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Activity-based Friend Recommendation System (ARS) Development in Location-based Social Network

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Abstract. Common friend and place recommendation services in Location-based Social Network (LBSN) is based on user's location tracking. However, since each user can do different activities even in the same place, location data is not enough to provide accurate recommendation for LSBN. To address this problem, Activity-based friend and place Recommendation System (ARS) is proposed. ARS considers two additional factors to improve recommendation accuracy: time and activity. ARS collects the time-related activity and location data from users through the developed scheduler application and then performs the recommendation for users based on the calculated similarity among them. Performance evaluation shows that ARS can provide accurate recommendation between users who have similar activity and location patterns according to time.

Keywords: Location-based Social Network, Friend Recommendation, Geofencing, Information Collection Service, Data mining

1. Introduction

With the development of smartphones and the growth of social networks, the location based social network (LBSN) has emerged which adds the location information to social networks. As many smartphones have built-in GPS sensor, a lot of location-based services have become possible including LBSN (e.g., personal health management program using GPS sensor (Jeong, 2020)). LBSN allows users to share their information in the same local community and to access more useful information. In addition, it enables users to share location-based information such as friend recommendation for social network service (SNS), point of interest (POI) recommendation, and the popularity of places. Especially, as increasing number of users participate in LBSN, the recommendation service has been attracted a lot.

To improve the accuracy for the recommendation, various algorithms such as a friend recommendation algorithm (Cho et al., 2011; Chu et al., 2013; Lin et al., 2016) and location recommendation algorithm (Yu et al., 2017; Wang et al., 2013) have been studied. Moreover, advanced algorithms using multi factors have been proposed. For example, users' opinions on different topics considering the asymmetric relations to enhance the accuracy of friend recommendation process was introduced (Samir, El-Tazi, 2020). However, previous works have focused on the location data without considerations on the users' activity which can be an important factor for the user context.

Therefore, this paper proposes an Activity-based friend and place Recommendation System (ARS) which considers the time-related activity as well as the location data to improve the recommendation accuracy. As the mobile application is widely used for the data collection (i.e., not offline or manual collection) due to its easy configuration and efficiency (Leocadio et al., 2018; Peart et al., 2019), a scheduler application is also developed for ARS to collect the user data. Based on the collected data, ARS provides an algorithm for the recommendation.

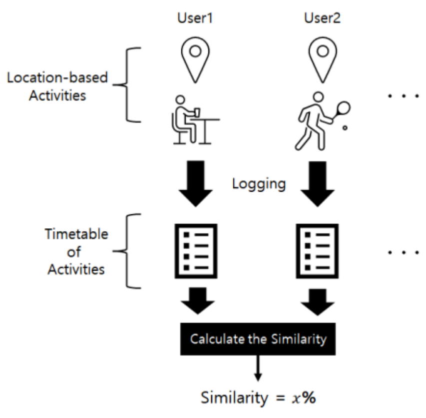


Fig. 1: Overview of ARS

2. Methods

Figure 1 shows an overview of ARS. First, ARS gathers user's location data and location-bases activities. To gather these data, ARS uses a schedular application which can easily collect data based on the simple operation. Second, ARS measures the similarity between users automatically by comparing logged users' daily timetable including location data, time, and activities. Finally, ARS recommends friends based on the similarity measured previously.

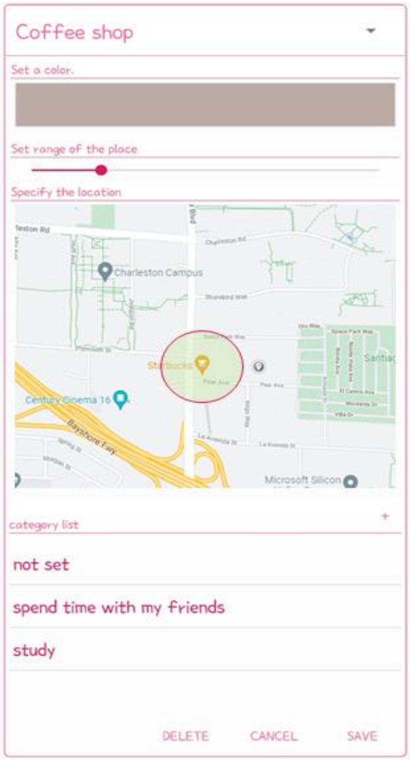
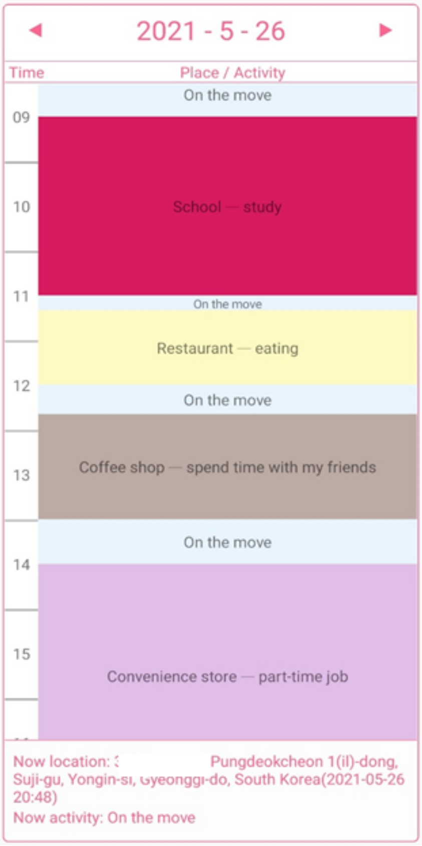


Fig. 2: Setting of activities based on location in our application interface.

Using GPS sensor which is a common method to check the current location, longitude and latitude can be determined. However, GPS does not work properly inside the building because the signals from satellite cannot delivered into the building. Therefore, in addition to the GPS sensor, ARS uses nearby Wi-Fi APs and Beacons information to determine the current location. In the building (e.g., shopping mall, offices, and university classes), there are usually more than one Wi-Fi APs and Beacons that can be public or private. Wi-Fi APs and Beacons (even for the private APs or Beacons) periodically send broadcast information such as basic service set identities (BSSIDs) which are usually unique. Consequently, a certain point of location can be defined by the set of broadcast information with signal strength from

Wi-Fi APs and Beacons (Kanaris et al., 2017; Varshney et al., 2016). Therefore, ARS uses these data (i.e., longitude and latitude from GPS sensor and broadcast information from Wi-Fi APs and Beacons) to determine the place which the user is in more precisely. Furthermore, for social similarity between users, ARS includes two more factors in addition to the location data: Time and Activity. Since people even in the same place can do different activities, it can be noticed that the more people perform the similar activities in the same place, the more there are possibilities to meet each other and become friends.

To collect the time-related activity and location data, we develop the scheduler application based on Android platform. As shown in Fig 2, the user can set activities for the current places with range and categories that can be defined by the user. When the user clicks a "save" button, location information as explained above are saved with a label according to the current location. To improve the reliability of the collected information, the application performs data collection repetitively and saves the average value of them. After the information are stored for the place, when the user enters a set place, the application automatically records the associated activity as shown in Fig 3. For example, after the user sets a location where the label is "School" and activity is "study" with collected location information, the application automatically can perform check-in when user is in the place based on the matching



of collected location information with currently scanned information and then records the activity to the current time (i.e., red square in Fig 3). Users can also modify logged activities manually.

Fig. 3: Automatically logged schedule in our application interface.

To determine the user's location, our application normally uses the location API of Android platform. As explained above, GPS sensors cannot determine location accurately in some places (e.g., floors in buildings). Therefore, ARS utilizes the place scanning phase according to location accuracy as shown in Fig 4. Specifically, the application can check the GPS performance based on the accuracy value from the location API. When location API accuracy is higher than the criteria (i.e., value x in Fig 4), current location can be determined by the result values of the location API (i.e., longitude and latitude from GPS sensor). Then, if the result values of location API are similar to those of the saved location information, the place matching is completed. On the other hand, if the accuracy is lower than the criteria, the application uses the scanning API of Android platform for Wi-Fi APs and Beacons. Finally, the result values of the location and scanning APIs are matched with saved information when the user set the activity to determine where the current location is.

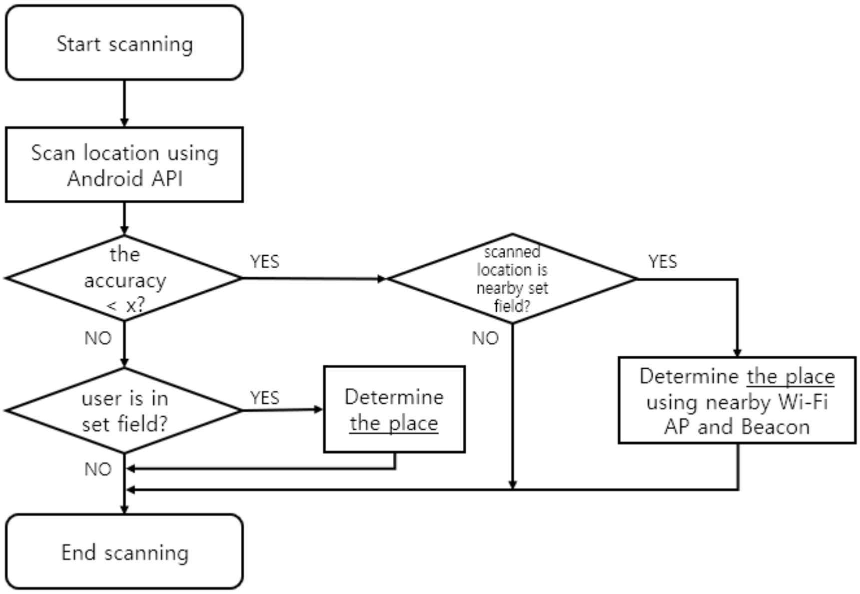


Fig. 4: Place scanning phase according to location accuracy.

With help of this scheduler application, we can track places, time, and activities data of users. Activities can be identified like hashtags. We can create a sequence of activities with time. The first element of the sequence refers to the activity at 00:00

(start of a day) and the last element refers to the activity at 23:50 (end of a day). Using these sequences, we can create a new comparison sequence between two users shown in Fig 5. The same activity means the value '1' and the different activity means '0'. The similarity between two users can be determined using sum of this new comparison sequence. We only apply this algorithm to people who have visited the overlapped activity area which is determined by the location information as mentioned above.

Time	User1's Activity	User2's Activity
09:00	study	sleep
09:10	study	study
...	...	...
11:50	study	study
12:00	eating	study
12:10	eating	eating
...	...	...
13:00	part-time job	play a game
13:10	part-time job	play a game
...	...	...
22:00	sleep	sleep

User1: ['study', 'study', ... 'study', 'eating', 'eating', ... 'part-time job', 'part-time job', ... 'sleep']

User2: ['sleep', 'study', ... 'study', 'study', 'eating', ... 'play a game', 'play a game', ... 'sleep']

comparison of two users: [0, 1, ..., 1, 0, 1, ..., 0, 0, ..., 1]

Fig. 5: Timetable and comparison sequence between two users.

Table 1. Comparison group.

Comp. 1	User A (Neighborhood friend with user B) (Not related to User C)	User B (Neighborhood friend with user A)
		User C (Not related to User A)
Comp. 2	User D (Hanshin Univ. School of Computer Engineering)	User E (Hanshin Univ. School of Computer Engineering)
		User F (Hanshin Univ. School of Economics)

3. Results

To validate our algorithm, we collect 6 people daily data using the developed scheduler application. The comparison groups are shown in Table 1.

For the Comparison 1 in Table 1, User A and User B are real friends. User A and User B usually study in café and exercise at the gym together. On the other hands, User A and User C don't know each other though they live in the same town. Fig 6 shows the summary of users' activity log. The green cell means the same activity, and the red cell means the different activity at the same time with User A. It should be noted that the activities "on the move" and "take a rest at home" were treated as different activities because they were not in the same place. The similarity between User A and User B is approximately 22.9% and that between User A and User C is approximately 4.8%. From this result, it can be found that the similarity is high for friends because of common activities between them.

Time	User A's Activity	User B's Activity	User C's Activity
09:00	study (at café)	study (at café)	sleep
09:10	study (at café)	study (at café)	sleep
...	...	...	...
12:00	eat (at AAA restaurant)	eat (at AAA restaurant)	play a computer game
...	...	...	...
13:00	do a part-time job	take a rest at home	play a computer game
...	...	...	...
18:00	working out (at AA GYM)	working out (at AA GYM)	on the move
...	...	...	...
18:20	working out (at AA GYM)	working out (at AA GYM)	working out (at AA GYM)
...	...	...	...
19:40	on the move	on the move	on the move
19:50	take a rest at home	take a rest at home	take a rest at home
...	...	...	...

Fig6: Comparison 1 activity log table.

Time	User D's Activity	User E's Activity	User F's Activity
09:00	on the move	on the move	on the move
...	...	...	...
09:30	take a lecture (at AA hall)	take a lecture (at AA hall)	take a lecture (at BB hall)
...	...	...	...
11:00	on the move	on the move	on the move
11:10	study (at the library)	study (at the library)	study (at the library)
...	...	...	...
12:00	on the move	on the move	on the move
12:10	eat (at AAA restaurant)	eat (at BBB restaurant)	eat (at CCC restaurant)
...	...	...	...
13:00	take a lecture (at CC hall)	take a lecture (at CC hall)	study (at the library)
...	...	...	...
14:30	take a lecture (at DD hall)	take a lecture (at DD hall)	take a lecture (at EE hall)
...	...	...	...
16:00	on the move	on the move	on the move

Fig. 7: Comparison 2 activity log table.

For the Comparison 2 in Table 1, User D, User E, and User F don't know each other. User D and User E belong to the same department and grade. On the other hands, User D and User E belong to different departments. Figure 7 shows the summary of users' activity log like Comp 1. It should be noted that the activity "take a lecture" was treated as same activity for User E and different activity for User F based on location. The similarity between User D and User E is approximately 22.2% and that between User D and User F is approximately 3.4%. From this result, ARS can determine that Users D and E can be potential friends based on the similarity.

4. Conclusion

This paper proposes an algorithm using location, time, and activity to improve recommendation accuracy. Users' interests or social characteristics with the specific location can be presented to the activity with certain time. This means that because users can do various activities according to time even for the same location, multi factors, not only location data but also time and activity data, should be considered for the recommendation services.

Therefore, this paper utilizes these factors to determine the similarity between users and performs recommendation based on the similarity. In addition, we developed a scheduler application that can gather these factors and calculate the similarity according to the proposed algorithm.

Performance evaluation shows that the proposed system can provide high similarity between users who have similar activity and location patterns. In our future work, we will integrate the proposed system into the SNS service to show the practical effect of the recommendations and consider more optimized algorithms.

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