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Zhijun Yan

Beijing Institute of Technology, yanzhijun@bit.edu.cn

Wenyang Liu

Beijing Institute of Technology, 1281909767@qq.com

Yaohui Pan

Beijing Institute of Technology, 734207068@qq.com

Tianmei Wang

Central University of Finance and Economics, wangtianmei@cufe.edu.cn

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THE EFFECT OF TRUST ON INFORMATION DIFFUSION IN ONLINE SOCIAL NETWORKS

Zhijun Yan, School of Management and Economics, Beijing Institute of Technology,
Beijing, China, yanzhijun@bit.edu.cn

Wenyang Liu, School of Management and Economics, Beijing Institute of
Technology, Beijing, China, 1281909767@qq.com

Yaohui Pan, School of Management and Economics, Beijing Institute of Technology,
Beijing, China, 734207068@qq.com

Tianmei Wang, School of Information, Central University of Finance and Economics,
Beijing, China, wangtianmei@cufe.edu.cn

Abstract

online social networks have a explosive growth in recent years and they provide a perfect platform for information diffusion. Many models have been given to explore the information diffusion procedure and its dynamics. But the trust relationship and memory effect are ignored. Based on the complex network theory, The information diffusion model is proposed and the network users, considered as agents, are classified into susceptible, infected and recovered individuals. The users' behaviour rule and diffusion process are designed. The proposed agent-based model is tested by simulation experiments in four different complex networks: regular network, small world network, random network and scale-free network. Moreover, the effect of four immunization strategies are explored. The research results show that the influence of users' trust relationship on different networks is varied, and the vertex weight priority immunization strategy is the best one in all four networks.

Key words: information diffusion, trust, immunization strategy, online social networks

1. INTRODUCTION

With the rapid development of internet and communication technology, China has made significant achievements in the information industry. Now the Internet and mobile communication network is becoming an essential part of people's daily life. By the end of year 2012, the number of Internet users (a.k.a. "netizens") in China has reached 564 million, and the number of cellphone netizens has reached 420 million (CNNIC 2013). As the fast development of Web2.0 technology, various online venues (e.g., forums, social networking sites, blogs, and so on) are emerging to provide users new convenient channels for mass information propagation. The global reach of the Internet inspires a far-reaching and astonishingly rapid movement of digital word of mouth, thereby changing the information diffusion patterns and users' knowledge-acquisition behaviours (Chang, Oh et al. 2010). And this diffusion procedure influence internet users' decision and action significantly (Hinz and Spann 2010). Given the importance of information diffusion in decision-making process and human behaviour selection, it is worth exploring the diffusion influencing factors and understanding the dynamics of information diffusion.

Information diffusion has been extensively studied in the field of epidemiology, sociology, system science, marketing and other areas. Biology and epidemiology has conducted in-depth study on epidemic spreading in early time , and the classical susceptible-infected-susceptible (SIS) model and susceptible–infected–recovered (SIR) model are proposed (Tebbens and Thompson 2009). Many marketing scholars explore the information diffusion process in product marketing and explore how the word-of-mouth works. Some research predict that social structure play a critical role in the spread of a viral message (Bampo, Ewing et al. 2008). And the influence factors on the information diffusion are investigated. The proposed factors include informational properties, network characteristic, social reinforcement, user characteristics, and so on (Zhou, Liu et al. 2007; Lü, Chen et al. 2011; Han and Niu 2013; Song, Hwang et al. 2013).

Users on social networking sites build and expand their social relationships with other users of similar interests and preferences. Social tie is very important for users to decide whether they adopt their neighbours' suggestions or not (Zeng and Wei 2013). And trust relationship is one kind of social ties. Then users would like to accept their trusted neighbours' message and retransmit them (Kim and Tran 2013). Moreover, previous contacts could impact the information spreading in current time (Dodds and Watts 2004). Such memory effects can improve the information acceptance probability directly, or enhance the tie strength between transmitter and receivers and also influence the spreading process. At the same time, the influence of memory effect also exists decay (Lü, Chen et al. 2011), namely the effect of previous contacts will decrease as the time goes on.

Different from previous studies, our study take both trust relationship and memory effect into consideration. Our research employs these two variables and other related variables as model parameters and explore their influence on the information diffusion dynamics. Considering the individual heterogeneity of users in online social network, we propose an agent-based model to investigate the dynamics of information diffusion (Rahmandad and Sterman 2008).

The difference of the strength of trust relationship on the diffusion process is analyzed. And four different immunization strategies to control negative information are compared in different network structure.

Our study contributes to the knowledge on information diffusion dynamics and provides managerial implications regarding the strategic utilization of online social networks for promoting positive information and blocking negative information. There are three-fold novel contributions of this study. First, we propose a variant of the SIR model for information diffusion, which incorporate several new diffusion factors which the standard SIR model doesn't include. Second, the simulation experiment show that in the small initial transmitting probability, the information spreads more effectively in regular networks than other networks. And high level trust relationship only influence the information diffusion under certain circumstance. Furthermore, we have analyzed the effect of four immunization strategies on different networks and provide insights on the blocking of information diffusion in online social networks.

The rest of the paper will be organized as follows. Section 2 introduces the related work on information diffusion model and the limitations of existing approaches. Then, we propose a new information diffusion model in Section 3. Section 4 describes the experiment result of the proposed model, followed by the major findings. Finally, the paper will discuss the implications of the study and conclude the paper in Section 5.

2. RELATED WORKS

By definition, information diffusion means utilizing possible channels for propagation without physical contact. The disseminated content may include viewpoints, rumours, knowledge, product marketing information, etc (Lü, Chen et al. 2011).

As one of the most important form of information, knowledge dissemination wins a large range of scholars' concern. The research topics include the efficiency of knowledge spreading, the direction of knowledge flows, the influence of knowledge spreading on organizational performance, and the influencing factors on knowledge spreading (Tsai 2008; Kaše, Paauwe et al. 2009; Tortoriello, Reagans et al. 2012). Multiple approaches such as cellular automaton, complex network models, questionnaire survey, and empirical study methods were used to analyze the impact of domain structure, aggregation and range of network and working mechanism on knowledge dissemination.

The spread of rumours is also a field of great interest in information diffusion. Equipped with complexity theory and simulation techniques, researchers analyzed the rumour spreading process, its relevant factors, and immunization and control strategies. Wang and Chen (2012) discussed the impact of multiple parameters, like rumour property and network structure, on the process of rumour propagation. Zhou (2007) studied the rumour propagation in complex networks using the SIR model. The mean-field theory is applied and the results show that the number of the total final infected nodes depends on the network topological structure. Huang (2011) proposed an immunization strategy against rumour spreading on small world networks.

Regarding the spread of public opinion or viewpoint in online social network sites, Han (2013) proposed an information propagation agent-based model for online social network. The simulation results showed that the number of initial infected nodes has a certain impact on the information propagation speed, but it doesn't affect the number of final infected and susceptible nodes. Son (2013) considered message characteristics and user identity as information diffusion factors and investigates their impact on information diffusion volume and speed in online social network. Song (2013) found that Informational properties, individual characteristic variables, as well as network characteristic variables, have a significant influence on the verbal acceptance. Qian (2012) built a weibo public opinion propagation model based on the traditional epidemic model, and further conducted an empirical study using data from Sina weibo.

Regarding information diffusion dynamics, Lü (2011) proposed an information spreading model and studied the dynamics process of information spreading. The model emphasized the essential difference between information spreading and epidemic spreading. The simulation results showed that the small-world networks could yield the most effective information spreading. And several other articles also explored the dynamics of information diffusion process (Yang, Yao et al. 2010).

Up to now, previous studies rarely take the influence of trust relationship among members (nodes) on information diffusion into consideration, and the memory decaying effect that takes place after receiving information is also ignored. However, trust is very important for people's relationship and can reduce uncertainty and hesitation in the communication process. It is a valuable mechanism to avoid opportunism actions and enhance cooperation. At the organizational level, trust relationship can directly boost the level of satisfaction and commitment, thus increasing organizational performance (Ye, Chen et al. 2008). Therefore, trust is one of major influencing factors on information propagation, and it will directly affect the information diffusion speed and depth. Meanwhile, previous contacts will influence the information spreading process in current time. The spreading speed and ranged are affect by such memory effects. At the same time, information receiver has the memory decay effect. The longer the information is received, the less the receiver is interested in. In other words, information will play a less and less important role as time goes on (Lü, Chen et al. 2011).

As a major research tool in transmission dynamics of complex network, epidemic model is being applied to a wide range of areas: computer virus control, public opinion analysis, information diffusion, behaviour prediction, social management, and so on (Newman 2003; Bampo, Ewing et al. 2008; Zhao, Cui et al. 2012). Based on epidemic model, this article presents an information diffusion model, which treats the propagation process as information being communicated among multiple agents in an agent-based social network. We further analyze the influence of trust relationship on networks with different topological structure, and discuss the advantages and disadvantages of different immunization strategies in the process of information diffusion.

3. INFORMATION DIFFUSION MODEL

3.1 Model Description

The process of information diffusion on online social networks can be resolved as information dissemination among different network agents. Each network node represents an individual (or agent) in the network community, and each network edge (or link) represents the neighbour relationship between two network nodes. Individuals will transmit the receiving information to neighbours according to their behaviour rules. And they will record their state, sending and receiving information behaviour in each step. We divide individuals (referred to as “nodes” below) into 3 categories according to their states: Susceptible Node, Infected Node and Recovered Node.

The susceptible node has not yet been infected, but is prone to be infected. That is, the node has not received the information yet, but will receive it when its neighbours transmit the information.

The infected node has received information, but has not transmitted it yet. If the node receives the same information again, the node will calculate the transmitting probability according to the times it receives this information. The transmitting probability will be higher as the increase of receiving times. After the node transmit the information to its neighbours, its state will be changed.

The recovered node has received the information and transmitted it to neighbours. For simplicity, we assume the recovered node isn't interested in the same information and will not be affected by the same information.

A susceptible node will become infected once receiving information from its infected neighbours, and an infected node will become recovered when it performs a transmission. Assume the average probability from susceptible state to infected state is α , and the average probability from infected state to recovered state is β . Then the network information diffusion model can be described as:

$$\begin{aligned}\frac{dI}{dt} &= \alpha S(t) - \beta I(t) \\ \frac{dR}{dt} &= \beta I(t) \\ \frac{dS}{dt} &= -\alpha S(t) \\ N &= S(t) + I(t) + R(t)\end{aligned}\tag{1}$$

In formula (1), $S(t)$ is the number of susceptible nodes, $I(t)$ is the number of infected nodes, and $R(t)$ is the number of recovered nodes. The total number of nodes in the network is N . we assume the network is composed of a fixed set of nodes and edges, thus the total number of nodes N remain unchanged, and there is no adding or removing of nodes during the entire process.

Formula (1) presents an information diffusion model based on the classic epidemic model. However, this model doesn't consider the difference among network nodes. In real world, the

individual will have different transmitting probability because of the personal characteristics.

The probability whether a node transmits the receiving information or not depends on various factors: the number of times it receives information, information strength, the social effect, memory effect, neighbour relationship, etc (Lü, Chen et al. 2011). First of all, the more times the node receives the same information, the more probable it transmits the receiving information. Secondly, the node will receive the same information from different neighbours. But the information strength will vary greatly because of the diversified relationship with different neighbours. High information strength will bring high transmitting probability. We think information strength is related with trust relationship among network nodes and define it as a function of trust relationship. Based on weighted network, the trust relationship can be modeled by edge weight. A large edge weight indicates a high level of trust between two neighbouring nodes, therefore resulting in a high probability to retransmit the receiving information. Thirdly, the transmitting probability is also associated with the information's social awareness, which represents how much the information get social concern. The information with high social concern will have more impact on information diffusion. Additionally, each node will have memory decay effect and the information received in the time $t-1$ will have less influence in the time t .

Thus, the transferring probability β_{it} of node i from infected state to recovered state is defined as (Lü, Chen et al. 2011):

$$\beta_{it} = 1 - (1 - \lambda)^{b * e^{(m_{it}-1) * h_{it}}} \quad (2)$$

In formula(2), b represents the information social effect coefficient, $\lambda = \beta_1$ ($0 \leq \lambda \leq 1$) is the initial transmitting probability that a node transmit the receiving information for the first receipt, m_{it} represents the times a node receive the information by time t , h_{it} is the cumulative amount of information strength, and e is the natural logarithm. The second item on the right side of formula(2) denotes the probability that node i will not transmit the information after it receive the information for m_{it} times and the accumulating information strength is h_{it} . When $m_{it}=1$ and $b=1$, β_{it} equals the initial transmitting probability λ .

The transferring probability α_{jt} of node j from susceptible state to infected state is relevant to its neighbours' information transmission action. The probability α_{jt} can be defined as:

$$\alpha_{jt} = 1 - \prod_{r=1}^{|C(j)|} (1 - \beta_r) \quad (3)$$

In formula(3), $C(j)$ denotes the set of node j 's neighbours, $|C(j)|$ denotes the number of node j 's neighbours. formula (3) indicates that whether node j transforms to infected state depends on whether its neighbours transmit the information. Once a neighbour performs transmission, node j becomes infected, and the more its neighbours perform transmission, the more frequently and abundantly node j receives the information.

3.2 Information Diffusion Process

Based on the diffusion model proposed above, we further design the node behaviour rules in

the information diffusion process and explore the diffusion result of different network structure through simulation experiment.

The information diffusion process is given as follows:

(1) Initially, a seed node is chosen randomly and its state is set as recovered, indicating that the seed has transmitted information to its neighbours. The seed's neighbours state are set as I (infected), and all other nodes' state in the network are set as S (susceptible).

(2) Different operations are conducted according to the node state at every moment.

(2.1) If the node is in the infected state, and it receives information from neighbours, then:

(2.1.1) Calculate the cumulative amount of information strength as follows:

$$h_t = h_{new} + \delta \times h_{t-1} \quad (4)$$

$$h_{new} = \sum_{j \in C(i)} \frac{w_{ij}}{\langle w \rangle} \quad (5)$$

In formula(4), h_{t-1} denotes the cumulative amount of information strength by time t-1, and δ denotes the memory decay effect coefficient ($0 \leq \delta \leq 1$), meaning that the influence the information strength on information diffusion decays as time goes on. From this formula, it is clear that the total impact of the same information, which is represented by h_t , is increasing. But the impact of last receiving behaviour is decreasing. In formula(5), h_{new} denotes the information strength at time t, which depends on the transmitting neighbour and their trust relationship. $C(i)$ represents the set of node i's neighbours that transmits information to node i. w_{ij} denotes the weight of the edge between node i and j (j transmits information to i), and $\langle w \rangle$ represents the level of trust between i and j. $\langle w \rangle$ is the average edge weight in the network.

(2.1.2) Calculate the cumulative number of times that a node has received information by time t:

$$m_t = m_{new} + \delta \times m_{t-1} \quad (6)$$

In formula(6), m_{t-1} denotes the cumulative number of times the node has received information by time t-1, and δ is the memory decay effect coefficient. m_{new} denotes the number of times the node receives information at time t, where each neighbour's transmission is counted as once. Formula (6) indicates that m_t implies the effect of information transmission times. The effect of information transmission taking place at time t-1 will decrease as δ times as much influence at time t.

(2.1.3) Decide whether to transmit the information or not according to the probability β_{it} . If the transmission takes place, the node state is changed to recovered.

(2.2) If the node is in the susceptible state, it will be changed to infected state if it receives information from its neighbours. And the information strength and number of transmission times will be recorded.

(2.3) If a node is in the recovered state, then nothing happens.

(3) Repeat the step two until no transmission is possible in the whole network.

Following the above process, the network nodes will transform between different states during the information diffusion process, and a stable final state will be reached.

3.3 Four Network Structures

The information diffusion model is applied in four complex network models: regular network, small world network, random network and scale-free network. And each network model has the same node degree k . In regular network, each node has the same degree, and the clustering coefficient and average path length are big. In random network, the node degree follows the Poisson distribution which brings a smaller clustering coefficient and average path length. Regular network and random network represent two extreme situations. And the small world network is a special network between them. The scale-free network is proposed by Barabasi in the study of hyperlink relationship among website pages. In this type of network, the node degree follows the power-law distribution.

We explore the influence of trust relationship on information diffusion in these four different network structures. Assume a network $G=\{A, E\}$, where A denotes the set of agents (nodes), and E denotes the set of edges. Each edge $e_{ij}=\{a_i, a_j, w_{ij}\}$ represents an undirected link between node a_i and a_j with a weight of w_{ij} . Methods to generate different network structures are given as follows (Lü, Chen et al. 2011; Wang, Li et al. 2012):

(1) Regular network. Each node is linked to its k nearest neighbours, that is, its $k/2$ nearest nodes clockwise and anti-clockwise.

(2) Small world network(SW). This network structure is generated by randomly rewiring a regular network by keeping the node degree unchanged. The edge-based rewiring method is applied to generate small world network. We randomly choose a pair of edges $A-B$ and $C-D$ from the original regular network, then the two edges are relinked to be $A-D$ and $B-C$. If the edge $A-D$ or $B-C$ already exists, randomly select a new pair of edges. Repeat the rewiring procedure for $p|E|$ ($0<p<1$) times to generate a small world network, where p is the randomness of the network.

(3) Random network. When $p\geq 1$, we will obtain a random network by repeating the above rewiring procedures.

(4) Scale-free network(BA). At first, we generate an initial network with n_0 nodes and $k*n_0/2$ edges. Then adding a new node to the network, and the new node will link to $k/2$ existing nodes. The adding operation is repeated until the total node number in the network is N . The probability that the new node connects to the existing node is proportional to the existing node's degree. For example, the probability that an existing node with degree k_i being chosen as the new node's neighbour is $k_i/\sum k_i$.

Meanwhile, Each kind of networks will include two different instances according to the edge weight distribution. High-weight network represents a high level of trust among nodes and low-weight network indicates a low level of trust among nodes.

4.EXPERIMENT AND RESULT ANALYSIS

4.1 Simulation Platform

Repast (Recursive Porous Agent Simulation Toolkit) is an agent-based modelling tool and adopted as the simulation platform. Repast is developed under the “Swarm-like” software architecture, with powerful features, good performance and a user-friendly interface. Highly customized models can be constructed by inheriting base classes and interfaces provided by Repast. And each agent in Repast can have their own behaviour rule and decision mechanism (Sabelli and Kovacevic 2006).

In the simulation, let $N=1000$, $n_0=100$ and $k=6$. The edge weight for high-weight networks are between 5 and 10, for low-weight networks are between 1 and 5. We denote by R the number of recovered nodes in the whole network. Larger R at the final state indicates broader information diffusion. All the simulation results are obtained by averaging over 500 independent realizations.

4.2 The Effect of Initial Transmitting Probability

The influence of initial transmitting probability on the information diffusion in different network described in Figure 1. It illustrates the changing procedure of R value in four networks with different λ ($\lambda=0.1, \lambda=0.2, \lambda=0.3$). For the sake of brevity, we set $b=1$ and $\delta=0.9$ in this analysis. Our result is similar to Centola (2010) and Lü (2011)’s results. With small λ , regular networks have a faster and broader diffusion than random and small world networks,

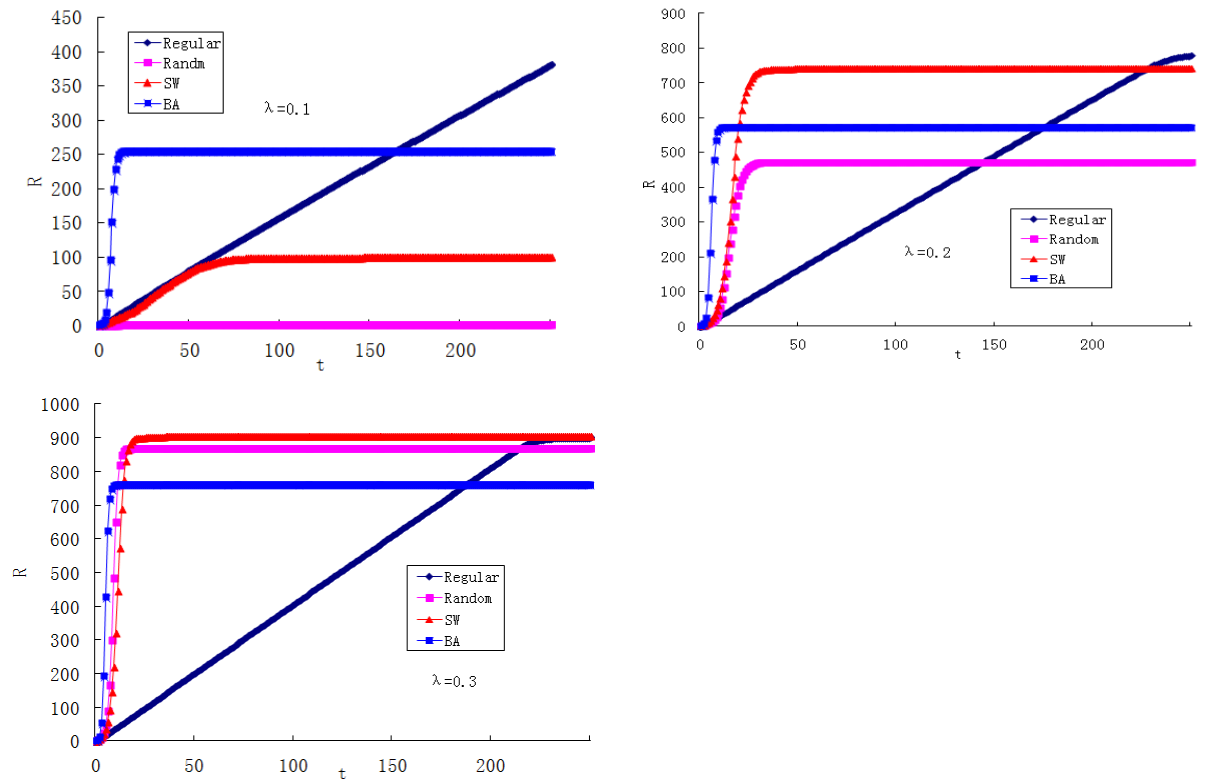


Figure 1 The effect of initial transmitting probability on information diffusion

but scale-free networks enjoy the largest diffusion speed in the early stage. As the increase of λ , information diffusion in small world and random networks is gradually faster and wider. And small world networks get the highest R value finally. Scale-free networks disseminate information fastest in the early stage because the hub nodes with large degree inspire diffusion significantly. However, most nodes' degree are small, so the diffusion speed drops quickly after reaching the peak.

4.3 The Effect of Trust Relationship

Trust is one of the basic factors in people's social activities. Individuals are willing to accept or adopt the suggestions from people they trust. This paper analyzes the influence of trust relationship on information diffusion and explores the difference of information diffusion in networks with different trust relationship.

Figure 2 shows the number of recovered nodes as a function of initial transmitting probability λ in high-weight and low-weight networks. The parameters are $b=1$ and $\delta=0.9$.

For regular and small world networks, the enhancing of trust relationship has obvious influence on information diffusion. When λ is small, the range of information diffusion is limited in random and scale-free networks. And the enhancing of trust relationship make network nodes more prone to their neighbours' behaviour. Thus the number of recovered nodes in high-weight networks is more than that of low-weight networks. When λ is large, however, the number of recovered nodes in different networks are similar, indicating that the effect of trust vanishes. For random networks, a high level of trust can only enhance the range of information diffusion significantly when λ belong to $[0.1, 0.3]$ interval. Scale-free networks also have the similar situation. An increase in trust level can significantly improve the range

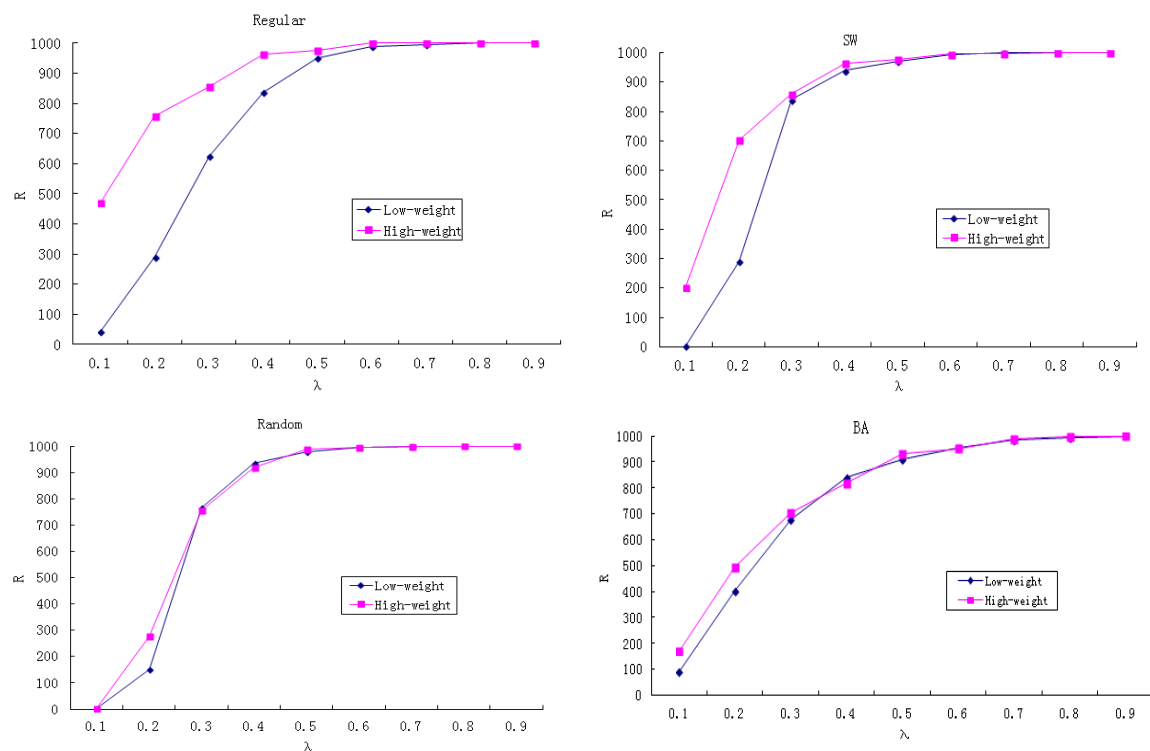


Figure.2 The effect of trust on diffusion range

of information diffusion only when initial transmitting probability is small. In conclusion, the trust relationship will relatively influence information diffusion on random and scale-free networks only under certain circumstances, and the nodes' own attributes play a more important role in the information diffusion process.

Trust relationship between nodes also affects the speed of information diffusion. We define V_t as a measure of diffusion speed:

$$V_t = R_t - R_{t-1} \quad (7)$$

V_t denotes the increase of number of recovered nodes at time t compared to time $t-1$.

Figure 3 shows diffusion speed in low-weight and high-weight networks across four different network structures. The parameters are $\lambda=0.2$, $b=1$ and $\delta=0.9$.

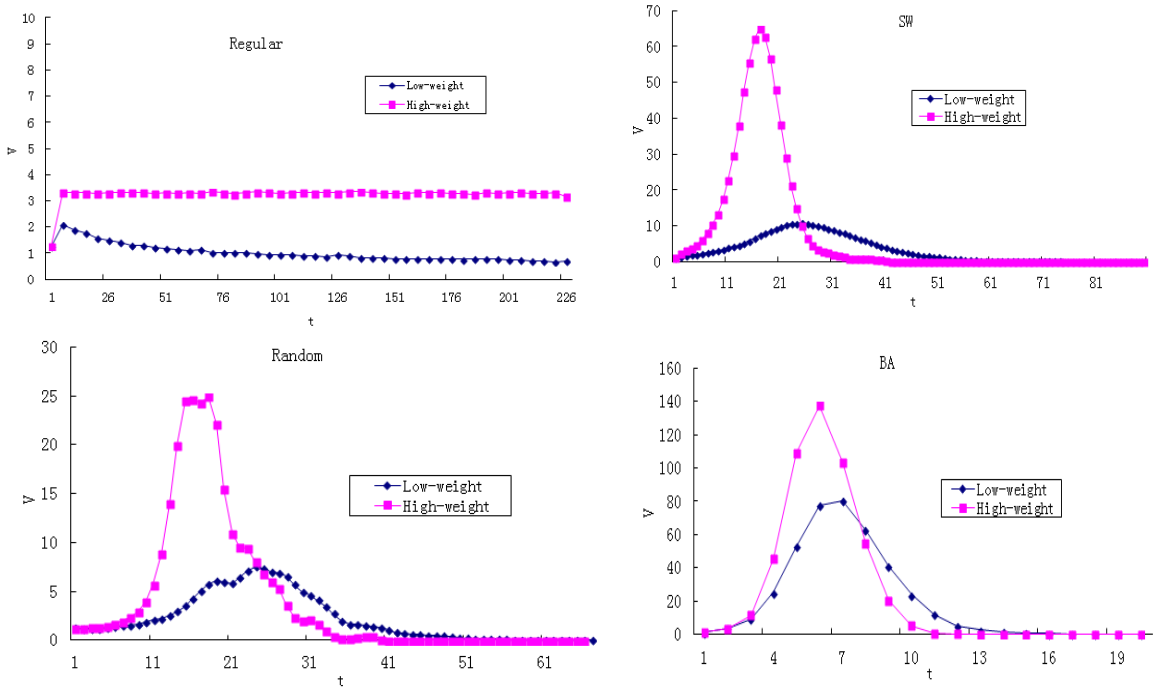


Figure.3 The effect of trust on diffusion speed

In regular networks, information always spreads faster on high-weight networks than low-weight networks, which indicates that trust relationship has a stable influence on information diffusion. On small world networks, high-weight networks reach a diffusion speed peak and falls back to a relatively low level. But the diffusion speed is relatively stable in low-weight network. Random networks have the similar phenomenon with small world networks, but the dropping speed for high-weight networks is slower than that of small world networks. Thus, the influence of trust increasing on information diffusion is only lasting for a short time. On scale-free networks, both the diffusion speed of high-weight and low-weight network have an obvious peak value, which is the result from high-degree nodes. However, the increase of trust level raises the speed peak value of information diffusion in high-weight networks. After reaching the peak, the diffusion speed in both low-weight and high-weight scale-free network drops quickly to a relative stable value.

4.4 Immunization Strategies

In the process of information diffusion, immunization strategies can be taken to control the propagation and prevent potential negative consequences. Common immunization strategies on weighted networks include random immunization, vertex weight priority immunization and weakened immunization (Ma, Li et al. 2010). Random immunization means randomly choosing a number of nodes to perform immunization, removing their links to neighbours so that they won't be affected. Vertex weight priority immunization prefers to immunize nodes with large strength, and remove their links to neighbours. Weakened immunization means randomly choosing a number of nodes to immunize, reducing their edges' weights to $1/q$ instead of simply removing them.

We tested the effects of four immunization strategies in our simulation, namely random immunization(Random), vertex weight priority immunization(WP), randomly weakened immunization(RW) and vertex weight priority weakened immunization(WW). To keep the network structure unchanged during the simulation, the weight of the edges connecting to immunized nodes is set 0.01 for random immunization and vertex weight priority immunization. Figure 4 displays the percentage of recovered nodes as a function of immunization rate. The parameters are $\lambda=0.2$, $b=1$ and $\delta=0.9$.

It shows that vertex weight priority immunization is the most effective strategy on all four networks. For scale-free networks, vertex weight priority weakened immunization is the second best strategy, whereas random immunization is the second best strategy on regular, small world and random networks. This is because vertex weight priority weakened immunization can effectively immunize the hub nodes on scale-free networks. We also observe that vertex weight priority weakened immunization always performs better than

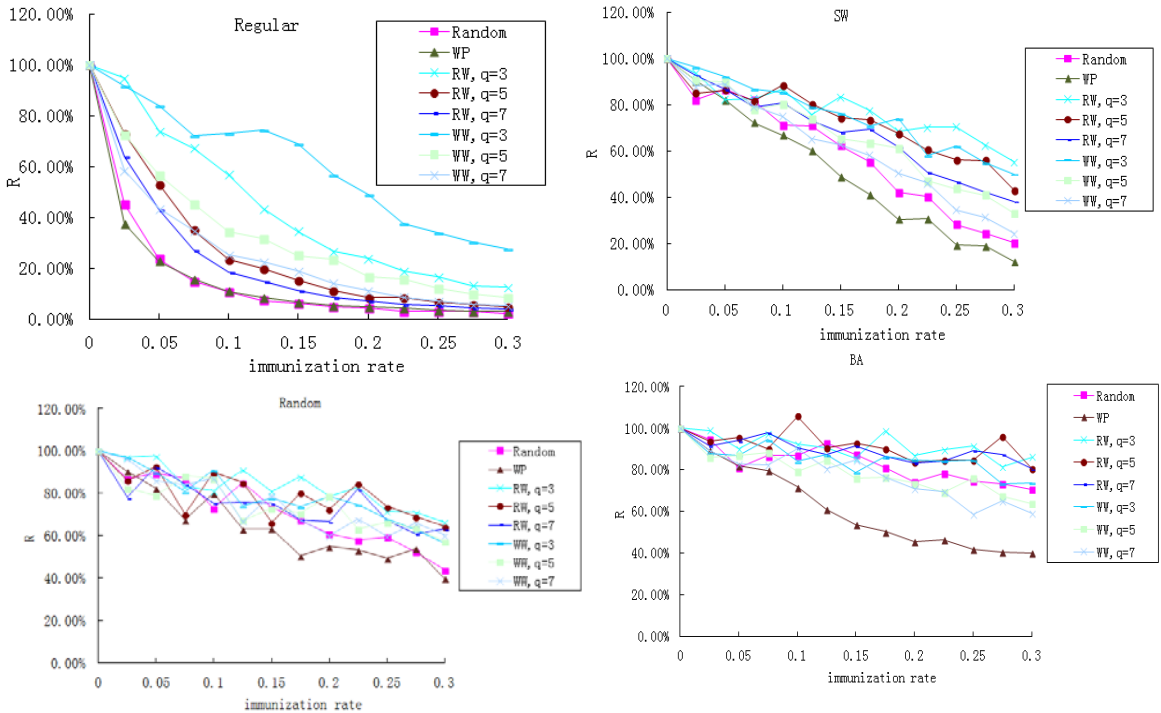


Figure.4 The immunization strategies effect in four networks

randomly weakened immunization, and the value q doesn't have a significant influence on the final number of recovered nodes. However, the smaller q is, the more efficient the whole network is (Ma, Li et al. 2010).

5. CONCLUSIONS

With the rapid development of social media, the Internet has become a major channel for information propagation and diffusion. It is well known that the information diffusion process is largely influenced by the number of neighbours and their relationship. Represented by different level of ties, the trust relationship is simulated in our proposed model and its influence on information diffusion is also explored. At the same time, the time decaying effect is normal phenomenon and no one is willing to spread news long time ago. That means the old information people received have a low probability to be transmitted and diffused. Social effects imply how much the society care about the information. It is stated that social effects play an important role in the propagation of opinions, news, innovations and fads. Our model also take the decaying effect and social effect into consideration.

The simulation results show that under small initial transmitting probabilities, regular networks can spread information faster and broader than random network, which to some extent is similar with the result of Centola (2010) and Lü (2011). As the increasing of initial transmitting probability, small world networks perform best, and the information diffusion is better than random, regular and scale-free networks. At the same time, the results show that the strength of trust relationship can influence the information diffusion greatly only in some special circumstances. High level of trust in the network really inspire the range of information diffusion, but the effect among different network structures varies greatly. Furthermore, four immunization strategies are applied to block the negative information diffusion in the network. The simulation results indicate that the vertex weight priority immunization is the most effective immunization strategy on all four kinds of network structures.

Our study have several implications on research and practice. Our study enriches the current knowledge about information diffusion. It incorporate several new factors into the information diffusion model and examine the diffusion dynamics. The research result supports some conclusions of several recent works and also gives us some new insights on the diffusion dynamics. For example, our results suggest that high level of trust relationship can only play an important role in some cases. Our results are also helpful for social network manager. Although the information diffusion is affected normally by people's disposition to sending message, it is also influenced by several other features. Small world networks can mostly spread information faster and broader. Improving mutual trust relationship can help motivate the information diffusion but it will not be effective all the time. Thus the network manager should apply other technique to encourage the information diffusion. In order to block negative information diffusion (e.g. rumour), vertex weight priority immunization strategy will be the first option for network manager.

There are several limitations in the study that should be noted. Firstly, although we incorporate the memory decay and social effect into consideration, we didn't analyze the

influence of the memory decay and social effect in detail. For example, how the memory decay coefficient δ affect the final number of recovered nodes. Secondly, the interaction effect of trust relationship, memory decay and social effect is missing in the study. Thirdly, agent-based model and simulation method are applied to examine the impact of individual heterogeneity and different network topologies, but we lack the empirical data from real online social networks to verify our result. Further research can be conducted in those directions to expand the current research.

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