IGTP: A Next Point-of-Interest Recommendation Method that Integrates Geospatial and Temporal Preferences

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IGTP: A Next Point-of-Interest Recommendation Method that Integrates Geospatial and Temporal Preferences

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Abstract With the rapid development of location-based social networks(LBSNs), point-of-interest(POI) recommendation has become an important way to meet the personalized needs of users. The purpose of POI recommendation is to provide personalized POI recommendation services for users. However, general POI recommendations cannot meet the individual needs of users. This is mainly because the decision-making process for users to choose POIs is very complicated and will be affected by various user contexts such as time, location, etc. This paper proposes a next POI recommendation method that integrates geospatial and temporal preferences, called IGTP. Compared with general POI recommendation, IGTP can provide more personalized recommendations for users according to their context information. First, IGTP uses users' preferences information to model users' check-in histories to effectively overcome the challenge of extremely sparse check-in data. Secondly, IGTP takes into account the geographic distance and density factors that affect people's choice of POIs, and limits POIs to be recommended to the potential activitive area centered on the current location of the target user. Finally, IGTP integrates geospatial and users' temporal preferences information into a unified recommendation process. Compared with six advanced baseline methods, the experimental results demonstrate that IGTP achieves much better performance.

Keywords Point of Interest · Next POI Recommendation · Tensor · Location Based Social Networks · Preference

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1 Introduction

In recent years, LBSNs as shown in Fig 1 and their services have emerged and developed rapidly. Location data bridges the gap between the physical world and the digital world, allowing people to gain a deeper understanding of users' preferences and behaviors. Location-based personalized recommendation services have become crucial in LBSNs and have received widespread attention in both academia and industry. POI recommendation is one of the most important tasks in LBSNs, it can help users discover new and interesting locations in LBSNs. POI recommendation usually recommends a list of POIs that a user is most likely to check-in in the future by mining the user's check-in history, location information and the user's social relationship. Currently, POI recommendation has become a new research hotspot in the field of recommendation systems and social networks.

Although POI recommendation has achieved great success, it still faces some difficulties and challenges, as follows:

- General POI recommendation only recommends POIs that a user may visit in the future, and cannot recommend POIs that a user may visit in the next

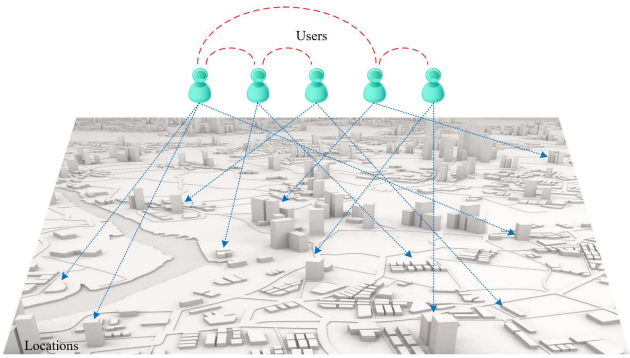


Fig. 1 location-based social networks

moment according to the user's current contextual information, such as the user's current time and current location. Therefore, general POI recommendations cannot make personalized recommendations for users based on their current context.

– POI recommendation system suffers from a serious problem of data sparse. Compared with the user-item matrix used by the traditional recommendation system, the user-POI matrix used by the POI recommendation system is extremely sparse. This is because the total number of POIs is quite large, the number of POIs accessed by a single user is very small.
– Various types of contextual information can be used to make POI recommendations, such as geographical coordinates of POIs, timestamps of check-ins, social relationships of users, categories of POIs, etc. Although most of the existing POI recommendation systems integrate a variety of contextual information. However, they did not construct a unified recommendation process to integrate these information, thus ignoring the implicit correlation between various contextual information.

In this paper, in order to solve the above problems, we propose a next POI recommendation method that integrates geospatial and temporal preferences, called IGTP. The main contributions of IGTP can be summarized as follows:

1. IGTP uses users' check-in frequency to model users' temporal preferences, which can effectively reflect users' preferences.
2. IGTP divides POIs according to users' preferences, and uses users' preferences information to model users' check-in histories, thereby overcoming the challenge of extremely sparse check-in data.
3. IGTP can dynamically predict users' preferences according to the change of time.
4. IGTP takes into account the geographic distance and geographic density factors that influence people's choice of POIs. IGTP improves the accuracy of recommendations by limiting the POIs to be recommended to potential active areas centered around the target user's current location.
5. IGTP effectively integrates geospatial and users' temporal preferences information into a unified recommendation process.
6. In this study, we experimented with IGTP on two real-world datasets of Foursquare and Gowalla. And six advanced POI recommendation methods are compared with IGTP as baseline methods.

2 Related Work

In recent years, LBSNs and related services have developed rapidly. In LBSNs, users generate a large amount of check-in data, which makes it possible to recommend POIs to users. POI recommendation can help users get familiar with unfamiliar cities as soon as possible and can also assist users in choosing travel destinations. Therefore, the POI recommendation is also of great commercial value and has been widely valued by industry and academia. This section briefly introduces POI recommendation from four perspectives: 1) datasets used by POI recommendation; 2) the influence of geographical factors; 3) the influence of temporal factors; 4) recommendation methods used by POI recommendation.

2.1 Datasets Used by POI Recommendation

The POI recommendation mainly uses users' check-in dataset (Yang et al (2014)) and users' GPS trajectory dataset (Zheng (2011)). A check-in dataset contains POIs with semantic information, rich user attributes and POI attributes information and also includes friend relationships between users. Therefore, check-in datasets have become the first choice of many POI recommendation researchers. However, the extremely sparse user check-in behavior is also an unavoidable problem of check-in datasets. Compared with the extremely sparse check-in data, GPS trajectory datasets do not have this problem. A GPS trajectory dataset contains the total time of user trajectory, user residence time in a location, speed, altitude, some corresponding distances and other geographical information. However, the first task to use GPS trajectory dataset is to mine the geographical information of POIs from the trajectory data. Moreover, how to match the semantic information of these mined POIs is also a challenging task.

2.2 The Influence of Geographical Factors

POI recommendations are affected by many factors. Geographical factors are the core factors that affect POI recommendations and they are extremely important for POI recommendations. Since users' check-in behavior in LBSNs presents a spatial clustering phenomenon, geographical influence can be modeled by the methods of probability distribution and kernel density estimation. Ye et al (2011) use a power-law distribution to simulate the check-in probability of two POIs visited by the same user. In reference Cheng et al (2012a), according to the characteristics of user check-in behavior, Gaussian distribution is used to model user check-in behavior and multi center Gaussian model (MGM) is proposed. Yu et al (2016a) believe that Gaussian distribution is more suitable for modeling users' rating behavior rather than users' check-in behavior and Poisson distribution is better than Gaussian distribution in fitting check-in frequency data. A Poisson matrix factorization POI recommendation based on ranking is proposed. Zhang and Chow (2013) believed that the geographical influence of a user's check-in behavior should be personalized rather than modeled with the same distribution (such as power law distribution, multi-center Gaussian distribution) and then proposed the iGSLR method using kernel density estimation, which uses the personalized distance distribution of each user to model geographical influence. Ren et al (2017) improved the kernel density estimation of the fixed bandwidth and adopted a decision-making method to adapt to the local bandwidth and achieved good results.

2.3 The Influence of Temporal Factors

In LBSNs, POI recommendations can be made for a specific time interval. The influence of temporal factors on POI recommendation is mainly manifested in the periodicity and non-uniformity of users' check-in behavior. Time periodicity means that users usually visit the same or similar POIs in the same time interval. Time non-uniformity usually shows that a user's check-in preference is different in different times of a day, different days of a week and different months of a year. References (Cho et al (2011a); Debnath et al (2016); Gao et al (2013); Ozsoy et al (2016); Yuan et al (2013a); Yuan and Li (2016); Zhang and Chow (2017)) respectively use temporal influence to recommend POIs for users. These methods divide a day into multiple time intervals, such as 24 hours or morning, noon, afternoon, evening, night, etc., and then use collaborative filtering and other recommendation technologies to infer users' preferences in each time interval.

2.4 Recommendation Methods Used by POI Recommendation

Many recommendation methods have been used since the development of POI recommendation, which are summarized as follows. In the early stage of POI recommendation, most of the POI recommendation methods directly match users' preference attributes with location features, that is, content-based recommendation method. With the emergence of PageRank and HITS algorithms, POI recommendation begins to adopt recommendation methods based on link analysis (Bagci and Karagoz (2016); Li et al (2016)). Since the idea of collaborative filtering was put forward, there have been many studies (Cui et al (2017); Jiao et al (2019c); Li et al (2021); Oppokhonov et al (2017); Si et al (2017); Yuan et al (2013b)) using collaborative filtering to recommend POIs for users. POI recommendation methods also include matrix factorization based recommendation method (Cheng et al (2012b); Rendle et al (2009); Yu et al (2016b)), tensor decomposition based recommendation method (Jiao et al (2019b); Kim et al (2014)), Markov chain based recommendation method (Zhang et al (2014)), embedding based recommendation method (Feng et al (2017, 2020); Qian et al (2019); Wu et al (2013); Xu et al (2019)) and so on. With the vigorous development of deep learning, the method of using deep learning (Feng et al (2018); Li et al (2019); Liu et al (2016, 2020); Sun et al (2020); Zhao et al (2019)) to recommend POIs to users is becoming a research hotspot, and has received extensive attention from academia and industry.

3 Problem Definition

In this paper, the problem of next POI recommendation is defined as: given the check-in history of a target user and the target user's current time and current location, the task of next POI recommendation is to recommend top k locations for the target user that the user may be interested in in the next time period.

In order to facilitate the description of the IGTP method, the symbols used in this paper are as follows:

1. U**:** the set of the entire users.
2. F**:** the set of all the preferences. There are many categories of POIs, such as medical center, coffee shop, music store and so on. Bao et al (2012) suggest that the category of a POI that a user has visited usually implies the user's travel preferences. In this paper, the categories of POIs are referred to as user preferences.

3. L**:** the set of the entire POIs. Each POI $l \in L$ is represented as $l =< x, y, f >$, where x denotes latitude, y represents longitude and $f \in F$ is the preference which l belongs to.
4. P**:** the set of all the check-ins. Specifically, each check-in $p \in P$ is represented as $p =< l, t, u >$, where l denotes the POI of check-in, t is the check-in time, and u is the check-in user.

Table 1 summarizes some symbols used in this paper.

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, $p \in P$
χ	a 3 order-tensor
$AR_{u,l}$	potential active area of user u with l as the center

4 IGTP Method

4.1 The General Idea

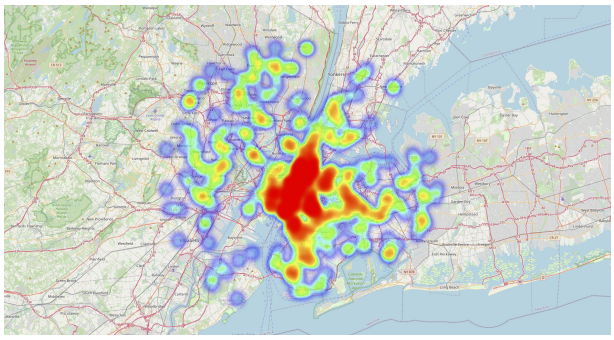
In real life, people face the choice of travel destination every day. In this paper, it is referred to as the choice of POIs. People's choice of POIs before traveling is a complex decision-making process, which is often affected by many factors, such as time, geography, weather, social relations and so on. Among them, time and geography are the two most important factors. First, the time factor will affect people's preferences. People's preferences will change over time. For example, people usually go to the library during the day and the bar at night. Secondly, geographical factors are also important factors that affect people's choice of POIs, such as geographic distance and geographic density. According to Tobler's first law: everything is related to everything else, but near things are more related to each other, it can be known that people always tend to visit locations closer to them, so geographic distance is one of the important factors that affect people's choice of POIs. The geographic density of POIs can also affect people's choice of POIs. For example, if a user wants to buy household appliances, he or she can choose a household appliance mall gathered by many household appliance stores(high geographic density) or isolated household appliance stores(low geographic density). Most users prefer a household appliance mall. This is because if a user is not satisfied with a certain store in the household appliance mall, he can easily visit many other household appliance stores nearby. Users who choose an isolated household appliance store will lose this convenience. Furthermore, based on real-world data, this study observed the influence of geographic density on people's choice of POIs. Specifically, for the same category of POIs, this study generated two heat maps: user check-in heat map and geographic density heat map. Due to space reasons, this paper only shows the heat maps generated by some POI categories. For example, for Coffee Shop category POIs and Electronics Store category POIs in New York, Fig. 2 shows the comparison results of two heat maps belonging to each category. For Spa Massage category POIs and Movie Theater category POIs in Tokyo, Fig. 3 shows the comparison results of two heat maps belonging to each category. We can obviously observe that the heat distributions of the two heat maps belonging to each category are consistent. This indicates that users tend to visit POIs in areas with high geographic density.

Based on the two most important factors that affect the choice of POIs, time factor and geographical factor, this paper designs a next POI recommendation method IGTP that integrates geospatial and temporal preferences. First, IGTP uses users' temporal preferences to model users' check-in histories, so as to dynamically predict a target user's preferences in different time interval. Secondly, IGTP generates POI recommendation candidate set according to the predicted temporal preferences of a target user and the user's current context such as current time and current location, and calculates the geographical score of each POI in the recommendation candidate set considering geographic distance and geographic density of POIs. Finally, IGTP generates the next POI recommendation list for a target user based on the predicted temporal preference score of the user and the geographical scores of POIs in the recommendation candidate set. The framework of IGTP is shown in the Fig. 4.

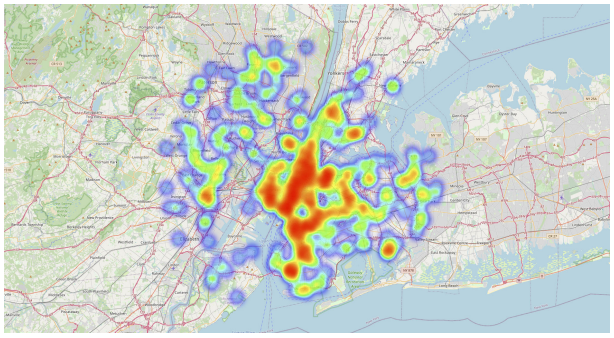
IGTP designed three modules: user temporal preferences modeling module, geographical factor influence module and next POI recommendation module. The specific details of the three modules are as follows.

4.2 User Temporal Preferences Modeling

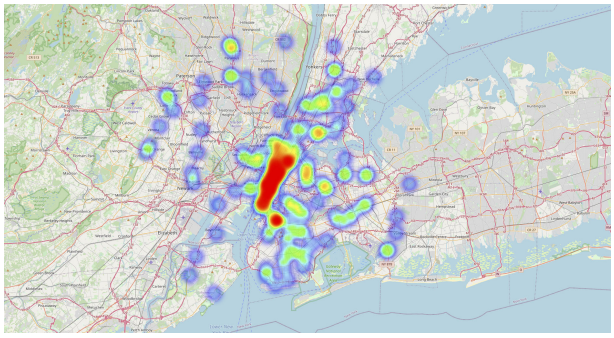
The user temporal preferences modeling module is an important part of the IGTP method. The accurate prediction of user preferences in different time slots will have a direct impact on the accuracy of IGTP method.



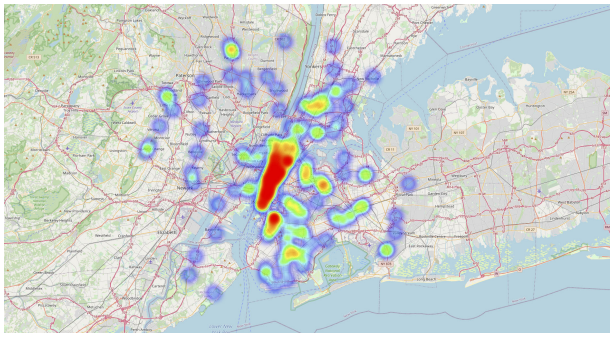
(a) user check-in heat map of POI category: Coffee Shop



(b) geographic density heat map of POI category: Coffee Shop

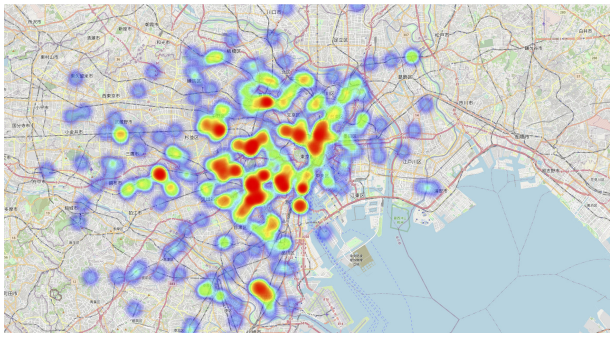


(c) user check-in heat map of POI category: Electronics Store

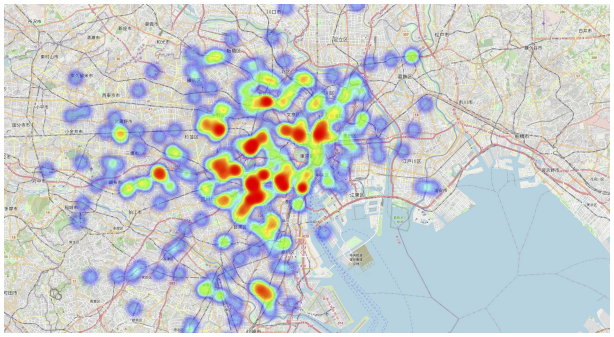


(d) geographic density heat map of POI category: Electronics Store

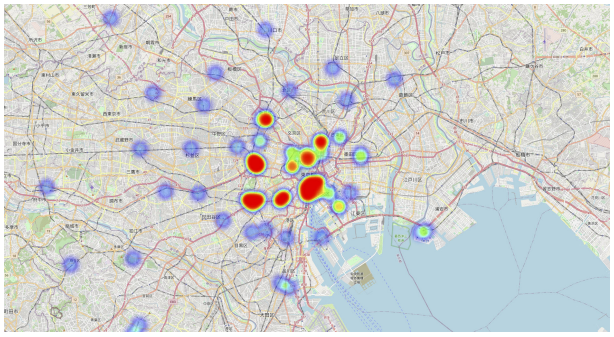
Fig. 2 comparison results of two heat maps of the same category of POIs in New York



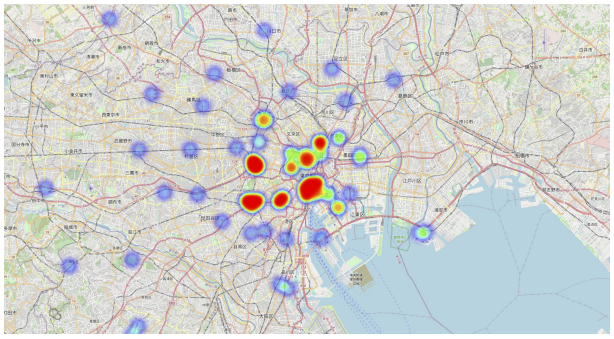
(a) user check-in heat map of POI category: Spa Massage



(b) geographic density heat map of POI category: Spa Massage



(c) user check-in heat map of POI category: Movie Theater



(d) geographic density heat map of POI category: Movie Theater

Fig. 3 comparison results of two heat maps of the same category of POIs in Tokyo

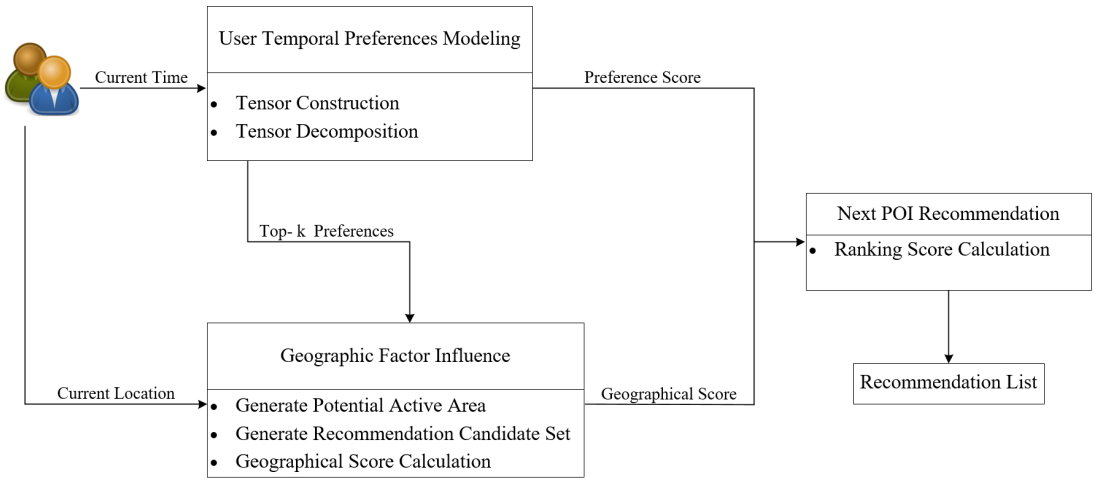


Fig. 4 framework of IGTP

The IGTP method chooses tensor modeling users' temporal preferences mainly based on two reasons. First, tensors can be used to recover lost or sparse data through tensor decomposition. Second, tensors can be used to analyze and isolate the patterns hidden in a dataset. The specific tensor construction and decomposition method are as follows.

IGTP uses a third-order tensor $\chi \in \mathbb{R}^{I \times J \times K}$ to model users' temporal preferences, as shown in Fig. 5. $\chi \in \mathbb{R}^{I \times J \times K}$ has three dimensions: user, time and preference. I, J and K respectively indicate the size of these three dimensions. Each element $\chi(i, j, k)$ of χ represents the sum of check-in frequencies of all POIs belonging to preference k visited by user i in time slot j. IGTP divides each day into six time slots according to 0:00-7:00, 7:00-9:00, 9:00-12:00, 12:00-14:00, 14:00-18:00 and 18:00-0:00. Obviously a week contains 42 time slots. Each time slot has a unique time ID. Many existing POI recommendation methods use POI as a dimension of the tensor model. It makes recommendation methods suffer from extremely sparse check-in data. This is mainly because there are a large number of POIs in the real world and only a small number of POIs have been visited by a single user. In reality, hundreds of preferences can describe people's lives in detail. Therefore, IGTP chooses preference as a dimension of the tensor model, which can effectively solve the challenge brought by the extremely sparse of check-in data.

After the tensor model is established, IGTP decomposes the tensor χ into a core tensor G and three factor matrices A, B, C to infer and complement missing elements in the tensor to extract the implicit features of users, time slots and preferences, as shown in Eq. 1. There are many methods for tensor decomposition. IGTP uses the high-order singular value decomposition method to obtain the approximate tensor $\hat{\chi}$, as shown

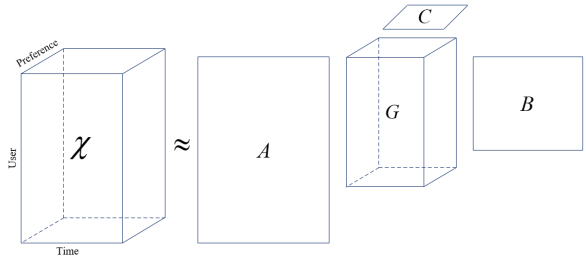


Fig. 5 user temporal preferences model and high-order singular value decomposition

in Fig. 5. The specific decomposition method is as follows:

$$\chi \approx G \times_1 A \times_2 B \times_3 C = \sum_{p=1}^{P} \sum_{q=1}^{Q} \sum_{r=1}^{R} g_{pqr} a_p \circ b_q \circ c_r \quad (1)$$

1. The initial tensor $\chi \in \mathbb{R}^{I \times J \times K}$ is constructed according to the three dimensions of user, time and preference. I, J and K respectively indicate the size of these three dimensions.
2. According to the tensor matricization method, the tensor χ is unfolded along three modes to obtain three corresponding matrices. Specifically, the mode-1 matricization of tensor χ is denoted by $X_{(1)}$. The mode-2 matricization of tensor χ is denoted by $X_{(2)}$. The mode-3 matricization of tensor χ is denoted by $X_{(3)}$.
3. The matrices $X_{(1)}$, $X_{(2)}$ and $X_{(3)}$ obtained by unfolding along three modes of tensor χ are singular value decomposed to obtain the corresponding left singular matrices A^1, B^2 and C^3.

4. Perform low-rank approximation on the left singular matrices A^1, B^2 and C^3 to obtain the corresponding reduced-rank dimension parameters α_1, α_2 and α_3.
5. The approximate matrices $A^1_{\alpha_1}, B^2_{\alpha_2}$ and $C^3_{\alpha_3}$ of left singular matrices A^1, B^2 and C^3 are calculated according to the corresponding rank-reduced dimension parameters α_1, α_2 and α_3 to filter the noise data caused by smaller singular values.
6. According to Eq. 2, the approximate matrices $A^1_{\alpha_1}, B^2_{\alpha_2}$ and $C^3_{\alpha_3}$ are used to construct the approximate core tensor $\hat{G}$.

$$\hat{G} = \chi \times_1 A^{1\,T}_{\alpha_1} \times_2 B^{2\,T}_{\alpha_2} \times_3 C^{3\,T}_{\alpha_3} \tag{2}$$

7. According to Eq. 3, the approximate tensor $\hat{\chi}$ of tensor χ is calculated by using the approximate core tensor $\hat{G}$.

$$\hat{\chi} \approx \hat{G} \times_1 A^1_{\alpha_1} \times_2 B^2_{\alpha_2} \times_3 C^3_{\alpha_3} \tag{3}$$

4.3 Geographical Factor Influence

In this part, IGTP considers the geographic density of POIs and calculates geographical scores for POIs to be recommended based on the current time t_c and the current location l_c of the target user u_i. As mentioned earlier, the geographic density of POIs can affect people's choice of POIs. And people tend to visit POIs that are located in areas with greater geographic density. Therefore, the POI geographical score calculation method of IGTP needs to allocate more geographical scores for the POIs in the area with greater geographic density. The specific calculation method of POI geographical score is as follows.

1. According to the target user u_i and the time slot of the current time t_c of u_i, the obtained approximate tensor $\hat{\chi}$ can be used to obtain preference probabilities of u_i at time t_c.
2. According to the preference probabilities, the preferences of the target user u_i at time time t_c are sorted in descending order. And the top k preferences are selected. The optimal value of k will be given in the experimental section. The set of k preferences is denoted by $F_{t_c} = \{f_1, f_2, \cdots, f_k\}$.
3. The potential activity area AR_{u_i,l_c} of the target user u_i is constructed with the current location l_c of u_i as the center and r as the radius, as shown in Fig. 6. P_{u_i} represents the set of all check-ins of user u_i. $P_{AR_{u_i,l_c}}$ denotes the set of user u_i's check-ins in AR_{u_i,l_c}. The value of the radius r is the smallest value that satisfies the Eq. 4, where η is a threshold.

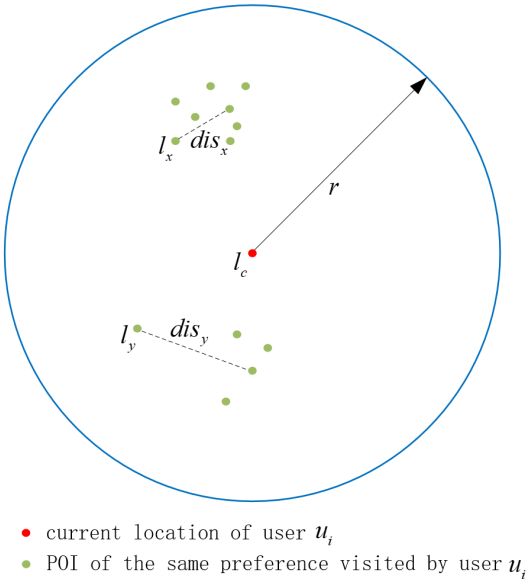


Fig. 6 potential activity area AR_{u_i,l_c} of user u_i

The optimal value of η will be given in the experimental section.

$$\frac{\left|P_{AR_{u_i,l_c}}\right|}{|P_{u_i}|} \geqslant \eta \tag{4}$$

4. In the potential activity area AR_{u_i,l_c} of the target user u_i, for each preference $f_m \in F_{t_c}, 1 \leqslant m \leqslant k$, if there are POIs belonging to f_m, these POIs constitute a set $L^m_{AR_{u_i,l_c}}$. $Z^m_{AR_{u_i,l_c}}$ represents the sum of the total number of POIs included in $L^m_{AR_{u_i,l_c}}$ that have been checked in by users.
5. For each $l_a \in L^m_{AR_{u_i,l_c}}, 1 \leqslant a \leqslant |L^m_{AR_{u_i,l_c}}|$, the Euclidean distance between l_a and each other POI in the set $L^m_{AR_{u_i,l_c}}$ is calculated.
6. According to the Euclidean distance calculated in step 5, the $|L^m_{AR_{u_i,l_c}}| - 1$ POIs in the set $L^m_{AR_{u_i,l_c}}$ except l_a are arranged in ascending order to obtain a new set $L^m_{AR_{u_i,l_c},l_a} = \{l_1, l_2, \cdots, l_j\}, j = |L^m_{AR_{u_i,l_c}}| -1$. Correspondingly, $N^m_{AR_{u_i,l_c},l_a} = \{N_1, N_2, \cdots, N_j\}$ is a set corresponding to the total number of check-ins for each POI in $L^m_{AR_{u_i,l_c},l_a}$.
7. Construct an array H of length j. Each element H_b of H stores the cumulative sum of the total number of check-ins for POIs from l_1 to $l_b, 1 \leqslant b \leqslant j$ in the set $L^m_{AR_{u_i,l_c},l_a}$, as shown in Eq. 5.

$$H_b = \begin{cases} N_1 & , b = 1 \\ N_1 + \cdots + N_b & , 2 \leqslant b \leqslant j \end{cases} \tag{5}$$

8. Given the threshold e, the optimal value of e will be given in the experimental section. Start from el-

ement H_1 of array H to find the first element H_b satisfying Eq. 6.

$$\frac{H_b}{Z^m_{AR_{u_i,l_c}}} \geqslant e \tag{6}$$

9. For the first element H_b satisfying Eq. 6, dis_a is used to denote the Euclidean distance between l_a and l_b.
10. Calculate the geographical score $GeoScore_{l_a}(u_i, t_c, l_c)$ of POI l_a as shown in Eq. 7.

$$GeoScore_{l_a}(u_i, t_c, l_c) = 1 - \frac{dis_a}{2r} \tag{7}$$

It can be seen from Fig. 6 that in the potential active area AR_{u_i,l_c} of user u_i, POI l_x is in an area with high geographic density and POI l_y is in an area with sparse geographic density. The dis_x required to calculate the geographical score of l_x is significantly shorter than the dis_y required to calculate the geographical score of l_y. Obviously, according to Eq. 7, the geographical score $GeoScore_{l_x}(u_i, t_c, l_c)$ of l_x is higher than the geographical score $GeoScore_{l_y}(u_i, t_c, l_c)$ of l_y.

4.4 Next POI Recommendation

The task of the next POI recommendation module is to generate a recommendation list for a target user. The next POI recommendation module comprehensively considers users' temporal preferences and geographical factors of POIs, as follows.

1. IGTP uses the user temporal preferences modeling module to predict the target user u_i's preferences at the current time t_c.
2. The recommendation candidate set CS_{u_i,t_c,l_c} is composed of POIs that belong to the predicted top k preferences and are located in the potential activity area AR_{u_i,l_c} of u_i centered on the current location l_c.
3. IGTP calculates a ranking score $RS_{l_j}(u_i, t_c, l_c)$ for each POI l_j in the recommendation candidate set CS_{u_i,t_c,l_c}.
4. IGTP sorts the recommendation candidate set CS_{u_i,t_c,l_c} in descending order according to ranking scores of POIs. The POIs with the same ranking score in CS_{u_i,t_c,l_c} are sorted in ascending order according to the distance between POI and l_c.
5. The recommendation list composed of top n POIs in the recommendation candidate set CS_{u_i,t_c,l_c} is recommended to the target user u_i.

The ranking score $RS_{l_j}(u_i, t_c, l_c)$ of each POI l_j in the recommendation candidate set CS_{u_i,t_c,l_c} is calculated according to Eq. 8.

$$RS_{l_j}(u_i, t_c, l_c) = PreScore_{l_j}(u_i, t_c) + GeoScore_{l_j}(u_i, t_c, l_c) \tag{8}$$

where $PreScore_{l_j}(u_i, t_c)$ represents the preference score and $GeoScore_{l_j}(u_i, t_c, l_c)$ denotes the geographical score.

Given the current time t_c and current location l_c of the target user u_i, the specific calculation methods of the preference score $PreScore_{l_j}(u_i, t_c)$ and the geographical score $GeoScore_{l_j}(u_i, t_c, l_c)$ are as follows.

- **Preference score.** According to the time slot t that the current time t_c of u_i belongs to, the approximate tensor $\hat{\chi}$ can be used to obtain a preference vector $v_{i,t}$. The approximate tensor $\hat{\chi}$ is obtained by user temporal preferences modeling module. Each entry of $v_{i,t}$ represents a preference score corresponding to a preference. Then the corresponding preference score $PreScore_{l_j}(u_i, t_c)$ can be obtained from the preference vector $v_{i,t}$ according to the preference that POI l_j belongs to.
- **Geographical score.** According to u_i's current time t_c and current location l_c, Eq. 7 is used to calculate the geographical score $GeoScore_{l_j}(u_i, t_c, l_c)$ of POI l_j.

5 Experiments

This experiment verifies the recommendation quality of the next POI recommendation method IGTP based on two real-world datasets through comparison with the baseline methods. This section first describes the various settings of the experiment and then analyzes the recommendation quality of IGTP method.

5.1 Experimental Setting

5.1.1 Datasets

This experiment uses two real-world datasets, Foursquare[1] (Yang et al (2014)) and Gowalla[2] (Cho et al (2011b)), to evaluate the recommendation quality of IGTP. The Foursquare dataset is composed of data generated in two cities, New York and Tokyo. The Gowalla dataset contains data from a city of New York. Foursquare

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

[2] http://snap.stanford.edu/data/loc-Gowalla.html

dataset is a dataset that has been filtered. The Gowalla dataset is a raw dataset. In reality, fake check-in data is inevitable. Large datasets suffer from fake check-in data. For this reason, this experiment first eliminated the fake check-in data and performed data preprocessing on the two datasets. For specific methods, please refer to Jiao et al (2019a). Finally, the statistics of the two datasets are shown in Table 2.

Table 2 Dataset Statistic

Dataset	New York (Foursquare)	Tokyo (Foursquare)	New York (Gowalla)
Users	807	1857	257
Venues	38196	60988	9762
Check-ins	225864	571812	97562

5.1.2 Experimental Data Partition

In order to evaluate the recommendation quality of IGTP, this experiment divides each dataset into two parts: training set and testing set. Specifically, the data of the last two months of each dataset is used for testing and the rest is used for training.

5.1.3 Evaluation Metrics

In order to evaluate the quality of IGTP, this experiment selected three evaluation metrics: Precision, Recall and F1 score, as follows.

$$Precision = \frac{No.\ of\ POIs\ correctly\ predicted}{No.\ of\ recommended\ POIs} \tag{9}$$

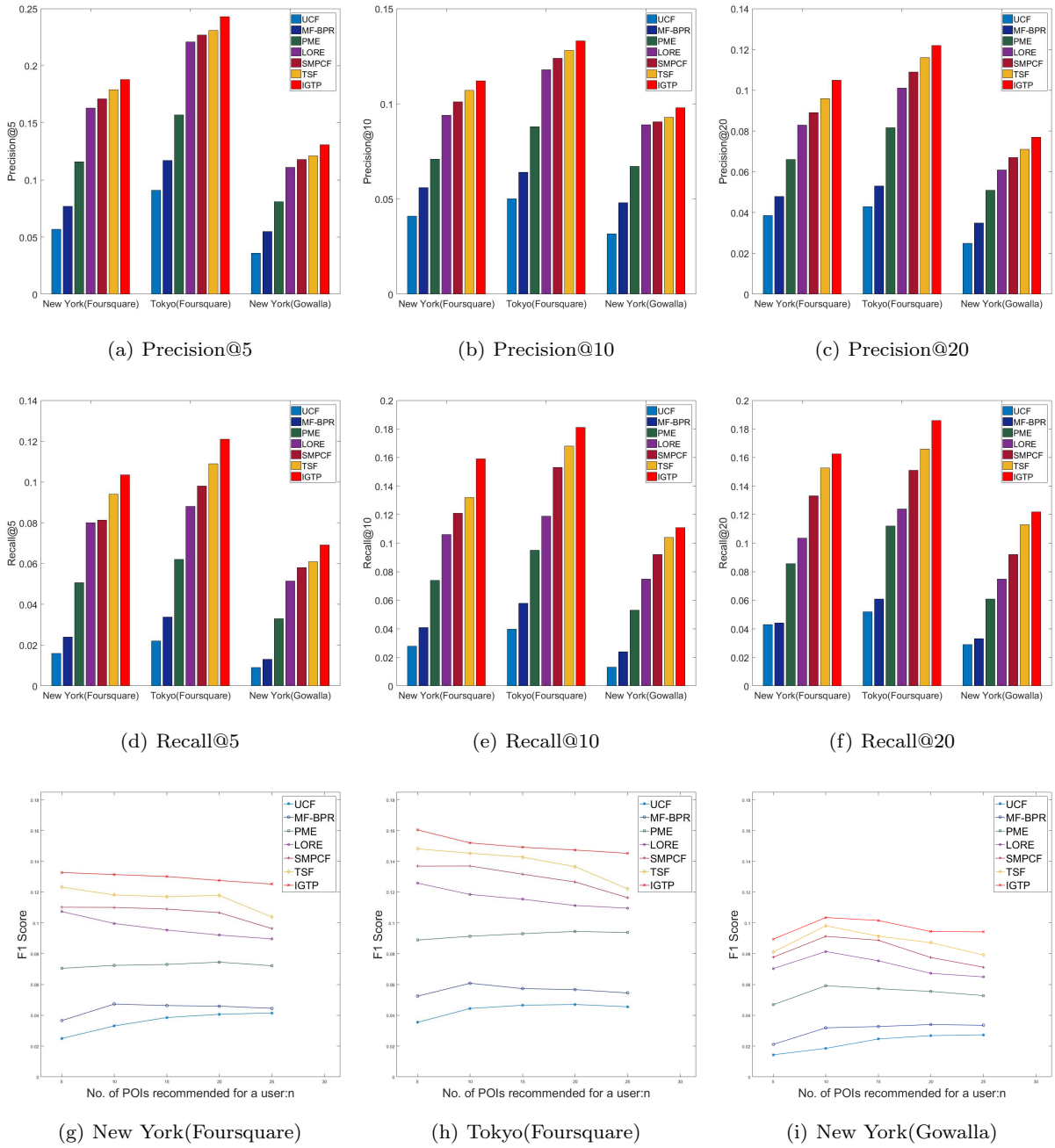
$$Recall = \frac{No.\ of\ POIs\ correctly\ predicted}{No.\ of\ POIs\ actually\ accessed} \tag{10}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{11}$$

5.1.4 Baseline Methods

To verify the performance of IGTP, this experiment select six representative baseline methods for comparison.

- UCF Yuan et al (2013b): UCF recommends POIs for a given user at a specified time in a day. To solve the problem, the authors develop a collaborative recommendation model that is able to incorporate temporal information.
- MF-BPR Rendle et al (2009): The authors present a generic optimization criterion BPR-Opt for personalized ranking that is the maximum posterior estimator derived from a Bayesian analysis of the recommendation problem. The authors also provide a generic learning algorithm for optimizing models with respect to BPR-Opt. The learning method is based on stochastic gradient descent with bootstrap sampling. And the authors apply this method to matrix factorization.
- PME Wu et al (2013): The authors propose Personalized Markov Embedding(PME), a next-song recommendation strategy for online karaoke users. PME is a personalized metric embedding method that projects users and POIs in a common latent space. As a baseline method of this experiment, PME is used to implement the next POI recommendation.
- LORE Zhang et al (2014): LORE exploits sequential influence on location recommendations. LORE incrementally mines sequential patterns from location sequences and represents the sequential patterns as a dynamic Location-Location Transition Graph(L2TG). LORE then predicts the probability of a user visiting a location by Additive Markov Chain(AMC) with L2TG. Finally, LORE fuses sequential influence with geographical influence and social influence into a unified recommendation framework.
- SMPCF Jiao et al (2019c): SMPCF is a personalized POI recommendation method based on collaborative filtering. SMPCF 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. SMPCF takes into account three features of the human mobility pattern: spatial, temporal, and sequential properties, and designs a personalized user mobility pattern similarity calculation method based on the features of human mobility pattern.
- TSF Li et al (2021): TSF is a next POI recommendation method using the Voronoi diagram. The authors 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. TSF designs an approach to dynamically generate different POI recommendation lists for a particular user according to different current context information of the user.



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

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

(g) New York(Foursquare) (h) Tokyo(Foursquare) (i) New York(Gowalla)

Fig. 7 comparison results of Precision, Recall and F1 score of $top-N$ between IGTP and baseline methods in two datasets Foursquare and Gowalla

5.2 Recommendation Effectiveness

This experiment compared the Precision, Recall and F1 score of IGTP and baseline methods in two datasets Foursquare and Gowalla. Through sufficient experiments, this experiment finally determined the optimal values of the three parameters of IGTP: $k = 5$, $\eta = 0.01$, $e = 0.2$. For the optimal values of the parameters of baseline methods, this experiment selects the values of the parameters when baseline methods have the best performance. Specifically, the comparison results of Precision, Recall and F1 score of $top-N$ between IGTP and baseline methods in the two datasets are shown in Fig. 7.

It can be seen from Fig. 7 that the two baseline methods UCF and MF-BPR have the worst performance in terms of Precision and Recall. Fig. 7 also shows that UCF and MF-BPR have the worst F1 scores of $top-N$. This is mainly because the two methods

UCF and MF-BPR do not effectively use the geographical influence of users' check-in behavior, but only focus on mining users' preference information from the users' check-in histories. The performance of the UCF method is the worst among all methods. This is mainly because in addition to the above shortcomings, UCF's user similarity calculation method relies on the traditional cosine similarity, which cannot accurately mine the similarity between users. And the extremely sparse check-in data also has a great impact on the collaborative filtering algorithm used by UCF.

The recommendation performance of PME method is slightly better. However, due to the mutual interference of sequential transition and user preference learning in a common latent space, the PME method does not have better performance.

LORE showed good recommendation performance. LORE uses the Additive Markov Chain(AMC) to predict the probability of a user visiting a POI. And LORE integrates sequential influence, geographical influence and social influence into a unified recommendation framework. The performance of LORE also shows that the sequential influence plays an important role in next POI recommendations, and also shows the effectiveness of the use of Markov chain on next POI recommendation methods. However, LORE does not limit the next POI to be recommended to a local area, that is, LORE ignores the geographical distance factor. This is an important factor limiting the recommendation performance of LORE.

The recommendation quality of SMPCF is good. This is mainly because: First, SMPCF designs a personalized user spatial similarity calculation method based on the target user's activity area. Secondly, SMPCF considers the three characteristics of people's mobility pattern: spatial, temporal and sequential properties and designs a personalized user mobility pattern similarity calculation method. Although SMPCF designs personalized user spatial similarity calculation method and user mobility pattern similarity calculation method, since collaborative filtering idea is the core of SMPCF method, SMPCF's recommendation performance is limited by the difficulty caused by extremely sparse check-in data. Moreover, SMPCF mainly focuses on users' spatial-temporal information and ignores users' travel preferences, which is also a reason for affecting the recommendation quality of SMPCF.

The recommended performance of TSF is better than other baseline methods. TSF constructs virtual trajectories of users. And TSF uses the Voronoi diagram to characterize the influences of temporal and spatial feature for users and designs a context-aware similarity calculation method. TSF also uses the idea of collaborative filtering, so it also suffers from extremely sparse check-in data. And TSF also ignores the user preferences which is an important factor affecting the performance of recommendation.

The performance of IGTP proposed in this paper is better than baseline methods in terms of Precision, Recall and and comprehensive evaluation metric F1 score of $top-N$. This is mainly because: First, IGTP method effectively integrates geographical and user preference information into a unified recommendation process. Secondly, IGTP divides POIs according to users' preferences and uses users' preferences to model users' check-in histories, so as to overcome the challenge of extremely sparse check-in data. Thirdly, IGTP can dynamically predict the target user's preference according to the change of time and limit the POIs to be recommended to the potential activity area centered on the current location of this user. And IGTP takes into account the geographic distance and geographic density factors that affect people's choice of POIs.

6 CONCLUSION

This paper proposes a next POI recommendation method IGTP that integrates geospatial and temporal preferences. This method dynamically predicts user preferences according to the change of time and also considers the geographic distance and geographic density factors that affect people's choice of POIs. IGTP uses users' preferences information to model users' check-in histories, which effectively overcomes the extremely sparse check-in data. The effectiveness of IGTP is proved by comparison with six baseline methods.

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Conflict of interest

The authors declare that they have no conflicts of interest.

Human participants or animals

This article does not contain any studies with human participants or animals performed by any of the authors.

Authorship contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Xu Jiao, Wenguang Zheng and Ke Zhu. The first draft of the manuscript was written by Xu Jiao and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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