What the fake? Assessing the extent of networked political spamming and bots in the propagation of #fakenews on Twitter

Abstract

This study examines one of the largest data sets on the hashtag use of #fakenews that comprises over 14 million tweets sent by more than 2.4 million users. Tweets referencing the hashtag (#fakenews) were collected for a period of over one year from January 3 to May 7 of 2018. Bot detection tools were employed, and the most retweeted posts, most mentions, and most hashtags as well as the top 50 most active users in terms of the frequency of their tweets were analyzed. The majority of the top 50 Twitter users are more likely to be automated bots, while certain users' posts like that that are sent by President Donald Trump dominate the most retweeted posts that always associate mainstream media with fake news. The most used words and hashtags show that major news organizations are frequently referenced with a focus on CNN that is often mentioned in negative ways. Though the data reported here does not prove direct effects, the implications of the research provide a vital framework for assessing and diagnosing the networked spammers and main actors that have been pivotal in shaping discourses around fake news on social media. These discourses, which are sometimes assisted by bots, can create a potential influence on audiences and their trust in mainstream media and understanding of what fake news is. This paper offers results on one of the first empirical research studies on the propagation of fake news discourse on social media by shedding light on the most active Twitter users who discuss and mention the term "#fakenews" in connection to other news organizations, parties, and related figures.

Keywords: Fake news; Twitter; social media; mainstream media; networked political spamming

Introduction

This study sheds light on the most active Twitter users who discuss and mention the term "#fakenews" in connection to other news organizations, parties, and related figures. It also investigates whether these users are more likely to be humans or bots in order to better understand the nature of the dissemination of discourses surrounding fake news discussion on social media. In this regard, there is also another category called cyborg that combines both artificial and human activity. For example, Daniel John Sobieski, a conservative activist on Twitter with the username @gerfingerpoken, uses algorithms to post over 1000 messages a day in order to further his agenda and reach a wider online public. This is just one of the actions that cyborgs can provide, and in this case Sobieski uses 'schedulers' which "work through stacks of his own prewritten posts in repetitive loops" (Timberg, 2017). Further, political bots tend to be developed and deployed in sensitive political moments when public opinion is polarized" (Kollanyi, Howard & Woolley, 2016, p. 1). For example, one study on Twitter found that "almost 50% of traffic is generated and propagated by a rapidly growing bot population" (Gilani, Crowcroft, Farahbakhsh & Tyson, 2017).

In the contemporary media environment, fake news is becoming more important than perhaps ever before as "political actors and governments worldwide have begun using bots to manipulate public opinion, choke off debate, and muddy political issues" (Forelle et al., 2015, p. 1). Indeed, fake news has become a highly partisan issue in the United States, so associating certain political figures or news organizations with making or spreading it can lead to undermining their credibility. This study attempts to examine the way some active Twitter users connect certain figures, parties, and sides with fake news, which can be regarded as part of their political spamming activities that are meant to discredit their ideological opponents. There is no doubt that there is an increasing interest by the general public in the issue of fake news especially due to its importance in influencing campaigns, shaping the perception of reality and potentially altering citizens' political decision making. In general, there seems to be a systematic and well-calculated attack on mainstream media by many political sides in the way it is associated with fake news (Cadwalladr, 2017).

The main issue here is that most social media sites like Twitter and Facebook allow bots to be used, which boost and enhance spamming or posting messages by repeatedly sending them to as many other users as possible (Chu, Gianvecchio, Wang & Jajodia, 2010). For example, Donald Trump's first presidential address was initially identified as the most tweeted event in history, but it has been observed that this online attention was partly due to the use of pro-Trump bots. To wit, "Even before they started trending…., the official hashtags — #JointAddress and #JointSession — accumulated decidedly inorganic traffic, including from some accounts that had never tweeted about any other topic" (Musgrave, 2017). Some of these accounts are not totally automated as there seems to be cyborgs or human spammers and bot activity as explained above, for such "accounts are often bots that see occasional human curation, or they are actively maintained by people who employ scheduling algorithms and other applications for automating social media communication" (Kollanyi, Howard & Woolley, 2016, p. 2). According to Pew Research Center, it has been estimated that 2/3 of "tweeted links to popular websites are posted by" bot that "share roughly 41% of links to political sites shared primarily by liberals and 44% of links to political sites shared primarily by conservatives" (Wojcik et al., 2018).

Theoretical framework

Since this study deals with online information, it is relevant to begin with the theoretical concept of political spamming, which we define as an *overflow of politically oriented online messages that are widely disseminated to serve the interest of a certain political party or figure.* In the context of this study, spamming is done with the way news organizations, political figures, and entities are repeatedly associated with fake news on Twitter. Further, we introduce here the concept of *networked political spamming* activity which is manifested in the way many active Twitter users collaboratively disseminate posts by retweeting political or ideological messages that often include hyperlinks in order to serve a certain agenda or political purpose.

In general, spamming is not a new phenomenon in politics. For example, during the time fax machines were still popular in the 1990s, a US company called Bonner and Associates was "able to send out 10,000 faxes overnight to a congressperson's office. When the firm is hired by a client, it isolates the 'swing votes' in Congress, does a scan of the corresponding districts, and identifies citizens whose profiles suggest that they are sympathetic to the cause" (Newman, 1999, p. 6). Other types of spam include commercial ones, pre-recorded telephone messages, and snail mail.

As for online spamming, it has been mostly done through emails to achieve unconventional political mobilization purposes, and it is considered a much cheaper option than political advertising on TV or radio (Sweet, 2003; Krueger, 2010). Online political spamming has become part of the new political reality. For example, during the 2002 US midterm elections, many politicians from different political affiliations sent voters many unsolicited e-mails, widely regarded as unregulated political speech (Sweet, 2003). In relation to political campaign activities in the year 2004, "it was estimated that over 1.25 billion political spam messages were sent during the campaign as many candidates used e-mail to supplement direct mail campaigns

(Quinn & Kivijarv, 2005, p. 136). However, the actual impact of such a strategy is uncertain as it is mostly expected to influence swing voters (Frankel & Hillygus, 2014, p. 184) and is widely regarded as a "bad politics" strategy (Krueger, 2006, p. 763). It is believed that "large scale political spamming" usually done through emails is unethical and can have a negative impact on democracy and political deliberation, so there should be some kind of regulation to control its impact on citizens (Grossman, 2004; Rooksby, 2007; Trere, 2016), while other scholars think that political spamming should be protected as part of the First Amendment (Sweet, 2003).

In relation to Twitter, spamming occurs in the way certain political campaigns are implemented and messages are repeatedly retweeted often with the use of cyborgs and bots (Gao et al., 2010; Sridharan, Shankar, & Gupta, 2012). It also works by including hyperlinks in the tweets "that a user would likely not visit otherwise" (Just et al., 2012, p. 16). Though a few previous studies showed that political spam was not prevalent on Twitter during the 2008 US Congressional Elections or in the discussion of certain controversial political topics (Metaxas & Mustafaraj, 2009; Himelboim, McCreery, & Smith, 2013), this research argues, based on the empirical findings, that political spamming is very prevalent in the context of discourse on fake news.

This position is in line with many other studies conducted on the Twitter spam use during the 2010 municipal elections in Ottawa, Canada (Raynauld & Greenberg, 2014) and the Massachusetts (MA) senate race between Martha Coakley and Scott Brown in 2010 (Mustafaraj & Metaxas, 2010). In relation to the latter elections, many spammers targeted "individual journalists and liberal media outlets" in order to discredit them (Just et al., 2012), and the examination of the top 200 most active accounts revealed that a small number of users attempted to game search engines as they "were responsible for many of the replies, in an attempt to flood the network with spam" (Mustafaraj & Metaxas, 2010, p. 2). Several other studies showed similar results on the impact of spamming on political deliberation and debates. For example, Verkamp and Gupta (2013) studied the popular hashtags around five political protests and events from 2011 and 2012 from different parts of the world and found that the hashtags were "inundated with spam tweets intended to overwhelm the original content" (p. 1) in an attempt to silence dissent.

After the 2016 US presidential election, some journalists and researchers divided the concept of "fake news" into different categories such as political bias, satire, parody, and misinformation (Tandoc, Lim, & Ling, 2017), while others prefer to reserve the phrase exclusively for a new category driven by computational propaganda due to the increasing use of political bots in many countries around the world (Woolley & Howard, 2017). In political campaigning literature, some scholars believe that a certain kind of hierarchy and centralization is needed in the micro-management of voters and control of elites (Howard, 2005), and that social media can greatly assist in the "greater coordination and centralization of campaign activities" (Smith, 2009, p. 560). This is often done with the assistance of some active spammers or bots that are examined here, precisely because they are considered to be influential actors on social media. In general, influentials are "central both in the overall communication network and in the domain-specific communication exchange of protest messages: other users direct their messages to them in the hope that they will pass them on and help them reach a larger number of people" (Gonza´lez-Bailo´n, Borge-Holthoefer, & Moreno, 2013). Among the advantages of having influentials operating within a social network or movement is that they will function as facilitators to augment the overall diffusion of messages due to the wide connections their own networks have. In the context of this study, it is actually the political spammers and bots that take on the role of influential due to the high number of tweets, retweets, and hyperlinks they distribute in order to further their political agenda. Bakshy et al. (2011) wrote that influentials usually “exhibit some combination of desirable attributes – whether personal attributes like credibility, expertise, or enthusiasm, or network attributes such as connectivity or centrality – that allows them to influence a disproportionately large number of others, possibly indirectly via a cascade of influence” (p. 9).

As mentioned above, there is a gap in literature with regard to empirically studying fake news, specifically fake news discourses whose audiences can be vastly increased by spammers, whether be bots or humans. On this front there are some studies that have examined bots during Brexit (Howard & Kollanyi, 2016; Gallacher et al., 2017) and the 2016 election (Kollanyi, Howard, & Woolley, 2016). These researchers examined election hashtags and found that “Twitter traffic on pro-Trump hashtags was roughly double that of the pro-Clinton hashtags, and about one third of the pro-Trump twitter traffic was driven by bots and highly automated accounts, compared to one fifth of the pro-Clinton twitter traffic”. Similarly, Bessi and Ferrara (2016) found that about 19% of all 2016 U.S. election tweets were sent by political bots, amounting to about one-fifth of the total communication on Twitter related to this topic.

Given the opaque and still-debated scope of fake news and the most-influential users referencing fake news, this study attempts to provide an understanding of fake news discussion on social media. While such an endeavor cannot prove effects of exposure to fake news, it very well can provide vital insights about fake news as a cultural phenomenon as it is debated on social media. As such, we therefore pose the following research questions:

RQ1: In relation to networked political spamming, what are the most associated users and hashtags that are linked to #fakenews mentions on Twitter as well as the most retweeted posts?

RQ2: Which Twitter accounts are the most active in spamming and disseminating #fakenews tweets, and what is the likelihood that they are bots?

Methods

In order to identify an appropriate time frame in which to study fake news, we rely on data from Google and Wikipedia search traffic. Here, according to a Google Trend search, the term "fake news" became popular online in January 2017, which corresponds with the highlighting of this term on various topics by the current U.S. President, Donald Trump, and many other politicians, journalists, and the general public following the U.S. elections (see Figure 1). The highest peak in Google searches for this term was, in fact, in mid-January 2018 when Donald Trump announced his fake news awards contest (Siddiqui, 2018). This denotes the way famous figures like the US President can popularize certain terms. On Wikipedia, the highest number of searches for the "fake news" entry occurred between October and November 2017 (see Figure 2). Since these are important periods for researching fake news, we have chosen to study this topic around these dates.

Our data on fake news tweets were collected from the Boston University Twitter Collection and Analysis Toolkit (BU-TCAT), where data collection remains ongoing (Borra & Rieder, 2014; Groshek, 2014). As indicated above, Google and Wikipedia searches indicate that there has been an increasing public interest in this topic starting from January and February 2017, so we collected tweets on the hashtag (#fakenews) for a period of over one year from January 3 to May 7 of 2018. In total, there were 14,300,463 tweets retrieved that were posted by

2,493,949 unique users, and the highest peak of tweets was found in January 11 with 151,735 units collected that day. On the whole, 49.6% of tweets have links to other sites (see Figure 3).

-- Insert Figures 1, 2, and 3 about here --

In the second stage of the study, we examined the most mentioned terms associated with the hashtag #fakenews on Twitter as well as the top 50 most active users in terms of the frequency of their tweets. Since there is a lot of noise and irrelevant content on social media, the choice was to select the top 50 users following previous research that examined large datasets (Wilkinson & Thelwall, 2012, Al-Rawi, 2017a & 2017b). We used Gephi (https://gephi.org/), an open source visualization software (Bastian, Heymann & Jacomy, 2009), in order to present a graph that models the influence and communities around the most mentioned users and their connections with other users mentioning each other in the network constructed around this topic. To take on additional analytic step, we used an online tool called botometer (https://botometer.iuni.iu.edu) in order to understand the bots' scores of the top Twitter accounts (Davis et al., 2016; Varol et al., 2016; Bessi & Ferrara, 2016; Shao et al., 2017; Ferrara, 2017a & 2017b). Previous research showed the effectiveness of this award-winning tool, and it can be regarded as a useful starting point for an exploratory study such as this.

The above methods are relevant in understanding the Twitter users that most actively spread information on fake news, their affiliations, the nature of such accounts in terms of being a bot or human. As far as the researchers' knowledge, this is the first empirical study that examines fake news using the above methodological procedures, which can altogether assist in filling an important gap in literature and advance future understanding of a growing sociopolitical concern.

Findings

To answer the first research question on the most associated @usernames that are linked to #fakenews mentions on Twitter, it can be observed that @realdonaldtrump with 1,330,141 such mentions ranks first followed by @CNN n=1,164,871 mentions followed by @potus (President of the United States) at 472,656, @nytimes with 212,092, and @foxnews with 209,476 mentions on Twitter. There is clear tendency towards Twitter handles that represent media organizations or politicians that can be further illustrated in the following ranking of mentions: (6) @donaldjtrumpjr n=201,600, (7) @msnbc n=145,621, (8) @washingtonpost n=144717, (16) @abc n=103,675, (17) @nbcnews n=90,838, (28) @thehill n=52,505, (32) @cnnpolitics n=48,118, (35) @cbsnews n=46,885, (36) @nbc n=46,705, (37) @hillaryclinton n=45,186, (38) @cbs n=45,135, and (41) @ap n=39,977.

Further, there are many other mentions of journalists working for media outlets that were referenced very frequently, specifically including Jake Tapper (CNN; n=76,210), Jim Acosta (CNN; n=47,023), Chris Cuomo (CNN; n=111,767), and Brian Stelter (CNN; n=38,492). However, there are many other references to users (either human or bot) that are linked to or supportive of Donald Trump, such as James Woods (n=142,020), Bill Mitchell (n=134,643), the host of YourVoice at http://www.yourvoiceamerica.tv, Kevin W. (n=127502) James Edward O'Keefe III (n=122,752), and Linda Suhler (n=107,359) who is regarded as one of “Trump's female Internet superfans” (Roller, 2016) but is believed to be an account with almost exclusively bot-like behavior (Bohannon, 2017) (See Table 1).

Beyond the simple frequency of user mentions, we also used network analysis to construct a social graph by mentions to identify especially influential users and communities of users with the network of discussion on this topic. Here, weighted degree metrics were used to size user nodes and thereby determine their influence in spreading messages through the network by their activity in mentioning and being mentioned by other users of influence. The modularity algorithm placed users in to communities within this network and are identified by color in the graph. The most active 1,500 nodes (connected with 56,505 edges) were spatialized using the Open Ord algorithm in Gephi, which is suitable to better distinguish clusters of users.

Summarized here as Figure 4, this graph is also available online in a dynamic interactive user interface at https://bit.ly/2zcIraL. When sorted by user influence, many of the same accounts appeared in this graph, specifically with the top 20 being @cnn, @potus, @realdonaldtrump, @trey_vondinkis, @deplorable80210, @siddonsdan, @americanvoterus, @kwilli1046, @jrcheneyjohn, @rodstryker, @lawriter33, @rosenchild, @drmartyfox, @jimiznhb, @nytimes, @lvnancy, @georgiadirtroad, @poetreeotic, @petefrt, and @msnbc.

-- Insert Figure 4 about here --

Though there is no simple obvious pattern, the majority of tweets reference mainstream media as there seems to be a systematic and ongoing identifications with mainstream news organizations, especially CNN, which is by far the most mentioned outlet. There is evidence suggesting that the current US President and many members of conservative, Republican and (far) right groups have been involved in attacking CNN, identifying it as fake news as explained below. This partly explains the high frequency of mentions to this news channel. However, many other users reference CNN in connection to fake news in order to defend it rather than attack the news outlet. By examining references to the names of other news organizations, we find that the overwhelming majority are considered liberal such as CBS, MSNBC, NBC, NYT, Washington Post, while only one is typically regarded as conservative, namely Fox News.

As can be seen above, the most mentioned news outlet that is often associated with #fakenews references is CNN. In order to dig deeper into the data and understand how CNN is connected, we further examined the most used hashtags in the dataset. Aside from the common ones, some of which are already covered above in the reporting on the most mentions such as #CNN (rank 4, n=439,095), we find that there are certain terms in the top 50 most used hashtags that are clearly negative such as #FakeNewsCNN (rank 10, n=106,168), #CNNBlackmail (rank 13, n=85,265), #FraudNewsCNN (rank 31, n=51,470), and #CnnIsIsis (rank 49, n=33,307). In other words, CNN is mostly associated with negative terms that are connected to fake news discourses probably to undermine its credibility and status as a well-known mainstream media outlet.

-- Insert Tables 1 and 2 about here --

In order to further understand the most prevalent messages found in the dataset, we investigated the top 25 most retweeted posts, which were retweeted 506,944 times in total. This examination is important and relevant because it provides an indication into the kind of messages Twitter users are mostly engaged with and interested in retweeting. Once more, we find that CNN is the most referenced news outlet (n=5) followed by ProPublica (n=2) and NBC (n=2) that are all framed in a negative manner, while Donald Trump @realDonaldTrump and his son @DonaldJTrumpJr have dominated the online chatter with 16 tweets that were retweeted 315,140 times, constituting 64% of the retweets volume of the top 25 tweets. In these 16 tweets, Trump and his son mostly accused mainstream media of being fake news, while many other top tweets were supportive of Trump and critical of mainstream media like user @yoiyakujimin, which happens to be a known bot that is currently suspended from Twitter, having stated: ProPublica - #fakenews & #HateGroup funded by @OpenSociety Main presstitutes…”. In response to the popularity of this particular automated post, ProPublica tweeted: “People also buy Twitter bots to harass journalists. We know because it happened to us” (See Angwin, 2017). Other accounts that are supportive of Trump include @kirstenkellogg_ and @kwilli1046, which both were suspended from Twitter possibly for being bots. Another user @RealAssange that questioned the fact that Hillary Clinton won the popular vote and treated it as fake news also got suspended from Twitter and the account itself is fake masquerading as, or at least leveraging the fame of the founder of Wikileaks (Digital Forensic Research Lab, 2017). As a matter of fact, only 3 top tweets are actually critical of Trump, accusing him or fabricating facts and/or disseminating fake news in order to serve his political agenda.

-- Insert Table 3 about here --

To answer the second research question on the Twitter accounts that are the most active in discussing tweets that mention # fakenews, Table 2 shows that these most active accounts sent a total of 305,364 tweets (average 6,107 tweets per user) referencing #fakenews, where @PropOrNotApp alone sent 23,863 tweets. It is important to note here that the latter account, which scored 1.3 as being a bot, is associated with the non-partisan group of researchers who run the website “Is It Propaganda Or Not?” (www.propornot.com). They describe themselves as follows: “We are an independent team of concerned American citizens with a wide range of backgrounds and expertise, including professional experience in computer science, statistics, public policy, and national security affairs. We are currently volunteering our time and skills to identify propaganda – particularly Russian propaganda - targeting a U.S. audience” (The PropOrNot Team, 2016). In fact, the list of Russian trolls that is provided by this group has been largely contested as some users have proved to be politically independent rather than partisan sides (Timberg, 2016).

In total, there are 18 accounts suspended by Twitter from this analysis as of May 2018 allegedly for violating Twitter's automation rules (https://support.twitter.com/articles/76915) which are related to "abuse[ing] the Twitter API or attempt to circumvent rate limits.". Out of the remaining 32 accounts, the majority (n=17) showed clear affiliation with, support for Trump, or conservative groups such as @Free_PressFail (n=11,676), @trey_vondinkis (n=6,926), and @avonsalez (n=19,280) who describes herself as follows: "I wreak havoc on Libtards with victim cards. #Navymom#Deplorables #MAGA #Americafirst #QArmy #PATRIOT". On the other hand, 6 Twitter users showed support the democrats or were anti-conservative such as @alternatfacts (n=9,822) that has Trump as part of his/her Twitter profile picture with the statement: "President of fake news", while @samir0403 (n=5,928) describes himself as follows: "I am an Indian. Got active on twitter on Nov 8th 2016. I was amazed how America can elect such a soulless pathetic human @POTUS". Finally, the remaining 9 users had either neutral or unclear political affiliations.

-- Insert Table 4 about here --

By using botometer (https://botometer.iuni.iu.edu), an API developed by a team from Indiana University, we investigated the top 32 accounts (see Table 2). The algorithm used indicates scores from 0 for being human-like and 5 for performing like a bot, while scores "in the middle of the scale is a signal that [the] classifier is uncertain about the classification" (BotorNot, 2018). For example, @gerfingerpoken, the Twitter account of Sobieski described earlier as a cyborg was determined by the botometer algorithm as having a score of 1.6 of being a bot; hence, a score 3 and above is more likely to be a bot. Accordingly, we found that the average bots' score is actually 2.3

which means that the classifier is generally not certain about the nature of these accounts. However, 12 accounts scored 3 and above with the highest being 4.6 such as @_breitbot_. If we take into consideration the suspended Twitter accounts (n=18), we conclude that the majority of the top Twitter users that disseminated posts referencing #fakenews are bots (n=30), constituting 60% of the total.

According to Kollanyi, Howard and Woolley, bots exhibit "a high level of automation as accounts that post at least 50 times a day, meaning 200 or more tweets, [for it] …. is difficult for human users to maintain this rapid pace of social media activity without some level of account automation" (Kollanyi, Howard & Woolley, 2016, pp. 2 & 3). In early August 2017, Twitter suspended the account of 'Nicole Mincey' who received praise from Donald Trump himself with the username @ProTrump45 for being his super fan. However, Phillip (2017) reported that this account was another bot used to amplify Trump's views and virally disseminate them on the online platform.

In order to further examine the data for the likelihood of being bots, we randomly selected two larger samples of Twitter accounts, each containing 102,000 Twitter users collected between January 3 to July 21 of 2017 and another sample collected between January 1 to May 7 of 2018 by using a Python package provided by botometer. It returns a metric of Bot-likelihood, including both overall score and scores in specific categories such as "content" and "temporal". Since its inception in late 2015, the Botometer API (originally named "Botornot") has undergone a few updates in its presentation and algorithm. In its May 10, 2018 update, the Complete Automation Probability (CAP) is introduced. Compared with other older metrics, the CAP value is better calibrated and reflects a more conservative estimation of the likelihood an account is completed automated (thus a real Bot).1 For our purpose, we choose the CAP in this study in order to minimize the likelihood of falsely labelling human accounts as bots.

We chose two datasets from two periods in order to examine whether Twitter's decision to crack down on bot accounts which started in June 2017 has been effective in limiting bots' use in the dissemination of #fakenews (Twitter Public Policy, 2018). Due to user security setting as well as Twitter policy (e.g. some accounts have been suspended and no longer available), the API does not return results for all accounts. Eventually, we obtained CAP of 78,132 accounts for the older dataset (mean=0.078, sd=0.21), and 93,322 for the newer dataset (mean=0.063, sd=0.17). Given a majority of accounts are not bots (thus with CAP of or close to 0), both datasets are highly skewed (kurtosis = 11.97 and 15.2, respectively). Figure (5) shows the density plot of the CAP for both datasets after log transformation. As indicated in the two analyses, the CAP value of the first sample is higher than that of the second sample, indicating that Twitter has actually achieved some success in decreasing, but not ending, bots' use.

-- Insert Figure 5 about here --

Discussion & conclusion

The dissemination of fake news discourses can be regarded as a method for networked spamming opponents for a variety of reasons. Most importantly, fake news propagation– much like propaganda models during the World Wars – serves the interests of some groups that benefit from this mistrust in mainstream media in order to further their political, economic, and other agendas. While it can be argued that "democracies depend on an informed public, totalitarian regimes on fake news" (Martinson, 2017), it is important to avoid hypodermic-needle theorizing

[1] https://botometer.iuni.iu.edu/#!/faq#what-is-cap

and to position the effects of fake news appropriately (Groshek & Koc-Michalska, 2017). Along these lines, however, and of particular importance to the study reported here, the use of bots is aimed at spreading fake news and enhancing a political party's messaging power, but it is also meant to "hack free speech and to hack public opinion" (Timberg, 2017). This is because fake news itself is considered as a potential public threat to the proper functioning of democratic discourse and decision making, and better understanding it is highly relevant today as fake news can undermine democracy and the public's faith in factual, watchdog news organizations. Most importantly, fake news references are used as part of networked political spamming that function as a proxy to undermine credibility and weaken the opponents' arguments by the association made between them and fake news references.

As can be seen from the above findings on the top 50 most recurrent mentions and hashtags, there is a clear focus on major liberal news organization especially CNN in the discourse surrounding fake news. While it is not possible to understand the tone of this discourse without detailed content analysis, the most frequent hashtags provide insight into the attitudes associated with CNN and fake news as we can clearly identify the salience of negative terms like #FakeNewsCNN, #CNNBlackmail, #FraudNewsCNN, and #CnnIsIsis (n= 276,210 in total). In fact, there is not a single positive attribute associated with CNN in the most recurrent hashtags. This is also collaborated in the examination of the 25 most retweeted posts as CNN in particular has received the lion's share in the accusations of being a fake news organization mostly due to the popular tweets of Donald Trump and his son, while their supporters have assisted in the propagation of fake news discourses and associating them with other liberal mainstream media like ProPublica and NBC. This shows that conservative groups that are linked to Trump and his administration have dominated the fake news discourses on Twitter due to their activity and use of bots. In fact, 4 top Twitter accounts that showed support for Trump while receiving the highest number of retweets got suspended from Twitter mostly due to being bots which shows the danger of automated accounts that can go viral and move online debates towards certain directions.

Bots aside, there are other subtle yet important mechanisms that ought to be taken into account when addressing the issue of fake news. To begin, although the impact of fake news has often been discussed above within the realm of social media, it is important to note that part of the disruptive power of fake news lies in its propagandistic and agenda-setting capacity on the entire mediascape that exists beyond social media – and this is reinforced by the fact that a majority of the most active accounts (n=30, 60%) including some that belonged to the most retweeted posts (n=4, 16%) in this study likely came from spamming bots. Though all social bots are essentially algorithms designed to accomplish simple informational tasks, they are by no means monolithic. Social media platforms are populated by multiple species of bot accounts, employed by entities and organizations with distinctly different agendas. As it relates, a recent study shows that, though not successful on all topics, fake news is especially capable of setting the agenda for key issues regarding international relations, the economy and religion (Vargo, Guo & Amazeen, 2017). Moreover, in 2016, such an influence is particularly strong on online partisan media, which increasingly serves as an effective conduit to reach legacy news organizations (Vargo & Guo, 2017). In other words, bots have the potential to influence people's agenda especially if the messages propagated by these automated accounts go viral such as the case of some of the most retweeted posts examined in this study, for there is a dominant online communication structure that is critical of liberal mainstream media in the way they are mostly associated with references to fake news.

At the same time, some observers see fake news as a problem posing imminent threat to democracy, others working in the area believe that part of the worry over fake news has been ballooned into a moral panic (Shaffer, 2016; Beckett, 2017; Carlson, 2017). As related to his more recent articulation on the public sphere, Habermas (2006, p. 415) wrote: "the public sphere is rooted in *networks* for the wild flows of messages – news, reports, commentaries, talks, scenes and images" (emphasis added). If social media platforms do offer insights into the latest evolution of the structural transformation of the public sphere (Habermas, 1989), they could hardly do so without this unprecedented computational capacities of networked political spamming, online spammers, and bots.

Fake news remains an important field of study for many contemporary areas of interest. It can instantaneously and easily spread on social media mostly due to the networked affordances. The increasing risk that is associated with fake news discourses has led many social media companies like Facebook to monitor and evaluate the spread of news stories on their platforms (Wingfield, Isaac & Benner, 2016), and Wikipedia's founder, Jimmy Wales, pledged to launch a new online publication called Wikitribune based on crowdfunding campaign to counter fake news (Hern, 2017). In addition, the Full Fact organization that uses an automated fact-checking system to detect fake news will soon provide its services to journalists in order to cross examine sources in real time (Booth, 2017), and the Knight Foundation recently sponsored a number of projects to help combat the spread of fake news. Though the peak of fake news stories online was thus far in the period immediately following the U.S. election, other fake reports periodically emerge. Here it worthwhile to reiterate that many accounts endorsing nearly all political factions and affiliations are responsible for spreading fake news in different levels. As one example, the factchecking website Snopes mentioned that in April 2017 fake anti-

Republican stories started outnumbering fake pro-Republican news stories (BBC Trending, 2017), and it also indicated that many fake stories do not easily cease being shared by people on social media (Criss, 2017), such as the “claim that HIV and AIDS are man-made diseases” (Grimes, 2017). The same applies to the findings of this study as fake news discourses on Twitter seems to be driven by people who belong to all political factions though Trump’s supporters remain dominant in the most active users category (n=17, 53%). The same finding is observed in the examined top mentions and hashtags which include the names of journalists and politicians from various affiliations and backgrounds.

In sum, this study has provided insight into Twitter users’ networked spamming accounts that influenced the discussion on fake news on Twitter. While there is no simple solution to the issue of fake news discourse dissemination, it is all but inevitable that the sophistication and reach of bots and cyborgs will only continue to improve. Our hope is that the reactions of scholars, developers, and policy makers can be informed by this contribution. More importantly, the discourses surrounding fake news on social media, which are often amplified by bots, can influence audiences especially in their understanding of what fake and factual news is and their general trust in mainstream media credibility. One of the findings of this study indicates that Twitter has recently succeeded in slightly limiting the use of bots on its platforms, but more efforts are needed to enhance these efforts with broader technical measures.

Of course, there are limitations to this study, including the sampling principally of Twitter and (to the extent possible) future research studies can explore the spread of #fakenews in other platforms like Instagram. Other theories such as selective exposure may also be relevant in understanding the reasons behind the circulation and sharing of fake news by certain users, and determining the effect size of fake news exposure is also critical, and that can be triangulated using big data approaches such as this one with audience surveys and interviews to better explore a still under-researched area of study.

References

Al-Rawi, A. (2017a). Viral News on Social Media. *Digital Journalism*, 1-17.

Al-Rawi, A. (2017b). Audience Preferences of News Stories on Social Media. *The Journal of Social Media in Society*, 6(2), 343-367.

Angwin, Julia. (2017, September 11). How Journalists Fought Back Against Crippling Email Bombs. Wired. Retrieved from https://www.wired.com/story/how-journalists-fought-back-against-crippling-email-bombs/

Bakshy, E., Hofman J, Mason W, et al. (2011) Everyone's an Influencer: Quantifying Influence on Twitter. *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining.* Hong Kong, China: ACM, 65-74.

BBC Trending. (2017, April 15). The rise of left-wing, Anti-Trump fake news. Retrieved from http://www.bbc.com/news/blogs-trending-39592010

Beckett, C. (2017). 'Fake news': the best thing that's happened to journalism. POLIS: journalism and society at the LSE.

Bessi, A., & Ferrara, E. (2016). Social bots distort the 2016 US Presidential election online discussion. *First Monday*, 21(11).

Bastian M., Heymann S., Jacomy M. (2009). Gephi: An open source software for exploring and manipulating networks. International AAAI Conference on Weblogs and Social Media.

Bohannon, J. (2017, February 2). Election polling is in trouble. Can internet data save it? *Science*. doi:10.1126/science.aal0695

Booth, Robert. (2017, August 8). Journalists to use 'immune system' software against fake news. The Guardian. Retrieved from https://www.theguardian.com/technology/2017/aug/08/fake-news-full-fact-software-immune-system-journalism-soros-omidyar

Borra, E. and Rieder, B. (2014). Programmed method: developing a toolset for capturing and analyzing tweets. *Aslib: Journal of Information Management*, *66*(3), 262 - 278.

Cadwalladr, Carole. (2016, December 4). Google, democracy and the truth about internet Search. The Guardian. Retrieved from https://www.theguardian.com/technology/2016/dec/04/google-democracy-truth-internet-search-facebook

Cadwalladr, Carole. (2017, February 26). Robert Mercer: the big data billionaire waging war on mainstream media. The Guardian. Retrieved from https://www.theguardian.com/politics/2017/feb/26/robert-mercer-breitbart-war-on-media-steve-bannon-donald-trump-nigel-farage

Carlson, Matt. (2017) Fake News as Information Moral Panic. Presentation at Journalism and the Search for Truth conference, Boston, 2017

Chu, Z., Gianvecchio, S., Wang, H., & Jajodia, S. (2010, December). Who is tweeting on Twitter: human, bot, or cyborg?. In *Proceedings of the 26th annual computer security applications conference* (pp. 21-30). ACM.

Criss, Doug. (2017, March 10). 5 fake stories that just won't go away. CNN. Retrieved from http://www.cnn.com/2017/03/10/us/snopes-five-fake-stories-trnd/

Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016). BotorNot: A system to evaluate social bots. In Proceedings of the 25th International Conference Companion on World Wide Web.

Digital Forensic Research Lab. (2017, September 5). Fake Assanges Drive Far-Right Messages. The Medium. Retrieved from https://medium.com/dfrlab/fake-assanges-drive-far-right-messages-604a8658bde8

Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM*, *59*(7), 96-104.

Ferrara, E. (2017a). Measuring social spam and the effect of bots on information diffusion in social media. *arXiv preprint arXiv:1708.08134*.

Ferrara, Emilio. (2017b). Disinformation and Social Bot Operations in the Run Up to the 2017 French Presidential Election. *First Monday* 22(8).

Forelle, M., Howard, P., Monroy-Hernández, A., & Savage, S. (2015). Political bots and the manipulation of public opinion in Venezuela. *arXiv preprint arXiv*:1507.07109.

Frankel, L. L., & Hillygus, D. S. (2014). Niche communication in political campaigns. In Kate Kenski & Kathleen Hall Jamieson (Eds.). *The Oxford Handbook of Political Communication*, (pp. 179-194). Oxford: Oxford University Press.

Gallacher, J., Kaminska, M., Kollanyi, B., Yasseri, T., & Howard, P. N. (2017). Social Media and News Sources during the 2017 UK General Election. Retrieved from comprop.oii.ox.ac.uk

Gao, H., Hu, J., Wilson, C., Li, Z., Chen, Y., & Zhao, B. Y. (2010, November). Detecting and characterizing social spam campaigns. In Proceedings of the 10th ACM SIGCOMM conference on Internet measurement (pp. 35-47). ACM.

Gilani, Z., Crowcroft, J., Farahbakhsh, R., & Tyson, G. (2017, August). The Implications of Twitterbot Generated Data Traffic on Networked Systems. In Proceedings of the SIGCOMM Posters and Demos (pp. 51-53). ACM.

Gonza´lez-Bailo´n, S., Borge-Holthoefer, J., & Moreno, Y. (2013). Broadcasters and hidden influentials in online protest diffusion. American Behavioral Scientist, 57(7), 943–965. doi:10.1177/0002764213479371

Grimes, David. (2017, June 14). Russian fake news is not new: Soviet Aids propaganda cost countless lives. The Guardian. Retrieved from https://www.theguardian.com/science/blog/2017/jun/14/russian-fake-news-is-not-new-soviet-aids-propaganda-cost-countless-lives

Groshek, J. (2014). Twitter Collection and Analysis Toolkit (TCAT) at Boston University. Retrieved from http://www.bu.edu/com/bu-tcat/

Groshek, J., & Koc-Michalska, K. (2017). Helping populism win? Social media use, filter bubbles, and support for populist presidential candidates in the 2016 US election campaign. *Information, Communication & Society*, 1-19.

Grossman, S. (2004). Keeping unwanted donkeys and elephants out of your inbox: the case for regulating political spam. *Berkeley Technology Law Journal*, 1533-1575.

Habermas, J. (1989) The Structural Transformation of the Public Sphere: An Inquiry into a Category of Bourgeois Society. Cambridge: Polity.

Habermas, J. (2006). Political communication in media society: Does democracy still enjoy an epistemic dimension? The impact of normative theory on empirical research. *Communication theory*, *16*(4), 411-426.

Hern, Alex. (2017. April 25). Wikipedia founder to fight fake news with new Wikitribune site. The Guardian. Retrieved from https://www.theguardian.com/technology/2017/apr/25/wikipedia-founder-jimmy-wales-to-fight-fake-news-with-new-wikitribune-site

Himelboim, I., McCreery, S., & Smith, M. (2013). Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of Computer-Mediated Communication*, 18(2), 154-174.

Howard, P. (2005). *New Media Campaigns and the Managed Citizen*. New York: Cambridge University Press.

Howard, P. N., & Kollanyi, B. (2016). Bots, #StrongerIn, and #Brexit: Computational Propaganda during the UK-EU Referendum. arXiv:1606.06356 [Physics]. Retrieved from http://arxiv.org/abs/1606.06356

Jun, Y., Meng, R., & Johar, G. V. (2017). Perceived social presence reduces fact-checking. *Proceedings of the National Academy of Sciences*, 201700175.

Just, M. R., Crigler, A. N., Metaxas, P. T., & Mustafaraj, E. (2012). 'It's Trending on Twitter'-An Analysis of the Twitter Manipulations in the Massachusetts 2010 Special Senate Election.

Kollanyi, B., Howard, P. N., & Woolley, S. C. (2016). Bots and automation over Twitter during the first US Presidential debate. *COMPROP Data Memo*. Retrieved from https://assets.documentcloud.org/documents/3144967/Trump-Clinton-Bots-Data.pdf

Krueger, B. S. (2006). A comparison of conventional and Internet political mobilization. *American Politics Research*, 34(6), 759-776.

Krueger, B. S. (2010). Opt in or tune out: Email mobilization and political participation. *International Journal of E-Politics (IJEP)*, 1(4), 55-76.

Martinson, Jane. (2017, June 18). A question for a dystopian age: what counts as fake news? The Guardian. Retrieved from https://www.theguardian.com/media/2017/jun/18/aquestionforadystopianagewhatcountsasfakenews?CMP=Share_iOSApp_Other

Metaxas, P., & Mustafaraj, E. (2009). The battle for the 2008 US Congressional Elections on the Web.

Musgrave, S. (2017, January 3). Trump address Twitter numbers appear to be boosted by 'bots'. Politico. Retrieved from http://www.politico.com/story/2017/03/trump-speech-twitter-235590

Mustafaraj, E., & Metaxas, P. T. (2010). From obscurity to prominence in minutes: Political speech and real-time search.

Newman, B. I. (1999). *The mass marketing of politics: Democracy in an age of manufactured images*. California: Sage Publications.

Nguyen, T. T., Hui, P. M., Harper, F. M., Terveen, L., & Konstan, J. A. (2014, April). Exploring the filter bubble: the effect of using recommender systems on content diversity. In *Proceedings of the 23rd international conference on World wide web* (pp. 677-686). ACM.

Phillip, Abby. (2017, August 7). The curious case of 'Nicole Mincey,' the Trump fan who may actually be a bot. The Washington Post. Retrieved from https://www.washingtonpost.com/politics/the-curious-case-of-nicole-mincey-the-trump-fan-who-may-actually-be-a-russian-bot/2017/08/07/7aa67410-7b96-11e7-9026-4a0a64977c92_story.html?utm_term=.aad28a95288f

Qiu, X., Oliveira, D. F., Shirazi, A. S., Flammini, A., & Menczer, F. (2017). Limited individual attention and online virality of low-quality information. *arXiv preprint arXiv:1701.02694*.

Quinn, P., & Kivijarv, L. (2005). US political media buying 2004. *International Journal of Advertising*, 24(1), 131-140.

Rampton, S., & Stauber, J. C. (2003). *Weapons of mass deception: The uses of propaganda in Bush's war on Iraq*. London: Penguin.

Raynauld, V., & Greenberg, J. (2014). Tweet, click, vote: Twitter and the 2010 Ottawa municipal election. *Journal of Information Technology & Politics*, 11(4), 412-434.

Roller, Emma. (2016, May 10). The Women Who Like Donald Trump. The New York Times. Retrieved from https://www.nytimes.com/2016/05/10/opinion/campaign-stops/the-women-who-like-donald-trump.html

Rooksby, E. (2007). The ethical status of non-commercial spam. *Ethics and Information Technology*, 9(2), 141-152.

Shao, C., Ciampaglia, G. L., Varol, O., Flammini, A., & Menczer, F. (2017). The spread of fake news by social bots. *arXiv preprint arXiv:1707.07592*.

Siddiqui, Sabrina. (2018, January 18). Donald Trump faces backlash as he reveals 'Fake News Awards' winners. The Guardian. Retrieved from https://www.theguardian.com/us-news/2018/jan/17/trump-fake-news-awards-winners

Smith, J. (2009). Campaigning and the catch-all party: The process of party transformation in Britain. *Party Politics 15*(3): 555–572.

Sridharan, V., Shankar, V., & Gupta, M. (2012, December). Twitter games: how successful spammers pick targets. In Proceedings of the 28th Annual Computer Security Applications Conference (pp. 389-398). ACM.

Sundar, S. (2016). Why Do We Fall For Fake News? The Conversation. URL: https://theconversation.com/why-do-we-fall-for-fake-news-69829

Sweet, M. (2003). Political E-Mail: Protected Speech or Unwelcome Spam?. *Duke Law & Technology Review*, 1(1), 1-9.

Tandoc Jr, E. C., Lim, Z. W., & Ling, R. (2017). Defining "Fake News" A typology of scholarly definitions. *Digital Journalism*, 1-17.

The PropOrNot Team. (2016). Black Friday Report: On Russian Propaganda Network Mapping. November 26. Retrieved from https://drive.google.com/file/d/0Byj_1ybuSGp_NmYtRF95VTJTeUk/view

Timberg, C. (2016, November 24). Russian propaganda effort helped spread 'fake news' during election, experts say. *Washington Post*. Retrieved from https://www.washingtonpost.com/business/economy/russian-propaganda-effort-helped-spread-fake-news-during-election-experts-say/2016/11/24/793903b6-8a40-4ca9-b712-716af66098fe_story.html?utm_term=.4fe0be44cf9b

Timberg, C. (2017, February 5). As a conservative Twitter user sleeps, his account is hard at work. The Washington Post. Retrieved from https://www.washingtonpost.com/business/economy/as-a-conservative-twitter-user-sleeps-his-account-is-hard-at-work/2017/02/05/18d5a532-df31-11e6-918c-99ede3c8cafa_story.html?utm_term=.6f32697a59e3

Treré, E. (2016). The dark side of digital politics: Understanding the algorithmic manufacturing of consent and the hindering of online dissidence. *IDS Bulletin*, 47(1).

Twitter Public Policy. (2018, January 19). Update on Twitter's Review of the 2016 U.S. Election. Retrieved from https://blog.twitter.com/official/en_us/topics/company/2018/2016-election-update.html

van der Linden, S., Leiserowitz, A., Rosenthal, S., & Maibach, E. (2017). Inoculating the public against misinformation about climate change. *Global Challenges*, *1*(2).

Vargo, C. J., Guo, L., & Amazeen, M. A. (2017). The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016. *new media & society*, 1461444817712086.

Vargo, C. J., & Guo, L. (2017). Networks, Big Data, and Intermedia Agenda Setting: An Analysis of Traditional, Partisan, and Emerging Online US News. *Journalism & Mass Communication Quarterly*, 1077699016679976.

Varol, O., Ferrara, E., Davis, C., Menczer, F., & Flammini, A. (2017). Online Human-Bot Interactions: Detection, Estimation, and Characterization. International AAAI Conference on Web and Social Media.

Verkamp, J. P., & Gupta, M. (2013, August). Five Incidents, One Theme: Twitter Spam as a Weapon to Drown Voices of Protest. In FOCI.

Wilkinson, D., & Thelwall, M. (2012). Trending Twitter topics in English: An international comparison. *Journal of the Association for Information Science and Technology*, 63(8), 1631-1646.

Wingfield, N., Isaac, M., & Benner, K. (2016, November 14). Google and Facebook Take Aim at Fake News Sites. *The New York Times*, *11*. Retrieved from https://www.nytimes.com/2016/11/15/technology/google-will-ban-websites-that-host-fake-news-from-using-its-ad-service.html

Wojcik, S., Messing, S., Smith, A., Rainie, E., Hitlin, P. (2018, April 9). Bots in the Twittersphere. Pew Research Center: Internet & Technology. Retrieved from http://www.pewinternet.org/2018/04/09/bots-in-the-twittersphere/

Woolley, S. & Howard, P. (2017). Computational Propaganda Worldwide: Executive Summary. Working Paper No. 11. Oxford, UK: Project on Computational Propaganda. comprop.oii.ox.ac.uk.

Figures and Tables

Figure 1: Google searches for “fake news” from January to May 2018

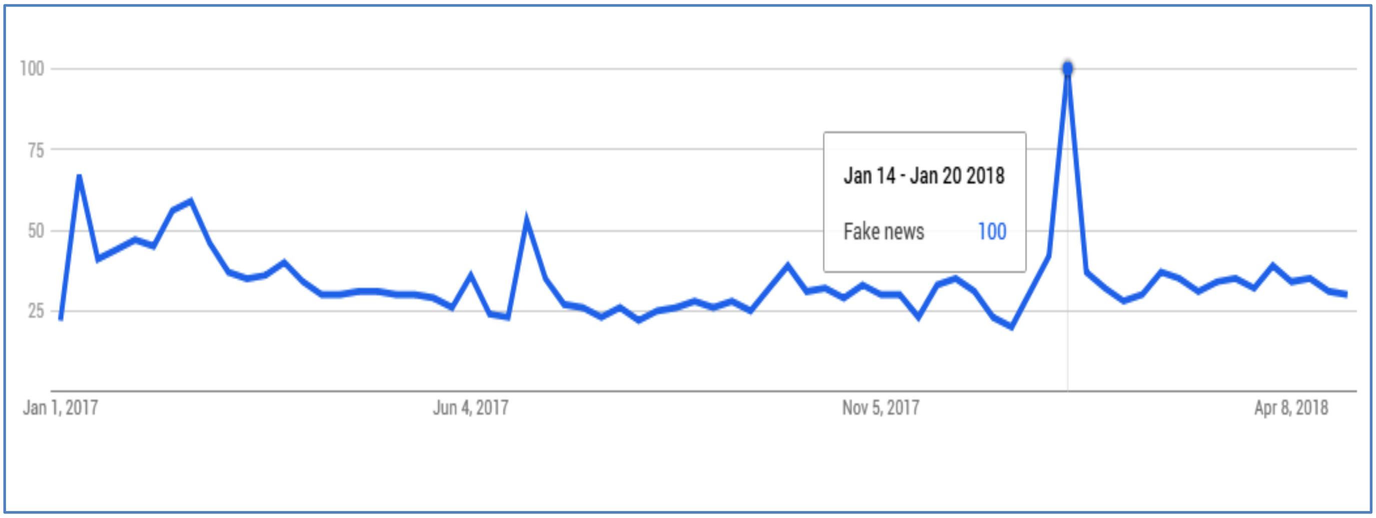


Figure 2: Wikipedia searches for “fake news” from July 2015 to May 2018

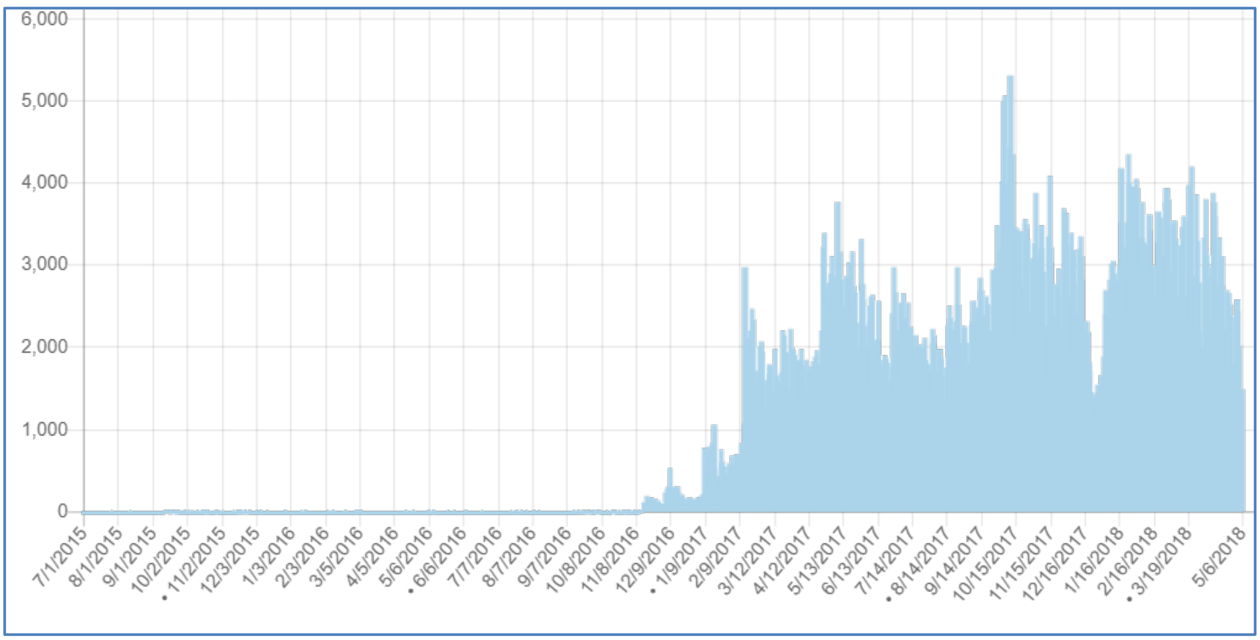


Figure 3: Distribution of tweets mentioning #fakenews from January 3, 2017 to May 7, 2018

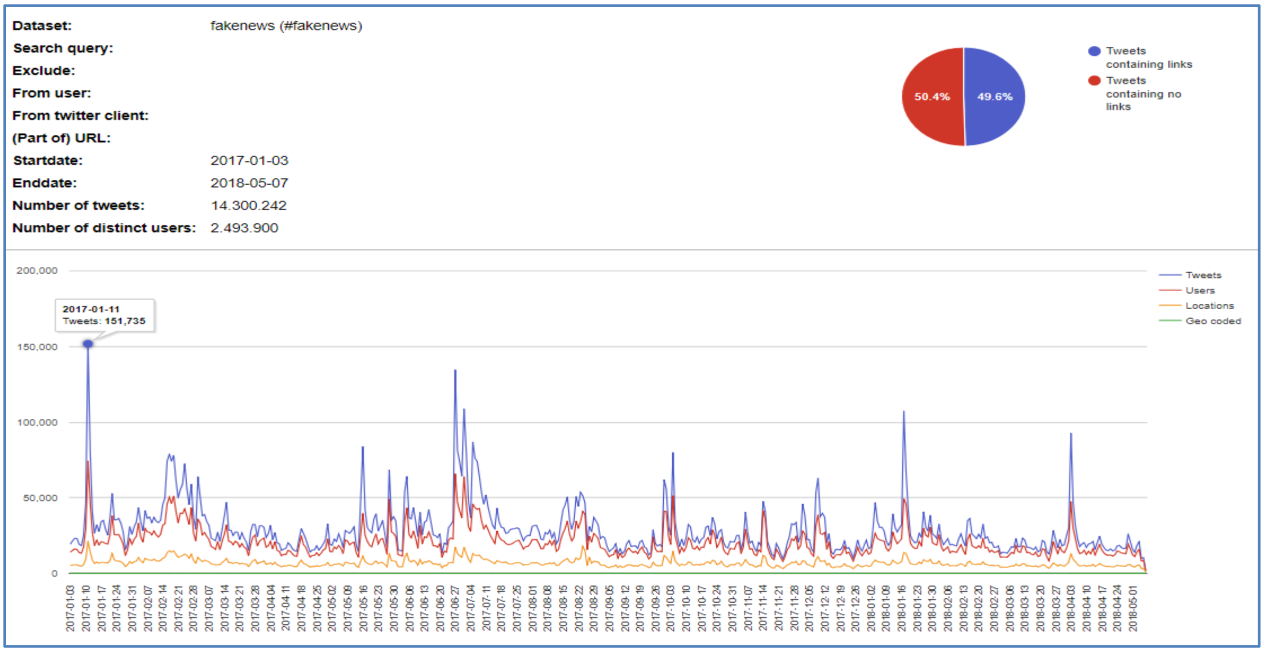
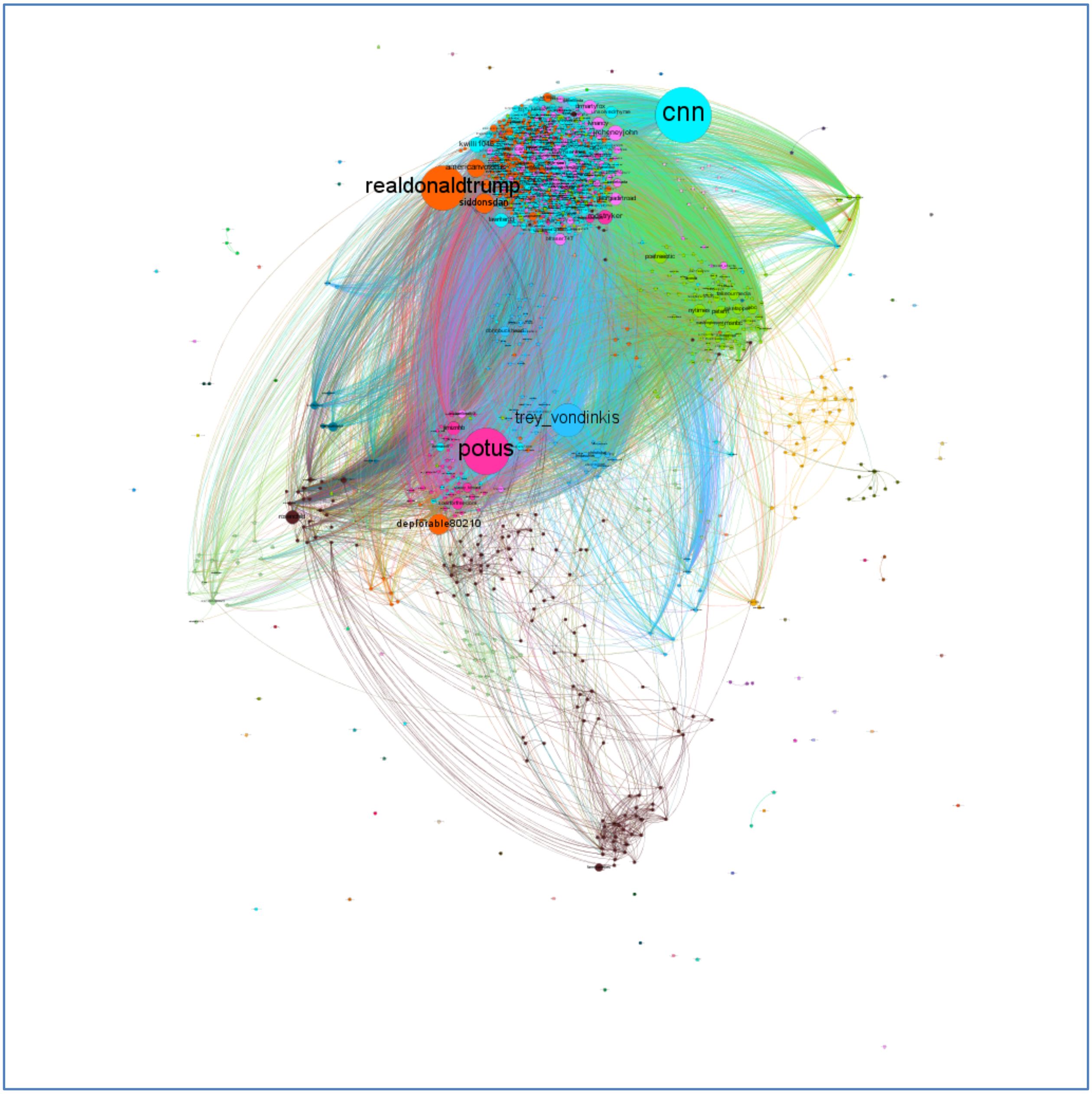


Figure 4: A social network graph by mentions identifying the most active 1,500 nodes connected with 56,505 edges*



*For a higher resolution and more detailed graph, see the following link: https://bit.ly/2zcIraL

Table 1: The top 50 most mentions in connection with #fakenews

Rank	Mention	frequency	Rank	Mention	frequency
1.	realdonaldtrump	1330141	26.	christichat	56572
2.	cnn	1164871	27.	drmartyfox	52675
3.	potus	472656	28.	thehill	52505
4.	nytimes	212092	29.	ingrahamangle	52081
5.	foxnews	209476	30.	teapainusa	49895
6.	donaldjtrumpjr	201600	31.	bfraser747	48873
7.	msnbc	145621	32.	cnnpolitics	48118
8.	washingtonpost	144717	33.	presssec	47785
9.	realjameswoods	142020	34.	johncardillo	47095
10.	mitchellvii	134643	35.	cbsnews	46885
11.	kwilli1046	127502	36.	nbc	46705
12.	jamesokeefeiii	122752	37.	hillaryclinton	45186
13.	jaketapper	111767	38.	cbs	45135
14.	lindasuhler	107359	39.	markdice	43253
15.	project_veritas	104271	40.	gmoneyrainmaker	42946
16.	abc	103675	41.	ap	39977
17.	nbcnews	90838	42.	wikileaks	39238
18.	acosta	89311	43.	realalexjones	38558
19.	seanhannity	88071	44.	brianstelter	38492
20.	sebgorka	75167	45.	donlemon	37028
21.	georgiadirtroad	71556	46.	_makada_	35885
22.	jrcheneyjohn	66822	47.	sandratxas	35734
23.	lvnancy	66003	48.	lkirchner	35615
24.	americanvoterus	63048	49.	thejefflarson	35615
25.	bocavista2016	56920	50.	repstevensmith	34864

Table 2: The top 50 most used hashtags in connection with #fakenews

Rank	hashtag	frequency	Rank	hashtag	frequency
1.	fakenews	14258909	26.	Trumprussia	59068
2.	MAGA	634624	27.	veryfakenews	57685
3.	Trump	470693	28.	AmericaFirst	56068
4.	CNN	439095	29.	MSNBC	54574
5.	MSM	249222	30.	DeepState	52308
6.	QAnon	138350	31.	FraudNewsCNN	51470
7.	WeThePeople	135556	32.	news	51305
8.	GreatAwakening	123834	33.	ReleaseTheCures	51014
9.	FakeNewsMedia	121284	34.	Treason	50831
10.	FakeNewsCNN	106168	35.	SethRich	50012
11.	obamagate	95340	36.	TheResistance	46102
12.	Russia	93881	37.	Obama	45715
13.	CNNBlackmail	85265	38.	FoxNews	43149
14.	Fakenewsawards	80650	39.	resist	41013
15.	Media	77967	40.	Macron	39177
16.	AmericanPravda	75528	41.	Facebook	36692
17.	POTUS	75105	42.	nbc	36624
18.	Propaganda	69705	43.	pizzagate	36416
19.	TCOT	69307	44.	HateGroup	35854
20.	TrumpTrain	69292	45.	wapo	35463
21.	DrainTheSwamp	63401	46.	antifa	34837
22.	AlternativeFacts	63216	47.	FakePresident	34141
23.	InternetBillofRights	60757	48.	wednesdaywisdom	33840
24.	PresidentTrump	60299	49.	CnnIsIsis	33307
25.	Democrats	59395	50.	realnews	33209

Table 3: Top 30 most retweeted posts

Rank	Retweets	Frequency
1.	RT @realDonaldTrump: I am extremely pleased to see that @CNN has finally been exposed as #FakeNews and garbage journalism. It's about time!	39,474
2.	RT @realDonaldTrump: Because of #FakeNews my people are not getting the credit they deserve for doing a great job. As seen here, they are ALL doing a GREAT JOB! https://t.co/1ltW2t3rwy	30,158
3.	RT @realDonaldTrump: I am thinking about changing the name #FakeNews CNN to #FraudNewsCNN!	29,640
4.	RT @MarkRuffalo: Every day it becomes clearer and clearer. The reason @realDonaldTrump labeled legit news #FakeNews early on was because he knew one day all of his deceit, cheating, and harassment, would come under scrutiny by them. The truth has always been his enemy and he knew it.	29,482
5.	RT @realDonaldTrump: We will fight the #FakeNews with you! https://t.co/zOMiXTeLJq	25,441
6.	RT @realDonaldTrump: The #FakeNews MSM doesn't report the great economic news since Election Day. #DOW up 16%. #NASDAQ up 19.5%. Drilling &…	21,496
7.	RT @realDonaldTrump: NBC news is #FakeNews and more dishonest than even CNN. They are a disgrace to good reporting. No wonder their news ra…	20,303
8.	RT @yoiyakujimin: ProPublica - #fakenews & #HateGroup funded by @OpenSociety Main presstitutes: @lkirchner @thejefflarson @JuliaAngwin @i…	18,788
9.	RT @kurteichenwald: Ive checked all of @realDonaldTrump's #fakenews declarations from Nov to March. All of them have since proved true in s…	17,842
10.	RT @realDonaldTrump: ....the 2016 election with interviews speeches and social media. I had to beat #FakeNews and did. We will continue t…	17,216
11.	RT @realDonaldTrump: The @NBCNews story has just been totally refuted by Sec. Tillerson and @VP Pence. It is #FakeNews. They should issue a…	16,985
12.	RT @kirstenkellogg_: ProPublica is alt-left #HateGroup and #FakeNews site funded by Soros. @ProPublica @lkirchner @thejefflarson @JuliaAng…	16,766
13.	RT @realDonaldTrump: .@CNN is #FakeNews. Just reported COS (John Kelly) was opposed to my stance on NFL players disrespecting FLAG ANTHEM …	16,132
14.	RT @markantro: CNN creating the narrative #FakeNews https://t.co/nwxizDhTED	16,086
15.	RT @realDonaldTrump: It is my opinion that many of the leaks coming out of the White House are fabricated lies made up by the #FakeNews med…	16,015
16.	RT @realDonaldTrump: To the people of Puerto Rico: Do not believe the #FakeNews! #PRStrong🇵🇷	15,435
17.	RT @kwilli1046: Isn't It Interesting How The #FakeNews Media Can't Get Off ""The Stormy Slept With Trump"" Story But Somehow Congress Never Provided The List Of "Congressional Sexual Predators" Who Used Tax Payer Money To Hide Their Indiscretions In Office. There's a Story That Needs Resolution!	15,111
18.	RT @realDonaldTrump: One of the most accurate polls last time around. But #FakeNews likes to say we're in the 30's. They are wrong. Some…	14,946
19.	RT @realDonaldTrump: 'BuzzFeed Runs Unverifiable Trump-Russia Claims' #FakeNews https://t.co/d6daCFZHNh	13,574
20.	RT @TeaPainUSA: Perfect example of Russian troll farms coordinatin' with far-right nutball blogs to generate #FakeNews and further Trump's attack on Mueller. Notice they are not RTs, but sent as original content. Yet, each tweet is identical. This is all cranked out by one Russian operator.	13,358
21.	RT @realDonaldTrump: Biggest story today between Clapper & Yates is on surveillance. Why doesn't the media report on this? #FakeNews!	13,199
22.	RT @DonaldJTrumpJr: Getting to read a #fakenews book excerpt at the Grammys seems like a great consolation prize for losing the presidency.…	13,068
23.	RT @realDonaldTrump: ....it is very possible that those sources don't exist but are made up by fake news writers. #FakeNews is the enemy!	12,058
24.	RT @MichaelCohen212: I have never been to Prague in my life. #fakenews https://t.co/CMil9Rha3D	11,924
25.	RT @RealAssange: Democrats and the #FakeNews: ""But @HillaryClinton won the popular vote!"" Fact: 7.2 million votes were cast by dead people.	11,572

Table 4: Summary of the 50 most active Twitter users and their bots' scores

Rank	@username	tweets	bot	Rank	@username	tweets	bot
1.	Grasslanddesign*	25692	---	26.	lawriter33	3339	1.4
2.	propornotapp	23863	1.3	27.	immoralreport	3204	1.8
3.	avonsalez	19280	1.5	28.	sealeney	3158	1.5
4.	politicalpopcu1	18628	4.5	29.	israeli101	3086	0.2
5.	johnnystarling	16851	3.3	30.	Idesignwis*	3059	---
6.	theproplist	14611	1.8	31.	_breitbot_	3047	4.6
7.	Plivecalmer*	12583	---	32.	fake___newz*	2848	---
8.	free_pressfail	11676	3.9	33.	Rharrisonfries*	2809	---
9.	alternatfacts	9822	0.6	34.	Hoffmanllisa*	2808	---
10.	Fauxnewslive	9723	3.8	35.	kianmcian	2641	2
11.	Portofaye*	7622	---	36.	pinkpinta13	2615	1.3
12.	Msmexposed*	7043	---	37.	teespringstores	2608	3.5
13.	trey_vondinkis	6926	4.1	38.	brrrrokkkk	2593	2.9
14.	fakenewsnews247	6112	3.5	39.	hetzbeweis	2588	1.8
15.	col_connaughton*	5975	---	40.	michellebullet1	2414	4.6
16.	samir0403	5928	0.5	41.	poetreeotic	2408	1.9
17.	milove131	5427	1.3	42.	yerissa_blondee*	2384	---
18.	deplorable80210	4943	3.2	43.	rosenchild	2378	1
19.	dumptrumpspace	4490	1.9	44.	rodstryker	2325	2.4
20.	somuchtest	4312	3.4	45.	unsolvedrhyme	2287	3
21.	saul42*	3664	---	46.	turtlewoman777	2287	1.6
22.	trend_auditor*	3641	---	47.	whiskey999111*	2274	---
23.	Siddonsdan*	3616	---	48.	draco333999*	2271	---
24.	macansharp	3536	1.4	49.	jedi_pite_bre*	2255	---
25.	Maconnal*	3470	---	50.	solomon99999000*	2244	---

*Account suspended and is no longer available. Data on bots' scores was retrieved from Botometer on 29 May, 2018

Figure 5: Bots' scores for two random samples of 204,000 Twitter accounts collected between January 3 to July 21 of 2017 as well as from January 1 to May 7 of 2018