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Personalized Recommendation for Network Teaching Courses Based on Combined Filtering of Deep Learning and K-Means

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Abstract. To meet the needs of students for personalized learning during the process of network teaching, a personalized recommendation scheme based on combined filtering is proposed. Firstly, based on the analysis of deep learning algorithm and existing personalized recommendation technology, a specific framework for teaching course recommendation is proposed. Using the advantages of deep learning in natural language processing, a neural network model is constructed and trained. Then the weights of different feature sequences are acquired through similarity calculation, which provides a data basis for the design of curriculum recommendation engine. Finally, a recommendation system based on feature weighted optimization is proposed, and its implementation process on Hadoop platform is also provided. The experiment takes the recommendation of psychology teaching resources as an example to test, which proves that the strategy can better complete the personalized recommendation task, and it has better accuracy and recall compared with similar algorithms.

Keywords. personalized recommendation; teaching course; deep learning; k-means; Hadoop

1. Introduction

With continuous development and popularization of network, online teaching has become an important way to cultivate talents and promote the development of scientific research and education. However, in order to make the network and information technology truly serve teaching and realize the optimization of teaching process and teaching resources, we must have the support of rich teaching resources. The prerequisite for the development of online teaching is to build a complete and substantial online teaching resource system [1]. In the face of information overload, Personalized Recommendation provides users with a fast and efficient intelligent choice. With the continuous development of artificial intelligence technology, personalized recommendation can predict users' interests and preferences according to users' previous browsing records and learning habits, so as to customize users in many teaching resources and filter out content more in line with users' needs [2].

For the current students' needs for personalized learning, based on deep neural network and clustering algorithm, this paper selects the information they may be interested in from a large number of target user behaviors. The program takes a large

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number of sample data of psychology courses as cases, and arranges the historical data of teachers' and students' online learning behavior, which is used as the basis to construct students' learner portraits. In the process of recommendation similarity calculation, combined with deep neural network and k-means algorithm, a personalized learning resource recommendation system integrating data mining and artificial intelligence is designed. Finally, the system performance is tested on the platform represented by Hadoop, which proves its feasibility and effectiveness, and is conducive to improving students' learning efficiency.

2. Related Technology

2.1 Personalized Recommendation

Personalized recommendation system is a subset of information filtering system. It can be used in many fields, such as film, music, e-commerce and feed stream recommendation. Personalized recommendation system finds the personalized needs and interest characteristics of users by analyzing and mining user behavior, and recommends the information or goods that users may be interested in to users. Unlike search engines, personalized recommendation systems do not require users to accurately describe their needs, but model according to users' historical behavior and actively provide information to meet users' interests and needs [3]. Among these personalized recommendation technologies, the common key technologies are: feature extraction, feature modeling, feature dimensionality reduction technology, similarity measurement method, singular value decomposition, clustering (K-means), collaborative filtering algorithm and so on. The architecture of the recommendation system can be basically divided into: user feature extraction module, related item retrieval module and recommendation result sorting module. A typical recommendation system flow is shown in figure 1.

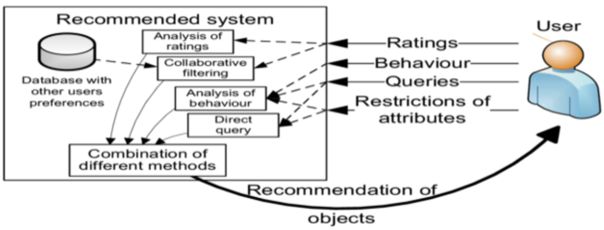

Figure 1. Recommendation system model.

2.2 Artificial Intelligence Technology and Its Application

With the rise of deep learning, neural network has been applied to various recommendation problems. In recent years, deep learning has achieved great success in many fields. Although one goal of deep learning is to design algorithms that can handle various tasks, up to now, the application of deep learning still needs a certain degree of specialization. In recent years, with the increase of data and the research and progress of deep learning neural network algorithm, it shows that deep learning is very effective Deep learning is a sub field of machine learning. It is an algorithm inspired by the structure and function of human brain or the interconnection of many neurons. These algorithms are called artificial neural networks (ANN) that simulate the biological structure of the brain. The recommendation system based on deep learning captures the deep-seated preferences of users by learning the potential characteristics of data. Compared with the traditional collaborative filtering, it can deal with all kinds of complex user data [4]. The deep learning models commonly used in recommendation system include recursive neural network, convolutional neural network, generative countermeasure network, etc. The principle of collaborative filtering based recommendation is simple, which is to discover the relevance of the item or content itself based on the user's preference for the item or information, or to discover the user's relevance, and then make recommendations based on these correlations. Collaborative filtering based recommendations can be divided into two simple subcategories: user based recommendations and item based recommendations.

3. Personalized Recommendation Based on Combined Filtering of Deep Learning and K-means

3.1 Overall Process

The scheme of this paper is to collect and count the learning data of students on the intelligent learning platform, and optimize it by using artificial intelligence neural network, so as to obtain the learning situation of students' knowledge points in different dimensions, and then provide data support for the construction of learner portrait and personalized learning resource recommendation [5-7], as shown in figure 2.

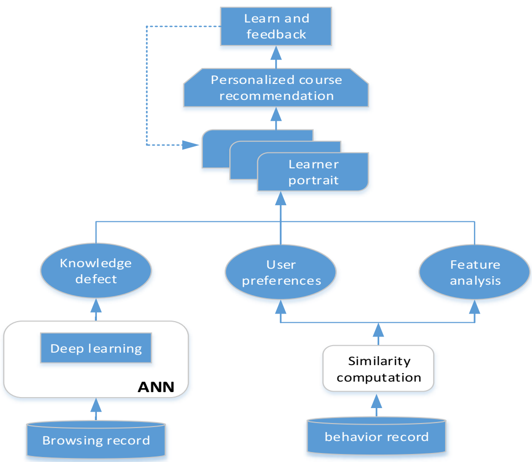

Figure 2. Adaptive recommendation system of learning resources based on artificial intelligence.

The system uses the deep learning function of artificial intelligence neural network to generate the algorithm mathematical model of distributed parallel information processing, and transforms the learning knowledge information into quantifiable attribute values. The browsing records and behavior characteristics of students' online learning platform are extracted to summarize the classification basis, to acquire their preference for different learning resources [8]. In this process, the algorithm classifies the polarity of recommendation basis based on two dimensions: one is the dynamic update of learner portrait, which provides useful enlightenment for personalized learning research; The other is the user's feedback, which can be further calculated by using intelligent algorithms such as k-mans or collaborative filtering. Finally, the two combine to get the final recommended system information, which is used to push it to the front-end customers and generate the corresponding learning interface.

3.2 Framework Deep Learning Model

The framework of deep neural network model proposed in this paper is mainly composed of two parts: in terms of user behavior analysis, how to match the adjustable weight of the model with the input features is how to assign the weight to these features according to how the neural network classifies and clusters the input; In the aspect of resource classification, the topological relationship between regions is used to describe the structural relationship between objects in the knowledge map represented by symbols, so as to construct a geometric cognitive space integrating numbers and symbols. This vector space satisfies some properties, for example, vectors with similar semantics are closer. It can be regarded as an abstract description of low-level text features extracted by neural network.

Assuming x is input vector, y is output vector, h_i is the hidden layer in neural network, W_i is the weight matrix in the network, b_i is the bias of the i_{th} layer, then

$$h_1 = \mathrm{W}_i x + \mathrm{b}_1 \tag{1}$$

$$\mathrm{h}_i = f(\mathrm{W}_i \mathrm{h}_{i-1} + \mathrm{b}_i) \tag{2}$$

$$y = f(\mathrm{W}_N \mathrm{h}_{N-1} + \mathrm{b}_N) \tag{3}$$

where $f(x)$ is activation function. *tanh* is adopted as the activation function of hidden layer and output layer and its equation is

$$f(x) = \frac{1-e^{2x}}{1+e^{2x}} \tag{4}$$

The semantic relevance of behavior U and interest V is computed as

$$R(U,V) = \cos ine(y_U, y_v) = \frac{{y_U}^T y_v}{\| y_U \| \, y_v \|} \tag{5}$$

where y_U and y_v denote the distributed vector of extracted user interest. After calculating the relevance of users, you can select the most similar n nearest neighbor users to calculate the score prediction value of a course, that is, n related courses are of value to users. Finally, select the top N products with the highest score of all products and recommend them to the current user.

3.3 Course Similarity Calculation

The main function of this module is to calculate the similarity between courses, and then obtain the list of similar courses of each course according to the similarity, to provide data support for relevant course recommendation. The user's topic based local interest view can be represented by implicit feature vectors. When calculating the similarity between courses, an algorithm similar to collaborative filtering is selected for calculation:

$$sim = \frac{course_i course_j}{\| course_i \| \| course_j \|} \tag{6}$$

where $course_i$ is the hidden feature vector of course i and $course_j$ is the hidden feature vector of course j.

A multi-dimension vector can be acquired by (6). Then we need to acquire a final weight information by the parameter in neural network and the computation is:

$$output = p^T \sum_{i=1}^{n} \sum_{j=i+1}^{n} a_{ij} \overline{h} \tag{7}$$

3.4 System Implementation

To verify the effectiveness of the algorithm on the data in this paper, we use k-means algorithm to cluster and store the user implicit feature vector and course implicit feature vector. Classify similar data samples into one class and different data samples into other classes K-means algorithm needs a MapReduce, which assigns each sample to the nearest center, and the reduce function is responsible for updating the cluster center [9]. To reduce the network responsibility, the combiner function is required to handle the partial merging of intermediate results of the same map and the same key. As described by the combine function, the input data includes the sum of some samples and the corresponding number of samples. Part of the key codes of such process are described as follows:

```
minDis=Double. MAX_ VALUE；
Index=-1；
For i=0 to centers. length do
        dis=ComputeDist(instance,centers[i]);
        If dis<minDis{
            minDis=dis;
            index=i;
        }
End For
Take index as key ';
Construct values of different dimensions into value ';
Output < key ', value' > pairs;
End
```

4. System Test Analysis

The resources on the personalized learning platform mainly come from the Mu class data on various networks, including teaching site pages and relevant videos. By providing learners with a mechanism of mutual cooperation, students can have a richer and comprehensive understanding and memory of learning content. This course is applicable not only to undergraduates, but also to teachers at all levels and schools. The recommendation algorithm in this paper is used to summarize and analyze the learners' behavior and browsing information, and the final top-N resource list form is obtained. In order to save system resources, the number of recommendations per user is limited to 50, and the items with too small similarity are shielded. The final visual interface of course recommendation results is shown in figure 3.

In order to verify whether the recommendation results meet the actual needs of learners, some students were randomly selected for questionnaire survey. Then the actual prediction results are compared with the output results of the algorithm. After adjusting the corresponding network parameters, recommend personalized resources for them. In order to realize the adaptive output of the recommendation results, HTML5 is used to process the front-end program. Figure 4 depicts the courses recommendation effect of the mobile terminal, and the system has set up the collection function, which can see the behavior records of other learners at the same time for later psychological course selection.

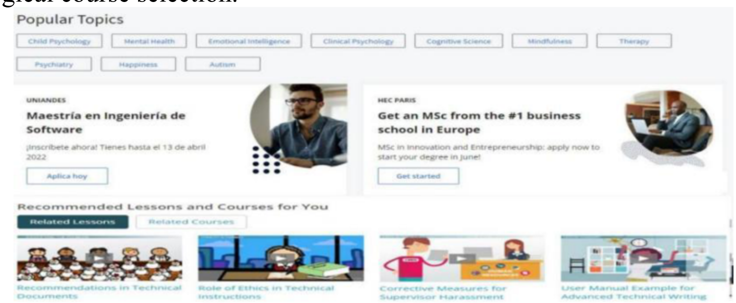

Figure 3. Personalized Course recommendation interface.

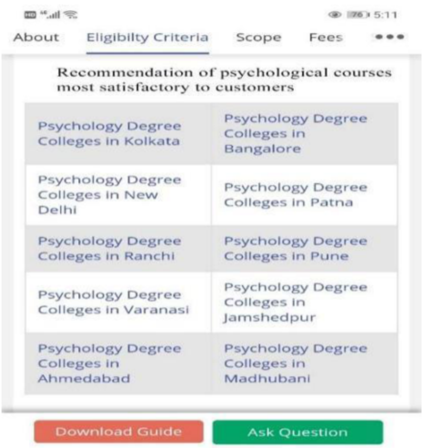

Figure 4. Mobile end recommendation result test.

To verify the performance improvement of the algorithm, the classical TF-IDF and collaborative filtering algorithm are compared. The test indexes are AUC, map and RMSE respectively. The final results are shown in Table 1. It can be seen that the three indexes of this algorithm are slightly better than other algorithms, which proves that it shows a good calculation accuracy in the recommendation process. Because the initial data scale of users is optimized by using deep learning, the training time advantage in calculating similarity is improved. Traditional algorithms often need to build a large-scale scoring matrix. At the same time, Hadoop method also has a good performance for the accuracy of feature extraction, which shows that this scheme has been tested in practical cases and has high feasibility and stability.

Table 1. Comparison of performance indexes of different algorithms

Algorithm	AUC	mAP	RMSE
Deep neural network	0.832	0.793	0.416
TF-IDF	0.754	0.730	0.404
Collaborative filtering	0.669	0.701	0.355

5. Conclusion

This study arranges the existing solutions to the recommendation problem of e-learning. Based on the discussion of the related technologies of personalized recommendation and artificial intelligence, a personalized teaching course recommendation model based on deep learning network is proposed. Firstly, the structure of the deep neural network and the adaptive adjustment strategy of its parameters are designed. Then, the large-scale input data is transformed into one-dimensional vector by deep learning. Then K-means clustering algorithm is used to calculate the neighbor users, and the user interest ranking is obtained through the calculation of their similarity. Finally, taking psychology course as an example, Hadoop platform is used to realize the above process, and the key implementation code is given. The test results show that the course accuracy of introducing artificial intelligence neural network and personalized learning resource recommendation model is significantly improved to meet the needs of students for adaptive learning resource recommendation.

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