Context-Aware Point-of-Interest Recommendation Algorithm with Interpretability

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Abstract. With the rapid development of mobile Internet, smart devices, and positioning technologies, location-based social networks (LBSNs) are growing rapidly. In LBSNs, point-of-interest (POI) recommendation is a crucial personalized location service that has become a research hotspot. To address extreme sparsity of user check-in data, a growing line of research exploits spatial-temporal information, social relationship, content information, popularity, and other factors to improve recommendation performance. However, the temporal and spatial transfers of user preferences are seldom mentioned in existing works, and interpretability, which is an important factor to enhance credibility of recommendation result, is overlooked. To cope with these issues, we propose a context-aware POI recommendation framework, which integrates users' long-term static and time-varying preferences to improve recommendation performance and provide explanations. Experimental results over two real-world LBSN datasets demonstrate that the proposed solution has better performance than other advanced POI recommendation approaches.

Keywords: Point-of-interest recommendation · Interpretability · Location based social network

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1 Introduction

Geographical location information has played an increasingly important role in people's lives with the popularization of smart terminals and development of geolocation technologies. Location-based social networks (LBSNs), combined with location-based services and online social networks, are emerging rapidly. In LBSNs, users can share their check-in activities as they visit point-of-interests (POIs) (e.g., supermarkets, restaurants, attractions, and hotels). Massive check-in data can be used to mine users' visit preferences and introduce personalized POI recommendation system, which not only helps users explore new areas and discover new POIs but also enables POIs to increase the revenue through smart location services (e.g., location-based advertising services). As a smart service based on big data [1,2], POI recommendation has recently attracted increasing attention from academics and industry [3–5].

POI recommendation is more complicated than traditional recommendation system. Information such as distance, time, social relationships, category, and popularity of POI must be considered in addition to user preferences and location attributes [5]. Moreover, a user check-in matrix has higher sparseness than a user-item matrix in traditional recommendation systems [6].

To alleviate data sparsity, existing approaches mainly utilize auxiliary information such as time, geographical location, and social relationship. The temporal and spatial transfers of user preferences are seldom mentioned. In current POI recommendation algorithms, user interest is assumed static, but people's interest actually change over time. The visit preferences of people usually change along with their workplace or accommodation. The POIs that they are interested in may also change after beginning a relationship. At the same time, people have static preferences because some interests are retained for a long time on the one hand. For example, users who like reading books tend to go to bookstores. On the other hand, some static interests are related to people's rational choice in nature. For example, people usually prefer to visit nearby POIs and famous POIs. In addition, the interpretability of the recommendation results is an important factor in the recommendation systems as it can increase the credibility of the recommendation. However, current research has overlooked this factor. Existing advanced POI recommendation algorithms typically take model-based methods to mine visit preferences of users by integrating auxiliary information, such as matrix factorization, which experiences difficulty in distinguishing the influence of different factors and explaining recommendation results.

In light of the above discussion, we propose a collaborative filtering POI recommendation approach (HWREC) in this study. The proposed approach uses improved Hawkes process to integrate user's long-term static and time-varying preferences, capitalizing on multiple contextual information, including spatial clustering, spatial distance, spatial sequence transformation, temporal, and POI popularity information, to improve performance of recommendation. More significantly, HWREC can explain recommendation results in several aspects according to the preferences and historical check-in records.

The remainder of this paper is organized as follows. Section 2 describes the preliminaries of the POI recommendation task. Section 3 presents the proposed POI recommendation method in detail. Section 4 evaluates the effectiveness of the proposed method. Section 5 reviews related work. Finally, Sect. 6 concludes this study.

2 Preliminaries

2.1 Notation

In a LBSN, assume a set of N users represented as $U = \{u_1, u_2, \ldots, u_N\}$ and a set of M POIs represented as $L = \{l_l, l_2, \ldots, l_M\}$. Each POI has a geographic coordinate $g = <longitude, latitude>$. The POIs can be clustered into K POI clusters by the coordinates, denoted as $C = \{c_l, c_2, \ldots, c_K\}$. Each check-in activity is a tuple $<u, l, t>$ that represents user $u \in U$ visiting POI $l \in L$ at time t.

2.2 Problem Statement

The goals of POI recommendation task in this study are to recommend to each user with top-k new POIs that he/she may be interested in but has not visited before by learning users' personalized preferences from their history check-in activities, and explain the recommendation results.

3 Methodology

In this section, we describe the proposed HWREC method in detail.

3.1 Select Candidate POIs

To reduce the commutating complexity of the proposed solution, we first select candidate POIs for users. Candidate POIs are obtained from similar users, which makes this method a user-based collaborative filtering approach. Similar users are believed to share similar behaviors. We analyze user behaviors according to the geospatial aggregation phenomenon of their check-in POIs [7] and then extract user features to compute similarity among users. The feature representation of a user is defined as follows:

Definition 1. *User feature representations. A vector of check-in frequencies in each POI cluster of a user.*

First, we determine clusters of POIs in a certain geographic area by applying the density-based spatial clustering of applications with noise (DBSCAN) algorithm whose inputs are geographic coordinates of POIs. The DBSCAN allocates a cluster to each POI and obtains noise POIs that do not belong to any cluster. The features of a user u_i are then expressed according to Eq. 1 expressed as follows:

$$F_i = \{f_0, f_1, f_2, \ldots, f_K\}(0 \leq i \leq N) \tag{1}$$

where f_0 indicates the check-in frequency of user u_i at noise points. f_1 to f_c indicate the respective check-in frequency of user u_i in clusters 1 to c. The check-in frequency of the user u_i in the cluster j is defined as Eq. 2:

$$f_j = \frac{k}{n}(1 \leq j \leq m) \tag{2}$$

where n_i is the total number of check-in records for user u_i. Similarly, the check-in frequency of the user u_i at the noise point is defined as Eq. 3:

$$f_0 = \frac{k_0}{n_i} \tag{3}$$

Finally, the similarity among users can be calculated as follows:

$$S_{ij} = \sum_{q \in Q} min(f_{iq}, f_{jq}) \tag{4}$$

where Q is a set of clusters that users u_i and u_j have visited. The index q must be positive, so the noise points will not be taken into account. According to Eq. 4, we can identify a group of similar users for each user, and the candidate POIs can be selected from his/her similar users' historical check-ins.

Algorithm 1 illustrates the functionality of candidate POI selection.

Algorithm 1. Candidate POIs Selecting

Input: Users U, POIs L with coordinates g
Output: Candidate POIs set P_i of each user
Run DBSCAN on L to get Clusters $C = \{c_l, c_2, \ldots, c_K\}$
for each $u_i \in U$ **do**
  calculate check-in count n_i
  for each $c_i \in C$ **do**
    calculate check-in count k_i in cluster c_i
    set check-in frequency $f_i = k_i/n_i$
  end for
  set user feature $F_i = \{f_0, f_1, f_2, \ldots, f_K\}$
end for
for each $u_i \in U$ **do**
  for each $u_j \in U$ **do**
    set $S_{ij} = \sum_{q \in Q} min(f_{iq}, f_{jq})$
  end for
  sorting S_{ij} in descending order
  get Candidate POIs P_i from top 1 similar user.
end for
return $P = \{P_1, P_2, \ldots, P_N\}$

3.2 Improved Hawkes Process

The Hawkes process is a linear self-excited point process model proposed by Hawkes in 1972 [8]. The model is widely used in various fields, such as economic analysis and forecasting and social network modeling. This model believes that previous events affect the probability of occurrence of future events, and the incentives of past events are positive, additive, and decay over time. We introduce the Hawkes process to model the spatio-temporal sequence of users' check-in records. The equation is as follows:

$$\lambda_{ul_k}(t) = \mu_{ul_k} + \sum_{l_i \in H_u} \alpha_{l_i l_k} e^{-\delta(t - t_{l_i})} \tag{5}$$

where $\lambda_{ul_k}(t)$ is the intensity of user u visiting POI l_k, μ_{ul_k} is the basic intensity (probability) of u visiting l_k, $\alpha_{l_i l_k}$ is the excited degree of historical check-in $<u, l_i>$, $e^{-\delta(t-t_{l_i})}$ indicates the time decay of the historical check-in $<u, l_i>$, and H_u is the set of POIs that user u has visited. The left part of the formula can be considered as long-term preferences of a user, and the right part can be considered as time-varying preferences.

Each user can have a personalized Hawkes process to estimate the probability of visiting candidate POIs based on his/her historical check-ins to obtain the top-k recommended POIs. The way of solving the parameters in Hawkes process is described in the following sections.

3.3 Basic Intensity $\boldsymbol{\mu_{ul_k}}$

The basic intensity μ_{ul_k} can be calculated in different ways. Considering that the distances from a user to POIs and the popularity of POIs are critical information, we utilize the improved Huff model to integrate distance and popularity to compute the basic intensity μ_{ul_k}.

The Huff model was proposed by David Huff. It attributes the attraction of a mall to customers in two factors [9]: (1) the area size of the mall and (2) the geographical distance between the mall and the customer. The original Huff model is expressed as follows:

$$P_{ij} = \frac{S_j d_{ij}^{-\gamma}}{\sum_{j=1}^{M} S_j d_{ij}^{-\gamma}} \tag{6}$$

where S_j represents the area size of mall j, d_{ij} is the distance between customer i and mall j, and γ is the distance attenuation coefficient.

In our study, the Huff model is improved to adapt to LBSN check-in datasets. The equation is expressed as follows:

$$P_{ij} = \frac{\upsilon_j^{\beta} Haversine(d_{ij}^{-\gamma})}{\sum_{j=1}^{M} \upsilon_j^{\beta} Haversine(d_{ij}^{-\gamma})} \tag{7}$$

where υ_j denotes the total number of check-ins of POI l_j, which reflects the POI popularity, and the exponential distribution υ_j^{β} is used instead of S_j, where β is an elasticity coefficient. $Haversine(d_{ij})$ is used to calculate the Haversine distance between the last check-in location of user u_i and the candidate POI l_j, and γ is the distance attenuation coefficient. Haversine distance is the great-circle distance between two points on a sphere given their longitudes and latitudes.

The Huff model is further normalized by the sigmod function to obtain the basic intensity μ_{ul_k} of improved Hawkes process:

$$\mu_{ul_k} = \frac{1}{1 + e^{-P_{ij}}} \tag{8}$$

3.4 Excited Degree $\alpha_{l_i} l_k$ and Time Decay Coefficient δ

The excited degree $\alpha_{l_i l_k}$ of historical check-in $<u, l_i>$ with respect to future check-in $<u, l_k>$ can be calculated by a POI transition graph.

Definition 2. *POI-to-POI Transition Graph [4]. Graph* $= (L, E)$*, where* L *is the set of vertices, and* E *is the set of edges. Each vertex* $l_i (l_i \in L)$ *represents a POI. Each POI has an out-degree, defined as* $OutDegree(l_i)$*, which represents the number of transitions from* l_i *to other POIs. Each edge* $(l_i, l_j) \in E$ *represents a transition* $l_i \rightarrow l_j$*. The number of transitions contained in each edge is defined as* $EdgeWeight(l_i, l_j)$*.*

Definition 3. *Transition probability. The transition probability of* $l_i \rightarrow l_j$ *is defined as* $TP(l_i \rightarrow l_j)$*, and calculated as follows:*

$$TP(l_i \rightarrow l_j) = \begin{cases} \frac{EdgeWeight(l_i, l_j)}{OutDegree(l_i)}, & \text{if } (OutDegree(l_i) > 0) \\ 0, & \text{other} \end{cases} \tag{9}$$

The excited degree $\alpha_{l_i l_k} = TP(l_i \rightarrow l_k)$ can be obtained by Eq. 9.

The time decay coefficient δ is a free parameter, we will discuss the tuning method of δ and analyze its value in the experimental section.

The detailed algorithm is illustrated in Algorithm 2.

Algorithm 2. POI Recommendation Based on Hawkes Process

Input: Users U, POIs L, check-in time T
Output: $top-k$ POIs for each user
Run Algorithm 1 to get candidate POIs $P = \{P_1, P_2, \ldots, P_N\}$ for each user
for each $u_i \in U$ **do**
  for each $l_k \in P_i$ **do**
    calculate $Haversine(d_{ik}^{-\gamma})$ between user u_i and candidate POI l_k
    calculate popularity υ_k for POI l_k
    calculate basic intensity $\mu_{u_i l_k}$ according to equation 7 and 8
    for each $l_m \in H_{u_i}$ **do**
      set $\alpha_{l_m l_j} = TP(l_m \rightarrow l_j)$
    end for
    calculate visit preference of l_k according to equation 5
  end for
  recommend to u_i with top-k POIs according to visit preference.
end for

4 Experiments

4.1 Dataset

Two datasets are used in our experiments.

Gowalla Dataset. The Gowalla dataset used in this experiment is obtained from Stanford University's public dataset collection site[1]. The check-in data cover different parts of the world, and the data densities vary from place to place, which makes data mining inconvenient. In the experiment, the Manhattan area of New York City, where user check-in is denser and data quality is higher, is selected as the study area. The geographic range is latitude 40.60° to 40.85° N and longitude 73.89° to 75.05° W. The contents of each check-in record in the dataset include user ID, POI ID, geographic coordinate of POI, and check-in time. The users whose check-in times are less than 5 and the POIs that have been visited less than 10 times are filtered out. After preprocessing, the dataset contains 59,336 check-in records made by 1,612 users at 2,299 POIs, and the check-in time span is from February 2009 to October 2010.

Foursquare Dataset. Foursquare is a mobile service website based on user geographical location information. It encourages mobile phone users to share information about their current geographical location with others. In the experiment, the Tokyo check-in dataset of Foursquare provided by [10] is used. The contents of each check-in record in the dataset include user ID, POI ID, category ID of POI, category name of POI, geographic coordinate of POI, and check-in time. After filtering out users who have checked in less than 10 times and the POIs that have been visited less than 10 times, the dataset contains 357,147

[1] http://snap.stanford.edu/data/loc-gowalla.html.

check-in records made by 2,293 users at 7,866 POIs, and the check-in time span is from April 2012 to February 2013.

Table 1 shows the statistics of the two datasets.

Table 1. Statistics of dataset

Dataset	Number of users	Number of POIs	Number of check-in records	Average number of check-ins	Check-in matrix density
Gowalla	1612	2299	59336	36.81	1.60%
Foursquare	2293	7866	357147	155.75	1.98%

4.2 Evaluation Metrics

For each user, the top 80% of the check-in data (sorted by check-in time in ascending order) are used as the training data, whereas the remaining 20% are used as the testing data. The visited probabilities of a user to the candidate POIs are calculated according to the proposed HWREC algorithm, and the top-k POIs sorted by visiting probability are recommended to the users.

To evaluate the performance of the proposed method, two metrics are used [11], namely, precision and recall, and the equations are defined in 10 and 11, respectively.

$$Precision = \frac{\sum_u |R_u \bigcap T_u|}{\sum_u |R_u|} \tag{10}$$

$$Recall = \frac{\sum_u |R_u \bigcap T_u|}{\sum_u |T_u|} \tag{11}$$

where R_u represents a set of POIs recommended for user u, and T_u represents a set of POIs that actually visited by user u in the testing data.

4.3 Baseline Methods

We compare the proposed HWREC with the following baseline algorithms.

- HUFF. It is the basic intensity of HWREC, which uses the distance and popularity information of POIs to obtain the long-term static preferences of users.
- AMC. It is the time-influencing part of HWREC, which uses additive Markov process to calculate the time-varying preferences of users.
- ASVD++ [12]. It is a combined model which improves the accuracy of top-k recommendation by utilizing the advantages of latent factor and neighborhood method. In this experiment, the number of user check-ins is normalized as implicit scores of $<user, POI>$ pairs when calculating.

- AOBPR [13]. It is an advanced Learning-to-Rank based algorithm for top-k recommendation, which studies the preferences of users from implicit feedback.
- LORE [4]. This algorithm integrates several contextual information, such as social relationships, spatial distance, POI popularity, and time information; it achieves better results compared with many other advanced methods, such as CoRe [14] and USG [15]. The Foursquare dataset does not contain social relationship information, so the similar users calculated in Sect. 3.1 are used instead in the experiment.

4.4 Parameter Settings

In the experiment, the radius of neighborhood and density threshold of DBSCAN clustering algorithm are set to 100 and 2, respectively.

The improved Huff model has two parameters: distance attenuation coefficient γ and elastic coefficient β of POI popularity. Parameter γ is set to 2 according to the modified Huff model in [9]. Parameter β is set to 3.5 in the Gowalla dataset and 5 in the Foursquare dataset.

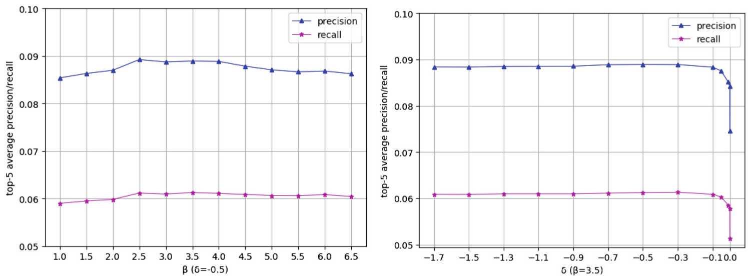
The excited degree $\alpha_{l_i l_k}$ of historical check-in $<u, l_i>$ is calculated according to the method presented in Sect. 3.4. The time decay coefficient δ is set to -0.5 in the Gowalla dataset and -0.001 in the Foursquare dataset. A smaller δ indicates a lower decay rate. The time differences between historical events and current events are calculated in scale of hours.

For the two free parameters, β and δ, we search for the optimal values by tuning the parameters alternately. First, β is fixed, and δ is tuned to obtain the best recommendation accuracy. Next, δ is fixed, and β is tuned to obtain the best recommendation accuracy. In general, this process is repeated 3 to 5 times to achieve the best results.

4.5 Parameter Discussion

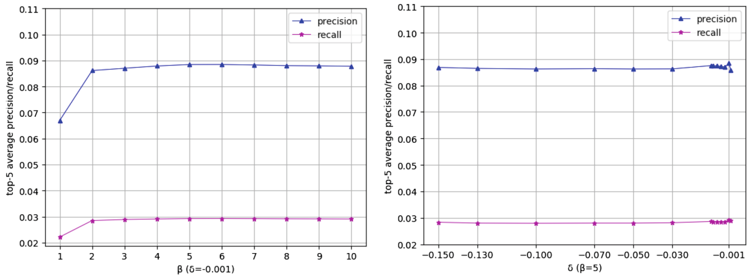
Two free parameters are used in our proposed algorithm: elastic coefficient β of POI popularity and time decay coefficient δ. Figures 1 and 2 show the effect of these parameters on the Gowalla and Foursquare datasets in terms of precision and recall, respectively. The experiment compares the average accuracy and recall of top-k (k = 1, 2, 3, 4, 5) recommendations when the parameters are varied.

The performance is poor in the both datasets when parameter $\beta \leq 2$ because the distance coefficient γ is fixed to 2. The best performance for the Gowalla dataset is obtained when $2.5 \leq \beta \leq 4$, after which the average accuracy and recall decrease slightly. On the Foursquare dataset, the best performance is achieved when $5 \leq \beta \leq 6$, and the performance changes are imperceptible thereafter. Therefore, the value of β can be generally selected from 3 to 5, which indicates that user check-in probability has an exponential relationship with the popularity of a POI. It also reflects actual phenomena, for example, the number of visitors who travel to famous attractions is usually dozens of times that of ordinary ones.



(a) Precision (b) Recall

Fig. 1. Influence of β and δ on recommendation of Gowalla dataset



(a) Precision (b) Recall

Fig. 2. Influence of β and δ on recommendation of Foursquare dataset

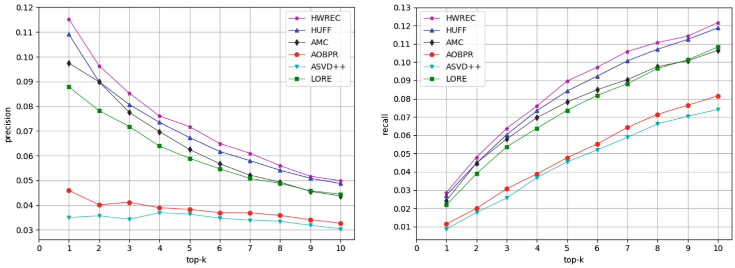
Parameter δ differs significantly between the two datasets. On the Gowalla dataset, the recommendation performance drops significantly when $\delta > -0.1$. When $\delta = 0$ (no decay), the result is the worst. When $\delta \leq -0.3$, not much difference is observed between the performances. On the Foursquare dataset, the best performance is obtained when $\delta = -0.001$. When $\delta = 0$ (no decay), the performance is slightly lower than the best value. When the value of δ decreases, the performance changes are minor because the time decays of historical check-ins on the Foursquare dataset are considerably lower than those on the Gowalla dataset. Therefore, the value of $|\delta|$ should be smaller on the datasets with lower time decays.

4.6 Performance Comparison

Figures 3 and 4 compare the proposed algorithm HWREC and other baseline methods on the Gowalla and Foursquare datasets, respectively. The results indicate that the accuracy decreases as the value of k increases, whereas the recall increases as the value of k increases. This is because the visit probability of recommended POIs decreases as the value of k increases.

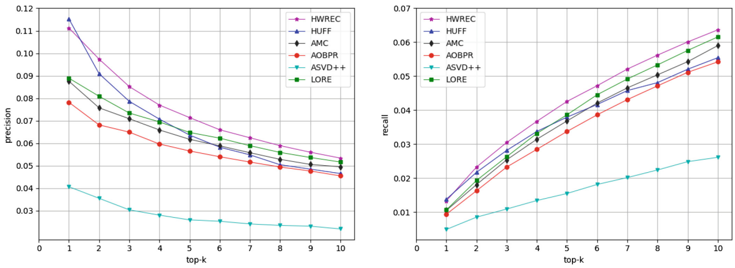
Figures 3 and 4 demonstrate that the proposed HWREC is far superior to matrix factorization based ASVD++ and Learning-to-Rank based AOBPR.

These algorithms consider only the check-in counts of users and do not use spatial and temporal information. Although the top-1 recommendation performance of the proposed HWREC is slightly lower than HUFF in the Gowalla dataset, the overall performance of HWREC is significantly better than the HUFF, which considers only static preferences of users, and the AMC, which considers only time-varying preferences of users. The LORE uses distance, popularity, time, and social relationship information, but HWREC achieves better results, particularly on the Gowalla dataset.



(a) Precision (b) Recall

Fig. 3. Recommendation performance with respect to top-k values on Gowalla dataset



(a) Precision (b) Recall

Fig. 4. Recommendation performance with respect to top-k values on Foursquare dataset

4.7 Interpretability

Different from existing methods, the proposed HWREC algorithm considers both static preferences and time-varying preferences, so it can easily explain the recommendation results.

First, let's consider the long-term static preferences. In the location-based mobile applications, such as Meituan, when you search for POIs according to the keywords, it will show you a list of POIs sorted by popularity or distance. In our proposed method, the popularity and distance of POIs are reflected in the static preferences part. We can tell users that "we recommend the POI to you according to its distance (e.g., 2 km from you) and popularity (e.g., 1000)."

Second, we consider the time-varying preferences. The influence of historical check-ins is related with multiple factors, including check-in count, check-in time and transition probability. For each POI that is recommended to users, an explicit score of every historical check-in can be calculated by the time-varying preferences part of the proposed method. Then we can tell users that "we recommend the POI to you because you have visited POIs a, b, and c (a, b, and c, are sorted by their scores in descending order)." Furthermore, we can provide the information, such as check-in count, check-in time, and transition probability, related with the score, which can enhance the explanation.

5 Related Work

POI recommendation has attracted lots of attention from academics and industry, and related works include collaborative filtering (CF) approaches [16], matrix factorization-based algorithms, geographical distance-based models, social relationships-based methods, and context-based method, etc. Different methods are suitable for different check-in datasets. For example, the CF method, which recommends POI by calculating similarity of users or POIs, is widely applicable. The geographical distance-based method, which is applicable for datasets with precise geographic locations, leverages the distance between users and POIs to characterize user behaviors. The social relationship-based methods can be applied to datasets that contain friend information of users. The recommendation is performed by mining the similarity between users and their friends. We summarize the related works as follows.

(1) Collaborative filtering (CF) methods. Most existing POI recommendations are based on CF algorithms [16,17], which assume that similar users usually visit similar POIs. There are two types of CF algorithms, user-based CF [17] and item-based CF (a POI is considered as an item) [16]. The former compares the similarity among users, whereas the latter compares the similarity among POIs.

(2) Geographical distance-based methods. Geographic location is an important factor for POI recommendation. POIs that are closer to the users tend to be visited. A study [18] analyzes the distance distribution of the users' check-in locations, and the results reveal that the distances of adjacent check-in locations present a power-law distribution. In [7], data sparsity is alleviated by modeling user activity areas and POI impact areas. The literature [14] uses kernel density estimation to analyze the influence of the 2D geographical coordinates of POIs to improve recommendation performance.

(3) Social relationship-based methods. The social relationship (e.g., friendship) between users is an important factor in the location based social networks. Friends tend to share common preferences. In [19], a friend-based CF method using the common check-in records of friends to recommend POIs is proposed. However, given that few users share information about check-in POIs, the improvement of recommendation performance is limited by only using social relationships [20].

(4) Time-aware methods. Time is an important factor for POI recommendations because the places users tend to visit vary with the time of the day. The literature [21] proposes a time-aware POI recommendation by considering the temporal influence of user activities.
(5) Content-based methods. Users can rate and comment on POIs in LBSNs. Modeling users' comments on the POIs [3] is useful to understand the preferences of users accurately and improve the recommendation performance.
(6) Methods integrated with multi-factors. The visit preferences of users are influenced by many factors, single-factor based recommendation algorithm can not archive good performance. Most studies have attempted to integrate geospatial information, time effects, social relationships, content information, popularity, and other factors to improve the recommendation performance [22].

In this study, we propose a new approach to model interests of users from both long-term static preferences and time-varying preferences. Unlike existing methods, our approach can provide satisfactory explanations for recommended POIs.

6 Conclusion

In this study, we propose a context-aware POI recommendation approach with interpretability based on improved Hawkes process. The proposed method exploits users' long-term static and time-varying preferences by using multiple context information to alleviate the problem of data sparsity and provide explanations to users for recommendation results in several aspects. Context information include spatial clustering, spatial distance, spatial sequence transformation, temporal, and POI popularity information. We conduct experiments over two real-world LBSNs datasets and compare our model with several baselines. The experimental results demonstrate that the proposed solution achieves better performance than other advanced POI recommendation algorithms.

In the future work, we intent to improve the performance and interpretability of POI recommendation by integrate more auxiliary information, such as POI category, comments of POI, etc. to the static and time-varying preferences of our model. Moreover, the recurrent neural network which is excellent at sequence modeling can be explored to mine the check-in sequences of users to study the time-varying preferences. Further, the time-varying part of our proposed model can be improved to do online POI recommendation based on deep reinforcement learning.

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