

A Novel Based Friend Recommendation System for Social Networks

*B.RAMYA SREE

**N.RAJENDER REDDY

*M.TECH student, Dept of CSE, VAAGDEVI COLLEGE OF ENGINEERING

**Assistant Professor, Dept of CSE, VAAGDEVI COLLEGE OF ENGINEERING

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. In this paper, 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 smartphones, 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 by using the Latent Dirichlet Allocation algorithm. We further propose a similarity metric to measure the similarity of life styles between users, and calculate users' impact in terms of life styles with a friend-matching graph. Upon receiving a request, Friendbook returns a list of people with highest recommendation scores to the query user. Finally, Friendbook integrates a feedback mechanism to further improve there commendation accuracy. We have implemented Friendbook on the Android-based smartphones, and evaluated its performance on both small-scale experiments and large-scale simulations. The results show that the recommendations accurately reflect the preferences of users in choosing friends.

Keywords: LDA, MIT, GPS.

I. INTRODUCTION

Twenty years ago, people typically made friends with others who live or work close to themselves, such as neighbors or colleagues. We call friends made through this traditional fashion as G-friends, which stands for geographical location-based friends because they are influenced by the geographical distances between each other. With the rapid advances in social networks, services such as Facebook, Twitter and Google+ have provided us revolutionary ways of making friends. According to Facebook statistics, a user has an average of 130 friends, perhaps larger than any other time in history [2]. One challenge with existing social networking services is how to recommend a good friend to a user. Most of them rely on pre-existing user relationships to pick friend candidates. For example, Facebook relies on a social link analysis among those who already share common friends and recommends symmetrical users as potential friends. Unfortunately, this approach may not be the most appropriate based on recent sociology findings [15]. According to these studies, the rules to group people together include: 1)

habits or life style; 2) attitudes; 3) tastes; 4) moral standards; 5) economic level; and 6) people they already know. Apparently, rule #3 and rule #6 are the mainstream factors considered by existing recommendation systems. Rule#1, although probably the most intuitive, is not widely used because users' life styles are difficult, if not impossible, to capture through web actions. Rather, life styles are usually closely correlated with daily routines and activities. Therefore, if we could gather information on users' daily routines and activities, we can exploit rule #1 and recommend friends to people based on their similar life styles. This recommendation mechanism can be deployed as a standalone app on smartphones or as an add-on to existing social network frameworks. In both cases, Friendbook can help mobile phone users find friends either among strangers or within a certain group as long as they share similar life styles. In our everyday lives, we may have hundreds of activities, which form meaningful sequences that shape our lives. In this paper, we use the word activity to specifically refer to the actions taken in the order of seconds, such as "sitting",

“walking”, or “typing”, while we use the phrase life style to refer to higher-level abstractions of daily lives, such as “office work” or “shopping”. For instance, the “shopping” life style mostly consists of the “walking” activity, but may also contain the “standing” or the “sitting” activities. To model daily lives properly, we draw an analogy between people’s daily lives and documents, as shown in Fig. 1. Previous research on probabilistic topic models in text mining has treated documents as mixtures of topics, and topics as mixtures of words [10]. Inspired by this, similarly, we can treat our daily lives (or life documents) as a mixture of life styles (or topics), and each life style as a mixture of activities (or words).

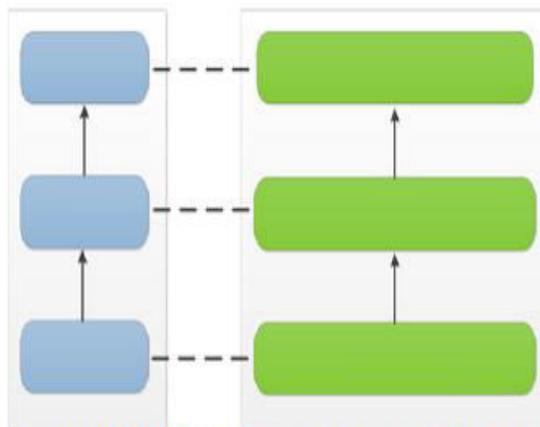
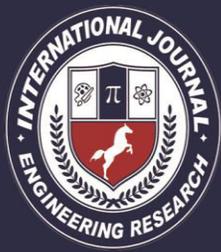


Fig. 1. An analogy between word documents and people daily lives.

Observe here, essentially, we represent daily lives with “life documents”, whose semantic meanings are reflected through their topics, which are life styles in our study. Just like words serve as the basis of documents, people’s activities naturally serve as the primitive vocabulary of these life documents. Our proposed solution is also motivated by the recent advances in smartphones, which have become more and more popular in people’s lives. These smartphones (e.g., iPhone or Android-based smartphones) are equipped with a rich set of embedded sensors, such as GPS, accelerometer, microphone, gyroscope, and camera. Thus, a smartphone is no longer simply a communication device, but also a powerful and environmental reality sensing platform from which we can extract rich context and content-aware information. From this perspective, smartphones serve as the ideal platform for sensing daily routines from which people’s life styles could be discovered recognition using the rich set of sensors on the smartphones. Reddy et al. [26] used the built-in GPS and the accelerometer on the smartphones to detect



the transportation mode of an individual. CenceMe [24] used multiple sensors on the smartphone to capture user's activities, state, habits and surroundings. SoundSense [23] used the microphone on the smartphone to recognize general sound types (e.g., music, +-voice) and discover user specific sound events.

Easy Tracker[7] 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 [12] and Farrahi and Gatica-Perez [14] tried to discover daily location-driven routines from large-scale location data. They could infer daily routines such as leaving from home to office and eating at a restaurant. However, they could not discover the daily routines of people who are staying at the same location. For instance, when one stays at home, his/her daily routines like "eating lunch" and "watching movie" could not be discovered if only using the location information. In [13],

Farrahi and Gatica-Perez took a step further and overcame the shortcoming 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 [9], 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. In our work, we attempt to use the probabilistic topic model to discover life styles using the smartphone. We further utilize patterns discovered from activities as a basis for friend recommendation that helps users find friends who have similar life styles as shown in Fig.2.

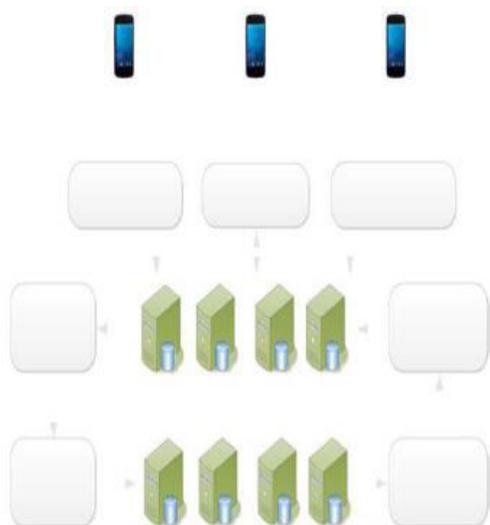


Fig. 2. System architecture of Friendbook.

Note that the work in this paper is significantly different from our preliminary demo work of Friendbook [31] recommended friends to users based on the similarity of pictures taken by users. Activity Recognition To derive $p_{\text{wi j dkP}}$, we need to first classify or recognize the activities of users. Life styles are usually reflected as a mixture of motion activities with different occurrence probability. Therefore, two motion sensors, accelerometer and gyroscope, are used to infer users' motion activities. Generally speaking, there are two mainstream approaches: supervised learning and unsupervised learning. For both approaches, mature techniques have been developed and

tested. In practice, the number of activities involved in the analysis is unpredictable and it is difficult to collect a large set of ground truth data for each activity, which makes supervised learning algorithms unsuitable for our system. Therefore, we use unsupervised learning approaches to recognize activities. Here, we adopt the popular K-means clustering algorithm [9] to group data into clusters, where each cluster represents an activity. Note that activity recognition is not the main concern of our paper. Other more complicated clustering algorithms can certainly be used. We choose K-means for its simplicity and effectiveness.

II. EXISTING SYSTEM

Most of the friend suggestions mechanism relies on pre-existing user relationships to pick friend candidates. For example, Facebook relies on a social link analysis among those who already share common friends and recommends symmetrical users as potential friends. The rules to group people together include:

- Habits or life style
- Attitudes
- Tastes

- Moral standards
- Economic level; and
- People they already know.

Apparently, rule #3 and rule #6 are the mainstream factors considered by existing recommendation systems.

Disadvantages of Existing System:

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

III. PROPOSED SYSTEM

- 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 smartphones, 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.
- We model a user's daily life as life documents, from which his/her life

styles are extracted by using the Latent Dirichlet Allocation algorithm.

- Similarity metric to measure the similarity of life styles between users, and calculate users'
- Impact in terms of life styles with a friend-matching graph.
- We integrate a linear feedback mechanism that exploits the user's feedback to improve recommendation accuracy.

Advantages of Proposed System:

- Recommend potential friends to users if they share similar life styles.
- The feedback mechanism allows us to measure the satisfaction of users, by providing a user interface that allows the user to rate the friend list.

IV. SYSTEM ARCHITECTURE

System architecture is as shown in bellow Fig.3.

A. Modules

- Life Style Modeling
- Activity Recognition

- Friend-matching Graph
- Construction
- User Impact Ranking

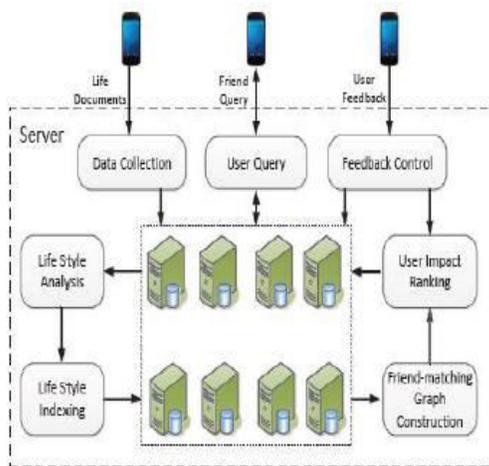
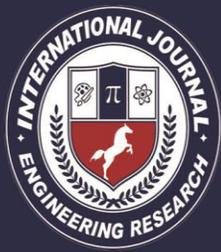


Fig.3. System Architecture.

V. CONCLUSION

In this paper, we presented the design and implementation of Friendbook, a semantic-based friend recommendation system for social networks. Different from the friend recommendation mechanisms relying on social graphs in existing social networking services, Friendbook extracted life styles from user-centric data collected from sensors on the smartphone and recommended potential friends to users if they share similar life styles. We implemented Friendbook on the Android-based smartphones, and evaluated its performance on both small-scale

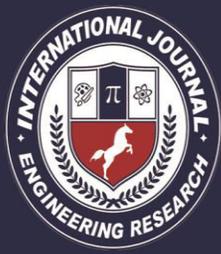
experiments and large-scale simulations. The results showed that the recommendations accurately reflect the preferences of users in choosing friends. Beyond the current prototype, the future work can be four-fold. First, we would like to evaluate our system on large-scale field experiments. Second, we intend to implement the life style extraction using LDA and the iterative matrix-vector multiplication method in user impact ranking incrementally, so that Friendbook would be scalable to large-scale systems. Third, the similarity threshold used for the friend-matching graph is fixed in our current prototype of Friendbook. It would be interesting to explore the adaption of the threshold for each edge and see whether it can better represent the similarity relationship on the friendmatching graph. At last, we plan to incorporate more sensors on the mobile phones into the system and also utilize the information from wearable equipments (e.g., Fitbit, iwatch, Google glass, Nike+, and Galaxy Gear) to discover more interesting and meaningful life styles. For example, we can incorporate the sensor data source from Fitbit, which extracts the



user's daily fitness info graph, and the user's place of interests from GPS traces to generate an infograph of the user as a "document". From the infograph, one can easily visualize a user's life style which will make more sense on the recommendation. Actually, we expect to incorporate Friendbook into existing social services (e.g., Facebook, m Twitter, LinkedIn) so that Friendbook can utilize more information for life discovery, which should improve the recommendation experience in the future.

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AUTHOR 1 :-

* B.Ramya Sree completed her B tech in Vaagdevi Engineering College in 2014 and pursuing M-Tech in Vaagdevi College of Engineering

AUTHOR 2:-

**N.Rajender Reddy is working as Assistant Professor in Dept of CSE, Vaagdevi College of Engineering