



Recommendations Based on Overlapping Communities for Location Based Social Networks (LBSNs)

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ABSTRACT: Today, Location Based Social Networks(LBSNs) have become a rapidly growing area which attracts millions of people towards itself. LBSN sites are Foursquare, Bright kite, Gowalla, City Sense etc. Due to diversity of user's interests and behaviours, community structures in LBSNs overlap. Based on the user check-in traces at venues and user/venue attributes, a coclustering framework is used to discover the overlapping communities of LBSNs users. Using both intermode and intramode features, the framework is not only able to group the users having similar interests from various social perspectives but also discover communities with explicit profiles indicating the interests of community members. Considering these interests, we proposed recommendations based on the overlapping communities structure. The users belonging to the same community can have a same area of interest and such users can form or naturally belong to an overlapping community structure. By following the recommendations which system provides, user can be aware about the location of his/her interest and also can join new friends from overlapping community. Hence, the proposed system tries to recommend the locations and friends based on the user check-in history and similarities respectively, that can be useful to the users in an overlapping community.

KEYWORDS: Location Based Social Networks(LBSNs), Communities, Overlapping Communities, Edge Clustering, Friend Recommendations, Location Recommendations,

I. INTRODUCTION

With the extensive use of mobile devices and location-based services in the world, there is new way for online social interaction, namely location-based social networks (LBSNs). Location-based social networking sites uses GPS, Web 2.0 technology and mobile devices to allow people to share their locations (usually referred to as "check-in"), find out local Points of Interest and discounts, leave comments on specific places, connect with their friends, and find other friends who are nearby. It also aims to provide location-based services such as location-based marketing and disaster relief.

People in LBSNs are structured in the form of community. Community is a group of nodes which has dense and sparse relations with other parts of a network. Identifying these communities helps to better understand the structure of social network. There are two types of communities, namely Disjoint and Overlapping Communities. In disjoint communities, each community has its own users, no other community users are overlapped with each other. Whereas, the user usually belongs to several social groups such as family, friends, colleges and therefore forms an overlapping community structure in a network. Disjoint communities are unable to represent the as it is structure of social network. But overlapping communities provides a clear understanding about the structural as well as semantic aspects of social networks. So, over the recent years, detection of overlapping communities is a key attention. With the business prospective the detection and analysis of overlapping communities is important.



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Based on these overlapping communities it is possible to generate a recommendations for users. Recommendations are designed to recommend friends and venues to users in various situations such as online shopping, dating, and social events. Recommendations helps users in overlapping nature for decision making by filtering the uninterested things. By recommendations, user can save time in selecting the item which he/she wants. In this paper, to assist the users to get advantage of being in overlapping community nature, recommendations based on overlapping communities is proposed.

II. RELATED WORK

The introduction to the location based social networks and also the details of different overlapping community detection algorithms as well as recommendation algorithms are reviewed in [2].

A. Understanding of the collective user behaviour

In location based social networks, Scellato et al. [3], [4] provides social, geographic, and geosocial details of Foursquare, Twitter, Brightkite, LiveJournal. Noulas et al. [5] gives details about a users behavior in foursquare. Noulas et al. [6] provides a way to group foursquare users based on venue categories. It helps to find user communities visiting to similar categories of places.

B. Overlapping Community Detection

The work on overlapping community detection was first started by Palla in 2005 [7]. He produced clique percolation method (CPM) as a deterministic community detection method which allows for finding overlapping communities. CPM exploits local topological properties of a network. Fuzzy detection algorithms such as fuzzy clustering and optimization of quality function by Zhang S [8] and Disjoint Community Detection by Wang X [9], calculates a soft membership vector, or belonging factor [Gregory 2010], for each node. There is a need to find out the dimensionality k of the membership vector, this is the drawback of such algorithms.

The above algorithms aims to find only disjoint communities by considering only the internal connectivity. These algorithms are unable to generate interpretable communities. The Framework by Zhu Wang et.al [1] focuses on community detection by considering both links and node attributes to have explicit semantic meanings that can be interpreted as community profiles.

C. Recommendations

Ye et.al [10] first introduced location recommendation. The research in location recommendation on LBSNs mainly focuses on the geospatial and temporal influence, and the social network information is usually utilized through traditional collaborative filtering[11], [12] which considers the location as an item such as that on Epinions[13],[14]. For evaluation, performance[15] is usually adopted to assess the location recommendation performance. It consider all the locations that should be recommended as uncovered locations, and the set of correctly recommended locations as recovered locations.

The work on friend recommendation vary in how to choose the feature space and classifier. To predict the link among two users having co-locations, logistic regression by Jonathan et al.[16] is used. Feature extraction was done using the tuples. Touples consist of place x , actor1, actor2. Touples indicates that actor1 and actor2 have checked-in into place x at least once. Based on the tuple, three features are extracted : 1. the total number of check-ins at place x , 2. Number of check-ins of first actor and 3. Number of check-ins of second actor. For each co-location inspection among two users Justin et al.[17] works for feature extraction on the data of Locaccino[18]. With respect to user attributes and co-location properties, extracted features include structure properties, location diversity, intensity and duration, mobility regularity, etc. Scellato et al.[19] utilizes the place features such as common check-ins, social features like common friends, and global features such as distance between homes, then selected various classifiers in WEKA for link prediction on Gowalla.

As seen, previous recommendation systems aims to finds the similarities explicitly but in our system users having similar features are implicitly club into a community at the time of overlapping community discovering and profiling.

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This saves the too much work on finding the similarities explicitly. So recommendations becomes efficient while considering the profiled communities.

III. PROBLEM STATEMENT

Detection of overlapping communities from an edge-centric perspective. Where each edge is viewed as a link between two modes, i.e., both user mode vertex and a venue mode vertex.

Recommendation analyzes the similar pattern between a target user and other users, and then recommends users with the most similar patterns to the target user. Here, the similar patterns may represent the common interests, shopping habits, traveling trajectories, etc. Also, users check-in history is analyzed for recommendation.

A. Input

- A check-in matrix $M(|U| * |V|)$, where $|U|$ and $|V|$ are the number of users and venue categories, respectively.
- A user attributes matrix $M(|U| * |A|)$, where $|A|$ is the number of user attributes.
- A venue category attributes matrix $M(|V| * |B|)$, where $|B|$ is the number of venue category attributes.
- The number of communities k , which is optional based on the clustering algorithm

B. Output

- k overlapping communities which consist of both users and venue categories.
- Friend and Location Recommendation based on discovered overlapping communities

IV. PROPOSED SYSTEM ARCHITECTURE

The key idea of overlapping community discovering, profiling and recommendations on overlapping communities is shown in Figure1. Architecture is divided into three phases such as data crawling, finding and profiling overlapping communities, recommendations. These phases are described below.

First phase is the data crawling based on the collected LBSNs dataset. Second phase finds and profiles the overlapping communities using feature selection, feature normalization, feature fusion and feature clustering. M^2 Clustering and HM^2 Clustering algorithms are used to find out the overlapping community structure. By combining the detected communities together along with user/venue metadata, we get the community profiles which possesses social and semantic meanings of communities. Third, by analyzing these detected community profiles recommendations are provided to the user.

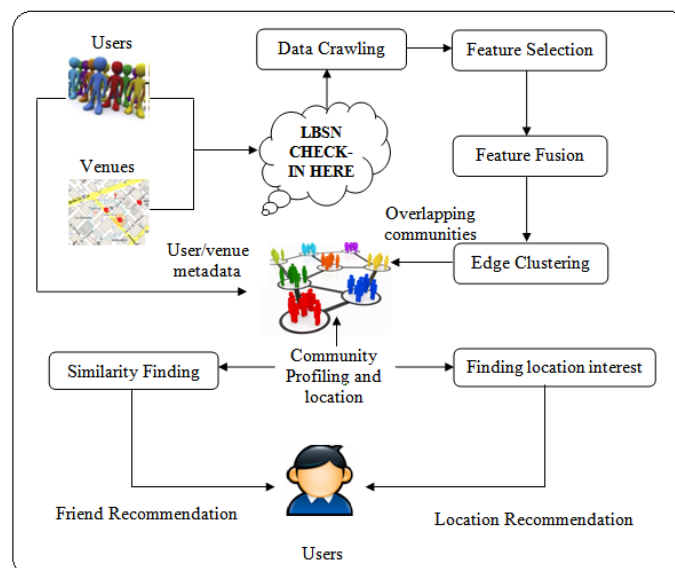


Fig.1 : Overlapping community discovering, profiling and recommendations framework.



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Phase 1 : Data Crawling

Data Crawling in this phase involves a. Preprocessing on check-ins data, b. Computation of check-in matrix, c. Calculation of user attribute matrix, d. Calculation of venue category attribute matrix.

Phase 2 : Finding and profiling overlapping communities

- A. *Feature Selection*: This is the phase of intermode and intramode feature selection. The intermode feature describes the structure similarity between a pair of edges based on the check-in relationships between users and venues. (i.e., user-venue similarity). The intramode feature depicts attributes similarity where each attribute corresponds to a certain social aspect of users or venues (i.e. users social influence similarity). They are selected based on the characteristics of the Foursquare data.
- B. *Feature Normalization*: For similarity features, there might be different value ranges in the results. So feature normalization is required to get the precise value of similarity measure.
- C. *Feature fusion*: By defining the user similarity and venue similarity of each edge, different features are to be fused. Based on the normalization and fusion defined above, various forms of edge similarities can be obtained which reveals the community structure in LBSNs.
- D. *Feature Clustering*: Following are the algorithms for feature clustering :
 - a) M^2 Clustering - Edge clustering based on k means
 - b) HM^2 Clustering - Two step hierarchical edge clustering

Phase 3: Recommendations

After finding Overlapping Communities, User profiles and preferences are matched with other community users in which user belongs. After getting matched result the result is ranked in descending order so that highest probable matches can be recommended. As per the user preferences, recommendations in specific category can be generated. Recommendations are categorized into two sections :

- A. *Location interest*: Based on users check-in history and rating recommend location to user where he never visited before and lies in overlapping communities.
- B. *Similarity between users*: By matching users highest rating similarity recommend users/friend to another user in overlapping communities.

V. MATHEMATICAL MODELING

The proposed system S is defined as follows :

$S : \{ U, V, C, M, F \}$

Where,

$U = (u_1, u_2, \dots, u_m)$: User set,

$V = (v_1, v_2, \dots, v_n)$: Venue category set,

$C = \text{set of } C_i (1 \leq i \leq k)$: Subset of users and venue categories and k is the number of communities,

$M = M_{ij} \in [1, \infty]$ of check-ins that u_i has performed over v_j ,

$F = (f_1, f_2, f_3, f_4)$

- A. f_1 : This function detects the communities having similar users and venues together by maximizing the intracluster similarity.
- B. f_2 : This function considers similarity between the corresponding pair of user vertices and venue vertices and returns similarity between a pair of edges.
- C. f_3 : This function returns similarity between an edge e_i and a community C_j .
- D. f_4 : This function calculates the user venue similarity for a pair of users. For user venue similarity, check-in patterns of two users must be similar to each other.

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VI. ALGORITHMS

There are four algorithms namely M^2 Clustering, HM^2 Clustering, Friend Recommendation & Location Recommendations. Consider the following notations for M^2 Clustering & HM^2 Clustering algorithms :

C_j : Each centroid

$E(C_j)$: list of instances within centroid

$E(A, C_j)$: list of instances assigned to centroid during last iteration

$E(R, C_j)$: list of instances removed from the centroid during last iteration

$Sim(E(P, C_j), E)$: similarity array between previous centroid and whole set of instances

Algorithm 1: M^2 Clustering - Edge clustering based on k - means

Input :

- E , an edge list $\{ e_i / 1 \leq i \leq n \}$
- k , the number of communities
- SM_u , the user-user similarity matrix
- SM_v , the venue-venue similarity matrix

Output:

- C , a set of detected communities

Steps :

```
1:  $k$  edges are randomly selected  $\{ e_j / 1 \leq j \leq k \}$ 
2: for each  $e_j$  do
3:    $E(C_j) \leftarrow \{ e_j \}$ 
4:    $E(A, C_j) \leftarrow E(C_j)$ 
5:    $E(R, C_j) \leftarrow \emptyset$ 
6:    $sim(E(P, C_j), E) \leftarrow zeros(|E|)$ 
7: end for
8:  $\{ maxsim_i | 1 \leq i \leq n \} \leftarrow 0$ 
9: repeat
10:   $Obj_{pre} \leftarrow maxsim_i$ 
11:  reset  $\{ maxsim_i \}$ 
12:  for each  $C_j$  do
13:    for each  $e_i$  in  $E$  do
14:      Calculate  $sim(E(A, C_j), e_i)$ 
15:      Calculate  $sim(E(R, C_j), e_i)$ 
16:       $sim(E(C_j), e_i) \leftarrow sim(E(P, C_j), e_i) + sim(E(A, C_j), e_i) - sim(E(R, C_j), e_i)$ 
17:      if  $sim(E(C_j), e_i) > maxsim_i$  then
18:         $maxsim_i \leftarrow sim(E(C_j), e_i)$ 
19:        assign  $e_i$  to  $C_j$ 
20:      end if
21:    end for
22:  end for
23:  Update the centroids
24:   $Obj_{cur} \leftarrow$  summation of  $maxsim_i$ 
25:   $d \leftarrow abs(Obj_{cur} - Obj_{pre})$ 
26: until  $d < e$ 
```

Algorithm 2 : HM^2 Clustering – Two step hierarchical edge clustering algorithm

Input:

- E , an edge list $\{ e_i | 1 \leq i \leq n \}$
- K , a large number which possess twice the no of communities than k
- SM_u , the user-user similarity matrix
- SM_v , the venue-venue similarity matrix

Output:



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- ED, an edge dendrogram

Steps:

- 1: Invoke Algorithm 1 to generate K edge groups $\{EG_j\}$
- 2: Calculate pairwise similarity ps for connected edge groups EG_a and EG_b
- 3: **repeat**
- 4: Find the largest ps
- 5: Merge EG_a and EG_b , update related weights
- 6: **until** $|EG| \leq 1$

Algorithm 3: Friend Recommendations based on Overlapping Communities

Input:

- Overlapping Communities
- User Rating

Output:

- Friend Recommendations

Steps:

- 1: Find the Overlapping Communities in which user belongs
- 2: Find user preference venue set V
- 3: **for** each venue V_i in V **do**
- 4: Identify other users for venue V_i
- 5: **end for**
- 6: Re-rank user list by comparing with user preferences
- 7: Suggest top k recommendations

The users having highest and same rating count depicts the similar interests towards venues in overlapping communities. So such type of users are recommended to each other.

Algorithm 4: Location Recommendations based on Overlapping Communities

Input:

- Overlapping Communities
- User Rating

Output:

- Location Recommendations

Steps:

- 1: Find the Overlapping Communities in which user belongs
- 2: Find user preference venue set V
- 3: **for** each venue V_i in V **do**
- 4: identify other users for venue V_i and add in U set
- 5: **end for**
- 6: **for** each user in U **do**
- 7: Find preferred venues $\notin V$
- 8: **end for**
- 9: Re-rank venue list
- 10: Suggest top k recommendations

The user who belongs to overlapping community nature and has an interest in art gallery, so the art gallery locations to which user has not visited before, are suggested to him/her.

VII. IMPLEMENTATION

The system is implanted in Java environment. We have created client server architecture. User interact with the system using Android application developed using android sdk and in eclipse environment. A web service is created in Java

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environment with Apache server to communicate with Android application. For Communication HTTP protocol is used. Data transfer is carried out using JSON. Client application uses GPS functionality to check-in at venues. Venue location is displayed on google map using google API V-3. To evaluate the performance of the proposed work Foursquare dataset is used.

VIII. ANALYSIS AND RESULTS

1) We have checked the user application functionality with GPS tracking and location detection. Result of GPS tracking is shown in Figure 2. Once user registered and login to the system, user check-in at a location and rate that location. Users' rating details will be save at server end. Server saves the data in the similar way as the preserved dataset.

2) We first distinguish the categorywise venues so that they can be quantitatively characterize the different areas or categories. The graph of categorywise venues is shown in Figure 3.

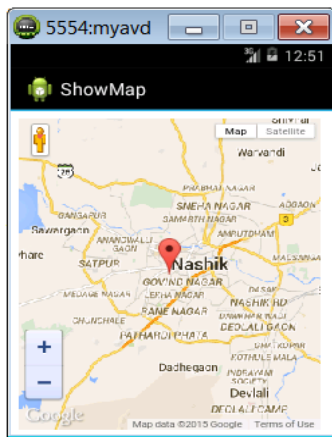


Fig.2 : Location detection using GPS tracking

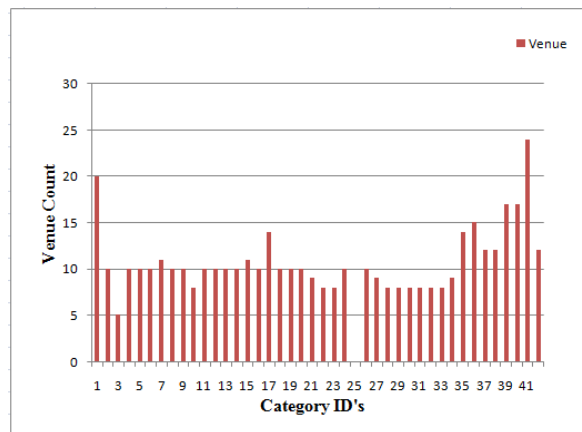


Fig. 3: Category Wise Venue Count

3) Venue wise user details are characterized by the check-in of users at venues which fall into the community. By using the user's liking i.e. rating to the venue, we have identified the category based communities of users. After the analysis of these communities we come across the following results as shown in Figure 4a and Figure 4b.

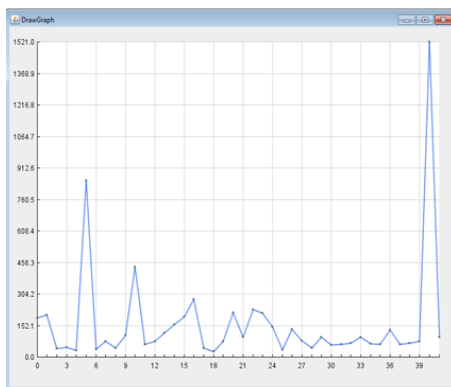


Fig. 4a: Community Specific User Count.
(X axis: Category Id, Y axis: User Count)

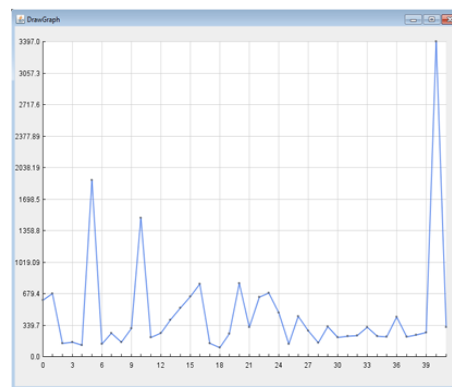


Fig. 4b: Community Specific Rating Count.
(X axis: Category Id, Y axis: Rating Count)

These graphs shows the comparative analysis between community users and their highest ratings. These graphs shows that the overall rating for a communities is higher than that of users. The highest peak of the user count shows that the

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maximum possible users of a community Id 41("pool hall") and the highest peak of the rating count of the same record shows that the interest of users towards that community and hence, depicts the popularity of the community.

4) The disjoint communities are identified based on the users check-ins and respective ratings. For this purpose M^2 Clustering algorithm is used. In this, the venues to which users are visited are clustered into predefined cluster k . Here, separate communities are formed for the different interest users. No relation between the two communities is considered while forming the disjoint communities. To achieve this overlapping communities are identified.

5) The overlapping communities are discovered from the disjoint communities. For this HM^2 Clustering algorithm is used. We have run this algorithm four times for different cluster inputs(5, 10, 15) and iterations(2, 4, 8) to test the execution time required for the formation of overlapping communities. Figure 5 shows the time required to execute the algorithm for different cluster inputs and iterations. We have analysed the overlapping nature of users based on their ratings between two communities and calculated the common users in terms of weights who lies in Overlapping Communities and merge the possible weights to reduce the clusters.

6) The comparison between the disjoint and overlapping communities for different execution and cluster counts is shown in Figure 6.

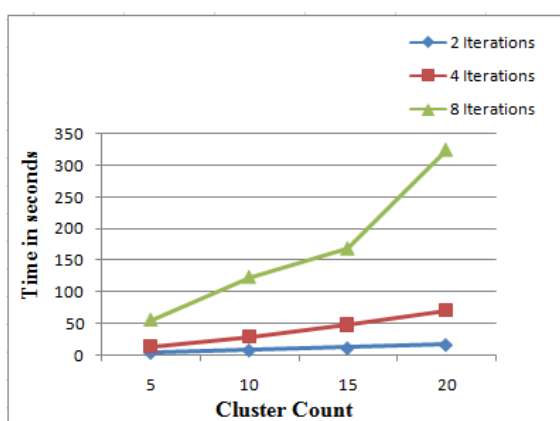


Fig. 5: Execution time for Overlapping Communities formation

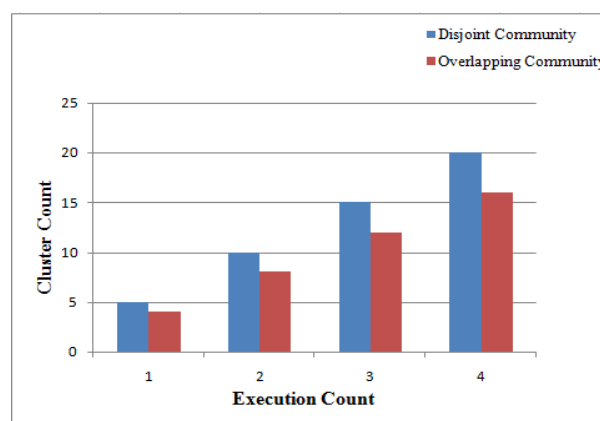


Fig. 6: Disjoint and Overlapping Communities difference

7) Further, we have generated Friend and Venue Recommendations for users based on overlapping communities. Figure 7 and Figure 8 shows all the possible friend and venue recommendations respectively for users having overlapping nature.

Friend Recommendation :

Friend Id	Friend Name	Email	Phone
1714	Christina	ClaudeMrwin@armyspy.com	913-570-8857
1713	Josephine	JoySavage@superrito.com	660-427-2344
10	John	BartLWade@gustr.com	812-596-7462
6	Cynthia	GwendolynGJohnson@einrot.com	201-861-1478
5	Jody	JorgeJCox@einrot.com	573-400-1700
4	Thelma	BeatriceBSchell@teleworm.us	240-215-9373
3	Kesha	EdithDBlack@rhyta.com	409-998-1606
2	Robert	MaryCSmith@superrito.com	484-299-3946

Fig. 7: Friends recommended to user



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Venue Recommended :

Venue Id	Venue Name	City	Email	Phone
564	maratha highschool	nashik	mar@gmail.com	0253-2453689
567	fame	nashik	fame@hotmail.com	0253-2415263
563	RJCB, nashik road	nashik	rjcb@gmil.com	0253-965287
570	geschscoe	nashik	gesrhscoe@gmail.com	0253-2556633
573	sony gift	nashik	sg@gmail.com	0253-2364879
567	fame	nashik	fame@hotmail.com	0253-2415263

Fig. 8: Venue recommended to user

IX. CONCLUSION AND FUTURE WORK

We proposed a recommendations based on multimode multi-attribute edge centric co-clustering framework for LBSNs users. The recommendations assists user to interact with the other users belonging to overlapping community. Recommendations help users in overlapping communities to know the locations as per their area of interest and reduce time to seek new things at a location nearer to user. Recommendations also assist users to find new friends. It can be also used to facilitate different applications, such as group advertising and marketing as the recommendations are based on overlapping communities. As users naturally forms overlapping communities among themselves so based on these, friend and location recommendations will surly beneficial to overlapping community users.

Providing a framework to guide the selection of different features and personalized profiling is one direction to work on. Further, comment processing is one another feature which can be consider to provide overlapping communities based recommendations to users.

ACKNOWLEDGEMENT

I would like to thank our project guide and Head of Computer Engineering Department. His valuable and skillful guidance, assessment and suggestions from time to time improved the quality of work in all respects. I would like to take this opportunity to express my deep sense of gratitude towards him, for his invaluable guidance in completion of this project. I would also thankful to all the staff members of Computer Engineering Department and Librarian, who rendered their valuable guidance to me.

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BIOGRAPHY



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