The Impact of Bots on Opinions in Social Networks

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We present an analysis of the impact of automated accounts, or bots, on opinions in a social network. We model the opinions using a variant of the famous DeGroot model, which connects opinions with network structure. We find a strong correlation between opinions based on this network model and based on the tweets of Twitter users discussing the 2016 U.S. presidential election between Hillary Clinton and Donald Trump, providing evidence supporting the validity of the model. We then utilize the network model to predict what the opinions would have been if the network did not contain any bots which may be trying to manipulate opinions. Using a bot detection algorithm, we identify bot accounts which comprise less than 1% of the network. By analyzing the bot posts, we find that there are twice as many bots supporting Donald Trump as there are supporting Hillary Clinton. We remove the bots from the network and recalculate the opinions using the network model. We find that the bots produce a significant shift in the opinions, with the Clinton bots producing almost twice as large a change as the Trump bots, despite being fewer in number. Analysis of the bot behavior reveals that the large shift is due to the fact that the bots post one hundred times more frequently than humans. The asymmetry in the opinion shift is due to the fact that the Clinton bots post 50% more frequently than the Trump bots. Our results suggest a small number of highly active bots in a social network can have a disproportionate impact on opinions.

Key words: Social networks, opinion dynamics, bots

1. Introduction

Social networks have given us the ability to spread messages and influence large populations very easily. Malicious actors can take advantage of social networks to manipulate opinions using artificial accounts, or bots. It is suspected that the 2016 U.S. presidential election was the victim of such social network interference, potentially by foreign actors [Parlapiano and Lee 2018]. Foreign
influence bots are also suspected of having attacked European elections (Ferrara 2017). The bots' main action was the sharing of politically polarized content in an effort to shift opinions (Shane 2018). The potential threat to election security from social networks has become a concern for the U.S. government. Members of Congress have not been satisfied with the response of major social networks (Fandos and Shane 2017) and have asked them to take actions to prevent future interference in the U.S. democratic process by foreign actors (Price 2018). In response, major social media companies have taken serious steps. Facebook has identified several pages and accounts tied to foreign actors (O'Sullivan and Herb 2018) and Twitter suspended over 70 million bot accounts (Timberg and Dwoskin 2018).

Despite all of the efforts taken to counter the threat posed by bots, one important question remains unanswered: how many people were impacted by these influence campaigns. More generally, how can we quantify the effect of bots on the opinions of users in a social network? Answering this question would allow one to assess the potential threat of an influence campaign. Also, it would allow one to test the efficacy of different responses to the threat. Studies have looked at the volume of content produced by bots and their social network reach during the 2016 election (Bessi and Ferrara 2016). However, this data alone does not indicate the effectiveness of the bots in shifting opinions. The challenge is we do not know what would have happened if the bots had not been there. Such a counterfactual analysis is only possible if there is a model which can predict the opinions of users in the presence or absence of bots. Such models do exist in the literature (DeGroot 1974, Ghaderi and Srikant 2013, Hunter and Zaman 2018). However, for a model to be useful in assessing the impact of bots, it must be validated on real social network data. Once validated, an opinion model can then be used to assess the impact of different groups of bots.

1.1. Our Contribution

In this work we present a method to quantify the impact of bots on the opinions of users in a social network. We focus our analysis on a network of Twitter users discussing the 2016 presidential election between Hillary Clinton and Donald Trump. The core of our approach is a model for opinion dynamics in a social network. First, we validate the model by showing that the user opinions predicted by the model align with the opinions of these users’ based on their social media posts. Second, we identify bots in the network using a state of the art algorithm. Third, we use the opinion model to calculate how the opinions shift when we remove the bots from the network. Our high level finding is that a small number of bots have a disproportionate impact on the network opinions, and this impact is primarily due to their elevated activity levels. In our dataset, we find that the bots which support Clinton cause a bigger shift in opinions than the bots which support Trump, even though there are more Trump bots in the network.
2. Literature Review

A detailed study of bots in the 2016 presidential election was conducted by Bessi and Ferrara (2016). The authors found a large fraction of the election discussion came from bots and the bots were connected to many users. Similar conclusions were reached for bots deployed in the run up to the Brexit vote (Bastos and Mercea 2017) and French elections (Ferrara 2017). A comprehensive survey of social bots is provided in (Ferrara et al. 2016).

The detection of bots is an active area of research. Algorithms which use predictive features of individual users have been developed (Benevenuto et al. 2010, Chu et al. 2012, Davis et al. 2016, Egele et al. 2013, Thomas et al. 2011, Viswanath et al. 2014, Wang 2010), but require extensive data about the users. Another approach utilizes network structure to identify coordinated groups of bots, also referred to as sybils (Aggarwal 2014, Alvisi et al. 2013, Benevenuto et al. 2009, Cao et al. 2012, 2014, Danezis and Mittal 2009, Ghosh et al. 2012, Mesnards and Zaman 2018, Tran et al. 2009, Wang et al. 2013, Yang et al. 2014, Yu et al. 2006, 2008). The network based approaches look for anomalous behavior in network interactions. They have the advantage of requiring less data about the users and also being able to simultaneously detect multiple bots, unlike the feature based approaches.

Bots are designed to shift opinions. A variety of models have been developed to quantify such opinion shifts in networks. One of the earliest is the DeGroot model (DeGroot 1974) where users’ opinions equal the weighted average of their neighbors’ opinions. This model has a similar flavor to many distributed consensus algorithms (Jadbabaie et al. 2003, Olshevsky and Tsitsiklis 2009, Tsitsiklis et al. 1986, Tsitsiklis 1984), as the goal of each user reach consensus with his neighbors. Related to the DeGroot model is the voter model (Clifford and Sudbury 1973, Holley and Liggett 1975) where users update their opinions to match a randomly chosen neighbor. There is a large body of theoretical research concerning the limiting behavior in the voter model (Cox and Griffeath 1986, Gray 1986, Krapivsky 1992, Liggett 2012, Sood and Redner 2005). Another class of models take a Bayesian perspective on how opinions evolve, where each message a user posts causes his neighbors to update their belief according to Bayes' theorem (Acemoglu et al. 2011, Banerjee and Fudenberg 2004, Banerjee 1992, Bikhchandani et al. 1992, Jackson 2010).

Some opinion models allow for stubborn users whose opinions do not evolve. The notion of stubborn users was introduced by Mobilia (2003). Analysis has been done of the impact of stubborn agents in various opinion models (Acemoglu et al. 2013, Chinellato et al. 2015, Galam and Jacobs 2007, Ghaderi and Srikant 2013, Mobilia et al. 2007, Wu and Huberman 2004, Yildiz et al. 2013). The model in Hunter and Zaman (2018) is similar in flavor to the DeGroot model, but allows for users to grow stubborn with time. Common to all of these models is an opinion equilibrium where the non-stubborn users’ opinions are determined by the stubborn users.
3. Network Opinion Model

We consider users in a directed social network where each user follows a set of individuals, which we refer to as his friends. The user can see any social media content posted by his friends. To model the opinions in a social network we utilize the model proposed by Hunter and Zaman (2018) which is a variant of the classic DeGroot model (DeGroot 1974). The model assumes that individuals in a social network update their opinions based upon the opinions contained in the social media posts of their friends. Another assumption of the model is that certain users in the network are stubborn, meaning that their opinions do not change. These stubborn users end up driving the opinions of the rest of the users in the network.

Let us define the opinion of a user $i$ in the network as $\theta_i$. We assume the opinions are between zero and one. As an example, in the 2016 U.S. presidential election, an opinion of zero indicates strong support for Hillary Clinton while an opinion of one indicates strong support for Donald Trump. Let us also define the posting rate of user $i$ as $\lambda_i$. The posting rate is in units of posts per day, and is easily measured. The network opinion model predicts that in equilibrium the opinion of a non-stubborn user $i$ satisfies the following condition:

$$\sum_{j \in \text{friends of } i} \lambda_i (\theta_i - \theta_j) = 0.$$  

(1)

This equilibrium condition has a natural interpretation in terms of electrical circuits. One can view the user opinions as the voltages of nodes in an electrical circuit and the posting rate as the conductance between pairs of nodes connected by a resistor. Using this analogy, and Ohm’s Law from circuit theory, the quantity in the summation is equal to the electrical current flowing into a user from all of his friends. The equilibrium condition simply states that the total current flowing into each user must be zero. This same equilibrium and circuit interpretation was obtained for a very similar opinion model by Ghaderi and Srikant (2013).

Equation (1) has a unique solution as long as each non-stubborn user can be reached by at least one stubborn user. This means that in equilibrium, the non-stubborn user opinions are determined by the stubborn users. Therefore, if the reachability condition is satisfied, then once the stubborn user opinions are known, the non-stubborn user opinions can be calculated using equation (1).

4. Social Network Data

To utilize the network opinion model for our analysis, we first need to confirm that the opinions it predicts align with the true opinions of users in the social network. The dataset we use to validate the model consists of Twitter users discussing the second debate of the 2016 presidential election. The selected users were those who had at least one post, or tweet, which mentioned the second debate. We then collected all tweets of these users which were related to the 2016 election. Details
on the dataset are provided in [Littman et al. (2016)]. In total this dataset consists of over 2.3 million tweets belonging to 77,563 users. In addition, we were able to build the follower graph for these users using the Twitter API [Twitter (2018)] which contains over 5.0 million edges.

For each user we want to calculate their opinion with respect to the two presidential candidates. We assume each user’s opinion is between zero and one, with a zero or one indicating strong support for Clinton or Trump, respectively. The opinion of a user is manifested in the content of their tweets. Therefore, we use the tweets to estimate each user’s opinion. We did this by training a neural network on the tweets’ opinions.

We first needed a set of tweets with opinions labeled to serve as training data for the neural network. We did this by identifying several extremely politically polarized hashtags, such as #ImWithHer or #LockHerUp. We manually labeled these hashtags as either pro-Clinton or pro-Trump. Anyone using these hashtags is given a similar label. Then, all tweets in the dataset belonging to any pro-Clinton users are given an opinion of zero, and all tweets of pro-Trump users are given an opinion of one. This process produced 200,000 labeled tweets which served as our training data.

Next, we trained a neural network on the text of these tweets to predict their opinion. The full details of the neural network are provided in the appendix. We train on 80% of the labeled data and tested on the remaining fraction. The neural network achieves an accuracy of 92% on the test set, indicating that it has good accuracy in predicting the opinions.

We then used the neural network to calculate tweet opinions for all users in our dataset. For each user we first find the neural network opinion of each of their tweets. We then average these values to obtain the user’s opinion. Looking at the distribution of the tweet opinions reveals some interesting properties about the data. For the 77,563 users in our follower graph, the mean opinion is 0.38, indicating a bias towards Clinton. Looking more closely at the opinion distribution, we find that there are 57,781 users whose opinion is below 0.5 (pro-Clinton) and 19,782 users whose opinion is above 0.5 (pro-Trump). It is not clear why this bias exists in the data. It is possible that pro-Clinton users were more likely to use the hashtags and keywords that were used to collect the tweets for the dataset.

5. Model Validation
We assessed the validity of the network opinion model in [Hunter and Zaman (2018)] based on its ability to reproduce the tweet based opinions of users in our dataset. We show a visualization of the follower network of these users in Figure 1. To calculate the network based opinions, we first determine which users are stubborn. We do this by setting lower and upper opinion intervals for Clinton and Trump supporters. Any user whose tweet opinion falls within either of these intervals
is declared stubborn. We set the network based opinions of these stubborn users equal to their
tweet based opinions. For the posting rates, we use the number of tweets of each user in the dataset.
This is a good estimate of the rates since the data covers the same period of time for each user.

We set the Clinton and Trump stubborn threshold intervals to be [0.0, 0.1] and [0.9, 1.0], respectively. Using these stubborn intervals, we have 69,861 non-stubborn users and 7,702 stubborn users.
The mean opinion of the stubborn users is 0.23, indicating that there is a greater number of stub-
born users supporting Clinton than Trump. In total, 6,147 users have opinions in [0.0, 0.1] and
1,555 users have opinions in [0.9, 1.0]. We then solve the system of equations given by (1) to obtain
the network opinions of the non-stubborn users.

To see how well the network model predicts the opinions, we look at the correlation between the
tweet and network based opinions. We find that the correlation coefficient is equal to 0.43 (p-value
< 10^{-6}). Thus, we find that there is a non-trivial relationship between the tweet and network based
opinions. We plot the two types of opinions for the non-stubborn users in Figure 2. As can be seen,
the network opinions have a similar mean as the tweet based opinions, but a lower variation. The
mean tweet based opinion of the non-stubborn users is 0.40 and the mean network based opinion
is 0.42. The standard deviation of the tweet based opinions is 0.19 and the standard deviation
of the network based opinions is 0.04. These differences may be due to properties of the network model. The equilibrium equation (1) states that the opinions adjust to create a zero net opinion “current” flow into each non-stubborn user. This makes the opinions come closer to each other. The net result is that the variation of non-stubborn opinions across the network is reduced.

Despite this difference in opinion variation, we still obtain a non-trivial correlation between the network model’s opinions and the tweet based opinions. Also, the mean opinions are very close. This indicates that the network model is useful for capturing the impact of stubborn users on the mean opinion of a population of non-stubborn users. For this reason, the network model will be sufficient for our analysis of how bots shift the mean opinion.

To make sure the network opinions were robust to the choice of stubborn interval, we recalculated the opinions using several different intervals. Overall we found that the opinions were highly correlated and did not change significantly. This indicates that our results are robust to the choice of stubborn intervals. We summarize the robustness results in Table 1.

6. Bot Impact on Opinions

Bots are automated accounts which most likely are not influenced by content in the social network, and so must be stubborn. We now investigate the effect social network bots have on user opinions. We do this by first identifying the bots, and then calculating the opinion distribution using the
network model when we remove the bots. To identify the bots, we use the algorithm of Mesnards and Zaman (2018). This algorithm looks for groups of accounts that retweet others often (a retweet is a forwarded tweet) but do not receive many retweets in the interaction network related to an event. In our case, we use the network of retweets related to the second presidential debate. We chose this algorithm because it was shown to have a higher accuracy than other state of the art algorithms and also required less data.

The bot detection algorithm assigns a likelihood of being a bot between zero and one. We declared any user whose likelihood was greater than or equal to 0.51 as a bot. However, we found on our dataset that the algorithm identified several humans who retweeted frequently but were not retweeted themselves as bots. Therefore, to be even more careful with our bot detection, we further refined the set of bots by eliminating any users that had verified Twitter accounts (a verified account has the user’s identity confirmed by Twitter). We also manually inspected the accounts of the users who had the top 30 follower counts and removed anyone who appeared not to be a bot. At the end of this process, we identified 396 bots, of which 260 supported Trump (tweet based opinion greater than 0.5) and 136 supported Clinton (tweet based opinion less than 0.5). These bots represent less than 0.5% of the users in our dataset.

When the bots are included, they are considered stubborn users, even if their tweet opinion is not within our stubborn thresholds of $[0.0, 0.1]$ and $[0.9, 1.0]$. We show a histogram of the bot opinions in Figure 3. It can be seen that most bots do not fall within our stubborn threshold. Therefore, despite not being persuadable, most of the bots would not be considered stubborn based on their tweet opinion alone. It is possible these bots are designed to sometimes post less polarized content in an attempt to appear more human.

We calculated the network model opinions for four different scenarios: no bots, only Trump bots, only Clinton bots, and all bots. The resulting opinion cumulative distributions for the different scenarios are shown in Figure 4. We see some striking features here. First, when all bots are

Table 1  
Statistics of the correlation coefficient between the non-stubborn opinions for different stubborn intervals. The mean and minimum correlation coefficient for each stubborn interval with all other stubborn intervals are shown.

| Lower stubborn interval | Upper stubborn interval | Minimum correlation coefficient | Mean correlation coefficient |
|-------------------------|-------------------------|--------------------------------|-----------------------------|
| [0.00, 0.10]            | [0.90, 1.00]            | 0.71                           | 0.85                        |
| [0.00, 0.10]            | [0.95, 1.00]            | 0.69                           | 0.78                        |
| [0.00, 0.10]            | [0.85, 1.00]            | 0.64                           | 0.80                        |
| [0.00, 0.15]            | [0.90, 1.00]            | 0.74                           | 0.85                        |
| [0.00, 0.05]            | [0.90, 1.00]            | 0.74                           | 0.81                        |
| [0.00, 0.15]            | [0.85, 1.00]            | 0.66                           | 0.80                        |
| [0.00, 0.05]            | [0.95, 1.00]            | 0.64                           | 0.76                        |
included, the opinions shift towards Clinton. The median opinion goes from 0.58 with no bots to 0.42 with both Trump and Clinton bots. This indicates an asymmetry in the influence of the bots. This is more striking given the fact that there are nearly twice as many Trump bots as Clinton bots. To emphasize this asymmetry, one can look at the shift caused by each group of bots operating without the opposing bots. The Clinton bots alone create a huge shift from 0.58 to 0.26, while the Trump bots alone only cause a shift from 0.58 to 0.76.

Our results indicate that the Clinton bots are more effective than the Trump bots at shifting opinions. To understand why, we looked closer at these two groups of bots. We focus on two hypotheses. One is that the Clinton bots are followed by more people, and therefore have greater reach. The second is that the Clinton bots post content more frequently, allowing them to be more effective in their influence. According to the network opinion model, either of these conditions will lead to the observed asymmetry. This can be seen by looking at equation (1). To satisfy the equilibrium condition, non-stubborn users will shift their opinion towards those with a higher posting rate or more followers.

We first consider the friend and follower count of the bots and non-bots in the entire Twitter network. For the non-bots, we separate the users into pro-Trump and pro-Clinton using their tweet based opinions. We choose the tweet based opinions as our separation criterion because this is a more accurate measure of opinion than the network model which distorts the variance of the opinion distribution. We show the resulting cumulative distributions in Figure 5. We see that both
Clinton and Trump bots are more connected than the non-bot users. We also see that there is no visible difference between these distributions for the two groups of bots. This is confirmed by a Kolmogorov-Smirnov (KS) test (no difference at the 1% level). Therefore, the connectivity of the bots does not seem to be the cause of the asymmetry.

Next, we consider at the posting rate. Recall that this is the number of tweets in our dataset posted by each user that are relevant to the election. Figure 6 shows the cumulative distribution of the rates for the bots and non-bots. The first observation is that the bots’ median posting rate is nearly two orders of magnitude larger than the non-bots. This would seem to explain why the model predicts that their removal creates such a large opinion shift, despite their small number. Second, it appears the Clinton bots post at a higher rate than the Trump bots. Not only is the median rate 50% higher for the Clinton bots, but their distribution has a fatter tail than the Trump bots. This means there are several Clinton bots that post at very high rates. A KS test shows that the Clinton and Trump bot rates have different distributions (significant at the 1% level). Third, there is no clear difference between the rate distribution for the non-bot Clinton and Trump supporters. The median rate is five and six for the Trump and Clinton supporters, respectively.

As a second test, we recalculated the network opinions, but this time we gave every user in the network the same posting rate. This would eliminate any advantage the Clinton bots had due to higher activity levels. The resulting opinion distributions are shown in Figure 7. As can be seen,
when the rates are equal, the bots ability to shift opinions is reduced considerably. The Clinton bots alone cause almost no opinion shift. The inclusion of all bots shifts the median opinion slightly towards Trump. When the rates are equalized, the Trump bots have an advantage, most likely due to the fact that there are twice as many of them as Clinton bots. Therefore it seems that the asymmetry between the influence of Clinton and Trump bots is due to the Clinton bots’ higher posting rate.

Another interesting observation about the uniform rates model is that the median opinion shifts towards Clinton compared to the model with the true posting rates. Recall that the rate distributions of Trump and Clinton supporters were very similar. This suggests that there are some Trump supporters with high posting rates who have an effective position in the network for influencing others.

7. Conclusion

It is important to understand the impact of bots on the opinions of users in social networks. The method we presented here shows how opinion dynamics models can be used to accomplish this. Validation of the model was done by comparing its predictions to those based on the content of users. Then we were able to evaluate different scenarios by removing bots from the network. We found that the bots had a disproportionate effect on the opinions. Also, we found that the Clinton bots had a much greater effect on opinions than Trump bots, and that this asymmetry was due to their increased posting rate. Effectively, the bots shout louder than the humans, and the Clinton bots were shouting louder than the Trump bots. Our results suggest that a small number of highly active bots could be sufficient to significantly shift opinions in a social network. Therefore, it is
Figure 6 Plot of cumulative distribution of the bots’ and non-bots’ posting rate.

Figure 7 Plot of cumulative distribution of non-stubborn user opinions based on the network opinion model with different types of bots removed. All users in the network are give uniform rates.

important to limit the presence of bots on major social networks as they can distort the public discourse on many important issues.
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Appendix

EC.1. Neural Network Details

We now present the details of the neural network used to calculate the tweet based opinions of the users. We used a convolutional neural network architecture with two channels for two versions of the same tweet. The model architecture was inspired by \textsuperscript{[Kim (2014)]}. Their approach was to train a text classification model on two different word embeddings of the same text: one static channel comprised of embeddings using word2vec \textsuperscript{Goldberg and Levy (2014)} and another channel which is the output of an embedding layer trained during back-propagation.

Each tweet goes through a processing phase where we remove punctuation, stopwords and convert it into a format that the model can process. Each processed tweet is then converted into two versions: one where hashtags are left as they are and another where hashtags have been split into actual words. For example, ”I hope @candidate\_x will be our next president #voteforcandidate\_x #hatersgonnahate.” will be converted into two versions: The dirty version “I hope candidate\_x will be our next president voteforcandidate\_x hatersgonnahate” and the clean version “I hope candidate\_x will be our next president vote for candidate\_x haters gonna hate”. We do this in order to prevent our model from being a lazy learner by learning only from the hashtags. The hashtag splitting was done using the WordSegment library in Python \textsuperscript{[Python]}. The sequence length of the tweets has been set to 20 tokens (i.e. words). Any tweet with more than 20 tokens is truncated, while tweets with less than 20 tokens are padded with zeros.

We show the complete neural network architecture in Figure \textsuperscript{[EC.1]}. Each version of the processed tweet goes through its own embedding layer (dimension dense embedding = 128) that will then output two separate channels, each of size (20, 128). Each channel will go through its own separate 32 1D-convolution filters (kernel size = 3, stride = 1, padding = valid) with a ReLU activation, 1D max-pooling layers (pool size = 2) and a flattening layer. The resulting output is two (288,1) layers that we concatenate to form a (576,1) layer. This layer then goes through two fully connected layers with a ReLU activation and 64 and 32 units, respectively. The final layer is a softmax layer that outputs the probability distribution over our labels (i.e. Clinton, Trump).
Figure EC.1  Convolutional neural network architecture used to learn tweet opinions with respect to Hillary Clinton and Donald Trump.