Design of Teaching Resource Recommendation Platform Based on Fuzzy Recommendation Algorithm in the Context of Education Informatization

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Abstract

With the popularity of online education platforms, the quantity and variety of teaching resources have rapidly increased. Due to the abundance and complexity of these teaching resources, an efficient recommendation system is needed to help users quickly find useful teaching content. In order to improve the updating speed and utilization efficiency of online teaching resources, the study proposes a teaching resource recommendation platform system combining Takagi-Sugeno fuzzy model and neuromatrix decomposition model to solve the lack of linear relationship in fuzzy recommendation algorithm. The results show that the Area Under Curve of the proposed model is 0.940, while the Area Under Curve of the graph neural network model is the smallest, only 0.892. The reason is that the graph neural network model cannot fully capture the correlation information between users and educational resources, leading to a decrease in recommendation performance. The accuracy of the model proposed within 0-500 iterations is 95.60%, which is 4.51% higher than the integrated model of convolutional neural networks and bidirectional long short-term memory networks. This indicates that the proposed model has good application effect and feasibility, achieving good teaching resource recommendation results. This has practical application value for improving the efficiency of recommending educational resources.

Keywords: NeuMF model, Recommendation platform design, Teaching resources, TS fuzzy algorithm.

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1. Introduction

With the booming development of big data technology, the demand for data analytics in various industries is expanding. As an important means of utilizing modern information technology to optimize the education process, the development of educational informatization has had a significant impact on learning modes, efficiency, and resource allocation. Al Shloul's team proposed combining activity-based learning to enhance students' learning motivation and engagement in order to verify the impact of ChatGPT on student education. The application of ChatGPT can enhance the educational experience [1]. With the integration of information technology, educational resources can be more widely disseminated, improving the accessibility and quality of education [2]. Meanwhile, intelligent technology and theory are often combined to assist student education. Mallek and other professionals designed to analyze the adoption of virtual reality in higher education by combining VR with theories such as collaborative learning and experiential learning. The results showed that this approach can improve learning outcomes [3]. Due to the uneven distribution of educational resources and the continuous growth of user base, the problem of low utilization of educational resources is becoming increasingly prominent. The emergence of machine learning solves the problem that people cannot extract the required information from complex and redundant data. Abideen et al. proposed a machine learning model that combines multiple linear regression, Random forest (RF), and decision tree to predict future enrollment rates and classify school target levels for the analysis of school enrollment rates. The results showed that the model is effective [4]. And the development of big data also promotes the development of machine learning technology. Among them, Yu's team considered the performance improvement of intelligent self powered devices, combined with machine learning and artificial intelligence to analyze the performance of nanogenerators, and collected device information to ensure efficiency [5]. In the field of education, recommendation algorithms can help students and teachers discover the most relevant and useful learning resources, thereby improving learning efficiency [6]. Takagi-Sugeno (TS) fuzzy model has the mapping ability of continuous function, and it can represent highly nonlinear complex systems with fewer fuzzy rules, but it cannot solve linear relationships. In order to improve the updating speed and utilization efficiency of online teaching resources, the research proposes a teaching resource recommendation platform system that combines TS fuzzy model and Neural Matrix Factorization (NeuMF) model. The research aims to utilize the ability of TS fuzzy model to handle nonlinear problems, and analyze a large amount of user project interaction data through NeuMF model to improve the accuracy of recommendations. This model helps to improve the updating speed and utilization efficiency of teaching resources, providing strong technical support for the education industry. The research mainly consists of four parts. The first part is a review of the current status of research related to recommendation algorithms. The second part is a teaching resource recommendation platform system combining TS fuzzy model and NeuMF model, the first section introduces the composition of NeuMF model, and the second section constructs the teaching resource recommendation platform system with TS fuzzy model and NeuMF model. The third section gets the performance analysis of the designed teaching resource recommendation platform. The fourth section concludes the teaching resource recommendation platform system with TS fuzzy model and NeuMF model. Abbreviations and their explanations are shown in **Table 1**.

Table 1. Abbreviations and Explanations

Abbreviation	Explanation
NeuMF	Neural Matrix Factorization
TS fuzzy model	Takagi-Sugeno fuzzy model
RF	Random forest
MSE	Mean square error
RNN	Recurrent neural network
SVM	Support vector machines
GMF	Generalized matrix factorization
MLP	Multi-layer perceptrons
GNNs	Graph Neural Networks
TS-KG	Takagi-Sugeno and Knowledge Graph
CNN-BiLSTM	Convolutional Neural Networks, and Bidirectional Long Short Term Memory Network

2. Related Works

With the increasing research on recommendation algorithms, domestic and foreign researchers have proposed different personalized recommendation algorithms and applied them in the field of e-learning resources recommendation [7]. Shaw R and other scholars designed a learning video recommendation system with a variational autoencoder to improve students' learning ability, recognizing their activities in the classroom and improving their attention level. The results showed that the system is feasible [8]. Peng and other professionals for the software crowdsourcing system in the task personalized recommendation problem, constructed a worker capacity correction long and short-term attention network recommendation framework extracted the long-term and short-term element layers, calculate the attention weights of the user's preference, and the results show the effectiveness of this method in improving the efficiency and quality of crowdsourcing recommendation [9]. Arik's team in order to meet the students' needs, developed a content-based collaborative filtering hybrid recommender system to provide suitable recommendations, avoiding the use of predefined association rules, and converted student and course text information into feature vectors using natural language processing methods [10]. Tlili et al. focused on the sustainable development of open education resources and used triangulation to determine the adoption mode of open education resources, thereby increasing the opportunities and quality of higher education. The results showed that this method has a certain positive effect [11]. Monsalve and other scholars have built a hybrid recommendation model to manage available information and coordinate requirements in order to achieve efficient recommendation of learning resources. The results show that the model has certain practicality [12].

Recommendation algorithms in the field of education are mainly used for learning paths, personalized learning material recommendations, and other aspects [13]. Phauk and other researchers, in order to improve the math performance of high school students, proposed an educational data mining method that combines the feature selection technique and the RF algorithm to find out the information features that affect the future performance of the students in mathematics, and the results show that the method has high accuracy and low mean square error (MSE) of prediction [14]. Bulathwela and other scholars targeting the Lifelong Learning Open Educational Resources, conceptualized an online Bayesian strategy to automatically extract the knowledge components of the educational resources and trained it on the Open Education Video Lecture dataset, and the results showed that the algorithm performs well [15].

Chen and other professionals in order to recommend the resources that users are interested in, through the recommended content and collaborative filtering on high-dimensional user behavior data to reduce the dimensionality, and establish the user writing topic matrix to obtain the user's interest list, the results show that the method has a better accuracy and effectiveness [16]. Saito's team for programming education, designed a combination of recurrent neural network (RNN) and sequential prediction model Saito's team designed a learning path recommendation system for programming education that combines recursive neural network and sequential prediction model which helped learners learn information technology skills on their own, and the results showed the practicality of the method [17]. In order to recommend the best learning courses more efficiently, researchers such as Bhanuse analyzed online courses using a mixed similarity method and obtained effective features under an improved horse swarm optimization algorithm. The results showed that the accuracy of this method reached 99.69% [18].

Fuzzy recommendation algorithms are often applied in fields such as healthcare services, educational resource matching, and social network services to handle and optimize fuzzy user preferences and uncertain decision-making environments [19, 20]. Nagaraj et al., in order to improve the accuracy of diabetes diagnosis, constructed a prediction model of fuzzy reasoning method to shorten the diagnosis time, determine the disease risk and provide treatment suggestions. The results show that the model has good practicability [21]. Iatrellis and other scholars have proposed an educational consultation system that combines semantic web technology and fuzzy logic to provide reliable suggestions for students based on their learning interests. The results show that the system has good feasibility [22]. Ouechtati constructed a fuzzy logic recommendation model to estimate the trust level of recommenders and improve sensitivity and recognition in order to reduce dishonest recommendations in the social Internet of Things. The results showed that the detection rate of the model reached 100% [23]. Liang and other researchers have designed a teaching resource balancing recommendation algorithm that combines support vector machines (SVM) and trust relationships to address the issue of low trust in teaching resources. The results show that the algorithm achieves a balancing degree of 96 [24]. Aghaei et al. used fuzzy recommendation algorithm and collaborative filtering to predict service quality and personalized recommendations according to user needs in order to improve the quality of recommendation systems. The results showed that the algorithm has practicality [25].

To summarize, recommendation algorithms in the education field face challenges of low universality and technical complexity. In addition, current recommendation algorithms still show shortcomings in dealing with diverse user behaviors and massive teaching resource information. In order to improve the updating speed and utilization efficiency of online teaching resources, the research proposes a teaching resource recommendation platform system that combines the TS fuzzy model and the NeuMF model to solve the lack of linear relationship in the fuzzy recommendation algorithm.

The proposed method combines TS fuzzy model and NeuMF model, the former is suitable for handling nonlinear relationships in large teaching resources, and the latter can integrate linear relationships between users and teaching resources. The combination of these two models has unique innovation compared to existing recommendation algorithms. By combining the advantages of the two models, it is possible to more accurately capture user interests and behavior patterns, thereby improving the accuracy of recommendations. This system can better cope with diverse user behaviors and complex teaching resource information, and has high adaptability and flexibility. Accurate recommendations can better meet user needs, enhance their learning experience and satisfaction.

The comparison of current recommendation algorithms and their limitations is shown in **Table 2**.

Table 2. Comparison of Recommended Algorithms

Researcher	Recommendation algorithm	Boundedness	Result
Phauk et al. [14]	Feature selection technology and RF algorithm	Low universality for other disciplines or educational stages	Improved accuracy and reduced MSE
Bulathwela et al. [15]	Online Bayesian Strategy	Only educational resources suitable for video lectures	Performed well
Chen et al. [16]	Collaborative filtering of high-dimensional user behavior data for dimensionality reduction	Processing high-dimensional data presents complexity	Accurate and effective
Saito et al. [17]	Combining RNN with Sequence Prediction Models	Limited applicability to non programming education fields	Practicality
Nagaraj et al. [21]	A predictive model for fuzzy reasoning methods	Limited application in non medical fields	Shorten diagnostic time and provide recommendations for disease treatment
Iatrellis et al. [22]	Semantic Web Technology and Fuzzy Logic	The complexity of technology	Provide reliable advice
Ouechtati et al. [23]	Fuzzy logic recommendation model	The performance in other applications is unclear	The model detection rate reaches 100%
Liang et al. [24]	Combining SVM with Trust Relationships	Neglecting safety factors	Balance degree reaches 96

3. Teaching Resources Recommendation Platform System Based on Fuzzy Recommendation Algorithm

The study first constructs the NeuMF model using the generalized matrix factorization model (GMF) and multi-layer perceptrons (MLP) models. Afterwards, with the support of Java open-source web scraping technology, a teaching resource recommendation platform system was designed by combining the designed NeuMF model with the TS fuzzy model. The technical roadmap flowchart for the research is shown in **Fig. 1**.

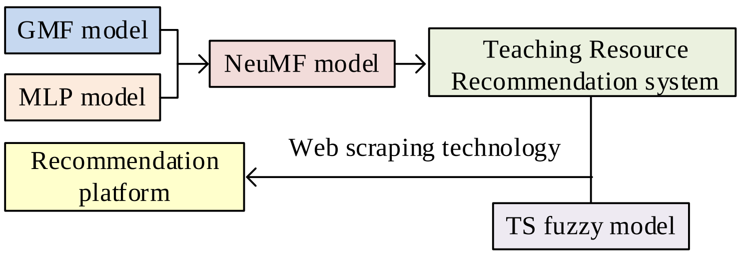


Fig. 1. Technical roadmap and flowchart of the research.

3.1 GMF model and MLP model

In the recommendation field, GMF is a technique commonly used to reduce the dimensionality by splitting the original matrix into the product of two or more matrices, which is used to make up for the defects of sparse matrices. It is specifically described as the dot product of the user's hermitian space vector and the item's hermitian space vector, which is then weighted and output [26]. The basic form of matrix decomposition, as shown in (1).

$$R \approx P^T \times Q = \hat{R} \tag{1}$$

In (1), R is the scoring matrix of N rows M columns, matrix P^T has matrix dimension $N*K$, matrix Q has matrix dimension $K*M$, and K is an adjustable parameter between 10 and 100. The values of the elements in the matrix $\hat{r}_{ij}$ are represented as shown in (2).

$$\hat{r}_{ij} = p_i^T q_j = \sum_{k=1}^{K} p_{ik} q_{kj} \tag{2}$$

In (2), $\hat{r}_{ij}$ is the value of the element in the i row of $\hat{R}$ and the j column. In order to avoid errors caused by overfitting, a regular term is attached and the loss function is used as a measure of how good the decomposition is, as shown in (3).

$$e_{ij}^2 = \left(r_{ij} - \sum_{k=1}^{K} p_{ik} q_{kj}\right)^2 + \frac{\beta}{2} \sum_{k=1}^{K} \left(\|p\|^2 + \|Q\|^2\right) \tag{3}$$

In (3), e_{ij} is the sum of each element given. The gradient descent method is used to determine the fastest descent direction by finding the partial derivatives of the parameters p_{ik} and q_{kj} to solve for the negative gradient of the loss function, as shown in (4).

$$\frac{\partial}{\partial p_{ik}} e_{ij}^2 = -2\left(r_{ij} - \hat{r}_{ij}\right)\left(q_{kj}\right) = -2e_{ij}q_{kj}, \quad \frac{\partial}{\partial q_{kj}} e_{ij}^2 = -2\left(r_{ij} - \hat{r}_{ij}\right)\left(p_{ik}\right) = -2e_{ij}p_{ik} \tag{4}$$

The variables are updated according to the direction of the negative gradient as shown in (5).

$$p'_{ik} = p_{ik} + \alpha \frac{\partial}{\partial p_{ik}} e_{ij}^2 = p_{ik} + \alpha\left(2e_{ij}q_{kj} - \beta p_{ik}\right), \quad q'_{kj} = q_{kj} + \alpha \frac{\partial}{\partial q_{kj}} e_{ij}^2 = q_{kj} + \alpha\left(2e_{ij}p_{ik} - \beta q_{kj}\right) \tag{5}$$

In (5), α is the learning rate, and the larger α is, the faster the iteration decreases. Through iterative calculations, the parameters are continuously optimized until the algorithm finally converges. After finding out the matrix elements of P and Q, the expression of the score of a user i on a target j is calculated, as shown in (6).

$$p(i,1) * q(1,j) + p(i,2) * q(2,j) + \ldots\ p(i,k) * q(k,j) \tag{6}$$

The expression of the predicted values in the user-teaching resource relationship matrix, as shown in (7).

$$\bar{y}_{u,e} = f\left(u, r \middle| p_u, q_r\right) = p_u^T q_r \tag{7}$$

In (7), p_u denotes the user potential characteristics, q_r denotes the potential characteristics of teaching resources, and $\hat{y}_{u,r}$ denotes the degree of conformity of educational resources to the user's needs, reflecting the user-teaching resource correlation.

MLP model can recognize non-linearly separable data. An MLP contains at least three node layers. Each node, except the input node, is a nonlinear activation function using the neural element [27]. Consider each input data as a vector $x = (x1, x2)$, and mathematically, define the weight vector as a and the vertical offset as b to get the transfer function as shown in (8).

$$f(x) = x \cdot a + b \tag{8}$$

In order to introduce nonlinearities and allow the perceptual machine to approximate any nonlinear function, an activation function is used to activate the result of the transfer function as shown in (9).

$$h(x) = \begin{cases} 1 : if f(x) = x \cdot a + b > 0 \\ 0 : other \end{cases} \tag{9}$$

In the application of multilayer perceptron, the algorithm for supervised training belongs to the back-propagation algorithm, where the samples are fed into the model to carry out the forward propagation computation. The MSE is then used to calculate the output error as shown in (10).

$$E = \frac{(t - y)^2}{2} \tag{10}$$

In (10), t denotes the target value and y denotes the actual calculated output. The error is minimized by the gradient descent method and the input error is used to update the inter-neuron weights in the back propagation algorithm as shown in Equation (11).

$$\Delta a_i = -\alpha \frac{\partial E}{\partial a_i} \tag{11}$$

In (11), E is the input error and a_i denotes the weight of input i. The weights of i are used to continuously correct the gradient direction, and the error is calculated through back propagation, and the weights are continuously updated during the training process to reach the ideal minimum value.

3.2 NeuMF model construction for recommendation system

The most basic thing in a recommender system is the data information of the system, and the more common data information in a general recommender system is the user-target rating matrix. According to the user's rating of the target to get a rating matrix about the user-item, but in this matrix in the real situation is very sparse, that is, in the user-item scoring matrix, there are only a small number of users to a small number of targets to rate the behavior. The user-target rating matrix, as shown in **Table 3**.

Table 3. User objective rating matrix

Classification	Goal 1	Goal 2	Goal 3	Goal 4
User 1	5	3	/	1
User 2	4	/	/	1
User 3	1	1	/	5
User 4	1	/	/	4
User 5	/	1	5	4

In **Table 3**, the user's score for the target is 1 to 5, and the user has no score for the target as "/". As a recommender system, the purpose is to predict the value of no rating and give recommendation to the user according to the size of the predicted score. The research dataset selected EdNet, which is a large student behavior dataset collected by Santa's artificial intelligence tutoring service, containing over two years of data from real online learning platforms. It includes detailed information such as user learning behavior, practice records, and exam scores. EdNet has the characteristics of rich diversity, large scale, cross platform, and clear structural hierarchy. The MLP model is a function approximation classification model, which can be used to solve the problem of matching the user and educational resources. The combination of the GMF model and the MLP model is the NeuMF model with a better performance in the training. The structural framework of the NeuMF model is shown in **Fig. 2**.

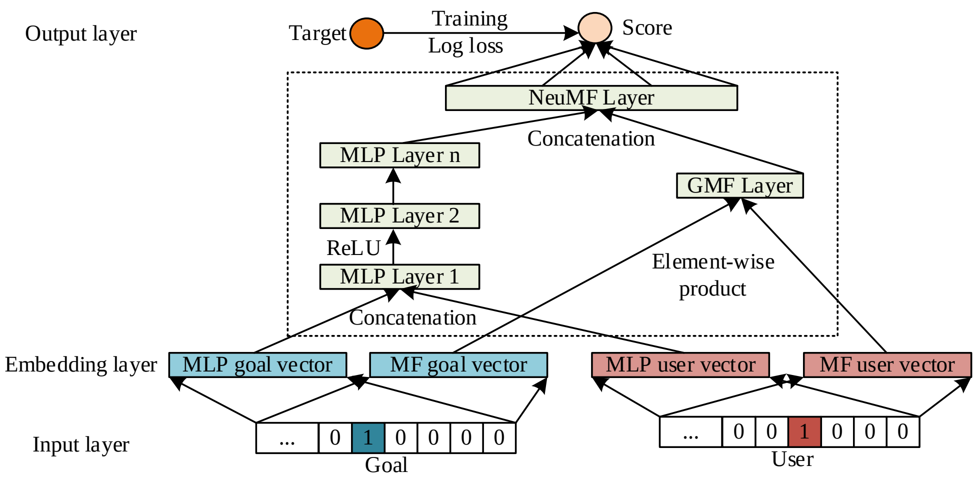


Fig. 2. The structural framework of NeuMF Model.

In **Fig. 2**, the input layer is the user and target information, the embedding layer is the target vector of MLP and MF, the user vector of GMF and MF, and the intermediate layer is the interaction link between MLP and **GMF** models, which are combined to form the NeuMF model, and finally the output score target object training. The NeuMF educational resource recommendation model flow, as shown in **Fig. 3**.

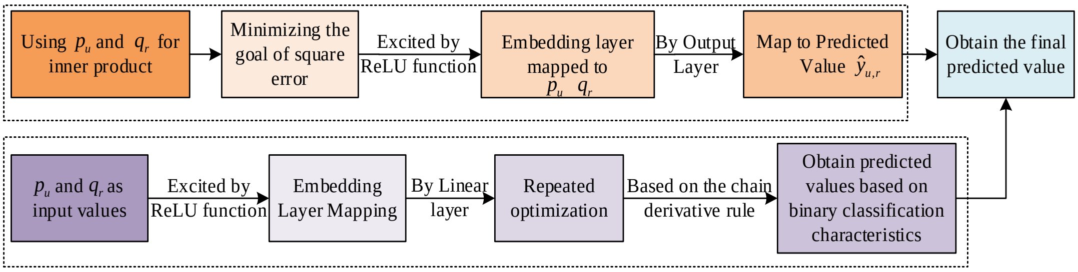


Fig. 3. NeuMF education resource recommendation model process.

In **Fig. 3**, in NeuMF educational resource recommendation model, the feature information such as user's ID, specialty information and educational resource's ID, belonging to the category are encoded and transformed, and passed to the input layer as the input of the model, and the predicted value of the user-teaching resource is output from the GMF model, which is denoted by y^{GMF}. The user-teaching resource prediction value is output by MLP model, which is denoted by y^{MLP}. The Sigmoid function is accurate in updating the weights in feature comparison, as shown in (12).

$$S(x) = \frac{1}{1+e^{-x}} \tag{12}$$

The Sigmoid function is used to activate y^{GMF} and y^{MLP} to get the final teaching resource prediction as shown in (13).

$$y_{u,r} = f_{out}\left(W_{out}\begin{bmatrix} y^{GMF} \\ y^{MLP} \end{bmatrix}\right) \tag{13}$$

The predicted value is in the interval [0, 1], and the predicted value indicates the probability of belonging to 1, i.e., the degree of conformity.

3.3 Teaching Resource Recommendation Platform System Based on TS Fuzzy Model and NeuMF Model

Dealing with nonlinear relationships in teaching resources is done using TS fuzzy model. TS (Takagi-Sugeno) fuzzy model proposed by two scholars Takagi and Sugeno in 1985 is a way of transforming a complex nonlinear problem into a problem that is on different small line segments. In order to obtain the data of teaching resources research, the study uses a kind of automatic crawling, according to certain rules, of the World Wide Web information of the program of the web crawler technology. Teaching resources Java open source crawler technology process, as shown in **Fig. 4**.

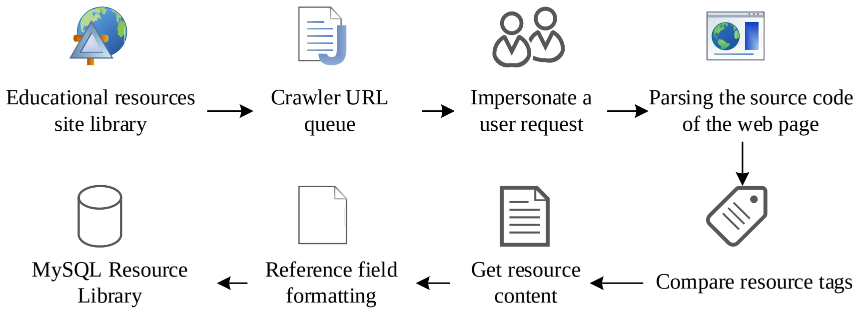


Fig. 4. Teaching resources: Crawler technical processes.

In **Fig. 4**, the educational resources web library to the crawler URL queue, simulating user requests, parsing web page source code, comparing resource tags, obtaining resource content, formatting with reference to fields, entering the MySQL repository, and periodically deleting resource data that has expired. Web crawler is a program that automatically extracts web pages for the search engine. Downloading web pages from the World Wide Web is an important component of a search engine. Controller, Parser, and Repository are the three core elements that make up the Crawler Framework. The repository is used to store the web pages obtained by the crawler and related data information [28]. In the modeling process, k-means classification algorithm is used to construct the user model. Two points are randomly selected as centroids, and based on the distance between the sample points and these two centroids, classification is performed, and the latest classification is repeated the previous steps and iterated to arrive at the final classification. The inputs are the number of user labels K and the set of user information to be classified $\left\{x^{(1)}, x^{(2)}, \ldots, x^{(m)}\right\}$. Initialize K tags to the cluster centroid $\mu_1, \mu_2, \ldots, \mu_K \in R^n$, keep iterating the process, when i goes from 1 to m, $c^{(i)} = \min_k \left\|x^{(i)} - \mu_k\right\|^2$, it means that the indexes of all the cluster centroid tags are nearest to the index of $x^{(i)}$ user information. When k goes from 1 to K, μ_k denotes the average of the values that are close to the center point of the cluster k. Minimization is performed using the cost function in k-means. $x^{(i)}$ The index of k is $c^{(i)}$, the clustering center of is μ_k and the clustering space to which the user information $x^{(i)}$ belongs is $\mu_{c^{(i)}}$. The cost function in k-means is represented as shown in (14).

$$J\left(c^{(i)}, \ldots, c^{(m)}, \mu_1, \ldots, \mu_k\right) = \frac{1}{m}\sum_{i=1}^{m}\left\|x^{(i)} - \mu_{c^{(i)}}\right\|^2 \tag{14}$$

In (14), J is a parameter and keeps changing as the algorithm is executed iteratively. $\frac{1}{m}\sum_{i=1}^{m}\left\|x^{(i)} - \mu_{c^{(i)}}\right\|^2$ denotes the square value of the distance of each user information to the center of the clustering space it belongs to. The user-teaching resource feature matching model is built using the user model and teaching resource model as foundations. The user ID, as well as the user's professional information, learning interests, etc., are all included in the user information in the user-teaching resource feature matching model. Similarly, the user-educational resource feature matching model also includes the user's ID, as well as the type and labelling category to which the educational resources belong. Input, embedding, linear, activation, and output layers make up the user-educational resource feature matching model. The model inputs user ID information, educational resource ID information and educational resource auxiliary information in the input layer of training. The output of the NeuMF model is not only related to the user and educational resource, but also related to the basic information of the user and educational resource. In TS model, its output is also affected by user and educational resource basic information. The output formula of the model is expressed as shown in (15).

$$\hat{y}_{u,r} = f_{out}\left(W_{out}\begin{bmatrix} y^{NF} \\ y^{TS} \end{bmatrix}\right) \tag{15}$$

In (15), W_{out} is the connection weight. The teaching resources recommendation system contains modules such as educational resources acquisition, educational resources, recommended resources, personal educational resources, and subject information management. Among them, the recommendation process, as shown in **Fig. 5**.

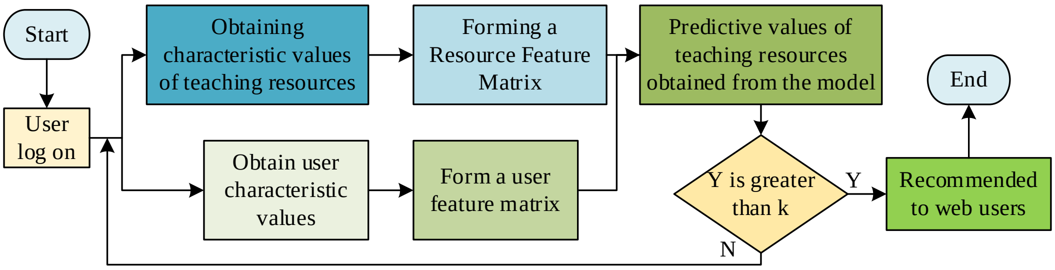


Fig. 5. Recommendation process.

In **Fig. 5**, the system is able to gather user data when the user logs into the instructional resources recommendation platform system. In order to examine the link between users and teaching resources in the database, the user eigenvalue u and teaching resource eigenvalue r are feature-matched to produce the parameters needed for the teaching resource recommendation model. This module is used to display the teaching resources recommended by the system to the user, and in the recommended page, the user can view, comment and other operations. With the help of artificial intelligence, the combination of intelligent systems can better provide personalized recommendations and enhance students' interest in learning [29, 30].

4. Analysis of the Results of the Teaching Resources Recommendation Platform System Based on Fuzzy Recommendation Algorithm

Teaching resources recommended platform system platform has been running stably in the actual environment for half a year, a total of five servers were used to build, the specific environment configuration, as shown in **Table 4**.

Table 4. Platform system test environment

Software environment	Hardware
Operating system: 64 bit Ubuntu version 14.04	CPU: AMD Ryzen 7 1700 Eight-Core Processor 8 cores and 16 threads
JDK version: 1.8.0_ 65	Memory: DDR4 16 GB
Spring Cloud version: Finchley.SR1	External network bandwidth 8 Mbps

By simulating the operation of the system user, after logging into the teaching resources recommendation system, the operation of each level 1 module and level 2 module functions are tested. The vector for setting the parameters of users and teaching resources in the experiment is 16. The number of hidden layers in the network and the number of neurons in each layer are 3 and 64, respectively. The activation function is participated by Sigmoid and ReLU, and the learning rate used in the optimization process is 0.01. The batch size is 1000, and the number of iterations on the training set is 200. Evaluation indicators include precision, recall, F1 value, ROC, and accuracy

As a result of the system function test, all the function test results of the first-level module and second-level module of the system have been passed, and the operation is normal and can run normally. Since the size of the parameter J take value will affect the effect of the recommendation algorithm, the study set J to take value from 1 to 7, and compared the precision rate, recall rate and F1 results of the TS-NeuMF model, as shown in **Fig. 6**.

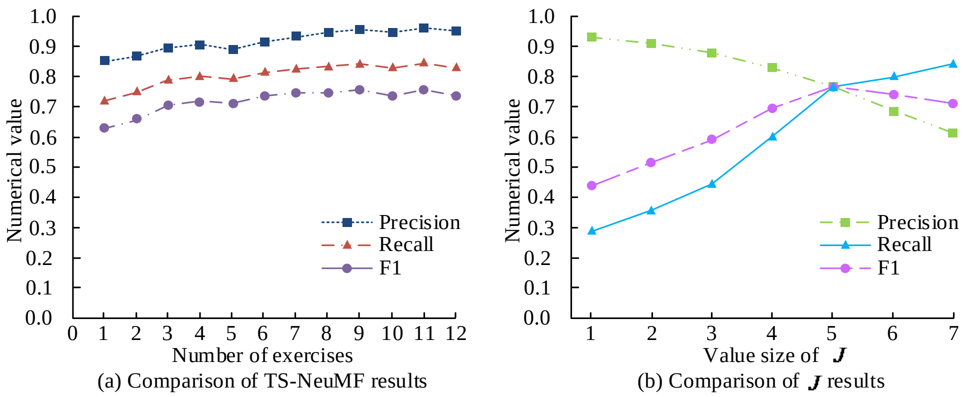


Fig. 6. Comparison of prediction performance results of FRA model.

In **Fig. 6(a)**, the model's precision, recall, and F1 value generally keep increasing as the number of student exercises increases. In the first two exercises, the model's precision and recall are low because of the severe early cold-start problem. However, in the later exercise assignments, the precision, recall and F1 values became stable. Especially in the last three exercise assignments the average precision reaches over 0.95, which further improves the accuracy of recommendations. In **Fig. 6(b)**, as the value of J increases, the precision rate of recommendation gradually decreases, and the recall rate and F1 value steadily increase. When the number of recommended exercises is 1, the probability of students answering correctly is high, and thus the precision rate is high. At the same time, the recommended recall rate is low because the number of recommended exercises is low. The actual difficulty of the exercises obtained from the students' correct answer rate was compared with the difficulty of the exercises obtained from the TS-NeuMF method in the students' 12 exercise assignments, and the results of the experimental evaluation of the difficulty of the exercises in the first, fifth and tenth assignments are shown in **Fig. 7**.

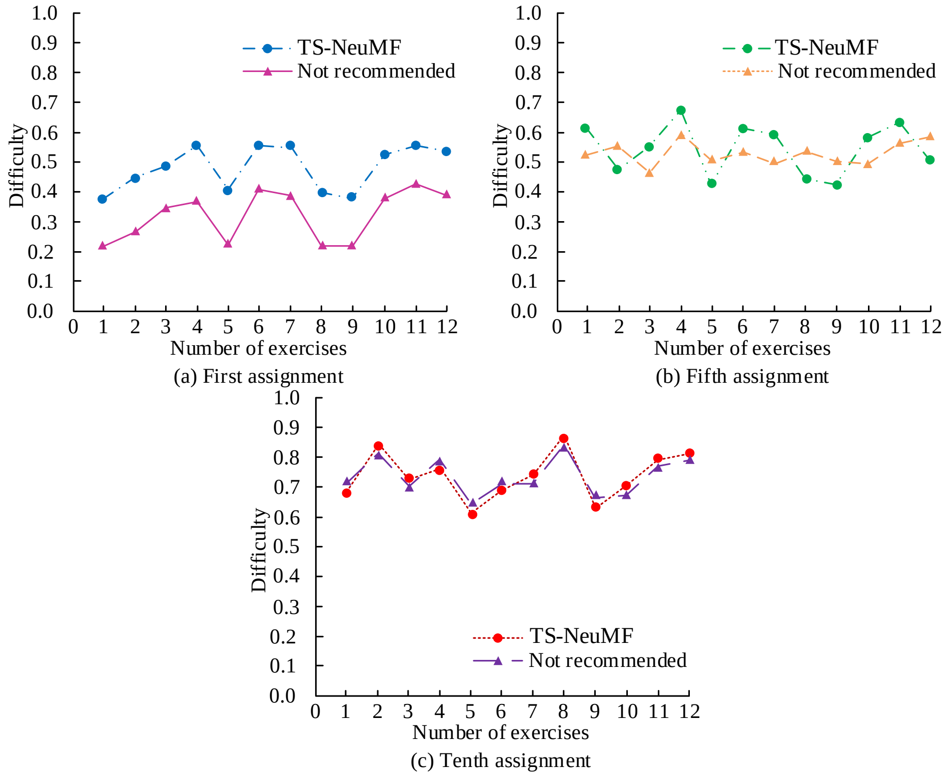


Fig. 7. Comparison of experimental evaluation results on the difficulty of exercises in the first, fifth, and tenth assignments.

In **Fig. 7(a)**, whereas in the first assignment, the difficulty of the exercises obtained without using the TS-NeuMF method of assessment is generally lower and closer to the real difficulty of the exercises. In **Fig. 7(b)**, in the fifth assignment, the exercise difficulty and the assessed difficulty fluctuated up and down across exercises. In **Fig. 7(c)**, the fit in the tenth assignment is clear. In the later assignments students familiarized themselves with the platform operation and mastered the knowledge points, and the difficulty of the exercises obtained through the correct rate of students' answers reflected the real difficulty of the exercises, which made the TS-NeuMF method fit better. In order to achieve the best recommendation effect, the user information similarity α is fused with weights w, and the weights w take the value of 0-1 each time in steps of 0.1 increment, 11 experiments are carried out, and each experiment is done 5 times to take the average to verify the accuracy. α The values were taken as 5, 10, 15, 20 and 30, and the recommendation accuracy obtained from 11 experiments under different α is shown in **Fig. 8**.

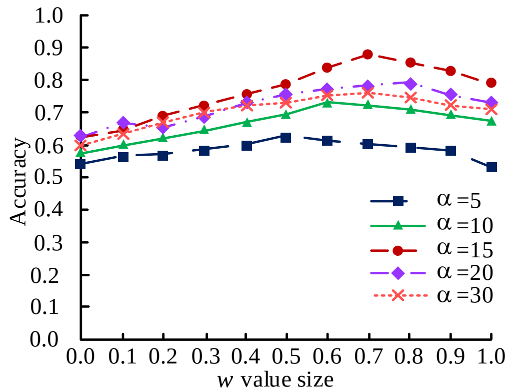
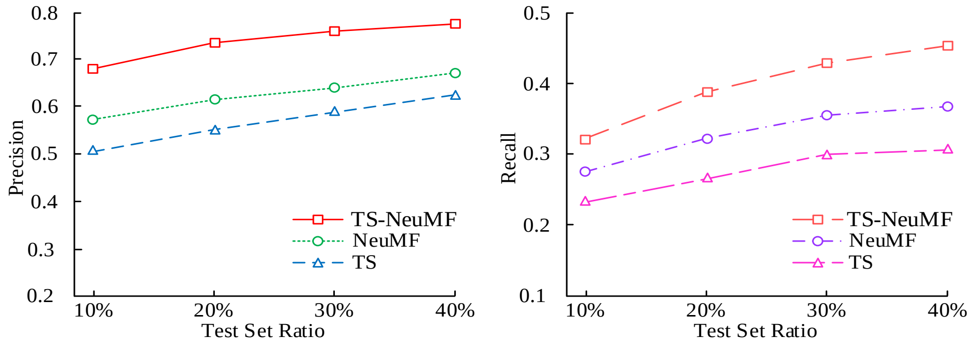
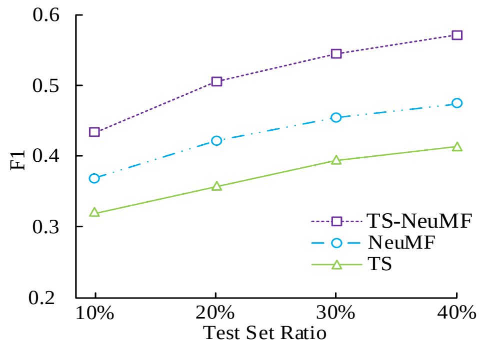


Fig. 8. Comparison of recommendation accuracy results obtained by different n and b methods.

In **Fig. 8**, the lowest accuracy rate is found when α =5. It is possible that the range of similar users' codes is too small, resulting in not covering as many learner-biased codes as possible. At this point, the ratio of code similarity and simplicity does not have a significant effect on the accuracy rate. When α >10, within a certain range, the larger the proportion of the weight w, the higher the recommendation accuracy. However, when w exceeds this range, the accuracy starts to decrease. This indicates that when the recommended code evolution fragment is similar to the user's code, the simpler the code is the more helpful for the learner to debug. The model performs best when α =15 and w=0.7. As α continues to increase, the accuracy gradually decreases. In order to verify the effectiveness of the TS-NeuMF model, 10%, 20%, 30% and 40% proportions from all the datasets were taken as the test set and compared with the TS fuzzy algorithm and NeuMF method, and the results are shown in **Fig. 9**.



(a) Comparison of precision results (b) Comparison of recall results



(c) Comparison of F1 results

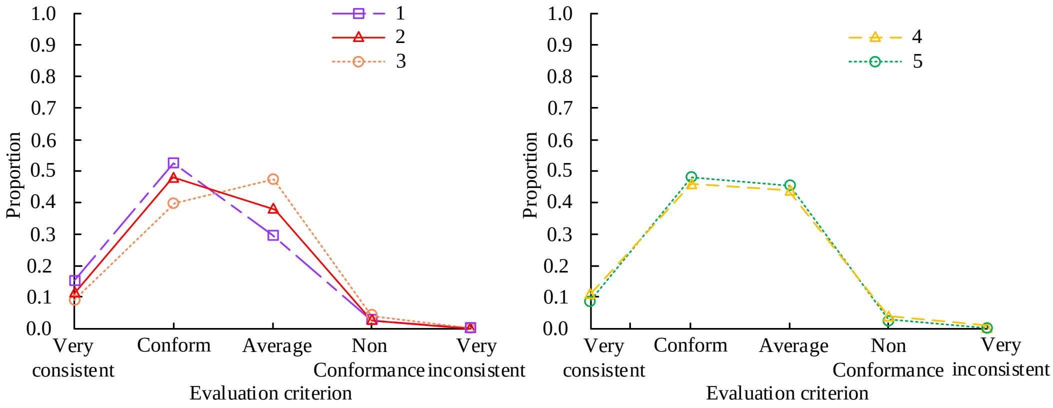
Fig. 9. Comparison of accuracy, recall, and F1 results for three different methods.

In **Fig. 9(a)**, TS-NeuMF precision rate for, recall and performance on F1 are better than the other two algorithms. The precision rate of TS-NeuMF reaches more than 77% when the proportion of exercise tests is 40%, and the recall rate of TS-NeuMF is more than 45% in **Fig. 9(b)**, both of which are significantly higher than the other two groups of algorithms. In **Fig. 9(c)**, the F1 results of TS-NeuMF are always the highest among the three methods. To further validate the recommendation effect of the improved model in a real teaching environment. The experiment will randomly select 300 students from the same major in the first year of a university and randomly group them into experimental group A and control group B, with 150 students in each group. All the selected students have made preliminary study of the examined knowledge points, and the students in each group are required to take the quiz and study in the online teaching platform within the specified time. Before and after the test, the teachers were asked to form a group of papers through the online teaching platform to conduct the test, and the difficulty distribution of the test questions was consistent with the knowledge points examined. During the independent study period, Group A used the improved modeling platform system to recommend teaching resources, while students in Group B independently studied the examined knowledge points through traditional search and browsing methods. The paired-sample t-test was used to compare the response result data, and the results are shown in **Table 5**.

Table 5. A and B t-test results

Stage	Average score	Standard deviation	Mean square error	Correlation coefficient	Significance	T	Difference significance
A Before the test	81.145	4.134	0.949	0.977	0.09%	-2.088	4.23%
A After testing	83.387	4.053	0.887				
B Before the test	81.287	5.355	1.321	0.742	0.04%	-1.752	6.41%
B After testing	81.958	5.041	1.029				

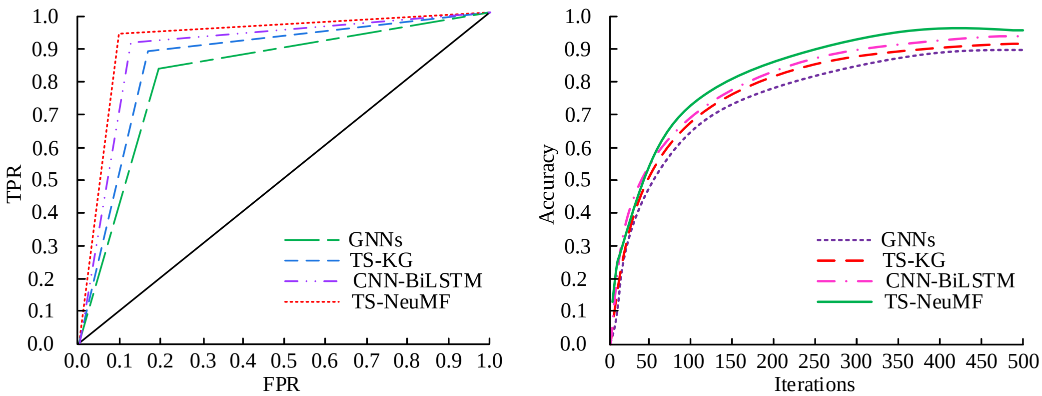
As shown in **Table 5**, the post-test mean score of 83.387 of group A is higher than the pre-test mean score of 81.145. Whereas the post-test mean score of 81.958 of group B is higher than the pre-test mean score of 81.287. The correlation coefficient of group A is 0.977 > 0.05 with a significance value of 0.09% < 5%, and the correlation coefficient of group B is 0.742 > 0.05, significance 0.04% < 5%, the data shows that there is a linear correlation between the mean scores of both groups of students before and after the test. The significance value of the difference between group A and group B is 4.23% and 6.41%, respectively, in comparison with 5%, then there is a significant difference between the group A and not a significant difference between the group B regarding the pre and post-test scores. The learning effect of group A using TS-NeuMF modeling platform system is better than group B not using TS-NeuMF modeling, which indicates that using TS-NeuMF modeling application is more effective and feasible. For the satisfaction of the teaching resource platform system, 536 students from the whole university were selected to do the questionnaire, and the ratio of freshmen to seniors was about 1:3:1, and the satisfaction survey of the platform's functional characteristics was carried out from the two perspectives of the platform's ease of use and the platform's interface, and the results are shown in **Fig. 10**.



(a) Convenience of platform use
(b) Platform interface

Fig. 10. Comparison of satisfaction survey results on platform functional characteristics.

In **Fig. 10(a)**, 1 indicates the satisfaction that the platform is easy to operate and easy to use without downloading updates, 2 indicates the satisfaction that the platform provides easy and quick access to teaching resources for various subjects, and 3 indicates the satisfaction that the platform answers questions. More than 50% of the students considered the ease of use of the platform to be compliant. In **Fig. 10(b)**, 4 indicates that the platform's interface is simple and uniform in style, which is in line with aesthetic habits and a good experience, and 5 indicates that the platform's navigation menu is reasonably designed and can be quickly adapted. Nearly 50% of the students believe that the platform interface design is relatively compliant. In order to further validate the effectiveness of the TS NeuMF model, a comparative experiment was conducted with deep learning recommendation models. Three recommendation systems, namely Graph Neural Networks (GNNs), TS and Knowledge Graph (TS-KG), Convolutional Neural Networks, and Bidirectional Long Short Term Memory Network (CNN-BiLSTM), were selected for comparison. The comparison of ROC curves and accuracy curves of different algorithms on the same dataset is shown in **Fig. 11**.



(a) Comparison of ROC curves
(b) Comparison of accuracy curves

Fig. 11. Comparison of ROC curves and accuracy curves of different algorithms

In **Fig. 11(a)**, the AUC of the TS NeuMF model is 0.940, while the AUC of TS KG and CNN-BiLSTM are 0.921 and 0.903, respectively. The AUC of the GNNs model is the smallest, only 0.892. The reason is that GNNs can effectively process graph structured data and solve data sparsity through the information of neighboring nodes. However, it cannot effectively integrate non graph structured information such as user attributes and the characteristics of multiple teaching resources. The TS NeuMF model can more effectively handle the complex nonlinear relationship between users and teaching resources, and better capture the correlation information between the two. In **Fig. 11(b)**, the accuracy of the TS NeuMF model is 95.60% within 0-500 iterations, which is 4.51% higher than that of CNN-BiLSTM. This is because the proposed model can better capture the association information between users and items, and can more effectively learn potential patterns in the data, thereby improving the accuracy of recommendations.

5. Conclusion

In order to improve the updating speed and utilization efficiency of online teaching resources, the study proposes a teaching resource recommendation platform system incorporating the TS-NeuMF model to solve the lack of linear relationship, and utilizes web crawler technology to obtain research data. The results showed that the average accuracy of the TS-NeuMF model reached over 95%. The AUC of the proposed model is 0.940, which shows an improvement of 0.019 and 0.037 compared to TS-KG and CNN BiLSTM, respectively. The AUC of the GNNs model is the smallest, only 0.892. The reason is that the proposed model can more effectively handle the complex nonlinear relationship between users and teaching resources, and better capture the correlation information between the two. This indicates the efficiency and reliability of the TS-NeuMF model in the field of teaching resource recommendation, and the significant differences in comparative experiments further validate the effectiveness of the model. However, this study did not consider the fun and user experience. In the future, various interactive designs and personalized content recommendations can be added to enhance the platform’s fun and user experience. At the same time, regularly collect user feedback and conduct user satisfaction surveys.

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