International Journal of Future Generation Communication and Networking
Vol. 9, No. 4 (2016), pp. 39-50
http://dx.doi.org/10.14257/ijfgcn.2016.9.4.04

Social Network Partition Method based on Concentricity-Controllable Routing

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Abstract

In allusion to issues that partitioning algorithm of traditional social network community is generally lacking in comprehensive consideration of node and link attributes as well as full expression of model and mechanism using attributes of node and link. This paper presents a social network community partitioning algorithm fusing node and link attributes. The algorithm has blended similarity of node properties, link weights between nodes and link attribute information, making definition of the similar weights, and on this basis, social networking community division is realized combined with condensation algorithms. Experiments show that the algorithm has remarkable effects on community partition with obvious attributes in social network.

Keywords*: Social Network, Social Network Partition, Centrality, Controllable Routing*

1. Introduction

With the rapid socio-economic development, people have conducted increasingly frequent exchanges and a variety of social activities related to work and life, and information exchange is also developing rapidly. In the process of information exchange, each person's social attributes, including social relations, social behavior, etc., can be shown explicitly or implicitly, gradually forming social networking such as instant messaging chat networks, telecommunication networks and microblog networks. The study has found that social networking prevails in "community structure" [1]. How to divide the community structure is of great significance to the study on social networks.

Traditional community partitioning algorithm includes: one is algorithm based on graph theory. The basic idea is that a network is given and is resolved into some sub-networks, and the number of nodes in each sub- node within the network is substantially equal, and the link between nodes in different subnets is very few. Famous algorithms include Kernighan-Lin algorithm [2] (referred to as KL algorithm), spectral bisection method based on Laplace image eigenvalues [3], clique percolation method and WH rapid spectral segmentation method [4]. The other is hierarchical clustering algorithm. The algorithm is a method of sociology. It mainly makes analysis of similarity between social networks or the strength of link between edges. Hierarchical clustering algorithm can be divided into two categories: agglomerative algorithm and splitting algorithm. The basis of partition is the addition or deletion of edges in networks. The one with edges is agglomerative algorithm, while the one without edges is splitting algorithm. Typical representative of agglomerative algorithm is Newman fast algorithm [5] and CNM algorithm [6], while that of splitting algorithm is GN algorithm [7].

Numerous community partition algorithms appeared later are also optimized and improved based on traditional algorithm. Because there are a large number of property information in relationship between nodes and links of the social network, while these property information are significant to the full presentation of network community structure. Hence, in recent years, a new direction has emerged in recent years: community partition of fusion property and link relations. For social networking, link relations between individuals with similar properties are more likely to occur and thus are likely to form community or group. In social network, members of the same organization often cannot only friends but also have common interests and hobbies, or other common individual properties.

Figure 1 is a comparison of results in small social network segmentation. (a) is the original link graph; (b) is the result based on property division; (c) is the result based on the partition of the link information; (d) the expected partition result. As can be seen from the (b) and (c), the divided result by mere consideration of property or link relationships is not what we want. Therefore, if both link and attribute information are taken into account, social networking community structure can be presented more truly [8].

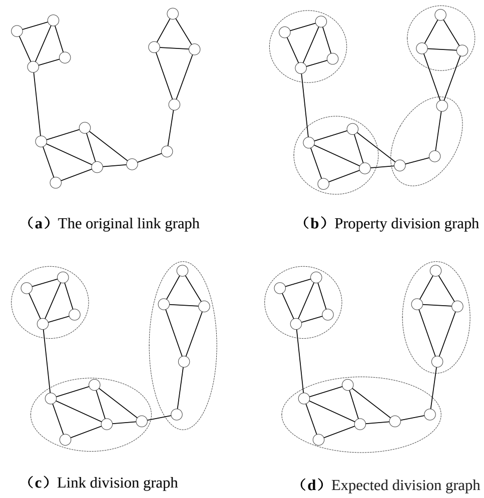

Figure 1. Instance Graph of Community Partition

Canada's Simon Fraser University, Martin Ester. [9] have proposed issue of CkC (Connected k-Center), seeing individual property as corresponding coordinate vector of the individual, and informative graph is established based on this. On the basis of CkC issue, Flavia Moser. has improved the limit of CkC algorithm that needs to give the number of clusters k in advance, and has presented CXC algorithm without pre-specified number of clusters [10]. CkC and CXC fail to address the issues of edge property use and similarity use between individuals without link relationships. Having integrated property information into the suggested tightness, Lin Youfang [11] has presented a model of edge stability coefficient and a complete informative graph model that can express tightness relationship between individuals. On this basis, an effective community partitioning algorithm has been designed and implemented, but edge stability factor proposed in this algorithm depends only on the local limited network environment without considering the differences of properties in the influence on nodes partition, which easily leads to low fidelity of the divided communities. The Anh Dang. [12] has defined the properties modularity, combining this modularity with the modularity [6] proposed by Newman in community partition. In addition, a KNN graph partitioning method has been proposed, but this method is limited by the value of K.

In social networks, nodes and links have rich attribute information such as individual properties, structural attributes, social attributes, network behavior attributes and so on. These properties play a very important role in location of communities that nodes lie in. This paper considers the impact of node and link attributes on community discovery, as well as the impact of similarity in boundless node attributes on community discovery. In design of algorithm, it is based on agglomerative algorithm, and function fitting of node attributes and links relations is conducted, and a community partitioning algorithm based on this fitting function fusing property and link relationships is designed. After the experimental simulation, the algorithm has significant effect on community division in social network with properties.

1. Model and Related Definitions

1.1. Social Networking Model and Definitions

Social networks are generally indicated by informative graph, and simple social network is shown in Figure 2:

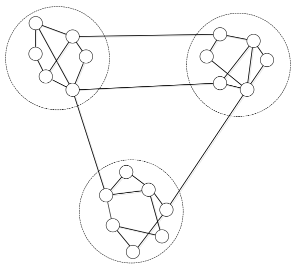

Figure 2. Simple Social Network Model

Definition 1. Informative graph. Assuming $G=\{V,E\}$ in the diagram, in which V is the individual (or node) in network. There is a total of n nodes in $V=\{v_1,v_2,...,v_n\}$. E is the set of node link (or edge) in the network, $E=\{e_1,e_2,...,e_m\}$, a total of m edges. There are p attributes in individual, and attribute set of node V is $V_{att}=\{a_1,a_2,...,a_p\}$. There is h attributes in link in total, and the attribute set of link E is $E_{att}=\{b_1,b_2,...,b_h\}$. From the above information, properties matrix of node and link in the graph can be built. Link matrix of informative graph can be expressed by the following matrix:

$$\begin{pmatrix} A_{11} & \cdots & \cdots & \cdots & A_{1n} \\ \vdots & \ddots & A_{ij} & \cdots & \cdots \\ \vdots & A_{ji} & \ddots & \cdots & \cdots \\ \vdots & \cdots & \cdots & \ddots & \cdots \\ A_{m1} & \cdots & \cdots & \cdots & A_{mn} \end{pmatrix}$$

Among them, A_{ij} is the link weight from node i to node j, and A_{ji} is the link weight from node j to node i. For powerless undirected graph, element value in the matrix is 0 or 1, and $A_{ij}=A_{ji}$.

1.2. Information Gain

Information gain is defined as the difference between the original information needs and new needs [13]. The original information needs refers to the desired information of original sample classification. The new requirements mean information needs of sample classification based on the partition of known property A.

Supposed that there are m sample categories in D, and the ratio of the ith category ($i=(1,2,...,m)$) to total number of samples is p_i, then:

$$Info(D)=-\sum_{i=1}^{m} p_i \log_2(p_i) \qquad (1)$$

Supposed that the samples in D are divided according to characteristics of A, D can be divided into v subsets with A, in which the sample in D_j has value a_j in terms of the A. According to this division of A division, the desired information required in sample partition of D is:

$$Info_A(D) = \sum_{j=1}^{v} \left(\frac{|D_j|}{|D|} \cdot Info(D_j)\right) \quad (2)$$

The information gain of attribute A is:

$$Gain(A) = Info(D) - Info_A(D) \quad (3)$$

Among it, $Gain(A)$ is information gain of attribute A; $Info(D)$ is original information need, and $Info_A(D)$ is new information need.

1.3. Modularity

Assumed that $G = \{V, E\}$ in the graph, there is a total of n nodes and m edges, and in powerless undirected graph, modularity Q on the node is defined [6] as:

$$Q = \frac{1}{2m} \sum_{i,j}^{n} \left(A_{ij} - \frac{k_i k_j}{2m}\right) \delta(C_i, C_j) \quad (4)$$

Among it, $k_i = \sum_{j=1}^{n} A_{ij}$ is the number of links (that is, the degree of V_i) owned by V_i . C_i is the community that node i belongs to. When the node i and node j is in the same community, $\delta(C_i, C_j) = 1$, otherwise it is zero. The role of module is mainly to evaluate the stand or fall of community partition and the strength of the network community structure. Q value is in the range of (0, 1). The greater value means better result of the division and more obvious community structure. For networks with modularity usually from 0.3 to 0.7, their communities' structures are more evident.

1.4. Normalized Mutual Information

NMI [14] is used to measure the difference between the divided community and real community. Assumed that the real community is divided into C_o , and the community obtained through algorithm is divided into C_e. NMI is defined as:

$$NMI(C_o, C_e) = \frac{H(C_o) + H(C_e) - H(C_o, C_e)}{\sqrt{H(C_o) H(C_e)}} \quad (5)$$

Among it, $H(C)$ represents the Shannon entropy of divided C . When C_e and C_o are fully consistent, $NMI(C_o, C_e) = 1$; when C_e and C_o are completely different, $NMI(C_o, C_e) = 0$. When $NMI(C_o, C_e)$ is between (0, 1), the greater value indicates that the divided result is closer to that of the real community.

2. Community Partitioning Algorithm Based on Similar Weights

2.1. General Idea of Algorithm

Based on attributes and links matrix of nodes, the similarity weights between nodes are calculated. Then combined with cohesion algorithm, community is divided. Initially, each node is a community. Firstly, two communities of largest similarity weights are merged into one community, and the modularity after combination is calculated. Then, the remaining two communities with maximum similar weight are merged into one community in turn to calculate the corresponding modularity. In the process of calculating the modularity, there is a maximum value point, and the community divided at the maximum value point is the optimal community.

2.2. Several Definitions Involved in Algorithm

2.2.1. Similar Measure on Node Attributes

In similar measure between attributes, we must firstly consider the impact of node properties on the community partition of the node, and greater weight shall be given to attribute of greater influence, while smaller weights can be given to less influential attribute. For determination of node attribute weights, this article makes use of information gain method. Similarity measure used in this paper is the Dice coefficient. Similarity measure function $(V_i, V_j)_{AS}$ between node and attribute is calculated as follows:

$$(V_i, V_j)_{AS} = 2 \cdot \sum_{p=1}^{k} (a_{ip} \cdot a_{jp}) / (\sum_{p=1}^{k} a_{ip}{}^2 + \sum_{p=1}^{k} a_{jp}{}^2) \qquad (6)$$

Among it, there are k attributes in each node, and a_{ip} and a_{jp} is the quantized attribute information of the p-th attribute in nodes V_i and V_j respectively.

Link attributes between nodes mainly include link weight, occurrence time of link, the frequency of link occurrence and others. Since the link attribute itself contains links between nodes, the link attribute cannot be characterized using the similarity measure here. Various attributes of link have diverse roles in link division, thus a measure mechanism must be firstly adopted to determine the contribution of each attribute to the link division. It is recorded that there are h attributes in total in each link, and the total neighbor nodes contribution is also taken as an attribute of link, and at this time, there are $(h+1)$ link attributes. Assumed that shared neighbor node degree of the two nodes is dg , but for similarity between these two nodes, their total neighbor nodes only play the role of $2/dg$. It is assumed that shared neighbor node set of two nodes is $(V_i, V_j)_{sum}$. It is defined that shared neighbor node contribution attribute L is: $L = \sum_{i \in (V_i, V_j)_{sum}} (2/dg_i)$. Quantized attribute information of link E_{ij} is $(b_{ij1}, b_{ij2}, ..., b_{ijh}, L)$, and the corresponding weight of each attribute is $(w_1, w_2, ..., w_h, w_{h+1})$, in which $w_1 + w_2 + ... + w_h + w_{h+1} = 1$. Computational formula of link attributes metric function $(E_{ij})_{LA}$ to be adopted in this paper is as follows:

$$(E_{ij})_{LA} = \sum_{q=1}^{h} (b_{ijq} \cdot w_q) + w_{h+1} \cdot L \qquad (7)$$

Among it, w_q can be set according to actual social network.

2.2.2. Similar Weights

Similar weights as defined herein are obtained based on the tightness [7] defined by Lin Youfang etc. The formula of similar weight function $(V_i,V_j)_{SW}$ of the node V_i and the weight V_j is as follows:

$$(V_i,V_j)_{SW} = \alpha \cdot (V_i,V_j)_{AS} + (1-\alpha)(E_{ij})_{LA} \qquad (8)$$

Similar weight calculation is based on the attribute matrix and link matrix, but for each node, attributes and links play different roles in the division. An adjustment parameter α is introduced here to adjust the role of node attributes and link attributes in similar weight calculation. In the formula (5), $(V_i,V_j)_{AS}$ is the similarity of node V_i and V_j attributes, and $(E_{ij})_{LA}$ is the link attributes measurement of nodes V_i and V_j.

2.2.3. Improved Modularity

Because the social networks studied in this paper are all powerful and directed, there should be appropriate improvements for the modularity. The formula of the improved modularity Q_{im} is as follows:

$$Q_{im} = \frac{1}{2m}\sum_{i,j}^{n}(\lambda_{ij} - \frac{k_i k_j}{2m})\delta(C_i,C_j) \qquad (9)$$

Among it, as to the parameter λ_{ij}, when there are links between nodes V_i and V_j, $\lambda_{ij}=1$; otherwise $\lambda_{ij}=0$. For powerful and directed graph, $k_i = \sum_{j=1}^{n} A_{ij}$ is the accumulation of all the links weights of the node V_i; A_{ij} is the link weights of i and j nodes and m is sum of all the links weights in the network. C_i is the community that node i belongs to, and when the node i and node j is in the same community, $\delta(C_i,C_j)=1$ and otherwise, it gets 0. The role of Q_{im} in powerful and directed network is equivalent to the Q in the powerless and undirected network.

2.3. Community Partitioning Algorithm Implementation Based on Similar Weights

Community Division Algorithm based on Similar Weights (CDASW) uses framework based on bordered agglomerative algorithm, with the aforementioned similar weights and modularity as basis design, and the core is to fuse similar weight and modularity to get bordered agglomerative algorithm in directed and powerful informative graph model. Algorithm processing block diagram is shown in Figure 3:

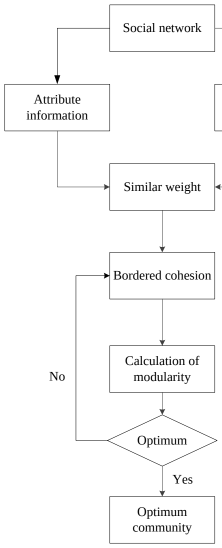

Figure 3. Algorithm Processing Block Diagram

Pseudo-code description of the algorithm is as follows:
Algorithm 1: CDASW

Initialization: $G=\{V(n),E(m)\}$, $V_{att}(k)$, $E_{att}(h+1)$ Initialization community: $C=\{C_1,C_2,...,C_n\}$. SW Matrix is initialized in accordance with Equation (6) (7) (8): (V_{SW}) .

1) Do
2) Figure out the largest element of (V_{SW}) , $(V_{SW})_{ij}=\max(V_{SW})$;
3) for $l=1:|C|$
5) end
6) Assumed that $(V_{SW})_{ij}=0$;
7) Delete the j row and j line of (V_{SW}) ;
8) $C \leftarrow C \setminus \{C_i,C_j\} \cup \{C_i \cup C_j\}$;
9) $C_{(|C|)} \leftarrow C$;
10) Update (V_{SW}) , return to 2) ;
11) Until $|C|=1$;
12) $C_{(tree)} \leftarrow \{C_{(n)},...,C_{(1)}\}$;
13) $C_m \leftarrow \arg\max_{C\in C_{(tree)}} Q(C)$;
14) Return to C_m as the result of community division.

By the design cycle of the above algorithm, it can be seen that the time complexity of the algorithm is $O(n^2)$, which is higher than $O(n\log^2 n)$ of CNM algorithm. Since the number of edges in the network are generally much larger than the number of nodes, the time complexity of this method is lower than that of GN algorithm.

3. Experiment and Analysis

3.1. Attribute-Based DBLP Data Sets Experiment

Due to the complexity, polytrope and privacy of social network itself, there exists prevailing difficulty in to verification in community partitioning algorithm. In order to verify the effect of community discovery algorithm based on similar weights, this paper has firstly conducted experiments on public data sets DBLP (Digital Bibliography & Library Project) to obtain co-authorship network data between authors.

3.1.1. Data Preprocessing

According to the analysis of the data, the data is 509 papers data, and it is parsed that the data has coauthored network, a total of 213 nodes and 1146 edges. It is obtained through analysis that node attributes are: interest, field of study, study groups; link attributes are: occurrence time of link, the times of link, the frequency of link and other features. This paper focuses on analysis of the above node attributes and link attributes.

3.1.2. Preferences

Preferences are mainly for in formula (8), which is primarily expressed as the weight ratio of node and link attributes in the community division. In social networks, since community-based timeshare node and link attributes has different emphasis, the value is also not the same. When node attribute is stressed, its value should be greater than 0.5; when the emphasis is on the link attribute, its value should be less than 0.5; when the both is of the time, its value should be near 0.5. We select six values (0.05, 0.25, 0.45, 0.55, 0.75 and 0.95 respectively) for experiment thereby to determine the approximate optional range of parameters.

As to issue of quality measurement on community partition results, the improved modularity is used to calculate the divided community modularity, and its value close to 1 indicates that the modularity of the divided result community has higher quality. Because this algorithm is designed based on agglomerative algorithm, comparison is made between the proposed algorithm and classic agglomerative algorithm--CNM algorithm. Specific results of experiment are shown in Table 1:

Table 1. Comparison in Experimental Results between CDASW and CNM

Algorithm	Parameter α	Q_{im}	Time consuming / ms
CDASW	0.05	0.6235	783
	0.25	0.6507	775
	0.45	0.6553	780
	0.55	0.6567	782
	0.75	0.6721	772
	0.95	0.6684	785
CNM	/	0.4087	347

3.1.3. Comparative Analysis of Experimental Results

From the experimental results, the proposed algorithm is obviously better than CNM algorithm without considering node and link attributes. Among the selected parameter, when = 0.05, it can be approximately thought that it is divided by the link attribute information at this time, while when = 0.95, it can be approximately thought that it is divided by the node attribute information. By the analysis of the data, it is obtained that the link attribute of this data set is more important than the node attribute in community division, and the corresponding link attribute weights should be greater than 0.5. From the experimental results, when = 0.75, dividing quality of CDASW algorithm is at best. We can draw that the real value of should be in the vicinity of 0.75. Experimental results show the importance of the link attribute for the data set in the partition.

From the experimental results, it can be seen that node attributes and link attributes in the social network also play a very important role in community discovery, and there exists significant deficiencies in community discovery relying on single link information. In the time complexity of algorithm, since CDASW is designed based on agglomerative algorithm, computational complexity is relatively low, and in the selected parameter, the time consumption is about 780ms.

3.2. Attribute-Based Telephone Network User Data Experiment

To validate the effect of real data on the proposed algorithm, the paper conducts experiment relying on work phone network data in a unit collected by the research group locally. Data content is Call Detail Record (CDR).for the telephone network in May 2012.

3.2.1. Data Preprocessing

According to the findings of the research group in advance, the test network users can be divided into 13 communities, and the paper has also been familiar with almost all of the user's age, interests, owned small work units and other individual properties. From CDR data in May, it can be analyzed that there are 263 nodes (telephone subscriber) and 1349 edges (call relationship, repeated call between two users is also considered as one call relationship) , and features have been obtained for each call, including the average call length, the average number of calls per day, talk time and so on. This paper focuses on analysis of the above users' attributes (node attributes) and call attributes (link attributes). Role of node attributes and link attributes is of the same when the data set is divided.

3.2.2. Preferences

Six values are also selected for parameter (0.05, 0.25, 0.45, 0.55, 0.75 and 0.95 respectively) to conduct experiment. Divided communities under each parameter value are as listed in Table 2:

Table 2. Comparison of the Number of Divided Communities in Different Parameters of

Parameter α	0.05	0.25	0.45	0.55	0.75	0.95
The number of divided communities	14	14	12	11	11	10

As can be seen from the table, when the parameter values are at 0.25 and 0.45, the number of divided communities is the closest to the real number of the divided community. Experimental results under selected parameter are shown in Figure 4:

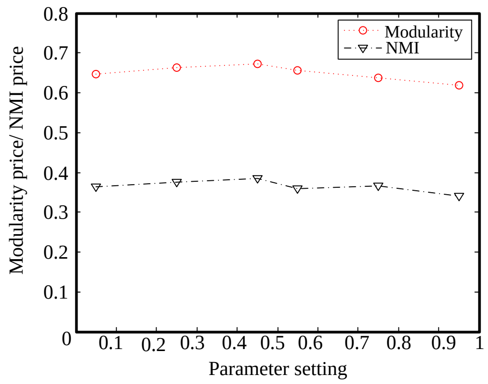

Figure 4. Comparison of the Experimental Results under Preferences of α

As for quality measure of the community partition results, the improved modularity and NMI values are employed to make measurement. We make comparison between CDASW algorithm and CNM algorithm when the parameter = 0.45. Specific results are shown in Figure 5:

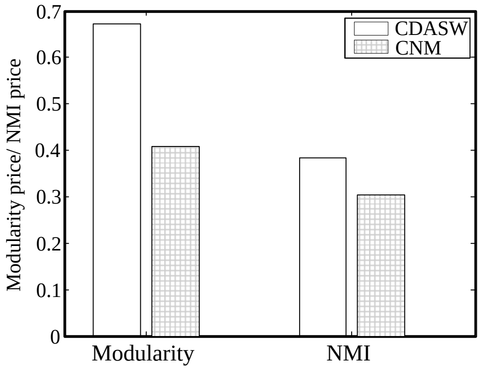

Figure 5. Comparison in Result between CDASW Algorithm and CNM Algorithm

3.2.3. Comparative Analysis of Experimental Results

Since node attributes and link attributes of the data set are of the same importance, the corresponding is valued at about 0.5. As can be seen from Fig. 4 when = 0.45, dividing quality of CDASW algorithm is better and is also closest to the real network community structures. The results have also proved the importance of node attributes and link attributes in the data set. As it can be seen from Figure 5, due to the added consideration of the node attributes and link attributes, the proposed method has obviously better division efficiency in community division of real social networks than CNM algorithm without considering node and link attributes.

4. Summary and Outlook

As for the community discovery of social networking, this paper has proposed community partitioning algorithm based on similar weights integrated with attributes, making appropriate improvements of modularity combined with powerful and directed network, and has applied this algorithm in community division issues of real social networking. With similar weight as the basis for dividing the community, the divided communities have higher modularity. The algorithm has commendable applicability and effectiveness, with more obvious effects particularly for network that node attribute information has greater impact on community partition. There has been no in-depth study on what to think when there are excessive node attributes and on the coefficient setting of link attributes in the algorithm currently, and in addition, the considerations of weight setting for link attributes are too simple. Issues on how to divide into more real and effective results and to improve the NMI value all need in-depth study in the next step.

Acknowledgements

This work was supported by the project of the Ministry of Housing and Urban-Rural Development (2012-K1-1), The scientific research project of department of education of Shaanxi province (12JK0999).

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