Research on the Realization of Travel Recommendations for Different Users Through Deep Learning Under Global Information Management

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ABSTRACT

This article is mainly to study the realization of travel recommendations for different users through deep learning under global information management. The personalized travel route recommendation is realized by establishing personalized travel dynamic interest (PTDR) algorithm and distributed lock manager (DLM) model. It is hoped that this model can provide more complete data information of tourist destinations on the basis of the past and can also meet the needs of users. The innovation of this article is to compare and analyze with a large number of baseline algorithms, highlighting the superiority of this model in personalized travel recommendation. In addition, the model incorporates the topic factor features, geographic factor features, and user preference features to make the data more in line with user needs and improve the efficiency and applicability of the model. It is hoped that the plan proposed in this article can help users make choices of tourist destinations more conveniently.

KEYWORDS

Deep Neural Networks, Feature Mining, Personalized Travel, PTDR Algorithm

1. INTRODUCTION

Under the current Internet + model, the tourism field has also been developed rapidly. More and more users are pursuing a more efficient and fast style of work, so they are more willing to make travel plans and find relevant travel destinations through the online travel system, and they shared their photos and published some opinions and other information in the process of traveling on the Internet (Lyu et al., 2019). These will undoubtedly promote people's understanding of various tourist destinations, but it causes the system information overload due to the explosive growth of this type of data (Liao and Nong, 2021; Du, 2021). Faced with complex and huge travel information, it is difficult for users to quickly extract their favorite travel information from the system. At present, most of the functions of online travel systems only provide basic information retrieval, and the functions are too single to satisfy the user's data analysis and extraction functions before traveling.

Chen et al. (2020) simulated the subway station building evacuation design based on a deep neural network (DNN) model, which is compared with the convolutional neural network (CNN) model, the

classification data set pre-training model, and the You Only Look Once (YOLO) algorithm to verify the accuracy and training speed of the model algorithm. Wang (2020) proposed a classification and processing method of tourism product information based on deep learning using the word embedding in the data preprocessing stage. The CNN is adopted to process user and travel service item review information, and the DNN is selected to process the necessary information of users and travel service items. The results show that the model can maintain an excellent accuracy of 64.2% when a personalized recommendation list for users is generated. Law et al. (2019) used deep learning methods to study the prediction framework of Macau's monthly visitor arrivals. The empirical results show that deep learning methods are significantly better than support vector regression (SVR) and artificial neural network (ANN) models. Feizollah et al. (2019) used deep learning algorithms to calculate and analyze Twitter sentiment in their research. The CNN, long and short-term memory neural networks (LSTM), and recurrent neural networks (RNN) are used to improve the prediction accuracy and build prediction models, so as to realize the sentiment calculation of Twitter in a specific topic. Shi et al. (2019) established the sentiment analysis experiments by analyzing the latest articles and techniques based on dictionaries, traditional machine learning, deep learning, and mixed sentiment analysis methods; and the most advanced results in different sentiment analysis experiments are obtained. Paolanti et al. (2021) established a social geographic data framework for deep learning to describe the spatial, temporal, and population tourist flow of this rural tourist area and its vast coastal areas. Four specially trained DNNs are used to recognize and evaluate emotions based on two words and two characters respectively. The rough data set is selected to reduce the dimensionality of the index, the number of neurons in the multi-layer structure of BPNN is optimized by QSIA, QSFOA, QPSO, and QGA, respectively, and the deep learning model is applied to establish the optimal neuron number prediction model under the three algorithms to predict the non-linear return rate of actual stocks. The results reveal that the QSFOA-BPNN model shows the highest prediction accuracy among all models. Fudholi et al. (2021) used cosine similarity to measure the similarity between a person's picture and the gallery of a tourist destination through their label vector. An image classifier model run from a mobile user device through Tensorflow Lite is applied to infer tags. There are a total of 40 tags, covering local tourist destination categories, activities, and objects. The model uses the most advanced mobile deep learning architecture EfficientNet Lite for training. Th EfficientNet Lite is undertaken as the basic architecture for several experiments, and it is obtained that the accuracy rate is more than 85% on average.

The objective of this article is to realize the personalized travel recommendation for users through deep learning under global information management. The personalized travel route recommendation is realized by establishing personalized travel dynamic interest (PTDR) algorithm and distributed lock manager (DLM) model. It is hoped that this model can provide more complete data information of tourist destinations on the basis of the past, and can also meet the needs of users. The innovation of this article is to compare and analyze with a large number of baseline algorithms, highlighting the superiority of this model in personalized travel recommendation. In addition, the model incorporates the topic factor features, geographic factor features, and user preference features to make the data more in line with user needs and improve the efficiency and applicability of the model. It is hoped that the plan proposed in this article can help users make choices of tourist destinations more conveniently.

2. DESIGN ON THE PLAN

2.1 The Personalized Recommendation Algorithm of Point of Interest (POI) Under Deep Learning

A.   Framework of the Model Recommended by DLM

DNN can input specific tasks into high-level features that can realize automatic adaptation and complete interactive tasks. Therefore, in this study, a deep learning model of DNN is established to achieve personalized travel POI recommendation. Figure 1 below is the structural framework of the deep learning model (Hu et al., 2019; Nguyen and Shin, 2019; Ma and Bennett, 2021). The DLM personalized POI recommendation model is mainly composed of two parts: the network learning

Figure 1. The structural framework of personalized recommendation algorithm of POI
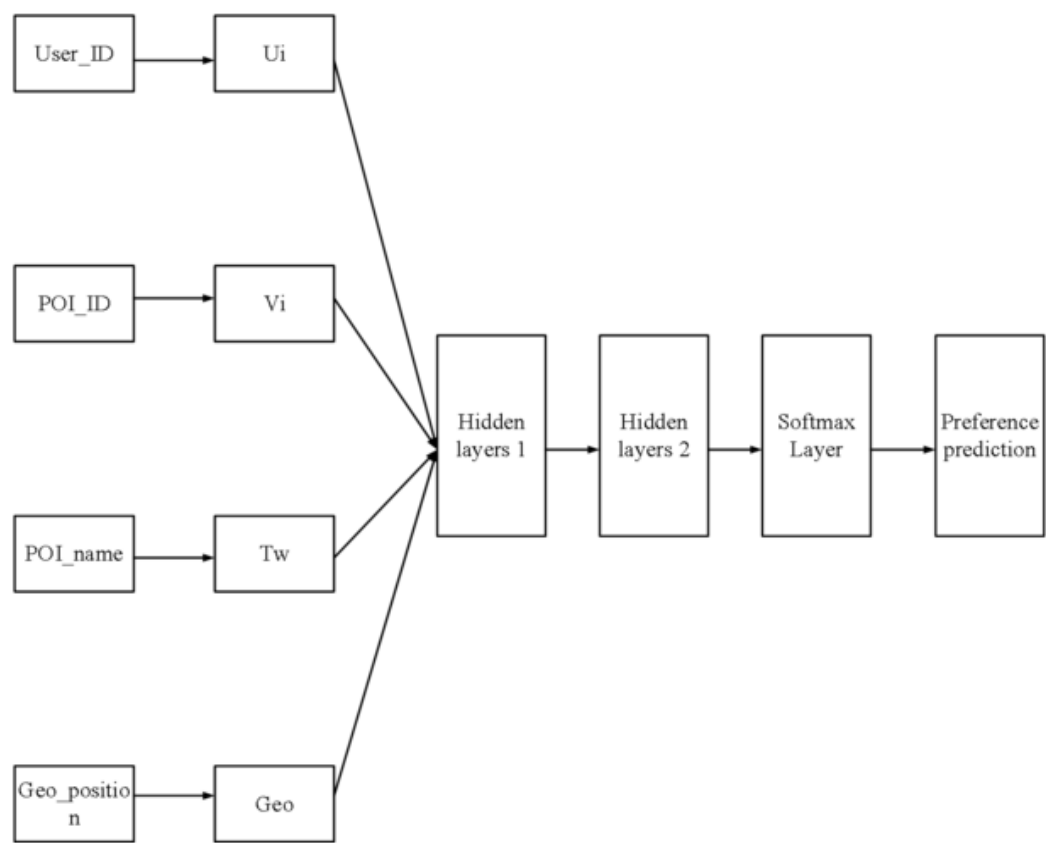
module and the feature extraction module. The network learning module in the model is mainly composed of a network layer and a network connection layer. The connection layer in this module can merge the extracted feature vectors according to different feature types. In addition, the module can use the network layer to recommend POI The hobby score in the model can be predicted, and the DLM recommendation model can also be trained (Huang et al., 2020). The feature extraction

and construction of the target can be completed by word embedding technology (Ye et al., 2020; Niu et al., 2021).

The feature extraction module can well complete the establishment of effective features in the POI recommendation model. The word embedding technology is adopted to extract feature vectors, geographic factor feature vectors, and topic feature vectors in user access records.

B.   Introduction to the Experimental Data Set

In this study, the Foursquare data set is used for experiments, covering 1,134 users and around 241,234 user check-in history records. The data set saves the historical record of every user who has checked in. The record has a timestamp, the location of a POI and the user identity document (ID). The information of each tourist location includes the location name and latitude and longitude information (Yan et al., 2019; Huo et al., 2021; Lv et al., 2020a; Lv et al., 2021b). The location of the clock-in data is extracted and undertaken as the experimental data for this study, and the preliminary processing (de-noising and pre-processing) of the obtained data is required. In the process of dividing the experimental data set, the past check-in history information of the user *ui* is extracted according to the ratio of 2:8. Among them, 20% of the test content is used to test the performance of the model, and the remaining 80% of the training set is to participate in the training of the model (Yha et al., 2021; Lv et al., 2021).

C.   Introductions of Baseline Algorithm

The method proposed in this article is compared and analyzed with the following baseline algorithms:

User-based collaborative filtering (UCF) is used to mine the mutual influence between users by calculating the similar interests of users (Kangethe and Oboko, 2020). It can improve the efficiency of POI recommendation by taking into account the influence of interest among similar users.

Probabilistic matrix factorization (PMF) explains the feasibility of matrix factorization from the perspective of the probability generation process, and then recommends it to users.

Library computer access and retrieval system (LCARS) integrates topic features into the recommendation system, and realizes POI recommendation to users by considering the comprehensive interests of personal interests and local preferences.

Rank-based matrix factorization method (Rank-GeoFM) adds POIs that the user has not visited when constructing the user's historical access POI matrix, which can increase the number of user access matrices, thereby alleviating the data sparsity. Finally, the matrix factorization method is adopted to implement POI recommendation to users (Naghizade et al., 2020).

Scaled group forwarding matrix (SGFM) designs a POI recommendation method based on social geographic factors under the social relationships and geographic influences between users, which can better recommend POI to users by combining the social relationships and geographic factors of users in social networks.

DLM is the algorithm used in this study, which combines the topic factor feature, geographic factor feature, and user preference feature to the feature fusion of the model (Hao et al., 2019).

DLM_MF is the algorithm used in this study, but in the process of fusion of the features of the model, only matrix decomposition can be used to obtain the characteristics of whether users have preferences for tourist locations.

DLM_MF+Geo is used in this study, but in the process of fusion of model features, only matrix decomposition can be used to obtain the user's preference for tourist locations and the geographic information characteristics of each tourist location (Bhaskar and Kumar, 2020).

D. Evaluation Criteria

In this study, two indicators are used to evaluate whether different recommendation algorithms have the performance of personalized travel recommendation, namely accuracy rate (pre@N) and recall rate (Rec@N), which can be calculated with equations (1) and (2), respectively.

$$pore @ N = \frac{1}{\delta} \sum_{u \in U} \frac{Top - N \cap K}{N} \tag{1}$$

$$\mathrm{Re} c @ N = \frac{1}{\delta} \sum_{u \in U} \frac{Top - N \cap K}{K} \tag{2}$$

In the two equations above, δ and N refers to the number of users and the number of recommended POIs, respectively; T*op-N* is the list of top N points of interest recommended by the recommendation model to the target user; and K is the actual check-in list in the user test set, that is, the actual historical access records of users and the set of POIs that the user has actually visited (Si et al., 2019).

2.2 Personalized Travel Route Recommendation Based on Dynamic Interests of Users

A. Construction of User Travel Sequence

In the data layer, the photos of travel locations are extracted from the network, and then the Haversine equation is adopted to calculate the distance between the user's shared photos and each point of interest in the travel destination (Skuratov et al., 2020). When the calculated distance is less than 300 meters, the model defaults to the point of interest of the user. In the historical visit records of user u, the set of historical visit records of user u can be set as below equation:

$$S = < (v_1, t_{v1}^s, t_{v1}^e)...(v_i, t_{vi}^s, t_{vi}^e) > \tag{3}$$

In the equation above, v_i represents the point of interest visited by the user, t_{vi}^s represents the time when user u arrives at the point of interest, and t_{vi}^e represents the time when user u leaves the point of interest.

$$t_{vi}^e - t_{vi}^s > \tau \tag{4}$$

The historical visit record S of user u is further divided into multiple travel sequences Seq, where $\tau = 8$ hours.

B. The Dynamic Interest of Users

It can identify the user's preference for various tourist locations and whether they are interested in the subject of the target location by mining each user's travel data, so as to collect, sort, and filter the obtained data into the model, and then establish the user's personalized travel interest vector (Luo et al., 2020). Then, a context information matrix is established for each tourist location, and the CNN is used to extract the features of the matrix, and the one-dimensional feature vector of the fully connected layer in the CNN network is used as the context vector of the interest point. The

characteristics of the user's travel target area are mined through the cosine similarity of the user interest vector and the context vector of the interest point. Finally, the user's dynamic interests during the travel process are obtained by weighting the user interest vector and the characteristics of the travel target area (Liu et al., 2020).

The user interest vector is calculated, which is derived from the user's historical visit records:

$$\text{int } P(u) = <\text{int}(c_1, p_1), \text{int}(c_2, p_2) \bullet\bullet\bullet (c_n, p_n) > \tag{5}$$

In the equation (5) above, ci represents the preference for the topic of interest vi of the user u, and pi represents the preference for the popularity of the interest vi of user u. The topic access preference of user u is calculated by equation (6).

$$u_{ci} = \sum_{vi \in V} \frac{t_{vi}^e - t_{vi}^s}{T_{vi}} \delta(\text{cat}(v_i) = c) \tag{6}$$

T_{vi} refers to the average visit time of all users on the point of interest vi, the popularity of the point of interest is normalized according to equation (7), and $pop_{num(vi)}$ is used as the popularity index of the point of interest vi.

$$pop_{num(vi)} = \frac{pop(v_i) - \min}{\max - \min} \tag{7}$$

In the above equation, max represents the largest popularity in the set of interest points, and min represents the smallest popularity in the set of interest points.

The popularity preference of user u can be calculated with equation (8) below.

$$u_{pi} = \sum_{vi \in V} \frac{t_{vi}^e - t_{vi}^s}{T_{vi}} \delta(P(v_i) = p) \tag{8}$$

Based on the above analysis, the k nearest neighbor users are selected for user u according to the cosine similarity of the user interest vector. According to equation 9, the user u's interest in the POI vi is obtained.

$$pred(u_a, v) = \bar{int}_a + \frac{\sum_{b \in N} \sin(u_a, u_b) * (int_b - \bar{int}_b)}{\sum_{b \in N} \sin(u_a, u_b)} \tag{9}$$

In the equation (9) above, $\bar{int}_a$ represents the average interest score of the user ua in the historical visit points of interest, N is the set of neighbor users, sin(ua, ub) represents the Pearson similarity between the user ua and the user ub, $Intb$ represents the user ub the interest score of the point of interest vi, and $Intb$ represents the user ub the average interest score of the historical visit point of interest (Du, 2021).

C. Personalized Travel Route Recommendation

The final travel route recommended to the user can be determined by maximizing the final score of the travel route, as shown in the following equation.

$$Max \sum_{i=2}^{N-1} \sum_{j=2}^{N} x_{i,j} Score(i) \tag{10}$$

When the path includes the sub-path from the point of interest vi to the point of in$_{te}$rest vj, xi,j = 1, while $xi,_j$ = 0 in other cases, ensuring that each point in the OP orientation problem can only be selected when constructing the route of the trip once.

$$\sum_{j=2}^{N} x_{i,j} = \sum_{i=2}^{N-1} x_{i,N} = 1 \tag{11}$$

$$\sum_{i=2}^{N-1} x_{i,N} = \sum_{j=2}^{N} x_{k,j} \leq 1, \forall k = 2,...,N-1 \tag{12}$$

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} Cost(i,j) x_{i,j} \tag{13}$$

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} x_{i,j} \delta(Cat_i = c_m) \geq 1, \forall c_m \in Cat \tag{14}$$

For the collection of points of interest V, it can recommend *a* travel route with the highest total score for the user according to the user's dynamic interest preferences $C(u,vi)$ and the popularity $P_{op}(vi)$ of the points of interest vi (Asrianda et al., 2021).

D. Descriptions of Baseline Algorithm

In this study, a leave-oneout cross-validation method is used to compare and analyze the PTDR algorithm used in previous studies with the personalized travel recommendation algorithm. The specific analysis method is described as follows.

Greedy nearest (GNear) selects points of interest by random selection. The requirement of the point of interest is the shortest distance to the user, and the user has never contacted the point of interest, so it is determined as the next user's upcoming selection POI.

Greedy most popular (GPop) selects points of interest by random selection. The point of interest is required to be the most popular, and the user has never contacted the point of interest, so it is determined as the POI of user.

Random selection (Rand) screens the points of interest and selects points of interest that the user has never contacted before, so as to determine the points of interest to be selected by the next user. The PersTour algorithm and the PTDR algorithm used in this study are introduced for comparative analysis. The characteristic of PersTour algorithm is that it can realize personalized travel route recommendation based on three aspects: user interest, visit time of POI, and recent visit POI of user .

The value of σ in PT−5F is 0.5: in the PersTour algorithm, the model is uniformly identified as the user's hobbies based on the user's visit frequency and the popularity of POI.

The value of σ in PT−5T is 0.5: in the PersTour algorithm, the model is uniformly identified as the user's hobbies based on the user's visit time and the popularity of POI.

The value of σ in PT−5U is 0.5: in the PersTour algorithm, the user's interests and hobbies of visit duration are updated through the weight. The model is uniformly identified as the user's hobbies based on the user's visit duration and the popularity of POI.

The value of σ in PT-1F is 1: in the PersTour algorithm, the mainstream hot spots in the society are not considered, and the only factor that can affect the POI score in the model is user interest preference - user visit frequency.

The value of σ in PT−1T is 1: in the PersTour algorithm, the mainstream hot spots in the society are not considered, and the only factor that can affect the score of interest points in the model is the user's interest preference - observation duration.

The value of σ in PT−1U is 1: in the PersTour algorithm, the mainstream hot spots in the society are not considered, and attention is paid by updating the weight. The attention angle is the duration of the user's observation of the target location according to his own interest preferences.

The algorithm used in this article is compared with other most advanced tourist location sequence recommendation algorithms based on three data sets (Foursquare, New York (NYC), and Tokyo (TKY) to prove that the scheme used in this study shows universality and effectiveness in personalized recommendation of the user's travel location sequence. Flickr is an experimental data set established by obtaining geo-tagged photos from the social network, and then sorts the sequence of the user's visiting attractions in chronological order.

NYC mainly includes long-term user check-in data (about 9 months) collected in New York, USA from May 2015 to May 2020. The records where the number of historical visits is less than 20 users and the number of visits is less than 20 The second travel locations are filtered. A total of 1,054 users participated in the experiment, and 4,548 tourist locations and 234,318 historical check-in records that can be experimented.

TKY is a data set collected in Tokyo. The data set is basically similar to NYC. It also filters the records of historical visits of less than 20 users and tourist locations that have been visited less than 20 times. Finally, there are 2,048 users participating in the experiment, and the total number of tourist locations is 7,562. The total number of historical check-in records that can be tested is 583,920.

2.3 Experimental Parameter Setting and Evaluation Criteria

In the personalized travel recommendation PTRD algorithm model used in this article, the POI score weight σ is undertaken to represent the weight of the user's dynamic interest preference and point-of-interest popularity in the PTDR model. According to the different weight values, there are the following methods:

The value of σ in PTDR-.5N is 0.5: in the PTDR algorithm, $Int\_P(ui)$ is set as the personal interest preferences of different users, but the model does not incorporate the mining of the characteristics of the tourism target area. When the POI is scored based on users, the personal interest preferences of different users and the popularity of this type of interest in the society account for the same proportions in the model, that is, the two aspects have the same weight value.

The value of σ in PTDR-.5C is 0.5: in the PTDR algorithm, $C(u,vi)$ is set as the personal interest preferences of different users, and the model integrates the mining of the characteristics of the tourism target area. When the POI is scored based on users, the personal interest preferences of different users and the popularity of this type of interest in the society account for the same proportions in the model, which means that the two aspects have the same weight value.

The value of σ in PTDR-1N is 1: in the PTDR algorithm, $Int\_P(ui)$ is set as the personal interest preferences of different users, but the model does not incorporate the mining of tourism target area features. When the POI is scored, it is not related to the popularity of this type of interest in society, so the model will focus more on user interest preferences.

The value of σ in PTDR-1C is 1: in the PTDR algorithm, $C(u,vi)$ is set as the user's preference for points of interest, and can be regarded as the personal interest preferences of different users. When the POI based on users, it is not related to the popularity of this type of interest in society. Therefore, the proportion of this model in calculating the points of interest scores of different users is higher than that of users' dynamic interests.

The value of σ in PTDR-.10N is 0.1: in the PTDR algorithm, *Int_P(ui)* is regarded as the personal interest preferences of different users, but the model does not incorporate the mining of tourist target area features. When the score is evaluated based on the popularity of certain interests in the society, the user does not pay attention to the points of interest, so the model will focus more on the mainstream interests of the society.

The value of σ in PTDR-.10C is 0.1: in the PTDR algorithm, *C(u,vi)* is set as the personal interest preferences of different users, and the model integrates the mining of the characteristics of the tourism target area. When the score is given based on the popularity of certain interests in the society, the user does not pay attention to the points of interest, so the model will focus more on the mainstream interests of the society. The following two evaluation methods are adopted to analyze the performance of different personalized travel recommendation algorithms.

Tour Recall is one of the detection indicators in the process of recommending travel routes to users. The recall rate of the personalized travel recommendation method used should be calculated, as given in equation (15) below.

$$recall = \frac{|\ \mathrm{p_r} \cap \mathrm{p_v}\ |}{|\ p_v\ |} \tag{15}$$

In the equation above, Pr represents all the points of interest in the recommended travel route using the PTDR method, and Pv represents all the points of interest visited by the user in the real travel route of the recommended user.

Tour Precision is one of the detection indicators in the process of recommending travel routes to users. The accuracy of the personalized travel recommendation method used should be calculated with below equation.

$$precision = \frac{|\ \mathrm{p_r} \cap \mathrm{p_v}\ |}{|\ p_r\ |} \tag{16}$$

The meanings of Pv and Pr in the above equation (16) are the same as those in the recall rate, and both are all the points of interest visited in the recommended route and the real route.

The comprehensive indicator Tour F1_Score is introduced to better evaluate the effectiveness of the algorithm. TourF1_Score is the harmonic average of Tour Recall and Tour Precision. The higher the F1 value, the better the overall effect of the recommendation algorithm, as shown below.

$$F1\_\text{Score} = \frac{2 \times precision \times recall}{precision + reacll} \tag{17}$$

The software environment used in the experiment is the Python3 and TensorFlow deep learning platform installed under the 64-bit Ubuntu16.04 operating system. The computer hardware configuration used in the experiment is defined as follows: Intel(R) Core(TM) i7 CPU and a single NVIDIA GTX TITAN GPU.

3. ANALYSIS ON EXPERIMENTAL RESULTS

3.1 Analysis of DLM Model Data Results

Figure 2 below shows the statistics of experimental results after adding user preference, geographic factor, and topic factor features to the DLM model.

Figure 2. Feature factors of DLM model
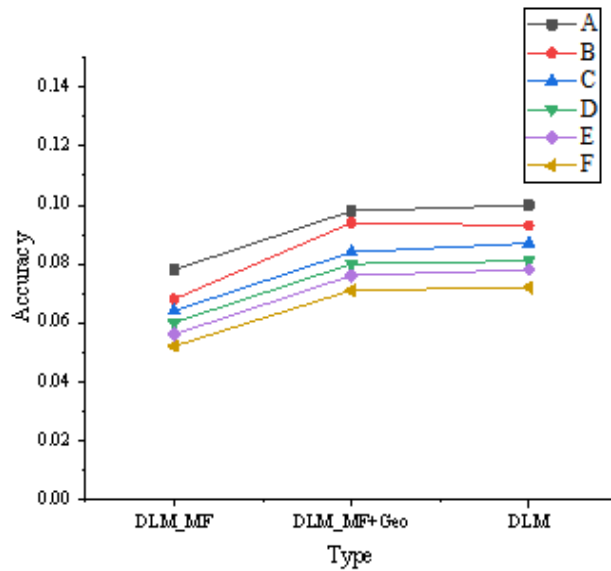
(A: Pre@5; B: Pre@10; C: Pre@15; D: Pre@20; E: Pre@25; F: Pre@30;)

As illustrated in Figure 2, the DLM algorithm that combines topic factor, geographic factor, and user preference features in the DLM model is better than the DLM_MF+Geo algorithm that only combines geographic factor and user preference, and the model combining the user preference feature and geographic factor feature is better than that only analyzing the user preference feature factor in terms of effect. Thus, geographic factor feature in the establishment of personalized travel recommendation for users is an important factor that can't be ignored. The DLM model achieves the best effect, which further shows that integrating the topic features in the model can optimize the effect of personalized travel recommendation. Figure 3 below shows a comparative analysis of the recall rate and accuracy rate on the three data sets.

Figure 3. Comparison and analysis of recall and accuracy data in three data sets
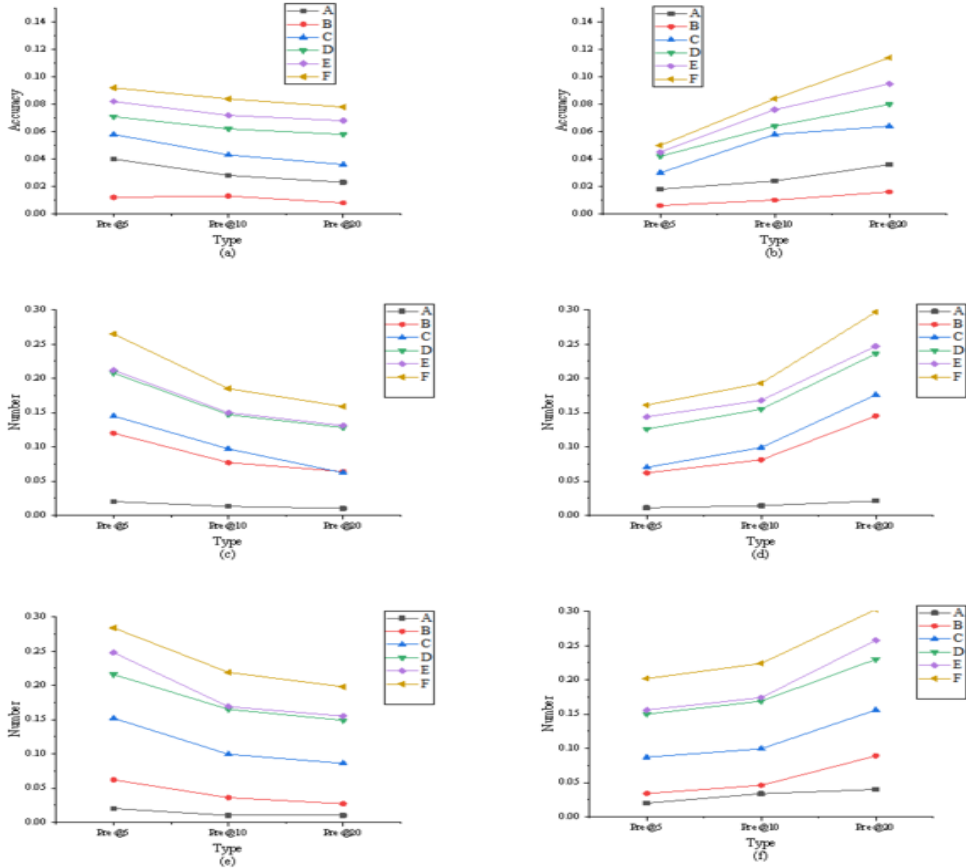

Note: a: the accuracy of different algorithms in the Fourquare dataset; b: the recall rate of different algorithms in the Fourquare dataset; c: the accuracy of different algorithms in the NYC dataset; d: the recall rate of different algorithms in the NYC dataset; e: the TKY dataset The accuracy of different algorithms; f: the recall rate of different algorithms in the TKY dataset; A: UCF; B: PMF; C: LCARS; D: Rank-GeoFM; E: SGFM; F: DLM.

The comparative analysis of the recall rate and accuracy rate in Figure 3 above illustrates that the performance superiority of the DLM algorithm is better than other algorithms. The recall rate and accuracy rate of this algorithm in different data sets are better than those of the other five algorithms. Therefore, the performance of the DLM algorithm model is better than other POI algorithms. When the number of POIs used is the top 20, the top 10, and the top 5, the accuracy rate has increased by nearly 7%, 7.3%, and 9.8%, respectively, and the recall rate has increased by 14.4%, 7.5%, and 4.2%, respectively. The reason why the DLM algorithm is superior to other algorithms is not only reflected in the recall rate and accuracy, but also in the efficiency of the construction of the geographic factor feature and user preference feature. Moreover, it also proves that the DNN can accurately identify the user behavior characteristics, which enables better personalized travel recommendation performance after feature fusion.

3.2 Experimental Analysis on Personalized Travel

Figure 4 below shows the statistics of the comparison between the PTDR algorithm and the traditional baseline algorithms (Rand, GPop, and GNear).

Figure 4. Statistics of comparative analysis results of PTDR and baseline algorithms
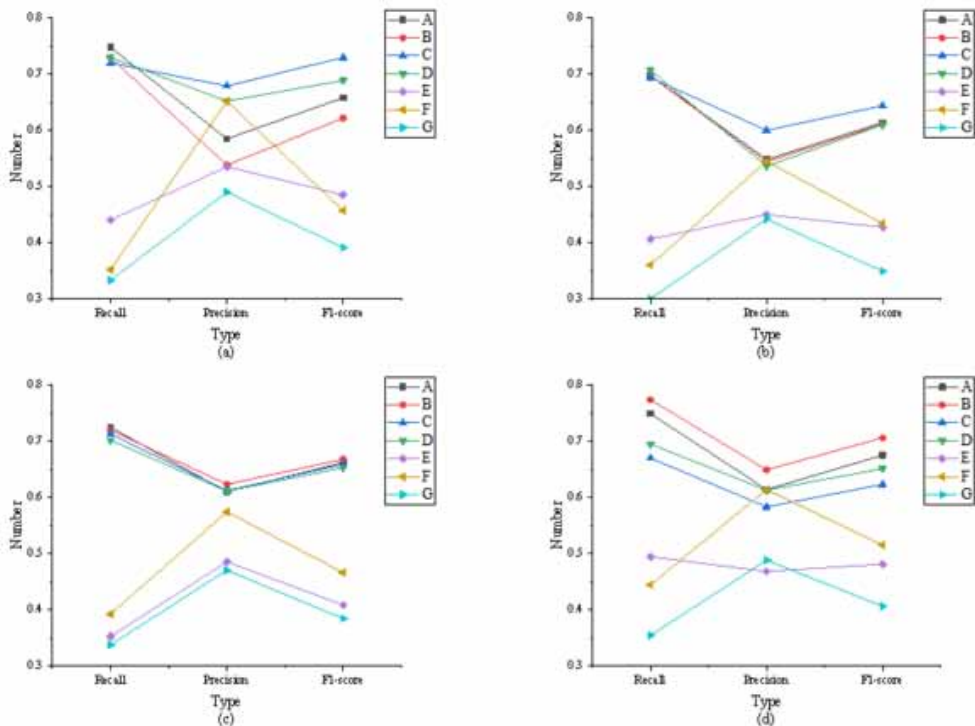
Note: a: Melbourne; b: Sydney; c: Moscow; d: Berlin; A: PTDR-.5N; B: PTDR-.5C; C: PTDR-1N; D: PTDR-1C; E: GNear; F: GPop; G: Rand.

After the results of the comparison between the PTDR and the baseline algorithms in Figure 4 above are analyzed, the following conclusion can be obtained. In the four selected cities (Melbourne, Sydney, Moscow, and Berlin), the PTDR personalized recommendation algorithm used in this article is superior to other baseline algorithms in terms of recall rate, F1 value, and accuracy rate. Because the baseline algorithms can launch personalized travel route recommendation according to different types of users, but currently this type of algorithm can only perform recommendation analysis on the distance of the tourist destination or whether the place meets the needs of the user. Each user shows different travel preferences and purpose, the algorithm currently used can't effectively realize the personalized travel route recommendation for each user. The results of the measurement based on the Flickr real data set this time show that PTDR can efficiently realize the mining of the features of

Figure 5. Comparison of PTDR and PersTour experimental data statistics
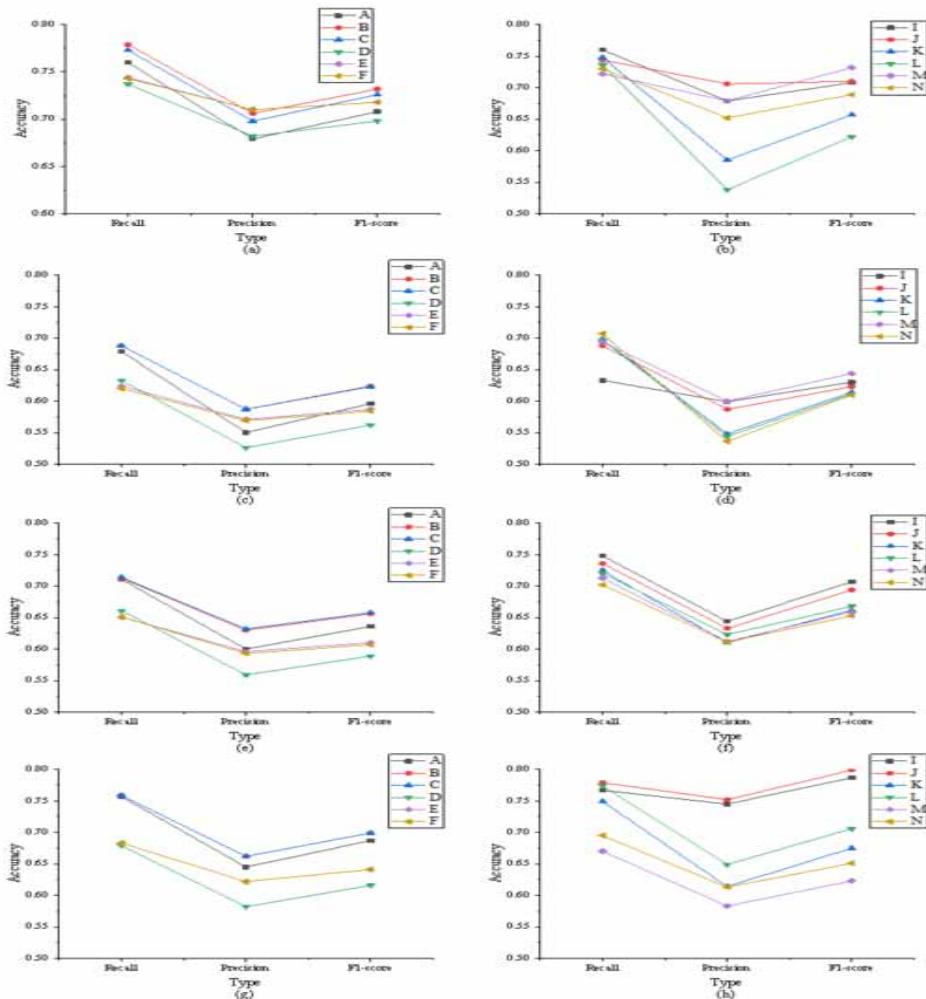
personalized preference of users in the personalized travel recommendation of different users. Figure 5 below shows the comparison of PTDR and PersTour experimental data statistics.

Note: a: Melbourne; b: Sydney; c: Moscow; d: Berlin; A: PT-.5F; B: PT-.5T; C: PT-.5U; D: PT-1F; E: PT-1T; F: PT-1U; I: PTDR-.10N; J: PTDR-.10C; K: PTDR-.5N; L: PTDR-.5C; M: PTDR-1N; N: PTDR-1C.

As revealed in above Figure 5, the PTDR used in this study is better than the PersTour algorithm in terms of F1 value and recall rate. In this experiment, more attention is paid to the change of F1 value than the recall rate and accuracy rate. Because the F1 value is a manifestation of the comprehensive ability of the algorithm, it can better illustrate the similarity between the actual travel route of user and the personalized route recommended by the algorithm. The data reveals that the personalized travel route recommended by the PTDR algorithm is closer to the actual travel route of user. In addition, the algorithm will further consider the interests of each user and mine the features of user interests. Therefore, the PTDR algorithm is closer to the user's interests in the recommendation of the user's personalized travel route, and the PTDR algorithm can plan more reasonable travel

recommendations based on the interests of different users, thereby greatly improving the accuracy of travel recommendations.

4. CONCLUSION

This article mainly studies the recommendation of personalized travel for users through deep learning under global information management. Firstly, a DLM model is constructed, which incorporates the topic factor, geographic factor, and user preference features to better understand the interests of users. Secondly, the PTDR algorithm model is established according to different user's hobbies to realize personalized travel route recommendation. The comparative analysis of different algorithms suggests that the performance superiority of the DLM algorithm is better in contrast to other algorithms, and the recall rate and accuracy rate of this algorithm in different data sets are better than those of the other five algorithms. The PTDR algorithm model can efficiently realize the mining of user's personalized preference features in the personalized travel recommendation of different users; and its data in the recall rate, F1 value, and accuracy rate are better than other baseline algorithms, making the recommended personalized travel information is more in line with the needs of users. However, there are some limitations for this study. Because people currently encounter many unexpected factors in the travel process, such as traffic conditions, scenic spots, and weather conditions, it is necessary to statistically analyze the data from multiple tourism platforms, so as to help users make the best travel guidance. Secondly, the current model is aimed at a single user, with a single goal, so it is not suitable for group travel users, such as graduating class travel and family travel. The above points should be paid attention to in future research, and it is hoped that this study can help users make choices of tourist destinations more conveniently.

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