

Retraction

Retracted: Design of Deep Learning Network Model for Personalized Music Emotional Recommendation

Security and Communication Networks

Received 25 July 2023; Accepted 25 July 2023; Published 26 July 2023

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] C. Chen, "Design of Deep Learning Network Model for Personalized Music Emotional Recommendation," *Security and Communication Networks*, vol. 2022, Article ID 4443277, 8 pages, 2022.

Research Article

Design of Deep Learning Network Model for Personalized Music Emotional Recommendation

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Received 11 November 2021; Accepted 14 March 2022; Published 2 May 2022

Academic Editor: Jian Su

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Music is a way for people to express their inner thoughts, and it is an art form to express their feelings and send their emotions. In modern society, people tend to listen to music more and more as a way of leisure and entertainment, and different types of music hold different feelings of listeners and trigger different emotional resonances. In this study, we propose an algorithmic model based on the two-layer attention mechanism, which includes the processing of textual convolutional neural network for music name and music label text data and the processing of two-layer attention mechanism, where the two-layer attention mechanism refers to the first layer of attention mechanism that learns the user's preference for each music feature from the feature level and the second layer of attention mechanism that learns the user's preference for each piece of music in the history listening list from the item level. The experiments show that the NDCG value of this method is improved by about 0.08, and the overall quality of the recommendation list is improved, which indicates that the user interest model constructed based on the fusion of various dings has good characterization ability and is helpful to alleviate data sparsity.

1. Introduction

Music is a way for people to express their inner thoughts, and it is an art form to express their feelings and send their emotions. In modern society, people are more and more inclined to listen to music as a form of leisure and entertainment, and different types of music hold different feelings of listeners and trigger different emotional resonance. Some studies have shown that people listen to music more frequently in their daily social life compared to the behaviors of reading books and watching fixed movies that require a fee [1–3]. At the same time, also because music generally lasts for a short period of time, and listening has a coherent nature. Users are more likely to finish listening to multiple pieces of music at once. In recent years, digital multimedia technology has enabled the rapid development of both online and mobile music. In earlier years, music existed mainly in the form of CD albums, but in recent years it is gradually changing to digital storage, and albums are mostly becoming digitally distributed, the size of music databases is expanding

rapidly, and the number of users of music websites and music applications is growing rapidly [4].

The application of a recommendation system in a certain field needs two bases: first, the data volume of the field is so large that users cannot select their favorite items by understanding and contacting all items; second, the user needs cannot be described exactly. Those that meet these two conditions are mainly concentrated in the pan-entertainment field, such as e-commerce, music, video, etc. The music field happens to have the above two characteristics [5]. First, the current library of each mainstream music platform contains at least tens of millions of different types of music, and the library is updated very fast, so it is unrealistic for users to listen to all the music and then choose their favorite music; second, the demand for listening to music is not clear, and usually in a certain context, users may like a certain type of music, but there is no specific demand for a certain music item that Fuzzy recommendations can be made [6]. For users, because listening to music online is generally free and the duration of each piece of music is short, the time cost and economic cost are lower compared to other forms of leisure

and entertainment that require a fee, such as books and movies. Online music websites can meet users' personalized listening needs through music recommendation systems, and music recommendation systems can also help improve service levels and user stickiness. Therefore, the research on personalized music recommendation systems has great practical value [7].

The effect of applying personalized music recommendation algorithms on domestic and international music websites is remarkable, and personalized music recommendations that meet users' emotional needs have helped music websites greatly increase the number of users and the length of time they use. The powerful role of personalized music recommendations cannot be underestimated [8].

Although a variety of music recommendation methods have emerged, there are still some common problems that have not been solved in the field of music recommendation, such as the real-time problem. Most of the existing recommendation methods only consider the basic information of users and combine with the overall historical behavior of users to achieve recommendations, but they do not divide the historical behavior of users into long-term and short-term, and short-term interest preferences are closer to the real-time needs of users. Therefore, the existing algorithms are less capable of making recommendations based on users' real-time emotions and state of mind, causing the problem of real-time recommendations [9].

2. Related Work

2.1. Music Recommendation. Initially, some attribute features of the music itself were analyzed to generate recommendation results, such as analyzing the acoustic data of the music's spectrum, short-time over-zero rate, etc. This method requires professional knowledge of signal processing and acoustics, and the complexity of the algorithm is also high. [10] Research was conducted on content-based recommendation methods to realize a personalized music recommendation system, which obtains information such as the rhythm and melody of the user's preference. The user's preference is obtained through the rhythm and melody of the user's preferred music, the music is classified according to the melody classifier, and then the classified music with a similar rhythm is recommended to the user. [11] The lyrics information was transformed and downscaled using the vector space model, the frequency cepstrum coefficient features of music was extracted, multimodal fusion with lyrics information as a complement to collaborative filtering recommendation was performed, and a multimodal-based music recommendation system was realized. [12] A dynamic music similarity metric strategy to recommend music through the tags of music using content features, as well as user access patterns was proposed. [13] A music recommendation model based on MFCC and GMM, combining frequency central coefficients and Gaussian mixture model to first extract the speech features of music was proposed, and then the GMM algorithm to generate templates for music was used. This method can also analyze the user rating and review data of music, and since these data are generated

by users, the recommendation results can be personalized [14]. The used text input is analyzed, including the user's personal information, and descriptive information about the music, and the user's own data is combined with content-based recommendations to recommend music that matches the user [7]. Music items and predicted users considering the Gaussian distribution of user ratings, in addition to also improving the performance of recommendations using audio features are grouped.

Tag-based music recommendation mainly refers to tags established for different types of music, such as music genres, music styles, etc. Tags can be generated either by experts or by users, tags make music libraries that can be structurally represented and can help to complete the recommendation of a certain type of music, but the generation of tags costs more and is also prone to tag imbalance [15] based on the social tags of music, which are first mapped into three semantic spaces of genre, sentiment, and contextual information, respectively, to calculate the user and the music. The similarity of users and music is calculated, and then the similarity of the three spaces is fused by different methods to recommend songs to users. [16] The user history and download records, combined with LDA method are analyzed [17], and a music recommendation model based on LDA-MURE is proposed. [18] A recommendation method combining LDA is proposed, which achieved better results.

2.2. Attentional Mechanisms. Attention mechanism is a mechanism used to improve the effectiveness of Encoder+Decoder model, which is summarized based on the habitual pattern of human observation. It was first proposed by Google Deep-Mind team in 2014 to solve the image processing problem, and the error rate of image classification was significantly reduced by introducing the attention mechanism in the recurrent neural network, and it was verified in the MNIST classification task [19], which reduced the error rate by 4%. This proved the effectiveness of adding the attention mechanism to image processing. After that, the attention mechanism also began to be applied to the field of machine translation, [12] was the first to apply the attention mechanism in the field of machine translation, used the attention mechanism to solve the problem of aligning source languages of different lengths in machine translation, and performed machine translation while aligning the source languages, which led to a significant improvement in the performance of neural network machine translation models, demonstrating the usefulness of the attention mechanism in the field of natural language processing. The attention mechanism was introduced based on [20], and the sentence modeling was implemented using the convolutional neural network with the addition of the attention mechanism [21]. Later, the Google machine translation team fused the attention mechanism and the sequence converter network [22] to achieve better text translation, which is different from the previous combination of attention mechanism and recurrent neural network or CNN, and proved the feasibility of the fusion method of multiple attention mechanisms. Li et al. [23] designed and implemented a dynamic attention

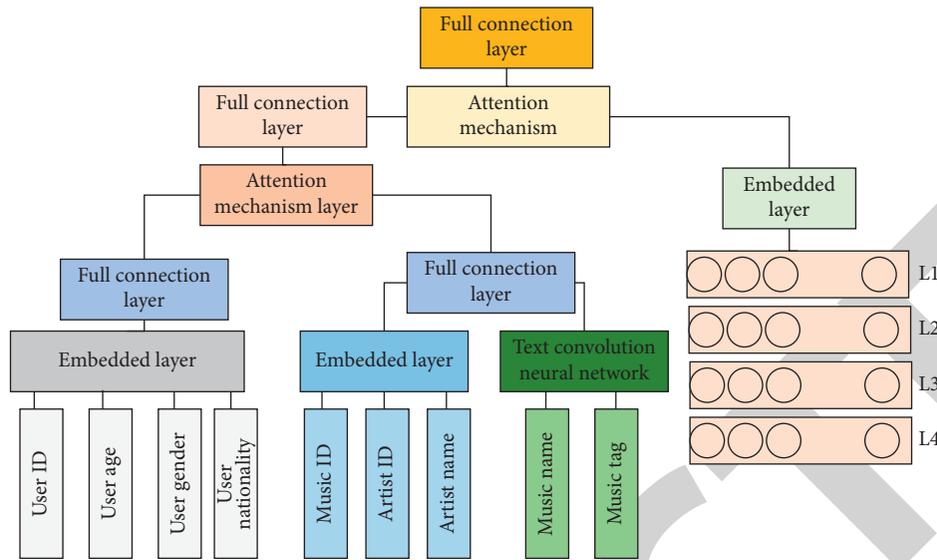


FIGURE 1: Structure diagram of two-layer attention mechanism model.

network based on cascading attention, borrowing the idea of alternating cooperative attention mechanisms, and the iterative process enabled the model to recover from the initial local maxima corresponding to wrong answers, achieving good results in a machine reading quiz task.

2.3. Music Recommendation Algorithm Based on a Two-Layer Attention Mechanism. To address the problems of sparse data and poor recommendation real-time of previous algorithms, this study combines a music recommendation system and a deep learning method and designs a music recommendation method based on a two-layer attention mechanism, which makes full use of multiple features of users and music, such as user gender, age, nationality, music name, music tag, artist, etc., as well as users' historical music listening records by adding a two-layer [24]. The deep learning model with attention mechanism learns multiple source data and processes the input multiple data from feature-level and item-level, respectively, with the feature set and music itself as minimum processing units to obtain a nonlinear multilevel abstract feature representation, combining the learned user's interest preference for each music feature and the user's interest preference for each music in the historical music listening list and constructs. Finally, the output of the attention mechanism is fed into the fully connected layer to calculate the music with higher similarity and generate a personalized music recommendation list for the user to achieve the final music personalization recommendation function [25].□

The main structure of the model is shown in Figure 1, which takes the user and music features and the user's historical music listening list as the input, extracts the features through the embedding layer of the neural network, and inputs them into the two-layer attention mechanism. The first layer of attention mechanism takes the user and music features as the input, learns user preferences for each music feature from the feature level, in which music name

and music label text data are converted into distributed word vectors by Word2vec technique in natural language processing, and inputs to the end of text CNN for feature processing to reduce the computation; after that, the second layer of attention mechanism processes the output of the first layer of attention mechanism and the user's historical music listening list to learn user preferences for each music in their music playlist; the output of the two-layer attention mechanism is the user's interest weight vector, and then the user's interest weight vector is sent to the fully connected layer, and the vector cosine similarity method is used to calculate the music with higher similarity and generate a personalized music recommendation list for the user to achieve the final music personalization recommendation function.

2.4. Music Text Feature Processing. In the field of machine learning, it is crucial to convert data into machine language that can be processed by computers and to represent the data effectively with features. In natural language processing problems, common approaches are Word Embedding or Distributional vectors, both of which transform the data into computationally understandable vectors or matrices. Training methods for word embedding are divided into unsupervised or weakly supervised pretraining and end-to-end supervised training. Word2vec and auto-encoder are typical representatives of unsupervised training methods, which can represent words in natural language as low-latitude distributed word vectors. Word2vec technique does not take the trained model results as the most important content, but characterizes the word vectors with the parameter matrix of the hidden layer. Each row of the word vector matrix represents a word, and the number of columns of the matrix indicates the dimensionality of the word vector, which is generally between 100 and 300. The unsupervised training process is relatively simple, and it is easy to obtain the implicit semantic information, but it is less

TABLE 1: Common word embedding training methods.

Unsupervised	Supervised
word2vec and auto-encoder	Embedding layer
Simple process and weak pertinence	Complex structure, high accuracy and strong pertinence

specific in dealing with different problems, and it needs to be adjusted by using manually labeled samples after training out the model, as shown in Table 1. The supervised training model, or end-to-end training model, is based on a deep neural network, where the natural language is input to the chin-in layer, and the semantic information is learned through multiple convolutional layers. The word embedding layer can be interpreted as a dictionary lookup, where different weights are assigned to different word vectors, adjusted by back-propagation, and finally, the trained word vectors are returned, but the algorithm is more expensive due to the complex structure [26].

Natural language texts, such as music names and music tags, contain some deep-level features of music, especially music tags, which can be generated by both experts and users, and can be used to distinguish genres and styles of music, as well as to describe the emotion of music and users' listening experience. If we only analyze music tags statistically, we can only get the user's interest information to a certain extent. By combining with neural networks, we can analyze these text data to learn deeper user preference characteristics, which can help to build a more complete user interest model.

In this study, for music name and music tag text data, unsupervised word vector training Word2vec technique is used to convert them into distributed word vectors for feature extraction, and then input to text CNN for feature processing; for other user features and music features, considering that the end-to-end training model has a clear task orientation and the learned word embedding vectors are often more accurate, therefore, the end-to-end model using the neural network word embedding layer is used for feature extraction.

The parameter matrix obtained after training is the word vector matrix, which represents the music name and music label, with low-dimensional dense characteristics, and the word vector is obtained with semantic information. Then, the word vectors of music names and labels obtained by Word2vec technique are input to the text of CNN for feature extraction since the convolutional neural network has the features of local connectivity, spatial sampling, and weight sharing. After the features of the music name and music label text are obtained in the convolutional layer, the features are further extracted and downsampled using the pooling layer spatial sampling method, which reduces the computational effort and enhances the robustness at the same time. Similar to biological neural networks, CNN also has the feature of weight sharing, which can avoid a large amount of data preprocessing work and complex data reconstruction process, and therefore has been more widely used in the field of natural language processing [7].

Therefore, in this study, text CNN is chosen to process music name and music label text.

2.4.1. Two-Tier Attention Mechanism

(1) *First layer attention mechanism.* After inputting the user feature set and music feature set into the word embedding layer respectively, the vectorized table of user features and music features is obtained.

The user set is represented as

$$U = \{u_1, u_2, u_3, \dots, u_m\}, \quad (1)$$

where

$$u_i = \sum_m u_{f_m}. \quad (2)$$

The user feature set is represented as

$$u_f = \{u_{f_1}, u_{f_2}, u_{f_3}, \dots, u_{f_m}\}. \quad (3)$$

The music collection is represented as

$$M = \{m_1, m_2, m_3, \dots, m_N\}. \quad (4)$$

Among them

$$m_j = \sum_n m_{f_n}. \quad (5)$$

The set of musical features is denoted as

$$m_f = \{m_{f_1}, m_{f_2}, m_{f_3}, \dots, m_{f_n}\}. \quad (6)$$

Through the fully connected network, the features of each user and each piece of music are obtained U_f . The attention mechanism learns the user's preference function for music features M_f , i.e., attention:

$$a_{ij} = \tanh(w_{ij}h_{m_j} + b_{ij}), \quad (7)$$

where $\{h_{m_1}, h_{m_2}, \dots, h_{m_n}\}$ is the hidden layer state value corresponding to the music feature set $\{m_{f_1}, m_{f_2}, m_{f_3}, \dots, m_{f_n}\}$, w_{ij} and b_{ij} are parameters obtained by model training, w_{ij} represents the weight of user u_i on the music m_k features, and b_{ij} represents the bias.

After normalization using the Softmax function:

$$a_{ki} = \frac{\exp(\sum_{j=1}^n a_{ij})}{\sum_{i=1}^m \exp(\sum_{j=1}^n a_{ij})}. \quad (8)$$

The preference C of the user u_i for the features of each music is obtained by multiplying and adding the hidden layer vector $\{h_{m_1}, h_{m_2}, \dots, h_{m_n}\}$ of the music features and the weight coefficient points:

$$C = \sum a_{ki}h_{m_j}. \quad (9)$$

The output of the first layer of attention mechanism results in different preferences of users for each music feature:

$$U_{a_i} = H\left(C, h_{m_j}, m_{f_j}\right). \quad (10)$$

(2) *Second layer of attention mechanism.* Input data: user's preference for each music feature $U_a = \{U_{a_1}, U_{a_2}, U_{a_3}, \dots, U_{a_n}\}$ user's historical music listening list $L_u = \{m_u^1, m_u^2, m_u^3, \dots, m_u^k\}$. Unlike the first layer of attention mechanism, this layer of attention mechanism takes each music as the minimum operational unit and learns from the music item level to get the user's preference for each music in the historical listening list.

The attention mechanism learns the different preferences of users for each track in the listening history list:

$$a_u^k = \tanh(w_k m_u^k + b_k), \quad (11)$$

where m_u^k denotes the k th track in the user's listening history list, w_k and b_k are the model parameters to be trained, w_k denotes the bias of user M towards a particular track, and m_u^k denotes the bias amount.

Normalization using the Softmax function yields u_i preferences for music k :

$$a_i = \frac{\exp(a_u^{iT} u_w)}{\sum_n \exp(a_u^{iT} u_w)}, \quad (12)$$

where u_w is the initialization weight and the final output of the second layer of the attention mechanism is a weight vector summed over the preferences of the user's u_i historical music listening list:

$$\varphi = \sum_k m_n^k a_i. \quad (13)$$

Then the weight vector output from the second layer of the attention mechanism is input to the fully connected layer, and the music vector with higher similarity is calculated and composed into a music recommendation list to realize the function of music recommendation. In the model training process, the adaptive moment estimation Adam optimization method is used. Adam algorithm is a first-order gradient optimization method for stochastic objective function, which has high computational efficiency and small memory requirement, and is suitable for attenuating the noise of the model, and the learning rate is set to 0.001 in this model.

3. Music Recommendation List Building

The output of the two-layer attention mechanism is the user's interest preference vector, which characterizes the user's recent music listening interest preference model. After obtaining this result, the next task is to generate a personalized recommendation list for the user based on the user's interest weight vector, and this paper uses the vector cosine similarity method to calculate the similarity between the user's interest weight vector and the music vector, and selects the Top- N music for users to generate personalized music recommendation list [14].

TABLE 2: Last.fm360Kusers dataset contains data.

Last. Fm360 users dataset	
Unique users	35,347
Artists with MBID	16,642
Artists with MBDID	10,373
Total lines	17,59,50

For the user interest vector φ_i , calculate the similarity with the music vector m_j :

$$\text{Sim}(\varphi, m) = \frac{\sum_{i \in U, j \in M} \varphi_i m_j}{\sqrt{\sum_{i \in U, j \in M} \varphi_i^2 \sum_{i \in U, j \in M} m_j^2}}. \quad (14)$$

In the above equation, φ_i represents the interest weight vector of user, m_j represents the vector representation of certain music, the music with higher similarity is calculated, and the top 7 music are selected to build the recommendation list for the user.

4. Experiment

4.1. *Data Set for This Study.* MSD [21] (Million Song Dataset), developed by Million Song organization, is the most authoritative and widely used dataset in the field of music recommendation, providing researchers with feature data information of nearly one million music songs for free. MSD dataset has collected and organized the information of some famous music websites, mainly including Second Hand Songs dataset and Musi Xnatch dataset. It contains comprehensive information about user characteristics and music characteristics. In this study, we use Foundation dataset, which contains basic information about users, music listening history, and various music characteristics. Since TheLast.Foretaste dataset contains a large amount of data that is inconvenient to handle, some researchers have trimmed down the data contained in it and taken some of the more complete user and music information to obtain Last.Fin360KiiSerS dataset, which contains the following data as shown in Table 2.

The Last.frn360Kusers dataset has two files.

- (1) listen to the song i self-record (userid-timestamp-artid-artname-traid-traname.tsv).
- (2) User information (userid-profile.tsv) The listening record file is the historical music listening records, playing time, playing times, etc. Of nearly 360,000 users, as well as information related to the music itself such as music name, artist, music ID, artist ID, etc. The user information file records all users' basic information such as user ID, age, gender, country, and registration time.

The listening record file contains field descriptions as shown in Table 3.

The user file contains field descriptions as shown in Table 4.

Since the Last. Fr360K users dataset does not contain music tag information, we need to extract music tags from

TABLE 3: Listening record file contains field descriptions.

Field	Field description
Userid	User ID
Timestamp	Playback time
Artid	Artist ID
Artname	Artist name
Traid	Music ID
Traname	

TABLE 4: User file contains field descriptions.

Field	Field description
Userid	User ID
Gender	Gender
Age	Age
Country	Country
Signup date	Registration time

TABLE 5: Experimental operating environment configuration.

Experimental environment	Environment configuration
Operating system	Windows8
Processor	Inter-core i7
Dominant frequency	3.2 Ghz
Memory	8 GB
Programing language	Python3.7
Development tool	Pycharm
Deep learning framework	Keras

The Last fantastic dataset. Since MSD has set a unified track id for the integration of music from different music sites, for the songs in the Last. Fr360 Users dataset, we only need to find its music tag according to the triad and create a new music ID-music tag file according to the traid-tag method.

5. Experimental Environment

Eras is an open-source neural network library that can be used as a high-level API for Tensor flow [20], which is the most widely used framework for deep learning. Eras is modular and scalable and contains algorithms commonly used in artificial intelligence, such as support vector machines and plain Bayes, as well as deep learning models such as CNN used in this study, which are convenient to use due to their highly integrated nature, and can also be switched between CPU and GPU, making it easy for researchers to efficiently construct the neural network structures needed for different tasks, as shown in Table 5. The neural network structure required for different tasks can be efficiently constructed.

6. Results and Comparative Analysis

For the two evaluation indexes, hit-rank and normalized discount cumulative gain (NDCG), this study takes the ranking list truncation index $K = 10$. Therefore, for the test set containing 1 positive case and 99 negative cases, hit-

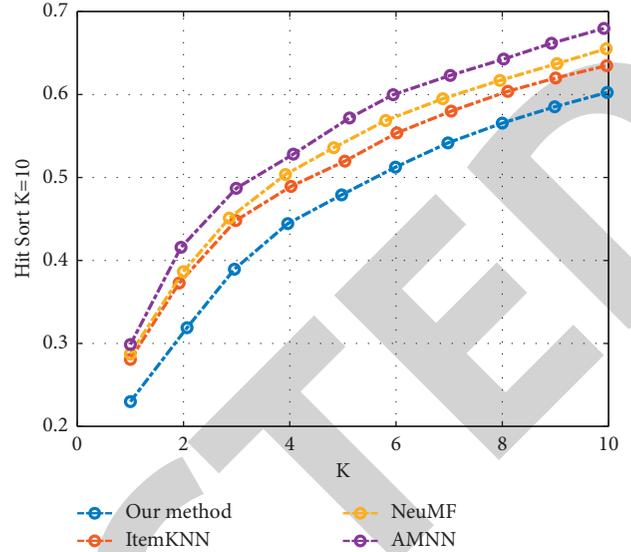


FIGURE 2: Comparison of hit-rank values of each algorithm.

rank measures whether a song that a user has listened to is in the top 10 items of the recommendation list, and can be used to measure the real-time of the recommendation results. The higher the value of the normalized discount cumulative gain, the better the overall quality of the recommendation list and the higher the relevance of the recommendation list to the user's interest model. The higher the value of the normalized discount cumulative gain, the better the overall quality of the recommendation list and the greater the correlation between the recommendation list and the user interest model.

Compared with the previous recommendation methods, the hit ranking value of this study decreases and the normalized discount cumulative gain index increases, indicating that both indexes are improved compared with the previous algorithms, and the NDCG value of this study improves by about 0.08 compared with the Itemknn method. Compared with the Neum method, the hit ranking decreases by 0.06 and the NDCG increases by 0.04, which shows that the attention mechanism in the model has a significant improvement. After adding music name and music label, the hit ranking and NDCG are further improved compared with the AMNN algorithm.

It can be seen from Figures 2 and 3 that the music recommendation model based on the two-layer attention mechanism proposed in this study has achieved better results in building music recommendation lists, and the quality of the generated recommendation lists has been improved to a certain extent compared with previous algorithms. The incorporation of the attention mechanism in the model makes the recommendation results more interpretable; by integrating with natural language processing technology to process music names and music tags, the feature information of the source data can be better obtained.

In addition, considering that the number of music in the user's history list may have an impact on the

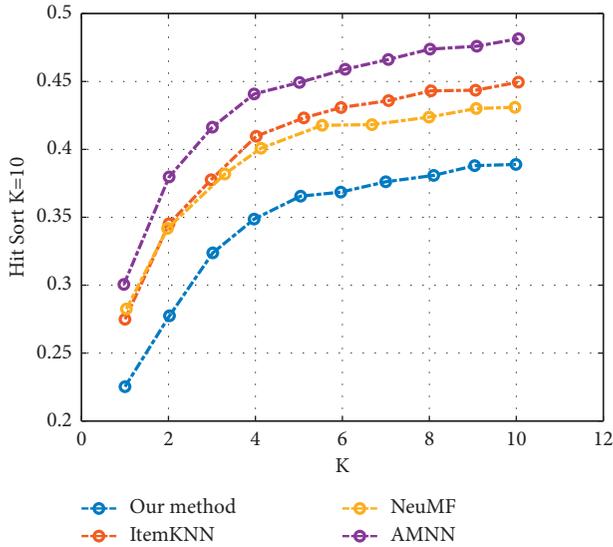


FIGURE 3: Comparison of NDCG values of each algorithm.

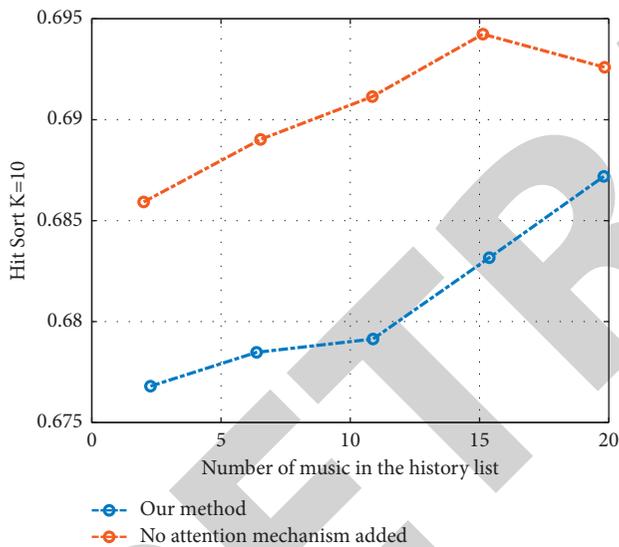


FIGURE 4: Effect of the number of music in the historical listening list on the hit-rank value.

recommendation list, we designed a comparison experiment, and the results are shown in Figures 4 and 5. For the deep learning method with the attention mechanism, when the number of music in the user's history list is greater than or equal to 15, a more complete user's interest preference can be obtained, and the method without the attention mechanism does not achieve the maximum value in the range of 0–20 songs. The method without the attention mechanism does not achieve the maximum value in 0–20 songs, and there is still room for improvement, which indicates that more user listening information is needed to get better recommendation results. This verifies the effectiveness of adding the attention mechanism to the deep learning method, which helps to improve the accuracy of the recommendation and reduce the complexity of the calculation.

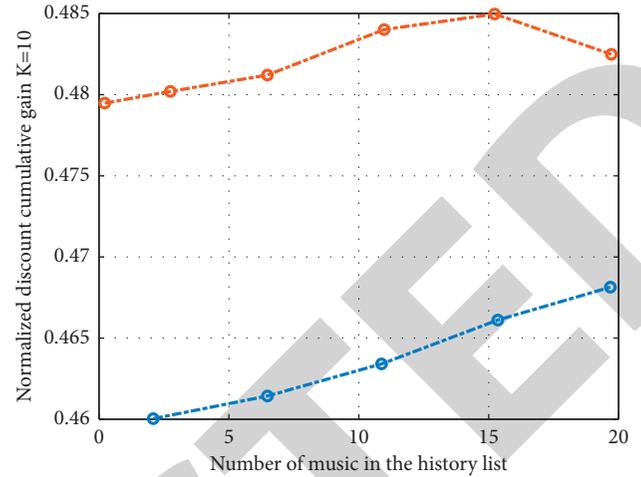


FIGURE 5: Effect of the number of music in the historical listening list on the NDCG value.

7. Conclusions

The proposed algorithm model based on the two-layer attention mechanism includes the processing of text convolutional neural networks for music name and music label text data. After obtaining the user's interest weight vector, the vector cosine similarity method is used to calculate the music with high similarity and generate personalized recommendation lists for the users. Experiments show that the NDCG value of this method is improved by about 0.08, and the overall quality of the recommendation list is greatly improved.

Data Availability

The dataset used in this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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