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#### ESTER DI SILVESTRO

Political Discourse and Digital Communication: A Critical Discourse Analysis of far-right Populism in Italy and in The United States

## Tesi di dottorato

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## INTRODUCTION

Populism is certainly not a new political phenomenon since it was identified for the first time during the 19th century in Russia (Canovan, 1981: 61). However, it is also undeniable that currently we are witnessing a revival of this phenomenon and especially of (far-)right populism. This strong reappearance in the international panorama is due to an overall atmosphere characterised by uncertainties and instabilities from political, social and economic perspectives. The financial crisis of 2008 (Tormey, 2019) is surely one of the main triggers of this climate of general instability and uncertainty, since it led to economic austerity measures (Tormey, 2019: 53) that obviously caused dissatisfaction among citizens who already distrusted mainstream parties that are perceived as being part of the political elite (Mudde and Kaltwasser, 2017: 99). In addition, we should not underestimate the populist leaders' strategical employment of topics concerning minorities – who threaten social order, traditions, religion, and culture – in order to gain people's consensus. On the one hand, the immigration phenomenon is probably the most popular topic used by (far-)right populist politicians because it is very easy to trigger anxieties, uncertainties and fears after all the terrorist attacks that followed 9/11. On the other hand, feminists and the LGBTQ+ community represent for (far-)right populists a real threat because they fight for a new and inclusive vision of the world that strongly jeopardises the social order - supported by these politicians - that involves notions such as traditional family and fixed gender roles (Mudde, 2019: 140). As a result, the uncertain atmosphere characterised by real or just perceived - political, social and economic - threats has favoured the rise of peculiar politicians and outsiders (Tormey, 2019) such as Donald J. Trump, Matteo Salvini, Nigel Farage and Jair Bolsonaro.

The study of the populist phenomenon is particularly relevant in order to understand why some events – that were considered nearly impossible – actually happened, such as Brexit and the election of President Donald J. Trump, and to place the (populist) implications of current events in the right perspective; consider, for instance, the Women Strike in Poland, Viktor Orbán's fight against the LGTBTQ+ community and their rights, and migration crises (e.g. the one caused by Lukashenko). Although many populists may have temporarily lost some consensus during the COVID-19 pandemic (e.g. Bolsonaro handled terribly the pandemic in Brazil), this does not mean that the populist phenomenon is permanently over (Müller, 2021). Indeed, populism thrives in times of crises (Brubaker, 2021: 79); and nowadays we are witnessing many protests concerning COVID-19 restrictions (Brubaker, 2021) around the

world. Consequently, it is important to carry out new and updated research about populism. In this regard, the present work aims to be a contribution to the broader field of study of populism – trying to give an additional insight of U.S. and Italian far-right populist discourse – from a linguistic and critical perspective.

Specifically, this dissertation aims to analyse and to compare the far-right populist discourses of Donald J. Trump and Matteo Salvini through a combined approach between Critical Discourse Analysis and Corpus Linguistics. The idea of this work emerged after Donald J. Trump's victory at the 2016 U.S. presidential election and increased even more after the 2018 Italian general election that led to a coalition Government formed by *Lega* and *Movimento 5 Stelle*. These events intensified my growing interest to analyse far-right populist discourse since I wanted to understand why and how populist leaders manage to be successful, especially through the exploitation of social media.

I decided to use a combined methodological approach that allowed me to take advantage of the positive outcomes of both qualitative and quantitative analyses. Indeed, the main focus of this analysis is to identify common patterns in Trump's and Salvini's employment of particular (populist) linguistic/rhetorical strategies, their ideological implications, and their possible outcomes. More precisely, the present study takes into consideration Donald J. Trump's and Matteo Salvini's tweets and traditional speeches during the timespan covering the last three months of electoral campaign and the first seven months in office (including the transition periods) in order to compare their populist discourses – highlighting the presence of similarities and differences –, and to investigate the evolution of populist discourse, which has to adapt to social media's peculiarities and constrains.

Chapter 1 provides a theoretical introduction to the populist phenomenon. Specifically, it focuses on the presentation of the main features that define populism – such as the people, the elite, the general will and the presence of a charismatic leader –, and the causes of the current revival of populism in the world, especially in Europe and in the United States. Moreover, the chapter examines the characteristics of (far-)right populism in depth, since it is the object of the present study. In addition to a summary of the approaches that have been used to study populism, the chapter introduces the current combination between social media and populist discourse – paying attention on how populist leaders strategically exploit these platforms at their own advantage – with a particular focus on the perfect synergy between Twitter and populist discourse. The last two sections of the chapter are dedicated to the contextualisation of the populist phenomenon in the United States and Italy through a synthetic overview of the rise and the evolution of this phenomenon.

An overview of the theoretical background concerning the methodology employed to carry out the analysis of this dissertation is presented in chapter 2, which introduces the macrocategories of Discourse Studies, Critical Discourse Analysis, with a specific focus on the Discourse-Historical Approach, Corpus Linguistics, and particularly Corpus-Assisted Discourse Studies, Systemic Functional Grammar, and Political Discourse Analysis.

Chapter 3 concerns data and the methodological approach used for this analysis. The first section provides a description of data selection and the building of corpora. The following sections are dedicated to the detailed aspects of the qualitative (metaphors, *topoi*, representational strategies and transitivity) and quantitative (keywords, concordances and collocates) analyses carried out with the support of the UAM Corpus Tool and Sketch Engine respectively. The last section introduces the research question of this linguistic analysis.

The results of the qualitative and quantitative analysis regarding Donald J. Trump are presented in chapter 4. The results are discussed and organised into six sections that correspond to the six macro-topics of the analysis (Donald Trump's in-group representations, the United States, the media, Europe, Mexico, immigrants, and refugees).

Chapter 5 presents the results of Matteo Salvini's qualitative and quantitative analysis. Similarly, the results are discussed and organised into five sections that correspond to the five macro-topics of the analysis (Matteo Salvini's in-group representations, Italy, the media, Europe, and immigrants and refugees).

Chapter 6 is dedicated to the comparative analysis of Donald J. Trump's and Matteo Salvini's populist discourses. The first part of the chapter provides a discussion of the findings of the individual analyses presented in chapters 4 and 5, and a comparison of these findings highlighting Trump's and Salvini's similarities and differences in the employment of specific linguistic strategies from a populist perspective. The second part of the chapter presents some insights concerning the employment of populist strategies in tweets and traditional speeches.

Finally, Conclusion provides concise answers to the two main research questions that have been at the center of the linguistic analysis of this dissertation. In addition, this last section tries to give causes for reflection regarding the powerfulness of language as a mean of social action and its possible negative outcomes in combination with the populist style of communication.

# CHAPTER 1 POPULISM

Populism is a heterogeneous political phenomenon that is present in many countries of the world. The heterogeneity is an inherent characteristic of this phenomenon but, at the same time, it is the reason why populism is a concept so difficult to define. Taggart (2000: 1) defines populism as a *difficult* and *slippery* concept; indeed, during the years the word *populism* has been used to describe different political movements, parties and leaders around the world such as left-wing presidents in Latin America, right-wing challenger parties in Europe, and both left-wing and right-wing presidential candidates in the United States (Mudde and Kaltwasser, 2017: 1). As a result, context becomes a crucial factor to understand and define this phenomenon (Mackert, 2018: 6). On the one hand, every populist movement differs in terms of context such as place, time (Taggart, 2000), causes, forms of mobilisation or even the presence of a charismatic leader. On the other hand, all populist movements have in common some basic characteristics that are the cornerstones of populism such as the opposition between the *people* and the *elite*.

During the years, many researchers have tried to define what populism is and what the term *populism* actually means (Ionescu and Gellner, 1969: 1). Moreover, as Mudde and Kaltwasser (2017: 2) highlight, the debate around populism is not limited to the definition of the phenomenon but it even questions the existence of populism itself. Consequently, they define populism as an *essentially contested concept* (Mudde and Kaltwasser 2017: 2; Panizza, 2005: 1). It is also important to specify that Mudde and Kaltwasser consider populism as an ideology, but populism has been considered as a discursive style, a political strategy and a global phenomenon as well (Hidalgo-Tenorio, Benítez-Castro and De Cesare, 2019: 2–5).

Even though a generalised and univocal definition of populism would be useful in order to understand better the phenomenon, the research for a perfect definition is an illusion (Taggart, 2000: 2) precisely because of the heterogenous nature of populism. Furthermore, Canovan (1981: 7) claims that the research for a precise definition of populism compromises its credibility since this research just leads to a series of "conflicting statements about what populism "basically" is". Canovan (1981: 13) highlights also how one definition of the term populism could not explain all the populist cases. For this reason, she provides a classification

of seven different types of populism that have their own peculiarities. This classification can be useful to have an overview of the main populist cases:

#### Agrarian populisms

- 1. Farmer's radicalism (e.g. The People's Party in the U.S.)
- 2. Peasant movements (e.g. The Eastern European Green Rising)
- 3. Intellectual agrarian socialism (e.g. the Russian Narodniki)

#### **Political Populisms**

- 4. Populist dictatorship (e.g. Peronism)
- 5. Populist democracy (call for direct democracy)
- 6. Reactionary populism (e.g. George Wallace)
- 7. Politicians' populism (appeal to the people)

Following the classification above, Canovan (1981: 13) makes a distinction between "agrarian" and "political" populisms. This distinction and the sub-classification in seven categories are particularly helpful in understanding the different forms of populist phenomena. The seventh type of populism – 'the politicians' populism' – is particularly interesting since it is in line with an approach that considers populism as a communicative political strategy (Moffitt and Tormey, 2013; Mudde and Kaltwasser, 2017: 4) that can be used by politicians who are not necessarily populist but take advantage of the populist style of communication. Canovan (1981: 15) suggests that this type of populism is a political technique that is characterised by the appeal to the people. It is important to highlight that this approach and this way of seeing the populist phenomenon could be risky because populism could be reduced to a mere political rhetoric. Other researchers such as Moffitt and Tormey (2013), have defined populism as a political style. They claim that nowadays politics is extremely characterised by performativity (Moffitt and Tormey, 2013: 388). Indeed, they define populism as "a style that is performed and enacted" (Moffitt and Tormey, 2013: 388) and that is based on the appeal to the people, the presence of instabilities (such as crises), and on politicians' employment of unprofessional language style (Moffitt and Tormey, 2013: 391–392).

Laclau (2005) – who was a post-Marxist philosopher – criticises Canovan's approach. Firstly, he criticises the distinction between the agrarian and political populisms and the assumption that agrarian populism is not political (Laclau, 2005: 6). Secondly, Laclau points out that Canovan seems to have collected randomly these movements through their features making a classification that is based upon their differences (Laclau, 2005: 6). The philosopher has a completely different approach: "[...] the question 'what is populism?' should be replaced by a different one [...]: 'of what social reality or situation is populism the expression?'" (Laclau, 2005: 16–17). In this way Laclau shifts the attention from the populist form (that at this point does not need any explanation) to the social contents expressed by populism (Laclau, 2005: 17).

The philosopher claims that populism has not a referential unity since it cannot be limited to just one phenomenon. Instead, populism relies on a social logic and its effects are attributable to a variety of phenomena. For this reason, Laclau defines populism as a socio-political logic and more precisely as *a way of constructing the political*. Furthermore, the philosopher has inspired many researchers who describe the phenomenon as a discursive style (Hidalgo-Tenorio, Benítez-Castro and De Cesare, 2019: 2–3; Moffitt and Tormey, 2013: 385).

According to Mudde and Kaltwasser (2017) – who follow the ideational approach – populism is:

a thin-centered ideology that considers society to be ultimately separated into two homogeneous and antagonistic camps, "the pure people" versus "the corrupt elite," and which argues that politics should be an expression of the volonté Générale (general will) of the people. (Mudde and Kaltwasser, 2017: 6)

The definition of populism as a thin-centered ideology is helpful to understand the heterogenous nature of the phenomenon. Indeed, a thin-centered ideology must be necessarily attached to another host ideology (e.g. nationalism, nativism, socialism etc.) (Hawkins and Kaltwasser, 2017: 2; Mudde and Kaltwasser, 2017: 6). Mudde and Kaltwasser (2017: 6) suggest that this is one of the reasons why populism has been considered as a transitory phenomenon, when it is simply shaped differently by other ideologies. As a result, this process of attachment (or even assimilation) can lead to the creation of populist sub-types (Mudde and Kaltwasser, 2017: 7).

Therefore, the literature about populism is quite heterogeneous. Even though this heterogeneity may be confusing, it has not necessarily a negative impact because it provides a variety of ideas and approaches (see section 1.3) that enrich the field of study. Moreover, it contributes to make perceive populism as a fascinating phenomenon that still needs contributions in order to be comprehended better.

## 1.1 The cornerstones of populism

Although it is impossible to find a univocal definition of populism, it is possible – at least – the identification of some basic characteristics that define this concept. The necessity of this identification arises from the fact that almost every politician could be labelled as *populist* because of the excessive vagueness of the term *populism* (Mudde and Kaltwasser, 2017: 1). The distinction between populist and non-populist social actors is extremely blurred since nowadays the majority of politicians use strategically the appeal to the people (Panizza, 2005: 5). Mudde and Kaltwasser (2017) highlight the three fundamental concepts that defines what populism is: the *people*, the *elite* and the *general will*. The combination of these three concepts

creates the dichotomic opposition *people* vs. *elite* that is crucial to comprehend the populist phenomenon (Taggart, 2000: 11).

#### 1.1.1 The people

The people is the most important cornerstone of populism since it is the first fundamental concept that all the populist movements share. This concept is so important because of its flexibility (Taggart, 2000: 92) that populist politicians can use at their own advantage (Canovan, 1981: 261). Mudde and Kaltwasser (2017) consider the people as a flexible concept as well that can be combined with three different meanings:

- 1. The people as a sovereign
- 2. The common people
- 3. The people as a nation

The idea of the people as a sovereign is strictly connected to the principles of the American and the French Revolutions; indeed, according to this perspective the people is both the source of power and the ruler (Mudde and Kaltwasser, 2017: 10). The second meaning characterises positively the common people who do not have access to power because of their socioeconomic and socio-cultural statuses (Mudde and Kaltwasser, 2017: 10). As a result, the common people is one of the most visible expressions of the populist anti-establishment attitude since this idea aims to create a sense of unity among a silent and angry majority (Mudde and Kaltwasser, 2017: 10–11). At the same time, it is useful to create an opposition between the majority and the establishment (Mudde and Kaltwasser, 2017: 10–11). Thirdly, the idea of the people as a nation relies on a conception of the people in terms of ethnicity (Mudde and Kaltwasser, 2017: 11). This type of representation is linked to the idea of a 'monolithic' nation where only one ethnicity can live. For obvious reasons, this idea of nation is a myth since two or more ethnicities coexist very often in the same nation.

This idea of a monolithic nation is very similar to Taggart's (2000: 95) *heartland*. Specifically, Taggart defines the heartland as an idealised place where the people as a unified and homogeneous group live (Taggart, 2000: 2). Furthermore, according to Taggart the heartland also justifies the populist leader's construction and the invocation of the people (Taggart, 2000: 3) since this powerful and idealised concept is able to trigger rational and irrational emotions (Taggart, 2000: 95). People's unity is particularly strengthened through the feeling of fear – represented by economic, political or immigration crises that could jeopardise the community – triggered by the leader who promise to actively defend the heartland (Taggart, 2000: 4). Moreover, populist leaders see themselves and their heartland at the 'heart of things';

therefore, they generally reject cosmopolitanism and globalisation (Taggart, 2000: 96) – especially right-wing leaders (Mudde and Kaltwasser, 2017: 101) – and embrace isolationism. This populist perspective highly neglects everything outside the borders of the heartland and, at the same time, reinforces people's unity as being part of the heartland (Taggart, 2000: 96).

In addition to Mudde and Kaltwasser's (2017) threefold interpretation, Laclau (2005) defines the people as an empty signifier. In order to understand what an empty signifier is, it is necessary to highlight that Laclau points out that the unity of the people is the result of the articulation of different demands. The post-Marxist philosopher claims that the empty signifier is the demand capable of including different demands (Laclau, 2005: 130). More precisely, Laclau explains that every demand is different from the others but, at the same time, all the demands are equivalent because they oppose the same oppressive regime (the philosopher uses the example of Tsarism). Just one of these demands will come up – as an empty signifier – and it will represent all the others (Laclau, 2005: 131).

Finally, another characteristic of the people, that is important to highlight, is its relationship with the charismatic leader (see section 1.1.4). The leader is the personification of the people and the people's general will since (s)he was born among them (Merker, 2009: 6). For this reason, (s)he can represent the values of the 'pure' people (Merker, 2009: 7). Populist leaders are also actively involved in the construction of the people that is also achieved through the opposition and exclusion towards other groups. Specifically, populist leaders facilitate people's unity and the construction of a strong identity (Taggart, 2000: 94; Moffitt, 2016: 115) through the opposition between this group and the others. In populist narratives the other is very often the common enemy (Mudde and Kaltwasser, 2017: 18) that jeopardises people's well-being, stability, and safety. Indeed, the main enemy is indisputably the corrupt establishment better known as the elite (Mudde and Kaltwasser, 2017: 11) - that could be political, economic, cultural or even a media elite (Mudde and Kaltwasser, 2017: 11; Tormey, 2019: 29) - because they are the ones who oppose to people's general will (Mudde and Kaltwasser, 2017: 12). However, in the case of far-right populism, otherness can be also embodied by other social actors such as immigrants and the LGBTQ+ community (Mudde and Kaltwasser, 2017: 25; Moghissi, 2018: 87).

#### 1.1.2 The elite

The concept of the elite includes and unifies the cultural, the economic and the media elites (Mudde and Kaltwasser, 2017: 11). However, populist politicians often refer to the elite as an abstract concept. This attitude shows one of the common features of populism which is an

oversimplification of social structures (Tormey, 2019). The elite is depicted as the source of all evils (Albertazzi and McDonnell, 2008: 5) such as crises and corruption (Moffitt and Tormey, 2013: 391). Moreover, it is primarily defined in terms of morality but also in terms of power, economy, and nationality. This privileged group is formed by people who diminish and obstruct the 'general will' of the people. Indeed, the fundamental dichotomy between the corrupt elite and the pure people (Mudde and Kaltwasser, 2017: 12) is understood primarily in terms of morality, but it can also be interpreted in terms of ethnicity since the elite seems to favour the minorities' interests (e.g. immigrants and refugees) at the expenses of the people's interests. For this reason, the elite is also perceived as distant from the common people and becomes the enemy against whom the people has to fight in order to get back its power. Finally, it is important to specify that the elite can be both an insider, e.g. political establishment, or an outsider enemy, e.g. the European Union (Panizza, 2005: 17) that the populist leaders promise to fight and defeat in order to protect the heartland, the people and their general will.

#### 1.1.3 The general will

The general will is a concept connected to the philosopher Jean-Jacques Rousseau who defined people's ability of building a community as *volonté générale* (Gerbaudo, 2017: 74), self-regulating and defending their common interests. From this perspective, the dichotomy (pure) people vs. (corrupt) elite confirms the existence of a general will (Mudde and Kaltwasser, 2017: 16). Consequently, populists shares both Rousseau's critique to the representative government (because citizens are treated as passive entities) and his utopian idea of self-government (Mudde and Kaltwasser, 2017: 17) since they often support direct democracy. Furthermore, the general will is connected to 'common sense'. This connection allows the formation of a strong popular identity through the aggregation of different demands (Mudde and Kaltwasser, 2017: 18); even in this case the concept of empty signifier (Laclau, 2005) should be remembered because it is crucial in the creation of popular identity.

#### 1.1.4 The leader

In addition to the three core concepts mentioned above, the presence of a charismatic leader is another important feature that is common to almost every populist movement (Tormey, 2019: 35). Moffitt (2016) claims that the leader should be the first concept on which researchers should focus on during the study of populism since nowadays politics is characterised by media exposure. Consequently, populist leaders are the *performers* of populism (Moffitt, 2016: 54).

Firstly, the leader is the *vox populi* (de la Torre, 2019: 2; Mudde and Kaltwasser, 2017: 68) who has a direct and personal relationship with the people (Hennessy, 1969: 33; Weyland, 2017: 86) because (s)he represents and protects people's general will against the elite. More precisely, populist leaders depict themselves as part of the common people and, for this reason, often claim to be able to take "common sense solution" (Mudde and Kaltwasser, 2017: 64) that actually represent just a strategy to gain consensus. Populist leaders often provide "simple solutions to complex problems" (Mudde and Kaltwasser, 2017: 101) representing themselves as the only leaders – with strong leadership – who have and can provide the solution (Moffitt, 2016: 117–118). On the other hand, they achieve this type of representation describing other political actors as incompetent (Moffitt, 2016: 117–118).

Secondly, the populist leader is often depicted as an independent strongman (Mudde and Kaltwasser, 2017: 63). This type of representation is obviously strictly connected to gender stereotypes; indeed, the strongman leader is represented as a very masculine man who could be violent as well (Mudde and Kaltwasser, 2017: 63). The employment of gender stereotypes is not surprising since they are still present in our society and shape our perception of women and men. In this specific case, gender stereotypes are used to portray a leader who can be trusted in his capability of leading firmly the country. However, it is also important to mention the presence of female populist leaders such as Marine Le Pen in France (Turner, 2018: 6), Sarah Palin in the United States and Giorgia Meloni in Italy. Women use gender stereotypes at their own advantage as well in the building of their figure as leaders. They can portray themselves as good women (Mudde and Kaltwasser, 2017: 70) but also as mothers (Abi-Hassan, 2017: 553; de Beauvoir, 2011) and wives (that are the two most common social roles used in the description of women). Specifically, the role of the mother seems to be the most appropriate since it allows female leaders to represent themselves as protective mothers of their countries and their citizens (Mudde and Kaltwasser, 2017: 70). Thus, they create a strong bond with the people and highlight the connection between populism and nationalism (Mudde and Rovira Kaltwasser 2017: 70) depicting themselves as the mothers of the Nation (Geva, 2018: 7).

Mudde and Kaltwasser (2017) provide a useful and clear classification of the most common sub-types of populist leaders:

- 1. Entrepreneurs
- 2. Ethnic leaders
- 3. The insider-outsider

The first category is the one of the entrepreneurs. These types of leaders are people who belong to the economic elite, but at the same time claim to represent the common people (Mudde and

Kaltwasser, 2017: 70). For instance, Donald J. Trump and Silvio Berlusconi are probably the most famous entrepreneurs who have become populist leaders. The key point is understanding how these leaders successfully manage to represent themselves as the vox populi since their wealth and their lifestyle are very distant from the economic means and the lifestyle of common people. They are able to do this representing themselves as political outsiders because as Mudde and Kaltwasser (2017) suggest: "The populist distinction between the people and the elite is not fundamentally based on socioeconomic criteria – like class or wealth – but rather on morality" (Mudde and Kaltwasser, 2017: 71). Both Trump and Berlusconi represent themselves as successful businessmen despite an unfavourable and unjust taxation regime. On the one hand, during the presidential campaign of 2016, Donald J. Trump focused a lot on economic matters highlighting how he would be capable of leading the United States and resolve the economic problems since he is a successful businessman. He is also notoriously inclined for misogynistic opinions (Prasad, 2019; Oppenheim, 2020). Even though these opinions are controversial, they allow Trump to relate with all those men (and women) whose life is shaped by toxic masculinity attitudes. On the other hand, Silvio Berlusconi relates to common people through soccer because he was the president of AC Milan and through the exaltation of his virility (Mudde and Kaltwasser, 2017: 71). Although he faced judicial proceedings for the Bunga Bunga scandal, he used this scandal at its own advantage to emphasise his virility even more (Mudde and Kaltwasser, 2017: 64).

Ethnic leaders show how complex the relationship between populism and ethnicity can be. There is generally a special focus on how populist movements in combination with other ideologies – such as nativism – can lead to xenophobic tendencies towards minorities, especially in Europe (Mudde and Kaltwasser, 2017: 71). Nevertheless, in some contexts – such as Latin America – ethnicity can become a crucial characteristic in representing the pure people. For instance, Evo Morales represents what is commonly known as ethnopopulism (Madrid, 2019). He was the first Bolivian President with indigenous heritage; indeed, he used his ethnicity to represent himself as an outsider and as part of the common people (Mudde and Kaltwasser, 2017: 71).

The insider-outsider is the most successful category of populist leaders since it includes both leaders who are not part of the political elite but have political connections (e.g. Berlusconi), or leaders who enter politics because of family connections (e.g. Marine Le Pen) (Mudde and Kaltwasser, 2017: 74). However, the status of the insider-outsider becomes more complex and challenging when these leaders are elected and stay in government (Mudde and Kaltwasser, 2017: 76) because at that point they become inevitably part of the political elite.

We should also highlight the existence of real outsiders – such as Chávez or Fujimori – who are a rare a category (Mudde and Kaltwasser, 2017: 75), and the presence of insider populist leaders – politicians who have been politically active for many years and are clearly part of the political elite – who claim to have nothing in common with the political establishment (Mudde and Kaltwasser, 2017: 71). They strategically represent themselves as outsiders who are different from other politicians characterised by corruption and incompetence (Mudde and Kaltwasser, 2017: 71).

#### 1.2 The causes of populism

The populist phenomenon was born in Russia during the 19<sup>th</sup> and the 20<sup>th</sup> centuries; as a result, the term *populism* comes from the Russian term *narodničestvo* (народничество) (Canovan, 1981: 61). Russian populism was theorised by Russian intellectuals who highlighted the positive characteristics of Russian peasantry. Indeed, Russian populism was deeply influenced by agrarian socialism (Canovan, 1981: 96). The movement aimed to cause a peasantry revolution against the Tsarist regime in order to establish a rural socialism (Taggart, 2000: 96). The movement failed to reach its aim, but the revolutionary ideas inspired the Russian Revolution in 1917 (Taggart, 2000: 96). In the 19<sup>th</sup> century – approximately at the same time when Russian populism was born – populism was present in the United States as well through the establishment of the Farmers Alliance and The People's Party (Canovan, 1981). In the following years, populism has spread around the world adapting to different contexts. For instance, in Latin America populism has been widely present since the early 1920s (Mudde and Kaltwasser, 2017: 28) till today. On the other hand, populism has not been really relevant in Europe until the late 1990s because of several reasons such as the first tensions due to the immigration phenomenon (Mudde and Kaltwasser, 2017: 34).

The presence of different forms of populism all over the world leads to a reflection upon the rise of this phenomenon. The appeal of populist politicians is comprehensible since many people around the globe share populist ideas such as the anti-establishment attitude. More precisely, these people believe to be unheard by the corrupt and dishonest elite (Mudde and Kaltwasser, 2017: 99). Consequently, the first cause of populism is the presence of the fracture and the opposition between the elite and the people. This is the reason why the dichotomic opposition is considered to be the essence of populism. Secondly, populism manifests itself when there are specific demands connected to certain socio-economic and socio-political circumstances (Mudde and Kaltwasser, 2017: 100). The economic conditions generally include

economic instability. Indeed, one of the reasons why populism has risen again in the last years is due to the financial crisis of 2008 and its effects around the world that led to austerity measures (Tormey, 2019: 53). These measures clearly created dissatisfaction among citizens – who started to blame governments – and favoured the rise of political outsiders such as Donald J. Trump who promised an economic revival (Tormey, 2019: 53–58).

Pasquino (2008) examined more in depth the social and the political conditions that favours the rise of populism. He claims that there are two main social conditions involved in the process. The first one regards individuals and their psycho-sociological characteristics. He highlights that people – who are involved in populist mobilisations or are attracted by a charismatic populist leader – share common features such as political isolation and a restricted number of human connections (especially outside the family and the workplace) (Pasquino, 2008: 23). The second one involves the society and its specific circumstances. He points out that a society creates a fertile soil for the rise of populism when there is an overall emotional discomfort. In the worst cases this discomfort can lead to an authoritarian type of populism since people feel reassured by the populist leader (Pasquino, 2008: 24-25). Regarding the political circumstances, he shares three conditions identified by Mény and Surel that are: the crisis of political intermediation and its structures, the personalisation of political power and the new role that media play in the political sphere (Surel, 2002: 141). However, Pasquino (2008: 27) suggests that these three conditions are common to almost every contemporary society. For this reason, he proposes to investigate the degrees of these conditions (in order to identify the causes of populism) such as how deep the crisis of intermediation is, how important the personalisation is, and how much pervasive media are (Pasquino, 2008: 27).

In addition to the socio-economic and the socio-political circumstances, the phenomenon of immigration and the presence of radical Islamic terrorist attacks favour the success of (far-)right populism. Indeed, this type of populism presents a polarised vision of the world (Wodak, 2015; 2018; Tormey, 2019: 64) where integration will never be possible. In this regard, we should mention that populism can be left-wing or right-wing (Gandesha, 2018). In the first stages populist movements usually present themselves as new political forces and the majority of them claim that they are neither right-wing nor left-wing since they just want to represent people's interests against the establishment (Albertazzi and McDonnell, 2008: 4), but in the end – after the evolution that transforms the movement in a structured party – almost every populist movement take a political orientation. It is also important to specify that some populist movements can integrate both right-wing and left-wing positions such as Peronism (Mackert, 2018: 6) and the *Movimento 5 Stelle* (5 Star Movement).

Nowadays populism is described and perceived mainly as a negative phenomenon; for instance, politicians often use *populist* as a derogatory term (Gerbaudo, 2017: 71; Mudde and Kaltwasser, 2017: 2; Rivero, 2019) to indicate and accuse their (political) opponents. This negative representation is due to the fact that in some circumstances this phenomenon could destabilise and threaten the democratic regime (Moffitt, 2016: 123) leading it to an authoritarian shift (Eatwell and Goodwin, 2018; Mudde and Kaltwasser, 2017: 87; Weyland, 2019). Nonetheless, populism can be seen from a different and even positive perspective as well. According to Laclau (2005) populism can be perceived as a process of democratisation since all the demands are represented by one (see section 1.1.1). This point of view focuses also on the increased and active citizens' interest and participation through mobilisation, and the call for direct democracy (Mudde and Kaltwasser, 2017: 79–87). As a result, it is undeniable that this is a positive effect of populism because it favours and increases citizens' involvement and interest in the political sphere.

#### 1.2.1 (Far-)right populism

Far-right populism is strictly connected to right-wing populism since they share common perspectives; however, these perspectives are extremely radical in the case of far-right populism. Far-right populism has to be considered as a heterogeneous phenomenon as well because it is influenced by national, political, economic and cultural contexts (Rucht, 2018: 74). Moreover, (far-)right populism is often combined with the ideologies of nativism, authoritarianism, and nationalism (Mudde and Kaltwasser, 2017: 21/72).

Although far-right populism is present in many parts of the world (such as the United States), it is particularly pervasive in the European continent (Zúquete, 2019: 425). Specifically, radical right populism appeared at the end of the 19<sup>th</sup> century (Loch, 2018: 87), it strongly reappeared at the end of the 20<sup>th</sup> century – especially during the 1990s (Betz, 1994: 3) – and at the beginning of the 21<sup>st</sup> century for several reasons such as the financial crises of 2008 and the migration crises (Vieten, 2018: 102). In this regard, it is important to briefly emphasise the social, economic and historical context that allowed the rise of (far-)right populism in Europe. After Second World War, Europe went through a period of political stability and economic prosperity (Betz, 1994: 1). However, Europe – starting from the 1960s – saw the emergence of new ideological, political, economic and social changes (such as the protests of 1968 and the fall of the Soviet Union) that eventually led to an ideological fracture and distrust towards the institutions (Betz, 1994: 1–2/37). The fertile soil for the appearance and the growth of far-right populism coincides with Eatwell and Goodwin's (2018) *Four Ds* of national populism:

- 1. Distrust (of politicians and institutions)
- 2. Destruction (of national identity threatened by immigrants)
- 3. Deprivation (due to wealth inequalities)
- 4. De-alignment (of people from traditional mainstream parties)

More precisely, Eatwell and Goodwin's (2018) *Four Ds* perfectly summarise the main reasons why far-right populism emerges such as the crisis of political representation, and social and economic instabilities. Furthermore, it is possible to highlight some basic features that far-right populist parties share. Generally, they aim to limit the power of the central state and support the free market, they firmly oppose to international and technocratic elite, e.g. the European Union (Fitzi, 2018: 5). They are also against (economic) globalisation (Rucht, 2018: 74) and have an anti-democratic attitude (Lochocki, 2018: 7). Far-right movements show hostility towards minorities' integration. Indeed, they are well-known for their xenophobic (Ruzza, 2019: 201) attitude (Betz, 1994: 4) and their opposition to women (e.g. abortion) and LGBTQ+ rights (Moghissi, 2018: 78/87). It could be said that (far-)right wing populists aim to re-establish an old (social and economic) order – always connotated as a positive period – against the new and negative order (Rucht, 2018: 68–69).

Far-right supporters are particularly attracted by these parties because their rhetoric aims to trigger the feelings of resentment (Betz, 2002: 198), anger (Moghissi, 2018: 78), and fear (Wodak, 2015) — among other general anxieties — that are crucial features of populist mobilisation (Betz, 2002: 202). The votes of the far-right electorate are defined as *floating votes* since these people claim to support and vote for these parties in order to protest and express their dissatisfaction (Betz, 1994: 59–60). Consequently, far-right populist parties manage to be successful because they are able to re-establish a sense of community — against the threats posed by immigration and by national and international elites — (Ruzza, 2019: 213), and to present themselves as the only ones capable to listen to people's needs and amplify their dissatisfaction in the political arena (Betz, 2002: 199).

The immigration phenomenon is surely one of the most important factors that contributes to the success of far-right populism. Many people decide to support these parties mainly because they openly oppose to immigration (Betz, 2002: 206). There are several reasons why people are attracted by anti-immigration appeal such as the belief that unemployment is associated with an increase of foreign immigration (Betz, 1994: 85), or the belief that immigrants represent a national threat to culture, religion and traditions (Lochocki, 2018: 9). We should also mention that the phenomenon of immigration and the elite are strictly connected since far-right populist politicians represent the elite as the one who favours and allows to immigration to be a dangerous national threat (Lochocki, 2018: 9). From this perspective, far-

right populism has a twofold exclusionary attitude. On the one hand, it separates the common people from the corrupt elite who favours immigrants and international financial interests (Wodak, 2018: 12). On the other hand, it opposes the people to the others (immigrants and refugees) since they have a highly exclusionary rhetoric and present a dichotomic vision – us vs. them – of society (Wodak, 2015: 91; 2018: 13). The people are represented as the real victims of an unjust system perpetrated by the elite (Wodak, 2015: 16). As a result, populist far-right politicians can represent themselves as the saviours (Wodak, 2015: 44; 2018: 12) who will protect the heartland (Taggart, 2000) and the citizens from any (foreign or domestic) threat, but especially from national, cultural and religious threats posed by immigrants (Loch, 2018: 92; Roberts, 2019: 152). Indeed, far-right populist ideology and rhetoric can be described synthetically through Ruth Wodak's (2015) words: *the politics of fear*.

## 1.3 Approaches to populism

The heterogeneity of the field of study of populism has caused the development of a very rich and extended variety of approaches that try to analyse almost every aspect of this phenomenon. An overview of the main approaches could be helpful in order to comprehend better the most important characteristics of populism. In this regard, Mudde and Kaltwasser (2017) provide a clear presentation of the main approaches to populism:

- 1. The ideational approach
- 2. The popular agency approach
- 3. The Laclauan approach
- 4. The socioeconomic approach
- 5. Populism as a political strategy
- 6. Populism as a style of politics

As mentioned in the first section of this chapter, the ideational approach – that is currently the dominant one (Moffitt and Tormey, 2013: 383) – describes populism as an ideology. Specifically, Mudde and Kaltwasser (2017) define populism as a thin-centered ideology that exists in combination or assimilation with other ideologies. The process of combination (or assimilation) perfectly explains the heterogeneous nature that characterises populism and the existence of various populist sub-categories. This approach is also strictly connected to the Laclauan approach; more precisely, the ideational approach shares Laclau's (2005) political theory on populism. Both approaches focuses on the importance of a popular identity (in contraposition with the elite) and define populism as a specific set of ideas (Hawkins and

Kaltwasser, 2017: 4). However, the ideational approach tries to go beyond and give other important contributions to the field of study (Hawkins and Kaltwasser, 2017: 2).

The popular agency approach presents populism as part of the democratic regime. Specifically, populism is seen as a positive force because it is capable of mobilising the people who feel more engaged in the political field (Mudde and Kaltwasser, 2017: 3). As a result, this approach focuses on one of the positive characteristics attributed to populism that is the involvement, the interest and the active participation of citizens in political processes. This approach was particularly present in North America during the 19<sup>th</sup> century (Mudde and Kaltwasser, 2017: 3).

The Laclauan approach concerns Ernesto Laclau (1977; 2005) and Chantal Mouffe's (2005) work. It is a political and post-Marxist approach that presents populism as the essence of politics, but at the same time as an emancipatory force that can lead to the achievement of radical democracy through the mobilisation of the people (especially the ones from the excluded social classes). Indeed, according to Laclau (2005) radical democracy represents the solutions to the problems created by liberal democracy (Mudde and Kaltwasser, 2017: 3).

The socioeconomic approach has been influential especially in the 1980s and the 1990s concerning populist studies in Latin America (Mudde and Kaltwasser, 2017: 3). This approach focuses on specific economic policies (Hawkins and Kaltwasser, 2017: 3) and it was linked to Latin America since Southern American populist leaders often favoured massive spending and hyperinflation (Mudde and Kaltwasser, 2017: 3).

Populism has been considered as a political strategy that is used by charismatic leaders who try to take power and rule through a direct connection with the people (Mudde and Kaltwasser, 2017: 4). This approach is common in Latin American studies (Moffitt and Tormey, 2013: 386) and it is also strictly connected to the pervasiveness of gender stereotypes – because it highlights the necessity of a strong, authoritative and reliable man who can lead the country – and to the massive use of social media (see section 1.4) that the populist leaders use in order to create an unmediated relationship with their followers.

The last approach to populism – according to Mudde and Kaltwasser (2017) – is the one that presents populism as a style of politics used by both leaders and parties in order to facilitate the mobilisation of the people (Mudde and Kaltwasser, 2017: 4) and their support. This approach focuses on the political behaviours of populist leaders who are intentionally unprofessional to gain popular support since they depict themselves as political outsiders and as the *vox populi* (de la Torre, 2019; Mudde and Kaltwasser, 2017: 4). Indeed, this approach

studies the *performances* – of populist leaders – that shape and influence political relations (Moffitt and Tormey, 2013: 387–388).

Obviously, these approaches are not separate from each other since they simply study populism from different perspectives giving useful contributions to the field of study. For this reason, the linguistic analysis carried out in this dissertation takes into consideration every approach.

#### 1.4 Populism and social media

Nowadays social media are part of the political sphere, and can influence the way political organisations and institutions work because political matters are represented and discussed in these platforms (Bouvier and Machin, 2018: 179). The powerfulness of social media relies on their extreme pervasiveness in our everyday life (van Dijk, 2005: 1) that is a key strategy for politicians to reinforce and increase their electorate (Pajnik and Sauer, 2018: 1). At the same time, the electorate is able to know more about the candidates' personality in order to estimate their reliability (Enli, 2017a: 59). For this reason, it is important to focus on how social media work and on how politicians – especially populist leaders – employ these platforms at their own advantage.

The birth – and the evolution – of social media is strictly connected to the evolution of the world wide web; indeed, social media were born in the early 2000s during the phase of the web 2.0 with the emergence of a specific type of social media: social networks (Golbeck, 2015: 7). In this regard, it important to specify that there are different types of social media. Golbeck (2015: 11–12) provides a useful classification of social media based on their features:

- 1. Social Networks (e.g. Facebook, Instagram and Twitter)
- 2. Photo and Video Sharing (e.g. Flickr, Instagram and YouTube)
- 3. Microblogging (e.g. Twitter and Tumblr)
- 4. Social Bookmarking (e.g. Pinterest)
- 5. Social Gaming (game consoles such as PlayStation and Xbox have social features that allow players to create friend lists and play with them online)
- 6. Apps (small applications/programs often integrated to other social media sites)

The classification does not provide a strict distinction between social media since the same social media can be part of two or even more categories (e.g. Facebook, Instagram and Twitter). This interdependence (van Dijck, 2013: 41) between platforms – that can be considered as an actual overlapping – is due primarily to the inner characteristics of the web such intertextuality, but most importantly to the fact that social networks are always expanding, and they incorporate

successful features of other social media (e.g. Facebook incorporated several features from WhatsApp, Instagram etc.).

The crucial role that social media play in the political arena is due to several reasons such as their free and cheap accessibility (Flew and Iosifidis, 2019: 9) in almost every part of the world. They also give people – who do not even know each other in real life – the possibility to create bonds (Murthy, 2013: 3). Furthermore, they can reach and engage with a large number of people, and especially the possibility for people to participate actively to some political processes (Ross and Rivers: 2017: 285). All these characteristics highlight social media as a part or even a new extension of the public sphere (Fuchs, 2014: 199).

The communication that takes place on social media is dynamic and follows the manyto-many model (Flew and Iosifidis, 2019: 9). This model challenges the power of traditional media for several reasons. Firstly, there is not a clear and strict distinction between producers and consumers (KhosraviNik, 2017: 582). Secondly, social media have created new - and interactive – spaces where citizens feel highly involved (KhosraviNik, 2017: 583). This particular characteristic of social media has caused utopian ideas regarding the political communication that takes place online. For instance, the idea that social media would have replaced traditional media and their old way to communicate with a new and participatory (Seargeant and Tagg, 2014: 2) form of communication capable to decentralise and democratise the access to discursive power (KhosraviNik, 2017: 582-583). Although these ideas remain a utopia, it important to recognise the role that social media have – and will continue to have in the future – in political communication because their employment has become increasingly central in political processes such as political campaigns or even the organisation of protests (e.g. the Arab Spring) and rebellions (Flew and Iosifidis, 2019: 10). Since Barack Obama started to use strategically social media (such as Facebook, Twitter and YouTube) during his first presidential campaign in 2008, social media have become an essential part of almost every political process. During the U.S. presidential campaign of 2016, the strategical employment of these platforms has continued to evolve. More precisely, social media (especially Twitter) have been used by both candidates (Clinton and Trump) as a direct source of news and as a mean to create a direct relationship with their (potential) voters (Enli, 2017a: 51/59; Krämer, 2014: 49).

In this regard, we should mention that all politicians take advantage of the strategical employment of social media. However, populist politicians seem to have a peculiar relationship with these platforms (Gerbaudo, 2018: 746; Postill, 2018: 761).

Firstly, populists employ social media as a direct source of news in order to perpetuate their discursive strategies based upon the dichotomic opposition people vs. elite. They usually communicate with a simple and clear style to disseminate their populist ideologies (Engesser *et al.*, 2017: 1123; Kreis, 2017). The use of social media as a direct source of news is also crucial in spreading fake news (Bergmann, 2020: 262; Hellinger, 2019: 81) – or even conspiracy theories (Bergmann, 2020: 254–255; Hellinger, 2019: 21–26) – that support populist politicians' points of view. These politicians – who should be trustable institutional figures – can help the spreading of fake news (Flew and Iosifidis, 2019: 13–14) for their own political game leading to a "post-truth politics" (Bergmann, 2018: 156; 2020: 252; Waisbord, 2018). This is clearly a dangerous path because this strategy leads to a high level of misinformation and to a manipulation of reality that cause confusion and division in an era where the polarisation (Enli, 2017b: 3) of political points of view is extremely pervasive.

Secondly, populist leaders are able to negotiate their own image (Enli, 2017a: 59) as they please through social media. They can easily present themselves as the perfect *vox populi* who can be trusted and they can even attract new and potential voters. Indeed, social media have been portrayed as the platforms where the people's voice can be heard against the elitist traditional media (Gerbaudo, 2018: 748–749). However, even if social media are easily accessible, they are not democratised platforms without commercial interests (Gerbaudo, 2018: 748–749).

Finally, one of the most important advantages of social media employment is the creation of a unique, personal, and direct bond between the populist leaders and their electorate (Ernst et al., 2017; Engesser et al., 2017: 1113; Flew and Iosifidis, 2019: 10). The establishment of this type of bond is based on the dichotomic opposition people vs. elite. On the one hand, the close relationship between the populist leader and the followers/supporters is strictly connected to the representation of the leader as the vox populi (de la Torre, 2019). The populist leader is the only and true representative of people's general will (Ernst et al., 2017); for this reason (s)he is a trustable politician who understand the needs of the common people and will defend their common interests. On the other hand, anti-elitism (Ernst et al., 2017) helps populist leaders to reinforce their followers' trust since the leader is the one who represent the people and will fight for them against the elite. Indeed, populist politicians try to challenge the political hegemonic system (Freedman, 2018: 5) through social media employing them in opposition to traditional ones that are portrayed as being part of the elite's corrupt and dishonest system (Krämer, 2018: 10).

#### 1.4.1 Populist Discourse on Twitter

Both populist and non-populist politicians can use social media in a clever way at their own advantage (Enli, 2017b; Gerbaudo, 2018: 746; Postill, 2018). However, populist politicians can exploit more easily the potential of social media because populist discourse is based intrinsically on the creation of a familiar bond with the people (Ernst *et al.*, 2017; Hixson, 2018: 49). Moreover, the perfect synergy between social media such as Twitter and populist discourse should be highlighted (Ott, 2017). The existence of this perfect synergy is due to the peculiarities and constrains of Twitter that are well-suited for the simple and aggressive populist language style of communication. It is also important to specify that Twitter can be defined as both a *tool of opposition* – against the elite – (Van Kessel and Castelein, 2016) and an *echo chamber* where political discourse can be easily polarised (Barberá *et al.*, 2015) favouring populist narratives that are often based on dichotomic oppositions. For instance, right-wing populists usually go beyond the traditional opposition of the people vs. the elite, and they extend the polarised opposition us vs. them to a collective other that involves media, migrants, LGBTQ+ people and feminists (Pajnik and Sauer, 2018: 2).

Nowadays politicians are expected to balance between the formal, institutional, and professional sphere, and the informal, unprofessional, personalised and familiar one (Enli, 2017a: 52). Twitter is particularly privileged by populist leaders because it is part of our everyday life (Zappavigna, 2012: 37), and it can be used for both institutional and amateur purposes.

On the one hand, Twitter is suitable for a breaking news format (Murthy, 2013: 51–52) that can be part of institutional communication. For instance, during the U.S. electoral campaign of 2016 Trump used Twitter as direct source of news (Enli, 2017a: 50–51) to communicate with his followers directly, bypassing traditional media (Van Kessel and Castelein, 2016; Enli, 2017a: 50) since in his view they are part of the elite corrupt system. In this regard, we should highlight that the employment of Twitter – as other social media – is favoured because it allows politicians to have complete control over the conveyed messages (Enli, 2017a: 53) and to challenge the establishment since it can be used as a tool of opposition (Van Kessel and Castelein, 2016).

On the other hand, Twitter provides a channel to establish a personal, direct, and strong bond with the electorate (Ernst *et al.*, 2017; Engesser *et al.*, 2017: 1113; Flew and Iosifidis, 2019: 10) through the sharing of familiar contents as any other person who belongs to the category of the people. Indeed, populist leaders employ Twitter to negotiate and convey strategically their self-representation (Enli, 2017a: 59) often associated with the cult of personality that characterises these charismatics leaders (Reyes, 2020). Specifically,

authenticity is the crucial aspect that populist leaders employ in their performances on Twitter (Kissas, 2019) in order to make their followers relate better and identify with them. For example, Donald J. Trump and Matteo Salvini use this strategy through the sharing of tweets (often with pictures attached) that involve their family role as fathers (in the case of Trump even as grandfather), food (e.g. Salvini usually use this strategy to promote Made in Italy food) and religion. We should emphasise that precisely through these contents, populist leaders are able to easily disseminate specific ideologies and beliefs such as their support for the 'traditional family', but also their nationalistic and protectionist political and economic views.

According to Ott (2017) Twitter can be defined – from a communicative perspective – through three main characteristics that are simplicity, impulsivity, and incivility (Ott, 2017: 60). These defining features prove to be particularly well-suited for populist discourse.

Firstly, Twitter is a microblogging platform (Golbeck, 2015) where users cannot post tweets that go beyond 280 characters. From a structural point of view, Ott (2017: 61) argues that Twitter cannot handle complex messages. For this reason, complex messages are tweeted with attachments such as videos, articles and reports (Ott, 2017: 61). However, the constraint of characters does not represent an actual limitation for populist discourse and its spread, since populist politicians always use straightforward language (Kreis, 2017) often trying to provide simple (and unreal) solutions to complex phenomena (Mudde and Kaltwasser, 2017: 118).

Secondly, the simplification of messages affects the possibility to reason and think about topics in a complex way favouring – at the same time – impulsive and uncivil discourse (Ott, 2017: 61; Jaidka, Zhou and Lelkes, 2019; Zompetti, 2019). Indeed, populist politicians usually employ an aggressive, strong, repetitive, sensationalist and provocative style of communication (Engesser *et al.*, 2017: 1123; Krämer, 2018: 10; Wang and Liu, 2017). Moreover, they are well-known for their discursive strategies that aim to trigger people's emotions (Wahl-Jorgensen, 2018), especially negative ones in order to gain consensus (Flew and Iosifidis, 2019: 11). For instance, Wignell *et al.* (2020) highlight – through a comparative study about tweets delivered by Trump and Obama that involves emotion and sentiment analysis – that Donald Trump is able to trigger and convey several negative emotions such as sadness and fear. In this regard, it is important to mention that according to Wahl-Jorgensen (2018) anger is an ideological resource and a defining characteristic of Trump's populism since this emotion is particularly effective in the generation of (emotional) bonds and to encourage collective mobilisation (Wahl-Jorgensen, 2018: 768–769). Lastly, Evolvi (2019) underlines – in her textual analysis and critical discourse analysis of Islamophobic tweets – how Salvini triggers and exploits

negative emotions (such as anger, fear and hate) in order to support both his far-right ideology and his strict immigration policies (e.g. through the hashtag #chiudiamoiporti).

### 1.5 Populism in the United States

The politics of the United States has always been strictly connected to populism. Taggart (2000) claims: "It is hard to understand politics in the United States without having some sense of populism. It is impossible to understand populism without having a sense of the populism in the USA" (Taggart, 2000: 1). According to Taggart (2000) this deep connection is due to the fact that populism emerges as a reaction to representative democracy; indeed, the nature of the U.S. political system and the U.S. national identity rely on the principles of representative democracy (Taggart, 2000: 1). In the United States populism has always been characterised by spontaneous – often weak and unorganised – mobilisation since the last decade of the 19<sup>th</sup> century (Mudde and Kaltwasser, 2017: 2).

#### 1.5.1 The Farmers' Alliance and The People's Party

During the last part of the 19<sup>th</sup> century the United States – after the Civil war – dealt with social and economic changes such infrastructural developments (e.g. the railway system extension) that led to a general discontent of the farmers (Canovan, 1981: 20). The farmers' discontent was also caused by the consequences of the Civil war and of an international price depression (Hofstadter, 1969: 15). The war left a deep fracture between the urban States of the North and the rural ones in the South (Taggart, 2000: 29). As a result, this situation led to the emergence of what is called *prairie* populism (Mudde and Kaltwasser, 2017: 23) an agrarian radical movement. We should underline that populism in the United Sates was different from other populist movements because it did not rely on a class of rural and poor peasantry, but rather on commercial farmers (Hofstadter, 1969: 9). This type of populism lacked the figure of a charismatic leader since it was basically a mass mobilisation that came from the bottom (Taggart, 2000: 26).

According to historians (Canovan, 1981: 25) in the United States populism was born with the institution of the Farmers' Alliance in Texas and then spread in the rest of the country, especially in Western and Southern States (Canovan, 1981: 25–26; Taggart, 2000: 31–32). The Alliance evolved and entered in politics with the establishment of The People's Party in 1892 (Canovan, 1981: 36; Taggart, 2000: 33–34) in occasion of the Presidential election of that year. Indeed, a national convention was organised in Omaha in order to elect the People's Party

presidential candidate (Taggart, 2000: 27). The party claimed to fight for the interests of the people (the farmers) against the elite (e.g. banks) who was to blame for the precarious conditions of the farmers (Hofstadter, 1969: 17-18; Green and White, 2019: 112). Moreover, the party aimed to challenge the two U.S. main parties; but the challenge was completely unsuccessful (Taggart, 2000: 27). It is important to emphasise that the People's Party was supported by people who had different – and often incompatible – positions (Canovan, 1981: 38). The party did not have a charismatic leader capable to unite all the supporters overcoming regional differences (Mudde and Kaltwasser, 2017: 23). During the presidential election of 1896, the People's Party supported the Democratic candidate William Jennings Bryan who lost the elections (Canovan, 1981: 44; Mudde and Kaltwasser, 2017: 23). Eventually, this is one of the reasons why the party dissolved (Canovan, 1981: 44; Taggart, 2000: 35; Mudde and Kaltwasser, 2017: 46) in 1909. The first U.S. populist movement dissolved quickly (Hofstadter, 1969: 24; Canovan, 1981: 17); but the populist phenomenon did not disappear with the dissolution of the Peoples' Party (Taggart, 2000: 35). Instead, the main U.S. parties absorbed some populist features (Green and White, 2019: 112). According to Kazin (2017: 4), during the first part of the 20<sup>th</sup> century, populism continued to exist through two different movements: a labor movement (that included socialists) and middle-class protestant believers. The former replaced the farmers in representing the common and virtuous people, the latter opposed to saloons and alcohol consumption (Kazin, 2017: 4). Kazin (2017: 4) points out that the U.S. populism of the early stages was oriented to left, but during the late 1940s it shifted towards right. Indeed, populism focused on opposing social and cultural changes since conservative groups and politicians changed the radicals' populist rhetoric (Kazin, 2017: 4).

#### 1.5.2 Huey Long, George Wallace and Richard Nixon

The U.S. populist tradition continued with Huey Long, who was a Democratic politician (Taggart, 2000: 38), Governor of the Louisiana and U.S. Senator – during the years of the Great Depression – (Lowndes, 2017: 300) until his assassination in 1935. Long was an authoritarian politician, who was very close to Latin American populist dictators (Lowndes, 2017: 300). According to Long, Wall Street and big corporations were the enemy (Green and White, 2019: 113). He aimed to redistribute U.S. wealth through the Share Our Wealth Society in order to ensure a basic income to the poor ones (Taggart, 2000: 38). Furthermore, Long – as many populist leaders – was very provocative and presented himself as a common man close to the people (Taggart, 2000: 39).

George Wallace was another Democratic politician and he was elected Governor of the Alabama (for the first time) in 1963 (Taggart, 2000: 39). Wallace is remembered mainly for being the representative of modern racial populism (Lowndes, 2019: 191). Indeed, Wallace supported the segregation (Taggart, 2000: 40). His political success was due to a series of black protests in the late 60ties (Lowndes, 2019: 191). In this occasion, Wallace claimed that the government was doing nothing to protect the American people from the disorders and he highlighted the importance of "law and order" (Lowndes, 2019: 191). In addition to his support to the segregation, Wallace opposed to the liberal political establishment and supported the ones who did not belong to this political system (Taggart, 2000: 40). For these reasons, he was able to gain the support of white people in the South, Midwest and West (Lowndes, 2017: 300). He was also able to gain support in the Northern states from (white) working- and middle-class people (Lowndes, 2017: 300). More precisely, he was supported by old white skilled workers - who feared black protests - and young production workers attracted by Wallace's opposition to the liberal establishment (Lowndes, 2019: 191). Wallace's populism was defensive and reactionary since he wanted to defend the heartland that was threatened by social (civil right movements) and governmental changes (Taggart, 2000: 40).

Richard Nixon competed with Wallace to gain more votes especially in the Southern States (Lowndes, 2019: 192). For this reason, Nixon strategically employed Wallace's populist style of communication (Lowndes, 2017: 300) and started to use the terms *Silent Majority*, *Forgotten Americans*, and *Middle America* to indicate a white majority forgotten by the government and threatened by rioters (Lowndes, 2019: 192). Nixon also used Wallace's theme of "law and order" that was particularly successful (Lowndes, 2019: 192).

#### 1.5.3 From Ronald Reagan to Ross Perot

After President Nixon, several U.S. politicians can be labelled as populist because Wallace's populist style became a frequent feature in the U.S politics (Taggart, 2000: 41). For instance, Ronald Reagan was able to unify different shades of conservative populism since he related to evangelical Protestants and Catholics' concerns such as abortion and communism (Kazin, 2017: 262). Reagan used a populist rhetoric – especially against intellectualism (Taggart, 2000: 41) – but his economic policy did not help the common people at all because he promoted deregulation and tax-cutting that eventually favoured the elites (Lowndes, 2019: 194). In addition to Reagan, Jimmy Carter used populist rhetoric in order to depict himself as an outsider (Taggart, 2000: 41). The Democratic Jesse Jackson – during his presidential campaigns in 1984

and 1988 – tried to create a black populist movement extended to Latinos and rural whites (Lowndes, 2019: 194).

In 1992 Pat Buchanan – who was Nixon's speechwriter – faced George H.W. Bush during the republican primaries (Lowndes, 2019: 194–195). Buchanan combined the populist anti-establishment attitude with racism and nativism (Lowndes, 2019: 195). Indeed, he was even supported by the Ku Klux Klan and Neo-Nazis groups (Lowndes, 2019: 195). He was antisemitic and against feminism, LGBTQ+ rights, pornography and liberalism (Lowndes, 2019: 194–195).

During the presidential election of 1992 Ross Perot – a Texas billionaire – faced George H.W. Bush and Bill Clinton as an independent candidate (Lowndes, 2017: 301; Taggart, 2000: 41). Although he was a very wealthy man, he succeeded in portraying himself as a populist candidate. As other entrepreneurs (Mudde and Kaltwasser, 2017: 70–71) he claimed to feel obligated to enter politics and to give his contribution as successful businessman (Taggart, 2000: 42). Perot was against the elitist Washington politicians (the insiders) (Lowndes, 2017: 301) and focused on the necessity to have a plan to face national debt (Taggart, 2000: 42).

#### 1.5.4 The Tea Party and Occupy Wall Street

During the beginning of the Great Recession – in the 21<sup>st</sup> century – two new populist movements emerged: the Tea Party and Occupy Wall Street (Mudde and Kaltwasser, 2017: 26). The emergence of the Tea Party – in 2009 – coincided with the economic crisis, the last period of Bush's second term presidency, and the first presidency of Barack Obama (Lowndes, 2019: 196). It is a right-wing movement that opposes to governmental intrusion in the life of American citizens, and excessive government spending and taxation (Green and White, 2019: 113; Lowndes, 2017: 302). The movement – as it is possible to assume from its name – looks back not just to the American Revolution (especially to the Boston Tea Party), but also to a historical period when the position of the white (rich) man was still completely hegemonic and above women, black and other whites (Lowndes, 2019: 196). Thus, race (and racism) plays a crucial role in the movement's rhetoric and ideology (Lowndes, 2019: 196).

Occupy Wall Street was a left-wing movement that complained about the excessive financial power of the elite (Green and White, 2019: 113). The movement manifested itself – in 2011 – through marches in the main cities and occupations (Green and White, 2019: 113) that escalated in violent protests (Lowndes, 2017: 303). Occupy Wall Street was a more inclusionary movement – especially in comparison to the Tea Party that is exclusionary towards elites and races – who claimed to speak for the 99% of the people (Mudde and Kaltwasser,

2017: 26; Savage, 2019: 403). Occupy Wall Street has weakened for several reasons such as the lack of leadership that eventually led to its disappearance. However, some parts of the movement populist rhetoric have been included in the rhetoric of the Democratic Senator Bernie Sanders (Green and White, 2019: 114; Mudde and Kaltwasser, 2017: 26).

#### 1.5.5 Donald J. Trump

Populism emerged once again in 2015 when Donald J. Trump announced his presidential candidacy for the election of 2016. Donald Trump is a famous tycoon and as such he can be classified as an entrepreneur and insider-outsider populist leader (Mudde and Kaltwasser, 2017: 70–71/73–76). Trump is also a (television) celebrity since he has often appeared on television and films, and for many years he also hosted the reality show The Apprentice (Street, 2019). His celebrity persona has surely influenced the spectacularization of his campaign and his presidency (Kellner, 2016: 4). Moreover, the spectacularization has been amplified by Trump's massive and peculiar use of social media (Kellner, 2016: 4), especially Twitter. This social network has been employed to disseminate freely – and without the interference of traditional media – his conservative far-right populist ideology (Kreis, 2017) with a simple and repetitive style of communication (Wang and Liu, 2017). Indeed, Trump has always used a clear and aggressive style of language (Kreis, 2017) perfectly suited to Twitter constrains (such as the limitation of characters). As an insider-outsider – and entrepreneur – populist leader (Mudde and Kaltwasser: 2017: 70/75), he claimed to fight against the Washington insiders corrupt politicians, and to save the American citizens from his political opponents' disastrous (economic) domestic and foreign policies. As a result, he managed to gain the votes of wealthy people – who wanted lower taxes – and votes from poor working people (Welfens, 2019: 7) representing himself as a successful businessman capable to run the country, fix all the problems and achieve a new economic revival. In addition to corrupt politicians, he opposes to traditional *fake media* that – according to him – are part of a broader elitist corrupt system. His populist far-right ideology and rhetoric are characterised by racism, xenophobia (especially Islamophobia), anti-immigration (Kellner, 2016: 24), anti-intellectualism (Higgins, 2019: 136), anti-environmentalism and a strict opposition to women's (e.g. abortion) and LGBTQ+ rights (Welfens, 2019: 156–157).

Although Trump does not depict himself as an ordinary politician, he is supported – as any other politician – by a communication team. During the years of his presidency his team has changed a lot; however, it is important to mention his campaign manager Brad Parscale, the digital strategy director Daniel Scavino, the social media manager Justin McConney and other

two personalities who had a great influence during Trump's first electoral campaign in 2016. Firstly, Steve Bannon who was the chief executive officer of the first Trump's presidential campaign. Bannon is also a former Hollywood producer and he is behind the right-wing Breitbart News website (BBC, 2020a). Breitbart News is well-known for spreading fake news and conspiracy theories, and to promote a neo-Nazi and white supremacist ideology (Guardian staff, 2020). Secondly, Roger Stone, an old and experienced political strategist who worked for Nixon, Reagan and George H. W. Bush, supported is long-term friend Trump during the first part of electoral campaign (BBC, 2020c; Guardian staff and agencies, 2020). Furthermore, Stone shares Bannon's attitude to spread conspiracy theories and fake news (Pilkington, 2019). Starting from these premises it is not surprising that Trump's electoral campaign (and his presidency) was pervaded by a post-truth climate (Cillizza, 2016).

Donald Trump lost the presidential election of 2020; consequently, he is one of the few one-term presidents of the history of the United Sates. He kept some of his electoral promises such as tax cut and the withdrawal from the Paris Climate Accord (BBC, 2020b); however, he did not deliver some of his crucial promises such as the replacement of Obamacare and the building of the Wall (BBC, 2020b). Trump administration officially built 452 miles of the wall, but only 80 miles are new barriers (Giles, 2021). Thus, the administration just reinforced the pre-existing barrier (Giles, 2021). Moreover, the Wall was not paid by Mexico but – predictably – by American taxpayers (Qiu and Karni, 2020).

Finally, we should highlight that Trump's populist authoritarian rhetoric and his conservative followers represent a dangerous combination. Trump has been able to gain the support of different conservative groups such as the alt-right Evangelicals, paleo-conservatives (Jutel, 2019: 250/252) and extremist groups such as the Proud Boys (Belam and Gabbatt, 2020) and QAnon supporters (Wong, 2020). Indeed, Trump's populist rhetoric aims to trigger people's emotion (Wahl-Jorgensen, 2018) and it has also caused physical attacks (Lowndes, 2019: 198). In 2015 – at the beginning of Trump's electoral campaign – two Trump's supporters were inspired by the tycoon to beat and urinate on a homeless Mexican man in Boston (The Guardian Associated Press, 2015). Trump – at the end of his presidency – also caused an attack on the United Stated Capitol perpetrated by his extremist supporters (e.g. Proud Boys and QAnon followers) (Gabbatt, 2021) in the attempt to stop the formalisation of Biden's victory. As a result, all social media platforms suspended Trump's official accounts. This ultimate shocking event should warn us on how powerful and dangerous the combination of populism, extremism and an unconscious employment of social media can be.

# 1.6 Populism in Italy

According to Tarchi (2008) Italy can be defined as "a country of many populisms" since it has been a fertile ground for the growth and the development of different types of populist movements, especially from the 1990s (Bobba and Legnante, 2016: 221; Tarchi, 2008: 84). Although Italy has this variegated populist history, it is important to mention a paradox highlighted by Bobba and Legnante (2016: 221) who argue that the Italian literature about populism lack of (empirical) studies focused exclusively on this topic particularly during the 1990s.

## 1.6.1 Fascism and Qualunquismo

Populism has spread in Italy mainly during the 20<sup>th</sup> century – as many others western European countries – but it is necessary to briefly look back to what happened before the 1990s in order to have a clear and complete picture of Italian populism.

The first appearance of Italian populism can be found during the first stages of fascism when it was a movement that aimed to gain popular support (Mudde and Kaltwasser, 2017: 33). However, fascism did not rely on a populist ideology, but rather on an elitist one (Mudde and Kaltwasser, 2017: 33) since just Mussolini (and few loyal party officials) held the power.

Populism appeared again during the last years of dictatorship when the journalist Guglielmo Giannini founded in 1944 the journal *L'Uomo Qualunque* (The Common Man). The journal led to the establishment of the *Fronte dell'Uomo Qualunque* (The Common Man's Front) a populist movement that perfectly expressed Italians' lack of trust in political institutions (Tarchi, 2008: 86). The movement was characterised by opposition to fascism, antifascism, to the monarchist, clerical or conservative Right and to the Republican, Socialist or Communist Left (Tarchi, 2002: 122). Giannini focused on the opposition between the people and the politicians (especially the ones from traditional parties) proposing a government formed by – neutral and competent – technicians and administrators (Tarchi, 2002: 122). According to Tarchi (2002) *Qualunquismo* is one of the clearest examples of the Italian populist potential. The movement involved some common populist features such as the lack of trust towards corrupt traditional parties and the ability to gain support from both left- and right-wing voters (Tarchi, 2002: 123). The movement started to dissolve in the late 1940s (Tarchi, 2002: 123) but populism strongly re-emerged during the last part of the 20<sup>th</sup> century.

#### 1.6.2 Lega Nord

The *Lega Nord* (Northern League) was born in the late 1980s with the unification of different northern regional and autonomist movements (Tarchi, 2002: 126) – such as the *Lega Lombarda* and the *Liga Veneta* (Cento Bull and Gilbert, 2001: 9–11) – characterised by ethno-nationalism and xenophobia (Aime, 2012: 48; Richardson and Colombo, 2013: 185). The birth of this populist political party is strictly connected to political, economic and social changes. Firstly, the crises of main ideologies and traditional parties during the post-Cold War (Cento Bull and Gilbert, 2001: 42). Secondly, the Italian economic situation was deeply influenced by the post-World War II gap between the poor South and the industrialised North, especially the North-West (Cento Bull and Gilbert, 2001: 2; Verbeek and Zaslove, 2015: 3). For this reason, in the 1980s the party was able to gain consensus offering to northern Italians a political program that aimed to achieve political and economic freedom from the central and corrupt government of Rome (Cento Bull and Gilbert, 2001: 5) during the increasing process of globalisation.

Umberto Bossi is the founder of the Lega Lombarda and then of the Lega Nord. Bossi managed to lead the party to its first electoral success in the general elections of 1987 (Cento Bull and Gilbert, 2001: 13). Indeed, Bossi was able to become Senator and continued the Lega Nord's campaign against the central government, the unproductive South of Italy (blamed to live at the expenses of northern Italian people) (Richardson and Colombo, 2013: 184) with its clientelism and organised crime (Cento Bull and Gilbert, 2001: 14), mass immigration (Richardson and Colombo, 2013: 181) and the threat of Islamisation (Tarchi, 2002: 130). Specifically, during 1980s immigrants came mainly from Maghreb and Albania. Their presence triggered the xenophobic attitude of the *Lega Nord* (already reserved to Southern Italians) since according to Leghisti a multicultural society will never be possible, especially if immigrants are privileged over Italians in terms of access to social services (Cento Bull and Gilbert, 2001: 20). From a linguistic perspective, the Lega Nord was (and it is still) characterised by the use of a direct, explicit, sarcastic and aggressive style of communication (Tarchi, 2002: 127). Specifically, Umberto Bossi used a simple and vulgar language (Mudde and Kaltwasser: 2017: 64-66) and expressions in dialect (Aime, 2012: 68) in order to relate better with common people.

After the successes of the European elections in 1989 and the local elections in Lombardy in 1990, Bossi decided to increase the autonomist attitude of the party (Cento Bull and Gilbert, 2001: 20). He aimed to replace the ideological opposition between communism and Catholicism with the Italian opposition between North and South (Cento Bull and Gilbert, 2001: 23), and – inspired by some Italian intellectuals such as Carlo Cattaneo and Gianfranco

Miglio – proposed the idea to separate Italy in three (Nord, Central and South) federal republics (Cento Bull and Gilbert, 2001: 24).

Even though the *Lega Nord* was in some way involved in the *Tangentopoli* scandal<sup>1</sup> in 1993, the *Leghisti* were still able to portray themselves as political outsiders. The *Tangentopoli* scandal played a crucial step in the rise of the *Lega Nord* (Anselmi, 2018: 67; Tarchi, 2002: 126). Indeed, the *Lega Nord* won –filling the void left by the party *Democrazia Cristiana* (Christian Democracy) – the general elections of 1994 with Silvio Berlusconi's *Forza Italia* (Forward Italy) and Fini's neo-fascist party *Movimento Sociale Italiano* (Italian Social Movement) (Cento Bull and Gilbert, 2001: 32; Richardson and Colombo, 2013: 184). However, Berlusconi did not satisfy the requests of *Lega Nord* such as the Federal Reform and this caused the end of the coalition government by the hand of Bossi (Tarchi, 2008: 90).

The Lega Nord can be defined as an ethno-populist party since it focused on the opposition of the northern people towards various social actors. First of all, the elite and especially Roma Ladrona (Thieving Rome) (Bianchini, 2012: 54). Secondly, all other Italians – who were not northerner – and obviously, immigrants. If the opposition between Italians and immigrants is quite easy to trigger, the opposition between Northern Italians and all the other Italians – especially from the South – required the construction of a well-thought northern identity (Tarchi, 2002: 128). The party claimed that northern Italians were genetically more similar to other northern European people rather than other Italians (Aime, 2012: 41; Cento Bull and Gilbert, 2001: 113). Leghisti argued to have Celtic heritage in order to claim the existence of a Padanian race (Cento Bull and Gilbert, 2001: 114). In this way, they depicted their ancestors as pure, rude, simple and honest people in opposition to the colonist, lazy and corrupt Romans (Aime, 2012: 27). A contraposition that clearly metaphorically recalls the opposition between northern Italians and Thieving Rome. Moreover, they reinforced this sense of belonging – and at the same time their exclusionary desire towards the rest of Italy – with historical references such as the name Carroccio - that is another name used to indicate the party and that recalls Alberto da Giussano and the battle of Legnano in 1176 - and the establishment of an annual party convention at Pontida where in 1167 the original Lega Lombarda (that was a military alliance) made an oath against the Holy Roman Empire (Cento Bull and Gilbert, 2001: 21). The construction of this identity was also crucial when Umberto Bossi decided to strategically shift the federalist attitude of the party to a secessionist one (Cento Bull and Gilbert, 2001: 106) since he even talked about the institution of the State of Padania (Tarchi, 2002: 131; Richardson and Colombo, 2013: 184). The secessionist attitude was

A scandal that revealed a corrupt network of Italian politicians and entrepreneurs in the early 1900s.

increased after the success of the *Lega Nord* during the election of 1996 (Cento Bull and Gilbert, 2001: 110). After the institution of its own Parliament, the State of *Padania* was symbolically founded by Bossi in 1996 when he walked by the river Po – followed by a procession of people (Cento Bull and Gilbert, 2001: 111) – in order to perform the ritual of the ampoule<sup>2</sup> (Aime, 2012: 35). Nevertheless, very few Italians took seriously the idea of secession from Italy (Cento Bull and Gilbert, 2001: 116).

The *Lega Nord* was once again part of Berlusconi's governments from 2001 to 2005, from 2005 to 2006, and from 2008 to 2011. After 2011 the party experienced a loss of support mainly because of various scandals (La Repubblica 2012a; 2012b; 2012c; Richardson and Colombo, 2013: 184). After the resignation of Umberto Bossi in 2012, Roberto Maroni was the Secretary of the party from 2012 to 2013. In 2013 – during the election of the new Secretary – Matteo Salvini became the new leader of the party.

#### 1.6.3 Silvio Berlusconi

In addition to a European context characterised by social and economic instabilities, during the 1990s Italy had to face a major corruption scandal called *Tangentopoli* (Bribersville) or *Mani Pulite* (Clean hands) that revealed a corrupt network of politicians and entrepreneurs. The scandal caused the end of the First Republic, an increasing negative reaction of the public opinion, an additional detachment of the people from the institutions, and people's opposition and lack of trust towards politics in general (Tarchi, 2008: 87). This context represented a breeding ground for the rise of both the *Lega Nord* (the Northern League) (Anselmi, 2018: 67) and Silvio Berlusconi (Mudde and Kaltwasser, 2017: 100).

In 1994 – for the political election of that year – Silvio Berlusconi decided to enter politics and founded the (centre)right-wing party *Forza Italia* (Tarchi, 2002: 131). Berlusconi managed to win the election in a favorable climate created by *Tangentopoli* since he was not a politician. However, the government did not last long because the *Lega Nord* withdrew its support. Later, he was Prime Minister again from 2001 to 2006, and from 2008 to 2011.

Berlusconi can be defined as both entrepreneur and insider-outsider populist leader (Mudde and Kaltwasser, 2017: 70–76). Firstly, he is a very wealthy businessman and – as any other populist leader that belongs to this category – he has always highlighted his temporary commitment to politics. He wanted to represent and save the Italian people, especially the ones neglected from the left and from the general corrupt old politics (Tarchi, 2008: 93–94).

Bossi took some water from the spring of the river Po and carried it – in an ampoule – to Venice in order to symbolise *Padani*'s unity (Aime, 2012: 35).

Moreover, he is an insider-outsider because – even before his political commitment – he had connections with Bettino Craxi (Diodato and Niglia, 2019: 24; Mudde and Kaltwasser, 2017: 100) the leader of the Italian Socialist Party.

Although his wealthy lifestyle, Berlusconi has been able to portray himself as a man of the people through the figure of the self-made man (Tarchi, 2002: 133) who did not forget his roots. Furthermore, he strategically used sport (e.g. AC Milan) and his virility (e.g. the *Bunga Bunga* scandal) (Mudde and Kaltwasser, 2017: 71/74) that allowed him to come closer to common people. Indeed, people's desire to identify with Berlusconi represents a crucial factor in the construction of his figure as leader (Amadori, 2002: 33; Tarchi, 2002: 133).

Berlusconi – advantaged by his own media empire – has embodied a plebiscitarian populism (Tarchi, 2002: 134; 2008: 95) or tele-populism (Anselmi, 2018). According to this perspective, the legitimisation or the delegitimisation of a government can be based upon surveys since they express the people's will (Amadori, 2002: 95; Tarchi, 2002: 134).

Finally, we should highlight that his charismatic and effective rhetoric is characterised by conciseness, linearity, and clarity (Amadori, 2002: 22) which are clearly common features of populist communication. Berlusconi strategically employed this simple and clear style of language in order to finally give to Italians the impression to understand something of politics (Tarchi, 2008: 94).

#### 1.6.4 Movimento 5 Stelle

The *Movimento 5 Stelle* (5 Star Movement) was founded by the comedian Beppe Grillo and Gianroberto Casaleggio – entrepreneur, marketing expert and founder of the publishing company Casaleggio Associati – in 2009 (Chiapponi, 2017: 104). However, the movement started to emerge in 2005 when Grillo opened his blog and promoted mobilisations such as the V-Day in 2007 (Biorcio, 2018: 141). The movement presents an innovative style of mobilisation; and its supporters are defined as activists (Anselmi, 2018: 68). The emergence and the rise of the movement was caused by the institutionalisation of previous populist party such as *Forza Italia* and the *Lega Nord* (Verbeek and Zaslove, 2015: 4), and the inability of both left- and right-wing parties to face a political, economic, and social crisis, especially in the timespan that goes from 1994 to 2008 (Biorcio, 2018: 140–141).

Nowadays the movement maintains its original ideology against partitocracy since the *Movimento 5 Stelle* is still defined as a movement or as a governmental force but never as party. Moreover, it has been presented as a post-ideological movement because it is not right nor left. Nevertheless, the movement actually integrates both left- and right-wing features. This

characteristic has been used strategically to attract disappointed left- and right-wing voters (Anselmi, 2018: 68). Indeed, the movement – starting from 2010 – has become the third political force in Italy (Anselmi, 2018: 68), especially in the South (Biorcio, 2018: 141). Furthermore, its chameleonic post-ideological nature has allowed the formation of two governments. Firstly, the sovranist government Conte I in 2018 formed by the *Movimento 5 Stelle* and Salvini's *Lega* that has apparently represented the end of the Second Republic and the beginning of the Third Republic (D'Esposito, 2018). Secondly, the centre left-wing government Conte II in 2019 formed by the *Movimento 5 Stelle* and *PD* (the Democratic Party).

In addition to its post-ideological position, the movement supports direct democracy since representative democracy is thought to be already dead. According to the movement direct democracy is possible through the employment of internet; therefore, the movement has already experimented forms of direct democracy among its supporters with the creation of the platform Rousseau where certified M5S (Movimento 5 Stelle) members can vote to express their preferences regarding the movement's decisions (Frequente, 2019). We should emphasise that the name of the platform voluntarily recalls the philosopher Jean-Jacques Rousseau who theorised the concept of general will and supported a utopian idea of self-government. The movement has also a particular interest in environmental topics (Anselmi, 2018: 68) and clearly to improve the access to internet. However, the main aspect that characterised the M5S is its hostility towards corruption and especially towards the political elite that Grillo and M5S politicians used to call *la Casta* (the caste) (Santoro, 2012: 49–52). *La Casta* involves every mainstream party, and it is opposed to honest Italian people (Verbeek and Zaslove, 2015: 4). Indeed, the movement itself is based upon the values of honesty and meritocracy. The value of honesty is a main and special value for M5S politicians. In addition to the Casta's lack of honesty, they care deeply about the movement's honesty in order to depict themselves as different from the traditional political elite. For instance, they fiercely and openly attack other members of the movement who dare to change party and betray the people who have elected them (Gagliardi, 2019). In this regard, we should emphasise that although the movement – especially at the beginning – promised to never ally with other parties, the M5S has been facing the reality of the political system where compromises are necessary. As a result, during the electoral campaign of 2018 the movement changed its approach. Luigi Di Maio – at the time leader of the movement – warned the supporters about the necessity to govern with other parties (Gallori, 2018) since the Italian electoral system does not allow to just one party to rule. If the government Conte I did not caused many problems to the movement in terms of consensus, the

same cannot be said for Conte II (Pregliasco, 2021) because M5S governed with PD that is one of the parties depicted as *la Casta*.

#### 1.6.5 Matteo Salvini

Matteo Salvini became a militant of the *Lega Nord* in 1990 when he was just seventeen years old (Madron, 2013). His political carrier began in 1993 when he became a city council member of Milan (Spinaci, 2018). At the beginning of his carrier, Salvini defined himself as a *Comunista Padano* and he clearly belonged to the left-wing current of the *Lega Nord* (before the establishment of the *Lega Nord* as a far-right wing populist party). In 1997 he was the top candidate of *Comunisti Padani* during the election of *Padania*'s Parliament (Madron, 2013). In the same year he started working as a journalist for the party's newspaper *Padania* and in 1999 he worked also for *Radio Padania* (Gatti, 2019: 105–109; Passarelli and Tuorto, 2018; Salvini, Pandini and Sala, 2016). Later, Salvini has been a member of the Italian Parliament, member of the European Parliament, and more recently Italian Minister of the Interior, Vice Prime Minister and Senator. However, the crucial moment in his carrier as politician is undoubtedly his election as Secretary of the *Lega Nord* in 2013.

Under Salvini's leadership the Lega Nord has gone through a process of change (Passarelli and Tuorto, 2018) starting from the rebranding of its name – since nowadays people refer to the party simply as la Lega – and its slogan that from Prima il Nord (North First!) has become Prima gli Italiani! (Italians First!). Indeed, Salvini has managed to turn the populist ethno-regionalist party into a successful national populist party (Renzi, 2016: 23). Despite the Lega Nord's long opposition to the South of Italy, Salvini has been able to gain consensus precisely in the South and in the central regions traditionally oriented towards left (Albertazzi, Giovannini and Seddone, 2018: 646). In order to reach this aim, Salvini has strategically maintained some original features of the party such as the achievement of federalism, but at the same time he has changed the representation of the people and the other. More precisely, now the people involves not just northern Italians but all Italians without any territorial difference. Consequently, the category of the other involves immigrants who are a national threat to all Italians. Nonetheless, Salvini never talks about Italy as patria (homeland) but as terra (land) or paese (country) in order to remind the original roots of the Lega as a Northern party (Albertazzi, Giovannini and Seddone, 2018: 650). The success of Salvini could be explained by his balancing attitude that aims to maintain the older supporters of the Lega Nord but at the same time to reach new ones.

Once abandoned ideas regarding the Celtic heritage and Pagan rituals, nowadays the Lega aims to defend Italy as a Catholic country threatened by Islamisation. In addition to the unchanged xenophobic approach towards immigration, Salvini tries to present himself as a tolerant man guided by common sense. Salvini's common sense involves conservative views about certain topics such as abortion, homosexuality and the phantomatic gender theory (a derogatory term to indicate gender studies) (Renzi, 2016: 110) because they threaten nonnegotiable Christian values, especially connected to the concept of traditional family. The Lega Nord has had a complex and ambiguous approach towards the Catholic Church essentially because religion has always been used as a propaganda instrument (Bianchini, 2012: 166). Nowadays Salvini continues to maintain an ambiguous approach. On the one hand, he seems to be critical towards the Church especially regarding the immigration phenomenon. On the other hand, he tries to sympathise with Catholics and especially with the most conservative wing of the Church (Renzi, 2015). Indeed, he has never hidden his preference for Pope Benedict XVI over Pope Francis (Gilioli and Nasso, 2016; Rame; 2016). The leader of the Lega perpetuates the exploitation of religion for propaganda in many ways; for instance, he often exhibits and kiss the rosary (Poletto, 2019; Pucciarelli, 2020) during his public appearances. It is worth mentioning that Salvini has gained not only the support of conservative Catholics, but also the support of neo-fascist parties and movements such as Forza Nuova and Casa Pound (Renzi, 2016:16; Piselli, 2019).

Salvini can be defined as an insider populist leader (Mudde and Kaltwasser, 2017: 75) since he has always been a politician, but he is still capable of representing himself as an outsider who fights with and for the common people against the elite (e.g. his political opponents, intellectuals and Europe). At the beginning, his figure as leader has been characterised by a very informal dressing style. Before and during his first years as Secretary of the *Lega Nord* Salvini wore very often sweatshirts. Nowadays his style has evolved. Although he maintains a casual style, he has worn formal dresses, especially after his election in 2018 as Vice Prime Minister and Minister of the Interior. However, he still uses strategically personalised sweatshirt (he often wears this clothing to convey messages) in social media pictures. His dressing style has clearly specific and strategical functions. For instance, he has worn several uniforms (Cerami, 2018; Tonacci, 2019) in order to highlight his figure as strong, masculine and firm leader. Moreover, since 2019 he tried to attract left-wing voters by wearing sometimes cloths that remind the style of left-wing intellectuals (Baldolini, 2019; Cavalli, 2019).

From a linguistic perspective, Salvini's style of communication has not changed so much. He surely does not talk in a derogatory way of terroni<sup>3</sup> anymore; but he still employs a simple, clear and direct populist style of language with xenophobic tendencies (Passarelli and Tuorto, 2018). Furthermore, the leader of the *Lega* is – among Italian politicians – the one who uses social media the most in a massive way. He has accounts in almost every social media, and he is the only Italian politician to even own a Tik Tok (Florio, 2019) account in order to reach younger supporters. Specifically, it is important to highlight Salvini's use of Twitter since – as almost every politician – he tweets on a daily basis and employs massively this social network (Vecchio, 2020). We should emphasise that his social media accounts are extremely interconnected – especially Twitter and Facebook – but Twitter deserves particular attention because it is the social platform that favours and reinforces the aggressive and simple populist style of communication (Ott, 2017). Salvini employs Twitter to spread his populist narratives, but at the same time to create a direct and empathetic relational bond with his electorate. He tries to build a direct connection with his supporters through the employment of a familiar and informal language. For instance, he uses emojis and he always refers to his followers using the word *amici* (friends) in order to build a strong community. He often posts picture of what he is eating. Nowadays sharing food pictures on social media is a common practice; for this reason, Salvini presents himself as a common man because he does what normal people do. Moreover, food – especially in Italy – reminds conviviality. Consequently, even food pictures have a strategical function in building a strong community of supporters and to reinforce his Eurosceptic narratives regarding Made in Italy products. In addition, he sometimes posts pictures of his children in order to portray himself as a loving father, as a trustable and reassuring man, and once again as a man of the people. Salvini's aim is clearly to reinforce the bond with his followers and to empathises with them, especially with divorced parents. In this regard, it is important to underline that the sharing of politicians' personal information is crucial for common citizens to both trust these politicians and identify with them (Mazzoni and Mincigrucci, 2020: 3–4). Tweets about religion should not be underestimated since Salvini tries to sympathise with Catholics - especially to older people who use social media - and particularly with the conservative Roman Catholic wing (Renzi, 2015). For instance, he has reserved particular attention to the Virgin Mary and especially to the Medjugorje one that is precisely connected to the conservative wing of the Catholic Church (Bibus, 2019; Misculin, 2019).

<sup>&</sup>lt;sup>3</sup> Derogatory term to indicate Southern Italian people.

Furthermore, social media have played a crucial role in Matteo Salvini's rise. Salvini has been able to reach success on social media (he is currently the populist right-wing politicians with more followers in Italy<sup>4</sup>) with the support of a strong communication team (Lorenzetti, 2020). More precisely, the social media strategist Luca Morisi<sup>5</sup> – head of Salvini's communication team until September 2021 (Foschini and Tonacci, 2021; Tedesco, 2021) – is the man behind Salvini's success on social media. Morisi was also Salvini's image consultant and precisely he is the one who invented Salvini's epithet il Capitano (the Captain). Salvini's communication team is called *la Bestia* (the Beast) and it is formed by 35 digital experts who portray Salvini' private and public life on social media on a daily basis (Gabanelli and Ravizza, 2019). Salvini's communication strategy is particularly enviable because of the followers' high level of engagement that the team manage to achieve through surveys, the employment of a software that identify the daily most discussed topic (in order to adjust Salvini' posts) and most importantly the choosing of divisive messages since they are the ones that create more participation and engagement (Gabanelli and Ravizza, 2019). In addition to strategically trigger negative emotions, Salvini and his Bestia favour a xenophobic climate and instigate hate towards minorities and the elites. Hate is favoured not only through words, but also through actions. For instance, in January 2020 Salvini rang the intercom of an alleged Tunisian drug dealer in Bologna, followed by a group of angry supporters (Prisco, 2020). Finally, the authoritarian populism promoted by Salvini is reflected on his social media accounts, where he spreads fake news at his own advantage and censors all the comments that contain specific words or hashtags with references to the *Lega*'s scandals (Gabanelli and Ravizza, 2019). People who dare to question Salvini and the Lega are blocked and bullied by Salvini's supporters (Bottura, 2021). The limitation of freedom of expression – among other things – perpetuated by Salvini and his team should represent an alarm bell to any democratic society.

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Salvini has 1.3 million followers on Twitter; 4.8 million on Facebook; 2.3 million on Instagram. The data are updated to the 3<sup>rd</sup> of February 2021.

Luca Morisi has a degree in philosophy, and at the beginning of his carrier he was a local politician for the Northern League. After his political experience he became a philosophy professor at the University of Verona (Marini, 2019). He returned in the political field as Matteo Salvini's spin doctor.

# CHAPTER 2 THEORETICAL BACKGROUND

This chapter is dedicated to the theoretical background of the analysis. The first section of the chapter explores Discourse Studies and the definition of discourse. The following sections focus on the different branches of Discourse Studies, such as Critical Discourse Analysis, on Corpus Linguistics, and on Corpus-assisted Discourse Studies. The last part of the chapter is dedicated to Political Discourse.

## 2.1 Discourse Studies

Discourse Studies (DS) emerged during the 1960s (Bhatia, Flowerdew and Jones, 2008: 1) through the merging of different disciplines that belong to the fields of social sciences and humanities (e.g. linguistics, sociology, philosophy, anthropology, etc.) (Angermuller, Maingueneau and Wodak, 2014: 1). Discourse Studies can be defined as an interdisciplinary field of study – that includes a considerable heterogeneity regarding fields of study, 'schools', and the types of data used by researchers (Angermuller, Maingueneau and Wodak, 2014: 2) – that focuses on the theory and analysis of text and talk (van Dijk, 1997a). More precisely, Discourse Studies analyses the linguistic behaviour – written and spoken – with a particular regard to the construction and the interpretation of meaning in specific social contexts (Bhatia, Flowerdew and Jones, 2008: 1).

From this perspective, it is crucial to understand what *discourse* is. According to van Dijk (1997b), discourse is "a form of language use" (van Dijk, 1997b: 1) in both spoken and written language (van Dijk, 1997b: 2–3). Specifically, Discourse Studies focuses on language that naturally occurs in text or talk in a specific context (van Dijk, 1997b: 29; 2008; 2009), and aims to understand how *language in use* is connected to beliefs (social cognition) and social interaction (van Dijk, 1997b: 2; 1998). Indeed, Discourse Studies looks primarily at the social dimension of language since discourse can be understood as a form of *social action* (van Dijk, 1997c: 2).

The social dimension of discourse is an essential element for two main reasons. Firstly, every Discourse Studies' branch assumes that meaning is the product of social practices (Angermuller, Maingueneau and Wodak, 2014: 3). This highlights the importance of the

concepts of *language in use* and *context* because language needs to be contextualised in order to have meaning (Angermuller, Maingueneau and Wodak, 2014: 3). Secondly, Discourse Studies investigates how discursive practice shapes society and social order (Angermuller, Maingueneau and Wodak, 2014: 3). The disciplines that converge in this field of study claim that it is possible to analyse language not only from an internal level structure (e.g. phonemes, morphemes, words, clauses etc.), but also as a *tool of social action* (Bhatia, Flowerdew and Jones, 2008: 1; Angermuller, Maingueneau and Wodak, 2014: 3).

## 2.2 Critical Discourse Analysis

Critical Discourse Analysis (CDA) is a branch of Discourse Studies that originated from Critical Linguistics (Flowerdew, 2008: 195; Machin and Mayr, 2012: 2). Critical Linguistics emerged in the late 1970s at the University of East Anglia (Flowerdew, 2008: 195; Machin and Mayr, 2012: 2) from the works of Fowler, Kress, Hodge and Trew (Fowler *et al.*, 1979). On the other hand, Critical Discourse Analysis was established during the early 1900s through the works of van Dijk, Fairclough, Kress, van Leeuwen and Wodak (Wodak, 2001a: 4).

Wodak (2001a: 1) suggests that Critical Linguistics and Critical Discourse Analysis are two terms that have been used as synonyms but there are actually some differences between the two disciplines. Even though CDA assumed the Critical Linguistics' conception of language as a social practice (Wodak, 2001a: 1) and the ideological potential of language (Machin and Mayr, 2012: 2), CDA implemented the analysis of the relationship between language, power and ideology (Machin and Mayr, 2012: 4). Indeed, CDA distinguishes itself for its particular interest in language and power (Wodak, 2001a: 2; Weiss and Wodak, 2003: 12), and for claiming that power relations are discursive (Machin and Mayr, 2012: 4). According to van Dijk:

One of the crucial tasks of Critical Discourse Analysis (CDA) is to account for the relationships between discourse and social power. More specifically, such an analysis should describe and explain how power abuse is enacted, reproduced or legitimised by the text and talk of dominant groups or institutions. (van Dijk, 1995: 84)

CDA aims to discover and highlight the hidden power and ideological relations inside language (Flowerdew, 2008: 195; Machin and Mayr, 2012: 5) because language – as a form of social action – can actively normalise, legitimise and perpetuate power inequalities in society. As a result, – as Fairclough (2018) suggests – CDA focuses not only "on power *in* discourse but also on power *behind* discourse" since it is both a critique of manipulation and ideology (Fairclough, 2018: 14). Consequently, CDA analyses specific discursive practices (Flowerdew, 2008: 196)

focusing mainly on issues regarding socio-political domination (Bhatia, Flowerdew and Jones, 2008: 11). According to Fairclough:

CDA is a form of *critical* social analysis. Critical social analysis shows how forms of social life can damage people unnecessarily, but also how they can be changed. CDA's contribution is elucidating how discourse is related to other social elements (power, ideologies, institutions, etc.) and offering critique of discourse as a way into wider critique of social reality. But the objective is not just critique, it is change 'for the better'. (Fairclough, 2018: 13)

CDA aims to highlight – through a *critical* approach to language – hidden ideological assumptions (Flowerdew, 2008: 195) and to questions the status quo pervaded by inequality and unfairness (Bhatia, Flowerdew and Jones, 2008: 11) to achieve a fairer social order (Kress, 1995: 15).

From this perspective, it is important to scrutinise more the *critical* aspect of Critical Discourse Analysis. CDA is critical not just from a methodological perspective but also because it plunges its roots in social relations' radical critique (Billig, 2003: 38). According to Wodak (2001a: 9) the notion of *critical* in CDA is very heterogeneous since scholars can follow different approaches such as the ones from the Frankfurt School, literary criticism or Marxism (Fowler, 1995: 4; Wodak, 2001a: 9). However, she claims that the critical approach should be understood as: "[...] having distance to the data, embedding the data in the social, taking a political stance explicitly, and a focus on self-reflection as scholars doing research" (Wodak, 2001a: 9).

As already mentioned, CDA has a particular focus on the role that language has in the perpetuation of domination, power abuse and inequalities (van Dijk, 2001: 96). Consequently, the critical aspect of CDA is strictly connected to the concepts of power and ideology. CDA has drawn a lot from the works of Michel Foucault and Antonio Gramsci regarding these concepts. On the one hand, CDA relies on Foucault's (1995; 2002) theory about power since he highlighted its pervasiveness in society and the importance of power relations in order to establish control (Flowerdew and Richardson, 2018: 3). On the other hand, Gramsci's importance in CDA is tied to his theory of hegemony. Gramsci suggested that power can be performed though ideology and discourse (Flowerdew and Richardson, 2018: 4); indeed, (cultural) hegemony represents a situation in which all the classes of a society accept and interiorise the ideology (values and beliefs) of the dominant class (Gramsci, 1971). For this reason, CDA claims that ideology is crucial for the establishment and reproduction of power inequalities (Wodak, 2001a: 10).

CDA distinguishes itself for other characteristics as well such as interdisciplinarity, intertextuality and multimodality.

Firstly, interdisciplinarity is one of the cornerstones of the macro-category of Discourse Studies. As a result, interdisciplinarity represents one of the defining characteristics of CDA as well. Weiss and Wodak (2003) suggest that CDA does not rely on a uniform theory but it is rather formed by several approaches (Weiss and Wodak, 2003: 6). CDA often combines linguistics with other disciplines such as sociology, cognitive science, psychology and ethnography. For instance, van Dijk combines CDA with a socio-cognitive approach that connects discourse structures to social structures (van Dijk, 2018: 27). The cognitive approach focuses on knowledge - that has often been backgrounded in linguistics - and on the relationship between knowledge and discourse (van Dijk, 2003: 85). This approach underlines the importance of mental representations and the essential cognitive aspect of discourse's structures (van Dijk, 2018: 28). Discourse's structures are shaped by models, knowledge, attitudes and ideologies (van Dijk, 2018: 39). More precisely, mental representations conciliate shared social cognition (e.g. knowledge or ideologies), societal structures and discourse (text and talk) (van Dijk, 2018: 28). Cognition is both individual (mental models) and social, since social actors own a sociocultural knowledge (e.g. values, ideologies, attitudes) that they share with other members of the same group or community (van Dijk, 2018: 30–31). Specifically, van Dijk (2018) suggests that there is a *cognitive interface* that relates discourse and society.

Secondly, through intertextuality and interdiscursivity CDA investigates the relationships between texts and discourses (Meyer, 2001: 15) because both are contextualised and can be connected to other past or present texts and discourses (Wodak and Weiss, 2005: 127). These two concepts are widely used in Wodak's Discourse Historical approach (see section 2.2.1); more precisely, Wodak (2009) suggests that intertextuality and interdiscursivity are crucial in the process of recontextualization. Recontextualization happens when an argument is decontextualised and then it is placed in a new context in which it assumes a new meaning (Wodak, 2009: 39) that can be easily manipulated (Flowerdew and Richardson, 2018: 6). Furthermore, the concept of intertextuality is linked to Fairclough's orders of discourse. Fairclough borrows Foucault's (1981) order of discourse (Fairclough, 1992: 68) to indicate the configuration of discourse practices in society (Fairclough, 1992: 9). Fairclough and Wodak claim that discourse is a social practice (Fairclough and Wodak, 1997: 258). This perspective entails that CDA is a dialectical reasoning since it focuses on the dialectical relations between discourse and other social elements (Fairclough, 2010: 3; 2018: 16) highlighting the relationship between critique, explanation and action (Fairclough, 2018: 16). The relationships between discourse, social and cultural structures are mediated by the orders of discourse (Fairclough and Wodak, 1997: 277) since they are "structured sets of discursive practices associated with particular social domains" (Fairclough and Wodak, 1997: 265). This concept is linked to intertextuality because discourse change can be caused by a change of the *orders of discourse* through the incorporation of different discourses and genres in texts that reorganises the relationships between social practices and social domains (such as institutions) (Fairclough and Wodak, 1997: 265).

Thirdly, CDA is not limited to the analysis of discourse understood just in terms of text and talk but it can involve non-verbal practices such as images, sounds and material design (van Leeuwen, 2014: 281; Ledin and Machin, 2018: 60). Specifically, Kress and van Leeuwen (2006) have developed a Multimodal Critical Discourse Analysis approach (MCDA) with a particular focus on images since they believe that the analysis of visual communication is a crucial aspect of disciplines that aim to be 'critical' (Kress and van Leeuwen, 2006: 14). Indeed, they argue that it is possible to analyse visual data from a lexical and grammatical perspective following the framework of social semiotics and the work of Michael Halliday (Kress and van Leeuwen, 2006: 1–6; see also section 2.5). Regarding the grammatical aspect of MCDA, Kress and van Leeuwen's visual grammar is not universal because visual language is culturally bound (Kress and van Leeuwen, 2006: 4). As a result, they propose a flexible set of resources in order to analyse visual data (Kress and van Leeuwen, 2006: 266). Furthermore, Machin and Mayr (2012) - following Kress and van Leeuwen's approach - provide a seminal overview of Multimodal Critical Discourse Analysis focusing on a variety of categories such as setting, salience (e.g. size, colour, tone etc.), gaze, pose, distance and angle. In addition, van Leeuwen's contribution to CDA is particularly relevant regarding the representation of social action and social actors (van Leeuwen, 2008). Van Leeuwen is interested in knowing "what are the ways in which social actors can be represented in (English) discourse" and "which choices does the (English) language give us for referring to people" (van Leeuwen, 1996: 32). For this reason, he proposes a sociosemantic inventory of the different and possible representation of social actors (van Leeuwen, 1996: 32) that includes a detailed classification of inclusionary and exclusionary strategies such as suppression, individualisation and aggregation (van Leeuwen, 2008).

This overview of CDA has highlighted the heterogeneity of this field of study that is highly characterised by interdisciplinarity. Consequently, the overview has focused just on the main approaches used in CDA with particular attention to Fairclough (1992; 2018), Wodak (2001b) (her approach will be scrutinised more in depth in the following section 2.2.1), van Leeuwen (1996; 2008) and van Dijk's socio-cognitive approach (2003; 2018). Although CDA is a very heterogenous field of study, it is important to remember that all CDA scholars agree

upon the interpretation of language as a social practice and as a tool of social action. More precisely, they believe – as Machin and Mayr suggest – that "language shapes and it is shaped by society" (Machin and Mayr, 2012: 4).

## 2.2.1 Discourse-Historical Approach

The Discourse-Historical Approach (DHA) is a branch of CDA theorised by Ruth Wodak (Wodak, 2001b; 2009; 2015; Reisigl and Wodak, 2001) that represents one of the most important critical approaches in the study of discourse (Reisigl, 2018: 44) with a particular focus on argumentation (Reisigl, 2014: 67). CDA and DHA share many characteristics such as the attention to language that occurs naturally in specific contexts (Reisigl, 2018: 49). However, DHA emphasises – as it is possible to assume from its label – the historical aspect (e.g. historical subjects, historical change etc.) of discourse (Reisigl, 2018: 49).

The Discourse-Historical Approach was originally developed to investigate the building of anti-Semitic stereotypes in public discourse that emerged during the Austrian Election Campaign of Kurt Waldheim in 1986 (Wodak, 2001b: 70; Reisigl, 2018: 44–45; Wodak and Reisigl, 2001: 41). In more than 30 years, the DHA has evolved, and nowadays scholars focus on fascist and right-wing populist discourses but also on discourses that concern other current topics such as environment and climate change (Reisigl, 2018: 47).

The Discourse-Historical Approach can be defined as a problem oriented, abductive and interdisciplinary approach – with strong roots in linguistics (Reisigl, 2018: 47) – that explores discourse and its diachronic change (Wodak, 2001b: 65, 69–70). The development of DHA has been influenced by van Dijk's (2003; 2018) socio-cognitive approach (Weiss and Wodak, 2003: 13; Wodak, 2009: 38) especially regarding some concepts such as the 'positive self-presentation' and 'negative other-presentation' (Reisigl and Wodak, 2001: 31).

DHA analyses discursive strategies and features through both qualitative and corpusbased quantitative approach (Reisigl, 2018: 52). According to Wodak (1995) DHA focuses on three aspects of *language in use* that are the topics or contents, the discursive strategies, and their linguist realisation (Wodak, 1995: 111; 2009: 38). Moreover, it is possible to identify five main discursive strategies on which DHA concentrates in order to investigate the positive selfand negative other- presentation that are particularly useful in the construction of identity and in the legitimisation of social actors' inclusion and exclusion (Wodak, 2009: 40). These discursive strategies are nomination (the discursive construction of social actors, objects, events, actions and processes), predication (the discursive characterisation attributed to social actors, objects etc.), argumentation (the arguments used in discourse), perspectivation (the author's point of view in the expression of nomination, predication and argumentation), and mitigation and intensification (the articulation of utterances and their illocutionary force) (Wodak, 2009: 40–42; Reisigl, 2018: 52; Reisigl and Wodak, 2001).

The strategy of argumentation is particularly relevant because it focuses on the process of persuasion through the employment of specific arguments that are thought to be true and normatively right (Reisigl, 2018: 52). Since the main aim of argumentation is persuasion (Reisigl, 2014: 70), argumentation is strictly connected to rhetoric with a particular focus on tropes such metaphors (Musolff, 2014) and *topoi* (Reisigl, 2018: 52). Specifically, *topoi* represent a crucial element in argumentation analysis (Reisigl, 2014: 75) because they connect an argument to a conclusion and, at the same time, justify this connection (see section 3.2.1.2) (Wodak, 2009: 42; 2015: 76). Thus, *topoi* can be defined as *warrants* or *conclusion rules* (Wodak, 2009: 42; 2015: 76). More precisely, the importance of *topoi* is attributable to their capability to justify and legitimise positive or negative statements (Wodak, 2009: 42; Reisigl and Wodak, 2001).

Since DHA investigates language in use, even in this approach, context has a crucial role; DHA distinguishes four types of contexts: the socio-political/historical context, the current context (e.g. a specific event), the co-text (e.g. a specific text) and the intertextual and interdiscursive relations (Wodak, 2009: 38; 2015). In this regard, Wodak makes a distinction between discourse and text arguing that a text is the specific realisation of a discourse (Wodak, 2009: 39). Intertextuality and interdiscursivity indicate the connection among texts and discourses through time (especially in the past and in the present) and space (Wodak, 2015: 75). For what concerns intertextuality, Wodak (2009) suggests that there are several types of connections between texts. For instance, a link can be established often mentioning the same topic, referring to the same events already mentioned in other texts or through the process of recontextualization (Wodak, 2009: 39). As already mentioned in the previous section, recontextualization consists in the decontextualization of an argument and in its introduction in another context where it assumes a new meaning (Wodak, 2009: 39). Even for what concerns interdiscursivity, there are different ways to connect discourses – with the same topic – to each other such as the employment of (sub-)topics present in other discourses or the employment of new sub-topics that can be always formed because of the hybrid nature of discourse (Wodak, 2009: 40) that favours the creation of new *fields of action* which are defined by Wodak (2009) as segments of the respective societal 'reality' (Wodak, 2001b; 2009). Indeed, the fields of action are involved in the process of building and shaping discourse's 'frame' (Wodak, 2001b:

66–68; 2009: 40–41) since discourses (and texts) can easily shift – through the process of intertextuality and interdiscursivity – from one field to another (Wodak, 2001b: 67–68).

# 2.3 Corpus Linguistics

Corpus Linguistics (CL) is described as *the study of real language in use* (McEnery and Wilson, 2001: 1) that is supported by the employment of computers (Baker and McEnery, 2015: 1). Specifically, CL studies language empirically (Biber and Reppen, 2015: 1) using bodies of texts (corpora) encoded electronically and adopting a quantitative methodology (Baker, 2006: 1). Even though there have been many debates about the status of Corpus Linguistics as a theory (Tognini-Bonelli, 2001: 1), it has been depicted mainly as a methodology (Baker and McEnery, 2015: 1) that can be integrated with other disciplines in the field of study of linguistics (McEnery and Wilson, 2001: 2).

Corpora are collections of texts used to carry out linguistic analysis (McEnery and Wilson, 2001: 29; Tognini-Bonelli, 2001: 2). There are several types of corpora since the body of texts is coherent to specific research questions (Baker, 2006: 26). For instance, reference corpora (Baker, 2014: 213) aim to be representative of a language variety (Tognini-Bonelli, 2001: 2; Baker, 2006: 30) that occurs naturally (Baker, 2006: 2) and, for this reason, they are generally large (Baker, 2006: 2). There are also specialised corpora that are usually smaller because their purpose is to focus on language in specific genres or in specific language varieties (Baker, 2006: 26; 2014: 213). In addition, there is a rich variety of types of corpora such as diachronic corpora that investigate a language in a particular timespan (Baker, 2006: 29) or learner corpora that are particularly useful in teaching since they highlight common patterns in student's writing (Tognini-Bonelli, 2001: 9). Corpora are encoded electronically to carry out quantitative analyses based mainly on frequency (Baker, 2006: 2) through specific software tools capable of identifying and highlighting linguistics behaviours (Baker, 2014: 213) and patterns (Baker, 2006: 2). Moreover, corpora are usually annotated – automatically by the software (Baker and McEnery, 2015: 1) – with further linguistic information (McEnery and Wilson, 2001: 32) such as part of speech (e.g. verbs, nouns etc.) to facilitate extensive grammatical analyses (Baker, 2006: 2).

Corpus Linguistic analyses are carried out through specific tools based on frequency and salience (Baker, 2006). More precisely, the most important tools are keywords, concordances and collocates<sup>6</sup> (Sinclair, 1991; Baker, 2006; Culpeper and Demmen, 2015; Xiao,

<sup>&</sup>lt;sup>6</sup> See chapter, 3 section 3.1.1.

2015). However, some software provides additional tools as well. For instance, Sketch Engine (Kilgarriff *et al.*, 2014) provides *Word Sketch* and *Words Sketch Difference*. The first tool gives a detailed analysis of words' employment, while the second one highlights the differences between two lemmas and their different use in a given corpus.

Corpus studies can follow a corpus-driven or a corpus-based approach (Tognini-Bonelli, 2001). The corpus-driven approach focuses just on the evidence provided by the corpus without any reference to previous theories or assumptions made by the researchers (Tognini-Bonelli, 2001: 84). On the other hand, the corpus-based approach indicates a methodological approach that takes advantage of corpora – as a source of examples (Baker, 2006: 16) – in order to support language theories (Tognini-Bonelli, 2001: 68). Even though Tognini-Bonelli (2001) suggests that this approach was used mainly when large corpora were not available (Tognini-Bonelli, 2001: 68), corpus-based studies are still used by scholars in order to investigate and verify quantitatively linguistic hypothesis.

Although in the past Corpus Linguistics was mainly a quantitative approach – that relied solely on computer software – focused just on specific techniques such as keywords and collocates (Baker and McEnery, 2015: 2), it has evolved during the following years. Nowadays CL has undergone a qualitative turn (Tognini-Bonelli, 2010: 17–18) since quantitative results need an interpretation (Baker and McEnery, 2015: 2) through qualitative analytical techniques (Biber and Reppen, 2015: 1).

CL has been used in many linguistic areas of study such as the creation of dictionaries, the interpretation of literary texts, language teaching and learning, language description, translation studies, sociolinguistics and forensic linguistics (Baker, 2006: 2-3; McCarthy and O'Keeffe, 2010: 7). Moreover, Baker (2006: 15-16) highlights the importance of triangulation in this field of study. Indeed, starting from the mid-2000s Corpus Linguistics approach has been integrated more often with Discourse Studies (McCarthy and O'Keeffe, 2010: 9; Baker and McEnery, 2015: 3–4/6–7) – especially with the Critical Discourse Analysis approach (Baker, 2014: 213) – developing a 'special synergy' (Baker et al., 2008: 274; Baker and McEnery, 2015: 6).

# 2.4 Corpus-Assisted Discourse Studies

Corpus-Assisted Discourse Studies combine (Critical) Discourse Analysis and Corpus Linguistics techniques (Baker *et al.*, 2008). There are two main related approaches in this field

of study: Corpus-Assisted Critical Discourse Analysis and Corpus-Assisted Discourse Studies (CADS).

On the one hand Baker *et al.* (2008) focus on Corpus-Assisted Critical Discourse Analysis that is highly influenced by the Discourse-Historical Approach (Baker, 2014: 213); Baker *et al.* (2008: 295) propose a model, formed by nine stages, that involves different levels of analysis (e.g. context-based analysis, corpus analysis of frequencies, analysis of intertextuality or interdiscursivity etc.) in order to develop and investigate hypotheses (Baker, 2014: 213). More precisely, Baker *et al.* (2008) claim – during their RAS project (Discourses of Refugees and Asylum Seekers in the UK Press 1996–2006) – that, in Corpus-Assisted Critical Discourse Analysis, CDA and CL form a methodological synergy since they equally give their contribution in spite of their differences (Baker *et al.*, 2008: 274). CL highlights quantitatively specific linguistic patterns while CDA – taking into consideration the social, political, historical, and cultural context – can reveal why those linguistic patterns were or were not found in the corpora (Baker *et al.*, 2008: 293); indeed, one of the most common criticism made to CL is that its methodology does not entirely include a proper identification of what is missing (Partington and Marchi, 2015: 224).

On the other hand, Partington (Partington, Duguid and Taylor, 2013) has developed the approach of Corpus-Assisted Discourse Studies (CADS) that distinguishes itself – from the previous approach, influenced by DHA, that allows researchers to take an explicit position during the analysis (Baker, 2014: 213) – as it takes a less ideological and more objective perspective (Baker, 2014: 213). CADS has a less critical approach (Baker and McEnery, 2015: 7) because it not bound to Critical Discourse Analysis nor to any other Discourse Analysis approach (Partington, Duguid and Taylor, 2013: 10). Partington, Duguid and Taylor (2013) define Corpus-Assisted Discourse Studies as a sub-category of Corpus Linguistics, a "set of studies into the form and/or function of language as communicative discourse which incorporate the use of computerised corpora in their analyses" (Partington, Duguid and Taylor, 2013: 10). According to Partington (2006), CADS is an interdisciplinary field of study (Partington, 2006: 3) that has a polyhedric approach since it combines quantitative and statistical tools - typically associated with Corpus Linguistics - in the study of discourse (Partington, 2006: 4; Partington, Duguid and Taylor, 2013: 10). Indeed, the main aim of CADS is to expose those linguistic patterns – what Partington calls *non-obvious meaning* – that are not visible without the help of corpus techniques (Partington, Duguid and Taylor, 2013: 11). Moreover, Partington, Duguid and Taylor (2013) suggest that CADS distinguishes itself from traditional Corpus Linguistics because researchers always engage and familiarise with their

corpora (Partington, Duguid and Taylor, 2013: 12) though the combination of CL tools with Discourse Studies qualitative methods (Partington, 2006: 4). In addition, CADS is characterised by the analysis of specialised corpora, the diachronic analysis of corpora, and its comparative nature since the only way to discover and expose specific discursive patterns is comparing them to other ones (Partington, Duguid and Taylor, 2013: 12–13). In this regard, we should highlight that the comparative nature of CADS is quite broad. For instance, CADS can be engaged with discourse type comparison (Partington and Marchi, 2015) and even in cross-linguistic analyses, that take the label of cross-linguistic corpus-assisted discourse studies (Taylor, 2014).

Even though CADS is not necessarily tied to CDA, their combined approach is a successful union of quantitative and qualitative tools that integrate each other (Partington, 2006: 3–4). Furthermore, as Taylor (2013) suggests, this combined approach can have two starting points. In the first case, the analysis could start from the examination of the corpus through the employment of a software (Taylor, 2013: 85). The second option is to previously establish a discourse-analytical frame and then move on to the collection of data – through the corpus – that will be categorised and understood in the light of that frame (Taylor, 2013: 85).

# 2.5 Systemic Functional Grammar

Systemic Functional Grammar (SFG) belongs to the field of Systemic Functional Linguistics (SFL) – an approach developed by Halliday (2009a) – and aims to establish what are the linguistic structures that are involved in the construction of meaning (Webster, 2009: 7).

According to Halliday (2009a), language is a *semiotic system* – based on grammar (Webster, 2009: 5) – deeply influenced by physical, physiological and social-semiotic factors (Halliday, 2009a). Firstly, the system is *linguistic* because language is the object of investigation (Halliday, 2009b: 59). For this reason, SFL can be defined as an open and dynamic system that reflects and adapts to language and its changes (Matthiessen, 2009: 12). Secondly, language is a *semogenic* system since it is capable to create meaning (Halliday, 2009b: 60). Halliday (2009b) claims that language involves both "the potential to mean and the act of meaning" (Halliday, 2009b: 60). Indeed, Halliday (2009a) highlights the social dimension of language – that it is strictly connected to the concept of *language in use* – since he focuses on how human beings employ language to build the world around them and perform social relationships (Webster, 2009: 1). More precisely, Halliday investigates the social functions of language defining social actors and their ideologies (Fowler, 1991: 4). SFL can be adapted and integrated with different fields of study and approaches such as Corpus Linguistics

(Matthiessen, 2009: 21), corpus-based research (Wu, 2009), Discourse Studies, and particularly Critical Discourse Analysis since they both focus on social semiotics (Matthiessen, 2009: 20), and because SFL is highly adaptable to multimodal approaches (Martin, 2009: 164). Both SLF and CDA see language as a social construct that is deeply influenced by contexts; and they have a particular focus on how history and culture can affect meaning (Young and Harrison, 2004: 1).

Halliday points out, through Systemic Functional Grammar, that in every language grammar is a system of choices (Machin and Mayr, 2012: 104). For this reason, people select the better options based on specific social circumstances (Machin and Mayr, 2012: 104). According to Halliday (2014) grammar is formed by three main metafunctions to which all the above-mentioned options belong (Thompson, 2013: 30). Firstly, the experiential or ideational metafunction is employed to talk about the world (Webster, 2009: 5–6; Fairclough, 2010: 92; Thompson, 2013: 30). Secondly, the interpersonal metafunction is used to interact with other people (Webster, 2009: 5–6; Fairclough, 2010: 92; Thompson, 2013: 30). Thirdly, the textual metafunction organises language in specific contexts (Webster, 2009: 5–6; Thompson, 2013: 30).

SFG can be easily integrated with Discourse Analysis and Critical Discourse Analysis (Bhatia, Flowerdew and Jones, 2008: 2–3; Thompson, 2013: 264–265) since not only does it aim to describe language but also to evaluate it (Thompson, 2013: 265). Moreover, SFG is particularly useful concerning the analysis of transitivity (see section 3.2.1.4) that investigates how people are described in the act of doing or not doing something (Machin and Mayr, 2012: 104). Consequently, transitivity is not limited to the description of the verb and its object but it aims to define the whole clause (Thompson, 2013: 94). The starting point is to identify the verbal group that is called process (e.g. material, verbal, mental process etc.) because it will establish what kind of doer (e.g. actor, goal, sayer, receiver, senser etc.) is present in the clause (Thompson, 2013: 94).

# 2.6 Political Discourse Analysis

Although Political Discourse Analysis (PDA) could be perceived as an ambiguous concept – since it is difficult to establish if a discourse is political or not – (van Dijk, 1997d: 11; Randour, Perrez and Reuchamps, 2020), PDA can be defined in a straightforward way as the analysis of discourses produced and delivered by politicians (van Dijk, 1997d: 12). We should mention that political discourse can be produced by other social actors as well, such as citizens involved

in political activities (van Dijk, 1997d: 13). For this reason, context is another crucial defining characteristic of political discourse because it is often produced during specific events such as election campaigns, rallies, parliamentary sessions, and protest demonstrations (van Dijk, 1997d: 14). According to this perspective, a discourse is defined *political* when it is possible to identify a political actor that produces a discourse with a political scope in an institutional context (Randour, Perrez and Reuchamps, 2020). Moreover, van Dijk (1997d) suggests that it is possible to identify political discourse through specific discourse structures – that are politically contextualised since they can have multiple functions adapting to different contexts (van Dijk, 1997d: 24) – such as topics (that will be mainly political because political discourse is highly self-referential), textual schemata (the schematic structure of a specific genre), local semantics and lexicon (that are linked to the realisation of specific strategies such as presupposition, entailment, polarisation etc.), syntax, rhetoric and speech acts (van Dijk, 1997d: 25–37).

According to van Dijk (1997d):

PDA is both about political discourse, and it is also a critical enterprise. In the spirit of contemporary approaches in CDA this would mean that critical-political discourse analysis deals especially with the reproduction of political power, power abuse or domination through political discourse, including the various forms of resistance or counter-power against such forms of discursive dominance. (van Dijk, 1997d: 11)

From a *critical* perspective, PDA is deeply embedded with power and hegemony since the exploitation of political power contributes to the perpetuation of the status quo (Wodak, 2009). Indeed, PDA is particularly relevant not only because discourse is seen as a form of political action (van Dijk, 1997d: 20) but also because the political process involves discursive practices (van Dijk, 1997d: 37).

Fairclough and Fairclough (2012) – who share van Dijk's (1997d) approach to political discourse and PDA – propose an approach to PDA that combines CDA with argumentation theory since they describe political discourse as an argumentative type of discourse (Fairclough and Fairclough, 2012: 17). Their approach privileges political action focusing on deliberation and decision-making in contrast to the following approaches that focus mainly on the analysis of representation (Fairclough and Fairclough, 2012: 17).

On the other hand, Wodak presents an approach (see section 2.2.1) to PDA primarily oriented towards the representation of political discourse but it also looks at argumentation through the employment of *topoi* (see section 3.2.1.2) that she describes as argumentative strategies (Wodak, 2009: 41). Specifically, Wodak (2009) proposes a multi-level approach that investigates political communication in its historical, socio-political and organizational

contexts, with a particular focus on the ideological representations that are hidden in political discourse (Wodak, 2009: 1). The notions of *fields of action* – already mentioned in section 2.2.1 – are particularly helpful in identifying the fields that define political discourse as a social practice (Wodak, 2009). More precisely, Wodak (2009) and Reisigl (2008) break up political discourse in different fields – such as law-making procedures, political advertising, political control etc. (Wodak, 2009: 41; Reisigl, 2008: 248) – where political discourse topics can easily shift in these fields through the process of intertextuality and interdiscursivity (Wodak, 2001b: 67–68).

A different approach to political discourse is Chilton's cognitive and evolutionary perspective (Chilton, 2004: 16). Chilton provides a twofold definition of politics. The first one describes politics as a struggle for power, while the second one presents politics as cooperation, in order to balance the clashes of interest present in society (Chilton, 2004: 3). Furthermore, he distinguishes between the micro (e.g. conflicts of interest, struggles for dominance, cooperation between various types of social groups etc.) and the macro dimension of power, involving the political institutions and their enactment of power (Chilton, 2004: 4). Concerning the relationship between language and politics, Chilton understands political action as language action through the employment of speech acts (Chilton, 2004: 30). In addition, he highlights the human capability of producing detached representations of things since human beings can both represent and meta-represent things (Chilton, 2004: 18). Indeed, the representation process is crucial for political actors who seek to legitimise their political discourse (Chilton, 2004: 23). Starting from Grice's maxims and Habermas' validity claims, Chilton illustrates a seminal classification of strategies used in political discourse such as coercion, legitimisation and delegitimisation, representation and misrepresentation (Chilton, 2004: 45-46). More precisely, representation involves the employment of frames (also known as schemata or conceptual models), metaphors and discourse worlds, that is coherent chains of propositions used by the speaker to meta-represent the reality (Chilton, 2004: 51-56). Moreover, Chilton describes strategies that convey meaning implicitly such as entailment and presupposition (Chilton, 2004: 61–64). Lastly, he focuses on indexicality and deixis that involve the cognitive positioning of social actors during the production and delivery of political discourse (Chilton, 2004: 56). Specifically, Chilton proposes a schematic representation of deixis that is formed by the deictic centre (where the actors are positioned) and three axes: space, time and modality (Chilton, 2004: 58; 2014: 30). The deictic dimension is particularly relevant in the conceptualisation of the perceived political discourse and, consequently, in the building of related mental representations (Chilton, 2004: 61).

Building on Chilton's deictic space theory, Cap (2010; 2013) has developed the proximization theory. More precisely, Cap (2010; 2013; 2014) defines proximization as a discursive strategy employed to depict temporally and physically distant events as imminent and dangerous in order to legitimise specific political actions (Cap, 2013: 3). Cap further investigates the three dimensions already identified by Chilton (2004) in terms of proximization (Cap, 2013: 74–99). However, Cap (2013) relies on the Spatial-Temporal-Axiological model of proximization (STA model). Specifically, the axiological proximization involves the representation of the ideological conflict between the values held by who is inside (us) and who is outside (the other) the deictic centre (Cap, 2013: 94).

# **CHAPTER 3**

## DATA AND METHODOLOGY

The first part of this chapter (section 3.1) is dedicated to data collection and their organisation into corpora. The second part (section 3.2) focuses on the combined approach (CDA and CL) that I used to analyse the data. Specifically, I focused my attention on Critical Discourse Analysis tools – such as metaphors, *topoi*, representational strategies and transitivity – and on Corpus Linguistics tools (e.g. keywords, concordances and collocations) used to carry out the analysis. Finally, the last part of this chapter (section 3.3) is dedicated to the research questions.

# 3.1 Corpora Building

The data collected for this analysis were organised into four corpora: two corpora are dedicated to tweets and the other two are dedicated to traditional speeches.

The timespan taken into consideration for the collection of Donald Trump's data goes from the 1<sup>st</sup> September 2016 to the 31<sup>st</sup> July 2017. The tweets were collected on the website Trump Twitter Archive (https://www.thetrumparchive.com/), while the traditional speeches were collected on the website The American Presidency **Project** (https://www.presidency.ucsb.edu/). The Trump Tweet Corpus counts 2,253 tweets, 39,901 words and 49,694 tokens. The Trump Traditional Corpus counts 10 traditional speeches, 32,628 words and 39,075 tokens. In order to analyse qualitatively the Trump Tweet Corpus, I built a sub-corpus of 50 tweets collected through the keywords Europe, E.U., west, border, immigration, immigrant/s, refugee/s and Mexico. During the selection of Trump's tweets regarding Europe, I also used the name of every European capital, the name of each Prime Minister, and the name of every European nation as keywords. Some keywords were not found in Trump Tweet Corpus. For instance, Germany, France, U.K./United Kingdom and Poland are the only keywords – among the ones used to look for European nations – that were found in the corpus. Furthermore, I used other keywords in order to have a wider and clearer picture of Trump's approach towards immigration, Europe, and foreign relations. The additional keywords are ISIS, security, travel ban and China.

Matteo Salvini's data were collected during the timespan that goes from the 1<sup>st</sup> January 2018 to the 31<sup>st</sup> October 2018. The tweets were selected through a Google Chrome tool called

Data Miner (https://dataminer.io/) on Matteo Salvini's official Twitter account @matteosalvinimi (https://twitter.com/matteosalvinimi). Regarding the traditional speeches, I did not find an Italian resource similar to The American Presidency Project. For this reason, I collected 10 videos of Matteo Salvini's speeches on his official Facebook page (https://www.facebook.com/salviniofficial) and I transcribed them. The Aquarius Senate Report is the only speech that I found already transcribed on the Italian Senate webpage (https://www.senato.it/home). The Salvini Tweet Corpus counts 1,597 tweets, 46,283 words and 59,112 tokens; while the Salvini Traditional Corpus counts 10 traditional speeches 37,987 words and 43,631 tokens. Even in this case, I created a Tweet sub-corpus – for the qualitative part of the analysis – that counts 50 tweets collected through the keywords *immigrazione* (immigration), *immigrato/i* (immigrant/s) and *Europa* (Europe).

To sum up, all the data were organised into four corpora and two sub-corpora:

- 1. Trump Tweet Corpus (2,253 tweets and 49,694 tokens) Trump Tweet Sub-Corpus (50 tweets)
- 2. Trump Traditional Corpus (10 speeches and 39,075 tokens)
- 3. Salvini Tweet Corpus (1,597 tweets and 59,112 tokens) Salvini Tweet Sub-Corpus (50 tweets)
- 4. Salvini Traditional Corpus (10 speeches and 43,631 tokens)

It is important to specify that all the tweets and the traditional speeches were transformed in .txt files and were tagged through the text editor TextPad before their upload on the software Sketch Engine (Kilgarriff *et al.*, 2014). Tweets were tagged encoding information concerning the author, the date, the retweets, the likes, and the tweet URL; the traditional speeches were tagged paying particular attention to the speaker (and turn-takings), the date, the place and the title of the speech.

Moreover, the two timespans taken into consideration do not cover the same span. This difference arises from the need to have two timespans that were as comparable as possible since this work aimed to compare discourses delivered in the same (political) context. More precisely, this comparative study analysed the populist discourses of Donald Trump and Matteo Salvini during the last three months of electoral campaign and the following seven months of government (the timespans include the transition periods as well).

# 3.2 Methodology

The analysis was carried out through a combination of qualitative and quantitative approaches. Specifically, I started to analyse the data with the Critical Discourse Analysis approach and then I continued the analysis with the Corpus Linguistics approach in order to compare the qualitative and the quantitative results. The reason why I decided to use this combined approach is to take advantage of the strong points of both approaches; indeed, CDA and CL can complement and integrate each other. The Critical Discourse Analysis approach has been criticised for the lack of quantitative and comparative tools (Machin and Mayr, 2012: 215) and the possible presence of cognitive biases (Baker, 2006: 11). At the same time, the Corpus Linguistics approach lacks a qualitative interpretation of the data that inevitably led to a qualitative turn (Tognini-Bonelli, 2010: 17–18; Baker and McEnery, 2015: 2). As a result, CL provides to CDA a quantitative and – almost – objective feedback for its qualitative hypothesis (Baker, 2006: 12; Machin and Mayr, 2012: 216), while CDA provides to CL qualitative tools for the interpretation of large amounts of data (Baker, 2006: 19). The combination of quantitative and quantitative approaches goes under the label of Corpus-Assisted Discourse Studies (CADS) (Partington, Duguid and Taylor, 2013).

#### 3.2.1 UAM Corpus Tool

The qualitative part of the analysis was carried out through the software UAM Corpus Tool<sup>7</sup> (O'Donnell, 2008) where I uploaded the two Tweet Sub-Corpora (for a total of 100 tweets), the Trump Traditional Corpus and the Salvini Traditional Corpus.

UAM Corpus Tool allowed me to manually annotate the data (that were uploaded as .txt files) and to calculate the percentages of the qualitative results. Therefore, this tool was particularly helpful during the comparative part of the analysis since it was possible to compare Trump's and Salvini's results (including the different percentages of tweets and traditional speeches).

It is necessary to highlight that although immigrants and refugees have two different legal statuses, in the following sections – but also during the quantitative part of the analysis – they were considered as one category because the distinction between immigrants and refugees is often ambiguous and blurred (Baker *et al.*, 2008).

During the qualitative part of the analysis I focused my attention of four main aspects: metaphors, *topoi*, representational strategies and transitivity.

## **3.2.1.1** *Metaphors*

Metaphors are deeply embedded in our everyday language since we use them continuously and unconsciously to organise our experiences (Lakoff and Johnson, 1980). According to Chilton

It is a software that allows users to annotate texts through the creation of layers.

(2004), metaphorical expressions are highly involved in the human cognitive process of shaping and understanding the world because they are a source of conceptualisation (Chilton 2004: 51).

The analysis of metaphors was carried out following Lakoff and Johnson's (1980) approach regarding conceptual metaphors. According to Lakoff and Johnson (1980), metaphors are the result of a conceptual process that involves a target domain and a source domain. On the one hand, the target domain is the concept that we want to represent through the metaphor. On the other hand, the source domain is the concept that we employ to actually create the metaphor.

Furthermore, metaphors have always been considered as crucial elements in political rhetoric (Chilton 2004: 51) – especially in terms of persuasion (Machin and Mayr, 2012: 163) – because they can be extremely powerful and effective in political discourse (Musolff, 2004; 2016; Charteris-Black, 2011).

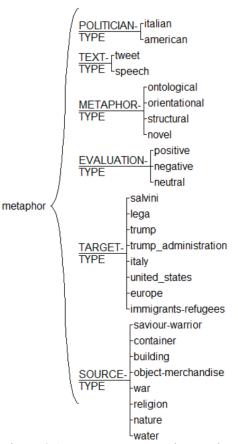


Figure 3.1 UAM Corpus Tool metaphor layer

On UAM Corpus Tool I created a layer that allowed me to annotate the metaphor type (ontological, orientational, structural and novel), the metaphor evaluation (positive, negative, and neutral), the target and the source domains. As it is possible to see in Figure 3.1 the layer also includes the text type and the politician type. This distinction is present in every layer since it allowed me to compare tweets and traditional speeches, and the qualitative results of Trump

and Salvini. In addition to the metaphor type and the evaluation type, it is important to focus on the target and the source domains. The target domains selected for the metaphor analysis are Matteo Salvini and his party, Donald Trump and his administration, Italy, the United States, Europe, immigrants and refugees. On the other hand, the source domains on which I focused on during the analysis are *saviour and warrior*, *container*, *building*, *object and merchandise*, *war*, *religion*, *nature* and *water*. The selection of these source domains – that was influenced by the investigation of the target domains from a populist perspective – tries to provide – thought the linguistic analysis – a clear picture of the metaphorical representation of social actors in Trump's and Salvini's discourses.

# 3.2.1.2 Topoi

During the analysis of *topoi* I followed Wodak's approach (2015). Ruth Wodak theorises *topoi* in her Discourse Historical Approach (DHA) (Wodak, 2001b; see also section 2.2.1) and defines *topoi* as *content-related warrants* or *conclusion rules* that connect an argument to a conclusion and at the same time justify this connection (Wodak, 2009: 42; 2015: 76). For this reason, *topoi* can be defined also as argumentative (Rubinelli, 2009) and persuasive (Wodak, 2009: 30) strategies that are particularly helpful in the strategical (and often negative) representation of social actors since they facilitate the production and the legitimisation of some statements (e.g. the dangerousness of immigrants and refugees). Moreover, *topoi* are always context-related because they are strictly connected to *past collective experiences* and *commonsense narratives* (Wodak, 2015: 62). According to Wodak the nature of *topoi* can be often *fallacious* and *manipulative* since they are *shortcuts* – based on collective knowledge – usually used in very complex contexts (Wodak, 2015: 77).

We should also mention that *topoi* actually come from classical argumentation theory; specifically, from Aristotle and Cicero's works (Žagar, 2010). For instance, Aristotle describes *topoi* as the places where we can look for arguments (Žagar, 2010, 13). The philosopher distinguished two main types of *topoi*: general (or common) and specific. This distinction involves context and rhetoric genres; indeed, general *topoi* can be used in every situation (regardless of context) while the employment of specific *topoi* is tied to judicial, deliberative, and epideictic genres (Žagar, 2010, 13–14).

Even though Wodak has provided a list of the most common types of *topoi* (Wodak, 2001b: 74; Wodak, 2009: 44), it is still difficult to create a unique and full list upon which scholars can agree (Bartley and Hidalgo-Tenorio, 2016: 6). For this reason, I decided to use some of the categories provided by Wodak (e.g. DTF, burden etc.) and other ones (that are not included in her list) in order to facilitate my analysis.

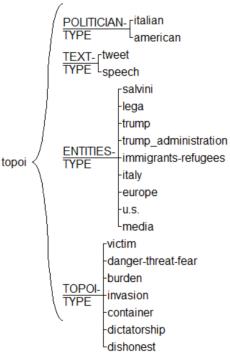


Figure 3.2 UAM Corpus Tool topoi layer

The UAM Corpus Tool layer – that I created to analyse *topoi* – includes just the entities type and the *topoi* type. The entities type selected for the analysis are Matteo Salvini and his party, Donald Trump and his administration, immigrants and refugees, Italy, Europe, the United States, and the media. The *topoi* that I took into consideration during the analysis are the *victim*, *danger*, *threat and fear (DTF)*, *burden*, *invasion* (sub-category of the DTF *topos*), *container*, *dictatorship*, and *dishonest*. The *topoi* of danger, threat and fear can be used separately but I decided to join them in one category because they often overlap. The selection of *topoi* tries to provide a full and variegated framework for the linguistic analysis of social actors' representation. Similarly to source domains, even the selection of *topoi* was influenced by the investigation of the entities type from a populist perspective. For this reason, almost all *topoi* imply the need of social actors' (e.g. the people) protection of from otherness (e.g. immigrants).

Finally, it is important to highlight that metaphors and *topoi* are strictly connected since metaphors' source domains and *topoi* often coincide and reinforce each other. *Topoi* are also connected to some of the representational strategies used to analyse the data.

# 3.2.1.3 Representational Strategies

The analysis of the representation of social actors was carried out following van Leeuwen's approach (1995; 1996; 2008) as he provides a seminal classification based upon a sociosemantic perspective (van Leeuwen, 2008: 23). First of all, van Leeuwen makes a distinction between inclusionary (e.g. specification) and exclusionary (e.g. suppression) representational strategies. Indeed, the main aim of these strategies is to include or exclude social actors (van

Leeuwen, 2008: 28). Van Leeuwen's classification is very detailed; for this reason, I decided to take into consideration just the categories best suited for this analysis (such as genericisation, specification, suppression and aggregation). In addition to van Leeuwen's approach, I also followed van Dijk's approach regarding the processes of legitimisation and delegitimisation (van Dijk, 1998).

The UAM Corpus Tool layer (Figure 3.3) dedicated to representational strategies involves the entities type, the representational strategies type and the agency type. The entities type taken into consideration are immigrants and refugees, Europe and Mexico. The aim of this part of the analysis is to understand how Donald Trump represents the U.S. foreign relationships (with particular attention to Europe and Mexico), how Matteo Salvini represents the European Union through his Eurosceptic discourse, and how both politicians represent immigrants and refugees.

The types of representational strategies –following van Leeuwen's approach (2008) – taken into consideration especially for the description of immigrants and refugees are aggregation, genericisation, specification and suppression. I also considered other strategies such as the association to crime and terrorism – that can be either explicit or implicit – for Mexico, immigrants and refugees. The representation of Europe was analysed through the categories of dictatorship – that can be general, financial or linked to immigration policies – and absent and useless institution. Moreover, these two strategies are strictly connected to some of the topoi previously mentioned such as danger, threat and fear, and dictatorship.

The opposition strategy is based upon the opposition between two social groups that involves a positive self-representation (us) and a negative representation of the otherness (them) (van Dijk, 1998; Oktar, 2001; Eriksson and Aronsson, 2005). Furthermore, in the layer (Figure 3.3) I included three different sub-types of opposition strategy: the cultural and religious opposition, the opposition strategy that opposes two suffering groups of people, and the opposition between the current immigration (in Italy) and Italian immigration (in other countries).

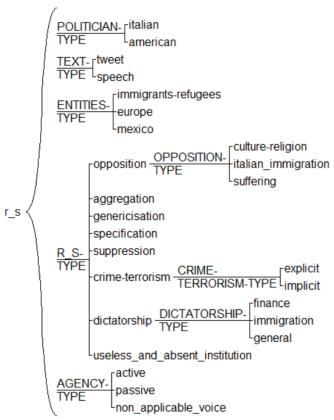


Figure 3.3 UAM Corpus Tool representational strategies layer

Finally, I decided to focus on the agency of the social actors. Specifically, I chose to include three different possibilities: active, passive or non-applicable voice. This particular aspect was further scrutinised with the analysis of transitivity.

### 3.2.1.4 Transitivity

The last main aspect of the qualitative analysis is transitivity. I decided to look at transitivity because it can be helpful to understand better how social actors are represented. Indeed, transitivity can influence the representation of social actors as passive or active entities. From a methodological perspective, I followed Halliday's Systemic Functional Grammar approach (Halliday, 2014) (see section 2.5).

In this case, I could not include the entire figure of the UAM Corpus Tool layer since it is too detailed. For this reason, I decided to show the layer divided into four figures and to provide a synthetic list of the categories present in the layer:

- 1. Process type
- 2. Polarity
- 3. Modality
- 4. Congruency
- 5. Voice type
- 6. Participant class type
- 7. Participant type
- 8. Evaluation

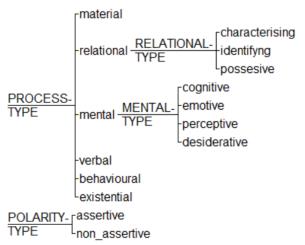


Figure 3.4 UAM Corpus Tool transitivity layer: processes and polarity

Figure 3.4 shows the processes and the polarity type. The category of process type involves material, mental, verbal, relational, behavioural and existential processes. Moreover, the mental and relational processes include sub-categories. On the other hand, polarity can be assertive or non-assertive.

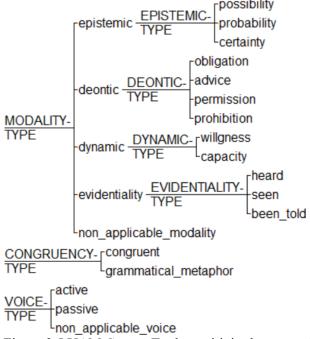


Figure 3.5 UAM Corpus Tool transitivity layer: modality, congruency and voice type

As shown in Figure 3.5, modality can be deontic, dynamic and evidential. Furthermore, I added – among the modality types – the possibility of non-applicable modality. Each type of modality has also its sub-categories. In addition, Figure 3.5 shows that the layer includes the congruency and the voice types.

```
PARTICIPANT-
CLASS-TYPE

-we_lega
-we_italians
-italy
-trump
-we_administration
-we_u.s.
-u.s.
-europe
-immigrants-refugees
```

Figure 3.6 UAM Corpus Tool transitivity layer: participant class type

Figure 3.6 shows what are the social actors (participant classes) taken into consideration for the analysis of transitivity (e.g. Donald Trump, Matteo Salvini, immigrants and refugees etc.). Indeed, as already mentioned, I decided to look at transitivity in order to understand if social actors are depicted as passive or active entities.

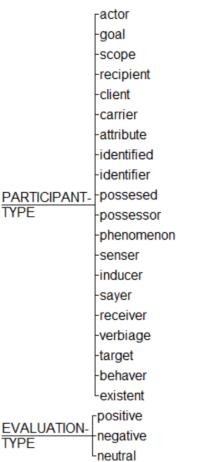


Figure 3.7 UAM Corpus Tool transitivity layer: participant and evaluation types

Finally, Figure 3.7 shows the evaluation type – that can be positive, negative, or neutral – and the long list of participant type that coincide with every type of process according to the systemic functional grammar analysis (Halliday, 2014) of clauses.

#### 3.2.2 Corpus Linguistics approach

The quantitative part of the analysis was carried out through the software Sketch Engine (Kilgarriff *et al.*, 2014) where I uploaded the four corpora. The analysis followed mainly a corpus-based approach (Tognini-Bonelli, 2001); therefore, the quantitative results were used to verify the results of the qualitative analysis. However, I did not completely omit the corpusdriven approach (Tognini-Bonelli, 2001) since I highlighted what are the quantitative patterns in contrast with the qualitative results. During the quantitative part of the analysis, I focused my attention on keywords, concordances and collocates.

### 3.2.2.1 Keywords

Keyness indicates the frequency of words in a given corpus – which is one of the most important factors in quantitative analysis – but also salience (Baker, 2006: 125); indeed, words' keyness is calculated through statistical tests comparing the focus corpus (e.g. the Trump Tweet Corpus) to a bigger reference corpus (e.g. English Web 2018). More precisely, Sketch Engine calculates keyness through the simple maths formula that works with normalised (per million) frequencies in the focus and reference corpora (Kilgarriff *et al.*, 2014).

In this analysis keywords were used to discover – from a quantitative perspective – what are the crucial topics in Trump and Salvini's discourses. The main aim was to highlight coherence or discrepancies in comparison to the qualitative results. Firstly, the analysis was carried out looking at keywords' position in the lists and their relative frequency. Secondly, keywords were categorised through concordance reading.

From a methodological perspective, it is important to mention the parameters that I used on Sketch Engine to select the keywords in each corpus. More precisely, I decided to set up 10 as the parameter for both the minimum frequency of keywords and to select the rare words inside the corpora. The Italian Web 2016 (itTenTen16) was used as the reference corpus for Salvini's corpora, while Trump's corpora were compared to the reference corpus English Web 2018 (enTenTen2018). Moreover, in this case, I had the possibility to select as reference subcorpus the US domain.

The lists of Donald Trump's single keywords count 356 items in his Tweet Corpus and 282 items in the Traditional one. On the other hand, the lists of Matteo Salvini's single keywords count 404 items in his Tweet Corpus and 352 items in his Traditional Corpus. I downloaded the lists as excel files, categorised each keyword, and then established 14 categories and 9 sub-categories (Table 3.1) in order to facilitate the analysis of keywords and their comparison with the qualitative results.

Subcategories
-
Invasion/Organised crime
Positive/Negative
-
Allies/Family
-
-
Fake
-
-
-
-
-
Us/Other

Table 3.1 Keywords categories and subcategories

Table 3.1 shows all the categories and sub-categories of keywords. As I have already mentioned, some of these categories were established in order to facilitate the comparison with the categories used for the qualitative analysis. Specifically, the categories of burden, danger, threat and fear (and the invasion sub-category), and victim are coherent with the topoi used during the qualitative part of the analysis on UAM Corpus Tool. The category of immigration was established in order to identify all the keywords that are generally connected to this topic. The *in group* category aimed to highlight the keywords connected to Donald Trump and his administration, Matteo Salvini and his party, their allies and family members. Italy and USA include all the keywords linked to these two countries and their citizens. The categories of law and order and security aimed to categorise those keywords connected to legal, institutional and security matters. The *opposition* category and its sub-category *fake* involve everything (such as media) and everyone who oppose to Trump and Salvini. The category of politics and economy clearly involves all the keywords about political and economic matters. The twitter category aimed to collect all those keywords that involve Twitter and its style of communication. Finally, I chose to include the evaluation and the other categories in order to categorise all the remaining keywords.

During the qualitative interpretation of keyword concordances, I noticed that some keywords were part of two or more categories simultaneously. For this reason, I created other four lists where I focused just on those keywords and I calculated the relative frequency of each keywords in each category. Moreover, in these lists I associated a specific shade of colour to each category in order to facilitate the process of categorisation.

#### 3.2.2.2 Concordances and collocates

In addition to keywords, during the analysis on Sketch Engine I relied on concordances and collocates which are other two important tools for the interpretation of the data. Baker defines concordances as:

[...] simply a list of all the occurrences of a particular search term in a corpus, presented within the context that they occur in; usually a few words to the left and right of the search term. A concordance is also sometimes referred to as key word in context or KWIC [...]. (Baker, 2006: 71)

Concordances represent a useful tool because they not only indicate the number of occurrences of a term in a corpus, but they also help us to understand how a specific term is used in context.

The concept of collocation is strictly connected to concordances; indeed, a collocate is a word that co-occurs regularly with another word (Baker, 2006: 95–96). However, we can identify the phenomenon of collocation just when the co-occurrence between two words is statistically relevant (Baker, 2006: 95–96).

The parameters used on Sketch Engine to calculate the collocates of specific terms were not particularly restrictive since the corpora used for this analysis are relatively small. Specifically, the parameter to calculate the minimum frequency in the corpora is 2, while 1 is the parameter that was set up for the minimum frequency in a given range (five words either side of the node). During the analysis collocates were statistically calculated through T-Score and MI3. On the one hand, T-Score shows with certainty that the co-occurrence between words is not random and its score is influenced by the frequency of the whole collocation (Kilgarriff *et al.*, 2014). On the other hand, the MI3 attributes higher scores to frequent words and lower scores to infrequent words through the cubing of frequencies (Oakes, 1998: 171–172).

The analyses of concordances and collocates were carried out to scrutinise specific terms in order to verify the results of the qualitative analysis. These two tools were also employed to analyse more in depth the keywords.

### 3.3 Research Questions

In light of the methodological premises, this study aims to answer to the following research questions:

- 1. Are there any similarities or differences between the Trump's and Salvini's populist discourse?
- 2. Are there any similarities or differences between these populist discourses on Twitter and on traditional speeches?

## **CHAPTER 4**

### **DONALD TRUMP**

This chapter is dedicated to the analysis of Donald Trump's discourse. The results are discussed and organised into six sections that correspond to the six macro-topics of the analysis (Donald Trump's in-group representations, the United States, the media, Europe, Mexico, immigrants and refugees). Each section begins with the qualitative part of the analysis – carried out through the software UAM Corpus Tool – that focuses on metaphors, *topoi*, representational strategies and transitivity. Some of these four categories can be missing in the following sections for two main reasons. Firstly, the qualitative analysis did not provide results. Secondly, a particular topic was investigated only through specific categories (see section 3.2.1). The second part of each section is dedicated to the quantitative analysis – carried out through the software Sketch Engine – that focuses on keywords, concordances and collocates. Specifically, the keyword lists are all categorised under established labels (see section 3.2.2.1). It is possible to observe the complete keyword lists in the Appendices A and B.

# 4.1 Donald Trump and Trump's administration

This section investigates Donald Trump's in-group representations, both his and his administration's.

### 4.1.1 Qualitative analysis

Trump's self-representation and the representation of his administration were qualitatively analysed through metaphors, *topoi* and transitivity.

### **4.1.1.1** *Metaphors*

Donald Trump employs just the saviour and warrior source domain; the Trump Tweet Corpus has just one occurrence and the Traditional one has 11, as shown in Table 4.1 below.

As it is possible to notice in the examples 1, 2, and 3 the saviour and warrior source domain allows Trump to depict himself as an outsider populist fighter who will save the United States and the American people. On the one hand, he aims to reassure his electorate talking about security and safety matters. On the other hand, he focuses on economic matters since he always emphasises his position as a successful businessman. Indeed, his main aim is to *Make America Great Again* especially from an economic perspective – promising an economic

revival – and from a geopolitical perspective assuring to regain U.S. hegemonic position (see examples 9, 11, and 19).

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
TTW <sup>8</sup>	$100\%^{9}(1)^{10}$	-	-	-	-	-	-	-
$TTS^{11}$	100% (11)	-	-	-	-	-	-	-

Table 4.1 Trump's source domains in Trump's corpora

- 1. Great day for America's future Security and Safety, courtesy of the U.S. Supreme Court. **I will keep <u>fighting</u>** for the American people, & WIN! [emphasis added] (Trump's Tweet 27 June 2017)
- 2. I will never back down from <u>fighting to save</u> American lives. I will never back down from <u>fighting to create</u> safety and wealth for our inner cities. [emphasis added] (Remarks at a Rally at the Mid-America Center in Council Bluffs Iowa 28 September 2016)

Regarding Trump's administration, metaphors were not found in the Trump Tweet Corpus. However, in the Trump Traditional Corpus there are 13 occurrences that – even in this case – belong to the saviour and warrior source domain.

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
TTW	-	-	-	-	-	-	-	-
TTS	100% (13)	-	-	-	-	-	-	-

Table 4.2 Trump's administration source domains in Trump's corpora

- 3. **We will <u>save</u>** American lives, <u>protect</u> American sovereignty, and **we will <u>ensure</u>** the forgotten men and women of our country are never forgotten again. [emphasis added] (Remarks at a "Celebrate Freedom" Rally 1 July 2017)
- 4. **We are going to <u>protect</u>** the integrity of the ballot box, and **we are going to <u>defend</u>** the votes of the American citizens. [emphasis added] (Remarks at the "Congress of Tomorrow" Republican Member Retreat in Philadelphia 26 January 2017)

It is important to mention that these 13 occurrences appear just in the timespan after Trump's election. As a result, he alternates his figure as the outsider and populist leader with a more institutional figure as president who works with his administration in order to achieve his goals. For this reason, examples 3 and 4 are very similar to examples 1 and 2. Nevertheless, we should notice that he uses the words *save*, *protect* and *defend* without the word *fight* when he talks about his administration because he probably aims to maintain his leading role as the powerful commander in chief able to fight alone as an outsider and to save his compatriots.

### 4.1.1.2 Transitivity

<sup>&</sup>lt;sup>8</sup> Trump Tweet Corpus.

<sup>9</sup> UAM Corpus Tool percentage.

Number of occurrences.

<sup>11</sup> Trump Traditional (speeches) Corpus.

The Trump Tweet Corpus counts 6 occurrences of processes, while in the Trump Traditional Corpus there are 703 occurrences. As it is possible to notice in Table 4.3 material processes have the highest percentages, especially in tweets. Moreover, in traditional speeches there is more heterogeneity than in tweets where there are just material and relational processes.

	Material	Relational	Mental	Verbal	Behavioural	Existential
TTW	67% (4)	33% (2)	-	-	-	-
TTS	38% (268)	10% (68)	14% (100)	37% (257)	1% (10)	-

Table 4.3 Trump's transitivity in Trump's corpora

- 5. Hillary Clinton is an insider fighting only for insiders. **I am** an outsider **fighting** for you. [emphasis added] (Remarks at a Rally at the Mid-America Center in Council Bluffs Iowa 28 September 2016)
- 6. We are here today to speak the truth, the whole truth, and nothing but the truth. **I hear** your demands, **I hear** your voices, and **I promise** you **I will deliver**. **I promise** that. [emphasis added] (Remarks at a "Make America Great Again" Rally in Melbourne 18 February 2017)

In example 5 it is possible to find a combination of material and relational processes (I *am* and *fighting*) in an extract of a traditional speech. Specifically, Trump describes himself once again as a warrior (and as a saviour) comparing himself to Clinton who is described and delegitimised as *an insider who fights for insiders*. Example 10 shows a combination of behavioural (*hear*), verbal (*promise*) and material processes (*deliver*). More precisely, Trump – in this last extract – presents himself as a leader who is close to the people, hears their needs, and will accomplish their requests.

Participant types <sup>12</sup>	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	37%	259	Senser	13%	93
Goal	2%	15	Inducer	1%	5
Recipient	1%	4	Sayer	35%	250
Carrier	6%	44	Receiver	1%	5
Identifier	1%	8	Target	1%	4
Possessor	1%	12	Behaver	1%	10

Table 4.4 Trump's participant types in Trump's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	98% (695)	1% (12)	1% (2)	-	-	-
Evaluation	_	_	-	52% (367)	3% (26)	45% (316)

Table 4.5 Trump's voice-type and evaluation-type in Trump's corpora

The self-representation of Trump as a commander in chief is supported by the high percentages of material processes. The participant type performed by Trump in processes is mainly the

The Table shows just the participant types performed by Trump. The empty categories – that is possible to observe in section 3.2.1.4 Figure 3.7 – have been omitted.

Actor (37%) and the Sayer (35%), while he is rarely the Goal  $(2\%)^{13}$ . The voice type of these processes is always active  $(98\%)^{14}$  with a positive evaluation  $(52\%)^{15}$ .

Trump's administration has just two occurrences of processes in the Trump Tweet Corpus and 422 occurrences in the traditional one. Even in this case material processes outnumber the other ones; moreover, they are the only type of processes present in tweets.

	Material	Relational	Mental	Verbal	Behavioural	Existential
TTW	100% (2)	-	-	-	-	-
TTS	84% (353)	9% (40)	5% (22)	2% (7)	-	-

Table 4.6 Trump's administration transitivity in Trump's corpora

- 7. Jobs are returning, illegal immigration is plummeting, law, order and justice are being restored. **We are truly making** America great again! [emphasis added] (Trump's Tweet 13 April 2017)
- 8. The story of America's men and women in uniform is the story of freedom and overcoming oppression, the strong protecting the weak, and the good defeating evil. There's a lot of evil out there, I want to tell you. There's a lot of evil. I was left a mess, the fact is. But we're cleaning it up. You watch. Cleaning it up. Cleaning it up. [emphasis added] (Remarks at a "Celebrate Freedom" Rally 1 July 2017)

Example 7 shows a tweet delivered by Trump during his presidency. This tweet contains a material processes (we are *making*) since the main aim of the tweet is a self-legitimisation of Trump and his administration that are keeping their electoral promises. The same circumstances can be found in example 8 – a traditional extract – where Trump – after a U.S. self-celebration – claims that his administration is *cleaning up* the mess left by the Obama administration.

Participant types	Percentage	Occurrence
Actor	82%	349
Goal	2%	8
Carrier	3%	12
Possessor	6%	27
Senser	5%	20
Sayer	1%	7
Receiver	1%	1

Table 4.7 Trump's administration participant-types in Trump's corpora

The representation of Trump's administration is strictly connected to Trump's self-representation. However, we should notice that when Trump talks about his administration he focuses mainly on achievements (e.g. example 7). As a result, the percentage of material process is higher; furthermore, the administration mainly performs the Actor (82%). In addition, the

UAM Corpus Tool percentages includes also other participant types (see Table 4.4 and section, 3.2.1.4).

Processes were categorised as active, passive or non-applicable voice (see Table 4.5 and section 3.2.1.4).

The evaluation of processes can be positive, negative or neutral (see Table 4.5 and section 3.2.1.4).

voice type of processes is always active (98%) with a positive evaluation  $(85\%)^{16}$  (e.g. example 7).

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	98% (421)	1% (1)	1% (2)	-	-	-
Evaluation	-	-	-	85% (359)	2% (9)	13% (57)

Table 4.8 Trump's administration voice-type and evaluation-type in Trump's corpora

### 4.1.2 Quantitative analysis

The quantitative part of the analysis involves the investigation of keywords, concordances and collocates. In this regard, further information about the selection of collocates should be mentioned. Firstly, the collocate lists show just the first 20 collocates – according to collocation scores – excluding articles, prepositions and punctuation. Secondly, the lists of collocates were calculated through specific parameters. On the one hand, the collocates of words with less than 50 occurrences in the corpora were calculated with 10 as the parameter for the minimum frequency in the corpus and 2 as the parameter for the minimum frequency in a given range. On the other hand, the collocates of words with more than 50 occurrences were determined with 10 as the parameter for the minimum frequency in the corpus and 5 as the parameter for the minimum frequency in a given range. Moreover, the following collocate lists are organised according to the MI3 score – that gives higher scores to frequent words and lower scores to infrequent words through the cubing of frequencies (see section 3.2.2.2) – (Oakes, 1998: 171-172). Finally, it is important to highlight that the reference corpus used for the selection of keywords is the English Web 2018 (enTenTen2018). Specifically, it was selected as reference sub-corpus the US domain.

### 4.1.2.1 Keywords in the Trump Tweet Corpus

The following keywords are those categorised under the label in group and they are the ones directly connected to Donald Trump. Indeed, all the keyword lists were created through their categorisation under specific label that it is possible to observe in section 3.2.2.1 while the complete keyword lists can be found in the Appendix A. As it is possible to notice from Table 4.9 these keywords involve Trump (*Trump*, *Donald*, *me*, *my*, *I*), his family (*Melania*), his political allies (*Pence*, *Mike* and *John*), his administration and political matters (*we*, *republican*, *campaign* and *administration*), and his supporters (*our* and *we*). Lastly, the keyword *judge* can be considered as being part of Trump's allies (see section 4.1.2.2).

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The evaluation of processes can be positive, negative or neutral (see section 3.2.1.4). In this specific case processes associated to Trump's administration have positive (85%), negative (2%) and neutral (13%) evaluation.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Trump	82.400	137	275.7	Mike	3.620	14	28.2
Melania	53.200	26	52.3	John	2.490	13	26.2
Pence	38.000	21	42.3	our	2.140	246	495.0
Donald	21.890	29	58.4	my	2.020	191	384.4
republican	9.800	51	102.6	judge	1.970	3	6.0
campaign	6.330	20	40.2	we	1.780	331	666.1
me	3.890	177	356.2	I	1.470	440	885.4
administration	3.410	12	24.1				

Table 4.9 In group keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

## 4.1.2.2 Concordances and collocates in the Trump Tweet Corpus

The analysis of collocates focuses mainly on the figure of Donald Trump. For this reason, the following Table shows the first 20 collocates of the word *Trump*.

The first collocate – not surprisingly – is *Donald*. However, the collocate list reveals – through the collocate *J*. – that Trump talks also about his son Donald Trump Jr. The word *Tower* is connected to Trump Tower that is the headquarter of the Trump Organization.

Collocate	Cooccurrences	Occurrences	T-score	MI3
Donald	24	29	4.88	17.40
Tower	9	10	2.99	14.69
J.	8	10	2.82	14.18
be	36	1,592	5.27	13.38
[number]	24	474	4.63	13.37
%	10	50	3.12	12.82
Clinton	12	139	3.35	12.14
Russia	8	59	2.77	11.62
election	9	95	2.91	11.44
win	9	104	2.90	11.31
poll	7	69	2.57	10.82
campaign	6	48	2.40	10.67
first	5	48	2.18	9.88
now	6	111	2.32	9.46
you	9	387	2.64	9.42
vote	6	120	2.31	9.35
not	8	324	2.51	9.16
go	6	139	2.29	9.14
all	6	164	2.26	8.90
just	5	140	2.06	8.34

Table 4.10 Collocates of the word *Trump* in the Trump Tweet Corpus

The collocates %, Clinton, [number], campaign, election, president and poll are connected to his electoral campaign and his election. The concordances of the word won reveal that this collocate is not connected to the saviour and warrior source domain and topos but it is rather linked to the electoral campaign with a particular reference to debates. Lastly, the collocate Russia indicates the alleged connection between Trump and Russia during the electoral campaign of 2016. Moreover, this word is also linked to the dishonest topos (see section 4.3).

The concordances of the word *judge* (Table 4.11) show that Trump refers to a judge that he nominated (Neil Gorsuch); as a result, the keyword *judge* is in the list of Trump's in group keywords. Nonetheless, the word *judge* is also connected to Trump's opposition (see section 4.3).

Hope you like my nomination of Judge Neil Gorsuch for the United States Supreme he had (major lie), now misrepresents what Judge Gorsuch told him? Chris Cuomo, in his inexpensive to quickly fix (fill in and top)! Judge Gorsuch will be sworn in at the Rose Garden Table 4.11 Concordances of the word *judge* in the Trump Tweet Corpus

In order to investigate in greater detail the representation of both Trump and his administration as saviours and warriors, the quantitative analysis focuses on the concordances of the word *fight* (Table 4.12) that is always associated to Trump except for the last concordance that involves his administration. These concordances confirm the results of the qualitative analysis in which Trump uses this word just in his self-representation as warrior and saviour.

Thank you High Point, NC! I will fight for every neglected part of this nation & I will for every neglected part of this nation & I will fight to bring us together as one American people! Hillary profits off the rigged system, I am fighting for you! Remember the simple phrase: have been taken off me and I can now for America the way I want to. With the fight fight D.C. LINK Great night in WI. I'm going to for every person in this country who believes Get out and vote! I am your voice and I will for you! We will make America great again! fight The Remembrance Project. I will for them everyday! #ImWithYou fight The journey begins and I will be working and fighting very hard to make it a great journey for ... the FIND NOW Going to CPAC! Trump vows to 'epidemic' of human trafficking FAKE NEWS fight if they don't get on the team, & fast. We must fight them, & Dems, in 2018! The failing @nytimes , the U.S. Supreme Court.I will keep fighting for the American people, & WIN! #USA???I will represent our country well and fight for its interests! Fake News Media will never Looking forward to day two! #USA We will fight the #FakeNews with you! The #G20Summit Table 4.12 Concordances of the word *fight* in the Trump Tweet Corpus

# 4.1.2.3 Keywords in the Trump Traditional Corpus

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Trump	36.880	18	46.1	Mike	4.250	13	33.3
Donald	25.850	4	10.2	campaign	2.720	7	17.9
Luis	20.220	14	35.8	me	2.460	88	225.2
Harry	16.100	20	51.2	I	2.300	542	1387.1
veteran	10.150	30	76.8	us	2.150	89	227.8
our	5.480	497	1271.9	judge	2.080	2	5.1
we	5.290	774	1980.8	government	2.040	4	10.2
agenda	5.250	7	17.9				

Table 4.13 In group keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

Table 4.13 shows the in group keywords found in the Trump Traditional Corpus. Traditional keywords includes words connected directly to Trump (*Trump*, *Donald*, *me* and *I*), allies (*Mike*), his administration and supporters (*our*, *we* and *us*), political matters (*agenda*, *campaign* and *government*) and veterans (*Luis*, *veteran* and *Harry*). Even in this list it is possible to notice the keyword *judge*.

### 4.1.2.4 Concordances and collocates in the Trump Traditional Corpus

Table 4.14 shows the collocates of the keyword *Trump*. The first collocate is precisely *Trump* since Trump likes to report his supporters' stories and opinions about him. Therefore, he uses the collocate *he* to refer to himself and the collocate *say* to quote people.

Collocate	Cooccurrences	Occurrences	T-score	MI3
Trump	11	48	3.30	14.46
vote	3	23	1.72	9.90
say	5	128	2.17	9.63
win	3	60	1.69	8.52
I	6	542	2.18	8.34
forget	2	23	1.39	8.15
states	3	82	1.67	8.07
united	3	82	1.67	8.07
state	2	31	1.39	7.71
love	2	36	1.38	7.50
they	4	295	1.82	7.46
let	2	44	1.38	7.21
look	2	45	1.38	7.18
take	2	90	1.34	6.18
do	3	314	1.51	6.13
your	2	104	1.32	5.97
want	2	131	1.30	5.64
he	2	138	1.29	5.56
great	2	148	1.29	5.46
thank	2	157	1.28	5.37

Table 4.14 Collocates of the word *Trump* in the Trump Traditional Corpus

Furthermore, traditional speeches include audience's ovations. The collocates *vote* and *win* refer to the electoral campaign. The collocates *states* and *united* are clearly linked to the United States, while the collocate *forget* refers to the American people (*the forgotten men and women*). The collocates *love*, *let*, *want* and *do* are processes connected to Trump, while *take* and *look* are linked to the audience (*take a look*). Finally, the collocate *they* is mainly used to refer to Trump's opposition.

Table 4.15 shows the concordances of the keyword *judge* that – even in traditional speeches – is used similarly to tweets since Trump talks about the judge Neil Gorsuch.

great Antonin Scalia. His name is Judge Neil Gorsuch. He will uphold and great Justice Scalia. His name is Judge Neil Gorsuch. And he comes from my list of Table 4.15 Concordances of the word *judge* in the Trump Traditional Corpus

In Table 4.16 it is possible to notice that – in the Trump Traditional Corpus – Trump uses more frequently (precisely four times) the word *fight* in association with the word *we* (his administration) than in tweets. However, it is clear that even in traditional speeches Trump employs this word mainly in his self-representation of strong populist leader.

I don't want anything to get in our way. I am	fighting	every day for the great people of this
In everything you do, Mr. President, you're	fighting	for the forgotten men and women across
You've been saying it. I will never stop	fighting	for you. I am delivering on trade, on the
who are not treated fairly. We're	fighting	for workers of all backgrounds and from all
look at our borders. We're going to	fight	this terrible ruling. We're going
our people defenseless. And I will not stop	fighting	for the safety of you and your families,
we're going to lower taxes. Big! And we will	fight	for the right of every American child to grow
Safety is a civil right, and we will	fight	to make America totally safe again.
that the American people had a President	fighting	as hard for its citizens as other countries do
Thank you. It's time that somebody	fought	for our country and didn't let anyone take
Fighting only for insiders. I am an outsider	fighting	for you. Everything you need to know about
I will never back down from	fighting	to save American lives. I will never back
I will never back down from	fighting	to create safety and wealth for our inner
steel into the spine of this country. I will	fight	for every neglected part of this nation and
part of this nation – and I will	fight	to bring us all together as Americans
Table 4.16 Canagadanasa af the assaul Galetin t	la a Tanana	Traditional Communa

Table 4.16 Concordances of the word *fight* in the Trump Traditional Corpus

### 4.2 The United States

This section explores how Donald Trump represents both the United States and the American people.

### 4.2.1 Qualitative analysis

Trump's representation of the United States and U.S. citizens was qualitatively investigated through metaphors, *topoi* and transitivity.

### **4.2.1.1** *Metaphors*

The Trump Tweet Corpus counts 4 occurrences that belong to the source domains of building, war and nature. In the Trump Traditional Corpus there are 39 occurrences that cover more source domains – in comparison to tweets – such as saviour and warrior and container.

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
TTW		_	25% (1)	-	50%(2)	-	25% (1)	_
TTS	23% (9)	18% (7)	36%(14)	-	13%(5)	-	10% (4)	-

Table 4.17 U.S. source domains in Trump's corpora

- 9. **We're <u>fighting</u>** battles that no longer help us. **We're <u>fighting</u>** battles that other people aren't treating us fairly in the fight. I'm a NATO fan, but many of the countries in NATO, many of the countries that **we <u>protect</u>**, many of these countries are very rich countries. They're not paying their bills. [emphasis added] (Remarks at a "Make America Greta Again" Rally in Melbourne Florida 18 February 2017)
- 10. **We are going to rebuild** America. We are going to revitalize America. And we are going to unite America. [emphasis added] (Remarks at Prescott Valley Center Arizona 4 October 2016).
- 11. The era of economic surrender has come to an end. It's come to an end. We have <u>surrendered</u>, as a country, to outside interests. The era of economic victory for our country has just begun.

- [emphasis added] (Remarks at the North America's Building Trades Unions 2017 Legislative Conference 4 April 2017)
- 12. **America will <u>flourish</u>** as long as our liberty—and in particular, our religious liberty—is allowed to flourish. America will succeed as long as our most vulnerable citizens—and we have some that are so vulnerable—have a path to success. And **America will <u>thrive</u>** as long as we continue to have faith in each other and faith in God. [emphasis added] (Remarks at the National Prayer Breakfast 2 February 2017)

Example 9 displays both the war and the saviour and warrior source domains applied to the American people who help and protect other countries that do not treat them fairly and take advantage of the United States underlining the *topos* of the victim (see section 4.2.1.2). On the one hand, in example 10 America is described as a building that needs to be rebuilt and restored highlighting Trump's aim to change the country and go back to an economic and geopolitical hegemonic position. On the other hand, in example 11 the war source domain is used to describe the United States' economic downfall that is also perfectly in line with the narrative used in the previous example since Trump promises to change this situation of *economic surrender*. Example 12 shows the nature source domain; indeed, Trump describes America as a garden (McCallum-Bayliss, 2019: 244) that can *flourish* and *thrive* just through the preservation of U.S. fundamental values such as freedom (see also example 27). Lastly, the container source domain can be observed in example 15.

### 4.2.1.2 Topoi

The victim *topos* occurs three times in the Trump Tweet Corpus. The Trump Traditional Corpus counts 25 occurrences that involve mainly the victim *topos* but also the container *topos*.

	Victim	DTF <sup>17</sup>	Burden	Invasion	Container	Dictatorship	Dishonest
TTW	100% (3)	-	-	-	-	-	-
TTS	72% (18)	-	-	-	28% (7)	-	-

Table 4.18 U.S. topoi in Trump's corpora

- 13. This agreement is less about the climate and more about other countries gaining a financial advantage over the United States. [...] The agreement is a massive redistribution of United States wealth to other countries. [emphasis added] (Remarks announcing United States withdrawal from the United Nations Framework Convention on Climate Change Paris Agreement 1 June 2017)
- 14. [...] they [Democrats] were clogging up the veins of our country with the environmental impact statements and all of the rules and regulations. [emphasis added] (Remarks at a "Make America Great Again" Rally in Melbourne, Florida 18 February 2017)
- 15. Our southern border will be protected always. It will have the wall. **Drugs will stop pouring in** and poisoning our youth, and that will happen very, very soon. [emphasis added] (Remarks at a "Make America Great Again" Rally in Nashville Tennessee 15 March 2017)

Danger, threat and fear.

The victim *topos* can be observed in examples 13 and 14. Example 13 is an extract of the U.S. withdrawal from the Paris accord; for this reason, Trump strategically uses this *topos* in order to legitimise this important choice. Specifically, he highlights how the U.S. have been economically exploited by other countries. On the other hand, example 26 shows a personification of the United States because the U. S. are described as a mistreated human being who is the victim of environmental regulations that prevent the economic revival. Finally, example 15 shows the container *topos* – strictly connected to the homonym source domain – that is used to describe a negative circumstance since the U.S. are represented as a container infiltrated by fluids – such as drugs but also terrorists, immigrants and refugees (e.g. examples 32 and 33) – that embody imminent (see section 2.6), unstoppable and dangerous threats.

### 4.2.1.3 Transitivity

Processes linked to the United States count just two occurrences in the Trump Tweet Corpus. In the Trump Traditional Corpus there are 78 occurrences that belong to each category of processes except for the behavioural ones. Moreover, the majority of U.S. processes found in traditional speeches are material processes.

	Material	Relational	Mental	Verbal	Behavioural	Existential
TTW	50% (1)	-	50% (1)	-	-	-
TTS	69% (54)	14% (11)	5% (4)	5% (4)	-	7% (5)

Table 4.19 U.S. transitivity in Trump's corpora

- 16. North Korea is behaving very badly. **They have been "playing" the United States** for years. China has done little to help! [emphasis added] (Trump's Tweet 17 March 2017)
- 17. Therefore, in order to fulfill my solemn duty to protect America and its citizens, the United States will withdraw from the Paris climate accord [applause] thank you, thank you—but begin negotiations to reenter either the Paris accord or an—really entirely new transaction on terms that are fair to the United States, its businesses, its workers, its people, its taxpayers. [emphasis added] (Remarks announcing United States withdrawal from the United Nations Framework Convention on Climate Change Paris Agreement 1 June 2017)
- 18. The nation-state remains the best model for human happiness, and the American nation **remains** the greatest symbol of liberty, of freedom, and justice on the face of God's Earth. And now we have spirit like we've never had before. [emphasis added] (Remarks at a "Make America Greta Again" Rally in Melbourne Florida 18 February 2017)

Examples 16 and 17 show two types of material processes. The former is a tweet where the United States are the Goal of the process; indeed, the U.S. – as already seen in the previous section – are described through the *topos* of the victim because they are subjected to the actions of foreign countries. The latter is an extract of a traditional speech delivered by Trump to announce the withdrawal of the United States from the Paris Agreement. As a result, the United States are represented by Trump as the Actor in order to underline its active agency under Trump administration. Lastly, example 18 present an existential process linked to the self-

celebration of the U.S. More precisely, in this traditional extract Trump praises the United States and its fundamental values such as freedom, liberty and justice.

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	26%	21	Identifier	4%	3
Goal	35%	28	Possessor	5%	4
Recipient	5%	4	Senser	6%	5
Client	3%	2	Sayer	5%	4
Carrier	5%	4	Existent	6%	5

Table 4.20 U.S. participant types in Trump's corpora

The voice type of U.S. processes is mainly active (95%). In addition, the U.S. perform more the Goal (35%) than the Actor (26%) since the *topos* of the victim is particularly pervasive. As a result, the positive (40%) evaluation percentage of processes is very similar to the negative (39%) one because the positive evaluation is linked to the representation of the U.S as the saviour and the negative one is connected to the victim.

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	95% (76)	4% (3)	1% (1)	-	-	-
Evaluation	-	-	-	40% (32)	39% (31)	21% (17)

Table 4.21 U.S. voice type and evaluation type in Trump's corpora

Processes that involve American citizens count 17 occurrences in the Trump Tweet Corpus, and the majority of them are material ones as it is possible to notice in Table 4.22. The Trump Traditional Corpus has 411 occurrences. Even in this case the majority of processes are material; moreover, in traditional speeches there are more categories of processes (except for the existential ones) than in tweets.

	Material	Relational	Mental	Verbal	Behavioural	Existential
TTW	70% (12)	12% (2)	18% (3)	-	-	-
TTS	53% (219)	24% (97)	17% (71)	4% (16)	2% (8)	-

Table 4.22 U.S. citizens' transitivity in Trump's corpora

- 19. **We will bring back** our jobs. **We will bring back** our borders. **We will bring back** our wealth and **we will bring back** our dreams! [emphasis added] (Trump's Tweet 20 January 2017)
- 20. **We also reflect** on everything we **cherish** as Americans: We **love** our country, we **love** our families, we **love** our freedom, and we **love** our God. [emphasis added] (Remarks at "Celebrate Freedom" Rally 1 July 2017)
- 21. A cynic would say the obvious reason for economic competitors and their wish to see us remain in the agreement is so that **we continue to suffer** this self-inflicted major economic wound. [emphasis added] (Remarks announcing United States withdrawal from the United Nations Framework Convention on Climate Change Paris Agreement 1 June 2017)

Example 19 shows a sequence of material processes that Trump employs to involve the American people. He aims to create a strong sense of community talking about a collective *we* that includes both himself and the American people. Specifically, the American people perform

the Actor of this sequence of material processes that aim to bring back the American dream, an economic revival and stop immigration. In example 20 there are some mental processes (reflect, cherish and love) that help Trump to praise American people and their values such as patriotism and freedom. In example 21 there is a behavioural process (suffer) that is also contextualised during the announcement of U.S. withdrawal from the Paris Agreement. This process is employed by Trump to legitimise his decision, otherwise American citizens will continue to suffer an economic disadvantage.

The representation of American citizens is characterised by high percentages of processes with an active voice type (98%) and a positive evaluation (60%). Consequently, U.S. citizens are represented more as saviours rather than victims.

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	50%	215	Senser	16%	70
Goal	4%	18	Inducer	1%	1
Recipient	1%	4	Sayer	3%	12
Carrier	7%	31	Receiver	1%	3
Identifier	2%	11	Behaver	2%	7
Possessor	13%	56			

Table 4.23 U.S. citizens' participant-types in Trump's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	98% (424)	1% (3)	1% (1)	-	_	-
Evaluation	-	-	<b>-</b>	60% (256)	19% (81)	21% (91)

Table 4.24 U.S. citizens' voice type and evaluation type in Trump's corpora

### 4.2.2 Quantitative analysis

### 4.2.2.1 Keywords in the Trump Tweet Corpus

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
America	10.470	143	287.8	Arizona	4.710	15	30.2
great	10.130	365	734.5	safe	4.590	36	72.4
Hampshire	9.980	12	24.1	Americans	4.400	24	48.3
Ohio	9.420	54	108.7	American	4.370	87	175.1
Pennsylvania	9.150	29	58.4	Georgia	4.210	12	24.1
Carolina	8.580	32	64.4	Washington	3.690	17	34.2
Florida	8.530	51	102.6	North	3.630	51	102.6
Iowa	8.470	19	38.2	united	3.200	44	88.5
Nevada	8.220	14	28.2	states	3.070	35	70.4
Michigan	7.710	21	42.3	military	2.970	26	52.3
Wisconsin	7.610	17	34.2	Virginia	2.810	12	24.1
again	7.150	70	140.9	woman	2.300	32	64.4
Colorado	6.220	19	38.2	make	1.840	71	142.9
hero	5.610	15	30.2	nation	1.800	13	26.2
country	5.000	88	177.1	worker	1.650	10	20.1

Table 4.25 USA keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

Table 4.25 above shows the keywords associated to the United States. The majority of the keywords present in Table 4.17 indicate U.S. States (e.g. Hampshire, Ohio etc.) since Trump used Twitter to announce local speeches, especially during the electoral campaign. It is important to mention that the first two keywords are *America* and *great*. Indeed, the keywords *America*, *great*, *again*, *safe* and *make* are strictly connected to Trump's slogans *Make America Great Again* and *Make America Safe Again* that are also combined in the slogan *Make America Safe and Great Again*. Not surprisingly among the keywords it is possible to find *country*, *American*, *united*, *states* and *nation*. American people are also involved in this list primarily through the keyword *Americans*.

Moreover, we should highlight that the two categories of American people that Trump mentions are *women* and *workers*. The concordances of the word *woman* reveal that Trump talks about American women who support him, but he also talks about the accusation against him and try to defend himself. Trump self-legitimises himself saying that nobody has more respect for women than him and delegitimises his opponents (such as Bill Clinton and Joe Biden) claiming that they are abusive to women. On the other hand, the concordances of the word *worker* highlight Trump's closeness to this category of U.S. citizens (that it is part of his populist narrative) and his efforts in order to improve U.S. economy. The keyword *military* is connected to U.S military forces and to security matters. Finally, the keyword *hero* involves American soldiers with a particular focus on veterans.

4.2.2.2 Concordances and collocates in the Trump Tweet Corpus

Collocate	Cooccurrences	Occurrences	T-score	MI3
again	86	113	9.24	20.90
make	82	179	9.00	20.03
great	88	365	9.27	19.31
safe	24	36	4.88	17.03
together	19	57	4.32	15.35
we	40	331	6.17	16.04
will	35	480	5.68	14.92
be	38	1,592	5.42	13.55
go	13	139	3.49	12.42
#americafirst	7	63	2.58	10.89
want	7	63	2.58	10.89
watch	7	88	2.55	10.40
let	6	56	2.38	10.39
day	6	70	2.37	10.07
here	5	42	2.18	10.01
world	5	43	2.18	9.98
job	7	138	2.50	9.75
thank	8	250	2.57	9.48
join	6	117	2.31	9.33
#maga	5	105	2.10	8.69

Table 4.26 Collocates of the word *America* in the Trump Tweet Corpus

In Table 4.26 it is possible to observe the collocates of the word *America*. The collocates *again*, *make*, *great*, *safe*, *together*, *we*, *will*, *go* and *let* are connected to Trump's slogans *Together*, *we* will make *America* (safe and) great again! and *Together*, we are going to make *America* (safe and) great again! or *Let's make America* (safe and) great again!. There are also some collocates directly connected to Twitter such as #americafirst, watch, here, join and #maga. The process want is linked to both Trump and his supporters regarding their determination in improving the state of the United States. Lastly, the words *world* and *job* are connected to Trump's electoral promises regarding the U.S. hegemonic (economic) position in the world.

In order to investigate Trump's different employment of the keywords *country* and *nation* to indicate the United States, the quantitative analysis focused on the concordances of both words.

```
to show Americans that Hillary will KILL our if elected, I will think big for our to be a terrorist who wants to destroy our Americans who want to take our our U.S. Navy for protecting our to keep Radical Islamic Terrorists out of our Drugs are pouring into this If we have no border, we have no No wonder companies flee Table 4.27 Concordances of the word country if elected, I will kILL our country !! Vote for Trump!!

**Country** to country !! Vote for Trump!!

**Country** to country !! Vote for Trump!!

**Country** to ever let the American people down country back. #BigLeagueTruth

**Country** to both in times of peace & war.

! #DrainTheSwamp

**Country** If we have no border, we have no country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not to the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to potential terrorists and others that do not the country to the country that the country to potential terrorists are country to potential terrorists.
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The word *country* occurs 88 times in the Trump Tweet Corpus – revealing that Trump uses more this word than *nation* –; for this reason, Table 4.27 shows just a random selection of 10 concordance lines. The concordances reveal Trump's employment of this word in different topics such as electoral campaign, military matters, terrorist and criminal affairs, and economic matters. However, we should notice that in the majority of the lines the word *country* is always preceded by the pronoun *our* suggesting the existence of a strong community of people who shares the same values and believes.

```
fight for every neglected part of this
                                               nation
                                                         & I will fight to bring us together as one
                          Such a great honor! Nation's
                                                        Immigration And Customs Enforcement
   With all of the jobs I am bringing back to our
                                                Nation
                                                         , that number ... will only get higher.
   the day the people became the rulers of this
                                                         again. The forgotten men and women of
                                                nation
                    THE SECURITY OF OUR NATION IS AT STAKE!
   hard work & dedication are ingrained in our
                                               nation's
                                                        fabric.
        to preserving the natural beauty of our
                                                nation
                                                         . I am committed to keeping our air and
               Pacific Islanders that enrich our
                                                Nation
                                                         #ICYMI
      Macron. The friendship between our two
                                               nations
                                                         and ourselves is unbreakable
     women our U.S. Armed Forces. A grateful
                                                         thanks you! I will be at the @USGA
                                                nation
     Youngstown, Ohio this evening. A grateful
                                                nation
                                                         salutes you! People of Ohio are
             Congratulations to Boys and Girls
                                                Nation
                                                         . It was my great honor to the WH
        It was my great HONOR to present our nation's highest award for a public safety officer
Table 4.28 Concordances of the word nation in the Trump Tweet Corpus
```

Table 4.28 shows the 13 occurrences of the word *nation* in the Trump Tweet Corpus. The concordances reveal that this word is used by Trump mainly regarding security and military matters. In addition, the different employment of *country* and *nation* in terms of occurrences is particularly relevant in tweets rather than in traditional speeches (see section 4.2.2.4).

Since the United States and U.S. citizens – according to the qualitative results – are represented as saviours and warriors, the quantitative analysis investigates once again the concordances of the word *fight*.

Table 4.29 reveals the presence of only three occurrences of this word in the Trump Tweet Corpus that are referred to both the U.S. and U.S. citizen with a particular focus on military and veterans. Finally, the quantitative analysis investigates more in depth the representation of the United States and American people as victims.

```
When will the U.S., and all countries, fight to take care of Veterans who have stand shoulder-to-shoulder with Poland in the Table 4.29 Concordances of the word fight in the Trump Tweet Corpus
```

```
condolences to all of the families and
                                               victims
                                                         of the horrible bombing in NYC.
                                                         . their families and all Americans!
                                 Thinking of
                                               victims
       rate is record setting - 4,331 shooting
                                                         with 762 murders in 2016.
                                               victims
  STATE of OHIO, to meet with ObamaCare
                                                         and talk Healthcare & also Infrastructure!
                                               victims
               We will NEVER FORGET the
                                                         who lost their lives one year ago in the
                                               victims
                                                         . Video: LINK While I greatly appreciate the
 North Korean regime as we mourn its latest
                                               victim
           The United States mourns for the
                                               victims
                                                         of Nice, France. We pledge our solidarity
Table 4.30 Concordances of the word victim in the Trump Tweet Corpus
```

Table 4.30 shows that the Trump Tweet Corpus counts 7 occurrences of the word *victim* that in the majority of the lines refers to American people, while there are some exceptions regarding foreign victims of regimes and terrorism.

### 4.2.2.3 Keywords in the Trump Traditional Corpus

Table 4.31 shows a lot of similarities to Table 4.25. Nevertheless, there are some differences that should be mentioned. The first keywords are *country*, *rebuild*, *nation* and *America*. These keywords reveal that in traditional speeches it is particular pervasive the source domain of building (the Trump Traditional Corpus includes the "Remarks at the North America's Building Trades Unions 2017 Legislative Conference" a speech in which the source domain of building is crucial). In this regard, we should mention that the keyword *build* is both connected to the source domain but also to the building of Trump Wall. On the one hand, the keyword *flag* indicates a strong patriotism. On the other hand, the keyword *dream* signals the common narrative of the American dream.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
country	12.450	116	424.8	Americans	5.350	23	58.9
rebuild	12.440	14	35.8	Pennsylvania	4.100	10	25.6
nation	11.290	79	202.2	military	4.040	28	71.7
America	10.800	116	296.9	again	3.880	48	122.8
states	9.060	82	209.9	dream	3.260	15	38.4
sacrifice	8.600	14	35.8	Washington	3.040	10	25.6
American	8.470	133	340.4	woman	2.690	34	87.0
united	7.530	82	209.9	thousand	2.540	10	25.6
worker	7.080	35	89.6	build	2.320	36	92.1
flag	6.930	16	40.9	man	1.930	36	92.1
citizen	6.720	35	89.6	make	1.440	28	71.7
hero	6.160	13	33.3				

Table 4.31 USA keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

For what concerns the keywords linked to American people, in traditional speeches Trump's discourse focuses again on the categories of *women* and *worker* but also on *citizens* and *men*. The keyword *thousand* involves mainly American people and jobs. In addition to *hero* and *military*, the veteran narrative in traditional speeches is reinforced by the keyword *sacrifice* that is also connected to the victim *topos*. Lastly, the keywords *America*, *again* and *make* signal the presence of Trump's slogan.

### 4.2.2.4 Concordances and collocates in the Trump Traditional Corpus

Table 4.32 shows the collocates of the word *America* in the Trump Traditional Corpus. Here it is possible to find once again the collocates *again*, *make*, *will*, *great*, *we*, *safe* and *go* that are connected to Trump's well-known slogans (already mentioned in section 4.2.2.2).

Collocate	Cooccurrences	Occurrences	T-score	MI3
again	26	48	5.07	16.91
make	29	110	5.32	16.19
we	34	774	5.44	14.06
will	25	325	4.81	13.98
be	38	1,670	5.36	13.43
states	13	82	3.54	13.14
first	10	46	3.12	12.84
united	12	82	3.39	12.79
you	22	613	4.30	12.51
great	13	153	3.48	12.24
bless	7	24	2.62	12.23
go	14	320	3.49	11.50
put	6	46	2.39	10.63
thank	9	157	2.84	10.61
safe	5	31	2.19	10.41
much	7	87	2.55	10.38
as	8	144	2.68	10.23
all	7	177	2.45	9.35
out	5	81	2.13	9.02
very	6	174	2.24	8.71

Table 4.32 Collocates of the word *America* in the Trump Traditional Corpus

The word *first* recalls *America First* – another important slogan – that is also connected to the word *put* (*put America first*). Finally, the collocates *states*, *united* and *bless* refer to the U.S. Even in the list of traditional keywords it is possible to find both the words *country* and *nation*. The word *country* has 166 occurrences.

fighting everyday for the great people of this country . Therefore, in order to fulfill my solemn lobbyists wish to keep our magnificent country tied up and bound down by this the most prosperous and productive country on Earth and with the highest standard of that have long sought to gain wealth at our country's expense. They don't put America first. rarely do we have a deal that works for this country, but they'll soon be under renegotiation. the forgotten men and women across this country . You're a champion for the hard- working We cherish as Americans: We love our country, we love our families, we love our freedom, terrorism and extremism to spread in our country or to find sanctuary on our shores or in our sure that anyone who seeks to join our country shares our values and has the capacity to those who would seek to enter our country for the purpose of spreading violence or Table 4.33 Concordances of the word *country* in the Trump Traditional Corpus

Table 4.33 shows a random selection of 10 concordances lines where *country* is used once again in different circumstances (e.g. economy matters) with particular reference to American community's values and believes. The word *nation* counts 79 occurrences. In Table 4.34 there are some random concordance lines that, even in this case, confirm Trump's employment of this word almost exclusively regarding protection and military matters.

taking away the great wealth of our Nation -it's great wealth, it's phenomenal wealth And it should be noted that we as a Nation do it better than anyone in the world in those who have proudly served our in uniform. Thank you very much. Nation and reminds us all of who we are: one under God. To First Baptist music Director Nation our great American flag. Your loyalty to our Nation is measured not merely in words, but in than 300 million people behind you. And our Nation is getting strong again. Do you notice? Together, we will protect our families, our , and our borders. And yes, by the way, for nations is the sum of its citizens: their hopes, their a country is more than just its geography. A nation God bless you. God bless our Nation's veterans. God bless the United States of was amazing. He died in defense of our Nation . He gave his life in defense of our people. Table 4.34 Concordances of the word *nation* in the Trump Traditional Corpus

In order to investigate the representation of U.S. and American people as saviours and warriors in traditional speeches, the analysis of concordances focuses once again on the word *fight*.

and ran past the gates of hell to fight and to win for America. And you Five hundred thousand American soldiers fought that pivotal battle of the Second World War. Private Miller was on his way to Europe to fight for our country. Great. A couple months to get them all set for action and ready to . And before long, those three tanks were fight Harry! Harry! Stand up! Harry through the battle and the rest of the war, fought love your country, and send your bravest to fight in our wars. All you want is a Government the tired echoes of yesterday's fights. We're fighting battles that no longer help us. that no longer help us. We're fighting battles that other people aren't treating us demand new solutions. Americans have and won wars together. Our heroes have fought service men and women who bravely in our name. You not only know the pain fight will always, always protect you. Americans fought and died to liberate Europe from the evils of Table 4.35 Concordances of the word *fight* in the Trump Traditional Corpus

The Trump Traditional Corpus counts 44 occurrences of this word; for this reason, the Table above provides a random selection of concordance lines where it is possible to notice that the word *fight* is mainly associated to soldiers and veterans representing them as heroes.

In addition to the word *fight*, the analysis of concordances focuses also on the keyword *sacrifice* that – as is it possible to observe in the following Table – is strictly connected to veterans as well.

We are awed by your service and your sacrifice . And so to the veterans here tonight received a Purple Heart for his service and sacrifice. To Luis and Claudia, we will never forget will never forget the courageous sacrifice that you made for all of us in this room and we will prove worthy of the sacrifice that our brave veterans have made. . Our freedom is won by their sacrifice, and our security has been earned with the in God has inspired men and women to sacrifice for the needy, to deploy to wars overseas, to take a moment to thank you all for the sacrifices you make on behalf of our country. or constant moves to the base, your sacrifices do not go unnoticed or unappreciated. Each of you makes these great sacrifices for our country as well. Let's hear it Military children also make great sacrifices for their country, and I want you all that You not only know the pain of sacrifice , but you also know the tremendous covenant of trust: to serve together to sacrifice together, and to fight together. And by the We honor their memory and their sacrifice . And we also hope to honor them with our our deeds to prove worthy of their sacrifice. Because there is no peace without Table 4.36 Concordances of the word *sacrifice* in the Trump Traditional Corpus

Lastly, the quantitative analysis investigates the representation of U.S. and American people as victims. Specifically, Trump – in Table 4.37 – associates the word *victim* just to American people who are mainly victims of criminal immigrants.

the day before. Also among the victims of the Obama-Clinton open borders was released from Federal Custody. Another victim is Kate Steinle, gunned down in the our already existing laws. These American victims were ignored by the media. They were to get it by. So I've met with so many victims of Obamacare, the people who have been so in Chicago since January. 60% of murder victims under the age of 22 in this country are Table 4.37 Concordances of the word *victim* in the Trump Traditional Corpus

### 4.3 The Media

Trump has distinguished himself for his harsh attacks to the mainstream media. Consequently, this section aims to investigate the linguistic strategies used by Trump in order to criticise the media.

### 4.3.1 Qualitative analysis

Trump's representation of the media was qualitatively investigated just through the category of *topoi*.

#### 4.3.1.1 Topoi

In the Trump Tweet Corpus there are 11 occurrences linked to the representation of the media, while the Trump Traditional Corpus counts 8 occurrences. As it is possible to notice from Table 4.38 all these occurrences belong to the category of the dishonest *topos*.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
TTW	-	-	-	-	-	-	100% (11)
TTS	-	-	-	-	-	-	100% (8)

Table 4.38 Media topoi in Trump's corpora

- 22. **The dishonest media does not report** that any money spent on building the Great Wall (for sake of speed), will be paid back by Mexico later! [emphasis added] (Trump's Tweet 6 January 2017)
- 23. At some point **the Fake News will be forced to discuss** our great jobs numbers, strong economy, success with ISIS, the border & so much else! [emphasis added] (Trump's Tweet 3 July 2017)
- 24. By the way—watch what happens. Now you just booed Obamacare. They will say, Trump got booed when he mentioned—they're bad people, folks. They're bad people. [...] Tonight I'll go home, I'll turn on, I'll say—listen, I'll turn on that television. My wife will say, "Darling, it's too bad you got booed." I said, I didn't get booed. This was a love fest—I said, no, no, they were booing Obamacare. Watch, a couple of them will actually do it, almost guaranteed. But when we call them out, it makes it harder for them to do it. So we'll see. It's the fake, fake media. [emphasis added] (Remarks at a "Make America Great Again" Rally in Nashville Tennessee 15 March 2017)
- 25. **The fake media is trying to silence us** but we will not let them, because the people know the truth. **The fake media tried to stop us** from going to the White House, but I'm President, and they're not. We won, and they lost. The fact is, the press has destroyed themselves, because they went too far. Instead of being subtle and smart, they used the hatchet, and the people saw it right from the beginning. **The dishonest media** will never keep us from accomplishing our objectives on behalf of our great American people. It will never happen. Their agenda is not your agenda. [emphasis added] (Remarks at "Celebrate Freedom" Rally 1 July 2017)

Examples 22, 23, 24 and 25 show the straightforward strategy that Donald Trump uses to discredit the media. Specifically, he employs the dishonest *topos* that – according to Trump – is part of the elite corrupt system. It is possible to observe that in each example he associates the words *dishonest* or *fake* to the media. In examples 22 and 23 Trump argues that the media omit important news such as information about Trump Wall and the achievements of Trump administration. In example 24 Trump claims that the media manipulate and will continue to manipulate news in order to attack and disadvantage him and his administration. Finally, in example 25 Trump incorporates the media to the elite corrupt system since he claims that not only the media do not give him enough visibility but also that the media have worked in order to prevent his election and consequently the people's will.

### 4.3.2 Quantitative analysis

### 4.3.2.1 Keywords in the Trump Tweet Corpus

The following keywords go under the label of fake (a sub-category of the macro-category opposition. See Table 4.40).

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
fake	73.250	97	195.2 hunt	6.790	16	32.2
dishonest	42.680	25	50.3 Russian	6.570	23	46.3
phony	28.440	17	34.2 medium	6.370	72	144.9
witch	16.970	16	32.2 media	6.200	26	52.3
Russia	16.190	46	92.6 false	5.490	11	22.1
rig	12.630	6	12.1 news	4.910	113	227.4
bias	11.440	13	26.2 Washington	3.690	6	12.1
nbc	11.150	14	28.2 Germany	3.630	3	6.0
cnn	9.970	13	26.2 press	2.590	4	8.0
leak	9.960	19	38.2 source	1.460	18	36.2
fail	9.090	53	106.7 low	1.360	6	12.1
rating	6.860	19	38.2			

Table 4.39 Media keywords (opposition-fake) in the Trump Tweet Corpus (ref. corpus enTenTen2018 US domain)

The keywords fake, dishonest, phony, witch, rig, bias, nbc, cnn, leak, fail, hunt, medium, media, false, news, Washington (Post) and source are all connected to the dishonest topos. The keywords Russia and Russian are linked to the attack to Trump regarding the alleged support from Russia during his presidential campaign. The keyword Germany refers to a specific episode – that happened during the G20 in Hamburg – concerning his meeting with Putin. Lastly, this keyword list is longer than the traditional one revealing that Trump's dishonest media narrative is more pervasive in tweets. Trump has always highlighted the usefulness and powerfulness of social media that allowed him to fight fake news and win the presidency.

The label fake is a sub-category of the macro-category opposition. The keywords categorised under the latter label can be observed in the following Table that involves mainly Trump's opponents such as Hillary and Bill Clinton, democrats, North Korea and Putin.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Hillary	123.760	166	334.0	refuse	3.820	11	22.1
crooked	107.470	66	132.8	dead	3.780	17	34.2
Trump	82.400	19	38.2	Iran	3.610	14	28.2
Obamacare	69.590	71	142.9	lose	3.600	26	52.3
dems	62.150	36	72.4	investigation	3.550	13	26.2
Clinton	52.600	139	279.7	despite	3.410	17	34.2
Comey	38.410	20	40.2	administration	3.410	12	24.1
repeal	33.430	35	70.4	total	3.340	21	42.3
dnc	28.730	16	32.2	Bill	3.330	17	34.2
dem	27.890	17	34.2	James	3.070	14	28.2
democrats	26.000	45	90.6	crime	2.990	13	26.2
Kaine	25.420	13	26.2	email	2.900	25	50.3
Podesta	23.310	12	24.1	insurance	2.650	5	10.1
FBI	22.790	31	62.4	wall	2.640	4	8.0
Donald	21.890	5	10.1	push	2.640	14	28.2
Schumer	17.940	10	20.1	John	2.490	11	22.1
WikiLeaks	15.590	10	20.1	secret	2.410	10	20.1
Bernie	14.030	11	22.1	server	2.320	14	28.2
Korea	11.550	23	46.3	woman	2.300	6	12.1
Putin	11.520	5	10.1	get	2.250	4	8.0
democrat	9.830	21		stop	2.220	6	12.1

disaster	8.250	23	46.3 act	2.140	5	10.1
weak	7.990	15	30.2 catch	2.060	11	22.1
mess	7.920	7	14.1 foreign	2.020	4	8.0
excuse	7.520	11	22.1 judge	1.970	5	10.1
hack	7.460	13	26.2 pay	1.800	11	22.1
Obama	7.320	67	134.8 political	1.760	15	30.2
fraud	6.730	11	22.1 hit	1.760	5	10.1
lie	6.580	31	62.4 major	1.610	5	10.1
campaign	6.330	28	56.3 foundation	on 1.550	11	22.1
replace	5.760	31	62.4 kill	1.540	2	4.0
Syria	5.200	5	10.1 official	1.480	9	18.1
crazy	5.070	11	22.1 she	1.460	83	167.0
intelligence	4.970	16	32.2 low	1.360	6	12.1
secretary	4.440	1	2.0 interest	1.310	7	14.1
China	4.370	31	62.4 force	1.310	7	14.1

Table 4.40 Opposition keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

### 4.3.2.2 Concordances and collocates in the Trump Tweet Corpus

Table 4.41 shows the collocates of the word *medium* that confirm – through the first collocates *fake*, *dishonest* and *news* – Trump's harsh attacks to the media.

Collocate	Cooccurrences	Occurrences	T-score	MI3
fake	22	97	4.66	16.21
dishonest	11	25	3.31	15.17
news	16	113	3.96	14.61
be	27	1,592	4.75	13.06
not	13	324	3.48	12.19
very	8	156	2.75	11.15
it	5	301	2.04	8.16
have	5	403	1.97	7.74

Table 4.41 Collocates of the word *medium* in the Trump Tweet Corpus

The word *medium* counts 72 occurrences in the Trump Tweet Corpus. The following Table provides a random selection of 10 concordance lines of this word. The analysis of concordances reveals – once again – the harsh attitude of Trump towards the media, especially through the dishonest *topos*. Indeed, the word *media* is often preceded by the words *dishonest* or *fake* news.

"sources said" by the VERY dishonest do them? Very little pick-up by the dishonest media being rigged by the dishonest and distorted for an interview with @chucktodd. Dishonest I out to @NBCNews. So serious! Dishonest our very civil conversation that FAKE NEWS and everyone knows it. Some FAKE NEWS lining the road that the FAKE NEWS of the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS and the public a break - The FAKE NEWS are the public a break - The FAKE NEWS and the public a break - The FAKE NEWS are the sources and incredible information provided by pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! lied about. Very nice! Meeting with biggest a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! lied about. Very nice! Meeting with biggest a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I in a pushing Crooked Hillary - but also at many cut out 9 of her 10 minutes. Terrible! I

The analysis of concordances focuses also on another keyword of *medium*, that is *witch*. The concordances in Table 4.43 reveals that this word is always used by Trump in combination with

the keyword *hunt* in order to create a metaphorical representation of his relationship with the media. Specifically, this metaphor is employed by Trump concerning his alleged connection to Russia to reject and delegitimise all the accusations. Although Trump does not represent himself explicitly as a victim, this metaphor allows Trump to present himself as a persecuted man without undermining his role as strong populist leader.

FAKE NEWS - A TOTAL POLITICAL WITCH HUNT! 'BuzzFeed Runs Unverifiable and other information. It is a total " witch hunt!" Nick Adams new book. Green Card Flynn should ask for immunity in that this is a witch hunt (excuse for big election loss), by media virtually everyone else with knowledge of the witch hunt, says there is no collusion, when does it This is the single greatest hunt of a politician in American history! witch by James Comey, John Brennan ... " Hunt! Kathy Griffin should be ashamed of Witch Nice You are witnessing the single greatest WITCH HUNT in American political history - led by I can go around them Despite the phony Hunt going on in America, the economic & Witch the man who told me to fire the FBI Director! Witch Hunt Great news! #MAGA LINK "Remarks by doing very well despite the distraction of the Witch Hunt. Many new jobs, high business election." Check out his statement -Witch Hunt! Great day for America's future and innocent. This is the greatest Hunt in political history. Sad! Remember, Witch Hunt continues, two groups are laughing at Luck & Godspeed! As the phony Russian Witch proving he did not collude with the Russians. Witch Hunt. Next up, 11 year old Barron Trump! So why doesn't Fake News report this? Witch Hunt! Purposely phony reporting. Big I want strong military & low oil prices. Witch Hunt! LINK Republican Senate must get rid Table 4.43 Concordances of the word *witch* in the Trump Tweet Corpus

### 4.3.2.3 Keywords in the Trump Traditional Corpus

Table 4.44 shows the list of *media* keywords in Trump Traditional Corpus that involves just two keywords.

Keyword	Score	Freq	Rel_freq
fake	12.800	13	33.3
medium	1.610	14	35.8

Table 4.44 Media keywords (opposition-fake) in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

The short keyword list in Table 4.44 suggests that Trump's attack to the media is more pervasive and aggressive in the Trump Tweet Corpus. Moreover, in the following Table there are the traditional keywords of the macro-category opposition.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Obamacare	37.620	30	76.8	Washington	3.040	7	17.9
Trump	36.880	6	15.4	criminal	2.870	2	5.1
Hillary	33.460	35	89.6	lie	2.760	10	25.6
Donald	25.850	1	2.6	campaign	2.720	4	10.2
Clinton	21.290	44	112.6	stop	2.710	2	5.1
democrats	15.550	21	53.7	woman	2.690	1	2.6
repeal	12.440	10	25.6	administration	2.610	4	10.2
disaster	8.210	8	20.5	interest	2.270	4	10.2
massive	5.910	1	2.6	judge	2.080	4	10.2
agenda	5.250	3	7.7	government	2.040	12	30.7
foreign	5.000	2	5.1	Bill	2.020	4	10.2

fail	4.410	20	51.2 lose	1.970	2	5.1
secretary	4.320	3	7.7 pay	1.830	3	7.7
wall	3.670	4	10.2 special	1.590	8	20.5
replace	3.110	10	25.6 Obama	1.570	11	28.2

Table 4.45 Opposition keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

### Concordances and collocates in the Trump Traditional Corpus

In Table 4.46 there are the collocates of the keyword *fake*. Not surprisingly the list involves the words news and medium. Furthermore, the presence of fake suggests a repetition of the word which is typical in Donald Trump's discourse.

Collocate	Cooccurrences	Occurrences	T-score	MI3
news	8	14	2.83	16.75
fake	6	13	2.45	15.61
medium	4	14	2.00	13.75
wall	3	22	1.73	11.85
try	2	13	1.41	10.85
folk	2	20	1.41	10.23
it	5	451	2.17	9.70
be	7	1,670	2.44	9.27
us	2	89	1.39	8.08
we	2	774	1.23	4.96

Table 4.46 Collocates of the word *fake* in the Trump Traditional Corpus

The collocate *wall* indicates that the building of Trump Wall is also connected to the dishonest media narrative since Trump accuses the media to report false information such as the possibility of not building the wall at all. The word try is linked to processes associated to the media and their attitude towards Trump. Finally, folks is a term that Trump uses to refer to the audience. The following Table shows the concordances of the word *fake*. In these lines it is possible to see how the collocates mentioned above are actually used by Trump.

it belongs: to the people. To the people. The fake media is trying to silence us but we because the people know the truth. The fake media tried to stop us from going to the if I said we're not going to build a wall? Fake news. It's fake, fake news. Fake news, going to build a wall? Fake news. It's fake, fake news. Fake news, folks, a lot of fake. No, fake, fake news, Fake news, folks, a lot of fake . No, the wall is way ahead of schedule in harder for them to do it. So we'll see. It's the fake , fake media. We want Americans to be able for them to do it. So we'll see. It's the fake, fake media. We want Americans to be able to want to speak to you without the filter of the fake news. The dishonest media, which has Table 4.47 Concordances of the word *fake* in the Trump Traditional Corpus

We're going to build the wall. Some of the fake news said, I don't think Donald Trump wants not going to build a wall? Fake news. It's fake , fake news. Fake news, folks, a lot of fake. a wall? Fake news. It's fake, fake news. Fake news, folks, a lot of fake. No, the wall is way to win, win, win. We are not going to let the fake news tell us what to do, how to live, or what didn't read it-of course, you're reading the fake news LAUGHTER but the Democrats were

For instance, we should observe the word try in combination with to silence and to stop. The third and the eighth lines show the dishonest topos in combination with Trump Wall. In addition, the massive repetition of the word *fake* – from line fourth to line seventh – should be highlighted.

In the following Table it is possible to look at the collocates of the word medium.

Collocate	Cooccurrences	Occurrences	T-score	MI3
fake	3	13	1.73	12.50
them	3	77	1.72	9.93
never	2	66	1.40	8.40
no	2	69	1.40	8.34
us	2	89	1.39	7.97
will	3	325	1.66	7.86
want	2	131	1.38	7.41
they	2	295	1.34	6.24
be	3	1,670	1.39	5.50
I	2	542	1.28	5.36
have	2	560	1.27	5.32
we	2	774	1.22	4.85

Table 4.48 Collocates of the word *medium* in the Trump Traditional Corpus

Even in this case – not surprisingly – the first collocate is *fake*. Moreover, the majority of the processes present in the list are exclusively associated to the media such as *want*, *will* and *have*. Lastly, the list includes the collocates *them*, *us*, *they*, *I* and *we* that suggest a strong narrative based on the opposition *us* (Trump and his supporters) vs. *them* (the media as part of the elite corrupt system) that it is possible to observe in the concordance lines in Table 4.49.

because the people know the truth. The fake it right from the beginning. The dishonest These American victims were ignored by the them to do it. So we'll see. It's the fake, fake the filter of the fake news. The dishonest of our greatest Presidents, fought with the started—they came at 4 in the morning. The The media will give them no credit. The so it's not fair, but nothing fair about the the lobbyists, and the corrupt corporate interests who control our politics and our Our campaign is taking on big business, big donors, the large corporations, and the Trump Traditional Corpus

The quantitative analysis also investigated the metaphor *witch hunt* that was found in tweets. However, the analysis did not provide results in the Trump Traditional Corpus.

# 4.4 Europe

This section focuses on the representation of Europe in Donald Trump's discourse.

#### 4.4.1 Qualitative analysis

The qualitative analysis dedicated to Europe involved the investigation of metaphors, *topoi*, representational strategies and transitivity. The analysis did not provide results concerning *topoi* and representational strategies. However, it is possible to find references to Europe's implicit connection to crime and terrorism in the section dedicated to immigration (see section 4.6. Example 33).

### **4.4.1.1 Metaphors**

In the Trump Tweet Corpus there are 5 occurrences of source domains connected to Europe that – as it is possible to notice from Table 4.50 – belong to the source domains of war, religion and nature. The Trump Traditional Corpus has no occurrences.

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
TTW	-	-	-	-	40% (2)	40% (2)	20% (1)	-
TTS	-	-	-	-	-	-	-	-

Table 4.50 E.U. source domains in Trump's corpora

- 26. A strong Poland is a **blessing** to the nations of Europe, and a strong Europe is a **blessing** to the West, and to the world. [emphasis added] (Trump's Tweet 6 July 2017)
- 27. THE WEST WILL NEVER BE BROKEN. Our values will **PREVAIL**. Our people will **THRIVE** and our civilization will **TRIUMPH!** [emphasis added] (Trump's Tweet 6 July 2017)

Example 26 – a tweet that contains an extract of a speech delivered by Trump in Poland– shows the religion source domain since Trump describes the stability of Europe as a *blessing*. In addition, in example 27 there is a combination of war and nature source domains. In this tweet – that is also an extract of the same speech delivered in Poland – Trump recalled the historical alliance between the U.S. and Poland (among other European countries) during the Second World War and the Cold War. During the speech he specified that nowadays communist threats have been replaced by terrorism; consequently, it is necessary to cooperate against this new enemy. He strategically opposes the western world to the Muslim one. Specifically, the verbs *prevail* and *triumph* clearly recall this opposition that has been reinforced during the years that followed 9/11. These verbs belong to the source domain of war and they are used by Trump to describe and perpetrate this conflict that involves religions, values ad cultures. The verb *thrive* metaphorically represents western society (more precisely European and American societies) as a garden (McCallum-Bayliss, 2019: 244) that will flourish after the defeat of the enemy.

28. **A new radical Islamic terrorist** has just attacked in Louvre Museum in **Paris**. Tourists were locked down. France on edge again. **GET SMART U.S**. [emphasis added] (Trump's Tweet 3 February 2017)

Finally, Trump often mentions Europe to talk about the immigration phenomenon mainly to inform the happening of terrorist attacks in order to remark the connection between radical Islamic terrorism (ISIS) and refugees present in Europe, and to comment the catastrophic effect of mass immigration (see example 33). In this regard, example 28 shows how Trump implicitly highlights the possible threats that the United States have to face if they do not *get smart* adopting different immigration policies.

### 4.4.1.2 Transitivity

The Trump Tweet Corpus counts two occurrences of relational processes linked to Europe, while there are no occurrences in the Trump Traditional Corpus.

	Material	Relational	Mental	Verbal	Behavioural	Existential
TTW	-	100% (2)	-	-	-	-
TTS	-	-	-	-	-	-

Table 4.51 E.U. transitivity in Trump's corpora

29. Working on major Trade Deal with the United Kingdom. Could be very big & exciting. JOBS! **The E.U. is very protectionist** with the U.S. STOP! [emphasis added] (Trump's Tweet 25 July 2017)

Example 29 shows one of the two relational processes found in Trump's Corpora (it is possible to observe the other one in example 26) that is strictly connected to the portrayal of the United States as a victim. Indeed, Trump uses this process to negatively depict the European Union's attitude towards the U.S. from an economic perspective.

### 4.4.2 Quantitative analysis

### 4.4.2.1 Keywords in the Trump Tweet Corpus

The following Table shows the keywords associated to Europe in the Trump Tweet Corpus. It is important to specify that these keywords were extracted from the Appendix A.

Keyword	Score	Freq	Rel_freq
France	4.330	12	24.1
Germany	3.630	11	22.1

Table 4.52 Europe keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

The only two keywords associated to Europe in the Trump Tweet Corpus are *France* and *Germany*. As it is possible to notice from Tables 4.53 and 4.54 both keywords are connected to a variety of topics such as immigration, terrorism, fake news and U.S. foreign relationships with these two countries.

### 4.4.2.2 Concordances and collocates in the Trump Tweet Corpus

The concordances of *France* – that can be scrutinised in Table 4.53 – reveal that this keyword is clearly associated to terrorism and politics with a particular focus on U.S. foreign relation with this European country.

Museum in Paris. Tourists were locked France on edge again. GET SMART U.S. We must will not take much more of this. Will have a terrorist attack in Paris. The people of France election currently taking place in . Thank you Lake Worth, Florida. France on his big win today as the next President of . I look very much forward to working with France this morning. Spoke yesterday with the King Will be speaking with Germany and France @ the invitation of President Macron to for agriculture." LINK Getting rdy to leave for France Senate must act! Just landed in Paris, with @FLOTUS Melania. LINK Melania and France to Eiffel Tower for dinner. Relationship with stronger than ever. LINK Republicans France United States mourns for the victims of Nice, France . We pledge our solidarity with France against terror. ??? LINK Great conversations Nice, France. We pledge our solidarity with France this afternoon. Just landed from Paris, France . It was an incredible visit with President and myself to such a historic celebration in France . #BastilleDay #14juillet LINK Honored to Table 4.53 Concordances of the word *France* in the Trump Tweet Corpus

Similarly, the keyword *Germany* – as it is possible to observe in Table 4.54 – is also connected to terrorist attacks. However, Trump focuses more on economic and political matters. Furthermore, the pervasive dishonest topos refers to a specific episode happened during the G20 in Hamburg.

were terror attacks in Turkey, Switzerland - and it is only getting worse. The civilized Germany Germany said just before crime, "by God's will we will The terrorist who killed so many people in ? We had a great News Conference at One last shot at me. Are we living in Nazi Germany Chancellor Angela Merkel. Nevertheless, Germany owes ... ... vast sums of money to NATO & , and very expensive, defense it provides to Germany ! #ICYMI: Weekly Address We have a MASSIVE trade deficit with Germany , plus they pay FAR LESS than they should EVIL! USA ?? Will be speaking with and France this morning. Spoke yesterday Germany leave for Poland, after which I will travel to for the G-20. Will be back on Saturday. Germany at the #G20Summit here in Hamburg. Germany . Looking forward to day two! #USA spouses, were invited by the Chancellor of Germany . Press knew! The Fake News is becoming Even a dinner arranged for top 20 leaders in is made to look sinister! I will be having Germany Table 4.54 Concordances of the word *Germany* in the Trump Tweet Corpus

Lastly, Table 4.55 shows the concordances of the word Europe that confirm once again the connection to political matters but also to immigration in combination to terrorism.

ISIS has infiltrated countries all over by posing as refugees, and @HillaryClinton Europe NOW. Look what is happening all over Europe and, indeed, the world - a horrible mess! </s> is very real, just look at what is happening in Europe and the Middle-East. Courts must act fast! I Montana for Republicans! Just returned from Europe . Trip was a great success for America. strong Poland is a blessing to the nations of Europe , and a strong Europe is a blessing to the to the nations of Europe, and a strong Europe is a blessing to the West, and to the world. Table 4.55 Concordances of the word *Europe* in the Trump Tweet Corpus

#### 4.4.2.3 Keywords in the Trump Traditional Corpus

The following Table shows the keyword list (extracted from the Appendix B) in the Trump Traditional Corpus that involves just the keyword *Paris*.

Keyword	Score	Freq	Rel_freq
Paris	13.300	26	66.5

Table 4.56 Europe keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

This keyword is mainly connected to the Paris Climate Accord, but also to U.S. foreign relationships with France, immigration, and terrorism.

### 4.4.2.4 Concordances and collocates in the Trump Traditional Corpus

In Table 4.57 there is a random selection of *Paris* concordances lines that confirms that this keyword is almost exclusively associated to the Paris Agreement and the U.S. withdrawal.

CONVENTION ON CLIMATE CHANGE PARIS AGREEMENT" Thank you very much. the United States will withdraw from the Paris climate accord thank you, thank you-Agreement-they went wild; they were so of the world applauded when we signed the Paris tremendous disadvantage. The fact that the Paris deal hamstrings the United States, while severe energy restrictions inflicted by the Paris accord, it includes yet another scheme to citizens are out of work. And yet, under the Paris accord, billions of dollars that ought to be that obligation is to the American people. The accord would undermine our economy, Paris countries of the world. It is time to exit the accord and time to pursue a new deal that Paris locations within our great country-before , France. It is time to make America great Paris the world. Take a look at Nice. Take a look at Paris . We've allowed thousands and thousands of Table 4.57 Concordances of the word *Paris* in the Trump Traditional Corpus

Nevertheless, the last line shows that the keyword is also associated to refugees proving even in traditional speeches the association between Europe, immigration and the consequent dangers.

We're supposed to get rid of ours. Even issues as well. Foreign leaders in stalling the advance of his Third Army across he enlisted, Private Miller was on his way to of our economic revival. China, Japan, and you. Americans fought and died to liberate Europe is allowed to continue construction of coal purpose. Asia, and across the world should not have in early December 1944—horrible weather—to fight for our country. APPLAUSE Great. A are printing huge sums of money – the from the evils of nazism—you know that—and Table 4.58 Concordances of the word *Europe* in the Trump Traditional Corpus

Finally, in Table 4.58 it is possible to observe the only concordance lines of *Europe* where Trump mentions Europe regarding economic matters, especially in order underline the position of the United States as a victim of other countries' unfair behaviours. Europe is also mentioned when Trump talks about veterans and their efforts during the Second World War.

### 4.5 Mexico

The following sections investigate – qualitatively and quantitatively – Trump's representation of Mexico.

### 4.5.1 Qualitative analysis

From a qualitative perspective the representation of Mexico was investigated just through Trump's employment of representational strategies.

# 4.5.1.1 Representational Strategies

There is just one occurrence of representational strategies connected to Mexico in the Trump Tweet Corpus. The Trump Traditional Corpus does not count occurrences.

	Opposition	Aggregation	Generecisation	Specification	Suppression	Crime and terrorism
TTW	-	-	-	-	-	100% (1)
TTS	-	-	-	-	-	<u>-</u>

Table 4.59 Mexico's representational strategies in Trump's corpora

30. **Mexico** was just ranked the **second deadliest country in the world**, after only Syria. **Drug trade** is largely the cause. We will BUILD THE WALL! [emphasis added] (Trump's Tweet 23 June 2017)

Example 30 shows the only occurrence found in the Trump Tweet Corpus. In this example Mexico is linked to crime because of drug trade. Moreover, it is interesting to notice how Trump strategically compares Mexico to Syria in order to make perceive Mexico as a war zone devastated by criminal cartels. Consequently, this representational strategy is used by Trump in order to legitimise his strict immigration policies and the building of the Wall (Demata, 2017). Therefore, the connection to crime and terrorism is useful to Trump to simply a complex phenomenon such as immigration through the physical exclusion of immigrants and refugees.

Although there is just one occurrences connected to the representational strategy of crime and terrorism, it is also important to underline that Trump often mentions Mexico regarding economic matters such as economic deals, trades and delocalisation as it is possible to observe in example 31.

31. Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! **Build plant in U.S. or pay big border tax**. [emphasis added] (Trump's Tweet 5 January 2017)

Specifically, examples 31 also includes a warning and threatening speech act (Chilton, 2004) in order to underline Trump's portrayal as a firm leader and to legitimise his capability in terms of economic matters since he is a successful businessman. Lastly, there is a complete suppression of Mexican people's representation in Trump' discourse; as a result, it would be more difficult to empathised with them or more generally with people that come from the southern border.

## 4.5.2 Quantitative analysis

## 4.5.2.1 Keywords in the Trump Tweet Corpus

Table 4.60 shows that the only keyword associated to Mexico in the Trump Tweet Corpus is *pay*. Specifically, as it is possible to notice in Tables 4.61 and 4.62 this keyword involves first of all the building of Trump Wall when it is associated to Mexico.

Keyword	Score	Freq	Rel_freq
pay	1.800	8	16.1

Table 4.60 Mexico keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

# 4.5.2.2 Concordances and collocates in the Trump Tweet Corpus

The following Table shows the collocate list of the keyword *pay*. As mentioned in the previous section this keyword involves first of all the building of Trump Wall when associated to Mexico. As a result, the first collocates of the list are precisely *wall* and *Mexico*.

Collocate	Cooccurrences	Occurrences	T-score	MI3
wall	6	20	2.44	14.13
Mexico	6	29	2.44	13.59
they	6	162	2.41	11.11
high	3	34	1.72	10.36
respect	2	13	1.41	9.99
tax	3	59	1.71	9.57
play	2	19	1.41	9.45
what	3	70	1.71	9.32
should	3	72	1.71	9.28
if	3	85	1.70	9.04
#imwithyou	2	28	1.40	8.89
pay	2	30	1.40	8.79
say	3	105	1.70	8.73
border	2	34	1.40	8.61
big	3	128	1.69	8.45
Hillary	3	166	1.67	8.07
must	2	55	1.39	7.91
back	2	65	1.39	7.67
look	2	86	1.38	7.27
more	2	89	1.38	7.22

Table 4.61 Collocates of the word pay in the Trump Tweet Corpus

The words *tax*, *border* and *big* are connected to Trump's threatening acts (see example 31) towards U.S factories delocalisation in Mexico. Finally, it is important to mention that some of the collocates – such as *high*, *play*, *#imwithyou*, *they*, *what*, *must*, *look*, *more* and *Hillary* – are not directly connected to representation of Mexico but just to the word *pay* used in different circumstance.

In Table 4.62 there is a random selection of concordances lines of the keyword *pay* when it is associated to Mexico (the third and the ninth lines show two examples of the keyword used in different contexts). The concordances confirm the strong association between *pay*, *Mexico* 

and wall. Indeed, Trump often repeats that the Wall will be paid by Mexico despite what the fake news says.

```
in Arizona! #ImWithYou LINK Mexico will
                                                       for the wall - 100%!
                                                 pay
 #AmericaFirst! #ImWithYou LINK Mexico will
                                                       for the wall! Thank you to @foxandfriends
                                                pay
                                                       $225,000 by a Brazilian bank for a speech
    #BigLeagueTruth LINK Moderator: Hillary
                                                paid
  cars for U.S. NO WAY! Build plant in U.S. or
                                                       big border tax. How did NBC get "an
                                                pay
    the Great Wall (for sake of speed), will be
                                                       back by Mexico later! Hillary and the Dems
                                                paid
       Dishonest media says Mexico won't be paying
                                                       for the wall if they pay a little later so the wall
    Mexico won't be paying for the wall if they
                                                       a little later so the wall can be built more
                                                pay
                                                       for the badly needed wall, then it would be
  and companies lost. If Mexico is unwilling to
                                                pay
     on the importance of getting countries to
                                                pay
                                                       their fair share & focus on the threat of
   so we can get started early, Mexico will be paying , in some form, for the badly needed border
Table 4.62 Concordances of the word pay in the Trump Tweet Corpus
```

The following Table explores the collocates of the word *Mexico* in the Trump Tweet Corpus. Some of the collocates are linked to economic matters such as *ford*, *dollar*, *billion* and *deal*. Furthermore, the collocates *plant*, *fire* and *move* are strictly connected to delocalisation.

Collocate	Cooccurrences	Occurrences	T-score	MI3
plant	5	13	2.23	14.01
pay	6	30	2.44	13.59
new	6	106	2.42	11.77
move	2	10	1.41	10.42
Ford	2	12	1.41	10.16
both	2	12	1.41	10.16
call	3	46	1.72	9.97
fire	2	15	1.41	9.84
dollar	2	19	1.41	9.49
billion	2	20	1.41	9.42
wall	2	20	1.41	9.42
#imwithyou	2	28	1.40	8.94
lose	2	40	1.40	8.42
very	3	156	1.68	8.21
deal	2	49	1.39	8.13
one	2	50	1.39	8.10
me	3	177	1.67	8.03
good	2	75	1.38	7.51
would	2	81	1.38	7.40
no	2	100	1.37	7.10

Table 4.63 Collocates of the word *Mexico* in the Trump Tweet Corpus

Table 4.64 provides a random selection of the concordances lines of the word *Mexico* in the Trump Tweet Corpus. In addition to confirm the analysis of keywords, the concordances show that Trump is more focused on economic matters rather than immigration concerning the word *Mexico*.

invitation of President Enrique Pena Nieto, of	Mexico	, and look very much forward to meeting him
Just arrived in Arizona! #ImWithYou LINK	Mexico	will pay for the wall - 100%!
, it's called #AmericaFirst! #ImWithYou LINK	Mexico	will pay for the wall! Thank you to
made wonderful deals together - where both	Mexico	and the US would have benefitted.

Will be in Nevada, Colorado and New	Mexico	tomorrow - join me! Tickets: LINK
#DTS "@DanScavino: Ford to scrap	Mexico	plant, invest in Michigan due to Trump
you to Ford for scrapping a new plant in	Mexico	and creating 700 new jobs in the U.S. This is
Motor said will build a new plant in Baja,	Mexico	, to build Corolla cars for U.S. NO WAY!
So serious! Dishonest media says	Mexico	won't be paying for the wall if they pay a little
instead of building a BILLION dollar plant in	Mexico	. Thank you Ford & Fiat C! An old picture
numbers of jobs and companies lost. If	Mexico	is unwilling to pay for the badly needed wall,
the Obama Administration to move to	Mexico	. Fired their employees. Tax product big
New Sugar deal negotiated with	Mexico	is a very good one for both Mexico and the
with Mexico is a very good one for both	Mexico	and the U.S. Had no deal for many years
Table 4.64 Concordances of the word <i>Mexico</i> in	the Trum	p Tweet Corpus

Table 4.64 Concordances of the word *Mexico* in the Trump Tweet Corpus

#### Keywords in the Trump Traditional Corpus 4.5.2.3

Table 4.65 displays that the only keyword associated to Mexico is pay that even in this Corpus - excluding economic matters - is mainly associated to Trump Wall (see Table 4.66).

Keyword	Score	Freq	Rel_freq
pay	1.830	3	7.7

Table 4.65 Mexico keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

#### 4.5.2.4 Concordances and collocates in the Trump Traditional Corpus

The following Table shows the collocate list of the word pay in the Trump Traditional Corpus. The majority of the collocates in this case are not directly connected to both the keyword pay and to Mexico. They are mainly associated to economic matters such as bill, share, cost, fair and tax. The only keyword directly linked to both pay and Mexico is wall.

Collocate	Cooccurrences	Occurrences	T-score	MI3
bill	4	17	1.99	12.58
share	3	11	1.73	11.96
their	5	100	2.21	10.99
they	7	295	2.58	10.89
not	6	338	2.36	10.02
cost	2	15	1.41	9.76
group	2	16	1.41	9.67
have	6	560	2.31	9.29
fair	2	21	1.41	9.28
wall	2	22	1.40	9.21
tax	2	34	1.40	8.58
more	2	54	1.39	7.91
those	2	56	1.39	7.86
other	2	62	1.39	7.71
them	2	77	1.38	7.40
states	2	82	1.38	7.31
go	3	320	1.62	7.10
will	3	325	1.62	7.08

Table 4.66 Collocates of the word pay in the Trump Traditional Corpus

Table 4.67 shows a random selection of the concordances lines of pay. Here it is possible to verify the analysis of collocates. Moreover, we should notice that the collocate bill is not used by Trump to indicate just economic matters but also to refer to Bill Clinton.

```
pipelines-and they failed. Didn't work. They
                                                paid
                                                        millions and millions and hundreds of millions
   Syria into absolute chaos. Our allies aren't paying their fair share, foreign countries like
      make this country run and run well. You
                                                        your taxes, follow our laws, support your
                                                 pay
   our allies pay their fair share. They have to
                                                        . We've begun a dramatic effort to eliminate
                                                 pay
                                                        for the wall, and I've made that clear to the
 many times that the American people will not
                                                 pay
   of dollars the U.S. taxpayers have spent to
                                                 pay
                                                        the cost of illegal immigration. Much of it has
   will generate revenue from Mexico that will
                                                        for the wall if we decide to go that route. It is
                                                 pay
   fees from financial firms. The same groups paying Bill and Hillary for their speeches were
Table 4.67 Concordances of the word pay in the Trump Traditional Corpus
```

Finally, in Table 4.68 there are the concordances of the word *Mexico* that confirms once again the pervasiveness of Trump's economic discourse.

```
, and so many others are moving their jobs to it's moving all of its small car production to money, believe me. We've reinstated the I've made that clear to the Government of us as much as $60 billion a year with To that end, the President of meeting scheduled for next week. Unless exports, and will generate revenue from Table 4.68 Concordances of the word Mexico in the Trump Traditional Corpus
```

# 4.6 Immigrants and Refugees

This section analyses Donald Trump's representation of immigrants and refugees.

## 4.6.1 Qualitative analysis

Immigrants and refugees' representation in Trump's discourse was investigated through metaphors, *topoi*, representational strategies and transitivity.

## **4.6.1.1** *Metaphors*

On the one hand, the Trump Tweet Corpus counts just one occurrence that belongs to the source domain of water. On the other hand, in the Trump Traditional Corpus there are no occurrences.

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
TTW	-	-	-	-	-	-	-	-
TTS	-	-	-	-	-	-	-	100% (1)

Table 4.69 Immigrants and refugees' source domains in Trump's corpora

32. I am going to end illegal immigration, stop **the massive <u>inflow</u> of refugees**, keep jobs from pouring out of our country, renegotiate our disastrous trade deals, and massively reduce taxes and regulations on our workers and our small businesses. [emphasis added] (Remarks at Prescott Valley Center Arizona 4 October 2016)

In example 32 it is possible to observe the only metaphor found in Trump's Corpora. Specifically, this metaphor concerns just refugees that are described as an *inflow*. This metaphor

allows Trump to represent refugees as an unstoppable, strong and powerful flow that could enter and destroy the United States since water is a dangerous force of nature. It is also important to highlight that the word *inflow* is combined with the word *massive*. This word gets worse the threatening perception of refugees because it suggests a huge number of people that continuously enter into the country with no way to stop them.

# 4.6.1.2 Topoi

In the Trump Tweet Corpus there are 14 occurrences of *topoi* linked to immigrants and refugees. More precisely, as shown in Table 4.70 the majority of the occurrences belong to the category of danger, threat and fear while the remaining occurrences belong to the invasion *topos*. The Trump Traditional Corpus counts 20 occurrences. Even in this case the majority of the occurrences belong to the danger, threat and fear *topos*. However, in traditional speeches the remaining occurrences belong to both the categories of burden and invasion.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
TTW	-	79% (11)	-	21% (3)	-	-	-
TTS	-	75% (15)	15% (3)	10% (2)	-	-	-

Table 4.70 Immigrants and refugees' topoi in Trump's corpora

- 33. **ISIS** has infiltrated countries all over Europe by posing as refugees, and @HillaryClinton will allow it to happen here, too! #BigLeagueTruth [emphasis added] (Trump's Tweet 20 October 2016)
- 34. On top of that, **illegal immigration costs our country more than \$113 billion a year**. For the money we are going to spend on illegal immigration over the next ten years, we could provide one million at-risk students with a school voucher. [emphasis added] (Remarks at Prescott Valley Center Arizona 4 October 2016)
- 35. Do you believe it? The Obama Administration **agreed to take thousands of illegal immigrants** from Australia. Why? I will study this dumb deal! [emphasis added] (Trump's Tweet 2 February 2017)

Example 33 shows the *topos* of danger, threat and fear. In this tweet Trump links refugees to terrorism claiming that Clinton will allow terrorist to easily pose as refugees and enter in the United States if she becomes President. Indeed, the tweet shows how Trump portrays – coherently with the proximization theory (section 2.6) – refugees as an imminent threat very close to the United States legitimising his presidential candidacy over Clinton's one. As a result, in this tweet we can also find a combination of delegitimisation and self-legitimisation because Trump aims to discredit Clinton and to presents himself as the firm leader that will protect the United States from terrorist threats. The tweet can be scrutinised in Figure 4.1 and it provides a video that is an extract from the third presidential debate of 2016. The DTF *topos* can be found also in examples 37, 38, 39 and 40. In example 34 it is possible to observe the burden *topoi* since Trump talks about how much illegal immigration costs to the United States and he

proposes to invest that money in other sectors more useful for American citizens such as school voucher. The *topos* of burden is also present in example 37 where Trump claims that refugees have free access to U.S. welfare and healthcare at the expense of American people disadvantaging some categories such as veterans. Lastly, example 35 shows the invasion *topos*; specifically, Trump combines the words *illegal immigrants* to the word *thousands* suggesting a huge number of people that are entering the United States. This *topos* can be also observed in examples 37 and 38. In example 37 Trump claims that *thousands of refugees* are entering into the United States without screening implying that they could pose economic and terrorist threats (since the invasion *topos* can be considered a sub-category of the danger, threat and fear *topos*). In Example 38 Trump talks about an increase of Syrian immigrants in terms of percentages underling once again the potential connection between refugees and terrorism.



Figure 4.1 Trump's tweet 19 October 2016

#### 4.6.1.3 Representational Strategies

In the Trump Tweet Corpus there are 27 occurrences of representational strategies connected to immigrants and refugees, while the Trump Traditional Corpus has 38 occurrences.

	Opposition	Aggregation	Generecisation	Specification	Suppression	Crime and terrorism
TTW	-	30% (8)	7% (2)	-	11% (3)	52% (14)
TTS	16% (6)	29% (11)	13% (5)	-	-	42% (16)

Table 4.71 Immigrants and refugees' representational strategies in Trump's corpora

- 36. So, in the coming days, we will develop a system to help ensure that **those admitted into our country fully embrace our values of religious and personal liberty and that they reject any form of oppression and discrimination**. We want people to come into our Nation, but we want people to love us and to love our values, not to hate us and to hate our values. [emphasis added] (Remarks at the National Prayer Breakfast 2 February 2017)
- 37. Thousands of refugees are being admitted, with no way to screen them, and are instantly made eligible for welfare and free healthcare even as our own Veterans die waiting for the

- **medical care they need**. [emphasis added] (Remarks at Prescott Valley Center Arizona 4 October 2016)
- 38. Hillary has called for **550% more Syrian immigrants**, but won't even mention "**radical Islamic terrorists**." [emphasis added] (Trump's Tweet 20 October 2016)
- 39. **ISIS** is taking credit for the terrible stabbing attack at Ohio State University by a Somali refugee who should not have been in our country. [emphasis added] (Trump's Tweet 30 November 2016)
- 40. Also among the victims of the Obama-Clinton open borders policies was Grant Ronnebeck, a 21-year-old convenience store clerk in Mesa, Arizona. He was murdered by **an illegal immigrant gang member** previously convicted of burglary who had also been released from Federal Custody. [emphasis added] (Remarks at Prescott Valley Center Arizona 4 October 2016)
- 41. ISIS is on the run & will soon be wiped out of Syria & Iraq, **illegal border crossings** are way down (75%) & MS 13 gangs are being removed. [emphasis added] (Trump's Tweet 12 July 2017)

Examples 36 and 37 shows two types of opposition strategy. The first one – in example 36 – is a traditional type of opposition strategy that opposes us vs. them from a cultural and religious perspective with a particular focus on values. The second one – in example 37 – is a type of opposition that opposes two categories of suffering social actors. In this case Trump opposes veterans to refugees (who represent a threat and exploit U.S. welfare and healthcare) since he aims to shift people's empathy towards their compatriots. Moreover, in example 37 it is possible to find the aggregation strategy (thousands of refugees) that is present in example 38 as well because Trump talks about refugees in terms of percentages aiming to dehumanise this category of social actors and to reduce once again empathy towards them. Example 38 also contains a connection to terrorism since Trump implies that Syrian immigrants have connection to radical Islamic terrorism. This tweet can be observed in Figure 4.3 where Trump's strategy of selflegitimation and other-delegitimisation is particularly evident from the attached Clinton's picture. In addition, in this picture the words will increase Syrian refugees by 550% are red in order to underline the danger that the U.S. could face once Clinton is elected. In example 39 (see Figure 4.2) the connection to terrorism is combined with the genericisation strategy (a Somali refugee) to increase the perception that any refugee could be a potential threat. On the other hand, in example 40 it is possible to notice a combination of genericisation (an illegal immigrant gang member) and the association to crime that has the same strategic function of the previous example. In this way, any immigrant can be perceived as a potential threat for U.S. citizens' safety. Lastly, in example 41 Trump employs the suppression strategy (illegal border crossing) in combination with the association to crime because he strategically does not differentiate between criminals and immigrants at the southern border in order to dehumanise them and erase empathy.



ISIS is taking credit for the terrible stabbing attack at Ohio State University by a Somali refugee who should not have been in our country.

12:20 PM · 30 nov 2016 · Twitter for Android

28.580 Retweet 92.985 Mi piace

Donald J. Trump

Figure 4.2 Trump's tweet 30 November 2016



Figure 4.3 Trump's tweet 19 October 2016

## 4.6.1.4 *Transitivity*

The Trump Tweet Corpus counts 3 occurrences of processes linked to immigrants and refugees, while in the Trump Traditional Corpus there are 40 occurrences. As it is possible to notice from Table 4.72 all the processes in tweets are material. Material processes represent the majority in traditional speeches but there are also relational and mental processes.

	Material	Relational	Mental	Verbal	Behavioural	Existential
TTW	100% (3)	-	-	-	-	-
TTS	85% (34)	10% (4)	5% (2)	-	-	-

Table 4.72 Immigrants and refugees' processes in Trump's corpora

42. Countless Americans who have died in recent years would be alive today if not for the open border policies of this Administration. This includes incredible Americans like 21-year-old Sarah Root. The man who killed her arrived at the border, entered federal custody, and then was released into a U.S. community under the policies of this White House. He was released again after the

crime, and **is** now at large. [emphasis added] (Remarks at Prescott Valley Center Arizona 4 October 2016)

Example 42 shows a sequence of material processes in which immigrants perform both Actor and Goal (see also example 35). These processes are mainly negative since Trump is talking about an immigrant who illegally entered the country and killed a young and brilliant American woman underling the *topos* of DTF. These material processes are also combined with a relational once (*is*). This traditional extract is used to delegitimise Hillary Clinton and Barack Obama since Trump blames the Obama administration for weak immigration policies.

Finally, it is important to mention immigrants and refugees' participant types in material processes because they can reveal the agency of these social actors. Immigrants and refugees are Actor for the 54% and Goal for the 35%. As a result, immigrants and refugees are described by Trump usually as active social actors who perpetrate negative actions. Therefore, the evaluation type of processes is mainly negative (86%) and the voice type is usually active (58%).

Participant types	Percentage	Occurrence
Actor	54%	23
Goal	35%	15
Carrier	5%	2
Identified	2%	1
Possessor	2%	1
Senser	2%	1

Table 4.73 Immigrants and refugees' participant types in Trump's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	58% (25)	40% (17)	2% (1)	-	-	-
Evaluation	-	-	-	12% (5)	86% (37)	2% (1)

Table 4.74 Immigrants and refugees' voice type and evaluation type in Trump's corpora

# 4.6.2 Quantitative analysis

# 4.6.2.1 Keywords in the Trump Tweet Corpus

The following Table shows the keywords associated to immigration in Trump Tweet Corpus.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
illegal	10.860	13	26.2	ban	6.090	16	32.2
immigration	7.690	11	22.1	stop	2.220	1	2.0

Table 4.75 Immigration keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

The first keyword *illegal* – as it is possible to notice in Table 4.80 – is strongly associated to immigration and immigrants. The keyword *ban* is linked to Trump's Travel ban towards dangerous countries.

In addition to keywords directly associated to immigration, this quantitative analysis investigates the categories of danger, threat and fear, invasion and burden that are also strictly connected to the topic of immigration. In this regard, we should mention that in the Trump Tweet Corpus there are no keywords associated to the category of burden.

The majority of keywords – in Table 4.76 – associated to DTF (*Isis*, *terrorism*, *terrorist*, *attack* and *kill*) are linked to terrorism because this topic is implicitly connected to immigration. Trump often mentions Europe in order to warn American people of the potential and catastrophic effects of immigration. For this reason, it is possible to notice in Table 4.76 the keywords *France* and *Germany*. The keywords *Syria* and *Iraq* are connected to both immigration and terrorism. In addition to terrorism, the association between immigration and crime through the keywords *gang*, *criminal* and *drug* should be highlighted.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
isis	9.470	15	30.2	Germany	3.630	2	4.0
immigration	7.690	4	8.0	criminal	2.280	10	20.1
gang	6.980	10	20.1	drug	2.240	14	28.2
terrorism	5.810	10	20.1	attack	2.190	21	42.3
Syria	5.200	3	6.0	Iraq	2.060	10	20.1
terrorist	4.980	16	32.2	kill	1.540	6	12.1
France	4.330	4	8.0				

Table 4.76 DTF keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

In Table 4.77 it is possible to observe the keyword *immigration* that is the only one associated to the category of invasion suggesting that it is not a very pervasive narrative in Trump discourse on Twitter (see also Table 4.81).

Keyword	Score	Freq	Rel_freq
immigration	7.690	1	2.0

Table 4.77 Invasion keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

Lastly, in Table 4.78 there are those keywords under the label security that also involve immigration since Trump – through the keywords *border*, *wall*, *security*, *protect* and *stop* – depicts immigrants (especially the ones who come from the southern border) as an imminent threat (see proximization in section 2.6) to national security that require immediate strict security measures.

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
border	8.410	34	68.4 stop	2.220	6	12.1
wall	2.640	16	32.2 national	1.580	33	66.4
security	2.590	35	70.4 safety	1.420	13	26.2
protect	2.450	21	42.3 force	1.310	11	22.1
general	2.230	19	38.2			

Table 4.78 Security keywords in the Trump Tweet Corpus (reference corpus enTenTen2018 US domain)

# 4.6.2.2 Concordances and collocates in the Trump Tweet Corpus

Table 4.79 shows the collocates of the keyword *illegal* in the Trump Tweet Corpus. The first collocate is *immigration* confirming that in Trump's discourse is particularly relevant the association of immigration with criminality. Indeed, the list includes the collocate *criminal*. This association aims to legitimise Trump's strict immigration policies that are possible to recognise in this list through the collocates *border*, *stop*, and *security*.

Collocate	Cooccurrences	Occurrences	T-score	MI3
immigration	8	16	2.83	15.85
leak	6	19	2.45	14.35
be	11	1,592	3.06	10.59
criminal	2	10	1.41	10.52
border	3	34	1.72	10.51
classified	2	12	1.41	10.26
weak	2	15	1.41	9.94
take	3	71	1.71	9.45
place	2	22	1.41	9.39
stop	2	26	1.40	9.15
act	2	27	1.40	9.09
totally	2	27	1.40	9.09
security	2	35	1.40	8.72
job	3	138	1.69	8.49
all	3	164	1.68	8.24
even	2	50	1.40	8.20
why	2	62	1.39	7.89
that	3	274	1.65	7.50
state	2	84	1.38	7.45
very	2	156	1.35	6.56

Table 4.79 Collocates of the word illegal in the Trump Tweet Corpus

The word *job* is present because Trump – during the electoral campaign – usually listed his electoral promises, while the collocates *classified* and *leak* are actually linked to media (see section 4.3). Finally, the collocates *act*, *weak* and *place* are connected to Trump's opposition. It is possible to verify the employment of these collocates in the following Table that provides a random selection of concordances of the keyword *illegal*.

```
illegal
                                                      immigration, stop the drugs, deport all
                                We will end
       should focus their energies on ISIS,
                                              illegal
                                                      immigration and border security instead
             The real story ... ... is all of the
                                              illegal
                                                      leaks of classified and other information.
                         Jobs are returning,
                                              illegal
                                                      immigration is plummeting, law, order and
                                                      immigration policies of the Obama Admin.
                                  The weak
                                              illegal
                                              illegal
                                                      immigration, bad for jobs and wants
                  VERY weak on crime and
                                             illegals to pour through our borders.
           border security – now they want
                                                      acts that took place in the Clinton
                              With all of the
                                              illegal
                                     Totally
                                              illegal! Fake News is at an all time high.
     will soon be wiped out of Syria & Iraq,
                                              illegal border crossings are way down (75%)
Table 4.80 Concordances of the word illegal in the Trump Tweet Corpus
```

Table 4.80 shows also how Trump uses the words illegals and illegal border crossing to suppress immigrants and strategically assimilate them to common criminals.

In Table 4.81 there are all the concordances of the keyword immigration. These concordances show the variety of topics connected to immigration such as immigration policies, and the connection to crime and terrorism.

for the great review of the speech on as @JeffFlake, if it is going to stop illegal Such a great honor! LINK Nation's balancing the budget, jobs and illegal #Debate TRUMP & CLINTON ON IMMIGRATION #Debate #BigLeagueTruth Thank you NH! We will end illegal ICE OFFICERS WARN HILLARY IMMIGRATION PLAN WILL UNLEASH GANGS, is wrong - they are sadly weak on focus their energies on ISIS, illegal and JOBS! #AmericaFirst ?? LINK LINK ' media is trying to say that large scale happening! Jobs are returning, illegal wants to protect criminals, allow illegal lower taxes & safety! The weak illegal VERY weak on crime and illegal Today, I hosted an

immigration immigration **Immigration** immigration immigration immigration immigration **Immigration** immigration immigration immigration immigration immigration immigration

last night. Thank you also to the great . The Great State of Arizona, where I just And Customs Enforcement Officers (ICE) and not waste his time on fighting stop the drugs, deport all criminal . The two ... ... Senators should focus and border security instead of always Ban Is One Of Trump's Most Popular in Sweden is working out just beautifully. is plummeting, law, order and justice are and raise taxes! TRUMP APPROVAL policies of the Obama Admin. allowed , bad for jobs and wants higher taxes. roundtable ahead of two votes taking

Table 4.81 Concordances of the word *immigration* in the Trump Tweet Corpus

In addition to the word *immigration*, the quantitative analysis focuses more in depth on this topic through the analysis of the concordances of the words immigrant and refugee.

in Washington State by a Middle Eastern immigrant . Many people died this weekend in Ohio Hillary has called for 550% more Syrian immigrants, but won't even mention "radical Islamic agreed to take thousands of illegal immigrants from Australia. Why? I will study this dumb was broadcast on @FoxNews concerning immigrants & Sweden. Give the public a break - The Table 4.82 Concordances of the word *immigrant* in the Trump Tweet Corpus

Table 4.82 shows that Trump tends to specify the ethnicity of immigrants and that in the majority of the cases they are connected to terrorism or more in general with the DTF and invasion topoi since it is also present the aggregation strategy (e.g. 550% more and thousands).

@realDonaldTrump @RogerRice10 Refugees from Syria over 10k plus more coming. Lots countries all over Europe by posing as refugees , and @HillaryClinton will allow it to happen attack at Ohio State University by a Somali refugee who should not have been in our country. I Our legal system is broken! "77% of refugees allowed into U.S. since travel reprieve hail dealers & others are being removed! 72% of refugees admitted into U.S. (2/3 -2/11) during Table 4.83 Concordances of the word *refugee* in the Trump Tweet Corpus

In Table 4.83 it is possible to notice that even refugees are strongly associated to terrorism and to the DTF and invasion topoi because they are often represented through numbers and high percentages (10k plus, 77% and 72%). The concordances in Tables 4.82 and 4.83 confirm that Trump does not use the specification strategy. Moreover, the quantitative analysis focused more in depth on the source domain of water since the qualitative analysis counts just one occurrence in the Traditional Corpus but none in tweets. Words such as *flow*, *inflow*, *sea*, *ocean* and *flood* were scrutinised but they did not provide results. Finally, it is important to mention that neither keywords nor collocates and concordances analyses provided results concerning the representation of immigrants and refugees as victims.

## 4.6.2.3 Keywords in the Trump Traditional Corpus

The following Table presents the keywords linked to the topic of immigration in the Trump Traditional Corpus.

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
Paris	13.300	1	2.6 massive	5.910	1	2.6
immigration	10.320	17	43.5 criminal	2.870	3	7.7
alien	9.460	12	30.7 stop	2.710	1	2.6
illegal	9.240	18	46.1			

Table 4.84 Immigration keywords in the Trump Traditional Corpus (ref. corpus enTenTen2018 US domain)

Table 4.84 shows keywords that were already present in Table 4.75 such as *immigration*, *illegal* and *stop*. However, it is possible to notice four new keywords that are present just in the Trump Traditional Corpus. The keyword *criminal* highlights Trump's connection between immigration and the DTF *topos* (it is possible to find it in both Tables 4.76 and 4.85). The word *Paris* has the same function of the keywords *France* and *Germany* in the Trump Tweet Corpus. The keyword *alien* is employed by Trump to indicate immigrants (and criminals). Lastly, the word *massive* (it is possible to look at its only occurrence in example 32) is connected to the *topos* of invasion.

Table 4.85 displays the DTF keywords in the Trump Traditional Corpus. These keywords are associated to immigration more directly in comparison to tweets through the keywords *immigration* and *immigrant*.

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
terrorism	15.770	22	56.3 terrorist	4.760	12	30.7
Paris	13.300	1	2.6 threat	3.950	13	33.3
immigration	10.320	1	2.6 criminal	2.870	10	25.6
pour	8.520	4	10.2 stop	2.710	4	10.2
immigrant	7.330	11	28.2 attack	1.740	7	17.9
foreign	5.000	2	5.1 cut	1.540	3	7.7

Table 4.85 DTF keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

Even in this case some keywords are associated to both terrorism (*terrorism*, *Paris*, *foreign*, *terrorist*, *threat*, *attack* and *cut*) and crime (*pour* and *criminal*). The keyword *stop* is referred to immigration but most of all to criminal activities (e.g. drugs).

The following Table focuses on the keywords that belong to the category of burden.

Keyword	Score	Freq	Rel_freq
immigration	10.320	3	7.7
spend	1.310	2	5.1

Table 4.86 Burden keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

The keywords *immigration* and *spend* (see example 34) are the only ones associated to the category of burden. The first one shows the direct and exclusive connection between this category and the topic of immigration. The second one indicates that Trump focuses mainly on the economic burden represented by immigrants and refugees.

Lastly, the following Table shows the traditional keywords under the label security that are – even in this case – connected to immigrants and refugees since Trump represents them as threats. As a result, he legitimises his strict immigration policies through the imminent need to protect U.S. citizens.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
border	11.600	37	94.7	stop	2.710	14	35.8
defend	8.630	17	43.5	defense	2.690	11	28.2
protect	5.850	40	102.4	safety	1.800	13	33.3
safe	5.020	31	79.3	force	1.740	19	48.6
wall	3.670	18	46.1	security	1.610	17	43.5
secure	3.230	12	30.7	general	1.480	11	28.2

Table 4.87 Security keywords in the Trump Traditional Corpus (reference corpus enTenTen2018 US domain)

# 4.6.2.4 Concordances and collocates in the Trump Traditional Corpus

Table 4.88 shows the collocate list of the word *illegal* in the Trump Traditional Corpus. Similarly to Table 4.79, even in Table 4.88 *immigration* is the first collocate of the keyword *illegal*. Furthermore, this time the connection between immigration and criminality is validated even more with the presence of *immigrant* that is the second collocate. The connection is also supported by the presence of the collocate *record*.

Collocate	Cooccurrences	Occurrences	T-score	MI3
immigration	9	17	3.00	16.51
immigrant	7	11	2.64	16.05
record	3	11	1.73	12.38
a	7	595	2.54	10.29
cost	2	15	1.41	10.18
end	2	21	1.41	9.69
our	5	497	2.13	9.09
government	2	34	1.40	9.00
border	2	37	1.40	8.87
who	2	111	1.38	7.29
country	2	208	1.35	6.38
go	2	320	1.31	5.76

Table 4.88 Collocates of the word illegal in the Trump Traditional Corpus

The word *cost* is connected to the *topos* of burden because Trump complains *about the cost of illegal immigration* (see Table 4.89). The collocates *end* and *go* are processes linked to Trump's promises concerning the stop of illegal immigration. Even though the lists do not include articles, this time it is possible to find the article *a* since it is particularly relevant in the identification of the genericisation strategy (see Table 4.90).

The following Table shows the concordances of the word *immigration* in the Trump Traditional Corpus.

rules, achieving a record reduction in illegal immigration on our southern border, or bringing jobs, Our Nation has the most generous immigration system in the world. But these are thosehas brought record reductions to illegal immigration . Record reductions. Down 61 percent I am going to end illegal immigration , stop the massive inflow of refugees, keep out, and quickly. On top of that, illegal immigration costs our country more than \$113 billion a money we are going to spend on illegal immigration over the next ten years, we could provide 40-percent reduction in illegal immigration on our southern border; 61 percent-61 an Executive order to temporarily suspend immigration from places where it cannot safely occur. give the President the power to suspend immigration when he deems-or she-or she. from the Federal statute, 212(f), of the Immigration and-you know what I'm talking about, You want us to enforce our immigration laws and to defend our borders. You want We've put in place the first steps in our immigration plan: ordering the immediate construction of America and its citizens. Most illegal immigration is coming from our southern border. I've s have spent to pay the cost of illegal immigration. Much of it has then been sent back, and cooperation on matters of both terrorism, immigration , migration, to protect our citizens. From policy, a new economic policy, a new immigration policy, a new trade policy. Hillary Clinton ; unleash American energy; end illegal immigration ; keep Radical Islamic terrorists out of our Table 4.89 Concordances of the word *immigration* in the Trump Traditional Corpus

The concordances indicate that – similarly to tweets – this topic is mainly connected to immigration policies, crime, and terrorism. However, it is possible to notice electoral promises that involve Trump's active agency.

Even in this case the quantitative analysis focuses on the analysis of immigrant and refugees' concordances analyses.

Arizona. He was murdered by an illegal City of San Francisco by an illegal in his home. The perpetrators were illegal was viciously shot and killed by an illegal infiltrated by terrorists. Just yesterday, an charged in another ISIS plot. Hundreds of were viciously and violently killed by illegal entry of all aliens, or any class of aliens as of Sarah Root, who was killed by an illegal Table 4.90 Concordances of the word *immigrant* immigrant immigrant immigrant immigrant immigrant immigrant immigrant gang member previously convicted of deported five previous times. Then there is immigrant with criminal records who did not meet the with three gun charges, as well as battery and other non-citizens in our prisons and from Bangladesh was charged in another from high-risk regions have been implicated immigrants or nonimmigrants, or impose on the entry of immigrant released into the country under the Obama Table 4.90 Concordances of the word *immigrant* in the Trump Traditional Corpus

The concordances of *immigrant* (Table 4.90) show a high association of this word with the word *illegal* that is preceded by the article *an* that signals the presence of the genericisation strategy. Indeed, even in the Traditional Corpus Trump does not use the specification strategy.

*Immigrant* is also associated to the word *alien* and to numbers (*hundreds*) that indicate the presence of the aggregation strategy and a complete dehumanisation of these social actors.

immigration, stop the massive inflow of our pouring into the country. Thousands of Clinton wants a 550% increase in Syrian investigations going on all over; hundreds of blocked our executive order on travel and is pushing for a 550% increase in Syrian Table 4.91 Concordances of the word *refugee* in the Trump Traditional Corpus

The concordances of refugees (Table 4.91) reveal that even in traditional speeches Trump tends to specify the ethnicity of these social actors. Moreover, it is also possible to notice the aggregation strategy (*thousands*, 550% and *hundreds*). Similarly to the Trump Tweet Corpus, refugees are associated to the *topoi* of DTF and invasion.

According to the qualitative analysis, the Trump Traditional Corpus counts just one occurrences of the water source domain. For this reason, the quantitative analysis aimed to verify this result through the research of words such as *flow*, *inflow*, *sea*, *ocean* and *flood* but they did not provide results. Finally, even in the Traditional Corpus immigrants and refugees are not represented as victims.

# **CHAPTER 5**

# MATTEO SALVINI

This chapter is dedicated to the analysis of Matteo Salvini's discourse. The results are discussed and organised into five sections that correspond to the five macro-topics of the analysis (Matteo Salvini's in-group representations, Italy, the media, Europe, and immigrants and refugees). Each section begins with the qualitative part of the analysis – carried out through the software UAM Corpus Tool – that focuses on metaphors, *topoi*, representational strategies and transitivity. Some of the four categories can lack in the following sections for two main reasons. Firstly, the qualitative analysis did not provide results. Secondly, a particular topic was investigated only through specific categories (see section 3.2.1). The second part of each section is dedicated to the quantitative analysis – carried out through the software Sketch Engine – that focuses on keywords, concordances and collocates. Specifically, the keyword lists are all categorised under established labels (see section 3.2.2.1). It is possible to observe the complete keyword lists in the Appendices C and D.

# 5.1 Matteo Salvini and la Lega

This section focuses on Matteo Salvini's in-group representations. More precisely, the analysis investigates Salvini's self-representation and the representation of his party.

#### 5.1.1 Qualitative analysis

Salvini's self-representation and the representation of his party were qualitatively analysed through metaphors, *topoi* and transitivity.

# **5.1.1.1** *Metaphors*

Matteo Salvini mainly represents himself as a saviour and warrior. This source domain counts 2 occurrences in the Salvini Tweet Corpus and 14 in the traditional one. The source domain of religion has got only one occurrence in the Salvini Traditional Corpus.

1. #Salvini: Posso **combattere** un miliardario speculatore [George Soros] che vuole riempire l'Europa di finti profughi? O sono un NAZISTA? #inonda [emphasis added] (Salvini's Tweet 3 July 2018)<sup>18</sup>

Can I fight against a millionaire speculator [George Soros] who wants to fill up Europe with fake refugees? Or am I a Nazi? #inonda.

2. [...] al Governo io voglio **difendere** i diritti di chi non ha voce per difendersi da solo, e penso ai bambini che hanno il diritto di avere una mamma e un papà. Gli uteri in affitto, gli ovuli in vendita, i bambini al supermercato. No! No! Altrimenti è la fine! Questo è egoismo degli adulti sulla pelle dei bambini. [emphasis added] (Salvini's speech in Rome 1 March 2018)<sup>19</sup>

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
$STW^{20}$	$100\%^{21}(2)^{22}$	-	-	-	-	-	-	-
$STS^{23}$	93% (13)	-	-	-	-	7%(1)	-	-

Table 5.1 Salvini's source domains in Salvini's corpora

Salvini depicts himself as a warrior who will save the Italian people from countless threats. Specifically, example 1 shows the main threat – according to Salvini – for the Italian people which is the immigrants' invasion favoured by George Soros. Indeed, Salvini – as other farright populist leaders – has the tendency to support and use at his own advantage fake news and conspiracy theories. In example 2 he promises to defend Italian society from another main threat which is the 'gender theory' (another topic connected to fake news) that will destroy traditional families and the integrity of children.

Source domains involved in the description of *Lega* count just one occurrence in the Salvini Tweet Corpus and 13 in the traditional one. Tweets involve just the saviour and warrior source domain, while in traditional speeches Salvini also uses the war, religion, nature and water source domains.

	Saviour and	Container	Building	Object and	War	Religion	Nature	Water
	Warrior			Merchandise				
STW	100% (1)	-	-	-	-	-	-	-
STS	68% (9)	-	-	-	8% (1)	8% (1)	8% (1)	8% (1)

Table 5.2 *Lega*'s source domains in Salvini's corpora

- 3. Prodotti contraffatti o tossici? NO, grazie. **Difendiamo** la nostra agricoltura, la nostra economia, la nostra salute. La Lega sempre in prima fila, anche in Europa, per la tutela del vero Made in Italy. [emphasis added] (Salvini's Tweet 15 April 2018)<sup>24</sup>
- 4. **Noi combatteremo** non per togliere l'autonomia a chi ce l'ha ma per darla a chi la vuole e che ancora non ce l'ha: alla Lombardia, al Veneto, alla Puglia, al Piemonte, alla Liguria o all'Abruzzo. L'autonomia di chi ce l'ha non si tocca. [emphasis added] (Salvini's speech in Pinzolo 25 August 2018)<sup>25</sup>

21 UAM Corpus Tool percentage.

<sup>23</sup> Salvini Traditional (speeches) Corpus.

<sup>[...]</sup> once in government I want to defend the rights who do not have the voice to defend him(/her) self. I think to those children who have the right to have a mother and a father. Womb for rent, egg sale, children at the supermarket. No! No! Otherwise this is the end! This is adults' selfishness at the expenses of children.

<sup>20</sup> Salvini Tweet Corpus.

Number of occurrences.

Counterfeit or toxic products? No, thanks. We defend our agriculture, our economy, our health. The League is always on the front line, even in Europe, for the protection of the true Made in Italy.

We will not fight to take away the autonomy to the ones who already have it, but we will fight to give autonomy to those who do not have it and want it: Lombardy, Veneto, Apulia, Piedmont, Liguria or Abruzzo. The autonomy already achieved will not be touched.

5. [...] hanno provato a metterci nell'angolino, non ci son riusciti. Stanno provando a fermare il **fiume in piena** con le mani, eh ma non riesci a fermare l'acqua che scende da monte a valle con le mani. [emphasis added] (Salvini's speech in Rome 1 March 2018)<sup>26</sup>

Examples 3 and 4 show how Salvini employs the saviour and warrior source domain in both tweets and traditional speeches. In example 3 Salvini talks about *Lega*'s defence of Made in Italy against European impositions, while in example 4 he focuses on one of the founding elements of his party which is the fight for regional independence. In example 5 the *Lega* is positively represented – through the water source domain – as an unstoppable river in flood. In this way, Salvini depicts his party as a strong and powerful force.

# 5.1.1.2 Topoi

The victim *topos* is the only one used by Salvini to represent himself. More precisely, he employs this *topos* 2 times in his Tweet Corpus and 21 times in his Traditional Corpus.

	Victim	DTF <sup>27</sup>	Burden	Invasion	Container	Dictatorship	Dishonest
STW	100% (2)	-	-	-	-	-	-
STS	100% (21)	-	-	-	-	-	-

Table 5.3 Salvini's topoi in Salvini's corpora

- 6. Ora **mi denunciano** anche per "danno erarariale" per aver bloccato le navi cariche di immigrati... Ma quanta pazienza serve? Comunque altra medaglia, non si molla! [emphasis added] (Salvini's Tweet 14 September 2018)<sup>28</sup>
- 7. Quattro milioni di processi arretrati hanno e **indagano Salvini** che difende i confini! [...]**Me ne han dette di tutti i colori sequestratore**, tor... **c'è uno che mi vuole indagare per tortura**. No! [emphasis added] (Salvini's speech in Pinzolo 25 August 2018)<sup>29</sup>

Salvini uses this *topos* mainly to discredit his opponents and to defend himself playing the innocent victim. In both examples 6 and 7 Salvini portrays himself as the victim of an unjust system since he was investigated for blocking the disembarkation of immigrants on board the NGO Diciotti. According to Salvini this action – as the then Minister of the Interior – was fair and legitimate.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
STW	-	-	-	-	-	-	-
STS	100% (7)	-	-	-	-	-	-

Table 5.4 *Lega*'s *topoi* in Salvini's corpora

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<sup>[...]</sup> they tried to put us in the corner but they did not succeed. They are trying to stop the river in flood with their hands, huh but you cannot stop with the hands the water that flows from upstream to downstream.

<sup>&</sup>lt;sup>27</sup> Danger, threat and fear.

Now I am going to be reported for "tax damage" for stopping the ships full of immigrants…how much patience is needed? However, this is another medal. I do not give in!

They [judges] have four millions backlogged trials and investigate Salvini who defends the borders! [...] They told to me all sort of things kidnapper, tort...there is someone who wants to investigate me for torture. No!

For what concern the representation of the *Lega*, even in this case the victim *topos* is the only one used by Salvini. As shown in the Table above, this *topos* occurs 7 times in the Salvini Traditional Corpus.

8. E a proposito di immigrazione, la stessa Simon Weil che non è accusabile di **populismo**, **sovranismo**, **fascismo**, **razzismo**, **nazismo** o marzianismo e tutto quello di cui veniamo accusati solitamente. [...] Son riusciti a dire, qualche sciacallo, qualche poveretto, qualche frustrato di sinistra, qualche giornalista, che perfino la tragedia nel Mar Mediterraneo dell'altro giorno è sostanzialmente colpa nostra. [emphasis added] (Salvini's speech in Pontida 1 July 2018)<sup>30</sup>

Example 8 is an extract from the speech that Salvini delivered in Pontida during *Lega*'s annual convention. For this reason, the *topos* employed is highly inclusive because Salvini not only refers to people who run the party but also to all the *Lega* followers and voters. In this first part of the example, it is possible to observe how Salvini ironically lists all the accusations that are usually made to *Lega*, while in the second part he blames his opponents – and especially the dishonest media – to treat the *Lega* as a scapegoat. Moreover, Salvini often employs quotations of influential people (sometimes people who even belong to political orientations far from the *Lega*) to support and legitimise his ideas and policies.

# 5.1.1.3 Transitivity

In the Salvini Tweet Corpus there are 33 occurrences of processes connected to Salvini, while in the Salvini Traditional Corpus there are 1,157 processes. Table 5.5 shows that material processes are the most used ones, especially in tweets. Furthermore, the table shows that Salvini employs every type of processes in traditional speeches.

	Material	Relational	Mental	Verbal	Behavioural	Existential
STW	73% (24)	6% (2)	-	21% (7)	-	-
STS	42% (490)	10% (122)	20% (231)	25% (288)	2% (24)	1% (2)

Table 5.5 Salvini's transitivity in Salvini's corpora

9. Con questo calduccio, uno spuntino a base

9. Con questo calduccio, uno spuntino a base di spettacolare mozzarella di bufala campana ci sta. Alla faccia dell'Europa che vuole portarci in tavola ogni tipo di schifezza, **io mangio** (e **bevo**) italiano! [emphasis added] (Salvini's Tweet 1 August 2018)<sup>31</sup>

10. Hanno SVENDUTO l'Italia, la metà delle nostre aziende ormai è in mani estere. A che cosa hanno portato quindici anni di lacrime e sangue e di sacrifici imposti dall'Europa agli italiani? IL

And speaking of immigration, Simone Weil who cannot be accused of populism, sovereigntism, fascism, racism, Nazism or 'martianism' and all that we are usually accused of. [...] They said – some jackals, some miserable people, some frustrated left-wing people, some journalists – that even the tragedy of the other day in the Mediterranean sea is substantially our fault.

A snack of spectacular buffalo mozzarella from Campania is perfect during this hot weather. I eat (and drink) Italian! In spite of Europe that wants to bring on our tables every type of junk.

- DISASTRO! Riprendiamoci il nostro Paese! Io dico #PRIMAGLIITALIANI! [emphasis added] (Salvini's Tweet 30 January 2018)<sup>32</sup>
- [...] quanti sardi io trovo in giro per il mondo a portare lavoro? Per questo che poi mi imbufalisco 11. quando paragonano l'immigrazione sarda all'immigrazione di adesso. Io non penso che a nessuno abbiano mai pagato colazione, pranzo e cena in albergo per un anno e per non fare un accidente dei nostri nonni. [emphasis added] (Salvini's speech in Cagliari 24 January 2018)<sup>33</sup>

Example 9 – a delegitimising tweet against Europe – shows two material processes (eat and drink), while in example 10 – another delegitimising tweet against Europe and the previous Italian governments – there is a verbal process (say). In example 11 Salvini exhibits his disappointment regarding the comparison between Italian immigration and the current immigration in Italy through a behavioural process (go up the wall) and a mental one (I don't think). Finally, in example 1 it is possible to observe a relational process (or am I a Nazi?). In examples 1 and 2 there are also other material processes (fight and defend) that are strictly connected to the figure of the warrior and saviour. Indeed, the participant type performed by Salvini is mainly the Actor  $(40\%)^{34}$ , the voice type is always active  $(99\%)^{35}$  and the evaluation is often positive  $(47\%)^{36}$ 

Participant types <sup>37</sup>	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	40%	482	Senser	18%	222
Goal	2%	28	Inducer	1%	8
Recipient	1%	5	Sayer	23%	272
Carrier	6%	70	Receiver	1%	23
Identifier	1%	10	Behaver	2%	24
Possessor	4%	44	Existent	1%	2

Table 5.6 Salvini's participant types in Salvini's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	99% (1,189)	1% (1)	-	-	-	-
Evaluation	-	-	-	47% (554)	4% (47)	49% (589)

Table 5.7 Salvini's voice-type and evaluation-type in Salvini's corpora

For what concerns processes linked to the *Lega*, there are 9 occurrences in the Salvini Tweet Corpus and 356 in the Salvini Traditional Corpus. Even in this case material processes have the highest percentages in both tweets and traditional speeches.

They sold cheaply Italy. Half of our companies is already owned by foreigners. What have 15 years of tears and sacrifices imposed by Europe to Italians led to? A DISASTER! We must get back our country! I say **#ITALIANSFIRST!** 

How many Sardinians are around the world bringing workforce? This is way I go up the wall when Sardinian immigration is compared to the current immigration in Italy. I do not think that our grandfathers had free breakfast, lunch and dinner at the hotel for an entire year and for doing nothing all day.

UAM Corpus Tool percentages includes also other participant types (see Table 5.6 and chapter 3).

Processes were categorised as active, passive or non-applicable voice (see Table 5.7 and chapter 3).

The evaluation of processes can be positive, negative or neutral (see Table 5.7 and chapter 3).

The Table shows just the participant types performed by Salvini. The empty categories – that is possible to observe in chapter 3 section 3.2.1.4 Figure 3.7 – have been omitted.

	Material	Relational	Mental	Verbal	Behavioural	Existential
STW	78% (7)	-	-	22% (2)	-	-
STS	80% (286)	30% (30)	6% (21)	5% (16)	1% (3)	-

Table 5.8 Lega's transitivity in Salvini's corpora

- 12. Non vorrei qualcuno avesse voglia di perdere tempo per imporre agli italiani un governo scelto dall'Europa, per entrare nei nostri conti correnti e per tassare le nostre case! Questo **la Lega non lo permetterà** MAI! #andiamoagovernare [emphasis added] (Salvini's Tweet 23 April 2018)<sup>38</sup>
- 13. Ora con la Lega al governo. Questa gente se ha preso denaro pubblico dei cittadini italiani per legge non potrà licenziare neanche un operaio in Italia per assumerlo dall'altra parte del mondo. Alle parole **noi preferiamo** i fatti. [emphasis added] (Salvini's speech in Milan 24 February 2018)<sup>39</sup>

Example 12 shows a material process (*will not allow*) that is also an electoral promise since Salvini claims that his party will always defend Italians from European unjust impositions. In example 4 it is possible to find another material process (*we will fight*) connected to the party that will fight to achieve one of its main goals. In example 13 there is a mental process (*we prefer*) through which Salvini represent himself and his party as a reliable and concrete option.

Finally, the *Lega* plays mainly the Actor (77%), it has always an active voice type (99%) and a positive evaluation (65%).

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	77%	281	Senser	5%	19
Goal	3%	11	Inducer	1%	1
Recipient	1%	5	Sayer	3%	13
Carrier	2%	8	Receiver	1%	4
Identifier	1%	1	Behaver	1%	3
Possessor	5%	19			

Table 5.9 Lega's participant types in Salvini's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	99% (363)	-	1% (2)	-	-	-
Evaluation	-	-	-	65% (236)	3% (13)	32% (116)

Table 5.10 *Lega*'s voice-type and evaluation-type in Salvini's corpora

## 5.1.2 Quantitative analysis

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The quantitative part of the analysis involves the investigation of keywords, concordances and collocates. In this regard, further information about the selection of collocates should be mentioned. Firstly, the collocate lists show just the first 20 collocates excluding articles, prepositions, and punctuation. Secondly, the lists of collocates were calculated through specific parameters. On the one hand, the collocates of words with less than 50 occurrences in the

I do not want that anyone wants to waste time imposing to Italians a government chosen by Europe in order to enter in our current accounts and to tax our houses! The League will NEVER allow this! #let'sgotogovern

Now with the League in government. If these people took public money of Italian citizens, they will not be able to fire even a worker in Italy – by law – to hire him/her in the other part of the world. We prefer facts to words.

corpora were calculated with 10 as the parameter for the minimum frequency in the corpus and 2 as the parameter for the minimum frequency in a given range. On the other hand, the collocates of words with more than 50 occurrences were determined with 10 as the parameter for the minimum frequency in the corpus and 5 as the parameter for the minimum frequency in a given range. Moreover, the following collocate lists are organised according to the MI3 score (Oakes, 1998: 171-172), that gives higher scores to frequent words and lower scores to infrequent words through the cubing of frequencies (see section 3.2.2.2). Finally, it is important to highlight that the reference corpus used for the selection of keywords is the Italian Web 2016 (itTenTen16).

# 5.1.2.1 Keywords in the Salvini Tweet Corpus

The following Table involves those keywords categorised under the label in group and directly connected to Matteo Salvini. Indeed, all the keyword lists were created through their categorisation under specific labels that it is possible to observe in chapter 3 (section 3.2.2.1) while the complete lists of keywords ca be found in the Appendix C.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Salvini	113.290	98	165.8	mi	2.840	219	370.5
Lega	39.910	123	208.1	nostro	2.800	205	346.8
Maio	15.750	2	3.4	noi	2.520	76	128.6
Giulia	5.550	5	8.5	ci	2.310	204	345.1
io	4.920	190	321.4	mio	2.300	135	228.4

Table 5.11 In group keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

As it is possible to observe in Table 5.11 this list involves Salvini – *Salvini*, *io* (*I*), *mi* (me), *mio* (my) –, his party – *Lega*, *nostro* (our), *noi* (we), *ci* (us) –, his party members – *Giulia* (Bongiorno), and political allies – (Luigi Di) *Maio* – during the coalition government between *Lega* and *Movimento 5 Stelle*.

## 5.1.2.2 Concordances and collocates in the Salvini Tweet Corpus

Collocate	Cooccurrences	Occurrences	T-score	MI3
governo	28	258	5.21	15.65
colpa	9	20	2.99	14.42
essere	31	1,272	5.19	13.79
ministro	6	54	2.41	11.24
fare	10	378	2.96	10.64
non	11	658	2.99	10.25
dire	7	189	2.53	10.10
avere	9	665	2.63	9.37
lega	5	123	2.14	9.26
andare	5	156	2.12	8.92

Table 5.12 Collocates of the word Salvini in the Salvini Tweet Corpus

The analysis of collocates focuses on the representation of Matteo Salvini; for this reason, Table 5.12 shows the collocates of the word *Salvini*. Firstly, this list reveals that there are some collocates linked to his work such as *governo* (government), *ministro* (minister) and *Lega*. Secondly, the collocate *colpa* (fault) is strictly connected to the *topos* of the victim that Salvini often uses to depict himself. Finally, the remaining collocates involves processes such as *dire* (to say), *essere* (to be), *fare* (to do), *andare* (to go) and *avere* (to have).

In order to investigate and confirm the results of the qualitative analysis regarding Salvini's employment of the source domain of saviour and warrior, the concordance analysis focuses on the words *combattere* (to fight) and *difendere* (to defend).

lavoratori e imprenditori, per ignoranza, povertà culturale. La Amici, io posso anche l'Italia ha già dato abbastanza. delinquenza sulle nostre spiagge si mollare il potere. Da ministro Da ministro combatto e io aiuto la mafia, una merda che mafiosi e scafisti si rassegnino, li economiche sottratte alle mafie per FINE. #inonda" #Salvini: Posso come uno che più di altri ha per colpa della Mafia, che l'ha ragazzi e alle loro famiglie. Voglio voglia di futuro, voglia di Da una parte gli operai dell'Ilva che liberiamo le nostre strade e

combattere combatteremo combattere Combatterò combatte combatto combatterò combatto combatteremo combattere combattere combattuto combattuta combattere combattere combattono combattiamo

corrotti e corruttori, per arrestare attraverso tutti i mezzi possibili, per bloccare barconi e scafisti, ma fino all'ultimo per mantenere gli con i FATTI. Abbiamo imboccato e combatterò ogni forma di violenza: ogni forma di violenza: non mi con tutte le mie forze, o di dire che con tutte le forze. Meno partenze, venditori abusivi, potenziare i un miliardario speculatore che vuole camorra, 'ndrangheta e mafia, ma non solo a parole come qualcun gli spacciatori di morte con ogni per ricostruire. per difendere il posto di lavoro, i trafficanti di esseri umani. Più

Table 5.13 Concordances of the word *combattere* (to fight) in the Salvini Tweet Corpus<sup>40</sup>

Table 5.13 shows all the concordances of the word *combattere* (to fight) in the Salvini Tweet Corpus where Salvini uses this word in order to depict both himself and his party as saviours and warriors. Moreover, he focuses mainly on immigration but also – as Minister of the Interior – on the fight against organised crime.

The following Table provides a random selection of the word *difendere* (to defend) (that in the Salvini Tweet Corpus has 64 occurrences) that confirms how Salvini depicts himself as

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<sup>1)</sup> workers and entrepreneurs, to fight corrupt people and briber, to arrest; 2) ignorance, lack of culture. We will fight it with all the necessary means; 3) Friends, I can fight to stop immigrants' ships and smuggles, but; 4) Italy has given enough. I will fight until the end to keep the; 5) criminality in our beaches is fought with FACTS. We took; 6) give in the power. As Minister I fight and I will fight every kind of violence: I do not; 8) I help mafia, a crap that I fight with all my strength, or to say that; 9) mafiosi and smugglers must give up, we will fight them with all our strength. Less departures; 10) economic stole to mafias to fight unauthorised sellers, reinforce the; 11) END. #inonda #Salvini: Can I fight against a millionaire speculator [George Soros] who wants to; 12) one that more than others has fought camorra, 'ndrangheta and mafia; 13) because of Mafia, that fought not only with words like someone; 14) boys and to their families. I want to fight deaths 'pushers with every; 15) the desire of future, the desire to fight in order to rebuild; 16) On the one hand the Ilva workers who fight to defend their job; 17) free our streets and fight human smugglers. More.

the saviour who will protect the Italian people from threats such as European interferences and especially from immigration.

il consenso a quanto stiamo facendo per difendere i confini e fermare barconi e barchini. Non Ho promesso che avrei fatto di tutto per difendere i confini e fermare l'invasione del nostro il diritto alla sicurezza degli Italiani? Rischio 30 anni di galera per avere difeso Sempre più determinato a difendere gli italiani, un brindisi a chi indaga, insulta inchiesta, bugia, insulto o minaccia perché difendo la sicurezza, i confini e il futuro degli lo sono FIERO di battermi per difendere i confini, tutelare la sicurezza degli "Ho promesso di difendere confini e sicurezza degli Italiani, questo quello che gli italiani mi hanno chiesto: difendere i confini, garantire la sicurezza del Paese, si vedano già risultati. Avevo promesso di difendere i confini, lo sto facendo con tutte le energie Ridurre partenze e morti, difendere i confini italiani. lo vado avanti! parole Stop ai trafficanti di esseri umani, difendiamo i confini: io non mollo, Amici. mangiare italiano, comprare italiano! Difendere le nostre imprese significa difendere il Table 5.14 Concordances of the word *difendere* (to defend) in the Salvini Tweet Corpus<sup>41</sup>

## 5.1.2.3 Keywords in the Salvini Traditional Corpus

The following Table shows the in group keywords found in the Salvini Traditional Corpus. These keywords involve mainly Salvini: *Salvini*, *Matteo*, *io* (I), *mi* (me), *mio* (my) – and his party – *Lega*, *ci* (us), *partito* (party), *nostro* (our); furthermore, the keywords *Pontida* and *Pinzolo* are also connected to the party since the annual convention of the *Lega* takes place in Pontida (Salvini's speech in Pontida 2018 is part of the Traditional Corpus).

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Salvini	101.870	14	32.1	ci	3.570	233	534.0
Lega	31.690	72	165.0	mi	3.510	200	458.4
Pontida	27.470	12	27.5	partito	3.220	6	13.8
Pinzolo	23.100	11	25.2	mio	2.770	120	275.0
Matteo	21.780	18	41.3	nostro	2.390	129	295.7
io	10.050	287	657.8	amico	2.100	9	20.6

Table 5.15 In group keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

In Pinzolo, Salvini delivered another speech (that it is part of the Traditional Corpus as well) during a *Lega*'s party. Finally, the keyword *amico* (friend) is referred to both the member of *Lega* and allies.

# 5.1.2.4 Concordances and collocates in the Salvini Traditional Corpus

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<sup>41 1)</sup> the consensus concerning what we are doing to defend the borders and stop big and small immigrants' ships; 2) I promised that I would have done anything to defend the borders and stop the invasion of our; 3) I am risking 30 years of jail because I defended the Italians' right to security?; 4) I am even more determined to defend Italians, a toast to those who investigate, insult; 5) investigation, lie, insult or threat because I defend the security, the border and the future of; 6) I am proud to fight in order to defend the border, and protect the security of; 7) I promised to defend Italians' borders and security, this; 8) what Italians asked me: to defend the borders, to guarantee the security of the country; 9) the results are already visible. I promised to defend the borders, I am doing it with all my energy; 10) To reduce departures and deaths, to defend the Italian borders. I go ahead!; 11) words stop to human smugglers, we defend the borders: I do not give in, Friends; 12) eat Italian, buy Italian! To defend our companies means defend the.

Table 5.16 displays the collocates of the word *Salvini* in the Traditional Corpus. As it is possible to notice at first glance, comparing Tables 5.12 and 5.11; Table 5.16 is shorter. However, even these collocates involve Salvini's work: *Matteo* and *governo* (government) and processes such as *dire* (to say), *avere* (to have) and *essere* (to be).

Collocate	Cooccurrences	Occurrences	T-score	MI3
Matteo	27	49	5.18	18.04
governo	10	94	3.12	12.80
essere	12	1,480	2.83	9.61
dire	5	240	2.08	8.45
non	7	692	2.26	8.38
avere	7	725	2.24	8.31

Table 5.16 Collocates of the word Salvini in the Salvini Traditional Corpus

Table 5.17 and Table 5.18 investigate Salvini's employment of the saviour and warrior source domain in traditional speeches. Specifically, in Table 5.17 there are all the occurrences of the word *combattere* (to fight) in the Salvini Traditional Corpus. The concordances reveal that in traditional speeches Salvini is more focused on protecting the Italian people from organised crime and economic difficulties.

la mafia, la camorra, la 'ndrangheta e li combatteremo con ogni mezzo necessario da nord a sud. a esempio chi ha dedicato una vita a combattere la malavita, non a parole, e c'è un hanno dato la vita per questo paese combattendo la mafia, la camorra e la 'ndrangheta È solo l'inizio di una guerra che combatteremo con tutte le armi che la democrazia mette a può essere uno spunto. Io sto combattendo da 137 giorni, perché ... poi vedo Dario dove ci avrebbe portati. Noi stiamo combattendo a colpi di spread. Ho visto le dichiarazioni Spingere le masse a combattere un nemico inesistente mentre il un Don, fatto da una donna che combatte in strada e io questo non lo mollo più in tutte le altre regioni italiane. Noi combatteremo non per togliere l'autonomia a chi ce l'ha Table 5.17 Concordances of the word *combattere* (to fight) in the Salvini Traditional Corpus<sup>42</sup>

In Table 5.18 there is a random selection of the word *diffendere* (to defend) through which Salvini depicts himself and his party as fighters against the threats posed by immigration, gender theory and economic difficulties.

Però al Governo io voglio difendere i diritti di chi non ha voce per difendersi che ha ritrovato il suo orgoglio. E per me ore che il buon Dio mi dona ogni giorno per avere cura delle nostre risorse, vuol dire città e magari pagano le tasse all'estero. Noi difenderemo i negozi perché i negozi sono vita.

difendere i diritti di chi non ha voce per difendersi i confini, la cultura, il lavoro di questo la storia di questo paese e vi posso difendere i negozi perché i negozi sono vita.

Difenderemo i commercianti perché i commercianti

<sup>&</sup>lt;sup>42</sup> 1) mafia, camorra, 'ndrangheta, and we will fight them with every necessary means from north to south; 2) for example, who dedicated his/her life to fight organised crime, not with words, and there is; 3) they gave their life for this country fighting mafia, camorra and 'ndrangheta; 4) This is just the beginning of a war that we will fight with all the weapons that democracy provides; 5) it can be an idea. I am fighting for 137 days because... then I will meet Dario; 6) where it would take us. We are fighting with 'spread' strokes. I saw the statements; 7) To push the masses to fight an unreal enemy while the; 8)a Father, made by a woman who fights in the street and I will never leave this; 9) in all the other Italian regions. We will fight not to take away the autonomy to the ones who already has it.

italiani del Family Day, che hanno detto che difendere la vita e i bambini è un sacro diritto per e indagano un Ministro che difende i confini di questo paese APPLAUSE e è un dovere, ma essere indagato per i diritti degli italiani è una vergogna! difendere arretrati hanno e indagano Salvini che i confini! Ma fate più in fretta a smaltire difende Table 5.18 Concordances of the word *difendere* (to defend) in the Salvini Traditional Corpus<sup>43</sup>

# 5.2 Italy

This section investigates how Matteo Salvini represents Italy and the Italian people.

#### 5.2.1 Qualitative analysis

Salvini's representation of Italy and Italians was qualitatively analysed through metaphors, topoi and transitivity.

#### 5.2.1.1 Metaphors

Source domains connected to Italy has just 12 occurrences in traditional speeches. Specifically, the building source domain – the predominant one – occurs 9 times. The container source domain occurs twice, while there is just one occurrence of the nature source domain.

	Saviour and	Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
STW	_		-	-	-	-	-	-	-
STS	-		17% (2)	75% (9)	-	-	-	8% (1)	-

Table 5.19 Italy's source domains in Salvini's corpora

14. Con 5 milioni di italiani in povertà, con 3 milioni di italiani disoccupati - io apro le porte di casa mia - però fino a che questi italiani non troveranno una casa e un lavoro, molto serenamente chi sceglie la Lega sceglie un concetto chiaro: prima gli italiani [emphasis added] (Salvini's speech in Milan 24 February 2018)<sup>44</sup>

15. [...] ci hanno messo in tasca una moneta tedesca, ci hanno dato regole tedesche, ci hanno riempito di immigrati e poi se l'artigiano non riesce più a vedere, il commerciante ha chiuso o il disoccupato il lavoro non lo trova, ci dicono pure in televisione: "Ma è colpa tua [...] [emphasis added] (Salvini's speech in Rome 1 March 2018)<sup>45</sup>

Questo fra Bruxelles, Berlino e Parigi hanno provato a fare in questi anni. Toglierci le radici da sottoterra, cancellare donne e uomini per avere numeri e consumatori al servizio di quelle

<sup>1)</sup> Once in government I want to defend the rights who do not have the voice to defend him(/her) self; 2) who has found again its pride. And for me to defend the borders, the culture, the word of this; 3) hours that the good Lord gives me every day to defend the history of this country and I can; 4) take care of our resources, it means to defend our mountains, our lakes, the; 5) cities and perhaps they even pay taxes abroad. We will defend the shops because the shops are life; 6) the shops because the shops are life. We will defend shop keepers because shop keepers; 7) the Italians of the Family Day, who said that defend life and children is a sacred right for; 8) and they investigate a Minister who defends the borders of this country and; 9) it is a duty, but being investigated for defending the Italians' right is a shame!; 10) backlogged [trials] and investigate Salvini who defend the borders! But hurry to dispose of.

There are 5 millions of Italians in poverty, there are 3 millions of unemployed Italians. I open the doors of my house but - very serenely - until these Italian find a home and a job, who choose the League choose a clear concept: Italians first.

<sup>[...]</sup> they gave us German money, they gave us German rules, they filled us up with immigrants. And then if the artisan cannot sell, if the shop keeper closed, if the unemployed does not find the job, they even say to us on television: "But this is your fault [...]

multinazionali come la Coca-Cola, che poi sponsorizzano le sfilate dell'orgoglio nelle varie città per conquistare nuovi consumatori e magari qualcuno ci spiega che fa meglio la Coca-Cola dell'olio d'oliva italiano. [emphasis added] (Salvini's speech in Pontida 1 July 2018)<sup>46</sup>

Both examples 14 and 15 involve a metaphorical representation of Italy regarding the topic of immigration. On the one hand, in example 14 Salvini employs the building source domain since he compares Italy to a house that will host immigrants once all Italian people live decently. On the other hand, in example 15 Italy is represented as a container that has been filled up with immigrants by Europe. Example 16 shows the only occurrence of the nature source domain. Indeed, Italians are described as plants uprooted from their native lands by Europe.

# 5.2.1.2 Topoi

In the Salvini Tweet Corpus there are 4 occurrences that belong to the victim *topos*, while Salvini Traditional Corpus counts 23 occurrences of the victim *topos* and 4 occurrences of the container one. As it is also possible to notice from the following Table, Salvini prefers to use the *topos* of the victim in order to represent Italy and the Italian people.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
STW	100% (4)	-	-	-	-	-	-
STS	85% (23)	-	-	-	15% (4)	-	-

Table 5.20 Italy's *topoi* in Salvini's corpora

- 17. Sono tre gli immigrati fermati con l'accusa di aver **ucciso e fatto a pezzi la povera PAMELA**. Ma oggi la sinistra manifesta "contro il razzismo", **Pamela e gli italiani vittime della violenza dei clandestini possono aspettare** ... #stopimmigrazione" [emphasis added] (Salvini's Tweet 10 February 2018)<sup>47</sup>
- 18. Io voglio tornare in questa terra, **non riempiendola di immigrati** che riempiono gli alberghi degli imprenditori falliti, ma riportando i ragazzi sardi che adesso sono in giro per il mondo a lavorare qua e a fare figli qua e a mettere su famiglia qua [emphasis added] (Salvini's speech in Cagliari 24 January 2018)<sup>48</sup>

Example 17 shows how Salvini employs the *topos* of the victim to describe Italian people. In this tweet Salvini reiterates the dangerous consequences of immigration and the topic of reverse racism. Moreover, this is also a delegitimising tweet against left-wing politicians who – according to Salvini – do not protect Italians and defend immigrants in any circumstances. In example 18 Salvini describes Sardinia as a land that has been filled up with immigrants, while

They have tried to do this during these years in Brussels, Berlin and Paris. They tried to remove our roots from the underground, they tried to erase women and men in order to have numbers and consumers at the service of those multinationals such as Coca-Cola that promote Gay prides in various cities to obtain new consumers; and then someone even explains to us that Coca-Cola is healthier than Italian olive oil.

There are three immigrants detained by the police with the accusation of killing and tearing apart the poor PAMELA. Instead, today left-wing politicians demonstrate "against racism". Pamela and the other Italians, who are the victims of illegals' violence, can wait.

I want to come back in this land. I do not want to fill it up with immigrants who fill up failed entrepreneurs' hotels, but I want to take back all the young Sardinians, who now are around the world, to work here, to start a family here and raise their children here.

young people from Sardinia (as other Italians from other regions) have been forced to move outside Italy in order to find a job and live decently. In addition, it is possible to observe the container *topos* in example 15 as well.

# 5.2.1.3 Transitivity

Processes linked to Italy count 6 occurrences in tweets and 37 occurrences in traditional speeches.

	Material	Relational	Mental	Verbal	Behavioural	Existential
STW	67% (4)	33% (2)	-	-	-	-
STS	68% (25)	13% (5)	16% (6)	-	3% (1)	-

Table 5.21 Italy's transitivity in Salvini's corpora

- 19. Oggi anche la nave Sea Watch 3, di Ong tedesca e battente bandiera olandese, è al largo delle coste libiche in attesa di effettuare l'ennesimo carico di immigrati, da portare in Italia. **L' Italia ha smesso di chinare il capo e di ubbidire**, stavolta C'È CHI DICE NO.#chiudiamoiporti [emphasis added] (Salvini's Tweet 11 June 2018)<sup>49</sup>
- 20. **L' Italia è composta** da 8.000 comunità, 8.000 santi patroni, 8.000 lingue, 8.000 profumi, 8.000 teatri, 8.000 cucine ed è quello che vogliono cancellare e che ci invidiano perché ... in Germania, che c'è? C'è il würstel. [...] [emphasis added] (Salvini's speech in Rome 1 March 2018)<sup>50</sup>

Example 19 shows two material processes (*has stopped to bend* and *obey*) connected to Italy. Specifically, this tweet was delivered when Salvini was part of the coalition government as Minister of the Interior after the ban for the NGO Aquarius to dock in any Italian harbour. Consequently, these material processes aim to represent Italy as a strong country – under the new government – that will not obey to European impositions. In example 20 it is possible to find a relational process (*is made up of*) useful to praising Italy; indeed, in this traditional extract Salvini is attacking once again Europe discrediting Germany which is one of the E.U. leading forces.

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	58%	25	Possessor	5%	2
Goal	7%	3	Senser	14%	6
Client	2%	1	Behaver	2%	1
Carrier	12%	5			

Table 5.22 Italy's participant types in Salvini's corpora

As it is possible to notice in Table 5.21, material processes are the ones with the highest percentages in both tweets and traditional speeches. Furthermore, Italy is mainly the Actor (58%). Processes have also a prevalent positive evaluation (65%) and exclusively an active voice type (100%).

Italy is formed by 8,000 communities, 8,000 patron saints, 8,000 languages, 8,000 scents, 8,000 theaters, 8,000 cuisines; and this is what they want to erase and what they envy us for because...what do they have in Germany? The würstel. [...]

Today even the ship Sea Watch 3, a German NGO flying the flag of Holland, is off the coast of Libya too, waiting to carry out the umpteenth load of immigrants to bring to Italy. Italy has stopped to bend the head and to obey, this time THERE IS SOMEONE WHO SAYS NO. #closetheharbours

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	100% (43)	-	-	-	-	-
Evaluation	-	-	-	65% (28)	12% (5)	23% (10)

Table 5.23 Italy's voice-type and evaluation-type in Salvini's corpora

Processes that involve Italian citizens occur 6 times in the Salvini Tweet Corpus and 90 times in the Salvini Traditional Corpus.

	Material	Relational	Mental	Verbal	Behavioural	Existential
STW	67% (4)	-	33% (2)	-	-	-
STS	72% (65)	17% (15)	4% (4)	7% (6)	-	-

Table 5.24 Italians' transitivity in Salvini's corpora in Salvini's corpora

- 21. #Salvini: ASSURDO. Con i ricongiungimenti familiari **paghiamo** un miliardo di euro all'anno di pensioni ad immigrati che non hanno mai versato una lira in Italia. Ci metteremo mano. #portaaporta [emphasis added] (Salvini's Tweet 11 September 2018)<sup>51</sup>
- 22. [...] e **noi ringraziamo** la Madonnina e chi vuole riportare un po' di serenità in Italia. Serenità che prevede che ci siano delle radici ben piantate per terra e un paese come il nostro come diceva Benedetto Croce non può che definirsi cristiano. [emphasis added] (Salvini's speech in Milan 24 February 2018)<sup>52</sup>

Example 21 shows a material process (*we pay*) that is clearly connected to the *topos* of burden (see also section 5.5). Example 15 shows another material process (*they filled us up*) but in this particular example, Italians – that involve once again immigration – play the Goal of this process. In example 22 it is possible to notice a verbal process (*to thank*) that concerns religious topics<sup>53</sup> mixed with cultural roots.

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	55%	53	Identifier	3%	3
Goal	7%	7	Possessor	9%	8
Recipient	10%	9	Senser	5%	5
Client	1%	1	Sayer	2%	2
Carrier	4%	4	Receiver	4%	4

Table 5.25 Italians' participant types in Salvini's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	97% (94)	-	2% (2)	-	-	-
Evaluation	-	-	-	40% (38)	42% (41)	18% (17)

Table 5.26 Italians' voice-type and evaluation-type in Salvini's corpora

Even in this case material processes are the ones with the highest percentages in both corpora. Italians play mainly the Actor (55%), while the processes have always an active voice type

#Salvini: RIDICOLOUS. Every year we pay a billion of euros for the pensions of immigrants, who have never deposited a *lira* in Italy, because of family reunification. We will handle this. #portaaporta

-

<sup>[...]</sup> and we thank the *Madonnina* and those who want to bring back a little bit of serenity in Italy. Serenity is possible if there are roots well planted on the ground; and a county like ours – as Benedetto Croce said – can only be defined as Christian.

He is referring to "La Madonnina" a statue of the Virgin Mary atop Milan's Cathedral.

(97%). The positive (40%) and negative (42%) evaluations have similar percentages implying that the former supports Italians as a strong community – especially under the new government – and the latter confirms the description of Italians as victims.

## 5.2.2 Quantitative analysis

## 5.2.2.1 Keywords in the Salvini Tweet Corpus

The following Table shows the keywords categorised under the label Italy that are associated to this country and the Italian people. Clearly among the keywords that go under the label Italy there are *Italiani* (Italians), *Italia* (Italy) and *italiano* (Italian). In addition, the word *milione* (million) is also associated to Italy because Salvini often talks about Italian people in terms of numbers (e.g. he often repeats "60 million of Italians"). The word paese (country) is used by Salvini to describe Italy as a country. *Perbene* (respectable) and *operaio* (worker) refer to categories of Italian people, while razzismo (racism), scappare (to escape), vittima (victim) indicate the employment of the victim topos and the topic of reverse racism in Salvini's narrative. The keyword porta (door) confirms the employment of the source domain of building in the representation of Italy. Lastly, the keywords duomo (Cathedral), Catania, piazza (square), Genova, Milano, quartiere (neighbourhood), Torino, Napoli, and (Friuli-Venezia) Giulia indicate specific parts and cities of Italy to talk about various topics or to talk about a speech that took place in these places.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
italiani	30.600	47	79.5	Catania	3.990	10	16.9
perbene	26.370	13	22.0	operaio	3.830	11	18.6
razzismo	17.510	3	5.1	piazza	3.550	42	71.1
scappare	13.870	8	13.5	vittima	3.450	16	27.1
duomo	11.180	19	32.1	Genova	3.130	11	18.6
Italia	8.540	316	534.6	Milano	2.840	42	71.1
italiano	7.760	296	500.7	quartiere	2.500	10	16.9
Giulia	5.550	7	11.8	Torino	2.100	14	23.7
paese	5.330	106	179.3	porta	1.920	9	15.2
milione	4.480	33		Napoli	1.570	11	18.6

Table 5.27 Italy keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

## 5.2.2.2 Concordances and collocates in the Salvini Tweet Corpus

In Table 5.28 it is possible to observe the collocates of the word *Italia* (Italy). The majority of collocates are processes linked to Italy such as *volere* (to want), *essere* (to be), *stare* (to stay), *avere* (to have), *potere* (can), *dare* (to give), and *dovere* (have to). The process *tornare* (to go back) is linked to Italy's comeback to a favourable (economic) condition through Salvini's work; indeed, the processes *fare* (to do) and *cambiare* (to change) are linked to both Italy and

Salvini. #salvini is a collocate that indicates Salvini's quotations when he talks about Italy in tweets, while *io* (I) introduces what he thinks and what he wants to do for the country. The word *immigrato* (immigrant) involves mainly the presence and the potential arrival of immigrants in Italy. The collocate *Europa* (Europe) regards the relationship between the European Union and Italy. Finally. #primagliitaliani (#Italiansfirst) is one of the most famous slogans of Salvini.

Collocate	Cooccurrences	Occurrences	T-score	MI3
essere	76	1,272	7.94	15.98
non	51	658	6.65	15.20
volere	26	188	4.90	14.09
più	25	239	4.74	13.58
tutto	23	201	4.57	13.47
avere	33	665	5.13	13.30
stare	16	126	3.83	12.57
#salvini	21	321	4.21	12.40
fare	21	378	4.14	12.16
ci	17	204	3.86	12.14
potere	14	145	3.53	11.79
dare	12	95	3.32	11.73
cambiare	11	77	3.19	11.66
Europa	11	95	3.16	11.36
immigrato	12	129	3.27	11.29
anche	12	136	3.25	11.21
dovere	10	110	2.98	10.73
tornare	8	63	2.71	10.57
io	11	190	3.01	10.36
#primagliitaliani	9	109	2.81	10.29

Table 5.28 Collocates of the word Italia (Italy) in the Salvini Tweet Corpus

In the previous Table there is the collocate *paese* (country) that is used to describe Italy. It is interesting to notice that this is the only word used by Salvini to indicate Italy because of *Lega*'s history regarding its fight for independence and secession. As a result, the word *nation* has just one occurrence in the Salvini Tweet Corpus and it does not refer to Italy.

studiano, lavorano e fanno figli qui, il Belle personcine. VIA dal nostro Belle personcine. VIA dal nostro all'estero sono tornati a vedere nel nostro migliaio di ragazzi e fare dell'Italia un i confini e fermare l'invasione del nostro cerca di sfiorarlo per mettere in sicurezza il nostre donne che DIFENDONO il nostro viene la sicurezza degli italiani. Voglio un operazione e via, via, VIA dal nostro in mano. Adesso l'Italia torna ad essere un Table 5.29 Concordances of the word paese (country) in the Salvini Tweet Corpus<sup>54</sup>

-

<sup>1)</sup> they study, the word and they raise children here, the country take off again. Luxembourg, Belgium and now; 2) Nice little people. Who wants to bring war in our home OUT of our country!; 3) abroad they consider again our country as a fortress that can lead to the reborn of; 4) thousands of young people and make Italy a safer country @emergenzavvf; 5) the borders and stop the invasion in our country and I am doing it. They can investigate me; 6) tries to almost reach it in order to secure our country and relaunch Italians' consumption;

Table 5.29 provides a random selection of the word paese (country) that shows how Salvini talks about Italy as a country mainly to discuss security and the defence of the homeland against immigration. The quantitative analysis also investigated the representation of Italy and Italian people through the word *combattere* (to fight). However, this word is not connected to these social actors but just to Salvini and his party.

On the other hand, Table 5.30 shows all the concordances of the word *vittima* (victim) that are associated to Italian people who were victims of bad weather, disastrous events (e.g. the collapse of Morandi bridge in Genoa), reverse racism – linked to immigration and various crime such as rape perpetrated by immigrants – and terrorism. It is also possible to observe the keywords that go under the label victim in Table 5.72 (in section 5.5). Specifically, in the Table it is present the word italiani (Italians) that confirms Salvini's employment of the respective topos in the representation of these social actors and the reverse racism narrative.

economia) a tutti voi Amici, soprattutto alle ondata di maltempo. Una preghiera per le : 9 morti, 4 feriti gravi, 1 disperso. Tra le torna il buonsenso. " #Salvini: le ""Se vedessi sulla strada il figlio di #Salvini oggi a #Genova, fra i parenti delle IL PORTAFOGLI per aiutare i parenti delle Da ore nei soccorsi e una preghiera per le è stra-finita! " Un pensiero alle spegnere i terribili incendi. Un pensiero alle Buon viaggio #Pamela, bellissima ragazza la nostra civiltà. Una preghiera per le "contro il razzismo", Pamela e gli italiani @nonelarena PICTURE #Salvini: Le prime gli italiani, soprattutto le donne spesso Table 5.30 Concordances of the word *vittima* (victim) in the Salvini Tweet Corpus<sup>55</sup>

vittime vittime vittime vittime vittima vittime vittime vittime vittime vittime vittima vittime vittime vittime vittime

del maltempo di queste ore, e grazie ai Vigili e un abbraccio ai loro cari. Seguiamo con anche un Vigile del Fuoco volontario. Un del razzismo in Italia sono gli italiani. Onu si di un incidente stradale, passerei avanti e tanti cittadini comuni: il mio impegno è , le persone coinvolte, gli sfollati e la città. e per le loro famiglie. Andremo fino in fondo e ai feriti della terribile esplosione di di questa tragedia e un grazie a donne e della ferocia di chi non merita di essere . #Francia #Trebes..." "Anche in tutelato il DELINQUENTE piuttosto che la VITTIMA . #Mattino5 @Mattino5 #Salvini: Se arrivi qua della violenza dei clandestini possono di un'immigrazione fuori controllo sono LE di violenza da parte di FINTI profughi. Dico

<sup>7)</sup> our women who defend our country and our sea, land and sky borders; 8) comes (first) Italians' security. I want a country that goes forward, I do not want a country that looks back!; 9) operation and these criminal illegals out, out, OUT of our country! Music is; 10) now Italy goes back to being a proud country with its borders and its.

<sup>1)</sup> economy) to all of you Friends, especially to the victims of bad weather in these hours and thanks to the firefighters; 2) wave of bad weather. A prayer for the victims and a hug to their loved ones. We follow with; 3) 9 dead people, 4 people severely injured, a missing person. Among the victims even a voluntary firefighter; 4) common sense is coming back." #Salvini: in Italy the victims of racism are the Italians. The UN; 5) "If I saw #Salvini's son victim of an accident in the street, I would move off; 6) today in #Genoa among victims' relatives and many common citizens. My commitment is; 7) THE WALLET in order to help victims' families, the people involved, the evacuees and the city; 8) for hours in first aid; and a prayer for the victims and their families. We will go all the way; 9) is super over! "A thought for the victim and the injured of the terrible explosion of; 10) extinguish the fire. A thought for the victims of this tragedy and thanks to women and; 11) Farewell #Pamela, beautiful girl victim of the cruelty of those [immigrants] who do not deserve of being; 12) our civilisation. A prayer for the victims #Francia #Trebes..." "Even in; 13) protected the CRIMINAL rather than the VICTIM. #Mattino5 @Mattino5 #Salvini: If you come here; 14) "against racism". Pamela and the other Italians, who are the victims of illegals' violence, can; 15) @nonelarena #Salvini: the first victims of an uncontrolled immigration are THE [women]; 16) Italians, especially women who are often the victims of fake refugees' violence. I say.

# 5.2.2.3 Keywords in the Salvini Traditional Corpus

Table 5.31 shows the list of keywords under the label Italy in the Salvini Traditional Corpus.

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
perbene	23.230	8	18.3 insegnante	5.000	16	36.7
scappare	13.230	10	22.9 Italia	4.290	117	268.2
sardo	12.490	16	36.7 milione	4.080	29	66.5
Sardegna	11.170	27	61.9 piazza	3.440	30	68.8
nonno	9.230	13	29.8 Roma	2.870	46	105.4
Trentino	8.800	13	29.8 Milano	2.570	28	64.2
paese	7.470	114	261.3 sud	2.470	7	16.0
disabile	7.350	12	27.5 terra	2.010	12	27.5
signora	6.830	14	32.1 porta	1.830	12	27.5
imprenditore	5.170	12	27.5 mare	1.410	12	27.5
italiano	5.050	142	325.5			

Table 5.31 Italy keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

Even in traditional speeches, among the keywords connected to Italy, it is possible to notice paese (country), italiano (Italian), Italia (Italy), milione (million). In addition to paese, this list reveals that Salvini – in his Traditional Corpus – also uses the word terra (land) to indicate Italy (see section 5.2.2.4). Sardegna, Trentino, Roma, Milano, piazza (square), sud (south) and mare (sea) refer to specific regions, cities of Italy or simply to Italian places where Salvini is delivering a speech. Porta (door) once again confirms Salvini's employment of the building source domain in the description of Italy. Perbene (respectable), sardo (people from Sardinia), nonno (grandfather), disabile (disabled), signora (lady), imprenditore (businessman), insegnante (teacher) are all categories of Italian people that Salvini mention during his speeches to create an empathetic bond with his electorate (because he gives the impression to care for every category, especially the disadvantaged ones). These keywords also indicate that Salvini employs the strategy of storytelling; indeed, he often reports his conversations with common people.

# 5.2.2.4 Concordances and collocates in the Salvini Traditional Corpus

In Table 5.32 on the next page, it is possible to observe the collocates of the word *Italia* (Italy) in the Salvini Traditional Corpus. *Paese* (country), *Sardegna* and *Italia* (Italy) are the first collocates that go under the label Italy and are directly connected to this nation and one of his regions (where Salvini delivered one of the speeches present in the Traditional Corpus). Even in this case *Europa* (Europe) involves the relationship between E.U. and Italy. The word *arrivare* (to arrive) regards mainly the immigration topic since it is especially connected to immigrants who reach Italy. The collocates *Lega* and *io* (I) regard Salvini's vision of Italy and what he and his party intent to do to improve the country. The collocate [number] indicates

characteristics of Italy and statistics, especially involving immigrants who arrive in the country. Lastly, there are also some processes connected to Italy such as *essere* (to be), *fare* (to do) and *avere* (to have).

Collocate	Cooccurrences	Occurrences	T-score	MI3
essere	49	1,480	6.43	14.86
non	20	692	4.06	12.07
tutto	10	141	3.04	11.37
paese	9	139	2.88	10.93
Sardegna	5	27	2.20	10.75
Italia	8	117	2.72	10.67
Europa	5	36	2.19	10.34
arrivare	6	67	2.38	10.23
avere	13	725	3.07	10.14
fare	11	474	2.93	10.03
io	9	287	2.74	9.89
perché	9	307	2.73	9.79
Lega	5	72	2.15	9.34
altro	5	93	2.12	8.97
[number]	7	255	2.39	8.97
chi	5	140	2.07	8.38
anno	5	146	2.06	8.32
come	5	154	2.05	8.24

Table 5.32 Collocates of the word *Italia* (Italy) in the Salvini Traditional Corpus

Even in this case, traditional speeches have just one occurrence of the word *nation* and it does not involve Italy. The following Table shows a random selection of the word *paese* in the Salvini Traditional Corpus. The concordances show that there are generally less references to the topic of immigration (in comparison to Table 5.29). However, here it is present Salvini's commitment against organised crime. *Paese* is also used to talk about various topic such as economy.

il lavoro è la vera emergenza di questo paese architettoniche, le medicine". Io nel mio i primi. Non esistono italiani ultimi nel Cancellare da questo splendido Perché questo non è il la loro vita per la sicurezza del nostro nella manovra economica di questo paese coalizione con cui governeremo questo di voi sia protagonista. Voglio un e col sorriso noi cambieremo questo Table 5.33 Concordances of the word paese . Il lavoro! E quindi per creare lavoro non lo fai voglio applicare quello che un Matteo molto più che ho in testa APPLAUSE. Tutti devono avere le schifezze che rispondono al nome di mafia, di chi aggredisce i poliziotti e i carabinieri. e quindi sappiate che come io conto su di voi, voi ognuno ha la sua identità. La Lega è la lega, gli che torni a marciare, a lavorare, a sorridere. La violenza non ha mai risolto nulla

56 1) work is the real emergency of this country. Work! And then toy cannot create work; 2) architectural [barriers], medications". In my country I want to apply what a Matteo more famous than me; 3) the firsts. In the country I have in mind there are not Italians left behind. Everyone must have; 4) Erase from this beautiful country the nastiness such as mafia; 5) Because this is not the country of people who attack policemen and carabinieri; 6) their lives for the security of our country; and then you should know that as I count on you,

In addition to *paese*, among traditional keywords there is the word *terra* (land) that is used by Salvini to talk about Italy. In Table 5.34 it is possible to notice that Salvini uses this word to talk about the defence of Italian products (such as food) and generally of Made in Italy, but also to talk about specific Italian regions. Moreover, the word is often associated to *nostra* (our) in order to create a strong sense of community.

mangiare i frutti che ci dà la nostra terra . lo sono stufo di dover bere l'olio che i miei figli mangino i prodotti della nostra terra terra, bevano i prodotti della nostra terra terra, bevano i prodotti della nostra terra e mangino i prodotti del nostro mare perché è , preferisco i frutti del mio mare e della mia Il buon Dio ci ha dato un mare e una Italia è il lavoro. lo voglio tornare in questa terra differenza fra chi parla e chi fa. lo giro tante qua e parlo della Sardegna perché è una Ripartire dal lavoro, ripartire dalla terra giorno di vacanza in questa splendida terra Viva la Lega e viva questa splendida terra (land) in the Salvini Traditional Corpus<sup>57</sup>

The quantitative analysis in traditional speeches – similarly to tweets – focused on the word *combattere* (to fight). Even in this case this word is not connected to these social actors but just to Salvini and his party.

The following Table shows the concordances of the word *vittima* (victim) that involves mainly Italian people (two concordances regards *true* refugees and illegal immigrants) that suffer from economic disadvantages, organised crime, and reverse racism.

come sono contenti, andate a chiedere alle vittime delle norme fiscali bancarie folli. Mi dicono: a Rosario Livatino morto a 38 anni, vittima della mafia. Un giudice integro, onesto, libero, dotato di autonome istituzioni, non è vittima di guerre, pestilenze o carestie, e quindi fuggono della guerra e che sono le prime vittime della confusione che stiamo vivendo. Perché qualche diritto in più, perché noi siamo vittime dell'unica forma di razzismo che ha Table 5.35 Concordances of the word *victim* (vittima) in the Salvini Traditional Corpus<sup>58</sup>

through which we will govern this country, everyone has its own identity. The League is the League the others; 9) of you will be the protagonist. I want a country that marches again, works again and smiles again; 10) and smiling we will change this country. Violence has never resolved something.

<sup>1)</sup> eat the fruits given by our land. I am sick and tired of drinking oil; 2) for my children to eat the products of our land, to drink the products of our land, to drink the products of our sea because; 4) I prefer the fruits of my sea and my land. Not numbers. Men, Women, with; 5) the good Lord gave us a sea and a land that produce all good things. Why; 6) Italy is work. I want to come back in this land, I do not want to fill it up with immigrants who fill up; 7) children must eat the fruits of our land and our sea. Because it means; 8) the difference among those who talk and those who act. I visit many lands of this beautiful country. For instance; 9) here and I am talking about Sardinia because it is a land that is suffering more than others the; 10) Starting again from work, starting again from the land. It can be done. However, during this week I; 11) some days off in this wonderful land that is Trentino, you should know that coming back home – without; 12) Hurrah for the League and hurrah for this wonderful land that is Trentino! I love Trentino, I love.

<sup>58 1)</sup> how happy they are, ask to those victims of the ridiculous banking and financial rules. They say to me; 2) to Rosario Livatino who died at the age of 38, victim of the mafia. An incorruptible and honest judge; 3) free, provided with independent institutions, it is not a victim of wars, pestilences or famines; and then; 4) flee from

### 5.3 The Media

This section explores how Matteo Salvini represents the media. Indeed, Salvini often criticises the media – especially the traditional ones that are dominated by the elite – and praises the freedom of speech in social media.

## 5.3.1 Qualitative analysis

Salvini's representation of the media was qualitatively investigated just through the category of *topoi*.

## 5.3.1.1 Topoi

The Salvini Tweet Corpus has 2 occurrences of the dishonest *topos*, while in the Traditional one there are 19 occurrences of the same *topos*.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
STW	-	-	-	-	-	-	100% (2)
STS	-	-	-	-	-	-	100% (19)

Table 5.36 Media topoi in Salvini's corpora

23. In 3 minuti il mio intervento **che nessun TG vi farà vedere.** Prima l'Europa? No, prima gli italiani! [emphasis added] (Salvini's Tweet 6 February 2018)<sup>59</sup>

- 24. [...] e io vi dico che noi vinceremo nonostante il vergognoso silenzio di gran parte dei giornali, delle radio e delle televisioni italiane, con giornalisti pubblici o privati che cancellano le idee, che hanno provato a cancellare una piazza stupenda come la piazza di Milano sabato scorso con 50.000 persone educate e perbene. Però fortunatamente siamo nell'epoca in cui c'è la rete, in cui la gente si confronta, in cui ci sono i social network, e quello che hanno cancellato i telegiornali della rai o di altre televisioni è stato visto in rete da 10 milioni di italiani, quindi noi vinceremo anche alla faccia di quei giornalisti servi che sono lì perché devono rispondere al padrone. Noi non abbiamo padroni, il bello è che noi non abbiam padroni, voi non avete padroni. [emphasis added] (Salvini's speech in Rome 1 March 2018)<sup>60</sup>
- 25. Io ricordo il ghigno di qualche giornalista. Averne di giornalisti così. La Lega è finita, un bacione a Gad Lerner! Veramente, lunga vita umana e professionale, lunga vita umana e professionale a lui, a Eugenio Scalfari, a Michele Santoro, a Fabio Fazio, a tutti i rosiconi che menano gramo, a tutti! Lunga vita! E un bacione affettuoso. [emphasis added] (Salvini's speech in Pontida 1 July 2018)<sup>61</sup>

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war and who are the first victim of the chaos we are living. Because; 5) a few more rights, because we are the victims of the only type of racism that has.

This is – in 3 minutes – my speech that news will not show you. Europe first? No, Italians first!

<sup>[...]</sup> and I say to you that we will win despite the shameful silence of the majority of newspapers, radios and Italian television, with journalists of public and private broadcasters who erase ideas, who tried to erase a wonderful square such as the square in Milan of last Saturday with 50.000 well-behaved and respectable people. Fortunately we live in an era where there is the internet, where people can discuss, where there are social networks. And what have been erased by rai news or other news in television, it has been watched by 10 millions of Italians on the web; therefore we will win to spite those servant journalists who are there because they have to answer to the master. We have no masters, the best part is that we have no masters, you do not have masters.

I remember some journalists' snigger. All should have journalists like that. The League is over, a big kiss to Gad Lerner! Truly, I wish to him a long human and professional life, a long human and professional life to

In example 23 Salvini suggests that the news censors him. As a result, he uses Twitter to freely share his short speech (against Europe regarding the topic of immigration and Italy's sovereignty also in terms of economic matters) at the European Parliament. Similarly, in example 24 Salvini says that televisions, radios and newspapers censor the success of his speeches during the electoral campaign. He also underlines the journalists' dependence from the elitist system. For this reason, he uses social media to spread his contents in order to win the campaign. Clearly, this attitude helps Salvini in spreading feelings of injustice and fear that encourage his supporters to act (e.g. share on social media those contents). Finally, example 25 contains a direct attack to famous journalists such as Lerner, Scalfari, Santoro, and Fazio.

## 5.3.2 Quantitative analysis

## 5.3.2.1 Keywords in the Salvini Tweet Corpus

The following keywords are the ones categorised under the label of fake in the Salvini Tweet Corpus.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
tivù	18.010	11	18.6	giornale	2.500	11	18.6
news	4.910	3	5.1	giornalista	2.050	8	13.5

Table 5.37 Media keywords (opposition-fake) in the Salvini Tweet Corpus (reference corpus itTenTen16)

*Tivù* (television), *news*, *giornale* (newspaper) and *giornalista* (journalist) summarise Salvini's narrative of the dishonest media; specifically, the keyword *news* is associated to the topic of the fake news. Moreover, he accuses journalists to be submissive to the system.

We should emphasise that the fake category belongs to the macro-category opposition, Table 5.38 below. Opposition keywords involve primarily Salvini's political opponents (Fornero, Boldrini, Di Maio, Renzi) but also intellectuals (Saviano), Europe and some European nations through the keywords Macron, Europa (Europe), Spagna (Spain), francese (French), Francia (France), UE (E.U.), tedesco (German), europeo (European) and Bruxelles (Brussels), and NGOs through ONG (NGO), nave (ship) and bandiera (Flag). In addition, the keywords Salvini and Lega show that Salvini talks about his personal attacks and the attacks to his party confirming his employment of the victim topos.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
Salvini	113.290	59	99.8	cancellare	5.960	8	13.5
Fornero	40.340	30	50.8	violento	4.880	6	10.2
ONG	40.010	36	60.9	straniero	4.750	10	16.9
lega	39.910	13	22.0	bandiera	4.680	10	16.9
Boldrini	38.380	27	45.7	denunciare	4.660	10	16.9

him, to Eugenio Scalfari, to Michele Santoro, to Fabio Fazio, and all those jinx haters, to all of them! Long life! And an affectionate big kiss.

buonista	35.080	22	37.2	violenza	4.240	4	6.8
Macron	29.310	17	28.8	Spagna	3.870	12	20.3
insulto	26.960	28	47.4	francese	3.820	24	40.6
insultare	26.100	23	38.9	Francia	3.750	18	30.5
spacciatore	25.840	3	5.1	democratico	3.670	13	22.0
Saviano	24.080	17	28.8	finanza	3.650	3	5.1
Bruxelles	19.290	29	49.1	UE	3.590	10	16.9
PD	18.400	76	128.6	attaccare	3.530	11	18.6
razzismo	17.510	18	30.5	tedesco	3.060	17	28.8
razzista	17.320	16	27.1	miliardo	2.830	7	11.8
Maio	15.750	9	15.2	legge	2.480	26	44.0
nave	15.350	52	88.0	europeo	2.440	41	69.4
Renzi	14.990	34	57.5	imporre	2.440	12	20.3
sinistra	11.040	82	138.7	signore	2.380	16	27.1
Europa	8.890	95	160.7	repubblica	2.260	5	8.5
indagare	8.510	17	28.8	finire	2.140	5	8.5
minaccia	7.890	18	30.5	lezione	1.960	10	16.9
fascista	7.690	13	22.0	arrivare	1.760	13	22.0
faccia	7.030	25	42.3	centro	1.310	37	62.6
presunto	6.300	5	8.5				

Table 5.38 Opposition keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

## 5.3.2.2 Concordances in the Salvini Tweet Corpus

The concordances in Table 5.39 shows that the word tivù (TV) is strictly associated to the idea of censorship. Salvini complains particularly about television silence about topics such as immigration (and its threats) and personal attacks to him. Furthermore, in the last concordance Salvini claims that television also attacks President Donald J. Trump.

votano per il cambiamento, e da giornali e tivù italiane parte il solito ritornello per cui "ha ! #lamafiamifaschifo" "Senatore del Pd in tivù con maglietta "Salvini sei solo un pistola"! i cittadini italiani. #EleggiloTu Tivù e giornali nasconderanno la notizia, aiutaci Fra insulti e minacce di tutti i giornali e le tivù italiane, apprezziamo l'obiettività di di governo". Basta bugie di giornali e tivù , ecco la realtà: vi piace?? Leggi: LINK "Penso di essere stato chiaro in tivù ! O si parte col governo e si lavora, con Di Avete visto queste immagini su qualche tivù ? #Salvini: 24 FEBBRAIO, dalle loro case. Perché quasi tutte le tivù e i giornali non ne parlano? Forse gualcuno Oltre 1.200 clandestini, nel SILENZIO delle tivù , sbarcati in Sicilia nelle ultime ore E a gola e mal di testa, ma si esce per portare in tivù da Floris (su @La7tv alle ore 23) la mia e #4marzovotoLega" "Tutte le tivù e i buonisti contro @realDonaldTrump. Forse Table 5.39 Concordances of the word *tivù* (TV) in the Salvini Tweet Corpus<sup>62</sup>

<sup>1)</sup> vote to change, and from the Italian newspapers and tv start the usual refrain according to; 2)! 
#Iamdisgustedbtmafia" "PD Senator in tv with a t-shirt "Salvini you are only a gun a; 3) the Italian citizens 
#YouElect Tv and newspapers will hide the news, help us; 4) Among all the insults and the threats of all the 
Italians newspapers and tv we appreciate the impartiality of; 5) of government". Stop with the lies of 
newspapers and tv, here there is the truth. Do you like it? Read; 6) "I think that I have been clear in tv! Or we 
start with the government and we work, with Di; 7) Have you seen these pictures on any tv? Salvini: 24 
FEBRUARY; 8) from their homes. Why almost all the tv and the newspapers do not talk about it? Maybe 
someone; 9) More than 1.200 illegals have disembarked in Sicily in the last hours in the SILENCE of tv; 10) 
sore throat and headache, but I go out to bring to Floris in tv (on @La7tv at 11 pm) my and; 11) 
#4marchIvoteLeague" "all the tv and do-gooders are against @realDonaldTrump. Maybe.

Similarly, the concordances of *giornale* (newspaper) in the following Table indicates Salvini attitude to talk about censorship and fake news. In Table 5.39 and 5.40 *giornale* and *tivù* often co-occur. As a result, Salvini reaffirms the existence of corruption in the mainstream traditional media perpetrated by the elite.

```
i cittadini votano per il cambiamento, e da c'è giorno in cui non siamo stati attaccati, da "ufficiale" ha occupato pagine di i cittadini italiani. #EleggiloTu Tivù e non abbiamo paura, e non molliamo! funzionare". Fra insulti e minacce di tutti i "contratto di governo". Basta bugie di dell'uomo. Mai più. Quello che i dalle loro case. Perché quasi tutte le tivù e i "Gli altri hanno televisioni, Table 5.40 Concordances of the word giornale (newspaper) in the Salvini Tweet Corpus<sup>63</sup>
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In the following Table it is possible to notice how Salvini attacks journalists who – according to him – are unjust and liars.

```
cambiando ovunque. Non capisco alcuni giornalisti
                                                            italiani che danno del
  fanno tutti i giorni, nel silenzio di buonisti, giornalisti
                                                            e compagni vari. #primagliitaliani
  Agosto 2018: tre tunisini in fuga. Ma per i giornalisti
                                                            c'è "il buco del Viminale". Anche grazie a
                      "Ricordo a politicanti e giornalisti
                                                            buonisti che io non giudico le persone in
        "Che cosa intenderà esattamente il giornalista
                                                            del Fatto quando dice che ""Salvini
     @poliziadistato " INCREDIBILE come i giornalisti
                                                            italiani riescano a inventarsi bugie dalla
   a vita! Esagero? Quanto rosicano alcuni giornalisti
                                                            di sinistra ??? "Cambia l'Italia,
  è cosa troppo leggera.). Complimenti al "" giornalista
                                                            "" Friedman! Amici, questi insulti mi dicono
Table 5.41 Concordances of the word giornalista (journalist) in the Salvini Tweet Corpus<sup>64</sup>
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## 5.3.2.3 Keywords in the Salvini Traditional Corpus

Table 5.42 shows the keywords categorised under the label fake in the Salvini Traditional Corpus.

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<sup>1)</sup> the Italian citizens vote to change, and from the Italian newspapers and tv start the usual refrain; 2) there has not been a day in which we have not received attacks from newspapers and various European commissioner; 3) "official" has occupied pages of newspapers and hours of news to report the; 4) the Italian citizens #YouElect Tv and newspapers will hide the news, help us!; 5) we are not scared, and we do not give in! Newspapers and German politicians insult: Italians; 6) Among all the insults and the threats of all the Italians newspapers and tv we appreciate the impartiality; 7) "agreement between government parties". Stop with the lies of newspapers and tv, here there is the truth. Do you like it? Read; 8) Never again. What newspapers do not say; 9) from their homes. Why almost all the tv and the newspapers do not talk about it? Maybe someone in the left-wing; 10) "The other ones have televisions, newspapers and radios. We have YOU! Subscribe now.

<sup>1)</sup> changing everywhere. I do not understand some Italian journalists who say that; 2) do every day, in the silence of do-gooders, journalists and various comrades. #Italiansfirst; 3) August 2018: three Tunisians on the run. Instead, for the journalists there is the "Viminale void". Even thanks to; 4) "I remind to petty politicians and do-gooders journalists that I do not judge people; 5) "What exactly does the *Fatto*'s journalist means when he says that "Salvini; 6) @statepolice UNBELIVABLE how the Italian journalists manage to make up lies; 7) to life! Am I exaggerating? How much do some left-wing journalists feel envy? "Change Italy; 8) I congratulate with the "journalist" Friedman! Friends, these insults make me understand.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
televisione	9.580	16	36.7	giornale	4.510	15	34.4
giornalista	5.620	11	25.2	-			

Table 5.42 Media keywords (opposition-fake) in the Salvini Traditional Corpus (reference corpus itTenTen16)

The list presents the same keywords (except for *news*) already found in Table 5.37: *televisione* (television), giornalista (journalist), and giornale (newspaper). Moreover, the frequency of these traditional keywords is slightly higher than the ones in Table 5.37.

The following Table involve those keyword categorised under the macro-category opposition. Even this Table is shorter compared to Table 5.38. Nevertheless, it is possible to notice the same narratives since there are keywords connected to Salvini's employment of the victim topos (e.g. Salvini and Lega), Salvini's political opponents: Fornero, Renzi, sinistra (left) and PD (democratic party); Europe: Bruxelles (Brussels), Europa (Europe) and europeo (European); and NGOs such as Aquarius and bandiera (flag).

Keyword	Score	Freq	Rel freq Keyword	Score	Freq	Rel freq
Salvini	101.870	15	34.4 sinistra	5.690	31	71.1
lega	31.690	4	9.2 pagare	5.620	8	18.3
Aquarius	30.140	13	29.8 Europa	4.590	36	82.5
Fornero	24.010	13	29.8 PD	4.050	12	27.5
Matteo	21.780	5	11.5 fermare	3.240	7	16.0
Renzi	13.760	23	52.7 partito	3.220	3	6.9
fascista	11.060	14	32.1 europeo	2.260	28	64.2
Bruxelles	10.980	12	27.5 legge	2.150	14	32.1
multinazionale	10.780	10	22.9 amico	2.100	7	16.0
indagare	10.120	15	34.4 sicuro	2.010	3	6.9
cancellare	9.470	11	25.2 usare	1.300	11	25.2
bandiera	8.640	1	2.3			

Table 5.43 Opposition keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

### 5.3.2.4 Concordances in the Salvini Traditional Corpus

The following Table shows that almost every concordance of the word *televisione* (television) focuses on the dishonest topos that Salvini associates to traditional media. Specifically, how the elite employs at its own advantage these media. The remaining concordances involve Salvini's TV appearances.

gran parte dei giornali, delle radio e delle televisioni italiane, con giornalisti pubblici o privati , guardare tutti lo stesso programma alla televisione , ascoltare tutti la stessa musica. In una maggioranza dei giornali e delle televisioni italiane, hanno soccorso più di 1.000

cancellato i telegiornali della rai o di altre televisioni è stato visto in rete da 10 milioni di italiani, elettorale stando o davanti a una televisione o dietro a un computer. Noi abbiam fatto, io il lavoro non lo trova, ci dicono pure in televisione : "Ma è colpa tua, perché non hai fatto i di cui ho provato sempre a parlare in televisione , l'ultima volta sono andato da Vespa che mi in un'intervista su un giornale, in una televisione , a radio radio, su Facebook. Ho capito, mi una lira, senza una banca, senza una televisione , senza amici potenti, ha vinto e ha ripreso onesto, coraggioso, che non andava in televisione, non faceva interviste sui giornali, non

bandiera del leone, sotto il traliccio delle televisioni . Arriviamo signora, cercheremo di essere una fiducia. Questo ho detto ieri sera in televisione , e chiudo, la fiducia perché la gente voterà mia figlia, che vede il papà più spesso in televisione che a casa, e passare ore e ore al telefono in galera i mafiosi, senza andare in televisione a finire sui giornali. Questa è la giustizia che vita grama che devono avere. E vanno in televisione e dicono: "Eh però, questo Governo non ha finanza, useranno i giornali, useranno le televisioni . Possono usare chi vogliono, se il popolo Table 5.44 Concordances of the word *televisione* (television) in the Salvini Traditional Corpus<sup>65</sup>

The concordances of *giornale* (newspaper) in Table 5.45 confirm Salvini's narrative regarding censorship and fake news even in the Traditional Corpus.

nelle maniere più varie, in un'intervista su un giornale , in una televisione, a radio radio, su e quindi abbiamo letto per quindici giorni sui giornali italiani: La Stampa, La Repubblica, il Fatto nel silenzio della stragrande maggioranza dei giornali e delle televisioni italiane, hanno soccorso Table 5.45 Concordances of the word *giornale* (newspaper) in the Salvini Traditional Corpus<sup>66</sup>

il vergognoso silenzio di gran parte dei giornali , delle radio e delle televisioni italiane, con No! Non mi sembra. Ovviamente sui giornali di oggi, proposte, ci sono anche belle Quindi voi avete letto mezza riga su un giornale oggi? No! Figurati! La Lega che parla di ai radical chic di salotto che domani sui giornali commenteranno la brutta gente che c'era a in televisione, non faceva interviste sui giornali , non aveva fatto i milioni di euro grazie all' reale, fra quello che si leggeva sui siti, sui giornali e sui social e quello che noi chiedevamo di dovuto essere qua e spero che qualche giornale non polemizzi perché c'è in corso ... infatti contestazione ma va bene! Lasciamo che i giornali , i telegiornali scrivano e dicano quello che si dovessero informare aspettando qualche giornale e qualche telegiornale campa il cavallo che l' che, alla faccia di quello che scrivono i giornali , è compatto come non mai. Ringrazio il , senza andare in televisione a finire sui giornali . Questa è la giustizia che mi piace e questa la borsa, useranno la finanza, useranno i giornali , useranno le televisioni. Possono usare chi

<sup>1)</sup> of the majority of newspapers, radios and Italian television, with journalists of public and private broadcasters; 2) erased by rai news or other news in television, it has been watched by 10 millions of Italians; 3) the electoral campaign staying in front of a television or behind a computer. We have done, I; 4) does not find the job, they even say to us on television: "But this is your fault because you have not done the; 5) of which I have always tried to talk about in television, the last time I went to Vespa who; 6) all watch the same program on television, all listen to the same music. In a; 7) on a newspaper interview, on a television, on radio radio, on Facebook. I understood; 8) without a lira, without a bank, without a television, without powerful friend. It has won and has; 9) honest, brave, who did not go on television, who did not grant interviews on newspapers; 10) the majority of Italian newspapers and televisions, they rescued more than 1,000; 11) the lion's flag, under the television trellis. We are coming Ms.; we will try to be; 12) a trust. This is what I said last evening in television, ad a stop here, the trust because people will vote; 13) my daughter, who see the father more in television than at home, and spend hours speaking at the telephone; 14) mafiosi in jail, without going on television or end up in the newspapers. This is the justice that; 15) unhappy life they probably have. And they go on television and say: "Huh but this government has not; 16) finance, they will use the newspapers, they will use the televisions. They can use whatever they want, if the people.

<sup>1)</sup> the shameful silence of the majority of newspapers, radios and Italian television, with; 2) No! I do not think so. Obviously on today newspapers there are proposals, even good; 3) did you read a half line about this on a newspaper today? No! Oh yes of course! The League that talks about; 4) in various manners, on a newspaper interview, on a television, on radio radio; 5) and then we have red for fifteen days on the Italian newspaper: La Stampa, La Repubblica, il Fatto; 6) to salon radical chic who tomorrow will comment the bad people that were; 7) who did not go on television, who did not grant interviews on newspapers, who did not make millions of euro thank to; 8) in the silence of the majority of Italian newspapers and televisions, they rescued; 9) among what was possible to read on the websites, on the newspapers and on social media and what we were asking to; 10) should not be here and I hope that some newspapers will not argue because there is...; 11) protest but it is ok! We let that the newspapers and the news write and say what; 12) should find out waiting some newspapers and some news live horse that; 13) that, in spite of what they write, is more solid than ever. I thank the; 14) without going on television or end up in the newspapers. This is the justice that I like and this is; 15) stock market, they will use the finance, they will use the newspapers, they will use the televisions. They can use whoever.

In both Table 5.44 and Table 5.45 televisione and giornale co-occur (similarly to Table 5.39 and Table 5.40) in order to represent a corrupt and dishonest system. In addition to television and newspaper, in traditional speeches it is possible to notice the presence of the word radio.

Finally, in Table 5.46 Salvini attacks journalists who – according to him – are *slaves* of the elite and their corrupt system.

radio e delle televisioni italiane, con giornalisti noi vinceremo anche alla faccia di quei giornalisti quello che è l'interesse del paese. Un giornalista , qualche frustrato di sinistra, qualche giornalista lo ricordo il ghigno di qualche giornalista di qualche giornalista. Averne di giornalisti che qualche ... prevedo qualche collega giornalista di festa assoluta e qualche collega giornalista politologi, di quei sondaggisti, di quei giornalisti anche i politici che li hanno coperti e i giornalisti i giornalisti che li hanno coperti, e i giornalisti

pubblici o privati che cancellano le idee, che servi che sono lì perché devono entrando m'ha chiesto: "Però in Europa , che perfino la tragedia nel Mar Mediterraneo . Averne di giornalisti così. La Lega è finita, così. La Lega è finita, un bacione a Gad : "Salvini non va al vertice, in polemica coi 5 - lo dico da giornalista - è riuscito a scrivere ma figurati! Salvini, brutto, cattivo no! Qua c che li hanno coperti, e i giornalisti che li che li hanno coperti. Chiedo troppo? Table 5.46 Concordances of the word *giornalista* (journalist) in the Salvini Traditional Corpus<sup>67</sup>

# 5.4 Europe

This section investigates Salvini's Eurosceptic discourse and how he represents Europe.

#### 5.4.1 Qualitative analysis

The qualitative analysis dedicated to Europe involved the investigation of metaphors, *topoi*, representational strategies and transitivity.

### 5.4.1.1 **Metaphors**

In both the Salvini Tweet Corpus and the Salvini Traditional Corpus there are 5 occurrences of metaphors linked to Europe. As it is possible to notice in the following Table all the metaphors in traditional speeches belong to the source domain of war, while the metaphors in tweets belong to the source domains of container, building and religion.

<sup>1)</sup> radios and Italian television, with public and private journalists who erase ideas, who; 2) therefore we will win to spite those servant journalists who are there because they have; 3) what is the interest of the country. A journalist asked my while he was coming in "But in Europe; 4) some frustrated left-wing people, some journalists – that even the tragedy of the other day in the Mediterranean sea; 5) I remember some journalists' snigger. All should have journalists like that. The League is over; 6) some journalists' snigger. All should have journalists like that. The League is over, a big kiss to Gad; 7) that some... I expect that some fellow journalists: "Salvini does not go to the meeting, in controversy with the 5; 8) absolute party and some fellow journalists - and I say this because I am a journalist - have even written; 9) political commentators, those pollsters, of those journalists. Oh yes of course! Salvini bad, evil, no! here; 10) even the politicians who covered them and the journalists who covered them, and the journalists who; 11) the journalists who covered them, and the journalists who covered them. Am I asking too much?

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
STW	-	20% (1)	60% (3)	-	-	20% (1)	-	-
STS	-	-	-	-	100% (5)	-	-	-

Table 5.47 E.U. source domains in Salvini's corpora

- 26. Incredibili e inaccettabili gli insulti e le minacce che ogni giorno arrivano da Bruxelles. Le uniche #macerie che dovrò raccogliere sono quelle del bel sogno europeo, distrutto da gente come #Juncker: sarò felice di ricostruire una nuova Europa con il voto popolare di maggio. [emphasis added] (Salvini's Tweet 5 October 2018)<sup>68</sup>
- 27. Insieme per un'Europa fondata sul lavoro e sulla sicurezza, recuperando i **valori sacrificati sull'altare** della speculazione e dell'immigrazione. #elezionieuropee2019 @MLP\_officiel [emphasis added] (Salvini's Tweet 8 October 2018)<sup>69</sup>
- 28. Far cadere il muro di Berlino una volta sarebbe stato impensabile e il prossimo **muro** che facciamo cadere è quello **di Bruxelles** restituendo ai popoli europei il diritto al lavoro, il diritto alla vita, il diritto alla salute, il diritto alla sicurezza. **Il muro di Bruxelles**, non dico a colpi di ruspa se no dicono che sono cattivo. [emphasis added] (Salvini's speech in Pontida 1 July 2018)<sup>70</sup>

Example 26 shows how Salvini uses the source domain of building. He compares the European dream to a destroyed house and claims to be happy to rebuild a new Europe after the European Election of 2018. In example 27 the word *altare* (altar) clearly belongs to the religion source domain. Since he is talking about values that have been sacrificed on this European altar characterised by speculation and immigration, the metaphorical representation recalls a heretical pagan sacrifice. The structure of the tweet should be also observed. Salvini's and Le Pen's (@MLP\_officiel) idea of Europe is (a positive and legitimising self-representation) based on jobs and security, while the current structure of Europe is represented negatively and delegitimised since Salvini describes it as based on wrong values such as flexible immigration policies, and wrong and risky economic policies. In example 28 Salvini talks about the *Brussels Wall* that clearly recalls the Belin Wall. In this way, he compares the relationship with the European Union to the Cold War. Moreover, he implies a liberation from this dictatorial and foreign institution (see also sections 5.4.1.2 and 5.4.1.3). Lastly, example 1 shows the container source domain because Salvini talks about the possibility to *fill up* Europe with fake refugees.

## 5.4.1.2 Topoi

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The Salvini Tweet Corpus counts 13 occurrences of *topoi*, while in the Salvini Traditional Corpus there are 21 occurrences. As shown in Table 5.48, the occurrences in tweets belong to

Unbelievable and unacceptable the threats that every day arrive from Brussels. The only #ruins that I will have to pick up are the ones of the beautiful European dream destroyed by people like #Junker: I will be happy to rebuild a new Europe with the popular vote in May.

Together for a Europe based on work and security, getting back the values sacrificed on the altar of speculation and immigration #Europeanelection2019 @MLP officiel.

Bringing down the Berlin Wall would have been unthinkable once and the next wall we are going to bring down is the Brussel one giving back to the European people the right to work, the right to life, the right to health, the right to security. The Brussel Wall, I do not say with bulldozer bumps otherwise they say that I am evil.

the container and the dictatorship *topoi*. All the occurrences in traditional speeches belong to the dictatorship one.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
STW	-	-	-	-	8% (1)	92% (12)	-
STS	-	-	-	-	=	100% (21)	-

Table 5.48 Europe topoi in Salvini's corpora

29. La nostra Europa sarà fondata sul diritto al lavoro, alla vita, alla salute e alla sicurezza. Basta con la **dittatura di finanza e immigrazione**. [emphasis added] (Salvini's Tweet 28 August 2018)<sup>71</sup>

On the one hand, example 1 is a clear example of the container *topos* in the representation of Europe. On the other hand, example 29 shows how straightforwardly Salvini employs the dictatorship *topos*. Looking at Figure 5.1, it is clear that Salvini uses the words *our Europe* to indicate the vision he shares with his European allies such as Victor Orbán (in the picture) and Marine Le Pen. The tweet (as already seen also in example 27) has a legitimising and delegitimising structure. Salvini and his allies' vision is a Europe founded on the people's will that focuses on important and concrete matters such as jobs, health and security, while the current elitist Europe is characterised by catastrophic budgetary and immigration policies. In addition, it is also possible to find the dictatorship *topos* in examples 9, 10, 12, 15 and 16 where Europe is negatively represented as an intrusive institution that imposes its decisions in every area.

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Our Europe will be founded on the right to work, to life, to health and to security. Enough with the dictatorship of finance and immigration.



La nostra Europa sarà fondata sul diritto al lavoro, alla vita, alla salute e alla sicurezza.

Basta con la dittatura di finanza e immigrazione.



8:57 PM · 28 ago 2018 · Twitter for iPhone

1.806 Retweet 196 Tweet di citazione 6.475 Mi piace

Figure 5.1 Salvini's tweet 28 August 2018

# 5.4.1.3 Representational strategies

Representational strategies connected to Europe count 17 occurrences in tweets and 32 occurrences in traditional speeches. In both corpora Europe is represented as a dictatorial, useless, and absent institution; therefore, as it is also possible to see in the following Table the percentages are uniform.

	Opposition	Aggregation	Suppression	Crime and terrorism	Dictatorship	Useless/absent institution
STW	_	-	-	-	88% (15)	12% (2)
STS	-	-	-	_	88% (28)	12% (4)

Table 5.49 Europe's representational strategies in Salvini's corpora

30. **In Europa non muovono un dito per accogliergli**, però si indignano se vanno in Albania perché ""**ci vuole il loro consenso**"". Dove siamo, in un villaggio vacanze??? Pazzesco... [emphasis added] (Salvini's Tweet 9 October 2018)<sup>72</sup>

Example 30 summarises the representational strategies mentioned above. Europe is a useless and absent institution because it does not support Italy in facing immigration. At the same time, Europe demands to decide and evaluate if decisions regarding immigrants are adequate. Other examples of Europe represented as a dictatorial institution can be observed in examples 28 and 29.

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In Europe [European politicians] do not move a finger to host them [immigrants], but they are outraged if they go to Albania because ""their consent is needed"". Where are we, in a tourists resort??? Madness...

## 5.4.1.4 Transitivity

In the Salvini Tweet Corpus there are 14 occurrences of processes linked to E.U., while in the Traditional one there are 34 occurrences.

	Material	Relational	Mental	Verbal	Behavioural	Existential
STW	72% (10)	7% (1)	7% (1)	14% (2)	-	-
STS	65% (22)	6% (2)	14% (5)	12% (4)	-	3% (1)

Table 5.50 Europe's transitivity in Salvini's corpora

31. L'Europa dei banchieri, quella fondata sull'immigrazione di massa e sulla precarietà, continua a **minacciare** e **insultare** gli Italiani e il loro governo? Tranquilli, fra sei mesi verranno licenziati da 500 milioni di elettori, noi tiriamo dritto! #primagliitaliani [emphasis added] (Salvini's Tweet 25 July 2017)<sup>73</sup>

Example 31 shows two verbal processes (*threaten* and *insult*) through which Salvini represents negatively the E.U. attitude towards Italy and Italians. Material processes can be observed in examples 9 (*wants to bring*), 10 (*imposed by*) and 30 (*don't move*). Material processes can also be found in examples 15 (*gave* and *filled up*) and 16 (*tried, remove* and *erase*). Example 29 shows a relational process (*will be*), while example 30 a mental one (*outraged*).

In both tweets and traditional speeches, most processes are material supporting especially the negative representation of Europe as a dictatorship. Consequently, Europe plays mainly the Actor (61%). Moreover, the voice type of processes is always active (98%) and the evaluation type is always negative (73%).

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	61%	29	Possessor	4%	2
Goal	4%	2	Senser	15%	7
Recipient	2%	1	Sayer	10%	5
Carrier	2%	1	Existent	2%	1

Table 5.51 Europe's participant types in Salvini's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	98% (47)	-	2% (1)	-	-	-
Evaluation	=	-	-	6% (3)	73% (35)	21% (10)

Table 5.52 Europe's voice-type and evaluation-type in Salvini's corpora

## 5.4.2 Quantitative analysis

# 5.4.2.1 Keywords in the Salvini Tweet Corpus

Does the Europe of bankers, the one founded on mass immigration and job insecurity, continue to threaten and insult Italians and their government? Stay calm, in six month they will be fired by 500 millions of voters, we go ahead! #Italiansfirst.

The following Table shows the keywords associated to Europe. It is important to specify that these keywords were extracted from Tables 5.38 and the Appendix C since Salvini is well-known for his Eurosceptical narratives. For this reason, the majority of keywords connected to Europe were categorised under the label opposition. Some of the keywords are also categorised under the label politics-economy because Salvini's Eurosceptical discourse involves not only immigration matters but also economic and political impositions.

Keyword	Score	Freq	Rel freq	Keyword	Score	Freq	Rel freq
Europa	8.890	95	160.7	europeo	2.440	41	69.4
Spagna	3.870	12	20.3	euro	1.770	40	67.7
miliardo	2.830	7	11.8				

Table 5.53 Europe keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

It is not surprisingly to find in this keyword list the words *Europa* (Europe), *europeo* (European) and euro. However, it is also possible to notice the presence of the words *miliardo* (billion) and *Spagna* (Spain). On the one hand, the keyword *miliardo* confirms Salvini's focus on economic matters. On the other hand, Salvini talks about Spain to complain about immigration and economic matters (see Table 5.56).

# 5.4.2.2 Concordances and collocates in the Salvini Tweet Corpus

Table 5.54 contains the collocates of the word *Europa* (Europe) in the Salvini Tweet Corpus. We can see processes such as *cambiare* (to change), *volere* (to want), *fare* (to do), *avere* (to have) and *essere* (to be). They are mainly linked to Europe but some of them – especially *cambiare* – are also linked to Salvini's actions and intentions. Indeed, in the list there is also the collocate *io* (I). The collocate *interesse* (interest) refers to both European elitist interests and Italians' interests – threatened by Europe – that Salvini aims to protect. Finally, *Italia* (Italy) and *italiano* (Italian) regard the relationship between Europe and Italy.

Collocate	Cooccurrences	Occurrences	T-score	MI3
cambiare	8	77	2.78	12.01
essere	20	1,272	4.02	11.93
non	16	658	3.74	11.92
interesse	5	22	2.22	11.79
Italia	11	316	3.16	11.36
volere	9	188	2.90	11.24
fare	11	378	3.13	11.10
io	8	190	2.72	10.71
avere	12	665	3.16	10.66
anche	6	136	2.36	9.95
più	7	239	2.50	9.80
chi	6	161	2.34	9.71
ci	6	204	2.32	9.36
italiano	5	296	2.02	8.04

Table 5.54 Collocates of the word Europa (Europe) in the Salvini Tweet Corpus

Table 5.55 shows a random selection of the concordances of the word *Europa* in Salvini's tweets that support the interpretation of collocates in Table 5.54. In Table 5.56 it is possible to observe all the concordances of the word Spagna (Spain) where Salvini talks about immigration, NGOs, and complains about how Europe treats unfairly – in terms of economic matters – Italy in comparison to other European countries such as Spain.

, risparmiatori truffati. Se la finanza e l' Europa cambiando l'Italia lavoreremo per cambiare l' Europa responsabile. Comunque, Europa o non Europa """Siamo tutti clandestini, l' Europa da chi ci ha preceduto, NO. "Ma in Europa come stiamo cambiando l'Italia, cambiare l' Europa di carcere), lavoro per cambiare l'Italia e l' Europa . GRAZIE! lo non mollo! "La nostra Europa di bufala campana ci sta. Alla faccia dell' Europa ROBA DA MATTI! Non è questa l' Europa

seguiranno l'economia REALE lo spread . lo ci sono, e voi? "È finito il tempo . io non cambio idea e seguo sempre lo non ha confini"". Questa mattina a Milano, non hanno altro di meglio da fare che e salvarne i valori è il nostro obiettivo. e mi bloccano tutti i conti correnti, per sarà fondata sul diritto al lavoro, alla vita, che vuole portarci in tavola ogni tipo di che vogliamo lasciare ai nostri figli.

Table 5.55 Concordances of the word *Europe* (Europe) in the Salvini Tweet Corpus<sup>74</sup>

, pregiudicato per spaccio). "Dopo la Spagna me e il governo! "Ma come, se Francia e Spagna internazionale di vent'anni fa. Se lo fa la Spagna migliaia di pensionati italiani che vanno in Spagna gli immigrati a bordo verranno distribuiti fra Spagna Ong con immigrati a bordo si dirige verso la Spagna di porti siciliani, la nave Ong va in Spagna porto più vicino Malta, Ong e bandiera della Spagna : si scordino di arrivare in un porto italiano. #Aquarius, quella che abbiamo mandato in Spagna . Per loro questa settimana niente scalo al " "E due! Dopo la Ong Aquarius spedita in Spagna , ora tocca alla Ong Lifeline che andrà a IO NON MOLLO! "La #Aquarius approda in Spagna . Per la prima volta una nave partita dalla "Mentre Aquarius naviga verso la Spagna , altre 2 navi di Ong con bandiera

sforano da anni il tetto del 3% nessuno va bene, ma se lo propongo io allora sono e Portogallo per non pagare la tassa su , Francia, Lussemburgo, Portogallo e : bene così!! PICTURE "Finalmente, , con donna ferita e due morti Non sarà

, ora anche la Grecia supera l'Italia per

Table 5.56 Concordances of the word *Spagna* (Spain) in the Salvini Tweet Corpus<sup>75</sup>

#### 5.4.2.3 Keywords in the Salvini Traditional Corpus

<sup>1)</sup> cheated account holders. If finance and Europe will follow REAL economy the spread; 2) changing Italy we will work to change Europe. I am here, and you? "The time is over; 3) responsible. However, Europe or no Europe, I do not change my mind and I always follow the; 4) ""We are all clandestine, Europe has no borders"". This morning in Milan; 5) from those who preceded us, NO. "But in Europe they do not have anything better than; 6) how we are changing Italy, our aim is to change Europe and save its values; 7) of jail) I work to change Italy and Europe and they block my back accounts; 8) THANK YOU! I do not give in! "Our Europe will be founded on the right to work, to life; 9) buffalo mozzarella from Campania is perfect. In spite of Europe that wants to bring on our tables every type; 10) SHEER MADDNESS! This is not the Europe we want to leave to our children.

<sup>1)</sup> convicted for pushing). "After Spain, now even Greece exceed Italy for; 2) me and the government! "But how, if France and Spain have been exceeding the limit of the 3% for years no one; 3) international of twenty years ago. If Spain does it that is fine, but if I propose it then I am a; 4) thousands of pensioned Italians who go in Spain and Portugal in order to avoid paying the tax on; 5) the immigrants on board will be distributed among Spain, France, Luxembourg, Portugal and; 6) NGO with immigrants on board is heading towards Spain: This is good!! "Finally; 7) of Sicilian harbours, the NGO goes to Spain, with an injured woman and two dead people it will not be; 8) the closest harbour to Malta, NGO and Spanish flag: can forget to arrive in an Italian harbour; 9) #Aquarius, that one that we sent to Spain. For them there will not be a seaport; 10) "And two! After the NGO Aquarius sent to Spain now it is the tur of the Lifeline NGO that will go to; 11) I DO NOT GIVE IN! "The #Aquarius lands in Spain. For the first time a ship that come from; 12) "While the #Aquarius is sailing towards Spain, other two NGO with flag.

In Table 5.57 there are the keywords associated to Europe in traditional speeches. Even in this case these keywords are primarily categorised under the labels opposition and politics-economy. For this reason, it is possible to find them in Table 5.43 and in the Appendix D.

Keyword	Score	Freq	Rel_freq
Europa	4.590	36	82.5
europeo	2.260	28	64.2
euro	2.040	34	77.9

Table 5.57 Europe keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

This list reveals that Salvini – in his traditional speeches – talks about Europe, European institutions, and economic matters. It is possible to scrutinise better these topics in Tables 5.58 and 5.59.

# 5.4.2.4 Concordances and collocates in the Salvini Traditional Corpus

Table 5.58 shows the collocate list of the word *Europa* (Europe) in the Salvini Traditional Corpus. The collocate *popolo* (people) indicates that Salvini makes appeal to the people and, at the same time, talks about Europe as a community that is not adequately represented by the European elite.

Collocate	Cooccurrences	Occurrences	T-score	MI3
Europa	4	36	1.99	11.07
popolo	4	37	1.98	11.03
Italia	5	117	2.19	10.34
non	9	692	2.81	10.32
più	5	160	2.18	9.89
obiettivo	2	11	1.41	9.78
voi	4	96	1.96	9.66
chiamare	2	13	1.41	9.54
comunità	2	13	1.41	9.54
speranza	2	14	1.41	9.44
porto	2	20	1.40	8.92
lega	3	72	1.70	8.83
solo	3	77	1.70	8.73
grazie	3	89	1.69	8.52
io	4	287	1.88	8.08
ultimo	2	36	1.39	8.07
andare	3	167	1.65	7.61
no	2	66	1.38	7.20
dare	2	90	1.36	6.75
lavoro	2	120	1.34	6.34

Table 5.58 Collocates of the word Europa (Europe) in the Salvini Traditional Corpus

Indeed, it is also possible to find the collocates *comunità* (community) and *voi* (you) (the latter collocate is linked to European people but especially to Italians). In the majority of cases, the collocate *chiamare* (to call) actually refers to an Italian party called +*Europa*. The word *Italia* (Italy) involves the relationship between Italy and Europe. The collocate *obiettivo* (goal) is

strictly connected to Salvini's aims regarding the building of a new Europe and a new relationship between the E.U. and Italy. There are also the collocates Lega and io (I), and some processes that are often linked to Salvini's actions and intentions such as *portare* (to bring), dare (to give) and andare (to go). Some of these collocates can be also observed in Table 5.59 that shows a random selection of the concordances of *Europa* (Europe) in traditional speeches.

Giorgetti, l'obiettivo è cambiare l' Europa . L'obiettivo è dar voce in Europa a quei questo noi faremo di modo che sia anche l' Europa e di quattro burocrati. Grazie alla Lega l' Europa perché qualcuno li illude che in Italia e in Europa non lo crea ... non lo crea l'Europa. L' Europa protegga i suoi cittadini e li difenda dall' Europa E noi da qua ripartiremo, andando in Europa Monti, Letta, Renzi, Gentiloni. Io porto in Europa il problema non l'abbiamo risolto grazie all' Europa o grazie ai soliti chiacchieroni. L'abbiamo abbiamo fatto valere le ragioni d'Italia in Europa , bloccando quella nave, bloccando quegli Table 5.59 Concordances of the word *Europa* (Europe) in the Salvini Traditional Corpus<sup>76</sup>

una comunità di popoli, non un'unità fondata tornerà ad essere una comunità di ci sia casa e lavoro per tutti! Sono stufo di dovrebbe fare meno cose e farle bene. Non è dei burocrati, dell'euro, delle banche, della , non col cappello in mano come hanno fatto voi. lo porto in Europa l'Italia, non vado a

# 5.5 Immigrants and Refugees

This section explores how Salvini represents immigrants and refugees in his corpora.

#### 5.5.1 **Qualitative analysis**

Immigrants and refugees' representation in Salvini's discourse was investigated through metaphors, topoi, representational strategies and transitivity.

### 5.5.1.1 **Metaphors**

The source domains linked to immigrants and refugees count 4 occurrences in the Salvini Tweet Corpus and 5 in the Salvini Traditional Corpus.

	Saviour and Warrior	Container	Building	Object and Merchandise	War	Religion	Nature	Water
STW	-	-	-	100% (4)	-	-	-	-
STS	-	-	-	60% (3)	-	-	40% (2)	-

Table 5.60 Immigrants and refugees' source domains in Salvini's corpora

<sup>1)</sup> Giorgetti, the aim is to change Europe. The aim is to give voice in Europe to those; 2) this is what we will do to make even Europe a community of people, not a unity founded on; 3) and of four bureaucrats. Thanks to the League Europe will be again a community of; 4) because someone deceive them saying that in Italy and in Europe there is home and work for everybody! I am tired of; 5) it is not created...it is not created by Europe. Europe should make less things and should do those things right; 6) protect its citizens and defend them from the Europe of bureaucrats, euro, banks; 7) And we will start again from here, going in Europe, not with cap in hand how; 8) Monti, Letta, Renzi, Gentiloni. I bring you in Europe. I bring Italy in Europe, I do not go; 9) we did not fix the problem thanks to Europe or thank to the usual big mouths. We fixed; 10) we asserted Italy' reasons in Europe, stopping that ship, stopping those.

32. [...] ed è stato confezionato questo rosario da una donna sfruttata, da una di quelle donne che erano state illuse che in Italia c'era il bengodi, che in Italia c'era casa e lavoro per tutti ed è stata sradicata dalla sua terra. [emphasis added] (Salvini's speech in Pontida 1 July 2018)<sup>77</sup>

Specifically, the only source domain presents in tweets is object and merchandise while in traditional speeches there is also the nature source domain. Example 32 shows the nature source domain since Salvini describes an immigrant woman as a plant that was uprooted from her native land; this woman is represented as a completely passive social actor without any type of human agency, a woman who had been deluded and brought to Italy by an unspecified entity. It is possible to observe the object and merchandise source domain in examples 6 and 19. Firstly, in example 6 Salvini talks about ships *loaded* with immigrants. Secondly, in example 19 – that is also possible to observe in Figure 5.2 – immigrants are represented as a *load of immigrants*. In both tweets Salvini represents immigrants as inanimate objects that are loaded and unloaded in the coasts of Italy. Consequently, he strategically aims to completely dehumanise these social actors in order to legitimise his strict immigration policies and delegitimise NGOs. Lastly, the visual strategy used by Salvini on Twitter should be highlighted. More precisely, Salvini usually attaches to tweets not only external links to newspaper articles, videos and pictures, but he also attaches the same Facebook post – that is usually longer – in order to bypass Twitter's limitation of characters (see Figure 5.2).

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<sup>[...]</sup> and this rosary was made by an exploited woman, by one of those women who had been deluded that in Italy there were homes and jobs for everyone. She was uprooted from her land.



Oggi anche la nave Sea Watch 3, di Ong tedesca e battente bandiera olandese, è al largo delle coste libiche in attesa di effettuare l'ennesimo carico di immigrati, da portare in Italia.

L'Italia ha smesso di chinare il capo e di ubbidire, stavolta C'È CHI DICE NO.#chiudiamoiporti



2.840 Retweet 487 Tweet di citazione 9.642 Mi piace

Figure 5.2 Salvini's tweet 11 June 2018

### 5.5.1.2 **Topoi**

In the Salvini Tweet Corpus there are 31 occurrences of topoi connected to immigrants and refugees, while the Salvini Traditional Corpus has 48 occurrences.

	Victim	DTF	Burden	Invasion	Container	Dictatorship	Dishonest
STW	3% (1)	45% (14)	16% (5)	36% (11)	-	-	-
STS	23% (11)	33% (16)	31% (15)	13% (6)	-	-	-

Table 5.61 Immigrants and refugees' topoi in Salvini's corpora

33. #Salvini: il colore della pelle non c'entra nulla, e #primagliitaliani è un principio che vale anche per gli immigrati regolari, integrati e perbene. Ma per chi ci porta in casa la guerra, #stopinvasione. #domenicalive [emphasis added] (Salvini's Tweet 18 February 2018)<sup>78</sup>

34. E per quanto riguarda i costi per ogni singolo richiedente asilo, io ricordo che i francesi spendono 25 euro al giorno, a cui aggiungono in qualche caso quattro euro di pocket money, i tedeschi 26, i croati 25, gli austriaci 23 e via dicendo. Quindi, cercheremo di portare i costi di questa immigrazione, per noi difficilmente sostenibili, al livello dei Paesi nostri simili in Europa. Non si vede perché noi dobbiamo spendere 35 euro per garantire servizi che in altri Paesi

<sup>#</sup>Salvini: the colour of the skin has nothing to do with it, and #Italiansfirst is a principle that counts even for legal immigrants who are integrated and respectable. But to those who bring war in our home, #stopinvasion. #domenicalive

**comportano una spesa molto minore**. [emphasis added] (Salvini's Aquarius speech in Senate 13 June 2018)<sup>79</sup>

Example 33 shows the *topoi* of DTF and invasion. Salvini claims that he is not racist but, at the same time, he underlines the presence of immigrants who cause trouble. Moreover, the hashtag #stopinvasion implies that immigrants are invading Italy. It is also possible to find the *topos* of DTF in examples 17 (where Salvini talks about immigrants who killed an Italian woman), examples 36 and 38 (immigrants are portrayed as a cultural and social threat), and in example 37 and 39 (immigrants are described as the perpetrators of criminal actions). Other examples of the invasion *topos* can be found in examples 1 and 15 (where immigrants are represented as a dangerous and unstoppable entity that fills up Italy), and in examples 6 and 19 (Salvini implies that NGOs are constantly unloading immigrants in Italy). Example 34 shows the *topos* of burden. Salvini is complaining during his speech at the Italian Senate about how much the Italian government spend daily for each asylum seeker<sup>80</sup>. This *topos* can be observed in examples 11 and 21 as well. Finally, Salvini uses the *topos* of the victim – as it is possible to notice in example 32 – just to refer to those people that he calls *true* refugees; indeed, in Tables 5.72 and 5.84 there is the keyword *guerra* (war) that involves those people – especially women and children – who escape from wars.

## 5.5.1.3 Representational Strategies

Representational strategies count 36 occurrences in tweets and 55 occurrences in traditional speeches.

	Opposition	Aggregation	Genericisation	Specification	Suppression	Crime and terrorism
STW	5% (2)	28% (10)	17% (6)	3% (1)	-	47% (17)
STS	22% (12)	47% (26)	7% (4)	-	-	24% (13)

Table 5.62 Immigrants and refugees' representational strategies in Salvini's corpora

35. Immigrati della #Diciotti in sciopero della fame? Facciano come credono. In Italia vivono 5 milioni di persone in POVERTÀ assoluta (1,2 milioni di BAMBINI) che lo sciopero della fame lo fanno tutti i giorni, nel silenzio di buonisti, giornalisti e compagni vari. #primagliitaliani [emphasis added] (Salvini's Tweet 24 August 2018)<sup>81</sup>

36. Io sono pronto a dare rispetto a chi porta rispetto. Questo però significa che sei il benvenuto in casa mia se scappi dalla guerra o se cerchi un futuro per i tuoi figli. Però **se arrivi** a Pinzolo o arrivi a Milano o arrivi a Torino o arrivi a Palermo, **e cominci a dire**: "E **non mi piace il** 

And for what concerns the costs for every asylum seeker, I remind you that the French spend 25 euro per day, to which they add 4 euro of pocket money, the Germans 26, the Croatians 25, the Austrians 23 etc. Therefore, we will try to bring the cost of this immigration, that are hardly sustainable for us, at the same level of other European countries. I do not understand why we have to spend 35 euro to guarantee serviced that other countries deliver with lower costs.

Salvini does not specify that 35 euros actually go to asylum seeker and refugees' centres (de Cesco, 2018).

<sup>#</sup>Diciotti immigrants on hunger-strike? Do as they please. In Italy 5 million of people live in absolute POVERTY (1.2 million of CHILDREN), who go on hunger-strike every day, in the silence of do-gooders, journalists and various comrades. #Italiansfirst.

crocifisso, e non mi piace Gesù bambino, non mi piacciono le campane", torna a casa tua e fai quello che vuoi e prega il Dio che vuoi, e mangia quello che vuoi, e bevi dove vuoi [...]. Chi ritiene che la donna ha meno diritti dell'uomo stia a casa sua perché l'Italia non è il paese che fa per lui. Stia a casa sua perché l'Italia non è il paese che fa per... e se vuoi coprirla con i tappeti lo fai a casa tua, perché io di gente che va vestita in giro da Batman in Italia non ne voglio. [emphasis added] (Salvini's speech in Pinzolo 25 August 2018)<sup>82</sup>

- 37. Nell' ultima settimana la @poliziadistato ha arrestato 528 persone, di cui più della metà immigrati, e ne ha denunciate 2.478, di cui oltre il 50% immigrati. Più immigrazione significa più delinquenza: aver ridotto sbarchi e arrivi, nonostante denunce, è per me motivo di orgoglio! [emphasis added] (Salvini's Tweet 7 September 2018)<sup>83</sup>
- 38. Ultime ore di lavoro per il governo, ce la stiamo mettendo tutta! Intanto la cronaca ci riporta alla dura realtà, con **un immigrato** che **SPENNA I PICCIONI** in pieno giorno e in mezzo alla strada ... A casa!!! [emphasis added] (Salvini's Tweet 31 May 2018)<sup>84</sup>
- 39. Arrestato questa notte dalla Polizia di Mestre **Mohamed Gueye**, **immigrato senegalese irregolare**, **accusato di avere STUPRATO** a Jesolo una ragazza di 15 ANNI. ROBA DA MATTI! Con il #DecretoSicurezza, se un clandestino stupra, ruba, uccide o spaccia, se ne torna a casa subito. [emphasis added] (Salvini's Tweet 25 August 2018)<sup>85</sup>

Examples 35 and 36 show two types of opposition strategies. Firstly, in example 35 there is a type of opposition strategy that opposes two suffering groups of social actors. Specifically, Salvini opposes immigrants to Italian suffering people in order to suggest to Italian people that they should be more empathetic towards their poor suffering compatriots rather than towards immigrants who are represented as ungrateful and capricious protesters. Moreover, this tweet reiterates Salvini's narrative of reverse racism. Secondly, example 36 presents a more traditional type of opposition strategy that involves cultural and religious opposition. In this way, Salvini underlines the impossibility of integration. We should emphasise that this traditional extract was delivered during Salvini's speech in Pinzolo in occasion of a League Party after he discovered that he was investigated for the abduction of immigrants on board the NGO Diciotti. This explains his excessive informal and aggressive style of communication that can be summarised in the derogatory comparison of the burqa to a Batman suit. This traditional extract also shows how immigrants – following the proximization theory (section 2.6) – are depicted by Salvini as a close and imminent threat that jeopardises Italians' religion and culture in order to legitimise his immigration policies, especially concerning the Diciotti case. In

want, and drink where you want. Therefore, respect for respect, I do not think that I am asking too much.

During the last week, @poliziadistato has arrested 528 people, of whom more than a half are immigrants, and reported 2,478 people, of whom over 50% are immigrants. More immigration means more criminality: having reduced disembarkations and arrivals, despite complaints, is a source of pride for me!

Last hours of work for the government, we are doing our best! In the meanwhile the news brig us back to the hard reality with an immigrant who plucks pigeons in broad daylight and in the middle of the street...To home!!!

I am ready to show respect to those who do the same. This means that you are welcome in my home if you are escaping from war or if you are looking for a future for your children. But if you arrive in Pinzolo, or Milan, or Turin, or Palermo and you start saying: "I don't like the crucifix, and I don't like baby Jesus, I don't like the bells", go back to your home and do what you want, and prey the God you want, and eat what you

This night Mohamed Gueye, illegal Senegalese immigrant, accused to have RAPED a 15 years old girl in Jesolo, has been arrested by Mestre Police. SHEER MADNESS! With #SecurityDecree if a clandestine rapes, steals, kills or pushes, he goes back home immediately.

example 37 it is possible to find a combination of the aggregation strategy and the association to crime that legitimises Salvini's immigration policies (as it is possible to notice in Figure 5.3 where Salvini proudly shake hands with police officers). Both examples 38 (see Figure 5.4. In this tweet Salvini even shares an amateur video) and 39 involve the connection to crime. In addition, in example 39 it is possible there is the specification strategy. Lastly, example 17 shows a combination of association to crime and genericisation.



Figure 5.3 Salvini's tweet 7 September 2018



Ultime ore di lavoro per il governo, ce la stiamo mettendo tutta! Intanto la cronaca ci riporta alla dura realtà, con un immigrato che SPENNA I PICCIONI in pieno giorno e in mezzo alla strada... A casa!!!



6:17 PM · 31 mag 2018 · Twitter for iPhone

843 Retweet 201 Tweet di citazione 2.652 Mi piace Figure 5.4 Salvini's tweet 31 May 2018

### 5.5.1.4 Transitivity

In the Salvini Tweet Corpus there are 31 processes connected to immigrants and refugees, while in the Salvini Traditional corpus there are 106 processes.

	Material	Relational	Mental	Verbal	Behavioural	Existential
STW	87% (27)	13% (4)	-	-	-	-
STS	85% (90)	9% (10)	5% (5)	1% (1)	-	-

Table 5.63 Immigrants and refugees' processes in Salvini's corpora

40. Quel richiedente asilo che a Foggia **ha aggredito** due poliziotti poche ore fa **rischiando di investirli** con la macchina, grazie al nuovo decreto viene preso, viene mandato in un centro per i rimpatri, viene rispedito al suo paese [emphasis added] (Matteo Salvini's speech in Rome at the 40<sup>th</sup> Anniversary of the Operational Security Core 10 October 2018)<sup>86</sup>

Example 40 presents two material processes (to attack and to run over) that Salvini typically associates to immigrants since he focuses mainly on criminal activities perpetrated by some of them in order to support his points of view and policies. Other similar material processes can be found in examples 17 (to kill and to cut into pieces), 38 (to pluck) and 39 (to rape). In example 17 it is also possible to look at a relational process (to be), while in example 32 there is a mental one (deluded). It is important to highlight that immigrants and refugees are usually associated to material processes – as it is possible to notice in Table 5.63 – and they play mainly the Actor (58%). The voice type of processes is always active (92%), while the evaluation is often negative (53%).

Participant types	Percentage	Occurrence	Participant types	Percentage	Occurrence
Actor	58%	80	Identified	4%	5
Goal	25%	34	Identifier	3%	4
Recipient	1%	1	Possessor	2%	4
Client	1%	2	Senser	4%	5
Carrier	1%	1	Sayer	1%	1

Table 5.64 Immigrants and refugees' participant types in Salvini's corpora

	Active	Passive	Non-applicable	Positive	Negative	Neutral
Voice	92% (126)	6% (8)	2% (3)	-	-	-
Evaluation	=	-	=	16% (22)	53% (73)	31% (42)

Table 5.65 Immigrants and refugees' voice-type and evaluation-type in Salvini's corpora

# 5.5.2 Quantitative analysis

# 5.5.2.1 Keywords in the Salvini Tweet Corpus

Table 5.66 below shows those keywords under the label immigration. These keywords are mainly words with a negative connotation highlighting how Salvini negatively describes

That asylum seeker who has attacked two policemen risking running over them with the car in Foggia, thanks to the new decree, he gets caught, he is brought to repatriation centre, he is sent back to his country.

immigration, immigrants and refugees. The keywords criminale (criminal), violento (violent), violenza (violence) and the processes stuprare (to rape), picchiare (to beat up), aggredire (to attack) and rubare (to steal) connect immigrants to criminal and violent actions. Specifically, ragazza (girl) and verme (worm) are used in rape cases perpetrated by immigrants, while guerra (war) is a metaphorical representation used by Salvini to describe illegal immigration repercussion on Italian society. The keywords scafista (people smuggler), sbarco (disembarkation), barcone (boat), business, porto (harbour) and traffico (trafficking) refers to illegal human trafficking and its connection to organised crime. Indeed, the words delinquente (delinquent), spacciatore (pusher), spaccio (dealing), mafia and droga (drugs) link immigrants to (Italian) organised crime. The keyword finto (fake) highlights Salvini's tendency to doubt about the truthfulness of the refugees' status. Finally, the words perbene (respectable), salvare (to rescue), umano (human) and persona (person) reveal that Salvini's talks also about immigrants and refugees as human beings. However, it is often a strategy in order to praise rescue operations and to attack other European countries that do not cooperate regarding immigration matters.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
clandestino	67.700	87	147.2	droga	7.420	8	13.5
immigrato	65.140	129	218.2	africano	6.520	11	18.6
immigrazione	49.340	82	138.7	presunto	6.300	7	11.8
delinquente	44.320	17	28.8	pagare	6.220	11	18.6
scafista	39.190	24	40.6	business	6.050	22	37.2
sbarco	27.450	27	45.7	bloccare	5.920	21	35.5
perbene	26.370	4	6.8	porto	5.500	31	52.4
spacciatore	25.840	12	20.3	salvare	5.410	28	47.4
profugo	21.280	26	44.0	criminale	5.410	10	16.9
libico	17.910	12	20.3	rubare	5.080	4	6.8
clandestini	17.780	10	16.9	violento	4.880	2	3.4
stuprare	16.820	10	16.9	denunciare	4.660	5	8.5
barcone	16.720	11	18.6	violenza	4.240	9	15.2
trafficante	16.350	11	18.6	accogliere	3.840	23	38.9
stop	15.650	25	42.3	traffico	3.740	10	16.9
schifoso	15.310	7	11.8	decina	3.430	6	10.2
immigrare	15.110	10	16.9	paesi	3.420	10	16.9
spaccio	14.570	9		guerra	3.190	28	47.4
scappare	13.870	14	23.7	ragazza	2.980	10	16.9
Libia	13.620	12	20.3	riportare	2.970	8	13.5
verme	12.940	10	16.9	partenza	2.320	13	22.0
picchiare	11.140	6		finire	2.140	12	20.3
finto	9.890	11	18.6	protezione	1.830	11	18.6
aggredire	9.700	6		arrivare	1.760	14	23.7
mafia	9.640	3	5.1	umano	1.580	16	27.1
pensione	8.470	9	15.2	persona	1.480	14	23.7
accoglienza	8.290	17	28.8	ospitare	1.460	10	16.9

Table 5.66 Immigration keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

Table 5.67 includes the DTF keywords. Although some of these keywords can also be found in the previous Table, it is important highlight some of the keywords that signal what – according to Salvini – is a threat to Italians. Firstly, we should notice those words such as *nigeriano* (Nigerian) and *Rom* that specify the ethnicity of dangerous people. Secondly, the word *islamico* (Islamic) introduces the topic of terrorism but also Islam as a cultural and religious threat to Italian society. Thirdly, *profugo* (refugee), *asilo* (asylum) and *richiedente* (seeker) indicate that Salvini links not only illegal immigrants to criminal actions, but also people who ask for the status of refugee.

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
clandestino	67.700	16	27.1 aggredire	9.700	10	16.9
immigrato	65.140	32	54.1 richiedente	7.700	11	18.6
immigrazione	49.340	15	25.4 reato	5.760	12	20.3
delinquente	44.320	18	30.5 rubare	5.080	4	6.8
pacchia	33.460	20	33.8 straniero	4.750	12	20.3
spacciatore	25.840	18	30.5 violenza	4.240	9	15.2
profugo	21.280	8	13.5 traffico	3.740	10	16.9
nigeriano	17.030	12	20.3 decina	3.430	3	5.1
stuprare	16.820	11	18.6 guerra	3.190	3	5.1
barcone	16.720	3	5.1 ragazza	2.980	10	16.9
rom	16.430	21	35.5 uccidere	2.230	10	16.9
islamico	15.150	28	47.4 finire	2.140	4	6.8
spaccio	14.570	11	18.6 morte	1.470	14	23.7
asilo	13.910	18	30.5			

Table 5.67 DTF keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

This strategy is also connected to Salvini's employment of *finto* (fake) when it comes to talk about refugees since he doubts of the truthfulness of their status and highlights their dangerousness. Fourthly, there are other negative and violent keywords that are not present in Table 5.66 such as *reato* (crime), *uccidere* (to kill) and *morte* (death). Lastly, the keyword *pacchia* (good times) is a common informal word that Salvini uses very often especially in relation to immigrants who take advantage of Italy and Italians, and to people connected to organised crime.

The following Table shows the keywords categorised under the invasion label that is a sub-category of the DTF category. This Table reveals that this category involves exclusively immigrants and refugees.

Keyword	Score	Freq	Rel_freq Keyword	Score	Freq	Rel_freq
clandestino	67.700	9	15.2 profugo	21.280	3	5.1
immigrato	65.140	12	20.3 sbarcare	20.060	24	40.6
immigrazione	49.340	3	5.1 invasione	11.140	14	23.7

Table 5.68 Invasion keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

In addition, in Table 5.69 there are the keywords categorised in the DTF sub-category organised crime (they were found just in the Salvini Tweet Corpus). These keywords focus on mafia, but also on the connection between organised crime and human trafficking linking this topic to the topic of immigration.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
mafioso	13.610	19	32.1	decina	3.430	3	5.1
mafia	9.640	19	32.1	guerra	3.190	3	5.1
violenza	4.240	1	1.7	finire	2.140	4	6.8

Table 5.69 Organised crime (DTF) keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

Table 5.70 presents the keywords connected to the burden category that confirm how Salvini represent both immigrants and refugees as people who take advantage of Italy and Italians.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
clandestino	67.700	3	5.1	richiedente	7.700	2	3.4
immigrato	65.140	15	25.4	pagare	6.220	5	8.5
immigrazione	49.340	3	5.1	miliardo	2.830	3	5.1
profugo	21.280	6	10.2	ospitare	1.460	5	8.5
asilo	13.910	4	6.8	mantenere	1.340	6	10.2

Table 5.70 Burden keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

The following Table presents those keywords categorised under the label security that are linked to immigration since Salvini aims to legitimise his immigration policies through the representation of immigrants and refugees as a close (see proximization in chapter 2 section 2.6) and dangerous threats for Italy.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
clandestino	67.700	16	27.1	sicurezza	6.260	85	143.8
immigrazione	49.340	2	3.4	frontiera	6.220	11	18.6
poliziadistato	28.060	16	27.1	legittimo	6.040	11	18.6
galera	25.620	23	38.9	guardia	5.900	18	30.5
espulsione	23.410	27	45.7	carabiniere	5.560	11	18.6
difendere	18.520	64	108.3	polizia	5.550	31	52.4
rispedire	16.350	11	18.6	difesa	4.510	28	47.4
arrestare	16.090	40	67.7	carcere	4.000	12	20.3
sequestrare	15.680	19	32.1	finanza	3.650	7	11.8
rimpatrio	14.350	10	16.9	ordine	3.290	44	74.4
poliziotto	13.430	19	32.1	agente	3.220	12	20.3
espellere	13.090	14	23.7	forza	2.910	48	81.2
confine	10.120	41	69.4	proteggere	2.500	10	16.9
legalità	8.810	14	23.7	fuoco	2.100	13	22.0
carabinieri	8.690	13	22.0	controllare	2.080	12	20.3
fermare	7.910	57	38.9	aumentare	1.690	7	11.8
droga	7.420	6	10.2	controllo	1.470	19	32.1
arresto	6.760	14	23.7				

Table 5.71 Security keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

As a result, there are keywords directly connected to immigration such as *clandestino* (illegal) and *immigrazione* (immigration). Moreover, Salvini's legitimisation strategies are supported by keywords such as *confine* and *frontiera* (border), *espulsione* (expulsion), *rispedire* (send back) and *rimpatrio* (repatriation). Security keywords involve also words connected to law enforcement; for instance, *polizia di stato* and *polizia* (police), *poliziotto*, *carabinieri*, *carabiniere* and *agente* (policeman/policemen), *guardia* (guard. E.g. Italian finance police), *fuoco* (firefighter), and words linked to organised crime – *legalità* (legality) and *droga* (drugs) – since Salvini was Minister of the Interior.

Finally, Table 5.72 involves those keywords categorised under the label victim. The only keywords that involve mainly refugees is the word *guerra* (war) because it supports Salvini's narrative regarding the few *true refugees* (women and children) that escape from war and deserve to be welcomed and do not be confused with illegal immigrants. On the other hand, the word *italiani* (Italians) supports Salvini's employment of the respective *topos* and the reverse racism narrative towards Italians (see section 5.1).

Keyword	Score	Freq	Rel_freq
italiani	30.600	7	11.8
guerra	3.190	6	10.2

Table 5.72 Victim keywords in the Salvini Tweet Corpus (reference corpus itTenTen16)

## 5.5.2.2 Concordances and collocates in the Salvini Tweet Corpus

The collocates of *immigrato* (immigrant) – in the following Table – show that this word does not often co-occurs with *clandestino* (illegal). This could be linked to the fact that Salvini uses the word *clandestino* alone as a synonym of *immigrato*. Furthermore, *clandestino* (illegal) co-occurs more often with the word *immigrazione* (immigration) (see Table 5.74).

Collocate	Cooccurrences	Occurrences	T-score	MI3
[number]	25	555	4.76	13.66
che	26	877	4.72	13.16
clandestino	11	87	3.26	12.78
essere	26	1,272	4.55	12.63
più	14	239	3.60	12.36
avere	16	665	3.64	11.46
Italia	12	316	3.27	11.29
riportare	5	28	2.21	11.00
nave	6	52	2.40	10.89
un	11	509	2.98	10.23
altro	6	93	2.37	10.06
meno	5	60	2.18	9.90
anche	6	136	2.33	9.51
non	10	658	2.71	9.44
italiano	6	296	2.19	8.39

Table 5.73 Collocates of the word immigrato (immigrant) in the Salvini Tweet Corpus

The collocate [number] confirms Salvini's employment of the aggregation strategy, while Italia (Italy) and italiano (Italian) signal immigrants' presence in Italy. Nave (ship) clearly regards their journey to Italy. Riportare (to take back) involves successful pushbacks of immigrants. It is also possible to notice the processes avere (to have) and essere (to be). Lastly, un (a) signals the genericisation strategy.

The following Table shows that *clandestino* (illegal) is primarily associated to *immigrazione* (immigration) which according to Salvini is a *business*. Indeed, it is also possible to notice the collocates *espellere* (to expel) and *fermare* (to stop). Even in this case, *[number]* confirms the employment of the aggregation strategy, while the article *un* (a) indicates the genericisation strategy.

Collocate	Cooccurrences	Occurrences	T-score	MI3
immigrazione	29	82	5.36	17.62
business	13	22	3.60	16.05
espellere	6	14	2.44	13.36
immigrato	11	129	3.26	12.78
fermare	6	57	2.42	11.33
essere	15	1,272	3.39	10.82
che	11	877	2.93	10.01
nostro	6	205	2.33	9.48
non	8	658	2.49	9.05
un	7	509	2.36	8.84
volere	5	188	2.11	8.82
tutto	5	201	2.10	8.72
[number]	7	555	2.34	8.71
ci	5	204	2.10	8.70
si	5	234	2.08	8.50
fare	5	378	1.99	7.81
avere	5	665	1.80	7.00

Table 5.74 Collocates of the word *clandestino* (illegal) in the Salvini Tweet Corpus

. Nuovo piano volontario per quasi 3.000 immigrati PICTURE "#Salvini: meno soldi per immigrati morte #Desirée. Si tratta (guarda caso) di un confine nazionale e del ""trasporto"" di per aver fermato in mare una nave carica di all'appello? PICTURE" "Roba da matti. Un ultime ore sono sbarcati a Lampedusa 135 immigrati #Salvini: Entro l'estate i 35 euro al giorno per sbarchi, 430.000 domande di asilo, 170.000 immigrati è ora in acque di Malta, col suo carico di 239 immigrati

irregolari. Rimpatrio obbligato attraverso e richiedenti asilo, piú soldi per sicurezza clandestino. Per lui, come per gli altri da parte dei francesi io non mollo di un . Ora l'indagine, partita da Agrigento, del Gambia, con precedenti penali, , quasi tutti tunisini, su 13 barchini. , scenderanno almeno a 25. Quello che mantenuti in case e alberghi. Ma per . Per sicurezza di equipaggio e

Table 5.75 Concordances of the word *immigrato* (immigrant) in the Salvini Tweet Corpus<sup>87</sup>

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<sup>1)</sup> New voluntary plan for almost 3,000 illegal immigrants. Forced repatriation through; 2) "#Salvini: less money for immigrants and asylum seekers, more money for security; 3)#Desirée's death. It involves (coincidentally) an illegal immigrant. For him, as for the others; 4) national border and of immigrants' ""transportation" by French I do not give in; 5) for stopping in the sea a ship loaded with immigrants. Now the investigation, started in Agrigento; 6) the call? "Sheer Madness. An immigrant from Gambia, with criminal record; 7) last hours 135 immigrants have disembarked in Lampedusa, almost all of them are Tunisians, on 13 little boats; 8) #Salvini: By summer the 35 euro per day for each immigrant will decrease at

Table 5.75 shows a random selection of concordances of the word *immigrato* (immigrant) in which it is possible to evaluate some of the collocates in Table 5.73 and some of the keywords in the previous section (5.5.2.1). For instance, here it is possible to observe the aggregation and the genericisation strategies, the specification of ethnicity and the employment of the burden topos.

In the Italian language the word refugee has two corresponding words that are rifugiato and profugo. In his Tweet Corpus, Salvini uses the word rifugiato just three times. On the other hand, the word *profugo* occurs 26 times. A random selection of concordances of this word is shown in Table 5.76 where it is possible to look at how it co-occurs with finto (fake) or with presunto (alleged), and how Salvini employs the burden and invasion topoi, and the association to crime.

senza limiti centinaia di migliaia di finti profughi invasione di centinaia di migliaia di presunti profughi governo del Pd è "pronto ad accogliere 200mila profughi è quello di accelerare il rimpatrio dei finti profughi invaso da centinaia di migliaia di presunti profughi : Oggi sono stato nel quartiere Aurelio, a Roma. Profughi volevano più SOLDI. Cosa farei io? #domenicalive Presunto profugo di un euro al giorno, mentre in Italia i finti profughi ci costano 35 euro al giorno. E a che in Italia non sbarca più nemmeno un finto profugo Salvini spalancherà le porte. Ma per i finti profughi che portano la guerra in Italia, biglietto Table 5.76 Concordances of the word *profugo* (refugee) in the Salvini Tweet Corpus<sup>88</sup>

che pretendono! Con #DecretoSalvini , consentita da chi ci ha preceduto, ". Agosto 2018: tre tunisini in fuga. Ma . Difesa dei confini ed espulsioni. Dalle . Sbaglio?? Vi assicuro che ce la sto tenta di violentare operatrice nel . #Corrierelive #Italia18 @corriere

Table 5.77 presents all the concordances of *richiedente asilo* (asylum seeker). In some of the concordances Salvini specifies the ethnicity, while in each concordance Salvini reports criminal actions perpetrated by these people.

meno soldi per immigrati e a calci e pugni da un gruppo di #DecretoSalvini #Salvini: alcuni un ventenne del Bangladesh RICHIEDENTE ASILO rimane lo stesso anche OGGI. (Lecce) sette IMMIGRATI nella piazza dello spaccio. " Reggio Emilia, arrestato un RICHIEDENTE ASILO

richiedenti asilo richiedenti asilo richiedenti asilo Richiedente asilo richiedenti asilo Richiedente asilo "Ultima notizia. Un RICHIEDENTE ASILO

, piú soldi per sicurezza e Forze per un semplice controllo ad un , dopo aver ricevuto lo status di . Grazie alla Polizia di Stato e alla nigeriano è stato arrestato per la , gambiani e senegalesi, per spaccio di " massacrato da suoi connazionali. , un africano del Mali è stato arrestato ucraino di 26 anni. Inaspriremo leggi

least to 25; 9) disembarkations, 430,000 asylum applications, 170,000 immigrants supported in houses and

hotels; 10) is now in Maltese waters, with load of 239 immigrants. For the security of the crew and. 1) without limits hundreds of thousands of fake refugees who demand! With #SalviniDecree; 2) invasion of hundreds of thousands of alleged refugees, allowed by those who preceded us; 3) PD government is "ready to host 200 thousands refugees". August 2018: three Tunisian on the run. But; 4) is of accelerating the repatriation of fake refugees. Defence of the border and expulsions. From; 5) invaded by hundreds of thousands of alleged refugees. Am I wrong?? I assure you that I am doing; 6) Today I have been in Aurelio neighborhood in Rome. Refugees wanted more money. What would I do?; 7) #domenicalive Alleged refugee tries to rape [female] worker in; 8) of one euro per day, while in Italy fake refugees cost to us 35 euro per day; 9) that in Italy not even a single fake refugee disembarks. #Corrierelive #Italia18 @corriere; 10) Salvini will open the doors wide. But for the fake refugees who bring the war in Italy, ticket.

sicurezza e più efficacia. "Tutti richiedenti asilo , tutti arrestati per spaccio. Via, via, ospita meno della metà dei richiedenti asilo che ospitiamo noi e spende 10 euro in non può essere espulso perché "richiedente asilo". Roba da matti. Ma la musica presto Table 5.77 Concordances of the word *richiedente asilo* (asylum seeker) in the Salvini Tweet Corpus<sup>89</sup>

The quantitative analysis also investigated the metaphorical representation of immigrants revealing that Salvini actually uses the water source domain. More precisely, there are two occurrences of *flusso migratorio* (migratory flow) and one occurrence of *flusso della morte* (flow of death).

In addition, the analysis investigated *topoi* confirming the low percentage of the victim *topos* in Table 5.78 since there are no occurrences of this word in the Salvini Tweet Corpus. It is also possible to observe how Salvini uses this *topos* through the word *schiavo* (slave) in the following Table.

e un futuro, non abbiamo bisogno di nuovi pronti a mettersi nelle mani di trafficanti di eviterebbe tante morti e tante nuovi schiavi dire impedire che queste ragazze diventino senza controllo che crea nuovi anche Malta. Bene, stop al traffico di nuovi schiavi Table 5.78 Concordances of the word *schiavo* (slave) in the Salvini Tweet Corpus<sup>90</sup> schiavi sfruttati dai trafficanti uomini e dalle mafie pensando che in Italia ci siano lavoro e exiteretta di trafficanti uomini e dalle mafie pensando che in Italia ci siano lavoro e . Ascoltate questa testimonianza, . "Bugie e insulti di qualche ONG straniera sfruttati dai trafficanti uomini e dalle mafie pensando che in Italia ci siano lavoro e . I'll leghisti di qualche ONG straniera sfruttati dai trafficanti uomini e dalle mafie pensando che in Italia ci siano lavoro e . Schiavi schiavi sfruttati dai trafficanti uomini e dalle mafie pensando che in Italia ci siano lavoro e . I'll leghisti dalla criminalità organizzata e ! "I'l leghisti le fanno paura e io non Italia ci siano lavoro e . I'll leghisti dalla criminalità organizzata e ! "I'l leghisti le fanno paura e io non Italia ci siano lavoro e . Ascoltate questa testimonianza, . "Bugie e insulti di qualche ONG straniera sfruttati dai trafficanti uomini e dalle mafie

## 5.5.2.3 Keywords in the Salvini Traditional Corpus

Table 5.79 presents the traditional keywords under the label immigration. Comparing Tables 5.66 and 5.79 it is possible to find some keywords in common. However, these traditional keywords – such as *nave* (ship), *soccorso* (recue), *coordinamento* (coordination), *porto* (harbour) and *mare* (sea) – indicate that Salvini seems to focus more on NGOs and immigrants' rescues (probably because at least two of the speeches inside the corpus are almost exclusively dedicated to this topic). Even in this case, immigrants are strategically humanised; indeed, there are the words *umano* (human) and *persona* (person). Furthermore, through the keyword *mercato* (market) Salvini compares immigration to human meat market.

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<sup>1)</sup> less money for immigrants and asylum seekers, more money for security and law; 2) kicked and punched by a group of asylum seekers, for a simple control at; 3) #SalviniDecree #Salvini: some asylum seekers, after receiving the status; 4) a twenty-year-old from Bangladesh ASYLUM SEEKER. Thanks to the state police and; 5) is the same even TODAY. Nigerian asylum seeker has been arrested for; 6) (Lecce) seven Gambian and Senegalese IMMIGRANTS asylum seekers, for pushing; 7) the dealing square. "Asylum seeker" massacred by his compatriots; 8) "Breaking news. An ASYLUM SEEKER, an African from Mali has been arrested; 9) Reggio Emilia, a 26-years-old Ukrainian ASYLUM SEEKER has been arrested. We will embitter laws; 10) security and more effectiveness. "All asylum seekers, all arrested for pushing. Go, go; 11) hosts less than the half of the asylum seekers that we host and it spend 10 euro in; 12) cannot be expelled because he is an "asylum seeker". Sheer madness. But soon the music.

<sup>1)</sup> and a future, we do not need new slaves exploited by human smugglers and from organised crime; 2) ready to trust slaves smugglers thinking that in Italy there work and; 3) would avoid lots of deaths and lots of new slaves. Listen to this testimony; 4) means to prevent that these girls become slaves. "Lies and insults of some foreign NGOs; 5) without control that produces new slaves exploited by organised crime and; 6) even Malta. Good, stop to the trafficking of new slaves!" She is afraid of Leghisti and I will never.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
immigrazione	25.440	31	71.1	pensione	4.050	1	2.3
perbene	23.230	3	6.9	accogliere	3.630	16	36.7
immigrato	21.410	31	71.1	arrivare	3.300	4	9.2
sbarcare	17.060	14	32.1	ragazza	2.860	3	6.9
scappare	13.230	5	11.5	sicuro	2.010	3	6.9
clandestino	10.930	10	22.9	terra	2.010	3	6.9
nave	8.470	21	48.1	guerra	1.900	12	27.5
pagare	5.620	3	6.9	umano	1.650	8	18.3
soccorso	5.530	11	25.2	mercato	1.480	2	4.6
coordinamento	5.430	12	27.5	persona	1.450	5	11.5
porto	4.820	20	45.8	mare	1.410	2	4.6
fatica	4.600	2	4.6	usare	1.300	2	4.6

Table 5.79 Immigration keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

Tables 5.80, 5.81, and 5.82 show the keywords in DTF category, the invasion sub-category and the burden category. Comparing these Tables to Tables 5.67, 5.68 and 5.70 it is possible to notice that the former ones are shorter, especially the invasion one suggesting that for Salvini is much easier to spread these threatening narratives on Twitter.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
immigrazione	25.440	4	9.2	ragazza	2.860	3	6.9
immigrato	21.410	4	9.2	guerra	1.900	4	9.2
clandestino	10.930	2	4.6	-			

Table 5.80 DTF keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
immigrazione	25.440	3	6.9	sbarcare	17.060	3	6.9
immigrato	21.410	3	6.9				

Table 5.81 Invasion keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
immigrazione	25.440	2	4.6	costo	1.870	7	16.0
immigrato	21.410	2	4.6	mantenere	1.790	1	2.3
pagare	5.620	3	6.9				

Table 5.82 Burden keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

The following Table involves the traditional keywords under the label security. Even in this case, comparing Table 5.71 and Table 5.83 we should highlight that the former is longer than the latter indicating that security matters are more pervasive in Salvini's tweet discourse.

Keyword	Score	Freq	Rel_freq	Keyword	Score	Freq	Rel_freq
immigrazione	25.440	4	9.2	confine	3.440	10	22.9
clandestino	10.930	2	4.6	sicuro	2.010	3	6.9
difendere	10.270	26	59.6	sicurezza	1.730	17	39.0
difesa	3.730	17	39.0				

Table 5.83 Security keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

Finally, Table 5.84 involves the keywords under the label victim in the Salvini Traditional Corpus that includes just the keyword *guerra* (war) confirming Salvini's narrative of the *true refugees* already mentioned in section 5.5.2.1 (Table 5.72).

Keyword	Score	Freq	Rel_freq
guerra	1.900	4	9.2

Table 5.84 Victim keywords in the Salvini Traditional Corpus (reference corpus itTenTen16)

## 5.5.2.4 Concordances and collocates in the Salvini Traditional Corpus

The following Table presents the collocate list of the word *immigrato* (immigrant). The comparison between this Table and Table 5.73 highlights some collocates in common such as *nave* (ship), *[number]* (that suggest the presence of the aggregation strategy), *essere* (to be) and *avere* (to have). However, the collocate *clandestino* (illegal) is not present in traditional collocates. The collocate *un* (an) – that suggests the presence of the genericisation strategy – is part of the list (and it has 3 occurrences) but it is not part of the first 20 collocates. The collocates *accogliere* (to host), *sbarcare* (to disembrak), *quanto* (how many), *portare* (to bring) and *andare* (to go) are strictly linked to immigrants' journey and their arrival in Italy. *Diritto* (right) is connected to Salvini's reverse racism narrative since according to him immigrants have more rights than Italians.

G 11				3.672
Collocate	Cooccurrences	Occurrences	T-score	MI3
accogliere	4	16	1.99	12.46
che	14	1,216	3.51	11.63
essere	12	1,480	3.16	10.68
[number]	6	255	2.38	10.22
sbarcare	2	15	1.41	9.55
quanto	2	20	1.40	9.14
nave	2	21	1.40	9.07
avere	6	725	2.24	8.71
altro	3	93	1.69	8.67
parte	2	28	1.40	8.65
prossimo	2	36	1.40	8.29
tutto	3	141	1.67	8.07
sapere	2	50	1.39	7.82
portare	2	54	1.39	7.70
si	3	187	1.66	7.67
diritto	2	68	1.38	7.37
dove	2	69	1.38	7.35
anno	2	146	1.34	6.27
se	2	167	1.33	6.08
andare	2	167	1.33	6.08

Table 5.85 Collocates of the word *immigrato* (immigrant) in the Salvini Traditional Corpus

Table 5.86 is considerably shorter than Table 5.74, even because *clandestino* (illegal) occurs 10 occurrences in the Salvini Traditional Corpus (see Table 5.87). As it is possible to notice

from Tables 5.86 and 5.87 this word co-occurs 9 times with *immigrazione* (immigration). This means that Salvini always uses these words to talk about immigration in general in his traditional speeches, while he uses the word just one time to indicate illegal immigrants. Moreover, there are two processes *avere* (to have) and *essere* (to be). *Avere* (to have) is also connected to Salvini's actions as it possible to deduce from the collocate *io* (I). We should highlight that the article *un* (an) is present in the original collocate list but it does not indicate the genericisation strategy since it does not refer to immigrants.

Collocate	Cooccurrences	Occurrences	T-score	MI3
immigrazione	9	31	3.00	16.65
io	2	287	1.37	6.93
essere	3	1,480	1.54	6.31
non	2	692	1.30	5.66
avere	2	725	1.30	5.59

Table 5.86 Collocates of the word clandestino (illegal) in the Salvini Traditional Corpus

The following Table shows all the concordances of the word *clandestino* (illegal) that confirm the strong co-occurrence among this word and the word *immigrazione* (immigration).

essere mischiate a una immigrazione clandestina miliardi di euro con l'immigrazione clandestina in Sardegna diminuirà, la presenza di arricchisce sfruttando l'immigrazione e chi favoreggia l'immigrazione significa bloccare l'immigrazione per contrastare l'immigrazione da noi per contrastare l'immigrazione un grande per bloccare l'immigrazione clandestina clandestina un grande per bloccare orbitatione di miliardi di euro con l'immigrazione clandestina clandes

Table 5.88 presents a random selection of the concordances of the word *immigrato* (immigrant) where it is possible to observe how Salvini employs the burden and invasion *topoi*, the aggregation strategy and the reverse racism narrative.

gli italiani che dormono in macchina e gli immigrati dato regole tedesche, ci hanno riempito di immigrati diritto di voto a qualche milione di immigrati un mondo al contrario dove ha più diritto l' immigrato . Mi riferisco, ad esempio, ai 170.000 immigrati sotto questo tendone. E devo dire che gli immigrati

che stanno in albergo a non fare un e poi se l'artigiano non riesce più a vedere, il e buonanotte! APPLAUSE E sono gli italiani rispetto all'italiano APPLAUSE, dove giocare , come detto, in accoglienza in questo a bordo della nave Diciotti sbarcheranno

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<sup>1)</sup> be mixed with illegal immigration that simply brings to social conflict; 2) billions of euro with illegal immigration, in spite of entrepreneurs; 3) in Sardinia will decrease, the presence of illegals will decrease in Sardinia and finally; 4) get rich exploiting illegal immigration. This is not generosity, this is; 5) Stopping illegal immigrations is not a Minister's right but it is a duty of; 6) and who favours illegal immigration. Because I remind to this; 7) means to stop illegal immigration and allow me to thank a Government; 8) to stop illegal immigration", and I asked: "But excuse me this; 9) to us to stop illegal immigration, of many immigrants has picked up?" "45,000"; 10) great to stop illegal immigration. In two month and a half of last year and the.

di Genova e presenti sulla nave degli immigrati , io ricordo sottovoce, ricordo l'immigrazione clandestina, quanti immigrati ha raccolto? ". "45.000". "E dove li ha una ragazza di quindici anni a lesolo è un immigrato senegalese che con precedenti penali per Boschi vada a rivendicare i diritti degli immigrati mentre si è dimenticata dei diritti dei Table 5.88 Concordances of the word *immigrato* (immigrato) in the Salvini Traditional Corpus<sup>92</sup>

In addition to the word *immigrato*, even in traditional speeches Salvini uses the words *profugo* (refugee), rifugiato (refugee) and richiedente asilo (asylum seeker). However, the word profugo occurs just once in this corpus and it is linked to the reverse racism narrative. Indeed, according to Salvini immigrants have more rights than Italians who are the real refugees in their own country.

ancor di più i tempi di distinzione fra i rifugiati e coloro che rifugiati non sono. Ricordo i di distinzione fra i rifugiati e coloro che rifugiati non sono. Ricordo i numeri - che amo - di fra le 42.000 domande esaminate il rifugiato politico - è stato riconosciuto come tale - in per dare voce a questi rifugiati veri, agli immigrati regolari e perbene che Table 5.89 Concordances of the word *rifugiato* (refugee) in the Salvini Traditional Corpus<sup>93</sup>

Table 5.89 presents the only 4 concordances of rifugiato (refugee). The first 3 occurrences show how Salvini doubts of the status of refugee, while the last one actually reveals Salvini's employment of the victim topos.

In the following Table it is possible to observe the only 3 concordances of the word richiedente asilo (asylum seeker) that confirm once again Salvini's use of the burden topos and the association to crime and the aggregation strategies.

gesti, di sorrisi, di ringraziamenti. Quel richiedente asilo che a Foggia ha aggredito due poliziotti quanto riguarda i costi per ogni singolo richiedente asilo , io ricordo che i francesi spendono 25 , l'Italia ospita circa 170.000 richiedenti asilo nelle strutture italiane. I numeri ci dicono Table 5.90 Concordances of the word richiedente asilo (asylum seeker) in the Salvini Traditional Corpus<sup>94</sup>

remind; 8) the illegal immigration, how many immigrants has picked up?" "45,000". "And where did it; 9) a fifteen-year-old girl in Iesolo, he is a Senegalese immigrant with criminal records for; 10) Boschi claims immigrants' rights, while she has forgotten of the rights of.

1) even more the selection process among refugees and those who are not refugees. I remind the; 2) selection

process among refugees and those who are not refugees. I remind the numbers – which I love – of; 3) among the 42,000 examined requests the political refugee – has been recognized as such – in; 4) to give voice to these

<sup>1)</sup> the Italians who sleep in the cars and the immigrants who stay in the hotels doing nothing; 2) gave us German rules, they filled us up with immigrants. And then if the artisan cannot sell; 3) right to vote to a few millions of immigrants and goodnight! And the Italians are; 4) an upside-down world where the immigrant has more rights than the Italian, where to play; 5) For example, I am referring to the 170,000 immigrants, as already said, in refuge in this; 6) under this big tent. And I have to say that the immigrants on board the NGO Diciotti will disembark; 7) of Genoa and present on board the immigrants' ship, I quietly remind to them, I

true refugees, to legal and decent immigrants who.

<sup>1)</sup> gestures, of smiles, of thanks. That asylum seeker who, in Foggia, has attacked two policemen; 2) And for what concerns the costs for every asylum seeker, I remind you that the French spend 25; 3) Italy host approximately 170,000 asylum seekers in Italian structures. The numbers say to us.

The quantitative analysis confirms that Salvini does not use the source domain of water in traditional speeches. In addition, the analysis proves the employment of the victim *topos* (see Tables 5.35 and 5.84) that is also supported by one occurrence of the word *schiavo* (slave).

# **CHAPTER 6**

# DISCUSSION OF FINDINGS

This chapter is dedicated to the discussion and the comparison of Donald J. Trump's and Matteo Salvini's findings, with a particular focus on populist strategies, in order to highlight the possible similarities and differences. The last section of the chapter involves the comparison between the different (or similar) employment of these strategies on Twitter and in traditional speeches.

# 6.1 Donald J. Trump

# 6.1.1 The populist leader in Trump's populist discourse

The results shown and discussed in chapter 4 reveal that Donald Trump represents himself as a strong populist leader through the employment of metaphors and active agency.

Trump's metaphorical self-representation (see Table 4.1) concerns exclusively the saviour and warrior source domain in both tweets and – especially – traditional speeches. Indeed, Trump represents himself as a strong man and warrior who will fight for the United States and for U.S. citizens' safety and economic interests (see chapter 4 examples 1 and 2). At the same time, his self-representation involves also the (religious) figure of the saviour, who will save – with his strict attitude – American people's future. In this regard, we should mention that Trump, as a populist entrepreneur leader (see section 1.1.4), exploits his working and social position in order to strategically legitimise his ability to run and fix the country, and especially to revitalise the United States' economy. Moreover, Tables 4.12 and 4.16 show that Trump employs this source domain to underline his figure as a populist outsider – who fights against the elitist system – but also as *vox populi* who hears and understands people's requests (especially the requests of neglected people left behind by the previous governments) and fiercely fights for their needs and safety, and for the United States' brighter future.

In addition to the warrior and saviour source domain, Trump implicitly legitimises his leadership through specific representations of Europe (see section 4.4). On the one hand, Europe is positively described by Trump since the old continent and the United States represent *the* west and share common values (see chapter 4 examples 26 and 27). However, Europe is also negatively represented by Trump in association to the consequences of wrong immigration

policies in order to affirm his position as the right leader to follow to prevent similar situations in the United States.

The self-representation of Trump as a commander in chief is also crucially supported by the massive presence of material processes (see Table 4.3), active voice type and positive evaluation (see Table 4.5) that contribute to build his figure as a concrete and resolute populist leader. In combination with his active agency, Trump's massive employment of material processes – to present both electoral promises and accomplishments after his election – supports his self-representation as a strong and pragmatic man who keeps his promises and succeeds in achieving his goals.

As it is possible to notice in Tables 4.9 and 4.13, some keywords (e.g. *Pence* and *administration*) suggest that the representation of Donald Trump as a strong leader – capable of *Mak[ing] America Great Again* – is reinforced by extending Trump's characteristics – already seen in his self-representation – to the other in-group representations and especially to his administration. As a result, the people who collaborate with Trump are represented as much resolute and determined as him in order to embody a valid alternative (against the elitist Hillary Clinton) capable of fixing the country. Consequently, Trump's administration is also metaphorically represented through the saviour and warrior source domain. Furthermore, Trump's administration is highly associated to material processes and has an active voice type and positive evaluation (see Tables 4.6 and 4.8). These linguistic choices are strategically used to support a populist narrative that presents Donald Trump as a convincing presidential candidate and a valid President who leads a strong administration that supports him in improving the United States' condition concerning domestic and foreign affairs.

## 6.1.2 The heartland and the people in Trump's populist discourse

The United States are Donald Trump's heartland (see section 1.1.1); specifically, his idealised heartland is formed by people who embody, cherish and celebrate American values such as freedom, justice and patriotism (see chapter 4 examples 18 and 20). Tables 4.25 and 4.31 highlight through some keywords such as *workers*, *woman* and *man* Trump's populist narrative concerning (*the forgotten*) common and honest American people – often neglected by the elitist previous governments – who work hard and deserve a President who understands their necessities and fight for their interests.

Trump invokes and celebrates both the heartland and the people through various strategies such as metaphors, *topoi* and transitivity.

Firstly, Trump employs the saviour and warrior, and the war source domains (see Table 4.17) in order to praise and glorify the American heartland formed by hardworking citizens who are able to make great efforts and sacrifices to preserve their fundamental values and to defend their country (see Table 4.36). Indeed, Trump's populist discourse often involves American auto celebration concerning the bravery of soldiers and veterans. American people's active and positive attitude is also confirmed by transitivity since they are mainly associated to material processes (see Table 4.22) and perform the Actor (see Table 4.23) with active voice type and positive evaluation (see Table 4.24).

Secondly, we should notice (see Tables 4.17 and 4.18) that Trump is more focused on representing the U.S. and the people as victims through the *topos* of the victim, the war source domain, the source domain and the *topos* of container. The heartland is strategically represented by Trump as a place where the people are mistreated and are suffering the consequences of the previous corrupt governments that not only were not able to manage domestic policies, but they were also unable to impose U.S. interests in foreign policies (see chapter 4 example 13) and to protect people's safety (see chapter 4 examples 35 and 40). The representation as victim is partially supported by the participant types associated to these social actors. On the one hand, Table 4.20 shows that the United States are mainly the Goal of processes suggesting that the United States – as a community – are subjected to actions that are often negative (see Table 4.21). On the other hand, Table 4.23 shows that the American people have a different description because they perform mainly the Actor with active voice and positive evaluation (see Table 4.24) recalling the saviour and warrior source domain and Trump's American self-praising.

The victimisation of the U.S. is also supported by the source domains of war and building, the source domain and the *topos* of container. The source domain of war (see chapter 4 example 11) is used by Trump to represent the economic condition of the United States that have *surrendered* – under previous governments – their wealth to foreign countries and have lost their geopolitical hegemonic position. The United States are described as a building where foreign people enter and could compromise American people's safety. This narrative is implemented through the representation of the U.S as a container that is exploited by Trump to describe the heartland as a community in jeopardy since it is vulnerable to infiltrations and penetrations of various threats (see chapter 4 example 15) such as terrorism, criminality and immigration (see Table 4.37). Moreover, these two representations are useful to support Trump's political and economic isolationism. Trump – as other right-wing leaders (Mudde and Kaltwasser, 2017: 101) – rejects cosmopolitanism and globalisation (Taggart, 2000: 96) and

embraces isolationism because he sees himself and his heartland at the 'heart of things' (Taggart, 2000: 96) (see section 1.1.1).

Finally, the source domains of building and nature are employed by Trump in order to describe the future of the United States and the American people under his leadership. Consequently, these are also strategies used to legitimise and support Trump's positive selfrepresentation as populist leader (already discussed in the previous section). More precisely, the United States are presented as a building that has been damaged by the elite and that could be restored and renewed by Trump. Instead, the nature source domain is used to represent the United States as a garden that will flourish and thrive once Trump will be President. As a result, these representations support Trump's role as saviour since he describes himself as the only one who will be able to save the United States' disastrous conditions. Specifically, he implies that the United States are a permeable and unsafe container, an old and unstable building, and a neglected and arid garden. At the same time, these representations are also delegitimising strategies against the elite and especially against Hillary Clinton who was his major opponent during the electoral campaign and who embodies the *insider*. These catastrophic representations are clearly strategies that Trump uses to promise the delivery of simple solutions (see section 1.1.4) such as isolationism to regain U.S. powerful hegemonic position in the world, to revitalise U.S. economy and protect the heartland from any dangerous threat.

## 6.1.3 Otherness in Trump's populist discourse

The others/enemies identified in Donald Trump's analysis are the elite – embodied by Hillary Clinton and the media –, Mexico, immigrants and refugees. The fear of the other and the anger towards the enemies are exploited by Trump not only to encourage people's unity, but also to establish himself as the *vox populi* leader who is the only one willing to fight to protect the people (see sections 1.1.1 and 1.1.4).

Firstly, Hillary Clinton was not only Trump's main enemy during the presidential campaign, but she also symbolises and embodies the corrupt establishment. Indeed, Clinton has always been involved in the political sphere occupying different positions such as Secretary of State. As shown in Tables 4.40 and 4.45, the lists of keywords under the label opposition highlight the massive and harsh attacks to Hillary Clinton (e.g. *crooked*). More precisely, the attacks involve her corruption and dishonesty concerning the email controversy (see Tables 4.40 and 4.45), and her inability to run the country properly (since she is also subjected to the interests of other members of the elite such as her donors; see chapter 4 example 5), especially concerning economic and immigration policies. Consequently, Clinton is described as a

politician who has failed in helping people and in creating wealth in the United States advantaging foreign countries with her support to wrong deals (such as NAFTA). Furthermore, she is represented as a politician who has failed overseas favouring the rise of ISIS and illegal immigration with wrong and weak immigration policies (see chapter 4 examples 33, 35, 38, 40, 42, and Figures 4.1, 4.2). As a result, the delegitimation of Clinton is always strategically combined with Trump self-legitimisation in order to present him as the right and well-suited presidential candidate (see chapter 4 examples 5 and 35).

Secondly, Trump has defined the mainstream traditional media as the enemies of the people (Smith, 2019) claiming that they spread fake news (Tormey, 2019: 89). This is a common characteristic among populist leaders since they represent the media as part of the corrupt establishment and as biased because they protect the elite disadvantaging populists (Mudde and Kaltwasser, 2017: 12). The results of the analysis in chapter 4 show how harshly Trump attacks the media through the dishonest *topos* (see chapter 4 Table 4.38 and examples 22, 23, 24, 25); specifically, he accuses the media of censoring him during and after the electoral campaign. According to Trump the media do not report – on purpose – his successes and achievements, misrepresented and continues to misrepresent news in order to disadvantage him and to protect the corrupt establishment. Trump's aim is to instil distrust in the media in order to gain people's trust since he opposes to the establishment – fighting for himself and the people – saying the truth. Indeed, it is possible to observe in Tables 4.39 and 4.44 the keywords (e.g. fake, dishonest and phony) that signal Trump's harsh opposition to the media as part of the elite (see also chapter 4 Tables 4.40 and 4.45). In addition, collocate and concordance analyses (see Tables 4.41, 4.42, 4.46, 4.47, 4.48 and 4.49) confirm both Trump's employment of the dishonest topos, and his hostile attitude. It is important to highlight (see Table 4.43) the metaphorical representation of media's behaviour towards Trump as a witch hunt that is particularly pervasive in his tweets. On the one hand, this representation is useful to delegitimise the media and their biased work in favour of the elite. On the other hand, this powerful metaphor contributes to implicitly depict Trump as a victim of the system.

Thirdly, Mexico is described by Trump as an unfair and dangerous neighbour. In this regard, Trump Wall (see Tables 4.62 and 4.64) is crucial and represents the symbolic and physical border between the people and otherness. The Wall symbolises primarily Trump's isolationist approach; more precisely, Mexico poses two main threats concerning immigration and economy. Mexicans and the majority of immigrants from South America pass through this country in order to reach the United States. For this reason, the Wall is also represented – and legitimised – by Trump as a protection that is useful to stop illegal immigration physically, and

to prevent Mexican criminals (e.g. gangs and cartels) from entering into the United States (see chapter 4 Table 4.59 and example 30). As it is possible to notice from Tables 4.61, 4.63, 4.64, 4.66 and 4.68, the collocate and concordance analyses show the centrality of economy in Trump's discourse concerning Mexico. The symbolic and physical separation represented by the Wall is both a promise and a threat to Mexico since this country takes advantage of the United States and *steals* U.S. work because of cheaper labour costs that lead to delocalisation (see chapter 4 example 31).

Finally, immigrants and refugees are represented by Trump as the dangerous other through a rich variety of strategies. The combination of the source domain of water, the invasion topos, and the aggregation strategy (see Tables 4.69, 4.70, 4.71, 4.77, 4.82, 4.83, 4.90 and 4.91) allows Trump to present these social actors as a massive and powerful threat that put at risk the United States and U.S. citizens. The danger, threat and fear topos (see Tables 4.70, 4.76, 4.82, 4.83, 4.85 and 4.91) includes all the strategies employed by Trump in order to trigger people's fear against the other and strategically legitimise his policies. More precisely, Trump exposes a variety of threats such as social and cultural ones with the topos of burden (see chapter 4 Table 4.70 and examples 34, 37 and Table 4.86), the opposition strategy (see chapter 4 Table 4.71 and examples 36 and 37), the genericisation strategy (see chapter 4 Tables 4.71, 4.90, and examples 39, 40), and threats to people's safety with the association to crime and terrorism (see chapter 4 Tables 4.71, 4.81, 4.83, 4.89 and examples 39, 40). The negative representation of these social actors is also supported by transitivity. Trump presents immigrants and refugees as Actors (see Table 4.73) who actively perpetrate bad actions since they are primarily associated to material processes (see Table 4.72), have an active voice type (see Table 4.74), and a negative evaluation (see Table 4.74). We should also notice that some strategies such as the metaphorical representation through the water source domain, the topos of DTF, the association to crime and terrorism, the aggregation strategy, the genericisation strategy, and especially the suppression strategy (see Tables 4.69, 4.70, 4.71, 4.76, 4.81, 4.82, 4.83, 4.85, 4.89, 4.90 and 4.91) are employed by Trump to suppress people's empathy towards immigrants and refugees in order to legitimise his immigration policies (see Tables 4.75, 4.78, 4.81, 4.84, 4.87 and 4.89). For instance, Trump Wall and the Travel Ban aim to the physical exclusion of immigrants and refugees from the heartland through their strategical dehumanisation.

## **6.2** Matteo Salvini

### 6.2.1 The populist leader in Salvini's populist discourse

Matteo Salvini's results – shown and discussed in chapter 5 – reveal that Salvini's self-representation as a strong populist leader is achieved primarily through metaphors and active agency.

Concerning metaphors, Salvini employs marginally the source domain of religion and more prominently the source domain of saviour and warrior (see Table 5.1). Specifically, Salvini presents himself as an ordinary man sensitive to common people's daily problems in order to affirm his position as an outsider (see section 1.6.5). Indeed, Salvini is actually part of that corrupt establishment – since he has always been a politician – that he claims to despise. As both a common man and a strong populist leader, Salvini describes himself as a warrior and a saviour that is willing to fight – what he considers – dangerous threats for Italian society such as immigration, European economic and political impositions, and LGBTQ+ civil rights (see chapter 5 examples 1 and 2) in order to save and protect the Italian people. As is possible to notice in Tables 5.13, 5.14, 5.17 and 5.18, this source domain is strictly connected to Matteo Salvini's role as Italian Minister of the Interior; consequently, there are a lot of references to Italian borders' protection and Italians' safety safeguard from immigration, but there are also references to the fight against organised crime.

Salvini's self-representation as a populist leader characterised by firmness and concreteness is sustained by the high percentage of material processes (see Table 5.5), Salvini's frequent performance as Actor (see Table 5.6), and the high percentages of active voice type and positive evaluation (see Table 5.7). The massive presence of material processes (see also Table 5.12) underlines Salvini's effort and willingness to achieve and maintain his goals mainly concerning the promise to assure and improve Italian people's safety and quality of life.

In addition to Salvini's self-representation as a strong populist commander in chief able to provide common sense solutions, the results show a strong victimisation of Salvini through the employment of the victim *topos* (see chapter 5 Tables 5.3, 5.12 and examples 6,7). This type of representation is useful to Salvini in order to delegitimise the corrupt elite – such as the media, political opponents and intellectuals (see chapter 5 example 25) – and legitimise his strong leadership since in spite of all the attacks he has to endure, he stands and persists to provide to the Italian people a better future. Furthermore, this strategy is also employed not only to legitimise his (immigration) policies but also to delegitimise the judges who investigate him concerning the Diciotti crisis (see chapter 5 examples 6 and 7).

Some keywords (e.g. *Lega*, *Giulia* and *Partito*) in Tables 5.11 and 5.15 suggest that Salvini's self-representation is strictly connected to the (in-group) representation of his party. Salvini extends (positive) characteristics – already seen in his self-representation – to *Lega* 

members' representation. As a result, the *Lega* – similarly to Salvini – is associated to a high percentage of material processes (see Table 5.8), to the Actor participant type (see Table 5.9), and it has an active voice type and a positive evaluation (see Table 5.10). Moreover, the *Lega* is represented both as a victim (see chapter 5 Table 5.4 and example 8), and as a warrior and saviour (see chapter 5 Tables 5.2, and examples 3,4). Specifically, the *Lega* is presented as a party that stands against the opponents' attacks and that under the leadership of Salvini will fight to protect Italians from internal (e.g. organised crime) and external (e.g. immigration) threats (see Tables 5.13, 5.14, 5.17 and 5.18).

## 6.2.2 The heartland and the people in Salvini's populist discourse

Matteo Salvini's heartland (Taggart, 2000) is currently Italy (see section 1.6.2); in his rhetoric, it is formed by honest, respectable and hardworking Italian people (see Tables 5.27 and 5.31) who are suffering the consequences of uncaring previous governments' political, economic, and immigration policies (see Tables 5.30 and 5.35). This representation is particularly useful to Salvini to trigger specific emotions (such as anger) in order to both present himself as a right Prime Minister (during the electoral campaign) and to legitimise his work as Minister of the Interior (after the electoral campaign).

On the one hand, Salvini invokes the people and stimulates their unity celebrating Italy's rich heterogeneousness (see chapter 5 example 20) but also Italians' common values concerning the heartland such as strong cultural and religious roots (see chapter 5 examples 16 and 22) – in particular through the nature source domain (see Table 5.19). On the other, the results in chapter 5 (see section 5.2) show that the victimisation of Italy and Italians is particularly pervasive in Salvini's discourse. This representation is achieved primarily through the employment of the victim topos (see Table 5.20), especially in combination with the source domain and topos of container. Salvini depicts Italy and Italians as the victims of unjust European impositions (see Tables 5.30 and 5.35) and as the victims of the dangerous and disastrous consequences of massive immigration (see chapter 5 Tables 5.30, 5.35 and example 17). For this reason, Italy is depicted as a container that has been filled with immigrants (presumably by the European elite with the tacit approval of the elitist Italian governments. See chapter 5 examples 15 and 18). In this regard, Salvini also underlines Italians' victimisation through the reverse racism narrative. Specifically, Salvini claims that the Italian people are the true victims of immigration impact on Italian society since they fear for their safety (see chapter 5 Table 5.27 and examples 17, 39). Furthermore, they have to bear economic burdens due to the costs of immigration (see chapter 5 examples 21 and 34) and they have to endure possible cultural religious and social instabilities (see chapter 5 examples 33, 36, 37 and 38). As a result, the building source domain is employed by Salvini concerning the legitimation of his immigration policies (see chapter 5 example 14). Italy is depicted as a home that will open its doors just to those people who truly are – according to Salvini – refugees (see chapter 5 example 36). Otherwise, Italy's doors will be shut to prevent the dangerous consequences of immigration (see chapter 5 example 36).

We should also highlight that the source domain and *topos* of container and the source domain of building are employed by Salvini to describe the current disastrous Italian condition in order to support his self-representation as saviour and warrior. More precisely, he describes Italy as a container completely open and vulnerable to foreign threats and as a home with wide open doors. Consequently, he legitimises himself – promising to change and improve Italy's condition – and delegitimises his opponents (see chapter 5 examples 3, 10, 15 and 18).

In addition, transitivity plays a crucial role in the representation of Italy and Italians, and in the legitimation of Salvini's leadership. Italy and Italians are mainly connected to material processes (see Table 5.21 and 5.24), perform the Actor (see Tables 5.22 and 5.25) and have an active voice type (see Tables 5.23 and 5.26); moreover, Italy has often a positive evaluation (see Table 5.23). Salvini exploits this strategy to indicate the positive changes that will happen and are happening during his time in government thanks to his strong leadership (see chapter 5 Table 5.28, 5.32 and example 19). Instead, the high percentage of negative evaluation associated to the Italian people (see Table 5.26) supports the employment of the victim *topos* because it indicates the connection of Italian people to processes that cause their suffering.

## 6.2.3 Otherness in Salvini's populist discourse

Salvini identifies specific social actors as otherness: 1) the elite, his (political) opponents, the media and the European Union; 2) immigrants; and 3) refugees. Their portrayal as otherness and enemies is crucial for Salvini in order to trigger people's negative emotions (such as anger, fear and uncertainty) and to stimulate their unity under his leadership.

Firstly, Tables 5.38 and 5.43 show some keywords that indicate Salvini's enemies. The keyword *Maio* refers to Luigi Di Maio – leader of the *Movimento 5 Stelle* – who was his major opponents during the electoral campaign in 2018, but who became his "ally" (see Table 5.11) when they formed a coalition government. The keywords *sinistra* (left), *PD*, *Boldrini* and *Renzi* indicate the *Partito Democratico* – the corrupt party who was in charge during the previous government and that according to Salvini is responsible for Italy's disastrous conditions concerning economic and immigration policies (see chapter 5 examples 10, 17, 18, 29 and 32)

– and they highlight Salvini's harsh attacks towards some politicians such as Matteo Renzi and Laura Boldrini. Lastly, *Fornero* refers to Elsa Fornero who was Minister of Labour, Social Policies, and Gender Equality in Monti's government and who perfectly embodies the corrupt establishment of bureaucrats submitted to the European Union since she reformed the Italian retirement system in order to cut the Italian public expenditure in the context of the European debt crisis. It is important to underline that the elite is also connected to other important topics concerning wrong immigration policies (see chapter 5 example 29 p, 142 and 32), wrong economic policies (often influenced by European imposition) that favour multinationals vis-a-vis local businesses (see chapter 5 Table 5.43 and examples 9, 10), and to their support to the LGBTQ+ community's achievements of civil rights that Salvini disapproves of, as other right-wing populist leaders (see chapter 5 example 2) (Mudde and Kaltwasser, 2017: 25; Moghissi, 2018: 87).

Secondly, Salvini portrays the media as the enemy through the dishonest topos (see Table 5.36). Specifically, he describes traditional media – especially newspapers, journalists and television (see chapter 5 Tables 5.39, 5.40, 5.41, 5.44, 5.45, 5.46 and examples 23 and 24) - as part of the corrupt elite. Salvini claims that the media spread fake news (see Tables 5.37, 5.40, 5.41 and 5.45) and censor his successes (see chapter 5 Tables 5.40, 5.41, 5.44, 5.45, 5.46 and examples 23, 24) because they are biased and aim to preserve the establishment, preventing him to win hiding the support he receives from the people (see chapter 5 Table 5.39 and example 24). For this reason, Salvini praises the power of social networks that allow him to spread the truth and whatever the traditional media hide (see chapter 5 examples 23 and 24). Salvini's harsh attacks to the media are also personal attacks because not only does he claim that journalists are subjugated by the elite (see chapter 5 example 24), but he also names journalists and intellectuals that he despises such as Lerner, Scalfari, Santoro, Fazio and Saviano (see chapter 5 Table 5.46 and example 25). In this way Salvini explicitly describes himself – and his party – as a victim of this system (see chapter 5 Tables 5.39. 5.40, 5.45, 5.46 and example 8), but he also implicitly portrays the people as victims (see chapter 5 example 35) of the same corrupt establishment. As a result, the portrayal of the media as an enemy is used by Salvini to trigger the scepticism of the people who will regard him as the true and right leader to follow.

Thirdly, Euroscepticism is particularly pervasive in Salvini's discourse (see Tables 5.38 and 5.43). The European Union is depicted as an elitist institution formed by technocrats and bureaucrats who impose — with the complicity of the Italian corrupt elite — wrong and disadvantaging economic and immigration policies to the Italian people. Salvini represents Europe mainly as a dictatorship (see chapter 5 Tables 5.48, 5.49 and examples 9, 10, 12, 15,

16, 29) that dictates rules and regulations that do not benefit Italian local businesses and that imposes to Italy the burden of dealing with the massive immigration phenomenon. Europe is also described as an absent and useless institution (see chapter 5 Table 5.49 and example 30) that pretends to intrude in Italian domestic policy but that does not really care about the wellbeing of the Italian people. The pervasiveness of these negative representations is supported by the keywords under the label opposition (see Tables 5.38 and 5.43) and the presence of words connected to the E.U. in the collocate lists of Italy (see Tables 5.28 and 5.32) that indicate a strong connection between Italy and Europe and, at the same time, sustain the victimisation of Italy and Italians by the hands of the European elite. Furthermore, Salvini depicts the E.U. as an absent and useless institution since not only does it leave the burden of helping immigrants to Italy, but it also complains about Salvini's decisions as Minister of the Interior (see chapter 5 examples 15 and 30). On the other hand, the representation of Europe as a dictatorship is supported by the source domain of war (see chapter 5 Table 5.47 and example 28) – that amplifies its negative representation as an institution that massacres Italians with its wrong regulations – and by the high percentage of material processes associated to E.U. (in comparison to other types of processes. See Table 5.50), the E.U. performance as an Actor (see Table 5.51) with active agency and negative evaluation (see chapter 5 Table 5.52 and example 31). The delegitimation of the European Union is obviously also useful to Salvini to create an odious common enemy as well as to legitimise his strong leadership. Consequently, he represents himself as the one who will save both Italy and Europe from the corrupt elite. Specifically, Salvini promises to safeguard Italian people's interests (see chapter 5 Table 5.59 and example 19) – including crucial right-wing values such as the protection of traditional families against the LGBTQ+ community (that also represents another type of dangerous otherness. See chapter 5 examples 2 and 16) –, to support Made in Italy (see chapter 5 example 9) against the European elite's excessive power, and to change and rebuild Europe (see chapter 5 example 29). For this reason, he describes Europe as a building (see chapter 5 Table 5.47 and example 26) that he promises to rebuild since it has been destroyed by the corrupt establishment, and as a container (see chapter 5 Tables 5.47, 5.48 and example 1) that should be protected by those people who can undermine European common Christian and cultural roots (see chapter 5 example 36). Lastly, it is important to mention that Salvini – as it is possible to observe in Tables 5.38, 5.33, 5.56 and examples 16, 20 (chapter 5) – attacks European countries that are thought to be particularly influential in the E.U. such as Germany and France or countries favoured concerning economic and immigration matters – by the E.U. elite such as Spain and France.

Finally, the results in chapter 5 suggest that immigration is actually the most pervasive topic in Salvini's populist discourse (see Tables 5.66 and 5.79); Salvini has the ability to intertwine this topic strategically with others such as his Eurosceptic discourse (see chapter 5 examples 15, 27 and 30). As keywords in Table 5.66 show, immigration is highly associated by Salvini to criminality. Indeed, immigrants and refugees are depicted as the dangerous other through several strategies. The DTF (see chapter 5 Tables 5.61, 5.67, 5.80 and example 33) and the invasion topoi (see chapter 5 Tables 5.61, 5.68, 5.81 and example 33), and the association to crime and terrorism (see chapter 5 Table 5.62 and examples 37, 38 and 39) aim to present these social actors as an impressive and imminent threat. The opposition strategy indicates a specific threat concerning the threatening of cultural and religious values (see chapter 5 Table 5.62 and examples 35, 36), but it also strategically opposes immigrants and refugees to Italian people. According to Salvini, the latter suffer from reverse racism since the elite favours the former neglecting the poor Italian people (see chapter 5 Tables 5.27, 5.30, 5.35 examples 17 and 35). In addition, transitivity plays a crucial role in this representation because immigrants and refugees are described as Actors (see Table 5.64) associated to a high percentages of material processes (see chapter 5 Table 5.63 and example 40), with active voice type and negative evaluation (see Table 5.65). Furthermore, Salvini sometimes uses some strategies to humanise these social actors and portray himself as a kind man sensitive to certain topics such as children safety (he also exploits his role as a father for the same reason, see section 1.6.5). In this case, immigrants and refugees are depicted through the victim topos (see chapter 5 Tables 5.35, 5.61, 5.78 and example 32) but also through the nature source domain (see chapter 5 Table 5.60 and example 32) since Salvini compares immigration to the uprooting of these people from their native countries. This strategy is useful to distinguish and separate who according to Salvini are true refugees – few boys, women, and children (see 5 Table 5.72) – and honest legal immigrants from the dishonest illegal immigrants who represent a real threat to Italians. Clearly this is a simplification of the complex immigration phenomenon because even desperate people can enter illegally Europe. Tables 5.77 and 5.90 show that he often associates the words richiedente asilo (asylum seeker) to criminality in order to prove that the majority of the requests are false and that he is right in applying his strict immigration policies. This strategical humanisation is also used to delegitimise other European countries, such as France (see Table 5.75), that do not share responsibilities and do not welcome these desperate people. However, in most cases Salvini aims to dehumanise immigrants and refugees to justify the need of security (see Tables 5.71 and 5.83) that legitimises his strong and strict leadership especially regarding immigration policies; he tries to dehumanise them through the object and

merchandise source domain (see chapter 5 Table 5.60, example 19 and Figure 5.2), the water source domain (see section 5.5.2.2) and the aggregation strategy (see chapter 5 Tables 5.62 and example 37) that allow him to talk about immigrants in terms of (numerous) inanimate objects that are unloaded in Italy. In addition, the burden *topos* (see chapter 5 Tables 5.61, 5.70, 5.82 and examples 11, 21 and 34) allows Salvini to represent immigrants and refugees simply as a cost that gravely impact on Italian people's finances. As a result, this *topos* depicts them as dangerous economic threats as well. Immigrants and refugees are also strictly connected to NGOs (see chapter 5 Tables 5.38, 5.56, 5.78, Figure 5.2 and example 19), which Salvini perceives as another intolerable enemy connected to the corrupt establishment.

# 6.3 Comparing Trump's and Salvini' populist narratives

This section provides a qualitative and quantitative comparison of Trump and Salvini's populist strategies. Specifically, the qualitative results focus mainly on the percentages of UAM Corpus Tool<sup>95</sup> comparative analysis. Furthermore, the following comparative discussion considers the comparative results but also the results of the individual analyses in chapters 4 and 5.

# **6.3.1** The populist leader

The self-representation of Donald Trump and Matteo Salvini as populist leaders is surely influenced by their different background. Trump is an entrepreneur populist leader (see sections 1.1.4 and 1.5.5), while Salvini is an insider since he has always been a politician (see section 1.6.5). Despite their different background, their self-representation as active and strong populist leaders is similarly achieved primarily through the employment of metaphors and active agency.

Concerning metaphors, they both use the saviour and warrior source domain <sup>96</sup>. The percentages of UAM Corpus Tool – in Table 6.1 – reveal that Salvini uses more this source domain than Trump (see also chapter 4 Table 4.1 and chapter 5 Table 5.1). Both qualitative and quantitative results show that these politicians represent themselves as the saviours that will help the citizens – especially the poor and neglected ones – (see chapter 4 examples 1, 2, 3 and Tables 4.25, 4.31; chapter 5 examples 14, 35 and Tables 5.27, 5.31), and that will protect their heartlands by inside and foreign threats (see chapter 4 examples 3, 4, 5, 15, 32, 36 and Tables 4.12, 4.16; chapter 5 examples 1, 2, 33, 36, 39, 40 and Tables 5.13, 5.14, 5.17, 5.18).

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<sup>95</sup> See section 3.2.1.

All the qualitative analytical categories are listed in chapter 3 section 3.2.1.

Target type	Trump <sup>97</sup>	Salvini <sup>98</sup>
Trump	$35\%^{99} (12)^{100}$	-
Trump administration	38% (13)	-
The United States	27% (9)	-
Salvini	-	60% (15)
Lega	-	40% (10)
Italy	-	-

Table 6.1 Saviour and warrior source domain comparison

In this regard, it is important to mention some differences highlighted by the quantitative approach. Firstly, Salvini seems to focus on a wider range of Italians (see Tables 5.27 and 5.31) than Trump does with Americans (see Tables 4.25 and 4.31). Secondly, Salvini's rhetoric – on Twitter – concerning the protection of the heartland from otherness is more pervasive (see Table 4.78; Table 5.71; sections 6.2.3 and 6.3.3). Thirdly, Donald Trump is more focused on the representation of himself as the saviour that will accomplish the revival of the American dream (see chapter 4 examples 7, 19 and Tables 4.25, 4.26, 4.32) summarised by his slogan *Make America Great Again*.

In order to support their representation as strong and concrete commander in chief, both Trump and Salvini are mainly associated to material processes (see Table 6.2; chapter 4 Table 4.3 and chapter 5 Table 5.5).

Participant class-type	Trump	Salvini
Trump	29% (272)	-
Trump administration	37% (355)	-
The United States	6% (55)	-
U.S. citizens	24% (231)	-
Salvini	-	49% (514)
Lega	-	28% (293)
Italy	-	3% (29)
Italian citizens	-	6% (69)
Europe	-	3% (32)
Immigrants and refugees	4% (37)	11% (117)

Table 6.2 Material processes comparison

They usually play the Actor role – according to UAM Corpus Tool comparative results Trump performs the Actor with the percentage of 30% (see the Appendix E Table E.1 and chapter 4 Table 4.4) while Salvini has a percentage of 51% (see the Appendix E Table E.1 and chapter 5 Table 5.6) – and have an active voice type (Trump 42% and Salvini 64%) and positive

The comparison percentages include both the Trump Tweet Corpus and the Trump Traditional Corpus data.

<sup>&</sup>lt;sup>98</sup> The comparison percentages include both the Salvini Tweet Corpus and the Salvini Traditional Corpus data.

Since each percentage (e.g. The United States 27%) is calculated in relation to the total percentage of the category (e.g. saviour and warrior source domain 100%) employed by each politician, the percentages have to be considered vertically.

Number of occurrences.

evaluation (Trump 36% and Salvini 63%) (see the Appendix E Tables E.2 and E.3, chapter 4 Tables 4.5, and chapter 5 Table 5.7). The considerable employment of material processes is, in both cases, connected to (electoral) promises and achievements of both politicians (see chapter 4 examples 2, 6 and chapter 5 example 2).

In addition to their representation as strong populist commanders in chief, we can see a victimisation of these politicians (see Table 6.3). On the one hand, Trump depicts implicitly himself as a victim of the elitist establishment especially through the metaphorical representation of the dishonest media's behaviour – that disadvantages him – as a *witch hunt* (see chapter 4 examples 22, 23, 24, 25 and Tables 4.42, 4.43, 4.47, 4.49). On the other hand, Salvini employs an explicit victimisation through the victim *topos* (see Tables 5.3, and 5.12) that he uses strategically to delegitimise his elitist opponents and to legitimise his leadership (see chapter 5 examples 6 and 7). Both the implicit and the explicit victimisation of Trump and Salvini somehow still support their representation as strong leaders who – despite all the attacks – fight for the people against the corrupt establishment.

Finally, both populist leaders strategically connect their self-representation with the ingroup representations of their administration and party (see Tables 4.9; 4.13; Tables 5.11 and 5.15) in order to reinforce and legitimise their leadership. As it is possible to notice from Table 6.2 both Trump's administration and *Lega* are connected to material processes (see also chapter 4 Table 4.6 and examples 7, 8; chapter 5 Table 5.8 and example 12). They perform the Actor; according to UAM Corpus Tool comparative analysis Trump administration performs this participant type for the 40% (see the Appendix E Table E.1 and chapter 4 Table 4.7) while the Lega has a percentage of 29% (see the Appendix E Table E.1 and chapter 5 Table 5.9). They also have an active voice type (Trump administration counts 25% while Lega has the 19%) and positive evaluation (Trump administration has the 35%; Lega counts the 27%. See the Appendix E Tables E.2 and E.3, chapter 4 Table 4.8 and chapter 5 Table 5.10). Moreover, Table 6.1 shows that both Trump's administration and the Lega are represented through the saviour and warrior source domain (see also chapter 4 Table 4.2 chapter 5 Table 5.2 and examples 3,4). For what concerns the topos of the victim, even in this case, Trump employs this topos implicitly (see chapter 4 examples 23 and 25) while – as shown in Table 6.3 – Salvini uses it in an explicit way (see chapter 5 Table 5.4 and example 8). Lastly, Salvini differs from Trump regarding his in-group representation that is more variegated since he also employs other source domains such as water to depict his party as a strong and unstoppable force of nature (see chapter 5 Table 5.2 and example 5).

### 6.3.2 The heartland and the people

Donald Trump and Matteo Salvini have a slightly different approach – revealed by the quantitative part of the analysis – towards the heartland that is influenced by their different political backgrounds. For instance, Tables 4.27, 4.28, 4.33, 4.34, 5.29, 5.33 and 5.34 reveal that Italy is not described by Salvini as a nation because the *Lega (Nord)* has a history of independent and secessionist claims. Despite some differences due to the different historical, political, and social background of the U.S. and Italy, Trump and Salvini portray their heartlands similarly. Indeed, both leaders appeal to those forgotten citizens neglected by the previous elitist governments (see Table 4.14; 5.30, and 5.35). However, Salvini seems to appeal to a wider range of Italians (see Tables 5.27 and 5.31) in comparison to Trump (see Tables 4.25 and 4.31).

The appeal to neglected U.S. and Italian people is strictly connected to the victimisation of the heartland. For this reason, Trump and Salvini employ primarily the *topos* of the victim (see Table 4.18 and 5.20) but also the source domain and the *topos* of container (see Tables 4.17, 4.18, 5.19, and 5.20). As Table 6.3 shows, Trump has a higher percentage because he employs this *topos* exclusively to support the victimisation of the United States and U.S. citizens, while Salvini uses this *topos* to support the victimisation of several social actors including himself.

Entities type	Trump	Salvini
Trump	-	-
Trump administration	-	-
The United States	100% (21)	-
Salvini	-	33% (23)
Lega	-	10% (7)
Italy	-	39% (27)
Immigrants	-	18% (12)
and refugees		

Table 6.3 Victim topos comparison

The source domain and the *topos* of container are useful to both politicians to depict their countries as vulnerable to a variety of threats such as terrorism, criminality and immigration (see chapter 4 Table 4.37 and example 15; chapter 5 Tables 5.30, 5.35 and examples 15, 18).

Although Trump and Salvini use these strategies to describe the heartland and the people similarly, there are some differences in their employment of additional strategies. For instance, Trump also uses the source domains of war and building (see Table 4.17) while Salvini is more focused on intertwining the victimisation to his Eurosceptic discourse (see Tables 5.30 and 5.35). Moreover, Salvini highlights the victimisation of the Italian people through the support

of the reverse racism narrative (see chapter 5 Table 5.27 and examples 17, 21 33, 34, 36, 37, 38 and 39).

The victimisation is also supported by transitivity that Trump and Salvini employ in a different way; Trump uses this strategy only concerning his country, and represents the U.S. as the Goal of negative processes (see Table 4.21). Instead, Salvini focuses on Italian citizens and their connection to negative evaluation suggesting that they are subjected to processes that cause their suffering (see Table 5.26). Both politicians represent the citizens as the victims of illegal immigrants (chapter 4 examples 39, 40 and 42; chapter 5 examples 17, 39 and 40) and previous elitist governments (chapter 4 example 14, 35 and 42); but there are still some differences because Trump focuses on negative actions - that disadvantage the U.S. perpetrated by foreign countries (see chapter 4 example 9, 13, 16 and 29), while Salvini focuses mainly on E.U. negative and intrusive actions (see chapter 5 examples 9, 12, 13, 16 and 31). In addition, transitivity supports other perspectives in the representation of the heartlands. The United States are praised and depicted by Trump through the saviour and warrior source domain (see Table 6.1) recalling their crucial contribution during and after the Second World War (see chapter 4 Table 4.17 and example 9); for this reason, U.S. citizens are linked to material processes (Table 6.2), and perform mainly the Actor with active voice type and positive evaluation (see Tables 4.23 and 4.24). In this regard, even Salvini praises Italy and the Italian people, but he does so through other strategies, that is the nature source domain (see Table 6.4) that he uses to describe Italy as a heterogenous country with strong cultural and religious roots (see chapter 5 Table 5.19 and examples 16, 22). Furthermore, even Italy and Italians (see Table 6.2) – similarly to U.S. citizens – are connected to material processes (see Table 5.21 and 5.24), perform the Actor (see Tables 5.22 and 5.25) and have an active voice type and positive evaluation (see Tables 5.23 and 5.26). However, this strategy is employed by Salvini to legitimise the representation of his strong leadership since the positive representation of Italy and Italians is connected to positive changes caused by his political decisions (see chapter 5 Table 5.28, 5.32 and example 19). Similarly, Trump achieves a similar result through the source domains of building and nature (see Table 6.4) that he employs to describe the bright future of the United States and American people under his leadership (see chapter 4 Tabe 4.17 and examples 10, 12). The representation of the heartland as a building (see Tables 4.17 and Table 5.19) is useful to both politicians to legitimise their leadership and to represent themselves as saviours and warriors as well. Trump describes the United States as a building that has been damaged by the corrupt establishment but that can be restored by himself (see chapter 4

example 10), while Salvini uses this source domain to depict Italy as a home that he will protect through his strict policies (see chapter 5 examples 14 and 36).

T	T.	G 1 · ·
Target type	Trump	Salvini
Trump	-	-
Trump administration	-	-
The United States	83% (5)	-
Salvini	-	-
Lega	-	25% (1)
Italy	-	25% (1)
Europe	17% (1)	-
Immigrants	- ' '	50% (2)
and refugees		

Table 6.4 Nature source domain comparison

#### 6.3.3 Otherness

Trump and Salvini share some similarities in the representation of otherness, as they both identify the corrupt establishment – embodied by the elite and the media –, immigrants and refugees as their enemies.

Firstly, as shown by the keywords under the label opposition (see Tables 4.40, 4.45, 5.38, and 5.43), both politicians attack the corrupt political elite. On the one hand, Donald Trump focuses his attention primarily on Hillary Clinton who was not only his main opponent during the presidential campaign of 2016, but who also symbolises and embodies the corrupt establishment. Consequently, Trump puts massive effort into the delegitimation of Clinton describing her as a dishonest and corrupt politicians (see Tables 4.40 and 4.45) who only cares about her interests and the interests of her donors (see chapter 4 example 5) and who is unable to properly run the United States and to fix the problem of the country, especially concerning economic and immigration policies (see chapter 4 Tables 4.40, 4.45, examples 33, 35, 38, 40, 44, and Figures 4.1, 4.2). Indeed, he often combines the delegitimation of Clinton with his selflegitimisation (see chapter 4 examples 5 and 35). On the other hand, Salvini focuses his attention on a wider range of political opponents (see Tables 5.38 and 5.43) because he competed with more than one political party during the electoral campaign of 2018. More precisely, Salvini attacks Luigi Di Maio leader of Movimento 5 Stelle – before Di Maio became his ally (see Table 5.11) during their coalition government -, Partito Democratico (the Democratic Party), politicians such as Matteo Renzi and Laura Boldrini, and members of previous governments such as Elsa Fornero (who was part of Monti's technocratic government). Moreover, Salvini considers Europe as part of the corrupt elite because it is an institution that imposes disadvantaging economic and immigration policies to Italy (see chapter 5 example 9, 10, and 29), intrudes in Italy's domestic policy (see chapter 5 examples 12 and

30) and supports values in contrast with the far-right populist agenda (e.g. LGBTQ+community's civil rights. See chapter 5 example 2).

Secondly, Trump and Salvini depict the media as part of the corrupt establishment since media censor and disadvantage them in order to support and protect their political opponents that are part of the same corrupt system. For this reason, both Trump and Salvini employ the dishonest topos (see chapter 4 Tables 4.38, 4.41, 4.42, 4.46, 4.47, 4.48, 4.49 and examples 22, 23, 24, and 25; chapter 5 Tables 5.36, 5.39, 5.40, 5.41, 5.44, 5.45, 5.46 and examples 23 and 24). Table 4.9 highlights that Trump's attacks to the media are more pervasive on Twitter in comparison to Salvini's attacks (see Table 5.37). Nevertheless, Salvini's attacks are harsh as well, focusing on journalists and intellectuals (see chapter 5 Table 5.46 and examples 24, 25). In both cases this strategy is useful to represent themselves as victims and saviours. Trump implicitly represents himself as a victim of a witch hunt perpetrated by the media (especially concerning his alleged Russian ties during the electoral campaign. See Table 4.43), while Salvini explicitly describes himself as a victim (see Table 6.3) of the system (see chapter 5 Tables 5.39. 5.40, 5.45, 5.46 and example 8). As a result, they present themselves as the reliable leaders who speak the truth in contrast with the media that just spread fake news (see chapter 4 Tables 4.42, 4.47, 4.49 and example 24; chapter 5 Tables 5.39, 5.40, 4.41, 5.44. 5.45 and 5.46). Consequently, these strategies aim to discredit the reliability of the media and, at the same time, to support the representation of Trump and Salvini as saviours who will fight to protect the people from this corrupt system (see chapter 4 example 25 and chapter 5 example 35).

Thirdly, immigrants and refugees are represented by both Trump and Salvini as the dangerous other through several strategies such as the danger, threat and fear (see Tables 4.70, 4.76, 4.85, 4.91, 5.61, 5.67, and 5.80), the invasion (see Tables 4.70 4.77, 5.61, 5.68, and 5.81) and the burden *topoi* (see Tables 4.70, 4.86, 5.61, 5.70, and 5.82). As it possible to notice from Table 6.5, these *topoi* are used with different percentages. According to the comparative analysis, Trump (76%) uses the DTF *topos* more than Salvini (38%), while Salvini employs more the invasion (22%) and burden (25%) *topoi* in comparison to Trump (invasion 15% and burden 9%). The quantitative part of the analyses (in chapters 4 and 5) confirms that the *topoi* of burden (see Tables 4.86, 5.70, and 5.82) and invasion (see Tables 5.68 and 5.81) are more pervasive in Salvini's discourse; however it also reveals that Salvini massively employs – especially in tweets – the DTF *topos* as well (see Tables 4.76, 4.85, 5.67, and 5.80).

In addition to *topoi*, immigrants' and refugees' dangerousness is supported by representational strategies such as the association to crime and terrorism, specification, and opposition.

Topoi type	Trump	Salvini
DTF	76% (26)	38% (30)
Invasion	15% (5)	22% (17)
Burden	9% (3)	25% (20)
Victim	- ` ´	15% (12)

Table 6.5 Immigrants and refugees' topoi comparison

R.S. type	Trump	Salvini
Opposition	9% (6)	15% (14)
Aggregation	29% (19)	40% (36)
Genericisation	11% (7)	11% (10)
Specification	-	1% (1)
Suppression	5% (3)	-
Crime/terrorism	46% (30)	33% (30)

Table 6.6 Immigrants and refugees' representational strategies comparison

The association to crime and terrorism (see chapter 4 Tables 4.71, 4.81, 4.83, 4.89 and examples 39, 40; chapter 5 Table 5.62 and examples 37, 38, 39) is employed similarly by both politicians (see Table 6.6). Nonetheless, some difference emerge; the specification strategy is employed only by Salvini (see also chapter 5 Table 5.62 and example 39). Moreover, the opposition strategy is used more by Salvini (15%) than Trump (9%) (see Table 6.6). In this regard, it is important to mention the different sub-types of the opposition strategy. As we can see from Table 6.7, Trump (8%) uses more than Salvini (3%) the common type of opposition strategy concerning cultural and religious incompatibilities (see chapter 4 Table 4.71 and example 36; chapter 5 Table 5.62 and example 36). Furthermore, Salvini (10%) employs more often than Trump (1%) the sub-type strategy that opposes immigrants and refugees to suffering citizens (see chapter 4 example 37 and chapter 5 example 35). Lastly, Salvini (2%) is the only one who compares (illegal) immigrants who arrive in Italy to Italian immigrants forced to leave their country (see Table 6.7 and chapter 5 example 18) highlighting the reverse racism narrative (see chapter 5 Tables 5.27, 5.30, 5.35 and examples 17, 35).

Opposition type	Trump	Salvini
Culture/religion	8% (5)	3% (3)
Suffering	1%(1)	10% (9)
Italian immigration	-	2% (2)

Table 6.7 Opposition sub-types comparison

The representation of immigrants and refugees as dangerous social actors is supported by transitivity as well. Tables 6.8, 6.9, 6.10 and 6.11 show how both Trump and Salvini represent them as Actors (Trump 53% and Salvini 58%) associated mainly to material processes (Trump 86% and Salvini 85%), with active voice type (Trump 58% and Salvini 92%) and negative

evaluation (Trump 86% and Salvini 53%) (see also chapter 4 Tables 4.72, 4.73, 4.74 and chapter 5 Tables 5.63, 5.64, 5.65).

Participant types <sup>101</sup>	Trump	Salvini
Actor	54% (23)	58% (80)
Goal	35% (15)	24% (34)
Recipient	-	1% (1)
Client	-	1% (2)
Carrier	5% (2)	1% (1)
Identified	2% (1)	4% (5)
Identifier	-	3% (4)
Possessor	2% (1)	3% (4)
Senser	2% (1)	4% (5)
Sayer	-	1% (1)

Table 6.8 Immigrants and refugees' participant type comparison

Process type <sup>102</sup>	Trump	Salvini
Material	86% (37)	85% (117)
Relational	9% (4)	10% (14)
Mental	5% (2)	4% (5)
Verbal	- ` `	1% (1)

Table 6.9 Immigrants and refugees' processes comparison

Voice type	Trump	Salvini
Active	58% (25)	92% (126)
Passive	40% (17)	6% (8)
Non applicable voice	2% (1)	2% (3)

Table 6.10 Immigrants and refugees' voice type comparison

Evaluation type	Trump	Salvini
Positive	12% (5)	16% (22)
Negative	86% (37)	53% (73)
Neutral	2% (1)	31% (42)

Table 6.11 Immigrants and refugees' evaluation comparison

Table 6.11 shows that sometimes Trump and Salvini associate immigrants and refugees to positive evaluation as well. We should specify that this positive evaluation is actually connected to the consequence of Trump and Salvini strict immigration policies that impact on immigrants and refugees' future actions (see chapter 4 example 36 and chapter 5 examples 39, 40). Moreover, immigrants and refugees are strategically dehumanised to avoid the possibility that U.S. and Italian citizens can empathise with them. In order to achieve this aim, Trump and Salvini employ metaphorical representations (see Table 6.12) and some representational strategies such as aggregation, genericisation and suppression (see Table 6). For what concerns

The Table shows just the participant types performed by immigrants and refugees. The empty categories – that is possible to observe in chapter 3 section 3.2.1.4 Figure 3.7 – have been omitted.

The Table shows just the process types performed by immigrants and refugees. The empty categories – that is possible to observe in chapter 3 section 3.2.1.4 Figure 3.4 – have been omitted.

metaphors, Trump uses just the source domain of water (see Table 4.69). The quantitative approach reveals that Salvini uses the source domain of water (section 5.5.2.2) as well but he is more focused on the source domain of object and merchandise (see Table 5.60).

Source domain type	Trump	Salvini
Object/merchandise	-	78% (7)
Nature	-	22% (2)
Water	100% (1)	-

Table 6.12 Immigrants and refugees' source domains comparison

The dehumanisation of immigrants and refugees is also achieved by both politicians through the aggregation (Trump 29% and Salvini 40%) and the genericisation (Trump 11% and Salvini 11%) strategies, while Trump is the only one who employs the suppression strategy (5%) (see Table 6.6). The aggregation strategy dehumanises these social actors reducing them to numbers, statistics, and percentages (see chapter 4 example 38 and chapter 5 example 37), the suppression erases their existence as subjects (see chapter 4 example 41), and the genericisation strategy deprives them from their individual identity and, at the same time, contributes to their representation as threats (especially when their identity is only characterised by their ethnicity. See chapter 4 Tables 4.71, 4.82, 4.83, 4.90, 4.91 and examples 39, 40; chapter 5 Tables 5.62, 5.74, 5.75, 5.77, 5.88, 5.90 and examples 38, 40).

It is important to mention that Salvini is the only one who portrays – strategically – legal immigrants and especially refugees as victims (see Table 6.3) through the *topos* of the victim (see Tables 5.35, 5.61, 5.72, and 5.78) and the source domain of nature (see Table 5.60 and example 32). However, this humanisation is strictly connected to delegitimation of opponents who – according to Salvini – favour immigration (see Table 5.75).

The comparative analysis shows that Trump and Salvini tend to combine the same strategies to describe immigrants and refugees as the dangerous other. Nevertheless, these strategies are used differently because there are some historical, social, and cultural differences between the United States and Italy. Trump is more systematic in the employment of the DTF *topos*, the association to crime and terrorism and the opposition strategy (especially the religious and cultural sub-type) since it is easier for him to trigger fear in U.S citizens in this way after 9/11. Instead, Salvini employs the DTF *topos* in combination with other ones such as invasion and burden, but also representational strategies such as aggregation and opposition, and the source domain of object and merchandise because not only has Italy witnessed all the terrorist attack after 9/11, but it is also subjected to immigrants' disembarkations. Consequently, Salvini employs more often a wider range of strategies, since immigrants and refugees can embody numerous and multiple types of threats. For instance, they could be potential terrorists (see

Table 5.67), criminals (see chapter 5 example 17, 37, and 39), invaders who want to impose their culture and religion (see chapter 5 example 33 and 36), or people who wants to live at the expense of the Italian people (see chapter 5 examples 18 and 21).

Finally, the representation of immigrants and refugees as the dangerous other is also useful for both populist leaders to support their representation as the saviours who will fight the enemy and save the people through their strict immigration policies. Moreover, this type of representation is achieved through proximization (Cap, 2013) (see section 2.6) that presents immigrants and refugees as close and imminent threats. As a result, strict immigration policies are legitimised by the presence of the dangerous other since it triggers citizens' fear and justify the necessity for populist leaders to act.

# 6.4 Comparing tweets and traditional speeches

This section is dedicated to the comparison of already investigated linguistic strategies in tweets and in traditional speeches. The first part (sections 6.4.1 and 6.4.2) focuses on the individual employment of Trump's and Salvini's strategies, while the second one (section 6.4.3) is dedicated to the comparison between Trump and Salvini. The comparison is limited to categories that have an interpretative relevance.

### 6.4.1 Trump's tweets and traditional speeches

In section 6.1.1 we have explored the self-representation of Trump as a populist leader and the in-group representation of his administration. However, it is necessary to further investigate this representation (and all the following ones in this last section) from a comparative perspective concerning the way the linguistic strategies are used in tweets and in traditional speeches.

The source domain of saviour and warrior is the only one employed in both the metaphorical self-representation of Trump and the representation of his administration (see Tables 4.1, 4.2, 4.12 and 4.16). Nonetheless, it is possible to notice some differences in the employment of this source domain in the Trump Tweet Corpus and the Trump Traditional one. Specifically, Table 4.2 shows that Trump does not use this source domain in the representation of his administration in his Tweet Corpus. Indeed, the quantitative analysis (see Tables 4.12 and 4.16) confirms that Trump is more focused on the representation of himself as a warrior and saviour, especially on Twitter.

	Trump		Administration	
Participant types <sup>103</sup>	TTW TTS		TTW	TTS
Actor	67% (4)	36% (255)	100% (2)	82% (347)
Goal	-	2% (15)	-	2% (8)
Recipient	-	1% (4)	-	-
Carrier	-	6% (44)	-	3% (12)
Identifier	-	1% (8)	-	-
Possessor	33% (2)	2% (10)	-	6% (27)
Senser	-	13% (93)	-	5% (20)
Inducer	-	1% (5)	-	-
Sayer	-	35% (250)	-	1% (7)
Receiver	-	1% (5)	-	1% (1)
Target	-	1% (4)	-	-
Behaver	-	2% (10)	-	-

Table 6.13 Trump and Trump's administration participant types

Transitivity is used similarly as well since both Trump and his administration are connected to material processes (see Tables 4.3 and 4.6), active voice type and positive evaluation (see Tables 4.5 and 4.8). Concerning processes, it is important to mention that Trump uses more types of processes in his self-representation than in his administration's representation (see Tables 4.3. and 4.6). We should also notice that the types of processes associated to both social actors are more varied in the Trump Traditional Corpus (see Tables 4.3. and 4.6).

	Trump		Administration	
	TTW	TTS	TTW	TTS
Active voice	100%(6)	98%(689)	100%(2)	99%
			, ,	(419)
Passive voice	-	1% (12)	-	1% (1)
Non-applicable	-	1% (2)	-	1% (2)
voice				
Positive evaluation	100%(6)	51%(361)	100%(2)	84%(356)
Negative	-	4% (26)	-	2% (9)
evaluation				
Neutral evaluation	-	45%(316)	-	14% (57)

Table 6.14 Trump and Trump's administration voice type and evaluation type

Finally, Tables 6.13 and 6.14 show that the representation of Trump and his administration is less heterogeneous on Twitter concerning participant types (that are strictly connected to the processes. See Tables 4.3. and 4.6), voice-type and evaluation. Specifically, in tweets Trump performs the role of the Actor and Possessor while his administration performs just the Actor. Regarding voice type and evaluation on Twitter, both social actors have exclusively an active voice combined with a positive evaluation.

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The Table shows just the participant types performed by Trump and his administration. The empty categories – that is possible to observe in chapter 3 section 3.2.1.4 Figure 3.7 – have been omitted.

The representation of Trump's heartland involves a rich variety of strategies, as it is possible to observe in section 6.1.2. Trump praises and glorifies his heartland through the saviour and warrior source domain that is employed mainly in the Trump Traditional Corpus (see Tables 4.17, 4.29 and 4.35). At the same time, he victimises the heartland in both corpora through the *topos* of the victim, the war source domain, the source domain and the *topos* of container (see Tables 4.17, 4.18 and 4.27). Furthermore, even the source domains of nature and building – that are both used to indicate the future of the United States and American people under Trump's leadership, while the building one is also employed in the victimisation of the U.S. (see section 6.1.2) – are present in both Trump's corpora.

	U.S.		U.S. citizens	
Participant types	TTW	TTS	TTW	TTS
Actor	-	27% (21)	65% (11)	50% (204)
Goal	50% (1)	35% (27)	6% (1)	4% (17)
Recipient	-	5% (4)	-	1% (4)
Client	-	3% (2)	-	-
Carrier		5% (4)		7% (31)
Identifier	-	4% (3)	-	3% (11)
Possessor	-	5% (4)	6% (1)	13% (55)
Senser	50% (1)	5% (4)	17% (3)	16% (67)
Inducer	-	-	-	1% (1)
Sayer	-	5% (4)	-	3% (12)
Receiver	-	-	-	1% (3)
Behaver	-	-	6% (1)	1% (6)
Existent	-	6% (5)	-	-

Table 6.15 U.S. and U.S. citizens' participant types

	U.S		U.S. o	citizens
	TTW	TTS	TTW	TTS
Active voice	50%(1)	96%(75)	94%(16)	99%(408)
Passive voice	-	4% (3)	-	1% (3)
Non-applicable voice	50%(1)	-	6% (1)	-
Positive evaluation	-	41%(32)	53% (9)	60%(247)
Negative evaluation	50% (1)	38% (30)	12% (2)	19% (79)
Neutral evaluation	50% (1)	21% (16)	35% (6)	21% (85)

Table 6.16 U.S. and U.S. citizens' voice type and evaluation type

Transitivity supports the representation of the United States and the U.S. citizens as both saviours and warriors, and victims (see sections 4.2.1.3 and 6.1.2). Table 6.16 shows the percentages of U.S. and U.S. citizens' positive and negative evaluation that are strictly linked to these types of representation. In addition, the United States and the U.S. citizens are connected to a wider range of processes in Trump Traditional Corpus (see Tables 4.19 and 4.21). Consequently, the U.S. and the U.S. citizens perform a richer variety of participant types in traditional speeches (see Table 6.15).

Trump's representation of otherness is very heterogeneous and involves the employment of different strategies (see section 6.1.3). Firstly, the media are described through the dishonest *topos*. Trump employs this *topos* in both corpora as it is possible to observe in Table 4.38. However, the quantitative analysis reveals that Trump's employment of the dishonest *topos* is more pervasive in his tweets (see Table 4.39) rather than traditional speeches (see Table 4.44). Indeed, even the metaphorical representation of the media's behaviour towards Trump as a witch hunt is present just in the Trump Tweet Corpus (see Table 4.43). Secondly, the representation of Mexico as a hostile neighbour - concerning especially economic matters – is present in both Trump's corpora, as shown mainly through the corpus linguistics approach (see Tables 4.64 and 4.68). Thirdly, the representation of immigrants and refugees is achieved through the combination of different strategies such as topoi, representational strategies and transitivity. Tables 4.70, 4.76, 4.77 and 4.85 show that topoi – specifically DTF, burden and invasion – are similarly employed in the Trump Tweet Corpus and in the Trump Traditional Corpus with the exception of the burden topos that is only used in traditional speeches (see Tables 4.70 and 4.86). Instead, Table 4.71 (see also Tables 4.82 and 4.83) reveals that representational strategies are used similarly in both Trump's Corpora. Nonetheless, the opposition strategy is employed just in traditional speeches while the suppression strategy is present just in tweets. Finally, transitivity supports Trump's negative representation of immigrants and refugees. Table 4.72 shows that immigrants and refugees are associated to different types of processes and with higher percentages in traditional speeches. As a result, the percentages in Tables 4.73 and 4.74 concerning voice type and evaluation are to be considered mainly in relation to traditional speeches.

### 6.4.2 Salvini's tweets and traditional speeches

Salvini – as seen in section 6.2.1– represents himself and his party through the saviour and warrior source domain with similar percentages in both tweets and traditional speeches (see 5.1, 5.2, 5.13, 5.14, 5.17 and 5.18). However, the *Lega* is also described through the source domain of war, religion, nature and water (see Table 5.2) only in the Salvini Traditional Corpus. Moreover, Salvini and the *Lega* are represented as victims through the respective *topos*. In this regard, it is important to specify that this *topos* is used more in Salvini's representation in both Salvini's corpora (see Table 5.3), while it is used in the representation of the *Lega* just in the Salvini Traditional Corpus (see Table 5.4). In addition, transitivity is employed similarly in both the Salvini Tweet Corpus and the Salvini Traditional Corpus since Salvini and the *Lega* are mainly associated to material processes (see Tables 5.5 and 5.8). Consequently, they also

generally perform the Actor (Table 6.17), with active voice type and positive evaluation (Table 6.18). Lastly, Table 6.17 shows that the representation of Salvini and his party – specifically concerning participant-types that are also strictly connected to the association of processes – is more heterogeneous in traditional speeches.

-	Salvini		Lega	
Participant types	STW	STS	STW	STS
Actor	70% (23)	39% (459)	78% (7)	77% (274)
Goal	3% (1)	2% (27)	-	3% (11)
Recipient	-	1% (5)	-	1% (5)
Carrier	3% (1)	6% (69)	-	2% (8)
Identifier	3% (1)	1% (9)	-	1% (1)
Possessor	-	3% (44)	-	5% (19)
Senser	-	19% (222)	-	5% (19)
Inducer	-	1% (8)	-	1% (1)
Sayer	18% (6)	23% (266)	22% (2)	3% (11)
Receiver	3% (1)	2% (22)	-	1% (4)
Behaver	-	2% (24)	-	1% (3)
Existent	-	1% (2)	-	-

Table 6.17 Salvini and Lega's participant types

	Salvini		Lega	
	STW	STS	STW	STS
Active voice	100% (33)	99% (1,156)	100% (9)	99% (354)
Passive voice	-	1% (1)	-	-
Non-applicable voice	-	-	-	1% (2)
Positive evaluation	79% (26)	46% (528)	100% (9)	64% (227)
Negative evaluation	9% (3)	4% (44)	-	4% (13)
Neutral evaluation	12% (4)	50% (585)	-	32% (116)

Table 6.18 Salvini and *Lega*'s voice type and evaluation type

The representation of the heartland and the people is characterised by the victimisation that Salvini achieves through several strategies (see section 6.2.2). Specifically, he uses the source domain and *topos* of container and the building source domain that – as it is possible to observe from Tables 5.19 and 5.20 – are present just in the Salvini Traditional Corpus. Instead, the victim *topos* – strictly connected to the reverse racism narrative – is pervasive in both Salvini's corpora (see Tables 5.20, 5.27, 5.30 and 5.35). Furthermore, transitivity supports the representation of Italy and Italians as victims especially through negative evaluation (see Table, 6. 20 and 5.26). Nevertheless, Italy and Italians are generally connected to material processes (see Tables 5.21 and 5.24); they perform the Actor (see Tables 6.19, 5.22, and 5.25), and have an active voice type together with positive evaluation (see Tables 6.20, 5.23, and 5.26). This type of representation is employed by Salvini not only to praise his heartland made of honest and hardworking people, but also to legitimise his leadership that will improve Italy and Italians' condition. Finally, both Italy and Italians are connected to a richer variety of processes

in the Salvini Traditional Corpus. As a result, they perform a wider variety of participant types (see Table 6.19) with different types of evaluation (see Table 6.20) in traditional speeches.

	Italy		Italian citizens	
Participant types	STW	STS	STW	STS
Actor	50% (3)	60% (22)	67% (4)	55% (49)
Goal	17% (1)	5% (2)	-	8% (7)
Recipient	-	-	-	10% (9)
Client	-	3% (1)	-	1% (1)
Carrier	33% (2)	8% (3)	-	4% (4)
Identifier	-	-	-	3% (3)
Possessor	-	5% (2)	-	9% (8)
Senser	-	16% (6)	33% (2)	3% (3)
Sayer	-	-	-	3% (2)
Receiver	-	-	-	4% (4)
Behaver	-	3% (1)	-	

Table 6.19 Italy and Italians citizens' participant types

	It	aly	Italian citizens	
	STW	STS	STW	STS
Active voice	100%(6)	100%(37)	100%(6)	98%(88)
Passive voice	-	-	-	-
Non-applicable voice	-	-	-	2% (2)
Positive evaluation	50% (3)	68% (25)	67% (4)	37%(34)
Negative evaluation	50% (3)	5% (2)	33% (2)	43%(39)
Neutral evaluation	-	27% (10)	-	20%(17)

Table 6.20 Salvini and *Lega*'s voice type and evaluation type

The dangerous other is represented by Salvini through a wide range of strategies (as already seen in section 6.2.3). Firstly, Salvini employs the dishonest topos to describe the media in both corpora (see Table 5.36). In addition, the quantitative analysis (see Tables 5.37, 5.39, 5.40, 5.41, 5.42, 5.44, 5.45 and 5.46) confirms that this *topos* is used similarly in both tweets and traditional speeches. Secondly, Salvini's Eurosceptic approach is supported by the negative representation of the E.U. achieved mainly through topoi and representational strategies. He describes the European Union as a dictatorship and an absent and useless institution in both corpora (see Tables 5.48 and 5.48). This representation is supported by the war source domain that is present just in the Salvini Traditional Corpus (see Table 5.47). Moreover, the quantitative results (see Tables 5.38, 5.43, 5.53, 5.55, 5.57 and 5.59) show that Salvini's Eurosceptic narrative is employed similarly in his corpora. Lastly, transitivity is crucial in the representation of the European Union as a dictatorship. Indeed, in both Salvini's corpora the E.U. is associated mainly to material processes, to the Actor participant type, to active voice type and negative evaluation (see Tables 5.50, 5.51 and 5.52). Thirdly, immigrants and refugees are described through the combination of several strategies since the immigration topic is particularly pervasive in Salvini's populist discourse (see Tables 5.66 and 5.79). Concerning topoi, Table 5.61 shows that the DTF, invasion, and burden topoi are used similarly in both Salvini's corpora. However, the quantitative analysis (Tables 5.67, 5.68, 5.70, 5.80, 5.8 and 5.82) reveals that the employment of these *topoi* is more pervasive in the Salvini Tweet Corpus. As a result, even the list of keywords under the label security is more considerable in the Salvini Tweet Corpus (see Tables 5. 71 and 5.83). In the same way, Table 5.62 shows that representational strategies linked to immigrants and refugees are used in both Salvini's corpora. We should specify that the suppression strategy is the only one present just in the Salvini Tweet Corpus. Furthermore, transitivity supports the negative representation of immigrants and refugees as social actors who are generally connected to material process in both Salvini's corpora (see Table 5.63). They also mainly perform the Actor with active voice type and negative evaluation (see Tables 5.64 and 5.65). In this regard, it is important to specify that the percentages present in Tables 5.64 and 5.65 have to be considered mainly in relation to traditional speeches since the occurrences of processes in Table 5.63 are higher in the Salvini Traditional Corpus. Finally, we should remember that Salvini employs other strategies to represent strategically immigrants and refugees that are not necessarily employed to describe them as enemies. On the one hand, he dehumanises immigrants through the source domain of water that - according to the quantitative analysis – is present just in the Salvini Tweet Corpus, and through the object and merchandise source domain that is employed in both Salvini's corpora (see Table 5.60). On the other hand, Salvini strategically represents these social actors (especially refugees) as victims at his own advantage (see sections 5.5. and 6.2.3). Specifically, Salvini uses the victim topos in both corpora (see Tables 5.35, 5.61 and 5.78) and the nature source domain just in the Salvini Traditional Corpus (see Table 5.60).

### 6.4.3 Comparing Trump's and Salvini's tweets and traditional speeches

Although both Trump and Salvini employ the saviour and warrior source domain in their self-representation as populist leaders and in the representation of their administration and party, we should notice that Trump does not often use this source domain in the description of his administration in his Tweet Corpus (see Tables 4.2 and 4.12) probably because he is more focused on his self-representation as strong man of action. In addition, Salvini is the only one who explicitly represents himself and his party as victims in both tweets and traditional speeches. Concerning transitivity, Salvini and the *Lega* are generally connected to more types of processes in comparison to Trump and his administration (see Tables 4.3, 4.6, 5.5, and 5.8). It is also possible to notice that in both cases the number of processes is higher in Trump's and Salvini's traditional corpora. Consequently, all social actors perform a wider range of

participant types in traditional speeches (see Tables 6.13 and 6.17). In the same way, these social actors are also connected to a richer variety of voice types and evaluation (see Tables 6.14 and 6.18) in traditional corpora. In this regard, it is important to highlight that Salvini is the only one who has a heterogeneous evaluation even in tweets (see Table 6.18). The reason why is attributable to his explicit self-victimisation that is pervasive in both tweets and traditional speeches (see Tables 5.3 and 5.12).

Trump and Salvini depict their heartlands and the people as victims. These politicians employ several strategies to achieve this aim. Specifically, they both use the source domain and the *topos* of container and the *topos* of the victim. They employ the source domain and the *topos* of container almost exclusively in their traditional corpora (see Tables 4.17, 4.18, 5.19 and 5.20), while the victim *topos* is clearly employed in both the Trump Tweet Corpus and the Salvini Tweet Corpus (see Tables 4.18, 4.30, 4.37, 5.20, 5.27, 5.30, and 5.35). Regarding transitivity, we should mention that even in this case the social actors considered are associated to more types of processes in traditional corpora (see Tables 4.19, 4.22, 5.21, and 5.24). Even the participant types, the voice types, and the evaluation are generally less heterogeneous in tweets (see Tables 6.15, 6.16, 6.19, 6.20). However, U.S. citizens have higher percentages in both Trump's corpora probably because they are depicted not only as victims but they are also praised as active saviours and warriors (see section 6.1.2). Indeed, U.S. citizens are connected to more material processes (especially in traditional speeches. See Tables 6.15 and 6.19), to higher percentages of active voice type and positive evaluation (see Tables 6.16 and 6.20).

Concerning the representation of otherness I focus – following an interpretative relevance – only on media, immigrants, and refugees.

On the one hand, Donald Trump and Matteo Salvini attack the media in a very similar way employing in their corpora the dishonest *topos* (see Tables 4.38 and 5.37). Nevertheless, the analysis – particularly the quantitative part – reveals that Trump (see Tables 4.38, 4.43, 4.44 and 4.45) employs this *topos* and attacks the media more than Salvini (see Tables 5.36, 5.37 and 5.42), especially in his Tweet Corpus (see Table 4.39).

On the other hand, immigrants and refugees are dehumanised by both politicians through the water source domain but with low percentages (see Table 4.69 and section 5.5.2.2). Moreover, Salvini particularly employs – qualitatively and quantitatively – strategies in order to make immigrants and refugees perceived as dangerous and imminent threats. Firstly, in both tweets and traditional speeches Salvini (see Tables 5.61, 5.67, 5.68, 5.70, 5.80, 5.81 and 5.82) employs massively *topoi* – such as DTF, invasion and burden – to describe these social actors in comparison to Trump (see Tables 5.70, 5.76, 5.77, 5.85 and 5.86). Secondly, Salvini (see

Table 5.62) employs more representational strategies – such as the opposition, the aggregation and the genericisation – than Trump (see Table 4.71) in both corpora. In this regard, we should mention that in terms of occurrences – according to the qualitative part of the analysis – they both use the association to crime and terrorism (see Tables 4.71 and 5.62) similarly. Thirdly, Salvini's massive representation of immigrants and refugees as imminent threats is supported by transitivity. Specifically, Salvini associates to these social actors more processes (especially material processes. See Table 5.63), the role of the Actor (see Table 5.64), active voice type and negative evaluation (see Table 5.65) in comparison to Trump (see Tables 4.72, 4.73, 4.74, 6.8., 6.9, 6.10 and 6.11) in both tweets and traditional speeches. However, they similarly associate more processes to immigrants and refugees in their traditional corpora. Consequently, even the occurrences and percentages concerning participant types, voice type and evaluation are to be considered mainly in relation to traditional speeches (see Tables 4.73, 4.74, 5.64, 5.65, 6.8., 6.9, 6.10, and 6.11). Finally, it is important to mention that the pervasiveness of these strategies in Salvini's corpora is probably due to the fact that Salvini employs more commonly the topic of immigration – and he is also able to strategically intertwine this topic to other ones - than Trump (see Tables 4.75, 4.84, 5.66, and 5.79).

# **CONCLUSION**

The main aim of this dissertation has been to analyse and to compare the far-right populist discourse of Donald J. Trump and Matteo Salvini – with a particular focus on discourses delivered on Twitter – through a combined approach that involves both Critical Discourse Analysis and Corpus Linguistics. The employment of this type of methodology is clearly not a random choice since I wanted to take advantage of the positive outcomes of qualitative and quantitative analyses' integration.

This work aimed to answer two main research questions (section 3.2.3) that were the at the centre of the linguistic analyses carried out in chapters 4, 5, and 6. Specifically, the first research question focuses on the identification of similarities and differences between Donald J. Trump's and Matteo Salvini's populist discourses. Instead, the second research question is concerned with the evolution of populist discourse comparing tweets and traditional speeches. This section provides concise but complete answers to these research question, as an outcome of the detailed and in depth (comparative) analysis carried out in chapter 6.

Concerning the first research question, chapter 6 has shown that Trump and Salvini share many common grounds regarding the realisation of their populist discourses employing specific linguistic strategies. These strategies follow the same populist pattern that gravitates around the dichotomic opposition *us vs. them*, foregrounding the role of the strong populist leader. Moreover, this dichotomy evidently enhances the polarisation of political discourses that can lead to negative and concrete actions (see sections 1.5.5 on Donald J. Trump and 1.6.5 on Matteo Salvini). In addition, not only has the comparative analysis revealed the presence of some differences in the employment of these strategies but also the existence of strategies that the two politicians do not share. All the highlighted differences can be attributed to the politicians' different social, cultural, and political background (e.g. Trump is an entrepreneur populist leader, while Salvini has always been a politician. See chapter 1), since the United States and Italy share some values and traditions – being part of *the west* – but they are two different countries with geographical, social, cultural, and religious peculiarities.

First of all, both politicians share common narratives in their self-representation as populist leaders. Specifically, they focus primarily on their metaphorical representation as saviours and warriors to depict themselves as the only ones capable of saving, protecting, and fighting for the people embodying the true *vox populi*. This linguistic strategy is part of a broader schema that contributes to their representation as strong, authoritarian, and active

populist leaders. Indeed, their representation as commanders in chief is supported by their strong, positive and active agency. Furthermore, even their self-representation as victims – of the overall elitist system – contributes to their portrayal as strong, reliable and tireless men because they endure all the attacks and never give in order to fulfil their promises. Both Trump and Salvini strategically extend all the strategies – already used and employed in their self-representation – to their administration/party to legitimise their leadership and to build a better option in comparison to their elitist rivals.

Secondly, the victimisation of their heartlands is crucial to represent the people as vulnerable to various threats (e.g. the elite and immigrants), and to further legitimise their leadership (especially the strict policies they support). Despite these similarities, there are also some differences, mainly connected to Trump's and Salvini's political and cultural backgrounds. For instance, Salvini does not describe Italy – his heartland – as a nation because the *Lega* (formerly *Lega Nord*) has a history of independent and secessionist claims. For the same reason, he praises Italy and Italians emphasising their regional peculiarities and richness. On the other hand, Trump is more focused on the (self-)praising of the United States and the American people concerning their role as warriors and saviours during and after the Second World War.

Thirdly, otherness is particularly relevant in both discourses since it enhances the ingroup identity of the people who live in the heartland under their leadership. For both politicians, otherness is represented by the corrupt elite, the dishonest media, and immigrants and refugees. Clearly, the elite is embodied by different social actors. Trump focuses primarily on Hillary Clinton, while Salvini attacks various politicians with a particular focus on left-wing ones. Consequently, Trump's and Salvini's delegitimising strategies are different because they rely on different (political) contexts. However, it is possible to identify a common attitude concerning the aggressive language employed to delegitimise the enemies, and the populist narratives involving corruption and incompetence. Trump tends to be aggressive towards Clinton with harsh and personal attacks, while Salvini focuses on incompetence as well as on the values supported by the elite (e.g. left-wing politicians and the E.U.) that contrast his farright populist agenda (e.g. LGBTQ+ rights).

For both Trump and Salvini, the media represent a dishonest enemy that censors them, spreads fake news, and disadvantages them in order to support and protect their political opponents, who are part and parcel of the same corrupt establishment. It is interesting to notice that even the strategic way in which Trump and Salvini represent the media is useful to support their representations as saviours. Indeed, Trump (implicitly) and Salvini (explicitly) represent

themselves as the victims of this corrupt establishment, victims that – despite the attacks – resist and continue to fight with the aim of disseminating their truth and saving the people's will thanks to their strength and reliability.

In addition to the elite and the media, otherness is perfectly embodied by immigrants and refugees. In this regard, the concept of proximization (see section 2.6) is particularly relevant in Trump's and Salvini's populist discourses since the representation of immigrants and refugees as potential and dangerous threats is achieved through strategies (e.g. the invasion topos) that make people perceive these social actors closer than they actually are, both in space and time. This clearly contributes to trigger fear and to legitimise strict policies, as well as the representation of these leaders as saviours. Specifically, Trump and Salvini share the employment of a wide range of strategies that are useful to dehumanise and to reduce immigrants and refugees to dangerous threats (e.g. metaphorical representations, topoi, representational strategies and transitivity). All these strategies are used by the two politicians in a slighter different way, accountable for the historical, social, cultural, and especially geographical differences between the United States and Italy. What happened during 9/11 was undoubtedly a turning point that has had a particular influence in the way otherness – especially Islamic immigrants/refugees – is represented. This explains why Trump is more systematic in combining some strategies (e.g. DTF topos, the association to crime and terrorism and the opposition strategy, especially the religious and cultural sub-type) aiming to highlight a possible terrorist threat. Salvini, on the other hand, often combines a wider range of strategies (e.g. DTF, invasion and burden *topoi*, opposition strategy, object and merchandise source domain etc.) because Italy has witnessed 9/11 (and all the following attacks) but it has also a different geographical position that makes it particularly vulnerable to the immigration phenomenon (specifically to immigrants' disembarkations). It is important to mention that there are additional dangerous others – that they do not share – connected to their different geographical and political contexts. On the one hand, Donald Trump describes Mexico as a dangerous and unfair neighbour (see section 4.5) linked to both criminal (e.g. criminal cartels and illegal immigration) and economic matters (e.g. delocalisation). On the other hand, Salvini's additional (elitist) enemy is the European Union represented as a dictatorial – but also as useless and absent - institution (see section 5.4) that imposes disadvantaging policies, especially in terms of economic and immigration matters.

Finally, all the strategies employed by Trump and Salvini support – even indirectly – their reliability as leaders. These strategies – as already mentioned at the beginning of this section – follow a simple structure concerning populist cornerstones (see chapter 1) such as the

omnipresent dichotomy *us* (the people) *vs. them* (elite, media, immigrants, and refugees etc.) and their validations as strong and authentic leaders. Specifically, the results of the analysis highlight that both Trump and Salvini are always focused on their self-legitimation. These politicians portray themselves as the embodiment of people's will and as the only ones who will fight and save this will. People should rely on them because they are resolute leaders who are able to solve every problem providing and delivering (simple) solutions.

Regarding the second research question, the analyses in chapters 4, 5 and 6 reveal that the populist discourse has not changed but it has just adapted to social media such as Twitter. As already mentioned (see section 1.4.1) populist discourse seems to have a perfect synergy with Twitter since it suits the simple, aggressive, and repetitive populist style of language. Twitter's limitation of characters does not represent a problem to populist politicians who tend to provide simple (and usually ureal) solutions to complex problems. For this reason, it is not necessary for populist politicians to provide additional argumentations because they usually rely on polarised schemata such as the common us vs. them dichotomy. Consequently, the individual and comparative analyses carried out in this dissertation show that there are no particular differences in the employment of linguistic strategies in tweets and traditional speeches from an ideological point of view. Nonetheless, it is undeniable that there are differences due to the limitation of characters which is the main peculiarity and constrain of Twitter. More precisely, almost all the linguistic strategies employed by Trump and Salvini count more occurrences and are generally more variegated in traditional speeches. This is particularly evident in the Tables dedicated to processes; indeed, in the Trump Traditional Corpus and in the Salvini Traditional Corpus there is generally a wider processes' variety and more occurrences connected to different social actors. It is interesting to notice how this happens despite the fact that both the Trump Tweet Corpus and the Salvini Tweet Corpus are bigger than the Trump Traditional Corpus and the Salvini Traditional Corpus (see section 3.1). This confirms precisely that the main difference relies on the possibility to disseminate simple, concise, powerful and effective messages on Twitter in a particularly successful manner. However, it is important to underline that this does not mean that populist politicians do not provide argumentations or reasoning at all. These leaders present simple, repetitive and according to them – common sense argumentations when they have enough time and space to do that, for instance when they deliver a speech. As a result, it is evident that not only has populist discourse easily adapted to Twitter (and other social media) but it is also capable of exploiting the peculiarities and constrains of this social network.

This dissertation tries to be a contribution in the study of populism paying particular attention to American and Italian far-right populist discourses. Specifically, the comparison among Donald J. Trump's and Matteo Salvini's populist discourses aimed to underline the presence of common populist features and to understand how these features are influenced and shaped by context that is a crucial key factor in making populism a heterogeneous phenomenon. Finally, this work also aimed to raise awareness about the language used by populist leaders and the possible negative consequences of this type of employment. The analysis carried out in this dissertation has shown that both Trump and Salvini use a repetitive, dehumanising, and aggressive style of communication. They employ a wide variety of strategies in order to dehumanise specific social actors spreading anger, fear and suspicion. In addition, their aggressivity is particularly visible in their personal attacks to political opponents and the media. Language is a mean of social action. Consequently, we should not underestimate the concrete consequences of far-right populist discourse that disseminates endlessly anger, fear and hate.

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## APPENDIX A KEYWORD LIST OF THE TRUMP TWEET CORPUS

Hillary	Keyword	Score	Freq	Ref freq	Rel freq	Rel ref freq
crooked         107.470         66         441         1328.128         2.451           Trump         82.400         137         4243         2756.872         23.579           fake         73.250         97         3020         1951.946         16.783           Obamacare         69.590         71         1921         1428.744         10.675           dems         62.150         36         327         724.434         1.817           Mclania         53.200         26         4         523.202         0.022           Clinton         52.600         139         7804         2797.118         43.368           dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.800         21         249         422.586         1384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194						
Trump         82.400         137         4243         2756.872         23.579           fake         73.250         97         3020         1951.946         16.783           Obamacare         69.590         71         1921         1428.744         10.675           dems         62.150         36         327         724.434         1.817           Mclania         53.200         26         4         523.202         0.022           Clinton         52.600         139         7804         2797.118         43.368           dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.384           repeal         33.433         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556 <td>•</td> <td></td> <td></td> <td></td> <td></td> <td></td>	•					
fake         73,250         97         3020         1951,946         16.783           Obamacare         69,590         71         1921         1428,744         10.678           dems         62,150         36         327         724,434         1.817           Melania         53,200         26         4         523,202         0.022           Clinton         52,600         139         7804         2797,118         43,868           dishonest         42,680         25         364         503,079         2.023           Comey         38,410         20         133         402,463         0.739           thank         38,250         250         21912         5030,788         121,769           Pence         38,000         21         249         422,586         138           repeal         33,430         35         2046         704,310         11,370           poll         29,020         69         6873         1388,498         38,194           denc         28,730         16         280         321,970         1.556           phony         28,440         17         428         342,094         2.378					2756.872	
Obamacare dems         69.590         71         1921         1428.744         10.675           dems         62.150         36         327         724.434         1.817           Melania         53.200         26         4         523.202         0.022           Clinton         52.600         139         7804         2797.118         43.368           dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dne         28.730         16         280         321.970         1.556           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         252.07     <						
dems         62.150         36         327         724.434         1.817           Melania         53.200         26         4         533.202         0.022           Clinton         52.600         139         7804         2797.118         43.368           dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         137           den         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.623           dem         27.890         17         472         342.094         2.623           dem         27.890         17         472         342.094         2.623           <						
Melania         53.200         26         4         523.202         0.022           Clinton         52.600         139         7804         2797.118         43.368           dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.348           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         1.067						
Clinton         52.600         139         7804         2797.118         43.368           dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           Pence         38.000         21         249         422.586         1.384           Pence         38.000         21         249         422.586         1.384           poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.378           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31859           Kaine         25.420         13         123         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844						
dishonest         42.680         25         364         503.079         2.023           Comey         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.378           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         0.684           Podesta         23.10         12         142         21.478         0.789						
Comey thank         38.410         20         133         402.463         0.739           thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dne         28.730         16         280         321.970         1.556           dem         27.890         17         472         342.094         2.378           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844 <tr< td=""><td></td><td></td><td></td><td></td><td></td><td></td></tr<>						
thank         38.250         250         21912         5030.788         121.769           Pence         38.000         21         249         422.586         1.384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.623           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         819         1247.636         45.119						
Pence         38.000         21         249         422.586         1.384           repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.378           dem         27.890         17         472         342.094         2.378           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119 <tr< td=""><td></td><td></td><td></td><td></td><td></td><td></td></tr<>						
repeal         33.430         35         2046         704.310         11.370           poll         29.020         69         6873         1388.498         38.194           dne         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.378           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345 <tr< td=""><td></td><td></td><td></td><td></td><td></td><td></td></tr<>						
poll         29.020         69         6873         1388.498         38.194           dnc         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.378           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.342           Donald         21.890         29         3081         583.571         17.122 <tr< td=""><td></td><td></td><td></td><td></td><td></td><td></td></tr<>						
dne         28.730         16         280         321.970         1.556           phony         28.440         17         428         342.094         2.378           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726 <tr< td=""><td>-</td><td></td><td></td><td></td><td></td><td></td></tr<>	-					
phony dem         28.440         17         428         342.094         2.378           dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089						
dem         27.890         17         472         342.094         2.623           democrats         26.000         45         4536         905.542         25.207           rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         10.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           bi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           terrible         18.520         27         3578         543.325         19.84						
democrats         26,000         45         4536         905.542         25.207           rally         25,720         53         5733         1066.527         31.859           Kaine         25,420         13         123         261.601         0.684           wh         24,540         13         192         261.601         1.067           tonight         23,410         54         6630         1086.650         36.844           Podesta         23,310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.						
rally         25.720         53         5733         1066.527         31.859           Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773<						
Kaine         25.420         13         123         261.601         0.684           wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564 <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>						
wh         24.540         13         192         261.601         1.067           tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.990         12         878         241.478         4.879						
tonight         23.410         54         6630         1086.650         36.844           Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         3.55						
Podesta         23.310         12         142         241.478         0.789           healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.990         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.95						
healthcare         22.820         62         8119         1247.636         45.119           fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.490         29         5094         583.571         2						
fbi         22.790         35         3841         704.310         21.345           Donald         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.990         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308						
Donald badly         21.890         29         3081         583.571         17.122           badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         <						
badly         21.760         23         2110         462.833         11.726           congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355 <t< td=""><td>Donald</td><td></td><td></td><td></td><td></td><td></td></t<>	Donald					
congratulation         21.730         32         3615         643.941         20.089           tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.030         11         1168         221.355						
tomorrow         19.700         57         8769         1147.020         48.731           terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.4	•					
terrible         18.520         27         3578         543.325         19.884           Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127	•					
Schumer         17.940         10         319         201.232         1.773           witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127.559           vote         13.700         120         30052         2414.778         167	terrible					
witch         16.970         16         1721         321.970         9.564           optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127.559           vote         13.700         120         30052         2414.778         167.004           honor         13.680         69         16597         1388.498						
optimism         16.900         12         878         241.478         4.879           abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127.559           vote         13.700         120         30052         2414.778         167.004           honor         13.680         69         16597         1388.498         92.232           apologize         13.660         13         1778         261.601		16.970				
abe         16.320         10         530         201.232         2.945           Russia         16.190         59         11509         1187.266         63.958           wikileaks         15.590         10         639         201.232         3.551           wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127.559           vote         13.700         120         30052         2414.778         167.004           honor         13.680         69         16597         1388.498         92.232           apologize         13.660         13         1778         261.601         9.881           rig         12.630         16         2929         321.970 <td< td=""><td>optimism</td><td>16.900</td><td>12</td><td>878</td><td></td><td>4.879</td></td<>	optimism	16.900	12	878		4.879
Russia       16.190       59       11509       1187.266       63.958         wikileaks       15.590       10       639       201.232       3.551         wow       15.490       29       5094       583.571       28.308         republicans       15.490       26       4393       523.202       24.413         unbelievable       15.160       11       947       221.355       5.263         classified       14.330       12       1358       241.478       7.547         Bernie       14.030       11       1168       221.355       6.491         election       13.970       95       22954       1911.700       127.559         vote       13.700       120       30052       2414.778       167.004         honor       13.680       69       16597       1388.498       92.232         apologize       13.660       13       1778       261.601       9.881         rig       12.630       16       2929       321.970       16.277	•	16.320	10	530	201.232	2.945
wow         15.490         29         5094         583.571         28.308           republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127.559           vote         13.700         120         30052         2414.778         167.004           honor         13.680         69         16597         1388.498         92.232           apologize         13.660         13         1778         261.601         9.881           rig         12.630         16         2929         321.970         16.277						
republicans         15.490         26         4393         523.202         24.413           unbelievable         15.160         11         947         221.355         5.263           classified         14.330         12         1358         241.478         7.547           Bernie         14.030         11         1168         221.355         6.491           election         13.970         95         22954         1911.700         127.559           vote         13.700         120         30052         2414.778         167.004           honor         13.680         69         16597         1388.498         92.232           apologize         13.660         13         1778         261.601         9.881           rig         12.630         16         2929         321.970         16.277	wikileaks	15.590	10	639	201.232	3.551
unbelievable classified       15.160       11       947       221.355       5.263         classified       14.330       12       1358       241.478       7.547         Bernie       14.030       11       1168       221.355       6.491         election       13.970       95       22954       1911.700       127.559         vote       13.700       120       30052       2414.778       167.004         honor       13.680       69       16597       1388.498       92.232         apologize       13.660       13       1778       261.601       9.881         rig       12.630       16       2929       321.970       16.277	wow	15.490	29	5094	583.571	28.308
unbelievable classified       15.160       11       947       221.355       5.263         classified       14.330       12       1358       241.478       7.547         Bernie       14.030       11       1168       221.355       6.491         election       13.970       95       22954       1911.700       127.559         vote       13.700       120       30052       2414.778       167.004         honor       13.680       69       16597       1388.498       92.232         apologize       13.660       13       1778       261.601       9.881         rig       12.630       16       2929       321.970       16.277	republicans	15.490	26	4393	523.202	24.413
Bernie       14.030       11       1168       221.355       6.491         election       13.970       95       22954       1911.700       127.559         vote       13.700       120       30052       2414.778       167.004         honor       13.680       69       16597       1388.498       92.232         apologize       13.660       13       1778       261.601       9.881         rig       12.630       16       2929       321.970       16.277		15.160	11	947	221.355	5.263
election       13.970       95       22954       1911.700       127.559         vote       13.700       120       30052       2414.778       167.004         honor       13.680       69       16597       1388.498       92.232         apologize       13.660       13       1778       261.601       9.881         rig       12.630       16       2929       321.970       16.277	classified	14.330	12	1358	241.478	7.547
vote     13.700     120     30052     2414.778     167.004       honor     13.680     69     16597     1388.498     92.232       apologize     13.660     13     1778     261.601     9.881       rig     12.630     16     2929     321.970     16.277	Bernie	14.030	11	1168	221.355	6.491
honor     13.680     69     16597     1388.498     92.232       apologize     13.660     13     1778     261.601     9.881       rig     12.630     16     2929     321.970     16.277	election	13.970	95	22954	1911.700	127.559
apologize 13.660 13 1778 261.601 9.881 rig 12.630 16 2929 321.970 16.277	vote	13.700	120	30052		167.004
apologize 13.660 13 1778 261.601 9.881 rig 12.630 16 2929 321.970 16.277						
rig 12.630 16 2929 321.970 16.277						
		11.720	20	4533	402.463	25.191

Korea	11.550	24	5882	482.956	32.687
supporter	11.530	25	6208	503.079	34.499
Putin	11.520	13	2442	261.601	13.571
bias	11.440	13	2472	261.601	13.737
nbc	11.150	14	2907	281.724	16.155
totally	11.070	27	7196	543.325	39.989
illegal	10.860	27	7367	543.325	40.940
debate	10.810	39	11432	784.803	63.530
America	10.470	143	47822	2877.611	265.755
tremendous	10.310	15	3644	301.847	20.250
great	10.130	365	128789	7344.951	715.703
join	10.030	117	40633	2354.409	225.805
Hampshire	9.980	12	2736	241.478	15.204
cnn	9.970	13	3102	261.601	17.238
leak	9.960	19	5286	382.340	29.375
democrat	9.830	21	6116	422.586	33.988
republican	9.800	51	17221	1026.281	95.700
presidential	9.760	26	8036	523.202	44.657
W	9.520	25	7899	503.079	43.896
isis	9.470	15	4124	301.847	22.918
horrible	9.470	10	2215	201.232	12.309
Ohio	9.420	54	19139	1086.650	106.359
crowd	9.210	28	9400	563.448	52.237
massive	9.200	26	8629	523.202	47.953
senator	9.160	26	8673	523.202	48.197
Pennsylvania	9.150	29	9877	583.571	54.888
fail	9.090	53	19508	1066.527	108.409
Carolina	8.580	32	11915	643.941	66.214
Florida	8.530	51	20070	1026.281	111.532
Iowa	8.470	19	6539	382.340	36.338
border	8.410	34	13046	684.187	72.499
remark	8.370	14	4470	281.724	24.841
prime	8.280	23	8480	462.833	47.125
disaster	8.250	23	8515	462.833	47.319
Nevada	8.220	14	4588	281.724	25.496
wonderful	8.200	35	13878	704.310	77.122
win	8.060	104	45134	2092.808	250.817
job	8.000	138	60870	2776.995	338.265
weak	7.990	15	5220	301.847	29.008
bad	7.980	88	38368	1770.838	213.218
mess	7.920	13	4371	261.601	24.290
Michigan	7.710	21	8300	422.586	46.125
immigration	7.690	16	5964	321.970	33.143
Wisconsin	7.610	17	6522	342.094	36.244
excuse	7.520	11	3736	221.355	20.762
hack	7.460	13	4751	261.601	26.402
yesterday	7.430	26	11118	523.202	61.785
ticket	7.390	34	15107	684.187	83.952
Obama	7.320	67	31575	1348.251	175.468
again	7.150	113	55658	2273.916	309.301
senate	7.080	27	12270	543.325	68.187
ford	7.040	12	4626	241.478	25.707
interview	6.990	41	19683	825.049	109.382
gang	6.980	10	3643	201.232	20.245
minister	6.930	25	11530	503.079	64.074
rating	6.860	19	8496	382.340	47.214
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hunt	6.790	16	7004	321.970	38.922
watch	6.780	88	45449	1770.838	252.568
fraud	6.730	11	4387	221.355	24.379
Mexico	6.720	29	14092	583.571	78.312
lie	6.580	31	15542	623.818	86.370
Russian	6.570	23	11145	462.833	61.935
victory	6.550	20	9526	402.463	52.938
medium	6.370	72	39385	1448.867	218.869
campaign	6.330	48	25959	965.911	144.259
fantastic	6.310	13	5948	261.601	33.054
premium	6.290	14	6546	281.724	36.377
today	6.250	140	79541	2817.242	442.023
speech	6.220	23	11869	462.833	65.958
Colorado	6.220	19	9549	382.340	53.065
media	6.200	26	13666	523.202	75.944
ban	6.090	17	8600	342.094	47.792
president	6.020	98	57458	1972.069	319.304
voter	5.880	21	11429	422.586	63.513
terrorism	5.810	10	4738	201.232	26.330
		31		623.818	
replace	5.760	128	18013 79622		100.101
big	5.710		8210	2575.764	442.473
hero	5.610	15 25		301.847	45.624
wrong	5.500	25	14985	503.079	83.274
movement	5.500	32	19615	643.941	109.004
false	5.490	11	5790	221.355	32.176
afternoon	5.480	19	11090	382.340	61.629
proud	5.380	18	10639	362.217	59.123
evening	5.300	26	16301	523.202	90.587
Syria	5.200	13	7594	261.601	42.201
crazy	5.070	11	6416	221.355	35.655
country	5.000	106	75273	2133.054	418.305
terrorist	4.980	16	10184	321.970	56.594
intelligence	4.970	17	10959	342.094	60.901
incredible	4.920	11	6658	221.355	37.000
news	4.910	113	81871	2273.916	454.971
confidence	4.780	11	6914	221.355	38.422
Arizona	4.710	15	10105	301.847	56.155
soon	4.710	36	26243	724.434	145.837
deal	4.660	49	36684	986.035	203.859
nothing	4.630	36	26754	724.434	148.677
safe	4.590	36	27017	724.434	150.138
welcome	4.540	30	22550	603.695	125.314
tax	4.510	59	45952	1187.266	255.363
forward	4.440	33	25531	664.064	141.880
secretary	4.440	17	12478	342.094	69.342
exciting	4.420	13	9263	261.601	51.476
americans	4.400	24	18339	482.956	101.913
tower	4.380	10	6877	201.232	38.217
China	4.370	31	24306	623.818	135.073
american	4.370	87	70743	1750.714	393.131
together	4.330	57	46324	1147.020	257.430
France	4.330	12	8661	241.478	48.131
trade	4.300	25	19652	503.079	109.210
never	4.210	68	57099	1368.374	317.309
Georgia	4.210	12	8960	241.478	49.792
supreme	4.170	11	8175	221.355	45.430
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happy	4.130	27	22322	543.325	124.047
very	4.110	156	136127	3139.212	756.481
truly	4.050	16	12968	321.970	72.065
info	4.010	10	7683	201.232	42.696
enjoy	3.980	48	42335	965.911	235.263
me	3.890	177	163551	3561.798	908.881
refuse	3.820	11	9086	221.355	50.492
dead	3.780	17	14963	342.094	83.152
ceo	3.770	13	11169	261.601	62.068
Washington	3.690	34	32098	684.187	178.374
amazing	3.680	19	17409	382.340	96.745
fight	3.650	29	27475	583.571	152.683
north	3.630	51	49552	1026.281	275.369
Germany	3.630	11	9667	221.355	53.721
meeting	3.630	51	49606	1026.281	275.669
why	3.620	62	60752	1247.636	337.609
Mike	3.620	14	12714	281.724	70.654
Iran	3.610	14	12726	281.724	70.721
lose	3.600	40	38886	804.926	216.096
Japan	3.580	11	9818	221.355	54.560
investigation	3.550	14	12981	281.724	72.138
prayer	3.500	11	10110	221.355	56.183
let	3.440	56	57750	1126.897	320.927
despite	3.410	17	16787	342.094	93.288
administration	3.410	25	25315	503.079	140.680
politics	3.400	10	9389	201.232	52.176
dollar	3.380	19	19058	382.340	105.909
total	3.340	29	30163	583.571	167.621
bill	3.330	36	37916	724.434	210.706
promise	3.290	15	15283	301.847	84.930
congress	3.230	17	17786	342.094	98.840
nice	3.210	22	23555	442.709	130.899
story	3.200	52	57530	1046.404	319.704
governor	3.200	13	13465	261.601	74.827
united	3.200	44	48573	885.419	269.929
respect	3.160	13	13654	261.601	75.878
morning	3.120	26	28974	523.202	161.014
remember	3.100	24	26794	482.956	148.899
states	3.070	35	40093	704.310	222.804
James	3.070	14	15312	281.724	85.091
reform	3.060	10	10613	201.232	58.978
night	3.040	45	52407	905.542	291.235
crime	2.990	13	14557	261.601	80.896
fix	2.980	16	18241	321.970	101.368
talk	2.970	42	49958	845.172	277.625
military	2.970	26	30543	523.202	169.733
strong	2.960	29	34242	583.571	190.289
hard	2.960	38	45373	764.680	252.146
billion	2.920	20	23617	402.463	131.244
email	2.900	25	30028	503.079	166.871
people	2.870	153	191808	3078.843	1065.910
statement	2.830	18	21858	362.217	121.469
agree	2.820	18	21927	362.217	121.852
true	2.820	22	27092	442.709	150.555
Virginia	2.810	12	14294	241.478	79.434
beginning	2.770	10	11945	201.232	66.380

everyone	2.750	26	33075	523.202	183.803
r	2.720	10	12161	201.232	67.581
will	2.710	480	639223	9659.114	3552.273
insurance	2.650	12	15268	241.478	84.847
ready	2.640	18	23565	362.217	130.955
wall	2.640	20	26315	402.463	146.237
push	2.640	14	18120	281.724	100.696
happen	2.600	31	42066	623.818	233.768
press	2.590	19	25461	382.340	141.491
security	2.590	35	47907	704.310	266.227
now	2.560	111	156214	2233.670	868.108
longer	2.550	12	15924	241.478	88.492
thought	2.500	12	16324	241.478	90.715
John	2.490	25	35330	503.079	196.335
just	2.460	140	205415	2817.242	1141.527
protect	2.450	21	29972	422.586	166.560
far	2.450	28	40350	563.448	224.232
leader	2.440	28	40451	563.448	224.793
secret	2.410	10	13944	201.232	77.489
announce	2.410	19	27493	382.340	152.783
beautiful	2.380	17	24795	342.094	137.790
white	2.350	28	42078	563.448	233.835
executive	2.340	16	23718	321.970	131.805
forget	2.340	10	14461	201.232	80.362
server	2.320	14	20800	281.724	115.589
must	2.320	55	84935	1106.773	471.998
woman	2.300	38	58752	764.680	326.495
discuss	2.280	17	26013	342.094	144.559
criminal	2.280	10	14900	201.232	82.802
get	2.250	173	277580	3481.306	1542.560
drug deliver	2.240 2.240	14 16	21661 24924	281.724 321.970	120.374 138.507
	2.240	17	24924 26599	342.094	138.307
Saturday general	2.230	29	46179	583.571	256.625
stop	2.220	26	40179	523.202	229.867
leadership	2.210	13	20305	261.601	112.838
ever	2.210	25	39996	503.079	222.265
attack	2.190	21	33706	422.586	187.310
speak	2.180	23	37194	462.833	206.693
look	2.160	86	143378	1730.591	796.776
act	2.140	27	44659	543.325	248.178
should	2.140	72	120757	1448.867	671.068
our	2.140	246	416077	4950.296	2312.212
go	2.120	139	236412	2797.118	1313.782
stock	2.120	10	16156	201.232	89.782
regulation	2.080	11	18197	221.355	101.124
cut	2.080	19	32221	382.340	179.058
Iraq	2.060	10	16655	201.232	92.555
catch	2.060	11	18433	221.355	102.435
save	2.050	20	34375	402.463	191.028
justice	2.040	11	18573	221.355	103.213
S	2.030	22	38264	442.709	212.640
foreign	2.020	10	16999	201.232	94.466
my	2.020	191	341332	3843.522	1896.841
house	1.990	44	79011	885.419	439.078
judge	1.970	12	21163	241.478	117.606

le e els	1.970	65	125022	1200 005	604.760
back	1.870	65	125022	1308.005	694.769
no	1.860	100	193627	2012.315	1076.019
anyone	1.860	13	24449	261.601	135.867
live	1.860	42 12	80954 22657	845.172	449.875
represent	1.850			241.478	125.909
do	1.840	296	580781	5956.453	3227.501
make	1.840	179	351069	3602.045	1950.951
decision	1.830	17	32748	342.094	181.986
economy	1.830	12	22926	241.478	127.404
want	1.820	63	124218	1267.759	690.301
pay	1.800	30	59423	603.695	330.224
nation	1.800	16	31401	321.970	174.501
finally	1.790	12	23414	241.478	130.116
we	1.780	331	672872	6660.764	3739.266
political	1.760	15	29995	301.847	166.687
hit	1.760	14	28070	281.724	155.990
SO	1.760	144	295956	2897.734	1644.679
chance	1.750	11	21973	221.355	122.108
last	1.750	55	113022	1106.773	628.083
out	1.750	132	272948	2656.256	1516.819
much	1.740	54	111362	1086.650	618.858
believe	1.730	22	45337	442.709	251.946
order	1.720	33	68815	664.064	382.417
state	1.720	84	176580	1690.345	981.286
sign	1.710	20	41681	402.463	231.629
you	1.700	387	823159	7787.660	4574.437
many	1.700	76	161130	1529.360	895.427
fact	1.700	21	44034	422.586	244.705
head	1.680	24	50973	482.956	283.266
worker	1.650	10	21234	201.232	118.001
million	1.650	28	60804	563.448	337.898
money	1.640	21	45639	422.586	253.624
host	1.640	14	30228	281.724	167.982
raise	1.630	15	32726	301.847	181.864
real	1.620	21	46114	422.586	256.263
Israel	1.620	12	26117	241.478	145.137
major	1.610	18	39850	362.217	221.453
national	1.580	33	74771	664.064	415.515
conference	1.560	14	31959	281.724	177.602
foundation	1.550	11	25103	221.355	139.502
kill	1.540	13	29962	261.601	166.504
ask	1.540	27	63001	543.325	350.107
court	1.520	21	49409	422.586	274.574
thing	1.510	42	100180	845.172	556.718
allow	1.490	31	74678	623.818	414.999
official	1.480	18	43383	362.217	241.087
hear	1.480	17	41116	342.094	228.489
stay	1.470	13	31440	261.601	174.718
I	1.470	440	1084305	8854.188	6025.671
history	1.470	20	48840	402.463	271.412
she	1.460	83	205506	1670.222	1142.032
source	1.460	18	44168	362.217	245.449
time	1.450	113	280948	2273.916	1561.277
November	1.450	11	26966	221.355	149.855
keep	1.450	34	84530	684.187	469.748
stand	1.440	14	34732	281.724	193.012

not	1.440	324	816527	6519.902	4537.582
policy	1.440	19	47378	382.340	263.288
future	1.430	19	47405	382.340	263.438
safety	1.420	13	32536	261.601	180.808
against	1.420	27	68163	543.325	378.794
give	1.420	57	145286	1147.020	807.379
run	1.400	35	90234	704.310	501.446
even	1.390	50	129448	1006.158	719.365
thanks	1.390	11	28195	221.355	156.684
call	1.380	46	120212	925.665	668.039
full	1.360	22	57891	442.709	321.710
low	1.360	18	47461	362.217	263.749
success	1.350	10	26378	201.232	146.587
support	1.350	46	123161	925.665	684.427
put	1.350	25	66807	503.079	371.258
Friday	1.340	11	29223	221.355	162.397
all	1.340	164	443016	3300.197	2461.917
	1.340	27	72794	543.325	404.529
really		35		704.310	525.136
down	1.330		94497		
plan	1.330	39	105390	784.803	585.670
after .	1.310	63	173091	1267.759	961.897
economic	1.310	12	32690	241.478	181.664
leave	1.310	28	76899	563.448	427.341
interest	1.310	13	35482	261.601	197.180
force	1.310	18	49410	362.217	274.580
they	1.310	162	449085	3259.951	2495.643
instead	1.300	11	30156	221.355	167.582
who	1.300	104	289946	2092.808	1611.280
travel	1.290	13	36023	261.601	200.186
final	1.290	10	27623	201.232	153.506
party	1.280	17	47554	342.094	264.266
pass	1.280	15	42097	301.847	233.940
reason	1.280	13	36516	261.601	202.926
always	1.270	19	53805	382.340	299.004
at	1.260	273	783049	5493.621	4351.539
say	1.260	105	301324	2112.931	1674.510
former	1.260	10	28371	201.232	157.663
day	1.250	70	201747	1408.621	1121.143
special	1.250	18	51621	362.217	286.867
plant	1.240	13	37462	261.601	208.183
fire	1.240	15	43532	301.847	241.915
meet	1.230	22	64483	442.709	358.343
spend	1.220	13	38128	261.601	211.884
come	1.220	59	174720	1187.266	970.949
guy	1.220	10	29386	201.232	163.303
concern	1.210	11	32722	221.355	181.842
focus	1.200	16	47906	321.970	266.222
long	1.190	27	81970	543.325	455.521
hope	1.190	15	45432	301.847	252.473
actually	1.190	11	33285	221.355	184.971
world	1.180	43	132092	865.296	734.058
on	1.160	388	1208359	7807.784	6715.060
here	1.160	42	130999	845.172	727.984
bring	1.150	24	75222	482.956	418.022
air	1.150	15	47090	301.847	261.687
race	1.150	11	34501	221.355	191.728
	1.100		5 1501		171.120

an	1.150	13	40859	261.601	227.061
new	1.130	106	338744	2133.054	1882.459
good	1.130	75	239732	1509.237	1332.232
know	1.130	52	166999	1046.404	928.042
friend	1.130	17	54480	342.094	302.755
would	1.120	81	261824	1629.975	1455.001
next	1.120	23	74293	462.833	412.859
report	1.120	32	103564	643.941	575.523
before	1.110	35	114178	704.310	634.507
take	1.100	71	233056	1428.744	1295.133
be	1.100	1592	5256613	32036.061	29211.908
see	1.080	62	206901	1247.636	1149.785
top	1.080	17	56770	342.094	315.481
continue	1.080	22	73576	442.709	408.875
important	1.080	16	53689	321.970	298.359
about	1.070	95	321621	1911.700	1787.304
problem	1.060	20	67926	402.463	377.477
up	1.060	82	279826	1650.099	1555.042
change	1.050	34	116650	684.187	648.244
try	1.040	22	76712	442.709	426.302
release	1.040	14	48817	281.724	271.285
expect	1.030	11	38451	221.355	213.679
year	1.030	89	313194	1790.961	1740.473
yet	1.020	12	42385	241.478	235.541
man	1.020	24	85041	482.956	472.588
way	1.010	43	153473	865.296	852.876
us	1.010	53	189503	1066.527	1053.101
think	1.010	32	114789	643.941	637.902
over	1.010	50	179414	1006.158	997.035
government	1.000	21	76000	422.586	422.345

## APPENDIX B KEYWORD LIST OF THE TRUMP TRADITIONAL CORPUS

Keyword	Score	Freq	Ref freq	Rel freq	Rel_ref_freq
Obamacare	37.620	30	1921	767.754	10.675
Trump	36.880	48	4243	1228.407	23.579
Hillary	33.460	35	3072	895.713	17.072
thank	30.570	157	21912	4017.914	121.769
Donald	25.850	27	3081	690.979	17.122
boo	23.700	12	608	307.102	3.379
Clinton	21.290	44	7804	1126.040	43.368
Luis	20.220	14	1478	358.285	8.214
incredible	17.090	31	6658	793.346	37.000
Harry	16.100	20	4033	511.836	22.412
terrorism	15.770	22	4738	563.020	26.330
democrats	15.550	21	4536	537.428	25.207
everybody	14.910	20	4500	511.836	25.007
nobody	14.660	18	3976	460.653	22.095
bless	14.160	24	6134	614.203	34.088
Paris	13.300	26	7338	665.387	40.779
okay	12.880	17	4418	435.061	24.552
fake	12.800	13	3020	332.694	16.783
anymore	12.460	15	3891	383.877	21.623
country	12.450	208	75273	5323.097	418.305
repeal	12.440	10	2046	255.918	11.370
rebuild	12.440	14	3529	358.285	19.611
tremendous	12.170	14	3644	358.285	20.250
border	11.600	37	13046	946.897	72.499
nation	11.290	81	31401	2072.937	174.501
America	10.800	116	47822	2968.650	265.755
immigration	10.320	17	5964	435.061	33.143
veteran	10.150	30	11990	767.754	66.631
tonight	10.050	18	6630	460.653	36.844
alien	9.460	12	4234	307.102	23.529
illegal	9.240	18	7367	460.653	40.940
states	9.060	82	40093	2098.528	222.804
defend	8.630	17	7479	435.061	41.562
sacrifice	8.600	14	5907	358.285	32.826
pour	8.520	12	4894	307.102	27.197
American	8.470	133	70743	3403.711	393.131
disaster	8.210	18	8515	460.653	47.319
trade	8.030	37	19652	946.897	109.210
job	7.670	104	60870	2661.548	338.265
promise	7.650	28	15283	716.571	84.930
proud	7.550	20	10639	511.836	59.123
united	7.530	82	48573	2098.528	269.929
liberty	7.460	14	7083	358.285	39.361
plane	7.400	14	7151	358.285	39.739
immigrant	7.330	11	5353	281.510	29.748
factory	7.270	13	6680	332.694	37.122
pipeline	7.220	11	5461	281.510	30.348

	7 120	12	6200	207 102	24.454
wealth worker	7.130 7.080	12 35	6200 21234	307.102 895.713	34.454
	6.980	44	27475		118.001 152.683
fight coal	6.930	13	7095	1126.040 332.694	39.428
	6.930	16	9091	409.469	50.520
flag folk	6.840	20	11937	511.836	66.336
citizen	6.720	35	22471	895.713	124.875
steel	6.710	17	10142	435.061	56.361
forget	6.620	23	14461	588.612	80.362
restriction	6.570	10	5482	255.918	30.464
faith	6.410	23	15007	588.612	83.396
freedom	6.300	24	16035	614.203	89.109
	6.190	320	236412	8189.379	1313.782
go hero	6.160	13	8210	332.694	45.624
win	5.930	60	45134	1535.509	250.817
	5.910	13	8629	332.694	47.953
massive	5.850	40	29972	1023.672	166.560
protect	5.820	174	136127	4452.975	756.481
very	5.710	13	9000	332.694	50.015
tough fair	5.650	21	15641	537.428	86.920
honor	5.610	22	16597	563.020	92.232
our	5.480	497	416077	12719.130	2312.212
great	5.410	153	128789	3915.547	715.703
Americans	5.350	23	18339	588.612	101.913
	5.290	50	42066	1279.591	233.768
happen we	5.290	774	672872	19808.061	3739.266
agenda	5.250	12	9078	307.102	50.448
believe	5.220	53	45337	1356.366	251.946
never	5.190	66	57099	1689.060	317.309
agreement	5.190	24	19862	614.203	110.377
billion	5.140	28	23617	716.571	131.244
remember	5.060	31	26794	793.346	148.899
safe	5.020	31	27017	793.346	150.138
president	5.000	64	57458	1637.876	319.304
foreign	5.000	20	16999	511.836	94.466
deal	4.950	41	36684	1049.264	203.859
want	4.800	131	124218	3352.527	690.301
terrorist	4.760	12	10184	307.102	56.594
strength	4.730	15	13170	383.877	73.188
regulation	4.700	20	18197	511.836	101.124
hundred	4.430	19	18358	486.244	102.019
fail	4.410	20	19508	511.836	108.409
people	4.360	183	191808	4683.301	1065.910
secretary	4.320	13	12478	332.694	69.342
Mike	4.250	13	12714	332.694	70.654
beautiful	4.220	24	24795	614.203	137.790
speech	4.170	12	11869	307.102	65.958
amazing	4.170	17	17409	435.061	96.745
amendment	4.130	10	9784	255.918	54.371
Pennsylvania	4.100	10	9877	255.918	54.888
congress	4.090	17	17786	435.061	98.840
dollar	4.060	18	19058	460.653	105.909
military	4.040	28	30543	716.571	169.733
oh	4.040	12	12340	307.102	68.576
prayer	4.020	10	10110	255.918	56.183
ever	4.010	36	39996	921.305	222.265
5 , 61	1.010	50	3,7,70	721.303	222.203

	2 000	12	12654	222 (04	75.070
respect	3.990	13	13654	332.694	75.878
together	3.960	41	46324	1049.264	257.430
threat	3.950	13	13831	332.694	76.861
again	3.880	48	55658	1228.407	309.301
senate	3.730	11	12270	281.510	68.187
peace	3.710	16	18538	409.469	103.019
wall	3.670	22	26315	563.020	146.237
much	3.560	87	111362	2226.488	618.858
fix	3.540	15	18241	383.877	101.368
right	3.440	88	116395	2252.079	646.827
let	3.430	44	57750	1126.040	320.927
you	3.420	613	823159	15687.780	4574.437
economic	3.390	25	32690	639.795	181.664
vote	3.380	23	30052	588.612	167.004
god	3.380	48	64210	1228.407	356.826
tell	3.370	55	73904	1407.550	410.697
wonderful	3.350	11	13878	281.510	77.122
speaker	3.330	10	12571	255.918	69.859
anything	3.330	20	26409	511.836	146.759
tax	3.320	34	45952	870.122	255.363
dream	3.260	15	19911	383.877	110.649
lot	3.260	47	65063	1202.815	361.566
infrastructure	3.250	10	12915	255.918	71.771
secure	3.230	12	15852	307.102	88.092
bad	3.140	27	38368	690.979	213.218
	3.110	46	66807	1177.223	371.258
put					
replace	3.110	13	18013	332.694	100.101
Washington	3.040	22	32098	563.020	178.374
they	3.020	295	449085	7549.584	2495.643
strong	2.990	23	34242	588.612	190.289
always	2.930	35	53805	895.713	299.004
SO	2.880	186	295956	4760.077	1644.679
criminal	2.870	10	14900	255.918	82.802
big	2.850	50	79622	1279.591	442.473
justice	2.800	12	18573	307.102	103.213
leader	2.770	25	40451	639.795	224.793
lie	2.760	10	15542	255.918	86.370
here	2.750	79	130999	2021.753	727.984
campaign	2.720	16	25959	409.469	144.259
represent	2.710	14	22657	358.285	125.909
stop	2.710	25	41364	639.795	229.867
longer	2.700	10	15924	255.918	88.492
stand	2.700	21	34732	537.428	193.012
woman	2.690	35	58752	895.713	326.495
defense	2.690	11	17714	281.510	98.440
nothing	2.640	16	26754	409.469	148.677
administration	2.610	15	25315	383.877	140.680
guy	2.570	17	29386	435.061	163.303
future	2.560	27	47405	690.979	263.438
know	2.550	93	166999	2380.038	928.042
thousand	2.540	12	20656	307.102	114.789
do	2.490	314	580781	8035.829	3227.501
me	2.460	88	163551	2252.079	908.881
million	2.460	33	60804	844.530	337.898
true	2.450	15	27092	383.877	150.555
	2.430	13	27092	332.694	130.899
nice	2.430	13	23333	332.094	130.899

	2.270	2.4	45(20	(14.202	252 (24
money	2.370	24	45639	614.203	253.624
percent	2.360	20	37960	511.836	210.950
many	2.360	83	161130	2124.120	895.427
will	2.340	325	639223 42362	8317.338	3552.273
across	2.330	22		563.020	235.413
everything	2.330	16	30551	409.469	169.777
climate	2.330	11	20698 70330	281.510	115.022
build I	2.320 2.300	36 542	1084305	921.305	390.836
=	2.300	21	41116	13870.761 537.428	6025.671
hear	2.300	18	35482	460.653	228.489 197.180
interest choice	2.270	13	26271	332.694	145.992
	2.200	73	153473	1868.202	852.876
way	2.150	73 89	189503	2277.671	1053.101
us actually	2.150	16	33285	409.469	184.971
actually	2.130	96	205415	2456.814	1141.527
just	2.140	73	156214	1868.202	868.108
now deliver	2.140	12	24924	307.102	138.507
those	2.140	56	120141	1433.141	667.644
history	2.130	23	48840	588.612	271.412
because	2.130	59	126784	1509.917	704.561
	2.130	11	22926	281.510	127.404
economy	2.120	41	89108	1049.264	495.189
every back	2.080	57	125022	1458.733	694.769
judge	2.080	10	21163	255.918	117.606
executive	2.060	10	23718	281.510	131.805
sign	2.050	19	41681	486.244	231.629
world	2.040	59	132092	1509.917	734.058
care	2.040	27	59976	690.979	333.297
accord	2.040	20	44302	511.836	246.194
what	2.040	116	261482	2968.650	1453.101
government	2.040	34	76000	870.122	422.345
love	2.030	36	80852	921.305	449.309
bill	2.020	17	37916	435.061	210.706
single	2.010	13	28904	332.694	160.625
matter	2.010	14	31235	358.285	173.578
keep	1.990	37	84530	946.897	469.748
come	1.990	76	174720	1944.978	970.949
understand	1.990	17	38415	435.061	213.479
reason	1.970	16	36516	409.469	202.926
lose	1.970	17	38886	435.061	216.096
heart	1.950	14	32133	358.285	178.569
think	1.950	49	114789	1253.999	637.902
say	1.950	128	301324	3275.752	1674.510
see	1.950	88	206901	2252.079	1149.785
down	1.930	40	94497	1023.672	525.136
man	1.930	36	85041	921.305	472.588
not	1.900	338	816527	8650.032	4537.582
talk	1.900	21	49958	537.428	277.625
get	1.900	115	277580	2943.058	1542.560
where	1.890	54	130516	1381.958	725.300
it	1.860	451	1113442	11541.907	6187.590
action	1.860	18	43738	460.653	243.060
clean	1.860	12	28948	307.102	160.869
under	1.840	32	79143	818.938	439.811
all	1.840	177	443016	4529.750	2461.917

pay	1.830	24	59423	614.203	330.224
period	1.830	11	26896	281.510	149.466
safety	1.800	13	32536	332.694	180.808
among	1.780	15	37979	383.877	211.056
take	1.770	90	233056	2303.263	1295.133
who	1.760	111	289946	2840.691	1611.280
force	1.740	19	49410	486.244	274.580
construction	1.740	12	30976	307.102	172.139
attack	1.740	13	33706	332.694	187.310
them	1.730	77	203903	1970.569	1133.124
have	1.720	560	1495684	14331.414	8311.775
law	1.700	26	69607	665.387	386.818
simple	1.690	11	29313	281.510	162.897
order	1.660	25	68815	639.795	382.417
fact	1.650	16	44034	409.469	244.705
middle	1.640	11	30204	281.510	167.849
mean	1.640	23	63964	588.612	355.459
no	1.640	69	193627	1765.835	1076.019
travel	1.630	13	36023	332.694	200.186
good	1.630	85	239732	2175.304	1332.232
reduce	1.610	13	36451	332.694	202.565
	1.610	17	47907	435.061	266.227
security		38			
start	1.610		107958	972.489	599.941
medium	1.610	14	39385	358.285	218.869
too	1.600	25	71169	639.795	395.498
friend	1.590	19	54480	486.244	302.755
special	1.590	18	51621	460.653	286.867
but	1.580	157	455658	4017.914	2532.170
why	1.570	21	60752	537.428	337.609
Obama	1.570	11	31575	281.510	175.468
that	1.570	504	1476719	12898.273	8206.383
already	1.560	15	43510	383.877	241.793
place	1.550	38	111937	972.489	622.053
cut	1.540	11	32221	281.510	179.058
almost	1.530	11	32505	281.510	180.636
send	1.520	15	44790	383.877	248.906
he	1.490	138	426675	3531.670	2371.107
before	1.480	37	114178	946.897	634.507
over	1.480	58	179414	1484.325	997.035
general	1.480	15	46179	383.877	256.625
would	1.470	84	261824	2149.712	1455.001
speak	1.460	12	37194	307.102	206.693
be	1.460	1670	5256613	42738.324	29211.908
thing	1.460	32	100180	818.938	556.718
join	1.450	13	40633	332.694	225.805
room	1.450	16	50209	409.469	279.020
really	1.440	23	72794	588.612	404.529
make	1.440	110	351069	2815.099	1950.951
look	1.440	45	143378	1151.631	796.776
today	1.440	25	79541	639.795	442.023
something	1.410	16	51711	409.469	287.367
same	1.410	25	81303	639.795	451.815
give	1.390	44	145286	1126.040	807.379
court	1.380	15	49409	383.877	274.574
real	1.380	14	46114	358.285	256.263
leave	1.370	23	76899	588.612	427.341
15410	1.570	<u> </u>	10077	200.012	127.571

out	1.360	81	272948	2072.937	1516.819
out begin	1.360	21	70582	537.428	392.236
even	1.350	38	129448	972.489	719.365
like	1.340	64	219241	1637.876	1218.360
rule	1.340	10	33991	255.918	188.894
since	1.330	25	86010	639.795	477.972
spend	1.310	11	38128	281.510	211.884
word	1.310	16	55673	409.469	309.384
ago	1.300	12	41999	307.102	233.396
value	1.280	12	42618	307.102	236.836
day	1.280	56	201747	1433.141	1121.143
family	1.270	29	105050	742.163	583.781
one	1.250	104	381961	2661.548	2122.623
to	1.220	1125	4233934	28790.787	23528.704
hard	1.210	123	45373	307.102	252.146
watch	1.210	12	45449	307.102	252.568
time	1.210	73	280948	1868.202	1561.277
important	1.190	14	53689	358.285	298.359
end	1.170	21	82235	537.428	456.994
	1.160	12	47205	307.102	262.326
away policy	1.160	12	47203	307.102	263.288
	1.160	19	75222	486.244	418.022
bring		19			
land	1.160		43469	281.510	241.565
and	1.150	1235	4944316	31605.886	27476.420
office	1.140	19	76408	486.244	424.612
work	1.130	66	268163	1689.060	1490.228
york	1.130	10	40665	255.918	225.982
this	1.120	208	851640	5323.097	4732.711
long	1.120	20	81970	511.836	455.521
support	1.120	30	123161	767.754	684.427
first	1.120	46	188989	1177.223	1050.245
up	1.120	68	279826	1740.243	1555.042
close	1.110	12	49378	307.102	274.402
your	1.110	104	432692	2661.548	2404.544
their	1.100	100	417003	2559.181	2317.358
life	1.100	30	125141	767.754	695.430
child	1.100	28	116900	716.571	649.634
white	1.090	10	42078	255.918	233.835
can	1.090	110	465083	2815.099	2584.547
war	1.080	11	46824	281.510	260.209
level	1.070	16	68423	409.469	380.238
serve	1.070	14	59988	358.285	333.364
call	1.070	28	120212	716.571	668.039
run	1.070	21	90234	537.428	501.446
meet	1.070	15	64483	383.877	358.343
another	1.070	19	82024	486.244	455.822
than	1.060	45	195084	1151.631	1084.116
cost	1.060	15	65132	383.877	361.950
fire	1.060	10	43532	255.918	241.915
into	1.050	48	210046	1228.407	1167.262
city	1.040	29	127880	742.163	710.651
energy	1.040	18	79525	460.653	441.934
face	1.030	11	48938	281.510	271.957
there	1.030	64	285064	1637.876	1584.150
she	1.030	46	205506	1177.223	1142.032
my	1.030	76	341332	1944.978	1896.841

class	1.030	13	58352	332.694	324.272
hope	1.010	10	45432	255.918	252.473
against	1.010	15	68163	383.877	378.794
early	1.010	11	50204	281.510	278.992
record	1.000	11	50407	281.510	280.120
these	1.000	43	197340	1100.448	1096.653

## APPENDIX C KEYWORD LIST OF THE SALVINI TWEET CORPUS

Keyword	Score	Freq	Ref freq	Rel freq	Rel ref freq
Salvini	113.290	98	27690	1657.870	4.722
buonsenso	77.170	52	8964	879.686	1.529
clandestino	67.700	87	69710	1471.782	11.887
immigrato	65.140	129	138735	2182.298	23.657
immigrazione	49.340	82	107428	1387.197	18.318
delinquente	44.320	38	27744	642.847	4.731
Fornero	40.340	30	16587	507.511	2.828
ong	40.010	36	32081	609.013	5.470
lega	39.910	123	248547	2080.796	42.382
scafista	39.190	24	3615	406.009	0.616
Boldrini	38.380	27	12675	456.760	2.161
buonista	35.080	22	5244	372.175	0.894
pacchia	33.460	20	2402	338.341	0.410
mollo	31.460	23	15760	389.092	2.687
italiani	30.600	47	95629	795.101	16.306
Macron	29.310	17	904	287.590	0.154
poliziadistato	28.060	16	16	270.673	0.003
sbarco	27.450	27	41088	456.760	7.006
insulto	26.960	28	46580	473.677	7.943
perbene	26.370	17	7527	287.590	1.283
insultare	26.100	23	31024	389.092	5.290
live	26.070	65	190959	1099.608	32.562
spacciatore	25.840	18	12735	304.507	2.172
galera	25.620	23	32707	389.092	5.577
amici	25.120	29	58240	490.594	9.931
Saviano	24.080	17	13823	287.590	2.357
espulsione	23.410	27	58273	456.760	9.937
rtl1025	22.990	13	9	219.922	0.002
profugo	21.280	26	65332	439.843	11.140
centrodestra	20.160	24	62350	406.009	10.632
sbarcare	20.060	24	62993	406.009	10.741
Bruxelles	19.290	29	93571	490.594	15.956
difendere	18.520	64	287413	1082.690	49.009
pd	18.400	76	354258	1285.695	60.407
tivù	18.010	11	5222	186.087	0.890
libico	17.910	15	27743	253.756	4.731
clandestini	17.780	10	447	169.170	0.076
matto	17.580	20	57551	338.341	9.813
orgoglioso	17.550	25	86035	422.926	14.670
razzismo	17.510	18	46688	304.507	7.961
razzista	17.320	16	36411	270.673	6.209
nigeriano	17.030	12	14723	203.004	2.511
stuprare	16.820	11	9720	186.087	1.657
barcone	16.720	11	10112	186.087	1.724
rom	16.430	21	71759	355.258	12.236
trafficante	16.350	11	11693	186.087	1.994
rispedire	16.350	11	11710	186.087	1.997

	16,000	40	101563	(7( (9)	22 665
arrestare	16.090	40 15	191562 38765	676.682	32.665
buona Maio	15.880 15.750	13	14391	253.756	6.610 2.454
	15.730	25	102936	186.087 422.926	17.552
roba	15.680	19	65293	321.424	11.134
sequestrare	15.660	32	147835	541.345	25.208
papà	15.650	25	103536	422.926	17.655
stop	15.570	13	27946	219.922	4.765
pazzesco votare	15.440	59	324350	998.105	55.307
nave	15.350	52	281354	879.686	47.976
schifoso	15.310	10	9985	169.170	1.703
islamico	15.150	28	128626	473.677	21.933
immigrare	15.110	10	10877	169.170	1.855
Renzi	14.990	34	170310	575.179	29.041
tassa	14.830	44	239723	744.350	40.877
spaccio	14.570	13	33922	219.922	5.784
rimpatrio	14.350	10	14561	169.170	2.483
sbaglio	14.190	17	64359	287.590	10.974
asilo	13.910	26	131061	439.843	22.348
	13.870	27	138747	456.760	23.659
scappare Libia	13.620	16	62186	270.673	10.604
mafioso	13.610	19	84177	321.424	14.354
poliziotto	13.430	19	86031	321.424	14.670
mollare	13.270	15	57896	253.756	9.872
espellere	13.090	14	51924	236.839	8.854
verme	12.940	10	22555	169.170	3.846
vergognare	12.240	11	35317	186.087	6.022
governo	11.760	173	1406059	2926.648	239.758
duomo	11.180	19	115143	321.424	19.634
invasione	11.140	14	71266	236.839	12.152
picchiare	11.140	11	44624	186.087	7.609
governare	11.110	23	151953	389.092	25.911
sinistra	11.040	82	683574	1387.197	116.561
confine	10.120	41	349154	693.599	59.537
finto	9.890	11	57600	186.087	9.822
aggredire	9.700	10	49664	169.170	8.469
mafia	9.640	19	142975	321.424	24.380
Europa	8.890	95	1007746	1607.119	171.838
legalità	8.810	14	105587	236.839	18.004
carabinieri	8.690	13	96461	219.922	16.448
priorità	8.600	18	155770	304.507	26.562
Italia	8.540	316	3620400	5345.784	617.342
indagare	8.510	17	146386	287.590	24.961
abbraccio	8.490	21	193708	355.258	33.031
pensione	8.470	29	288000	490.594	49.109
accoglienza	8.290	24	235515	406.009	40.159
buongiorno	8.120	14	119684	236.839	20.408
fermare	7.910	57	663620	964.271	113.159
minaccia	7.890	18	175119	304.507	29.861
sondaggio	7.780	12	101969	203.004	17.388
italiano	7.760	296	3733480	5007.443	636.624
richiedente	7.700	11	90631	186.087	15.454
fascista	7.690	13	116737	219.922	19.906
dritto	7.670	11	91296	186.087	15.568
ministro	7.600	54	653563	913.520	111.444
vergogna	7.600	10	79615	169.170	13.576

è	7.530	12	107210	203.004	18.281
sorriso	7.450	19	202153	321.424	34.471
droga	7.420	15	149708	253.756	25.528
orgoglio	7.400	12	110263	203.004	18.802
migliaio	7.360	29	340016	490.594	57.979
restituire	7.120	20	228369	338.341	38.941
avanti	7.070	55	721070	930.437	122.955
faccia	7.030	25	302410	422.926	51.566
mandare	6.980	37	475485	625.930	81.079
coerenza	6.850	10	94727	169.170	16.153
voi	6.850	80	1108720	1353.363	189.056
arresto	6.760	14	155564	236.839	26.526
disastro	6.560	10	101607	169.170	17.326
soldo	6.550	34	465642	575.179	79.400
africano	6.520	11	117863	186.087	20.098
presunto	6.300	12	139479	203.004	23.784
sicurezza	6.260	85	1296740	1437.948	221.117
frontiera	6.220	11	126218	186.087	21.522
pagare	6.220	57	860358	964.271	146.706
voto	6.120	39	582844	659.765	99.385
pena	6.120	24	339833	406.009	57.948
viva	6.080	13	163291	219.922	27.844
business	6.050	22	311788	372.175	53.165
legittimo	6.040	11	131736	186.087	22.463
cancellare	5.960	16	217306	270.673	37.055
bloccare	5.920	21	303399	355.258	51.735
guardia	5.900	18	253731	304.507	43.266
paura	5.870	38	593627	642.847	101.224
amico	5.860	88	1442457	1488.699	245.964
odio	5.810	10	122303	169.170	20.855
promettere	5.800	15	208153	253.756	35.494
finalmente	5.770	34	535894	575.179	91.379
bimbo	5.770	15	209491	253.756	35.722
reato	5.760	19	278728	321.424	47.528
cambiare	5.750	77	1280176	1302.612	218.293
video	5.740	57	936541	964.271	159.697
centinaio	5.660	20	302563	338.341	51.592
colpa	5.640	20	303864	338.341	51.814
carabiniere	5.560	11	148038	186.087	25.243
Giulia	5.550	12	166362	203.004	28.368
polizia	5.550	31	506474	524.428	86.363
porto	5.500	31	510736	524.428	87.090
salvare	5.410	28	465453	473.677	79.368
criminale	5.410	10	135700	169.170	23.139
paese	5.330	134	2448753	2266.883	417.556
sbagliare	5.300	20	326518	338.341	55.677
incredibile	5.280	15	234546	253.756	39.994
ieri	5.110	41	749496	693.599	127.802
rubare	5.080	10	148382	169.170	25.302
questi	5.040	16	267701	270.673	45.648
fiducia	5.030	21	366788	355.258	62.544
meritare	4.940	17	294428	287.590	50.205
10	4.920	190	3786521	3214.237	645.669
news	4.910	13	215727	219.922	36.785
violento	4.880	11	176943	186.087	30.172
qualcuno	4.870	43	828628	727.433	141.296

intervista	4.790	20	368041	338.341	62.757
straniero	4.750	25	475763	422.926	81.126
onore	4.740	15	267436	253.756	45.603
bandiera	4.680	10	165885	169.170	28.286
denunciare	4.660	15	273572	253.756	46.649
domani	4.640	24	467345	406.009	79.691
difesa	4.510	28	570110	473.677	97.214
milione	4.480	58	1239186	981.188	211.303
combattere	4.400	17	338138	287.590	57.658
questa	4.340	30	640074	507.511	109.144
complimento	4.330	13	252617	219.922	43.076
augurare	4.290	11	209141	186.087	35.662
estero	4.290	25	533712	422.926	91.007
violenza	4.240	19	399444	321.424	68.112
lavorare	4.230	63	1433175	1065.773	244.382
	4.190	22	475862	372.175	81.143
giustizia	4.180	14	287627	236.839	49.045
preghiera					
tornare	4.180	63 13	1451109	1065.773	247.440
imprenditore	4.170		264534	219.922	45.108
gente	4.170	34	764544	575.179	130.368
testa	4.130	33	749165	558.262	127.746
parola	4.100	83	1965746	1404.114	335.194
voglia	4.080	18	393746	304.507	67.141
mattina	4.030	22	498104	372.175	84.936
carcere	4.000	12	254010	203.004	43.313
figlio	3.990	59	1421219	998.105	242.343
Catania	3.990	10	204702	169.170	34.905
coraggio	3.950	12	257272	203.004	43.869
debito	3.910	13	285937	219.922	48.757
Spagna	3.870	12	263744	203.004	44.973
mamma	3.860	20	470666	338.341	80.257
fiscale	3.850	16	368609	270.673	62.854
no	3.850	47	1167200	795.101	199.028
accogliere	3.840	23	550504	389.092	93.871
operaio	3.830	11	241445	186.087	41.171
solidarietà	3.820	13	293954	219.922	50.124
chi	3.820	161	4136650	2723.643	705.372
francese	3.820	24	580540	406.009	98.992
buon	3.790	38	950748	642.847	162.119
ce	3.770	28	693480	473.677	118.251
Francia	3.750	18	433659	304.507	73.947
smettere	3.740	10	222060	169.170	37.865
traffico	3.740	14	328475	236.839	56.011
grazie	3.680	109	2892427	1843.957	493.210
democratico	3.670	13	308694	219.922	52.638
finanza	3.650	10	229295	169.170	39.099
incontrare	3.590	30	785863	507.511	134.004
ue	3.590	10	234234	169.170	39.941
vincere	3.580	32	844530	541.345	144.007
sera	3.560	31	821729	524.428	140.119
piazza	3.550	42	1132199	710.516	193.060
attaccare	3.530	11	267252	186.087	45.571
grazia	3.520	12	295972	203.004	50.468
splendido	3.510	17	438537	287.590	74.778
rispettare	3.460	16	416696	270.673	71.054
pronto	3.460	30	818273	507.511	139.530

affetto	3.450	11	274523	186.087	46.811
vittima	3.450	16	419072	270.673	71.459
presto	3.440	23	620890	389.092	105.873
preoccupare	3.430	11	276783	186.087	47.196
decina	3.430	11	277049	186.087	47.242
paesi	3.420	10	248461	169.170	42.367
sperare	3.420	31	857967	524.428	146.299
nessuno	3.350	32	906166	541.345	154.517
ascoltare	3.320	21	586671	355.258	100.038
domenica	3.310	34	978210	575.179	166.802
ordine	3.290	44	1285449	744.350	219.192
ringraziare	3.260	16	445614	270.673	75.985
cittadino	3.230	50	1493759	845.852	254.712
agente	3.220	12	329345	203.004	56.159
guerra	3.190	39	1173002	659.765	200.018
Genova	3.130	11	308244	186.087	52.561
serio	3.130	14	403564	236.839	68.815
regalare	3.100	12	344519	203.004	58.747
tedesco	3.060	17	512049	287.590	87.313
ragazza	2.980	17	526308	287.590	89.745
riportare	2.970	28	896505	473.677	152.870
volere	2.960	188	6271953	3180.403	1069.479
futuro	2.930	38	1247713	642.847	212.757
vi	2.910	94	3162634	1590.202	539.285
forza	2.910	48	1596345	812.018	272.205
oggi	2.890	102	3464482	1725.538	590.755
pace	2.890	19	614524	321.424	104.787
chiedere	2.870	66	2240208	1116.525	381.995
Milano	2.840	42	1428604	710.516	243.602
mi	2.840	219	7610568	3704.832	1297.736
miliardo	2.830	13	417510	219.922	71.193
bastare	2.830	32	1084147	541.345	184.866
aiutare	2.800	33	1130934	558.262	192.844
nostro	2.800	205	7225076	3467.993	1232.003
ridurre	2.790	27	923634	456.760	157.496
prima	2.760	74	2618866	1251.861	446.563
bene	2.730	84	3012449	1421.031	513.676
impegno	2.730	24	834714	406.009	142.333
elezione	2.730	11	362506	186.087	61.814
preferire	2.710	16	549261	270.673	93.659
scegliere	2.680	42	1515642	710.516	258.444
ecco	2.680	30	1072561	507.511	182.891
regola	2.660	21	745138	355.258	127.059
tagliare	2.650	11	375827	186.087	64.085
diritto	2.620	54	2011117	913.520	342.931
andare	2.610	156	5892187	2639.058	1004.722
marzo	2.610	29	1068103	490.594	182.130
normale	2.600	15	535621	253.756	91.333
nessun	2.560	25	932285	422.926	158.971
ragazzo	2.530	32	1217698	541.345	207.639
servire	2.530	36	1378125	609.013	234.995
girare	2.520	13	477050	219.922	81.345
noi	2.520	76	2960379	1285.695	504.797
li	2.510	41	1584931	693.599	270.259
gli	2.500	47	1829089	795.101	311.892
quartiere	2.500	10	361833	169.170	61.699
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. 1	2.500	1.1	401057	106.007	(0.524
giornale	2.500	11	401857	186.087	68.524
proteggere	2.500	10	362296	169.170	61.778
meno	2.500	60	2350438	1015.022	400.791
me	2.490	61	2391270	1031.939	407.754
duro	2.490	13	483136	219.922	82.383
legge	2.480	47	1842442	795.101	314.169
genitore	2.480	17	645249	287.590	110.026
lavoro	2.470	128	5103847	2165.381	870.296
stare	2.460	126	5041411	2131.547	859.650
europeo	2.440	41	1630685	693.599	278.061
imporre	2.440	12	453773	203.004	77.376
fatto	2.430	53	2128419	896.603	362.933
casa	2.410	84	3424249	1421.031	583.895
principio	2.400	12	462327	203.004	78.835
dire	2.390	189	7822155	3197.320	1333.815
signore	2.380	16	632098	270.673	107.784
adesso	2.370	18	718951	304.507	122.594
accordo	2.370	23	930515	389.092	158.669
vostro	2.340	43	1793177	727.433	305.768
sostegno	2.320	13	521825	219.922	88.980
partenza	2.320	13	523693	219.922	89.299
sindaco	2.310	22	911095	372.175	155.358
ci	2.310	204	8739893	3451.076	1490.306
mio	2.300	135	5790351	2283.800	987.357
libertà	2.290	17	704643	287.590	120.154
repubblica	2.260	13	539265	219.922	91.954
donna	2.240	47	2047976	795.101	349.216
uccidere	2.230	10	412275	169.170	70.300
minuto	2.220	26	1129070	439.843	192.526
obiettivo	2.210	30	1317242	507.511	224.613
mille	2.160	10	427912	169.170	72.967
finire	2.140	25	1127974	422.926	192.339
piacere	2.130	33	1508452	558.262	257.218
crescere	2.120	17	764618	287.590	130.381
felice	2.110	11	487361	186.087	83.104
fuoco	2.100	13	582915	219.922	99.397
Torino	2.100	14	631518	236.839	107.685
controllare	2.080	12	541645	203.004	92.360
idea	2.070	33	1549193	558.262	264.165
altri	2.070	27	1262040	456.760	215.200
mano	2.070	37	1746079	625.930	297.737
giornalista	2.050	10	453938	169.170	77.404
economia	2.040	14	650322	236.839	110.891
chiaro	2.010	19	910087	321.424	155.186
contro	2.000	44	2153044	744.350	367.132
	1.970	15	726805	253.756	123.933
popolo	1.970	47	2339174	795.101	
mese					398.870
lezione	1.960	10	476735	169.170	81.292
toccare	1.960	10	477284	169.170	81.385
morire	1.950	17	834436	287.590	142.286
rispondere	1.940	22	1096172	372.175	186.917
cambiamento	1.930	11	536817	186.087	91.537
fare	1.930	378	19426221	6394.641	3312.513
porta	1.920	17	852391	287.590	145.348
pensiero	1.900	16	806601	270.673	137.540
condividere	1.860	15	771845	253.756	131.613

perdere	1.860	24	1252064	406.009	213.499
protezione	1.830	11	569479	186.087	97.106
dare	1.820	95	5152243	1607.119	878.548
i	1.810	22	1177110	372.175	200.718
contrario	1.800	10	523935	169.170	89.340
semplicemente	1.790	10	528352	169.170	90.093
ora	1.780	111	6173605	1877.791	1052.709
euro	1.770	40	2215303	676.682	377.748
portare	1.760	57	3180770	964.271	542.377
arrivare	1.760	48	2687767	812.018	458.312
garantire	1.750	20	1108670	338.341	189.048
giusto	1.750	20	1109273	338.341	189.151
valere	1.740	12	659531	203.004	112.462
pensare	1.740	51	2885281	862.769	491.991
tanto	1.730	73	4162203	1234.944	709.729
col	1.720	23	1300134	389.092	221.696
chiudere	1.720	16	900973	270.673	153.632
decreto	1.700	11	617014	186.087	105.212
aspettare	1.690	15	856051	253.756	145.972
aumentare	1.690	14	799086	236.839	136.258
niente	1.680	15	861100	253.756	146.833
prossimo	1.670	25	1464902	422.926	249.792
interesse	1.660	22	1288768	372.175	219.758
mettere	1.660	63	3746484	1065.773	638.842
ne	1.660	63	3747093	1065.773	638.945
problema	1.650	43	2559166	727.433	436.383
notte	1.640	16	946046	270.673	161.318
occupare	1.630	15	890898	253.756	151.914
presidente	1.630	34	2048555	575.179	349.315
uomo	1.620	46	2787198	778.184	475.266
parere	1.600	17	1035399	287.590	176.554
sabato	1.590	15	912272	253.756	155.558
mai	1.590	46	2847652	778.184	485.575
umano	1.580	22	1361118	372.175	232.095
non	1.580	658	41414206	11131.412	7061.853
nulla	1.570	18	1117759	304.507	190.598
Napoli	1.570	11	675283	186.087	115.148
continuare	1.540	31	1971139	524.428	336.114
cuore	1.540	20	1269962	338.341	216.551
libero	1.500	18	1172874	304.507	199.996
qualche	1.490	38	2512439	642.847	428.415
bambino	1.490	31	2050021	524.428	349.565
tutti	1.480	39	2598823	659.765	443.145
persona	1.480	58	3881836	981.188	661.922
rispetto	1.470	32	2136359	541.345	364.287
dimostrare	1.470	14	926034	236.839	157.905
morte	1.470	14	927758	236.839	158.199
controllo	1.470	19	1267981	321.424	216.213
ospitare	1.460	10	660264	169.170	112.587
giro	1.450	11	736303	186.087	125.553
prendere	1.440	41	2802949	693.599	477.952
buono	1.440	30	2052290	507.511	349.952
bisogno	1.430	17	1165378	287.590	198.718
perché	1.410	93	6538180	1573.285	1114.875
senza	1.400	70	4930818	1184.193	840.791
settimana	1.400	19	1331917	321.424	227.115

fuori	1.400	19	1332140	321.424	227.153
quelli	1.380	25	1787389	422.926	304.781
se	1.370	177	12768671	2994.316	2177.284
lo	1.370	73	5281227	1234.944	900.542
p	1.360	17	1221696	287.590	208.321
solo	1.360	113	8209599	1911.625	1399.881
giorno	1.360	69	5029918	1167.276	857.690
mantenere	1.340	12	873939	203.004	149.022
fa	1.330	18	1323396	304.507	225.662
differenza	1.330	10	731835	169.170	124.791
nonostante	1.320	11	810358	186.087	138.180
avere	1.320	665	50024970	11249.831	8530.140
loro	1.320	89	6688269	1505.616	1140.468
interessare	1.320	10	740233	169.170	126.223
troppo	1.310	20	1496654	338.341	255.206
centro	1.310	37	2789639	625.930	475.683
questo	1.300	320	24345325	5413.452	4151.308
ultimo	1.300	47	3571246	795.101	608.960
caro	1.300	10	749746	169.170	127.845
davanti	1.290	10	753305	169.170	128.452
male	1.290	13	984634	219.922	167.897
rete	1.290	19	1445880	321.424	246.548
cominciare	1.290	13	989116	219.922	168.662
mare	1.290	16	1222215	270.673	208.409
sì	1.280	10 26	759395	169.170	129.490
famiglia	1.270 1.270		2015950	439.843	343.755
tutto	1.270	201 11	15673327	3400.325	2672.579
festa	1.270	30	848239 2346420	186.087	144.640
scuola	1.250	30 11	2346420 857761	507.511 186.087	400.106 146.263
passato unico	1.250	27	2128709	456.760	362.982
rischio	1.250	14	1099945	236.839	187.560
	1.240	901	72005360	15242.252	12278.184
a insieme	1.240	24	1911370	406.009	325.922
	1.230	25	1999655	422.926	340.976
giovane	1.230	130	1999055	2199.215	1783.233
anno parlare	1.230	36	2897595	609.013	494.091
né	1.220	11	882434	186.087	150.471
migliore	1.220	18	1454893	304.507	248.085
Roma	1.210	26	2113120	439.843	360.324
aspetto	1.210	15	1219212	253.756	207.897
precedente	1.200	12	978106	203.004	166.784
viaggio	1.200	13	1066521	219.922	181.861
notizia	1.190	10	827617	169.170	141.123
scorso	1.180	14	1164131	236.839	198.505
cosa	1.180	62	5192669	1048.856	885.442
più	1.180	239	20085903	4043.172	3425.001
ma	1.180	215	18104913	3637.163	3087.207
contratto	1.180	10	834886	169.170	142.363
capire	1.170	20	1688659	338.341	287.946
esistere	1.170	16	1354017	270.673	230.884
lavoratore	1.160	10	844161	169.170	143.944
strada	1.150	20	1715439	338.341	292.513
passare	1.150	24	2064392	406.009	352.015
rimanere	1.150	16	1374986	270.673	234.459
forte	1.140	17	1468973	287.590	250.486
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credere	1.140	20	1738678	338.341	296.475
comunità	1.130	11	957192	186.087	163.218
dopo	1.130	63	5532893	1065.773	943.456
bello	1.120	28	2465871	473.677	420.475
le	1.110	24	2131576	406.009	363.471
dovere	1.110	110	9806951	1860.874	1672.258
qui	1.110	30	2675714	507.511	456.256
commissione	1.110	10	888540	169.170	151.512
lei	1.110	14	1248456	236.839	212.884
vicino	1.110	13	1161120	219.922	197.991
ragione	1.100	11	985495	186.087	168.044
giornata	1.100	15	1352028	253.756	230.545
dalla	1.090	124	11272840	2097.713	1922.218
lui	1.090	23	2096402	389.092	357.474
ricordare	1.070	21	1938811	355.258	330.601
permettere	1.070	21	1939050	355.258	330.642
per	1.070	739	68783056	12501.692	11728.725
mancare	1.060	10	928836	169.170	158.383
al	1.060	429	40237687	7257.410	6861.236
consiglio	1.050	19	1788898	321.424	305.039
spesa	1.050	10	942350	169.170	160.687
via	1.040	42	3985191	710.516	679.545
bisognare	1.040	10	948250	169.170	161.693
programma	1.040	20	1902996	338.341	324.494
ancora	1.040	49	4685889	828.935	799.027
lasciare	1.040	24	2294196	406.009	391.201
campo	1.040	19	1816956	321.424	309.823
essere	1.030	1272	122308133	21518.473	20855.695
politico	1.030	19	1828900	321.424	311.860
conto	1.010	11	1078551	186.087	183.912
c	1.010	53	5228680	896.603	891.582
su	1.000	91	9011627	1539.451	1536.641

## APPENDIX D KEYWORD LIST OF THE SALVINI TRADITIONAL CORPUS

Keyword	Score	Freq	Ref freq	Rel freq	Rel ref freq
Salvini	101.870	65	27690	1489.766	4.722
abbiam	43.800	21	7135	481.309	1.217
qua	40.980	85	221602	1948.156	37.787
lega	31.690	72	248547	1650.203	42.382
eh	30.290	45	142976	1031.377	24.380
Aquarius	30.140	13	1276	297.953	0.218
Pontida	27.470	12	2201	275.034	0.375
immigrazione	25.440	31	107428	710.504	18.318
Fornero	24.010	13	16587	297.953	2.828
perbene	23.230	11	7527	252.114	1.283
Pinzolo	23.100	11	7889	252.114	1.345
comizio	22.720	13	20843	297.953	3.554
Matteo	21.780	49	246425	1123.055	42.020
immigrato	21.410	31	138735	710.504	23.657
ringraziare	17.180	64	445614	1466.847	75.985
sbarcare	17.060	15	62993	343.792	10.741
aldilà	16.160	10	28178	229.195	4.805
orgoglio	14.670	18	110263	412.551	18.802
Renzi	13.760	23	170310	527.148	29.041
scappare	13.230	19	138747	435.470	23.659
bimba	13.230	11	57578	252.114	9.818
votare	13.140	37	324350	848.021	55.307
applauso	12.790	12	72022	275.034	12.281
sardo	12.490	16	118258	366.712	20.165
gente	12.480	76	764544	1741.881	130.368
tassa	12.360	27	239723	618.826	40.877
papà	11.350	17	147835	389.631	25.208
giurare	11.270	10	65795	229.195	11.219
Sardegna	11.170	27	271550	618.826	46.304
voi	11.100	96	1108720	2200.270	189.056
fascista	11.060	14	116737	320.873	19.906
beh	11.020	19	178446	435.470	30.428
Bruxelles	10.980	12	93571	275.034	15.956
clandestino	10.930	10	69710	229.195	11.887
multinazionale	10.780	11	83935	252.114	14.312
vent	10.570	12	99488	275.034	16.964
difendere	10.270	26	287413	595.907	49.009
indagare	10.120	15	146386	343.792	24.961
io	10.050	287	3786521	6577.892	645.669
ministro	9.900	52	653563	1191.813	111.444
bimbo	9.740	19	209491	435.470	35.722
televisione	9.580	16	172005	366.712	29.330
cancellare	9.470	19	217306	435.470	37.055
carità	9.420	13	133077	297.953	22.692
onore	9.250	22	267436	504.229	45.603
nonno	9.230	13	136983	297.953	23.358
vincere	8.990	60	844530	1375.169	144.007

palco	8.970	15	172780	343.792	29.462
Trentino	8.800	13	146545	297.953	24.989
sondaggio	8.730	10	101969	229.195	17.388
governo	8.670	94	1406059	2154.431	239.758
bandiera	8.640	14	165885	320.873	28.286
nave	8.470	21	281354	481.309	47.976
qualcuno	8.400	55	828628	1260.572	141.296
dignità	8.380	15	189068	343.792	32.239
governare	7.940	12	151953	275.034	25.911
evidentemente	7.500	12	164203	275.034	28.000
paese	7.470	139	2448753	3185.808	417.556
disabile	7.350	12	168801	275.034	28.784
no	7.280	66	1167200	1512.686	199.028
lupo	7.220	11	154282	252.114	26.308
colpa	7.210	19	303864	435.470	51.814
però	7.090	124	2300642	2842.016	392.300
signora	6.830	14	225456	320.873	38.444
bravo	6.760	23	407271	527.148	69.447
popolo	6.410	37	726805	848.021	123.933
viva	6.320	10	163291	229.195	27.844
perché	6.260	307	6538180	7036.282	1114.875
mamma	6.210	24	470666	550.068	80.257
quindi	6.200	170	3633847	3896.312	619.635
domani	5.990	23	467345	527.148	79.691
sorriso	5.890	11	202153	252.114	34.471
migliaio	5.880	17	340016	389.631	57.979
collega	5.870	18	363488	412.551	61.981
giù	5.870	10	180489	229.195	30.777
questa	5.850	30	640074	687.585	109.144
ciascuno	5.840	14	273545	320.873	46.644
zero	5.780	14	277158	320.873	47.260
autonomia	5.780	15	300422	343.792	51.227
coraggio	5.720	13	257272	297.953	43.869
sinistra	5.690	31	683574	710.504	116.561
pagare	5.620	38	860358	870.940	146.706
giornalista	5.620	21	453938	481.309	77.404
elettorale	5.560	15	314300	343.792	53.594
soccorso	5.530	11	219090	252.114	37.359
parlamentare	5.520	11	219683	252.114	37.460
coordinamento	5.430	12	249346	275.034	42.518
voto	5.330	25	582844	572.987	99.385
alzare	5.220	14	313066	320.873	53.383
mattina	5.180	21	498104	481.309	84.936
imprenditore	5.170	12	264534	275.034	45.108
mandare	5.140	20	475485	458.390	81.079
ce	5.080	28	693480	641.746	118.251
italiano	5.050	142	3733480	3254.567	636.624
tornare	5.020	56	1451109	1283.491	247.440
noi	5.010	112	2960379	2566.982	504.797
insegnante	5.000	16	382945	366.712	65.299
sì	5.000	30	759395	687.585	129.490
sette	4.960	15	359873	343.792	61.365
figlio	4.940	54	1421219	1237.652	242.343
col	4.890	49	1300134	1123.055	221.696
impegno	4.880	32	834714	733.423	142.333
porto	4.820	20	510736	458.390	87.090

dormire	4.820	11	259994	252.114	44.334
lavorare	4.810	53	1433175	1214.733	244.382
ragazzo	4.780	45	1217698	1031.377	207.639
là .	4.780	18	460254	412.551	78.481
segretario	4.770	14	347893	320.873	59.322
testa	4.730	28	749165	641.746	127.746
negozio	4.670	19	500519	435.470	85.347
nessuno	4.660	33	906166	756.343	154.517
giustizia	4.640	18	475862	412.551	81.143
fatica	4.600	11	275786	252.114	47.026
Europa	4.590	36	1007746	825.101	171.838
voglia	4.590	15	393746	343.792	67.141
lì	4.570	20	541767	458.390	92.381
cambiare	4.560	45	1280176	1031.377	218.293
bocca	4.550	13	338608	297.953	57.739
stare	4.540	172	5041411	3942.151	859.650
giornale	4.510	15	401857	343.792	68.524
chi	4.500	140	4136650	3208.728	705.372
diritto	4.440	68	2011117	1558.525	342.931
me	4.360	79 11	2391270	1810.639	407.754
meritare	4.350	11	294428	252.114	50.205
cinque	4.340	25	729073	572.987	124.320
pensare	4.310	94	2885281	2154.431	491.991
c Italia	4.310 4.290	169 117	5228680	3873.393	891.582
adesso	4.220	24	3620400 718951	2681.580 550.068	617.342 122.594
	4.220	13	369003	297.953	62.922
gioia missione	4.190	13	339915	297.933	57.962
dire	4.190	240	7822155	5500.676	1333.815
milione	4.080	39	1239186	893.860	211.303
grazie	4.070	89	2892427	2039.834	493.210
pd	4.050	12	354258	275.034	60.407
pensione	4.050	10	288000	229.195	49.109
paura	4.010	19	593627	435.470	101.224
soldo	3.960	15	465642	343.792	79.400
magari	3.920	22	710073	504.229	121.080
regola	3.920	23	745138	527.148	127.059
faccia	3.890	10	302410	229.195	51.566
andare	3.780	167	5892187	3827.554	1004.722
difesa	3.730	17	570110	389.631	97.214
accogliere	3.630	16	550504	366.712	93.871
mano	3.610	48	1746079	1100.135	297.737
ci	3.570	233	8739893	5340.240	1490.306
davanti	3.550	21	753305	481.309	128.452
speranza	3.530	14	490816	320.873	83.693
mi	3.510	200	7610568	4583.897	1297.736
responsabilità	3.490	17	612202	389.631	104.391
casa	3.490	90	3424249	2062.754	583.895
ovviamente	3.480	19	691176	435.470	117.858
giro	3.460	20	736303	458.390	125.553
confine	3.440	10	349154	229.195	59.537
piazza	3.440	30	1132199	687.585	193.060
niente	3.420	23	861100	527.148	146.833
dieci	3.420	13	470095	297.953	80.159
battaglia	3.380	11	395483	252.114	67.437
futuro	3.340	32	1247713	733.423	212.757

. 1	2 220	1.5	500050	2.42.702	06.625
risolvere ·	3.320	15	566656	343.792	96.625
sei	3.310	27	1054959	618.826	179.889
arrivare	3.300	67	2687767	1535.605	458.312
chiedere	3.300	56	2240208	1283.491	381.995
rischiare	3.300	10	366915	229.195	62.565
pesce	3.290	11	408157	252.114	69.598
scegliere	3.280	38	1515642	870.940	258.444
fare	3.270	474	19426221	10863.835	3312.513
mettere	3.270	92	3746484	2108.593	638.842
finalmente	3.260	14	535894	320.873	91.379
valere	3.260	17	659531	389.631	112.462
fermare	3.240	17	663620	389.631	113.159
riforma	3.230	12	459382	275.034	78.333
vostro	3.230	44	1793177	1008.457	305.768
li	3.230	39	1584931	893.860	270.259
partito	3.220	20	795606	458.390	135.665
ascoltare	3.220	15	586671	343.792	100.038
prossimo	3.210	36	1464902	825.101	249.792
lavoro	3.140	120	5103847	2750.338	870.296
vi	3.110	74	3162634	1696.042	539.285
guardare	3.050	29	1239840	664.665	211.415
normale	3.040	13	535621	297.953	91.333
anzi	3.030	14	581745	320.873	99.198
donna	3.030	47	2047976	1077.216	349.216
bisogno	3.010	27	1165378	618.826	198.718
cuore	2.980	29	1269962	664.665	216.551
tanto	2.910	91	4162203	2085.673	709.729
Roma	2.870	46	2113120	1054.296	360.324
ragazza	2.860	12	526308	275.034	89.745
volere	2.850	134	6271953	3071.211	1069.479
felice	2.820	11	487361	252.114	83.104
sera	2.810	18	821729	412.551	140.119
marzo	2.800	23	1068103	527.148	182.130
parlare	2.790	61	2897595	1398.089	494.091
domenica	2.780	21	978210	481.309	166.802
mese	2.770	49	2339174	1123.055	398.870
mio	2.770	120	5790351	2750.338	987.357
chiudere	2.770	19	900973	435.470	153.632
buon	2.720	20	950748	458.390	162.119
bello	2.690	50	2465871	1145.974	420.475
	2.640	10	473613	229.195	80.759
comprare	2.620	16	785863	366.712	134.004
incontrare	2.600	51	2598823	1168.894	443.145
tutti		36			
politico	2.590		1828900	825.101	311.860
mangiare	2.590	13	639074	297.953	108.973
prima	2.580	51	2618866	1168.894	446.563
repubblica	2.570	11	539265	252.114	91.954
Milano	2.570	28	1428604	641.746	243.602
sindaco	2.560	18	911095	412.551	155.358
qualche	2.530	48	2512439	1100.135	428.415
fatto	2.490	40	2128419	916.779	362.933
morire	2.470	16	834436	366.712	142.286
sud	2.470	12	618939	275.034	105.540
lo	2.450	97	5281227	2223.190	900.542
ricordare	2.450	36	1938811	825.101	330.601
lavoratore	2.450	16	844161	366.712	143.944

qualcosa	2.420	22	1188353	504.229	202.635
rispetto	2.410	39	2136359	893.860	364.287
nostro	2.390	129	7225076	2956.613	1232.003
altri	2.390	23	1262040	527.148	215.200
fa	2.380	24	1323396	550.068	225.662
crescere	2.360	14	764618	320.873	130.381
	2.350	20	1108670	458.390	189.048
garantire dare	2.330	90	5152243	2062.754	878.548
dove	2.320	69	3956255	1581.444	674.611
	2.320	20	1124527	458.390	191.752
quattro scuola	2.320			939.699	
finire	2.310	41 20	2346420 1127974		400.106 192.339
				458.390	
perdere	2.300	22	1252064	504.229	213.499
mai	2.290	49	2847652	1123.055	485.575
decreto	2.280	11	617014	252.114	105.212
settimana	2.270	23	1331917	527.148	227.115
capire	2.260	29	1688659	664.665	287.946
sperare	2.260	15	857967	343.792	146.299
europeo	2.260	28	1630685	641.746	278.061
portare	2.260	54	3180770	1237.652	542.377
merito	2.240	11	626238	252.114	106.785
non	2.240	692	41414206	15860.283	7061.853
nessun	2.230	16	932285	366.712	158.971
cosa	2.210	86	5192669	1971.076	885.442
idea	2.210	26	1549193	595.907	264.165
questo	2.210	400	24345325	9167.794	4151.308
aiutare	2.200	19	1130934	435.470	192.844
vita	2.180	69	4221142	1581.444	719.779
legge	2.150	30	1842442	687.585	314.169
chiaro	2.140	15	910087	343.792	155.186
visto	2.140	26	1602550	595.907	273.263
quello	2.140	151	9472411	3460.842	1615.213
fra	2.130	32	1987336	733.423	338.876
buono	2.130	33	2052290	756.343	349.952
problema	2.130	41	2559166	939.699	436.383
passato	2.120	14	857761	320.873	146.263
differenza	2.110	12	731835	275.034	124.791
amico	2.100	23	1442457	527.148	245.964
parola	2.090	31	1965746	710.504	335.194
ieri	2.070	12	749496	275.034	127.802
bambino	2.070	32	2050021	733.423	349.565
mezzo	2.060	27	1728253	618.826	294.698
pronto	2.060	13	818273	297.953	139.530
euro	2.040	34	2215303	779.262	377.748
sicuro	2.010	12	771918	275.034	131.626
terra	2.010	25	1645687	572.987	280.619
cominciare	1.980	15	989116	343.792	168.662
avere	1.950	725	50024970	16616.626	8530.140
bene	1.940	44	3012449	1008.457	513.676
esistere	1.940	20	1354017	458.390	230.884
interessare	1.920	11	740233	252.114	126.223
poi	1.920	74	5164908	1696.042	880.708
giorno	1.910	72	5029918	1650.203	857.690
significare	1.910	11	746673	252.114	127.321
guerra	1.900	17	1173002	389.631	200.018
dio	1.890	24	1675163	550.068	285.645

oggi	1.890	49	3464482	1123.055	590.755
anno	1.870	146	10457762	3346.245	1783.233
costo	1.870	17	1195632	389.631	203.876
che	1.860	1216	87725754	27870.092	14958.789
ritenere	1.860	15	1056703	343.792	180.187
prendere	1.850	39	2802949	893.860	477.952
quelli	1.850	25	1787389	572.987	304.781
porta	1.830	12	852391	275.034	145.348
servire	1.820	19	1378125	435.470	234.995
ne	1.820	51	3747093	1168.894	638.945
meno	1.810	32	2350438	733.423	400.791
vedere	1.810	60	4440750	1375.169	757.226
mantenere	1.790	12	873939	275.034	149.022
comunità	1.780	13	957192	297.953	163.218
ormai	1.770	16	1190517	366.712	203.004
sentire	1.760	27	2032428	618.826	346.565
dovere	1.760	129	9806951	2956.613	1672.258
ufficio	1.760	15	1121701	343.792	191.270
	1.750	167			2177.284
se			12768671	3827.554	
piacere	1.750	20	1508452	458.390	257.218
riuscire	1.740	30	2293695	687.585	391.115
entrare ·	1.730	18	1371377	412.551	233.844
sicurezza	1.730	17	1296740	389.631	221.117
uomo	1.720	36	2787198	825.101	475.266
provare	1.720	17	1307546	389.631	222.960
nome	1.710	24	1862632	550.068	317.612
data	1.710	13	999087	297.953	170.362
bastare	1.700	14	1084147	320.873	184.866
preparare	1.660	11	865625	252.114	147.604
umano	1.650	17	1361118	389.631	232.095
stato	1.640	26	2103262	595.907	358.643
uno	1.640	37	3008277	848.021	512.964
amare	1.630	12	966148	275.034	164.745
essere	1.630	1480	122308133	33920.836	20855.695
occupare	1.620	11	890898	252.114	151.914
ecco	1.600	13	1072561	297.953	182.891
a	1.590	854	72005360	19573.239	12278.184
politica	1.590	13	1076109	297.953	183.496
fuori	1.590	16	1332140	366.712	227.153
famiglia	1.580	24	2015950	550.068	343.755
cercare	1.580	28	2360117	641.746	402.442
mondo	1.570	44	3733785	1008.457	636.676
giusto	1.550	13	1109273	297.953	189.151
cultura	1.520	15	1303674	343.792	222.299
sapere	1.510	50	4429761	1145.974	755.352
aprire	1.500	20	1769745	458.390	301.773
economico	1.490	18	1600153	412.551	272.854
mercato	1.480	18	1611931	412.551	274.863
te	1.480	14	1250589	320.873	213.247
scorso	1.480	13	1164131	297.953	198.505
gran	1.480	10	891566	229.195	152.028
strada	1.470	19	1715439	435.470	292.513
ben	1.470	21	1901546	481.309	324.247
riportare	1.470	10	896505	229.195	152.870
impresa	1.470	15	1354294	343.792	230.931
persona	1.450	42	3881836	962.618	661.922

scrivere	1.430	28	2609526	641.746	444.970
ma	1.430	193	18104913	4423.460	3087.207
tu	1.420	13	1209203	297.953	206.190
ti	1.420	30	2816570	687.585	480.275
passare	1.420	22	2064392	504.229	352.015
mare	1.410	13	1222215	297.953	208.409
tre	1.400	28	2664270	641.746	454.305
scelta	1.400	15	1428528	343.792	243.589
bisognare	1.390	10	948250	229.195	161.693
permettere	1.380	20	1939050	458.390	330.642
disposizione	1.360	12	1174209	275.034	200.223
ultimo	1.350	36	3571246	825.101	608.960
loro	1.340	67	6688269	1535.605	1140.468
ragione	1.340	10	985495	229.195	168.044
esempio	1.340	21	2087912	481.309	356.026
fronte	1.330	11	1098505	252.114	187.314
usare	1.300	19	1944475	435.470	331.567
storia	1.280	27	2815918	618.826	480.164
lei	1.280	12	1248456	275.034	212.884
percorso	1.270	14	1470357	320.873	250.722
altro	1.270	93	9842692	2131.512	1678.353
solo	1.260	77	8209599	1764.800	1399.881
quando	1.240	48	5180873	1100.135	883.430
venire	1.240	74	8005211	1696.042	1365.030
rispondere	1.210	10	1096172	229.195	186.917
tutto	1.210	141	15673327	3231.647	2672.579
consiglio	1.200	16	1788898	366.712	305.039
ora	1.200	55	6173605	1260.572	1052.709
insieme	1.190	17	1911370	389.631	325.922
partire	1.180	14	1579110	320.873	269.266
due	1.170	59	6765918	1352.250	1153.708
gli	1.170	16	1829089	366.712	311.892
•	1.170	18			
soprattutto		1274	2064989 147122730	412.551 29199.422	352.117 25087.022
e	1.160				
un	1.160	514	59553559	11780.615	10154.933
centro	1.150	24	2789639	550.068	475.683
giugno	1.140	11	1285960	252.114	219.279
meglio	1.140	15	1761131	343.792	300.304
libero	1.140	10	1172874	229.195	199.996
regione	1.130	15	1770722	343.792	301.939
su	1.120	75	9011627	1718.961	1536.641
obiettivo	1.120	11	1317242	252.114	224.613
volta	1.120	38	4570956	870.940	779.429
momento	1.110	22	2665342	504.229	454.488
vero	1.090	21	2578363	481.309	439.656
come	1.080	154	19155252	3529.601	3266.308
cittadino	1.080	12	1493759	275.034	254.712
una	1.070	314	39279978	7196.718	6697.929
più	1.070	160	20085903	3667.117	3425.001
settore	1.060	14	1765578	320.873	301.062
senza	1.060	39	4930818	893.860	840.791
chiamare	1.060	13	1648712	297.953	281.134
presidente	1.050	16	2048555	366.712	349.315
tenere	1.050	19	2439473	435.470	415.973
leggere	1.040	17	2187941	389.631	373.083
interesse	1.040	10	1288768	229.195	219.758

0	1.040	122	15763313	2796.177	2687.923
tempo	1.020	43	5647031	985.538	962.918
fino	1.020	24	3153602	550.068	537.745
vivere	1.020	16	2114052	366.712	360.483
migliore	1.020	11	1454893	252.114	248.085
il	1.010	1201	159077049	27526.300	27125.444
primo	1.010	65	8620819	1489.766	1470.002
forza	1.010	12	1596345	275.034	272.205
trovare	1.000	39	5220874	893.860	890.251
nascere	1.000	13	1745960	297.953	297.717

## **APPENDIX E**

Participant class-type	Trump	Salvini
Trump	30%(259)	-
Trump administration	40%(349)	-
The United States	2% (21)	-
U.S. citizens	25%(215)	-
Salvini	-	51%(482)
Lega	-	29%(281)
Italy	-	3% (25)
Italian citizens	-	6% (53)
Europe	-	3% (29)
Immigrants	3% (23)	8%(80)
and refugees		

Table E.1 Actors' comparison

Participant class-type	Trump	Salvini
Trump	42%(695)	-
Trump administration	25%(421)	-
The United States	5% (76)	-
U.S. citizens	26%(424)	-
Salvini	-	64%(1,189)
Lega	-	19%(363)
Italy	-	2% (43)
Italian citizens	-	5% (94)
Europe	1%(2)	3% (47)
Immigrants	1% (25)	7%(126)
and refugees		

Table E.2 Active voice-type comparison

Participant class-type	Trump	Salvini
Trump	36%(367)	-
Trump administration	35%(358)	-
The United States	2% (32)	-
U.S. citizens	25%(256)	-
Salvini	-	63%(554)
Lega	-	27%(236)
Italy	-	3% (28)
Italian citizens	-	4% (38)
Europe	1%(1)	1% (3)
Immigrants	1% (5)	2%(22)
and refugees		

Table E.3 Positive evaluation comparison