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Research on Personalized Music Recommendation Model Based on Personal Emotion and Collaborative Filtering Algorithm

Yingqiang Wang
School of Information Technology, Mapua University
School of Electronic Information Engineering, Xi'an Siyuan University

Elcid A.Serrano* YINGQIANGWANG@MYMAIL.MAPUA.EDU.PH
School of Information Technology, Mapua University

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Abstract

In today's digital age, music plays an important role in people's lives, but the current music recommendation system is mainly based on content, the use of collaborative filtering and other algorithms, can not according to the user's real-time emotional state, recommend suitable for the current mood of the music. This paper aims to design and implement a personalized music recommendation model based on personal emotional information and collaborative filtering algorithm. The model mainly includes two sub-models: the emotion and music selection tendency model and the music recommendation model based on collaborative filtering algorithm. By analyzing the user's emotional state and music preference, the model provides music recommendation services that are more in line with the user's psychological state, so as to improve the user experience and recommendation accuracy. The model designed in this paper can effectively solve the problem that personalized music recommendation cannot be performed according to the user's real-time emotion. At the same time, it can also be used as a reference for other personalized recommendation models.

Keywords: personalized music recommendation, personal emotion, collaborative filtering algorithm

1. Introduction

In today's digital age, music recommendation system play an increasingly important role in helping people discover new music, expand music taste, and enhance music experience. However, the traditional music recommendation system often has some problems, such as the recommended music is too general, and it cannot accurately capture the personalized needs of users. These problems mainly stem from the fact that the system cannot well understand the user's emotion and mood, which is one of the important factors that affect people's music preferences and choices. One of the key challenges in personalized music recommendation systems is how to effectively integrate users' emotional information. People will have different preferences for music in different emotional states, for example, they may prefer lively and upbeat music when they are happy, while they may prefer lyrical tunes when they are melancholy. Therefore, it is of great significance to combine personal emotional information to improve the accuracy and personalization of music recommendation systems.

This study aims to explore how to use users' emotional information to improve the performance of music recommendation systems. By analyzing the correlation between users' emotional states and music preferences, music recommendation systems can provide users with more personalized music recommendation services that are consistent with their psychological states, thereby enhancing user experience and user satisfaction, and further promoting the development of personalized recommendation systems in the field of music.

This paper mainly includes the following parts: the first part introduces the research background, the second part introduces the research status, the third part introduces the data set used in this paper, the fourth part introduces the design and implementation of the model, and the fifth part introduces the experimental results of the algorithm and analyzes the results.

2. Research status

2.1. Research status of personalized music recommendation system

Personalized music recommendation systems have been widely developed and applied in the past few years and researchers are constantly exploring new methods and technologies to improve the performance and user experience of recommendation systems. At present, many scholars have carried out various studies on music personalized recommendation systems.

In view of the low user satisfaction of the current personalized music intelligent recommendation system, Guo (2023) designed a personalized music intelligent recommendation system oriented to user preferences. Mao (2023) conducted research on the problems of low recommendation accuracy, lack of personalization, cold start, and sparse data in traditional recommendation methods. In order to improve user experience and improve recommendation efficiency, he conducted sentiment analysis on user comment texts and proposed a hybrid recommendation method that introduces sentiment weights, achieving personalized music recommendation based on sentiment analysis. Yao (2023) used deep learning technology to focus on the essential characteristics of music such as audio and lyrics, used content-based recommendation method to recommend music matching each user's hobbies, and improved the recommendation algorithm to improve the accuracy of the recommendation system. Kostrzewa et al. (2024) built a content-based recommendation system based on three basic factors: genre classification of neural network, Mel-frequency cepstral coefficient (MFCCs) and song rhythm . Based on the KDEF dataset, Sharath et al. (2023) used Caffemodel to detect faces and mlp classifier to detect facial emotions respectively and proposed playlists that could improve their emotions. Zhang (2024) proposed a personalized music recommendation method based on tag information and recurrent neural network, the accuracy of personalized music recommendation is always above 93%, and the recommendation time is always less than 0.6s. Liu et al. (2023) designed an LSTM-based model to select the most appropriate music according to the user's previous mood and current emotional stimuli to help improve their mental state. De Prisco et al. (2022) proposed Moodify, a new music recommendation system based on reinforcement learning (RL), given a target emotional state, and starting from the assumption that an emotional state is completely determined by the sequence of recently played music tracks, the proposed RL method aims to learn how to select a list of music clips that better "match" the target emotional state.

2.2. A Survey of Collaborative Filtering Algorithms

Collaborative filtering algorithm is a common method in personalized recommendation system, which makes recommendations based on user behavior data (such as user's historical behavior, preferences, etc.). At present, many scholars have carried out a number of studies on collaborative filtering algorithm and its applications.

Garanayak et al. (2022) Mamata mainly focuses on content-based, population-based and collaboration-based filtering algorithms, and tries to combine them using hybrid methods to develop a recommendation system using the popularity and rhythmic content of songs. Magron and Févotte (2022) introduced neural content aware collaborative filtering, which uses deep learning to extract content information from low-level acoustic features and models the interaction between the user and the song embedding, effectively solving the hot-start and cold-start problems in music recommendation tasks. Niu (2022) studied how to use Spark to achieve efficient music system recommendation, the item-based collaborative filtering algorithm realizes music recommendation by avoiding the user's personal information, and the optimized performance is improved by 54.8% compared with that without optimization. Valera et al. (2021) proposed a group recommendation system in the field of music and conducted an extensive comparative study of different collaborative filtering algorithms and aggregation methods.

3. Introduction to the Dataset

In this model, the data sets that need to be used mainly include two:

1) Emotion and music selection dataset. Through searching and researching, the author did not find a suitable dataset for emotion and music selection. In this paper, the author self-built a dataset for emotion and music selection through questionnaire survey. When designing the questionnaire, the authors mainly investigated the selection tendency of music genre based on the nine emotional categories (happiness, excitement, anger, stress, sadness, fear, surprise, calm, and boredom) in the DEAP dataset, such as: what type of music do you want to listen to when you feel excited, etc. To facilitate the analysis of the dataset, each person's choice of music in each emotion is treated as a row in the dataset, which means that each person's survey data corresponds to nine rows of data in the dataset. In the end, a total of 1024 people were surveyed. The dataset has a total of 9216 rows of data. Among the individuals surveyed, there were 494 males, accounting for 48.24%, and 530 females, accounting for 51.76%. In the survey, the largest number of individuals aged between 18 and 25 were 854, as this questionnaire mainly targeted university students. The dataset structure is shown in Table 1 and has been uploaded to pan.baidu.con[1].

Table 1: The Emotion and music selection dataset structure

Id	Emotion	sad	sweet	happy	lonely	quiet	catharsis	inspirational	cure	miss	other
1	happy	0	1	1	0	0	0	0	0	0	0
2	excited	0	0	1	0	0	0	0	0	0	0
3	angry	0	0	0	0	1	0	0	1	0	0
4	stressed	0	0	0	0	1	0	0	1	0	0
5	sad	0	0	0	0	1	0	0	1	0	0
6	fear	0	1	1	0	0	0	0	0	0	0
7	surprise	0	0	0	0	1	0	0	1	0	0
8	calm	0	0	1	0	1	0	0	0	0	0
9	boring	0	0	1	0	0	0	0	0	0	0

1. https://pan.baidu.com/s/1uVbbgjghHcGY5KcxGD6H-Q?pwd=33sz

2) User music dataset Last.fm. The Last.fm is a public dataset that can be downloaded from www.kaggle.com . It contains user data (user ID, username, registration time, etc.), music data (music tracks, artists, album information, etc.), user listening history (records the user's listening history of music tracks and artists, including the number of plays, listening time, etc.), user tags (tags added by users to music tracks and artists, etc.), Used to describe the style, emotion and other characteristics of the music), social network relationships (social relationships between users, such as friend relationships, follow relationships, etc.). Therefore, Last.fm dataset is widely used in the research and development of music recommendation systems. Researchers and data scientists can use these datasets to analyze users' music preferences, build personalized recommendation models, and explore user behavior patterns and social network structures.

4. Model Design

4.1. Algorithm Description

Collaborative filtering recommendation algorithms are mainly divided into user-based collaborative filtering recommendation and item-based collaborative filtering recommendation. It predicts a user's rating or liking degree for an item according to the user's historical behavior and the similarity between multiple users. It is mainly used to mine association rules between users and between items, and make recommendations according to the obtained association rules. The Similarity calculation methods generally include Jaccard similarity, Cosine Similarity, Pearson Correlation Coefficient, and Euclidean Distance. This article uses Pearson Correlation Coefficient to calculate similarity, and the Pearson Correlation Coefficient calculation formula is as follow.

$$\mathrm{r} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{1}$$

4.2. Model design

The personalized music recommendation model designed in this paper combines personal emotion and collaborative filtering algorithm to provide users with music recommendations that are more in line with their preferences and emotions. Firstly, the model of emotion and music selection tendency is established, which aims to recommend the music that matches the user emotionally according to the user's emotional state. Secondly, a user-based collaborative filtering algorithm is used to build a recommendation model according to the user's listening history social network relationships etc. The process of the model designed in this paper is shown in figure 1.

(1) Emotion and music preference model based on collaborative filtering algorithm

In this model, the user's emotion is matched with the emotion label of the music, and the mapping model between the user's emotion and the music's emotion is constructed. The input of the model is the user's emotional state, and the output is the emotional type of music the user tends to listen to. For this dataset, we use a user-based collaborative filtering algorithm to model the emotion and music preference. The process of building the model is as follows:

1)The data of each emotion type were cyclically screened from the data set to form a sub-data set of emotional states.

2) Pearson correlation coefficient was used to calculate the similarity of selected music types in the emotional sub-data set.

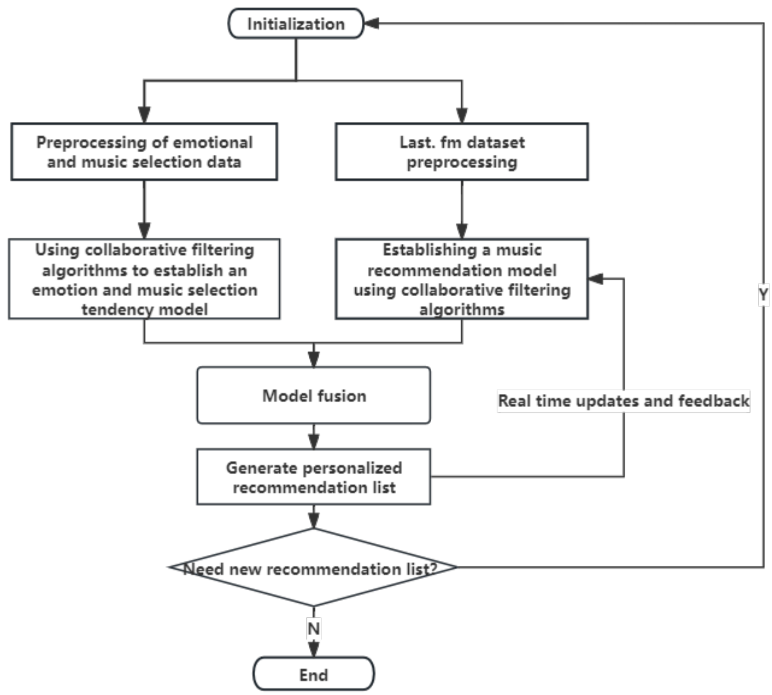

Figure 1: Implementation process of personalized music recommendation model.

3) The top two music genres are selected from the results and used as the output of the model.

(2) Music recommendation model based on collaborative filtering algorithm

This thesis mainly use user-based collaborative filtering algorithm to recommend music to users according to their listening history and tags. The building process of the model is as follows:

1) Preprocess the Last.fm dataset: clean and process the collected data, remove incomplete or erroneous data, unify the format, etc.

2) Similarity calculation of computer user listening history: Pearson correlation coefficient is selected to calculate the similarity between songs.

3) Generate user recommendation list: According to the similarity calculation results and the user's preference data, generate the user's recommendation list.

4) Recommendation ranking: Sort the recommendation results to ensure that the most relevant and emotionally relevant music is prioritized for recommendation.

(3) Model fusion and recommendations

In order to recommend music to users more effectively and improve the accuracy of music recommendation, this paper combines the emotion and music selection tendency model with the music recommendation model based on collaborative filtering algorithm. The combination method is as follows:

1) The user's emotional input (which can be perceived in real time through deep learning and other methods) is input into the emotion and music preference model, and the emotional type of music the user tends to listen to is output.

2) A music recommendation model based on collaborative filtering algorithm is used to generate a list of recommended music for users.

3) The recommended music is filtered from the recommendation list to match the emotional type of music that users tend to listen to.

4) Ranking of recommendation results: The recommendation results are ranked to ensure that the most relevant and consistent with the user's mood music is recommended first.

(4) Real-time update and feedback

In order to improve the accuracy of the model, the model provides a user feedback channel for the recommendation results, collects user preferences and emotional feedback, and continuously updates the emotion model and recommendation algorithm according to user real-time behavior and feedback to improve the accuracy of the recommendation.

5. Experimental results and discussion

5.1. Analysis of experimental results of Emotion and Music choice tendency model

In this paper, the Pearson correlation coefficient is used to calculate the similarity, and the user-based collaborative filtering algorithm is used to generate the recommended music types. The recommended music types are ranked, and then the first two types are selected for ranking. The experimental results are shown in Table 2.

In the previous study, the author used statistical methods to recommend music selection types, and the statistical results are shown in Table 3. After comparing the two results, this paper found that the recommendation results were basically consistent. However, the algorithm designed in this paper is more suitable for large-scale data calculation, and with the increase of data scale, the data model can be updated in real time, and the accuracy of recommendation is higher.

Table 2: Experimental results

Emotional types Recommended results	The first recommended music type	The second recommended music type
happy	happy	sweet
excited	happy	inspirational
angry	quiet	cure
stressed	quiet	cure
sad	quiet	cure
fear	sweet	happy
surprise	happy	quiet
calm	quiet	happy
boring	happy	quiet

5.2. Analysis of Experimental results of music recommendation model based on Collaborative filtering algorithm

In this paper, the Pearson correlation coefficient is used to calculate the similarity, and the recommendation analysis is carried out on the Last.fm dataset based on the user collaborative filtering

Table 3: Mood and music selection type

mood state \ music type	sad	sweet	happy	lonely	quiet	catharsis	inspirational	cure	miss	other
happy	19.1	36.2	72.0	9.7	34.7	10.7	31.3	37.1	11.7	5.7
excited	14.9	23.0	66.8	7.6	21.5	17.2	30.2	19.6	7.7	5.3
angry	28.4	10.4	21.9	13.3	36.5	36.3	14.5	31.7	7.3	6.4
stressed	27.7	10.3	26.6	14.5	40.2	24.0	25	38.1	10.7	3.6
sad	43.8	11.7	25.2	19.0	35.3	15.2	16.0	35.1	14.9	4.2
fear	16.4	15.7	40.0	11.9	31.0	12.8	24.3	28.9	9.08	7.2
surprise	15.1	13.4	39.2	11.6	35.9	13.7	19.0	26.2	9.57	7.9
calm	18.1	17.8	38.4	13.2	55.7	11.0	19.8	31.0	11.9	4.2
boring	26.2	23.8	50.3	20.4	40.9	19.0	27.3	31.8	18.0	5.2

algorithm. In this experiment, 80% of the dataset is used as the training set, and the remaining 20% is used as the test set. In order to measure the effectiveness of the algorithm designed in this paper, the Precision and Recall of the algorithm are calculated according to the actual listening records and the recommendation results. Precision actually refers to the proportion of the user's preferred items in the recommendation list, while Recall actually refers to the proportion of the user's preferred items in all the users' preferred items in the whole system.

After many experiments, the number of nearest neighbor users in the algorithm is 30, the number of recommended lists is [5,30], and the step size is 5. The results of precision and recall are shown in Figures 2 and 3 respectively. The results show that the user-based collaborative filtering recommendation algorithm designed in this paper can improve the quality of music personalized recommendation and prediction.

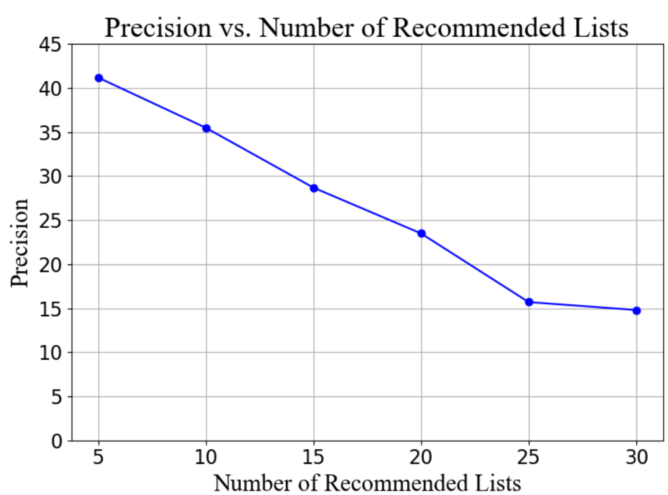

Figure 2: Accuracy Results.

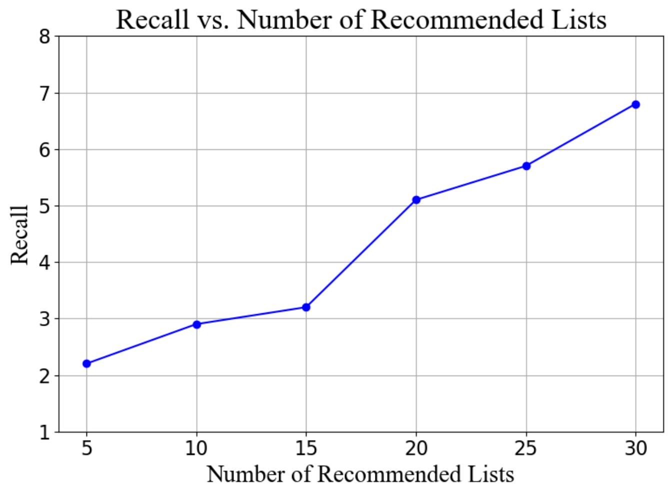

Figure 3: Recall Results.

6. Conclusion and Prospect

Aiming at the situation that the current personalized music recommendation system cannot effectively recommend according to the user's emotion, this paper designs a personalized music recommendation model based on personal emotion and collaborative filtering. The model includes the emotion and music selection tendency model and the music recommendation model based on collaborative filtering algorithm, which can recommend the music list suitable for the current mood according to the user's real-time emotional state and the user's preference, so as to make personalized recommendation to the user more effectively. There are still some shortcomings in this paper. For example, in this paper, it is assumed that the music in the music library has used emotion tags. In the subsequent research, methods such as deep learning can be used to generate emotion labels for music libraries. The user emotion perception model and algorithm still need further research.

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