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Location Recommendation based on location-based social networks for Entertainment services

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Abstract

Recent advances in mobile devices permit the use of geographic data in online social networks based on traditional Web site. Which leads to the formation of location based social networks. One of the services provided in these networks is personal location recommendation. While real-world users follow time patterns when they visit the places, so far little attention has been taken to role of the time as an influential factor in users decisions. First, we study user's behavior based on temporal-spatial patterns and social dimensions of how user's friend affects user's decision. Then we model the social, geographical and temporal patterns. We provide a model to recommend location to users. The proposed model examine on real world data of online location social network Foursquare. The results show improvements of our model compare to pervious works.

Keywords: *Location recommender systems, Location Based Social network, geo-temporal influence.*

1. Introduction

Recent advances in technology of mobile devices and Global Positioning System allows the formation and evolution of the location-based social networks. In other words, it provides the geographical dimensions to the web. Foursquare and Yelp are some of location based social networks that provide location based services. They allow their users to take advantage of their services, with a focus on massive amounts of personal data with geographical information of users. As of this writing, Foursquare has more than 55 million users and more than 6 billion Check-ins worldwide. These Social networks tell user's location and places that user's friends have been visited before. In this paper, we use Foursquare data set available online[1].

Considering breadth and complexity of location-based social networks and facilities provided by them users always need to easily fit between their interests and content from the network. As far as user satisfaction and location based marketing has become an essential task in location based social networks [1, 2].

Location based social network sites can be driven by three dimensions: users, location and time. Figure 1 Shows the status of each of these factors on a location based social network.

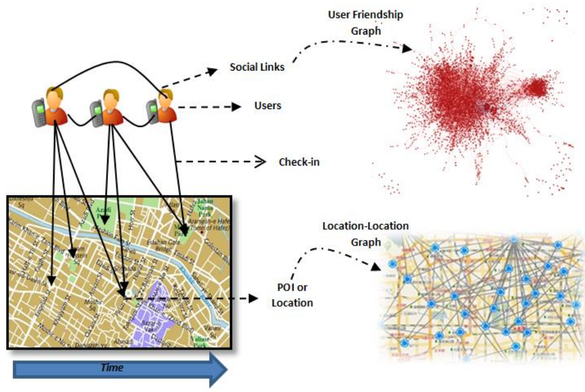

Fig. 1 dimensions of location based social networks.

Relationship and social interactions, social network integration with recommendation systems theoretically can take to improve the performance of the recommendation system. In other word, a recommender system can provide a recommendation based on user's friend preferences and settings. Evidence show that people tend to rely more on the advice of his friends to advise from similar people but unknown [1,2,3,4,5,6,7]. Generally, inspired by social influence theory which states that "social friends have similar behavior." [2,8] The effects of online social relations in location based social network can be examined. In Figure 2, We have examined check-ins behavior of two friends in terms of spatial and temporal patterns. Two friends have a similar check-ins pattern. They usually visit the same place in similar time. The reason could be that friends visiting places with each

[1] http://www.public.asu.edu/~hgao16/dataset.html

other. For example, two friends visit a gallery together. Meanwhile, friends usually taste similar to each other.

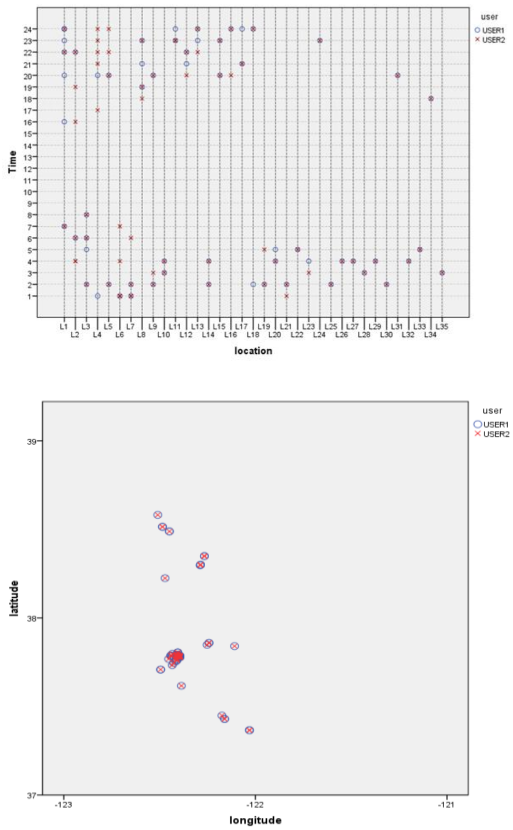

Fig. 2 check-ins behavior of two friends in terms of spatial and temporal patterns.

The effects of geographical distance of users and places; Research shows that users are interested in visiting places close to where they live and work or the distance between the workplace and the place they live.
We examine the distribution of distance between visited places by users on real world data set obtained from Foursquare. We observed that the majority of check-ins made by users within 11 km from each other which are conformance with previous findings [2, 9]. Figure 3. Shows the geographical distribution of the distance between places on our data set.

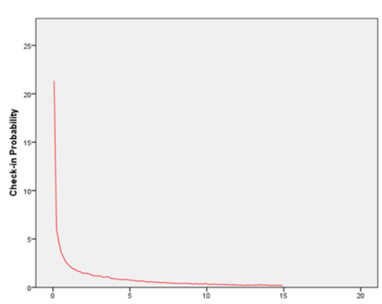

Fig. 3 geographical distribution of the distance between places.

Almost all previous studies distance distribution globally and considered by all users which follow a normal distribution [2, 9]. While the geographical effects in the real world is personal. We considered the geographical distance distribution between each pair of locations visited by a user personal [11]. Figure 4, Shows distance distribution of check-ins for two users in our data set. Distribution of check-ins for each user is different and is purely personal. User 2 visits focused on the United States of America with few trips to Europe. While User 1 visits are limited to a specific area in the United States of America. It can be explained so that users visit places according to their mood, Income, home, work, and many others. For example, a person traveled widely to different parts of the world because of his work or because of appropriate income level.

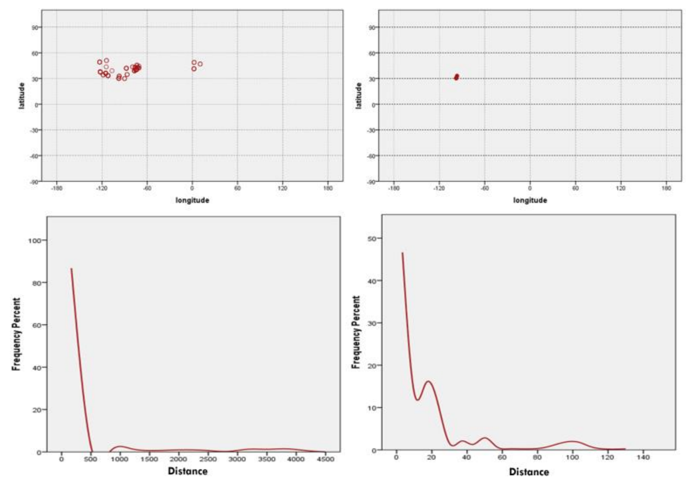

Fig. 4 distance distribution of check-ins for two users.

Human geographical displacement show major time patterns [11,12,13] and have effective relation to location features. For example, a user goes to work at 8:00, goes to restaurant about 12:00 for lunch, at about 19:00 he goes for dinner, and then goes out to the movies. So we can say the daily patterns of check-ins are one of the fundamental patterns that represent user displacement behavior [14]. Study the features that are included in the daily patterns can help us to understand the people displacement behavior better. And therefore, it can improve the location recommendation systems. In Figure 5, we studied check-ins behavior of user U in New York City and user V in Milan at different times of the day for 5 users' favorite places.
Check-ins behavior patterns of users changes during the day. Check-ins number increase from morning until lunch at noon that reaches their peak. Then the check-ins number decrease until we again observe a growth in the number of visits carried out in evening. Also the check-ins behavior

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patterns of users are different according to the local culture and habits of users.

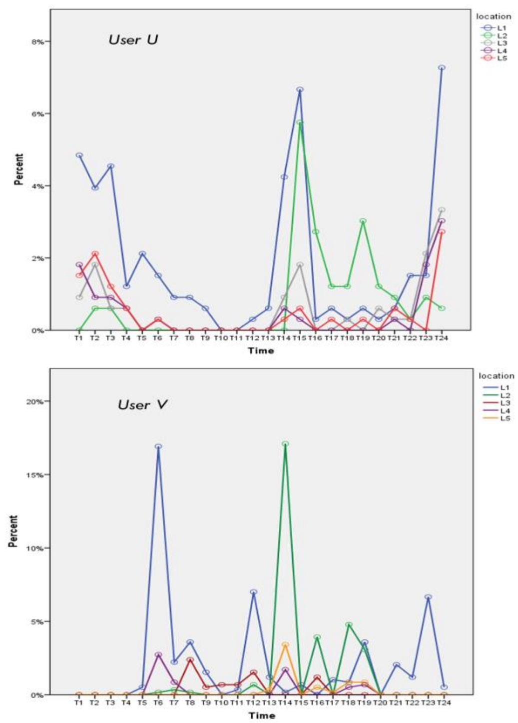


Fig. 5 check-ins behavior of user U in New York City and user V in Milan.

In Figure 6, we compare temporal distribution of check-in behavior in several countries with each other. People in Italy raising early morning compared to other countries and are more active in morning, and their activity reduce overnight While in New York City visiting of places continues during the night.

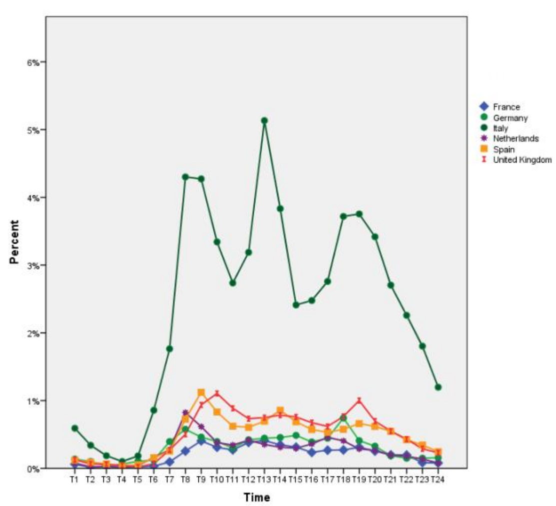


Fig. 6-a temporal distribution of check-in behavior in Europe.

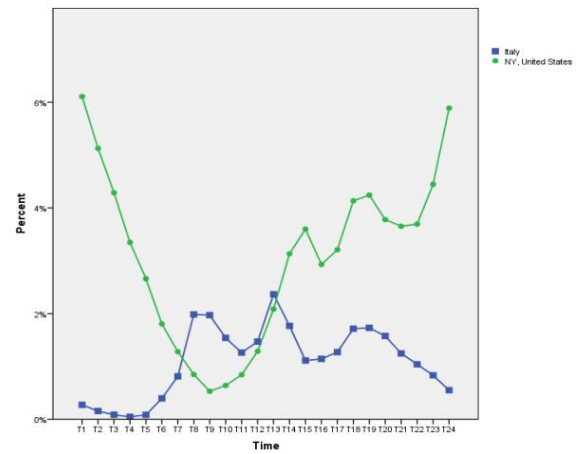
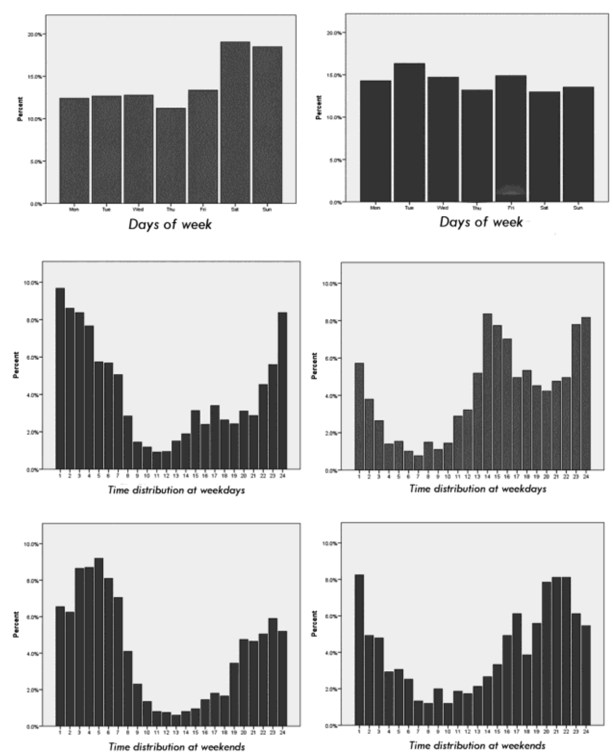


Fig. 6-b. temporal distribution of check-in behavior in NY & Milan.

We compare time distribution and days distribution of different activities. Figure 7, shows Time and daily distribution of two category food and bar. more Check-ins in bar occur in weekends than week days. On the other hand, Time distributions during the week for both bar and food categories are at late hours of the day.



a) b)

Fig. 7 Time and daily distribution of two category a) Bar and b) Food

Since users check-ins behavior related to users activities, and the activities of users related to time we divided 24 hours a day into 6 equal slots: 00:00- 04:00 ، 04:00-08:00 ، 08:00-12:00 ، 12:00-16:00 ، 16:00-20:00 ، 20:00- 24:00.

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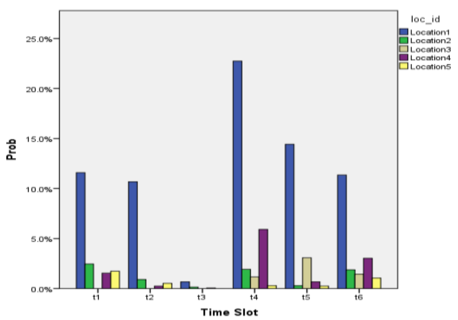
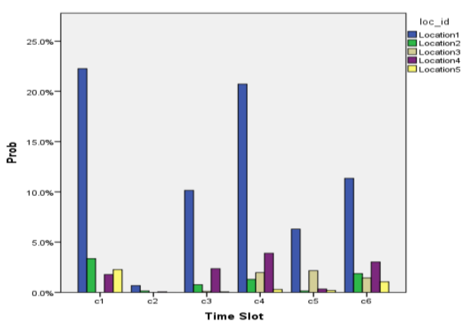
The corresponding time intervals are displayed by t_1 ، t_2 ، t_3 ، t_4 ، t_5 ، t_6. Then we examine check-ins behavior for 5 most popular visited places by user with respect to time slots. Figure 8-a shows a diagram of the check-in behavior of user U visiting 5 most popular places at intervals of t_1 to t_6. In a second experiment, 24 hours a day, divided into six unequal slots: 00:00–08:00 ،08:00–12:00 ،12:00–14:00، 14:00–18:00،18:00–20:00, 0:00–24:00. The corresponding time intervals are displayed by c_1 ، c_2 ، c_3 ، c_4 ، c_5 ، c_6. Then we examine check-ins behavior for 5 most popular visited places by user with respect to time slots. Figure 8-b shows a diagram of the check-in behavior of user U visiting 5 most popular places at intervals of c_1 to c_6. The reason for the different length of intervals is that the amounts of activities in each period are different.

Generally it can be said that different similarity between different time periods is visible in user check-ins behavior that we calculate that in proposed algorithm and use it in location recommendation.



a)



b)

Fig. 8 diagram of the check-in behavior of user U visiting 5 most popular places at a) equal time slots, b) unequal time slots

2. Modeling

2.1 Social Collaborative Filtering

The aim of CF is to find patterns that users rate items**.** CF is based on this argument that if the user has been agreed with his neighbor, he will continue it in the future [18].

Because friends are interested in shearing common interest, CF models social influence as user-user matrix to improve the recommendation quality. This type of technique is known as SCF.

Let U be a set of users, L be a set of locations (i.e., POIs), and C be a user-location rating matrix derived from check-in activities, each C_{ij} denotes the frequency of u_i visiting location l_j . the rating of u_i to unvisited location l_j , denoted as $\widehat{c_{ij}}$, can be predicted using the user-based SCF method[15,16]:

$$\begin{cases} c_{i,j} = 1 & \text{Visited} \\ c_{i,j} = 0 & \text{otherwise} \end{cases}$$

$$\widehat{c_{ij}} = \frac{\sum_{u_k \in U \wedge k \neq i} SocSim(u_i, u_k).c_{kj}}{\sum_{u_k \in U \wedge k \neq i} SocSim(u_i, u_k)} \qquad (1)$$

$SocSim(u_i, u_k)$ in equation (1) is the similarity between user u_i and u_k , taken from the social influence matrix between users instead of user-based CF.

To calculate the degree of similarity between two friends we define 3 social relationships factors. In a LBSN data, the most important information is user's common check-ins, users common social ties and distance among users for user similarity measurement.

One way to estimate the similarity between two friends is Calculating their common social circles[9]. For this purpose we calculate similarities between social friend using the following method:

$$FriendshipSim(u_i, u_k) = \begin{cases} \frac{|F(u_i) \cap F(u_k)|}{|F(u_i) \cup F(u_k)|} & \text{, if } u_i \text{ and } u_k \text{ are friends} \\ 0 & \text{, otherwise} \end{cases} \qquad (2)$$

In Equation 2, $F(u_i)$ specifies a set of users who have a social relationship with user u_i.

We considered similar location check-ins as similarity of two users who have a social relationship and calculate their similarity and social influence using the following method[17]:

$$ChechSim(u_i, u_k) = \begin{cases} \frac{|L(U_i) \cap L(U_k)|}{|L(U_i) \cup L(U_k)|} & \text{, if } u_i \text{ and } u_k \text{ are friends} \\ 0 & \text{, otherwise} \end{cases} \qquad (3)$$

In Equation 3, (U_i) specifies a set of locations which were visited by user u_i.

Also to utilizes the users geographical effect we considered the distance between friend's home to adjust the weight of similar users in the SCF [7]. We calculate the similarity between two users u_i and u_k based on social and geographical distance between their homes using the following method:

$$\mathrm{SGSim}(u_i,u_k)=\begin{cases}1-\frac{\mathrm{distance}\,(u_i,u_k)}{\max_{u_f\in F(u_i)}\mathrm{distane}\,(u_i,u_f)} & \text{, if } u_i \text{ and } u_k \text{ are friends}\\ 0 & \text{, otherwise}\end{cases} \tag{4}$$

In Equation 4, distance (u_i, u_k) specified Geographic distance between u_i and u_k home. $u_f \in F(u_i)$ also is the set of users that have social relationship with user u_i.
Finally similarity between users u_i and u_k estimates as follow:

$$\begin{aligned}\mathrm{SocSim}(u_i,u_k) = & (1-\eta-\delta).\,\mathrm{FriendshipSim}(u_i,u_k)\\ & +\eta.\,\mathrm{ChechSim}(u_i,u_k)\\ & +\delta.\,\mathrm{SGSim}(u_i,u_k)\end{aligned} \tag{5}$$

where η and δ are a tuning parameters ranging within [0, 1], if $\delta = 1$ and $\eta = 0$ we will only have the geographical influence. If $\delta = 0$ and $\eta = 1$ we will only have check-in similarity and if $\delta = 0$ and $\eta = 0$ we will only have the social influence. For ease of calculation, the Influence coefficient of each factor is considered equal. we, use the output of equation 5 for input in equation 1 to calculate the user rating of user u_I to new location l_j:

$$\hat{c_{ij}} = \frac{\sum_{u_k\in F(u_i)} \mathrm{SocSim}(u_i,u_k)\,.\,c_{kj}}{\sum_{u_k\in F(u_i)} \mathrm{SocSim}(u_i,u_k)} \tag{6}$$

2.2 Modeling temporal effect

To calculate the temporal effect, we split a day into 6 equal/unequal time slots based on hour. To represent the temporal check-in behavior of users, we introduce the time dimension into the conventional user-location matrix. Specifically, we use user-time-location cube to represent the temporal check-in records. Let U be a set of users, L be a set of locations (i.e., POIs), and C be a user-time-location rating matrix derived from check-in activities, each $C_{u,t,l}$ denotes the frequency of u_i visiting location l_j at time slot t . Then, the rating of u_i to unvisited location l_j at time slot t, denoted as $\hat{c}^{(t)}_{u,t,l}$, can be predicted using following equation:

$$\hat{c}^{(t)}_{u,t,l} = \frac{\sum_{v\in U, v\neq u} \mathrm{CoSim}^{(t)}_{u,v}\, c_{v,t,l}}{\sum_{v\in U, v\neq u} \mathrm{CoSim}^{(t)}_{u,v}} \tag{7}$$

In this case, if two users visit the same places at the same time the similarity of users will be high. Expanding the cosine similarity, the similarity between two users u and v can be calculated as follows:

$$\mathrm{CoSim}^{(t)}_{u,v} = \frac{\sum_{t=1}^{T}\sum_{l\in L} c_{u,t,l}c_{v,t,l}}{\sqrt{\sum_{t=1}^{T}\sum_{l\in L} c^2_{u,t,l}}\sqrt{\sum_{t=1}^{T}\sum_{l\in L} c^2_{v,t,l}}} \tag{8}$$

The user-time-location matrix is much sparser than the user-location matrix.

By considering the time to compute the similarity between two users visiting same places at different times, similarity between users will be 0 according to equation 8.
To overcome this problem, Let $c_{u,t} = \{c_{u,t,1}, c_{u,t,2}, \dots, c_{u,t,L}\}$ be the check-in vector of user u at time t, which is extracted from user-time-location cube. For each user u, we calculate the cosine similarity between every pair of check-in vectors c_{u,t_i} and c_{u,t_j} at time t_i and t_j respectively. Then, we calculate the similarity value between two time slots t_i and t_j to be the average of the similarity values of all users between these two time slots t_j and t_j. For example, for 6 time slot and N users, for each user u_i we calculate cosine similarity between each pair of 6 time slot And then the average similarity for each pair of intervals are calculated for N user. We calculate the similarity between time slots, for two time slots t and t' , using following equation:

$$\mathrm{CoSim}_{t,t'} = \frac{\sum_{u_i\in U}\sum_{l_j\in L} c^{(t)}_{u_i,l_j}\, c^{(t')}_{u_i,l_j}}{\sqrt{\sum_{u_i\in U}\sum_{l_j\in L} {c^{(t)}_{u_i,l_j}}^2}\sqrt{\sum_{u_i\in U}\sum_{l_j\in L} {c^{(t')}_{u_i,l_j}}^2}} \tag{9}$$

Now we can compute the new rating $c_{u,t,l}$ using user base CF:

$$\tilde{c}_{u,t,l} = \sum_{t'=1}^{T} \frac{\rho_{t,t'}}{\sum_{t''=1}^{T}\rho_{t,t''}}\, c_{u,t',l} \tag{10}$$

Then the similarity between user u and v using cosine similarity and the similarity between time slots ρ is calculated as follows:

$$\mathrm{SoSim}^{(ts)}_{u,v} = \frac{\sum_{t=1}^{T}\sum_{l\in L} \tilde{c}_{u,t,l}.\,\tilde{c}_{v,t,l}}{\sqrt{\sum_{t=1}^{T}\sum_{l\in L}\tilde{c}^2_{u,t,l}}\sqrt{\sum_{t=1}^{T}\sum_{l\in L}\tilde{c}^2_{v,t,l}}} \tag{11}$$

Finally, rating for not visited place *l* by user *u* at time *t* using user-based CF is estimated as follows:

$$\hat{c}^{(ts)}_{u,t,l} = \frac{\sum_{v\in U, v\neq u} \mathrm{SoSim}^{(ts)}_{u,v} \sum_{t'\in T} \tilde{c}_{v,t',l}\cdot\rho_{t,t'}}{\sum_{v\in U, v\neq u} \mathrm{SoSim}^{(ts)}_{u,v}} \tag{12}$$

2.3 MODELING PERSONALIZED GEO-TEMPORAL INFLUENCE WITH KERNEL DENSITY ESTIMATION

Most of the previous research assumed that the geographical distance between two locations visited by the same user following a power-law distribution[4].
In this study we expand the proposed model [10] based on time influence to model the distribution of geographical distance using kernel density estimation.

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The kernel density estimation process consists of two steps: distance sample collection and distance distribution estimation.
First step, Distance sample collection: We can acquire a sample for a user by computing the distance between every pair of locations that have been checked in by the user at time slot t, In particular, for a cold-start user with only one check-in, we instead employ the distance between the only visited location and her residence as the sample. To avoid the loss of valuable check-ins data at similar time slots, we use the user-time-location matrix obtained from equation 10 . for user *u* and location *l* in time slot *t*, $\tilde{C}_{u,t,l} = 1$ if $\tilde{C}_{u,t,l} \geq \text{avg}$ .otherwise $\tilde{C}_{u,t,l} = 0$. Avg represents the average value of check-ins taken by the user in the user-time-location matrix. This way, if user u visited location l at time t'' similar to time t'. location l considered visited for time slot t'.
Second step, Let $D^{(t)}$ be the distance sample for a certain user that is drawn from some distribution with an unknown density f. Its kernel density estimator $\hat{f}$ over distance d using $D^{(t)}$ is given by:

$$\hat{f}(d^{(t)}) = \frac{1}{|D^{(t)}|h} \sum_{d' \in D^{(t)}} K(\frac{d^{(t)} - d'}{h}) \tag{13}$$

In this paper we apply the most p opular normal kernel and the optimal bandwidth [19]:

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}} \quad , \quad h = (\frac{4\hat{\sigma}^5}{3n})^{\frac{1}{5}} \approx 1.06\,\hat{\sigma} n^{\frac{-1}{5}}$$

where $\hat{\sigma}$ is the standard deviation of the sample in $D^{(t)}$.
After we find a distance distribution based on kernel density estimation, we design a method based on Equation (13) to derive the probability of a user u_i visiting a new location l_j in time slot t. given u_i 's set of visited locations at time t, $L_i^{(t)} = \{l_{1,t}, l_{2,t}, \ldots, l_{n,t}\}$. First, we compute the distance of every pair of locations in l_i and l_j as follows:

$$d_{ij}^{(t)} = \text{distance}(l_i, l_j) \quad \forall l_i \in L_i^{(t)} \tag{14}$$

Each $d_{ij}^{(t)}$ is then used to derive a probability based on Equation (13) as follows:

$$\hat{f}(d_{ij}^{(t)}) = \frac{1}{|D^{(t)}|h} \sum_{d' \in D^{(t)}} K(\frac{d_{ij}^{(t)} - d'}{h}) \tag{15}$$

Finally, the probability of u_i visiting a new location l_j can be obtained by taking the mean probability as follows:

$$p(l_j | l_i) = \frac{1}{n} \sum_{i=1}^{n} \hat{f}(d_{ij}^{(t)}) \tag{16}$$

Eventually, we can exploit the personalized geographical influence of locations to make location recommendation for u_i by returning the top-k locations l_j with the highest probability $p(l_j | l_i)$ according to Equation (16).

2.4 A unified framework for personalized location recommendation

The purpose of this step is to integrate the results from equations 6 and 12 with results from the equation 16.
First we normalized the rating obtained from equation 6 and 12 using min-max normalization.

$$\bar{p}_{i,j} = \frac{\hat{c}_{i,j} - \min_{l \in L}(\hat{c}_{i,l})}{\max_{l \in L}(\hat{c}_{i,l}) - \min_{l \in L}(\hat{c}_{i,l})} \tag{17}$$

$$\bar{p}_{i,t,j}^{(t)} = \frac{\hat{c}_{i,t,j}^{(t)} - \min_{l' \in L}(\hat{c}_{i,t,l'}^{(t)})}{\max_{l' \in L}(\hat{c}_{i,t,l'}^{(t)}) - \min_{l' \in L}(\hat{c}_{i,t,l'}^{(t)})} \tag{18}$$

In the above equations, $\max_{l \in L}(\hat{c}_{i,l})$ and $\min_{l \in L}(\hat{c}_{i,l})$ denote the maximum and minimum check-in scores of u across all POIs. And $\max_{l' \in L}(\hat{c}_{i,t,l'}^{(t)})$ and $\min_{l' \in L}(\hat{c}_{i,t,l'}^{(t)})$ denote the maximum and minimum check in scores of u at t across all POIs.

$$\tilde{s}_{ij} = \frac{\bar{p}_{i,j} + \bar{p}_{i,t,j}^{(t)} + p(l_j | l_i)}{3} \tag{19}$$

3. Conclusions

We use real world data set obtained from a Foursquare, which is available online. Information about the data is given in Table 1.
To increase recommendation performance we omit users with less than 10 understandable check-ins. Also places that were visited by less than two unique users omitted in final data set. We split each data set into the training set and the testing set because in practice we can only utilize the past check-in data to predict the future check-in events. 90% of check-in data with earlier timestamp are used as the training set and the remaining check-in data are used as the testing set.
In general, recommendation techniques compute a score for each candidate item regarding a target user and return POIs with the top-k highest scores as a recommendation result to the target user.
In this study, to evaluate the proposed method, we use stringent approach To obtain the overall performance of

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Precision and coverage. We take averaged over all user for different values of k from 5 to 50 [20].

Table 1: Information about our data set

Time duration	January-2011 to March- 2011
#Users	6937
#check-ins	326595
# unique locations	25216
Avg. No. of visited POIs per user	47
User-location matrix density	7.45×10-4

User-based collaborative filtering (U), is a state-of-the-art approach for recommender systems[21]. This method only considered the user preferences to make recommendation.
Social collaborative filtering(S), it integrates Social friendship with user preferences to offer the location to the user.
Social and Geographical collaborative filtering (SG), it integrates Social friendship with user preferences and geographical influence to offer the location to the user.
Collaborative filtering with modeling geographical distance with power-law distribution (PD) [2].
Collaborative filtering with modeling geographical distance with multi-center Gaussian distribution (MGM) [4].
Our experiment results on variety of recommendation techniques (listed above) on large scale real data set collected from Foursquare compare to our proposed method called USGT will be discussed.
Figure 9 depicts the overall performance of a variety of recommendation techniques. Our proposed method USGT always exhibits the best accuracy based on precision and recall for all the values of k, where k denotes the number of recommended locations. The details are demonstrated as follows:
U has the worst performance in terms of precision and recall, and loses almost all places visited by the target user. Ignoring the social effects can causes low efficiency. Another reason could be related to sparseness problem of large-scale real world data set.
Considering social effects causes significant improvements in quality in terms of precision and recall on all values of k, significant improvements in S and SG toward U can be seen. These results show that social influence benefits location recommendation. SG has better performance to S by taking to account additional residence information of users to adjust the similarity between users with social friendships. Results shows that geographical influence of user can improve the quality of recommendation because users tend to visit location close to their home so they would like to visit locations with their nearby friends.

PD and MGM improve the recommendations quality by considering the geographical influence of POIs in terms of precision and recall. PD has better quality performance toward MGM technique because of modeling the geographical influence by normal distribution. We can say modeling geographical influence by normal distribution is more accurate than modeling using multi-center Gaussian distribution. More importantly, our proposed model USGT shows better performance toward all the techniques in terms of precisions and recall. It shows that considering temporal influence in recommendation can improve the performance. Also modeling geographical distribution using kernel density is more precise than the normal distribution model uses in PD.

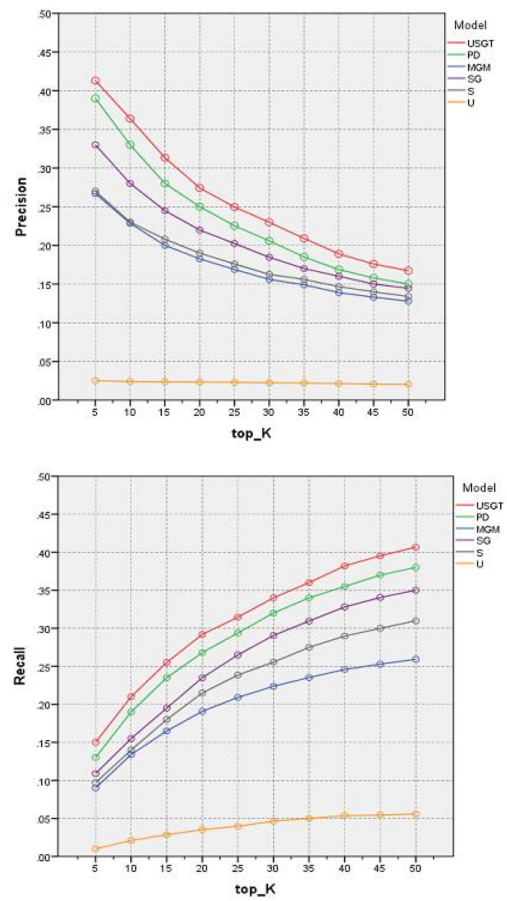

Fig. 9 overall performance of a variety of recommendation techniques

We further study how USGT deals with the data sparsity problem by using only 50% of the check-in data as the training sets. This experiment is in line with the previous work [25].
Figure 10. Shows performance variety of techniques on sparse data. Recall for all techniques and all k- highest values decrease. This is because of the density of the data has been significantly reduced in the test data set and the number of places visited by users in the test data set has

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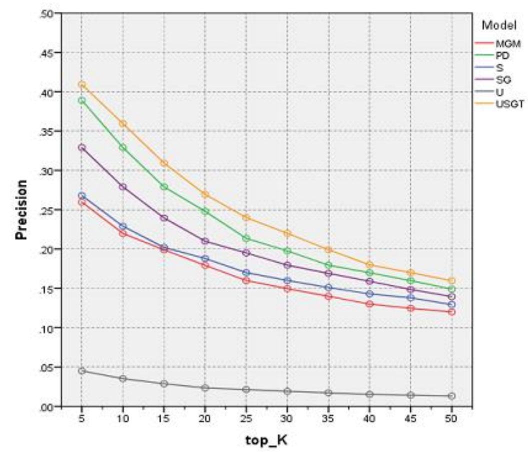
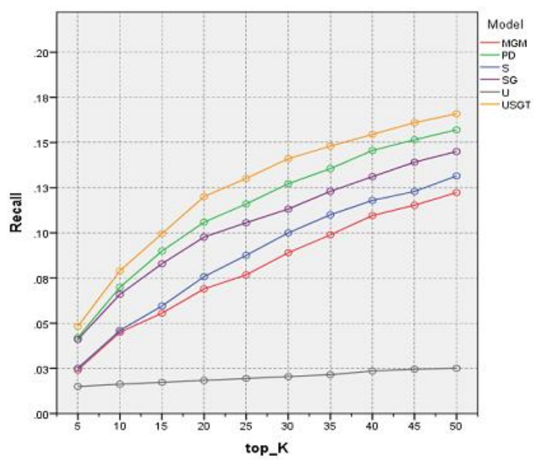
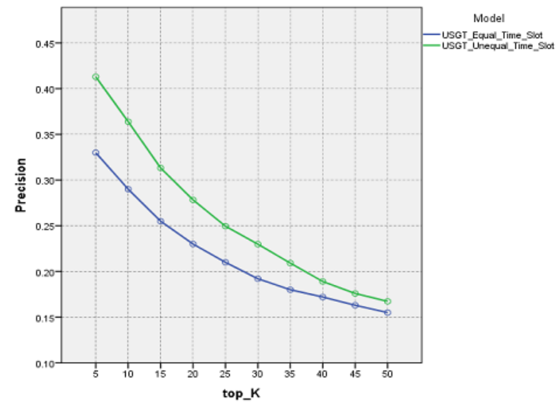
increased. their precisions increases to some extent. Our explanation is that, with the decrease of the proportion of the training data, the lower density decrease the precision, but the larger number of positive POIs in the testing set increases the prior possibility of any recommended location being a positive POI and then contributes to the improvement on precision. Also results of our proposed technique USGT are reduced. That it can be stated that, by involving temporal influence in recommendations our data set will become sparser. As a result we are seeing a reduction in the precision and recall from previous levels.





In Figure 11. We measure precision and recall for the cases when the time slots are divided equally and when they are divided unequally. We explain the results below: the unequal division will improve performance. Because the unequal division will cause the check-ins data denser and will improve the prediction performance. For example, it can be stated that the check-ins behavior in 8:00 to 12:00 and 14:00 to 16:00 is more similar because they usually work in this time period and have similar check-ins towards the time period 12:00-14:00 that is lunch time period.



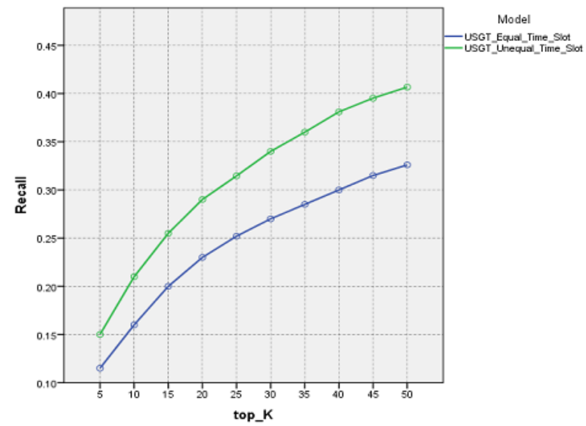


Fig. 11 precision and recall for different time slots

4. Future work

In this paper, we have explored the temporal influence on users' check-in behaviors in location-based social networks (LBSNs). Aiming at overcoming the limitation that the state-of-the-art techniques merely consider the temporal influence as important factor in studying human displacement behavior, we have proposed USGT to consider the user preference, social influence and geo-temporal influence on a user's check-in behavior. In this study, the strength of relationship between friends defined by three factors. For simplicity, we considered each factor equally while each of these factors in fact have a different influence coefficient which can be examined in future studies. We have conducted experiments to evaluate the performance of USGT using large-scale real data set collected from Foursquare. Experimental results show that USGT provides significantly superior location recommendation compared to all other recommendation techniques evaluated in our experiments. In addition to hour, humans' check-in behavior is also influenced by the day of a week and even the month of a year. Hence we plan to exploit other time dimensions in POI recommendations.

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