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

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Abstract

Purpose – The purpose of this paper is to examine one of the largest data sets on the hashtag use of #fakenews that comprises over 14m tweets sent by more than 2.4m users.

Design/methodology/approach – 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.

Findings – The majority of the top 50 Twitter users are more likely to be automated bots, while certain users' posts like 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.

Research limitations/implications – The research study is limited to the examination of Twitter data, while ethnographic methods like interviews or surveys are further needed to complement these findings. Though the data reported here do 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.

Originality/value – 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 Twitter, Fake news, Bots, Networked political spamming

Paper type Research paper

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 1,000 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 *et al.*, 2016, p. 1). For example, one

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study on Twitter found that "almost 50% of traffic is generated and propagated by a rapidly growing bot population" (Gilani *et al.*, 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 USA, 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 a 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 *et al.*, 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 *et al.*, 2016, p. 2). According to Pew Research Center, it has been estimated that two-thirds of "tweeted links to popular websites are posted by" bots 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. The majority of previous studies on political spamming did not offer a clear conceptual definition of this online activity, while the networked and collaborative aspect has been largely overlooked. This is a networked activity because there is a collective collaboration in disseminating spam, and those involved might not always be aware of their spamming activity. Though spam is not always defined as a form of false information, it is somehow similar to the spread of misinformation which refers to the "inadvertent sharing" of wrong information when users are not aware of the nature of messages they disseminate (Born and Edgington, 2017; Jackson, 2017). In other words, networked political spamming includes the intentional and unintentional spread of spam messages by social media users whose general aim is to serve a particular political side and attack or silence the opponent(s).

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 e-mails 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 and Kivijarv, 2005, p. 136). However, the actual impact of such a strategy is uncertain as it is mostly expected to influence swing voters (Frankel and 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 e-mails 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; Treré, 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 *et al.*, 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 and Mustafaraj, 2009; Himelboim *et al.*, 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 and Greenberg, 2014) and the Massachusetts (MA) senate race between Martha Coakley and Scott Brown in 2010 (Mustafaraj and 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 and 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" in an attempt to silence dissent.

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 and Kollanyi, 2016; Gallacher *et al.*, 2017) and the 2016 election (Kollanyi *et al.*, 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 percent of all 2016 US 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 US President, Donald Trump, and many other politicians, journalists, and the general public following the US 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, where data collection remains ongoing (Borra and 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 percent of tweets have links to other sites (see Figure 3).

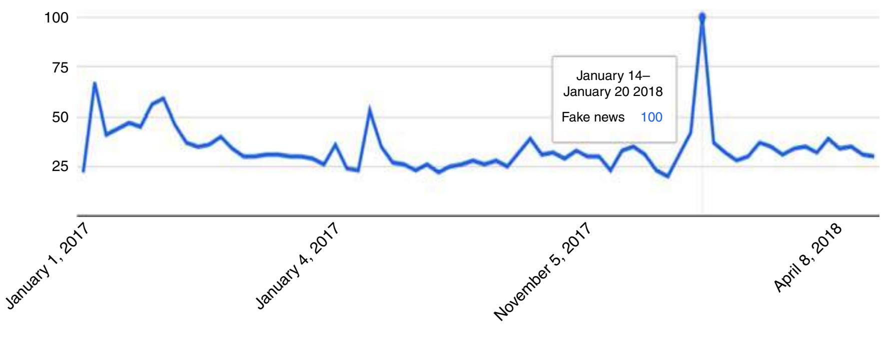

Figure 1.
Google searches for "fake news" from January to May 2018

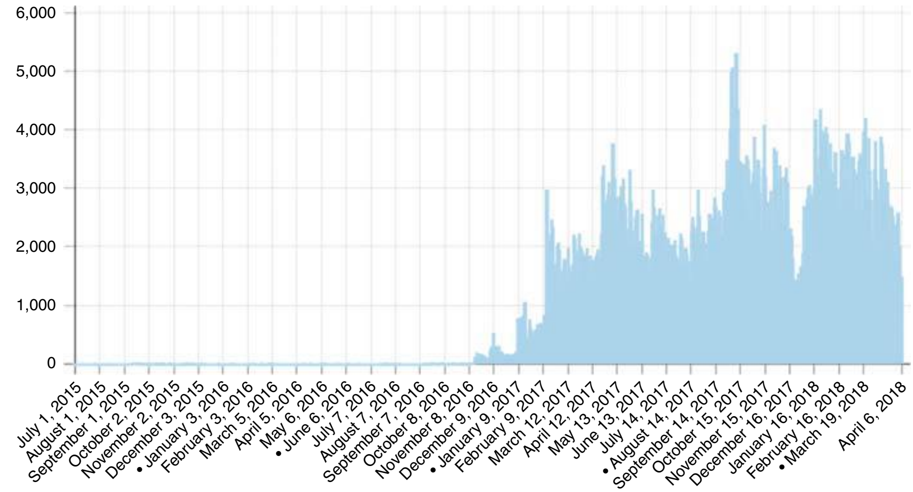

Figure 2.
Wikipedia searches for "fake news" from July 2015 to May 2018

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 data sets (Wilkinson and Thelwall, 2012; Al-Rawi, 2017a, b). We used Gephi (https://gephi.org/), an open source visualization software (Bastian *et al.*, 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; Bessi and Ferrara, 2016; Shao *et al.*, 2017; Ferrara, 2017, 2018). 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 USA) at 472,656, @nytimes with 212,092 and @foxnews with 209,476 mentions on Twitter. There is clear tendency toward 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 $n = 144{,}717$, (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 $n = 39{,}977$.

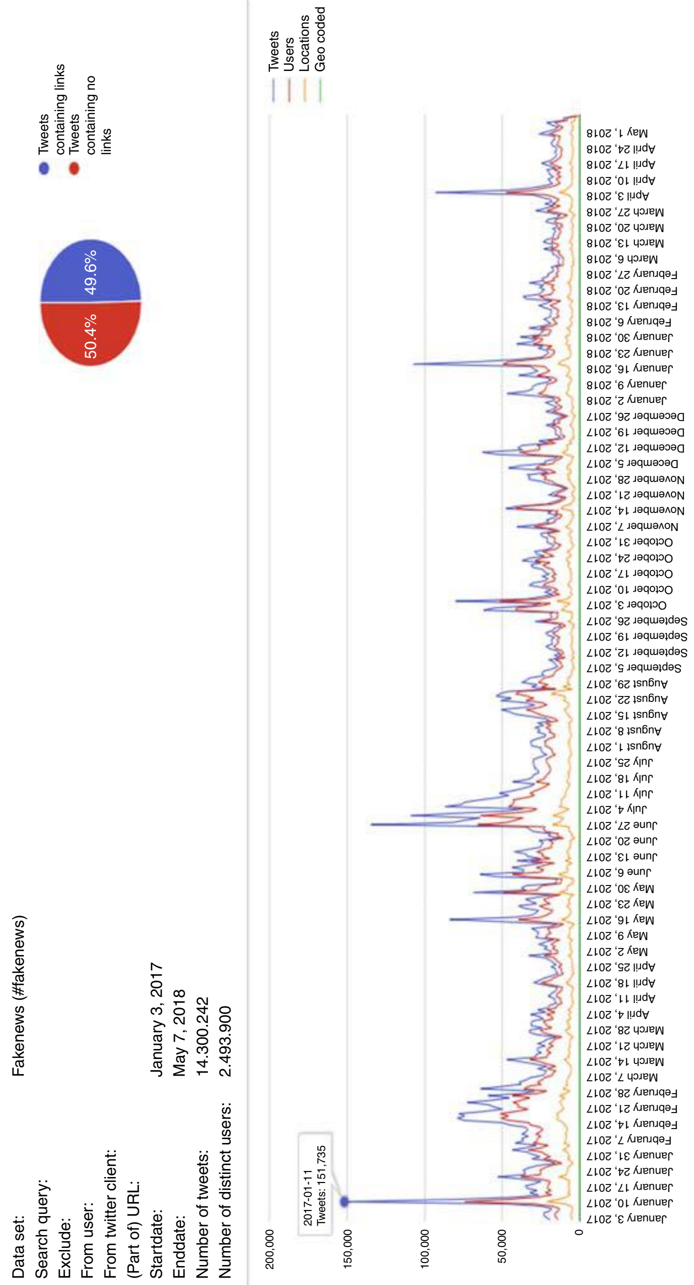

Figure 3.
Distribution of tweets mentioning #fakenews from January 3, 2017 to May 7, 2018

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 www.yourvoiceamerica.tv, Kevin W. ($n = 1{,}27{,}502$) 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 I).

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 into communities within this network and is 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.

As shown in 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.

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

Rank	Mention	Frequency	Rank	Mention	Frequency
1.	realdonaldtrump	1,330,141	26.	christichat	56,572
2.	cnn	1,164,871	27.	drmartyfox	52,675
3.	potus	472,656	28.	thehill	52,505
4.	nytimes	212,092	29.	ingrahamangle	52,081
5.	foxnews	209,476	30.	teapainusa	49,895
6.	donaldjtrumpjr	201,600	31.	bfraser747	48,873
7.	msnbc	145,621	32.	cnnpolitics	48,118
8.	washingtonpost	144,717	33.	presssec	47,785
9.	realjameswoods	142,020	34.	johncardillo	47,095
10.	mitchellvii	134,643	35.	cbsnews	46,885
11.	kwilli1046	127,502	36.	nbc	46,705
12.	jamesokeefeiii	122,752	37.	hillaryclinton	45,186
13.	jaketapper	111,767	38.	cbs	45,135
14.	lindasuhler	107,359	39.	markdice	43,253
15.	project_veritas	104,271	40.	gmoneyrainmaker	42,946
16.	abc	103,675	41.	ap	39,977
17.	nbcnews	90,838	42.	wikileaks	39,238
18.	acosta	89,311	43.	realalexjones	38,558
19.	seanhannity	88,071	44.	brianstelter	38,492
20.	sebgorka	75,167	45.	donlemon	37,028
21.	georgiadirtroad	71,556	46.	_makada_	35,885
22.	jrcheneyjohn	66,822	47.	sandratxas	35,734
23.	lvnancy	66,003	48.	lkirchner	35,615
24.	americanvoterus	63,048	49.	thejefflarson	35,615
25.	bocavista2016	56,920	50.	repstevensmith	34,864

Table I. The top 50 most mentions in connection with #fakenews

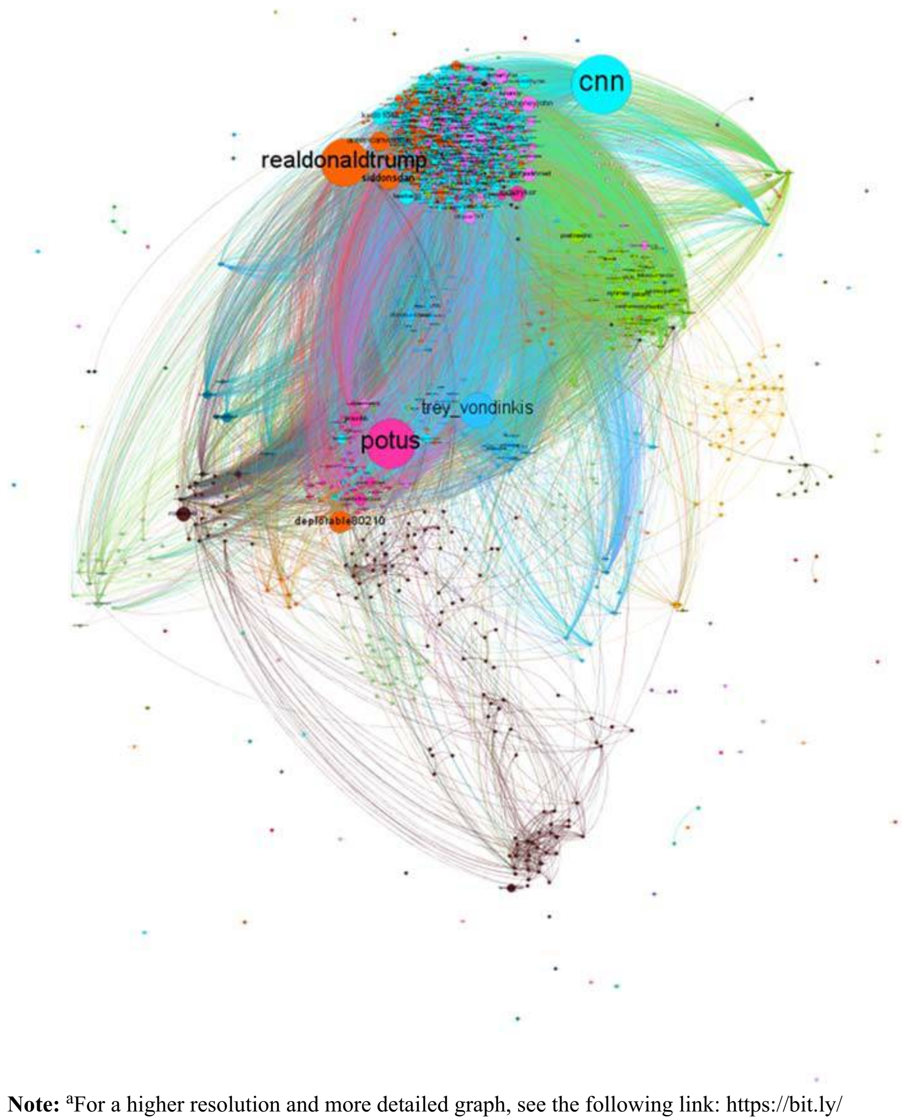

Figure 4.
A social network graph by mentions identifying the most active 1,500 nodes connected with 56,505 edges[a]

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

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* and *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 data set. 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 (Tables I and II).

In order to further understand the most prevalent messages found in the data set, 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 percent 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

Rank	Hashtag	Frequency	Rank	Hashtag	Frequency
1.	fakenews	14,258,909	26.	Trumprussia	59,068
2.	MAGA	634,624	27.	veryfakenews	57,685
3.	Trump	470,693	28.	AmericaFirst	56,068
4.	CNN	439,095	29.	MSNBC	54,574
5.	MSM	249,222	30.	DeepState	52,308
6.	QAnon	138,350	31.	FraudNewsCNN	51,470
7.	WeThePeople	135,556	32.	news	51,305
8.	GreatAwakening	123,834	33.	ReleaseTheCures	51,014
9.	FakeNewsMedia	121,284	34.	Treason	50,831
10.	FakeNewsCNN	106,168	35.	SethRich	50,012
11.	obamagate	95,340	36.	TheResistance	46,102
12.	Russia	93,881	37.	Obama	45,715
13.	CNNBlackmail	85,265	38.	FoxNews	43,149
14.	Fakenewsawards	80,650	39.	resist	41,013
15.	Media	77,967	40.	Macron	39,177
16.	AmericanPravda	75,528	41.	Facebook	36,692
17.	POTUS	75,105	42.	nbc	36,624
18.	Propaganda	69,705	43.	pizzagate	36,416
19.	TCOT	69,307	44.	HateGroup	35,854
20.	TrumpTrain	69,292	45.	wapo	35,463
21.	DrainTheSwamp	63,401	46.	antifa	34,837
22.	AlternativeFacts	63,216	47.	FakePresident	34,141
23.	InternetBillofRights	60,757	48.	wednesdaywisdom	33,840
24.	PresidentTrump	60,299	49.	CnnIsIsis	33,307
25.	Democrats	59,395	50.	realnews	33,209

Table II. The top 50 most used hashtags in connection with #fakenews 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 top 3 tweets are actually critical of Trump, accusing him or fabricating facts and/or disseminating fake news in order to serve his political agenda (Table III).

To answer the second research question on the Twitter accounts that are the most active in discussing tweets that mention #fakenews, Table II 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 US 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, six 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 nine users had either neutral or unclear political affiliations (Table IV).

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 II). 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 percent 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*et al.*, 2016, pp. 2 and 3). In early August 2017, Twitter suspended the account of "Nicole Mincey" who received praise from Donald Trump himself

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$_{PR}$	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 III. Top 30 most retweeted posts

Rank	@username	Tweets	Bot	Rank	@username	Tweets	Bot
1.	Grasslanddesign[a]	25,692	–	26.	lawriter33	3,339	1.4
2.	propornotapp	23,863	1.3	27.	immoralreport	3,204	1.8
3.	avonsalez	19,280	1.5	28.	sealeney	3,158	1.5
4.	politicalpopcu1	18,628	4.5	29.	israeli101	3,086	0.2
5.	johnnystarling	16,851	3.3	30.	Idesignwis[a]	3,059	–
6.	theproplist	14,611	1.8	31.	_breitbot_	3,047	4.6
7.	Plivecalmer[a]	12,583	–	32.	fake___newz[a]	2,848	–
8.	free_pressfail	11,676	3.9	33.	Rharrisonfries[a]	2,809	–
9.	alternatfacts	9,822	0.6	34.	Hoffmanllisa[a]	2,808	–
10.	Fauxnewslive	9,723	3.8	35.	kianmcian	2,641	2
11.	Portofaye[a]	7,622	–	36.	pinkpinta13	2,615	1.3
12.	Msmexposed[a]	7,043	–	37.	teespringstores	2,608	3.5
13.	trey_vondinkis	6,926	4.1	38.	brrrrokkkk	2,593	2.9
14.	fakenewsnews247	6,112	3.5	39.	hetzbeweis	2,588	1.8
15.	col_connaughton[a]	5,975	–	40.	michellebullet1	2,414	4.6
16.	samir0403	5,928	0.5	41.	poetreeotic	2,408	1.9
17.	milove131	5,427	1.3	42.	yerissa_blondee[a]	2,384	–
18.	deplorable80210	4,943	3.2	43.	rosenchild	2,378	1
19.	dumptrumpspace	4,490	1.9	44.	rodstryker	2,325	2.4
20.	somuchtest	4,312	3.4	45.	unsolvedrhyme	2,287	3
21.	saul42[a]	3,664	–	46.	turtlewoman777	2,287	1.6
22.	trend_auditor[a]	3,641	–	47.	whiskey999111[a]	2,274	–
23.	Siddonsdan[a]	3,616	–	48.	draco333999[a]	2,271	–
24.	macansharp	3,536	1.4	49.	jedi_pite_bre[a]	2,255	–
25.	Maconnal[a]	3,470	–	50.	solomon99999000[a]	2,244	–

Notes: [a]Account suspended and is no longer available. Data on bots' scores were retrieved from Botometer on May 29, 2018

Table IV.
Summary of the 50 most active Twitter users and their bots' scores

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 and July 21 of 2017 and another sample collected between January 1 and 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 labeling human accounts as bots.

We chose two data sets 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 data set (mean = 0.078, SD = 0.21), and 93,322 for the newer data set (mean = 0.063, SD = 0.17). Given a majority of accounts are not bots (thus with CAP of or close to 0), both data sets are highly skewed (kurtosis = 11.97 and 15.2, respectively). Figure 5 shows the density plot of the CAP for both data sets 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.

Discussion and 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 and to position the effects of fake news appropriately (Groshek and Koc-Michalska, 2017). Along these lines, however, and of particular importance to the study reported here, the use of bots is not only 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 have become weaponized tools (Al-Rawi, 2018) used as a part of networked political spamming that functions as a proxy to undermine credibility and weaken the opponents' arguments by the association that is made. Here, social media users, who actively support political figures interested in attacking their opponents online, might be unwittingly acting as political spammers in their supportive dissemination activities, while bots greatly enhance this spamming effort.

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

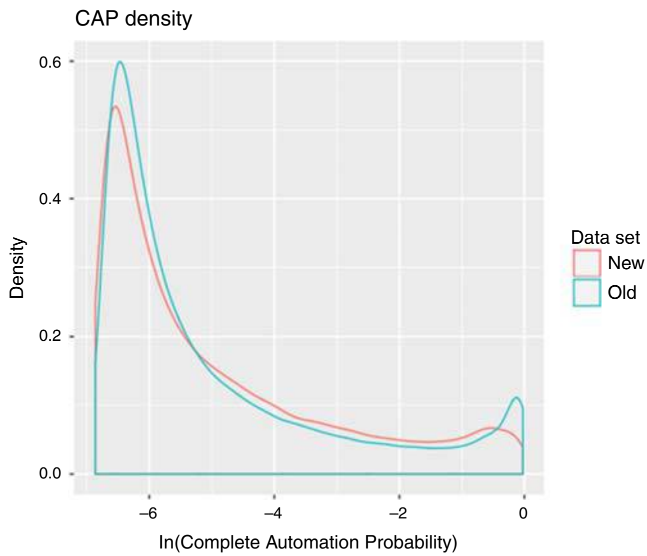

Figure 5.
Bots' scores for two random samples of 204,000 Twitter accounts collected between January 3 to July 21 of 2017 as well as from January 1 to May 7 of 2018

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, top 4 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 toward certain directions. The above attacks against CNN and other mainstream media outlets would not have been clearly visible without the success of networked political spamming, whether by bots or humans.

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 a 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 percent) including some that belonged to the most retweeted posts ($n = 4$, 16 percent) 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 *et al.*, 2018). 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 and Guo, 2017). In other words, bots have the potential to influence people's agenda especially if the networked spamming 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 a part of the worry over fake news has been ballooned into a moral panic (Beckett, 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 propaganda afforded by networked political spamming.

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 its networked affordances and the relative ease of spreading information. Though the peak of fake news stories online was thus far in the period immediately following the US 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 percent). 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 that sheds light on why fake news discourses are repeatedly referenced on Twitter and how they are currently used as a weapon to spam opponents. 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. Media educators can make use of this study to further enlighten the public and possibly networked political spammers who are not aware of the nature of their online behavior, by highlighting the potential impact or effect of their online spamming activity.

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. Finally, spamming and networked discourses of fake news are limited here to the study of news and politics, but there are other important and vital issues that can be explored using the same or different methodology, since spammers are also active in spreading (dis)information on the environment, health and science.

Note

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

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