Opinion Mining Hybrid Approach. An Application to Investigate the Users' Political Positions in Disinformative Echo Chambers

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Abstract Although the definition is not yet conceptually well defined, the image of echo chambers ((Quattrociocchi & Vicini. *Misinformation. Guida alla società dell'informazione e della credulità*. Franco Angeli, Roma, 2016); (Terren, L., & Borge-Bravo, R., *Review of Communication Research* 9:99–118, 2021)) aims to convey the idea that people who use social media platforms are exposed largely (or exclusively) to one type of pro-attitudinal content that polarizes their opinions to the point of extremes. This type of exposure raises much concern in the academic community concerning the information consumption, which plays a fundamental role in the construction of public opinion. Despite studies ((Mocanu et al. *Computers in Human Behavior* 51:1198–1204, 2015); (Bessi et al. Social determinants of content selection in the age of (mis)information. International conference on social informatics (pp. 259–268). Springer, Cham, 2014). (Bessi et al. Science vs conspiracy: Collective narratives in the age of misinformation. PLoS One, 10(2), 2015)) that have contributed to understanding the social dynamics of user behavior in social media in relation to disinformative content, an exclusively data-driven approach seems to reduce the complexity of the disinformation phenomenon to a simple true/false dichotomy and considers individuals and their complex social behaviors as a single subject with undifferentiated behavior. The aim of this work is to use an epistemological theory-driven approach and a hybrid opinion-mining approach to analyze opinions of Italian users who consume disinformative content, and to reconstruct their narratives and worldviews to identify any elements that guide users' opinions and their experience in disinformative echo chambers. The papers contain part of the results of a broader analysis that was conducted on two sequential levels. The results of the first level will be mentioned, useful for understanding the results that will be seen here which refer to the second level of analysis.

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1 Disinformation: A Difficult Phenomenon to Define

Social media has completely changed our communication, political debates, and access to information. In recent years, fake news, disinformation, and conspiracy theories have spread very easily and become a danger to the democratic process. Indeed, the expression "fake news" has become relevant because it has characterized two significant political events: the US electoral process, which elected Donald Trump as president, and the UK Brexit referendum. During these two political processes there was a strong wave of false information used in an attempt—in both cases successful—to obtain advantages and achieve political objectives. In a society where we are called to decide and have an opinion on very sensitive and technical issues (such as the recent COVID-19 vaccination campaign), the presence of fake news and disinformation impacts upon the democratic system (World Economic Forum, 2016, 2017).

The workings of social media are based on news feed algorithms that are programmed to show only what is in line with users' preferences (Hagey & Horwitz, 2021). Hence, users immersed in these digital spaces view almost exclusively only content in line with their opinions and beliefs, interacting only with other users who have the same preferences and ideas. This mechanism creates a state of ideological isolation and opinion polarization (Mocanu et al., 2015). The image of echo chambers aims to convey the idea that the people who use social media platforms are exposed largely (or exclusively) to one type of pro-aptitude content. Regarding echo chambers, we know from the literature that social media communities are polarized in their opinions around specific topics (Quattrociocchi & Vicini, 2016).

Inside the echo chambers, it is difficult to discern the difference between "real news" and "fake news" because our trust in the content we see is so strong that it does not make us doubt. In this way, the construction of consensus within public opinion is obstructed by disinformation and opinions are instead polarized (Quattrociocchi & Vicini, 2016; Bentivegna & Boccia Artieri, 2019). For this reason, the scientific community is questioning—in an interdisciplinary way—how to analyze and contrast the phenomenon of disinformation. A fruitful series of studies has aimed to understand the social dynamics that emerge between users who consume disinformation on social media platforms. This research—based on a data-driven approach—has detected empirically the existence of echo chambers on social media and demonstrated their impact on information selection and opinion polarization (Bessi et al., 2014, 2015; Mocanu et al., 2015). Although users' radicalized behavior in these echo chambers is well attested, the empirical methodology that tries to investigate how and in what direction these opinions are radicalized is relatively poor. The data-driven approach seems to consider individuals and their complex social behaviors as a single subject with undifferentiated behavior. This work, by contrast, exploits the potential of combining approaches of text analysis and opinion mining in an epistemological theory-driven approach in order to analyze opinions of Italian users, seeking to identify the elements that guide these opinions and shape users' experiences in the disinformative echo chambers.

2 Methodology and Data Collection

This study contains part of the results of a broader analysis that was conducted on two sequential levels. The results of the first level will be mentioned, useful for understanding the results that will be seen in this paper which refer to the second level of analysis.

The analysis was conducted on two levels: the first level is the analysis of the disinformative message (stimulus) and the second level is the analysis of the comments related to the disinformative message (response to the stimulus message). The two levels are linked together by an anchor variable produced by the API which is a numeric ID that identifies: page, message, and user who replies to the message. This paper will report the results of the second level of analysis (comments) which shares some variables with the first level. In fact, it is important to know that in the first level of analysis a disinformation risk index (high, medium, or low) was constructed: each post in the sample was analyzed individually on the basis of content, context, and visual clues and then labeled according to categories of misinformation drawn from the reference literature. Furthermore, in the first level an LDA Topic Model (Blei et al., 2003) was conducted which extracted 18 Topics: in this way we know which topics are covered in the disinformative messages to which users reply. Topics found that the messages convey politically well-defined content and use highly polarizing trending topics. This result highlighted an unexpected element that is not present in the literature, namely political orientation, which was thus inserted as a further variable in the second level of analysis, where the users' judgment is at the center of attention. The results of the first level of analysis (misinformation risk, content construction strategy, and message topic) are reported in the second level of analysis where users' opinions and their narratives are analyzed. The analysis uses two standard opinion mining approaches: the supervised machine learning approach based on the Naive Bayes probabilistic classifier (Hasan et al., 2015; Singh & Dubey, 2014; Vangara et al., 2020) and an unsupervised approach using the LIWIC dictionary (Tausczik & Pennebaker, 2010), useful for labeling texts based on words associated with psychologically and emotionally significant categories. Eventually, a hybrid approach was implemented to address the inability of the chosen classifier to label the political orientation expressed by users.

3 A Hybrid Approach Proposal to Opinion Mining

In the supervised machine learning approach, the Naive Bayes probabilistic classifier was chosen, one of the most widely used algorithms in automatic text classification. Bayesian classification uses Bayes' Theorem to predict the occurrence of any event. Bayesian classifiers are statistical classifiers within the Bayesian concept of probability, which expresses how a level of belief may be expressed as a probability. The theorem itself, due to Thomas Bayes, utilizes conditional probability to provide an algorithm that uses evidence to calculate bounds for an unknown parameter. Bayes' theorem is expressed mathematically by the following formula:

$$\mathrm{P}\,(\mathrm{x}|\mathrm{y}) = \frac{\mathrm{P}\,(\mathrm{y}|\mathrm{x})\,\mathrm{P}\,(\mathrm{x})}{\mathrm{P}\,(\mathrm{x})} \tag{1}$$

where x and y are events such that $P(y) \neq 0$, $P(x|y)$ is a conditional probability that describes the occurrence of event X is given that Y is true, $P(y|x)$ is a conditional probability that describes the occurrence of event Y is given that X is true, and P(x) and P(y) are the probabilities of observing X and Y independently of each other (known as the marginal probabilities) (Berrar, 2018).

The training set is composed of 5604 comments (equal to 5% of comments of the sample) which were manually labeled based on the sentiment expressed (positive, negative, neutral) and on the political orientation expressed (right-wing, left-wing, center, political orientation rejected or not expressed). The classification capacity of the algorithm was verified through synthetic indicators based on the confusion matrix, which contain information on a classifier's predictive capacity. The Bayesian classifier had a mean accuracy of 82% in forecasting the sentiment variable, with a 95% confidence interval (0.80, 0.83) and an accuracy of over 80% on the three classes, which refers to the ability of the classifier not to label an instance with one label when it belongs to another. There is a certain difficulty in predicting neutral and positive sentiments; this is because the randomly extracted training set was composed of only 3% neutral and 20% positive against 77% from the negative class (Table 1).

The accuracy of the classifier decreased drastically in predicting political orientation (53% with a NIR of 72%).

Despite an accuracy of 84.8% in identifying the right political orientation, it had difficulty in predicting the other orientations (34.4% not expressed; 10.5% refuse political orientation; 0.66% on the left). The problems with the classifier may be due to the composition of the training set,[1] but also to the political scenario that has characterized Italy in recent years, which has brought together disparate political positions: the presence of two conflicting political positions (such as Lega-5Stelle or

[1] The training set consists of 4% refuse placement; 8% Left; 44% Right; 44% not expressed.

Table 1 Statistics of accurate Naive Bayes classification by "sentiment"

Overall statistics			
Accuracy:	0.82		
95% CI:	(0.801, 0.8379)		
No information rate:	0.7391		
P-value (Acc > NIR):	1,27E-12		
Kappa:	0.4479		
Mcnemar's test *P*-value:	< 2.2e-16		
Statistics by class			
	Negativo	Neutro	Positivo
Sensitivity	0.9779	0.42105	0.36290
Specificity	0.3862	0.99573	0.97993
Pos Pred value	0.8186	0.82051	0.83333
Neg Pred value	0.8607	0.97378	0.84759
Precision	0.8186	0.82051	0.83333
Recall	0.9779	0.42105	0.36290
F1	0.8912	0.55652	0.50562

Table 2 Naive Bayes Classification on "political orientation"

Overall statistics				
Accuracy:	0.5393			
95% CI:	(0.5145, 0.5639)			
No information rate:	0.7219			
P-value [Acc > NIR]:	1,00E+00			
Kappa:	0.2005			
Mcnemar's test *P*-value:	<2e-16			
Statistics by class				
	Right-wing	Not expressed	Refused	Left-wing
Sensitivity	0.5285	0.6723	0.333333	0.121622
Specificity	0.7556	0.6384	0.967844	0.916993
Pos Pred value	0.8488	0.3449	0.105263	0.066176
Neg Pred value	0.3817	0.8731	0.992243	0.955722
Precision	0.8488	0.3449	0.105263	0.066176
Recall	0.5285	0.6723	0.333333	0.121622
F1	0.6514	0.4559	0.160000	0.085714

PD-5Stelle) treated in the same way within a comment may have created difficulties in the disambiguation process (Table 2).

For this reason, a hybrid approach was developed with a novel combination of a supervised approach to machine learning and an unsupervised dictionary-based approach. This path exploits convergence to overcome the limits of one approach with the advantages of the other and vice versa (Amaturo & Punziano, 2016). Thus, starting from the labeled training set, a vocabulary of political orientation was built, thanks to which it was possible to classify comments by extracting their features. However, the extraction of features is not so immediate because, while

Table 3 Classification accuracy of the hybrid model on "political orientation"

Overall statistics				
Accuracy:	0.781			
95% CI:	(0.77, 0.7918)			
No information rate:	0.4863			
P-value (Acc > NIR):	< 2.2e-16			
Kappa:	0.652			
Mcnemar's test *P*-value:	<2e-16			
Statistics by class				
	Right-wing	Not expressed	Refused	Left-wing
Sensitivity	0.9026	0.7728	0.34944	0.83801
Specificity	0.7850	0.8864	0.99585	0.98483
Pos Pred value	0.6791	0.8656	0.89952	0.83262
Neg Pred value	0.9411	0.8048	0.93513	0.98540
Precision	0.6791	0.8656	0.89952	0.83262
Recall	0.9026	0.7728	0.34944	0.83801
F1	0.7750	0.8166	0.50335	0.83531

on the one hand the procedure must discriminate and describe the original text as much as possible, on the other hand it must also reduce the large size of the source data and avoid redundancies. For this reason, the function considered most suitable was TF-IDF (Silge & Robinson, 2017). This function is widely used in the information retrieval field to measure the importance of a word for an individual document in relation to a wider collection of documents. In computational linguistic studies, it is commonly highlighted how classical measures of frequency place too much emphasis on high-frequency terms, whereas measures of specificity assign too much weight to low-frequency terms (Manning & Schutze, 1999). The challenge in the selection or weighting of terms lies in establishing a good balance between frequency and specificity (Aizawa, 2003). The TF-IDF statistic appears to be a suitable compromise.

The overall statistics of the model show us that the results were improved using a hybrid approach (Table 3).

In the end, the comments were labeled on psychologically and emotionally significant categories through the LIWC dictionary. The dictionary consists of several categories, with a number of words assigned to one or more of these categories that have a psychological, emotional, or related meaning to cognitive processes and life concerns. In this analysis, five categories considered relevant were selected to investigate the psychological dimensions underlying the users' corpus: optimism, anxiety, anger, sadness, and certainty; the "bad words" category was also exploited to analyze the degree of language formality. The score assigned by LIWC to each selected dimension was categorized into: "high," "medium," "low," and "absent" starting from the analysis of the position indices. The sample's comments were thus labeled according to the sentiment expressed (through Naive Bayes), according to the emotions expressed as anger, anxiety, etc. (through the LIWIC lexicon), and according to political orientation (via the hybrid approach described above).

4 The Users' Political Orientation

The factorial analysis brought two synthetic dimensions of meaning to the data, characterized by a dimension of high and low emotionality, the first factor (horizontal axis) and high and low conviction toward one's ideas (second factor, vertical axis). The first two factorial axes altogether explain 63.91% of the total inertia with Benzécrì's correction.[2]

Along the first axis, high emotionality contained in user messages corresponded to interaction with high-risk disinformation content that negatively polarized sentiment and generated very high user engagement (high engagement). The conviction expressed toward the opinions expressed by these users was also high. This negative communication, polarized and convinced of one's own opinions characterized the political position of the right. The associated feelings were anger and anxiety, the two emotions most frequently associated with populism and with major episodes of conspiratorial thinking and anti-elite attitudes (Grzesiak-Feldman, 2013). On the opposite side of the factorial plane, however, low emotionality expressed in users' comments corresponded to an interaction with content with a lower risk of disinformation that generated medium-low engagement. Here users expressed left-oriented political positions or expressed no political positions and had positive or neutral feelings. Along the second axis, however, low conviction and low emotionality characterized users who reject political positions: we are talking about the "5 Stelle Movement," which although it is considered a populist movement appears (in this disinformative environment) less radicalized than right-wing political positions. The high conviction with which right-wing users express their opinions makes possible comparison with other positions difficult. Their levels of interaction make these contents viral, keeping alive open debates on delicate topics (extracted in the first level of analysis) such as immigration, Islam, LGBT rights, media, and climate. A cluster analysis brings out the differences between different users, who appear as many small tribes that express different convictions and emotions, discuss different topics in different languages, and expose themselves in different ways to the risk of disinformation (Table 4).

To the high disinformation risk already highlighted is added the use of informal language, consistent with negative sentiment and high emotionality expressed in the comments. Involvement decreases for users with left-leaning political positions (15%), as does the disinformation risk to which they are exposed, and the

[2] The active variables are sentiment (three modalities), political orientation (four modalities), engagement (three modalities), and disinformation risk (three modalities). In the graph 2, the active variables are indicated with the triangle symbol.

Table 4 Cluster of opinions, feelings, and positions of users who consume disinformative content

	Engagement	language	Conviction	Emotionally	Sentiment	Disinformation risk	Themes' resumed
Right-wing support (20%)	High	Informal	High	High (high anger, high anxiety); optimism absent	Negative	High, medium	Immigration; nationalism; politics (Italian and foreign), climate; LGBT
Left-wing support (15%)	Medium	Formal	High	Medium (medium optimism; medium anxiety; medium anger)	Positive, Neutral	Low	Politics (Italian and foreign), job, climate
Rejected PP support (15%)	Low	Moderately Formal	Medium	Low (low anger, low anxiety, low optimism)	Neutral, Negative	Medium	Economy, politics (Italian and Foreign)
Not expressed (50%)	Low	Informal	High	Absent	Neutral, Negative	Low	Gossip, Chronicle

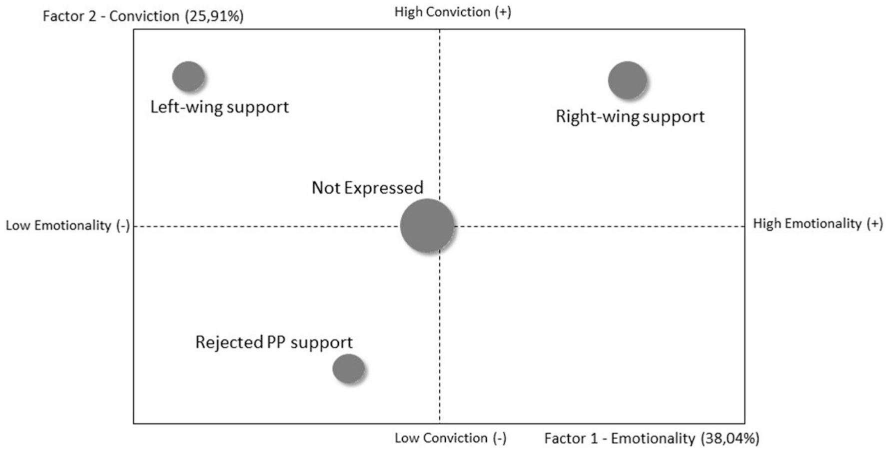

Fig. 1 Clusters on the factorial plane from ACM (axes 1–2)

emotionality of communication, which tends to be positive and optimistic and expressed in more formal language. Convictions toward positions expressed on issues such as work, politics, and the environment remain high. Low involvement and low conviction instead characterize users who reject a political orientation (15%) (Fig. 1).

Projecting clusters of users at a factorial level, it becomes clear how much political positions—with varying degrees of conviction and emotion—polarize and differentiate responses to users' disinformative content in the echo chambers, and thus become a guiding mechanism in the complex disinformative universe. Furthermore, the polarization of sentiment is not only an important component in the study of the effects of disinformation but also seems to be linked to the support of the populist political orientation and how this negatively affects the users' emotions.

5 The Users' Polarized Narratives in the Disinformative Echo Chambers

To understand in which issues the users' positions are polarized, the narratives of different political orientations have been reconstructed through the visualization of a Markov chain: a common model in Text Mining to establish a semantic-oriented discussion network, where each word depends only on the previous word. To make the network interpretable, it was chosen to show only the most common word-to-word connections by setting a different frequency threshold for each user group (Fig. 2).

The narrative carried out by right-wing users in disinformative echo chambers can be summarized into six elements that are characterized by strong radicalization

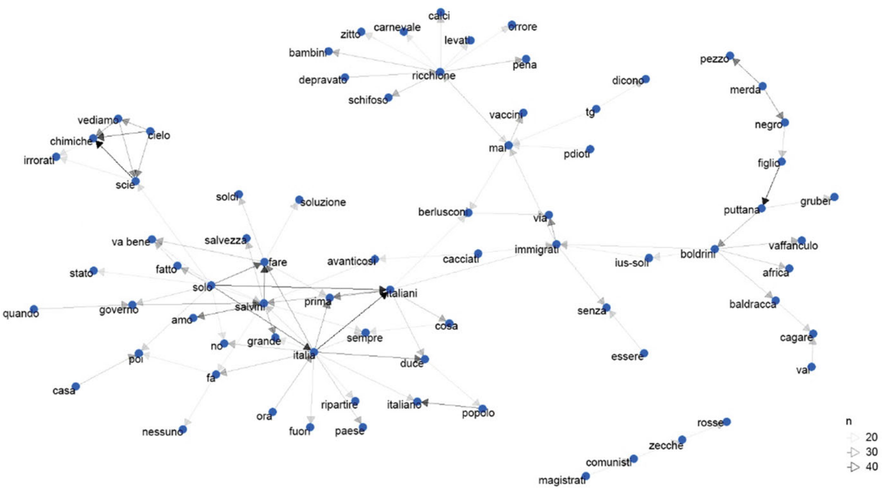

Fig. 2 Markov chain. Narrative of right-wing users (word frequency ≥ 20). Italian idiom

and frequent references to hatred: nationalism, conspiracy, homophobia, racism, misogyny, and political opposition. In the central part of the network, the nationalist consciousness is supported by the figure of Salvini and taken to extremes by the fascist drift evidenced by the presence of the word “Duce” (Mussolini); the same pro-Salvini nationalist soul that detaches itself from the old right-wing politics is testified by the succession of words “Italy,” “Berlusconi,” “via” (go home). The conspiracy element is located in different parts of the network: on the left is the narrative linked to chemtrails, characterized by the words “cielo” (sky), “vediamo” (let’s see), “irrorate” (sprayed), “scie” (trails), “chimiche” (chemicals. On the right of the network, however, the conspiracy narrative focuses on the topic of vaccines “mai,” “vaccini” (never vaccines) and mainstream information “mai,” “notizie,” and “dicono” (never, news, they say). The extremism of the right-wing positions is testified by the homophobic element on the upper part of the network, characterized by the semantic universe that leads to violence and hate speech “ricchione” (faggot), “schifoso“ (lousy), ”depravato“ (depraved), “bambini” (children), “orrore” (horror), “calci” “kick”, and “levati” (get up”). Violence and hatred are also poured out toward immigrants, underlining a racist attitude “negro” (nigga), “pezzo” (piece), “shit” (merda), “figlio” (son), “puttana” (whore) and toward women, where hatred targets two female figures: Laura Boldrini (left-wing politics), linked to traditional and opposition politics (anti-establishment attitude) and Lilli Gruber (journalist), linked to the world of mainstream information (users’ skepticism toward the media). Finally, the clique at the bottom of the network expresses an anti-elitist political opposition that is also negatively polarized and given by the presence of the word “magistrate” (magistrates) linked to “comunisti” (communists), “zecche rosse” (reds ticks), typical insult against those with leftist political positions (Fig. 3).

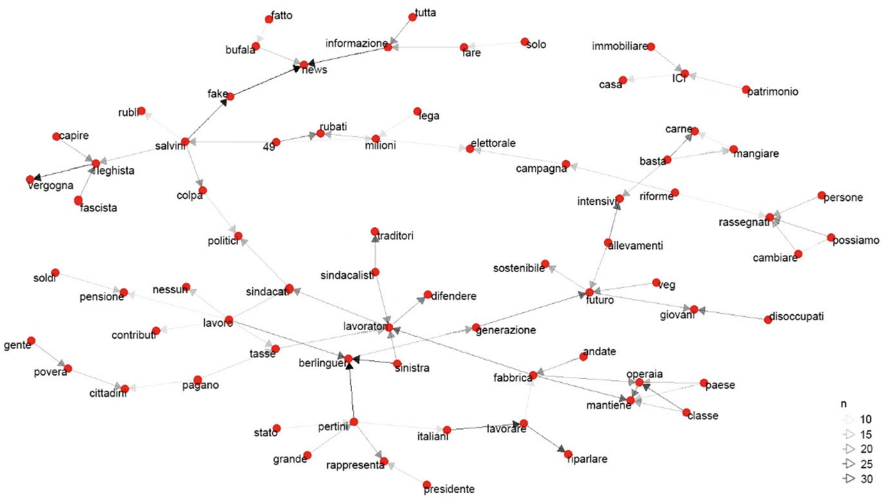

Fig. 3 Markov chain. Narrative of left-wing users (words frequency ≥ 10). Italian idiom

The narrative shared by left-wing users appears moderate, not very radicalized, and rather positive. It is characterized by five elements: the reference to the historical left, the condition of the workers, the detachment from the trade unions, a vision of a sustainable future, and the awareness of disinformation. The strong reference to the Italian historical left is visible in the central part of the network and well represented by the semantic group "Berlinguer," "Pertini," "great," "President," in turn linked by the word "labor" to its traditional battles: "tasse," "pensioni," "povertà," "operai" (taxes, pensions, poverty, and working class), upon which the burdens of the country and the conditions in the "fabbriche" (factories) would fall. Users detach themselves completely from the historical institution of the trade union and from the role of the trade unionist, considered a traitor to the workers. Looking toward the future features strongly and visibly at the top right of the network, referring to the issues of environmental sustainability but also to the concerns about rampant youth unemployment. From the word "riforma" (reform) opens a semantic group "persone," "possiamo," "cambiare," and "rassegnato" (people, we can, change, resigned) that refers to a positive vision toward change, possible only collectively and by overcoming feelings of resignation. The political opposition is above all toward Salvini and his party (Lega), of which their fascist positions are condemned. Low radicalization can also be seen in this context, however, the semantic universe of political opposition never flows into a language of hatred, as it does in the political position referred to previously. The most interesting thing that emerges from this narrative is the awareness of disinformation that opens starting from the word "Salvini" (right-wing Italian politician), as if to attribute the blame for it to him. The presence of high-frequency words such as "fake," "news," "bufala (another Italian word meaning fake news), "informazione" (information), and "fatto" (fact) refers to the practice of commenting on disinformative contents

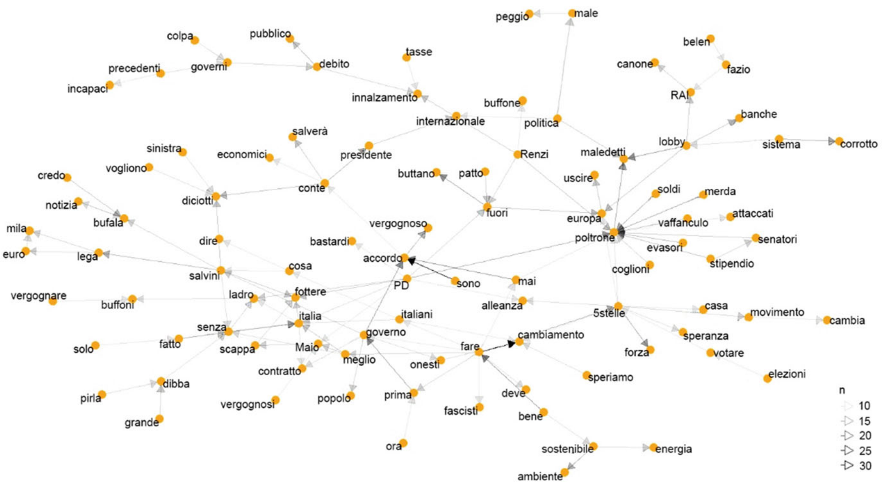

Fig. 4 Markov chain. Narrative of users rejecting political orientation (frequency $\geq$ 10). Italian idiom

by signaling them as fakes. This awareness is absent in the network discussed previously (Fig. 4).

The narrative of users who reject a political location is more polarized than the previous one but less polarized of right-wing users. The topics covered are many and concern anti-establishment, anti-elite, and pro-environmentalism positions. Users seem to split into two positions: on the one hand, opposition toward the PD (left party) and the Lega (right party), which results in both cases in a refusal of any government pact, and, on the other, sympathy toward President Conte, who symbolizes of this pact. On the right side of the network, negatively polarized language underlines the anti-establishment sentiment which, with the word "poltrone" (armchairs)—expression used to make people understand the attachment to their privileged place that these people defend at all costs—opens a semantic whole that refers to theme of senators' salaries and tax evasion. From the word "poltrone" there also opens anti-European sentiment: "uscire," "italexit" (going out, italexit), and anti-elitist: "lobby," "banche," "sistema-corrotto," and "politica-internazionale" (lobby, banks, corrupt-system, international-politics). RAI (Italian State TV) is also included in these lobbies, whose governance reform is one of the cornerstones of Movimento 5 Stelle. This political opposition focuses on blaming previous governments for public debt and the inability to improve the conditions of the country. A particularly harsh attack is aimed above all at Matteo Renzi's PD. The two souls of the movement emerge clearly: the one in favor of Conte, expressed by a very positive semantic set: "presidente-salverà" (president-will save); and the opposite, as testified by the words "contratto-vergogna," "accordo-vergognoso" (contract-shame, agreement-shameful), and the clique above in which there is a pessimism toward the second Conte government. Attention to environmentalism

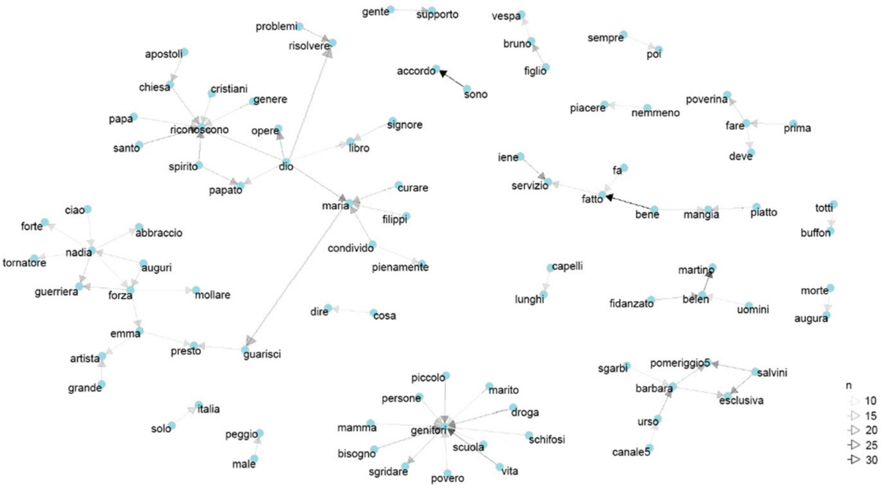

Fig. 5 Markov chain. Narrative of users who do not express political orientation (frequency ≥ 10). Italian idiom

has positive semantics, featuring the terms "sostenibile," "energia," "ambiente," and "rivoluzione-verde" (sustainable, energy, environment, green revolution). The narrative toward Salvini (on the right of the network) branches out in three directions with different feelings: on the story of the Diciotti ship, the positions of the users seem rather in agreement with the line of the League, considering their use of words very close to the communication strategies of Salvini, such as "sinistra-buonista" (left-feelgood), "sinistra-vogliono-immigrati (left-want-immigrants); the disagreement with Salvini is expressed instead by the accusation of fascism and with the question of the 49 million euros stolen by the party. The interesting thing is the presence (once again) of the theme of fake news linked to Salvini (Fig. 5).

With this last network, it is clear that users who comment on content without expressing political positions have opinions that are not radicalized and expressed with a rather neutral sentiment. The topics of discussion are generic and related to the Church, the family, and characters in TV shows such as "Nadia" (Nadia Toffa), "Emma" (Emma Marrone) and "Belen," "Barbara D'Urso" (well-known personalities of Italian TV.

6 First Conclusions and Future Work

Through this methodology, we can say that we have made a gradual and tentative exploration of disinformative echo chambers. By focusing our study inside these disinformation echo chambers, it emerges that disinformation is moderately associated with support for populist communication. In this regard, we can refer to echo chambers as chambers of political similarity both in information (first level of analysis) and in discussion (second level of analysis). In the light of what has emerged, it is possible to provide disinformation with another interpretative aspect, framing it in terms of an ideological split. The work certainly has limits, but the use of different approaches to opinion mining, the construction of a hybrid approach, and the subsequent multidimensional analyzes were useful to point out empirically how the political positions of the users are the guiding mechanism of users in the complex disinformative universe, and also what differentiates them in the consumption of false content. Furthermore, our analysis shows that disinformative content and media populism feed the same type of topics and sometimes overlap. Populist arguments reflect the values, opinions and sometimes frustrations of users, contributing to the consolidation of misperceptions about political facts and perceptions out-groups by harboring stereotypes and attributing blame. These are also characteristics that emerged in the disinformative messages that generate a mobilizing effect on users who share anti-establishment, anti-immigrant, and anti-media sentiments. As they are received, heated debates are triggered that at times become offensive. In fact, the second element common to disinformation and populism is the use of emotions. Populist communication constructs messages that trigger very powerful emotional responses such as anger and hatred in users; the emotional and provocative nature of much disinformative content makes users indignant and favors the consolidation of an in-group identity (of those who think the same things) that radicalizes their opinions. Another connection to emerge is that emotionality is also related to virality: similar world views and a high belief in one's own positions are sufficient elements to viralize content that spreads thanks to the support of homophilic environments.

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