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Community Discovery Optimization Algorithm in Social Network

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Abstract
As for the present community discovery and compression algorithm ignoring the issue of network community structures, this paper proposes a community discovery GS algorithm and community compression SNC algorithm. On the basis of proposing the theorems and corollaries related to the importance of the nodes in community discovered by topological method. GS algorithm discoveries the important nodes on different levels in community, and then through social networks compresses SNC algorithm and according the importance of the node compresses the community. Experimental results show that: the proposed algorithm can maintain the relationship between the communities during the compression process. It has a good community compression, in which the ratio can up to 0.95, and at the same time it can retain the important nodes in the community or community basic structures.
Keywords: FIGURE COMPRESSION, COMMUNITY CISCOVERY, ROUTING SELECTION, NODE

1. Introduction

Online social networking communities are some unique teams consisted by very closely linked units or individuals, which usually have the common interests and share the same theme. Community represents of the social activities of user in the network; the in-depth study of the community can learn the knowledge of online social networking information and its organizational structure; it can help network service providers effectively organize portals and product manufacturers to accurately find their interest groups.

In the real world, there are many network models, which range between complete rule and complete random called as complex networks, such as national transport networks, ecological networks, scientists cooperation network and social relations networks. Complex network has the properties as with small world and scale-free, but also it has a community structure characteristic. Links between nodes within the community is relatively close, while the links between communities is relatively sparse. Discovery of community structures in network is helpful for understanding and applying the complex network. For example, in social networks, community structure can provide friends referral services for community members, and it can also be used for social network analysis, network culture security early warning and so on. Thus, community discovery in social network has very important practical value. Online social networking community is divided into two kinds: artificial community and potential community. Human community is found and maintained by artificial, however, it is difficult to manage these artificial communities through artificial means; the number of potential communities is greatly larger than the artificial communities, and it is still growing [8]. Therefore, it is necessary to study a community automatic discovery technology for those potential, or is about to be the community,

Discovery and research in online Community is attracting wide attention from researchers of complex networks. In recent years, there is the emergence of a number of methods; from data mining level, the essence of network discovery is clustering learning based on community network link, and its goal is to divide the network nodes several clusters, in which it's internal links are close, while it's external links are sparse. From the standpoint of learning clustering, the quality of the discovery algorithm of online communities largely depends on the design ideas and optimization strategies of the quality evaluation indexes on network community structures. Currently, the online community discoveries that the solving optimization strategies of objective function (quality evaluation index on network community structure) in algorithm can be broadly divided into two categories: basic heuristic method and meta-heuristic method. The former transfer the problem discovered by complex network community into the design problem of the predefined heuristic rules; according to the characteristics of various community quality index, the strategies is designed and optimized; the latter uses a variety of ultra-heuristic operator in network community to find the problem in the problem community space and search optimization for community quality evaluation index.

Currently, there are many algorithms found by community, in which Kernighan-Lin algorithm, spectrum diagram dichotomy with Laplace eigen-value and GN algorithm are classical algorithms belong to the community found. KL algorithm is an application of graph partitioning method. According to the principles of the greedy algorithm, the network is divided into two communities with known scale. Spectrum dichotomy of Laplace graph Eigen-value find the community structures in network by analyzing the eigenvalues of the Laplace matrix. GN algorithm is belong to the hierarchical clustering category, which is the split method based on edge betweenness. Hierarchical clustering algorithm mainly uses the similarity calculation to search the community discovery, and it is consider that two nodes in the same community are equivalent or with a high degree of similarity, and also the algorithm uses the edge clustering coefficient to divide the network. For examples, Radicchi algorithm determines the community by make the largest coefficient of edge aggregation; GN algorithm uses betweenness to divide image based on the structure characteristics of pictures, and by removing the side of the communication concentration to obtain two communities. These algorithms usually need to know beforehand the number of existing communities and the clear network structure, etc. Most community discovery algorithms are considered from the overall network topology, in which the amount of computation is large and the performance of algorithm has different degrees of impairment. Therefore, the research of community discovery is far from perfect and need to be explored further.

With the advent of the era of social networks, it is the necessary requirements made by the times conducting the in-depth research on the social networks. The researches on visualization and knowledge discovery for social network will be involved to the social network compression. With the increasing of social network scale, the community discovery has

become an indispensable step in the process of social networking application. As an important structural feature of social networks, community retains the important nods or basic structure and maintains the relationship between them in the compression process, which has an important and meaningful value. However, from the point of view of existing figure compression method, the research taking community as compress object is still very rare.

Figure compression is widely used in semantic label network, important node discovery, network retrieval, network visualization, network analysis and other fields. In recent years, some relative typical figure compression method is appeared. The current figure compression methods can be divided into no right figure compression and right figure compression; the used compression method is generally as the combined similarity nodes. For example, when node A and node B has the same or similar common neighboring nodes, they can be merged and generated the so-called super-node; the edge merges between super nodes is called super edge. Thus, this method will produce some edges between the super nodes which does not exist in the original network, and then cause errors when decompressed. Therefore, these methods damage the compression method. Besides, there are other shortcomings of these methods, such as the need to pay a higher time cost to balance the similarity between nodes and prior knowledge of merger thresholds set required for more parameters to meet different situations.

For these problems, the thesis proposes the social network compression method based on the importance of community nodes. This approach consists of a community discovery algorithm (GS) based on greedy strategy and social network compression algorithm (SNC); social network compression, in essence, is a figure compression. However, in order to distinguish it from other networks approach, which do not consider the premise of community, the approach is called as the social network compression method. This method first uses the social network topology theory to research the community discovery of social network, and on this basis to find the importance of distinguishing community nodes, and then the important compression based on community nodes are conducted.

2. Network Community

2.1. Network Community Nodes

The topology potential theory is derived from the nuclear physics, which is used to guide the community discovery on social networks. In the nuclear physics, the non-contact interaction nuclear between the nucleons is characterized through nuclear field. Topology potential theory draws on the field theory, which considers that there is interaction of direct or indirect relationship between nodes mutual. This interaction between nodes in the topology potential theory is known as topology potential force, just like between the acting forces between nucleons, with the increasing of the distance, it is continue to decay until the decay is zero. From the community structure level, the importance of nodes between communities discovered by using the topology potential method exist difference. To illustrate the difference of importance of community nodes, firstly the theorems and corollaries are given as following.

Theorem 1 Let node u and node v locating in an attractive chain of the community representatives point v^* in social network, and u is the a_{-th} jump of v^*; v is located in $a+1_{-th}$ jump of v^*; $a=0,1,2...,h-1$, so the contribution ratio of the topology potential of u and v to v^* is as follows:

$$R_{u\leftarrow v}(a,a+1)=e^{\frac{2a+1}{\sigma^2_{opt}}} \tag{1}$$

Proof: The contribution ratio of the topology potential of any node p in the attraction chain to the community representative point v^* is:

$$A_{v^*\leftarrow p}(\sigma_{opt},l)=\frac{1}{n}e^{-(\frac{l}{\sigma_{opt}})^2} \tag{2}$$

l is minimal hops of p leaving v^*.

From the formula (2), it is easy to know that the contribution ratio of the topology potential of u and v to v^* is:

$$A_{v^*\leftarrow u}(\sigma_{opt},a)=\frac{1}{n}e^{-(\frac{a}{\sigma_{opt}})^2} \tag{3}$$

$$A_{v^*\leftarrow v}(\sigma_{opt},a+1)=\frac{1}{n}e^{-(\frac{a+1}{\sigma_{opt}})^2} \tag{4}$$

Therefore, the contribution ratio of the two is:

$$R_{u\leftarrow v}(a,a+1)=\frac{A_{v^*\leftarrow u}(\sigma_{opt},a)}{A_{v^*\leftarrow v}(\sigma_{opt},a+1)}=e^{\frac{2a+1}{\sigma^2_{opt}}} \tag{5}$$

Corollary 1 Let node u and node v locating in an attractive chain of the community representatives point v^* in social network, and u is the a_{-th} jump of v^*; v is located in $a+1_{-th}$ jump of v^*; $a=0,1,2...,h-1$, so the contribution ratio of the topology potential of u and v to v^* is $R_u\leftarrow v(a,a+1)\succ 1$.

Proof From the theorem 1, $Ru\leftarrow v=e^{\frac{2a+1}{\sigma^2_{opt}}}$; $a=0,1,2...,h-1$, $\sigma opt\succ 0$, so $2a+1\succ 0$.

$\sigma_{opt}^{2} > 0, \frac{2a+1}{\sigma_{opt}^{2}} > 0,\ Ru \leftarrow v(a,a+1) = e^{\frac{2a+1}{\sigma_{opt}^{2}}} > 1$

Corollary 2 Let node u, node v and node y are in an attractive chain of the social network community representatives point v^*; y is the a_{-th} jump of v^*; v is $a+1_{-th}$ jump of v^*; m is $a+2_{-th}$ jump of v^*; $a = 0,1,2...,h-1$, so:

$$R_{v\leftarrow w}(a+1,a+2) > R_{u\leftarrow v}(a,a+1) \quad (6)$$

Proof Because $\sigma_{opt}^{2} \succ 0$ and a is the non-negative integer, for a given network $\sigma_{opt}^{'}$ is a constant value, so $\frac{2(a+1)+1}{\sigma_{opt}^{2}} > \frac{2a+1}{\sigma_{opt}^{2}}$. From the Theorem, it can be known that $Ru \leftarrow v(a,a+1) = e^{\frac{2a+1}{\sigma_{opt}^{2}}}$, $Ru \leftarrow v(a+1,a+2) = e^{\frac{2a+1}{\sigma_{opt}^{2}}}$; and ex (x>0) is a strictly monotonic increasing function, therefore $Ru \leftarrow v(a+1,a+2) > Ru \leftarrow v(a,a+1)$.

Corollary 3 Let node u, node v and node w are in an attractive chain of the social network community representatives point v^*; u is the a_{-th} jump of v^*; v is $a+1_{-th}$ jump of v^*; w is $a+2_{-th}$ jump of v^*; $a = 0,1,2...,h-1$, so:

$$R_{v\leftarrow w}(a+1,a+2) = e^{\frac{2}{\sigma^{2}_{opt}}} R_{u\leftarrow v}(a,a+1) \quad (7)$$

Proof From Theorem 1

$Ru \leftarrow v(a,a+1) = e^{\frac{2a+1}{\sigma_{opt}^{2}}}$, $Ru \leftarrow v(a+1,a+2) = e^{\frac{2a+1}{\sigma_{opt}^{2}}}$,

so $Ru \leftarrow v(a+1,a+2) / Ru \leftarrow v(a,a+1) = e^{\frac{2}{\sigma_{opt}^{2}}} Ru \leftarrow v(a,a+1)$, that is:

$$R_{v\leftarrow w}(a+2,a+1) = e^{\frac{2}{\sigma^{2}_{opt}}} R_{u\leftarrow v}(a,a+1) \quad (8)$$

Corollary 4 Let node u, node v and node w are in an attractive chain of the social network community representatives point v^*; u is the a-th jump of v^*; v is a + 1-th jump of v^*; w is $a+2_{-th}$ jump of v^*; $a = 0,1,2...,h-2$ and $b \succ a$, so:

$$R_{x\leftarrow y}(b,b+1) = e^{\frac{2(b-a)}{\sigma^{2}_{opt}}} R_{u\leftarrow v}(a,a+1) \quad (9)$$

Proof From Theorem 1

$Rx \leftarrow y(b,b+1) = e^{\frac{2b+1}{\sigma_{opt}^{2}}}$, $Ru \leftarrow v(a+1,a+2) = e^{\frac{2a+1}{\sigma_{opt}^{2}}}$,

so

$$Rx \leftarrow y(b,b+1) / Ru \leftarrow v(a,a+1) = e^{\frac{2b+1}{\sigma_{opt}^{2}}} / e^{\frac{2a+1}{\sigma_{opt}^{2}}} = e^{\frac{2(b-a)}{\sigma_{opt}^{2}}},$$

that is:

$$R_{x\leftarrow y}(b,b+1) = e^{\frac{2(b-a)}{\sigma^{2}_{opt}}} R_{u\leftarrow v}(a,a+1) \quad (10)$$

Table 1 lists the contribution ratio of a number of nodes in network which is distant away 1 hop to the representative point; the above theorems and corollaries can be used to verify the correctness. Theorem 1 and its corollaries fully demonstrate that in the community discovered by topology potential method compared to distant neighbor nodes, the neighbor nodes have larger contribution to the topology potential of the representatives; with the increasing distance from the representative points, the contribution of the nodes is exponentially decreased. Therefore, with more community representatives of local extreme value, the number of its neighbor nodes is larger, so their links are also more closely, which forms core structure of the community. The topology potential's contribution of distant neighbors to preventatives is relatively smaller, the numbers are relatively less, and their links are sparser. In summary, from the community level, compared to the distant nodes, the neighbor nodes of the representatives are more importance.

Table 1. Ru ←v (A,A+1)Values Of Number Of The Networks

The hopes of node u when leaving representative v^*	The hopes of node v when leaving representative v^*	Scene People Network	Karate Club Network	Dolphin social networks
1	2	19.789	16.873	15.852
2	3	146.432	138.421	98.063
3	4	165432	820.863	620.931

The above conclusions are exactly the same with intuitive feel of people for the community. In addition, some other aspects can also be used to illustrate the importance of community representatives' neighbor nodes is far more important than the importance of neighbors. For example, the study found that robustness and fragile is one of the basic characteristics of complex systems and complex networks, while the other important mean to trigger the vulnerability of complex networks is consciously attacking the nodes with high number. With this attack strategy, the network connectivity is damaged and the flow of information is clogged. According to this attack strategy, a conscious attack on the first hop neighbors of nodes with high number of degree, which can also destroy the network connectivity; conversely, if the distant neighbors of a high number of nodes launch the attacking, it is difficult to destroy the network connec-

tivity. This shows that a high number of nodes and their neighbors in the network are more important than the distant neighbors. Empirical research, aforementioned topological theorems and corollaries indicate that the community representatives discovered by the topology potential method are the high number of nodes in the network, so the importance of the nodes in the community discovered by the topology potential method are also different.

2.2. Network Community Structures

Community structure is an important characteristic of complex network, which has become a hot research. After a lot of research work of scientists, the current research on community structure in complex network has made great achievements. In 2002, Newman proposed the concept of community structures in complex network; community is the collection of nodes in the network. Nodes in the communities have a close connection, while the nodes between the communities are loose. A reasonable community division of a network should satisfy that the connection rate within the community is greater than the average network connection rate, and inter-community connection rate is less than the average connection rate.

Let the undirected network $G(V,E)$; the set of network nodes as V; the set of network edge is as $E=\{E=(u,v)|u\in v, v\in V\}$; G is presented by the matrix A with a size as $|V|\times|A|$; if the edge $e=(i,j)\in E$, $A_{ij}=1$, otherwise, $A_{ij}=0$. Internet community structure is an m division scheme $p=(v_1,v_2,...v_m)$ of the set V of network nodes, in which V_i should meet four conditions:

$V_i \neq \varnothing (i=1,2,\cdots,m)$;

$\bigcup_{i=1}^{m} V_i = V$;

$V_i \cap V_j = \varnothing (i \neq j)$.

2.3. Evaluation Index of Network Community

1) Modularity function R

Several definitions of community structures can not be directly applied to probe the structure of complex networks in the community and can not evaluate the quality of community structures obtained by algorithm. Therefore, Girvan and Newman proposed the modularity R function, which quantitatively describes the advantage and disadvantage of the division of community structure.

2) Module density G

Module density G represents the difference of the edges within the community and between the community and the ratio of with the total number of the community nodes. The yard stick of module density the total number of nodes in the community takes into account and to overcomes the defects of modularity R can not detect small community.

3) Community level C

This thesis makes improvements in the defects of modularity function R and proposes the concept of community level. Community level index is defined as:

$$C=\frac{1}{m}\sum_{i=1}^{m}\frac{C_{in}}{n_c-(n_c-1)/2}-\frac{C_{oat}}{n_c(n-n_c)}$$

From the above formula, m is the number of communities; n is the number of nodes throughout the network; N_c is the number of nodes in community i; C in is the number of edges within the community I; Cout is the number of edges connected by the nodes in community I and the nodes outside the community.

2.4. Community Structure Detection Algorithms

The current existing division method of complex network of community can be divided into two categories: optimization-based method and heuristic methods. Optimization-based algorithm: Kernighan-Lin algorithm is a temptation optimization algorithm, which is the dichotomy based on the principle of greedy algorithm and the algorithm divide the network into two communities with known size. It's basic idea is introducing a gain function R, which is defined as the two variables within the community minus the variables linked two communities, and then looks for the best ways to make the maximum Q value; Spectral method completes segmentation through analyzing the eigenvectors of Laplace operator in network. Heuristic methods: The basic idea of G-N algorithm is to continually remove the edges with biggest betweenness from the network. First of all, the betweeness of all edges in the network is computed, and then the edge with the highest betweeness is found and removed until each node is a degraded community. This algorithm makes up the deficiencies of the traditional algorithm, but there are still some problems like the decomposition step is not sure. To solve this problem, Newman et al introduced the concept of modularity to measure the standards of community division quality. MFC algorithm is the minimum cut theorems based on the maximum flow in graph theory. The algorithm assumes that the maximum flow in the network is determined by the network the capacity of the "bottleneck", while in the network with community structure the network "bottleneck" is constituted by the connection between the communities. By the maximum flow- minimum cut theorem, the maximum flow in the network is equal to the capacity of minimal cut sets. Therefore, by cal-

culating the minimum cut sets it can identify connections between communities, and through repeatedly identifying and removing the connection between the communities the online communities can be gradually separated. The efficiency of the proposed algorithm depends on the time calculating the minimum cut sets. Tasgin algorithm uses the genetic algorithm to the division of community structures and proposes a symbolic coding method of community ID number, which randomly assigns the community ID number to each node.

3. Algorithm Description

The proposed method is conducted by the way of compression of relative representatives from the outside to the inside; it can be compressed only leaving representative points in the network at maximum. One of the advantages of the method is embodied as follows: during the compression process, it can compress out some relatively unimportant node, which effectively reduce network size, but also keep the necessary important nodes in the community or the basic structure of the community. Different from other general figure compression method, this method need not using the experience parameters specified by the user in the compression process, but only need to assign the hops should be compressed under the guidance of the optimization range of influence determined by the automatically method. Figure 1 presents the compression sketch map of the community with the optimization range of influence as 2 hops, in which the one-way arrows represent that some hops can be compressed to another hop.

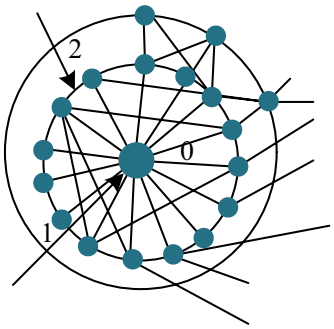

Figure 1. Compression Sketch Map of Community

3.1. Data Structures

In order to achieve lossless compression, the proposed method in the community discovering process indicates the hops of all nodes between representative points, and these markers is marked in the list structure in the memory community. For there is possible that the relationships between communities may be loosed in the compression process, the chain table of relationships between memory communities is designed. The basic data structure used in the methods used is as follows:

```
// List structure in various communities
Typedef struct CommNode {
 int  Node
 int  hop
Struct CommNode*next node
} CommNode
Typedef struct {
 int  Re pNode
 int  totalhop
CommNode*FirstNode
} VexNode . Community  Arr [maxSize]
// List structure in various communities
Typedef struct  Comm Re lation  {
 int  c1
 int  c2
Struct  Comm Re lation *next
} Comm Re lation
```

3.2. GS Algorithm

When processing some nodes (especially the nodes in the edge) in community, the current social network discovery method artificially separates the relationship of these nodes with the nodes in another community in essential. To vividly illustrate the problem, the karate network shown in Figure 2 is as criminal networks, and node 3 is the criminal who should be emphasized suspect. Node 3 is a node which is easy divided; generally it is believed that it should be included in the right community, but some algorithms include it to the left community (such as GN algorithm, modularity optimization algorithm and spectral dichotomy), while some other algorithms include it into both the right of the left communities (such as some overlapping communities algorithm). However, regardless of which communities it classified, they are all take consider of node 3 as the edge node in community, which will not take analysis of the nodes in another community related closely at the same range. In the analysis of criminal networks, the traditional approach easily misses some important clues and splits the relationship between some nodes and the other communities (gangs) resulting in loss of information.

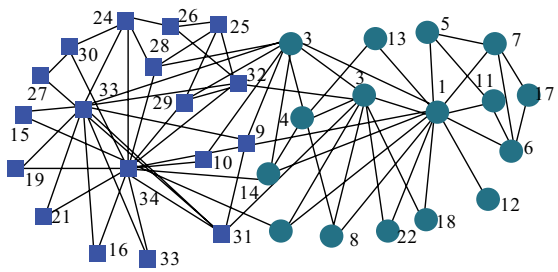

Figure 2. Karate club network

In addition, due to the benefit function used in the current topology potential community method to determine the community ownership of the overlapping nodes is too strict, the discovered overlapping community nodes are too scarce, which exists greater difference in the real world that the individuals are belong to multiple communities situation.

3.3. SNC Algorithm

On the basis of the GS algorithm discovering the community, social network compression algorism (SNC) obtains the number of hops need to compressed through the interactively method, and then conducts the compression operation. The specific description of SN_c algorithm is as follows:

Input network $G=(v,e)$, $|v|=n$, $|E|=m$, $Opstigma$

Output compressed community C_i (i is the number of the community representatives, and for each community C_i it only indicates the nodes within a user-specified number of hops)

Disover Community()

$h=(\text{int})(3*Optsigma/sprt(2))$

Count<<" $/n$ Optimization range of infuluence of the current network" n "

Count>>hop

For $i=0, i<\max Size, i++)$

P= $G.Comm[i]$

While $(p)\{$

If $(p->hop<=hop)$ display $(p->Node)$

$p=p->next\,node$

}

}

$r=G.CommR->next$

while $(r)\{$

display $(r->c_1, r->c_2)$

r=r->next

}

4. Experimental simulation and analysis

4.1. Experimental Environment and Setup

To verify the feasibility and effectiveness of this method, it is tested in two widely used sets of data: the karate club network and dolphin social networks. The node number in the two networks is the same with the number offered by Newman.

4.2. Analysis of Experimental Results

1) Compression Test in Karate Club Network

Karate club network is drawn by Zachary according to the interaction of its members. The club eventually split into two respective groups which as the core of coaches and the core of management, shown in Figure 2.

GS algorithm is applied on the karate club network to make community discovery, and the results are shown in Figure 3. In Figure 3, the circular and the square are used to mark two different communities; large icons are used to identify the community representatives; the triangle icons are used to identify communities overlap between nodes. The meaning of the icons IN Figures 4 ~ 6 are the same with Figure 3.

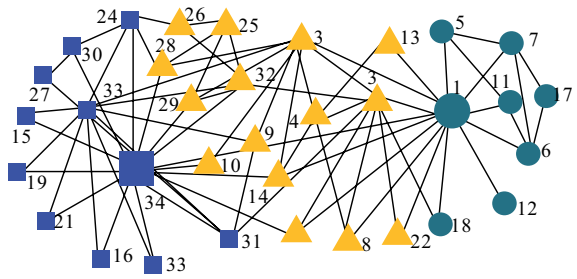

Figure 3. GS algorithm used in karate club network to discovery community

In the community found by GS algorithm, the SNC algorithm is applied to find the compression of the community with 2 hops, 1 hop skip and 0 hops, and the compression results are shown in Figure 4~6. The double-headed arrow in Figure 4~6 are used to identify the relationships between the two communities.

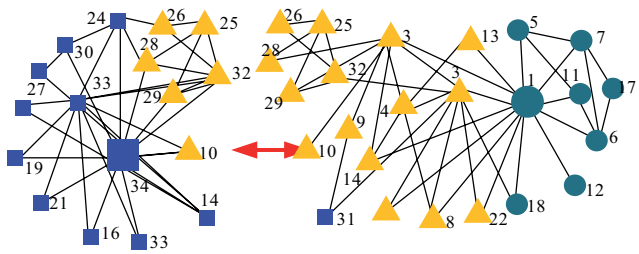

Figure 4. 2 hops compression in karate club network

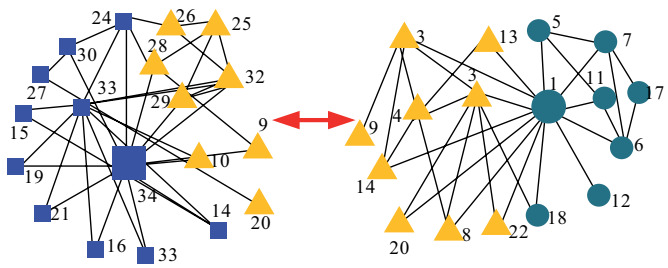

Figure 5. 1 hops compression in karate club network

Figure 6. 0 hops compression in karate club network

2) Compression Test on Dolphin Social Networks

Dolphin social network shown in Figure 7 reflects THE interaction between two dolphins family relationship; the larger number of family members is 42, while the smaller one is as 20.

GS algorithm is applied on dolphins social networks to discovery community, the results are shown

in Figure 8. In Figure 8 the round, square and star icons are used to indicate three different communities; the large icons are used to identify community representatives; the triangle icon are used to identify overlapping nodes in communities. The meanings of the icons in Figure 9~11 are the same Figure 8.

In the community found by GS algorithm, the SNC algorithm is applied to find the compression of the community with 2 hops, 1 hop skip and 0 hops, and the compression results are shown in Figure 9~11. The double-headed arrow in Figure 9~11 are used to identify the relationships between the two communities.

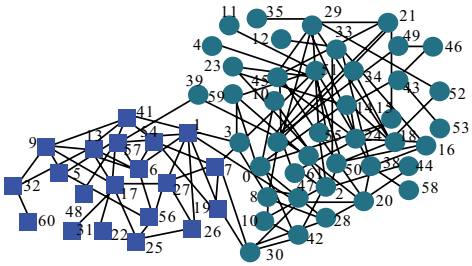

Figure 7. Dolphin social networks

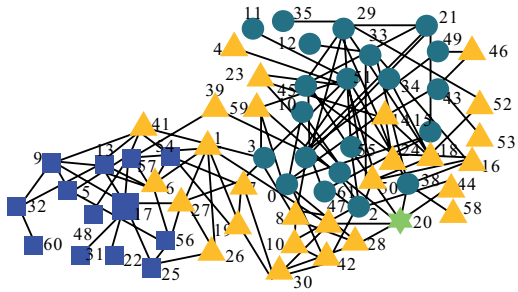

Figure 8. Communities discovered by GS algorithm in dolphin social network

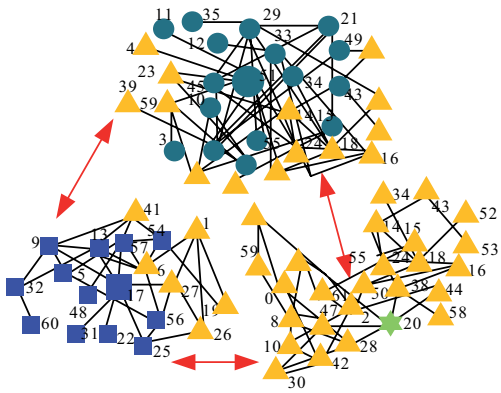

Figure 9. 2 hops compression Figure in dolphin social network

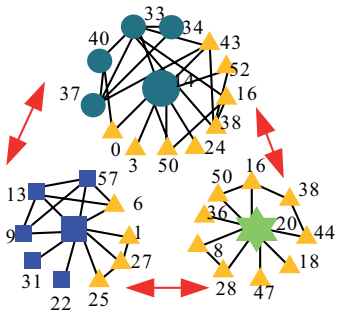

Figure 10. 1 hops compression Figure in dolphin social network

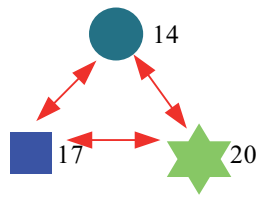

Figure 11. 0 hops compression Figure in dolphin social network

3) Results Analysis

Experiments on classic datasets show that after the application of community discovery algorithm GS based on greedy strategy and social networks compression algorithm SNC, the number of nodes in the community can be effectively compressed. Table 2 lists the compression ratio of each community in karate club network and dolphin social network with 2 hops, 1 hop and a 0 hop data (the code of community in the second column are the same with the code of the community representatives). The compression rate is defined below.

Table 2. Data sheet of community compression ratio

Network name	Community Name	Number of community nodes	Hops of compression		
			3	2	0
KarateClub Network	C_1	23	0.2964	0.3210	0.9712
	C_{13}	28	0.23451	0.33415	0.9641
Dolphin social network	C_{16}	53	0.2671	0.7421	0.9842
	C_{22}	24	0.1601	0.5542	0.9512
	C_{23}	42	0.4631	0.7513	0.9731

If the network $G' = (v', e')$ is a network compression network $G = (v, e)$, then $R = \frac{|G| - |G'|}{|G|}$ is called as network the compression ratio G.

Since the optimization scope of influence of the two networks are $h = 3$, they may cause that some nodes in the communities cannot attract other nodes in other communities and then the compression ratio is as 0. For example, when the community C_1

in karate club network is compressed to 2 hops, the compression ratio is belong to such a situation. Under normal circumstances, some nodes in the optimization community will still have the ability to attract other communities, so when community C_{23} in karate club network and communities C_{13}, C_{16} and C_{22} in dolphin social network is compressed to 2 hops, the compression ratio is not as 0, but the highest compression rate is up to 0.4401. Compared with the identified community from Network Community Discovery Methods Based on Topology Potential by Gan Wenyan, when the community compressed to 1 hop, it still remains the basic structure or the important nodes, and this time the maximum compression ratio is 0.77 and the minimum is 0.3014; when it is compressed to 0 hops, the compression ratio of each community is above the highest 0.95.

5. Conclusion

With the wide use of the figure compression methods and techniques in semantic label network, network retrieval and other fields, the related researches are growingly concerned. In order to solve the problems of figure compression methods like high time complexity, depending on prior knowledge to set the parameters, too many parameters need to be adjusted, compression beneath and ignoring network community structures, this paper presents a new compression method - the social network compression method based on the importance of community nodes. On the basis of proposing the theorems and corollaries related to the importance of community nodes discovered by the topology potential method, this method makes community discovery through the GS algorithm based on greedy strategy, excavates important nodes with different levels in community, through the social networks compresses SNC algorithm and based on the importance of nodes compresses the community. Through the experiments in classic data sets the feasibility and effectiveness of this method are verified. The experimental results show that this method can keep the relationships between communities in the compression process, has the ideal community compression ratio, in which the highest can be up to 0.95, and if necessary can reserve the important nodes in the community or community basic structures.

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Application of Multi Feature Watermarking Algorithm for Ownership Protection in the Judicial Authentication and Copyright

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Abstract
Aiming the problem of the poor robustness of software watermarking, the low efficiency of the implementation of Watermarking Sharing Algorithm, we put forward a kind of software watermarking scheme based on chaotic optimization. The scheme by introducing chaos system, taking matrix partition, chaotic scrambling on the watermark information to form the sharing watermarking; when watermarking embedding, encoding the sharing watermarking as DPPCT topology one by one, and filling the Info domain of every DPPCT with the watermark information treated by Hash; after embedding the watermark, encrypted by chaotic, to protect all the code and prevent the damage brought by the reverse engineering and other means to the software watermarking. Theoretical analysis and