Hindawi
Security and Communication Networks
Volume 2023, Article ID 9834514, 1 page
https://doi.org/10.1155/2023/9834514

Retraction

Retracted: Exploratory Research on the Practice of College English Classroom Teaching Based on Internet and Artificial Intelligence

Security and Communication Networks

Received 26 December 2023; Accepted 26 December 2023; Published 29 December 2023

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] Y. Jia, "Exploratory Research on the Practice of College English Classroom Teaching Based on Internet and Artificial Intelligence," *Security and Communication Networks*, vol. 2022, Article ID 7133654, 9 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 7133654, 9 pages
https://doi.org/10.1155/2022/7133654

Research Article

Exploratory Research on the Practice of College English Classroom Teaching Based on Internet and Artificial Intelligence

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Received 12 May 2022; Accepted 21 June 2022; Published 12 July 2022

Academic Editor: Tao Cui

With the rapid development of cloud computing and mobile Internet technology, the information of optional services in the network is exploding and the problem of information overload is becoming more and more serious. The recommendation system can recommend suitable English online classes for students according to their interests and needs, effectively reduce the data load, help students extract effective information from the mass of information, and make accurate recommendations. Aiming at the problems of data sparsity and cold start in the recommendation system, this paper proposes a recommendation method to improve the collaborative recommendation algorithm in college English online classroom teaching practice. Based on the extracted student tag feature information, this method uses spectral clustering algorithm to cluster similar students and transforms the original high-dimension scoring matrix into several lower-dimension subscoring matrices. Then, the implicit meaning model is used to locally predict the missing score in the subscore matrix. Finally, after obtaining the missing score, the improved neighborhood-based collaborative recommendation algorithm is used to predict the global score of the target student. Experiments are performed on commonly used public data sets. Compared with the traditional recommendation algorithm, the proposed algorithm has higher recommendation accuracy and better RMSE performance.

1. Introduction

In the era of "Internet plus," students have a broad vision, are not afraid of authority, and no longer blindly accept the indoctrination of books and teachers. The penetration of the Internet, the application of artificial intelligence, and the popularity of smart phones have also changed students' learning concepts and ways [1]. Students' learning input is no longer limited to classroom and relying on teachers, and they can use the abundant resources of the Internet to obtain the knowledge they need [2].

In today's era of rapid scientific and technological development, all walks of life continue to reform and innovate and education industry is also subjected to the baptism of the tide of The Times, facing unprecedented challenges. With the continuous advancement of teaching reform in colleges and universities, innovative teaching methods have gradually infiltrated. Information-based classroom software platforms represented by university's "Rain Classroom," "Blue Ink Cloud Class," and "UMU Interactive Learning Platform" have emerged in an endless stream [3]. How to introduce the information-based classroom teaching methods under the influence of "Internet+" thinking into traditional course teaching has become the focus of teaching reform and innovation in various disciplines.

Due to the epidemic and other reasons, the demand for online teaching in universities at home and abroad has increased sharply. According to data release report, more than 2,000 colleges and universities in China have adopted online teaching tools such as Tencent Classroom and Rain Classroom for online teaching [4]. However, the Special Research Report on the Evaluation of the Effect of Online School Resumption in China in the Spring of 2020 by Imedia pointed out that the current online teaching tools in colleges and universities can only rely on teachers to recommend and release human resources and cannot integrate and utilize the teaching resources in schools automatically. Due to copyright problems, internal teaching resources can only be accessed externally by teachers and students through VPN and other ways but cannot provide good internal search and query tools.

This leads to the seemingly contradictory problem of "too many idle resources on campus and insufficient demand satisfaction," which seriously affects the effectiveness of online teaching [5]. Although a series of new mobile Internet technologies, such as knowledge recommendation engine, have provided solutions to this problem to a certain extent, the relative isolation of resources in the campus network leads to the reduced efficiency of these solutions.

In recent years, the scale of student and English online courses in the network is getting larger, and the huge data information becomes rich resources, which also brings great challenges to the existing collaborative recommendation algorithm [6]. In the face of massive, multisource, heterogeneous, and sparse students' behaviour data, the traditional neighborhood model-based collaborative recommendation algorithm [7] and the matrix factor-based latent factor model (LFM) are unable to do so. The traditional neighborhood-based collaborative recommendation model needs to mine the similarity information of students on the basis of calculating the similarity between all student pairs or English online course pairs, so as to determine the similar historical students of target students [8]. However, in the face of student comment information with high dimension, large scale, and sparse data substituted with context information, there is a huge amount of calculation and the efficiency of recommendation algorithm is one of the bottlenecks, affecting the further improvement of recommendation performance. Meanwhile, the problem of cold start is also one of the urgent problems to be solved in collaborative recommendation methods.

At the psychological level, domestic and foreign scholars have concluded that the individual differences of each learning individual make personalized curriculum planning have positive significance for learning [9]. Although the personalized curriculum recommendation algorithm started late in China, there are many achievements in the optimization and improvement of recommendation algorithm. Through the collaborative prediction method of learning resources in literature [10], problems such as extensibility calculation and loose calculation in collaborative recommendation algorithm are basically alleviated. Literature [11] improves the collaborative filtering algorithm based on English online courses through communication between teachers and students. By analysing the characteristics of students, a personalized recommendation algorithm suitable for students is proposed to alleviate the problem of low fit between recommendation results and learners. Literature [12] obtained and analysed the dynamic data of online learners in the learning process, extracted the personalized learning needs of learners, and made an overall course planning through professional teachers. Finally, the genetic hierarchical recommendation algorithm was used to recommend courses for learners, significantly improving the accuracy of course recommendation.

However, the above methods often involve the problem of cold start of recommendation algorithm, which makes it impossible to establish a recommendation model with good performance and accurate recommendation without initial data. This paper proposes an intelligent collaborative recommendation algorithm based on spectral clustering and cryptic model. On the basis of mining similar information between students or items using spectral clustering algorithm, the algorithm combines the recommendation model based on cryptic meaning model with the collaborative recommendation model based on neighborhood, so as to solve the bottleneck problem in the traditional collaborative recommendation algorithm and improve the recommendation performance.

The contributions of this paper are as follows:

(1) On the basis of obtaining the label feature vectors of students (or English online courses), the spectral clustering algorithm is used to cluster students to obtain similar students of the target students. Meanwhile, the original scoring matrix can be divided into several lower-dimension subscoring matrices based on the spectral clustering algorithm

(2) In each subscoring matrix, the matrix decomposition model based on cryptic meaning model is used to locally predict the missing score to solve the data sparsity

(3) The improved neighborhood-based collaborative recommendation algorithm is used to predict the global score of the target students

This paper consists of four main parts: Section 1 is the introduction, Section 2 is the state of the art, Section 3 is methodology, Section 4 is result analysis and discussion, and Section 5 is the conclusion.

2. State of the Art

2.1. Collaborative Recommendation Method Based on the Neighborhood Model. The neighborhood model-based collaborative recommendation method is mainly based on the user's historical behavior information to find the nearest neighbors with similar preferences for the user. It is based on the idea of "people are divided into groups" or "things are clustered together" to recommend items that may be of interest to users. At present, many scholars at home and abroad have improved the basic nearest neighbor model in different degrees to improve the model recommendation effect [11, 13]. Literature [11] proposes a QoS-aware personalized service recommendation method based on users' rating of service quality attributes of services. It finds near-neighbor objects with similar QoS preferences for users by building a region model. Literature [13] constructs a user preference model by mining user text comment data and extracting keyword vectors to improve the scoring-based similarity calculation in the original nearest neighbor model based on semantic information. The idea of constructing the nearest neighbor model is simple and easy to understand, but the model has poor recommendation effect for sample data sparse or cold start scenarios and does not have good scalability.

2.2. Recommendation Method Based on the Hidden Semantic Model. Compared with the neighborhood-based collaborative recommendation model, the implicit semantic model based on matrix decomposition technique can better cope with the data sparsity problem. Moreover, it takes into account the influence of the implicit information in the scoring matrix on the recommendation effect. Literature [14] adds binarized user attributes to the implicit semantic model and uses the classification model to evaluate the importance of other user attributes and find out the similar users of the target user. Then, it combines the rating information of the target users to make predictions and recommendations. Based on the BERT model, deep nonlinear feature vectors of users and items can be extracted from the reviews, and the deep feature vectors of users and items are combined with potential hidden vectors to generate deep feature terms for predictive recommendations [15].

2.3. Collaborative Recommendation Method Based on Clustering Algorithm. The clustering algorithm belongs to an unsupervised learning method in machine learning, which can group sample data effectively. Therefore, clustering algorithms can be used in collaborative recommendation models to search for similar users of the target user. Literature [16] clusters label features to generate topic label clusters and constructs an item-topic association matrix combined with the original scoring matrix, to calculate the similarity between items. Finally, it uses a collaborative neighborhood-based recommendation model for predictive recommendation. Literature [17], on the other hand, improves the traditional recommendation model based on K-medoids clustering algorithm and probabilistic model to enhance the recommendation accuracy. By introducing a time decay function to preprocess the rating information, it proposed a collaborative recommendation model based on a clustering algorithm. Users and items are clustered based on user feature vectors and item attribute vectors, and then, an improved similarity calculation method is used to find similar users of the target user for predictive recommendation.

3. Methodology

3.1. Problem Description. Given a sample data set, each sample (p, x, r_{px}) represents a r_{px} grade for college English online course x given by student p. The sample data also contain the characteristics of student tags $[F_1, F_2, \ldots, F_n]$. Each student p has a tag feature vector corresponding to it, and n represents the dimension of the tag feature vector of the student. The task of this paper is to mine the interactive information of student-student and student college English online courses from the information of student label characteristics and scoring and predict the score of target students on candidate college English online courses.

As shown in Figure 1, there are three modules. The first module uses spectral clustering algorithm to cluster students based on the characteristic vector of student tags obtained from sample data. In module 2, the score matrix is constructed in each subcluster and the cryptic meaning model based on matrix decomposition is used to locally predict missing score in each subcluster. Module 3 uses the improved collaborative recommendation model to make global prediction recommendation. This algorithm mines similar information among students, based on the characteristic information of students' tags, and can find similar students without excessive comments, so it can solve the cold start. At the same time, the missing score is locally predicted in each submatrix in module 2, which solves the problem of data sparsity.

3.2. Spectral Clustering. In spectral clustering, all sample data are regarded as points in space and these points can be connected to form an undirected weighted graph. And, the weight of each edge is the similarity of the two vertices. The adjacency matrix can be obtained based on the similarity matrix. Then, the eigenvectors of the Laplacian matrix constructed by the sample data are clustered. In spectral clustering algorithm, there are three main methods to construct the adjacency matrix. They are ε-neighborhood method, k nearest neighbor method, and full connection method. In this paper, we use the symmetric k nearest neighbor method.

The KNN algorithm is used to traverse all sample points, and the k points closest to each sample point (the distance is measured by Gaussian kernel function) are taken as their nearest neighbors. It can be constructed as a symmetric adjacency matrix in the following two ways:

(1) As long as a point is in the k nearest neighbor of another point, $m_{xy} = \exp(-(\|i_x - i_y\|_2^2/2\sigma^2))$; otherwise, $m_{xy} = 0$
(2) Only when two points are k-nearest neighbors to each other, $m_{xy} = \exp(-(\|i_x - i_y\|_2^2/2\sigma^2))$; otherwise, $m_{xy} = 0$

3.3. Cryptic Meaning Model Based on Matrix Decomposition Technology. The implicit meaning model is derived from Simon Funk's improvement of singular value decomposition (SVD) algorithm by using gradient descent (GD). From the perspective of matrix decomposition, the cryptic meaning model decomposed the scoring matrix R into the product of two low-dimensional matrices related to student characteristics and college English online course characteristics, respectively.

$$R = U^N V. \tag{1}$$

$U \in R^{f\times t}$, $V \in R^{f\times w}$, and t and w are the number of students and the number of college English online courses, respectively. The student p's score of college English online course x can be expressed as follows:

$$\widehat{r}_{px} = \sum u_{pf} \cdot v_{xf}. \tag{2}$$

Here, u_{pf} represents the f-th eigenvalue of student p. v_{xf} represents the f-th eigenvalue of college English online course x. To obtain the parameters u_{pf} and v_{xf}, we have the following formula:

$$L(u, v) = \sum_{(p,x)\in \text{Train}} \left(r_{px} - \widehat{r}_{px}\right)^2. \tag{3}$$

Train is the training set. Random gradient descent, least square method, coordinate descent, and other methods can

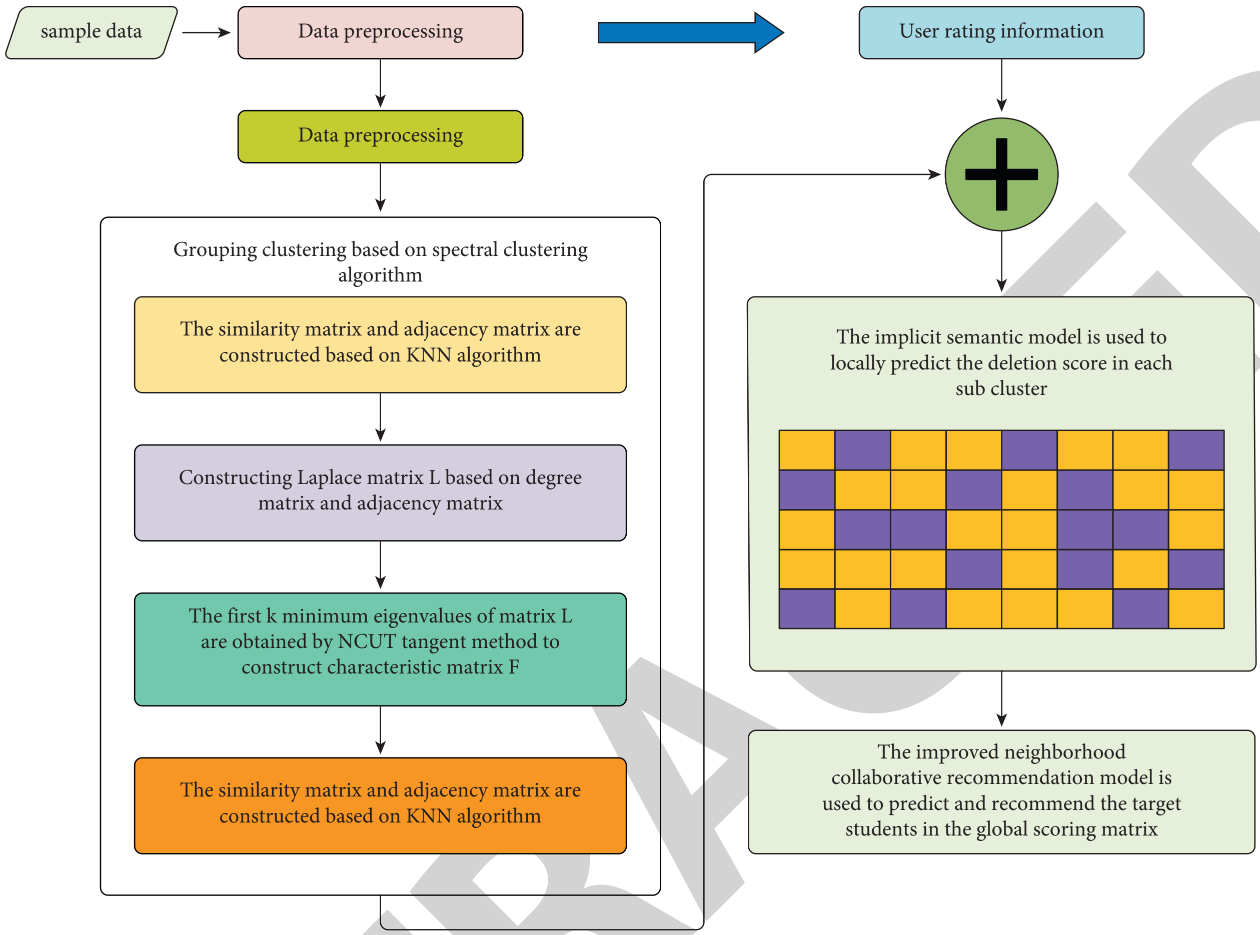

Figure 1: The framework model of the proposed algorithm.

be used to learn. In addition, in order to prevent overfitting, the overfitting term can be added to the loss function $\lambda(\|u_p\|^2 + \|v_x\|^2)$, λ is the regularization parameter.

In addition, in practice, some attributes of students have nothing to do with college English online courses and some attributes of college English online courses have nothing to do with students. Therefore, bias items can be added to the prediction model, and SVD models with bias items added are called BiasSVD models.

3.4. *Cluster Students Based on Student Characteristics and Spectral Clustering Algorithm*

(1) The sample point $I = \{i_1, i_2, \ldots, i_t\}$ and then the student similarity matrix $S = \{s_{xy}\}_{t\times n}$ are calculated by using the K-nearest neighbor algorithm based on Gaussian kernel function and the student tag feature vector. Here, n is the label feature dimension.

$$s_{xy} = \exp\left(-\frac{\|i_x - i_y\|_2^2}{2\sigma^2}\right). \tag{4}$$

Then, the adjacency matrix $M = \{m_{xy}\}_{t\times n}$ is constructed. The similarity matrix constructed by the K-nearest neighbor method is not symmetric. Therefore, a symmetric K-nearest neighbor similarity matrix is constructed in the following way. As long as a point is in another point's k-nearest neighbor, S_{xy} is retained.

$$m_{xy} = \begin{cases} 0, & i_x \notin ZTT(i_y) \& i_y \notin ZTT(i_x), \\ \exp\left(-\dfrac{\|i_x - i_y\|_2^2}{2\sigma^2}\right), & i_x \in ZTT(i_y) | i_y \in ZTT(i_x). \end{cases} \tag{5}$$

(2) We construct degree matrix D_{wt} according to the connection matrix; degree matrix D is a diagonal matrix.

(3) We calculate the Laplace matrix L: $L = \mathrm{d} - \mathrm{m}$.

(4) We use Ncut to find k minimum eigenvalues of Laplace matrix L to construct the characteristic matrix F.

First, the normalized Laplace matrix L_s is constructed, $L_s = D^{-1/2} L D^{-1/2} = I - D^{-1/2} W D^{-1/2}$, where x is the identity matrix.

We calculate the eigenvalues of normalized Laplacian matrix L_s, select the first k minimum eigenvalues, and calculate the corresponding eigenvectors $f_1, f_2, \ldots, f_k$.

The matrix composed of the above k feature vectors as column vectors is normalized according to rows, and finally, the feature matrix $N = \{f_1, f_2, \ldots, f_k\}$ and $N \in R^{t\times k}$ with dimension $t \times k$ are formed.

(5) Let $b_x \in R^k$ be the i-th row vector of the characteristic matrix n as the new intermediate data sample point, where $x = 1,2, \ldots, t$, and then, we use the k-means clustering to cluster the new sample points $B = \{b_1, b_2, \ldots, b_t\}$ into clusters $\{G_1, G_2, \ldots, G_k\}$.

(6) The cluster of the new sample points is transformed into the original student cluster $C = \{C_1, C_2, \ldots, C_k\}$, where $C_x = \{y|b_y \in G_x\}$.

3.5. Missing Score of Local Prediction Based on the Cryptic Model. After grouping and clustering students based on the above steps, the original scoring matrix with a higher dimension can be divided into k smaller subscoring matrices. The cryptic meaning model based on matrix decomposition will be used to fill the missing score in the scoring matrix to solve data sparsity. The operations for each subscoring matrix are as follows.

Suppose $R_{a\times w}$ is a subscoring matrix, a is the number of students in the corresponding subcluster, and w is the number of college English online courses in the sample. In this paper, BiasSVD algorithm is used to decompose and predict the scoring matrix. The BiasSVD algorithm assumes that the scoring system includes two parts, bias term and interaction factor between students and college English online courses, as shown in

$$\hat{r}_{px} = \mu + h_p + h_x + \sum_f u_{pf} \cdot v_{xf}. \tag{6}$$

Among them, the bias items include global mean μ, student bias item h_p, and college English online course bias item h_x.

In the cryptic model, the parameters h_p, h_x, u_{pf}, and v_{xf} in Formula (6) are obtained by minimizing the loss function in

$$\begin{aligned} L = &\sum_{(p,x)\in \mathrm{train}} \left(r_{px} - \mu - h_p - h_x - \sum_f u_{pf} \cdot v_{xf} \right)^2 \\ &+ \lambda\left(\left\|u_p\right\|^2 + \left\|v_x\right\|^2 + \left\|h_p\right\|^2 + \left\|h_x\right\|^2 \right). \end{aligned} \tag{7}$$

Here, $\lambda(\|u_p\|^2 + \|v_x\|^2 + \|h_p\|^2 + \|h_x\|^2)$ is a regular term added to prevent overfitting.

Then, the stochastic gradient descent (SGD) method is used to solve the above loss function, and the partial derivative of each parameter can be obtained as follows:

$$\begin{aligned} \frac{\partial L}{\partial u_{pf}} &= -2\rho_{px} \cdot v_{xf} + 2\lambda u_{pf}, \\ \frac{\partial L}{\partial v_{xf}} &= -2\rho_{px} \cdot u_{pf} + 2\lambda v_{xf}, \\ \frac{\partial L}{\partial h_p} &= -2\rho_{px} + 2\lambda h_p, \\ \frac{\partial L}{\partial h_x} &= -2\rho_{px} + 2\lambda h_x, \end{aligned} \tag{8}$$

where $\rho_{px} = r_{px} - r_{px} = r_{px} - \mu \quad -h_p - h_x - \sum_f u_{pf} \cdot v_{xf}$.Therefore, parameters h_p, h_x, u_{pf}, and v_{xf} can be obtained iteratively by the following recursive formula:

$$\begin{aligned} h_p &\leftarrow h_p + \gamma\left(\rho_{px} - \lambda h_p\right), \\ h_x &\leftarrow h_x + \gamma\left(\rho_{px} - \lambda h_x\right), \\ u_{pf} &\leftarrow u_{pf} + \gamma\left(v_{xf} \cdot \rho_{px} - \lambda u_{pf}\right), \\ v_{xf} &\leftarrow v_{xf} + \gamma\left(u_{pf} \cdot \rho_{px} - \lambda v_{xf}\right). \end{aligned} \tag{9}$$

Here, γ is the learning rate. Through the above implicit semantic model based on BiasSVD algorithm, the missing score can be locally predicted in each subscoring moment.

3.6. Score Prediction. After the local initial prediction of missing score in each subcluster, the subscore matrix was combined into the original score matrix and the improved neighborhood-based collaborative recommendation model was used to make the quadratic global prediction. The scoring matrix becomes very dense after missing scoring through local filling. If the traditional neighborhood-based collaborative recommendation model is used, the similarity value between all pairs of students needs to be calculated, which requires a large amount of calculation. Therefore, this paper uses k-means clustering algorithm again to cluster students based on student scoring vector and divides the student set into k classes again. Then, in the cluster where the target student is located, the similarity between the target student p and other students in the subcluster is calculated based on the Pearson Correlation Coefficient (PCC). The calculation equation is as follows:

$$sxw(p,q) = \frac{\sum_{x\in X_{PQ}} \left(r_{px} - r_p\right) \cdot \left(r_{px} - r_q\right)}{\sqrt{\sum_{x\in X_{PQ}} \left(r_{px} - r_p\right)^2} \sqrt{\sum_{x\in X_{PQ}} \left(r_{px} - r_q\right)^2}}, \tag{10}$$

where r_{px} and r_{px} represent the scores of student p and student q for college English online course x, respectively. X_{pq} represents a collection of online college English courses that are all graded p and q by students. r_p and r_q represent the mean of student p and student q scores, respectively.

Here, to set a threshold value of δ, $Tex(p) = \{q|stxnwq(p,q)h \geq_{\delta} x, 7qC \in ; P\}$. P is the whole set of students, so the score of target student p on college English online course x can be predicted by

$$ur_{px} = r_l + \frac{\sum_{q \in Tex(p)} \left(r_{qx} - r_l\right) \cdot sxw(p,q)}{\sum_{q \in Tex(p)} |sxw(p,q)|}. \tag{11}$$

4. Result Analysis and Discussion

The experimental data set is from the actual operation data of an online teaching website, with 13,680 students and a total of 737 courses, mainly college English-related courses. The data included students' learning records and scoring records from May 2014 to July 2017, with a total of 148,170 records. The training set accounted for 80%, about 118,000 records, and the test set accounted for 20%, about 30,000 records. First, the data are simplified into triples (student id, study time, and course id).

The evaluation index of the algorithm is precision, which refers to the proportion of the courses actually learned by students among all the courses recommended for display, as shown in

$$\text{precision} = \frac{\sum_{p \subseteq P} R(p) \cap N(p)}{\sum_{p \subseteq P} R(p)}, \tag{12}$$

where $N(p)$ represents all courses actually learned by student p and $R(p)$ represents all courses recommended to student p. The higher the accuracy rate is, the better the recommended courses meet students' expectations.

We input the course sequence that students have learned in the test set, output a course sequence after model processing, take the last course as the recommended course of students, and judge whether the recommended result is accurate compared with the courses that students actually learn.

All courses are divided into three categories: English reading, English listening and speaking, and English writing. The data set is divided into three subsets accordingly. Table 1 records the recommendation results based on the traditional collaborative algorithm under the manual classification of websites.

The recommendation results of all categories are generally better than those of all courses after classification.

The algorithm in this paper is used for automatic classification of courses, and three course categories are obtained. Table 2 shows the corresponding recommendations.

Compared with the results of manual classification in Table 1, the recommendation algorithm performs better than manual classification in most categories divided and the accuracy of weighting is increased by 8.2%.

The comparison of the accuracy of the proposed algorithm with those in literature [11, 18–20] and literature [21] in the same data set is shown in Table 3 and Figure 2.

Except for all course categories, the accuracy index of the proposed algorithm is much higher than of the other five

Table 1: Recommended results based on artificial classification of websites.

Category	Number of courses	Accuracy
All courses	137	0.126
English reading	38	0.298
English listening and speaking	47	0.373
English writing	52	0.387
Weighted accuracy	—	0.206

Table 2: Recommended results based on the proposed algorithm.

Category	Number of courses	Accuracy
All courses	137	0.126
Course 1	29	0.211
Course 2	45	0.369
Course 3	63	0.406
Weighted accuracy	—	0.288

algorithms. Compared with the other five algorithms, the proposed algorithm is more suitable for the recommendation of courses with strong temporal dependence.

The performance of the intelligent collaborative recommendation method based on the spectral clustering and cryptic model is not only related to the structure size of the collaborative recommendation algorithm but also highly dependent on the training sample size. Therefore, the sample size of training participants was set differently to verify its recommended performance, and the results are shown in Table 4 and Figure 3. The initial training and testing sample ratio is 8 : 2.

When the number of training samples decreases, the recommended RMSE values of the three data sets all rise. When the proportion of the training set decreased from 80% to 20%, the RMSE performance of English reading, English listening and speaking, and English writing decreased by 34.11%, 36.77%, and 42.93%, respectively. By comparison, the personalized recommendation of English writing is most sensitive to the sparsity of the training sample set, followed by the sparsity of English listening and speaking, and the sparsity of the sample set has the least influence on the sparsity of English reading. In conclusion, when the proportion of the training set is 80%, the optimal personalized recommendation performance can be obtained.

To verify the recommended performance of different algorithms for three kinds of data sets, six algorithms were used to train the three kinds of data sets, respectively. Figures 4–6 show the results. According to the results in Table 4, the number of nodes involved in training for the six algorithms is 80% of the total sample number.

RMSE in this paper includes all the lowest values, which indicates that the proposed algorithm has the highest recommendation accuracy for these three data sets. In terms of order of accuracy of personalized recommendation, the algorithm in this paper has the best performance, followed by literature [20], and those in literature [18] and literature [21] have the worst RMSE performance. In terms of running time, algorithms in literature [18] and literature [21] are the best, while the algorithm in this paper and literature [20]

Table 3: Accuracy comparison of six algorithms.

Category	Literature [18]	Literature [19]	Literature [20]	Literature [11]	Literature [21]	Proposed
All courses	0.031	0.016	0.045	0.022	0.077	0.126
Course 1	0.016	0.021	0.015	0.012	0.019	0.038
Course 2	0.055	0.028	0.062	0.069	0.079	0.098
Course 3	0.112	0.141	0.122	0.137	0.155	0.186

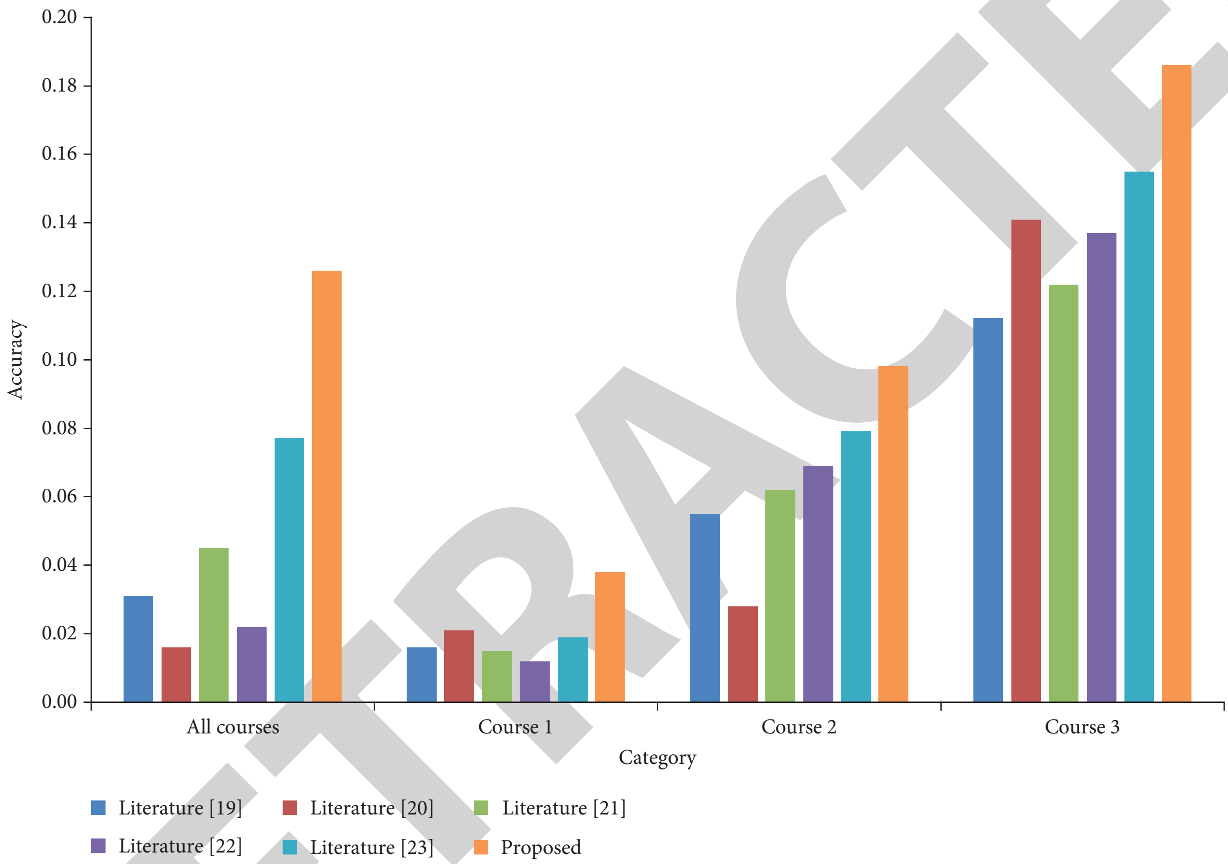

Figure 2: Accuracy comparison of six algorithms.

Table 4: RMSE of different training sample sizes.

⟶Data set	Training set ratio/%	RMSE
English reading	80	0.8248
	60	0.8969
	40	0.9255
	20	1.1659
English listening and speaking	80	0.839
	60	0.9194
	40	0.9391
	20	1.2067
English writing	80	0.9685
	60	1.0011
	40	1.1506
	20	1.3978

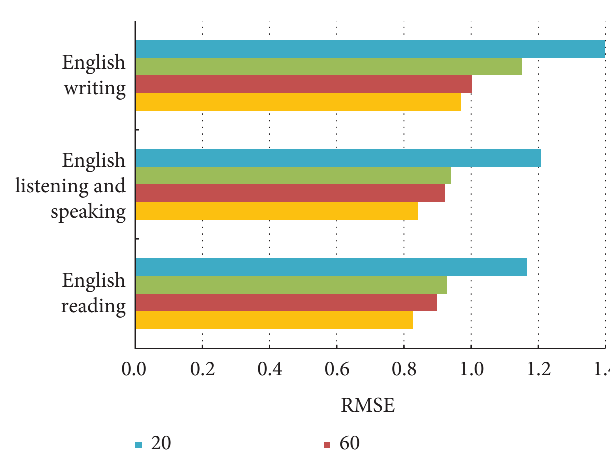

Figure 3: RMSE with different training sample sizes.

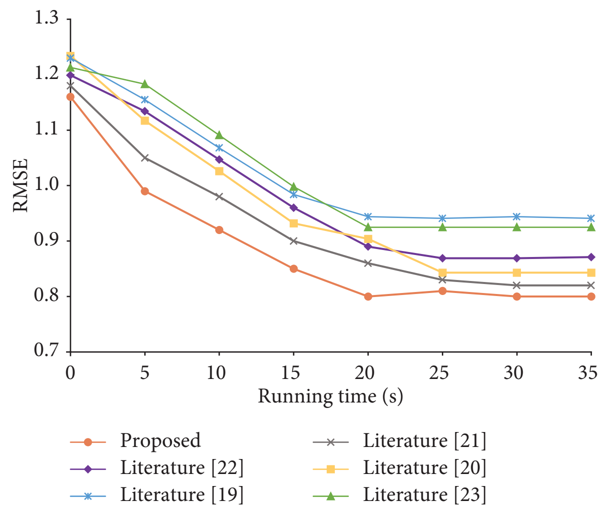

Figure 4: RMSE of six algorithms (English reading).

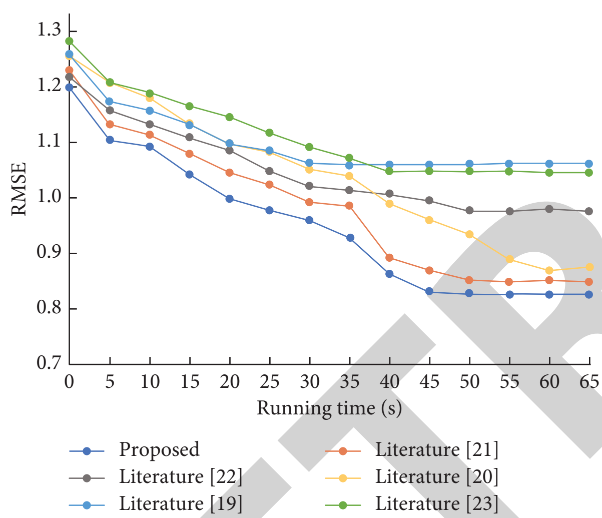

Figure 5: RMSE of six algorithms (English listening and speaking).

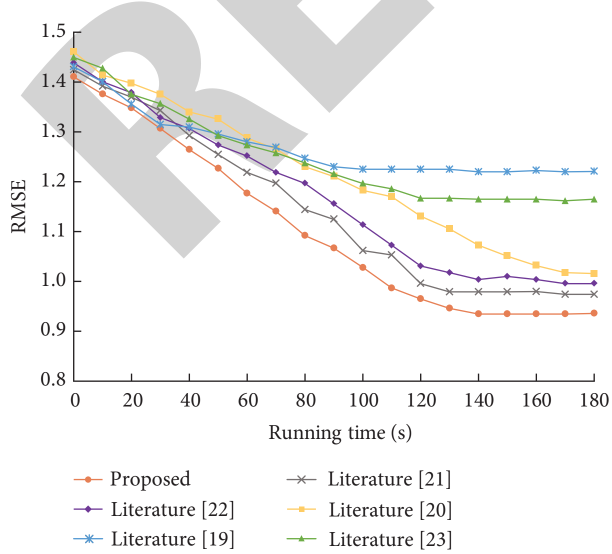

Figure 6: RMSE of six algorithms (English writing).

perform poorly. The main reason is that the operation of the deep learning framework requires multiple positive and negative updates, resulting in high operation time consuming steps.

5. Conclusion

No recommendation algorithm is absolutely superior to another recommendation algorithm. Therefore, multiple recommendation models can be effectively integrated to build a hybrid recommendation model with higher performance. Based on this, an intelligent collaborative recommendation method based on spectral clustering and cryptic model is proposed. The method uses the KNN model-based spectral clustering algorithm to mine similar information among students and then groups the students into clusters. Then, the original scoring matrix is divided into several subscoring matrices with lower dimensions based on clustering. Then, a matrix decomposition model based on the cryptic meaning model is used to locally predict the missing score in each subscore matrix. Finally, the improved neighborhood-based collaborative recommendation algorithm is used to predict the global score of the target students. Experimental results show that the proposed algorithm effectively solves the problem of data sparsity and cold start and accelerates the efficiency of the recommendation algorithm while improving the accuracy of prediction. The next step mainly includes constructing the relationship diagram between students and English online courses by using a knowledge graph to obtain more specific characteristics of students and English online courses and constructing a prediction model by using the deep learning method to further improve recommendation accuracy.

Data Availability

The labeled data set used to support the findings of this study is available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

This study was sponsored by English Department, Taiyuan University.

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