#Populism on Twitter: Statistical Analysis of the Correlation between Tweet Popularity and "Populist" Discursive Features

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Abstract
Recent political events, such as the Brexit or Donald Trump's electoral success, have led to a proliferation of studies focusing on populism nature (Müller 2017; Mudde and Kaltwasser 2017). Part of the literature has also investigated communicative aspects of populism, highlighting how populists are benefitting from the use of social media (Bartlett 2014; Gerbaudo 2018). This research offers further insights on the subject by analyzing populist discourse on Twitter and exploring the correlation between the presence of linguistic features linked to populism, such as emotionalization, simplified rhetoric and intensified claims (Canovan 1999; Heinisch 2008), and tweet popularity. The use of linear mixed effects models revealed a positive correlation between the linguistic elements of interest and tweet popularity, not only in the populist sample, but also in the control group composed by establishment politicians. Surprisingly, reference tweets received more popularity than populist messages when the discursive features analyzed were present.

Key words
Social media; populism; linear mixed effects models; discourse analysis; appraisal framework

1. Introduction

Populism has been present throughout the centuries in several different countries. Historically, the first instances of populism have been identified in the late 19th century, with the People's Party in the United States of America, and the *narodnichestvo* movement in the czarist Russia (Taggart 2000). Since then, its presence has been rather erratic, with persistent governmental expressions in particular areas such as Latin America, but decades of minority politics in most of European countries. However, things seem to have been changing, especially in the Western world. In Europe, the recent populist wave to the detriment of the more established parties has been shown by different events. In 2016, the UK Independent Party (UKIP) successfully supported the Brexit campaign to withdraw the United Kingdom from the European Union, despite having only one seat in the British parliament. Shortly thereafter, the leader of the French nationalist party Front National, Marine Le Pen, managed to achieve the most successful result in the party history by arriving second to the presidential ballot in 2017. Lastly, the Italian populist party Movimento 5 Stelle, founded in 2009 by the comedian Beppe Grillo, became the largest individual party in the Italian parliament during the 2018 general election in Italy, obtaining 32.7% of the votes. In addition, they entered in coalition with the right-wing regionalist party Lega Nord, stipulating a "government contract" which includes, among other proposals, stricter immigration rules, support for direct democracy practices, and cuts to politics' costs.[1]

In general, the diffusion of social issues such as immigration, racism, terrorism and economic crisis in the Western world can be considered a major reason for the rise of populist ideas during these last decades. However, what seems to be different in comparison with older examples of populism is the role that new instruments have played in populist and, more generally, political communication. In particular, social media have given political actors the possibility to cultivate a personal image thanks to profiles and personal pages, as well as to be in closer contact with their audience. Nonetheless, as suggested by Bartlett (2014: 100), it seems that "[...] populist parties in Europe have been quicker to spot the opportunities these new technologies present to reach out and mobilize an increasingly disenchanted electorate." Through the use of social networks such as Twitter or Facebook, populists had the chance to bypass media intermediaries and possible censorship, and to express their thoughts directly, often enhancing their texts with images or videos to better appeal to the online audience. Moreover, the importance that social media had (and have) for the spread of populism was sometimes underlined by the populist leaders themselves, as stated by Nigel Farage and Marine Le Pen in the following tweets:

(1) "Without the internet, the development and growth of UKIP in Britain would have been far tougher." (Farage 2016)

(2) "Les réseaux sociaux permettent de s'adresser directement au peuple. Ma campagne sera innovante en ce domaine." ["Social networks allow to speak directly to the people. My campaign will be innovative in this domain."] (Le Pen, 2017)

The advantageous relationship between populism and social media has been examined by several studies (cf. Bartlett 2014; Trottier and Fuchs 2015; Engesser et al. 2017; Gerbaudo 2018). However, it seems that the correlation between populists' popularity on social media and the language they use has remained rather unclear. Therefore, the aim of this essay is to examine the discourse of four European populist leaders (Luigi Di Maio, Matteo Salvini, Marine Le Pen and Nigel Farage) on Twitter in order to offer new insights regarding not only the main elements of populist style, but above all the effects that these have on the digital spread of the populist discourse. We decided to opt for a quantitative methodology to give more reliable and less biased results when observing the correlation between language and popularity. To conduct the research, we collected 10,365 messages from the official Twitter accounts of the four above-mentioned politicians. Next, we analyzed the tweets using the Appraisal Framework (Martin and White 2005), which allowed to ascertain the presence of linguistic features (mostly emotionalization, simplified rhetoric and intensifications) that previous studies link to populism (Heinisch 2008; Bos et al. 2011). We also created a reference corpus consisting of tweets collected from the accounts of Matteo Renzi, David Cameron and François Hollande in order to verify the presence and the effects of populist discursive elements in establishment discourse as well. Lastly, we chose to adopt statistical methods, using linear mixed effects models (Bates et al. 2015), to observe possible significant correlations between the presence of specific linguistic elements and each tweet popularity value, this latter being the sum of "favorites" and "retweets" (namely the number of people who respectively liked or quoted the message).

The first part of this paper illustrates the relevant background studies that have been considered for the research. The second part describes data collection and the methodology used. The third section summarizes the findings of the research. Finally, the essay offers conclusions, limitations and directions for future studies.[2]

2. Literature Review

Defining what is populism seems a rather controversial process. The challenge is even harder for linguists who are often interested in its communicative traits, since it is mainly analyzed as a political phenomenon. Generally, scholars tend to agree on the main aspect constituting populism, being the contrast between the "good" people against the "bad" elites. When right-wing populism is considered, a third element can be often added, that is the threat represented by the "others" (primarily immigrants or minorities in general), who are not included in the concept of "pure" people (Canovan 1999; Taggart 2000; Mudde 2004, 2007; Jagers and Walgrave 2007). In this regard, a comprehensive definition has been given by Albertazzi and McDonnell (2008: 3), who defined populism as "[...] an ideology which pits a virtuous and homogeneous people against a set of elites and dangerous 'others' who are together depicted as depriving (or attempting to deprive) the sovereign people of their rights, values, prosperity, identity and voice."

However, what seems to be contentious is the actual nature of populism (Kriesi 2015; Aslanidis 2016). On this subject, most of the studies are divided in two different trends which respectively consider populism to be an ideology or a political style. The first stance generally affirms that populism is a "thin-centered" ideology since it is not characterized by a coherent position when compared to "full" ideologies such as nationalism, liberalism or socialism (Mudde 2004, 2007; Stanley 2008; Mudde and Kaltwasser 2012). In particular, Cas Mudde (2004: 543) considers populism as "an ideology that considers society to be ultimately separated in two homogenous and antagonistic groups, the 'pure' people versus the 'corrupt' elites, and which argues that politics should be an expression of the *volonté générale* (general will) of the people." According to Mudde (2004), the reason why populism should not be considered as a style is that phenomena like demagogy or opportunism, often expressed through emotional discourse or cunning electoral promises, risk to be conflated with populism.

On the other hand, several scholars criticized the idea of populism as an ideology. Jagers and Walgrave (2007) affirm that the core of populism, represented by the identification and the appeal to the people, cannot be considered itself an ideology as it characterizes the majority of (if not all) the political parties. In addition, Canovan (1999) states that populism should not be defined in terms of ideology, as it merely consists of a reaction to the establishment in power, meaning that it changes according to the political and social context to which it is set against. Moreover, the "thin-centered" definition itself has been considered fallacious from a methodological and classificational point of view (Aslanidis 2016). Therefore, populism is also conceived as "[...] a political communication style of political actors that refers to the people" (Jagers and Walgrave 2007: 3). Similarly, Aslanidis (2016) considers populism to be a discursive frame, a view which, on the one hand, seems to resonate better with the interpretational schemes spread of corruption, crisis and danger spread by populists, while on the other hand it provides a precise methodological framework of analysis.

A possible third stance is illustrated by de Vreese et al. (2018), who combines Mudde's (2004) ideology-centred and Hawkins's (2010) discourse-centered ideas of populism, thus proposing what seems to be a convenient compromise between the two "historical" stances. According to the authors, populism can be considered "as a discursive manifestation of a thin-centered ideology" (de Vreese et al. 2018: 3). Therefore, the communication aspects through which populist ideas are spread have as much importance as the populist ideas themselves. This shift allows to focus on how the ideology of populism is communicated, rather than to concentrate on what populism is. This means that what defines populism can be observed and measured in the discourses produced by the political actors, which also seems to be more appealing from a linguistic perspective.

When political discourse is analyzed, the interest is often on how political actors communicate with the audiences, and this is mainly done through the use of media and communication technologies. However, it cannot be ignored how these instruments have evolved, changing the way in which politicians present themselves and are presented to the public. Spina (2012) illustrates this evolution describing three chronological paradigms and how these have influenced political communication. The first paradigm is represented by the vertical transmission depicted in TVs and newspapers, where political actors talk to the audience unidirectionally. The second paradigm is characterized by the first generation web, where static political messages, as well as information in general, are shared through a many-to-many transmission. Finally, "interaction" summarizes the third paradigm, where users share contents in real-time. This latter paradigm can be considered a major change in political discourse, since politicians are directly linked with their audience (and potential electorate) and can express their ideas without intermediaries or gatekeepers. Although they are nowadays used by politicians of all parties, social media have played an important role in the spread of populism for several reasons. Firstly, websites such as Twitter and

Facebook allow a simple and rather uncontrolled communication between online audience and populists, who often criticize the role of more traditional means of communication. Secondly, social media users tend to select information and opinions that reinforce their own stances, creating a “filter-bubble” effect (Pariser 2011), while, on the other hand, they tend to surround themselves with people who share their own views, consequently generating an “echo-chamber” effect (Jamieson and Cappella 2008). Together, these two elements seem to match the populist exclusivist behavior, where individuals not belonging to the populist idea of people are depicted as a danger through in-group favoritism and out-group discrimination. Also, the possibility to create a personal online profile instead of a generic party account also allows populist leaders to focus users’ attention on their personas and their communicative style. Finally, as suggested by Shoemaker and Cohen (2006), populist discursive style seems to be particularly effective in catching the ephemeral attention of online users, as it often consists of emotional language, oversimplified rhetoric and intensifications (Canovan 1999; Kramer 2014; Engesser et al. 2017) as exemplified by the following tweets:

(3) “I now fear every attempt will be made to block or delay triggering Article 50. They have no idea level of public anger they will provoke.” (Farage 2016)

(4) “Ecco chi sono i veri razzisti! Le tivù lo censurano, fai girare tu.” [“Here’s who the real racists are! The TVs censor it, spread it yourself.”] (Salvini 2016)

(5) “‘La bataille que nous allons mener est la plus belle, la plus grande: la bataille pour la France!’ #Brachay” [“The battle we are going to fight is the most beautiful, the greatest: the battle for France! #Brachay”] (Le Pen 2016)

Therefore, the evidence reviewed here seems to suggest an important relation between populism and social media. However, the actual effect that the populist style and its linguistic features have on the widespread digital popularity enjoyed by populist leaders in Europe is not fully investigated. Hence, this study hopes to offer new perspectives on populism, social media and their relation by determining the extent to which the presence of specific discursive elements attributed to populism may or may not favor the popularity of an online message.

3. Methodology

3.1 Data Collection

This study focuses its interest on four European populist politicians, namely Luigi Di Maio, Matteo Salvini, Marine Le Pen and Nigel Farage. The first three subjects are the leaders of their parties, respectively Movimento 5 Stelle, Lega Nord and

Front National. The same cannot be said anymore for Nigel Farage, who definitely left the party at the end of 2016. However, he still seems to have a considerable resonance for both UKIP and its electorate (McCrum 2017; Lowles 2018; Cohen 2018), and his tweets are still far more popular than any other member of the British party. Although the four politicians and the parties they represent have their own differences, there are some similarities that justify the choice of grouping them together in this research. First, they seem to share the same spectrum of populist views, encouraging the sovereignty of the people over the role of institutional politics, expressing skepticism towards traditional mass media and criticizing excessive immigration and taxation (Albertazzi and McDonnell 2008; Otjes and Louwerse 2015). In addition, the four parties are also allied in the European Parliament. Specifically, Lega Nord and Front National represent the majority of the Europe of Nation and Freedom Group (ENF), a populist-nationalist coalition that also include two former members of Movimento 5 Stelle and UKIP, respectively Marco Zanni and Janice Atkinson. On the other hand, the Eurosceptic union called Europe of Freedom and Direct Democracy Group (EFDD) is mostly formed by politicians belonging to UKIP and Movimento 5 Stelle. Moreover, neither ENF nor EFDD include members of European left-wing populist parties such as Podemos (Spain), Syriza (Greece), Socialist Party (Netherlands) or the Party of Democratic Socialism (Germany). Finally, the four subjects of interest also differentiate themselves from more extremist politicians and parties, as they benefit from a greater electorate, at least at a national level (Hanley et al. 2017). These aspects corroborate the idea that there should be common political goals, which are hopefully reflected in the language that Di Maio, Salvini, Le Pen and Farage tend to use.

We gathered tweets from the official Twitter accounts of the four above-mentioned politicians using FireAnt (Anthony and Hardaker 2017), an application that, through the Twitter API, collects and organizes a limited amount of tweets per account.[3] Later, FireAnt was also used to exclude retweets from the study, as texts written by other people could have spoiled the research in terms of popularity. The final populist corpus consists of 10,365 tweets, which cover a temporal spectrum ranging from less than one year to almost four years, as illustrated by Table 1.

POLITICIAN NAME	USER NAME	COLLECTED TWEETS	EARLIEST COLLECTED TWEET	LATEST COLLECTED TWEET
Luigi Di Maio	@luigidimaio	2,117	11/06/2014	02/03/2018
Matteo Salvini	@matteosalvinimi	2,871	26/05/2016	16/02/2017
Marine Le Pen	@MLP_officiel	3,056	02/12/2015	16/02/2017
Nigel Farage	@Nigel_Farage	2,321	04/04/2015	16/02/2017

Table 1. Populist tweets corpus

Next, we created a reference corpus using tweets collected from a control group composed by three establishment politicians and former institutional figures, namely Matteo Renzi, David Cameron and François Hollande. The reason why these subjects were included is represented by the "standard" political language that should characterize their tweets, which should be stylistically opposed to the populist ones. However, the time span covered by reference tweets overcomes the periods when the three subjects were Prime Ministers or Presidents. This means that, for example, the earliest messages written by Matteo Renzi refer to the time he was the Major of Florence. If, on one hand, this makes the language used less "standard" for a reference corpus, on the other hand it guarantees that the data had not been manipulated in order to force a particular result. The reference corpus comprises 8,209 tweets, and it is further described by Table 2.

POLITICIAN NAME	USER NAME	COLLECTED TWEETS	EARLIEST COLLECTED TWEET	LATEST COLLECTED TWEET
Matteo Renzi	@matteorenzi	2,622	20/11/2012	11/01/2017
François Hollande	@fhollande	3,225	12/02/2012	07/01/2018
David Cameron	@David_Cameron	2,362	06/10/2012	18/01/2017

Table 2. Reference tweets corpus

Tweets were manually annotated using UAM CorpusTool (O'Donnell 2011). The theoretical model adopted for the annotation was the Appraisal Framework, based on the Systemic Functional Linguistics (Halliday et al. 2004) and designed by Martin and White (2005) to analyze degrees of evaluation in discourse. More specifically, it focuses on "[...] exploring, describing and explaining the way language is used to evaluate, to adopt stances, to construct textual personas and to manage interpersonal positionings and relationships" (White 2001: 1). The framework has a "tree" structure characterized by three main nodes: attitude, engagement and graduation. The first element mainly concerns emotional language, behavioral judgements and aesthetic evaluations. The second feature regards how authors support, disclaim or ignore stances different from theirs. The third characteristic focuses on the intensifications included in the text. These three elements seem to adequately match what are considered to be the main features of populist style, namely emotionalization, simplified rhetoric and intensified claims (Canovan 1999; Heinisch 2008; Bos et al. 2011). Since the framework was not originally designed to analyze texts on social media, we added different features in order to make it more functional. This means that, whenever we cite the framework designed by Martin and White, we are actually referring to an edited version of the model. More specifically, the 'empathy' feature was included in the 'attitude' node, as a considerable number of populist tweets empathized with the bad conditions in which the people lived because of natural disasters, terrorist attacks or the elites. The 'hashtag', 'mention' and 'retweet' elements were added to the 'engagement' node in order to include metalinguistic markers used in Twitter with specific functions. Finally, 'graphical' and 'repetition' were added to the 'graduation' node. The former comprises all the graphical forms used in computer-mediated communication in order to convey paralinguistic meanings, such as emoticons, exclamation marks or capitalized letters. The latter is composed by the repetition of similar or identical words with the aim to emphasize the message.

3.2 Statistical Model Fitting

Considering the aim of this study, specifically to ascertain and possibly measure the correlation between the presence of linguistic features related to populism and the popularity of a tweet, we decided to make use of statistical analysis. These methodologies are becoming more and more widespread in most of linguistics sub-fields as they allow, among other advantages, to observe the significance of predictors over one or more variables of interest (Gries 2013; Cunnings and Finlayson 2015). In particular, we chose to adopt mixed effects models because, on one hand, they can cope better with noisy and unbalanced data (Gries 2015) and, on the other hand, they manage to account for subject diversity in a study, represented in this case by the different politicians, especially when multiple observations for each subject are concerned.

In our investigation, specific linguistic features were considered to be independent variables, while the popularity of a tweet, intended as the arithmetical sum of "favorites" and "retweets" received by the message, was set as dependent variable.[4] At the same time, both populist and establishment politicians were set as random effects to take into account stylistic differences among the subjects. We used R version 3.4.2 (2017) to generate two different linear mixed effects models, one for the populist corpus and another one for the reference group, using the **lmertest** package (Kuznetsova et al. 2017) which, differently from other packages, has the advantage of showing the *p* values (hence the significance) for each predictor of the model. In view of the considerable number of features included in the Appraisal Framework, we decided to consider only the most comprehensive ones, often merging smaller sub-nodes with their parent items. This process allowed us to include fourteen independent variables, described in detail in Table 3. We were aware that a relatively high number of variables could make the model less accurate, but the simulations we performed with fewer variables did not provide significantly more reliable results.

Independent Variable	Parent Node	Description
Affect	Attitude	Emotional language such as fear, joy, hope, displeasure.
Judgement	Attitude	Praise or criticism of human behavior.
Appreciation	Attitude	Judgements regarding state of affairs, artefacts or human aesthetics.
Positive	Attitude	A trait referring to affect, judgement or appreciation.
Negative	Attitude	A trait referring to affect, judgement or appreciation.
Contract	Engagement	Suppression of divergent positions by the authors.
Expand	Engagement	Acceptance of the existence of alternative assertions by the authors.
Hashtag	Engagement	Metadata tag used on Twitter to group tweets and create user affiliation.
Mention	Engagement	Metadata tag used on Twitter to address one or more particular users.

Independent Variable	Parent Node	Description
Vigree	Graduation	Blend category which accounts for "vigour" and "degree", respectively indicating assessments of degree of intensity over processes or qualities.
Repetition	Graduation	Lists of terms composed by the same lexical items or by closely related words.
Graphical	Graduation	Emoticons, exclamation points or capitalization.
Focus	Graduation	Graduation regarding the prototypicality of non-scalable terms.
Quantification	Graduation	Scaling with respect to amount of size, weight, number or extent of time and space.

Table 3. Independent variables included in the study

In addition, we also decided to observe how two predictors together might affect tweet popularity. Therefore, we also included variables such as "Affect:Graphical" in order to obtain a more detailed and inclusive view of the correlations. However, in order to decrease the total number of predictors considered, sub-nodes belonging to the same parent item were not paired. For example, correlations such as "Contract:Expand" were not included as they both belong to the Engagement system, and they also relate to opposite linguistic elements, whose presence is difficult to find in a single tweet. The only exception was represented by the correlations including "Positive" and "Negative", which were paired with intra-system elements as well, since they are not considered as predictors on their own, but rather traits of other Attitude predictors such as "Affect", "Judgement" and "Appreciation".

We used the **qqnorm()** function in R to verify the distribution of the dependent variable, together with the **qqline()** function which graphically illustrates with a gray line the hypothetical normal distribution that the data should follow. Since performing a variable transformation is discouraged by some studies (O'Hara and Kotze 2010; Feng et al. 2014), we tried to adopt a Generalized Linear Mixed Model (GLMM) both with Negative-Binomial and Poisson distribution which would have accounted for the dependent variable distribution in our study. However, since REML values and residual distributions were not satisfying, we decided to design a Linear Mixed Model (LMM) and to perform a logit transformation of the dependent continuous variable (Tweet Popularity), in order to normalize its distribution. Figures 1 and 2 show the results respectively for non-transformed and logarithmically transformed dependent variables in both groups.

Figure 1. Dependent variable distributions

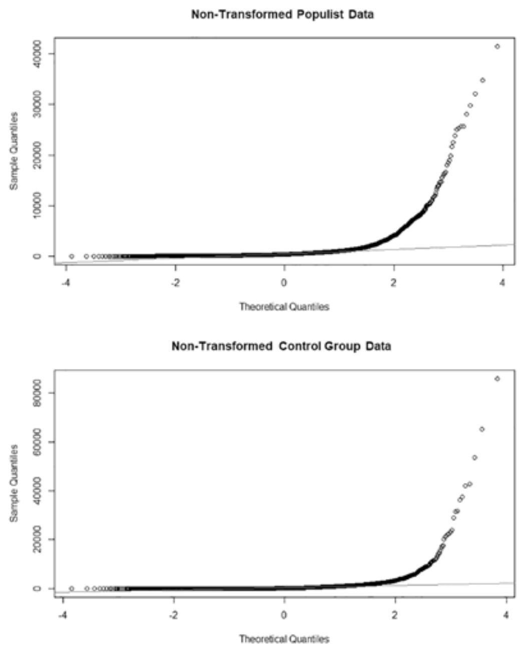
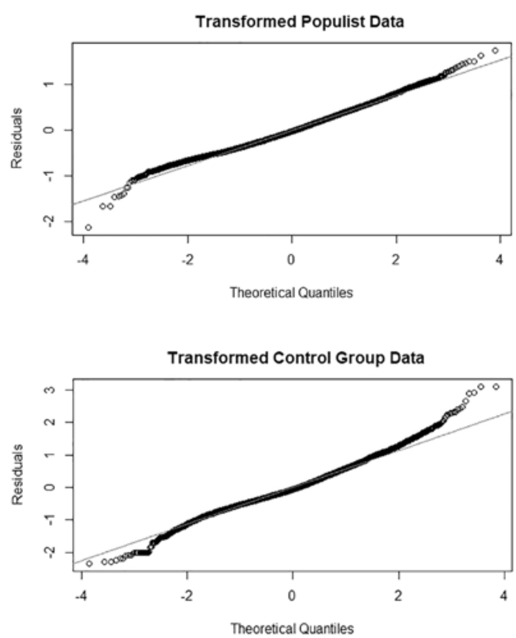
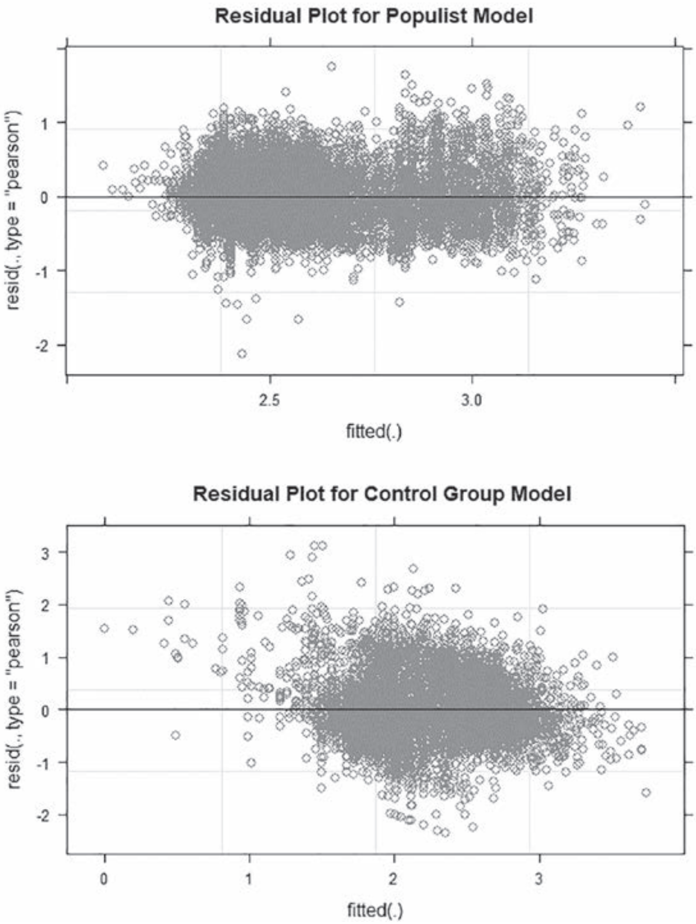


Figure 2. Transformed dependent variable distributions



Despite the presence of some outliers, the data showed in Figure 2 better resemble the expected distribution represented by the gray diagonal line when compared to the plots in Figure 1. Next, Figure 3 illustrates the residual plots for populist and control group linear mixed models. Strong graphical patterns in the plots might signal assumption violations when computing the model (Gelman and Hill 2007). In our case, the residuals of the two models were plotted in a rather symmetrical distribution, and there were no visible strong patterns.

Figure 3. Residual plots for populist and control group models



4. Results

In this section, findings are presented for both populist and control models. Due to the considerable number of predictors, we only decided to show independent variables having a *p* value smaller than 0.001 (***), 0.01 (**) or 0.05 (*). However, non-significant variables were still included in the models when outcomes were calculated. The summary of the populist model is presented below.

```
> summary (PopulistModel)
REML criterion at convergence: 9708.1
Scaled residuals:
   Min       1Q       Median       3Q       Max
-5.6159   -0.7125    -0.0681     0.6591    4.6124

Random effects:
 Groups   Name         Variance  Std.Dev.
 USER    (Intercept)  0.04771    0.2184
 Residual             0.14405    0.3795
Number of obs: 10367, groups:  USER, 4

Fixed effects:
                         Estimate   Std. Error    t value   Pr(>|t|)
(Intercept)              2.544e+00   1.097e-01    23.183   0.000159 ***
AFFECT                   1.486e-01   3.503e-02    4.241    2.25e-05 ***
JUDGEMENT                9.849e-02   2.499e-02    3.942    8.15e-05 ***
NEGATIVE                 5.586e-02   2.302e-02    2.427    0.015257 *
CONTRACT                 6.041e-02   1.173e-02    5.151    2.64e-07 ***
EXPAND                   5.167e-02   1.384e-02    3.735    0.000189 ***
HASHTAG                 -1.698e-02   6.723e-03   -2.526    0.011567 *
MENTION                 -3.112e-02   1.155e-02   -2.695    0.007045 **
GRAPHICAL                5.515e-02   1.386e-02    3.980    6.94e-05 ***
FOCUS                    1.045e-01   4.771e-02    2.191    0.028487 *
AFFECT:HASHTAG          -3.582e-02   1.289e-02   -2.779    0.005463 **
AFFECT:MENTION          -4.970e-02   2.240e-02   -2.219    0.026527 *
AFFECT:FOCUS            -1.681e-01   8.563e-02   -1.963    0.049657 *
JUDGEMENT:CONTRACT      -2.657e-02   1.181e-02   -2.249    0.024551 *
JUDGEMENT:EXPAND         4.033e-02   1.674e-02    2.409    0.016013 *
JUDGEMENT:HASHTAG       -2.957e-02   7.374e-03   -4.010    6.11e-05 ***
JUDGEMENT:VIGREE        -3.269e-02   1.551e-02   -2.107    0.035125 *
JUDGEMENT:REPETITION    -9.645e-02   3.481e-02   -2.771    0.005594 **
JUDGEMENT:GRAPHICAL     -2.141e-02   1.034e-02   -2.070    0.038480 *
CONTRACT:VIGREE         -5.441e-02   2.030e-02   -2.681    0.007358 **
HASHTAG:QUANTIFICATION  -2.169e-02   1.028e-02   -2.110    0.034848 *
MENTION:GRAPHICAL        4.857e-02   2.080e-02    2.335    0.019542 *
MENTION:FOCUS           -1.737e-01   6.574e-02   -2.643    0.008239 **
```

The model estimates represent the effect that the predictors have on the dependent variable. For example, the fact that 'affect' has an estimate of 0.148 means that for every one-unit increment that 'affect' has in a tweet, the (logit transformed) popularity value of the tweet increases by 0.148. Here, we can see that all the main significant predictors, with the exception of "Hashtag" and "Mention", positively affect tweet popularity when present in a message. More specifically, the highest positive values are obtained by "Affect" (0.148), "Focus" (0.104) and "Judgement" (0.098). On the other hand, pairwise interactions between predictors generally show negative effects on the number of favorites and retweets received by the tweets. In this context, we find the highest negative estimates, represented by "Mention:Focus" (-0.173), "Affect:Focus" (-0.168) and "Judgement:Repetition" (-0.096). Next, summary outcomes for the control group model are illustrated below:

```
> summary(ControlGroupModel)
REML criterion at convergence: 15184.6
Scaled residuals:
    Min       1Q      Median       3Q       Max
-3.9157    -0.6420    -0.1066     0.6267   5.1860

Random effects:
 Groups   Name        Variance  Std.Dev.
 USER    (Intercept)  0.1211    0.3481
 Residual             0.3620    0.6016
Number of obs: 8185, groups:  USER, 3

Fixed effects:
                       Estimate   Std. Error   t value   Pr(>|t|)
(Intercept)            2.344e+00   2.018e-01   11.612    0.006957 **
AFFECT                 1.543e-01   5.604e-02    2.753    0.005913 **
POSITIVE               1.377e-01   4.128e-02    3.335    0.000856 ***
NEGATIVE               2.058e-01   4.723e-02    4.357    1.34e-05 ***
EXPAND                -4.243e-02   2.107e-02   -2.013    0.044108 *
HASHTAG               -1.130e-01   1.282e-02   -8.816     < 2e-16 ***
MENTION               -5.048e-01   1.752e-02  -28.812     < 2e-16 ***
VIGREE                 1.342e-01   3.578e-02    3.751    0.000177 ***
REPETITION             2.108e-01   9.198e-02    2.291    0.021971 *
FOCUS                 -4.043e-01   1.477e-01   -2.738    0.006186 **
AFFECT:HASHTAG        -1.383e-01   2.014e-02   -6.865    7.13e-12 ***
AFFECT:MENTION         6.877e-02   3.059e-02    2.248    0.024613 *
JUDGEMENT:HASHTAG     -4.187e-02   1.615e-02   -2.592    0.009559 **
JUDGEMENT:MENTION      1.035e-01   2.510e-02    4.123    3.78e-05 ***
JUDGEMENT:GRAPHICAL    3.217e-01   1.089e-01    2.955    0.003136 **
APPRECIATION:MENTION   1.118e-01   2.336e-02    4.785    1.74e-06 ***
CONTRACT:GRAPHICAL    -3.374e-01   9.207e-02   -3.665    0.000249 ***
EXPAND:GRAPHICAL      -4.216e-01   1.585e-01   -2.659    0.007844 **
HASHTAG:REPETITION    -1.798e-01   5.057e-02   -3.556    0.000379 ***
HASHTAG:GRAPHICAL      3.383e-01   8.625e-02    3.922    8.84e-05 ***
HASHTAG:FOCUS          2.022e-01   8.163e-02    2.478    0.013245 *
MENTION:GRAPHICAL      1.795e-01   7.313e-02    2.455    0.014117 *
```

Despite an overall similarity in quantity and quality of significant predictors between the two models, the outcomes illustrate a more positive effect of predictor interactions for the control group when compared to the populist model. Another major difference is represented by the range of the estimates, both on the positive and the negative side. While the averages of the positive and negative estimates for the populist group are respectively 0.074 and -0.058, the control group model shows averages of 0.18 and -0.24. More specifically, the highest positive estimate values are represented by two interactions, "Hashtag:Graphical" (0.338) and "Judgement:Graphical" (0.321), followed by "Repetition" (0.21) and

"Negative" (0.205). On the other side of the spectrum, estimates values are even higher, as showed by "Mention" (-0.504), "Expand:Graphical" (-0.421) and "Focus" (-0.404).

5. Conclusions

The main purpose of this investigation was to ascertain and analyze the correlation between the presence of linguistic elements related to populism and the popularity received by tweets written by populist politicians. These elements are often represented as emotional language, simplified rhetoric and intensified claims (Canovan 1999; Heinisch 2008; Bos et al. 2011). The statistical model designed for the study revealed that the majority of the predictors included in the research have a positive or a negative effect on the dependent variable. In addition, it also confirmed results obtained in previous studies with different methodologies (Carrella 2018).

First, the fact that features from the Appraisal Framework related to the "Attitude" node and, consequently, to emotional language, mostly have a positive effect on tweet popularity confirms previous findings (Zappavigna 2011; Stieglitz and Dang-Xuan 2013). In particular, "Affect", "Judgement" and "Negative" are the three significant traits which seem to grab more attention when present in a message. The presence of "Negative" among these variables indicates that the "populist" audience is more attracted to negative emotions or behavioral judgements, traits that often characterize populist discourses. Second, "Engagement" features, namely "Hashtag" and "Mention", negatively affect the number of favorites and retweets received. This could be counterintuitive, since both are markers that characterize the general user experience on Twitter and should favor the spread of a tweet (especially in the case of hashtags). This unexpected outcome may be explained by the fact that hashtags are often used to promote political campaigns, while mentions address specific users on Twitter. Therefore, these two elements may characterize uninteresting tweets for the audience. Finally, as far as intensified language is concerned, predictors related to "Graduation" seem to have a restricted but positive effect. Only two variables out of five have a significant effect, with "Focus" having more resonance over "Graphical". With regard to interactions between predictors, the majority of these negatively affect populist tweet popularity. A possible explanation for this could be that tweets characterized by several elements might be more "rhetorically" structured when compared to simpler tweets, therefore less successful in catching users' volatile attention.

Next, the analysis of the control group brought unanticipated results. As for the populist model, the control study revealed positive correlations between emotional language and tweet popularity as well. In particular, we found "Affect", "Positive" and "Negative" to have a positive effect on the dependent variable. Surprisingly, the latter had the highest effect among the three, possibly indicating that audiences from all the political spectrum might be more interested in negative language. "Engagement" traits, represented by "Hashtag", "Mention" and "Expand", are characterized by negative estimates. Notably, the presence of "Mention" is detrimental for tweet popularity. On one hand, we already explained that tweets with mentions are addressed to one or more specific user, hence restricting the interested audience. On the other, the establishment politicians who composed the control group seemed to be more inclined to directly interact with their followers. In addition, "Graduation" features present inconsistent behavior, since the presence of "Focus" decreases tweet popularity, whereas "Vigree" and "Repetition" corroborate it. Finally, a further difference between the populist and the control group is suggested by the fact that the majority of predictor interactions have a positive impact on tweet popularity. This might indicate a possible difference in the control group audience, which could show interest in more complex tweets as well.

In conclusion, this study has shown that linguistic elements often linked to populism have a correlation with populist tweet popularity. In most cases, this correlation is positive, meaning that the presence of features such as emotions, negative judgements or some types of intensifications make the tweet more appealing to the followers. Moreover, the fact that pairwise interactions between two predictors mostly have negative effects on tweet popularity seems to corroborate the idea that populist style works better when rhetorically simplified, at least on social media.

On the other hand, the research also suggests that "populist" linguistic elements characterize non-populist messages online, reinforcing the idea that populism resembles a style more than an ideology, and that therefore this style could be adopted by any politicians (Jagers and Walgrave 2007). Moreover, the fact that predictors receive higher estimates in the control group model rather than in the populist model could imply that also establishment politicians take advantage from the "populist" style, probably because their audience is more sensitive to it and gives more resonance to uncommon tweets that have emotional or intensified linguistic elements.

Overall, this study seems to discourage the analysis of populism in purely stylistic terms, since the differences between populist and non-populist groups can sometimes become rather thin, and there is the risk to see traces of populism in every political actor. Nonetheless, it is possible that this proximity is not due to the ephemeral definability of populism, but rather to the fact that non-populist politicians are attracted by the modern populist success and try to emulate their opponents.

In terms of limitations, the main weakness of this study is that the corpora were manually annotated by a single author and not double coded. This occasionally caused ambiguity issues during features categorization, and it partially undermined the scientific rigor of the research which, however, was supported by the consistency in the methodological application. In addition, the paucity of groups and subjects considered, both for the corpus of interest and the control group, also makes these findings less generalizable.

In spite of its shortcomings, we believe that this study can offer new insights regarding the relationship between populism, populist language and social media. Further research might enlarge the sample population in order to capture a wider description of the populist and the political linguistic behavior online. In addition, authors could choose to focus on some specific areas of the Appraisal Framework, on other particular Twitter metadata tags such as hashtags or retweets, or on the role that multimedia contents, mainly pictures and videos, have on tweet diffusion. Finally, other social media, such as Facebook or Instagram, are characterized by different peculiarities when compared to Twitter, and they could be therefore considered for similar research.

Notes

1 Both Front National and Lega Nord have recently decided to change their party names. The former is now known as Rassemblement National, the latter as Lega. However, we decided to keep the names they had when the research started. Obviously this choice does not reflect any ideological or political interest of the authors, but it only wants to treat the subjects of the study consistently, starting from their names.

2 This study is part of a larger doctoral research which examines with different methodologies the relationship between populism and social media. Therefore, there could be theoretical similarities between this article and other publications by the same author. However, the present examination represents a unique contribution since it is separated from the others by the use of different methodologies and the presentation of new insights.

3 The fact that the number of collectable tweets is limited does not depends on the use of Fireant, rather on the type of permissions given by the API.

4 For those who are not familiar with Twitter, a person (or user) can choose to express his/her preference for a message (or tweet) by clicking on the “favorite” button. At the same time, the person can quote what other users have said by “retweeting” that message. Therefore, the more “favorites” and “retweets” a tweet has received, the more that tweet can be considered to be popular.

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