Who is Spreading Misinformation?

Social Bots, Misinformation, and 2020 U.S. Presidential Election

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Abstract

This study aims to investigate the social bots' role in misinformation spreading, and its influence on the issue topics of elite media (the combination of professional news organizations accounts and journalists or reporters accounts) and average users on social media by analyzing 926, 845 tweets discussing about 2020 U.S. Presidential Election related misinformation from November 1st, 2020 to January 20th, 2021. Through intermedia agenda setting theory, the study uses unsupervised machine learning method (LDA topic model) combining with topic issues comparison to compare topics generated by social bots accounts, elite media accounts and average users accounts during this election period. Results showed that both social bots accounts and average users accounts took active part in spreading or engaging (retweet) in fraud, illegal, or illegitimate related misinformation around the 2020 election; conversely, elite media accounts were less likely to spread or engage in election related misinformation. And social bots accounts, elite media accounts, and average users accounts have the possibility to influence each other's topic issues of election race, justice & law, capitol attack & violence, and news & media. But in terms of the topic issue of overturn election results, the convergence relationship only appears between social bots accounts and elite media accounts. And in terms of voting process topic, only social bots accounts and average users accounts have the convergence. The study advances the intermedia agenda setting theory through adding the social bots – non-human social media accounts into intermedia agenda analysis.

Keywords: social bots, misinformation, issue topics, elite media, social media

Introduction

Recent years, social media has become a breeding ground for spreading fake news and misinformation. "Misinformation is when false information is shared, but no harm is meant" (Wardle & Derakhshan, 2017). Many previous research examined how fake news and misinformation spread over social media platforms (Allcott et al., 2019; Vosoughi et al., 2018). Other studies tried to reveal why social media platforms facilitate the emergence and spread of misinformation, some of them attributed this problem to the algorithms; and some of studies pointed out that the filter bubble and recommendation feature of social media cause people expose more frequently to misinformation.

However, some scholars provided alternative explanation, their work found that social bots might also play a role in producing and disseminating misinformation over social media platforms. Social bots are fake accounts that pretend to be real users' accounts, they are controlled by the computer algorithm that automatically produces content and interacts with humans on social media, trying to emulate and possibly alter users' behavior (Ferrara et al., 2016).

Social bots are caught more and more attention from academia, industry, and governments recent years, especially after the 2016 U.S. Presidential Election. Although more and more social media companies are involved in reducing social bots in their platforms, it is still challenging for them to detect and delete bots due to both technical and financial constraints. The fast-developing AI technology make social bots be able to produce human-like language, as such it is harder to distinguish them from real accounts (Guglielmi, 2020). Therefore, bots remain active in major social media platforms such as Twitter, Facebook, Reddit, and Sina Weibo. And they are typically active in special events or time periods like important political elections, social movements, and COVID-19 pandemic. This study uses the significant political event —— 2020 U.S. Presidential Election as a case study to examine to what extent social bots have involved in spreading misinformation surrounding this election, and whether social bots have the effect to influence issue topics of elite media accounts and average users account through the lens of intermedia agenda setting theory. There are many misinformation and rumors surrounding this election over social media platforms, even the election candidate such as former president Donald Trump also spread this election was "fraud" and tried to overturn the election results on Twitter during the election period. Thus the 2020 U.S. Presidential Election is a best fit context for this study.

Literature Review

Bots have existed for many years since the emergence of Internet in the early period, one of the typical cases is the Chatbots——a computer-controlled software that could mimic real person to chat or communicate with users online via text or text-to-speech. Along with the popularity of social media, bots also are widely used in various social media platforms such as Twitter and Facebook (Subrahmanian et al., 2016; Santia et al., 2019). There are many different kinds of social bots active across different social media platforms, overall, they can be aggregated into two higher level categories: legitimate social bots and malicious social bots. Legitimate social bots are bots that being produced and used with innocuous or even helpful purposes on social media (Ferrara et al., 2016). For example, some professional news agencies or news organizations are using news bots to produce or disseminate news automatically. While malicious social bots are bots that being created to harm, by tampering with, manipulating, and deceiving social media users (Ferrara et al., 2016). Malicious bots can deceptively impersonate humans to manipulate and pollute the information ecosystem by spreading low-credibility content, misinformation, and fake new etc (Yang et al., 2022; Shao et al., 2018). Therefore, malicious bots are often being used with unfavorable even harmful intentions such as intervening in political discourse, spreading misinformation, and manipulating the stock market.

Given the diversity and ongoing evolution nature of social bots, researchers have not achieved the agreement on social bots' universal definition until now. Ferrara et al. (2016) defined the social bots are fake accounts that pretend to be real users' accounts, they are controlled by the computer algorithm that automatically produces content and interacts with humans on social media, trying to emulate and possibly alter their behavior. This study will use Ferrara et al. (2016)'s definition of social bots.

The Rise of Social Bots Research

Although research work on social bots increased rapidly after the 2016 U.S. presidential election, the rise of social bots related research could date back to 2010 United States midterm elections. In this midterm elections, politically-motivated individuals and organizations used multiple centrally-controlled accounts to create the appearance of widespread support for a candidate or opinion (Ratkiewicz et al., 2011). In 2016 U.S. presidential election, many research found that numerous social bots were used in intervening and distorting this election (Bessi & Ferrara, 2016; Shao et al, 2018; Gorodnichenko et al, 2021), since then, social bots are attracting more and more attention from academia, government and the public.

Social Bots Detection

In the early periods, social bots used simple strategies that were easy for researchers or social media companies to detect. For example, researchers could detect whether one social media account is bot or not based on how many posts it produced in 24 hours or the language it used. However, as artificial intelligence tools advance to produce human-like language, today's social bots are becoming more and more complicated (Guglielmi, 2020). How to detect social bots on social media is the first and also an important step when conducting social bots research. Many work have focused on social bots detection, particularly in computer science field. In Ferrara et al. (2016) and Alothali et al. (2018)'s work, they summarized three main approaches to detect social bots: Graph based method which examines the social bots accounts' social graph structure and networks on social media; crowdsourcing approach which recruits a large number of humans to detect social bots accounts; and machine learning approach which uses the machine machine learning methods to identify social bots based on some general features and behaviors patterns on social media. Martini et al. (2021) compared three widely-used social bots detection tools that are Botometer, Tweetbotornot and "heavy automation", and found that Botometer's detection results are more reliable than the other two tools.

Social Bots in Health Context

Since the outbreak of COVID-19 pandemic in 2020, it is obvious that abundant misinformation around this pandemic are disseminated rapidly and broadly over various social media platforms. In February 2020, The World Health Organization used a term "infodemic" to alarm the severity of COVID-19 related misinformation. An "infodemic" is too much false and misleading information mixed with accurate and scientifical information circulated in digital and physical environments during a disease outbreak (WHO, 2020).

Who are the active actors that generate and disseminate COVID-19 related misinformation on social media platforms? Many recent studies showed that social bots also played a role in amplifying COVID-19 infodemic. Shi et al. (2020) found that social bots contributed to as much as 9.27 percent of COVID-19 diccussions on Twitter. Himelein-Wachowiak et al. (2021) found that up to 66% of bots were discussing COVID-19 according to analyze a large dataset of social bots accounts. Ferrara’s (2020) research found that high bot score accounts are used to promote political conspiracies and divisive hashtags alongside with COVID-19 content and enable participatory activism to shed light on issues that may otherwise be censored in China during the early periods of COVID-19. The research by Yang et al. (2020) also revealed that social bots were involved in both posting and amplifying low- credibility information on social media during the pandemic. Work by Xu and Sasahara (2021) examined the social bots’ role in spreading the COVID-19 pandemic by analyzing retweet networks and retweeted items.

Social bots in Political Context

Social bots research popularized after the 2016 U.S. presidential election, some previous research tried to investigate how social bots interfered in this election and manipulated public opinion. Bessi and Ferrara (2016) found that almost 19 percent of all tweets about the U.S. presidential election in 2016 were generated by social bots, they concluded that social bots greatly affected political discussion around the 2016 U.S. presidential election. Shao et al. (2018) found evidence that social bots played a disproportionate role in spreading articles from low-credibility sources from 2016 to 2017. Bots amplify such content in the early spreading moments, before an article goes viral. Ferrara (2018) discussed how social bots have been used during the 2016 U.S. Presidential Election to sway the conversation around the presidential candidates. And the work by Woolley and Howard (2017) revealed how governments and politicians in different countries used social bots to serve their political propaganda, including spreading misinformation and conspiracy theories.

Intermedia Agenda Setting Theory

Hence, previous research mainly focused on how prevalence of social bots on social media platforms, how to detect social bots, or how to improve social bots detection tool's performance. Few of them pays attention to the content and topics discussed by social bots accounts. thus, this study proposes the first research question:

RQ1: What topics and keywords around 2020 U.S. Presidential Election related misinformation were spread mostly by social bots?

Also, few prior research work investigated the correlation among social bots, elite media (elite media is the combination of news organizations and professional journalists or reporters on social media), and general real users on social media. When studying the public opinion or public discourse on social media, researchers often grouped all posts or contents published on social media platforms as a whole, they presumed all posts or contents were published by real users accounts, which might cause their findings biased. Since more and more research had found out the prevalence of social bots on social media, the posts or contents published by those fake users accounts should not be accounted into the public opinion or public discourse. Therefore, this study separates social bots accounts from elite media accounts, average real users accounts, and treats those three types of accounts as three different subjects, through introducing the intermedia agenda setting theory, this study tries to examine the correlation among social bots, elite media and general real users on social media in regarding for the issues they discussed during the 2020 U.S. presidential election period.

The agenda setting theory refers to media has the power to set public agenda. (McCombs & Shaw, 1972; McCombs, 2004). Media could transfer agenda to the public agenda regarding the salience of issues, political figures and other objects of attention, which is the first level of agenda setting (Coleman et al., 2009; McCombs et al., 2014). The second level agenda setting is concerning the impact of the media agenda on the public agenda regarding the salience of the attributes of these objects (McCombs et al., 2014). And the third level of agenda setting asserts the news media is also able to transfer the relationships, or the connections, between the attribute agendas to the public, which is also called the network agenda setting theory (NAS)(Guo & McCombs, 2011; Guo, 2013).

Above three levels of agenda setting theories all concentrate on the impact of media agenda on the public agenda, while there is another line of agenda setting research that cares about who sets the media agenda? Different media organizations can influence each others' news agenda, this is described as intermedia agenda setting theory (IAS) (McCombs, 2004). Many research has certified the flow and influence of agenda among different traditional media, some of them found that traditional elite media such as leading newspapers, TV programs, or radio stations often influenced the agenda of other small media outlets (Reese & Danielian,1 989; Meraz, 2011); while some other research found that the agenda could flow among different media types, for example, newspapers, televisions, and advertisements could affect each others' agenda (Boyle, 2001).

When entering into digital media era, intermedia agenda setting research not only limited to traditional media, but also expanded to the online media, and social media. Some studies focused on the agenda flow among different online news websites (Guo & Vargo, 2020); some studied about the agenda transferred among online news media and traditional news media such as newspaper and TV news programs (Vonbun, 2016; Harder, 2017). And some other studies also investigated the agenda convergence between social media such as Twitter and traditional media (Rogstad, 2016; Valenzuela et al., 2017).

Social media has brought many challenges to the traditional intermedia agenda setting theory, for example, “media” subjects needed to be re-defined. Along with more and more people turn to social media to acquire news, more and more professional news organizations and journalists/reporters also create accounts on different social media platforms, they published news information on social media instead of through news platforms. Thus, those professional news organizations and journalists/reporters on social media also could be regarded as media. Additionally, different from traditional one-directional news flow that news organizations/journalists/reporters are the only news sources to the public, social media provided the platforms for the general public to create/publish content on social media, which referred to “user generated content” (UGC). Those user generated contents also could become news sources to other average users even professional news media or journalists/reporters. In this case, average users accounts on social media also could be counted as media. However, as argued before, social media is proliferating with many social bots accounts, they are always controlled by computer algorithms rather than real persons, and they also mimic real users to publish news or information on social media. Thus, they also could be separated as another type of media on social media.

During current multimedia environment, the agenda flow among different media is also multi-directional. Focused on Twitter, this study tries to examine agenda flow among social bots accounts, elite media accounts, and average users accounts, and to see whether there will be issues convergence correlations among those three different media subjects. Hereby, two other research questions proposed as below:

RQ2: Are there any differences/similarities regarding the topics discussed by social bots accounts, news media accounts, and average real users accounts during the election?

RQ3: Whether social bots accounts, news media's accounts, and average real users accounts influenced each other's topic issues during the election?

Methods

Data Collection

This study used the R package "academictwitteR" to retrieve tweets (including retweets) discussing about stolen or fraudulent or illegal claims of 2020 U.S. Presidential Election related misinformation through the Twitter Academic Research Product Track V2 API Endpoint. As all data collection work were completed by November 16, 2022, this project was not affected by Twitter's changing API policy luckily. Query used in search is: "election steal", "election stolen", "election fraud", "election fraudulent ", "election illegal", "election illegitimate", "#stopthesteal","#voterfraud","#fraud". Language was set as English, and all countries were included. After doing literature review and exploratory tweets review, keywords like "steal", " stolen", "fraud", "fraudulent ", " illegal", " illegitimate", and hashtags such as "#stopthesteal", "#voterfraud","#fraud" are associated closely with 2020 U.S. Presidential Election related misinformation, and those misinformation have been widely fact-checked as false and misleading.

Time window was set from November 1st, 2020 (The deadline for early in-person voting in Delaware, Florida, and New York) to January 20th, 2021(Inauguration of the president Joe Biden and the Vice President Kamala Harris).

In total, 12 million tweets were retrieved, and due to the limitation of the researcher's computer power and labor capacity, the researcher randomly selected 1.2 million tweets (applying 10% sample rate). Among the 1.2 million randomly sampling tweets, 273, 155 tweets are not available as a result of accounts being protected or deleted. After removing those unavailable tweets, 926, 845 tweets were used in the final data analysis (dataset is named "election2020"). Although some tweets among the 926, 845 tweets are indeed correcting, alerting, or fact-cheking misinformation around the 2020 election, the researcher still kept those tweets for analysis. As those corrections, alerting and fact-checking tweets are also part of online debates or discussions about this election related misinformation.

Data Analysis

Firstly, the researcher classified social bots accounts from average real users accounts, and elite media accounts. In order to categorize accounts into above three categories, the researcher first counted and sorted all tweets by unique username (or called handles), in total, there are 366, 549 unique user accounts. As the dataset is comprised of all English tweets discussing about false claims of the 2020 U.S. election from all around the world, researcher then count and sort tweets by courtiers, among all 926, 845 tweets, 428, 595 tweets (46.2%) did not disclose the locations, and the top 10 countries are: United States (41.2%), Canada (2.5%), United Kingdom (1.7%), Australia(0.8%), France(0.5%), Japan(0.5%), Germany(0.4%), Colombia(0.3%), Brazil(0.3%), Spain(0.3%) (See Table A1 in Appendix). As tweets from United States, Canada, United Kingdom, and Australia account for 86% of all tweets with locations disclosure (N total=926, 845 – 428, 595= 498,250), the researcher decided to collect handles of elite media accounts from those top 4 countries (See Table A2 in Appendix), another factor to pick up those 4 countries is that they are all major English spoken countries in the world.

In terms of elite media accounts' handles in the United States, this paper directly used the handles collection list in the paper of Wells et al. (2016). In this paper, they collected 97 major media organizations and professional journalists active on Twitter. Apart from the 97 handles, the researcher also added 3 news organizations through self-searching on Twitter, therefore elite media accounts' handles in the United States are 100 in total. In regarding for handles of elite media accounts in the other three countries, the researcher hand picked up 17 media in Canada, 17 media in the United Kingdom, and 13 media in the Australia through searching on Twitter platform. (See Table A3 in Appendix).

Next step, the researcher searched all 147 elite media handles from the United States, Canada, United Kingdom, and the Australia in the "election2020" dataset to identify elite media accounts. In total, 29 elite media accounts were identified in the "election2020" dataset. (See Appendix Table A4)

Then the 29 elite media accounts with their tweets were subset from the "election2020" dataset, the researcher used the Botometer which is a machine learning bot detection tool to identify bots accounts from the remaining 366, 520 accounts. Botometer is managed by the Observatory on Social Media (OSoMe) and the Network Science Institute (IUNI) at Indiana University, it is a supervised machine learning classifier that distinguishes bot-like and human-like accounts based on their over 1000 features that being categorized into six classes: user profile, friends, network, temporal, content and language, and sentiment (Yang, 2022).

Compared to other bot detection tools such as tweetbotornot and Bot Sentinel, Botometer has three advantages: it provides service for longer time; it is easier to access through either web interface and an application programming interface (API); and it is maintained and updated by a research team regularly. For above reasons, this study selected Botometer as the bots detection tool.

The researcher used both the Botometer web interface and queried Botometer Pro API in Python to check the remaining 366, 520 accounts as Botometer Pro API has data limitation per day. The Botometer will return back the bot scores to each account that are displayed on a 0-to-5 scale with zero being most human-like and five being the most bot-like. The researcher first tested 367 samples (0.1% sample rate) by setting the score 3 as the threshold as the middle score 2.5 means that Botometer classifier is uncertain about the classification. After human checking all score 3 above accounts' profiles, tweets contents as well as tweet activities, the researcher found that 70% of accounts which scores between 3 to 3.9 are more human like accounts, therefore, the researchers decided to improve the threshold to the score 4, that is all accounts with Botometer bot scores larger or equal to 4.0 will be regarded as bots like accounts. Finally, 34, 136 social bots like accounts were detected, and 332,384 remaining accounts are average users accounts (see Appendix Table A4).

After classifying elite media accounts, social bots accounts, and average users accounts, the author then subset tweets by usernames of elite media accounts, social bots accounts, and average users accounts respectively in R, and saved them into three different datafiles for later analysis.

In order to address the first and second research questions, the author extracted tweets from elite media accounts data file, social bots accounts data file, and average users accounts data file and converted them into three different Corpuses. "tm", "NLP", "SnowballC", "textstem", "SparseM", "tidytext" R packages were used to do basic cleaning for the elite media accounts Corpus, social bots accounts Corpus, and average users accounts Corpus including: removing punctuation, numbers, digits, URLs, white spaces, special characters such as emoji, transferring uppercase to lower case, stemming, and lemmatization. The researcher also removed stopwords from the three Corpuses, in addition to the default English stopwords, after exploring 100 sample tweets, bellowing context-based stopwords also added to the stopwords bag and applied to three Corpuses: "now","can","claim", "rt", "election","will","say","president", "presidential election","trump","donald trump", "steal" , "stolen", "fraud", "fraudulent", "illegal", "illegitimate", "biden","joe biden","joe".

Then researcher built up three term document matrix based on three above well cleaned Corpuses, and calculated word frequencies for elite media accounts tweets, social bots accounts tweets, and average users accounts tweets respectively.

The next step was to build up three document term matrix based on well cleaned elite media accounts Corpus, social bots accounts Corpus, and average users accounts Corpus and run topic models with them. LDA (Latent Dirichlet allocation) method was used, different K topics numbers from 2 to 30 were tried to evaluate models for elite media accounts DTM (document term matrix), social bots accounts DTM, and average users accounts DTM respectively. Blei, et al. (2003) tested perplexity is a good measure of performance for LDA, the lower perplexity score indicates better generalization performance. The researcher calculated perplexity scores with different K topics numbers from 2 to 30 with package "topicmodels" and found that 18 is the best K topic number for elite media accounts DTM, 12 is the best K topic number for social bots accounts DTM, and 10 is the best K topic number for average users accounts DTM (See Appendix Figure 1). Thus, the researcher ran the LDA topic model with 18 topic numbers for elite media accounts DTM, 12 topic numbers for social bots accounts DTM, and 10 topic numbers for average users accounts DTM.

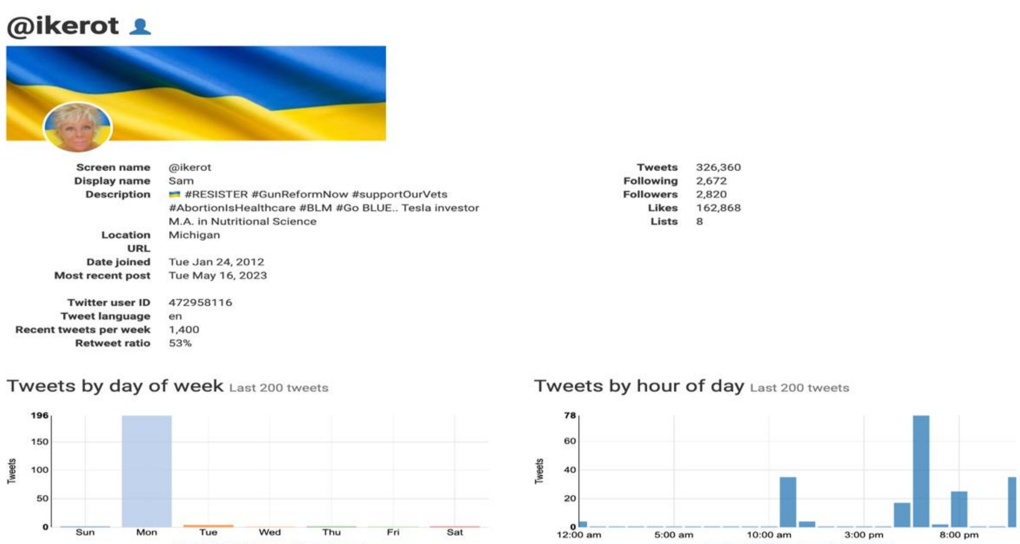
For the third research question that tries to examine whether social bots accounts, news media's accounts, and average real users accounts influenced each other's topic issues during the election? The researcher used the topics prediction results from the RQ1 and RQ2, and human labeled those topics in three accounts respectively. Then the researcher compared and found out convergence topics among three accounts types.

Findings and Results

Qualitative analysis results

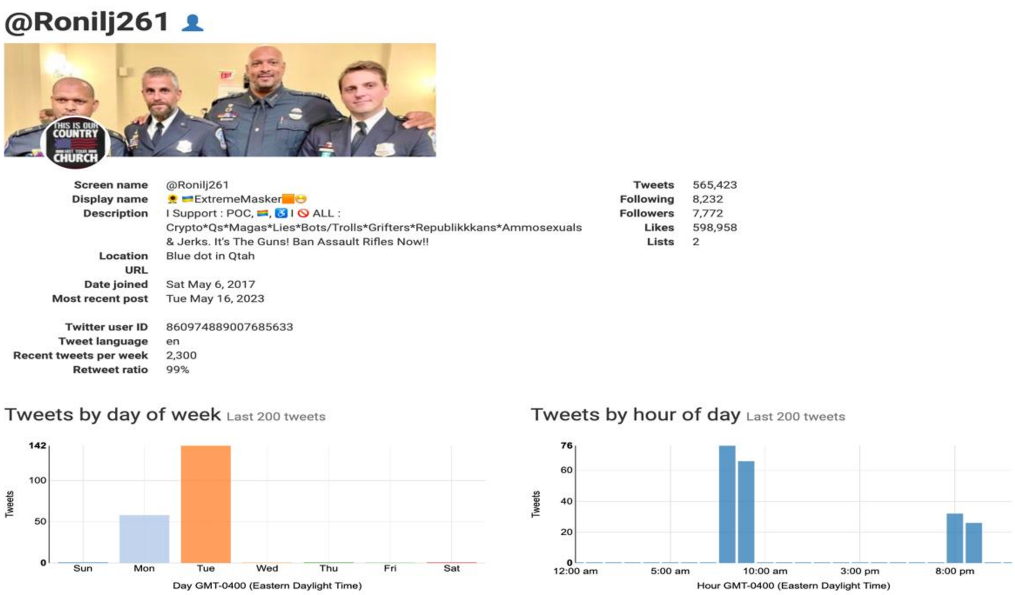
Through human checking social bots accounts' profiles, tweets contents, and tweet activities, this study found that social bots accounts are more likely to use virtual or fake profile pictures, their profile introduction are always very vague or displaying with extreme political ideology. Besides that, their tweet frequencies are also always high, they often post tweets every day, during some special periods, they even post more than hundreds and thousands of tweets. (See three social bots accounts examples in Figure 2, Figure 3, and Figure 4).

Figure 2: The sample bots accounts' profile and account details of @ikerot.



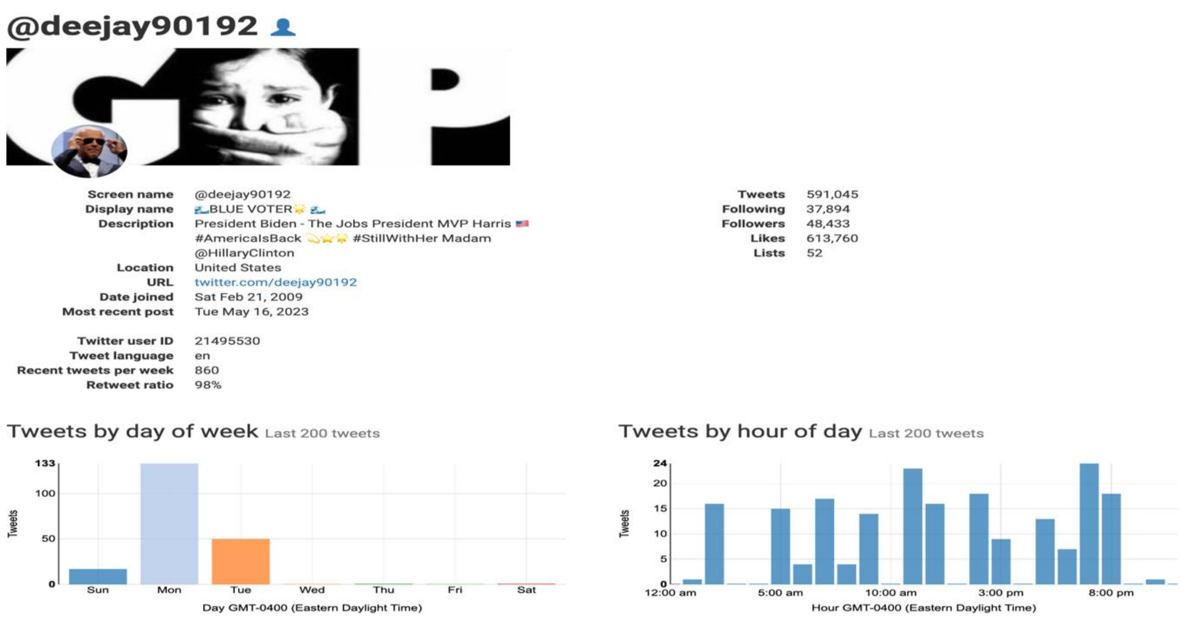
Note. The information is provided by Botometer web interface.

Figure 3: The sample bots accounts' profile and account details of @Ronilj261.



Note. The information is provided by Botometer web interface.

Figure 4: The sample bots accounts' profile and account details of @deejay90192.



Note. The information is provided by Botometer web interface.

Quantitative and computational analysis results

In the 1,144 most active accounts that posted at least 30 tweets about fraud or illegal misinformation around the 2020 U.S. presidential election during Nov 1, 2020 to January 20, 2021, around 33.2% (380) are social bots accounts. In comparison, during the same period, among 29 elite media accounts that were identified in the “election2020” dataset, none of them posted more than 10 tweets about 2020 U.S. presidential election fraud, illegitimate, or illegal related misinformation except for two accounts: @brianstelter posted 15 tweets, and @GlennKesslerWP posted 11 tweets. In total, 29 elite media accounts only posted 78 tweets (including retweets) about election fraud, illegal or illegitimate related misinformation during the who election period. Thus, during the 2020 election, social bots accounts were more active in posting or engaging (sharing by retweet) in with fraud or illegal related misinformation around this election than elite media accounts. Which indicates that social bots do play an active role in spreading misinformation on social media platforms. Comparatively, professional news organizations and journalists or reporters are less likely to discuss or engage with misinformation on social media.

In terms of the RQ1: What topics and keywords around 2020 U.S. Presidential Election related misinformation were spread mostly by social bots? As shown in Table 1, the top 30 keywords that social bots accounts generated most are: “vote”, “voter”, “state”,” “evid”, “republican”, “lie”, “win”,” georgia”,” peopl”, “just”, “senat”, “court”, “result”, “go”, “one”, “alleg”, “get”, “investig”, “gop”, “ballot”, “hear”, “make”, “tell”, “elect”, “american”, “offici”, “lose”, “us”, “know”, “like”. Comparted to top 30 keywords of elite media accounts and average users accounts, all three accounts have convergence of keywords that are related to election terms such as “Vote”, “ballot”; social bots accounts and average users accounts also have convergence of keywords “georgia” (the state that President Trump pressed to overturn election results). Additionally, all three accounts also share keywords convergence that are about justice or conspiracy theories surrounding this election such as “lie”, “evid” (meaning evidence), “court”, “investig”, “lose”.

Table 1: Top 30 keywords by social bots accounts, elite media accounts, average users accounts.

Social bots accounts	Elite media accounts	Average users accounts
Vote	vote	vote
voter	peopl	voter
state	offici	state
evid	result	evid
republican	evid	republican
lie	go	lie
win	fal	peopl
georgia	investig	win
peopl	republican	claim
just	one	just
senat	tell	georgia
court	us	senat
result	law	result
go	lie	one
one	tri	go
alleg	alleg	ballot
get	american	us
investig	conspiraci	elect
gop	day	alleg
ballot	state	hear
hear	win	court
make	attorney	investig
tell	believ	american
elect	campaign	tell
american	capitol	offici
offici	court	make
lose	elect	call
us	fact	democrat
know	find	know
like	fox	lose

Note. Words were stemmed in the preparation of the document corpus.

The LDA topic model returned back 12 topics with keywords under each topic for social bots accounts, 18 topics with keywords associated with each topic for elite media accounts, and 10 topics with keywords under each topic for average users accounts. The researcher human labelled all topics through checking their associated keywords as well as searching for related background information and key events of the 2020 election. The criterions for labelling topics presented in Table 2,

Table 2: Criterions for labelling topics

Topic	**Keywords**
Overturn election results	overturn, throw,
Voting process	vote, voter, ballot, count, machine, mail, poll, cast
Election race	win, lose, result, lead, different states like Georgia, Michigan, Arizona, Wisconsin, democrat, republican
Justice & law	evid, legal, secure, court, lawsuit, lawyer judge, investigate, attorney, justice, hear, arrest
Capitol attack & violence	attack, capitol, conspiracy, lie, riot, rioter, dead, violent, storm
News & media	news, medium, speak, fox, twitter, tweet, video
N/A	Keywords are meaningless or unrelated to each other, could not be assign to any topic issue

Note. Words were stemmed in the preparation of the document corpus.

Based on above labelling basis, 6 topics were identified in social bots accounts' tweets, they are: overturn election results, voting process, election race, justice & law, capitol attack & violence, news & media (see Appendix Figure 5); and 5 topics were found in elite media accounts' tweets : justice & law, overturn election results, election race, capitol attack & violence, news & media (see Appendix Figure 6); in terms of average users' accounts' tweets, 5 topics were identified, they are: election race, justice & law, news & media, capitol attack & violence, voting process (see Appendix Figure 7).

Then, the researcher compared and found out the convergence topics among three accounts types, or between any two accounts types. Results showed that all social bots accounts, elite media accounts, and average users accounts have four convergence topics that are: election race, justice & law, capitol attack & violence, news & media; and in regarding for the topic of overturn election results, the convergence only appeared between social bots accounts and elite media accounts. And in terms of the "voting process" topic, only social bots accounts and average users accounts have the convergence (see Table 3). Based on the results, the second and third questions were addressed. Social bots accounts do have convergence topics with both the elite media accounts, and average users accounts, all three accounts might influence each other's topic issues when it comes to election race, justice & law, capitol attack & violence, and news &

media. Social bots accounts and elite media accounts might affect each other in terms of the topic of overturn election results, and social bots accounts and average users accounts may influence each other in terms of voting process topic.

Table 3: Topic issues convergence among social bots accounts, elite media accounts, or average users accounts.

Accounts	**Topic issues convergence**
social bots accounts & elite media accounts & average users accounts	election race, justice & law, capitol attack & violence, news & media
social bots accounts & elite media accounts	overturn election results
social bots accounts & average users accounts	voting process

Conclusion and Discussion

This study found that a large number of social bots do exist on social media platforms such as Twitter, for example, in our "election2020 dataset", 34, 136 out of 366, 549 accounts (9.3%) are social bots like accounts. Compared to real users-controlled accounts, social bots accounts are more likely to use virtual or fake profile pictures, their profile introduction are always very vague or displaying with extreme political ideology, and they always tweet with very high frequency than normal real users accounts. This implicates that future research which use social media data should pay attention to the social bots accounts, and their roles in shaping public discourse on social media should not be ignored. If social bots accounts' posts were grouped together with real users accounts, we should doubt that are they truly represent real public or individual's opinion or thoughts?

The study also found that both social bots accounts and average users accounts played a great role in spreading misinformation during the 2020 U.S. presidential election period. For example, during the election period, in the 1,144 most active accounts that posted at least 30 tweets about fraud, illegitimate or illegal misinformation around this election, around 33.2% (380) are social bots accounts, remain 66.8% are average users account, none of them are elite media accounts. The total 29 elite media accounts only posted 78 tweets (including retweets) discussing about illegal, illegitimate, or fraud related misinformation around the 2020 election. Therefore, elite media are more vigilance about misinformation than social bots accounts and average users accounts, and they are less likely to patriciate in spreading or discussing misinformation than social bots accounts and average users accounts.

In terms of the topic issues convergence among three accounts types, the study results showed that social bots accounts, elite media accounts, and average users accounts have the possibility to influence each other's topic issues of election race, justice & law, capitol attack & violence, and news & media. But in terms of the topic issue of overturn election results, the convergence relationship only appears between social bots accounts and elite media accounts. And in terms of voting process topic, only social bots accounts and average users accounts have the convergence.

Limitations

However, this study also has some limitations. First, elite media handles for the United States, Canada, United Kindom, and Australia are not complete, especially for the latter three countries. Due to the time and labor limitation on working for this paper, the researcher was not able to collect more comprehensive elite media handles lists, which might cause the research results are not fully accurate. If future research which intend to use the "election2020" dataset to study about elite media's discourse or agenda around the election related misinformation, they should try to search for more complete elite media handles.

Additionally, the bots detection results also not be fully accurate due to following reasons: Firstly, when checking for accounts' activities on Twitter, Botometer only check account's 200 recent tweets. This might cause missing some social bots accounts as some bots accounts which were very active during the 2020 election period might calm down recently; Secondly, the researcher only human checked 367 samples at 0.1% sample rate to set the threshold score as 4.0, as threshold is the key component in running Botometer detection, and machine learning never can replace human judge, future work should try to human checking for more sample (maybe increase to 1% sample rate) to set a better threshold; Thirdly, some accounts in the "election2020 dataset" have already been suspended or protected for some reasons, the Botometer could not access those accounts' profiles and activities through twitter API, plus the upheaval policy changing of Twitter API recently, all those factors might cause miss some social bots.

Besides that, when predicting topics for social bots accounts' tweets, elite media accounts' tweets, and average users accounts' tweets, this study only used the unsupervised machine learning approach – LDA topic model. When evaluating LDA topic models with different K topic numbers, this study solely relied on perplexity score. However, through human checking 18 topics along with their associated keywords in elite media accounts' tweets, the researcher found that different topics' keywords mixed together under one topic, under this situation, the study should shrink K topic numbers. perplexity score can not guarantee the best fit model, future research should combine both the perplexity score and human check to tune model and find the best fit topic models to your study.

Additionally, LDA topic model is a good way to explore the hidden latent topics of the whole dataset at the first stage. If the research wanted to make more accurate topics prediction and agenda issues comparison/correlation, future work could combine the topics prediction results with literature review to make a full list of issue topics for the 2020 election and recruit human coders to do content analysis or called human annotation for sample tweets, and then introduce supervised machine learning method to predict topics. Apart from that, in order to examine the correlations among three accounts, comparing the topics issues convergence is not solid enough, future work should further run time series analysis of convergence topics of each account, and calculated correlation between each of these time series.

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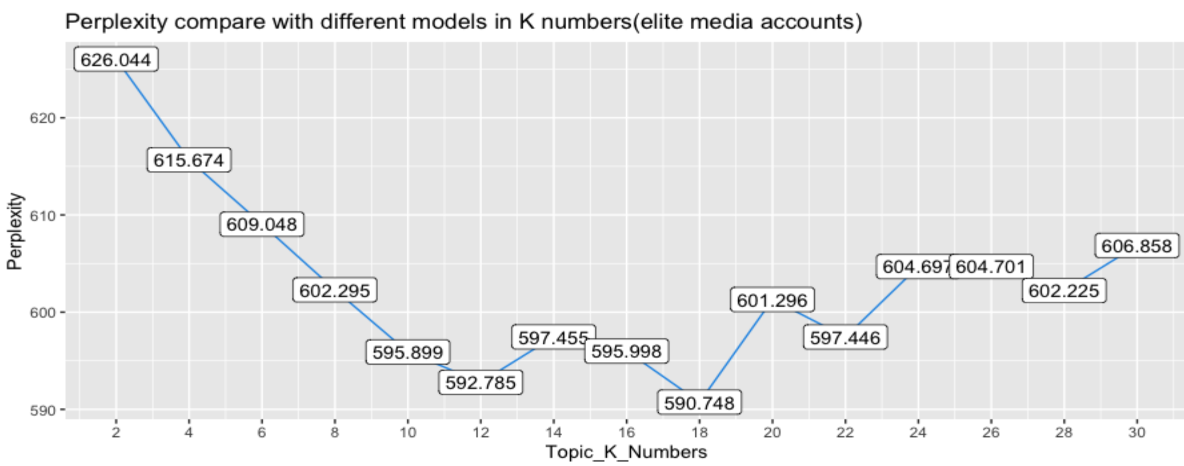
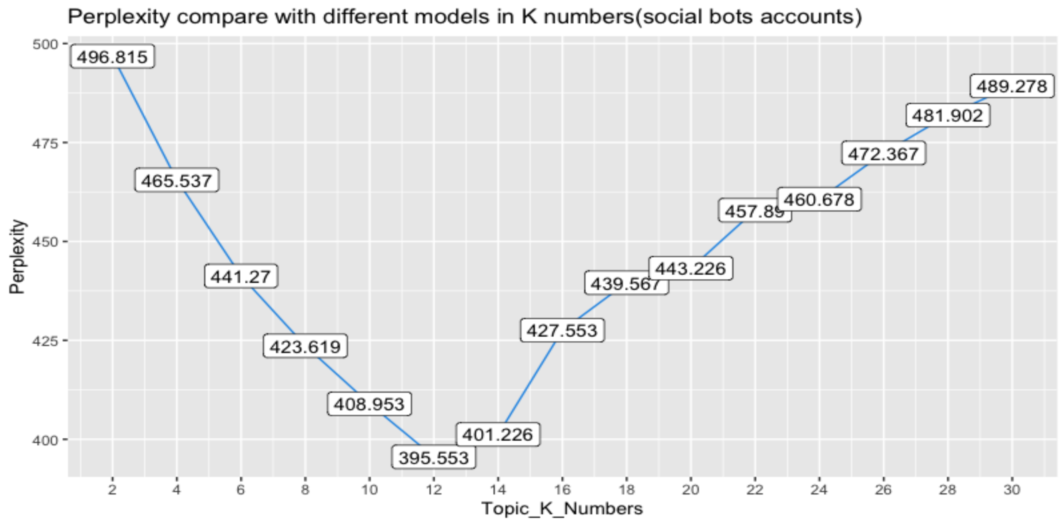
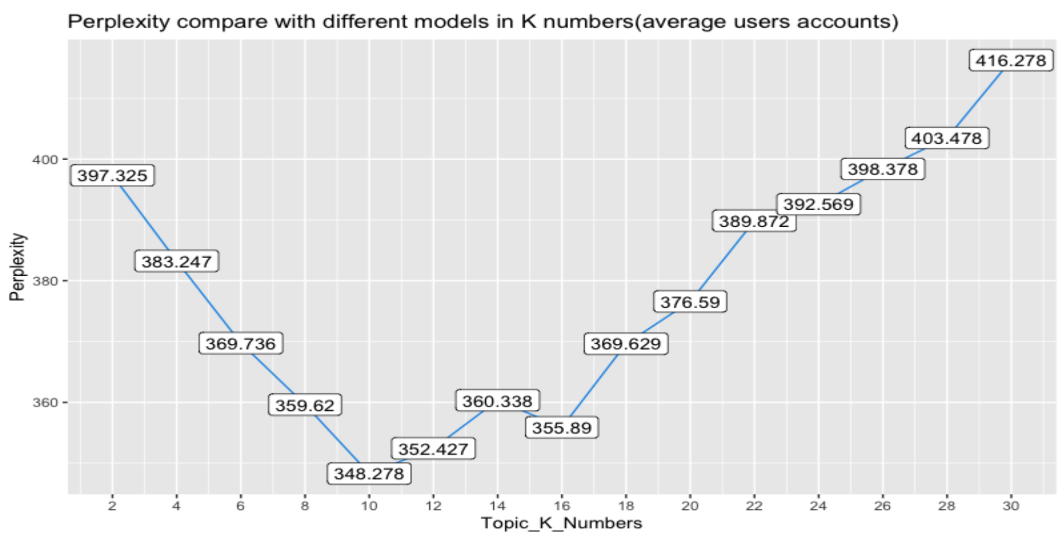
Appendix

Figure 1: LDA Topic Model evaluation with perplexity scores for elite media DTM, social bots DTM, and average users DTM.

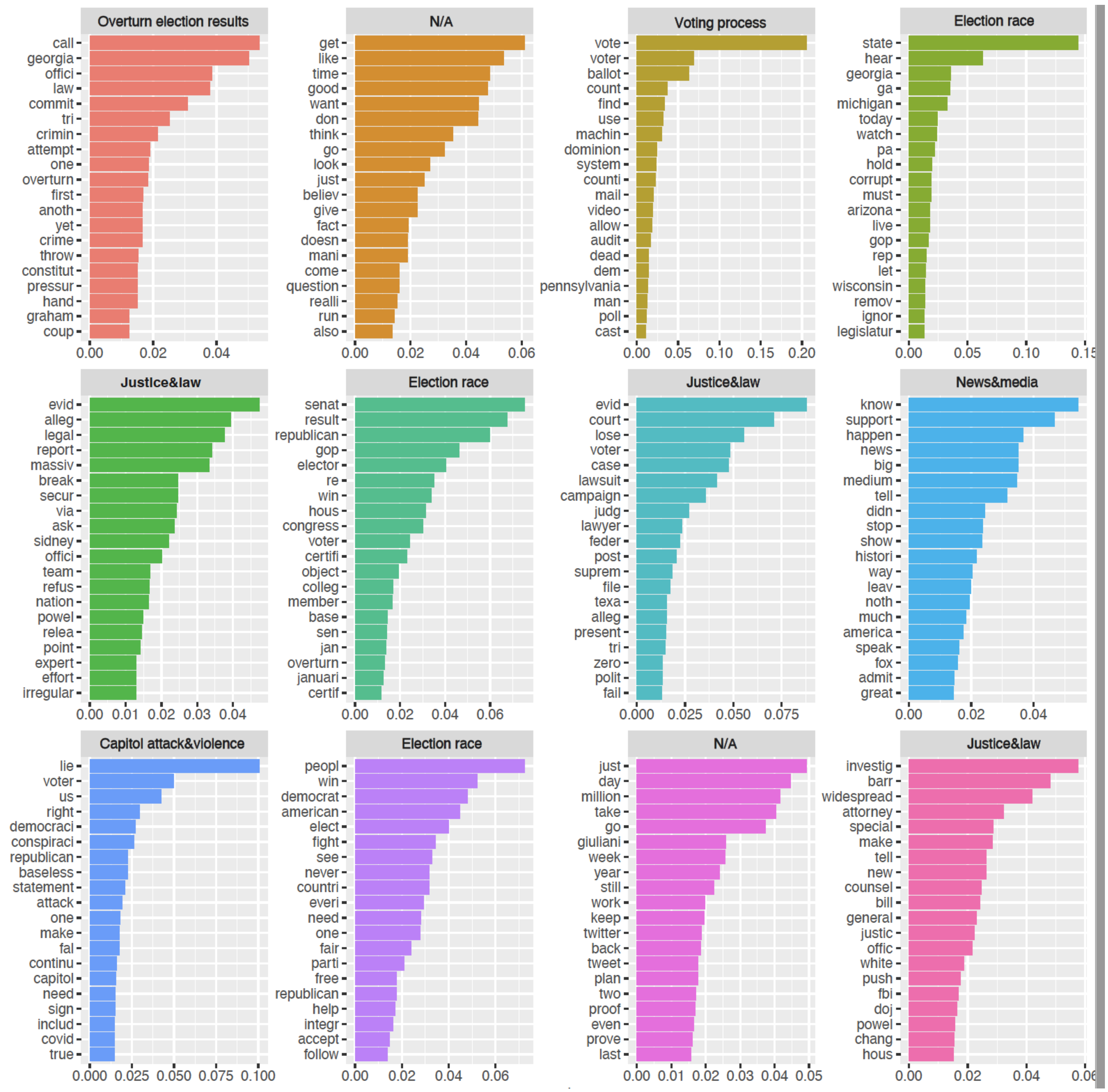






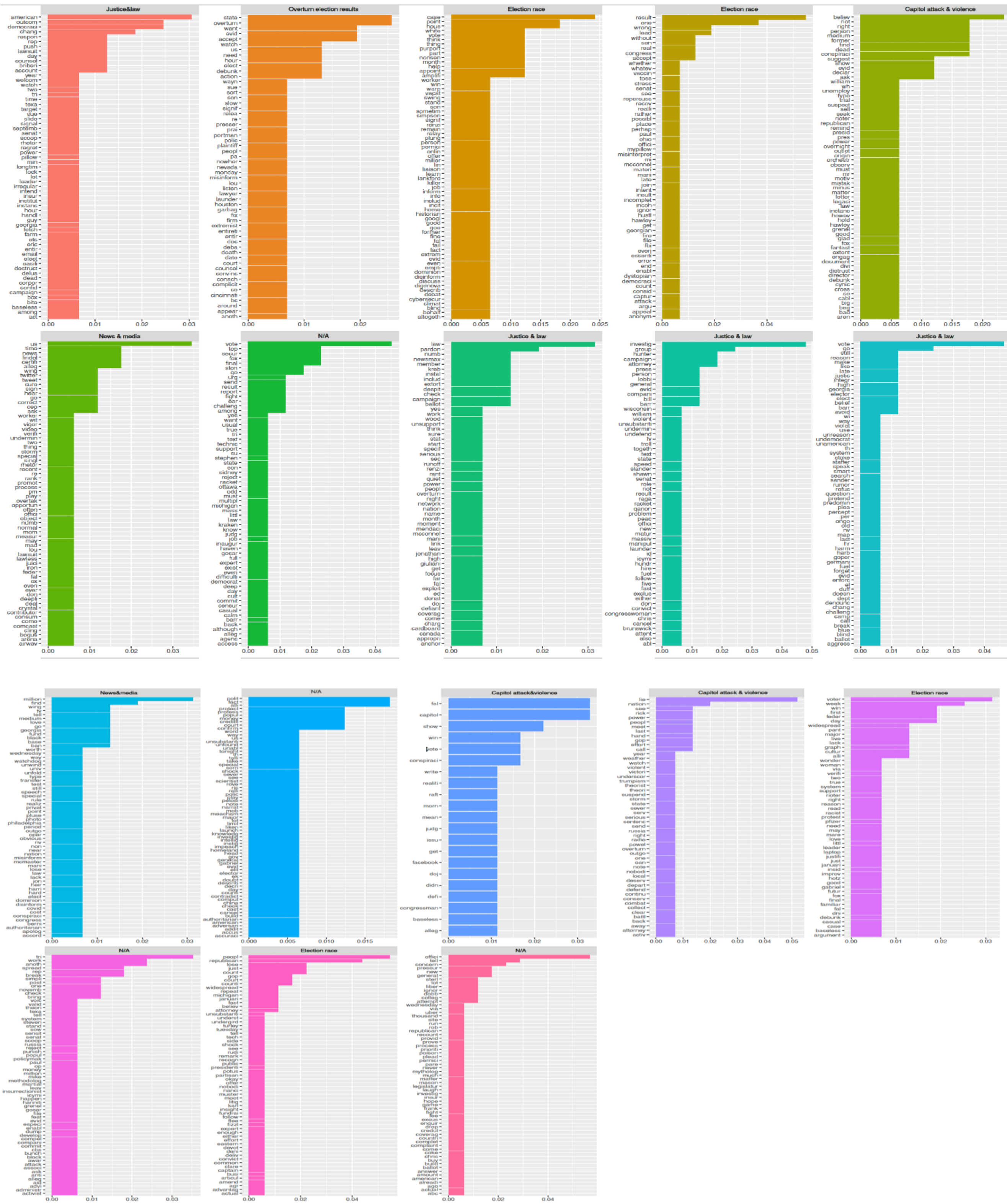
Note. All three plots were plotted with “ggplot2” package in R.

Figure 5: LDA Topic Model with human labels in social bots accounts' tweets



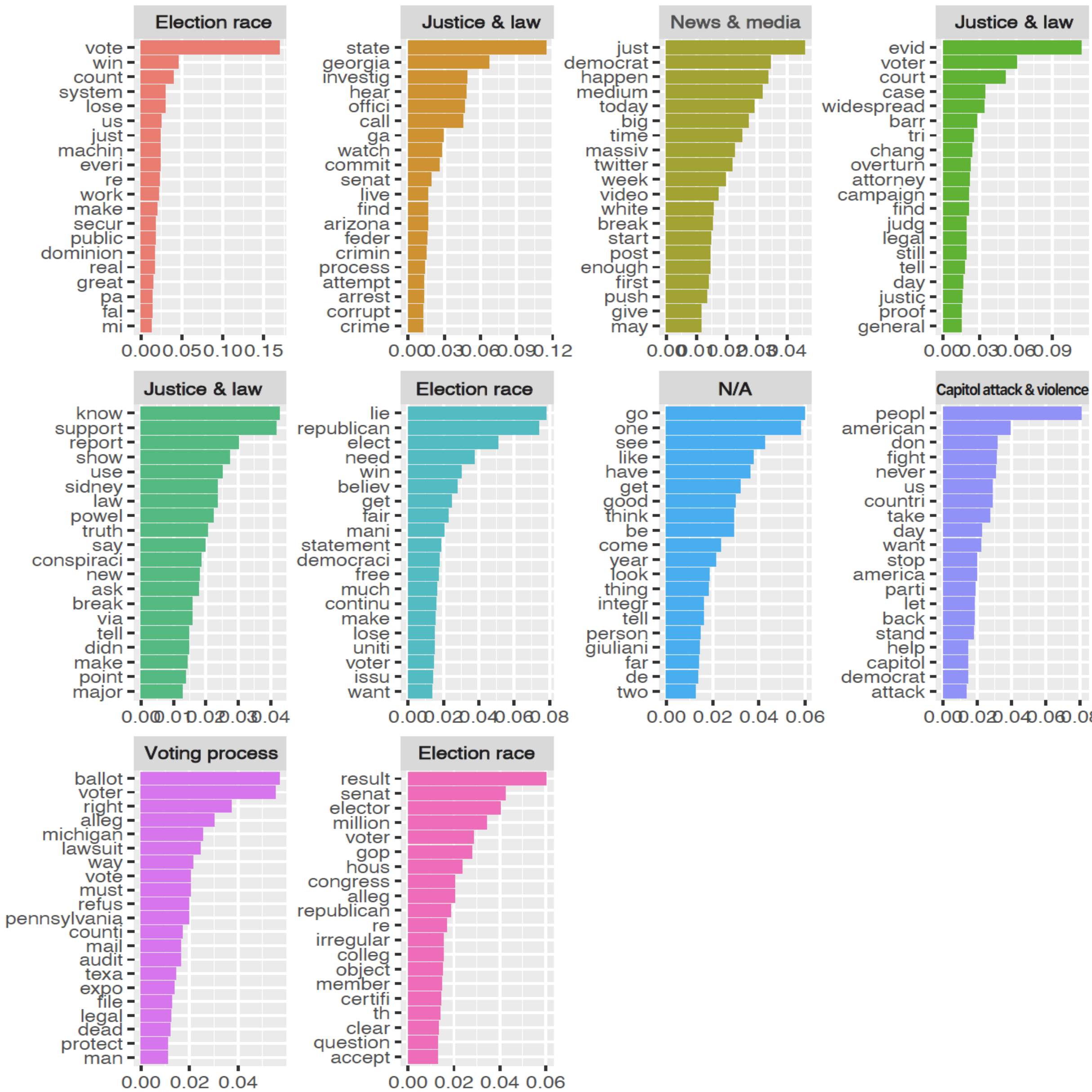
Note. Plot was plotted with "ggplot2" package in R.

Figure 6: LDA Topic Model with human labels in elite media accounts' tweets



Note. Plot was plotted with "ggplot2" package in R.

Figure 7: LDA Topic Model with human labels in average users accounts' tweets



Note. Plot was plotted with "ggplot2" package in R.

Table A1: Top 10 countries & percentage in all tweets

Country	N	Percentage
Not available	428595	46.2%

United States	381703	41.2%
Canada	23112	2.5%
United Kingdom	16087	1.7%
Australia	7455	0.8%
France	4299	0.5%
Japan	4293	0.5%
Germany	3492	0.4%
Colombia	2710	0.3%
Brazil	2446	0.3%
Spain	2333	0.3%
Total	876525	95%

Note. N total = 926, 845, Percentage= N/N total

Table A2: Top 4 countries & percentage in all location available tweets

Country	N	Percentage
United States	381703	76.6%
Canada	23112	4.6%
United Kingdom	16087	3.2%
Australia	7455	1.5%
Total	428357	86%

Note. N total =926, 845 – 428595= 498250, Percentage= N/N total

Table A3: Elite media handles selected for United States, Canada, United Kindom, Australia, by country

United States (100)	Canada(17)	United Kindom(17)	Australia (13)
@abc	@CdnPressNews	@NewsUK	@newscomauHQ
@abcfactcheck	@CBCNews	@BBCNews	@abcnews
@AJEnglish	@CTVNews	@GBNEWS	@9NewsAUS
@andersoncooper	@globalnews	@SkyNews	@SkyNewsAust
@anncurry	@NewsroomGC	@BBCWorld	@aus_media
@bbcworld	@TrueNorthCentre	@BBCBreaking	@10NewsFirst

@bloomberg	@nationalpost	@PA	@7NewsAustralia
@bostonglobe	@CBC	@DailyMailUK	@australian
@bretbaier	@RebelNewsOnline	@itvnews	@AAPNewswire
@brianstelter	@CanadianPM	@Telegraph	@SBSNews
@BuzzFeed	@globeandmail	@bbcpress	@news_australian
@BuzzFeedNews	@CMF_FMC	@Independent	@crikey_news
@BuzzFeedBen	@CBCAlerts	@theipaper	@RebelNews_AU
@cbsnews	@CP24	@thetimes	—
@chucktodd	@CANADALAND	@TheSun	—
@cjr	@CBCRadioCanada	@guardian	—
@cnetnews	@CBCNB	@GMB	—
@cnn	—	—	—
@CNNPolitics	—	—	—
@CNN_word	—	—	—
@current	—	—	—
@DailyCaller	—	—	—
@davidgregory	—	—	—
@edshow	—	—	—
@enews	—	—	—
@ethanklapper	—	—	—
@factcheckdotorg	—	—	—
@FAIRmediawatch	—	—	—
@FoxNews	—	—	—
@gallupnews	—	—	—
@GlennKesslerWP	—	—	—
@gstephanopoulos	—	—	—
@guardiannews	—	—	—
@HuffingtonPost	—	—	—
@HuffPostPol	—	—	—
@jaketapper	—	—	—
@jdickerson	—	—	—
@jeffjarvis	—	—	—
@jimcramer	—	—	—
@kasie	—	—	—
@latimes	—	—	—
@LATimesbiz	—	—	—
@latinopolitics	—	—	—
@markknoller	—	—	—
@mattbai	—	—	—
@mediaite	—	—	—
@megynkelly	—	—	—
@mehdirhasan	—	—	—
@michele_norris	—	—	—
@mmfa	—	—	—
@msnbc	—	—	—
@MysteryPollster	—	—	—
@nationaljourna	—	—	—
@NBCNews	—	—	—
@newsbusters	—	—	—
@newshour	—	—	—
@Newsupdate_25	—	—	—
@nickconfessore	—	—	—
@nprnews	—	—	—
@NYTimes	—	—	—
@onthemedia	—	—	—
@OpenSecretsDC	—	—	—

@Politico	—	—	—
@politifact	—	—	—
@postpolitics	—	—	—
@postpolls	—	—	—
@Poynter	—	—	—
@PranayGupte	—	—	—
@radiobabe	—	—	—
@ralstonflash	—	—	—
@RasmussenPoll	—	—	—
@reuters	—	—	—
@RollCall	—	—	—
@Slate	—	—	—
@snopes	—	—	—
@soledad_obrien	—	—	—
@streetkode	—	—	—
@sunfoundation	—	—	—
@terrymoran	—	—	—
@TheAtlantic	—	—	—
@thecaucus	—	—	—
@TheDailyBeast	—	—	—
@theeconomist	—	—	—
@thefix	—	—	—
@thehill	—	—	—
@TIME	—	—	—
@TPM	—	—	—
@tw_top_politics	—	—	—
@TWCBreaking	—	—	—
@UnivisionNews	—	—	—
@usatoday	—	—	—
@usnews	—	—	—
@washingtonpost	—	—	—
@weeklystandard	—	—	—
@WestWingReport	—	—	—
@wolfblitzercnn	—	—	—
@wsj	—	—	—
@WSJPolitics	—	—	—
@wsjwashington	—	—	—
@yahoonews	—	—	—

Table A4 Accounts numbers by three categories in the “election2020” dataset

Elite media accounts (N=29)	Social bots accounts (N=34136)	Average users accounts (N=332,384)
@ BBCWorld	@ bellausa17 (bot score 4.8/5)	—
@brianstelter	@ TonyHussein4 (bot score 4.3/5)	—
@BuzzFeedNews	@ ConcernedHigh(bot score 4.8/5)	—
@ CBSNews	@ JimLHorn1 (bot score 4.4/5)	—
@CNN_word	@ joey52509403(bot score 4.1/5)	—

@DailyCaller	@ deathtocrazy(bot score 4.1/5)	—
@FAIRmediawatch	@ Elizabe29599604(bot score 4.3/5)	—
@GlennKesslerWP	@ MtRushmore2016(bot score 4.2/5)	—
@jaketapper	@ BellaDonaModels(bot score 4.2/5)	—
@jdickerson	@ melodyisdestiny(bot score 4.1/5)	—
@jeffjarvis	@ jjauthor(bot score 4.1/5)	—
@latimes	@ DonnaMu17526414(bot score 4.1/5)	—
@mehdirhasan	@fantasticlegs (bot score 4.3/5)	—
@michele_norris	@29361RMSM (bot score 4.4/5)	—
@mmfa	@kenkircher1(bot score 4.4/5)	—
@newshour	@RonnieMotes8(bot score 4.0/5)	—
@nickconfessore	@UROCKlive1(bot score4.4/5)	—
@NYTimes	@proudCanadavet(bot score 4.3/5)	—
@OpenSecretsDC	@SylviaZ1913(bot score 4.6/5)	—
@politifact	@Fightkidscancer (bot score 4.0/5)	—
@snopes	@PatriotMarie(bot score 4.0/5)	—
@terrymoran	@missb62(bot score 4.1/5)	—
@TheDailyBeast	@davidpsdem(bot score 4.8/5)	—
@usatoday	@CFraase(bot score 4.1/5)	—
@WSJPolitics	@Tanis42(bot score 4.7/5)	—
@RebelNewsOnline	@netbacker(bot score 4.1/5)	—
@CBCNB	@4tybin(bot score 4.1/5)	—
@BBCNews	@AmyAyers16(bot score 4.0/5)	—
@DailyMailUK	@Joni_Looking(bot score 4.5/5)	—
—	@LorraineJDion(bot score 4.4/5)	—
—	@MarthaLynneOwe1(bot score 4.4/5)	—
—	@mcarsonaos(bot score 4.1/5)	—
—	@stephphilip8(bot score 4.9/5)	—
—	@chinwind1(bot score 4.8/5)	—
—	@RDTBook(bot score 4.8/5)	—
—	@WarnockWarrior(bot score 4.9/5)	—
—	@carrybeyond(bot score 4.8/5)	—
—	@garden4u_wa(bot score 4.4/5)	—
—	@lolli55(bot score 4.1/5)	—
—	@snw106(bot score 4.1/5)	—
—	@Alexblx(bot score 4.1/5)	—
—	@bannerite(bot score 4.6/5)	—
—	@Enrico056(bot score 4.6/5)	—
—	@sea5(bot score 4.0/5)	—
—	@arch1com(bot score 4.8/5)	—
—	@shellneal2501 (bot score 4.4/5)	—
—	@ soultravelers3(bot score 4.1/5)	—
—	@cagney1991(bot score 4.6/5)	—
—	@ElkeHollings(bot score 4.2/5)	—
—	@RayneNGrace(bot score 4.2/5)	—
—	@Sesimbra5(bot score 4.4/5)	—
—	@kbackous(bot score 4.4/5)	—
—	@lizditz(bot score 4.2/5)	—
—	@PaulaJanL (bot score 4.3/5)	—
—	@ rleas(bot score 4.6/5)	—
—	@BeHappyandCivil (bot score 4.6/5)	—
—	@ Gillis9Rose(bot score 4.2/5)	—
—	@JamesGibson1138(bot score 4.1/5)	—
—	@rstrok71(bot score 4.7/5)	—
—	@TinaMarie_80s(bot score 4.6/5)	—
—	@1stacyphillips(bot score 4.4/5)	—

—	@freddyatton(bot score 4.3/5)	—
—	@NanaOxford(bot score 4.2/5)	—
—	@Willsdarlin(bot score 4.4/5)	—
—	@awelab1956(bot score 4.6/5)	—
—	@katz_mum(bot score 4.3/5)	—
—	@mercenarygraphi(bot score 4.0/5)	—
—	@bigplaincircle(bot score 4.4/5)	—
—	@DianeEugenio(bot score 4.0/5)	—
—	@GodessofChaos71(bot score 4.8/5)	—
—	@MikeVaden2(bot score 4.3/5)	—
—	@stockguy61(bot score 4.8/5)	—
—	@1artniece2(bot score 4.4/5)	—
—	@BentleyK(bot score 4.2/5)	—
—	@CarolLaRue(bot score 4.6/5)	—
—	@DragonFly34343(bot score 4.4/5)	—
—	@FreeThinkerDona(bot score 4.1/5)	—
—	@iamforeverblue2(bot score 4.5/5)	—
—	@JeffreyMeursing(bot score 4.4/5)	—
—	@JoeSixpackSays(bot score 4.2/5)	—
—	@spunkkee(bot score 4.1/5)	—
—	@Studpardee(bot score 4.4/5)	—
—	@barbcast60(bot score 4.4/5)	—
—	@CnBsNana(bot score 4.2/5)	—
—	@ikerot(bot score 5.0/5)	—
—	@MikeReeseM(bot score 4.7/5)	—
—	@Montpellier21(bot score 4.6/5)	—
—	@PVTrump(bot score 4.6/5)	—
—	@Teram323Tere(bot score 4.6/5)	—
—	@TrumpWatchNews(bot score 4.3/5)	—
—	@alice4u2010(bot score 4.7/5)	—
—	@cheezwitham(bot score 4.4/5)	—
—	@GabrielleMary55(bot score 4.1/5)	—
—	@KathleeRowlands(bot score 4.6/5)	—
—	@melinwy(bot score 4.6/5)	—
—	@MendiolaGrandma(bot score 4.6/5)	—
—	@morgfair(bot score 4.3/5)	—
—	@__Sassafras_(bot score 4.3/5)	—
—	@carolyn86452721(bot score 4.8/5)	—
—	@debsomewhere(bot score 4.7/5)	—
—	@drseid(bot score 4.3/5)	—
—	@ewindham3(bot score 4.5/5)	—
—	@JeaniefaetroonJ(bot score 4.6/5)	—
—	@jeanneenabottle (bot score 4.4/5)	—
—	@lsferguson(bot score 4.2/5)	—
—	@Ronilj261(bot score 5.0/5)	—
—	@RosieM1919(bot score 4.8/5)	—
—	@social_seer(bot score 4.4/5)	—
—	@YockeyWendy(bot score 4.6/5)	—
—	@Juliet_notRomeo(bot score 4.2/5)	—
—	@peace1(bot score 4.5/5)	—
—	@suzie462(bot score 4.5/5)	—
—	@textifyer59(bot score 4.4/5)	—
—	@Twinsfan811(bot score 4.9/5)	—
—	@WitmerCarl(bot score 4.6/5)	—
—	@DullDianna(bot score 4.1/5)	—
—	@Hoodyshit1981(bot score 4.1/5)	—

—	@JenniferThePart(bot score 5/5)	—
—	@LorenzoCastane3(bot score 4.7/5)	—
—	@MyraDSirois1(bot score 4.8/5)	—
—	@mzee26 (bot score 4.0/5)	—
—	@ RN_JW733(bot score 4.4/5)	—
—	@ryan102857(bot score 4.0/5)	—
—	@tina10004359(bot score 4.1/5)	—
—	@trustingmyvibes(bot score 4.6/5)	—
—	@ZiffyKat(bot score 4.9/5)	—
—	@0scar1709(bot score 4.6/5)	—
—	@coop22089074(bot score 4/5)	—
—	@crt39437(bot score 4.8/5)	—
—	@dbble5(bot score 4.2/5)	—
—	@dbluewave20(bot score 4.7/5)	—
—	@EileenDiana(bot score 4.6/5)	—
—	@Elgianne(bot score 4.1/5)	—
—	@Eliz_Hightower(bot score 4.6/5)	—
—	@KatCapps(bot score 4.0/5)	—
—	@LeBonTravel(bot score 4.4/5)	—
—	@NewsJunkie60(bot score 4.4/5)	—
—	@Nvania(bot score 4.2/5)	—
—	@panolan2(bot score 4.4/5)	—
—	@SaveRDemocrazy(bot score 4.3/5)	—
—	@suekhi(bot score 4.0/5)	—
—	@ungubunugu1274(bot score 4.4/5)	—
—	@VoiceOverPerson(bot score 4.4/5)	—
—	@1015_cookie(bot score 4.9/5)	—
—	@Alan_R2A(bot score 4.6/5)	—
—	@BildSteve(bot score 4.0/5)	—
—	@dachapman4(bot score 4.5/5)	—
—	@Genies_world(bot score 4.2/5)	—
—	@gratefulAC19(bot score 4.8/5)	—
—	@jkdeppe(bot score 4.0/5)	—
—	@LindaLawrey(bot score 4.1/5)	—
—	@LoraAneM(bot score 4.4/5)	—
—	@nstark1959(bot score 5/5)	—
—	@on_bender(bot score 4.1/5)	—
—	@ParryPierce(bot score 4.8/5)	—
—	@StandUp4USA2(bot score 4.6/5)	—
—	@AliAdair22(bot score 4.8/5)	—
—	@Britpoptarts(bot score 4.4/5)	—
—	@chinster2017(bot score 4.1/5)	—
—	@Deb90243593(bot score 4.8/5)	—
—	@Draggen75(bot score 4.0/5)	—
—	@DsOchoa(bot score 4.1/5)	—
—	@klgrube(bot score 4.1/5)	—
—	@LaurenDownSouth(bot score 4.0/5)	—
—	@MichaelFrankie6(bot score 4.8/5)	—
—	@NetworksManager(bot score 4.1/5)	—
—	@nobsamerican1(bot score 4.0/5)	—
—	@notComey(bot score 4.4/5)	—
—	@PennyWafford(bot score 4.2/5)	—
—	@rcarr57(bot score 4.6/5)	—
—	@RN549(bot score 4.6/5)	—
—	@sharonflink (bot score 4.6/5)	—
—	@ 16PawsWY(bot score 4.1/5)	—

—	@AnotherOne_c011(bot score 4.8/5)	—
—	@Arbara0728B(bot score 4.2/5)	—
—	@AZPerspectives(bot score 4.0/5)	—
—	@banjoscrambler(bot score 4.3/5)	—
—	@ClaySharps(bot score 4.8/5)	—
—	@clemmiesmom(bot score 4.8/5)	—
—	@CMargaronis(bot score 4.1/5)	—
—	@EricMoo91919605(bot score 5.0/5)	—
—	@HanselSchatzi(bot score 4.6/5)	—
—	@jssacramento(bot score 4.9/5)	—
—	@LeChatNoire4(bot score 4.2/5)	—
—	@LindaLarsonKemp(bot score 4.1/5)	—
—	@MarianCantwellF(bot score 4.2/5)	—
—	@mcgee_mom(bot score 4.7/5)	—
—	@Pissed_Woman(bot score 4.8/5)	—
—	@ScienceMilk(bot score 4.0/5)	—
—	@sigstarget(bot score 4.7/5)	—
—	@Stoptheinsani20(bot score 4.1/5)	—
—	@SueDinNY(bot score 4.2/5)	—
—	@theleightons327(bot score 4.2/5)	—
—	@tnmtnlake(bot score 5.0/5)	—
—	@WoodwardWoodw11(bot score 4.9/5)	—
—	@AMS0035(bot score 4.4/5)	—
—	@behe_2020(bot score 4.0/5)	—
—	@CharmaxHutt(bot score 4.4/5)	—
—	@CovfefeTwaffle(bot score 4.0/5)	—
—	@Cubfan13241(bot score 4.4/5)	—
—	@JeffZou14(bot score 4.4/5)	—
—	@jjj5819(bot score 4.4/5)	—
—	@justjo2(bot score 4.8/5)	—
—	@Lauraseriously1(bot score 4.4/5)	—
—	@Mitchie02435305(bot score 4.1/5)	—
—	@mog7546(bot score 4.7/5)	—
—	@Rosa1234tejana(bot score 4.7/5)	—
—	@THE_OG_G_MA(bot score 4.4/5)	—
—	@ziyaziba(bot score 4.2/5)	—
—	@1catherinesiena(bot score 4.1/5)	—
—	@cannoneerfour(bot score 4.4/5)	—
—	@cliffhangerCA(bot score 4.4/5)	—
—	@dan81359(bot score 4.4/5)	—
—	@ecclesias(bot score 4.4/5)	—
—	@Emaxx2044(bot score 4.1/5)	—
—	@GNRtruth(bot score 4.3/5)	—
—	@HunterdonMan(bot score 4.2/5)	—
—	@JamieRJN(bot score 4.4/5)	—
—	@MariJoDeLeon(bot score 4.2/5)	—
—	@MayIrmamay14(bot score 4.6/5)	—
—	@nakesha_horsey(bot score 4.4/5)	—
—	@proudtigerlsu(bot score 4.7/5)	—
—	@weskusgogga(bot score 4.4/5)	—
—	@amidthetumult(bot score 4.3/5)	—
—	@braschen1(bot score 4.7/5)	—
—	@CyrilDeLaPerri2(bot score 4.0/5)	—
—	@d_oversole(bot score 4.6/5)	—
—	@deejay90192(bot score 5.0/5)	—
—	@dianerocks52(bot score 4.1/5)	—

—	@frankmueller101(bot score 4.1/5)	—
—	@grace2bfree(bot score 4.0/5)	—
—	@grammy620(bot score 4.6/5)	—
—	@itsweezie(bot score 4.4/5)	—
—	@JackySinAZ(bot score 4.6/5)	—
—	@jengrimes8(bot score 4.6/5)	—
—	@kfkeys(bot score 4.1/5)	—
—	@KiritoKirto(bot score 4.3/5)	—
—	@lachic288(bot score 4.2/5)	—
—	@Lisa_Lisa_NJ(bot score 4.7/5)	—
—	@lkjtexas(bot score 4.1/5)	—
—	@louiedadawg(bot score 4.0/5)	—
—	@MinnesotaMaryS(bot score 4.4/5)	—
—	@pollsstar(bot score 4.2/5)	—
—	@RaeMargaret61(bot score 4.6/5)	—
—	@saangus(bot score 4.0/5)	—
—	@Skel531(bot score 4.0/5)	—
—	@txsguy09(bot score 4.2/5)	—
—	@24baseballReed(bot score 4.4/5)	—
—	@AmeriGirlTN(bot score 4.0/5)	—
—	@Antoinotabot(bot score 4.6/5)	—
—	@Billis4rox(bot score 4.3/5)	—
—	@bob_levitt(bot score 4.4/5)	—
—	@christi73224817(bot score 4.1/5)	—
—	@CindyCinnis(bot score 4.6/5)	—
—	@DAndalora_Bella(bot score 4.1/5)	—
—	@DebH63951470(bot score 4.0/5)	—
—	@DemNevada(bot score 4.4/5)	—
—	@FN92(bot score 4.6/5)	—
—	@Frippin2(bot score 4.4/5)	—
—	@game_changer1(bot score 4.0/5)	—
—	@GreenSkyDeb(bot score 4.1/5)	—
—	@gretathegreek(bot score 4.1/5)	—
—	@Jerri47(bot score 4.6/5)	—
—	@JoyBell75174267(bot score 4.2/5)	—
—	@Ladude2014(bot score 4.8/5)	—
—	@lapham923(bot score 4.9/5)	—
—	@MonicaRivpin(bot score 4.6/5)	—
—	@NancyTaylor5(bot score 4.5/5)	—
—	@NanfromSC(bot score 4.4/5)	—
—	@ptialex77(bot score 4.4/5)	—
—	@Real_Charlene_C(bot score 4.1/5)	—
—	@sasky19591(bot score 4.3/5)	—
—	@stanspak(bot score 4.7/5)	—
—	@suzannekeith71(bot score 4.2/5)	—
—	@Tom_Larry2u(bot score 4.4/5)	—
—	@verticalrepeat(bot score 4.2/5)	—
—	@Vmbritsch(bot score 4.5/5)	—
—	@_realSasquatch(bot score 4.1/5)	—
—	@bengin1003(bot score 4.8/5)	—
—	@BeverlyEra1(bot score 4.1/5)	—
—	@bstovalljr(bot score 4.8/5)	—
—	@c_dm1377(bot score 4.4/5)	—
—	@CDEKeane(bot score 4.5/5)	—
—	@CherokeeNative3(bot score 4.6/5)	—
—	@debr3322(bot score 4.1/5)	—

—	@DianeOl64825469(bot score 4.6/5)	—
—	@DWDrummer13(bot score 4.8/5)	—
—	@eegarim(bot score 4.2/5)	—
—	@FriedasMom7(bot score 4.2/5)	—
—	@houstonsupertec(bot score 4.0/5)	—
—	@howgreatJr(bot score 4.1/5)	—
—	@Irenejaeger9(bot score 4.4/5)	—
—	@Jeannie22757716(bot score 4.1/5)	—
—	@JorgeSignoret2(bot score 4.1/5)	—
—	@kak089(bot score 4.8/5)	—
—	@KentRademacher1(bot score 4.5/5)	—
—	@KMCaton(bot score 4.7/5)	—
—	@kskm126_susan (bot score 4.0/5)	—
—	@Lindy255(bot score 4.7/5)	—
—	@Lori74458665(bot score 4.1/5)	—
—	@navyChiefalways (bot score 4.8/5)	—
—	@Nick_Clamorgan(bot score 4.0/5)	—
—	@noxa_nonne(bot score 4.7/5)	—
—	@politiwars(bot score 4.6/5)	—
—	@rdrgz_l(bot score 4.1/5)	—
—	@Reggiebub(bot score 4.2/5)	—
—	@Revel7272Daniel(bot score 4.6/5)	—
—	@SuzyCampbell20(bot score 4.0/5)	—
—	@theresamax(bot score 4.4/5)	—
—	@upchuck66(bot score 4.4/5)	—
—	@4annegs(bot score 4.6/5)	—
—	@79topper(bot score 4.9/5)	—
—	@abe_american(bot score 4.0/5)	—
—	@AndersonCheri (bot score 4.4/5)	—
—	@ angela_dummett(bot score 4.0/5)	—
—	@Backstorymom1(bot score 4.0/5)	—
—	@BBBudget(bot score 4.2/5)	—
—	@BenniBizati(bot score 4.4/5)	—
—	@CielNow(bot score 4.6/5)	—
—	@Claudyconn(bot score 4.8/5)	—
—	@dire_donald(bot score 4.4/5)	—
—	@DziadoszS(bot score 4.0/5)	—
—	@fl_tax_lady(bot score 4.6/5)	—
—	@Gustoe16(bot score 4.2/5)	—
—	@hlpryor(bot score 4.8/5)	—
—	@Inspect54932104(bot score 4.4/5)	—
—	@JacquieWells4(bot score 4.1/5)	—
—	@Jinxy_Minxy(bot score 4.3/5)	—
—	@Jmh6543Jimmy(bot score 4.1/5)	—
—	@KettleCorn1234(bot score 4.4/5)	—
—	@ladydshops(bot score 4.6/5)	—
—	@Locou9(bot score 4.8/5)	—
—	@LydiaLynn89(bot score 4.0/5)	—
—	@mliz77(bot score 4.2/5)	—
—	@my3monkees(bot score 4.7/5)	—
—	@nicole_bertrand(bot score 4.0/5)	—
—	@RamonaEid(bot score 4.5/5)	—
—	@SandraC42595084(bot score 4.6/5)	—
—	@Siadasha(bot score 5.0/5)	—
—	@sivan1040(bot score 4.6/5)	—
—	@Terri2cat(bot score 4.4/5)	—

—	@TexasteaPeggy(bot score 4.2/5)	—
—	@Trumpgot2go(bot score 4.6/5)	—
—	@UPROAR23(bot score 4.4/5)	—
—	@webb_carrie(bot score 4.3/5)	—
—	@xbrooklynite21(bot score 4.3/5)	—
—	@ad1140(bot score 4.6/5)	—
—	@AllieinMO(bot score 4.1/5)	—
—	@AnnH1958(bot score 4.1/5)	—
—	@Avonan(bot score 4.2/5)	—
—	@Barbtomko1(bot score 4.7/5)	—
—	@BetsysUSofA1776(bot score 4.4/5)	—
—	@Beverly21811568(bot score 4.0/5)	—
—	@BillyBoysDaddy(bot score 4.8/5)	—
—	@cardon_brian(bot score 4.8/5)	—
—	@CathyJoeGPT(bot score 4.6/5)	—
—	@crusader4US(bot score 4.5/5)	—
—	@CynicalVision50(bot score 4.6/5)	—
—	@DLP75902038(bot score 4.4/5)	—
—	@edwards_lill(bot score 4.2/5)	—
—	@ellieofa(bot score 4.0/5)	—
—	@Emkayoh1(bot score 4.4/5)	—
—	@GabyDore(bot score 4.6/5)	—
—	@Ihelpu2c(bot score 4.6/5)	—
—	@Istandfortheru1(bot score 4.2/5)	—
—	@kandieg19652000(bot score 4.2/5)	—
—	@KrattMike(bot score 4.0/5)	—
—	@larryfd(bot score 4.1/5)	—
—	@LeCorsaire(bot score 4.1/5)	—
—	@lewing99(bot score 4.1/5)	—
—	@MarciaBunney(bot score 4.1/5)	—
—	@Margaret_ADuffy(bot score 4.4/5)	—
—	@MatthewCronin9 (bot score 4.2/5)	—
—	@ obligatoryasian(bot score 4.1/5)	—
—	@QuillWalter(bot score 4.8/5)	—
—	@ReneeMcCone(bot score 4.1/5)	—
—	@STCHauck(bot score 5.0/5)	—
—	@Urdchan(bot score 4.7/5)	—
—	@yvonnecody1326(bot score 4.4/5)	—
—	@AdrianaCothran(bot score 4.8/5)	—
—	…	—

Note. This table only listed the most active 380 social bots accounts that posted more than 30 tweets during election period.