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Research Article

Music Personalized Label Clustering and Recommendation Visualization

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With the advent of big data, the performance of traditional recommendation algorithms is no longer enough to meet the demand. Most people do not leave too many comments and other data when using the application. In this case, the user data are too scattered and discrete, with obvious data sparsity problems. First, this paper describes the main ideas and methods used in current recommendation systems and summarizes the areas that need attention and consideration. Based on these algorithms and based on the user history data information and music data information that can be found now, the paper aims to build a personalized music recommendation system based on directed tags, which can provide basic music services to users and push them personalized music recommendation lists. Then, the collaborative filtering algorithm based on tags is introduced. Usually this method uses discrete tags, and the user tags and music tags are juxtaposed and leveled with each other, which does not reflect the importance and ranking order relationship of each tag and does not reflect the cognitive sequence of users when they listen to and annotate music. In order to improve this problem and increase the accuracy of recommendations, the user-tag and music-tag data are correlated through the tag sequence of tag and music-tag data are correlated and modeled analytically, and feature directed graphs are constructed.

1. Introduction

In recent years, the mobile network has developed very rapidly and, at the same time, driven the rapid development of digital multimedia technology; the young people after 90 have become the main consumer, and digital music has become one of their favorite consumer content. Users can access large music databases in these services; when users want specific music, they can enter the song title or artist or other information to easily search for the desired music, but if there is no clear query, that is, when users want music systems to give them music that matches their preferences without a clear target, music recommendations for personalization can be a better solution to this problem. The massive and huge heterogeneous music data generated in music databases undoubtedly exceed the basic needs and affordability in hand, which in turn triggers user information fatigue [1]. Ordinary music users are often unable to quickly identify songs that meet their preferences when faced with the massive amount of music data in music databases and

have many personalized requirements that are not met by the music libraries recommended by others [2]. At present, information overload is an urgent problem, that is, users cannot understand or grasp the information of too many items or users do not have a clear goal in a certain field but only a vague demand, and the purpose of personalized music recommendation is to help users quickly filter out the interested music in the huge music information database [3].

Currently, the mainstream large music portals usually contain massive music libraries with various genres and types of music, and new music is being added at a high growth rate every month [4]. First, music libraries contain hundreds of millions of songs and it is impossible for users to have enough time to listen to all the songs and then choose their favorite music from them; second, music services are nonimmersive so users can listen to music while doing other things, and music is only used as a kind of background sound, which leads to the ambiguity of users' needs, such as "suggest me or recommend me a good song or songs" [5–10]. In terms of a single song, the cost of time

spent by users to listen to a piece of music is low, and most online music services in China are currently free of charge and do not have too many copyright issues. These characteristics show that music as a spiritual enjoyment is a very suitable item for recommendation compared to movies, which have a certain cost, or books, which require a higher time cost [11]. The future market for music recommendation is very broad, is perfectly suited to the needs of users, and is more fully accepted by them [12]. With the rise of music services, there have been many research results on music recommendation techniques related to music services. Nowadays, many music radio stations not only provide basic music service functions but also can push personalized song lists for users, among which the more famous ones are Pandora and Last.fm. However, because of the unique and emotional characteristics of music itself, the current recommendation results lack personalization and do not have a high coverage rate [13-17]. Music mark and user mark make it orderly, and a music recommendation system that is more in line with individual needs can be designed and implemented based on the functional directed graph of the two, as shown in Figure 1. In this topic, music recommendation system has the following issues to be considered during the design and development: how to track the user preferences; how to make a system with good reliability, scalability, and faster responsiveness [18]. The algorithm will implement a personalized music recommendation system based on directed tags, taking into account historical user behavior data, music tagging data, and tag sequences to improve the accuracy of recommendations [19]. In recent years, with the rapid development of mobile communication, people are more inclined to use mobiles for entertainment and communication, and the recommendation system based on social networks has obvious market prospects. Social networks contain a huge amount of user information, and people are usually willing to share items with their friends, and using this relationship helps to increase the recommendation success rate [20–23].

Because of the rapid development of mobile terminals, digital music becomes mainstream and major Internet companies are increasing investment in the music sector. There are 894 million Internet users in China, and demand for music is a very big market. The current mobile music player is very convenient. Huge demand is a focus on the competition of major Internet music vendors, providing enormous traffic and providing music to users in a large music database. To this end, personalized music recommendation algorithms have been developed for decades since their emergence. There are countless excellent researchers who combine advanced mathematical and statistical ideas with computers with high-speed processing power to provide music recommendation services. Each of the mainstream recommendation algorithms has its own advantages and disadvantages, and combining them will result in better recommendations. With today's open datasets being more readily available, collaborative filtering algorithms will cost less compared to content-based algorithms and have better results when performing clustered recommendations.

2. Related Work

The need for recommendation systems originates from people's lives. Because of the highly social nature of human beings, people always want to refer to other people's opinions when making decisions, and providing accurate and meaningful suggestions to users can effectively deal with information overload and bring rich benefits to the industry. The world's first music recommendation system was developed in 1995, called "Ringo", which pioneered the use of a rating system that predicted user ratings for music and then pushed lists of music that users might like based on their ratings. For a long time, music recommendations were based on basic information about the music tracks, such as artist, genre, and song style, and the results were largely similar, uniform, and lacking in relevance and personalization.

In the subsequent development, researchers have proposed content-based recommendation algorithms and collaborative filtering-based recommendation algorithms, and these two recommendation algorithms and their various improved versions are the most common ones and are commonly used today. Content-based recommendation is based on the user's history to find items that are similar to the item or have a certain contextual relationship to make recommendations and requires the item's content information or expert labeling. The representative example is the famous foreign Internet radio station Pandora, and this "Music Genome Project" was launched in 2001. "Music gene" is dependent on 400 musical features such as melody, harmony, rhythm, form, and lyrics. These are quantified to a specific value; then, the similarity between features is calculated and the similarity between music is precisely determined. The collaborative filtering-based algorithm has a social feature based primarily on user interests, behavior records, collection history, and so on. The SecondHand-Songs website is one of the representatives. When users listen to music, they generate many behaviors, such as listening to music, socializing, music collecting, and rating music. Human behavioral activities are not meaningless, so these recorded historical behavioral data all imply information about users' interests, which can be used as a basis for mining users with similar interests or music with more similar characteristics. We can divide users into many groups, and each group of users has similar interests, so that we can push other users' favorite music to each other in the user group. Both methods have both advantages and disadvantages; the former requires considerable expertise to classify music data and is extremely complex, while the latter has two main disadvantages:

- (1) When users first use it, we do not have any data to work with and how to convey music information is a problem, often called the cold-start problem.
- (2) Not all users will comment and tag their favorite contents, so there is an obvious data sparsity problem. However, users' trial and download records are more likely to be retained, so there are some solutions to the cold-start problem in the actual algorithm system design, such as using a mixture of

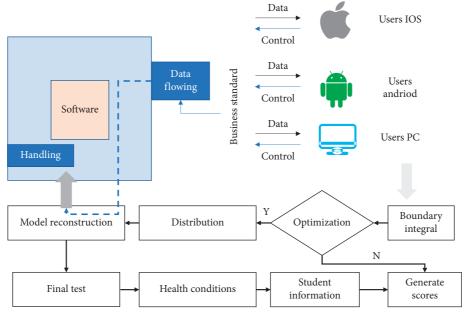


FIGURE 1: Feature directed graph based on user labels.

multiple data sources and multiple recommendation methods to fuse the two in order to achieve better results. In order to improve the algorithm by addressing the shortcomings mentioned above, researchers have improved the algorithm, and the rise of deep learning has led to new research directions.

3. Tag-Based Personalized Music Recommendation Algorithm Research

3.1. Label-Based Collaborative Filtering Algorithm. Users use tags to label music to express their opinions. The tags of music represent the genre of music, style, the psychology of users when listening to songs, and other contents, so it can be said that tags are the bridge between users and music. In many music radio stations, you can see that there are corresponding tags under each music, which provides a basis for users to judge whether they want to try this music or not. Usually, each user's tag record usually consists of a triad of recorded behaviors: user, music, and tag. We can write this as (u,m,t), which means that user u tagged music m with tag t. Using the idea of TF-IDF, we denote the frequency of users tagging tag t by TF (u,t), whose value is calculated as the number of times users tag t/total number of times users tag; the frequency of files with tag t about user u is denoted by IDF (u,t), and the value is logarithmic to the value of (total number of users/number of users who have labeled label *t*). Then, the tag-user association degree is calculated as

$$U_{x}K = TF(u,t) * DF(u,t). \tag{1}$$

Similarly, the tag-music association is calculated as

$$U_m K = TF(x,t) \bullet DF(x,t), \tag{2}$$

where TF (m,t) denotes the frequency of music m tagged by tag t and IDF(m,i) denotes the logarithmic value of (total

number of music/number of music tagged by tag *i*); after obtaining these two values, the model of users' interest in music is constructed as follows:

$$\operatorname{Im}(u,x) = \frac{\sum_{i=0}^{l} U_x K \times U_m K}{x+m}.$$
 (3)

Then, the Jaccard formula is used to calculate the resource similarity, as shown in the following equation:

$$T_{x}(u,x) = \frac{\sum_{i=1}^{n} x_{i} y_{i}}{\sqrt{x+m}}.$$
 (4)

Here, we mainly consider two pieces of music that have been tagged with the same label by multiple users. Theoretically, the more times they have been tagged with the same label, the more similar the two pieces of music are. After obtaining the interest model of users and then calculating the similarity between music models, we can calculate the interest of users to other music, as in the following equation:

$$E_x(u,x) = \sum_{i=1}^n x_i y_i \otimes T(i,j).$$
 (5)

The algorithm first calculates the TF-IDF values of user-to-tag and music-to-tag, which are used to calculate the user's interest model for music and the similarity between music, and finally calculates the user's interest in other music based on the interest model and music similarity to obtain a list of recommendable music.

3.2. Collaborative Filtering Algorithm Based on Directed Labels. Music tags can reflect music content information, and in tag-based music recommendation, we mainly use the information correlation between tags to classify tags in a flat way. However, tags are independent of each other and are discrete in distribution, so we cannot access what users have in mind when labeling or categorizing music and we cannot

directly access their cognitive order of tags. To solve this problem, we can improve the situation by vectorizing the tags. We collect the behavioral data such as time and number of times when users categorize and label music and vectorize them to reflect the relationship between users, music, tags, and cognitive order, so as to improve the accuracy of music recommendation. The main scheme is shown in Figure 2.

For this program process, the following points need to be elaborated and explained:

- (1) First, we collect the annotation records of music by users when they receive music services and organize the data into an ordered tagging dataset. This tagging dataset records the annotations made by each user while listening to music, and we organize this dataset to obtain an ordered sequence of annotations; from the music side, the records include the content of the music annotated by each different user, which may be the same or similar or completely different. These data can be obtained from millions of music databases. In each music tag, there are both the musician's knowledge of his music and various different users' perceptions of it, and these perceptions exist in an order; the more the number of tags with the same perception, the more the annotation reflects the characteristics of the music. Compared with the basic algorithm, a step of tag serialization is added here, which makes our recommendation results more accurate.
- (2) In feature modeling, the user's interest features and music features are to be mined from the user's tag sequence set and the music's tag sequence set, respectively. Mining user features can count his labeled content and times; the higher the frequency of occurrence, the more the user may be interested. In the same way, we need to mine and extract the directed graph of music features from the set of music tags.
- (3) Based on the directed graphs we obtained in the previous step, here we mainly use the theory of isomorphic graphs to complete the clustering division of the set of music feature directed graphs and form clusters. This allows us to match the user feature directed graph with the content in the clusters with the highest similarity when making aggregated recommendations, thus reducing the time cost of matching and obtaining the music recommendation results more quickly. Usually, we use tags to describe the characteristics of an item, which are usually in the form of text and possess hierarchy-free characteristics.

When we perform content-based recommendations, items such as music, which can be characterized in multiple ways, are more suitable. Content-based recommendation methods usually start by classifying music according to tags based on a certain feature, modeling its features, and then reclustering similar songs as a topic or genre based on similarity. This method has more complete and clear criteria, takes into account the relationship between tags and content, and has clear tag semantics, but lacks thinking about the

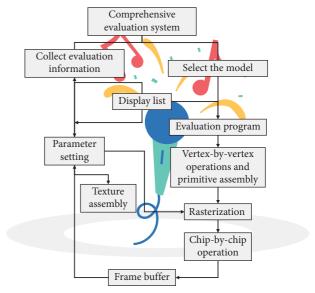


FIGURE 2: Flowchart of the collaborative filtering algorithm based on directed labels.

user's topic; correspondingly, the collaborative filteringbased tag recommendation technology mainly obtains the user's labeling behavior data and infers music that is more similar to that user's needs or more similar to that user's interests based on the data laws. The association between the user and the label is utilized, and the label is used to find similar users first. Then, according to the similar users, the corresponding items are recommended, but this will have an obvious drawback that there is no description of the descriptive characteristics of the music itself. The principle of recommendation based on directed graph combines the parts of the first two algorithms; there is a three-dimensional relationship between users, music, and tags, users label music to describe music features, tags reflect music features, and if users repeatedly use the same tags for labeled music, then he must be interested in the music, and the same reasoning can be inferred in reverse; the three-dimensional relationship affects each other, forming a three-dimensional relationship structure chart. This method is similar to the algorithm based on collaborative filtering and has a certain similarity with the algorithm based on user similarity, but there is no direct analysis of the content of the music and no focus on the user's preferences.

4. Collaborative Filtering Algorithm Based on Visualization of Directed Labels

4.1. Get Tags. Music radio provides a service that allows users to comment and rate music. The keywords in users' comments can then become tags for the music and provide users with a number of optional tags to label the music. The first few tags of a piece of music are usually labeled according to the description, theme, and emotion provided by the artist and combined with the album genre. When users play music, according to their own feelings about the music, they can choose the corresponding tags in the tag category of music

or complete their own labeling by creating their own tags for the music, users may have completely different feelings about the same song after repeatedly trying it, and accordingly users may have completely different feelings about the same song after repeatedly listening to it. Accordingly there may be multiple tags with large gaps, and each tagging by users will be recorded. Repeated tagging and multiple comments will increase the weight. To obtain these tags, we need to text process the data information after obtaining the user's annotation information and comment content. Tag information should usually be able to visually reflect the content of a piece of music, such as artist, album name, era, style, genre, and theme. The details of the processing are detailed. Usually, the music tags provided by radio stations are sequential in nature, and the more advanced the tags are, the better they reflect the music characteristics. The dataset of this paper comes from Million Song Dataset (MSD), a music resource integration platform. It collects data from seven well-known and authoritative foreign music communities (e.g., MAGD dataset and 7 digital) and organizes and analyzes the data, giving researchers offline datasets and analysis results obtained using various algorithms. The data for the optimization algorithms in this chapter are mainly from the offline dataset provided by Last.fm, which we divided 2/8 into a training set and a test set because the site provides song-level tags and similarity, which helps later studies to conduct comparative exploration. As Figure 3 shows the information displayed for a particular music in Last.fm, we can see how many users are currently listening to the music, and below are the popular tags of the music, with the tags arranged in the order of hotness.

For artists, they will have albums with different themes, and these albums will have different song lists with different tags. For music, each piece of music may be tagged by multiple users, and these tags may be similar or different, so the music will exist in different song lists according to different tags. We are able to obtain the tag sequence of the artist's album and the tag sequence of the music tagged by multiple users. It is important to note that, in the song list, users' perceptions are reflected in their tagged sequences, and the more prominent the music is in the song list, the more it should be tagged and positioned at the top of the song list.

4.2. Visualization of Clustering Information. In the Last.fm dataset, there are 943,347 matched tracks, of which 505,216 contain at least one tag and 584,897 have at least one corresponding similar music, containing a total of 522,366 unique tags, with a total of 859,863 track-tag pairs. Based on the number of tags and their corresponding popularity, we can get the following chart, as shown in Figure 4.

As can be seen from Figure 4, the more frequently the tag appears, the more people love the tag, which can be called a popular tag, and correspondingly the smaller the number of such tags. The set of music feature digraphs is divided into *K* clusters. We know the target user's interest feature digraph and the cluster center digraph of each cluster. First, we calculate the isomorphism degree one by one and put the isomorphism degree beyond the critical value into a new cluster. Then, we calculate the target user's interest feature

digraph and the music feature digraph contained in each cluster in turn and compare them. According to isomorphism, the total number of music is not large enough. Since we recommend music to users, we do not need to recommend all the music that meets the requirements. Therefore, if the total amount of music is enough, matching with the cluster with the highest isomorphism can meet the requirements. For users with a large number of tags, we can use the directed graph of user interest features and the directed graph of music features to calculate their isomorphism and provide the corresponding music recommendation list according to the level of isomorphism. The database records the music tags of users and musicians, so the data are extremely large, with the number of titles reaching more than 200,000. The top 20 tags and their popularity are shown in Figure 5.

Every user generates behaviors when listening to a song; clicking, skipping, adding to the collection, looping, downloading, forwarding, commenting, and the operation time of the above behaviors will leave a record, and these behaviors will make the connection between the user and the tag. The information of the tag represents the user's view of the music. Through the tag, we can discover the music that the user is more likely to be interested in, and in the case of fuzzy queries, we will be able to determine whether the music is what they need by the tag of the music. The purpose of this step correlates the user and the tag sequence according to certain laws and reflects this relationship in the equation. Useri is the current i-th user number, and assuming that there are a total of x tags, $\langle k1, ... k_x \rangle$ denotes the tag sequence, guseri denotes the associated user's tag sequence, and k_{ix} denotes the xth tag tagged by the i-th user, the associated user forms the following record:

$$g_i = |\operatorname{User}_i: k_1, k_2, \dots k_i\rangle, \tag{6}$$

where gi denotes the tag sequence after associating the user. Then, by obtaining the different music and tag sequences collected and tagged by the user, we can obtain the set of m tagged sequences for that user, as shown in the following equation:

$$g_i = \{ \text{guest}_i, \dots \text{guest}_q.$$
 (7)

We identify these sorted labels with the following formula:

$$gset = (music_1, ... music_i).$$
 (8)

Then, we assume that there is some sequential relationship between the labels, and the vast majority of users will not make labels without any order and meaning. In the whole relationship graph, each node is a label. The association between tags is represented by node-to-node lines as connecting edges.

5. Results and Discussion

If the user has initiated the search behavior, then it must be purposeful and have clear interest characteristics because search without purpose brings high time cost and low

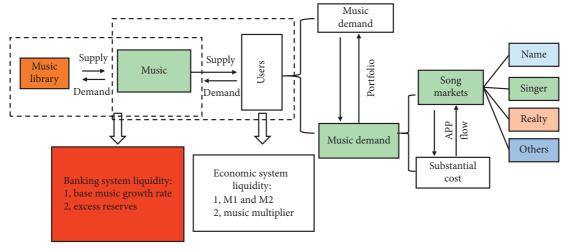


FIGURE 3: Music information display.

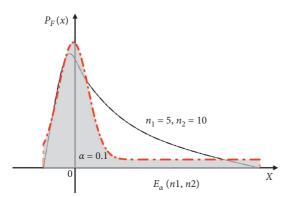


FIGURE 4: Corresponding popularity $(P_F(x))$.

benefit. Typically, there are two scenarios if the user uses the search function in the music system. Users can perform accurate searches and provide accurate music names, artists, or lyrics in detail. These can be quickly matched through the text in the music feature database, although the user who wants to listen to a particular song does not have a clear purpose, but simply listens to a certain kind of music and does not know the genre or wants to search and listen to songs on different web pages in the outdoors, but does not know the name of the music or the artist or remember the exact lyrics, and the impression of the melody is just a little. It is a recent practice to optimize services using smart word associations and search phrasal recommendations. This allows users to listen to specific music in other social platforms or life scenarios, but they do not know the names and may make ambiguous searches. Precise music search usually utilizes reduced search, that is, the more information the user inputs, the higher the matching precision demanded, the fewer results that match the conditions, but the higher the search precision, as shown in Figure 6.

The set of music feature directed graphs is divided into k clusters. As we know the interest feature directed graph of the target user and the cluster center directed graph of each cluster, first calculate the isomorphism degree one by one, put the clusters whose isomorphism degree exceeds the

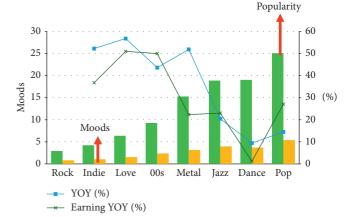


FIGURE 5: Moods and corresponding popularity.

critical value into a new cluster set, calculate the interest feature directed graph of the target user and the music feature directed graph contained in each cluster in that cluster set in turn, and rank the clusters according to isomorphism, which is the case when the total amount of music is not large enough. Since we are recommending music to users, we do not need to recommend all the music that meet the conditions to users. Therefore, if the total amount of music is enough, matching with the cluster with the highest isomorphism can satisfy the requirement. For users with a large number of tags, we can calculate their isomorphism using the directed graph of user interest features and the directed graph of music features, as shown in Figure 7, and provide a corresponding list of music recommendations according to the level of isomorphism. Users with few tags but more audition and download records can be called inactive users, for which the collaborative filtering based on directed tags is not effective due to the lack of tagging data. We can supplement the DTSCF algorithm by using the LDA-MURE model-based algorithm for music recommendation based on the user's listening and downloading records, that is, hybrid recommendation is used.

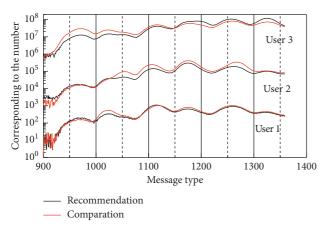


FIGURE 6: Relationship between matching accuracy and input information.

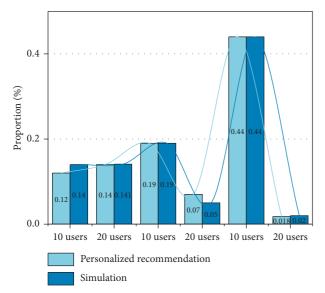


FIGURE 7: Comparison of isomorphism in clusters of clusters.

Both recommendation algorithms in this paper provide music list recommendations, i.e., top N recommendations. Because of user activity and the long-tail effect of music, we mainly divide all sample music into popular music and longtail music. Top music is music with more than 15 tags, and long-tail music is music with less than 5 tags, which provides a clear distinction. When evaluating the performance of the algorithm, three evaluation metrics are used, recall, accuracy, and F-measure, which are shown in Figure 8, for the collaborative filtering algorithm based on the labeled directed graph. In the implementation of music recommendation function, first we need to obtain the data information and model the data information with features (including user feature directed graph modeling and music feature directed graph modeling), and the specific code has been described in detail earlier.

Then, we train the algorithm model, and after the similarity matching, we get the music feature directed graph for the user and form the recommendation list by matching it with the music in the music list. Then, we can push it to the

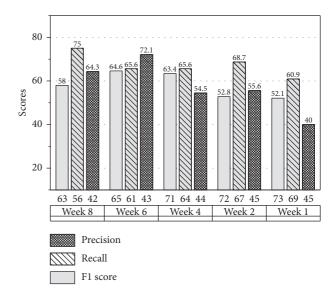


FIGURE 8: Recall and accuracy metrics statistics.

user to achieve personalized music recommendation. In particular, the question of when to deliver true information and when to deliver false information in order to maximize their own benefits is the primary consideration for poor quality corporate think tanks. It is recommended that IoT security companies do a good job of division of labor and collaboration, and product-based companies pay attention to market segments and provide specific network information security issues for the IoT with detailed solutions; channelbased enterprises build a public network information security service platform to undertake the realization and distribution of commercial benefits, thereby realizing the IoT network information security ecosystem. The construction of the IoT network information security ecosystem faces the technical complexity and operational complexity of the IoT business industry chain, and there are a lot of problems to be solved.

This process is well illustrated by the signaling game. In other words, the enterprise think tank will choose its own strategy according to its own actual situation, weighing the relationship between the benefits and costs of sending signals; at the same time, the public information service platform will also consider which specific action is the most beneficial to itself, whether to collaborate or not, according to the balance of signals sent by the enterprise think tank. Under the condition of information asymmetry, the signaling mechanism is crucial for the future development of enterprises and governments as a path that indirectly affects the development of participants. To this end, this chapter constructs a signaling game model of enterprise think tanks and public information service platforms based on signaling game theory and analyzes the equilibrium results to summarize and propose relevant countermeasures.

6. Conclusion

This paper introduces a tag-based collaborative filtering algorithm and optimizes and improves it to improve the accuracy of recommendation. The feature modeling of

music-tag and user-tag is carried out, respectively, and a directed graph of music features and a directed graph of user interest features are constructed. The music feature directed graph is divided into clusters, so that the clusters can be clearly distinguished, and at the same time, the music in each cluster is guaranteed to be the most isomorphic with the cluster center feature directed graph, and the music list is performed. When recommending, it is only necessary to match the directed graph of user characteristics with the music in the cluster with the highest degree of adaptation. Detailed requirement analysis and design of each function in the personalized music recommendation system are carried out, and functions such as music playback control, music list, music retrieval, user comments and annotations, and music recommendation are realized. When the sparseness is too large and it is difficult for long-tail music and low-activity users to obtain a good recommendation effect, an algorithm based on the LDA model can be used as a remedy. The algorithm can make corresponding recommendations based on the user's audition and download records.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] D. Kulibert, A. Ebert, S. Preman, and S. H. Mcfadden, "In-Home use of personalized music for persons with dementia," *Dementia*, vol. 18, no. 7-8, pp. 2971–2984, 2019.
- [2] K. Murphy, W. W. Liu, D. Goltz et al., "Implementation of personalized music listening for assisted living residents with dementia," *Geriatric Nursing*, vol. 39, no. 5, pp. 560–565, 2018.
- [3] M. Wang and A. Nehorai, "Coarrays, MUSIC, and the cramér-rao bound," *Ieee Transactions on Signal Processing*, vol. 65, no. 4, pp. 933–946, 2017.
- [4] A. Salunke, R. Kukreja, J. Kharche, and A. Nerurkar, "Personalized suggestion for music based on collaborative filtering," *International Journal of Engineering and Computer Science*, vol. 9, no. 5, pp. 25047–25051, 2020.
- [5] F. S. Collins and R. Fleming, "Sound health," The Journal of the American Medical Association, vol. 317, no. 24, pp. 2470-2471, 2017.
- [6] S. Garrido, C. J. Stevens, E. Chang, L. Dunne, and J. Perz, "Music and dementia: individual differences in response to personalized playlists," *Journal of Alzheimer's Disease*, vol. 64, no. 3, pp. 933–941, 2018.
- [7] C.-Y. Wang, Y.-C. Wang, and S.-C. T. Chou, "A context and emotion aware system for personalized music recommendation," *Journal of Internet Technology*, vol. 19, no. 3, pp. 765–779, 2018.
- [8] K. Archambault, K. Vaugon, V. Deumié et al., "MAP: a personalized receptive music therapy intervention to improve the affective well-being of youths hospitalized in a mental

- health unit," Journal of Music Therapy, vol. 56, no. 4, pp. 381-402, 2019.
- [9] N. Sharda, E. Mattoon, L. Matters et al., "Bach to the basics: implementation and impact of a postoperative, inpatient personalized music program for older adults," *Journal of Perianesthesia Nursing*, vol. 34, no. 2, pp. 347–353, 2018.
- [10] R. Kyriakides, P. Jones, R. Geraghty et al., "Effect of music on outpatient urological procedures: a systematic review and meta-analysis from the European association of urology section of uro-technology," *The Journal of Urology*, vol. 199, no. 5, pp. 1319–1327, 2017.
- [11] E. Liebman, M. Saar-Tsechansky, and P. Stone, "The right music at the right time: adaptive personalized playlists based on sequence modeling," *MIS Quarterly*, vol. 43, no. 3, pp. 765–786, 2019.
- [12] H.-Y. Chang, S.-C. Huang, and J.-H. Wu, "A personalized music recommendation system based on electroencephalography feedback," *Multimedia Tools and Applications*, vol. 76, no. 19, pp. 19523–19542, 2017.
- [13] M.-C. Chiu and L.-W. Ko, "Develop a personalized intelligent music selection system based on heart rate variability and machine learning," *Multimedia Tools and Applications*, vol. 76, no. 14, pp. 15607–15639, 2017.
- [14] D. Kang and S. Seo, "Personalized smart home audio system with automatic music selection based on emotion," *Multi-media Tools and Applications*, vol. 78, no. 3, pp. 3267–3276, 2019.
- [15] N. Ding, A. D. Patel, L. Chen, H. Butler, C. Luo, and D. Poeppel, "Temporal modulations in speech and music," *Neuroscience & Biobehavioral Reviews*, vol. 81, pp. 181–187, 2017.
- [16] P. Investigators, K. M. Rowan, D. C. Angus et al., "Early, goal-directed therapy for septic shock-a patient-level meta-analysis," *The New England Journal of Medicine*, vol. 376, no. 23, pp. 2223–2234, 2017.
- [17] E. M. Long and K. White, "Using personalized music playlists for patients with dementia as a teaching innovation," *Nursing Education Perspectives*, vol. 40, no. 6, pp. 384-385, 2019.
- [18] E. Hoffman, "When composers draw: personalized music, formalized thought," *Perspectives of New Music*, vol. 57, no. 1, pp. 149–190, 2019.
- [19] D. Miao, X. Lu, Q. Dong, and D. Hong, "Humming-query and reinforcement-learning based modeling approach for personalized music recommendation," *Procedia Computer Science*, vol. 176, pp. 2154–2163, 2020.
- [20] S. Koelsch, P. Vuust, and K. Friston, "Predictive processes and the peculiar case of music," *Trends In Cognitive Sciences*, vol. 23, no. 1, pp. 63–77, 2019.
- [21] M. Tkalčič, M. Schedl, and P. Knees, "Preface to the special issue on user modeling for personalized interaction with music," *User Modeling and User Adapted Interaction*, vol. 30, no. 2, pp. 195–198, 2020.
- [22] J.-H. Su, C.-Y. Chin, Y.-W. Liao, H.-C. Yang, V. S. Tseng, and S.-Y. Hsieh, "A personalized music recommender system using user contents, music contents and preference ratings," *Vietnam Journal of Computer Science*, vol. 7, no. 1, pp. 77–92, 2020.
- [23] L. Quinn-Lee and D. Mowry, "Effects of personalized music on caregivers of older adults with dementia in the community," WMJ Official Publication of the State Medical Society of Wisconsin, vol. 118, no. 2, pp. 80–83, 2019.