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APPLICATION ANALYSIS OF ENGLISH PERSONALIZED LEARNING BASED ON LARGE-SCALE OPEN NETWORK COURSES

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Abstract. In the context of Big data, large-scale open online courses increase learning paths for learners, but in the face of countless high-quality curriculum resources, it is easy for derivative learners to face the dilemma of rich curriculum resources but difficult to choose resources, which leads to information maze for learners. How to help learners quickly and accurately find their own learning resources in the explosive growth of MOOC resources is an urgent problem in the field of education Big data. However, the traditional Collaborative filtering recommendation technology does not perform well when dealing with sparse data and cold start. The recommendation content is repeated and can not effectively deal with high-dimensional and nonlinear data of online learning users, resulting in low efficiency of resource recommendation. Therefore, the study adopts a deep belief network (DBN) to construct a personalized resource recommendation model. The model combines the learner behavior characteristics with the curriculum resource content attribute characteristics to form the learner feature vector. The parameters of the model are adjusted according to the characteristics of learners. Through experiments, the proposed model has shown good performance. The experiment explored the effects of training set size, learner characteristics, and GPU on model performance. The experimental results show that when the training set proportion is 100%, the RMSE, Accuracy, Recall, and F1 values of the model are 0.76, 0.946, 0.957, and 0.951, respectively. When the model is trained using a training set containing learner features, the RMSE, Accuracy, Recall, and F1 values of the model are 0.75, 0.962, 0.908, and 0.958, respectively. After using GPU to accelerate the model, the running time of the model decreased from 360 minutes to 90 minutes. The results indicate that the model cannot effectively mine data information when the degree of correlation between sample information is low. The richer the relationships between samples, the better the performance of the model. Simultaneously learning hunger feature vectors and learner behavior feature vectors for training can significantly improve the recommendation accuracy of the model. The main contribution of this study is to propose a recommendation method based on DBN classification to replace traditional similarity calculation methods, using DBN's efficient feature abstraction and feature extraction capabilities to fully explore learners' interest and preference for course resources. In addition, in view of the common problems of cold start and data sparsity in traditional Collaborative filtering recommendation methods, the research deeply mines the characteristics of learners' Demographics and curriculum resources' content attributes, and constructs a learner interest model based on DBN combined with learners' behavior characteristics, which effectively solves the problems of cold start and data sparsity, as well as the inaccurate expression of learners' interest preferences for curriculum resources.

Key words: Open network courses; Deep belief network; Restricted Boltzmann machine; Back propagation neural network; Personalized recommendation

1. Introduction. There are many teaching methods in the current society, and the emerging personalized learning method of English based on large-scale open network courses has gradually become the focus of social attention. Due to the differences in students' knowledge structure and individual learning needs, they cannot quickly and accurately find their own curriculum resources. Therefore, it has caused a huge waste of manpower, material resources and time. In this case, the recommendation system can solve this problem well. The Personal Recommendation System (PRS), as the name implies, is to establish a personalized user model based on the characteristics and interests of users. After systematic calculation, the model finally realizes the user's requirements [1, 2]. Unlike search engines, users can obtain personalized suggestions by artificial means without consciously. However, due to the exponential growth of learners and teaching resources, the traditional collaborative filtering algorithm is not efficient in processing sparse data and cold start. In addition, the duplication of recommendation content and the inability to effectively process high-dimensional and non-linear data will lead to inefficient resource recommendation. On the basis of the DBN model, the research conducted an in-depth discussion on the RBM and BP of each component of the DBN [3, 4]. In the process of in-depth modeling, the feature vector based on "learner-course resources" and the relevant course scores

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provide a training example for students. On this basis, the feature vector of "learner curriculum resources" is introduced. This method mainly regards learners' evaluation of the course as a supervised marker, and fine-tune the whole network using unsupervised pre-training and supervised feedback, and finally form a complete DBN personalized recommendation model. The classification result is learners' preference for curriculum resources.

The main theoretical contribution of the study is to improve the accuracy of DBN-MCPR scoring prediction by optimizing the initial values of model parameters and parameter setting rules based on DBN-MCPR. Verify the classification accuracy of DBN-MCPR using public datasets and compare it with several traditional recommendation methods to highlight its excellent recommendation accuracy; Then, the DBN-MCPR is used to train the real dataset of the M0OC platform of the Teacher's College, mining recommendation rules between learners and course resources, further completing learners' predictive scoring of courses, and verifying the effects of the training dataset, learner feature vectors, and GPU acceleration on the performance of DBN-MCPR. The practical significance and potential contributions of the study have four aspects. Firstly, enhancing personalized learning experience. By using the DBN-MCPR model, tailored course recommendations can be provided for each learner based on their interests and needs. This will enable learners to more efficiently choose suitable learning resources, improve their learning experience and effectiveness. Secondly, to enhance learner engagement, personalized recommendation models can help improve learner engagement and motivation. By providing relevant and challenging course resources based on learners' interests and learning needs, it can stimulate learners' learning motivation and encourage them to participate more deeply in the learning process. Thirdly, the improvement of automated evaluation systems. The DBN-MCPR model can provide more accurate and personalized suggestions for automated evaluation systems, thereby helping learners better evaluate their learning progress and understanding. This will have a positive impact on the improvement and optimization of automated evaluation systems. Fourthly, educational decision-making support, utilizing the DBN-MCPR model, can analyze learners' learning preferences and behavioral characteristics, and provide valuable data and insights for educational decision-making. This information can be used for the formulation of educational policies, allocation of teaching resources, and other aspects, helping educational institutions make more intelligent and effective decisions. This method solves the Hard problem of consciousness problem of resource selection faced by learners in the context of large-scale open online courses, and improves the shortcomings of traditional Collaborative filtering recommendation technology. The use of deep belief networks to construct feature fusion and recommendation models is a relatively new method in the field of education Big data.

The research mainly consists of four parts. The first part is to summarize the research results of domestic and foreign scholars on personalized recommendation algorithm and DBN model; The second part is to build a personalized recommendation model based on DBN, and introduce the DBN model and the operation of the personalized recommendation model in detail; The third part is to test the proposed model and analyze its performance; The last part is the summary of the full text, the analysis of the deficiencies in the study, and the recommendations for the follow-up study.

2. Related Work. The essence of personalized English learning based on large-scale open online courses is personalized recommendation based on learners' characteristics. Many scholars at home and abroad have relatively mature research on personalized recommendation model. Zhong L et al. proposed a personalized news recommendation algorithm based on the topic model and the finite Boltzmann machine. Based on the LDA2vec topic model, the topic information and audience rating data are used as the condition layer and visual layer to achieve the purpose of news recommendation. Experiments had proved that taking the news theme of LDA2vec as a prerequisite layer can better predict and enhance the effect of news recommendation [5]. Chen Y team constructed a personalized recommendation model based on attention flow network. It proposed a weighted attention flow net, and then recommended products according to the transfer probability of the attention flow net. The algorithm was tested with several sets of actual data, which proved its superiority [6]. A location identification and customized suggestion technique for tourism sites based on image processing was suggested by Zhang Q and other academics. This method was based on hashing and consists of offline and online phases. In addition, a personalized recommendation model based on geographical location and time was also presented in the experiment. It was obviously that the proposed method has high precision and efficiency [7]. Naserian E and other researchers proposed a local personalized recommendation model based on classification. The model was divided into several local models, each of which had several characteristics. Other strategies

Table 2.1: Overview Table

Reference	Research direction	Research results
Reference [5]	Personalized news recommendation algorithm	Enhance news prediction and recommendation effectiveness
Reference [6]	Personalized recommendation algorithm based on attention flow network	The algorithm has superiority in experiments
Reference [7]	Image Processing Based Location Recognition and Personalized Recommendation Method for Tourist Attractions	The proposed method has high accuracy and efficiency
Reference [8]	Classification based local personalized recommendation mode	Tested using data on Foursquare and achieved better recommendation results
Reference [9]	Proposed an intelligent agent model that supports deep learning	This algorithm has good economy and effectiveness in use
Reference [10]	Taylor based T-DBN classifier	The specificity of this model reaches 90.757%, sensitivity is 92.225%, and accuracy is 92.122%
Reference [11]	A New Fuzzy Fusion Method Based on FG-SMOTE	The performance of this method was evaluated using a DBN classifier, and the AUC using Fuzzy SMOTE technology reached 93.7%; The predicted value of F1 score is 94.2%; The geometric average score is 93.6%

were also implemented to support the development of individual local patterns. On this basis, a new method of extracting hidden patterns from geographical clusters was proposed. On Foursquare, the data on Foursquare were used for testing, it was verified that the model performed better effect than the existing algorithm [8]. The DBN model used in the study is also the focus of current social research. Su T et al. proposed an agent model that supports deep learning, which could effectively improve the computational efficiency while ensuring high accuracy. For this reason, the experiment combined the deep belief network (DBN) with the reference frame based non-dominant sequence genetic algorithm (NSGA-III) to establish a new prevention and control system. Through a large number of simulations of IEEE experimental system, the effectiveness and economy of the algorithm were verified[9]. Vijay G and other researchers proposed a Taylor based T-DBN classifier, which could accurately locate the lesions and features in retinal fundus images. The specificity of the model reached 90.757%, the sensitivity was 92.225%, and the accuracy was 92.122% [9]. Hemalatha P and other scholars proposed a new fuzzy fusion method based on FG-SMOTE for processing unbalanced data. The algorithm was composed of a few oversampling based on fuzzy Gaussian synthesis and a deep belief network classifier. DBN classifier was applied to evaluate the function of this method. The results show that the AUC using Fuzzy SMOTE technology reaches 93.7%; The predicted value of F1 achievement is 94.2%; The geometric average score is 93.6% [11].

In summary, many scholars have conducted research and analysis on the DBN model and achieved good classification results. The key directions in each study are shown in Table 2.1. Due to the limited application of the DBN model in personalized recommendation in the field of education, the study is the first to combine the two for exploration, aiming to improve the learning quality of learners in a large-scale open online learning environment.

3. Construction of personalized learning recommendation model based on DBN in MOOC environment.

3.1. Construction of deep belief network model. The research optimizes the personalized English learning of the current large-scale open online courses through the deep belief network (DBN) [12, 13, 14]. DBN is a probability generation model, which consists of multiple hidden layers and a display layer to form a deep hybrid neural network. The DBN used in the study is composed of the unsupervised restricted Boltzmann machine (RBM) and the back propagation neural network (BPNN). Figure 3.1 indicates its structure [5, 16, 17].

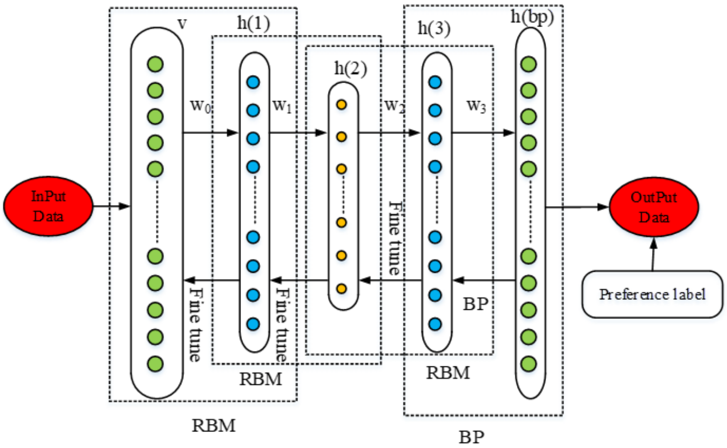


Fig. 3.1: DBN model structure

Figure 3.1 shows the training process of the DBN model, where v represents the state vector of the visible layer; b represents the visible layer bias vector; h represents the hidden layer state vector; c represents the hidden layer bias vector; W represents the connection weight. The DBN training process mainly involves unsupervised pre training and supervised parameter tuning. Among them, unsupervised pre training uses unlabeled training sets to train each layer's RBM layer by layer, independently, and unsupervised from bottom to top. After Input Data, initialize the first layer RBM visible layer unit using the original sample data, and ensure that the features of the input data are well mapped onto the first layer RBM hidden layer unit through abstraction, enabling the model to extract the most essential original features of the data. Then, the hidden layer of the first layer RBM is used as the visible layer input of the second layer RBM. After training to obtain the nth layer, the output of the nth layer is used as the input of the n+1 layer, and the RBM parameter sets of each layer are obtained repeatedly. Supervised parameter adjustment involves fine-tuning network parameters using labeled data from top to bottom, globally, and with supervision. By comparing the expected values of Oup Daa with Preene label, the error is fed back to the network for weight adjustment. BP weights and thresholds are corrected by the quickest descent method, which is more suitable for global optimization of DBN network parameters and can avoid the optimal characteristics of a single RBM network. The learning process of this model is comparable to the startup process of the BP weight, which compensates the defect that the weight matrix and deviation in BP network are random initialization. The model formalizes the traditional BP neural network into an optimized BP neural network, fine-tuning the network using BP back-propagation algorithm to achieve the best classification effect, effectively solving the issue that BP network takes a long time. RBM is the core architecture of DBN, mainly composed of visible layer and hidden layer. Its feature is that neurons are not interconnected, but are interconnected between the visible layer and the hidden layer. In the visual layer, each neuron is used to describe a feature or attribute of the training sample. The hidden layer neurons are used to extract the corresponding features. The core of RBM learning is to correctly describe the characteristics of the observable stratum by adjusting the parameters. The RBM network structure is shown in Figure 3.2.

In Figure 3.2, there are m neurons and hidden neurons in RBM. The energy based model (EBM) is the core of RBM. For a group of known states, the energy of this state can be described by equation 3.1.

$$E(v,h|\theta) = -\sum_{i=1}^{m} b_i v_i - \sum_{j=1}^{n} c_j h_j - \sum_{i=1}^{m}\sum_{j=1}^{n} v_i w_{ij} h_j \tag{3.1}$$

The matrix vector form of the known state is shown in equation 3.2.

$$E(v,h) = -b^T v - c^T h - h^T W v \tag{3.2}$$

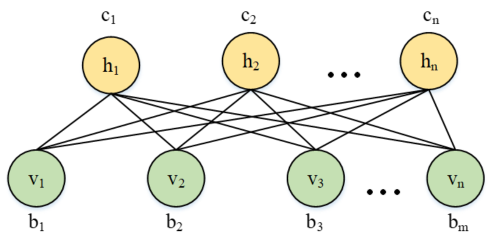


Fig. 3.2: RBM structure diagram

In equation 3.1, (v, h) is the description of the known state; v indicates the visible layer state vector; b indicates the visible layer offset vector; h indicates the hidden layer state vector; c indicates the hidden layer offset vector; W indicates the connection weight. Because RBM is the connection between visible layer and hidden layer, the weight of W is the connection weight between visible layer unit and hidden layer unit; $E(v, h|\theta$ Indicates the energy of the current state of the system; And θ is the parameter set of W, b, c. When the value of θ is determined, the joint probability distribution of RBM at a certain time is shown in equation 3.3.

$$\begin{cases} p(v,h|\theta) = \frac{e^{-E(v,h|\theta)}}{Z(\theta)} \\ z(\theta)) = \sum_{v,h} e^{-E(v,h)} \end{cases} \tag{3.3}$$

In equation 3.4, p represents the joint probability of a given parameter model; $Z(\theta)$ represents the partition function. If the state vector v of the visible layer is known, the neuron activation possibility of the concealed layer is shown in equation 3.4.

$$p(h_j = 1|v) = \text{sigmoid}\left(c_j + \sum_i v_i w_{ij}\right) \tag{3.4}$$

Similarly, if the hidden layer state vector h is known, the neuron activation possibility of the visible layer is shown in equation 3.5.

$$p(v_j = 1|h) = \text{sigmoid}\left(b_j + \sum_i h_i w_{ij}\right) \tag{3.5}$$

In equation 3.4 and equation 3.5, *sigmoid* represents the activation function, and its value range is from 0 to 1. When analyzing a practical problem, the essence of solving the problem is to solve the probability allocation of the visible layer v. The edge allocation of visible layer v is shown in equation 3.6.

$$p(v) = \frac{1}{Z(\theta)} \sum_h e^{-E(v,h|\theta)} \tag{3.6}$$

In equation 3.6, $p(v)$ represents the edge distribution of the visible layer. Similarly, the edge distribution formula of hidden layer h can be gotten, as shown in equation 3.7.

$$p(h) = \frac{1}{Z(\theta)} \sum_v e^{-E(v,h|\theta)} \tag{3.7}$$

It can be seen from the above formula that the main goal of training the RBM model is to modify θ to make the probability distribution represented by the model as consistent as feasible with the probability distribution of the training sample. Because the model is difficult to calculate $Z(\theta)$, the result of $p(v, h|\theta)$ is difficult to obtain. Traditional solving methods have seriously reduced the training efficiency of the model, and

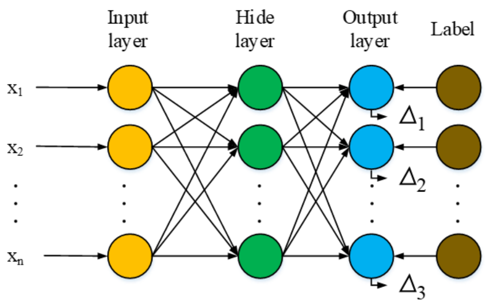


Fig. 3.3: Structure diagram of BPNN

the convergence velocity is also slow, so the learning efficiency of RBM model is low. To handle the above issues, the research applies the Contrast Divergence (CD) algorithm to initialize the neuron states of all visible layers [18, 19, 20]. CD algorithm only needs one Gibbs sampling to get a better approximation, so it is popular in RBM model. As a supervised learning classifier in DBN, BPNN uses a combination of forward propagation of signals and reverse fine tuning of errors to conduct autonomous learning [3, 4, 12]. Figure 3.3 demonstrates the structure of BPNN.

BPNN model consists of forward propagation and back propagation. Forward propagation is the training data from the input to the output layer through the middle layer to get the output Y; At this time, Y is a function of X and W. Back propagation is that when the output layer fails to get the expected value, W is modified by the minimum principle to reduce the model error. As long as appropriate hidden layer neurons are set, BPNN can approximate the nonlinear function of any discontinuous point. Calculate the error gradient between the actual output and the ideal output of the output node as shown in equation 3.8.

$$\delta_k = v_i'(1 - v_i')(v_i - v_i') \tag{3.8}$$

In equation 3.8, v_i' represents the actual output; v_i indicates the desired output. The gradient error of h is shown in equation 3.9.

$$\delta_h = v_h'(1 - v_h')\theta_{hk}\delta_k \tag{3.9}$$

In equation 3.9, θ represents the connection weight value. The update method of calculation weight is shown in equation 3.10.

$$\theta_{ij} = \theta_{ij} + \Delta\theta_{ij} = \theta_{ij} + \epsilon o_i \delta_j \tag{3.10}$$

In equation 3.10, ϵ represents the learning rate; o_i represents node output. The minimum value of output error is calculated as shown in equation 3.11.

$$E = \sum_S \left(\sum_Z (d_{sz} - o_{SZ}) \right)^2 \tag{3.11}$$

4. English personalized learning recommendation based on DBN classification. Study the application of the constructed DBN model to personalized resource recommendation in the education big data environment. In the experiment, a personalized recommendation model on the bias of DBN classification (DBN-MCPR) was established in the MOOC environment. Personalized recommendation are seen as a categorization prediction issue, and DBN-MCPR is the key to personalized recommendation. Figure 4.1 is the structure of the DBN-MCPR.

The data preprocessing module shown in Figure 4.1 refers to the data acquired by the data collection component, which cannot be directly imported into the DBN classification model for data feature extraction.

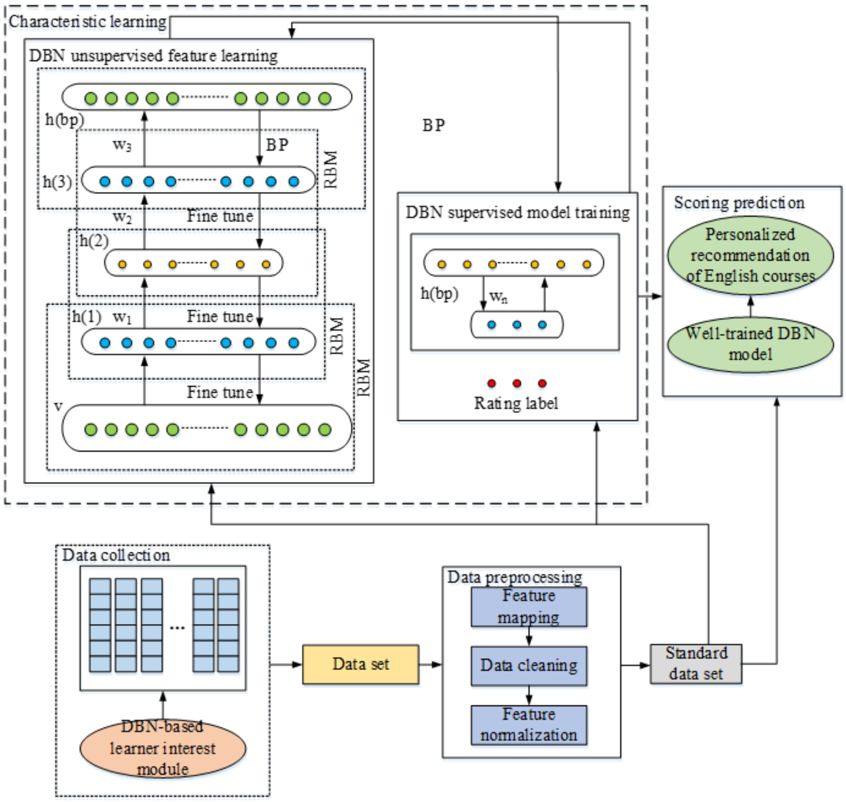


Fig. 4.1: Structure of DBN-MCPR model

Because there are many bad data in the data collected in the early stage, it is necessary to carry out analysis and categorization, characteristic mapping, noise processing, pseudo-data or null value cleaning, characteristic normalization and other operations. Data preprocessing usually affects the learning effect of the model. After the preliminary statistics, analysis and collection of data, the data with large deviation will be eliminated, and then the data will be digitized to eliminate the data that is meaningless for model training. The data will be standardized with equation 4.1.

$$x^* = \frac{x - x_{\min}}{x\ \min_{\max}} \tag{4.1}$$

In equation 4.1, x^* represents the normalized value; x indicates raw data; x_{min} and x_{max} represent the extreme value of a single attribute. The performance of DBN-MCPR model mainly depends on the training of DBN classification model, and its goal is to fit the data extracted from DBN depth feature to the maximum extent. The training of the model consists of two types: supervised and unsupervised.

$$W = W + \epsilon\left(\frac{1}{\text{dataset}}\Delta W\right) \tag{4.2}$$

Figure 4.2 demonstrates the training of DBN-MCPR.

In formula (2.13), ϵ represents the learning rate. Similarly, as indicated in formula (2.14), both the concealed layer offset vector and the apparent layer offset vector are changed.

$$\begin{cases} b = b + \epsilon\left(\frac{1}{\text{dataset}} \Delta\ b\right) \\ c = c + \epsilon\left(\frac{1}{\text{dataset}} \Delta\ c\right) \end{cases} \tag{4.3}$$

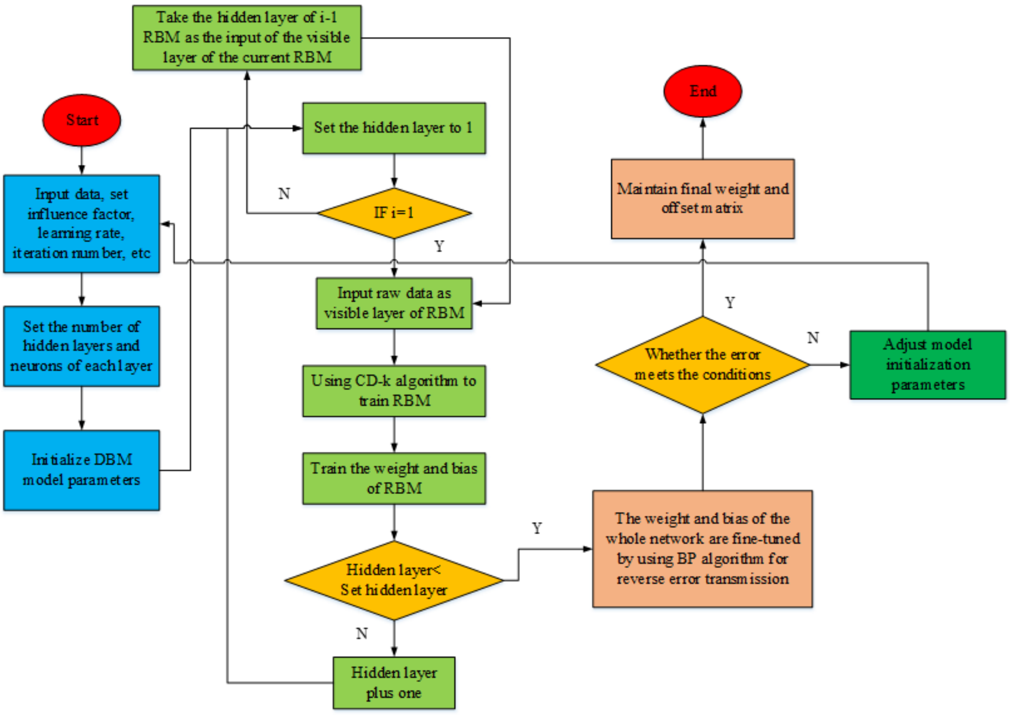


Fig. 4.2: Training the DBN-MCPR

To improve the recommended effect of DBN-MCPR, all parameters must be set effectively before the model runs. These settings usually include initialization and parameter settings. The model implicit weight matrix is initialized using the activation function. The main goal of model weight initialization is to ensure that the initialization neurons can work under the activation function's influence in the initial state, so as to ensure the transmission of information. Because the reverse propagation of gradient is invalid for the offset of hidden layer, the offset of this layer is 0, and the initialization of this value is also 0. In the training of DBN classification model, learning rate is very important. A good learning rate strategy can efficiently shorten the training time of the model and accelerate the convergence of the algorithm. Momentum is introduced into parameter updating, and the direction of parameter updating after two iterations is combined to avoid local extremum problem. In addition, the algorithm not only accelerates the convergence speed, but also greatly enhances the robustness of the model. The formula after adding momentum is shown in equation 4.4.

$$\theta := \varphi\theta + \epsilon\frac{\partial \ln L_s}{\partial \theta} \tag{4.4}$$

In equation 4.4, φ represents the learning rate of momentum. The research first sets φ to 0.5, and then adjusts it according to the reconstruction error during the training process. The number of iterations is the same as the learning rate setting strategy. According to the situation of training data,The quantity of initial pre-training iteration is 100, and the quantity of iterations in the fine-tuning stage is 200. Theoretically, increasing the quantity of hidden layers and hidden layer nodes can effectively improve the efficiency of feature extraction of the model, but there is no clear theoretical basis for specific parameter settings. And it needs to be set according to different models. The smaller quantity of hidden layers and nodes will weaken the ability of feature extraction, resulting in under-fitting; The quantity of hidden layers and nodes in the network is large, which makes the network structure more complex and vulnerable to local minimization, resulting in over-fitting.

Table 5.1: File Information of MovieLens 1M Dataset

Filename	Description	Field
Users.dat	User information files that include demographic characteristics	UserID, gender, age, occupation, zip-code
Movies.dat	A movie information file that includes movie content properties	MovieID, movietitle, genres
Ratings.dat	A file that contains information about the user's rating of the movie	UserID, movied, rating, timestamp

Therefore, according to Kolmogorov's law, the hidden layer is decided to be 3 layers and the neurons meet the $(2n+1)/n$ condition.

5. Effect analysis of deep belief network in personalized English learning under MOOC environment.

5.1. Analysis of personalized recommendation effect of DBN-MCPR model. Through the construction and analysis of the above model, detailed settings for experiments, materials, and data collection will be studied. The experiment was conducted using the MovieLens 1M dataset; Compare the performance of DBN based recommendation method, matrix factorization based Collaborative filtering recommendation method, BP network based recommendation method, and RBM based hybrid recommendation algorithm; Set the top-level feature dimension to 5; Examining the variation of RMSE values of different algorithms with the number of iterations; For the DBN-MCPR model, further parameter analysis is carried out, including the number of iterations, Learning rate, number of hidden layers, hierarchical settings, and training data set size. The materials and data were collected from the MovieLens 1M dataset, including users. dat, movies. dat, and ratings. dat files; Parsing dataset files to extract information about users, movies, and ratings; Collect demographic characteristics data such as gender, age, occupation, etc. based on user information; Collect film content attribute data for film information, such as categories, directors, actors, etc; Associate user rating data for movies with demographic characteristics and movie content attribute data to construct a dataset for model training; Organize and preprocess the dataset, such as removing duplicate data, handling missing values, etc. MovieLens 1 M was chosen as the test data to simulate the test data to the maximum extent. The experiment uses the demographic characteristics of users and the film content attributes for model training. This data set includes 6040 users of MovieLens, who evaluated 3952 films with 5-star rating and provided free text annotation. The data set mainly includes three parts: users.dat, movies data and ratings data. The details of each file are shown in Table 5.1 below.

The recommendation methods based on DBN and the collaborative algorithm of matrix decomposition are compared; The recommendation methods based on BP network and matrix decomposition are compared. Figure 5.1 shows the performance of different recommended algorithms in the MovieLens1M data set.

The top feature dimension of each recommended method is set to 5 in the experiment. Figure 5.1 illustrates how, when the upper dimension is the same, the RMSE values of various suggestion algorithms vary with the number of repetitions. In Figure 5.1, the number of repetitions has no effect on the User-CF and Item-suggestion CF's precision. With a rise in iterations, the RMSE graph greatly changes. However, in this data set, it is estimated that it will take more than 90 iterations to get better results. The more iterations of the recommended algorithm of BP network, the lower the RMSE; The smaller the RMSE is after 12 iterations. The more BP repeats, the lower RMSE. The RMSE value of BP fluctuates around 87.4%. From this point, we can see that the recommendation quality of BP is not high. After more than 60 iterations, the RBM hybrid recommendation algorithm has achieved good recommendation results; After 100 repetitions, the RMSE of the RBM recommended algorithm can reach 0.83. The RMSE value decreases and the recommendation's precision increases with the number of repetitions. From the experimental results, when there are more than 200 rounds, the precision of the recommendations is unaffected by the number of repetitions, and the recommendations outperform the RBM technique.When there are a set amount of repeats, the hybrid recommendation algorithm based on RBM is much better than the DBN classification method. In the hybrid recommendation of RBM, the result of recommendation is much worse than that of DBN classification because there is no supervised

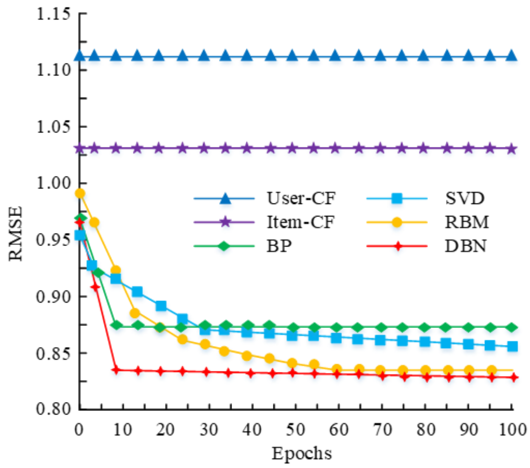


Fig. 5.1: Recommended performance of different algorithms

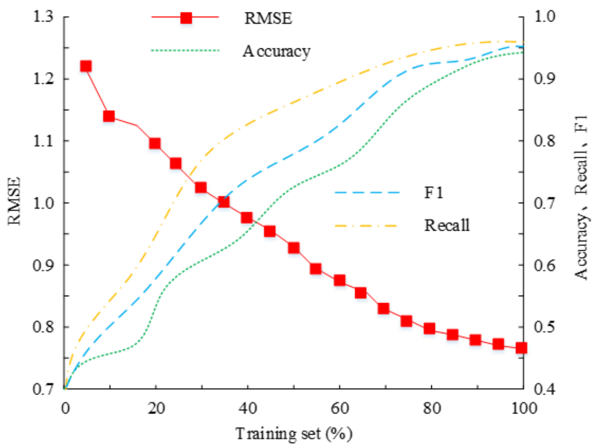
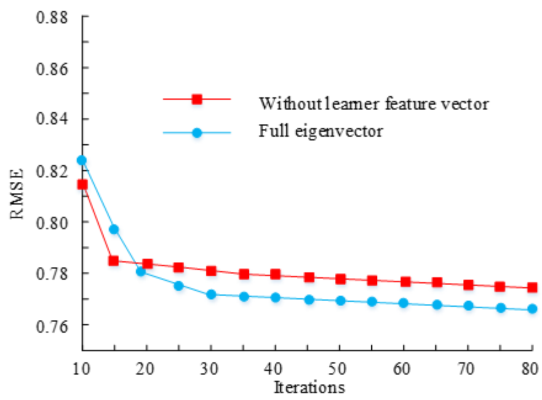


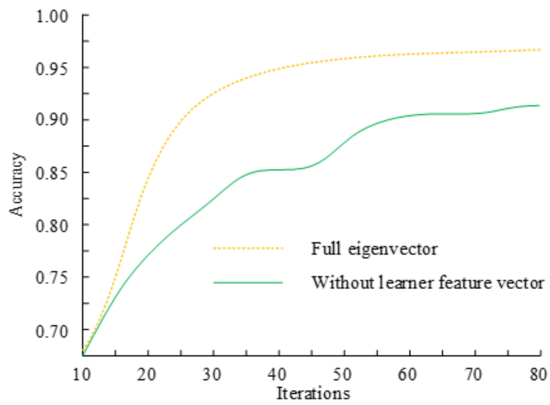
Fig. 5.2: Change of DBN-MCPR model performance with training set size

back-propagation algorithm. Moreover, the recommendation method based on DBN classification is superior to other recommendation methods in terms of convergence speed.

5.2. Performance analysis of parameters on DBN-MCPR model. In the experiment, the correctness of the recommendation algorithm of DBN classification is tested. The results show that the correct rate of the model is different with the adjustment of each parameter. It contains the quantity of training rounds, the quantity of feedback iterations for fine-tuning, the setting of learning rate, the quantity of concealed layers, and the layer setting. The size of the training data set will also have a great effect on the recommendation precision of the model. The data set of MovieLens1M is more about the demographic characteristics of users and the attributes of films. So in the evaluation of the film, there is no more about the user's behavior. This is very disadvantageous to deeply mining the user preference relationship model. For this reason, the research uses the actual student course selection data of the normal university to test the DBN-MCPR to achieve higher recommendation accuracy. The parameters of the DBN model are initialized by the proposed method.The batch size is 10; The pre-training learning rate was 0.01; Fine tuning learning rate is 0.1; The number of pre-training



(a) Effect of training set size on model RMSE



(b) Effect of training set size on model Accuracy

Fig. 5.3: Effect of learner feature vector on RMSE and Accuracy of DBN-MCPR model

iterations is 100; The quantity of fine-tuning iterations is 200; The characteristic dimension is 40; The output neuron is 5; The median neurons were 81, 163 and 327, respectively. The experiment will verify the influence of training data set, learner feature vector and GPU accelerator on the performance of the model. The RMSE, Accuracy, Recall and F1 values were selected as the criteria for judging the performance of the model.

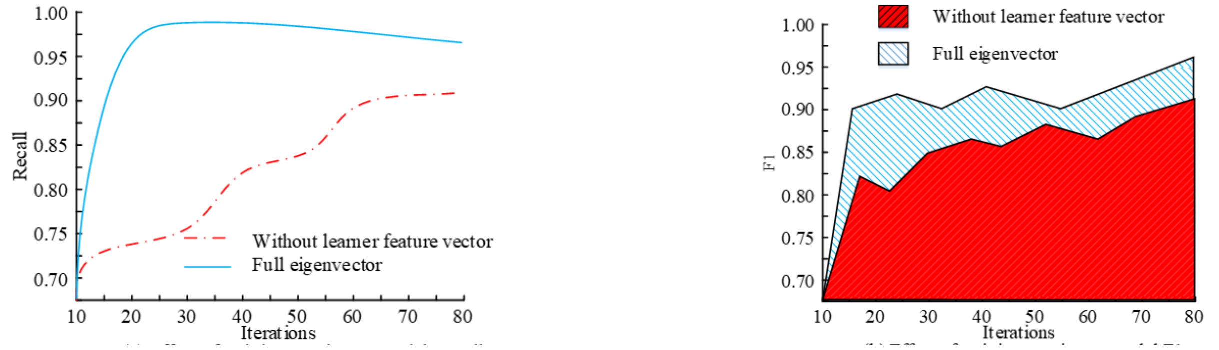
Figure 5.2 shows the impact of training set size on DBN-MCPR model. In Figure 5.2, the RMSE of the model is directly influenced by the percentage of the training sample. The higher the proportion of the training set, the lower the RMSE value. When the training set proportion reaches 100%, the RMSE value of the model is 0.76. From the analysis of the accuracy results, the higher the training set proportion, the higher the precision value. When the training set proportion reaches 100%, the accuracy value of the model is 0.946. From the analysis of Recall results, the higher the proportion of training set, the higher the Recall value of the model. When the training set proportion reaches 100%, the Recall value of the model is 0.957. From the analysis of F1 value results, the higher the proportion of training set, the higher the F1 value. When the training set proportion reaches 100%, the F1 value is 0.951.

Figure 5.3 shows the effect of learner feature vectors on the model. In Figure 5.3a, when the iterations of the model achieves to 80, the RMSE value is 0.79 when the training data set without the learner feature vector is trained. When the training data set of learner feature vector is used for training, the RMSE value of the model is 0.75. In Figure 5.3b, when the iterations of the model achieves to 80, the precision value is 0.917 when the training data set without the learner feature vector is trained. When the training data set of learner feature vector is applied for training, the accuracy value of the model is 0.962.

Figure 5.4 shows the effect of learner feature vectors on the Recall and F1 values of the model. In Figure 5.4a, the Recall value of the model is 0.908 when the training data set without the learner's feature vector is trained. The Recall value of the model is 0.966 when the training data set of the learner feature vector is used for training. In Figure 5.4b, the F1 value is 0.913 when the training data set without the learner feature vector is trained. The F1 value is 0.958 when the training data set of the learner feature vector is used for training.

Figure 5.5 depicts how the Processor affects how effectively the model runs.. In Figure 5.5, the running time of the model increases with iterations. When iterations reaches 100, the running time is about 360 minutes. The RMSE value is also increasing, and the final RMSE value is 0.92.

Figure 5.6 depicts how the Processor affects how effectively the model runs. In Figure 5.6, the running time increases with the iterations. However, when iterations reaches 100, the running time is only about 90 minutes. The RMSE value is also increasing, and the final RMSE value is 0.75.



(a) Effect of training set size on model Recall

(b) Effect of training set size on model F1

Fig. 5.4: Effect of learner's feature vector on Recall and F1 values of DBN-MCPR model

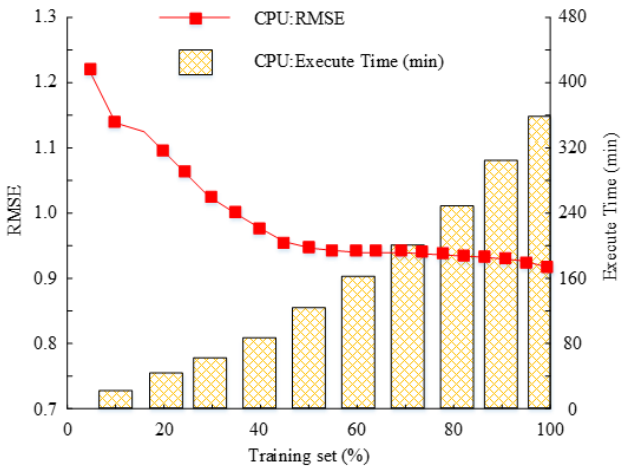


Fig. 5.5: Effect of CPU on the running efficiency of DBN-MCPR model

6. Discussion. Based on the experimental results, we conducted a comprehensive analysis and explanation of the performance of the DBN-MCPR model on the MovieLens 1M dataset, and linked it to research questions and existing literature. First, by comparing the performance of different recommendation methods, it is found that the recommendation method of DBN classification is superior to other recommendation methods in Rate of convergence. Specifically, when the number of repetitions is fixed, the hybrid recommendation algorithm based on RBM performs slightly worse than the recommendation algorithm based on DBN classification. This shows that although the hybrid recommendation algorithm can improve the recommendation accuracy to a certain extent, the DBN based classification method performs better in Rate of convergence and recommendation quality. Secondly, a detailed analysis was conducted on the parameters of the DBN-MCPR model. It is found that the recommendation accuracy of the model is affected by several parameters, including the number of iterations during training, the number of iterations during feedback fine-tuning, the setting of Learning rate, the number of hidden layers and layers, and the size of the training dataset. In the experiment, gradually debug the combination of these parameters and evaluate the performance of the model. The experimental results show that a higher proportion of training sets, the use of learner feature vectors for training, and GPU acceleration can significantly improve the recommendation accuracy and performance of the model. The

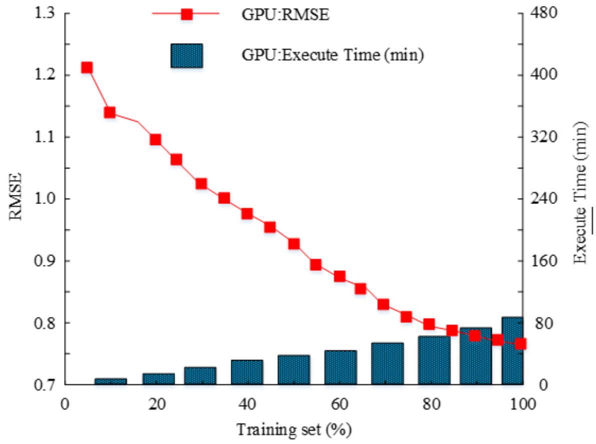


Fig. 5.6: Effect of GPU on the operation efficiency of DBN-MCPR model

experimental results show that the DBN based recommendation method has advantages over other methods in Rate of convergence and recommendation quality. This is consistent with the expected advantages of DBN in the research question.

7. Conclusion. The study explores the application effect of personalized English learning based on large-scale open online courses, and uses DBN to construct a personalized resource recommendation model. This model integrates learner behavior features with course resource content attribute features to form learner feature vectors. The parameters of the model are adjusted based on the learner's characteristics. Through experiments, the DBN-MCPR model showed the best performance when compared with other models, with an RMSE value of 0.83. At the same time, the effects of the size of training set, learner characteristics and GPU on the function of the model are also discussed. The experimental results indicate that the RMSE, Accuracy, Recall and F1 values of the model are 0.76, 0.946, 0.957 and 0.951 respectively when the training set is 100%. When the model uses the training set containing learner characteristics for training, the RMSE, Accuracy, Recall and F1 values of the model are 0.75, 0.962, 0.908 and 0.958, respectively. When GPU is used to accelerate the model, the running time of the model is reduced from 360 min to 90 min. The results show that the model cannot well mine data information when the degree of sample information association is low. The richer the relationship between samples, the better the performance of the model. Meanwhile, the learner characteristic vector and the learner behavior characteristic vector are trained together, which can significantly improve the recommendation accuracy of the model. There are still some deficiencies in the experiment carried out in the study. At present, the score data of learners on the MOOC platform on English curriculum resources are few. The DBN model has some difficulties in mining information, which leads to the improvement of model performance. Therefore, the follow-up research can explore how to effectively use the learner feedback information as the original training data set, so as to train a more efficient personalized recommendation model.

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