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Optimization and realization path of moral education flipped classroom teaching model based on intelligent computing in colleges and universities

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ABSTRACT

Flipped classroom teaching puts forward new requirements on the enthusiasm of students' independent learning, however, the traditional independent learning lacks scientific aids and cannot meet the individual needs of students in the process of self-study. Therefore, this paper exploits the neural network technology in intelligent computing technology to extract the deep implicit semantic representation, combines the implicit semantic indexing (LSI) to improve the traditional collaborative filtering algorithm, and explores an optimized implementation path of the flipped classroom teaching mode. The improved ICF algorithm outperforms the comparison algorithm in terms of recommendation accuracy, average recall, and average coverage in the three datasets. The computational time consumed is reduced by 44.85%, 57.34%, and 73.68%, respectively, compared with UCF. Incorporating the learning resource recommendation model constructed in this paper in a traditional flipped classroom, it is found that the post-test scores of the experimental class in Moral Education are significantly higher than those of the control class ($p<0.01$), and its post-test scores are significantly higher than its pre-test scores ($p<0.01$). The collaborative filtering algorithm optimized by intelligent computing technology facilitates students' personalized independent learning, innovates the general flipped classroom teaching mode, and receives the expected results.

Keywords: intelligent computing, moral education, flipped classroom, collaborative filtering algorithm, learning resource recommendation

1. Introduction

Advantages and Realization Path of Flipped Classroom Teaching Model Flipped classroom teaching model is a kind of teaching model that reverses the arrangement of teaching content and learning activities in traditional classroom. Students take the initiative to participate, explore and think in the

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classroom, while the teacher plays more of a guiding role. The advantage of the flipped classroom teaching mode is that it can improve students' learning effect and learning interest, and can promote students' independent learning and creative thinking. In the information age, integrating information technology into the flipped classroom teaching activities to optimize the flipped classroom is conducive to amplifying the advantages of the flipped classroom, so as to better enhance the effect of classroom teaching [1-4].

The optimization of intelligent computing flipped classroom teaching mode is a teaching mode that enables students to actively participate in learning, independent inquiry, cooperative learning and personality development both inside and outside the classroom through the use of information technology tools and resources. This teaching mode subverts the traditional teacher-led and student-passive teaching method, which helps to improve students' learning interest and learning effect. In the current era of information technology, information technology has become an indispensable and important resource and tool in education and teaching. Information technology can provide teachers and students with more learning resources, teaching support and learning tools, making teaching more lively, interesting, efficient and personalized [5-8].

Literature [9] conducted a review of the literature on the flipped classroom in order to examine the advantages and challenges of the flipped classroom for both teachers and students, and the results indicated that the advantages of the flipped classroom are its ability to improve student performance, while its challenges are mainly focused on extracurricular activities. Literature [10] describes the application of the flipped classroom as a teaching and learning model, indicating that, it can be used to address the gap between teaching and performance in clinical practice and pointing out the evidence for the application of the flipped classroom in the health professions education, and also suggesting strategies for applying the flipped classroom in other medical education programs. Literature [11] lies in exploring the application of artificial intelligence in the flipped classroom for teaching English listening and proposes to apply particle swarm algorithms to the flipped classroom so as to make learning smarter and easier for students. The results of the study show that the flipped classroom with artificial intelligence is conducive to improving students' learning performance. Literature [12] outlined a flipped classroom teaching model using Google, stating that the teacher is able to send various types of learning materials to students through Google Classroom. The effectiveness of this teaching model was also demonstrated in experiments where it facilitated the development of students' thinking skills and optimized their learning outcomes. Literature [13] investigated 26 freshmen in order to study the effectiveness of ChatGPT in the flipped classroom, and the results proved that students can better utilize ChatGPT with proficiency in ChatGPT's prompted engineering sessions, thus promoting their learning efficiency in the flipped classroom. Literature [14] constructed a flipped classroom teaching model by utilizing adaptive teaching techniques and conducted a study on students by developing different flipped learning environments with the aim of demonstrating the benefits of adaptive technology for flipped classroom teaching. The results of the experiment revealed that students' academic performance was affected by the adaptive and adaptive levels of the flipped classroom. Literature [15] introduces an intelligent assisted learning algorithm for English flipped classroom with recurrent neural networks, and its use in teaching practice reveals that students' motivation and interest in learning have as well as the overall teaching effectiveness of the flipped classroom are significantly improved. Literature [16] emphasizes the interactivity of artificial intelligence and the resource storage advantage of e-commerce technology, and explores the integration of the two into the flipped classroom, aiming to promote flipped teaching in colleges and universities. And new optimization algorithms for flipped teaching are proposed to analyze the dataset of UCI repository.

Literature [17] studied the English translation teaching mode of flipped classroom based on the fusion algorithm of network communication and artificial intelligence, and proposed to construct an Internet learning platform to meet the needs of flipped classroom. The test results concluded that the teaching quality was effectively improved by combining the flipped classroom teaching mode with English translation teaching through this Internet learning platform. Literature [18] describes the effects, advantages and challenges of the integration of artificial intelligence into the flipped classroom based on existing resources. It indicates that the application of AI in the flipped classroom helps to improve the teaching effect, but there are difficulties such as technical facilities and teacher preparation. Literature [19] synthesizes the challenges faced by higher education institutions under the trend of flexible learning and provides feasible suggestions based on the example of flipped classroom in Mooc, aiming at enriching the learning experience through innovative pedagogical strategies. Literature [20] describes the advantages of the 6G web-based flipped classroom teaching model in terms of providing effective pedagogical suggestions for English language teachers. A comparative test between traditional teaching methods and the 6G web-flipped classroom teaching model emphasized that the latter is more effective. Literature [21] reveals teachers' experiences and perceptions of using the flipped classroom model in teaching through qualitative case studies. Structured interviews were conducted with a number of teachers who had used the flipped classroom model in order to understand the aspects of improvement, benefits and challenges to teaching and learning. Literature [22] outlines the basic concepts of flipped classroom and flipped classroom teaching model and discusses the effective application of flipped classroom teaching model in practice teaching. In order to better improve the quality and efficiency of practice teaching.

According to the advantages of intelligent computing in flipped classroom, this paper constructs a learning resource personalized recommendation model based on an improved collaborative filtering algorithm. The popular implicit semantic indexing is utilized for dimensionality reduction of item recommendations. The sparse matrix is filled and the singular value decomposition of the dense matrix is performed to obtain the user factor matrix and item factor matrix and the user's predicted ratings of the items. Exercise the user and item entities together to build recommendation information using the hidden semantic model. The multi-layer user hidden semantics and an item hidden semantics are combined to obtain a deep hidden semantic model based on neural network, and the loss function is solved using the projected gradient method to complete the algorithmic framework construction. And a method of alternating projection of constraints is proposed to solve the model parameters. Finally, based on the optimized collaborative algorithm, a personalized recommendation model of learning resources for flipped classroom is constructed, and relevant experiments are set up to verify the improved algorithm and the new teaching method.

2. Smart computing in the flipped classroom

2.1. Intelligent Computing

With the accelerating process of informatization in the college classroom, the teaching information processing affairs are becoming increasingly complex, and there is often a large amount of data and information that need to be counted, classified, decided and optimized. And intelligent computing methods are applied in information processing technology by simulating the biochemical process of intelligent systems in nature, mainly including fuzzy computing, artificial neural networks, genetic algorithms and other methods.

Any computation that is constructed in imitation of the laws of nature can be referred to as intelligent computing or sometimes soft computing. Among them, neural network is one of the intelligent computing technologies. Neural networks are built by simulating the human brain's nervous system, which is a network composed of simple information processing units interconnected, and its advantages are: 1) Neural networks can approximate any function with arbitrary accuracy. 2) It adopts parallel and distributed storage and processing of information, which is very fault-tolerant and robust, and it is very suitable for dealing with complex information system. 3) Neural network has strong learning ability, can realize online or offline learning, so that it can meet certain control requirements, with great flexibility. 4) Neural network draws on the physical structure and mechanism of the human brain, and can simulate some of the functions of the human brain, with the characteristics of "intelligence". Therefore, neural networks have great potential for application in the field of education.

2.2. Personalized Recommendation Technology of Teaching Resources for Flipped Classroom

Flipped classroom is a new teaching mode relative to the traditional classroom, which interchanges the processes of knowledge transmission, absorption, internalization and transfer in time and space. The teacher's knowledge transfer process is front-loaded in the front of the classroom and completed through students' independent learning, while the process of knowledge internalization and transfer is back-loaded to the middle of the classroom and completed through the teacher's well-designed active learning activities based on the social interactions between the teacher and the students, and between the students and the students. The basic essence of the flipped classroom is the advancement of knowledge transfer and the optimization of knowledge internalization brought about by changes in the teaching process.

Flipped classroom allows learners to make their own learning plans, then study outside the classroom according to their own plans and record the problems they encounter, and finally solve these problems together with the teacher in the classroom, which undoubtedly provides learners with an open, autonomous, student-oriented learning platform and rich resources. However, although the flipped classroom teaching model has been applied in actual classes, and teachers have a certain understanding of each student, the lack of data leads to the inability to use big data analytics technology to carry out effective computational analysis, and can only rely on the teacher's experience to provide personalized guidance, which is not conducive to students' independent learning in a targeted manner. For this reason, this paper combines intelligent computing and collaborative filtering algorithms to design a personalized recommendation model of educational resources based on deep learning, which provides a feasible path for the optimization and implementation of the teaching mode of the flipped classroom.

3. Personalized recommendation models for learning resources

3.1. General Recommendation Process for Collaborative Filtering Algorithms

When the collaborative filtering algorithm recommends users, the main process is divided into three parts: constructing the scoring matrix, finding nearest neighbors, and generating recommendations [23], and its recommendation process is shown in Figure 1.

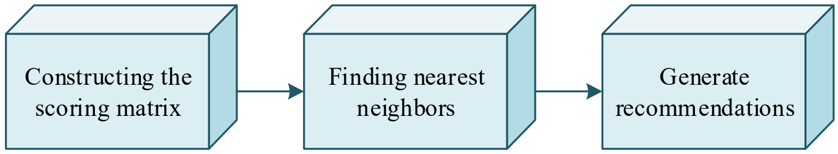

Fig. 1. Process of Collaborative Filtering Recommendation Algorithm

3.1.1. Constructing the scoring matrix. The rating data collected from the users is transformed to obtain a rating matrix R of $m \times n$. m represents the number of users, n represents the number of items, and R_{ui} represents the ratings given by the users u to item i. R_{ui} can be valued in various ways, either as 0 and 1 for dislikes and likes, or as 1 to 5, with higher scores indicating more favoritism for items. If the user has no rating for an item it can be replaced by 0 or null. In the rating matrix R, the row vectors represent the ratings of each user for all items and the column vectors represent the scores for each item.

3.1.2. Finding the nearest neighbor. Collaborative filtering recommendation algorithm produces recommendation for the target user through the preferences of the nearest neighbors, when selecting the nearest neighbors, first calculate the similarity between the target user and other users in the user group, and then select the K users with the largest similarity to constitute the nearest neighbors of the target user. From the above, it can be seen that the user similarity calculation in the collaborative filtering recommendation algorithm has a crucial role, and its accuracy plays a decisive role in the recommendation quality of the recommendation algorithm. Commonly used similarity measures are: cosine similarity, Pearson correlation coefficient and modified cosine similarity.

1) Cosine similarity. Cosine similarity measures the similarity by the cosine of the angle between two vectors, the larger the value the higher the degree of similarity. In a collaborative filtering recommender system, the rating matrix can be viewed as a n-dimensional vector space, where each row is viewed as a row vector, and items with no ratings are filled with zeros by default. Let the rating vectors of users u and v be $\vec{u}$ and $\vec{v}$, then the similarity $sim(u,v)$ of the two users can be expressed as:

$$sim(u,v) = \cos(\vec{u},\vec{v}) = \frac{\vec{u}\cdot\vec{v}}{\|\vec{u}\|\times\|\vec{v}\|} \tag{1}$$

2) Pearson's correlation coefficient. Pearson correlation coefficient can be used to measure the degree of linear correlation between two variables, it is between 1 and -1. The larger the value, the greater the similarity between the two variables, and the smaller the value, the lower the similarity between the two variables. If the set of items jointly rated by users u and v is I_{uv}, the rating of user u for item i is R_{ui}, and the average rating of user u is $\bar{R}_u$, then the similarity between the two users is:

$$sim(u,v) = \frac{\sum_{i\in f_{lv}}\left(R_{ut}-\bar{R}_u\right)\left(R_{vi}-\bar{R}_v\right)}{\sqrt{\sum_{i\in f_{lvr}}\left(R_{ui}-\bar{R}_u\right)^2}\sqrt{\sum_{i\in f_{lvv}}\left(R_{vi}-\bar{R}_v\right)^2}} \tag{2}$$

3) Modified cosine similarity. The cosine similarity algorithm is calculated ignoring the problem that different users score on different scales, i.e., some users score generally high while others score generally low. Modified cosine similarity improves on traditional cosine similarity by averaging user ratings to eliminate differences in user ratings. Let the set of items jointly rated by users u and v be I_{uv}, user u's rating of item i be denoted as R_{ui}, user u's average rating be denoted as $\bar{R}_u$, and the set of items rated by user u be denoted as I_u, then the similarity of users u and v is:

$$sim(u,v)=\frac{\sum_{i=1}^{n}\left(R_{ui}-\bar{R}_u\right)\left(R_{vi}-\bar{R}_v\right)}{\sqrt{\sum_{i=1}^{n}\left(R_{ui}-\bar{R}_u\right)^2}\sqrt{\sum_{i=1}^{n}\left(R_{vi}-\bar{R}_v\right)^2}} \tag{3}$$

After obtaining the similarity between users, the similarity between the target user and other users is sorted in descending order to select the nearest neighbors, and usually K user with the largest similarity is selected as its nearest neighbor.

3.1.3. Generating recommendations. After obtaining the set of nearest neighbors, the target user's ratings for unrated items can be predicted based on the ratings of users in the nearest neighbors, and the top N highest rated item recommendations are selected for recommendation. Currently, two commonly used prediction methods are shown in Equation (4) and Equation (5).

$$P_{uj}=\frac{\sum_{v\in KNB} sim(u,v)\times R_{vi}}{\sum_{v\in KNB}\left(sim(u,v)\right)} \tag{4}$$

$$P_{ui}=\bar{R}_u+\frac{\sum_{v\in KNB} sim(u,v)\times\left(R_{vi}-\bar{R}_u\right)}{\sum_{v\in KNB}\left(sim(u,v)\right)} \tag{5}$$

where P_{ui} denotes the predicted rating of user u for item i, and KNB denotes the set of nearest neighbors of target user u. Equation (5) better overcomes the problem of inconsistent evaluation habits and rating scales of different users in Equation (4), so this paper chooses Equation (5), which has higher prediction accuracy, to predict the ratings of target users.

3.2. Improvement of Collaborative Filtering Algorithm

3.2.1. Singular value decomposition. In response to the shortcomings of traditional collaborative filtering algorithms, methods based on dimensionality reduction have been proposed. Implicit semantic indexing (LSI) is a popular method for dimensionality reduction of item recommendations. In this method, first the sparse matrix needs to be filled with the elements that are not scored to complete the filling so that the original sparse matrix is called a dense matrix, and then the singular value decomposition is performed on the filled matrix. The main components of the filled matrix are kept as constant as possible, i.e., the eigenvalues of the new matrix are close to the eigenvalues of the original matrix. The padding can be a fixed value or the average value of each row or the average value of each column [24].

With m user and n items, the populated rating matrix is R, which is obtained by performing a singular value decomposition for R:

$$R=U\Sigma V^T \tag{6}$$

where the decomposition yields U as the matrix of $m\times m$, and the vectors in U intersect two by two and are called the left singular vectors. V is the matrix of $n\times n$, and the vectors in V intersect twice and are called the right singular vectors. Σ is the diagonal matrix of $m\times n$, where the diagonal elements are the singular values and the diagonal elements are arranged in descending order.

The magnitude of the singular values indicates the importance of the implicit factors in each hidden semantic space to the original matrix. Keep k largest singular value and round off the rest, i.e., keep the first k rows and k columns in Σ to get Σ_k, keep the first k columns in U to get U_k, and keep the first k columns in V to get V_k. The selection of the value of k determines the proximity of the downsampled matrix to the original matrix, if k is too large, it will cause insufficient downsampling to achieve the desired effect. If k is too small, it will cause too much information loss. Normally k value selection should be satisfied:

$$\frac{\sum_{i=1}^{k}\lambda_i}{\sum_{\lambda_i\in\Sigma}\lambda_i} \geq 90\% \tag{7}$$

where λ_i is the i nd singular value. The matrix R' obtained after dimensionality reduction is approximately equal to R:

$$R' \approx R = U_k\Sigma_k V_k^T \tag{8}$$

After the decomposition is completed, the user factor matrix and item factor matrix can be obtained, denoted as: $P = U_k\sqrt{\Sigma_k}$, $Q = V_k\sqrt{\Sigma}$. Then the rating r_{ui} of item i by a particular user u is predicted as:

$$r_{ui} = p_u q_i^T \tag{9}$$

3.2.2. Deep Hidden Semantic Modeling. In order to build recommendations, collaborative filtering systems need to relate two qualitatively different entities, namely users and items. There are two main approaches to facilitate the comparison of these two entities, which constitute the two main techniques of collaborative filtering: neighborhood-based approaches and hidden semantic models.

A deep learning based model for cryptosemantic collaborative filtering recommendation is shown in Fig. 2, where the hidden layer can be extended to a deeper level. Theoretically, as the network deepens, deeper levels of hidden semantic representations will be extracted. For example, when we choose a book or a movie, only a small portion of the hidden semantics for the ordinary hidden semantics model will affect the user's choice. However, for deep cryptosemantics, not only the above cryptosemantics can be captured, but also other deeper features. For example, deeper neural network nodes may capture the user's personality traits: introversion, extroversion, neutrality, etc., or some deeper features of the items, which are captured without human intervention, and the deep neural network will do it automatically according to different datasets [25]. Based on these more abstract features, the model in this paper has better robustness and accuracy than other models.

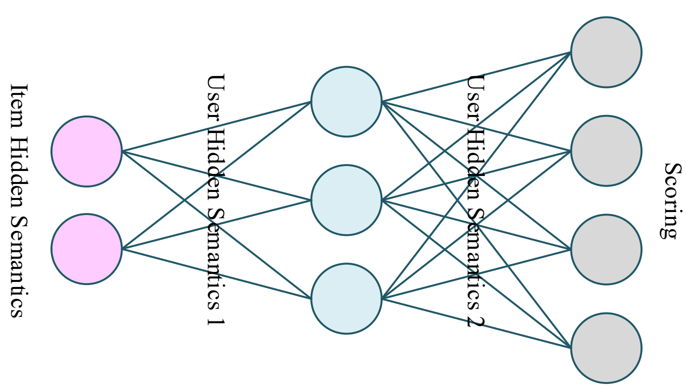

Fig. 2. A collaborative filtering recommendation model based on deep learning

In the standard implicit semantic model, the rating matrix can be seen as the product of the user implicit matrix and the item implicit matrix.

$$R = PQ \tag{10}$$

In the deep cryptosemantic model of this paper, we combine multiple layers of user cryptosemantics and one item cryptosemantics, which can be expressed as follows, assuming there are 2 user cryptosemantics:

$$R = P_1 P_2 Q \tag{11}$$

where: P_1 and P_2 are the 2-layer user cryptosemantics matrices and Q is the item cryptosemantics matrix. Therefore the model can be easily extended to N layers of user hidden semantics as shown in Eq:

$$R = P_1 P_2 \cdots P_N Q \tag{12}$$

Since R is the scoring matrix, and in the actual dataset, many values in the matrix are missing, we fill all the positions of the missing values with zeros, which can be formalized as Eq:

$$Y = I \cdot R \tag{13}$$

where: $\cdot$ denotes dot product and I is a matrix containing only 0 or 1. Combined with Eq. (12) the deep hidden semantic model of this paper can be formed:

$$Y = I \cdot R = I \cdot \left(P_1 P_2 \cdots P_N Q\right) \tag{14}$$

Therefore, we need to optimally solve the following loss function:

$$\begin{gathered} \min_{P_1 P_2 \cdots P_N Q} \frac{1}{2} \left\| Y - I \cdot \left(P_1 P_2 \cdots P_N Q\right) \right\|_2^2 \\ P_1 \geq 0, P_2 \geq 0, \cdots, P_N \geq 0, Q \geq 0, R = P_1 P_2 \cdots P_N Q \end{gathered} \tag{15}$$

In this paper, the projected gradient method is used to solve the above problem, which leads to the algorithmic framework of this paper [26]:

$$\begin{aligned} &Initialize: R^0, P_1^0, P_2^0, P_3^0, \cdots, P_N^0, Q^0 \\ &For\ k = 1, 2, \cdots \end{aligned} \tag{16}$$

1) $\overline{R}^k = R^k - \gamma\left(I^T \cdot \left(I \cdot R^k - Y\right)\right)$.

2) Iterate to get $\left(R^{k+1}, P_1^{k+1}, P_2^{k+1}, P_3^{k+1}, \cdots, P_N^{k+1}, Q^{k+1}\right)$.

Solve:

$\underset{X, P_1, P_2, \cdots, P_N,}{R} \left\| \overline{R}^k - R \right\|_2^2$, of which $P_1 P_2 \cdots P_N Q = R$, $X \geq 0$, $P_1 \geq 0$, $P_2 \geq 0, \cdots, P_N \geq 0$, $Q \geq 0$

The key of the above algorithm is how to iteratively solve R^{k+1}, P_1^{k+1}, P_2^{k+1}, P_3^{k+1}, ..., P_N^{k+1}, Q^{k+1}. Since the solution is performed on a non-convex set, it is difficult to obtain the global minimum directly. Therefore, this paper proposes a method of alternating projections of the constraints to arrive at an approximate solution to the problem. Each variable will be processed sequentially in a Gauss-Seidel fashion and then projected onto its associated set of constraints. The specific formalization is represented as follows:

$$\begin{cases} R^{k+1} = \Pr ojection_{+}\left(\overline{R}^{k}\right) \\ P_1^{k+1} = \Pr ojection_{+}\left(\Pr ojection_{\left\{P_1^2 P_2^k P_3^k \ldots P_N^k Q^k = R^{k+1}\right\}}\left(P_1^k\right)\right) \\ P_2^{k+1} = \Pr ojection_{+}\left(\Pr ojection_{\left\{P_1^{k+1} P_2 P_3^k \cdots P_k^k \hat{k}^k = R^{k+1}\right\}}\left(P_2^k\right)\right) \\ \ldots \\ P_N^{k+1} = \Pr ojection_{+}\left(\Pr ojection_{\left\{P_1^{k+1} P_2^{k+1} P_1^{k+1} \ldots P_N Q^k = R^{k+1}\right\}}\left(P_N^k\right)\right) \\ Q^{k+1} = \Pr ojection_{+}\left(\Pr ojection_{\left\{P_1^{k+1} + P_2^{k+1} P_3^{k+1} \ldots P_x^{k+1} Q^k = R^{k+1}\right\}}\left(Q^k\right)\right) \end{cases} \tag{17}$$

The $Projection_{+}$ in the formula denotes the projection in the positive direction, i.e. if the value appears negative we will set it to 0 (this can be done using the ReLU function). The general properties of the projection $R = A \cup B$ of a matrix P on a linear constraint R can then be applied as follows:

$$Projection = P - A^{+}\left(A \cup B - R\right)B^{+} \tag{18}$$

The + sign in Eq. denotes the pseudo-inverse matrix, so the specific expansion of Eq. (17) is calculated in Eq. (19):

$$\begin{cases} R^{k+1} = \Pr ojection_{+}\left(\overline{R}^{k}\right) \\ P_1^{k+1} = \Pr ojection_{+}\begin{pmatrix} P_1^k - \left(P_1^k P_2^k P_3^k \cdots P_N^k Q^k - R^{k+1}\right) \\ \left(P_2^k P_3^k \cdots P_N^k Q^k\right)^{+} \end{pmatrix} \\ P_2^{k+1} = \Pr ojection_{+}\begin{pmatrix} \left(P_2^k - \left(P_1^{k+1}\right)^{+}\right. \\ \left(P_1^{k+1} P_2^k P_3^k \cdots P_N^k Q^k - R^{k+1}\right) \\ \left(P_3^k \cdots P_N^k Q^k\right)^{+} \end{pmatrix} \\ P_3^{k+1} = \Pr ojection_{+}\begin{pmatrix} P_3^k - \left(P_1^{k+1} P_2^{k+1}\right)^{+} \\ \left(P_1^{k+1} P_2^{k+1} P_3^k \cdots P_N^k Q^k - R^{k+1}\right) \\ \left(P_4^k \cdots P_N^k Q^k\right)^{+} \end{pmatrix} \\ P_N^{k+1} = \Pr ojection_{+}\begin{pmatrix} P_N^k - \left(P_1^{k+1} P_2^{k+1} \cdots P_{N-1}^{k+1}\right)^{+} \\ \left(P_1^{k+1} P_2^{k+1} P_3^{k+1} \cdots P_{N-1}^{k+1} P_N^k Q^k - R^{k+1}\right) \\ \left(Q^k\right)^{+} \end{pmatrix} \\ Q^{k+1} = \Pr ojection_{+}\begin{pmatrix} Q^k - \left(P_1^{k+1} P_2^{k+1} \cdots P_N^{k+1}\right)^{+} \\ \left(P_1^{k+1} P_2^{k+1} P_3^{k+1} \cdots P_N^{k+1} Q^k - R^{k+1}\right) \end{pmatrix} \end{cases} \tag{19}$$

Combining the algorithmic framework of this paper and Eq. (17) completes the solution of the model parameters.

3.2.3. Personalized Recommendation Model for Learning Resources. After modeling users, educational resources and knowledge points, a personalized recommendation model can be obtained.

The model mainly consists of two aspects: online work and offline work. The main task of online work is to collect students' behavioral data, which include students' problem records, prep work, class performance, etc. Students' behavioral data provide data support for student modeling. The main task of the offline work is to analyze the student's interest model and use the recommendation algorithm to calculate the recommendation results.

The overall personalized recommendation model of educational resources is shown in Figure 3.

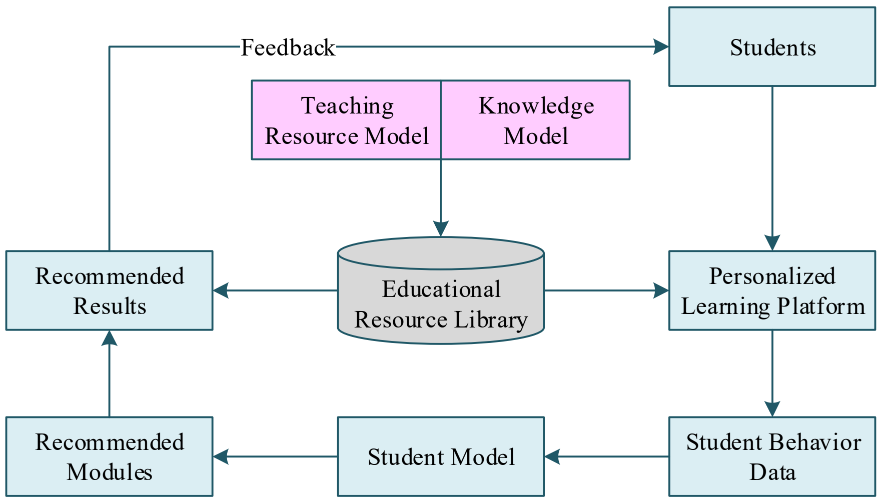

Fig. 3. Education resource personalized recommendation model

Students learn by learning in the personalized learning platform, and the educational resource library provides data support for the learning platform, in which the educational resource model and knowledge point model can be constructed. In the process of student learning, the platform will record the student's behavioral data as a way to construct the student model, and then use these data as the input data for the recommendation module, which will be analyzed and calculated by the recommendation engine to get the recommendation results and feedback the results to the students.

4. Experimentation and analysis

4.1. Algorithm performance experiment

4.1.1. Experimental data. In order to verify the recommendation effect of the proposed improvement scheme, three datasets are selected for comparison experiments, namely MovieLens 100K dataset, MovieLens1M dataset and Book-Crossing dataset. Considering the time factor of recommendation, the datasets are divided into training and testing sets according to the order of user interaction time. The item that is the latest in terms of time of interaction with the user u is selected as the test set, and the ratio of the training set to the test set is 4:1. By testing different values of α and K. The test set is divided into the training set and test set. The scoring information and parameter values for the three datasets are shown in Table 1.

Table 1. Data set information and parameters

Dataset	User	Project	Scoring	α	K
MovieLens-100K	957	1682	110000	0.4	5
MovieLens-1M	6047	3971	1000354	0.45	5
Book-Crossing	278381	278135	1138471	0.35	4

4.1.2. Experimental design and analysis of results. Four recommendation algorithms such as UCF, TimeSVD++, CDAE and xDeepFM are selected for comparison experiments, and the algorithm proposed in this paper is named as ICF for the convenience of experimental data presentation.In the comparison experiments, the number of recommended movies is used as the independent variable. Figure 4 shows the results of the comparison experiments of the accuracy of different algorithms on three datasets.

In the figure, the x-axis indicates that the number of items recommended to the user is 5, 10, 15, 20, 25, and 30 respectively. Figures (a), (b), and (c) represent the recommendation results on three different datasets, respectively. The average accuracy of this paper's improved ICF recommendation algorithm is 6.6%, 8.1%, and 3.7% higher than the second-place xDeepFM algorithm in the three datasets, respectively, and more significantly higher than the other compared algorithms. Among them, UFC performs the worst, with an average recommendation accuracy of only 0.226 in the three datasets.

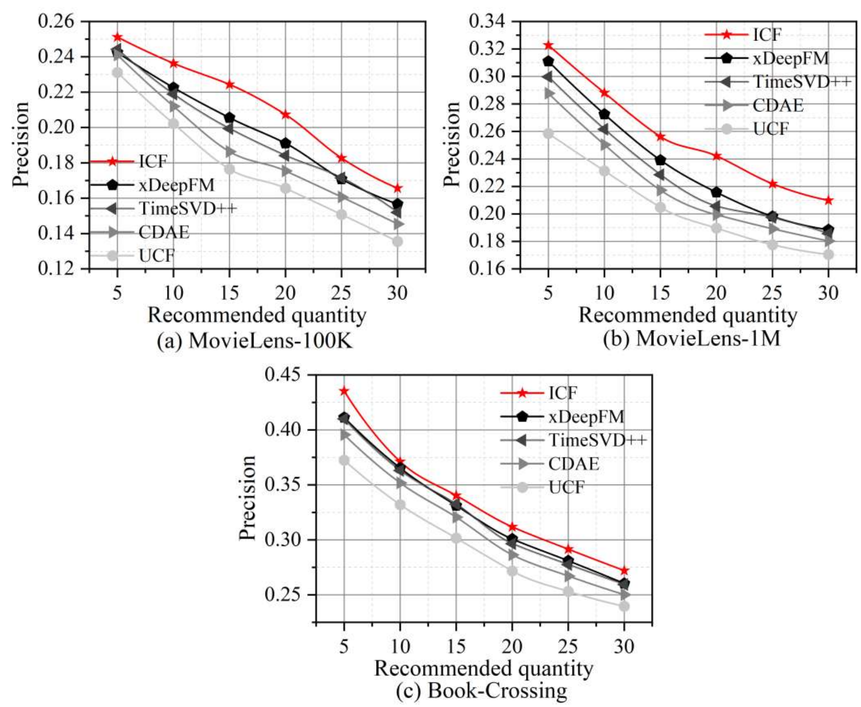

Fig. 4. The comparison of the accuracy

Fig. 5 shows the comparison results of the recall of different algorithms on the three datasets. It can be seen that the ICF recommendation algorithm has a higher recall than the comparison algorithms on all three datasets. The average recall on all datasets is 0.191, while the average recalls of xDeepFM, TimeSVD++, CDAE and UCF algorithms are 0.170, 0.155, 0.145, and 0.123, respectively. It can be seen that the collaborative filtering algorithms improved by using the singular value decomposition and the neural network have a better performance in terms of recall.

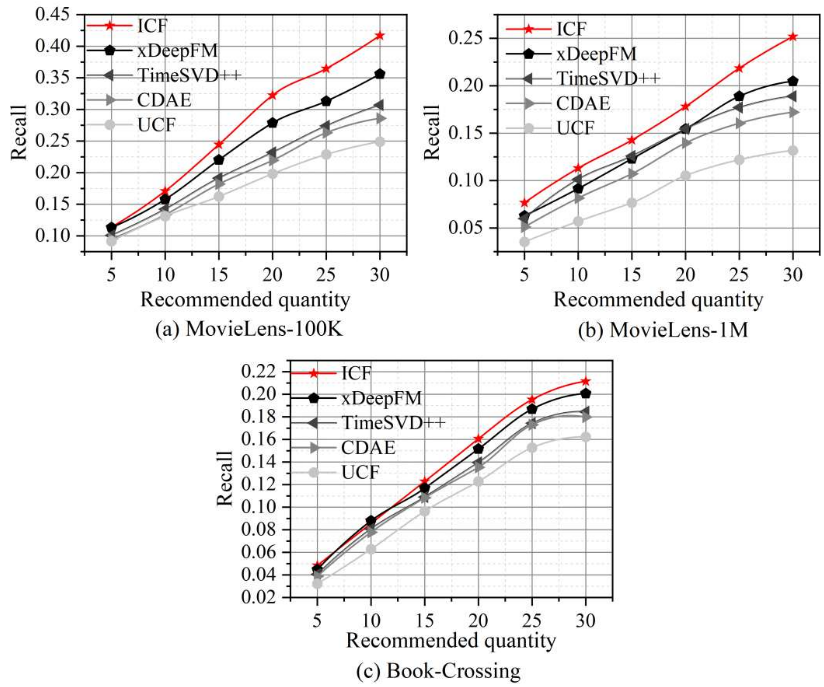

Fig. 5. The comparison of the recall rate

Figure 6 shows the comparison results of the coverage on the three datasets. From the figure, it can be seen that the coverage rate of this paper's algorithm is higher than that of other comparison algorithms, and the average coverage rate on all datasets is 0.367. It can be seen that after the dimensionality reduction of the item recommendation by implicit semantic indexing and the singular value decomposition of the filled matrix, this paper's collaborative filtering algorithm improves the coverage rate. The experimental results verify the rationality and effectiveness of the improved algorithm in this paper.

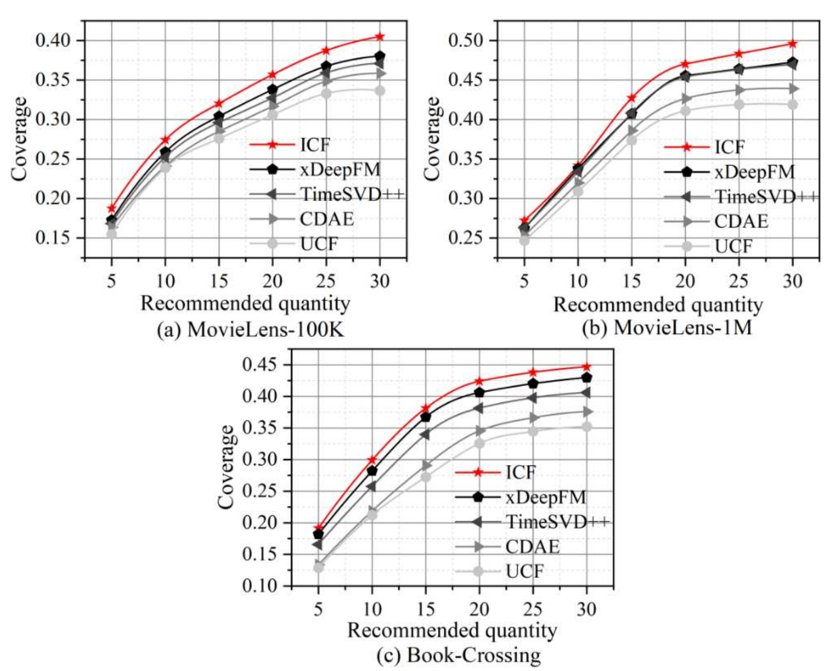

Fig. 6. The comparison of the coverage

Figure 7 shows the comparison results on the evaluation index MAP. From the experimental results, it can be seen that our proposed recommendation algorithm not only outperforms other algorithms on the traditional evaluation metrics, but also performs well on the ranking order of the recommendation results, with an average MAP value of 0.421, and performs the best on every dataset.

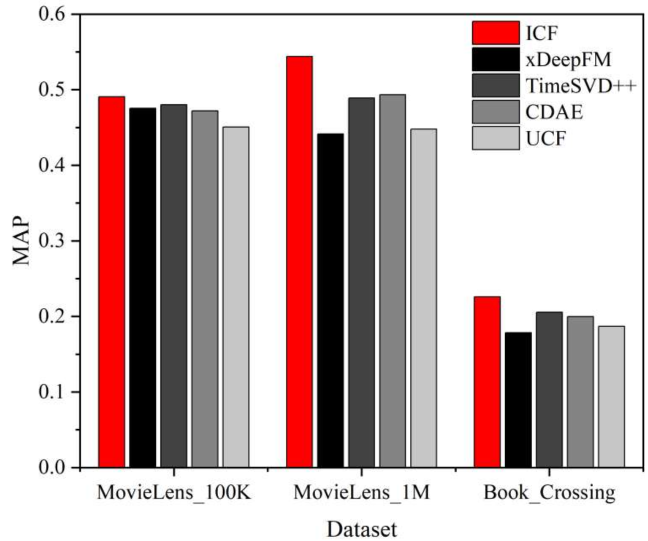

Fig. 7. The comparison of MAP

In order to improve the time-consuming improvement of the improved collaborative filtering algorithm, Table 2 demonstrates the comparison of the running time of the ICF algorithm of this paper and the UCF and TimeSVD++ algorithms on the three datasets. The same running environment is used in the experiments, and the data in the table are in "seconds". Since CDAE and xDeepFM use a multi-layer neural network model to compute the recommendation list, which takes longer time, the comparison experiment is not set up here.

From the table, it can be seen that under the same computational conditions, the time consumption of this paper's ICF algorithm is significantly lower than that of other collaborative filtering computational methods. Compared with UCF, this paper's algorithm reduces 44.85%, 57.34% and 73.68% of the computational time in MovieLens_100K, MovieLens_1M and Book_Crossing datasets, respectively, compared with UCF, which greatly saves the time of calculating the user's nearest neighbor, which consumes the most time share in collaborative filtering computational methods.

Table 2. The results of the running time comparison

Data set	UCF	TimeSVD++	ICF
MovieLens_100K	6.89	18.17	3.8
MovieLens_1M	323.71	728.47	138.11
Book_Crossing	93.87	329.33	24.71

4.2. Personalized Recommendation Model Application Effect

4.2.1. Experimental design. The implementation effect of the flipped classroom teaching model incorporating the learning resource recommendation model is examined in the case of the "Moral Education" course. This experiment was selected from two second-year classes of higher education institutions in a city T, and the experimental and control classes were determined through random assignment. The number of the control class was 50 students, who received the traditional flipped classroom teaching mode. And the number of experimental class is 50 students, using the optimized learning resources personalized recommendation method designed in this paper as an aid for the new flipped classroom learning. The pre- and post-test scores of the Moral Education course were compared to determine the practical utility of the new teaching model.

4.2.2. Analysis of student achievement data. After a semester of experimental teaching, the author used IBMSPSS data analysis software to statistically analyze the pre-test scores and post-test scores of the two "Moral Education" course classes participating in the experimental study respectively. Since this secondary school adopts process assessment and the teaching content of this teaching is a total of six project teaching, the average score of the six process assessment scores is taken as the final final assessment score, and the final assessment score is taken as the post-test score. The assessment work order is prepared by the teacher of the class, and the total score is 100 points, the time is 60 minutes, and the place of assessment is the machine room of the school. Since both classes were taught using the traditional teaching method during the teaching, so the assessment scores were used as the pre-test scores.

Using IBM SPSS data analysis software, independent samples tests were conducted on the pre-test scores and post-test scores respectively, aiming to examine whether the learning levels of the two classes, the experimental class and the control class, were basically the same before the implementation of the new flipped classroom teaching mode and the extent of the difference in the learning achievements of the two classes, the experimental class and the control class, after the implementation of the flipped classroom teaching mode, respectively.

Table 3 shows that the pre-test score of the control group is 62.98, the standard deviation is 5.187, and the mean of standard error is 0.843. The pre-test score of the experimental group is 63.55, the standard deviation is 4.382, and the mean of standard error is 0.791. The mean score of the experimental group is higher than that of the control group by 0.57, and the difference of standard deviation of the two groups is 0.805<1, so we can think that the average score and standard deviation of the two groups are higher than those of the control group. Control group have basically the same mean score and standard deviation. In terms of significance in the table, the sig values are 0.187 and 0.183 (>0.05) for equal and unequal variance cases respectively. The results show that the difference between the data of the two classes is not significant, which means that there is no significant difference in the learning level of the students in the two classes, therefore, the two classes can be used as parallel classes for the control experiment.

Table 3. Test of pre-test results

Descriptive statistics				
Group	N	Mean	SD	SE
Control group	50	62.98	5.187	0.843
Experimental group	50	63.55	4.382	0.791

T test result									
	Levine variance equivalence test		T test						
	F	Sig.	t	df	Sig.(2-tails)	d(mean)	d(SE)	95% confidence interval	
								U-limit.	L-limit.
Assumed equal variance	3.872	0.05	-1.582	100	0.187	-0.57	1.058	-3.841	0.687
Unassuming equal variance			-1.357	94.84	0.183	-0.57	1.068	-3.817	0.673

The results of the independent sample test of the posttest are shown in Table 4. As can be seen from Table 4, the posttest score of the control group is 71.42 The posttest score of the experimental group is 79.84 The mean score of the experimental group is 8.42 points higher than that of the control group, which indicates that the teaching effect of the experimental group that implements the new flipped classroom teaching mode is better than that of the control group that implements the traditional teaching mode to a certain extent. In terms of significance, p=0.000 (<0.001), the results show that there is a very obvious difference between the data of the two groups, and it can be considered that the post-test scores of the experimental class are significantly better than those of the control class.

Table 4. Test of post-test results

<table>
<tr><td colspan="10">Descriptive statistics</td></tr>
<tr><td colspan="2">Group</td><td colspan="2">N</td><td>Mean</td><td colspan="2">SD</td><td colspan="3">SE</td></tr>
<tr><td colspan="2">Control group</td><td colspan="2">50</td><td>71.42</td><td colspan="2">8.874</td><td colspan="3">1.315</td></tr>
<tr><td colspan="2">Experimental group</td><td colspan="2">50</td><td>79.84</td><td colspan="2">5.381</td><td colspan="3">0.783</td></tr>
<tr><td colspan="10">T test result</td></tr>
<tr><td></td><td colspan="4">Levine variance equivalence test</td><td colspan="5">T test</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">F</td><td rowspan="2">Sig.</td><td rowspan="2">t</td><td rowspan="2">df</td><td rowspan="2">Sig.(2-tails)</td><td rowspan="2">d(mean)</td><td rowspan="2">d(SE)</td><td colspan="2">95% confidence interval</td></tr>
<tr><td>U-limit.</td><td>L-limit.</td></tr>
<tr><td>Assumed equal variance</td><td>10.578</td><td>0.01</td><td>-5.681</td><td>100</td><td>0.00</td><td>-8.42</td><td>1.058</td><td>-11.321</td><td>-5.857</td></tr>
<tr><td>Unassuming equal variance</td><td></td><td></td><td>-5.547</td><td>89.857</td><td>0.00</td><td>-8.42</td><td>1.068</td><td>-11.235</td><td>-5.138</td></tr>
</table>

The paired samples test was conducted on the pre and post-test scores of the two classes respectively, with the purpose of verifying whether the changes in the pre and post-test scores of the two classes respectively were significant or not, and the results of the paired samples test are shown in Table 5. The mean score of the control group increased by 8.44 points, while the mean score of the experimental group increased by 16.29 points, which indicates that using the new flipped classroom teaching model can improve the students' academic performance to a certain extent more than the traditional flipped classroom teaching model in the learning of "Moral Education" course. The standard deviation of the control group is 8.874 and that of the experimental group is 5.381, which indicates that the students in the experimental class are more concentrated in their course performance. The p-value of the pre- and post-test scores of the experimental class is less than 0.001, which indicates that the difference between the pre- and post-test scores of the experimental class under the new flipped classroom teaching mode is very significant. Although the difference between the pre- and post-test scores of the control group was also very significant (p<0.01), the improvement of the post-test scores was not as large as that of the experimental class. In conclusion, it shows that adopting the optimized flipped classroom teaching mode of this paper will produce better results than the traditional flipped classroom teaching mode in the intermediate "Moral Education" course, and it also shows that the personalized recommendation model of teaching resources has certain feasibility and effectiveness.

Table 5. Paired sample t test

		Mean			N	SD			SE
Control group	Pretest	62.98			50	5.187			0.843
	Posttest	71.42			50	8.874			1.315
Experimental group	Pretest	63.55			50	4.382			0.791
	Posttest	79.84			50	5.381			0.783
Paired sample t test									
		Pair difference			95% confidence interval		t	df	Sig.(2-tails)
		Mean	SD	SE	U-limit.	L-limit.			
Control group	Pretest-posttest	-8.44	4.398	0.783	-11.652	-7.685	-12.581	49	0.00
Experimental group	Pretest-posttest	-16.29	5.872	0.738	-17.508	-14.628	-20.385	49	0.00

5. Conclusion

In this paper, the collaborative filtering algorithm is improved to construct a personalized recommendation model for learning resources for flipped classrooms. The improved ICF algorithm outperforms the xDeepFM algorithm by 6.6%, 8.1%, and 3.7% in the three datasets in terms of mean recommendation accuracy, with an average recall of 0.191 and an average coverage of 0.367, which is the best among all the compared algorithms.ICF also excels in terms of both the sorting of learning resources and the consumption of computation time.

The teaching effect of applying the personalized recommendation model of learning resources in flipped classroom is examined in the course of “Moral Education” as an example. With no significant difference between the pretest performance of the experimental class and the control class, the average posttest score of the experimental class reaches 79.84, which is significantly better than the average posttest score of the control class ($p<0.01$). The paired t-test showed that the posttest scores of both classes were significantly higher than the pretest scores, indicating that both the traditional flipped classroom teaching model and the optimized teaching mode have teaching effects, and the new teaching mode has more obvious effects.

Recommendation algorithms applying intelligent computing technology can accurately recommend learning resources for students' individuality, which fits the essential requirement of flipped classroom to improve students' learning initiative, and is a feasible path for teaching optimization of moral education teaching in universities.

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