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Bovet, Alexandre; Makse, Hernan A.

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Influence of fake news in Twitter during the 2016 US presidential election

Alexandre Bovet[1,2,3], Hernán A. Makse[3]

1) naXys and Department of Mathematics, Université de Namur, Rempart de la Vierge 8, 5000 Namur, Belgium.

2) ICTEAM, Université Catholique de Louvain, Avenue George Lemaître 4, 1348 Louvain-la-Neuve, Belgium

alexandre.bovet@unamur.be

3) Levich Institute and Physics Department, City College of New York, New York, New York 10031, USA

Abstract

We investigate the influence of fake and traditional, fact-based, news outlets on Twitter during the 2016 US presidential election. Using a comprehensive dataset of 171 million tweets covering the five months preceding election day, we identify 30 million tweets, sent by 2.2 million users, which are classified as spreading fake and extremely biased news, based on a list of news outlets curated from independent fact-checking organizations, and traditional news from right to left. We find that 29% of these tweets disseminate fake or extremely biased news. We fully characterize the networks of users spreading fake and traditional news and find the most influential users. Contrary to traditional news, where influencers are mainly journalists or news outlets with verified Twitter accounts, e.g. @FoxNews and @CNN, the majority of fake news influencers have unverified or deleted accounts. In particular, accounts with seemingly deceiving profiles are found among the top fake and extremely biased influencers. We find that the three top influencers spreading (i.e. re-tweeting) fake news websites are @PrisonPlanet, @RealAlexJones and @zerohedge and re-tweeting extremely bias news websites are @realDonaldTrump, @DailyCaller and @BreitbartNews. To understand how fake news influenced Twitter opinion during the presidential election, we perform a Granger-causality test between the time series of activity of influencers and the supporters of each presidential candidate: Trump and Clinton. Two different news spreading mechanisms are revealed: *(i)* The influencers spreading traditional center and left leaning news largely determine (Granger-cause) the opinion of the Clinton supporters. *(ii)* Remarkably, this causality is reversed for the fake news: the opinion of Trump supporters largely Granger-causes the dynamics of influencers spreading fake and extremely biased news.

1 Introduction

Recent social and political events, such as the 2016 US presidential election [1], have been marked by a growing number of so-called "fake news", i.e. deliberate misinformation, shared on social media platforms. While misinformation and propaganda have existed since ancient times [2], their importance and influence in the age of social media is still not clear. Indeed, massive digital misinformation has been designated as a major technological and geopolitical risk by the 2013 report of the World Economic Forum [3]. A substantial number of studies have recently investigated the phenomena of misinformation in online social networks such as Facebook [4–9] Twitter [10, 11], YouTube [12] or Wikipedia [13]. These investigations, as well as theoretical modeling [14,15], suggest that confirmation bias [16] and social influence results in the emergence, in online social networks, of user communities with homogeneous beliefs, i.e. echo chambers, where unsubstantiated claims are as likely to propagate virally than other information [6, 17]. A comprehensive investigation of the spread of true and false news in Twitter also showed that false news is characterized by a faster and broader diffusion than true news mainly due to the attraction of people to the novelty of false news [11]. The polarization in communities is also observed in the consumption of news in general [18, 19] and corresponds with political alignment [20]. Recent works also revealed the role of bots, i.e. automated accounts, in the spread of misinformation [11, 21, 22]. In particular, Shao *et al.* [23] found that, during the 2016 US presidential election on Twitter, bots were responsible for the early promotion of misinformation and that they targeted influential users through replies and mentions. These results have raised the question of whether such misinformation campaigns could alter public opinion and endanger the integrity of the presidential election [22].

Here, we use a dataset of 171 million tweets sent by 11 million users covering almost the whole activity of users regarding the two main US presidential candidates, Hillary Clinton and Donald Trump, collected during the five months preceding election day. This dataset was collected using the Twitter Search API using the two following queries: *trump OR realdonaldtrump OR donaldtrump* and *hillary OR clinton OR hillaryclinton* and was used to extract and analyze Twitter opinion trend in our previous work [24]. Instead of investigating a set of specific true or false stories as has been done in several previous work [5, 11, 25], we are interested in the differential influence of the entire media landscape on Twitter activity. We compare the spread of news coming from websites known to display fake news with the spread of news coming from traditional, fact-based, news outlets with different political orientations. We investigate the diffusion in Twitter of each type of media to understand what is their relative importance, who are the news influencers and how they drive the dynamics of Twitter opinion.

We find that, among the 30 million tweets containing an URL directing to a news outlet website, 29% point toward websites containing fake news, conspiracy theory or extremely biased news. In order to estimate the importance of automated accounts, We separate tweets posted from official Twitter clients from the other third-party clients (non-official clients). Third-party clients represents a variety of applications, form applications mainly used by professional for automating some tasks (e.g. `www.sprinklr.com` or `dlvrit.com`) to manually programmed bots, and are used to post $\leq 8\%$ of the total number of tweets. When considering only tweets originating from non-official Twitter clients, we see a tweeting rate for users tweeting links to websites containing fake news more than four times larger than for traditional media, suggesting a larger role of bots in the diffusion of fake news. We classify 30 million tweets with URLs according to the type of media they direct to. Based on a professionally curated list of online information sources (available at `www.opensources.co`), we consider two categories of misinformation, *fake news* and *extremely biased news*, and we separate the traditional, fact-based, news outlets in five categories according to their political orientation. We detail our classification in Section (2.1). We reconstruct the information flow networks by following retweets tree for each type of media. We find that user diffusing fake news form more connected networks with less heterogeneous connectivity than users in traditional news diffusion networks. While influencers, identified using collective influence algorithm [26], of traditional news outlets are journalists and public figures with verified Twitter accounts, we find that a large number of influencers of fake news and extremely biased websites are unknown users or users with deleted Twitter accounts. The activity of each candidate supporters is measured thanks to a machine learning approach previously validates in Ref. [24]. The presence of two clusters of media sources and their relation with the supporters of each candidate is revealed by the analysis of the correlation of their activity. Finally, we explore the dynamics between the influencers and the supporters activity with a Granger-causality analysis. Granger-causality allows to estimate how the information in a first time series can be used to predict future values of a second time series [27]. We find two different mechanisms for the dynamics of fake news and traditional news. For traditional news, we find that the influencers of center and left-leaning news outlets, who are mainly journalists, are driving the activity of Clinton supporters, who represent the majority in Twitter [24]. For fake and extremely biased news, we find that it is the activity of Trump supporters that governs their dynamics and influencers of fake and extremely biased news are merely following it.

Using a novel approach, we show the polarization of the users' activity in different clusters and we provide new insights into the dynamics of news diffusion, the role of media influencers and the importance of misinformation on Twitter opinion dynamics.

2 Results

2.1 News spreading in Twitter

To characterize the spreading of news in Twitter we analyze all the tweets in our dataset that contained at least one URL (Uniform Resource Locator, i.e. web addresses) linking to a website outside of Twitter. We first separate URL in two main categories based on the websites they link to: websites containing misinformation and traditional, fact-based, news outlets. We use the term traditional in the sense that news outlets in this category follow the traditional rules of fact-based journalism and therefore also include recently created news outlets (e.g. `vox.com`). Classifying outlets as spreading misinformation or reliable information is inherently subject to a level of subjectivity and imprecision that should be kept in mind when interpreting our results. We include a finer classification of news outlets spreading misinformation in two sub-categories: *fake news* and *extremely biased news*. We base our classification of misinformation websites on a curated list of fake, false, conspiratorial, and misleading news websites compiled by a research team of Merrimack College, USA, freely available at `www.opensources.co`. Fake news websites are websites that have been flagged as spreading fabricated news or conspiracy theories by several fact-checking groups. Extremely biased websites include more controversial websites that do not necessarily publish fabricated information but "distort facts and may rely on propaganda, decontextualized information, or opinions distorted as facts" (see `www.opensources.co`). Opensources.co classify websites by analyzing several aspects, such as if they try to imitate existing reliable websites, if they were flagged by fact-checking groups (`www.snopes.com`, `www.hoax-slayer.net` or `www.factcheck.org`), or by analyzing the sources cited in articles (the full explanation of their methods is available at `www.opensources.co`). More details about our classification of websites spreading misinformation is available in the Methods section.

We also use a finer classification for traditional news websites based on their political orientation. We identify the most important traditional news outlets by manually inspecting the list of top 150 URL's hostnames, representing 71% of all URLs, shared on Twitter. We only take into account the top 150 hostnames since adding a less popular hostnames would change the total amount of considered URLs by less than 0.2%. Based on information from the websites `www.allsides.com`, which rates media bias using a combination of several methods such as blind surveys, community feedback and independent research (see `www.allsides.com/media-bias/media-bias-rating-methods` for a detailed explanation of the media bias rating methodology used by AllSides), and `mediabiasfactcheck.com`, which scores media bias by evaluating wording, sourcing and story choices as well as political endorsement (see `mediabiasfactcheck.com/methodology/` for an explanation of Media Bias Fact Check methodology), we classified each news outlet according to their political orientation in the following five categories: left, left-leaning, center, right-leaning and right. The detail of our classification could be discussed, for example some media that we considered as center may be thought to be left-leaning or some left-leaning media could be classified as left, and this fact has to be kept in mind while interpreting our results. However, as we will see, the details of the media political classification do not influence greatly our results as we see patterns encompassing several media categories emerging.

We report the hostnames in each categories along with the number of tweets with a URL pointing toward them in Tables 6 and 7. Using this final separation in seven classes, we identify in our dataset (we give the top hostname as en example in parenthesis): 330 hostnames corresponding to fake news websites (e.g. `thegatewaypundit.com`), 110 hostnames for extremely biased news websites (e.g. `breitbart.com`), 13 hostnames for left news websites (e.g. `huffingtonpost.com`), 17 hostnames for left leaning news websites (e.g. `nytimes.com`), 15 hostnames for center news websites (e.g. `cnn.com`), 2 hostnames for right leaning websites (e.g. `washingtontimes.com`) and 13 hostnames for right websites (e.g. `foxnews.com`). We only found two media websites in the right leaning category, which reflects the fact that right medias seem to have a stronger polarization than left media on Twitter. Consequently, we group right leaning and right media in a unique category during our analysis.

We identified 30 million tweets with an URLs directing to a news outlet website, sent by 2.2 million users. An important point when comparing the absolute number of tweets and users contributing to the spread of different types of news is the bias introduced by the keywords selected during the data collection. Indeed, if we had used keywords or targeting specific news outlets or hashtags concerning specific news event, it would be impossible to perfectly control the bias toward fake and reliable news or the political orientation representation of the tweet sample. Here, we used neutral keywords in term of media representation, the names of the two main candidates to the presidential election (see Methods), in order to collect a sample representative of the real coverage of the election on Twitter by all media sources.

Table 1 shows the number of tweets and the number of users having sent tweets with a URL pointing to a website belonging to one of the seven media categories we defined. Figure 1 shows the number of tweets and users grouped in four categories: fake & extremely biased news, right & right leaning news, center news and left & left leaning news. We see a large number of tweets linking to fake news websites, 3.8 million, and extremely biased news websites, 4.7 million. However, the majority of tweets linking to news outlets points toward left leaning news websites, 7.1 million, closely followed by center news websites with 6.8 million. Tweets directing to left and left leaning news websites represent together 35% of the total and tweets directing towards center news outlets represents 32% (see Fig. 1a). Tweets directing to fake and extremely biased news websites representing a considerable share of 29%. When considering the number of distinct users having sent the tweets instead of the number of tweets, the share of left and left leaning websites increases to 42% and the share of center news to 32%, while the share going to fake news and extremely biased news is equal to 14% (see Fig. 1b). Our first results show that the number of tweets linking to websites producing fake and extremely biased news is comparable with the number for center, left and left leaning media outlets. However, when taking into account the heterogeneous activity of users, a different picture

	N_t	p_t	N_u	p_u	N_t/N_u	$p_{t,n/o}$	$p_{u,n/o}$	$N_{t,n/o}/N_{u,n/o}$
fake news	3 837 826	0.13	248 937	0.06	15.42	0.19	0.04	79.32
extremely biased news	4 698 708	0.16	374 387	0.10	12.55	0.09	0.03	33.31
right news	3 419 828	0.12	388 150	0.10	8.81	0.10	0.04	22.11
right leaning news	272 395	0.01	91 720	0.02	2.97	0.14	0.05	8.30
center news	6 774 099	0.23	1 062 149	0.27	6.38	0.18	0.04	27.01
left leaning news	7 137 544	0.24	1 214 721	0.31	5.88	0.13	0.04	17.91
left news	3 241 973	0.11	539 800	0.14	6.01	0.12	0.05	14.01

Table 1: Tweet and user volume corresponding to each media category in Twitter. Number, N_t, and proportion, p_t, of tweets with a URL pointing to a website belonging to one of the seven media categories. Number, N_u, and proportion, p_u, of users having sent the corresponding tweets, and average number of tweets per user, N_t/N_u, for each category. Proportion of tweets sent by non-official clients, $p_{t,n/o}$, proportion of users having sent at least one tweet from an non-official client, $p_{u,n/o}$, and average number of tweets per user sent from non-official clients, $N_{t,n/o}/N_{u,n/o}$.

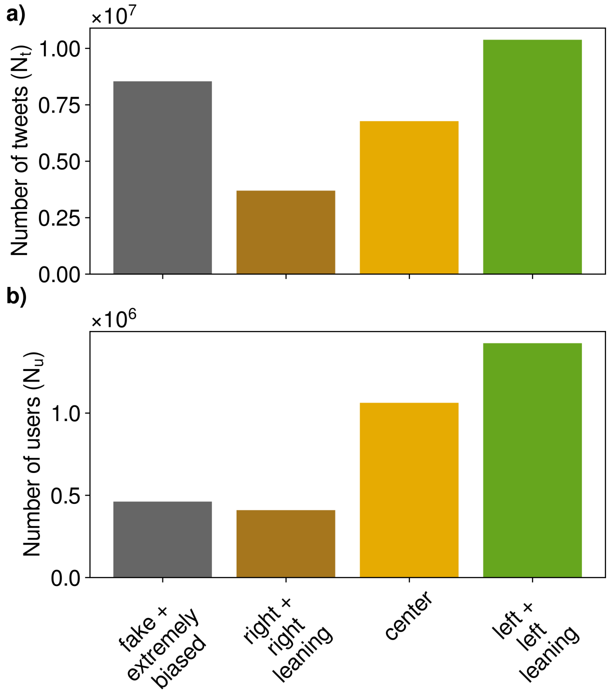

Figure 1: Importance of different types of news outlets in Twitter. Number of distinct tweets (a) and number of distinct users having sent tweets (b) with a URL pointing to a website belonging to one of following categories: fake or extremely biased, right or right leaning, center and left or left-leaning news outlets. While the tweet volume of fake and extremely biased news is comparable to the tweet volumes of center and left & left volume (a), users posting fake and extremely biased news are around twice more active (see Tab. 1). Consequently, the share of users posting fake and extremely biased news (b) is smaller (14%) than the share of tweets directing toward fake and extremely biased news websites (29%).

emerges. Indeed, users posting links to fake news or extremely biased websites are, in average, more active than users posting links to other news websites (see Tab. 1). In particular, they post around twice the number of tweets compared to users posting links towards center or left leaning news outlets.

Table 1 also shows the proportion of tweets sent by, and users using, non-official Twitter clients. This allows to evaluate the importance of automated posting in each category. We detail our classification of official Twitter clients in the Methods. We see that the two top categories are fake news and center news with almost 20% of tweets being sent from non-official accounts. When considering the proportion of users sending tweets from non-official clients, the number are very similar for all categories, around 4%, showing that the automation of posting plays an important role across media categories. Indeed, non-official clients includes a broad range of clients, from “social bots” to applications used to facilitate the management of professional Twitter accounts. However, a large discrepancy between sources arises when we consider the average number of tweets per users sent from non-official clients (see Tab. 1). Users using non-official clients to send tweets with links directing to websites displaying fake news tweeted an average of 79.32 times during the collection period, which is more than twice the value for other types of news outlets. This high activity from non-official clients suggest an abnormal presence of bots. The role of bots in the diffusion of fake news has already been documented [23] as well as their presence in the Twitter discussions during 2016 US election [22] using a machine learning classification to detect bots [28].

2.2 Networks of information flow

To investigate the flow of information we build the retweet networks for each category of news websites, i.e. when a user u retweets (a retweet allows a user to rebroadcast the tweet of an other user) the tweet of a user v that contains a URL linking to a website belonging to one of the news media category, we add a link, or edge, going from node v to node u in the network. We do not consider multiple links with the same direction between the same two users and neither consider self-links, i.e. when a user retweet her/his own tweet. Directed links of such networks represent the flow of information between Twitter users. The out-degree of a node is its number of out-going links and is equal to the number of different users that have retweeted at least one of her/his tweets. Its in-degree is its number of in-going links and represents the number of different users she/he retweeted.

Figure 2 shows the networks formed by the top 100 influencers of each retweet graph. We explain in Section (2.3) and in the Methods how the influencers are identified. The characteristics of each retweet graphs are shown in Table 2. A clear difference is apparent between the graphs representing the flow of fake and extremely biased news and the graphs for left, left leaning and center news. The left, left leaning and center news outlets correspond to larger networks in term of number of nodes and edges, revealing their larger reach and influence in Twitter. However the retweet networks corresponding to fake and extremely biased news outlets are the most dense with an average degree $\langle k \rangle$ between 6 and 7, more than twice the number for left, left leaning and center news. The retweet network for right & right leaning news has characteristics in between those two groups with a slightly larger size than the networks for fake and extremely biased news and a larger average degree than left, left leaning and center news. These results show that users spreading fake and extremely biased news, although in smaller numbers, are not only more active in average, as shown in Tab. 1, but also more connected indicating that the audience of fake and extremely biased news form tighter community structures which may facilitate the spread of misinformation among themselves. Table 2 also shows that the center and left leaning networks have the most heterogeneous out-degree distribution and the fake news retweet networks has the less heterogeneous out-degree distribution. The heterogeneity of the degree distribution plays an important role in spreading processes on networks as a larger degree heterogeneity indicates the presence of high degree nodes that accelerate the diffusion in the entire networks [29,30]. This suggests that different mechanisms of information diffusion could be at play in the center and left leaning news networks, where high degree nodes may play a more important role, than in the fake and extremely biased news networks.

	N nodes	N edges	$\langle k \rangle$	$\sigma(k_{\text{out}})/\langle k \rangle$	$\sigma(k_{\text{in}})/\langle k \rangle$	$\max(k_{\text{out}})$	$\max(k_{\text{in}})$
fake news	207 222	1 465 265	7.07	28 ± 2	2.70 ± 0.03	42 977	1232
extremely biased	306 919	1 953 136	6.36	34 ± 4	2.80 ± 0.02	51 845	648
right & right leaning	337 772	1 665 718	4.93	47 ± 8	2.68 ± 0.02	84 739	464
center	894 899	2 762 013	3.09	92 ± 38	2.80 ± 0.04	229 605	559
left leaning	998 438	3 416 201	3.42	67 ± 17	3.36 ± 0.06	145 047	826
left	421 415	1 320 756	3.13	50 ± 10	3.42 ± 0.05	58 832	622

Table 2: Retweet networks characteristics for each news source categories. We show the number of nodes and edges (links) of the networks, the average degree, $\langle k \rangle = \langle k_{\text{in}} \rangle = \langle k_{\text{out}} \rangle$, (the in-/out-degree of a node is the number of in-going/out-going links attached to it). The out-degree of a node, i.e. a user, is equal to the number of different users that have retweeted at least one of her/his tweets. Its in-degree represents the number of different users she/he retweeted. The ratio of the standard deviation and the average of the in- and out-degree distribution, $\sigma(k_{\text{in}})/\langle k \rangle$ and $\sigma(k_{\text{out}})/\langle k \rangle$, measures the heterogeneity of the connectivity of each networks. As the standard deviation of heavy-tailed degree distributions can depend on the network size, we computed the values of $\sigma(k_{\text{in}})/\langle k \rangle$ and $\sigma(k_{\text{out}})/\langle k \rangle$ by taking the average, and standard error, of 1000 independent samples, of 200 000 values each, drawn from the in- and out- degree distributions of each network.

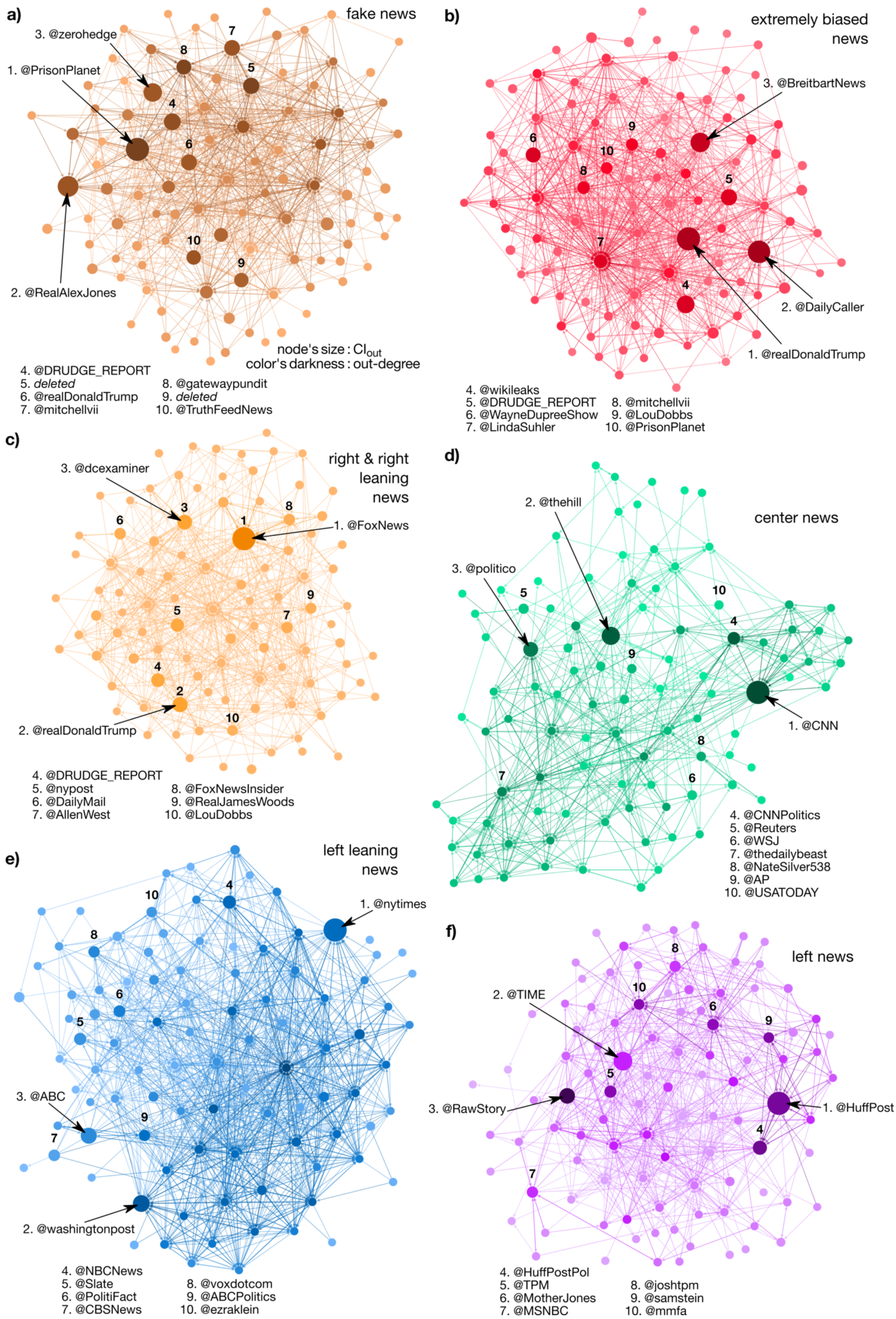

Figure 2: Retweet networks formed by the top 100 influencers of each media category. Retweet networks for fake news (a), extremely biased news (b) right & right leaning news (c), center news (d), left leaning news (e) and left news (f) showing only the top 100 influencers ranked according to their collective influence. The direction of the links represents the flow of information between users. The size of the nodes is proportional to their CI_{out} values and the shade of the nodes' color represents their out-degree from dark (high out-degree) to light (low out-degree). The network of fake (a) and extremely biased (b) are characterized by a connectivity that is larger in average and less heterogeneous than for networks of traditional news (see also Tab. 2).

The difference in degree heterogeneity is also visible in the difference between the in- and out-degrees maxima. The out-degree maxima of the center and left leaning news graphs are the largest revealing the existence of highly retweeted users, while it is the fake news graph that has the largest in-degree maximum due to the presence of a user having retweeted more than 1000 other users posting links toward fake news websites. While inspecting specific accounts is not the goal of this study, looking at the two accounts with the maximum k_{out} and k_{in} reveals an interesting contrast between users of both graphs. The user with the largest out-degree of the center news graph is the verified account of the Cable News Network, CNN, (*@CNN*), which posts regularly links towards its own website using mainly the non-official professional client Sprinklr (`www.sprinklr.com`). The user with the largest in-degree of the fake news graph is the user *@Patriotic_Folks*, which, at the moment of this writing, seems to belong to a fake, or at least deceiving user, whose profile description contains the hashtag *#MAGA* and refer to a website belonging to our fake news website list (`thetruthdivision.com`). The name of the account is "Annabelle Trump" and its profile picture is a young woman wearing cow-boy clothes (a reverse image search on the web reveals that this profile image is not authentic as it comes in fact from the catalog of a website selling western clothes). Most of its tweet are sent from the official Twitter Web Client, suggesting that a real person is managing the account, and contains URLs directing to the same fake news website. However, having a high in-degree does not indicate that this user has an important influence. Indeed, its out-degree is approximately 3.5 times smaller than its in-degree and, as we explain in the next section, influence is poorly measured by local network properties such as in- or out-degree.

2.3 Media influencers

In order to uncover the most influential users of each retweet network, we use the Collective Influence (CI) algorithm [26] which is based on the solution of the optimal network percolation, i.e. the problem of finding the minimal number of nodes to remove in order to destroy the network's giant component. The CI algorithm considers influence as an emergent collective property, not as a local property such as the node's degree, and has been shown to be able to identify super-spreaders of information in social networks [31, 32]. We apply here the CI algorithm to directed networks, by only considering the out-degree of a node and therefore identifying the most influential sources of information in each networks (see Methods). For a Twitter user to be highly ranked by the CI algorithm, she/he does not necessarily need to be directly retweeted by many users, but she/he needs to have several highly retweeted users at close network distance from her/him (see Methods).

Table 3 shows the top 25 influencers, ranked using CI, for each media category. The top influencers for each category are: @PrisonPlanet for fake news, @realDonaldTrump for extremely biased, @FoxNews for right & right leaning, @CNN for center, @nytimes for left leaning and @HuffPost for left news. A check-mark (✓) is added next to the accounts that are verified by Twitter. Verifying its accounts is a feature offered by Twitter, that "lets people know that an account of public interest is authentic" (`help.twitter.com/en/managing-your-account/about-twitter-verified-accounts`). We also show the number of verified, unverified and deleted accounts among the top 100 influencers of each category in Fig. 3 and the networks they form are shown in Fig. 2.

We find that top influencers of left, left-leaning and center news are almost uniquely verified accounts belonging to news outlets or journalists. A very different situation for influencers of the fake news and extremely biased news websites is revealed, where, among official accounts of websites and journalists, we also find a large number of unknown, unverified, users that are not public figures but are important influencers in Twitter. We also find deleted accounts, that could have been deleted either by Twitter for infringing their rules and policies or by the users themselves, in the fake and extremely biased news influencers. The list of the right & right leaning news top influencers form a mix of verified

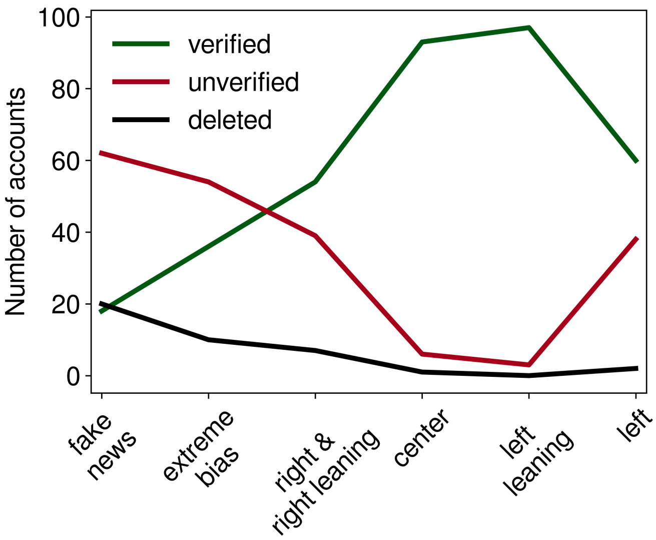

Figure 3: Types of top influencers accounts per media category. Proportion of verified (green), unverified (red) and deleted (black) accounts among the top 100 influencers in each media category.

rank	fake news (7 verified, 2 deleted, 19 unverified)	extremely biased news (14 verified, 1 deleted, 10 unverified)	right & right leaning news (22 verified, 0 deleted, 3 unverified)
1	@PrisonPlanet ✓	@realDonaldTrump ✓	@FoxNews ✓
2	@RealAlexJones ✓	@DailyCaller ✓	@realDonaldTrump ✓
3	@zerohedge	@BreitbartNews ✓	@dcexaminer ✓
4	@DRUDGE_REPORT	@wikileaks ✓	@DRUDGE_REPORT
5	deleted	@DRUDGE_REPORT	@nypost ✓
6	@realDonaldTrump ✓	@WayneDupreeShow ✓	@DailyMail ✓
7	@mitchellvii ✓	@LindaSuhler	@AllenWest ✓
8	@gatewaypundit ✓	@mitchellvii ✓	@FoxNewsInsider ✓
9	deleted	@LouDobbs ✓	@RealJamesWoods ✓
10	@TruthFeedNews	@PrisonPlanet ✓	@LouDobbs ✓
11	@RickRWells	@FreeBeacon ✓	@KellyannePolls ✓
12	@V_of_Europe	@DonaldJTrumpJr ✓	@foxandfriends ✓
13	@Lagartija_Nix	@benshapiro ✓	@WashTimes ✓
14	@DonaldJTrumpJr ✓	@gerfingerpoken	@PrisonPlanet ✓
15	@ThePatriot143	@TeamTrump ✓	@TeamTrump ✓
16	@infowars	@Italians4Trump	@wikileaks ✓
17	@KitDaniels1776	deleted	@FoxBusiness ✓
18	@Italians4Trump	@KellyannePolls ✓	@IngrahamAngle ✓
19	@_Makada_	@JohnFromCranber	@LifeZette ✓
20	@BigStick2013	@DanScavino ✓	@theblaze ✓
21	@Miami4Trump	@gerfingerpoken2	@foxnewspolitics ✓
22	@JayS2629	@ThePatriot143	@BIZPACReview
23	@conserv_tribune ✓	@true_pundit	@TheLastRefuge2
24	@MONAKatOILS	@ARnews1936	@JasonMillerinDC ✓
25	@ARnews1936	@Lagartija_Nix	@DonaldJTrumpJr ✓

rank	center news (24 verified, 0 deleted, 1 unverified)	left leaning news (25 verified, 0 deleted, 0 unverified)	left news (21 verified, 0 deleted, 4 unverified)
1	@CNN ✓	@nytimes ✓	@HuffPost ✓
2	@thehill ✓	@washingtonpost ✓	@TIME ✓
3	@politico ✓	@ABC ✓	@RawStory ✓
4	@CNNPolitics ✓	@NBCNews ✓	@HuffPostPol ✓
5	@Reuters ✓	@Slate ✓	@TPM ✓
6	@WSJ ✓	@PolitiFact ✓	@MotherJones ✓
7	@thedailybeast ✓	@CBSNews ✓	@MSNBC ✓
8	@NateSilver538 ✓	@voxdotcom ✓	@joshtpm ✓
9	@AP ✓	@ABCPolitics ✓	@samstein ✓
10	@USATODAY ✓	@ezraklein ✓	@mmfa ✓
11	@business ✓	@guardian ✓	@DavidCornDC ✓
12	@AP_Politics ✓	@nytpolitics ✓	@dailykos ✓
13	@bpolitics ✓	@NYDailyNews ✓	@thinkprogress ✓
14	@FiveThirtyEight ✓	@BuzzFeedNews ✓	@JuddLegum ✓
15	@DRUDGE_REPORT	@Mediaite ✓	@nxthompson ✓
16	@jaketapper ✓	@nytopinion ✓	@ariannahuff ✓
17	@cnnbrk ✓	@CillizzaCNN ✓	@jonathanchait ✓
18	@businessinsider ✓	@HillaryClinton ✓	@blackvoices ✓
19	@AC360 ✓	@MSNBC ✓	@WeNeededHillary
20	@cnni ✓	@KFILE ✓	@activist360
21	@KellyannePolls ✓	@TheAtlantic ✓	@politicususa
22	@BBCWorld ✓	@SopanDeb ✓	@JoyAnnReid ✓
23	@brianstelter ✓	@BuzzFeed ✓	@PoliticusSarah ✓
24	@KFILE ✓	@Newsweek ✓	@aterkel ✓
25	@realDonaldTrump ✓	@Fahrenthold ✓	@mcspocky

Table 3: Top 25 CI influencers of the retweet networks corresponding to each media category. Verified users are in green and have a checkmark (✓) next to their user name. Verifying an accounts is a feature offered by Twitter for public figures. Unverified accounts are shown in red and accounts that have been deleted, either bu Twitter or by the users themselves are shown in black.

and unverified accounts and share many influencers with the lists of fake and extremely biased news influencers. The overlap between the different set of top 100 influencers is given in Tab. 5.

We distinguish three categories of unverified accounts: 1) unverified accounts that are not necessarily misleading or deceiving, for example @zerohedge, @DRUDGE_REPORT or @TruthFeedNews make their affiliation to their respective news websites clear, although their identities or the ones of their websites administrators is not always clear; 2) unverified accounts that make their motif clear in their choice of screen-name, e.g. @Italians4Trump, @Miami4Trump or @WeNeededHillary, although the real identity of the persons behind such accounts is also usually undisclosed; 3) finally, unverified accounts that seem to be real persons with profile pictures and user names, e.g @Lagartija_Nix, @ThePatriot143, @BigStick2013, @LindaSuhler or @gerfingerpoken, but are not public figures. Whether such users are authentic, social bots or fake users operated by someone else is not clear. However, our results show that such users are not present in the top influencers of the center and left-leaning news, while they have a high prevalence in the fake, extremely biased, right and right leaning categories.

2.4 News spreading dynamics

To investigate the news spreading dynamics of the different media categories on Twitter, we analyze the correlations between the time series of tweeting rate measured for each category. The Twitter activity time series are constructed by counting the number of tweets with a URL directing toward a website belonging to each of the media category at a 15 minute resolution. We find that a 15 minute resolution offers a sufficiently detailed sampling of Twitter activity. Indeed, a representative time scale of Twitter activity is given by the characteristic retweet delay time, i.e. the typical time between an original tweet and its retweet. We find that the median time of the retweet delay distribution in our dataset is 1 h 57 min and the distribution has a log-normal shape (first quartile at 20 min and third quartile at 9 h 11 min). We tested the consistency of our results using a resolution of 5 min and 1 h and did not see significant changes. In addition to the activity related to each media group, we also consider the time series of the activity of the supporters of each presidential candidates. Supporters are identified using a combination of machine learning, natural language processing based on the hashtag co-occurrence network [24].

We removed the trend and circadian cycles present in the time series with widely used STL (seasonal-trend decomposition procedure based on Loess) method [33], which is a robust iterative filtering method allowing to separate a time series in seasonal (in this case, daily), trend and remainder components (see Methods). Figure 4 shows examples of the residual component of activity time series for the top 100 left leaning influencers the Clinton supporters, the top 100 fake news influencers and the Trump supporters.

Figure 5a shows the Pearson correlation coefficient computed between the activity time series corresponding to each media group and to the activity of each supporters. The separation of the media sources in two correlated clusters is revealed when using a threshold of $r = 0.50$ on the cross-correlation coefficients. Figure 5b shows the graph obtained when considering only correlation coefficients larger than $r = 0.50$. The first activity cluster (indicated by a red square) comprises the fake, extremely and right & right leaning news with cross-correlation coefficients $0.51 \leq r \leq 0.57$. The second activity cluster (indicated by a blue square) is made of the center, left and left leaning news sources ($0.57 \leq r \leq 0.63$). We observe the following patterns between the media groups and the supporters dynamics: the activity of Clinton supporters has a higher correlation with the second cluster ($0.66 \leq r \leq 0.71$) than with the first one ($0.33 \leq r \leq 0.39$) while the activity of Trump supporters is equally correlated with the two clusters ($0.55 \leq r \leq 0.60$). The total activity of supporters, computed as the sum of the activity of both supporter groups, has a larger correlation with the second cluster ($0.67 \leq r \leq 0.70$) than with the first one ($0.45 \leq r \leq 0.50$), revealing that Clinton supporters dominate Twitter activity.

These results indicate that the media included in the two clusters respond to two different news dynamics and show that the polarization of news observed in previous works [18–20] is also visible in a

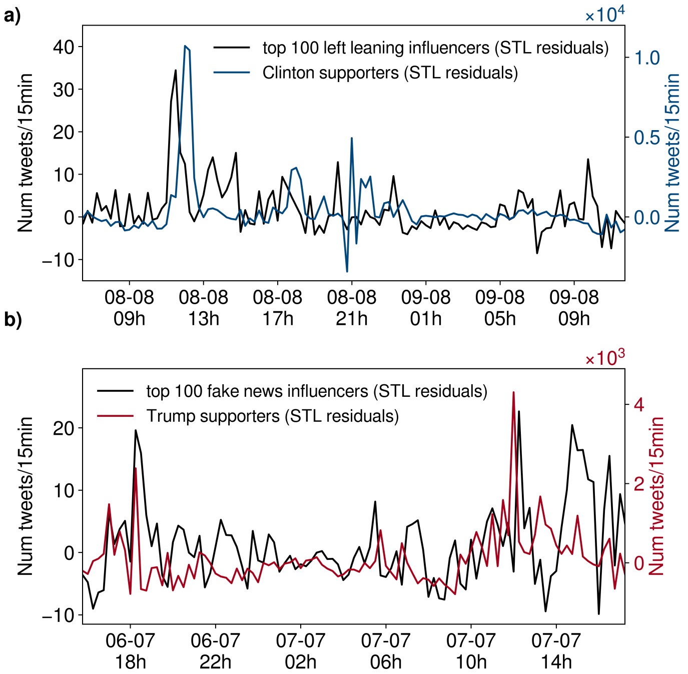

Figure 4: Example of Granger-causality relation between the activity of influencers and supporters. (a) Activity time series corresponding to the top 100 left leaning influencers (black) and the Clinton supporters (blue, right vertical axis). (b) Activity time series of the top 100 fake news influencers (black) and the Trump supporters (red, right vertical axis). We show the residuals of the STL filtering after the removal of the seasonal (daily) and trend components. A Granger-causality relation is apparent from the top 100 left leaning influencers to the Clinton supporters (a), i.e. the information of the influencers time series helps predict the Clinton activity time series. This is apparent as peaks in the left leaning influencers activity (black) tend to precede peaks in the activity of Clinton supporters (blue). A Granger-causality relation from the Trump supporters to the the top 100 fake news influencers (b) is also apparent.

separation in their activity

The cross-correlations between activity time series informs us about their temporal relation, however they do not allow to draw conclusions about causation between time series. In order to investigate the causal relations between news media sources and Twitter dynamics, we use the statistical test of Granger-causality [27] between the activity of news influencers and supporters of the presidential candidates. A stationary stochastic process, represented by a time series Y_t, is said to Granger-cause a stochastic process X_t when a regression using the past values of Y_t and X_t is better able to predict X_t than the same regression model using only the past values of X_t [27]. We use a linear autoregressive model for the time series:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \epsilon_t, \tag{1}$$

where ϵ_t is a white noise and m is the order of model. The null-hypothesis of the test is that the predictive error of this model is not significantly decreased when adding the lagged values of Y_t up to lag l in the regression

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{l} b_j Y_{t-j} + \epsilon_t, \tag{2}$$

in other words, that the coefficients b_j for $i = 1, ..., l$ of the regression are equal to zero. As for the cross-correlation analysis, we use the residuals of the STL filtering of the 15 min tweet volume time series. The STL procedure removes the trend and circadian pattern in the time series, resulting in stationary time series (the stationarity of each time series is confirmed by an augmented Dickey–Fuller

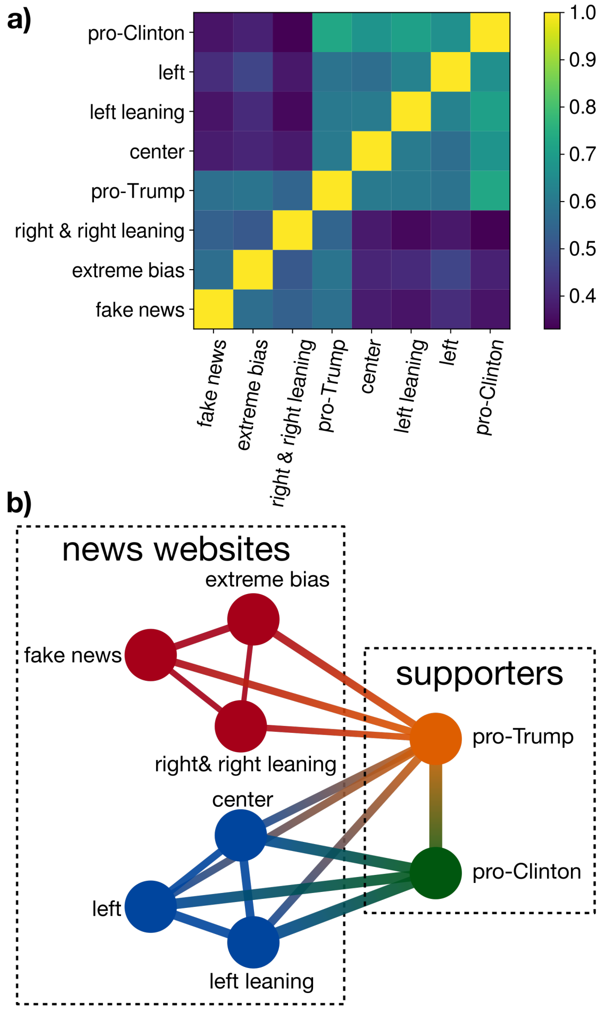

Figure 5: Activity correlation between news outlets and supporters. (a) Pearson cross-correlation coefficients between activity time series related to the different types of news outlets, Trump supporters and Clinton supporters. (b) Graph showing the correlation relations between the types of news websites and the supporters. The edges of the graph represent correlations larger than $r_0 = 0.5$. Fake news, extremely biased and right websites form a first cluster, indicated by a red square in (a) and shown in red in (b), while center, left leaning and left news websites form a second cluster, indicated by a blue square in (a) and shown in blue in (b). The activity of Trump supporters is equally correlated with all news sources, except for right leaning news, and the activity of Clinton supporters, which represents the largest activity, is mainly correlated with the second media cluster and only poorly with the first one.

test [34]).

Figure 6 shows the Granger-causality relations between the activity of the top 100 media influencers of each news source category and the supporters. The p-values of the null hypothesis obtained with a F-test between the activity of the top 100 influencers of each news source category and the activity of the supporters are reported in Tab. 4. We consider only the activity of the top influencers since, by the definition of CI, they are the most important sources of information and we assume that they are the ones triggering the activity of the rest of the population. We do not include the Granger-causality relations in-between influencers groups as the groups do not form disjoint sets. As can be seen in Tab. 3, some influencers appear in several groups. We report the amount of overlap between pairs of sets formed by the top 100 influencers of each category in Tab.5. The overlap between influencers groups should be kept in mind while interpreting the Granger causality results, however, as shown in Fig. 6, we find significantly different results for each influencers group. The value of the lag is chosen with an information criterion by fitting a bi-variate autoregressive model to the pairs of time

a)			*influencers*			
$\swarrow$	fake news	extremely biased	right & right leaning	center	left leaning	left
supporters						
pro-Clinton	1.8×10^{-3}	8.1×10^{-1}	8.8×10^{-2}	7.9×10^{-37}	1.4×10^{-45}	2.2×10^{-9}
pro-Trump	7.4×10^{-9}	4.9×10^{-1}	1.1×10^{-2}	3.3×10^{-13}	2.2×10^{-15}	2.0×10^{-7}

b)	*supporters*	
$\swarrow$	pro-Clinton	pro-Trump
influencers		
fake news	2.1×10^{-11}	8.6×10^{-36}
extremely biased	2.2×10^{-9}	8.9×10^{-22}
right & right leaning	2.6×10^{-6}	5.6×10^{-10}
center	3.4×10^{-6}	9.4×10^{-2}
left leaning	1.3×10^{-6}	2.8×10^{-2}
left	1.4×10^{-22}	1.9×10^{-7}

Table 4: p- values of the Granger causality analysis between the activity of the top 100 influencers of each media category and the activity of the presidential candidate supporters. a) p-values obtained with a F-test for the direction influencers Granger-cause supporters activity. b) p-values obtained with a F-test for the direction supporters activity Granger-cause influencers activity. Smaller values of the p-values indicate a stronger rejection of the hypothesis and therefore a stronger evidence of Granger-causality between the two time series.

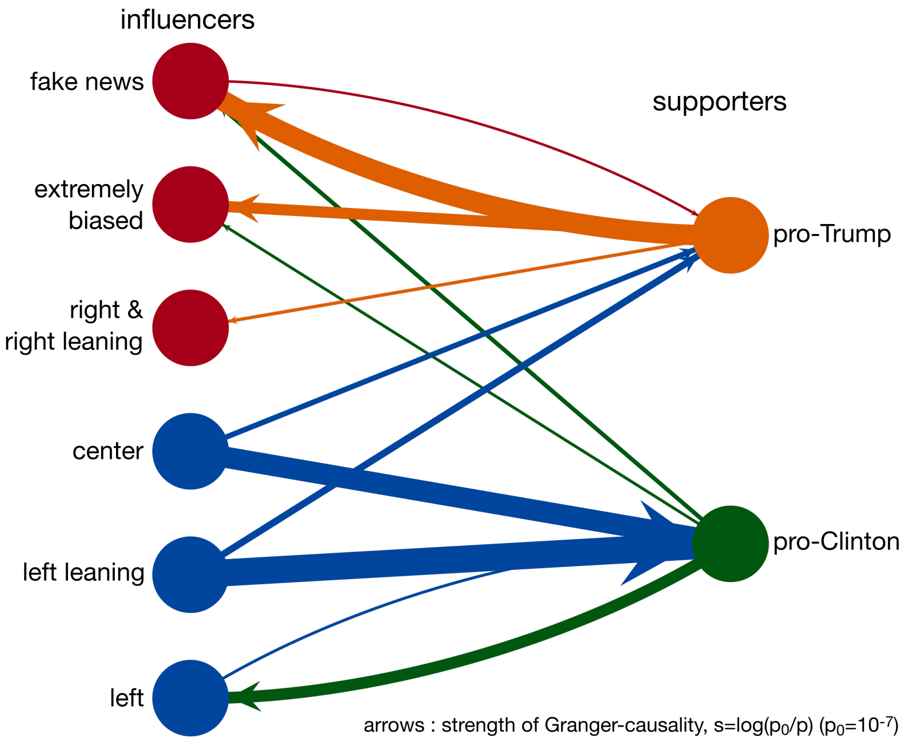

Figure 6: Granger causality relations between influencers and supporters activity. Graph showing the Granger causality relations between the activity of the top 100 influencers of each media category (left) and the activity of the presidential candidate supporters (right). Arrows indicate the direction of a statistically significant ($p < p_0 = 10^{-7}$) Granger-causation between two activity time series. The width of each arrows is proportional to the strength of the causation computed as $s = \log_{10} p_0/p$. The activity of center and left leaning news influencers show the strongest Granger-causation of the supporters activity, whereas fake, extremely biased as well as right & right leaning news influencers are shown to be following the activity of Trump supporters. The p-values of the null hypothesis for each pair of activity time series are shown in Tab. 4.

series. We find that the Bayesian information criterion (BIC) gives the smallest lag (22), the Akaike information criterion (AIC) gives the largest (48) and the Hannan–Quinn information criterion (HQC) gives a lag of 37. We choose to include up to 37 lagged values, i.e. up to 9.25 h, as including more values does not significantly changes the results. This value is consistent with our observation of the retweet delay distribution as approximately 75% of the retweets happen during this lag. Smaller values of the p-values indicate a stronger rejection of the null hypothesis and therefore a stronger evidence of Granger-causality between the two time series. We only consider p-values smaller than $p_0 = 10^{-7}$ in Fig. 6 and observe that this condition is fulfilled for several pairs of time series revealing the interdependence of the different media. However, a broad range of p-values smaller than p_0 is observed which allows us to compare the strength of the causal relations and reveals interesting patterns.

The center and left leaning news influencers have the strongest causation on the supporters activity, with a stronger effect on the Clinton supporters than on the Trump supporters. Since the Clinton supporters dominate Twitter activity, they also are the main drivers of the global activity. The influencers of right & right leaning and extremely biased news have no significant effect on the supporters activity. The influencers of left news and of fake news have a smaller effect on the supporters activity. In particular, fake news influencers have Granger-causal effect on Trump supporters and no significant effect on Clinton supporters.

The reverse Granger causality relations are also shown in Fig. 6 and in Tab. 4b revealing the presence of feedback loops, when two time series have a significant Granger causality relation in both directions, between the fake news influencers and the Trump supporters and between the left news influencers and the Clinton supporters. No significant causation is revealed from the Trump or Clinton supporters activity toward the center and left leaning influencers. This indicate that left leaning and center news influencers are the ones driving Twitter activity. All the other influencers are more strongly influenced by supporters activity than are influencing it. This suggest that they are in fact following Twitter activity rather than driving it. In particular, the activity of fake and extremely biased news influencers is influenced by the activity of Trump supporters. These results reveal two very different dynamics of news diffusion for traditional, center and left leaning, news and misinformation. While traditional news dynamics is governed by journalists, fake and extremely biased news dynamics seem to be governed by the ensemble of Trump supporters rather than by a small group of users.

3 Discussion

Using a dataset of tweets collected during the five months preceding the 2016 presidential elections, we investigated the spread of fake news and compared its importance and influence with traditional, fact-based, media. This dataset was previously used to analyze the opinion dynamics of Twitter users during the 2016 election in Ref. [24] where we developed a framework to infer the opinion of each tweet and users, based on machine learning, that we validated with national polling aggregates.
Here, we find that fake and extremely biased news represent 29% of the tweets linking to a news outlet media. However, taking into account the difference in user activity, decreases the share of fake and extremely biased news to 14%. Although we find approximately the same ratio of users using automated Twitter clients in each media category, we find that automated accounts diffusing fake news are much more active than the automated accounts diffusing other types of news. This results confirms the role of bots in the diffusion of fake news, that has been shown using a different method of bot detection [23], and shows that automated accounts also play a role, although smaller, in the diffusion of traditional news.

We analyzed the structure of the information diffusion network of each category of news and found that fake and extremely biased news diffusion networks are more densely connected and have less heterogeneous connectivity distributions than traditional, center and left-leaning, news diffusion networks. The heterogeneity of the degree distribution is known to play an important role in in spreading processes on networks [29, 30]. Spreading in networks with heterogeneous connectivity usually follows a hierarchical dynamics in which the information propagates from higher-degree to lower-degree classes [30].

We discovered the influencers of each type of news by computing their collective influence [26] and found very different profiles of fake and extremely biased news influencers compared to traditional news influencers. While traditional news influencers are mostly journalists with verified Twitter accounts, fake and extremely biased news influencers include unverified accounts with deceiving profiles.

Analyzing the Twitter activity dynamics of the news diffusion corresponding to each media category, we reveal the existence of two main clusters of media in term of activity correlation which is consistent with the findings of previous works [4–9] that revealed the separation in polarized communities of on-

	fake news	extremely biased	right & right leaning	center	left leaning	left
fake news	100	41	36	9	3	0
extremely biased	41	100	43	14	3	0
right & right leaning	36	43	100	17	3	0
center	9	14	17	100	19	8
left leaning	3	3	3	19	100	14
left	0	0	0	8	14	100

Table 5: Pairwise overlap of the sets of top 100 influencers of each media category.

line social media news consumers. We also show that right news media outlets are clustered together with fake and extremely biased news. Finally, a Granger-causality analysis between the influencers activity and the activity of presidential candidate supporters revealed that influencers of center and left-leaning news outlets are the ones driving Twitter activity while influencers of fake and extremely biased news are in fact following Twitter activity, particularly Trump supporters activity.

Our investigation provides new insights into the dynamics of news diffusion in Twitter, namely our results suggests that fake and extremely biased news are governed by a different diffusion mechanisms than traditional center and left-leaning news. Center and left leaning news diffusion is driven by a small number of influential users, mainly journalists, and follow a diffusion cascade in a network with heterogeneous degree distribution which is typical of diffusion in social networks [30], while the diffusion of fake and extremely biased news seem to not be controlled by a small set of influencers but rather to take place in a tightly connected cluster of users that do not influence the rest of Twitter activity.

Methods

Twitter data collection and processing

We collected tweets continuously using the Twitter Search API from June 1st, 2016 to November 8th, 2016. We gather a total of 171 million tweets in the English language, mentioning the two top candidates from the Republican Party (Donald J. Trump) and Democratic Party (Hillary Clinton) by using two different queries with the following keywords: *hillary OR clinton OR hillaryclinton* and *trump OR realdonaldtrump OR donaldtrump*.

We extracted the URLs from tweets by using the `expanded_url` field attached to each tweet containing at least one URL. A large number of URL were redirecting links using URL shortening services (e.g. `bit.ly`, `dlvr.it` or `ift.tt`). News websites sometimes also uses shortened versions of their hostnames (e.g. `cnn.it`, `nyti.ms`, `hill.cm` or `politi.co`). We programmatically resolved shortened URLs, using the Python Requests library, in order to find their final destination URL and extracted the hostname of each final URL in our dataset.
Among the 55 million tweets with URLs linking outside of Twitter, we identified tweets directing to websites containing fake news by matching the URLs' hostname with a curated list of fake, false, conspiratorial, and misleading news websites compiled by a research team headed by Melissa Zimdars of Merrimack College, USA, freely available at `www.opensources.co`. This list classifies websites in several categories, such as "Fake News", "Satire" or "Junk Science". For our study, we construct two non-overlapping set of websites: *fake news* websites and *extremely biased* websites. The set of fake news website is constructed by joining the hostnames from the categories "Fake News", "Conspiracy Theory" and "Hate News" from `www.opensources.co`. The following definitions of these three categories are given on `www.opensources.co`

- "Fake News": sources that entirely fabricate information, disseminate deceptive content, or grossly distort actual news reports,
- "Conspiracy Theory": sources that are well-known promoters of kooky conspiracy theories,
- "Hate News": sources that actively promote racism, misogyny, homophobia, and other forms of discrimination.

The set of extremely biased websites contains hostnames appearing in the category "Extreme Bias" (defined as "sources that come from a particular point of view and may rely on propaganda, decontextualized information, and opinions distorted as facts") but not in any of the categories used to construct the set of fake news.

To identify tweets that may originate from bots, we extract the name of the Twitter client used to post each tweet from their *source* field and kept only tweets originating from an official twitter client. When a programmatic access to Twitter is gained through its API to send tweets, the value of the *source* field of automated tweets corresponds to the name, which must be unique, given to the "App" during the creation of access tokens. Table 8 shows the clients we consider as official and the corresponding number of tweets with URLs originating from each client. The number of tweets with a URL originating from official clients represents 82% of the total number of tweets with a URL. This simple method allows to identify tweets that have not been automated and scales very easily to

fake news		extremely biased news		right news	
hostnames	N	hostnames	N	hostnames	N
thegatewaypundit.com	761 756	breitbart.com	1 854 920	foxnews.com	970 322
truthfeed.com	554 955	dailycaller.com	759 504	dailymail.co.uk	474 846
infowars.com	478 872	dailynewsbin.com	189 257	washingtonexaminer.com	462 769
therealstrategy.com	241 354	americanthinker.com	138 321	nypost.com	441 648
conservativetribune.com	212 273	freebeacon.com	129 077	bizpacreview.com	170 770
zerohedge.com	186 706	newsninja2012.com	127 251	nationalreview.com	164 036
rickwells.us	78 736	wnd.com	103 919	lifezette.com	139 257
departed.co	72 773	newsmax.com	94 882	redstate.com	105 912
therightscoop.com	63 852	endingthefed.com	88 376	allenbwest.com	104 857
teaparty.org	48 757	truepundit.com	84 967	theconservativetreehouse.com	102 515
usapoliticsnow.com	46 252	westernjournalism.com	77 717	townhall.com	10 240
clashdaily.com	45 970	occupydemocrats.com	73 143	theblaze.com	99 029
thefederalistpapers.org	45 831	ijr.com	71 558	theamericanmirror.com	91 538
redflagnews.com	45 423	dailywire.com	67 893		
thetruthdivision.com	44 486	bipartisanreport.com	66 360		
thepoliticalinsider.com	36 779	ilovemyfreedom.org	54 772		
donaldtrumpnews.co	29 332	100percentfedup.com	54 596	right leaning news	
sputniknews.com	27 440	shareblue.com	50 880	hostnames	N
angrypatriotmovement.com	27 400	pjmedia.com	46 542	washingtontimes.com	178 861
dcclothesline.com	27 072	weaselzippers.us	45 199	rt.com	93 771
frontpagemag.com	25 457	redstatewatcher.com	38 499		
conservativedailypost.com	25 393	youngcons.com	35 793		
beforeitsnews.com	24 827	lifenews.com	32 004		
bb4sp.com	23 143	americanlookout.com	29 888		
madworldnews.com	22 334	libertywritersnews.com	28 577		
freedomoutpost.com	18 791	usuncut.com	27 653		
investmentwatchblog.com	17 930	heatst.com	24 657		
pamelageller.com	17 182	regated.com	23 825		
truthrevolt.org	17 121	usapoliticstoday.com	21 969		
shoebat.com	16 940	weeklystandard.com	20 807		
theantimedia.org	16 399	liberalamerica.org	18 534		
wearechange.org	16 330	winningdemocrats.com	15 272		
usherald.com	16 135	worldnewspolitics.com	13 886		
christiantimesnewspaper.com	15 881	counterjihad.com	13 031		
yesimright.com	15 759	freakoutnation.com	12 504		
freedomdaily.com	15 699	cnsnews.com	11 802		
jewsnews.co.il	14 518	nevo.news	10 904		
globalresearch.ca	14 417	rightwingnews.com	10 828		
conservativebyte.com	14 203	russia-insider.com	10 550		
thefreethoughtproject.com	12 821	americasfreedomfighters.com	10 255		
prntly.com	12 760	chicksontheright.com	9607		
usanewsinsider.com	12 671	eaglerising.com	9068		
canadafreepress.com	11 810	drudgereport.com	7400		
jihadwatch.org	11 786	charismanews.com	6721		
usatwentyfour.com	10 347	newcenturytimes.com	6361		
proudcons.com	9717	americablog.com	6179		
downtrend.com	9667	lewrockwell.com	5467		
eutimes.net	9033	lifesitenews.com	4877		
barenakedislam.com	9031	thenewamerican.com	4867		
readconservatives.news	9007	americannewsx.com	3907		

Table 6: Top 50 hostnames in the categories fake, extremely biased, right and right leaning news. We also show the number of tweets with a URL pointing toward each hostname. Tweets with several URLs are counted multiple times.

large datasets contrary to more sophisticated methods [28]. Advanced bots might not be detected by our method, but this is also a problem for more advanced methods that relies on a training set of known bots [28]. We remove all tweets sent from non-official clients when computing the activity of supporters but we keep them when building the retweet networks, as we want to include automated accounts that play a role in the diffusion of news.

3.1 Collective influence algorithm in directed networks

We use the Collective Influence (CI) algorithm [26] applied to directed networks to find the most influential nodes of the information retweet networks. The Collective Influence algorithm is based on the solution of the optimal percolation of random networks which consists of identifying the minimal set of nodes, the *super-spreaders*, whose removal would dismember the network in many disconnected and non-extensive components. The fragmentation of the network is measured by the size of the

center news		left leaning news		left news	
hostnames	N	hostnames	N	hostnames	N
cnn.com	2 126 941	nytimes.com	1 811 627	huffingtonpost.com	996 546
thehill.com	1 200 123	washingtonpost.com	1 640 088	rawstory.com	297 256
politico.com	1 173 717	nbcnews.com	512 056	politicususa.com	293 419
thedailybeast.com	378 931	abcnews.go.com	467 533	dailykos.com	270 509
wsj.com	310 416	theguardian.com	439 580	time.com	252 468
usatoday.com	303 928	vox.com	369 789	talkingpointsmemo.com	199 346
bloomberg.com	266 662	slate.com	279 438	motherjones.com	179 685
reuters.com	248 753	buzzfeed.com	278 642	msnbc.com	177 090
businessinsider.com	239 423	cbsnews.com	232 889	mediamatters.org	152 160
apnews.com	138 496	politifact.com	198 095	newyorker.com	131 695
realclearpolitics.com	128 417	nydailynews.com	188 769	thinkprogress.org	107 776
observer.com	128 043	theatlantic.com	177 637	salon.com	104 199
fivethirtyeight.com	124 268	mediaite.com	152 877	nymag.com	89 077
bbc.com	118 176	newsweek.com	149 490		
npr.org	59 931	latimes.com	122 741		
		cnb.cx	87 094		
		cnbc.com	68 830		

Table 7: Hostnames of the websites in the categories center, left leaning, and left news media. We also report the number of tweets with a URL pointing toward each hostname. Tweets with several URLs are counted multiple times.

client name	number of tweets with a URL
Twitter for iPhone	14 215 411
Twitter Web Client	13 045 560
Twitter for Android	10 192 781
Twitter for iPad	3 355 197
Facebook	1 254 619
TweetDeck	1 079 637
Mobile Web (M5)	951 749
Mobile Web	452 812
Google	410 514
Twitter for Windows	200 088
Twitter for Windows Phone	170 529
Mobile Web (M2)	161 682
Twitter for BlackBerry	93 937
iOS	72 334
Twitter for Android Tablets	56 007
Twitter for Mac	43 993
OS X	40 642
Twitter for BlackBerry	25 140

Table 8: List of Twitter official clients. We also display the number of tweets containing a URL and originating from each official client. The number of tweets with a URL originating from official clients represent 82% of the total number of tweets with a URL.

largest connected component, called the giant component of the network.
Here, we consider a directed version of the algorithm corresponding to a percolation of the weakly-connected giant component, the largest maximal set of nodes where there exists a path in at least one direction between each pair of nodes, where we target the *super-sources* of information.
Following the procedure described in Ref. [31], we first compute the value of $\mathrm{CI}_{\ell,\mathrm{out}}(i)$ for all nodes $i = 1, ..., N$ as

$$\mathrm{CI}_{\ell,\mathrm{out}}(i) = (k_{\mathrm{out}}(i) - 1) \sum_{\substack{j \in \partial B_{\mathrm{out}}(i,\ell) \\ k_{\mathrm{out}}(j)>0}} (k_{\mathrm{out}}(j) - 1)\,, \tag{3}$$

where ℓ is the radius of the ball around each node we consider, here we use $\ell = 2$, $k_{\mathrm{out}}(i)$ is the out-degree of node i and $\partial B_{\mathrm{out}}(i, \ell)$ is the set of nodes situated at a distance ℓ from node i computed by following outgoing paths from i. The node with the largest $\mathrm{CI}_{\ell,\mathrm{out}}$ value is then removed from the network and the value of $\mathrm{CI}_{\ell,\mathrm{out}}$ of nodes whose value is changed by this removal is recomputed. This procedure is repeated until the size of the weakly connected largest component becomes negligible. The order of removal of the nodes corresponds to the final ranking of the network influencers shown in Tab. 3.

3.2 Time series processing

In order to perform the cross-correlation and Granger-causality analysis of the activity time series, we had to process the time series to remove the trend and circadian activity cycles and to deal with missing data points. For each missing data points, we remove the entire day corresponding to the missing observation in order to keep the period of the circadian activity consistent over the entire time series. This is necessary to apply filtering technique to remove the periodic component of the time series. When removing an entire day, we consider that the day starts and ends at 4 am, corresponding to the time of the day with lowest Twitter activity. We removed a total of 24 days, representing 15% of our observation period. We then applied a STL (seasonal-trend decomposition procedure based on Loess) [33] procedure to extract the trend, seasonal and remainder components of each activity time series. We only consider the remainder components for the cross-correlation and Granger-causality analysis. We set the seasonal period of the STL filter equal to the number of observations per day, $n_p = 96$, and the seasonal smoothing period to $n_s = 95$, such that the seasonal component is smooth and the remainder component retains the higher frequency signal containing the activity of interest. Varying the value of the smoothing period to $n_s = 47$ does not change significantly the results.

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