EAI Endorsed Transactions
on Scalable Informations Systems

Research Article EAI.EU

An Improved Intelligent Machine Learning Approach to Music Recommendation Based on Big Data Techniques and DSO Algorithms

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Abstract

INTRODUCTION: In an effort to enhance the quality of user experience in using music services and improve the efficiency of music recommendation platforms, researching accurate and efficient music recommendation methods and constructing an accurate real-time online recommendation platform are the key points for the success of a high-quality music website platform.
OBJECTIVES: To address the problems of incomplete signal feature capture, insufficient classification efficiency and poor generalization of current music recommendation methods.
METHODS: Improve the deep confidence network to construct music recommendation algorithm by using big data and intelligent optimization algorithm. Firstly, music features are extracted by analyzing the principle of music recommendation algorithm, and evaluation indexes of music recommendation algorithm are proposed at the same time; then, combined with the deep sleep optimization algorithm, a music recommendation method based on improved deep confidence network is proposed; finally, the efficiency of the proposed method is verified through the analysis of simulation experiments.
RESULTS: While meeting the real-time requirements, the proposed method improves the music recommendation accuracy, recall, and coverage.
CONCLUSION: Solves the questions of incomplete signal feature capture, insufficient classification efficiency, and poor generalization of current music recommendation algorithms.

Keywords: music recommendation method, deep confidence network, music feature extraction, deep sleep optimization algorithm

Received on 22 February 2024, accepted on 27 March 2024, published on 08 April 2024

doi: 10.4108/eetsis.5176

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1. Introduction

With the vigorous development of Internet technology, digital music products using the Internet as a carrier have gradually entered people's daily lives [1]. With the Internet's fast and effective dissemination methods, the demand and supply of digital music is increasing, making the music database massive surge leads to user retrieval needs are not satisfied, the user retrieval difficulty increases [2]. In order to improve the quality of data music services, a music recommendation system that actively provides users with loads of user interests has been proposed [3]. Currently, in terms of storage and computational efficiency, traditional machine learning methods to deal with music raw data, the overhead are very large, while a large number of redundant data with noise data has a negative impact on the results [4]. In order to improve the quality of user experience in using music services and improve the efficiency of music recommendation platforms, researching accurate and efficient music recommendation methods and constructing accurate real-time online recommendation platforms are the key points for the success of a high-quality music website platform [5].

The core idea of music recommendation methods is to make similar recommendations by measuring the similarity between users or items [6]. Music recommendation system usually consists of three aspects: user preference information, music description information and recommendation algorithm [7]. Recommendation algorithms, as the key technology of music recommendation system, generally include collaborative filtering algorithms, content-based recommendation algorithms and hybrid recommendation algorithms according to the specificity of the music recommendation problem [8]. Music recommendation algorithms will not only rely on data such as user behavior, preferences and ratings, but also take into account the characterization of items that users like [9]. Content-based music recommendation algorithms will get the set of user preferred features based on the user's characterization of the evaluated music, and the similarity will be calculated to complete the recommendation by comparing such a feature set with the features of the music to be recommended [10]. Content-based music recommendation algorithms are usually divided into two ways based on labeled content and based on music features [11]. Content-based recommendation algorithms make full use of the correlation between music, can well solve the cold start and sparsity problems, and the recommendation results are more convincing, but the content description is inaccurate, and can't tap the user's potential hobbies [12]. Collaborative filtering-based music recommendation algorithm searches for users whose hobbies are the same as those of the target user based on the similarity between users, and then decides the target recommendation candidate set based on the behaviors of similar users [13]. Collaborative filtering based music recommendation algorithms can be categorized into two algorithms based on user similarity and item similarity [14]. Collaborative filtering based music recommendation algorithms are generally adaptable and able to discover new user interests, but suffer from the cold-start problem and sparsity problem [15]. Literature [16] uses deep confidence network to extract vectorized features from the spectrogram of audio and incorporates these features into the probability matrix decomposition; literature [17] proposes a music recommendation algorithm based on convolutional neural network, which extracts log-compressed Meier spectral image from the side that audio file as CNN input and outputs the hidden features of each song; literature [18], on the basis of collaborative subject modeling based, a new Bayesian probabilistic hybrid recommendation model, the collaborative depth model, is proposed; literature [19] uses the basic feature attributes of music to calculate the similarity between music; literature [20] applies the listening habits and collection habits between users to find out the users with high similarity and recommend music with common preferences for them; literature [21] groups the music efficiently and utilizes the user ratings to apply the probabilistic model processing, proposed a collaborative filtering-based music recommendation method. Whether content-based recommendation algorithms or collaborative filtering algorithms, with the increase in the amount of book data and user requirements, it is difficult to get user-satisfied recommendation results, for this reason, combined with a variety of recommendation algorithms, to achieve satisfactory recommendation results [22]. For the above literature analysis, the existing recommendation algorithm methods have the following defects [23]:

1) Incomplete capture of the essential signaling characteristics of music;

2) Insufficient efficiency in categorizing music recommendations;

3) Poor generalization of recommendation algorithms.

Aiming at the problems of the current music recommendation algorithm method, this paper proposes a music recommendation method based on big data technology and machine learning algorithm. The main contributions of this paper are (1) to analyze the principle of music recommendation algorithm with music features and evaluation indexes; (2) to optimize the parameters of deep confidence network using deep sleep optimization algorithm, and to construct the music advancement method based on DSO-DBN algorithm; and (3) to use music dataset to analyze and practice the proposed method.

2. Principle of Music Recommendation Algorithm and Feature Extraction Analysis

2.1. Principle analysis of music recommendation algorithm

Music recommendation algorithm is to analyze the songs preferred by the users of the music platform, calculate the similarity of different users of the platform, get the other music users in the platform with the largest similarity, and then find the songs that the user may be interested in according to the taste of the other music users' music styles, and recommend the songs to the current user [24].

In this paper, based on the user's listening habits and the correspondence of music information, we obtain the user's interest degree and recommend the music in the music library that matches the user's interest degree model to the user [25].

User interest level information

It is assumed that users will click to listen to the music which they are interested in, and the action behavior on a piece of music represents the user's interest level in the music, while similar users have the same interest level in an unknown piece of music.

To facilitate the calculation, the music in the music library can be numbered to define the percentage of listening time:

$$\rho_{ij} = \frac{t_{ij} - \alpha_{ij}}{\beta_{ij} - \alpha_{ij}} \qquad \left(i = 1,2,\cdots,n; j = 1,2,\cdots,m\right) \tag{1}$$

In Eq. (1), ρ_{ij} denotes the proportion of time users spend listening to the jth music in the ith category, n denotes the total number of all music in the music library, and m denotes the total number of music in the ith category.

$$t_{ij} = \begin{cases} \rho_{ij}, t'_{ij} \in R & \text{Collect songs} \\ \begin{cases} \alpha_{ij}, t'_{ij} \le \alpha_{ij} \\ t'_{ij}, \alpha_{ij} \le t'_{ij} \le \beta_{ij} \\ \beta_{ij}, t'_{ij} \ge \beta_{ij} \end{cases} & else \end{cases} \tag{2}$$

In Eq. (2), α_{ij} and β_{ij} are the thresholds for the maximum and minimum listening time of the music, respectively.

The user's interest in music of category i is calculated in equation (3) below:

$$Int_i = \frac{\sum_{j=1}^{m} t_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} t_{ij}} \tag{3}$$

Music Recommendation Process

Based on the calculation of the user's interest level and the music information, the music content of interest is recommended to the user [26], and the overall music recommendation process is shown in Figure 1.

1) Extract music features

The method in this paper segments the involved music audio into audio segments and performs feature extraction on the segmented audio;

2) Labeling music

In music information labeling, this paper uses the genre-emotion two-dimensional attribute as music labels, including 10 categories of music information: pop-sentimental, pop-lonely, pop-romantic, rap-easy, rap-inspirational, rock-passionate, dance-joyful, country-quiet, folk-sweet, and jazz-missing;

3) Constructing a prediction model for categorizing music information

Based on music features and music labels, machine learning algorithms are used to construct music information classification prediction models;

4) Calculate the user-song rating matrix

Based on the music information categorization as well as the user interest degree, the calculation is converted to the user degree song rating to get the user-song rating matrix.

5) Calculate user similarity

Based on the user-song rating matrix, the user similarity is computed to obtain the k most similar users in terms of song preferences.

6) Predicting user preference for songs

Based on the k users with the most similar song preferences and according to the user-song rating matrix, the user ratings of the uncollected songs are calculated and the ratings are sorted.

7) Song Recommendations

Based on the size of the predicted score, n recommended songs are removed from the sorted heap and the song ID is the algorithmic recommendation result.

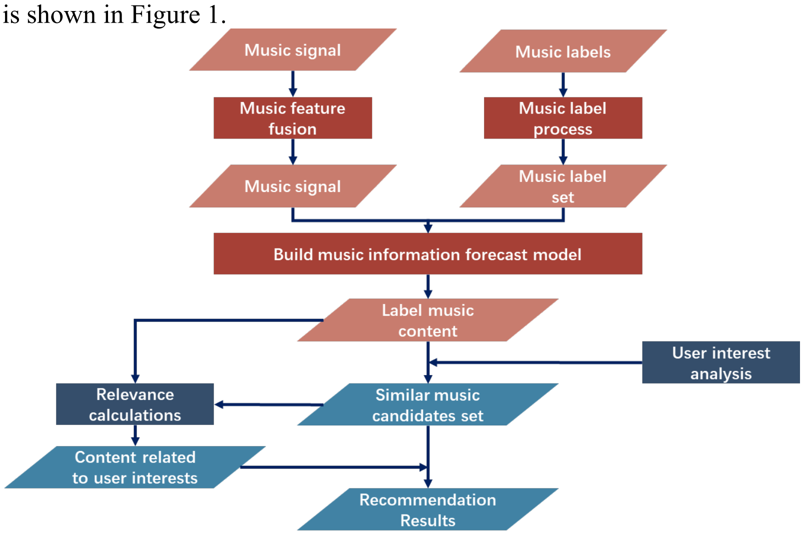

Figure 1. Music Recommendation Process

2.2. Music Feature Extraction

In traditional music classification, manual labeling or single feature expression suffers from the problem of one-sided understanding of music. For this reason, this paper adopts a hybrid feature approach to describe music information [27].

The extraction and expression of music feature parameters is the basis of music information prediction technology, and the music content is divided into three parts, namely, bottom layer features, middle layer features, and high level features. The bottom features and middle features are symbolic features that exist objectively, and the high-level information is the information that relies on the human senses for specific labeling, including music emotion, music genre and other contents. The schematic diagram of music feature parameter extraction is shown in Figure 2.

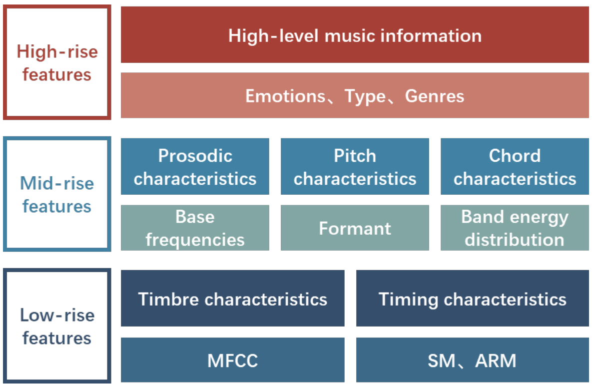

Figure 2. Music feature extraction

3. Recommendation Algorithm Evaluation Metrics

In order to evaluate the performance of music recommendation methods, this paper uses evaluation metrics such as precision rate, recall rate, and coverage rate [26].

3.1 Accuracy

Accuracy rate indicates the degree of accuracy, for the recommendation prediction result, the ratio of the number of recommendation accuracy to the total number of recommendations in the final recommendation list. The specific calculation equation is as follows in equation (4):

$$precision = \frac{\sum \left| R(u) \cap T(u) \right|}{\left| R(u) \right|}, u \in U \tag{4}$$

In Eq. (4), $R(u)$ represents the list of recommendations made to the user by the training data, and $T(u)$ represents the recommendations made to the user by the user based on the test data.

3.2 Recall rate

Recall is the ratio of the number of recommendations that are accurate to the true number of recommendations that need to be recommended in the final recommendation list for the original sample, indicating the number of positive examples predicted correctly. The specific calculation method equation (5):

$$recall = \frac{\sum \left| R(u) \cap T(u) \right|}{\left| T(u) \right|}, u \in U \tag{5}$$

3.3 Coverage

The coverage rate mainly describes the discovery ability of a recommender system, the list of songs between the years of the recommender system, as a proportion of all the songs in the recommender system. The specific calculation method is shown in equation (6):

$$coverage = \frac{\sum \left| R(u) \right|}{\left| S \right|}, u \in U \tag{6}$$

where *coverage* denotes the ratio of the concatenated set of recommended songs of u users to the total set of songs, and S denotes the total set of songs.

4. Deep Sleep Optimization Algorithm Improved K-means Clustering Algorithm

4.1. Deep Sleep Optimization Algorithm

Sleep can be divided into four stages: non-REM1 (N1), non-REM2 (N2), non-REM3 (N3) and Rapid eye movement (REM), as shown in Figure 3. At the beginning of sleep, an individual feels a gradual sense of unconsciousness, which is similar to gradually descending into a hole, while the depth to which an individual reaches the "sleep hole" depends on the sleep stage acquired during sleep. At the end of sleep, the deeper a person sleeps, the easier it is for the intelligence to enter the sleep hole. By simulating the sleep pattern of the intelligent individual, i.e., descending into the sleep hole, as an optimization process. The deep sleep optimization algorithm is mainly inspired by the swarm intelligence sleep pattern, which determines the neighborhood optimum and optimal solution of the optimization problem by obtaining the deep sleep duration.

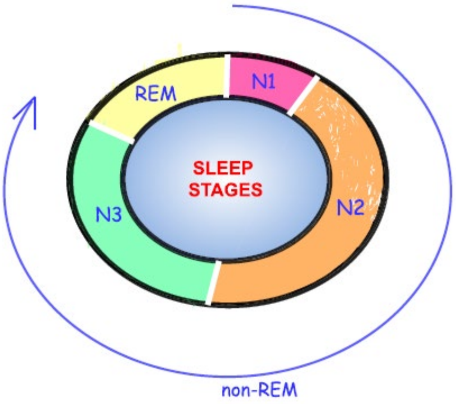

Figure 3 Four stages of sleep

Deep sleep optimizer (DSO) algorithm [28] is based on the dual-process sleep regulation model. The dual-process sleep regulation model is to be subjected to the sleep-wakefulness cycle principle, which consists of: a constant action operator and a physiological rhythm operator. In the constant action operator, the wakefulness stage increases and so does the need for sleep; in the physiological rhythm operator, sleep and wakefulness rhythmically vary, determining that a small period of sleep begins at the end. A schematic of the sleep rule optimization model is shown in Figure 4.

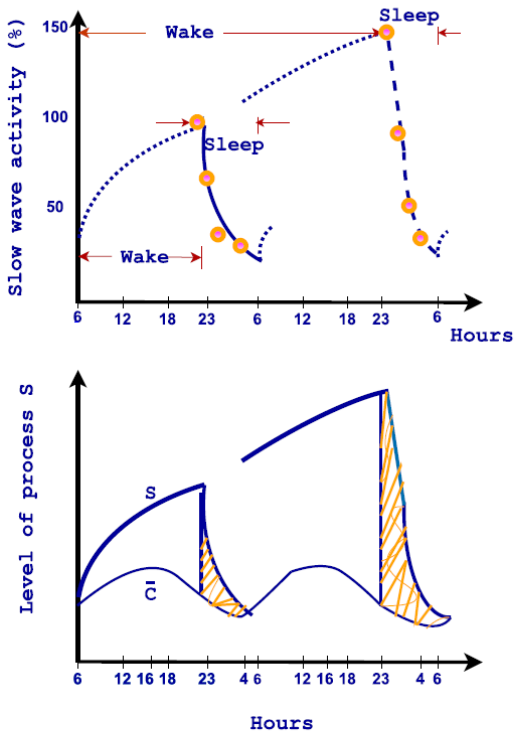

Figure 4 Dual-process sleep regulation model

Algorithmic optimization mathematical model

In the dual-process sleep regulation model, an intelligent individual can be in either sleep or awake state. $H(t)$ The time t steady state pressure of an intelligent individual can be defined as:

$$H(t)=\begin{cases} H_0(t)\cdot e^{(t_0-t)/x_s} & \textit{sleep state} \\ \mu(t)+\left(H_0(t)-\mu(t)\right)\cdot e^{(t_0-t)/x_w} & \textit{wake state} \end{cases} \tag{7}$$

In Eq. (7), x_s and x_w denote the sleep power index and wakefulness power index, respectively; $H_0(t)$ denotes the initial stabilization value; $\mu(t)$ denotes the arousal threshold, and $\mu(t)=0$ denotes the upper proximity line if the intelligent individual is in the wakefulness state and , and $\mu(t)=1$ denotes the lower proximity line if the individual is in the sleep state. $H(t)$ must be within the maximum threshold value $H(t)^{\max}$ and the minimum threshold value $H(t)^{\min}$, and the equation for calculating the maximum threshold value and the minimum threshold value is as follows:

$$H(t)^{\max}=H_0^{+}+a\times C(t) \tag{8}$$

$$H(t)^{\min}=H_0^{-}+a\times C(t) \tag{9}$$

where a and $C(t)$ denote the physiological rhythm value of the periodic equation and the physiological rhythm periodic equation, respectively. In addition, H_0^{+} and H_0^{-} denote the maximum and minimum initial state stabilization values, respectively. The physiological rhythmic periodic equation is defined as follows:

$$C(t)=\sin\left(\frac{2\pi}{T}(t-\alpha)\right) \tag{10}$$

Where, α denotes the physiological rhythm time conversion variable, which is mainly used to specify the physiological rhythm maximum value conversion. It is a uniformly distributed random number α located between 0 and 1. $H_0(t)$ The initial stabilization value is defined as follows:

$$H_0(t)=\gamma+r\cdot\left(X_{best}-\mu(t)\cdot X_{mean}\right) \tag{11}$$

Eq. (11), X_{mean} denotes the average steady state value of the intelligent individual. X_{best} denotes the optimal candidate solution. r denotes a uniformly distributed random value between 0 and 1. γ denotes the initial population.

At the beginning of the state, $\mu(t)$ denotes the threshold of the distribution between 0 and 1. It can help to regulate the equational capacity $\mu(t)$ of exploration and exploitation. When the value $\mu(t)$ of tends to 1, the exploration capability increases and avoids falling into a local optimum; when the value of tends $\mu(t)$ to 0, the exploitation capability comes into play. The DSO algorithm escapes from the local optimum by ensuring that the intelligent individuals move flexibly. In the DSO algorithm, each candidate solution exists in a sleep-wake cycle. During the deep sleep phase, the steady state increases and during the awake phase, the steady state decreases. Meanwhile, the DSO algorithm employs a greedy selection strategy to select new candidate solutions.

Algorithm Pseudo-Code

The DSO algorithm is a global optimization algorithm that uses natural sleep-wakefulness physiological activity to simulate exploration and exploitation of search capabilities. In the DSO algorithm, intelligent individuals carry out the optimization process by simulating the entry into the sleep hole model, and the optimization is judged by the sleep depth and pressure values. During the exploration process, the intelligent individual stabilizes the pressure increase to simulate the awake state. In each sleep-wake cycle, the intelligent individual shares the fitness value and position to guide the individual into the optimization process.

According to the optimization strategy of DSO algorithm, the pseudo-code of DSO algorithm is shown in Figure 5. An initial solution is randomly generated, and the final optimal solution is continuously obtained by evaluation with greedy selection strategy.

Algorithm 1: Deep sleep optimizer algorithm	
1	Initialize DSO algorithm parameters;
2	Initialize DSO algorithm population position;
3	Evaluate the fitness of all agents, obtain best solution;
4	While t < T_max
5	Randomly select asymptote value,
6	Compute candidate solution based on sleep-wake cycle;
7	Bound violating variables to their ranges;
8	Evaluate the new solution fitness value, update and obtain best fitness;
9	End
10	Ouput best solution and fitness value.

Figure 5. Pseudo-code of DSO algorithm

4.2. Deep Confidence Networks

Deep Belief Networks (DBN) [29] consist of multiple Restricted Boltzmann Machines (RBM) layers, a typical type of neural network is shown in Figure These networks are restricted to a visible layer and a hidden layer with connections between the layers but not between the units within the layers. The hidden layer units are trained to capture correlations of higher-order data exhibited in the visual layer, the exact structure of which is shown in Figure 6. As can be seen from Figure 6, the input layer v and the hidden layer h^1 constitute the first layer of the RBM, and the input data is mapped through the activation equation to the hidden layer , which is inputted to the second layer of the RBM (the hidden layer h_1 and the hidden layer h_2), and the data is passed through the hidden layer sequentially to reach the output layer.

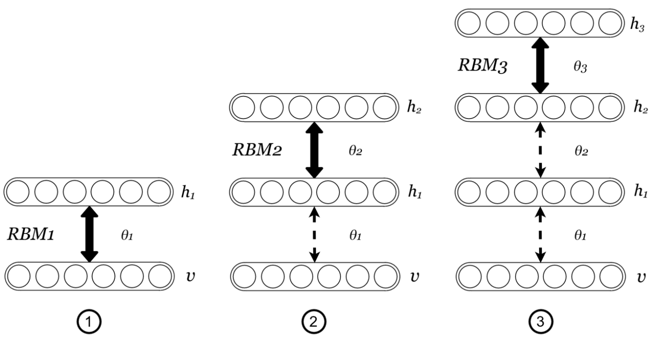

Figure 6.DBN structure

Step 1: Calculate the RBM energy equation. $\theta=(\omega,a,b)$ Assuming that is the DBN network parameter, the energy equation of RBM is expressed as:

$$E(v,h|\theta)=-\sum_{i=1}^{n}a_iv_i-\sum_{j=1}^{m}b_jh_j-\sum_{i=1}^{n}\sum_{j=1}^{m}v_i\omega_{ij}h_j \tag{12}$$

where (v,h) is the state value of DBN, ω is the connection weight of the visible and hidden layers, a and b are the bias of the visible and hidden layers, respectively, and the hidden and visible layer states are binary states, i.e., $v\in\{0,1\}$ and $h\in\{0,1\}$.

Step 2: Solve the DBN network parameters using stochastic gradient method θ . θ^* The corresponding parameters are obtained by solving the maximum of the log-likelihood equation:

$$\theta^*=\arg_\theta\max L(\theta)=\arg_\theta\max\sum_{k=1}^{K}\ln p\left(v^k|\theta\right) \tag{13}$$

where K is the number of training samples.

Step 3: The joint probability distribution equation can be determined from the energy equation:

$$p(v,h|\theta)=\frac{e^{-E(v,h|\theta)}}{Z(\theta)} \tag{14}$$

$$Z(\theta)=\sum_v\sum_h e^{-E(v,h|\theta)} \tag{15}$$

Step 4: Determine the visual layer state. The activation probability of the jth network node of the hidden layer is

$$p(h_j=1|v,\theta)=sigmoid\left(b_j+\sum_{i=1}^{n}v_i\omega_{ij}\right) \tag{16}$$

Step 5: Determine the hidden layer state. The activation probability of the ith network node of the visualization layer is

$$p(v_i=1|h,\theta)=sigmoid\left(a_i+\sum_{i=1}^{n}h_j\omega_{ij}\right) \tag{17}$$

Step 6: According to Gibbs sampling theorem, the RBM θ parameter is updated with the following equation:

$$\Delta\omega_{ij}=\frac{\partial\log p(v)}{\partial\omega_{ij}}=\varepsilon\left(\langle v_ih_j\rangle_{data}-\langle v_ih_j\rangle_{predict}\right) \tag{18}$$

$$\Delta a_i=\frac{\partial\log p(v)}{\partial a_i}=\varepsilon\left(\langle v_i\rangle_{data}-\langle v_i\rangle_{predict}\right) \tag{19}$$

$$\Delta b_j=\frac{\partial\log p(v)}{\partial b_j}=\varepsilon\left(\langle h_j\rangle_{data}-\langle h_j\rangle_{predict}\right) \tag{20}$$

where $\langle\square\rangle_{data}$ denotes the learning rate, ε is the expectation of training after input data, and $\langle\square\rangle_{predict}$ is the expectation of the model itself.

4.3. Improved DBN network optimization ideas based on DSO algorithm

(1) Decision-making variables

The traditional iterative method of DBN network optimization can easily cause the optimization of DBN network parameters to fall into local optimum. $\theta=(\omega,a,b)$ In order to overcome the above problems, this paper adopts the DSO algorithm to optimize the DBN network parameters, i.e., the connection weights of visible and hidden layers, and the bias of visible and hidden layers. The optimization decision variables of the DSO algorithm are .

(2) Objective equation

In order to overcome the DBN training precision, the precision, recall, and coverage equations are used as the objective equations of the DSO-DBN algorithm and are calculated as follows:

$$\min Fitness(X)=\alpha\cdot(1-precision)+\beta\cdot(1-recall)+\gamma\cdot(1-coverage) \tag{21}$$

In Eq. (21), $\alpha+\beta+\gamma=1$; $\alpha=0.4$, $\beta=0.4$, $\gamma=0.2$.

(3) Steps and Processes

The classification recognition method based on DSO algorithm optimized DBN network is mainly based on the mapping relationship between features and recognition types with features as input and recognition types as output. The flowchart of the classification and recognition method based on DSO-DBN algorithm is shown in Figure 7. The specific steps are as follows:

Step 1: Extract music features; use principal component analysis to downsize the features; divide the dataset into training set, validation set and test set;

Step 2: The initial DBN parameters are encoded using the DSO algorithm, and the algorithm parameters such as population parameters and iteration times are initialized; the population is initialized and the objective equation value is calculated;

Step 3: Position update according to the sleep-wake physiological cycle strategy;

Step 4: Calculate the fitness value and update the optimal solution;

Step 5: Judge whether the termination condition is satisfied, if so, exit the iteration, output the optimal DBN network parameters, and execute step 3, otherwise continue to execute step 6;

Step 6: Decode the optimized DBN parameters based on the DSO algorithm, obtain the optimal DBN parameters, and construct the DSO-DBN based recognition model;

Step 7: Use the trained recognition prediction model to perform recognition analysis on the current test set and output the corresponding category results.

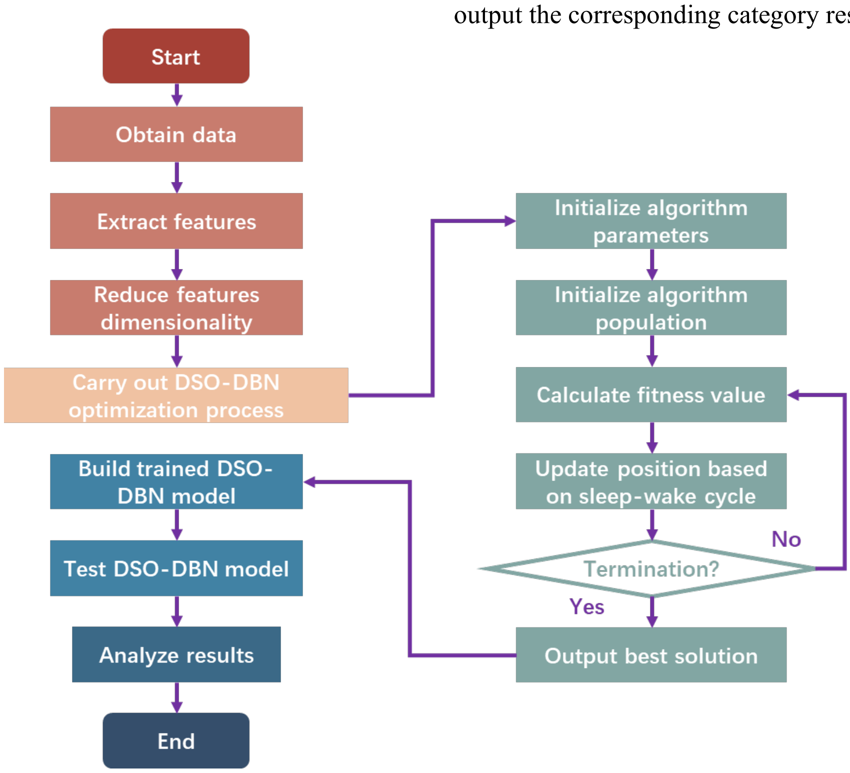

Figure 7. Flow chart of improved DBN network optimization based on DSO algorithm

5. Music Recommendation Method Based on DSO-DBN Network Modeling

In order to improve the music recommendation accuracy, combining the content-based music recommendation method and DSO-DBN music information prediction model, this paper proposes a music recommendation method based on the DSO-DBN network model, the specific flowchart is shown in Figure 8, and the specific steps are as follows:

Step 1: Music data feature extraction as well as labeling. The involved music audio is segmented into audio clips and the segmented audio is feature extracted; genre-emotion 2D attributes are used as music labels;

Step 2: Construct music information classification prediction model. According to the music features and music labels, the deep sleep optimization algorithm is used to improve the classification recognition model of deep confidence network to construct the music information classification prediction model;

Step 3: Calculating the user-song rating matrix. According to the music information categorization as well as the user interest degree, calculate the score converted to the user degree song to get the user-song score matrix;

Step 4: Calculate the user similarity as well as evaluate the user's preference for the song.

Step 5: Generate recommendation results. Based on the size of the predicted score, n recommended songs are taken from the sorted heap and the song ID is the algorithmic recommendation result.

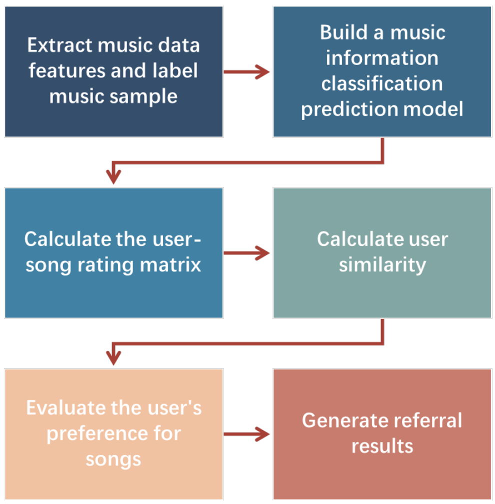

Figure 8. Flowchart of music recommendation based on DSO algorithm to improve DBN network

6. Results and Discussion

In order to verify the advantages and disadvantages of the recommendation algorithms proposed in this paper, five recommendation algorithms are selected for comparison, and the specific parameter settings of each algorithm are shown in Table 1.The recommendation algorithms used in the experiments are based on the implementation of Hadoop with Mahout algorithmic framework [27].

Table 1. Recommended algorithm parameter settings

arithmetic	parameterization
DBN	Three hidden layers with 100, 100, 100 nodes in each layer
PSO-DBN	Three hidden layers, the number of nodes is determined by Section 6.4; the PSO algorithm has an inertia factor of 0.3, c1 = 1, c2 = 1, and the number of populations is determined by Section 6.4
TLBO-DBN	Three hidden layers, the number of nodes is determined by Section 6.4; the TLBO algorithm teaches factor T = 1 or 2, the number of populations is determined by Section 6.4
GWO-DBN	Three hidden layers, the number of nodes is determined by Section 6.4; the GWO algorithm converges with a decreasing value of constant a from 2 to 0 and the number of populations is determined by Section 6.4
BBO-DBN	Three hidden layers, the number of nodes is determined by Section 6.4; the BBO algorithm has a habitat modification probability of 1, a migration probability restriction range of [0,1], a step size of 1, I=1, E=1, a mutation probability of 0.005, and a population size determined by Section 6.4
DSO-DBN	Three hidden layers, the number of nodes is determined by Section 6.4; the DSO algorithm has initial stabilization values of maximum and minimum of 0.17 and 0.85, a = 0.1, Xs = 4.2, Xw = 18.2, T = 24, and the number of populations is determined by Section 6.4

6.1. Experimental environment setup

The experiments were all run on a server configured with CPU: Xeon Intel e5 2620v4; RAM: 80G; Graphics: Nvidia TitanX Pascal; OS: Ubuntu 16.04; Runtime environment: python 3.6 and pytorch 0.3 and cuda 9.0.

6.2. Description of the experimental data set

In this paper, we use the public data of Last.fm, a music website that supports users to customize adding tags to music and records the listening information of each user. Currently, the published information contains 360,000 user records, from which we randomly selected 4128 user information containing 231,453 music tracks and 13,246 music tags in our experiments.

6.3. Performance Analysis of DSO Algorithm Optimization

In order to analyze the optimization performance and process of the DSO algorithm, this paper tests the DSO algorithm using the multimode criterion equation. The multimode standard equation is defined as equation (22):

$$F(x)=10n+\sum_{i=1}^{n}\left(x_i^2-10\cos\left(2\pi x_i\right)\right) \quad (22)$$

In Eq. (22), n is 30, the equation search space is $[-5.12,5.12]$, and the optimal value is 0. The process of optimizing the standard equation by the DSO algorithm is given in Figure 9.

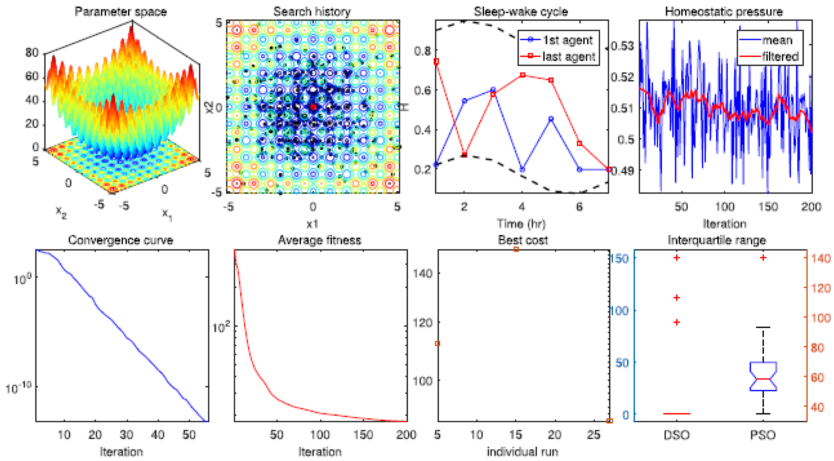

Figure 9. DSO optimization process

6.4. Performance Analysis of Music Recommendation Algorithms

Parameter impact analysis

In order to analyze the impact of the population size of DSO algorithm and the number of hidden layer nodes of DBN network on the music recommendation method, this paper compares and analyzes the performance of the music recommendation method under the conditions of different population sizes and different numbers of hidden layer nodes of the network, respectively. Figure 10 and Figure 11 give the graphs of the influence of different population sizes and different numbers of network hidden layer nodes on the accuracy and time of the music recommendation method, respectively.

From Figure 10, it can be seen that as the number of DSO algorithm populations increases, the music recommendation accuracy also increases gradually; as the number of DBN hidden layer nodes increases, the music recommendation accuracy also increases gradually. From Figure 11, it can be seen that as the number of populations of optimization algorithms increases, the music recommendation time also increases gradually; as the number of DBN hidden layer nodes increases, the music recommendation time also increases gradually. In summary, the population size of the intelligent optimization algorithm selected in this paper is 50, and the number of hidden nodes of DBN network is 110.

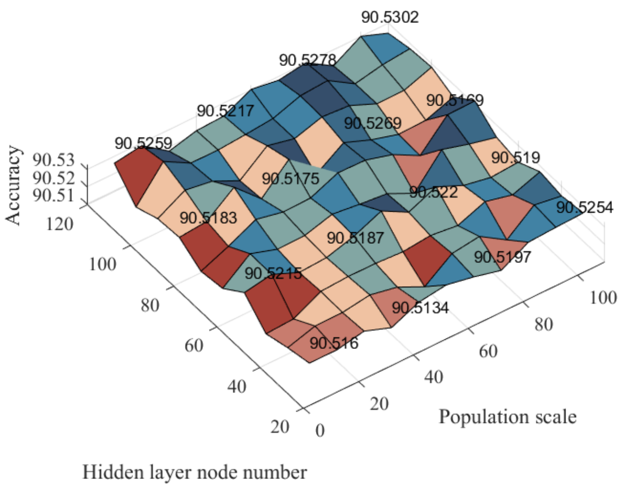

Figure 10. Effect of different population sizes and different number of hidden nodes on music recommendation accuracy

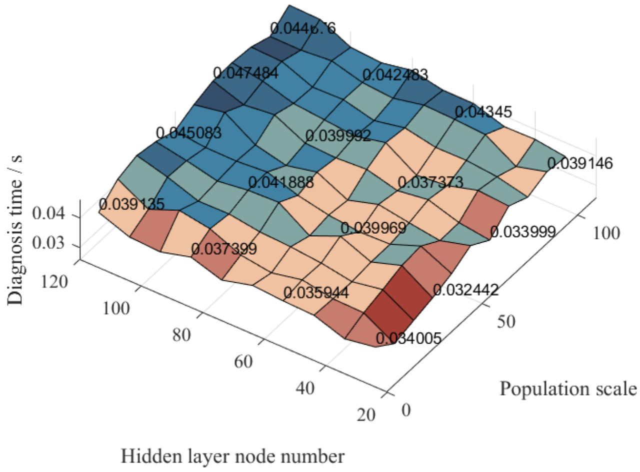

Figure 11 Effect of different population sizes and different number of hidden nodes on music recommendation time

Comparative analysis of algorithms

In order to verify the effectiveness and superiority of the music recommendation method based on the DSO-DBN algorithm, the music recommendation method based on the DSO-DBN algorithm is compared with the music recommendation algorithms based on the DBN, PSO-DBN, TLBO-DBN, GWO-DBN, and BBO-DBN, and the performance results of each model are shown in Figures 12, 13, 14, and 15.Figures 12, 13, 14, and 15 give the results of accuracy rate, recall rate, coverage rate, and recommendation time of music recommendation methods based on each algorithm, respectively. From Figure 12, it can be seen that the DSO-DBN based algorithm has the highest mean accuracy rate and the smallest standard deviation of accuracy rate, and the ranking of the mean accuracy rate is DSO-DBN, GWO-DBN, BBO-DBN, TLBO-DBN, PSO-DBN, and DBN, and the ranking of the standard deviation of the accuracy rate is DSO-DBN, BBO-DBN, GWO-DBN, in that order, TLBO-DBN, DBN, PSO-DBN, indicating that the DSO-DBN algorithm has the best accuracy and the best robustness; as can be seen from Figure 13, the ranking of the mean of the recall rate of each music recommendation method is DSO-DBN, BBO-DBN, GWO-DBN, TLBO-DBN, PSO-DBN, DBN, and the ranking of the standard deviation of the recall rate of each music recommendation method is DSO-DBN, BBO-DBN, GWO-DBN, DBN, PSO-DBN, TLBO-DBN in order, indicating that the DSO-DBN algorithm has the largest mean recall rate and the smallest standard deviation, and has good stability; as can be seen from Figure 14, the rankings of each algorithm's mean coverage rate are DSO-DBN, BBO-DBN, GWO-DBN, TLBO- DBN, PSO-DBN, and DBN, and the ranking of the standard deviation of the coverage rate of each algorithm is DSO-DBN, BBO-DBN, GWO-DBN, TLBO-DBN, PSO-DBN, and DBN in order, which indicates that the DSO-DBN algorithm has the largest coverage rate mean and the smallest standard deviation, and has good stability; as can be seen in Figure 15, the ranking of the mean of the recommendation time of each algorithm is DSO-DBN, GWO-DBN, BBO-DBN, TLBO-DBN, PSO-DBN, DBN, and the ranking of the standard deviation of the recommendation time of each algorithm is DSO-DBN, BBO-DBN, TLBO-DBN, GWO-DBN, PSO-DBN, DBN in the following order, which indicates that DSO-DBN algorithm has the least mean value of the recommendation time, the smallest standard deviation and the best real-time robustness.

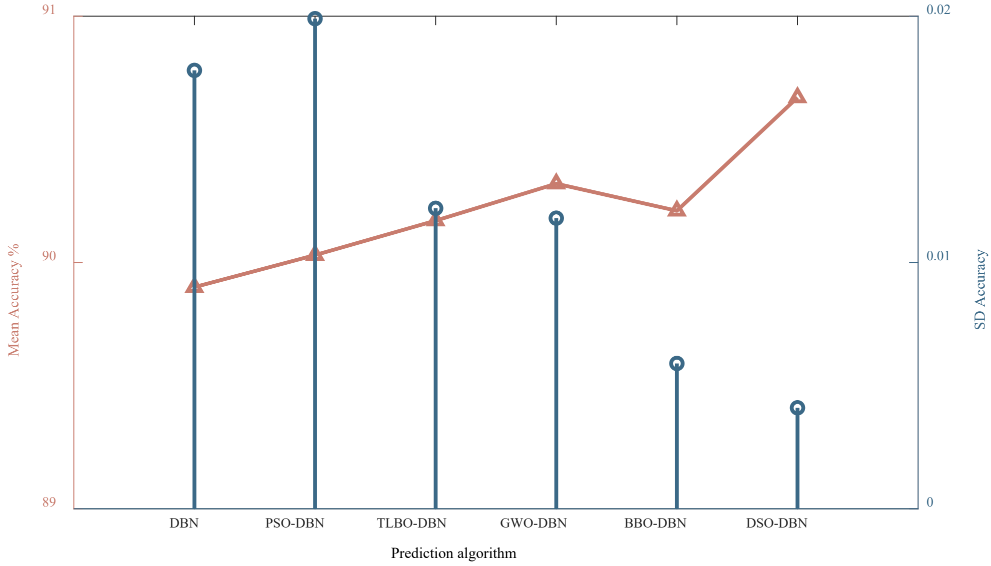

Figure 12. Accuracy rate results of music recommendation methods based on each algorithm

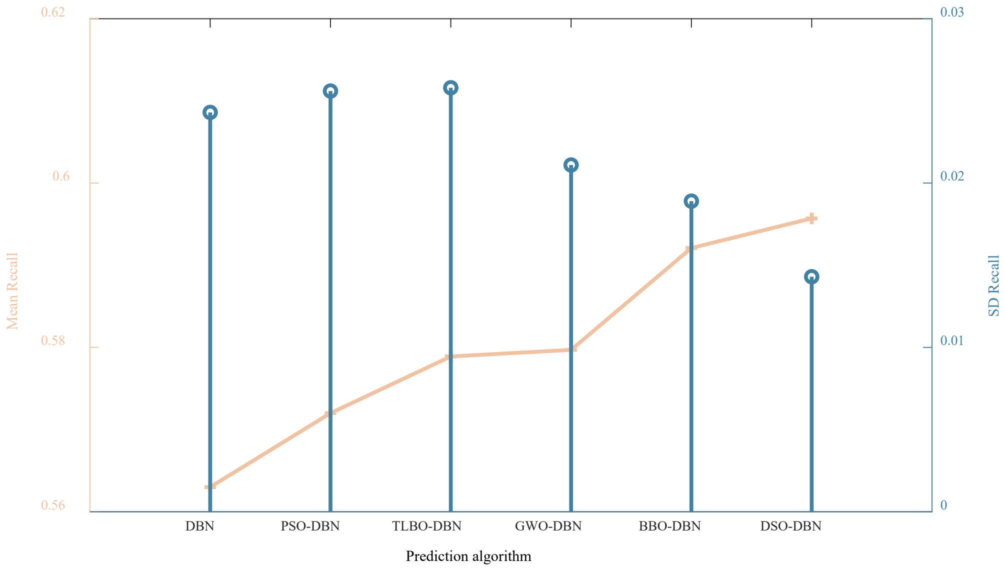

Figure 13. Recall results of music recommendation methods based on each algorithm

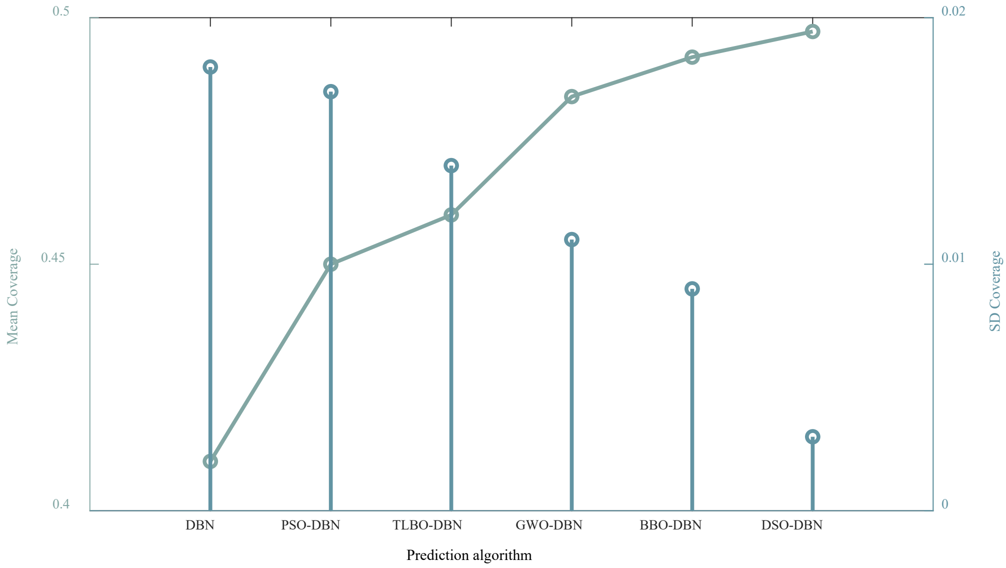

Figure 14. Coverage results of music recommendation methods based on each algorithm

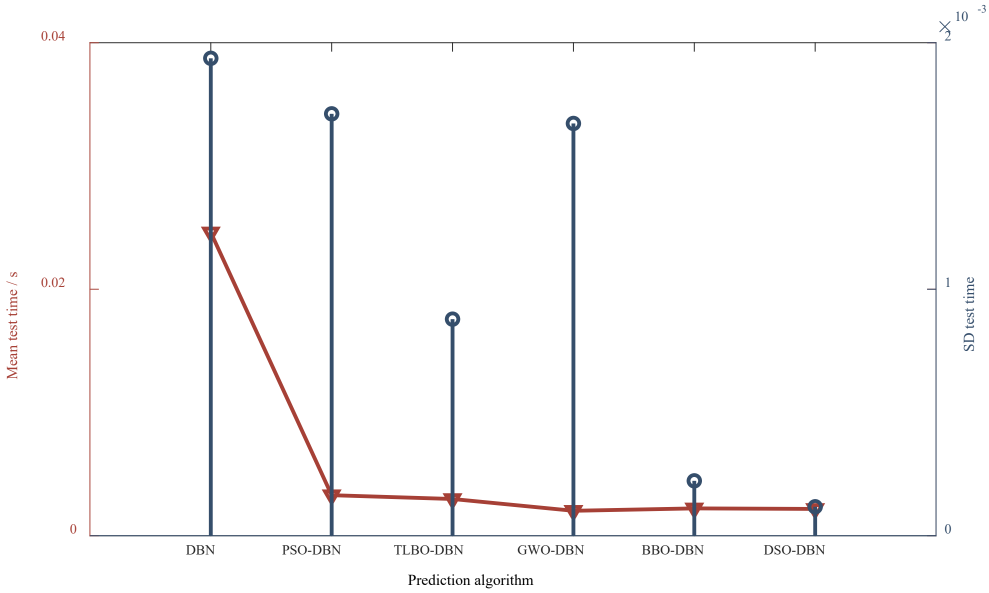

Figure 15 Recommendation time results of music recommendation methods based on each algorithm

7. Conclusion

In order to solve the current music recommendation algorithm's lack of accuracy and effectiveness, this paper adopts an improved machine learning algorithm to construct a music recommendation algorithm. The method proposes a music recommendation method based on DSO-DBN algorithm by analyzing the principle of music recommendation algorithm and feature extraction process, proposing the evaluation index of recommendation algorithm, and optimizing the deep confidence network using deep sleep algorithm. Simulation experiments are conducted using Last.fm public data, and by comparing the recommendation performance of DSO-DBN with that of DBN, PSO-DBN, TLBO-DBN, GWO-DBN, and BBO-DBN, it is found that the method proposed in this paper has a better recommendation precision rate, recall rate, and coverage rate, and meets the real-time requirements.

In this paper, the proposed method uses the DSO algorithm to optimize the DBN making the recommendation efficiency subject to certain limitations. In future work, optimization of DBN network will be considered to improve the recommendation efficiency of the algorithm.

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