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How social bots can influence public opinion more effectively: Right connection strategy

Yaozeng Zhang [1], Jing Ma [*], Fanshu Fang

College of Economics & Management, Nanjing University of Aeronautics & Astronautics, Nanjing 211106, China

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ABSTRACT

The advent of online social networks (OSNs) has facilitated the exchange of opinions and information, but the prevalence of social bots that manipulate opinions through human-like behavior demands attention. In response, we present a novel approach that utilizes a virtual corpus to analyze the impact of social bots on public opinion in OSNs. By developing behavior rules for both bots and human users, we aim to identify optimal strategies for social bots to increase their effectiveness. This work reveals that the success of social bots on OSNs depends on their connectivity strategy to corresponding OSN topologies. We found that simply increasing the number of social bots is not always effective, and dense communication links in target OSNs can dilute the impact of information posted by social bots. As a result, we explored other factors, such as the walking speed of bots in OSNs, to provide rules that inspire the development of smarter and more effective social bots. Our research sheds light on the intricate dynamics between social bots and human users in OSNs and provides valuable insights into social bots' behaviors, informing effective strategies for their design and deployment.

1. Introduction

Social media platforms such as Twitter, Facebook, and Instagram have revolutionized communication by enabling rapid content creation and exchange among thousands of users. However, with the increasing recognition of social media's influence, social bots - driven by algorithms that simulate human behavior – have been heavily invested in online social networks (OSNs) to pursue influence and profit [1]. For instance, bots participate in discussions on vaccination by reposting biased content with the aim of swaying public opinion [2]. Recent advancements in artificial intelligence technologies, such as ChatGPT, have demonstrated the remarkable flexibility of bots in their interactions with human users, making it challenging for humans to distinguish them from genuine users. Consequently, social bots have become a focal point of intense research interest due to their capacity to influence public opinion effectively [3,4]. Although the large-scale use of bots necessitates substantial computing resources [5], there is still much to explore in designing and using social bots at a macro level considering input-output rates.

Social bots are increasingly being used across various domains to achieve objectives such as political elections, market manipulation, content generation, user behavior cloning, and group opinion steering, among others [6]. For instance, during the 2016 US presidential election, bots infiltrated Twitter to attack candidates during midterm discussions, generating approximately 20% of the content on the platform [7]. Similarly, Ferrara's analysis of the Twitter dataset from the 2017 French presidential election revealed

* Corresponding author.
E-mail addresses: zhangyaozeng@foxmail.com (Y. Zhang), majing5525@126.com (J. Ma).
[1] https://github.com/yaozengzhang

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anomalous account usage patterns, suggesting a possible black market for reusable political disinformation bots [8]. Research also indicates that automated accounts generate 70–80 % of tweets mentioning e-cigarettes, influencing smokers' buying preferences based on the content of these tweets [9]. In addition, social bots are also used for financial information manipulation, with studies showing the effectiveness of coordinated social bots for stock market speculation [10]. Furthermore, social bot retweeting may have a limited and different association with stock prices, volatility, and liquidity, according to Fan et al. [11].

Current research on social bots has explored a wide range of topics, including bot detection systems, political manipulation, behavioral analysis, cybersecurity, and information diffusion [12]. Significant progress has been made in understanding the behavioral patterns of social bots. Automated social bots tend to behave more consistently and actively in OSNs, while human users have shorter sessions and exhibit more flexible behavior, often engaging in social interactions when exposed to posts and messages from other users [13]. Bots can play a role in opinion formation similar to that of stubborn individuals [14]. During the COVID-19 pandemic, Shi et al. found that social bots coexisted with human users on social networks and were more polarized in their expression, particularly on negative topics. However, their contagious emotions on most topics were weaker than those of humans, and their language tended to be stiff and uninspiring [15]. Grimme et al. analyzed the complexity of human-bot interaction, presented the challenges of detecting hybrid social bots [16], while Ross et al. have shown that even a small number of social bots can influence the climate of opinion, changing the majority opinion in a group [3]. Cheng et al. have studied the influence of social bots in OSNs with different topologies [17]. Social bots played a disproportionate role in the early spread of disinformation, leading many researchers to view them as a means of achieving the interests of certain groups or even as a threat [18]. At the same time, those with ulterior motives continue to upgrade the connectivity strategy of social bots and their anti-detection capabilities to avoid being caught, creating an arms race [19,20]. However, the more social bots behave like humans, the more likely users are to be fooled [21]. Some researchers are focusing on detecting the misuse of social bots, while others are exploring how they can be used beneficially, for example, to correct harmful tendencies held by groups on OSNs or to dispel rumors. Understanding the complex dynamics between social bots and human users in online social networks from a complexity science perspective could inspire researchers to develop strategies for detecting and mitigating the negative effects of social bots, as well as exploring their potential to have a positive impact.

Agent-based modeling is an efficacious framework that has proven invaluable in the simulation of intricate social phenomena and the comprehensive understanding of the nuanced, emergent patterns of inter-individual interactions. It has been widely used to study various social realities involving multiple agents. For example, Wei et al. utilized the gravitational theory to analyze the diffusion mechanism of consumer agents' acceptance of new products within groups [22]. Agent-based and population-based trust schemes have been applied in the field of collaborative artificial intelligence of things to evaluate communication models [23]. Shin et al. used an agent-based model to estimate exposure to non-exhaust emissions on roads in central Seoul [24]. Given the heterogeneity of individuals in social networks, much of the related research on opinion formation is also based on agent-based modeling. Recent studies on public opinion evolution based on agent-based models have gained prominence in the relevant field [25–28]. Domino et al. proposed an infection propagation model based on three channels of propagation to construct the wave-like dynamics of collective opinions and other phenomena [29]. Peng et al. established a corresponding bounded confidence model considering the relationship between opinion evolution and community structure [30]. Li et al. constructed a mathematical model of opinion dynamics under media influence and analyzed the impact of media on opinion formation formulated by public agents [31]. Similarity, Lee et al. consider the influence of the media on opinion formation and explain the formation of polarized opinions in this context [32]. Agent-based modeling have also been employed to study social bots in OSNs. Social bots, as emerging agents of public opinion participation, have received relatively little research attention at the macro level and from a complexity science perspective. Ross et al. and Cheng et al. have constructed models based on this approach to analyze the impact of the number of social bots on opinion formation, but lacked consideration for the social bot dynamically walk in the OSNs [3,17]. Furthermore, Given the large number of users acting as agents in social networks infiltrated by social bots, and the consideration of research cost and diversity, agent-based modeling remains the primary method in this work.

Table 1 presents an overview of recent research examining the impact of external factors on the dynamics of public opinion. While past studies have explored the role of external factors in shaping public opinion, they have mostly focused on discrete opinions and the quantity of bots. In contrast, our research focuses on the impact of social bots on continuous opinion dynamics, considering the unique characteristics of social bots and how they walking in OSNs, and their effects on the evolution of public opinion across different network topologies. Moreover, we also consider the words that characterize the tendencies expressed in the various types of comments made by human users during the dissemination of information as a basis for opinion formation.

Additionally, measuring individual opinions in models of collective behavior remains a challenging task, with limited effective

Table 1
Comparison of previous studies on the external factor of opinion dynamics.

References	Opinion value	External factor	Effectiveness of the guiding role of external factors	The impact of the number of external factors	External factors dynamically walking	Content of interaction model
[29]	State	No	No	No	No	Numerical
[30]	Continuous	No	No	No	No	Numerical
[31]	Continuous	Media	Yes	No	No	Numerical
[32]	Continuous	Media	Yes	Yes	No	Numerical
[3]	Discrete	Social bot	No	Yes	No	Numerical
[17]	Discrete	Social bot	No	Yes	No	Numerical
Ours	Continuous	Social bot	Yes	Yes	Yes	Feature word

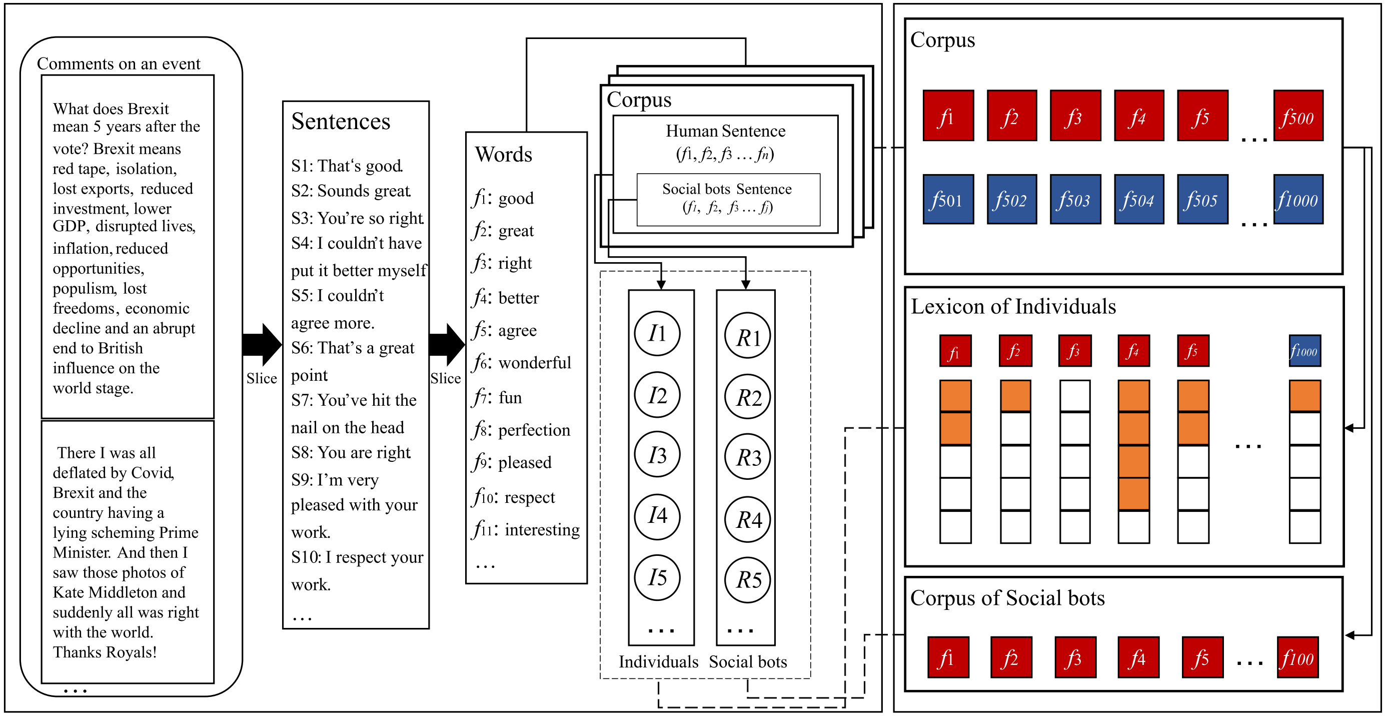

Fig. 1. Construction of the virtual corpus.

methods available. One common approach involves defining an individual's opinion as a value between 0 and 1, indicating their tendency towards being pro or anti [33,34]. However, this method is more abstract. Researchers have proposed several alternative methods for opinion evaluation or attitude analysis, such as corpus-based semantic analysis [35]. This method involves collecting words from groups on a particular topic, eliminating meaningless information, counting words that appear at a certain granularity, scoring the words, and assigning weights to them to calculate the attitude of groups [36]. For example, attitudes towards vaccines have been analyzed by counting the frequency of words appearing in comments on COVID-19 in newspapers or magazines in over 20 countries [37]. Similarly, Clayton et al. conducted a corpus-based thematic analysis to study the attitudes of related topic groups, such as political leanings [38]. It is worth noting that individuals have a limited amount of effective commentary content on events, beyond which information becomes redundant and meaningless [39]. Thus, using a virtual corpus can enable the calculation of the opinion of each individual in the group. These properties allow the introduction of the virtual corpus proposed in this work to model construction, which can better describe the existence of utterance exchange processes in the interaction of opinions between individuals.

Overall, social bots are emerging agents in shaping public opinion on modern social network platforms. Their performance and behavior are manipulated by algorithms, and they play different roles in various targeted OSNs. Designing them to be more effective by analyzing the role of social bots based on a multi-agent model can be cost-saving and more efficient, facilitating their development in beneficial ways. While some current research exists on the extent of influence of social bots, there is a lack of research on their effectiveness and depth in guiding public opinion [3,17]. Our aim is to construct behavioral patterns of social bots to explore their optimal application strategies and reveal corresponding mechanisms in several networks with different constructures. The main contents of this paper are: (a) constructing an opinion interaction mechanism based on a virtual corpus, (b) designing the behavioral patterns of social bots and human users to investigate how bots influence public opinions, and (c) exploring the impact of social bots on various social networks and summarizing the findings.

The rest of this paper is structured as follows: In Section 2, we explain the modeling framework and define the roles of the virtual corpus, human users, and social bots. Next, in Section 3, we use large numerical simulations to investigate the proposed model on networks of different types and various cases. Finally, in Section 4, we provide a discussion and conclusion of this study.

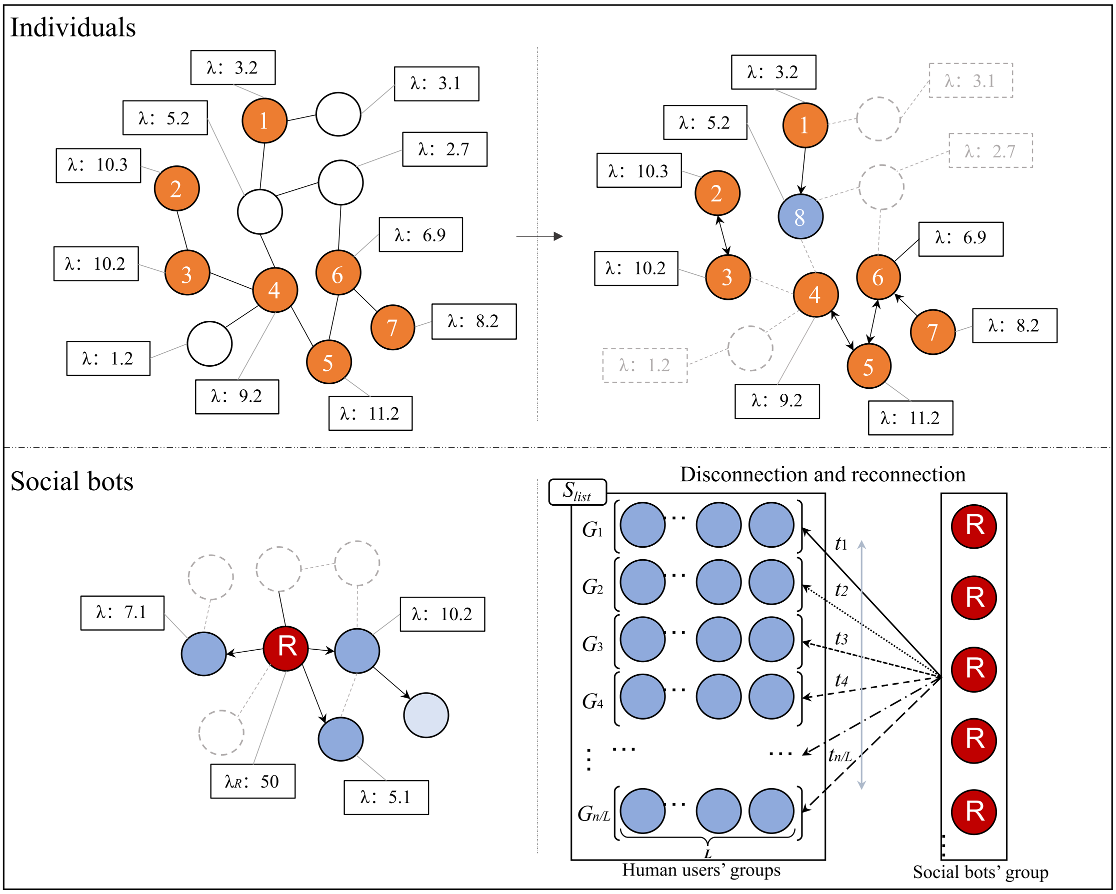

Fig. 2. The figure above represents the behaviors of users and social bots. The top half of the figure shows the tendency of agents to select more active neighbors to establish communication links when activated. The bottom half of the figure indicates that social bots are one-way communicators in the OSNs, disseminating information outwards to different human users' groups as they walk in the target OSNs driven by the algorithm.

2. Model formation

2.1. Model framework

Three main elements of the model constructed in this work are described here.

2.1.1. Virtual corpus

It is considered that the words expressing attitudes of the comments from groups in the OSNs, constituted by the target topic, are known and numbered by one-hot encoding method. Users' comments on an event can be collected and organized into a corpus. As shown in Fig. 1, each comment on an event can be sliced into sentences and words. The words express the attitude defined as feature words f_i ($i = 1, 2, 3, \ldots, 1000$) in this work and formed the virtual corpus. The virtual corpus for the given topic is defined as $C_{all} = \{f_1, f_2, ., f_{1000}\}$, which $C_{all\text{-}p} = \{f_1, f_2, \ldots, f_{500}\}$ as positive feature words and $C_{all\text{-}n} = \{f_{501}, f_{502}, \ldots, f_{1000}\}$ as negative one, $C_{all\text{-}p} \cup C_{all\text{-}n} = C_{all}$.

The lexicon is a collection of feature words found in recently posted comments by human users on a particular topic. Since many users may comment on a particular topic, the frequency of certain feature words can be high. To ensure the validity of the comment content, we set an upper limit on the number of feature words each user can have in their lexicon from a linguistic research perspective [39]. In this study, we set the maximum number of feature words per user to 500, and each user's initial lexicon contains 100 feature words. If an individual receives the same feature word multiple times, its impact may be reinforced. However, if the individual's lexicon exceeds the limit, the earliest words in their lexicon are discarded to reflect the idea that old opinions become outdated over time.

According to research, social bots account for less than 0.3% of the total corpus user population [40]. It is evident that the linguistic complexity of human commentary on events exceeds that of bots [41,42]. Social bots do not engage with the message but rather export it outwardly, thus not forming a lexicon, but only their specific corpus. Therefore, we assume that each feature word of social bots will appear only once in the single message they send.

This virtual corpus answers the question of what content of the message is passed between users and social bots during opinion evolution, particularizing the numerical values of the relevant kinetic model. To the best of our knowledge, we are the first to apply this method to opinion evolution.

2.1.2. Individuals

Individuals in OSNs, also called human users/agents in this work, make recent comments expressing their opinions. The less the agent deviates from their friends' opinions, the more likely they are to be activated to participate in the discussion or remain silent. If a human agent chooses to communicate, they are most likely to discuss with a friend whose activity level is the highest. As shown in Fig. 2, the opinion interaction between agents may be one-way or two-way. In summary, the behavioral flow of an individual is as follows: (a). Observe the climate of public opinion. (b) Judge willingness to send a message based on self-confidence. (c) Choose a friend user with a high activity level as the target of their communication. (d) Send a certain amount of information (feature words), based on the individual's activity level. (e) Increase individual activity level [13]. Sometimes, in the process (b), the individual chooses to be silent, which leads to a decrease in its activity level, and subsequent behavior does not occur. Whether an individual chooses to remain silent or not, completing a round of behavior leads back to behavior (a) and initiates it once again. The behavioral process described above is a closed loop.

2.1.3. Social bots

The social behavior of bots (also called bot agents) in OSNs includes (1) posting status updates, (2) posting comments, (3) adding friends, (4) adding likes, and (5) auto-adding [43]. However, only posting comments and establishing communication links affect the diffusion of information. Bots decide whether to intervene in the currently connected group by detecting the difference between the opinion of the target group and the preset goal (i.e., the difference between the opinion expressed by the human users and the target opinion). To maximize the efficiency of information diffusion, bots sometimes seek out users with great influence to send messages depend on the algorithms. Social bots send more messages in OSNs than human users, and therefore, tend to attract the attention of users.

As shown in Fig. 2, human users are likely to retweet or distribute the content of the social bot's comments, which also contain feature words. It is worth noting that social bots seeking new human users to send messages do not delete the original target users lists and close the communication channels. Social bots require server hardware facilities to function, and their batch processing power is related to the performance of their algorithms and the level of hardware. Therefore, it is difficult for social bots to send messages to all human users in target OSNs simultaneously. Sending messages to all users at the same time not only changes the nature of social bots as external factors, but this behavior pattern is also easily detected by users, reducing the credibility of the messages that bots send, which we try to avoid. If the social bots notice that the target groups' opinion is within the expected range $\boldsymbol{\theta}$ (called social bot tolerance), then they consider the intervention of the group constructed by human agents to have achieved the goal, and the bots seek new human users to send messages to, and so on. Moreover, if these social bots are programmed to move at a faster speed (bigger $\boldsymbol{\theta}$), they may be able to reach more users within a shorter time frame.

The previous studies often selected random nodes in the network as special actors, such as social bots or media [3,17]. However, it is important to note that social bots are not always present in the target OSNs. They are typically used for a specific topic under which a social network is formed, and then people embed social bots in the target networks to post information. As a result, social bots are usually embedded posteriorly in the target OSNs, and it makes more sense for them to access the social network from the outside. This aspect will also be reflected in our work.

A more detailed explanation: For a given target OSN, there are n human users $i\in$OSN ($i = 1, 2, 3,., n$). Based on the social bots' ability to send a message at once (i.e., the number of target users L for a single message, which is constant due to computer power stability), there is a list $S_{list} = \{G_1, G_2, G_3,., G_{n/L}\}$, and agent $i\in Gc$ ($c = 1, 2, 3, \ldots, n/L$), where the number of agents i is L. The group of users to which the social bots send a single message is taken from S_{list}. If all G_c in the list have been used once by social bots, they are reused for the original S_{list}. The ordering of the users' IDs within G_c and S_{list} depends on the design of the social bot behaviors. By default, in the S_{list} used in this paper, the sorting method of users is based on their degree in networks in descending order. As shown in Fig. 2, there is a dynamic change in the communication links of social bots to the users' groups. If the social bots detect that the difference between the opinions of the connected users' group and the preset opinion value falls within the predetermined range $\boldsymbol{\theta}$, they will temporarily pause their operations and allocate their limited computational resources to transmit messages to a new group Gc in the S_{list}. This process of switching between human users' groups is referred to as social bots "walking" within the target OSN.

2.2. Individual behavior pattern

2.2.1. Evaluation method for individual opinion

In the context of OSNs, user comments on events provide valuable insights into their attitudes and opinions. For instance, a simple sentence such as "Coffee is good, but it keeps you up at night" can be analyzed to extract two feature words: "good" and "but." The weight of these words is then calculated to arrive at an opinion value of 0.5 for the user. However, given the complex nature of human attitudes, opinions expressed in OSNs are seldom as straightforward as this example. Hence, the constructed opinion model takes into account a user's recent comment history, which helps to capture a broader range of attitudes and opinions. The model maps the number of feature words to the [0,1] interval, which reflects the user's agreement or opposition tendencies towards a particular topic. Moreover, the opinions expressed by users' social circles can also influence their opinions. If a majority of the feature words in their comments are supportive, the user's opinion is likely to lean towards 1.

Let the opinion value of agent i at time t be denoted as $O_i(t)$. Let the set of P^n positive feature words held by agent i at time t be denoted as P_i (P^n, t), and the set of N^n negative feature words be denoted as N_i (N^n, t). Then the measure of opinion support is shown in below:

$$O_i(t) = \frac{card(P_i(P^n, t))}{card(P_i(P^n, t) \cup N_i(N^n, t))} \tag{1}$$

Although there are differences in the intensity of emotions expressed by different words, we ignore them as they do not affect the emergence of overall patterns in the evolutionary process.

As this work is concerned with guiding the group opinion towards a target value of 1, the formula is biased towards calculating positive comments, although it is equally possible to calculate the negative opinions held by agents. This method also applies to social bots. However, in this work, social bots are programmed to post messages containing only positive feature words, so all social bots have an opinion value of 1 and are constant.

2.2.2. Measurement of individual expressions of willingness

We assume that individuals' opinion values are continuously distributed in the range [0,1], indicating the degree of propensity, rather than simply [+ , -] expressing approval or disapproval [44,45]. Individuals in social networks decide whether to participate in discussions based on the difference between their own opinions and those of their friends, which can be determined by observing the comments recently posted on OSNs. In this work, individuals attempt to achieve consensus in their opinions, and the greater the divergence of opinions, the more likely interaction occurs [46]. At the same time, the topology composed of user nodes and their neighbors, although appearing random at the microscopic level, has certain patterns in the macroscopic perspective of the group, such as the small-world property and the scale-free property, which will be described later. We define all neighbors j of agent i as $j\in\delta_i$, where δ_i is the set of neighbors of agent i. i or j can also be called the user ID in OSNs, and the number of neighbors is N (δ_i, t) at time t. Therefore, considering that each user has their particular opinion value, the opinion climate $\pi_i(t)\in[0,1]$ computation metric is given by Eq.(2):

$$\pi_i(t) = \left| \frac{\sum_{j\in\delta i}(O_i(t) - O_j(t))}{N(\delta_i, t)} \right| \tag{2}$$

In Eq. (2), large differences in opinions can mutually cancel. To determine the net effect of significant differences in opinions that cancel each other out, calculate the sum of the differences and take the absolute value of the result. This method accurately reflects the cancellation of the differences, whereas taking the sum of absolute values does not.

According to research by Sohn [47], the willingness of expression $I_i(t)$ is defined as a sigmoid function about $\pi_i(t)$. To delineate expressing willingness $I_i(t)$ to include opinion climate in opinion participation [17]. The original related model was rescaled and is demonstrated in Eq.(3):

$$I_i(t) = l * (1 + e^{-k\pi_i(t)})^{-1} - \frac{l}{2} \tag{3}$$

The equation reflects the probability of agent i expressing comments at moment t. This is consistent with prior research in the field

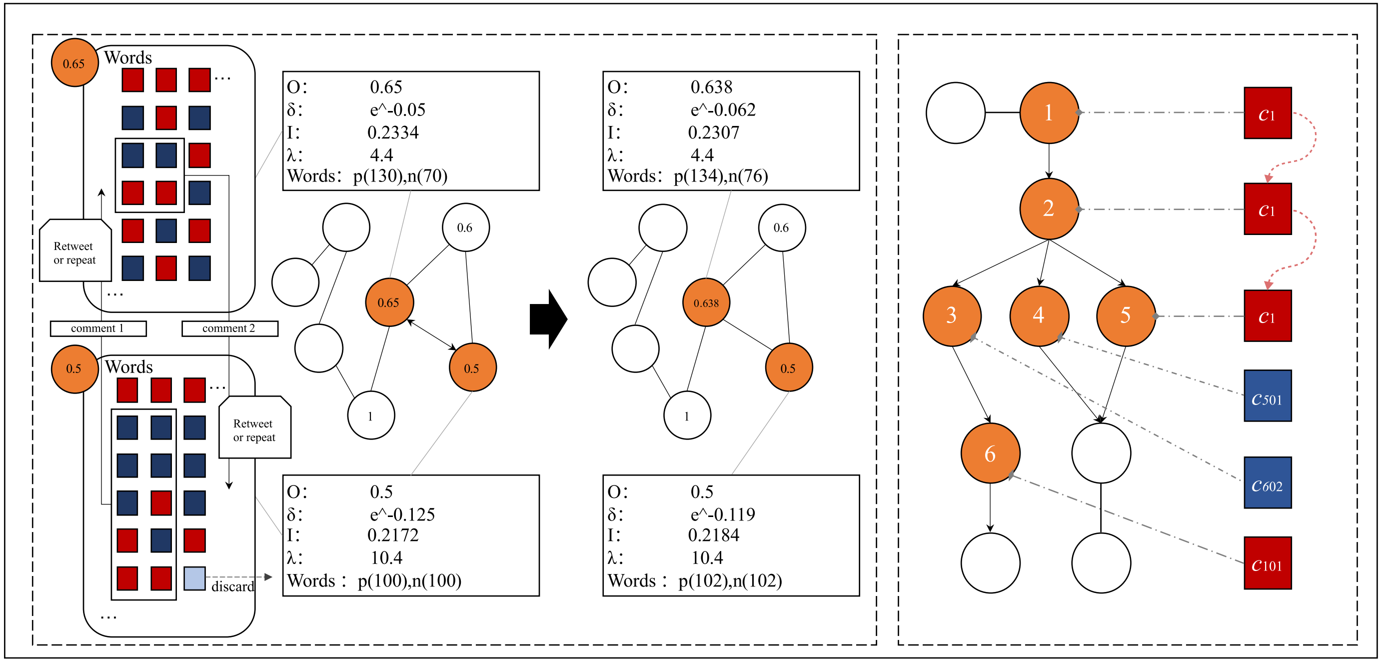

Fig. 3. The left-hand side of the figure shows the communication model between two agents who exchange messages containing feature words. The number of feature words in each message is controlled by the activity λ. The agents update their lexicon and opinion values based on the received messages, which they either forward or repeat. However, it is observed that the lexicon of an agent with an opinion of 0.5 has a feature word that has exceeded the storage limit and has been squeezed out by new additions. This is indicated by a light blue rectangle in the figure. On the right-hand side, it is shown that a feature word C_1 spreads through the network under this mechanism, but it doesn't spread all the way because of the phenomenon of information loss in chain propagation.

of social interaction that has reported a diminishing marginal impact of the input variable [48,49]. Here, l= 2 and k = 2 are suitable values derived from pre-simulation. We assume that individuals will not remain silent, and agent i is more likely to participate in the discussion and absorb the opinions of their friends as their opinions become more different. This process is dynamic. We do not specify the number of individuals involved in the dissemination of information at each time, but rather the number of individuals in the OSNs willing to publish information is dynamically changed after the above calculation.

2.2.3. Definition of individual activeness

Activeness reflects the degree to which individuals are active on OSNs and indicates their likelihood of participating in discussions and the number of messages they send. In real social networks, people tend to interact more with those who are more active in seeking information. However, there is a forgetting effect on human users. For instance, a user who was highly active in the past may have become less active because they have not engaged in discussions for a long time, which reduces their influence in the public [50]. In contrast, the activity of social bots remains constant, providing a consistent presence in OSNs.

The Hawkes process is able to capture the self-exciting nature of social interactions, in which the occurrence of one event can trigger a cascade of additional events [51,52]. In the context of this model, the Hawkes process is used to describe the way in which past communication events increase the probability of future events occurring during the activation period. Specifically, for the sequence of events $t_i \in \{t_1, t_2, t_3, \ldots\}$, the Hawkes process takes the form of Eq.(4):

$$\lambda_k(t) = v + \sum_{t_i < t} h(t - t_i) \tag{4}$$

$\lambda_k(t)$ denotes the magnitude of the activity of individual k at moment t. The activity value, $\lambda_k(t)$, indicates the probability that the individual is currently selected for communication by their neighbors, with larger values being more likely to be sent messages by friends. This value is also used as a basis for the amount of information sent by individual k. In this paper, v is the initial base strength, i.e., the initial activity of the agent. The kernel function $h = \alpha e^{-\beta t}$, where $\alpha = 1$, represents the influence of a new event on the original event. That is, the individual's activity is increased by 1 for each communication occurrence, and $\beta = 1$ controls the decay rate as the forgetting influence parameter. The formula describes how an individual's future activity grows with the occurrence of a communication event, but its activity decays over time during the interval between communication events. When individuals tend to choose friends to communicate with, the probability of individual i establishing a communication link with neighbor k is:

$$\eta_{ik} = \frac{\lambda_{k \in \delta_i}(t)}{\sum\limits_{j \in \delta_i} \lambda_j(t)} \tag{5}$$

Considering that users in OSNs cannot distinguish between their neighbors being human users or social bots, and that social bots are more active, so they are more likely to receive messages from bots.

2.2.4. The rule of interaction

Agents, whether human users or social bots, are the actors in OSNs. There are two forms of information posting of them in real OSNs: one-to-many (posts) or one-to-one (private chats). This increases the complexity of the model and reduces its applicability, so in this work, the two types of information posting are merged. We assume that users under a certain topic have commented and are discussing it below the comments, with social bots participating in the interactions to influence the group's opinion.

As shown in Fig. 3, if a human user chooses to participate in a discussion, they are most likely to communicate with the neighbor whose activity level is highest. In this process, the user who gets the message is the target user and the user who posts the information is the source user. The number of feature words in the message of communication depends on the value of the source user's activity value $\lambda_k(t)$, and rounded down. The higher the level of the source user's activity, the more messages are made, and the more feature words

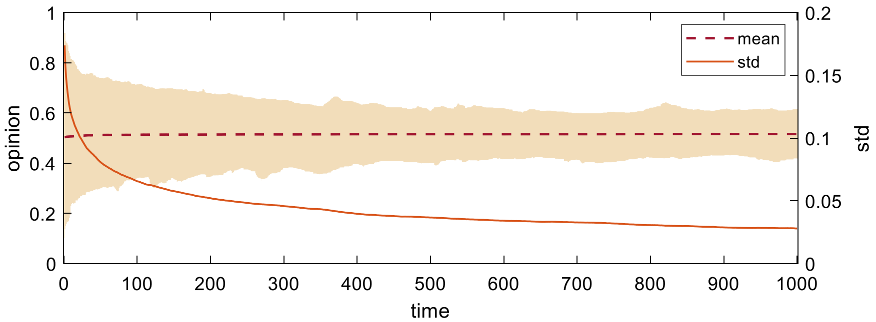

Fig. 4. Based on the corpus and the above-mentioned interaction method, the evolution process of the group opinions without the influence of social bots has shown in this figure. This process is implemented in a scale-free network using the BA model with 1000 nodes, each user starting with an activity level of 1. The filled sections of the figure represent the range of differences in opinions within the group at each moment in time. Mean and std of group opinion also have shown in the figure. It can be observed that there is always a change in individual opinions within the group, although the group's overall opinion tends to remain stable at 0.5.

are acquired by the target user. After receiving the message containing the feature words, the target user organizes them for forwarding or repeating and saves them in its lexicon. When the individual is activated, the feature words sent are selected from the lexicon and used to compose the message. During agent-to-agent interactions, feature words expressing tendencies are spread. Considering that individuals' opinions are dynamic, we only count feature words in comments recently posted by individuals to measure its opinion.

In addition, the propagation of feature words between agents in the OSN simulates the decay of the information content in the propagation chain, because as the chain gets longer, the more likely it is that some feature words will no longer exist in the propagation process. We refer to this process as the phenomenon of information loss in chain propagation.

The generation, reception, and amount of useful information contained in messages spread between individuals are all complex processes. To simplify the model and make it more practical, we ignore the complex processes described above. Therefore, we assume that the content of the comments generated according to the lexicon that individuals pass to their friends is entirely received. This simplification does not affect the macro trends in opinion evolution. We have also documented the evolution of opinions under this model to demonstrate its similarity to classical opinion evolution models, as shown in Fig. 4. This method enhances the interpretability of the opinion evolution model.

2.3. Social bot behavior pattern

Social bots are driven by algorithms and programs. Unlike humans, they do not consider the pressures brought about by the opinion climate and mechanically follow pre-determined goals in their activities in OSNs. When social bots are arranged to enter the target OSNs, they actively seek out agents to establish communication links ($\boldsymbol{L}$ bars). A study found that measuring the length and number of high-frequency tweet sequences was an effective way to detect social bots, indicating that social bots interact more frequently in OSNs than human users [53]. To reduce the risk of detection, social bots should avoid simply repeating messages. Instead, they can choose to remain silent or become active based on the degree of difference between the opinions of connected agents and a predefined opinion goal.

Let $O_R = 1$ be the predetermined value of the social bots' opinion. Let $j \in G_c \subseteq S_{list}$ denote the users who establish communication links for these bots. Similar to Eq.(2), the difference between the opinion of human user j and the preset opinion O_R of the social bots is detected using Eq.(6):

$$\omega_R(t) = \left| \frac{\sum_{j \in G_c} (O_R - O_j(t))}{L} \right| \tag{6}$$

Inputting the target-actual opinions variance $\omega_R(t)$ into the activation function (a common sigmoid function), and whether a social bot will activate to intervene in group G_c opinion depends on the Eq.(7):

$$S(\omega_R(t)) = \frac{1}{1 + e^{-\omega_R(t)}} \tag{7}$$

Under this activation function, the larger the value of $\omega_R(t)$, the more likely the bot is to send the message. The above process has been illustrated in Fig. 2. Due to the complexity of the role of social bots in influencing human users at the micro level, we have simplified the process to increase the model's universality.

3. Simulation and discussion

In this section, we discuss the role played by the social bots constructed in this paper in networks with different types. We also examine how various attributes of the bots affect opinion shaping in OSNs. Due to the difficulty of obtaining a significant amount of real-world data, we primarily rely on large-scale simulations as the main research method. The focus of this study is to investigate the average opinion value of the target OSN at the end of the given simulation time (500 time steps) affected by social bots. The effectiveness of social bots and their corresponding strategies is directly proportional to the average opinion value, where a higher value (with a maximum of 1) indicates a more effective strategy. To reduce the impact of noise on our findings, each outcome is an average of ten simulation runs of the same experiment.

3.1. Network construction

Two types of networks were constructed as carrier networks to simulate target OSNs. Each node represents a human user, and the connected edges represent the communication links established between users. To explore the differences in the role of social bots in networks with different structures, several carrier networks were constructed as part of the subsequent simulation. As the speed of

Table 2
Carrier networks parameters of simulations.

Network topology	m_0	m	K	Pr	N
scale-free	6	[1, 6]	-	-	1000
small-world	-	-	[4, 10]	[0, 1]	1000

information dissemination far exceeds changes in network structure, we assume that the network topology of target OSN remains fixed during opinion formation. However, the connected edges formed by the social bots are dynamic due to their frequent actions. The structure of most real social networks can be described by BA scale-free networks and WS small-world networks. Table 2 shows the carrier network parameters of simulations in this paper. Different communication edge densities represent social networks that have existed for different lengths of time, with fewer edges indicating a younger social network.

BA scale-free networks [54]. A high degree of self-organization exists in many networks, characterized by the large-scale nature of complex networks resulting in a scale-free state, including many social networks. This network model starts with a connected network with $\boldsymbol{m_0}$ nodes, where new node with $\boldsymbol{m}$ ($\boldsymbol{m} \leq \boldsymbol{m_0}$) edges is connected to the existing nodes according to the rule of preferential attachment. The result is a scale-free network with $\boldsymbol{N}$ nodes. Due to preferential attachment, a node that gains more links than another will increase its connectivity at a higher rate, which reflects the uneven distribution of connections among individuals in OSNs.

WS small-world networks [55]. There are also many social network topologies that lie somewhere between completely regular and completely random. To construct a WS small-world network, a toroidal nearest-neighbor coupling network containing $\boldsymbol{N}$ nodes is first created, where each node is connected to $\boldsymbol{K}/2$ neighbors. Then, every original edge in the network is randomly reconnected with a probability of $\boldsymbol{P_r}$. Since there are $\boldsymbol{NK}/2$ edges in the entire graph, the rewiring process stops after $\boldsymbol{K}/2$ turns.

Additionally, it has been shown that social bots form the sparsest network structure among themselves when compared to the normal user population [56]. Recent research has estimated the bot population on Twitter to be between 8 % and 18 % [57]. Therefore, by means of several pre-simulations, we adjusted the number of social bots as a percentage of the number of social network users to

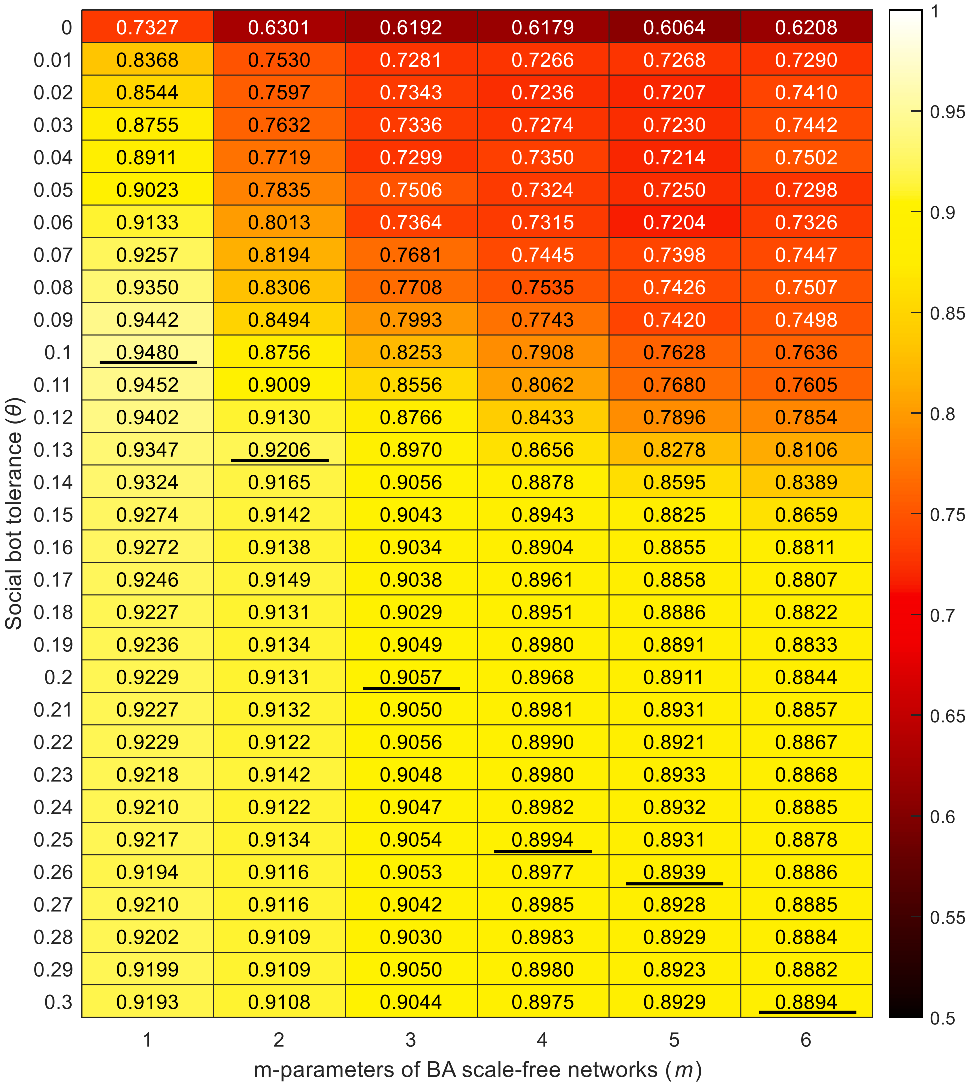

Fig. 5. Results of simulations of social bots in different BA networks with different tolerances. Here, R=L= 50, λ_R= 100. Each grid represents a result of corresponding situation. The final average opinion value of the group influenced by social bots is also marked. The optimal results achieved by social bots at different walking speeds in various networks are also indicated with horizontal lines.

between 1 % and 10 %. This is both realistic and facilitates following up.

3.2. Result of simulations

In this simulation, we examine the effect of social bot tolerance $\boldsymbol{\theta}$ on the evolution of group opinions. We set up six scale-free BA networks with varying densities of connected edges. The number of social bots $\boldsymbol{R}$ and the number of communication links $\boldsymbol{L}$ established by bots with the carrier network at each moment are set to 50. To ensure effective guidance and clear results, we set the social bot activity $\lambda_{\boldsymbol{R}}$ to 100, which means that bots send 100 feature words indicating a positive attitude in each communication with the individuals they interact with.

Fig. 5 shows that as the social bot tolerance $\boldsymbol{\theta}$ increases, the guiding effect on target OSN becomes progressively more obvious. However, increasing $\boldsymbol{\theta}$ beyond a certain value does not lead to further improvements. This indicates that there is an upper limit of $\boldsymbol{\theta}$ in the BA network such that social bot tolerance beyond this value leads to similar walking speeds resulting in equal influence. Overall, social bots that walk faster through the target OSN have a wider reach, and their messages are received by more users. However, the optimal walking speed of social bots varies depending on the OSN, and the bots that appeared to have the best results did not necessarily have the greatest walking speed. Additionally, the optimal walking speed of the bots increases in networks with a higher density of connected edges.

In Fig. 6, it can be seen that as the density of communication links in the BA scale-free network increases (m increases from 1 to 6), the influence of social bots becomes progressively weaker. We believe that increasing the number of communication links shortens the length of links in the process of information dissemination. However, it also means that individuals have more access to messages, which weakens the role of messages sent by social bots. There are differences in the performance that social bots can exhibit in social networks with different link densities. In social networks with dense communication connections, there is more scope for variation in the role of social bots. This is illustrated by the variation in std in Fig. 6. It emphasizes that the earlier the impact on the target OSN the better, avoiding the formation of more communication links reducing the usefulness of social bots.

While the above exploration initially suggests that social bots are more effective in guiding public opinion as their tolerance level increases, this conclusion is subject to debate.

After conducting multiple simulations, we discovered several sets of unusual results, which we present in Fig. 7. The remaining simulation results are variations of these special cases, and we have chosen not to present them to avoid redundancy.

Increasing the parameters $\boldsymbol{R}$, $\boldsymbol{L}$, and $\lambda_{\boldsymbol{R}}$ of social bots is more effective in influencing public opinion. However, in exceptional cases such as $\boldsymbol{m}=1$ in Fig. 7**(a)** above, the impact of social bots on the OSN weakens as $\boldsymbol{\theta}$ increases. In a scale-free network, users with higher degrees are connected to most individuals in the group. When $\boldsymbol{\theta}=0$, it implies that social bots are most effective in guiding public opinion when they send messages only to individuals with the highest degrees and do not walk in the social network. But when $\boldsymbol{R}$, $\boldsymbol{L}$, $\lambda_{\boldsymbol{R}}$ and $\boldsymbol{m}$ are set to larger values, this trend is reversed. In other cases, there is an optimal $\boldsymbol{\theta}$ (which may be larger or smaller) that determines the most effective walking speed for a social bot to influence group opinion. In summary, given that the behavior mechanism of social bots can directly influence individuals as they navigate through the target OSN, the optimal value of $\boldsymbol{\theta}$ should take into account both the impact on influential users and general users.

In summary, when the capability of social bots is weak (both $\boldsymbol{R}$, $\boldsymbol{L}$ and $\lambda_{\boldsymbol{R}}$ is small), it is more effective to maintain a stable message output and concentrate on sending messages to users with higher influence, especially in social networks where communication connections are sparse. The effect of social bots on OSNs is also more pronounced when their performance becomes more superior (greater $\boldsymbol{L}$ and $\lambda_{\boldsymbol{R}}$, compare Fig. 7(a) and (c), (b) and (d)). This tells us that the earlier social networks are formed, the lower the performance requirements and costs of the social bots needed to achieve a specific purpose.

In addition, we have found that increasing the number of social bots is not always effective (compare Fig. 7(a) and (b), (c) and (d)). To our surprise, when social bots are slower to walk (smaller $\boldsymbol{\theta}$), more social bots cause a worse outcome instead. One point to note in the mechanism of our work constructed is the concept of opinion climate (Eq. (2)). It is the excess of social bots that makes individuals feel a worse opinion climate and thus inhibits their willingness to engage in discussion and keeping silence, which also leads to a decrease in the effectiveness of social bots in influencing group opinion. This has led to increased antagonism towards social bots among users in online social networks: when there are multiple social bots influencing opinion from different perspectives, which can lead to controversy and disagreement among users. This can lead to users no longer trusting the words and advice of these bots, reducing the bots' influence on public opinion. However, the impact of the quantity of social bots becomes apparent when the walking

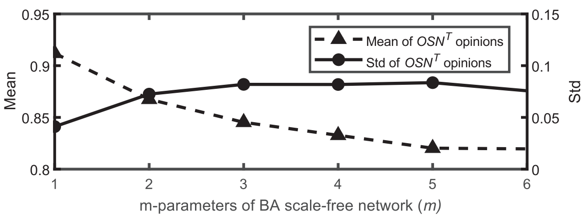

Fig. 6. Mean and std of results of target OSN (OSN^T) in different BA networks with different social bot tolerances. It is clear that as the density of communicating edges increases, the less effective the social bot becomes. The increase in std reflects the fact that social bots have more room to improve their effectiveness in social networks with denser communication links.

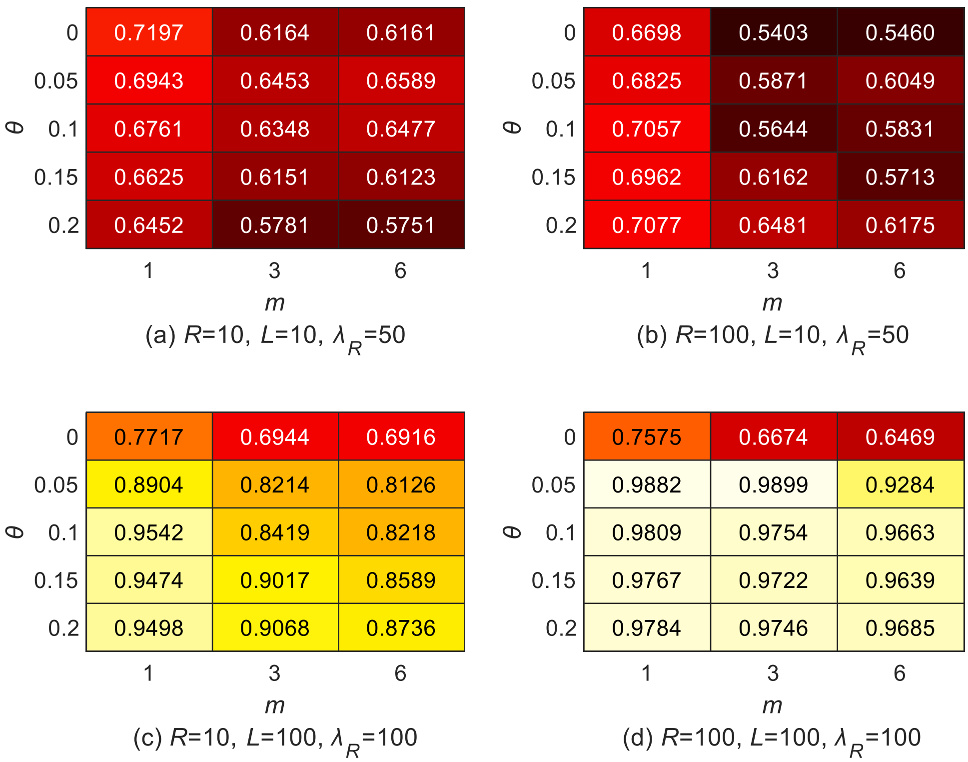

Fig. 7. The BA scale-free network m= 1,3,6 was chosen and the size of R, L, λ_R was varied, with each grid representing the results of the social bots' influence on the given situation. Each plot represents the result of a set of data. For instance, in Fig. 8(a), the grid with $m = 1$ and $\theta = 0$ represents the results of the influence of a social bot group with $R = 10$, $L = 10$, $\lambda_R = 50$, and $\theta = 0$ in a BA scale-free network with $m = 1$.

speed of these bots increases. By reducing the duration of the influence on specific users' groups, the increase in the number of social bots can be effectively leveraged to enhance their impact.

This insight suggests that in designing and deploying social bots, it is important to control their quantity and focus on personalization and alignment with user perspectives to increase their influence on public opinion. The behavior of the bots should respect user opinions, rather than attempting to forcibly impose a certain stance or opinion (merely by increasing their quantity and the duration of their influence on users). This approach can lead to more effective and trustworthy social bots in online social networks.

The small-world character of social networks is also present in abundance. Similarly, to examine the role of the walking speed of social bots in small-world networks in guiding public opinion, as shown in Fig. 8, the following results were obtained from simulations.

In Fig. 8, as the density of network connections, represented by $\boldsymbol{K}$, increases, the influence of social bots on public opinion decreases (also shown in Fig. 9 (a)). Similarly, in the WS network, as the density of network connections increases, the space in which social bots can exert their influence decreases (Fig. 9 (b)). This finding reinforces the notion that social bots are less effective when they intervene in the target OSN too late. The optimal performance of social bots is achieved when $\boldsymbol{P_r}$ equals 0, indicating that they are in a toroidal nearest-neighbor coupling network. Note that the degree priority is maintained in groups G_c and list S_{list}. However, when the users' degrees are uniform in the social network at $\boldsymbol{P_r}$= 0, the connection strategy becomes random selection, this makes the effectiveness of social bots better. We will discuss this phenomenon in detail later. Increasing $\boldsymbol{P_r}$ does not significantly change the impact of social bots. Instead, it results in the edges in the WS network becoming more randomized, which increases the diversity of information sources available to users and weakens the ability of social bots to shape public opinion. Additionally, the faster the walking speed of social bots, the greater their impact on public opinion.

We still further explored the effects of social bots on public opinion by varying $\boldsymbol{\theta}$, $\boldsymbol{R}$, $\boldsymbol{L}$, and $\boldsymbol{\lambda_R}$, as shown in Fig. 10 and Fig. 11. Increasing $\boldsymbol{L}$ and $\boldsymbol{\lambda_R}$ is more effective in promoting the guidance of public opinion. When $\boldsymbol{\theta} = 0$ and $\boldsymbol{P_r} = 0$, it is most difficult to advance opinion guidance to the target OSN. This is because social bots only focus on a few users in small-world networks, and the shortest path in the toroidal nearest-neighbor coupling network is longer. The ring structure of the network leads to an averaging of node degrees, making it difficult for individuals to have significant influence, which hinders social bots from spreading information.

In Fig. 10 **(a)**, we observe that when $\boldsymbol{P_r} = 0$, social bots with lower performance achieve better results as their tolerance increases. However, this trend reverses with increasing $\boldsymbol{P_r}$, which suggests that the rewiring of connections in WS small-world networks gives some users greater influence, allowing them to disseminate information to more users. Consequently, social bots that focus on influencing these influential users achieve better results. On the other hand, social bots with lower performance can have a negative impact when they move faster in WS small-world networks with some randomness in their connections, as observed previously in scale-free networks. Neglecting influential users in networks with specific structures can lead to worse results. Additionally, an

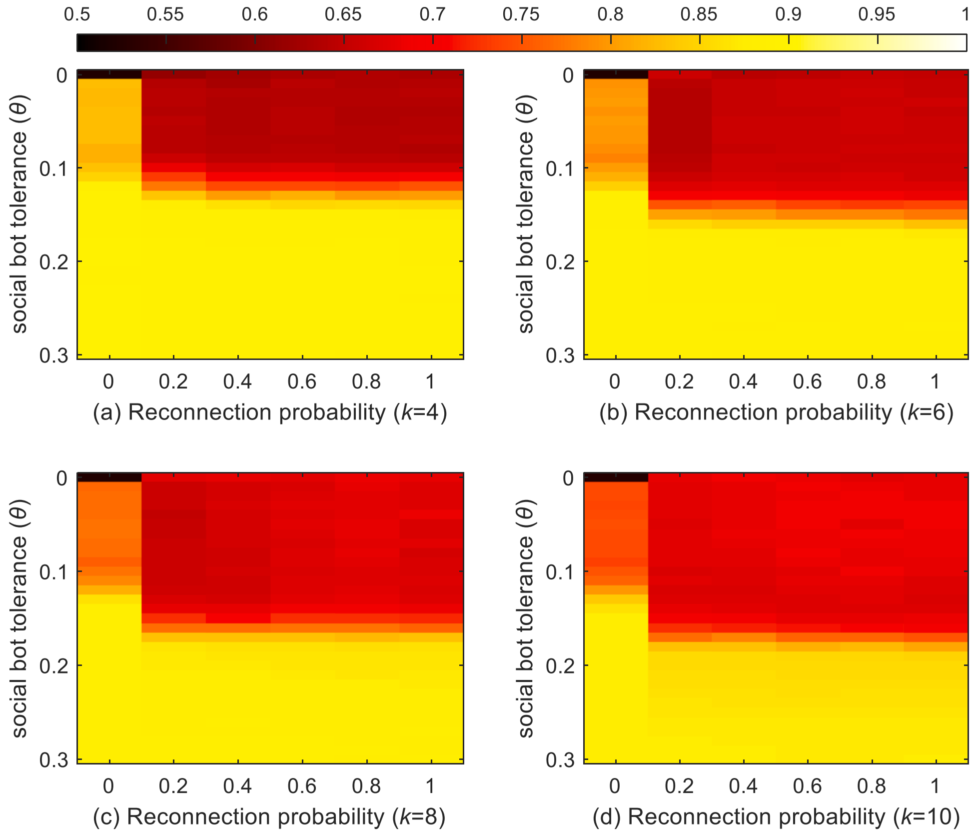

Fig. 8. Results of simulations of social bots in different WS small-world networks with different tolerances. Here, R=L= 50, λ_R= 100. Each plot represents the result of a different WS small world network (with different values of k). Each grid represents the result of corresponding situation, the values represented by each color are indicated in the color bar in the figure.

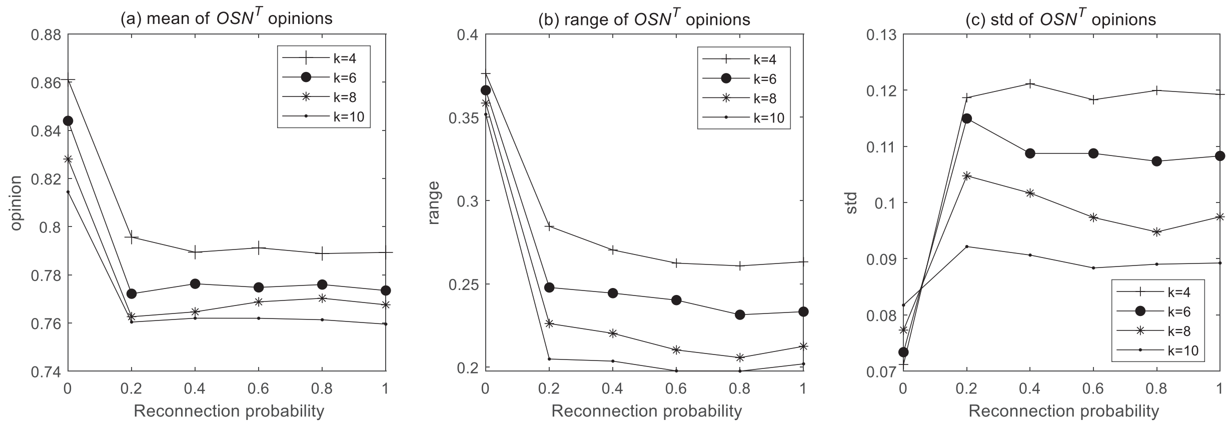

Fig. 9. Mean, range, and std of the impact of social bots on the group in different WS networks with different social bot tolerance levels.

increase in the number of social bots can also decrease users' willingness to exchange information in small-world networks (compare Fig. 10**(a)** and **(b)**, Fig. 10**(c)** and **(d)**, when $\boldsymbol{\theta}$= 0). However, as the tolerance of social bots increases, their numerical advantage and rapid walking in social networks allow them to exert more influence. Certainly, when the performance and quantity of social bots are both strong, it still depends on the optimal tolerance to achieve the best results.

Fig. 11 provides a comparison of small-world networks with more connections. The overall trend shown in this is not different from Fig. 10, only the difference in communication links density leads to different overall performance of social bots. This leads to an interesting conclusion: the impact of social bots in scale-free networks differs due to differences in network link density. Whereas in small-world networks, social bots exhibit corresponding patterns due to differences in the randomness of network connections, rather

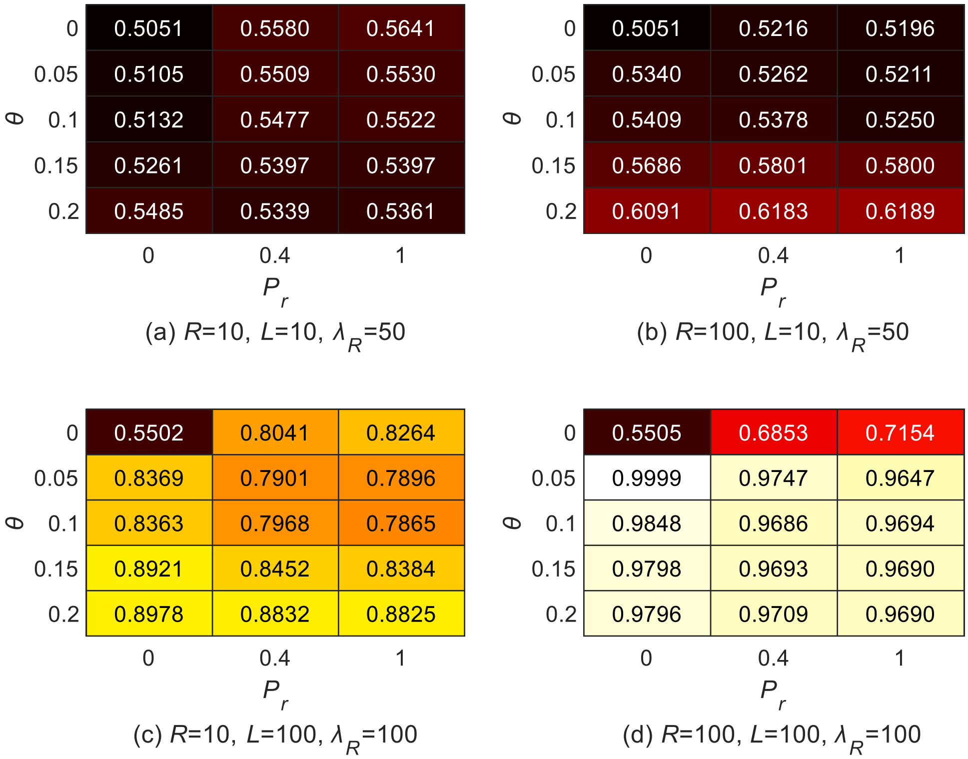

Fig. 10. WS small world network K= 4 when varying the size of R, L, λ_R, yielded the above figures of results, with each grid representing the results of the social bots' influence for a given situation.

than just link density.

The conclusions drawn from our simulations provide insights for designing social bot behavior. While we previously assumed a homogeneous tolerance θ for the social bot group, varying the walking speed based on the allocation of computational resources can improve performance. Additionally, sorting of S_{list} does not need to prioritize by degree. To better understand the implications of social bot connection strategies, we conducted additional simulations using general social networks and appropriate configuration parameters, without considering weak social bot power or optimal tolerance.

In Fig. 12, we examined the differences in the impact of social bot tolerance values on public opinion under various settings. We divide social bot tolerance into two modes: one with a fixed value of θ and the other with a uniform distribution between 0 and a maximum value θ'. Our simulations reveal that the impact of social bot tolerance heterogeneity is distinct from that of tolerance fixation on the public evolution of OSN. Interestingly, the results indicate that social bots with lower tolerance values have similar effects on public opinion, regardless of whether their tolerance is uniformly distributed or fixed. Notably, fixed bot tolerance above 0.1 yielded better results than the other way. To further optimize the performance of social bots, we propose a simple yet effective strategy of assigning different walking speeds to some social bots. By allocating more computational resources to these faster bots, we can intentionally bias their impact on the network and enhance their ability to influence public opinion.

Sorting user IDs in S_{list} based on degree priority may appear to be the best choice, especially in scale-free networks. However, in small-world networks, social bots tend to have more success when randomly selecting nodes to send messages. This may be due to the shorter paths between nodes in small-world networks, which reduce the likelihood of lost messages. As shouwn in Fig. 13. In scale-free networks, as seen in the case of $\theta\in[0.06, 0.09]$, there is little difference in the impact of random selection versus degree prioritization. This suggests that degree-first selection may not always be the most effective strategy, and the choice should depend on the network's characteristics and task requirements.

Although degree-first selection requires a social network search calculation that consumes computational resources, it is not always necessary for social bots to prioritize users based on degree. In some cases, randomly selecting users may be a more feasible strategy, particularly when resources are limited. For example, in smaller social networks, random user selection may be more appropriate, whereas in larger networks, a balance between computational resources and network impact is required to find the optimal strategy. It has real-world applications, such as in social media advertising, where advertisers seek to target the most appropriate audience. If the algorithm is too complex, the cost may be too high or the effectiveness may be limited.

Overall, the results may be similar regardless of the sorting method used for the list of users, as long as the social bots can move quickly enough. However, there may be some differences in certain cases. The optimal strategy for social bots to choose users depends on the network structure of the target social network and the computational resources that are available to them.

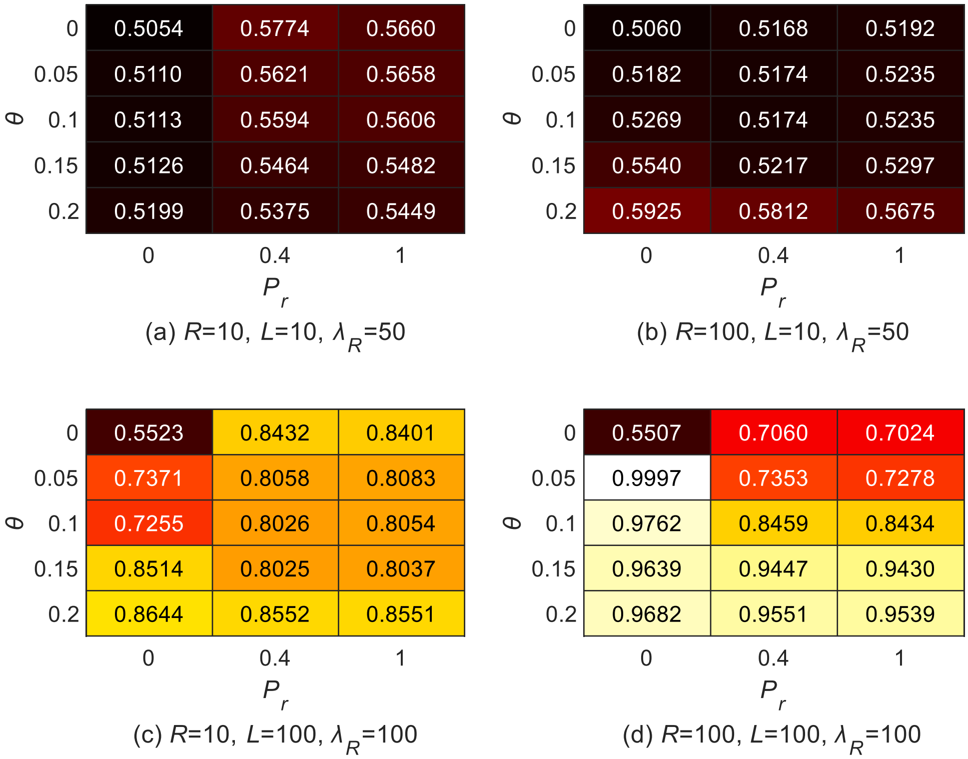

Fig. 11. WS small world network K= 6 when varying the size of R, L, λ_R, yielded the above results, with each grid representing the results of the social bots' influence for a given situation.

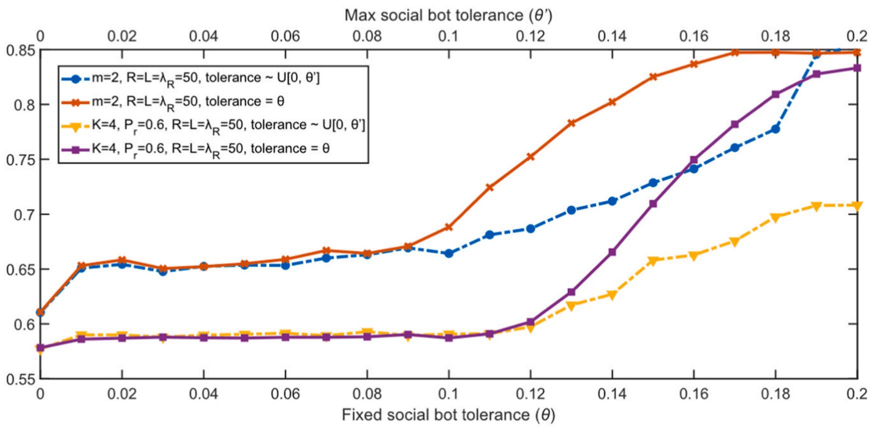

Fig. 12. Differences in the influence of heterogeneous versus fixed social bot tolerance values on public opinion were investigated. A WS small-world network (K=4, Pr=0.6) and a BA scale-free network (m=2) were selected. Tolerance fixed refers to all social bots having the same tolerance value, θ, as shown on the x-axis. Tolerance uniformly means that social bot tolerance varies uniformly between 0 and θ', with θ' being the maximum value shown on the x-axis.

4. Conclusion

This paper delved into the impact of social bots on public opinions of target social networks, measured in terms of continuous opinions, through designed behavioral patterns. The mechanism for the interaction of opinions between individuals is based on a virtual corpus which was first proposed in this study. The impact of social bots has been studied in a variety of different types of networks, providing insights into the use and design of social bots. Our findings offer a new perspective and approach to the study of the evolution of public opinion, as well as the optimal behavioral strategies of social bots and their macro-level influence on the online social network. Choosing the right connection strategy (such as social bot tolerance and sort strategies) is crucial in enhancing the

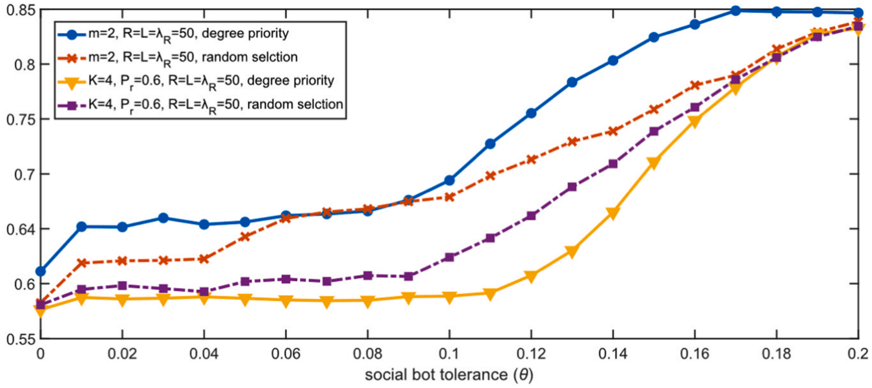

Fig. 13. Differences in the effectiveness of social bot node degree priority versus random selection in influencing group opinion were investigated by selecting a WS small-world network (K=4, P_r=0.6) and a BA scale-free network (m=2), with user degree priority meaning that all social bots intervened in descending order of degree and user random selection meaning that all social bots randomly selected nodes to influence.

effectiveness of social bots.

The denser the network's connected edges, the less effective it is in guiding public opinion. This once again emphasizes the importance of early intervention in the target OSN. The speed at which social bots walk in the social network varies significantly in terms of their effect on public opinion, and generally, the faster the social bots walk, the better the effect on group opinion. However, in some cases, there is an optimal walking speed to achieve the best effect. Even in cases where the performance of social bots is poor, it is not advisable for social bots to walk too fast in the target social network, as this may result in worse outcomes. Therefore, if the operator cannot create social bots with strong conversational abilities, it is recommended that they focus on social network users with certain influence instead of attempting to send messages to a large number of users through social bots in order to achieve the best results.

Increasing the number of users influenced in a single session (i.e., the number of communication links established by social bots) and the amount of information sent to users at once are effective ways to enhance social bots' ability to influence public opinion. However, having an excessive number of social bots can lead to the suppression of expression by human users in social networks, which decreases the effectiveness of social bots. In such cases, it is suggested to increase the walking speed of social bots in the social network to reduce the amount of time they continuously impact each human user.

After considering the costs, our study suggests that the behavioral intensity of social bots can be flexibly adjusted to optimize their performance in a given situation. Some computing resources can be allocated to certain social bots to speed up their walking compared to their peers, resulting in better results. If computing resources are limited and a higher tolerance for social bots cannot be set to support faster walking speeds in OSNs, randomly selecting users in the social network to influence may achieve a better input-output ratio than a priority strategy based on node degree, especially in small-world networks.

In summary, the way to make social bots more effective comes down to either having sufficient computational resources and good algorithms to make social bots perform well or having the flexibility to set the behavior of social bots to work better with limited resources, i.e., the bigger the better and the right amount of flexibility.

However, individual behavioral flow and opinion interactions are complex processes, which we ignore to make the model more applicable. Many of the studies in question consider multiple scenarios, resulting in models that are only applicable to a few specific situations. In fact, individual behavioral patterns are difficult to determine, and its base on a variety of attributes, such as income, education level, cultural background, etc. Perhaps the introduction of artificial intelligence can open up new horizons for agent-based models, making simulation more adaptive and intelligent [58]. The next step in the research will be to consider collecting behavioral features of real individuals based on deep learning and analysing the behavior flow of individuals in social networks.

CRediT authorship contribution statement

Yaozeng Zhang : Conceptualization, Methodology, Original draft preparation, Software. **Jing Ma**: Supervision. **Fanshu Fang**: Validation, Visualization.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, "How social bots can influence public opinion more effectively: right connection strategy".

Data availability

Model, as well as more example demonstrations of the results, can be found on GitHub. https://github.com/yaozengzhang/How-social-bots-can-influence-public-opinion-more-effectively-right-connection-strategy

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