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PDOC in Location – Based Social Networks

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Abstract: ***Now a days the usage of social network such as facebook , flicker increases day by day. Most of the social networking sites support Location Based Services (LBS). Location based social network used to identify the friend's location and the current location details of the user. The Increasing availability of the smartphone makes the location based services more flexible. Most of the location based social networks do not have an explicit community structure. All the social network users belongs to at least any one of the community depending upon their behavior and interest. Sometime the community structure may overlap. In this paper, by tracing the user locations use a multimode multi-attribute edge centric co-clustering framework to detect the overlapping community .The proposed framework uses both inter-mode and intra-mode features. By evaluating the collected dataset we can analyze the efficiency of our approach.***

Keywords: Location Based Service (LBS),community structure, overlap, Social network, clustering

1. Introduction

In social network detecting communities is still an open problem. Social networks have different groups for users to join or to subscribe. In location based social networks users can write their reviews, upload new photos and explore places. A community is typically thought of as a group of users with more and/or better interactions amongst its members than between its members and the remainder of the network [1], [2].In the case of large number of users community profiling and community detection approaches are needed. Each social network user have multiple community memberships. It is better to cluster different users into overlapping communities.

All the existing community detection approaches are based on structural features [3] ,but the structural information of online social networks is often sparse and weak ; thus, it is difficult to detect interpretable overlapping communities by considering only network structural information [4].

In this paper, the main contributions are

1) Each edge is viewed as a link between two modes first mode is user mode vertex and the second mode is venue mode vertex. Inter-mode and intra-mode features are needed.
2) Consider both community profiling and detection in one unified framework and obtain communities containing venue and user simultaneously.

From the aspect of service provider, it is important to identify communities with same interests and identify what each community is interested in. It is very essential to characterize communities in a semantic way to accurately support the real-world applications. Community profiling is affected by limitation of available node information. The venue metadata and rich user available in LBS, especially the hierarchical structure of venue categories

2. Related Work

Existing community detection approaches are classified into three categories. The first category uses user behavior for detecting communities. By using clustering methods user behaviors are clustered. The second category defines the work on community detection that is a essential task in complex network analysis. In order to detect communities from a network uses an objective function based on intuition that a cluster is a set of nodes with better internal connectivity than external connectivity. Heuristic algorithms are used to extract node clusters by optimizing the objective function. Third category focuses on community detection by considering node attributes.

Community detection approaches are classified into two approaches. Overlapping approaches and non overlapping approaches. Community detection is very complex task in the case of weak and sparse relations .In the third category main idea is to find the similarity measure for vertex pairs that combine both structural and attribute information about the nodes. k-medoids and spectral clustering algorithms are applied.

3. Proposed Framework

In this paper propose a profiling work and discovering of overlapped communities in location based social networks. Proposed system detect the overlapping communities by viewing both inter-mode links and intra-mode attribute. Detected communities have same semantic meanings that can be interpreted as community profiles.

3.1 Multimode multi-attribute edge co-clustering framework

In the first step the data set is selected from different location based social networks. Here the preferable data set used is twitter accounts. Features are selected depending upon the characteristics of the collected dataset. Next step feature selection is carried out. In the feature fusion stage the selected features are converted into normalized values. Overlapping community structure is detected using the edge clustering algorithm.

Community in location based social networks can be defined as a group of users who are similar with users within the group than users outside the group. Communities which aggregate same users and venues together is detected by maximizing intra-cluster similarity. In the case of user venue check-in networks each edge is connected with a venue vertex and user vertex. In an edge-centric view ,every edge can be viewed as n instances with its two vertices as features.

3.2 Overall architecture

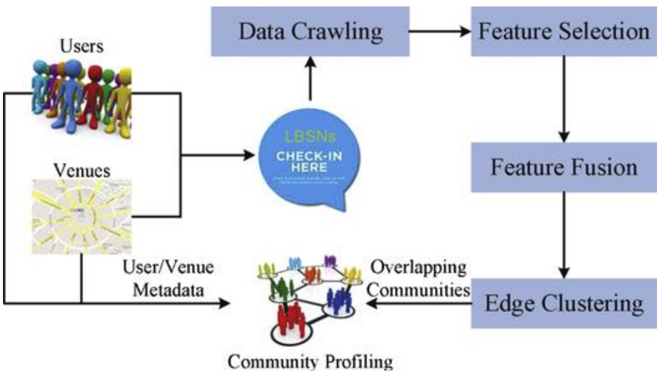

Figure 1: Discovering and profiling of community

By considering the overall architecture it contain mainly 4 phases. First phase is data crawling. From different twitter users dataset is selected. The selected data is used for feature selection. Different features are selected from the data set. B oth inter-mode and intra-mode are considered. In the feature fusion absolute values are normalized. Finally the clustering algorithms are applied into the dataset for profiling different clusters.

3.3 Modules of the framework

Mainly four modules are presented in this paper.
1) data crawling
2) feature description
3) feature fusion
4) clustering algorithm

First phase is data crawling. from the different social network users dataset is collected from the user's account and the friends of users and friends of friends. The next step is feature description. In this both inter-mode and intra-mode are considered. According to [5], we adopt two inter-mode features (i.e., user-venue similarity and venue-user similarity) in this paper, where each user is represented as a vector of venue categories and each venue category is denoted as a vector of users. The intra-mode feature depicts attributes similarity where each attribute corresponds to a certain social aspect of users or venues. We select three intra-mode features based on the characteristics of the Foursquare data, which is partially inspired by [10].

1) Inter-mode feature user-venue similarity: According to [5], cosine similarity is effective in characterizing inter-mode feature similarities.
2) Inter-mode feature venue-user similarity: venue user similarity explained using cosine similarity.
3) Intra-mode feature: user social influence similarity. Intra-mode feature is also known as social influence similarity or social influence metric. follow list and following list is present in each LBSN profile .social influence is the ratio of number of followers to number of followings.
4) Intra-mode feature: user geo-span similarity. It is also called radius of gyration.it is used to distinguish the life cycle of users which can be explained as a standard deviation of distance between user's check-in and home location.

In the feature fusion absolute values of features are normalized. Social influence similarity and geo span similarity is not change after normalization, because the original values are fall into interval 0,1 .Last module is clustering algorithm. Hierarchical multimode multi-attribute algorithm is used. First step edges are clustered into large no of groups. Then the next step groups are aggregated into larger clusters. Here use average linkage for accuracy.

3.4 Screenshots

These are the model output screenshots of my work.

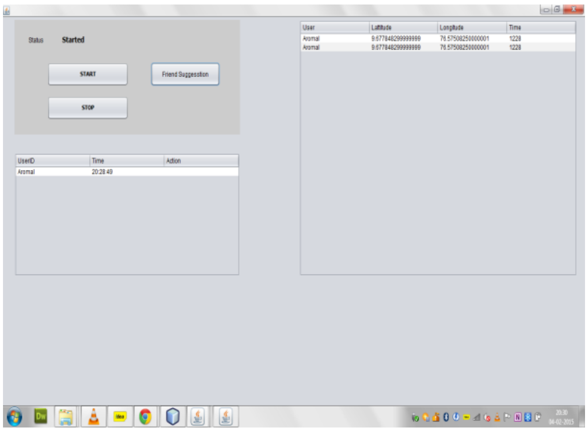

Figure 2: It is the home page,shows the connection with server.

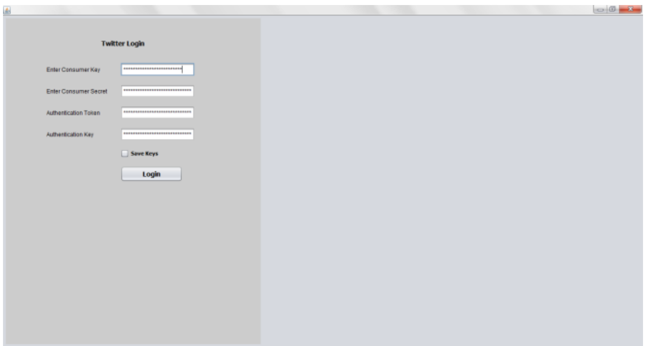

Figure 3: log in page, log in into the twitter account using the 4 tokens.

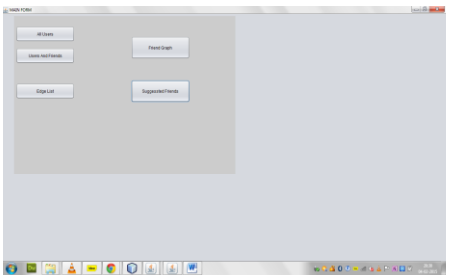

Figure 4: main form, conatin the buttons all users ,users and friends, edge list, friend graph, suggested friends.

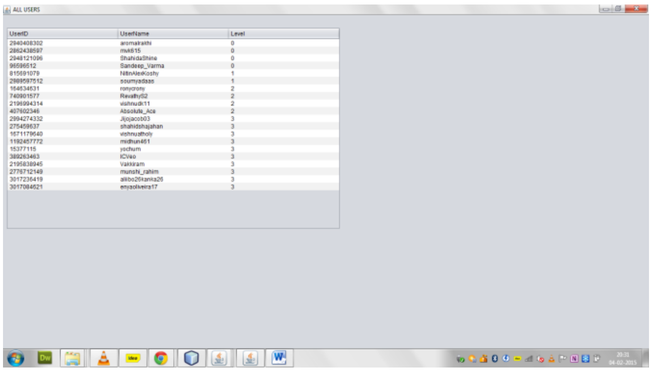

Figure 5: display of all the users.

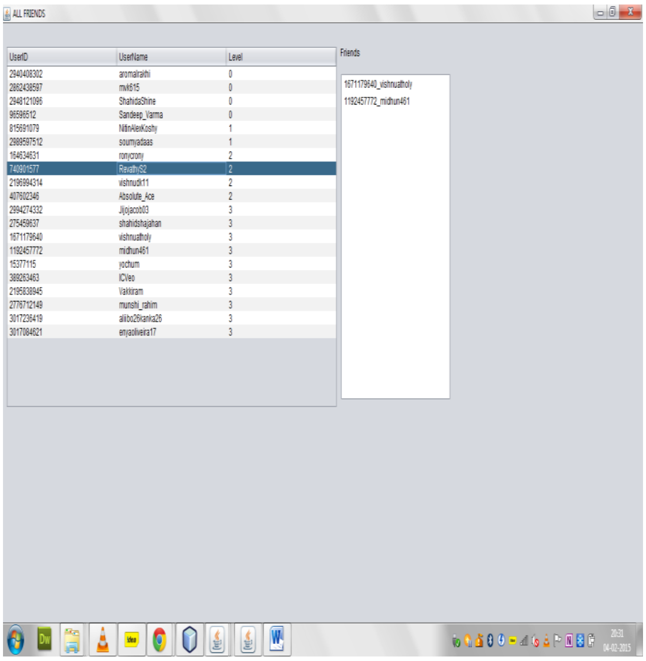

Figure 6: Route of friendship

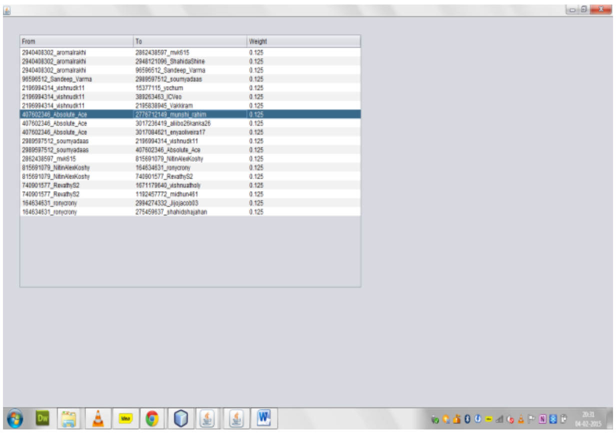

Figure 7: Calculation of weight

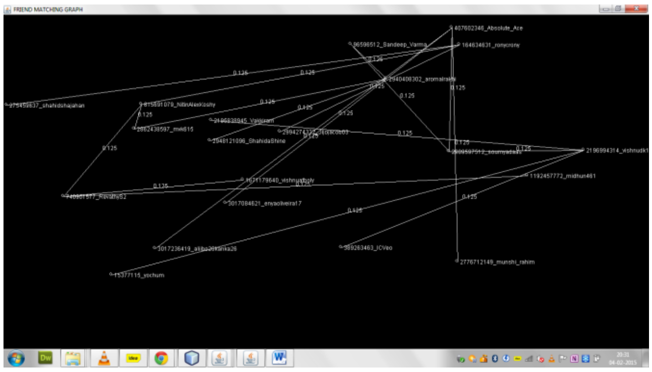

Figure 8: Friend Graph

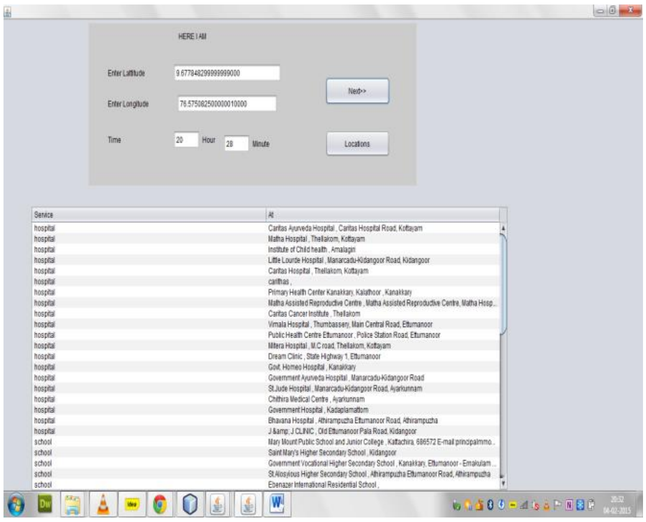

Figure 9: Location details

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Aromal Rakhi received the B.TECH degree in Computer science Engineering from Sreebuddha College of Engineering in 2013 and now doing M.TECH under M.G university.