Accurate Recommendation of Personalized Mobile Teaching Resources for Piano Playing and Singing Based on Collaborative Filtering Algorithm

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Abstract. With the rapid development of education informatization, online education resources are growing explosively. In order to avoid the waste of resources and enable piano playing and singing learners to accurately and quickly find the mobile teaching resources courses they are interested in the massive resources, this paper proposes a precise recommendation method of personalized piano playing and singing mobile teaching resources based on collaborative filtering algorithm. Through the context awareness method, we can obtain the demand information of learners in real time, store it in the database, and calculate the degree of interest of piano playing and singing learners on this basis. Based on the collaborative filtering algorithm, we can constantly optimize the accuracy of the algorithm through the analysis of the degree of interest of learners and other information, accurately recommend learning resources for piano playing and singing, and improve the learning effect and interests of learners. The experimental results show that the proposed method has achieved good application results in practice, and has certain reference and guidance value for enhancing the learning interest of piano playing and singing learners and cultivating autonomous learning ability.

Keywords: Collaborative Filtering Algorithm · Individualization · Piano Playing And Singing · Mobile Teaching Resources · Situational Awareness · Gray Level Correlation Algorithm · Similarity

1 Introduction

The rich network resources facilitate users to search for target resources from massive resources through retrieval, and it has become the main way for people to obtain target resources. However, the explosive growth of network resources has brought convenience to users while also causing a series of problems. For example, when faced with a large amount of learning materials, learners face certain difficulties in finding learning resources that meet their own needs. Even if target resources are found, they may not necessarily be suitable for their own learning. How to recommend massive learning

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resources to learners is currently a challenge faced by traditional education. The research on precise recommendation methods for personalized piano playing and singing mobile teaching resources [1, 2] can recommend piano playing and singing mobile teaching resources based on users' personalized needs and interests, thereby improving learning efficiency and results, and meeting users' needs and expectations [3, 4]. In addition, it is also of great significance for the development of the education field, providing reference and support for the intelligence and informatization of piano teaching. This paper mainly introduces the research status, recommendation algorithms, advantages and disadvantages of collaborative filtering, which is the most common recommendation algorithm. Let us understand the main idea of collaborative filtering through simple examples. Personalized learning involves analyzing, processing, and mining a large amount of student learning log data, and recommending the mining results. Based on learners' basic knowledge mastery, interests, learning abilities, and other characteristics, personalized chemistry learning models are designed to support teaching, providing personalized learning resources and paths for piano and singing learners.

Reference [5] aims to improve the efficiency of online learners in selecting appropriate high-quality courses from a vast amount of similar learning resources. On the basis of fully mining the value of online comment data, corresponding learning resource profiling and recommendation methods were designed and proposed: based on Apriori algorithm and text sentiment analysis, information such as frequent term itemsets, course features, user emotional tendencies, and online learning platform service quality hidden in online comment information were mined, establish a multi-dimensional feature system for learning resources, and then use the Topsis method to conduct a comprehensive analysis of multiple indicators for alternative courses, exploring the proximity of each object to the optimal ideal solution and the distance from the worst ideal solution, ultimately completing the ranking and recommendation of courses.

Reference [6] proposes a learning resource recommendation method based on multidimensional association ontology. Construct a multi-dimensional association ontology model (MCOM) for learning resource recommendation, and achieve the association of learning resource ontology, learner ontology, and situational ontology through semantic relationships. Then, a dynamic self-balancing binary particle swarm optimization algorithm (DSEBPSO) is designed, and the MCOM ontology model and DSEBPSO algorithm are integrated and applied to implement a learning resource recommendation method based on multi-dimensional associated ontology (MCOM-LROM), which provides learners with optimal learning resources or learning paths.

Reference [7] proposes a multi granularity cloud manufacturing resource combination recommendation method based on self-organizing mapping. By clustering and analyzing the scheduling logs of manufacturing resources from the requester, manufacturing resources are classified into different types based on QoS indicators; Then, sliding window analysis is used to statistically analyze various types of resource scheduling methods, calculate the proportion of different resource scheduling methods in the entire resource scheduling process, and obtain the commonly used scheduling combinations for the requester in the manufacturing process. This is used as a recommended resource combination for the requester to achieve cloud manufacturing resource combination recommendation.

In the current era of information overload, people are facing a massive amount of learning resources, and how to quickly and accurately find suitable teaching resources has become an important issue for learners. However, ordinary learning resource recommendation algorithms lack specificity and cannot effectively meet the personalized needs of learners. Therefore, it is of great significance to study the precise recommendation method of personalized piano playing and singing mobile teaching resources based on collaborative filtering algorithm. By using context awareness method and combining collaborative filtering algorithm to constantly analyze and optimize learners' interests and preferences, learners can find their own learning resources more quickly and accurately, thus improving learning effects and interests. At the same time, the application value of this study is not limited to the learning field of piano playing and singing, but can also provide certain reference and reference for personalized mobile teaching in other disciplines.

2 Design of Personalized Piano Playing and Singing Mobile Teaching Resource Recommendation Method

2.1 A Method for Collecting Information of Piano Singing Learners Based on Contextual Perception

Context awareness refers to the process of perceiving and understanding information such as objects, people, and events in the surrounding environment, enabling machines to understand and adapt to different contexts [8]. Based on this, they decide what data to collect and what methods to use to collect data, and establish a close connection between the collected data and the context.

The data collection process of researchers is an advanced context awareness process [9, 10], This process essentially belongs to the category of human cognition and can be described using models in cognitive psychology. Many models have been proposed in cognitive psychology to describe human cognitive processes. Although these models have significant differences in details, they all describe the cognitive process as three basic stages: first, the brain receives stimuli; Secondly, handle the stimulus; Finally, make a response. Based on these three basic stages, the data collection process of researchers can also be described as three stages:

(1) Perceiving the context related to user activities;
(2) Filter and organize these situations in the brain to identify the situations they are interested in;
(3) Choose appropriate data collection methods. The current situational awareness process in the computer field can also be roughly divided into three stages:
(4) Context acquisition: perceiving and collecting contexts;
(5) Scenario processing: Formalize contextual representations and use contextual reasoning to construct a complete user context;
(6) Service invocation: Using context to trigger the invocation of specific services. This paper will model the situational awareness process of researchers using three processes of situational awareness technology, as shown in Fig. 1.

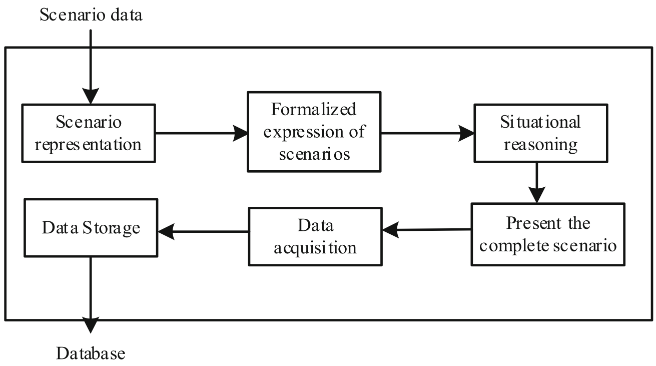

Fig. 1. Context aware data collection model

2.2 Calculation of Interest for Piano Singing Learners

Based on the data collection model, assign an initial value of interest to the target user, their own favorite resources, and the labels used, that is, assign an initial interest to the corresponding vertices in the tripartite graph [11]. These vertices with initial interest will be used as the diffusion origin for the first diffusion.

In the study, it is assumed that the initial interest of the target user towards themselves is 1, and the interest towards other users is 0. Therefore, if y is the target user, the initial interest vector for all users is Y_0. Assuming that users have no difference in their interest in resources, initially, y is only interested in his own favorite resources and has a zero interest in other resources, then y's interest in his favorite resources z can be expressed as:

$$X = \frac{Y_0 z}{n}\left[z \in I(y)\right] \tag{1}$$

In the formula, $I(y)$ is the collection of resources that target user y has collected, and n is the number of resources that target user y has collected.

In public classification systems, users often use the same label multiple times to label different resources. To this end, drawing inspiration from the TF-IDF method, a metric was defined to measure the user's interest in different tags, that is, the target user's interest in the tags they use.

Initially, assuming that the target user is only interested in the tags they use and has a zero interest in other tags, the user's interest in tags can be calculated by the following equation:

$$B = y' \times \lg Y_0 z \tag{2}$$

In the formula, y' represents the number of users using labels.

2.3 Collaborative Filtering Based Recommendation Method for Piano Playing and Singing Teaching Resources

In traditional piano playing and singing teaching, the problem of randomization and arbitrariness in the application of online resources is relatively obvious, leading to a decrease in the efficiency of resource application, and the separation of online and offline teaching. Therefore, a precise recommendation method of personalized mobile teaching resources for piano playing and singing based on a collaborative filtering algorithm is proposed.

The main idea of collaborative filtering recommendation method [12, 13] is to use the past behavior of existing user groups to analyze and predict which users will be interested in such items in the future. Generally speaking, collaborative filtering recommendations are divided into three types: user based collaborative filtering, item based collaborative filtering, and model based collaborative filtering.

The implementation of user based collaborative filtering technology mainly includes three steps, namely, finding a set of users with similar interests to the target users, calculating the similarity between items using Pearson correlation coefficient, cosine similarity, Jaccard and other methods, and filtering out the nearest neighbor of the target users by TOP-N method, which refers to taking the first N data after sorting according to certain indicators (such as recommendation, quantity, etc.). This method is usually used in scenarios such as data analysis and leaderboard production, or to filter the nearest neighbor of the target user by setting a threshold. The processing flow of this algorithm is shown in Fig. 2.

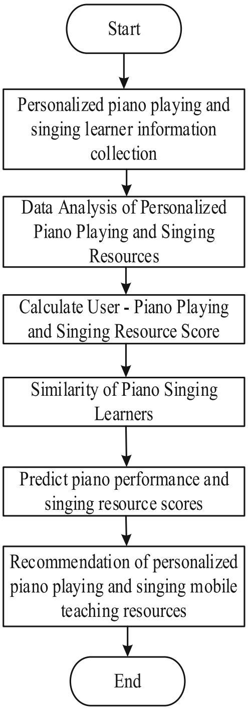

Fig. 2. Recommended flow chart of collaborative filtering algorithm

From Fig. 2, it can be seen that this algorithm collects learner information and conducts data analysis. Based on this, it calculates the score of playing and singing resources, obtains the similarity of learners, predicts scores, and achieves high-precision recommendation of learning resources.

In order to achieve the goal of personalized learning recommendation, students can be divided into two categories. For students without foundation, they can complete knowledge learning in an orderly manner according to the requirements of the curriculum outline. By mastering basic knowledge, they can have a more comprehensive understanding of the content they have learned.

The higher the quality of recommended learning resources, the better the recommendation technology of personalized learning resources [14, 15]. This paper proposes personalized learning resources recommendation based on user preference collaborative filtering algorithm. The algorithm implementation process is shown in Fig. 3.

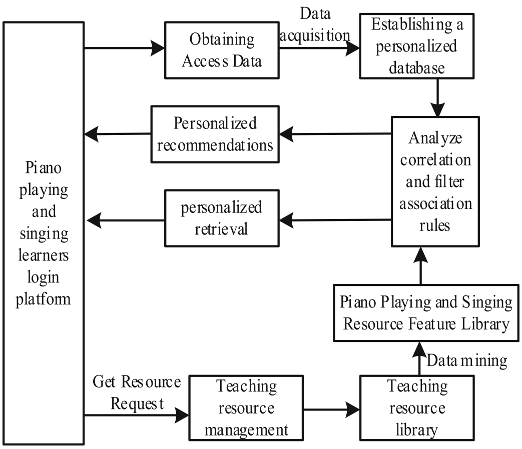

Fig. 3. Flow Chart of Recommended Teaching Resources for Piano Playing and Singing

The core content of teaching resource recommendation is the feature extraction of user data and teaching resources, as well as the analysis or rule association of their features. Feature extraction quantifies and digitizes the user data and teaching resource attribute features of online teaching platforms through data mining, and conducts correlation analysis or association analysis on the user feature library and resource feature library composed of user features and teaching resource features to achieve accurate matching and recommendation of teaching resources. Select user and resource characteristics based on the characteristics of online teaching platforms. The main algorithms are as follows:

Firstly, assuming that the internal and external keywords (requirement features) are a_1 and a_2, with text lengths of δ_1 and δ_2, respectively, where the length of similar strings is δ. Therefore, the similarity $Z(a_1, a_2)$ between the two can be defined as:

$$Z(a_1, a_2) = \begin{cases} \frac{\delta}{\delta_1+\delta_2-\delta} & \delta > 2 \\ 0 & \delta \leq 2 \end{cases} \tag{3}$$

From the above equation, it can be seen that $Z(a_1, a_2) \in [0, 1]$. This formula simulates the similarity between the "requirements vs. resources" part inside and outside the school, thereby improving the matching accuracy of similarity between requirements and resource keywords. All resources in the system have several personalized feature words that describe them. Combining the frequency of feature words (keywords), the following processing can be performed:

Firstly, obtain the frequency of feature words for a certain resource:

$$R(\delta_{n+1}) = [R(\delta_1), R(\delta_2), \ldots, R(\delta_n)] \tag{4}$$

From this, Eq. (5) can be obtained:

$$Z(\delta_{n+1}) = [Z(\delta_1), Z(\delta_2), \ldots, Z(\delta_n)] \tag{5}$$

Subsequently, take the maximum value in formula (5) and define it as $Z(\delta_n)_{\max}$ to obtain the final value calculated by similarity weighting:

$$H(\delta_n) = Z(\delta_n)_{\max} \times (Z(\delta_{n+1}) + 1) \tag{6}$$

Secondly, assuming there are several teaching resources with a total of m feature words, the expression form of their space vector matrix is as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{7}$$

The spatial feature component of a resource is the similarity between its feature words and the core feature words (requirements) multiplied by the frequency of the feature words appearing in the abstract, then weighted by 1, and the maximum value is taken. Next, sort them to obtain the recommended resources that are currently ranked high. Subsequently, this system adopts a direct scoring measurement method to describe its evaluation values:

$$\Upsilon(\delta) = a_{nn} H(\delta_n) d + M_t^g v_t, t = 1, 2, \ldots, n \tag{8}$$

In the formula, M_t^g is the evaluation value of the resource by the g-th evaluator (faculty) at time t, where d is the true value, and correspondingly, v_t is the evaluation noise generated by subjective factors at time t. There is unknown prior knowledge in the formula. In the subsequent processing, the gray correlation algorithm [16, 17] is used to calculate the gray correlation degree of the two. This algorithm is a multivariable non parametric statistics statistical analysis method, which can be used to find the relationship between multiple input variables and an output variable. It is mainly used to establish mathematical models and carry out prediction analysis. It is suitable for data with different scales, distributions and intervals standardize the data of distribution and interval, then calculate the correlation degree and analyze it, and provide its similarity

[18, 19]. The grey correlation degree L_{ij} between the recommendation sequence i and the demand sequence j at time t in the system can be expressed as:

$$L_{ij} = \begin{cases} 1 & , i = j \\ \sum\limits_{i=1,j=1} \frac{\min\limits_{i}\min\limits_{j}\left|\Upsilon(\delta)+M_t^g\right|}{\max\limits_{i}\max\limits_{j}\left|\Upsilon(\delta)+M_t^g\right|} & , i \neq j \end{cases} \tag{9}$$

From this, it can be concluded that the similarity between the recommendation sequence and the requirement sequence (grouping of teachers, managers, students, etc.) at time t constitutes a matrix W_l, as shown in formula (8):

$$W_l(t) = \begin{bmatrix} 1 & w_{12}(t) & \cdots & w_{1n}(t) \\ w_{21}(t) & 1 & \cdots & w_{2n}(t) \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1}(t) & w_{n2}(t) & \cdots & 1 \end{bmatrix} \tag{10}$$

If there is a large number of elements in matrix W_l, it indicates that it is close to most requirements at time t in the system. From this, it can be further defined that the correlation $T_i(t)$ between the i-th recommendation sequence at time t and the sequence is:

$$T_i(t) = \frac{\sum\limits_{i=1} w_{ij}(t)}{n} \tag{11}$$

In the formula, $w_{ij}(t)$ represents the similarity between the recommendation sequence i and the requirement sequence j at time t. At this point, sorting their correlation values and selecting a recommendation sequence with higher correlation can obtain more accurate recommendation targets.

3 Experiment and Analysis

In order to verify the application effect of the personalized piano playing and singing mobile teaching resources precise recommendation method based on the collaborative filtering algorithm, experimental tests were carried out. The experimental environment is shown in Table 1.

The above configuration is a common configuration for online course resource recommendation systems, ensuring the universality of the experiment. The experiment used the proposed method, the method of reference [4], and the method of reference [5] to test recommendation coverage, recommendation time, and recommendation accuracy in sequence. The test content is as follows:

3.1 Recommended Coverage Test

In order to test the recommendation level of different recommendation methods, 1000 students were selected as the recommendation target to test the recommendation coverage

Table 1. Experimental environment

Configuration	Parameter
CPU	Intel(R) Core(TM) i5–9400
Frequency	2.90GHz
The server	Associate SR550
Operating System	Windows 10
Version	18362.1082 Professional Edition
Digit	64bit
Hard disk	8TB
Database	MySQL

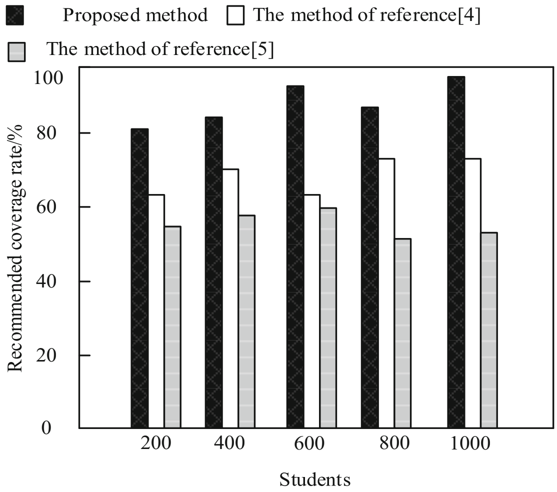

Fig. 4. Recommended Coverage Test Results

of the three methods. The higher the coverage, the better the recommendation ability of the method. The test results are shown in Fig. 4.

From Fig. 4, it can be seen that the recommendation coverage rate using the comparison method is relatively low, while the recommendation coverage rate using the proposed method is always higher than 80%, which can effectively achieve accurate recommendation of personalized piano playing and singing mobile teaching resources.

3.2 Recommended Time Test

In order to test the resource recommendation efficiency of different recommendation methods, 15 sets of tests were conducted on three different methods using recommendation time as the testing indicator. The test results are shown in Table 2.

Table 2. Resource recommendation time for different methods

Number of experimental groups/group	Recommended time/ms		
	Proposed method	The method of reference [4]	The method of reference [5]
1	20.5	46.7	39.9
2	21.2	45.3	39.6
3	20.8	46.6	39.9
4	20.1	46.7	40.2
5	20.8	46.2	39.4
6	20.4	45.9	39.6
7	21.7	46.8	39.8
8	20.9	46.1	40.1
9	21.1	45.8	39.4
10	20.5	45.4	38.8
11	21.8	46.3	40.1
12	20.6	44.5	40.5
13	19.9	45	39.9
14	20.3	44.6	41
15	21	46	40.2

From Table 2, it can be seen that during the experimental process of 15 groups, the recommended time of the method of reference [4] and method of reference [5] fluctuated around 45.7 ms and 39.5 ms, respectively. However, the resource recommendation time of the proposed method was always less than 22 ms, which was lower than the comparison method, indicating a higher resource recommendation efficiency.

3.3 Recommended Accuracy Testing

In order to further test the resource recommendation effectiveness of the three methods, using recommendation accuracy as an evaluation indicator, the resource recommendation accuracy of the three methods for 1000 students was tested. The calculation formula for recommendation accuracy is as follows:

$$\varpi = \frac{\varpi_1}{\varpi_2} \times 100\% \tag{12}$$

In the formula, ϖ_2 represents the total recommended resources, and ϖ_1 represents the actual received recommended resources.

The higher the recommendation accuracy, the better the recommendation accuracy and resource recommendation effect. The test results are shown in Fig. 5.

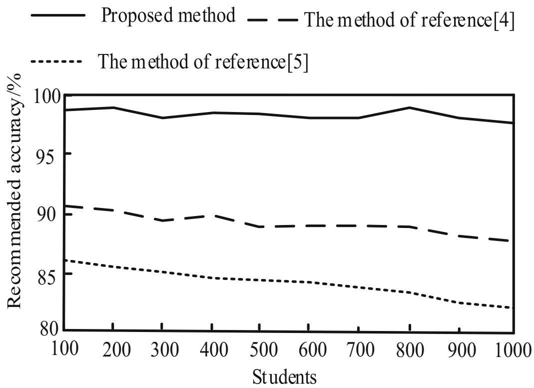

Fig. 5. Recommended Accuracy Test

Figure 5 shows the recommendation accuracy of different methods. From the test results, it can be seen that as the number of students increases, the recommendation accuracy of each method continues to decrease. When the number of students reaches 500, the recommendation accuracy of the method of reference [4] and the method of reference [5] decreases to 87% and 83%, respectively. Although the resource recommendation accuracy of the proposed method shows a decreasing trend, its resource recommendation accuracy always exceeds 97%, it can effectively improve the precise recommendation effect of personalized piano playing and singing mobile teaching resources.

4 Conclusion

This paper proposes a precise recommendation method for personalized mobile teaching resources of piano playing and singing based on collaborative filtering algorithm. Collect the information of piano playing and singing learners based on context awareness method, and calculate the learners' interest in recommended resources. Aiming at the problems of low resource utilization and poor recommendation effect, accurate recommendation of piano playing and singing resources is achieved through Collaborative filtering algorithm. The experimental results indicate that:

1) In the recommendation coverage tests of the three methods, the proposed method consistently achieved a recommendation coverage rate of over 80%, which can effectively complete the precise recommendation task of personalized piano playing and singing mobile teaching resources and has good practicality.
2) In the recommendation time test, the resource recommendation time of the proposed method is always less than 22ms, indicating high recommendation efficiency.
3) When the number of students reaches 500, the recommendation accuracy of the comparison method is less than 90%. Although the resource recommendation accuracy of the proposed method shows a decreasing trend, the overall resource recommendation accuracy is always higher than 97%, indicating good recommendation results.

From the above results, it can be seen that this method has high recommendation coverage and accuracy, and low recommendation time, can quickly and accurately recommend learning resources that learners are interested in, effectively improving learning effectiveness and hobbies. In addition, this method also has certain universality, and the corresponding algorithm can be applied to other mobile teaching fields, which has certain theoretical and practical significance. In summary, this method provides a new approach and approach for personalized recommendation of mobile teaching resources, which can better meet the personalized needs of learners and provide a certain reference for the development of mobile education.

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