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Global Multi-Source Information Fusion Management and Deep Learning Optimization for Tourism:
Personalized Location-Based Service

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ABSTRACT

The purpose is to solve the problems of sparse data information, low recommendation precision and recall rate, and cold start of the current tourism personalized recommendation system. First, a context-based personalized recommendation model (CPRM) is established by using the labeled-LDA (labeled latent Dirichlet allocation) algorithm. The precision and recall of interest point recommendation are improved by mining the context information in unstructured text. Then, the interest point recommendation framework based on convolutional neural network (IPRC) is established. The semantic and emotional information in the comment text is extracted to identify user preferences, and the score of interest points in the target location is predicted combined with the influence factors of geographical location. Finally, real datasets are adopted to evaluate the recommendation precision and recall of the above two models and their performance of solving the cold start problem.

KEYWORDS

Deep Learning, Information Fusion Management, Location-Based Services, Recommendation System

INTRODUCTION

People's material life has been satisfied with the progress and development of society. However, the overall rhythm of life and work becomes increasingly faster, followed by the pressure from all aspects (Chen, 2019). Excessive social pressure will seriously affect people's mental health and work efficiency. Hence, people will be eager to meet the needs of spiritual life after work (Bussing et al., 2018). As one of the preferred ways of relaxation and entertainment, tourism has also entered a high-speed development stage with the development of China's economy and the improvement of people's quality of life (Yan et al., 2019). Everyone can get unlimited information in the digital age. Before traveling, people often spend a lot of time looking for information of tourist attractions they are interested in in in various search engines. At present, mobile positioning technology (MPT), global positioning system (GPS), geographic information system (GIS) and Internet technology (IT) have been popularized all over the world (Yuan et al., 2020). Location based services (LBS) is a value-added service based on the user's location. It is mainly use to obtain user's location information through a mobile communication network or GPS, providing users with location-related information services

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with the support of an electronic map and business platform (Huang et al., 2018). For example, the introduction, photos, location information and evaluation of various tourist attractions around the world can be queried on the network. The best traffic path can be directly generated by one click of the navigation system, so that people can have a panoramic view of the hotels and restaurants around the scenic spot, which greatly saves time and allows people to fully enjoy the beautiful experience brought by tourism. Thereby, people increasingly hope that they can obtain personalized information and services with the help of the above technologies in the process of tourism and customize a personal exclusive tourism strategy (Renjith et al., 2020). For example, they can recommend personal preferred scenic spots, travel routes, hotels and restaurants according to the location information of the selected destination.

In recent years, the amount of multi-source heterogeneous data is increasingly exponential with the increase of the Internet scale. However, the research on personalized LBS for tourism lags behind, accompanied by the low quality of LBS and the overload of tourism information (Du et al., 2019). This requires a sufficiently intelligent search engine to collect user needs according to historical information and relevant information should be found from unlimited information. Multi-source information fusion technology can integrate and process multi-source information, make different data information complementary, and obtain a deeper understanding of the same goal. Recommendation system based on multi-source information fusion technology has attracted an increasing attention of researchers. The recommendation system mainly helps to understand users' interests and preferences through the analysis of users' historical behavior information, predict users' preference index for specific items and provides a personalized recommendation list, without users' accurate description of their needs (Cui et al., 2020). However, tourists only sign in at a few points of interest, resulting in sparse data information; when a new user joins the recommendation system, the system cannot extract its historical information, resulting in the cold start of the user (Tahmasebi et al., 2021). The above problems make the tourism personalized recommendation system face more serious problems such as data sparsity and user cold start than other recommendation fields. Deep learning is a crucial technology to solve the needs of personalized recommendations (Sharma et al., 2021). It can extract the complex relationship among data from multi-source information and more accurately express user preferences. A recommendation system based on deep learning has attracted much attention in recent years (Wang, 2020).

Unger et al. (2016) used unsupervised deep learning technology and principal component analysis (PCA) technology to automatically learn the user's potential context data collected from the user's mobile phone. The data extracted from high-dimensional sensors were integrated into a new potential context-aware recommendation algorithm, which improves the recommendation precision by 20% (Unger et al., 2016). Tourism personalized LBS can be divided into tour route recommendation and interest point recommendation (Zhang et al., 2017). Based on the recommendation of interest points, the research on global multi-source information fusion management and deep learning optimization for tourism personalized LBS is conducted. First, the context based personalized recommendation model (CPRM) and the interest point recommendation framework based on convolutional neural network (CNN) are established with the Labeled-LDA (Labeled Latent Dirichlet Allocation) algorithm. The purpose of this exploration is to provide crucial technical support for solving the challenges and problems encountered in the application of tourism personalized LBS in reality.

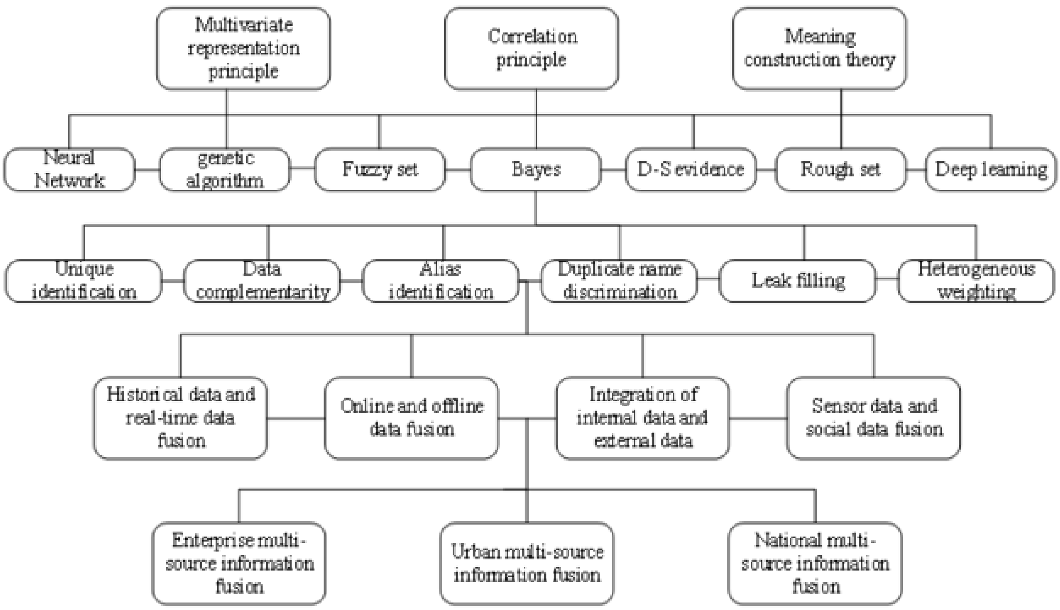
METHODS OF MODEL CONSTRUCTION AND EVALUATION

Key Technology Analysis

(1)Multi-source information fusion technology

Multi-source information fusion technology is widely used in the military in the early stage. At present, its application scope has been extended to the fields of sensors, geospatial, intelligence analysis and recommendation systems (Wang & Chen, 2021). Multi-source information fusion is an information processing technology that automatically processes the data from multiple information sources in some effective ways and transforms data into a support for human decision-making. It is generated from different channels and presented in various forms (text, image, audio, and numerical value), and it is a process of data fusion describing the same subject (Zhou et al., 2019; Ma & Bennett, 2021). There are multiple multi-source information fusion methods, which can be classified according to three criteria: information fusion processing hierarchy, structural model and fusion information type. Figure 1 displays its specific classification.

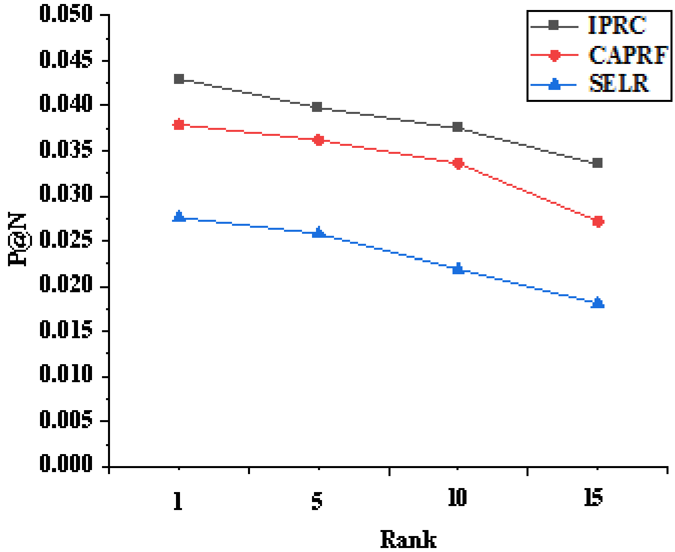
Figure 1. Classification of multi-source information fusion methods



Academic circles have studied the methods and technologies related to multi-source data fusion. Wang et al. (2018) proposed an information fusion method based on the Baire function. The similarity evaluation model based on the Baire function was introduced to improve the consistency between the basic probability distribution and the real probability, and a new digital signal modulation recognition scheme based on information fusion was proposed. Experiments show that the model has excellent recognition performance (Wang et al., 2018; Niu et al., 2021). Ye et al. (2019) proposed a new information fusion method that can make full use of various prediction information and improve prediction performance, and applied it to oil price prediction fusion. The experimental results show that this method does not need training data, with little restriction on the source data and without complex calculation, and it shows stable and good performance, and provides a solution to the combinatorial problem (Ye et al., 2019; Lv & Wu, 2021). Figure 2 presents the theoretical system of multi-source information fusion.

(2) Labeled-LDA model

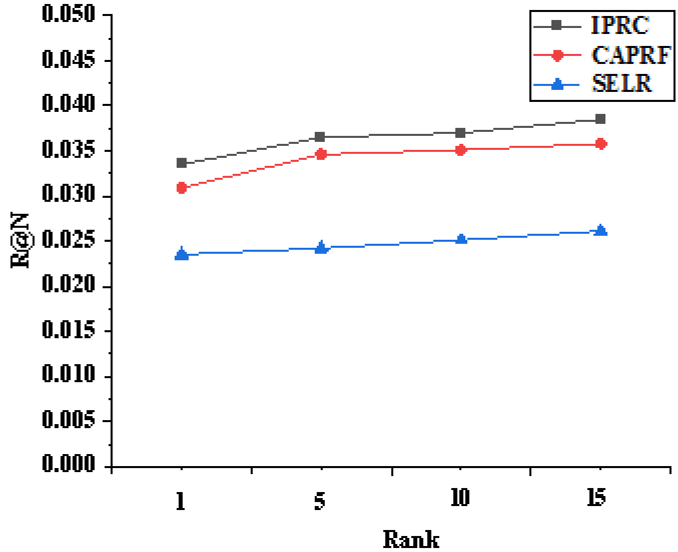
Figure 2. Theoretical system of multi-source information fusion



The Latent Dirichlet Allocation (LDA) is an unsupervised topic model for feature extraction of ordinary text (Jelodar et al., 2019; Lv et al., 2021a;). However, in practical application, each document corresponds to some other content, such as tags comments and scores in the document. Hence, when text features are extracted, the LDA model has some problems, such as unclear subject recognition, and its use has certain limitations. The Labeled-LDA model is a supervised topic model, which is mainly used to model labelled documents to make up for the defects of the LDA model (Wang et al., 2021; Lv et al., 2021b). Figure 3 displays the basic flow of text feature extraction based on Labelled-LDA model.

Figure 3 shows that the first step of extracting text features is to use data mining to obtain text data in the Internet. Data mining refers to the process of searching hidden information from massive data through algorithms (Liu & Chen, 2021; Lv et al., 2020). After the initial data are pre-processed, the unstructured text is transformed into structured text. Meanwhile, the combination of supervised and unsupervised learning is adopted to calculate and extract the similarity of text feature values, so as to obtain the optimal text feature extraction. The Labelled-LDA model has been applied to social networks, recommendation systems and other fields, which has brought more convenience to people's life. To solve the problem that it is difficult to find the interests of ordinary users with fewer posts in social networks, He et al. (2020) proposed a double Labelled-LDA probabilistic topic model. The model was to simulate the social relationship between well-known users and non-well-known users, and infer the interest tags of non-well-known users from the interest topics of well-known users. Real datasets were used to test the performance of the model. The results show that the performance of the model is better than the most advanced method (He et al., 2020; Yi, 2021, Yu et al., 2021). In order to more effectively solve health-related queries, Youneng and Xiuli (2020) proposed an online medical expert recommendation model based on Labelled-LDA, which mainly uses the Labelled-LDA model to identify potential topics of online health problems and match them with doctors' specialties. Experiments show that this method has high recommendation precision, recall rate and corresponding adoption rate.

Figure 3. Basic flow chart of text feature extraction

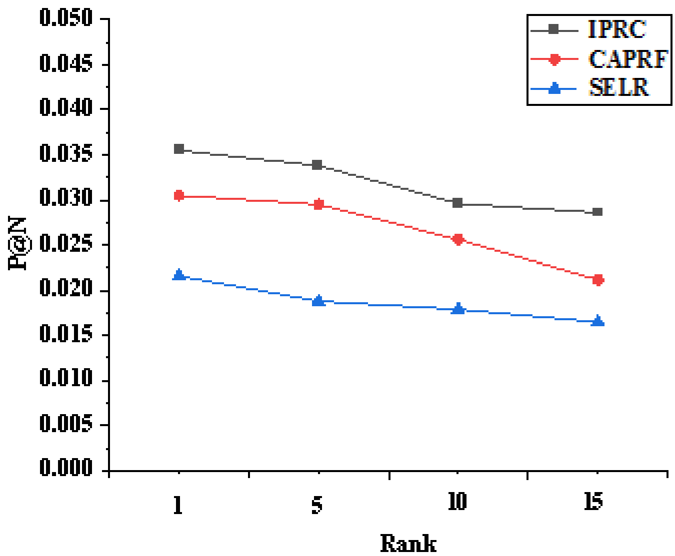


(3)Convolutional neural network (CNN)

CNN is one of the popular neural networks and a typical differentiated depth structure based on minimizing the requirements of pre-processing data. It is one of the representative algorithms of deep learning and is mainly used in research fields such as computer vision and natural language processing (Dhillon &Verma, 2020). CNN is mainly inspired by the human visual structure and can carry out supervised learning and unsupervised learning. The sharing of convolutional kernel parameters in the hidden layer and the sparsity of inter-layer connections enable CNN to characterize grid-like topology with less computation (Pires de Lima & Marfurt, 2020). CNN's representational learning ability enables it to learn the effective internal representation of data, and optimize the model structure and parameters. At present, there are relatively mature research results on CNN. Sun et al. (2019) proposed a new method to solve the problem of image classification by using the genetic algorithm to evolve the structure and connection weight initialization value of deep CNN. A new representation method was also proposed to effectively initialize the connection weights of the deep CNN to avoid the network falling into a local minimum. The experimental results show that the algorithm is superior to the existing design in terms of classification error rate and parameter number (weight) (Sun et al., 2019). To solve the problem that the recommendation system based on collaborative filtering is vulnerable to shilling attack, Tong et al. (2018) proposed a CNN - shilling attack detector (CNN-SAD) method. This method uses the transformed network structure to mine deep features from user rating files. Unlike the manually designed function, its deep function can describe the user rating more accurately and detect the shilling attack more effectively. Experimental results show that this method can accurately detect most fuzzy attacks, and its performance is better than other methods (Tong et al., 2018; Liu et al., 2021). Typical CNN mainly includes three parts: convolutional layer, pooling layer and fully connected layer. Figure 4 displays its architecture.

In CNN architecture, the convolutional layer is mainly responsible for extracting data features, and the pooling layer is responsible for reducing the parameter magnitude. Finally, the underlying

Figure 4. Typical CNN architecture



parameters are mapped to a new space in the fully connected layer, so as to collect parameters and further calculate the sample score, thus the feature information of data can be obtained quickly, effectively and accurately.

Construction of Personalized Recommendation Model Based on Context Information Fusion

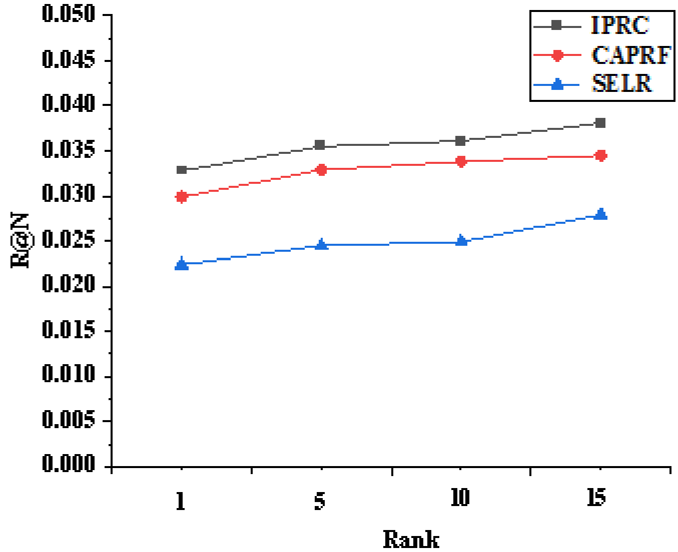
CPRM is designed to mine context data from unstructured text comment information. It is applied to the recommendation system according to the evaluation context information of tourists' points of interest. This model includes three modules: context reasoning module, grade prediction module and utility function calculation module. The role of context reasoning in the model is a classifier. After training, the user's current context can be inferred according to the given information; grade prediction can be any prediction algorithm for predicting project grade; finally, based on the data information provided by the first two modules, the utility value of the utility function is calculated and sorted, and the recommendation is given according to its order. The three modules will be described and analysed in detail below.

(1) Context reasoning module

LDA algorithm mainly regards the text information as the word probability distribution in the title, and generates a new document based on the determination of the title distribution θ_d. θ_d determines the choice of each word in the document title x. φ_x is set as the polynomial distribution of words in title x. A word is selected to add to the document according to the distribution. Figure 5 presents a description of LDA.

In Figure 5, the rectangle represents repeated execution; M means M document; N represents the process of instantiating words in N document.

Figure 5. LDA Algorithm diagram



LDA model assumes that title hybrid θ is a k-dimensional random variable, which can be expressed as:

$$Y\left(,_{d}(\pm)\right) = \frac{``\left(\sum_{i=1}^{k} \pm_{i}\right)}{\prod_{i=1}^{k} ``\left(\pm_{i}\right)} ,_{1}^{\pm_{1}-1} \cdots ,_{k}^{\pm_{k}-1} \tag{1}$$

α: k-dimensional vector with element $\alpha_i > 0$; Γ(x): γ function.

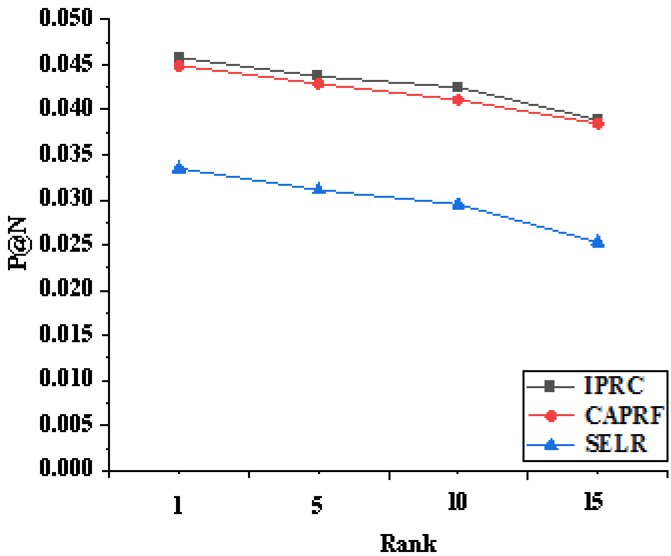
Labelled-LDA modelling is similar to LDA, with k unique tags in the document. In each document, Λ is a k-dimensional binary vector, indicating whether each title appears or does not appear in the document tag set. In the case of a priori probability vector σ, Λ is generated by the Bernoulli experiment. Figure 6 is a description of Labelled-LDA.

(2)Grade prediction module

Equation (2) is the context calculation of prediction:

$$A\left(j,\ i\right) = \frac{\sum_{k \in N(i)} A_{j}^{i} \cdot B\left(k,\ i\right)}{\sum_{k \in N(i)} \left|B\left(k,\ i\right)\right|} \tag{2}$$

Figure 6. Illustration of Labelled-LDA algorithm



A_j^k : the k-th adjacent context related to user j; B(i, μ) can be obtained from the following equation (3):

$$B\left(i,¼\right) = \frac{\sum_j L\left(i,\ ¼\right)}{\sqrt{\sum_j \left|l\left(i\right)\right| \times \left|l\left(¼\right)\right|}} \tag{3}$$

L (i, μ) is the number of times the user assigns the same type to i and μ, and l (i) is the number of times of all user types given i. Through this calculation, the project i biological adjacent project can be obtained.

2) User j calculates the context value of item i

Equation (4) is the context value calculation equation of user j for item i:

$$B\left(j,\ i\right) = \frac{IA_J.PA_j^i}{IA_J PA_j^i} \tag{4}$$

IA_j: derivation context of user j; PA_j^i : it describes the prediction context.

(3)Utility function calculation

Equation (5) is the calculation of prediction grade value:

$$u\left(i,\ ¼\right) = \pm A\left(j,\ i\right) + \left(1 - \pm\right) B\left(j,\ i\right) \tag{5}$$

α is the weight of the prediction grade.

Construction of Interest Point Recommendation Model Based on CNN

It is set that $A=\{a_1, a_2, \cdots\cdots, a_n\}$ is the user, $B=\{b_1, b_2, \cdots\cdots, b_m\}$ is the point of interest, and $C=\{c_1, c_2, \cdots\cdots, c_o\}$ is the comment text set. n, m and o represent the number of the three. D represents the user - interest sign in matrix, and D_{ij} represents the frequency and score of user u_i sign-in at l_j.

(1)User emotion category modelking

The emotional categories in the comment text are divided into three categories: -1 for dislike, 0 for neutrality and 1 for like. A function is adopted to reconstruct emotion category $\hat{I}$, as shown in equation (6):

$$\hat{I} = I + \hat{A}^{*}P,\ \ \cdot \epsilon \left[0, 1\right] \tag{6}$$

ς: Scalar, controlling user emotion weight; I: $I \epsilon R^{m \times n}$, check-in matrix; S: emotion score, $S \epsilon \left(-1, 1\right)$.

(2)User preference and interest point attribute modelling

CNN can use the pre-trained word embedding model to more deeply understand the location interest point comment text content.

$$P\left(f_{is} = 1(u_i,\ c_s\right) = \frac{\exp\left(u_i^T \cdot E \cdot CNN\left(W,\ C_s\right)\right)}{\sum_{C_{k \epsilon C}} \exp\left(u_i^T \cdot E \cdot CNN\left(W,\ C_s\right)\right)} \tag{7}$$

C_s: comment text set; c_s: user comments; f_{is}: whether the comment c_s is published by the user u_i; W: weight; C: comment on the interaction matrix between text content features and user potential features.

To extract the user's potential feature vector u_i, the probability function in equation (7) is converted into the objective function in equation (8), so as to obtain the user's potential feature vector:

$$\sum_{i=1}^{n} \sum_{c_{k \epsilon C_{u_i}}} \log P\left(f_{ik} = 1(u_i,\ c_k\right) \tag{8}$$

Similarly, the probability of comment c_p related to location l_j is defined as:

$$P\left(h_{jp} = 1(l_j,\ c_p\right) = \frac{\exp\left(l_j^T \cdot P \cdot CNN\left(W,\ C_p\right)\right)}{\sum_{C_{k\epsilon C}} \exp\left(l_j^T \cdot P \cdot CNN\left(W,\ C_k\right)\right)} \tag{9}$$

h_{jp}: whether comment c_p is associated with location l_j; P: the interaction matrix between comment content features and potential features of location interest points.

The probability function in equation (8) is converted into the objective function in equation (10), so as to obtain the position potential feature vector:

$$\sum_{j=1}^{m}\sum_{c_{k\epsilon C_{l_j}}} \log P\left(h_{jk} = 1(l_j,\ c_k\right) \tag{10}$$

(3)Geographic information modelling

The minimization problem of the objective function can be expressed as the following equation:

$$\min_{U,\ L} \frac{1}{2}\left(I \odot \left(R - UHL^T\right)^2\right) \tag{11}$$

$$H = {}^2\, UL^T + \left(1 - {}^2\right)G^T,\ \ G\epsilon R^{n \times n},\ \ G_{j,\ k} = \frac{sim\left(l_j,\ l_k\right)}{Z\left(l_j\right)} \tag{12}$$

B: the weight to control the influence of adjacent positions; sim(l_j, l_k): geographical weight of location l_j and adjacent location l_k; Z(l_j) is defined as:

$$Z\left(lj\right) = \sum_{l_k \epsilon E\left(l_j\right)} sim\left(l_j,\ l_k\right) \tag{13}$$

Sim(l_j, l_k) adopts Gaussian function, as shown in equation (14):

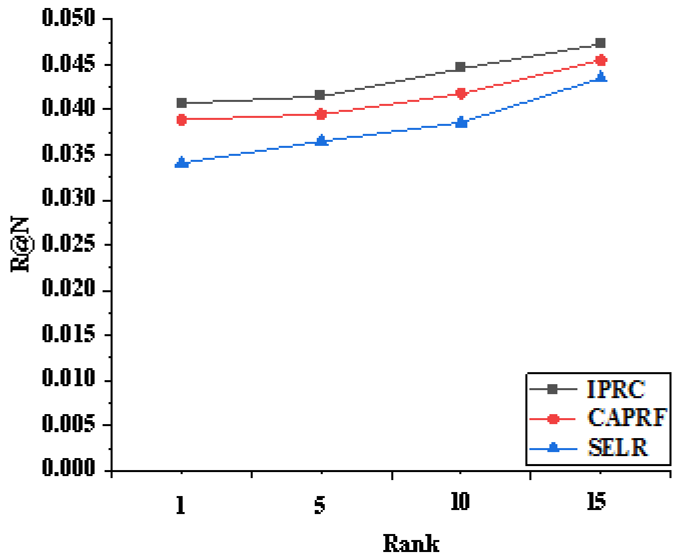
$$sim\left(l_j,\ l_k\right) = e^{\frac{l_j - l_k{}^2}{{}^2{}^2}},\ \ \forall l_k \epsilon E\left(l_j\right) \tag{14}$$

E(l_j) indicates the adjacent position of l_j.

(4)Interest point recommendation model based on CNN

Figure 7 shows the interest point recommendation model based on CNN.

Figure 7. Interest point recommendation model based on CNN



In Figure 7, S, U and L respectively represent user emotion classification factor, potential factor and interest point potential factor, which are all learned from CNN. R is the check-in behaviour, and H is the influencing factor of geographical location.

Analysis of Experimental Methods

(1)Experimental dataset

The mobile service website Foursquare based on users' geographical location information is selected as the data source to mine implicit context data from tourists' comments on points of interest, and the check-in records and comment text information of Chicago and San Francisco are collected as a dataset. Three kinds of data are collected: users, points of interest and comment information. Table 1 displays the specific statistical data of the two cities.

Table 1. Statistical data of the experimental dataset

City	Number of users	Number of points of interest	Number of comments
Chicago	50215	70169	201598
San Francisco	62589	89657	345896

(2)Experimental setup

1) CPRM Performance Verification

Tourists' comments on points of interest usually mention contextual clues such as whether the location of scenic spots is easy to find, the grade and type of scenic spots, and whether the ticket price is reasonable. These contents are of great significance to the recommendation system (Hassannia et al., 2019). Relevant data information is extracted from the dataset to build B dataset. Each comment text in this dataset contains a global level value, a comment text and 7 attribute types (scenic spot location, scenic spot level, tourist score, playing time, ticket price, scenic spot type and suitable playing season). Finally, the most commonly used data mining classification algorithm, the project-based standard kNN (K Nearest Neighbors) algorithm (Huang et al., 2019), is selected to compare the recommendation hit rate with the recommendation model designed in the same running environment.

2) Evaluation of interest point recommendation framework based on CNN

Precision and recall will be adopted to evaluate the performance of the point of interest recommendation framework. The two are replaced by P@N and R@N, separately. Equation (15) and equation (16) are the definitions.

$$\mathrm{P@N} = \frac{\mathrm{A}}{\mathrm{B}} \tag{15}$$

$$\mathrm{R@N} = \frac{\mathrm{A}}{\mathrm{C}} \tag{16}$$

A: the number of locations where users sign-in in the recommendation list; B: recommended list length.

Finally, two mainstream interest point recommendation methods, SELR (Sentiment Enhanced Personalized Location Recommendation) algorithm and CAPRF (Feedforward classification network pattern recognition) algorithm, are selected to compare with the IPRC designed in terms of performance, the recommendation accuracy and recall in the face of cold start under the same conditions (Tang & Zeng, 2021; Sharif et al., 2020).

RESULTS OF MODEL EVALUATION

Experimental Results of CPRM Performance Verification

CPRM algorithm and kNN algorithm run on Chicago dataset and San Francisco dataset respectively. Figure 8 and Figure 9 show the hit rates of the two under different numbers of recommended items.

The above figures reveal that the recommended hit rate of CPRM and kNN algorithms shows an upward trend, indicating that the hit rate of the two algorithms increases with the increase of the number of recommended items. When running on the Chicago dataset, the hit rate of the kNN algorithm increases from 0.051 to 0.481; CPRM hit rate increases from 0.053 to 0.585. When running on the San Francisco dataset, the hit rate of the kNN algorithm increases from 0.045 to 0.469, and the hit rate of CPRM increases from 0.049 to 0.542. It suggests that when the number of recommended items is the same, the recommended hit rate of CPRM is significantly higher than that of the kNN algorithm, and has better performance.

To sum up, the designed CPRM can provide a more accurate point of interest recommendation method by mining the context information in unstructured text, which can greatly improve the level of tourism personalized LBS and bring convenience to people.

Figure 8. Comparison of recommended hit rate between kNN and CPRM algorithms based on Chicago dataset

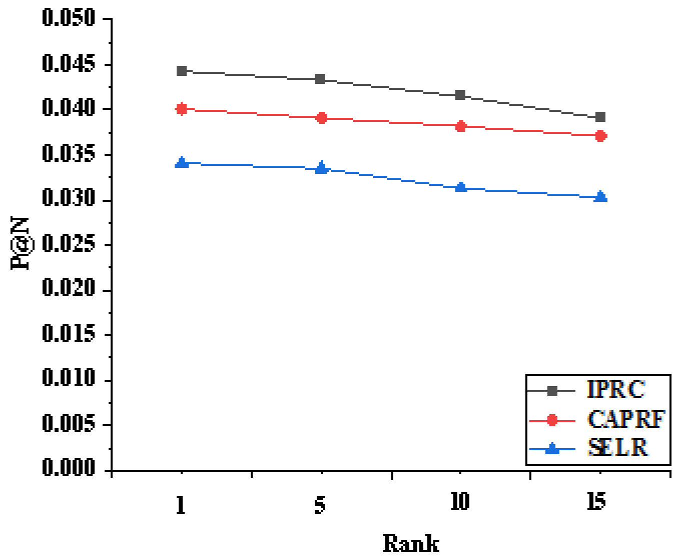


Figure 9. Comparison of recommended hit rate between KNN and CPRM algorithms based on San Francisco dataset

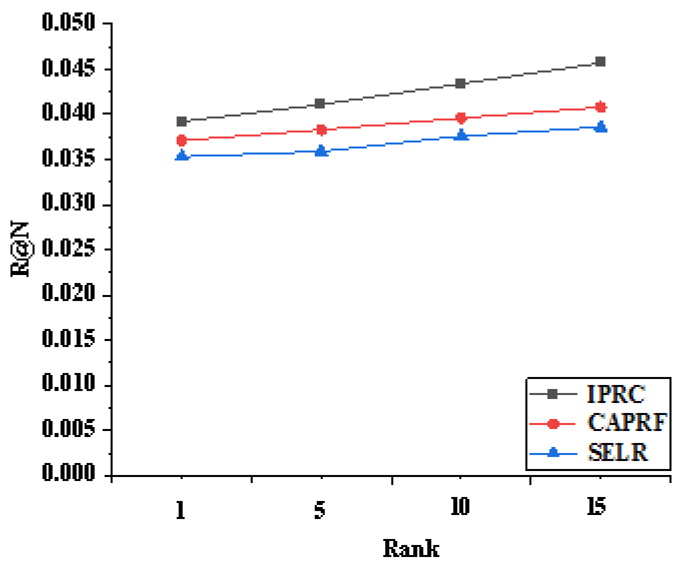


Figure 10a. Experimental performance comparison based on Chicago dataset

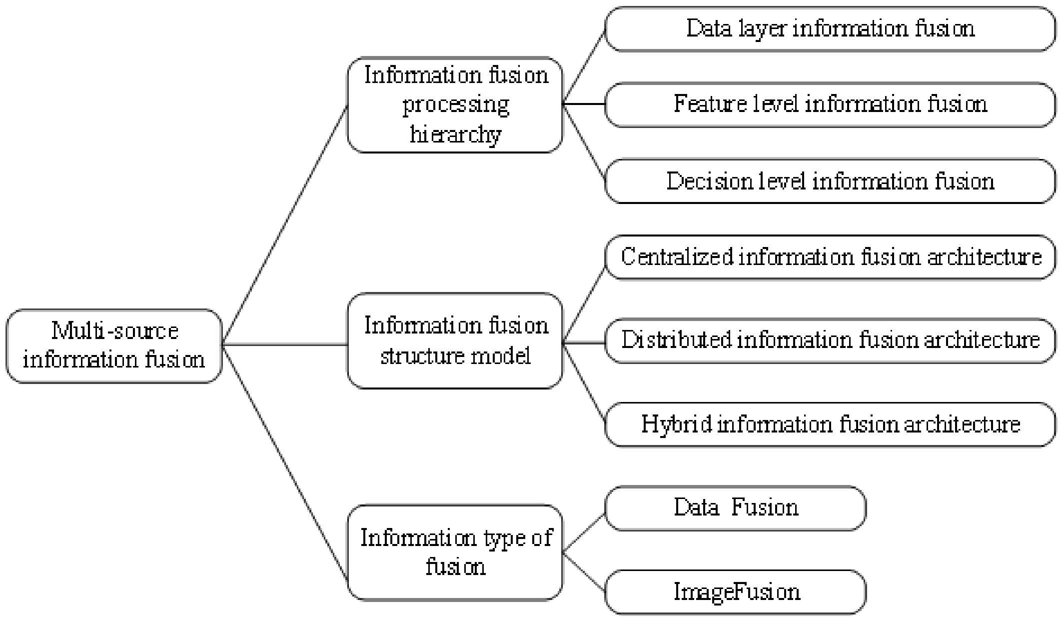
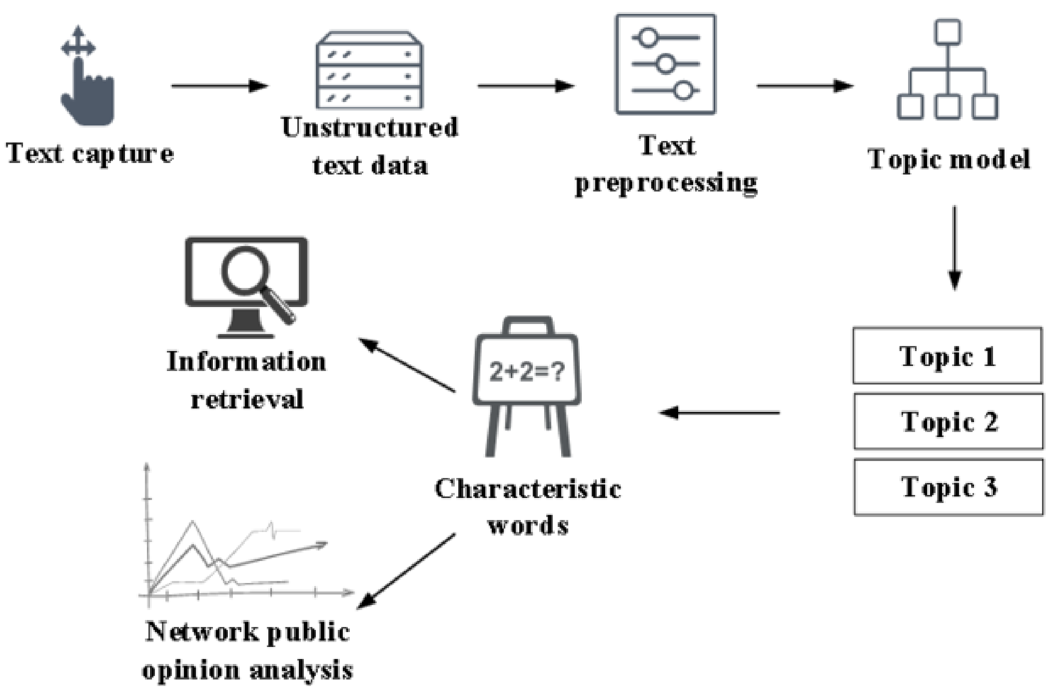


Figure 10b. Experimental performance comparison based on Chicago dataset



Evaluation Results of Interest Point Recommendation Framework Based on CNN

IPRC, SELR algorithm and CAPRF algorithm run on Chicago dataset and San Francisco dataset respectively. Figure 10 and Figure 11 are the experimental results of the precision and recall of the three.

(a)precision (b) recall

Figure 11a. Experimental performance comparison based on San Francisco dataset

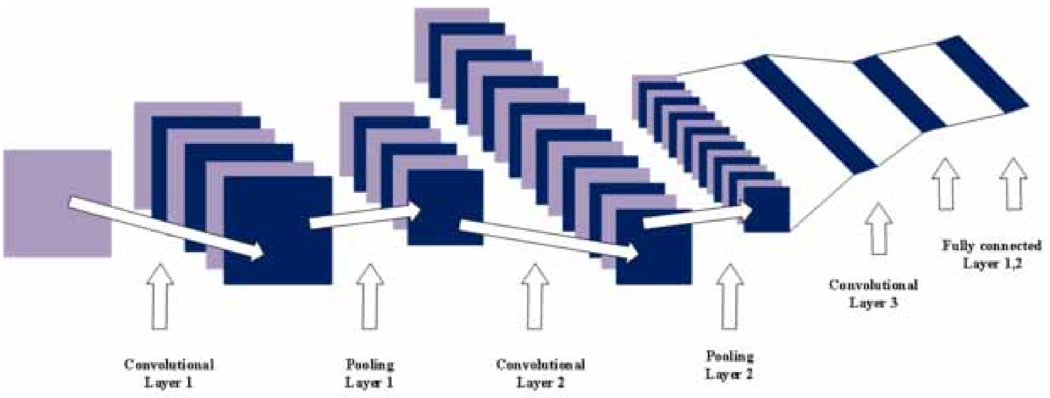
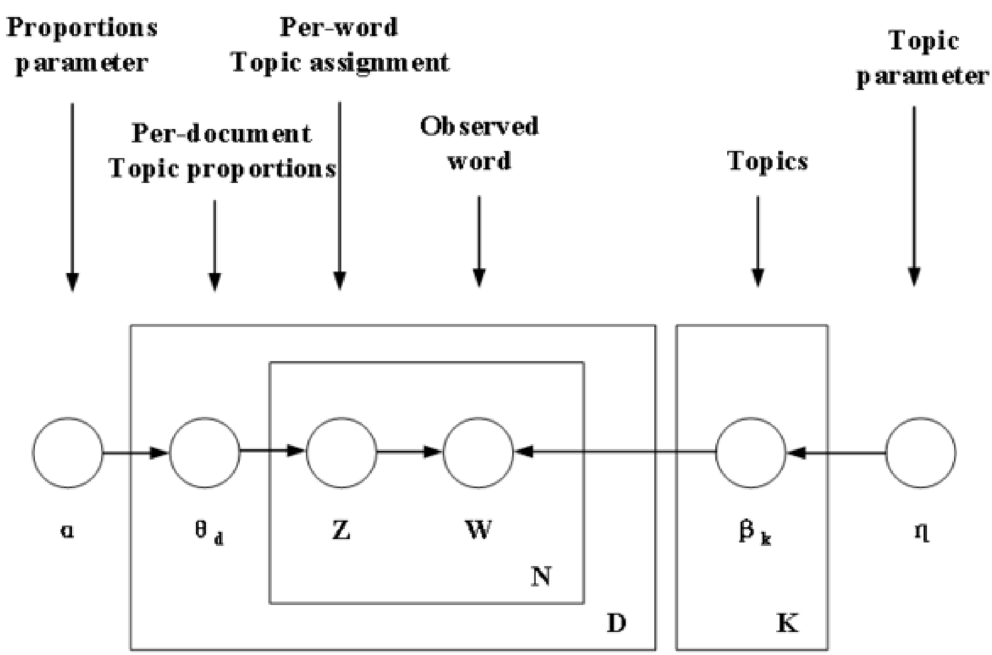


Figure 11b. Experimental performance comparison based on San Francisco dataset



The figures above show the designed IPRC, SELR algorithm and CAPRF algorithm. When they run on the two datasets, the precision shows a downward trend, while the recall rate shows an upward trend. It shows that the precision of the three algorithms decreases with the increase of the operation range, and the recall rate increases with the increase of the operation range. However, the comparative analysis shows that in the same range, the precision and recall of the three algorithms are as follows: IPRC > CAPRF > SELR. The precision rate of IPRC is up to 0.0430 and the recall rate is up to 0.0385. Thereby, under the same conditions, the designed IPRC has higher precision and recall than the SELR algorithm and CAPRF algorithm. In order to solve the cold start problem in point of interest recommendation, the recommendation precision and recall of the three algorithms in the face of cold start are compared through experiments. Figure 12 and Figure 13 are the experimental results.

Figure 12a. Performance comparison of cold start problem based on Chicago dataset

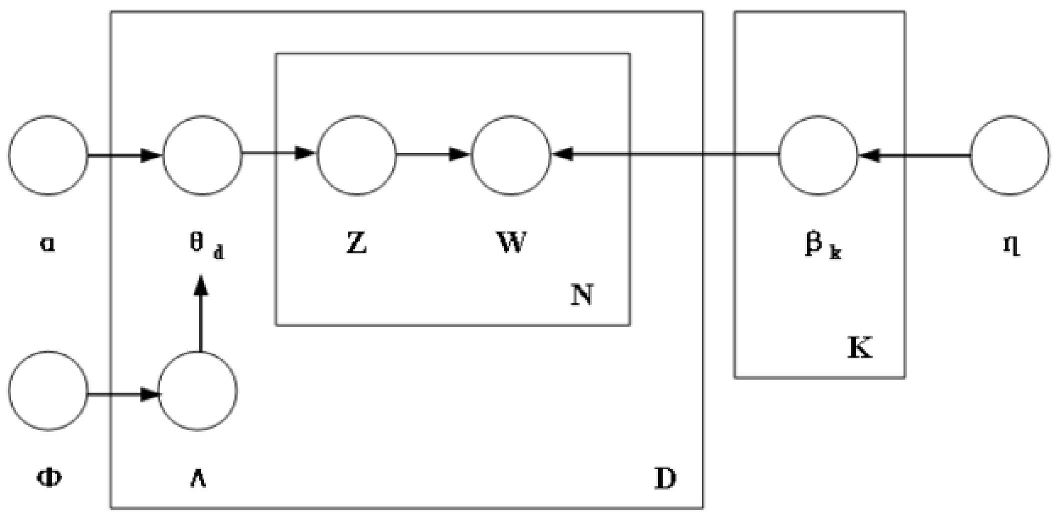


Figure 12b. Performance comparison of cold start problem based on Chicago dataset

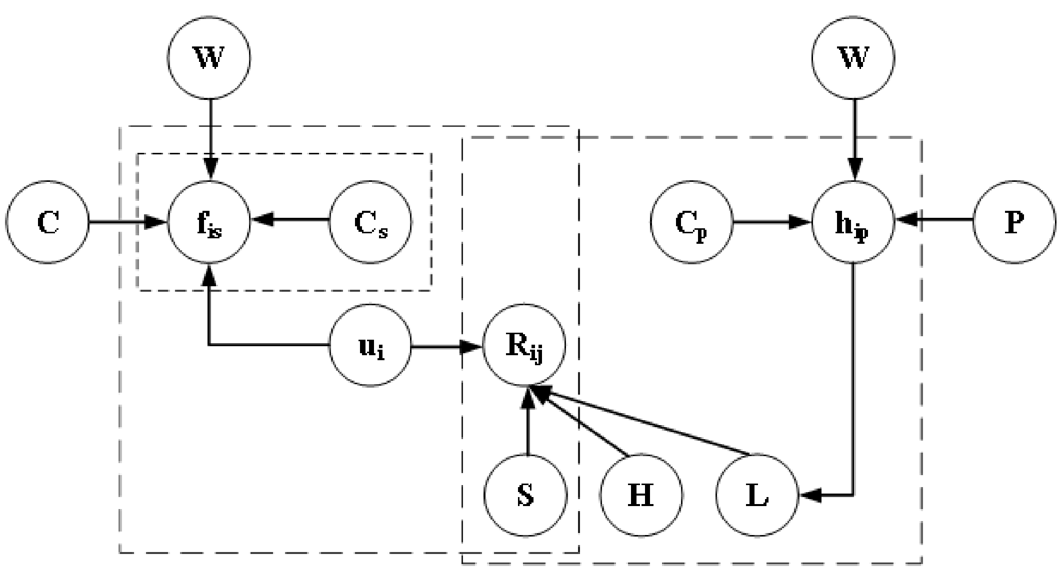


Figure 13a. Performance comparison of cold start problem based on San Francisco dataset

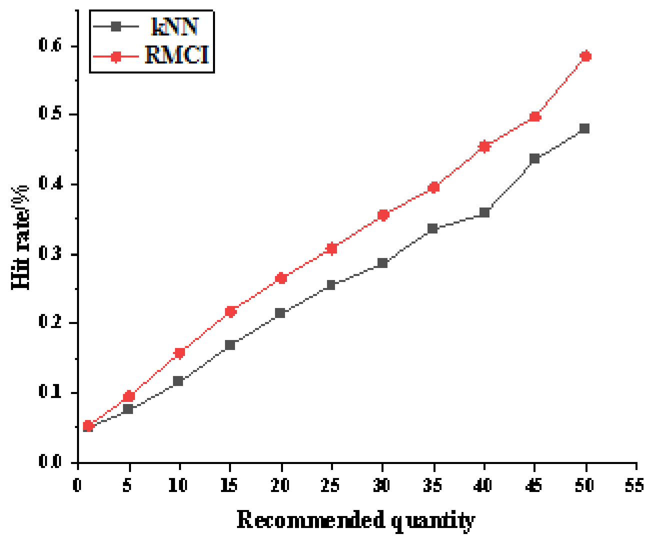
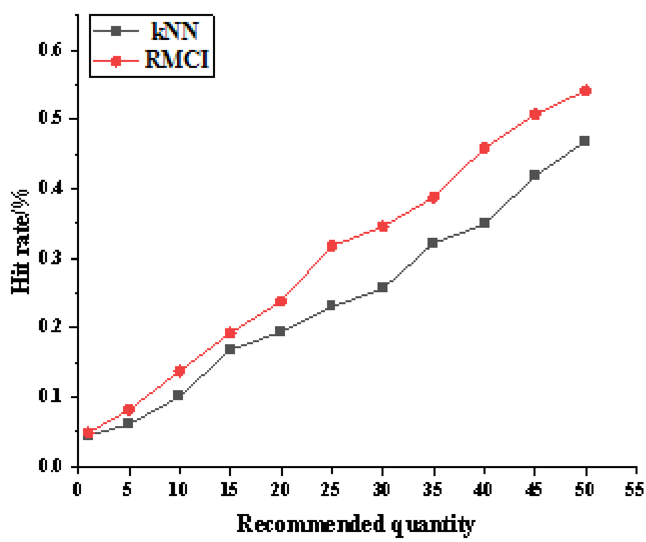


Figure 13b. Performance comparison of cold start problem based on San Francisco dataset



The above figures show that the recommendation precision of the three algorithms when running on the dataset shows a downward trend, and the recall rate shows an upward trend. It shows that in the face of cold start problem, the recommendation precision of the three algorithms decreases with the increase of operation range, and the recall rate increases with the increase of operation range. The observation and analysis show that the recommended precision and recall of the three algorithms are: IPRC > CAPRF > SELR. The precision of IPRC is up to 0.0458 and the recall rate is up to 0.0473. Thus, under the same conditions, IPRC shows better performance than the other two algorithms.

To sum up, the application of CNN based interest point recommendation framework to the recommendation system can improve the precision and recall rate of interest point recommendation, effectively alleviate the cold start problem in interest recommendation, and provide crucial technical support for bringing more high-quality tourism personalized LBS to people.

CONCLUSION

Tourism has become one of the crucial ways for people to meet their spiritual needs, and has developed very rapidly in recent years. However, in the past, people used to spend a lot of time looking for destinations, making plans and planning traffic routes. Therefore, it is of great significance to establish a recommendation system that can provide more high-quality tourism personalized LBS. In this context, first, the CPRM is established by using the Labelled-LDA algorithm. The precision and recall of interest point recommendations are improved by mining the context information in unstructured text. Then, an interest point recommendation framework based on CNN is established. The semantic and emotional information in the comment text is extracted to identify user preferences, and the score of interest points in the target location is predicted combined with the influence factors of geographical location. Finally, real datasets are used to evaluate the recommendation precision and recall of the above two models and the performance of solving the cold start problem. The experimental results show that: (1) compared with other popular algorithms, the designed CPRM and IPRC have better recommendation precision and recall when running on the dataset; (2) IPRC can effectively alleviate the cold start problem in point of interest recommendation. Applying the two models proposed to the recommendation system can improve the level of tourism personalized LBS to a great extent and bring convenience to people. The research deficiency is that the selected dataset has less information and is not representative. Model evaluation based on more datasets needs further research. The purpose of this exploration is to provide crucial technical support for solving the challenges and problems encountered in the application of tourism personalized LBS in reality.

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