Personalized Recommendation Method of Maternal and Child Health Education Resources Based on Association Rule Mining Algorithm

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Abstract. Some personalized recommendation methods of maternal and child health education resources have the problem of long response time of resource recommendation. A personalized recommendation method of maternal and child health education resources based on association rule mining algorithm is designed to improve the above defects. Automatically obtain the text content within the marking range, obtain the characteristics of digital teaching resources, use the session log to record various behaviors of users, build the user interest preference model, extract the core language concept knowledge in the language concept lattice, establish the maternal and child health knowledge base, calculate the maximum likelihood function of the ability parameter, and design the personalized recommendation method based on the association rule mining algorithm. Experimental results: the response times of the personalized recommendation method of maternal and child health education resources in this paper and the other two personalized recommendation methods of maternal and child health education resources are 5.055s, 7.119s and 7.508s respectively, which shows that the personalized recommendation method of maternal and child health education resources in this paper is more feasible after fully combining the association rule mining algorithm.

Keywords: Association rules · Mining algorithm · Maternal and child health care · Teaching resources · Personalized recommendation · Article characteristics

1 Introduction

With the progress of science and technology, the network and education inevitably collide. Especially in recent years, the number of educational websites has increased geometrically, and the educational resources in the network are also growing rapidly. Therefore, a lot of human and material resources have been invested in all aspects of

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online education at home and abroad, aiming to use computer technology and educational data to improve learning efficiency or teachers' educational quality. However, a large number of maternal and child health care teaching resources are published on the network, which leads to the rapid growth of the number of teaching resources. It is difficult for students to find suitable learning resources in the massive maternal and child health care teaching resources, resulting in problems such as learning loss and information overload. Nowadays, information technology in the field of maternal and child health care teaching has developed rapidly, and a lot of experience has been accumulated in daily life and production. Summing up these experiences has produced a large number of data texts in the field of maternal and child health education. Among them, personalized learning through the analysis of students' learning behavior is one of the current research hotspots. Knowledge-based recommendation depends on the knowledge of item characteristics and user knowledge. The user knowledge here is not necessarily the browsing records and scoring information of users, but the search information of users or the description information of items. By making full use of these data texts through existing science and technology, it can play a huge medical guiding value, effectively assist doctors in diagnosis, and effectively improve the efficiency of clinicians and patients in obtaining high-quality reference resources. Therefore, some researchers have introduced relevant technologies in the recommendation field into online teaching to recommend maternal and child health care teaching resources, which can automatically recommend teaching resources for students that meet their learning characteristics, knowledge level, cognitive ability and other traits according to students' historical learning and historical response records. In the knowledge base system, acquiring knowledge is a major difficulty in the knowledge base. In the field of maternal and child health care, the characteristics of obvious differences in the distribution of knowledge structure, unclear concepts, wide sources of resources, complexity and strong subjectivity make it very difficult to build the knowledge base in the field of maternal and child health care. Combined with the machine learning technology of artificial intelligence, we can achieve the structured storage of multi-source knowledge in the field of personalized recommendation of maternal and child health care teaching resources, achieve the goal of reuse and sharing between the fields of maternal and child health care, and lay the foundation for the construction of maternal and child health care knowledge base system. Recommendation based on association rule mining algorithm must clarify user needs, and then the system matches whether the characteristics of items meet user needs, and establishes the association between recommended items and user needs. Compared with information retrieval technology, maternal and child health care teaching resource recommendation can better meet the personalized needs of students, greatly save students' time to find suitable teaching resources, and effectively alleviate the problems of information overload and learning loss caused by massive teaching resources. Just like pesonallogic, it allows users to describe the characteristics of items they need through conversation. In addition, it also adopts decision support or case-based recommendation methods. Teaching resource recommendation service is gradually becoming an important research topic and hot spot in the fields of online education and artificial intelligence, and has attracted more and more researchers' attention. Reference [1] proposed a recommendation model of educational resources based on collaborative filtering algorithm, incorporating the attribute feature information of learning users, and constructed a learning user model and a resource model; The learning user learning resource scoring matrix is constructed, and the modified cosine similarity algorithm is used to calculate the behavior information similarity of learning users, so as to achieve personalized recommendation of resources. Reference [2] proposed a personalized educational resource recommendation algorithm based on high-dimensional tensor decomposition. Preserve the information integrity of high-dimensional space and realize personalized learning resource recommendation. Reference [3] proposed a multi task feature recommendation algorithm that integrates knowledge maps. Using multi task feature learning tools to embed knowledge maps into tasks; Through the cross compression unit, the high-level relationship between potential features and entities is established, and the recommendation model is constructed to realize the recommendation of curriculum resources. However, the above educational resource recommendation method has the problem of long recommendation and response time. In order to solve this problem, a personalized maternal and child health education resource recommendation method based on the association rule mining algorithm is designed.

2 Get the Characteristics of Digital Teaching Resources

With the development of educational informatization, teaching resource platforms are also increasing, which promotes the wide dissemination and sharing of high-quality resources. Different from commodities in e-commerce, digital teaching resources in the platform have their inherent characteristics. In the past, in traditional teaching methods, teachers mostly wrote test questions by hand, which is not only difficult to share, but also inefficient, and difficult to save. Although there are many ways to classify resources: according to the teaching level, they can be divided into basic teaching resources and higher teaching resources. According to disciplines and majors, it can be divided into science and engineering teaching resources, Reference and history teaching resources, etc. [4]. Nowadays, although teachers have entered the era of electronic information. Usually, teachers use computer office word software to edit test questions, but due to the powerful function of office software, many teachers are not proficient in using it, which leads to low efficiency. At the same time, most of the storage of test questions is in the form of documents, which is too large to be flexible, and usually requires manual test paper generation. However, no matter which classification, teaching resources are used to teach knowledge. Each teaching resource has its own knowledge and skill points, which constitute the core of this resource and represent the essential attributes of digital teaching resources. This leads to the characteristics of digital teaching resources, as shown in Fig. 1:

It can be seen from Fig. 1 that the characteristics of digital teaching resources include: linear progressive characteristics, real-time characteristics, diversity characteristics and interactive characteristics. In addition, in order to meet the various needs of teachers for the generation of test questions, facilitate teachers' operation, improve the efficiency of question production, and reduce the granularity of resource storage, this paper studies and implements a variety of ways to generate test questions resources, so that the test questions resources can be stored in the unit of small questions. Moreover, the knowledge point information of each teaching resource is marked by experts and scholars,

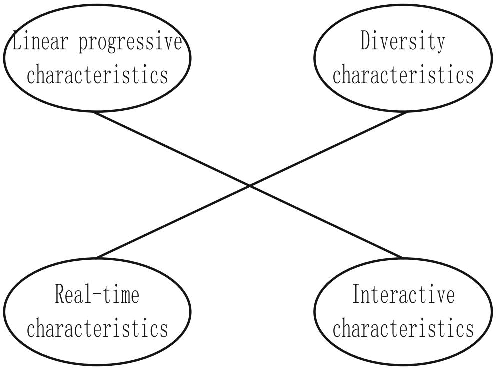

Fig. 1. Characteristics of digital teaching resources

which has a certain authority. For example, if you log on to the China University open course website, each course in the resource sharing course lists the course knowledge point information. After automatically obtaining the start and end positions of the test book, for a test document downloaded from the Internet or edited by the teacher, mark the test text, and then automatically obtain the text content within the marked range, and automatically analyze the questions, options, answers and analysis. Knowledge point information among resources may overlap, so resources can be linked through knowledge points. At the same time, users' preferences for resources also represent users' preferences for the attributes of knowledge points contained in resources to a certain extent [5, 6]. In addition, in order to improve the traditional test paper generation process, it is difficult for teachers to grasp the difficulty of the test paper and the comprehensiveness of the knowledge points examined by the test paper. Users share digital resources through the teaching platform, learn relevant knowledge, and are users of teaching resources. Personalization is the most important feature of digital education resources. Many digital education resources are selective and can effectively meet the personalized needs of learners. In order to ensure the independence of personal teaching resources among teachers and facilitate the effective sharing and reuse of teaching resources. Specifically, each teacher corresponds to a personal storage space, that is, each teacher has a personal resource library, and the test question resources and teaching courseware in the personal storage space are only used by teachers or users authorized by the owner of the library. Users generally have certain pertinence when learning, and the classification is relatively clear. For example, a science and engineering student is more inclined to learn science and engineering knowledge and choose science and engineering resources, while a Reference and history student is more inclined to choose Reference and history resources, that is, the user's own characteristic information has a certain connection with the selected resources. Resource providers provide learners with accurately pushed digital education resources through diversified service methods to meet learners' preferences, work and life, give full play to learners' potential, form learners' independent personality, and realize the personalization and customization of universal education and lifelong education. Therefore, students can be granted the right to upload their homework by teachers, which is convenient to upload it to teachers' personal space for teachers to download and review. At the same time, Teachers can also upload personal information and other teaching resources that are inconvenient to share to the personal resource library. Therefore, the similarity of choosing users of similar resources is much higher than that of choosing users of different resources. At the same time, big data technology is used to collect learners' learning tracks and data, build behavior models, match with knowledge maps, and accurately recommend digital education resources for learners.

3 Build a User Interest Preference Model

The data used in the recommended methods are generally divided into two categories. One is the attribute information of the user or the item itself, and the other is the interaction information between the user and the item. Personalized recommendation for users requires interactive information between users and items. When selecting resources, users' interests and preferences are usually concentrated in one or several types of resources, and the knowledge point attribute information of similar resources is also relatively similar. The knowledge point attribute connects different maternal and child health care teaching resources. Therefore, users' preference for resources also represents users' preference for the attributes contained in resources to a certain extent. This is the only way for users to have a relationship with items. However, most recommendation algorithms only use interactive information. When a new user just enters a new system, there is no interaction temporarily. Naturally, there is no interactive information. At this time, the user's attribute information can play a key role. Using the user model learned from the attribute information provided by the newly registered user to design the recommendation algorithm, it is easier to meet the needs of personalized recommendation [7, 8]. At the same time, the number of resource attributes in the method is far less than the number of resources. Transforming the user's preference for resources into the user's preference for resource attributes can map the high-dimensional scoring matrix to a relatively low dimensional space, which improves the response speed and reduces the sparsity of data. User's attribute information refers to the information that users need to provide when they visit the new platform for the first time, including gender, age, occupation, geographical location, etc. The platform can infer users' interests and preferences by analyzing these attribute information provided by users. Under the condition that the data of the user feature layer and the interest characteristics based on time series information are known, the data obtained from the user portrait layer is the combination of user attribute characteristics and user interest characteristics. The mathematical expression formula is as follows:

$$G_\delta = h_\delta + \frac{(1-h)}{2}\phi \tag{1}$$

In formula (1), h represents the weight of the user feature model, ϕ represents the data of the user feature layer, δ represents the set of user interest features.

Therefore, the scoring and resource attributes are fused to calculate the user similarity. In the process of user clustering, this model is used to calculate the similarity between users, which not only excavates the potential interests of users, but also alleviates the problem of data sparsity, making the clustering effect better. The discrete feature corresponds to each position of the coding vector, that is, how many discrete features there are, the number of bits of the coding vector will take value, and the value on the vector position is determined by the characteristic value corresponding to this position, so the value corresponding to this characteristic position will be set to 1, and the value not belonging to this characteristic position will be set to 0. When calculating users' preferences for resource attributes, users' specific ratings should be taken into account. The larger the proportion of the sum of users' ratings of resources with a certain attribute to the total of all their ratings, the more users prefer this attribute. Because the user clustering method belongs to unsupervised clustering, using the clustering method based on the peak density can determine the number of clusters according to the size of the density, so as to obtain the optimal number of clusters. For each user in the user model, the local density and distance should be calculated. Based on formula (1), the calculation formula of local density is obtained:

$$g = \sum_{i=1} \gamma |\gamma_i - \eta| \tag{2}$$

In formula (2), γ represents the truncated distance, η represents the number of data points smaller than the truncated distance, i represents the weight of all the scoring resources.

This determines that the coding vectors corresponding to each feature are orthogonal to each other and the distance is equal. The interaction information between users and items is the most important data in the recommendation method. This data mainly includes two forms: explicit interaction and implicit interaction. However, users' preferences cannot be comprehensively measured only by their ratings, because each resource has different attributes and the number of attributes, and the ratings are easily affected by other factors such as resource quality, evaluation scale and so on. Explicit interactive information refers to the information that can clearly see the user's preference for items, such as scoring, collection, attention, likes, purchases, etc. This type of data is easy to obtain, but it is also prone to dirty data. Implicit interaction is the user's objective operation of the object, such as user login, click, browse, search and other behaviors. Generally speaking, the more users prefer a certain attribute, the more they evaluate it. For example, if users prefer science fiction books, the number of science fiction books accounts for a large proportion of all evaluated books. At present, the more popular way to use implicit interaction is the mining of session log data. Various user behaviors are recorded in the session log, from which specific information can be extracted. Under comprehensive consideration, the expression formula of users' preference for resource attributes is:

$$K = \frac{|r - \mu_j|}{|\mu|} \times \sum_{j=1} |\gamma_i - \eta| \tag{3}$$

In formula (3), r represents the entire resource space, μ represents the set of resources scored by the user, j represents the resource attribute.

Therefore, the greater the weight of the resource containing a certain attribute in the user's scoring resource set, the more users prefer the attribute of the resource. Considering the dynamic relationship between the popularity of items and time. When calculating the user's interest in the item, add the weight parameter of the item over time:

$$Q = V^{\frac{y_\varepsilon - w_{\varepsilon-1}}{y}} \tag{4}$$

In formula (4), V represents the total amount of items, w is the time when the item is scored the first time, y is the total length of the item online, ε is the time complexity.

Due to the various types of operations of users, the types of implicit interactive information of users are more complex and diverse than the explicit interactive information. The advantage of implicit interaction is that it can avoid directly asking users for data of others' preferences and improve the goodwill of users.

4 Establish Maternal and Child Health Care Knowledge Base

The knowledge base model in the field of maternal and child health care is constructed. The knowledge base expresses the maternal and child health care knowledge in a standardized structural form, provides data model support for the entire upper application, assists the entire treatment process, and enables the maternal and child population and users to independently and quickly obtain relevant knowledge in the professional field. The number of language concept knowledge in language concept lattice is much larger than that in classical concept lattice, and the partial order relationship and data analysis work are also more complex. Therefore, in this section, the Boolean factor analysis method is used to simplify the language concept lattice. The field of maternal and child health care is further combined with the existing high-tech mobile Internet technology, big data technology, artificial intelligence technology and other computer technologies to realize the digitalization, standardization and informatization of maternal and child health care services. Combining the formal background of Boolean matrix and language concept, a knowledge reduction algorithm based on Boolean matrix for language concept lattice is proposed. By calculating the similarity of language concept knowledge in mandatory language concept knowledge, the core language concept knowledge in language concept lattice is extracted. From a practical point of view, we can simply regard the knowledge graph as a multi relationship graph. Determine the field and scope of maternal and child health care knowledge, including what knowledge will be covered by maternal and child health care knowledge, and what questions should be answered by the knowledge in the maternal and child health care ontology knowledge base. In the formal context of language concepts, language values are used to describe attributes, so the data dimensions are greatly increased compared with the classical formal context, so the lattice structure of language concept lattice is more complex than that of concept lattice. Reuse the created maternal and child health care ontology knowledge base, search and query the ontology knowledge base related to the field of maternal and child health care, and learn from the relevant concepts and relationships in the ontology or reuse in building a new maternal and child health care ontology knowledge base. This paper studies the problem of language concept reduction in the formal context of language concepts, and extracts the knowledge base of language concepts from the language concept lattice. A language concept knowledge reduction algorithm is proposed, which processes the mandatory language concept knowledge by calculating the similarity of language concept knowledge, so as to extract the core language concept knowledge base and simplify the language concept lattice. Find out all domain related terms in maternal and child health care, list the terms and give the attributes and concepts contained in the ontology at the same time. The more perfect the domain terms are, the more robust the knowledge base is. In the context of incomplete language concepts, define the similarity between fuzzy objects:

$$S = \frac{|e - d| + f|Inc(\alpha, \beta)|}{d|\alpha, \beta|} \tag{5}$$

In formula (5), e represents the complete lattice of the language concepts, d represents the language concept set, f represents the language order, α, β represents the upper and lower bounds of the language concepts, respectively.

In the formal context of incomplete language concepts, whether language concepts can be used to describe different fuzzy objects has uncertainty. Therefore, it is used to describe the relationship between fuzzy objects and language concepts, which is closer to human understanding. Determine the hierarchical relationship between classes in the maternal and child health knowledge base, and the hierarchical relationship between classes can be determined by bottom-up, top-down or a mixture of two methods. Determine the attributes of the class in the maternal and child health knowledge base, and the internal structure of the class is described by attributes. The formula for calculating the multi granularity similarity relationship of language concepts is:

$$M = \frac{\left\| e^2 - d^2 \right\|}{2} \times d|\alpha, \beta| \tag{6}$$

In formula (6), e represents the multi-granular language concept coordination set, d represents the similarity threshold.

However, when expressing the same information, compared with the dimension of attributes in the formal context, the dimension of language concepts in the formal context is greatly increased. Given the similarity threshold, the identification function is transformed into the minimum disjunctive normal form by using the absorption law and the distribution law. Determine the constraints between attributes in the maternal and child health knowledge base. Create instances in the maternal and child health knowledge base, build each instance through the created classes in the maternal and child field, and confirm whether the instance has corresponding attribute values. The convolution neural network structure of maternal and child health knowledge base is composed of four layers: input layer, multiple convolution layers, output layer and full connection layer. First, the maternal and child knowledge data is preprocessed, and the text data is converted into multi-dimensional vectors. Each conjunctive term of the minimum disjunctive normal form is a reduction under granularity, and all its conjunctive terms constitute all the reductions of the formal background of incomplete language concepts under granularity. After the input of the input layer, the multidimensional vector is processed by convolution neurons. A single convolution neural network structure can contain multiple convolution layers and multiple output layers.

5 Design Personalized Recommendation Method Based on Association Rule Mining Algorithm

Workflow of association rule recommendation function: when the user requests to browse resources from the server, the server generates session information, and the session information recording module first judges the content information accessed by the user. The essence of data fusion based on association is to establish semantic relationships between a large number of heterogeneous data. RDF data model is mainly used, that is, heterogeneous digital education resources can be transformed into standard format, so that each knowledge unit is related, and the relationship between existing knowledge bases can be established. Semantic analysis is mainly through processing and analyzing digital resources to obtain valuable content. If the access information has been browsed, it will not be written into the session. If the access information is new, it will be written into the session. There are many kinds of teaching resources in the network. Content-based recommendation is difficult to recommend unstructured resources such as audio and video, and it is difficult to recommend across fields. Association rule-based recommendation has a low degree of personalization, and it is difficult to get better personalized recommendation results. Then, the association rule reading and processing program module is used to find the content information accessed by users in the association rule table, read out the recommended content information, and hand it to the foreground display program related to the recommended content to find and display the recommended content [9]. The system structure of personalized recommendation method of teaching resources is shown in Fig. 2:

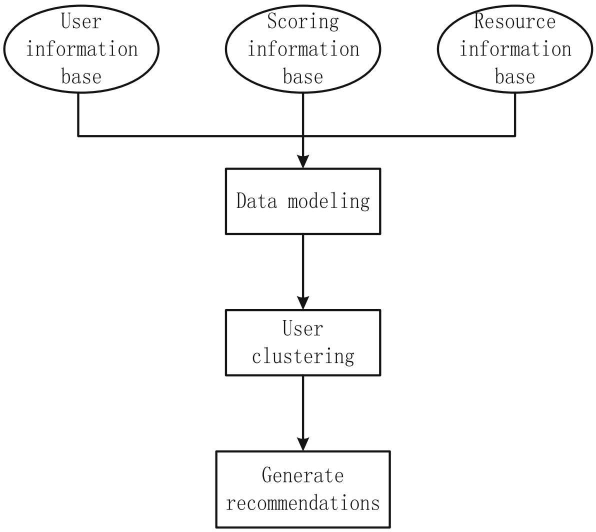

Fig. 2. Architecture of personalized recommendation of teaching methods for Maternal and Child Health care teaching resources

It can be seen from Fig. 2 that the recommendation method inputs the basic information and scoring data of users and resources, and outputs the recommendation results. Return the page data containing the recommended content to the client. When the user leaves the system, the storage access log module stores the contents accessed by the user into the access log table of the database. Workflow of association rule mining function: teachers or administrators log in to the background of the system, select association rule mining algorithm, set basic parameter values such as minimum support and minimum confidence, realize association rule mining, and store the mining results of association rules in the association rule table. Personalized recommendation can be divided into three steps: data processing, recommendation calculation and prediction recommendation. The first unit is to preprocess the data in the user information base, resource information base and scoring information base, and build a data model, that is, get the user feature vector, resource attribute vector, resource attribute preference vector, etc., so as to calculate the user similarity later. In the personalized recommendation method of maternal and child health care teaching resources designed this time, the concept of parameter estimation is introduced. If the difficulty coefficient, guess coefficient and discrimination coefficient of the current project are known, then the answer result data in the score matrix and the known difficulty coefficient, guess coefficient and discrimination coefficient are substituted into the IRT model to establish the maximum likelihood function of capability parameters, as shown in formula (7):

$$N = \prod_{j=1}^{\sigma} (z - \sigma)^{1-j} \tag{7}$$

In formula (7), z represents the positive answer probability obtained by the IRT model function, σ represents the true answer situation of the tested user in the score matrix, j represents the difficulty coefficient of the knowledge point.

Apriori algorithm module realizes content recommendation, that is, when users access the content in the theoretical learning video module, it realizes the function of recommending other learning content to users according to association rules. Besides content recommendation, ml-sh module can also realize the function of recommending access to the user. The second unit is to calculate the similarity of users and find the nearest neighbors according to the recommended method on the basis of the first unit, in which new users are based on user characteristics and information entropy model, and other users are based on scoring and resource attribute preference model. Take logarithm on both sides of formula (7) to get:

$$\ln(N) = \sum_{j=1} \ln\left(\lambda_j\right) + \ln\left(1 - \lambda_j\right) \tag{8}$$

In formula (8), λ represents the maximum likelihood estimator.

Using association rules to realize content recommendation is the key content of this paper. This paper describes the mining of association rules and the method of using association rules to realize content recommendation. The method is mainly composed of content recommendation and association rule mining module. The third unit is responsible for users' prediction scores and the final top-N recommended resources. There are both registered users and unregistered users in the personalized recommendation method of teaching resources. Unregistered users can retrieve and browse resources and non personalized recommendation services. The content recommendation module of association rules mainly realizes the recommendation function of other content according to the page content accessed by the user and the association rules. The association rules mining module mainly realizes the function that the background administrator uses the association rules mining algorithm to mine the association rules according to the user's access log, and stores the mining results in the database. In addition, for registered users, they can evaluate resources and manage personal information in addition to the rights of unlisted users. At the same time, the recommendation strategies for new registered users and rated users are different.

6 Simulation Experiments

6.1 Build up the Experimental Environment

The verification of the recommended scheme in this paper is realized through the system, using the classic windows + mysql + apache + PHP environment. The personalized recommendation method proposed in this paper is implemented in the development environment equipped with 3.1 GHz Intel Core i5 processor and 8 GB 2133 MHz LPDDR 3. The package management software anaconda and sublime 3 editor are used as development tools, and the programming language is python. The software and hardware environments are as follows: client: IE 4G memory, operating system: Windows, Web server: Apache/2.4.23(Win32), database product: MySQL, server script: PHP, development tool: MyEclipse2020, JDK support: JDK. External network bandwidth 8mbps, memory: DDR4 16 GB, CPU: AMD Ryzen 71700 Eight Core Processor 8-core 16 threads.

6.2 Experimental Results

Select reference [1] method, reference [2] method, reference [3] method as a contrast method, and compare it with the personalized recommendation method of maternal and child health education resources designed this time. Test the response time of Resource Recommendation of the three personalized recommendation methods of maternal and child health education resources under different user numbers, The shorter the time, the better the concurrency performance of the method is proved. The experimental results are shown in Table 1, 2, 3 and 4:

It can be seen from Table 1 that the response time of the personalized recommendation method of maternal and child health teaching resources in this paper and the other two personalized recommendation methods of maternal and child health teaching resources are 1.051 s, 1.540 s and 1.814 s respectively; It can be seen from Table 2 that the response time of the personalized recommendation method of maternal and child health teaching resources in this paper and the other two personalized recommendation methods of maternal and child health teaching resources are 2.851 s, 4.596 s and 4.855 s respectively; It can be seen from Table 3 that the response time of the personalized recommendation

Table 1. Number of users 200 resource recommended response time (s)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
1	1.332	1.779	1.515	1.006
2	1.659	1.802	1.822	1.114
3	1.483	1.714	1.977	0.978
4	1.326	1.936	1.549	0.845
5	1.515	1.825	1.866	0.994
6	1.584	1.774	1.917	1.312
7	1.316	1.830	1.833	1.125
8	1.847	1.944	1.892	0.977
9	1.315	1.855	1.847	1.331
10	1.549	1.731	1.779	1.025
11	1.447	1.822	1.685	1.009
12	1.631	1.915	1.793	1.014
13	1.585	1.993	1.689	0.847
14	1.713	1.548	1.943	1.113
15	1.805	1.745	1.982	1.074

Table 2. Number of users 400 resource recommended response time (s)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
1	5.616	4.878	4.784	3.415
2	4.878	4.966	5.386	2.748
3	4.316	5.132	4.895	2.495
4	3.997	5.031	5.012	3.006
5	4.022	4.667	4.877	2.142
6	4.116	4.515	4.941	3.475

(*continued*)

Table 2. (*continued*)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
7	4.198	5.121	4.978	2.199
8	5.121	4.948	4.976	3.114
9	4.774	4.677	4.997	2.087
10	5.336	4.531	4.822	2.746
11	4.815	5.016	5.748	3.143
12	4.012	4.751	5.495	3.255
13	4.377	5.220	5.006	3.149
14	4.241	4.866	5.142	2.914
15	5.122	4.513	5.475	2.878

Table 3. Number of users 600 resource recommended response time (s)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
1	9.487	7.548	9.512	6.544
2	8.645	8.316	9.147	6.483
3	8.991	8.487	9.351	6.102
4	9.612	8.615	8.948	5.947
5	8.147	7.948	9.275	6.314
6	8.351	9.364	8.771	5.349
7	7.948	9.788	9.123	5.717
8	9.215	9.487	8.802	5.612
9	9.336	8.115	8.665	5.318
10	9.148	8.212	8.319	6.771

(*continued*)

Table 3. (*continued*)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
11	8.999	8.366	8.771	6.123
12	9.103	9.154	8.544	5.802
13	9.215	9.477	9.483	5.665
14	8.144	9.202	9.102	6.319
15	7.946	8.746	8.947	6.411

Table 4. Number of users 800 resource recommended response time (s)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
1	12.301	13.457	13.616	9.154
2	13.548	12.748	13.878	10.031
3	14.917	14.159	13.316	11.120
4	13.645	13.747	13.997	9.748
5	13.747	15.166	15.022	9.789
6	12.871	14.199	15.116	10.551
7	14.522	16.742	14.198	10.374
8	15.334	15.213	15.121	11.885
9	12.008	14.779	14.515	9.677
10	13.494	13.552	15.121	9.644
11	12.548	16.415	14.948	11.122

(*continued*)

Table 4. (*continued*)

The number of experiments	Reference [1] method	Reference [2] method	Reference [3] method	The personalized recommendation method of maternal and child health care teaching resources in the article
12	14.183	15.412	14.677	9.748
13	13.455	14.733	14.531	9.647
14	12.748	15.120	14.585	10.488
15	13.489	14.144	15.191	11.316

method of maternal and child health teaching resources in this paper and the other two personalized recommendation methods of maternal and child health teaching resources are 6.032 s, 8.819 s and 8.721 s respectively; It can be seen from Table 4 that the response time of the personalized recommendation method of maternal and child health teaching resources in the text and the other two personalized recommendation methods of maternal and child health teaching resources are 10.286 s, 13.521 s and 14.639 s respectively. According to the experimental results, it can be analyzed that the less the number of users, the faster the response of the resource recommendation of the three personalized recommendation methods of maternal and child health care teaching resources. In the four experimental scenarios, compared to the other three methods, the performance of the personalized recommendation method of maternal and child health teaching resources in this paper is better.

7 Conclusion

The personalized recommendation method of maternal and child health care teaching resources in this paper provides users with personalized language association rules, and constructs different fuzzy object language formal backgrounds for different users. In the whole learning process, the error prone knowledge points of middle school students' users have been consolidated, and the difficulties have been broken through, so as to improve the learning level of students, promote the personalized development of users of maternal and child health education resources, and further improve the development and utilization of high-quality teaching resources. On this basis, from the perspective of connotation and extension, a cognitive system of fuzzy object language concept lattice is established to better reflect users' cognitive process and provide exploratory suggestions for users. In the subsequent improvement process, the dependence on user participation will be minimized.

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