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Computer-Aided Design of Personalized Recommendation in Teaching System

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Abstract. The traditional education model has been unable to adapt to the needs of talents in the new era. In order to improve teaching efficiency and promote the coordination of teaching mode and computer technology development, this paper used artificial intelligence, fuzzy mathematics, XML and other technologies to form a network teaching system with certain intelligence under the guidance of new constructivist theory. At the same time, this paper designed an educational resource topic push system and transplanted it to a secondary education cloud platform in Zunyi City. This thesis provides a reference example for promoting the application of recommendation system in teaching aid system and the development of teaching aid system, and also improves the auxiliary quality of teaching aid system and provides theoretical reference for subsequent related research.

Keywords: personalization; recommendation system; computer aided; teaching; system construction.
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1 INTRODUCTION

In the field of education and teaching, the teaching aid system has been widely used, and teachers and students can communicate and share resources through the teaching aid system. Teachers can share the teaching resources of teaching through the auxiliary system, and students can also access and share teaching resources through the auxiliary system. Therefore, in the teaching aid system, it is very necessary to build a recommendation system for integrated teaching resources. This can improve the utilization of teaching resources, especially in the case of a large number of shared teaching resources in the teaching aid system. This recommendation system can help students find the teaching resources that they are interested in, which is very helpful to improve students' interest in learning and quality of learning [1].

In foreign countries, especially the United States, the popularity of the Internet is very high, and the application of recommended system technology is also very mature. Therefore, the integration of some website recommendation systems in the United States is very high. The personalized recommendation system was first created by Goldberg et al. at the XeroxPARC Research Center, and based on the collaborative filtering prototype Tapestry, they conducted mail filtering and news recommendation [2]. Subsequently, American Association of Artificial Intelligence (AAAI) conference, Carnegie Mellon University and the Massachusetts Institute of Technology each proposed their own recommendation systems WebWatcher and LIRA. In August of the same year, at the International Artificial Intelligence Conference, the Massachusetts Institute of Technology proposed a personalized navigation body recommendation system, Lefizia. The introduction of these three systems marks the beginning of personalized recommendation services [3]. In the following years, the personalized recommendation system received extensive attention from the academic community and the business community. Researchers at the University of Minnesota in the United States established a research-based film recommendation system website based on collaborative filtering algorithms and promoted the development and application of collaborative filtering algorithms. Foreign commercial websites use the recommendation system earlier [4], and even some well-known recommendation algorithms are invented by enterprises. For example, Alllazon (Amazon) first applied the collaborative filtering algorithm to its own products, and the recommendation algorithm based on project collaborative filtering was proposed by Amazon [5]. It can be seen that the driving of commercial interests has contributed greatly to the development of recommendation algorithms.

The most famous websites that use recommended algorithms in foreign countries are Amazon, Nefflix, Hulu, etc. Among them, Amazon makes recommendations for its products to increase the user's purchase rate, which contributes to Amazon's annual revenue growth of at least 20%.On the Amazon website, the use of the recommendation system can be seen everywhere [6]. For example, Amazon's Today recommendation module can recommend some new items to the user according to the current popular products, the user's recent purchase records and browsing records, which can solve the cold start problem based on the item recommendation. The bundled sales module analyzes the user's purchase behavior through machine learning technology and recommends some products that are often bought together to the user [7]. The product modules purchased by other users are a typical application based on the item collaborative filtering recommendation algorithm to help users find products of interest. It can be seen that the success of Amazon is inseparable from the widespread use of recommendation algorithms. Netflix is an online video rental provider in the United States. The company offers a huge number of DVDs for users to choose from and distribute them for free. In order to increase the user's rental rate and reduce the user's rent to the dissatisfied movie replacement DVD, Netflix also uses a recommendation system to recommend movies that users may like to users, reducing the user's dissatisfaction with the rental movie and increasing the number of users renting movies. Netflix takes the recommendation system very seriously, it hosted the Referral Engine Grand Prix to reward teams that can improve the Netflix recommendation engine. The event not only improved the accuracy of the Netflix recommendation system, but also increased the visibility of Netflix and attracted talents who are proficient in the recommendation engine algorithm to work at Netflix. Therefore, foreign attention to the recommendation system research can be seen [8].

After investigation, it is found that the popularity of the teaching aid system in the domestic education field is not very high. Although some colleges have their own teaching aid system, these teaching aid systems rarely include the teaching resource recommendation subsystem. In domestic commercial websites, due to the serious competition in the industry and the good user experience of the website, it has a significant effect on improving the company's efficiency. Therefore, commercial websites use a wide range of machine learning technologies such as recommendation systems. In particular, the integration system of e-commerce and social networking sites is relatively high. E-commerce websites are represented by C2C and B2C websites such as Taobao, Jingdong Mall and Dangdang [9]. In such sites, the recommendation system can improve the cross-selling ability of the website, increase the transaction conversion rate, and can improve the loyalty of the user and help the user to quickly find the product. Taking Taobao as an example, it contains shop recommendation for similar or related products, bought it after bought it, see it after seeing it, group information disclosure, popular rankings, etc. These products cover a lot of application scenarios, including browsing and browsing, favorites recommendation, shopping cart recommendations, goods already bought, goods that you may be interested, Taobao wireless applications, etc. [10]. It is

Taobao's extensive application of recommendation systems, making it the first C2C e-commerce platform in China and even in Asia. The recommendation system of social networking websites mainly focuses on social recommendation, which helps users to find people, movies, songs, etc. of interest, and is represented by Douban and Youku. In particular, Douban is now a relatively successful social networking site in China, and its wide application in recommendation algorithms makes it a very good and diverse social networking platform. The recommended system can be seen almost anywhere in the watercress network. For example, after the latest revision of the Douban homepage, users will be interested in articles, books, photo albums, movies and other resources, and then follow up the user's feedback to correct the recommendation model, so that its recommendations are closer to the user's preferences. Another excellent example of a personalized recommendation for Douban is the Douban FM Music Radio. The recommendation system of Douban Music Radio's back end recommends a series of songs to the user, and then follow up the user's feedback to recommend the songs that the user may like. The more user feedback, the more accurate the Douban music station's recommendation. Douban Radio has become a very good choice for Chinese users to listen to songs [11].

The research content of this subject provides a solution for the individualized recommendation of the teaching resources of the teaching aid system. At this stage, although the recommended algorithm has been widely used in commercial websites and has been greatly developed. However, in the field of education and teaching, the teaching aid system is at the stage of initial development. It is a good idea to promote the development of teaching aids and improve the quality of teaching aids by using the mature recommendation algorithm technology and experience on existing commercial websites. Moreover, it can be foreseen that with the development of the teaching aid system, resource search and resource recommendation will inevitably become an indispensable important function, and this has a great impact on the user experience of the teaching aid system. Therefore, this topic is an attempt to recommend teaching resources. According to the characteristics of teaching resources recommendation in the teaching aid system and the mature technology of existing recommendation systems, a solution to meet the recommendation requirements of teaching resources is designed and implemented. This is very meaningful for improving the teaching assistant quality of the teaching aid system, improving the quality of teachers' teaching and the efficiency of students' learning.

2 RESEARCH METHODS

2.1 Fuzzy relation and fuzzy matrix

There are many concepts in the teaching system that are highly subjective and ambiguous, such as students' cognitive ability and teaching strategies, which cannot be accurately described by traditional mathematical methods. Fuzzy mathematics is an emerging branch of mathematics that can quantify and mathematically deal with fuzzy phenomena and fuzzy concepts.

The relationship is a mathematical model that describes the connection between things, represented by the letter R.

In the general set theory, one element is taken from the set A and the set B, respectively. The set of all these ordered pairs is called the direct product set of set A and set B, denoted as [12]:

$$A \times B = \left\{ (x, y) \middle| x \in A, y \in B \right\} \tag{1}$$

Among them, (x, y) is an ordered pair and their order cannot be changed, that is: $(x, y) \neq (y, x)$

A subset of the set of direct products A×B of sets A and B is called the binary relationship of A to B, referred to as the relationship.

There are only two values when a normal relationship describes the relationship between elements: yes or no. However, fuzzy relationships can quantitatively describe the closeness of the relationship between elements.

A fuzzy relation R from ordinary set A to ordinary set B is a fuzzy set $\underset{\sim}{R}$ on the direct product space. The membership function of $\underset{\sim}{R}$ is represented by $\mu_R(x,y)$ [13].

$$R=\begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mm} \end{bmatrix} \tag{2}$$

Among them, $0 \le r_{ij} \le 1, 1 \le i \le m, 1 \le j \le n$. The fuzzy relationship and the fuzzy matrix are one-to-one correspondence and are all represented by $\underset{\sim}{R}$.

The rules of ordinary sets are easily extended to fuzzy sets [14].

$F_{n\times m}$ is the set of all fuzzy relation matrices of the domain U(n) to V(m).

$\underset{\sim}{R}, \underset{\sim}{S} \times F_{n\times m}, \underset{\sim}{R} = (r_{ij})_{n\times m}, , \underset{\sim}{S} = (s_{ij})_{n\times m}$, for $\forall i, j$,there is

$$\begin{aligned} &\underset{\sim}{R} \bigcup \underset{\sim}{S} = (r_{ij} \vee s_{ij})_{n\times m} \\ &\underset{\sim}{R} \bigcap \underset{\sim}{S} = (r_{ij} \wedge s_{ij})_{n\times m} \\ &\underset{\sim}{R}^c = (1 - r_{ij})_{n\times m} \end{aligned} \tag{3}$$

Among them, " $\vee$ " indicates that the larger value is selected after comparing r_{ij} and s_{ij}, and "h" indicates that the smaller value is selected after comparing r_{ij} and s_{ij}.

In the real world, there are a large number of complex relationships synthesized by various basic relationships. For example, the "uncle" relationship is a synthesis of the "brother" relationship and the "father and son" relationship. The synthesis of fuzzy relations can be achieved by multiplication operations like ordinary relational synthesis. This is the basis for implementing fuzzy reasoning [15].

Assuming $\underset{\sim}{R}(r_{ij}) \in F_{n\times m}, \underset{\sim}{S}(s_{ij}) \in F_{m\times 1}$, the fuzzy product of $\underset{\sim}{R}$ and $\underset{\sim}{S}$ is

$$\underset{\sim}{T} = \underset{\sim}{R} \circ \underset{\sim}{S} \tag{4}$$

2.2 Fuzzy comprehensive evaluation principle

(1) Determine indicator sets and review sets. The set of factors of n numbers that affect the evaluation object is called the indicator set and is recorded as $U=\{u_1,u_2,\cdots,u_n\}$. The set of evaluation levels of m categories as evaluation criteria is called a comment set and is recorded as $V=\{v_1,v_2,\cdots,v_m\}$ [16].

(2) Determine the weight of each factor. The weight distribution set of each factor is $A=\{a_1,a_2,\cdots,a_n\}$. Among them, $a_i\,(0 \le a_i \le 1)$ is the weight of u_i, that is, the membership of u_i to $\underset{\sim}{A}$.

(3) Determine the single factor evaluation matrix $\underset{\sim}{R}$. If the element $u_i\{i=1,2,\cdots,\mathrm{n}\}$ in the indicator set U forms a fuzzy subset of V on the membership degree r_{ij} of $v_j\{j=1,2,\cdots,\mathrm{m}\}$ in the comment set V, which is recorded as $R_i=\{r_{i1},r_{i2},\cdots,r_{im}\}$, then

$$\underset{\sim}{R}=\begin{bmatrix}\underset{\sim}{R_1}\\ \vdots\\ \underset{\sim}{R_2}\end{bmatrix}=\begin{bmatrix}r_{11} & \cdots & r_{1n}\\ \vdots & \ddots & \vdots\\ r_{m1} & \cdots & r_{mm}\end{bmatrix} \tag{5}$$

(4) Solve the judgment result set. When the fuzzy vector $\underset{\sim}{A}$ and the fuzzy relation matrix $\underset{\sim}{R}$ are known, taking the direct product of the fuzzy matrix can obtain the following formula:

$$\underset{\sim}{B}=\underset{\sim}{A}\circ\underset{\sim}{R}=(a_1,a_2,\cdots,a_n)\circ\begin{bmatrix}r_{11} & \cdots & r_{1m}\\ \vdots & \ddots & \vdots\\ r_{1n} & \cdots & r_{nm}\end{bmatrix}=(b_1,\cdots,b_m) \tag{6}$$

$\underset{\sim}{B}$ is called a fuzzy evaluation set, and $b_j\{j=1,2,\cdots,\mathrm{m}\}$ is a judgment indicator.

(5) Operator Analysis of Fuzzy Comprehensive Evaluation Model

For the allocation of weights $\underset{\sim}{A}$, the corresponding comprehensive evaluation is $\underset{\sim}{B}=\underset{\sim}{A}\circ\underset{\sim}{R}$.

$$\underset{\sim}{A}=\{a_1,a_2,\cdots,a_n\},\underset{\sim}{B}=\{b_1,b_2,\cdots,b_m\} \tag{7}$$

$\underset{\sim}{A}=\{a_1,a_2,\cdots,a_n\},\underset{\sim}{B}=\{b_1,b_2,\cdots,b_m\}$ Among them, $b_j=\overset{m}{\underset{k=1}{\vee}}{}^*\left(\mathrm{a}_k\wedge^*\mathrm{r}_{kj}\right)$. The commonly used operator $M(\wedge^*,\vee^*)$ of b_{ij} has four factors: main factor determination type $M(\wedge,\vee)$, main factor prominent type I $M(\bullet,\vee)$, main factor prominent type II $M(\wedge,\otimes)$, and weighted average type $M(\bullet,+)$. Among them, the weighted average type $M(\bullet,+)$ is more accurate.

(6) Determination of fuzzy comprehensive evaluation results

There are two ways to determine the final evaluation result by evaluation result set $\underset{\sim}{B}$:

(1) Maximum membership method

The element of the evaluation set corresponding to the solution with the largest degree of membership in the evaluation result set $\underset{\sim}{B}$ is the evaluation result.

(2) Weighted average method

The evaluation result set $\underset{\sim}{B}=\{b_1,b_2,\cdots,b_m\}$ is normalized to $\underset{\sim}{\bar{B}}=\{J_1,J_2,\cdots,J_m\}$.Among them,

$$J_i=b_i\Big/\sum_{j=1}^{m}b_j\,(i=1,2,\cdots,m) \tag{8}$$

Then, the evaluation result set is $V=\sum_{j=1}^{m}J_jV_i$

The influencing factors are divided into several levels. First, the lower-level factors are evaluated by single-level fuzzy comprehensive evaluation, and then multi-level evaluation is carried out.

This paper assumes that $U=\{u_1,u_2,\cdots,u_n\}$ is a secondary evaluation indicator set. Among them,

$$\begin{aligned} &U_1=\{u_{11},u_{12},\cdots,u_{1m}\} \\ &U_2=\{u_{21},u_{22},\cdots,u_{2m}\} \\ &\cdots\cdots \\ &U_n=\{u_{n1},u_{n2},\cdots,u_{nm}\} \end{aligned} \tag{9}$$

$V=\{v_1,v_2,\cdots,v_r\}$ is the evaluation set.

The first step: the second level is first judged

(1) Judgment matrix $\underset{\sim}{R_i}$ and weight distribution set $\underset{\sim}{A_i}$ are sought

(2) $\underset{\sim}{B_i}=\underset{\sim}{A_i}\circ\underset{\sim}{R_i}$ $\underset{\sim}{B_i}=\{b_{i1},b_{i2},\cdots,b_{ik}\}$.

Step 2: The first level is judged.

The result obtained in the first step is formed into a judgment matrix $\underset{\sim}{R}$, that is,

$$\underset{\sim}{R}=\begin{bmatrix}\underset{\sim}{R_2}\\ \vdots \\ \underset{\sim}{R_n}\end{bmatrix} \tag{10}$$

Weight set $A=(a_1,a_2,\cdots,a_n)$. Among them, a_i is the weight of the i-th factor U_i in the first level. $\underset{\sim}{B}=\underset{\sim}{A}\circ\underset{\sim}{R}$ is calculated, then $\underset{\sim}{B}=\{b_{i1},b_{i2},\cdots,b_{ik}\}$.

3 ALGORITHM VERIFICATION RESULTS AND SYSTEM CONSTRUCTION

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3.1 Algorithm verification

Experimental environment: The processor is Intel Xeon E5620 or above, the memory is 8G, the hard disk is 1T, and the development environment is Python. Experimental protocol: The experiment was tested on the MovieLens dataset along with the classic algorithms Slope One and Weighted Slope One. Contrast experiments and verification algorithms were performed to reduce the recommended mean absolute error. The experiment was conducted using the five-fold cross-validation method. The data set was divided into five parts, four of which were training sets, and the remaining one was the test set. The average of the results obtained in the five experiments is the experimental result. Experimental data set: DataSets The MovieLens dataset was downloaded from the Grouplens website (http://www.grouplens.org/node/12). The selected data set contains 100,000 pieces of data that scored nearly 900 users for 1683 movies. The number of movies each user can watch varies from 1 to 20. The downloaded data set is simply processed and saved as u.data.

Experimental analysis: The average error of MAE of AW-Slope One and W-Slope One and W-Slope One proposed in this paper is shown in the figure:

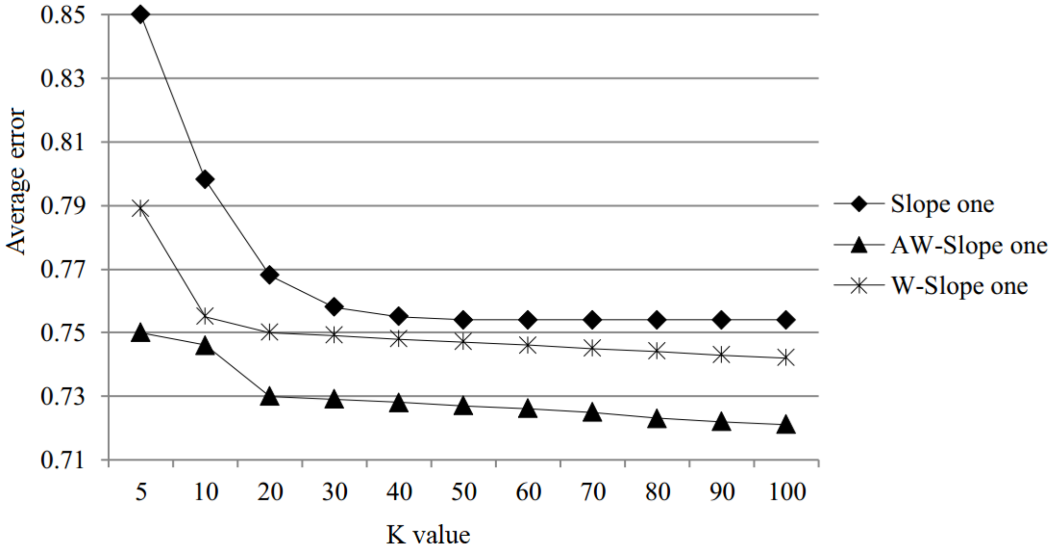

Figure 1: MAE evaluation line graph of each algorithm.

The experimental results show that the AW-Slope One algorithm has a significantly lower mean absolute error (MAE) value than the W-Slope One and Slope One algorithms. As the data increases, the value of the absolute value error MAE of the AW-Slope One algorithm and the W-Slope One Slope One algorithm is decreasing. Obviously, the proposed AW-Slope One algorithm is far superior to the W-Slope One and Slope One algorithms. It is concluded that the proposed AW-Slope One algorithm greatly reduces the recommended mean absolute error compared to the traditional algorithms W-Slope One and Slope One.

3.2 System function requirement analysis

(1) Obtain educational resource topic information and user behavior information. The AW-Slope One algorithm model proposed in the third chapter is limited to explicit feedback data, which is the specific score information, which does not conform to the design idea that the system calculates the similarity of the topic according to the error situation of the topic and the similarity of the content. Therefore, the system adopts the second hybrid recommendation algorithm model CB-ItemCF. Therefore, the acquisition of information also needs to be divided into two branches: The content-based recommendation algorithm needs to collect the wrong questions of the student users and the text content information of these topics. The ItemCF algorithm needs to collect the user's correct questions and score information for the questions.

(2) Clean and sort the input data. After obtaining the topic information and user behavior information, the data cannot be directly applied to the recommendation algorithm. It is also necessary to clean and organize the data and eliminate the redundant part of the algorithm calculation in the topic feature information and the student user title score information, and at the same time, the format is unified.

(3) Recommended algorithm model. This is the most important part of the recommendation system. The recommended model must be consistent with the system requirements and the goals are the same. The choice of recommendation algorithm and the choice of model will directly affect the performance of the entire recommendation system.

(4) The recommended result generation. After obtaining the topic to be recommended according to the recommendation algorithm, it is necessary to display the information to the user in

a suitable scenario to obtain a greater approval rate and satisfaction. Figure 2 is an interaction relationship between various components in the recommendation system.

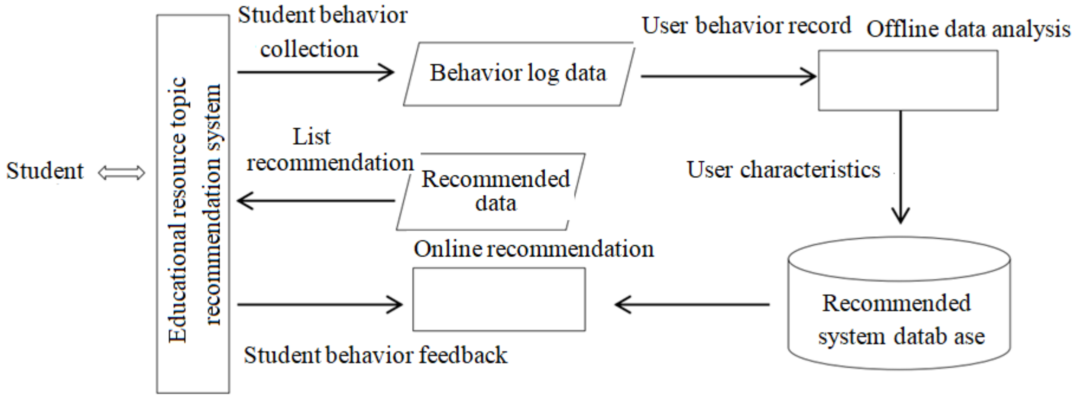

Figure 2: Component interaction of the education resource topic recommendation system.

When a new user is registered in the recommendation system, the system first collects basic information of the user through a preset registration page, including account personal information and preferences or demand topic label information. After that, the online layer transmits the information to the data analysis layer, and after the data analysis layer sorts and sorts the information, the account personal information is stored in the student user information database. If the user has selected a tag for a personal preference or a topic of interest, then the personalized interest information is transmitted to the recommendation generation module. After that, the user's personal information is collected for subsequent system upgrades.

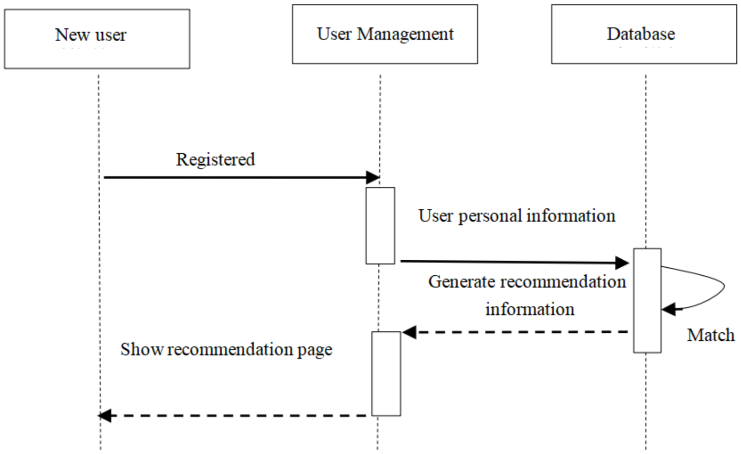

Figure 3: New user registration.

The user's preference for the topic is the core data of the topic recommendation system, and the business process is related to the recommendation accuracy. Considering that the real-time requirement of the topic recommendation does not have to be too high, in order to facilitate the processing, the system uses the offline calculation mode, that is, the user does not immediately process the user after updating the demand for the topic (favorite) but updates the user recommendation at a fixed daily time. At the time of daily settlement, after the user uses the browser feedback to do the problem, the user management module acquires the demand (favorite) degree of the problem through the program logic and transmits the data to the recommendation generation module. The recommendation generation module is responsible for calculating and updating the topic similarity and recalculating the target user's preference for the new recommended topic using the CB-ItemCF recommendation model and updating the user's recommendation list.

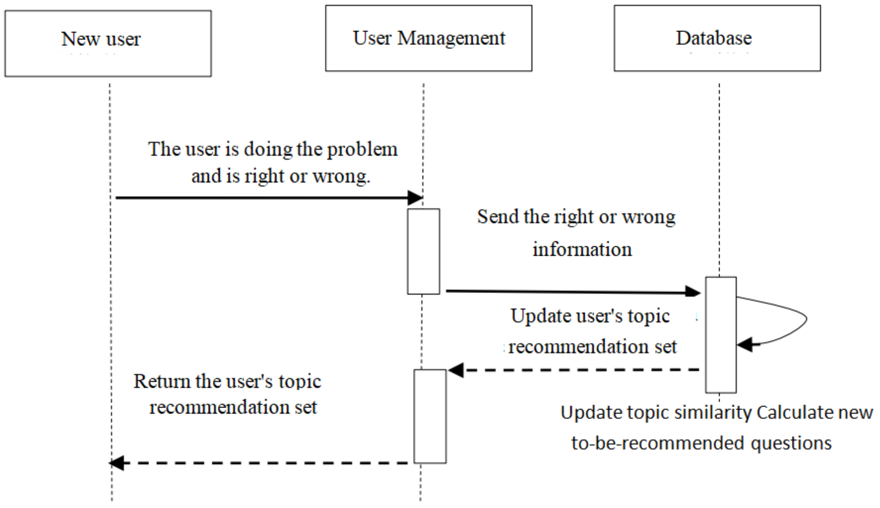

Figure 4: Recommended list of updates by doing the title.

The method of topological sorting is as follows: Step 1: construct a weighted directed graph; second step; vertices with an input degree of 0; and third step: delete the vertex and its directed edges. Loop through the second and third steps, ending when all vertices are output. The linear sequence formed by the output vertices is the topological sequence. The specific steps are shown in Figures 5 to 7.

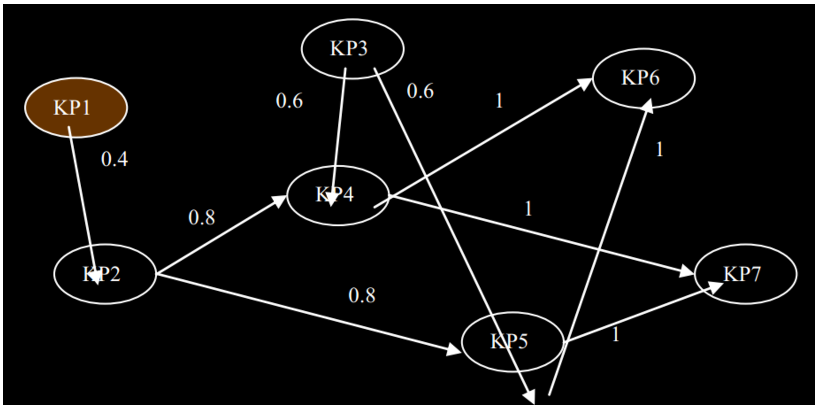

Figure 5: Output vertex KP1.

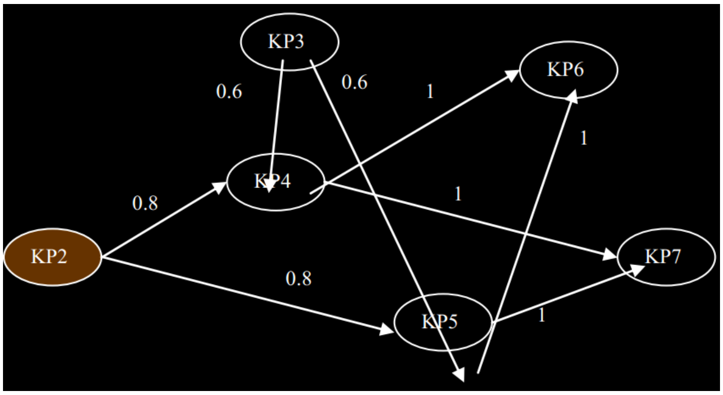

Figure 6: Output vertex KP2.

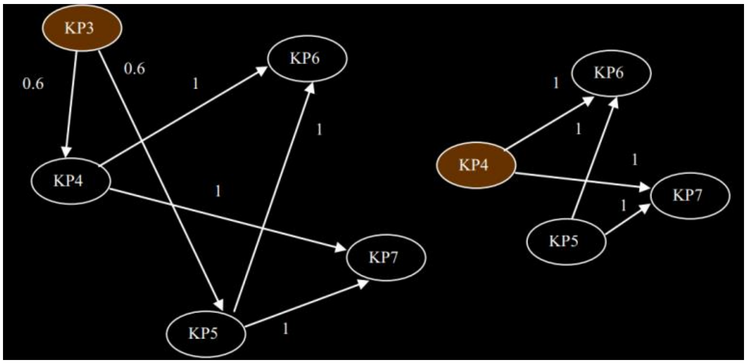

Figure 7: Output vertices KP3 and KP4.

The database of this educational resource recommendation system uses Oracle. The advantage of Oracle database is that Oracle's stability is better. Moreover, Oracle's data logging tool sqlload.exe is more powerful than Sqlserver's Bcp, and Oracle can import text file data according to conditions and the security mechanism is better. The main table structure of the system database is designed as follows. The student basic information form is used to store regular personal information of the system students, such as student ID (primary key, uniquely determined student identity), student name, account password, student gender, student class, student age, registration time, and the like.

Field	*Type*
stu_ID	varchar(30)
stu_NAME	varchar(80)
stu_PSW	varchar(30)
stu_SEX	varchar(8)
stu_CLASS	varchar(8)
stu_AGE	int(10)
stu_RDATE	datetime

Table 1: User Information Table.

The topic basic information table is used to store basic information of all the questions in the system, including the title ID (primary key), title name, title type, title content, topic knowledge point, title difficulty, title release time and title picture path.

Field	*Type*
title_ID	varchar(30)
title_NAME	varchar(80)
title_TYPE	varchar(30)
title_CONTENT	text
title_POINT	varchar(30)
title_DIFF	float(10)
title_RDATE	datetime
title_IMAGE	varchar(100)

Table 2: Basic information table of the title.

The student's problem information table is used to store the correctness and score information of the student's topic and is mainly used to call the recommendation generation module. It includes the user ID, the title ID, the correct question, and the title score. The user ID and the title ID together form a primary key.

Field	*Type*
user_ID	varchar(30)
title_ID	varchar(30)
title_RIGHT	bit
title_GRADE	Float(10)

Table 3: Student's problem information table.

The teacher information table is used to store teacher related information, including teacher ID, teacher name, account password, teaching course, number of questions added, and time added. The teacher ID is the primary key, which uniquely identifies the user.

Field	*Type*
teach_ID	varchar(30)
teach	_NAME
teach_PSW	varchar(30)
teach_COURSE	varchar(8)
teach	_RDATE
teach	_numb

Table 4: Teacher Information Table.

4 ANALYSIS AND DISCUSSION

The two mixed recommendation algorithm models studied in this thesis are: the hybrid recommendation algorithm of the fusion association rules Apriori and Weighted-Slope One and the hybrid recommendation algorithm combining ItemCF and CB. The hybrid strategy used by the hybrid recommendation algorithm of the fusion association rules Apriori and Weighted-Slope One is cascading and uses the results of the previous recommendation algorithm as input to the next recommendation algorithm. Frequent patterns can mine the Apriori algorithm part. The popular meaning is to find N items that are close to the target score, so that the calculation range can be narrowed, and the data credibility can be improved to achieve the purpose of improving the recommendation accuracy. The result set obtained by the association rule is introduced into the Weighted-Slope One algorithm model whose associated project confidence is weight, and the scoring estimate of the target item by the current active user is calculated. Finally, the Top-N recommendation item is submitted to the user according to the predicted value of the user's rating on the item. The second hybrid recommendation model is a hybrid recommendation algorithm that combines ItemCF and CB: it also uses a cascaded recommendation strategy. The meaning of the content-based recommendation algorithm part in this project is to use the text analysis method TF-IDF algorithm to find M topics similar to the title content. The item-based collaborative filtering part analyzes the user's previous behavior, constructs a matrix of M questions, calculates the similarity between the student user's wrong topic and the M topics, and sorts the similar topics to do Top-N recommendation. In practical applications, the similar items calculated by the content-based recommendation algorithm may be of a large order of magnitude, and the similarity is not much different. Therefore, on the basis of this, the item-based collaborative filtering algorithm is used for the second filtering, it can match the problem, and the difficulty of the topic is similar to the difficulty of wrong question of the student user. This greatly reduces the number of similar topics, improves the accuracy of recommendations, and the recommended topics are more in line with the needs of student users.

This chapter proposes a recommendation algorithm combining Apriori and Weighted-Slope One based on association rules. Firstly, the data is analyzed and mined, and the calculation of the correlation values of the N items associated with the target project is mined, the matrix is reduced, and the interpretability is enhanced. In theory, it can solve the problem that the similarity of the items that are neglected when using the weighted Slope One algorithm to calculate the predicted value has a greater impact on the project score. The hybrid recommendation model replaces the number of users who have jointly evaluated the project in the traditional form by using the relevance of the project association. This method not only calculates the predicted value of the user for the target project, but also enhances the credibility of the recommendation.

5 CONCLUSION

Starting from the recommendation of educational resources, this paper introduced the research background, research significance, current situation at home and abroad, challenges and development trends of educational resources recommendation. At the same time, this paper briefly introduced the structure of the personalized recommendation system, the commonly used recommendation algorithm, the mixed recommendation strategy and the evaluation of the recommendation system. Moreover, the idea, flow and implementation steps of the fusion association rules Apriori and Weighted-Slope One were introduced, and the experimental results showed that the fusion effect of the method is good. In addition, this paper also introduced a combination of item and content-based collaborative filtering algorithms, which combines content-based recommendation algorithm and item-based collaborative filtering algorithm through Cascade combination, and the idea and algorithm flow were described in detail. Meanwhile, this paper introduced the functional architecture of the detailed design system of the education resource topic recommendation system, database design and functional module design, and system implementation. Finally, the paper used the interface design of the system function module and elaborated the implementation of the system.

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