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Research Article

A Dynamic Microblog Network and Information Dissemination in "@" Mode

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Social media, especially the microblogs, emerge as a part of our daily life and become a key way to information spread. Thus, information dissemination in the microblog became a research hotspot. Based on some principles that are summarized from the microblog users' behaviors, this paper proposes a dynamic microblog network model. Through simulations this network has the features of periodicity of average degree, high clustering coefficient, high degree of modularity, and community. Besides, an information dissemination model through "@" in the microblog has been presented. With the microblog network model and the zombie-city model, this paper has modelled an artificial microblog and has simulated the information dissemination in the artificial microblog with different scenes. Therefore, some interesting findings have been presented. (1) Due to a better connectivity, information could spread widely in a random network; (2) information spreads more quickly in a stable microblog network; (3) the decay rate of the relationships will have an effect on information dissemination; that is, with a lower decay rate, information spreads more quickly and widely; (4) the higher active level of users in microblog could promote information spread widely and quickly; (5) the "@" mode of information dissemination makes a high modularity of the information diffusion network.

1. Introduction

With the development of information and communication technology, social media are emerging. Social media become an important channel for information spread, especially microblogs. For example, in China, there are around 618,000,000 Internet users and the number of the microblog users is larger than 281,000,000 [1]. People could receive real-time information from the microblog, which is a novel and quicker way than traditional modes like newspaper. The microblog is changing the mode of information dissemination and even has an important impact on the real society. As one knows, microblog platforms such as Twitter have played an important role in Arab Spring [2, 3], and people could transmit and get the crucial information based on the microblog, which has promoted revolutionary information spread and social progress. Information spreads in microblog platforms through several ways such as posting microblogs, retweeting microblogs, and comments on microblogs. In addition, a user could use the "@" mode to "@" his/her followers (who follow this user) or followings (who are followed by this user), when he/she posts, retweets, or comments in the microblogs. This "@" mode could improve information dissemination in microblog platforms. Thus, studying the information dissemination through the "@" mode is a meaningful and interesting work.

The motivation of this paper is to research into the information dissemination in a microblog through "@" mode, including the effectiveness of information spread and factors affecting information spread. However, the microblog is a mapping of the real society, and the changes and evolutions of the microblog may have effects on the real society. Experiments on the microblog also result in negative impacts on the real society, and these experiments are also unrepeatable. Due the high cost and nonrepeatability of experiments in the real microblog platforms, we should borrow the idea of social computing and artificial society to research into information dissemination and the corresponding issues in the microblog. As the social network of the microblog plays a key role in information dissemination and is also an important part of artificial societies, firstly we should study how a microblog network dynamically evolves. Through the analysis of the microblog users' behaviors, we could acquire some principles of the microblog network: (1) people have different limited abilities to follow others (different maximum out-degree); (2) mutual following or connecting; (3) people prefer to follow others with larger followers; (4) transitivity—people prefer to follow their followings' followings; (5) following relationships will decay with time. Based upon these characteristics, we could propose a microblog network model to reconstruct such a microblog network in the computer world. Moreover, the information dissemination model will affect the information spread, and we should also study on how information spreads. Some modes could aid in information dissemination in the microblog, and the "@" mode is an important mode for information diffusion in the microblog, which means that information is transmitted from user A to user B when user A "@" user B. Hence, the "@" mode is our focus, and we propose a model of information dissemination in "@" mode. In order to research into information spread in "@" mode, we need a general model to construct an artificial society, including users, social network, and the environment. Recently, there are some artificial society models, such as the classical artificial society model—sugarscape [4]. These models could not intuitively aid to construct artificial societies. Zombie-city model [5–7] is a new artificial society model and more suitable for the issues like infectious diseases spread and information dissemination. Based on the proposed microblog network and the information dissemination model, we could construct an artificial microblog with the zombie-city model, and then study the information dissemination in the microblog with different scenes. In this case study, some valuable and interesting results and findings could be seen.

Main contributions of this paper are as follows: (1) proposing a model for the dynamical microblog network based on the analysis of characteristics of the real microblog network; (2) aiming at the "@" mode in microblogs and borrowing the existing model for infectious disease spread, proposing the information dissemination model in "@" mode; (3) borrowing social computing and artificial society, acquiring some meaningful findings through experimental simulations in different scenes.

The remaining sections of this paper are organized as follows. Section 2 analyzes the characteristics of the real microblog networks and proposes a dynamic microblog network model based on the features of the microblog users' behaviors. Section 3 presents the information dissemination model through "@" mode in the microblog. Based on the zombie-city model, Section 4 makes some experiments for the information dissemination in an artificial microblog, and then experimental simulations and analysis show some interesting results. Section 5 summarizes the work of this paper and presents some conclusions and looks forward to the future works.

2. Dynamic Microblog Network

Like the friendship network (JGN) [8, 9] in the real society, the microblog network is dynamically growing. Based on three simple principles, we could acquire models of the friendship network and this network is an undirected network. A social network model is presented based on the analysis of microblog users' behaviors [10], which also shows the distributions of out-degree of the microblog network presenting power-law characters and the microblog has a high average clustering coefficient. As we know, the microblog network is a directed graph and the JGN network is not suitable for the microblog network because of an undirected graph. The microblog network is a directed network and is different from the friendship network. Therefore, we should summarize some characteristics about the real microblog network to reconstruct this network in computer world.

2.1. Characteristics of Microblog Networks. An increasing number of people use microblog platform to broadcast their news and express their mood. There are many connections between these users, that is, following relationships. When user A wants to get news from another user, B, then user A could follow user B in the microblog and user A could receive the microblog of user B in real time. The relationship from user A to user B is a following relationship that is directed. Thus the microblog users and their relationships could form a social network, which is similar to the friend social network (JGN). However, the microblog network is a directed graph; that is, the links or connections between users are directed. As for the dynamical behaviors of users, the microblog network is a complex and growing network and users dynamically follow other users or stop to follow other users. There are some characteristics about the dynamical microblog network. As we know, there will be an increasing number of users in microblog platform, but in a short time we could consider that the number of users is stable; that is, the population dynamics will not be mentioned.

(1) Different Abilities of Users. Each user has his/her own abilities or power (one user could not follow a great number of users), and abilities of users are distinct. As we know, fewer people have powerful abilities; that is, fewer users follow a large number of users and more users follow a small number of users. Different abilities of users bring the different max out-degree of users. The distribution of max out-degree may follow power-law distribution with the scaling feature [11].

(2) Mutual Following. A microblog user is inclined to follow the users who have followed this microblog user. As shown in Figure 1, user B has followed user A, and then it is more possible that user A may follow user B. Due to the mutual following, one user in a microblog platform may follow several fans or followers of this user.

(3) Transitivity of Following Relationships. Users may be interested in whom their followings follow, and these users more possibly want to follow their followings' followings. These following relationships have the characteristic of transitivity. As seen in Figure 2, user C is a following of user A and user B is a following of user C. Hence, user A is inclined to follow the users who are followed by user C; that is, user A will more probably follow user B. This situation is similar to the scene

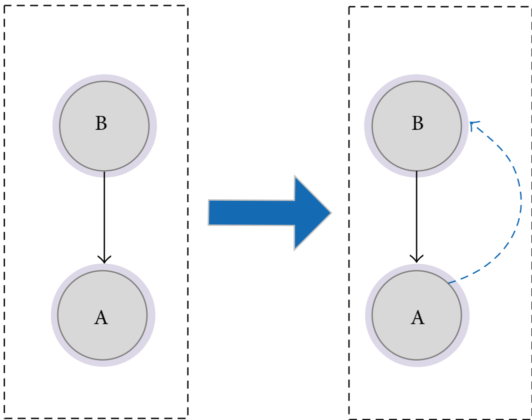


FIGURE 1: Mutual following.

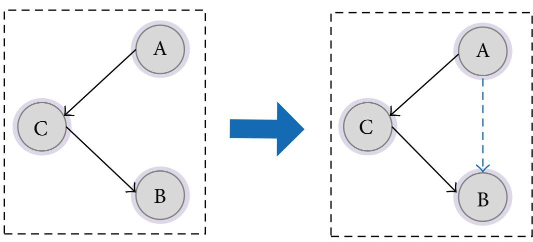


FIGURE 2: Transitivity of following relationships.

in real society, and people more possibly make friends with their friends' friends.

(4) Preferential Following (Matthew Effect). Usually, Matthew effect is used to describe the phenomenon that the rich will get richer and the poor will become poorer. Similarly, users in a microblog with a large number of followers will have more and more followers due to Mattew effect. As shown in Figure 3, users may more probably follow the users who have been followed by many users, which will make some users become the star users who have a large amount of fans, for example, the president of USA, Obama, in Twitter.

(5) Decay of Following Relationships. Like friendships in the real society, following relationships may decay with time. Because interests of users are developing and changing, some users may not be interested in their followings any more, and then users may cancel the following relationships. The stability of a microblog network connects with the decay rate of these following relationships. When the decay rate is higher, the stability will be worse and vice versa.

2.2. Mathematical Model of a Dynamic Microblog Network. Based on the above characteristics, whether node i connects to node j depends on the following factors: (1) the out-degree of node i; (2) whether node j has connected to node i; (3) the in-degree of node j; (4) the number of nodes, which are the out-neighbors of node i and also are the in-neighbors of

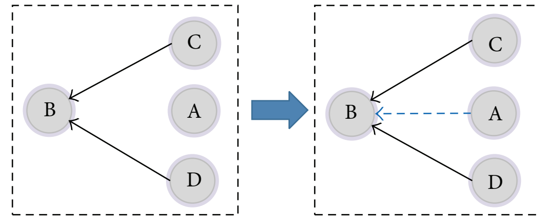


FIGURE 3: Preferential following (Matthew effect).

node j. Hence, the probability of node i connecting to node j could be expressed by the math equation

$$p_{ij} = f_1(z_{i\rightarrow}) f_2(\mathrm{link}_{ji}) f_3(z_{j\leftarrow}) g(m). \tag{1}$$

The function $f_1(z_{i\rightarrow})$ is larger for small $z_{i\rightarrow}$ (the out-degree of node i) and decreases sharply around the transition value $\mathrm{ownz}^*_{i\rightarrow}$. The distribution of $\mathrm{ownz}^*_{i\rightarrow}$ follows the power-law exponential distribution ($P(\kappa) \propto e^{-\kappa/\mu}$). This represents that each node has a limit ability to connect to another node and their abilities are different. One possible formation of this function is as follows:

$$f_1(z_{i\rightarrow}) = \frac{1}{e^{\beta(z_{i\rightarrow} - \mathrm{ownz}^*_{i\rightarrow})} + 1}. \tag{2}$$

The function $f_2(\mathrm{link}_{ji})$ is presumably large for $\mathrm{link}_{ji} = 1$ (that means node j has connected to node i) and then falls off sharply with $\mathrm{link}_{ji} = 0$. This means that a node will more probably connect to the node that has connected to itself. The possible functional form can be described as

$$f_2(\mathrm{link}_{ji}) = 1 - \frac{p_0}{e^{\varepsilon \mathrm{link}_{ji}}}. \tag{3}$$

The function $f_3(z_{j\leftarrow})$ is small for small $z_{i\leftarrow}$ (the in-degree of node j) and increases with the value $z_{i\leftarrow}$ heightening. This presents that the nodes, in which a larger number of nodes are connecting to, will attract more nodes to connect to themselves. The possible function can be formed as

$$f_3(z_{j\leftarrow}) = \frac{1}{1 + e^{-\lambda z_{j\leftarrow}}}. \tag{4}$$

The function $g(m)$ increases with the value m growing. The value m represents the number of nodes in which node i has connected to and has connected to node j. The functional form could be depicted as

$$g(m) = 1 - (1 - p_1) e^{-\alpha m}. \tag{5}$$

Above these situations, there is another situation that microblog users may cancel the following relationships. We could give the strength of this following relationship, and s_{ij} represents the strength of following relationship from user i to j. If node i begins to follow node j, then s_{ij} is set to 1. If node i has not connected to node j, then $s_{ij} = 0$. As time passes, the strength decreases exponentially as $s_{ij} = e^{-\kappa\Delta t}$. When s_{ij} is less than a threshold, node i will cancel the connection to node j. At the moment, the active level of Sina (Chinese largest microblog platform) users is around 0.7, so we could set the threshold to 0.3. If $s_{ij} < 0.3$, then node i will cancel the connection to node j.

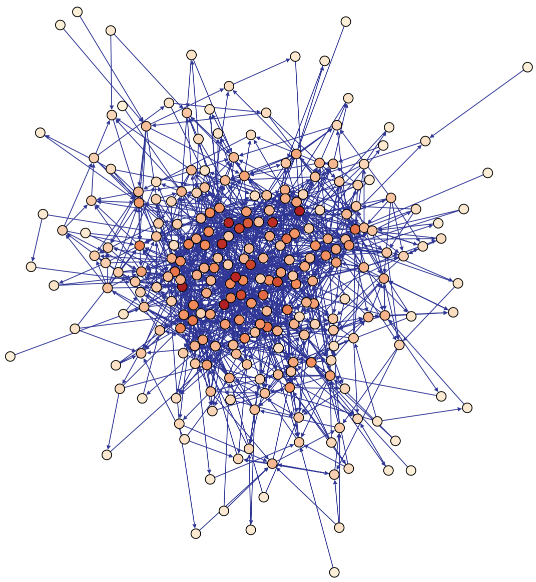


FIGURE 4: A snapshot of the growing microblog network ($N = 250$, $\beta = 10$, $p_0 = 0.9$, $\varepsilon = 100$, $\lambda = 0.05$, $p_1 = 0.005$, $\alpha = 10$, and $\kappa = 0.001$).

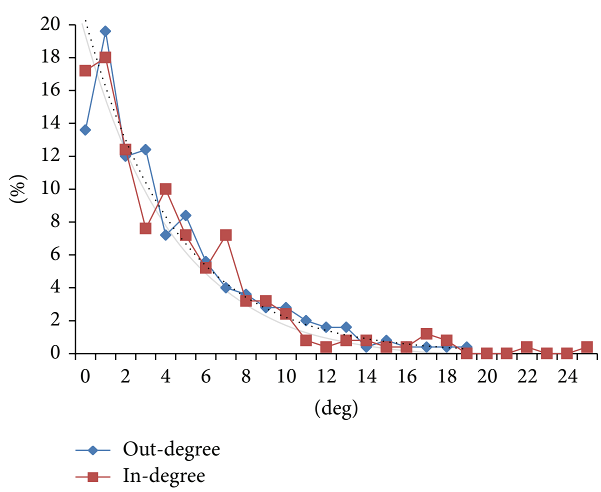


FIGURE 5: A snapshot of degree distribution.

2.3. Features. We could study the features and behaviors of the dynamical microblog network model through experimental simulations. In our simulations, we have initialized these simulations with an empty network (i.e., no edges or links). In the first simulation, we have set $N = 250$, $\beta = 10$, $p_0 = 0.9$, $\varepsilon = 100$, $\lambda = 0.05$, $p_1 = 0.005$, $\alpha = 10$, $\kappa = 0.001$, $\mu = 5$, and threshold (the strength threshold of connections) = 0.3, and Figure 4 presents a snapshot of this growing microblog network.

2.3.1. Degree Distribution. Since the growing microblog network is dynamic, the degree distribution is also mutative. Figure 5 shows a snapshot of degree distribution of this growing microblog network, including out-degree distribution and in-degree distribution. x-axis represents the degrees,

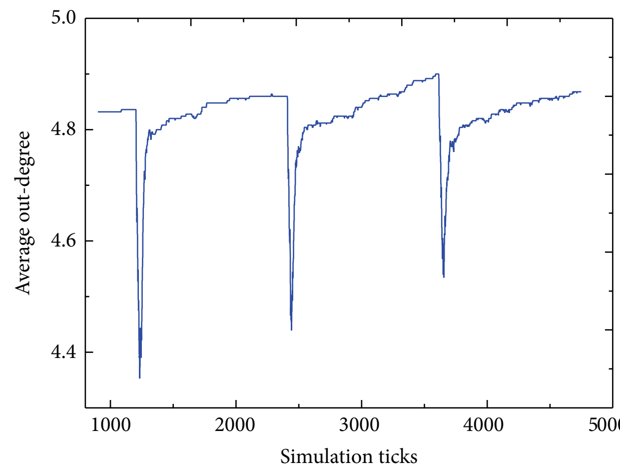


FIGURE 6: Average out-degree of the microblog network.

and y-axis expresses the percentage of the vertexes with the corresponding degree. It represents in-degree with more flexibility for no limits for in-degree of a node or vertex. However, for the out-degree of each vertex or node, there is a limit or maximum out-degree, and the distribution of these maximum out-degrees should follow the power-law exponential distribution. As seen in the figure, we could fit the out-degree distribution curve with an exponential fitting curve.

2.3.2. Average Degree. The microblog network has periodical behaviors that users could periodically release or broadcast their microblogs and could periodically skim these microblogs of their following users [12]. Figure 6 displays the average degree, and we could see that the fluctuations periodically appear with tranquillizations between these fluctuations. The periodical decay of connections results in these periodical fluctuations. With $\beta = 10$, out-degree of each vertex strictly complies with each out-degree limit. While decreasing the value of β with other parameters being fixed, the average degree will be larger.

2.3.3. Clustering Coefficient. For the clustering behavior of the dynamic microblog network, clustering coefficient is a directed way and method. For undirected networks, the clustering coefficient [13] of vertex i could be defined as follows, where a_{ij} means node i links with node j and d_i denotes the degree of node i:

$$C_i = \frac{\sum_{j,k} a_{ij}a_{jk}a_{ik}}{\sum_{j,k} a_{ij}a_{ik}} = \frac{\sum_{j,k} a_{ij}a_{jk}a_{ik}}{d_i\left(d_i - 1\right)/2}. \quad (6)$$

However, for direct networks, there are more ways to form a triangle and it is more complex to calculate the clustering coefficient [14]. For triangles, we could divide these triangles into four types, as depicted in Figure 7. The global clustering

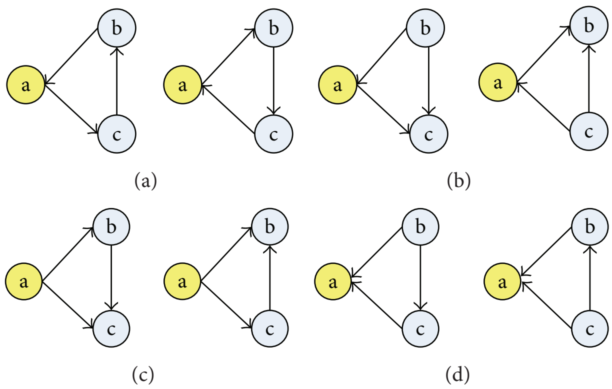


Figure 7: Potential triangles of the directed network.

coefficients $C(C(\text{loop}), C(\text{in\_out}), C(\text{all\_out}), C(\text{all\_in}))$ could be defined as follows:

$$\begin{aligned} C_i(\text{loop}) &= \frac{\sum_{j\neq k} a_{ij}a_{jk}a_{ki}}{d_i(\text{in})\, d_i(\text{out}) - \text{pairs}_i}, \\ C_i(\text{in\_out}) &= \frac{\sum_{j\neq k} a_{ij}a_{kj}a_{ki}}{d_i(\text{in})\, d_i(\text{out}) - \sum_j a_{ij}a_{ji}}, \\ C_i(\text{all\_out}) &= \frac{\sum_{j\neq k} \left(a_{ij}a_{ik}a_{kj+}a_{ij}a_{ik}a_{jk}\right)}{d_i(\text{out})\left(d_i(\text{out})-1\right)}, \\ C_i(\text{all\_in}) &= \frac{\sum_{j\neq k} \left(a_{ji}a_{ki}a_{kj+}a_{ji}a_{ki}a_{jk}\right)}{d_i(\text{in})\left(d_i(\text{in})-1\right)}. \end{aligned} \tag{7}$$

As seen in (7), each subclustering coefficient has been defined and $d_i(\text{in})$ represents the in-degree of vertex i and $d_i(\text{out})$ expresses the out-degree of vertex i. Then, the global clustering coefficient could be depicted as

$$C = \frac{\sum_{i=1}^{N} \left(C_i(\text{loop}), C_i(\text{in\_out}), C_i(\text{all\_out}), C_i(\text{all\_in})\right)}{N}, \tag{8}$$

with $N = 250$, $\beta = 10$, $p_0 = 0.9$, $\varepsilon = 100$, $\lambda = 0.05$, $p_1 = 0.005$, $\alpha = 10$, $\kappa = 0.001$, $\mu = 5$, and threshold $= 0.3$. Figure 8 shows the global coefficient. All these global subclustering coefficients are higher than clustering coefficients of the corresponding random network (especially the value of $C(\text{all\_out})$), and most subclustering of the random network is less than 0.04. The periodical behaviors of microblog network could also be observed through the periodicity of the global clustering coefficient. As seen in Figure 8, there are periodical fluctuations and between these fluctuations the clustering coefficients are stable. In this simulation, the $C(\text{all\_out})$ is greater than other subclustering coefficients, and it could be mapped in the real microblog network. Most users of microblog will follow the stars (the users are stars or presidents) and one user may follow several stars, and these stars may not follow the general users and they may be apt to follow other stars. So this situation causes greater $C(\text{all\_out})$. Through adjusting these parameters, we could get different global clustering coefficients.

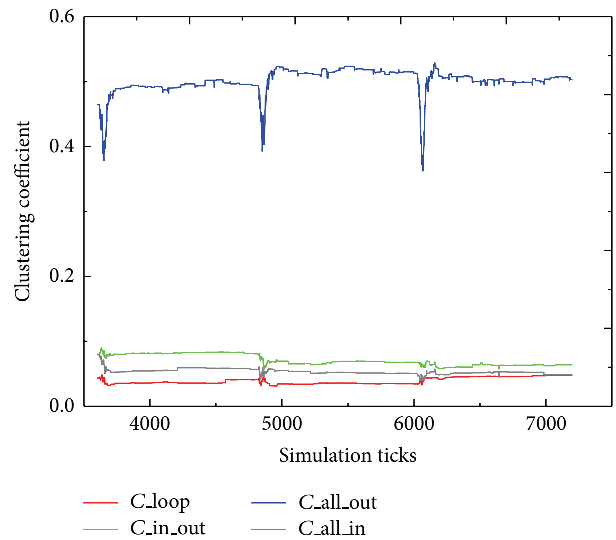


Figure 8: Global clustering coefficient of the dynamic microblog network ($N = 250$, $\beta = 10$, $p_0 = 0.9$, $\varepsilon = 100$, $\lambda = 0.05$, $p_1 = 0.005$, $\alpha = 10$, and $\kappa = 0.001$).

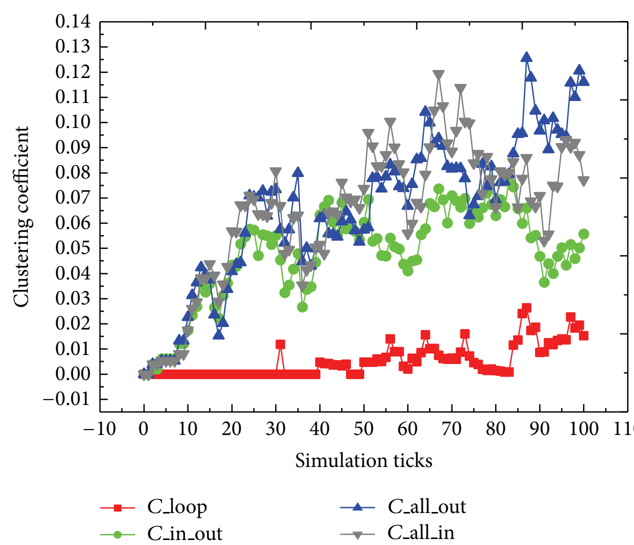


Figure 9: Global clustering coefficient with $\kappa = 0.1$.

Through changing the parameter κ to 0.1 ($\kappa = 0.1$) and fixing other parameters, the clustering coefficients sharply fluctuate with time, as shown in Figure 9. Adjusting parameter κ with a larger value, the clustering coefficients will rise and fall more sharply. Meanwhile, the average degree will also fluctuate sharply. There are many parameters in this dynamic microblog network model. Different β could give each node with different flexibilities about its out-degree. Less p_0 and ε will bring more mutual connections between vertexes. Larger λ will easily bring Matthew effect. Then, through adjusting the parameter α, we could control the transitivity of the network and bigger α could cause higher transitivity.

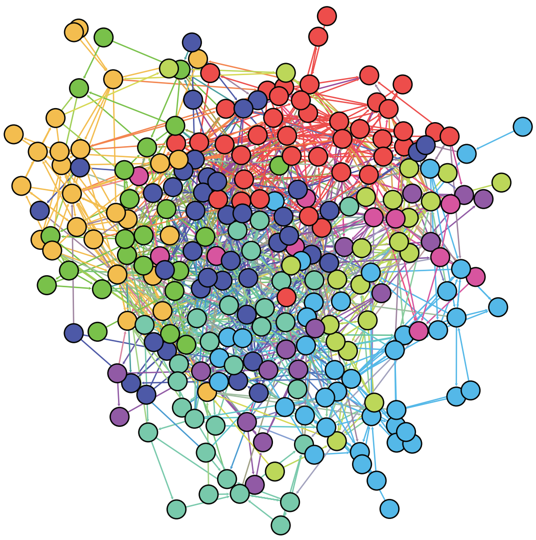


Figure 10: Communities with different colors (splitted by modularity classes).

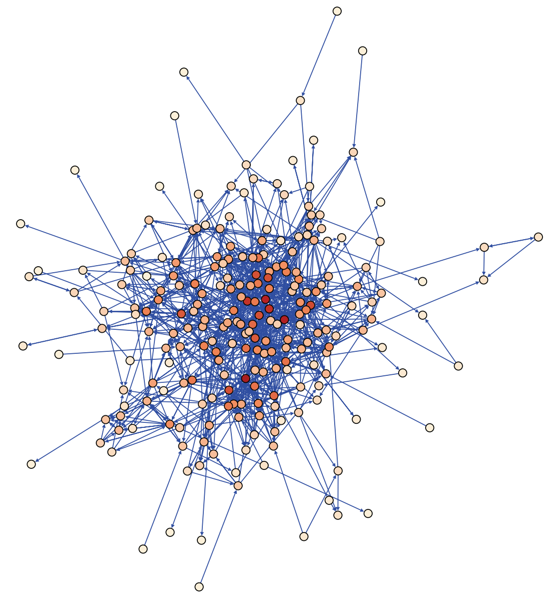


Figure 11: A snapshot of the dynamic microblog network ($N = 250$, $\mu = 5$, $r_0 = 0.0015$, $r_1 = 0.9$, $r_2 = 0.001$, $r_3 = 2$, $\gamma = 0.001$).

2.3.4. Community. Another measure for the structure of complex networks is the modularity [15, 16], which measures the strength of dividing a network into modules, groups, clusters, or communities. For the microblog networks, a high modularity denotes that the network has dense connections between the users within the same communities and sparse connections between users in different communities. Modularity of the network in Figure 4 is about 0.401, which is a high degree of modularity. Based on the modularity classes, this network could be divided into 9 communities, as shown in Figure 10. Nodes with different colors represent nodes in different communities. Compared with a random social network, with the same average degree, the modularity of the random network is about 0.28. The mechanism of dynamic microblog network results in a higher modularity.

2.4. Another Model for the Microblogging Network. In order to facilitate simulating such a dynamic microblog network, we provide another way to construct this microblog network. As seen in the former model, we could know that in each time the network will create new edges following specific rules and periodically cancel several edges. So we could propose a novel model equivalent with the former one; the algorithm is as follows.

Let N denote the number of nodes in the microblog social network, the maximum out-degree (signed as n_p) of the whole social network is $N(N-1)$, and existed out-degree number is $n_e = (1/2)\sum Z_{i\rightarrow}$ ($z_{i\rightarrow}$ is the out-degree of node i). The number of neighborhood links is $n_m = (1/2)\sum Z_{i\rightarrow}(Z_{i\rightarrow}-1)$. Then, $\mathrm{ownz}^{*}_{i\rightarrow}$ is the max out-degree limit of node i, and maximum out-degree of all nodes follows a power law as the exponential distribution ($P(\kappa) \propto e^{-\kappa/\mu}$). Consider the following.

(a) In each step, randomly choose $n_p r_0$ pairs of nodes. For each pair of nodes, randomly choose one of these pairs of nodes signed as node i. If out-degree of node i is less than $\mathrm{ownz}^{*}_{i\rightarrow}$, then node i will connect to the other one.

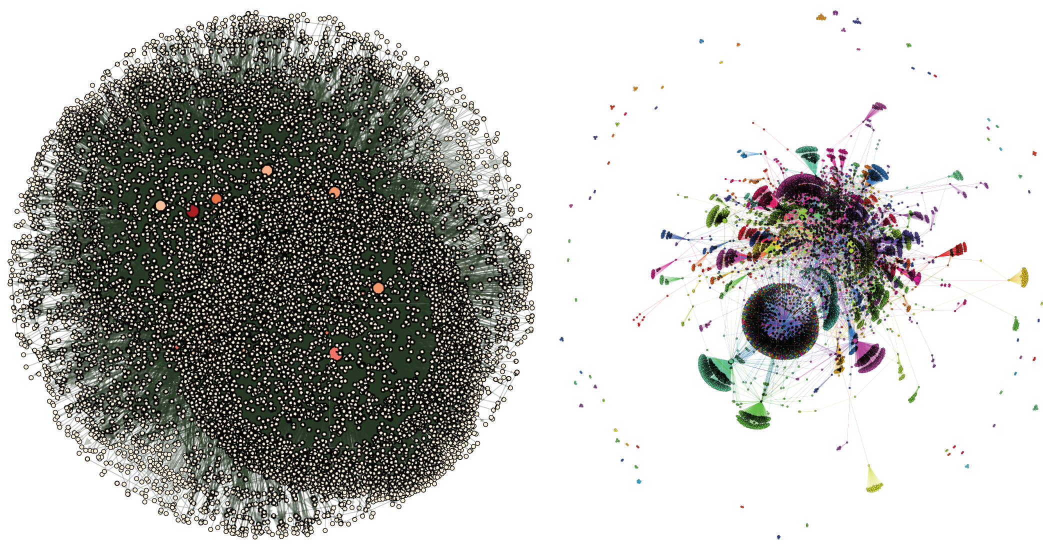
(b) In each step, randomly choose $n_p r_1$ pairs of nodes. If one of the chosen nodes (node j) has connected to the other (node i), and node i has not connected to node j and out-degree of the node i is less than $\mathrm{ownz}^{*}_{i\rightarrow}$, then node i will connect to node j.

(c) In each step, randomly choose $n_p r_2$ pairs of nodes. For each pair of nodes, if this chosen node i with the minimum in-degree has not connected to the other node and the minimum in-degree of these two nodes is less than $\mathrm{ownz}^{*}_{i\rightarrow}$, then node i will connect to the other one.

(d) In each step, proportionate to $z_{i\rightarrow}(z_{i\rightarrow}-1)$, randomly choose $n_m r_3$ nodes. For each node, randomly choose one of nodes from its in-neighbor nodes which are connected to this node as node i, and randomly choose one of nodes from its out-neighbor nodes signed as node j. If node i has not connected to node j and out-degree of node i is less than $\mathrm{ownz}^{*}_{i\rightarrow}$, then node i will connect to node j.

(e) In each step, with probability proportionate to $z_{i\rightarrow}$, randomly choose $n_e \gamma$ nodes (γ is a constant). For each node, randomly choose one of out-neighbor nodes and cancel the connection from this node to the out-neighbor node.

Most behaviors and features shown in the former model could also be reproduced with appropriate values of these parameters in this method, including the periodical behaviors and community. Figure 11 presents a snapshot of microblog network with this model.



(a) A part of "@" network in Sina Weibo (b) The "@" network after splitting with communities

Figure 12: A part of the "@" network in Sina Weibo (including 11,073 nodes and 13,046 links).

3. Information Dissemination Model in "@" Mode

Social media, especially the microblogs, have become an important channel for disseminating information, and with the social network model of microblog in Section 2 we could study several issues in the computer system, including the issue of information dissemination. Users of a microblog (like Sina Weibo) could transmit information mainly through the following methods or ways: posting on a microblog, retweeting on a microblog, and commenting on a microblog. If one user has posted, retweeted, or commented on a microblog, all of his/her fans (followers) will see this microblog in their man-machine interfaces of the microblogging platform. However, these fans may not pay attention to this microblog and miss the information in this microblog. Another mode could provide a stronger way to disseminate the information, called as "@" mode, and users could make some or all of their followers or followings know the information through posting, retweeting, or commenting on a microblog using "@". For example, when user A posts, retweets, or comments on a microblog with "@" user B, user B will prior read this microblog. The "@" mode is a more effective way to disseminate information. In order to better understand this mode, we have collected several microblog data especially the "@" relationships between users from the Sina with the open APIs released by Sina, and Figure 12(a) shows a snapshot of the "@" network in Sina, including 11,073 nodes and 13,046 links. The nodes represent the users in Sina Weibo, and the links denote the "@" relationships between users, which are directed edges; for example, the directed link from user A to user B means that user A already "@" user B. Figure 12(b) presents the feature of community and clustering of the "@" network, where modularity is 0.848, modularity with resolution is 0.848, and number of communities is 2,896.

The "@" mode is a stronger, more effective, and important way for information spread; thus the "@" mode is our focus in this paper. As one knows, the social network plays a key role in information dissemination in the microblog [17]. In order to research into information dissemination, some diffusion mathematical models [18–20] have been proposed, and some infectious disease spread models [21–24] could be applied in information diffusion. These works could not directly be used to research into information dissemination in the microblog, for the specificity of "@" mode. As shown in Figure 13, there are three situations that user A could "@" user B: (a) A is a follower of B; (b) B is a follower of A; (c) A is a follower of B and B is also a follower of A. If the user C is not the follower of A and A is not a follower of C, then A cannot send any information to user C through "@" mode. A user prefers "@" the users who are followers or followings of this user. Therefore, three parameters could be defined to distinguish the probability of user A "@" user B in these three situations, as shown in Figure 13. Parameters ρ, ς, and σ denote the probability of user A "@" user B in the situations (a), (b), and (c), respectively.

When a user wants to diffuse information in "@" mode, he/she will choose some users from his/her followers and followings to retweet a microblog with "@." The process of information dissemination through "@" mode in microblog is similar to the *SIR* model of disease propagation [21–24]. Classic disease propagation models are based upon the basic assumptions that initially a person is susceptible (S) to the disease and could become a host of the infectious disease. If he/she is exposed to the disease by an infectious contact, then the person will become infected (I) with a probability; with several medical measures or his/her immunity, he/she will become recovered (R). Information spread in microblog is similar to this *SIR* model. However, the kernel meaning of these three states (*SIR*) of information dissemination in

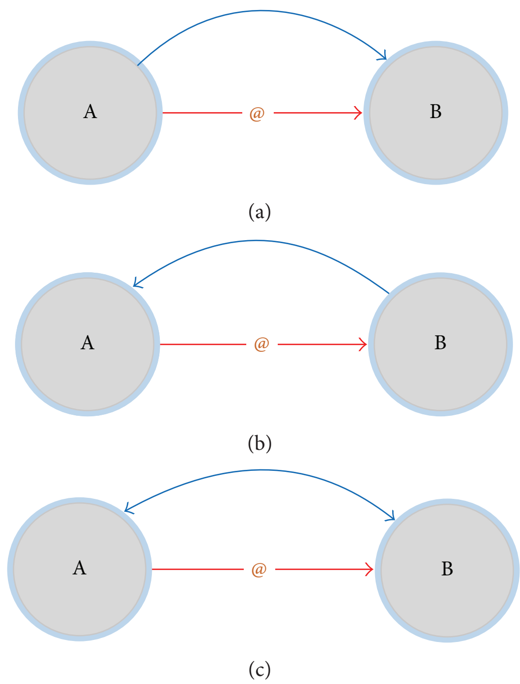


Figure 13: Three situations of user A “@” user B.

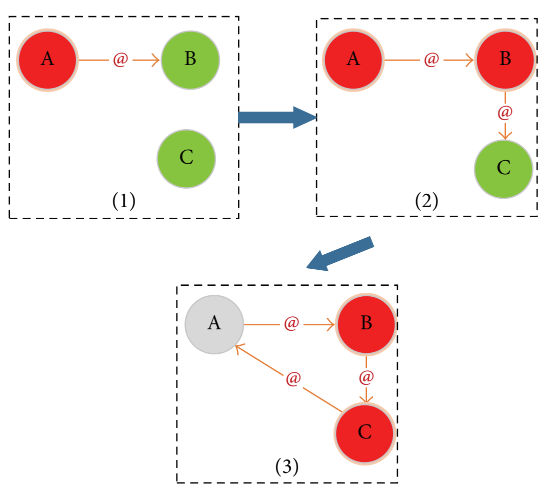


Figure 14: The process of information dissemination in “@” mode.

“@” mode has some differences with disease propagation. Figure 14 depicts the process of information dissemination from node A in “@” mode, and these nodes denote users of the microblog. A node with the green color indicates the person who is ignorant and interested to disseminate the information, a node with the red color means the person who is informed and still interested to disseminate the information, and a node with the gray color means the person who is informed and loses the interest to diffuse the information. These situations denote users in state S (green color), state I (red color), and state R (gray color), respectively.

For the previous research of information dissemination, we could assume that if a person receives the information and he/she will become informed ($I(i)$) then he/she will post on a microblog and diffuse the information into one of his/her neighbors with “@” mode. If the neighbor mentioned with “@” in this microblog has not known the information ($S(j)$), then the neighbor will acquire the information and become informed ($I(j)$). If the neighbor has known this information and has been informed and “@” for q times, then this neighbor will lose the interest to diffuse to any other users and become recovered ($R(j)$), as shown in Figure 14. The process could be described as follows:

$$\begin{aligned} I(i) + S(j) &\longrightarrow I(i) + I(j), \\ I(i) + I(j) &\longrightarrow I(i) + R(j), \\ I(i) + R(j) &\longrightarrow I(i) + R(j). \end{aligned} \tag{9}$$

4. Experiments

4.1. Method. To research into information spread in the microblog, we could construct an artificial microblog based on the zombie-city model. Zombie-city model [5–7] is a general model for modeling artificial societies. Agent, role, social network, environment, and rule are included. Rules could constrain agents, environments, and social network; that is, the agents, the environment, and social network must conform to these rules. Besides, agents have their own capabilities (e.g., move), and agents may be infected with viruses through interactions (e.g., “@” in microblogs) so that they will carry viruses. Agents could dynamically play different roles to adapt to various changes with the mechanism of dynamically playing roles [25]. Figure 15 depicts the metamodel of the zombie-city model.

Based upon the zombie-city model, we could abstract the users of the microblog as agents, with the characteristics of proactivity, sociality, self-adaption, and interactivity. The following relationships between these users could be considered as the directed links of the social network. Then, in the circle of information dissemination, we could define three roles: S (is ignorant for the information), I (is informed to the information and interested to disseminate the information), and R (loses the interest to diffuse the information). Agents could dynamically play different roles with distinctive situations. Besides, there are some rules restricting the agents and social networks. However, in this case, the environment of agents could not be considered, because agents only interact with others through the social network. Above all, we could model this case as the following aspects.

(i) *Agents*. It is assumed that the number of agents is 1000.

(ii) *Role*. It is assumed that there are three roles: S (green color), I (red color), and R (gray color).

(iii) *Rules*. It includes rules of agents and rules of the social network.

Rules of the social network are used to construct a dynamic microblog network, as described in Section 2. All the directed links between agents constitute a social network. A link on the social network could be described

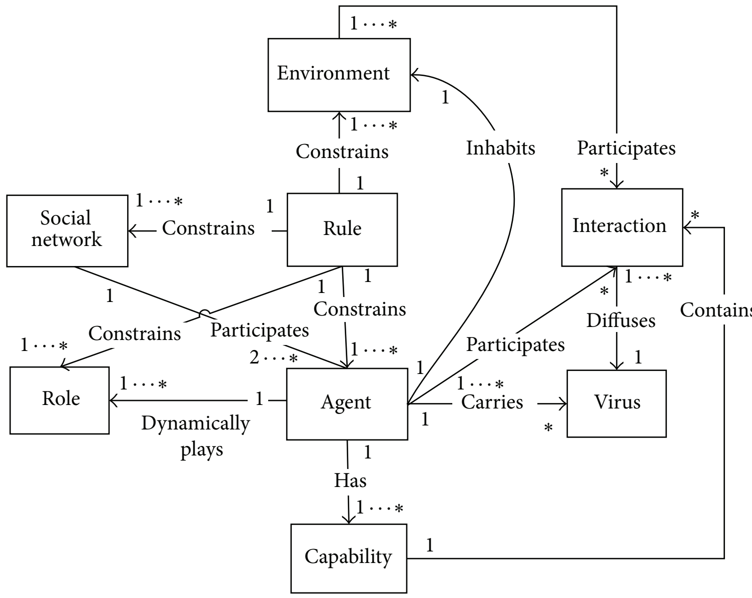


Figure 15: Metamodel of the zombie-city model.

Parameters input: $\alpha, \beta, \lambda, \varepsilon, \kappa, \mu, p_0, p_1$

While $t \in T$
  $t \leftarrow t + 1$
  for $a_i \leftarrow a_1$ to a_N
    $z_{i\rightarrow} \leftarrow \left|LINK^S{}_{ai,t}\right|$
    for $a_j \leftarrow a_1$ to a_N
      $z_{j\leftarrow} \leftarrow \left|LINK^T{}_{aj,t}\right|$
      for $a_k \leftarrow a_1$ to a_N
      $m \leftarrow \Sigma\,\mathrm{Min}\left(\left|LINK^S{}_{ak,t} \cap LINK^T{}_{aj,t}\right|, \left|LINK^S{}_{ai,t} \cap LINK^T{}_{ak,t}\right|\right)$
      if $a_i \in LINK^S{}_{aj,t}$
        then $link_{ji} \leftarrow 1$
      if $a_i \notin LINK^S{}_{aj,t}$
        then $link_{ji} \leftarrow 0$
      $p_{ij} \leftarrow (1-(p_0/e^{\varepsilon link_{ji}}))(1/(e^{\beta(z_{i\rightarrow}-\text{ownz}^*{}_{i\rightarrow})}+1))(1/(1+e^{-\lambda z_{j\leftarrow}}))(1-(1-p_1)\,e^{-\alpha m})$
      if $a_j \notin LINK^S{}_{ai,t} \wedge p_{ij} \geq Random(1) \wedge \left|LINK^S{}_{ai,t}\right| < \text{ownz}^*{}_{i\rightarrow}$
        then $Create(a_i, a_j) \wedge \Delta t \leftarrow 0$ // Create Link
      if $a_j \in LINK^S{}_{ai,t} \wedge s_{ij} < 0.3$
        then $Delete(a_i, a_j)$ // Delete Link
      $s_{ij} \leftarrow e^{-\kappa\Delta t}$
      if $s_{ij} \geq 0.3$
        then $\Delta t \leftarrow \Delta t + 1$
end

Pseudocode 1: Pseudocode of constructing the dynamic mircoblogging social network.

as $l ::= \langle cid, s_{ij}, (a_i, a_j)\rangle$. The property s_{ij} ($s_{ij} = e^{-\kappa\Delta t}$) denotes the strength of this link, which will decay with the time Δt, and Δt means the age of the link. At any time, randomly choose an agent a_i and also randomly choose an agent a_j from others; if a_i does not connect to a_j, p_{ij} ($p_{ij} = f_1(z_{i\rightarrow})f_2(\text{link}_{ji})f_3(z_{j\leftarrow})g(m)$) is greater than a random number (less than 1), and out-degree of a_i is less than the threshold of out-degree of a_i ($\text{ownz}^*_{i\rightarrow}$), then a_i will create a link from a_i to a_j. If there is a link from a_i to a_j and s_{ij} is less than a threshold (in this case we set the threshold as 0.3), then a_i will delete the link from a_i to a_j. This process of constructing the dynamical social network could be described by pseudocode, as shown in Pseudocode 1. For any agent a_i, $\text{LINK}^S_{ai,t}$ means an agents set. If a_i links to agent b, then b will belongs to $\text{LINK}^S_{ai,t}$. Meanwhile, $\text{LINK}^T_{ai,t}$ is also an agent set. $|\text{LINK}^S_{ai,t}|$ means the total number of agents belonging to this set. When any agent a links to a_i, agent

```
Parameters input: ψ, ρ, ς, σ
While t ∈ T
    t ← t + 1
//Initialization & PostMicroblog
    if Average_degree > 4 ∧ a_i = Random(AG) ∧ Total(S) = |AG|
        then a_i.Quit(S) ∧ a_i.Play(I)
    for a_i ← a_1 to a_N
        for a_j ← a_1 to a_N
//Microblog Dissemination
            if ψ ≥ Random(1) ∧ a_i⫰_t I ∧ a_j ∈ LINK^S_{ai,t} ∧ a_j ∉ LINK^T_{ai,t} ∧ a_j⫰_t S ∧ Random(1) < ρ
                then a_i.Post_Blog_@(a_j) ∧ a_i.Quit(S) ∧ a_i.Play(I) ∧ a_j.Quit(S) ∧ a_j.Play(I) ∧ a_j.weight++
            if ψ ≥ Random(1) ∧ a_i⫰_t I ∧ a_j ∈ LINK^T_{ai,t} ∧ a_j ∉ LINK^S_{ai,t} ∧ a_j⫰_t S ∧ Random(1) < ς
                then a_i.Post_Blog_@(a_j) ∧ a_i.Quit(S) ∧ a_i.Play(I) ∧ a_j.Quit(S) ∧ a_j.Play(I) ∧ a_j.weight++
            if ψ ≥ Random(1) ∧ a_i⫰_t I ∧ a_j ∈ LINK^S_{ai,t} ∧ a_j ∈ LINK^T_{ai,t} ∧ a_j⫰_t S ∧ Random(1) < σ
                then a_i.Post_Blog_@(a_j) ∧ a_i.Quit(S) ∧ a_i.Play(I) ∧ a_j.Quit(S) ∧ a_j.Play(I) ∧ a_j.weight++
//Lose Interest
            if ψ ≥ Random(1) ∧ a_i⫰_t I ∧ a_j ∈ LINK^S_{ai,t} ∧ a_j ∉ LINK^T_{ai,t} ∧ a_j⫰_t I ∧ Random(1) < ρ ∧ weight > q
                then a_j.Quit(I) ∧ a_j.Play(R)
            if ψ ≥ Random(1) ∧ a_i⫰_t I ∧ a_j ∈ LINK^T_{ai,t} ∧ a_j ∉ LINK^S_{ai,t} ∧ a_j⫰_t I ∧ Random(1) < ς ∧ weight > q
                then a_j.Quit(I) ∧ a_j.Play(R)
            if ψ ≥ Random(1) ∧ a_i⫰_t I ∧ a_j ∈ LINK^S_{ai,t} ∧ a_j ∈ LINK^T_{ai,t} ∧ a_j⫰_t I ∧ Random(1) < σ ∧ weight > q
                then a_j.Quit(I) ∧ a_j.Play(R)
end
```

Pseudocode 2: Pseudocode of agents' behaviors.

a will belong to $\mathrm{LINK}^{T}_{ai,t}$. The functions *Create*(a_i, a_j) and *Delete*(a_i, a_j) represent to create a link from a_i to a_j and to delete the link from a_i to a_j, respectively.

Agents in the artificial microblog model are used to map users of the microblog, and initially all agents are playing S role; that is, all agents are ignorant to the information in the initial.

When the average degree of this microblog network reaches 4, randomly select an agent to get and post the information, and then this agent a_i will quit the role S and start to play the role I, which means that agent a_i has known and posted the information. The rules of retweeting the microblog with the information are complex. If the active level of a_i (any infected agent) is greater than ψ (i.e., $Random(1) < \psi$), and then a_i may spread information to others (signed as a_j). But one of the following situations should be satisfied: (1) a_j is one of the out-neighbors of a_i and a_j does not connect to a_i, meanwhile, a_j is playing role S and the random probability is less than ρ; (2) a_j connects to a_i and a_i does not link to a_j. Besides, a_j is playing role S and the random probability is less than ς; (3) a_j connects to a_i and a_i links to a_j, and a_j is playing role S and the random probability is less than σ. If a_i posts or retweets the information to a_j through "@" mode, then a_j will quit role S but play role I. When agents have been informed for q times with "@", they will lose the interest to retweet the information. Pseudocode 2 shows the pseudocode of agents' behaviors. *Total*(S) means the total number of agents who play the role S, and $|AG|$ denotes the population of agents in this artificial microblog. $a_i.Quit(S)$ and $a_i.Play(I)$ denote that agent a_i stops to play role S and agent a_i plays role I. Function $a_i.Post\_Blog\_@(a_j)$ means agent a_i posts or retweets a microblog with the information through "@" a_j. Meanwhile, the parameter *weight* denotes the total "@" times of an agent received. When the *weight* value of any agent a_i is greater than q, agent a_i will lose the interest to retweet the information to other agents.

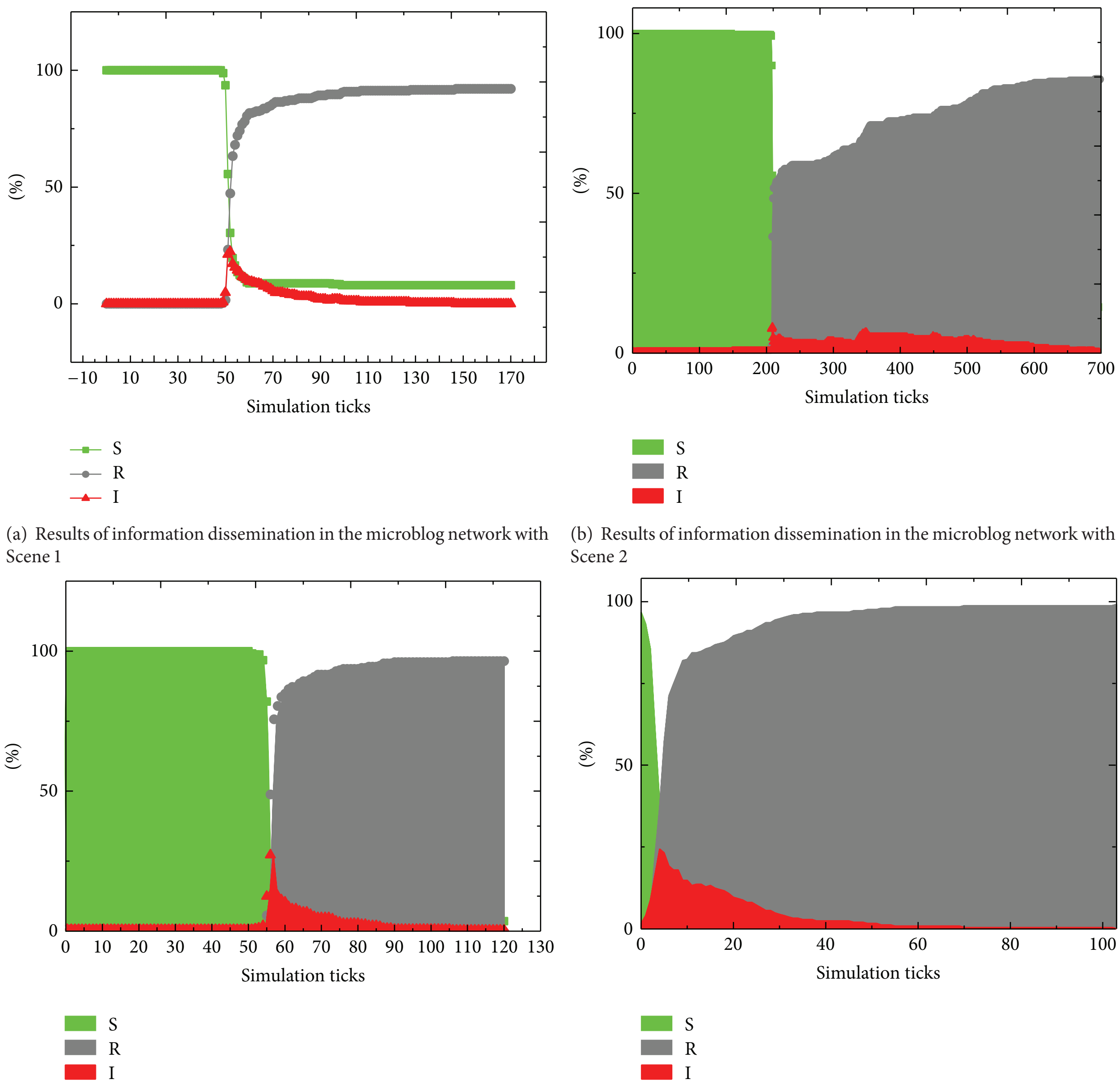
In order to compare the effectiveness of information dissemination in different scenes and situations, four scenes are defined as follows.

(1) Scene 1. Information spreads in a microblog network through "@" mode. We could assume these parameters as follows: $N = 250$, $\beta = 10$, $p_0 = 0.9$, $\varepsilon = 100$, $\lambda = 0.05$, $p_1 = 0.005$, $\alpha = 10$, $\kappa = 0.005$, $\psi = 0.7$, $\mu = 5$, $\rho = 0.05$, $\varsigma = 0.2$, and $\sigma = 0.5$, so the average out-degree of the microblog network is about 5.

(2) Scene 2. In order to illustrate that whether and how the stability of the microblog network affects the information diffusion, we could change κ from 0.005 to 0.1, and other parameters are the same as (1). In this paper, it is assumed that the number of nodes in the microblog network will not increase or decrease. The stability of the microblog network is related to links of the network, and a better stability means fewer links will be deleted in each time.

(3) Scene 3. As one knows, the active level of agents may affect the information diffusion, so in this scene we set these three parameters as $\rho = 0.1$, $\varsigma = 0.3$, and $\sigma = 0.7$, and the other parameters are the same as (1).

(4) Scene 4. Information disseminates in a random network through "@" mode. In order to depict the characteristics of



(a) Results of information dissemination in the microblog network with Scene 1

(b) Results of information dissemination in the microblog network with Scene 2

(c) Results of information dissemination in the microblog network with Scene 3

(d) Results of information dissemination in a random network with Scene 4

Figure 16: Results of information dissemination in different scenes.

the information dissemination on the microblog network, we could compare it with information spread in a random network. In this scene, we should set the average degree of this random network as 5. Thus, the conditions are as follows: $N = 250$, average degree $= 5$, $q = 10$, $\rho = 0.1$, $\varsigma = 0.3$, and $\sigma = 0.7$.

4.2. Results and Analysis. We have implemented the experimental simulations in Netlogo (widely used in simulation of multiagents systems), and these experiments are executed on a workstation with a 4 GB RAM and a 2.60 GHZ Intel Core i5 in Win 8 operation system. To compare the information dissemination in the microblog network with the information spread in the random network, we could define a random directed network with average out-degree = 5. Figure 16(a) presents the information dissemination in the microblog network with the defined parameters: $N = 250$, $\beta = 10$, $p_0 = 0.9$, $\varepsilon = 100$, $\lambda = 0.05$, $p_1 = 0.005$, $\alpha = 10$, $\kappa = 0.005$, $\psi = 0.7$, $\mu = 5$, $\rho = 0.05$, $\varsigma = 0.2$, and $\sigma = 0.5$. Figure 16(b) depicts the information dissemination in the microblog with only changing the parameter κ to 0.1. Figure 16(c) shows the information diffusion in the microblog with changing ρ, ς, and σ to 0.1, 0.3, and 0.7, respectively. Figure 16(d) illustrates the information dissemination in the random network with average degree = 5. x-axis denotes the simulation ticks, and y-axis indicates the percent of three roles that agents play.

Table 1: Comparisons of information spread in different scenes.

	Time cost	ϑ	ϱ
Scene 1	99 ticks (49~147 ticks)	8%	22.4%
Scene 2	514 ticks (148~691 ticks)	14.4%	6.4%
Scene 3	47 ticks (50~96 ticks)	4.4%	27.6%
Scene 4	104 ticks (0~103 ticks)	0.8%	24.4%

Table 1 quantitatively analyzes and compares the effectiveness of information spread in these four scenes. Time cost means the time consumption from the first time of posting information to the end time when no informed users have interest to spread the information. The time cost expresses the speed of information dissemination, and a smaller time cost represents higher speed of information spread. The metrical parameter ϑ (min percent of S) means the minimum percent of agents who play the role S (i.e., agents who are ignorant to the information). A larger ϑ indicates that a greater number of agents have not known the information. In addition, the metrical parameter ϱ (max percent of I) denotes the maximum percent of agents who play the role I (i.e., agents who know the information and do not lose interest to retweet the information). A larger ϱ means more agents are informed and interested in retweeting the information.

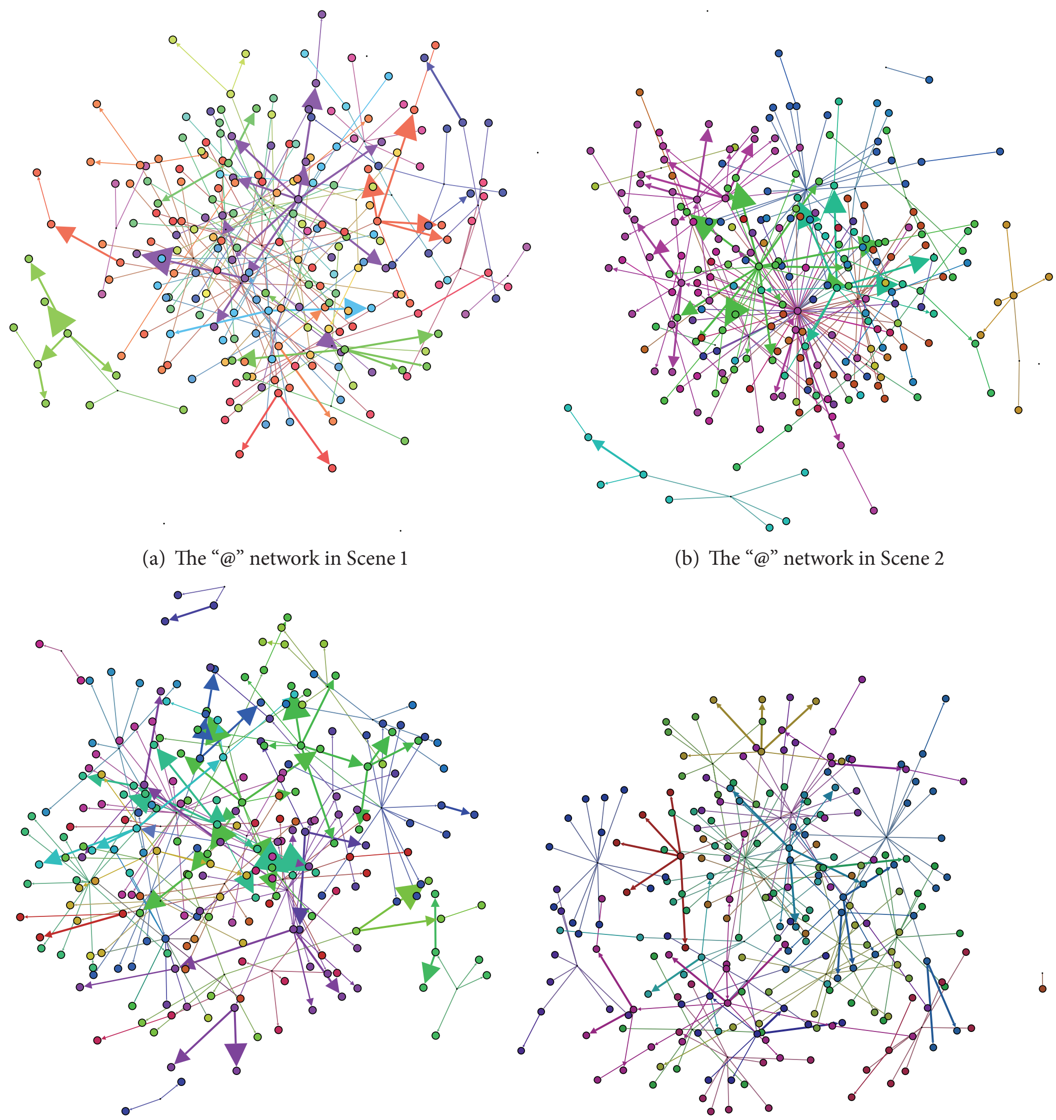
Compared with Scene 1, Scene 2 only has increased the value of parameter κ from 0.005 to 0.1, which is related to the stability of the social network. A larger κ denotes the worse stability of the social network. As shown in Table 1, in Scene 2, the time cost is 514 ticks, ϑ is 14.4%, and ϱ is only 6.4%. However, in Scene 1, the time cost is 99 ticks, ϑ is 8%, and ϱ is only 22.4%. Hence, information spread more widely and quickly in Scene 1; that is, a better stability of the social network is beneficial to improve information dissemination. Compared with Scene 1, Scene 3 only has adjusted the values of parameters ρ, ς, and σ from 0.05, 0.2, and 0.5 to 0.1, 0.3, and 0.7, respectively. We could see that in Scene 3 information spreads more quickly and widely than in Scene 1, which means the higher active level of agents will promote information spread. Scene 4 describes information dissemination in a random social network, and the values of parameters ρ, ς, and σ in Scene 4 are the same with the values of the corresponding parameters in Scene 3. Meanwhile, the average degree of the random network is 5. As presented in Table 1, we could get a conclusion that information spreads quickly in Scene 3 but spreads widely in Scene 4. That is, with a similar average degree, information could spread more quickly in a microblog network, and information may spread more widely in a random network.

We could collect the data of the "@" networks, which are also the information diffusion networks. Figure 17 shows the networks of information dissemination in different scenes. Figures 17(a), 17(b), 17(c), and 17(d) illustrate the information diffusion networks according to Scenes (1), (2), (3), and (4), respectively. This network also reflects the "@" network, because information diffusion in this case is based on the "@" mode. Modularity of the network (a) is 0.924, modularity of network (b) is 0.897, modularity of network (c) is 0.925, and modularity of network (d) is 0.922. All these information dissemination networks have the characteristic of community. The "@" mode of information dissemination determines the bigger modularity of the information diffusion networks. In this case, we only consider the "@" mode for information diffusion. For the real data, we could see that the modularity of information diffusion network (i.e., "@" network) of the real microblog network is 0.848, as seen in Section 2.3.4. Hence, the modularity of these information dissemination networks coincides to the real data. When we adjusted the values of ρ, ς, and σ in Scene 4 from 0.1, 0.3, and 0.7 to 0.05, 0.2, and 0.5, the modularity of "@" network became 0.877, which is less than 0.922. The higher active level of users may make a larger modularity. However, the smaller values of ρ, ς, and σ also bring a high modularity due to the information dissemination mode—the "@" mode.

Above these data and analyses, we could get some conclusions. (1) A random network is more conducive for diffusing the information widely; (2) information spread more quickly in a stable microblog network; (3) the decay rate of the relationships will have an effect on information dissemination; that is, information spreads more quickly and widely with a lower decay rate; (4) the higher active level of users in microblog could also promote information spread; (5) the "@" mode of information dissemination makes a high modularity of the information diffusion network.

4.3. Discussion. Why the random network is more conducive for widely diffusing the information? As shown in Figure 18, (a) shows the process of the information dissemination in a random network, and (b) presents the process of the information dissemination in a microblog network constructed by our model. The average out-degree of this random network and the dynamic microblog network both are 1. For this random network, in Figure 18(a), each node has some following or followed nodes. This results in better connectivity of this random network, which is beneficial to promote information diffusion on the network. For this microblog network in Figure 18(b), the microblog network has a bigger clustering coefficient. However, these nodes a, b, and c of the microblog network have not connected with nodes e, f, and g. Information could not be disseminated to nodes of e, f, and g. Better connectivity of the random network makes information spread widely in the random network.

Why does information spread more quickly in the microblog network? As presented in Figure 18, both nodes "a" in these two figures are original promoters of posting information. As one knows, the max distance between node a and other nodes in the random network is 3, that is, the distance between node "a" and node "c" or the distance between node "a" and node "d", as shown in Figure 18(a). However, the max distance between node "a" and other nodes is 1, that is, the distance between node "a" and node "b" or the distance between node "a" and node "f." This max distance affects the speed of information spread. Smaller max distance



(a) The "@" network in Scene 1

(b) The "@" network in Scene 2

(c) The "@" network in Scene 3

(d) The "@" network in Scene 4

Figure 17: The "@" networks of information dissemination in four scenes.

of the microblog network makes information spread more quickly.

These models and conclusions in this paper could also be used to explain some phenomena of social media. For example, the Sina Weibo is more popular than Renren (a social media platform like Facebook), and we could explain this phenomenon with our model. The reason may be the Matthew effect described in our model. Because many famous stars or persons do not have Renren accounts but have Sina Weibo accounts. For example, Kun Chen (陈坤) is a very famous movie star in China, and he does not have a Renren account but the number of his fans in Sina Weibo is more than 70 million (the number of Sina Weibo users over the world is about 500 million), which means that about 14% users in Sina Weibo have followed Kun Chen. As shown in Figure 19, Kun Chen looks like the node "s", some persons like node "1" and node "2" want to follow the node "s." Hence, both node "1" and node "2" will register in Sina Weibo, and then an increasing number of people will register as the users in Sina Weibo for Matthew effect.

5. Conclusion

Borrowing the ideas of social computing and artificial society, we could make several experiments in artificial societies that are the mappings of the microblogs or real societies. As we know, the social network plays the key role in the information dissemination. This paper has proposed a dynamic growing microblog network based upon the characteristics of the real microblog such as the Sina Weibo. The microblog network is a directed network with the characteristics of higher clustering coefficient, higher modularity, community, and power-law degree distribution. Meanwhile, to facilitate simulations, we have provided another microblog model, which is similar

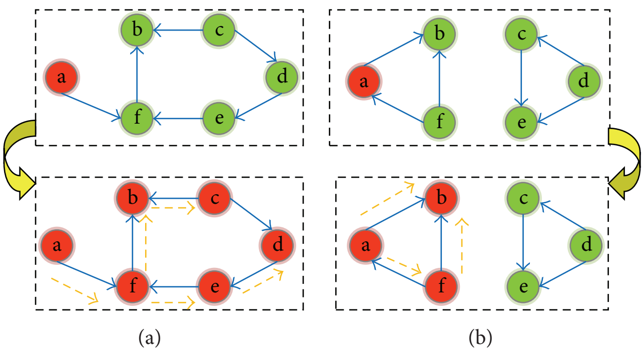


FIGURE 18: (a) The information dissemination in the random network (average out-degree is 1); (b) The information dissemination in the microblog network (average out-degree is 1).

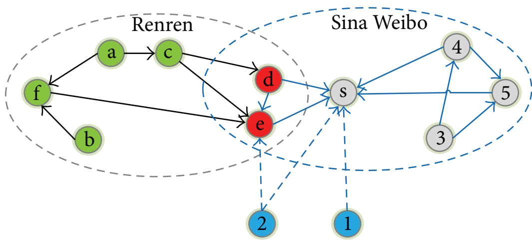


FIGURE 19: Why Sina Weibo is more popular than Renren.

to the former model. Information could be transmitted through several ways or modes, and the "@" mode is an important and stronger way for information dissemination in the microblog. In order to research into information dissemination with "@" mode in the microblog, aid in modeling artificial societies, and quantitatively and qualitatively analyzing the information dissemination and emerging phenomenon, we have introduced a proposed general artificial society model—zombie-city. Based on the microblog network and the zombie-city model, this paper has modeled the artificial microblog with the zombie-city and analyzed the information dissemination in "@" mode with different scenes. Therefore, through these experimental simulations and analysis, we have acquired some general and interesting conclusions. (1) A random network is more conducive for diffusing the information widely; (2) information spread more quickly in a stable microblog network; (3) the decay rate of the relationships will have an effect on information dissemination; that is, information spreads more quickly and widely with a lower decay rate; (4) the higher active level of users in microblog could also promote information spread; (5) the "@" mode of information dissemination makes a high modularity of the information diffusion network.

In addition, some works should be done or improved. Our future works are foreseen as follows: (1) collecting some real data about social network and information dissemination in Sina Weibo to verify the models proposed in this paper; (2) studying other modes of information dissemination in social media, and (3) synthetically considering all these modes to research into information dissemination in social media based on the zombie-city model research into control and management of information dissemination in the microblog.

Conflict of Interests

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

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