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Research and Practice of E-Learning Education and Teaching Mode Based on Data Mining Technology

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Abstract. The advent of the era of big data has led to changes in learning concepts and methods. Modern distance education breaks traditional education limitations and space limitations, makes learners' autonomous learning possible, and realizes the sharing of excellent schools, teachers, and courses by society. This paper establishes the DM(data mining) distance education teaching mode model. The association among various internal attributes is found in the mining part of association rules, which will guide future learners. At the same time, the design of the learner model mainly includes three characteristics: cognitive ability, knowledge level, and learning resource preference. The CF(collaborative filtering) recommendation algorithm generates the recommendation list of learning resource objects. The results show that the clustering accuracy test results can verify that the clustering accuracy of the algorithm is above 85.36%, and the accuracy of this algorithm reaches 96.03% when the number of neighbors is 80. The experimental results show that the recommendation algorithm proposed in this paper has a better recommendation effect.

Keywords: Data mining; Distance education; Personalized recommendation; Association rule; E-Learning Education
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1 INTRODUCTION

Today's society has entered the era of big data, and cloud computing and DM(data mining) technology have become essential technologies in economic, cultural, medical, and other application fields, which are of great significance to promoting the development of all sectors of society. The development of modern distance education is not only the change of contemporary teaching methods but also the change of educational concepts and theories and the re-understanding and re-recognition of educational models and systems. How to correctly and effectively use the network education resources to acquire knowledge. And explore the basic framework of the talent training mode of junior college education and undergraduate education under the condition of modern distance education, as well as the corresponding teaching mode, management mode, and operation mechanism, to cultivate a large number of applied higher specialized talents who can get down, stay and be used to meet the needs of local and grass-roots levels for China's economic construction and social development. Distance education is a general term for the educational forms organized by various colleges or social organizations, realizing the sharing of excellent schools, excellent teachers, and excellent courses by the whole society so that more people can enjoy quality education [16]. In modern society, with the intensification of social employment competition, learning separated from production no longer exists. People often start to learn according to their work needs and the need to increase their competitive weight, and learning becomes an individual activity of the learning subject. Therefore, autonomous learning has become essential to modern educational learning theory [4]. The development of current distance education is not only the change of contemporary teaching means but also the change of academic concepts and theory, and it is also the re-understanding and re-recognition of educational modes and systems. Students can systematically learn essential knowledge and skills through the teaching CD provided by the school and know the important and difficult points of the course, even simulation experiments, simulation exercises, simulation exams, etc. so that students have more freedom in learning. According to the requirements of modern distance education teaching mode, students must have a considerable level of computer application ability and network foundation and master the ability to obtain learning information, analyze information, and comprehensively process information through the network, as well as students who need to have stronger self-monitoring and restraint ability and the ability to communicate with teachers and classmates through the network than those trained by traditional adult education teaching mode. This amalgamation of data mining technology and e-learning aims to address several critical facets of education, including early identification of struggling students, customization of learning materials, and creation of tailored learning experiences that cater to individual learning styles.

DM can help people extract interesting knowledge, rules, or higher-level information from relevant data in databases, especially data warehouses, and also help people analyze them in different degrees so that they can make more effective use of data. The arrival of the era of big data has led to a change in learning ideas and learning methods. Students have changed from content digesters to content creators, and learning has moved from classroom to environment [20]. The essence of distance education is the separation of time and space between teaching behavior and learning behavior, which determines that the key to distance education practice is how to realize the re-integration of teaching and learning. Because these network platforms have sound teaching effects and distinctive teaching interaction modes and can represent the first-class level of teaching interaction in modern distance education in China, many have been rated nationally excellent courses. Theoretically speaking, combining and summarizing the interaction in contemporary distance education is conducive to promoting the in-depth development of the basic theory of distance education and providing a reference for the better development of distance education.

Innovation of this research:

1. Modern distance education is an educational form with learners as the main body and modern technologies such as computer technology; this paper puts forward the reform idea of implementing quality control management and formative evaluation for distance education, which has certain reference functions and reference value for the current distance education pilot work.

2. based on a comprehensive analysis of a personalized learning environment, this study puts forward a customized learning environment that pays attention to learners' emotional experiences in the learning process. It uses DM technology to analyze and extract learners' personalized characteristics and a CF recommendation algorithm to explore resources and recommend customized learning resources.

The structure of this paper is as follows:

The first chapter introduces the background work of the research. The second chapter mainly introduces the present situation of this research. The third chapter puts forward the DM model of distance education teaching mode. The fourth chapter verifies the performance of the model studied in this paper. The fifth chapter is the conclusion.

2 RELATED WORK

2.1 DM Related Research

WU et al. discussed a kind of resource-based learning based on DM technology by understanding DM technology, knowledge discovery, and resource-based learning [17]. Lin et al. used association rules to get the association between grades four and six, the relationship between teachers' classroom teaching effect and teachers' age and professional title, and the factors that affect course grades [9]. Nguyen et al., guided by knowledge points and using various DM algorithms, constructed an intelligent, personalized online learning system to meet the targeted educational needs of learners and improve teaching quality [15].

DM is a technology. Like other technologies, DM needs time and energy to be researched, developed, gradually matured, and finally accepted by people. There are currently many general DM systems, but they can't reach the desired intelligent system. Olorunnimbe et al., on the premise of using modern computer network teaching technology, give full play to the advantages of online resources as the main channel and achieve the goal of improving students' autonomous learning ability by combining the trinity of "curriculum responsibility teacher-led, guidance teacher-assisted, and student-centered" [11]. Karkina et al. put forward the concept of clustering technology, the main point of which is that when dividing objects, not only the distance between objects is considered, but also the classified class is required to have a specific connotation description, thus avoiding some one-sidedness of the traditional technology [7]. Arquilla et al. found out the types of learners and learning rules through DM to better serve learners [2]. Pecori made a slight improvement on the ID3 algorithm and designed the concepts of equivalent infinitesimal and user interest degree to simplify the calculation formula and the bias of feature values [12]. Compared with the ID3 algorithm, the improved new algorithm realizes the fast calculation of information gain through the actual sample test, and the selection of eigenvalues is in line with the expectation under the condition of the same selected report eigenvalues.

2.2 Research on Personalized Recommendation Technology of Distance Education

Distance education has entered the third generation, that is, the stage of modern distance education. The outstanding features of current distance education are that the educated can choose more abundant teaching resources, and The teaching form has changed from teaching to learning. The network-based teaching mode separates teaching time, and resource recommendation is a primary technical means to improve students' learning efficiency without teachers' guidance and supervision.

Fernandes et al. established a personalized service model using mathematical statistics and association rules and introduced personalized recommendation technology into the teaching system for the first time [3]. Xiang et al. brought personalized recommendation technology into the learning community to meet the individual needs of members of the virtual community [18]. Kim et al. improved the CF(collaborative filtering) algorithm through two processes of dimension reduction and itemset similarity calculation, which improved the sparseness of the original algorithm [8]. Si et al. combined the data weights based on time and resources and introduced them into the recommendation process of a resource-based collaborative filtering algorithm, which improved the recommendation accuracy [14].

Early practice is storing the learning resources on the web server so learners can study, ask questions, do homework, take exams independently through browsers anytime and anywhere, and communicate with teachers or classmates through the computer network. Aliannejadi et al. use the hybrid CF method of user similarity and items to recommend personalized learning resources that match their characteristics to learners [1]; Guo et al. Used collaborative tagging technology to model and analyze learners' learning preferences and knowledge levels. The learning style model constructed uses clustering technology to reduce tag space, improve execution time, and reduce memory requirements, thus improving the system's personalized recommendation performance [5]. Saeed et al. solved the problems of "information overload" and "resource loss" on the Internet by using personalized intelligent recommendation services mined by association rules [13]. Linda et al. tried to use the structural features of the knowledge map to integrate ontology into the CF algorithm [10].

3 METHODOLOGY

3.1 DM Model of Distance Education Teaching Mode

In modern distance education, educational technology is the means, teaching application is the purpose, and distance education mode is the teaching organization form of distance education, which varies according to the teaching tasks and contents and simultaneously has cross-emphasis. In the traditional teaching process, the most essential teaching mode is teacher-centered, with teachers speaking and students listening. It is a one-way communication teaching mode. The most significant advantage of using this teaching mode in distance education is that it breaks through the limitation of the number of people and places in the traditional classroom. This requires not only a high network transmission rate but also some hardware devices to achieve real-time interaction. Most distance education pilot universities in China have realized the real-time interactive function. However, due to many factors, its practical teaching application scope is not enormous, and it is mainly used in remote meetings in off-campus learning centers, counseling, and answering questions before exams and other occasions.

The requirements for students and the nature of learning monitor the teaching process, learning process, and learning quality. Through the reorganization and structural optimization of educational resources, the teaching point implements the whole process of aiding students, and the situation of students' autonomous learning is monitored by the teaching point nearby. Some tutors are hired at the teaching point to implement the nearby tutoring and practice link organization. Therefore, on the premise that learners' internal factors play a decisive role, external factors play a vital role in learners' learning activities. A successful learning guidance mode is one of the critical factors in ensuring the teaching quality of distance education. Teachers' online forums can help learners discuss their learning objectives in a timely manner and answer common problems in time, which shows the practical teaching function of online forums.

Specifically, in the practice of distance and open education, learners' autonomous learning can be carried out by independent individualized learning activities based on online course material resources without teacher-student communication or by cooperative learning among learners. From the perspective of learners, no one is born to learn autonomously. Of course, some students can master and learn autonomously. However, in a learning process without other learners' face-to-face participation, persistence in learning is a great challenge for them. These teaching links include autonomous learning, information technology media assistance, homework and formative assessment, group cooperative learning, practical teaching, examination, etc. Among them, independent learning is the most critical link, and implementing other teaching links aims to promote the smooth and effective implementation of autonomous learning.

E-learning can realize the interaction between learners through various learning platforms, and knowledge can be shared in the interaction process. Consultation and cooperation are essential, and they can also supervise and evaluate their peers' learning. How to objectively, indeed, and comprehensively assess the effect of online learning is another complex problem faced by education and teaching reform. With the popularization and deepening of DM technology applications, we can further analyze the data of online course learning platforms by using mining technology and provide timely learning guidance for students.

Currently, the more active research field is the scalability of clustering methods [19]. Euclidean distance is defined as follows:

$$d(i,j)=\sqrt{(x_{i1},x_{j1})^2+(x_{i2},x_{j2})^2+\cdots+(x_{in},x_{jn})^2} \tag{1}$$

Where $i=(x_{i1},x_{i2},\cdots,x_{in}), j=(x_{j1},x_{j2},\cdots,x_{jn})$ are two n-dimensional data objects.

A learner's test score is an essential factor to comprehensively measure a learner's learning characteristics because the final result of the comprehensive effect of other factors is still reflected in the test score. In the DT(Decision tree) method, DT is first constructed from the instance set, a guided learning method. The technique first forms DT according to the training set data.

Let s_i be the number of samples in $C_i$class.

$$I(s_1,s_2,\cdots,s_m)=-\sum_{i=1}^{m}p_i\,log_2(p_i) \tag{2}$$

Where p_i is the probability that any sample belongs to C_i, estimated by s_i/s.

Assuming the transaction database has four items, there are six possible 2-item sets. Calculate whether the confidence of frequent itemsets meets the requirement of minimum confidence by formula (3):

$$Confidence(A\Rightarrow B)=P(A\cup B)=\frac{support\_count(A\cup B)}{support\_count(A)} \tag{3}$$

The process of DM is a complicated one. When DM is carried out, it needs to be repeated many times. In the process of repetition, things can gradually approach its essence, and the best solution to the problem can be found constantly. According to the characteristics of online course learning, this paper adopts the mining model, as shown in Figure 1.

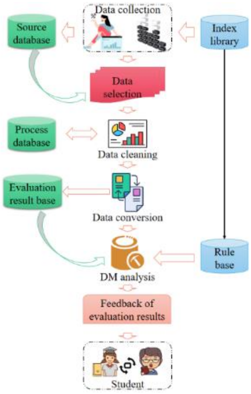

Figure 1: DM model of distance education teaching mode.

The k-means algorithm takes k as a parameter and divides n objects into clusters, which are defined as follows:

$$E = \sum_{i=1}^{i} \sum_{p \subset c_i} |p - m_i|^2 \tag{4}$$

Where E is the sum of the mean square deviations of all objects in the database and the corresponding cluster centers, p is a point in the representative object space, and m is the mean value of cluster C.

Find all frequent item sets that satisfy all item subsets with support at least the minimum support. The forms of support and confidence c are defined as follows:

$$s(X \to Y) = \frac{\sigma(X \cup Y)}{N} \tag{5}$$

$$c(X \to Y) = \frac{\sigma(X \cup Y)}{\sigma(X)} \tag{6}$$

3.2 Recommendation Model of Personalized Learning Resources in Distance Education

Each visual three-dimensional object represents an experimental object. In addition to the basic requirements, the realization of a virtual laboratory should also pay attention to the communication and feedback between the interactive parties and the collaborative activities among learners. Collaboration is based on communication. Besides providing a series of tools for users to communicate conveniently, collaboration also requires the synchronous display of experimental results.

Study the personalized learning resource recommendation model, realize the precise connection between high-quality educational resources and learners' customized learning needs, and improve learners' academic performance and learning effect. Using educational DM technology to analyze learners' data, pre-process, clean, integrate and standardize the data.

Different users have evaluated various learning resources and core concepts. According to the domain knowledge, there are some similarities between learning resources and core concepts, so users have similar interests. Users' interest can be gained through their browsing behavior and evaluation of resources and ideas. When students learn online, the system automatically records students' learning behavior, analyzes learners' learning process and access resources through a learning analysis engine, and establishes a characteristic model of learners' knowledge structure and corresponding cognitive level.

The probability of mastering knowledge points can be maximized by maximizing the expectation to obtain the parameters of guessing error rate and error rate. By maximizing the test correct probability of learners, it is determined that:

$$\hat{\beta}_u = argmax_{\beta}\, L\,(W_u | \beta, \hat{s}_v, \hat{g}_v) \tag{7}$$

For numerical attributes, there are significant differences in the comparability (similarity) of the average absolute difference of characteristics due to different attribute measurement units. Standardize it according to formula (8) to eliminate the influence of measurement units.

$$S_{a_i} = \frac{a_i - \frac{1}{n}\sum_{i=1}^{n} a_i}{\frac{1}{n}\sum_{i=1}^{n} |a_i - M_A|} \tag{8}$$

Where S_{a_i} represents the standardized attribute, a_i represents the ith numerical attribute, and M_A represents the average value of attributes.

Traditional recommendation technology is sought after by educational researchers because of its wide application and good performance in e-commerce platforms. As a result, the direct transplantation algorithm is inefficient and can't meet the personalized needs of online learning system [6]. Currently, online learning recommendation algorithms mostly use CF, which can't accurately recommend when students browse fewer data in the early stage of the system, and there is a cold start problem.

According to the target learners' prediction scores, learner clusters, and learning resource clusters, the CF recommendation algorithm generates the recommendation list of learning resource objects. The personalized learning resource recommendation model established in this paper is shown in Figure 2.

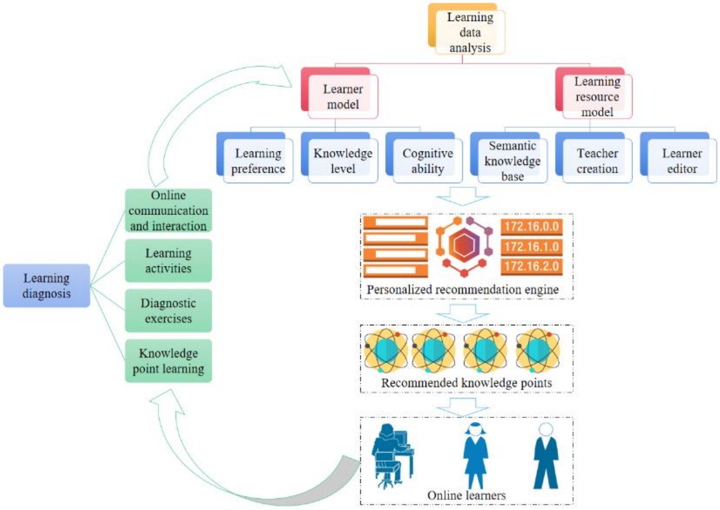

Figure 2: Personalized learning resource recommendation model.

The basic idea of the CF recommendation algorithm is that users with the same or similar hobbies and interests may like the same type of resources. Recommend resources according to their interests. The calculation method in the case of N-dimensional space assumes vectors $A = (A_1, \ A2 \cdots, A_n)$, $B = (B_1, \ B2 \cdots, B_n)$. The cosine formula is:

$$cos\,\theta = \frac{\sum_1^n A_i B_i}{\sqrt{\sum_1^n A_i^2}\sqrt{\sum_1^n B_i^2}} \tag{9}$$

Multiple learners may select a specific learning resource, and the learning resources selected by different learners are related. In this way, the relationship between vertices and edges in the bipartite graph can be transformed into the flow allocation of learning resources. If the amount of resources allocated by a certain learning resource r_i to another learning resource r_j is defined as w_{ij}, then w_{ij} is calculated as shown in formula (10):

$$w_{ij} = \frac{1}{k_j} \sum_n^m \frac{a_{iu} a_{ju}}{k_u} \tag{10}$$

Where k_j represents the degree of learning resource j, that is, how many users have selected it, andk_u ku means the degree of learner u, that is, how many learning resources the user has selected.

When a theme appears in most students' learning paths, the reference significance of this theme to the construction of each student's interest model will be weaker. This paper defines the following formula (11) to calculate the interest weight of each topic:

$$w_{v_i} = ln\left(\frac{N+\delta}{n_{v_i}}\right) \tag{11}$$

In the formula, N is the number of all students, $n_{v_i}$is the number of all students including topic v_i, and $\delta > 0$ is a constant, and the weight of avoidance is 0. w_{v_i} topic decreases with the increase of the number of students learning.

4 EXPERIMENT AND RESULTS

The experimental data types include personal information of learners, information of learning resources, information of teaching resources of learners, etc. The data sets are substituted into this paper's traditional CF and situational recommendation methods and tested, respectively. Cross-validation is conducted between learners and knowledge points in the selected data set.

Remove the course number field, only keep the average value field, and cluster the data by using a clustering algorithm (such as the K-Means algorithm). The results are shown in Table 1, and the center point of the whole training data set is 88.9036.

Avg	*K-Means*	*Class center*
90	*3*	*89.6679*
84	*4*	*93.4382*
90	*0*	*89.2398*
89	*2*	*86.7461*
88	*0*	*89.2398*
88	*2*	*86.7461*
89	*3*	*85.8271*
85	*2*	*86.9471*
82	*4*	*93.4382*
86	*0*	*89.2398*
84	*3*	*89.6679*

Table 1: The result of the clustering algorithm.

Let the center point of the whole training data set be 88.9036 as the influence factor "1", calculate all kinds of influence factors by formula, and add this field to the curriculum to get the result set as shown in Table 2. According to the historical data, the influencing factors of each course can be used for teaching evaluation in the new semester.

Course number	*Influence factor*
002010	*1.39*
002011	*1.13*
002012	*1.28*
002013	*1.08*
002014	*0.98*
002015	*1.21*
002016	*1.17*
002017	*1.38*
002018	*1.06*

002019	*1.25*
002020	*1.38*
002021	*1.17*

Table 2: Influencing factors of each course.

To compare the performance of the CF algorithm and hierarchical clustering algorithm, we use the CF algorithm and hierarchical clustering algorithm to cluster students' features and follow up on the implementation. The results are shown in Figure 3:

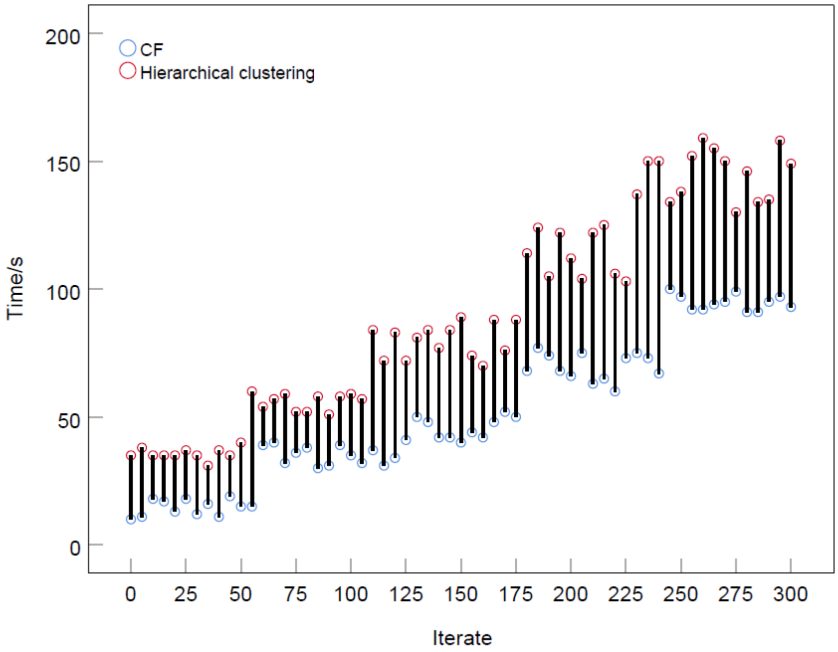

Figure 3: Tracking algorithm execution process.

The hierarchical clustering algorithm takes 150 seconds, while the CF algorithm runs for 100 seconds. CF algorithm saves more time than the hierarchical clustering algorithm. Find the internal correlation between the pages users visit when the minimum support and confidence are met. Then, analyze and record learners' personalized learning habits based on the found frequent paths. Facilitate learners' continuous learning, enable instructors to grasp learners' learning progress and habits in real-time, and work out suitable learning plans and teaching progress for each learner.

After generating the transaction database D, we atotale minimum support is 20%, $|D| = 8$, $I = \{I01, I02 \cdots, and\ I08\}$. Find k subsets with only one item, then connect them to generate a subset with two items until finally connecting them into a subset of $k-1$ items. Figure 4 shows some association rules selected from frequent itemsets.

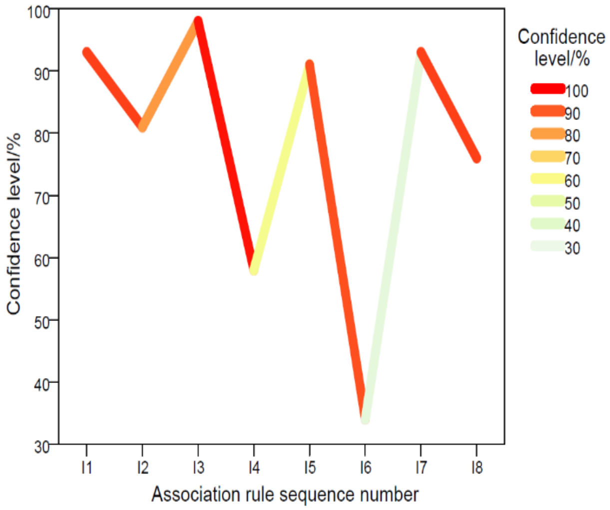

Figure 4: Association rules generated by transactions in the database.

In the personalized learning system, we set the minimum confidence threshold to 80%, so the strong rule in the above table is $I01 \wedge I08 \Rightarrow I02$. Association rule analysis can not only dig out the hidden association between the contents of learning courses but also find out what learning strategies people with different learning styles can use to learn efficiently. In addition, we can also make a correlation analysis on the topics selected by users and find out the association rules between the topics answered correctly by learners, which can be recommended to learners who need to cultivate their abilities in this field to concentrate on practice.

Learners with this style can learn best when information is presented in the form of visualization and images or charts. They like information stimulation of charts, pictures, graphs, animations, flow charts, arrows, colors, gestures, etc. In classroom teaching, learners will benefit a lot from listening to lectures or participating in group discussions, and they can also get a lot of knowledge from tapes. This dimension shows learners' preference for receiving auditory information. For example, some people learn best when listening to speeches, lectures, or discussing with other students.

The learning layer embodies the essential characteristics of personalized learning, and its material entity is the learning content and learning support tools carefully prepared by the learning system. Besides general information, such as name, gender, age, etc., it also includes learners' estimated values of their cognitive abilities, such as their knowledge level, mental ability level, learning style, preferred learning strategies, etc. In the learning process, learners do not learn the fixed courseware prepared by teachers in advance, nor do they adopt a particular learning strategy, but dynamically form the learning resources that are most suitable for learners' learning characteristics according to their learning characteristics and learning styles. Figure 5 shows the clustering results of different categories.

Through the clustering accuracy test experiment, the clustering accuracy of the algorithm can be verified to be above 85.36%. It can be seen that the accuracy of the clustering results is high, and the clustering results are within a high acceptable range, which is suitable for subsequent clustering research.

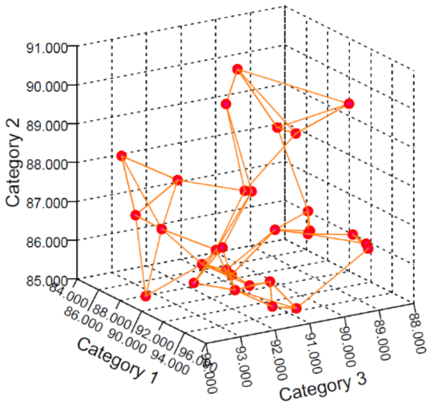

Figure 5: Clustering results of different categories.

The number of K-nearest neighbors in the CF algorithm based on resources is set to 10; the optimal experimental results can be achieved after 1000 training iterations. The results of comparing this algorithm with the traditional recommendation algorithm are shown in Figure 6.

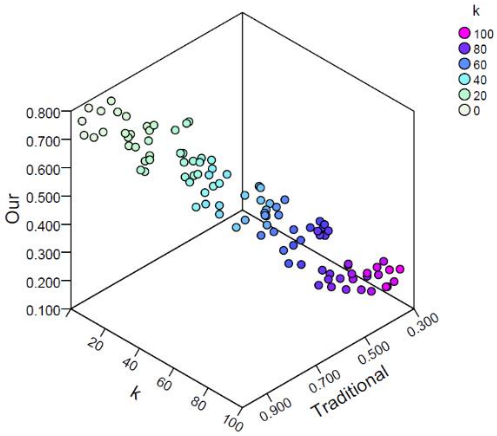

Figure 6: Comparison chart of MAE values of different algorithms.

It can be seen that the MAE (Mean Absolute Error) value of this algorithm is lower than that of the traditional algorithm under different numbers of neighbors k.

As shown in Figure 7, the precision values of the two algorithms all show an upward trend. When $k > 50$, the upward trend of the precision of this algorithm and the comparison algorithm tends to be gentle with the increase of the number of neighbors. The accuracy of this algorithm is 96.03% when the number of neighbors is 80. Network course construction project is an important part of excellent course projects, and it is also the most representative open and shared project of educational resources in modern distance education. A series of measures can be taken to promote content exchange in the teaching interaction mode in distance education. For example, the organizers and managers of online education courses can emphasize the necessity of strengthening this interaction at the beginning of the construction of online courses.

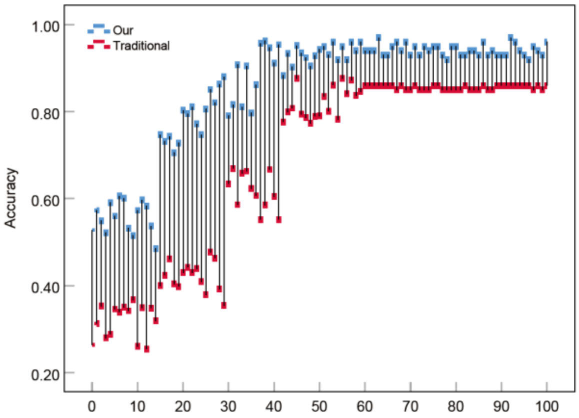

Figure 7: A line chart showing the accuracy of the algorithms involved in the experiment under different values.

Therefore, knowledge management tools can be embedded in online education courses, such as adding a blog application board, so that participating learners can record their learning experience and reflection in time, thus promoting learning and the construction of a teaching interaction mode. The construction of the interactive mode of distance teaching is a never-ending process that will not stop or come to an end. Its construction is a process of advancing with the times and developing continuously.

5 CONCLUSIONS

The development of modern distance education is not only the change of contemporary teaching means but also the change of educational concepts. The process of DM is a complicated one. Combined with the characteristics of online course learning, this paper establishes the DM model of distance education teaching mode. By analyzing learners' learning activities, a database of learners' personality characteristics is constructed, and the data in the database is DM to obtain learners' personality characteristics to guide learning. According to the target learner's prediction score, learner clustering, and learning resource clustering, the CF recommendation algorithm is used to generate the recommendation list of learning resource objects. The results show that the clustering accuracy of this algorithm is above 85.36%, and the accuracy of this algorithm reaches 96.03% when the number of neighbors is 80.

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