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Exploring Spatial and Mobility Pattern's Effects for Collaborative Point-of-Interest Recommendation

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ABSTRACT In recent years, researches on the mining of user check-in behaviors for point-of-interest(POI) recommendations has attracted a lot of attention. Personalized POI recommendation is a significant task in location-based social networks(LBSNs) because it helps target users explore their surrounding environment and greatly benefits the business in real life. Although a personalized POI recommendation system can significantly facilitate users' outdoor activities, it faces many challenging problems, such as the hardness to model human mobility and the difficulty to address data sparsity. Moreover, geographical influence on users should be personalized, but current studies only model the geographical influence on all users' check-in behaviors in a universal way. In this paper, we design a novel and effective personalized POI recommendation system. First, our system mines the target user's active area based on his or her check-in history, and designs a personalized user spatial similarity calculation method based on the target user's active area. Secondly, our system takes into account three features of the human mobility pattern: spatial, temporal, and sequential properties. Furthermore, our system designs a novel personalized user mobility pattern similarity calculation method based on the features of human mobility pattern. Finally, a recommendation list is generated based on the idea of collaborative filtering. Compared with the state-of-the-art POI recommendation approaches, the experimental results demonstrate that our system achieves much better performance.

INDEX TERMS POI recommendation, user active area, user mobility pattern, the minimum enclosing circle.

I. INTRODUCTION

With the rapid emergence of location-aware social media, location-based social networks (LBSNs) as shown in Figure 1 are becoming more and more popular with users. LBSNs enable users to easily share content associated with locations. There are numerous types of popular LBSNs. One type of LBSNs represented by Foursquare and Gowalla mainly provides check-in services that attract millions of users to check in their favorite POIs and share their experience in accessing these POIs with friends.

Through in-depth understanding of LBSNs, it can be found that LBSNs are heterogeneous networks, in which there are two nodes with different attributes, namely, location nodes and user nodes. According to these two kinds of nodes, there are three kinds of relationships among LBSNs: location-to-location relationship, user-to-user relationship, location-to-user relationship. And there are three different distances corresponding to the three relationships: the distance between the two locations, the distance between the two users(refers to the geographical distance between the current location of two users), and the distance between a user and a location(refers to the geographical distance between a user's current location and a location). In LBSNs, the distance between two locations directly reflects the degree of correlation between the two locations. For example, many shopping malls are adjacent to each other to form a commercial center. The distance between two users can reflect the similarity between the two users. For example, multiple POIs in each user's travel trajectory are relatively close, that is, the trajectories of the two users are

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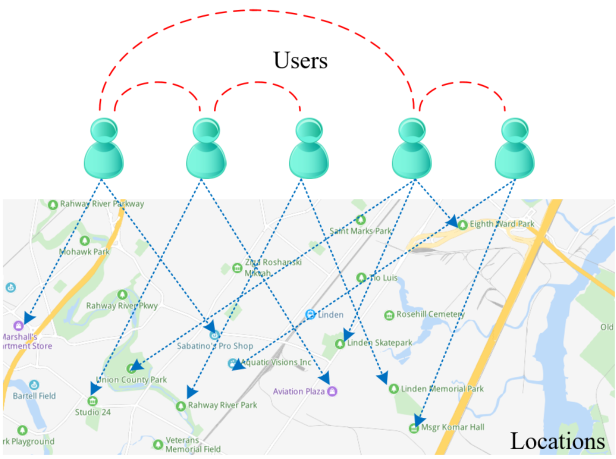


FIGURE 1. Location-based social network.

similar, indicating that the two users have similar preference or mobility pattern. The distance between the user and the location can affect the probability of the user accessing the location. This is because, according to Tobler's First Law of Geography: everything is related to everything else, but near things are more related than distant things, we can know that people are more inclined to visit places closer to themselves. Therefore, it is not difficult to find that locations and users are interdependent in LBSNs. When we study a location, we can't ignore users' access behaviors to this location, and we can't ignore locations that a user has visited when we study this user.

Location information is the most important attribute of LBSNs, which is the link between the physical and digital worlds that closes the distance between the two worlds. Location information also provides conditions for researchers to better explore users' preferences and behaviors. For example, a large amount of check-in data generated by users in LBSNs making it possible to recommend locations that users might be interested in. POI recommendation refers to recommending POIs to users has become a very popular research direction in LBSNs. POI recommendation can help users understand unfamiliar cities as soon as possible and can also help them to choose their travel destinations. POI recommendation is also of great commercial value, such as helping companies choose where to place their ads in a city.

Compared with the traditional recommendation system, due to the dependence of users and locations and the unique properties of locations in LBSNs, the POI recommendation system has become more complex. There are many difficulties and challenges different from the traditional recommendation system, as follows:

- **Implicit user feedback.** The ranking data used in traditional recommendation systems(such as music recommendation system or movie recommendation system) is a kind of explicit feedback, that is, users directly express their "like" or "dislike" of an item by ranking. The check-in data used in the POI recommendation system is an implicit feedback, which makes POI recommendations more difficult. The check-in data only provides positive examples that a user likes and POIs that are not checked in. A POI that is not checked in by a user means that the user dose not like or has not found this POI.
- **Data scarcity.** The data scarcity problem suffered by POI recommendation system is much worse compared with traditional recommendation system. The user-POI check-in matrix is extremely sparse compared to the user-item matrix of the traditional recommendation system. Because the total number of POIs is quite large, the number of POIs visited by a single user is very small.
- **Contextual diversity.** Compared to traditional recommendations, the POI recommendation system can obtain different types of context information, such as geographical coordinates of POIs, timestamps of check-ins, friendship of users, categories of POIs, etc. Using contextual information to improve recommendation accuracy is a challenging task.
- **User mobility.** In daily life, people's choice of travel destinations changes with context, so modeling user mobility is a very challenging task.

In this paper, we design a novel and effective personalized POI recommendation system based on the idea of collaborative filtering. The main contributions of this paper can be summarized as follows:

1) Our system uses clustering and minimum enclosing circle techniques to mine the target user's active area based on his or her check-in history. Using the target user's active area for recommendation has the following advantages.
   - We limit the POIs recommended to the target user to his or her active area instead of the entire map, which can make our recommendations more accurate and personalized.
   - We limit the POIs recommended to the target user to his or her active area instead of minimum enclosing circles. This ensures the diversity of recommendations.
2) Our system designs a personalized user spatial similarity calculation method based on the target user's active area.
3) We take into account three features of the human mobility pattern: spatial, temporal, and sequential properties and design a novel personalized user mobility pattern similarity calculation method based on the features of human mobility pattern.
4) We use six advanced methods as baseline methods and make a comprehensive comparison with them in the two real-world datasets of Foursquare and Gowalla.

II. RELATED WORK

POI recommendation as one of the crucial tasks in LBSNs has become a popular research direction and has been widely concerned by the academic community. Most previous studies recommended POIs for users based on their check-in history.

Since people's travel is affected by many factors, how to use these factors in POI recommendation has become the key to improve the accuracy of recommendation. These factors include the following.

- **Geographical influence.** As the most important attribute of LBSNs, geographic information is an important feature of POI recommendation that differs from traditional recommendation. Since users' check-in behaviors present spatial clustering phenomenon, previous studies often use a certain distribution or method to uniformly model users' check-in behaviors, such as power law distribution [1], Gaussian distribution [2], Poisson distribution [3], [4] and kernel density estimation [5]–[8].
- **Temporal influence.** Temporal influence [9]–[16] is an important factor affecting POI recommendation. This is because people's travel preferences change over time. For example, people's travel preferences are different on weekdays and weekends and even at different times of a day. Temporal influence is mainly manifested in two aspects of periodicity and non-uniformity.
- **Sequential influence.** The properties of POIs, the geographical adjacency of POIs, the periodicity of time and the habits of humans acting together on POI recommendation are expressed as sequential influence [17]–[19].
- **Social influence.** In LBSNs, friends share more experience in accessing POIs, so using social influence [8], [20]–[22] is also an effective way to improve the quality of POI recommendations.

The POI recommendation system uses a variety of recommendation methods, which are summarized as follows.

The content-based recommendation method mainly refers to a recommendation method that directly matches the user's preference attribute with the feature of the location. The advantage of this method is that it is not plagued by cold start problems. The disadvantage is that the location information and user information need to be structured, and it is very costly to do this in LBSNs.

The recommendation method based on link analysis [22]–[25] mainly refers to predicting the possibility of a link between two unlinked nodes by analyzing the known network structure information. Typical representations of this method are PageRank, HITS and Random Walk. The advantage of this method is that it is not plagued by cold start problems and takes into account users' experience. The disadvantage is that because this method ignores users' preferences, it can only do general recommendations and cannot personalize the recommendations.

The recommendation methods based on collaborative filtering [10], [20], [26]–[28] are mainly divided into user-based collaborative filtering and location-based collaborative filtering. The POI recommendation system uses the collaborative filtering method mainly into the following three steps: generating recommendation candidate sets, calculating similarity and calculating recommendation scores of POIs. The advantage of this method is that it does not require structured location information and user information and utilizes community opinion information. The disadvantage is that this method is easily plagued by cold start problem and data sparse problem and because of the large number of users and locations, the cost of similarity calculations is also enormous.

Since the great success of the Netfix Grand Prix, the recommendation method based on matrix factorization has received extensive attention from academia and industry. In the POI recommendation system, the recommendation method based on matrix factorization [2], [3], [29]–[33] maps feature vectors of users and locations to the low-dimensional hidden factor space simultaneously. In the low-dimensional hidden factor space, since the correlation between user preference and location feature can be directly calculated, the matrix factorization recommendation method uses the inner product of low-dimensional feature vectors of users and locations to predict a user's evaluation score for a POI.

Other recommendation methods used by the POI recommendation system include recommendation method based on tensor decomposition [34]–[37], recommendation method based on meta-path, recommendation method based on neural networks [38] and so on.

III. THE FRAMEWORK FOR POI RECOMMENDATION

A. PROBLEM DEFINITION

In this paper, the problem of POI recommendation is defined as: given the check-in history of a target user, the task of POI recommendation is to recommend top k locations that the user might be interested in. Table 1 summarizes some symbols used in this paper. Let U denote a set of users in LBSN, F represent a set of POI categories, L be a set of POIs and P denote a set of check-ins.

Each POI l belonging to L is represented as $< x, y, f >$, where x and y are the longitude and latitude of l respectively and $f \in F$ is the POI category of l. Each check-in p belonging to P is represented as $< l, t, u >$, where l is the POI that is checked in, t indicates the check-in time and u is the check-in user. And P_u represents a set of all check-ins of user u.

For the convenience of later, we first give the definition of user's check-in history here.

Definition 1 (Check-in History): For each user $u_i \in U$, u_i's check-in history H_{u_i} is a sequence of check-ins formatted as $H_{u_i} = p_1 \xrightarrow{\Delta t_1} p_2 \xrightarrow{\Delta t_2} \ldots p_j \xrightarrow{\Delta t_j} p_{j+1} \xrightarrow{\Delta t_{j+1}} \ldots \xrightarrow{\Delta t_{n-1}} p_n$, where $p_j \in P_{u_i}$, $1 \leq j < n$, $\Delta t_j = p_{j+1}.t - p_j.t$ and $p_{j+1}.t > p_j.t$.

B. THE GENERAL IDEA

In real life we can observe two phenomena: First, many POIs with similar services in a city are clustered in the same geographical area. For example, the shopping mall of a city gathers a large number of shops, restaurants and cinemas. A city's Cultural Center is home to art galleries, concert halls and museums. Second, the types of POIs that a person has visited during a day are only a limited number. For example,

TABLE 1. Frequently used symbols.

Symbol	Description
U	the set of users
u	a user, $u \in U$
F	the set of all the categories of POIs
f	a category of POIs
L	the set of POIs
l	a POI, $l \in L$
P	the set of check-ins
P_u	the set of all check-ins of user u
p	a check-in, $p \in P$
$p.t$	the check-in time of p
AR_u	active area of user u
L_u	the set of all POIs that user u has visited
UA_u	the set of users with similar active area to user u
H_u	a check-in history of user u
SEQ	the set of continual check-in sequences
seq	a continual check-in sequence
len	the length of a continual check-in sequence
T	a time interval of a continual check-in sequence
cmp	a common mobility pattern sequence
UAM_u	the set of users with similar active area and similar mobility pattern to user u

on weekdays, most people only visit limited types of POIs such as companies, restaurants and gyms. Through the above two observed phenomena, it is not difficult to find and understand that a person's check-in history is usually limited to certain geographical areas. And through the observation of users' check-in history, it is not difficult to find some hidden mobility patterns behind a large number of physical human movements.

In this paper, our system solves the POI recommendation problem based on the above observation of a person's check-in history, the general idea is as follows: Given the target user u_i, first look for the active area AR_{u_i} of u_i and a set UA_{u_i} of users with similar active area of u_i. Then, look for a subset UAM_{u_i} of users in UA_{u_i} that have a similar mobility pattern to u_i. So the users in UAM_{u_i} have similar active area and similar mobility pattern to u_i. Finally, the POIs are recommended for u_i based on the users in UAM_{u_i}.

Our system has designed three modules: user active area and user spatial similarity module, user mobility pattern similarity module, and POI recommendation module. The specific details of the three modules are as follows.

C. USER ACTIVE AREA AND USER SPATIAL SIMILARITY

In order to find users with similar active area to the target user u_i, our system finds the active area of the target user u_i, and designs a personalized user spatial similarity calculation method.

1) USER ACTIVE AREA

In this section, we look for the active area of the target user u_i based on u_i's check-in history. The specific steps are as follows:

1) A user's active area is composed of multiple small active areas, so our approach first cluster all the POIs that u_i has accessed based on his or her check-in history. We use the MeanShift algorithm [39] to cluster these POIs according to latitude and longitude. Then we get a collection C_{u_i} of clusters belonging to u_i.
2) For each cluster belonging to C_{u_i}, its shape is irregular. For ease of representation and use, our approach uses a minimum circle containing all the points in a cluster to represent the shape of the cluster. Finding a minimum circle that contains all points in a given set of points is a problem that people are very interested in both theory and practice. Our approach first removes clusters containing fewer than 3 points from C_{u_i}, and then obtains the minimum enclosing circle for each cluster using the method in [40]. The specific details are as follows:
    a) Arbitrarily take three points a, b, c in a cluster.
    b) Make a minimum circle k containing a, b, c.
    c) Find the farthest point d in the cluster from the center of k. If point d is inside the circle k or on the circumference of k, then k is the desired minimum enclosing circle. Otherwise step d).
    d) Select 3 points in a, b, c, d to minimize the circle that contains the 4 points. The three selected points become the new three points a, b and c, and return to step b).

    When the minimum enclosing circle of each cluster is generated, the minimum enclosing circle set K_{u_i} of u_i is obtained.
3) A plane coordinate system is established based on longitude and latitude. Each minimum enclosing circle contained in K_{u_i} is represented on the coordinate plane based on longitude and latitude. On the coordinate plane, make a vertical tangent to the left boundary of the leftmost minimum enclosing circle. Make a vertical tangent to the right boundary of the rightmost minimum enclosing circle. Make a horizontal tangent to the upper boundary of the uppermost minimum enclosing circle. Make a horizontal tangent to the lower boundary of the lowermost minimum enclosing circle. The rectangular area enclosed by these four tangent lines is the active area AR_{u_i} of u_i. The active area is shown in the Figure 2.

2) USER SPATIAL SIMILARITY

After finding the active area of u_i, in order to find users with similar active area with u_i, our system designed a personalized user spatial similarity calculation method to calculate the spatial similarity between target user u_i and other user u_j. The specific details are as follows:

According to a user's check-in history, all the POIs that the user has visited can be obtained. Use L_{u_i} to represent a set of all POIs that u_i has visited. Use L_{u_j} to represent a set of all POIs that u_j has visited. The POIs belonging to AR_{u_i} in L_{u_j} constitute a subset $L^i_{u_j}$ of L_{u_j}. Our method divides the POIs in $L^i_{u_j}$ into the following three categories.

- The POI that u_j has visited is inside a certain minimum enclosing circle in AR_{u_i}, and u_i has also accessed this POI. Such as POI l_a in Figure 2. Use S_1 to represent this category of POIs, $S_1 = \{l : l \in L_{u_i} \cap L^i_{u_j}\}$.

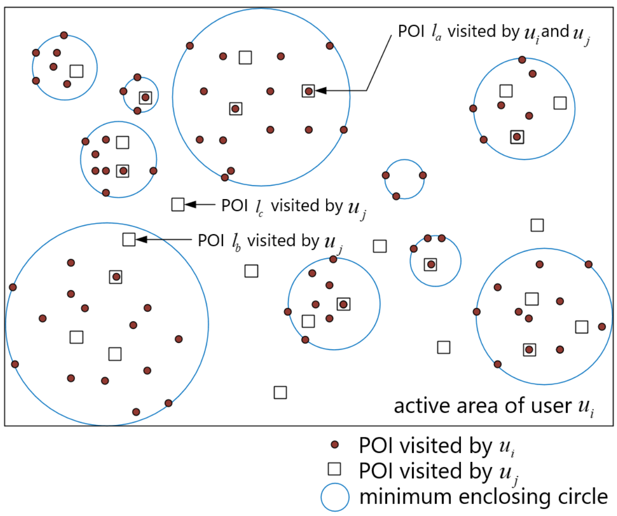


FIGURE 2. The active area AR_{u_i} of user u_i and the explanation of the three categories of POIs S_1, S_2 and S_3.

- The POI that u_j has visited is inside a certain minimum enclosing circle in AR_{u_i}, but u_i has not accessed this POI. Such as POI l_b in Figure 2. Use S_2 to represent this category of POIs, $S_2 = \{l : l \in L^i_{u_j}$ *and* l *inside a minimum enclosing circle, but* $l \notin L_{u_i}\}$.
- The POI that u_j has visited is in AR_{u_i} but does not belong to any minimum enclosing circle. Such as POI l_c in Figure 2. Use S_3 to represent this category of POIs, $S_3 = \{l : l \in L^i_{u_j} - S_1 - S_2\}$.

Obviously, these three categories of POIs imply a different degree of spatial similarity between u_i and u_j. The POIs in S_1 imply that the spatial similarity is the strongest. The POIs in S_3 imply that the spatial similarity is the weakest.

Our method calculates the spatial similarity between the target user u_i and other user u_j based on these three categories of POIs as follows:

$$sim_S(u_i, u_j) = \frac{Fre_{S_1} + Fre_{S_2} + Fre_{S_3}}{Fre_{u_j}} \tag{1}$$

$$Fre_{S_2} = \sum_{i=1}^{|K_{u_i}|} \frac{1}{r_i} Fre_i \tag{2}$$

$$Fre_{S_3} = \sum_{k=1}^{|S_3|} \frac{1}{d_k} Fre_k \tag{3}$$

Specifically, in Equation 1, Fre_{S_1} indicates the total number of times the POIs in S_1 are checked-in by u_j. Fre_{u_j} represents the total number of check-ins for u_j in his or her check-in history H_{u_j}. In Equation 2, Fre_i represents the total number of times all POIs in the i-th minimum enclosing circle that belong to S_2 are checked-in by u_j. r_i denotes the radius of the i-th minimum enclosing circle. In Equation 3, Fre_k indicates the number of times the k-th POI in S_3 is checked-in by u_j. d_k represents the distance from the k-th POI in S_3 to the center of the minimum enclosing circle closest to this POI. Specifically, we use the distance from a POI to the center of a minimum enclosing circle minus the radius of this minimum enclosing circle to calculate the distance between the POI and the minimum enclosing circle. The distance from the k-th POI to each minimum enclosing circle is calculated, and the minimum enclosing circle with the smallest distance is the minimum enclosing circle closest to the k-th POI.

Given the target user u_i and other user u_j, our method of calculating user spatial similarity is to first divide the POIs that u_j has visited in the active area of u_i into three categories, and then accumulate the total number of check-ins of these three categories of POIs Fre_{S_1}, Fre_{S_2} and Fre_{S_3}, finally calculate the ratio of the cumulative and the total number of check-ins Fre_{u_j} for u_j in his or her check-in history.

Since these three categories of POIs imply a different degree of spatial similarity between u_i and u_j, our method is handled as follows. In Equation 2, the POI in S_2 is weighted by the reciprocal of the radius of the minimum enclosing circle in which it is located. In Equation 3, the POI in S_3 is weighted by the reciprocal of the distance of the POI to the center of the minimum enclosing circle closest to it.

According to our user spatial similarity calculation method, the spatial similarity between the target user u_i and each of the other users can be calculated, and a set UA_{u_i} of users having similar activity area with u_i can be obtained.

D. USER MOBILITY PATTERN SIMILARITY

After obtaining the active area AR_{u_i} of the target user u_i and the set UA_{u_i} composed of users having similar active area with u_i, our task is to find the user in the set UA_{u_i} having a similar mobility pattern with u_i in AR_{u_i}. Then a personalized and effective user mobility pattern similarity calculation method becomes the key to accomplish the above task. In this section, we will first briefly introduce the characteristics of the user mobility pattern, and then we will describe in detail our personalized user mobility pattern similarity calculation method.

1) USER MOBILITY PATTERN CHARACTERISTICS

In daily life, people's choice of travel destinations changes with context, so modeling human mobility is a very challenging task. Although modeling human mobility is very difficult, it is not difficult to find some hidden mobility patterns behind a large number of physical human movements. For example, on the morning of weekdays people usually move from home to work or school. And on weekend nights, people usually go to the movies after dinner. To deeply analyze the human mobility pattern, you first need to know what features the human mobility pattern has. In this paper, we attribute the most important features of the human mobility pattern to three points: spatial, temporal, and sequential properties.

- **Spatial features:** Spatial features refers to the location information of the user's movements and the distribution of these locations in the physical space. Brockmann *et al.* [41] research shows that human movement on many spatial scales is not random, but shows a high level of spatial regularity, and the probability distribution of displacements over all users can be well approximated by a truncated power-law. And according to Tobler's First Law, it is not difficult to find that people are more inclined to visit places closer to themselves. Therefore, the user's travel distance is an important feature of the user's movement in the spatial dimension, which can reflect the user's active range in the spatial dimension.

- **Temporal features:** The user's movement exhibits a periodicity of time in the time dimension. The time periodicity of user movement means that the user usually visits the same or similar location within the same time interval. For example, people usually go to the library during the day, go to restaurants in the evening and go to bars at night.
- **Sequential features:** Sequential features refers to the highly correlated between the continuous movement of users. The study in [17] found that more than 40% and 60% of continuous movement occurred within 4 hours of the last movement of Foursquare and Gowalla. And about 90% of the continuous movements in Foursquare and Gowalla occur within 32km. This also reflects that the sequential features of the user's movement are spatial-temporal related, which is the result of time periodicity, the proximity of moving positions in geospatial, and the attributes of the moving position and human habits(for example, people usually go to the gym first and then go to the restaurant for dinner, if the opposite is not good for people's health).

2) USER MOBILITY PATTERN SIMILARITY

In this subsection, we describe the details of our method to calculate the user mobility pattern similarity based on the three features mentioned above. Most previous similarity calculation methods ignore the sequential features of check-in records and separately consider each single check-in record to calculate the similarity. Instead, our method comprehensively considers spatial, temporal and sequential properties to investigate the similarity between users based on sequences of continual check-ins. Therefore, our method is more strict and effective for the reason that similar users defined in our method means that they successively visit POIs with similar spatial and temporal features.

Our user mobility pattern similarity calculation method first finds continual check-in sequences of target user u_i. Then common mobility pattern sequences belonging to u_i and other user u_q are constructed according to continual check-in sequences of u_i. Finally, the mobility pattern similarity of u_i and u_q is calculated according to common mobility pattern sequences. The construction process of a common mobility pattern sequence is as follows.

1) **Continual Check-in Sequence:** Continual check-in sequences can be viewed as segments in a user's check-in history based on the time threshold $\triangle t'$. The definition of continual check-ins and how to find u_i's continual check-in sequences according to u_i's check-in history H_{u_i} can refer to our previous work [36]. Let $SEQ = \{seq_1, seq_2, \ldots, seq_m\}$ denote the continual check-in sequence set of u_i. Each seq_j, $1 \leqslant j \leqslant m$ belonging to SEQ is a continual check-in sequence. And $LEN = \{len_1, len_2, \ldots, len_m\}$ is a set of the length of the corresponding continual check-in sequence of SEQ.

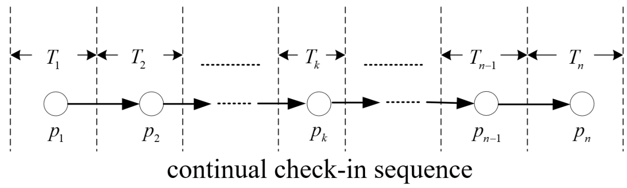


FIGURE 3. Time interval.

2) **Time Interval Calculation:** For each $seq_j = \{p_1, p_2, \ldots p_n\}$ belonging to SEQ, we consider the first check-in p_1, last check-in p_n and intermediate check-in p_k, $1 < k < n$ to divide time intervals as shown in Figure 3. Equation 4, 5, and 6 give specific calculations.

$$T_1 = [p_1.t - \frac{p_2.t - p_1.t}{2}, p_1.t + \frac{p_2.t - p_1.t}{2}] \tag{4}$$

$$T_n = [p_n.t - \frac{p_n.t - p_{n-1}.t}{2}, p_n.t + \frac{p_n.t - p_{n-1}.t}{2}] \tag{5}$$

$$T_k = [p_k.t - \frac{p_k.t - p_{k-1}.t}{2}, p_k.t + \frac{p_{k+1}.t - p_k.t}{2}] \tag{6}$$

3) **Common Mobility Pattern Sequence Construction:** According to each seq_j of target user u_i, we construct common mobility pattern sequence of user u_i and u_q, denoted by $cmp_j^{iq} = \{f_1, f_2, \ldots f_n\}$, where each $f_k \in cmp_j^{iq}$ is a category of POI. The method of generating f_k according to $p_k \in seq_j$ is as follows:
   a) Calculate the corresponding time interval T_k according to $p_k.t$.
   b) Construct a set CI_k contains all the check-ins of user u_q in the active area AR_{u_i} of the target user u_i during the time interval T_k.
   c) Construct a subset of F, denoted by F_k. F_k contains the categories of POIs for all check-in records in CI_k.
   d) Construct an array A of length $|F_k|$. Each element A_r in A stores the total number of check-ins in the CI_k of the POIs belonging to the category $f_r(f_r \in F_k)$. And f_{max} is used to indicate the POI category with the largest number of check-ins in CI_k(the POI category with the largest element value in A).
   e) Calculate the probability $h(f_r)$ that u_q checked in POIs of each category in AR_{u_i} during the time interval T_k by Equation 7.

$$h(f_r) = \frac{A_r}{|CI_k|} \tag{7}$$

f) Calculate the entropy $H(CI_k)$ of the category distribution of POIs checked in by u_q in AR_{u_i} during the time interval T_k by Equation 8.

$$H(CI_k) = -\sum_{r=1}^{|F_k|} h(f_r)\, log_2 h(f_r) \tag{8}$$

g) Calculate the maximum entropy $H_{max}(CI_k)$ of the category distribution of POIs checked in by u_q in AR_{u_i} during the time interval T_k by Equation 9. The maximum entropy corresponds to the situation in which u_q visits each category of POIs with equal probability during the time interval T_k.

$$H_{max}(CI_k) = log_2|CI_k| \tag{9}$$

h) Due to the difference in the category distribution of POIs checked in by different users, we normalize $H(CI_k)$ using the maximum entropy $H_{max}(CI_k)$. As is shown in Equation 10.

$$H^{'}(CI_k) = \frac{H(CI_k)}{H_{max}(CI_k)} \tag{10}$$

i) Given a threshold e.
   i) If $H^{'}(CI_k) > e$, it means that the POIs that checked in by u_q in AR_{u_i} during the time interval T_k have no clear category tendency. Therefore, u_q does not have the same check-in POI category as the target user u_i, then $f_k = \phi$.
   ii) If $H^{'}(CI_k) \leqslant e$, it means that u_q's check-in in AR_{u_i} during the time interval T_k obviously tend to the category f_{max} with the most check-in. The category of $p_k.l$ is indicated by f'.
      A) If $f_{max} = f'$, it means that u_q and the target user u_i have the same check-in POI category in AR_{u_i} during the time interval T_k, then $f_k = f'$.
      B) If $f_{max} \neq f'$, it means that u_q and the target user u_i do not have the same check-in POI category in AR_{u_i} during the time interval T_k, then $f_k = \phi$.

The algorithm for generating f_k according to $p_k \in seq_j$ is shown in Algorithm 1.

The common mobility pattern sequence is a valid representation of the common part of the two user's mobility patterns. Based on the characteristics of common mobility pattern sequence, we consider the sequential property and visited popularity of POI category to calculate the mobility pattern similarity between the target user u_i and other user u_q.

1) **Sequential property:** Our mobility pattern similarity calculation takes into account the sequential property. That is, the more continuous the two users' common mobility pattern is, the more similar the mobility pattern of the two users. The continuity of the two users' common mobility pattern is expressed as the length of their common mobility pattern sequence.

Algorithm 1 Generate f_k According to $p_k \in seq_j$

Input: p_k: $p_k \in seq_j$, seq_j is a continual check-in sequence of target user u_i
f': the category of $p_k.l$
AR_{u_i}: active area of target user u_i
e: a threshold
Output: f_k
begin
    Calculate T_k according to $p_k.t$;
    Construct $CI_k = \{p_r: p_r$ belongs to u_q and $p_r.l \in AR_{u_i}, p_r.t \in T_k\}$
    Construct $F_k = \{f_r: f_r \in F$ and check-in records of POIs belonging to f_r belongs to $CI_k\}$
    Construct an array A of length $|F_k|$
    for $r: 1 \to |F_k|$ **do**
        Construct a set c_r which contains all the check-ins in the CI_k of the POIs belonging to category $f_r (f_r \in F_k)$
        $A_r = |c_r|$
    end
    Find the largest value A_k in the array A
    $f_{max} = f_k$
    Construct an array h of length $|F_k|$
    for $r: 1 \to |F_k|$ **do**
        $h_r = \frac{A_r}{|CI_k|}$
    end
    $H = -\sum_{r=1}^{|F_k|} h_r log_2 h_r$
    $H_{max} = log_2|CI_k|$
    $H^{'} = \frac{H}{H_{max}}$
    if $H^{'} \leqslant e$ **then**
        if $f_{max} = f'$ **then**
            $f_k = f'$
        end
        else
            $f_k = \phi$
        end
    end
    else
        $f_k = \phi$
    end
end

2) **Visited popularity of POI category:** Our mobility pattern similarity calculation considers visited popularity of POI category. Inspired by the inverse document frequency (IDF), two users have accessed POIs belonging to a certain category, and only a few people have visited POIs of this category, then the two users might be more correlated.

The mobility pattern similarity between target user u_i and other user u_q is calculated as follows:

$$sim_M(u_i, u_q) = \sum_{j=1}^{m} f(len1[j])\, sim(cmp_j^{iq}) \tag{11}$$

$$sim(cmp_j^{iq}) = \frac{\sum_{k=1}^{len_j} V(f_k)}{len1[j]} \tag{12}$$

$$V(f) = \begin{cases} \log \frac{|U|}{n_f}, & f \neq \emptyset \\ 0, & f = \emptyset \end{cases} \tag{13}$$

Specifically, in Equation 11, m represents the number of u_i's continual check-in sequence. $len1[j]$ denotes the length of a common mobility pattern sequence, that is, the number of consecutive common mobility pattern. In Equation 13, n_f is the number of users who accessed POIs belonging to category f.

Our method calculates their mobility pattern similarity by summing the similarity scores of all common mobility pattern sequences of two users in a weighted way. The function $f(len1[j])$ is used to assign larger weights to longer common mobility pattern sequences, e.g., $f(len1[j]) = 2^{len1[j]-1}$.

The calculation of similarity score $sim(cmp_j^{iq})$ of a common mobility pattern sequence is shown in Equation 12. $sim(cmp_j^{iq})$ is calculated by summing up the visited popularity $V(f_k)$ of each POI category f_k contained in cmp_j^{iq}. Meanwhile, $sim(cmp_j^{iq})$ is normalized by $len1[j]$.

The algorithm for calculating user mobility pattern similarity is shown in Algorithm 2. According to our user mobility pattern similarity calculation method, the mobility pattern similarity between the target user u_i and each user in UA_{u_i} can be calculated, and a set UAM_{u_i} of users having similar activity area and similar mobility pattern with u_i can be obtained.

E. POI RECOMMENDATION

After obtaining the active area AR_{u_i} of the target user u_i and the set UAM_{u_i} of users having similar activity area and similar mobility pattern with u_i, our system will recommend POIs for the target user u_i in AR_{u_i} according to the users in UAM_{u_i}. The details are as follows:

1) The POIs accessed by the users in UAM_{u_i} in AR_{u_i} are grouped into the recommended candidate set RC_{u_i} of the target user u_i.
2) The pseudo-rating of the POI l_m in RC_{u_i} by the user u_k in UAM_{u_i} is calculated by the Equation 14.

$$pr(u_k, l_m) = \frac{w}{CT_{u_k}} \tag{14}$$

where w indicates the number of times u_k has visited l_m. CT_{u_k} represents the total number of check-in records for user u_k in his or her check-in history H_{u_k}.
3) The pseudo-rating of the POI l_m in RC_{u_i} by the target user u_i is calculated by the Equation 15.

$$pr(u_i, l_m) = \sum_{k=1}^{|UAM_{u_i}|} sim_S(u_i, u_k) sim_M(u_i, u_k) pr(u_k, l_m) \tag{15}$$

4) After obtaining the pseudo-rating of each POI in RC_{u_i} by the target user u_i, the RC_{u_i} is arranged in descending order according to the pseudo-rating. Finally, the top-n POIs are recommended to the target user u_i.

Algorithm 2 User Mobility Pattern Similarity Calculation Method

```
Input: u_i: the target user
       UA_{u_i}: the set of users with similar active area to
       the target user u_i
       U: the set of entire users
       SEQ: the set of continual check-in sequences of
       target user u_i, SEQ = {seq_1, seq_2, ..., seq_m}
       LEN: the set of the length of the corresponding
       continual check-in sequence of SEQ,
       LEN = {len_1, len_2, ..., len_m}
Output: sim: the similarity between target user u_i and
        other user u_q
begin
  for each u_q ∈ UA_{u_i} do
    Construct an empty array len1 and initialize to 0;
    /*len1 stores the length of each common
    mobility pattern sequence.*/
    Construct an empty array d and initialize to 0;
    /*d stores similarity score of a common mobility
    pattern sequence.*/
    for each seq_j ∈ SEQ do
      Construct an empty array v and initialize to
      0; /*v stores the visited popularity of each
      f_k.*/
      for each p_k ∈ seq_j do
        Construct f_k; /* Using algorithm 1. */
        if f_k ≠ ∅ then
          len1[j] = len1[j] + 1;
          Initialize n with 0;
          Construct a set B which contains all
          the users who accessed POIs
          belonging to category f_k;
          n = |B|;
          v[k] = log |U|/n;
        end
        else
          v[k] = 0;
        end
      end
      d[j] = (Σ_{k=1}^{len_j} v[k]) / len1[j]
    end
    sim = Σ_{j=1}^{m} f(len1[j]) * d[j];
  end
end
```

IV. EXPERIMENTS

In this section, we evaluate the recommendation quality of our system with baseline methods on two real-world datasets. We first present the experimental setting and then analyze the quality of our POI recommendation system.

TABLE 2. Dataset statistic.

Dataset	New York (Foursquare)	Tokyo (Foursquare)	New York (Gowalla)
Users	833	2071	328
Venues	38274	61009	9874
Check-ins	237846	584511	986124

A. EXPERIMENTAL SETTING

1) DATASETS

At present, large-scale datasets with POI classification information are still very difficult to obtain. In this paper, we use two datasets Foursquare[1] [42] and Gowalla[2] [9] to evaluate the quality of our proposed POI recommendation system. The Foursquare dataset consists of two cities, New York and Tokyo. And the Foursquare dataset is a dataset that has been data filtered. The Gowalla dataset is a raw dataset that contains a city of New York. Even though Gowalla is able to verify whether a user is actually near the place when they check in, fake check-in data is still inevitable in large dataset. We removed the fake check-ins (consecutive check-ins with a speed faster than 1200 km/h: the common airplane speed). In both datasets we only select users who have performed at least three check-ins per week. We use the MeanShift algorithm to cluster all POIs that a user has visited based on longitude and latitude. If each cluster contains less than 3 POIs, we remove such users from both datasets. The basic statistics of them are shown in Table 2.

2) EXPERIMENTAL DATA PARTITION

In order to evaluate our system, we split each dataset into the training set and the testing set in terms of time. The data generated in the last two months is used for testing and the rest of the data is used for training.

3) EVALUATION METRICS

In order to evaluate the quality of the POI recommendation system we proposed, we selected the following three evaluation metrics.

$$Precision = \frac{No.\ of\ POIs\ correctly\ predicted}{No.\ of\ recommended\ POIs} \tag{16}$$

$$Recall = \frac{No.\ of\ POIs\ correctly\ predicted}{No.\ of\ POIs\ actually\ accessed} \tag{17}$$

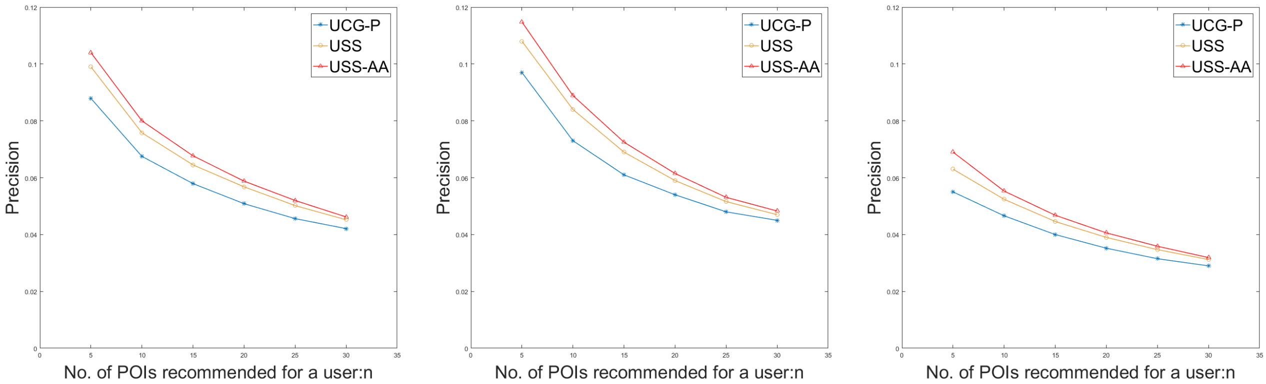
$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{18}$$

4) BASELINE METHODS

To verify the performance of our system, we select six representative baseline methods for comparison.

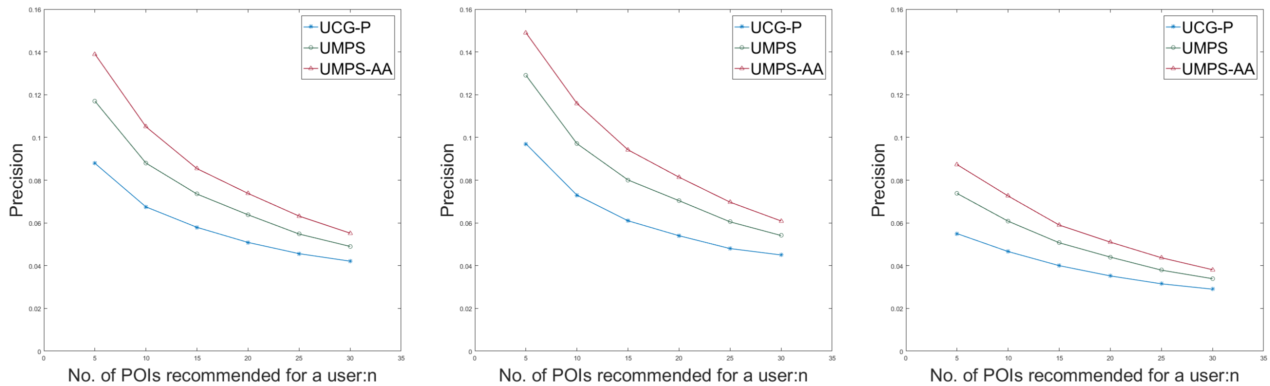
- USG [1]: A unified location recommendation framework is implemented which linearly fuses three factors: user preference, social influence and geographical influence. The user preference component of USG is implemented by a traditional user-based collaborative filtering technique, and the geographical influence is computed by a power-law probabilistic model that aims to capture the geographical clustering phenomenon that POIs visited by the same user tend to be clustered geographically. The USG can select the factors to be included by controlling the weight parameters. In this paper, USG-P represents a USG that only contains a factor of user preference, which is a traditional user-based collaborative filtering technology. And USG-PG denotes the USG considering both user preference and geographic influence.
- CoRe [7]: This method fuses social collaborative filtering and geographical check-in distribution using kernel density estimation with a fixed bandwidth. CoRe is divided into three versions. We use the geographical category version of CoRe as the baseline method. Specifically, CoRe estimate a personalized two-dimensional check-in probability density over the latitude and longitude coordinates for each user rather than using a common one-dimensional distance distribution for all users.
- GeoSoCa [8]: This method exploits geographical correlations, social correlations and categorical correlations among users and POIs. GeoSoCa uses a kernel estimation method with an adaptive bandwidth to determine a personalized check-in distribution. And GeoSoCa applies the bias of a user on a POI category to weigh the popularity of a POI in the corresponding category and models the weighed popularity as a power-law distribution to leverage the categorical correlations between POIs. We use GeoSoCa that does not contain the social correlation component as the baseline method, represented by GeoSoCa-GC.
- Geo-PFM [4]: The authors propose a general geographical probabilistic factor model (Geo-PFM) framework which strategically takes various factors into consideration. This framework can capture the geographical influences on a user's check-in behaviors, can effectively model the user mobility patterns, and can deal with the skewed distribution of check-in count data. Moreover, based Geo-PFM framework, the authors further develop a Poisson Geo-PFM which provides a more rigorous probabilistic generative process for the entire model and is effective in modeling the skewed user check-in count data as implicit feedback for better POI recommendations.
- ASMF [22]: ASMF is a two-step framework to elaborate friends' check-ins. In the first step, the authors design two approaches (i.e., a linear aggregation based and a random walk based) to learn a set of friends' locations that each user most potentially prefers and she never visited. In the second step, the authors develop two loss functions to model these three kinds of check-ins: the square error based loss function and the ranking

[1] https://sites.google.com/site/yangdingqi/home/foursquare-dataset
[2] http://snap.stanford.edu/data/loc-Gowalla.html



(a) New York (Foursquare) (b) Tokyo (Foursquare) (c) New York (Gowalla)

FIGURE 4. Comparison of recommended results of user-based collaborative filtering technology using user spatial similarity and user active area with traditional user-based collaborative filtering technology.



(a) New York (Foursquare) (b) Tokyo (Foursquare) (c) New York (Gowalla)

FIGURE 5. Comparison of recommended results of user-based collaborative filtering technology using user mobility pattern similarity and user active area with traditional user-based collaborative filtering technology.

error based loss function. ASMF define three types of friends (i.e., social friends, location friends, and neighboring friends) in LBSN. Due to the datasets, we only used location friends to implement ASMF as a baseline method.

- Rank-GeoFM [32]: Rank-GeoFM is a ranking based geographical factorization method, which incorporates the geographical and temporal influence in a latent ranking model. Rank-GeoFM consider that the check-in frequency characterizes users' visiting preference and learn the factorization by ranking the POIs correctly. And in this model, POIs both with and without check-ins will contribute to learning the ranking and thus the data sparsity problem can be alleviated.

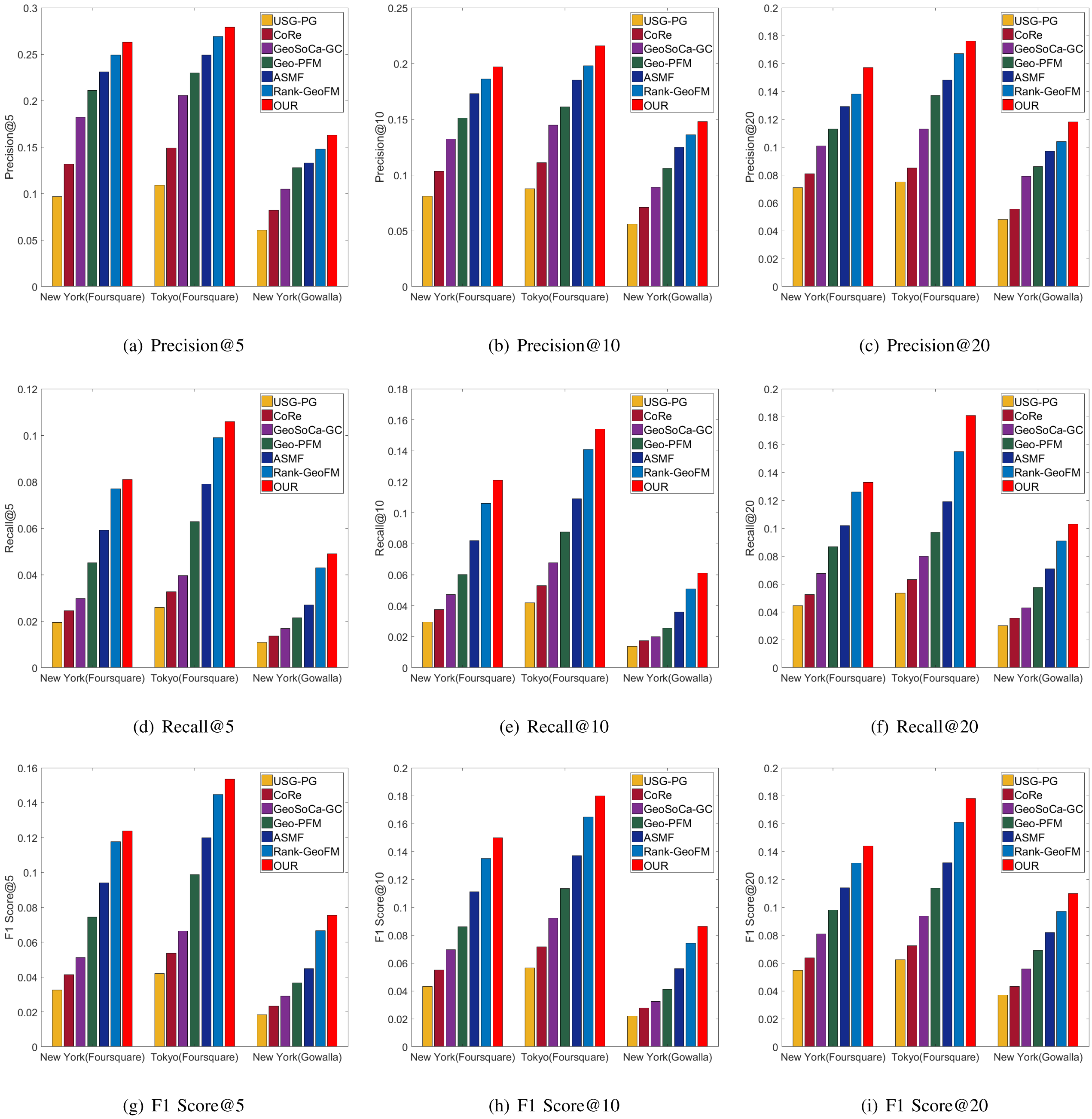
B. RECOMMENDATION EFFECTIVENESS

Our system designs the calculation methods of user active area, user spatial similarity and user mobility pattern similarity. In order to verify the performance of our system, we first verify the effectiveness of each functional module, and finally verify the overall performance of the system by comparing with baseline methods.

1) THE EFFECTIVENESS OF FUNCTION MODULES

We use user-based collaborative filtering technology to verify the validity of user active area, user spatial similarity and user mobility pattern similarity calculation methods. The baseline method USG is a traditional user-based collaborative filtering technology when only considering the user preference factor, and is represented by USG-P. The USG-P uses the cosine similarity method to calculate similarities between users. Using USG-P as the baseline method, we replace the cosine similarity with our user spatial similarity and user mobility pattern similarity respectively, and use the user-based collaborative filtering method to verify the effectiveness of the two user similarity calculation methods proposed in this paper. Furthermore, based on the above methods, we limit the POIs to be recommended to the user active area to further verify the effectiveness of our proposed user active area calculation method. Figure 4 and Figure 5 show the experimental results in two datasets, respectively.

In Figure 4, USS represents a user-based collaborative filtering method using user spatial similarity, and USS-AA represents a USS method that limits POIs to be recommended in the user active area. In the three subgraphs of Figure 4, USS



(a) Precision@5 (b) Precision@10 (c) Precision@20

(d) Recall@5 (e) Recall@10 (f) Recall@20

(g) F1 Score@5 (h) F1 Score@10 (i) F1 Score@20

FIGURE 6. Comparison with baselines under different datasets.

has better performance than UCG-P, which indicates that our user spatial similarity more accurately reflects the similarity between users than cosine similarity. USS-AA performs slightly better than USS. This is because USS has considered the user's spatial factor, and the performance improvement brought by limiting the POIs to be recommended to the user active area is bound to be limited.

In Figure 5, UMPS represents a user-based collaborative filtering method using user mobility pattern similarity, and UMPS-AA represents a UMPS method that limits POIs to be recommended in the user active area. In the three subgraphs of Figure 5, the performance of UMPS is significantly higher than that of UCG-P, which indicates that our user mobility pattern similarity reflects the similarity between users very well. This is because our user mobility pattern similarity is personalized and considers three features of the human mobility pattern: spatial, temporal, and sequential properties. Compared with UMPS, the performance of UMPS-AA is also greatly improved, because limiting the POIs to be recommended in the user activity area is equivalent to adding the consideration of user spatial factor in the recommendation process.

TABLE 3. The effect of time threshold.

Time Threshold (hour)	Pre@5	Pre@10	Pre@20	Pre@5	Pre@10	Pre@20	Time Threshold (hours)	Pre@5	Pre@10	Pre@20
	New York (Foursquare)			Tokyo (Foursquare)				New York (Gowalla)		
2	0.161	0.116	0.085	0.165	0.122	0.105	1	0.081	0.062	0.051
4	0.171	0.131	0.107	0.187	0.158	0.127	**5**	**0.161**	**0.142**	**0.113**
6	**0.263**	**0.197**	**0.157**	**0.279**	**0.216**	**0.176**	10	0.093	0.089	0.074
8	0.201	0.152	0.123	0.236	0.175	0.153	15	0.089	0.084	0.062
10	0.109	0.087	0.062	0.125	0.106	0.095	20	0.088	0.073	0.054
∞	0.089	0.071	0.057	0.115	0.083	0.075	∞	0.073	0.065	0.041

The above experimental results show that our proposed user active area, user spatial similarity and user mobility pattern similarity calculation methods are effective.

2) COMPARISON OF METHODS

In this paragraph, we present the performance of our system on both Foursquare and Gowalla datasets and make a comprehensive comparison with the six baseline methods. To ensure fairness, we set the parameters in baseline methods to the values when they perform best. We set the time threshold $\triangle t'$ to 6 hours. When our system performs best, we take the parameter e as 0.57. Figure 6 shows the comparison of our system and baseline methods in two datasets.

The experimental results show that the performance of USG-PG is the worst. This is because the weights of the USG-PG for linear fusion of user preference and geographic influence are universal and cannot be personalized according to the specific user, which means that the USG-PG cannot be personalized. And USG-PG does not consider the category and popularity information of POIs is also a factor of its poor performance. CoRe gives the second worst recommendation performance. This is mainly because the bandwidth used by CoRe to estimate the geographical check-in distribution based on the method of kernel density estimation is fixed. Due to the large difference in check-in density between different geographical regions, the fixed global bandwidth does not well reflect the local geographical check-in distribution characteristics. Moreover, CoRe also does not consider the category and popularity information of POIs. GeoSoCa-GC outperformes CoRe. This is mainly due to GeoSoCa models the geographical correlation using a kernel estimation method with an adaptive bandwidth determining a personalized check-in distribution. But the performance of GeoSoCa-GC is still unacceptable. This is because GeoSoCa-GC uses geographical, sequential and categorical information to indirectly characterize user preferences, but it does not directly model user preference. And GeoSoCa-GC needs to have enough common POIs in the training set and test set. But the data set used is highly sparse. The recommended results of Geo-PFM are acceptable. First, Geo-PFM uses a hierarchical approach to analyzing user preferences. Geo-PFM jointly learns geographical influence and user preference. Joint learning can make better use of context information than separately modeling. Geo-PFM uses Poisson distribution to better model users' check-in behaviors, but it ignores the partial order of POIs. And Geo-PFM attributes the check-in behaviors of all users to the same distribution that ignores the difference in check-in behaviors between different users. ASMF has relatively good performance. Although ASMF considers geographical influence and category information of POIs, it relies on social information to cause the Matrix Factorization model to perform not well enough. Rank-GeoFM shows a good recommendation performance for several reasons. First, Rank-GeoFM is designed for implicit feedback data. This indicates that modeling users check-ins as implicit feedback is more appropriate in POI recommendations. Second, in this model, POIs both with and without check-ins will contribute to learning the ranking and thus the data sparsity problem can be alleviated. But Rank-GeoFM ignores the effectiveness of sequential modeling. The sequential information of users' check-in behaviors is an important factor for POI recommendation.

Compared to baseline methods, our POI recommendation system has a higher recommendation quality, mainly because: Our system effectively utilizes the category information of POIs and the popularity information of POI categories. Our system mines the target user's active area based on his or her check-in history, and designs a personalized user spatial similarity calculation method based on the target user's active area. Our system takes into account three features of the human mobility pattern: spatial, temporal, and sequential properties. Furthermore, our system design a novel personalized user mobility pattern similarity calculation method based on the features of human mobility pattern.

3) IMPACT OF TIME THRESHOLD

The time threshold $\triangle t'$ has a direct impact on the performance of our system. Table 3 presents specific changes in the recommendation precision of our system as time threshold $\triangle t'$ change. In the Foursquare dataset, our system's recommendation precision gradually reaches the highest level as the time threshold $\triangle t'$ increases from 2 to 6. As $\triangle t'$ continues to increase, the performance of our system begins to decline. In the Gowalla dataset, our system gradually performs at its best as the time threshold $\triangle t'$ increases from 1 to 5. As $\triangle t'$ continues to increase, the recommendation precision of our system begins to slowly decline. This is because $\triangle t'$ is too small to result in a smaller number of continual check-in sequences and shorter sequence lengths. Then common mobility pattern sequences constructed according to these continual check-in sequences are of low quality and cannot fully reflect the similarity of the mobility pattern between the target user and each other user. Conversely, too much value of $\triangle t'$ causes continual check-in sequences to be too coarse to ignore the mobility pattern information of the target user at the next time interval.

V. CONCLUSION

In this paper, we explore the effects of spatial and mobility pattern for collaborative POI recommendation. Our system mines the target user's active area based on his or her check-in history, and designs a personalized user spatial similarity calculation method based on the target user's active area. And our system designs a novel personalized user mobility pattern similarity calculation method based on the features of human mobility pattern.

Our recommendation method is straightforward. In the future, we will consider using some more advanced technologies, such as deep learning. And we look forward to doing some work on the interpretability of POI recommendation system. Interpretability can better facilitate the use of POI recommendation system.

REFERENCES

[1] M. Ye, P. Yin, W.-C. Lee, and D.-L. Lee, "Exploiting geographical influence for collaborative point-of-interest recommendation," in *Proc. Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2011, pp. 325–334.

[2] C. Cheng, H. Yang, I. King, and M. R. Lyu, "Fused matrix factorization with geographical and social influence in location-based social networks," in *Proc. AAAI Conf. Artif. Intell.*, Nov. 2012, pp. 17–23.

[3] Y. Yu, G. Yang, and W. Hao, "A ranking based poisson matrix factorization model for point-of-interest recommendation," *J. Comput. Res. Develop.*, vol. 53, no. 8, pp. 1651–1663, 2016.

[4] B. Liu, H. Xiong, S. Papadimitriou, Y. Fu, and Z. Yao, "A general geographical probabilistic factor model for point of interest recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 5, pp. 1167–1179, May 2015.

[5] J.-D. Zhang and C.-Y. Chow, "iGSLR: Personalized geo-social location recommendation: A kernel density estimation approach," in *Proc. ACM SIGSPATIAL Int. Conf. Adv. Geographic Inf. Syst.*, Nov. 2013, pp. 334–343.

[6] X. Y. Ren, M. N. Song, and J. D. Song, "Context-aware point-of-interest recommendation in location-based social networks," *Chin. J. Comput.*, vol. 40, no. 4, pp. 824–841, 2017.

[7] J.-D. Zhang and C. Y. Chow, "CoRe: Exploiting the personalized influence of two-dimensional geographic coordinates for location recommendations," *Inf. Sci.*, vol. 293, pp. 163–181, Feb. 2015.

[8] J.-D. Zhang and C. Y. Chow, "GeoSoCa: Exploiting geographical, social and categorical correlations for point-of-interest recommendations," in *Proc. Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, 2015, pp. 443–452.

[9] E. Cho, S. A. Myers, and J. Leskovec, "Friendship and mobility: User movement in location-based social networks," in *Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, San Diego, CA, USA, Aug. 2011, pp. 1082–1090.

[10] Q. Yuan, G. Cong, Z. Ma, A. Sun, and N. Magnenat-Thalmann, "Time-aware point-of-interest recommendation," in *Proc. Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Aug. 2013, pp. 363–372.

[11] H. Gao, J. Tang, X. Hu, and H. Liu, "Exploring temporal effects for location recommendation on location-based social networks," in *Proc. ACM Conf. Recommender Syst.*, Oct. 2013, pp. 93–100.

[12] J.-D. Zhang and C.-Y. Chow, "TICRec: A probabilistic framework to utilize temporal influence correlations for time-aware location recommendations," *IEEE Trans. Serv. Comput.*, vol. 9, no. 4, pp. 633–646, Jul./Aug. 2016.

[13] M. Debnath, P. K. Tripathi, and R. Elmasri, "Preference-aware poi recommendation with temporal and spatial influence," in *Proc. 29th Int. Florida Artif. Intell. Res. Soc. Conf. (FLAIRS)*, Mar. 2016, pp. 548–553.

[14] M. G. Ozsoy, F. Polat, and R. Alhajj, "Time preference aware dynamic recommendation enhanced with location, social network and temporal information," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining*, Aug. 2016, pp. 909–916.

[15] Z. Yuan and H. Li, "Location recommendation algorithm based on temporal and geographical similarity in location-based social networks," in *Proc. World Congr. Intell. Control Automat.*, Jun. 2016, pp. 1697–1702.

[16] Y. Liu, C. Liu, B. Liu, M. Qu, and H. Xiong, "Unified point-of-interest recommendation with temporal interval assessment," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 1015–1024.

[17] S. Zhao, T. Zhao, H. Yang, M. R. Lyu, and I. King, "STELLAR: Spatial-temporal latent ranking for successive point-of-interest recommendation," in *Proc. AAAI Conf. Artif. Intell. (AAAI)*, Feb. 2016, pp. 315–321.

[18] J.-D. Zhang, C.-Y. Chow, and Y. Li, "LORE: Exploiting sequential influence for location recommendations," in *Proc. ACM SIGSPATIAL Int. Conf. Adv. Geographic Inf. Syst.*, Nov. 2014, pp. 103–112.

[19] J.-D. Zhang and C.-Y. Chow, "Spatiotemporal sequential influence modeling for location recommendations: A gravity-based approach," *ACM Trans. Intell. Syst. Technol.*, vol. 7, no. 1, Oct. 2015, Art. no. 11.

[20] M. Ye, P. Yin, and W.-C. Lee, "Location recommendation for location-based social networks," in *Proc. ACM SIGSPATIAL Int. Symp. Adv. Geographic Inf. Syst.*, San Jose, CA, USA, Nov. 2010, pp. 458–461.

[21] L. Cui, P. Dechang, and L. Hui, "Periodic and successive point-of-interest recommendation under dual social group influences with matrix factorization," *Rev. Fac. Ing.*, vol. 31, no. 3, pp. 255–269, 2016.

[22] H. Li, Y. Ge, R. Hong, and H. Zhu, "Point-of-interest recommendations: Learning potential check-ins from friends," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 975–984.

[23] Y. Zheng, L. Zhang, X. Xie, and W.-Y. Ma, "Mining interesting locations and travel sequences from GPS trajectories," in *Proc. 18th Int. Conf. World Wide Web*, Apr. 2009, pp. 791–800.

[24] X. Cao, G. Cong, and C. S. Jensen, "Mining significant semantic locations from GPS data," *Proc. VLDB Endowment*, vol. 3, no. 1, pp. 1009–1020, 2010.

[25] H. Bagci and P. Karagoz, "Context-aware friend recommendation for location based social networks using random walk," in *Proc. Int. Conf. Companion World Wide Web*, San Jose, CA, USA, Apr. 2016, pp. 531–536.

[26] C. Cui, J. Shen, L. Nie, R. Hong, and J. Ma, "Augmented collaborative filtering for sparseness reduction in personalized POI recommendation," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 5, 2017, Art. no. 71.

[27] Y. Si, F. Zhang, and W. Liu, "CTF-ARA: An adaptive method for poi recommendation based on check-in and temporal features," *Knowl.-Based Syst.*, vol. 128, pp. 59–70, Jul. 2017.

[28] S. Oppokhonov, S. Park, and I. K. E. Ampomah, "Current location-based next POI recommendation," in *Proc. Int. Conf. Web Intell.*, Aug. 2017, pp. 831–836.

[29] V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang, "Collaborative location and activity recommendations with GPS history data," in *Proc. Int. Conf. World Wide Web.* Raleigh, NC, USA, Apr. 2010, pp. 1029–1038

[30] B. Berjani and T. Strufe, "A recommendation system for spots in location-based online social networks," in *Workshop Social Netw. Syst.*, Apr. 2011, Art. no. 4.

[31] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian personalized ranking from implicit feedback," in *Proc. Conf. Uncertainty Artif. Intell.*, Jun. 2009, pp. 452–461.

[32] X. Li, G. Cong, X.-L. Li, T.-A. Nguyen, and P. S. Krishnaswamy, "Rank-GeoFM: A ranking based geographical factorization method for point of interest recommendation," in *Proc. 38th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, 2015, pp. 433–442.

[33] P. Zhao, X. Xu, Y. Liu, Z. Zhou, K. Zheng, V. S. Sheng, and H. Xiong, "Exploiting hierarchical structures for POI recommendation," in *Proc. IEEE Int. Conf. Data Mining (ICDM)*, Nov. 2017, pp. 655–664.

[34] J. Kim, Y. He, and H. Park, "Algorithms for nonnegative matrix and tensor factorizations: A unified view based on block coordinate descent framework," *J. Global Optim.*, vol. 58, no. 2, pp. 285–319, 2014.

[35] J. Kim and H. Park, "Fast nonnegative tensor factorization with an active-set-like method," in *High-Performance Scientific Computing*. London, U.K.: Springer, 2012, pp. 311–326.

[36] X. Jiao, Y. Xiao, W. Zheng, H. Wang, and C.-H. Hsu, "A novel next new point-of-interest recommendation system based on simulated user travel decision-making process," *Future Gener. Comput. Syst.*, vol. 100, pp. 982–993, Nov. 2019.

[37] X. Jiao, Y. Xiao, W. Zheng, H. Wang, and Y. Jin, "R2SIGTP: A novel real-time recommendation system with integration of geography and temporal preference for next point-of-interest," in *Proc. Int. Conf. World Wide Web*, San Francisco, CA, USA, May 2019, pp. 3560–3563

[38] P. Zhao, H. Zhu, Y. Liu, J. Xu, Z. Li, F. Zhuang, V. S. Sheng, and X. Zhou, "Where to go next: A spatio-temporal gated network for next POI recommendation," in *Proc. 33th AAAI Conf. Artif. Intell.*, vol. 33, pp. 5877–5884, Jul. 2019.

[39] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 5, pp. 603–619, May 2002.

[40] W. Wang, W. Wang, and J. Wang, "Algorithm for finding the smallest circle containing all points in a given point set," *J. Softw.*, vol. 11, no. 9, pp. 1237–1240, 2000.

[41] D. Brockmann, L. Hufnagel, and T. Geisel, "The scaling laws of human travel," *Nature*, vol. 439, no. 7075, p. 462, Jan. 2006.

[42] D. Yang, D. Zhang, V. W. Zheng, and Z. Yu, "Modeling user activity preference by leveraging user spatial temporal characteristics in LBSNs," *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 45, no. 1, pp. 129–142, Jan. 2015.

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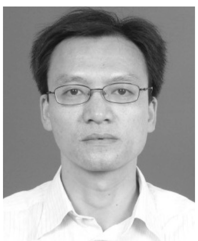

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