Design of the College Students’ Music Big Data Management System Based on Computer Assistance

Peng Cheng

College of Arts, Henan Institute of Science and Technology, Xinxiang 453003, Henan, China

Correspondence should be addressed to Peng Cheng; cppiano@hist.edu.cn

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With the rapid development of science and technology, the college music big data management system also needs a computer-aided data model for optimization. In order to improve the efficiency of computer-aided teaching of the music big data management system in colleges and universities, this paper analyzes and processes the music database of music software based on the computer-aided Bayesian algorithm and establishes a Bayesian model. Firstly, this paper introduces the principle and function theorem of the Bayesian algorithm. The data is divided into original music and new music, and a college music data management system with search recommendations as the core is established. We iteratively calculate the optimal hidden semantic matrix and finally select ReLU function as the activation function of this experiment. After the model of the music management system is established, it is applied to a university. The experimental results show that the experiment has reached the expected standard. When the hidden factor dimension is 11, the system model has the best representation of music features. Students’ use of the music search and the recommendation system has greatly improved their music literacy and music coverage.

1. Introduction

The 21st century is an era of rapid development of computer technology. At the same time, with the popularization of computers and smartphones, the number of Internet users has shown explosive growth. Technological progress has also led to the rapid development of the Internet. Today’s human beings get dozens or even hundreds of times more information every day than before. Mankind has fully entered the era of big data. According to the report of the International Institute of Data, the total amount of data in the world is expected to reach 50zb by 2030 [1].

Massive information brings convenience but also brings the problem of information overload. Both producers and users of information are facing great challenges. For information producers, the content they produce is easy to be submerged in a huge amount of data and cannot stand out without attention. Faced with a large amount of information, it is difficult for information users to screen out really useful information, which wastes time and energy. This problem is particularly prominent in colleges and universities. Teachers can use too many information resources and need to work hard to screen out the content suitable for teaching. Students have not yet formed a stable world outlook, outlook on life, and values. The information they receive is mixed, and it is difficult to distinguish between good and bad [2]. The computer-aided search and the recommendation system came into being, which provides users with certain convenience, but users have various needs, especially efficient students have their unique requirements for the search and recommendation of music data. Music, as the carrier of expressing human emotions and transmitting information, is also developing with human history [3]. It has become an indispensable spiritual food for many people. With the advent of the era of big data, storage and communication media have also undergone revolutionary changes. From black glue to magnetic tape, then to CD, until today’s electrification (usually MP3 and AAC format), music and audio-visual show ease of availability and convenience with the development of science and technology [4]. For college students, especially teachers and students majoring in music, the search and recommendation of music data is the key to
the growth of academic and personal ability. Music computing science came into being under this background. It is a new discipline based on the algorithm, which carries out theoretical research, information storage, intelligent analysis, and fuzzy recognition of music audio and video [5].

2. Related Work

At present, search engines are widely used in daily life, except that traditional search engines provide users with basic and comprehensive search services [6]. The built-in search engines of social software, knowledge Q&A software, video software, and music software have also attracted more and more attention. Providing faster, more convenient, and more accurate search results is a great challenge for this software [7]. A computer-aided college music system is the basis of search function. Only by doing a good job in the search of music data, teachers and students can benefit from it. The recommendation system is developed from streaming the media service, and now it is most commonly used in commodity recommendation of e-commerce software [8]. The application in the music market and the addition of a recommendation system not only improve the good degree of user experience but also increase the number of active users of the product. It also increases user stickiness, so that more different music works can be heard by users, and finally, it greatly improves commercial interests [9]. In the college students’ music system, with the continuous development and application of computer multimedia technology, many music industries prefer to provide online music services. Teachers and students can easily obtain music resources through music platform online listening, online downloading, and other ways. However, the music database is becoming larger and larger. It takes a lot of time and energy for college students to find their own music. In the past, users can only search music through keywords, such as music name, singer, and genre, and then the search results do not take into account the differences of users, so there is a deviation in the results [10]. A college music recommendation system makes up for the shortcomings of the search system. This intelligent recommendation system can predict the behavior preferences of teachers and students according to the behavior information and music data characteristics of teachers and students and actively push music that meets their tastes and learning needs to college students.

The two main functions of music computing science are search and recommendation, which are two important aspects of music management in urgent need of upgrading and optimization, so it has aroused great interest in academia and music industry [11]. Music computer-aided is not only an important means to obtain music semantic information but also an important part of music management. Traditional music audio-visual search is based on the general information of songs, such as song name, singer or band name, word author, song author, and file format [12]. This search method is accurate and efficient, but it can no longer meet the needs of the current music market. Nowadays, users of online listening software prefer to get retrieval and recommendation based on personal preferences, which requires a more humanized intelligent search of music audio-visual in terms of style, emotion, genre, and song theme. Before entering the era of big data, classification based on style, emotion, genre, and song theme was carried out manually. Although the accuracy can meet the requirements, it is inefficient and the cost of manpower and time is huge [13]. And with the development of data explosion, labor has been increasingly unable to keep up with the growth of data. The use of computer-aided automatic classification began to enter the public’s field of vision and began to play its own efficient and irreplaceable role [14].

The increasing amount of music data and the demand of teachers and students in colleges and universities pose a more stringent challenge to the research of music search and recommendation algorithms. Traditional recommendation systems include content-based recommendation, collaborative filtering recommendation, and hybrid recommendation combining the two [15]. Although the three basic recommendation methods have been developed and mature, they have some problems to be solved, such as slow startup. In addition, with the development of social media, recommendation based on the emotional state has also entered the public’s vision, which is the result of in-depth learning in the computer industry and full mining of users’ potential hobbies [16]. Based on the naive Bayes theory, starting from the analysis of the characteristic data of college teachers, students, and music, this paper designs an accurate music search system and a personalized music recommendation system, which can not only bring great convenience to the daily learning of teachers and students but also the goal that every college hopes to achieve. Therefore, it has an important research significance and broad application prospects.

3. Principle and Selection of the Bayesian Algorithm

In the last century, people usually thought that the probability of something happening was 50%, and the probability of not happening was 50%, that is, non-0 was 1. I do not think about the probability that this thing will happen and the probability that it will not happen. For example, a bag contains a number of black balls and white balls. People in the past thought that taking a ball, the probability of getting a white ball and a black ball was half, and they would not consider the impact of other factors on the results [17]. In academic circles, such a theory was called the frequency experiential school, which was a simple and limited theory until Thomas Bayes proposed the Bayesian theorem. Returning to the example of taking a black-and-white ball from a bag, Bayes believes that the probability of obtaining a ball of a certain color is uncertain and affected by many factors. The frequency experiential school believes that the factors affecting the probability are unknown, but the value is a fixed value. At the same time, the frequency school believes that the samples are random, and its research focuses on the distribution of samples. Bayesian believes that the sample is a random variable, so it is necessary to calculate to understand its distribution [18]. The distribution
determined before the experiment is called a priori distribution. Bayesian theory is based on the priori distribution and then deduces the posterior distribution of the sample [19]. So, the Bayesian theorem is also called a posteriori probability, which is the probability of event A after event B, which can be expressed by the following formula:

\[ P(A|B) = \frac{P(A \cap B)}{P(B)} \]  

(1)

The joint probability and a priori probability are different from a posteriori probability. It represents the probability that two events A and B occur at the same time [20]. Contrary to a posteriori probability is a priori probability. The Bayesian theorem can get another expression by marginalizing a priori probability, that is, as shown in the following formula:

\[ P(A|B) = \frac{P(B|A)P(A)}{P(B)}, \]  

(2)

where \( P(A|B) \) represents the probability of event A when event B occurs.

4. Using the Bayesian Algorithm to Establish the Management System

4.1. Overall Design of the Music Data System. The data warehouse comprehensive project of music data center in colleges and universities is mainly aimed at the data collected in the past, such as students’ on-demand and music purchase (including business data and user behavior data). It provides decision-making service support for the healthier development of colleges and universities. In intelligent management, more reports are mainly displayed for the reference of school operators. Another application is data service, which is mainly used to provide the analysis result data to the business system in the form of interface for access. It recommends songs according to singers or students.

At present, the Bayesian algorithm has been widely used in text, image, and video recommendation systems. The college students’ music content search and the recommendation system in this study is actually a hybrid recommendation model based on college students’ user behavior and music data information. The core content of this set of search and recommendation is to use the Bayesian algorithm to iteratively calculate the implicit features of music data, and then get the low-dimensional vector information of music data through marginalization [21]. These low-dimensional vector information can be added to the search to optimize the search results and can also be combined with the implicit preference characteristics of college student users to make reasonable music recommendation. This experiment directly extracts the music features from the audio files, which can fundamentally avoid the problem of cold start and be as close to the user’s intuitive feeling of music as possible. This hybrid system is based on the traditional matrix decomposition model, and it is improved in the algorithm. The flowchart of the overall system design is shown in Figure 1.

As can be seen from Figure 1, this model uses the hidden semantic matrix to project the user’s hidden features and music audio information into a shared space through the Bayesian algorithm and finally outputs the search and recommendation results. The college music data system includes user feature module, music audio information module, search engine module, and recommendation algorithm module. The main function of the user feature module is to collect and store the behavior history data of college student users in the music system and then establish the student user preference model. Due to the preprocessing of music data and the extraction of frequency and other features, music audio information prepares for training the Bayesian dynamic model to calculate search and recommendation data. The search engine module outputs the user’s personalized search results according to the extracted features. The recommendation algorithm module is applied to calculate the matching degree between hidden features and student users, and finally, it dynamically recommends music that users may be interested in. The operation of the whole system can be divided into two parts: Bayesian model training and search recommendation. The arrow in the figure shows the process of collection, prediction, and collection. The specific process can be divided into the following steps: first, the system collects the historical behavior of college student users using music software and unifies it, so as to use the appropriate semantic matrix for analysis; then the original music data is restored, and the spectrum features are extracted; using the data obtained in the first two steps to build a Bayesian dynamic model, and then input the obtained data to continuously carry out machine learning to obtain a more perfect Bayesian model. Finally, if the system adds new music data, it also restores the spectrum characteristics first, then uses the perfect Bayesian model to calculate the user’s interest in the new music data combined with the preferences of college student users, and finally judges whether to recommend it to the user.

The system also needs to classify the original music and new music data. The traditional music audio-visual classification is based on the song name, singer or band name, lyric author, composer, and file format. It has some similarities with the automatic music classification method based on genre and emotion, which is, it needs three steps: the Bayesian algorithm to extract features, select optimal features, and classification training. However, there are great differences between the two. The definition of music by genre and emotion is abstract, which is different from the qualitative characteristics of traditional music classification. Music genre and emotion are based on human subjective feelings. It is an advanced way of music description. The establishment of genre is classified according to the common points and starting points of different artists when creating music works, which can be used as a simplified summary of some artists’ works. As the theme of music expression, emotion plays a decisive role in arousing the feeling of the audience. According to the setting of melody and section, it can also be used as a simplified summary of the common points of some music works. With the development of the music industry, the number of music materials also
increased. When searching the required music, college teachers and students quickly associate and list the data based on genre and emotional classification, which determines the advantages and disadvantages of a music database, which is of great significance to the development of the music industry. The music works created by the same artist in different periods will have different styles and belong to different schools. The subsets of features extracted by the Bayesian algorithm can form a hierarchical relationship graph of music audio-visual cognition based on genre and emotion.

4.2. System Hidden Semantic Matrix. The hidden semantic matrix used in the college students’ music big data management system is a basic factorization matrix (BFM). Unlike the classical singular decomposition matrix, it no longer decomposes the scoring matrix into the form of the product of three matrices. The hidden semantic matrix decomposes several users and several items into the hidden factor matrix corresponding to users and the hidden factor matrix corresponding to items, and there is no need to complete the original matrix. Finally, the obtained hidden factor is used to fit the matrix to obtain the prediction score. This process can be expressed by the following formula:

\[ R_{\text{new}} \approx R_{\text{new}}^{2} = P_{\text{new}} Q_{\text{new}}^{T}, \]  

where \( m \) is the number of student users, \( n \) is the number of music, and \( R_{\text{new}}^{2} \) is the approximate square matrix of the decomposed two matrices, also known as the estimated score matrix. To calculate the predicted score of a student user on a song, we can use the following formula:

\[ R_{ui} = \sum_{k=1}^{K} P_{uk} Q_{ki}. \]  

Hidden semantic matrix can make good use of hidden factors to express the preferences of students and users for the potential characteristics of music, and reduce the complexity of matrix decomposition. The next step is to calculate the two hidden factor matrices \( P \) and \( Q \). First we initialize them and then use the random gradient rising method to iterate continuously until the local optimal value is reached. The scoring error of each student user can be defined by the following formula:

\[ e_{ui}^2 = \left( r_{ui} - \sum_{k=1}^{K} P_{uk} Q_{ki} \right)^2. \] (5)

In this study, the square error is used to reduce the difference between the predicted score and the actual score. Firstly, the loss function is defined as

\[ \text{argLoss} = \sum_{i} e_{ui}^2 = \sum_{i} \left( r_{ui} - \sum_{k=1}^{K} P_{uk} Q_{ki} \right)^2. \] (6)

Then find out the positive gradient direction of the current value and use the variables in two directions to distinguish.

\[
\begin{align*}
\frac{\partial}{\partial P_{uk}} e_{ui}^2 &= -2q_{ki} = -2e_{ui} q_{ki}, \\
\frac{\partial}{\partial Q_{ki}^T} e_{ui}^2 &= -2q_{ki} = -2e_{ui} q_{ki}.
\end{align*}
\] (7)

Then, formulate update rules to iterate the rising direction of the gradient.

\[
\begin{align*}
P_{uk} + \alpha \frac{\partial}{\partial P_{uk}} e_{ui}^2 &= P_{uk} + 2\alpha e_{ui} q_{ki}, \\
Q_{ki}^T + \alpha \frac{\partial}{\partial Q_{ki}^T} e_{ui}^2 &= Q_{ki}^T + 2\alpha e_{ui} P_{uk}.
\end{align*}
\] (8)

\( \alpha \) in the above formula is a constant with a small value, which determines the minimum value of the machine learning rate. Continue the iterative operation of gradient rise until the minimum error is reached. When the error of
the loss function is less than the set threshold e, the iteration stops, and finally two matrices are obtained as

$$E = \sum e_{ui}^2 = \sum \left( r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki} \right)^2 \leq e.$$  

\(10\)

The above formula is the most basic method for hidden semantic matrix decomposition and cannot directly optimize the loss function because it is easy to lead to overfitting. In this experiment, the regularization term is added to the original loss function, that is, regularization is introduced, and the subsequent loss function is expressed as

$$e_{ui}^2 = \left( r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki} \right)^2 + \lambda \left( \| p_u \|^2 + \| q_k \|^2 \right),$$  

\(11\)

Then, the least square method alternately makes the parameters \(p_{uk}\) and \(q_{ki}\) in the above two formulas rise along the minimum value of speed for iterative optimization, and the optimal parameter value can be obtained as

$$\bar{p}_{uk} = p_{uk} + \alpha (e_{ui} q_{ki} - \lambda p_{uk}),$$  

\(12\)

$$\bar{q}_{ki} = q_{ki} + \alpha (e_{ui} p_{uk} - \lambda q_{ki}).$$  

\(13\)

In this way, the optimal hidden semantic matrix is obtained, and then the parameters of various functions are selected.

4.3. Selection of Music System Activation Function. If an activation function is not added to a Bayesian model, it is only equivalent to a linear regression model and cannot deal with more complex logical problems. In the process of introducing the activation function into the dynamic system, the single thread processing mode is changed into nonlinear, which can represent and calculate more complex music data. At present, the commonly used monotone functions mainly include sigmoid function, tanh function, and ReLU function. Their respective function diagrams are shown in Figure 2.

This design attempts to use JSP to build an online music website management system on the network, so as to promote the development of electronic information management process and intelligent management of music websites. From the perspective of theory and practice, this paper analyzes the design and implementation of a music website management system with data analysis function. Choosing different activation functions to apply to the music management system will affect the training and prediction and then affect the search and recommendation results. When using sigmoid function or tanh function to calculate large-scale data, it will produce large errors, while using ReLU activation function can converge quickly, so as to save the amount of calculation and improve the training efficiency. Moreover, for the dynamic deep music model, the gradient of ReLU function is constant, and the gradient will not disappear like sigmoid function. As mentioned above, this study finally selects ReLU function as the activation function of the music management system.

5. System Experiment and Result Analysis

In the deep learning of machine dynamics, there are many free and open benchmark databases, but most of them are text and pictures. The music data required in this experiment usually involves the ownership of copyright, so it was authorized with music software and applied to a university for the practical use of the system. First, the predicted characteristic coefficients are substituted into the Bayesian algorithm to preprocess the data of a music library. The steps are shown in Figure 3.

As can be seen from Figure 3, firstly, the original music data is randomly divided into two parts, and data set 1 is trained by the Bayesian algorithm to obtain a strong
classifier composed of several data subsets. Data set 2 is reconstructed directly using output vector $W$ and then merged with data set 1. Finally, the combined data set is classified into two categories to predict the search and recommendation of college students in the music audio-visual data set.

As described in the previous section, this experiment uses the square error as the loss function and uses the preprocessed music data above to train the Bayesian dynamic music model. The training results are shown in Figure 4.

It can be seen from the result chart that the loss error decreases rapidly in the initial stage of training. When the iteration round epoch exceeds 10, the downward trend of the function slows down obviously. Compared with the ideal loss value, the experimental results meet the expected standard, and the prediction error of the Bayesian algorithm model is within the acceptable range. In theory, the naive Bayesian model has the least error rate compared with other classification methods. However, this is not always the case because naive Bayesian models assume that attributes are independent of each other. This assumption is often not true in practical applications. When there are many attributes or the correlation between attributes is large, the classification effect is not good.

Then, the hidden factor dimension is used to comprehensively evaluate epoch. The output dimension of the hidden factor is directly determined by the number of feature vectors of the music audio file. The number of college students using the music data system is 130, and the number of iteration rounds affected when the dimension of the hidden factor increases from 3 to 11. The results are shown in Figure 5.

As can be seen from Figure 5, when the hidden factor dimension is 3, the maximum RMSE value is obtained, indicating that the representation of music features is insufficient when the dimension is small. As the dimension increases, the RMSE value also decreases steadily. When the hidden factor dimension is 11, the system model has the best representation of music features. The timbre effect of music is the best and the classification is the clearest.
In order to verify the feasibility of the Bayesian algorithm in this experiment, the accuracy and recall of system models under different search and recommendation lists are tested. The results obtained are plotted as shown below.

On the left side of Figure 6 is the comparison of accuracy. It can be found from the figure that the Bayesian algorithm model is used to filter the characteristics of music audio and recommend directly without this method. The accuracy of the recommendation effect of the Bayesian algorithm model is significantly higher than that of the standard collaborative filtering recommendation. On the right side of Figure 6 is the comparison of recall rates obtained by two different algorithms. It can be seen from the figure that with the growth of the music search and the recommendation list, the recall rate of both algorithms gradually increases. When the recommendation list is 45, the acceptable recall rate is reached. At this time, the music data search and the recommendation recall rate using the logistic regression model is 4.62%, while the music data search and the recommendation recall rate of nonstandard collaborative filtering is about 6.29%. The comparison shows that the recommendation effect filtered by the Bayesian algorithm model is better than that of the nonstandard collaborative filtering recommendation system.

After putting the music data management system for college students based on the Bayesian algorithm into use for decades, the ability of music majors was tested through the music classroom test. It can be found from the results in Figure 7 that students majoring in music have greatly improved their sound sense, music literacy, music scope, and music performance level by using this system.

College students’ music data has the characteristics of three dimensions. In order to optimize management, the dimension of the data is reduced so that the database can be represented by one-dimensional data. It is faster and more convenient to calculate the search and recommendation results based on the data because the one-dimensional data has no redundant features and can accurately reflect the results, as shown in Figure 8.

Figure 8 describes the peak value of search and push data of music in the whole day. It can be seen that the peak value of recommendation data of college students in the whole day remains at about 40%. This shows that the data system of this experiment is stable and can use low resources to calculate and output recommendation results, which meets the needs of teachers and students. The peak value of search data will appear two peaks at 15:00 and 21:00. This paper infers that these two periods may be the most frequent periods of
students' demand for entertainment, so there is such a peak value of search.

Results after a period of use, the feedback of teachers and students in a university was obtained through the questionnaire survey. The results are shown in Figure 9.

As can be seen from the data in the figure, more than 67% of teachers and student users actually feel the improvement of the new system for music audio-visual archives management, and about 62% of users think the optimization effect is obvious. At the same time, less than 40% of the respondents said that the system needs to be further improved. This shows that the model based on the Bayesian algorithm has made a good optimization of the college music big data management system.

6. Conclusion

In today’s era, with the progress of computer technology, the university music big data management system also needs to introduce a scientific and an effective data model for optimization. Based on the computer-aided Bayesian algorithm, the music database of music software is analyzed and processed, and a Bayesian model is established, which provides a scientific research method for this complex system. Firstly, this paper introduces the principle and function theorem of the Bayesian algorithm. Then, different from the classification of traditional music, the data is divided into original music and new music, and a college music data management system with search and recommendation as the two core is established. The optimal hidden semantic matrix is calculated iteratively, and the advantages and disadvantages of sigmoid, tanh, and ReLU, the three most commonly used functions, are compared. Finally, ReLU function is selected as the activation function of this experiment.

After completing the establishment of the music management system model, we obtained the authorization of music software and applied it to a university. Firstly, we preprocessed the original data. Compared with the ideal loss value, the experimental results meet the expected standard, and the prediction error of the Bayesian algorithm model is within the acceptable range. With the increase of the hidden factor dimension, the RMSE value also decreases steadily. It can be seen that when the hidden factor dimension is 11, the system model performs best in the representation of music features. The comparison shows that the recommendation effect filtered by the Bayesian algorithm model is better than that of the nonstandard collaborative filtering recommendation system. By using the experimental music search and the recommendation system, music majors have greatly improved their sound sense, music literacy, music coverage, and music performance level. The final questionnaire survey shows that college students are satisfied with the system as a whole.

However, the efficiency of the Bayesian mining algorithm needs to be further improved. There is also the risk of data leakage. When the number of Bayesian attributes is large or the correlation between attributes is large, the classification effect is not good. There are still many actual situations where the feature correlation is very small, so this model still needs further analysis and modification. In the future, college music users should also use the analysis results reasonably. Further analysis is needed.

Data Availability

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

The author declares no conflicts of interest.

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