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Characterizing the roles of bots during the COVID-19 infodemic on Twitter

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Abstract An infodemic is an emerging phenomenon caused by an overabundance of information online. This proliferation of information makes it difficult for the public to identify trustworthy news and credible information from untrustworthy sites and non-credible sources. The perils of an infodemic debuted with the outbreak of the COVID-19 and bots (i.e., automated accounts controlled by a set of algorithms) that are suspected of involving the infodemic. Although previous research has revealed that bots played a central role in spreading misinformation during major political events, it is unclear how bots behaved during the infodemic. In this paper, we examined the roles of bots in the case of the COVID-19 infodemic and the diffusion of non-credible information such as "5G" and "Bill Gates" conspiracy theories and "Trump" and "WHO" related contents by analyzing retweet networks and retweeted items. We show the bipartite topology of their retweet networks, which indicates that right-wing self-medium accounts and conspiracy theorists may lead to this opinion cleavage, while malicious bots might favor amplification of the diffusion of non-credible information. Although the basic influence of information diffusion could be larger in human users than bots, the effects of bots are non-negligible under an infodemic situation.

1 Introduction

It was estimated that of all tweeted links to popular websites, 66% were shared by bots [1]. The most recent research about social media manipulation in the 2020 U.S. presidential election characterized the differences between right and

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left-leaning bot behavior [2]. Given this context, an important research question is how bots behaved in the spread of misinformation during the COVID-19 infodemic. To study this, we focused on Twitter retweets as misinformation vectors. Conspiracy theories related to "5G", "Bill Gates", "WHO" and "Trump" (the 45th U.S. president) were analyzed. In this paper, we firstly characterized the credible and non-credible humans and bots around the four topics in the retweet networks. We then compared the retweet activities as well as other features in the four topics considered. Our results may help us understand how bots played a role during the COVID-19 infodemic, providing insights into a mitigation strategy.

2 Data and Methods

2.1 Data collection and preprocessing

We collected 279,538,960 English tweets from Feb 20 to May 31 by querying COVID-19 related keywords: "corona virus", "coronavirus", "covid19", "2019-nCoV", "SARS-CoV-2", "wuhanpneumonia" using the Twitter Search API. As aforementioned , we focused on four topics in our analyses: "WHO", "Trump", "Bill Gates", and "5G". According to domains information publihsed on MisinfoMe [1], [3] and [4], we obtained 893 non-credible domains and 32 credible domains. After extracting tweets regarding the four topics, we obtained a total of 37,219,979 tweets, in which 23,1515,441 (82.8%) were retweets. The breakdown of this dataset is shown in Table 1. We used the Botometer API to compute user bot scores. According to [5,6], we set the threshold to 0.43 in the human/bot classification. This means that a user was considered to be a bot if the bot score was larger than 0.43, and if otherwise, a human user.

Table 1: Overview of COVID-19 tweets by topic.

	Unique users (U)	Unique Users with Bot score (US)	Percentage (US/S)	# Tweets	# Retweets
WHO	88,719	73,704	83.1	128,016	46,650
Trump	1,125,366	947,694	84.2	5,631,459	2,322,036
5G	67,524	55,315	81.9	97,638	31,814
Bill Gates	94,597	77,896	82.3	138,042	75,885

2.2 Retweet behavior analysis

The retweet network was visualized by the network analysis tool Gephi [7]. We used different colors to represent credible and non-credible bots; red nodes are

[1] `https://misinfo.me`

non-credible bots, green nodes are credible bots, and purple nodes are others that can be humans or unlabeled bots. Edge colors are the same as the target node colors. We highlighted users with large a indegree, including important politicians, well-known mainstream medium, right-wing medium, and so on. Moreover, we compared temporal patterns of retweet activities among four types of users: credible humans and bots, non-credible humans and bots.

2.3 Retweeted contents analysis

To compare important terms used in articles retweeted by credible and non-credible users, we summarized TF-IDF values by using the Laterality Index (LI) [8], defined as follows:

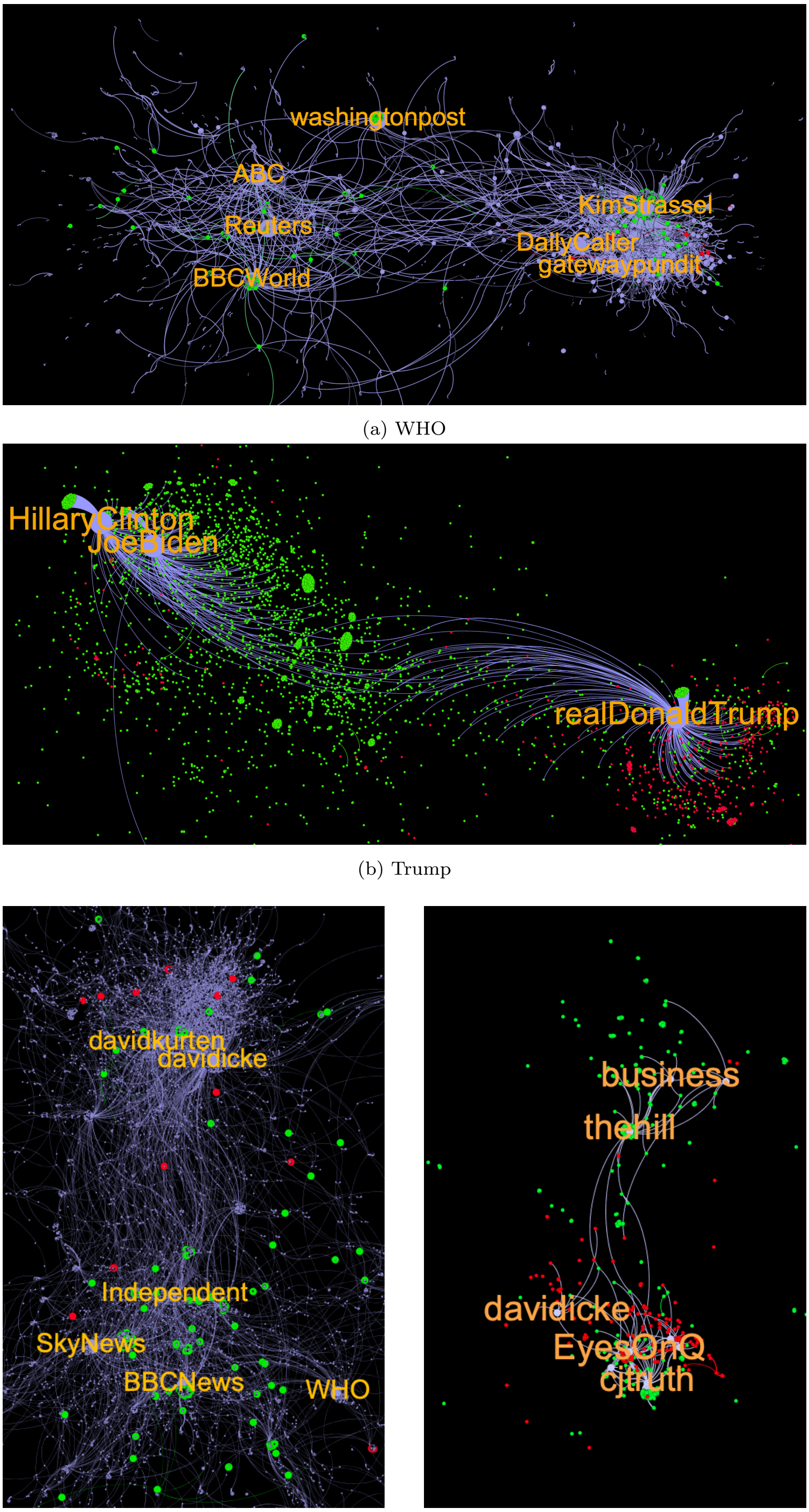
$$LI = \frac{C - NC}{C + NC}, LI \in [-1, 1], \tag{1}$$

where C is the TF-IDF score for terms used in articles retweeted by credible users and NC is one for terms used in articles retweeted by non-credible users. LI compares the importance of a term between credible sites and non-credible sites. For this analysis, we limited our research to the top 30 most popular terms in the collected articles.

3 Results

3.1 Bipartite structures of retweet networks

The resulting retweet networks are shown in Fig. 1. It is notable that bipartite structures emerged in all the topics considered, with dense connections inside and sparse connections in-between. Previous research has found that the retweet network of the 2010 US midterm election showed typical "left" and "right" segregated groups [9]. We thus examined whether the "Trump" reteweet network shares the similar features. Fig. 1b shows the Trump network ($n = 1,125,366$) with 694 non-credible bots and 5,400 credible bots. Here "@HillaryClinton" (Hillary Clinton) and "@JoeBiden" (Joe Biden) representing the progressive clustered together, were distant from the conservative cluster with "@realDonaldTrump" (Donald Trump). A notable finding is that "@realDonaldTrump" was mostly retweeted by non-credible bots, whereas "Hillary Clinton" and "Biden Joe" were less so.

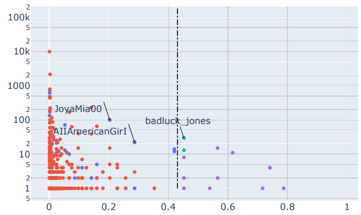


(a) WHO

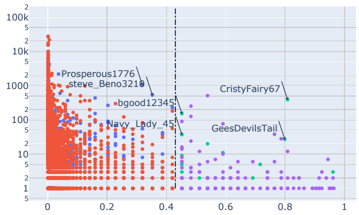
(b) Trump

(c) 5G (d) Bill Gates

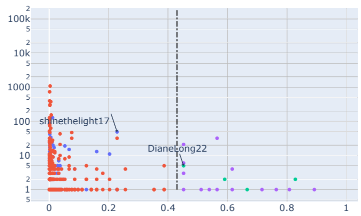
Fig. 1: Retweet networks related to "WHO","Trump", "5G", and "Bill Gates". Red shows non-credible bots, green shows credible bots, and purple can be humans or unlabeled bots. To improve visibility, in (b) "Trump" and (d) "Bill Gates", only credible bots, non-credible bots, and users with large indegrees are shown (purple nodes are not shown).



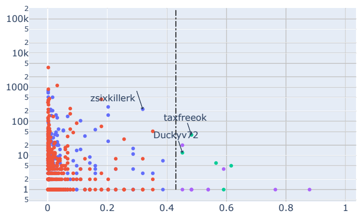
(a) WHO



(b) Trump



(c) 5G



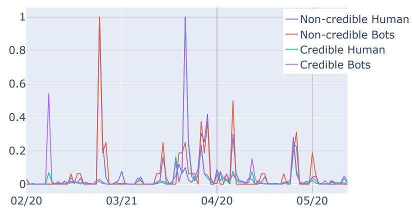
(d) Bill Gates

Fig. 2: Indegrees (Y-axis) vs. bot scores (X-axis) in “WHO”, “Trump”, “5G” and “Bill Gates” topics. Red indicates credible humans; Blue indicates non-credible humans; Green indicates non-credible bots; purple indicates credible bots. The users pointed out by arrows are seemingly outliers. The text indicates the username of that node. The black dot dash line is the threshold of 0.43 for a bot score.

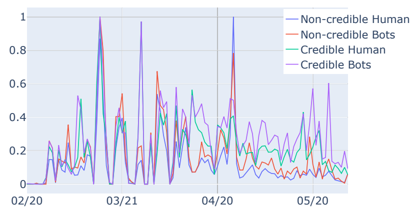
Then, we quantified indegrees (the numbers of retweeted posts by different users, used as a measure for engagement) as a function of the bot score. The resulting scatter plots are shown in Fig. 2, in which the majority of users are obviously credible humans and most of them fall in the bot score range $[0, 0.2]$. It turns out that the indegrees tend to be inversely proportional to the bot score and on average, indegrees for humans are larger than those for bots in all the topics.

3.2 Temporal patterns of retweets in humans and bots

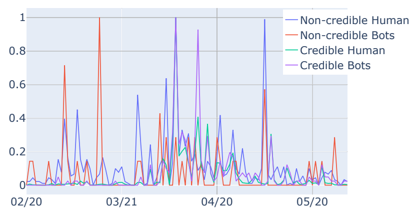
We assumed that non-credible bots were following non-credible humans rather than credible humans, because the intention of non-credible bots would be on amplifying the spread of misinformation including conspiracy theories. Thus, we quantified temporal patterns of retweet behaviors in humans and bots. For a comparison among credible/non-credible humans and bots, we scaled daily retweet counts between 0 and 1, respectively. Fig. 3 shows daily retweet series by humans and bots for each topic, in which the patterns of retweet increases follow the similar trends. To confirm this observation, we measured the correlation coefficient of temporal oscillations of retweets generated by these users. The results are summarized in Table 2. This reveals that all the topic retweet series by non-credible bots correlated with those by non-credible humans much better than by credible humans. The above assumption is therefore partially supported. We further consider this assumption in the next section by looking at commonality in retweets generated by humans and bots.



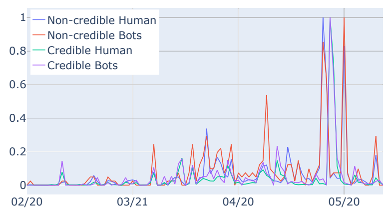
(a) WHO



(b) Trump



(c) 5G



(d) Bill Gates

Fig. 3: Retweet series generated by humans and bots in "WHO","Trump", "5G" and "Bill Gates" topics. Daily retweet counts are scaled between 0 to 1, respectively. Here 1 represents the maximum retweet count while 0 represents the minimum retweet count in each topic.

Table 2: Correlation coefficients of retweets between Non-credible Bots (NB), Credible Humans (CH), Non-credible Humans (NH).

Topic	Category	Correlation Coefficient	P-value
Bill Gates	NB & CH	0.02	0.83974369
	NB & NH	0.93	1.91E-44
5G	NB & CH	0.11	0.240689586
	NB & NH	0.49	1.57E-07
Trump	NB & CH	0.67	1.84E-14
	NB & NH	0.95	1.26E-51
WHO	NB & CH	0.26	0.009576659
	NB & NH	0.93	2.23E-46

3.3 Commonality in retweets by humans and bots

Finally, we examined terms (nouns), domains (URLs), and users that commonly appeared in retweets generated by humans and bots. Fig. **??** shows an example comparing term importance (measured by TF-IDF) on 5G-related articles retweeted by humans and bots. In the 5G topic, “china” was a characteristic term used in the articles retweeted by non-credible humans as well as non-credible bots. Overall, the non-credible bots and non-credible humans share 71%, 50%, 80% and 50% terms (nouns) used in the retweeted articles related to the “WHO”,“Trump”,“5G” and “Bill Gates” topics, respectively.

We also found that both non-credible humans and bots exhibit high commonality in retweeted domains (URLs) and users; the same is true for credible humans and bots. Take the 5G topic as an example, both non-credible humans and bots tend to share the same domains and retweeted users. This indicates that both humans and bots tended to follow common influential users. Taken together, non-credible bots shared many in common with respect to the top 15 retweeted domains and the top 15 retweeted users. These findings further support the assumption that non-credible bots were following non-credible humans rather than credible humans.

4 Discussion

In this paper, we investigated the roles of bots by analyzing retweet networks, temporal patterns of retweets as well as retweeted contents and users during the COVID-19 infodemic. For analysis, we focused on misinformation and conspiracy theory related topics, such as “WHO”, “Trump”, “5G” and “Bill Gates”. We found that the retweet networks exhibited a bipartite topology in all of the four topics. According to the indegrees, the basic influence of retweets by non-credible humans can be much larger than those by non-credible bots. Thus, bots may not play as important a role during the COVID-19 infodemic as they did in previous political events, including 2016 US presidential election. The clustering of non-credible bots may reflect a partisan asymmetry and that non-credible bots follow non-credible humans call for the necessity of continuously monitoring the information ecosystem of bots. This is especially important to detect their coordinated acts, though we did not find evidence of such events in the current settings, but this could still be a future threat that has a negative societal impact.

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