Web Based Online Hybrid Teaching Method of Network Music Course

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Abstract—Today, with the rapid development of online course teaching, the demand for online courses is increasing day by day, and the demand for online mixed teaching of online music courses is also increasing rapidly. In the context of big data, the lengthy personalized screening process of users has become one of the problems to be solved. Based on Web data mining, an improved algorithm of hybrid hierarchical recommendation algorithm and genetic algorithm is used in the experiment, and compared with the other two algorithms in the experiment. The experimental results show that the average accuracy of the improved algorithm is 79.63% in the limited training times, and has better adaptability. It can be applied to the online hybrid teaching recommendation and screening of online music courses in dynamic changes.

Keywords—web, data mining, hierarchical recommendation algorithm, genetic algorithm

1 Introduction

In recent years, the number of users of online courses has increased rapidly, and the teaching methods of online music courses have been difficult to meet the needs of current users [1]. Users often have difficulty making choices in the face of big data [1]. At present, the research on data mining and recommendation algorithm of online courses is also gradually increasing. These studies are mainly to shorten the recommendation time and improve the accuracy [2]. However, in these studies, there are relatively few online teaching methods aimed at the dynamic changes of online courses [3]. At the same time, the current conventional recommendation algorithms also have various disadvantages, such as data sparsity, cold start problem, too many iterations and too much computation [4]. Therefore, the experiment uses the improved recommendation algorithm combined with genetic algorithm to achieve the desired dynamic recommendation effect.

The innovation of the research is that while using the recommendation algorithm, genetic algorithm is applied and combined with it to form a new algorithm combining hierarchical recommendation and genetic algorithm, which can have the advantages of hierarchical recommendation and genetic algorithm at the same time.

The whole article is mainly divided into four parts. The first part describes the research background and feasibility, that is, to improve the current hybrid music curriculum based on the algorithm; The second part is the related literature of other scholars, mainly about the methods used in the study; The third part describes the main methods used in the study, that is, combining the hierarchical recommendation algorithm with the genetic algorithm to form a new improved algorithm, which is used to complete the recommendation in the changing classroom situation; The fourth part is the simulation results of the experiment, and summarizes the results and shortcomings of the research.

2 Related work

At present, many domestic and foreign scholars have studied data mining and various recommendation algorithms. Aiming at the problems of too sparse and poor timeliness of conventional recommendation algorithms, Chen's team proposed a dynamic clustering recommendation algorithm based on double-layer network, which uses the new hierarchical clustering method for dynamic evolution. The experimental results show that the speed of the algorithm is improved compared with the traditional algorithm [5]. Zhou et al. Adopted a personalized preference collaborative filtering recommendation algorithm and introduced Bayesian personalized sorting and other methods to recommend jobs for graduates because graduates lack work experience and are difficult to recommend jobs with conventional algorithms. The experimental results show that this method has high satisfaction in obtaining feedback [6]. Das and other scholars proposed a collaborative filtering method based on clustering, which uses two hierarchical spaces to divide the data. The experimental results show that this method not only improves the operation speed, but also ensures the recommendation quality [7]. Wang's team used the improved factor decomposition machine model to design a new hierarchical decomposition machine, and used the generalized Kalman filter and expectation maximization algorithm for recommendation. Experiments show that the model has a significant improvement effect on recommendation [8]. Chen's team calculates the similarity between users through the combination of collaborative filtering algorithm and other algorithms, and calculates the similarity between users' calligraphy words and main recommended calligraphy words based on the preliminary recommendation results, so as to obtain the final recommendation results [9]. Zhang et al. Designed a coverage based collaborative filtering algorithm to provide personalized recommendations for new users, reconstructed a decision class to improve the previous collaborative filtering through detailed analysis of the characteristics of new users, and used the coverage reduction algorithm based on coverage rough set to remove redundant candidates of new users. The results show that the improved algorithm is significantly better than the existing working algorithm [10].

Yu et al. Proposed a cross domain collaborative filtering algorithm based on feature construction and locally weighted linear regression. By constructing features in different domains and using these features to represent different auxiliary domains. Experimental results show that the regression algorithm can effectively solve the problem of data sparsity by transferring useful knowledge from the auxiliary domain [11].

Xu and other scholars recommend the results by calculating the dependency between the features of the classification set and the features of the target object by introducing a new dependency function based on Gaussian kernel and extended classification method. Data experiments show that the new hybrid algorithm has high efficiency and good performance [12]. Han and other scholars proposed a time weighted collaborative filtering algorithm based on improved small batch K-means clustering. When Pearson correlation coefficient is combined with k-means algorithm, Newton cooling time weighting is introduced to improve user similarity. The experimental results show that the performance of this algorithm is significantly better than the traditional algorithm [13]. On the basis of Web mining, Nian et al. Used the filtering method to select the appropriate colorectal cancer detection instruments and methods, and used the bivariate mixing effect to enhance the detection function. The experimental results show that the detection accuracy of this method has been improved [14]. Ruan and other scholars combine the k-means algorithm with the hierarchical recommendation algorithm, apply the improved algorithm to the detection of athletes' stress, establish a user preference model and recommend coping strategies for athletes with corresponding stress characteristics. The experimental results show that this method has a good relieving effect on Athletes' stress [15].

From the above research results, it can be found that there are a large number of researches on the application of different types of recommendation algorithms and data mining to personalized technology, and a considerable number of researches in different fields are used to improve the traditional recommendation algorithms, but there are relatively few researches on the personalized teaching technology of online music courses based on hierarchical recommendation algorithms. Therefore, the research is based on Web data mining, using hierarchical recommendation algorithm, online music courses and online mixed teaching mode for different target users are designed to improve the learning interest and learning ability of target users, and consider the curriculum arrangement of teachers.

3 Hierarchical recommendation algorithm and improved algorithm based on Web Data Mining

3.1 Web based layered recommendation algorithm and its application in online music courses

At present, the network resources related to music courses are very rich. For these massive data, data mining technology is usually used. In order to enable the online music course to carry out online hybrid teaching, the experiment will use Web Mining to mine and analyze massive data. According to the different objects processed by data mining, web mining is divided into three categories: Web content mining, web structure mining and Web Log Mining [16]. Web content mining is mainly to extract useful music network course knowledge from web document information, which is suitable for processing structured and semi-structured data. Web content mining is divided into text mining and multimedia mining according to the required carrier form, which helps to improve the quality of information and help course users filter useless information. In terms of resource search, both text resources and multimedia resources are necessary for online music courses. At the same time, semi-structured documents also provide additional information data such as hyperlinks and HTML [17]. The data mining classification structure of the whole web is shown in Figure 1.

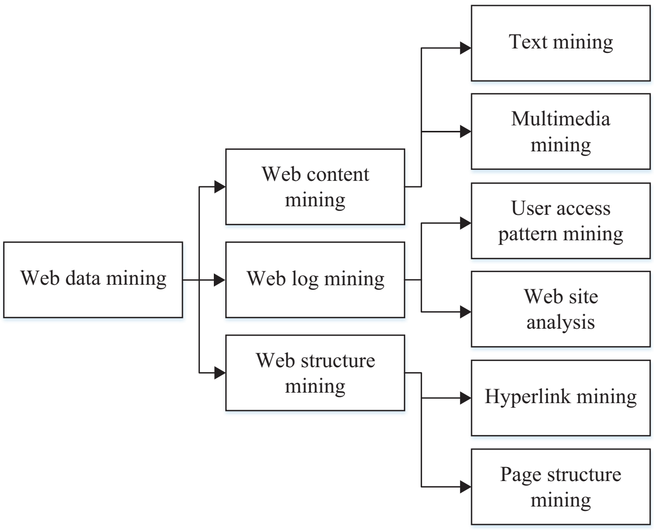


Fig. 1. Schematic diagram of Web mining classification

Based on the classification and various characteristics of Web mining, web data mining usually uses hierarchical recommendation algorithm to generate corresponding personalized courses and personalized teaching resource recommendations. The recommendation algorithm based on layering is mainly divided into three layers. The first layer is the overall teaching plan for music teachers, which extracts the same or related concepts of the subject words of the course. The extraction source is the knowledge base, and the original page relationship of the knowledge base will also be inherited; The second layer is the core of the target users of the course. According to the current attributes of the users, such as knowledge level, concept mastery and learning ability, the relevant concepts are filtered from the knowledge base and recommended to the target users. At the same time, the corresponding personalized knowledge structure chart is constructed; The third layer is the improvement of personalized knowledge structure chart. Objects with the same or related concepts in the current knowledge structure chart are extracted and filtered, and then the corresponding personalized teaching course resource base is formed. The structure diagram of hierarchical recommendation algorithm is shown in Figure 2.

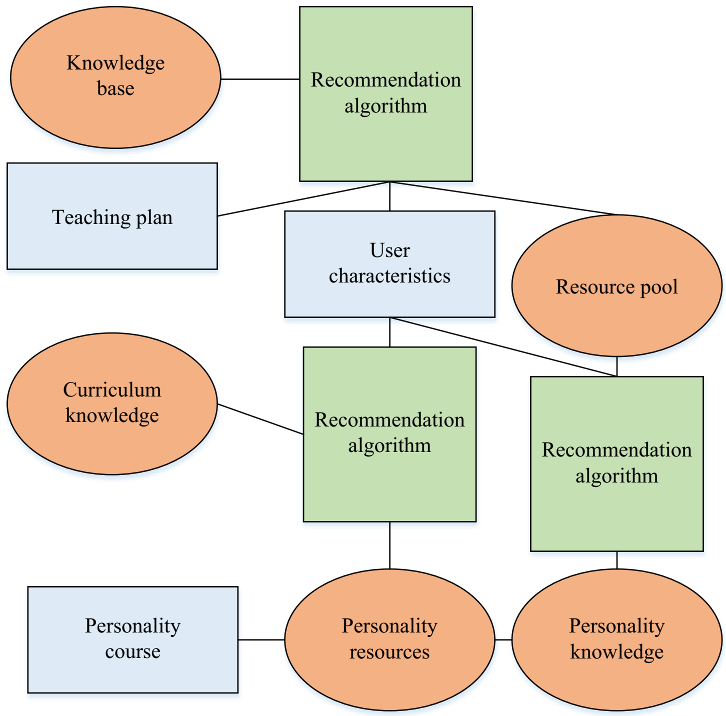


Fig. 2. Structural framework of hierarchical recommendation algorithm

The resources contained in the web pages are diversified. They not only recommend the related concepts in the knowledge base, but also recommend the learning objects in the learning resource base. The hierarchical recommendation algorithm has unique properties, which is different from the conventional recommendation algorithm. The hierarchical recommendation algorithm will not only consider the interests and hobbies of the target users, but also combine the knowledge characteristics of the target users on the target of the resource base, including the theoretical knowledge level, the actual ability level and the local characteristics of the target, and take the above characteristics as the main recommendation. The advantage of this recommendation algorithm is that it considers the interests and abilities of the target users, the teaching level and methods of the course teachers, and the music course itself has different requirements for the theoretical level and actual performance level of the target users, so as to form a more accurate and three-dimensional teaching recommendation with a deeper degree of fit [18].

Since algorithm execution generates corresponding recommendations based on learners' personality characteristics, it is necessary to establish a conceptual model and extract features for target users [19]. Generally, user feature extraction based on vector space model is used. It is assumed that the user model is a n dimensional feature vector $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, a feature keyword and a corresponding weight form each corresponding sub vector, and the weight is expressed as the degree of user interest in a concept. If the concept set in the knowledge structure diagram of a course is $C = (c_1, c_2, ..., c_n)$, of which c_i is naturally its knowledge vector, while the corresponding knowledge score vector *S*, ability vector *A* and target vector *O* are represented as s_i, a_i and o_i respectively, that is, there is a quad (c_i, s_i, a_i, o_i) to represent the learning characteristics of the target user on concept *c*. At this time, the personality characteristic model of the target user is shown in equation (1).

$$F = \{(c_1, s_1, a_1, o_1), (c_2, s_2, a_2, o_2), ..., (c_n, s_n, a_n, o_n)\} \tag{1}$$

For the learning object model, using a similar method, for example, the concept set of the knowledge structure diagram of the course is $C = (c_1, c_2, ..., c_n)$ and the set of all learning objects in the resource database is $L = (l_1, l_2, ..., l_n)$. At this time, the correlation coefficient between the *i* learning object l_i and the *k* Concept c_k is obtained, and the calculation is shown in formula (2).

$$v_{ik} = tf_{ik} \cdot \log \frac{m}{df_{ik}} \tag{2}$$

Formula (2) represents the weight of the *k* concept in the *i* learning target objects, that is, the correlation coefficient between the learning object and the concept; tf_{ik} represents the frequency of concept *k* in goal *i*, df_{ik} represents the frequency of concept *k* in all courses, and *m* represents the total number of courses to be studied. At this time, for the learning object l_i, the expression of the association relationship between the *n* concepts in the concept set in the course is shown in equation (3).

$$l_i = (v_1, v_2, ..., v_n) \tag{3}$$

At this time, a matrix of $m \times n$ is used to represent *m* learning objects and n concept indexes in the course. The index matrix formed is shown in equation (4).

$$R(m,n) = \begin{bmatrix} v_{1,1} & v_{1,2} & v_{1,3} & v_{1,4} & \cdots & v_{1,n} \\ v_{2,1} & v_{2,2} & v_{2,3} & v_{2,4} & \cdots & v_{2,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ v_{m,1} & v_{m,2} & v_{m,3} & v_{m,4} & \cdots & v_{m,n} \end{bmatrix} \tag{4}$$

At this time, the correlation degree between the two learning objects can be expressed by the cosine value of the two vectors, as shown in equation (5).

$$l_{ij} = \frac{\sum_{k=1}^{n} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{n} v_{ik}^2 \sum_{k=1}^{n} v_{jk}^2}} \tag{5}$$

On the basis of the above, the expression of the incidence matrix obtained from the correlation degree between all m learning object is shown in equation (6).

$$R(m,n)=\begin{bmatrix} l_{1,1} & l_{1,2} & l_{1,3} & l_{1,4} & \cdots & l_{1,m} \\ l_{2,1} & l_{2,2} & l_{2,3} & l_{2,4} & \cdots & l_{2,m} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ l_{m,1} & l_{m,2} & l_{m,3} & l_{m,4} & \cdots & l_{m,m} \end{bmatrix} \tag{6}$$

According to the above model calculation, the form of each learning object is defined as shown in Table 1.

Table 1. Definition form of learning object

Metadata	ID, Title, Author, Duration
Keywords	Key feature word vector of learning object
Learning goal	Target characteristics, value according to learning methods
Difficulty	From low difficulty to high difficulty, the value is 1–5
Content	Content information presented directly on the course page
Practice	Exercise content after learning
Evaluation	Evaluation content after learning

3.2 Improved layering and improved layering algorithm combined with genetic algorithm and its application

In the whole web knowledge base, due to the large number of concepts and knowledge points, the vector space of user models and learning objects also expands rapidly. At this time, only using the conventional hierarchical recommendation algorithm will lead to many problems, such as slow operation and low accuracy [20]. In order to solve this problem, the experiment will improve the algorithm, that is, using the combination of genetic algorithm and hierarchical recommendation algorithm, and improving the original hierarchical algorithm to form a new improved algorithm.

The structure of the improved algorithm is also divided into three layers. The first layer is the knowledge structure. The generation of the structure is based on the teacher's overall teaching plan on the course knowledge structure. The second layer is the personalized recommendation to the target user. The recommendation is based on the knowledge structure characteristics of the target user. The third layer is divided into two parts, that is, the learning object recommendation according to the learning object association matrix and the concept, and recommendation algorithm based on user characteristics and related content. The main contents to be completed for each layer are shown in Figure 3.

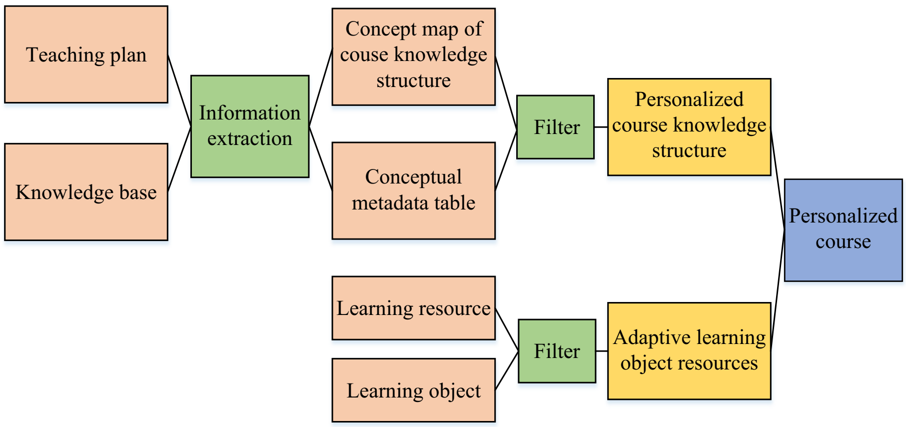


Fig. 3. Structure diagram of improved algorithm

In order to realize the improved stratification, the course knowledge structure is generated first, then the personalized knowledge structure is generated, then the adaptive learning object resources are generated, and finally the adaptive personalized knowledge structure is generated. The improved layering not only realizes the dimensionality reduction operation, but also considers the needs of teachers and target users, that is, the overall teaching plan of teachers and the characteristics of learners, distributes the relevant content at different levels, reduces the amount of calculation, and provides the possibility for the mixed application of multiple algorithms [21].

The whole algorithm is represented by spatial vector model based on knowledge base concept map and learning object. Assuming that the concept set is C, the constraint relationship set between concepts is R, and there are N different concepts in set C, set C is expressed as formula (7).

$$C = (c_1, c_2, ..., c_N) \tag{7}$$

The teacher's teaching plan is divided into M document record, which is represented by set D as $D = (d_1, d_2, ... d_M)$. Therefore, the core of the algorithm is to select the relevant feature keyword subspace in the feature space C according to the document set D, and extract the relevant concepts in the process of learning the course from set C according to the teaching plan of a course formulated by the teacher. The weight method is applied to calculate the feature vector of document d_i, in which the weight w_{ij} of feature concept c_j corresponding to document d_i is calculated as shown in equation (8). In equation (8), dc_j is the number of documents with characteristic concepts.

$$w_{ij} = \frac{c_{ij}}{\sum_{k=1}^{M} c_{kj}} \cdot \log \frac{M}{dc_j} \tag{8}$$

The greater the value of weight w_{ij}, the greater the role of the characteristic concept in the teaching plan. The weight of feature concept C to teaching plan document D in the whole knowledge base is shown in equation (9).

$$\lambda = \sum_{i=1}^{N} d_{iN} \sum_{i=1}^{M} w_{iM} \tag{9}$$

Measure the importance of each feature concept relative to the teaching plan document D, and calculate the weight of feature concept c_j in the whole teaching plan D, as shown in equation (10). In equation (10), k is the number of elements contained in the document set.

$$Dc_j = \sum_{k=1}^{M} w_{kj} \tag{10}$$

Set the threshold f. For the feature concept subset $C`$ of the selected quota teaching plan, it is shown in equation (11).

$$C`=\{c_j \,\middle|\, Dc_j \geq d, 1 \leq j \leq N, c_j \in C\} \tag{11}$$

Find subset $R`$ of relation $R$ in subse $C`$, as shown in equation (12). Then the knowledge structure of the target course can be formed.

$$R`=\{r \,\middle|\, r \leq c_i, c_i < c_j, c_j \in C`, c_j \in C`, 1 \leq i, j \leq N, r \in R\} \tag{12}$$

There is a big gap in the knowledge level, learning ability, learning efficiency and learning progress of the target users in a certain course, and the differences of users in various aspects will make the individual needs for the course learning content different in the overall learning process. At this time, it is necessary to build a personalized knowledge state diagram for the target users in the whole dynamic process, and build a user's knowledge model in the learning process of the target users [22]. In this case, it is best to use genetic algorithm for adaptive change, and continuously evolve on the basis of the initial course to generate a series of course sequences suitable for users at each stage to meet users' personalized needs.

Genetic algorithm (GA) is a kind of randomized recommendation algorithm evolved from the evolution law of biology, which is a method of bionics. The main feature of genetic algorithm is that it operates on structural objects without derivation and function continuity, and has inherent implicit parallelism and better global optimization ability. It adopts probabilistic optimization method to automatically obtain and guide the optimized search space, and can adaptively adjust the search direction without determining rules [23]. Genetic algorithm is often used to find an appropriate course learning path in the solution space and generate a dynamic personalized course learning sequence to achieve the purpose of personalized teaching [24].

On the basis of the improved hierarchical recommendation algorithm, genetic algorithm is applied to adaptively extract the personality characteristics of learners, so as to achieve the dynamic tracking of user personalization, so as to form a new improved evolutionary algorithm, namely personalized hierarchical recommendation algorithm based on genetic algorithm (PHRA-GA). In PHRA-GA, the difficulty of learning content, learning time, user's knowledge level, performance level and local target characteristics are defined into the metadata of concepts and learning objects. At the same time, the adaptability function is constructed in the user model. The sequence based on fitness sorting is used to eliminate the fittest, and the crossover operation is completed by the partial matching crossover algorithm. At this time, in order to complete the adaptive operation of genetic algorithm, it is necessary to build a system of related disciplines. First, create a concept system of the discipline, define the relationship between concepts and build a concept map of the discipline, then collect knowledge points for each concept of the discipline through teachers and design learning objects, and then establish a learning resource base based on the web, and then establish the relationship between learning objects and concepts, the knowledge domain resource base of corresponding disciplines will also be built accordingly. Finally, test questions will be designed for each concept and a test question base will be built. The schematic diagram of the course structure system is shown in Figure 4.

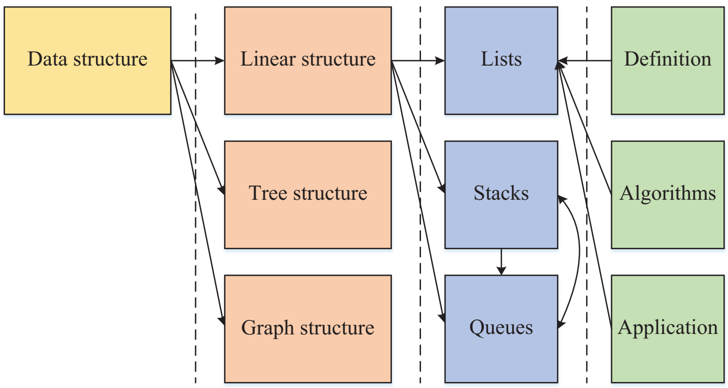


Fig. 4. Schematic diagram of course structure system

The initialization course is the basis of the whole algorithm. In order to make the genetic algorithm continuously update the learning content of the evolution course during the learning process, make use of the random convergence of the genetic algorithm, and quickly converge in the multi-objective rearrangement problem until the optimal solution is obtained, it is necessary to avoid losing the prior relationship between the concept knowledge points on the above basis. Therefore, the experiment introduces the method of hierarchical topology sorting. There is a relation R, which represents the partial order relation on set X, and its vertex sequence is $A(x_1, x_2, ..., x_n)$, which is a topological ordering sequence of nodes on set X to relation R. Each vertex element x in sequence Y has a corresponding weight w to represent the hierarchy of vertices in the directed acyclic graph, and a binary (x, w) is used to represent the node. At this time, a new sequence is obtained, as shown in formula (13).

$$Y` = \{(x_1, w_1), (x_2, w_2), \dots (x_n, w_n)\} \tag{13}$$

If the difference between the weights of two adjacent nodes in the sequence is within the [0,1] interval, the sequence is a hierarchical topological ranking relative to relationship R, and the weight is the layer in the defined directed acyclic graph. The exchangeable nodes have equal weights, and the higher the priority, the smaller the weight of the node. The partial order relationship in the hierarchical topology sorting sequence is guaranteed by the sorting method.

After that, the user model is updated and the main parameters are defined. Then, according to the idea of formative evaluation in pedagogy, the experiment standardizes and defines the evaluation method according to the metadata of learning objects. On this basis, an evaluation matrix UR of user learning objects is set. The value of each score in the matrix is 0-1/Na, which indicates the score value or no learning respectively, as shown in Table 2.

A cognitive diagnosis model based on Bayesian probability is used to evaluate and obtain the value of the matrix, as shown in equation (14). In equation (14), ω_{ij} represents the judgment value of whether the target user i has mastered all the concepts of the learning object j. If he has mastered all the concepts, it is 1, otherwise it is 0, s_j is the smoothing parameter, and g_j is the guessing parameter

$$P(Y_{ij} = 1 \middle| \omega_{ij}, s_j, g_j) = (1-s)^{\omega_{ij}} g_j^{1-\omega_{ij}} \tag{14}$$

In the knowledge state evaluation, the user concept matrix is obtained by using the learning object concept correlation matrix. Each element z_{ij} in the matrix represents the score evaluation result of the i user on a certain concept. The inner product of the m components of the user's scores on the m learning objects and the correlation components of the corresponding concept and the learning object are used to measure the user's mastery of the concept, as shown in equation (15).

$$z_{ij} = \sum_{k=1}^{m} y_{ik} v_{kj} \tag{15}$$

Finally, the ability assessment is carried out, including the cognitive ability of learning and their own performance level. The matrix construction method is similar. The whole evolutionary algorithm flow is shown in Figure 5.

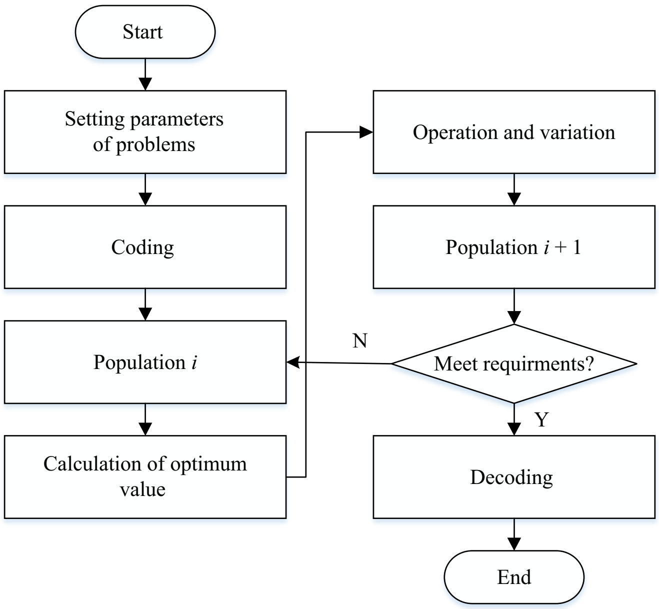
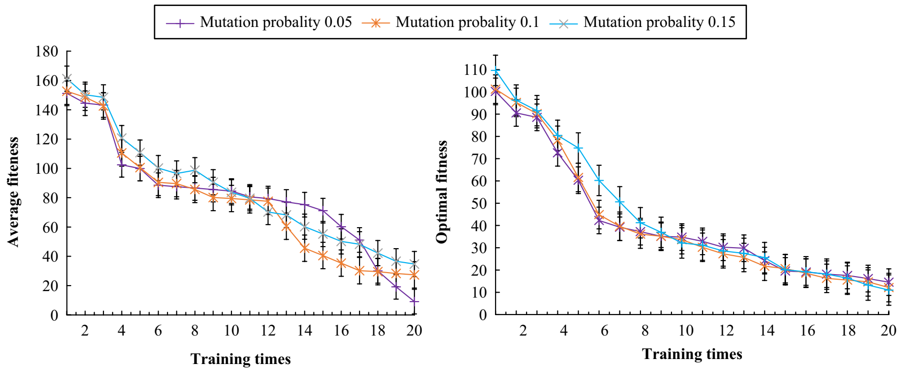


Fig. 5. Evolution flow chart of genetic algorithm

4 Comprehensive comparative analysis of experimental result

4.1 Determination of crossover probability and mutation probability

In the improved algorithm, the initial population is set to 50, and several experiments are carried out to determine the crossover probability and mutation probability. Set the crossover probability to 0.5, and the results of the impact of the variation probability on the average adaptation are shown in Figure 6. It can be seen from Figure 6 that the increase of mutation probability will improve the average fitness of the population as a whole, but it has little impact on the average fitness of the population, and the change is not significant, indicating that it is sufficient to set a stable mutation probability in the improved algorithm. It can be seen from Figure 6 and the variance of the three that it is the best when the mutation probability is set to 0.15.



(a) Effect of mutation probability on average fitness

(b) Effect of mutation probability on optimal fitness

Fig. 6. Effect of mutation probability on average fitness and optimal fitness

Using a similar method, set the mutation probability to 0.15, and the results related to the average adaptation of the crossover probability are shown in Table 2. It can be seen intuitively from Table 2 that when the crossing probability is greater, the average adaptability is greater and more stable. Therefore, the maximum crossing probability, i.e. 0.5, should be selected. To sum up, the mutation probability selected in the experiment is 0.15 and the crossover probability is 0.5.

Table 2. Effect of crossover probability on average fitness

	Crossover Probability 0.3	Crossover Probability 0.4	Crossover Probability 0.5
2	144.48	148.56	150.26
4	102.45	110.56	120.69
6	88.54	90.46	100.23
8	86.62	85.65	98.78
10	84.54	79.46	83.69
12	79.45	77.56	70.26
14	75.25	45.55	60.23
16	60.23	35.36	50.21
18	30.08	29.55	42.22
20	9.12	27.36	34.74

Considering the above two cases comprehensively, since the priority of average fitness is higher than the best fitness, the case with variation probability of 0.15 should be selected.

4.2 Comparison and analysis of algorithm performance results

At the same time, the experiment compares three algorithms: the traditional hierarchical recommendation algorithm (PRA), the improved hierarchical recommendation algorithm (HPRA) without genetic algorithm, and the comprehensive improved algorithm PRA-GA proposed and adopted in the experiment. Under the same experimental conditions, the influence of different algorithms on the average fitness is shown in Figure 7. As can be seen from Figure 7, the average adaptation result of PRA-GA is generally higher than that of the other two algorithms. The average values of each group of results obtained by the three algorithms are calculated. The results of PHR, IPHR and PRA-GA are 77.69,81.37 and 85.34 respectively, which further illustrates the superior performance of PRA-GA in average fitness.

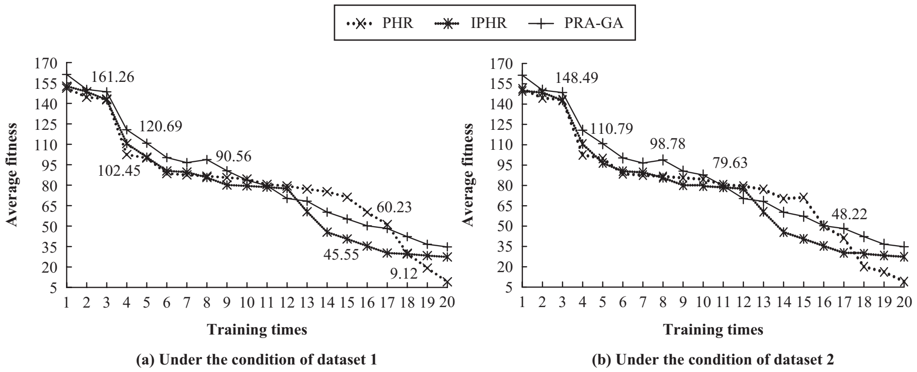


Fig. 7. Effect of different algorithms on average fitness

The accuracy results of different algorithms are shown in Figure 8. It is obvious from Figure 8 that the average accuracy of PRA-GA is significantly higher than that of the other two algorithms, and with the increase of training times, the growth rate of the average accuracy of PRA-GA is also significantly higher than that of the other two algorithms. Among the three algorithms, the average values of PHR, IPHR and PRA-GA are 72.42, 75.57 and 79.63 respectively, and the maximum values are 80.51, 83.31 and 93.36 respectively, which further shows the superiority of PRA-GA algorithm.

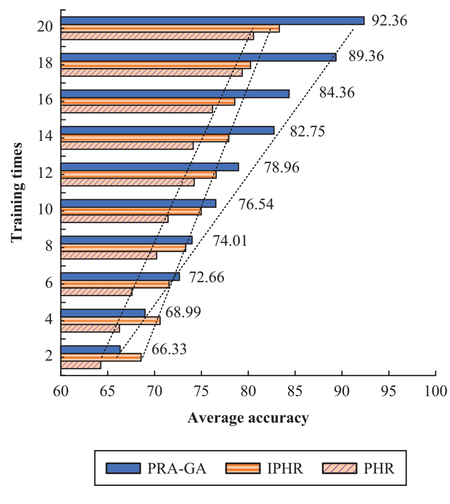


Fig. 8. Effect of different algorithms on average accuracy

The two groups of results of average operation rate of different algorithms are shown in Figure 9. As can be seen from Figure 9, with the increase of training times, the operation speed has an upward trend. The operation speed of PRA-GA is significantly higher than that of the other two algorithms, and with the increase of training times, the operation speed of PRA-GA is also significantly faster than that of the other two algorithms.

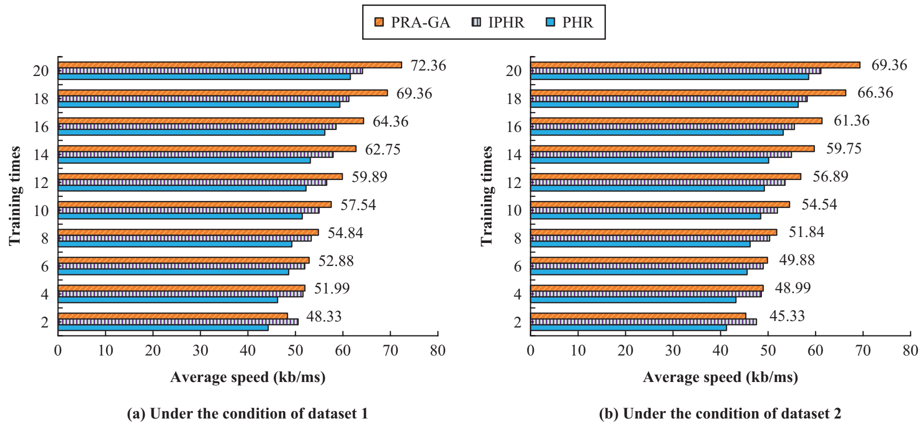


Fig. 9. Effect of different algorithms on average running speed

The adaptive rate results of the three algorithms obtained according to the change operation are shown in Figure 10. As can be seen from Figure 10, the overall adaptive rate of PRA-GA is significantly higher than that of the other two algorithms. With the increase of training times, the growth rate of the adaptive rate of PRA-GA is also significantly higher than that of the other two algorithms, indicating that the algorithm is significantly better than the other two algorithms in terms of evolution.

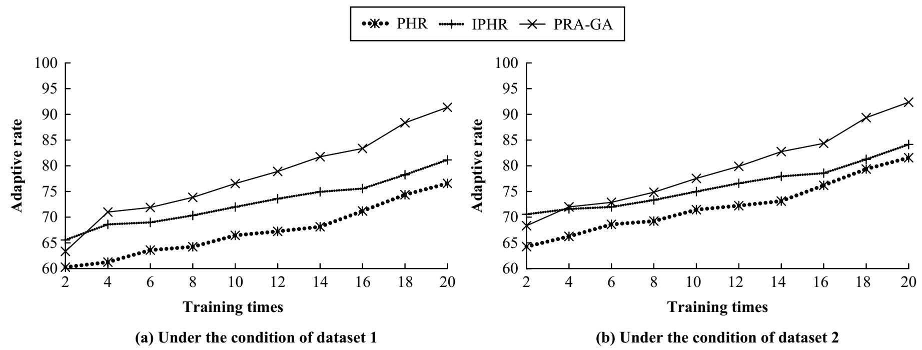


Fig. 10. Effect of different algorithms on adaptive rate

The above experimental results show that PRA-GA algorithm has better performance in adaptability and recommendation accuracy, which is significantly better than the traditional hierarchical recommendation algorithm and the improved hierarchical recommendation algorithm without genetic algorithm

5 Conclusion

Aiming at the problem of personalized recommendation for each target user in online music course according to the actual situation, a hierarchical recommendation algorithm combined with genetic algorithm is adopted and improved on the basis of Web data mining. At the same time, it is compared with the traditional hierarchical recommendation algorithm and the improved hierarchical recommendation algorithm without genetic algorithm. The experimental results show that within 20 training times, the average fitness of the improved algorithm is 85.34 and the average accuracy is 79.63%, which are significantly higher than the other two algorithms. The experimental results show that the improved algorithm has good performance in recommendation adaptability and accuracy in dynamic changes, and can be applied to online mixed teaching of online music courses. Although the research has achieved certain results, the results are lack of universality due to the small number of training times. In addition, when trying to increase the number of samples to a large number or greatly increase the number of training times, the algorithm is difficult to support, which is also the main subject to be optimized in further research in the future.

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