Haters gonna (make you) hate
Semantic, hashtags and topic network analysis of the hate during the 2019 European elections

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***Abstract*—In the last period mass media and social networks have acquired more and more relevance in political speech, specially due to their effects on real world and on the change of language register which very often slipped into hate speech.**

In this report we deal mainly with Twitter/Facebook activities occurred during European Elections political campaign in 2019, analyzing network of Posts and Comments that have been already categorized by Amnesty International activists and some other researchers form Padova University according to, for instance, their level of hate, the type of campaign, the target and topics.

We worked on two levels: semantic and content levels. In the former we exploited a NLP fashioned-like processing in order to retrieve unique lemmas that were used. Then some variables were created, according to the aforementioned manual categorization of post/comment, and the outputs of two different sentiment dictionaries (Sentix and LIWC). In the latter instead, we decided to focus on two different aspects: topics, already present in the database and hashtags that we recovered directly from the comments' and posts' text. An important variable we took into consideration was the level of hate, that was manually coded into the database for each comment and post.

In order to better perform statistics and analyze the networks, the main database was divided into subsets according to type of political campaign (positive/negative), political orientation (left/right), and content type (posts/comments). On each of these, algorithms for network characterization were run and the obtained data was compared for the various pairs of subdataframes.

The main results we found consist in the fact that hate speech is apparently more central in right posts/comments and in the negative campaign. This was obtained through node removal analysis by sentiment. Moreover, we discovered that manual categorization provides the most meaningful and accurate results in terms of highlighting the presence of hate speech. An additional interesting finding is that using cluster topic modelling, the communities holding the most hateful/problematic words were about immigrants and ethnic-religious topics, with a difference between Left and Right subnetworks.

***Index Terms*—Social Network analysis, Content analysis, Semantic analysis, hate speech, sentiment analysis**

I. Introduction

A. *Politics on social media*

For at least thirty years now, institutions have undergone continuous evolution, also dictated by the progressive increase in their dependence on the mass media. Even before the advent of social media, Mezzoleni and Schulz questioned this process of *mediatization* of politics [1] and how it could become a positive or negative change for democracies around the world.

Social media has changed the nature of political discussion. From likes, retweets, shares, and memes, everyday users have an amplified voice in the online, public-political sphere. Since the 2008 USA elections, when Obama decided to create a blog to communicate better with new generations, political campaign progressively moved from traditional media to new media like social media.

In the last few years, the effects of hate generated online during political discussions have been discussed, trying to define some techniques to reduce this phenomenon, both with automatic contents moderation and the removal of some specific account. This is, for example, the case of Trump's account.

Studies on social media demonstrate that the *emotional contagion* can be manipulated, changing the news feed of the users [2]. Consequently, also the political communication made by candidates influence their followers' emotions.

B. The hate speech

*1) **Definition**:* The definition of hate speech is unambiguous and differs depending on the context. Amnesty International's study, based on which this research was built, uses the definition that the European Commission gives against Racism and Intolerance in 2015 [3]:

" [...] hate speech is defined as fomenting, promoting or encouraging, in any form of denigration, hatred or defamation of a person or group, as well as subjecting a person or group to bullying, insults, negative stereotyping, stigmatization or threats, and the justification of all such forms or expressions of hatred as mentioned above, based on "race," color, ancestry, national or ethnic origin, age, disability, language, religion or belief, sex, gender, gender identity, sexual orientation, and other characteristics or personal status."

In the meaning proposed by the European Commission, therefore, hate is not reducible to the simple generic insults. It has the particularity of addressing a specific minority already the victim of discrimination.

A study published by UNESCO provides a clear picture of the context in which the definition of hate is placed, also regarding its online version [4]. It is explained how what is stated in the Declaration of Human Rights (UDHR) within the "International Covenant on Civil and Political Rights" (ICCPR) of 1966 [5] is the real foundation of the fight against hate, despite the transformations of society and its communicative forms that have occurred in the last 60 years.

It is also emphasized that it is essential for digital platforms to reach, in addition to a standard definition of hate speech, an agreement on the initiatives to be taken to limit its spread.

*2) **The hate spread and its consequences**:* Hate online is dangerous for at least two reasons other than the direct effects on the victims: it can generate offline hate crimes and create more hate online.

In fact, the effects of this type of comments online can due to serious hate crime offline. As demonstrated in a 2019 study conducted in London through the use of Computational Criminology techniques [6], an association can be found between hate speech about race and religion recorded on Twitter and hate crimes aggravated by same-sex discrimination that occurred in a given location.

In a similar study in Germany, where discrimination directed at refugees was analyzed, the conclusions are also the same: anti-refugee sentiment detected on Facebook predicts the number of hate crimes related to this category of people [7].

We also know that exposure to hate speech increases prejudice through desensitization [8]. Soral et Al. explored the effects of exposure to hate speech on outgroup prejudice. Following the General Aggression Model, they show how exposure to hate speech leads to desensitization to it and subsequently increasing outgroup prejudice, generating a lack of emotional arousal in the subject exposed to this type of communication.

In another paper, this time analyzing Youtube's comments [9], the diffusion of the hate against ethnic minority seems to increase as the number of previous insulting comments in the same trend increases.

In this project we will investigate how the type of political communication can have similar effects on the hate diffusion. To do that, we used the Negative Campaign theory.

C. The negative campaign

*1) **Definition**:* Some authors [10] [11] proposed a tripartite directional definition, taking into account comparative separate from negative and positive campaigns. Specifically, a division has been proposed: "advocacy" for political campaign's arguments in favor of the candidate, "attacks" with references to opponents, and "comparison" which would combine both of the first two types of campaigns. This definition is applied to the study of individual commercials by U.S. politicians during the '96 election. In this campaign, very significant differences are found between the two politicians considering comparative campaigns, in particular, demonstrating how this category is not superfluous but rather crucial for discerning negative electoral messages that mention the opponent without mentioning their own position.

Lau and Pomper [12] criticize this subdivision by citing as an explanation that all campaigns are inherently comparative and make this definition susceptible to subjective interpretations. Thus, an evaluation is proposed to span a continuum in which the two opposites are positive and negative campaigns. These terms are preferred over the previous ones because they are more explanatory. In all definitional meanings, only communication related to political content is considered.

When analyzing traditional media, this emphasis is superfluous since all the discourses considered are entirely political. On the other hand, when investigating social media content, it happens quite often to come across externals that have nothing to do with political content, that has nothing to do with the electoral campaign. For this reason, in this study we use a directional definition with four categories: positive, neutral, comparative, and negative campaigning.

*2) **The type of campaign and its consequences**:* Although it is reasonably clear that negative campaigns are more effective in spreading the message and going viral, as shown by a research on Facebook during the Hungarian's elections in 2014 [13], the literature does not indicate that these attacks are always more electorally effective, as reflected in the review by Lau and colleagues [14]. Indeed, it appears that such campaigns can mobilize radical voters in favor of the subject that is being attacked [15], thus obtaining results that are opposite to those desired.

D. Network analysis

Many researchers used the network analysis to deal with text corpus retrieved on social media.

Network analysis can be used to see the polarization of the discussion on social media, highlighting the re-tweets network. But it could also be used to synthesize a discussion creating hashtags networks or topic networks. Finally, it can also generate a semantic network where nodes are the words, and their edges are the co-occurrence of those words in the online contents like posts and tweets. For this project we took as references 5 papers.

1) Re-tweet networks: Investigating specifically the Twitter platform, Conover and colleagues [16], through clustering of users and network analysis of 355 million tweets published during the U.S. midterm elections, show how the two types of interactions (retweets and mentions) can produce very different and differently conflicting reactions. Those who use retweets predominantly discuss with people with whom they already agree. On the other hand, they are also used to discuss with people who are far from their perspective, increasing the possibility of even heated confrontations.

2) Topic networks: Casada et Al. [17] create the network of 1000 Italian political leaders' tweets, investigating the relation between politicians and negative/positive sentiment toward immigrants. The graphs, in this case, is generated after a manual coding of the topic present in the tweets, with a technique similar to the one we will use in this study.

3) Hashtag network: Suitner et Al. [18] compared the hashtag network on the climate change topic across different years. As in this case, retrieving data from Twitter allows us to make an exact idea of the discussion in social media. For example, in this case, it is interesting to see how we can spot the change in the climate action keywords, comparing those semantic transformations with real events that happened in society.

Eddington [19] shows how Trump's supports hashtag networks developed and united around particular organizing processes and White nationalist language, and provide insights into how these networks discursively create and connect White supremacists'organizations to Trump's campaign.

4) Semantic network: One of the most cited article about text analysis in the political sphere has been wrote by Grimmer and Stewart [20]. They made a comprehensive guide for automated text analysis highlight how it can substantially reduces the costs of analyzing large collections of text, concluding that automated text methods could become a standard tool for political scientists.

Another temporal comparison, but using semantic network analysis instead of hashtag network, is the one performed by Rule et AL. [21]. In this case, the researchers develop a strategy for identifying meaningful categories in textual corpora: terms, concepts, and language use changes. Using this text analysis method characterized by co-occurrence approaches, they induce categories by relying on terms' joint appearance over a particular unit of text. This project will use a similar methodology but analyzing social media text instead of the traditional media ones.

II. Research questions

The overall research's central question is highlighted in the project title: "hater gonna hate" or "haters gonna make you hate"? We want to find out cues for the correspondence between the discussion carried out in the politicians' posts/tweets and in the comments/retweets, primarily focusing on the hate levels. Then, we want to understand how the hate is differently generated across political orientations and types of political campaigns to point out where the hate and the negativity are mostly concentrated.

Our main research questions are:

- Which is the best variable to detect hateful contents? (manual coding vs. sentiment vs. LIWC)
- Where is the hate speech more relevant? (left vs. right parties, positive vs. negative campaign, post vs. comments)
- How can we qualitatively describe the topics discussed in the different data frames and their relation? (cluster analysis, topic comparison)

In the following sections, we will specify those main questions according to the different analyses performed.

A. Type of analysis

We analyzed the database according to three main techniques:

- Topic analysis: we used the manual coded variable provided by amnesty international
- Hashtag analysis: we consider the adjacency matrix of the hashtags.
- Semantic analysis: we consider the adjacency matrix of the words.

B. Sub-networks comparison

We decided to compare the post and comments separately, according to two database division:

- Political orientation (left parties against right parties)
- Type of political campaign used (neutral and positive campaign against comparative and negative campaign)

In the Semantic Group's analysis, we also added analysis on the type of target used in the negative and comparative campaign. In the Content Group's analysis, we also compared all the posts against all the comments.

C. Nodes attributes

We then set, as depending variable, different quantification of the sentiment as nodes' attributes.

- Hate/problematic/positive index: the frequency of a specific word/hashtag in the hate/problematic/positive comments or posts. The value range is from 0 to infinite.
- Sentix polarity: a sentiment value for each word taken from the Sentix dictionary. Values range is from -1 to +1.

- LIWC: words can belong to a specific class of words representing a particular type of emotion. This is a double variable.

In the following sections, each type of attributes will be described deeply.

III. The database

A. "Il Barometro dell'Odio": research by Amnesty International

In this project, we used the data retrieved by "Il Barometro dell'Odio" [22] during the 2019 European elections in Italy. Il Barometro dell'Odio is part the Amnesty International's campaign" Contrasto all hate speech online". This campaign aims to contrast the hate speech online, providing researches on the topic, social media monitoring, educational projects, and advocacy and lobby actions coordinate with the" Rete Nazionale per il contrasto ai discorsi e ai fenomeni d'odio."

The original database contains the contents posted during the last 40 days of the political campaign (15/04/2019 - 24/05/2019) on Facebook and Twitter by the candidates participating in the European elections 2019. In addition to the politicians' contents, all the relative comments and re-tweets have been retrieved. From the initial database of 4 million total contents, 100 thousand have been chosen to be part of the final data collection. The final analysis considers the 40 most active politicians on the two platforms, adjusting the selections assuring at least 4 politicians for each party and at least one girl and one man each. The final collection considers 77 politicians and 21.596 posts/tweets plus a proportionate set of comments/re-tweets each, from a minimum of 4 answers/posts to a maximum of 2 thousand answers/posts.

Each content retrieved has been qualitatively coded by 180 Amnesty International's activists. Each content was coded 3 times, and in case of difference between each other evaluations, an expert coder would review the classification. The variables that were added to the database are:

- "Topic": 14 categories according to the topic of the comments/posts (women, LGBTI, disability, migrants and refugees, rom, religious minorities, solidarity, poverty, other)
- "Rating": the level of hate of comments/posts (neutral/positive, negative, problematic containing insults and swear words and hate speech)

It is important to say that this is one of the most complete data collections on Italian elections ever made. Its particularity is to connect political advertisements on social media with the comments/re-tweets generated, enabling cause-effect analysis.

B. "Haters gonna (make you hate)": a master thesis

The Amnesty international's database has been further analyzed in a master thesis [23]. For this work, other 10 researchers were involved in classifying each politician's post/tweet according to the type of political campaign (neutral, positive, comparative, and negative). The negative and comparative campaigns also have another value specifying the attacks' target (private citizen, public figure, political figure, category of people, non-political group, and political group). Each content has been categorized twice; if the two classifications differ, an expert coded the post/tweet to assign the proper label.

IV. Methods - Semantic analysis group

A. Text cleaning

Before performing any text analysis, it is necessary to perform text cleaning to organize and describe the data in details. Our project involves construction of a word-context network, where nodes are words and edges are links connecting two words occurring together in a text. For a general overview of the code about text and cluster analysis, one can refer to [24]. We performed the following text cleaning on the posts and comments data base before performing any network analysis.

- removal of NaN-type content from the original database;
- lowercasing;
- removal of patterns (user tags, emojis, laughter and numbers);
- removal of punctuation, except for the "#" symbol to preserve hashtags;
- manually adjustment for special characters;
- removal of stopwords;
- removal of words shorter than 4 letters, taking care to preserve meaningful words and party names;
- removal of repeated characters at word endings;
- tokenization;
- lemmatization.

Tokenization and lemmatization procedures, were performed using Spacy, a free open-source library for Natural Language Processing in Python. In particular, it is one of the few libraries with an available trained pipeline for Italian language. However, Spacy has some limitations, despite having a 99.96% accuracy in tokenization and 73.80% accuracy in lemmatization, since it is trained on Wikipedia and consequently it does not have the same accuracy on social network texts [25]. One possibility we considered was to create a network just considering nouns, as some other research have done [26]. Indeed, Spacy's model for Italian language also allows to analyse the part of speech (POS). However, since we could not rely on good accuracy for our type of text, we chose to keep as many words as possible, thereby making a trade off between precision and complexity of the network.

After the text-cleaning phase, each content (post or comment) in the initial database was associated with the corresponding ordered list of lemmas, from which the adjacency matrix for the network was constructed.

B. Variables creation

In order to analyze the network, we proceeded to create some variables that were independent of each other.

1) hate_index and problematic_index: The first variable was *hate_index* indicating how many times a word appeared in comments replying to a Tweet that was manually rated as *hate speech*. The posts database did not have the hate index hence we agreed to use *problematic index* instead which showed the count of the number of times a word appears in a post that was rated as *problematic*.

The remaining two variables were instead introduced using some already implemented tools, namely the Sentix (Sentiment Italian Lexicon) [27] and the LIWC (Linguistic Inquiry and Word Count). [28].

2) Sentix - polarity: With regards to the former, its lexicon was the result of the alignment of several resources: *WordNet*, *MultiWordNet*, *BabelNet*, *SentiWordNet*. Every word contained in its database was assigned a positive and a negative score: two real numbers $\in [0, 1]$. Using these values, one could compute the *polarity*: $\theta = tan^{-1}\left(\frac{n}{p}\right)$ and the *intensity* $I = \sqrt{p^2 + n^2}$. Our work consisted to try to assign every lemma previously obtained a positive and a negative score in the according to the following arguments. For every single word in the lemmas database, we first tried and use pandas function $fullmatch$ to check whether it was present in the *sentix* database. If there was a unique correspondence, then it simply returned its values assigning them to that word. However, it also happened that exact correspondences could be more than a single one, therefore we decided to average the positive and negative scores found, thus assigning them to our word. Nevertheless it might happen that no exact was found, therefore we exploited pandas function $match$. Depending on how many correspondences were found, we either take the single row or the average as we previously did. However, if there were still no correspondences, we used pandas $contains$ function, and followed the same algorithm as before. If results were still none, we either return a row with all the set of values {positive score, negative score, polarity, intensity} set to 0.0 or exploit the function $get\_close\_matches$ present in the library *difflib*. It computes the similarity of the words actually taken into account with all the ones contained in sentix dictionary, and returned the most similar one only if above a certain threshold which was set arbitrarily to 0.8. This would help us in assigning sentiment even to words that were slightly mispelled.

3) LIWC - Total Negativity: The LIWC [28] is a psycholinguistic dictionary that groups the words according to a specific emotion they are related to. This dictionary has primarily been thought to attribute values to entire corpus of text. Instead, we exploited it to assign a value to every lemmas we extracted from our database. However, by doing this, we were not able to use all the variables and the complexity included in the dictionary. Indeed when applying it to already lemmatized words, the information regarding the singular and plural for nouns or the 1°/2°/3° person for the conjugation of verbs was lost. We then used just the following categories regarding the general emotions related to words, in particular the negative ones (Emo_Neg, Ansia, Rabbia, parolac, tristez, ansia). Moreover, to decrease the complexity of our network we used as a variable the sum of the scores of related to {Emo_Neg, Ansia, Rabbia, parolac, tristez, ansia}, which could take values either 0 or 100 and we referred to this variable as *total negativity*.

C. Adjacency matrix

As a first trial we built our network in such way that two nodes (i.e. words) were linked when they appeared in the text of a single Tweet, with the results that all lemmas in the same Tweet were linked between each other. The resulting network, however, was too large to be handled due to hardware limitations: number of edges reached several millions for some datasets. Therefore a second way was introduced: we decided to consider as linked two consecutive words appearing in the same Tweet. Following this argument, the number of edges was drastically reduced and could be successfully imported and analyzed in Gephi using our notebooks. All these links were saved in an adjacency list format.

D. Node attributes

In order to analyze the text, we had to create some variables required for assessment of the sentiment and hate level in the posts and comments. The following variables were considered as node attributes.

- **counts-hate** : the number of times a specific words appeared in a comment labeled as hate speech;
- **counts-prob** : the number of times a specific word appeared in a comment labeled as problematic in the context of hate speech;
- **counts-problematico** : the number of times a specific word appeared in a post labeled as problematic in the context of hate speech;
- **counts-pos** : the number of times a specific words appeared in a comment labeled as positive in the context of hate speech;
- **counts-positivo** : the number of times a specific words appeared in a posts labeled as positive in the context of hate speech;
- **counts-negativo** : the number of times a specific words appeared in a posts labeled as negative in the context of hate speech;
- **counts-ambiguo** : the number of times a specific words appeared in a posts labeled as ambiguos in the context of hate speech;
- **emo-neg** : a specific score representing the sentiment negativeness of a specific word based on the LIWC sentiment dictionary;
- **rabbia** : a specific score representing the sentiment of anger of a specific word based on the LIWC sentiment dictionary;
- **tristez** : a specific score representing the sentiment of sadness of a specific word based on the LIWC sentiment dictionary;

- **ansia** : a specific score representing the sentiment of anxiety of a specific word based on the LIWC sentiment dictionary;
- **tristez** : a specific score representing the sentiment of sadness of a specific word based on the LIWC sentiment dictionary;
- **parolac** : a specific label for italian swear words;
- **polarity** : a specific score in the range [-1,1] representing the degree in which a word's sentiment is considered as negative (-1), neutral (0) or positive (1);

E. Summary of the analysis carried out

1) Nodes removal: Nodes Removal aims at exploring the stability and robustness of the networks by gradually removing nodes following three main approaches. The goal is to determine the node-removal strategy that has the greatest impact on the network structure. Additionally, it is important to conduct a comparison between left and right parties's posts to assess which of the two is more resistant to the disruptions we are introducing. The first approach is node removal by problematic and positive indices; starting with words of high occurrence in problematic and positive posts respectively. The second approach is node removal by the polarity associated to each word; starting by the ones with the most negative polarity according to 'Sentix'. The final strategy, is node removal by the sentiments extracted using LIWC dictionary namely Emo_Neg, Ansia, Rabbia,parolac, tristez that take values of 0 or 100 as a maximum score. An extra LIWC variable was created from the mentioned sentiments, which is Total Negativity that sums up all the scores, and that allows us to have a non-binary score of overall negativity.

The following paragraph provides a legend about how to interpret a quantity that later will be introduced. It is the difference between densities of different subsets at every timestep, that is to say every time we remove a node. For instance, let us consider two different subsets: Left (L) and Right (R), as we will do in the next section (see Fig. 21). According to values taken by this difference $\text{den}(R) - \text{den}(L) := x$ and recalling that initially $x = 1$, we have different situations:

- $x \geqslant 1$: we observe that density of Right network increases faster that Left one, therefore difference between the two increases.
- $0 < x < 1$: density of Right network has increased slower that Left one, however the former is still denser than the latter one.
- $x = 0$: densities for Right and Left networks are equal, since their difference is null.
- $-1 < x < 0$: density of Left network has become larger than the Right network, but their difference, in modulus, is still less than the initial one
- $x \leqslant -1$: density of Left network is larger than the Right network. Their difference is, in modulus, larger than the initial value when Right network was denser.

2) Gephi visualization and cluster analysis: Gephi is a free network analysis and visualisation tool that enables exploration and manipulation of graph data such as networks. The goal is to help data analysts to make a hypothesis, intuitively discover patterns, isolate structure singularities or faults during data sourcing. We are able to interact with the representation, manipulate the structures, shapes and colors to reveal hidden patterns [29]. In our project we performed network analysis in Gephi using Modularity_Class which measures the structure of networks or graphs and is often used in optimization methods for detecting community structure in networks. We also used page rank which indicates the importance score of a node considering hate/problematic words in our network. The Multigravity Force Atlas 2 layout was useful in controling the scale and applying stronger repulsive forces to hubs of the graph. The Circle Pack layout enabled us to rearrange nodes according to attributes(Modularity_Class and Page rank) thus creating relevant clusters.

V. Methods - Semantic analysis group

For this group, the methods will be discussed in each participants' individual report.

VI. Results

Yasmine El Khaloufi
Left and Right Parties Posts

Our aim in this section is to further inspect posts published by politicians belonging to left and right parties prior to the 2019 European elections. Basing our main analysis on the different types of sentiments attributed to each node/word used in the posts, our goal is to extract meaningful distinctions between the language employed in social media by each political wing.

Two sub-networks representing left and right parties were thoroughly analyzed and compared. Table I shows some statistics relative to each network. In the original database,

	Nodes	Edges	Avg. Degree	Density	Estim.γ
Left Parties	13513	79062	11.70	0.000866	2.68
Right Parties	9784	45846	9.9235	0.00101	2.61

Table I: Network Structure Statistics: left Right Posts

the number of right posts "**1046**" exceeds that of left"**954**" by a small margin, which implies that the number of posts is balanced across parties. However, it is noticeable from table I that the number of words used in left parties is higher than that of right parties as well as the number of edges corresponding to the count of co-occurrences of adjacent words in the same post. This means that left parties politicians use more words to express their ideas in the social network. Moreover, the average degree of left parties' posts exceeds that of right parties, while the density of the latter is higher than that of left parties' posts. We can confidently say that both our networks have the scale-free property as confirmed by their respective γ exponent between 2 and 3 confirming that the degree distribution follows a power law, at least asymptotically as shown in figures 1 and 2 . Moreover, both networks are connected except from two small components in each network representing a negligible amount of noise and therefore the giant connected components of both networks exceed 99% of the total number of nodes.

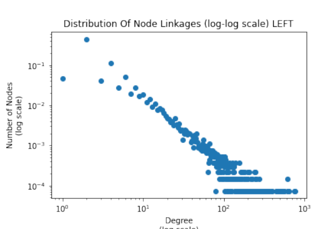


Figure 1: Distribution of Nodes'degrees (LEFT)

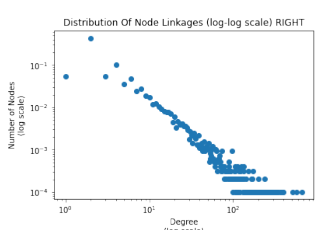


Figure 2: Distribution of Nodes'degrees (RIGHT)

A. *Nodes Removal Analysis*

- **Node Removal by Degree**

We first start by performing the most typical node removal strategy to get a glance at the overall robustness of the networks without accounting on the sentiments of the word. The nodes removal is done by degree starting by nodes with the highest degree for both left and right parties. We notice from figure 3 that the structure of both networks is affected in the same way meaning that they lose their robustness in the same fashion. Finally, both networks lose more than 80% of their initial robustness after removing nearly 4000 nodes.

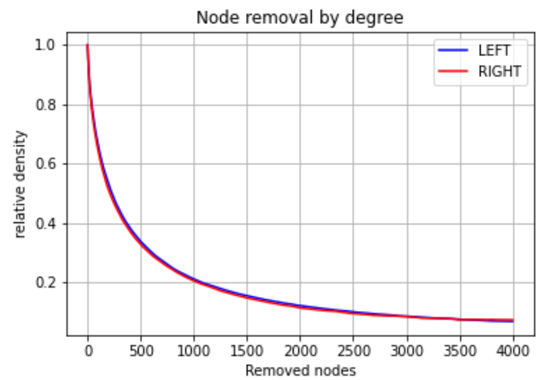


Figure 3: Node removal by degree (Left and Right posts)

- **Node Removal by Problematic Count Index**
  It can be seen from figure 4 that the curve of the right network decreases faster than the left one, the latter loses just 5% of its initial density up to 50 removed nodes while the right network's density is reduced by 25% removing the same number of nodes. The left wing speech network is therefore more resistant to removing nodes by their problematic index. In other words, the words used in problematic speech are more central in the right wing posts and that explains why it breaks faster than the left wing network. This node removal approach was compared to the nodes removal by degree starting by nodes with the highest degree (Fig.5). We observe that we can see a clear difference between removing by degree and removing by problematic index, the latter being the most impactful one highlighting the differences between the two parties.

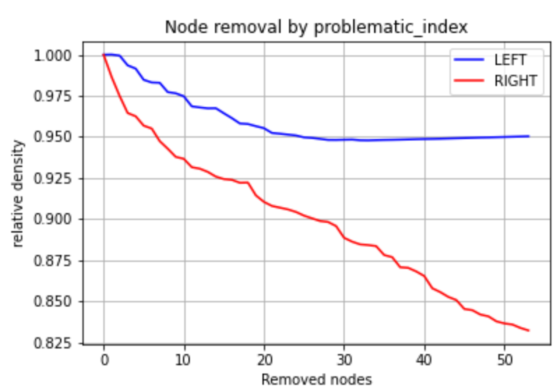


Figure 4: Probl.index node removal (Left and Right)

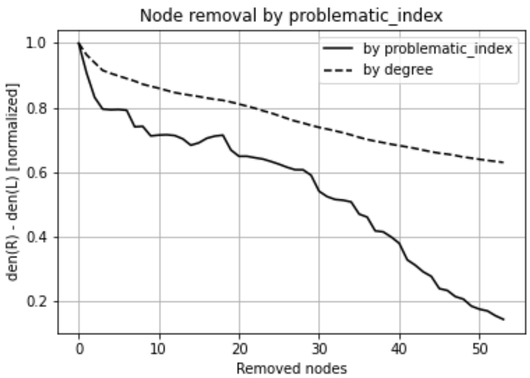


Figure 5: Probl.index node removal and Degree node removal

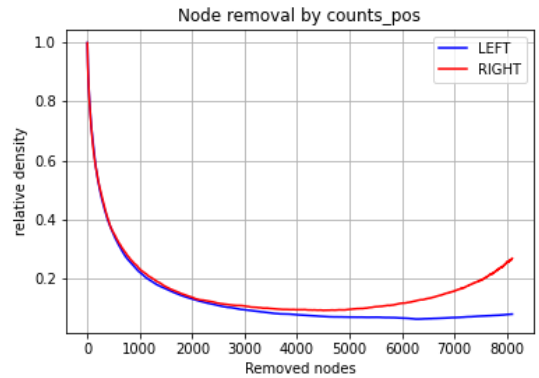


Figure 6: Positive index node removal (Left and Right)

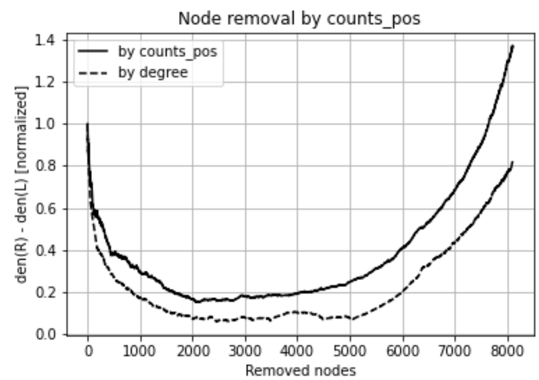


Figure 7: Positive index node removal and Degree node removal

- **Node Removal by Positive Count Index**
To provide a valid comparison ground, we also removed nodes by their positive index starting by words with the highest occurrence in positive posts. From figure 6 it seems that the behavior of the two curves is almost the same up to approximately to when 4000 nodes were removed, where we start to see that the Right network's density starts increasing contrary to the Left one. This confirms that the nodes removed in the right network have lowest degrees or are located at the periphery. Moreover, the positive words seem to be more central in the left wing's posts. This approach confirms our ' node removal by problematic index' findings. This node removal approach was compared to the nodes removal by degree starting by nodes with the highest degree 7. We observe that we can see a clear difference between removing by degree and removing by problematic index, the latter being the most impactful one highlighting the differences between the two parties.
- **Node Removal by Polarity Sentix**
For this approach, we start by removing nodes with the lowest polarity, from -1 to 0. An abnormal behavior is noticeable when we reach 500 removed nodes as the density starts increasing again (Fig.8). This is because the nodes with the same polarity are removed starting by those with the highest degrees. Then we reach the lowest degrees nodes, the relative density increases once again. We notice that the difference is not significant after all between the two political parties considering polarity attribute. Left and Right networks lose 2% and 4% of their initial density respectively. This is also confirmed by looking at the comparison with removing nodes by degree (fig.9), as no clear trend is observed.
- **Node Removal by LIWC's Total Negativity**
Finally, we performed node removal using LIWC sentiment dictionary's attributes namely the Total negativity obtained by summing the scores of the 5 variables. The total negativity score does not exceed 300. The plot shown in figure was obtained by removing nodes starting from those with 300 total score then 200, and finally 100. Therefore, we can easily observe that the graph is somehow divided into three parts corresponding to the three sets of nodes with scores 100, 200 and 300, where each set contains. The first part of the plot (fig. 38, shows that both right and left parties densities increase relative to their initial densities, meaning that those nodes(with 300 score) are not central in both networks. The second section of the plot corresponding to nodes with a total score of 200 shows an initial decrease in the density for both networks then a sudden increase. Finally, in the last section, the nodes with score equal to 100 follow the same behavior as in the second section of the plot. In general, we can see that in all the phases the density did not decrease by more than 0.015% for both networks. Therefore, we cannot say that there is a difference between the two parties in terms of the Total Negativity attribute of the LIWC dictionary. This is also confirmed by looking at figure 39 that compares node removal by degree and by total negativity.
- **Summary of Node Removal Analysis**
From the analysis above we can say that the only relevant node removal strategies are the ones associated to nodes removal by problematic index and by positive index. Using the first, the difference between the 'speech' employed in the two types of political parties is clear

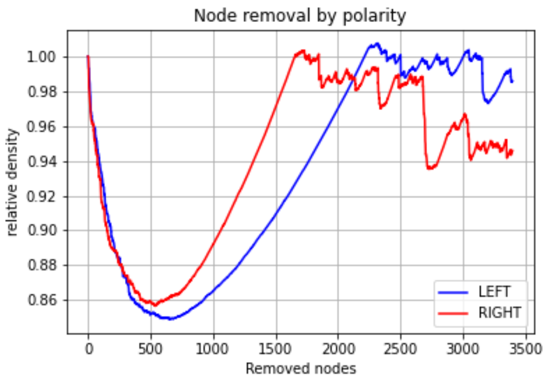


Figure 8: Sentix Polarity node removal (Left and Right)

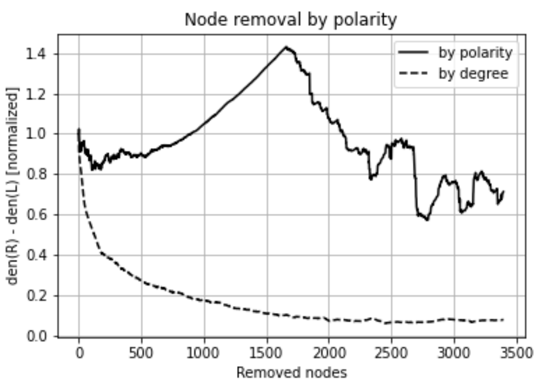


Figure 9: Polarity node removal and Degree node removal

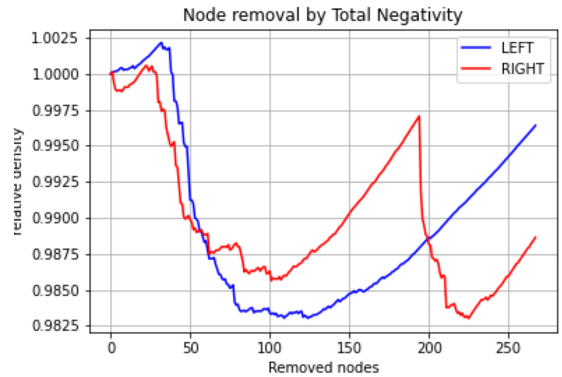


Figure 10: LIWC Total Negativity Node Removal (Left and Right)

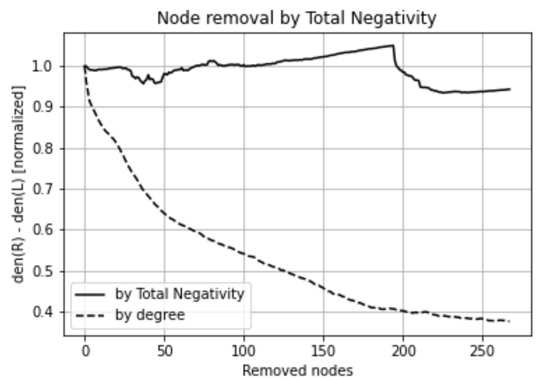


Figure 11: Total Negativity Node Removal and Degree Node Removal

leading us to conclude that the nodes used in problematic speech are more central in the right parties posts. Note that, for LIWC all the other 5 attributes were analyzed and are shown in the appendix.

B. *Modularity: Left- Right Graphs Representation in Gephi*

Since our networks are large, we made use of 'Gephi' software to provide a meaningful visualization. As we are also interested in highlighting the communities present in each network, we run the modularity algorithm with the default value of 1.0. A distinct color for each class was applied and the node size was set according to the page rank. Figure 12 and figure 14 show the results obtained for left and right respectively. Figure 13 and 15 show the results obtained by setting the node size according to the problematic index.

We can easily notice that one of the most significant communities in the right wing posts contains words such as "immigrati"," islamico" and " clandestino" by page rank and also problematic count, contrary to the left posts' communities where we see that when we set node size = problematic count, most of the words have the same count (very small) because the network contains few words with a high problematic count. Since most of the topics discussed revolve around immigrants, refugees and religion, we decided to give a closer look into specific clusters. We started by inspecting the cluster that contains word "clandestino" for both political parties.

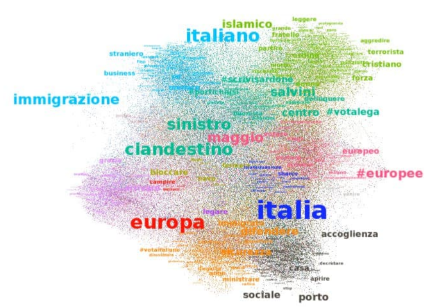


Figure 12: Right wing Communities, node size = page rank

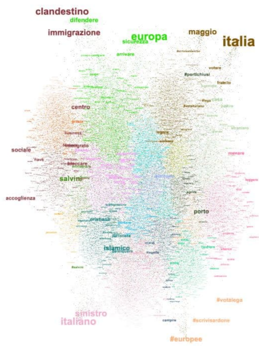


Figure 13: Right wing Communities, node size = problematic count

Figure 14: Left wing Communities, node size = page rank

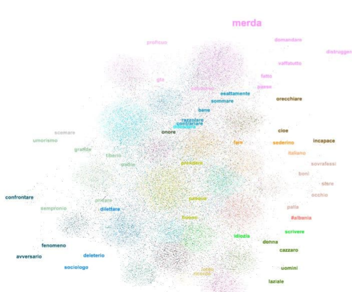


Figure 15: Left wing Communities, node size = problematic count

C. Clusters Analysis

- **Left Posts 'Clandestino' Cluster**

First, figure 16 shows the cluster that contains "clandestino" for left wing parties where the color of the nodes is according to the count problematic index. The black background was useful to see that most of the words have light color meaning that the problematic index is very low for the majority of those words. The average problematic count for this cluster is 0.0044 that is very low, this number will be compared to its equivalent in the right posts' "clandestino" cluster. Note that the cluster with the highest problematic count in the left posts does not convey any useful information but was nevertheless included in the appendix.

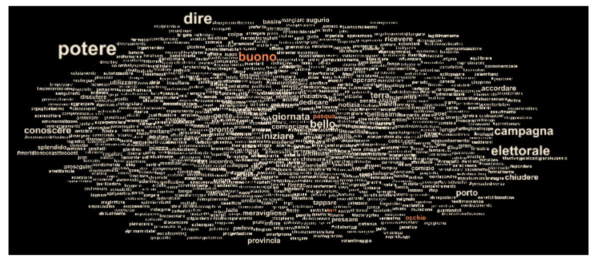


Figure 16: Left wing 'clandestino' cluster

- **Right Posts 'Clandestino' Cluster**

The topic of the cluster shown in figure 17 revolves around religion (Islam), and immigrants. Moreover this cluster is the one with highest average problematic count out of all the clusters in the right posts network. The color of the node is according to the problematic index while the size is the page rank. Interestingly enough, the words "immigrazione", "clandestino", "delinquere" and "islamico" have a high page rank and also high problematic count and are therefore used in problematic speech in right wing politicians' posts on social media as shown in table II and by page rank in table III. The average problematic count for this cluster is 1.51 that is clearly higher than the cluster containing 'clandestino' in left posts.

Word	Problematic Count
Clandestino	50.0
Immigrazione	42.0
Islamico	33.0
Centro	31.0
Sociale	29.0
Accoglienza	26.0
Bloccare	24.0
Immigrato	24.0
Delinquere	20.0
Terrorista	20.0

Table II: TOP 10 words by problematic count in "clandestino" cluster for right parties- 1st most hateful cluster

- **Left Posts 'Salvini' Cluster**

Another interesting cluster was detected in the left posts network while inspecting the modularity output that has "Salvini"

Word	Page Rank
Immigrazione	0.034
Clandestino	0.022
Centro	0.020
Sociale	0.019
Accoliengza	0.014
Islamico	0.014
Lottera	0.012
Delinquere	0.012
Business	0.011

Table III: TOP 10 words by page rank in "clandestino" cluster for right parties- 1st most hateful cluster

Figure 17: Right wing 'clandestino' cluster

who is a politician from the right wing parties as the node with the highest page rank. Although, that word appears frequently, it is not associated with any problematic speech as shown in figures 18 and 179 as the word is colored with white which means low problematic count. We can say that Salvini's ideas are a topic of discussion in the left posts but do not involve any kind problematic speech.

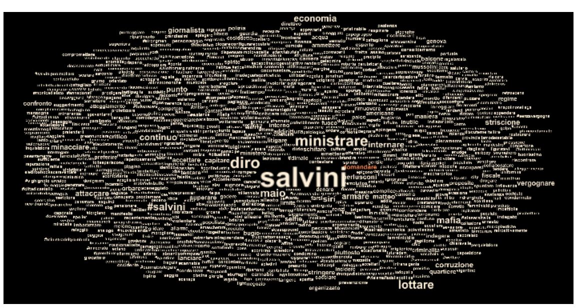


Figure 18: Left wing 'salvini' cluster, node color = prob.index

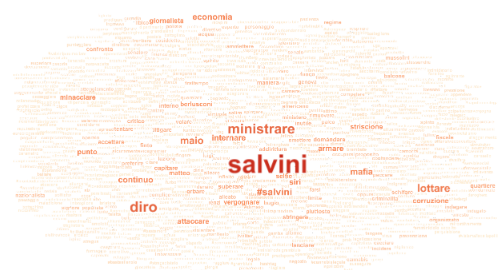


Figure 19: Left wing 'salvini' cluster, node size and color = page rank

ANDREA NICOLAI
LEFT AND RIGHT WING PARTY COMMENTS ANALYSIS

Our analysis proceeded then to divide the comments dataset according to whether comments were replying to posts published by Left or Right wing members. A very general analysis for the two subsets returned the results stated in table IV, in addition we found that for both networks the giant component included around 99% of the total number of nodes. One can note as the number of unique lemmas is more in the Left dataset, as well as the number of edges. The average degree is slightly larger in the left subset, and fitting the degree distribution using a power law returns an estimation for γ that is between 2 and 3, pointing out that network is scale-free. Finally, density is almost equal for both.

	Nodes	Edges	Avg Degree	Density	Estim. γ
Left	29509	210178	14.24	0.00048	2.96
Right	23861	140087	11.74	0.00049	2.92

Table IV: Networks Structure General Measurements
SUBSET Left/Right comments

- **Node Removal by hate index**
We proceeded then to sort nodes by their attributes, specially the aforementioned variables we created. As one can spot from Fig. 20, number of words with hate index more different from zero is way more in the comments that reply to Right wing politicians. They are almost double in numbers. Moreover, removing all the latter ones leads to a density that is decreased up to 40% of its initial value, while for Left comments the density of the network once all nodes with non null hate index are removed stops at around 55% of its initial density. Following this argument and with help of Fig. 21, one can state that words appearing in hate speech are more central in comments replying to Right wing politicians: indeed density fur such network decreases faster as the number of removed node increases, even faster than what would happen removing nodes according to their degree and starting from largest ones.

- **Node Removal by polarity**
Instead by removing the nodes according to the second variable we introduced, namely the polarity, and starting from the most negative ones we obtained the graph shown in Fig. 22, thus remaining with a network with only words that were either neutral or positive (polarity $\geqslant 0$). The odd behavior one can easily note, that is to say the paraboloidal shape, is due to the fact that we were, on average, firstly removing nodes sharing equal polarity (i.e. -1.0) and higher degree, thus decreasing the density of the network up to a minimum value. On the other hand later on we started removing, on average, nodes with still polarity equal to -1.0 but smaller degree that were more peripheric, with the result that network becomes denser. When compared to the node removal by degree of 23, we noted that this second variable was not so meaningful, since we did not observe a general trend as we previously did in Fig. 21. At the end, we see that both networks lost the same percentage of initial density ($\sim 15\%$), and showed the same trend. Last to be noted is that Left subset actually contained a larger number of words with negative polarity, compared to the Right one.

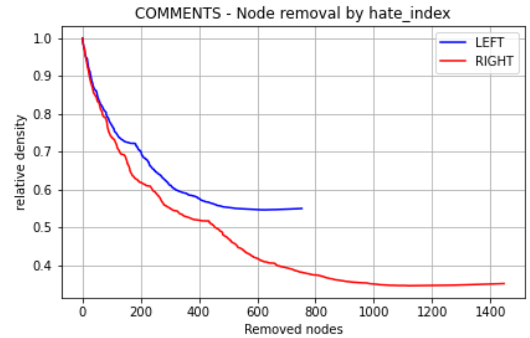


Figure 20: Relative density at each timestep by removing nodes sequentially according to their hate index. Densities are normalized to their initial values, where no nodes were removed.

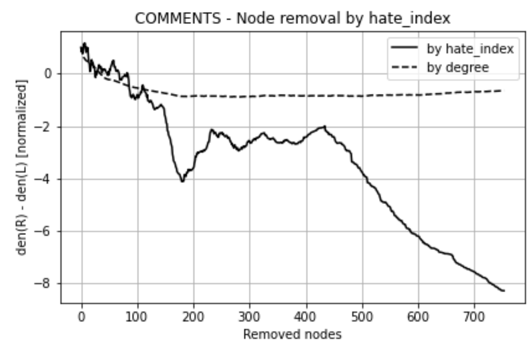


Figure 21: Difference $\text{den}(R) - \text{den}(L)$ of the density at each timestep by removing nodes sequentially according to their hate index. Difference is normalized to its initial value, where no nodes were removed and is compared to the density obtained by removing nodes by their degree.

- **Node Removal by Total Negativity**
We proceeded then to remove nodes according to *total negativity*, the last variable we created. Since we were summing up 5 variables, that we recall are {Emo_Neg, Ansia, Rabbia, parolac, tristez, ansia} with every of them taking values either 0.0 or 100.0, we expected their sum to be at most 500.0. We indeed removed nodes that had this new variable different from 0.0. Actually, we observed that the largest value total negativity could take is 300.0. As it occurred before, we observed in Fig. 24 that the curve was shaped in such way that one could think of three parabulas, each of them corresponding to

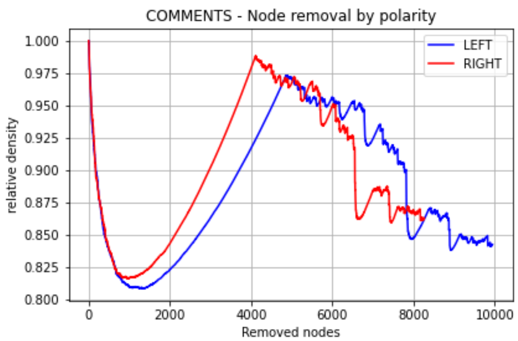


Figure 22: Relative density at each timestep by removing nodes sequentially according to their polarity. Densities are normalized to their initial values, where no nodes were removed.

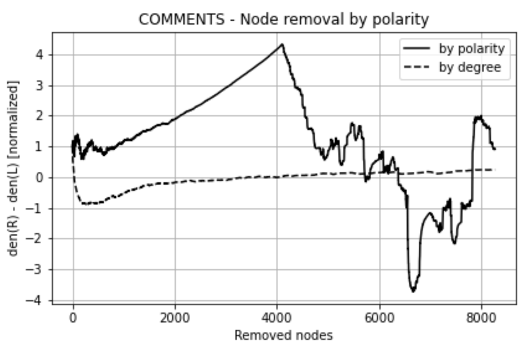


Figure 23: Difference $\mathrm{den}(R) - \mathrm{den}(L)$ of the density at each timestep by removing nodes sequentially according to their polarity. Difference is normalized to its initial value, where no nodes were removed and is compared to the density obtained by removing nodes by their degree.

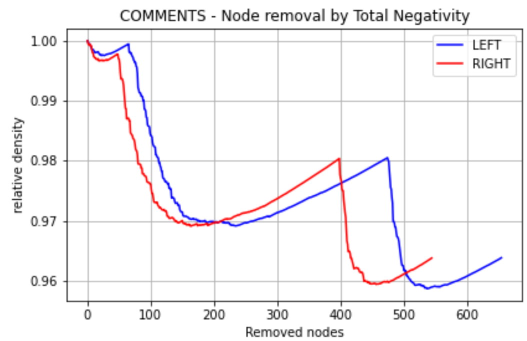


Figure 24: Relative density at each timestep by removing nodes sequentially according to their Total Negativity. Density are normalized to their initial values, where no nodes were removed.

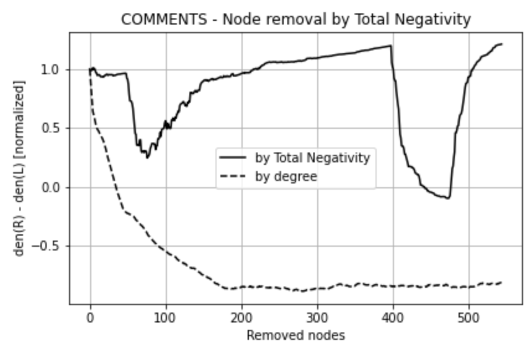


Figure 25: Difference $\mathrm{den}(R) - \mathrm{den}(L)$ of the density at each timestep by removing nodes sequentially according to their Total Negativity. Difference is normalized to its initial value, where no nodes were removed and is compared to the density obtained by removing nodes by their degree.

the three values present for total negativity: 300.0, 200.0, and 100.0. For each of these values, initially, nodes with higher degree were removed on average thus the density decreasing, and then nodes with smaller degree, making density increase again. Still, one could note as we were not losing much density wrt the initial one ($\sim 5\%$) and, thanks to Fig. 25, we can state that in both networks words flagged as negative by LIWC were used in really a similar way. In addition, negative words seem to be more present in Left subset, rather than the Right one.

- **Node Removal summary**
  As for now, and for these specific subsets, the most significant variable in our analysis turned out to be the manually encoded one, namely the hate index. From now on, hence, we are going to use it to proceed to a further analysis in Left/Right comments subsets. Moreover, comparing these last results with node removal by positive index (see Fig. 144 and Fig. 145), and problematic index (see Fig. 146 and Fig. 147) one could see that the only significant variable was the hate index, as just stated.

  Some more considerations may involve "swear words" (see Fig. 148 and Fig. 149), where one can see that despite the larger use of swearing words in the comments replying to Left wing posts is larger, its usage in both networks is really similar. The same arguments can be applied to "anger" (see Fig. 152 and Fig. 153) and "anxiety" (see Fig. 150 and Fig. 151), they are both present in the networks and are used in the same way for both networks. However, nodes exhibiting "anger" sentiment are more in numbers, rather than "anxiety" ones. Both of them are more present in Left subset, but a possible explanation could be due to the larger dataset.

Finally, another important statistics is that the Pearson correlation coefficient (see table V) between the drop in network density and the hate index attribute is, respectively, for Left and Right networks -0.62 and -0.60. This moderated

	Left	*Right*
$\rho_{\Delta_{density}, hate\_index}$	-0.62	-0.60
$\rho_{\Delta_{density}, polarity}$	-0.05	0.02
$\rho_{\Delta_{density}, tot\_neg}$	0.24	0.08

Table V: Pearson correlation coefficients for the difference in density when a node is removed according to its attribute, for different attribute and different subset.

negative correlation implies that the larger the hate index, the larger the drop in density. No conclusion of this kind can be made for the other variables, since the Pearson coefficient is closer to zero.

- **Cluster analysis**
  Later on, we imported the aforementioned graphs in Gephi and tried to visually identify and label communities, using *modularity* statistics provided by the software. Using resolution equal to 1.0 for Right and Left subsets, we obtained the results respectively depicted in figures 26 and 28. Here, we colored labels (i.e. the words) according to the modularity class they belong to, while their size was set to be the hate index variable.
  Another choice one would make, was to set the size of the labels according to their global pagerank score, computed by the means of Gephi function and related to the whole network. Results for this procedure are shown in figures 27 and 29.
  For instance, one can see from these two analysis that adjective "Italiano" ["Italian"] and "Italia" ["Italy"] are always present in both subsets with both high hate index and global page rank. Other words that are quite often present are "politico" ["politician"], "paese" ["country"] or "casa" ["home"]. As already pointed out in [23], the majority of hate speech mainly deals with immigrants and ethnic-religious related arguments. Therefore, we procedeed to spot the cluster the word "clandestino" ["illegal immigrant"] belongs to, and run some analysis on it by using Python and networkx library [30]. The main goal was to check whether this cluster was indeed among the ones with the largest average hate index.
  For Right parties, the word "clandestino" was indeed belonging to the 4-th meaningful cluster with highest average hate index (i.e. 0.15). For "meaningful cluster" we refer to cluster with more than 10-20 nodes, over which it was meaningful to average hate index variable. Specially regarding this cluster: its number of nodes and edges was respectively 1424 and 2369, while its average degree 3.33. Top 10 words ordered by cluster page rank score and hate index for this cluster are shown in VI. In order to have a look at the other three clusters with higher average hate index, please refer to the appendix IX-B.
  It was interesting to note that both words "clandestino" and "immigrato", words that come from two different speech levels, actually belong to the same cluster regardless the subset we were considering at that moment. This

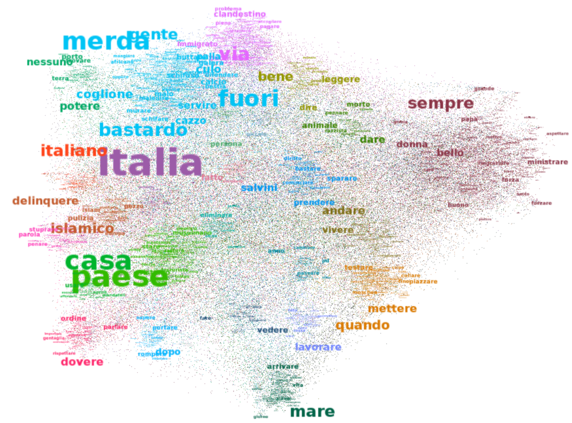


Figure 26: Network highlighting Gephi's modularity output for subset of Right parties comments. Size of the words is set according to its hate index.

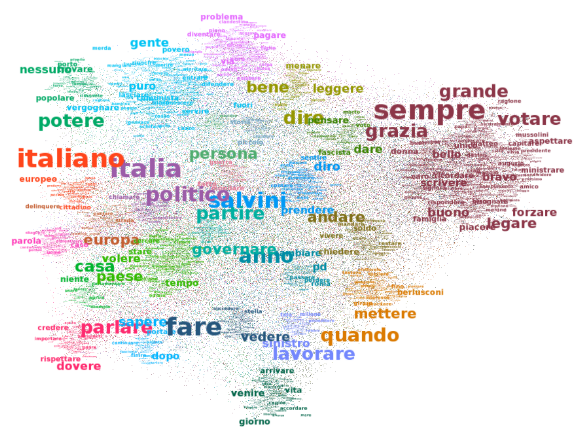


Figure 27: Network highlighting Gephi's modularity output for subset of Right parties comments. Size of the words is set according to its global page rank score.

however proves once more the goodness of Gephi modularity analysis, exploited in order to spot communities. The same analysis can be pursued with referral to Left comments, where instead we found that the cluster containing the word "clandestino" was indeed the one that had the highest average hate index (0.08). The number of nodes of this cluster was 4195, while the number of edges 20915 and average degree of the network 9.97. Top 10 words for this cluster, according to hate index and local page rank score are shown in VII. However, some words do not even exist in Italian language, e.g. "ministrare", that was the output returned by lemmatization of word "ministro". Nevertheless, its overall meaning can still be understood.

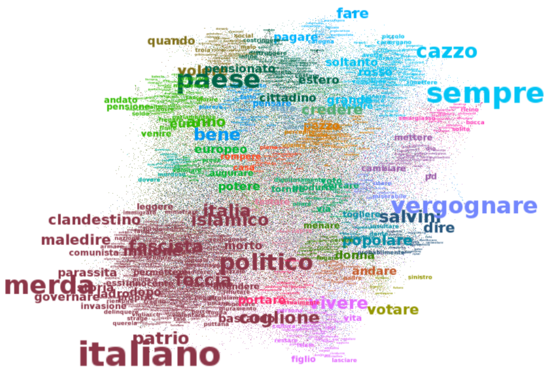


Figure 28: Network highlighting Gephi's modularity output for subset of Left parties comments. Size of the words is set according to its hate index.

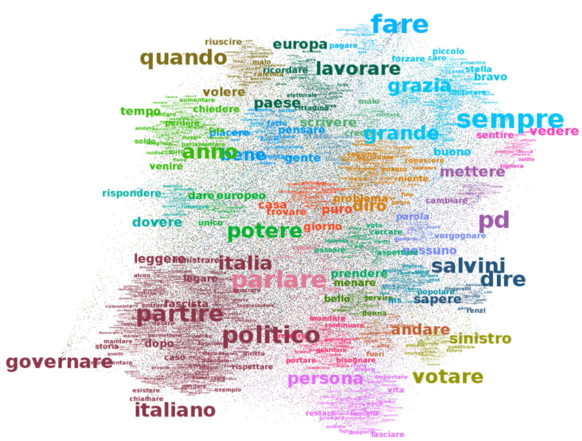


Figure 29: Network highlighting Gephi's modularity output for subset of Left parties comments. Size of the words is set according to its global page rank score.

Left Comments - "clandestino" cluster

Pagerank Score	Word	Hate index	Word
0.016026	*partire*	12.0	*italiano*
0.014124	*politico*	9.0	*merda*
0.012381	*italia*	8.0	*politico*
0.012167	*italiano*	6.0	*feccia*
0.011550	*governare*	6.0	*italia*
0.007750	*fascista*	6.0	*fascista*
0.007182	*leggere*	6.0	*patrio*
0.005588	*legare*	6.0	*coglione*
0.005449	*dopo*	6.0	*islamico*
0.004581	*ministrare*	5.0	*milione*

Table VII: Top 10 words for cluster Page Rank score and hate index in the cluster that contains the word "clandestino" ["illegal immigrant"] in Left comments network.

Right Comments - "clandestino" cluster

Pagerank Score	Word	Hate index	Word
0.014797	*problema*	19.0	*via*
0.014664	*via*	8.0	*clandestino*
0.013994	*pagare*	7.0	*buonista*
0.012877	*euro*	7.0	*immigrato*
0.010131	*clandestino*	5.0	*problema*
0.009761	*certo*	5.0	*pagare*
0.008792	*migrare*	5.0	*pieno*
0.008780	*diventare*	4.0	*accogliere*
0.008006	*risolvere*	4.0	*straniero*
0.007590	*figlio*	3.0	*portato*

Table VI: Top 10 words for cluster Page Rank score and hate index in the cluster that contains the word "clandestino" ["illegal immigrant"] in Right comments network.

Diego Pilutti
Type of Campaign comments analysis

This part of the analysis is intended to investigate differences in political discussion based on sentiment analysis and level of hate-speech. In particular, we analyzed comments generated by posts belonging to different types of political campaign collected in Italy before the European elections of 2019: Positive Campaign and Negative-Comparative Campaign. Two networks of comments' words have been generated with the same methodology in order to enable an efficient comparison between the two types of campaign: edges of the networks have been constructed by counting the occurrences of two adjacent words in different comments from the original database according to the type of political campaign; nodes are constituted by each word contained in the comments. In the analysis the following variables have been considered as attributes: counts-hate, counts-prob, counts-pos, emo-neg, rabbia, tristez, ansia, parolac and polarity. By the use of this approach for constructing the edges, it's possible to focus on both the content of each word and its related context within the comments. Moreover, it resulted in a more efficient representation of the language structure of the comments and it enhanced processing capability of the data.

D. Negative-Comparative and Positive Campaign Networks

From the original database of comments, 40762 referred to posts belonging to Positive Campaign and 37413 referred to Negative-Comparative Campaign posts. To generate the two networks a specific procedure for text cleaning, pre-processing and lemmatization has been applied so as to capture relevant and meaningful words. After cleaning the number of comments for the Positive Campaign was 39235 and 36421 for the Negative-Comparative one.

The resulting networks consisted respectively of 27530 nodes and 187926 edges for the Negative-Comparative Campaign comments, with an average degree of 13.65, and 26664 nodes and 162783 edges for the Positive Campaign comments, with an average degree of 12.21. So, generally, the structure of the networks is comparable in dimension, the Negative-Comparative one has slightly more nodes and edges than the Positive one and shows a relatively more connected structure. Evaluating the ratio between the actual number of connections in the networks and the potential number of connections resulted in comparable densities, 0.000496 for the Negative-Comparative network and 0.000458 for the Positive one. This reflects the fact that both structures are weakly connected, which is predictable considering the scale of the networks.

The degree distribution of the two graphs shows evidence that both are scale-free networks: their distributions follows a power law, as observed in figures 30 and 31. Furthermore the gamma representing this power law has been estimated: 2.95 for the Neg-Comp Campaign and 2.94 for the Positive one. Both these values are in between the interval [2,3], confirming the scale-free hypothesis.

	Nodes	Edges	Avg Degree	Density	Estim. γ
Neg-Comp	27530	187926	13.65	0.000496	2.95
Positive	26664	162783	12.21	0.000458	2.94

Table VIII: Networks Structure General Measurements

Neg-Comp			
degree	**pagerank**	**hate**	**polarity**
fare - 1524	italiano - 0.0046	italia - 29	volontariato
salvini - 1422	fare - 0.0045	paese - 25	calcolare
italiano - 1410	salvini - 0.0044	merda - 24	giovane
politico -1393	italia - 0.0044	casa - 23	merda
parlare - 1344	politico - 0.0040	italiano - 20	denunciare
partire - 1322	governare - 0.0039	fuori - 17	citta
italia - 1288	parlare - 0.0039	bene - 16	dovere
governare - 1241	partire - 0.0039	via - 15	lavorare
dire - 1240	pd - 0.0035	bastardo - 14	usare
pd - 1195	dire - 0.0033	vivere - 13	esasperare
potere - 1175	potere - 0.0033	salvini - 12	accadere
lavorare - 1007	votare - 0.0033	gente - 12	mica
persona - 1001	lavorare - 0.0031	islamico - 12	investrire
anno - 973	anno - 0.0029	mare - 12	sinistro

Table IX: Top 15 nodes for Negative-Campaign Network

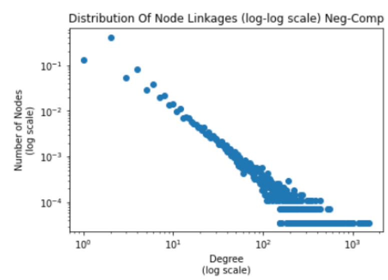


Figure 30: Distribution of Degree Neg-Comp Campaign

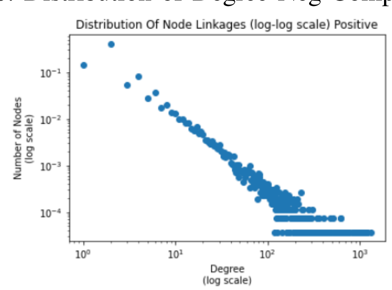


Figure 31: Distribution of Degrees Positive Campaign

As a preliminary step for the analysis, we considered some statistics about the nodes' characteristics: the degree, the Pagerank score, the hate index and the polarity measure. Top 15 nodes are presented in tables IX and X.

From the table we can see that relevant nodes according to the degree and the Pagerank score appear in the top 15 for both networks (fare, italia, italiano, italiano, politico, italiano, lavorare, potere, dire, salvini). This reflects the strong political nature of the discussion with respect to the European political elections. On the other hand some of these central words present also a high score of hate in both the networks (italia,italiano,) even if the scale of the score is lower for the Positive Campaign Network compared to the Negative-Comparative one. In general there are fewer hate-speech

Positive			
degree	**pagerank**	**hate**	**polarity**
fare - 1330	italia - 0.0048	italia - 15	giornalista
italia - 1203	grande - 0.0048	paese - 14	stronzo
politico - 1200	buono - 0.0044	merda - 10	umano
italiano -1172	fare - 0.0044	italiano - 8	mentire
votare - 1127	grazia - 0.0044	bastardo - 8	conduttore
grande - 1126	italiano - 0.0044	islamico - 8	arricchire
grazia - 1120	lavorare - 0.0042	donna - 7	pseudo
partire - 1099	votare - 0.0040	fatto - 7	scrivere
lavorare - 1089	politico - 0.0038	nessuno - 7	colpa
parlare - 1029	partire - 0.0036	via - 7	sostituire
potere - 999	salvini - 0.0033	coglione - 7	lavorare
dire - 970	votare - 0.0033	ministrare - 7	sorgere
anno - 934	lavorare - 0.0031	fuori - 7	bagheria
salvini - 928	anno - 0.0029	cazzo - 7	inchiesta

Table X: Top 15 nodes for Negative-Campaign Network

related words in the Positive Campaign Network (784) than in the Negative-Comparitive one (1484). Considering both hate and polarity attributes, we can notice that some words are present in the top 15 across the two networks, which are principally swear words and insults (merda, bastardo, stronzo).

*1) **Nodes Removal Analysis** :* Since the aim of this analysis is to examine relevant patterns in the context of the political discussion on social-media, in this section some experiments were performed on the robustness of the network. We systematically analyzed the relative changes in the density of the networks by performing node removal. The selection of nodes of the experiments has been implemented by importance of specific attributes and statistics. Starting from a list of nodes ranked by degree, attributes regarding the level of hate (hate index, problematic index and positive index) and sentiment (emo neg, rabbia, ansia, tristez, parolac) have also been considered. In the following the most relevant findings will be briefly discussed.

- **Node Removal by Degree**
  The comparison of the networks' behaviour in relative change of density by performing node removal by degree shows, as in 32, that removal of the first 4000 nodes with highest degree leads to a similar reduction in the density of the network for both campaigns. Also, it reflects commonalities in their structure, as highlighted in the statistics discussed above. In the analysis of the curve of relative change per node removed between the density of the Neg-Comp network and the Positive one in (Fig.33) there are no substantial differences. Given this, from now on the analysis will take into account this result to foster comparability and interpretability of our experiments across attributes.
- **Node Removal by Hate Count Index**
  Relevant differences has been detected performing node removal by hate score resulted as shown in figure 34 and 35. Even though in the Negative-Comparative Campaign network there are more hate-speech related words appearing more frequently with respect to the positive one, we compared the relative change in the density for the first 784 most hateful words. We observed that after the first

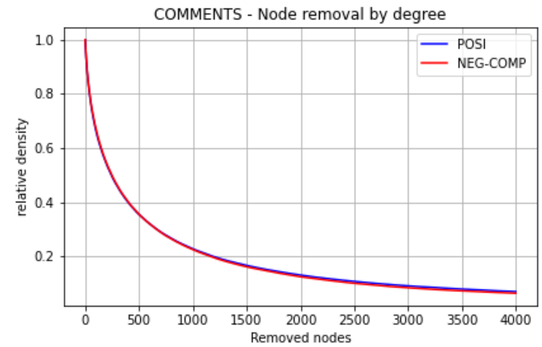


Figure 32: Degree node removal Neg-Comp vs. Positive Campaign

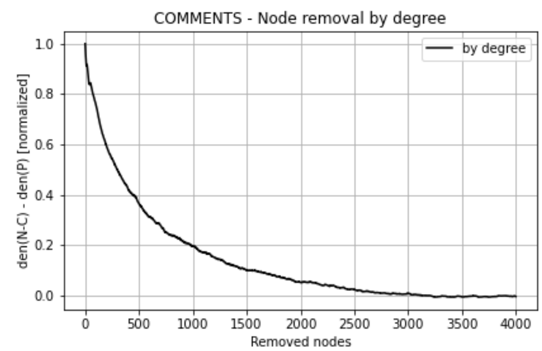


Figure 33: Relative Change Neg-Comp vs. Positive Campaign

  400 words there is a divergence between the two density curves: the Neg-Comparative network looses its structure in a faster fashion. This reflects that hate-related words are more central with respect to the political discussion of Negative-Comparative Campaign than in the Positive Campaign.
- **Node Removal by Positive Count Index**
  To assess the hypothesis of the centrality of hate-speech words in the narrative of Negative-Comparative political campaigns, we compared also the effect on the densities by removing the most positive words. As shown in figures 36 and 37 we noted that the relevance of changes in the 20000 most positive words for both networks behaved in the same way, It began with a steep drop in density for the most positive words, a steady decrease and finally a tiny increase for the least positive ones. As for the comparison with the node removal based on the degree, no relevant changes were identified. This strengthened our hypothesis that to highlight which type of campaign generated more hate speech in political discussion we should focus on the variable hate counts that we generated.
- **Node Removal by Total Negativity**
  To compare characteristics and differences of the two networks with respect to sentiments we analyzed the variable 'total negativity'. This variables is composed of 5 variables representing sentiments scores in the LIWC dictionary: emo neg, anxiety, anger, swear words, sad-

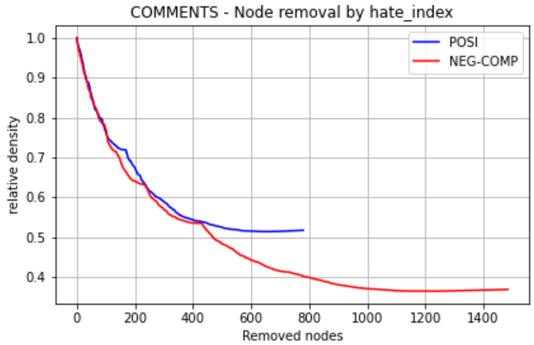


Figure 34: Node removal Hate Neg-Comp vs. Positive Campaign

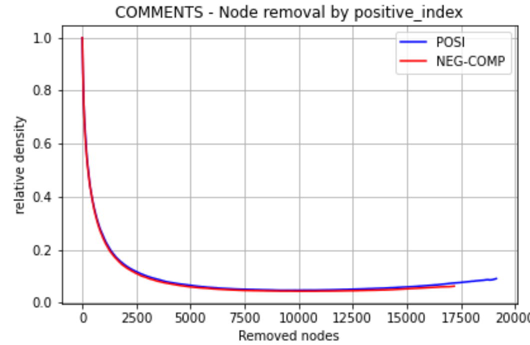


Figure 36: Node removal Positive Counts Neg-Comp vs. Positive Campaign

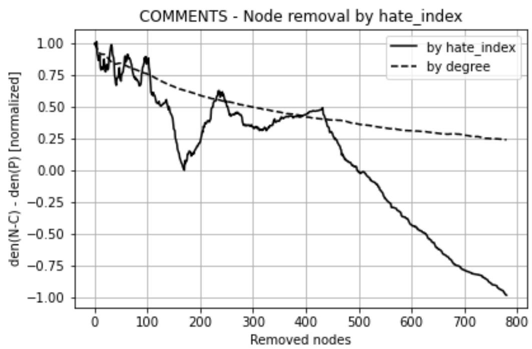


Figure 35: Relative Change Neg-Comp vs. Positive Campaign

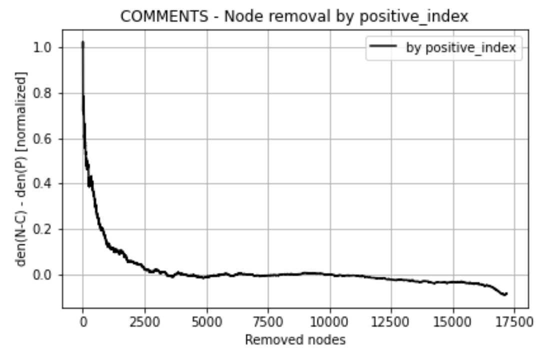


Figure 37: Relative Change Neg-Comp vs. Positive Campaign

ness. The variable takes values in a range between 0 and 300 in our network of words so when applying node removal, we can see the behaviour of the decrease in density following the shape of three parabolas, each of them corresponding to the three values present for total negativity: 300.0, 200.0, and 100.0. We can see from figures 38 and 39 that, when removing almost the same amount of nodes, the structure of the Negative-Comparative Campaign Network deteriorates faster than the Positive one.

- **Node Removal by LIWC Negative Emotions**
  To explore more in depth the effect of the different emotions involved in the discussion of the campaigns, we compared single instances of the variables composing the above mentioned total negativity. Concerning the impact over the density, from the figures 40 and 41, we can see that the two networks respond differently when systematically removing the words with highest negative emotions score, even if the number of emo-neg nodes is almost the same (542 for the Positive Camapaign and 644 for the Negative-Comparative one).
- **Node Removal by Anxiety and Anger**
  Another variable involved in total negativity is anxiety, whose presence is not that significant across the two networks (78 words for the Positive Campaign and 90 for the Negative Comparative one). Node removal by anxiety shows a coherent behaviour when comparing the two types of campaigns. In fact the Positive campaign network density decreases less than the one of the Negative-Comparative Campaign as showed in figures 42 and 43. The same behaviour is true and can be observed for the anger sentiment as in figures 44 and 45 even if a larger number of nodes has been considered (233 for the Positive Campaign and 301 for the Negative-Comparative Campaign).
- **Summary of Node Removal Analysis**
  From the analysis above we can say that the only relevant node-removal strategy to identify which variables affects more the two networks is the one related to hate counts variable. In fact from our comparisons we can conclude that the nodes used in hate speech are more central in the Negative-Comparative campaign comments with respect to the Positive Campaign Network and constitute a relevant part of the structure of the network. On the other side even if the node-removal experiments based on the sentiment highlighted some different behaviours, the results on the aforementioned variables need still to be investigated more in detail. Moreover was difficult to make conclusions considering the sentiments since only a small portion of the datasets presented relevant LIWC sentiments scores.

*2) **Cluster Analysis** :* In this last part of the analysis we want to investigate which are the relevant patterns that can capture the context and content of the hate speech words

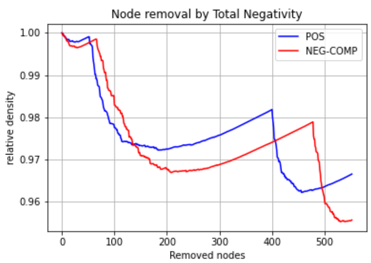


Figure 38: Node removal Total Negativity Neg-Comp vs. Positive Campaign

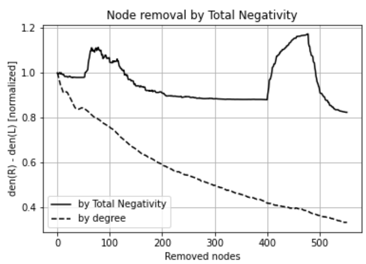


Figure 39: Relative Change Neg-Comp vs. Positive Campaign

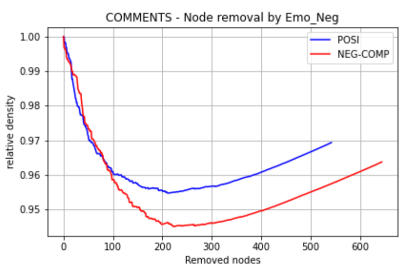


Figure 40: Neg. Emo. node removal Neg-Comp vs. Positive Campaign

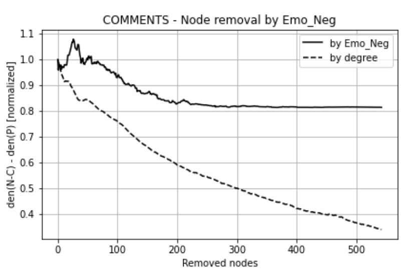


Figure 41: Relative Change Neg-Comp vs. Positive Campaign

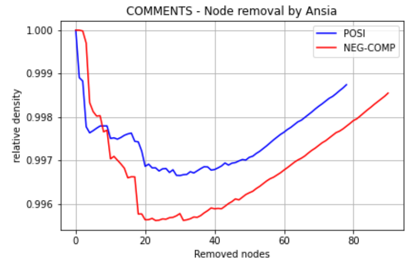


Figure 42: LIWC Anxiety node removal Neg-Comp vs. Positive Campaign

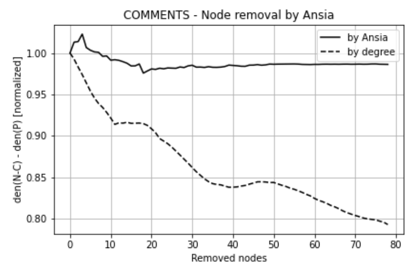


Figure 43: Relative Change Neg-Comp vs. Positive Campaign

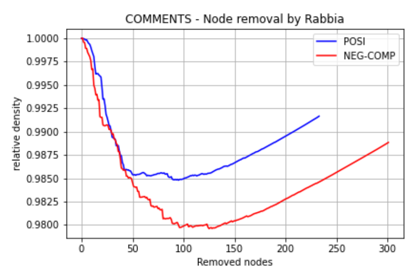


Figure 44: LIWC Anxiety node removal Neg-Comp vs. Positive Campaign

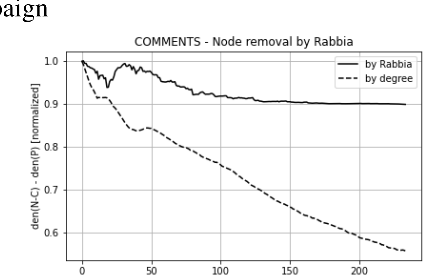


Figure 45: Relative Change Neg-Comp vs. Positive Campaign

across the two different networks. Following the results of the experiments for node-removal we focused on the variable hate counts. To do so we applied the Louvain community detection algorithm implemented in Gephi to visually identify and label communities, using modularity statistics provided by the software. To ensure common ground for comparison we used the same resolution parameter (1.0) for Negative-Comparative and Positive Campaign networks. The results are depicted in figures 46 and 48. Here, we colored words according to the modularity class they belong to, while their size was set to be the degree variable. To better visualize the relevance of hate speech words in both campaigns, we also set the size of the labels according to their hate score to identify their role in the network. Results for this procedure are shown in figures 47 and 49.

All these issues are in particular part of the right-wing political rhetoric and the presence of insults and swear words gives in general a negative connotation of the discussion, highlighting the negative-comparative political perspective. This results are more evident considering the PageRank scores

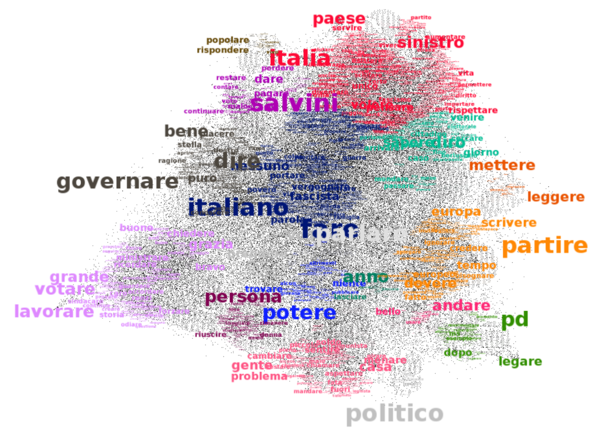


Figure 46: Network for Gephi's modularity communities the Negative-Competitive Campaign comments. Size of the words is set according to its degree.

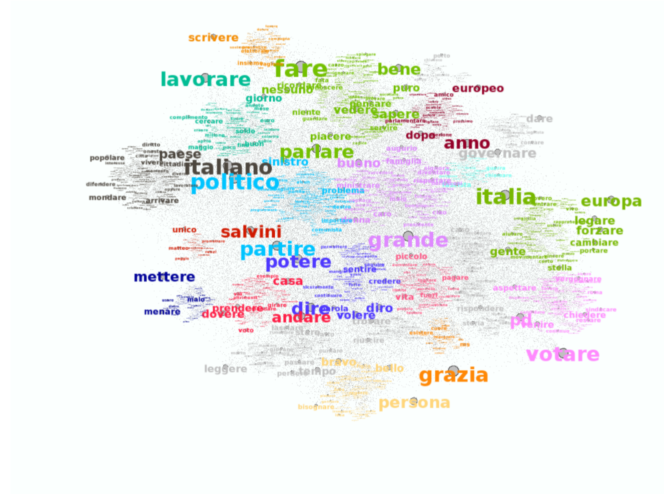


Figure 48: Network for Gephi's modularity communities the Positive Campaign comments. Size of the words is set according to their degree.

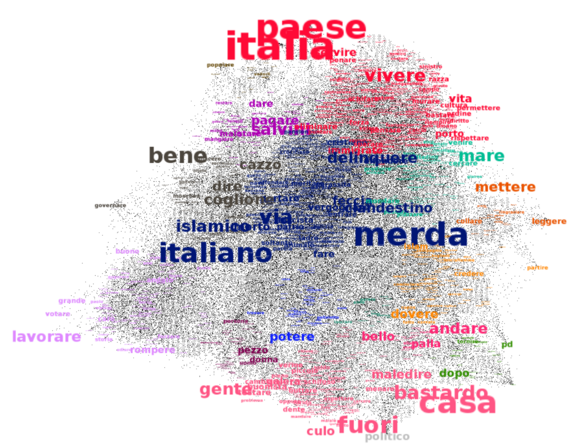


Figure 47: Network for Gephi's modularity communities the Negative-Competitive Campaign comments. Size of the words is set according to the level of hate.

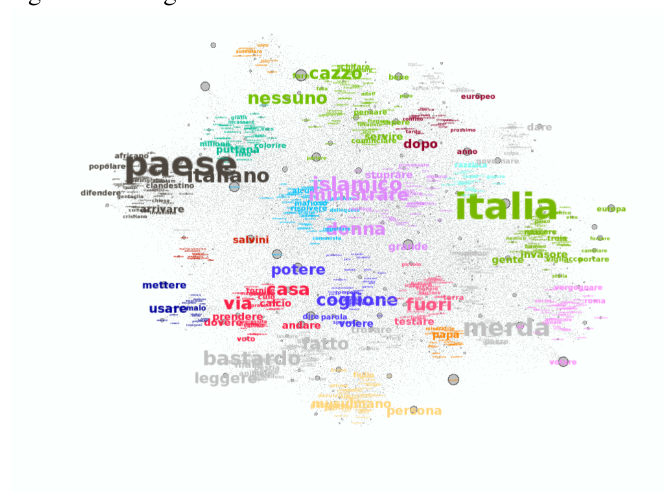


Figure 49: Network highlighting Gephi's modularity output for subset of Left parties comments. Size of the words is set according to its hate score.

of the nodes within the community and by sorting the most relevant words according to their hate counts as showed in XII. As we can see from the visualization the detected partition differs in the size and number of the communities detected: for the Positive Campaign we have more clusters (426) and the most relevant ones are similar in size, on the other hand for the Negative-Comparative Campaign has fewer clusters (349) which are bigger in size.

Among the different communities detected, in order to identify which topics and part of the discussion generated more hate speech, we selected the more relevant communities ranking them according to their size and compared by the total average hate score. Then we ranked the communities with respect to their average hate as shown in XI. As we can see from the tables in general the communities of the Negative-Comparative campaign have a higher average hate with respect to the ones from the Positive Campaign. Moreover, from the data we can affirm that more relevant communities in the Negative-Comparative campaign show a high collection of hateful words, strengthening therefore our results obtained with node removal. To better understand the topics and the words that generated more hate speech comments we visually inspected the more hateful clusters individuate by the algorithm. The community with the higher level of hate for the network of the comments referring to Negative-Comparative Campaign posts has 3335 nodes and 10775 edges with an average degree of 6.46. In the community with the higher number of average hate per word for the Negative-Comparative Campaign, taking as a reference the degree of the nodes inside the community, we can see that the most relevant words are: 'italiano', 'fare', 'fascista', 'vergognare', 'nessuno', 'difendere', 'delinquere', 'colpa', 'migrare', 'guerra', 'difendere',

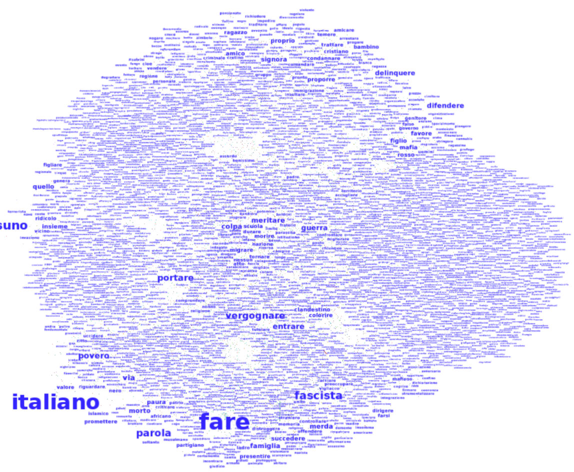


Figure 50: The community of the Negative-Competitive Campaign with higher level of average hate. Size of the labels by degree

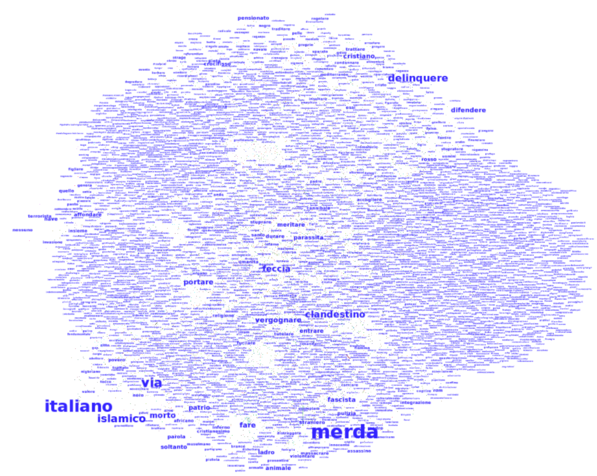


Figure 51: The community of the Negative-Competitive Campaign with higher level of average hate. Size of the labels by level of hate.

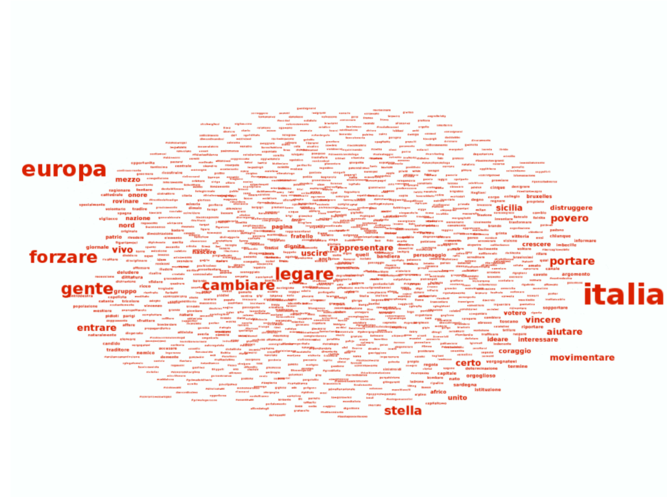


Figure 52: The community of the Positive Campaign with higher level of average hate. Size of the labels by degree

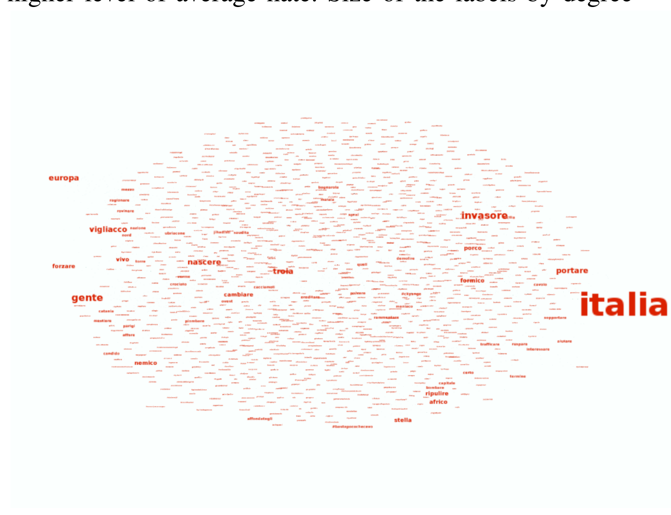


Figure 53: The community of the Positive with higher level of average hate. Size of the labels by level of hate.

'mafia','clandestino', 'colorire','scuola', 'figliare', 'merda, as shown in figure 50. In general it seems that the topic captured by the community refers to internal politics issues ranging from immigration, school and education, defense of national borders and family. All these issues are in particular part of the right-wing political rhetoric and the presence of insults and swear words gives in general a negative connotation of the discussion, highlighting the negative-comparative political perspective. This results are more evident considering the PageRank scores of the nodes within the community and by sorting the most relevant words according to their hate counts as showed in XII. When visualizing the same community according to the level of hate for each words, we can see that some words that were identified as relevant in the structure of the community are also correlated to their level of hate. In fact from the figure 51 we can clearly distinguish words such as 'merda', 'italiano', 'islamico', 'clandestino', 'feccia', 'delinquere', 'difendere', 'parassita', 'via', 'ladro', 'animale', 'affondare'. From this considerations therefore we can affirm that the relevant patterns in the discussion of the comments generated by Negative-Comparative Campaign posts concerning internal politics issues are highly correlated with respect to the level of hate-speech targeting migrants and religious minorities, and that in this context the attacks on these categories polarize the general political discussion on internal topics. The most hateful community for the Positive Campaign comments network is smaller in size compared to the one of the Negative-Comparative Campaign, in fact it consists of 1216 nodes and 2307 edges with an average degree of 3.8. Considering the community with higher level of hate per word on average for the positive campaign we can observe that with respect to the degree of the nodes words such as 'italia','europa', 'legare', 'forzare','gente', 'cambiare', 'movimentare', 'stella','sicilia', 'nord', 'povero', 'portare' are central with respect to the pattern identified by the algorithm. The general topic of this community varies across different relevant political topics: foreign and internal policies ('europa','italia','cambiare', 'nazione', 'nord', 'bruxelles') and political confrontation between Italian parties ('legare' lemmatization mismatch for 'Lega', 'movimentare' and 'stella' lemmatization mismatch for Movimento 5 Stelle). In this cluster shown in figure 52, differently for the previous one, no clear assumption can be made on the type of discussion captured by the community, since there are no relevant words that have a clear negative meaning. When analyzing the words with the higher hate score in this community, as shown in figure 53, we identify words such as 'italia','gente', 'vigliacco', 'invasore', 'africo', 'troia', 'ripulire', 'nemico', 'ruspare', 'jihadisti', 'stella'. From this we can align also this results with the conclusions for the Negative-Comparative Campaign bur remarking that in the case of the Positive campaign the general level of hate is lower and the hateful words are less central and significant with respect to the political discussion and when present they target principally words related to internal politics issues such as attacks on opposed parties and just a small part of the discussion is related to migrants and religious minorities such as Muslims and African people, as also confirmed from the more specific results showed in table XIII.

Positive Network		
community class	**percentage**	**average hate**
14	4.5%	0.08
10	6.18%	0.06
2	7.47%	0.05
6	5.1%	0.045
3	5%	0.045
26	5%	0.042
1	7.79%	0.04
5	5.1%	0.04
0	7.37%	0.03
19	5.47%	0.02
Negative-Comparative Network		
community class	**percentage**	**average hate**
12	12.11%	0.19
1	12.02%	0.16
2	7.46%	0.15
0	6.85%	0.08
4	7.64%	0.08
16	7.57%	0.06
10	4.3%	0.06
8	12.51%	0.05
5	4%	0.05
23	3.84%	0.03

Table XI: Top 10 communities for Positive Campaign and Negative-Comparative Network according to hate

Negative-Comparative Campaign - most hateful cluster

Pagerank Score	Word	Hate index	Word
0.02082	*italiano*	24.0	*merda*
0.01914	*fare*	20.0	*italiano*
0.00815	*fascista*	15.0	*via*
0.0779	*nessuno*	12.0	*islamico*
0.0063	*povero*	11.0	*delinquere*
0.0059	*vergognare*	10.0	*clandestino*
0.0058	*guerra*	9.0	*feccia*
0.0056	*entrare*	8.0	*morto*
0.0054	*via*	7.0	*fare*
0.0054	*portare*	7.0	*vergognare*

Table XII: Top 10 words for cluster Page Rank score and hate index in the most hateful cluster in Negative-Comparative campaign comments network.

Positive Campaign - most hateful cluster

Pagerank Score	Word	Hate index	Word
0.0727	*italia*	15.0	*italia*
0.04421	*forzare*	4.0	*gente*
0.034	*europa*	4.0	*invasore*
0.0249	*legare*	3.0	*troia*
0.0233	*stella*	3.0	*europa*
0.0202	*cambiare*	3.0	*vigliacco*
0.01719	*gente*	3.0	*portare*
0.01409	*povero*	3.0	*nascere*
0.0139	*movimentare*	2.0	*vivo*
0.0121	*vincere*	2.0	*stella*

Table XIII: Top 10 words for cluster PageRank score and hate index in the most hateful cluster in Positive campaign comments network.

Lynda Wainaina
Type of Campaign Posts Analysis (Negative vs Positive)

This part of the project describes the politicians posts made for the type of campaign that is; Negative-Comparative and Positive in the social media context of Facebook posts and tweets. We aimed at investigating the differences in level of hate from the posts of the two types of campaign (negative and positive) made by politicians. We also investigated the sentiment corresponding to polarity, Emo-Neg, Ansia, Rabbia, Tristez, Parolac.

Our main variable of interest from the data base was *p-camapagna*2 indicating the two types of campaign which had a total of $10,103$ posts before cleaning ($6,507$ for positive type of campaign and $3,596$ for negative campaign) and $10,043$ posts after cleaning($6,447$ for positive type of campaign and $3,596$ for the negative type of campaign). The data base for the positive type of campaign is bigger compared to the negative type of campaign however, we considered the two classes to be balanced since the balance ratio is $1 : 1.8$ which is not significant for class imbalance.

The variable *p-rating* indicated the level of hate *(problematico, negativo, ambiguo, positive)* ranging from the most hateful to the least hateful posts. These attributes enabled us to perform sentiment analysis comparing which data base had the most hateful posts. Since the posts did not have a hate index, we focused on the problematico attribute as our hate index. Text cleaning was perfomed on all posts from which we obtained lemmas used to extract nodes and edges using the package network x in python. The final output from network x contained $12,947$ nodes and $67,833$ edges for the positive type of campaign and $10,984$ nodes and $61,856$ edges for the negative type of campaign. We used co-occurencies of adjacent words to obtain the edges which was a great reduction of the original total edges($1,019,720$ and $1,095,195$ for the positive and negative type of campaign respectively). This reduction was of significance since we were able to visualize better the graphs in Gephi.

We performed network analysis using python and from Figure 54 and 55 we observe the probability of degree distribution over the whole network on a log log scale. From the plots we conclude that the networks for the Negative and Positive type of campaign are scale free networks. Moreover, the gamma representing the power law exponent was estimated as: 2.759 for the Neg-Comp Campaign and 2.717 for the Positive one as seen in table XIV. Both these values are in between the interval [2,3], confirming the scale-free hypothesis.

*3) **Nodes Removal Analysis For Posts Type of Campaign**:* In our project we were interested in observing how the network robustness and stability changes with respect to removal of the most important nodes. We aim at observing which node removal strategy greatly affects the negative and positive type of network while taking note of the changes in the density as we attack the network. These observations are important as they enable us to know the importance of these variables in political dialogues.

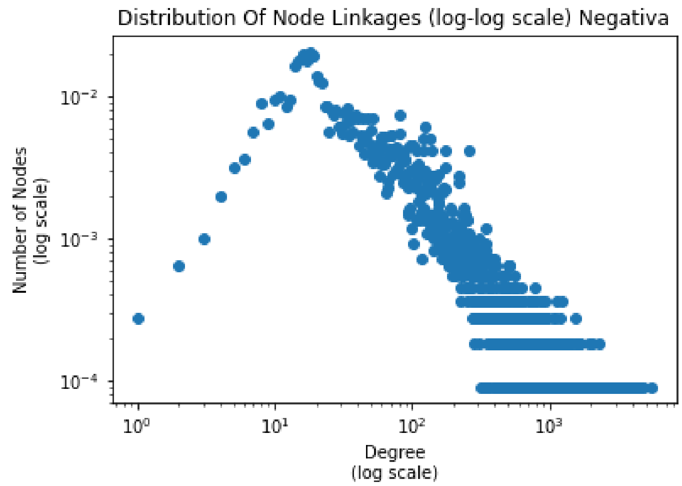


Figure 54: Distribution of Nodes' degrees Neg-Comp Campaign

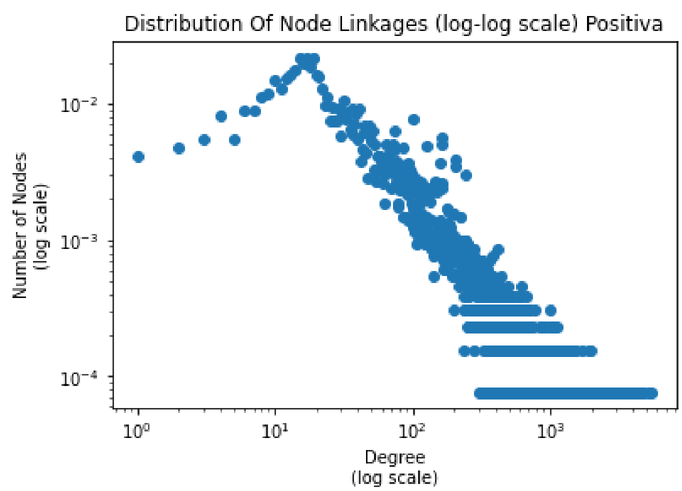


Figure 55: Distribution of Nodes' degrees Positive Campaign

We performed the following node removal corresponding to:

- Node Removal by Degree

  In this approach we remove nodes by degree starting with words having a high degree. We observe from fig. 56 that the density decreases drastically as we remove the nodes for both negative type of campaign and the positive one. Particularly, we observe that from the node 2000 the change in density is constant for the negative and positive type of campaign. Moreover, we observe that there is no significant difference between the two types of campaign with regards to node removal by density as seen in fig. 57.
- Node Removal by Problematic Count Index
  In this approach we remove nodes by problematic index;

	Nodes	Edges	Avg Degree	Density	Estim. γ
Neg-Comp	10984	61856	11.261	0.01816	2.759
Positive	12947	67833	10.479	0.0122	2.717

Table XIV: Posts type of campaign General Network Structure

starting with words of high occurrence in problematic posts. We observe from fig. 58 that the density decreases drastically as we remove the nodes for the negative type of campaign compared to the positive one. This shows the problematic words are more central in the negative network since we are removing the most appearing nodes hence the network loses its robustness more quickly. The positive Network loses approximately 30% of its density while the negative looses over 60% considering the first 300 nodes removed. Fig 60 shows a clear difference between node removal by degree and node removal by problematic index. The problematic index confirms our observations from 58 that the problematic posts are more significant in the negative type of campaign.

- Node Removal by Positive Count Index
  We remove nodes by positive index starting with words having high occurrence in positive posts to provide a valid ground for comparison. We observe from fig 59 that the behavior of the two curves is almost the same up to around 5500 removed nodes where we see that the negative network's density starts increasing contrary to the positive one. This confirms that the nodes removed in the negative network have lowest degrees or are located at the periphery. Moreover, the positive words seem to be more central in the positive type of campaign thus confirming findings from node removal by problematic index. Fig 61 shows a clear difference in node removal of the positive index and degree starting from 2000 node removed. From this plot we can conclude that positive words are more central in the positive type of campaign which supports our conclusions that problematic words are more central in the negative type of campaign.

- Node Removal by Sentix Polarity
  For this approach, we start by removing nodes with the lowest polarity, from -1 to 0 which correspond to the most negative words . An abnormal behavior is noticeable when we reach 500 removed nodes as the density starts increasing again. (Fig.63). This is because the nodes with the same polarity are removed starting by those with the highest degrees thus reducing the density upto the minimum. Then we reach the lowest degrees nodes, the relative density increases once again. We notice that the difference is not significant after all between the two types of campaign considering polarity attribute. Negative and Positive types of camapaign networks lose 4% and 6% of their initial density respectively. This is also confirmed by looking at the comparison with removing nodes by degree as no clear trend is observed.

- Node Removal by LIWC's Total Negativity
  We performed node removal using LIWC sentiment dictionary's attributes namely the Total negativity obtained by summing the scores of the five LIWC variables. The plot shown in figure 64 was obtained by removing nodes starting from those with 300 total score then 200, and finally 100. Therefore, we can easily observe that the graph is somehow divided into three parts corresponding to the three sets of nodes. The first part of the plot (fig. 64), shows that both negative and positive type of campaign densities increase relative to their initial densities, meaning that those nodes with 300 score are not central in both networks. The second section of the plot corresponding to nodes with a total score of 200 shows an initial decrease in the density for both networks then a sudden increase. Finally, in the last section, the nodes with score equal to 100 follow the same behavior as in the second section of the plot. In general, we can see that in all the phases the density did not decrease by more than 0.015% for both networks. Therefore, we cannot say that there is a difference between the two types of campaign in terms of the Total Negativity attribute of the LIWC dictionary. This is also confirmed by looking at figure 65 that compares node removal by degree and by total negativity.

To sum up the above results, we conclude that the problematic and positive index are the most important in determining the level of hate in posts for the negative and positive type of campaign. In particular the negative type of campaign generates more hate in accordance to problematic index. We included the other graphs corresponding to the LIWC attributes in the appendix.

*4) **Negative-Comparative vs Right Graphs Representation in Gephi** :* Network Graph Analysis and Visualization with Gephi enabled us to visualize better the graphs and perform cluster analysis using Multi Gravity Force Atlas 2 and Circular pack layouts. We used Modularity_class with the default resolution 1.0 and colored the nodes using this attribute.

- Negative-Comparative Type of Camapign General Graph:Problematic Index
  We obtained 27 communities using modularity score 0.280. The graph in fig. 66 shows the Negative-Comparative type of campaign communities with the attributes; node color = modularity_class and node size = problematico index. We used the attributes modularity_class and counts_problematico with the circular pack layout to obtain the final graph.

- Positive Type of Camapign General Graph:Problematic Index
  We obtained 58 communities using modularity score 0.314 The graph in fig. 67 shows the Positive type of campaign communities with the attributes; node color = modularity_class and node size = problematico index. We used the attributes modularity_class and counts_problematico with the circular pack layout to obtain the final graph.

- Negative-Comparative Type of Camapign General Graph:Page Rank
  The graph in fig. 68 shows the Negative-Comparative type of campaign communities with the attributes; node color = modularity_class and node size = page rank. We used the attributes modularity_class and page rank were used with the circular pack layout.

- Positive Type of Camapign General Graph:Page rank
  The graph in fig. 69 shows the Positive type of campaign communities with the attributes node color = modularity_class and node size = page rank. We used the attributes modularity_class and page rank with the circular pack layout.

We can observe from the graphs that the that adjective "Italiano" ["Italian"] and "Italia" ["Italy"] are always present in both subsets with both high problematic index and global page rank. We also see the words such as "Europa" ["Europe"] and "Immigrazione"["Immigration"] are most frequent both in the negative and positive network. This shows that these words are frequently used in the political dialogues context.

*5) **Communities Detection and Analysis**:* Detecting communities is of great importance in network analysis as we can analyze the independent clusters in the graph and understand more about a cluster. In our project we aimed at analyzing the patterns that can capture hate speech content in the negative and positive type of campaign. We selected some relevant clusters to better understand the topic discussed and how the words contributed in generating hate.

As described in the introduction, most of the hate speech contents mainly deals with immigrants and ethnic-religious related arguments. We identified the cluster containing the word "clandestino" ["illegal immigrant"] and run some analysis on it by using Python and networkx library [30]. The main goal was to check whether this cluster was indeed among the ones with the largest average hate index.

We observe from fig. 70 that the cluster containing the word "clandestino" was indeed the one that had the highest average problematic index. The number of nodes of this cluster was 812, while the number of edges 1182 and average degree of the network 2.9113. We observe from table XV that the words in the clandestino cluster have a higher level of hate considering the problematic index. With this we can conclude that the negative type of campaign generates more hate.

We also observe from fig. 71 that the cluster containing the words "immigrazione" and "clandestino" had indeed a high average problematic index in both types of campaign. The number of nodes of this cluster was 2055, while the number of edges 8354 and average degree of the network 8.1304. The table XVI shows the words in the "clandestino" cluster indicating the level of hate. We can clearly see that the words have a lower level of hate comparing it to table XV of the negative type of campaign.

The results obtained below clearly support our hypothesis that the type of campaign is an important variable in determining the level of hate in political posts. In particular, the negative type of campaign generates more hate compared to the positive type of campaign.

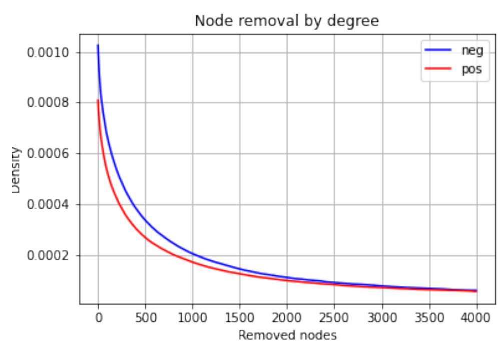


Figure 56: Node removal by degree (Negative and positive

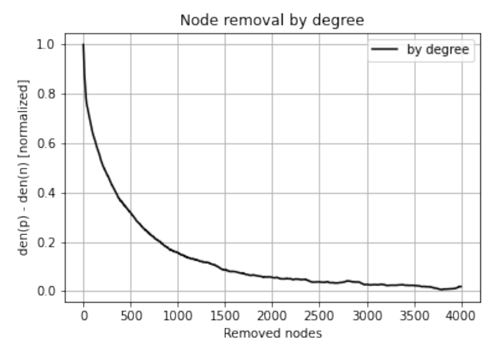


Figure 57: Relative change Neg-Comp vs Positive Campaign

Negative-Comparative Campaign - most hateful cluster

Pagerank Score	Word	Problematic index	Word
0.0316	*sinistro*	46.0	*sinistro*
0.01818	*centro*	42.0	*clandestino*
0.01809	*sociale*	31.0	*immigrazione*
0.01627	*immigrazione*	31.0	*centro*
0.0147	*clandestino*	29.0	*sociale*
0.0128	*destro*	25.0	*accoglienza*
0.01057	*accoglienza*	23.0	*immigrato*
0.01015	*delinquere*	20.0	*delinquere*
0.009269	*sentire*	19.0	*business*
0.0077	*centrare*	18.0	*straniero*

Table XV: Top 10 words for cluster Page Rank score and hate index in the most hateful cluster in Negative-Comparative campaign comments network.

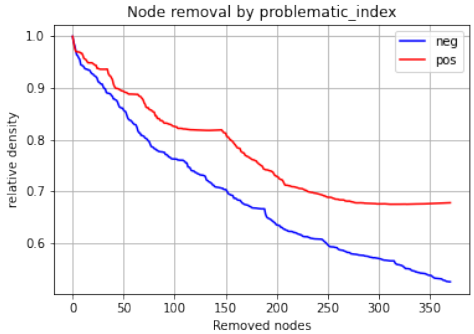


Figure 58: Problematic index Node removal(Negative and positive

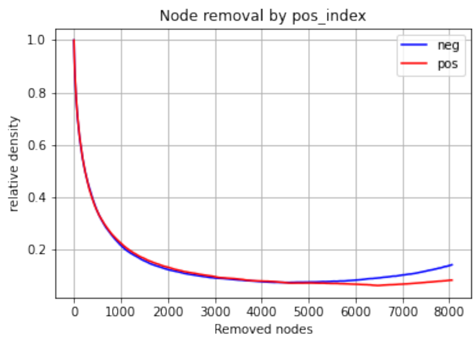


Figure 59: Positive index node removal(Negative and positive)

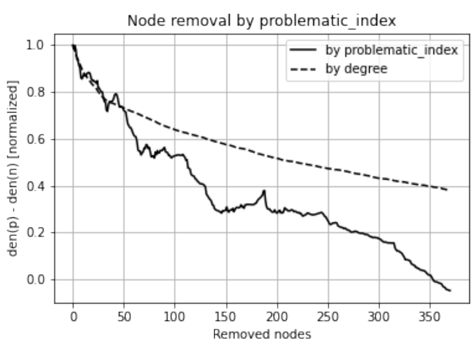


Figure 60: Problematic index vs Degree Node removal

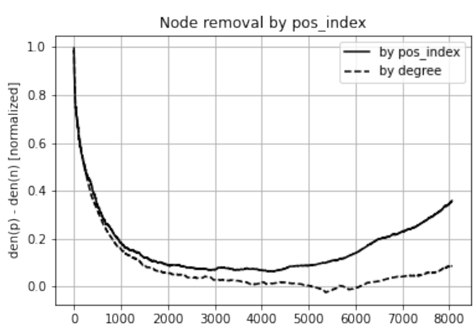


Figure 61: Positive index vs Degree node removal

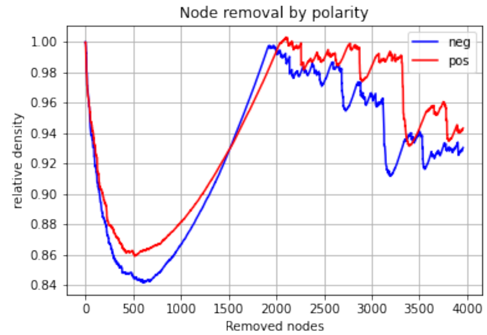


Figure 62: Sentix Polarity Node Removal (Negtaive and Positive)

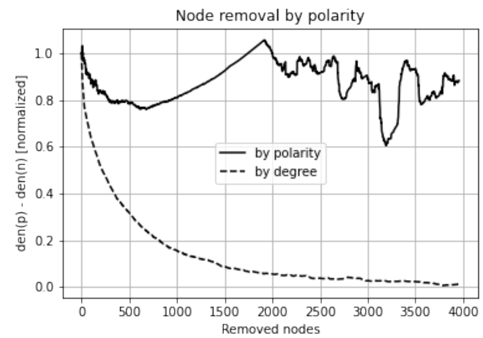


Figure 63: Sentix Polarity node removal

Positive Campaign - most hateful cluster

Pagerank Score	Word	Problematic index	Word
0.01792	*lavorare*	11.0	*italiano*
0.0122	*italiano*	11.0	*immigrazione*
0.01124	*persona*	8.0	*clandestino*
0.00868	*paese*	7.0	*confino*
0.00752	*diritto*	6.0	*sicurezza*
0.00706	*vita*	5.0	*islamico*
0.0070	*piccolo*	5.0	*sbarco*
0.0065	*cittadino*	5.0	*ungheria*
0.006205	*tutelare*	4.0	*morto*
0.005918	*leggere*	4.0	*galera*

Table XVI: Top 10 words for cluster PageRank score and problematic index in the most hateful cluster in Positive campaign comments network.

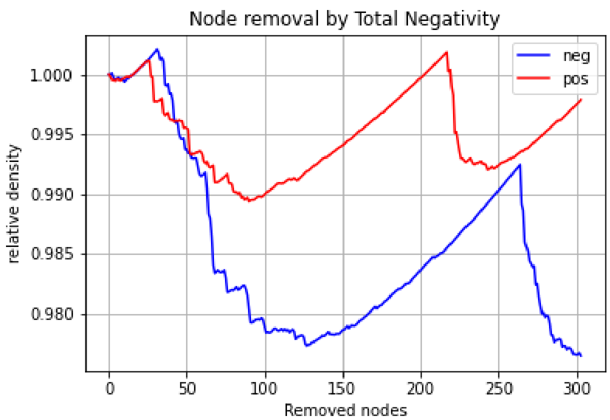


Figure 64: LIWC Total negativity node removal (Negative and Positive)

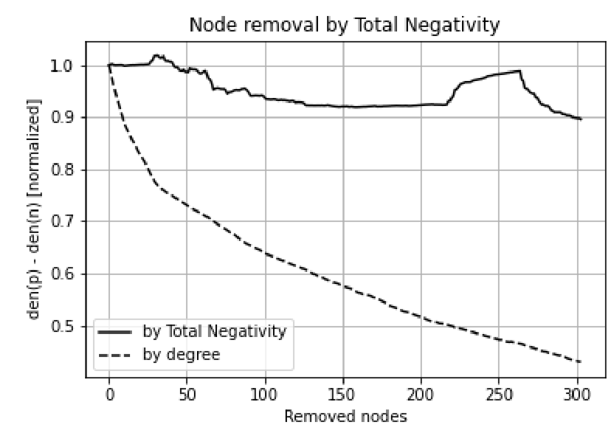


Figure 65: LIWC Total negativity node removal

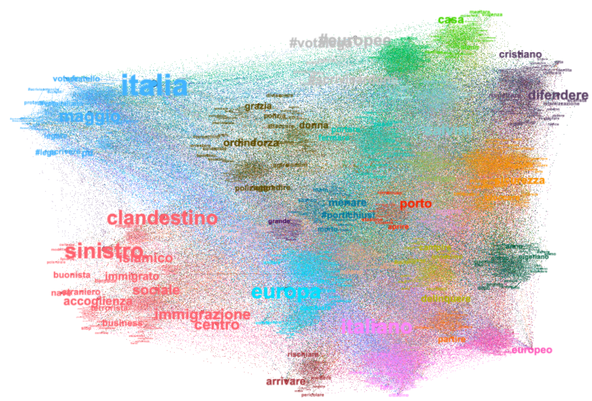


Figure 66: Negative-Comparative type of campaign Cluster with size of words indicating the problematic index.

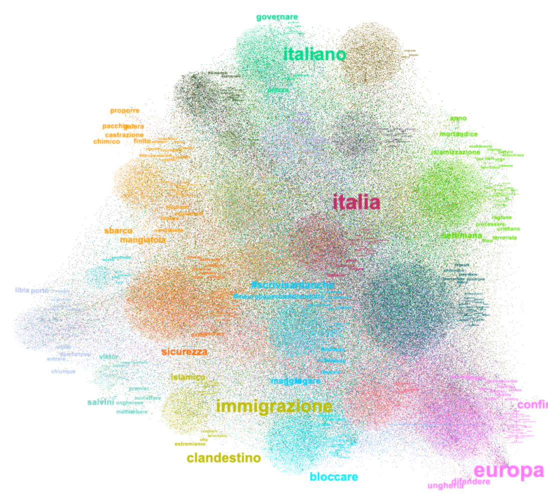


Figure 67: Positive type of campaign Cluster with size of words indicating problematic index.

Figure 68: Negative-Comparative type of campaign network - size of words indicating the page rank

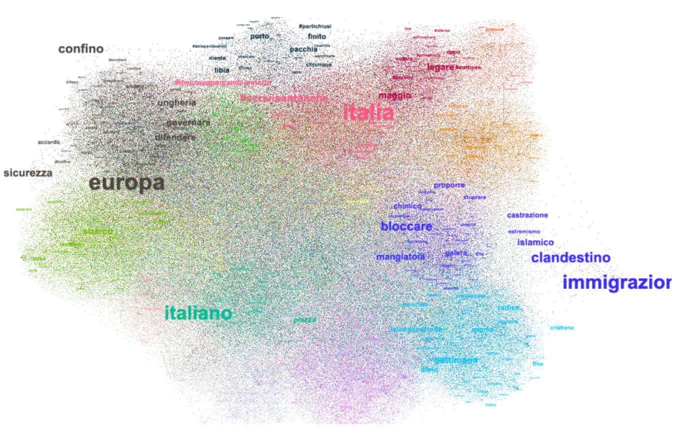


Figure 69: Positive type of campaign network - size of words indicating page rank

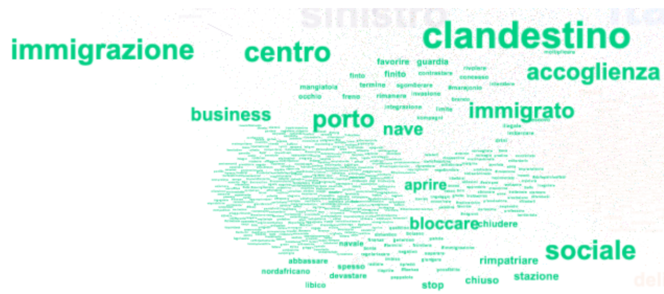


Figure 70: Negative-Comparative type of campaign Immigrazione Cluster

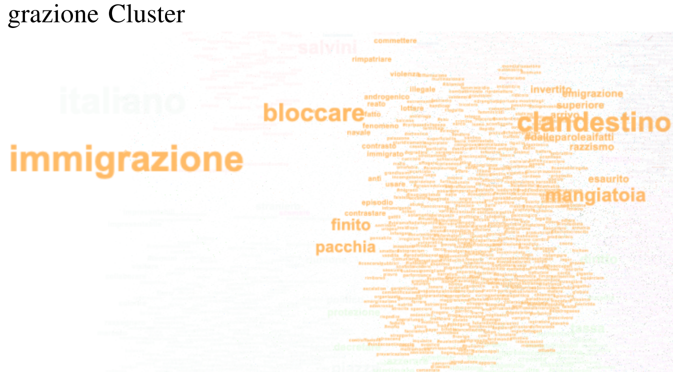


Figure 71: Positive type of campaign Cluster Immigrazione Cluster.

Natascia Caria
Campaign Target Division Comments Analysis

This part of the project is devoted to the analysis of the division with respect to the target of attacks in politicians' post contents. More in details, we want to assess whether or not the difference in attacks on individuals or groups of people are reflected in the spread of hate speech in users comments. With this in mind, we consider the following networks:

- the word-context network of comments on posts with attacks on group target;
- the word-context network of comments on posts with attacks on individual target.

Note that the target classification in the original database only concerns posts related to the Comparative or Negative campaign, therefore here we are considering two sub-networks of the previously studied network of comments associated with the Comparative-Negative campaign.

There are 20963 comments in the original database on posts with a group target, however the remaining ones after text-cleaning are 16344. Whereas in the case of individual target, there are 15930 out of 20423 remaining comments. In table XVII some metrics related to the networks structure are shown.

Networks Structure: The two networks have no significant differences: the number of nodes and the number of edges are comparable, as are the average degree and density. Furthermore, looking at the degree distributions in log-log scale (Fig. 72), it can be seen that asymptotically these follow a power law $p(k) = Ck^{-\gamma}$. The estimated γ parameters are between 2 and 3, therefore they are both scale-free.

The Group and Single networks are disconnected; they respectively consists of 210 and 195 components. In both cases the largest component makes up approximately 98.6% of the nodes and the other components to follow have 4 to 1 nodes.

	Nodes	Edges	Avg Degree	Density	Estim. γ
Group	20025	114768	11.4625	0.00057	2.83
Single	17260	86915	10.0713	0.00058	2.82

Table XVII: Target Networks General Structure Measurements

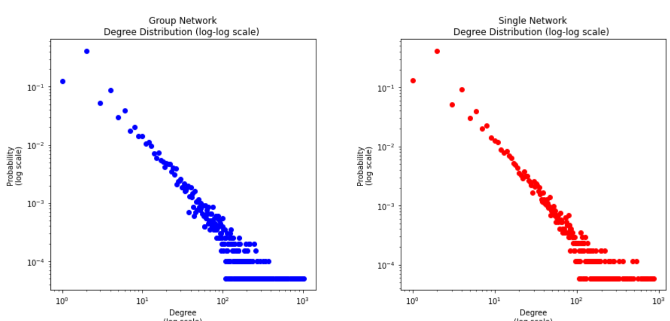


Figure 72: Degree distribution

Nodes Removal: As in previous sessions, we analyse the effect of nodes removal on network density according to different sentiment indices. What we know from [23] is that attacking singular targets compared to groups generates more negative comments than positive ones, but not a higher percentage of uncivil language and hate speech. Therefore, what we expect is that the removal of hate speech will have an equal effect in the two networks' structure.

*a) **Node removal by hate index:*** Indeed, this is exactly what happens if we perform a node removal according to decreasing hate index (Fig. 74). At the very beginning of the process, the density decreases more rapidly for the Group target network and thus their difference in density increases. However, after the removal of the first nodes, the density in the Single target starts decreasing more rapidly, resulting in a network that is less dense in the Single target and more dense in the Group target. But after the removal of few more than 200 nodes, the roles are reversed again, resulting at the end of the process in a denser network in the case of the Single target and with a difference 2.5 times greater than the initial one, which is not considered significant.

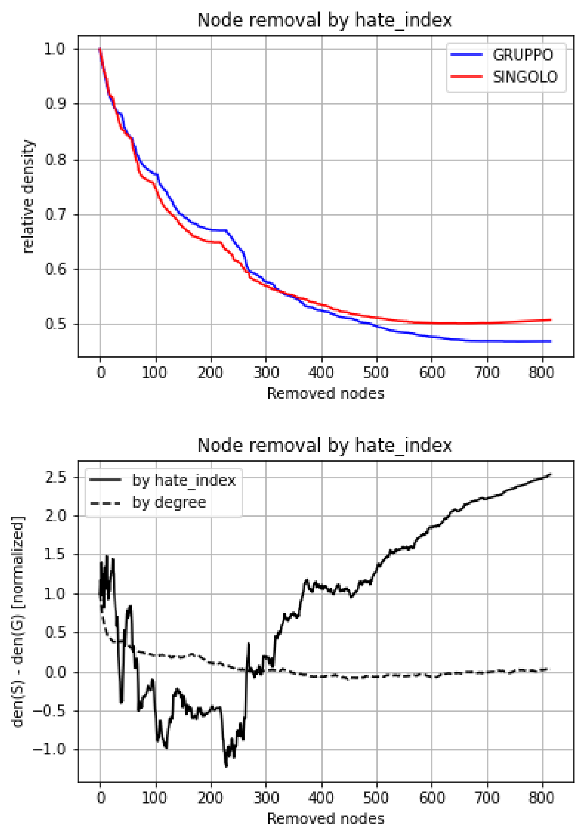


Figure 73: Density variation with node removal based on hate-index

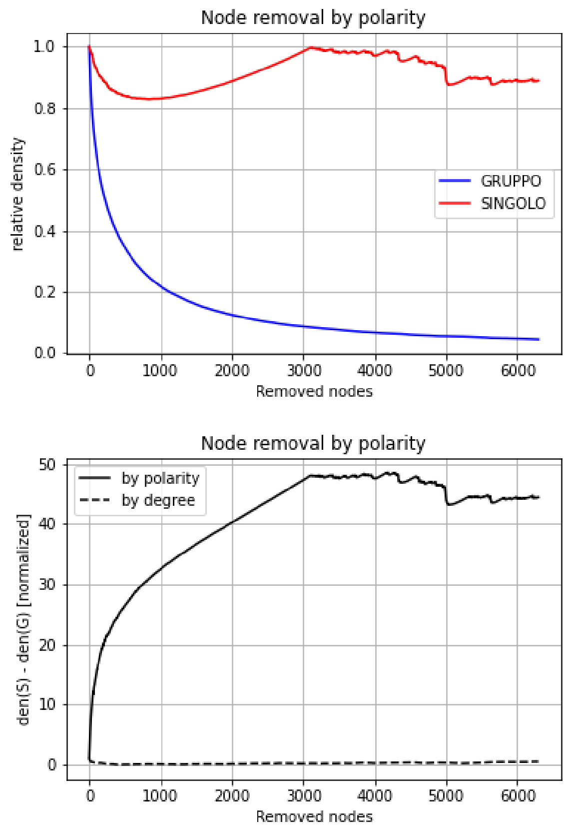


Figure 74: Density variation with node removal based on Polarity index

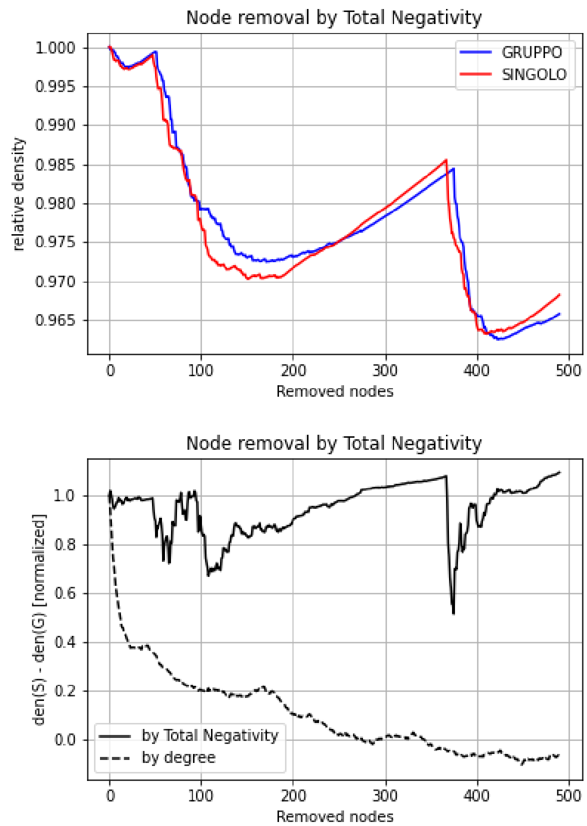


Figure 75: Density variation with node removal based on Total Negativity index

*b) **Node removal by polarity index**:* On the other hand, our initial hypothesis that attacking singular targets compared to groups generates more negative comments, is not confirmed when removing nodes according to polarity score. In this case, the density of the Group-target network decreases significantly faster than in the Single-target one and, after removing all words with polarity less than 0, the difference in density between the two networks is 50 times greater than the initial one. This is exactly the opposite of the expected result. Indeed, since attacks on individuals generate more negative comments, we would have expected the network of groups to be more robust.

*c) **Node removal by LIWC's Total Negativity**:* Finally, we perform the node removal analysis using the total negativity value obtained from the LIWC scores. As already mentioned in the previous sections, since this score is the result of the sum of 5 variables with value 0 or 100, the total negativity can vary between 0 and 500, but even in our case there are no values higher than 300. We therefore sequentially remove the variables that have total negativity equal to 300, 200 and 100. These steps are highlighted by the presence of the 3 parabolic trends in Figure 75; indeed, for equal scores, nodes are removed with a decreasing degree on average. Therefore, as peripheral nodes begin to be extracted, the density increases. In this case, as in that of the hate-index, we can see that there are no significant differences between the two networks, confirming our initial hypothesis that there is no evident distinction in the generation of hate content between attacks on groups or individuals.

***Summary of Nodes Removal Analysis**:* Summarising the obtained results, the nodes removal according to hate-index and total-negativity has equal effect in the two networks' structure, in compliance with the hypothesis that there is no obvious difference in the generation of hate comments from group or individual attacks in posts. While the removal of words on the basis of the negative polarity value decreases more the density in the network of comments from group attacks, in contradiction with the assumption that more negative comments are generated from posts with attacks on individuals. In addition to the analyses described above, node removal by problematic-index and positive-index was also carried out with similar results to removal by hate-index. Furthermore, with regard to the LIWC score, removal was also tested on the basis of the individual components of total negativity (negative emotion, sadness, anxiety, anger and swearing) and each showed no significant differences according to the variation of the density of the two networks.

Clusters Analysis: To conclude the analysis of the subdivision into Group and Single target, we investigate modularity and cluster components. The analysis was performed in Gephi; the modularity algorithm implemented in Gephi looks for the nodes that are more densely connected together than to the rest of the network. Therefore, considering the way our networks are constructed, a cluster should give us a more general view of the context in which a word is used in the comments.

Figure 78 shows the graphs obtained by performing modularity with a resoultion value equal to 1 on the Group target network. In the left visualisation, the size of nodes and labels is proportional to the pagerank value and their colour is that of the corresponding cluster. On the right, a different visualisation is proposed: the nodes and labels size increases with pagerank, the labels' colour varies from green to red according to the hate-index (min-max) rescaled value. The same applies to the single target network in Figure 79. As a matter of fact, we can see that words with high pagerank are common in the vocabulary of Italian political discussions and it can also be noted that many of these words also have a significant involvement in hate speech.

According to [22] and [23], focusing on content concerning immigration (8% of the total), 42% of this is discriminatory or hate speech. We are therefore interested in investigating a specific cluster, the one containing the words "clandestino" (clandestine) or "immigrato" (immigrant). Both in Group and Single target network, these words appear in the same cluster, displayed respectively in Figures 76 and 77. Furthermore, Tables XVIII and XIX show the words of the respective clusters sorted by pagerank and hate-index. The words "immigrato" and "clandestino" play different roles in the two sub-networks. Indeed, in the case of the Target Group, the word "clandestino" has a high importance in terms of pagerank, whereas this is not the case for the Target Single network. It is also worth noting that the hate words in this cluster are different across the target division: for the Group network many words are from hate comments in the religion topic. It is also worth noting that the hate words in this cluster are different across the target division: for the sub-network Group many words are from hate comments in the religion topic. For the Single network, on the other hand, the hate words seem to be related to delinquency and some polemics about Italians' pension. This suggests that the modularity algorithm probably placed the words "immigrato" and "clandestino" in two different contexts.

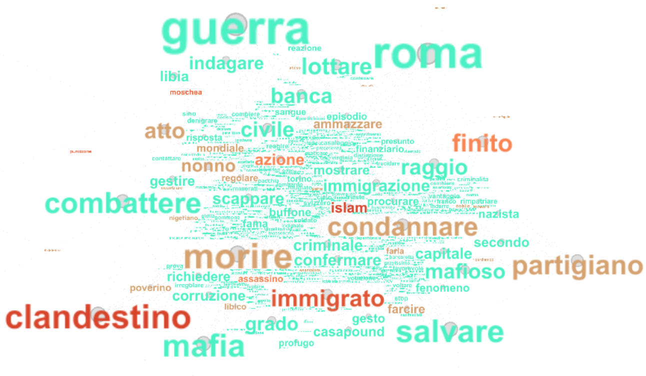


Figure 76: Group Target Network -"Clandestino" Cluster

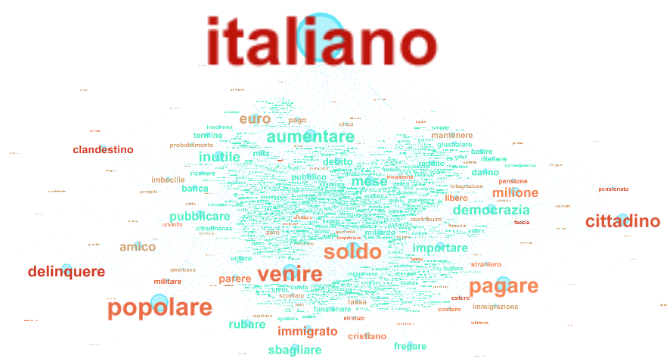


Figure 77: Single Target Network - "Clandestino" Cluster

Sorted by Pagerank			Sorted by Hate-index		
Word	Pagerank	Hate-index	Word	Hate-index	Pagerank
guerra	0.00084	0	clandestino	5	0.00058
roma	0.00079	0	islam	5	0.00023
morire	0.00061	1	immigrato	4	0.00040
clandestino	0.00058	5	punizione	3	6e-05
mafia	0.00054	0	lanciafiamme	3	2e-05
salvare	0.00054	0	moschea	3	0.00011
combattere	0.00050	0	azione	2	0.00026
partigiano	0.00047	1	finito	2	0.00042
condannare	0.00045	1	assassino	2	0.00014
finito	0.00042	2	disinfettare	1	3e-05

Table XVIII: Target Group Network - "Clandestino" Cluster.
Words sorted by pagerank and hate index.

Sorted by Pagerank			Sorted by Hate-index		
Word	Pagerank	Hate-index	Word	Hate-index	Pagerank
italiano	0.00367	10	italiano	10	0.00367
popolare	0.00131	3	feccia	6	0.0002
venire	0.00116	3	delinquere	6	0.00077
soldo	0.00114	2	clandestino	5	0.00052
pagare	0.00111	2	pensionato	4	0.00022
cittadino	0.00092	4	cittadino	4	0.00092
aumentare	0.00088	0	estero	4	0.00024
delinquere	0.00077	6	essi	3	5e-05
euro	0.00072	1	pensione	3	0.00028
mese	0.00070	0	stronzo	3	0.00023

Table XIX: Target Single Network - "Clandestino" Cluster.
Words sorted by pagerank and hate-index.

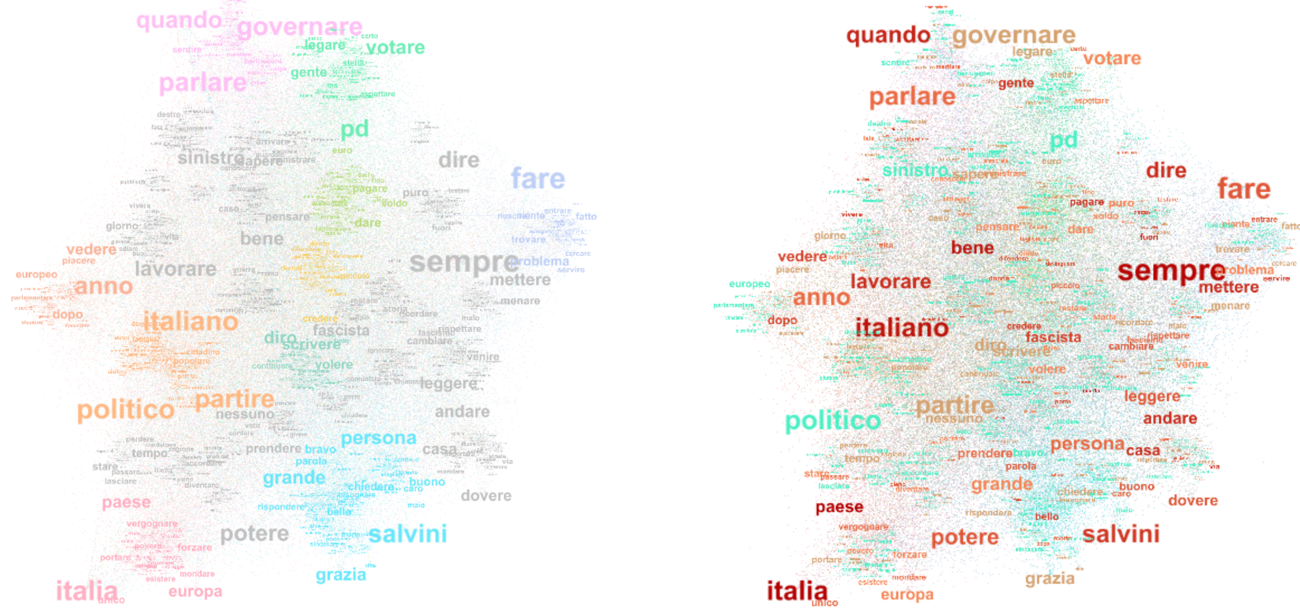


Figure 78: Group Target Network. Left: Nodes and labels proportional to pagerank, colored according to cluster. Right: Labels size and color according to hate index.

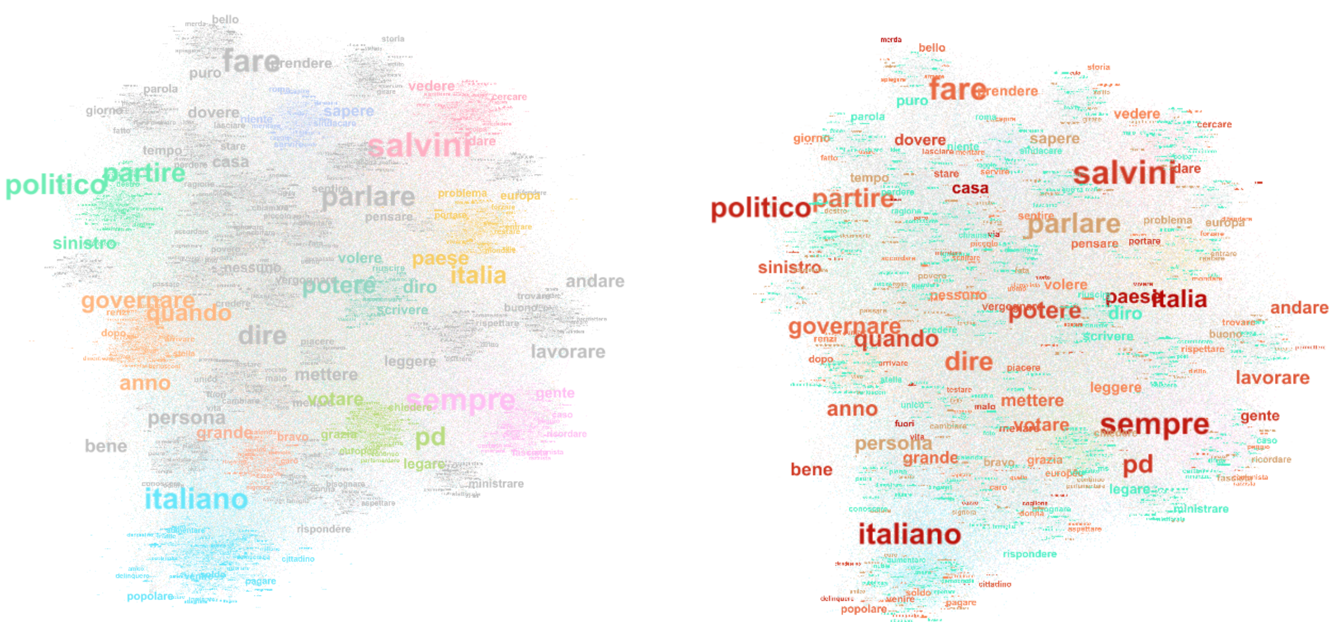


Figure 79: Single Target Network. Left: Nodes and labels proportional to pagerank, colored according to cluster. Right: Labels size and color according to hate index.

Laura Soccol, Gabriella Buosi
Type of Campaign: Comments' Analysis

E. Networks

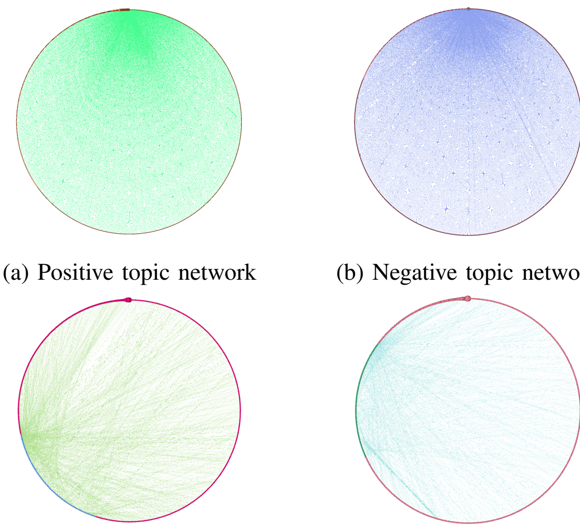
In this project, we examine two different types of networks: topics and hashtags. In the first case, we consider topics and comments, while in the latter, hashtags and comments. For each one, we construct both bipartite and projection networks. We perform statistical analysis on the hashtag network, considering mostly the projection, while only a few statistics are run on the bipartite. We use the topic network to make some considerations on the content of the comments, and how topics are related to each other.

The variables we consider are: topics, comments, and hashtags. We take topics and comments directly from the provided database *com_liwc.csv*. Each line of this file corresponds to a comment, that can be either the answer to a post or to another comment. Moreover, in the column *c_topic* we find the topic related to each comment. Topics were manually assigned to comments based on their specific content, and each comment may have from one to three different comments. We decided to discard comments that have as topic only the word 'Other' and to disregard it in comments that have it in their *c_topic* columns since this word does not define a specific feature. Hashtags, instead, are selected from comments, considering the columns *c_text* in the database. We first extract from comments' text all the present hashtags, we count them, and then we select only those that appear more than twice to avoid having too many disconnected components in the network.

The networks we evaluate for this project are the following:

- **Bipartite topic network:** the two sets of nodes are topics and comments. A comment node is linked to a topic one if the content of the considered comment refers to that topic.
- **Projection topic network:** we have only topic nodes. Two topic nodes are linked if they appear in the same comment.
- **Bipartite hashtag network:** the two sets of nodes are hashtags and comments. A comment node is linked to a hashtag one if the hashtag appears in the comment.
- **Projection hashtag network:** we have only hashtag nodes, and they are linked together if they appear in the same comment.

Then, to perform our analysis, we divide the given database into two smaller ones, based on the value *p_campagna2*. It can be either positive or negative and refers to the type of campaign for each specific comment. Our analysis aims to compare the network created with the two different databases. One important variable we consider in our analysis is negative emotion. Each comment in the database has its own level of negative emotion, which was manually assigned based on the comment's characteristics, and we retrieve it from the database's column *c_Emo_Neg*. To assign a level of emotion to hashtags too, we sum for each hashtag the value of emotion we find in all comments linked to it, and then normalize the level of hashtag emotion to obtain values between 0 and 1.



(a) Positive topic network (b) Negative topic network

(c) Positive hashtag network (d) Negative hashtag network

Figure 80: Bipartite networks

Bipartite networks are shown in Fig. 100. In the first row, we display topic bipartite networks. Blue nodes are the topics, while red ones represent the comments. In the second row, we have hashtag bipartite networks. As before, red nodes are comments, while blue ones represent hashtags. The size of the nodes depends, in the first row on the degree while in the second on the level of negative emotion. As a result, nodes with a higher degree or higher negative emotion, are bigger.

The general parameters of the bipartite topic network, that are topic nodes, comment nodes, and number of links between the two sets, and those of bipartite hashtag network, that are hashtag nodes, comment nodes, and number of links between them, are presented in Table XXVIII

	Pos topic	**Neg topic**	**Pos hash**	**Neg hash**
Topics/hash	13	13	183	160
Comments	22816	17828	905	774
Links	26552	20921	1392	1165

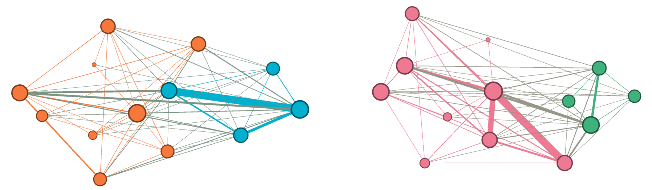
Table XX: Bipartite networks parameters

The **projection** networks are shown in Fig. 81. In the first row, we display the topic projection networks. Nodes' colors are set by considering modularity classes to which these nodes belong, while the size is related to the degree of each node. In the second row, we have hashtag projection networks. Here as well, colors depend on modularity, while node size depends on the negative emotion of the considered hashtag.

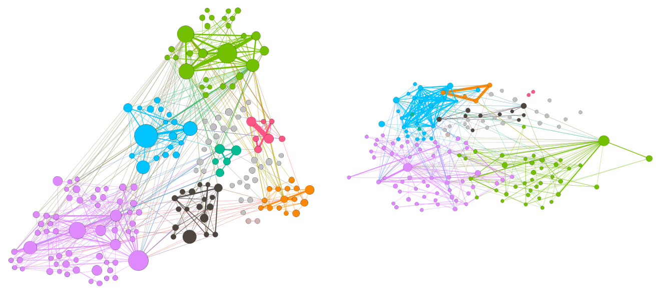
General parameters of projection networks, number of nodes, and links are reported in Table XXI.

	Pos topic	**Neg topic**	**Pos hash**	**Neg hash**
Nodes	13	13	183	160
Links	60	56	452	360

Table XXI: Projection networks parameters



(a) Positive topic network (b) Negative topic network



(c) Positive hashtag network (d) Negative hashtag network

Figure 81: Projection networks

F. General Network Parameters

We hereby describe the networks' general parameters, their definitions, and the methodology followed to obtain them.

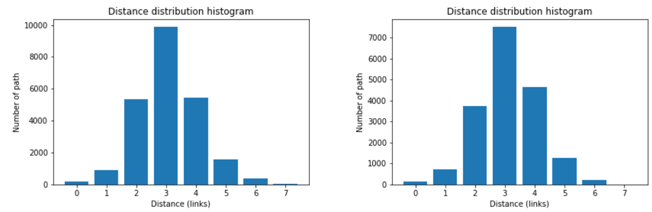
1) Diameter and Average Path Length: The diameter of a network can be defined as the shortest path between the two most distant nodes in the network. Once the shortest path length is calculated from each node to every other node, it can be obtained as the longest of all the shortest paths, where the shortest path (also called "distance") is the minimum number of links between any two nodes. The diameter of a network is a useful way of representing its linear size.

The diameter and average path length of the first set of subnetworks that we take into consideration, the positive and negative ones, is shown in Table XXII. The distance distributions are instead displayed in Figure 82.

	Positive	**Negative**
Diameter	7	7
Average path length	3.1186	3.1466

Table XXII: Diameter and average distance of the Positive and Negative networks

Although both of the networks present disconnected components, which would therefore lead to an infinite diameter, we consider only the giant connected components in order to obtain relevant measurements. The two networks present the same diameter and very similar average path lengths.



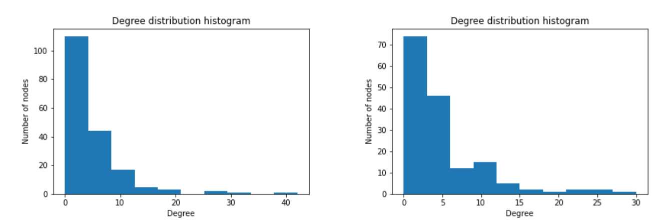
(a) Positive (b) Negative

Figure 82: Distance Distribution

G. Degree Distribution

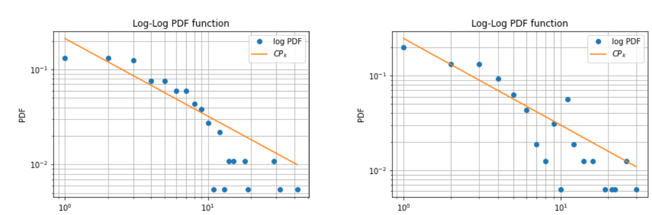
The degree of a node in a network is the number of links it has to other nodes, while the degree distribution of a network is the average number of nodes having a certain degree k. The general parameters related to the positive and negative networks' degrees are summarized in Table XXIII, and their respective degree distributions are shown in Figure 83.

We can observe that the average degrees for both networks are close in value, although it is slightly bigger for the positive network as a consequence of it having a higher maximum degree. This also leads to higher variance. The power law coefficient γ, which lies in the interval $[2, 4]$ in the two cases, shows they behave like scale-free networks, in which the degree distribution is heavy-tailed because of the presence of hubs (highly connected nodes). This fact can be seen in the log-log scale PDFs (Probability Density Functions) of Figure 84 but can be better appreciated in the CCDFs (Complementary Cumulative Distribution Functions) represented in Figure 85.



(a) Positive (b) Negative

Figure 83: Histogram of the degree distributions

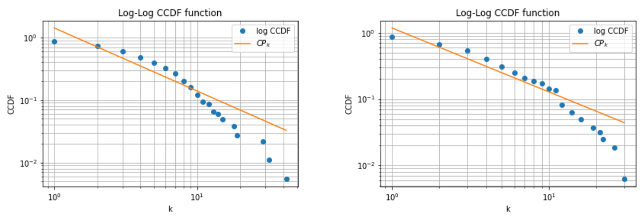


(a) Positive (b) Negative

Figure 84: Degree Distribution PDF in log-log scale

	Positive	Negative
Average degree $\langle k \rangle$	4.9399	4.5000
Second moment degree $\langle k^2 \rangle$	57.9344	48.6875
Third moment degree $\langle k^3 \rangle$	1205.8251	818.4375
Variance σ^2	33.5319	28.4375
Max degree k_{max}	42	30
Min degree k_{min}	0	0
Power law coefficient γ	3.4254	2.4294

Table XXIII: Degree and general parameters



(a) Positive (b) Negative

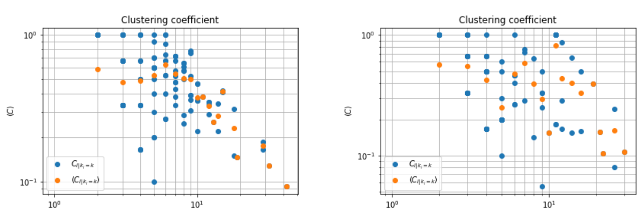
Figure 85: Degree Distribution CCDF in log-log scale

H. Clustering Coefficient

We study the clustering coefficients on both the bipartite and the projection networks.

the local clustering coefficient represents, for each node, how close its neighbors are to forming a clique, and in general, it measures how strongly connected the network is locally. Therefore, having a node and two neighbors, this measure represents how likely it is that the neighbors are connected forming a triangle. In this way, coefficients are obtained counting for each node in the network the fraction of pairs of neighbors that form a clique with the considered node.

For the **projection** network, we compute local clustering coefficients for each node using the algorithm implemented in Python's networkx package, the average clustering coefficient over all nodes with the same degree, and the average coefficient value on the whole network. In Fig. 86 we can see the comparison between the clustering coefficient of the two databases on log-log scale. Blue dots represent the local clustering coefficient for each node according to its degree while orange dots represent the average clustering coefficient for all nodes with the same degree. Moreover, the average clustering coefficients for the two networks are presented in Table XXIV.



(a) Positive (b) Negative

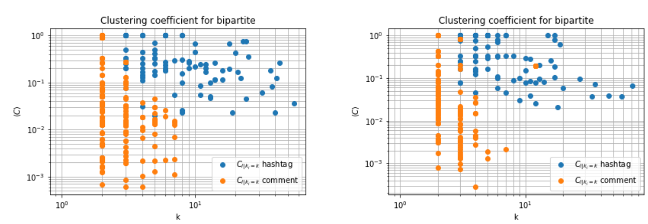
Figure 86: Clustering coefficient in log-log scale for the projection networks

	Positive	Negative
Avg. clustering coefficient $\langle C_{i\|k_i=k} \rangle$	0.4294	0.3796

Table XXIV: Average clustering coefficient parameters

From the graphs, we can observe that the nodes whit smaller degrees have a bigger clustering coefficient. This means that a hashtag with a high degree appears in different comments together with other hashtags, but the different hashtags with which it appears are not present in the same comment. Therefore, a more general hashtag can be used with more specific ones that do not appear together. Instead, hashtags with smaller degrees, more specific ones, tend to be clustered together that is, they appear in the same comments. This behavior is the same for both networks.

For the **bipartite** network, due to the fact we have two different sets of nodes, with the nodes of one set connected to the nodes of the other set but not among each themselves, we define the clustering coefficient based on the number of existing squares. A square is made up of a node, a pair of neighbors to the node, and a common neighbor of the previously mentioned two nodes. We compute the square clustering coefficients using Python's networkx package for each node of the two different sets in bipartite. In Fig. 87 we can see the comparison between the clustering coefficient of the two databases on log-log scale. Blue dots represent the clustering coefficient for each node according to its degree for hashtag nodes while orange dots represents the clustering coefficient for each node according to its degree for comments nodes.



(a) Positive (b) Negative

Figure 87: Clustering coefficient in log-log scale for the bipartite networks

In both diagrams we can see the same behavior, hashtag nodes have higher degrees and higher clustering coefficients, while comments have smaller degrees and in general smaller coefficient values. If we look at comments' values, we see that as the degree increases, the clustering coefficient values decrease. This means that as the number of hashtags increases in a comment, the probability of finding those same hashtags together in another comment decreases, while there are more comments with less hashtags but with the same ones present in their text.

I. Assortativity

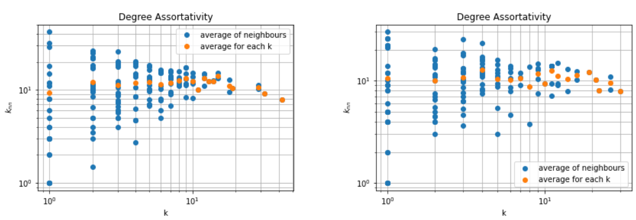
An assortative network is one in which high-degree nodes tend to connect with other high-degree nodes, and avoid lower-degree ones. On the other hand, a disassortative network, which is actually our case, is one that presents the opposite behavior.

In order to asses the assortativity of the positive and negative networks we are considering, we have studied them separately according to two different criteria: degree (on which assortativity is most often based off) and the "level of hate" (here defined as a value between 0 and 100 that quantifies negativity in an emotional sense) of a node. For this analysis, we consider only the projection networks.

The assortativity coefficients, obtained by applying an algorithm from Python's networkx package that is based on the calculation of Pearson's correlation coefficient r (that lies in the [-1,1] range), are shown in Table XXXI for the two networks, and consider the two aforementioned parameters for each. Additionally, Figure 88 and Figure 89 show the average degree of neighbors of a node with degree k and the average for each degree. In the graphs, the normalized value is taken into account.

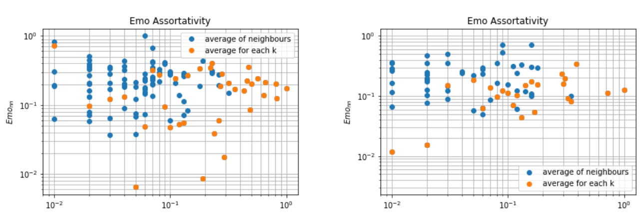
	Positive	Negative
Degree assortativity	-0.0808	-0.0699
Emotion assortativity	-0.0013	0.0892

Table XXV: Assortativity coefficients



(a) Positive (b) Negative

Figure 88: Degree assortativity



(a) Positive (b) Negative

Figure 89: Emotion assortativity

1) Degree Assortativity: From Table XXXI and Figure 88 we can observe that the fact that both the positive and negative networks have a negative assortativity coefficient means that they are actually disassortative. Since we are considering the hashtag projection network, we can conclude that popular hashtags are often used along other less-popular or more specific ones.

2) Emotion Assortativity: As for the assortativity coefficients obtained by taking into account the "level of hate" (on XXXI) in place of the degrees of the nodes, we can see that there is a difference between the two networks. While the positive network presents a slightly negative value, hinting it tends to be dissassortative, the positive value for the negative network shows it is instead assortative.

From these results we could say that strong negative emotions (higher value for the level of hate) will likely be connected to similar levels of such, while the same is not necessarily true for the positive case. Using a hashtag with a positive emotion does not imply another one of the same kind will be used in a comment. However, negative hashtags are more often used along with others containing similar negativity values.

J. Robustness

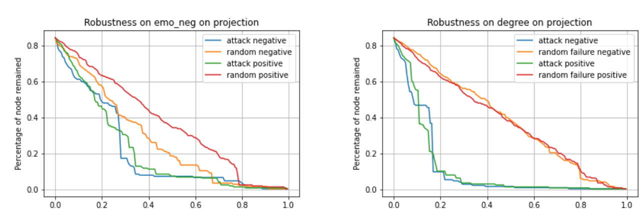
We study robustness on both bipartite and projection networks.

Robustness is a measure that is used to understand how a network behaves when a certain percentage of nodes is removed, due to failures or planned perturbation, and also how a network is connected. In the robustness algorithm, we remove one node at time, in a random way, either by removing specific nodes first, those with higher "negative emotion" or degree, as to assess how many nodes we need in order to break down the network into disconnected components.

In particular, we consider:

- robustness to random failure
- robustness to attacks by removing hubs (nodes with higher degree) first
- robustness to attacks by removing nodes with the highest value of negative emotion first

The obtained results for **projection** network are shown in Fig. 90. In the first graph, we display failure and attack robustness concerning the negative emotion value, while in the second we make the same computation but considering the node degree instead. Green and blue lines refer to attack robustness for positive and negative databases, while red and orange lines refer to the failure ones.

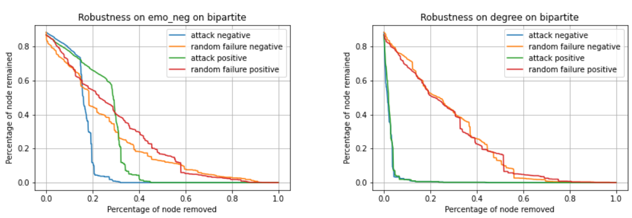


(a) Emo based robustness (b) Degree based robustness

Figure 90: Attack and failure robustness on projection networks

With regards to the first graph, we can see that the two databases perform quite similarly when we gradually remove the nodes with higher negative emotion. For both databases, we need to remove from around 25% of the nodes in the negative database to 35% in the positive to have a disconnected network. This means that in the negative network there are more nodes connected to the more negative ones, and when these are removed, the network separates quickly, while in the positive database negative nodes are less central. Regarding robustness on degrees, we found the same behavior in both networks, and the percentage of removed nodes necessary to separate the network decreases to less than 20%. This means that in both networks there are few hubs, whit lots of nodes connected to them. Now, concerning the random failure curves, we see a similar behavior on both, and this can be explained through the fact that the networks are scale-free, so we have some hubs that keep the network connected and other nodes whose removal does not affect the stability of the network.

The result for **bipartite** network are shown in Fig. 111. The graph order and the colors of the curve are kept the same as in the previous figure.



(a) Emo based robustness (b) Degree based robustness

Figure 91: Attack and failure robustness on bipartite networks

In this case, we have again the same behavior as before. Indeed, for the robustness to attacks computed on the negative emotion, we need about 30% of removed nodes in the positive database, and somewhat less than 20% in the negative one, while in degree-based attacks we have again a similar behavior but need, in both cases, less than 10% of removed nodes to separate the network. Failure curves are all comparable to each other but show a different behavior if compared with the previous ones.

K. Centrality Measures

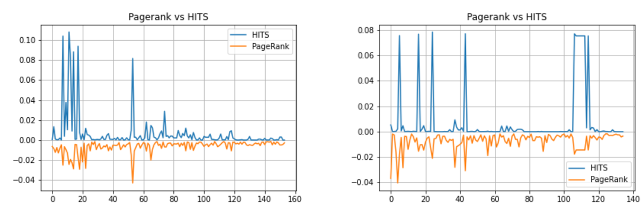
Centrality is a measure of how important a node is in a network. It takes into account the number and relevance of incoming and outgoing edges to do so. Two approaches are often considered when aiming at determining the importance of a vertex: PagaRank and HITS. Although our networks are undirected, and therefore edges are neither incoming nor outgoing, we still apply these two algorithms on the projected hashtag networks in order to be able to make a classification of the most frequently used hashtags. It is important to note that only the giant connected component of each network is being used.

1) PageRank Centrality: PageRank's rationale is based on the fact that important nodes are more likely to have a higher number of incoming links. It counts the number and quality of the edges to give an estimate of how important a node is. To determine the PageRank value of each node we used the algorithm implemented in Python's networkx package, which takes the undirected graph given as input (in this case) and transforms it into a directed one by replacing each undirected edge with two directed ones.

2) HITS Centrality: Similarly to PageRank, the Hyperlink Induced Topic Search (HITS) algorithm determines the prominence of a node in a network. It defines two types of "pages" (for it was originally intended to rank websites when the Internet was blooming):

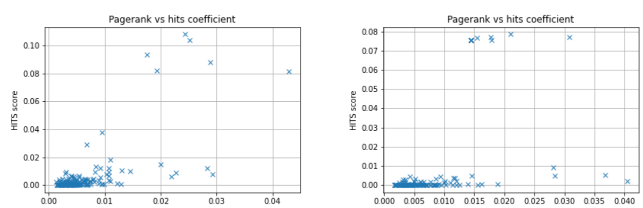
- **Authorities**: nodes with a high number of incoming edges, that contain useful information. Are linked by many hubs.
- **Hubs**: trustworthy nodes with a high number of outgoing edges. They link to many authorities.

Since we are once again considering undirected networks, the authority and hub scores will coincide.



(a) Positive (b) Negative

Figure 92: PageRank vs HITS algorithms

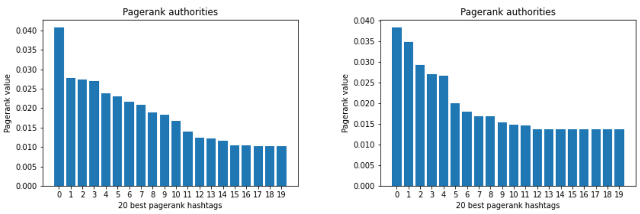


(a) Positive (b) Negative

Figure 93: PageRank vs HITS scores

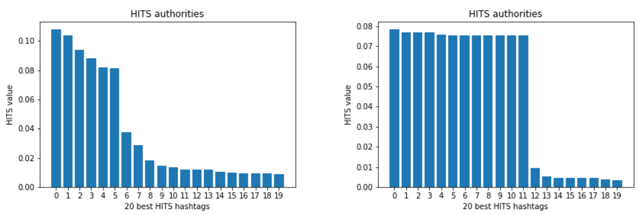
We can observe in Figure 92 the comparison between the two algorithms in terms of the importance score (y axis) they give to each hashtag (x axis), here identified by a number for ease of representation. It is to be noted that the HITS score is a positive value too but has been inverted to prevent overlapping between the two plotted lines. Despite the fact that the magnitudes of the scores assigned by each algorithm differ, the curves' trends are quite similar. The maxima and minima are located in the same positions, meaning that they both agree on which nodes, or in this case hashtags, are respectively the highest or lowest ranked.

Figure 93 compares the scores given by each algorithm. Though very similar values are assigned for less important nodes, they differ quite significantly when a higher score is to be set. On average, the HITS score is lower than that of Pagerank.



(a) Positive (b) Negative

Figure 94: PageRank top 20 ranked hashtags



(a) Positive (b) Negative

Figure 95: HITS top 20 ranked hashtags

The top 20 hashtags obtained for both the positive and negative networks, as sorted by Pagerank, are displayed in Figure 96. Since from the graph in Figure 92 we observe that the peaks do match, as previously mentioned, the results for HITS are omitted. We can observe that the frequency with which the hashtags are used does not necessarily influence their position in the ranking since other variables are also considered to determine their importance.

Although some hashtags are common to both networks, most of them differ. The particular hashtag *#facciamorete* is the top ranked in both networks. We can observe that the negative network's most used hashtags refer directly to public political figures while the positive network's ones are related to the general political environment.

L. Modularity

Modularity is a measure of how well a network is divided into distinguishable communities, with a community being a set of tightly connected nodes. Networks with high modularity have a large number of connections between nodes belonging to the same group and only a few between nodes that belong to different ones.

In order to graphically divide our networks into communities, we ran on them Gephi's modularity tool which in turn implements Louvain's method. On the other hand, in order to obtain the modularity value Q and be able to compare the previous results to the theoretical ones, we applied Python's implementation of the same algorithm (Louvain's) on the hashtag projection networks. The partition into communities for each projected network can be observed in Figure 81.

Hashtags	Frequency
#facciamorete	59
#iostoconsalvini	6
#propagandalive	4
#milano	9
#maiconsalvini	3
#votafdi	4
#instagram	4
#dantetop	3
#italia	11
#governo	6
#lariachetirala7	3
#selfini	7
#tolleranzazero	7
#piueuropa	3
#italexit	8
#europee2019	18
#stopinvasione	3
#pizzarotti	7
#25aprile	14
#formigli	5

(a) Positive

Hashtags	Frequency
#facciamorete	59
#salvini	73
#m5s	37
#lega	28
#pd	46
#renzi	17
#salvinidimettiti	19
#calenda	11
#ue	10
#portichiusi	20
#fascismo	12
#grillo	6
#europa	12
#parma	7
#pilotta	5
#pizzarotti	7
#formigli	5
#carofiglio	5
#federicopizzarotti	5
#pizzatotto	5

(b) Negative

Figure 96: Top 20 ranked hashtags

In it, we can see that both the positive and negative topic networks are split into two distinct groups while the the hashtag networks, consisting of a higher number of nodes, are instead organized into approximately 8 communities each. The fact that the modularity coefficients Q, shown in Table XXVI, are $\sim$0.6 for both the positive and negative hashtag projection networks indicates that significant community structures have been found. For this to be true, $Q \in [0.3, 0.7]$, which is the case.

	Positive	Negative
Modularity Q	0.5948	0.5530

Table XXVI: Modularity coefficients

M. Considerations on the Topic Network

We use the projection network on topics to make some general considerations about the two different networks. In fact, topics and comments are two parameters that have been once again taken from the main database, but with this representation, we can well understand the main difference between the two considered datasets. In Table XXXIV we report the average degrees and modularity values that, together with the parameters of Table XXI, allow to characterize these networks.

The first thing we can notice is that in both networks there are several highly connected nodes. This means that all of these topics, represented by said nodes, are recurrent in the comments.

	Positive	**Negative**
Average degree	9.231	8.615
Modularity Q	0.068	0.104

Table XXVII: Diameter and average distance for projection topics networks

'Politico' is the central topic together with *'altroPolitico'*, and they are strongly related to *'Europa'*. In the negative network, *'solidarietà'* and *'rifugiati'* are well related to each other, which means they appear together in many comments, *'rifugiati'* is well linked together with *'Politico'* and *'altroPolitico'*, while *'solidarietà'* is well linked only with *'Politico'*. We can find a similar behavior in the positive network, even if in this case *'solidarietà'* is not well linked to the *'Politico'* term. Regarding the *'religioni'* topic, we have that in the positive network it is mostly connected with *'rifugiati'*, while in the negative one it is mostly connect with *'Politico'*. *'Donne'* and *'povertà'* are more connected to *'Politico'* and *'altroPolitico'* in the negative than in the positive network. Other topics, like *'lgbti'*, *'rom'*, *'clima'*, *'disabili'* and in particular *'amnesty'*, are not commonly-used topics.

N. Final Considerations

In our project we have compared two different databases related to the type of campaign used by politicians: positive and negative. Our aim was to find if there were any features that identified such databases and that would allow us to distinguish them. We wanted to know how the two apparently different sets differ in their content, focusing in particular on hate speech characterization, and did this through the topics and hashtags databases we have previously described. From the statistical analysis, we can osberve some different behavior in the assortativity measure. In fact, we can see that the positive network is disassortative, while the negative one is assortative, if we consider emotion. This shows different behavior in the way the nodes are connected within each other: in the negative database, nodes with a higher level of hate are more connected with one another, while this is not true for positive ones.

If we instead consider topics, we can see that the covered subjects are the same in both networks, with *'Politico'*, *'altroPolitico'*, and *'Europa'* being the main topics.These are also strongly related among themselves. However, in the negative network, topics like *'religioni'* or *'rifugiati'* are more central, while in the positive we have *'solidarietà'*.

From a topological point of view, the positive and negative datasets present a very similar structure, both when comparing hashtags and topics, and when considering the bipartite and the projected networks. Each of them is divided into distinct communities that coincide with the negativity they each transmit. A higher number of communities can be observed for the hashtag network due to the higher number of nodes present in it, while since topics are fewer in number, nodes are only separated into two groups.

When analyzing robustness, we could appreciate the fact that based on the parameter we consider for the breakdown of the network, different behaviors were obtained. Both the positive and negative networks present a steeper behavior when robustness to attacks based on emotion is considered, implying that the so-called “level-of hate” does have a strong impact on how fast the network becomes disconnected. In the bipartite networks we can especially see how, by removing hashtags with a higher negative emotion first, the negative network's robustness decreases earlier with respect to the positive one.

(a) Positive (b) Negative

Figure 97: Topics Networks with labels

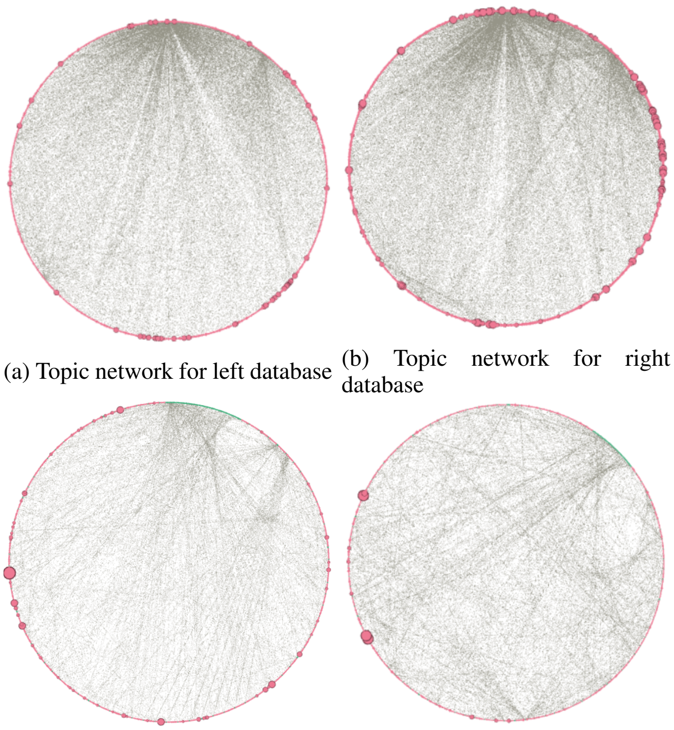
Figure 98: Hashtag network for the positive database with labels

Figure 99: Hashtag network for the negative database with labels

Luca Dalla Gassa , Matteo Piva

Left and right comments analysis

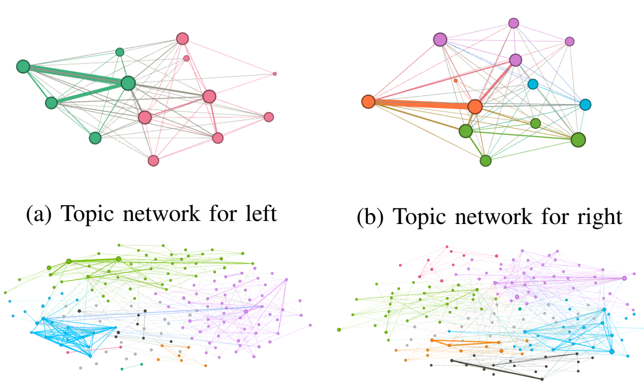
In this chapter we are going to analyze networks of Left and Right Italian parties, focusing on the network model and its general features. We are considering two types of networks, topic and hashtag ones. Then, for each one, we have built both bipartite and projection. Most of the analyses have been done on the hashtag projection network and some on the hashtag bipartite network. Instead, the topic projection network will be used only for some general considerations.



(a) Topic network for left database (b) Topic network for right database

(c) Hashtag network for left (d) Hashtag network for right

Figure 100: Bipartite topic and hashtag networks for left and right databases



(a) Topic network for left (b) Topic network for right

(c) Hashtag network for left (d) Hashtag network for right

Figure 101: Projection topic and hashtag networks for left and right databases

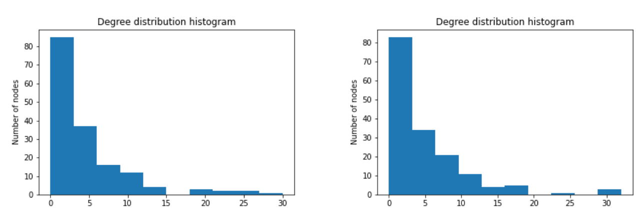
O. General parameter

Table XXVIII summarizes the parameters of the two hashtag projection networks. The sizes of the Left and Right networks are similar in the number of nodes, while the right network has a bigger number of edges. We can notice that the average degree is higher in the Right network than in the Left. It has a slightly higher maximum degree, 32 instead of 30, and looking at Fig. 102, that represent the degree distribution of the two networks we can notice that the Right network has a slightly higher number of nodes with higher degrees.

The Power law coefficient is smaller in the Left network and it is $2 < \gamma < 3$, so the Left network is scale-free. Instead, the Right network has a power law coefficient >3 so it is not a scale-free network. However, if we look at the log-log scale degree distribution plots in Fig. 103 its behavior seems to follow a power law distribution closely. In fact, in such graphs, there are lots of nodes with small degree and a few nodes with a higher degree (hubs), and we can notice that Right and Left graphs show a similar trend. The similarities between the two networks can also be seen in the log-log scale Complementary cumulative density function (CCDF) plots of Fig. 104, in which the value of the cumulative sum decrease when the degree increase, in a similar way both in left and right.

	Left	**Right**
Number of nodes	162	162
Number of edges	352	420
Average degree	4.3457	5.1852
Second order average degree	46.9876	50.6913
Third order average degree	801.3457	1056.5926
Variance	28.1027	31.8052
Min degree k_{min}	0	0
Max degree k_{max}	30	32
Power law coefficient	2.2821	3.6095
Density	0.0270	0.0322

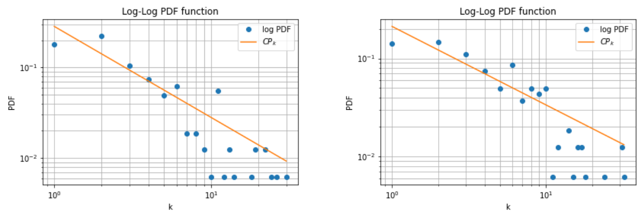
Table XXVIII: Network parameters



(a) Degree distribution histogram for left (b) Degree distribution histogram for right

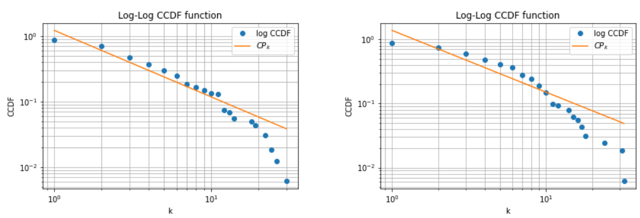
Figure 102: Degree distribution histogram for left and right

1) diameter, average path: Table XXIX reports the diameter and average path length for the left and right networks, while histogram in Fig. 105 shows the related distance distribution. We can see that the diameter is slightly bigger in the Right network, while the average path length is very similar between the two networks. This is confirmed in the distance distribution histogram, where we can see a similar trend. Since



(a) Probability density function (PDF) for left (b) Probability density function (PDF) for right

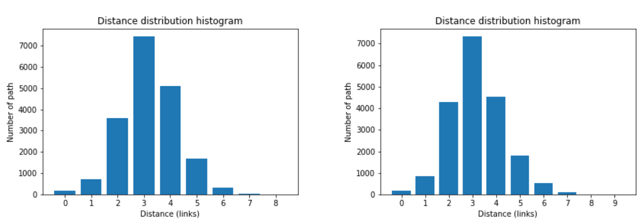
Figure 103: Probability density function (PDF) for left and right



(a) Complementary cumulative density function (CCDF) for left (b) Complementary cumulative density function (CCDF) for right

Figure 104: Complementary cumulative density function (CCDF) for left and right

our networks have some disconnected components, that lead to an infinite diameter, we decided to compute these parameters only on the giant one.



(a) Distance distribution histogram for left (b) Distance distribution histogram for right

Figure 105: Distance distribution histogram for left and right

	Left	Right
Diameter	8	9
Average path length	3.2462	3.2188

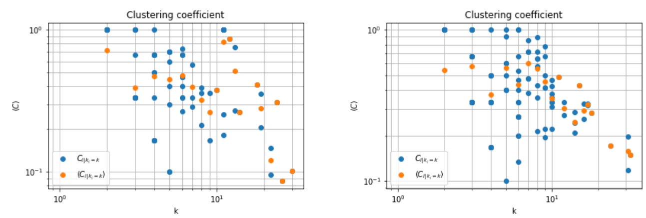
Table XXIX: Diameter and average path length

P. Cluster coefficient

Clustering coefficients were studied both on the projection and the bipartite networks.

The result on the projection networks are shown in Fig. 106. In this graphs blue dots represent the clustering coefficient of the hashtag w.r.t. its degree, while orange dots represent the average clustering coefficient of all the hashtags with the same degree. We can notice that the clustering coefficient is inversely proportional to the hashtags degrees and this trend is very similar in both two networks. This means that if we consider a hashtag connected to many others, so with a high degree, its neighbors are not connected within each other, while the neighbors of a hashtag with less connections tend to be more clustered together.

Moreover, the average clustering coefficients for the two networks are presented in Table XXX



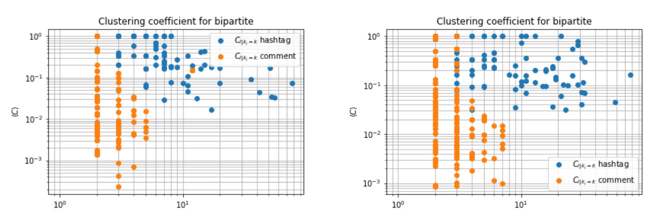
(a) Clustering coefficient for left (b) Clustering coefficient for right

Figure 106: Clustering coefficients of projection networks for left and right

	Left	Right
Average clustering coefficient	0.4427	0.4064

Table XXX: Average clustering coefficients

In Fig.107 we can observe the result for bipartite networks. In this case, blue dots represent the clustering coefficient of hashtag nodes w.r.t. their degree, while orange dots represent the clustering coefficient of all the comment nodes. Comments hold a similar behavior between left and right, thus as the degree of nodes increases the clustering coefficient decreases. For hashtag instead, we found the inversely proportional relation in the left network, while the hashtags clustering coefficients are more uniform in the right network.



(a) Clustering coefficient for left (b) Clustering coefficient for right

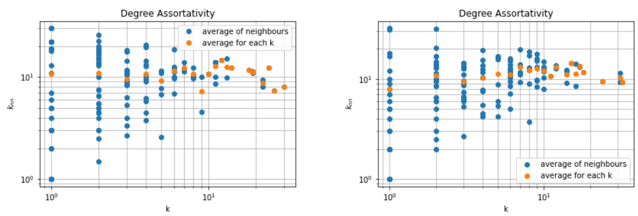
Figure 107: Clustering coefficients of bipartite networks for left and right

Q. Assortativity

We perform assortativity taking into account only the projection network, and we have decided to study it on two different variables:

- nodes degree, that is the usual variable
- negative emotion level defined as a value between 0 and 1

1) On degree: From Fig. 108 and Table XXXI we observe that both the databases have a quite disassortative behavior, with the left database which is slightly more disassortative than the right one. This means that hashtags with higher degree tend to connect with those that have smaller one. Therefore there are some more general or more used hashtags, thus with higher degrees, that are connected with those that are less used or more specific, with smaller.

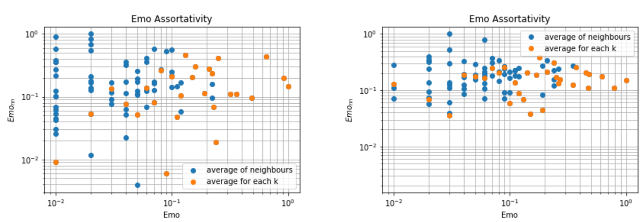


(a) Degree assortativity for left (b) Degree assortativity for right

Figure 108: Degree assortativity for left and right

2) On emo: In Fig. 109 we can observe results for negative emotion level variable. In both cases, we have an assortative behavior with the left dataset which is a bit more assortative than the right one. Therefore this implies that hashtags with the same level of hate tend to connect within each other.

However, all assortativity coefficients have a value that is close to zero so we can consider both cases as quite neutral networks.



(a) Negative emotion assortativity for left (b) Negative emotion assortativity for right

Figure 109: Negative emotion assortativity for left and right

	Left	Right
Degree assortativity	-0.0512	-0.0157
Emotion assortativity	0.0589	0.0211

Table XXXI: Assortativity coefficients

R. Robustness

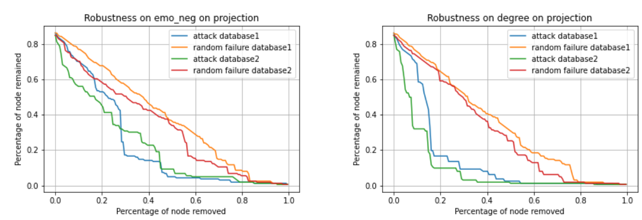
For this analysis, we consider both projection and bipartite network, and we decide to investigate the robustness of our network by using the following criteria:

- robustness to random failure
- robustness to attack on degree
- robustness to attack on level of hate

Fig. 110 refers to the robustness computed on the projection networks. Blue and green line refers to robustness to attack on right and left network respectively while orange and red lines refer to random failure. Moreover, the left graph represents the robustness on level of hate, while the right one on the degree.

From the left graph, we can see different behavior in the curves, in particular looking at the attack. At the beginning, the left dataset is less robust than the right one, but when the percentage of node removed is around 30% the right dataset becomes less robust, passing rapidly from 45% to 17-18% of remaining nodes. In any case, the networks are disconnected when about 40% of nodes are removed. About the random failure, the trend is similar for both politicians 'side with the left dataset which is still slightly less robust with respect to the right one.

If we look at the robustness on the degree we get that the left database is less robust than the right one with respect to the attack. For the first network, we need to remove less than 20% to have a disconnected network, while for the latter this value increases up to around 25%. This means that left parties use fewer different hashtags and removing those with the highest degree the percentage of node remained decreases very fast. The random failure shows a trend that is similar for the two curves but also similar for that we have found in the negative emotion graphs.



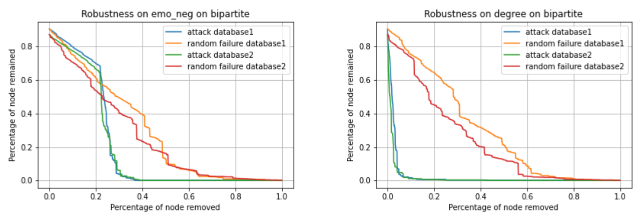
(a) Negative emotion robustness (b) Degree robustness

Figure 110: Attack and failure robustness on projection network

In Fig. 111 we show the results of the same analysis but on the bipartite network, thus the graph order and the colors of the curves are the same as in the previous figure.

In the first graph, we can see that both networks show similar behavior to attack. We need around 30% of removed nodes to have a disconnected network, confirming the fact that scale free networks are not so robust to attack. The same behavior between curves is kept also for attack on degree but in this case, the effect of the attack is stronger with respect to that on negative emotion and, we need less than 10% of removed nodes to separate the network, thus revealing the presence of hubs in both datasets. Considering random failure, in the graph on the left side we still have similar behavior with a small difference in the middle when the percentage of node removed is between 20-50%. The left political side is slightly less robust, but the trend is moreless equal. In the right side graph, we observe a similar trend for both datasets.

A general comment that can be made is that on projection the left dataset is slightly more robust with respect to the bipartite analysis, while the right one is constant.



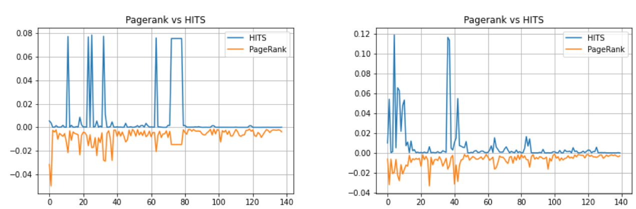
(a) Negative emotion robustness (b) Degree robustness

Figure 111: Attack and failure robustness on projection network

S. Pagerank

We apply Pagerank and HITS algorithms on projection networks, in order to find the most commonly used hashtags in the two different political sides and evaluate their importance. Due to the fact that our networks are undirected and edges are neither incoming or outgoing, we can just consider all the edges that belong to a node, and in the case of HITS hubs and authorities coincide.

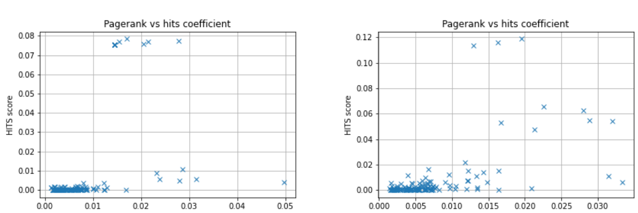
Fig. 112 shows the comparison between Pagerank, that is the orange line inverted to prevent overlap, and HITS, which is the blue one. We perform comparison in terms of score: the important the hashtag, here represented by their Id in the x axis, the higher the score



(a) Left network (b) Right network

Figure 112: PageRank vs HITS algorithm for left and right

In Figure 113 we can see the comparison between scores obtained with the two different algorithms for the same hashtag. We can observe a quite linear behavior at the beginning, thus hashtags with a lower score, less central, have very similar scores while for the more central ones the two scores differ.



(a) Left network (b) Right network

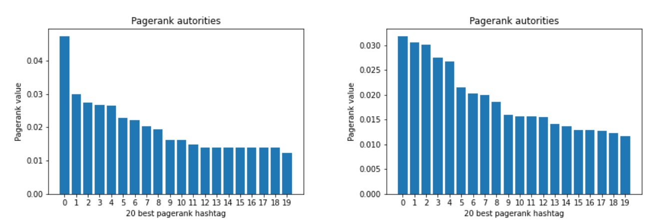
Figure 113: PageRank vs HITS scores for left and right

In Fig. 114 and Fig. 115 we highlight the 20 hashtag with higher Pagerank and HITS, that are the more central hashtags and their related scores. In Table XXXII we report the name of such hashtags.

Left hashtag	Right hashtag
facciamo rete	salvini
salvini	europa
pd	lega
siamoeuropei	europee2019
m5s	scrivimussolini
europee2019	26maggio
lega	italia
calenda	portichiusi
ue	europee
renzi	eu2019"
25aprile	forzaitalia
grillo	salvinidimettiti
pizzatotto	votalega
pizzarotti	pd
parma	libia
pilotta	salvininonmollare
formigli	facciamorete
carofiglio	ineuropapercambiaretutto
federicopizzarotti	mussolini
facciamovotare	votaitaliano

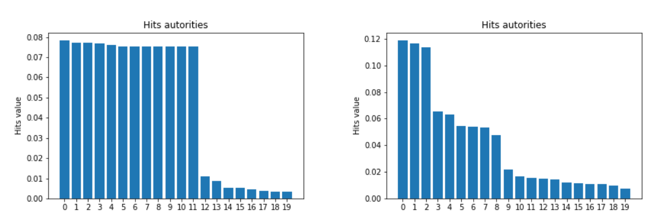
Table XXXII: Top 20 central hashtag

Therefore there is a difference in the topics that are treated between right and left dataset, we can notice for example that right parties are more focused than left parties on elections, considering that in the first top ten PageRank values there are five different hashtags concerning european elections (*europa*, *europee2019*, *26maggio*, *europee*, *eu2019*) while in left dataset only two different hashtags (*siamo europei*, *europee*).



(a) Left network (b) Right network

Figure 114: Top 10 PageRank hashtag



(a) Left network (b) Right network

Figure 115: Top 20 HITS hashtag

T. Modularity

We perform this analysis on the projection matrix using both python-louvain package to find an accurate modularity value reported in Table XXXIII and Gephi for a visual representation (see the lower row of Fig.101).

Both datasets have a similar modularity value and they are in the range [0.3-0.7], showing a significant community structure. About the community, we can fin 8 different significative communities in Right network and 7 in Left ones on the giant component. We made our analysis on the giant component while we decide to discard communities of the disconnected component that usually consists of a single node community.

	Left	**Right**
Modularity value	0.5583	0.5802

Table XXXIII: Modularity values

U. *Consideration on topic network*

Now we make some general consideration on the topics that characterize all those comments using the projection topic network.

In Table XXXIV we report the average degrees and modularity values that, together with the result shown in Fig. 101 in upper row, allow to characterize these networks.

	Left	**Right**
Nodes	13	13
Edges	58	59
Average degree	8.923	9.077
Modularity value	0.0076	0.006

Table XXXIV: Diameter and average distance for projection topics networks

Looking at the average degree of both network we can observe that their nodes are very strongly connected, so the topics we have are highly related in the comments.

In left network *'Politico'* is the central topic.It has the higher degree and it is linked together with all other topics. Then, it is strongly connected with *'altroPolitico'* and *'Europa'*, and those two are well related between each other. Other two relevant topics are *'solidarietà'* and *'rifugiati'*, They are connected within each other and with *'Politico'* and *'altroPolitico'*. Then *'rifugiati'* share a strong edge also with *'Europa'*. *'Povertà'* and *'religioni'* are a bit less central even if they have a well defined link with *'Politico'* and *'rifugiati'* rispectively. Also *'donne'* is well connected, but it does not have very strong link, showing that topic is less central if compared to the previous ones. Finally, other topics, like *'lgbti'*, *'rom'*, *'clima'*, *'disabili'* and in particular *'amnesty'*, are not commonly used topics.

In right network we have can do the same consideration about *'Politico'*, *'altroPolitico'* and *'Europa'*: that topic are very strongly connected even if in this case *'Europa'* is not in the same class of the other two. Also *'solidarietà'*, *'rifugiati'* and *'Povertà* are relevant topics in this network, however only *'rifugiati'* shows a strong link with *'Politico'* and *'altroPolitico'*. For *'religioni'* and *donne* we have that they are less central and well connected only with *'rifugiati'* the first, while the latter does not shows any strong link with the other topics. Also in this case, *'lgbti'*, *'rom'*, *'clima'*, *'disabili'* and *'amnesty'*, are not the central topics of this database.

V. *Final consideration*

The sizes of the Left and Right networks are similar in the number of nodes, while the right network has a bigger number of edges meaning that right parties social networks are more active than left ones.

The Power law coefficient is smaller in the Left network Which is scale-free while the Right network has a power law coefficient > 3 so it is not a scale-free network. However, if we look at the log-log scale degree distribution plots its behavior seems to follow a power law distribution closely. In fact, in such graphs, there are lots of nodes with small degree and a few nodes with a higher degree (hubs), and we can notice that Right and Left graphs show a similar trend.

Therefore there is a difference in the topics that are treated between right and left dataset, we can notice for example that right parties are more focused than left parties on elections, considering that in the first top ten PageRank values there are five different hashtags concerning european elections while in left dataset only two different hashtags.

Looking at the projection topic Network we notice that in both networks the topics *'Politico'*, *'altropolitico'* and *'europa'* are linked together but in the case of right network *'europa'* is not in the same class of the other two. The same for *'povertà'* which is in the same class of *'Politico'* for Left network and in a different class for Right networks. Finally in both networks we have the same not commonly used topics which are *'lgbti'*, *'rom'*, *'clima'*, *'disabili'* and in particular *'amnesty'*

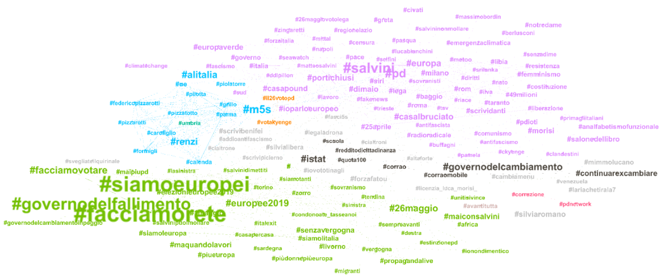


Figure 116: Hashtag network for left database with label

Figure 117: Hashtag network for right database with label

Figure 118: Topic network for left database with label

Figure 119: Topic network for right database with label

W. Network analysis

*1) **Topic Network Analysis: Bipartite :*** In this section we are comparing the comment and post databases by linking each of the two sets by topics, which means that if some comments, or some posts, share a common topic, a link is created between them (fig: 120 e 121) At first sight the graphs look very similar, in fact the same number of communities (seven) is identified by the modularity algorithm, but there are some meaningful differences to be highlighted. First of all, some communities are composed by different topic members: this is showed by comparing the “donne, LGBTI, rom, amnesty” community of the post network with the communities in the comment network where “donne, LGBTI” that form a community while “rom” is a member of the “rifugiati, rom, religioni” community. Secondly, the “clima” topic cluster is in a different topological position: in fact, in the post network this community is more related to topics such as “politico” and “europa” while, in the comment network, the same cluster is closer to “rifugiati, rom, religone” community and “altroPolitico” but further with respect to the “politico” module. In addition, the “povertà” cluster in the post network is connected to “rifugiati, solidarietà, religioni” and “europa” topics, while in the comment network it is mainly linked to “europa”, “donne” and “altroPolitico” clusters. These are the main differences between the two networks, even if some slight differences in topological position can be detected by a visual inspection. The comparison of some general measures of the two networks is reported in the table XXXV

*2) **Topic Network Analysis: Projection :*** The above compact representation is provided by computing the projection among topics of the comment and post bipartite networks. It has to be highlighted that we have the same number of communities (two) for both the projection networks but the members composing the two clusters are different. In fact, as it can be seen, the “povertà” topic in the post network is in the same community with “politico, europa, altroPolitico, clima”, while in the comment network is in the other one (pink). In addition, in the comment network the “povertà” node is more connected to “solidarietà”, “amnesty”, “rifugiati” nodes and significantly bigger, in terms of degree, while in the post network is mainly connected to “europa” and “altroPolitico” and it has less connections. Moreover, the "disabili" and "clima" have a higher degree in the comment projection network compared with their respective in the post one. Finally, the "amnesty" node is more related to the "religioni" and "rifugiati" topics in the comment network while in the topic one is linked to "donne" and "politico" nodes. From these graphical representations we did not extract any measure regarding the emo_neg information because we decided to first give a general informative representation in order to inspect the distribution of the available data according to topics and discarding the “other” topic. The analysis concerning the

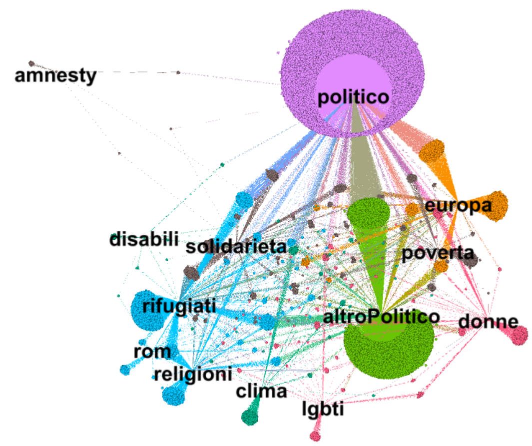


Figure 120: Comments bipartite topic network.

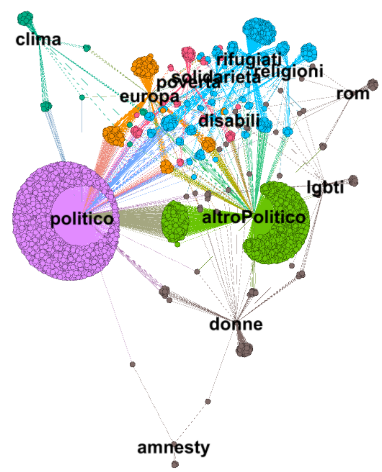


Figure 121: Posts bipartite topic network.

emo_neg information was carried out in the hashtag network, comparing the comment and the post databases. The general measures for the networks comparison are reported in the table XXXV. In this section

X. *Hashtag Network general comparison for posts and comments*

*1) **Hashtag Network Analysis: Bipartite:*** In the hashtag network we are not only providing a cluster representation by coloring the nodes, but also an emo_neg information visualization through the change of the nodes’ size and label. As it can be noticed, the comment hashtag network is significantly bigger than the post hashtag and the reason is that more hashtags are contained in the comments than in the post network, but we can identify eight major communities for both the networks created. Since the hashtags in the comments

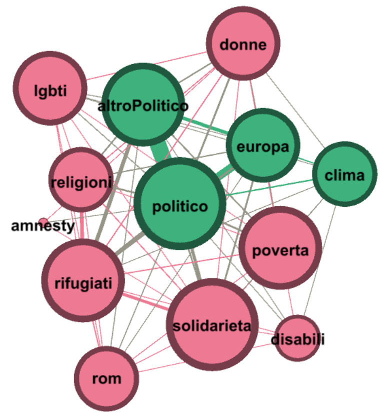


Figure 122: Comments projection topic network.

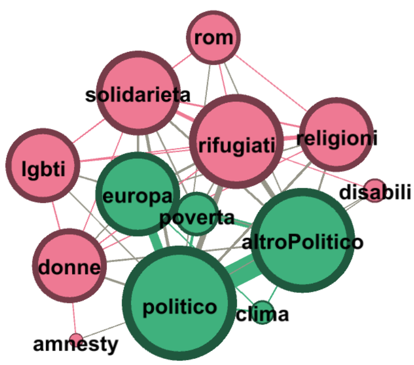


Figure 123: Posts projection topic network.

	Comments	Posts
Nodes	40657	5512
Edges	47473	6396
Average Degree	2.3353	2.3208
Average Degree (Second Order)	19720.0013	2737.7053
Average Degree (Third Order)	446100866.9694	8301429.0925
Variance	19714.5477	2732.3194
Min degree k_{min}	1	1
Max degree k_{max}	25536	3435
Average path length	1.2051	1.3974
Diameter	2	2
Density	5.7440	0.0004

Table XXXV: Topics Bipartite networks parameters

and in the posts are lexically different, we are comparing the emo_neg information differences represented with different sizes of the nodes. In the comment hashtag network, the bigger nodes, which are carrying the higher emo_neg, are governodelcambiamento, portichiusi, facciamorete, bimbominkia, scrivimussolini, tuttidante, while in the post hashtag network the main nodes are europa, facciamorete, ioparloeuropeo and portichiusi. We can notice that some of these nodes that are relevant for extracting the emo_neg information, are the same for both networks, in particular this concept concerns the hashtags portichiusi and facciamorete.

	Comments	Posts
Nodes	171	25
Edges	407	25
Average Degree	4.7602	2.0000
Second Order Average Degree	54.6315	7.2800
Third Order Average Degree	952.9005	36.32
Variance	31.9717	3.2800
Min degree k_{min}	0	0
Max degree k_{max}	31	8
Average path length	3.1872	2.3626
Diameter	7	5
Power law coefficient γ	6.8771	9.6561
NETWORK DENSITY	0.02800	0.0833

Table XXXVI: Hashtag Projection Networks parameters

2) ***Hashtag Network Analysis: Projection*** *:* With the same graphical methodology we computed the comment and post hashtag network projections with respect to hashtags and extracting as before the community and emoneg information in order to compare the two networks. In the projection comments network, it can be recognized that there are more nodes carrying much emo_neg information, such as scrivimussolini, facciamorete, salvini, governodelcambiamento, votalega, pd, europa, m5s, portichiusi, bimbominkia, scrivisantanchè and ineuropapercambiaretutto. Instead, for the post hashtag projection network the main nodes are europa, ioparloeuropeo, scrivimussolini, facciamorete, portichiusi and m5s. For both networks, the nodes with a significant emo_neg information are the same such as europa, portichiusi, facciamorete, scrivimussolini and m5s, but we identified a different community structure between the two projection networks. In fact, the post hashtag projection is composed by 7 communities while the comment one is composed by 4 communities, 2 principal and 2 less relevant that could be embraced in the two bigger ones. The network statistics extracted below refer to the comparison of the comment hashtag projection network with the respective post one.

Y. Degree distribution

1) ***Histogram****:* The degree distribution of the two networks is compared through the histograms of the degree distribution: the majority of the nodes composing both networks have a low degree value while there is a little fraction of them that have larger degrees.
By comparing the different scales of the x-axis, it can be noticed that only in the comment hashtag network there are a few hubs while this is not occurring in the post one.
Furthermore, the average degree is 4.7 for the comments network and 2 for the posts one which shows that the second one is less connected.

2) ***PDF e CCDF****:* Concerning the probability density function and the complementary cumulative density function of

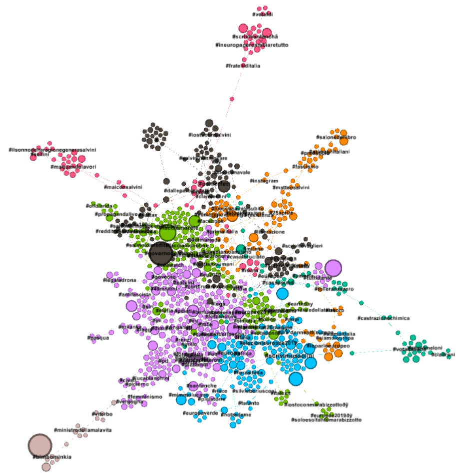


Figure 124: Comments bipartite hashtag network.

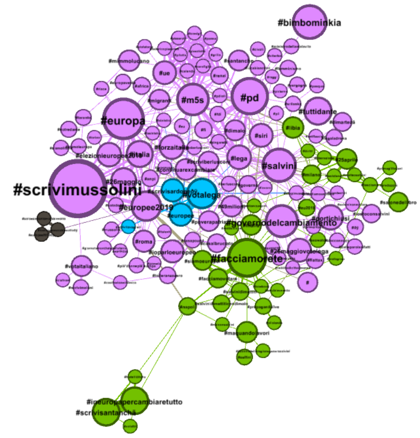


Figure 126: Comments projection hashtag network.

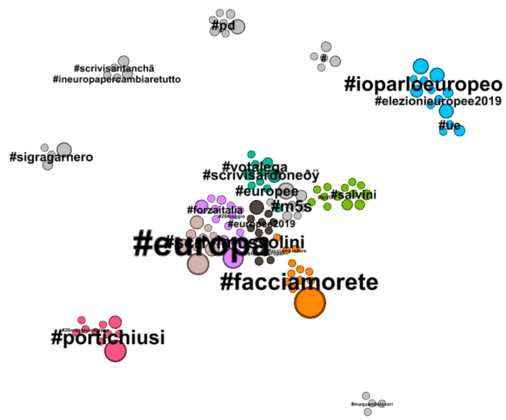


Figure 125: Posts bipartite hashtag network.

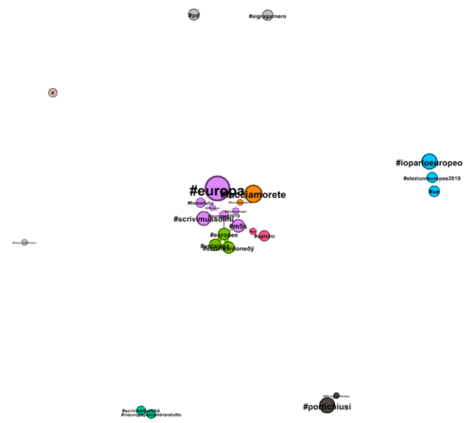


Figure 127: Posts projection hashtag network.

the hashtag projection networks are similar: in fact, even if the γ coefficients are a little bit different, as it can be seen from the table XXXVII, they do not show a scale-free network behaviour. In particular it has to be highlighted the fact that the plots and the measures in the post hashtag network could be biased by the lack of data.

	Comments	Posts
Average clustering coefficient:	0.3284	0.2766

Table XXXVII: Average clustering coefficient

Z. Cluster Analysis on projection

In the comment network we can notice that the cluster coefficient is decreasing according to the increasing degrees of the hashtags nodes meaning that hubs have less connections within its neighbours with respect to nodes that have lower degree but more connected neighbours. Unfortunately, the low dimension of the post projection network does not allow to identify a defined behaviour.

. Assortativity on projection

1) Assortativity on degree and emo: As it can be noticed from both the scatter plots and the degree and emo assortativity coefficients computation, both of the networks do not show an assortative or disassortative behaviour. In fact, for both the parameters for which the assortativity measure was extracted, the networks exhibit a similar behaviour that is likely to be random. This is explained also by looking at the assortativity coefficients that are almost equal to zero (table XXXVIII), meaning that no preferential behaviour is displayed.

	Comments	Posts
Degree assortativity	-0.0510	0.1691
Emo assortativity	0.0487	0.0658

Table XXXVIII: Degree and Emo assortativity

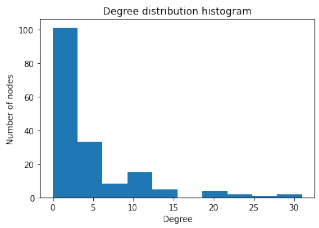


Figure 128: Comments degree distribution hashtag network.

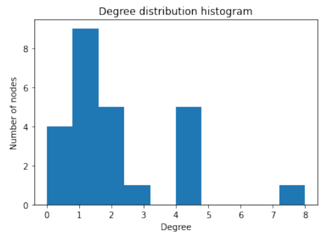


Figure 129: Posts degree distribution hashtag network.

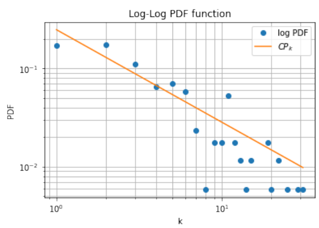


Figure 130: Comments PDF hashtag network.

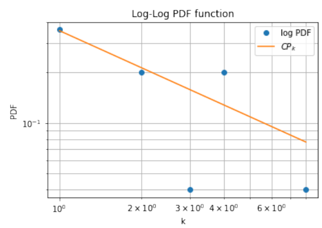


Figure 131: Posts PDF hashtag network .

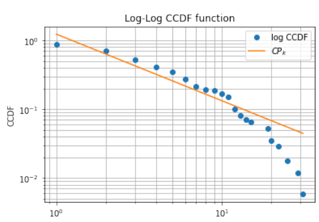


Figure 132: Comments CCDF hashtag network.

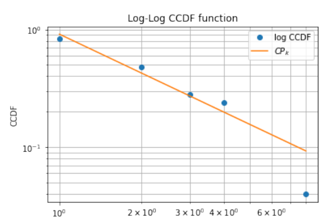


Figure 133: Posts CCDF hashtag network.

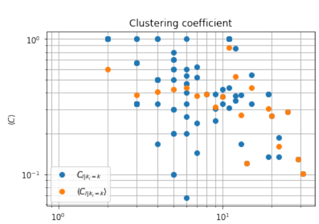


Figure 134: Comments Cluster coeff. on projection hashtag network.

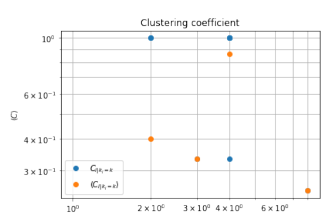


Figure 135: Posts Cluster coeff. on projection hashtag network.

Comments	Posts
#m5s	#europee
#renzi	#scrivisardone
#ue	#votalega
#calenda	#europee2019
#grillo	#m5s
#federicopizzarotti	#europa
#carofiglio	#scrivimussolini
#formigli	#26maggio
#pizzarotti	#forzaitalia
#pilotta	#facciamovotare

Table XXXIX: Top 10 hits autorities

. *Robustness*

Robustness aims to study the response of a network to node removal. We wanted to investigate the difference of robustness in the post and comment bipartite networks based on different attack criteria which are: negative emotion (depicted by the emo_neg field of our database) and node degree (figure 140).

As one would expect, node removal by degree quickly breaks the network down in both cases and robustness is thus almost the same. They are very fragile to degree attacks. The more interesting analysis is when removal by degree is performed. For the comment database, at 25% of nodes removed the robustness drops drastically whereas robustness for post follows a global linear curve until 30% and then decreases with a smaller slope. Therefore, the comment network relies more on fewer nodes with more negative emotions: nodes with more negative emotion have a bigger hub role than for post.

Global robustness without any node removed is also smaller for post network which can be explained by the fact that the graph is less connected by construction (there are more comments than posts so more nodes are connected to several hashtags at the same time). Therefore the biggest component does not include all the nodes in the post network.

Robustness applied on the networks projected on hashtags underlines a strong similarity between them (figure 141). However, even if the networks respond in a related way, we couldn't say that the same nodes of the same importance in both cases. This is due to the fact that there arrangement are really different (post have less hashtags than comments).

. *Pagerank*

Pagerank and hits algorithms return pretty similar results on the hashtag projected networks. They allow us to point out the most important nodes in the network. If we extract the top 10 most relevant words for the networks we've got the result of the tables XXXIX and XL. However, as it appears there is not a straight relationship between the most relevant hashtags of the 2 networks, even if some topics are shared among them (europa, m5s, immigration).

VII. Final considerations

Considering the whole database, comparing the post with the comments, we found that the networks might look similar from a graphical point of view, but they are quite different both

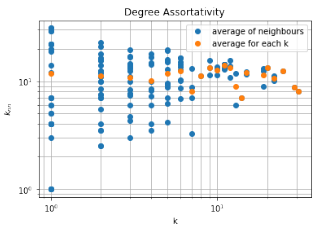


Figure 136: Comments Assortativity on degree hashtag network.

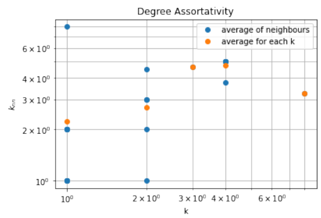


Figure 137: Posts Assortativity on degree hashtag network.

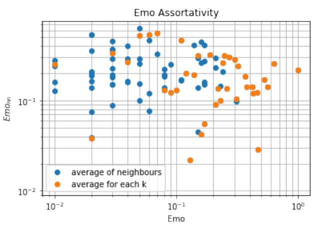


Figure 138: Comments Assortativity on emo hashtag network.

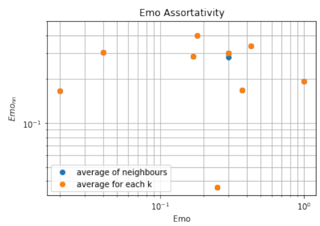


Figure 139: Posts Assortativity on emo hashtag network.

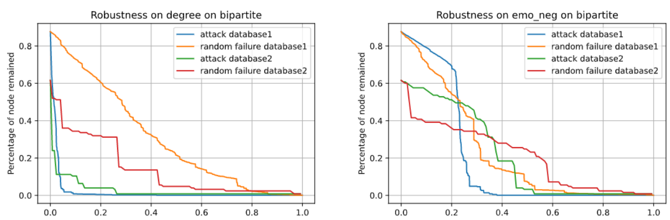


Figure 140: Robustness on bipartite graph

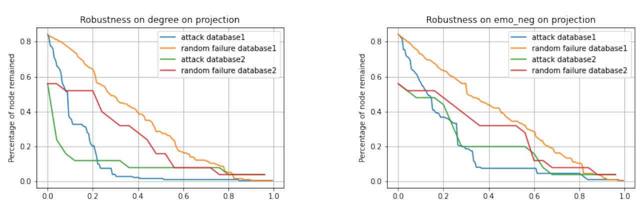


Figure 141: Robustness on projected networks

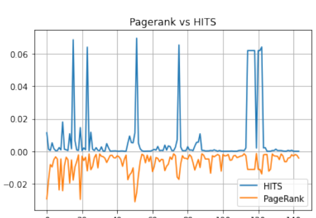


Figure 142: Pagerank vs HITS comments.

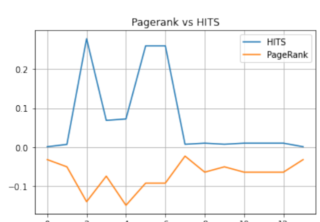


Figure 143: Pagerank vs HITS posts.

Comments	Posts
#europee2019	#europee2019
#pd	#europee
#salvini	#elezionieuropee2019
#m5s	#voltalega
#lega	#scrivisardone
#facciamorete	#m5s
#europa	#26maggiovotolega
#renzi	#portichiusi
#portichiusi	#ineuropapercambiaretutto
#scrivimussolini	#scrivisantanchã

Table XL: Top 10 pagerank

in terms of shape and measures, since the comments network is larger than the post one, but there are some similar features such as minimum degree, average path length and diameter. From a structural point of view, we can highlight some meaningful topological differences that resemble a different type of discussion in the two kinds of data sets available, such as different community organization structure, different topic connected neighbors and different degree sizes of the same nodes but in different networks. Some examples of these behaviours are given by the comparison of the nodes in both the bipartite and projection networks: in the projection it has to be highlighted that we have the same number of communities (two) for both the projection networks but the members composing the two clusters are different. In fact, as it can be seen, the “povertà” topic in the post network is in the same community with “politico, europa, altroPolitico, clima”,while in the comment network is in the other one (pink).In addition, in the comment network the “povertà” node is more connected to “solidarietà”, “amnesty”, “rifugiati” nodes and significantly bigger, in terms of degree, while in the post network is mainly connected to “europa” and “altroPolitico” and it has less connections. Moreover, the "disabili" and "clima" have a higher degree in the comment projection network compared with their respective in the post one. Finally, the "amnesty" node is more related to the "religioni" and "rifugiati" topics in the comment network while in the topic one is linked to "donne" and "politico" nodes. On the other hand, in the bipartite network, some communities are composed by different topic members: this is showed by comparing the “donne, LGBTI, rom, amnesty” community of the post network with the communities in the comment network where “donne, LGBTI” that form a community while “rom” is a member of the “rifugiati, rom, religioni” community. Secondly, the “clima” topic cluster is in a different topological position: in fact, in the post network this community is more related to topics such as “politico” and “europa” while, in the comment network, the same cluster is closer to “rifugiati, rom, religone” community and “altroPolitico” but further with respect to the “politico” module. In addition, the “povertà” cluster in the post network is connected to “rifugiati, solidarità, religioni” and “europa” topics, while in the comment network it is mainly linked to “europa”, “donne” and “altroPolitico” clusters.

Regarding instead the comparison between comment and post hashtag networks, the results on degree distribution, cluster analysis and degree/emo assortativity are quite similar. In fact, even if the γ coefficients are a little bit different, they do not show a scale-free network behaviour. Moreover, in both networks, the clustering coefficients are in an inverse relationship according to the increasing degree value of the nodes. Concerning the degree and emo assortativity, the networks do not show an assortative or disassortative behaviour. In fact, for both the parameters for which the assortativity measure was extracted, the networks exhibit a similar behaviour that is likely to be random.

VIII. Conclusions

A. Semantic group

- **general Results:** We found out that both posts and comments networks were scale-free, being the γ exponent less than 3 and more than 2. Moreover, often the largest components covered almost the totality of the network.
- **Node removal:** In the analysis we carried out in this paper, we discovered that the most meaningful variable to highlight hate speech is the manual coding, beside the more effort required, returns the most relevant results. In particular, manual coding was used to label every comment/post as problematic, hate speech, positive, ambiguous or neutral once having read it more than once. Therefore, we found that hate/problematic index is the most meaningful variable among the ones we have used. It allows us to conclude that software and sentiment dictionaries, applied along with lemmatization, are not good tools to highlight where hate is.
  In addition it helped us out to understand and predict where the hate is more relevant, that is to say in right parties and negative type of campaign networks, being this general conclusion valid both for posts and comments.
  Moreover, for both wings parties comments, the drop in density when applying node removal is mildly correlated to the hate index variable. Thus meaning that the higher the hate index for a given word, the larger will be such drop. This can be a consequence that hate speech words tend to have higher degree: the larger the hate index the more often they appear by construction, thus being more central in both networks. The words with higher hate index are either general words (like verbs, "fare" ["to do"], "dire" ["to say"], or "quando" ["when"] or words related to immigration (for instance "clandestino" ["illegal immigrant"], "immigrato" ["immigrant"], religious-ethnic (for instance "islamico ["islamic"]) topics and swear words. It is indeed what we would expect from literature already acquired results.
  For left and right posts, the decrease in density/robustness is tied to the node removal by problematic index that is manually encoded; the rest of the LIWC and Sentix dictionaries attributes were not significant in our analysis as they didn't highlight any differences between left and right posts' levels of problematic speech. We can say that the words with high problematic count are more central in the right posts speech. This result is also reinforced by the fact that the problematic words have higher degrees in right posts compared to the left posts.
  For the posts - type of campaign categorization, we observed that the negative type of campaign generated more hate compared to the positive type of campaign, considering that the problematic nodes with the highest degree were more central in the negative campaign network. In addition the analysis on Gephi showed that the negative campaign graph had a higher level of hate compared to the positive type of campaign.
  For target division analysis on comments, the nodes removal according to hate-index and LIWC variables has equal effect in the two networks' structure, in compliance with the hypothesis that there is no evident difference in the generation of hate comments from group or individual attacks in posts. While the removal of words by negative polarity value results are in contradiction with the assumption that more negative comments are generated from posts with attacks on individuals, since density decreases much faster in the group network.
- **Cluster Analysis:** As already pointed out in [23], most negative clusters are always about immigrants and ethnic-religious topics, holding this for both subsets. One more interesting point aspect that our analysis pointed out is that trying to model the topic of different clusters leads to different results depending on the subset we are analyzing. Indeed one of the clusters contained in left parties network is a topic related to Salvini's political aspects and decisions. Moreover, the clusters contained in the left posts do not differ that much in terms of the level of hate. On the other hand, for Right subset, the most hateful cluster mainly discusses about immigrants, race-ethnic related topics and religion.

B. Content group

- **Topic network** Comparing the posts and comments in the whole database in the projection post network the *'povertà'* topic is in the same community with *'politico'*, *'europa'*, *'altroPolitico'*, *'clima'*, while in the comment network it is in the other one. In addition, in the comment network the *'povertà'* node is more connected to *'solidarietà'*, *'amnesty'*, *'rifugiati'* nodes, and it is significantly bigger in terms of degree, while in the post network it is mainly connected to *'europa* and *'altroPolitico'* and it has less connections. Moreover, the *'disabili'* and *'clima'* have a higher degree in the comment projection network compared with their respective in the post one. Finally, the *'amnesty'* node is more related to the *'religioni'* and *'rifugiati'* topics in the comment network while in the topic one is linked to *'donne* and *'politico'* nodes.
  On the other hand, in the bipartite network some communities are composed by different topic members: this is showed by comparing the *'donne'*, *'LGBTI'*, *'rom'*, *'amnesty'* community of the post network with the communities in the comment network where *'donne'* and *'LGBTI'* form a community while *'rom'* is a member of the *'fugiati'*, *'rom'* and *'religioni'* community. Secondly, the *'clima'* topics cluster is in a different topological position: in the post network this community is more related to topics such as *'politico'* and *'europa'* while, in the comment network, the same cluster is closer to *'fugiati'*, *'rom'* and *'religioni'* community and *'altroPolitico'* but further with respect to the *'politico'* module. In addition, the *'povertà'* cluster in the post network is connected to *'rifugiati'*, *'solidarità'*, *'religioni'* and *'europa'* topics, while in the comment network it is mainly linked to

'europa', *'donne'* and *'altroPolitico'* clusters.

In the left politicians network *'Politico'* is strongly connected with *'altroPolitico'* and *'Europa'*, and these two are well related between each other. Other two relevant topics are *'solidarietà'* and *'rifugiati'*. They are connected within each other and with *'Politico'* and *'altroPolitico'*. Then *'rifugiati'* share a strong edge also with *'Europa'*. *'Povertà'* and *'religioni'* are a bit less central even if they have a well defined link with *'Politico'* and *'rifugiati'* respectively. Also *'donne'* is well connected, but it does not have very strong link, showing that topic is less central if compared to the previous ones. Finally, other topics, like *'lgbti'*, *'rom'*, *'clima'*, *'disabili'* and in particular *'amnesty'*, are not commonly used topics. In right network we can do the same consideration about *'Politico'*, *'altroPolitico'* and *'Europa'*: these topics are very strongly connected even if in this case *'Europa'* is not in the same class of the other two. Also *'solidarietà'*, *'rifugiati'* and *'Povertà* are relevant topics in this network, however only *'rifugiati'* shows a strong link with *'Politico'* and *'altroPolitico'*. For *'religioni'* and *donne* we have that they are less central and well connected only with *'rifugiati'* the first, while the latter does not shows any strong link with the other topics. Also in this case, *'lgbti'*, *'rom'*, *'clima'*, *'disabili'* and *'amnesty'*, are not the central topics of this database.

If instead we consider the negative and positive campaigns, we can see that the covered subjects are the same and in both networks, with *'Politico'*, *'altroPolitico'*, and *'Europa'* being the main topics. These are also strongly related among themselves. However, in the negative networks, topics like *'religioni'* or *'rifugiati'* are more central, while in the positive we have *'solidarietà'*.

- **Hashtag network** Comparing the posts and comments overall database, what is interesting is that they share really similar behaviours in terms of robustness and pagerank. In fact, the most important nodes (with respect to pagerank) share some common topics (mainly europa and immigration). But the distribution and shape of the post network prevent us to extract a lot of meaningful values to compare as it contains very few nodes and is less connected.

  Comparing the robustness removing by negative emotions (emo_neg) we found that the graphs for left and right division of the databases do not show significant differences, while the same techniques applied to negative and positive campaign databases are significantly different. That confirm one of the general hypothesis: the negativity driven more by the type of political communication than political orientation.

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IX. Appendix

A. Graphs

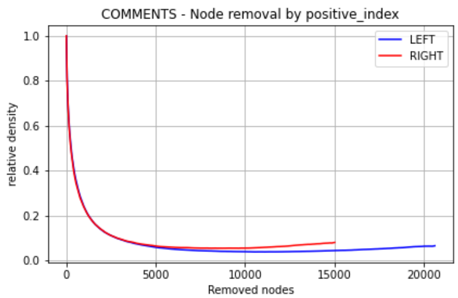

Figure 144: Relative density at each timestep by removing nodes sequentially according to their positive index normalized to its initial value.

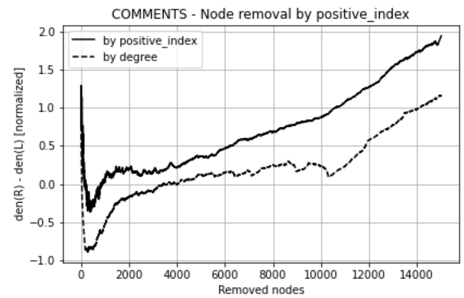

Figure 145: Difference $\mathrm{den}(R) - \mathrm{den}(L)$ of the density at each timestep by removing nodes sequentially according to their positive index. Difference is normalized to its initial value.

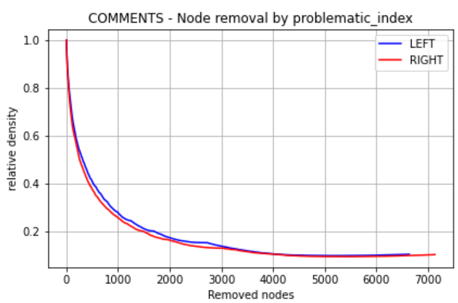

Figure 146: Relative density at each timestep by removing nodes sequentially according to their positive index. Density are normalized to its initial values.

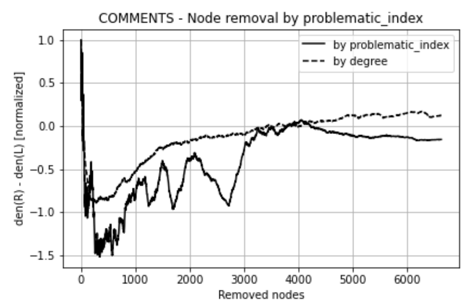

Figure 147: Difference $\mathrm{den}(R) - \mathrm{den}(L)$ of the density at each timestep by removing nodes sequentially according to their problematic index. Difference is normalized to its initial value.

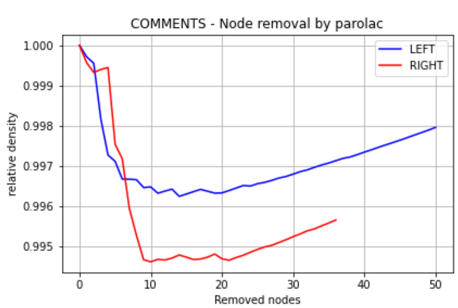

Figure 148: Relative density at each timestep by removing nodes sequentially according to whether they are a swearword normalized to its initial values.

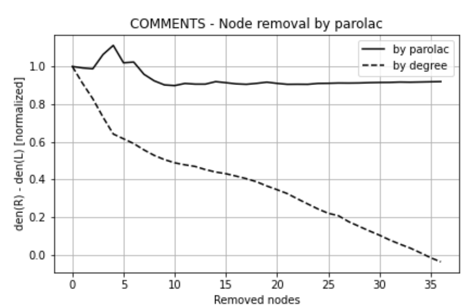

Figure 149: Difference $\mathrm{den}(R) - \mathrm{den}(L)$ of the density at each timestep by removing nodes sequentially according to whether they are a swearword. Difference is normalized to its initial value.

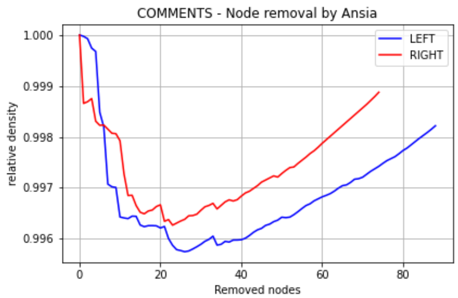

Figure 150: Relative density at each timestep by removing nodes sequentially according to whether they express Anxiety normalized to its initial values.

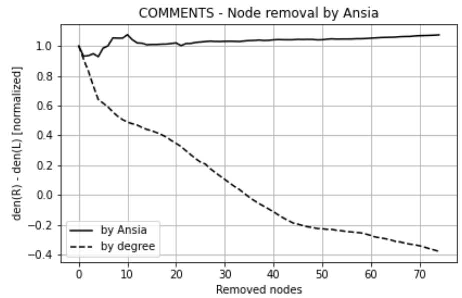

Figure 151: Difference $\text{den}(R) - \text{den}(L)$ of the density at each timestep by removing nodes sequentially according to whether they express Anxiety. Difference is normalized to its initial value.

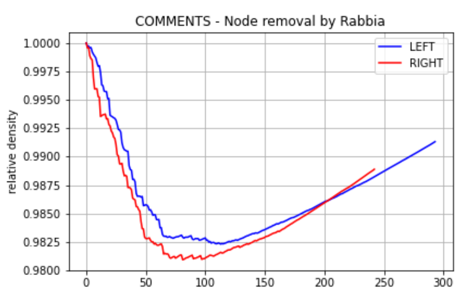

Figure 152: Relative density at each timestep by removing nodes sequentially according to whether they express Anger normalized to its initial values.

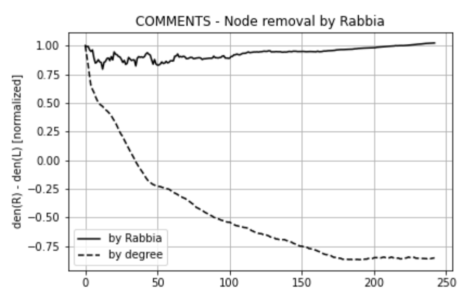

Figure 153: Difference $\text{den}(R) - \text{den}(L)$ of the density at each timestep by removing nodes sequentially according to whether they express Anger. Difference is normalized to its initial value.

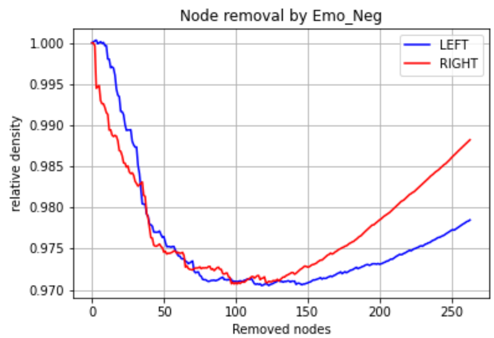

Figure 154: Negative Emotion (LIWC) node removal (Left and Right Posts)

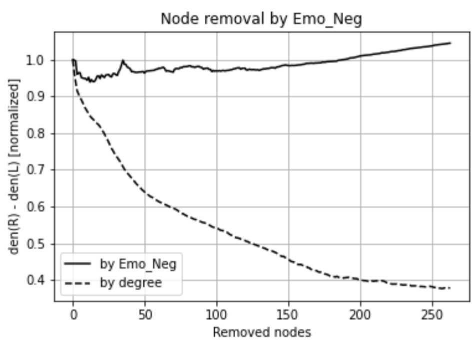

Figure 155: Difference between Negative Emotion (LIWC) node removal and Degree node removal, Left and Right Posts

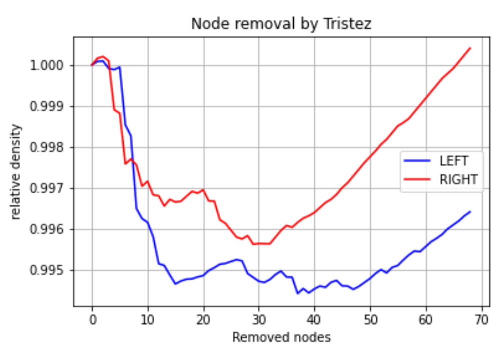

Figure 156: Tristez (LIWC) node removal (Left and Right Posts)

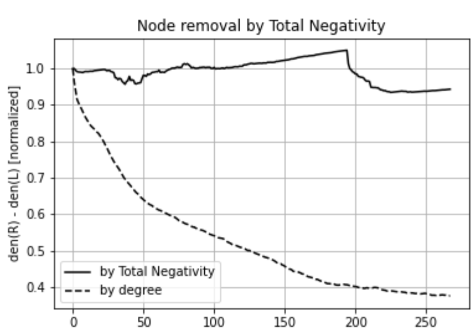

Figure 157: Difference between Tristez (LIWC) node removal and Degree node removal, Left and Right Posts

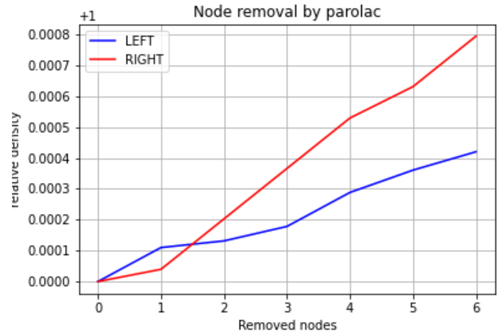

Figure 158: Parolaci (LIWC) node removal (Left and Right Posts)

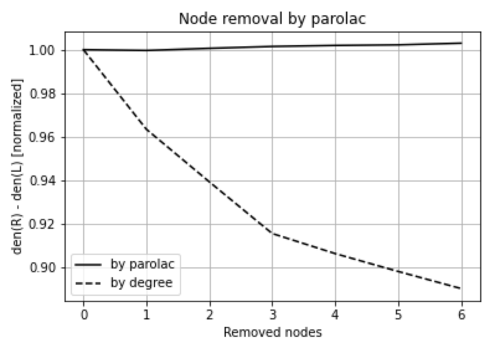

Figure 159: Difference between Parolaci (LIWC) node removal and Degree node removal, Left and Right Posts

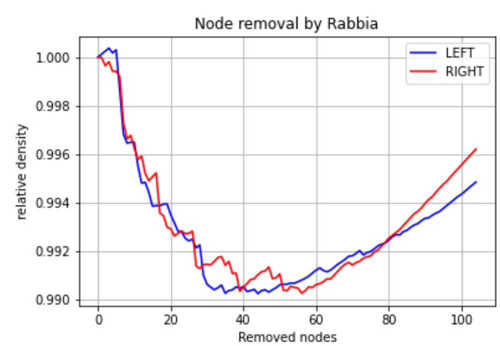

Figure 160: Rabbia (LIWC) node removal (Left and Right Posts)

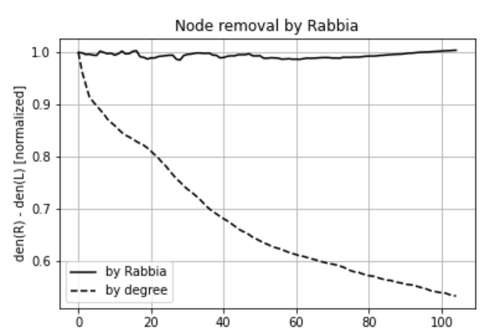

Figure 161: Difference between Rabbia (LIWC) node removal and Degree node removal, Left and Right Posts

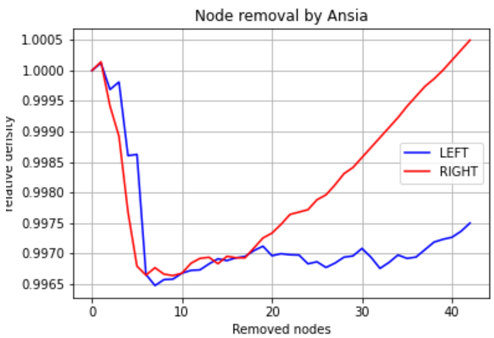

Figure 162: Ansia (LIWC) node removal (Left and Right Posts)

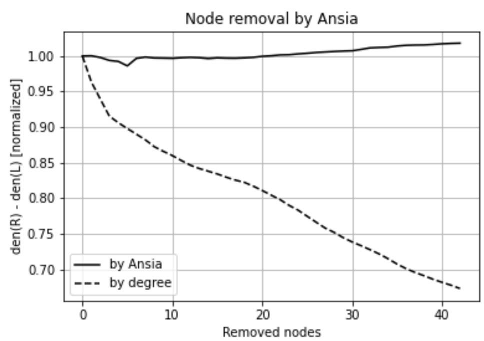

Figure 163: Difference between Ansia (LIWC) node removal and Degree node removal, Left and Right Posts

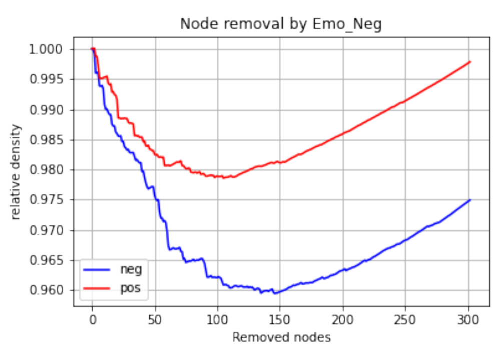

Figure 164: Emo-neg (LIWC) node removal (Negative and positive Type of campaign)

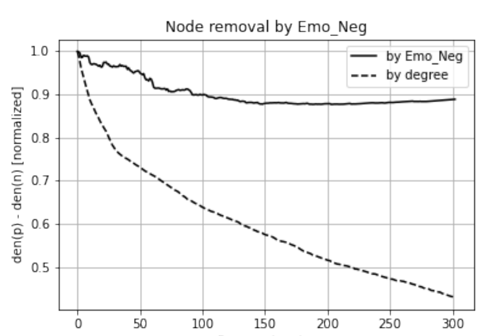

Figure 165: Difference between Emo-neg (LIWC) node removal and Degree node removal, Positive and Negative posts

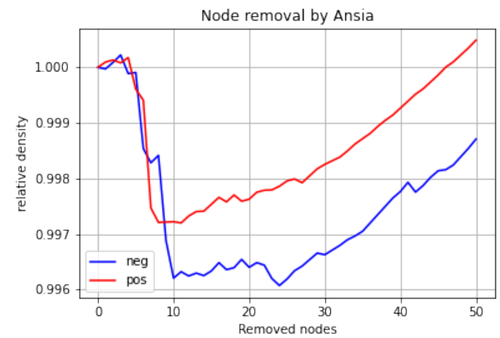

Figure 166: Ansia (LIWC) node removal (Negative and positive Type of campaign)

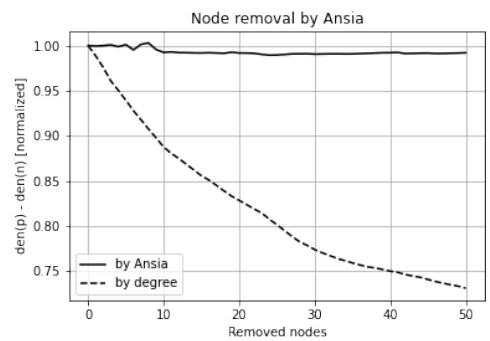

Figure 167: Difference between Ansia (LIWC) node removal and Degree node removal, Positive and Negative posts

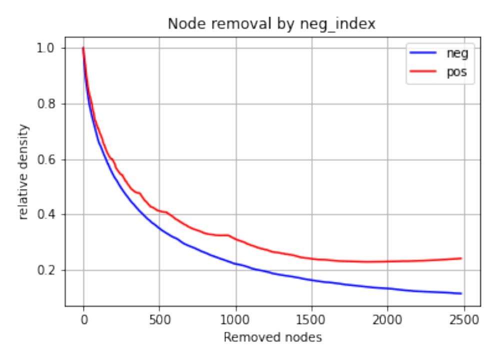

Figure 168: Negative index node removal (Negative and positive Type of campaign)

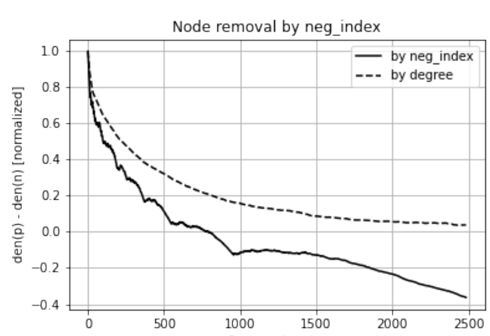

Figure 169: Difference between Negative Index node removal and Degree node removal, Positive and Negative posts

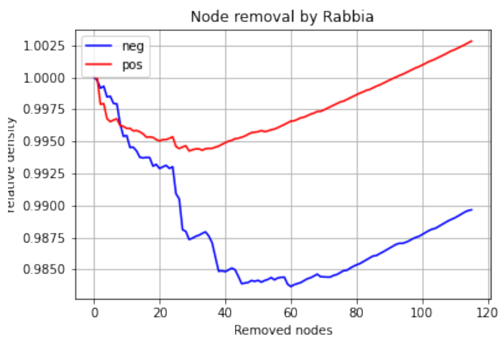

Figure 170: Rabbia(LIWC) node removal (Negative and positive Type of campaign)

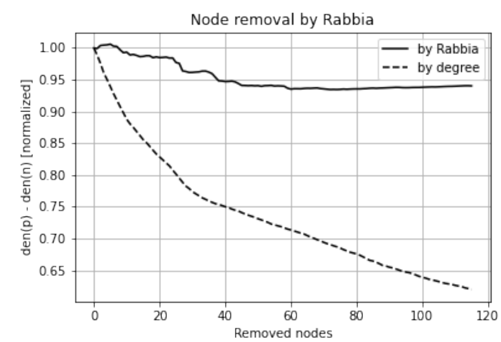

Figure 171: Difference between Rabbia(LIWC) node removal and Degree node removal, Positive and Negative posts

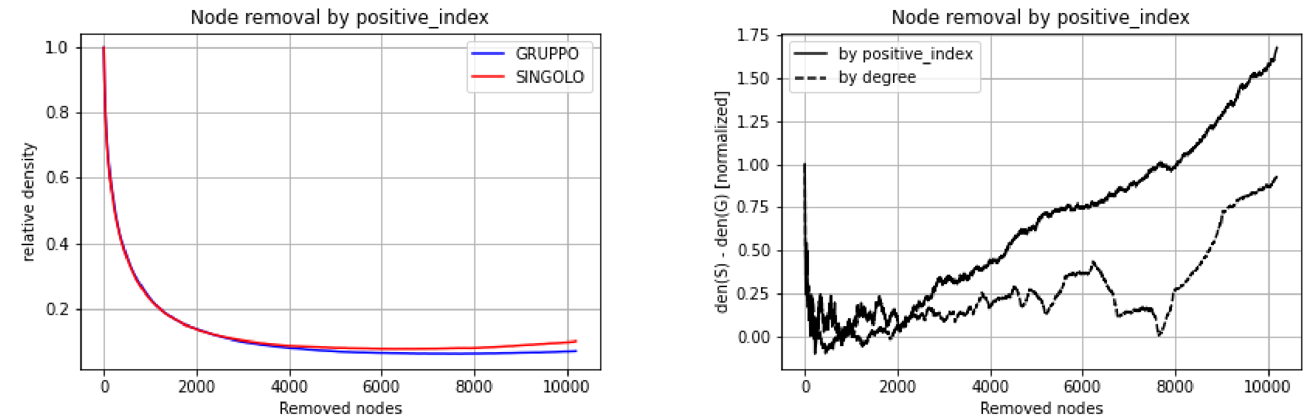

Figure 172: Target Networks - Node Removal by positive index

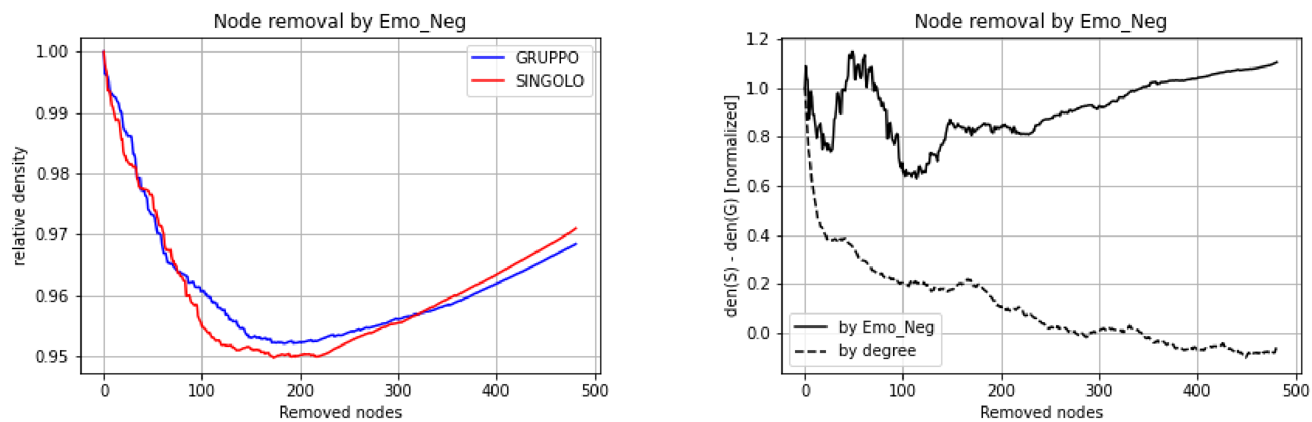

Figure 173: Target Networks - Node Removal by Negative Emotion

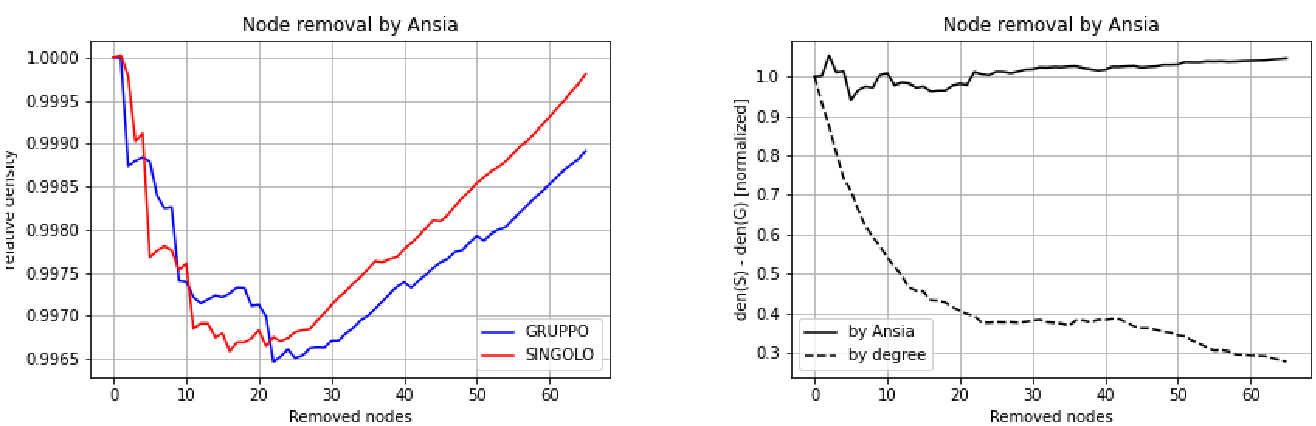

Figure 174: Target Networks - Node Removal by Anxiety

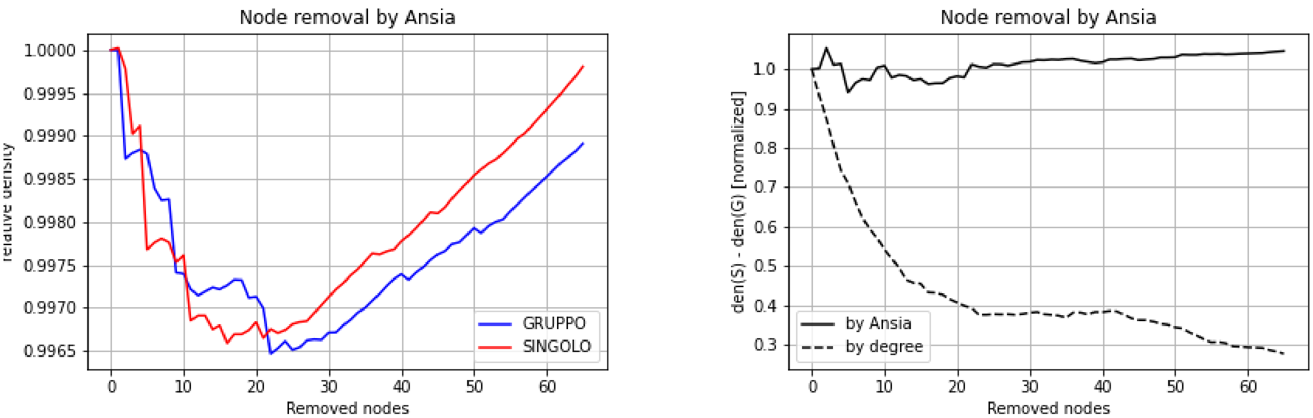

Figure 175: Target Networks - Node Removal by Anxiety

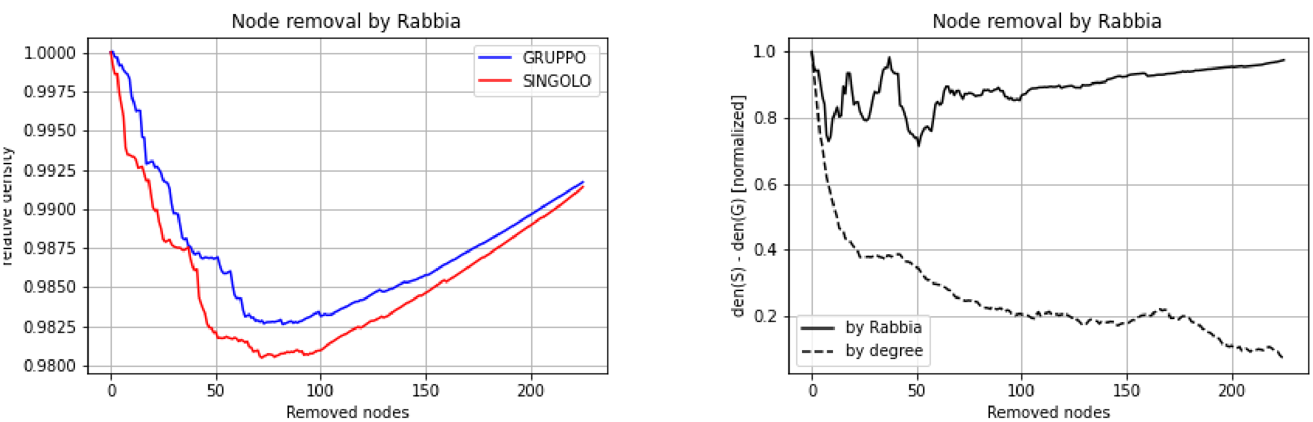

Figure 176: Target Networks - Node Removal by Anger

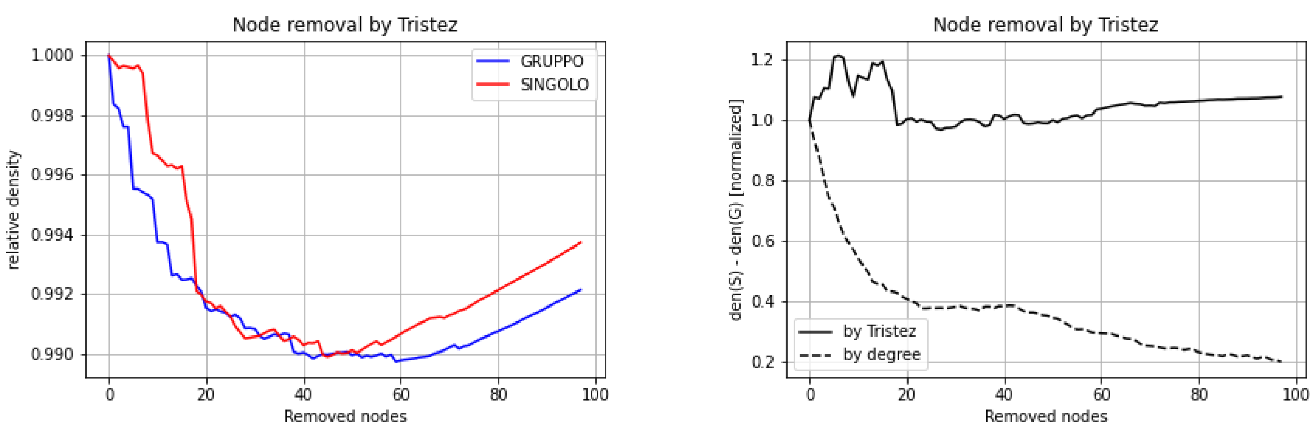

Figure 177: Target Networks - Node Removal by Sadness

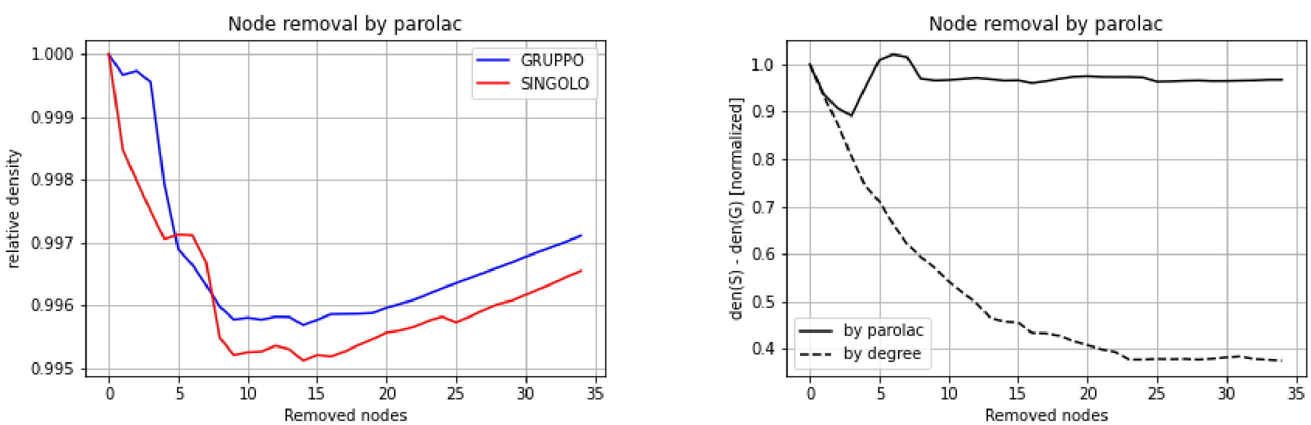

Figure 178: Target Networks - Node Removal by Swearing

B. Tables

Right Comments - 1st most hateful cluster

Pagerank Score	Word	Hate index	Word
0.013928	*gente*	25.0	*merda*
0.011894	*fuori*	23.0	*fuori*
0.011018	*comunista*	18.0	*bastardo*
0.010028	*puro*	15.0	*gente*
0.009662	*vergognare*	12.0	*coglione*
0.008553	*povero*	11.0	*culo*
0.007924	*merda*	10.0	*servire*
0.007641	*coglione*	10.0	*cazzo*
0.007561	*malo*	9.0	*palla*
0.007528	*lasciare*	8.0	*calcio*

Table XLI: Top 10 words for cluster Page Rank score and hate index for the 1st largest average hate index score in Right comments network. Average hate index for this cluster is 0.21.

Right Comments - 2nd most hateful cluster

Pagerank Score	Word	Hate index	Word
0.048703	*europa*	14.0	*islamico*
0.020789	*delinquere*	11.0	*delinquere*
0.017462	*strada*	7.0	*pulizia*
0.011896	*islamico*	6.0	*islam*
0.011742	*mafioso*	6.0	*pezzo*
0.011533	*evitare*	5.0	*europa*
0.009952	*puntare*	4.0	*puntare*
0.009465	*associazione*	4.0	*farli*
0.00934	*pezzo*	3.0	*massacrare*
0.00762	*piazza*	3.0	*durare*

Table XLII: Top 10 words for cluster Page Rank score and hate index for the 2nd largest average hate index score in Right comments network. Topic seems to be religion. Average hate index for this cluster is 0.18.

Right Comments - 3rd most hateful cluster

Pagerank Score	Word	Hate index	Word
0.061868	*casa*	27.0	*casa*
0.017501	*aprire*	6.0	*usare*
0.016751	*esempio*	4.0	*aprire*
0.015368	*niente*	4.0	*mandateli*
0.015211	*usare*	3.0	*tenere*
0.012763	*tenere*	3.0	*affondare*
0.011706	*parlamentare*	3.0	*niente*
0.011252	*dubbio*	3.0	*zoccolare*
0.009219	*sede*	2.0	*terremoto*
0.008798	*cioe*	2.0	*pensata*

Table XLIII: Top 10 words for cluster Page Rank score and hate index for the 3rd largest average hate index score in Right comments network. Topic seems to be religion. Average hate index for this cluster is 0.16.

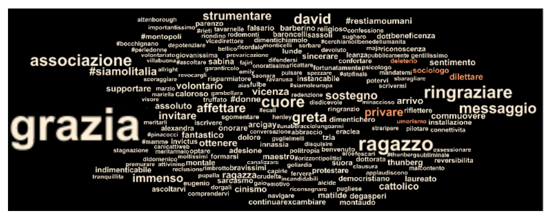

Figure 179: Left Wing Cluster with The Highest average Problematic Count, node size=page rank, node color=problematic count