Computer Aided Music Instructional Resource Recommendation System Based on Knowledge Map and Collaborative Filtering

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Abstract. In the current music teaching, computer-aided music teaching is a new instructional method. This instructional method makes up for the shortcomings of traditional music teaching to a certain extent, and integrates all music instructional resources. In this study, we designed and implemented a music CAI resource recommendation system based on knowledge map and collaborative filtering (CF). The goal of the system is to provide individualized and high-quality music instructional resources recommendation to meet the needs of different learners. In order to achieve this goal, a knowledge map in the field of music is first constructed. Then, combining CF method with knowledge map, a hybrid recommendation algorithm is proposed to comprehensively consider users' individualized preferences and entity relationships in knowledge map. The results show that the system can effectively recommend high-quality music instructional resources and improve users' satisfaction. In addition, compared with the recommendation system based on CF, the proposed system can make better use of the knowledge in the music field and provide more accurate and individualized recommendation results. The system can effectively improve the utilization rate of music instructional resources, improve learners' learning efficiency and interest, and has high practical value and broad application prospects.

Keywords: Knowledge Map; Collaborative Filtering; Computer-Aided Instruction; Resource Recommendation
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1 INTRODUCTION

As an important part of educational resources, music instructional resources are of great significance for improving students' music literacy and skills. Chicaiza and Valdiviezo-Diza [1] analyzed information sparsity and performance issues based on knowledge graphs. The development of recommendation systems has gone through multiple stages, from initial content-based recommendations to collaborative filtering recommendations, and then to machine learning based recommendations. With the continuous development of artificial intelligence technology, deep learning has also been applied in recommendation systems, achieving good results. As a method of describing the real world, knowledge maps can also be applied in recommendation systems to improve the accuracy and effectiveness of recommendations. The recommendation system based on knowledge graph has been widely applied and researched in recent years, and has achieved good results. In the future, with the continuous development of knowledge graph technology, recommendation systems based on knowledge graphs will also continuously improve the accuracy and effectiveness of recommendations. A knowledge graph-based recommendation system can provide more accurate and reliable support for personalized recommendations, improving the effectiveness of recommendations and user satisfaction. At the same time, recommendation systems based on knowledge graphs can also provide support and assistance for the improvement and development of knowledge graphs. However, in the actual teaching process, students often find it difficult to find suitable learning resources from a large quantity of music instructional resources, which affects the learning effect. Therefore, how to effectively recommend music instructional resources has become an urgent problem to be solved. The personalized recommendation system service computing based on collaborative filtering in IoT scenarios is a method that utilizes IoT technology and collaborative filtering methods to achieve personalized recommendations. In IoT scenarios, there are a large number of sensors and devices that can collect a large amount of data. These data include user behavior data, product information, etc., which can provide important support for personalized recommendations. Cui et al. [2] collect user behavior data and product information through sensors and devices in the Internet of Things. It processes the collected data and extracts features and information related to recommendations. Using collaborative filtering methods, personalized recommendations are made to users based on their historical behavior and preferences, as well as product features and information. At the same time, the recommendation results are provided to users through services to achieve personalized service calculation. The advantage of personalized recommendation system service computing based on collaborative filtering in IoT scenarios is that it can collect a large amount of data using IoT technology and achieve personalized recommendations through collaborative filtering methods. At the same time, this method can also improve the accuracy of services and user satisfaction, providing important support for the development of personalized services. This instructional method makes up for the shortcomings of traditional music teaching to a certain extent, and integrates all music instructional resources. With the help of computer software, it changes the instructional mode of traditional music classroom and optimizes music courses by using modern technical means. The basic idea of recommendation system is to predict the future needs of users by analyzing their historical behaviors and interest preferences, so as to provide individualized recommendation services for users. CF and recommendation method based on knowledge map are two commonly used technologies in recommendation system. The knowledge graph provides a rich description of domain knowledge, which can be used to enhance the accuracy and diversity of recommendation algorithms. When combined with project recommendations, knowledge graphs can help the system better understand users' interests and needs, and provide recommendations that better meet user expectations. Du et al. [3] constructed an effective joint framework for knowledge graph and project recommendation interaction. Firstly, collect and organize data from relevant field data sources to construct a knowledge graph. The graph should contain information such as entities, relationships, and attributes, and be able to express the knowledge structure within the domain.

The collaborative filtering recommendation algorithm based on DeepWalk and self-attention can effectively process user behavior data, capture complex relationships between users and items, and consider personalized local information to achieve more accurate recommendations. At the same time, this algorithm has good scalability and interpretability, and is suitable for large-scale recommendation scenarios. Guo et al. [4] transformed user behavior data into a sequence of nodes with rich contextual information through random walk and negative sampling techniques. Then, a neural network model is used to transform the node sequence into a low dimensional vector representation. This representation can capture the complex relationship between users and items, thereby improving the accuracy of recommendations. CF finds similar user groups by analyzing users' behaviors and interest preferences, and uses group behaviors to recommend users. CF algorithms can be divided into user-based CF and model-based CF. Among them, the user-based CF algorithm judges the similarity between users by calculating the similarity between them, so as to make recommendations. The model-based CF algorithm describes users' interest preferences by constructing a model, and makes recommendations according to the model. In practical application, model-based CF algorithm can usually achieve better recommendation effect, but it also needs more computing resources and data support. The recommendation method based on knowledge map analyzes the relationship between users and knowledge nodes by constructing domain knowledge map, and provides users with more accurate recommendations. Knowledge map is a graphical representation of domain knowledge base, including entities, attributes and their relationships. The purpose of this article is to study and implement a music CAI resource recommendation system based on knowledge map and CF, and to provide individualized and accurate music instructional resource recommendation service for students. Through the research and implementation of this system, it can help students to obtain music instructional resources suitable for them more efficiently, improve the learning effect, and also provide reference for the optimal allocation of music education resources.

With the popularity of online applications, information overload has become an increasingly serious problem. To address this issue, recommendation systems are widely used to provide personalized recommendations by predicting users' interests and preferences. However, traditional recommendation systems mainly rely on user behavior data and collaborative filtering, which largely ignores the semantic information of knowledge. In recent years, recommendation systems based on knowledge graphs have been proposed, aiming to utilize the semantic information of knowledge graphs to improve recommendation performance. Guo et al. [5] understand and predict user preferences and needs by constructing and utilizing a knowledge graph that includes entities, relationships, and attributes. This recommendation method not only provides accurate recommendations, but also enhances users' trust in recommendation results. By utilizing the semantic information of knowledge graphs, users' preferences and needs can be better understood, thereby improving the accuracy of recommendations. Knowledge map is a heterogeneous information network that can be understood by machines and stores objective facts in the real world in the form of graphs. Knowledge map constructs links between projects through different types of relationships, thus capturing the semantic relevance between projects and expanding the inherent characteristics of projects. According to the relationship shown in the knowledge map, other resources that are directly or indirectly related to the current learning resources are recommended, so that learners do not need to learn knowledge points step by step according to the traditional online learning method, but pay more attention to the structural relationship between the corresponding resources, and at the same time enrich the selectivity of resources. The significance of this study is not only to solve the problem of recommending music instructional resources, but also to promote the digital transformation and growth of music education. In this regard, the research has made the following innovations:

This article will use CF algorithm to model and analyze users' behaviors and interest preferences, find similar user groups, and make recommendations according to users' behaviors and interest preferences.

⊜ Using the recommendation method based on knowledge map to analyze and model the relationship between users and knowledge nodes, so as to provide users with more accurate recommendations.

⊛ Comprehensive use of CF and recommendation method based on knowledge map to provide individualized and accurate music instructional resource recommendation service for users.

This article introduces the significance of CF algorithm and knowledge map technology in music instructional resource recommendation, and puts forward a music CAI resource recommendation system based on knowledge map and CF. The feasibility of the system is verified by simulation test. Finally, the research results and the direction that the system can be further improved are summarized.

2 RELATED WORK

Guo et al. [6] constructed a hybrid recommendation system based on automatic encoder and latent feature analysis. This recommendation system combines automatic encoders and latent feature analysis to achieve more accurate recommendations by capturing latent features between users and projects. Automatic encoder is a deep learning model used to learn effective representations from data. In this system, an automatic encoder is used to extract potential features from user behavior data and project information, generating low dimensional embedding vectors. This module discovers potential relationships between users and projects by analyzing potential features extracted by automatic encoders. Specifically, it uses clustering algorithms to group potential features, identify users and projects with similar features, and further reveal the deeper features of users and projects. Based on the results of latent feature analysis, this module uses a hybrid recommendation method to generate the final recommendation list. Specifically, it combines project-based recommendations, user-based recommendations, and social network-based recommendations, taking into account user, project, and social network information to generate personalized recommendation lists. Huang and Jia [7] analyzed a network model that combines rating systems and user interests to achieve personalized recommendations. The rating system establishes a rating matrix for items by collecting user rating data. The user interest association network constructs a user interest model by analyzing user behavior data and feedback information, and identifies other users and items with similar interests to the target user. This model can reflect users' interests, preferences, and needs. Using a rating system, calculate the similarity between items, and then generate a recommendation list based on the user's rating and similarity of the items. By analyzing the user interest association network, identify other users and items with similar interests to the target user, and then generate a recommendation list based on similarity and user history behavior. Li et al. [8] studied a recommendation algorithm that combines heterogeneous graph convolutional networks and multi behavior enhancement. This algorithm improves the accuracy and diversity of recommendations by introducing feature interaction and multi behavior enhancement. Heterogeneous graph convolutional network is a convolutional neural network model for heterogeneous data, which can handle different types of data, such as user behavior data, item information, etc.

In the multi behavior enhanced heterogeneous graph convolutional network recommendation algorithm based on feature interaction, heterogeneous graph convolutional networks are used to extract and fuse different types of data features. Utilize heterogeneous graph convolutional networks to interact and fuse features between different nodes to extract and enrich feature information. Taking into account the different behavioral data of users, a weighted approach is used to enhance different behaviors to enhance the accuracy and diversity of recommendations. Liang et al. [9] analyzed a recommendation algorithm that combines deep neural networks and collaborative filtering, aiming to improve the accuracy and security of service recommendations in intelligent network-physical systems. The advantage of this scheme is that it combines the advantages of deep neural networks and collaborative filtering, which can improve recommendation accuracy and personalization. Meanwhile, by introducing a network security collaborative filtering mechanism, the security and credibility of recommendation results can be enhanced. However, this solution also faces some challenges, such as data sparsity, model complexity, and security and privacy issues. Future research can optimize and improve these issues to improve the efficiency and security of algorithms. Knowledge graph embedding is a method of mapping entities and relationships in a knowledge graph to a low dimensional space, which provides an effective means for reasoning and querying knowledge graphs. In service recommendation, knowledge graph embedding can help the system better understand user needs and semantic information of services, thereby providing more accurate and personalized recommendations. Mezni et al. [10] conducted context aware service recommendations. This recommendation method can better meet the actual needs of users and improve the quality and efficiency of recommendations. In context aware service recommendation based on knowledge graph embedding, the system first constructs a service model using knowledge graph. Then provide recommendations to users based on the current contextual information and service model. This recommendation method combines knowledge and contextual information to better understand user needs and provide more accurate and personalized service recommendations. Ojagh et al. [11] analyzed a personalized recommendation system that utilizes data from users' personal intelligent devices and combines social network information. The system collects device usage data for some users, such as search records, browsing records, purchase records, etc. The social network information integration section is responsible for obtaining users' social network information, such as friend relationships, interactive information, etc. The recommendation algorithm section conducts personalized recommendations based on the collected data. Transform social network information into a format suitable for recommendation algorithms and establish a social relationship matrix between users. Based on user personal intelligent device data, identify other users with similar interests to the target user, and then provide recommendations to the target user based on their preferences and behaviors. The cold start issue of recommendation systems is a long-standing challenge, mainly involving the initial recommendation quality for new users or projects. Panda and Ray [12] use user behavior data, such as browsing history and purchase records, to infer user interests. This method is mainly used for recommending new users. By analyzing the attributes, content, and other aspects of a new project, identify the most similar historical project to use as a recommendation basis.

Overall, alleviating the cold start problem of recommendation systems requires the comprehensive use of multiple methods and algorithms to understand user and item information from multiple perspectives in order to make more accurate recommendations. Future research can further explore the possibilities of these methods to improve the accuracy and personalization of recommendations. Comment text can provide rich information about users' opinions and emotions about items, thus providing valuable data sources for improving recommendation systems. Srifi et al. [13] utilize collaborative filtering based on comment text to improve the accuracy and personalization of recommendations. Firstly, preprocess the comment text data, including noise removal, word segmentation, feature extraction, and other operations. The purpose of this step is to convert the comment text into a form that can be understood by machines. Construct a user profile by analyzing user comment text and other behavioral data. User profiles should reflect information such as users' interests, preferences, and emotional tendencies. Construct an item portrait by analyzing the comment text and other relevant information of the item. The portrait of an item should reflect its characteristics, advantages and disadvantages, popularity, and other information. Generate recommendation lists using user profiles and item profiles, combined with collaborative filtering algorithms. Consider using user based collaborative filtering, item based collaborative filtering, or hybrid based collaborative filtering. The intelligent recommendation model for tourist attractions based on collaborative filtering and user preferences is a model that utilizes artificial intelligence technology to provide personalized recommendations for tourists based on user preferences and behavioral data. Wang [14] analyzes user behavior data to identify other users who are similar to the target user, and then provides recommendations to the target user based on their preferences and behaviors. User preferences are based on the user's historical behavior and feedback data, constructing a user's travel preference model to provide recommendations that better meet their needs for target users. By analyzing user behavior data, identify other users who are similar to the target user. Based on the preferences and behaviors of these similar users, recommend tourist attractions to target users. Zhang et al. [15] analyzed the neighborhood aggregation collaborative filtering recommendation algorithm based on knowledge graph. It aims to solve the problem of data sparsity in collaborative filtering and more accurately represent user preferences and item features, thereby improving recommendation performance. Personalize the ranking of tourist attractions by combining user preference models and collaborative filtering of recommendation results. The main basis for sorting includes user preferences, attributes of tourist attractions, and evaluations from other users. Zhang et al. [16]

captured semantic relationships between entities through bilinear pooling operations and knowledge perception layers, and utilized graph convolutional networks for recommendation prediction. Specifically, the bilinear knowledge perception graph neural network first utilizes a word embedding model to transform text information into a fixed dimensional vector representation. Then, these vectors are fused with entity and relationship embeddings in the knowledge graph to form composite embeddings. Next, through bilinear pooling operation, calculate the bilinear matrix between composite embeddings to capture the interaction relationship between entity and text information. Finally, recommendation prediction is performed using knowledge perception layers and graph convolutional networks. The advantage of this model is that it can simultaneously utilize both text information and knowledge graph information, improving the accuracy and diversity of recommendations.

3 CONSTRUCTION OF RECOMMENDATION MODEL BASED ON KNOWLEDGE MAP AND CF

The core goal of recommendation system is to create a good user experience and help users find relevant content that they are interested in. Recommendation system can solve this problem by collecting information from users and products, which includes the attributes of users and products, the context of time and geographical location, users' social networks and users' feedback on products. Among them, user feedback is the most extensive and direct reflection of user interests and provides one of the most valuable information about user preferences.

With the arrival of big data, the hidden value in data is gradually excavated. Especially in the field of education, by analyzing a large quantity of students' data, we can understand students' learning behavior and characteristics more deeply. Among them, CF algorithm is a commonly used recommendation algorithm, which is widely used in individualized recommendation in e-business, movies, music and other fields. This section will discuss how to apply CF algorithm to student feature extraction, and propose the system structure of instructional resource database as shown in Figure 1.

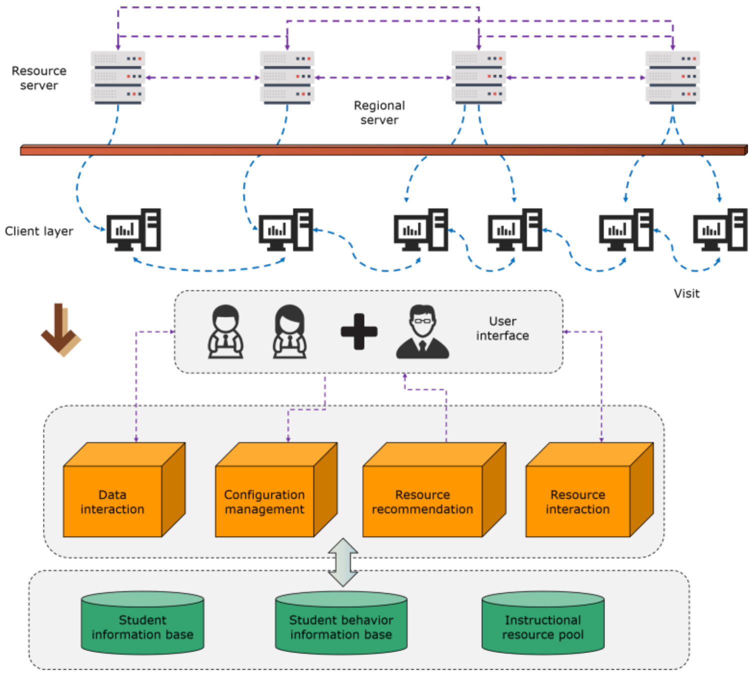

Figure 1: System structure of instructional resource library.

First of all, it is needed to collect all kinds of data of students, including but not limited to course participation, homework completion, test scores, discussion forum activity and so on. These data can be obtained through the school's educational administration system and online education platform. Moreover, in order to obtain more comprehensive characteristics of students, we also need to collect students' personal information, such as age, gender, major and so on.

After obtaining the data, we need to extract the features of these data to facilitate the subsequent CF analysis. For example, we can convert behavioral data such as course participation and homework completion into numerical features, and personal information such as age and gender into classification features. Let the n -dimensional feature vectors of student u,v be $U=\{X_{u1},X_{u2},\cdots,X_{un}\}$ and $V=\{X_{v1},X_{v2},\cdots,X_{vn}\}$ respectively, then the feature distance of student U,V is as follows:

$$d_{uv}=\sqrt{\sum_{k}^{n}\left|x_{uk}-x_{vk}\right|^{2}} \tag{1}$$

The similarity of students' characteristics can be obtained through the transformation of distance and similarity coefficient:

$$Sim_{uv}=\frac{1}{1+d_{uv}}=\frac{1}{1+\sum_{k}^{n}\left|x_{uk}-x_{vk}\right|^{2}} \tag{2}$$

Some features have a greater impact, while others have a smaller impact. In previous student teaching recommendation systems, the issue of student feature weights was not considered. In this article, when constructing teaching recommendation models, student feature weights were added to make clustering analysis more realistic. Transform the similarity of student features through distance and similarity coefficient:

$$Sim_{uv}=\frac{1}{1+d_{uv}}=\frac{1}{1+\sum_{k=1}^{n}\theta_{k}\left|x_{uk}-x_{vk}\right|^{2}} \tag{3}$$

A recommendation list can be generated according to the similarity calculation results. Rank according to the similarity from high to low, and then generate individualized recommendation list according to preset recommendation strategy (such as weighted average based on score). In practical application, we may need to adjust the recommendation strategy according to the specific needs. For example, for some special groups (such as students with poor academic performance), we can adopt stricter recommendation standards to ensure the accuracy of recommendation results.

Knowledge map is a graphical representation of knowledge, which covers entities, attributes and relationships among entities. In the music instructional resource recommendation system, the construction of knowledge map includes the following steps: entity identification: identifying all kinds of entities in music instructional resources, such as songs, tracks, musicians, musicians, etc. Relationship extraction: extract the relationship between entities from the text description and audio characteristics of music instructional resources, such as the relationship between composers and works, the relationship between works and music schools, etc. Attribute perfection: add corresponding attributes for each entity, such as song attributes including track name, composer, release time, etc. Knowledge map construction: integrate the identified entities, relationships and attributes into a complete knowledge map. In order to handle the tasks of entity prediction and relationship prediction under the same mapping framework, an additional symbol traceability task module is introduced for the semantic symbol mapping embedding model. The basic structure is shown in Figure 2.

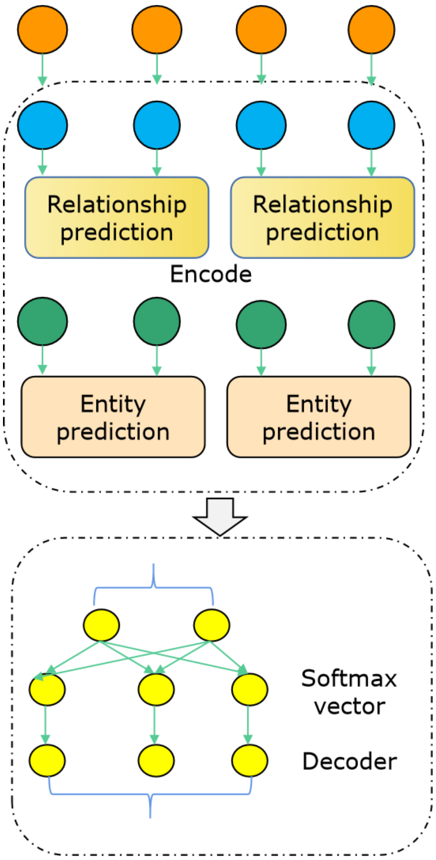

Figure 2: Schematic diagram of model network structure.

The multi-relationship knowledge map can be regarded as a three-dimensional binary tensor G, and the adjacency matrix corresponding to rel relationship types is established. By using triples to represent facts, the head entity is represented by $head$, the tail entity is represented by $tail$, the entity set is represented by E, and a certain relationship category existing in the relationship type set R is represented by rel.

In this article, the basic model is called entity prediction module, this model is relationship prediction module, and the basic structure is encoder structure. Because the structure of this module is close to the basic module, but the output vector achieved by this module is too small, and the parameters of the two modules exist independently of each other, it is possible to construct a representation by completing the mapping from different perspectives:

$$L(head, rel, tail) = L\{\hat{y}(tail) | head, rel\} + L\{\hat{y}(rel) | head, tail\} \tag{4}$$

The two addition parts after the equation respectively represent the average cross-entropy loss of each module and can be superimposed on each other, so the cross-entropy loss is explained as the probability negative logarithmic likelihood of observing the target under the given input. In the stage of expanding model training, the parameters of quantity module can be updated by back propagation according to the above formula. By introducing an inverse relationship for each relationship in the knowledge map, the model can solve the problems of symmetry and asymmetry modeling of relationships in the real number domain. This mechanism can flexibly support the learning model of various structural diagrams and can be applied to a wide range of downstream applications.

The application of knowledge map in recommendation system mainly carries out feature mining in two ways. One is to vectorize the knowledge map by graph mining, or to obtain the vector representation of users and projects by using the traditional vectorization model of knowledge map, so as to construct the recommendation matrix. Second, the primary task of recommendation based on knowledge map is to construct knowledge map, which needs to be based on data. The whole recommendation process includes data layer and mode layer. The data layer refers to the data source, data processing and data conversion for constructing knowledge map. The pattern layer is the principle of establishing knowledge map and the recommended pattern after forming the map. On the basis of constructing knowledge map, it is needed to implement an effective recommendation algorithm to realize individualized recommendation of resources. Convert entities and relationships in knowledge map into graph structure. Calculate the similarity between each node and other nodes. The higher the similarity, the more similar the two nodes are. Rank the nodes according to their similarity. According to the ranking results, the nodes with high similarity to the target nodes are selected as recommended instructional resources.

The distance between any two points P_i, P_j in G is defined as the usual Euclidean distance $d(P_i, P_j)$. On this basis, the square wave function is used to construct the kernel density function of the recommended model:

$$\hat{f}(P_j) = \sum_{i=1}^{N} K_{spuare,\sigma}(d(P_i, P_j)), \qquad j = 1,2,\cdots,N \tag{5}$$

σ is a predetermined positive value, which controls the radius of influence from one point to its surrounding points, and $N = w \times h$ is the total quantity of data points.

Through which the uniform distribution of can be transformed. At this time, the enhanced conversion equation is:

$$tk = EH(sk) = \sum (ni/n) = \sum ps(si), \qquad k = 0,1,\cdots,L-1 \tag{6}$$

The basic gene comes from a randomly selected gene, and a weighted differential value is added to the basic gene:

$$V_i(t+1) = X_{o1}(t) + F \times (X_{o2}(t) - X_{o3}(t)) \tag{7}$$

Among them, the $o1, o2, o3, i$ values are all different. We call X_{o1} the main individual of variation, and the part after the plus sign is called the difference part.

According to the structural characteristics of knowledge map, the path-based knowledge map feature representation model uses the method of meta-path design to mine the relational semantics of knowledge map. Although these ideas have a good performance in the stage of vectorization of knowledge map, there are also many problems such as unsatisfactory handling of complex relationships and difficult meta-path setting. In order to distribute the influence degree among triples reasonably, the wandering strategy can be used to distribute the weights, and the important entity relationship nodes will get higher weights through the wandering strategy. However, the knowledge map belongs to a heterogeneous network structure, in which entity nodes are connected through different types of relationships.

The length of individuals may be different. For clustering results, the more similar the data objects in a cluster are, the greater the similarity between them and the central data and the smaller the distance between them and the central data. Different clusters have great dissimilarity, that is to say, the centers of different clusters should be as small as possible, that is, the greater the distance, the better. Then we define the following functions:

$$fit(P_i)=\sum_{i=1}^{k} dist(c_i, c_j) \Big/ \left(2 \times k \times \sum_{i=1}^{k} \sum_{d_j \in c_i} dist(d_j, c_i) \right) \tag{8}$$

Among them, the numerator part is the sum of distances between different centers, and the denominator is the product of k value and the sum of intra-cluster distances of all clusters. This function is inversely proportional to k value and intra-cluster distance, and directly proportional to inter-cluster distance.

4 RESULT ANALYSIS AND DISCUSSION

In order to verify the effectiveness and accuracy of music CAI recommendation system based on CF algorithm and knowledge map, a series of experiments were carried out. The results show that the recommendation accuracy of the system is significantly improved compared with the traditional recommendation method, and the user satisfaction is also significantly improved. The research selected a representative data set of music field, including data of various music types, styles and genres. This data set covers a wide range of music resources and can meet the needs of different learners. During the experiment, the data set was preprocessed and cleaned, and the invalid and repeated data were removed. Then, CF method and knowledge map are used to extract features and build entity relationships.

In order to develop knowledge-aware recommendation system, the key problem is how to obtain rich structured knowledge base information for recommended projects. Existing data sets or methods either use various types of auxiliary information from the original recommendation system to enhance the semantic representation of the project, or use private knowledge base to enrich the structural information of the project. Taking the wandering sequence of knowledge map as the input of recommendation unit directly can avoid the loss of information in the quantization process and improve the accuracy of recommendation results. Moreover, the construction stage of adjacency matrix is balanced through the two angles of depth propagation and breadth propagation. Figure 3 depicts students' evaluation results of traditional resource acquisition methods and the music CAI resource recommendation model proposed in this article.

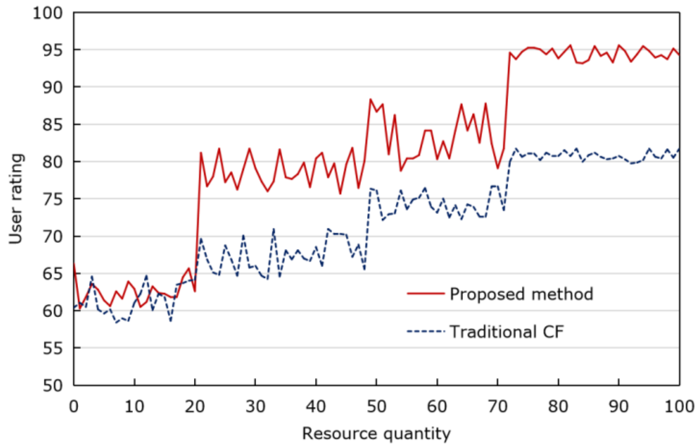

Figure 3: Students' subjective score.

Most students said that the music CAI resource recommendation model in this article can accurately locate the information they need in the huge music curriculum resources, which not only meets their needs, but also stimulates their potential interest.

After obtaining the data, it is needed to cluster the knowledge, and the principles of clustering are similar characters, similar attributes and similar structures. When vectorizing the links or relationships of knowledge maps, it will affect the efficiency of the model because of the difficulty in setting meta-paths or the high complexity of training time and space. Therefore, it is needed to design a knowledge map wandering strategy that does not use the concept of metapath to make the model more universal. Knowledge map information is usually expressed in the form of low-dimensional vectors, but this low-dimensional mapping will cause some information loss and affect the final recommendation results. Therefore, it is recommended that the system input adopts knowledge map sequence instead of low-dimensional mapping, so as to preserve the topological structure and semantic information of knowledge map to the maximum extent. Figure 4 and Figure 5 respectively show the simulation test results of recommendation using the traditional CF algorithm and the hybrid recommendation algorithm in this article.

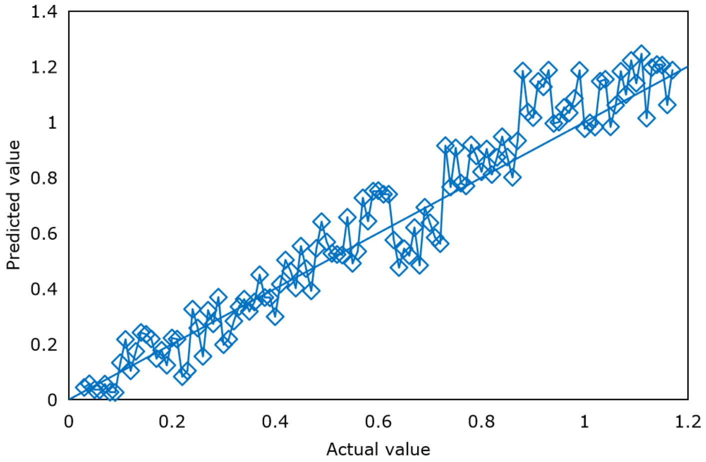

Figure 4: Traditional CF algorithm recommendation simulation.

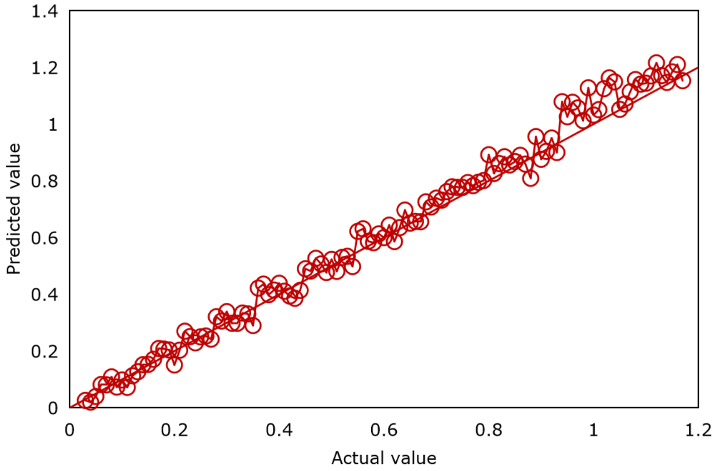

Figure 5: Simulation of algorithm recommendation in this article.

After detailed analysis, the music CAI resource recommendation model based on this algorithm is significantly superior to the traditional CF algorithm in accuracy and efficiency. Students' resource scores can reflect their preference for resources, so the resources presented to students are likely to be a collection of resources they are interested in. After the initial node is given in the model training process, the context sequence is constructed according to the unified quantity of walks. For the knowledge map, not all nodes are suitable to be the initial nodes. Secondly, the fixed traversal times of each node lead to the over-balanced resource allocation, and the nodes with great influence are not encouraged, and the nodes with little influence are not punished.

Obtaining users' needs and interests and accurately describing users' interests are the key to providing high-quality individualized recommendation services. Only by accurately grasping the interests of users can we provide individualized educational information services according to their interests. Individualized service of educational information is an important branch of individualized information service based on network, which is a concrete application of individualized information service in educational resource service. What they have in common is the quantification of information and the dynamic nature of information sources. By mining search logs, the latest entities and attributes can be obtained. This method focuses on keywords and the titles and abstracts of open web pages to extract entities and attributes, and uses timestamps to ensure the real-time updating of knowledge maps. Figures 6 and 7 show the average absolute error and recall results of different recommendation algorithms, respectively.

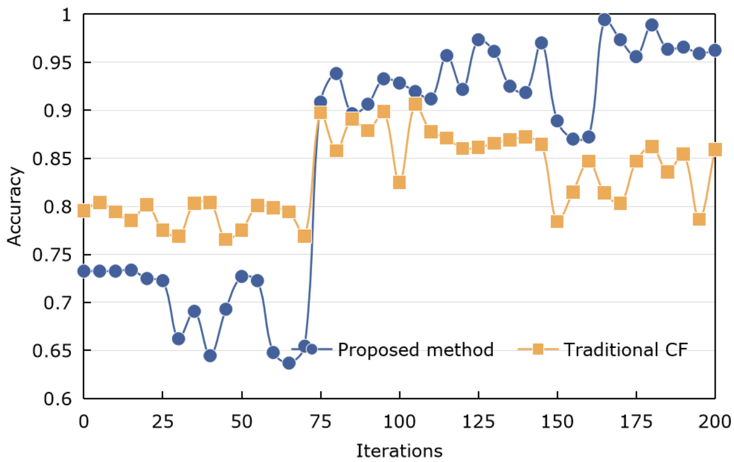

Figure 6: Average absolute error test.

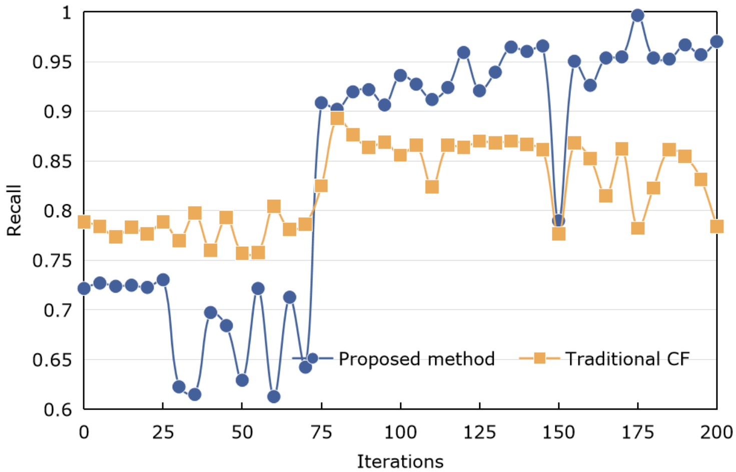

Figure 7: Recall test.

The results show that the error of the music CAI resource recommendation model in this article is reduced by more than 00%, and the recall is increased by more than 15%. Compared with the traditional CF algorithm, its performance is better. By designing and implementing a music CAI resource recommendation system based on knowledge map and CF, we can provide individualized and high-quality music instructional resource recommendation for different learners and improve their learning efficiency and interest. Driven by big data, digitalization and intelligent educational resources have become an important trend of educational growth of. Through this study, we can further explore the construction and application of digital educational resources and provide beneficial exploration and practice for the digital transformation of music education. Moreover, the results of this study can also provide reference for resource recommendation in other disciplines, and promote the digital transformation and growth of educational resources.

5 CONCLUSIONS

In the field of music teaching, computer-assisted music teaching, as a new instructional method, has become an indispensable part of teaching practice. There are some limitations in the traditional music instructional resource recommendation methods, such as unable to meet the individual needs and low recommendation quality. Aiming at these problems, this article designs and implements a music CAI resource recommendation system based on knowledge map and CF. The realization of the system is based on the knowledge map in the music field, and a hybrid recommendation algorithm is proposed by combining CF method and knowledge map. The results show that the system can effectively recommend high-quality music instructional resources and improve users' satisfaction. Compared with the traditional CF recommendation algorithm, the proposed algorithm can make better use of the knowledge in the music field and provide more accurate and individualized recommendation results. The music CAI resource recommendation system in this article provides a new and effective resource recommendation method for the music teaching field. The system can improve the utilization rate of music instructional resources, improve learners' learning efficiency and interest, and has high practical value and broad application prospects. The implementation of this system is only aimed at a specific music field, and the application in other fields is not considered. Future research needs to further expand the application field of the system, improve its recommendation performance and user experience, and make greater contributions to the growth of music teaching.

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