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Research Article

Construction and Push of Financial Instructional Resource Bank Based on Rough Set Theory

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A perfect resource bank for financial education that can foster resource exchange and charitable work must be established. The traditional recommendation algorithm is improved in this paper based on the rough set theory, avoiding the issue where the traditional similarity calculation does not match the actual similarity judgement. When used in the field of resource clustering for financial education, the improved algorithm has the concept of an approximate set for boundary problems. It can more accurately describe the boundary groups of resource classification. When the model is offline, a rough K-means user clustering algorithm is used; users are assigned to the upper and lower approximations of K classes based on how similar they are to cluster centers, creating the initial neighbor set of users. Find the target user's nearest neighbor from the initial nearest neighbor set online, predict the item's score, and offer suggestions to it. The evaluation's findings indicate that this system can achieve a precision rate of 94.35 percent. Additionally, compared to the conventional method, the recommended recall rate is higher at 95.94 percent. This algorithm can effectively provide high-quality resources for financial teaching while overcoming the drawbacks of traditional recommendation algorithms, increasing recommendation accuracy.

1. Introduction

The construction of a professional instructional resource database in colleges and universities is an important measure for the state to promote the reform of education and teaching and improve the quality of personnel training and social serviceability and is an important task of colleges and universities at present [1]. Under the background of the rapid development of educational informatization, it is of great practical significance to build a network instructional resource platform with a reasonable structure and complete system. Its significance is mainly manifested in the following aspects: (1) promoting the integration of information technology and curriculum and improving the teaching quality; (2) improving the knowledge structure and promoting autonomous learning; (3) realizing resource sharing and strengthening the sense of cooperation. As an established major in economic management, with the continuous opening and development of the financial market, finance is not only widely favored in universities but also has an increasingly strong demand for financial knowledge in the society [2]. The financial resource bank organically combines professional teaching standards, course library, teaching content, experimental training, learning evaluation, and other elements to build a learning platform to meet the learning, research and teaching needs of students, teachers, and the public. However, with the deepening of the construction of professional instructional resource databases, some problems gradually emerge [3]. At the same time, the state emphasizes that it is necessary to improve the level of model colleges as a whole, strengthen professional construction, and enhance the overall social serviceability. This puts forward higher requirements for the construction of resource banks for various teaching specialties [4]. With more and more financial instructional resources and wider sources, it is difficult for people to quickly retrieve the resources they need, and they often spend a lot of time but fail to find the resources they need.

A personalized learning resource recommendation system was created in response to these circumstances to address the urgent needs of users, education, and teaching while also paying attention to each user's unique needs and preferences [5]. It gives the two sides a platform for effective information exchange and effectively solves the issues of resource disorientation and information filtering. However, the conventional collaborative filtering recommendation algorithm is experiencing some significant issues due to the rapid growth in users and projects such as real-time recommendation, cold start, scalable algorithms, and sparse data [6]. These issues contribute, either directly or indirectly, to the sharp decline in recommendation quality and accuracy. It is a crucial piece of clustering data mining technology. If an algorithm can reasonably cluster educational resources, the results of the clustering can be used by students to locate the needed information quickly [7]. Using clustering to search the outcomes of educational resources is a trend in the development of educational resource retrieval. Uncertainty and incompleteness can be expressed using the rough set theory. It can analyze and handle all types of incomplete information, including information that is inaccurate, inconsistent, or incomplete, and can also uncover hidden knowledge and suggest potential laws. The knowledge push model of financial education resources and the creation of a push-oriented resource database are studied in this paper, which also introduces a rough set theory to the clustering problem. Users should be able to quickly, accurately, and effectively locate the financial resources they require. The main contributions of this paper are as follows:

(1) From the perspective of the construction and management of a professional instructional resource database system, this paper reflects on the positioning, content, and management of an instructional resource database, finds out the problems, and puts forward some countermeasures and suggestions. In the aspect of algorithm, the traditional recommendation algorithm is improved to avoid the phenomenon that the traditional similarity calculation is inconsistent with the actual similarity judgment. The improved algorithm has the concept of approximate set in dealing with boundary problems, and it can better describe the boundary groups of resource classification when it is used in the field of financial education resource clustering.

(2) In this paper, the application of the rough equivalence class method in clustering and filling is extended to the personalized recommendation method, and the corresponding algorithm and new model are formed after improvement combined with the new application background. The evaluation results show that the precision rate of this system can reach 94.35%. And, the recommended recall rate is as high as 95.94%, which is higher than the traditional method. This model can effectively improve the recommendation accuracy and has strong feasibility and practical significance.

According to the research needs, this paper is divided into five parts. The specific arrangements are as follows: introduction is the first section. This section explains the content, importance, methods, and definitions of related concepts from the research and creates a straightforward diagram of the paper's structure. The literature review comes next. This chapter provides the research concepts and techniques used in this paper, as well as a summary of the pertinent domestic and international literature. The method part is the third component. The related theories of recommendation algorithms are outlined in this section, along with the benefits and drawbacks of the current recommendation models. The corresponding improvement is put forward, and a rough set method is suggested to deal with it based on the user's multi-interest and the utilization method of the user's indirect rating information. The implementation process is then provided, followed by the construction of a financial instructional resource management system based on the rough set theory. Section 4 conducts an experiment with the model developed in this paper and evaluates its results and effects on practical application. The paper's summary and the prospect are included in Section 5. This section presents the potential directions for future research, summarizes the work done in this paper, and analyses its flaws.

2. Related Work

With the acceleration of educational informatization reform, online teaching has developed vigorously, and the construction of an online instructional resource database has become increasingly mature. At present, many scholars have studied the construction of instructional resource databases.

JND Silva Júnior et al. proposed a collaborative recommendation model based on rough sets. It is mainly aimed at the low precision of personalized recommendation, and it is believed that the multi-interest of users and the insufficient utilization of user indirect scores lead to the traditional calculation of user similarity which cannot reflect the similarity between users well. Therefore, it is proposed to introduce the rough set method into the collaborative filtering recommendation method [8]. Zhu designed the knowledge management tool development model diagram and discussed the application of knowledge management tools in network teaching [9]. Sun discusses the construction strategy and implementation method of the university teaching information resource platform from the aspects of service objectives, information organization principles, resource collection, localization technology, database structure, and website framework [10]. To solve the sparsity problem in collaborative filtering recommendation, Almohammadi et al. used the rough set theory to predict and fill the unrated item values of target users and then perform fuzzy user clustering based on user-item ratings [11]. Clarke et al. introduced rough sets into the clustering problem and proposed a rough clustering algorithm [12]. The algorithm introduces the idea of upper and lower approximation when calculating the attribution of samples and divides the samples into the upper or lower approximation of a cluster to describe that the sample belongs or may belong to this cluster and to improve the clustering boundary of the cluster class precision. Li et al. proposed a collaborative recommendation model based on rough sets, which applied the rough set theory to both user clustering and item value prediction and filling and achieved good recommendation results [13]. Bing et al. proposed a resource push model based on the Bayesian model and a resource fusion and network construction mechanism based on the fuzzy C-means theory [14]. It focuses on the openness, expansion, and renewal of financial instructional resources. Use the data mining method to find out the relationship between resources and effectively realize the integration of resources, so that they can be quickly and effectively pushed to the users who need them. Sun pointed out that since the orientation of the construction of the instructional resource library lies in the "learning center," it is necessary to establish the construction concept of "people-oriented." The writing, production, and design of all materials should be based on the overall planning and overall design from the perspective of students, teachers, and the general public [15]. Xie et al. introduced rough sets into collaborative filtering based on user clustering to improve recommendation quality [16]. Nicky proposed a rough clustering method to cluster user transaction data to analyze user transaction behavior and alleviate the sparsity problem [17]. Jalkanen et al. proposed a recommendation algorithm based on rough sets and collaborative filtering [18]. Based on rough sets, it integrates collaborative information and content features to jointly predict user preferences to solve the shortcomings of traditional recommendation algorithms. To improve the retrieval efficiency and accuracy of educational resources, Yz et al. proposed an educational resource retrieval model based on ontology and rough sets [19].

In this paper, the related literature on rough set theory and the creation of educational resources is thoroughly examined, and the topic of personalized recommendation technology is covered. Based on this, a rough set theory-based financial instructional resource management system is created. The use of data with a low preference for items in rating data is newly expanded in this paper from the perspective of user participation mode and effective utilization of rating data in the recommendation system. When the model is offline, a rough K-means user clustering algorithm is used; users are assigned to the upper and lower approximations of K classes based on how similar they are to cluster centers, which creates the initial neighbor set of users. Find the target user's closest neighbor from the initial nearest neighbor set online, predict the item's score, and generate recommendations for it. The evaluation's findings indicate that this system performs better than the conventional model. The model has strong reliability and feasibility and can effectively increase recommendation accuracy.

3. Methodology

3.1. Financial Instructional Resource Base and Rough Set Theory. With the deepening of education and teaching reform, information technology is more and more widely used in teaching, which has become an effective way to promote the leap-forward development of education. As the carrier of network information dissemination, it provides necessary technical support for educational informatization. The construction of information resources is the premise and foundation of educational informatization. Therefore, the construction of a network instructional resource database is the core content and important component of realizing educational informatization. In recent years, the creation of a shared instructional resource database has become the focus of many colleges and universities. Sharing professional instructional resource database is an important embodiment of the application of information technology in education. Using information technology [20], high-quality instructional resources will be shared all over the world, giving full play to the exemplary and leading role of high-quality resources and promoting the overall development of colleges and universities. In teaching practice, teachers often collect some project examples for students to make self-study references after class. However, how to accurately locate and classify project examples and make users search for the corresponding resources comprehensively and accurately is an urgent problem to be solved. At the same time, how to rationally integrate resources and make effective use of them becomes the key. The purpose of the construction of an instructional resource database is to integrate the complicated network of instructional resources and provide users with convenient and quick access functions. Provide efficient storage management for managers, thereby realizing the wide sharing of instructional resources and promoting the exchange and renewal of resources and improving the utilization rate of instructional resources, so that instructional resources can better serve teaching activities.

In today's society, the Internet has become a massive information resource bank, and users can publish and share information conveniently. In the implementation process of online education, educational resources are an important part of the whole system. It breaks through the multiple limitations of traditional educational resources in terms of personnel, region, time, and space and provides a large number of comprehensive and open resources, which provides the necessary guarantee for the successful development of online education. In online teaching, students can log on to the platform at any time and make use of resources such as documents, courseware, microcourses, exercises, and platform assignments for autonomous learning and training. If you encounter problems in learning and training, you can ask questions from the lecturer on the platform and get a quick response. This teaching method provides a convenient service for learners to use the fragmented time to learn professional knowledge and skills. Network instructional resources have their unique characteristics. It mainly includes (1) a large amount of information; (2) rich content and various forms; (3) wide sharing range; (4) strong interactivity; (5) uneven distribution and uneven quality; and (6) update speed is fast. The financial instructional resource database collects the instructional resources of hundreds of teachers in many schools, and it is constantly being updated. The content of the resource pool is continuously updated, injecting living water into the

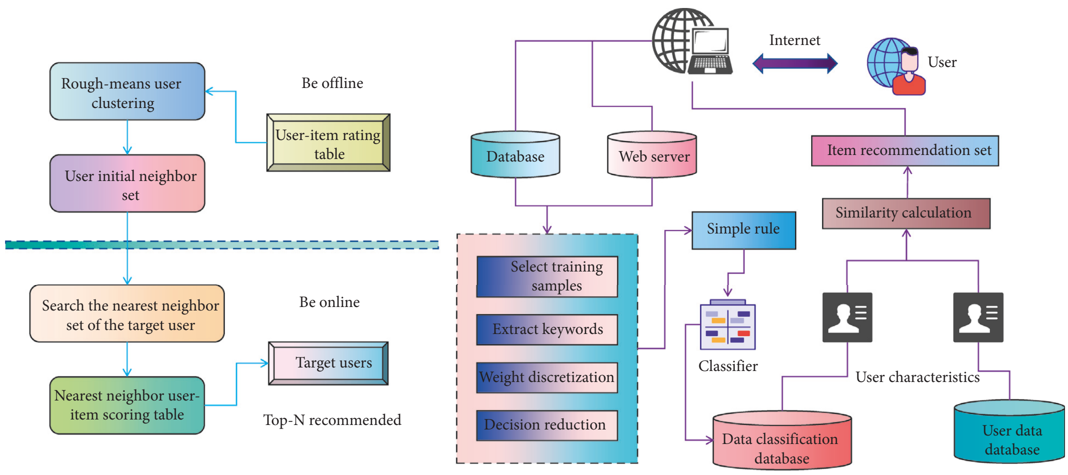

Figure 1: Architecture of the financial instructional resource recommendation model based on the rough set theory.

construction of the resource pool. Improve the construction and management mechanism of professional instructional resource bank, and realize the continuous updating of teaching materials of the financial professional resource bank. This requires the integration of resources from different sources, finding out the relationship between resources and building a resource network. The framework of financial instructional resource recommendation model based on the rough set theory is shown in Figure 1.

Clustering is based on the simple idea of "birds of a feather flock together." Its data objects are classified into several classes or clusters according to their similarity, so that the objects belonging to the same class have high similarity, while the objects in different classes are quite different. The traditional K-means clustering algorithm recognizes that each object only belongs to one class, that is, the class features are consistent. However, in real life, an object may belong to this category because of a series of features because other features belong to another category and even a large number of objects in a class overlap with each other. It belongs to hard clustering. In this clustering method, a data object is strictly divided into certain clusters and has nothing to do with other clusters. The cluster analysis problem can be described as follows: given n vectors in the m dimensional space Rm, each vector is assigned to one of the S clusters, so that the "distance" between each vector and its cluster center is the smallest. The essence of cluster analysis is a global optimization problem. The recommendation algorithm based on user clustering uses the similarity of users' ratings to cluster users, and users with greater similarity are in the same user cluster. When the target user appears, the nearest neighbor is searched in the user cluster where the target user is located, which greatly reduces the search space and improves the recommendation speed and the scalability of the algorithm and alleviates the sparsity problem to some extent. However, there are some shortcomings when using this method, for example, the similarity between the user at the edge of the cluster and the center of the cluster is low, and the recommendation accuracy of the algorithm for this user will be low. Rough set theory is used to deal with imprecise, inconsistent, and incomplete information, discover hidden knowledge, and explain its potential laws. At the same time, the rough set theory, as an effective conceptual model modeling tool to describe information systems semantically, can describe the essence of things. The construction of a network instructional resource database is a heavy systematic project, which is characterized by a large amount of data, complex structure, and difficult classification. So far, there is no unified standard for the construction of resource pools in the world. Through rough set theory and clustering method, this paper realizes resource integration and network construction.

3.2. Construction of Financial Instructional Resource Management System Based on Rough Set Theory. As an important part of campus digital construction, the instructional resource database system provides teachers and students with services such as collection, retrieval, and application of instructional resources. It is required that the system can not only meet the requirements of course teaching in terms of the number of resources but also take into account the problems of large user visits and heavy system load in terms of functions. To realize the rapid and effective push of financial instructional resources, it is necessary to first decompose the user's resource requirements. Because users have a demand for instructional resources for different purposes, this demand can be decomposed into several subdemands. Different users, according to their knowledge composition, industry, etc., need different levels of resources and content for the same goal. This paper designs the model into two parts: offline and online. When offline, judge the user affiliation to form an initial neighbor set. Searching the nearest neighbor in the upper and lower approximations of the user's class online can effectively shorten the search space and time and improve the recommendation speed. Based on user-project preference, this paper uses the advantages of incomplete data filling based on a rough set to deal with user similarity classes. At the same time, score fuzzification is used to sort the fuzzy similarity between the users in the cluster and the target users. It is better to combine the two methods to fill the ungraded items' values than to use only the scoring domain value statistics to fill the ungraded items' values or based on tolerance equivalence. The idea of a rough clustering algorithm thinks that the polymorphism of data object attributes leads to the uncertainty of cluster boundary, which is very similar to the description of users' multi-interest. In the financial instructional resources pushing system, users input the purpose of inquiry, and the system pushes out the most suitable instructional resources according to their situation. The content of this financial resource database includes six aspects. Specifically, it is (1) course instructional resources, (2) material tool resources, (3) exercises and test questions resources, (4) practical training resources, (5) research paper resources, and (6) multimedia case resources. Given a knowledge representation system S; for each object subset $X \subseteq U$ and indistinct relation B, the lower approximation set and the upper approximation set X can be defined by the basic set B as follows:

$$\begin{aligned}\underline{B}(X) &= \cup\{Y_i|(Y_i \in U|IN\ D(B)\Lambda Y_i \subseteq X)\},\\ \overline{B}(X) &= \cup\{Y_i|(Y_i \in U|IN\ D(B)\Lambda Y_i \cap X \neq \Phi)\}.\end{aligned} \tag{1}$$

Among them, $U|IN\ D(B) = \{X|(X \subseteq U \Lambda \forall x \forall y \forall b(b(x) = b(y)))\}$ is the division of U by the indistinct relation B, and it is also the set of B basic sets of the universe of discourse U. The concepts of lower approximation set and upper approximation set can also be defined by sets:

$$\begin{aligned}\underline{B}(X) &= \{x|(x \in U\Lambda[x]_B \subseteq X)\},\\ \underline{B}(X) &= \{x|(x \in U\Lambda[x]_B \cap X \neq \Phi)\}.\end{aligned} \tag{2}$$

That is, if and only if $[x]_B \subseteq X, x \in \underline{B(X)}$ and if and only if $[x]_B \cap X \neq \Phi, x \in \overline{B}(X)$. The set X can be described in the rough set form according to the equivalence relation $\mathrm{IND}(B)$. For rough set-based clustering, the publicity of the cluster center can be modified as follows:

$$\begin{aligned}c_j &= e_{\text{low}} \times \frac{1}{N_{\text{low}}} \sum_{x \in w_{\text{low}}} X + e_{ip} \times \frac{1}{N_{\text{low}}} \sum_{x \in w_{up}} X.\\ j &= 1, 2, 3, \ldots, k, e_{\text{low}} + e_{up} = 1\end{aligned} \tag{3}$$

Among them, w_{low} and w_{up}, respectively, represent the lower approximation set and the upper approximation set of the j th cluster; e_{low} and e_{up}, respectively, represent the weights of the lower approximation set and the upper approximation set of the j th cluster when finding the cluster center, where $e_{\text{low}} + e_{up} = 1$. And, because the lower approximation set has a greater impact on the cluster center than the upper approximation set, generally $e_{\text{low}} > e_{up}$. N_{low} and N_{up} represent the number of objects in the lower approximation set and the upper approximation set of the j th cluster, respectively.

The basic principle of K-means clustering, which expands on the original K-means concept, is to treat each cluster as an interval or rough set. To achieve the goal of a quick and precise push, the rough set theory is used in this paper to retrieve usage data from already existing financial instructional resources on the Internet. The rough K-means method is also used to model, and the correlation between user information and instructional resources is examined. Additionally, the model has both offline and online components. When users are offline, the modified cosine similarity method is used to calculate their similarity to the cluster center. Users are then roughly clustered according to this similarity using the rough K-means user clustering algorithm. All users are then assigned to the upper and lower approximations of the K user clusters to create the initial neighbor set of users. Find the target user's nearest neighbor online, make a prediction about the user's item score, and produce a top-N recommendation. The relationship between educational resources and knowledge points is closest, it is discovered after analyzing the gathered educational resources, and the consideration of knowledge points is frequently the searchers' starting point to improve understanding and application of a particular knowledge point. It is important to check the quality of resource construction as it is being done. The resources can be evaluated through the following aspects: (1) educational nature of resources, (2) scientific nature of resources, (3) technical nature of resources, (4) the artistry of resources, and (5) scientific nature of resources. For the rough set clustering proposed in this paper, the clustering result is no longer a cluster with a definite boundary, and each cluster consists of two parts, the lower approximation set, and the upper approximation set. The lower approximation set contains certain objects belonging to the cluster, which can be obtained by its properties. Objects in the lower approximation set must be contained in the upper approximation set. The objects contained in the upper approximation set include not only the objects contained in a lower approximation set but also the objects on some other approximation sets. In this paper, the modified cosine similarity is used to calculate the similarity in the rough K-means user clustering algorithm. The calculation formula is as follows:

$$\mathrm{Sim}(i,j) = \sum\nolimits_{c \in I_{ij}} \left(R_{i,c} - \overline{R_i} \right) \left(\frac{R_{j,c} - \overline{R_j})}{\sum_{c \in I_i} \left(R_{i,c} - \overline{R_i} \right)^2 \sum_{c \in I_j} \left(R_{j,c} - \overline{R_j} \right)^2.} \right) \tag{4}$$

Among them, $R_{i,c}$ represents the rating of item c by user i; $\overline{R_i}$ and $\overline{R_j}$ represent the average rating of the item by user i and user j, respectively; I_{ij} represents the set of items jointly rated by user i and user j; I_i and I_j represent user i and user j, respectively, a set of items scored by JJ. The similarity of documents to be recommended can be described in two ways:

$$W\langle C, T\rangle. \tag{5}$$

Among them, C represents the weight of cosine similarity, and T represents the weight of time. The formalized formula of time importance is described as follows:

$$W\langle t_i\rangle = \log \frac{|T|}{|T_i|}. \tag{6}$$

Among them, T represents the most frequent existence time of the document in the resource library and T_i

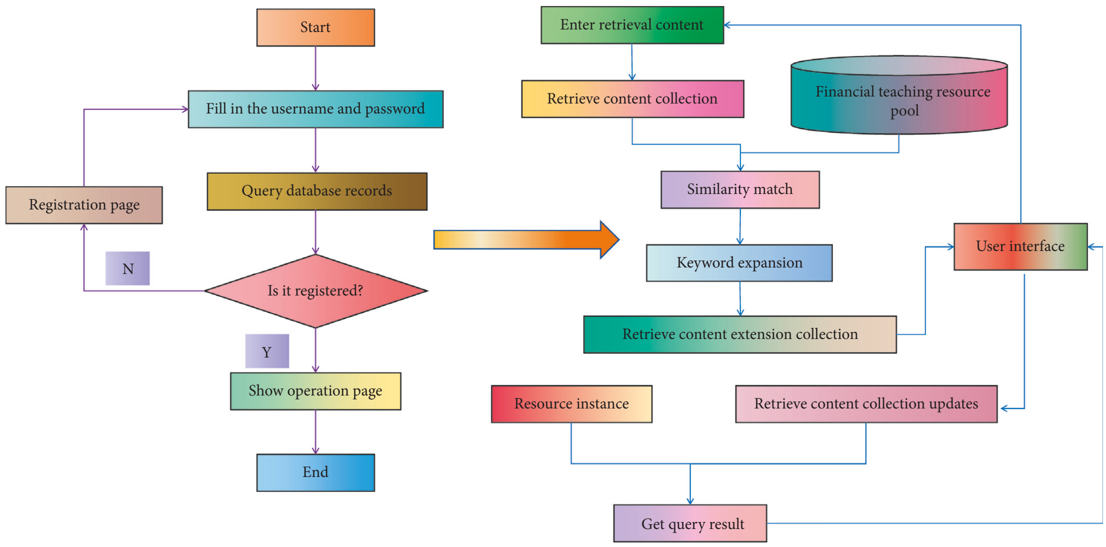

FIGURE 2: User registration and retrieval process of the system.

represents the existence time of the document resource to be recommended. The formula for calculating similarity with time weight is

$$\mathrm{Sim}\left(p_i, u_a\right) = C_{aj} \cdot q_{ij} \cdot W\left(t_i\right) \cdot \mathrm{cosine}\left(D_i, S_a\right). \tag{7}$$

Among them, D_i is the keyword vector of the document resource; S_a is the user's interest degree vector; C_{aj} is the user's interest degree in this category of resources; Q_{ij} is the affiliation of the document to be recommended in this category; and $W\left(t_i\right)$ is the time important of the document to be recommended. In this paper, a commonly used measurement method for evaluating the recommendation quality of recommender systems, that is, the mean absolute deviation is used as the measurement standard. Its formula is as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} p_i - q_i}{N}. \tag{8}$$

The domain is a vocabulary of related domain terms and their relationships, which enables people to reach a common understanding of terminology rules in related domains, that is, "ontology can be defined as a form of specification of a shared conceptualization." The financial ontology library is the basis of retrieval model. The financial management system includes six modules: resource storage module, resource management module, resource retrieval module, resource push module, resource demand module, and push task module. The user registration and retrieval process of this system are shown in Figure 2.

In this paper, users with different similarities are divided into the lower approximation of this class. Users with small similarity differences are divided into the upper approximation of the class. This avoids the situation that users are on the edge of the class. In addition, users in the upper approximation often belong to multiple classes, to reflect users' multi-interest. Applying cluster analysis to the retrieval results of educational resources can make users locate the educational resources they need more quickly, which is conducive to the full use of educational resources. For those educational resources that do not belong to strict categories, people hope to find them in two or more categories. Using the clustering algorithm based on the rough set in this paper, this problem can be easily solved. In this paper, when the rough K-means algorithm is used to cluster users, some definitions in the rough K-means algorithm are revised in consideration of the problem of users' multiple interest. Therefore, the lower approximation and the upper approximation can be used to describe users' multi-interest and interest persistence from the attention and preference of attribute values, and the usability of clustering results can be improved. The difference between the rough clustering algorithm and the general clustering algorithm is that the idea of upper and lower approximations is introduced when calculating the attribution relationship of samples. According to the similarity between users and clustering centers, samples that are certain to belong to a certain class are attributed to their corresponding lower approximations, and samples that are uncertain to belong to this class are attributed to their corresponding upper approximations.

4. Result Analysis and Discussion

After implementing the English instructional resource management recommendation system, this paper designs an evaluation experiment for the model and algorithm. The main content of this chapter is the comparative experiment of the model and algorithm and the analysis of its results. The validity of the database construction and push model proposed in this paper is verified by a course related to finance in an open class. Search the keyword "finance" in the system, and extract the related attributes of the course. In addition, 500 users' personal information, their courses, and 100,000 scoring records are selected, and they are divided into five disjoint subdatasets. Four of them are combined as the base set and the other as the test set. Select the top 200

Table 1: Statistics of experimental data.

Serial number	Index	Data
1	Subscriber number	500/person
2	Quantity of resources	1325/PC
3	Scoring quantity	100000/piece
4	Sparse grade	93.16%

users and their corresponding project scores for the experiment. The statistics of experimental data are shown in Table 1.

It can be seen from the data in the table that the data sparsity level reaches 93.16%, indicating that it is extremely sparse. The granularity division of keywords is related to the user's search results for instances. To better describe the example, the granularity of keywords is determined. The granularity of keyword division follows two principles: pertinence and independence. That is, there is no obvious inclusion relationship between keywords, and it can correctly describe the characteristics of examples. The running time of different systems is shown in Figure 3.

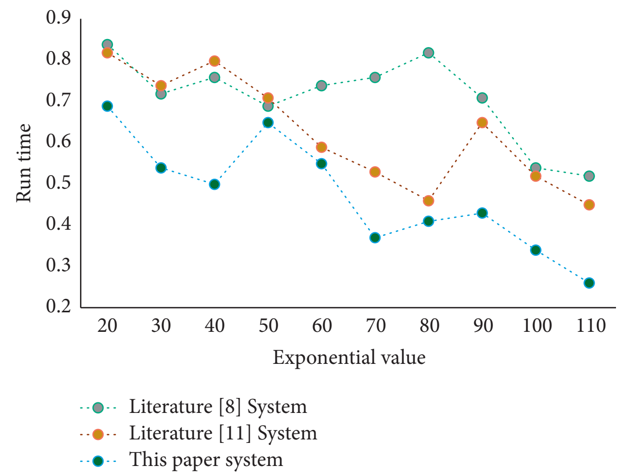

Figure 3: Comparison of running time of different systems.

It can be seen from Figure 3 that this method runs faster. And, the users in the lower approximation have a greater influence on the calculation of clustering centers than those in the upper approximation, which is also consistent with reality. In this paper, the improved rough K-means clustering is used to cluster users, and the initial neighbor classes of users are formed. Each class consists of a lower approximation set and an upper approximation set and is labeled. The absolute difference of similarity is used to reflect the difference between similarities, which is very suitable for rough user clustering as the basis for judging user affiliation. A large similarity difference means that the attribution relationship is clear, while a small similarity difference means that the attribution relationship is not clear. The MAE (mean absolute error) results of different algorithms are shown in Figure 4.

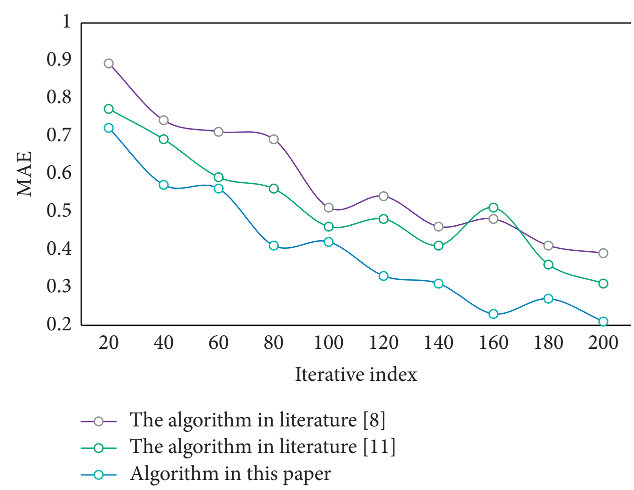

Figure 4: MAE results of different algorithms.

The smaller the MAE value, the more accurate the score prediction is, and the higher the recommendation quality is. It can be seen from Figure 4 that the method proposed in this paper is superior to other comparative recommendation methods in the accuracy of recommendation. 100 users were selected to rate the use of this system, and the results were compared with those of the other two systems. The result is shown in Figure 5.

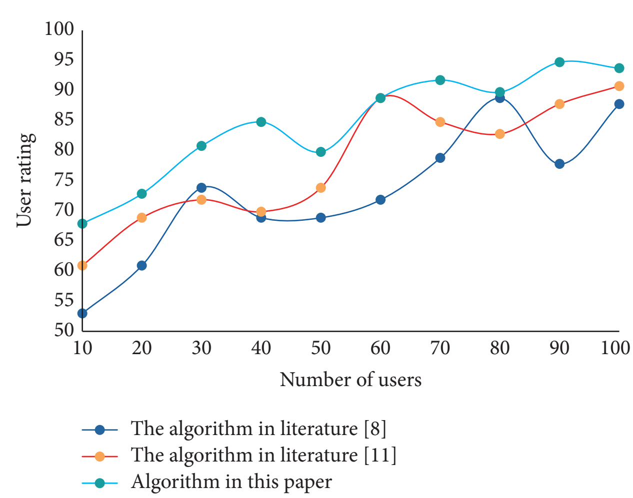

Figure 5: User's subjective rating results.

It can be seen from the results of users' subjective ratings that user satisfaction with this system is high. It can better meet the needs of users. In this paper, the two most applicable indexes in the recommendation model—precision and recall—are selected to verify the recommendation quality of this model. Table 2 shows the experimental results of the two evaluation indexes.

In this algorithm, users are roughly clustered according to the similarity between them and the clustering center, and users are assigned to the upper approximation and the lower approximation of K users' clusters, which allows overlapping between classes, thus reflecting users' multi-interest and avoiding the situation that users are on the edge of classes. According to the relevant data, the instructional resources

Table 2: Experimental results of evaluation indicators.

Model	Precision ratio (%)	Recall ratio (%)
Traditional recommendation model	88.64	89.31
Rule-based recommendation model	86.39	89.97
Content-based recommendation model	89.13	90.34
Recommended model in this paper	94.35	95.94

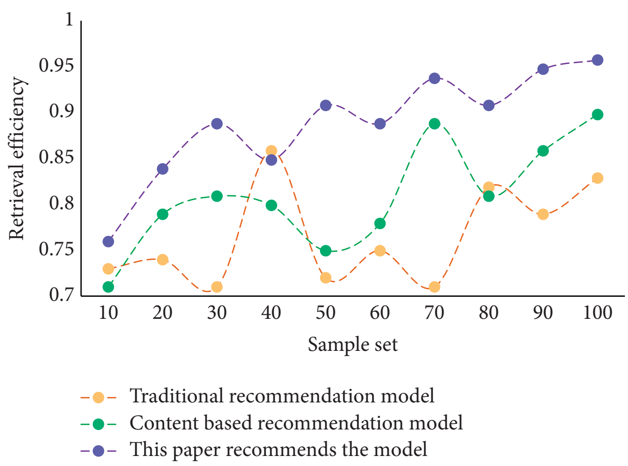

Figure 6: Retrieval efficiency results of the model.

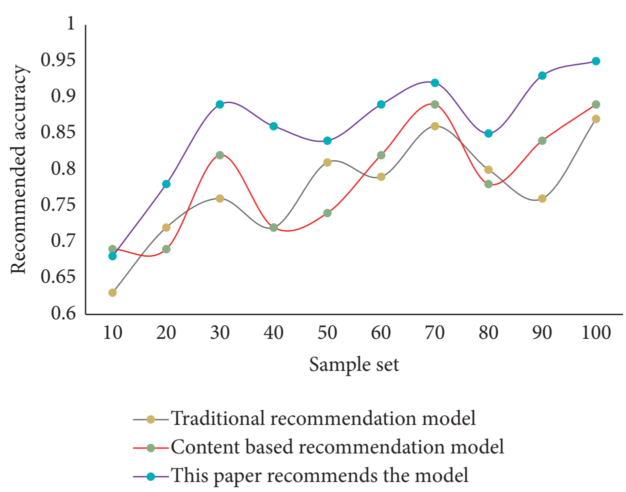

Figure 7: Comparison of recommended accuracy of different models.

suitable for users can be predicted. The retrieval efficiency of the model is shown in Figure 6.

Experiments show that the system can achieve high retrieval efficiency, and the introduction of user feedback makes the retrieval results more accurate. A comparison of recommended accuracy of different models is shown in Figure 7.

From the data in Figure 7, it can be seen that the financial instructional resource management recommendation system in this paper can quickly and accurately predict users' demand for instructional resources, push suitable resources for them, and improve the query speed and utilization efficiency of the resource pool. Its performance is superior to that of the comparison system. Through a large number of experimental data analyses in this chapter, it can be seen that the financial instructional resource management system based on rough set theory is stable. The recommended precision rate can reach 94.35%; And, the recommended recall rate is as high as 95.94%, which is higher than the traditional method. The financial instructional resource management system based on the rough set theory has good performance. And, using this system can effectively improve users' satisfaction. It can effectively provide suitable high-quality resources for financial teaching and can better meet the user experience.

5. Conclusions

The management and storage of resource data are gradually emerging as a new area for resource database development as a result of the growing development of resource database construction. Reasonable data storage and resource management techniques can help administrators manage and maintain the system more easily while using less hardware and staff. They can also significantly increase the speed of the network and the efficiency of resource access. Additionally, individualized resource recommendations can boost learning effectiveness by assisting students in quickly and accurately locating relevant, high-quality resources. The construction and implementation of a financial instructional resource management system based on the rough set theory are the main subjects of this paper. First, this paper analyses the current state of resource pool construction, draws lessons from the successful resource pool construction methods and experience, and proposes specific actions for resource pool application and promotion. It then looks at the development of a financial instructional resource pool, which serves as a reference for the subsequent projects for different majors. The study demonstrates that this system's precision can reach 94.35 percent. Additionally, the recommended recall rate is higher than the conventional method at 95.94 percent. The rough set theory-based system for managing financial educational resources is reliable. Furthermore, it effectively satisfies a variety of user experiences and increases resource users' satisfaction. However, given that the financial instructional resource system is a complex learning platform and is constrained by both technological and time constraints, there are still some issues that need to be resolved in the research and development of this system. The financial instructional resource management system will be further enhanced by taking into account how different initial clustering centers affected the clustering outcomes. This study is intended to increase teaching support and aid in raising student achievement.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author does not have any possible conflicts of interest.

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References

[1] Q. Yuan, "Network education recommendation and teaching resource sharing based on improved neural network," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 4, pp. 5511–5520, 2020.
[2] H. Wang and W. Fu, "Personalized Learning resource recommendation method based on dynamic collaborative filtering[J]," *Mobile Networks and Applications*, vol. 26, pp. 1–15, 2020.
[3] C. Klupiec, S. Pope, R. Taylor, D. Carroll, M. Ward, and P. Celi, "Development and evaluation of online video teaching resources to enhance student knowledge of livestock handling," *Australian Veterinary Journal*, vol. 92, no. 7, pp. 235–239, 2014.
[4] M. Minano, E. U. Grande, D. P. Ezama, and M. J. R. Menendez, "Multimedia teaching resources for financial accounting in bilingual degrees[J]," *Educación XX1*, vol. 19, no. 1, pp. 63–89, 2016.
[5] M. A. Jan and F. Khan, Eds., in *Proceedings of the First EAI International Conference, BigIoT-EDU 2021, Virtual Event*, vol. 392, Springer Nature, Cham, August 2021.
[6] M. Luehrmann, M. Serra-Garcia, and J. Winter, "Teaching teenagers in finance: does it work?[J]," *Journal of Banking & Finance*, vol. 54, no. 5, pp. 160–174, 2015.
[7] C. K. Hsu, G. J. Hwang, and C. K. Chang, "A personalized recommendation-based mobile learning approach to improving the reading performance of EFL students," *Computers & Education*, vol. 63, no. 4, pp. 327–336, 2013.
[8] J. N. da Silva, S. Lima, M. Anne et al., "KinChem: a Computational resource for teaching and Learning Chemical Kinetics[J]," *Journal of Chemical Education*, vol. 91, no. 12, pp. 2203–2205, 2014.
[9] H. Zhu, "Research on Human resource recommendation algorithm based on Machine Learning," *Scientific Programming*, vol. 2021, no. 3, pp. 1–10, 2021.
[10] Q. Sun, "Evaluation model of classroom teaching quality based on improved RVM algorithm and knowledge recommendation[J]," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 2457–2467, 2021.
[11] K. Almohammadi, H. Hagras, B. Yao, A. Alzahrani, D. Alghazzawi, and G. Aldabbagh, "A type-2 fuzzy logic recommendation system for adaptive teaching[J]," *Soft Computing*, vol. 21, no. 4, pp. 1–15, 2015.
[12] D. C. Clarke and P. F. Skiba, "Rationale and resources for teaching the mathematical modeling of athletic training and performance," *Advances in Physiology Education*, vol. 37, no. 2, pp. 134–152, 2013.
[13] S. Li and T. Li, "Incremental update of approximations in dominance-based rough sets approach under the variation of attribute values," *Information Sciences*, vol. 294, pp. 348–361, 2015.
[14] H. Bing, Y. L. Zhuang, H. X. Li, and D. K. Wei, "A dominance intuitionistic fuzzy-rough set approach and its applications [J]," *Applied Mathematical Modelling*, vol. 37, no. 12-13, pp. 7128–7141, 2013.
[15] B. Sun, W. Ma, and X. Xiao, "Three-way group decision making based on multigranulation fuzzy decision-theoretic rough set over two universes[J]," *International Journal of Approximate Reasoning*, vol. 81, pp. 87–102, 2016.
[16] K. Xie, G. Di Tosto, S. B. Chen, and V. W. Vongkulluksn, "A systematic review of design and technology components of educational digital resources," *Computers & Education*, vol. 127, pp. 90–106, 2018.
[17] H. Nicky, "Digital technologies in low-resource ELT contexts [J]," *ELT Journal*, vol. 68, no. 1, pp. 79–84, 2014.
[18] J. Jalkanen and H. Vaarala, "Digital texts for learning Finnish: shared resources and emerging practices[J]," *Language, Learning and Technology*, vol. 17, no. 1, pp. 107–124, 2013.
[19] Y. Zhu, H. Lu, P. Qiu, K. Shi, J. Chambua, and Z. Niu, "Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization," *Neurocomputing*, vol. 415, pp. 84–95, 2020.
[20] E. Q. Wu, D. Hu, P. Y. Deng et al., "Nonparametric bayesian prior inducing deep network for automatic detection of cognitive status," *IEEE Transactions on Cybernetics*, vol. 51, no. 11, pp. 5483–5496, 2021.