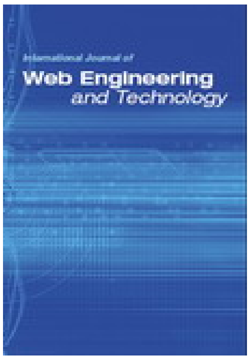

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PRMF: point of interest recommendation method integrating multiple factors

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Abstract: Point-of-interest (POI) recommendation plays an increasingly important role in location-based social networks (LBSNs) and is widely used in various e-commerce websites. However, due to the high sparsity of user check-in information, it is still challenging to recommend appropriate and accurate locations to users. As people decide where to visit based on numerous factors, recommendation systems need to consider check-in records and data on POI popularity and POI locations. In this paper, we propose a POI recommendation method that integrates multiple factors by analysing users' check-in records, POI category, location, and POI popularity, called PRMF. Firstly, we employ a neural network algorithm to calculate user preferences. Activity centres are then calculated based on the users' historical check-in history, and geographical preferences for each POI are calculated according to the activity centre. By combining the popularity of POIs in this study, we calculate POI popularity preferences, and the above three parts were obtained by linear fusion to calculate the users' final preference. Extensive experiments (based on real datasets, including long-term check-in data for locations in New York and Tokyo collected from Foursquare) show that our proposed method was superior to the baselines.

Keywords: point of interest; POI; recommendation methods; location social network; neural network; feature extraction; geographical location; popularity; MLP; user preferences; multi-factor.

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1 Introduction

With the advent of Web 2.0, a new form of social network services, location-based social networks (LBSNs), is gradually emerging. Mobile devices can be used to check into venues or POIs, and users can share their route and journey experience online so that users around the world can track and share their location in the real world in LBSNs. The combination of the natural world and network services has aroused great interest in the industry. Various LBSNs such as Foursquare, Gowalla and Facebook Places can be deployed at home and abroad. Users can check into restaurants, tourist attractions, and other POIs to share life experiences at any time. Utilising users' existing check-in history for personalised recommendations can help users understand relevant contextual information more efficiently and enable them to explore their surroundings.

Traditional recommendation systems rely heavily on the richness of user data, so they are more suitable for movie or music recommendations. All movies have a clear score and detailed content. However, based on social location, the POI recommendation system requires users to score a particular place they visit using the traditional recommendation method. The process is quite expensive. In most cases, even if users visit a particular POI, they may not check-in. Therefore, recommendation systems based on social location (Zhao et al., 2022; Xu et al., 2021; Ding and Chen, 2018) has greater sparsity than traditional recommendation system. Compared with the traditional recommendation system, POI recommendation needs to consider user preferences and factors such as popularity and the location of POIs.

In this paper, we propose a POI recommendation method integrating multiple factors called PRMF. The main contributions are as follows:

- We design a multi-layer learning network (with multi-layer perceptron architecture) based on a social location network that considers various contextual factors.
- We design a unified multi-factor POI recommendation model, which considers the influence of user preference, POI popularity, and geographical factors on POI recommendations.
- The empirical evidence from experiments on public datasets shows that the proposed method can improve POI recommendations.

The remainder of the paper is organised as follows. After Section 2 discusses the related work, Section 3 introduces our proposed method in detail. Section 4 discusses the extensive experimental results on real datasets crawled from Foursquare. Section 5 concludes the paper and briefly discusses future work.

2 Related works

In recent years, POI recommendation systems have made it possible to improve user experience and promote product sales, and they have attracted the attention of many researchers. Standard recommendation methods include the recommendation method based on collaborative filtering, the recommendation method based on matrix factorisation, and hybrid recommendation method.

2.1 Recommendation method based on collaborative filtering

The recommendation method based on collaborative filtering captures users' implicit preferences from their usage history and is widely used in POI recommendations. The main idea of the collaborative filtering recommendation method is to use other users' history or item scores to recommend items or predict item scores for target users. Wang et al. (2019a) proposed a trust-enhanced user similarity method in collaborative filtering based on network representation learning. At the same time, due to the importance of geographical and temporal influences, these two factors were integrated into POI recommendations using a fusion model. Zhang et al. (2020) developed a personalised geographical influence modelling (PGIM) method, which can capture the user's diversity preference and geographical preference at the same time. Firstly, the PGIM model introduces diversity preference regardless of the popularity of the POI. Secondly, considering geographical information relating to POIs, the PGIM establishes the user's geographical preference model. He et al. (2021) proposed a linear graph convolutional-based collaborative filtering that takes advantage of social relationships as side information to improve recommendation performance. Liu et al. (2022) defined a heterogeneous information network-based POI recommendation model to model various heterogeneous context features. However, the recommendation method based on collaborative filtering has a natural defect: limited ability to process sparse data; the head effect is relatively apparent, and the generalisation ability is relatively poor.

2.2 Recommendation method based on matrix factorisation

In order to solve the significant defects of data sparsity and information redundancy in traditional methods, some scholars have proposed a matrix factorisation method for recommendation systems. The basic idea of matrix factorisation methods is to factorise the user-POI matrix into two latent matrices which represent the characteristics of users and POIs. These two latent matrices are used to predict the score and generate the recommendation list. Xu et al. (2018) emphasised that geographical factors and user factors play a crucial role in POI recommendation. Based on this, a POI recommendation model named geographical and user matrix factorisation (GeoUMF) based on matrix factorisation is proposed by taking advantage of the above factors. The model analysed the difference between the ranking generated in the recommendation model and the actual ranking in the check-in data. In addition, GeoUMF defines an approximate approach in the objective function, which considers differences in POI access frequencies. He et al. (2017) have argued that computation of predicted scores by inner product has some limitations and proposed the NeuMF model to solve this problem by computing predicted scores with MLP instead of the inner product. A check-in matrix of user-POI is constructed by checking users' historical data. Davtalab and Alesheikh (2021) proposed that auxiliary information such as category, geographical influence, working time, and people's opinions are helpful for POI recommendation. A social spatio-temporal probabilistic matrix factorisation model named SSTPMF has been proposed to integrate all the above information into the recommendation model. Huang et al. (2022) proposed a federated learning (FL) approach to geographical POI recommendation. An optimisation problem of matrix factorisation formulates the POI recommendation, and the singular value decomposition (SVD) technique is applied for matrix factorisation. However, the recommendation method based on matrix factorisation has poor interpretability.

2.3 Hybrid recommendation method

In the hybrid recommendation methods, various models are combined to form a more powerful and accurate recommendation system with better robustness. To address the next POI recommendation problem, Wu et al. (2020) proposed a novel method named personalised long- and short-term preference learning (PLSPL) to learn users' preferences jointly. At the same time, this model especially learned the personalisation weights of different users for the long-term and short-term modules. In the long-term module, they described the context characteristics of the POI and captured the long-term preferences through the attention mechanism. They learned location-level and category-level preference in the short-term module through two parallel LSTM models. Wang et al. (2019b) proposed neural graph collaborative filtering (NGCF), which uses graph convolutional network to obtain decomposed embeddings of users and items, and improves recommending results. Xue et al. (2019) combined item-based collaborative filtering with neural networks to learn higher-order interactions among items. Liu et al. (2019) proposed a geographical information-based adversarial learning model, namely GeoALM. This method takes advantage of adversarial learning mechanisms and geographic information. Sheng et al. (2021) proposed a hierarchical time series attention network, which uses a multi-dimensional attention mechanism to learn fine-grained user intention from different check-in sessions. At the same time, it integrates the time-based directed attention mechanism into RNN to obtain dynamic preference characteristics. However, most of the existing POI recommendation work lacks the learning of abstract interactions between the user and POI characteristics. Given the heterogeneity of social location networks, designing an appropriate framework to integrate multi-source heterogeneous POI information has been a critical issue in recent years to improve the effectiveness of the recommendation model. In this study, we conducted an in-depth analysis of data relating to user check-ins, POI categories, and geographical locations, along with the popularity of POIs. We integrated different factors into the POI recommendation framework, alleviating data sparsity and improving the recommendation effect.

3 Proposed method

In this paper, we constructed a multi-factor POI recommendation method called PRMF, which uniformly utilises POIs, user check-in records, spatial distance, and POI popularity. Through user check-in records, making POI recommendations combined with the spatial distance and popularity models. Finally, experiments on real-world datasets show that our proposed method can make more accurate POI recommendations than other methods.

3.1 Problem description

This section will give a definition of the POI recommendation problem. Table 1 lists the symbols and their definitions used in this paper.

Table 1 Symbols and their definitions

Symbol	*Meaning*
U, P, C	User set, POI set, category set
u_i, p_l, c_z	User i, POI l, category z
u^i_{attr}, p^l_{attr}	User attribute, POI attribute
$p_l^{u_i}$	User u_i's preference for POI p_l
$d_{p_l}^{u_i}$	Distance between the centre distance of user u_i and the POI p_l to be visited
$p^g(u_i, l)$	The check-in probability of user u_i, which is affected by geography
p_l^p	Popularity preference of POI p_l
$p(u_i, l)$	User u_i's overall preference for POI p_l

Definition 1 [point of interest (POI)]: POI refers to a place whose location can be uniquely identified, e.g., restaurants or scenic spots. In this paper, a POI has the following attributes: identifier ID, location p_l, and category c_z. p_l is composed of longitude and latitude. In addition, each POI belongs to a category, predefined by a specific LBSN platform (such as Foursquare or Facebook Places), represented by c_z.

Definition 2 (user): The symbol U represents the user set in the LBSN. Each user u_i in set U has a unique identifier ID.

Definition 3 (user check-in): Assuming that the user is u_i, the POI is p_l, and the category information is c_z. The check-in history of user u_i at the POI p_l can be represented by a triplet $< u_i, p_l, c_z >$, indicating that the user u_i has checked in to the POI p_l, where the category of POI p_l is c_z.

Definition 4 (POI recommendation): A recommendation is made as to the most likely new POI for a given user through an analysis of the user's historical check-in records. The POI recommendation predicts the user's preference for all POIs, and the top-k POIs, sorted by preference, are the recommendation result for the user.

3.2 Overall framework of PRMF

Figure 1 shows the overall framework of the POI recommendation method proposed in this paper. When a user checks into a POI, the check-in data is generated, which contains the user ID, POI ID, and POI category. These check-in data form an LBSN. This method integrates three parts: user preference, popularity influence and geographical location influence. The user preference model uses a neural network algorithm to predict the user's preference for POIs according to users' check-in records. The spatial distance model calculates the distance between the POI to be checked and the user centre. The user's centre is obtained according to the user's historical check-in records. The closer they are, the greater the likelihood of a visit by the user. The popularity of a POI will affect users' decisions about where to go, i.e., users are more likely to visit famous places. The popularity model uses the POI entropy method to calculate the influence of the popularity of POIs. When generating the final recommendation list, our model uses a linear framework to combine the influence of user preference, spatial distance and popularity.

Figure 1 Framework of our proposed method (see online version for colours)

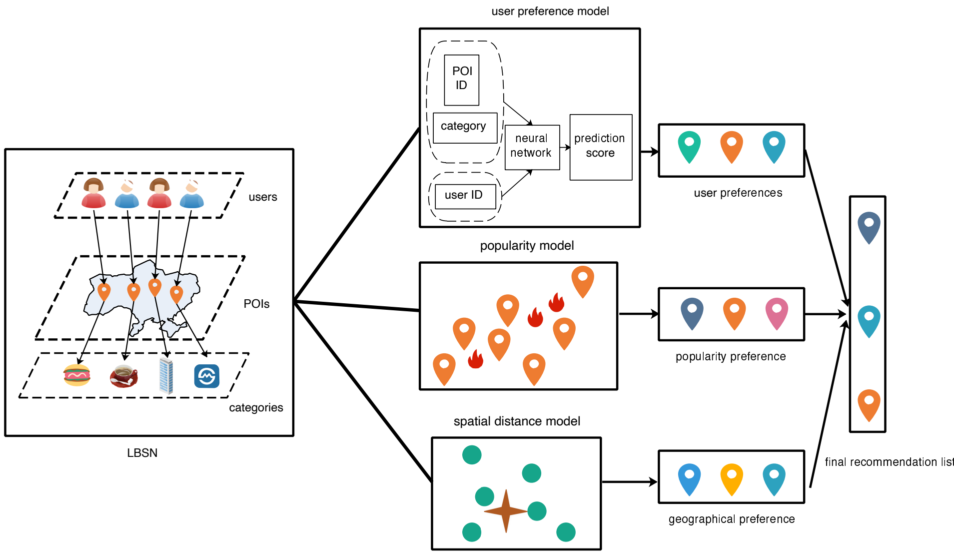
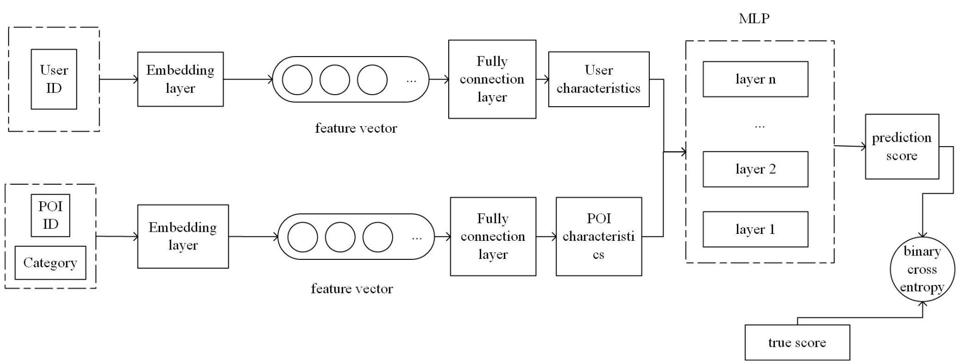


Figure 2 User preference model



3.3 User preference model

The user preference model obtains the user attributes and POI attributes and employs MLP to predict user preference for a specific POI. The framework of the user preference model is shown in Figure 2. User and POI attributes are inputted into the user preference model to obtain the user attribute features and POI attribute features.

Embeddings are vector representations of an entity. Any discrete entity can be represented in a continuous space through embeddings. Each user/POI represents a feature or a combination of features for the particular entity. In our model, POI IDs and user IDs are used to generate corresponding embeddings. These embeddings are generated through the model training process, along with other parameters. As shown in Figure 2, the embedding layer initialises the embedding weights based on the embedding_initialiser parameter. These embedding layers are trained along with the network, and the output of these layers is updated.

Suppose that the attribute of user u_i is expressed as u^i_{attr} = $\{u^i_{attr_1}, u^i_{attr_2}, ..., u^i_{attr_x}\}$, and $u^i_{attr_j}$ represents an attribute of user u_i, such as user ID. The attribute of POI p_l is expressed as u^l_{attr} = $\{u^l_{attr_1}, u^l_{attr_2}, ..., u^l_{attr_y}\}$, and $p^l_{attr_j}$ represents an attribute of POI, such as POI ID. The attributes of users and POIs are then inputted into the embedding layer to obtain the feature vector of the attributes, where the vector length is dim. The process can be expressed as:

$$\overline{u^i_{attr_{dim}}} = f(w_1 u^i_{attr} + b_1) \tag{1}$$

$$\overline{p^l_{attr_{dim}}} = f(w_2 p^l_{attr} + b_2) \tag{2}$$

where w_1 and w_2 represent weight, b_1 and b_2 represent bias, and $f(\cdot)$ represents activation function. Then, each attribute of the user and POI are fused by the connection function to obtain the user feature and POI feature. The process can be expressed as:

$$u^i_{attr} = concatenate(\overline{u^i_{attr_{dim}}}) \tag{3}$$

$$p^l_{attr} = concatenate(\overline{p^l_{attr_{dim}}}) \tag{4}$$

where $concatenate(\cdot)$ means concatenating the attributes. After obtaining the user and POI feature, the score is predicted by MLP. The input of MLP is the connection of the user feature and the POI feature, which can be expressed as equation (5):

$$x_0 = concatenate(u^i_{attr}, p^l_{attr}) \tag{5}$$

After passing through the first layer, the output can be expressed as equation (6):

$$x_1 = f(W_1 x_0 + b^{'}_1) \tag{6}$$

where W_1 represents the weight matrix between the output layer and the hidden layer, and $b^{'}_1$ represents the bias. Finally, the output passing through n layers can be expressed as the following equation (7):

$$x_n = f(W_n x_{n-1} + b^{'}_n). \tag{7}$$

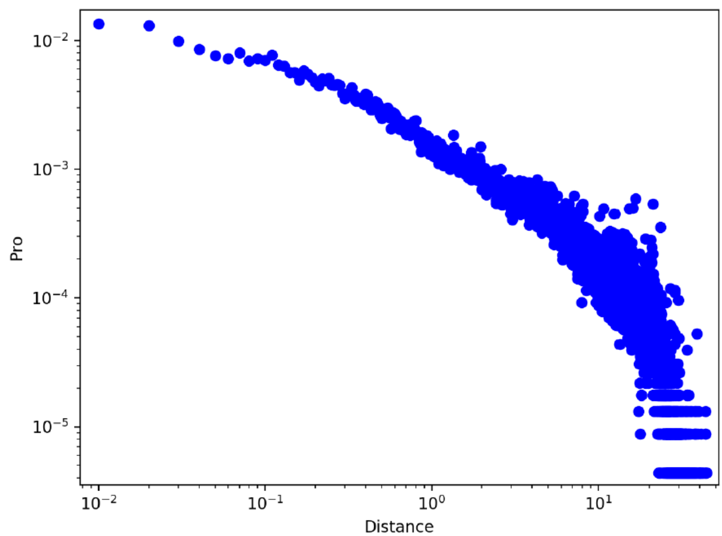
The user u_i's score on the POI p_l can be finally expressed as equation (8):

$$p^{u_i}_l = x_n. \tag{8}$$

3.4 Spatial distance model

Users' movement behaviour is often affected by spatial distance. When the spatial distance is short, users will be more influenced by the transfer relationship between the POIs. When the spatial distance is long, users will be more influenced by the user's potential preference than the transfer relationship between the POIs. In addition, differences in user behaviour patterns can also be seen in different regions. For example, in some cities, users are more influenced by short-term preferences, while in others, users pay more attention to long-term preferences. To better understand the impact of geographical location on users, we analysed the user behaviour of the dataset. The geographic location probability distribution is shown in Figure 3.

Figure 3 Geographic probability distribution between consecutive check-in records (New York dataset) (see online version for colours)



As can be seen from Figure 3, our results are consistent with findings reported in the literature (e.g., see Ye et al., 2011; Shi and Jiang, 2017), that is, users' movement behaviour is often affected by spatial distance follows specific rules. Less distance means users will be more affected by the transfer relationship between POIs. If the distance is greater, users will be more affected by users' potential preferences than the transfer relationship between POIs.

Thus, the geographic check-in probability of user u_i to POI p_l is shown as equation (9):

$$p_u(i,l) = \rho \times (d_{p_l}^{u_i})^k \tag{9}$$

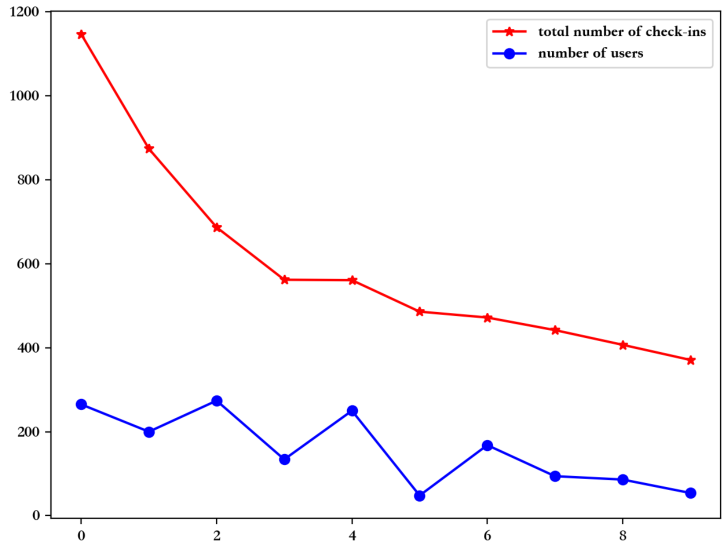
where ρ and k are parameters to be estimated, and the least square regression method is used to learn the parameters ρ and k. $d_{p_l}^{u_i}$ indicating the distance between the current POI p_l of user u_i and the user u_i's centre distance.

The standardised geographic check-in probability of user u_i can be calculated according to equation (10):

$$p^g(u_i,l) = \frac{p_u(i,l)}{Max(p_{u_i})} \tag{10}$$

where $Max(p_{u_i})$ represents the maximum transition probability in the historical check-in records of user u_i.

Figure 4 Number of check-ins and number of users for the top 10 POIs (see online version for colours)



3.5 Popularity model

The popularity characteristic of a POI refers to the popularity of the POI among users, that is, the number of users going to the POI. It is evaluated based on the number of users who check in at the POI in the social dataset. The greater the number of visits and check-ins times, the more popular it is, and the easier it is to be recommended to users. Figure 4 shows the number of check-ins and the corresponding number of users in the top 10 POIs. Popular locations usually attract more attention and are visited more often. These observations suggest that the prevalence of POIs depends on the total number of check-ins.

Therefore, if a restaurant is a popular online restaurant, it may attract more people. In other words, the popularity of POIs has a significant impact on users' decisions about where to go.

The entropy of a POI is used to calculate the impact of popularity on POI recommendations. Suppose that a collection of check-in records of each user in POI p_l is represented as $F_l = \{f_{u_1,l}, f_{u_2,l}, ..., f_{u_n,l}\}$, where n represents the total number of users that have checked POI p_l, and $p(u,l) = \{p_{u_1,l}, p_{u_2,l}, ..., p_{u_n,l}\}$ represents the check-in probability of users to POI p_l. The definition of $p_{u_i,l}$ is shown in equation (11):

$$p_{u_i,l} = \frac{f_{u_i,l}}{\sum_{j=1}^{n} f_{u_j,l}}. \tag{11}$$

The popularity entropy of POI is expressed as the following:

$$P_l^p = -\sum_{i=1}^{n} (p_{u_i,l} \times \log p_{u_i,l}). \tag{12}$$

The higher the value of POI entropy, the more different users will check into the location.

3.6 Model fusion

We propose a linear fusion framework, which effectively integrates user preference, spatial distance, and popularity and simulates the decision-making process of users' check-in behaviour to recommend POIs for users. Therefore, the final check-in probability of users can be expressed as:

$$P(u_i, l) = (1 - \alpha - \beta) \times P_l^u + \alpha \times P^g(u_i, l) + \beta \times P_l^p \qquad \alpha + \beta \leq 1. \tag{13}$$

The weighting parameter α represents the proportion of geographical factors in the overall preference, and β represents the proportion of popularity influence in the overall preference.

4 Analysis of experimental results

All experiments were developed in Python and carried out on a PC with an Intel Core i5 CPU with 2.4 GHz and 8 GB RAM. In this section, we will conduct a series of experiments to evaluate our proposed methods and answer the three research questions.

RQ1 How does PRMF perform against the baseline models?

RQ2 How do the parameters in PRMF influence the recommendation results?

RQ3 Does the user preference model, the spatial distance model, and the popularity model contribute to the performance of PRMF?

4.1 Dataset

We used a Foursquare (Yang et al., 2014) dataset for evaluation, containing data from two megacities, New York and Tokyo. The dataset of New York contains 227,428 check-in records, and the dataset of Tokyo contains 573,703 check-in records (as shown in Table 2). Each check-in record has longitude and latitude coordinates, POI category, and other information. In order to ensure data quality, users who have checked in less than ten times and POIs have been checked less than ten times are filtered out. After preprocessing, the dataset of New York contains 134,827 check-in records of 1,083 users and 4,753 POIs, and the dataset of Tokyo contains 447,570 check-in records of 2,293 users and 7,873 POIs (as shown in Table 2). We evaluated different recommendation approaches using the five-fold cross-validation technique. In other words, the dataset was divided into five folds. For each time, one-fold was used for testing, and the other four for training. Then, we averaged the results of five folds and took them as the final one.

4.2 Evaluating metrics

Precision and recall of top-k recommendation were used to evaluate the POI recommendation performance, defined as equations (14) and (15). These are also the most common indicators in the field of recommendation systems. Precision refers to the ratio of the number of correctly recommended POIs to the total number of recommended

POIs. Recall refers to the ratio of the number of correctly recommended POIs to the total number of POIs the user has visited.

$$Precision@k = \frac{1}{m}\sum_{u=1}^{m}\frac{|top_u(k) \cap test_u|}{k} \tag{14}$$

$$Recall@k = \frac{1}{m}\sum_{u=1}^{m}\frac{|top_u(k) \cap test_u|}{|test_u|} \tag{15}$$

where $top_u(k)$ represents the top k POIs recommended to user u, and $test_u$ is the POIs actually visited by user u in the test set.

Table 2 Statistics on the datasets

City	*#check-ins*	*#users*	*#POIs*	*Sparsity*
New York (NYC) (before pre-processing)	227,428	1,083	38,333	99.45%
Tokyo (TKY) (before pre-processing)	573,703	2,293	61,858	99.60%
New York (NYC) (after pre-processing)	147,938	1,083	5,135	97.34%
Tokyo (TKY) (after pre-processing)	447,570	2,293	7,873	97.52%

4.3 Baselines

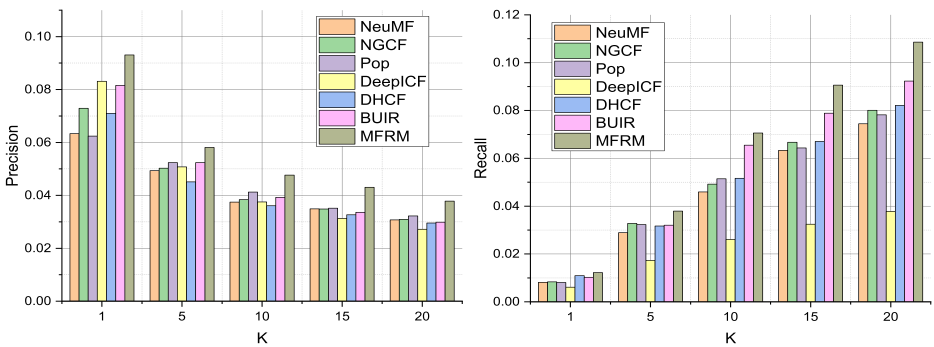
The proposed method combines geographical location, POI popularity, and user preference to improve the recommendation model of POIs. Therefore, the comparison methods selected in the study are as follows:

- NeuMF (He et al., 2017): Short for neural matrix factorisation, aims to solve personalised ranking tasks through implicit feedback. The model uses the flexibility and nonlinearity of a neural network to replace the dot product of matrix factorisation to enhance the model's expression ability.
- NGCF (Wang et al., 2019b): Acronymous for neural graph collaborative filtering, this method employs graph structure to express the interactive information of users and POIs, models the high-order connectivity of user and POI in graph network, and then aggregates and embeds for POI recommendation.
- Pop: This method utilises the popularity of POIs to make recommendations.
- DeepICF (Xue et al., 2019): The collaborative filtering method is based on a deep neural network. It learns the binary relationship and high-level relationship between POIs to recommend POIs at the same time.
- DHCF (Ji et al., 2020): DHCF is a new recommendation method based on hypergraph, which uses the hypergraph to model high-order correlation information.
- BUIR (Lee et al., 2021): BUIR only uses positive samples to guide model training and alleviates the problem of data sparsity through random data augmentation. This method is a predictive self-supervised learning model.

- PRMF: A multi-factor POI recommendation method is proposed in this paper.

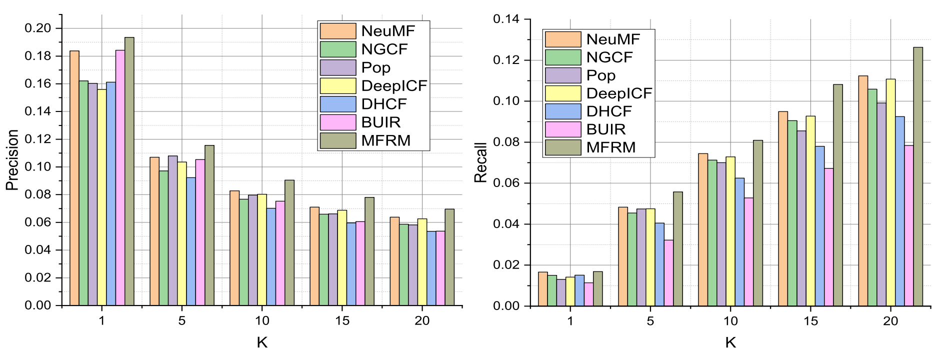
All baseline methods are implemented using the NeuRec framework (https://github.com/wubinzzu/NeuRec).

Figure 5 Performance comparison between the proposed method and the baselines (New York dataset), (a) precision (b) recall (see online version for colours)



(a) (b)

Figure 6 Performance comparison between the proposed method and the baselines (Tokyo dataset), (a) precision (b) recall (see online version for colours)



(a) (b)

4.4 Result analysis (RQ1)

This section presents the results of an analysis of the PRMF's performance, compared with the baseline methods. Figures 5 and 6 show a performance comparison of different methods using the Foursquare dataset on precision and recall metrics. Due to the low check-in of users, the POI recommendation method does not have a high level of precision. It was clear that all comparison methods performed better on the Tokyo dataset than the New York dataset because the number of check-in records in the Tokyo dataset was much larger than that in the New York dataset. The datasets are shown in Table 2. As can be seen from Figure 5, the PRMF method performed significantly better than the other comparison methods. Compared with the best comparison method (the BUIR method), the PRMF achieved a 14.12% improvement on Precision@1 and a 19.41% improvement on Recall@1. Similar results also appeared with the Tokyo dataset. As can be seen from Figure 6, the PRMF method also performed significantly better than other comparison methods. Compared with the best comparison method (the NeuMF method), the PRMF achieves a 5.28% improvement on Precision@1 and 1.57% improvement on Recall@1. With the New York dataset, DeepICF has the worst performance. DeepICF is an item-based collaborative filtering method used to solve the problem of the higher-order relationship between items. The data in the New York dataset were too sparse, which led to the poor performance of DeepICF. In the Tokyo dataset, the Pop model had the worst performance. This model counted the number of times that POI has been visited and recommended the most popular POIs, but it failed to capture the nonlinear relationship between users and POIs.

Figure 7 Impact of potential dimensions (see online version for colours)

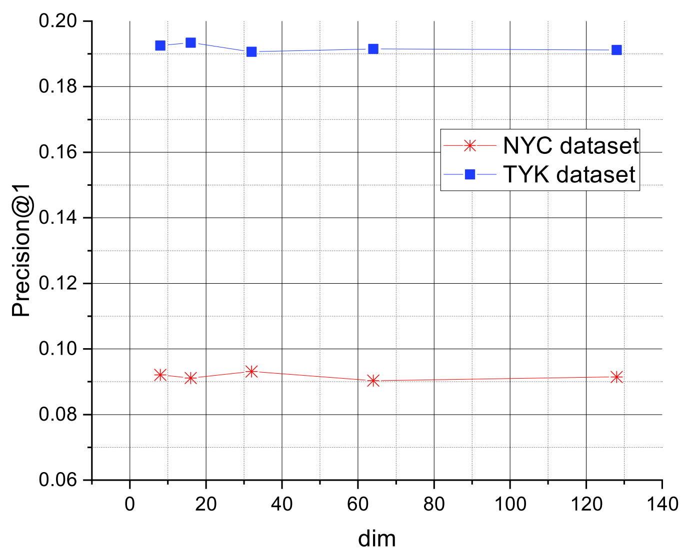


Figure 8 Impact of α and β on method precision, (a) New York dataset (b) Tokyo dataset (see online version for colours)

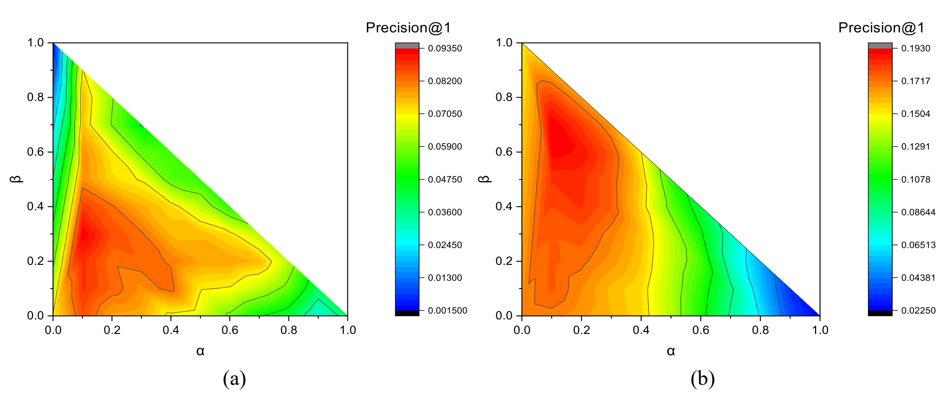
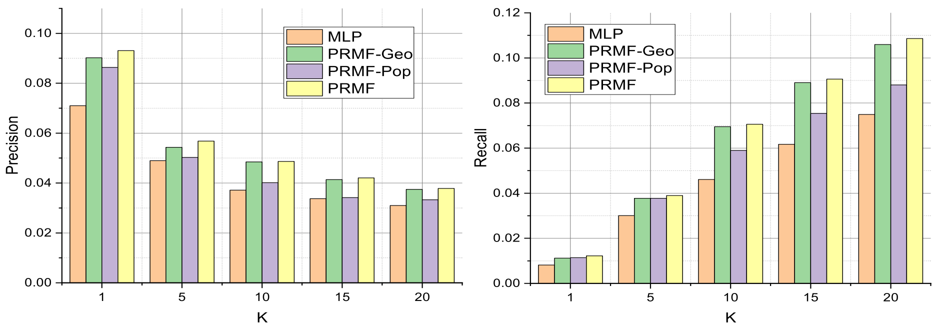
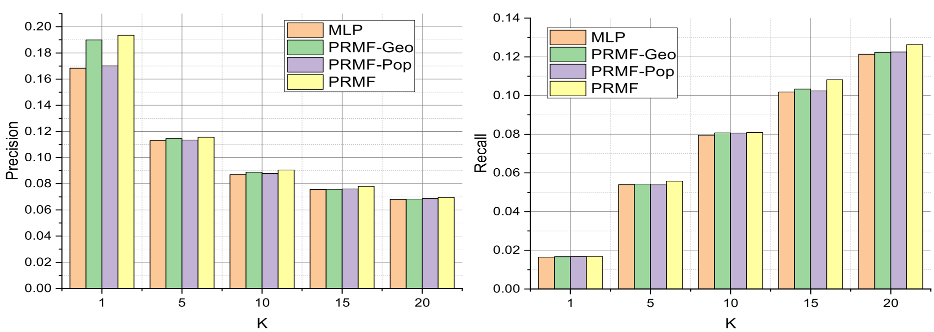


Figure 9 Ablation experimental results (New York dataset), (a) precision (b) recall (see online version for colours)



(a) (b)

Figure 10 Ablation experimental results (Tokyo dataset), (a) precision (b) recall (see online version for colours)



(a) (b)

4.5 *Experimental parameters (RQ2)*

4.5.1 *Impact of dimensions*

Figure 7 shows the impact of vector potential dimensions on the PRMF model. The influence of the potential dimensions on the experimental results was not apparent. As can be seen, once precision reached the highest value, and it gradually decreased with an increase in the value of dim. More specifically, this meant that more relevant shared information could be extracted. It also makes sense that having too few potential features (for example, $d = 10$) will limit the model's ability to extract relevant information, thus leading to poor performance. However, an excessive number of potential features will lead to overfitting, which reduces the performance of the model. The optimal value of dim obtained from different datasets was different, which may be caused by the sparsity of data. When the data are sparse, fewer potential features need to be outlined, so the length of dim will be shorter. In the case of the New York dataset, when the potential dimension of the vector was 32, the model performed slightly better than other vector dimensions; in the case of the Tokyo dataset, when the potential dimension of the vector was 16, the model performed slightly better than other vector dimensions.

4.5.2 Impact of α and β

There were two other important parameters, namely α and β, representing the relative importance of geographical and popularity influences for POI recommendation. Here, we set α and β from 0 to 1 to observe the role of geographical influence and popularity influence. Figure 8 shows the $precision@1$ results for the two datasets under different α and β values. As can be seen from Figure 8, geographical location and popularity played the leading roles in driving optimal performance. Specifically, the New York dataset's best settings were α = 0.1, β = 0.3. With the Tokyo dataset, the best settings were α = 0.1, β = 0.6. All the experiments indicate that both geographical location and popularity play a positive role in the final results of the POI recommendation.

4.6 Ablation study (RQ3)

An ablation study is conducted to understand the effect of a component on the whole recommendation system by studying the performance of the recommendation system after removing a component. In the case of the PRMF, three components were of interest. In order to study the importance of user preference, spatial distance, and the popularity of POIs, these three factors were removed in PRMF as follows:

- MLP: The user preference model proposed in the study was used to recommend POIs.
- PRMF-Geo: The multi-factor fusion method proposed in this paper was used for POI recommendation, but geographic information was ignored.
- PRMF-Pop: The multi-factor fusion method proposed in this paper was used for POI recommendation, but the popularity was ignored.
- PRMF: The multi-factor POI recommendation method proposed in this paper.

Figures 9 and 10 show the comparison results for various indicators of the PRMF model after removing the spatial distance module and popularity module. The comparison results showed that after introducing the spatial distance module and popularity module, the recommendation results increased by varying degrees, indicating the effectiveness of the model proposed in this paper. The PRMF-Geo model performed better than the PRMF-Pop model, indicating that the popularity model was better than the spatial distance module in terms of improving the recommendation results. The performance of the PRMF model with the Tokyo dataset was more accurate than that with the New York dataset. The result may be due to the Tokyo dataset was larger than the New York dataset, and the number of POIs in the New York dataset was small and sparse. After introducing the spatial distance module, the performance only increased slightly, possibly due to the potential distance information contained in the vector of POIs. The introduction of the spatial distance module only enlarged the distance relationship, so the improvement was slight.

5 Conclusions

In this paper, we have presented a POI recommendation method, called PRMF, which uses different factors, such as check-in records, POI category, geographic/spatial distance and POI popularity, to make POI recommendations. Experiments conducted on two public datasets showed that the proposed method is superior to other comparison methods in precision and recall. However, current AI technology does not have the capability to make completely accurate POI recommendations, and more research work is needed. In short, this method still has some directions worth exploring so that improvements can be made. In the future, more neural network methods and attention mechanism algorithms will be integrated into our user preference model to improve the recommendation effect. Attempts will also be made to use comment information for sentiment analysis. Moreover, we will explore the possibility of using a multitasking model in POI recommendations.

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