

Retraction

Retracted: Research on Students' Adaptive Learning System Based on Deep Learning Model

Scientific Programming

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] X. Yang, Z. Zhou, and Y. Xiao, "Research on Students' Adaptive Learning System Based on Deep Learning Model," *Scientific Programming*, vol. 2021, Article ID 6593438, 13 pages, 2021.

Research Article

Research on Students' Adaptive Learning System Based on Deep Learning Model

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With the rapid development of deep learning in recent years, recommendation algorithm combined with deep learning model has become an important direction in the field of recommendation in the future. Personalized learning resource recommendation is the main way to realize students' adaptation to the learning system. Based on the in-depth learning mode, students' online learning action data are obtained, and further learning analysis technology is used to construct students' special learning mode and provide suitable learning resources. The traditional method of introducing learning resources mainly stays at the level of examination questions. What ignores the essence of students' learning is the learning of knowledge points. Students' learning process is affected by "before" and "after" learning behavior, which has the characteristics of time. Among them, bidirectional length cyclic neural network is good at considering the "front" and "back" states of recommended nodes when recommending prediction results. For the above situation, this paper proposes a recommendation method of students' learning resources based on bidirectional long-term and short-term memory cyclic neural network. Firstly, recommend the second examination according to the knowledge points, predict the scores of important steps including the accuracy of the recommended examination of the target students and the knowledge points of the recommended examination, and finally cooperate with the above two prediction results to judge whether the examination questions are finally recommended. Through the comparative experiment with the traditional recommendation algorithm, it is found that the student adaptive learning system based on the deep learning model proposed in this paper has better stability and interpretability in the recommendation results.

1. Introduction

With the advent of the era of big data, combining the educational big data generated in the field of education with the deep learning model [1] can find internal characteristics from a large number of educational data, thus optimizing the educational model and carrying out more efficient teaching activities. The essence of education big data is big data in the field of education. Its data sources include not only learners' learning data, but also all people's behavior data in daily educational activities. It has the characteristics of multi-theme, multielement, and multiform. If we deviate from the adaptive learning of educational big data, we can solve the problems of unbalanced educational resources and educational model planning in traditional education, pay attention to students themselves, and realize personalized learning.

On the basis of the continuous development of information technology, distance education to overcome the limitation of time and space began to appear [2]. Adaptive learning system dynamically adjusts the generation of learning resources according to students' learning conditions, which overcomes the problems of unbalanced distribution of educational resources and single educational model in Chinese traditional education, and is of great significance to the realization of high-quality education. However, compared with foreign countries, there are more mature systems, such as Moodle Learning Management System and Knewton Personalized Learning Platform [3]. In China, the research on students' adaptive learning system is still in the theoretical stage. The research, design, development, and implementation of adaptive learning system are one of the research hotspots in the future education field.

With the rise of artificial intelligence, more and more people use data and machine learning to help and assist students to learn, which is used to detect emotional state and transfer negative state. We propose to use multimodal sensor data and machine learning system, which can improve the learning speed and keep the learner in the optimal emotional state [4]. Adaptive learning rate algorithm is an automatic method to set learning rate manually. We study Barzilai–Borwein step size method and extend it to adaptive learning rate problem. Through experiments, it is found that this method has great advantages in the learning speed and generalization performance compared with other methods [5]. With the popularity of the Internet, people are increasingly accepting online learning. It can provide learners with various learning materials and acquire knowledge in various fields. Based on the adaptive learning management system based on real-time personalization and personalized page ranking algorithm, we complete the skill test evaluation report and use Navies Bayes classifier to classify the learners' test results. Jagadeesan and Subbiah [6] provided learning content according to the level differences of learners and combined different learning methods and time for effective management.

Each learner has different abilities and preferences, which leads to the lack of a good way to support learners' needs in online education system, which is a challenge we face. Therefore, we adjust the teaching decisions according to the different needs of learners and develop an adaptive learning system that can generate learning paths according to learners' personal data. Q-learning algorithm is a reinforcement learning technique in this system, which provides learners with necessary contents and courses based on learners' feedback [7]. Adaptive learning management system can solve this problem by choosing suitable learning methods according to learners' learning conditions. This system can create courses with customized content and update them constantly during learning. The learning materials come from the knowledge base, which is searched, updated, and ranked for relevance by using the network. In order to verify its effectiveness, we test and evaluate the system, and the results show that the real-time test of the system shows its most advanced performance [8].

2. Recommendation Algorithm Based on Deep Learning

2.1. Traditional Recommendation Algorithm

2.1.1. Recommendation Algorithm Based on Popularity. Popularity-based recommendation algorithm is the simplest and most direct recommendation algorithm, which is widely used in various sites. It is mainly recommended to sort items based on PV, UV, and other data [9], where PV is page view. Its advantage is that it has no cold start problem and is suitable for new users. The disadvantage is that it cannot be customized for users.

2.1.2. Collaborative Filtering Recommendation Algorithm. At present, the cooperative filter recommendation algorithm is the most successful and widely used recommendation

algorithm, mainly including user-based common filtering recommendation algorithm and project-based common filtering recommendation algorithm. The common filter recommendation algorithm based on users first analyzes the evaluation records between users and items, calculates the similarity between users based on the evaluation records, and then selects M users who are most similar to the current users. Finally, the similar user group has the highest evaluation and selects the target users not to use N items in the records to recommend. The project-based joint filter recommendation algorithm firstly analyzes the evaluation records of users and projects, calculates the similarity of each project according to the evaluation records, and finally finds out N projects with the highest similarity of the projects evaluated by target users for recommendation. The principle of filtering recommendation algorithm is simple, and the evaluation indexes such as accuracy and recall rate are also very good. However, there is also the problem of relying too much on user ratings. When there are few records of cold start, new projects, and new users, the recommendation effect is poor.

2.1.3. Content-Based Recommendation Algorithm. Its principle is to analyze the content of the items used by the user to generate the content selection of the user's preference and recommend other items with high similarity of the items used [10]. Its advantage is to solve the problem of cold start, but its disadvantage is that users directly recommend items closely related to reading content, and the recommended content is more single.

2.1.4. Model-Based Recommendation Algorithm. Make a model to predict the user's score according to which is recommended [11]. The greatest advantage of this recommended method is that it is correct and fast. The disadvantage is that in order to maintain a better recommendation effect, the online recommendation mode is often maintained and updated to adapt to the changes of users and projects.

2.1.5. Hybrid Recommendation Algorithm. Recommendation methods have their own advantages and disadvantages. In order to get better recommendation results, hybrid recommendation strategies are often used in the real world [12]; there are often mixed recommendation strategies, such as conversion, crowding, and so on. Crowding is to return the recommendation results of various recommendation technologies to users for selection.

2.1.6. Comparison of Recommendation Algorithms. A comparison of the advantages and disadvantages of the above recommended algorithms is shown in Table 1.

2.2. Recommendation Algorithm Based on Deep Learning Model. Deep learning can directly extract features from content, process noise data, have better noise resistance [13],

TABLE 1: Comparison of the commonly used recommendation algorithms.

Recommended technology	Advantages	Disadvantages
Recommendation algorithm based on popularity	Simple and easy to operate, without the problem of cold start	Unable to make personalized recommendations
Collaborative filtering recommendation algorithm	Simple and easy to implement, with high recommendation accuracy	Too much reliance on user ratings; cold start; low project coverage
Content-based recommendation algorithm	No cold start problem	The recommended content is relatively simple
Model-based recommendation algorithm	Fast and accurate, especially suitable for high real-time business	Models need to be maintained frequently

and can realize dynamic or sequential data modeling. Because of the characteristics of this neural network, it is also very effective to import the recommendation system.

2.2.1. Recommendation Model Based on Multilayer Perceptron. The MLP network structure of a three-tier structure is shown in Figure 1.

2.2.2. Recommendation Model Based on Automatic Encoder. The data conversion from the input layer to the hidden layer is a program φ after decoding the data conversion from the hidden layer to the output layer, and the calculation method is as shown in the following formulas:

$$\phi: X \longrightarrow Z: x \mapsto \phi(x) = \sigma(Wx + b) = z, \quad (1)$$

$$\varphi: Z \longrightarrow X: z \mapsto \phi(z) = \sigma(\tilde{W}z + \tilde{b}) = x. \quad (2)$$

The first layer of the encoder can learn the primary features of the original input, and the second layer can learn the secondary features corresponding to the primary features.

2.2.3. The Model Based on Convolution Neural Network. It is assumed that the neural network is an I input unit and a K output unit, the implicit layer is a layer, and the J unit is shared. The formula for the sum of squared errors is as follows:

$$E = \frac{1}{2} \sum_{k=1}^k (d_k - o_k)^2. \quad (3)$$

Among them, the following hold:

$o_k = f(\text{net}_k)$ is the actual output value of neuron k in the output layer.

d_k is the desired output value of the output layer neuron k .

y_j is the output value of hidden layer neuron j .

For the E -value, in order to achieve the goal of the ideal value, it is necessary to change the weight value of the network. First, adjust the connection weights between the implicit layer and the output layer.

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj}. \quad (4)$$

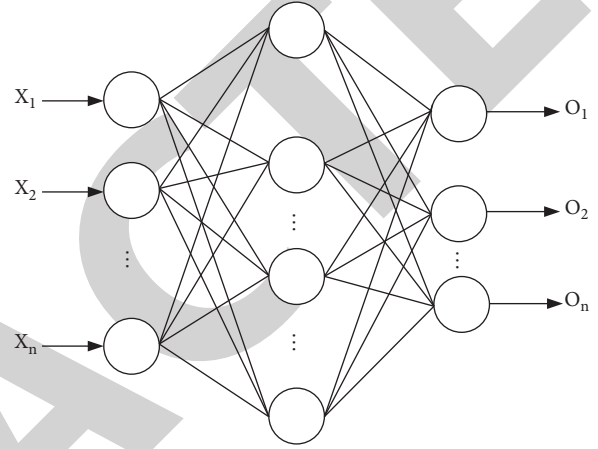


FIGURE 1: Multilayer perceptron network structure.

In the above formula, the value obtained by the gradient method is the adjusted value of the connection weight between the implicit layer and the output layer.

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} = \eta (d_k - o_k) f'(\text{net}_k) y_j. \quad (5)$$

In the above formula, η is the normal value, which is expressed as the iteration step.

In a similar manner, you can adjust the connection weights between the input layer and the implicit layer. Formula adjustment:

$$v_{ji}(t+1) = v_{ji}(t) + \Delta v_{ji}. \quad (6)$$

In the above formula, Δv_{ji} is the adjustment amount for determining the connection weight between the input layer and the implicit layer by the gradient method. It can be obtained from the following formula:

$$\Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}} = \eta \sum_{k=1}^k (d_k - o_k) f'(\text{net}_k) w_{kj} f'(\text{net}_j) x_i. \quad (7)$$

When there are samples, if there are P training samples, the total error sum form of the above calculation method is

$$E_p = \frac{1}{2} \sum_{p=1}^P \sum_{k=1}^K (d_k - o_k)^2. \quad (8)$$

As long as the operation is repeated for P samples as described above, Ep reaches the minimum requested value, and the algorithm ends.

The workflow is shown in Figure 2.

2.2.4. Recommendation Model Based on Recurrent Neural Network. Recent progress shows that RNN can effectively solve this part of the problem. Unlike feedforward neural networks, RNN has previous calculations, such as LSTM and GRU, which are usually used to overcome gradient disappearance in practical use.

2.2.5. Recommendation Model Based on Deep Semantic Similarity Model. In this model, different items are projected into a common low-dimensional space, and the similarity of items is calculated by cosine similarity calculation method. The details are shown in Figure 3.

2.2.6. Emerging Methods: Neural Autoregressive Distribution Estimation and Generative Countermeasure Network. Compared with other recommendation models based on deep learning, these two methods can obtain the best recommendation accuracy and good recommendation effect.

3. Research on Adaptive Learning System Based on Personalized Learning Resource Recommendation Algorithm

3.1. Personalized Learning Resource Recommendation Algorithm Based on Deep Learning Model. This section proposes a personalized learning resource recommendation algorithm based on deep learning. Specifically, the algorithm [14, 15] does not simply carry out TOP-N recommendation, but considers students' learning progress and current situation, predicts students' actions according to time information, and recommends learning resources.

3.1.1. Problem Description. The purpose of the introduction of personality test questions is to analyze students' logs, obtain students' learning status, and provide high-quality test questions exercises with personality so as to help students get rid of monotonous and repeated mechanical exercises.

Howard Gedina, an American educator, believes that quality intelligence can be developed and that anyone's intelligence can be improved by learning. When introducing personalized examination questions, students' learning situation and cognitive ability should be considered, and corresponding recommendations should be made according to their actual conditions. If the difficulty of the problem is not set properly, it is the students' "cognitive loss." Appropriate organization of learning resource sequence can stimulate students' learning enthusiasm and learning efficiency. It is extremely important to determine the difficulty of learning resources and the sequence of the most effective learning resources in students' learning process, which is also called the principle of procedure. Therefore, when

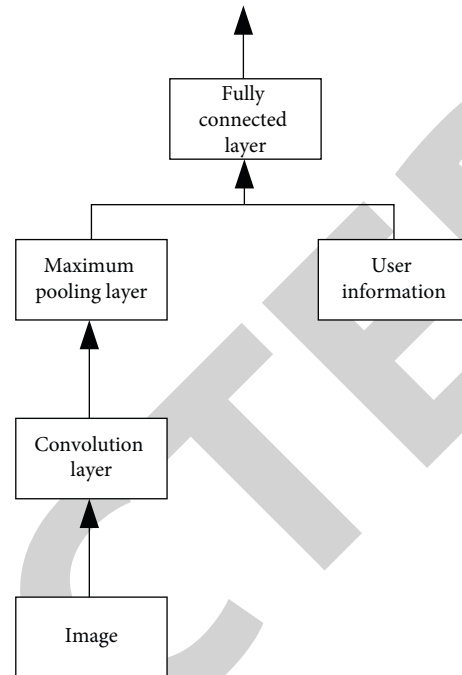


FIGURE 2: Workflow chart of attention-based convolution neural network recommendation model.

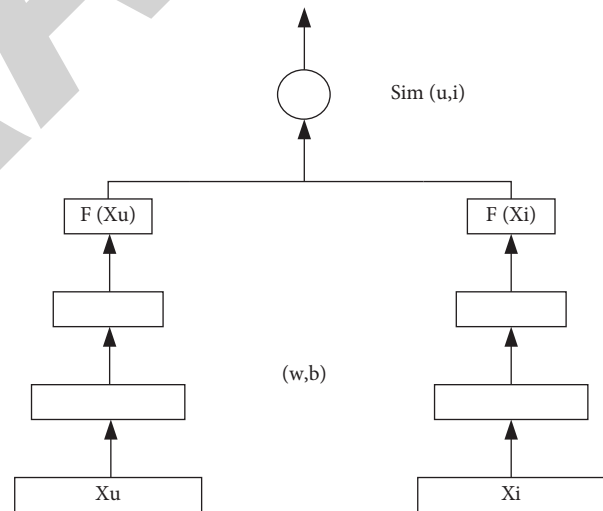


FIGURE 3: DSSM workflow chart.

making exam recommendations, we should bravely jump out of the comfort zone of the target students and cannot practice between the knowledge points we have been learning. Proper development can improve students' enthusiasm and initiative.

3.1.2. Algorithm Framework. Figure 4 shows the framework of the algorithm proposed in this paper.

The main flow of the method proposed in this paper is defined:

- (1) Analyze the data set, obtain the interactive records between students and exam questions, and construct

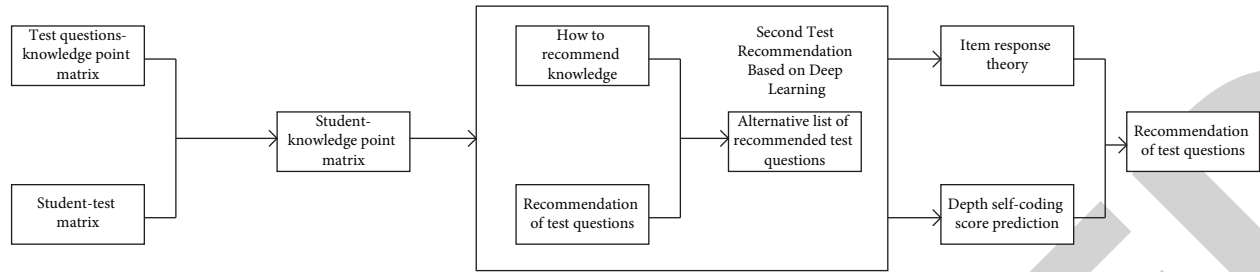


FIGURE 4: Personalized test recommendation algorithm framework.

the correlation matrix between questions and knowledge points.

- (2) This paper introduces the detection problem of quadratic cooperative filter based on knowledge points. Firstly, knowledge points are recommended according to the knowledge point matrix of students, and then test questions containing recommended knowledge points are introduced on the basis of recommended knowledge points.
- (3) According to the structural prediction model of IRT, judge whether the steps of using this knowledge point in the recommended examination are correct.
- (4) Predict the recommended test questions according to the scores and judge the correct rate of each test question.
- (5) Determine the final test question introduction list, control the difficulty range of the recommended test, and the final recommended test questions are not difficult.

3.1.3. Algorithm Implementation

Constructing Student-Knowledge Matrix. Firstly, the students' learning log is processed, and the interactive records between students and examination questions are obtained. The data format of each line of the student-exam question record seems to be "studentuid: probemuid: ratimestamp". Use the correct rate of exam questions to express students' grasp of this problem. A question contains many knowledge points, so students' exercises on examination questions are classified as exercises on students' knowledge points. The mapping relationship between student-examination question matrix and examination question-calculation knowledge point matrix is obtained, and the interactive matrix related to student-knowledge points is standardized and uniformly processed, and the interactive records are integrated. Students use the correct rate of all questions including a certain knowledge point to express their mastery of the knowledge point and record it as a time stamp of dialogue with the knowledge point in the maximum time, and finally get the student-knowledge point column. The interactive record of student-examination questions is further changed into the interactive record of student-knowledge point, and "studentuid: kcuid: ratimestamp" is recorded. Finally, according to the chapters with knowledge points, ECharts is used to show the processed results. Organize the

knowledge points of learning and understand the overall grasp of the situation.

Bi-LSTM Collaborative Filtering. The Long Short-Term Memory Network (LSTM) [16, 17] is a special RNN of the network structure shown in Figure 5. LSTM model is used to overcome the increase of long-term storage calculation index of RNN. Besides the basic structure of RNN, valve nodes of each layer are added to determine whether the model storage state is added to the calculation of this layer.

In LSTM model training, the state transfer is carried out from the back direction to one direction, but in some problems, the output of the current time is not only related to the previous state, but also related to the subsequent state. In this case, a bidirectional LSTM (Bi-LSTM) model is needed. Bi-LSTM is composed of two parts of one-way LSTM. The basic flow of secondary recommendation based on knowledge points using Bi-LSTM is as follows:

- (1) Raw data conversion

Generate a model training data set. After the data set is thermally encoded separately, sparse data with m binary features will be formed. By using single hot coding, the problem that the classifier cannot deal with attribute data well can be overcome.
- (2) Confirmation and adjustment of network model structure

After a series of experimental studies, we can determine the Bi-LSTM network model [18], determine the obsolescence rate of each layer, the repeated updating mode of weighting parameters, and the best model training including epoch and batch size. Finally, we decided to recommend the most effective Bi-SLSTM network model structure for personalization problems [19].
- (3) Prediction of model training results

In the recommended method of submitting test questions, firstly, knowledge points are recommended according to the interaction records between students and knowledge points. In addition, on the basis of recommending knowledge points, according to the alternate records of students and examination questions, personalized examination questions based on knowledge points are recommended, and the candidate recommendation list of personalized examination based on knowledge points is determined.

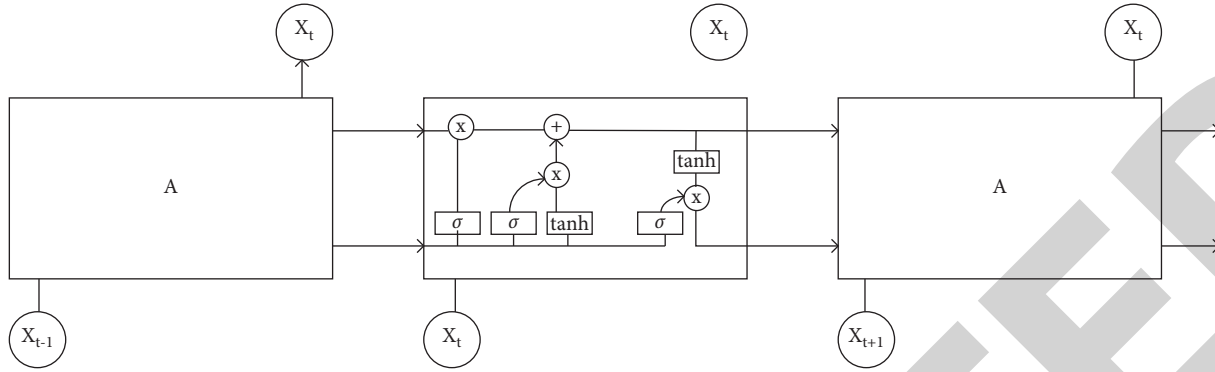


FIGURE 5: LSTM model structure diagram.

Item Response Theory Model. The original data is processed to obtain cognitive diagnosis data set. In the case of model training, weights are assigned to each sample data, and these weights constitute vector D . The error rate calculation method is defined as follows [20]:

$$\varepsilon = \frac{\text{Number of samples incorrectly classified}}{\text{Number of all samples}}. \quad (9)$$

The change formula of error sample weight is as follows:

$$D_i^{(t+1)} = \frac{D_i^{(t)} e}{\text{Sum}(D)}. \quad (10)$$

The correct sample weight is changed as follows:

$$D_i^{(t+1)} = \frac{D_i^{(t)} e^{-a}}{\text{Sum}(D)}. \quad (11)$$

t is the current classifier and i indicates the i th sample. Then, the updated sample weight training is used to repeat the above process. The weighting calculation formula of classifier is as follows:

$$a = \frac{1}{2} \ln \left(\frac{1 - \varepsilon}{\varepsilon} \right). \quad (12)$$

Use the last trained model to predict students' learning resources in Figure 6.

3.2. Students' Adaptive Learning System. Adaptive learning system is divided into online learning subsystem, individual test subsystem, learning information analysis subsystem, and resource management subsystem according to business functions. In the online learning subsystem, students order and study courses according to their needs, and when they learn to a certain stage, they can take the exams published by the course teachers to achieve the purpose of consolidating exercises in Figure 7.

Business service model is a module that provides substantive operations and applies specific business operation processes. The course management mainly depends on the business service module to process and supplement the business service. The storage side is the efficiency of storing and submitting data management for related data.

4. Experiment

4.1. Data Collection and Processing. Table 2 is the record data, which contains a series of question record information, such as student ID, question grade, and question name. According to the problem log information, the cognitive status of students' knowledge points is obtained.

Data sets are processed and analyzed through deep learning model. On the other hand, by extracting the information recorded for each problem, the right and wrong information of students' knowledge points and steps corresponding to specific problems can be obtained. According to the statistics of knowledge points, understand the knowledge points of students (correct rate). Finally, through the interaction between students and the knowledge points, the timestamp information can be recorded, and the students and examination questions, knowledge points, cognitive status, and timestamp information can be obtained. On the other hand, by processing the whole data set based on knowledge points, we can obtain the relevant information that the number of occurrences of knowledge points represents the weight of knowledge points. It is important to express the error rate of students' knowledge points.

4.1.1. Precision. Accuracy is one of the important indexes of students' adaptive learning system. Introductory problems applied to individualized learning problems. That is, it represents the ratio of the number of questions hit practiced by the user in the test set to the total number of recommended tests R .

$$\text{Precision} = \frac{\text{hit}}{R}. \quad (13)$$

4.1.2. Recall. Recall rate is another important indicator for evaluating students' adaptive learning system, and it is suitable for recommending questions of personality test questions. That is, it represents the ratio of the number of questions hit practiced by the user to the number of questions T practiced by the user in the test question. Specific definition formula is

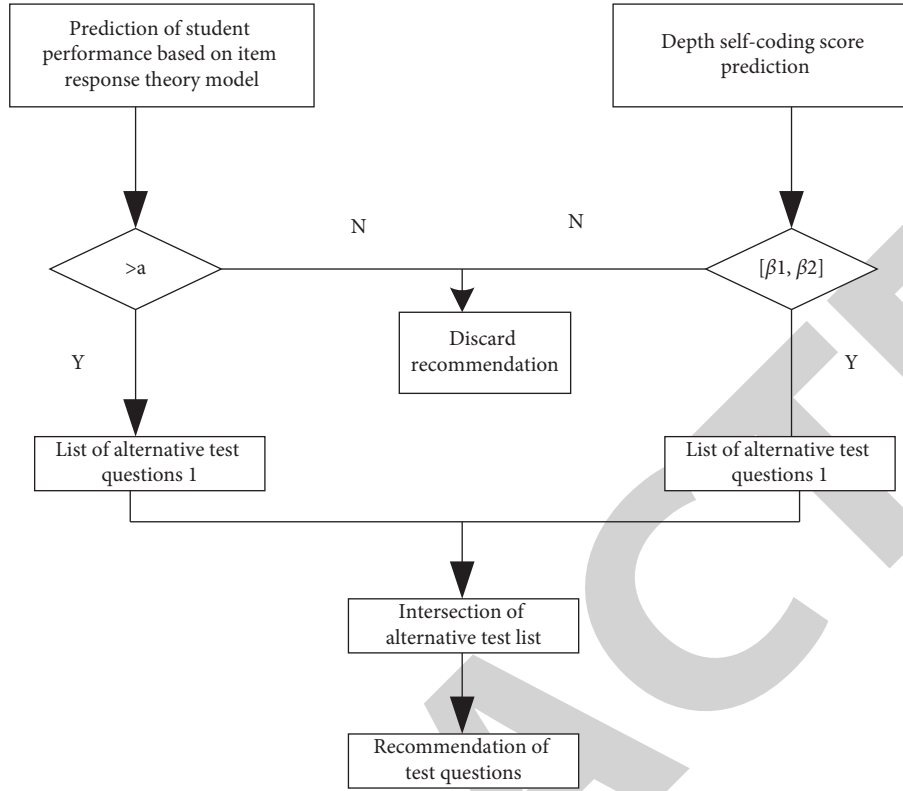


FIGURE 6: Flowchart of determining the recommended list of test questions.

$$\text{recall} = \frac{\text{hit}}{T}. \quad (14)$$

4.1.3. *Item_Coverage*. Project coverage is to measure the mining ability of the final project recommendation system. Excellent recommendation improves the user experience, improves the possibility of users using the project to achieve their goals, and should have the opportunity to recommend each project in the system as much as possible. Item_Coverage is numerically equal to the total number of recommended different items.

4.1.4. *Average Difficulty (AD)*. Different from the introduction of traditional movies and music, the essence of the problem is the actual grasp of knowledge points introduced by students. Therefore, only using the evaluation parameters (correct rate, recall rate, and F1) based on the previous TOP-N or evaluation prediction idea is not comprehensive enough. Therefore, in order to evaluate the recommendation results of test questions, this paper puts forward the average difficulty of test questions AD.

$$AD = \frac{\sum_{i=1}^n D}{n}, \quad (15)$$

where D is the difficulty of each test question and n is the number of recommended test questions. AD indicates the average difficulty of the test question, but the smaller the AD value, the simpler the recommended test, and the purpose of

practice cannot be achieved. If the AD value is small, it is difficult to recommend the exam, which means that the correct rate of students is low. The AD value of the recommended result should be kept within an appropriate range.

4.2. *Comparison of Algorithms*. In this paper, the proposed test problem recommendation method is verified by comparative experiments, including user-based collaborative filtering recommendation algorithm, potential trajectory modeling recommendation method, and Markov chain comparison. User-based common filtering recommendation algorithm is one of the most classical recommendation algorithms. Markov chain is a recommendation algorithm based on classical sequence. In addition, the recommendation method of personalized test questions based on deep learning proposed in this paper is also the recommendation of test questions based on sequential questions. The selection of Markov chain can better show the efficiency of the recommended method proposed in this paper.

4.2.1. *User-Based Collaborative Filtering Recommendation Algorithm (UserCF)*.

$$\text{sim}(u, v) = \sum_{i \in (Pu \cap Pv)} \frac{(R_{u,i} - \bar{R}_t) \times (R_{v,i} - \bar{R}_t)}{\sqrt{(R_{u,i} - \bar{R}_t)^2} \times \sqrt{(R_{v,i} - \bar{R}_t)^2}} \quad (16)$$

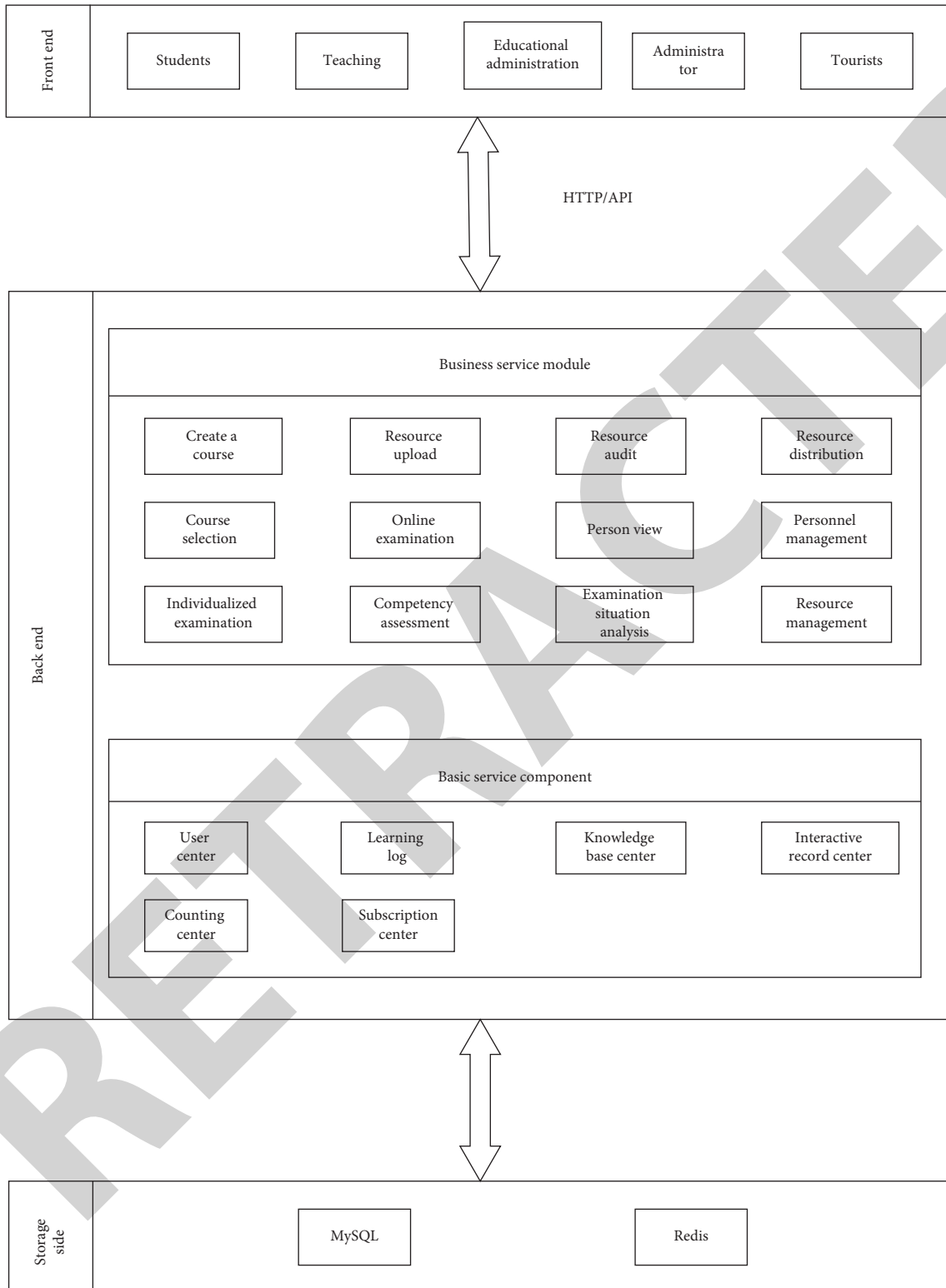


FIGURE 7: Architecture diagram of students' adaptive learning system.

TABLE 2: Data set field description.

Field name	Remarks	Field name	Remarks
Anon student ID	Student ID	Step duration	Step time
Problem hierarchy	Chapter	Correct step duration	Correct step time
Problem name	Test questions	Error step duration	Error step time
Problem view	Number of problems encountered	Correct first attempt	First attempt time
Step name	Step name	Incorrects	Number of errors

where P_u is the set of exercise questions for student u ; P_v is the set of exercise questions for student v ; and $R_{u,i}$ is the score of student u on test i .

After determining the similar student groups of the target students, the performance of the test questions of the target students is predicted according to the weighting of the similar student groups and the scores of the test questions, and the test questions recommendation list is obtained to recommend the test questions.

4.2.2. Latent Trajectory Modeling Recommendation Algorithm (LTM). Latent trajectory modeling (LM)

$$P(X_{n+1} = x | X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = P(X_{n+1} = x | X_n = x_n). \quad (17)$$

According to the Markov chain test questions, the test questions that predict the students' next state and practice are recommended.

4.3. Result Analysis. Firstly, the Bi-LSTM model is adjusted, including learning rate, dropout, and batch size. The quality of the model is judged from four angles: recall rate, sps, project coverage, and ndcg, and the structure of the model is finally determined.

4.3.1. Learning Rate (*learning_rate*). Learning rate determines whether the training of deep learning model can converge to local minimum and convergence speed. In order to select the best learning rate, 1, 0.1, 0.01, 0.001, and 0.0001 were selected in turn for comparative experiments. Experimental results (Figure 8) show the evaluation of experimental results of *learning_rate*.

It can be observed through Figure 8 that when the learning rate is 0.0001, the training mode is obviously dominant in the recall rate, and with the training, the recall rate is significantly improved. When the learning rate is 0.001 and 0.0001, although the growth trend of sps, item_coverage, and ndcg is the same, the performance of 0.0001 learning rate is better than 0.001. On the other hand, when the learning rate is 1, 0.1, and 0.01, the other evaluation indexes have no obvious improvement with the training. Therefore, 0.0001 is the learning rate of the final model.

4.3.2. Dropout. In order to avoid the overfitting phenomenon in deep learning mode training, that is, the trained model shows excellent performance in training data, but due to poor performance and low accuracy of test data, the method of adjusting Dropout parameters is adopted. In this adjustment of Dropout, a comparative experiment was performed using 0.4, 0.5, 0.6, 0.7, and 0.8, and the experimental results are shown in the evaluation of experimental results of Dropout in Figure 9.

It can be seen from Figures 9(a)–9(d) that with the training, recall, sps, item_coverage, and ndcg have similar

recommendation algorithm is an effective method to introduce time element into the recommendation method.

4.2.3. Markov Chain Prediction Algorithm (MarkovChain).

First of all, model the practice records of students' examination questions, make examination questions with different states, and write X1, X2, X3, and X4.... The value of X_n is a matter of practice at time n . X_{n+1} is a function of the conditional probability of the past state X_n . The calculation formula is as follows:

changes when dropout is 0.4, 0.5, 0.6, 0.7, and 0.8. But dropout was unstable at 0.7 and 0.8. Combining the performances of recall, sps, item_coverage, and ndcg, the final dropout is determined to be 0.5.

4.3.3. *batch_size*. *batch_size* is one of the important parameters of deep learning. Appropriate *batch_size* can improve memory utilization, while inappropriate *batch_size* will lead to slow convergence and other problems. Choose 16, 32, 64, 128, and 256 for comparative experiments, and the experimental results are shown in Figure 10.

As can be seen from Figures 10(a)–10(d), with the training, *batch_size* tends to change like recall, sps, and dcg at 16, 32, 64, 128, and 256. The item_cover with *batch_size* of 256 performs well at the start of the training and has a steady tendency thereafter. When *batch_size* is 16,256, the performance of recall, sps, item_cover, and ndcg is fluctuating. Combining all the results and their stability, the value of *batch_size* is finally determined to be 32.

The data set is divided into 0.6, 0.7, 0.8, and 0.9 for training, and the segmentation results are displayed in the experimental data set in Table 3.

Specific comparative experimental results are shown in Figure 11; with the increase of training groups, the accuracy of the previous UserCF began to decrease significantly, the accuracy of LTM has been at a low level, MC and the method proposed in this paper are relatively stable, and the comparison has been improved to a certain extent. According to Figure 11(b), the recall values of UserCF and MC methods change obviously with the increase of the proportion of training groups, but although the recall values of the methods proposed in this paper and LTM are low, the values are always stable. As can be seen from MC method (Figure 11(c)), with the expansion of training set, item_coverages decreases like a cliff, which is not conducive to new learning resources. The project coverage of this method has always maintained stable and excellent performance. As can be seen from Figure 11(d), the examination question resources of the method proposed in this paper are relatively stable, and it has better applicability considering whether

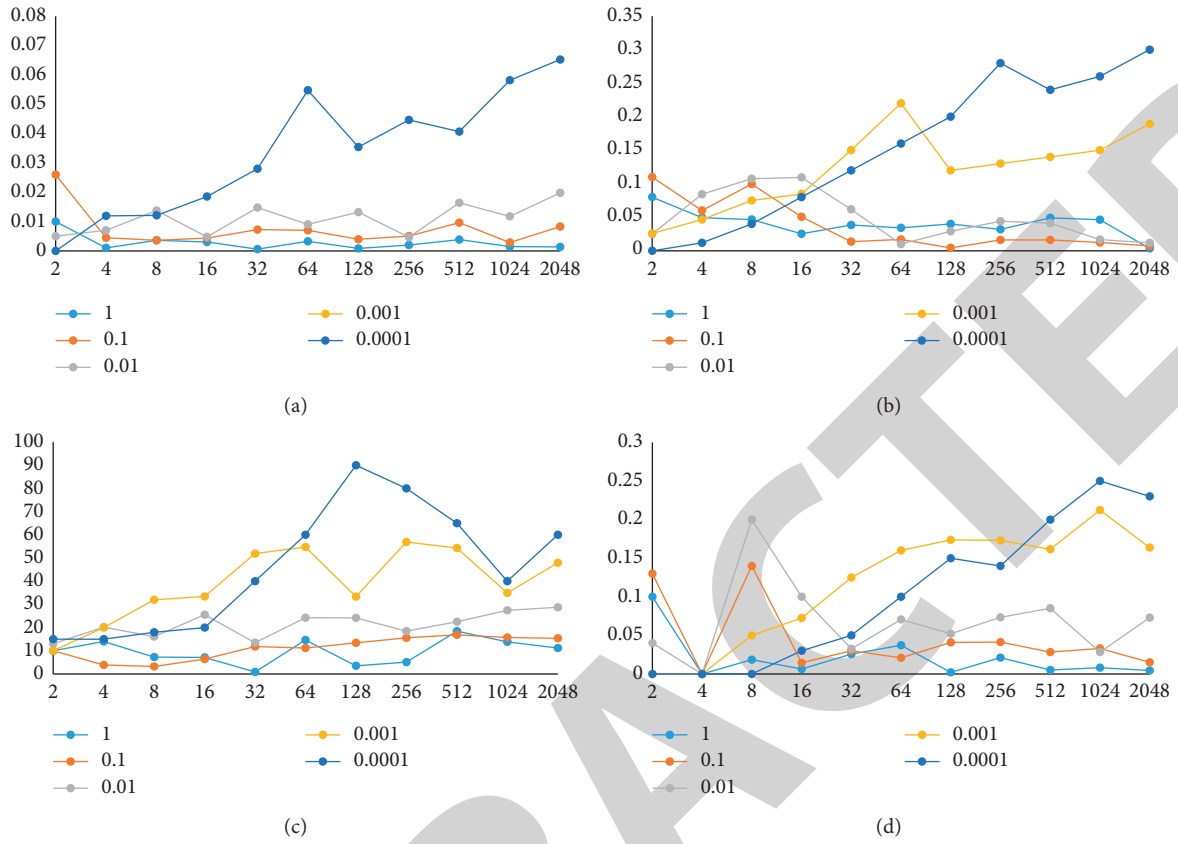


FIGURE 8: Evaluation of learning_rate experimental results. (a) Recall. (b) sps. (c) item_coverage. (d) ndcg.

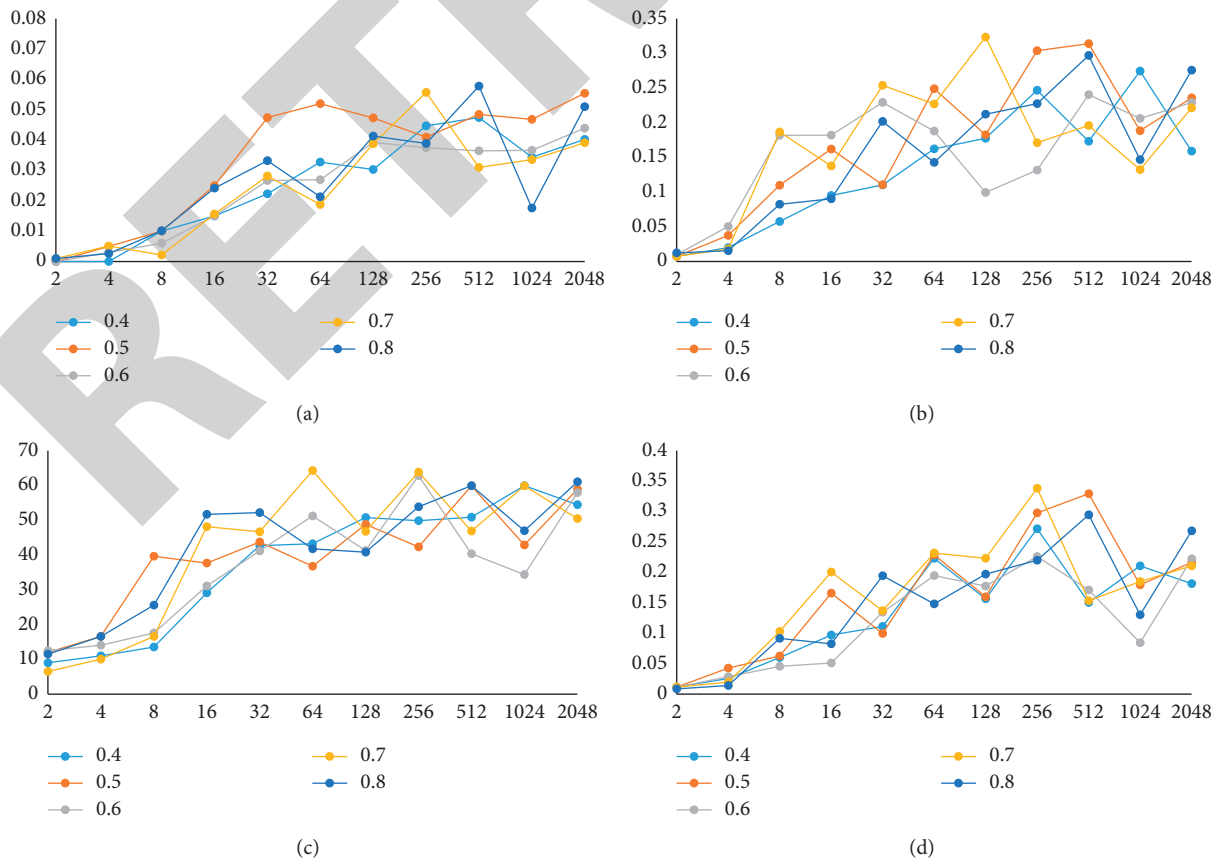


FIGURE 9: Evaluation of Dropout experimental results. (a) Recall. (b) sps. (c) item_coverage. (d) ndcg.

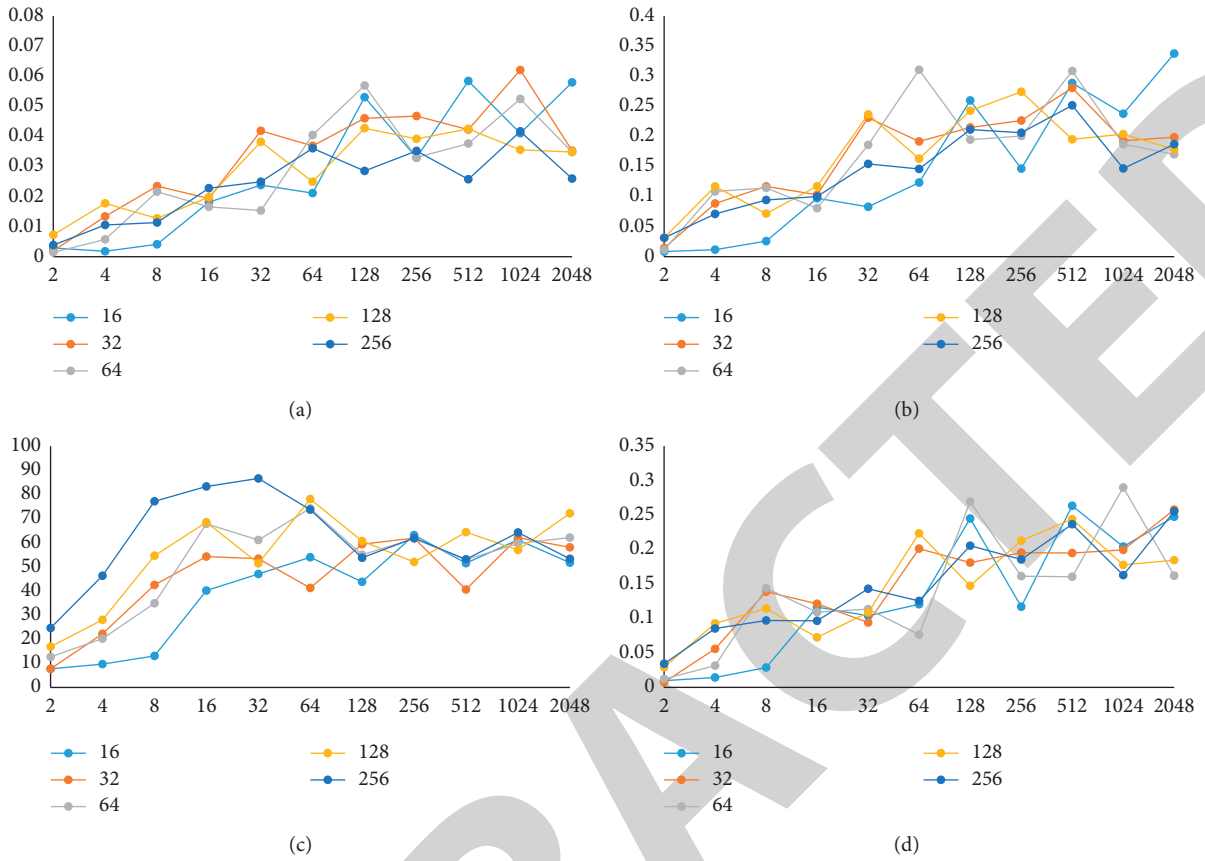


FIGURE 10: Evaluation of batch_size experimental results. (a) Recall. (b) sps. (c) item_coverage. (d) ndcg.

TABLE 3: Experimental data set.

Training set ratio	0.6			0.7			0.8			0.9		
	Full	Train	Test	Full	Train	Test	Full	Train	Test	Full	Train	Test
Users	2913	1874	1040	2913	2121	793	2915	2364	552	2912	2915	274
Items	15046	15028	12984	15045	15042	11807	15044	15044	9920	15043	15044	9982
Interaction	418291	265417	152873	418291	302817	115473	418291	338273	80019	418291	418291	39488

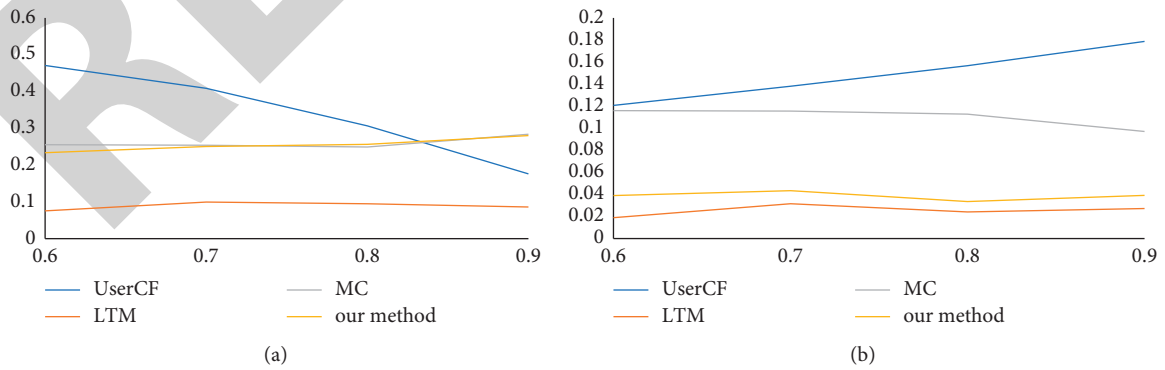


FIGURE 11: Continued.

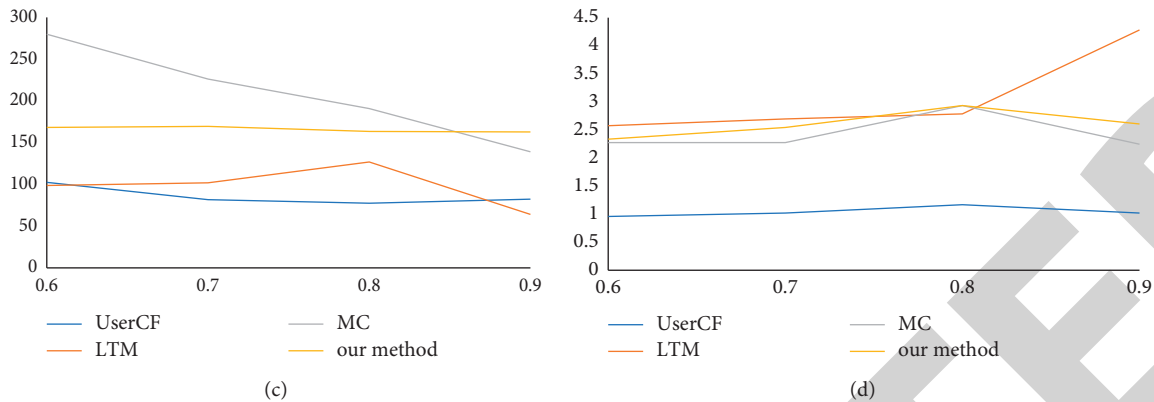


FIGURE 11: Evaluation of comparative experimental results. (a) Precision. (b) Recall. (c) item_coverage. (d) AD.

students adapt or not. The topics recommended by UserCF are not practical. The Markov Chain Prediction Algorithm is not more practical because of its unstable difficulty in the test questions recommended by the Markov Chain Prediction Algorithm. According to the above analysis, the recommendation method of personalized learning resources based on deep learning proposed in this paper has high stability even if the training data are different in size and can recommend corresponding topics to students with personality. The recommendation results can be further explained.

5. Conclusion

This paper discusses some disadvantages of Chinese traditional education and introduces students' self-adaptive learning system to solve these problems by understanding the definition, principle, research status, and key technologies of adaptive learning system. By studying the core part of personalized recommendation in adaptive learning system, a personalized learning resource recommendation algorithm based on deep learning model is proposed. The effectiveness of recommending learning resources is proved by comparative experiments, and it is integrated into students' adaptive learning system. At the same time, personalized learning in the field of education is one of the hot research topics at present, but it is still in the stage of theoretical research and faces many problems. The key research work in the future is to study the personalized recommendation methods for individual learners. Different behaviors, interests, and habits can improve the accuracy of recommendation.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this work.

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