POIs Category Recommendation for Cultural Country Travel Enterprises Based on Check-In Information

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ABSTRACT

With the ever-increasing popularity of traveling markets, more people are willing to spend their time and enjoy life by visiting some points of interest (POI) especially for the citizens living in cities. Therefore, it is of practical and significant value for travel enterprises to recommend appropriate country POIs to target travelers. However, the massive POIs as well as their diversity place a heavy burden on the POIs recommendation decision making especially when the available historical traveler-POIs check-in data are very sparse. In view of this challenge, the authors put forward a novel cultural country POIs category recommendation method based on historical knowledge and experienced information (e.g., check-in time and POIs category, i.e., CPCR). At last, CPCR method is evaluated via experiments on WS-DREAM dataset.

KEYWORDS

Check-In Records, Cultural Country POIs, POIs Category, Recommender System, Travel Enterprises

INTRODUCTION

With the economic and social progress of whole world, people are more interested in improving their living condition and life manner. In this situation, travelling has emerged as a promising way to achieve the goal of healthcare (Azrour, M., et al, 2020; Liu, Y., et al, 2021; Hazarika, B. B., 2021; Nitu P., 2022). Currently, travelling has become a crucial and significant part of human production and life. As a consequence, a number of travelling-related enterprises, business and services have emerged rapidly, such as ctrip.com, TripAdvisor, and so on. Such travelling websites as well as their interactions with massive travelers have formed the so-called big traveling data (Huang H., 2022; Liu, Y., et al, 2021; Kou, H., 2021). Deep mining and analysis of such big traveling data are of positive significance for improving the traveling market (Kumari, R., 2021; Li, L., 2021). However, due to the big volume of POIs (Point of Interest) as well as their diverse categories, how to recommend appropriate POIs to potential travelers based on experience knowledge have become a practical and significant research topic for travel enterprises.

Among the massive candidate POIs in traveling market, country POIs have constituted an important part due to their distinct characteristics in reflecting specific country culture. Especially...
for the citizens who are not familiar with the country POIs or cultures, they often live in busy cities and therefore, are generally curious with beautiful and interesting country culture and scenes. Today, many citizens in China or abroad are willing to travel to nearby country POIs to loosen their body and nerve at their free time such as weekends and holidays. Therefore, it is becoming a necessity to develop a specific recommender system that targets country POIs market.

However, such a recommender system is often confronted with several difficulties and challenges. First, country POIs are often massive and each POI has its specific knowledge and features (Wang, F., et al, 2021; Wang, F., et al, 2020). In this situation, how to recommend a set of appropriate country POIs with rich culture information to prospective travelers is practical but challenging (Xu, Y., et al, 2021; Zhu, K., et al, 2021). Second, the massive country POIs are often diverse in categories. For example, some country POIs are famous for their mountains and some are famous for rivers or lakes. Such a category diversity of country POIs places a heavy burden on the selection of travelers and further makes the recommendation task harder. Third, for massive travelers, their historical POIs access records are often time-aware. For example, travelers are more like to play in seas in hot summer but like skating in cold winter. Such hidden knowledge is helpful for recommendation decisions. Fourth, recommender systems need to analyze travelers’ historical check-in information to make accurate country POIs recommendation; however, the available check-in data are often sparse (Zhou, X., et al, 2021), which further influences the recommendation performances.

To tackle the above issues, we propose a novel knowledge-driven cultural country POIs category recommendation method based on check-in time and POIs category. In summary, the academic contributions of this work are three-fold, which are briefly introduced as follows.

(1) We recognize the check-in time and category information of country POIs as important decision-making basis for recommending appropriate country POIs. And we introduce such supplement information into country POIs recommendation.

(2) We put forward a novel algorithm named CPCR to solve the cultural country POIs recommendation problem based on valuable knowledge, e.g., traveler’s check-in time and POIs category. The recommendation algorithm is mainly based on hashing technologies including Simhash and Minhash.

(3) A set of experiments on a real-world dataset is constructed and we validate the feasibility of the proposed recommendation algorithm through the experiments. Through the experiment comparison, we further explain the advantages of our proposal.

The reminder of this research work is organized as follows. Current literatures associated with country POIs recommendation are summarized briefly in the Related Work section (i.e., Section 2). In Section 3, an intuitive example from real world is presented to demonstrate the research background and challenges. Detailed steps and pseudo code of the proposed recommendation algorithm are presented in Section 4. To prove the effectiveness and efficiency of the proposal, we have designed a set of experiments based on a real-world dataset. At last, we conclude the whole paper and point out the possible research directions and challenges in future work.

**RELATED WORK**

Cultural country POIs recommendation is of special significance and value towards the healthy and fast development of traveling industry all over the world. Many researchers have devoted themselves to the related investigation. In this section, we briefly introduce and summarize the current research outcomes related to country POIs recommendation, from the following aspects.
Recommendations Based on Location and Regional Differences

In (Zhang, C., et al, 2016), the authors recommend a set of POIs to users based on their current location and historical activity. Most of the previously proposed methods for predicting POI tend to recommend POI to users in cities they have visited in the past, so these methods are not conducive to recommending POI to users in a new city. To address this problem, the authors of this article distinguish between user preferences for POI content and user preferences for the POI itself. User preferences for POI content are long-term, regardless of the region or location of the POI. The user’s preference for the POI itself is short-term and is influenced by the distance between the user’s current location and the POI location. In this paper, the authors model the location of user POI content preferences and user POI location preferences independently, and then complete the recommendation of POI based on the prediction of content and the POI location.

In (Stefancova, E., 2020), the authors propose a new method for recommending points of interest to users, which takes into account both annual seasonality and long-term trends of points of interest. The work of this paper is to deal with time sensitivity in location-based social networks and complete recommendations. Therefore, the method proposed by the authors considers both location and time factors. Experimental results show that the introduction of site-specific seasonality can significantly improve recommendation performance compared with global schemes.

In (Islam, M., et al, 2020), Location-Based Social Networks (LBSNs) allow users to socialize by sharing historical information such as their clicks and comments with friends. The massive data generated by LNSNs has brought new development space for recommendation system, and derived a new field-POI recommendation. POI recommendation is essentially to recommend the next set of POI to users based on their historical check-in or other historical operation information. In the early days, a lot of work was mostly made use of traditional machine learning technology. Now, with the rise and development of deep learning, deep learning technology also begins to enter the field of POI recommendation. In this paper, based on different deep learning methods and other relevant characteristics, the authors analyze and evaluate the POI recommendation methods in recent years.

Spatial and Temporal Factors on Recommendations

In (Lim, N., et al. 2020), how to accurately recommend users’ interested POIs is a long-standing problem in the LSBN domain. In this paper, the authors propose a Spatial-Temporal Preference User Dimension Graph Attention Network (STP-UDGAT). Personalized user preferences are used to find the location of new global spatial-grey-preference POIs (STP), and in this method, users are allowed to selectively learn from other users according to conditions. In addition, random walk is proposed as a self-attentional option to exploit the structure of STP graphs.

In (Oppokhonov, S., et al, 2017), massive users’ location data opens up new research possibilities in the field of recommendation. In this paper, the authors propose a new recommendation system that can recommend new POIs to users within the next few hours. Specifically, the first is to find users with similar history check-in sequences, turn the embedded sequence into a directed graph, and then find the user’s current location. In order to complete the task of recommending a new POI for the next hour, the authors can use the created directed graph as a basis. In general, the method takes into account both the temporal factor (recommended time) and the spatial factor (distance).

In (Wang, Y., et al, 2020), the authors propose a multilingual analysis method of Twitter recommendation POIs based on psychological preference. This method is based on the reality that people in different countries speak different languages and have different behavior habits. In order to solve this problem, the authors aim to judge the psychological preferences of users’ behaviors by time, place and language label. In this method, firstly, the authors extract the language of tweets and determine the country according to the location of users when they send tweets. Then, TF-IDF method is used to extract feature words from the language of tweets. One of the most important aspects of this approach is that the system can recommend POIs for users in an area where there are few geo-tagged tweets, based on weighted similarity of other users’ preferences. In this paper, the POI preferences of users in different regions are discussed according to the correlation between tweets features in different regions.
POI Recommendation Based on Historical Access Data

In (Sarkar, J. L., et al. 2021), with the improvement of living standards, tourism has become a huge industry in the world and an important source of income for almost every country. In this case, tourism service recommendation gradually develops, but it is still a big challenge how to accurately recommend satisfactory travel routes to users. The recommended routes should meet users’ wishes and be planned within a limited time. To solve this problem, the authors propose an algorithm called TRIPTOUR, which generates multiple recommended routes based on POI visit times, tourist attractions, the costs involved in the routes, and the popularity of different routes. The results show that the TRIPTOUR method is superior to the benchmark method based on precision, recall rate and recommended trips.

In (Mishra, R. K., et al, 2020), users search for interested POIs based on the details of the POI of the tourist attractions they want to visit, so that they can make choices based on their interests. However, due to the large amount of information, it is difficult for users to make a correct choice on the POI, so the recommendation system comes into being. Recommendation system through user behavior to provide users with tourist attractions in line with their interests. However, most of the previous studies were based on users’ numerical ratings of the POIs they visited. In this paper, the authors use comment data generated by the Emotional Intensity Analyzer (SIA) to recommend POI for users.

In (Ahmedi, L., et al. 2017), as computers and users play an increasingly important role in social networks, social network analytics (SNS) is gaining more and more attention. In this paper, the authors propose a SNS based approach to estimate tourists’ satisfaction with POIs in order to determine whether to recommend these points of interest to the tourists. In addition, this article also puts forward a kind of based on the strength of the bimodal network links corresponding algorithm, in this algorithm, the authors will be the most similar commentators grouping for target visitors “islands”, and then the ranking algorithm based on level or authority centricity to get “islands” on the highest ranked reviewers, and recommend their favorite POIs to target visitors.

In (30), the country of origin (COO) effect—the influence of a brand’s perceived association with a country on consumer attitudes—is linked to consumer perception. Inspired by this observation, in this paper, the authors aim to identify origin as a feature derived from consumer perceived associations and to propose that such associations are of varying degrees, rather than merely a binary attribute, affecting consumer attitudes. The authors clearly demonstrate the moderating effect of national brand association strength COO on brand equity.

In view of the above analysis, current research work associated with country POIs recommendation is also confronted with several challenges. Motivated by such challenges, we put forward a novel algorithm to solve the cultural country POIs recommendation problem, which is mainly solved by considering the traveler’s check-in time and POIs category. Concrete procedure or process of this algorithm will be clarified clearly in the following sections.

MOTIVATION DESCRIPTION

In this section, we construct an intuitive example from real-world country POIs recommendation scenario to further describe the research background, research challenges and significance. The example is presented in Fig.1, in which the horizontal line denotes the different time points (e.g., 01, 02, 03, 04, 05) and each time point is corresponding to a set of country POIs belonging to different categories. Thus, each traveler is corresponding to a set of time-aware and category-aware country POIs check-in historical records. Generally, through analyzing such historical country POIs check-in records, we can predict the preferences of travelers and then make corresponding country POIs recommendations.

However, compared to the massive country POIs, the available POIs check-in historical records are relatively sparse. In this situation, with such sparse decision-making data for country POIs recommendation, the recommendation performances (especially recommendation accuracy) would be decreased considerably. In view of this challenge, we make full use of the available check-in records.
information (e.g., check-in time, POIs category tag, and so on) to aid the country POIs recommendation decision-makings. Concretely, we put forward a novel cultural Country POIs Category prediction and Recommendation method, named CPCR based on the check-in time and POIs category. The detailed steps and procedure of our proposal will be introduced in the following sections.

**METHOD: CPCR**

In this section, we introduce the major steps of the proposed cultural country POIs category prediction and recommendation method, i.e., CPCR. In general, the proposed algorithm mainly consists of the following three steps as described in Fig.2.

1. **Step 1: Time-Aware POIs Check-In Category Matrix Construction.**
   As analyzed in the example of fig.1, each traveler has left a series of country pois check-in records which contain some valuable information such as check-in time and pois name. For example, Alex is a traveler and his pois check-in records are: {(2009-12-20, Yellow River), (2012-01-25, Danxia Mountain), (2019-07-15, Disney Park), …}. With such historical pois check-in records, we can get a pois check-in matrix $M$ as formalized in (1) where each row denotes a user or traveler and each column represents a time point.

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**Figure 1. Time-aware and Category-based POIs recommendation: an example**

![Time-aware and Category-based POIs recommendation: an example](image)

**Figure 2. Main procedure of the proposed CPCR method**

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1. **Step 1: Time-aware POIs check-in category matrix construction.** According to the historical POIs check-in records of travelers (e.g., check-in time and POIs category), we construct a time-aware POIs check-in category matrix.
2. **Step 2: Traveler index creation based on hash technologies.** According to the time-aware POIs check-in category matrix in Step 1, we create an index for each traveler based on hash technology including Simhash and Minhash.
3. **Step 3: Similar travelers finding and POIs recommendation.** According to the traveler indexes created in Step 2, we divide the travelers into different clusters and groups. Then according to the POIs check-in records of similar travelers, we make POIs recommendations for a target traveler.
Thus, in matrix $M$, each entry $p_{oi,j}$ means the concrete POIs visited by $u_i$ ($1 \leq i \leq m$) at time point $t_j$ ($1 \leq j \leq n$). Please note that if $u_i$ did not visit $p_{oi,j}$ at time point $t_j$, then the corresponding entry value would be equal to zero, i.e., $p_{oi,j} = 0$ (in this situation, such 0-value entries will not take part in the subsequent calculation and processing). Generally, through analyzing the matrix $M$ in (1), we can evaluate and predict the personalized preferences of travelers and then make corresponding POIs recommendation to them according to their preferences.

$$M = \begin{bmatrix}
    t_1 & \cdots & t_n \\
    p_{oi_1,1} & \cdots & p_{oi_1,n} \\
    \vdots & \ddots & \vdots \\
    p_{oi_m,1} & \cdots & p_{oi_m,n}
\end{bmatrix}$$  \hspace{1cm} (1)

However, citizens living in city are often very busy in weekdays or weekends and as a consequence, they do not visit country POIs very frequently. Therefore, the available country POIs check-in records of travelers are often rare and the resulted matrix $M$ is very sparse, which significantly decreases the accuracy of the final recommended results. In this situation, we need to make the matrix $M$ denser so that the recommendation accuracy could be improved. To achieve this goal, we neglect the concrete POIs names that travelers have ever visited in the past; instead, we only record the POIs category information for each historical check-in record. Thus, the example in the last paragraph could be abbreviated considerably, for example, Alex’s POIs check-in records would be { (2009-12-20, River), (2012-01-25, Mountain), (2019-07-15, Park), ... }. Afterwards, we update the matrix $M$ to be a new matrix $M^*$ in (2), in which each entry $cat_{ij}$ means the category of the POIs visited by $u_i$ ($1 \leq i \leq m$) at time point $t_j$ ($1 \leq j \leq n$). Since a POIs category can include many POIs with the identical category, the matrix $M^*$ in (2) would be denser than the matrix $M$ in (1).

$$M^* = \begin{bmatrix}
    t_1 & \cdots & t_n \\
    cat_{i_1,1} & \cdots & cat_{i_1,n} \\
    \vdots & \ddots & \vdots \\
    cat_{i_m,1} & \cdots & cat_{i_m,n}
\end{bmatrix}$$  \hspace{1cm} (2)

(2) Step 2: Traveler Index Creation Based on Hash Technologies

As discussed in Step 1, each user $u_i$ ($1 \leq i \leq m$) in matrix $M^*$ is corresponding to a row constituted by $n$ discrete values $cat_{ij}$ which denotes the category of POIs such as river, mountain, park, zoo and so on. Next, to predict and recommend appropriate POIs to a target traveler (denoted by $u_t$) who expects a list of recommended POIs, we need to search for the similar travelers of $u_t$. Therefore, we need to calculate the similarity between $u_i$ ($1 \leq i \leq m$) and $u_t$ based on their respective vectors $u_i = (cat_{i_1}, \ldots, cat_{i_n})$ and $u_t = (cat_{t_1}, \ldots, cat_{t_n})$. Since $cat_{ij}$ is a discrete category tag, we cannot compare $u_i = (cat_{i_1}, \ldots, cat_{i_n})$ and $u_t = (cat_{t_1}, \ldots, cat_{t_n})$ directly. Next, we introduce how to use hash technologies to calculate the similarity between $u_i$ and $u_t$.

In concrete, for each category of POIs, we assign a concrete Boolean vector to delegate the category tag. For example, we can take the coding solution presented in Table 1 in which each category of POIs is corresponding to a 6-dimensional vector. Please note that the coding vectors for POIs category in Table 1 are defined beforehand. With these coding vectors, the $n$-dimensional vector $u_i = (cat_{i_1}, \ldots, cat_{i_n})$ can be converted into a $6^*n$-dimensional vector in which each entry is a Boolean value. Likewise, the target user’s corresponding vector $u_t = (cat_{t_1}, \ldots, cat_{t_n})$ can be further
converted into a $6^n$-dimensional Boolean vector. Here, we take the $6^n$-dimensional Boolean vector as the index for a traveler.

(3) Step 3: Similar Travelers Finding and Pois Category Recommendation

Next, to search for the similar travelers with close preferences, we need to calculate the similarity between the two $6^n$-dimensional Boolean vectors, i.e., $u_i$ and $u_t$ based on the Simhash technique. For better specifications, we use two $6^n$-dimensional vectors $X(x_{i1}, \ldots, x_{i6^n})$ and $Y(y_{t1}, \ldots, y_{6^n})$ to introduce the concrete calculation process of traveler similarity. More formally, the similarity between $X$ and $Y$, i.e., $\text{Sim}(X, Y)$ can be calculated by (3)-(5). Here, equation (5) denotes the XOR operation between two values;

$\text{Sim}(X, Y) = \begin{cases} 
1 & \text{if } \text{Sum} \leq 3 \\
0 & \text{if } \text{Sum} > 3 
\end{cases}$  \hspace{1cm} (3)

$\text{SUM} = \sum_{i=1}^{6^n} x_i \oplus y_i$ \hspace{1cm} (4)

$x_i \oplus y_i = \begin{cases} 
1 & \text{if } x_i \neq y_i \\
0 & \text{if } x_i = y_i 
\end{cases}$ \hspace{1cm} (5)

According to (3)-(5), we can find out all the similar friends of a target traveler $u_t$, assumed $\text{Sim}_U = \{u_1, \ldots, u_k\}$ (here, we repeat the random generation process of category codes (see Table 1) $R$ times; if a traveler $u_i$ is similar with $u_t$ in any of the $R$ repetitions, then $u_i$ would be put into set $\text{Sim}_U$). Next, we need to further discriminate all the $k$ similar friends of $u_t$, which is achieved by Minhash technique. Concretely, assume $u_i$ and $u_b$ are two similar friends of $u_t$, then the similarity between $u_a$ and $u_t$ is larger than that between $u_b$ and $u_t$, iff $\text{InterS}_{(a|t)}$ in (6) is larger than $\text{InterS}_{(b|t)}$ in (7); therefore, $u_a$ should be assigned a larger weight than $u_b$. Here, $\text{InterS}_{(a|t)}$ denotes the size of category intersection between the POIs visited by $u_a$ and $u_t$, respectively; $\text{InterS}_{(b|t)}$ denotes the size of category intersection between the POIs visited by $u_b$ and $u_t$, respectively.

**Table 1. Coding vector of POIs category**

| POIs category | Boolean code |
|---------------|--------------|
| River         | 000001       |
| Mountain      | 000010       |
| Park          | 000011       |
| ...           | ...          |
| Zoo           | 111111       |
To depict the above observation quantitatively, we introduce Minhash technique into the weighting process for each similar friend of the target traveler $u_i$. Here, we denote the weight of $u_i$ as $w_i$ which can be calculated by (8), where $|\cdot|$ denotes the size of a set. As (8) indicates, the value range of weight $w_i$ is $(0, 1)$. Thus, with the weights, we can discriminate all the similar friends the target traveler $u_i$.

Next, we predict the probability that target traveler $u_i$ will visit a POI with category $c_j$ (denoted by $P_{t,j}$) based on the similar friends in set $\text{Sim}_U_i$ as well as their weights. Formally, the prediction is made by (9).

\[
W_i = 2\times \frac{|\text{Cat}_{i,j} \cap \text{Cat}_{t}|}{|\text{Cat}_{i}| + |\text{Cat}_{t}|}
\]  

\[
P_{t,j} = \left(\sum_{i=1}^{\text{Sim}_U_i} w_i\right) / |\text{Sim}_U_i|
\]  

Next, we describe the abovementioned three steps of the introduced CPCR method with the pseudo code in Algorithm 1.

**Algorithm 1: CPCR**

-----------------------------------------------------------------
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Inputs:
1. $M$: traveler-time check-in matrix
2. $u_i$ ($1 \leq i \leq m$): travelers or users
3. $t_j$ ($1 \leq j \leq n$): time points
4. $u_t$: a target traveler
Output:
1. $c_{\text{max}}$: the POIs category that preferred most by $u_t$
---
1. Convert $M$ to $M^*$ by (1)-(2)
---
2. POIs category coding by Table 1
3. for $i = 1$ to $m$ do
4. \hspace{1em} $u_i = (\text{cat}_{i,1}, \ldots, \text{cat}_{i,n})$
5. \hspace{2em} for $j = 1$ to $n$ do
6. \hspace{3em} $\text{cat}_{i,j} = \text{Code}_j$ by Table 1
7. \hspace{2em} end for
8. end for
9. for i = 1 to m do
10. calculate Sim (uᵢ, uᵢ)
11. if Sim (uᵢ, uᵢ) £ 3
12. then put uᵢ into Set_Ut
13. end if
14. end for
15. for j = 1 to n do
16. calculate Pᵢ,j by (8)-(9)
17. end for
18. c_max = { cⱼ | Pᵢ,j = max Pᵢ,j, 1 £ j £ n}
19. return c_max

EXPERIMENTS

Configuration

We have deployed a set of experiments based on the time-aware service performance dataset WS-DREAM. The dataset records the user-service performance variation with time. Therefore, we use this dataset to simulate the traveler-POI category variation scenario with time. To prove the effectiveness of the CPCR method in this paper, we compare it with PPICF (Li, D., et al, 2016) and P-UIPCC (Zhu, J., et al, 2015). In terms of evaluation metrics, we test and compare the MAE and Time Cost of different methods. Involved parameters include: m (volume of travelers), n (volume of time points), R (times of repetitions in Step 3). The experiment hardware settings include a computer with 2.40 GHz CPU and 12.0 GB RAM; software settings include Windows 10 and Java programming language. We repeat each test 100 times and finally register their average performances for demonstrations.

Performance Comparisons

(1) MAE Comparison

In this profile, we compare the prediction performances of three methods: CPCR, PPICF and P-UIPCC. Here, we use MAE to measure the prediction accuracy (smaller MAE is better). Parameters are set as follows: m is varied from 100 to 300, n = 64, R = 10. Evaluation results are presented in Fig.3. As the report shows, the MAE value of CPCR method is much smaller than those of the rest two methods, whose reason is that the Simhash and Minhash techniques adopted in CPCR method can guarantee to return the really similar travelers of the target traveler; Moreover, more valuable information is used for POIs recommendation, such as check-in time, POIs category and so on. As
a result, the POIs prediction accuracy would be high in CPCR and the MAE value would be small. In addition, the MAE values of the three methods do not reflect an obvious variation tendency with the increment of parameter $m$.

(2) Consumed Time Comparison

In this profile, we test the time costs of three methods: CPCR, PPICF and P-UIPCC. Parameters are set as follows: $m$ is varied from 100 to 300, $n = 64$, $R = 10$. Evaluation reports are presented in Fig.4. Evaluation results show that the consumed time of CPCR method is much smaller than those of the rest two method. The reason is that the traveler index creation process by Simhash and Minhash techniques adopted in CPCR method can be done offline, which means the time complexity of this step is $O(1)$. Therefore, time consumed time of CPCR method is rather small compared to the other two methods of PPICF and P-UIPCC. Another observation from Fig.4 is that the time cost of CPCR method stays stably with the growth of $m$ while the time costs of PPICF and P-UIPCC increase linearly with the increment of parameter $m$, which also indicates a good performance of the proposed CPCR method.

Figure 4. Computational time comparison of three methods

(3) Accuracy of CPCR

As introduced in Section 4, the algorithm performance of CPCR method is related to the parameter $R$. In this profile, we observe the relationship between the MAE of CPCR method and parameter $R$, whose results are depicted in Fig.5. Parameters are set as follows: $m = 300$, $n = 64$, $R$ is varied from 2 to 10. As the results show, the MAE increases with the growth of parameter $R$. The reason is that a larger $R$ means more hash functions, while more hash functions indicate more relaxed search condition of similar travelers according to Step 3 of CPCR method; so the returned neighboring traveler of the target traveler are actually not very similar when $R$ is large and hence accuracy is decreased.

(4) Consumed Time of CPCR.

This profile demonstrates the correlation between consumed time and $R$. Parameters are set as follows: $m = 300$, $n = 64$, $R$ is varied from 2 to 10. Concrete evaluation results are show in Fig.6. As the figure indicates, the time cost of CPCR method stays approximately stable with the rising of $R$ when $R$ is larger than 2. The reason is that the traveler index creation process by Simhash and Minhash techniques adopted in CPCR method can be done offline, which means the time complexity of this step is $O(1)$. Therefore, time consumed time of CPCR method is rather small and stable.
CONCLUSION

With the ever-increasing popularity of traveling market, more and more people are willing to spend their time and enjoy life by visiting some Point Of Interests (POI) especially for the citizens living in city. Therefore, it is of practical and significant value to recommend appropriate country POIs to target travelers. However, the massive POIs as well as their diversity place a heavy burden on the POIs recommendation decision-makings especially when the available historical traveler-POIs check-in data are very sparse. In view of this challenge, we put forward a novel cultural country POIs category recommendation method based on valuable knowledge, e.g., check-in time and POIs category, i.e., CPCR. At last, CPCR method is evaluated via experiments on WS-DREAM dataset.

However, we only consider the check-in time of POIs when making an optimal POIs recommendation decision, while neglect other important context factors as well as their different weight information (Li J. et al, 2021; Lu, Z., et al, 2021; Malek, Y. N., et al, 2021; Tang, G., et al, 2021; Zhang, W., et al, 2021; Zhou, X., et al, 2021). Therefore, we will further improve CPCR method by adding more context factors and weights. Moreover, the historical POIs check-in data are often sensitive to travelers (Cai, Z., et al, 2021; Cai, Z., et al, 2018; Liu, H., et al, 2019; Kong, L., et al, 2021; Peng, C., et al, 2022; Vedadi, A., et al, 2021; Xu, Y., et al, 2017; Zheng, X., et al, 2020; Zhou, X., et al, 2021). Therefore, privacy issue would be taken into consideration in our future research. In
addition, big data often leads to big computational cost especially in the pre-processing phase and therefore, calls for efficient offloading operations (He, Q., et al, 2020; He, Q., et al, 2017; Lai, P., et al, 2018; Xia, X., et al, 2021; Yuan L., et al, 2021). Therefore, we will further optimize the CPCR method by accommodating the heavy computation load caused by big data. At last, our proposed CPCR method based on Simhash and Minhash is actually a probability-based approximate neighbor searching method. Therefore, it is inevitable to produce false-positive or false-negative recommendation results, especially when the POIs category data distribution is not average. We will further refine our CPCR method to minimize the probability of false-positive or false-negative recommendation.

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