Enhancing Music Recommender Systems with Personality Information and Emotional States: A Proposal

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Abstract. This position paper describes the initial research assumptions to improve music recommendations by including personality and emotional states. By including these psychological factors, we believe that the accuracy of the recommendation can be enhanced. We will give attention to how people use music to regulate their emotional states, and how this regulation is related to their personality. Furthermore, we will focus on how to acquire data from social media (i.e., microblogging sites such as Twitter) to predict the current emotional state of users. Finally, we will discuss how we plan to connect the correct emotionally laden music pieces to support the emotion regulation style of users.

Keywords: Music recommender systems, personality, emotional states, emotion regulation

1 Introduction

Research on recommender systems have shown increased interest to incorporate psychological aspects. Especially the relationship between personality and user preferences has gained a lot of attention. For example, knowledge about the influence of personality traits on music taste [25], and diversity in item recommendations [39] have been exploited to improve the user tailored recommendation. As personality is defined as the individual differences in enduring emotional, interpersonal, experiential, attitudinal and motivational styles [12, 17], one can expect to be able to infer much more based on personality traits to improve the recommendation.

The goal of this project is to improve music recommendations by incorporating additional psychological factors. More specifically, we focus on emotional states and their relationship with personality to infer music taste and preferences. By knowing the user's current emotional state, a system can anticipate its recommendation with an emotionally laden song that is in line with the user's style of emotion regulation (e.g., changing or maintaining their emotional state).

In the following sections we give a brief introduction about what is known about personality and emotional states, and work towards how we are planning to use it to improve recommendations.

2 Personality

Personality has shown to be an enduring factor that influences an individual's behavior [13], interest, and tastes [14, 25]. As personality plays such a prominent role in shaping human preferences, one can expect similar patterns (i.e., behavior, interest, and tastes) to emerge between similar personality traits [2].

Different models have been created to categorize personality, where the five-factor model (FFM) is most well known and widely used [17]. The FFM consists of five general dimensions that describe personality. Each of the five dimensions consist clusters of correlated primary factors. Table 1 shows the general dimensions with the corresponding primary factors.

General dimensions	Primary factors
Openness	artistic, curious, imaginative, insightful, original, wide interest
Conscientiousness	efficient, organized, planful, reliable, responsible, thorough
Extraversion	active, assertive, energetic, enthusiastic, outgoing, talkative
Agreeableness	appreciative, forgiving, generous, kind, sympathetic, trusting
Neuroticism	anxious, self-pitying, tense, touchy, unstable, worrying

Table 1. Five-factor model

There is an emerging interest in how personality relates to user preferences in different domains. This provide valuable information for the development of domain specific recommender systems. Knowing someone's personality can help to infer their preferences [23–25], and can therefore contribute to a more accurate recommendation. For example, music preferences were found to be correlated with personality traits [25]. Rentfrow and Gosling [25] categorized music pieces into 4 music-preference dimensions (reflective and complex, intense and rebellious, upbeat and conventional, and energetic and rhythmic), and found correlations with the FFM general dimensions, such as, a relation between energetic and rhythmic music and extraversion and agreeableness.

The prediction of personality parameters is starting to establish by either using implicit acquisition (e.g., personality prediction by extracting data from social media [8, 16, 22]), or explicit acquisition by letting users answering a personality quiz [10]. Although the implicit method is unobtrusive, accuracy is compromised as it dependents on the quality of the source (e.g., frequency of expressing on social media). On the other hand, the explicit method is more accurate, but intrusive and time consuming.

3 Emotional States

We can find emotions in every facet of our life, such as during: decision making, objective and subjective thinking, creativity. To categorize the emotional states we experience, Ekman [5] defined six basic emotional states in which we can categorize experienced emotion: anger, disgust, fear, happiness, sadness, and surprise. Others on the other hand believe that emotions are a mix of dimensions of emotional states [35].

To deal with our emotional states throughout the day, we adapt different strategies. Parkinson and Totterdell [21] defined 162 different strategies (e.g., exercising, music listening, taking a bath). Especially listening to music plays an important role. Research has found that music is the second most strategy used [36, 7]. It can change, create, maintain, or enhance emotions [3]. This suggest that music can play an important supportive role when people dealing with their emotions in daily life.

Just as with personality, there is also an implicit (e.g., blog text) and an explicit way to detect emotion with the same drawbacks. Although the implicit detection has advanced, it goes without saying that automatic capturing of online emotional states remain challenging. As Scherer [28] noted "The inherent fuzziness and the constant evolution of language categories as well as inter-language, inter-cultural, and inter-individual differences make it difficult to define central working concepts".

4 Personality & Emotional States

How we regulate our emotions have been investigated with relation to our personality. Of particular interest are the neuroticism and extraversion dimensions. These dimensions are associated with experiencing negative and positive affect consistently. For example, Tamir [32] found that people scoring high on the neuroticism dimension tend to increase their level of worry. Similarly, people who score low on the extraversion dimension tend to be less motivated to increase their happiness [33].

While most studies are focusing on personality traits in relation to emotion regulation, there is a small area that argues that the emotion regulation style can be explained by one's implicit theory of emotion. In other words whether someone beliefs that emotions are fixed (entity theorist), or more malleable (incremental theorist). Entity theorists experience more negative emotions, that is, less favorable emotion experiences, lower well-being, greater depression, more loneliness, and poorer social adjustments compared to incremental theorists [34].

Music has the ability to induce intense emotions (positive and negative) [40]. Some studies have investigated how, and whether the emotion that consist in music is used by people in their emotion regulation. Thoma et al. [38] categorized different music pieces on valence and arousal, and found that different pieces were preferred depending on the emotionally laden situation. Similarly, Van Goethem and Sloboda [7] found that people use music to support their regulation strategy. For example, music is used to help to distract from the affect or situation, or can help to think about it in a rational way. Despite findings on an individual level (i.e., personality) and how music is used as a regulation strategy, there is still a gap in connecting these two. That is, it is still unknown how music is used to regulate emotions on an individual level.

5 How to improve recommendations?

As music plays a role in emotion regulation of people, and the way how people regulate their emotions seem to be dependent on their personality (or their implicit theories of emotion), the music that people use to support their emotion regulation may also be dependent on their personality.

Whereas personality is usually used to alleviate the cold-start problem in recommender systems (i.e., new users and sparse data sets) [11], or to determine the amount of diversity in the recommendation [39], including emotional states can help to improve music recommendations on the fly. Currently, music recommender systems anticipate their subsequent recommendations on the music that the user currently listens to. The recommendation is based on similarity by comparing what others with similar taste have listened before (collaborative filtering), or by matching properties (e.g., genre, artist) of the music pieces (content-based filtering). This can result in that recommendations given may fit the user's taste, but may not match the user's actual *needs* at that moment. For example, the systems knows that a user likes Beyoncé. Beyoncé has a range of different emotionally laden songs from up-tempo to ballads. By knowing the user's emotion at a specific moment, the recommender system can anticipate and propose a piece of emotion-laden music that lies within the taste of the user that can support the regulation of the experienced emotion.

5.1 A Scenario

Anna is a 22 year old student. When she listens to music, she often makes use of an online radio. This online radio knows Anna's taste so it can anticipate on the next song to play for Anna. Besides knowing Anna's taste, the system knows that Anna is a little bit neurotic.

On one day Anna is at home, listening to an up-tempo song of Beyoncé. The next song that the radio put in the cue is another up-tempo song, but this time by Katy Perry. Suddenly Anna receives some bad news that makes her sad. She post her feelings on Twitter. The radio system notices this and based on her personality (neuroticsm), it adjust the song in the cue. Instead of playing an up-tempo song, it replaces it with a sad song of Katy Perry. By knowing how Anna likes to regulate her emotions, the system can anticipate the play-list accordingly.

6 Proposal

In the following sections we discuss the initial ideas that we have to improve recommender systems by incorporating the user's personality and current emotional state. We start with describing how we plan to investigate the relationship between personality and emotion regulation through music. After that we discuss the methods for the personality and emotion acquisition from social media, and finally we discuss how we plan to find the emotionally laden songs. For the incorporation of emotion and personality, we assume that system already initiated the user's music taste.

6.1 Step 1: User Study

The first step would be to investigate how people prefer to regulate their emotions and the relationship with their personality. For example, people scoring high on neuroticism tend to increase their level of worry [32]. Therefore, they may not want to listen to music that tries to change their worry state, but want music that is in line with that state instead.

Although there is much research done on the inducing effect of emotional laden music [4, 27], not much is known about how people use music to regulate their emotions. We plan to conduct a online user study using participants on Amazon Mechanical Turk. In this user study we will use the set of film clips (see Figure 1 for the experiment work flow), developed by Hewig et al. [9] to induce one of the basic emotional states. Presenting film clips is one of the methods that is frequently used to induce emotions in psychological experiments. For the user study, we will assign participants randomly to a emotionally laden film clip (anger, disgust, fear, happiness, sadness, or neutral). After showing participants the film clip, we will ask as a control the emotion the film clip induced. In the next step we will present different emotionally laden music fragments (anger, fear, happiness, sadness, and tenderness) and ask participants the likelihood that they would listen to such music when being in the just induced emotional state. The music fragments we will use are categorized by Eerola and Vuoskoski [4] based on the basic emotions they bear. As a control question we will ask in addition what kind of emotion the music pieces induce. To conclude we will ask the FFM questions, implicit theory of emotions questions, and demographics (i.e., age and gender). This will give us information about how music is used in different emotional states and how this is related to personality traits.

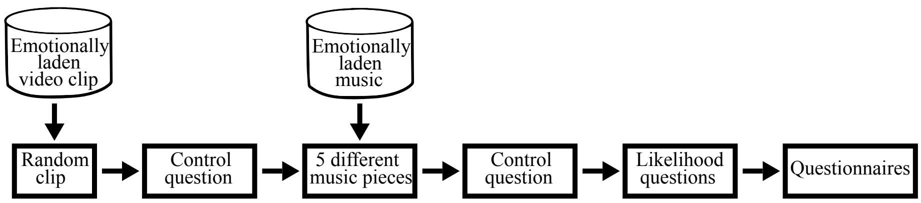

Fig. 1. User study work flow

With the results of the aforementioned user study we will create a model to predict the emotionally laden music pieces that users would like to listen to when in a certain emotional state. A second user study will be carried out to create the dataset for testing the model. The dataset will contain data about their current emotional states of users and the emotional laden songs they want to listen to. A 10-fold cross-validation method will be used for validation.

Once the model is created and verified, we will know how people prefer to regulate their emotional states with music throughout the day, and how this is related to their personality. In the next step we will move toward the extraction of personality and emotional states from social media.

6.2 Step 2: Personality & Emotional State Acquisition

We will use Twitter as our main source to extract the personality and emotional state parameters from. Tweets are crawled by using the Twitter API. Furthermore, we will limit ourselves to tweets with English as the main language.

Personality Acquisition For the acquisition of personality we will work toward an implicit detection of the parameters, i.e., without the need of a questionnaire. Results of previous research of extracting personality parameters from tweets are promising. Golbeck et al. [8] were able to predict personality parameters from Twitter within 11%-18% of their actual value by looking at the content of users' tweets. Other research done by Quercia et al. [22] were able to estimate personality parameters (RMSE below 0.88 on a [1, 5] scale) by only looking at the users' characteristics (e.g., listeners, popular, highly-read, and influential users). We plan to explore the techniques used by prior research and possibly combining them to improve predictions. Another direction that may be worth taking into account would be to incorporate historical tweets that reflect listening behavior of users. Rentfrow and Gosling [25] found relations between personality and music genres. By looking at historical music tweets of users, we are able to extract the genre of the song which in turn can provide us personality information.

Emotional State Acquisition Although we realize that emotional states are not expressed constantly, we do believe that social media is a platform that is increasingly used by users to express themselves. This includes emotional states depicting personal (e.g., anger, frustrations) to global topics (e.g., politics, sport events) [1, 37].

The acquisition of the emotional states from textual collections of user-generated data on the web has been well established (for an overview of this field see [20]). Results indicate that emotional indicators can be extracted accurately. However, acquisition of these indicators from microblogging sites has been done scarcely. Most of the studies focus on the polarity (positive, negative, or neutral) [20] or try to include the magnitude of the emotion (mild and strong) [30]. Only a few have tried to categorize microblogging text based on existing emotional categorizations [1, 29].

One approach that we bear in mind that to build upon is the use of emotion lexicons. These lexicons consist of terms related to an emotion. Several lexicons have been created based on different emotion categorizations and have been tested on tweets. Such as, Sintsova, Musat, and Pu [29] created a lexicon compatible with the Geneva Emotion Wheel categorization of emotions, Roberts et al. [26] based their emotion lexicon on Ekman's categorization, and Suttles, and Ide [31] on Plutchik's. Especially the work of Roberts et al. [26] would be suitable to build upon as the Ekman's categorization is on the basis of our work. We will be able to complement the predictability of emotions by including metadata that have shown to consist of emotional indicators, for example, hashtags [18, 19], traditional emoticons [6], and emoji [26].

6.3 Step 3: Emotion Classification of Songs

The user study (see §6.1) will give us insights in how emotionally laden songs are used in the emotion regulation process. For the system to be able to anticipate its recommendation, we need to find the right emotional annotated song.

The field of emotion classification in music is still evolving (see for an overview [15]). Currently, different methods are used to annotate music pieces on their emotion: direct human annotation (e.g., surveys, social tags, games), indirect human annotation (e.g., web documents, social tag clouds, lyrics), or content-based analysis (e.g., audio, images, video). As Kim et al. [15] noted "Recognizing musical mood remains a challenging problem primarily due to the inherent ambiguities of human emotions." To find the right emotionally laden song within a collection in this project, we will initially turn to the tags provided by Last.FM website. Last.FM currently provide songs with the tags happy, sad, angry, and relaxed. Based on these tags we can make a first attempt to match emotionally laden songs with the user's way of regulating their emotional state.

7 Conclusion

By including the user's current emotional state, we propose that music recommendations can be improved. Our next efforts will be to investigate how people regulate their emotions with music. That is, what kind of emotionally laden music people are listening when being in a specific emotional state. Additionally, we will investigate how emotion regulation with music is related to their personality.

For the acquisition of personality and emotion, we will focus on microblogging sites. As social media generates a constant stream of communication, we believe that microblogging sites as Twitter are suitable to extract personality and emotional states of users. Although accurate results are achieved from textual collections of user-generated data on the web, analyzing microblogging sites remains challenging. The amount of text is scarce as the text posted on Twitter is limited to 140 characters. However, the ability to express oneself in a short and fast way lend itself to post content more often. To extract personality and emotional states from Twitter feeds we will initially trust on different existing methods and combine them to improve predictability of the parameters.

With the findings of the aforementioned steps, we can start matching music that fits the user's way of emotion regulation. To find suitable music, we will initially rely on the emotional tags that Last.FM provides.

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