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*Research Article*

# Modeling and Simulation of Polarization in Internet Group Opinions Based on Cellular Automata

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Hot events on Internet always attract many people who usually form one or several opinion camps through discussion. For the problem of polarization in Internet group opinions, we propose a new model based on Cellular Automata by considering neighbors, opinion leaders, and external influences. Simulation results show the following: (1) It is easy to form the polarization for both continuous opinions and discrete opinions when we only consider neighbors influence, and continuous opinions are more effective in speeding the polarization of group. (2) Coevolution mechanism takes more time to make the system stable, and the global coupling mechanism leads the system to consensus. (3) Opinion leaders play an important role in the development of consensus in Internet group opinions. However, both taking the opinion leaders as zealots and taking some randomly selected individuals as zealots are not conductive to the consensus. (4) Double opinion leaders with consistent opinions will accelerate the formation of group consensus, but the opposite opinions will lead to group polarization. (5) Only small external influences can change the evolutionary direction of Internet group opinions.

## 1. Introduction

During the last years, a paradigm in computer simulation studies of social sciences problems is the emergence of consensus [1–4]. The question is to find out the dynamics of a set of interacting agents that can choose among several options (political vote, opinion, cultural features, etc.) [5]. In community environment, each individual affects his neighbors but also is affected by his neighbors, and individual's options evolve dynamically by learning, imitation and conformity, which will result in the emergence of consensus.

Usually, the dynamical models of consensus can be divided into two main categories: discrete dynamical model (the value of opinions is integer numbers of +1 or −1) and continuous dynamical model (the value of opinions is real numbers between 0 and 1). The discrete dynamical model of consensus includes Ising model [6], Vote model [7], Sznajd model, and other classical models [2], and continuous model includes Deffuant model [4] and Krause-Hegselmann model [8]. A standard review on consensus models can be found in [9].

When scholars pay their attention to the emergence of consensus, another important subject of options formation which is polarization [10, 11] attracts a great interest of them. When a group of people participates in a discussion, individuals tend to endorse a position in the direction already favored by the group and more extreme. This phenomenon is called polarization [10]. The difference between consensus and polarization is that the consensus refers to a single spatial domain which grows occupying the whole system, while polarization corresponds to a situation in which the system is disordered and competition exists among different spatial domains [5].

From group discussion to president election and from culture spread to Internet group opinions, polarization is widely observed in human society. In recent decades, scholars try to find the reasons and mechanisms that result in polarization; probably the earliest study is proposed by Stoner

[12] in the study of group decision in 1961. Since then, group polarization has been widely studied in psychology [13], sociology [14], political science [15], physics [16], and so on. One inspired model is suggested by Axelrod [17] who introduced an agent-based model to explore mechanisms of competition between globalization (consensus) and coexistence of several cultural options (polarization). Based on this model, various extensions are proposed [18]. For example, Klemm et al. carried out a series of studies on Axelrod's model from regular networks to complex networks [19–22]. Other extensions include the consideration of quantitative instead of qualitative values for the cultural traits [23], the model to simulation of technology assimilation [24], the consideration of specific historical contexts [25], or the effect of a fixed external cultural influence [26]. Macy et al. [27] introduced continuous values of the cultural traits to describe the group polarization problem. Li and Tang assign specific social influence implication to dyadic [28] and triadic structure [29] of social ties.

All these studies have led to a new direction of the study on polarization. However, most of them pay little attention to the real world [16] and ignore the fact that polarization shows new features with the development of Internet. In general, there are three new features in the process of Internet group polarization. The first is the coevolution of the networks and opinions. Usually, the opinions evolution on Internet is beginning with few people, but, as time goes on, there will be more and more people taking part in the networks discussion. So, the nodes of networks will grow with the evolution of group opinions. However, most of the previous studies [8, 17, 19–21, 27–29] start the opinions evolution from a fix scale lattice or networks in their simulation experiments. The second is the emergence of opinion leaders who usually refer to the higher concerned individuals, such as the popular influential Bulletin Board System (BBS) or government official website and Twitters of celebrities. Sometimes, opinion leaders can determine the process of opinions dynamics [30]. The third is the fact that Internet has no boundaries and the scale is huge, so it is impossible for individuals to interact with everyone on Internet; individuals can only communicate with neighbors they like to talk with.

Based on the above three points, we established a new model of group polarization in Internet group opinions based on Cellular Automata (CA) [31, 32]. Firstly, we set up a growth networks model which has the characteristic of being scale-free [33]; all of the interactions of opinions are conducted on the networks, and the networks grow with the interaction of opinions. Then, we introduced three factors in the opinions interaction rules; the inner pressure comes from neighbors, the pressure comes from opinion leaders, and the external pressure comes from external environment, such as government or newspaper. Based on the opinions spread networks model and the Cellular Automata model, we numerically investigate how the three factors of inner influence, opinion leader's influence, and external influence affect the dynamics of group polarization in Internet.

There are four differences between existing researches and our model. Firstly, the opinion value in our model is real numbers between −1 and 1 (continuous opinions), but the previous studies adopt values of −1 or 1 (discrete opinions). Secondly, opinions spread networks proposed in this paper are coevolving with opinions of group; it is very different from the previous studies which fix the networks and only evolve opinions. Thirdly, in previous studies, each individual connects to all of other individuals in group (global coupling). Considering the large scale of Internet networks, no one may interact with all other individuals, so each individual only interacts with his neighbors (local coupling) in our model. Finally, we introduce the opinion leaders to adapt to the new features of Internet in our model.

By simulation experiments, we find that both continuous opinions and discrete opinions can promote the polarization of group opinions under the influences of neighbors, and continuous opinions are faster than discrete opinions in making the polarization. However, the coevolution of networks and opinions takes more time to make the system stable than fixed networks. By further analysis, we find that it is different from the results of local coupling mechanism which leads to the polarization of group opinions; the system shows consensus under global coupling. The results of simulation experiments also show that the opinion leaders break the polarization but promote the emergence of consensus. However, different from the existing conclusion in literature [34], both taking the opinion leaders as zealots and taking some randomly selected individuals as zealots are not conductive to the consensus. In addition, we find that only small external influences can change the evolutionary direction of Internet group opinions.

The paper is structured as follows. In the next section, we will present the networks model and the Cellular Automata model of opinions spread in Internet. Then, we will analyze the simulation results in Section 3 where we only consider the influences of neighbors first and then introduce the opinion leaders and external intervention into the system gradually. Finally, we will draw the conclusions with a brief discussion in the last section.

## 2. The Model

As we introduced before, the development of the opinions in Internet is determined by the coupling evolution of the relationship networks and individuals' opinions; the interactions of opinions are conducted on the networks. So, we will establish a networks model of opinions spread based on social networks structure of discussion group firstly, and then we will propose a simulation model of group polarization based on Cellular Automata.

*2.1. Networks Model of Opinions Spread.* The spread process of opinions in Internet is "occurrence of hot event, delivery of few people, discussion of netizen, and spread of opinions." In order to describe the process from which only few people get the initial information of hot event to information rapidly spreading, we represent the individual who first publishes the information on a forum or on Twitter as point $i$ ($i = 1, 2, 3, \ldots$), and $i$ will pass this information to another individual $j$ ($j = 1, 2, 3, \ldots$). This process results in the formation of networks of opinions spread (Figure 1).

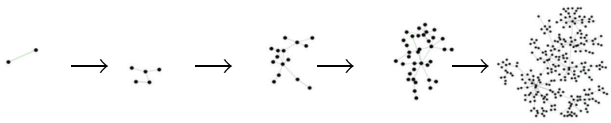


Figure 1: The formation of networks model of opinions spread.

It is necessary to emphasize that the relationship between networks of computers does not mean the relationship between the people who use the computers; adjacent computer users will not necessarily browse the same websites or contact by online communications, and they are not even online at the same time. Therefore, we need to reconsider the structure of dynamic networks of information dissemination on Internet rather than simply replacing it with the topology structure of Internet.

As the Internet group opinions often begin from a hot event after the initial networks news have been reported or posted, the information will be commented on and forwarded, and then more and more people will be involved in the topic. Obviously, during this process, people who have a higher degree of concern will more likely become the concerned object of subsequent partner. So there is preferential attachment [33] feature in the process of group opinions spread, namely, the individual priority access to the high popular websites, forums, or Twitters. Taking into account this feature, we establish the following networks model of opinions spread:

(1) Generate the first node which represents the revelator of hot event.

(2) Generate another new node $m$; connect $m$ with one existing node by a certain probability. The probability can be calculated as follows:

  (1) Calculate the total degree of networks; we note it as $T = \sum_{i=1}^{N} \sum_{j=1}^{N} l_{ij}$, where if $i$ and $j$ are not connected, $l_{ij} = 0$; otherwise $l_{ij} = 1$.

  (2) Generate a random number $R$ $(0 \le R \le T)$, and randomly select one existent node $n_1$; calculate its degree $d_{n_1} = \sum_{j=1}^{N} l_{n_1 j}$; if $d_{n_1} > R$, then connect $m$ and $n_1$; if $d_{n_1} < R$, let $R' = R - d_{n_1}$. Select another existent node $n_2$; calculate its degree and repeat above comparing process. Stop the calculation until we find that an existent node connects to $m$.

Repeat step (2); we can generate opinions spread networks (Figure 2) which obviously keeps the scale-free characteristic (Figure 3), where the larger size node represents a higher degree individual, such as high popular Twitters or forums. In fact, during the formation of the networks, those individuals who are not interested in the discussed topic are automatically filtered out, and the remainders will keep interest in the topic and maintain the activity to participate in the discussion. If the discussion group has tendentious attitude for the hot event at the beginning, the spread of Internet opinions is likely to form the polarization.

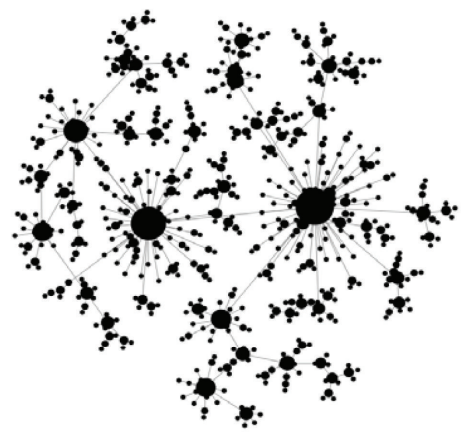


Figure 2: Networks of opinions spread.

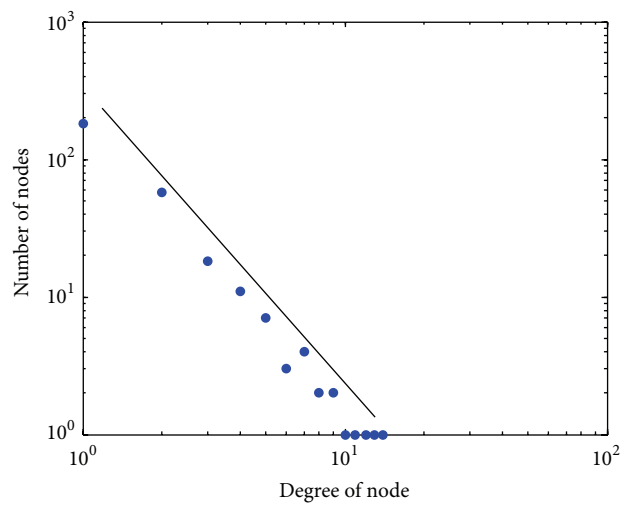



Figure 3: Scale-free feature of networks.

The above opinions spread networks are the social relational structure of the discussion group on Internet, and opinions spread networks are the physical framework of this study. On this physical framework, individuals' opinions are evolving through the communication.

*2.2. Cellular Automata Model.* How and why consensus emerges is an intensely investigated subject in recent years. Methods of agent-based modeling, such as Cellular Automata (CA) [31, 32], have been applied successfully and with much effect recently to shed the light on the problem from many different perspectives and also to outline many different ways on how polarization and convergence to consensus can be achieved [35, 36].

As an important simulation method, CA is first proposed by Neumann [31] and Ulam [32], and Ulam thinks CA is a physical space model defined by mathematics, which includes geometry and conversion function defined by a series of local rules. Back in the 1980s, Langton firstly used CA to study artificial life [37]; results show that almost all CA calculations are included in the scope of emergent computation [38]. CA

has played an indispensable role in the study of complex systems as a kind of fairly representative model [39, 40]. Since the 1990s, Crutchfield et al. have made innovations in exploring the mechanism of emergent computation through the evolution of CA [41] and achieved some research fruits [42, 43]. Holland established a universal framework for the study of emergence by considering the macro-micro mechanism as Constrained Generating Procedures (CGP) [44]; he pointed out that Cellular Automata (CA) is the basic approach of CGP. The most famous examples of CA include Game of Life designed by Conway in the late 1960s, Boids model [45], and Vicsek model [46].

Because of the powerful computing capabilities, inherent parallel computing capabilities, highly dynamic concept of space, and other features, CA has become a powerful tool for studying self-organizing systems, so it has been widely applied to various research fields. Here, we will use Cellular Automata (CA) to establish a stochastic model of polarization in Internet group opinions by further considering the randomness of opinions interact.

Usually, we can define Cellular Automata as a four-element array:

$$\mathrm{CA} = (S, X, V, f), \tag{1}$$

where $S$ is cellular space, $X$ is cellular status, $V$ is cellular neighborhood, and $f$ is the conversion rules of cellular status.

The key to establish a Cellular Automata model is to define the above four elements reasonably. In this paper, what is important during the process of defining the elements is that the dynamic evolution Cellular Automata model is based on the physical topology of opinions spread networks; it is very different from the traditional Cellular Automata based on two-dimensional lattice which is inconsistent with Internet group structure [17, 18]. Another point that needs to be noticed is that the networks growth and opinions interaction are evolving at the same time in our model; this is different from the previous studies which begin the opinions interaction from one fixed scale of lattice or networks [17, 19–22, 27–29]. We will take full account of this factor in the following modeling process.

*Cellular Space S*. Different from traditional Cellular Automata, we use the networks of opinions spread as cellular space. According to the algorithm in Section 2.1, we can get a network which contains $N$ nodes; if we denote node $i$ as cellular $a_i$ ($i = 1, 2, 3, \ldots, N$), then the cellular space is composed with $N$ cellular.

*Cellular Status X*. The nature of opinions spread in Internet is the spread of personal opinions, attitudes, or views; we refer to these as personal opinions. In considering the value of opinions space, there are two ways: discrete [47] and continuous [4]. When the individual participates in a discussion, personal opinions often exhibit different degrees of inclination towards Internet events, so we let $X \in [-1, 1]$ represent different opinions on a certain event. $x_i(t)$ ($x_i(t) \in X$) represents the attitude of individual $i$ at time $t$, and then $-1 \leq x_i(t) \leq 1$. When $0 < x_i(t) \leq 1$, individual tends to support the Internet event; when $-1 \leq x_i(t) < 0$, individual tends to oppose the Internet event.

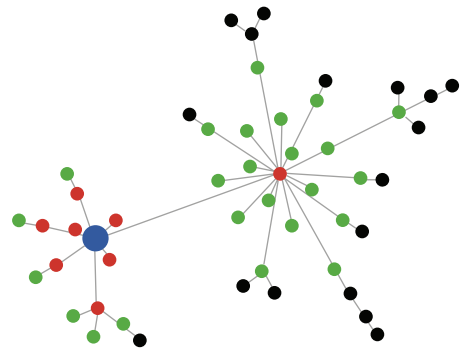


Figure 4: Neighborhood for $n = 2$. The neighbors of blue cellular include direct connect red cellular and indirect connect green cellular.

*Cellular Neighborhood V*. In traditional Cellular Automata, neighborhood of cellular is determined by nearest neighbors. The most popular forms are Von Neumann type and Moore type which is obviously different from the global spread of Internet group opinions. It is unrelated with spatial distance for individuals exchanging information in Internet group opinions, and the number of neighbors for each individual is heterogeneous too. To express this spatial characteristic, we define neighborhood of cellular $i$ as

$$V_i = \left\{a_j \mid d\left\|a_i, a_j\right\| \leq n,\ \ j = 1, 2, 3, \ldots, N\right\}, \tag{2}$$

where the neighbors of $i$ include not only the direct connect cellular but also indirect connect cellular (distance is $n$; Figure 4 is the example when $n = 2$) and $d\|\cdot\|$ is the number of passed edges from $a_i$ to $a_j$, that is, the distance from $a_i$ to $a_j$.

*Conversion Rules of Cellular Status f*. Conversion rules are the key elements of Cellular Automata, and they are based on the local interaction rules of every cellular. We will propose the mathematic function as follows.

Most traditional models only consider two factors of population pressure and external pressure [27, 48], where the population pressure comes from the entire participation group. However, it is often impossible for individuals to carry out opinion interaction with every individual for large-scale group. In fact, individual's neighbor group is the more important objects of opinion interaction. Moreover, the effects of external influences, such as government and other information through Internet, television, radio, and newspapers, are also an important factor for group opinions evolution, and they have been addressed by many researchers [48, 49]. In addition, the higher concerned opinion leaders such as the influential Twitter or websites cannot be ignored; opinion leaders can determine the process of opinions dynamics sometimes [30, 34].

In the process of the evolution of Internet group opinions, opinion leaders and external intervention are not involved at beginning but are involved gradually. So, the process can be

divided into three stages. The first stage is the formation of Internet group opinions without opinion leaders and external intervention; polarization process is only affected by the neighbors in group. The second stage is when the opinion leaders emerge and influence the polarization process. The third stage is the external intervention such as the government or newspapers beginning to influence the trend of polarization.

Based on the above analysis and according to the social impact theory [30, 50], we use $I_i$ to represent the public influences of individual $i$, then $i$'s opinion on hot event mainly affected by three aspects. The first is from individual's neighbors; we call it neighbors influence $I_{\mathrm{Ni}}$. Different from previous studies [17–21, 27, 28] where individuals interact with whole group, individuals' opinions are only impacted by their neighbors in this paper. The second is opinion leader's influence $I_{\mathrm{Li}}$ [30]. The third is external influence $I_{\mathrm{Oi}}$ [48, 49]. The evolution trend of group opinions will be determined by these three aspects.

Except the influences of individual's opinion [17], there are two other main factors that determine an individual's ability to influence others. One is individual influence scope; we use the proportion of individual degree of the total degree to measure this influence; for example, if individual $j$ is one of individual $i$'s neighbors, the influence of individual $j$ on individual $i$ is determined by the ratio of $d_j/d_{it}$, where $d_j$ is $j$'s degree, and $d_{it}$ is the total degrees of all $i$'s neighbors. Another is the differences of opinion. Because individuals always like to talk with others standing on the same camp, the different views are ignored [4, 8, 51]. If opinions $x_i$ and $x_j$ differ by more than a fixed parameter $\varepsilon$, nothing happens because the two agents think too differently to interact [51]. So, with the enlargement of opinion's difference, the opinion's influence reduces. Consistent with the references [51], we use $e^{-|x_i-x_j|}$ representing the influence of opinion differences. Based on the above analysis, we define the neighbors influence as

$$I_{\mathrm{Ni}} = \frac{1}{n_i - 1}\sum_{i=1}^{n_i}\frac{d_j}{d_{it}}e^{-|x_i-x_j|}x_j, \tag{3}$$

where $x_j$ is the opinion of individual $j$ and $n_i$ is the neighbor number of $i$. $d_j/d_{it}$ is the ratio of individual degree of total degree; its value determines the influence of $j$ on $i$.

We select one of the individuals $l$ which has biggest degree in Internet group as opinion leader. Because of their authority and influence, opinion leaders have an impact not only on their neighbor groups but also on the entire Internet groups [30]. We define the influence of opinion leaders as

$$I_{\mathrm{Li}} = \frac{d_l}{d_{it}}x_l, \tag{4}$$

where $x_l$ is the opinion of opinion leaders and there is maybe not only one opinion leader in the Internet group opinions spread.

Finally, we define the external influence [48, 49] as

$$I_{\mathrm{Oi}} = x_o. \tag{5}$$

Considering the above three kinds of influence together, we give $I_i$ as

$$\begin{aligned} I_i &= aI_{\mathrm{Ni}} + bI_{\mathrm{Li}} + cI_{\mathrm{Oi}} \\ &= a\frac{1}{n_i - 1}\sum_{i=1}^{n_i}\frac{d_j}{d_{it}}e^{-|x_i-x_j|}x_j + b\frac{d_l}{d_{it}}x_l + cx_o, \end{aligned} \tag{6}$$

where $a$, $b$, and $c$ are the ratio parameters of three influences, $0 \le a, b, c \le 1$, and $a + b + c = 1$.

According to the social impact theory [30, 50], when $I_i > 0$, the overall influence tends to support the hot event. Then, under this situation, it is possible that individual tends to change opinion to support, and the bigger $I_i$ is the bigger opinion changing probability is. On the contrary, when $I_i < 0$, the overall influence tends to oppose the hot event. Now, individual maybe tends to change the opinion to opposition, and the smaller $I_i$ is the bigger opinion changing probability is. So, we present the conversion rules of opinions as follows.

For individual $i$, when $I_i > 0$, add a small positive $\varepsilon$ ($\varepsilon > 0$) on its opinion according to the probability $P_1 = 1/(1 + e^{-I})$. Consider

$$x_i(t+1) = x_i(t) + \varepsilon. \tag{7}$$

On the contrary, when $I_i < 0$, subtract a small positive $\varepsilon$ ($\varepsilon > 0$) on its opinion according to the probability $P_2 = 1/(1 + e^{I})$. Consider

$$x_i(t+1) = x_i(t) - \varepsilon. \tag{8}$$

On the networks of opinions spread, individuals interact on the basis of conversion rules (7) and (8). The detailed algorithm is as follows.

*Step 1.* Generate the networks of opinions spread according to the algorithm in Section 2.1; every node represents one cellular; initialize $x$ of every cellular.

*Step 2.* Initialize the parameters $a$, $b$, $c$, $\varepsilon$, and $x_o$.

*Step 3.* Generate a new cellular; initialize its opinion $x$.

*Step 4.* Calculate $d_i$, $d_{it}$, and $I_i$.

*Step 5.* When $I_i > 0$, generate a random number $r_1 \in [0, 1]$; if $r_1 < P_1$, change opinion by formula (7). When $I_i < 0$, generate a random number $r_2 \in [0, 1]$; if $r_2 < P_2$, change opinion by formula (8).

*Step 6.* Repeat Steps 3–5 until the system tends to become stable.

The standard of system stability is that the opinions of individuals do not change anymore at the last 100 steps. When the system reaches stability, the simulation will terminate. It is important to note that the conformity or herding effect of individuals is an important factor which affects the system evolution, and it will determine where the system terminates during the evolution sometimes [52, 53]. In this paper, the

conformity is comprehensively determined by neighbor state, opinion leaders, and the outside environment. We will reveal the complex dynamics as follows.

## 3. Simulation and Results Analysis

In this paper, we take $\varepsilon = 0.01$, $x \in [-1, 1]$, and $x_o \in [-1, 1]$. It is worth emphasizing that different values of $\varepsilon$ may influence the evolutionary process of system. High values of $\varepsilon$ significantly accelerate the convergence process, and small $\varepsilon$ will take more time to achieve stability. We start from a random initial distribution of the states of individuals. Because the Internet topic is usually launched from the initial several people and expands to a certain scale at last, in the simulation experiments of this paper, we begin the opinion interaction after there are 10 nodes in networks of opinions spread and suppose that no one else will join in the discussion after $N = 100$. That is to say, the network does not develop anymore after $N = 100$. The simulation results are obtained by averaging over 30 samples. The system reaches a dynamic stable state when the opinions of cellular do not change anymore at the last 100 steps. We experiment for $N = 300, 500, 1000$, respectively, and get similar results.

The process of Internet group opinions evolution can be divided into three stages; opinion leaders and external intervention are involved gradually. At the first stage, system is only affected by inner neighbors and then opinion leaders emerge at the second stage; external intervention such as the government and newspapers makes influences at last. We will analyze the impacts of neighbors, opinion leaders, and external intervention, respectively, as follows.

*3.1. Influence of Neighbors.* In order to analyze the different influences of different roles, we first only observe the influence of neighbors, regardless of influences of opinion leaders and external intervention. Take $a = 1$ and $b = c = 0$; when the networks reached 100 nodes, individual opinions are quite different (Figures 5 and 6).

As the system evolved into 1000 time steps, polarization of group opinions is obvious. One part of the group takes supportive opinions, while the other part opposes (Figure 5). As can be seen from Figure 6, group with randomly distributed initial opinions is split into two opposing camps gradually.

The results displayed by Figures 5 and 6 are consistent with the conclusions of literatures [17, 27, 29, 48]. However, there are many differences between existing researches and our model. The continuous opinions ($x \in [-1, 1]$) adopted in our model are different from the discrete opinions ($x = \pm 1$) used by previous studies. Different from the previous studies which fix the networks and only let opinions evolve, opinions spread networks in this paper coevolve with opinions of group. In previous studies, each individual connects to all other individuals in group (global coupling), but each individual only interacts with its neighbors (local coupling) in our model. We will further analyze the impact of the three differences on polarization.

First, we set $x = \pm 1$ in our model and keep other conditions unchanged. The experiment results are shown in Figure 7. As can be seen from Figure 7, similar to the results of continuous opinions (Figure 6), the polarization phenomenon can also be observed in the case of discrete opinions. Figure 8 shows the time in which system reaches stable state for discrete opinions and continuous opinions under different networks scales, respectively. Obviously, the case of continuous opinions is faster than the case of discrete opinions in making the system stable.

Then, we analyze the influences of coevolution of networks and opinions. Figure 9 shows the system stable times of 30 random experiments under two situations: one is individual's opinions beginning to interact after 100 nodes generated in a fixed network and another is the networks coevolution with opinions since there are only 10 nodes. As can be seen from Figure 9, coevolution case takes more time to make the system stable than fixed networks.

Finally, we extend the local coupling relationship of the individuals to the global coupling. Figure 10 shows that it is significantly different from the results of local coupling (polarization); the system shows synchronization under global coupling (consensus). This is because the global coupling breaks the boundaries between cliques in the online community and then the exchange of information promotes the emergence of consensus.

*3.2. Influence of Opinion Leaders.* Influence of neighbors is one of the important facts in group polarization [27, 48], while a special type of individuals in the group usually tends to be ignored, that is, opinion leaders who usually emerge sometimes during the evolution of group opinions. Though few researchers begin to care for the issue in recent years [30], they did not consider the new situation and new features of the Internet. Here, according to the important role in the Internet group opinions, we take the factor of opinion leaders into account. We will focus effort on how the opinion leaders influence group polarization as follows.

Take $a = 0.7$, $b = 0.3$, and $c = 0$; we find that opinion leaders (the bigger nodes in Figures 11(a) and 11(b)) play an important role in the development trend of group opinions. The appearance of opinion leaders breaks the polarization which has two poles and leads to consensus of group opinions (Figures 11(b), 11(c), and 11(d)). In addition, from Figure 11(a), we can see that the opinion leader's opinion is $-0.45$ when the size of the networks reaches 100 nodes; obviously, when opinion leader opposes the events, whole groups also tend to oppose the events under the widespread influence of opinion leader. When we take the experiments where opinion leader takes supportive opinion, we get similar results.

In addition, compared with the situation of no opinion leader, the join of opinion leaders can promote the emergence of consensus in Internet group opinions (Figure 12). This is because the big and wide range of influence of opinion leader can lead the direction of the whole group so as to promote the formation of consensus [30].

Literature [54] introduced the participants who have different teaching capabilities into the model of evolution of cooperation. In accordance with the result of Figure 12, it was found in [54] that the join of opinion leaders can promote the emergence of consensus. Both literatures [30, 54] as well as the results of this paper suggest that the opinion leaders can

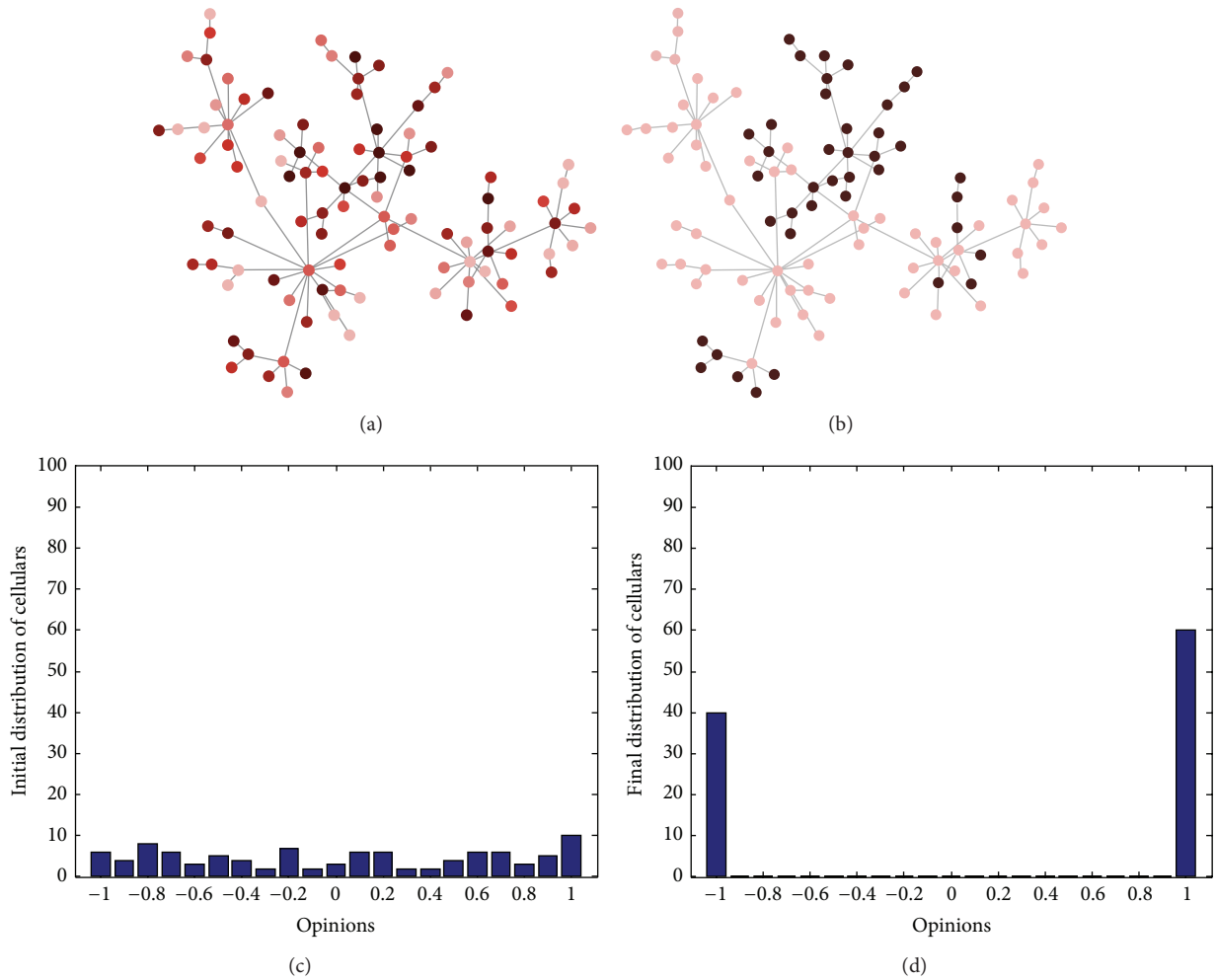



FIGURE 5: When $a = 1$, $b = c = 0$, and $N = 100$, the group shows polarization. In (a) and (b), the color of cellular represents individual's opinion to Internet events, with more dark meaning more opposition and more light meaning more support. (a) Initial status of group opinions. (b) Distribution of group opinions after 1000 time steps. (c) Histogram of initial distribution of group opinions. (d) Histogram of final distribution of group opinions.

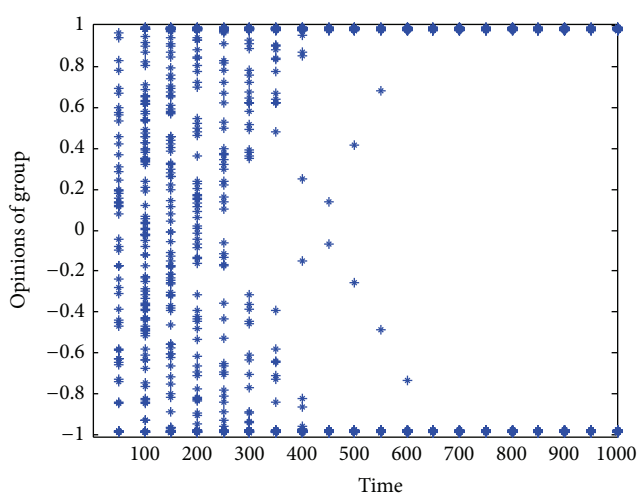



FIGURE 6: Group opinions change with time. $a = 1$, $b = c = 0$, and $x \in [-1, 1]$ (continuous opinions).

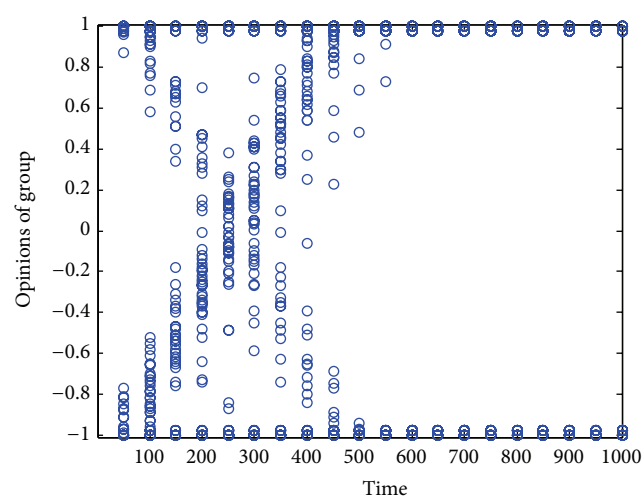



FIGURE 7: Group opinions change with time. $a = 1$, $b = c = 0$, and $x = \pm 1$ (discrete opinions).

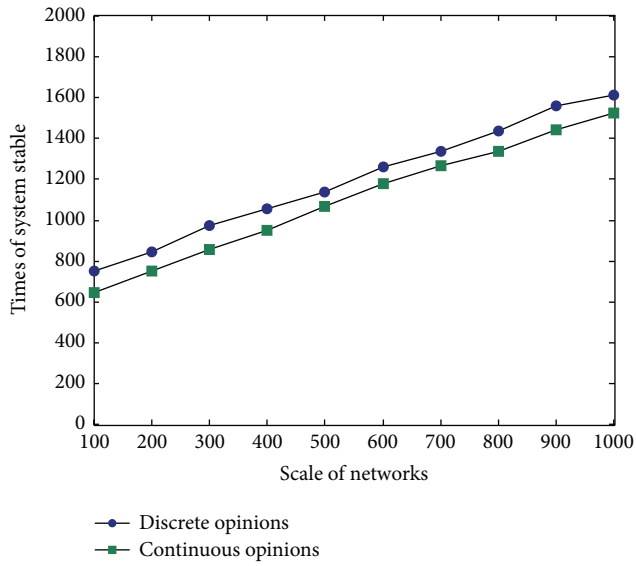



Figure 8: Times of system stable under different scale of networks for discrete opinions and continuous opinions. Each data point is an average over 30 independent experiments.

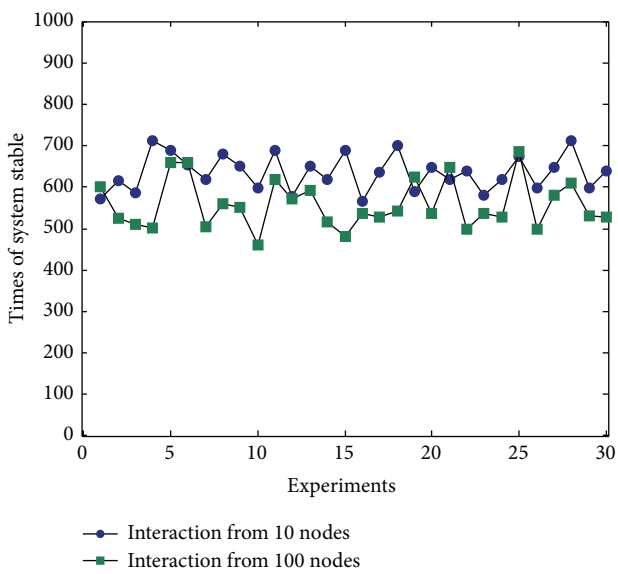
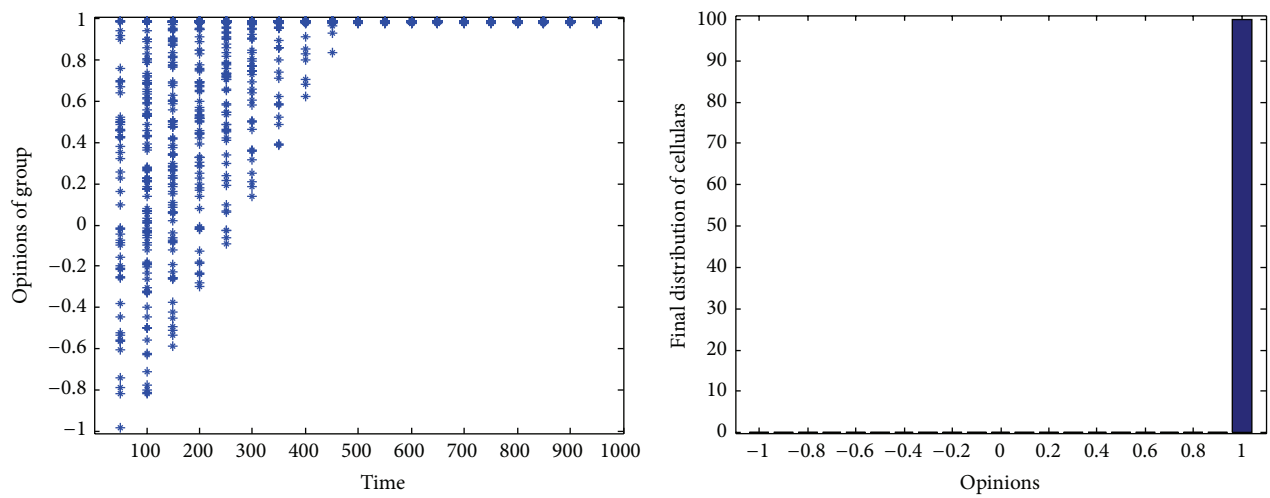



Figure 9: Times of system stable under 30 random experiments for interaction from 10 nodes and 100 nodes, respectively.

promote the formation of consensus under different topology and parameters.

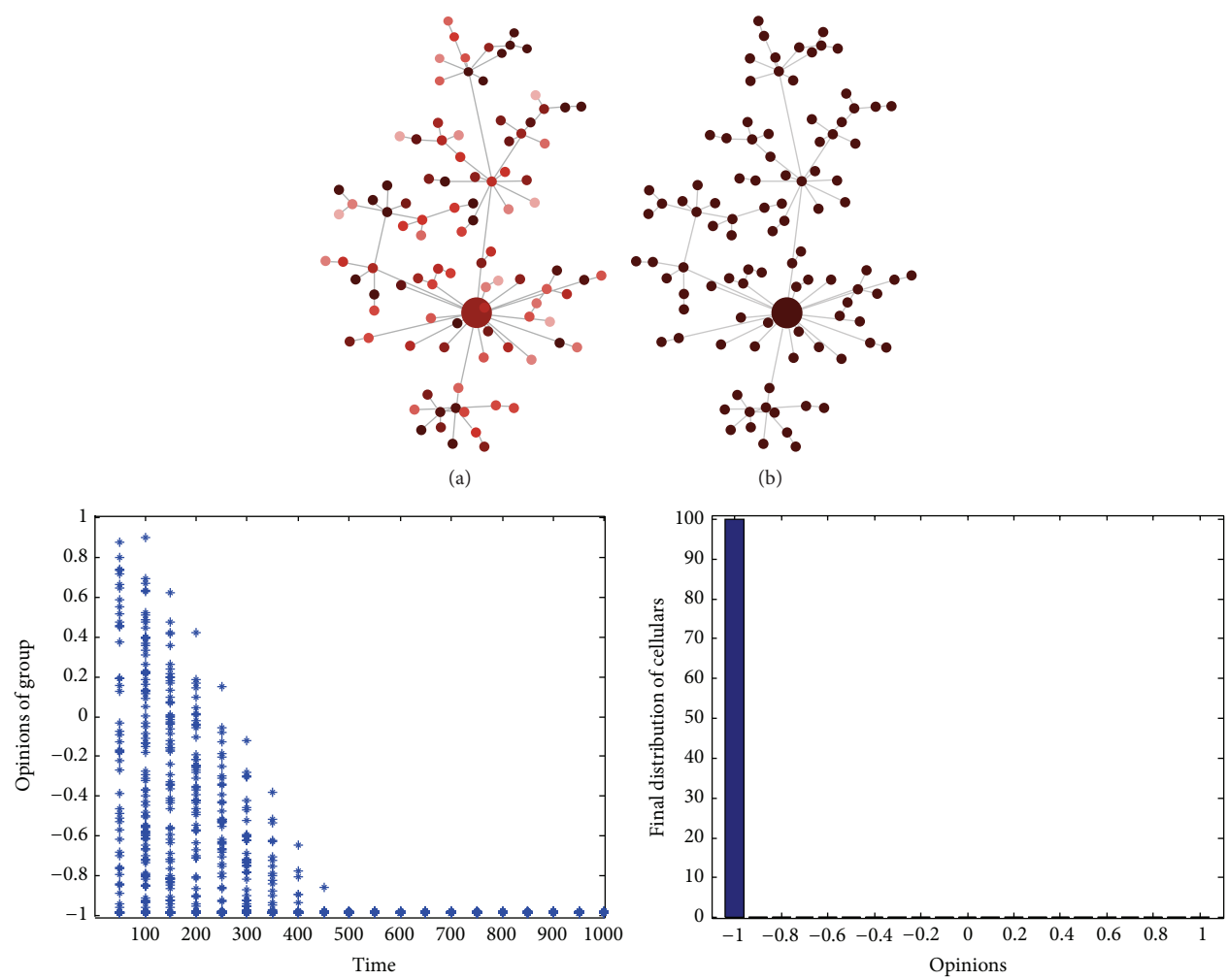
The above experiments are taken under the conditions that opinion leader can change its opinion with the evolution of system. In fact, someone in group may be a "zealot" [34] or facilitator [55] who always keeps his opinion unchanged, and zealot can affect the polarization of group opinions sometimes [34]. Facilitators introduced in literature [55] will cooperate with cooperators and defect with defectors, but they do not participate in the exchange of strategies. Different from the zealot in literature [34], the facilitators take the strategy of tit-for-tat during the dynamic process, and the simulation results show that the specific position of facilitators on scale-free networks could be a decisive factor influencing the evolution of cooperation. That is to say, different degrees of facilitators will affect the stable rate of cooperation.

To test whether the zealot will work in our model as it did in previous studies, we take some experiments under two conditions. One is the opinion leader as a zealot (Figure 13(a)) and the other is a random selection of 5% individuals as zealots (Figure 13(b)). Different from the existing conclusion in literature [34], both conditions show that the join of zealots does not play a role in promoting the consensus of group opinions, and we do not get different results by enlarging the randomly selected proportion of zealots. The reason




(a) (b)

FIGURE 10: When $a = 1$, $b = c = 0$, and $N = 100$, the group shows consensus in fully connected networks. (a) Opinions of group change with times. (b) Histogram of final distribution of group opinions.




(a) (b)

(c) (d)

FIGURE 11: When $a = 0.7$, $b = 0.3$, and $c = 0$, opinion leader influences the polarization of Internet group opinions. (a) Opinions distribution at 100 time steps; the opinion of opinion leader is −0.45 now. (b) Opinions distribution at 1000 time steps; the opinion of opinion leader changes to −1. (c) Opinions of group change with times. (d) Histogram of final distribution of group opinions.

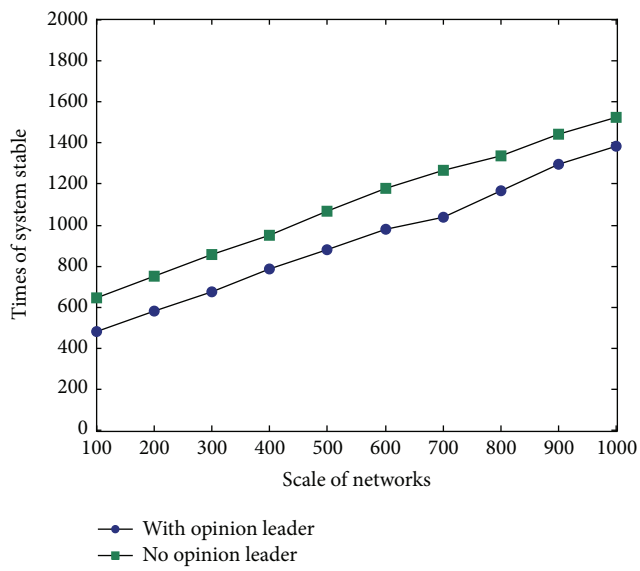



Figure 12: Influence of opinion leader on the times of system stable under different scale of networks. It takes less time to achieve system stable after appearance of opinion leader. Each data point is an average over 30 independent experiments.

of the results may be the coevolution and local coupling mechanisms in our model. Because of the coevolution of group opinions and networks, zealots do not appear at the beginning but join in the group gradually, so the mainstream direction of group opinions has formed before the advent of zealots. Coupled with the mechanism of local coupling in our model, the emergence of the zealots can only play a role in a small scope, so they cannot produce a wide range of influence. Therefore, they do little to promote the formation of group consensus.

To further analyze the opinion leader's influence on the group polarization in Internet group opinions, we take $x$ of opinion leaders as a constant (rather than a random value) from $-1$ to 1 and observe how the supportive ratio changes. The results are shown in Figure 14 where we keep parameters $a = 0.7$, $b = 0.3$, and $c = 0$ unchanged, and the time evolution steps are 1000 for each experiment. With the increase of $x$ of opinion leaders, supportive ratio gradually increased. Figure 14 also shows that, during the communication process of networks opinions, if opinion leader takes supportive opinion ($0 < x_l \leq 1$), the group will finally tend to the supporting direction of polarization. Conversely, if opinion leader takes opposed opinion ($-1 \leq x_l < 0$), the group will finally tend to opposed direction of polarization.

At the end of this subsection, we will take the double opinion leaders as an example of multiopinion leaders so as to analyze the polarization of group opinions further. When both of the initial opinions of the two opinion leaders are inclined to support or oppose the events, the group opinions also accordingly tend to support or oppose. Here, we mainly give the simulation results of inconsistent status where one opinion leader supports the events but another opposes (Figure 15).

We can find that polarization emerges when the opinions of two opinion leaders are inconsistent. Literature [56] uses the linear feedback method to control a small number of nodes in the networks so as to promote the networks evolving into two or more stable equilibriums. In fact, the controlled nodes in literature [56] have characterized substantially opinion leaders in our model; the difference is that the controlled nodes respond through getting the average information of whole group, but opinion leaders in this paper influence Internet group opinions by wide scope impact and high degree. Because opinion leaders are also affected by other individuals, group opinions evolve toward the polarization of absolute support or opposition.

*3.3. Influence of External Intervention.* In many Internet events, external intervention such as the government or newspapers will have influences on the polarization of group opinions. So, we will test the external influence in this subsection.

When $a = 0.6$, $b = 0.2$, and $c = 0.2$, we find that only a small external influence $I_o = 0.1$ can change the trend of Internet group opinions (Figure 16). Even though the opinion of opinion leaders is $-0.6$, it can be changed to support by the external influence. The results show that the government can more effectively prevent the diffusion of negative effects by handling hot events actively and carrying out a wide range of positive publicity through Internet, television, radio, and newspapers.

In order to observe the comprehensive effect of neighbors, opinion leaders, and external influences, we present Figure 17. By adjusting the parameters of model, we get three areas of A, B, and C. Area A corresponds to the first stage of the evolution process of group opinions ($a = 1$, $b = 0$, and $c = 0$); that is to say, there are no opinion leaders and outside interventions at this stage; polarization process is only influenced by neighbors. Obviously, the polarization has already emerged in this stage. By adjusting the parameters to $a = 0.8$, $b = 0.2$, and $c = 0$, we get area B which represents the opinion leaders join in the group. As can be seen from area B, the appearance of opinion leaders can lead to the opinions shift successfully. At last, we introduce the external influence by modifying the parameters to $a = 0.6$, $b = 0.2$, and $c = 0.2$, and set $I_o = 0.1$. We can see from area C that the external interaction can shift the direction of Internet consensus easily.

## 4. Conclusions

Many common phenomena in human society such as the polarization have been researched for a long time in social psychology [13, 57]. With the rapid development of the Internet, people's living habits and ways of communication are undergoing great changes. Many classic studies of social psychology problems have been given a new form especially since the complex networks are proposed. Due to its advantage for reflecting the reality of social networks features, more and more social psychology issues take complex networks as a new physical framework [58], such as evolution of cooperation [59–62] and dissemination of group opinions spread. In

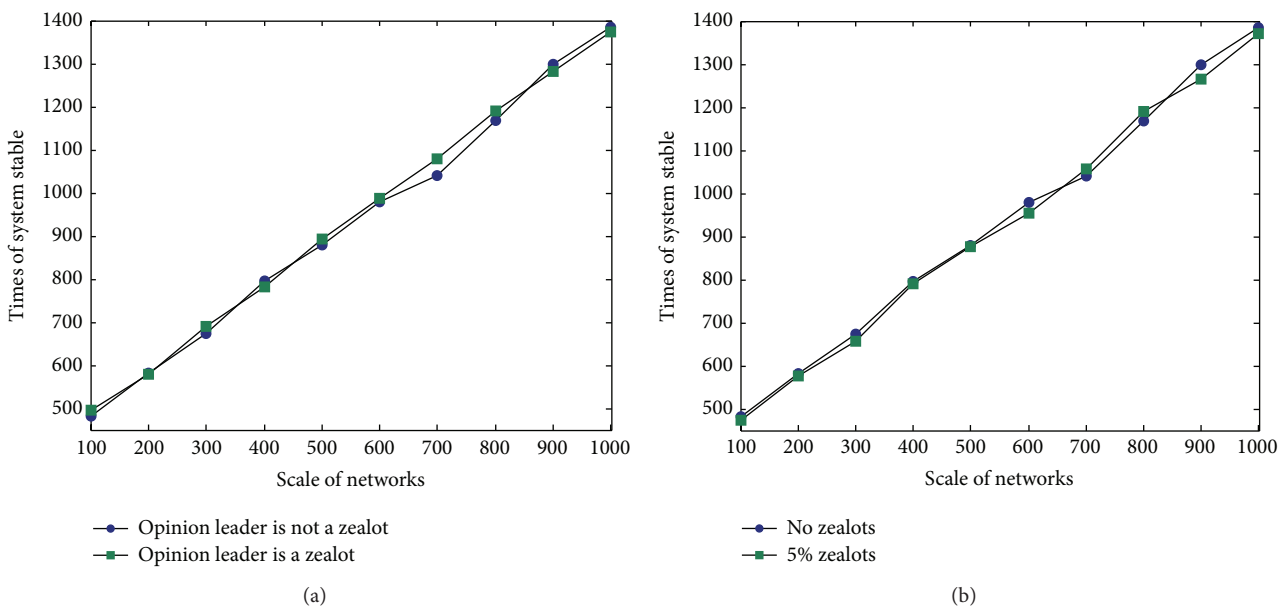



Figure 13: Influence of zealots on the times of system stable under different scale of networks. (a) It is not obviously different for promoting group consensus when the opinion leader is a zealot. (b) It is not obviously different for promoting group consensus in the case of random selection of 5% individuals as zealots. Both in (a) and (b), zealot's opinion is 1. Each data point is an average over 30 independent experiments.

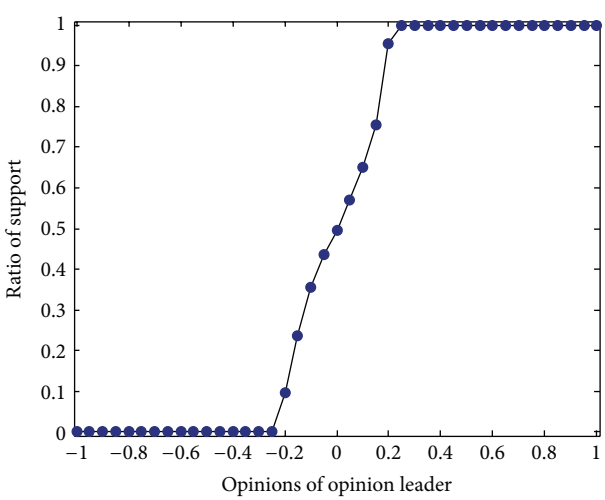



Figure 14: When $a = 0.7$, $b = 0.3$, and $c = 0$, supportive ratio changes with the opinion of opinion leaders. Each data point is an average over 30 independent experiments.

fact, networks of opinions spread are also a form of complex networks. As more and more people are communicating through Internet, polarization in Internet group opinions has become increasingly common phenomenon.

Different from traditional methods of qualitative analysis, synthetically considering the influence of neighbors, opinion leaders, and external influences, this paper studies polarization problem in Internet group opinions based on Cellular Automata simulation technology, and we made the following findings:

(1) Unlike the previous simulation experiments which take on two-dimensional periodic boundary lattice, this paper established a networks model of Internet group opinions spread, on which a new Cellular Automata simulation model is proposed.

(2) Both continuous opinions and discrete opinions can promote the polarization of group opinions when we only consider the influences of neighbors, and continuous opinions are faster than discrete opinions in making the system stable.

(3) Coevolution of networks and opinions takes more time to make the system stable than fixed networks. Different from the results of local coupling which lead to the polarization of group opinions, the system shows consensus under global coupling.

(4) The appearance of opinion leaders breaks the polarization and promotes the emergence of consensus in Internet group opinions. However, different from the existing conclusion in [34], both taking the opinion leaders as zealots and taking some randomly selected individuals as zealots are not conductive to the consensus.

(5) Double opinion leaders with consistent opinions will accelerate the formation of group consensus, but the opposite opinions will lead to group polarization.

(6) Only small external influences can change the evolutionary direction of Internet group opinions.

The study of opinions polarization has been introduced in the past decade [10–17], and many research results have emerged. Compared with the previous models, the model

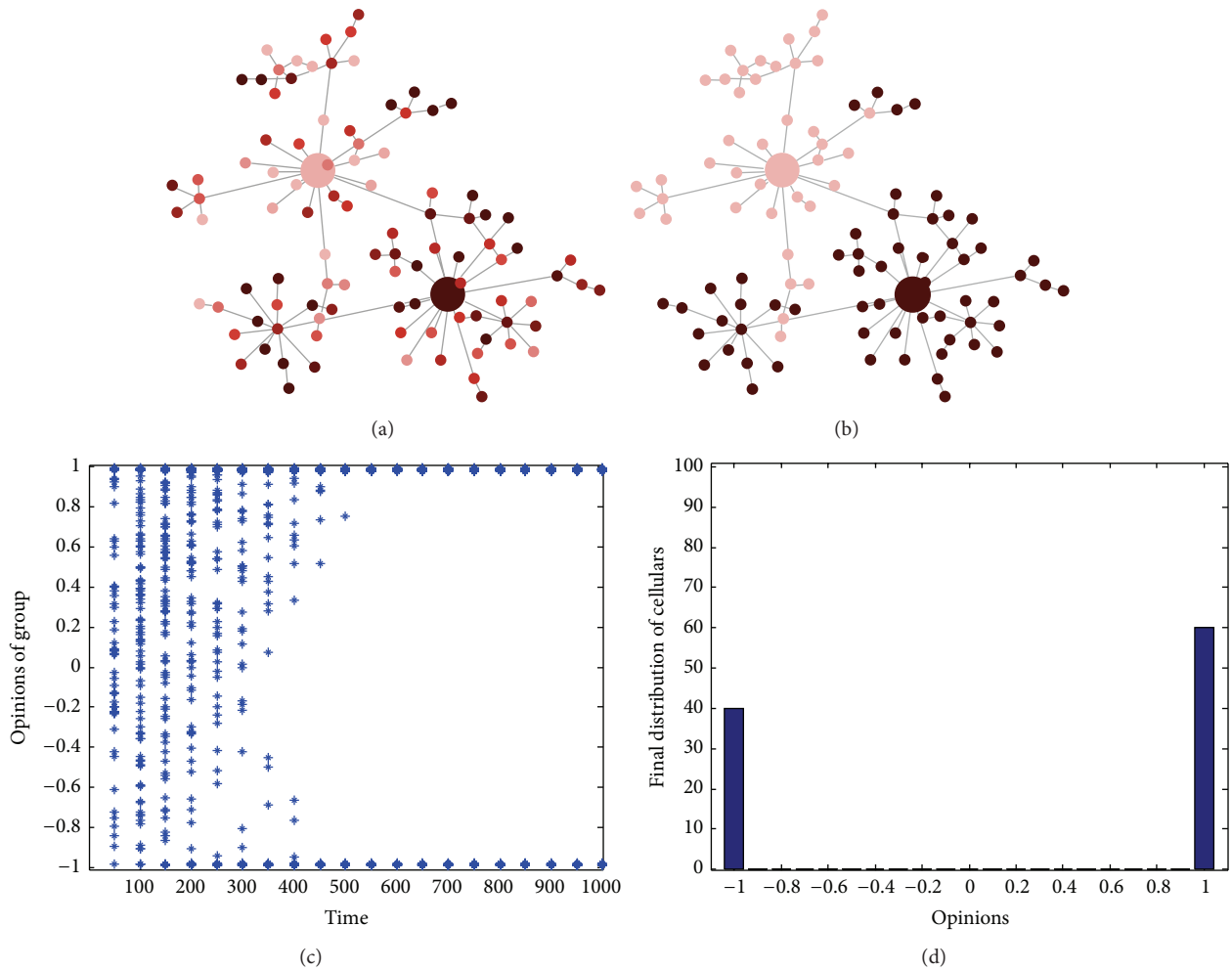



FIGURE 15: When $a = 0.7$, $b = 0.3$, and $c = 0$, two opinion leaders influence the polarization of Internet group opinions. (a) Opinions distribution at 100 time steps; the opinion of two opinion leaders is −0.6 and 0.8, respectively. (b) Opinions distribution at 1000 time steps; the opinion of two opinion leaders changes to −1 and 1, respectively. (c) Opinions of group change with time when there are two opinion leaders. (d) Histogram of final distribution of group opinions.

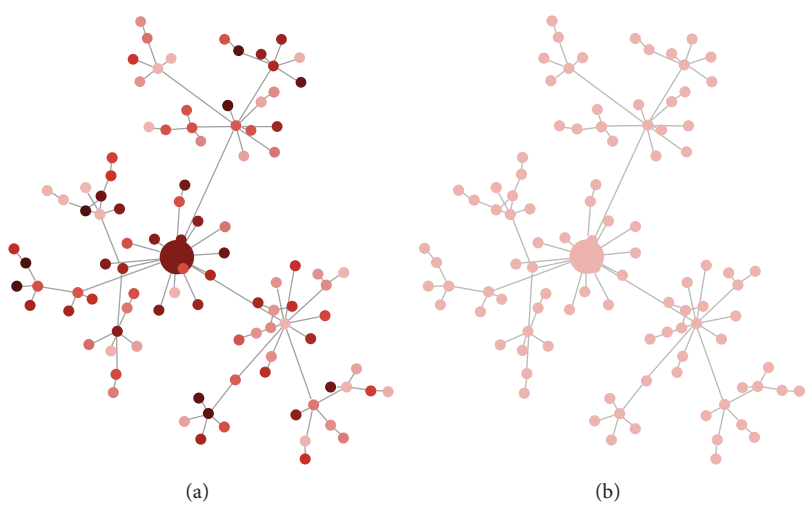



FIGURE 16: When $a = 0.6$, $b = 0.2$, $c = 0.2$, and $I_o = 0.1$, external intervention influences the polarization of Internet group opinions. (a) Opinions distribution at 100 time steps; the opinion of opinion leader is −0.6 now. (b) Opinions distribution at 1000 time steps; the opinion of opinion leader changes to 1.

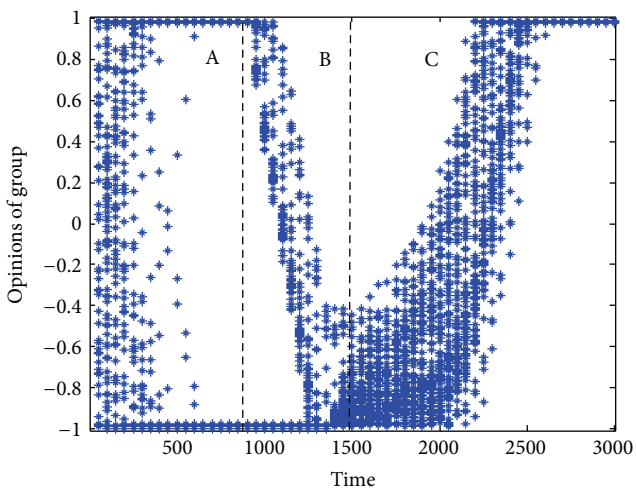



Figure 17: Group opinions change with time. Areas A, B, and C correspond to the three stages of the evolution process of group opinions by adjusting the parameters of $a$, $b$, $c$, and $I_o$. The parameters in area A are $a = 1$, $b = 0$, and $c = 0$; in area B they are $a = 0.8$, $b = 0.2$, and $c = 0$; in area C they are $a = 0.6$, $b = 0.2$, $c = 0.2$, and $I_o = 0.1$.

proposed in this paper is reflecting more the actual background of Internet group opinions; in spite of considering the neighbors influence and external influence, we add the important factor of opinion leaders. We hope this study succeeds in providing a framework that is very much susceptible to this phenomenon. The next work will further consider influence of opinion leaders on population differentiation and the role of the convergence and the control of polarization in Internet group opinions. In addition, because the topology of networks could also be a key factor when information spreads among individuals, the networks model in this study may be replaced by Small-World networks [63], regular networks [64], or interdependent networks [65].

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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