Research Article

Research on Music Content Recognition and Recommendation Technology Based on Deep Learning

Gao Yang

Qilu Normal University, Shandong 250200, China

Correspondence should be addressed to Gao Yang; 20156378@qlnu.edu.cn

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With the development of information technology, various cloud music services are gradually emerging, which has fully changed and enriched people's music life. How to propose the songs that consumers anticipate from the enormous song data is one of the key goals of the music recommendation system. This research aims to create a better music algorithm that incorporates user data for deep learning, a candidate matrix compression technique for suggestion improvement, accuracy, recall rate, and other metrics as evaluation criteria. In terms of recommendation methods, the music-music recommendation method based on predicting user behavior data and the recommendation method based on automatic tag generation are proposed. The music features obtained by audio processing are fully utilized, and the depth content information in music audio data is combined with other data for recommendation, which improves the tag quality and avoids the problem of low coverage. The results show that this model can extract the effective feature representation of songs in different classification criteria and achieve a good classification effect simultaneously.

1. Introduction

With the rapid development of music streaming media service industry, users can easily hear any songs on mobile devices, and the Internet has become a huge music storage platform [1]. In the face of the ever-increasing massive music database, relying on the traditional search method to find the music you are interested in has become increasingly unable to meet the needs of users. At the same time, how to find favorite songs from massive data has become a rather thorny problem [2]. Faced with this dilemma, the area of digital music is progressively introducing recommendation systems. Users may acquire the music they wish to listen to without having to search by actively relying on the recommendation system’s capacity. In a cloud music service, song suggestion is crucial [3]. However, as user demand grows, straightforward application of standard recommendation algorithms to digital music has proven insufficient to fulfill people’s requirements, and a slew of issues have arisen as a result [4]. First and foremost, there is the issue of a cold start created by the addition of fresh resources and the problem of niche unpopular music being recommended. Second, the basic base for describing music material is the music tagging system. The openness and unpredictability of user tagging resources have resulted in a flood of tags, lowering the system's tag quality and affecting the recommendation impact indirectly [5]. In the recommendation results, most of the recommendation sets obtained by users are focused on the same music type, which makes it difficult to tap users’ interests. Music recommendation should pay more attention to the content of the music itself, while the traditional recommendation technology for general items is mainly based on the related attributes other than the content, which is insufficient in applicability [6].

With the rapid development of the Internet, the Internet has become the main way for people to obtain multimedia resources, including books, movies, and music [7]. Listening to music, as one of people’s main entertainment activities, has always played an important role in people’s lives. With the rapid growth of the music streaming media service industry and the rapid progress of portable equipment technology, thousands of music become within reach, but it
becomes more and more difficult to find the music you want [8]. Today’s society has become more inclusive, and different fields are also showing unique individualization and diversification. Personalized recommendation system can meet the needs of different users and provide users with a better experience accurately, which has produced great commercial value and became the “cake” that Internet companies scramble for [9]. As the simple information retrieval system can no longer meet the needs of users, the recommendation system came into being [10]. In recent years, deep learning has achieved great success in many fields, but it is seldom used in recommendation system. Therefore, this paper mainly aims at music content identification and recommendation and proposes a music recommendation system based on deep learning.

For music lovers, as the song library becomes larger and larger, and the song resources become more and more abundant, users need to spend some time and cost to find music that suits their interests [11]. In the conventional sense, music is for listening [12]. Music visualization is a new type of music entertainment from the perspective of creativity and innovation. Music visualization can extract some intrinsic features of audio and display them in a certain visual form to bring users both auditory and visual enjoyment [13]. With the rapid rise of Internet technology and electronic information technology, it is becoming more and more important and valuable to find the required information quickly and accurately in such a huge amount of information [14]. The resultant recommendation engine has evolved into a link between users’ wants and material, allowing users to not only locate possible content they are interested in, but also better present unpopular content and discover new people [15]. The use of recommendation system technology to music is a significant one. The goal of this study is to develop and construct a music feature extraction strategy that may be used in music recommendation contexts. With the training set of music bottom feature set and deep confidence network, a music information prediction model is created. The article-side automated encoder learns audio features using the convolution layer and lyrics features using the full connection layer; the user-side automatic encoder learns the user item score vector using the full connection layer. After pretraining, combine matrix decomposition to train the tight coupling model. Combining the characteristics of melody and sound quality, and according to the scenes with large amount of data, the music features can be obtained efficiently, which complements the resource data.

2. Related Work

Literature [16] uses MSD dataset to provide input data, which includes audio features and metadata of songs. This paper introduces the current mainstream ways of learning music audio characteristics. Literature [4] holds that music recommendation system can help users find the music they want to listen to according to their past behaviors, provide users with a series of song lists, and at the same time increase the sales of digital music. Literature [5] suggests that there are two recommendation systems in major music websites at present. One is list recommendation, and the other is personalized recommendation of different music for users. Literature [17] pointed out that the current music recommendation has been widely used in the cloud music scene, but its recommendation results still have some shortcomings, the most important of which is the low coverage rate. Literature [13] designed a personalized music recommendation system. Taking some data from music websites as analysis samples, experiments were conducted on selected music according to personalized music recommendation. The results show that the recommendation effect of this method is better. Literature [1] holds that the relationship between music and users is a potential related information relationship. The database contains a large number of music pieces and users. Some people can only listen to a single piece of music, while others can only listen to a certain amount of songs in the collection. However, each user has a preference tendency, which means that a user may favor particular types of music and that there is a link between them. The topic relevant to deep learning is introduced in [18]. Self-encoder and convolutional neural network, two widely used deep learning techniques, are discussed, as well as their underlying principles and training procedure. Literature [2] examines the current state of music recommendation technology and comprehends its use in key music platforms via hands-on experience and consultancy resources. Analyze and describe the flaws in existing music recommendation techniques, as well as the sources of these flaws.

A trained hybrid depth neural network model extracts the characteristics of each song, a sequence of feature engineering produces a realistic user picture, and a machine learning algorithm predicts the likelihood that users would be interested in each song.

3. Methodology

3.1. Application of Deep Learning in Recommendation System.

Deep learning is developed with the research on the cognitive and thinking process of human brain nervous system in biology. Because of the strong nonlinear fitting ability of deep neural network and good results in many fields, more and more scholars apply deep learning to the extraction of music audio features [19]. In deep learning, processors are used to replace neurons in the human brain. To build the link between the lower layer of features and the higher layer of things, each layer of processors gets the features extracted by the upper layer of processors and extracts additional features for the next layer of processors.

With the development of information network, the amount of data is increasing geometrically, and the feature dimension of things is expanding rapidly. In the face of this situation, the traditional recommendation algorithm will inevitably be unable to meet the demand [20]. In the practical application of deep learning, no matter what structure is adopted, we cannot clearly set the specific parameters at the beginning, but we need to determine them according to the situation in the training of neural network,
which is also an important part of deep learning. The output result \( O \) may be tailored to match people’s needs by modifying the parameters. It should be noted that we can seldom make the output \( O \) precisely equal to the input \( I \) in practice, although it is an abstract idea [21]. The music audio attributes we are aiming to leverage in the content-based music recommendation system need to include global information that can represent the qualities of the whole song. Music audio is merely a particular event for tasks in several disciplines of music information retrieval, such as music chord identification, noise segmentation, and other tasks.

At present, the recommendation based on deep learning overcomes the obstacles of traditional linear model, thus significantly improving the recommendation quality. Deep learning can effectively capture the nonlinear relationship between users and items and obtain the vector representation of users or items by vectorization or coding. In the general training process, the process of deep learning is usually divided into supervised learning and unsupervised learning [22]. As illustrated in Figure 1, the recommendation engine contains a recommendation algorithm and a recommendation rationale that will construct a link between the user characteristics and the things to be suggested in order to propose the target items of interest to users based on the established link. The recommendation engine comprehensively calculates the information of the user’s education, age, label, and gene description of the item to be recommended and then combines the user’s preference for the item: depending on the item itself, it may include the user’s rating of the item, the user’s click record, etc. and finally forms the recommendation result.

Self-encoder is an important basic model of deep learning. Its basic realization process encodes the input information, extracts the main information, and reproduces the input signal as much as possible. Then, in the concrete realization process, the system needs to be able to capture the main factors that can represent the input information. The general structure includes the visible, hidden, and encoder and decoder between them [23]. The basic idea of content-based recommendation algorithm is to analyze the characteristics of users’ preference behaviors according to the historical information of users, get user preference sets, and match these sets with the recommended content to achieve recommendation. Commonly used music recommendation algorithms include the recommendation algorithm based on labeled content and music based on music features.

The traditional content-based recommendation algorithm first gets the items that have interacted with users and then gets the user’s preference model through similar user’s active behaviors such as users’ likes or ratings of items. User feedback on the project includes implicit and explicit ones [24, 25]. The former is the log of users’ marks when using the system, which reflects users’ interest in the project, such as browsing the lyrics of songs and the number of times the songs are played repeatedly. The latter is the user’s display of embodied content in addition to ordinary browsing on the system. The flowchart of music content identification and recommendation based on deep learning is shown in Figure 2.

In order to make the recommendation of songs more in line with the user’s taste, it is necessary to extract the spectrogram of songs and the audio sequences contained in them and then classify them [26, 27]. The traditional recommendation algorithm classifies songs after processing pictures and audio sequence information, and there is a technical bottleneck in integrating the classified data into the recommendation model. How to make good use of these picture data and audio time series plays an important role in the generation of recommendation results. The picture data and audio time series can be processed by neural network recommendation algorithm, so as to classify songs, and at the same time, the classified data can be integrated into the recommendation model to achieve more accurate recommendation results.

### 3.2. Music Content Identification and Recommendation Technology

Most of the music information prediction is carried out in a specific range, and the research of the method is based on the music feature extraction extracted from the music signal itself. During the development of this field, a large number of feature vectors have been explored to better express the musical characteristics of music itself. Selection and extraction of these features are the basis of music information prediction. In the task of music classification, the model needs to extract the features that reflect the overall characteristics of music, so that it can be better applied in the recommendation task. Therefore, we mainly focus on the task of music classification. Feature extraction is carried out for items in the recommended field, and the feature information extracted by different elements is different. For example, documents, posts, and short messages are mainly divided into words, and the weight of keywords in the whole text is calculated. Music, fitness, and books are the main features of extracting labels and classification.

Music is a kind of tuned audio. The change pattern of pitch is called pitch, and different music has different tones. If the same person sings the same phrase, the pitch frequency will alter with varied music, such as singing environment, emotional state, physical condition, and so on. These contents may be overlooked while recording music data, yet they are a significant factor for individuals when selecting music; hence pitch frequency conveys critical music data. The item we wish to promote is music, and the audio content of music is the most essential component in determining whether or not consumers will like it; thus the processing of audio characteristics is crucial.

The first stage in making a music suggestion is determining the user’s preferences. To make the calculation easier, the music in the music library must first be classified and numbered, and then the time for the user to enjoy the \( j \)-th song in the \( i \)-type songs accounts for the overall time for music enjoyment, as shown in

\[
y_i = f \left( \sum_j w_{ij} x_j - \theta_i \right),
\]

where \( w_i \) is the maximum listening time, \( x_i \) is the minimum listening time, and the value of \( f \) is shown in
According to the proportion of users’ listening time to different music in formula (2), the user’s interest in class \( i \) music can be calculated as shown in

\[
O_i = f \left( \sum_1^T_t \theta_i - \theta_j \right). \quad (2)
\]

In the parameter selection of pool layer, the size of compromise is used. Because the pool area is too large, it will lead to the lack of information, and too small cannot bring enough distortion invariance. As a result, pooling on the time axis may provide its distortion without distortion to the chord identification task, making the training network more compact and robust. On the other hand, pooling on the time axis will degrade the time resolution in the border detection job. When the support degree is high, the scanning times of the database will be less and the spatial complexity will be low. The formant frequency, referred to as formant for short, is a frequency component whose energy becomes stronger due to resonance. It directly reflects the source of sound in music and is an important parameter reflecting the physical characteristics of vocal tract. In music, if the music contains different emotional information or rhythm information, the shape of the audio channel will change differently, so formant is an important factor that can reflect the change of music information.

The value of absolute error represents the prediction accuracy, and there is an inverse relationship between them. The absolute error calculation process is as follows:

\[
\text{MAE} = \frac{\sum_{j=1}^N |R_j - R_j^{\text{pre}}|}{N}. \quad (4)
\]

After audio preprocessing, the music features that we pay attention to mainly include melody and sound quality. Melody refers to the overall characteristics of the tone and rhythm changes of music over a long period of time. The aspect of sound quality is the local feature of sound in a short time. After the feature extraction of the above two aspects is completed, the results are composed into features.
representing the whole music. After getting the audio characteristics of music, the second stage in the content-based music recommendation system is to propose acceptable songs to consumers using various methodologies. In general, it is important to compute the similarity between songs and favorite songs in a user’s history listening records and then to propose songs to users with comparable similarity.

For the least square method, it is directly solved by gradient descent. The optimized loss function is shown in the following formula, and \( u_{ij} \) is indicator function, which means that only the items existing in matrix \( T \) are considered. \( Q \) generally uses the square loss function; \( g_{ij} \) is a penalty factor, and overfitting is avoided by using the two-norm regular term, as shown in

\[
Q(u_{ij}) = \sum_{i=1}^{n} \max \{ g_{ij}(T) \}. \tag{5}
\]

Music is composed of vibrations with different frequencies and amplitudes emitted by the pronunciation body, in which the lowest frequency sound is called pitch frequency. It determines the pitch of the whole piece of music and is an important feature of music information expression, combining the obtained vectors of global features and local features, and finally obtaining sixteen-dimensional vectors as music content features corresponding to the audio. Classification models obtained according to different classification standards can extract the features of music from different angles. Consumers may get more tailored recommendations in the suggestion stage thanks to these capabilities. Because the pretrained corpus differs from our recommendations in the suggestion stage thanks to these cold start scenes, the popularity of new music is naturally zero. Preprocess the music data set by converting all music files to 30s audio files at a sampling rate of 22.05 KHz and extracting 40-dimensional feature parameters such as 14 mel-frequency cepstral coefficients, 8 wiki audio rate, 12-dimensional formant, and 6-dimensional frequency band energy distribution. The number of iterations should be kept to a minimum in practice to prevent wasting time and producing inefficiencies. In this experiment, the relationship between prediction accuracy and iteration times is shown in Figure 3.

The highly relevant music is recommended to users from the music library through music information prediction and user interest degree calculation, based on the corresponding relationship between music information such as music tags and music tags based on users’ interests, to meet the personalized needs of users. The suggestion of new users primarily assumes that new users like a certain genre and then picks 100 pieces of music from a variety of genres at random as the user’s favorite music. Recommend an additional 500 pieces of music by using the recommendation model and analyze the distribution of the recommended music styles to see if they are consistent with their favorite styles. Take three test cases of pop, rock, and roll and electronic music as examples, test the system, and evaluate the quality of recommendation from the visual angle. The receiver operation characteristic curve of Group 5 experimental results is shown in Figure 4.

It can be seen from the figure that, with the increase of the number of our features, the effect is better. It is explained...
that adding the statistical features of users and the audio features of music is beneficial for classifiers to discriminate the preferences of users. At the same time, it can help the model find out the potential reasons why users will like the music. In the process of generating frequent item sets, many candidate item sets will be generated, and the database needs to be scanned many times. This problem arises because the algorithm treats all items as equal in the calculation process, without considering the importance of items. To solve this problem, the compressed matrix method is used to quickly store the item sets, and the items are weighted according to their importance, so as to realize matrix storage by scanning once and then generate scoring item sets according to weights by pruning technology, so that candidate sets are not generated in the process, and the efficiency and accuracy are improved.

Recommend new users, analyze and evaluate the quality of the recommendation, and recommend music for cold start users, which requires users to listen to music data. However, because of the huge amount of music, it does not support retrieval and playback. Therefore, the system supports randomly generating a list of users’ favorite music directly for users and using this list as scoring data to make recommendations and evaluate the recommendation quality. Initialize network structure, offset, and other model parameters, then set learning rate, number of training rounds, and batch size, read training samples, calculate network output after input to the network, and get the error between output and expected value. If the error reaches the expectation, the training is finished. On the contrary, samples are extracted from the training set, the relevant output values are calculated, the optimizer calculates the gradient, the weight equivalence is reversely updated, and the sample training is continued. Figure 5 shows the similarity of music collections recommended by different methods.

Datasets provide labels. The tag’s value is either 0 or 1, with 1 indicating that the user purchased the music several times within one month of first hearing it, indicating that the user likes it. A label of 0, on the other hand, indicates that the on-demand will not be repeated. To test the method’s universal adaptability to diverse types of music information, we utilized the genre-emotion two-dimensional characteristic as the music label in the experiment and totaled 10 distinct types of music information. In the music recommendation system, recommending similar music for users is only a part of it. It is also an important part of the recommendation system to make diverse recommendations for users so that users can have different experiences. This study will use the deep learning algorithm to calculate the relevance of music information. It can improve the accuracy of recommended music and solve the problem of diversity of recommended results. Figure 6 shows the recall curves of different models on data sets. Figure 7 shows the accuracy curves of different models on data sets.

As can be seen from the above figure, the recall rate and accuracy of this model are higher than the other two. This also verifies the conjecture of this paper, and the method of this paper has certain advantages. In the generation of music tags, if the unsupervised learning method is used to cluster according to music features, then a clear tag cannot be given for each cluster. Therefore, we adopt the method of supervised learning and use the idea of classification to deal with the problem of music label generation. Take a group of music with clear labels as a training set, their musical characteristics as input, and the probability of containing a label as output and then predict the labels of other music after training. In the content-based recommendation system, another intuitive recommendation method can be adopted. If the characteristics of users and items are obtained at the same time, we can match similar users and items to achieve the purpose of recommendation. In this way, the effectiveness of user characteristics is particularly important, and the behavior of mining user characteristics has a special name, called user portrait. Users always have a preference for listening to music, either for the genre or for a certain singer. Therefore, counting the recommendation list can directly observe whether the recommended results have practical significance.

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**Figure 3:** Relationship between iteration times and prediction accuracy.

**Figure 4:** The receiver operating characteristic curve of Group 5 experimental results.
5. Conclusions

Music has gradually become an inseparable and important part of people’s lives. With the rapid development of network digital music industry, music recommendation system has become the focus of major music websites. The quality of content recommended by users directly affects the user experience. It can be said that the quality of music recommendation system is related to the operation of music websites to a certain extent, and designers have paid the research on this aspect more and more attention. Deep learning has achieved great success in many fields, such as computer vision, speech recognition, and natural language processing. Because deep learning can provide end-to-end learning and is good at dealing with complex tasks, academia and industry have been applying deep learning to more fields. The research value and importance of data recommendation technology and the music recommendation sector are examined in this work. In the realm of data recommendation, it summarises the application and development status of music recommendation technology and deep learning. This study investigates the recommendation technique and audio processing technology and combines them to address some of the problems of the present music platform’s recommendation system. A new method of in-depth music recommendation combined with music content analysis is proposed, which makes music recommendation pay more attention to the content of music itself and make more music have a chance to be heard by people. The weight of the collaborative filtering model is increased when users have a rich history of listening to songs. The weight of the music attribute model increases when users have less history of listening to songs, which is highly flexible in different music recommendation scenarios.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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