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An Evolution Model of Rumor Spreading Based on WeChat Social Circle

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Abstract

With the rapid development of the Internet and the Mobile Internet, social communication based on the network has become a life style for many people. WeChat is an online social platform, for about one billion users, therefore, it is meaningful to study the spreading and evolution mechanism of the rumor on the WeChat social circle. The Rumor was injected into the WeChat social circle by certain individuals, and the communication and the evolution occur among the nodes within the circle; after the refuting-rumor-information injected into the circle, subsequently, the density of four types of nodes, including the *Susceptible*, the *Latent*, the *Infective*, and the *Recovery* changes, which results in evolving the WeChat social circle system. In the study, the evolution characteristics of the four node types are analyzed, through construction of the evolution equation. The evolution process of the rumor injection and the refuting-rumor-information injection is simulated through the structure of the virtual social network, and the evolution laws of the four states are depicted by figures. The significant results from this study suggest that the spreading and evolving of the rumors are closely related to the nodes degree on the WeChat social circle.

Keywords

Evolution Equation, Rumor Spreading, Social Networking, WeChat Social Circle

1. Introduction

Network social, as a kind of virtual social, is considered as the expansion of the real social networking in the internet space. Multimedia-on-demand system in the network has increased the social people's links by the virtual network [1] and the behavior of people on the network is a kind of mapping of the real behavior. As a part of their social activities, people play different roles and accept, inject and spread information in different social networking circles, by joining different social networking platforms. The current literature suggest that the social network structure has the small world effect [2], or the scale-free characteristic on the degree distribution [3]. The topology association between individuals is formed, due to information dissemination between the individuals, and the topology of different social networks has been studied by many scholars. The previous research [4-7] studied the structure of social network from the perspective of complex network. The topological structure of social network, including the property of degree distribution, the clustering coefficient, the vertex degree, and the correlation coefficient, have been subjected to study by many researchers.

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The spread of rumors on social networks has become one of the research hotspots, during the past ten years. The studies of rumors in the fields of communication, psychology, sociology and other fields mainly analyze the connotation of the rumor [8], the influence factors of the rumor transmission [9], and the psychological motivation [10], by means of investigation or experiment. Daleya and Kenda [11] and Maki and Thompson [12] studied the spread of rumors from the perspective of epidemic-like spreading models. The DK model proposed by Daley and Kendal [11] divides the population into three different categories including people who do not know the rumor (*Susceptible*), people who know and disseminate the rumor (*Infective*), and people who know but do not spread the rumor (*Recovery*). The number of people who eventually heard rumors is almost unrelated to the number of first unknowns in the spread of rumor, that is, there is no critical value of the spread of rumors [11]. Maki and Thompson [12] suggested that rumors are spread through the direct contact between the communicator and the other individuals. The MT model proposed by these researchers suggests that only the initial communicator will become recovery when one communicator encounters another communicator [12]. However, both research on the DK model and the MK model lacks the deep consideration of the structure of the rumor spreading network. The later scholars have performed a great deal of expansion to address this issue. Doerr et al. [13] studied the impact of the network topology on the spread of rumors. Zanette [14,15] proposed the rumor spreading model, in the small world network and suggested the threshold of the rumor spreading. Moreno et al. [16] studied the dynamic mechanism of the rumor spreading in the scale-free networks. Based on the classical rumor spreading model, Pan et al. [17] studied the rumor spreading in the scale-free network with power law distribution and variable clustering coefficient. The findings from their research show the higher the clustering coefficient, the better the suppression of rumor spread [17]. Thus, the research of the rumor spreading is transformed from study of the propagation characteristics based on the model itself, to the research on the propagation oriented network topology structure.

The study of the rumor communication based on various indicators (i.e., the degree, the clustering coefficient, the distance, etc.) of network structure has a realistic basis, but the platform for the spreading rumors is the social medium, such as Twitter, Sina microblog, WeChat and other similar platforms. The communication law of information in the virtual communities and blogs is analyzed by name of authors [18]. The environment of the blog communication preserve some of the characteristics of a social network, therefore, we can see the blog network as a social network based on every blogger node. The literature [19] extracted characteristic factors from four aspects, including the publishing users, the receiving user, the user intimacy, and the timeliness of information, which affect the user's forwarding behavior. On the basis of the dynamic model of infectious disease, the user behavior analysis and contact nodes were introduced, subsequently, a SCIR model was proposed, based on the user behavior analysis. The proposed model was used to analyze the association and evolution among nodes, in micro-blog social network. A two stage A-SC1 C2IR model was constructed by Song et al. [20] and introduced the dynamic equation of the model. The simulation results suggested that the prematurely intervention of authoritative information can effectively control the spread of micro-blog rumor. Lu et al. [21] studied the crowd of WeChat rumor spread and constructed the S1S2IR double S rumor spreading model, consequently, they provided the steady state value of the mean field equation of the model. Luo [22] compared the causes and governance schemes of the rumor spread between the micro-blog and the WeChat. Therefore, after the propagation research oriented to network topology structure, some literatures began to pay attention to the rumor spreading research, based on the real social background or the social platform.

The above literatures have carried out a more in-depth study on the related fields of the rumor, such as the social network, the communication model, and the rumor communication platform, as the main factors in this field. Due to the huge number of users and the huge information flow of WeChat, the research value of the rumor spread based on the WeChat platform is particularly prominent. In the study of WeChat rumors in [21], the two states of S1 S2 match the channels of rumors (i.e., the public number and the common node). However, in reality, most of the information published by the public number is the content of the common node transmission and the WeChat's Circle, therefore, the display of this WeChat's Circle is an important channel for the spread of rumors. Because common node transmission is a one to one transmission, and the spread of WeChat's Circle is a display for all friends. This display is generally persistent and affects the friends' nodes, repeatedly. Therefore, taking into account the particularity of WeChat's Circle, this research creates a SLIR (Susceptible, Latent, Infective, Recovery) model for the rumor spreading. Subsequently, the rumor spreading law is deduced and the real data simulation is carried out based on the model.

2. Rumor Spreading Model SLIR

Tencent's WeChat mobile dating software is the most popular and influential universal social application software. In this study, the rumor evolution model in the social network is based on the user functions and privileges of the WeChat's dating software. Of course, the functions and user permissions of the WeChat and other social software will change throughout the time, but the basic functions of information sharing and information acquisition remains relatively unchanged. At present, the WeChat basically share and obtain the information through sending WeChat's Circles, and information are released from friends group, and information transmission between the friends.

Based on the reality of WeChat social network, it constructs an undirected and unweighted attribute graph $\mathrm{G(V, A, E)}$, in which V represents the set of nodes of the graph $\mathrm{V} = \{V_i | i \in N\}$. And E is a set of the edge of $\mathrm{E} = \{\overline{V_iV_j} | i, j \in N \wedge i \neq j\}$, where $\overline{V_iV_j}$ indicates that V_i and V_j have an edge connection, in other words, the information between the two nodes is connected； and A is a collection of attributes of all nodes of the graph, and a set of attributes is defined as the four states in $\mathrm{A} = \{S, L, I, R\}$, which is corresponded to: *S* is a healthy and susceptible state[*Susceptible*], *L* is a latent state[*Latent*], *I* is the state of spreading[*Infective*], and *R* is an immune state[*Recovery*], respectively.

According to the spreading law of rumor information in social network, the basic situation of the four kinds of nodes of *S, L, I,* and *R* in the network are as follows: susceptible node S indicate that no information about rumors is received in a social network; The infective node I indicates that the node accepts the rumor information from its neighbor nodes and implements activities to propagate the information, such as sending information in WeChat's Circles. The latent node L indicates that the rumor information has been received or seen, but the nodes themselves do not share or disseminate information, however, they may share information or disseminate information at any time (now or later); recovery node R indicates that the node has accepted the message of refuting the rumor, which comes from the neighbor nodes (Refute the rumor by asking or looking at WeChat's Circles).

The transfer between nodes in susceptible state, latent state, infective state, and recovery state, which depends not only on the state of the node itself, but also on the state of its neighbor nodes. On this basis, the following spreading rules are defined:

(1) If a susceptible Node S is contacted with an infective node I, the node S will convert to node L with the probability p_1. The latent node L will be converted to the infective node I with the probability p_3, and it is necessary to explain that the probability p_3 : p_3 is no related to topology structure between nodes, the conversion $V_j(L) \to V_j(I)$ of the node V_j state L to the I is completely subject to the subjective factors of the node itself (psychological factors);

(2) When the infective node *I* meets the recovery node R, it converts to the node R by probability p_2; when the latent node L meets the recovery node R it will be converted to the node R by probability p_2;

(3) The rumor comes from outside and is injected into a point V_j that makes $V_j(S) \to V_j(I)$. In other words, if there is no external injection, the closed social network has no so-called rumors. In the same way, the information of refuting the rumor also comes from the external injection.

Fig. 1 represents the rules of communication. It needs to be explained that the probability p_3 reflects the subjective state of the node itself. Some people see the rumor and believe it, hence they spread the rumor, while some people believe the rumor, but they reject to spread it. So, the probability p_3 is generally less than 1 in the real-world scenario. As for the "external injection" in Rule 3 is that the rumor does not come from the "social network circle", but it comes from the acquisition of the individual outside the "social network circle", perhaps, Injected into "the social network circle" by somebody after being coined.

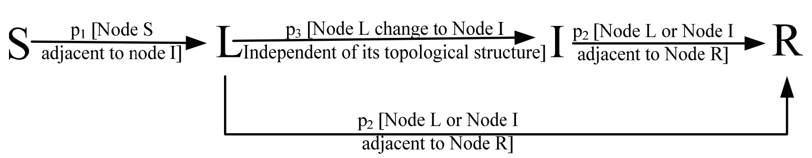

Fig. 1. The relation figure of node state conversion.

In the transformation rule of the spreading model (1), "if a susceptible node *S* is in contact with a infective node *I*, node S converts to the latent node *L* with the probability p_1. The latent node *L* will be converted to the infective node *I* with the probability p_3." It can be understood as, $V_j(S) \xrightarrow{p_1} V_j(L)$, and the converted result $V_j(L)$ will be converted to infective node *I* with the probability p_3, and still is a latent node *L* with the probability 1- p_3, as shown in Fig. 2.

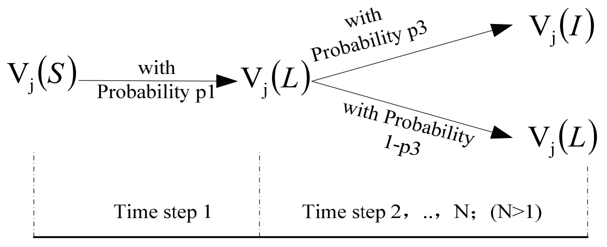

Fig. 2. Explanatory drawing of node S, L, I state conversion illustration.

The reality is that the conversion of $V_j(L) \xrightarrow{p_3} V_j(I)$ is usually happened while $V_j(S) \xrightarrow{p_1} V_j(L)$ changes. Since, a node *S* is contacted with rumor node *I*, if node *S* trusts the rumor, and the rumor is forwarded in no time (node *S* becomes *I*); if node *S* does not trust the rumor, and the rumor is not forwarded (node *S* will be latent node *L*), at that time and afterwards. So we can think of the approximation of the spreading model, as shown in Fig. 3 (the revised rule provides convenience for the subsequent equation description).

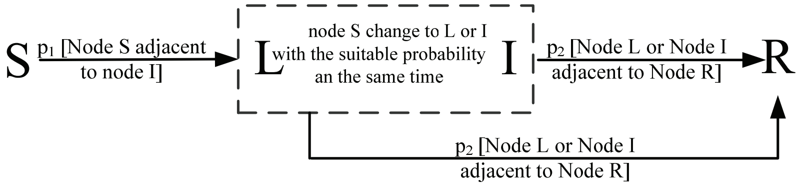

Fig. 3. Revised drawing of node state transformation relationship.

In this way, the spreading model transformation rules (1) can also be expressed as: If a susceptible node S is contacted with a infective node *I,* the susceptible node will convert to the infective node *I* with the probability $p_1 * \alpha$, and will convert to the latent node L with the probability $p_1 * \beta$ (among them, $\beta = 1-\alpha$).

3. Dynamic Analysis of Spreading Model

3.1 Average Transfer Probability of Node State

Assume that a node V^j is a susceptible node, which is expressed as $V^j(S)$. $P^j{}_{SS}$ indicates the probability that node $V^j(S)$ is still in a susceptible state in the time period of $[t, t+\Delta t]$. Accordingly, $P^j{}_{SL}$ represents the probability of the transition of node $V^j(S)$ into the latent node $V^j(L)$ in the time period of $[t, t+\Delta t]$. $P^j{}_{SI}$ represents the probability that the node $V^j(S)$ is transformed into the infective node $V^j(I)$ in the time period of $[t, t+\Delta t]$. In similar tags, the probability expression of the node state invariance is also $P^j{}_{LL}$ $P^j{}_{II}$, and the probability expression of the node state change is $P^j{}_{LI}$, $P^j{}_{LR}$, $P^j{}_{IR}$, with the similar meaning to the above explanation. Then,

$$P^j{}_{SS} = (1-\Delta t * p1)^G \tag{1}$$

Among them, $G = G(t)$ indicates the number of infective nodes in the neighbor of the $V^j(S)$ node at the t moment. It is assumed that the node $V^j(S)$ contains K edges, and $G(t)$ is a random variable with two distribution, as follows:

$$\prod(G,t) = \binom{k}{G} \omega(k,t)^G (1-\omega(k,t))^{(k-G)} \tag{2}$$

where, $\omega(k,t)$ represents the probability of connecting a susceptible node with a K edge to an infective node at *t* time. $\omega(k,t)$ can be written as:

$$\omega(k,t)=\sum_{k'} p(k'|k)p(I_{k'}|S_k)\approx\sum_{k'} p(k'|k)\rho^I(k',t) \tag{3}$$

where, $\sum_{k'} p(k'|k)$ is a degree correlation function, which represents the conditional probability of a node with a degree of k and a node with a degree of k' ; $p(I_{k'}|S_k)$ represents the probability of being in a infective state under the condition of a node with a k' edges that are connected to a susceptible node with a degree of k . $\rho^I(k',t)$ represents the density of the infective nodes of the scale of k' at the time of t .

Therefore, the average transfer probability $\overline{p}_{SS}(k,t)$ of a susceptible node with a degree of K, during the $[t,t+\Delta t]$ period can be calculated as follows:

$$\begin{aligned}\overline{p}_{SS}(k,t)&=\sum_{G=0}^{k}\binom{k}{G}\omega(k,t)^G(1-\omega(k,t))^{(k-G)}(1-\Delta t*p_1)^G\\&=\sum_{G=0}^{k}\binom{k}{G}((1-\Delta t*p_1)\omega(k,t))^G(1-\omega(k,t))^{(k-G)}\\&=((1-\Delta t*p_1)\omega(k,t)+(1-\omega(k,t)))^k=(1-\Delta t*p_1\omega(k,t))^k\\&=\left(1-\Delta t*p_1\sum_{k'}p(k'|k)\rho^I(k',t)\right)^k\end{aligned} \tag{4}$$

In the same way, it can be concluded that the conversion probability of the latent node $V^j(L)$, neighbored with the recovery $V(R)$, is $p_{LL}^j=(1-\Delta t*p_2)^G$. Meanwhile, the infective node $V^j(I)$ has the same state change probability $p_{II}^j=(1-\Delta t*p_2)^G$ with the recovery node $V(R)$ around it.

As a result, it can be concluded that the average transfer probability of a node with a degree of k in the latent state or infective state within a period of time $[t,t+\Delta t]$ is:

$$\begin{aligned}\overline{p}_{LL}(k,t)&=\sum_{G=0}^{k}\binom{k}{G}\omega(k,t)^G(1-\omega(k,t))^{(k-G)}(1-\Delta t*p_2)\\&=\sum_{G=0}^{k}\binom{k}{G}((1-\Delta t*p_2)\omega(k,t))^G(1-\omega(k,t))^{(k-G)}\\&=((1-\Delta t*p_2)\omega(k,t)+(1-\omega(k,t)))^k=(1-\Delta t*p_2\omega(k,t))^k\\&=\left(1-\Delta t*p_2\sum_{k'}p(k'|k)\rho^R(k',t)\right)^k\end{aligned} \tag{5}$$

Therefore, the average transfer probability of a node with a degree of k in the infective state within a period of time $[t,t+\Delta t]$ is:

$$\begin{aligned}\overline{p}_{II}(k,t)&=(1-\Delta t*p_2\omega(k,t))^k\\&=\left(1-\Delta t*p_2\sum_{k'}p(k'|k)\rho^R(k',t)\right)^k\end{aligned} \tag{6}$$

3.2 The Density Change Rate of Each State

$N(k,t)$ is used to express the total number of the nodes in the network with the degree of k, and $S(k,t)$, $L(k,t)$, $I(k,t)$, $R(k,t)$ represent the number of the susceptible nodes, the latent nodes, the infective nodes, and the recovery nodes, respectively. The total number of the nodes in the network is as follows:

$$S(k,t)+L(k,t)+I(k,t)+R(k,t)=N(k,t)$$

The changes of the number of the susceptible node with a degree of K in the network in the period of time $[t,t+\Delta t]$ are:

$$\begin{aligned} S(k,t+\Delta t) &= S(k,t)-S(k,t)\left(1-\overline{p}_{SS}(k,t)\right) \\ &= S(k,t)-S(k,t)\left(1-\left(1-\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right)\right)^k\right) \end{aligned} \tag{7}$$

There are:

$$S(k,t+\Delta t)-S(k,t)=-S(k,t)\left(1-\left(1-\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right)\right)^k\right)$$

There are:

$$\frac{S(k,t+\Delta t)-S(k,t)}{N(k,t)}=-\frac{S(k,t)}{N(k,t)}\left(1-\left(1-\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right)\right)^k\right) \tag{8}$$

By the binomial theorem:

$$\begin{aligned} \left(1-\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right)\right)^k &= \sum_{i=0}^{k}\binom{k}{i}\left[-\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right)\right]^i \\ &\approx 1-k\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right) \end{aligned}$$

The higher order power is skipped here.

Then:

$$\frac{S(k,t+\Delta t)-S(k,t)}{N(k,t)}=-\frac{S(k,t)}{N(k,t)}k\Delta t * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right) \tag{9}$$

Then:

$$\frac{\left(\dfrac{S(k,t+\Delta t)}{N(k,t)}-\dfrac{S(k,t)}{N(k,t)}\right)}{\Delta t}=-\frac{S(k,t)}{N(k,t)}k * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right) \tag{10}$$

In Eq. (10), when $\Delta t \to 0$, the density change immediate rate of the susceptible node is obtained as follows:

$$\frac{\partial \rho^S(k,t)}{\partial t}=-\rho^S(k,t)k * p_1\sum_{k'} p\left(k'|k\right)\rho^I\left(k',t\right) \tag{11}$$

The changes in the number of latent nodes with a degree of k in the network during the period of time $[t, t+\Delta t]$ are:

$$L(k,t+\Delta t) = L(k,t) + S(k,t)\left(1-\overline{p}_{SS}(k,t)\right) - N(L \to I) - L(k,t)\left(1-\overline{p}_{LL}(k,t)\right) \tag{12}$$

The changes in the number of infective nodes with a degree of k in the network during the period of time $[t, t+\Delta t]$ are:

$$I(k,t+\Delta t) = I(k,t) + S(k,t)\left(1-\overline{p}_{SS}(k,t)\right) + N(L \to I) - I(k,t)\left(1-\overline{p}_{II}(k,t)\right) \tag{13}$$

According to the description and interpretation of the model rules (1) in Figs. 2 and 3, the equations (12) and (13) are further analyzed as follows:

It needs to be explained: $N(L \to I) = S(k,t)\left(1-\overline{p}_{SS}(k,t)\right) * \alpha$

Among them: $\alpha \in (0,1)$

[Note: $N(L \to I)$ is the number of latent nodes changing to the number of infective nodes]

then： $L(k,t+\Delta t) - L(k,t) = S(k,t)\left(1-\overline{p}_{SS}(k,t)\right)\beta - L(k,t)\left(1-\overline{p}_{LL}(k,t)\right)$，（$\beta = 1-\alpha$）

Among them：

$$\left(1-\overline{p}_{SS}(k,t)\right) \approx k\Delta t * p_1 \sum_{k'} p(k'|k)\rho^I(k',t)$$

$$\left(1-\overline{p}_{LL}(k,t)\right) \approx k\Delta t * p_2 \sum_{k'} p(k'|k)\rho^R(k',t)$$

There are:

$$L(k,t+\Delta t) - L(k,t) = S(k,t)k\Delta t * p_1 \sum_{k'} p(k'|k)\rho^I(k',t)\beta - L(k,t)k\Delta t * p_2 \sum_{k'} p(k'|k)\rho^R(k',t) \tag{14}$$

Then:

$$\frac{\partial \rho^L(k,t)}{\partial t} = \rho^S(k,t)k * p_1 \sum_{k'} p(k'|k)\rho^I(k',t)\beta - \rho^L(k,t)k * p_2 \sum_{k'} p(k'|k)\rho^R(k',t) \tag{15}$$

Likewise, with the conversion of Eq. (13), we can achieve the following equation:

$$I(k,t+\Delta t) = I(k,t) + S(k,t)\left(1-\overline{p}_{SS}(k,t)\right) + N(L \to I) - I(k,t)\left(1-\overline{p}_{II}(k,t)\right)$$

There are:

$$I(k,t+\Delta t) = I(k,t) + S(k,t)\left(1-\overline{p}_{SS}(k,t)\right)\alpha - I(k,t)\left(1-\overline{p}_{II}(k,t)\right)$$

There are:

$$I(k,t+\Delta t) - I(k,t) = S(k,t)k\Delta t * p_1 \sum_{k'} p(k'|k)\rho^I(k',t)\alpha - I(k,t)k\Delta t * p_2 \sum_{k'} p(k'|k)\rho^R(k',t) \tag{16}$$

Then:

$$\frac{\partial \rho^{\mathrm{I}}(k,t)}{\partial t} = \rho^S(k,t)k * p_1 \sum_{k'} p(k'|k)\rho^I(k',t)\alpha - \rho^I(k,t)k * p_2 \sum_{k'} p(k'|k)\rho^R(k',t) \tag{17}$$

Finally, the density change immediate rate of the R nodes:

$$R(k,t+\Delta t) = R(k,t) + L(k,t)\left(1-\overline{p}_{LL}(k,t)\right) + I(k,t)\left(1-\overline{p}_{II}(k,t)\right)$$
$$\left(1-\overline{p}_{LL}(k,t)\right) \approx k\Delta t * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right)$$

and,

$$\left(1-\overline{p}_{II}(k,t)\right) \approx k\Delta t * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right)$$

Then:

$$R(k,t+\Delta t) - R(k,t) = \left[L(k,t) + I(k,t)\right]k\Delta t * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right) \tag{18}$$

The final results are as follows:

$$\frac{\partial \rho^R(k,t)}{\partial t} = \left[\rho^L(k,t) + \rho^I(k,t)\right]k * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right) \tag{19}$$

3.3 Analysis of Dynamic Equation

From the above formulas (11), (15), (17), (19), the dynamic equations set are obtained:

$$\begin{cases} \dfrac{\partial \rho^S(k,t)}{\partial t} = -\rho^S(k,t)k * p_1 \sum_{k'} p\left(k'\middle|k\right)\rho^I\left(k',t\right) & (11) \\ \dfrac{\partial \rho^L(k,t)}{\partial t} = \rho^S(k,t)k * p_1 \sum_{k'} p\left(k'\middle|k\right)\rho^I\left(k',t\right)\beta - \rho^L(k,t)k * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right) & (15) \\ \dfrac{\partial \rho^I(k,t)}{\partial t} = \rho^S(k,t)k * p_1 \sum_{k'} p\left(k'\middle|k\right)\rho^I\left(k',t\right)\alpha - \rho^I(k,t)k * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right) & (17) \\ \dfrac{\partial \rho^R(k,t)}{\partial t} = \left[\rho^L(k,t) + \rho^I(k,t)\right]k * p_2 \sum_{k'} p\left(k'\middle|k\right)\rho^R\left(k',t\right) & (19) \end{cases}$$

From Eq. (11), we know that the density change rate of susceptible nodes $\frac{\partial \rho^S(k,t)}{\partial t}$ is positively related to the amount of the susceptible nodes (density) $\rho^S(k,t)$, the relative amount of infective nodes $\sum_{k'} p\left(k'\middle|k\right)\rho^I\left(k',t\right)$ and k and p_1 in closed system.

On the one hand, the composite parameter $\sum_{k'} p\left(k'\middle|k\right)\rho^I\left(k',t\right)$ reflects the total quantity (density) of the infective nodes, and on the other hand it is related to the topology of the susceptible node. In general, the more the $V^j(S)$ connection nodes, the greater the probability of touching the rumor. The most extreme case is when $V^j(S)$ is an isolated node, it can only be infected by the rumors outside the social system, but not the social network. Hence, the parameter p_1 reaction is the sensitivity of the system node to the rumor, which has a lot of sociality, for instance, it is difficult for the knowledgeable people to easily believe the rumor.

It is known from Eq. (19) that the density change rate of the recovery nodes $\frac{\partial \rho^{R}(k,t)}{\partial t}$ is positively related to the amount of the sum of density of the latent nodes $\rho^{L}(k,t)$ and the density of the infective nodes $\rho^{I}(k,t)$. Also, $\frac{\partial \rho^{R}(k,t)}{\partial t}$ is positively related to the total population density of the recovery nodes $\sum_{k'} p(k'|k)\rho^{R}(k',t)$ and the k and p_2. Also, the measure of $\frac{\partial \rho^{R}(k,t)}{\partial t}$ is related to the topology of $V^{j}(L)$ and $V^{j}(I)$, and is also related to the sensitivity of the rumor and refuting rumors of the social groups' nodes.

The analyses of Eqs. (15) and (17) can also confirm that two density conversion rates are all related to the topological structure of social network interior points and the sensitivity of social network nodes to the rumors and the refuting information. It is necessary to add that the parameters α and β in the system have basic conditions: $\alpha+\beta=1$, α and β are rational numbers greater than 0, and less than 1. The value of α and β is subject to a complex psychological factor, subjected to further study, in future.

4. Data Simulation Analysis

4.1 Network Construction

In this study, a virtual network is built based on WeChat social circles, using simulation. This network is constructed by building node connections through the WeChat social circle in real life, subsequently, four states (i.e., the SLIR) of some nodes are set, the evolution of states are analyzed, accordingly. The details are as follows:

The WeChat is a social network tool which has become popular during recent years. According to Tencent's mid-2016 performance report, the number of active users in the WeChat is 806 million. Therefore, it is of practical significance to use the social network built by the WeChat users to analyze the evolution simulation of the rumors and the refuting rumors. However, the related information between the WeChat users involves the business confidentiality of the Tencent, the acquisition of one hand data and the experiment violate of the relevant laws and regulations.

Considering the feasibility of the experiment, a small social circle of about 1,000 people are considered to do the experiment and create a virtual social network, through sample data and fictitious data. On this basis, the experiment forms a social network by a moderate fictitious association of nodes, based on a modest fictitious node association based on the ZZ street WeChat social network in the YY town of XX city. The constructed social network for simulation experiments is about 1000 nodes. Finding out some institutions or companies from the ZZ street, through questionnaires and visits, we can basically identify which units have a group of employees on the scale of the WeChat, and which unit employees have frequent WeChat contacts. On the basis, based on the data from more than 700 people, a number of freelancers are added to the social network, to identify the connections between this group and the main group (i.e., 700 people)—relatives, neighbors, trade, etc. The person is numbered by a unit if he belongs to a unit, or, he is numbered by a freelance organization if he does not belong to any unit. On this basis, a WeChat community with 1,002 members is formed.

The survey revealed that this 1,002-member community has a typical small world network characteristics, for example, the employees of the same unit are closely related (large clustering coefficient), hence, the randomly connected freelancer is enough to make the flow of information fast (short path). Following the literature [23-25], the 1,002 network nodes allowed to have a small world characteristics. On the other hand, based on the survey, there are a few people which were especially "get along fine", and were able to chat with many people (individual nodes have a large degree). In contrast, some extremely introverted personality defects, were often unable to even contact their office colleague (individual nodes have extremely small degrees), which are identified as the characteristics of scale free network.

Therefore, following the theory proposed in the literature [3], in combination with the investigation of several unusual nodes, the degree of association of individual nodes (which is the few "most active individuals" in the survey) is appropriately increased. In contrast, the degree of association of individual nodes (which is the few "extremely introverted individuals" in the survey) is reduced. On this basis, some characteristics of the scale-free degree are formed within the WeChat community (the WeChat social circle). In addition to the above requirements, ensuring that each node is not an isolated node (if it is isolated, it is deleted), the virtual network with 1,002 nodes is finally formed. The minimum nodal degree is 11, the maximum is 390, the average is 80.56, and the median of the nodal degree is 71. The general situation of node association is presented in Fig. 4.

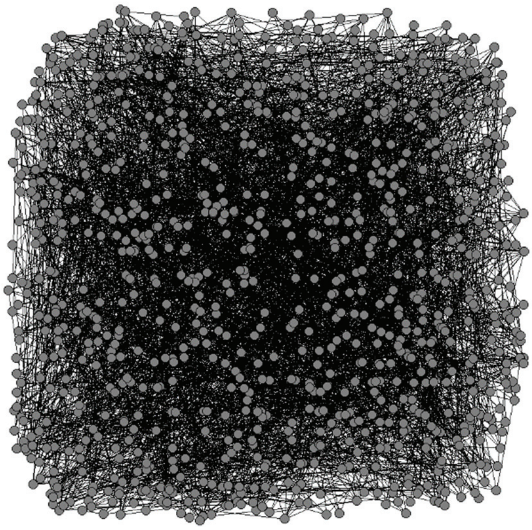

Fig. 4. The virtual social network of 1,002 nodes of the construction.

4.2 Simulation Data Analysis

The image of the degree distribution function is drawn by the statistics of the correlation degree of the 1,002 nodes, as shown in Fig. 5. As it can be observed in Fig. 5, the nodes and associations based on reality have a certain degree of scale-free characteristics on the basis of a modest fictitious basis.

Subsequently, the rumor is injected into the system, through three different ways: (1) a class of nodes with smaller degrees (the degree is near the minimum); (2) a class of nodes with larger degrees (the degree is near the maximum); and (3) a class of nodes in the vicinity of the average (the degree is near the median). In the next stage, 5 points taken from each of these three types of nodes which were infused the rumors. Consequently, the change of the density of the infective nodes and the latent nodes are obtained, as shown in Fig. 6 (The value of p_3 is 0.6, The value of p_1 is 0.2, The value of p_2 is 0.1).

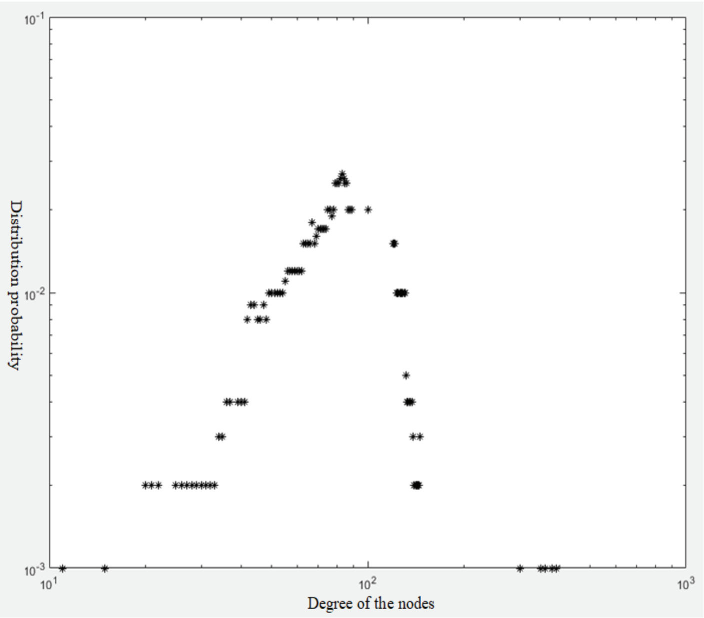

Fig. 5. degree distribution of virtual social network nodes.

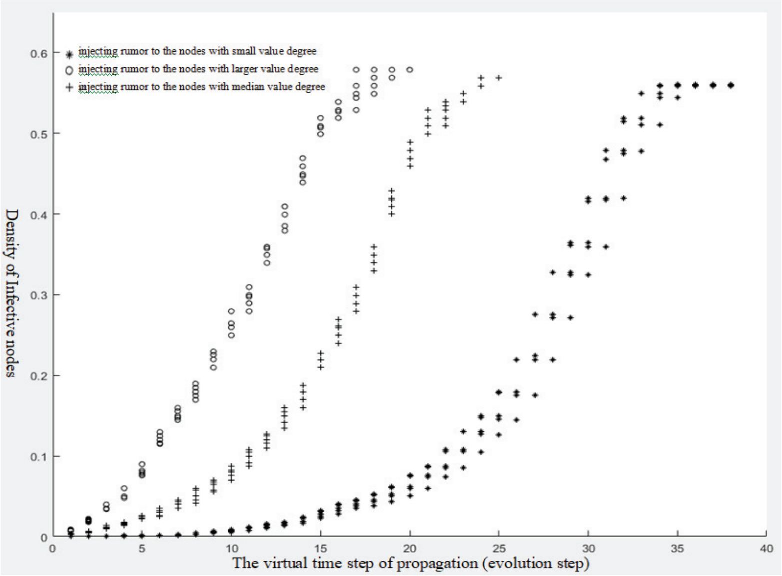

Fig. 6. Density variation of the three classes of infective nodes.

The rumors are injected into the system in three categories, when the number of infective nodes reaches the peak. Subsequently, the information of refuting the rumor was injected into three types of nodes. Fig. 7 represents the changes in the density of recovery nodes after the three types of nodes are injected.

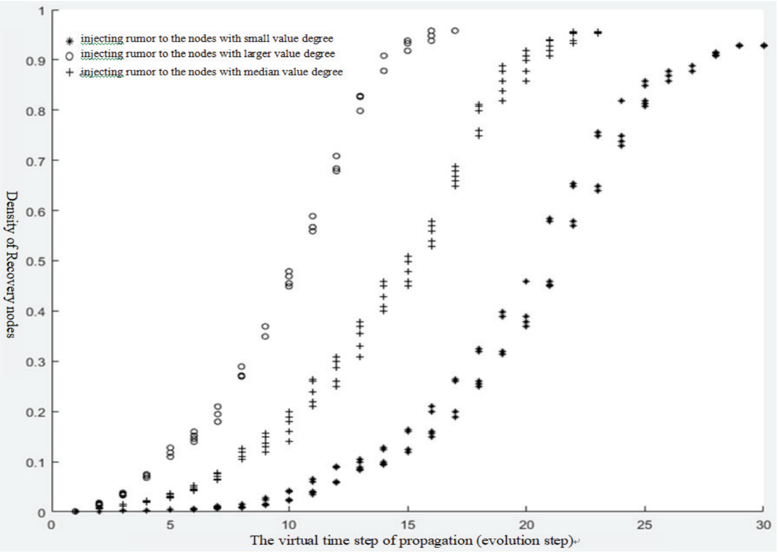

Fig. 7. Density variation of the three classes of recovery nodes in a virtual social network.

The above two types of experiments, regardless of being the injection of rumors or the injection of refuting-rumor-information, suggest that the evolution of the system after injection is significantly associated with the degree distribution of the injected node. The rumor information is injected from some nodes with node degree greater than 350, and the density growth of infective nodes is much larger. While, the injection from other nodes with node degree less than 20, hence, the density growth of infective nodes is much slower. In addition, the refuting-rumor-information is injected from some nodes with larger value degree, and the density growth of recovery nodes is much faster. While, the injection from other nodes with smaller value degree, hence, the density growth of recovery nodes is much slower.

The parameter $\sum_{k'} p(k'|k)\rho^{I}(k',t)$ of Eq. (11) explains the relationship between the evolution of the system and the topology of the node, after the rumor injection. The same applies to the parameter $\sum_{k'} p(k'|k)\rho^{R}(k',t)$ in the Eqs. (15), (17), and (19). A clear conclusion is that the selection of information injection nodes of the rumor and the refuting-rumor-information affect the subsequent evolution of the various nodes in the system.

The situation can be more complicated, when the rumor and the refuting-rumor-information are injected into the system, at the same time. The other possibility is that to select a number of nodes near the median degree to infuse the rumor and the refuting-rumor-information, and select the average of the 20 trials by many experiments. The density variations of the four types of nodes in SLIR are presented in Fig. 8 (the value of p_3 is 0.5, the value of p_1 is 0.2, the value of p_2 is 0.1).

The result of the experiment identify that the influence of the early spread of the rumor is obviously higher than the influence of the refuting-rumor-information, in case of injecting the rumor and the refuting-rumor-information at the same time (the total density of the infective nodes and the latent nodes is obviously larger than the density of the recovery nodes, at first). With the expansion of the transmission range and the increase of the total density of the affected nodes, the influence of the recovery nodes is bigger and bigger. Finally, the recovery nodes occupy the absolute superiority of the whole system. Surprisingly, always a part of the susceptible nodes in the system remains uninfected. This is probably because the rumors and the refuting-rumor-information are almost simultaneously injected, some nodes with small degrees are earlier to be immunized (being recovery nodes), and some other nodes that are closely related to it, may have no chance of being infected by rumors (never being infective nodes).

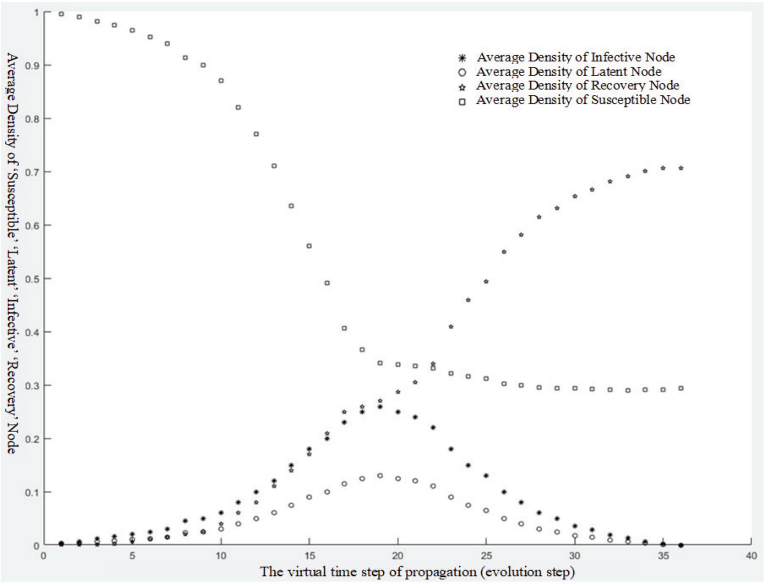

Fig. 8. The average density changes after the injection of rumor and refuting-rumor-information.

5. Summary and Prospect

In this research, an evolution model of rumor spreading is subjected to study, based on WeChat social circle. The evolution of rumor spreading is depicted through the propagation dynamics equation, where, the evolution of the four nodes in the SLIR model is subject to the topology of the nodes, the density of the four kinds of nodes, the information sensitivity of the nodes (p_1 , p_2), and some psychological factors (p_3). The relative factors, about the evolution of the four states, are obtained through different equations. Subsequently, the four states in the form of mutual cause and effect, form a dynamic evolution process. This study constructs a social network through a realistic WeChat community, and simulates the spread of the rumors in the WeChat's social circle, based on this social network. The simulation results show that the spreading efficiency of the nodes with various node degrees is significantly different, which also confirms the early deduction from the dynamic equation. In addition, the node degree affects the efficiency of evolution. However, the final density of I nodes or the R nodes are not significantly affected. This result can be related to the total number of nodes in the simulation network and the topology of the whole network.

In the era of Internet and mobile Internet, the dissemination of information in social networks, including the rumors, has become a norm. Current literature review suggest significant studies are performed in regards to the rumor spreading, However, this research stands out from the the existing literature, due to providing an evolution model, based on the reality oriented simulation. The construction of the rumor evolution model SLIR and the construction and deduction of propagation dynamics equation in this study provide a significant reference for the future studies on the rumor spreading model. The simulation realization facing the real background, especially for the injection of the rumors or the refuting-rumor-information, provides a valuable method for tracking and controlling of the rumors in the real-world scenarios. The background of this article is mainly the social network constructed by the WeChat social circle, which is obviously different from the social circle based on the portal platform, as well as the micro-blog dating for mutual attention and information display. Effective equation deduction solves the problem of logical trust and provides the certainty in research. In addition, simulation of realistic social networks is more believable for authenticity. This information interaction on the WeChat platform, in a larger scale, is considered as a limitation for this kind of research, due to the privacy of citizens' personal information and the highly confidential information of the Tencent Inc. Subsequent research can be carried out on other platforms, such as Facebook or a new social platform in China, called "Douyin". Furthermore, some parameters of this model, such as p_1, p_2, α and β ,can be studied in depth. In particular, studying the psychological factors, α and β , helps to identify the influence of various factors on them, through comprehensive methods of statistics and social psychology, such as the individual age, the education, the work experience, and the work nature influence.

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