Personalized Recommendation Method of POI Based on Deep Neural Network

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***Abstract*—With the rapid development of Location-based social networks (LBSN), there is a growing demand for location services. How to use the users' historical check-in data for exploring their visit patterns and preference characteristics to realize personalized point-of-interest (POI) recommendation has become an important topic. Finding valid features from the check-in data is the key to POI recommendation. Deep learning is a multi-level representation learning method, which can better explore the relationship between features. Therefore, a new POI recommendation model named DLM based on deep neural network is proposed in this paper. This model incorporates topic features, user preference features and geographical factor features in the LBSN into the POI recommendation tasks, thereby it improves the efficiency of users' personalized POI recommendation. A lot of experiments on public data set Foursquare have proved the advantages and effectiveness of the proposed method.**

Keywords*—*POI recommendation, LBSN, Deep Learning

I. INTRODUCTION

With the wide application of mobile devices, the location-based network services constitute a new type of social network, which meets the needs of people's service application about location. Yelp, Foursquare, and Gowalla, for example, have attracted millions of users who explore their surroundings and share their life experiences by means of "check-in". These historical data contain abundant information of users and POI, providing new opportunities for exploring users' location-based visit preferences. Based on the high-value information set of location-based services, the research on data discovery and implementation of personalized POI recommendation have become a research focus[1].

In the traditional POI recommendation problems, recommendations are usually made according to the relationship between users, the location information, and users' check-in records [2]–[4]. However, in the practical applications, users have personalized differences in the preferences of the POI categories. For example, User U loves shopping and often visits shopping malls, while User V is a food lover with no interest in shopping. Then U is significantly fonder of shopping centers than V. That is, gourmets may be more interested in food, while shopaholics are more concerned with shopping centers. Most of the existing methods adapt conventional memory or model-based collaborative filtering for POI recommendation with little consideration of the theme of POIs and the relationships between themes [5]–[7]. In addition, in the application of the LBSN, since each individual user accesses only a small portion of the POIs, which makes the check-ins very sparse. The check-in data density of users is usually around 0.1% [8], and the sparsity of the user-POI matrix reduces the quality of the recommendation results [4],[9]. Therefore, how to combine more effective features from limited users and location information in the combination of theme factors of the POI, alleviate the data sparsity problem in the POI recommendation and select an appropriate model to implement differentiated user preference modeling is the key to successfully achieve personalized POI recommendation.

Finding effective features from check-in data is the key to improve the quality of POI recommendation. Traditional methods based on collaborative filtering and matrix factorization (MF) only learn linear or low-order interactions between features rather than the rich information contained in the features [10]. In recent years, deep neural network (DNN) has achieved great success as it can self-adaptively learn the high-order features and their interactions from the input of particular tasks[11]. Therefore, this paper presents a DNN recommendation framework for fusion of DNN network[12] ,Latent Dirichlet Allocation (LDA) theme model and MF algorithm, which is named DLM. The user preference characteristics, geographical factor features, and probabilistic theme features in LBSN are incorporated into the POI recommendation task and then recommended to the user. The experimental results on the real data set Foursquare show that DLM can realize effective feature fusion, alleviate the problem of data sparsity, and better realize the personalized recommendation of users.

To sum up, the main contributions of this paper are as follows:

1) This paper defines a new probabilistic topic model for modeling of topic information about user preference and obtaining of topic vector representation of POI. In addition, we introduce the feature embedding method of MF to model the relationship between users and POIs. More specifically, user's visit matrix to POI in LBSN is exploited to converted into a potential vector representation of user and POI through the MF, which is used to represent user preference features.

2) This paper proposes a DNN-based personalized POI recommendation model named DLM. The algorithm combines the topic features, user preference features, geographical factor features in LBSN to alleviate the problem of data sparsity. A DNN is used to learn the

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feature interaction among the users and POIs, so as to achieve effective recommendation of the user interest points.

3) The DLM recommendation model proposed in this paper is evaluated on public data set, and compared with the existing POI recommendation methods. The effectiveness of the proposed method is verified by experiments.

II. RELATE WORK

In POI recommendation studies, most of the existing methods are based on Collaborative Filtering (CF) and by use of exploring users' features and the similarity of them to realize the recommendation. Ma et al. used the CF method to find out the neighboring users with similar interests to predict the user's score on the check-in places, and recommended those places with higher scores to the users [2]; Quan et al. defined the popularity of POI in different periods in combination with temporal information based on the collaborative filtering, and recommended it to users by use of the popularity of POI in different time periods, thereby improving the effectiveness of the recommendation [13]; Zheng et al. realized the recommendation after the research of coordination relationship between users and locations and the calculation of similarity among users according to their historical information of locations [3]. The above methods adopted the collaborative filtering learning and the similarity among users to realize recommendation according to the historical information of the same object visited by different users, but they didn't fully consider that there was also item-based collaborative filtering of the similarity among the visited objects. Yin et al. proposed to model the cooperative similarity among the visited objects based on the Latent Dirichlet distribution model (LDA) which combines the personal interests and location preferences to realize recommendations, and the research has shown that the thematic features of the visited locations contributed to improve recommendation results[14]. Li suggested that how to extract more effective features from limited information of users and locations has always been a challenging issue for POI recommendation. They designed and implemented a ranking-based geographical factorization method called Rank-GeoFM, where POIs both with and without check-ins participate in modeling learning of the ordering of recommended locations [4]. The above-mentioned methods try to adopt the context information related to variety of user-POI related context so as to construct a similarity CF model to realize the POI recommendation, and certain effects have been obtained. However, the influential factors of users' destination selection in the collaborative similarity relationship among recommendation objects were not being properly considered. So there are still challenges for the personalized POI recommendation of users as follows: Firstly, how can we design effective feature engineering to realize the personalized POI recommendation of users and form content feature sets by extracting more effective features on the basis of limited information of users and locations to alleviate the data sparsity in POI recommendation? Secondly, how can we fuse related content features of the user-POI, select appropriate learning model, extract key factors that can differentiate user preference, and realize accurate personalized POI recommendation?

In recent years, deep learning has made progress in many research fields. It has shown great potential in feature selection and high-level semantic feature learning in the problems of feature engineering construction on unstructured data sets such as computer vision and natural language processing, etc.[15]–[17]. Some scholars began to use deep learning techniques to solve POI recommendation problems. Zhao et al.[18] and Wang et al.[19] modeled the context sequence by using Long Short-Term Memory, and predicted the next check-in according to the users' information of spatiotemporal sequence. RNN was used to model according to the users' check-in sequences by Zhao et al.[20] and Xia et al.[21] to achieve POI recommendation. However, most of these methods based on deep learning were designed for particular applications which mainly focus on temporal and sequential context. In addition, Covington et al.[22] used the DNN model for YouTube video recommendations; Cheng et al.[23] used the DNN model for mobile application recommendations, and He et al.[24] proposed a generic framework combining DNN and MF for item recommendation in order to obtain more accurate recommendation results. The aforementioned researches show that the DNN network has the capability of learning advanced characteristics and interactions from the unstructured data and improving the effectiveness of POI recommendation.

Combined with the learning ability of DNN, this paper proposes a POI recommendation method which uses the DNN to solve the challenging problems. Firstly, in the stage of feature construction, the method considers the influential factors of the coordinative relationship existing among recommended objects on users' destination selection, designs probability topic model, obtains the theme information of POI, and models the topic features. Then the feature embedding method based on MF is used to extract users' preference features, and the geographical location information is taken as the geographic factor features. Secondly, the features extracted in the previous stage are learned as input vectors of the DNN neural network to improve the efficiency of users' personalized POI recommendation.

III. METHOD

A. DLM Model

The overall frame of the proposed model DLM based on DNN is shown in Figure 1. The model is divided into feature extraction module and network learning module.

The feature extraction module implements the construction of effective features for POI recommendation. We define a new LDA-based topic model to retrieve the topic vector of each POI, and the potential eigenvector of user preference is obtained by MF according to the visit matrix of user-POI. Also, the latitude and longitude of the POI are taken as the geographic factor features.

The network learning module is composed of network connection layer and network layer. The network connection layer fully connects the POI topic features, user preference features and geographic factor features and feed them into DNN network. The connection layer ensures the scalability of the entire model. Other relevant context information needed in the application can be connected automatically through the full connection layer and features of input layer can be sent to the network training.

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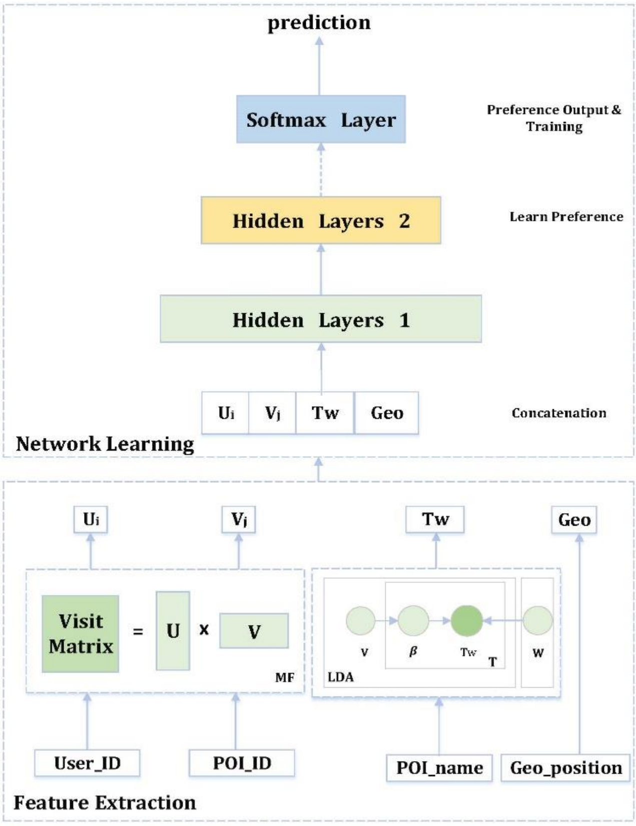

Fig. 1. The framework of the DLM model

The network layer of the network learning module includes two parts: training and prediction. In the training stage, DNN network is used to extract implicit features. The output of the hidden layer is used as the input of the softmax layer to learn the classification task. The POI recommendation task is transformed into a two-category classification task, in which the user's check-in record is defined as a positive sample. The output of the softmax layer is a probability vector with two elements, one is the visit probability of the user to the POI while another is the non-visit probability. The cross entropy loss function is constructed according to the network output result and the positive and negative samples. In the prediction stage, the network will output a probability vector after the information from the user and POI are analyzed. Then the top-k ranking will be recommending to the user according to the output probability.

B. *Feature Engineering*

a) *Topic Feature*

There are personalized difference of users in POI category preferences. In this paper, we define a new LDA-based thematic model to obtain the topic vector features of each POI and represent the users' category preference for POI. According to different users, this topic model can get different topic preferences.

The probabilistic topic model figures out personal preferences for POI according to the frequency of users' historical visits to different topics. The set of topics T[t1,t2,…tn] is given first, then according to all keyword sets V appearing in the check-in record, the keyword distribution β_t corresponding to each topic t will be calculated by using the potential Dirichlet distribution model, as shown in Formula (1).

$$\beta_t = \mathrm{T} \times V_t \tag{1}$$

Where V_t represents the keyword matrix of the topic t. For user i, each check-in records has its probability topic distribution P[t_1, t_2, ..., t_n] in the topic set T. The distribution describes the probability of each check-in record for the topic in the set T and represents the relevance between the POI and the topic.

For the check-in record w in the check-in record set W of a certain user in the data set, the probability $T_W[t]$ of the check-in record w belonging to the topic t can be obtained according to the Formula (2). Tw is used as the topic vector feature of check-in record ω to reflect how often the user access to different topics.

$$T_W[t] = \frac{N_{\omega\in(W\cap V_t)}+\alpha}{|W|+|T|*\alpha} \tag{2}$$

$N_{\omega\in(W\cap V_t)}$ indicates the number of keywords which belongs to V_t in the record W, and α is the prior probability of symmetric Dirichlet. Generally, α=0.1, $|W|$ and $|T|$ represent the number of keywords ω and the number of potential subjects t in the check-in record W respectively. Here, the probability of a potential topic of any check-in record satisfies the equation $\sum_{t\in T} \mathrm{T}_W[t] = 1$. In this paper, a topic model based LDA is designed: firstly, the probability distribution of keywords associated to each topic is obtained, and then the topic probability distribution of each check-in record is gotten according to Formula (2).

b) *User Preference Feature*

User's check-in records to POI constitutes user-POI check-in matrix $R_{N\times M}$, where N represents the number of users, M represents the number of POIs, and the value in the matrix represents the frequency of user's visit. MF by SVD is introduced in this paper to decompose the users' visit matrix.

Users with similar check-ins are closer to each other in the vector space. The visit matrices of users are performed with MF according to Formula(3) to obtain a potential vector representation of the user-POI records in the lower dimension space for characterizing the preference of users.

$$R_{N\times M} = U_{N\times N} \Sigma_{N\times M} V_{M\times M}^T \tag{3}$$

U and V are the potential vector matrices for users and POIs respectively, where U is an $N\times N$ matrix called a left singular matrix. Each row in U represents a user's potential vector. Σ is an $N\times M$ diagonal matrix, where the elements are singular values, V^T is an $M\times N$ matrix, called the right singular matrix, in which each row represents the potential vector of a POI.

In general, the singular matrix has an attenuation characteristic for the sum of the first 10% or even 1% singular values accounts for more than 99% of the sum of all singular values. Therefore, the top K singular values and the corresponding left and right singular vectors can be used to approximate the description matrix, as shown in Formula (4).

$$R_{N\times M} \approx U_{N\times K} \Sigma_{K\times K} V_{K\times M}^T \tag{4}$$

The matrices $U_{N\times K}$ and $V_{K\times M}^T$ are the user potential vector matrix and the POI potential vector matrix after singular value factorization respectively. The loss function is constructed according to Formula (5), and optimized it to minimum.

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$$Loss\_MF = \sum_{(n,m)\epsilon R}(r_{n,m} - \sum_{k}^{K} U_{n,k}V_{m,k})^2 \quad (5)$$

$r_{n,m}$ is the real value of the user-POI check-in matrix, and $\sum_{k}^{K} U_{n,k}V_{m,k}$ is the predicted value after the MF.

An effective vector representation of the features should be obtained in LBSN during the training of the neural network, so that the network can learn the features effectively. However, when the feature dimension is huge, the traditional One-Hot coding representation to demonstrate features is usually very sparse. Therefore, feature embedding method on the basis of MF is adopted to learn features and obtain a more efficient vector representation than One-Hot coding.

Since the user ID and the POI_ID are uniquely represented items, which means each ID can identify a single user and POI. However, the ID is a categorical variable and cannot be computed effectively. Thus, the ID is re-encoded using the One-Hot encoding method to obtain the latent feature vector $< U_i, V_j >$. Where U_i is the user potential vector and V_j is the POI potential vector, as shown in equations (6).

$$U_i = U(OneHot(i)) \quad and \quad V_j = V(OneHot(j)) \quad (6)$$

c) Geographical Feature

According to the first law of geography, the geographical distance affects the selection of human behaviors. Users generally like to visit POIs in the vicinity. The closer the POIs are, the more likely users are to choose[9]. Therefore, the location information of POIs is an important factor to be taken into account. In LBSN, each POI contains a unique longitude and latitude information to describe the location information. However, the original location information is singular sample data. In order to exclude singular sample data, the longitude and latitude of the original data are standardized respectively according to Formula (7). The data is normalized to an appropriate range and input into the model as the geographic factor feature for each POI.

$$Geo = \frac{(loc - loc_{min})}{(loc_{max} - loc_{min})} \quad (7)$$

Where loc is the longitude or latitude of the POI, loc_{max} is the maximum value in the longitude or dimension of the position information, loc_{min} is the minimum value in the longitude or latitude, and Geo is the normalized data as the POI geographic feature.

C. Training Model

The neural network learning module in DLM recommendation model proposed in this paper takes the user preference features, topic features and geographical factor features constructed in the previous stage as the input, and finally obtains the prediction results of POI recommendation after training.

For any user-POI pair $< U_i, V_j >$, the vector of its full connection is shown in Formula (8).

$$X0 = Merge\ (< U_i, V_j >, T_W, Geo) \quad (8)$$

where the user-POI potential vector $< U_i, V_j >$ represents the user preference feature, the T_W is the topic feature and the Geo is the geographic feature. Merge fully connects all features into the model, feeds it into the DNN and calculated in the hidden layer of the model according to Formula (9).

$$\mathrm{X1} = Dropout\ (Relu\ (H^{\theta}\ X0 + b^{\theta})) \quad (9)$$

Where θ represents the number of hidden layers and $Relu$ is used as the activation function. For the non-linear function, the calculation of gradient is simpler than other activation functions. There is no problem of gradient disappearance, so that the convergence rate of the model is maintained in a stable state[12]. Besides, dropout technology is added in each hidden layer to prevent over-fitting and improve generalization ability of DNN. In the output layer of the model, the user's predicted score is obtained as shown in Formula (10).

$$Y = Softmax\ (H_{out} * X1 + b_{out}) \quad (10)$$

In this paper, softmax function is used to classify the results. Softmax outputs two probability values at the output layer, which represent the positive and negative sample probabilities, respectively. Cross entropy is used as the loss function for model adjustment:

$$E = \sum_{i=1}^{N} -y_i log y'_i - (1 - y_i) log(1 - y'_i) \quad (11)$$

The number of summations of the loss function is related to the dimension of the input data. The model is optimized by minimizing the Formula (11), and output the sorted Top-k recommendations.

IV. EXPERMENTS

A. Datasets

The real data set Foursquare used in the experiment which includes 5076 users and 230316 check-in records. Each check-in record includes a user-ID, a POI location ID and a timestamp. Each location has longitude, latitude which contains location information and POI-context with semantic information.

We selected the users with check-ins in Beijing as the experimental dataset. The data was preprocessed to exclude users with less than 5 check-ins and POI with less than 5 check-ins. For each user's data, we randomly selected 80% as training set and the remaining 20% as testing set. Then we use the testing set to verify the feasibility of the proposed model.

B. Evaluation Criterion

In this paper, two widely used indicators, precision@N and recall@N, are used to evaluate the performance of different recommendation algorithms, as shown in Formula(12) and Formula(13).

$$Pre@N = \frac{1}{\delta} \sum_{u \in U} \frac{Top{-}N \cap K}{N} \quad (12)$$

$$Rec@N = \frac{1}{\delta} \sum_{u \in U} \frac{Top{-}N \cap K}{K} \quad (13)$$

Where δ represents the number of users, U is the user set, N represents the number of recommended POIs, $Top - N$ represents the list of top N points-of-interest by recommendation model to the target users, and K is the number of users' true check-ins in the testing set.

C. Baseline Methods

The method presented in this paer is compared with the following methods:

UCF: It is a user-based Collaborative Filtering method calculating the similarity among users and considering the impact between similar users to improve recommendation efficiency.

PMF: It explains the feasibility of MF from the perspective of probability generation process for recommendation.

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LCARS: It integrates topic features into recommendation model, considering personal interests and local preferences.

Rank-GeoFM: It is a ranking-based MF method, which adds POIs that users have not visited to alleviate the problem of data sparsity.

SGFM: it is a recommended method, combining social and geographical factors based on social relationships and geographical influences among users[25].

DLM: It is proposed in this paper, combining user preference feature, geographical feature and topic feature.

DLM_MF: It adopts the recommended method proposed in this paper, but the features sent into the model for learning only include the user preference features obtained by MF.

DLM_MF+Geo: It adopts the recommended method proposed in this paper, but the features sent into the model for learning only include the user preference features and geographical feature.

D. Experimental Results

In the experiment, the effect of each feature in the DLM model is compared for recommendation results. User preference features, geographical factor features and thematic features are added successively in the model, and these features are carried out into experiment and compared in Pre@5, Pre@10 and Pre@20.

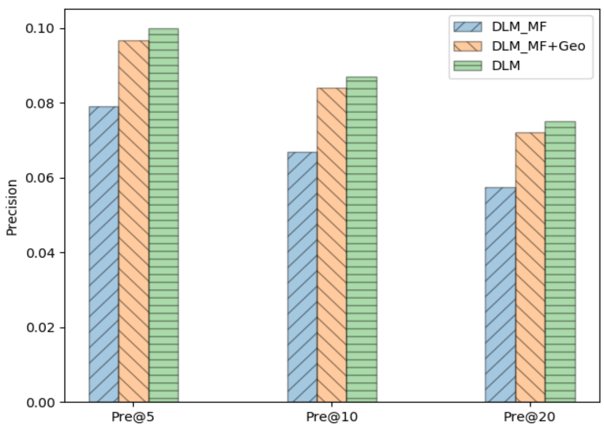

Fig. 2. Feature comparison of model

The experiment results are shown in Figure 2. First, the DLM method which combines the user preference features, geographical factor features and thematic factor features is superior to the DLM_MF+Geo which only adds the user preference and geographic factors. In addition, the effect of adding geographical factor features and user preference features in the model is obviously better than adding the user preference features only, which indicates the importance of the geographical factor features in the recommendation system. The whole experiment results show that DLM has the best effect, which shows that adding thematic features can optimize the recommendation effect and the DLM model can effectively and deeply learn the features, so as to better recommend to users.

Furthermore, we compare the DLM with other baseline methods on the Foursquare dataset for the rate of accuracy and recall. The experiments were conducted under the conditions of Pre@5, Pre@10 and Pre@20 respectively. The experiment results are shown in Figure 3 and Figure 4.

The results show that the precision and recall of DLM algorithm are superior to other POI recommendation algorithms in Foursquare data, which represents DLM is effective for personalized recommendation of POI. Both UCF and PMF lag behind other algorithms since UCF only utilizes the similarity among users to make recommendations and PMF only factorizes the user-POI matrix, which means none of them makes use of geographical influences or other features in the LBSN to make effective POI recommendation. The LCARS algorithm is better than UCF and PMF by adding subject factors to the model. Rank-GeoFM and SGFM are superior to UCF and PMF, both of which add geographical factors to the model, thus indicating the importance of geographical factors in POI recommendation tasks.

SGFM integrates the social relationship and geographical influence among users. Although the recommendation performance is not as good as DLM, it is sufficient to explain that the better integration of the features of LBSN in the POI recommendation task is the key to improve the recommendation performance. The fact that DLM is superior to other baseline algorithms compared in the experiment shows, on the one hand, the validity of the construction based on topic features, user preference features and geographical factor features proposed in this paper, and at the same time it also shows the advantages that DNN network can better learn the joint influence of features on user behavior in LSBN, proving a better recommendation performance after feature fusion.

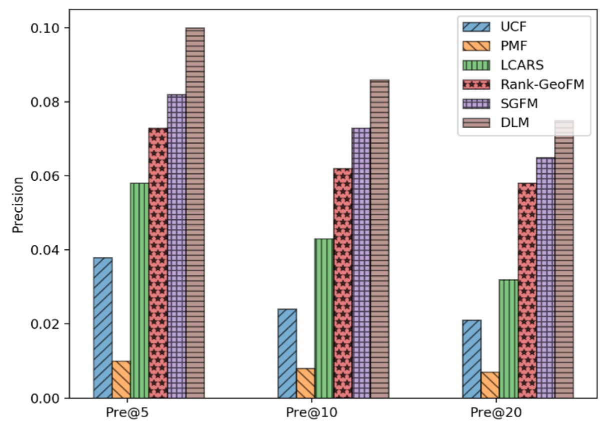

Fig. 3. Precision on Foursquare

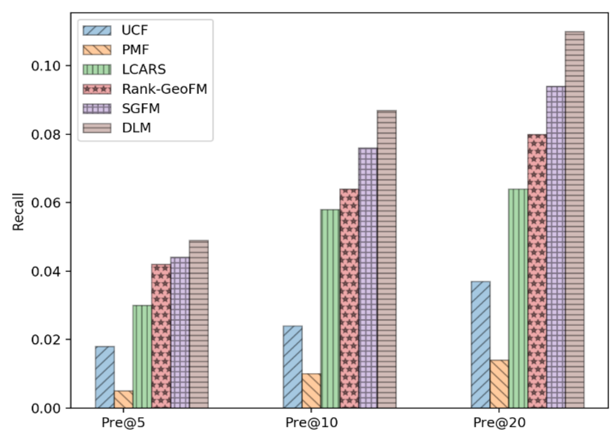

Fig. 4. Recall on Foursquare

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V. Conclusion

A deep learning model based on DNN is proposed for POI recommendation in this paper. User preference features, geographical factor features and POI thematic features in the LSBN are effectively integrated into the DLM model to alleviate the data sparsity problem in the POI recommendation. In addition, we adopt feature embedding method in the model for learning features effectively. The performance of DLM is verified by the results of experiments as the recommendation accuracy of DLM model is significantly higher than that of other POI recommendation methods.

In future research, we will pay attention to the influence of the temporal characteristics visited by users to POI on recommendation results and try to add the temporal factor in the model. Additionally, we would consider the time sequential relationship of different users accessing POI and then mine the rules of the access time sequence of each user, so as to further improve the personalized recommendation effect of users.

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