Personalized Recommendation System of E-learning Resources Based on Bayesian Classification Algorithm

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This article addresses the problem of learners' information trek as well as overload and meet the learners' personalized learning needs by realizing learners' personalized development. In this article, the development scheme of e-learning resources personalized recommendation system based on Bayesian algorithm is proposed. This paper studies the personalized Association recommendation model integrating association rule mining and Bayesian network, thereby improving the association rule mining algorithm by combining historical record pruning and Bayesian network verification. In the process of association rule mining, the proposed methodology is combined with user history and the frequent item sets in association rules are filtered. The item sets below the given threshold are pruned. The pruned item set is input into the Bayesian verification network for personalized verification, and the verification results are sorted and recommended according to the ranking. This is done to give priority to the readers who really like the books. The recommendation model solves the problem of weak personalization in the existing recommendation system to a certain extent. The experiments show that Bayesian network can improve the personalization of association recommendation.

Povzetek: Članek obravnava personalizacijo e-učenja z uporabo Bayesovega algoritma in učenjem asociativnih pravil, ki izboljšuje personalizacijo priporočil in povečuje učinkovitost.

1 Introduction

Recommendation system is a new information discovery mode. It models users' interests and preferences by analyzing users' historical behavior information, and recommends items conforming to their preferences to users according to users' preferences. In this process, users do not need to provide any demand information, and the recommendation system actively pushes information to users [1]. The emergence of the recommendation system solves the problem of how to select items from a large amount of item information when the user's needs are not clear or cannot accurately describe the needs. The emergence of the recommendation system also transforms the way of information acquisition from data search to higher-level information discovery. After the emergence of recommendation system, it has gradually proved to be an effective tool to solve the problem of information overload. In essence, the recommendation system solves the problem of information overload by recommending new items unfamiliar to the user, and the recommended new items are likely to be related to the needs of the user. For each request of the user, the recommendation system uses different recommendation methods and the environment and needs of the user at that time to generate recommendation results according to the user, available items, user historical transaction data and various types of additional information stored in the system. Users may or may not accept these recommended items, and may give explicit or implicit feedback immediately, or give feedback over a period of time [2].

All these user behaviors and feedback information are stored in the recommendation system and become the data source of recommendation when users interact with the recommendation system in the future. With the advent of the education informatization 2.0 era and the rapid development of education big data, learning analysis, artificial intelligence and other technologies, the educational form will change profoundly, and promoting students' personalized development has become the core demand. The realization of students' personalized development is inseparable from the support of personalized learning. However, education is still dominated by the traditional class teaching system. Due to the large number of students, it is difficult for teachers to "teach students according to their aptitude" with their personal ability. As a result, it is difficult to meet learners' personalized learning needs and hinder students' personalized development. At the same time, the explosive growth of e-learning resources also brings the problem of information Trek and overload to learners, which hinders learners from accurately positioning their own learning resources. Relevant studies believe that the intelligent service of personalized recommendation of e-learning resources can not only solve the problem of students' personalized needs, but also effectively avoid information loss and overload [3]. Therefore, the related research has been widely concerned by scholars in the field of education. Therefore, from the perspective of academic research or practical application, the research on personalized recommendation of e-learning resources is of great significance to educational development. It is an effective method and key way to support learners' personalized development and solve the problem of information Trek and overload. Figure 1 is the conceptual diagram of personalized recommendation system.

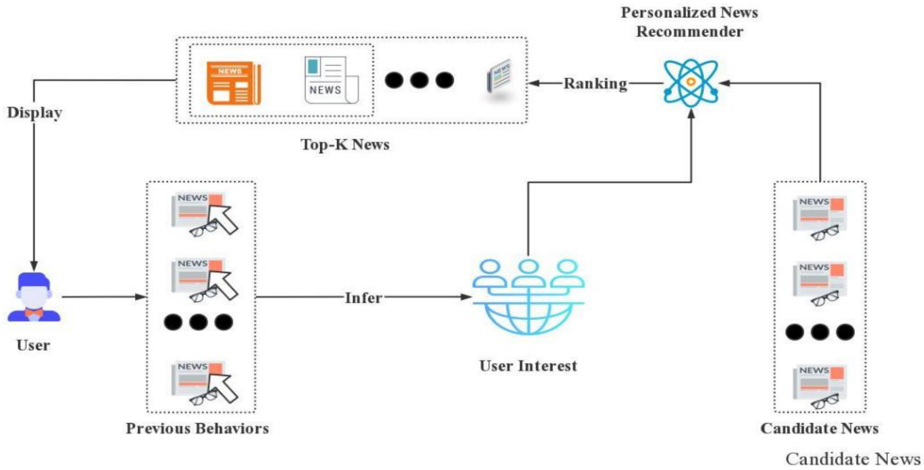

Figure 1: Personalized recommendation system.

This article contributes in the development scheme of e-learning resources personalized recommendation system based on Bayesian algorithm. The personalized Association recommendation model is studies which integrates association rule mining and Bayesian network, thereby improving the association rule mining algorithm by combining historical record pruning and Bayesian network verification. In the process of association rule mining, the proposed methodology is combined with user history and the frequent item sets in association rules are filtered. The item sets below the given threshold are pruned. The pruned item set is input into the Bayesian verification network for personalized verification, and the verification results are sorted and recommended according to the ranking. The recommendation model solves the problem of weak personalization in the existing recommendation system.

The rest of this article is organized as: Literature is presented in section 2 followed by the methodology section discussing the personalized association recommendation model based on Bayesian network in section 3. Results are analyzed in section 4 followed by conclusion in section 5.

2 Related work

In this section various recent work done in the field of recommendation system of e-learning related studies are explored and discussed.

At present, there are many theories and research methods on recommendation system. Rawat and Dwivedi studied the recommendation system based on association rules, compared a series of products purchased by current customers with a series of products purchased by other customers, selected the intersection of products purchased by customers and the product set purchased by current customers, and presented them to customers as recommended products [4]. Zhong proposed a personalized information filtering recommendation method based on simple Bayesian classifier to smooth user rating, which can alleviate sparsity and improve the accuracy of searching nearest neighbors [5]. Benhamdi, *et al.* others proposed a Bayesian network classification algorithm bncar based on association rules. The algorithm uses the association rule mining algorithm to extract the initial candidate edges, and obtains a better Bayesian network structure through the greedy algorithm. Bncar can obtain higher classification performance. Wang and others proposed an eye movement trajectory semantic extraction algorithm by collecting the eye movement parameters of customers observing an object and referring to the idea of find-s algorithm. The algorithm maximizes the distance between positive and negative examples by learning a priori knowledge, determines the weight of eye movement parameters, including gaze time, pupil size, blink times and look back times, uses sebet algorithm to judge whether customers like a commodity according to the distance, and realizes semantic extraction from eye movement trajectory. The study did not consider personalized relevance recommendation [6].

Chao *et al.* proposed an association rule extraction method using improved genetic algorithm, gave a specific algorithm, applied this knowledge to students' teaching management, and made corresponding adjustments to the original teaching system and plan. The algorithm has certain application value in promoting student training and education. This research fails to deeply study the user personalized semantics [7]. Kumar *et al.* proposed ar-sem algorithm based on association rules. Firstly, the algorithm uses association rules to analyze the causal relationship between variables, and combines it with the initial prior knowledge and the opinions of domain experts to further remove meaningless rules and form a knowledge base. Finally, the knowledge base is combined with SEM algorithm to construct Bayesian network. Although this method can improve the accuracy of Bayesian network structure learning to a certain extent, there is no personalized test on the mined association rules [8]. In terms of application, Sharma and Suryavanshi established a Bayesian network model of Anabaena bloom in dams. In the model, the monitoring data is stored in a unified database. By "learning" the relationship probability between factors, such as nutrient load, nutrient concentration of lake water body and fishy concentration, it can be convenient for nonprofessional modelers to use, so as to significantly reduce water treatment costs and operating expenses [9]. Zhang *et al.* put forward the concept of interest degree of attribute set through massive data and data flow analysis, studied the characteristic difference of attribute set as data, and deduced an accurate algorithm to find that the interest degree of all attribute sets exceeds the given threshold. The algorithm finds the most interesting attribute set by specifying similarity and confidence probability [10].

Chinna Gounder Dhanajayan, summarized the research of Bayesian network reasoning algorithms and their development and function expansion in recent 30 years, and compared them from the aspects of complexity, applicability and accuracy. The key links of each algorithm are pointed out, the application of Bayesian network in the field of engineering technology is analyzed and reviewed, and the shortcomings and future research trend of BN are summarized and prospected [11]. Aiming at the problem that traditional association rule mining cannot reflect the semantic measurement between items, Zhu *et al.* studied how to use the utility confidence framework to find association rules, studied a dense representation of mining all minimum antecedent and maximum antecedent association rules, and realized it by using closed itemset (HUCI) and its generator efficiently. In terms of personalized Preference Research [12], Zhang *et al.* use ontology to organize user and service information, and find the content they are interested in according to the user's preference [13]. One similar study that uses wavelet frames for measuring micropolar fluid flow is used for high mass transfer and some other relevant studies also studied that uses various approaches for measuring vibrations, space time fraction [14-16]. This work can be considered for future development by using integration approaches of Artificial Intelligence and Machine learning as studied from several studies [17-19].

3 Research methodology

This section includes the discussion of personalized association recommendation model on the basis of Bayesian network.

3.1 Personalized association recommendation model based on bayesian network

The recommendation model established by association rule mining, historical data pruning and Bayesian network verification is shown in Figure 2. The model includes four functional modules:

1. Module A is the association rule mining module, and the algorithm used in this module is Apriori algorithm.
2. Module B is a history pruning module, which prunes the of association rules with history data, and the item set lower than the given threshold is pruned.
3. Module C is a Bayesian network verification module, which uses Bayesian network to verify the semantics of association rules and sort the associated item sets according to probability priority.
4. Module D is the recommendation strategy formulation module, which formulates the recommendation strategy according to the output results of Bayesian verification network [20]. Apriori algorithm is a frequent itemset algorithm for mining association rules.

The algorithm is divided into two steps: the first step is to retrieve all frequent itemset in the transaction database through iteration, that is, itemset with support not lower than the threshold set by the user; The second step uses frequent itemset to construct rules that meet the minimum trust of users [21]. The specific method is: first, find out the frequent 1-itemset and record it as L_1; Then, L_1 is used to generate candidate itemset C_2, the items in C_2 are determined, and L_2, that is, frequent 2-itemset, is mined; This cycle continues until no more frequent k-itemset can be found. Bayesian network is a probabilistic network. It is a graphical network based on probabilistic reasoning. It obtains other probabilistic information through the information of some variables to solve the uncertainty and incompleteness of some facts in application. It has been widely used in many fields, and Bayesian theorem is the basis of Bayesian network [22]. Bayesian theorem is used to describe the relationship between two conditional probabilities, such as $P(A|B)$ and $P(B|A)$. According to the multiplication rule:

$$P(A \cap B) = P(A) * P(B \mid A) = P(B) * P(A \mid B) \tag{1}$$

Bayesian formula can be derived:

$$P(B \mid A) = P(A \mid B) * P(B) / P(A) \tag{2}$$

This formula is generally generalized to obtain the general Bayesian formula [23]:

$$P(A_i \mid B) = \frac{P(B \mid A_i)P(A_i)}{\sum_{i=1}^{n} P(B \mid A_i)P(A_i)} \tag{3}$$

Where, $A_1, \ldots, A_n$ is the complete event group [24], that is: $U_{i=1}^{n} A_i = \Omega, A_j = \varphi, P(A_i) > 0$.

Taking e-book borrowing as an example, D_1 is the borrowing record of readers. The algorithm mines association rules from D_1, and then prunes the mined frequent large itemsets by using the user's historical information [25]. The pruning results are verified by Bayesian network to obtain the verified frequent large itemset, so as to formulate the recommendation strategy. In the following algorithm, algorithm 1 calls algorithm 2 [26].

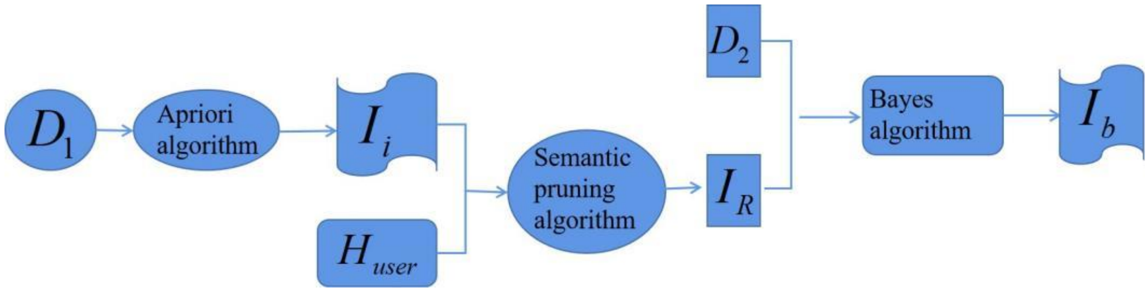

Figure 2: Model diagram

Algorithm 1 Bayesian personalized Association recommendation algorithm

Input: D_1;
Output: I_b;
Begin

1. Sort out readers' borrowing records and get D_1.
2. Set the support according to the Apriori algorithm_Degree, generate k itemsets, and calculate the large itemset $I_i, I_x \in I_i, i, k \in [1, n]$to recommend content to user R_i, n is the number of items [27].
3. The historical data of the user is recorded as H_{user}. combined with $H_{user,} prue(I_i, H_{user})$ is called to perform personalized semantic pruning on I_i and output $I_R = \{I_r | I_r \in I_i\}$.
4. If I_R meets the set k itemset requirements, execute (5), otherwise execute (2) until the requirements are met.
5. Build D_2, which is a borrowing record database that can reflect users' preferences.
6. Take I_R as the input of N, run Bayes algorithm, and output I_b and $I_b = \{I_y | I_y \in I_i\}$ sorted by readers' preference.
7. Return(I_b); I_b is the content to be recommended to the user [28].

End

In algorithm 1, when building D_2, it is necessary to ensure the scientificity of D_2. each record contains the basic information of the user as set u. The basic information of the user includes gender, age and other contents. The basic information of the user needs to be determined according to the actual situation. This algorithm prunes the large itemset mined by using the historical records to delete the records that are not in good agreement with the historical records. When calculating the degree of coincidence with the historical records, compare the large itemset with the historical records, and prune the records lower than the average value [29].

Algorithm 2 personalized pruning algorithm $\boldsymbol{prue(I_i, H_{user})}$

Input: $I_i, H_{user}, I_x \in I_i$;
Output:

1. $num = \text{count}(I_i)$; num is the number of large itemset items.
2. For $\omega = 1$: num.
3. $T_1 = total(I_w)$; $I_w = \{I_x^w\}, I_x^w \in I_x$.
4. $T_2 = count(H_{user})$; T_2 is the number recorded in H_{user}.
5. $T_3 = T_1/T_2$.
6. $T_4 = num/count(H_{user})$.
7. If $(T_3 < T_4)$; less than the average are pruned.

Delete I_w; Delete I_x from I_i.

8. Return(I_R).

End

T_4 in algorithm 2 is the threshold selected for this study [30].

Generally, the recommended results can be evaluated according to accuracy and re call [31]. Recall rate refers to the proportion of recommended books that meet readers' interests in the concentration of readers' interests; Accuracy refers to the proportion of recommended books in line with readers' interests in the total recommended book collection [32]. The calculation formulas of recall rate and accuracy rate are shown in formula 4, formula 5 and formula 6.

$$\text{Recall rate: } R_e = \sum_{i=1}^{u} \frac{L_i}{M \times P_i} \quad (4)$$

$$\text{Accuracy: } P_r = \frac{\sum_{i=1}^{M} L_i}{M \times N} \quad (5)$$

$$\text{Harmonic average of the two: } F = \frac{2 \times R_e \times P_r}{R_e + P_r} \quad (6)$$

Where, P_i is the total number of books in the reader's interest concentration, L_i is the recommended books that meet the reader's interest, M is the total number of readers, and N is the total number of recommended books. The higher the F value, the better the recommendation effect [33].

4 Results and analysis

This section presents the result analysis obtained from the proposed recommendation model and presents its discussion and summary in conclusion section.

The Bayesian algorithm is tested, and the accuracy, recall and F index are used to judge the quality of recommendation. The specific design of the experiment is as follows. In this experiment, the number of neighbors is 10. The change trend of F index, accuracy and recall is shown in Figures 3, 4 and 5 [35, 35].

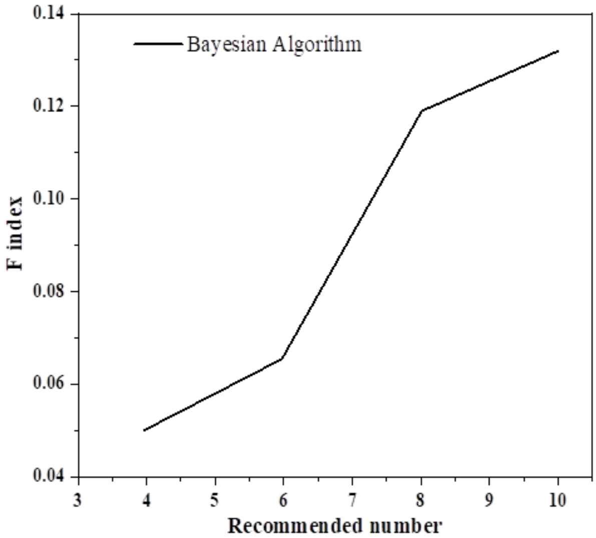

Figure 3: Change trend of F index.

It can be seen from Figure 3 that the f index based on Bayesian algorithm reaches about 14%, so it can be concluded that the recommendation effect based on Bayesian algorithm is better.

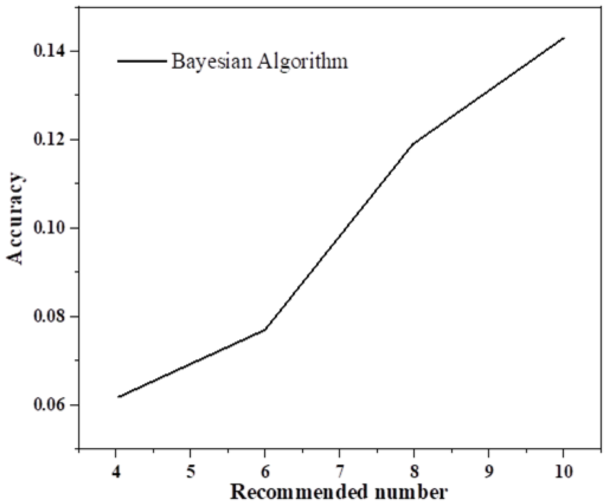

Figure 4: Variation Trend of accuracy.

As can be seen from Figure 4, the highest accuracy based on Bayesian algorithm is about 15%. As can be seen from Figure 5, the highest recall rate based on Bayesian algorithm is about 13%. The hybrid recommendation algorithm combining the recommendation results of Apriori algorithm and Bayesian algorithm is designed to judge the recommendation effect of the hybrid recommendation algorithm. The average absolute error, accuracy, recall and f index are used to judge the recommendation quality [36, 37]. The experimental design and result analysis are described below.

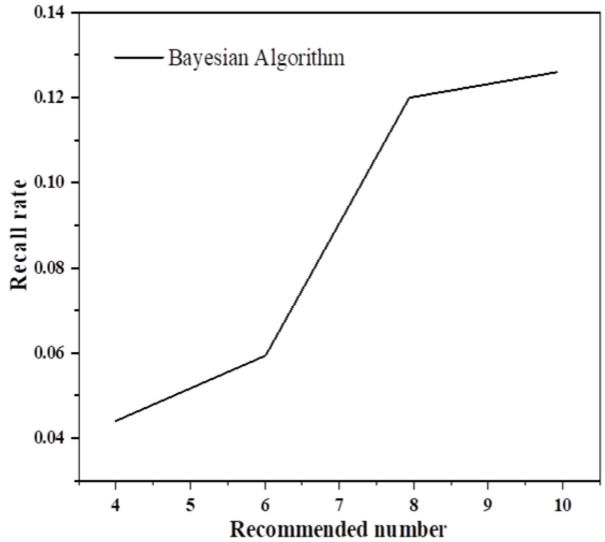

Figure 5: Change trend of recall rate.

Experiment 1: In this experiment, a hybrid recommendation algorithm combining Apriori algorithm and Bayesian algorithm is used to verify the recommendation effect of the hybrid recommendation algorithm. According to the design of Experiment 1, the change trend of F index, accuracy and recall of hybrid recommendation algorithm is shown in Figures 6, Figure 7 and Figure 8 [38, 39].

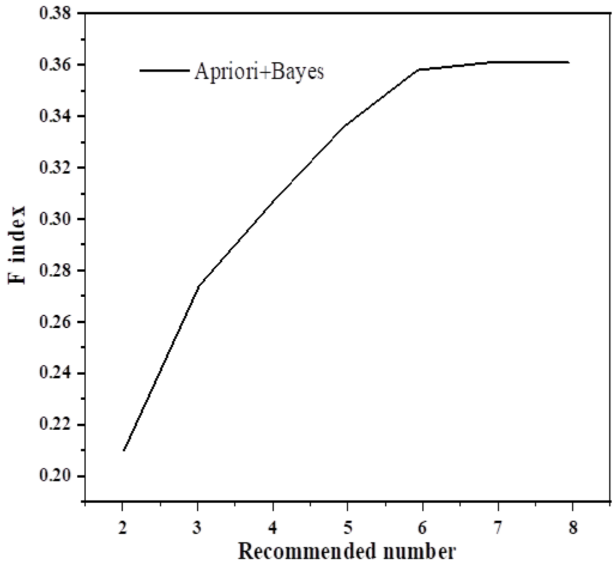

Figure 6: Change trend of F index.

As can be seen from Figure 6, the F index of the hybrid recommendation algorithm based on Apriori algorithm and Bayesian algorithm reaches about 34%, which is about 20% higher than that of the Bayesian algorithm alone, and improves the accuracy of recommendation to a certain extent.

As can be seen from Figure 7, the accuracy of the hybrid estimation method of Apriori algorithm and Bayesian algorithm is basically stable at about 33%, which is about 20% higher than that of Bayesian algorithm alone.

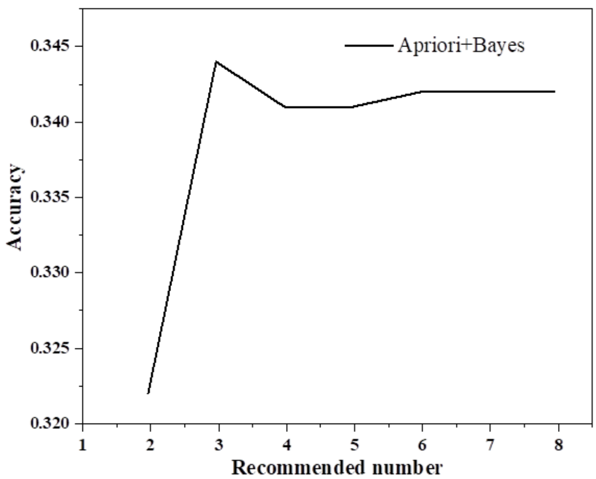

Figure 7: Variation Trend of accuracy.

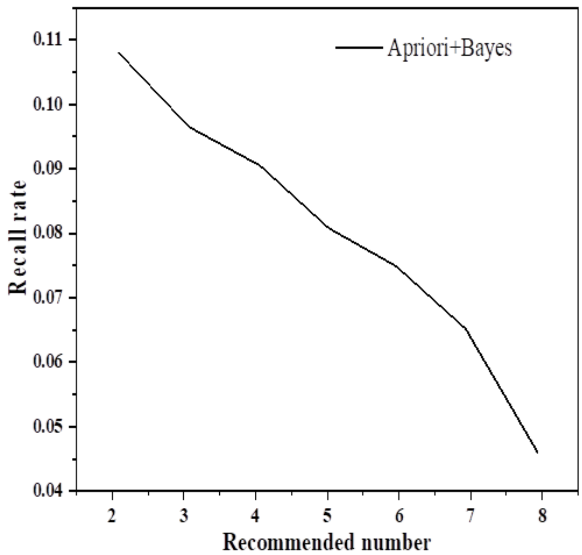

Figure 8: Change trend of recall rate.

As can be seen from figure 8, the highest recall rate of Apriori algorithm and Bayesian algorithm is about 11%, which is about 2% lower than that of Bayesian algorithm alone, which fully shows that better results can be obtained by combining the two algorithms.

5 Conclusions

This study successfully combines user history information with Bayesian network verification, and obtains an effective personalized Association recommendation model. The proposed model can solve the problem of weak personalization in the existing recommendation system to a certain extent. The model can eliminate the recommended goods with low probability of "preference" and highlight the goods with high probability of "preference", so as to give priority to the learning resources that readers really like. Further research includes optimizing the pruning method of association rule mining from user historical data, improving the mining algorithm of association rules. It describes the personalization and semantics, such as the method of introducing ontology. The research on personalized recommendation of e-learning resources is fundamental from the perspective of education, which is the necessity of the development of technology and learning environment. To fundamentally solve learners' learning needs and improve the effect of recommendation, it is inseparable from the guidance of educational theory. Secondly, the research on personalized recommendation of e-learning resources should be combined with the educational process. Learners' needs are not only for specific learning resources, but also for various personalized learning services in the learning process. The research on personalized recommendation of e-learning resources is still in the development stage. The research perspective for the future scope should focus on the application of these system models in specific education and teaching practice, so as to fundamentally promote teaching reform and innovation.

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