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Research on Process Modeling of Information Dissemination Based on Social Network

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Abstract

According to the retweeting mechanism based on user relations, we introduce the contacted state of an agent, and build a model of information propagation process in social networks. In the model, agents have two absorbing states, that is, the infected and refractory state. Experimental prove that small spreading rete can make information diffuse widely, and the degree based density of infected agents increases with the degree monotonously. The influence between information occurs only when different information originates in the same local neighborhood.

Keywords: *Social network, Network consensus, Information dissemination*

1. Introduction

Social network is a network application which emerges over recent years [1-3]. It provides convenient platform for users to share and spread information, view exchange, and emotional expression. By virtue of its unique information broadcasting pattern, easy and quick information distribution mode, scalability of open API, cross-platform and multi-terminal flexibility, as well as accessible interactivity any time anywhere, social network gains general concerns since its appearance [4-6]. With the number of users growing up exponentially, it becomes one of major network media. Social network information is disseminated through user social network [7-8]. User is creator and disseminator of network information. American social network website Facebook has more than 800,000,000 active users [9] as of July 2013. As another representation of social network, micro-blog posts a message which strictly contains less than 140 words. Longer text needs transferring to picture and displaying in the form of picture. As to December 2013, Chinese micro-blog users reach up to 360,000,000, increasing by 287.0% than last year end. Netizens who use micro-blog takes 52.7% [10].

When a piece of message is posted on social network website, it may be forwarded tremendously in a very short time, which would affect wide-range users. Hence social network becomes the media which spread information the fastest. Some false and negative words would diffuse rapidly through social network. Even though some original messages are removed, they have plentiful recipients. The resulted negative influence is immeasurable. Hence, studies on the dissemination of social network information are helpful to understand well the essence of the outbreak of social network public opinion and analyze causation to social network emergent group incidents. The research about relationship between user relation network and information spreading will help find out factors that affect the propagation of information, laying foundations for information propagation tendency and hot topic prediction.

At present, scholars have studied information spreading process of network media. They often investigated such process on actual network topology by virtue of epidemic dynamics, rumor propagation dynamics theory such as email forwarding, microblog network information share, microblog topic spreading and diffusion. Information

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propagation currently is analyzed by relying on different under-layer complex network, with more attention attached to reveal influences of topological structure on spreading scale. The remodeling of spreading mechanism is largely based on its own extension model. In social network, the effective way of information communication is message transmitting. When user finds an interesting message, he/she will forward it to his/her friends, together with comments. The message keeps its completeness. Obviously, message forwarding mechanism of social network is unlike traditional SIR model. To be specific, in former one, forwarding can co-exist with immune procedure and forwarding and immunity can both be stable state; in SIR model, single unit become immune only after being infected.

Here we'll create information communicate mode of social network and introduce node's contact status. Contact status means a post is read by nodes but not known whether it's forwarded. Contact status can further be converted to spreading message or negative message. Only after it's forwarded, the message can spread to friends. Next, we make numerical simulation analysis of the model and investigate impacts of different network topologies on communication speed and scale. That will help understand information forwarding behavior of social network.

2. Information Forwarding Mechanism of Social Network

In social network, new posted message by a user will be pushed by system to its relative friends so that they can instantly read the message. When friends read it, they will consider whether it's necessary to relay it. If the message is meaningful, some neighbors will forward it. Hence, the author's neighbor's neighbors will possibly read the message. Till this moment, influence range of the message goes beyond expectation of the origin author and it's probably transmitted in a large scale. On the contrary, if the author's neighbors have no interest in the message, it will be forgotten, affecting very few persons. Once a reader forwards the message, it will list on its page for long. Meanwhile, it will be pushed to the reader's neighbors. Even though the reader does not concern it any more, neighbors are still able to read the message. The message keeps its infectious state unchanged after being relayed, unless it's deleted in a special case by network administrator. If the message is not immediately forwarded after neighbors read, they will become less enthusiasm about spreading it till they become indifferent to it.

The message information process involves studying a given message and confirming its forwarding range and spread speed by users. In social network message broadcasting, individuals have a few of possible states: ignorant, contact, infected, immune state. Ignorant means individual never reads the message. Those who read the message and forward it are in an immune state. After individuals read the message and have not decided if to transmit the message, they go to a contact state. When individuals are completely unwilling to spread the message, they turn to an immune state. It is shown in Figure1.

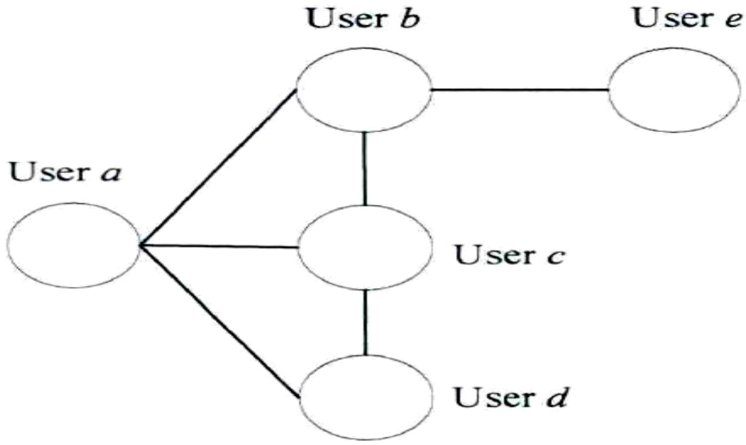

Figure 1. Map of Social Network Information Dissemination

In the model, the first rule indicates individual's intention to accept message at certain probability. However, in actual social network, the probability is decisive on many factors like message content, writer authority. Individual in the model has two possible absorbing states: affected and immune state. In traditional SIR model, infected nodes will get immune and stop spreading message. Opposite to SIR model, contact state of nodes is introduced in the paper. Only nodes in contact state can get immunity. Contact state is a temporary condition. In evolving telophase of the system, infected and immune units co-exist in it.

In the paper, we do mean-field analysis of the model. Message communication process is greatly concerned with network topology. We define: at time period t, ignorant node, contact node, infected node and immune node have density $i(k,t), s(k,t), c(k,t), r(k,t)$ at degree k. Set probability $p_{si}(k,t)$, $p_{ci}(k,t)$ of k-degree ignorant-state nodes and contact-state nodes being affected in the time interval $[t, t+\Delta t]$. Ignorant-state nodes can only be infected by communicating nodes. So the average density [11] of infected neighbors of k-degree nodes is:

$$\sum_{k'} P(k' \mid k) i(k', t) \tag{1}$$

If an individual has k neighbors, it will be affected by k times and the probability $p_{si}(k,t)$ is:

$$p_{si}(k,t) = 1 - \left(1 - \lambda \Delta t \sum_{k'} P(k' \mid k) i(k', t)\right) \tag{2}$$

It is noted that the contact state node that does not have immediate access to the immune system may be infected. Transition probability $p_{ci}(k,t)$ is

$$p_{ci}(k,t) = \lambda k \Delta t (1-\delta) \sum_{k'} P(k' \mid k) i(k', t) \tag{3}$$

$i(k,t)$ is due to ignorance of the node or the contact node is infected, $i(k,t)$ change quantity is

$$i(k, t+\Delta t) = i(k,t) + s(k,t) p_{si}(k,t) + c(k,t) p_{ci}(k,t) \tag{4}$$

Similarly, we can get the variation rate of $s(k,t), c(k,t), r(k,t)$ as follows:

$$\begin{aligned}
&\partial_1 s(k,t) = -k.s(k,t)\sum_{k'} i(k' \mid t)P(k',k) \\
&\partial_1 c(k,t) = (1-\lambda)k.s(k,t)\sum_{k'} i(k' \mid t)P(k',k) - \lambda k(1-\delta) \\
&\partial_1 i(k,t) = \lambda k.s(k,t)\sum_{k'} i(k' \mid t)P(k',k) + \lambda k(1-\delta) \\
&\partial_1 r(k,t) = \delta.c(k,t)
\end{aligned} \tag{5}$$

After integration of two sides of the first equation in equation 5 [12], we can obtain:

$$s(k,t) = s(k,0)\exp(-k\phi(t)) \tag{6}$$

According to formula 5, $i(k,t)$ the steady state value should be satisfied.

$$\lambda \le i(k,\infty) \le 1 - \frac{(1-\lambda)\delta}{\lambda k(1-\lambda)\phi'_{\infty} + \delta} \tag{7}$$

Clearly from formula 7, when λ is bigger, $i(k,\infty) \approx 1$; when δ is bigger, $i(k,\infty) \approx \lambda$. Therefore, the result shows that message's spreading threshold in network is 0. The infected probability λ being smaller can make message get rid of limited scope and diffuse in a wider area. To understand better basic features of the model, we now consider the spreading procedure in uniform network. Assume the scale in uniform network is k. Equation5 is simplified further to:

$$\begin{aligned}
&\partial_1 s(k,t) = -k.s(k,t).i(t) \\
&\partial_1 c(k,t) = (1-\lambda)k.s(t).i(t) - \lambda k(1-\delta) \\
&\partial_1 i(k,t) = \lambda k.s(t).i(t) + \lambda k(1-\delta) \\
&\partial_1 r(k,t) = \delta.c(t)
\end{aligned} \tag{8}$$

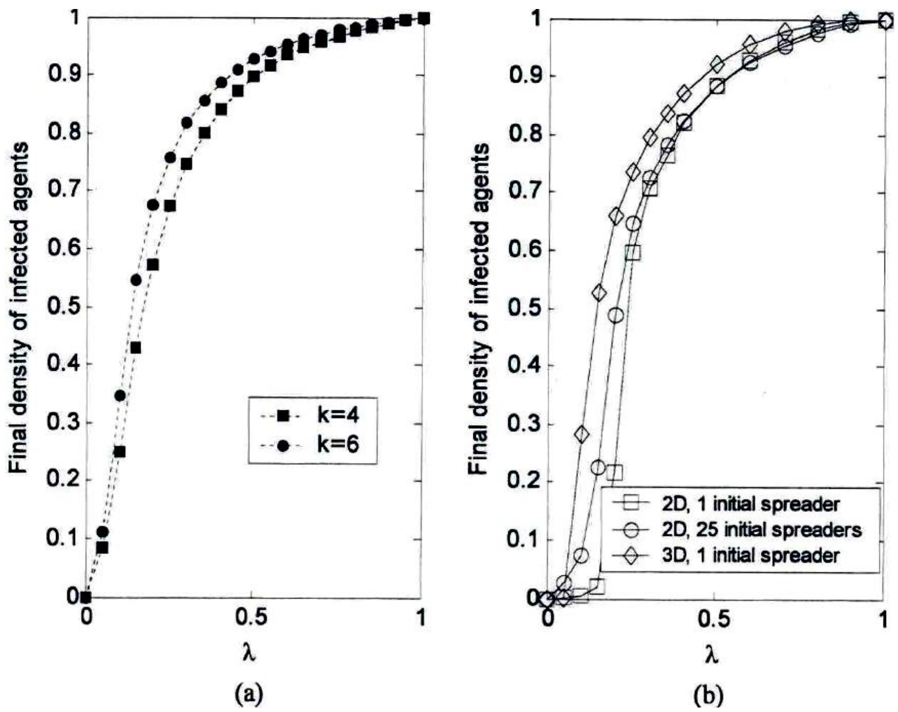

Figure 2. The Final Density of Infected Nodes of Analysis (a) and Simulation (b)

In Figure2(a), the figure indicates the relationship between $i(t)$ the steady state and λ ,the initial density of infected node is $0.11, \delta = 0.2$. Because the infection state of the node is absorbed, it is easy to spread the information in the global scope.

3. Experiment Design and Discussion

We conduct numerical simulation of message communication model of social network. For a network of N size, update it for N times according to above communication rules, with time telophase plus 1. In the simulation, we utilize scale-free network and multi-dimensional rule grid as interactive topology. Before each simulation, we choose randomly individuals as initial communicating nodes; all other units are ignorant.

3.1. Infected Degree in Stable State

Figure2 (b) presents how the density of infected nodes in stable state varying with λ during numerical simulation in regular grid. It lists mean value of 100 times of simulation. $N = 2500, \delta = 0.2$ .Obviously, message communication probability λ 's threshold is nearly 0. When λ is bigger than threshold, message can spread in a wider scope. That's in agreement with mean-field analysis. When λ is a little bigger, numerical simulation in regular network reaches identical result to the analysis. When λ is very small, infected node density in terminal state after simulation is smaller than the analyzed. That is because, during random fluctuation, lower communication probability makes all neighbors of communicator get immune. So the dynamic course is soon frozen and that nodes far away from communicator are uninformed. Ignorant units never view message, which remains in a confined area. Besides, increasing network connectivity or density of initial affected nodes will reduce the gap between simulation and analysis results. Particularly in 3D network grid, the final infected density in simulation is almost equal to mean-field analysis.

3.2. Time Evolution of Node Density

Give only one infected node in initial network. Figure3 displays the time evolution of node density in ignorant/contact/infected/immune state. $N = 2500, \lambda = 0.2, \delta = 0.2$. The mean scale of scale-free network is 4. Apparently, transient behavior of dynamics in regular network differs from scale-free network. In the former, infected node density grows slowly till up to a stable value; in latter network, infected node density keeps unchanging in the beginning; but after certain time, infected density booms and gets stable soon. Since scale-free network has small average shortest path length, there'll have more infected nodes in terminal system. At early stage, very few people spread message; but after some high-density nodes are infected, message grows explosively and spreads into a global scope. During the evolution, there're hardly nodes in contact state in regular grid, suggesting that contact-state nodes are rapidly infected or get immune. In scale-free network, when ignorant-state nodes are more than infected nodes, contact-state nodes will grow gradually; but they will decrease till disappear along with declining ignorant nodes.

The message communication in social network is just like in scale-free network. In social network, a piece of message may be published by some grass roots. On the early days, the message spreads in limited small area, with little influence. But after relayed by "celebrities" or "opinion leaders", their vast friends will read it. Pushed by those influential units, the message is forwarded quickly, becoming a group event and causing big social impacts. Some false opinions can gain lots of attentions even if it's posted by an ordinary person. That's studies on social network communication mechanism is helpful to understand the nature of sudden incidents in social network.

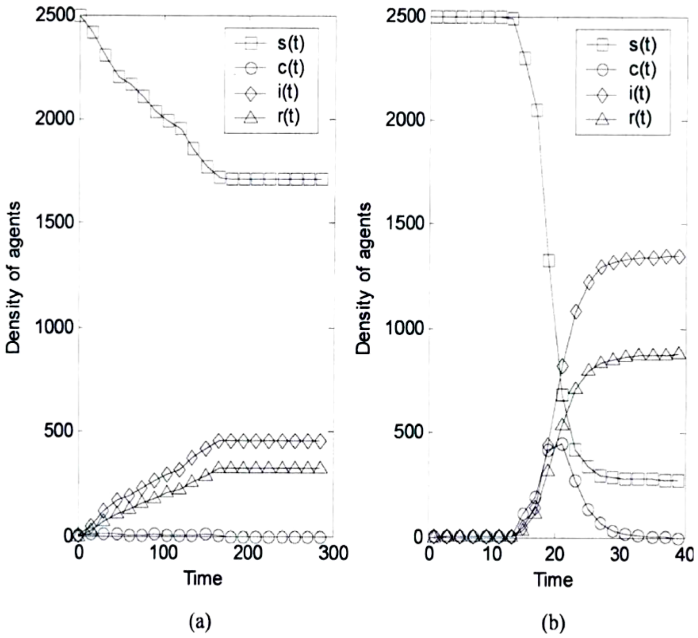

Figure 3. The Time Evolution of the Density of Four States, Two-Dimensional Grid (a), Scale Free Network (b)

3.3. Dependence of Network Structure

The message spreading is closely associated with network topology as medium. For scale-free network, adding edges of new nodes at each time step in the network constructing process is good to improve average degree of network. In Figure 4, when the average degree of network is low, the final infected unit density accelerates rapidly with upgrading network connectivity. Figure 4 is average result of 100 simulations, where the used topological structure is scale-free network. $N = 2500, \lambda = 0.2$ .When a unit has more neighbors, ignorant and contact-state nodes are easily infected and join in relaying the message. In this case, units in contact state will be soon affected for very short time; thus the final state units reduce remarkably. Infected node density won't grow up to 1 along with improving network connectivity. When network average density increases over 30, the proportion of infected units becomes steady. Therefore, even though network average density is big, there still have immune units which refuse to diffuse message. The point is when network is highly connected, communicating units in the final state system are still a big majority despite individuals have higher immune probability λ . It's the same with practical case. Real social network has higher connectivity and bigger cluster coefficient. So in social network, message spreading speed and influence region is bigger than in true society.

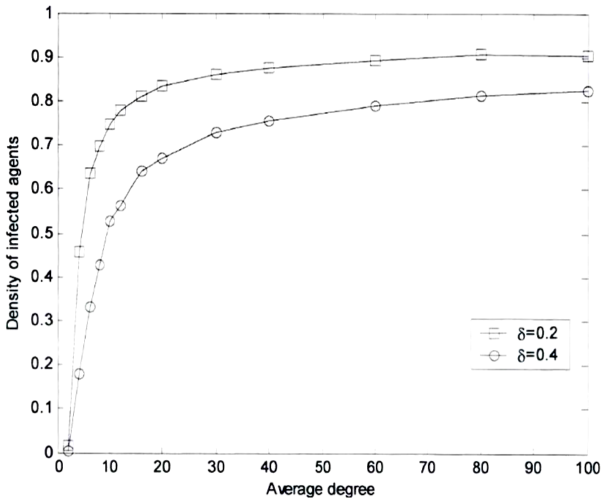

Figure 4. The Relationship of the Density of the Final Infected Nodes and the Average Degree of the Network

Intuitively, different nodes' infected density varies largely. As seen in Figure 5, different nodes' infected density increases non-linearly with growing degree, where network average degree is 4. $N = 2500, \lambda = 0.2$ .It shows average value of 100 simulations. When node density K<20, infected individual density increases monotonically with node density; when K>20, infected density would undulate during growth, for the reason that some high-degree central nodes are surrounded totally by smaller nodes. In the case of bigger immune probability, message communication may stop soon. As a result, message is not forwarded to nodes with higher degree, as their neighbors are nodes of lower degree and in ignorant state. Such phenomenon exists in social network, because some "opinion leaders" are not all inter-connected and they would add "grass roots" as friends. Furthermore, higher immune probability will bring down notably all-degree nodes' infected density on the whole; and partial topological structure of the initial communicator will impact the density of infected nodes in steady state.

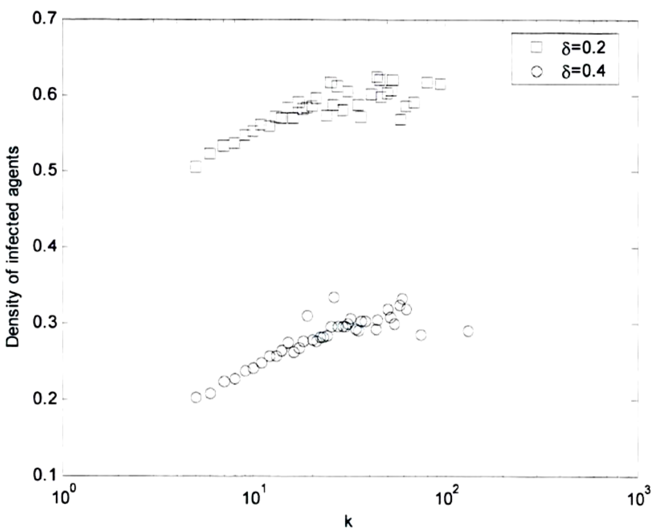

Figure 5. The Relationship of the Final Infection Node Density and the Node Degree in the Scale Free Network

3.4. Relaxation Time in the Communication Process

The system's relaxation time refers to what's required for the system evolving to become stable. That time being shorter means faster message spreading. In Figure 6, when individual infected probability and immune possibility is similar, the system's relaxation time is bigger. In Figure6, $\delta = 0.2$; under-level network is scale-free. Lower or higher infected probability λ will lead to quicker communication of message. Certainly, the two cases differ essentially in dynamics. When λ is smaller, all neighbors of a communicator soon become immune, so that the dynamics process terminates. When λ is bigger, the ignorant and contactors are more easily infected. With increasing infected nodes, the relaxation process will speed up. Especially when λ >0.8, the evolution will stop after a few time steps. What's out of expectation is higher network connectivity will enhance the density of final infected nodes, which, however, does not indicate faster communication process. When network average degree is 10, $\lambda = 0.05, \delta = 0.2$, the system evolves more slowly, because the entire dynamics can't be dominated either by infectious or immune factor.

4. Conclusion

The paper discussed message communication dynamics in social network, with special attentions to the message spreading process based on post forwarding mechanism in social network. Through analysis of such forwarding mechanism, the message communication model of social network was built to simulate communication rules of information sharing among users. Individuals in the network have two stable absorption states: communication and immune state. After being affected and spreading message, an individual won't transfer to other states but only becoming immune after contacting another individual which doesn't forward message. The created model reveals better properties of social network. Next, mean-field analysis and numerical simulation were conducted on the message communication mode and comparative results were obtained. Also, the paper found factors which affect information spreading speed and influence scope. The competition and influence relation was modelled among several information in the end.

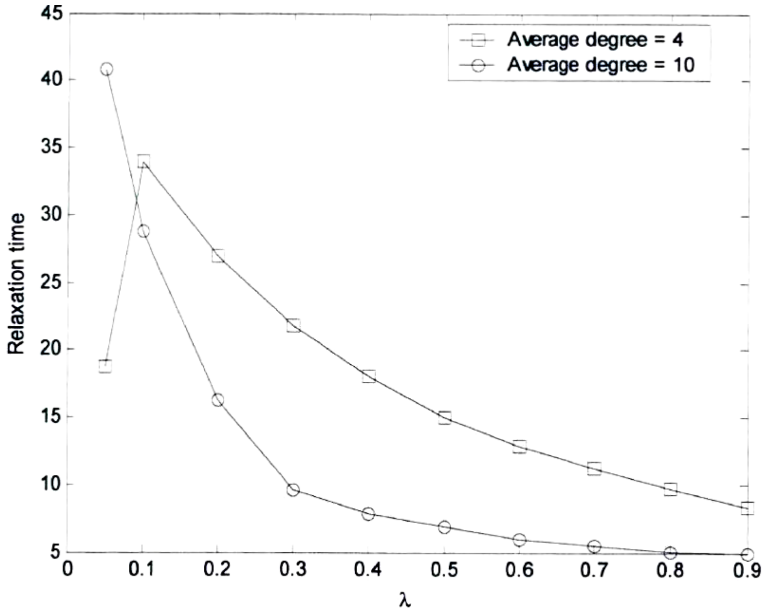

Figure 6. The Relationship of Relaxation Time and λ

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