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Research Article

University English Network Teaching Resource Bank Construction Based on Cooperative Filter Algorithm

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In recent years, with the rapid development of the network, related applications have also been greatly developed. Online-based online learning systems allow learners to ignore the difference in time and more convenient learning. It does not stick to the characteristics of classroom learning, which greatly meets the characteristics of contemporary education, and also enriches the diversity of education. This paper optimizes the recommendation technology of the personalized recommendation system of college English network teaching resource library, which is to propose a recommended model for the synergistic filtering algorithm using a combination of project properties and user attributes. Based on the detailed analysis of the network teaching resource construction platform, the algorithm is applied to the network teaching system, filled into the original matrix to obtain a dense pseudocomment matrix, and then find the user's own attribute information and rating information in the pseudocommentary matrix. The recent neighbor of the target user calculates the target user's preevaluation project for the nonscore item based on the nearest neighboring rating information and finally receives the highest recommendation list. After experimental analysis, the collaborative filtering algorithm proposed in this article was significantly higher than that of the remaining two, and the precision and recall values were also slightly more than about 0.2 in the *F*-measure evaluation criteria, bounded about 2%.

1. Introduction

In recent years, with the rapid development of the network, related applications have also been greatly developed. Based on the Internet-based college English network teaching system, it enables learners to ignore the differentiation of time and more convenient learning. It does not stick to the characteristics of classroom learning, which greatly meets the characteristics of contemporary education, and also enriches the diversity of education. With the gradual application of college English network teaching system in society, students can learn from the peer-to-end digital learning and generalization of the platform exhibition [1]. Research on Collaborative Filter Recommendation Technology is as follows: first, the traditional collaborative filtering recommendation technique is introduced and the problems existing in the technology; then, the optimized scheme is then introduced, respectively, and prepares it later. Combined with the recommendation algorithm based on attribute and time weight, the principles and steps of the combined recommendation algorithm proposed in this paper are described in detail, and the algorithm is verified by experiments. Analysis and Design of Learning Resources Personalization Recommendation System is as follows: analysis and design are a learning resource personalized recommendation system, apply the algorithm proposed in Chapter 4 to the system, and implement the combination of theory and practice. The traditional college English network teaching system is more focused on the integration of educational resources, but there is no personalized resource recommendation for different students. When the traditional web recommendation algorithm is transplanted to a college English network teaching system, because there is no consider the migration of students' interest, complete personalization is poor [2]. In response to the shortcomings of traditional recommendations, this paper introduces time weighted synergies filtering the probability distribution of the user's resource interest, combined with time interest factor that calculates the similarity of the user to complete collaborative recommendation; in order to solve the cold start problem of the collaborative algorithm and consideration of the relationship between knowledge, introduce knowledge unit closures, and complete the final recommendation analysis with the former combination [3], this paper compares the analysis of several common recommended algorithms, based on time dimensional interest migration and knowledge unit closure, a mixed recommendation algorithm for meeting the recommendation requirements of college English network teaching system.

This article has made in-depth research on personalized teaching resource recommendation and related recommendation technology. In response to the cold start in collaborative filtering technology, the score matrix sparse problem is proposed based on the analysis of the improved plan, and the synergistic filtering algorithm based on attribute and time weighting is proposed. In order to relieve cold start problems, use the combination of project properties and user attributes, combined with the recommended algorithm, for new projects and new users. It is a similar neighbor to the score matrix: in order to alleviate the sparseness of the evaluation matrix, this paper is designed with the scheme of filling the score matrix; that is, the project attribute and time weight will be predicted to preevaluate the unrecognizable subitem and fill in the original matrix. The dense pseudocomroom then finds the nearest neighbors of the target user through the user's own attribute information and rating information in the pseudocommentary matrix, based on the nearest adjacent score information, and the target user's preevaluation project is the highest. Recommended list [4] is as follows. This paper considers that user interest will change over time, adding psychology forgetting functions to change the ratio of different times in similarity calculation.

With the development of the network, network teaching has also become a new learning model, but there are still many defects in the current network learning resource system: teaching resource utilization is not high; learning resources are more like walrings, and learners, such as sea fishing needles, cannot be found quickly The resources needed the following; learners need to manually enter the description of the vocabulary for searching, and the system cannot be actively recommended according to the user's own information. These defects have lost the network teaching with the original advantages; so, it is urgent to integrate personalized services into online teaching [5]. This allows the user to quickly and accurately obtain the required resources quickly and accurately, not to retrieve itself, to find resources, thus improving the efficiency of users to find resources, saving users a lot of time. In addition, by personalized recommendation techniques, the quality of the recommendations can be guaranteed, the resource utilization is improved, and the learning direction is specified for the lost learners.

Innovative points of this article are as follows: recommended algorithms are the core part of the recommendation system, and the performance of the algorithm determines the quality of recommendations; so, how to better improve the algorithm will be worthy of research. The recommended algorithm for comparison includes the recommendation, content-based, based on the recommendation, label recommendation, and collaborative filtering recommendation, in which the collaborative filtering is recommended, but the algorithm has a scalar sparse problem, cold start problem, and poor extensibility. This article will conduct research on the collaborative filtering algorithm for these issues, which is to find ways to alleviate these issues, and ultimately reach the purpose of improving the quality of recommendation, and this is the focus of this article is also an innovative point.

The chapter arrangement of this article is as follows: the first chapter introduces the relevant research on collaboration algorithm; the second chapter introduces the relevant concepts of collaborative filtering algorithm and the design of the system process; the fourth chapter is a full-text summary.

2. Related Work

Personalized information recommended services have caused a lot of education researchers' concerns and research, but it is mature in the field of e-commerce in the field of education. Long first proposes a synergy filtering and applies it to spam filtration and news-recommended systems [6]. Zhou and Zhang propose a method of using a vector space model to represent user interest and feedback according to user behavior feedback to improve the system's automatic learning ability, thereby increasing the recommended accuracy. They introduce the body into the recommended system, using the ontology to provide a resource query to provide resource queries, replacing the relying on keyword queries [7]. Liu et al. take the lead in integrating personalized recommendations into network distance education, after overcoming a difficult relationship, completing the personalized service model of distance education, which is a major in the field of education at the time of education. Digital teaching development has made a good development in the early 21st century [8]. Liao analyzes the learners in the digital learning, summarizing the personalization of digital learning, constructing a set of support learners' personalized recommended digital learning systems [9]. Li proposes a method based on learner learning progress to determine the approximate learner method, track Internet learner learning behavior, dynamic, and dynamic recommendation learning resources [10]. Wang et al. are integrated with the learning model in the Internet environment with current mature digital learning models, and construct Internet learning personalized recommendation services that conform to user learning habits [11]. Mou and Huang propose a smart *E*-learning recommendation system that can evolve and achieve adaptive to learners and open network environments [12]. Wang takes personalized recommendation technology to people's daily lives, uses personalized recommendation algorithms to calculate the similarity of the product, and puts the juice calculation results to each user. It recommends a consolidated car and excited purchase desires [13]. Huang and Dong propose techniques for the interest of user interests to constantly modify the original configuration file and compare the user's interest and the content of the web stream file [14]. For problems in traditional collaborative filtration, Wang et al. propose to use the singular value decomposition (SVD) method to discover potential factors in documentation, reduce user project score dimensions, and better solve the problem, but recommended accuracy drop [15]. Chen et al. propose to analyze user history browsing records with K-means and neural network algorithms to solve cold boot problems, but only solve the cold start problem of new projects [16]. Yi and Yang refer to improving the recommended real-time [17] by reducing matrix dimensions and breaking matrices [17]. Zhou and Tan stated the isometrist based on model recommendation based on the use of line and column vector mean combination clustering method [18], Fang proposed to consider user access time affected by adjusting the hobbies of the user's different times in recommendation algorithm proportion and improve recommendation quality [19].

This paper mainly conducts research on the recommendation algorithm in the college English learning platform, introduces a cognitive capacity assessment model and English knowledge map, and gives an assessment model of the difficult coefficient of English learning resources and a cognitive basis. The design and implementation of the ability and difficulty collaborative filtering recommendation algorithm have improved the accuracy, targeted, and applicability of learning resources recommended and can effectively help the school students improve the efficiency of English learning. Cultivate self-confidence and develop good learning habits. The quality of the recommended resources has a degradation, as the user's collaborative filtering technology is recommended from the user's level, and the principle of similar users is similar. This cannot save the sectors of the recommended resources. Therefore, there is a need to establish a scoring system to ensure the recommended quality.

3. Resource Library and Collaborative Filter Algorithm

3.1. Construction of Network Teaching Resource Bank. The traditional collaborative filtering recommendation algorithm framework is based on the "behavioral consistency," that is, "the more purchased the same item, the more similar users, the more similar users," and in the university network English learning platform system, only according to the "consistent" behavior. It is difficult to recommend learning content that matches its knowledge, cognitive ability, and difficult coefficients. In order to solve the problem of recommendation difficulty, this paper first analyzes the external performance of the characteristics of knowledge, cognitive ability, etc. and quantizes it through a group. Multidimensional Abstract Data Make Description Table Exquisite Users' Knowledge Levels and Cognitiveilities and Implicit One-Some Home Attributes [20]. In addition, in order to solve the content association and learning path of English learning and the accuracy of search and recommendation, this article refers to the basic theory of knowledge maps, and the basic theory of knowledge map has established a college English knowledge base. Then, this paper records the user's learning log through the system, updating the user, pronunciation, continuous learning time, unit test case, etc., and updated the user's knowledge level and metric data of the user's knowledge level and cognitive capacity. In addition, this paper is difficult and similar to abstract modeling of English learning resources, spelling, pronunciation, sentence length, interpretation, matching, concept, field, etc. [21]. Finally, by calculating the European distance between the learner user, the user is classified, and the difficult coefficient of learning resources and learning records is integrated according to the ability of the learner user. The research ideas and methods of this paper are shown below.

Figure 1 The bottom layer represents the basic data of the system, which is derived from the system after the establishment of the submission of the user registration and social English resources.

Figure 1 The data discreced to in this article is mainly three categories: one is the user-related data, the other is the data related to English learning resources, and the other data is the user's learning behavior record. Learning behavioral data is used to record all kinds of behaviors of system users, mainly including data, test, and social data, as well as part of the system user submits the behavior record of English learning resources. Since the college English learning platform system is different from the general e-commerce system, through some questionnaire surveys can more accurately understand and evaluate the user's knowledge, the level of cognitive ability, and the knowledge of subsequent learners and the precision recommendation of resources. Good help [22].

The third layer illustrates the research angle selected in this paper. On the basis of initial data, the system extracts and analyzes the data of the user and the learning resources, and the assessment of it is evaluated, and then according to the user's learning behavior, the ability model of the corresponding user is as follows. The horizontal model and the difficulty model of the resource are dynamically updated.

This layer specifically illustrates four main models of this paper: English knowledge model, cognitive capacity model, interest family model, and difficulty model of learning resource. These four models are the core model for the recommendation system in the recommendation system and the recommended resource recommendation.

The fourth layer mainly illustrates the main solutions of this paper, namely, the user recommendation of the same class (capability level) and the search and recommendation of the learning resource.

3.2. General Framework for Preparation Resource Recommended Model. Through the above analysis, there are two aspects of the recommended method of the existing preparation system: the recommended resource is insufficient, and the quality of the recommended resources is low. These article research goals provide teachers with resources associated with specific knowledge points as you present, and its island has high quality resources. First, in order to ensure the recommended resources, there are the preparation resources of a certain grade of teachers' interested in a certain level of knowledge points. Then, in terms of preparation resources, you need to classify the existing

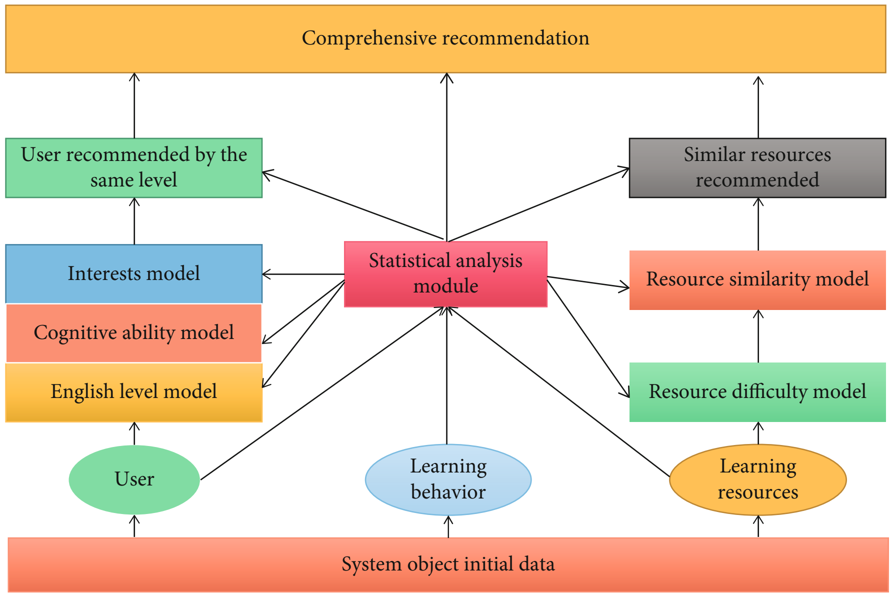

Figure 1: Model architecture.

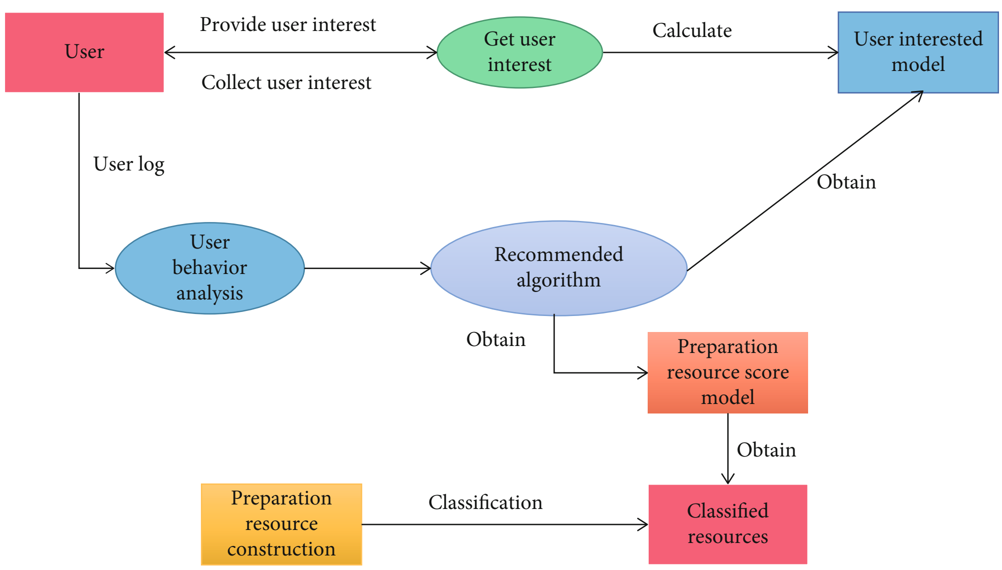

Figure 2: Recommended model of preparation resources.

resources to be classified, so that the resources they want to recommend is more accurate and the need for prepared resource modeling needs [23]. Secondly, a nuclear part based on the user's collaborative filtering algorithm is how to build user interest models, and the user interest model is the basis for the recommendation of resources, and this article should abstract a user-point model. Again, in order to solve the cold start problem based on the user-based collaboration algorithm, the vector, the new user is established for the new user, the resource classification match is made, and the recommended resources are given to the new user, because the quality of resources is required to guarantee of the user's view, download, recommendation, and collection behavior of a resource that represents an evaluation of this resource; so, you need to build a presence resource scoring model [24]. By collaborating the recommended algorithm, combined with the model of the previous section, the similarity between teachers is calculated, the similar user collection is found, and then the resources like users are pushed to the current user. Next, a structure of a preparatory resource system model with personalized recommendation is given below as shown in Figure 2.

3.3. Cooperative Filter Algorithm Based on User. The core idea of this algorithm is to recommend those of the user of user groups similar to the user; so, the user-project score matrix of user behavior score data is described, and the calculation of user similarities is the key step of the algorithm. Overall, the recommended process of this algorithm can be divided into three steps: users and project scoring matrices, user-mounted anxious calculation, and prediction recommendation. This step is based on the user score data mining and processing section of the user's collaborative filtering algorithm. By collecting the user-project score matrix by collecting the score data of the project, the Matrix $m \times n$ is represented by the user and the project score, as in the formula (1). Distance is as follows:

$$R(m, n) = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m1} & \cdots & r_{mn} \end{bmatrix}. \quad (1)$$

The number of m line represents the number of users, the number of column n represents the number of items, and the value r_{mn} in the matrix represents the score data of the user m to the project n; usually, the value of the value of 0 to 5 is between 0 and 5. The higher the integer value, the higher the value of the score of the project, but also to the project, the smaller the integer value, the lower the user's score value for the project; that is, the degree of interest in the project is relatively low, when the score value is at 0, the representative users did not evaluate the project. Of course, in most user-based collaboration algorithms, users and project score matrices typically use binary variables (0, 1) in the project score matrix, where 0 represents, 1 representative, and this A representation method is convenient for data collection and finishing and is convenient to calculate.

By calculating the similarity between the user, the first few users with the highest similarity as the neighbor user of the user, the formation of neighbor users is an important premise and foundation of the recommended result generation; for similar users, currently, most of the personality. The recommended system is mainly used: cosine similarity, corrected cosine similarity, and related similarity, where the cosine similarity is calculating two user rating vector in the vector space model and the cosine value of the vector angle, with score vector clip. The cosine value of the angle represents the similarities between the user. The corrected cosine similarity is mainly to solve the problem of user affected by itself or other factors, resulting in the unstable score data, and calculates the similarity between the user and the cosine similarity, and the corrected cosine similarity calculation is more than the factor. To accurate. Related Similarity. The efficiency of the calculation is higher because the calculated efficiency is higher, the results are also more accurate, and the relevant formula is also more accurate.

Cosine similarity (2) is as follows:

$$\operatorname{sim}(u, v) = \cos\left(\vec{u}, \vec{v}\right) = \frac{\vec{u} \cdot \vec{v}}{\left|\vec{u}\right|\left|\vec{v}\right|}. \quad (2)$$

Fixed cosine similarity (3) is as follows:

$$\operatorname{sim}(u, v) = \frac{\sum_{i \in Iu,v}\left(r_{u,i} - \bar{r}_u\right)\left(r_{v,i} - \bar{r}_v\right)}{\sqrt{\sum_{i \in Iu}\left(r_{u,i} - \bar{r}_u\right)^2}\sqrt{\sum_{i \in Iv}\left(r_{v,i} - \bar{r}_v\right)^2}}. \quad (3)$$

Relevance (4) is as follows:

$$\operatorname{sim}(u, v) = \frac{\sum_{i \in Iu,v}\left(r_{u,i} - \bar{r}_u\right)\left(r_{v,i} - \bar{r}_v\right)}{\sqrt{\sum_{i \in Iu,v}\left(r_{u,i} - \bar{r}_u\right)^2}\sqrt{\sum_{i \in Iv,v}\left(r_{v,i} - \bar{r}_v\right)^2}}, \quad (4)$$

where $\vec{u}$, $\vec{v}_{,}a$, represents the vector value of the user u and the user v in the spatial vector model. The project collection represented by $I_{u,v}$ represents projects that have scored those u and users v, $\bar{r}_u$, $\bar{r}_{v,}$a represents the user u and user v project score mean, and $r_{u,i}$, $r_{v,i,}$a represents user u and user $v_{,}$s score value for projects. The I_u, I_v represents user u and user v, a collection of score of the project.

As a final step of the user's collaborative filtering algorithm, it is mainly responsible for predicting the user's evaluation value of the unspeve item I and the N recommendations found through neighbor users. Since the data of most personalized recommended systems is high, the predicted evaluation value of the predicted evaluation is larger than the actual user evaluation value; so, it is more important than the N recommended by neighbor users. The formula (5) can be used.

$$P_{u,j} = \bar{r}_u + \frac{\sum_{v \in N(u)} \operatorname{sim}(u, v) \cdot \left(r_{v,i} - \bar{r}_v\right)}{\sum_{v \in N(u)} \left|\operatorname{sim}(u, v)\right|}, \quad (5)$$

where $N(u)$ is the nearest neighbor user set of users that represents the similarity of user u and user v. Finally, all users are sorted from large-to-small predictive score $P_{u,j}$ and ultimately scored higher nik. A project is recommended to the user to complete personalized recommendation.

The calculation ideology of the project-based collaboration algorithm and the user-based collaboration algorithm are very similar, and the step of user-based synergistic filtering algorithm is as follows: the construction of the predictive score matrix, similar users look up, predictive results, recommended, and correspondingly based on. The step of the collaboration algorithm of the project is as follows: the predictive score matrix is predicted to find a similar item lookup, predictive results, and recommendation. It can be found that the calculation idea of the two algorithms is substantially the same, and the only difference is that the user's collaborative filtering algorithm is to calculate the similarity between the user and the recommendation of the similar user, and the project-based collaborative filtering algorithm is calculated. Similarity, recommending the similar items like the project, the final prediction and recommendation also calculate the user's forecast score for unsubgraduated projects and then recommend the prepredictive score higher N items.

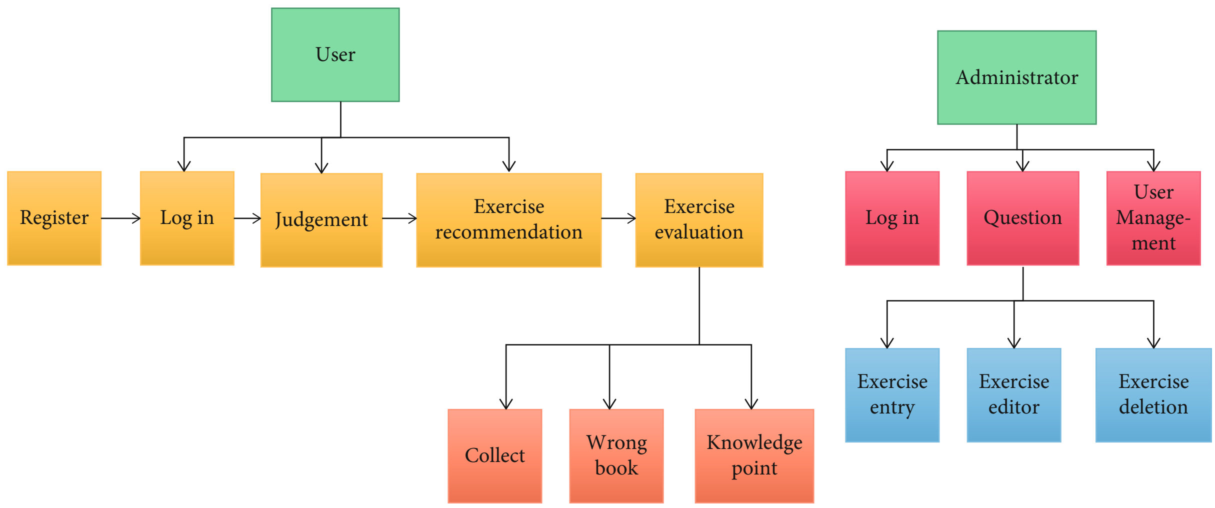

FIGURE 3: General flow diagram of university English teaching resource recommendation.

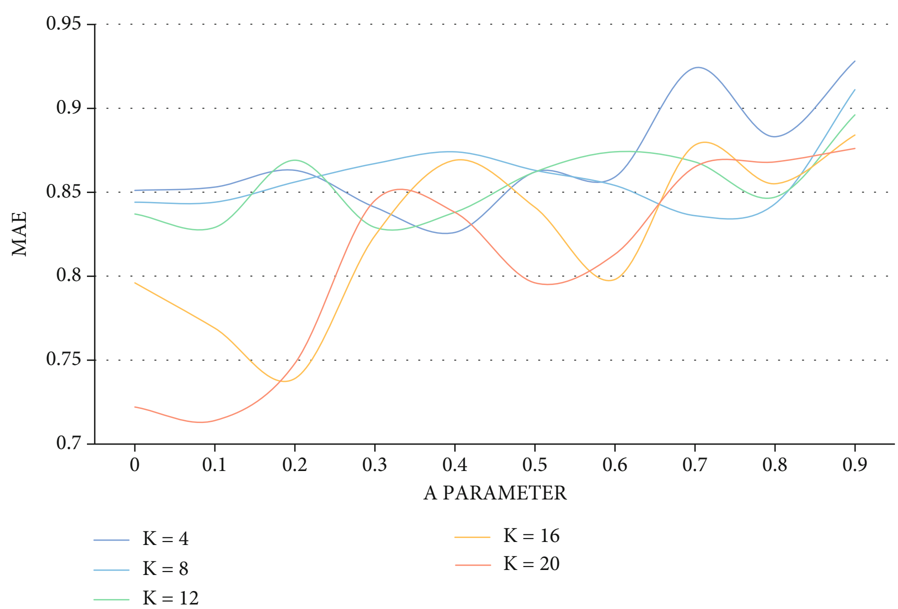

FIGURE 4: Amplified impact of parameters on comprehensive similarities.

3.4. University English Network Teaching Resource Bank Process Analysis. College English personalized recommendation system is mainly to meet the exercises and exercises recommendations for users, and the exercises are mainly enjoined by the background administrator, based on the above demand analysis and the personalized college English recommendation process and the system's business. The process mainly includes two parts; first of all, for the user, its business process is registration, login, diagnostic test, exercise recommendation, exercise evaluation, and users can use the collection, praise, and the wrong problem added to the system's own fault. The question is coming to evaluate the exercise. Secondly, for administrators, the main function is the management of users and question banks, and the question bank is the basis of the system and affects the quality and accuracy of the application recommendation. The administrator is the management of question bank that is mainly divided into three major aspects of exercises, exercise editing, and exercises, and the business process of college English personalized recommendation system is shown in Figure 3.

4. Experimental Analysis and Conclusion

4.1. Influencing Analysis of Parameters. In order to compare the performance of the coordinated filtering algorithm proposed in this paper, this chapter compares it to the ATCF recommendation algorithm and the UCF recommendation algorithm. In order to eliminate the impact of the nearest neighbor scale on the results, this paper selects 5 most adjacent scales: 4, 8, 12, 16, and 20. Experimental data sets use the training set and test set in the download package, and

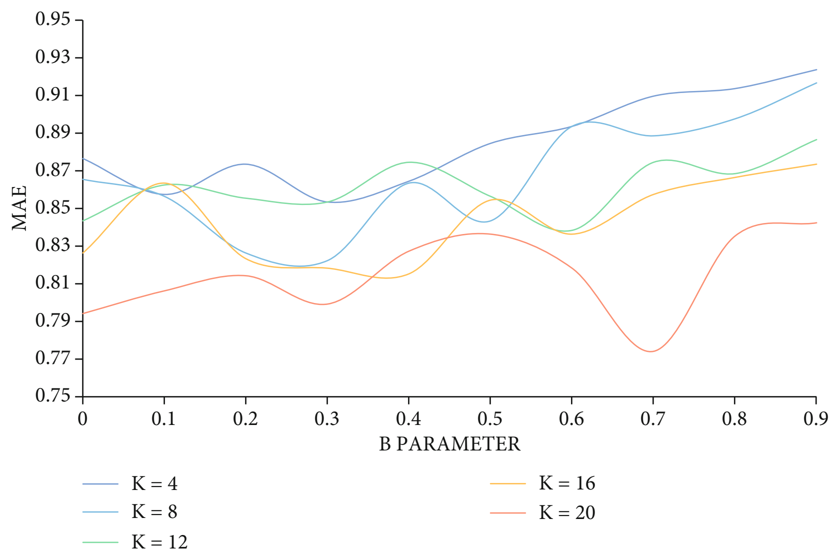

FIGURE 5: Better influence on the integrated similarity.

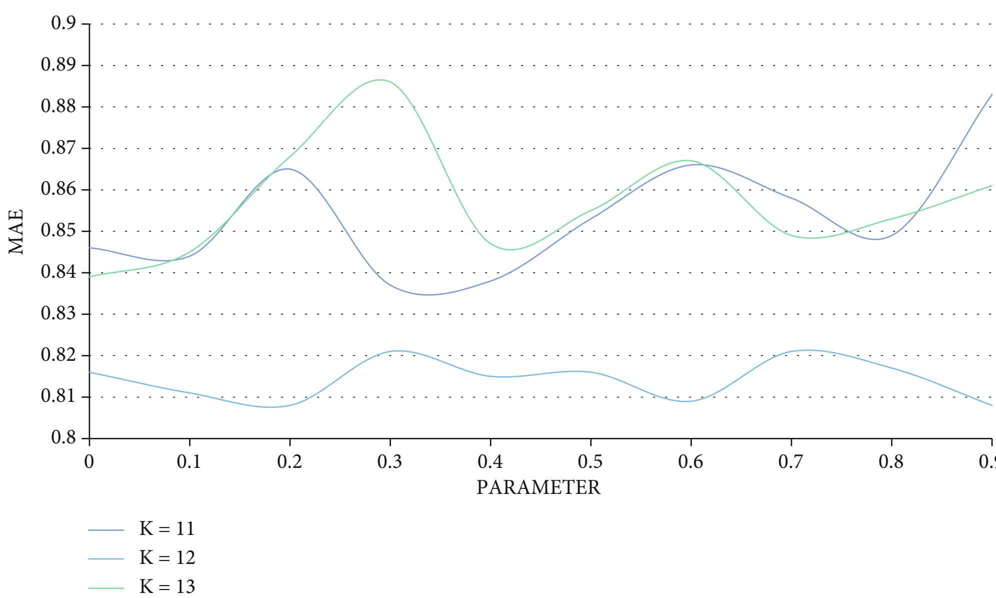

FIGURE 6: Comparison of algorithm in different users.

the data ratio is 4: 1 Multiple random division data sets repeat the experiment to reduce the error of data division.

The parameter A represents the ratio of the similarity of the project attribute in the comprehensive similarity, and the value of the value is 0 to 1; first, the parameter B in the forgotten function in the integrated similarity is 1, that is, considering the impact of the project attribute and project score. Then, A is experimentally in five similar user sets, and the optimum value is found through the size of MAE, as shown in FIG.

As can be seen from Figure 4, when a is approximately 0.1 or so, the MAE value is close to the smallest, and the algorithm reaches the optimal accuracy. Note that the comprehensive similarity does improve the accuracy of the recommended algorithm, the impact of the project attribute information is relatively small, and the impact of score information on the similarity is large.

Parameter b represents the proportion of user self-attribute information in the integrated similarity. The parameter B is also tested on the 5 nearest neighboring shapes, and the optimal value is found through the size of the MAE, as shown in Figure 5.

As can be seen from Figure 5, when b is approximately 0.2 or so, the MAE value is close to the smallest in various sizes. Note that comprehensive similarity makes the accuracy of the algorithm, and the impact of user attributes on comprehensive similarities is large. Figure 6 is a comparison of two algorithms of several users who are nearest neighbor B parameters, forgetting, randomly selected several users.

The value of the parameter B reflects the degree of forgetting with the user's interest, and the greater the B, the more you forget, and the smaller B, the slower. Through experiments, the accuracy of the algorithm that has been

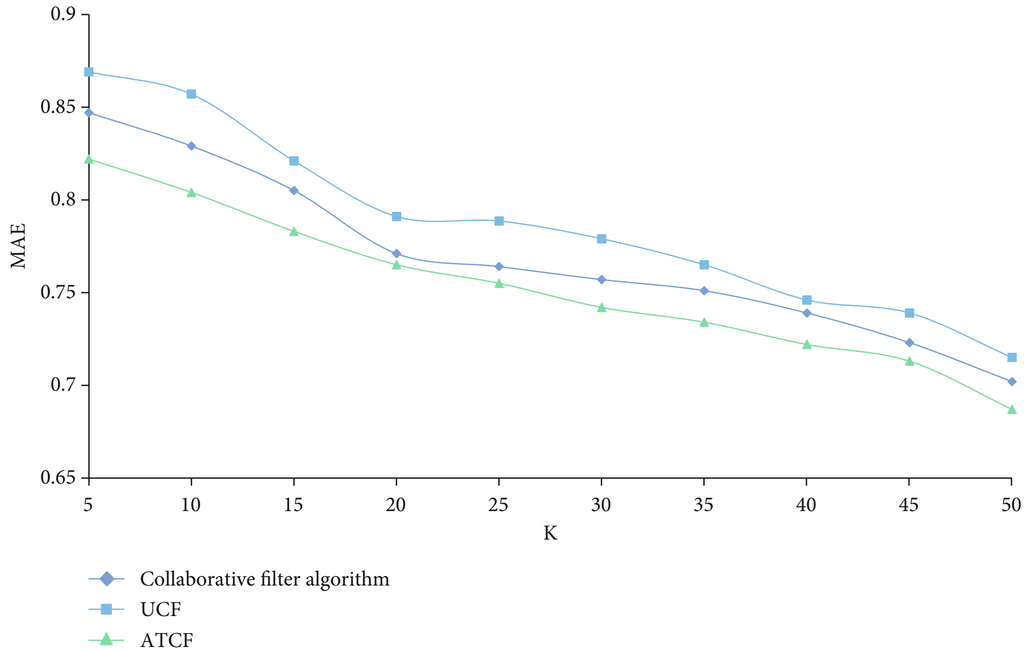

Figure 7: Different algorithms and different K values in the MAE line diagram.

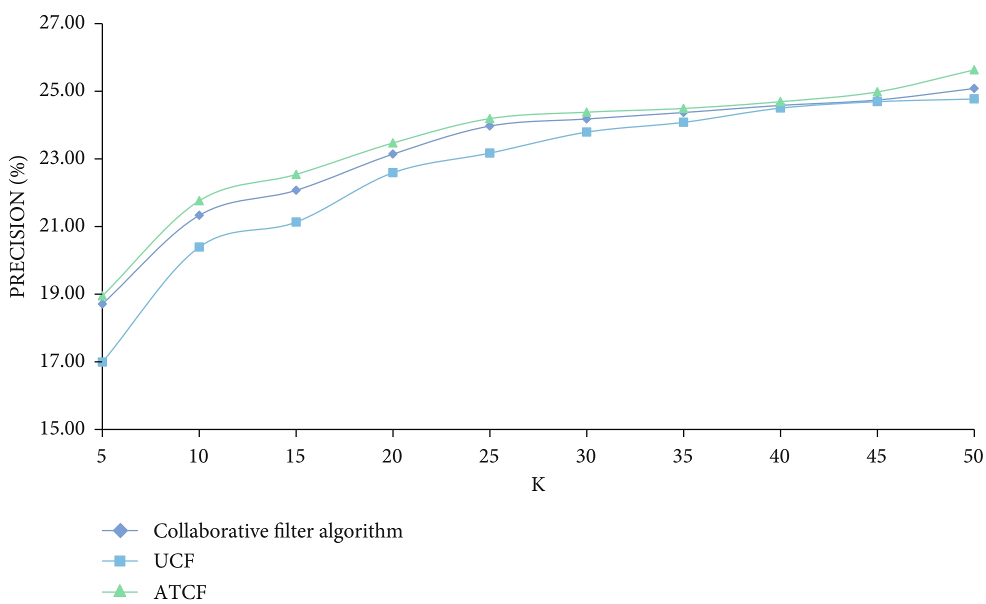

Figure 8: Precision line diagram of different algorithms.

improved by the forgotten function is higher than the traditional algorithm.

4.2. Coordinating Filter Algorithm and Traditional Algorithm MAE Comparison. In order to verify the recommended accuracy of the collaborative filter algorithm, the general evaluation standard MAE is used to compare the MAE value of the traditional ATCF and UCF. In addition to the method of neighbor similarity, the nearest neighbor is also reflected in the quality of the recommended quality. Therefore, this experiment chooses that the nearest neighbor is increased from 5 to 50, and the interval is 5. And the three algorithms are shown in Figure 7 under different K values.

It is known from Figure 7 that the improved synergistic algorithm is smaller than the MAE value of the ATCF and UCF. Since the smaller the MAE value is, the higher the prediction accuracy, the collaboration algorithm is higher than the ATCF, the UCF test is high, and the improved method has improved the prediction accuracy. Recent neighbors also affect algorithm performance, as the nearest neighbor k (user reflecting the latest interest of the target user) continues to increase, the MAE value is constantly decreasing, and the

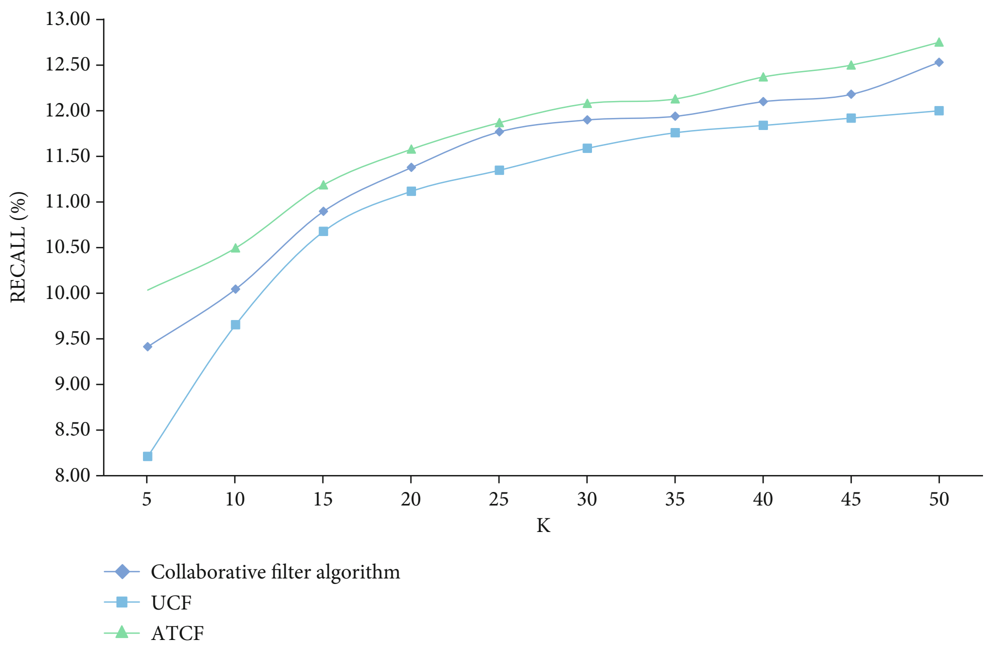

Figure 9: Recall line diagram of different algorithms.

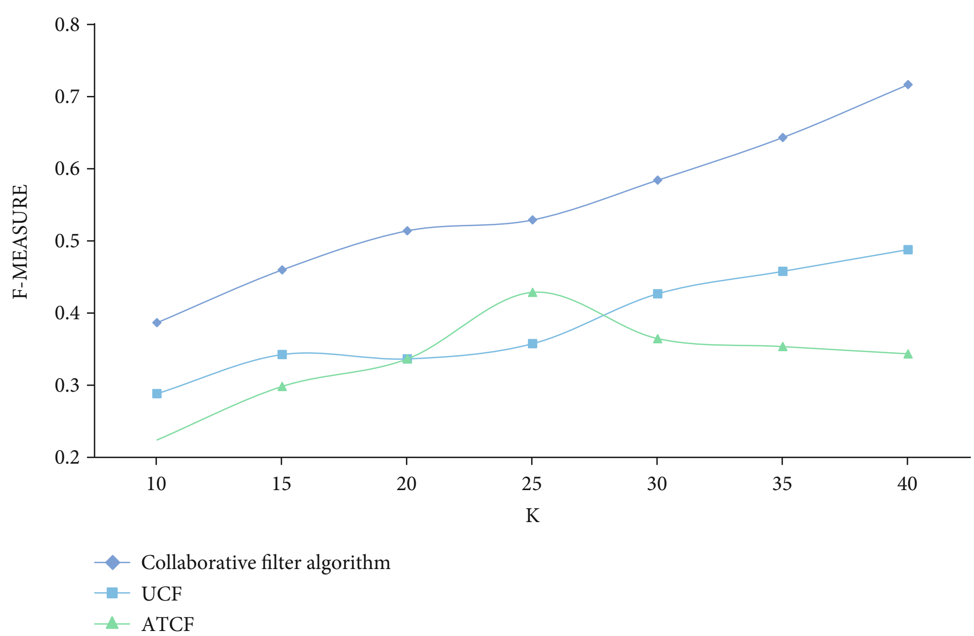

Figure 10: Different algorithms of F-measure values.

recommended accuracy is constantly improving, verifying that the collaboration algorithm recommended algorithm has indeed improved the system recommended quality.

4.3. Comparison of Precision and Recall of Traditional Algorithm. In order to continue to verify the predictive accuracy of the collaboration algorithm, the comparison experiment is performed using precision and recall evaluation criteria. The nearest neighbor K can also increase from 5 to 50, interval is 5, and ATCF, UCF, and synergistic algorithm were in different algorithms. The experimental results of precision and recall are shown in Figures 8 and 9 when the K value is shown in Figures 8 and 9.

As can be seen from Figures 8 and 9, a collaborative filter algorithm is higher than the ATCF and UCF's precision, the recall value is high, the accuracy of the three is coordinated with filter algorithm > ATCF > UCF, with K increases, and precision and recall value also were slightly increased. The increase is about 2%, and precision is significantly greater than the recall value, which indicates that the cofiltering algorithm significantly improves the recommended accuracy. The reason is that the collaborative filtering algorithm introduces the project attribute information, and the user's own attribute information improves the nearest neighbor calculation method, which is combined into the nearest neighboring formula based on oscitation information, and is more accurate nearest neighbor; use the improved ATCF algorithm to the system; in the system, some score matrices are filled, ease the sparse, and cold start problems; use improved UCF algorithms to add forgetting functions when predicting scores, more highlighting the proportion of the user's interest for forgetting updates. These improvements are effectively combined to form a new synergistic filter algorithm and mitigate problems in the traditional recommendation algorithm.

This chapter is for cold start and score matrix sparse problems and does not distinguish problems such as users' interest in different time periods. It is proposed that project attribute information, user self-attribute information, and time forgetting function were combined with collaborative filtering recommendation algorithm and coordinating filtering. The algorithm is an improved algorithm in which the UCF and ATCF are organically combined in a nonlinear combination. First, the improved ATCF is preevaluated for unsubstructed projects and fills into a strategic matrix in the original score matrix, effectively reducing sparseness and cold start question, and then uses improved UCF in the matrix to get the recommended list provided by the system for the target user. Compared to the traditional algorithm, the calculation time of the collaboration algorithm is constant. It is different that it is not a linear combination of the two in the past to be combined, but the attribute information of the project, the user's attribute information, improves the project. User similarity calculation formulas get a more accurate neighbor set. In calculating the predictive score, the time forgetting function is also added, focusing on the recent interest in users and weakening the user's long-term interest. Through the above links, the algorithm formed is alleviated by the traditional problems. The F-measure value is calculated for the three algorithm results to obtain a line diagram of Figure 10.

It will be apparent from Figure 10 that the collaborative filtering algorithm proposed in this article is significantly higher than that of the remaining two of F-measure evaluation criteria within the range of the K value. A better recommendation effect is achieved with respect to the coordinating filter algorithm of UCF and ATCF.

5. Conclusions

This paper will coordinate the filtering algorithm technology to the construction of college English network teaching resource library, using personalized recommended algorithms to guide students to learn. Based on the comparison of various technological analyses, it proposed a recommendation algorithm suitable for online learning. The algorithm combines a coordinated filtering and association rule algorithm based on knowledge unit closure. Introducing time weight into student learning path analysis, through time attenuation rights reconstructing students' interest distribution model, construct a similarity of similarity formulas based on time interest factor, using learning resources, and test score prediction to complete collaborative recommendation. Through the consideration of the relationship between knowledge points, avoiding the recommendation of the resources leads to the occurrence of student learning obstacles. For the score matrix sparsiness problem, the comprehensive similarity based on project attribute information and time weight is used to preevaluate and fill the original score matrix to obtain a dense pseudocommentary matrix: in the pseudocommentary matrix, using user attribute information and score information. Similarity identifies the nearest neighbor of the target user, obtaining the preevaluation of the nonscore item through the nearest neighboring rating information, eventually getting a recommended list.

This article is designed to be applied to the computer field, while the actual network learning resource website involves multidoor technology, in a variety of fields; so, in the future, we need to continuously improve the system, which makes the system more powerful and more applicable and promote the development of network education.

Data Availability

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

Conflicts of Interest

No competing interests exist concerning this study.

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