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AN OPINION EVOLUTION MODEL BASED ON SOCIAL REINFORCEMENT OF MICROBLOG NETWORK

Quan Liu and Lili Rong

Institute of Systems Engineering
Dalian University of Technology
No. 2, Linggong Rd., Dalian 116024, P. R. China
quanshuilq2005@163.com; llrong@dlut.edu.cn

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Abstract. *Microblog plays an important role in the evolution of the public opinion. This paper proposes an opinion evolution model of microblog network, in which the memory effects and social reinforcement on opinion spreading are taken into account. The following conclusions are reached through simulation. When the proportion of two initial opinions diverges largely among individuals, the opinions are more likely to evolve to dictatorship state. The opinions distribution in final state is closely related to the proportion of initial opinions, spreading rate, memory effects and social reinforcement, while irrelevant to the out-degree and opinion of initial infected agent. This work provides a new insight into the opinion evolution on social media, and gives reference to the guidance of public opinions.*
Keywords: Social reinforcement, Opinion evolution, Information diffusion, Microblog network

1. **Introduction.** With the arrival of Web2.0 age, microblog network (Twitter, Sina microblog, etc.) and online social network (Facebook, Renren, etc.) are developing rapidly. Information diffusion and sharing are becoming faster and more convenient, which makes people interact on the Internet more frequently. Information diffusion on the microblog network and online social network has attracted more and more concerns of researchers. Xiong et al. [1] proposed an information diffusion model on microblog network considering four possible states: susceptible, contacted, infected and refractory, which shows that scale-free network has more contacted state comparing with regular network. Lü et al. [2] constructed an information spreading model which took memory effects and social reinforcement into account, and carried out simulation experiments on the small-world network as well as regular network. Basically, the existing information diffusion models were transformed from the epidemic model [1-4], combining the feature of information diffusion.

In the numerous high-profile incidents in China, such as "Yao Jiaxin murder case in China", network public opinion has played a powerful role on influencing the development and final results of these incidents. The researches on the formation and evolution of public opinion attract more and more attention. Related dynamical models of public opinion include Sznajd model [5,6], Deffuant model with bounded trust [7-10], KH model [11-13], and so on. Although the existing research explained some factors of public opinion diffusion and formation, they ignored an important psychological characteristic in the public opinion diffusion, which is social reinforcement. At the same time, research on the opinion evolution on microblog network is relatively rare.

Individual's choice can be reinforced by his or her friends, for example, Microsoft's dominance of the operating system market and eBay's dominance of the online auction market [14]. The so-called social reinforcement is defined as the situation in which an individual requires multiple prompts from neighbors before adopting an opinion or behavior [15]. Some recent works indicate that social reinforcement plays an important role in the propagation of opinions, news, innovations and fads [16,17]. The rapid growth in popularity of social networking sites, such as Facebook and MySpace, also illustrates the importance of social reinforcement: people join because their friends have already done so [18]. Social reinforcement also exists in the opinion evolution.

Microblog has functions such as retweeting, and comments, which allow users to express their opinions in the information diffusion, meanwhile the public opinion is formed in the information diffusion and real-time interaction of opinions. So this paper pays more attention to the memory effects and social reinforcement and makes a research on the interaction, diffusion and evolution of opinions on microblog network. The simulation experiments show that: when the divergence of the proportion of two initial opinions is large among individuals, social reinforcement makes the opinions more likely evolve to dictatorship state; the opinions distribution in final state is closely tied to the proportion of initial opinions, spreading rate, memory effects and social reinforcement, while irrelevant to the out-degree and opinion of initial infected agent; when the spreading rate of information reaches a certain threshold, the probability of forming the public opinion will reach a steady state.

2. **Model Construction of Opinion Evolution on Microblog Network.** On microblog network, every user can be a publisher, recipient or sharer of information. When a user posts a message or expresses an opinion, his or her audiences will have certain behaviors after receiving the message: if interested, they spread it with certain probability attaching some comments; if not, they will not spread this information. This mechanism constitutes a channel for the exchange of opinions. When a user receives a similar opinion from his or her friends for several times, he or she will be more likely to accept it. As the opinions constantly are interacted among agents, a public opinion may gradually form.

Centola's experiment indicates that redundant signals significantly increased the likelihood of adoption; social reinforcement from multiple health buddies made participants much more willing to adopt the behavior [16]. So, the probability for microblog users to accept the opinion when receiving it for several times is higher than for only one time. With the introduction of social reinforcement and memory effects to opinion evolution, considering the characteristics of opinion spreading on microblog network, we construct this opinion evolution model of microblog network.

We define users of microblog network as nodes, the relationships between them as directed edges, which mean: an edge from node B to node A represents user A is a follower of user B, and information and opinions can only spread along the directed edges. Using the epidemic model for reference, on basis of analyzing the characteristics of information and opinions spreading, we divide the nodes in microblog network into four categories: susceptible, contacted, infected and refractory. Susceptible nodes represent users who have the opportunity to receive the message but have not received yet; contacted nodes represent users who have already received the message from neighbors but do not spread it, and may spread next time if receiving the message again; infected nodes will spread their opinion on the message after receiving it; refractory nodes represent the users have lost interest in the information and will never spread it.

We set the assumptions of model as the following. Firstly, each user has his own original opinion toward a topic, which is determined by his education background, social status, etc. Secondly, there are two kinds of opinions towards a topic: support (A or 1) or against (B or -1). At last, infected agents spread the opinions along with their spreading of information (we temporarily only consider the opinions spreading brought by retweet feature).

Agent's opinion and state are updated asynchronously, which means every agent's opinion and state are successively updated every time step. During a time step, we randomly select an agent from the network, whose opinion and state are determined by last step's opinions and states of itself and its neighbors. Every time step ended with all agents updated.

(1) Susceptible agents have a probability of λ being infected by its infected neighbor nodes, and update to infected state, otherwise have a probability of $1-\lambda$ updating to the contacted state. Infected agents will spread their opinions when spreading information, which can be support (A or 1) or against (B or -1). Susceptible agents' opinion can be infected by infected agents' opinion with the probability of $P(m)$ if their opinion differs; while receiving the same opinion, agents' opinion remains unchanged. Here we define $P(m) = (\alpha - T)e^{-b(m-1)} + T$, α is the probability to accept the opposite opinion for the first receipt [2]; T is the upper bound of the probability indicating maximal approving probability ($T = 1$, in this paper); b reflects the social reinforcement effect ($b > 0$), larger b indicates stronger social reinforcement; m represents cumulative times that nodes receive opposite opinions from last time step to the t time step, and the node will at least receive the opposite opinion for one time at time step t; the memory effects are embodied by $m(t)$.

(2) Contacted agents will gradually lose their interest in spreading information, and some of them spontaneously turn into refractory state with probability of β, the remaining contacted agents have the probability of λ being infected by their infected neighbors and turn into infected state, or keep in contacted state otherwise. When contacted agents have been infected, their opinion can be changed with probability of $P(m)$, and only the infected agents can infect the opinion of their neighbor agents. When agents updated from contacted state to refractory state, their opinion will not change any more. So there are only two states in the final states: susceptible state and refractory state.

(3) Infected agents automatically update to contacted state when going to the next time step, with their opinions staying unchanged.

(4) Refractory agents' state and opinion remain unchanged.

3. **Model Simulation and Analysis.** In order to study the opinion evolution on microblog network, firstly we built a microblog network based on the cognitive-costed agent model [19]. We define the whole microblog network is an un-weighted digraph notated as $G(V, E)$, where V means node set, and E means the directed edge between agents that have followed relation. Total number of nodes is 4031, average out-degree is 2.45 and maximum out-degree is 94. Out-degree distribution of nodes is shown in Figure 1, which presents a power-law distribution.

Figure 2 shows the agents' states transformation rules between four possible states and opinion evolution rules.

We define $S(t)$, $C(t)$, $I(t)$, $R(t)$ as the proportion of susceptible, contacted, infected and refractory agents respectively. In Figure 3, out-degree of initial infected agent is $k_0 = 55$, while the rest agents are susceptible state. Set the parameters as follows: $\lambda = 0.4$, $\beta = 0.01$; iterations number is 500; simulation number n is 100. Through the simulations, we obtained the density evolution over time of susceptible agents, contacted agents, infected agents and refractory agents (Figure 3). In Figure 3, abscissa t is the time step while the ordinate is the proportion of four-state agents in total agents. A large area of the information spread occurs at about $t = 10$.

In the beginning, information spread fast in the network. The susceptible agents decreased rapidly with growth of the quantity of infected agents and contacted agents, and gradually tended to zero. Infected agents and contacted agents grew rapidly at initial stage while reaching maximum at about $t = 10$, then gradually decreased until approaching zero. Refractory agents grew rapidly at initial stage, then slowly increased with the

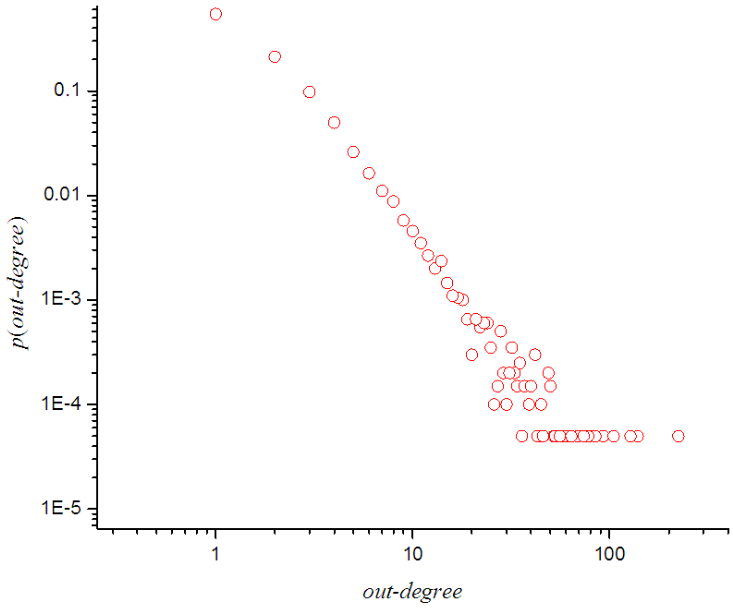

FIGURE 1. Out-degree distribution of microblog network

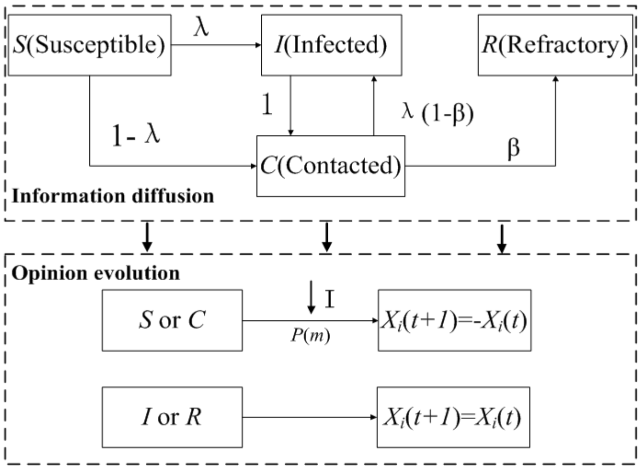

FIGURE 2. The process of information diffusion and opinion evolution

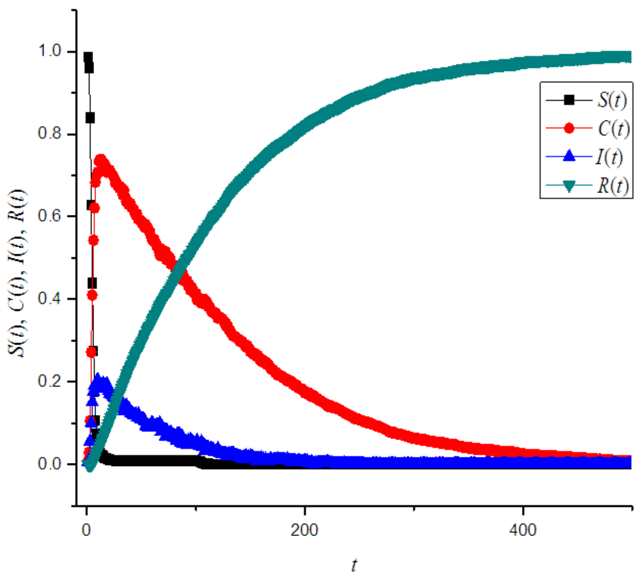

FIGURE 3. Time plots for density of susceptible, contacted, infected and refractory agents

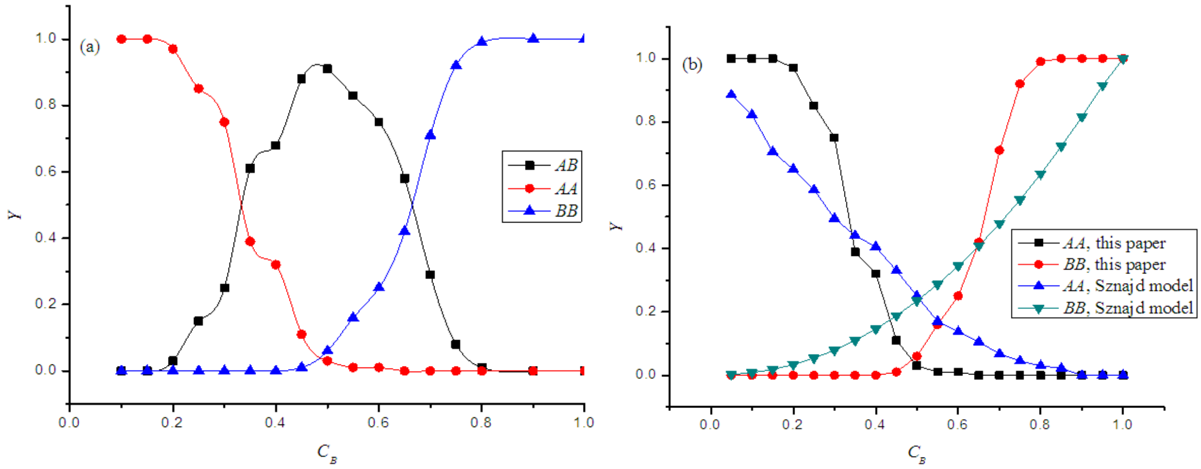

FIGURE 4. Relations between initial opinion distribution and final state ($\lambda = 0.4$, $\beta = 0.01$, $\alpha = 0.1$, $b = 0.8$, $k_0 = 55$)

decrease of contacted agents, gradually tended to N. When t tended to 200, infected agents and susceptible agents gradually reached a plateau, opinion interactions and evolution gradually came to an end, which implied that people have lost interest in the concerns of this information, and left only the contacted agents transfered to the refractory agents. At the initial stage, information spread to the whole network due to the virus-spreading way of microblog. At this moment hot debate was aroused, and opinion collision was fierce. Along with people concern decreased as well as opinions on microblog tended to unify, information and opinion evolution gradually calmed down.

Keeping other factors constant, only take the effect of initial opinion distribution on final evolution state into account. In Figure 4, AA and BB represent the states of consensus and AB represents the state of stalemate at final state. The abscissa C_B is the proportion of opinion B in initial opinion distribution. The ordinate Y is the probability of AA, BB or AB. The initial opinions of agents are uniformly distributed. Conclusions can be reached from Figure 4(a): When the initial proportion of B is more than 45%, opinion B is likely to become the state of consensus (BB); if the initial proportion of B exceeds 80%, B is bound to become the state of consensus (BB). We compared our results with Sznajd model [5] in Figure 4(b). Although the numerical results of the two models have some differences, the curvilinear trend is almost consistent. When $C_B > 0.65$ or $C_B < 0.35$, the probability that opinions become the state of consensus is greater than Sznajd model. When $0.35 < C_B < 0.65$, the probability that opinions become the state of consensus is lower than Sznajd model. As the above results indicate, when one opinion has the advantage with the social reinforcement, the opinion evolution is more likely to become unified. Considering the opinion evolution stage, there are agents converting to refractory agents continuously, in which the opinions may be A or B. There are susceptible agents in the final stage as well, as their opinions are not affected by the evolution. Therefore, there must be two opinions in the final state. In this paper, we choose opinion (A or B) more than 90% of the total number of nodes as the approximate dictatorship state (express as AA or BB). Hereinafter we adopt this approximation if there is no special explanation.

Keeping other factors constant, only consider the effect of social reinforcement on final opinion distribution. The abscissa b and ordinate Y of Figure 5 respectively represent the social reinforcement strength and the probability of A in the state of consensus (AA) at final state. When the value of social reinforcement is 0, then $P(m) = \alpha$, a unified opinion could not be reached at this time, all in stalemate. If the social reinforcement strength is low (lower than 0.3), Y increases with the increasing of b, the effect of social

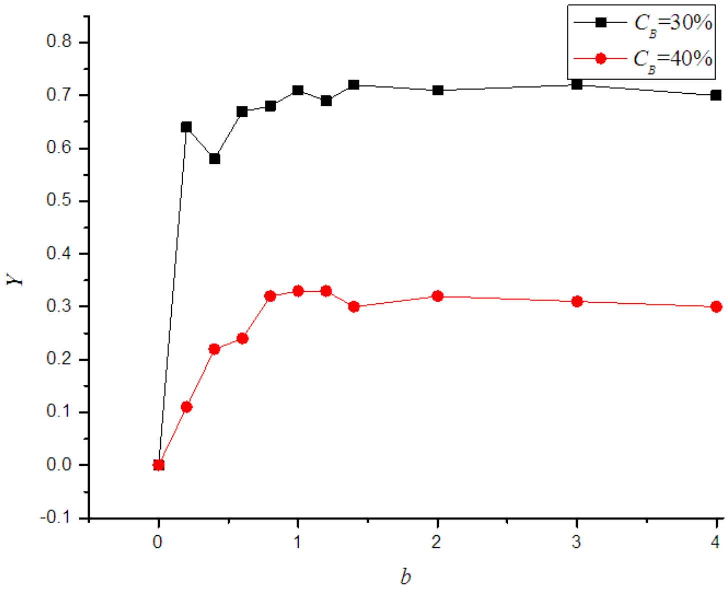

FIGURE 5. Relations between b and final state ($\lambda = 0.4$, $\beta = 0.01$, $\alpha = 0.1$, $k_0 = 55$)

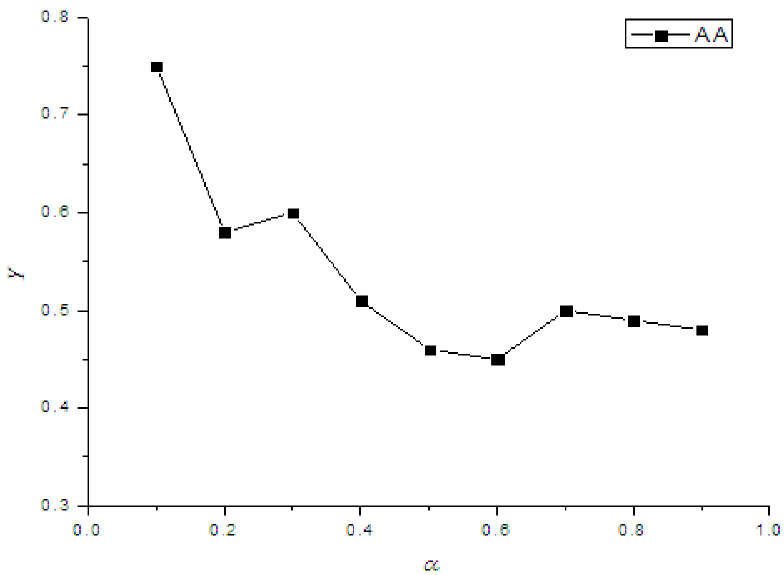

FIGURE 6. Relations between α and final state ($\lambda = 0.4$, $\beta = 0.01$, $b = 0.8$, $k_0 = 55$, $C_B = 0.3$)

reinforcement is obvious. When social reinforcement reaches a certain level of 0.8, its effect will gradually be in a stable state. When $C_B = 0.3$ and $C_B = 0.4$, the curvilinear trends are consistent.

Keeping other factors constant, only consider the effect of the probability to accept the opposite opinion for the first receipt. In Figure 6, the abscissa α is the probability to accept the opposite opinion for the first reception, and ordinate Y represents the probability of A in the state of consensus (AA) at final state. As shown in Figure 6, when α is between 0 and 0.4, the effect of α at final state decreases with the increasing of α; when α is higher than 0.4, its effect is small.

Keeping other factors constant, only consider the effect of the spreading rate on final state. In Figure 7, abscissa λ represents the spreading rate (high spreading rate means high interaction intensity of opinion spreading), ordinate Y represents the probability of A in the state of consensus (AA) at final state. We simulate two situations where the

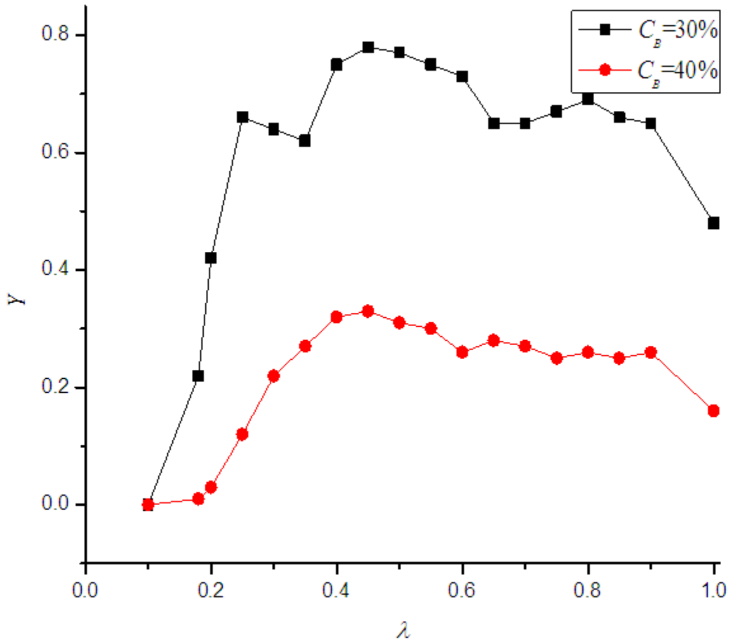

FIGURE 7. Relations between spreading rate and final state ($\alpha = 0.1$, $\beta = 0.01$, $b = 0.8$, $k_0 = 55$)

initial opinion distribution $C_B = 0.3$ and $C_B = 0.4$ respectively. As we can see from Figure 7, when the spreading rate is low (lower than 0.3), Y increases with the increasing of λ; when the spreading rate is high enough (higher than 0.3), there is no significant change of Y with the increasing of λ. When $C_B = 0.3$ and $C_B = 0.4$, the curvilinear trends are consistent.

4. **Conclusions.** Microblog is playing an increasingly important role in the formation of public opinion, and the public opinion dynamics based on microblog has attracted much attention. We study the opinion evolution mechanism on microblog network by proposing an opinion evolution model of microblog network, in which considering the social reinforcement and memory effects, then simulate it using the theory of complex network. Our model explains the group polarization phenomenon in microblog network. The simulation results show that: Firstly, information diffusion and opinions spreading grow rapidly at initial stage, then the growth rate declines slowly into stable stage. Secondly, when the proportion of initial opinions differs, social reinforcement and memory effects make the opinions more likely to evolve into the state of consensus. At last, the opinions distribution in final state is closely tied to initial proportion of opinions, spreading rate and social reinforcement strength, while irrelevant to the out-degree and opinions of initial infected nodes.

As the online social network is similar to microblog network, the results of this model can also be applied to online social network. Our work aids better understanding of the mechanisms of opinion evolution and how public opinion formed. Determining how network structure affects opinion evolution and considering feasible methods to intervene public opinion evolution are two possible directions for future research.

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