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Deep Learning in Urban Tourism Route Decision Suort

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Abstract: Users' demand for personalized travel services is becoming stronger and stronger. Providing more intelligent travel suggestions to users has become a hot topic in academia and industry. This paper mainly studies the alication of deep learning in urban tourism route decision suort. Due to the advantages of CNN network in text feature extraction, the design uses CNN network to process user comment information and tourism service project comment information respectively. The network is designed with four layers: input layer, convolution layer, pooling layer, and fully connected layer. A set of tourism service recommendation model based on deep learning is constructed and implemented. Through the experimental comparison with the common traditional recommendation methods, it can be found from the experimental results that the proposed model method is significantly better than the traditional recommendation methods, which verifies the superiority of the model.

1. Introduction

In recent years, the rapid development of science and technology has made a great contribution to the progress of society and greatly facilitated all aspects of People's Daily life [1]. With the development of The Times, people have higher standards for the quality of life. The exploration and pursuit of the world is not limited to using mobile phones, surfing on computers or working hard in office buildings, but more inclined to go out to see and feel the world. With the continuous development and improvement of the fields covered by the Internet, tourism relying on the theme of "Internet +" has become a hot field. As a new research direction to facilitate the masses' leisure and vacation and promote urban economic development, it is a convenient and effective new way to adapt to the development of The Times [2]. Therefore, the development and design of a tourism recommendation system based on a variety of tourism service data has become a hotspot and focus of current research in the field of smart tourism. Under the people's growing tourism travel demand stimulus, the travel company, travel platform, all recommended under the background of the surging ahead, want to grab market as early as possible, following is a variety of online network to represent the user data has increased dramatically in a short time phenomenon, this kind of situation to help users can learn more tourist information anytime and anywhere, In addition, I can have a more diversified understanding of the scenic spots and characteristics of the destination city before the actual trip, so as to make better planning and design of the trip scheme [3, 4].

With the rapid development in recent years, each kind of technology, all kinds of alication, due to the deep learning have become more widely used in every field and obtained more achievements, such as computer vision, speech recognition, natural language processing, and other fields, makes deep learning technology gradually become a very hot in the study of artificial intelligence tuyere, This is also a new oortunity for the research of recommendation system. Many scholars have also tried to aly deep learning technology to traditional models and made some good achievements [5]. Because deep learning technology has unique advantages in extracting content features and can effectively process inevitable noise data, it has been widely used in the research of recommendation [6]. Recommendation system based on depth study and recommendation on the use of traditional have similarities, they are in building the model input is project about the user and different types of data, can be explicitly score or implicit feedback data, can also be the basic information of the user or project, as well as comments and other auxiliary information as input for model training and learning; However, the difference between them lies in that when the deep learning model is used to learn the implicit representation of users and items, the deep characteristics of users and items and the complex interaction between them can be learned based on the implicit representation containing deep meaning [7]. In the recommender system based on deep learning, the commonly used models include autoencoder (AE) multi-layer perceptron (MLP) restricted Boltzmann machine (RBM) convolutional neural network (CNN) recurrent neural network (RNN) etc. With more and more researches on deep learning and recommendation algorithms, many scholars combine deep learning technology with recommendation algorithms and aly them to various fields to achieve good recommendation effects [8]. The alications of Deep learning in recommendation systems mainly include Deep Collaborative filtering and hybrid Hybird Combination Algorithm [9].

For tourists, the information load is too heavy, which seriously reduces the efficiency of tourist planning. Therefore, how to quickly and conveniently generate a travel plan that meets the needs and interests of tourists, tourism budget and time arrangement has become an urgent problem to be solved in the development of local tourism.

2. Construction of Tourism Route Decision Suort Model

2.1. Data Crawling and Preprocessing

(1) Data crawling and cleaning

Web crawler technology is an effective tool to collect information and data in Web pages. The basic process of Web crawler is shown in Figure 1.

Scrapy web crawler framework based on Python is adopted in this paper. The TourInterest dataset is built by crawling user information, scenic spot information and user comments data from two major tourism website information sources, Tuniu.com and Qiantou.com.

To ensure the accuracy of the recommendation results. First of all, you should clean the crawling data, filter out duplicate data and data with missing key information, and delete users with less than five ratings and comment records. Secondly, irrelevant comments are filtered. By observing the captured comment data, it can be found that generally there is only one word in the comments, but the words that do not represent good or bad mood can be filtered out as spam comments [10, 11]. Finally, the content of comments is filtered to filter out repeated comments, special symbols in comments and wrong data. To ensure data integrity and reliability, perform the preceding steps. After data cleaning is completed, complete and reliable data are obtained and further processed [12].

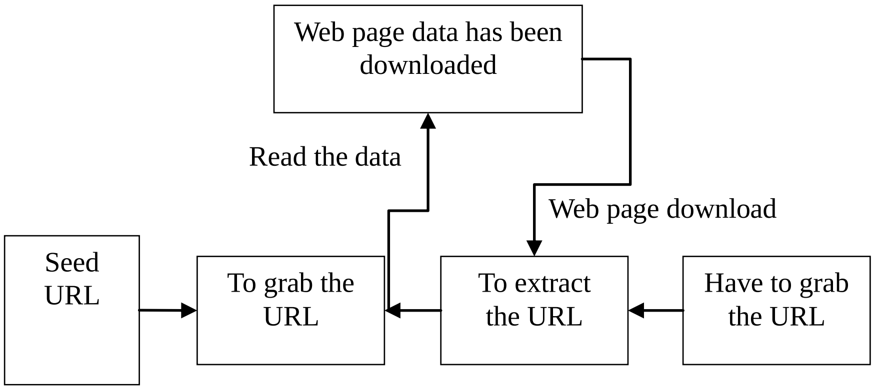

Figure 1. Basic process of web crawler

(2) Data preprocessing

The user's comment data is composed of Chinese text, which must be converted into word vectors before input into the model. Therefore, first perform word segmentation on it, and jieba is adopted as the Chinese word segmentation tool. Jieba word segmentation tool was developed based on Python and widely used in the field of word segmentation [13].

After word segmentation is completed, the text needs to be converted into word vectors, and the common way is to use unique hot coding for word vector conversion. One-hot coding is one-hot coding. Each word corresponds to a unique word vector, in which only one position is 1 and the other positions are 0. Although the word vectors processed by One-hot coding can be directly input into the model, there are two problems in the word vectors after One-hot coding: first, the dimension of the word vectors is large and the sparsity is high, which will lead to the excessive dimension of the vocabulary and bring dimensional disaster. Secondly, the word vector encoded by One-HOT cannot represent the similarity between words, ignoring the semantic information of sentences [14].

Word embedding can well solve the above problems in one-hot coding. Word embedding is to convert the sparse word vectors with higher dimensions into dense word vectors with lower dimensions. By calculating the distance between two words, the semantic information between words can be obtained [15].

Actual gender values of male and female users are converted to 0 and 1 respectively. Then the user ID, user gender and age are converted into vector word embedding, and user travel preference is converted into vector word embedding after word segmentation.

Then, the graphical point identifier, graphical point name and graphical point score are converted into word embedding vectors, and graphical point address and graphical point input are converted into embedding vectors words after word segmentation.

2.2. Construction of Deep Prediction Network Model

The depth prediction model proposed in this thesis consists of three parts: user review information network, information network for the review of tourist services projects and other information networks. The various vectors obtained after data pretreatment are used as network input. These bodies can be regarded as various expressions of information for users and tourist services projects.

In the co-action layer, this paper uses factorization technology to construct model function to score and predict items. Because we need to mine and learn the interaction between each vector, we can predict the score of the target item through these interactions, and the factorization machine can complete this task well.

User Comment information network is a network architecture based on convolutional neural network. Convolutional Neural Networks, also known as Convolutional Networks, is a kind of Neural network that specializes in processing data with similar grid structure [16]. Convolutional neural network has a good effect on the extraction of hidden features of text information [17].

In this paper, M neurons are used to perform convolution operation on the comment information vector matrix of user U in the convolution layer. In each neuron j, there is a convolution kernel Kj of size C ×t, where C represents the word vector dimension in the input user review information vector matrix, and T represents the window size of the convolution kernel. For the input user comment information vector, we use formula (1) for convolution calculation. As for each convolution kernel in the volume base, we use this formula for calculation.

$$z_j = g\left(V_{1:n}^{u} * K_j + b_j\right) \tag{1}$$

The ✳ representative is the convolution operation mentioned above, bj represent an offset, function g said an activation function. The reasonable Satisfaction Linear Units (ReLU) are used as the activation function here. The rectifying linear unit is a kind of activation function commonly used in neural networks. Its definition is shown in Equation (2).

$$g(x) = \max\{0, x\} \tag{2}$$

For the offset, you can initialize it with a small positive real value, such as 0.1. Doing so allows the rectified linear unit to be activated for a large number of training set inputs during the initialization phase and allows derivatives to pass through. Compared with other activation functions, the convergence speed of the rectified linear element is much faster, and the calculation is simple. Only a threshold is needed to activate the rectified linear element, eliminating a lot of complex operations [18].

For the output of the convolution operation, a set of real number vectors will be obtained after a convolution kernel is computed. This vector represents the result of the convolution operation of the input vector matrix. The size of this real vector depends on the window size of the convolution kernel. In general, the output size is shown in Equation (3).

$$O = \frac{(W - K + 2P)}{S} + 1 \tag{3}$$

Where W is the input size, O is the output size, K is the window size, P is the fill, and S is the stride length.

In this paper, the size of the convolution kernel is c×t, the size of the input user comment information vector matrix is c×n, the step is 1, and the filling is 0. Therefore, the output size through the convolution kernel is :(n-t+0) /1+1, namely n-t+1.

3. Model Simulation Experiment

3.1. Experimental Setting

In this paper, the MFW and Ubicomp datasets are taken as examples for verifying the effectiveness of the proposed method, where the MFW is a self-assembled dataset. Ubicomp is a widely used set of public restaurant recommendation data, and the universality of the algorithm is verified through Ubicomp.

3.2. Experimental Comparison

To verify the effectiveness of the model, the proposed method shall be compared with the following key recommended methods. The method adopts pair of personalized screening loss optimization model. The method uses the encoder to create the vector representation of users and projects, and takes into account only the nearest neighbor.

In order to better assess the overall performance of classification operations, there are three representative top recommended indicators, namely accuracy, recall and normalised cumulative loss gain (NDCG).

4. Analysis of Simulation Results

4.1. MFW Data Set

Table 1. Comparison of hot-start user recommendation performance on MFW dataset

	Recall	Precision	NDCG
BPR	0.217	0.259	0.243
GCMC	0.258	0.261	0.343
Our model	0.337	0.324	0.431

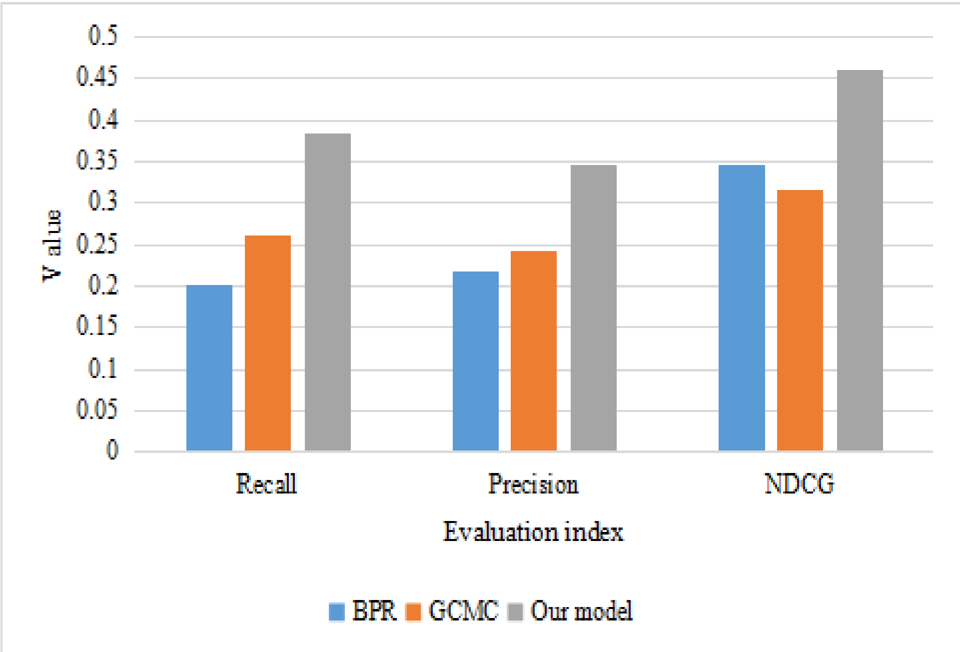

Figure 2. Comparison of cold-start users with different algorithms on the MFW dataset

As shown in table 1 and figure 2, this paper puts forward the method of cold start users heat start tourism recommendation performance is better, because the algorithm takes advantage of the deep potential links between nodes, because of the warm start users connect directly to the scenic spots are relatively cold start users, local neighborhood, in the training process may over fitting result in performance degradation, Therefore, the method proposed in this paper is more suitable for cold start users.

4.2. Ubicomp Data Set

Table 2. Hot start user comparison between different models on the Ubicomp dataset

	Recall	Precision	NDCG
BPR	0.004	0.002	0.003
GCMC	0.042	0.017	0.053
Our model	0.067	0.145	0.153

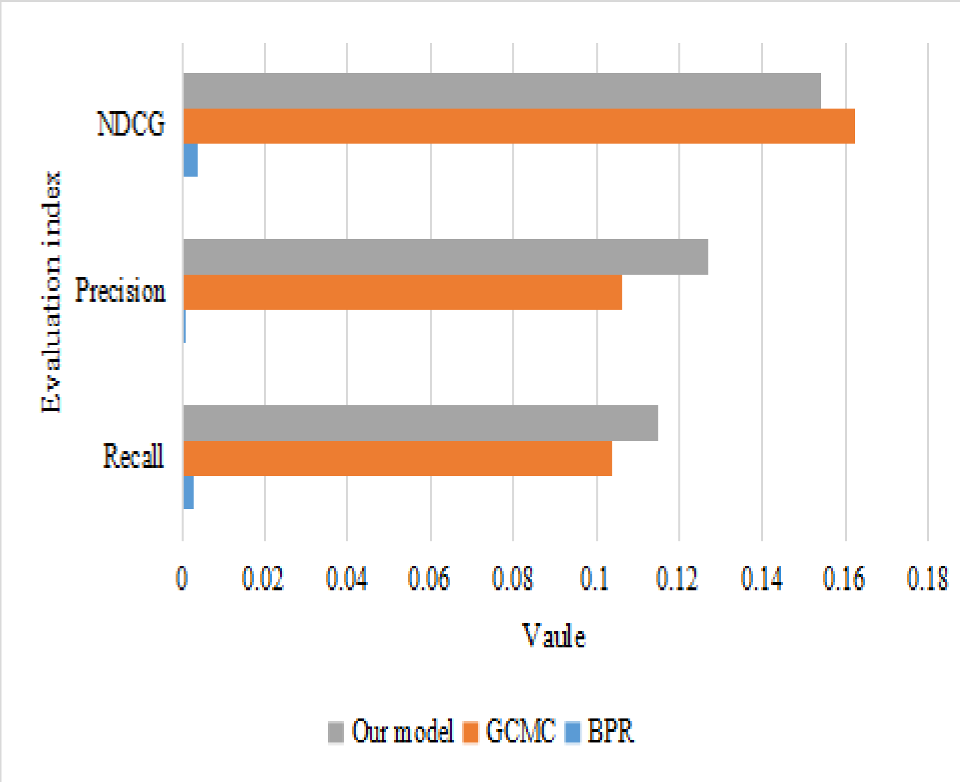

Figure 3. Comparison of cold start users with different algorithms on Ubicomp dataset

As shown in Table 2 and Figure 3, due to the sparse access records of cold-start users, BPR and GCMC methods have low accuracy due to the limitation of data sparsity. Therefore, the proposed method can effectively improve the recommendation performance of cold start users on the basis of maintaining the recommendation performance of hot start users.

5. Conclusion

Facing the huge and complex tourism data, it is difficult for people to quickly find the tourism information they want. However, the existing online tourism system only provides simple information retrieval and single service, which cannot meet people's increasingly strong personalized services for travel. In view of the problems existing in the existing personalized travel recommendation methods, this paper adopts the knowledge of deep learning and machine learning to conduct in-depth research on personalized travel recommendation, including how to effectively use multi-modal heterogeneous tourism information to mine users' multiple preferences and simulate the user's travel decision-making process. How to effectively solve the problems of data sparsity and user cold start to improve the recommendation accuracy, and how to provide effective tourism series recommendation for users with a long travel time span and dynamic changes in user preferences.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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