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Local Activity and Social Similarity based Data Forwarding Scheme

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Abstract: Existing social networking services recommend friends to users based on their social graphs, which may not be the most appropriate to reflect a user's preferences on friend selection in real life. we present Friendbook, a novel semantic-based friend recommendation system for social networks, which recommends friends to users based on their life styles instead of social graphs. By taking advantage of sensor-rich smart phones, Friendbook discovers life styles of users from user-centric sensor data, measures the similarity of life styles between users, and recommends friends to users if their life styles have high similarity. Inspired by text mining, we model a user's daily life as life documents, from which his/her life styles are extracted.

Keywords: GCM- Google Cloud Messaging, JSON- Java Script Object Notation, GPS- Global Positioning System, Text mining.

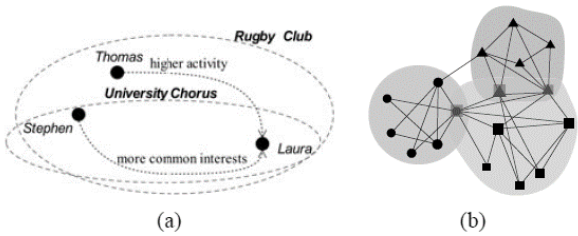
I. INTRODUCTION

Mobile social networks (MSNs) combine techniques in social science and wireless communications for mobile networking. In a broader sense, a mobile social network is a mobile communications system which involves the social relationship of the users. In such a network, users can publish and share information based on the social connections/relations among them. Due to the ubiquitous availability of mobile devices, mobile social networks can fully take advantage of human interaction and physical proximity to achieve efficient and effective data delivery services. In mobile social networks, there exist many encounter based data forwarding algorithms. Recently, people have found that social information has big impact on data forwarding. Thus, some social-aware and encounter-based forwarding schemes receive enormous attention.

In the literature, one common implicit and critical assumption has been widely utilized: two nodes can contact with a higher probability if they have more social similarity. The measurement of social similarity differs in different approaches and one of the most popular methods is using common interests or common communities.

In this project, we show that the measurement of social similarity based on the number of common communities ignores the fact that the members within the same community usually have different levels of local activity. A low local activity will result in a potentially low efficiency in terms of delivery ratio and latency due to the misalignment on the estimation of nodes' contact probability. Here, the concept of local activity is associated with a certain community. The local activity of node ***u*** in its belonging community ***i*** is the ratio of node ***u***'s encounter probability with other nodes in community ***i*** to any two nodes' encounter probability in community ***i***.

(a) depicts the relay selection between Thomas and Stephen in message delivery. In (b), different sizes of icons represent each node's different levels of local activity in its communities. In the overlapping area, one node has different local activity in each belonging communities respectively, depicted by overlapping icons of square and triangle or square and circle.



II. RELATED WORK

Recently, with the advance of social networking systems, friend recommendation has received a lot of attention. Generally speaking, existing friend recommendation in social networking systems, e.g., Facebook, LinkedIn and Twitter, recommend friends of users if, according to their social relations, they share common friends.

Meanwhile, other recommendation mechanisms have also been proposed by researchers. For example, Bian and Holtzman presented MatchMaker, a collaborative filtering friend recommendation system based on personality matching. Kwon and Kim proposed a friend recommendation method using physical and social context. However, the authors did not explain what the physical and social context is and how to obtain the information. Yu recommended geographically related friends in social network by combining GPS information and social network structure. Hsu studied the problem of link recommendation in weblogs and similar social networks, and proposed an approach based on collaborative recommendation using the link structure of a social network and content-based recommendation using mutual declared interests. Gou et al. proposed a visual system, SFViz, to support users to explore and find friends interactively under the context of interest, and reported a

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case study using the system to explore the recommendation of friends based on people's tagging behaviours in a music community. These existing friend recommendation systems, however, are significantly different from our work, as we exploit recent sociology findings to recommend friends based on their similar life styles instead of social relations.

Activity recognition serves as the basis for extracting high-level daily routines (in close correlation with life styles) from low-level sensor data, which has been widely studied using various types of wearable sensors.Zheng used GPS data to understand the transportation mode of users. Lester used data from wearable sensors to recognize activities based on the Hidden Markov Model (HMM). Li recognized static postures and dynamic transitions by using accelerometers and gyroscopes. The advance of smartphones enables activity recognition using the rich set of sensors on the smartphones. Reddy used the built-in GPS and the accelerometer on the smartphones to detect the transportation mode of an individual. CenceMe used multiple sensors on the smartphone to capture user's activities, state, habits and surroundings. SoundSense used the microphone on the smartphone to recognize general sound types (e.g., music, voice) and discover user specific sound events.EasyTracker used GPS traces collected from smartphones that are installed on transit vehicles to determine routes served, locate stops, and infer schedules.

Although a lot of work has been done for activity recognition using smartphones, there is relatively little work on discovery of daily routines using smartphones.

The MIT Reality Mining project and Farrahi and Gatica-Perez tried to discover daily location-driven routines from large-scale location data. Farrahi and Gatica-Perez took a step further and overcame the short-coming of discovering daily routines of people staying in the same location by considering combined location and physical proximity sensed by the mobile phone. Another closely related work was presented in, which used a topic model to extract activity patterns from sensor data.

However, they used two wearable sensors, but not smartphones, to discover the daily routines.

III. PROBLEM FORMULATION

a. Let 'S' be the | Friendbook system as the final set

S = {…………

b.Identify the inputs as D , L, I, P, G

S = {D, L, I, P,G …
D = {D1, D2, D3,D4, …| 'D' gives lifestyle data}
L= {L1, L2, L3, … | 'L' gives the matched friendlist}
I = {I1, I2,… |'I' gives user ID for login}
P= {P1, P2, … |'P' gives the respective password for login ID}
G= {G1, G2, G3 …|'G' gives Google chat service i.e. GSM}

c. Identify the outputs as

S = {D, L, I, P, G, R, C…
D = {D1, D2, D3, D4, …| 'D' gives lifestyle data}
L= {L1, L2, L3, … | 'L' gives the matched friendlist}
R= {R1, R2 …| 'R' is the friend request}
C= {C1, C2, C3 …|'C' is the chat}

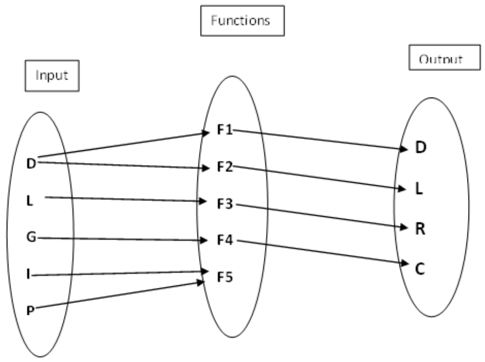
d.Identify the functions as 'F'

S = {D, Q, I, P, N, R, F…

F = {F1(), F2(), F3(), F4(), F5()}

F1(D) :: Fetch lifestyle data
F2 (D) :: Find similarities in lifestyles
F3 (L) :: Suggest friends
F4 (G) :: Chatting with GSM
F5(I,P) :: login

Hence the functionality can be shown as,



IV. PROPOSED SYSTEM

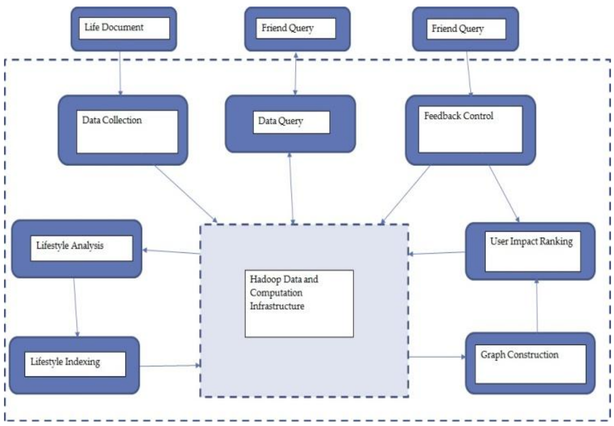


Figure 1. System Architecture

It is proposed that the architecture of the application be modular, in order to facilitate the expansion of analysis techniques without requiring changes to core functionality, as well as to allow future projects to reasonably modify core components of the system without adversely affecting the overall process. The system's target audience includes online social network users. Running the system over the web allows for an easy architecture for distribution, without incurring high operating cost on the client. All that would be required on the client side is an Internet browser and a smartphone. Hence, it would be easy to configure a terminal in a museum in order to use the system. As can be seen, the system is distributed using a web browser on the remote clients. These clients can access the central application server through normal HTTP requests. The application can then process the requests and forward

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them onto the Server, which contains all the code for image processing and retrieval. The android application requires a smartphone and embedded sensors in it. This server has two storage mechanisms as its back-end:

Hadoop MapReduce for our computation infrastructure, and a database for all other storage.

1. Web based GUI:

Server will be web based application and this module will be responsible to take inputs from admin. The GUI will be developed in HTML and Java-script

2. Android Client:

An android application will be needed for the user to provide sensor related data. User will run the application in order to provide activity information image of to server. This module will take care of sensors capturing life activity that needs to be perform to generate life documents.

3. Life style extraction using Probabilistic topic model:

Life styles and activities are reflections of daily lives at two different levels where daily lives can be treated as a mixture of life styles and life styles as a mixture of activities. We propose the "bag-of-activity" model to replace the original sequences of activities recognized based on the raw data with their probability distributions. This, however, requires activity recognition techniques. We particularly use unsupervised machine learning method of K-means clustering for this prpose.

4. Friend-matching Graph:

We model the relations between users in real life as a friend-matching graph.

5. User Impact Ranking:

The friend-matching graph has been constructed to reflect life style relations among users. However, we still lack a measurement to identify the impact ranking of a user quantitatively. Intuitively, the impact ranking means a user's capability to establish friendships in the network.

In other words, the higher the ranking, the easier the user can be made friends with, because he/she shares broader life styles with others. We form the idea that a user's ranking is reflected by his neighbors in the friend-matching graph and how much his neighbors endorse the user as a friend. Once the ranking of a user is obtained, it provides guidelines to those who receive the recommendation list on how to choose friends.

6. Database Manager:

This module will help to handle all database related activity. All the SQL queries will be taken care in this module. A database connection polling system will be present to avoid repeatedly opening and closing database connection.

ALGORITHM

■ **Input:** The query user i, the recommendation coefficient and the required number of recommended friends from the system p.

■ **Output:** Friend list F_i.

1: F_i Ø , Q Ø ;
2: extracts *i*'s life style vector L_i using the LDA algorithm.
3: **for** each life style z_k the probability of which in L_i is not zero **do**
4: put users in the entry of z_k into Q
5: **end for**
6: **for** each user j € Q **do**
7: S(i , j) 0
8: **end for**
9: **for** each user j in the database **do**
10: $R(i,j) = {}_{\beta}S(i, j) + (1 - {}_{\beta})r_j k$
11: **end for**
12: sort all users in decreasing order according to $R_i(j)$
13: put the top *p* users in the sorted list to F_i

V. CONCLUSION

In this paper, we described the implementation of a semantic based friend recommendation system for online social networks. This system uses a different approach from the existing recommendation systems as it relies on the concepts which are highly abstract and more socially compatible such as using "lifestyles" of the user. The System extracts the sensor data embedded in the smartphones which are in abundance in today's lifestyle of a person. Thus , the system is applicable on a large scale. User profiling and feedback control system enhances the efficiency of the system which allows comparison of the present users on the basis of their 'life documents'. Thus the system is practically presents a virtual method for the real world mechanisms for making friends. Still, the project has expandability to other industrial and other fields such as healthcare and e-commerce. The Project also multiplies the ever increasing need of mobile computing Hence, the project provides certain advancements to the automation and digitalisation of sociology.

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