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Research on Personalized Recommendation Algorithm for Smart Tourism Based on Deep Attention Interest Collaborative Filtering (DAICF)

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Abstract This paper proposes a smart tourism personalized recommendation algorithm based on Deep Attention Interest Collaborative Filtering (DAICF), which solves the sparsity and cold-start problems in tourism recommendation by fusing geo-tagged photo data with deep learning techniques to mine explicit and implicit relationships of user interests. The research utilizes P-DBSCAN clustering algorithm to identify hotspot locations, constructs user-tour route binary association matrix, and designs deep collaborative filtering model, combining shallow linear interaction with deep nonlinear interaction, to synchronously mine the low-order and high-order relationships between user and item features. Based on the real dataset Yelp, DAICF performed well in the Top-N recommendation task: the Precision@5 was 20.13% and the Recall@15 was 35.26%, which was significantly higher than that of the baseline models such as EPT-GCN and ASGNN. In addition, the ablation experiments show that key components such as social relations and temporal context contribute prominently to the model performance. In practical application tests, the DAICF-generated travel routes shorten the total distance of the trip by 52.5% and improve the time-to-time ratio by 41.9%, which verifies its efficiency and practicality in trip planning.

Index Terms deep attention interest collaborative filtering, personalized travel recommendation, user interest feature change, smart tourism

I. Introduction

With the continuous turnover of modern information technology, the operation mode and management of the traditional tourism industry gradually transformed to informationization, intelligence and personalization, fully reflecting the core position of computer information technology in the pace of development of the field of intelligent tourism [1]-[3]. Intelligent tourism is based on the traditional way of tourism, providing tourism intelligent service platform, around the personalized user experience, combined with a new generation of computer technology to form a huge tourism service system [4]. It can meet people's personalized demand for tourism products, while improving the quality and satisfaction of the tourism service industry, is a new revolution to achieve the tourism industry, human resources to share with each other and to achieve the efficient application in terms of integration and intensification [5]-[7]. Due to the rise of Internet communication technology, a large number of users share their travel experiences online, and photos and videos account for a large proportion of online information and are constantly being added or updated, which provides new research opportunities and challenges for multimedia, data mining, and geo-related research and applications [8]-[10].

Personalized recommendation based on data mining has been a popular research topic in recent years, which has received extensive attention from scholars at home and abroad. Literature [11] pointed out that the establishment of a tourism recommendation system based on data mining technology is a necessary measure to face the increasingly personalized demand for tourism, which can provide personalized tourism recommendations based on information such as user tour data, and also provide services for users with the same preferences. Literature [12] uses data mining techniques to extract user travel characteristics present in text data, combining attraction characteristics and location information to recommend highly personalized and adaptable tourist attractions and travel routes for tourists. It can be seen that data mining technology still plays an important role in the field of tourism personalized recommendation.

Some scholars have explored the specific application of collaborative filtering recommendation algorithm in personalized tourism recommendation, and realized personalized tourism recommendation by comprehensively analyzing the user rating data of tourist attractions and the similarity between users. Literature [13] establishes a large-scale decision-making framework for intelligent tourism, and combines multi-attribute collaborative filtering and social network analysis methods to recommend tourism expert recommendations that meet tourists' personalized needs, and at the same time, solves the cold-start problem of the recommender system through the tourists' interaction process. Literature [14] proposes two personalized tourism recommendation methods based on user travel behavior data, and the proposed collaborative filtering route recommendation method achieves good results by mining tourists' travel preferences in order to calculate the probability of different travel routes, and at the same time introduces the distance calculation to solve the cold-start problem. Literature [15], supported by the knowledge transfer learning model, can recommend tours with high adaptability for tourists by fully mining the historical behavioral data accumulated by users in travel, expenditure and other information, while combining with contextual data analysis techniques. Literature [16] established a collaborative filtering recommendation algorithm model for tourist attractions based on user preferences to address the data sparsity problem and the lack of common rating items in traditional tourism recommendation methods, using global and local rating information to extract and integrate user interest preferences to improve the accuracy of the recommendation system. Literature [17] developed a location-aware personalized traveler assistance (LAPTA) system, which employs a collaborative filtering K-nearest neighbor algorithm to analyze travel data based on the GPS positioning system and preference data based on users' input behaviors, and ultimately generates reliable and accurate travel recommendation results. The above study shows that the collaborative filtering algorithm can take into account the user's ratings and preferences for attractions, combined with the behavioral patterns of similar users, so as to provide users with personalized recommendations for tourist attractions, which is an indispensable means to promote the development of the tourism industry.

This paper proposes an intelligent travel recommendation algorithm based on Deep Attention Interest Collaborative Filtering (DAICF), aiming at solving the sparsity and cold-start problems in travel recommendation by fusing geotagged photo data with deep learning techniques to mine the explicit and implicit relationships of user interests. The research revolves around the construction and optimization of personalized tourism recommendation system, through basic data modeling, defining the association relationship between user behaviors and tourism locations based on a collection of geo-tagged photos, identifying hotspot locations using P-DBSCAN clustering algorithm, and constructing a database of tourist attractions through semantic annotation. On this basis, a deep collaborative filtering model is proposed, combining shallow linear interaction and deep nonlinear interaction, to synchronously mine the low-order and high-order relationships between user and item features, and to enhance the feature expression through bilateral neighbor information. The binary cross-entropy loss function and Adagrad optimization algorithm are adopted, combined with regularization technology to enhance the model generalization ability, and the effect of negative sampling rate on performance is experimentally verified. At the same time, we construct the binary correlation matrix of tourists-tourist routes, quantify the user activity and route popularity, and reveal its power law distribution characteristics, which provides theoretical support for the cold route mining of the recommender system.

II. Construction of personalized tourism recommendation system based on deep attention interest collaborative filtering

II. A. Basic concepts and terminology

Before introducing personalized travel recommendation system, some basic concepts and terms are given.

Definition 1: (Geo-tagged photo) A geo-tagged photo p can be defined as $p=(id,t,g,X,u)$, where id is the unique identifier of the photo. g is a geotag indicating the geographical area where the photo was taken. t is the timestamp. u is the identification of the user who contributed the photo. Each photo p can be annotated with a set of text tokens x.

Definition 2: (Collection of photos) The collection of photos contributed by all visitors can be represented as $P=\{P_1,P_2,\cdots,P_n,\cdots,P_n\}$, where P_a is the collection of photos contributed by user u.

Definition 3: (Location) Location t denotes the geographic area of a hotspot tour or attraction, such as a park, lake or museum.

Definition 4: (Context-aware query) Context-aware query Q is defined as $Q=(t,w)$, t denotes the time context and w denotes the weather context.

The data mining based personalized travel recommendation system aims to locate and summarize travel locations based on a user's given collection of geotagged photos and to build up each user's travel history in order to obtain his/her travel preferences, so as to perform a context-aware personalized query to recommend the travel locations that best suit his/her interests.

II. B.Personalized Tourism Recommendation System

After clarifying the basic concepts of geotagged photos and location, this section will identify tourist locations from the collection of user-contributed photos based on the P-DBSCAN clustering algorithm, and further complete the semantic annotation and location analysis to support the construction of the data base for the recommendation system.'

II. B. 1) Identifying tourism locations

Identifying tourist locations from a collection of geotagged photos is a typical clustering problem. Given a set of photos P, this study uses P-DBSCAN to cluster the photos to identify tourist locations based on the geotags of the photos.The output of P-DBSCAN is a set of locations (photo clusters) $L = \{I_1, I_2, \cdots, I_n\}$. Each element $l = \{P_i g_i\}$, where P_i is a set of geographically clustered photographs, and g_i denotes the center-of-mass geographic coordinates of the cluster of photographs P_i.

II. B. 2) Semantic annotation of locations

Tourist locations identified using spatial proximity based clustering algorithm can be visualized on user UI interface. In order to give a semantic annotation for identifying tourist locations from a collection of geotagged photos that are a canonical location, the study provides a new approach to the clustering problem of the method type. Given a set of photos P, this study uses P- Annotate the photos using text tags and combine them with information provided by an online Web service to automatically generate a textual description of each tourist location.

II. B. 3) Analyzing positions

When finished using the spatial proximity of the photos to cluster the photos will be analyzed for location to create a tourist attraction profile and a database of preferred tourist attractions.

Firstly, the location information of users is recognized from the photos taken by different users at tourist attractions. For each location $l \in L$, the photos are sorted according to the time u the photos were taken by each user. At time t, the photo p taken by user u at location l is noted as user visit v. Note that user u may take multiple photos at the same location in the same v. Therefore, if the difference between the timestamps of 2 photos $(p_2, t - p_1, t)$ taken by the same user at the same location is less than the access duration threshold T_s, the two photos are considered to belong to the same visit. In addition, the median of the timestamps associated with the photos is noted as a particular access duration v, t of the user.

II. C.Deep Attention Interest-based Collaborative Filtering DAICF Modeling

After completing the recognition and semantic annotation of tourist locations, it becomes crucial to mine personalized interests from user behavioral data. This section proposes a model based on Deep Attention Interest Collaborative Filtering DAICF, which realizes efficient interaction between users and item features by fusing shallow and deep components.

II. C. 1) Model Composition

After constructing the features of users and items, it is necessary to choose appropriate models to interact with these features. The current traditional methods are simple and easy to implement, but they can only use linear models to model the explicit relationship between features, and there are even cases where features need to be combined manually, which not only consumes manpower, but also has limited performance and lacks the generalization of the models, such as the MF model, the FISM model, the FM model, and so on. Deep learning methods based on interaction function learning can use deep neural networks as interaction functions to model nonlinear interactions between features, thus mining implicit relationships between features, but lose sight of the other side of the coin, and most of the models that use this method ignore low-order interactions between features, e.g., the DMF model, the DELF model, etc., which lacks the memory of the model, or the synergistic signals mining of the low-order interaction is Inadequate, e.g., NeuMF model, DeepICF model, NAIS model, etc. Based on this, this chapter proposes a collaborative filtering-based deep interest recommendation model DAICF, whose overall model structure is shown in Fig. 1.

The basic idea of the model is to adopt user and item features extracted from personalized features based on bilateral neighbor information as inputs, and interact user and item features with interest preferences simultaneously in second-order linear and higher-order nonlinear ways, to excavate explicit and implicit relationships between features, so as to allow the system to achieve more accurate personalized recommendations, and to vigorously improve the accuracy and interpretability of recommendations.

This subsection mainly introduces the composition of the DAICF model, in particular, this paper divides the model into six sub-modules and shows how the model obtains the predicted value of the user's preference for an item by introducing each sub-module in the model layer by layer, preparing the recommender system to make personalized recommendations to the corresponding users using this predicted value.

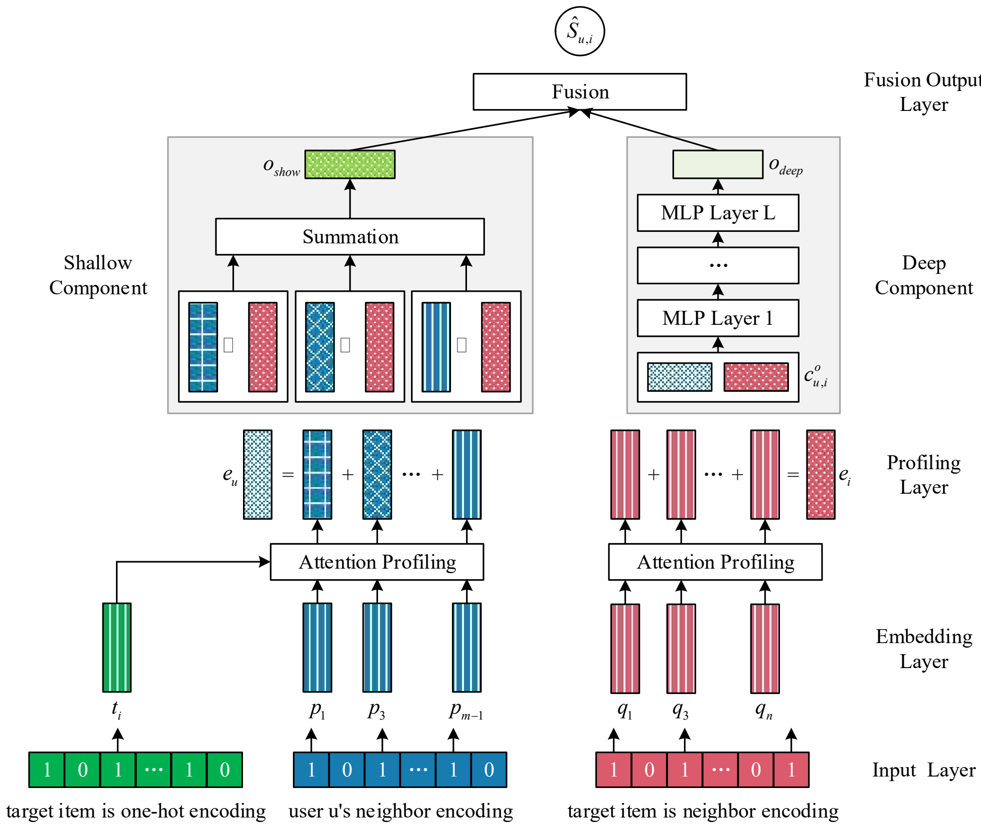

Figure 1: Overall structure of DAICF based on collaborative filtering

As shown in Fig. 1, the DAICF model is composed of an input layer, an embedding layer, a representation layer, a shallow component, a deep component, and a fusion output layer from bottom to top. Among them, the vectors input to the input layer include the encoding of the user using the user's neighbor information, the encoding of the item using the item's neighbor information, and the uniquely hot encoding of the item using the item's ID value. The shallow and deep components are structured in parallel to synchronize the mining of displayed linear and implicit nonlinear relationships between features. These network structures are further described below.

II. C. 2) Model training

In addition to the selection of features and model construction, another important aspect of the performance of the recommender system is the objective function constructed during the training of the model, and the selection of the objective function that meets the model in order to optimize the model by using the set of observed user-item interaction pairs H^{+} and the set of unobserved user-item interaction pairs H^{-} for the optimization of the model, with a generic formulation of the objective function:

$$\mathrm{L}_c = \sum_{(u,i)\in \mathrm{H}^{+}\cup \mathrm{H}^{-}} l(s_{u,i}, \hat{s}_{u,i}) + \lambda\Omega(\Theta) \tag{1}$$

where $l(\cdot)$ is the loss function, $\Omega(\Theta)$ is the regularization function of the parameter Θ, and λ is the regularization coefficient.

For the selection of the loss function $l(\cdot)$, there are two mainstream approaches in the recommendation domain, single sample-based and sample pair-based. The single-sample based approach usually assigns predefined target values to user-item interaction pairs in R^{+} (i.e., positive samples) and user-item interaction pairs in H^{-} (i.e., negative samples), and then trains the model parameters so that it outputs values similar to the target values, which is suitable for the use of implicit feedback data in the binary classification problems. The sample pair-based approach assumes that the interaction pairs in $\Re^{+}$ have higher prediction scores than the interaction pairs in H^{-}, optimizes for differences between positive and negative samples, and is suitable for regression problems using display feedback data. These two methods are not good or bad, and each model needs to choose the loss function according to its own situation.

According to the previous definition, the DAICF model is used to predict whether the user will interact with the target item, so the learning can be pushed to the binary classification problem, so in this paper, we choose the logarithmic loss function based on a single sample, which has been widely used to optimize neural recommender system models and has shown good performance. The computational formula of the objective function chosen in this paper is:

$$\mathrm{L}_{c} = \sum_{(u,i)\in \mathrm{H}^{+}} \log \hat{s}_{u,i} + \sum_{(u,i)\in \mathrm{H}^{-}} \log(1-\hat{s}_{u,i}) + \lambda \,\|\, \Theta \,\|^{2} \tag{2}$$

where $\sum_{(u,i)} \in \mathrm{H}^{+} \log \hat{s}_{u,i} + \sum_{(u,i)} \in \mathrm{H}^{-}(u,i) \log(1-\hat{s}_{u,i})$ is the binary cross-entropy loss function, and Θ is the parameter to be regularized in the model, in this model, this part of the parameter includes the user-side embedding matrix P and item-side embedding matrix Q in the embedding layer, and the weighting matrix in the deeper components $\{W^{(1)}, W^{(2)}, \ldots, W^{(L)}\}$. $\|\, \Theta \,\|^{2}$ denotes the L_2 regularization of the parameter Θ . λ is a hyperparameter used to control the strength of the regularization of L_2 and to regulate the model's fitting ability. In the shallow component, the regularization function of this module is only L_2 regularization because there is no activation function involved and its learning ability is limited, but in the deep component, in order to prevent the overfitting of the neural network, this paper also utilizes the batch normalization technique to regularize the parameters, and the use of this method also has some acceleration effect.

When training the model, each positive sample corresponding to H^{+} needs to select a certain number of negative samples corresponding to H^{-} together as the training data input to the model, and the ratio between the positive samples and the negative samples is known as the negative sampling rate of the model, which is denoted by NS. In this paper, we find that the negative sampling rate has an important effect on the model performance, which is demonstrated experimentally in the next chapter.

Currently, there are many kinds of optimization algorithms for the objective function, such as the momentum method, Adagrad algorithm, Rmsprop algorithm, Adam algorithm and so on. Each optimization algorithm has its advantages and disadvantages, and after experiments, it is found that the model proposed in this paper is optimized best using Adagrad algorithm. The Adagrad algorithm dynamically changes the learning rate of each dimension according to the magnitude of the gradient of the independent variable of each dimension, thus avoiding the problem that a single learning rate is not flexible enough, and it is suitable for dealing with sparse data, which matches the sparse implicit feedback data used in this paper, so Adagrad is used as the optimization algorithm for the objective function L_{c} in this paper.

After training the parameters of the model, the DAICF model can solve the preference of a specified user for a specified item, at which time the recommender system calculates the user's preference for the candidate item, and then sorts according to the calculated multiple preference scores, and selects the top N items to be recommended to the user. In summary, the personalized recommendation process implemented based on DAICF model in this paper is shown in Figure 2.

II. D.Personalized Recommendation of Travel Route Based on Changes in User Interest Characteristics

The training and optimization of DAICF model provides technical guarantee for the recommendation system, while accurate user interest modeling is the core of the reliability of recommendation results. In this section, we will combine the explicit selection behavior and implicit history interaction to construct the user-tour route association matrix and analyze its long-tail distribution characteristics to further optimize the recommendation strategy.

II. D. 1) Modeling of user interest features

Whether the expression and establishment of user interest feature model can correctly and objectively respond to the interest orientation of tourists has a direct impact on the recommendation results of tourism routes, so the establishment of an accurate user interest feature model adapted to the recommendation algorithm is the basis of the recommendation process, which is even more important. Most of the traditional collaborative filtering algorithms only apply the user's explicit rating data to build the corresponding interest feature vector model, and they do not take the user's implicit behavioral information into consideration. Based on this, this paper proposes a combination of tourists' explicit interest features and implicit information based on tourists' historical interaction information to establish a spatial vector model of users' interest preferences, i.e., a binary association matrix model of user-tour routes, and the correlation relationship between tourists and tour routes is defined as follows:

Definition 1: (The association relationship between tourists and tourist routes) A tourist u who makes a valid choice behavior for a tourist route r indicates that the association degree b_w between the tourist u and the tourist route r is 1, otherwise it is written as b_w is 0.

Here is a special note on the choice relationship between tourists and routes: in order to make the algorithm appear concise, as long as the tourists are considered to be very satisfied with the tourist route after the tourists have made a choice of the tourist route, therefore, this paper temporarily agrees that the value of the tourists' interests and preferences with the route is 1.

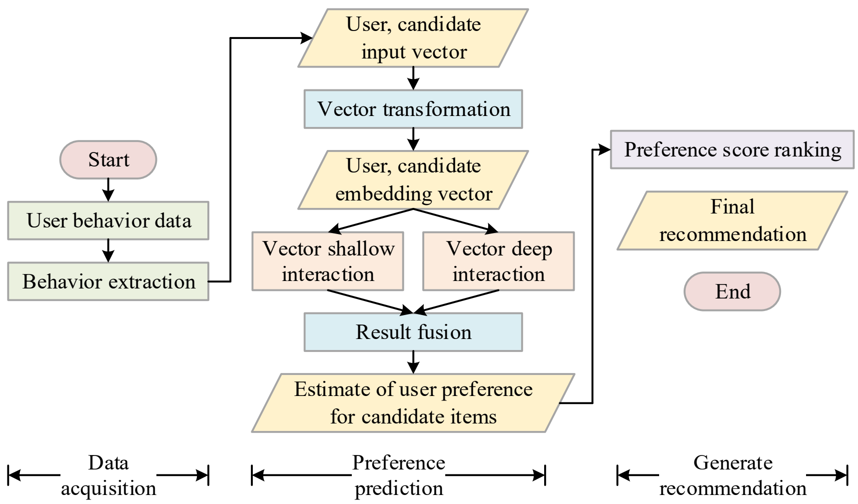

Figure 2: Personalized recommendation process based on DAICF

From the above definition, the association relationship between m tourists and n tourist routes can be expressed as a tourist-tourist route binary association matrix $B(m,n)$, whose relationship is expressed as shown in the following equation (3).

$$B(m,n)=\begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \dots & \dots & \dots & \dots \\ b_{m1} & b_{m2} & \dots & b_{mn} \end{bmatrix} \tag{3}$$

The matrix in Eq. (3) contains binary associative data of m tourists to n tour routes, with rows corresponding to tourists and columns corresponding to tour routes.

II. D. 2) Popularity of Tourist Routes and Tourist Activity

On the basis of establishing the user interest feature model, this section further explores the distribution law of the popularity of tourist routes and the activity of tourists, reveals its power law characteristics, and provides theoretical basis for dealing with the cold route recommendation and data sparsity problems.

A large number of studies on the distribution of Intent data have found that many data distributions of Intent have power law distribution characteristics, which are also called long-tailed distributions in many other fields. If the frequency of occurrence of variable x obeys:

$$f(x)=cx^{-a} \tag{4}$$

Then the variable x obeys a power law distribution. The formula for the long-tailed distribution is obtained by taking logarithms on both sides simultaneously:

$$\log f(x)=\log c+(-a)\log x \tag{5}$$

Equation (5) states that the frequency of x is distributed in a straight line in logarithmic coordinates, which can also be used to determine whether a distribution obeys a long-tailed distribution. By ranking the frequency of each English word in the article from highest to lowest, the frequency of each English word is inversely proportional to the parameter power of its ranked ordinal number; such a distribution is known as the Zipf distribution. This phenomenon is consistent with the long-tailed distribution property that most words are rarely applied and only a very few words are used frequently.

The recommendation method constrained by the long-tailed distribution points out that the user behavior data also harbors the law of long-tailed distribution, where the definitions of popularity of tourist routes and tourist activity are given first:

Definition 2: (Tourist Route Popularity) The total number of tourists who effectively choose a tourist route is the popularity of that tourist route.

Definition 3: (Tourist activity) The total number of all tourist routes effectively selected by a tourist is the activity of that tourist.

From the above two definitions, it can be seen that analyzing the data of tourists' historical choices of travel routes can obtain the popularity of travel routes and the activity of tourists. Based on the binary correlation matrix model of tourists-tourist routes, the popularity of a tourist route is the number of "1s" in the corresponding column of a route in the matrix, i.e., the total number of tourists who have validly chosen the tourist route; Tourist activity is the number of "1's" in the corresponding row of the matrix for a given tourist, i.e., the total number of tour routes effectively selected by that tourist in all history. The study shows that the popularity of tourist routes and the activity of tourists obey the power law distribution. This paper analyzes the popularity of obtaining tourist routes, draws the frequency distribution of their effective selection by tourists on logarithmic coordinates, and obtains that the popularity of randomly selected tourist routes is characterized by a long-tailed distribution.

As the frequency of tourist routes decreases, the corresponding route data distribution is more scattered, indicating that in the frequency of tourist routes appear very small, tourists choose the route of the randomness of the larger, in the figure deviates from the straight line distance is also larger; remove the edge of the very small amount of noise data, the vast majority of the data arrangement has linear characteristics, so the number of times a sufficient amount of tourist routes are effectively selected by tourists, that is, the popularity of tourist routes and power law distribution is very similar: routes popularized by the majority of tourists account for a small proportion of all tourist routes, while cold tourist routes occupy a large proportion.

III. Experimental validation and performance analysis of DAICF-based travel recommendation system

Chapter 2 completes the construction of a personalized recommendation system based on collaborative filtering of geotagged photos and deep attention interests, and achieves efficient mining of user interests through the DAICF model. In order to further verify the actual performance and generalization ability of the model, this chapter will comprehensively evaluate the effectiveness of DAICF in travel recommendation tasks through comparative experiments, ablation experiments, and system tests based on the real dataset Yelp and user behavior data.

III. A. Attraction recommendation based on similar users

According to the acquired user travel text data for LDA theme analysis, extract the user's tourism interest theme feature words, and then calculate the interest similarity between users, for easy representation, the user is numbered using USER, and some of the user interest similarity is shown in Table 1 below.

Table 1 shows the interest similarity matrix between the 15 users, with values ranging from 0 to 1. For example, the similarity between user1 and user8 is as high as 0.966, indicating that their interests are highly consistent, while the similarity between user1 and user3 and user4 is 0, indicating that the interests are completely unrelated. In addition, the similarity of some users shows a complex distribution, user11 has a similarity of 0.000 with user12, but a similarity of 0.999 with user13, reflecting the diversity and nonlinear association of user interests. This discrepancy suggests that recommender systems need to incorporate fine-grained interest modeling to avoid relying on a single similarity metric.

The user's comment data is processed and analyzed to extract the user's attribute word-emotion word pairs about the attractions, the attribute word-emotion word pairs of the attractions are subjected to emotion scoring and emotion polarity determination to obtain the user's scores of the attribute word-emotion about the attractions, the attribute word-emotion scores of the same attribute facet in the same user's comment are summed and then averaged to obtain the user's scores of the attribute facet of the attractions and the scores of each user's attribute facet of the attractions are obtained by calculation. Each user's emotional score about different attribute facets of attractions, and the emotional values of some users' attribute facets of attractions are shown in Table 2 below.

Table 1: Some users interest similarity

	user1	user2	user3	user4	user5	user6	user7	user8	user9	user10	user11	user12	user13	user14	user15
user1	1.000														
user2	0.136	1.000													
user3	0.000	0.258	1.000												
user4	0.000	0.000	0.438	1.000											
user5	0.199	0.000	0.511	0.000	1.000										
user6	0.311	0.741	0.000	0.990	0.058	1.000									
user7	0.000	0.525	0.252	0.000	0.314	0.300	1.000								
user8	0.966	0.279	0.000	0.000	0.768	0.194	0.347	1.000							
user9	0.198	0.291	0.140	0.291	0.793	0.000	0.000	0.000	1.000						
user10	0.000	0.734	0.000	0.274	0.305	0.452	0.000	0.091	0.830	1.000					
user11	0.000	0.929	0.953	0.746	0.209	0.000	0.041	0.647	0.721	0.796	1.000				
user12	0.761	0.000	0.000	0.000	0.409	0.684	0.549	0.995	0.296	0.891	0.000	1.000			
user13	0.586	0.689	0.549	0.000	0.652	0.100	0.336	0.303	0.822	0.282	0.999	0.704	1.000		
user14	0.000	0.586	0.974	0.000	0.000	0.000	0.574	0.863	0.330	0.540	0.051	0.097	0.818	1.000	
user15	0.610	0.672	0.899	0.286	0.000	0.000	0.920	0.000	0.000	0.000	0.000	0.255	0.993	0.554	1.000

Table 2: Some users attraction attribute surface emotion value

User	View	Price	Catering	Put up	Traffic	Service
user1	0.91	0.99	1.81	0.19	0	0.15
user2	0.31	1.14	0.24	0.43	1.55	-0.19
user3	1.40	0	-0.64	0.26	0.34	1.76
user4	1	1.59	0.23	1.97	0.78	0
user5	0.52	0.21	1.42	-0.18	0	1
user6	0.22	1.03	1.82	0.50	1.25	1.61
user7	0	0	1	1.49	0.44	1.79
user8	0.47	0.17	0.44	1.95	1.30	-1.32
user9	0	1.44	0.97	0.78	1.47	0.07
user10	0.15	0	1.73	-1.92	0	0
user11	-0.85	0.99	0.89	1.91	1.65	0.41
user12	1.97	0.45	1	0.38	1	-0.14
user13	-1.06	0.76	0.68	-1.78	0.56	1.04
user14	0.71	1	1.83	1.31	1	0
user15	0.18	0.62	1.21	0.76	0.25	1.89

Table 2 records the users' sentiment ratings for different attributes of the attraction such as view, price, and food and beverage. For example, user1 scored 0.91 on the "Landscape" attribute but 0 on the "Transportation" attribute, while user7 scored up to 1.79 on the "Service" attribute. Some users have extreme differences in sentiment values, such as user13 with a score of -1.06 in the "price" attribute and user14 with a score of 1.83 in the "food" attribute. These data show that there are significant differences in users' attention and emotional tendency towards attraction attributes, and it is necessary to improve the recommendation accuracy through multi-dimensional feature fusion.

The sentiment scores are then used to calculate the sentiment similarity between users regarding the attraction-attribute facets, and the sentiment similarity of some users is shown in Table 3 below.

Table 3: Emotional similarity of some users

	user1	user2	user3	user4	user5	user6	user7	user8	user9	user10	user11	user12	user13	user14	user15
user1	1.070														
user2	0.000	1.000													
user3	0.000	0.098	1.000												
user4	0.276	0.673	0.780	1.000											
user5	0.176	0.102	0.000	0.047	1.000										
user6	0.492	0.688	0.000	0.843	0.781	1.000									
user7	0.873	0.061	0.268	0.000	0.808	0.629	1.000								
user8	0.026	0.632	0.000	0.153	0.000	0.011	0.370	1.000							
user9	0.000	0.606	0.000	0.328	0.580	0.069	0.000	0.113	1.000						
user10	0.000	0.000	0.000	0.898	0.354	0.000	0.452	0.150	0.082	1.000					
user11	0.994	0.086	0.208	0.229	0.351	0.739	0.997	0.718	0.563	0.882	1.000				
user12	0.058	0.867	0.000	0.641	0.356	0.073	0.935	0.464	0.165	0.142	0.339	1.000			
user13	0.395	0.954	0.482	0.910	0.116	0.000	0.000	0.148	0.555	0.518	0.956	0.000	1.000		
user14	0.617	0.438	0.006	0.352	0.697	0.132	0.782	0.753	0.091	0.000	0.654	0.211	0.769	1.000	
user15	0.000	0.412	0.000	0.724	0.691	0.216	0.000	0.000	0.543	0.063	0.265	0.000	0.287	0.968	1.000

Table 3 calculates the emotional similarity between users based on their emotional ratings of attraction attributes. For example, the similarity between user11 and user1 is 0.994, which is almost identical, while the similarity between user15 and user1 is 0, which is completely unrelated. In addition, certain user pairs such as user4 have a similarity of 0.843 with user6, showing moderate similarity. Notably, some user pairs such as user7 have a low emotional similarity of 0.370 with user8, and their interest similarity is 0.347, suggesting that the interest and emotional dimensions are synergistically modeled to comprehensively capture user preferences.

III. B. Contrasting Experimental Designs and Baseline Model Performance Assessment

After analyzing attraction recommendations based on similar users, it becomes critical to quantify the recommendation performance of the model. In this section, we will introduce the Yelp dataset, design multi-group comparison experiments, and systematically evaluate the recommendation effectiveness of DAICF and the baseline model through accuracy and recall metrics.

III. B. 1) Data sets

This paper uses the real dataset Yelp dataset contains 30,173 users, 18,326 POIs (Points of Interest) and 862,832 travel records.

III. B. 2) Comparison algorithms

In order to validate the effectiveness of the models designed in this paper, this section selects eight models in the travel recommendation task that are classic

The classical models and the latest models in this task are used as the baseline models, and the models proposed in this study are compared and validated with the baseline models in order to assess the advantages of the models proposed in this chapter in terms of performance. These eight baseline models are described as follows:

(1) User-based collaborative filtering method DCF: This method is a user-based collaborative filtering method that uses the K-Means algorithm to discover the potential preferences of users and provide enough information for similarity metrics to improve the recommendation performance.

(2) POI2Vec: This method fully considers the distance factor between POIs, clusters nearby POIs into the same region by constructing a binary tree, and allows a POI to be assigned to multiple regions to enhance its spatial influence, which effectively captures spatial correlation.

(3) Distance2Pre: This method also takes the distance factor into account to predict the next possible POI by using the spatial distance between POIs in a user's historical check-in sequence as one of the features.

(4) DAN-SNR: This method considers the target user social relationships and uses the self-attention mechanism to model the user social relationships and sequence factors, and captures the long and short-term interests.

(5) G-DAN-SNR: This method improves the DAN-SNR model and improves the recommendation effect by introducing a self-attention mechanism that incorporates a gating mechanism.

(6) DeepMove: this method combines the gated loop unit and the attention mechanism to efficiently process sequential data and capture long-term dependencies to better understand user behavior, thus enabling the prediction of POIs that users are going to.

(7) ASGNN: This method utilizes a graph neural network to learn the hidden representations of each POI node on the user's historical check-in sequence graph, effectively capturing the relationships and contextual information between the nodes, thus improving the recommendation performance of this model.

(8) EPT-GCN: This method utilizes graph convolutional neural networks to capture richer temporal information and improve recommendation performance by dividing the user history check-in sequence by time periods.

Table 4: Precision and Recall of Top-N recommendations list

	Precision			Recall		
	Precision@5	Precision@10	Precision@15	Recall@5	Recall@10	Recall@15
DCF	5.16	4.69	3.15	3.69	5.42	12.20
POI2Vec	10.78	9.79	8.15	12.27	13.17	15.91
Distence2Pre	12.37	9.13	7.69	13.86	13.27	16.05
DAN-SNR	14.76	11.49	8.28	20.59	21.28	25.89
G-DAN-SAR	15.20	11.94	8.94	20.73	23.03	26.31
DeepMove	18.34	13.47	10.60	21.26	24.77	26.84
ASGNN	17.71	14.48	11.45	24.23	26.73	27.01
ETP-GCN	18.24	14.17	13.91	25.58	27.04	33.98
DAICF	20.13	16.35	13.81	27.77	29.47	35.26

III. B. 3) Evaluation indicators

The evaluation metrics used in this section are accuracy (P) and recall (Re), which are two widely used evaluation metrics in POI recommendation tasks, and the performance of the model is evaluated by the results of these two metrics, which are usually evaluated by utilizing different values of N in the top-N. Recall indicates the ratio between the number of successfully predicted POIs and the total number of POIs to be predicted, taking N in the top-N list of predictions as 5, 10, and 15.Accuracy indicates the percentage of the number of successfully predicted POIs out of the total number of recommended results, again, taking N in the top-N list of predictions as 5, 10, and 15.

III. B. 4) Comparative Experimental Results and Analysis

This section compares the article's proposed Deep Attention Interest Based Collaborative Filtering DAICF model with eight baseline models on the Yelp dataset. Table 4 demonstrates the accuracy and recall of Top-N recommendation lists on the Yelp dataset. In order to show the performance comparison among the models more clearly, line and bar graphs of the accuracy and recall of Top-N recommendation lists on the Yelp dataset are plotted as shown in Figure 3. Where the bar represents the accuracy rate of each model and the line represents the recall rate of each model.

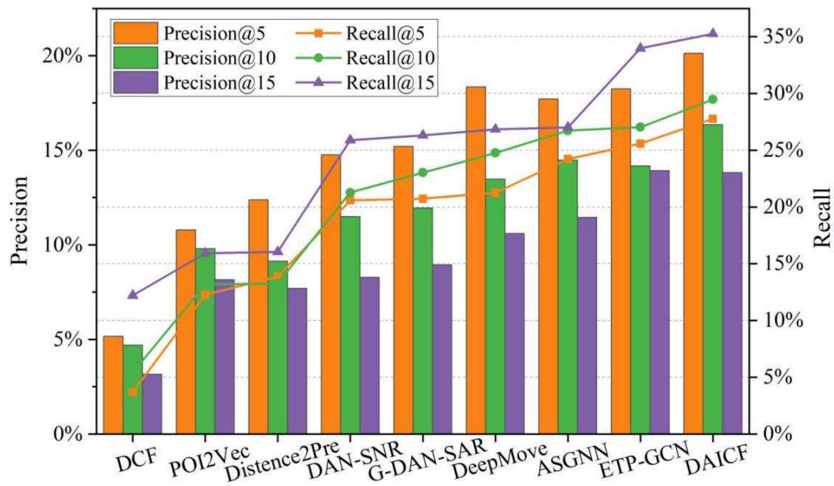

Figure 3: Precision and Recall of Top-N recommendations list

Table 4 compares the Top-N recommendation performance of DAICF with 8 baseline models on the Yelp dataset. The accuracy rate of DAICF is 20.13% and the recall rate is 27.77% when the recommended number is 5. When the number of recommendations is 15, the accuracy rate is 13.81%, and the recall rate is 35.26%, and its indicators are leading. For example, its Precision@5 increased by 10.4% from the second place EPT-GCN of 18.24%, and Recall@15 increased by 30.6% from ASGNN's 27.01%. This result verifies the design advantages of DAICF by fusing shallow linear interaction and deep nonlinear interaction. In addition, the performance of traditional models such as DCF and POI2Vec lags behind significantly, highlighting the necessity of deep learning methods in complex tourism recommendation scenarios.

Table 5: Experimental result of diagram on Yelp dataset

	Precision			Recall		
	Precision@5	Precision@10	Precision@15	Recall@5	Recall@10	Recall@15
Model-n DGAT	20.91	17.68	13.09	26.13	30.03	34.99
Model-n Time	17.88	15.81	12.07	24.03	26.19	33.29
Model-n User_sp	15.05	12.49	8.08	20.75	24.54	31.11
Model-n2h	19.15	16.38	13.31	25.81	29.09	35.08
Model-n Cg	18.91	15.85	12.82	24.51	27.48	33.41
DAICF	20.13	16.35	13.81	27.77	29.47	35.26

III. C. Ablation experiment results and analysis

Comparison experiments verify the overall performance advantages of DAICF, but the contributions of components inside the model still need to be further dissected. In this section, key components of DAICF such as social relations and timestamps are removed one by one through ablation experiments to analyze their impact on recommendation performance and reveal the necessity of multi-module co-design.

In this section, ablation experiments are conducted on each component of the model and the performance of each component is analyzed by removing one component of the model respectively to form five variants, namely Model-nDGAT, Model-nTime, Model-nUser_sp, Model-n2h, and Model-nCg. where Model-nDGAT denotes the removal of the variant of the DGAT de-dimensionalization component, Model-nTime denotes the variant of the de-dimensionalization of the user timestamp component, Model-nUser_sp denotes the variant of the de-dimensionalization of the buddy-user co-check-in component, Model-n2h denotes the variant of the de-dimensionalization of the updating of the POI component in the second isomorphic graph, and Model-nCg denotes the variant of the de-dimensionalization of the category component.Yelp The results of the ablation experiments on the dataset are shown in Table 5 and Figure 4.

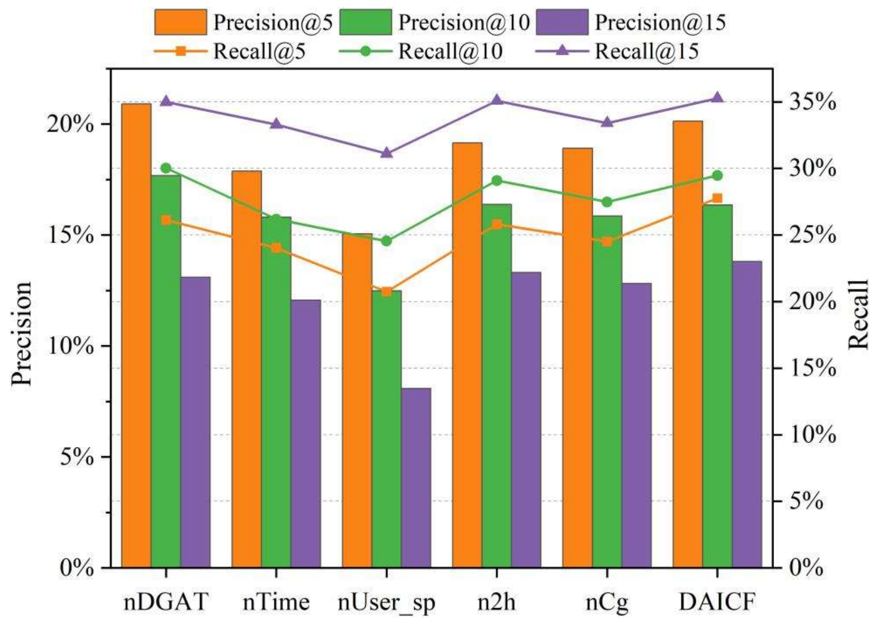

Figure 4: Experimental result of diagram on Yelp dataset

Ablation experiments on the Yelp dataset demonstrated the effectiveness and necessity of the components in the model designed in this study. The removal of the "Friend User Sign-in" component (Model-nUser_sp) resulted in a sharp drop in Precision@5 of 15.05% and a recall rate of about 7 percentage points, indicating that social relationships are the core of user interest modeling. After removing the "Timestamp" component (Model-nTime), the Precision@10 decreased from 16.35% to 15.81%, indicating that the time context has a significant impact on the recommendation performance. In addition, the removal of the "POI Category" component (Model-nCg) reduced the Recall@15 by 1.85%, indicating that the category information can effectively improve the coverage of long-tail recommendations. The analysis of the ablation experiment is described below:

(1) Effectiveness of buddy-user co-check-ins

The experiments show that using the POI of buddy-user co-check-in to strengthen the social relationships of modeled users is necessary and plays the largest role among all the components of the ablation experiments described above. This component can better tap into the user's interests, suggesting that portraying the user's own portrait is important for the model's recommendation performance.

(2) Modeling the effectiveness of user timestamps

From the above experimental results, it can be seen that the performance of the variants of Model-nTime with user timestamps removed are all lagging behind, indicating that access to POIs is strongly time-bound. In general, users refer to the current timestamp as an important consideration when choosing to go to the next POI.

(3) Effectiveness of Considering POI Categories

Considering POI category can significantly improve the model performance, this is because in practical scenarios, when users choose to go to the next POI, they often can not decide the specific POI immediately, but determine the category first, and then choose the specific POI from the category according to other constraints. Considering POI category is more in line with the breadth of the user's choice, and has universal applicability.

(4) Effectiveness of constructing the second kind of user-POI heterogeneous map

From the results, it can be seen that the learning of advanced POI representations on the second kind of user-POI heterogeneous graph is necessary and helps to improve the performance of the model, however, it does not improve much compared to the other components mentioned before. The reason may be that the advanced learned POI representation does capture the spatio-temporal relationship of neighboring POIs in the user's historical check-in sequence, which improves the model performance, but because the secondary modeling of POIs improves the model complexity, the magnitude of performance improvement is relatively small.

(5) Effectiveness on GAT Dimensionalization

From the experimental results, it can be seen that DGAT can improve the model performance compared to the traditional GAT, but the improvement is not obvious. The reason may be that dimensionalizing the traditional GAT on the attention mechanism improves the complexity of the model and increases the overhead. But overall the model performance is improved compared to traditional GAT.

III. D. Testing and validation of DAICF-based personalized recommendation system for smart tourism

On the basis of theoretical validation, this chapter further starts from practical application scenarios, designing travel route test experiments based on real user tips, and verifying the practicality and optimization effect of DAICF recommender system in itinerary planning through the comparison of time-to-moment ratio and other indexes.

III. D. 1) Experimental design

100 users' travel tips about a city within a city are collected through the popular review website, which constitutes the dataset S. Then the attraction information in it is extracted for the multi-dimension based attraction rating calculation. The final specific experimental steps are as follows.

Step 1: The itinerary of each travel guide is extracted, including the date of the trip, the total time of the trip, the time of the attraction tour, and the total distance between attractions (total distance of the trip).

Step 2: For the attractions extracted from each travel guide, calculate the recommended scores of the attractions based on the multidimensional attraction scores.

Step 3: For each travel guide, after obtaining the set of attractions with recommended scores, use the smart tourism personalized recommendation algorithm based on deep attention collaborative filtering constructed in this paper to carry out travel thread planning.

Step 4: For each travel guide, after obtaining the travel itinerary calculated according to the DAICF itinerary planning algorithm, calculate the attraction playing time of the itinerary, and the total distance between attractions (total distance of the itinerary), respectively.

Step 5: For the travel itinerary recommended by the system and the travel itinerary in the original travel guide, calculate its time efficiency (time/travel, i.e., play time divided by the total distance spent between attractions, the higher the time efficiency ratio, the better it represents the route), respectively.

III. D. 2) Experimental results and analysis

Table 6 shows the travel routes under the original travel guide and this paper's smart travel recommendation system.

Table 6: Travel routes of the original and smart travel recommendation system

Tour Itinerary (days)		1	2	3	4	5	Total
Original travel guide	Distance between scenic spots/km	8.08	48.75	35.54	26.11	10.08	128.56
	Sightseeing time/h	8.4	11.3	7.4	6.2	4.3	37.60
	Aging ratio	1.04	0.23	0.21	0.24	0.43	0.43
Travel routes under the smart travel recommendation system	Distance between scenic spots/km	3.85	23.82	16.51	10.48	6.41	61.07
	Sightseeing time/h	4.6	9.5	7	5.9	3.1	30.10
	Aging ratio	1.19	0.40	0.42	0.56	0.48	0.61

Table 6 compares the differences between the original travel strategy and the travel routes generated based on the DAICF recommendation system in terms of travel distance, tour time and time-to-time ratio. The total distance of the original route is 128.56 kilometers, the total tour time is 37.6 hours, and the time-to-time ratio is 0.43; while the total distance of the recommended route is significantly reduced to 61.07 kilometers, a decrease of 52.5%, the total tour time is reduced to 30.1 hours, a decrease of 20.0%, and the time-to-time ratio is improved to 0.61, an increase of 41.9%. Specifically for daily trips, the recommender system's routes are significantly optimized in terms of distance between attractions, such as from 8.08 kilometers to 3.85 kilometers on day 1, and tour time, such as from 11.3 hours to 9.5 hours on day 2, and the time-to-time ratio is higher than that of the original routes on each day, for example, from 0.24 to 0.56 on day 4. These data show that the DAICF recommender system, through intelligent planning, has effectively reduced redundant travel time and improves the tour efficiency, which verifies its practical application value in personalized tourism route optimization.

IV. Conclusion

The DAICF model proposed in this study effectively solves the problem of sparsity and cold start in travel recommendation by fusing geotagging data and deep attention mechanism. Experiments show that the recommendation performance of DAICF on the Yelp dataset is significantly better than that of the existing baseline model, with its Precision@5 and Recall@15 reaching 20.13% and 35.26%, respectively. The ablation experiment further verified the core effects of social relationship (Precision@5 plummeted to 15.05% after removal) and temporal context (Precision@10 decreased to 15.81% after removal) on the model. In the actual scenario test, the optimization effect of the tourism route generated by DAICF is significant: the total travel distance is shortened to 61.07 km, a decrease of 52.5%, and the timeliness ratio is increased to 0.61, an increase of 41.9%, which proves its practical value in improving the tourist experience and itinerary efficiency.

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