Measuring the Interference Effect of Bots in Disseminating Opposing Viewpoints Related to COVID-19 on Twitter Using Epidemiological Modeling

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Abstract

The activity of bots can influence the opinions and behavior of people, especially within the political landscape where hot-button issues are debated. To evaluate the bot presence among the propagation trends of opposing politically-charged viewpoints on Twitter, we collected a comprehensive set of hashtags related to COVID-19. We then applied both the SIR (Susceptible, Infected, Recovered) and the SEIZ (Susceptible, Exposed, Infected, Skeptics) epidemiological models to three different dataset states including, total tweets in a dataset, tweets by bots, and tweets by humans. Our results show the ability of both models to model the diffusion of opposing viewpoints on Twitter, with the SEIZ model outperforming the SIR. Additionally, although our results show that both models can model the diffusion of information spread by bots with some difficulty, the SEIZ model outperforms. Our analysis also reveals that the magnitude of the bot-induced diffusion of this type of information varies by subject.

Keywords: Epidemiological modeling, COVID-19, Misinformation, Social network analysis, Botometer.

1. Introduction

Twitter is an open platform wherein users argue opposing viewpoints. While some of these viewpoints are backed by scientific evidence, other viewpoints may not be. The non-scientifically backed viewpoints may tend to feed misinformation. Although being exposed to public discourse that contains varying viewpoints can be healthy in terms of gaining reciprocal understanding and situational awareness, these arguments often contain misinformation. Spreading misinformation and confusion within public arguments about healthcare subjects can be dangerous and poses a serious threat to people's health (Van Bavel et al., 2020). Unfortunately, the social media information regarding the novel coronavirus of 2019 (SARS-CoV-2) and its resultant disease (COVID-19) that caused a global pandemic is a profound example. In addition, the activity of bots and botnets have the ability to impact the opinions, choices, and behavior of humans, especially within the political landscape where hot-button issues are debated such as politically related healthcare issues. This study is motivated by the influence of the propagation of polarizing viewpoints on social media in people's behavior, specifically related to public health issues. In this study, we attempt to identify the impact of bots on the ability of epidemiological models to model the propagation of opposing viewpoints on Twitter. Using viewpoints related to COVID-19 on Twitter, we examined three different diffusion cases: all users, bots, and humans (after removing the bots from the datasets). We studied the diffusion trend of six different narratives including Biden virus, Biden vaccine, Trump virus, Trump vaccine, 5G, and Bill Gates from a misinformation perspective during the peak time of the COVID-19 pandemic (i.e., January 1, 2020 - June 30, 2021).

The primary research questions we study include: Are the epidemiological models able to evaluate the propagation trends of polarizing viewpoints spread by bots? What are the differences? Which epidemiological model is more capable of modeling the online social network diffusion trends of opposing viewpoints spread by all users, by bots, and by humans? Epidemiological models can help researchers to understand the influence of bots in the spread of opposing viewpoints. In these models, the Infected compartment is the most important since it is composed of the users who actively spread the viewpoint. The remainder of this paper is presented as follows. Section 2 presents the related work that is germane to the influence of bots, bot, and applying epidemiological models to the spread of misinformation on social networks. In Section 3, the methodology used in this work is described, including our data collection process, Botometer bot detection approach, and the models applied. Section 4 discusses

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our analysis and results and highlights the findings from our research. Finally, Section 5 discusses our overall conclusions and the impact of our research. We also discuss directions for future work.

2. Literature Review

Not all bots are bad. Yang et al. (Yang et al., 2019) provides a review of the types of bots and their impact on society as well as bot detection methods and tools. Bots can be very simple in that they are programmed to simply post content automatically. Bots can also be very complex in that they are programmed to impersonate humans by employing strategies to mimic human behavior (Keller & Klinger, 2018). Kaplan and Haeniein (Kaplan & Haenlein, 2010) explain that bots engaged in such activities as promotions for products or services or helpline bots such as those used in suicide prevention are benign and do not pose a threat to society. However, those referred to as influence bots are of great concern and have become increasingly active during times of significant events such as political campaigns and elections. Researchers ("Social Bots Distort the 2016 US Presidential Election") warn of the power of bots to amplify information in the form of retweets, and how it is difficult to differentiate human and bot activity, which often occurs at the same rate. Primarily to manipulate social media discourse, these bots are used to spread fake news and misinformation (Shao et al., 2018), and sometimes spam in order to distract attention away from otherwise factual information. In this section, we discuss extant literature relevant to the concepts involved in this work, including the influence of bots, bot detection and the use of the Botometer tool, and applying epidemiological models to the spread of information on social networks.

2.1. The Influence of Bots

There are economic and political incentives for interjecting social bots into online ecosystems (Ferrara, Varol, Davis, Menczer, & Flammini, 2016). Some bots act with the objective of forming and growing an audience with the goal being to exert influence. Bots vary across social media platforms. Twitter bots tend to be more political, for example, while Facebook bots are primarily conversational in nature (Adewale Obadimu, Mead, Al-Khateeb, & Agarwal, 2019). Evidence of the use of bots to exert influence has been found in other domains beyond the political mainstream, such as in the promotion of terrorism and extremism (Al-Khateeb & Agarwal, 2016) financial markets (Fan, Talavera, & Tran, 2020), (Adahali & Hall, 2020), and public health (Jamison, Broniatowski, & Quinn, 2019). Many of these issues that bots target has a tendency to be politicized and lead to polarization, such as vaccination (Ferrara et al., 2016), (Yuan, Schuchard, & Crooks, 2019), which has become increasingly prevalent during the spread of COVID-19 and often includes the spread of misinformation (Egli, Rosati, Lynn, Sinclair, & Lynn, 2021) and hate speech (Uyheng & Carley, 2020). Although bots often spread true and false news at the same rate (Vosoughi, Roy, & Aral, 2018), they tend to amplify low-credibility (Shao et al., 2018) and negative content (Stella, Ferrara, & De Domenico, 2018) in the early stage of its dissemination, right before the content goes viral; therefore, identifying and eliminating malicious bots can aid in the stemming of the spread of online misinformation. Khaund et al. (Khaund, Kirdemir, Agarwal, Liu, & Morstatter, 2022) conducted an extensive literature review regarding bots and their use in online coordinated influence campaigns.

2.2. Bot Detection

In addition to influence, bots also introduce a source of bias in studies of Twitter data (Allem & Ferrara, 2016). Bot detection tools use machine learning classification algorithms to evaluate the probability that a given social media account is controlled by a machine (a bot) or a human (Rodrigues & Fonseca, 2016). Reported estimations of bot presence vary. A 2009 report estimated that 24% of all tweets on Twitter were spread by bots ("Twitter Zombies: 24% of Tweets Created by Bots | Mashable," n.d.), ("The Invasion of the Twitter Bots," n.d.). In 2017 and 2021 the estimate of Twitter bots rose to 15% of users ("Online Human-Bot Interactions: Detection, Estimation, and Characterization | Proceedings of the International AAAI Conference on Web and Social Media," n.d.), (Martini, Samula, Keller, & Klinger, 2021). Twitter itself reports that it detects about 25 million suspected bots per month ("The secret world of good bots," n.d.). Bot detection is not flawless. There is the issue of the "false positive problem" (labeling a human account as a bot) that plagues detection tools. On the flip side is the problem of false negatives, which is labeling a bot account as human. Additionally, bots continually evolve to evade detection (Al-Khateeb & Agarwal, 2016). Nonetheless, researchers provide estimates for the suspected bot presence within their datasets. Berger and Morgan identified 6,216 accounts (out of 90,000) as suspected bots within a "ISIS supporters" dataset, responsible for at least 20% of the tweets ("The ISIS Twitter census: defining and describing the population of ISIS supporters on Twitter," n.d.). Bessi and Ferrara

(“Social Bots Distort the 2016 US Presidential Election Online Discussion by Alessandro Bessi, Emilio Ferrara :: SSRN,” n.d.) found 7,183 bots in their 2016 US Presidential election dataset of 50,000 accounts, responsible for 2,330,252 tweets, while 40,163 accounts were labeled as humans, responsible for 10.3 million tweets. Uyheng and Carley (Uyheng & Carley, 2020) found a 14.9% and 15.7% bot presence in two different datasets regarding online hate during the COVID-19 pandemic, being responsible for 26.31% and 21.73% of the tweets, respectively (3.026M and 3.436M tweets). And Egli et al. (Egli et al., 2021) reported a 1% to 2% bot presence, responsible for 3.5% to 5% of the tweets.

2.3. Epidemiological Models Evaluating the Spread of Information on Social Networks

Applying a mathematical model to evaluate the spread of information on an Online Social Network (OSN) can provide us with the opportunity to acquire effective information toward its propagation. As a result, we can set the stage for useful approaches and policies to control this propagation when needed. The findings of several subsequent works support the hypothesis that there is a similarity between the propagation of disease in a community and the spread and virality of information on social media platforms (Rodrigues & Fonseca, 2016), wherein several types of information have been considered from the epidemiological perspective; rumor (Zhao et al., 2012), news (Jin, Dougherty, Saraf, Cao, & Ramakrishnan, 2013), misinformation (Maleki, Arani, Buchholz, Mead, & Agarwal, 2021) (Holme & Rocha, 2019), and toxicity (A Obadimu, Mead, Maleki, on, & 2020, 2020) (Maleki et al., 2022). To date, there are no known works that evaluate the application of epidemiological models in an online social network that is infested with bots. To that end, this work is novel in that it serves to fill that void and to provide quantitative evidence as it applies to the modern digital landscape while also being based on strong theoretical foundations. The next section details the methodology used in this research.

3. Methodology

Methods of data collection are initially described, followed by the application of the Botometer tool and epidemiological models. To provide the proper background, we compare the structure and components of two epidemiological models including the SIR and the SEIZ models.

3.1. Data Collection and Processing

We used the Twitter Academic API to collect tweets related to COVID-19 from January 1, 2020, to June 30, 2021. We collected data for different sets of hashtags that are politically related to COVID-19. For every category, we collected a broad range of hashtags to be able to include as much as possible data for every category. These topics included Biden virus, Biden vaccine, Trump virus, Trump vaccine, 5G, and Bill Gates. Our datasets include original tweets, retweets, and replies. Due to the large size of the Trump virus dataset, we used the Random Python library to create 5 different 10% random samples. We applied both the SIR an SEIZ models to each sample and calculated the average errors for reporting. A sample of hashtags we collected for each dataset is shown in Table 1.

Table 1. Sample of list of hashtags for every dataset

Dataset	Sample of hashtags
Biden virus	#BidenCovid19, #BidenVirus2020, #BidenCoronavirus, #BidenfakedCorona,
Biden vaccine	#BidenVaccine, #BidenCovidVaccine
Trump virus	#TrumpPlandemic, #TrumpCovidscam, #TrumpCoronaVirus, #TrumpCorona
Trump vaccine	#TrumpVaccine, #TrumpCovidVaccine
5G	#5Gvirus, #5Gcovid19, #5Gcoronavirus, #5Gplandemic, #Corona5G
Bill Gates	#BillGatesCovid19, #BillGatesCorona, #BillGatesCoronaVirus, #BillGatesVirus

3.2. Botometer tool

In this study we used Botometer which is a Python library that calculates a probability score on a scale of [0, 1] using a machine learning algorithm. The Botometer API takes the user ID as an input and then compares it to tens of thousands of labeled examples. In the output, low scores represent a likelihood that the account is a human, while high scores represent a likelihood that the account is a bot. Although the bot scores are useful for visualization and behavior analysis, they do not provide enough information by themselves to classify an account. A more significant way to interpret a score is to ask: "What is the probability that an account with a bot score higher than this account is human, or bot?" To answer this question, the Botometer API provides the so-called CAP (Complete Automation Probability), defined as the probability, that a user with this score or greater is controlled by software, i.e., is a bot. (“Botometer® by OSoMe,” n.d.).

3.3. Epidemiological Models

To evaluate the propagation of different sets of opposing viewpoints on Twitter based on indicative hashtags, we applied and evaluated the results of the two most common epidemiological models for evaluating the spread of information, the SIR and SEIZ.

SIR Model: The SIR model is an oft-used fundamental epidemiological model. The SIR model partitions members of a population into three compartments: Susceptible (S), Infected (I), and Recovered (R) (Figure1). In the SIR model, people in the Infected compartment are those who have been determined to have contracted a specific infection or disease and can spread the infection to other members of the population. The Susceptible compartment includes those members of the population who are considered at risk of contracting the infection from the Infected members. The Recovered compartment consists of those members of the population who are immune from contracting the infection or who have died from the infection (Abdullah & Wu, 2011). By allocating new definitions to these terms, the SIR model can be adjusted to consider the spread of information on Twitter, treating "information" as the "infection", and Twitter users as the population. In this revised SIR setting, and for the data used in this current work, the use of a specific hashtag can be considered as the information and the "infection". Therefore, a user who has posted using the specific hashtag can be considered Infected. Further, a user can be considered Susceptible if they follow an infected user but have not yet posted using that specific hashtag themselves. Finally, a user can be considered Recovered if they have not made additional posts containing the specific hashtag within a certain defined time frame. The following system of Ordinary Differential Equations (ODE) represents the SIR model (Abdullah & Wu, 2011).

$$\frac{dS}{dt} = -\lambda S$$

$$\frac{dI}{dt} = \lambda S$$

$$\frac{dR}{dt} = \gamma I$$

Figure 1. SIR model

SEIZ Model: Basic epidemiological models such as SIR contain the limitation of accounting for only one possible path from the Susceptible compartment, which is to enter into the Infected compartment. In the case of the spread of information as the infection, however, users in the Susceptible compartment have additional paths possible for transition. Yes, they can transition to the Infected compartment by deciding to post the information using the specific hashtag. But they can also decide not to post, but continue to follow the infected user, and therefore move into an Exposed compartment, meaning that they are still at risk. In addition, some users may need some time to decide if they believe the information and should spread the hashtags related to them. Additionally, users in the Susceptible compartment can indicate that they are decidedly skeptical of the information. Further, some users in the Susceptible compartment show no indication of any reaction that they have had to their exposure to the information. These additional possibilities are not considered via the basic SIR epidemiological model but are accounted for in the more robust SEIZ model. We applied both the SIR and SEIZ model to our data for this current work to illustrate the comparative ability to model the propagation of information on Twitter.

When applying the SEIZ epidemiological model to Twitter data with the objective of analyzing the propagation of information, the composition of the compartments (Figure 2) can be considered as follows: Infected (I) consists of the users who have posted a Tweet containing a specific hashtag. Susceptible (S) consists of the users who follow the Infected users. Exposed (E) consists of the users who have been exposed to a hashtag-specific tweet and after some delay in time also posted a tweet using the specific hashtag. Skeptic (Z) consists of users who have been exposed to the hashtag-specific tweet but have decided not to post a tweet using the specific hashtag (Jin et al., 2013).

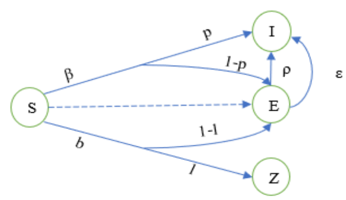

Figure 2. SEIZ model

The following system of Ordinary Differential Equations (ODE) represents the SEIZ model.

$$\frac{dS}{dt} = -\beta S\frac{I}{N} - bS\frac{Z}{N}$$

$$\frac{dE}{dt} = (1-p)\,\beta S\frac{I}{N} + (1-l)bS\frac{Z}{N} - \rho E\frac{I}{N} - \varepsilon E$$

$$\frac{dI}{dt} = p\beta S\frac{I}{N} + \rho E\frac{I}{N} + \varepsilon E$$

$$\frac{dZ}{dt} = lbS\frac{Z}{N}$$

4. Analysis and Results

This section presents the research findings in three parts. First, a preliminary analysis evaluates the usage frequency of hashtags in general over time. Then the frequency of hashtags spread by bots are evaluated, and finally, the SIR and SEIZ models were applied to fit our different datasets to the Infected (I) compartment of the models.

4.1. Diffusion Trends for All Users

Before applying any bot analysis, we first examined the information diffusion trend and cumulative sum of tweets for every dataset during January 2020 to June 2021 (Figure 3 group). The blue lines in each figure represent the diffusion trend of tweets and the red lines show the cumulative sum of tweets. Due to space limitations, frequency and cumulative sum figures for datasets that are not included here are available upon request.

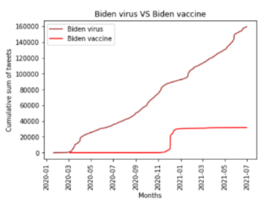

Figure 4.a. Biden virus vs. Biden vaccine (Biden campaign)

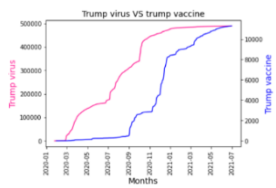

Figure 4.b. Trump virus vs. Trump vaccine (Trump campaign)

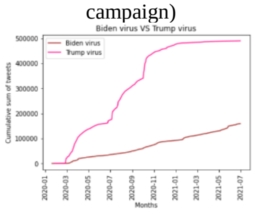

Figure 4.c. Biden virus vs. Trump virus (virus campaign)

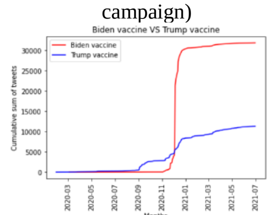

Figure 4.d. Biden vaccine vs. Trump vaccine (vaccine campaign)

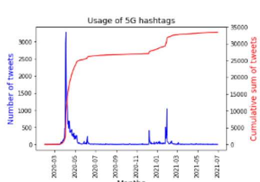

Figure 3.a. 5G

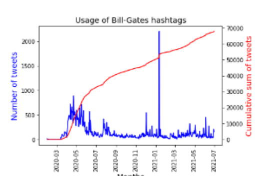

Figure 3.b. Bill Gates

Figure Group 3. Diffusion trends of tweets (blue line) and the cumulative sum of tweets (red line)

Examining the cumulative usage of tweets allows us to identify the overall rate of change of each information campaign (hashtag groups). Usage of 5G hashtags (Figure 3a) was most pronounced around April of 2020, which was the beginning of the pandemic and there were numerous rumors regarding the influence of 5G technology on the spread of the COVID-19 on different social media platforms, (Ahmed, Vidal-Alaball, Downing, & Seguí, 2020) declining sharply afterward through the end of May. Usage seemed to drop off the chart between the end of June through the end of November 2020. We then see three spikes in usage. Usage of Bill Gates hashtags (Figure 3b) had great fluctuation over our timeframe of analysis, with the first obvious increases being between the beginning of February and the end of April of 2020, and the most pronounced spike in usage being around the first weeks of January 2021, shortly after the presidential election in the US. During this time, conspiracy theories about Bill Gates were circulating on social media, such as the idea that he was working on embedding tracking devices in COVID-19 vaccines (Goodman & Carmichael, 2020).

A comparison of the usage of virus and vaccine hashtags from a political perspective are presented in (Figure group 4). We visualized a comparison between the cumulative sum of tweets for the virus and vaccine information campaigns for the Trump and Biden subjects (Figure group 4). Comparing the usage of the Biden virus and Trump virus hashtags with the usage of their respective vaccine hashtags reveals that the virus category absorbs more attention than the vaccine category. It is assumed that the spread of virus per se is not related to politics, and it is categorized as misinformation, therefore the spread of misinformation seems to be higher than the legitimate information related to vaccines. There is a pronounced spike wherein the usage of Biden virus hashtags surged as compared to the usage of Trump virus hashtags (Figure 4c).

Figure 4b compares the virus vs vaccine information campaigns only for Trump. Clearly, the virus subject was tweeted more often than the vaccine and could suggest more focus on the cause of the virus versus the discussions around the vaccine. However, we must consider that the vaccine discussions for COVID-19 didn't begin until late summer of 2020. Furthermore, the comparison reveals that both campaigns take on an s-shape, which shows a clear beginning, amplification, and flattening or slowing of the campaigns, as reported by Spann et al. (Spann et al., 2021). It is interesting that the Trump vaccine messaging was significantly amplified after the November 2020 elections.

Comparing the Trump information campaigns and Biden information campaigns around the virus subject over the same timeframe, we see that the Trump virus hashtags experienced significantly more usage (Figure 4c). The cumulative sum visualization comparing the usage of Biden vaccine and Trump vaccine hashtags (Figure 4.d.) reveals the magnitude of the usage differentiation. From the beginning of the usage of the Biden vaccine and Trump vaccine hashtags, the usage frequency of both sets was comparably low. However, the usage frequencies began to become notably divergent around the beginning of September of 2020, with the usage of Trump vaccine hashtags usurping that of the Biden vaccine hashtags.

4.2. Information Diffusion Trends for Detected Bot Activity

We used the Botometer tool to identify the tweets that spread by suspected bots. We used the "raw_scores.english.overall" and "cap.english" scores to find the tweets that are spread by suspected bots. The dataset was primarily in English, hence the English model was chosen. In this study, we used the threshold CAP>= 0.9 and raw score>= 0.9 for bot detection. A small sample of tweets spread by suspected bots is presented in the table 2.

Table2. Sample of tweets spread by highly likely bots

Text	CAP	Raw score
#BillGatesBioTerrorist **#BillGatesVirus** Do NOT take the vaccine! Do NOT trust #BillGatesIsEvil	0.92	0.96
#bidenvaccine is crushing **#trumpvirus**	0.93	0.97
I think we can improve our chances of surviving **#TrumpVirus** if we nail some 2x4's across the @whitehouse doors. What do you think?	1	1
Rather than let anything called the "**#TrumpVaccine**" be injected into myself, I would prefer to just deal with #Covid again	1	1

The diffusion trends of tweets spread by suspected bots are illustrated in Figure Group 5. Most of the temporal usage peaks in the plots contained in Figure Group 5 reveal that bots were suspected as being at least partially responsible for the amplification of usage of the subject hashtags for the corresponding date points or range. When using a high bot-detection threshold (i.e., CAP and raw score >=0.9), pronounced temporal spikes of suspected bot activity can be identified among the usage of the Biden virus hashtags group in April of 2020 and then again in various weeks between May through June of 2021 (Figure 5a). For the Biden vaccine hashtags, bot activity was clearly playing a prominent role in the diffusion of the information during the first week of December of 2020 (Figure 5b).

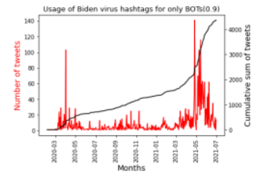

Figure 5.a. Biden virus

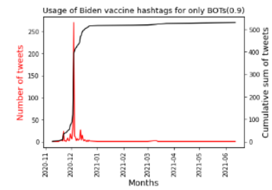

Figure 5.b. Biden vaccine

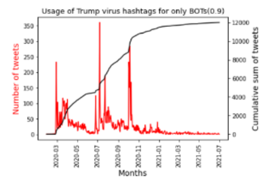

Figure 5.c. Trump virus

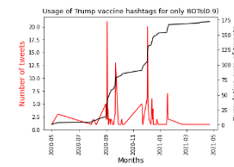

Figure 5.d. Trump vaccine

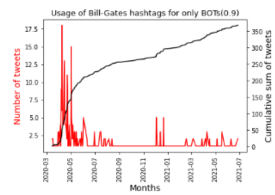

Figure 5.e. Bill Gates

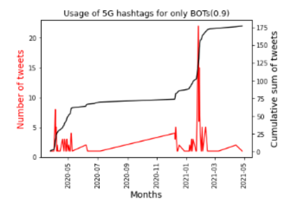

Figure 5.f. 5G

Figure Group 6. Diffusion trends of tweets spread by bots (red). Cumulative sum of tweets spread by bots(black)

Spikes in bot activity were evident during several months among the usage of the Trump virus hashtags (Figure 5c). Usage peaks correspond to March, the end of June, both the beginning and end of July, and October all in 2020. Suspected bot activity among the Trump vaccine hashtags usage seems to have been less evident (Figure 5d).

When detected, the bot activity appears to have occurred within visual spikes corresponding to the beginning of September, October, and December of 2020, and then again in February of 2021. For the 5G hashtags (Figure 5f), there are clear temporal spikes in bot activity. The first occurred around the first weeks of April of 2020, followed by another series of short bursts between around the last week of that same month and the first week of May 2020. The next temporal spike in detected bot activity is rather pronounced and occurs around the end of December of 2020. The final and most pronounced temporal spike in bot activity within the 5G dataset occurred around the first weeks of February of 2021.

4.3. Composition of Suspected Bots Within Datasets

Now, let's examine the composition of suspected bots within the datasets used in this work. Table 3 provides a summary of the general information about the number and percentage of bots and tweets by bots for the CAP Threshold >= 0.9 and raw score >= 0.9 threshold. Table 3 shows that, overall, the Trump_Vaccine, Biden_Virus, and Biden_Vaccine datasets had the largest bot presence (1.79%, 1.52%, and 1.51% of unique user count, respectively). Additionally, the datasets pertaining to "virus" had the largest number of tweets generated by bots, 12,002 within the Trump_Virus_10% and 4,365 within Biden_Virus.

Table 3. General information about the number and percentage of bots and tweets by bots

Dataset	Total number of Tweets	Total number of users	#of tweets by bots	%of tweets by bots	Total number of	% of users are bots
Biden_Virus	159,448	67,361	4,365	2.74	102	1.52
Biden_Vaccine	31,874	18,266	273	0.86	275	1.51
Trump_Virus_10%	489,896	186,618	12,002	2.45	1696	0.91
Trump_Vacci	11,311	6,523	172	1.52	117	1.79
5G	33,403	22,867	177	0.53	133	0.58
BillGates	67,780	32,306	368	0.54	169	0.52

Although the Trump_Virus_10% dataset had a smaller overall percentage of users detected as bots than three of the six datasets, those Trump_Virus bots were disseminating tweets throughout the dataset at a greater magnitude (2.45%) than were the bots within all other datasets except for the Biden_Virus dataset (2.74%). In the next section, we discuss the results of applying the SIR and SEIZ epidemiological models for evaluating information diffusion in networks infested with bots, and the impact of bots on the information diffusion process.

4.4. Modeling the Infected (I) compartments

In this section, we discuss the results of our applications of the SIR and SEIZ epidemiological models to each of the datasets used in this work. We fit the number of Infected people (those users who used the hashtags of interest in each experiment) in each 24-hour time interval for all datasets as the Infected (I) compartment in the SIR and the SEIZ model using Python. Model fit results for hashtags were graphed in Figure Groups 8 through 12 and will be discussed in the subsequent section. The nonlinear least square curve fitting MatLab function called lsqnonlin was applied to each of the datasets used in this work. Table 4 summarizes the SIR and SEIZ errors for three states for each dataset using the Botometer CAP threshold = (0.9, 1] and Botometer raw score interval (0.9, 1]: a) original dataset (before removing bots), b) after removing bots, and c) containing only bots. The error indicates the difference between the actual number of users who spread the tweets and the Infected compartment of our models. To be able to quantify this difference, we used relative error in 2-norm (Jin et al., 2013).

$$\frac{||I(t) - tweets\ (t)||_2}{||tweets(t)||_2}$$

Table 4. SIR and SEIZ errors for original datasets (before removing bots), after removing bots, and for only bots

Dataset:	SIR error (before removing bots)	SIR error (after removing bots)	SIR error (only bots)	SEIZ error (before removing bots)	SEIZ error (after removing bots)	SEIZ error (only bots)
Biden_Virus	20.2%	19.8%	36.1%	7.2%	7.2%	33.7%
Biden_Vaccine	25.3%	18.7%	36.9%	7.4%	7.4%	28.5%
Trump_Virus_10%	23.3%	19.1%	19.7%	5.3%	5.3%	14.7%
Trump_Vaccine	22.8%	22.6%	40.0%	6.6%	6.6%	18.4%
5G	26.9%	22.1%	39.1%	10.5%	10.2%	26.7%
BillGates	16.4%	16.3%	20.4%	7.9%	7.9%	14.4%

Our analysis reveals that the SEIZ model performed best for all datasets. For all six datasets, the SEIZ model is least impacted by the presence of bots as compared to the SIR model. SIR model showed a performance gain when bots were removed, demonstrating its higher vulnerability to bot infested information environment as compared to SEIZ model. For three of the datasets (Biden_Vaccine, 5G, Trump_Virus_10%) this improvement was pronounced from about 4% to more than 6%. For all six datasets, the SIR model had a more difficult time modeling the behavior when the dataset consisted of only bots than it did when the datasets consisted of no bots. For all but the Trump_Virius_10% dataset, this difficulty was very pronounced with increases in error ranging from 4.1% (BillGates) to about 18.2% (Biden_Vaccine). For all datasets the SEIZ model was not able to model the behavior any better after suspected bots were removed than it did when the datasets consisted of bots. Additionally, for all six datasets, the SEIZ model had a more difficult time modeling the behavior when the datasets consisted of only bots than it did when the datasets consisted of no bots. This difficulty was very pronounced with increases in error ranging from 14.4% (BillGates) to 28.5% (Biden_Vaccine).

Our analysis also reveals differences in model performances regarding bot presence when looking at individual datasets. For the Biden_Virus dataset, the presence of bots had no apparent impact on the performance of either the SIR and SEIZ models (a reduction in error of 0.40% and 0.00%, respectively). For the Biden_Vaccine dataset, however, there is a pronounced improvement in the performance of the SIR model in the form of a 6.60% reduction in error after bots have been removed. Additionally for the Biden_Vaccine dataset, although not very pronounced, the SEIZ model also realized an improvement in performance when bots were removed (a 1.90% reduction in error). For the Trump virus_10% dataset, there is a pronounced improvement in the performance of the SIR model in the form of a 4.2% reduction in error after bots have been removed. In answer to our research objectives, both the SIR and SEIZ models are able to model the diffusion trends of opposing viewpoints spread by users in general. But the SEIZ model is more capable of modeling the diffusion trends of opposing viewpoints spread by bots. Regardless of bot presence, the SEIZ model performed best for all datasets. On its own, the SIR model was better able to model behavior after suspected bots were removed than it was when bots were present.

4.5. Fitting datasets to Infected (I) Compartment of the SIR and SEIZ Models

Figures 6 through 8 reveal the model fit for the SIR and SEIZ epidemiological models when applied to our Biden_Virus datasets in each of three dataset states: 1) in their original state (before removing bots), 2) after removing bots, 3) bots only. Each of the SIR model fits (left panels) reveal that the trends tend to form S-shape lines, resulting in higher error levels in comparison to the corresponding SEIZ model fits (right panels). Due to space limitations, model fit for the SIR and SEIZ epidemiological models figures for all datasets are available upon request. Figure 6 reveals the model fit for the SIR (left panel) and SEIZ (right panel) models when applied to the original Biden_Virus dataset (before removing bots). For the Biden_Virus original dataset, the SEIZ model outperformed the SIR model with 7.2% and 20.2% error levels, respectively. In this case, the SIR model fit has almost three times as much error as the SEIZ model fit.

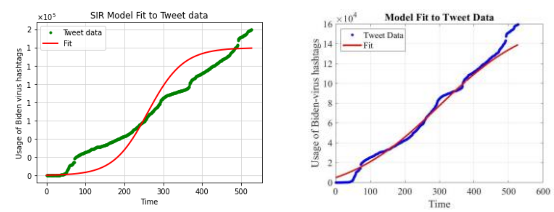

Figure 6. Model fit for the SIR (left panel) and SEIZ (right panel) when applied to the original Biden_Virus dataset (before removing bots).

Figure 7 reveals the model fit for the SIR and SEIZ models when applied to the Biden_Virus dataset after removing bots. For this Biden_Virus no-bot dataset, the SEIZ model outperformed the SIR model with 7.2% and 19.8% error levels, respectively. In this case, the SIR model has over twice the level of the SEIZ model fit.

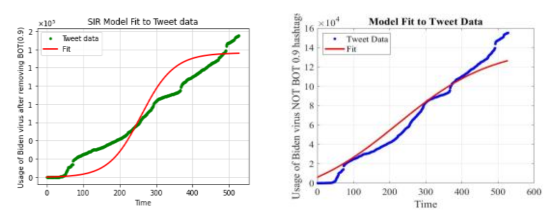

Figure 7. Model fit for the SIR (left panel) and SEIZ (right panel) when applied to the Biden_Virus dataset after removing bots.

Figure 8 reveals the model fit for the SIR and SEIZ models when applied to the Biden_Virus dataset when it consists of only bots. Although both models performed poorly in this case, for this bot-only dataset, the SEIZ model slightly outperformed the SIR model with 33.7% and 36.1% error levels, respectively. In this case, neither of the two models were able to react to changes in the posting behavior in a timely manner. It is important to note that the percentage of bots in the data was very low (<2%) in all six datasets. Further work is needed to rigorously evaluate the impact of bot infestation on performance of SIR and SEIZ models, when the number of bots is varied. This constitutes as one of our future research directions.

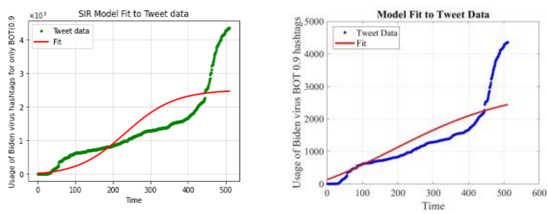

Figure 8. Model fit for the SIR (left panel) and SEIZ (right panel) when applied to the Biden_Virus dataset when it consists of only bots

5. Conclusions and Future Work

In this study, we presented the influence of bots in the trend of spread of politically-charged opposing viewpoints related to COVID-19. These topics included Biden virus, Biden vaccine, Trump virus, Trump vaccine, 5G, and Bill Gates. To extract the tweets propagated by suspected bots, we used the Botometer tool with the (0.9,1] threshold for “CAP” and “raw score”. To evaluate and characterize the diffusion trends of opposing viewpoints by bots, we applied two epidemiological models (viz., SIR and SEIZ) to all datasets in three different states containing tweets spread by users in general, those by suspected bots, and after removing those by suspected bots. We compared the results of the SIR and the SEIZ epidemiological models.

Our findings demonstrated that overall, the Trump_Vaccine, Biden_Virus, and Bident_Vaccine datasets had the largest bot presence (1.79%, 1.52%, and 1.51% of unique user count, respectively). Additionally, the datasets pertaining to "virus" had the largest number of tweets generated by bots. Although the Trump_Virus_10% dataset had a smaller overall percentage of users detected as bots than three of the six datasets, those Trump_Virus bots were disseminating tweets throughout the dataset at a greater magnitude (2.45%) than were the bots within all other datasets except for the Biden_Virus dataset (2.74%). For all the datasets, both SIR and SEIZ models had a more difficult time modeling the behavior when the datasets consisted of only bots. In addition, The SEIZ model outperformed for all datasets in all three states mentioned earlier. While SIR model gained performance after suspected bots were removed, the performance of the SEIZ model was not influenced by bots. We will continue to study the impact of bots on online diffusion dynamics in future work. We will also apply NLP to evaluate the belief or doubt of users who spread tweet using a specific hashtag. We are planning to apply other mathematical models to these and other datasets from different domains to compare with the epidemiological models. Further research can also include the influence of bots in the propagation of toxicity on online social networks such as Twitter.

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