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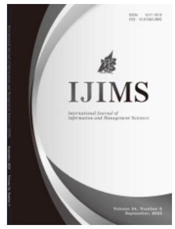


Establishment of Recommender System Based on Collaborative Filtering Algorithm and Design and Implementation of Educational Platform for Computer Courses

Shaocui Guo[*]
The Open University of Yantai, Yantai Vocational College, Yantai 264670, China

Keywords

collaborative filtering algorithms; recommender systems; computer course education; personalised recommendations; platform operations.

Abstract

Both user collaborative filtering and project collaborative filtering have problems such as data sparsity and cold start research using collaborative filtering, to solve such problems, this study builds an efficient recommender system and applies it to the design and implementation of the computer course education platform. The design of the platform includes several modules such as user management, course management, learning record management, recommendation system, etc. Through data mining and analysis, personalised learning experience is provided for each student. Through experimental verification, the improved collaborative filtering algorithm reaches 71.03% in the learning goal achievement rate, while the traditional collaborative filtering algorithm is only 59.55%. This indicates that the improved algorithm is more effective in recommending learning materials, and the platform can effectively improve students' learning outcomes and satisfaction. It can provide a certain reference and information for the design of recommender systems and educational platforms in other fields.

1. Introduction

With the rapid development of Internet technology, people are faced with a huge amount of information and resources, and how to sift through them to find the right content for them has become an important challenge (Mic & Zezula, 2022). Especially in the field of education, traditional education methods can no longer meet the individual needs of different students (Duan & Hou, 2021). Collaborative filtering algorithm is a kind of recommendation algorithm based on users' historical behaviours and preferences, and its basic idea is to predict users' needs for untouched items or services by analysing the behavioural similarity between users or the similarity between item (Sun et al., 2022; Mkinen et al., 2021). It has a wide range of applications in e-commerce services, news recommendations, online travel guidance, and education (Alsaadi et al., 2022). In the field of education, the design and implementation of computer course

*corresponding author. Email: gscytvc@126.com

education platforms have also become an important means to promote educational informatization (Vamos et al., 2020). Although traditional collaborative filtering algorithms have strong processing capabilities for coefficient data, user behavior data is often sparse, leading to accuracy and computational complexity issues in processing sparse data. In addition, changes in user interests at different times can also pose challenges to algorithm similarity calculation, affecting the final recommendation effect. Therefore, the study will introduce the basic principles and advantages of collaborative filtering algorithms, explore how to apply them to the design and implementation of computer course education platforms, and improve traditional collaborative filtering algorithm problems to enhance students' learning effectiveness and interest. Introducing collaborative filtering algorithms to build a course recommendation system to improve student learning efficiency and satisfaction.

This research is divided into four parts, the first part provides an overview of the research background and summarises the research in related fields. The second part describes the methodology of establishing a recommender system based on collaborative filtering algorithm. The third part applies and experimentally verifies the collaborative filtering algorithm based recommender system in computer course education. The last part summarises and outlooks the whole research.

2. Related Works

Collaborative filtering algorithms are recommendation algorithms based on users' historical behaviours and preferences, and the basic idea is to predict users' demand for untouched items or services by analysing the behavioural similarity between users or the similarity between items. Collaborative filtering algorithms are widely used in personalised recommendation, advertisement recommendation, search ranking and many other fields.

The collaborative filtering methods based on graph convolutional networks suffer from the problem of information loss, and the autoencoder-based collaborative filtering methods obtain the prediction results by reconstructing the interaction matrix between the user and the item without deep mining the behavioural patterns, which leads to limited expressive power. To solve the above problems, Xiong et al. (2022) proposed Variational Autoencoder-Augmented Graph Convolutional Network for Collaborative Filtering by removing redundant feature transformations and nonlinear activation functions, optimising the structure of the GCN and completing the multilevel information interactions using the Variational Autoencoder-Augmented Graph Convolutional Network. The basic paradigm of collaborative and sequential information describes each user's profile only in terms of their sequential behaviour, thus limiting its capability, Sun et al. (2022) proposed a generic vectorisation algorithm to cope with the challenge of multiple edges. The algorithm can implement arbitrary attention networks on complex graphs without simplifying the graph. Pre-training of graph neural networks for recommendation faces challenges. Successful mechanisms often used in natural language processing and computer vision to transfer knowledge from a pre-training task to a downstream task are not directly applicable to existing recommendation models based on graph neural networks. Wang et al. (2023) designed an adaptive graph pre-training framework for localised collaborative filtering without transferring users, capable of capturing both common knowledge across different graphs and the uniqueness of each graph. Experimental results demonstrate the effectiveness and superiority of the adaptive graph pre-training framework for localised collaborative filtering. The model focuses only on extracting domain-shared features among multiple domains. Liu et al. (2021) designed a novel framework that tightly integrates matrix factorisation-based collaborative filtering with deep adversarial domain adaptation via an attention network. The domain shared features between two domains are captured by common user embedding in the domain adversarial paradigm. Wang et al. (2021) proposed a collaborative filtering method based on lightweight relational graph convolutional networks with heterogeneous graphs, designed a prediction network combining graph-based representation learning with neural matching function learning, and demonstrated that this architecture can significantly improve performance.

Recommendation system is established on the basis of various types of recommendation algorithms, in which the algorithms have many unique properties and use scenarios, many scholars have studied them, Zhang et al. (2021) proposed a hybrid recommendation model based on causal neuro-fuzzy reasoning. Technically fuzzy set theory is used to represent the influencing factors. A causal neuro-fuzzy inference network is applied to learn the weights of fuzzy rules. Zhang et al. (2020) proposed a hybrid probabilistic matrix factorisation model. There are two sub-components, one that attempts to predict user ratings by capturing the user's personal preferences extracted from auxiliary information, and the second that attempts to model the textual attractiveness of items to different users through an attention-based convolutional neural network. A global objective function is then proposed and optimised for both subcomponents under a unified framework. Recommending points of interest to people with autism spectrum disorders is a challenge for recommender systems research because of the explicit need to take into account users' preferences and aversions in item evaluation. To address this problem, Mauro et al. (2022) proposed a Top-N recommendation model that combines user-specific aversion information with their preferences in a personalised way. The goal is to recommend to the user places that are both enjoyable and smooth to experience to properly take these aspects into account. Traditional recommender system approaches basically rely on static user feature vectors and ignore fine-grained user-item interactions, which may affect the accuracy of the recommender system. Da'U et al. (2021) proposed an RS model that learns adaptive user/item representations and fine-grained user-item interactions using neural attention techniques to improve the accuracy of item recommendations. The results show that the proposed model outperforms existing methods in both rating prediction and ranking. Systems equipped with only two strategies lack the flexibility to solve such uncertain decision-making problems. As a result, far-fetched recommendations with uncertainty tend to degrade the quality of recommendations. Wu et al. (2021) proposed a three-way recommendation model based on a novel shaded set to reduce the decision risk and improve the quality of recommendations. This helps to avoid the uncertainty arising from the prediction rating assignment process. The validity and reliability of the proposed model is verified on two Movielens datasets through comparative analysis.

In summary, in the academic field, collaborative filtering algorithms have a wide range of applications, and the establishment of recommender systems is based on many kinds of algorithms. Among them, the collaborative filtering algorithm its application in recommender systems and its application in course recommendation is an innovative and practical research direction.

3. Establishment of Recommender System Based on Collaborative Filtering Algorithm

The study identifies the work that needs to be done by the system by analysing the work competency requirements and non-work competency requirements of the existing web-based teaching platform for computer courses to provide a solid foundation for the subsequent coding and design.

3.1 Collaborative filtering algorithm based system requirements analysis and recommendation system module

To develop a system that meets the needs and expectations of users, it is critical to complete a system requirements analysis by communicating and interacting with users. The process of requirements analysis helps to clarify the scope and objectives of system development, helps to identify and solve potential system problems, and reduces communication costs in the development process (Bhosle & Musande, 2023). According to the user requirement analysis, the research-designed online learning platform contains a user management module, a course management module, a video and audio learning module, an interaction and discussion module, a resource recommendation and information notification, and a user feedback and support module. Table 1 shows the user role structure of the online computer course teaching platform.

Table 1 *Platform Operation Module Interface*

User (User Location)	Platform Role (System Corresponding Function Module)	Module Functionality
University leaders	Functional module for university leadership	Online
		Managing learning space
Course teacher	Functional modules for course teachers	Search for academic information
		Choose class time
		Online teaching
Class teacher	Teacher function module for class management	Textbook and homework management
		Classroom supervision
		Search for academic information
Operations personnel	Functional module for system operation managers	Maintain course sales information
		Manage teaching node information
		Customer service subsystem management
Platform administrator	Integrated manager function module for system platforms	Basic information of management platform users
		Course scheduling management
		Course consumption statistics

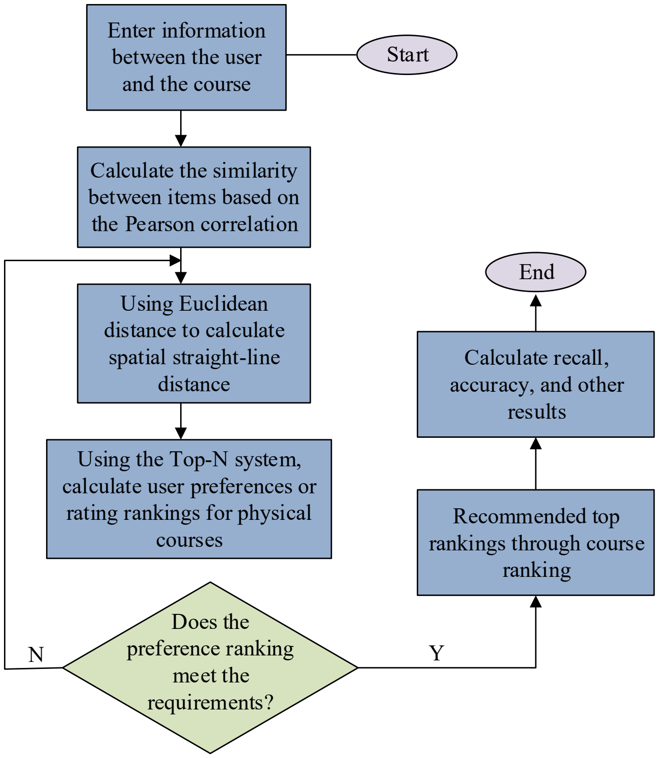


Figure 1 *Recommendation Process for Teaching systems*

In Figure 1, the collaborative recommendation technology process of the teaching system lies in the ability to utilize the correlation between user data and courses. By calculating and sorting the correlation between similar courses and users, the recommended content of courses and resources with high correlation can be obtained, thereby meeting the learning and development requirements of users and achieving effective management and teaching work. Typically, user data is sparse, resulting in poor recommendation accuracy of traditional collaborative filtering algorithms; in the face of new users and projects, the algorithms lack sufficient historical data to establish associations (He et al., 2023; Group, 2020). In collaborative filtering algorithms, cosine similarity is often used to calculate the degree of similarity between users, to assess the user's interest in the course, and to complete the recommendation (Falato et al., 2022). The cosine similarity is calculated as shown in Equation (1).

$$similarity = \cos(\theta) = \frac{A * B}{\|A\| * \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2 \times \sum_{i=1}^{n} (B_i)^2}} \tag{1}$$

In Equation (1), A_i and B_i represent the respective components of the two. The Pearson similarity evaluates the degree of similarity between two vectors and is calculated as shown in Equation (2).

$$\rho(X,Y) = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{2}$$

In Equation (2), X Y denote the degree of preference of different users for courses, respectively, and the Pearson coefficient measures the degree of association by the covariance of the two vectors. The simplest way to determine the degree of user similarity is the Euclidean distance, considered as the straight line distance between two points in space.

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i, y_i)^2} \tag{3}$$

Next, the Top-N recommendation system will be used to rank N items of interest for users. It can sort the interests of the target object based on user historical data and preferences, and reflect the system's recommendation accuracy through recall rate, as shown in equation (4).

$$\mathrm{Re}\,call = \frac{Tp}{Tp + Fn} \tag{4}$$

In Equation (4), Tp denotes the number of true prediction pairs, and Fn denotes the number of true categories misclassified as other categories, and recall can be used as a measure of recommendation accuracy. The score calculation method for assessing the similarity between users is shown in Equation (5).

$$S\mathrm{imI}(u,v) = \frac{\sum_{i \in K_{MN}} (S_{u,i} - \bar{S}_u) \times (S_{v,i} - \bar{S}_v)}{\sqrt{\sum_{i \in K_{M,v}} (S_{u,i} - \bar{S}_u)^2} \times \sqrt{\sum_{i \in K_{M,y}} (S_{v,i} - \bar{S}_v)^2}} \tag{5}$$

In Equation (5), $S_{u,i}$ and $S_{v,i}$ denote the total value of ratings of the items by different users, $\bar{S}_u$ and $\bar{S}_v$ denote the mean value of ratings of the items by different users, and $S\mathrm{im}(u,v)$ denotes the similarity between the items. u The change value of interest in the project is calculated as shown in Equation (6).

$$W_{\mathrm{i}}^{u} = e^{-\frac{t_i - t_1}{T}} \tag{6}$$

In Equation (6), t_1 and t_{i} represent the initial time and current moment of the user's rating of the line item, respectively, and T represents the user's time of using the system. Considering that there are differences in user interest in commercial fragrance projects during different periods, which can affect the effectiveness of system recommendations, in order to improve the accuracy of system recommendations, the similarity calculation method was improved by using interest change weights in the study. The improved similarity calculation is shown in equation (7).

$$SimT(u,v)=\frac{\sum_{ieK_{u,v}}(N_{\mathrm{u},i}\times W_i^u-N_{\mathrm{u}}^w)\times(N_{v,i}\times W_i^v-N_v^w)}{\sqrt{\sum_{ieK_{u,v}}(N_{u,i}\times W_i^u-N_u^w)}\times\sqrt{\sum_{ieK_{u,v}}(N_{v,i}\times W_i^v-N_v^w)}} \tag{7}$$

In Equation (7), $N_{\mathrm{u},i}$ and $N_{v,i}$ denote the user ratings of the items, and, N_{u}^w N_v^w denote the average ratings obtained by combining the user ratings with the interest change weights. Finally, the improved similarity calculation method is integrated with the preference similarity calculation, and the final similarity calculation process is shown in Equation (8).

$$S\mathrm{imI}(u,v)=\lambda SimI(u,v)+(1-\lambda)SimT(u,v) \tag{8}$$

In Equation (8), $S\mathrm{imI}(u,v)$ denotes the preference similarity, and $SimT(u,v)$ denotes the similarity improved by introducing interest change weights. The improved comprehensive score is shown in equation (9).

$$\mathrm{c}=\sum_{(u,i)\in R_0}(R_{ui}-\hat{R}_{ui})+R\mathrm{e} \tag{9}$$

In Equation (9), R_{ui} denotes the user's original rating and $\hat{R}_{ui}$ denotes the predicted rating. Continue regularization on equation (9), as shown in equation (10).

$$\mathrm{c}=\sum_{(N,i)\in R_0}(R_{\mathrm{ui}}-X_N^T\cdot Y_i)^2+\lambda\sum_N\|X_u\|^2+\lambda\|Y_i\|^2 \tag{10}$$

In Equation (10), $\lambda\sum_N\|X_u\|^2+\lambda\|Y_i\|^2$ is the regularisation term. Each user feature vector can be solved individually as shown in Equation (11).

$$F_N(X_N)=\sum_{\mathrm{i}}(R_{ui}-X_N^T\cdot Y_i)^2+\lambda\|X_u\|^2 \tag{11}$$

In Equation (11), To minimise the function, a partial derivative is applied to it as shown in Equation (12).

$$\frac{\partial F_u}{\partial X_u}=2(\sum_{\mathrm{i}}X_{\mathrm{u}}^T Y_i Y_i-\sum_{\mathrm{i}}R_{ui}Y_i-\lambda X_u) \tag{12}$$

In Equation (12), X_u is the user feature vector and Y_i is the course feature vector. As shown in Equation (13).

$$\sum_i X_N^T Y_i Y_i-\sum_i R_{Ni}Y_i+\lambda X_N=0 \tag{13}$$

Equation (13) can be equated as shown in Equation (14).

$$(\sum_{\mathrm{i}}Y_i Y_i^T+\lambda I)X_u=\sum_i R_{\mathrm{u}i}Y_i \tag{14}$$

In Equation (14), equating it as shown in Equation (15), the

$$X_{\mathrm{u}}=(YY^T+\lambda I)^{-1}YR_u \tag{15}$$

The function of the online teaching module is to provide students with online video and audio teaching, interactive Q&A with teachers, and video playback after class. Students want to learn on this platform, the first need to log on this platform, and then book the course they are interested in, students choose to play online or watch the purchase of the course to learn, colleague system needs to be retained to ensure that the learning behaviour of students to provide learning feedback. The main role of the network video teaching module is to realise the live webcast of the online teacher, and its flow chart is shown in Figure 2.

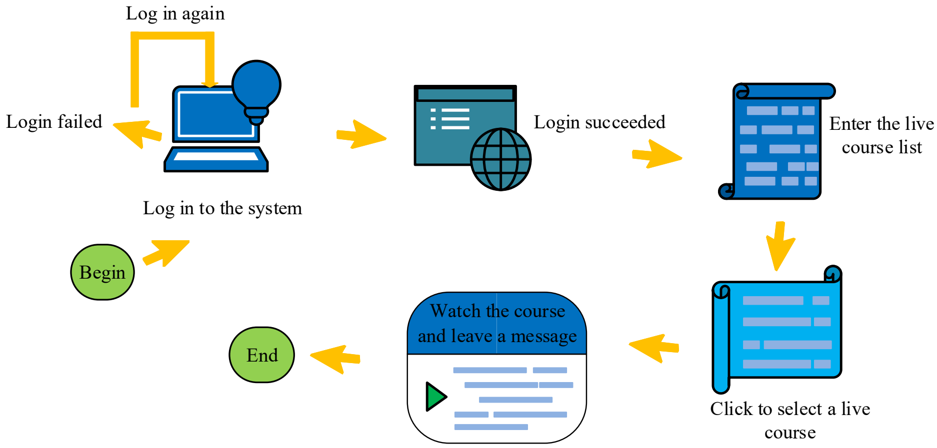


Figure 2 *Online Video Teaching Flowchart*

As can be seen in Figure 2, the process of online video teaching: firstly, determine the content of the learning course, then log in the online learning platform, browse and select courses and resources according to the learning needs. Based on the online recommendation module, students can query and retrieve the courses and resources recommended by the system as well as learning discussions.

3.2 Educational platform design for computer programmes

In this computer course education platform, the system will be based on the list of open course curriculum recommended by the system and comment on it, so that it can more accurately understand the user's psychology and interest, recommend and develop a more suitable course for them, and further optimise the course recommendation function. The example diagram of the recommendation system based on collaborative filtering algorithm is shown in Figure 3.

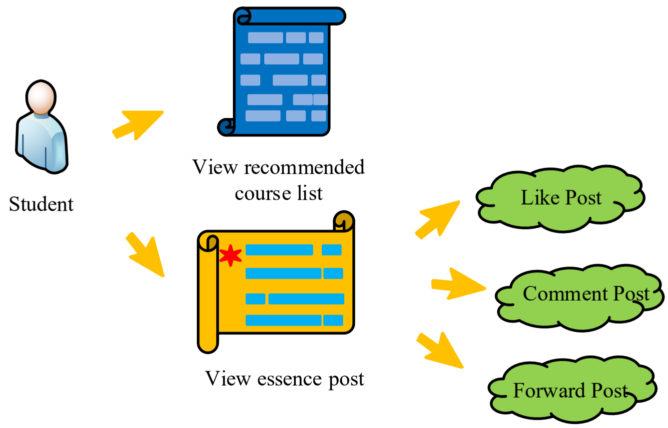


Figure 3 *Example of Recommendation System*

In Figure 3, it can be seen that students can retrieve the list of recommended courses based on the system query and select courses to add based on their study plan and needs. They can view the best discussion and sharing posts in the learning social area, and can actively participate in the discussion and sharing, and the system will recommend the next step according to the heat of the post.

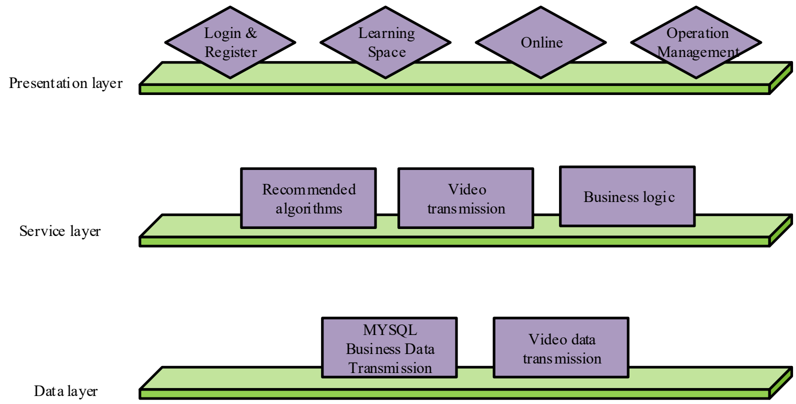


Figure 4 *System Three-Layer Architecture Diagram*

Figure 4 shows the overall architecture of the recommendation system, which includes the presentation layer, service layer, and data persistence layer. The service layer mainly includes recommendation algorithms, video transmission, and business logic, which is the key to implementing system services. The overall technical architecture of the system is shown in Figure 5.

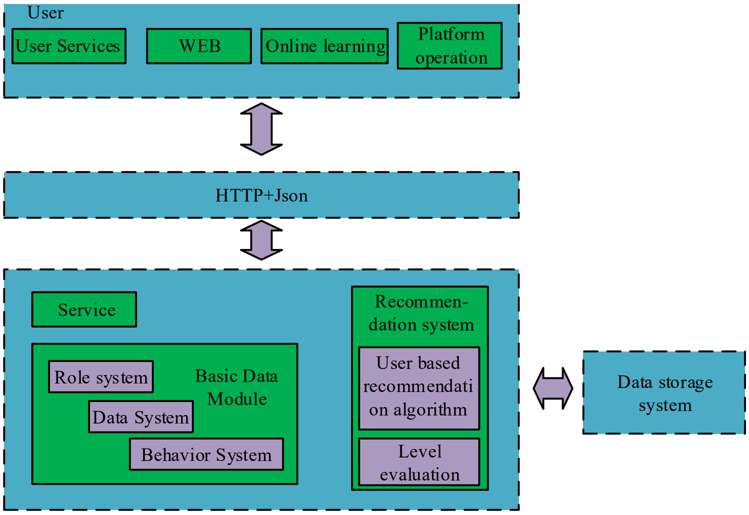


Figure 5 *Overall Technical Architecture of the System*

In Figure 5, it can be seen that in this system, the user service module, the faculty management module, the online learning module, and the platform operation module, all interact with the user through the browser and communicate with the server by submitting forms, sending request links, and so on. The backend server, on the other hand, plays the core role of the website or application, providing the necessary functions and services to ensure the normal operation of the system and user satisfaction. This includes storing and managing data, processing business logic, providing interfaces and services, and completing the configuration of recommendation algorithms; structured business logic data stored in MySQL database tables.

4. Analysis of the Performance of Collaborative Filtering Recommendation Algorithm and Its Recommendation Effect in Computer Course Education Platforms

In the computer course education platform, the course recommendation accuracy can be fed back by the actual click rate of the users after a long period of time, for which the study carried out the performance analysis and application testing of the model.

4.1 Performance analysis of collaborative filtering recommendation algorithm

On this basis, user similarity was measured using two methods, Pearson correlation and improved Jarka similarity. Firstly, researchers tend to take the set of items that are highly rated by two users and ignore the set of items that are not rated, leading to imprecise neighbouring users found, which is particularly evident when video rating data is scarce. Regarding user similarity: when two people review a high number of items together, they are considered to have a high degree of similarity; if one user has a high rating and the other has a low rating, there is little similarity between the two. As a result, the similarity of Jaccard is improved. In the study, movielens data was used as the training basis, which included rating data from 6040 users on 3900 movies. In addition, the files of this dataset include movies. dat, ratings. dat, and user. dat, where the ratings. dat file stores the user's rating information for movies, and divides it into high sparse and low sparse data for training. At the same time, root mean square error

(RMSE), recommendation accuracy (Accuracy), response time, and throughput are introduced as testing benchmarks to evaluate the practical application effects of different methods. The experimental parameters are shown in Table 2.

Table 2 *Basic Experimental Parameters*

Parameter	Type
Number of neighbors	50
Similar coefficient	0.5
Number of user categories	10
Experimental system	WINDOWS 10
Development language	Python 2.7
Development environment	JetBrains PyCharm 2.7.3

In user collaborative filtering algorithms, the first step is to calculate the similarity between users, and then search for targets and similar users based on their drug use habits. Therefore, historical data needs to be processed through Pearson correlation coefficient and Euclidean distance before the experiment. In addition, the number of neighbouring users selected has an effect on the calculation results, and its accuracy improves as the number of neighbours increases. To investigate the trend of the influence of the number of neighbours on the recommendation accuracy, the study gradually grows the number of neighbours from 0 to 50, and the corresponding accuracy is recorded every 5 neighbourhood growths. Thus the trend of accuracy with the growth of the number of neighbours under different sparsity conditions is shown in Figure 6.

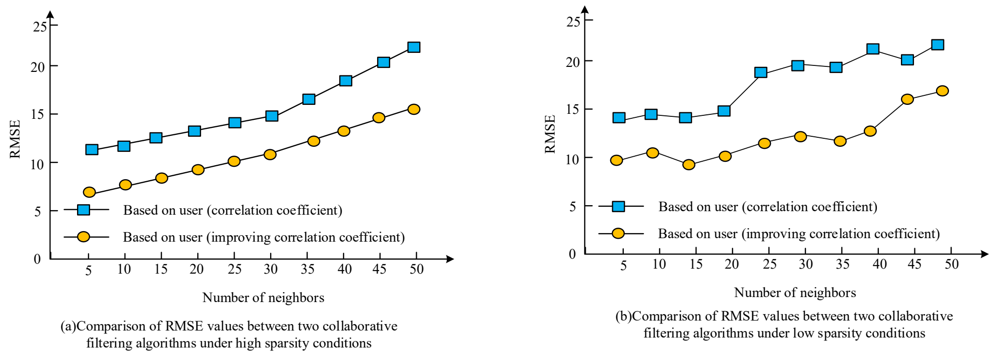


Figure 6 *Comparison of RMSE Values between Two Collaborative Filtering Algorithms*

In Figure 6, it can be seen that the prediction error after the algorithm improvement is significantly reduced, but the computational efficiency is also reduced and the computation takes longer. The study of the improved similarity metric has superior utility for the improvement of prediction accuracy. Figure 6(a) and (b) represent the comparison of the number of neighbours on accuracy in the case of higher sparsity and lower sparsity, respectively, but it can be clearly seen that the change with the number of neighbours is smoother in the case of higher sparsity, and the ups and downs with the number of neighbours are larger in the case of lower sparsity; thus the data fluctuation is smaller in the case of higher sparsity, and the accuracy transforms are smoother. Because there are a large number of teaching resources on the platform, a large number of resources are recommended to users at the initial stage, however, in reality, users tend to pay attention to only a very small part of the recommended resources, and they are more concerned about the items that are ranked high in the recommended results. Therefore, in the recommender system, more attention is paid to the accuracy of the recommended resources in the selected Top-N (correct rate = the ratio of the number of correct entries/the expected number of all entries) to evaluate the performance of the promoted recommender system, and the higher the accuracy rate of the data, the higher the quality of the recommendation. After calculation, the accuracy comparison of the algorithms is shown in Figure 7.

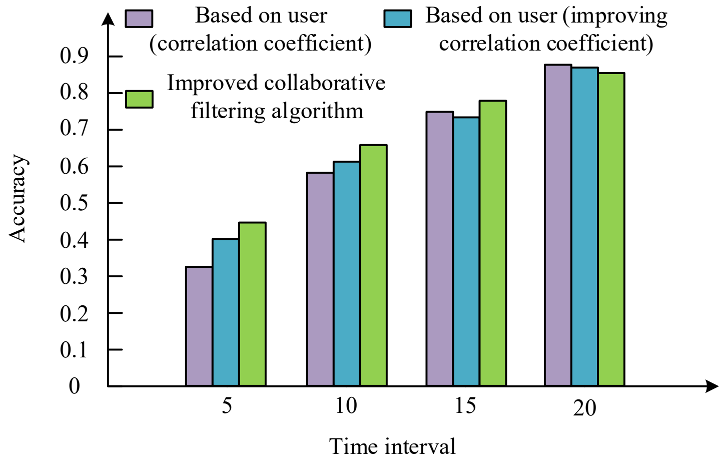


Figure 7 *Comparison of Accuracy of Various Algorithms*

In Figure 7, by comparing the recommendation accuracy of different algorithms, it can be seen that the video resources before the recommended resources are higher than the algorithms without improvement in terms of accuracy after improvement, and the accuracy gap between the two is getting smaller and smaller with the passage of time, but in the practical application, the user's attention is focused on the forefront, so that such an improvement, in the practical application, is more valuable. Collaborative filtering algorithm in the recommendation system role in the recommendation accuracy is higher than other algorithms, and in the time node of 5 ms when the accuracy of the superiority of the strongest, the difference is most obvious. In the user's assessment of the recommendation results, the user assessment can be considered from three aspects: whether it meets the purpose of learning, whether it meets the interest of learning, whether it meets the recommendation results, and analyses the effectiveness of the recommendation results of various algorithms, the specific structure is shown in Table 3.

Table 3 *Satisfaction Analysis*

Recommendation algorithm	Learning objectives	Interest in learning	Satisfaction with recommendation results
Traditional collaborative filtering algorithm	59.55%	69.56%	72.6%
Improved collaborative filtering algorithm	71.03%	79.4%	93.45%

In Table 3, it can be seen that the improved collaborative filtering algorithm outperforms the traditional collaborative filtering algorithm in terms of the rate of learning goal attainment, the level of interest in learning, and the satisfaction with the recommendation results. Specifically: the improved collaborative filtering algorithm reaches 71.03% in the learning goal achievement rate, while the traditional collaborative filtering algorithm is only 59.55%. This indicates that the improved algorithm is more effective in recommending learning materials that are closer to the learners' learning goals. The improved collaborative filtering algorithm in the level of interest in learning is 79.4% compared to 69.56% for the traditional collaborative filtering algorithm. This indicates that the improved algorithm not only recommends materials that are more in line with the learning objectives, but also stimulates learners' interest and enthusiasm in learning. The study achieved 93.45% satisfaction with the improved collaborative filtering algorithm compared to 72.6% with the traditional collaborative filtering algorithm. This indicates that learners are very satisfied with the recommendation results of the improved collaborative filtering algorithm, compared to the traditional collaborative filtering algorithm which has a lower satisfaction level. It can be seen that the percentage shown in the table is the percentage of users. The results of the subjective and objective tests show that the student users are more satisfied with the improved algorithm, which indicates that the improved algorithm improves their level of personalisation.

4.2 System performance testing

The response time of the system was first tested and recorded before conducting the system performance test and the results are shown in Table 4.

Table 4 *Main Operation Response Time*

Behavior	Time (ms)
Login	1066
Ask questions	242
Chat: text	235
Chat: images	380
Video requests	1857
Schedule classes	164
Develop courses	180

In Table 4, it can be seen that different behaviours take different amounts of time, with video requests taking the longest time at 1857 milliseconds, and scheduling lessons taking the shortest time at 164 milliseconds. It can be seen that the system runs more smoothly. To explore the persistence of the collaborative filtering algorithm in response time changes to explore, the number of iterations to 5 times as a division of the time consumed by seven types of operational behaviour, the initial time as shown in Table 4, record the response time required by the seven types of operations, when the number of iterations to reach 50 times until.

In Figure 8, it can be seen that with the increase of the number of iterations, the behaviours of the seven types of operations have different degrees of growth. In Figure 8(a), it represents the response time change of the response time of the application type request in the seven operations, in which the response time of the login operation grows from 1066 ms to 1796 ms, the response time of the ask operation grows from 242 ms to 1325 ms, the response time of the text operation in chat grows from 235 ms to 800 ms, and the response time of the picture operation in chat grows from 380 ms to 1289 ms. the response time of text operation in chat grows from 235 ms to 800 ms, and the response time of picture operation in chat grows from 380 ms to 1289 ms; in 8(b), it represents the response time change of course type request in 7 operations, in which the response time of video request operation grows from 1857 ms to 1997 ms, the response time of plan class operation grows from 164 ms grows to 1584 ms, and the response time of the development course operation in chat grows from 180 ms to 906 ms. The system is stress tested with a focus on the server side, and the server side services are divided into two categories, i.e., Http requests and WebSocket requests, and they are stress tested separately. The comparison of throughput between HTTP and WebSocket tests and the ratio of outliers occurring under HTTP and WebSocket tests in the test results are shown in Figure 9.

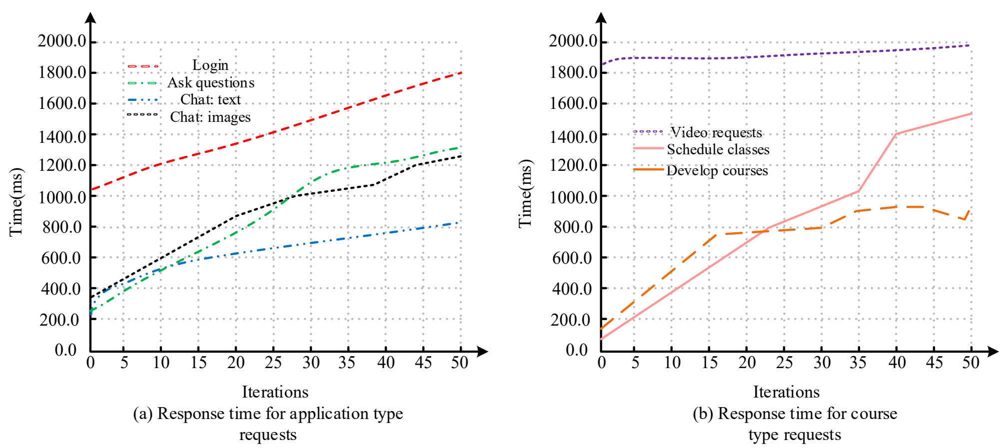
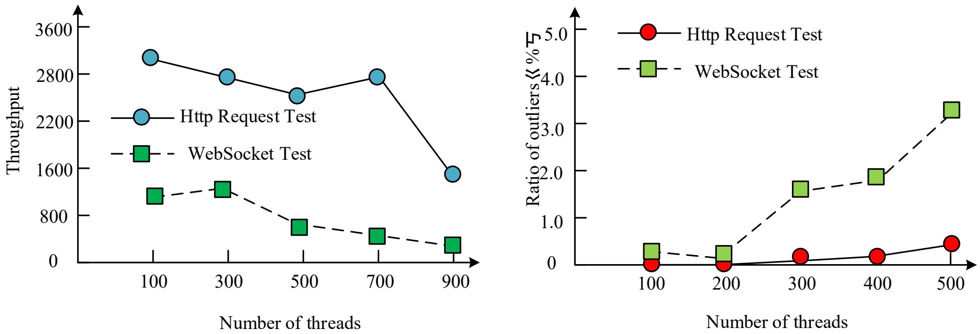


Figure 8 *System Login is Compared to Runtime Changes*



(a) Comparison of Throughput between HTTP and WebSocket Testing

(b) Comparison of the number of exceptions between HTTP and webSocket testing

Figure 9 *Comparison of Throughput between HTTP and WebSocket Testing*

In Figure 9, the horizontal axis is the number of threads that emulate the number of users making requests at the same time, 100 cycles, with the number of requests that will be made at the same time 100. the dashed line indicates the processing capacity per second, and the solid line indicates the number of exceptions that occur. In Figure 9(a), when the number of threads increases, the proportion of exceptions increases while the throughput decreases. The performance is better when the parallelism is lower than 400; the throughput is 362 when the number of threads in WebSocket reaches 900, and 1436 when the number of threads in Request Text reaches 900.The web socket request also uses the WebSocket heartbeat request, which is common in applications. The request has a length of 41 bytes and a return of 16 bytes. In Figure 9(b) the results of the experiment are shown, the system has a lower percentage of outliers at parallelism below 200 and WebSocket has a higher percentage of outliers compared to Http Request Text, with 3.36% of outliers at 500 threads, while Request Text has a lower percentage of outliers at 500 threads, with the percentage of outliers at 500 threads throwing less than 1.36%. The rate of exceptions is less than 1%, which is about 0.5%-6%. Therefore, it can be seen that Request Text has more superior performance and can play a better role in practical applications.

5. Conclusion

The research constructs a recommendation system based on collaborative filtering algorithm and applies it to the design and implementation of computer course education platform. Through experimental verification and practical application, we proved the effectiveness and superiority of the recommendation system and computer course education platform. This provides new ideas and methods for the reform and innovation of computer course education. The improved collaborative filtering algorithm reaches 71.03% in the learning goal achievement rate, while the traditional collaborative filtering algorithm is only 59.55%. This shows that the improved algorithm is more effective in recommending learning materials; and the time needed for the system to log in is 2056 milliseconds; the time needed for scheduling a course is the shortest, only 164 ms. it can be seen that the system runs more smoothly. It can be seen that the technology proposed by the research institute has better performance in practical applications, with smaller errors, higher recommendation accuracy, and better performance in different scenarios, meeting the requirements of education platform systems. This technology will also further improve the education system and enhance the effectiveness of students in utilizing learning resources. However, there are still shortcomings in the research, as the study did not utilize context aware information. In the future, it is necessary to further consider other contextual information of users, improve the accuracy of user decision-making, and further optimize the effectiveness of system education resource recommendations.

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Shaocui Guo
The Open University of Yantai, Yantai Vocational College, Yantai 264670, China
E-mail address: gscytvc@126.com
Major area(s): computer, course education.

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