Human-Computer Interactive Design of Education Information Recommendation System for Private Colleges Based on AI-Powered CAD Technology

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Abstract: With the gradual deepening of educational informatization work and the explosive growth of online teaching information, how to accurately extract the educational information required by users from a large number of educational resources is an urgent problem to be solved in the process of teaching and learning. As a basic subject, college plays a vital role in people's lives, studies, and work. The fuzzy recommendation algorithm is one part of AI-powered CAD technology. This paper starts with the advantages of applying modern educational information technology in private colleges, analyzes the problems existing in my country's current education in private colleges, and designs a recommendation system for education information in private colleges based on a fuzzy recommendation algorithm. The user retrieval instruction is transmitted to the database module, and the database module extracts the education information with the highest recommendation degree according to the user preference through the multivariate mixed criterion fuzzy decision model and transmits it to the recommendation display module. The recommendation display module feeds the recommendation information to the user in the resource list. The recommendation system aims to give full play to the role of modern educational information technology and improve the quality of education in private colleges.

Keywords: AI-powered CAD; Private College education; Educational information recommendation; Fuzzy recommendation algorithm; Human-Computer Interactive Design
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1 INTRODUCTION

With the development of information technology, the construction of education informatization has achieved remarkable results. However, with more and more technologies being integrated into the smart campus, the campus has gradually become an area with complicated information, which not only causes information waste but also affects the daily life and study of teachers and students in school due to excessive information, which makes the development of higher education enter the dilemma of the rapid development of campus informatization and the redundancy of campus information. Therefore, how to make effective use of campus information so that campus information can give full play to its effective value in its effective period, further improve the information utilization rate, and at the same time meet the construction of educational informatization, the development of private colleges, and the daily needs of teachers and students, is an urgent problem to be solved in the process of smart campus construction.

Mature network technology and diversified network education resources can solve the problem of lack of education resources in the previous teaching environment. However, in a complex network environment, the retrieval accuracy of educational information is low, and it takes more time. Therefore, the university education information recommendation system has become a tool for mining education resources that are urgently needed in the current education field. The traditional education information recommendation system mostly uses the similarity between the education information groups as the judgment basis and uses clustering or association mining to achieve information recommendation and less analysis of user preferences. The recommendation system predicts the items that users may be interested in and is a useful tool for solving information overload. In recent years, the recommendation system has played an increasingly important role in the process of digitization, such as friends' recommendations on Weibo, product recommendations on Taobao, movie recommendations on Netflix, music recommendations on Pandora, etc.

In view of the above problems, the main work and innovations of this paper include:

(1) The system combines the search engine with the characteristics of teaching resources, analyzes the retrieval results by using content extraction and fusion of various information technologies, calculates the similarity between the information content and the user interest model by using information retrieval technology, and then recommends valuable online teaching resources for users according to the ranking of the calculation results. At the same time, by recording and analyzing the user's access behavior, the common interests of the user group, as well as the preferences, habits, and patterns of individual users, are mined. At the same time, mathematical teaching information is recommended for users according to fuzzy algorithms.

(2) This paper designs and implements the recommendation system of education information and studies the system requirements analysis, recommendation algorithm, and system implementation. In the system requirements analysis part, according to different scenarios used by users, the requirements list is sorted out, and the functional modules of the system are divided and verified according to the requirements list.

(3) Focus on the content recommendation algorithm and collaborative filtering recommendation algorithm of educational information. In the process of researching recommendation algorithms, the principles, steps, and performances of the two kinds of algorithms are compared, and the performances of various hybrid recommendation algorithms are analyzed. In the introduction of content recommendation algorithms, the basic knowledge of educational information is briefly introduced.

In this paper, the university education information recommendation system is designed based on multiple mixed criteria and a fuzzy algorithm. The architecture is as follows:

The first chapter is the introduction. This part mainly expounds on the research background and significance of the education information retrieval system, which has low precision and large information overload problems and puts forward the research purpose, method, and innovation of this paper. The second chapter is an overview of the related work, the introduction of the recommendation system, and the background of the fuzzy algorithm, summarizes the advantages and problems, and puts forward the research ideas of this paper. The third chapter is the system design part, which focuses on the design of the university information recommendation system based on the fuzzy recommendation algorithm. In the process of research, the principle and performance of other algorithms are compared to obtain the optimized system. The fourth chapter is the analysis of experimental results. This part is verified by experiments after the users of the system use and analyze the performance and problems of the system so as to achieve the completion of the recommendation algorithm and present diversified information. The fifth chapter is the conclusion and prospect. This part mainly reviews the main contents and results of this paper, analyzes the shortcomings of this paper, summarizes the research conclusions, and points out the further research direction of the recommendation system.

2 RELATED WORK

With the explosive growth of Internet data and the coexistence of "rich" and "sparse" information, information retrieval is the main way for users to find and locate interesting information. The booming Internet from the 1980s to the 1990s has provided an unprecedented public information environment for the whole world, and how to extract useful information from massive data has become more and more difficult. A recommendation system is an intelligent agent system proposed to solve the problem of information overload on the Internet. It can automatically recommend resources that meet users' interests, preferences, or needs from a large amount of information on the Internet. The recommendation system can recommend related content to users online according to their interests, hobbies, habits, and the correlation between users, provide browsing suggestions, and provide personalized services for users.

The recommendation system can be understood as a system with information filtering and selection functions. It mainly has two parts of functions. The first part is to obtain the relevant preference information of users and items and obtain the potential relationship between users and items; The second part is to actively recommend the objects or items of interest to the target user through the potential connection between the user and the objects. In 1992, Goldberg proposed the first (personalized e-mail) recommendation system, taperstry191, which first proposed the idea of collaborative filtering, and reordered the e-mails using the user's annotation and behavior information. In 1994, Resnick et al. proposed GroupLens, a collaborative filtering system for news messages. Collaborative filtering algorithms can be seen in social networks, e-shopping, information service websites, online learning, and other fields. The recommendation system was originally developed by the groups of the University of Minnesota. The main content of the system is to put forward the idea of completing the recommendation task based on system filtering for the first time and establishing an appropriate model for the recommendation problem. On the basis of this research, the recommendation technology has developed vigorously.

Academic researchers have done much research in the field of recommendation systems, and many theories about recommendation systems have been established constantly. Information retrieval, cognitive science, and prediction-related knowledge should be used in recommendation. Because the recommendation system has brought such an obvious recommendation effect, researchers in academic circles have been keeping a high research heat on it. Cyber Dialogue in New York conducted a survey and statistics on users' attitudes and frequency of using personalized recommendation systems in online shopping in 2001. The survey results show that the use of a personalized recommendation system in e-commerce has an important impact on increasing sales. Among all the interviewed users, more than 55% of those who designed and studied the parallel recommendation algorithm based on fuzzy clustering think that using a recommendation system in an e-commerce website can make their willingness to browse the website more obvious, and 64.5% think that their personalized recommendation service is willing to register the website.

Personalized information push service is a service that can meet the individual information needs of users, that is, according to the clear requirements of users, through the analysis of user registration information and browsing record information, establish user interest model, and adaptively provide users with information services that may be needed. The randomness of the results caused by the fuzziness and uncertainty of information in social networks directly affects the user experience. It is particularly important to mine the actual preferences of users from uncertain information.

3 METHODOLOGY

3.1 Obtain the Image Information of the Informatization Construction of Education and Conduct Noise Reduction Processing of the Image Information

The single data information collection network is converted into a sensor collection network, and the wireless sensor is used to collect image and voice information. The collected information is denoised by the fuzzy algorithm. The common fuzzy algorithm contains many contents, so choosing the method suitable for image information is the key issue in this section. There are many kinds of common fuzzy algorithms. Through the comparison of various methods, this paper uses the mean fuzzy algorithm combined with multivariate mixed criteria to complete the information processing process. Set the image information to be processed as a matrix, name it W, and set the dimension of the information vector as $C_i \; i=1,2,\ldots,n$, n as the number of vectors. When the image is initialized, it can be known that its average area is J_i , and there are:

$$\sum_{\mathrm{i=1}}^{\mathrm{w}} \mathrm{J_i} = 1 \tag{1}$$

Set the fuzzy center as Z and the information serial number as L, and there are:

$$Z_i = \frac{\sum_{i=1}^{w} J_i}{\sum_{i}^{w} I} \tag{2}$$

The image blur processing center is obtained by equation (2), and the image information is processed with this as the reference point to obtain the processing result. If the processing information is y and H is the frame length of the image information, then:

$$Y = \left\{ \left(\frac{1}{H \;\; C_i Z_i} \right)^i \right\} \Big/ \left\{ \sum_{i=1}^{w} \left(\frac{1}{H} \right)^i \right\} \tag{3}$$

3.2 System Module Design

In this paper, the recommendation system of education information in private colleges based on a fuzzy algorithm is a system that needs a retrieval engine. The system is divided into three parts: database template, retrieval template, recommended display template. Among them, the search module focuses on the use of Web search engines, so as to achieve educational information search and efficient transmission of educational data. The system composition is shown in Figure 1.

(1) Retrieval module: The user logs in to the system first, enters this module, and then selects the corresponding language system according to his commonly used language. This recommendation system supports multiple languages, such as Korean, Chinese, Japanese, English, Mongolian, etc. The user inputs the type of educational information, corresponding keywords, and subject information in the retrieval interface to retrieve educational information.

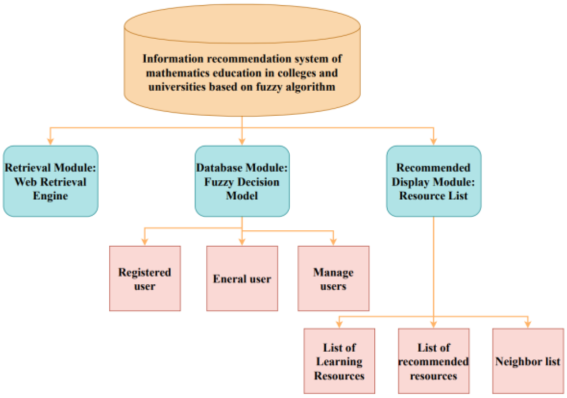

Figure 1: The composition diagram of the mathematical information recommendation system under the fuzzy algorithm.

(2) Database module: This module has various management methods for educational information. Users are divided into registered users, ordinary users, and administrative users. The composition of user information is shown in Figure 2. At the same time, different users can experience different functions. Registered users can search for relevant information and browse. The most important thing for ordinary users is downloading relevant information; administrative users have administrative rights to the database.

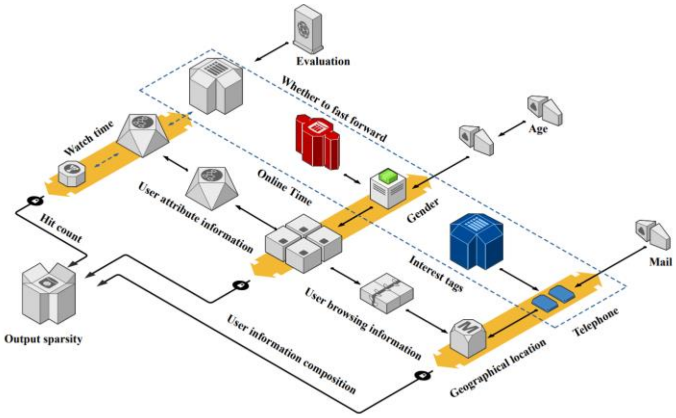

Figure 2: User information composition system.

(3) Recommended display module: this module is the core module of this system. The recommendation display module has three content partitions: ① List of learning resources, ② List of recommended resources, ③ Neighbor list. Click each list name in the recommendation display module panel, and the corresponding function will be activated. In the database, the keywords extracted from the questions need to be searched by the maximum matching algorithm. Among all kinds of retrieval algorithms, this system adopts the forward maximum matching Chinese word segmentation algorithm. The process of intelligent question-answering interaction in the system is divided into three parts, as shown in Figure 3.

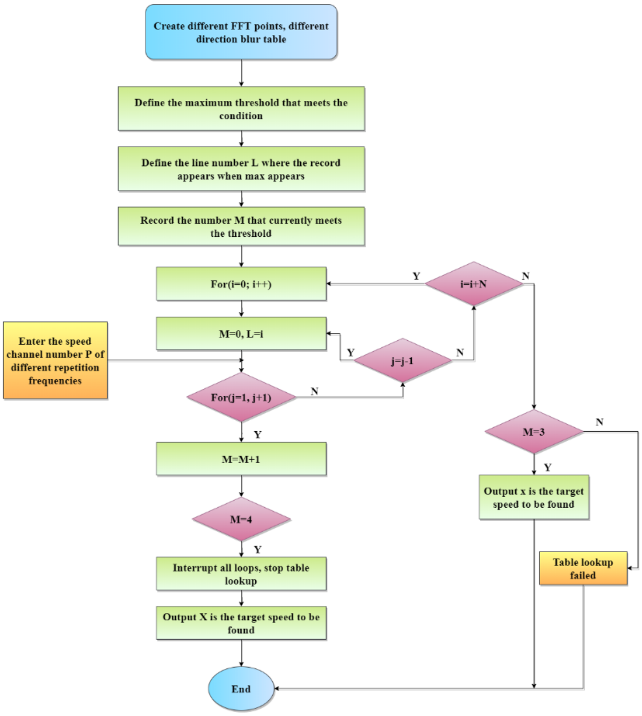

Figure 3: Recommended algorithm operation flow chart.

3.3 Fuzzy Set and User Interest Measurement

A fuzzy set is a form of dealing with uncertain information. By setting a threshold, we can judge whether an element belongs to this set. In fuzzy concentration, the user's preference is expressed in language terms, such as extremely high, high, and low. In the real world, there are many problems that can not be evaluated in quantitative form, but qualitative analysis is in fuzzy or imprecise form. Wu et al. Introduced fuzzy sets on the basis of traditional cosine similarity to solve the problem of data sparsity. Kant et al. Blurred the user's age and reasonably expressed the user's attributes. Jimenez et al. verified the effectiveness of the classification method based on fuzzy rules. Zhang Bing and others obtained reasonable clustering results based on fuzzy evaluation information. At the same time, many researchers have applied fuzzy set theory to medical diagnosis, image processing, and other tasks. The membership function of triangular fuzzy number f is calculated as shown in formula (4):

$$f=\begin{cases} 0, x<a \\ \dfrac{x-a}{b-a}, a\le x\le b \\ \dfrac{c-x}{c-b}, b\le x\le c \\ 0, x>c \end{cases} \tag{4}$$

Among the documents that users have read, because users have read these documents, they can think that users are interested in these documents and regard them as related documents so as to obtain users' interest information. Here, the document weight is adjusted by calculating the similarity between the target document and the documents in the read document class. If it is very relevant, it means that the target document also contains the content that users are interested in, thus increasing the weight of the target document. The similarity score between the target document and the read document can be expressed as:

$$sore\ d\ =\frac{c}{n_{read}}Sim\ d\ =\frac{c}{n_{read}}\frac{\sum_{i=1}^{n}W_{ij}}{\sqrt{\sum_{i=1}^{n}w\times\sum_{i=1}^{n}W_{i}^{2}}} \tag{5}$$

For the document class deleted by the user, deleting this document indicates that the content in this document does not meet the user's requirements. If the target document is similar to the deleted document, the content of this document also does not meet the user's requirements. Therefore, the weight of this document needs to be appropriately reduced. Similarly, the similarity score between the target document and the deleted document can be expressed as:

$$sore\ d\ =\frac{1}{n_{read}}Sim\ d\ =\frac{1}{n_{read}}\frac{\sum_{i=1}^{n}W_{ij}}{\sqrt{\sum_{i=1}^{n}w\times\sum_{i=1}^{n}W_{i}^{2}}} \tag{6}$$

Among the user's favorite documents, the user's collection of this document shows that the content in this document is in line with the user's interest. If the destination document is similar to the favorite document, it shows that the content of this document also meets the user's needs, so it is necessary to appropriately increase the weight of this document. The similarity measure between the target document and the favorite document can be expressed as follows:

$$\begin{aligned}sore\ d,d_{save}\ &=\frac{1}{n_{save}}Sim\ d,d_{save}\\&=\frac{1}{n_{save}}\frac{\sum_{i=1}^{n}W_{ij}}{\sqrt{\sum_{i=1}^{n}w\times\sum_{i=1}^{n}W_{save}^{2}}}\end{aligned} \tag{7}$$

According to the user's behavior log information, the following similarity model for calculating the user's behavior log information can be obtained:

$$\left.\begin{aligned}LogInfo\ q\ &=\mu_{1}score\ d,d_{read}\\&+\mu_{2}score\ d,d_{save}\\&-\mu_{3}score\ d,d_{read}\end{aligned}\right\} \tag{8}$$

To sum up, the user's interest model can be calculated in two parts. One is the static part, which calculates the similarity between the current document and the user's background, represented by D. The other is the dynamic part, which is calculated by the user's log and represented by LogInfo. Its processing methods include the change of document similarity caused by collection, reading, and deletion. The following interest model can be obtained:

$$Interest\ q\ =\lambda Sim\ d\ +\ 1-\lambda\ LogInfo\ q \tag{9}$$

among λ Is the weight of the user's background information. At the same time, in the fusion model of multiple information, we define that the measure of similarity between a document and a user query keyword can be expressed by the following formula:

$$Sim\ q,d\ =aSim\ q.d\ +\beta Simd+1-\alpha-\beta Sim(LogInfoq,\ d) \tag{10}$$

4 EXPERIMENTAL TEST

4.1 Analysis and Comparison of Recommended Algorithms

Users can open any browsing interface of the recommendation learning system through the browser, and the real data can well reflect the accuracy and credibility of the recommendation algorithm in this paper. The datasets in this paper are all from the teaching information dataset on the Internet, with a total of about 700,000 scoring data from 1,500 pieces of teaching information from 2,000 users. In this paper, data sets are divided into two categories: test set and training set. The division rule is that the user correlation coefficient shows a regular change (that is, it gradually decreases from the highest). 70% of the original data set is randomly selected as the training set, and the remaining 30% is the test set. Last, the coefficients of the data sets are 97.8%, 89.2%, 83.8%, 83.5%, 72.5%, 62.9%, 56.3%, 55.7%, and 52.3%, respectively. By inputting the data set into the prototype system, we can analyze the comparison results of different algorithms in the following aspects.

(1) Compare the data with scores under different sparseness. The trend of prediction based on scores can be seen in Figure 4.

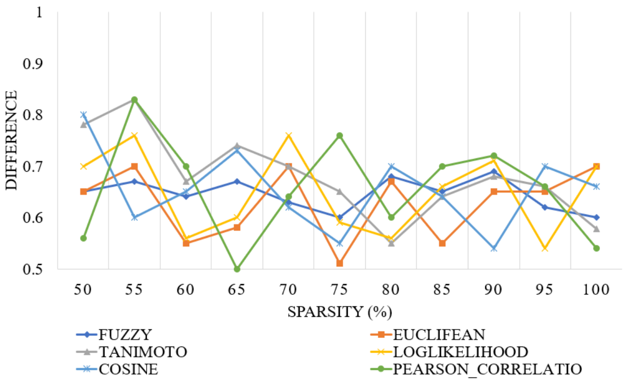

Figure 4: Comparison data of scoring similarity algorithm under different sparsity.

Therefore, the Euclidean algorithm is generally considered. Because the number of training sets added to the score is certain, and the data matrix related to the current user is sparse, the prediction ability of the fuzzy algorithm is the best. Therefore, when the matrix is sparse, the fuzzy algorithm can be considered. You can also consider adjusting the number of recommendations, increasing the preference of recommendation data, improving the filtering threshold, and enhancing the recommendation effect.

(2) Compare the data with different sparseness by ignoring the score. In our actual learning environment, users may not give a specific score to a learning resource but click or pay attention to a learning resource; that is, we only know whether users prefer it or not, but we don't score it. In this case, we can complete the learning resource. The recommendation effect of ignoring the score is shown in Figure 5. It can be seen from the figure that the Euclidean algorithm is considered when there is no scoring item for a recommendation. Although the fuzzy algorithm in the previous algorithm is better than the eu-clean algorithm when there is a score, the algorithm must rely on the score. Otherwise, the error is too large, and the Pearson_ Correlation completely depends on the score, so no recommendation data is generated in this case.

(3) Comparison of the time required for a single node to obtain results in different data sets and different algorithms from Fig. 6, it can be seen that the time required for various algorithms is different, and their average time is Pearson_ Correlation < Tanimoto < cosine < Euclidean <

loglikelihood > fuzzy algorithm. Therefore, to a certain extent, mixed recommendations can be considered, or different algorithms can be selected according to the size of the data set and correlation sparsity.

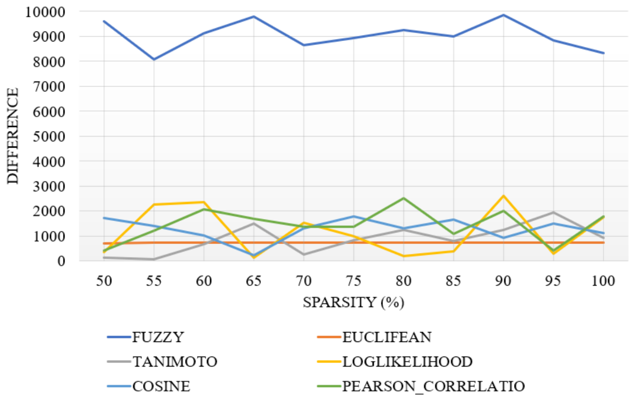

Figure 5: Comparison data of different sparsity algorithms without considering score similarity.

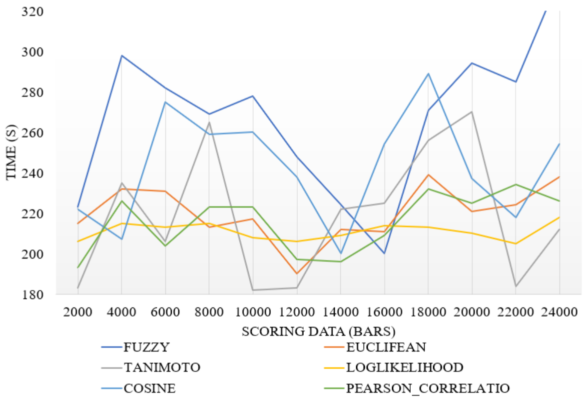

Figure 6: Time comparison of different algorithms for a single node.

At present, there are many kinds of recommendation algorithms which cannot be generalized. To deal with different situations, we need to consider many things, such as parameters, hardware, environment, and so on. Generally speaking, the similarity calculation methods of common recommendation algorithms are the above, but their suitable application ranges are different, and the fuzzy algorithm proposed in this paper has relative advantages in many aspects, so based on this fuzzy recommendation algorithm, a recommendation system for college information is designed.

4.2 Determine the Optimal Similarity Method and Determine the Number of Nearest Neighbors and the Optimal Clustering Items

In this experiment, three common similarity calculation methods, cosine similarity adjusted by cosine similarity and Pearson correlation coefficient, are considered as the test objectives of this experiment: the three similarity calculation methods are tested under different nearest neighbors by MAE to observe the optimal number of neighbors and the similarity calculation function. Assuming the number of fuzzy clusters C = 200, it can be found that the corresponding Mae value of the Pearson correlation coefficient is the smallest compared with the other two similarity calculation methods. Therefore, the Pearson correlation coefficient is used as the calculation method of the similarity between users. From the experimental objectives, it can be seen that the optimal result of fuzzy clustering is that the distance between clusters is far, the distance between samples in the cluster is as close as possible, and the higher the objective function L (c), the better. Therefore, it is mainly through iterative calculation of the number of clusters that the optimal number of clusters and the maximum value of L (c) are found. When the number of clusters is 200, the value of L (c) is the largest; that is, at this time, the samples in the cluster are relatively dense, and the distance between different clusters is relatively far, achieving a better clustering effect.

4.3 Comparison Results of Average Absolute Deviation MAE and Recommended Recall Rate

The average absolute deviation MAE is used as a metric to compare the performance of this algorithm with the traditional collaborative filtering algorithm. The comparative experiment is shown in Figure 7.

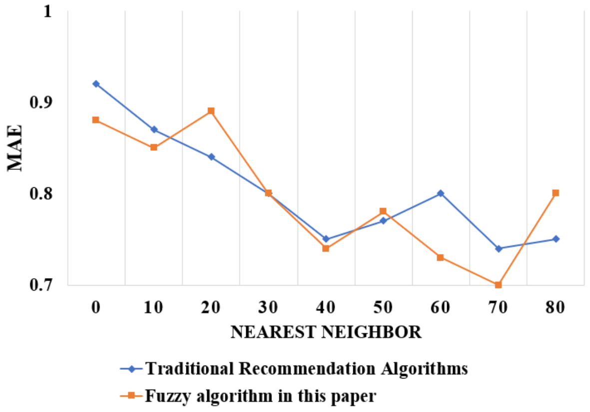

Figure 7: MAE of recommended algorithm.

Finally, this paper compares and analyzes the improved recommendation algorithm and the traditional recommendation algorithm and judges whether the recommendation degree of the proposed fuzzy model algorithm is improved under different numbers of nearest neighbors by their MAE. The figure shows that the recommendation results of the two algorithms are roughly the same. It can be seen from the data set experiment that under the setting of 10 different nearest neighbors, 7 corresponding MAEs are more accurate based on fuzzy reasoning, and 3 corresponding MAEs are more accurate based on traditional algorithms. However, it is impossible to explain which method is more accurate statistically.

In the actual e-commerce transaction scoring, Web customers often have very serious uncertainty and fuzziness in scoring items. In addition, the items scored by customers often have obvious category information. The multiple fuzzy implication fuzzy reasoning method just takes this information into account, which is more applicable. In order to test the effectiveness of the system, this paper conducts a performance comparison experiment between the system, the personalized education information recommendation system, and the recommendation system based on ElasticSearch based on the user's recommended accuracy and recall rate. The recommendation rate refers to the ratio of the amount of educational information recommended by the user system to the total amount of educational information applied by the user. The following experiments test the recall rates of the three systems, and the comparison results can be seen in Figure 8.

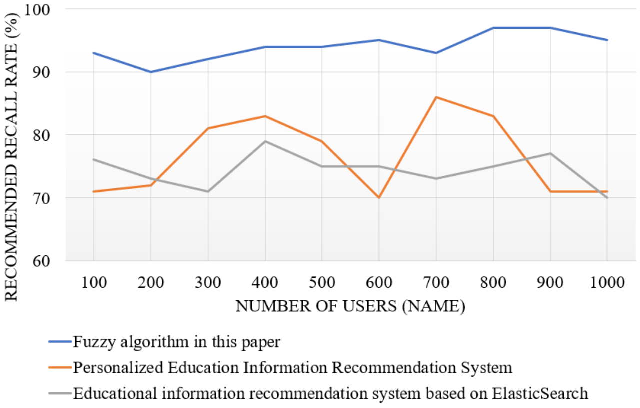

Figure 8: Comparison results of recommended recall rates of three systems.

With the increase in the number of users, it always ranks above the other two systems, and the fluctuation range is very small. The lowest recommended recall rate of the other two systems fell below 0.7. Most of the education information recommended by the system in this paper is adopted by users.

5 CONCLUSIONS

The application of modern educational information technology in education in private colleges marks the progress of education in the times, and it is also the inevitable trend of the development of the times. In the actual teaching of private colleges, teachers should be good at applying various new means and technologies to assist teaching so as to make abstract knowledge concrete, help students to have a deeper understanding, and improve their comprehensive literacy. In this paper, a fuzzy algorithm recommendation system for college education information is designed, in which each functional module performs its own duties, and the system content covers a wide range. On the basis of the traditional fuzzy recommendation algorithm, Hadoop is added. In the algorithm, online real-time recommendation, offline calculation, and cloud stack resource scheduling monitoring are adopted to make up for the shortcomings of the traditional algorithm, such as insufficient real-time recommendation, insufficient recommendation accuracy, and invisible resource scheduling. Aiming at the problem of data sparseness existing in traditional collaborative filtering recommendation algorithms, the fuzzy recommendation algorithm in this paper has a better performance compared with other recommendation system algorithms by fusing various relationship types of users and considering the fuzziness of users' ratings.

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