MemoMusic: A Personalized Music Recommendation Framework Based on Emotion and Memory

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***Abstract*—Music is universally recognized as an effective way for human to express emotion and regulate emotional states. But perceived music emotion is subjective and much dependent on culture, environment, and life experience. Therefore, personalized music recommendation is necessary to gain user satisfaction and navigate a listener to a more positive emotional state as well. Existing work on emotion-based music recommendation and personalized music recommendation often lack of considering the impact of past life experiences on music emotion perceiving. We argue that memories associated with music could play a vital role in determining the new emotional states after music listening. To verify our hypothesis, we propose a personalized music recommendation framework called MemoMusic, which estimates the new emotional state of a listener based on an individual's current emotional state and possible memory associated with the music being listened to. For the preliminary experiment, a dataset of 60 piano music was collected and labelled using the Valence-Arousal model from three categories of Classical, Popular, and Yanni music. Experimental results demonstrate that memory is actually an important factor in determining perceived music emotion. And MemoMusic based on emotion and memory achieves a good performance in terms of improving a listener's emotional states.**

Keywords—Personalized, music recommendation, emotion, memory, valence, arousal

I. Introduction

Music is one of the most ancient and popular art forms in the human world. Musicians compose music to express their emotions; performers play music to deliver music emotion and their own feelings; audiences listen to music to get engaged and resonated. While music is universally recognized as an effective channel to express emotion and to regulate emotional states, perceived music emotion is highly subjective and varies from person to person [1, 2]. Major factors that affect emotion induced by music include culture, environment, and life experience [3]. While cultural and environmental impacts are widely discussed, the factor of life experience is seldom explored. The reason could be that, to some extent, life experience often determines one's cognitive ability, which is hard to measure and assess. Since life experience is much diversified and individual, only those life experiences that directly involve music listening will be considered here. That is, whenever the same music is heard, people will recall the memory associated with music, or vice versa [4]. And the music emotion is much dependent on the event happening then and there. For example, one may enter similar emotional states just because the music being heard is the one played on his or her wedding ceremony. From this perspective, we argue that memories associated with music could play a vital role in determining the new emotional states after music listening.

Yet, existing research work in neither emotion-based music recommendation [5, 6] nor personalized music recommendation [7] has given enough attention to individual memory. Emotion-based music recommendation usually assumes that the listener's next emotional state is completely determined by the music being listened to. And personalized music recommendation depends too much on the history playlist of the listener, thus falls short of fresh and exciting emotional experience. Therefore, we propose a novel personalized music recommendation framework called MemoMusic, which estimate a listener's next emotional state by considering both the current emotional state and the individual's memory associated with the music being listened to.

To preliminarily verify our hypothesis, we have gathered 60 piano music from the Internet composed of three categories, namely, Classical, Popular, and Yanni music [8]. One reason for choosing Yanni music is that it is a unique label between Classical and Popular. The other is that Yanni music is very inspiring and full of the sense of pictures. Experimental results from 56 subjects demonstrate that memory is a major contributing factor for music emotion, and MemoMusic can navigate listeners to more positive emotional states.

The rest of the paper is organized as follows. Section 2 briefly reviews related work in emotion-based music recommendation and personalized music recommendation. Section 3 details the proposed framework of MemoMusic. The experiment is described and analyzed in Section 4, while Section 5 concludes the paper with future work.

II. Related Work

This section reviews the previous work on emotion-based music recommendation, personalized music recommendation, as well as exploring the relationship among memory, emotion, and music.

A. Emotion-based Music Recommendation

There have been many previous attempts to conduct emotion-based music recommendations. One classical approach that recommends music based on emotion includes matching music features with emotion. One attempt using this approach is a research conducted by Kuo in which a recommendation model is constructed from music in animation [5]. To get the emotion of the music, they first manually labelled the emotion each piece of music retrieved from the 20 animations. Then they extracted several music features (such as melody, rhythm, and harmony) and matched the emotion with the music features. Finally, they used the music features to recommend the music that contains certain emotion.

Other attempts involve getting users' current emotional states such as using physiological input. Ayata et al. used a wearable computing device that is integrated with a galvanic skin response (GSR) and photoplethysmography (PPG) physiological sensors to get accurate user emotion state and conduct music recommendations based on that data [8].

One recent research in this field that builds a music recommendation system by extracting the emotional features of music and estimates audiences' emotional states was conducted by Deng from Hong Kong Baptist University [9]. In this approach, a resonance-arousal-valence (RAV) model is built to map the musical features and their emotional impact. Then, an emotion-intensity-decay (EID) model and an emotion-state-transition (EST) model are built to predict the listener's changing emotional state. Finally, a ranked list of music is recommended to match with an assumed emotional state.

B. Personalized Music Recommendation

There are also some previous attempts to build personalized music recommendations. As pointed out by Adomavicius, three approaches widely used for building recommender systems are content-based, collaborative, and hybrid recommendations [10]. Since content-based and collaborative approaches each has its shortcoming, the hybrid approach usually gives a better outcome and is thus more welcomed by researchers.

There are several ways of recommending music using the hybrid approach. One straightforward method is to combine the collaborative approach with the music genre [11], while other more complex methods include combining content-based, collaborative, and music emotion [12]. To deal with cold start and grey sheep users that are common problems in the collaborative recommendation approach, researchers also come up with different approaches, such as using playing coefficients for artists and users [13].

C. Music, Emotion and Memory

None of the music recommendation systems presented above used user memory as a factor to determine the next music. However, as many research works have shown, memory evoked by music is one important factor that influences users' emotion after listening to music.

One research done by Maksimainen [14] concerning how memory induces pleasant emotions with musical and pictorial stimuli shows that memory strongly influences the emotion induced. Her paper states that "stimuli chosen based on memories were more inductive of joy, kinship, tenderness, sadness, and melancholia than stimuli chosen based on the stimulus features," which is a good indicator that memory is an important factor to consider when predicting users' emotion after listening to music.

Another research done by Baumgartner [15] on which kind of memory is likely to be induced by music also shows that hearing music evokes memories of the original episodes. He further claims that those memories of personal experiences induced by music were strongly affectively charged, and "the recollections triggered by the music were described as vivid and emotional and as involving a reliving of, and being accompanied by imagery descriptive of, the original episode". Other findings of this research include that "there was a fairly strong correlation between a person's evaluation of the piece of music and his or her evaluation of the autobiographical episode" and that "people's ratings of the affective characteristics of the personal experience corresponded to the feelings induced by hearing the piece of music." These findings directly support that the memory induced by the music that people hear directly correlates to the emotion perceived when the user listens to the music, which shows the significance of considering user memory when building emotion based and personalized music recommendation systems.

Finally, there is also evidence that familiarity with music is linked to increases in the intensity of emotional response, perceived meaning in music, the vividness of mental imagery, and detailed recollection of memory [16, 17]. This finding is another proof of how memory may affect participants' emotion after listening to a piece of music.

In view of the above-mentioned unresolved issues by emotion-based music recommendation and personalized music recommendation, and the interaction among music, emotion and memory, we argue that memory is an important factor to consider in order to achieve real personalized music recommendation. Therefore, we propose a new approach called MemoMusic to personalized music recommendation, which considers not only emotion, but also memory in music recommendation. This new approach will be detailed in the next section.

III. Proposed Method

To start with, two assumptions are made. As mentioned above, emotion can be influenced by many factors such as time, location, weather, people being with, and things happening around. Since these factors are dynamic and complex, it is difficult to accommodate all factors into one single model. We simply assume that the current emotional state of a listener before music listening can be obtained by user feedback or other means. And the second assumption is that the next emotional state of the listener will be determined by the current emotional state, the emotion expressed by the music being listened to, and possible individual memory triggered by the music.

Like many previous existing works in this field, we used the Valence-Arousal model to represent both the emotion a piece of music expresses and the emotion of a listener. In the following parts of this section, we will introduce the proposed method and system of the personalized music recommendation system MemoMusic in detail. First, we will describe the general picture of the framework. Then, we will detail how emotion is extracted from memory and integrated into the system to help with estimating the listener's current emotional state during music listening. And finally, based on the estimated current emotion of the listener, the next music for the listener will be recommended.

A. A Personalized Music Recommendation Framework

The proposed personalized music recommendation framework named MemoMusic is shown in Figure 1. The workflow of MemoMusic is as follows. First, the system retrieves a listener's current emotional state before listening to music. Then, by considering the listener's interest, previous listening behavior, the system will recommend the first music with similar valence and arousal values to the emotional state of the listener. Further, MemoMusic collects possible memory in text input by the listener during music listening and estimates the next emotional state of the listener. Finally, MemoMusic recommends the next music that has a higher valence and a similar arousal to the next emotional state of the listener. In this way, the listener can reach a more positive emotion state after listening to a list of recommended music. Two core algorithms will be described in subsections B and C.

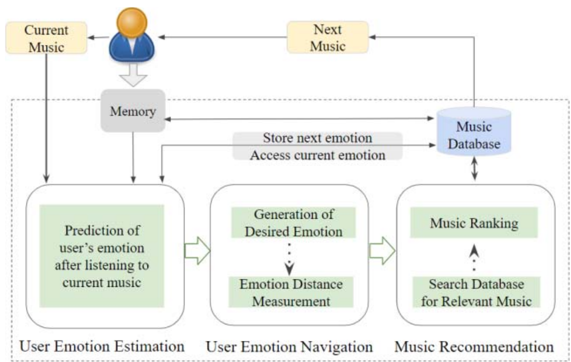


Fig. 1. The framework of MemoMusic.

B. Emotional State Estimation Based on the Memory Triggered by the Music

Memory is collected as the user listens to the music. Since memory can influence one's perception of music, considering users' memory related to the music may give the system a more effective and accurate way of recommending the music. Collecting memory can be difficult since not all users hope to share their memory with the platform. Currently, MemoMusic collects user memory from the comments the users give to the music during music listening.

In MemoMusic, memory works in the system as an important element to help determine whether the music brings positive or negative emotion to the listener. To get the emotional value of memory, we utilize a service from Baidu called "sentiment classify". When given a sentence or paragraph, this service provides whether this sentence is positive or negative and by what percentage. Then a weight is assigned to this value and the weighted value is added to the valence component of the current emotional state of the user to get an estimation of the user's next emotional state values after listening to the music. The formula used to calculate the final valence is:

$$V_f = V_{predict} + weight \ * V_{memory} \ , (1)$$

where $V_{predict}$ is the valence value calculated by the system to predict the user's emotional state after listening to the music but without the consideration of the memory and V_{memory} is the value returned by Baidu.

The weight should be dynamic and different based on each individual listener. Therefore, one algorithm is used to calculate the values of the estimated emotional state after listening to the music. To collect data as the basis of this calculation, the first two rounds of our experiment used 5 as the weight and a dynamic weight based on the user's previous feedback after the two rounds. Here we also give out the formula to calculate the weight:

$$\text{weight} = \frac{\sum_{\text{i\_mem}} \left(\frac{V_{after} - V_{before}}{V_{mem} - 0.5}\right)}{N_{mem}}, (2)$$

where $\sum_{\text{i\_mem}}(\ )$ sums up all cases in the previous rounds when the user has a memory input. V_{after} is the user's self-reported valence after listening to the music and V_{before} is the user's self-reported valence before listening to the music. This differs from the $V_{predict}$ on the top in that the latter one is predicted by the system while the former one is self-reported by the user. $V_{memory} - 0.5$ is used because the value returned from Baidu has a range of [0, 1] where 0 is the most negative and 1 is the most positive.

C. Music Recommendation for Navigating a Listener to More Positive Emotional States

Although the ultimate goal is to guide the user to a more positive emotional state, we suggest recommending a piece of music that has a similar Valence-Arousal value to the user's self-reported emotional state as the first piece of music that the user listens to. This expression of similar emotion can give the user a feeling of compassion. Especially when a user is experiencing a depressed mood, the attempt to positively influence the user by a piece of music that shows the expression of compassion may be more effective than trying to directly influence the user by playing a piece of music that is joyful and exciting.

After the warm-up, MemoMusic will attempt to cheer up the listener little by little and the goal is to navigate the listener to a more positive emotional state, which is taken as having a relatively high Valence value and a relatively low Arousal value. Since memory plays a key role in determining the next emotional state, MemoMusic assigns significant weights to memory when estimating the next emotional state of a listener.

As the next emotional state of a listener has been estimated, the next music will be recommended accordingly. That is, to look up the music corpus for a piece of music that is the closest in terms of VA values. The distance metric used is Euclidean Distance.

Like our approach to assigning weight to memory, the algorithm that decides to what extent a piece of music may affect the listener is given as follows:

$$\Delta V = \frac{\sum_{i\_exp}\left(\sum_{i\_music}\left(\frac{V_{after} - V_{before}}{V_{music} - V_{before}}\right) / 4\right)}{N_{exp}} \times (V_{music} - V_{prev}), \quad (3)$$

where ΔV calculates the estimated change of valence considering the user's previous listening behavior, the previous emotion state, and the valence of the music. Then the user's predicted new valence after listening to the music $V_{predict}$ can be calculated by adding ΔV to the previously estimated valence:

$$V_{predict} = \Delta V + V_{prev} \,. \quad (4)$$

After $V_{predict}$ is calculated, V_f is then calculated when the user inputs a piece of memory while listening to the current music. The calculation of arousal works in the same way. This is important because it helps with estimating a user's emotion after listening to a piece of music.

IV. Experiment

To evaluate the effectiveness of the proposed personalized music recommendation framework, we have developed an online system to carry out the experiment. In the experiment, 56 participants were invited to use MemoMusic that collects the Valence-Arousal values of their emotional states and recommends music based on their self-reported initial emotional states and possible memories associated with music being listened to.

A. Dataset and Music V-A Labelling

The dataset consists of 60 pieces of piano music from the Internet (see Table I) from three categories: Classical, Pop, and Yanni music. Yanni music is the music composed by the world-renowned composer Yanni, who says “Music is an incredibly direct language. It bypasses language and logic, and speaks directly to your soul.” So, music is the way Yanni communicates his feelings of life with his audiences. In general, Yanni music is very emotional, inspiring, and imagery. Thus, Yanni music is speculated as easy to trigger memories.

As mentioned above, we used Valence-Arousal model as the model to represent the emotion of music and the self-reported emotional states of the participants after listening to the music as well. The valence has an integer value in the range of [-5, 5], while arousal is in the range of [0, 10]. Nine volunteers who are either music professionals or experienced music fans helped label the V-A value of each piece of music, resulting in the final V-A values taking the medians.

TABLE I. MEMOMUSIC DATASET AND CORRESPONDING V-A VALUES

music name（Classical）	***V***	***A***		***music name（Pop）***	***V***	***A***		***music name（Yanni）***	***V***	***A***
BWV 807	3	5		A Comme Amour	-3	3		Almost A Whisper	1	4
Canon In D	4	4		Always With Me	3	3		Blue	3	6
Chopin C Sharp	-2	1		Castle In The Sky	-3	1		Breathe	2	5
Chopin E Flat	5	8		Da Yu	-2	2		Butterfly Dance	5	7
KV 265	4	4		Despacito	3	7		Enchantment	4	6
La Campanella	4	9		Kiss The Rain	-2	2		Farewell	-4	6
La Plus Que Lente	2	5		My Heart Will Go On	2	4		If I Could Tell You	-3	8
None Shall Sleep	1	4		Pirates Of The Caribbean	4	10		In The Mirror	3	7
The Blue Danube	5	10		Remember Me	-2	6		In The Morning Light	2	6
The Swan	4	6		Rhapsody In Blue	1	5		In Your Eyes	3	6
Trumpet Voluntary	3	5		River Flows In You	2	3		Marching Season	0	10
Turkish March	5	9		Summer	5	5		Nightingale	2	7
Brahms Lullaby	3	3		This Is The Moment	2	3		Nostalgia	-2	9
Clair De Lune	1	6		Three Inches Of Heaven	-3	3		One Man's Dream	1	6
Moonlight Sonata	-4	7		Spirited Away Theme	-2	4		The Flame Within	0	5
Love’S Sorrow	3	6		Melody Of The Night 5	-3	3		The Mermaid	-2	7
Minuet In G Major	3	5		When Love Became The Past	-4	3		The Rain Must Fall	4	7
Prelude And Fugue	1	5		Mariage D’Amour	-4	2		To The One Who Knows	3	5
Sonata No.17 In D Minor	-3	8		Those Bygone Years	-2	4		When Dreams Come True	2	6
Standchen	-1	5		Farewell	-4	2		Whispers In The Dark	1	5

B. Experiment Description

The experiment consists of five rounds of music recommendations. The participants are recommended to finish the experiment in a continuous five-day time range but no more than one round each day. During the register stage, the participants need to provide their genders, occupations, age ranges (10~20, 20~30, 30~40, 40~50, 50~60, or 60+), favor level of music (range in [1, 5], 1 for not interested in music and 5 means music is essential for their everyday life), as well as the music genre they prefer the most (Classical, Pop, or Yanni music). In each round of the experiment, the participants will be recommended with four pieces of music one by one. After logging into the system, the participants will be required to input their current Valence and Arousal values by clicking a value on a coordinate map with Valence on the x-axis within [-5, 5], representing a mood from much depressed to extremely joyful and Arousal on the y-axis within [0, 10], from being calm to highly excited.

Then, the participants will be recommended with the first music of the current round. While each music is playing, the participants can input by text their memory triggered by the music. When the current music comes to an end, the post-listening V-A value needs to be input as a red dot on the coordinate map. The pre-listening V-A value will be provided as a blue dot for reference. Feedback on whether they are familiar with the music is also needed as within a range of [1, 5], with 1 for not familiar and 5 for very familiar. But the feedback will not affect the music recommendation of the current round to simulate a real music recommendation system without frequent user feedback. At the end of each round, the participants should provide the music they like the most for the current round as well as an overall rating to the music recommendation within the range [1, 5] with 1 for not satisfied and 5 for very satisfied.

C. Experimental Results

The experimental results are analyzed as a whole and as individual cases, respectively.

a) Overall Statistical Analysis

The experiment has several interesting findings in general. Fig. 2 is a heatmap reflecting the rating participants gave to each round of the experiment. The y-axis represents the round, whereas the x-axis shows the rating. The shade on the map represents the number of votes for a specific score for the round. The largest number is rating 4 ("pretty satisfied") in the 4th round with a total of 32 votes. For each round, most participants voted for 4, and the colors go darker from top to bottom which means more votes for the rating 4 at rounds 4 and 5. Yet, due to the website access issue, MemoMusic only achieved a humble satisfaction of 65%.

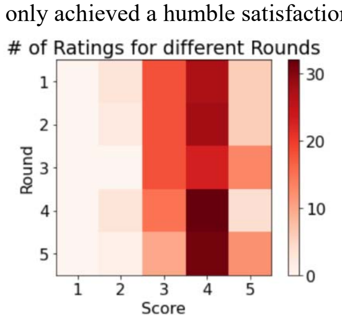
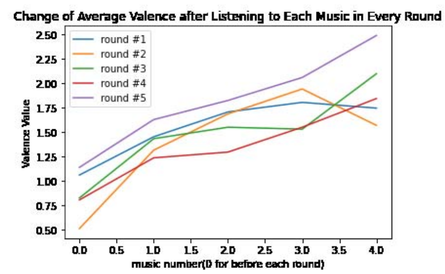
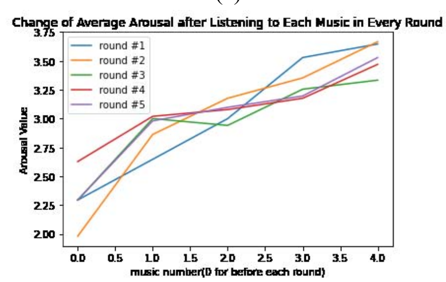


Figure 2. Heatmap of the rating participants gave to each round of the experiment.

Another interesting observation is the tendencies of average Valence and Arousal values of each round. Generally speaking, it is obvious to see that both Valence and Arousal values have increased in each round (see Figure 3). Since the final Valence values are all higher than the beginning values, the listeners are expected to have transferred from a relatively unpleasant state to a more joyful state. But, in round one and especially round two, the final Arousal values encountered a drop (Fig. 3a). There could be several reasons for this drop such as bad quality of experience due to disfluency of streaming and repeat of music pieces. However, a more likely reason could be that the weight of how much a memory attached to the former music affects the listener's V-A value. In the first two rounds the weight is set to a constant value of 0.5, but in the next three rounds it is calculated by V-A values reported by the listener in the first two rounds. Different from Valence values, Arousal values are expected to be controlled in an intermediate range so that the listener can remain in a relatively peaceful state. In this sense, the final Arousal values look ideal (Fig. 3b).



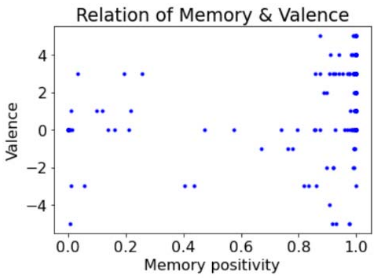
(a)



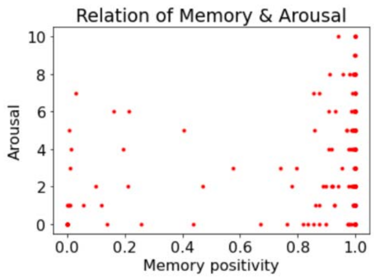
(b)

Figure 3. Emotion change due to music listening in each round.

Figure 4 below represents the relation between the positivity of memory and valence (Fig. 4a) and arousal (Fig. 4b). Memory here takes a value from 0-1, where 0 represents a very negative memory and 1 means the memory is delightful. When compared with valence, with the value of memory goes very high, the valence tends to be joyful. However, when the value of valence is negative, the memory can be either very positive or negative. On the contrary, there are not as many findings in the relation of memory compared with arousal. The participants stayed rather calm throughout the experiment process (with 92% reported arousal values below 6). However, it is obvious to see that when the participants do get very excited about a piece of music (8-10), their memories tend to be very positive (shown in the top right corner of Fig. 4b).



a)



b)

Figure 4. Correlation between memory positivity and valence (a) / arousal (b).

We further explored the relation by looking at how the positivity of the participants' memories affects the valence and arousal value. By calculating and comparing these values (see Fig. 5), we have found that when the memory is negative, despite the V-A of the music itself, the participants have a greater chance to turn into a lower mood (i.e., lower V-A). On the contrary, when the memory is positive, the participants generally have higher V-A. In Fig. 5, the x-axis represents ΔV, and the y-axis represents ΔA. We get the Δ(V-A) value by comparing the V-A feedback after music listening to the V-A taken before music listening. The blue dots represent Δ(V-A) of negative memories while the red dots represent Δ(V-A) of positive memories. The larger the dot means the bigger portion the Δ(V-A) pair-value takes in the memory group. It is obvious that the blue dots are gathering at the lower left corner, which means the negative memory negatively affected the users' mood, while the red dots are towards the upper right corner, meaning that positive memories gave positive influence at music listening.

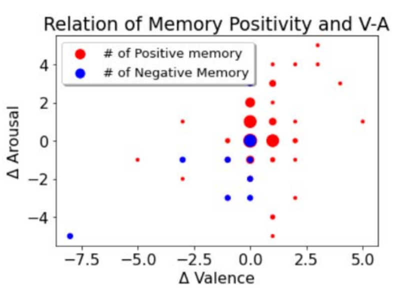


Figure 5. Correlation between between memory positivity and V-A of participates.

b) Typical Cases Analysis

A case for the negative memory is when listening to "Canon in D" a participant shared that the piece was her ex-boyfriend's favorite piece so that she'd skip the music every time she heard it. "Canon in D" was marked with a pretty high valence as 4 and arousal also as 4. However, after listening to the music, the participant's valence value dropped from 3 to 0, and her arousal value also dropped from 3 to 2.

Another case involving negatively marked music but leading to a participant's better V-A performance is found when a participant listened to the music "City in the Sky". The music's V-A is marked pretty low as -3 and 1. However, the participant wrote that he recalled the peaceful and warm atmosphere when he first watched the film on his own, and he even anticipated this music when he was listening to the prior music. Not surprisingly, the valence value of the participant boosted by 5 after listening to this somewhat sad music.

Another more typical case though, is when participants listened to a piece of music with a positive V-A value and resulted in an improved V-A for the participants themselves. An example is when a participant listened to "Almost a Whisper". The participant recalled the summer of his freshman year, which was delightful and improved his valence value by 2.

V. Conclusion and Future Work

In this paper, we have proposed a novel framework for personalized music recommendation by considering the memory triggered by the music listened to. Experimental results on MemoMusic demonstrate that memory actually contribute greatly in determining the emotional state of a listener after music listening.

Currently we are using the traditional and wide applied Valence-Arousal model to analyze the participants' emotions. However, although the model is good for emotion analysis, it is not a wonderful tool for music emotion analysis. There could be more complicated emotions involved within a piece of music. For example, nostalgia is bitter and sweet at the same time. Therefore a new model involving composite basic emotions might be a better option for analyzing music emotions. Additionally, using smart devices to monitor the participants' environmental or health condition will be considered as the experiment gets into a deeper phase. A device such as a smart watch can provide us with in-time feedback of a participant's current state so that we can recommend a music for them based on different and more complicated factors.

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