Hindawi
Mobile Information Systems
Volume 2022, Article ID 4504779, 10 pages
https://doi.org/10.1155/2022/4504779

Research Article

College English Precise Teaching Model Using Combination Optimization Collaborative Filtering Algorithm

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Received 2 April 2022; Revised 11 May 2022; Accepted 13 May 2022; Published 30 June 2022

Academic Editor: Liping Zhang

With the rapid development of the Internet and various learning platforms, the explosive growth of resources in the field of education has made the recommendation of learning resources increasingly important, and it has gradually become the research focus of academic circles. This article develops an English precision teaching platform based on the CF algorithm of combinatorial optimization to accurately recommend English learning materials that meet the learners' personal preferences and achieve precision teaching. This optimization algorithm takes full advantage of the background information of users, calculates the similarity between users, and forms the best neighbor set, and then recommends the learning resources evaluated by neighbors with similar interests to the target users, addressing the problem of data sparseness and cold start, which leads to a decline in recommendation accuracy. On different data sets, experimental results show that this method's recommendation accuracy is 94.6%, which is higher than the CF algorithm of multifeature fusion by 4.5% and the traditional CF algorithm by 9.7%. The findings show that when applied to English instructional resources, this method is accurate and practical and that it can effectively recommend resources that are appropriate for users to achieve accurate CET.

1. Introduction

With the explosive development of the Internet, the data related to human behavior in the Internet is becoming more and more abundant and diverse. At the same time, information technology has made the development of various industries advance by leaps and bounds, and the application of various technologies in the field of education has also been reflected [1]. In the field of education, the penetration of intelligence will inevitably bring about a high degree of integration of technology and the classroom. Developing smart classrooms, carrying out precision teaching, and providing accurate decision-making will surely become the new trend of educational informationizention in the future. This has a great influence on the profound changes in the field of education [2]. Quasi-teaching can improve teaching efficiency and ensure the quality of our teaching. How to achieve precision teaching is a problem that educators have been discussing for many years [3]. Accurate testing is applied to teaching practice, and students' learning changes are measured with appropriate tools. It aims at tracking students' learning performance and providing data decision support by designing the measurement process, providing data reference for subsequent teaching by further analysis, and guiding teaching work accurately [4]. To realize the accurate development of the whole course teaching, the choice of teaching platform should be combined with the advantages of the modern Internet, and the online and offline teaching methods should be actively adopted to systematically analyze students' learning behaviors.

The popular method of providing information can no longer meet the individual needs of differentiated users as society evolves [5]. The user's active conscious behavior is the traditional information acquisition method, and the user is the subject. A personalized recommendation is the intelligent recommendation prediction and related decision-making subject, as opposed to the traditional information acquisition method. The core component of a recommendation system is recommendation technology, which can influence the quality and effectiveness of the system's recommendations. Information retrieval and information filtering technology underpin personalized recommendation technology [6]. A personalized recommendation technology has been widely used and recognized as the primary technology for meeting the personalized needs of Internet users. This recommendation system can actively recommend information to users that they are interested in, reducing the time spent searching for information and increasing the efficiency with which users obtain information [7]. CF (collaborative filtering) recommendation technology is currently the most widely used personalized recommendation technology, and it has been successfully applied in a wide range of Internet fields. However, as the Internet grows in popularity and the number of users and products grows, CF recommendation technology is running into some serious issues. Data sparsity, cold start, scalability, accuracy, diversity, dynamics, and other issues are all part of it [8].

This article addresses these issues one by one, constructing a personalized instructional resource recommendation model based on the CF recommendation algorithm of combinatorial optimization. This model's resources are more efficient and accurate, and they can effectively provide some technical support for precise college English teaching. The following are the article's innovations: (1) it innovatively combines the research of the CF algorithm and the English precision teaching model, and constructs an English teaching platform based on the combinatorial optimization CF algorithm. The platform takes full advantage of the benefits of mobile learning while also recommending learning resources to meet the needs of various learners. (2) The personalized recommendation technologies are examined and compared in this article, as well as the general CF recommendation technology. Also, based on the existing issues, improve the CF algorithm. In the face of data scarcity, this article does not rely solely on the project's user rating data but also includes the user's background information attribute. The experimental results show that when compared with the traditional collaborative algorithm, the optimization algorithm improves recommendation accuracy, proving that the optimized recommendation algorithm is effective.

2. Related Work

Personalized recommendation technology has already been widely used in e-commerce, movies, music, and other fields and achieved good results. Nowadays, with the development of online education, personalized recommendation technology has gradually attracted the attention and application demand in the field of education. Compared with foreign research on recommendation system, domestic research started late. Most of the domestic researches is summarized based on the CF algorithm proposed by foreign scholars, or some improvements and optimizations are made to the original algorithm. This article studies the current development of the CF algorithm and lays a theoretical foundation for the recommendation of instructional resources in this article.

Liu et al. proposed a CF recommendation method based on user influence relationship for a personalized recommendation of learning resources. This method is not limited by the organizational heterogeneity and diversity of learning resources [9]. Yu and Li analyzed the working principle of the clustering algorithm and genetic algorithm, understood the advantages and disadvantages of the algorithm, and introduced the genetic K-means algorithm. Genetic K-means and collaborative algorithm are combined to calculate the similarity between user attributes, and then form the best neighbor set between users [10]. Based on CF recommendation technology, Zhou and Zhang studied the recommendation model of learning resource groups [11]. Dong et al. studied the implementation strategy of precision teaching under the background of educational reform and the rapid development of information technology [12]. Wang believed that in the reform of teaching mode, teachers can provide feedback and analyze a large amount of data such as teaching platforms, digital resources, and teaching evaluation to find out the commonalities and differences of students' learning; make adjustments to the classroom teaching process and knowledge points [13]. By analyzing the traditional teaching methods, Bradford believed that the shortcomings of the previous teaching methods in colleges and universities are the teachers are in a relatively closed situation when imparting knowledge. Long-term course teaching in such an environment is likely to cause information asymmetry in the grasp of teaching information, which has a certain impact on teachers' course teaching and students' knowledge absorption [14]. Thompson and others believe that the coverage of knowledge points by pretest questions pushed by teachers before class is the core of precision teaching, and the teaching wisdom and strategies generated after the analysis of pretest data are crucial to precision teaching [15]. In the precise teaching model proposed by Johnes and Johnes, the evaluation model mainly analyzes the students' learning situation through intelligent technical means, and generates a visual evaluation report [16]. Cazden achieved full coverage of precision teaching in the entire online and offline teaching links of college English. Through the overall data analysis chart of the class, it is judged whether the students have reached the preset teaching goals [17]. To effectively utilize the user-item rating matrix in the collaborative algorithm, Baena-Extremera and Granero-Gallegos refined the characteristics of user-based and item-based similarity calculation, and combined the advantages of the two calculations similarity to optimize the calculation similarity formula [18].

This article summarizes the advantages and disadvantages of each method and proposes a CF recommendation algorithm for combinatorial optimization based on an in-depth review of related literature. Users are classified optimally by learners' background information in this article, and efficient and accurate recommendation services are realized, as well as a personalized recommendation system suitable for use in the field of learning resources. For the data sparsity problem of the traditional CF algorithm, the item score prediction algorithm, before CF recommendation, predicts the score of unrated items based on the scores of similar users, thereby improving the resource score rate. Simultaneously, the grey relational degree is chosen as the method of similarity measurement in the CF recommendation, which reduces the impact of low distinguishability and sparsity of data to some extent. This method can recommend learning resources to meet different learners' learning needs, according to the research, which saves time and energy for learners and has some practical implications.

3. Methodology

3.1. Personalized Recommendation and CF Algorithm. Recommendation algorithms can be divided into CF, content filtering, and social filtering according to the data used. CF recommendation is the most widely used and accepted technical scheme in personalized recommendation system, and its application and research fields are the focus of attention [19]. The basic idea of CF is very intuitive: in daily life, people often make some choices according to the recommendations of relatives and friends. CF technology is to apply this idea to information recommendation and recommend to a certain user based on other users' evaluations of certain information. The main content of collaborative recommendation is that the system uses the historical behaviors, comments, and opinions of known user groups to predict the tendency of certain learning resources that target users may be interested in or will buy. CF recommendation algorithm establishes a user interest model by analyzing the historical behavior data of users and predicts the interest of target users in items that have not been browsed before, to make recommendations for them. This kind of method can be said to use swarm intelligence to explore users' potential interests, which is the embodiment of "collaboration." The CF recommendation method has several characteristics. Specifically, (1) good universality, (2) good recommendation accuracy, and (3) sharing neighbor's experiences make recommendations more efficient and targeted. CF algorithm is based on the assumption that providing the target users with the resource content they are interested in is to first find other user groups with similar interests and hobbies to the target users, and then recommend the resource content that the user groups are interested into the target users.

The most basic method in information filtering is content filtering recommendation technology, which is also a recommendation technology. Content filtering recommendation technology is suitable for recommending text-based learning resources, but not for recommending multimedia-based learning resources. Information retrieval and filtering technology are used to develop content-based recommendation algorithms. The research of text direction recommendation is primarily devoted to information retrieval and information filtering technology, both of which are widely used today, and the content-based recommendation algorithm also has important applications in this regard. The content-based recommendation does not rely on users' previous project scores or feedback information but instead creates an interest feature model for them based on the content feature information of projects they've been interested in. The system then selects the products that are most similar to the items that users have previously liked, i.e., different candidate items are compared with the items that users have previously liked, and the items with the highest matching degree are recommended. Alternatively, the user can be directly recommended items that are most similar to their preferences. Today's content-based recommendation can extract the feature vectors of the processed objects more accurately, thanks to the continuous development of machine learning [20–22] and statistical analysis technology. Bayesian classification neural networks and principal component analysis are two of the most commonly used technologies. The core of a content-based recommendation algorithm is to provide users with recommended items based on the relationship between resource content and user interests. Content-based recommendation algorithm has some advantages. Specifically, (1) it can deal with the cold start of new projects, (2) it cannot be constrained by the problem of the sparsity of scoring, and (3) it has good interpretability.

The term "CF recommendation algorithm" refers to a group of algorithms that make recommendations by constructing user interest models based on historical user behavior data, with neighbor-based and model-based algorithms being the most common [23]. The core of the CF recommendation algorithm based on nearest neighbor is a type of algorithm that makes recommendations based on nearest neighbor information. The model-based CF algorithm creates a user-project evaluation model before making item recommendations based on it. The model-based method is based on a model generated by applying statistics and machine learning to existing data, rather than on some heuristic rules for prediction calculation. The collection of user data, which will affect the recommendation effect of the recommendation algorithm, is an important foundation of the CF recommendation algorithm. The users themselves provide the recommendations based on CF recommendations. Users' recommendation accuracy is related to the generated neighbor sets and influenced by similar users, and their recommendation results are frequently related to their own scoring records. Without analyzing product content and attributes, the CF recommendation algorithm is said to use swarm intelligence to discover users' potential interests. It has a wide range of applications in the field and has gotten a lot of attention from researchers. Related technologies have also been very successful and widely adopted.

3.2. English Precision Teaching Platform Based on Combinatorial Optimization CF Algorithm. Learning resources refer to information resources formed by planning and summarizing according to education and teaching standards. The construction of learning resources is also the basic content of modern distance education. In the online education system, the organization of resources is not uniform, some resources are outlined and some resources are non-outlined. It mainly includes building basic learning materials, building a network resource database, developing a learning resource system, and developing a distance instructional resource platform. CF can only predict the products that users may like according to their historical behavior data, and it also gains a good recommendation effect in practical application. When a resource gets enough evaluation, the average value of this resource evaluation can be used to measure the real quality or quality of the resource. If the average value is high, it means that the resources are of good quality, which is very helpful for learners to understand the knowledge of the major. Therefore, for the recommendation of high-quality resources, we will select and recommend the resources with the highest average value from the users. The English learning platform based on the CF algorithm mainly includes four functional modules, namely, the learning module, resource search module, personal center, and personalized recommendation module. A personalized recommendation module is the core module in this platform. The difficulty of this module lies in which way and rules to recommend interesting materials to learners. The flow of this algorithm is shown in Figure 1.

Calculating the similarity between two users is used to find users with similar interests, and the user's interest is expressed in the project by the user's interest vector. The essence of content filtering in the vector space model is to match the resource model with the user model, that is, to calculate the similarity between the resource and user models. The interest value of items that have given positive feedback in this article is set to 1 only for the data set of item sets for which users have given positive feedback, otherwise it is 0. New resources will be added to the recommendation system on a regular basis, allowing users to learn new information. You can recommend the latest resources of your major to students regardless of their hobbies when recommending the latest resources. Although the traditional CF algorithm can make corresponding recommendations, it frequently relies solely on the user's rating or positive feedback information, ignoring related time series behavior data, and user- or project-related data. However, making effective use of this data can help the recommendation algorithm perform even better. The use of a fitness function is a factor in the genetic algorithm's calculation process, which drives the algorithm to find the best population. The lack of scoring data for the CF recommendation algorithm causes the cold start problem. In this regard, content filtering recommendations can be a beneficial addition to the CF algorithm.

Let formula (1) be the set of learners and formula (2) be the set of learning resources. The interestingness function $g_{l,m}$ can be used to predict the user l_i's rating for the resource m_j.

$$L = \{l_1, l_2, \ldots, l_i, \ldots, l_N\}, \tag{1}$$

$$M = \{m_1, m_2, \ldots, m_j, \ldots, m_n\}. \tag{2}$$

The correlation similarity method is used to calculate the similarity between learners:

$$\mathrm{sim}(x, y) = \frac{\sum_{m\in m_{zy}} \left(g_{x,m} - \overline{g}_x\right)\left(g_{y,m} - \overline{g}_y\right)}{\sqrt{\sum_{m\in m_{zy}} \left(g_{x,m} - \overline{g}_x\right)^2 \sum_{m\in m_{xy}} \left(g_{y,m} - \overline{g}_y\right)^2}}. \tag{3}$$

Among them, $x \in L$, $y \in L$, $g_{x,m}$, and $g_{y,m}$ are the scores of learner x and learner y on resource m, respectively; $\overline{g}_x$ and $\overline{g}_y$ are the average scores of learner x and learner y, respectively, and:

$$\begin{aligned} \overline{g}_x &= \left(\frac{1}{|m_x|}\right) \sum_{m\in m_x} g_{x,m}, \\ \overline{g}_y &= \left(\frac{1}{|m_y|}\right) \sum_{m\in m_y} g_{y,m}. \end{aligned} \tag{4}$$

Among them:

$$\begin{aligned} m_x &= \left\{m \in M | g_{x,m} \neq 0\right\}, \\ m_y &= \left\{m \in M | g_{y,m} \neq 0\right\}. \end{aligned} \tag{5}$$

Among them, m_{xy} is a collection of resources jointly scored by the learner x and the learner y.

In this article, the user influence relationship is obtained by mining the user's time series comment and reply behavior data. Assuming the user influence relationship mined from this time series behavior data, the sparse user-item interest matrix is filled in according to the obtained user influence relationship, to improve the accuracy and recall rate of recommendation. The function of a genetic operator is to drive the searching process of the algorithm, and crossover and mutation are two basic genetic operators. Crossover enables each individual to inherit some information from the parent chromosome, and then recombine and exchange it to generate new individuals. The intersection of two points produces two random positions, and then the genes inherited from parents' chromosomes are exchanged. In the recommendation process of the CF system, the historical behavior of users is dynamic. That is to say, the data used in the recommendation process will change after the recommendation or the change in the user's rating behavior. And its user-item scoring matrix is sparse, that is, with the increase of matrix dimensions, the proportion of its scoring value in the matrix scale becomes smaller and smaller. Therefore, for the problem of data sparseness, we can use the item score prediction algorithm, which can predict the score of unrated items through the scores of similar users before CF recommendation, to improve the scoring rate of resources. At the same time, in the CF recommendation, the grey relational degree is chosen as the method of similarity measurement, which can reduce the influence of low data distinguishability and sparsity to a certain extent. Predict the user's score on the target project by the target user's score on the resources in the similar project set, and present the top N items with the highest predicted score, namely Top-N, to the user as the recommended result. The formula for predicting the user's rating of resources is as follows:

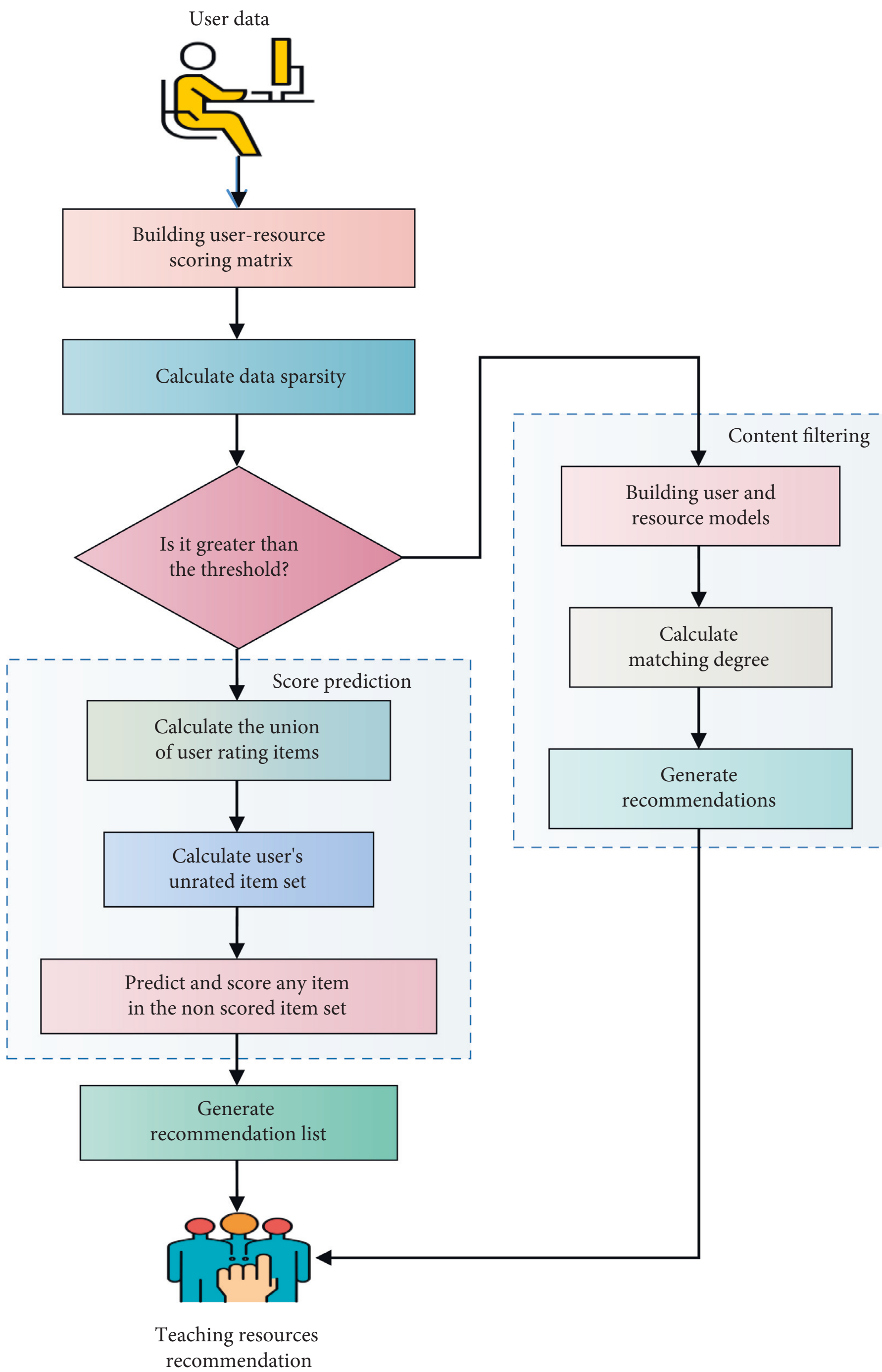

Figure 1: Algorithm flow chart.

$$R_{i,s} = \frac{1}{T} \sum_{j \in X} \bullet R_{j,s},$$
$$R_{i,s} = \Theta \sum_{j \in X} \mathrm{Sim}(x, y) \bullet R_{j,s}, \tag{6}$$
$$R_{i,s} = \overline{R}_i + \Theta \sum_{j \in X} \mathrm{Sim}(x, y) \bullet \left(R_{j,s} - \overline{R}_j\right).$$

The user's predicted score is $R = \{r_1, r_2, r_3, \ldots, r_m\}$, the user's actual score is $P = \{p_1, p_2, p_3, \ldots, p_m\}$, and MAE (mean absolute error) is calculated.

$$A = \frac{\sum_{i=1}^{m} \left| r_i - p_i \right|}{m}. \tag{7}$$

Among them, r_i is the recommended value of item u and p_i is the real score of the user.

When preprocessing the data set, it counts the time series comments and replies between users. After calculating the similarity between users and resources, the N resources with the highest similarity are recommended to users. Content filtering is not the ultimate goal here, but just a process, to generate certain resource recommendations for newly registered users. The so-called degree of association is essentially the degree of difference in scoring segmented polylines, so the interpolation size between segmented polylines can be used as a measure of the degree of association. This system includes learners' behaviors of learning, browsing, downloading, collecting, and scoring resources. Teachers are mainly responsible for resource construction, including adding new English learning resources and maintaining English learning resources. In the data set of this article, there is only the data on whether users like a certain resource. Therefore, when initializing the user interest matrix in this article, the interest value of the resources that the user likes is 1, and the default value that the user does not like is 0. In this article, a threshold is set to determine what state the system is currently in. When the sparsity of the score is greater than the threshold, the system is considered to be in a "cold start" state. Then use content filtering recommendations to push resources to users. When the score sparsity is less than a given threshold, the score of the unrated items in the library is predicted by the method of item score prediction.

3.3. Implementation Strategy of Precise Teaching. The smooth progress of precision teaching is predicated on the English instructional resources systematically pushed by teachers in this article before class. Teachers prepare for accurate data mining by uploading English instructional resources and assigning advanced homework based on teaching objectives, students' learning results, learning process, and personalized data. Because data is intuitive and authentic, it can best reflect reality in a scientific experiment. Teachers used to disregard the importance of teaching data when teaching the curriculum. Even if the teacher has processed and analyzed some data during the course, it is difficult to judge the validity of the entire data analysis. The student side of the teaching platform in this article comprehensively records the students' current learning track and effect, creates a data source that accurately reflects students' learning situation, reflects timely feedback on learning effect, and provides data for students' accurate learning. Teachers receive test results and use them to guide their precision teaching. Teachers gather comprehensive pre-learning data from students, dig and analyze data in-depth, make timely adjustments to teaching difficulties, and solve common problems. Add advanced English instructional resources based on individual teacher preferences, assist students in completing selective learning by removing barriers, and lay the groundwork for offline classroom instruction.

The first factor that teachers should consider when designing teaching is that students' learning ability matches the difficulty of professional knowledge, to teach students in accordance with their aptitude and individualized teaching. Teaching analysis includes learning situation analysis, objective analysis, and content analysis. Under the traditional teaching mode, it takes a lot of time and energy to analyze students' knowledge with personalized data. Only the most direct result analysis can be obtained by testing methods such as examination papers, but all kinds of behaviors of students in the learning process cannot be reflected, and it is difficult to realize personalized and accurate data analysis. At the same time, there is a gap between theory and practice in the analysis of learning situations in traditional teaching, which leads to the failure of "student-centered" teaching design. To test the implementation effect of teachers' precise teaching more timely, we need to establish a scientific teaching evaluation system. Teaching evaluation should include students' evaluation of teachers' teaching and teachers' evaluation of students' learning. Through the establishment of the two-way evaluation system, we can count the data, adjust and implement precise teaching, and improve the teaching quality. Instructional resource recommendation based on CF algorithm and its precise teaching process are shown in Figure 2.

The core elements of constructing teaching are instructional resources. All of the resources that users can use in the learning process to help them improve their knowledge level are referred to as instructional resources in this article. Texts, courseware, videos, test questions, small applications, and other resources that can help students meet their learning goals are all examples of English instructional resources. Precision teaching based on instructional resource recommendations adheres to the humanistic theory. By guiding students, pre-class students help teachers understand the differences in students' cognitive levels. When collating relevant knowledge of English majors, teachers can use the advantages of network resources to screen the network question bank resources according to big data. Furthermore, teachers should collect and sort network resources in a variety of ways, as well as combine data analysis of teaching feedback classify and screen reasonable resources, reconstruct knowledge points and teaching processes, and truly teach students according to their aptitude. The platform in this article automatically records each student's learning activities both inside and outside the classroom, generates accurate personalized data sources, and obtains quantitative values for improving students' autonomous learning ability and knowledge application ability in all aspects of teaching through data analysis. Teachers can accurately grasp the learning situation, judge the problems, and design teaching around the analysis of the learning situation using a large amount of structured and unstructured data. Empiricism and textbook-centered teaching design and implementation are avoided. When implementing precise teaching, teachers need to design scientific teaching plans based on educational data before teaching, which includes scientific teaching analysis, teaching strategies, and teaching process design. This is the key factor to implement precise course teaching. The data of CET (College English teaching) platform can reasonably refine the corresponding teaching objectives and clarify the final teaching effect. For English teaching, accurately explain and describe students' knowledge or skill level, and

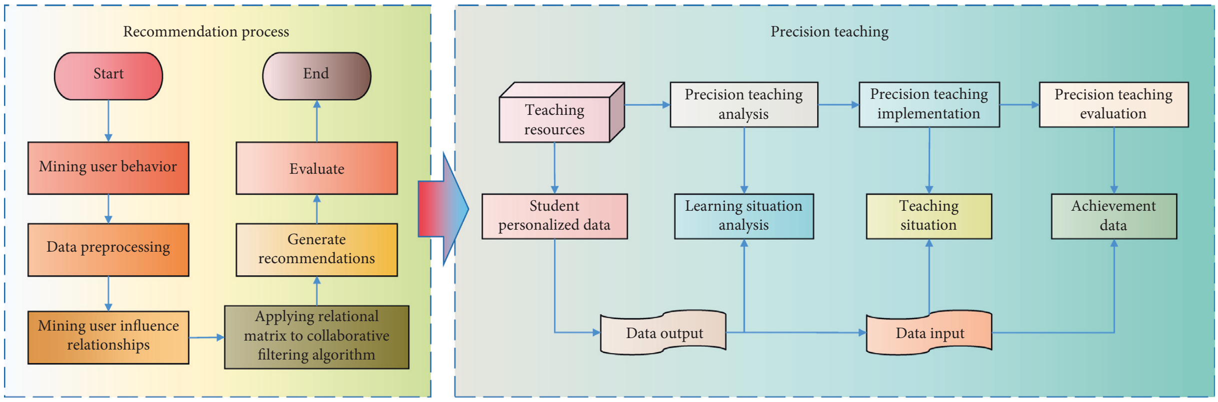

Figure 2: Instructional resource recommendation based on CF algorithm and its precise teaching process.

correspondingly decompose and refine each general goal into quantifiable goals. To help students improve their language knowledge and skills, teachers help students create online and offline multilingual environments through classroom teaching. By advocating the establishment of the network connection between knowledge systems, students can make up for the doubts and difficulties encountered in the process of self-learning before class through multiparty interaction and collaborative discussion in class. Teachers should make corresponding adjustments to the progress of classroom teaching, teaching emphases and difficulties according to the similarities and differences in students' existing knowledge, and study habits and personality characteristics. At the same time, teachers should scientifically analyze students' thinking habits and learning behaviors through effective teaching feedback data, improve classroom teaching modes and methods, and enhance the teaching effect.

4. Result Analysis and Discussion

Evaluating recommender systems and their algorithms is inherently difficult for two main reasons: (1) different algorithms may work better or worse on different datasets and (2) the goals to be achieved by the evaluation are different. Therefore, to obtain the reliability of the experimental results, this article uses different algorithms to conduct multi-index experiments on different data sets. The experiments of the method proposed in this article are validated on the Movie Lens dataset collected by Group Lens Research and the TED dataset. The data table set in this experiment contains three tables: user data table, item data table, and rate data table. The configuration of the server used in the experiment is Windows operating system; Mobile Dual Core AMD Athlon 64X2TK-571900 MHz processor; 36 G memory, 1 TB hard disk. The experiment uses 1286 pieces of data randomly selected from the data set, including the ratings given by 421 users to 512 items. The sparsity of the data is 21.6%, and each user has scored more than 50 items. This experiment adopts most of the experiments to set the ratio of the training set and test set, that is, 8/1.

The statistics of resource usage shows the download, recommendation, and collection of resources in the knowledge base, ranking according to the number of times. By switching the tabs, the corresponding ranking situation can be displayed. Clicking the specific resource entry can display the user's rating of resources and the recommendation list of similar resources. Because of the different sizes of data in the data set, and with the large amount of input data, the calculation performance of the algorithm is affected by the experimental environment, so it cannot complete the calculation task. User satisfaction is the most important index to evaluate the recommendation system, which can directly reflect the user's satisfaction with the recommendation results as the recommended person. However, it cannot be calculated offline, but can only be obtained through user surveys or online feedback. The user satisfaction of different algorithms on different data sets is shown in Table 1.

In the experiment, the data set is divided into the training set and the test set. The algorithm works in the training set, and the items in the test set are predicted by the data in the training set. The confirmation test, also known as the qualification test, mainly tests whether the functions of the personalized recommendation system of learning resources meet the requirements of users. It is mainly divided into two links: validity test and configuration review. The validity test is conducted by the users of the system. Coverage is the percentage of items that a recommendation system can recommend to at least one user. This index describes the ability of a recommendation system to explore the long tail of items. A good recommendation system should not only recommend items that users are satisfied with, but also cover as many items as possible. The coverage rate is between (0,1), and the greater the coverage rate, the better the long tail can be discovered. The coverage of different algorithms is shown in Figure 3.

In this section, the traditional CF algorithm and the multi-feature fusion CF algorithm use several different data sets, calculate on different data sets, and compare recommendation quality under the same experimental conditions. Diversity is the difference between every two items in the

TABLE 1: User satisfaction of different algorithms on different datasets.

Algorithm	Data set Movie lens dataset (%)	TED dataset (%)
Optimized CF recommendation algorithm	92.6	91.4
CF algorithm of multi-feature fusion	89.9	90.8
Traditional CF algorithm	84.5	81.4

TABLE 2: Diversity of different algorithms on different datasets.

Algorithm	Data set Movie lens dataset	TED dataset
Optimized CF recommendation algorithm	0.947	0.952
CF algorithm of multi-feature fusion	0.924	0.946
Traditional CF algorithm	0.845	0.852

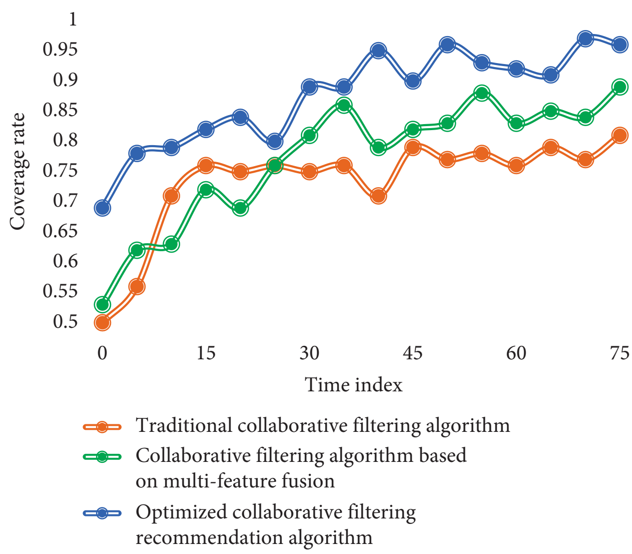

FIGURE 3: Coverage of different algorithms.

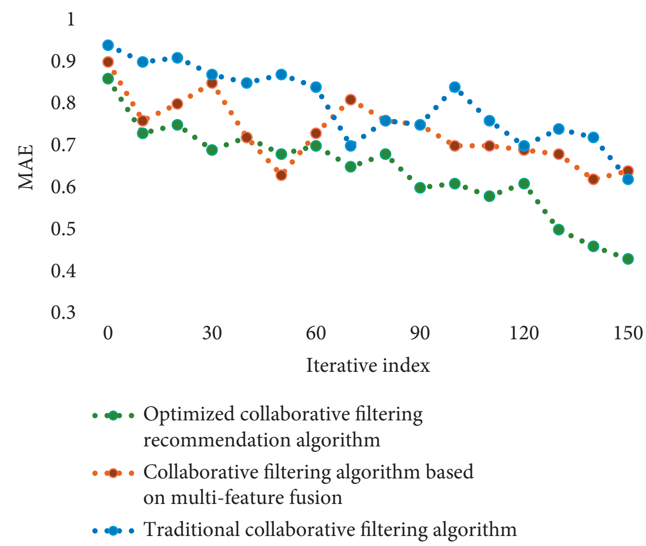

FIGURE 4: Comparison of MAE values of the different algorithms-MovieLens dataset.

recommendation list; diversity and similarity are inversely proportional, and a lack of diversity will negatively impact the user experience. User satisfaction will be reduced if the recommendation list only covers one of the user's interests, and the recommended interest is not the user's current interest. If the recommendation list covers a wide range of user interests, it will increase the likelihood that users will find items that they are interested in. Table 2 depicts the diversity of different algorithms on various data sets.

In this test, MAE is used to measure the recommendation performance of the personalized recommendation system of learning resources. MAE value is one of the most commonly used standards to measure the performance of a recommendation system. At present, almost all scholars refer to this standard when predicting the accuracy of the CF algorithm. In this article, different algorithms are tested on different test sets, and the results are shown in Figures 4 and 5.

The smaller the MAE value, the higher the recommendation accuracy, that is, the higher the recommendation performance. The selection of similar user groups has a great influence on the final recommendation results. The stability of algorithm recommendation accuracy is a major index to measure the efficiency of the CF recommendation algorithm when different neighbor sets are selected. It can be seen from Figure 5 that the improved CF algorithm has a small value, which shows that the improved algorithm effectively solves

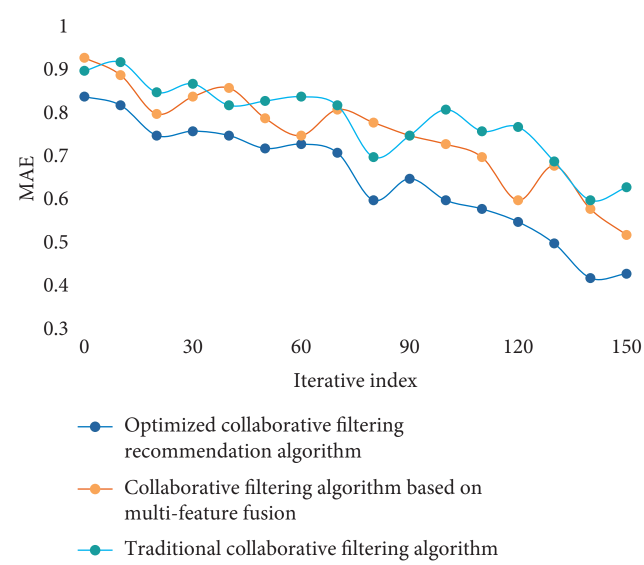

FIGURE 5: Comparison of MAE values of the different algorithms-TED dataset.

the problem that the user-item evaluation matrix cannot measure the similarity between users and items well by the traditional similarity algorithm when it is extremely sparse.

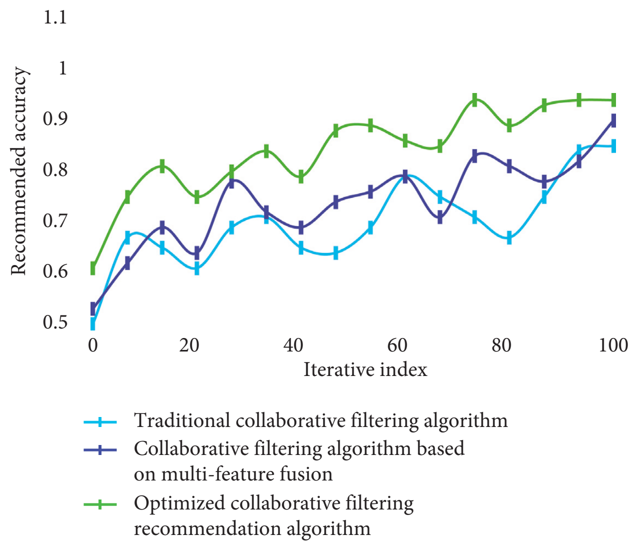

Figure 6: Comparison of recommendation accuracy of different algorithms-MovieLens dataset.

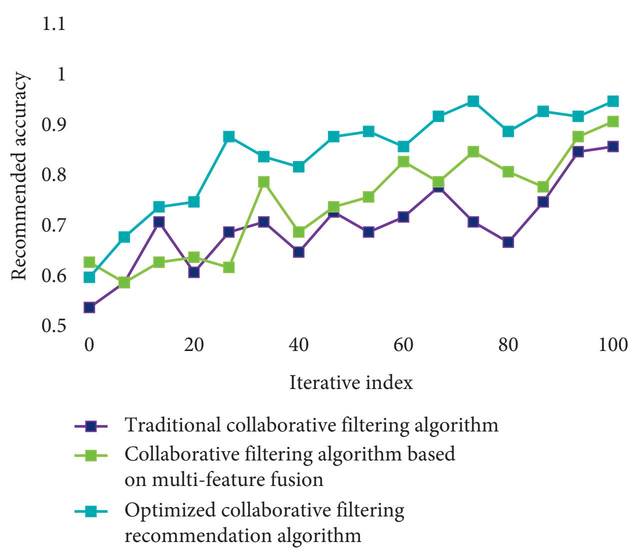

Figure 7: Comparison of recommendation accuracy of different algorithms-TED dataset.

The experimental goal of this article is to prove that the system can provide more accurate recommendation resources to users by using the optimized algorithm, and recommendation accuracy is an important criterion for evaluating the recommendation algorithm. Prediction accuracy is a measure of the ability of a recommendation algorithm to predict user behavior. When calculating this index, it is usually given an offline data set containing the user's historical behavior records. In the offline experiment, the data set needs to be divided into two parts: the training set and the test set. By building a model on the training set and predicting the user's behavior, and finally comparing the calculated and predicted results with the proportion of the user's actual behavior on the test set, it is measured. On different test sets, select neighbor sets of different sizes, and test and compare the traditional CF recommendation algorithm, multi-feature fusion CF algorithm, and the optimized recommendation algorithm in this article. The comparison results are shown in Figures 6 and 7.

According to the data in Figure 7, the recommendation accuracy of this method is 94.6%, which is higher than the CF algorithm of multi-feature fusion by 4.5% and the traditional CF algorithm by 9.7%. On the whole, the recommendation accuracy of this algorithm is the highest, followed by the multi-feature fusion CF algorithm, and the recommendation accuracy of the traditional CF algorithm is the lowest. This shows that the performance of this algorithm is better. Methods In the calculation of similarity, this article uses the effective information, predicts the score, and then calculates the similarity by seeking union instead of intersection. This algorithm improves the accuracy in calculating the similarity set of items, thus effectively improving the recommendation quality of the recommendation algorithm.

5. Conclusion

Precision teaching has two components: precision teaching by teachers and accurate learning by students. This article proposes and builds an English precision teaching platform based on the CF algorithm of combinatorial optimization to accurately recommend English learning materials that meet learners' personal preferences and achieve precision teaching. The grey relational degree is used as the method of similarity measurement in this article, which can reduce the impact of low distinguishability and sparsity of data to some extent. On various data sets, experimental results show that this method's recommendation accuracy is 94.6%, which is higher than the CF algorithm of multi-feature fusion by 4.5% and the traditional CF algorithm by 9.7%. It has been proven that using time series interaction behavior data between users, mining hidden user influence relationship information can improve prediction accuracy. Testing students' knowledge mastery through paper test questions is time-consuming in traditional English teaching, and the accuracy of the feedback information collected is low. Students' knowledge and abilities can be tested and immediate feedback can be obtained using information technology in the field of education, with the help of the platform built in this article. Teachers can quickly formulate targeted learning plans, implement accurate teaching strategy transformations, and improve teaching efficiency. With the support of the system constructed in this article, the shortcomings of traditional teaching can be overcome. Teachers can make statistical analysis on students' mastery of knowledge points, and explain the important and difficult points, so that students can avoid detours in the learning process. Obviously, some achievements have been made in this research, but further research is needed on the characteristics of instructional resources.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author does not have any possible conflicts of interest.

Acknowledgments

This study was supported in part by the Humanistic and Social Science Youth Fund Project of Ministry of Education, Research on Grammaticalization and Cognitive Motivation of Chinese and English Verbal Measurement Constructions (20YJC740013), and in part by the General Project of Humanistic and Social Science Research in Colleges and Universities of Henan Province, Research on Grammaticalization of English and Chinese Verbal Measurement Constructions from Cognitive Perspective (2021-ZZJH-151).

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