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An Efficient Method for Restraining Information Cascades on Mobile Social Networks*

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Information cascades are recognized as a major factor in catastrophic social network phenomena. Network structure and user behavior have important impacts on information cascades. In particular, homogeneity often becomes a barrier to the spread of new things, making it difficult to adopt new ideas and behaviors from outside closely connected communities. In this paper, we use cluster structure to precise densely connected community, and there exist the similar tendencies of behaviors between individuals and their neighbors in the cluster. A model of information cascades is proposed to emphasize individual decision-making based on the choices of their neighbors and the content of spreading. On the basis of this model, an efficient method is developed for restraining information cascades by reconfiguring clusters with links logically removed (termed CLLR). By limited links with high betweenness being logically removed, the CLLR method enhances the cluster density of a network, thereby effectively block information cascades. Experimental results show that the CLLR method significantly reconfigure the cluster structure with limited links removed, efficiently restrain the speed and scope of information cascades in mobile social networks.

Keywords: information cascades, cluster reconfiguration, limited links removed, cluster density, restrain negative information

1. INTRODUCTION

With the boom of the Internet and the rapid popularization of intelligent mobile devices, the audience of mobile social networks represented by Weibo, WeChat, Facebook and Twitter continues to expand [1]. Mobile social networks (MSNs) are wireless and convenient, individuals have more social interaction for information spread. At the same time, negative information will ferment rapidly through wireless mobile devices in a short time, such as rumors, false information, *etc.*, which will threaten users' security and have a huge negative impact on social stability and national security [2-4]. Therefore, how to effectively control the negative information spread has emerged as a challenging issue [5-8].

In many cases, individuals tend to ignore their own information and choose to join the crowd, when the information provided by neighbors is more convincing. This situation is called information cascades [9]. The experiments designed by Anderson and Holt showed that the cascade is very easy to occur, and is also very fragile [10]. Therefore, it is of great significance to explore the characteristics of user behavior and reveal the influence of cascading effects on information spread.

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Individuals tend to keep consistent with their neighbors when making decisions, which is called homogeneity. In particular, homogeneity often becomes a barrier to the spread of new things, making it difficult to adopt new ideas and behaviors from outside closely connected communities. In this paper, we use cluster structure to precise densely connected community, and there exist the similar tendencies of behaviors between individuals and their neighbors in the cluster. Furthermore, a model of information cascades is proposed to emphasize individual decision-making based on the choices of their neighbors and the content of spreading.

Network structure has an important impact on the information spread. For example, cluster structure of networks affects the spread of viruses and information to a certain extent [11, 12]. On the premise of ensuring the network coverage and connectivity, due to the wireless characteristics of MSNs, links logically removed is equivalent to controlling and cutting off the communication links between some qualified mobile devices, and individuals cannot communicate temporarily. In this paper, an efficient method is developed for restraining negative information cascades by reconfiguring clusters with limited links removed.

The main contributions of this paper are as follows,

- A model of information cascades is proposed to emphasize individual decision-making based on the choices of their neighbors and the content of spreading. Individuals tend to keep consistent with their neighbors when making decisions.
- Clusters with the high-density can block information cascades. Individuals in the same cluster have similar behavior tendencies, and new ideas and behaviors are difficult to enter the high-density clusters from the outside.
- An efficient method for restraining negative information cascades by reconfiguring clusters with links logically removed (termed CLLR). By limited links with high betweenness being logically removed, the CLLR method enhances the cluster density in a network, thereby effectively block information cascades.

2. RELATED WORKS

In the existing relevant research, most scholars use independent cascade (IC) models, linear threshold (LT) models, infectious disease models and other extended models to model the information spread process [13]. In 2010, Damon published a research result on the spread of behavior in Science journal [14], which aroused people's attention to the role of behavior in the process of information spread. The study found that behavior spread has social reinforcement effect. Therefore, more and more scholars are committed to exploring the impact of social reinforcement on behavior spread [15-19]. However, most of the current studies haven't considered the interaction between information content and behavior spreading.

In the real MSNs, information content and user behavior interact and influence each other. On the one hand, the user behavior will be affected by the information spread, that is, information drives behavior. When the received stimulus accumulates to a certain extent, the individual is likely to produce the behavior corresponding to the information. The cumulative effect of this stimulus is the social reinforcement effect. On the other hand, the user behavior itself will have a demonstration effect on the people around, so as to influence the decision-making of the surrounding neighbors and make them produce imitation behavior.

Behavior spread in MSNs is different from general information spread. When an individual adopts a new behavior, he not only needs to receive and adopt the information, but also involves the benefits or costs of participating in the behavior spread. The information forwarding threshold introduced to evaluate the cost of forwarding information. In the process of modeling information spread and evolution, the influence of similar behaviors' tendencies of direct neighbor nodes on individual decision-making is considered.

In view of the control of the information spread process, scholars generally adopt the method based on optimizing network topology to control information spread. Li *et al.* optimized the network structure based on the edge intermediary property and proposed a virus control strategy with limited-temporary-links removed. The experiment results proved that the method is effective on the network with small-world property [20]. Yao *et al.* formulated a set of novel group immunization problems for multiple natural settings on a network with groups, and developed multiple efficient algorithms, including provably approximate solutions [21]. Cao *et al.* proposed three selection algorithms of seed nodes, which make the immune information is widely spread in the network by injecting immune information into the seed nodes, so as to suppress the spread of specific information [22].

Clustering structure is ubiquitous in networks. In this paper, we use cluster structure to precise densely connected community, and there exist the similar tendencies of behaviors between individuals and their neighbors in the cluster. The waterfall will stop when it encounters a high-density cluster, which is the only reason why the waterfall stops spread [23]. That is to say, cascading and clustering are naturally opposites, and clustering can block cascading. In addition, this conclusion also provides a theoretical basis for the intuitive understanding of restraining negative information cascades in the network.

In this paper, a model of information cascades is proposed to emphasize individual decision-making based on the choices of their neighbors and the content of spreading. Furthermore, an efficient method is developed for restraining negative information cascades by reconfiguring clusters with links logically removed (termed CLLR).

3. MODEL FOR INFORMATION CASCADES

3.1 Information Cascades

When people are connected by MSNs, user behavior and decision-making are likely to be affected by others. In this paper, we believe that information spreading is a part behavior spreading process. In order to avoid confusion, we only use the concept of information spreading in the discussion of information cascades and the behavior spreading in the following narration. Information cascade is a very common phenomenon in groups. In short, information cascade is a process of behavior spreading, namely individuals are more likely to adopt the behavior when more neighbors choose to accept the behavior.

As we are known, a joke or funny short video spreads very fast, however some information spreads relatively slowly in a large-scale social network with weak ties. Social activities tend to be inherently risky undertakings and individuals tend have a higher proportion of neighbors to support their decisions. In our model, the information forwarding threshold to evaluate the cost of individual participating in information spread is introduced. Different information contents correspond to different information forwarding thresholds. The lower the information forwarding threshold, the more likely the information is forwarded by individuals, that is, the higher information spread probability. Individual forwards a joke or short video doesn't need to be supported by a higher proportion of neighbors, while individual who forwards unreliable information needs to be supported by a higher proportion of neighbors. Because of the user's behavior tends to keep consistent with the surrounding neighbors, when receiving the information, he decides whether to adopt the information and participate in the information spreading by comparing the proportion of neighbors who forward the information with the value of the cost of participating in the information spread.

Let's consider an example of the process of information cascades in Fig. 1. Suppose that nodes 7 and 8 are initial spreaders of the information, and individuals who make decision to forward the information need to be supported by at least 40% of neighbors. We believe that each node in the network decides whether to forward the information according to its own decision. First, nodes 5 and 10 choose to forward the information because 67% and 50% of their neighbors support forwarding. In addition, 67% and 50% proportion of neighbors' support is greater than the given 40%. Then nodes 4 and 9, and finally node 6 also chooses to forward the information. Note, there is a cascading process of the information with a certain threshold value. Since the information requires a high proportion of neighbors' supports, we see the information can not be spread more widely through nodes 2 and 11.

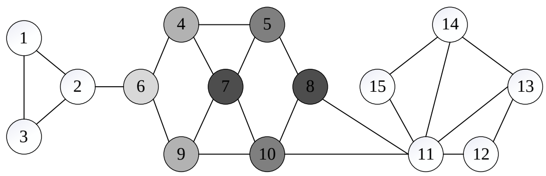


Fig. 1. An example of the process of information cascades.

3.2 Model Description

Consider a network with N nodes and E links representing the individuals and their interactions, respectively. Our model can be applied to the spreading of many kinds of information such as rumors and opinions. At each time step, each individual adopts one of two states. *Susceptible* (S) means an individual has not received the information, or he has received the information, but has not yet decided whether to forward the information; *Infected* (I) means an individual has adopted the information and then forwarded it to all his neighbors.

We describe the behavior spread process in MSNs as follows: At the beginning, one node is randomly selected from the network as the "seed" and all others are susceptible state. This seed will forward the information to all his neighbors. Once an individual (in a susceptible state) receives the information, he will decide whether to adopt and forward the information according to the impact of the information content itself and the neighbor's decision-making – a rumor is more likely to be adopted if a higher proportion of neighbors' supports forwarding. As time goes on, the infected node will recover to the susceptible state with a certain probability and participate in the next information spreading again. The present rules imply two features of information spreading, namely memory effects and social reinforcement, which reflected by the accumulative process of received information stimulus. In our model, only infected nodes can forward information. Therefore, we consider the proportion of infected nodes among neighbors in the process of modeling state transition rules. The higher the proportion of infected neighbors around an individual, the more likely the individual to adopt and forward the information. In general, information cascade occurs when most nodes in the network participate in the information spreading. When the proportion of infected nodes in the network is stable, the spread ends.

In our model, forwarding negative information with certain risks, and individual judge whether to adopt and participate in the information spreading by comparing the proportion of neighbors who forward the information with the value of the cost of participating in the information spread. The information forwarding threshold $q(q \in (0,1))$ is used to evaluate the cost of individual participating in information spread is introduced. Different information contents correspond to different information forwarding thresholds. The lower value of q, the more likely the information is forwarded by individuals, that is, the lower cost of individual participating in information spread, the higher information spread probability. Therefore, the lower information forwarding threshold confirms that information with higher attention and is easier to spread in the network.

In summary, this paper focuses on how the individuals decide whether to participate in the information spread, that is, the transformation rules from the S state to the I state. From the concept of information forwarding threshold, forwarding unreliable information has certain risks, and individual decision-making tends to be supported by a higher proportion of its neighbors. In this paper, a model of information cascades is proposed to emphasize individual decision-making based on the choices of their neighbors and the content of spreading.

4. RECONFIGURING CLUSTERS WITH LINKS LOGICALLY REMOVUED METHOD

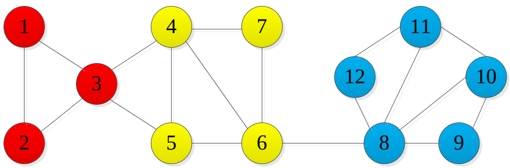
Based on the above model, an efficient method is developed for restraining negative information cascades by reconfiguring clusters with links logically removed (termed CLLR). By limited links with high betweenness being logically removed, CLLR method enhances the cluster density in a network, thereby effectively block information cascades.

4.1 Cluster Structure

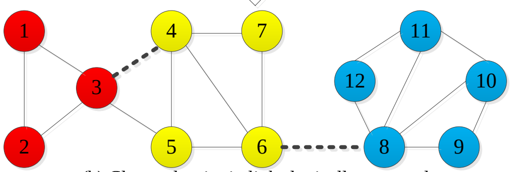
The cluster structure of a network precise a densely connected community, which has the characteristics of dense interconnection between nodes in the same cluster and sparse interconnection between nodes in different clusters. The cluster structure proposed in this paper emphasizes the similar tendencies of behaviors between individuals and their neighbors in the cluster. Each node in the cluster has some friends living in the cluster, which means internal "cohesion" level. To characterize this cohesion, we introduce cluster density.

Definition 1 Cluster density: Cluster density can be used to quantify the cohesion level of a cluster structure. The cluster density ρ means that each node in the cluster has at least a proportion ρ of neighbors with similar behaviors' tendencies in this cluster.

Fig. 2 illustrates the change of cluster density. According to the definition of cluster density, there are three clusters in Fig. 2. The cluster 1 with a cluster density of 0.5 on the left, including nodes 1, 2 and 3. The middle cluster 2 with a cluster density of 0.66 includes nodes 4, 5, 6 and 7. The cluster 3 with a cluster density of 0.8 on the right, including nodes 8, 9, 10, 11 and 12.



(a) Cluster density in the initial graph is 0.5(left 1)、0.66(middle 2) and 0.8(right 3)



(b) Cluster density in links logically removed is 0.66(left 1)、0.66(middle 2) and 1.0(right 3)

Fig. 2. An example of the change in cluster density.

Densely connected regions and weak connections between regions have an important impact on information cascades [9]. The links between different clusters in the network are weak connections, which are generally have larger link betweenness. Link betweenness is often defined as the ratio of the number of paths passing through the link to the total number of the shortest paths among all the shortest paths in the network [24]. If you consider the problem of graph partitioning, according to Girvan-Newman theory, it is an effective method to continuously remove links with high betweenness [25].

As shown in Fig. 2, the connecting link (6-8) between nodes 6 and 8 with the largest link betweenness. The cluster density of the three communities in Fig. 2 changed after removing the two links (6-8) and (4-3) with the largest link betweenness. And the cluster density of cluster 1 and cluster 3 increased by 0.16 and 0.2, respectively. It can be seen that when temporarily removing or controlling links with large betweenness, it means removing the connection between the cluster structures. If there are no such connecting links between clusters, the paths between many nodes will change, which will lead to longer propagation distances; at the same time, it can also be observed that reconfigure clusters by removing links with high betweenness is an effective method to rapidly increase the cluster density of the network. In view of the fact that links with high betweenness are usually weak connections between different clusters in the network. Removing the links with high betweenness means that the cluster density of the communities where the two end nodes connected by the link are located is increased.

4.2 Clustering Blocking Cascades

Interactions between individuals tend to be localized, that is, individuals tend to communicate with someone who closed to them, such as neighbors, friends, and colleagues. In MSNs, if an individual belongs to a cluster, most of his neighbors also belong to the same cluster. When faced with a specific event, different individuals in the same cluster often hold the same or similar views and behaviors. It should be noted that homogeneity often becomes a barrier to the spread of new things, making it difficult to adopt new ideas and behaviors from outside closely connected communities [9].

4.3 CLLR Algorithm

It is known that the problem of influential links identification is NP-hard. So, we propose an effective heuristic restaring method based on reconfiguring clusters with links logically removed to restrain negative information cascades. By limited links with high betweenness being logically removed, the CLLR method enhances the cluster density in a network, thereby effectively block information cascades.

Given a network graph $G(V, E)$ with n nodes and m links. The basic steps of the CLLR algorithm are as follows:

Step 1: First, use the classical GN algorithm [25] to obtain the descending links removed order based on link betweenness in graph G;
Step 2: In the case of ensuring the network connectivity, use the BFS algorithm to determine the number k_1 of removed links;
Step 3: Given the information forwarding threshold q, remove the links in sequence through the link betweenness in descending order, count the cluster density change of the largest cluster, and determine the number k_2 of removed links;
Step 4: Take the smaller value of k_1 and k_2 to determine the number k of removed links;
Step 5: Then logically remove a link that satisfies the condition according to the descending link remove order;
Step 6: Repeat Step 5 until the number of removed links reaches k.

Specifically, the CLLR method has the following characteristics:

- Logically remove links. The CLLR method refers to temporarily removing links logically, and isn't equivalent to physically removing links. In the process of information spread, it may mean temporary control and cut off the communication links.
- A limited number of links are removed. The number of links logically removed is jointly determined by the basic function of the network and the information forwarding threshold.
- Practical and effective method. The CLLR method doesn't completely cut off the connection between individuals; and links logically removed is easy to implement. This method efficiently restrains the speed and scope of information cascades.

5. SIMULATION RESULTS AND ANALYSIS

In this section, we first evaluate the diffusion efficiency of different information with a certain threshold value. Then, we show the essence of the CLLR method for restraining negative information cascades based on cluster density analysis. Finally, we validate the performance of the CLLR method by comparing with typical links removed blocking methods.

5.1 Datasets and Parameters Setting

Four real networks are from Konect's open databases, which are Zachary network, Political Books network, Oz network and Email network. The topology features of each network are shown in Table 1. Randomly select 4% nodes as the initial spreader, set the recovery rate to 0.20, and the information adoption threshold $q = 0.20$. Each curve value represents the average value of running more than 100 runs.

Table 1. Network topology features of each network.

Network	Node	Link	Average degree	Cluster
Zachary	34	78	4.59	2
Political Books	105	441	8.40	4
Oz	217	1839	16.95	6
Email	1133	5451	9.62	8

5.2 Analysis of Information Forwarding Threshold

In this section, the information forwarding threshold q is used to evaluate the cost of individual participating in information spread. We describe the dynamic evolution of the proportions ($I(t)$) of individuals who decide to forward the information during a period of time. Fig. 3 depicts the changing trend of $I(t)$ on different networks under different information forwarding threshold q.

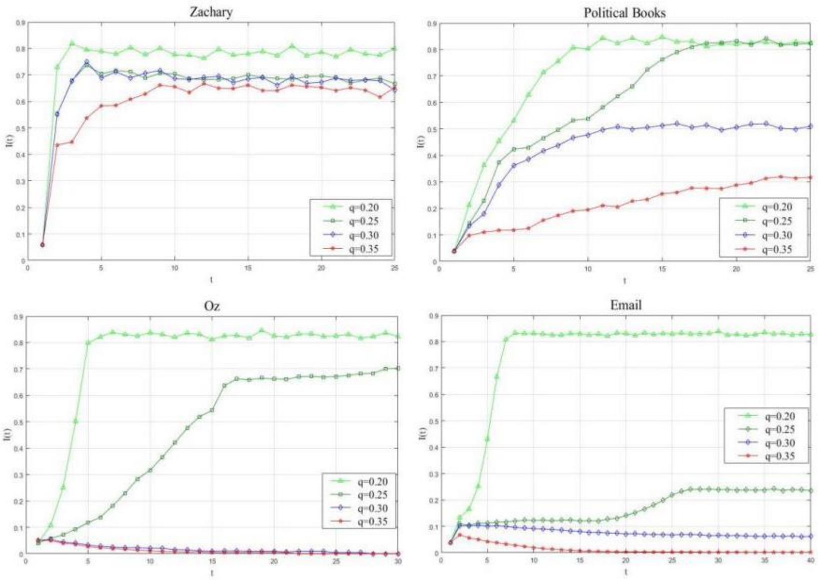


Fig. 3. The changing trend of $I(t)$ on different networks under different information forwarding threshold q.

It can be seen from Fig. 3 that (1) When the information forwarding threshold is low, as long as a low proportion of neighbors chooses to participate in the information spread, the individual will be followed, and change from *S* state to *I* state. That is to say, the lower the information forwarding threshold, the lower the cost of participating in information spread, and the information is easier to spread in the network; (2) As the information forwarding threshold increases, the cost of participating in information spread is also increasing, each individual tend to participate in the forwarding behaviors with more neighbors. In general, the lower information forwarding threshold confirms that information with higher attention and is easier to spread in the network.

5.3 Analysis of the Change of Cluster Density

Table 2 shows the comparison of cluster density changes of each network with links logically removed by the CLLR method. We see that the cluster density in reconfigured networks by the CLLR method is higher initial networks in Table 2. By limited links with high betweenness being logically removed, the CLLR method enhances the cluster density of networks. Clusters with the high-density will became a barrier to information cascades. We can draw that the change of cluster density is the essence of the CLLR method for restraining information cascades in a network.

Table 2. Comparison of cluster density changes of networks with links logically removed by the CLLR method.

<table>
<tr><th>Network</th><th colspan="7">Comparison of cluster density changes with links logically removed</th></tr>
<tr><td rowspan="3">Zachary</td><td></td><td colspan="3">Cluster 1</td><td colspan="3">Cluster 2</td></tr>
<tr><td>Initial cluster density</td><td colspan="3">0.40</td><td colspan="3">0.60</td></tr>
<tr><td>Reconfigured cluster</td><td colspan="3">0.80</td><td colspan="3">0.75</td></tr>
<tr><td rowspan="3">Political Books</td><td></td><td>Cluster 1</td><td colspan="2">Cluster 2</td><td>Cluster 3</td><td colspan="2">Cluster 4</td></tr>
<tr><td>Initial cluster density</td><td>0.37</td><td colspan="2">0.50</td><td>0.40</td><td colspan="2">0.67</td></tr>
<tr><td>Reconfigured cluster</td><td>0.40</td><td colspan="2">0.60</td><td>0.50</td><td colspan="2">0.83</td></tr>
<tr><td rowspan="3">Oz</td><td></td><td>Cluster 1</td><td>Cluster 2</td><td>Cluster 3</td><td>Cluster 4</td><td>Cluster 5</td><td>Cluster 6</td></tr>
<tr><td>Initial cluster density</td><td>0.25</td><td>0.25</td><td>0.21</td><td>0.17</td><td>0.38</td><td>0.35</td></tr>
<tr><td>Reconfigured cluster</td><td>0.31</td><td>0.38</td><td>0.33</td><td>0.46</td><td>0.50</td><td>0.33</td></tr>
</table>

5.4 Performance Analysis Based on Simulation Experiments

Fig. 4 depicts the changing trend of $I(t)$ on different networks by different blocking methods with the same number of links removed. We compare the CLLR method with the no-strategy method, the random links removed method, the degree-product links removed method and the Jaccard coefficient links removed method [26]. It can be seen from Fig. 4, the $I(t)$ curve under the CLLR method shows that the proportion of nodes participating in information spread in the network is controlled within a small range, indicating that the CLLR method has significant advantages in restraining the speed and range of information cascades. Our method enhancing the cluster density in a network by reconfiguring clusters with links logically removed. The higher cluster density, the closer the cluster structure is. Clusters with the high-density can block information cascades. It is difficult for new information to spread into the closer cluster structure when the information forwarding threshold is given. And compared with other blocking methods, our method is optimal when the same number of links are logically removed.

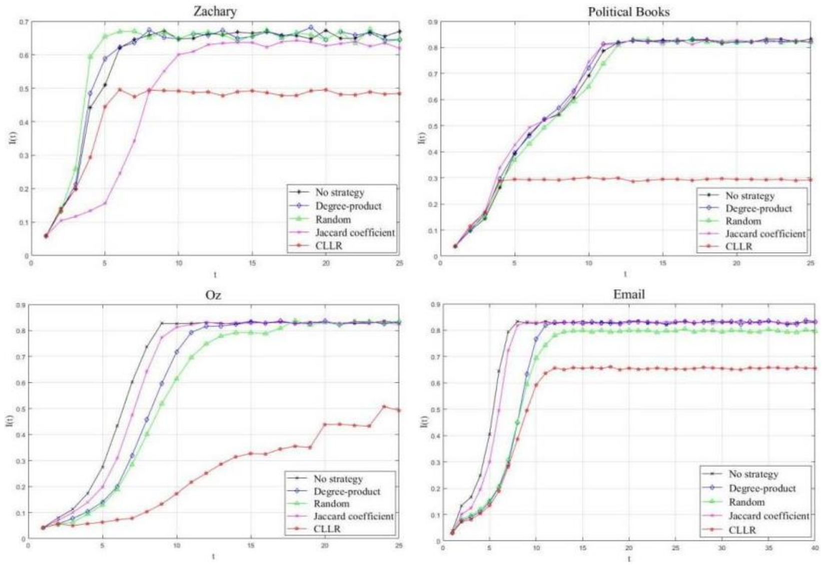


Fig. 4. The changing trend of $I(t)$ on different networks by different restraining methods.

6. CONCLUDING REMARKS

Information cascades are recognized as a major factor in disastrous social network phenomenons. Network structure and user behavior have an important impact on information cascades. Considering that different information contents correspond to different information forwarding threshold, and individuals tend to keep consistent with their neighbors when making decisions. In this paper, a model of information cascades is proposed to emphasize individual decision-making based on the choices of their neighbors and the content of spreading. On the basis of this model, an efficient method is developed for restraining negative information cascades by reconfiguring clusters with links logically removed (termed CLLR). By limited links with high betweenness being logically removed, CLLR method enhances the cluster density in a network, thereby effectively block information cascades. This paper validates the performance of the CLLR method with four real datasets. Experimental results show that the CLLR method proposed in this paper significantly reconfigure the cluster structure with limited links logically removed, efficiently restrain the speed and scope of information cascades in MSNs.

The next step is mainly reflected on two aspects: On the one hand, a more universal behavior spread model will be established according to the characteristics of information-driven behavior spread in real MSNs. On the other hand, on the basis of this paper, further research on behavior spread control methods based on interaction of network structure optimization and cascading behavior in large-scale network environment is carried out.

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