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Research on the Development Strategy of NetEase Cloud Music Based on Decision Tree Algorithm

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ABSTRACT: *With the rapid development of the internet and digital music, competition among music platforms has become intense. This study focuses on NetEase Cloud Music and proposes a development strategy based on the decision tree algorithm. By collecting user behavior data and constructing decision tree models, the study predicts user preferences and needs, providing personalized recommendations and services on the music platform. Experimental results of this strategy show that it effectively improves user satisfaction and platform profitability. Compared to traditional recommendation algorithms, the decision tree algorithm exhibits better interpretability and accuracy, enabling a deeper understanding of user preferences and behavior patterns, thus providing more precise content recommendations. This innovative development strategy for music platforms helps better meet user demands, achieve sustained growth, and gain competitive advantages.*

Subject Categories and Descriptors: [D.2.2 Design Tools and Techniques]; Decision tables: [E.1 DATA STRUCTURES]; Trees: [H.5.5 Sound and Music Computing]; Modeling

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1. Introduction

The rapid development of the internet and digital music has profoundly changed the landscape of the music industry, with music platforms becoming one of the main channels for music consumption. As one of China's leading music platforms, NetEase Cloud Music has achieved significant success in this field. Since its establishment, NetEase Cloud Music has been committed to providing users with high-quality music content, personalized recommendation services, and interactive community experiences [1]. However, with increasing competition and evolving user demands, NetEase Cloud Music needs continuous innovation and optimization to maintain its leading position.

Numerous research efforts have backed the idea that music can impact grammar and meaning processing in young children [2,3,4] . Specifically, investigations involving children with special needs have revealed that those with music-related challenges can enhance their language abilities through musical activities [5]. Consequently, incorporating music into children with special needs education has gained notable interest. [6] Many researchers from diverse disciplines and backgrounds have examined the challenge of expanding a decision tree based on accessible data, including machine learning, digital audio, pattern recognition, and statistical analysis. [7] As a common machine learning method, the decision tree algorithm has broad potential applications in music software [8] Mobile phones handle the music score information without much technical knowledge [8]. Further music rhythm trees lead to the creation of novel vertical partitioning techniques. [9,10,11,12]. The decision tree algorithm represented in a tree-like structure employs data analysis and mining to predict users' music preferences, behavior habits, and needs, offering personalized recommendations and services. Its advantage lies in its strong interpretability, providing clear logic behind recommendation decisions and making it easier for users to understand and accept the recommended results.

In the development of music platforms, personalized recommendations have become a crucial competitive advantage. By understanding users' interests and preferences, music platforms can recommend songs, artists, albums, and playlists that users may find interesting, enhancing user experience, promoting platform activity, and increasing user retention rates [13]. The decision tree algorithm can extract useful features from vast user behavior data and construct corresponding recommendation models, providing a feasible solution for implementing personalized recommendations on music platforms. Although the decision tree algorithm has been widely applied in the music recommendation field, many issues are still worth exploring and researching [14]. For instance, it is important to fully utilize users' social relationships and music community information in decision tree algorithms to enhance recommendation accuracy and diversity and address efficiency concerns when processing large-scale data [15]. Therefore, this study aims to explore a development strategy based on the decision tree algorithm to further improve user experience and competitive advantage on NetEase Cloud Music.

2. Progress in the Application of Decision Tree Algorithm in the Field of Music Software

Decision tree algorithms in music software have been extensively studied and applied domestically and interna tionally. Decision tree algorithms can be used to mine user interest on music platforms. By analyzing users' historical behavior data, such as play records, playlist collections, comments, etc., decision tree models can be constructed to infer users' music preferences and interests [16]. For example, decision tree algorithms can predict users' preferences for music styles, genres, or artists, providing more personalized content recommendations. Decision tree algorithms can also be applied to music genre classification, categorizing music into different styles or genres [17]. By analyzing music features such as rhythm, chords, timbre, etc., decision tree models can automatically classify music. This classification result can be used to recommend similar-styled music to users, enriching their music experience. Decision tree algorithms can also be utilized for song emotion analysis [18]. By analyzing song lyrics, music features, and emotion tags, decision tree models can identify the emotional states of songs, such as happiness, sadness, excitement, etc. The results of emotion analysis can be used to recommend music that matches the user's emotional state, enhancing their emotional experience.

However, in applying decision tree algorithms in music software, there are challenges and issues to address. User behavior data on music platforms is typically highly sparse, meaning that user behavior data for most music is missing [19]. This can limit the accuracy of decision tree models in the recommendation process. One method to address this problem is to introduce collaborative filtering and matrix factorization techniques to fill and complement user behavior data, thereby improving the effectiveness of recommendations. As music platforms develop and user scales grow, decision tree models can become very large and complex, making them difficult to understand and explain. Therefore, finding ways to simplify and optimize decision tree models to improve their interpretability and efficiency is a problem to solve. For newly registered users or users with insufficient behavior data, decision tree models cannot accurately infer their preferences and interests. One solution to this problem is introducing content-based recommendation algorithms that utilize music features and tags for recommendations [20,21].

Bagging refers to a method that utilizes a collection of classifiers and merges them through a majority voting approach to determine the class label [22] [23]. Similarly, an Info-fuzzy network has been introduced to create robust decision trees and is evaluated against a meta-learning framework [24]. Another research presents the Fuzzy min-max decision tree-HB (FMMDT-HB), which aims to enhance structural stability, with nodes divided according to the Hoeffding bound. [25] A boosting method known as the cross-split technique is employed to reinforce the stability of the decision tree [26]. Baranauskas notes that datasets containing fewer than five classes yield more stable decision trees [27]. The enhancement of structural stability is achieved through region compatibility within the decision tree, utilizing probability assignments derived from evidence theory to assess stability [29].

In conclusion, while decision tree algorithms have broad application prospects in music software, some issues remain to be addressed. Future research can focus on overcoming data sparsity, simplifying decision tree models, and integrating other algorithms and techniques to achieve more accurate and personalized music recommendations.

3. Establishing a User Analysis System Using the Decision Tree Algorithm

3.1. Overall Design of the Music Data System

The decision tree algorithm has been widely used in text, images, videos, and more recommendation systems. The NetEase Cloud Music content search and recommendation system developed in this study is a hybrid recommendation model based on user behavior and music data information. The core of this search and recommendation system is to use the decision tree algorithm to iteratively compute the latent features of music data and then obtain the low-dimensional vector information of the music data through marginalization. These low-dimensional vector information can be incorporated into the search to optimize search results and combined with users' implicit preference features for reasonable music recommendations. In this experiment, audio features are directly extracted from audio files, which fundamentally avoids the cold-start problem and closely aligns with users' intuitive feelings towards music. This hybrid system is built on the traditional matrix factorization model, and algorithmic improvements have been made. The flowchart of the overall system design is shown in Figure 1.

Figure 1 shows that this model utilizes a latent semantic matrix and projects the hidden features of users and audio information of music into a shared space using the decision tree algorithm, ultimately generating search and recommendation results. The music data system includes a user feature module, music audio information, search engine module, and recommendation algorithm module, among others. The user feature module collects and stores users' historical behavior data within the music system and establishes user preference models. The music audio information undergoes preprocessing and feature extraction to train dynamic models in calculating search and recommendation data. The search engine module outputs personalized search results based on extracted features. The recommendation algorithm module is responsible for computing the matching degree between hidden features and the preferences of student users, ultimately providing dynamic recommendations of music they might be interested in. The entire system operation can be divided into two main parts: decision tree model training and search recommendation, as indicated by the arrows representing processes such as collection, prediction, and aggregation. The specific process can be broken down into the following steps: firstly, the system gathers users' historical behaviors while using the music software and normalizes the data to facilitate analysis using an appropriate semantic matrix; next, the original music data is restored, and spectral features are extracted; using the data obtained from the first two steps, a dynamic model is built, and machine learning is continuously conducted to obtain a more sophisticated model; finally, if new music data is added to the system, it undergoes restoration to obtain spectral features, and the advanced model, combined with the preferences of university student users, calculates the degree of interest in the new music data, determining whether it should be recommended to the user.

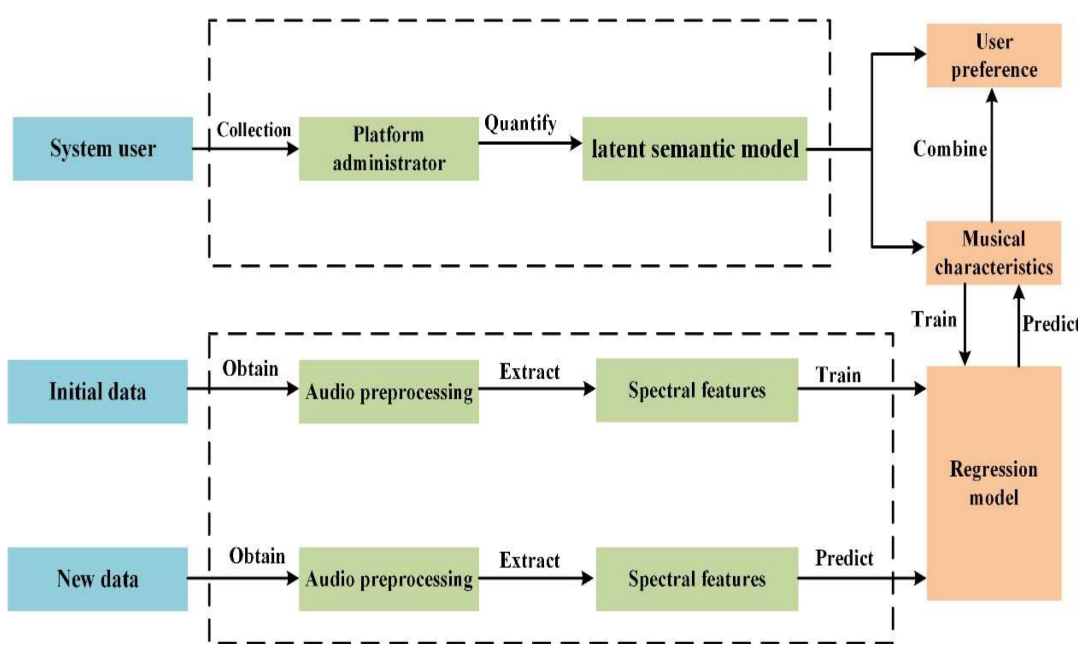

Figure 1. Overall Design Flowchart of the Music Software Data Management System

The system also requires classification of the original music and new music data. Traditional music indexing is based on the song's name, the artist or band's name, lyricist, composer, and file format. Automatic music classification methods based on genres and emotions share some similarities, as they both require feature extraction, optimal feature selection, and classification training using the decision tree algorithm. However, they also have significant differences, as genres and emotions define music in abstract terms, unlike the qualitative features of traditional music classification. Music genres and emotions are based on human subjective perceptions and represent a more advanced way of describing music. The establishment of genres is based on commonalities and starting points when artists create music, and it can serve as a simplified summary of the works of certain artists. Emotions, as the theme of music expression, play a decisive role in evoking feelings for the appreciators of the work, and based on the conventions of melody and rhythm, they can also serve as a simplified summary of common features in certain music works. With the development of the music industry, the quantity of music data has increased, and users quickly associate and list data based on genres and emotions when searching for desired music. This determines the quality of a music database and has significant implications for the development of the music industry. The same artist's music works created during different periods may belong to different styles and genres. The subset of features extracted by the decision tree algorithm can form a hierarchical relationship diagram for music indexing based on genres and emotions.

3.2. System Latent Semantic Matrix

The latent semantic matrix used in the online music software data management system is a Basic Factorization Matrix (BFM), which differs from the classical Singular Value Decomposition (SVD) matrix. It no longer decomposes the rating matrix into the product of three matrices. Instead, the latent semantic matrix decomposes several users and items into corresponding hidden factor matrices for users and items, without requiring completion of the original matrix. Finally, the obtained hidden factors are used to fit and predict ratings in the matrix. This process can be represented by the following formula:

$$R_{m\times n} \approx R^2_{m\times n} = P_{m\times k} Q^T_{n\times k} \quad (1)$$

In the equation, m represents the number of users, n represents the number of music, and R represents the approximate square matrix of the decomposed two matrices, also known as the estimated rating matrix. To calculate a user's predicted rating for a song, the following formula can be used:

$$p_u q_i^T = \sum_{k=1}^{K} p_{uk} q_{ki} \quad (2)$$

The latent semantic matrix can effectively utilize hidden factors to represent users' preferences for the latent features of music and reduce the complexity of matrix factorization. The next step is to calculate the two hidden factor matrices. Firstly, they are initialized, and then the random gradient ascent method is used for iterative optimization until reaching a local optimum value. The rating error for each user can be defined as follows:

$$e^2_{ui} = (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 \quad (3)$$

This study uses the squared error to minimize the difference between predicted and actual ratings. Firstly, the loss function is defined as:

$$\arg Loss = \sum e^2_{ui} = \sum (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 \quad (4)$$

Then, the positive gradient direction of the current value is found and distinguished using two direction variables. Alternately using the least squares method, the parameters and are iteratively optimized along the direction of the steepest ascent in the minimum value, obtaining the optimal parameter values. In this way, the experiment obtains the optimized latent semantic matrix and proceeds to select parameters for various required functions.

4. Application of the Data Model to Music Software

Firstly, the established algorithm model is applied to evaluate the epoch to the dimensionality of the hidden factors in a more comprehensive manner. The output dimensionality of the hidden factors is directly determined by the number of feature vectors in the music audio files. In the experiment, the number of high school students using the music data system is 130, and the impact of the iteration rounds is evaluated when the dimensionality of the hidden factors increases from 3 to 11, as shown in the figure 2.

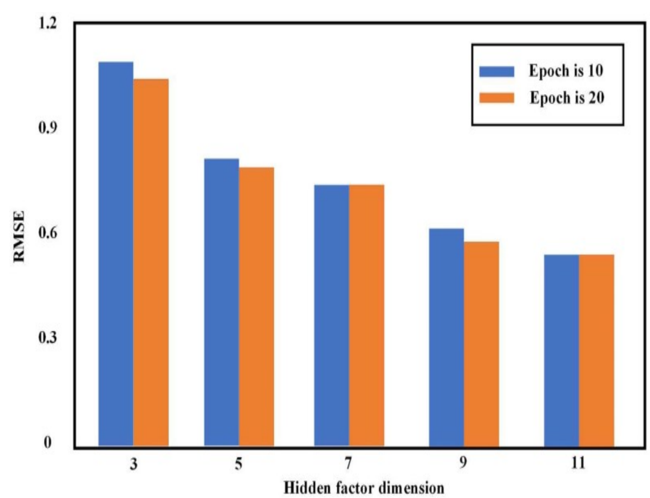

Figure 2. RMSE of Predicted Scores at Different k and Epochs

Figure 2 shows that the highest RMSE value is obtained when the hidden factor dimension is set to 3, indicating an insufficient representation of music features at lower dimensions. The RMSE values steadily decrease as the dimension increases, suggesting that the system model

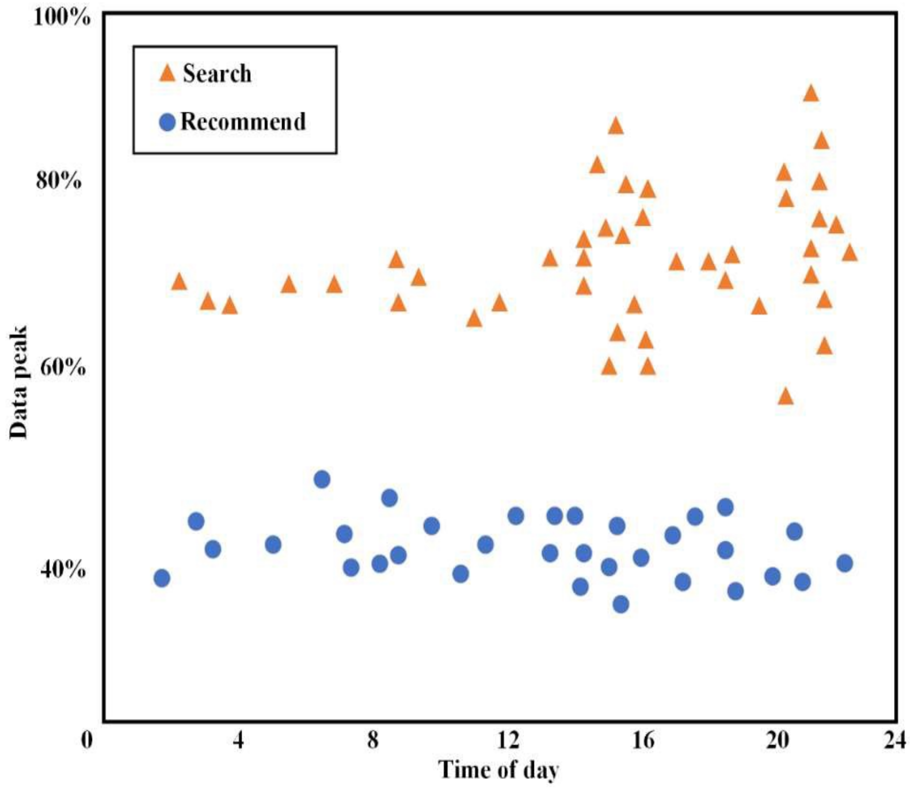

Figure 3. Peak Data of Searches and Recommendations Throughout the Day

performs best in representing music features when the hidden factor dimension is 11.

The data of NetEase Cloud Music users has three-dimensional features. To optimize management, the data is dimensionally reduced, allowing the database to use one-dimensional data representation. Calculating search and recommendation results using one-dimensional data becomes faster and more convenient because there are no redundant features, ensuring accurate outcomes, as shown in Figure 3.

Figure 3 illustrates the peak data of searches and recommendations in the NetEase Cloud Music platform throughout the day. It can be observed that the peak data for recommendation remains at around 40%, indicating the stability of the experimental data system. This suggests that the system can efficiently compute and output recommendation results with lower resources, meeting user demands. On the other hand, the search data exhibits two peaks at 15:00 and 21:00. It is speculated that these two time periods are when users have the highest entertainment demands, leading to the search peaks during those times.

By collecting legitimate user data in the background, it was found that the number of software users steadily increased, and the average usage time per user increased by 23 minutes. This indicates that the model based on the decision tree algorithm has significantly optimised the NetEase Cloud Music data management system and has positively impacted its development.

5. Conclusions

This study explored the development strategy of NetEase Cloud Music based on the decision tree algorithm. By collecting user behavior data and building decision tree models, the aim was to predict users' music preferences and demands, providing personalized recommendations and services on the music platform. Research progressed both domestically and internationally, showing that the decision tree algorithm has wide applications in music software, including user interest mining, music genre classification, and song sentiment analysis.

However, its application still has challenges, such as data sparsity, decision tree complexity, and cold-start issues. Future research can focus on solving these problems to improve recommendation accuracy and user experience.

Although this study achieved certain results in music recommendation based on the decision tree algorithm, there are still some limitations and areas for improvement. Firstly, this research primarily focused on applying the decision tree algorithm and did not fully consider the integration of other recommendation algorithms and technologies. Future work can explore combining the decision tree algorithm with collaborative filtering, deep learning, and other methods to enhance recommendation accuracy and diversity.

Secondly, due to the typically sparse nature of user behavior data on music platforms, the decision tree model has certain limitations during the recommendation process. Future research can address data sparsity by introducing more refined feature engineering, incorporating user feedback mechanisms, or using other data imputation methods to improve the recommendation effectiveness of the decision tree model. Additionally, the complexity and interpretability of the decision tree model are also areas that need attention. Future work can investigate how to optimize the structure and parameter settings of the decision tree model to make it more concise and efficient, thus enhancing the model's interpretability and user understanding. Future research can also explore combining content-based recommendation algorithms with decision tree algorithms to leverage music features and tags, providing more accurate recommendation results.

In conclusion, the development strategy of NetEase Cloud Music based on the decision tree algorithm presented in this study offers a promising solution. However, there are still limitations and areas that require further improvement. Future research can address the issues as mentioned earlier to enhance music recommendation accuracy, diversity, and user experience, thereby driving the development of music platforms.

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