Modeling the Impact of Social Media Bots for Information Dissemination *

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Abstract. This work describes the research involved in modeling the impact of the social media bot for information dissemination. It covers concepts of bot detection, bot behavior models, information spread techniques and agent based modeling, finally concluding with a discussion of the future of modeling information dissemination strategies by social media bots, and understanding the impact.

Keywords: modeling · bot · coordination · information dissemination

1 Introduction

Social media is an essential system component for communication. A November 2023 survey showed that at least 50% of Americans consume their news from social media [10]. However, how much information are deliberately planted? The intentional assembly of fake news, or disinformation, is one of the top global risks in 2024 defined by the World Economic Forum [1]. While some amount of disinformation stemmed from humans, bots are known to work in synchrony to amplify the narratives, increasing the spread of disinformation [19]. Bots leverage on automation, many of which can be performed with platform-provided APIs [23, 9], to increase the volume and reach of their messages, thereby disrupting international and national discourse [17, 16].

My research models the interactions of bots in social media as a socio-technical system. This system consists of three elements interacting with social media technology: users, content, and relationships. Users, represented by their virtual accounts, are actors driving the system. Content is information generated by users on the platform. Relationships are formed from user-user, user-content and content-content interactions. I perform empirical analysis on an unprecedented scale: terabytes of data, spanning 200million agents and 5billion posts across 5 platforms. I use machine learning (ML) methods that consider text and

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[1] https://www.weforum.org/press/2024/01/global-risks-report-2024-press-release/

network (narrative, community) features for bot detection and classification, social network analysis methods to analyze interaction patterns, and Agent Based Modeling for forecasting within the societal context.

2 Modeling The Bot

Modeling Users I begin my journey by modeling the bot agent. I extend literature algorithms to multiple platforms, and account for incomplete data collection. The bot model forms the basis of modeling its techniques and impact. Following which, I define and model subtypes of commonly occuring bots.

The General Bot is modeled extensively by work such as Botometer [29] and BotHunter [21]. These models only work for the Twitter platform, and do not deal with incomplete data. To that end, I designed BotBuster, a mixture-of-experts architecture that statistically aggregates fine-tuned deep-learning models, each responsible for producing a probability distribution of bot from a different data facet [14]. Using this model, I observed the dynamics of disinformation spread on Telegram during covid19. With a temporal message sharing graph, I find that while influential humans seed disinformation, bots actively engage in specific narratives, fueling desired conversations [19].

Beyond the `General Bot`, there are several subtypes of bots [7]. One type is the self-declared bot, an overt bot where the bot's meta-data (i.e., name, description) reveals their automated feature and intent. A news bot alerts its audience to fresh articles from their parent website, or aggregates articles of a certain genre. It is used within geopolitical and nationwide dialogue (e.g., US-China discourse, COVID updates) to provide news reports [16]. An announcer bot blasts out reports, e.g. when a website is down, and can be detected from having templated posts.

The `Bridging Bot` connects ideologies and messages between multiple communication clusters, and removal of the bot creates a more fragmented network topology. It is identified with a graph-theoretic method involving network community clustering, and identifying users that straddle multiple clusters. The bridging bot's effectiveness is observed in a US-China diplomacy conflict, connecting disinformation from both regions [16].

The `Amplifier Bot` network excessively shares tweets in a network topology that can be decomposed into a dense core with a loosely connected periphery. This structure floods social feeds, playing on illusory truth and availability biases, proliferating disinformation. Bots in the Taiwan-China discourse consistently amplify ideological narratives in this fashion [8].

The `Repeater Bot` amplifies posts not by the sharing behavior but by a copy-pasting behavior. Russian's IRA used this technique to spread disinformation [6], and bots in the Israel-Palestine discourse added 4-character hashtags to their copy-pasta to spread ideologies [5].

Finally, there is a class of bots that are half-bot, half-human. `Cyborgs` are typically used for strategic communication purposes by influential people and activists. Their bot-like automation persona provides relief to the operator from manual work, while their human-side provides an approachable persona to connect with their audience [22].

3 Modeling Bot Techniques

Bots frequently incorporate triggers of cognitive biases as dissemination techniques. Incorporates behavioral cues through psycholinguistic [3, 1] and ML [28, 25] methods, I find that bot disinformation tweets have a significant impact on engagement when these tactics are employed, while humans use minimal tactics. For example, triggering availability bias reduced retweets by 32%, while affect bias increased retweets by 5%.

Modeling Content Social media campaigns shape public opinion. Bots actively participate in information campaigns, drawing attention to their cause. Moving beyond generic text clustering and analysis, I used the BEND framework to describe narrative and network maneuvers within the online community context [2]. I map out the patterns of techniques used in information operations. Within the US-China discourse, bots opted for positive maneuvers like Boost and Excite, to portray a favorable image of their country within the tension [16]. Within the Indonesian discourse, bots also use a lot of negative maneuvers, especially the Distract maneuver to steer conversations away from the prevailing topic and towards desired narratives [5]. Lastly, within the Kashmir discourse, bots dominated images that have calls for action, inciting offline protests [11].

I also model co-occurring sets of content. Similar sets of content authored by bots can be connected through user-to-text and text-to-text network graphs, and reduced through matrix transformation to extract out the skeleton clusters [18]. This Coordinating Narratives Framework reveals distinct subgraphs of separate disinformation narratives. In a related fashion, images put forth by state-sponsored accounts can be related in terms of their objects and content, constructing a view of the group setup of information dissemination [20].

Modeling Relationships. Bots typically form relationships with each other through coordinated behavior, which is the heart of successful information campaigns [27]. Bots leverage on automation to increase the reach and effectiveness of information spread. Beyond analysis of coordination in singular dimensions, I developed the Combined Synchronized Index [15] to quantitatively rank the extent of each coordination modeled along each of the three dimensions: referral, semantic and social [12]. Across six events, we find that bots are more centrally placed than human users (i.e., higher total degree/ eigenvector centrality), signifying they have high connectivity and act as information brokers or transmitters. Of concern is that the bot-human relationship is extensive, showing the influence bots have over humans [15]. Persuasion metrics that factors in network influence (i.e., number of followers, network relationships) to model the potential Resonance of a post reveals that bot posts resonate 1.16x more, and misinformation posts spread by bots resonate up to 6.89x with the audience, as compared to human-authored posts.

4 Agent-Based Modeling

Lastly, I forecast bot impact with Agent-Based Modeling (ABM), with parameters informed by the ML models of the previous sections. Using an agent-based framework called Construct [24], I model the collective behavior of bots. An ABM represents individual users as agents that interact with each other and change their attributes accordingly. The ABM is a bottom-up view that provides a probabilistic model of the individual agents, and a general view of the aggregation of these interactions. I use this simulation method because the ABM unifies the space between agents with the continuum of temporal dynamics, allowing flexibility of simulation at a micro level.

Sufficient and simultaneous bot pressure can cause a user to change his stance. I modeled this phenomenon using a year's worth of COVID-19 vaccine discussion using a social influence model [13]. I first construct a ML model to discover how individualistic homogeneous traits and collectivist hetereogeneous features affect susceptibility to opinion changes, then model the effects of the stance flipping phenomenon over time across the network. Through empirical comparison, I find that bots have a higher opinion dynamic than humans. This is likely to increase homophily with their target audience. Simulations of this Social Influence Model with network perturbation strategies that deliberately change the leaning of a particular agent show that influential agents are the best confederates, and opinion converge through cascades that slowly tip local ego-networks [4]. Since bots generally occupy influential positions within the network, they are very likely to initiate waves of opinion changes.

I next simulate these socio-technical systems in a multi-agent network to examine the long term effects of coevolution of bot/human agent interactions. I first derive coefficients of bivariate interactions between properties of bot behavior and impact (ego-interactions, semantic, post engagement). Then, I model the posting behavior of different types of bots and simulate the effects towards the popularity of the posts and agents. In spreading ideologies and narratives, bots aim to make themselves and their posts viral. With simulation models, I can analyze how the behavioral techniques affect virality, which is important for policy makers to spot the emerging signs of the (mis/dis)information that is likely to go viral, and formulate counter measures or preventive strategies.

5 Conclusions

The social media bot is a species that coexist along with us humans on the social media space. Modeling the general bot behavior and its subtypes allow us to better spot this species through bot detection algorithms, and construct countermeasures against malicious bots. Modeling is especially useful for the social media domain, where one cannot always ethically perform experiments, for any information inject changes the system. Therefore, modeling information dissemination strategies provides us an empirical methodology to predict and analyze the impact of the agents, especially malicious bot users. These predictions can aid in analyst understanding of complex online social processes and policy formulations [26].

Future research brings me to identify atomic structures of bot disinformation strategies, recognize graph isomorphisms within real-world data, and studying network-level effects through time-series agent-based simulations.

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