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ABSTRACT

Social network analysis is a new research field in data mining. The clustering in social network analysis is different from traditional clustering. It requires grouping objects into classes based on their links as well as their attributes. While traditional clustering algorithms group objects only based on objects' similarity, and it can't be applied to social network analysis. So on the basis of BSP (business system planning) clustering algorithm, a social network clustering analysis algorithm is proposed. The proposed algorithm, different from traditional clustering algorithms, can group objects in a social network into different classes based on their links and identify relation among classes.

INTRODUCTION

Social network analysis, which can be applied to analysis of the structure and the property of personal relationship, web page links, and the spread of messages, is a research field in sociology. Recently social network analysis has attracted increasing attention in the data mining research community. From the viewpoint of data mining, a social network is a heterogeneous and multi-relational dataset represented by graph (Han & Kamber, 2006).

Research on social network analysis in the data mining community includes following areas: clustering analysis (Bhattacharya & Getoor, 2005; Kubica, Moore and Schneider, 2003), classification (Lu & Getoor, 2003), link prediction (Liben-Nowell & Kleinberg, 2003; Krebs, 2002). Other achievements include PageRank (Page, Brin, Motwani and Winograd, 1998) and Hub-Authority (Kleinberg, 1999) in web search engine.

In this paper, clustering analysis of social network is studied. In the second section, a social network clustering algorithm is proposed based on BSP clustering algorithm. The algorithm can group objects in a social network into different classes based on their links, and it can also identify the relations among classes. In the third section, an example of social network clustering algorithm is presented, and then the conclusion and the future work direction are given.

SOCIAL NETWORK ANALYSIS BASED ON BSP CLUSTERING

There has been extensive research work on clustering in data mining. Traditional clustering algorithms (Han & Kamber, 2006) divide objects into classes based on their similarity. Objects in a class are similar to each other and are very dissimilar from objects in different classes.

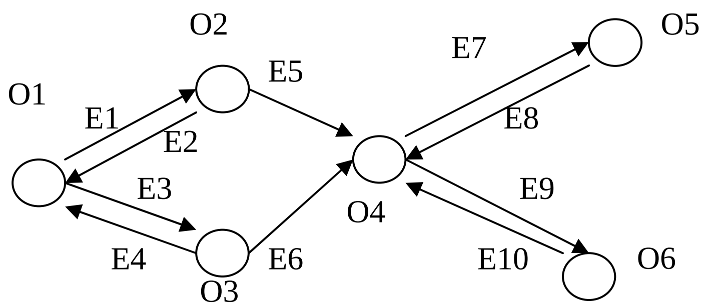
Social network clustering analysis, which is different from traditional clustering problem, divides objects into classes based on their links as well as their attributes. The biggest challenge of social network clustering analysis is how to divide objects into classes based on objects' links, thus we need find algorithms that can meet this challenge.

The BSP (business system planning) clustering algorithm (Gao, Wu and Yu, 2002) is proposed by IBM. It designed to define information architecture for the firm in business system planning. This algorithm analyses business process and their data classes, cluster business process into sub-systems, and define the relationship of these sub-systems.

Basically BSP clustering algorithm uses objects (business processes) and links among objects (data classes) to make clustering analysis. Similarly social network also includes objects and links among these objects. In view of the same pre-condition, the BSP clustering algorithm can be used in social network clustering analysis.

According to graph theory, social network is a directed graph composed by objects and their relationship. Figure 1 shows a sample of social network, the circle in the figure represents an object; the line with arrow is an edge of the graph, and it represents directed link between two objects, so a social network is a directed graph.

Figure 1: A sample of social network.



In figure 1, Let O_i be an object in social network ($i = 1...m$), let E_j which means directed link between two objects, be a directed edge of the graph ($j = 1...n$).

After definition of objects and directed edges, we can also define reachable relation between two objects. There are two kinds of reachable relation among objects, shown as following:

1) One-step reachable relation: if there has directed link from O_i to O_j through one and only one directed edge, then O_i to O_j is a one-step reachable relation. For instance in figure 1 there has a directed link from O_1 to O_2 through the directed edge E_1, O_1 to O_2 is one-step reachable relation.

2) Multi-steps reachable relation: if there has directed link from O_i to O_j through two or more directed edges, then O_i to O_j is a multi-steps reachable relation. For instance in figure 1 has a directed link from O_1 to O_4 through directed edges E_1 and E_5, then O_1 to O_4 is a 2-steps reachable relation.

After these definitions, we can use BSP clustering algorithm to analyses a social network. The analysis processes are as following steps:

Generate edge creation matrix and edge pointed matrix

First according to the objects and edges in the graph, define two matrix L_c and L_p.

Let L_c be a $m \times n$ matrix which means the creation of edges. In the matrix, $L_c(i, j)$ =1 denotes object O_i connects with the tail of edge E_j, which means that object O_i creates the directed edge E_j. $L_c(i, j)$ =0 denotes O_i doesn't connect with the tail of edge E_j, which means E_j isn't created by object O_i.

For example in figure 1 object O_1 connects with the tail of E_1, then it means O_1 creates E_1, so $L_c(1,1) = 1$; O_1 doesn't connect with the tail of edge E_2, then it means E_2 is not created by O_1, so $L_c(1,2) = 0$.

Let L_p be a $m \times n$ matrix which means the pointed relations of edges. In the matrix, $L_p(i, j)$ =1 denotes object O_i connects with the head of edge E_j, which means object O_i is pointed to by the directed edge E_j. $L_p(i, j)$ =0 denotes O_i doesn't connect with the head of edge E_j, which means E_j doesn't point to O_i.

For example in figure 1 object O_2 connects with the head of E_1, which means O_2 is pointed to by E_1, so $L_p(2,1)=1$. But O_2 doesn't connect with the head of edge E_2, then it means E_2 doesn't point to O_2, so $L_p(2,2)=0$.

Calculate one-step reachable matrix between objects

After the definition of L_c and L_p, we can calculate one-step reachable matrix between objects through the following equation.

$$G = L_c \bullet L_p^T = \left(g_{i,j} = \bigvee_{k=1}^{n} (l_c(i,k) \wedge l_p^T(k, j)), i = 1,..., m, j = 1,..., m \right) \qquad (1)$$

$\wedge$ is Boolean product, $\vee$ is Boolean sum.

$G(i, j) = 1$ means O_i to O_j is a one-step reachable relation, $G(i, j) = 0$ means there hasn't a one-step reachable relation from O_i to O_j. Through G, we can calculate all one-step reachable relation between objects.

Calculate multi-steps reachable matrix between objects

Besides one-step reachable relation, there are multi-steps reachable relations between objects too. We also need calculate multi-steps reachable matrices (2-steps, 3-steps, …, *m*-1-steps).

According to graph theory and the BSP clustering algorithm, we can calculate multi-steps reachable matrix $G^2, G^3, G^4,..., G^{m-1}$. Following equations show the calculation of multi-steps reachable matrix:

$$G^2 = G \bullet G = \left(g^2{}_{i,j} = \bigvee_{k=1}^{m} (g(i,k) \wedge g(k, j)), i = 1,..., m, j = 1,..., m \right) \qquad (2)$$

$$G^3 = G^2 \bullet G$$

$$G^4 = G^3 \bullet G$$

……

$$G^{m-1} = G^{m-2} \bullet G$$

These matrices include 2-steps, 3-steps… *m*-1-steps reachable relations between objects. Now we can know *n*-steps reachable relation between two objects through $G^2, G^3, G^4,..., G^{m-1}$.

Calculate reachable matrix

Because we only consider whether reachable relations exist between two objects, but do not care these relations are one-step or multi-steps, so we need calculate reachable matrix R based on $G, G^2, G^3, G^4,..., G^{m-1}$. The calculation of R is shown as following equation:

$$R = I \vee G \vee G^2 ... \vee G^{m-1} \qquad (3)$$

$\vee$ is Boolean sum, I is unit matrix.

$R(i, j) = 1$ means reachable relation exists from O_i to O_j, but the reachable relations existing in matrix R is not mutual, for instance $R(i, j) = 1$ means reachable relation exists from O_i to O_j,but it doesn't means reachable relation exists from O_j to O_i. Mutual reachable relations between two objects are important in a social network, so we need calculate mutual reachable matrix based on R.

Calculate mutual reachable matrix and generate clusters

The mutual reachable matrix can be calculated through following calculate equation.

$$Q = R \wedge R^T \quad (4)$$

$\wedge$ means Boolean product

In the matrix $Q(i, j) = 1$ means there are mutual reachable relation between O_i and O_j. In a social network if two objects that have mutual reachable relation, they should belong to the same class, thus we can cluster based on Q.

Thus according to mutual reachable matrix Q, we can divide a social network into classes based on strong sub-matrices in Q or adjusted Q. While strong sub-matrix is defined as follows.

Strong sub-matrix: if all elements in a sub-matrix of Q are 1, this sub matrix is strong sub-matrix.

Identify relationships among classes

After clustering of social network, we also need identify relationship among clusters. This can be done through generated clusters and one-step reachable matrix G. If there is one-step reachable relation between two objects in different classes, we can say directed links exist between classes. Through G we can identify all relations among classes.

After pervious 6 steps, we can divide a social network into classes. Social network clustering analysis algorithm can be given:

Input:

L_c : Edge creation Matrix

L_p : Edge pointed matrix

Begin

$G = L_c \bullet L_u^T$

for k=3 to m do

$G^{k-1} = G^{k-2} \bullet G$

$R = I \vee G \vee G^2 ... \vee G^{m-1}$

$Q = R \wedge R^T$

$Q -> C_k$

(C_k, Q)->Relation (C_k)

End

$Q->C_k$ means generating clusters through mutual reachable matrix Q , and (C_k , Q)->Relation(C_k) means identifying relationships among clusters base on clusters and one-step reachable matrix G .

EXAMPLE

Now an example is given to show process of the cluster analysis of social network. Suppose a social network as figure 1 shows. According to the figure, we can give the edge creation matrix L_c and edge pointed matrix L_p as following.

$$L_c = \begin{pmatrix} 1&0&1&0&0&0&0&0&0&0\\ 0&1&0&0&1&0&0&0&0&0\\ 0&0&0&1&0&1&0&0&0&0\\ 0&0&0&0&0&0&1&0&1&0\\ 0&0&0&0&0&0&0&1&0&0\\ 0&0&0&0&0&0&0&0&0&1 \end{pmatrix} \quad L_p = \begin{pmatrix} 0&1&0&1&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0&0\\ 0&0&0&0&1&1&0&1&0&1\\ 0&0&0&0&0&0&1&0&0&0\\ 0&0&0&0&0&0&0&0&1&0 \end{pmatrix}$$

According to the social network clustering algorithm, L_c and L_p , clustering the social network show as following steps:

Calculate one-step reachable matrix between objects

$$G = \begin{pmatrix} 1&0&1&0&0&0&0&0&0&0\\ 0&1&0&0&1&0&0&0&0&0\\ 0&0&0&1&0&1&0&0&0&0\\ 0&0&0&0&0&0&1&0&1&0\\ 0&0&0&0&0&0&0&1&0&0\\ 0&0&0&0&0&0&0&0&0&1 \end{pmatrix} \bullet \begin{pmatrix} 0&1&0&1&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0&0\\ 0&0&0&0&1&1&0&1&0&1\\ 0&0&0&0&0&0&1&0&0&0\\ 0&0&0&0&0&0&0&0&1&0 \end{pmatrix}^T = \begin{pmatrix} 0&1&1&0&0&0\\ 1&0&0&1&0&0\\ 1&0&0&1&0&0\\ 0&0&0&0&1&1\\ 0&0&0&1&0&0\\ 0&0&0&1&0&0 \end{pmatrix}$$

Calculate multi-steps reachable matrix between objects

$$G^2 = G \bullet G = \begin{pmatrix} 1&0&0&1&0&0\\ 0&1&1&0&1&1\\ 0&1&1&0&1&1\\ 0&0&0&1&0&0\\ 0&0&0&0&1&1\\ 0&0&0&0&1&1 \end{pmatrix} \quad G^3 = G^2 \bullet G = \begin{pmatrix} 0&1&1&0&1&1\\ 1&0&0&1&0&0\\ 1&0&0&1&0&0\\ 0&0&0&0&1&1\\ 0&0&0&1&0&0\\ 0&0&0&1&0&0 \end{pmatrix}$$

$$G^4 = G^3 \bullet G = \begin{pmatrix} 1&0&0&1&0&0\\ 0&1&1&0&1&1\\ 0&1&1&0&1&1\\ 0&0&0&1&0&0\\ 0&0&0&0&1&1\\ 0&0&0&0&1&1 \end{pmatrix} \quad G^5 = G^4 \bullet G = \begin{pmatrix} 0&1&1&0&1&1\\ 1&0&0&1&0&0\\ 1&0&0&1&0&0\\ 0&0&0&0&1&1\\ 0&0&0&1&0&0\\ 0&0&0&1&0&0 \end{pmatrix}$$

Calculate reachable matrix based on one-step and multi-steps reachable matrix

$$R = I \vee G \vee G^2 \ldots \vee G^5 = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix}$$

Calculate mutual reachable matrix , generate clusters

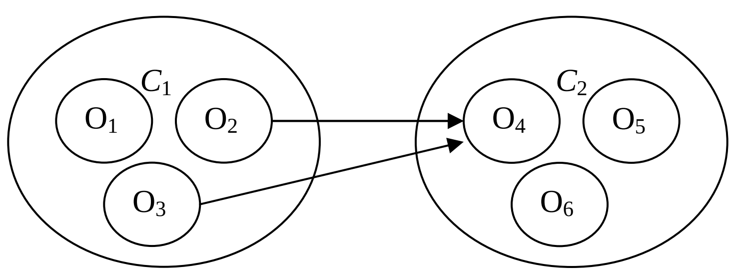
$$Q = R \wedge R^T = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix} \wedge \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix}$$

According the mutual reachable matrix Q, it includes two strong sub matrices. So we can divide figure 1 to two classes, the first class C_1 includes object O_1, O_2, O_3, and the second class C_2 includes O_4, O_5, O_6.

Identify relationships among classes

According to one-step reachable matrix G , there have one-step reachable relations between to classes ($O_2 -> O_4$ and $O_3 -> O_4$), so we can identify relations between two clusters C_1 and C_2 , as figure 2 shows.

Figure 2: Identify relationships between two clusters.



C_1 points to C_2 In figure 2, but C_2 not points to C_1, so we can identify relations between two classes.

CONCLUSION

In this paper based on BSP clustering algorithm, an algorithm of social network clustering analysis is proposed. It divides a social network into different classes according to objects in the social network and links between objects, and it also can identify relations among clusters.

Main disadvantage of this algorithm is that it uses matrices to store edges and reachable relations, in a real social network these matrices will be very huge, can't load into main memory. But because these matrices are very sparse, so we can design an efficient data structure to overcome this shortcoming.

Also in our algorithm the edges between objects have same weight, however in real world such edges may have different weights. Meanwhile the property of each cluster has not been analyzed. these will be solved in our future research.

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