GeoSocialRec : Explaining Recommendations in Location-based Social Networks

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Abstract. Social networks have evolved with the combination of geographical data, into location-based social networks (LBSNs). LBSNs give users the opportunity, not only to communicate with each other, but also to share images, videos, locations, and activities. In this paper, we have implemented an online recommender system for LBSNs, called GeoSocialRec, where users can get explanations along with the recommendations on friends, locations and activities. We have conducted a user study, which shows that users tend to prefer their friends opinion more than the overall users' opinion. Moreover, in friend recommendation, the users' favorite explanation style is the one that presents all human chains (i.e. pathways of more than length 2) that connect a person with his candidate friends.

1 Introduction

Over the past few years, social networks have attracted a huge attention after the widespread adoption of Web 2.0 technology. Social networks combined with geographical data, have evolved into location-based social networks (LBSNs). LBSNs such as Facebook Places, Foursquare.com, etc., which allow users with mobile phones to contribute valuable information, have increased both in popularity and size. These systems are considered to be the next big thing on the web [4].

LBSNs allow users to use their GPS-enabled device, to "check in" at various locations and record their experience. In particular, users submit ratings or personal comments for the location/activity they visited/performed. That is, they "check in" at various places, to publish their location online, and see where their friends are. Moreover, they can either comment on a friend's location or comment on their own. These LBSN systems, based on a user's "check in" profile, can also provide activity and location recommendations. For an activity recommendation, if a user plans to visit some place, the LBSN system can recommend an activity (i.e. dance, eat, etc.). For a location recommendation, if a user wants to do something, the LBSN system can recommend a place to go.

* This work has been partially funded by the Greek GSRT (project number 10TUR/4-3-3) and the Turkish TUBITAK (project number 109E282) national agencies as part of Greek-Turkey 2011-2012 bilateral scientific cooperation.

Our prototype system GeoSocialRec is an online recommender system that relies on user check-ins to provide friend, location and activity recommendations. It provides also explanations along with the recommendations based on the democratic nature of users' voting. That is, GeoSocialRec interprets a rating by a user for an activity in a specific location, as a positive/negative vote for the "interestingness" of the location. Every registered user is presented with the option of checking in. The procedure involves selecting the location he is currently at, the activity he is performing there, and finally rating that activity. Based on the users' "check in" history and friendship network, GeoSocialRec provides friend, location and activity recommendations. Friends are recommended based on the FriendLink algorithm [7] and the average geographical distances between users' "check-ins", which are used as link weights. Users, locations and activities are also inserted into a 3-order tensor, which is then used to provide location and activity recommendations.

In this paper, we conduct a user study to measure the user satisfaction with different explanation styles. In particular, we have conducted a survey to measure user satisfaction against two styles of explanation. The first regards the "Peoples' Check-ins" style, which is based on all users' check ins, whereas the second is the "Friends' Check-ins" style, which relies only on the user's friends check-ins. As will be shown later, users tend to prefer the latter style. Moreover, in friend recommendation, the users' favorite explanation style is the one that presents all human chains (i.e. pathways of more than length 2) that connect a person with his candidate friends.

The remainder of this paper is organized as follows. Section 2 summarizes the related work. Section 3 describes the GeoSocialRec recommender system and its components. Section 4.1 presents experimental results for the evaluation of the accuracy of the recommendations. In Sections 4.2 and 4.3, we conduct two surveys to measure user satisfaction against the explanation styles in all three types of recommendations (friend, activity, location). Finally, Section 5 concludes the paper and proposes possible future work.

2 Related Work

Recently emerged LBSNs (i.e. Gowalla.com, Foursquare.com, Facebook Places etc.) provide to users activity or location recommendation. For example, in Gowalla.com a target user can provide to the system the activity he wants to do and the place he is (e.g. coffee in New York). Then, the system provides a map with coffee places which are nearby the user's location and were visited many times from people he knows. Moreover, Facebook Places allows users to see where their friends are and share their location in the real world.

There is a little research on the scientific field of LBSNs. Backstrom et al. [1] use user-supplied address data and the network of associations between members of the Facebook social network to measure the relationship between geography and friendship. Using these measurements, they can predict the location of an individual. Scellato et al. [10] proposed a graph analysis based approach to study social networks with geographic information. They also applied new geo-social metrics to four large-scale Online Social Network data sets (i.e. Liveljournal, Twitter, FourSquare, BrightKite). Quercia et al. [8] address the mobile cold-start problem when recommending social events to users without any location history.

Leung et al. [5] propose the Collaborative Location Recommendation (CLR) framework for location recommendation. The framework considers activities and different user classes to generate more precise and refined recommendations. The authors also incorporate a dynamic clustering algorithm, namely Community-based Agglomerative-Divisive Clustering (CADC), into the framework to cluster the trajectory data into groups of similar users, similar activities and similar locations. The algorithm can also be updated incrementally when new GPS trajectory data is available.

Ye et al. [11] believe that user preferences, social influence and geographical influence should be considered when providing Point of Interest recommendations. They study the geographical clustering phenomenon and propose a power-law probabilistic model to capture the geographical influence among Points of Interest. Finally, the authors evaluate their proposed method over the Foursquare and Whrrl datasets and discover, among others, that geographical influence is more important than social influence and that item similarity is not as accurate as user similarity due to a lack of user check-ins.

Moreover, there are tensor-based approaches. For example, Biancalana et al. [2] implemented a social recommender system based on a tensor that is able to identify user preferences and information needs and suggests personalized recommendations for possible points of interest (POI). Furthermore, Zheng et al. [13] proposed a method, where geographical data is combined with social data to provide location and activity recommendations. The authors used GPS location data, user ratings and user activities to propose location and activity recommendations to interested users and explain them accordingly. Moreover, Zheng et al. [12] proposed a User Collaborative Location and Activity Filtering (UCLAF) system, which is based on Tensor decomposition.

In contrast to the aforementioned tensor-based methods, our GeoSocialRec recommender system provides (i) location and activity recommendations (ii) friend recommendations by combining FriendLink algorithm [7] with the geographical distance between users. Moreover, our tensor method includes an incremental stage, where newly created data is inserted into the tensor by incremental solutions [9, 3].

3 GeoSocialRec System Description

Our GeoSocialRec system consists of several components. The system's architecture is illustrated in Figure 1, where three main sub-systems are described: (i) the Web Site, (ii) the Database Profiles and (iii) the Recommendation Engine. In the following sections, we describe each sub-system of GeoSocialRec in detail.

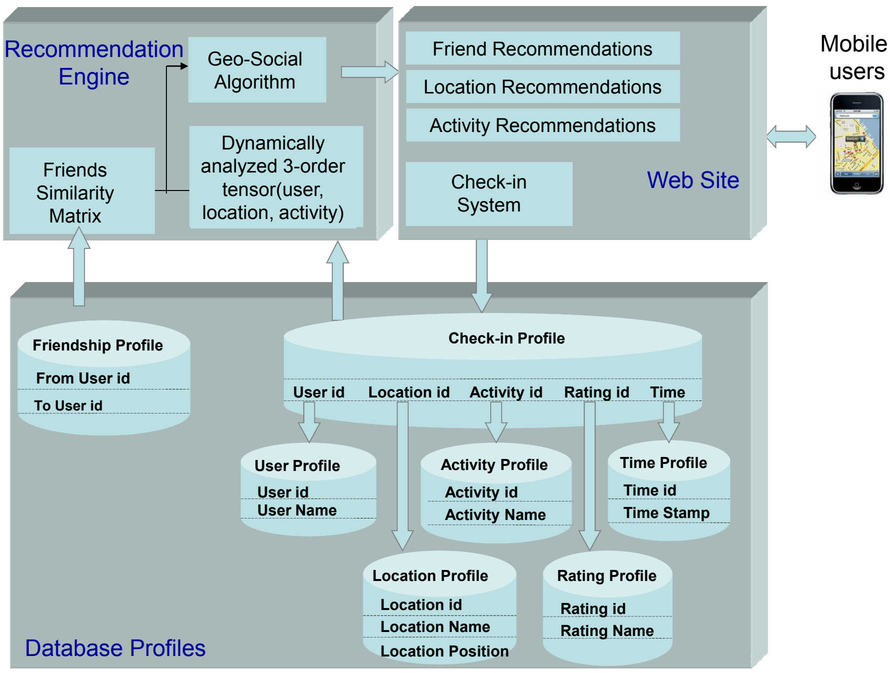


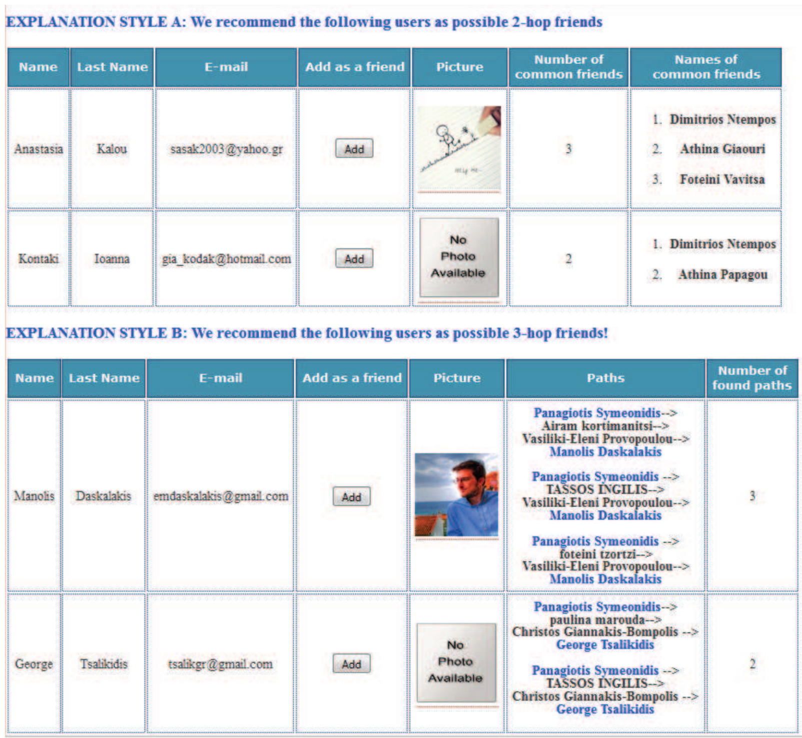
Fig. 1. Components of the GeoSocialRec recommender system.

3.1 GeoSocialRec web site

The GeoSocialRec system uses a web site[1] to interact with the users. The web site consists of four subsystems: (i) the friend recommendation, (ii) the location recommendation, (iii) the activity recommendation, and (iv) the check-in subsystem. The friend recommendation subsystem is responsible for evaluating incoming data from the Recommendation Engine of GeoSocialRec and providing updated friend recommendations. To provide such recommendations, the web site subsystem implements the FriendLink algorithm [7] and also considers the geographical distance between users and check-in points. The same applies to the location and activity recommendation sub-systems, where new and updated location and activity recommendations are presented to the user as new check-ins are stored in the Database profiles. Finally, the check-in subsystem is responsible for passing the data inserted by the users to the respective Database profiles.

Figure 2 presents a scenario where the GeoSocialRec system recommends four possible friends to user *Panagiotis Symeonidis*. As shown, the first table recommends Anastasia Kalou and Ioanna Kontaki, who are connected to him with 2-hop paths. The results are ordered based on the second to last column

[1] `http://delab.csd.auth.gr/geosocialrec`



EXPLANATION STYLE A: We recommend the following users as possible 2-hop friends

Name	Last Name	E-mail	Add as a friend	Picture	Number of common friends	Names of common friends
Anastasia	Kalou	sasak2003@yahoo.gr	Add		3	1. Dimitrios Ntempos 2. Athina Giaouri 3. Foteini Vavitsa
Kontaki	Ioanna	gia_kodak@hotmail.com	Add	No Photo Available	2	1. Dimitrios Ntempos 2. Athina Papagou

EXPLANATION STYLE B: We recommend the following users as possible 3-hop friends!

Name	Last Name	E-mail	Add as a friend	Picture	Paths	Number of found paths
Manolis	Daskalakis	emdaskalakis@gmail.com	Add		Panagiotis Symeonidis--> Airam kortimanitsi--> Vasiliki-Eleni Provopoulou--> Manolis Daskalakis Panagiotis Symeonidis --> TASSOS INGILIS--> Vasiliki-Eleni Provopoulou--> Manolis Daskalakis Panagiotis Symeonidis --> foteini tzortzi--> Vasiliki-Eleni Provopoulou--> Manolis Daskalakis	3
George	Tsalikidis	tsalikgr@gmail.com	Add	No Photo Available	Panagiotis Symeonidis--> paulina marouda--> Christos Giannakis-Bompolis --> George Tsalikidis Panagiotis Symeonidis --> TASSOS INGILIS--> Christos Giannakis-Bompolis --> George Tsalikidis	2

Fig. 2. Friend recommendations provided by the GeoSocialRec system

of the table, which indicates the number of common friends that the target user shares with each possible friend. As shown in Figure 2, Anastasia Kalou is the top recommendation because she shares 3 common friends with the target user. The common friends are then presented in the last column of the table. The second table contains two users, namely Manolis Daskalakis and George Tsalikidis, who are connected to the target user via 3-hop paths. The last column of the second table indicates the number of found paths that connect the target user with the recommended friends. Manolis Daskalakis is now the top recommendation, because he is connected to Panagiotis Symeonidis via three 3-hop paths. It is obvious that the second explanation style is more analytical and detailed, since users can see, in a transparent way, the paths that connect them with the recommended friends.

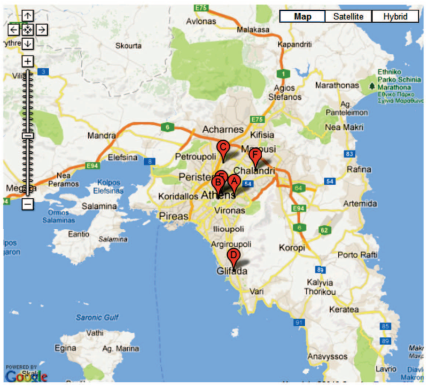
Figure 3a shows a location recommendation, while Figure 3b depicts an activity recommendation. As shown in Figure 3a, the target user can provide to the system the activity she wants to do and the place she is (i.e. Bar in Athens). Then, the system provides a map with bar places (i.e. place A, place B, place C, etc.) along with a table, where these places are ranked based on the number of users' check-ins and their average rating. As shown in Figure 3a, the top recommended Bar is Mojo (i.e. place A), which is visited 3 times (from the target user's friends) and is rated highly (i.e. 5 stars). Regarding the activity recommendation, as shown in Figure 3b, the user selects a nearby city (i.e. Thessaloniki) and the system provides activities that she could perform. In this case, the top recommended activity is sightseeing the White Tower of Thessaloniki, because it is visited 14 times and has an average rating of 4.36.

We recommend the following Point(s) of Interest
for the Activity: Bar
in the city of:Athens

EXPLANATION STYLE A:

We recommend the following POI's (Point of Interest) based on total Check-ins!

A/A	Point Of Interest	POI Address	Explanation Style A: Total Check-Ins	Average Rating from style A	Go To
A	Mojo	Παπαδιαμαντοπούλου 8, Ζωγράφου 157 71, Ελλάδα	3	5.0000	Move!
B	A for Athens	Ερμού 82, Αθήνα 105 55, Ελλάδα	3	3.6667	Move!
C	Rox Box	Ειρήνης 2-10, Φιλαδέλφεια Χαλκηδόνα 143 41, Ελλάδα	2	4.5000	Move!
D	Holy Spirit	Λαοδικης 18, Γλυφάδα 166 74, Ελλάδα	2	4.0000	Move!
E	Mo Better	Κωλέττη 28-42, Αθήνα, Ελλάδα	2	4.0000	Move!
F	Allo Bar	Thoukydidou 9-13, Chalandri 15232, Greece	2	2.0000	Move!



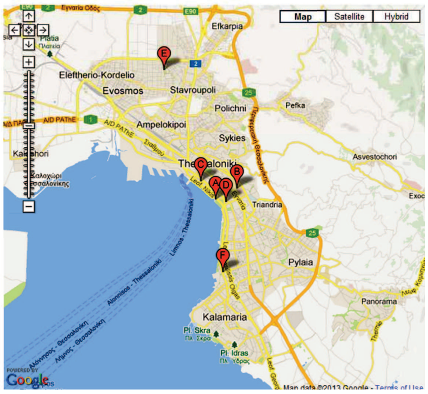
(a)

We recommend the following Activities
in the city of:Thessaloniki

EXPLANATION STYLE A:

We recommend the following activities based on total Check-ins!

A/A	Activity	Point Of Interest	POI Address	Explanation Style A: Total Check-Ins	Average Rating from style A	Go To
A	Sight-seeing	White Tower	Nikis Avenue--Paralia Thessalonikis	14	4.3571	Move!
B	Education	Aristotle University of Thessaloniki	Egnatia & Kondriktonos--Aristotle Campus	13	4.2308	Move!
C	Sight-seeing	Aristotelous Square	Aristotle Square--City Center	11	4.1818	Move!
D	Museums	Archaeological Museum of Thessaloniki	Ανδρόνικου, Θεσσαλονίκη 54621, Ελλάς--	8	4.0000	Move!
E	Cinema	Video Land	Ιθάκης 63-71, Εύοσμο 56224, Ελλάς--	8	2.6250	Move!
F	Bar	BRISTOL	George Papandreou 24--Poseidonio	7	4.2857	Move!



(b)

Fig. 3. Location and activity recommendations made by the Geo-social recommender system.

3.2 GeoSocialRec database profiles

The database that supports the GeoSocialRec system is a MySQL (v.5.5.8)[2] database. MySQL is an established Database Management System (DBMS), which is widely used in on-line, dynamic, database driven websites.

The database profile sub-system contains five profiles where data about the users, locations, activities and their corresponding ratings are stored. As shown in Figure 1, this data are received by the Check-In profile and along with the Friendship profile, they provide the input for the Recommendation Engine sub-system. Each table field represents the respective data that is collected by the Check-In profile. User-id, Location-id and Activity-id refer to specific ids given to users, locations and activities respectively.

3.3 GeoSocialRec recommendation engine

The recommendation engine is responsible for collecting the data from the database and producing the recommendations, which will then be displayed on the web site. As shown in Figure 1, the recommendation engine constructs a friends similarity matrix by implementing the FriendLink algorithm proposed in [7]. The average geographical distances between users' check-ins are used as link weights. To obtain the weights, we calculate the average distance between all pairs of POIs that two users have checked-in. The recommendation engine also produces a dynamically analyzed 3-order tensor, which is firstly constructed by the HOSVD algorithm and is then updated using incremental methods [9], both of which are explained in later sections.

4 Experimental Results

In this section, we study the performance of FriendLink and ITR approaches in terms of friend, location and activity recommendations. To evaluate the aforementioned recommendations we have chosen two real data sets. The first one, denoted as GeoSocialRec data set, is extracted from the GeoSocialRec site [3]. It consists of 102 users, 46 locations and 18 activities. The second data set, denoted as UCLAF [13], consists of 164 users, 168 locations and 5 different types of activities, including "Food and Drink", "Shopping", "Movies and Shows", "Sports and Exercise", and "Tourism and Amusement".

The numbers c_1, c_2, and c_3 of left singular vectors of matrices $U^{(1)}, U^{(2)}, U^{(3)}$ for ITR, after appropriate tuning, are set to 25, 12 and 8 for the GeoSocialRec dataset, and to 40, 35, 5 for the UCLAF data set. Due to lack of space we do not present experiments for the tuning of c_1, c_2, and c_3 parameters. The core tensor dimensions are fixed, based on the aforementioned c_1, c_2, and c_3 values.

We perform 4-fold cross validation and the default size of the training set is 75% (we pick, for each user, 75% of his check-ins and friends randomly).

[2] `http://www.mysql.com`

[3] http://delab.csd.auth.gr/~symeon

The task of all three recommendation types (i.e. friend, location, activity) is to predict the friends/locations/activities of the user's 25% remaining check-ins and friends, respectively. As performance measures we use precision and recall, which are standard in such scenarios.

4.1 Comparison results

In this section, we study the accuracy performance of ITR in terms of precision and recall. This reveals the robustness of ITR in attaining high recall with minimal losses in terms of precision. We examine the top-N ranked list, which is recommended to a test user, starting from the top friend/location/activity. In this situation, the recall and precision vary as we proceed with the examination of the top-N list. In Figure 4, we plot a precision versus recall curve.

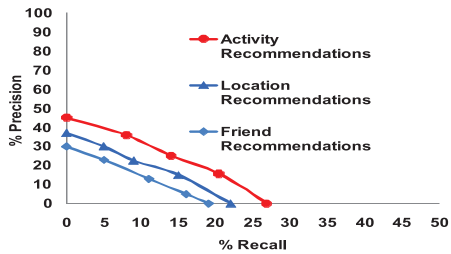


Fig. 4. Precision Recall diagram of ITR and FriendLink for activity, location and friend recommendations on the GeoSocialRec data set

As it can be seen, the ITR approach presents high accuracy. The reason is that we exploit altogether the information that concerns the three entities (friends, locations, and activities) and thus, we are able to provide accurate location/activity recommendations. Notice that activity recommendations are more accurate than location recommendations. A possible explanation could be the fact that the number of locations is bigger than the number of activities. That is, it is easier to predict accurately an activity than a location. Notice that for the task of friend recommendation, the performance of Friendlink is not so high. The main reason is data sparsity. In particular, the friendship network has average nodes' degree equal to 2.7 and average shortest distance between nodes 4.7, which means that the friendship network cannot be considered as a "small world" network and friend recommendations can not be so accurate.

For the UCLAF data set, as shown in Figure 5, the ITR algorithm attains analogous results. Notice that the recall for the activity recommendations, reaches 100% because the total number of activities is 5. Moreover, notice that in this diagram, we do not present results for the friend recommendation task, since there is no friendship network in the corresponding UCLAF data set.

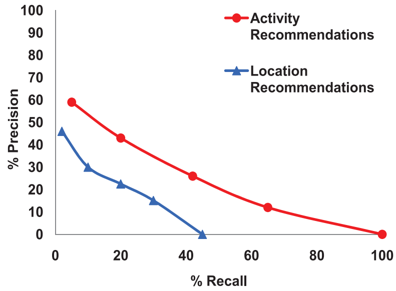


Fig. 5. Precision Recall diagram of ITR for activity and location recommendations on the UCLAF data set

4.2 User study for location and activity recommendations

We conducted a survey to measure user satisfaction against two styles of explanation. The first concerns the "Peoples' Check-ins" style (denoted as style A), and the second is the "Friends' Check-ins" style (denoted as style B). For the activity recommendation, Figure 6a shows the explanation style A of the GeoSocialRec[4] site, while Figure 6b depicts the explanation style B.

Figure 6a depicts 3 recommended activities (Sightseeing, Education, Sightseeing) based on the explanation style A. As shown in the first row of Figure 6a, the first recommended activity to the target user is "sightseeing" to the monument of White Tower (the first and the second column). The explanation for this recommendation is the fact that White Tower has been visited by 14 different people and got an average rating of 4.3571 in [0-5] rating scale, as shown in the last two columns of the first row in Figure 6a.

Figure 6b depicts also a top-3 (Bar-Restaurant, Sightseeing, Transports) list of recommended activities. As shown in Figure 6b, the first recommended activity to the target user is eating to a bar-restaurant named Dishcotto (the first and the second column). The explanation for this recommendation is the fact that 6 check-ins in Dischotto have been made by the target user's friends and it got an average rating of 3 in [0-5] rating scale, as shown in the last two columns of the first row in Figure 6b. Notice that, for the location recommendation, the explanation styles A and B are similar to the aforementioned ones.

We designed the user study with 50 pre- and post-graduate students of Aristotle University, who filled out an on-line survey. The survey was conducted as follows: Firstly, we asked each target user to provide the system with ratings and comments for at least five point of interests (POIs), so that a decent recommendation along with some meaningful explanations could be provided by our system. Secondly, we asked them to rate separately, from 1 (dislike) to 5 (like), each recommended location/activity list based on the two different styles of explanations. In other words, we asked target users to rate separately each

[4] `http://delab.csd.auth.gr/geosocialrec`

EXPLANATION STYLE A:

We recommend the following activities based on total Check-ins!

Activity	Point Of Interest	POI Address	Explanation Style A: Total Check-Ins	Average Rating from style A
Sight-seeing	White Tower	Nikis Avenue–Paralia Thessalonikis	14	4.3571
Education	Aristotle University of Thessaloniki	Egnatia & Kondriktonos–Aristotle Campus	13	4.2308
Sight-seeing	Aristotelous Square	Aristotle Square–City Center	11	4.1818

(a)

EXPLANATION STYLE B:

We recommend the following activities based on the Check-Ins made by your friends!

Activity	Point Of Interest	POI Address	Explanation Style B: Check-Ins made by your friends	Average Rating from style B
Bar-Restaurant	Dishcotto	Analipseos 6-20, Panorama 55236, Greece–	6	3.0000
Sight-seeing	Aristotelous Square	Aristotle Square–City Center	4	3.7500
Transports	International Airport 'Makedonia' (Thessaloniki)	Kalamaria Thessaloniki–Kalamaria	4	2.7500

(b)

Fig. 6. Explaining recommendations based on (a) total peoples' check-ins, and (b) target user's friends' check-ins.

explanation style to explicitly express their actual preference among the two styles.

We assume that, explanation style B will be the users' favorite choice, since it relies on their friends' check-ins. Notice that according to homophily theory [6] (i.e., "love of the same") individuals tend to prefer the same things that similar other users do like.

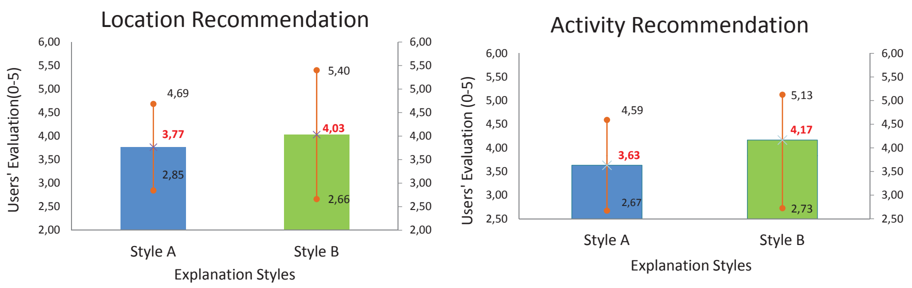
Our results are illustrated in Table 1. The second and third columns contain for explanation style A, the mean μ_A and standard deviation σ_A of the ratings provided by users for location and activity recommendations, respectively. As shown, the mean value of ratings μ_A for location recommendation is 3.77, whereas μ_A for activity recommendation is 3.63. The fact that the mean of ratings is higher than 2.5 in the [0-5] rating scale means that the quality of recommendations is good. The fourth and fifth columns contain for explanation style B, the mean μ_B and standard deviation σ_B of the ratings provided by users. As shown, the mean value of ratings μ_B for location recommendation is 4.03, whereas μ_B for activity recommendation is 4.17. This is a clear support of the assumption that explanation style B is the users' favorite choice.

Moreover, we computed the distribution of the difference between means of explanation styles A and B, to verify that it is statistically significant. That is, the difference between ratings of style A and B should not be centered around 0. Thus, we measured the mean μ_d and standard deviation σ_d of the differences

Table 1. Results of the user survey for location/activity recommendations.

Recommendation Type	μ_A	σ_A	μ_B	σ_B	μ_d	σ_d
Location	3.77	1.13	**4.03**	1.40	0.26	0.32
Activity	3.63	0.96	**4.17**	1.44	0.54	0.31

between ratings of explanation style A and ratings of explanation style B. These values, for each recommendation type, are presented in the sixth and seventh columns of Table 1. We run paired t-tests with the null hypothesis $H_0(\mu_d = 0)$ for the two recommendation types (i.e. location and activity). We found that for both location and activity recommendations, $H_0(\mu_d = 0)$ is rejected at the 0.05 significance level. This verifies the assumption that explanation style B is the users' favorite choice. Finally, Figures 7a and 7b show a visual representation of the mean and standard deviation of users' ratings, evaluating the explanation styles A and B for both location and activity recommendation, respectively. As expected, style B outperforms A in both recommendation types (i.e. location and activity recommendation). That is, likes of our friends have a greater impact in our own choices.



(a) (b)

Fig. 7. Mean and standard deviation of users' ratings evaluating explanation styles A and B for (a) location recommendation, and (b) activity recommendation.

4.3 User study for friend recommendations

We conducted a second survey to measure user satisfaction against the explanation styles in friend recommendation. We have also tested two styles of explanation. Explanation style A justifies friend recommendations based on the number of common friends between the target user and his candidate friends. That is, explanation style A considers only pathways of maximum length 2 between a target user and his candidate friends. Explanation style B can provide more robust explanations, by presenting as explanation, all human chains (i.e. pathways of more than length 2) that connect a person with his candidate friends.

For instance, an example of a social network is shown in Figure 8. The explanation style A for recommending new friends to a target user U_1 is as follows: "People you may know : (i) user U_7 because you have two common friends (user U_5 and user U_6) (ii) user U_9 because you have one common friend (user U_8) ...". The list of recommended friends is ranked based on the number of common friends each candidate friend has with the target user.

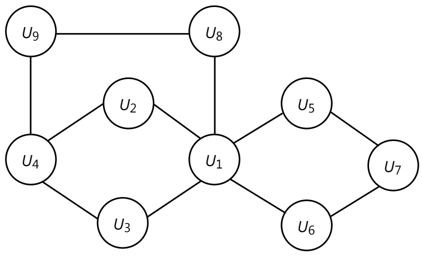


Fig. 8. Social Network Example.

Based on explanation style B, a user can also get, along with a friend recommendation, a more robust explanation. This explanation contains all human chains that connect him with the recommended person. For instance, in our running example, U_1 would get as explanation for recommending to him U_4 the following human chains that connect them:

1. $U_1 \rightarrow U_2 \rightarrow U_4$
2. $U_1 \rightarrow U_3 \rightarrow U_4$
3. $U_1 \rightarrow U_8 \rightarrow U_9 \rightarrow U_4$

This means that U_4 is connected with U_1 with two pathways of length 2 and 1 pathway of length 3. It is obvious that explanation style B is analytic and informative.

We designed the same user study with the one described in Section 4.2. We assumed that explanation style B will be the users' favorite one, because it is more transparent and informative than explanation style A. Our results are illustrated in Table 2. As shown, the mean value of ratings μ_B of style B is 4.10, whereas μ_A is 3.8. This is a first indication supporting our assumption that explanation style B is the users' favorite choice. Moreover, we measured the mean μ_d and standard deviation σ_d of the differences between means of explanation style A and ratings of explanation style B. These values are presented in the sixth and seventh columns of Table 2. We run paired t-tests with the null hypothesis $H_0(\mu_d = 0)$. We found that the null hypothesis is rejected at the 0.05 significance level. This verifies our assumption that explanation style B is the users' favorite choice.

Table 2. Results of the user survey for friend recommendations.

Recommendation Type	μ_A	σ_A	μ_B	σ_B	μ_d	σ_d
Friend	3.8	1.13	**4.10**	0.99	0.30	0.47

Finally, Figure 9 shows a visual representation of the mean and standard deviation of users' ratings, evaluating the explanation styles A and B for friend recommendation. As expected, style B outperforms A. That is, explanation style B increases the acceptance of a recommender system, since users can understand the strengths and limitations of the recommendation process.

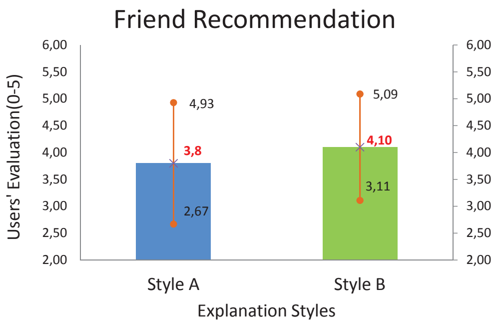


Fig. 9. Mean and standard deviation of users' ratings evaluating explanation styles A and B for friend recommendation.

5 Conclusion and Future Work

In this paper, we have proposed the GeoSocialRec recommender system, which is capable of recommending friends, locations and activities and simultaneously provides explanations along with the recommendations. We have conducted a user study, which has shown that users tend to prefer their friends opinion more than the overall users' opinion. Moreover, in friend recommendation, the users' favorite explanation style is the one that uses all human chains (i.e. pathways of more than length 2) that connect a person with his candidate friends. As future work, we are planning on comparing our explanation styles with other hybrid explanation styles, which combine more features for justifying their recommendation.

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