

## Precise Recommendation Algorithm for Online Sports Video Teaching Resources

Xu Zhu<sup>1</sup>, Zhaofa Zhang<sup>2,\*</sup>

<sup>1</sup> College of Public Finance and Administration, Jiangxi University of Finance and Economics, Nanchang 330044, China

<sup>2</sup> Institute of Physical Education, Nanchang Hangkong University, Nanchang 330036, China

### Abstract

**INTRODUCTION:** With the development of the epidemic, online teaching has gradually become a hot topic. However, unlike traditional teaching programs, there are many types of physical education resources, and the recommendation of related content has always been a difficulty in online teaching.

**OBJECTIVES:** Therefore, this paper designs an accurate recommendation algorithm for online video teaching resources of sports to meet the personalized needs of online learning of sports majors. The data layer of the entire recommendation algorithm stores the video in the database and transmits it to the service processing layer after receiving the data.

**METHODS:** This study was conducted using techniques from social network analysis. After receiving the data, the data layer of the recommendation algorithm stores the video in the database and transmits it to the business processing layer at the same time. The business processing layer uses the designed collaborative filtering resource recommendation algorithm to formulate recommendation results for different users, and push the recommended results to the user display interface of the user layer.

**RESULTS:** The test results of the algorithm show that the designed system has a high recommendation success rate, and the system can still maintain stable running performance when the concurrent users are 500. The average precision of resource recommendation of this method is 98.21%, the average recall rate is 98.35%, and the average F1 value is 95.37%.

**CONCLUSION:** The proposed resource recommendation algorithm realizes accurate recommendation of sports online video teaching resources through efficient recommendation algorithms.

**Keywords:** sports, online video, teaching resources, precise recommendation, collaborative filtering, algorithm test.

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\*Corresponding author. Email: [zhangzhaofa@nchu.edu.cn](mailto:zhangzhaofa@nchu.edu.cn)

### 1. Introduction

In the network era, people can obtain a large amount of information with the help of fast communication tools such as powerful search engines to improve the dynamic education effect, and the education resource recommendation system has gradually become a hotspot [1]. Due to the explosion of information and the diversity of individual needs, it is difficult to find the information you

need accurately and quickly. Therefore, in order to meet the needs of individual customers, people deal with the problem of information overload by turning to the outside world. This facilitates the development of recommender systems [2-3].

Online video is an important resource of sports teaching, which has high technical analysis value and application prospect [4]. In physical education teaching, the intelligent sports application system composed of Internet of things, cloud platform and mobile client [5] that can decompose the movements of athletes effectively in sports online video,

analyzes and utilizes sports online video resources scientifically and effectively, which has important reference significance for improving the level of sports teaching.

Physical education is a kind of maximum exercise for all aspects of the human body, which requires access to scientific and reliable data. There are various types of online sports videos, which have some similarities. Through the development and exploration of sports behaviors, the nonlinear learning ability can be effectively improved [6]. Therefore, the transmission and storage of online sports video and data analysis on the Internet can provide accurate online education resources for different audiences, playing a very important role in improving the quality of physical education in colleges and universities [7-8].

In the current era, the demand for individualized education is growing. With the acceleration of the process of education informatization, distance teaching has developed rapidly, and information technology with network communication technology and multimedia technology as the core has also developed rapidly, which promotes the application of teaching management information system in colleges and universities [9]. However, the current network sports teaching technology is mostly homogeneous, which does not take into account the personal characteristics of students, and can not adapt to the personalized learning needs of students.

At present, there are many studies on the recommendation of teaching resources. Cohenmiller et al. studied the multi-stage search and classification of the open video library for the online teaching resources of Social and Natural Sciences. A useful device for integrating multimedia into online and blended teaching is the Open Video Repository. It mainly offers curated videos that are freely accessible. And often offers advice on applying these videos to student learning [10]. Geng et al. studied the recommendation of teaching resources by using the similarity method. This method adopts the least squares collaborative filtering recommendation algorithm to optimize the use on the Spark big data analysis platform. Furthermore, the parallel method is adopted to improve the workload completed per unit time and the accuracy of the recommendation [11]. Chen studied the recommendation method of reinforcement learning resources based on online learning style model. First, the method creates clusters of learners based on online learning styles. Second, it applies collaborative filtering and association rule mining to extract the preferences and behavioral patterns of each cluster. Finally, it generates a variable-size personalized recommendation set for resource recommendation [12].

The above research methods apply the recommendation method to teaching, and provide an effective theoretical basis for personalized teaching. Personalized recommendation is a research hotspot in the field of online learning. However, there are many types of sports resources, and there are some similarities with online sports videos. Therefore, the current resource recommendation method has the problem of low recommendation accuracy when recommending physical education resources.

In order to meet the personalized learning needs of sports major students, this paper designs an accurate recommendation algorithm of sports online video teaching resources based on collaborative filtering, which uses collaborative filtering technology to achieve personalized sports online teaching resources recommendation, and realizes accurate recommendation of sports online video teaching resources through efficient recommendation algorithms.

## 2. Logical structure design of precise recommendation algorithm for sports online video teaching resources

This paper designs the overall structure of the precise recommendation algorithm for online sports video teaching resources based on collaborative filtering, which mainly includes the following four levels:

### User layer

The proposed algorithm uses the user layer to provide users with some interfaces that users can directly operate. Users can directly access the services provided by the algorithm through the interface. The algorithm includes user login registration, online sports video teaching resource retrieval and online sports video teaching resource recommendation interface, etc.

### Business processing layer

The proposed algorithm uses the business processing layer to receive the request submitted by the user, and then queries the relevant result set, which is finally sent back to the display interface of the user layer for display. At the same time, the algorithm uses this layer to collect the user behavior data set in real time. The business processing layer of the algorithm mainly includes the interface design module, the resource recommendation module and the sports online video collection module.

### Data layer

The data layer is used to store the online sports teaching video in the database, and the data is transferred to the business processing layer for the business logic layer to invoke. The database in the data layer can store massive historical data of user behavior, and provide data basis for accurate recommendation of resources according to the historical data of user behavior.

The video acquisition module on the sports line uses FPGA as the processing chip [13], and the FPGA device has on-chip resources, which can use on-chip resources to design FIFO (first in first out) as the data read/write buffer [14], so as to realize the multiport control of synchronous dynamic random access memory (SDRAM), and can store

and output data in multiple directions. SDRAM memory devices have three types of pins [15], control signal, address signal and data, which needs certain hardware support. Comprehensive analysis of the algorithm structure, the user layer is to provide users with basic operations. The designed algorithm transmits the online sports teaching video to the data layer, and the data layer stores the video in the database and transmits it to the business processing layer. The business processing layer uses the resource recommendation algorithm based on collaborative filtering to accurately push the sports online teaching video to the user interface.

### 3. Algorithm design of Resource Recommendation software based on collaborative filtering

The resource recommendation module of the system adopts the resource recommendation algorithm based on collaborative filtering to realize the accurate recommendation of sports online video teaching resources [16]. The recommendation based on collaborative filtering is the most widely used recommendation strategy in the current personalized recommendation technology. The key of collaborative filtering is to analyze the users' interests through the users' historical data [17], so as to mine the association between items or users, and then some algorithms are used to calculate these association relationships to obtain the recommendation value, and finally the items with high recommendation value are recommend to specific users. Collaborative filtering recommendation needs to find rules according to the behavior characteristics and interests of users, and the first task is to collect user preference data. According to the recommendation requirements of sports online video teaching resources [18], it analyzes some user behaviors which accurately represent user preferences, and finally these data are obtained and saved for future analysis. The specific process is as follows.

#### 3.1. Construction of judgment matrix

Pairwise comparison of all the influencing factors and unified quantification and comparison of different unit dimensions through relative scale comparison method are the core of collaborative filtering method. The judgment matrix is used to describe all the influencing factors in the current layer and the comparison results of the relative criticality of certain influencing factors in the upper layer during the recommendation process can be expressed by the 1-9 scale method. All elements in the judgment matrix need

$$\frac{n(n-1)}{2}$$

to be compared  $\frac{n(n-1)}{2}$  times (where  $n$  represents the number of all influencing factors). Considering that the absolute consistency of the matrix is difficult to achieve, the weight of different influencing factors on an influencing factor in the upper layer can be determined under the

condition of incomplete consistency. The consistency of the judgment matrix is determined based on the consistency index  $R_{CI}$ , the calculation formula is as follows:

$$R_{CI} = \frac{\lambda_{\max} - n}{n - 1} \quad (1)$$

In formula (1),  $\lambda_{\max}$  represents the upper limit value of the characteristic of the judgment matrix.

When the  $R_{CI}$  value is 0, it is defined that the matrix has complete consistency. Therefore, under the condition that the order of the matrix is less than or equal to 2, it has complete consistency. When the order of the matrix is greater than 2, the random consistency ratio  $R_{CR}$  can be taken as the standard. Under the condition that the  $R_{CR}$  value is less than 0.1, the judgment matrix can be defined as approximate consistency; otherwise, the judgment matrix needs to be constructed again to make it meet the consistency standard.

#### 3.2. Weight vector calculation

The judgment matrix constructed in this paper is used to describe all the influencing factors in the current layer in the recommendation process. Make the resource judgment result meet the consistency standard. On this basis, the weight vector calculation is performed to avoid the influence of expert experience and the subjectivity of decision makers. In the design process of collaborative filtering method, the expert experience and the preference of decision makers are emphasized, so the weight value obtained from this method is relatively reasonable, but it has obvious subjectivity problem. As an objective evaluation method, entropy weight method uses information entropy to determine the entropy weight of different influencing factors according to the variation level of different influencing factors in the application process, so as to optimize different influencing factors, finally the objective weight of influencing factors is obtained. The entropy weight method is used to improve the calculation process of the weight vector in the analytic hierarchy process to obtain the comprehensive weight value.

If the recommendation results have several development trends, the probabilities of various trends can be described by  $P_i (i = 1, 2, \dots, m)$ , and thus the entropy of things is

$$e = -\sum_{i=1}^m P_i \cdot \ln P_i \quad . \quad \text{Under the condition of } P_i = \frac{1}{m}, \text{ the entropy is}$$

$$\text{the largest, which is } e_{mm} = \ln m .$$

The entropy of an influencing factor is inversely proportional to its variation level, and inversely proportional to the index information and criticality. In other words, the larger the entropy of an influencing factor, the smaller the variation level, and the lower the information and criticality, which also indicates that the weight of this influencing factor is smaller. In the actual evaluation process, the

entropy weight of different influence factors is determined through entropy according to the variation level of different influence factors, and all influence factors are analyzed and evaluated based on the entropy weight of different influence factors to improve the accuracy of the final evaluation results. The specific process of judgment matrix construction and weight vector calculation is as follows:

For  $m$  video recommendation schemes to be evaluated and  $n$  evaluation indexes, an initial judgment matrix  $R = (r_{ij})$  is constructed:

$$R = \begin{pmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \vdots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{pmatrix} \quad (2)$$

In formula (2),  $a_{ij}$  represents the evaluation value of the  $i$ th recommended scheme under the  $j$ th influencing factor.

Formula (3) is used to determine the proportion of the index value of the  $i$ th video recommendation scheme under the  $j$ th influencing factor:

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \quad (3)$$

The entropy value of the  $j$ th influencing factor is determined by formula (4):

$$e_j = -k \sum_{i=1}^m p_{ij} \cdot \ln p_{ij} \quad (4)$$

In formula (4),  $k$  is  $\frac{1}{\ln m}$ .

The entropy weight of the  $j$ th influencing factor is determined by formula (5):

$$w_j'' = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (5)$$

The comprehensive weight can be obtained by combining the subjective weight obtained by the entropy weight collaborative filtering method. According to the concept of minimum relative information entropy, the comprehensive weight is determined by formula (6):

$$w_i = \frac{(w_i' w_i'')^{\frac{1}{2}}}{\sum_{i=1}^m (w_i' w_i'')^{\frac{1}{2}}} \quad (6)$$

The above process indicates that the weights of different influencing factors in the collaborative filtering recommendation evaluation system can be obtained.

The process of resource recommendation algorithm based on collaborative filtering to recommend online sports video teaching resources for users is as shown in Figure 3.

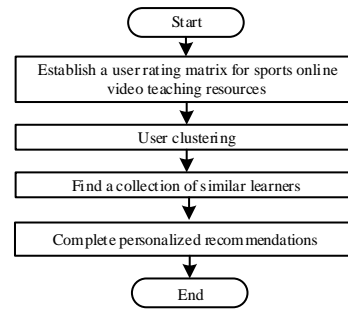


Figure 3. The process of sports online video teaching resources

### Establish the scoring matrix of users for online sports video teaching resources

Through the analysis of users' behavior, the user's rating of online sports video teaching resources is determined, and the scoring matrix is obtained. The scoring matrix of the  $M$  users on the  $N$  sports online video teaching resources is  $P(M \times N)$ , where the  $P_i$  in the  $i$ th row and the  $j$ th column represents the interest of the  $i$ th user on the  $j$ th sports online video teaching resources.

When users register the system, the system initializes their basic information, interests and preferences according to the registration information and the scale, thus solving this problem effectively. In order to solve the sparsity problem in collaborative filtering, this paper proposes a method based on the sparsity degree of fractional matrix. The sparsity calculation formula is as follows:

$$\text{Sparsity} = \frac{ENum}{LNum \times RNum} \quad (7)$$

In formula (7), ENum is the number of users' evaluation of sports online video teaching resources, LNum is the number of users, and RNum is the number of sports online video teaching resources. When the sparsity is lower than the minimum sparsity, it indicates that the user's evaluation matrix of online sports video teaching resources is too small [19]. At this point, the score is assigned an initial value. According to the characteristics of the recommendation system, the weighted average value of online sports teaching

resources is taken as the evaluation index, while non online education resources are scored by traditional methods.

### User clustering

Users are first clustered before finding similar users, which can reduce the search neighborhood and the time-consuming of the algorithm. According to the recommendation characteristics of the recommendation system, the users are classified, and k-means clustering algorithm [20] is used to process the recommended users. Figure 3 shows the clustering process of K-means clustering algorithm.

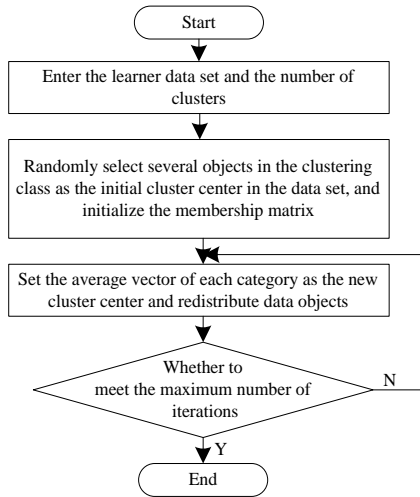


Figure 3. Caption to go below figure

The steps of K-means clustering algorithm are as follows:

The learner data set is represented by  $M$ ,  $N$  is the number of specified clusters, and  $P$  is the set maximum number of cycles. The evaluation standard of K-means clustering algorithm is shown in formula (8):

$$J(c, \mu) = \sum_{i=1}^M \|x^i - \mu N^i\|^2 \quad (8)$$

The sum of squares of the difference between the data in each class and the cluster center is calculated, and  $J$  is the smallest; the cluster segmentation effect is the best. In the formula,  $\mu$  is the cluster center,  $M$  is the number of data sources, and  $N$  is the number of cluster centers.

### The similar sets of learners

In the collaborative filtering algorithm, The computation and finding of similar neighborhood sets are the most important step. By clustering the recommended users, the nearest object can be selected as the neighborhood of the data set, which reduces the calculation speed greatly. Therefore, this paper proposes a new method based on similarity, that is similarity algorithm and improved cosine similarity algorithm.

### 1. Cosine similarity algorithm

In the calculation of similarity, the most representative is the cosine similarity. This method regards the user's evaluation of the item as a dimension vector, and calculates the remaining chord angle, so as to obtain the similarity among users. The specific algorithm is expressed in equation (9).

$$sim(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| \cdot \|\vec{j}\|} = \frac{\sum_{k=1}^n R_{i,k} R_{j,k}}{\sqrt{\sum_{k=1}^n R_{i,k}^2} \sqrt{\sum_{k=1}^n R_{j,k}^2}} \quad (9)$$

### 2. Modified cosine similarity algorithm

The algorithm subtracts all the scores of the user from the score of the item, thereby improving the data isolation point in the cosine similarity method. The specific algorithm is shown in the following formula (10).

$$sim(i, j) = \frac{\sum_{k=1}^n (R_{i,k} - \bar{R}_i)(R_{j,k} - \bar{R}_j)}{\sqrt{\sum_{k=1}^n (R_{i,k} - \bar{R}_i)^2} \sqrt{\sum_{k=1}^n (R_{j,k} - \bar{R}_j)^2}} \quad (10)$$

After the similarity calculation is completed, a set of  $n$  neighbors nearest to the user is obtained, as shown in the following formula (11):

$$Z = \{User_1, User_2, L, User_n\} \quad (11)$$

### Personalized recommendation is formed

Through the evaluation of the learners in the nearest adjacent group  $Z$ , the evaluation of object  $a$  can be obtained, and then the final recommendation result is get. The personalized recommendation formula of online video resources is as follows:

$$R_{a,i} = \bar{R}_a + \frac{\sum_{b=1}^n sim(a,b)(R_{b,i} - \bar{R}_b)}{\sum_{b=1}^n |sim(a,b)|} \quad (12)$$

In formula (12),  $R_{a,i}$  is the recommendation degree of user  $a$  to resource  $i$ ,  $n$  is the number of neighbors in the nearest neighbor set  $Z$ ,  $sim(a,b)$  is the similarity between user  $a$  and user  $b$ , and  $R_{b,i}$  is the interest degree of user  $b$  to resource  $i$ , that is the scoring weight of user  $b$  to resource  $i$ . Through the above process, the recommendation results of sports online video teaching resources of different users can be obtained.

In the collaborative filtering algorithm, the computation and finding of similar neighborhood sets are the most important step. By clustering the recommended users, the nearest object can be selected as the neighborhood of the data set, which reduces the calculation speed greatly. Therefore, this paper proposes a new method based on

similarity, that is similarity algorithm and improved cosine similarity algorithm.

### 4. Experimental analysis

In order to verify the accuracy of the proposed algorithm for the recommendation of sports online video teaching resources, the algorithm is built according to the algorithm design process and applied to a sports college.

In order to further test the recommended performance of the designed algorithm, 50 testers are selected to test the algorithm, all of whom are students majoring in physical education. The basic process of the test is as follows: Firstly, the user registers the algorithm, then logs in the algorithm, enters the personal center page, and fills in the personal basic attribute information. Then the course is browsed to select the course that you are interested in. People can also quickly select the courses in the navigation bar and start learning the courses. The system records the recommended resource information each time. In this test data set, a total of 50 students learn and score 20 sports online video teaching resources. The main purpose of this test is to test the recommendation effect of the algorithm. Due to the limitations of the experimental environment and conditions, the quality of the testers does not reach the expected effect, and the number is relatively limited, but the overall recommendation effect is relatively obvious, which reaches the expected value.

The proposed algorithm is used to recommend resources for users, first the average dwell time and mouse clicks of the algorithm users on the recommended resources are counted, and then 10 points as the scoring standard are selected to let students score the recommended sports online video teaching resources. The statistical results are shown in Table 1.

Table 1. Resource recommendation results

Tester serial number	Average time on page/s	Mouse clicks	score
1	10.52	6	7.5
2	11.64	7	8.1
3	12.34	8	7.6
4	12.84	6	8.2
5	13.64	5	8.4
6	10.85	7	8.4
7	13.46	7	7.8
8	14.58	9	7.3
9	16.52	8	7.2
10	13.45	8	7.5

It can be seen from the experimental results in Table 1 that the algorithm provides users with recommended resources. The average stay time of the user's page is more than 10s, the number of mouse clicks is more than 5, and the score of the recommended online sports video teaching

resources is higher than 7 points, which verifies that the algorithm in this paper has high recommendation effectiveness.

The accuracy of sports online video teaching resources recommendation is extremely important. With the wide application of recommendation algorithms, the real effect and role of recommendation algorithms are extremely important. The accuracy rate and recovery rate and other indicators are used to measure the performance of the recommended resource algorithm. The accuracy rate refers to the ratio of the number of accurately recommended resources to the total number of recommendations. The higher the accuracy, the better the recommendation effect. Recall rate refers to the ratio of the number of accurately recommended resources to the total number of relevant resources. The higher the recall rate, the better the effect of resource recommendation. The F1 value is the metric that neutralizes precision and recall. The algorithm in Refs 11-12 are selected as comparison algorithms, and the comparison results of resource recommendation accuracy and recall of different algorithms are shown in Fig. 4 and Fig. 5.

In practical application, there is a high contradiction between accuracy and recall. In order to accurately evaluate the performance of resource recommendation, The F1 value measurement index is selected to calculate the evaluation result, and the F1 value of the online sports video teaching resources recommended by the three algorithms is counted. The statistical results are shown in Fig. 6.

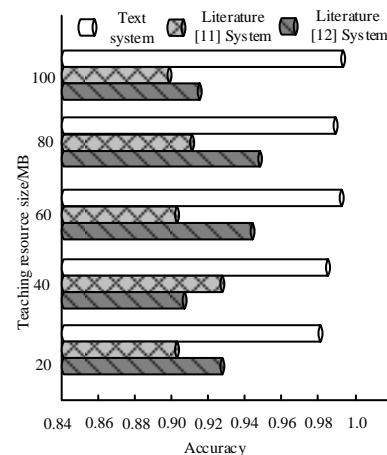


Figure 4. Precision comparison results

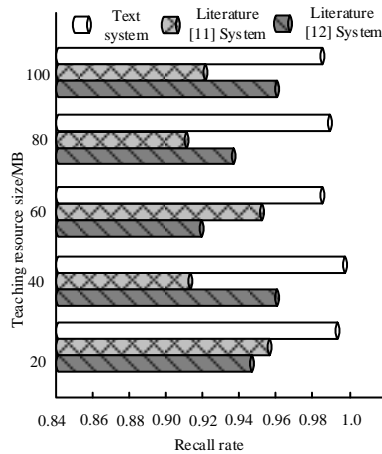


Figure 5. Recall comparison results

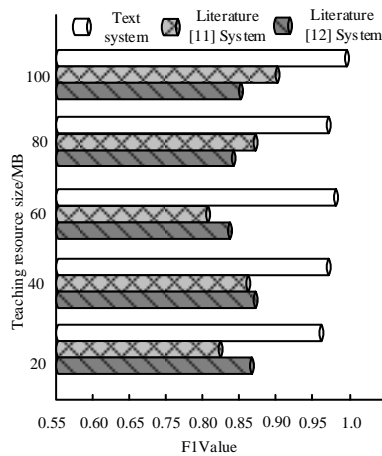


Figure 6. Comparison results of F1 values

Through comprehensive analysis of the experimental results in Fig. 4 -Fig. 6, it can be seen that compared with the other two algorithms, the recommendation algorithm adopted in this paper has a certain improvement in the recommendation success rate. The resource recommendation of the proposed method has an average accuracy of 98.21%, an average recall rate of 98.35%, and an average F1 value of 95.37%. With the increase of the number of recommended resources, the recommendation success rate of this algorithm does not decrease. Obviously, the recommendation success rate of this algorithm is higher than the other two algorithms. When the number of recommended resources increases to a certain extent, the recommendation algorithm will recommend more pages that are not related to learners' interests and preferences, and the recommendation success rate will inevitably decrease. In the case of a high number of recommended resources, the proposed algorithm can still maintain a high

recommendation accuracy, which verifies that the proposed algorithm has a high recommendation performance.

In order to further verify the recommended performance of the algorithm in this paper, MAE (Mean Absolute Error) is selected as another evaluation standard for the recommended performance of the algorithm. At present, almost all researches on personalized recommendation choose MAE as the evaluation standard, and MAE can determine whether the recommendation is accurate by comparing the degree of deviation. The deviation degree refers to the result of predicting the user's real score by the recommendation algorithm. The lower the MAE value is, the smaller the deviation between the estimated score and the actual score is, and the more accurate the recommendation is. When the MAE is high, it indicates that the error is large and the effect of the recommendation is poor. The number of resources scored is defined by the user as  $n$ , the algorithm predicts that the user's score on the resource  $i$  is  $X$ , and the actual score on the resource  $i$  is  $Y$ , then the calculation formula of MAE is as follows:

$$MEA = \left( \sum_{i=1}^n |x_i - y_i| \right) / n \quad (7)$$

The MAE comparison results of online video teaching resources recommended by the three algorithms are shown in Figure 7.

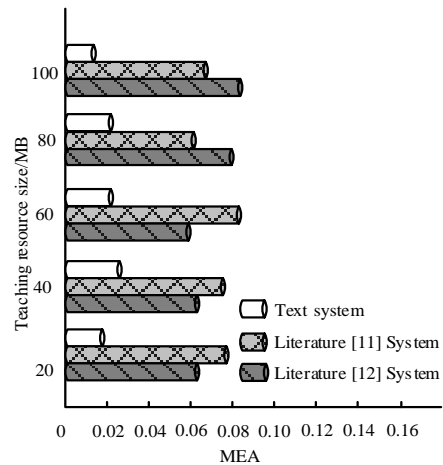


Figure 7. MEA value comparison results

As can be seen from Figure 7, with the increase of the number of online video teaching resources, the average absolute error of the algorithm in this paper is still significantly higher than that of the other two algorithms, which indicates that the error of the recommendation algorithm used in this paper is smaller than that of the other two algorithms and the recommendation result is more accurate when the number of users continues to increase.

Performance testing is a key step to ensure the quality of algorithms. Good performance testing can find problems in time, solve hidden dangers, provide more security, predict possible load problems and concurrent problems, and optimize the code in advance to make a good response plan.

The performance test indicators of this algorithm are described in detail below.

- (i) Concurrent number refers to the number of all users performing the same operation at the same time.
- (ii) Average response time refers to the average transaction processing time per second during the test. This indicator can reflect the number of transactions in different reaction times during the test.
- (iii) Average running time refers to the average time that transactions are actually executed at each time in the test. This method can analyze the performance trend of the algorithm.
- (iv) Throughput refers to the number of transactions per second of the server during the test execution. Its unit of measurement is one byte, which represents the amount of data obtained by the virtual user from the server at any given time per second.

- (v) Transaction overview refers to judging the success and failure of user transactions during the test.
- (vi) Network transmission rate refers to the average traffic per second of the network, which is used to detect whether there is a response of network delay caused by excessive network traffic.

When the number of concurrent users is 500, the test results of various performance indicators of the algorithm are shown in Table 2.

Through the performance test results, it can be seen that the performance index values of the algorithm are not significantly different under different concurrent numbers, and the overall state of the algorithm is relatively stable. Although it is normal for the algorithm to run slowly when a large number of users access the algorithm at the same time, the algorithm in this paper still has access failure, because there are two access failures when the concurrent number is 500. This shows that the algorithm still has room for improvement and optimization. In order to achieve better performance, maintenance and optimization are required in the later stage.

Table 2. Algorithm performance index test results

Concurrent number	Average response time/ms	Average running time/ms	Throughput/Mbps	Network transfer rate/(kb/s)	Business summary
50	58.64	231.52	9.52	345.62	success50
100	63.85	256.46	10.54	411.65	success100
150	72.54	285.64	11.64	456.85	success150
200	81.64	305.52	12.58	496.52	success200
250	92.64	356.46	13.64	534.65	success250
300	101.25	398.54	14.85	584.52	success299
350	126.54	425.61	16.85	654.85	success349
400	134.52	495.64	17.84	702.54	success399
450	156.48	581.52	18.56	756.84	success448
500	195.64	684.56	21.56	815.32	success498

#### 4. Experimental analysis

Individualized learning is the basic trend of the development of physical education in the future, and how to guide students to individualized learning is a research hotspot. In order to meet the individual needs of online learning of physical education students, this paper designs an accurate recommendation algorithm for online sports video teaching resources based on collaborative filtering, and personalized recommendation technology is applied to the field of online sports learning. After receiving the data, the data layer of the entire recommendation algorithm stores the video in the database and transmits it to the business processing layer at the same time. The business processing layer utilizes the designed collaborative filtering resource recommendation algorithm. The recommendation results are formulated for

different users, and the recommendation results are pushed to the user display interface of the user layer. It is hoped to provide ideal learning resources for students' personalized sports learning. The algorithm uses collaborative filtering recommendation algorithm to recommend sports online video teaching resources for users. The recommendation is mainly based on collaborative filtering recommendation algorithm, which converts user attribute feature values into interest models, and calculates neighbor users according to the interest models, thus improving the problems of user cold start and data sparsity. The resource recommendation algorithm based on the above recommendation algorithm includes the functions of browsing courses, course learning, recommending sports online video teaching resources, and managing sports online video teaching resources.



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