POI Recommendation System using Hypergraph Embedding and Logical Matrix Factorization

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Abstract

Aiming at the problems of inaccurate recommendation and single consideration in the traditional Points of Interest (POI) recommendation model, a POI Recommendation System using Hypergraph Embedding and Logical Matrix Factorization (HE-LMF) has been proposed. The user's check-in points of interest and time information are sampled by hypergraph embedding technology, and users with similar points of interest to the target user are found, and their points of interest are recommended to the target user. At the same time, through the geographic recommendation model based on logical matrix decomposition, the regions with many user check-in times and the correlation of each region are considered. The results of the two models are weighted, and top-k is selected to recommend to the user. Finally, experiments are carried out on the two datasets of gowalla and foursquare, and compared with the three models USG, PFMMGM and LRT. The experimental results show that the HE-LMF algorithm can effectively improve the accuracy and recall rate of POI recommendation.

Keywords: POI recommendation, hypergraph embedding technology, logical matrix decomposition, friend similarity, time factor, local geographic location

1. Introduction

More recently, Location-Based Social Network (LBSN)[1-5] has developed fleetly. Users can check in and comment on points of interest through smart devices such as mobile phones and computers to share their experience and help other users find locations and places of interest. The POI recommendation [6-8] service cannot only provide users with attractive

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places to benefit them, but also promote relevant enterprises to put targeted advertisements, which can significantly improve their corporate benefits.

Some researchers have proposed POI recommendation algorithm based on the Graph embedding (GE) model [9-11], which can embed massive information into a low-dimensional vector space and ensure that each node can be represented by low-dimensional feature vectors. In addition, since the users in social networks have similar check-in behaviors and common interests, the introduction of user similarity model into the recommendation system can effectively solve the problems of data sparsity. A simple user’s check-in operation is not only affected by the interest of the check-in person, but also by geographical factors. Since things are connected to a certain degree, the two closer together are more relevant. Therefore, the user's decision-making behavior is often restricted by the geographic location of the POI. Users are more inclined to choose to visit POI that is closer. Yang et al. [12] proposed a random walk scheme and combined sampled user check-in and social relations, which recommended points of interest by the similarity of hyper-edges. Ye et al. [13] employed power law distribution to model geographic influence. Afterwards, behaviors of similar users are calculated based on social relationships, meanwhile, the geographic and social influences are incorporated into the collaborative filtering algorithm for recommendation.

However, the traditional graph embedding technology has some shortcomings, such as low information density, inability to fully grasp the overly complex structure, easy to cause loss of information, and inaccurate recommendation results due to the sparseness of the data. Moreover, traditional location recommendation algorithms rarely consider combining the relevance of the user's visit location with the similarity of users. Hence, it is impossible to explore the relationship between the user's own interests and location. To handle the above problems, a point-of-interest recommendation model (HE-LMF) based on hypergraph embedding and logical matrix factorization is proposed in this paper. The proposed model comprehensively considers the information of users, POI, time and geographic location information, accordingly, the problem of inaccurate recommendation caused by sparse data and single consideration is solved, and personalized recommendation POI is realized.

2. Related Work

In LBSN, there are many kinds of interest points, but the user sign-in data is scarce, which leads to data sparseness. User similarity is to calculate the similarity between POIs visited by users through their historical check-in information, which can solve the problem of sparse data. In addition, researchers pay more and more attention to graph embedding technology [14] in LBSN, which embeds large-scale high-dimensional network information into low latitude space while keeping the original structure information of the network. Its main function is to ensure that each node can be represented by a low-dimensional feature vector.

The accuracy and recall of recommendations are improved by combining it with a friend-based similarity algorithm. Typical graph embedding techniques include DeepWalk [15], Graph Factorization [16] and LINE [17] etc. Users will generate a large amount of check-in information in LBSNs, and most POI recommendations mainly use the user's daily check-in data information and combine with various context information content.

The common type of context information [18] content is location information. Research [19] based on location information found that when people choose points of interest, they often choose points of interest that are closer to their own location.

Zeng et al.[20] clustered locations into different regions by using collaborative filtering based on regions and mobile context based on users. The traditional collaborative filtering is enhanced by using regional factors so as to capture users' preference for mobile context, and finally top-k locations are recommended to users.

The traditional recommendation algorithm just considers one or two factors to recommend POI, and cannot solve the problem of data sparseness. To solve this problem, hypergraph embedding technology is adopted to embed high-dimensional check-in information into low-dimensional information.

The similarity of points of interest between users is calculated through cosine similarity. Moreover the geographic location recommendation based on logical matrix decomposition is integrated, which considers the places where users check in frequently, that is, the user’s main activity area and the correlation of each location.

The proposed method can recommend points of interest individually. The model proposed in this paper integrates user check-in information, geographic location information and time information to improve the traditional model and the accuracy of recommendation.

3. HE-LMF Recommended Model

3.1 The impact of user similarity and time factors on POI recommendation

By analyzing the historical data of the interest preference of the target user to find other users who have the same or similar interests, subsequently, POIs that have not been searched before but may generate interest are recommended. That is, whether there is the same or similar behavior hobby depends on whether both users have visited (checked in) certain projects. If both parties have checked in for certain projects, the two users are likely to be interested in the projects visited by the other, which proves that they are likely to have similar hobbies.

In addition to the similarity of friends, POI recommendation is also largely subject to time factors. For example, users like to go to the breakfast shop in the morning, the store at noon and the night market at night. The user's behavior is closely related to time. LBSN's research shows that users have certain regularities in their daily check-in activities, that is, users have certain regularities on rest days and working days. According to the POI visited by the user in a time domain, users who are similar to their POI can be more accurately recommended for the next possible interest point visited by users. As shown in Fig. 1, two users visit some points of interest at certain times, which means that the two users have similar hobbies.

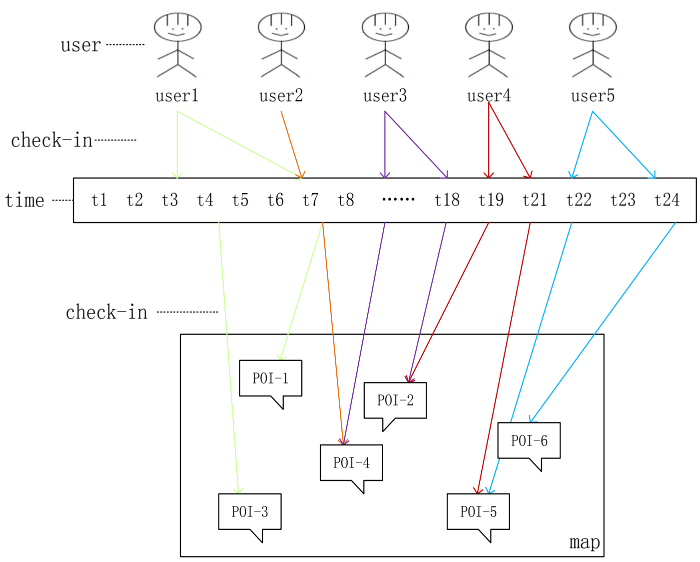

Figure 1. User-time check-in diagram

As shown in Figure 1, a user checks in a POI at a certain time, and then forms a user's historical check-in data set, and then calculates the similarity between two users.

3.2 User similarity point of interest recommendation based on hypergraph embedding

In traditional collaborative filtering algorithms based on social networks, the accuracy of data recommendation is low since there are fewer categories of similar relationships between users (only 0 and 1 can be used to represent), and traditional algorithms often have data missing and the new process. In this paper, the hypergraph embedding technology is used to transform the high-dimensional sparse check-in matrix into a low-dimensional matrix to maximize the retention of the original check-in information. The POI recommendation algorithm based on hypergraph embedding takes the point of interest category and time as the vertices of the hypergraph, and takes the similar relationship between the user and the point of interest and the time domain as the hyper-edge. The hyper-edge similarity is calculated by randomly walking on the vertices (users). The users who are similar to their interest points are found and recommended.

The LBSN hypergraph embedding technology adopted in this paper contains three vertices: social domain (user), semantic domain (POI) and time domain (hourly); and two kinds of edges: classic edges connecting user node pairs and user vertices connecting POI and the super side of time. In order to extract super edges, a random walk scheme is used to extract user vertices and check in super edges. As shown in Fig. 2, the model performs a classic random walk on user nodes, and a group of super edges are extracted when passing each user node.

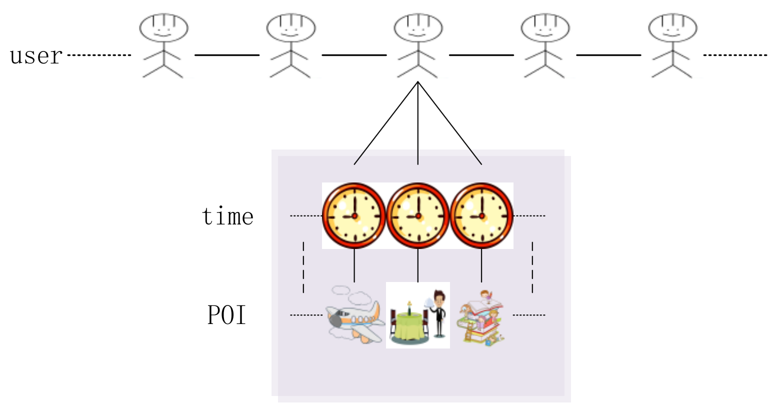

Figure 2. User-based random walk in hypergraph

Specifically, in the process of node embedding learning, the POI of the surrounding user nodes and the corresponding time of visiting the POI are sampled when a user is traversed every time, and then POI recommendation is made by calculating the similarity of POI between users.

3.3 Similarity Calculation

The specific numerical value of the similarity of the users indicates the magnitude of the similarity of the two users. The commonly used similarity calculation method affects the prediction accuracy and the quality of the recommendation. For example, there are three user nodes A, B, and C. If you want to recommend a node with higher similarity to user node A, you can check the relationship between the super edge of user node B and C and the super edge of user node A.

If the super edge where user node B is located is exactly the same as the super edge where user node A is located, and only part of the super edge of user node C is the same as user node A. It is obvious that user node B has a higher value than user nodes C and A. Hence, it will choose to recommend interest points of user node B to user node A. In the process of obtaining user similarity values, Euclidean similarity, Pearson correlation coefficient, and cosine similarity are usually used to calculate the user similarity value.

(1) Euclidean metric

The meaning of Euclidean metric is to calculate the distance between two points in a multi-dimensional space, which is also called the natural degree. The specific calculation is as follows

$$\mathrm{H}(u,v) = d(u,v) = \sqrt{\sum_{i=1}^{n}(u_i - v_i)^2} \tag{1}$$

where u and v are two users.

(2) Pearson Correlation Coefficient (PCC)

The Pearson correlation coefficient is used to measure the degree of similarity between two variables, as follows

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$$H(u,v)=\frac{\sum_{i=1}^{n}(u_i-\bar{u})(v_i-\bar{v})}{\sqrt{\sum_{i=1}^{n}(u_i-\bar{u})^2}\sqrt{\sum_{i=1}^{n}(v_i-\bar{v})^2}} \tag{2}$$

According to formula (2), the value range of Pearson's similarity is [-1,1]. When the value is [-1,0), the two user preferences are negatively correlated; when the value is (0,1], the two user preferences are positively correlated. The degree of correlation depends on its absolute value.

(3) Cosine Similarity (COS)

Cosine similarity evaluates the similarity of two vectors by calculating the cosine value of the angle between two vectors. As shown below

$$H(u,v)=\frac{\vec{u}\cdot\vec{v}}{\|u\|\times\|v\|} \tag{3}$$

where and represents the user's check-in vector, and represents the modulus of the user's label vector.

Although the above three algorithms are widely used in research, two users in the PCC algorithm will have the same score. Even if the similarity between the two is calculated to be 1, it may be far from the actual situation.

When using the Euclidean metric algorithm, if the evaluation is quite different from the average, it will not be able to better show a more real situation between the two users. Therefore, the cosine similarity is applied to calculate the similarity of the user's POI in this paper. Finally, the embedding vectors of user, POI and time calculated by the hypergraph embedding model are used to calculate the sum of cosine similarity between user-POI and POI-time.

3.4 Location recommendation based on logical matrix factorization

Since the user's behavior is closely related to his geographic location, users are susceptible to geographic factors, hence, geographic factors are considered in this paper. When a user chooses services related to him, he usually takes distance as a filter, and sometimes he even sacrifices his own preferences to choose a closer point of interest.

The user's personal preferences and geographic location information are firstly captured, and then the geographical model is incorporated into the logical matrix decomposition method to improve the accuracy of POI recommendations by taking into account the areas where the user has checked in frequently and the relevance of each location. Specifically, the area where the user has checked in the most times is regarded as the most interesting place for the user. The less POI check-ins around the POI, the less relevant the POI, thus the most interesting point of interest is worth recommending.

Let U={u_1,u_2,u_3,…,u_m} denotes the set of users and P={p_1,p_2,p_3,…,p_n} denotes the set of POIs. Given a set of points of interest P={p_1,p_2,p_3,…,p_n}, the priority of each p_i (p_i∈P) relative to its neighbor check-in is:

$$M_i^u = 1 - \frac{L_p^u}{|P^u|} \tag{4}$$

where represents the number of neighbors of p_i visited by user u. |P^u | is the set of POIs that user u has visited.

The preference of user u on POI p is:

$$P(x_u, y_p, \beta_u, \beta_p) = \frac{\exp(x_u y_p^{\mathrm{T}} + \beta_u + \beta_p)}{1 + \exp(x_u y_p^{\mathrm{T}} + \beta_u + \beta_p)} \tag{5}$$

The parameters x_u and β_u are the potential factors and deviations of the user, and y_p and β_p are the potential factors and deviations of the POI. The parameters x, y, and β can be optimized by formula (6):

$$\begin{aligned} &\arg\max_{x,y,\beta} (\sum_{u,p} \alpha c_{u,p} (x_u y_p^{\mathrm{T}} + \beta_u + \beta_p) - (1 + \alpha c_{u,p}) \\ &\log(1 + \exp(x_u y_p^{\mathrm{T}} + \beta_u + \beta_p)) - \frac{\lambda}{2} \| x_u \|^2 - \frac{\lambda}{2} \| y_p \|^2 \end{aligned} \tag{6}$$

where C∈R^(m×n) is the check-in frequency matrix of users (m)-POI (n), and c_up∈C is the check-in frequency of user u at POI p. The formula (5) is integrated into the logical matrix decomposition method (4), and the probability that the user u accesses the POI p is as follows:

$$L_{up} = P(x_u, y_p, \beta_u, \beta_p) \times M_i^u \tag{7}$$

Taking the first Li POI values, the model not only takes into account the location factor of the POI, but also considers the contextual information factor of the POI.

3.5 HE-LMF recommended model

To accurately recommend POI to users, four correlations are taken into account simultaneously: (1) the similarity between users; (2) the correlation between users and POI; (3) the correlation between time and POI; (4) the correlation between location information and POI. The whole framework consists of three parts: friend similarity point of interest recommendation based on hypergraph embedding, location recommendation model based on logical matrix factorization, and integration model. Fig. 3 shows the HE-LMF recommendation model designed in this paper.

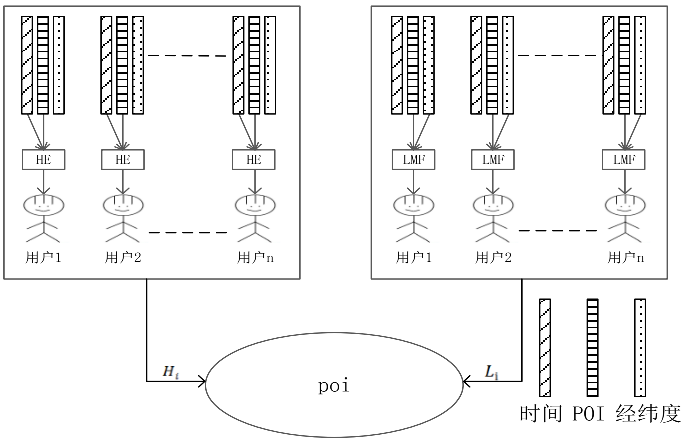


Figure 3. HE-LMF recommended model

In Figure 3, H_i is the first i POI calculated in the graph embedding technology, while L_i is the first i POI calculated by the logical matrix decomposition model. Taking i=100, the interest points of top-k is calculated to recommend to users by multiplying two weights. The calculation formula is as follows:

$$POI_k = \alpha H_i + (1 - \alpha)L_i \tag{8}$$

Here α dynamically adjusts the weight between user similarity and friend trust.

In summary, the proposed point-of-interest recommendation (HE-LMF) model based on hypergraph embedding and logical matrix factorization effectively integrates friend similarity, time and geographic influence, which can output the user's personalized prediction preferences for all POIs. Top-k candidate POIs can be recommended for users by sorting the predicted preference values.

4. Experiment and analysis

4.1 Experimental data set

The check-in data sets on gowalla1 from February 2009 to October 2010 and on foursquare2 from April 2012 to September 2013 are collected. To avoid the problem of missing data, the data of user check-in times and POI visits times less than 10 times are deleted, and the check-in time stamp is transformed into a time domain with 168 hours a week as a periodic change. In the experiment, 80%, 20% of all data sets are selected as the training set and test set respectively. The relevant information of the data is shown in Table 1.

Table 1. Relevant information of the experimental data set

Datasets	User	Check-in	POI	User-POI Matrix Density
gowalla	4465	353293	10001	99.21%
foursquare	5028	252874	11998	99.58%

4.2 Evaluation Index

Precision and Recall are used to evaluate the effect of POI recommendation. The larger the value is, the better the recommendation performance gets. The evaluation indicators are shown below:

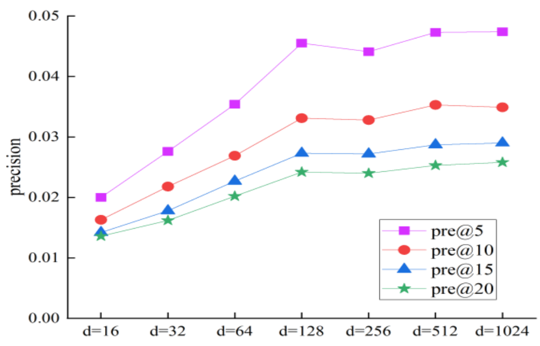
$$precision@k = \frac{|test \cap top_k|}{|top_k|} \tag{9}$$

$$recall@k = \frac{|test \cap top_k|}{|test|} \tag{10}$$

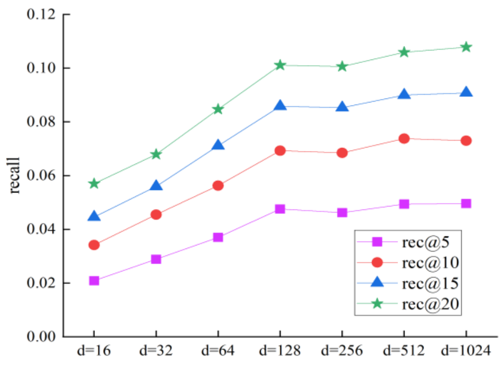
where topk are the POI of the calculated recommendation list, and test is the item list of the users in the verification set. |test| is the scale of the verification set, and |test∩〖top〗_k | is the set of the same items in the verification set and the recommendation list.

4.3 The influence of hypergraph embedding dimension d on experimental results

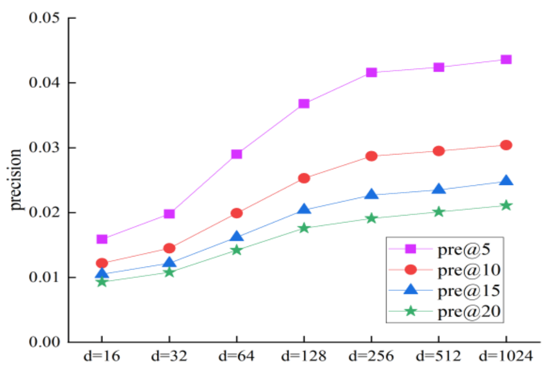
The influence of different dimension d on precision and recall performance is compared, as shown in Fig. 4. Use different pre@k and re@k(k=5,10,15,20) to infer the performance, the higher the value, the better the performance. Figure 4 shows that the precision and recall increase with the increase of d on gowalla and foursquare data sets. The precision and recall vary little after d=128, while the larger the dimension d is, the longer the program runs, so d=128.



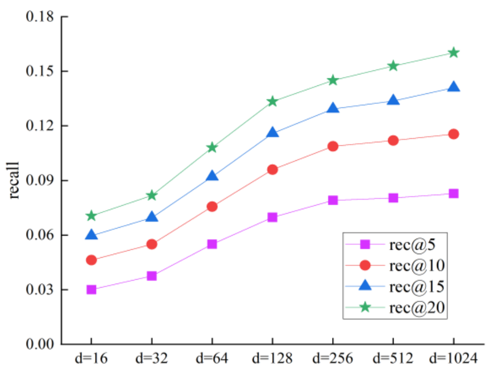
(a) gowalla-precision



(b) gowalla-recall



(c) foursquare-precision



(d) foursquare-recall

Figure 4. The influence of different dimensions d on precision and recall

4.4 Analysis of the influence of different factors in HE-LMF

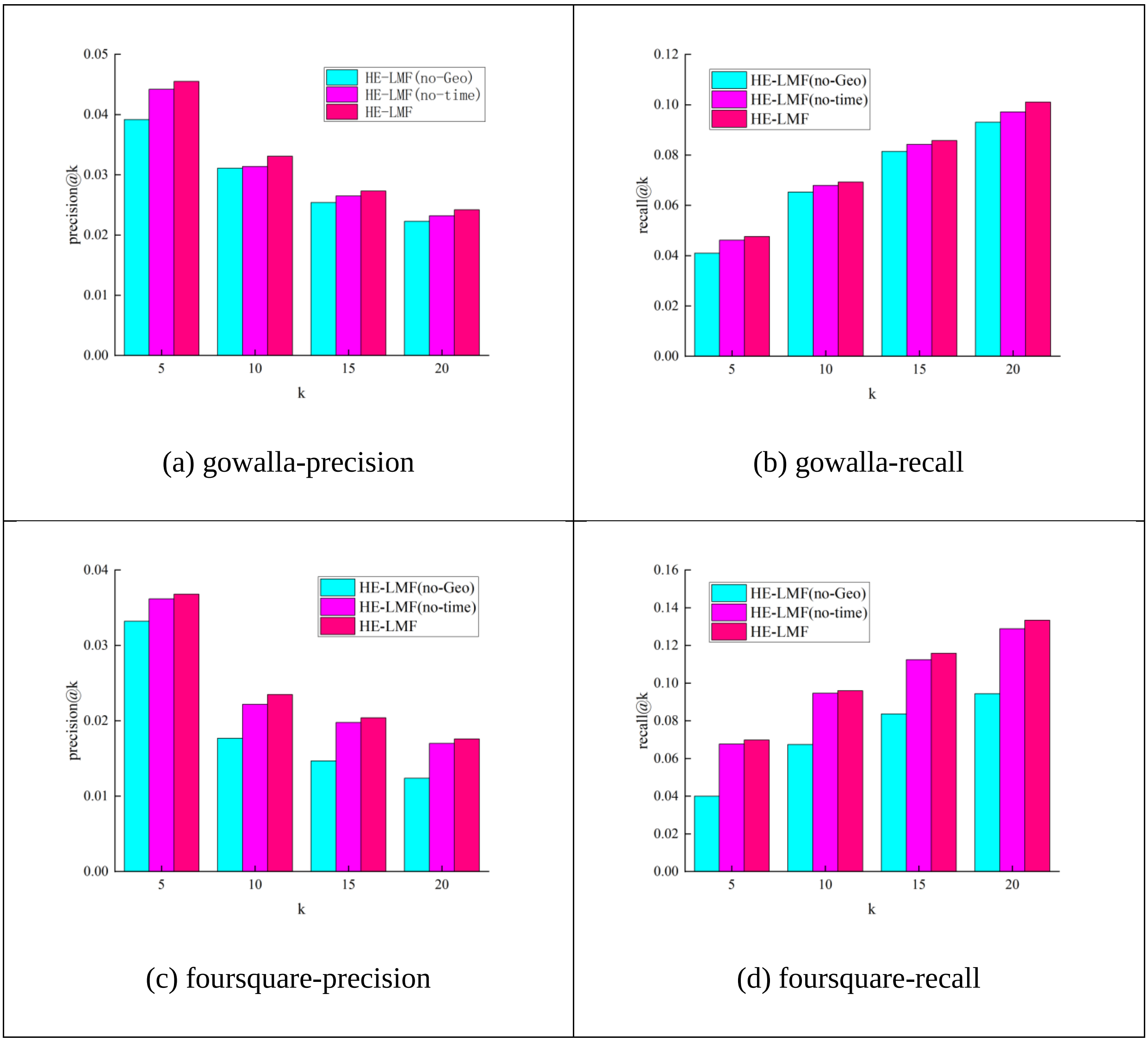
In order to analyze the influence of friend similarity and geographic factors in the HE-LMF model, two comparison models were constructed by deleting the corresponding components of the HE-LMF model. The three models tested in the experiment are as follows:

(1) HE-LMF (Lack of Geo): Geographical influence is not considered.

(2) HE-LMF (Lack of time): Time influence is not considered.

(3) HE-LMF: The proposed complete recommendation model, which includes the influence of friend similarity, time and geographic factors.

The recommendation effects of the HE-LMF model and the contract model are compared on the gowalla and foursquare data sets, the results are shown in Fig. 5.



(a) gowalla-precision

(b) gowalla-recall

(c) foursquare-precision

(d) foursquare-recall

Figure 5. Performance comparison of different factors in HE-LMF

Experimental results show that points of interest cannot be recommended for users more accurately when geographical factors or time factors are not taken into account. User's visit points of interest are affected by many factors. The proposed method considers friend similarity, time factors, and geographic factors simultaneously. The results show that HE-LMF with many factors has better recommendation effect.

4.5 Performance comparison with other methods

In order to verify the accuracy of the HE-LMF model proposed in this paper, the value of d is set to 128, and USG, PFMMGM, and LRT are selected for performance comparison. The points of interest recommended by each model are selected as top-k (k=5, 10, 15, 20) to compare the precision rate and recall rate.

USG [13]: The method is a collaborative filtering algorithm based on Bayesian geographic influence, which integrates geographic and social influence into the collaborative filtering algorithm for recommendation.

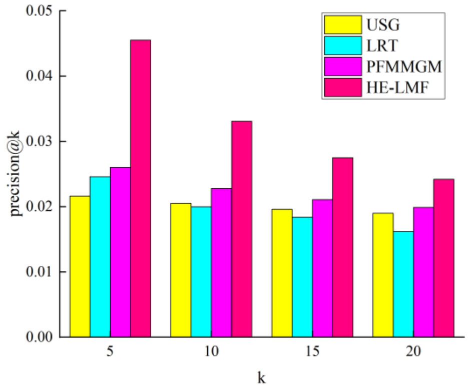
LRT [3]: The method studies the time characteristics of users' check-in behavior on location-based social networks, and uses them to generate a time-effect location recommendation framework.

PFMMGM [21]: The method integrates geographic and social influences. User’s check-in frequency is firstly modeled as a multi-center Gaussian model to obtain geographic influences, and then social information and geographic influences are integrated into the matrix factorization framework.

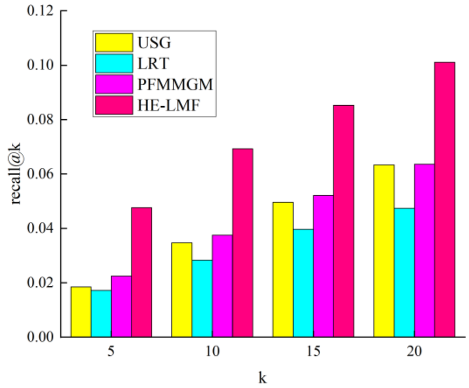
HE-LMF: The point-of-interest recommendation model proposed in this paper combines friend similarity point-of-interest recommendation based on hypergraph embedding and location recommendation based on logical matrix factorization to personally recommend points of interest.

Experiments show that the performance of HE-LMF is superior to the other three comparison algorithms on both data sets. Among them, both LRT and HE-LMF are location-based point-of-interest recommendation algorithms about time. The HE-LMF proposed in this paper takes into account the user’s main activity area and the location relevance of each area in the area, so it has better performance.

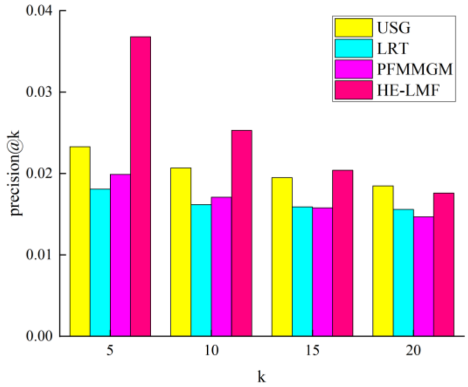
The comparison results are shown in Fig. 6.



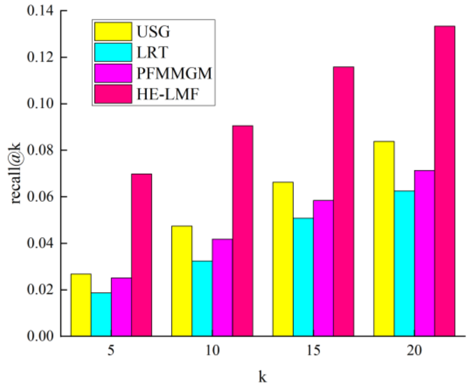
(a) gowalla-precision



(b) gowalla-recall



(c) foursquare-precision



(d) foursquare-recall

Figure 6. Performance comparison of comparison algorithms

It can be seen that the location recommendation by adding logic matrix plays a positive role in improving the accuracy rate and recall rate of the recommendation. While FMMGM, USG, and HE-LMF are all recommendation models based on geographic factors, and they all contain social information, however, PFMMGM and USG do not consider the influence of time factors on the recommendation of POI. A person's check-in behavior is closely related to time, which shows that adding the time factor plays an important role in the accuracy and recall of the model.

The effectiveness of the proposed HE-LMF recommendation algorithm is verified through experiments on gowalla and foursquare datasets, and the advantages of HE-LMF in personalized POI recommendation tasks are demonstrated.

5. Conclusion

In this paper, HE-LMF point of interest recommendation model is proposed, which adopts hypergraph technology to calculate the similarity of user points of interest based on its historical check-in information, and calculates the correlation of location information through a logical matrix factorization model. Finally, the two models are combined, which comprehensively considers the factors such as friend similarity, time, and geographical location, and conducts experiments on the most representative data sets gowalla and foursquare. The experimental results show that the accuracy and recall rate of the HE-LMF recommendation model outdo USG, LRT and FMFMGM. The future work will add friend trust factors to the recommendation model to improve the diversity of points of interest recommendation.

Acknowledgments

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