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DYNAMIC EVOLUTION MODEL BASED ON SOCIAL NETWORK SERVICES

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Based on the analysis of evolutionary characteristics of public opinion in social networking services (SNS), in the paper we propose a dynamic evolution model, in which opinions are coupled with topology. This model shows the clustering phenomenon of opinions in dynamic network evolution. The simulation results show that the model can fit the data from a social network site. The dynamic evolution of networks accelerates the opinion, separation and aggregation. The scale and the number of clusters are influenced by confidence limit and rewiring probability. Dynamic changes of the topology reduce the number of isolated nodes, while the increased confidence limit allows nodes to communicate more sufficiently. The two effects make the distribution of opinion more neutral. The dynamic evolution of networks generates central clusters with high connectivity and high betweenness, which make it difficult to control public opinions in SNS.

Keywords: Complex networks; social networking services; dynamic evolution; central cluster.

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1. Introduction

The last few years have witnessed a rapid development in the globalization of information and social networks. The formation and evolution of public opinion, has attracted wide attention from social physicists.[1] Currently, a series of social physics models[2,3] have played an important role in exploring the formation and evolution mechanism of public opinion, including Ising Model,[4,5] Sznajd Model,[6,7] Deffuant Model,[8] Krause–Hegselmann Model[9] and rumor diffusion Model.[10] Moreover, considerable efforts have been made to understand the opinion evolution on complex networks with typical topology,[11–14] such as small-world networks[15] and scale-free networks.[16–18]

Social Networking Services (SNS),[19] as the product of Web 2.0, is a new medium in which "interaction" is regarded as its core. Strictly speaking, SNS typically refers to social networking sites, including its derived product (microblog). In recent years, SNS sites are developing rapidly, from Facebook to Twitter, which are all favored by a large number of internet users of all ages. Those users, who are not only information receivers but also producers, releasers and disseminators of information, become an essential part of the process of formation and evolution of public opinion in networks.

The paper analyzes evolution characteristics of public opinion in SNS, and then proposes a dynamic model in which opinions are coupled with topology. This model shows the clustering phenomenon of opinion in dynamic networks. When confidence limit is small, dynamic network tends to produce several opinion clusters, while the corresponding static network is apt to be unanimous. Dynamic changes of the topology reduce the number of isolated nodes and the increase in confidence limit allows nodes to communicate more sufficiently. The two effects make the distribution of opinion more neutral. In addition, the paper analyzes the influence of model parameters on the scale of clusters, the number of clusters and the relaxation time. The dynamic evolution of networks generates central clusters with high connectivity and high betweenness, which make it difficult to control public opinions in SNS.

2. Model

In this paper, data were extracted from a famous SNS site, including 4221 users. The average degree is 10.8, and clustering coefficient is 0.13. Degree distribution obeys power law (see Fig. 1).[20,21]

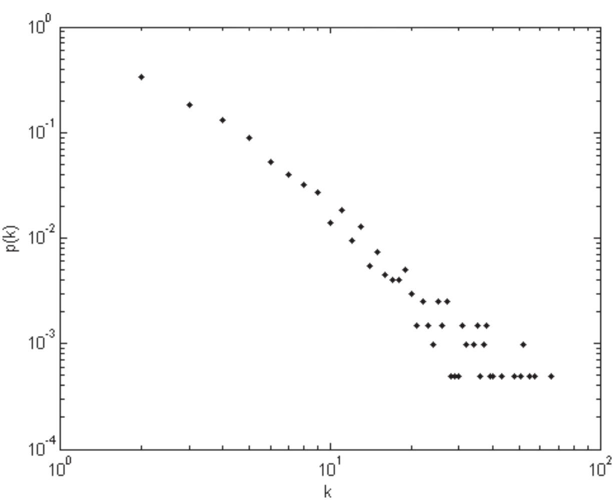

Fig. 1. Degree distribution on SNS.

Then, we extracted all the comments on a hot event in this website. During the process, 719 users make 5770 comments on the event. After removing redundant information, we obtained the following characteristics from the extracted data:

(i) To establish his opinion, a user will consult friends who are directly linked to him. The opinions of these friends should be close to his opinion.
(ii) If the opinions of two adjacent users are in conflict, the two may be disconnected with each other. Meanwhile, if the opinions of two users are close, the two may be connected with each other.
(iii) Users in the center of the network are usually celebrities. Some of them own mature and original thoughts, and make incisive comments on an event; the others are sports stars or pop stars who only share his/her working status or family life. For a specific event, just one of the two types is taken into consideration. These users are connected with each other, while they may have no similar opinions. They have great impact on other users in the network, and play a decisive role in the evolution of an event. These users are hardly influenced and hold their views.

The initial network is composed of N nodes and M edges, and each node holds a random opinion value between 0 and 1. A dynamic evolution process of network can be described as follows:

(i) Opinion evolution. In each step, we seek the weighted average of each node in the network successively, i.e.

$$S_i(t+1) = \sum_{|s_i - s_j| \le d} \frac{k_j}{\sum k_j} S_j(t), \tag{1}$$

where k_j is the degree of an adjacent node involved in the summation; d is called confidence limit. When each node of the network completes the step according to Eq. (1) for one time, we call it a round. This equation means: to each adjacent node j of node i, if opinion difference $|s_i - s_j| \le d$, the opinion of node i will be the weighted average of the opinions of adjacent nodes which match the above condition, as well as the node i itself. The weight will be the percentage of the degree of the adjacent nodes. Actually, in many instances, the opinion of a node has more influence on its subsequent opinion than those of its neighbors. To simplify the model, it is not taken into consideration.
(ii) Opinion rewiring. If the opinion difference of node i and its adjacent node j obeys $|s_i - s_j| > d$, disconnection probability of i and j is p; If the opinion difference of node i and its nonadjacent node j obeys $|s_i - s_j| \le d$, connection probability of i and j is p.
(iii) Emergence of a central cluster. Nodes with the degree larger than k_0 and the betweenness larger than B_0 will be connected with each other and generate a central cluster. Nodes of the central cluster stop updating their opinions, while they still change the opinions of others.

Betweenness centrality[22] is a measure of a node's centrality in a network. It is equal to the number of the shortest paths from all nodes to other nodes that pass through that central node. Betweenness centrality is a more useful measure of the load and importance of a node than connectivity. The betweenness centrality of a node is given by the expression:

$$C_B(x) = \frac{2\sum_{j<k} g_{jk}(x)}{(n-1)(n-2)g_{jk}}, \tag{2}$$

where g_{jk} is the total number of shortest paths from node j to node k; and $g_{jk}(x)$ is the number of the shortest paths passing through x. $(n-1)(n-2)/2$ represents the largest possible betweenness of nodes, where node x is crossed by every single shortest path.

3. Results and Discussion

Steps (ii) and (iii) tend to separate the nodes from other nodes with different opinions, and aggregate nodes with similar opinions. The evolutionary processes of public opinion in static and dynamic networks are show in Fig. 2.

As shown in Fig. 2, nodes in a static network tend to be evolved to a single opinion to form an opinion cluster, except that several nodes enter the isolated state, because they cannot communicate with neighbors.

In a dynamic network, topology is evolved with opinion changes. The nodes will be separated from other nodes with different opinions, while the nodes with similar opinions will approach each other. The opinions of nodes will show new features during topology change, such as the emergence of opposite opinion clusters with similar scales.

Figure 3 shows the occurrence probability of every opinion in static and dynamic networks ($d = 0.4$). It is obvious that in a static network, the nodes with extreme opinions (near 0 or 1), which have a great opinion difference with their neighbors, can exceed the confidence limit easily. These nodes finally exist in the isolated state.

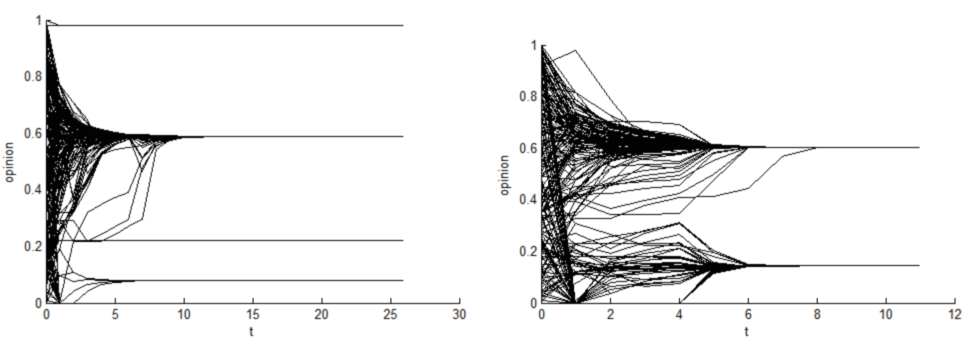

Fig. 2. Evolution process of public opinion in static and dynamic networks. $d = 0.15$. The left figure represents a static network, and the right figure represents a dynamic network.

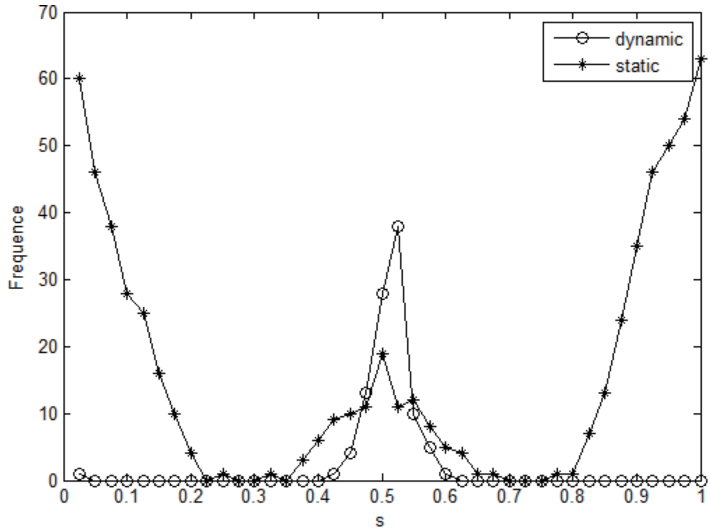

Fig. 3. Opinion distribution of static and dynamic networks, $d = 0.4$.

On the contrary, isolated nodes in a dynamic network can be reconnected with the nodes with similar opinions through rewiring. The nodes of the entire network can participate in the discussion, which makes the opinion distribution of a dynamic network to be completely in the central area.

Figure 4 shows opinion distribution of a dynamic network in the stable state for d with different values. When $d \geq 0.3$, the network will eventually be evolved into an opinion cluster including all nodes, and the final opinion distribution obeys the symmetric distribution with 0.5 in the center. When d is gradually reduced, the separation of opinions lead to the emergence of numerous opinion clusters which hold opinions far away from the neutrality. The opinion clusters are increasing with the decreasing d.

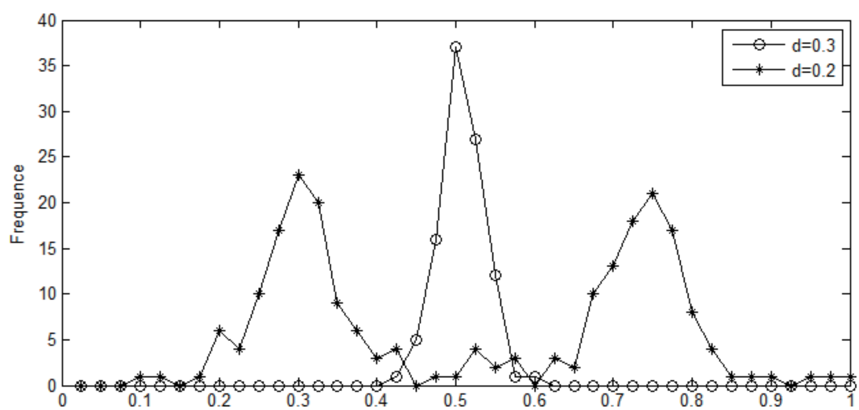

Fig. 4. Opinion distribution of dynamic network in the stable state for d with different values.

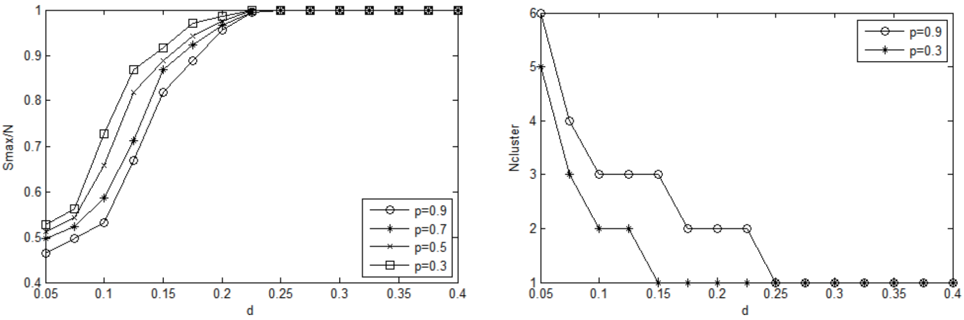

Fig. 5. Changes of the number of nodes in the largest cluster (left figure) and the number of clusters (right figure), when d and p take different values in dynamic networks.

The probabilities p represent the frequencies of dynamic evolution and are called rewiring probability. The larger the p is, the higher the frequency of dynamic evolution is. Figure 5 shows the changes of the number of nodes in the largest cluster and the number of clusters in the stable state, when d and p takes different values.

As shown in Fig. 5, when d is increased, the number of nodes in the largest cluster becomes greater. When rewiring probability p gets greater, this trend is more significant. When d has the same value, the larger the p is, the less the nodes in the largest cluster are. This is because large p leads nodes to be separated and aggregated easily. Small d makes a network to be divided into more and smaller clusters. When $d \geq 0.25$, the opinions of all the nodes in stable state are unanimous and the entire network becomes a single cluster.

The evolution time for a network system from the initial state to the stable state is called relaxation time or μ. Figure 6 shows the changes of μ with d for t_0 with different values.

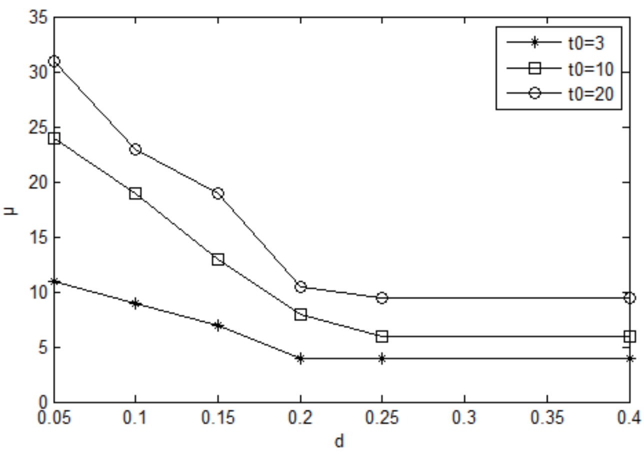

Fig. 6. Distribution of μ, when t_0 and d take different values.

Fig. 7. The dynamic evolution of network generates a central cluster, which will affect the opinions of the whole network. (left figure) Initial network of SNS. (central figure) In the case of central cluster with the same opinion. After rewiring, the whole network is evolved to the same opinion. (right figure) In the case of the central cluster with opposite opinions. After rewiring, the nodes of the entire network will be in the opposite positions.

As shown in Fig. 6, when t_0 is a definite value, the larger the d is, the smaller the μ is; when d is a specific value, the larger the t_0 is, the larger the μ is. The small d means smaller and more opinion clusters and the dynamic evolution requires a long time. When d is large, the central nodes can influence their neighbors and make them to get close. Large t_0 delays the changes of topology and makes opinions stable after a long time.

According to Ref. 21, a SNS network initially consists of clusters like the left figure of Fig. 7. The central figure of Fig. 7 shows node distribution after numerous steps of evolution. Some nodes have both large degrees and large betweenness. They are connected with each other to form a central cluster. The difference of interests or opinions causes rewiring. Meanwhile, through topology evolution, propagation path of information and opinion varies with time. With mutual influence between the opinions and topology, a completely stable state is not available.

The central and right figures of Fig. 7 show the role of the central cluster in the propagation of opinions. When nodes in the central cluster own the same opinion, the whole network can easily achieve consensus. The spread of positive and negative opinions in SNS, is related to the promotion of network celebrities. A large betweenness supports rapid spread of opinion in a network, and a large degree expands the influence scope of the central cluster. On the contrary, when central nodes have different opinions, supporters of opposite sides will participate in drastic debates. Debates may occur between different clusters or in the same cluster. In any case, the opinions of the central cluster represent "authoritative" voice.

The probability distribution function of betweenness centrality of all the nodes in the network is shown in Fig. 8. The curve approximately follows the piecewise power-law degree distribution. Obviously "gap" between the largest set of C_B and other nodes shows that, betweenness centrality of any node of the central cluster is much larger than that of other nodes. They play a bridge role in the opinion propagation. Meanwhile, dynamic rewiring generates the nodes with distinct roles in every cluster. The inset shows the normalized characteristic path length $L(t)/L(\infty)$ as a function of time t, where the normalizing factor is $L(\infty) = 3.3$. Every single shortest path gets

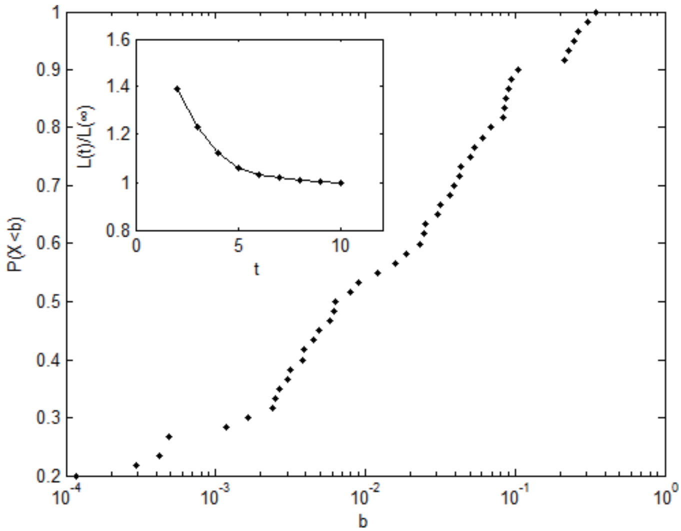

Fig. 8. Probability distribution function of betweenness centrality of all the nodes in the network. Inset: Normalized characteristic path length $L(t)/L(\infty)$ as a function of time t.

shorter when the central cluster gets larger. The entire network has the characteristics of "little world, more centers." It has not only short paths like random networks, but also a large clustering coefficient which is the same to that before evolution.

4. Conclusion

With gradually deep research on the complex network (including SNS), the coupling dynamics of public opinion and topology becomes a hotspot. Opinion spread and evolution based on SNS is a complicated process with various characteristics and various factors. The paper aims to find an appropriate method to monitor, forecast and guide public opinions, according to the spreading rules of network information.

In this paper, the dynamic evolution mode is based on SNS, in which opinions are coupled with topology, shows the clustering phenomenon of opinion evolution in dynamic networks. The dynamic evolution of networks accelerates the separation and aggregation, and the scale and number of clusters are affected by confidence limit and rewiring probability. The dynamic evolution of networks generates central clusters with high connectivity and high betweenness, which make it difficult to control public opinions in SNS. The outcome of this paper is conducive to further understanding and studying the spreading law of public opinion in SNS.

Acknowledgments

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