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Exploring Temporal and Spatial Features for Next POI Recommendation in LBSNs

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ABSTRACT With the increasing popularity of Location-Based Social Networks (LBSNs), a significant volume of check-in data of users has been generated. Such massive data brings difficulties for the users to efficiently retrieve their desired point-of-interest (POI). As a result, POI recommendation systems have received extensive attention from academia and industry. Currently, most existing POI recommendation approaches only provide users with a fixed set of recommended POIs based on the historical check-in records of the users, and cannot achieve flexible and feasible recommendations according to different spatial and temporal situations of the users. In this paper, we propose a next POI recommendation model that will predict POIs to be visited by users in the next few hours according to their historical check-in data and current contextual information (such as the current time and locations of the users). In our model, we propose a unified approach to calculate context-aware similarities between different users by investigating the influences of both temporal and spatial features for the users. We also propose an approach to dynamically generate different POI recommendation lists for a particular user according to different current context information of the user. 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 system, trajectory similarity.

I. INTRODUCTION

with the perfect combination of smartphones and the Internet, Location-Based Social Networks (LBSNs) have emerged, such as Foursquare, Gowalla, GeoLife, and Bikely, which furnish millions of users with platforms for displaying their check-ins at point-of-interests (POIs) and sharing life experiences in the physical world. The large-scale data generated by LBSNs supplies users with rich resources and extensive choices but brings difficulties for users to efficiently pick their really desired POIs. Thus, POI recommendation has become increasingly significant for users to navigate massive POIs and find the most satisfied ones.

Due to the importance of the POI recommendation, a bunch of approaches has been proposed to enhance the POI recommendation system. However, most existing POI recommendation approaches only explore the static preferences of the users from their check-in records and generate a fixed recommendation list of POIs, ignoring the current context of the users, such as the current location and time. Such approaches only focus on users' preference for POI recommendation, and do not care where are these recommended POIs located and when will the users visit them. Sometimes, such preference-aware POI recommendation approaches may provide useless suggestions. Concretely, ignoring the current context information, the traditional POI recommendation systems suffer from two major drawbacks: inflexible and unfeasible.

- **Inflexible problem:** A user's preference for POIs is dynamically changed according to different contexts. However, the traditional POI recommendation systems only archive a static preference estimation of the users. Thus, the generated recommendations fail to track the changing of users' preference on POIs, and remain fixed as long as check-in records of the users are not updated, causing the inflexible problem.
- **Unfeasible problem:** Without considering the current context information, the traditional POI recommenda-

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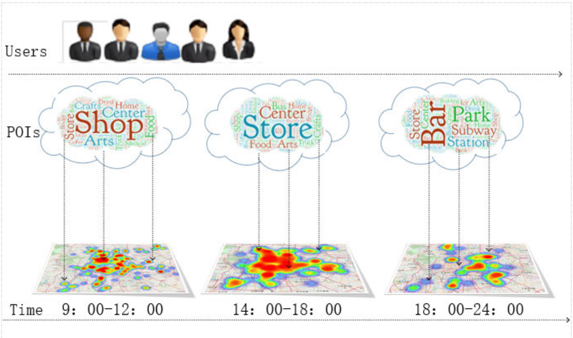


FIGURE 1. User check-in behavior is affected by time.

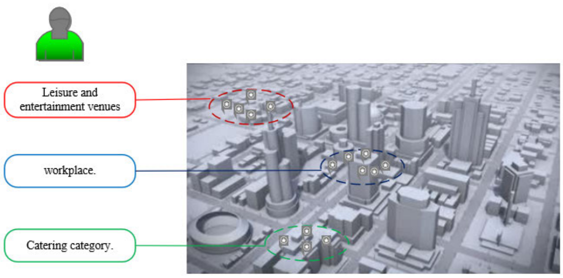


FIGURE 2. User check-in behavior is affected by geography.

tion systems may generate unfeasible suggestions. For example, they may recommend a restaurant located extremely far from the current location of the user, or recommend a bar at the working hours of the users.

Actually, what the users really need is a specific spatial and temporal constrained POI recommendation system which could answer the following question: "which POIs will the users visit next given his current context, including time and location?" Without loss of generality, temporal and spatial information will affect a user's decision to visit a certain location.

1) TEMPORAL INFLUENCE
The human geographical movement exhibits significant temporal patterns on LBSNs. For example, users generally exhibit distinct check-in preferences at different hours of the day as shown in Fig.1.

2) SPATIAL INFLUENCE
The geographical proximity between POIs will affect users' check-in behavior on the POIs. For example, we observe that most users' check-in records are concentrated in certain geographic areas as shown in Fig.2. Besides, the check-ins of each area are limited to several categories. Thus, a user may show different POI preferences in different areas.

In this paper, we investigate the problem of the next POI recommendation. In traditional POI recommendation, as long as the user has visited a certain place in the recommendation list, this recommendation is regarded as a correct recommendation. However, the next POI recommendation problem imposes more stringent restrictions on the generation of recommendation lists. What we recommend are locations where a user is likely to visit during the next few hours. Thus, the next POI recommendation is more challenging for the simple reason that different POI recommendation lists should be dynamically generated according to users' current location and the current time.

To address the next POI recommendation problem, we propose a novel and effective recommendation approach which contains the following contributions:

1) We first propose a method to construct virtual trajectories of users which fusing both temporal and spatial features. Similarity between different users can be measured by comparing their virtual trajectories.
2) Based on the constructed virtual trajectories, we propose a trajectory grouping method and a Voronoi diagram based method to characterize the influences of temporal features and spatial feature for users, respectively. Then, a fusion approach is proposed to combine them to calculate context-aware similarities between different users.
3) Finally, we propose collaborative filtering based approach to generate a POI recommendation list which contains top-k POIs likely to be visited by a particular user in the next few hours according to the current time and current location of the user.
4) Extensive experiments conducted on the two real-world datasets show that our model is effective and clearly outperforms the state-of-the-art methods.

The rest of the paper is organized as follows: We first present the related work in Section II. Section III describes the details of our next POI recommendation model. Experimental evaluation is shown in Section IV. Section V concludes this paper.

II. RELATED WORK
In LBSNs, POI recommendation is a crucial and challenging task. In this section, we briefly survey related research works from three perspectives: 1) temporal influence; 2) spatial influence; 3) next POI recommendation. Besides, we also introduce the Voronoi diagram which is applied in this paper, including notions and related research works.

A. TEMPORAL INFLUENCE
The temporal factor affects the choices of POIs of users to a great extent, because the determination of visiting a particular POI is time dependent [1]. Therefore, how to effectively combine the temporal factor to improve the recommendation efficiency of the recommendation system is a hot issue in current research. Yuan *et al.* [2] pointed out that the user's check-in behavior has temporal continuity. Based on this feature, a collaborative filtering recommendation model that incorporates time information is designed to provide users with a POI recommendation list. Gao *et al.* [3] proposed that users' personal preferences are not uniform in time, that is, users will show different check-in preferences at different

times of the day. To evaluate the time effects of location recommendations, they introduced four temporal aggregation strategies to integrate a user's check-in preferences of different temporal states. Cheng *et al.* [4] considered the sequence transfer mode between POIs at different time periods, and a tensor factorization based FPMC-LR model was proposed.

B. SPATIAL INFLUENCE

The spatial factor is an essential factor for the generation of POI recommendation list. Chen *et al.* [5] pointed out that users tend to check in around one or several central points and the probability that a user visits a location is inversely proportional to the distance from the nearest center point. Based on this phenomenon, many methods have been proposed to model geographic impacts. Zhang and Chow [6] proposed the iGSLR model which employed kernel density estimation (KDE) to model geographic impacts. Furthermore, they proposed an improved CoRe [7] method by using two-dimensional geographic coordinates to model the geographic impact. Ye *et al.* [8] proposed a power-law probabilistic model to capture the geographical influence, and realized POI recommendations via the naive Bayesian method. Liu *et al.* [9] developed a geographical-temporal awareness hierarchical attention network (GT-HAN), which can capture the great variation in geographical influence across POIs. Zhao *et al.* [10] proposed a SEER embedding model, which can improve the recommendation efficiency by learning pairwise preference features. Lian *et al.* [11] proposed a scalable and flexible framework, dubbed GeoMF++, for joint geographical modeling and implicit feedback based matrix factorization. They also proposed a Geography-aware sequential recommender based on the Self-Attention Network (GeoSAN for short) for location recommendation. In order to make better use of geographical information, GeoSAN [12] represented the hierarchical gridding of each GPS point with a self-attention based geography encoder. Zhao *et al.* [13] use of the mobile users' location sensitive characteristics to carry out rating prediction. The novelties of this paper are user-item and user-user geographical connections, i.e., they explore users' rating behaviors through their geographical location distances. In addition, They also explored sentimental attributes of locations and proposed a POI mining method and a personalized recommendation model by fusing sentimental spatial context [14]. However, the author did not thoroughly consider the impact of time factors on the emotional attributes of a location. For example, as time goes by, the emotional attributes of a certain location are a dynamic change process, which means that the emotional attributes of the location change dynamically. Not fixed.

C. NEXT POI RECOMMENDATION

At present, the next POI recommendation has become a new research direction. Jiao *et al.* [15] proposed a novel and effective next POI recommendation system by simulating the user travel decision-making process. They also considered two important factors that influence people's choice of travel destination: preference and geographic factors, and integrates them into a unified recommendation process. Ding *et al.* [16] proposed a spatial-temporal activity preference (STAP) model can capture the spatial and temporal influence separately. They also have put forward a text-aware fusion framework to combine the spatial and temporal activity preference models for preference inference. He *et al.* [17] proposed a third-rank tensor to model the successive check-in behaviors. By incorporating a function to fuse the personalized Markov chain with a latent pattern, they furnished a Bayesian Personalized Ranking (BPR) approach and derive the optimization criterion accordingly. Wu *et al.* [18] proposed a long-and short-term preference learning model (LSPL) considering the sequential and context information. In addition, to better learn the different influence of location and category of POIs, they trained two LSTM models for location-based sequence and category-based sequence, respectively. Then combined the long and short-term results to recommend next POI for users.

D. VORONOI DIAGRAM

Consider a set of discrete points, called generation points, in the plane. The Voronoi diagram can divide the space into adjacent but non-overlapping polygon regions according to Euclidean distance. Each polygon region is called Voronoi polygon or Voronoi cell, and each Voronoi cell contains only one generation point. The boundaries of the polygon are called Voronoi edges. The Voronoi polygons that share the same edges are called adjacent polygons and their generators are called adjacent generators [19]. In this paper, the two-dimensional position coordinates of each check-in point are used as generation point, and the space region is effectively divided.

Since the Voronoi diagram is sensitive to spatial distance, it can effectively reflect the spatial distance of the user's check-in location, it is mostly used in network research based on location data. Kolahdouzan and Shahabi [19] proposed a KNN query processing method for location data based on Voronoi division, which solved the problem of KNN query for large-scale location data. Xiao *et al.* [20] based on Voronoi diagram, he proposed a privacy protection method for stay point road network trajectory in view of offline trajectory data publishing scenario. Gao *et al.* [21] by constructing Voronoi diagram of road network under the road network, he proposed a V_k privacy model, which effectively protected the quality of service.

III. THE NEXT POI RECOMMENDATION SYSTEM

In this paper, we propose a next POI recommendation system. For a target user, the main objective of our model is to recommend top-k POIs which are likely to be visited next by the user according to the current time and location of the users. In this section, we describe details of our model, and Fig.3 illustrates the framework of the entire system. As depicted in the figure, our next POI recommendation system consists of two major components: context-aware similarity

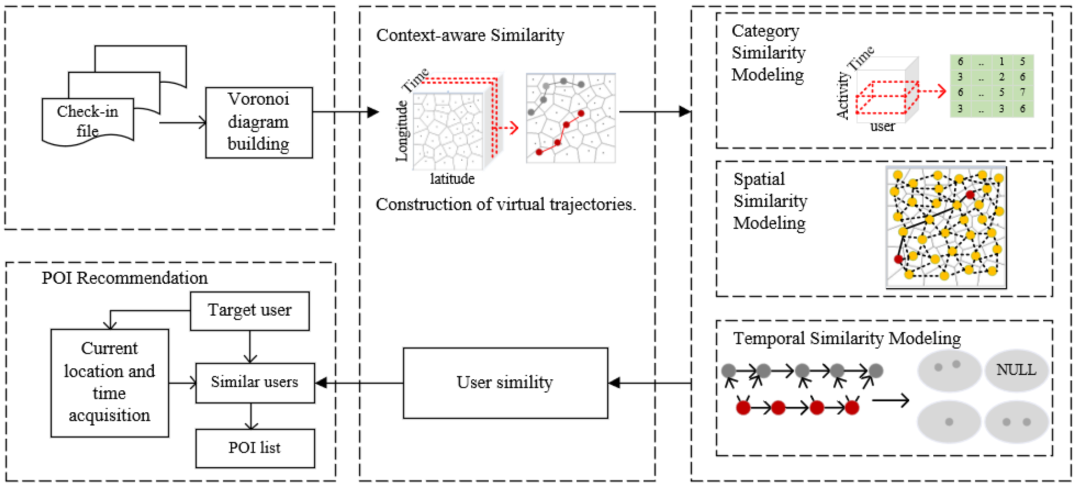


FIGURE 3. System framework.

module, and POI recommendation list generation module. In the context-aware similarity module, we propose a method to construct virtual trajectories of users, and a novel approach to calculate similarities between different users by comparing their corresponding virtual trajectories from three aspects: temporal feature, spatial feature, and category feature. At the POI recommendation list generation module, we propose a method to dynamically generate different POI recommendation list for a target user according to his current location and the current time. The details of the system will be described in the following sections.

A. CONTEXT-AWARE SIMILARITY CALCULATION

In this section, we describe the details of our approach to calculate context-aware similarities between different users. We define similar users as users whose check-in histories simultaneously satisfy three types of similarities: temporal similarity, spatial similarity, and category similarity. Specifically, our similarity calculation approach aims to explore the users who visit POIs with similar categories and similar geographical locations during similar time intervals.

In order to estimate the context-aware similarity between different users, we propose an approach to construct virtual trajectories of each user as follows:

1) We first divide a day into 6-time intervals, (i.e. 0:00-7:00, 7:00-9:00, 9:00-12:00, 12:00-14:00, 14:00-18:00, 18:00-0:00). The entire check-in records of the users are allocated to a certain time interval according to their check-in time stamp. Thus, the data set is divided into 6 groups.
2) For each time interval, we construct a Voronoi diagram according to the latitude and longitude of the check-in records that belong to this time interval.
3) For a particular user, we connect all the check-in records in chronological order to construct his virtual trajectory. Thus, each user has 6 trajectories corresponding to 6-time intervals.

Fig.4 shows an example of users' virtual trajectories construction. Voronoi diagrams are constructed by using the context information of the check-in records such as time, latitude, and longitude. For the time dimension, instead of using real timestamps of the check-in, we merge all the timestamps into 6 intervals. Notice that such trajectories are not the real movement tracks of the users for the reason that we only focus on time information to construct users' trajectories, ignoring date information (i.e. day, month, year). The users' virtual trajectories are only artificially constructed for similarity calculation.

Given a target user u_i, we construct his virtual trajectory for each corresponding time interval T_q, denoted by $L_i^q = \{p_1, p_2, p_k, \ldots, p_n\}$. Each $p_k \in L_i^q$ denotes a certain check-in point of user u_i during the time interval T_q, and can be expressed by $< l_k, t_k, c_k >$. l_k represents the geographical location of the POI p_k, t_k is the specific check-in time and c_k denotes the category of p_k.

Given a specific time interval, we first construct virtual trajectories for target user u_i and each other user u_j. Then, the similarity between u_i and u_j is calculated by comparing the constructed virtual trajectories of u_i and u_j. We consider three factors to estimate similarities between different trajectories: temporal factor, spatial factor, and category factor. In the following sections, we describe the details of our context-aware similarity calculation.

1) TEMPORAL SIMILARITY MODELING

Given the virtual trajectory $L_i^q = \{p_1, p_2, p_k, \ldots, p_n\}$ of the target user u_i, we divide the virtual trajectory of each other user u_j into n groups, where n denotes the length of L_i^q. Details are shown as follows:

1) For each check-in point $p_k \in L_i^q$ of u_i, construct an empty set, named $group_k$.

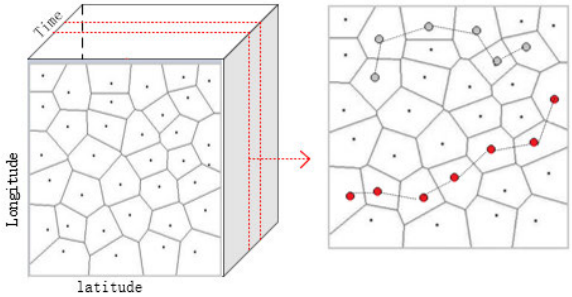


FIGURE 4. **The construction of virtual trajectories of users in different time periods.**

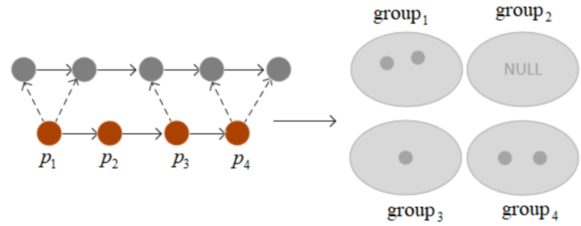


FIGURE 5. **Calculate the trajectory similarity between users through trajectory grouping.**

2) For u_j, construct his virtual trajectory, denoted by L_j^q.
3) Repeat the following to assign each check-in point $p_m \in L_j^q$ to a certain constructed set.
   a) Calculate $|t_m - t_k|$ for each $p_k \in L_i^q$, where t_m and t_k represent the check-in time of p_m and p_k, respectively.
   b) Compare each temporal distance, and find a point $p_{min} \in L_i^q$ which is the closest to p_m in time.
   c) Assign p_m to the corresponding set $group_{min}$.

Finally, we construct n groups according to n check-in points of u_i in L_i^q. Figure 5 shows an example of trajectory division. Obviously, an empty set may exist.

By considering the temporal feature, our approach successfully converts the calculation of trajectory similarity into the calculation of similarity between each $p_k \in L_i^q$ and the check-in points in his corresponding group.

Equation (1) and (2) give specific calculations.

$$simuser(u_i, u_j) = \frac{\sum_{k=1}^{n} sim(p_k, group_k)}{n} \tag{1}$$

$$sim(p_k, group_k) = \frac{\sum_{p_m \in gourp_k} simpoint(p_k, p_m)}{|group_k|} \tag{2}$$

Specifically, in Equation (1), $simuser(u_i, u_j)$ represents the similarity between u_i and u_j for the given time interval, and n is the length of the virtual trajectory of u_i. $sim(p_k, group_k)$ denotes similarity between $p_k \in L_i^q$ and his corresponding constructed set $group_k$. In Equation (2), $simpoint(p_k, p_m)$ represents the similarity between check-in point p_k of u_i and $p_m \in group_k$.

After successfully dividing trajectories, our research focuses on the similarity calculation of check-in points by considering spatial constraints and category features.

2) SPATIAL SIMILARITY MODELING

In order to model user spatial similarity, we construct a Voronoi diagram by using the geographical locations of all the POIs. Specifically, the entire city in the dataset is divided into multiple units, and each unit contains one and only one POI. Thus, users' spatial related preference can be reflected by the group of the units which contains their visited POIs. Voronoi diagram is more reasonable than Euclidean distance to define whether two POIs are nearby POIs. In different areas of the city, POIs have different distributions, sparse or dense. Obviously, the size of Voronoi units is relatively larger in sparse areas and smaller in dense areas. Thus, two POIs located at the sparse area may be adjacent POIs in the Voronoi diagram even though the Euclidean distance between them is large. Consequently, the Voronoi diagram provides an adaptive estimation of the distance between POIs according to different distributions.

In this subsection, we will describe the details of the Voronoi diagram based geographic similarity calculation approach.

Given a time interval T_q, we first transfer the corresponding Voronoi diagram into an undirected graph G_q as follows:

1) For each point of the Voronoi diagram, determine its adjacent points. If the Voronoi polygons of two points share a common edge, we define them as adjacent points.
2) For each pair of the adjacent points in the Voronoi diagram, add an undirected edge.
3) The weight of each undirected edge of the graph is 1.

For each $p_k \in L_i^q$ of the target user u_i, we have constructed its corresponding temporal similar set $group_k$ in the section III-A1. Then, we calculate the geographic similarity between p_k and each $p_m \in group_k$ by using Equation (3).

$$\omega_{(p_k, p_m)} = \begin{cases} 1, & s = 0 \\ \dfrac{e^{-d}}{2^{s-1}}, & s \geq 1 \end{cases} \tag{3}$$

Specifically, d represents the Euclidean distance between two points. s represents the shortest path length from p_k to p_m in the undirected graph G_p. $s = 0$ implies that p_k and p_m are actually the same point in the Voronoi diagram. The *Dijkstra* algorithm is employed to find the shortest path form p_k to p_m. Figure 6 shows an example of construction the undirected graph and determination of the variable s in Equation (3). In Figure 6, the shortest path length for p_k to p_m is 4, and $s = 4$.

3) CATEGORY SIMILARITY MODELING

In this subsection, we will describe how to calculate the category similarity between two check-in points. Obviously, a check-in point belongs to a certain category, such as a restaurant, cinema, or shopping mall. We do not directly calculate the similarity between two specific check-in points.

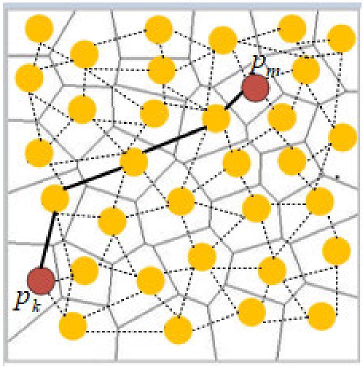


FIGURE 6. The undirected graph calculates the shortest distance between two points.

Instead, we calculate the similarities between different categories. The category similarity between two check-in points is actually the similarity between their corresponding categories.

We first construct a user-category matrix, and the matrix factorization technique is employed to recover lost or sparse data. In order to avoid the negative value in the recovered matrix which is meaningless, we use the non-negative matrix factorization technique [22]. Finally, we obtain a user-category matrix $Q \in R^{U \times C}$, where U represents the total number of users and C is the entire number of the categories. Each element q_{ij} of the matrix Q denotes the check-in frequency of user u_i at the POIs which belong to category c_j. Thus, each column of Q represents the check-in frequency of each user at a certain category and can be regarded as a feature vector of this category. After achieving the feature vector of each category, the similarity between different categories can be calculated.

For each $p_k \in L_i^q$ of the target user u_i, we calculate category similarity between p_k and each $p_m \in group_k$ by using Equation (4).

$$\varphi_{(p_k,p_m)} = \frac{\vec{c_{p_k}} \cdot \vec{c}_{p_m}}{\sqrt{|\vec{c}_{p_k}|^2} \cdot \sqrt{|\vec{c}_{p_m}|^2}} \tag{4}$$

In Equation (4), $\vec{c_{p_k}}$ and $\vec{c}_{p_m}$ represent feature vectors of categories of p_k and p_m, respectively.

4) CONTEXT FUSION MODEL

Given a target user u_i, we consider three features to calculate the context-aware similarity between u_i and each other user u_j. Details are shown as follows:

1) Construct virtual trajectories of u_i and u_j according to the given time interval T_q. Let L_i^q be the virtual trajectory of u_i, and L_j^q is the virtual trajectory of u_j.
2) For each $p_k \in L_i^q$, repeat the followings:
    a) Construct a set $gourp_k$ by using check-in points of L_j^q as described in Section III-A1. Each $p_m \in gourp_k$ shares similar temporal feature with p_k.
    b) For each $p_m \in gourp_k$, do the followings:
        i) Calculate spatial similarity $\omega_{(p_k,p_m)}$ by using Equation (3) as described in Section III-A2.
        ii) Calculate category similarity $\varphi_{(p_k,p_m)}$ by using Equation (4) as described in Section III-A3.
        iii) Calculate similarity between p_k and p_m as follows:

$$simpoint(p_k, p_m) = \omega_{(p_k,p_m)}\varphi_{(p_k,p_m)} \tag{5}$$

    c) Calculate similarity $sim(p_k, group_k)$ between p_k and its corresponding set $group_k$ by using Equation (2).
3) Calculate context-aware similarity $simuser(u_i, u_j)$ between u_i and u_j by using Equation (1).

The algorithm for Context-aware similarity is shown in Algorithm 1.

Algorithm 1 Context-Aware Similarity Calculation

Input:
  u_i: the target user
  u_j: another user
  T_q:the current time interval
Output:
  $simuser(u_i, u_j)$: the context-aware similarity between u_i and u_j

```
Construct the virtual trajectory L_i^q of u_i;
Construct the virtual trajectory L_j^q of u_j;
for each p_k ∈ L_i^q; do
    Construct an empty set group_k;
end for
for each p_m ∈ L_j^q; do
    Compare check-in time of p_m with each p_k ∈ L_i^q;
    Find the POI p_r ∈ L_i^q with the smallest temporal distance to p_m;
    Insert p_m to group_r;
end for
Initialize n with the length of L_i^q;
for each p_k in L_i^q; do
    for each p_m in group_k; do
        simpoint(p_k, p_m) = ω_(p_k,p_m) φ_(p_k,p_m);
    end for
    sim(p_k, group_k) = (Σ_{p_m ∈ gourp_k} simpoint(p_k,p_m)) / |group_k|;
end for
simuser(u_i, u_j) = (Σ_{k=1}^{n} sim(p_k,group_k)) / n;
```

Finally, we obtain the context-aware similarity between the target user u_i and each other user u_j by considering three types of features: temporal feature, spatial feature, and category feature. Next, we propose collaborative filtering based approach to recommend POIs to the target user.

B. POI RECOMMENDATION

After calculating the similarities between the target user u_i and each other user, we construct a set S_{u_i} to store the top k most similar users for u_i. Thus, $|S_{u_i}| = k$.

Then, a collaborative filtering based approach is proposed to generate a recommendation list for u_i. Details are shown as follows:

1) Construct a set CP_{u_i} which contains all the POIs accessed by the users in S_{u_i}.
2) Define a distance threshold λ to determine the recommendation region. Such a region is a circle and the current location of u_i is the center and λ is the radius.
3) For each check-in point $p_m \in CP_{u_i}$, we propose the following weight function:

$$\psi_{(l,p_m)} = \begin{cases} \lambda^{-1}, & d_{(l,p_m)} \leq \lambda \\ d^{-1}_{(l,p_m)}, & d_{(l,p_m)} > \lambda \end{cases} \tag{6}$$

Specifically, l denotes the user u_i's current location. $d_{(l,p_m)}$ denotes Euclidean distance between l and geographical location of p_m.

4) For a check-in point $p_m \in CP_{u_i}$, and a user $u_k \in S_{u_i}$, without considering the distance, the pseudo score of the POI p_m by the target user u_i is calculate by using Equation (7).

$$pscore(u_i, p_m) = simuser(u_i, u_k) f(u_k, p_m) \tag{7}$$

5) For each check-in point $p_m \in CP_{u_i}$, add the distance limit, the pseudo score of the POI p_m by the target user u_i is calculate by using Equation (8).

$$score(u_i, p_m) = \sum_{k=1}^{|S_{u_i}|} pscore(u_i, p_m)\psi(l, p_m) \tag{8}$$

where, $f(u_k, p_m)$ denotes the pseudo score of the POI p_m by a user $u_k \in S_{u_i}$ and can be calculated by Equation (9).

$$f(u_k, p_m) = \frac{N(u_k, p_m)}{L^q_k} \tag{9}$$

$N(u_k, p_m)$ indicates the number of times u_k has visited p_m. L^q_k represents the total number of check-in records for user u_k in his or her check-in history.

6) After getting the pseudo score of each POI in CP_{u_i} by the target user u_i, the CP_{u_i} arranged in descending order according to pseudo score, the top-k POIs are recommended to the target user u_i.

The algorithm for POI recommendation is shown in Algorithm 2.

Algorithm 2 The Approach of POI Recommendation

Input:
u_i: the target user
S_{u_i}: a set which contains top-α most similar users for u_i
CP_{u_i}: a set of POIs that accessed by the users in S_{u_i}
Output:
Recommendation list for u_i
Determine l represents the current location of u_i;
Initialize distance threshold λ;
Draw a circle;
Determine the recommendation region $Reg^{\lambda}_{u_i}$; /* a circle: the current location of u_i is the center and distance threshold λ is the radius. */
for each p_m in $CP^{\lambda}_{u_i}$; **do**
  for each $u_k \in S_{u_i}$; **do**
    $f(u_k, p_m) = \frac{N(u_k,p_m)}{L^q_k}$
    if $p_m \in CP_{u_i}$ and p_m is located in $Reg^{\lambda}_{u_i}$ **then**
      $\psi_{(l,p_m)} = \lambda^{-1}$
    else
      $\psi_{(l,p_m)} = d^{-1}_{(l,p_m)}$
    end if
  end for
  $score(u_i, p_m) = \sum_{k=1}^{|SIM_{u_i}|}(simuser(u_i, u_k) f(u_k, p_m)\psi_{(l,p_m)})$
end for
Compare $score(u_i, p_m)$ of each $p_m \in CP_{u_i}$, and select top-k POIs to generate recommendation list for u_i;

IV. EXPERIMENTS

A. EXPERIMENTAL SETTING

1) DATASETS

We use a publicly available dataset from Foursquare [1] [16] to evaluate the effectiveness of our proposed POI recommendation model. The Foursquare dataset contains two cities, New York and Tokyo. The dataset in New York contains consecutive check-ins from July 2012 to December 2013. The dataset in Tokyo contains consecutive check-ins from April 2012 to May 2013. In two data sets, a complete check-in record contains check-in time, user ID, POI ID, longitude, latitude of the POI, and category ID to which the POI belongs. We do the same data preprocessing on two datasets to reduce the impact of some noise and invalid data on the recommendation results. We eliminated users with less than 10 POI check-ins and POI with less than 10 visitors from two datasets. The basic statistics of them are shown in Table 1.

2) EXPERIMENT DATA PARTITION

In order to evaluate the performance of our system, we split each dataset into the training set and the testing set in terms of user check-in time. We use the check-in records generated by users in the last two months for the test set and the rest for the training set.

3) EVALUATION METRIC

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

$$Precision = \frac{No.\ of\ POIs\ correctly\ predicted}{No.\ of\ recommended\ POIs} \tag{10}$$

$$Recall = \frac{No.\ of\ POIs\ correctly\ predicted}{No.\ of\ POIs\ actually\ accessed} \tag{11}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{12}$$

[1] https://sites.google.com/site/yangdingqi/home/foursquare-dataset

TABLE 1. Dataset statistic.

Dataset	New York (Foursquare)	Tykyo (Foursquare)
Users	1083	800
Venues	38196	9762
Check-ins	225864	97562

4) COMPARISON OF VARIOUS APPROACH

- SMP [23]: The authors explore the effects of spatial and mobility pattern for collaborative POI recommendation. SMP determines the active area of the target user based on the check-in history, and designs a personalized user space similarity calculation method based on the active area of the target user. In addition, the authors also design a novel personalized user mobility pattern similarity calculation method based on the features of human mobility pattern.
- Rank-GeoFM [24]: The authors propose a ranking based geographical factorization method for POI recommendation, Rank-GeoFM consider that the check-in frequency can characterize users' visiting preference and learn the factorization by ranking the POIs correctly. Moreover, POIs both with and without check-ins will contribute to learning the ranking and thus the data sparsity problem can be alleviated In addition, the authors also propose a stochastic gradient descent based algorithm to learn the factorization.
- PFMMGM [5]: The authors propose a model framework which fuses MF(matrix factorization) with geographical and social influence for POI recommendation. This model can capture the geographical influence via modeling the probability of a user's check-in on a location as a Multi-center Gaussian Model (MGM).
- USG [8]: The authors propose a unified POI recommendation framework, which fuses user preference to a POI with social influence and geographical influence. The authors consider that the geographical influence among POIs plays an important role in user check-in behaviors and model it by the power-law distribution, and the user preference section of USG is realized through a traditional user-based collaborative filtering technique. The USG can adjust the weight parameters to select the considerations to be included. In this paper, USG-PG denotes the USG considering both user preference and geographical influence.
- PFM [25]: The authors propose a novel probabilistic factor model based on dimensionality reduction techniques. which can model the frequency data directly.

B. RECOMMENDATION EFFECTIVENESS

1) COMPARISON OF METHODS

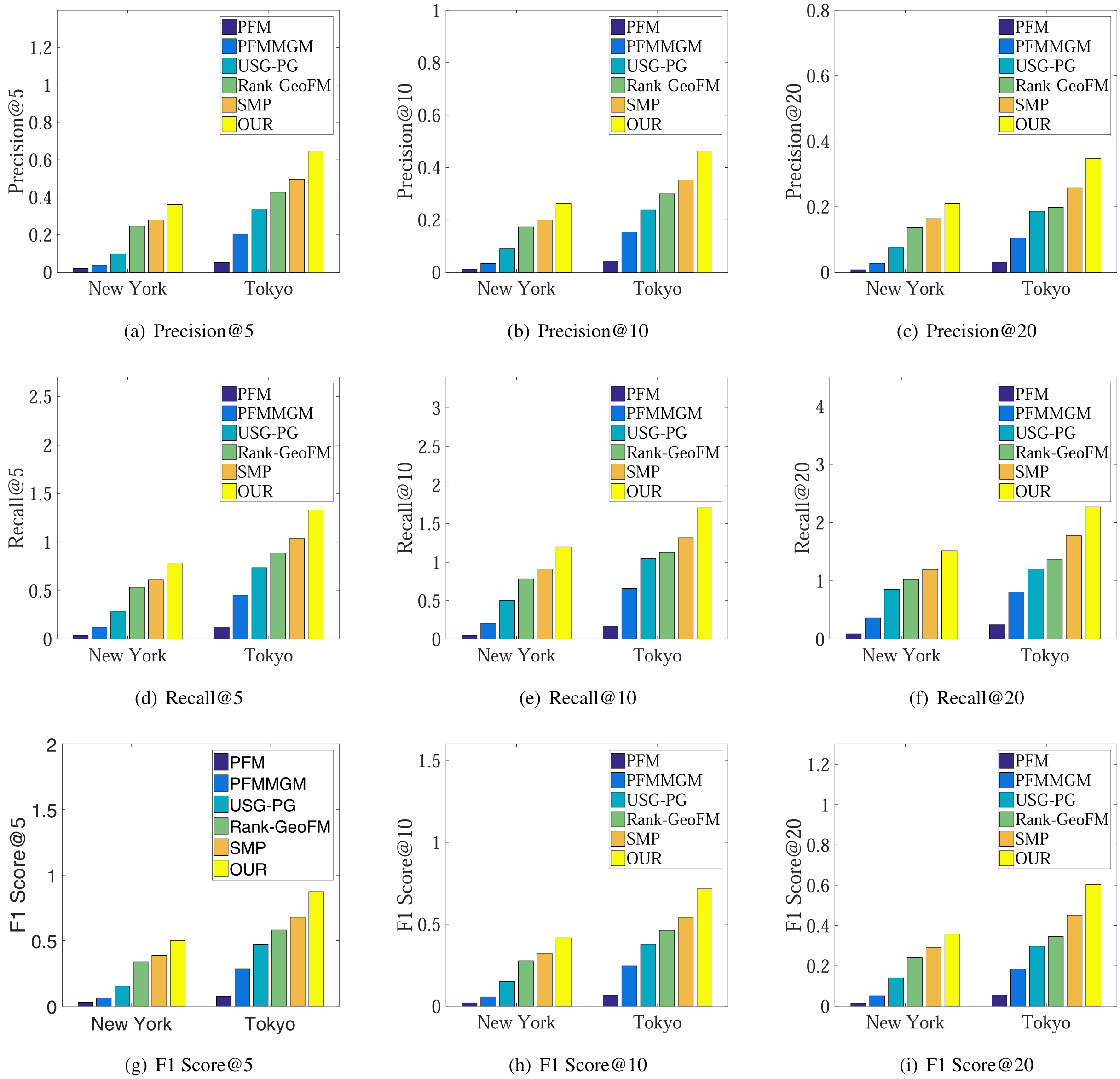
In this section, we will introduce the performance of our model, and make a comprehensive comparison with the six baseline methods. In order to ensure the fairness of the comparison, we have to constantly adjust the parameters in the baseline method, set the value of the parameters for the best performance. Fig.7 show the results of experiments. Our approach obtains higher performance than the other POI recommendation methods based on both of the datasets.

The experimental results show that the performance of PFM is the worst. This is mainly because PFM based on matrix factorization is more focused on mining user preference information, and do not effectively utilize the geographical influence and temporal influence of use's check-in behavior. Besides, the model is easily vulnerable to data sparsity. MGMPFM is improved based on the PFM model, and a Multi-center Gaussian Model (MGM) is proposed to model the user's check-in behavior. But the performance of MGMPFM is still unacceptable. This is mainly because FMFMGM constructs the Gaussian distribution by looking for the active region of the user, ignoring the regional integrity structure. Moreover, MGMPFM also does not consider the category information of POIs. The performance of USG-PG is slightly higher than MGMPFM. This is because the USG-PG model linearly combines the two factors of user preference and geographical influence, which effectively improves the recommendation efficiency. However, the model cannot set personalized weights for these two factors, which means the model ignores the different characteristics of users. The result of Rank-GeoFM is acceptable for several reasons. First, Rank-GeoFM can effectively model implicit feedback data. Second, Instead of fitting the check-in frequency as conventional matrix factorization based methods do, Rank-GeoFM fits the users' preference rankings for POIs to learn the latent factors of users and POIs. And the unvisited POIs also contribute to the learning, which will help alleviate the sparsity problem. But Rank-GeoFM ignores the modeling of user sequential check-ins. In the field of POI recommendation, the user's sequential check-in behavior is an important source of mining user movement patterns. SMP shows a good recommendation performance for several reasons. First, SMP effectively utilizes the category information of POIs and the popularity information of POI categories. Second, SMP takes into account three features of the human mobility pattern: spatial, temporal, and sequential properties. But the disadvantage of SMP is that it does not consider the implicit position association between POIs.

Compared to baseline methods, our POI recommendation system has a higher recommendation quality, mainly because: Our system effectively considers the implicit position association between POIs. Secondly, our system models the three characteristics of temporal, spatial, and category, and designs a personalized trajectory similarity calculation method. Finally, we designed a personalized location recommendation model based on a user's current context (i.e. location and time).

2) IMPACT OF THE NUMBER OF SIMILAR USERS

The number of similar users N has a direct impact on the performance of our system, it is a vital factor to control the types of recommended lists. Fig.8 presents specific changes in the recommendation performance of our model as N change. Just

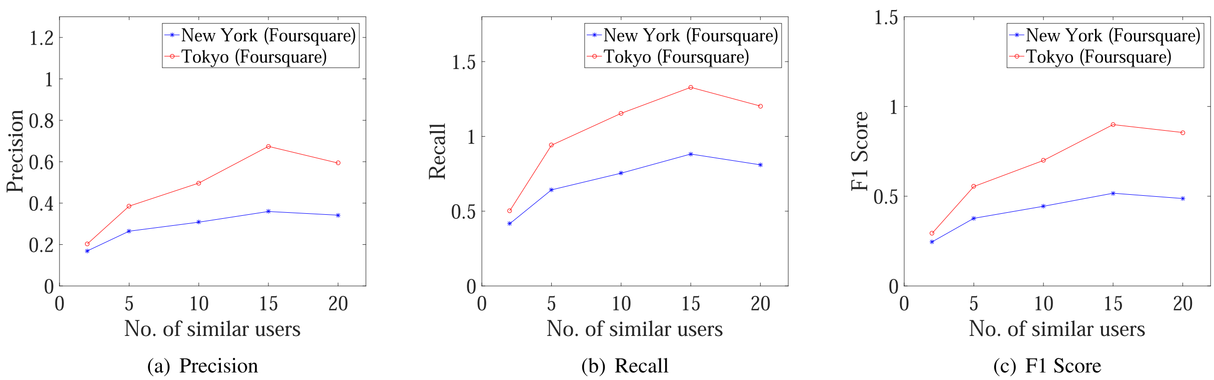


(a) Precision@5 (b) Precision@10 (c) Precision@20

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

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

FIGURE 7. Comparison with baselines under different datasets.



(a) Precision (b) Recall (c) F1 Score

FIGURE 8. The impact of the number of similar users on recommendation performance.

as the result shows, our system's recommendation performance gradually reaches the highest level when the number of similar users N is 15. As N continues to increase, the performance of our system begins to decline.

TABLE 2. Compare the impact of distance thresholds on recommendation performance under different datasets.

Distance Threshold (km)	Pre@5	Pre@10	Pre@20	Pre@5	Pre@10	Pre@20
	New York (Foursquare)			Tokyo (Foursquare)		
10	0.351	0.249	0.211	0.438	0.301	0.237
30	**0.367**	**0.261**	**0.219**	0.573	0.385	0.301
50	0.341	0.245	0.207	**0.683**	**0.481**	**0.360**
70	0.327	0.242	0.201	0.652	0.463	0.340
90	0.311	0.227	0.187	0.532	0.414	0.297

This is because too small a value of N will result in fewer POIs to be selected in the recommendation list, which is not enough to reflect the similar relationship between the check-in information of similar user groups and the recommendation of POIs for the target user. When the N value is too large, some users who have low similarities with the target are also considered in our model, which reduces the efficiency and the accuracy of the system.

3) IMPACT OF DISTANCE THRESHOLD

The distance threshold λ has a direct impact on the performance of our system, it is a vital factor to control the radius of user's active area in the next time. Table 2 presents specific changes in the recommendation precision of our model as the distance threshold change. Firstly, it can be observed that the accuracy values of two different datasets of Foursquare are greatly different, because the user check-in data in New York (Foursquare) dataset is relatively sparse, which cannot fully capture the similarity of the movement trajectory between the target user and other users, while the user check-in data in Tokyo (Foursquare) dataset is of good quality. Secondly, in New York (Foursquare) dataset, our system's recommendation precision gradually reaches the highest level as the distance threshold increases from 10 to 30. As continues to increase, the performance of our system begins to slowly decline. In Tokyo (Foursquare) dataset, our system gradually performs at its best as the distance threshold λ increase from 10 to 50. As continues to increase, the recommendation precision of our system begins to decline. This is because when λ is small, we only consider a very small radius of the recommendation region which do not include enough information and yield suboptimal performance. While when λ is too large, this model may introduce more noisy information which yields poor performance.

V. CONCLUSION

In this paper, we design a novel and effective next POI recommendation system by analyzing user historical travel records. Our system mines the user's check-in records in different time slots and designs a personalized user similarity calculation method that integrates spatiotemporal features. We first propose a method to construct virtual trajectories of users which fusing both temporal and spatial features. Then, based on the constructed virtual trajectories, we propose a trajectory grouping method and a Voronoi diagram based method to characterize the influences of temporal features and spatial feature for users, respectively. Finally, we propose collaborative filtering based approach to generate a POI recommendation list which contains top-k POIs likely to be visited by a particular user in the next few hours according to the current time and current location of the user.

In the future, we look forward to doing some work on the semantic analysis of POI recommendation, for example, user comment information. This will better understand the needs of users and make the POI recommendation system better serve users.

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