The Building Blocks of Music based User Mood Recognition: A Review

[1]Sharwin Bobde, [1]Shamla Mantri, [2]Pankaj Agrawal, [3]Dipti Patil, [4]Vijay Wadhai

[1]Department of Information Technology, MIT College of Engineering, Pune, India
[2]G. H. Raisoni Academy of Engineering and Technology, Nagpur, India
[3]MKSSS' Cummins College of Engineering for Women, Pune, India
[4]DY Patil College of Engineering, Akurdi , Pune, India.

Abstract : Research aimed towards sentiment analysis has gained popularity with the increase in computational power and rise of Big Data, but a negligible part of it covers music based User Mood Recognition (UMR); most methods stem from social media analytics and Natural Language Processing. This paper elucidates the significance of UMR using audio analysis and music listening behaviour. The underlying relations between music listening behaviour and user's emotions are described to create a strong case for such research. Various research methodologies for Music Emotion Recognition (MER) have been illustrated, which use variations of neural networks for the problem task. A music based UMR system which uses Music Information Retrieval (MIR) and text analysis has also been described. This paper is a review of basic concepts and real-world implementations that support music based UMR, and acts as a precursor to a cloud based system for music listening behaviour based User Mood Recognition, which is currently under development.

***IndexTerms* - User Mood Recognition, Sentiment Analysis, Music Information Retrieval, Music Emotion Recognition, Neural Networks.**

I. INTRODUCTION

Our music listening experience has changed a lot through the decades; since 1877, when phonographs were invented to play physical records, we have come today to streaming digital lossless FLACs(Free Lossless Audio Codec) for a truly immersive audio experience. In this time, recorded music has become more available, which has in turn changed how and why we listen to music. Today the music we choose to listen is greatly determined by artist's social presence and marketing campaigns by the record labels. This has separated us why we listen to music; because it resonates with how we feel our how it makes us feel. Enter, Music Emotion Recognition (MER) and music based User Mood Recognition (UMR). MER is a classification problem, in which signal processing methods and machine learning algorithms are applied to learn the association between emotion tags and features that characterize certain musical piece(s). On the other hand, music based UMR deals with identifying the transient emotion an individual actually feels in response to an auditory stimulus (music in this case) by taking various features of the musical piece into consideration.

Today music analysis through Music Information Retrieval (MIR) is popularizing. MIR is an interdisciplinary research area which encompasses to various disciplines such as signal processing, information retrieval, machine learning, multimedia engineering, library science, cognitive science, musicology, and humanities [1]. In this study we shall see why sentiment analysis on the basis of the user's mood is actually a significant problem, and how people have tried to tackle it. In general, past works focus mainly only on either MER [2-4] or UMR [5] and only partially overlap for the dealing with the problem in question.

This paper can be summarized as follows: First a strong case will be built up for music based UMR in Section 2, by analyzing various findings in observing findings from various publications related to psychology, music research and cognition. Various popular methods of representation of human emotions will be explained in Section 3. Computational methods of modelling human emotions for analysis and association with music which hold promise will be explained in Section 4. A case study of gamified data collection for the problem statement will explained in Section 5. Methodologies in MER which can facilitate UMR with fundamentally distinct approaches for a diverse explanation have been stated in Section 6. Section 7 will deal with the findings of a study which draws relations between people's music listening behaviour and their mood. The conclusion summarizes the information in the paper and showcases the significance of each finding, while also informing about the purpose of this review.

II. THE CASE FOR MUSIC BASED UMR

This section will state findings from literature in the domains of psychology, cognitive science, etc. to justify the use of music listening behaviour data for UMR. The findings will also establish some premises for this paper about the relation between quality or features of music and their affect.

A. EMOTIONS AS A NATURAL PART OF THE MUSIC LISTENING EXPERIENCE

There have been extensive studies which have elaborated on the relation between the part played by emotions in music listening behaviour. For instance, [6] has shown results which can explain why music is perceived as expressive of emotion, and how they are consistent with an evolutionary perspective on vocal expression of emotions. They have outlined theory that supports the following seven premises:

- Emotions may be regarded as adaptive reactions to certain evolutionarily relevant, and recurrent life problems that are common to many living organisms.
- What makes emotions adaptive is that they are communicated nonverbally, thereby transmitting important information without the need for language.
- Vocal expression (sounds, not linguistic) [7] is the most evolutionarily continuous of all forms of nonverbal communication.

- Vocal expressions of discrete emotions usually occur in similar types of life situations in different organisms.
- The form of the vocal expressions of emotion indirectly reflects the situation of the organism.
- Physiological reactions affect an organism’s voice production in different ways.
- By imitating the acoustic characteristics of these patterns of vocal expression, music performers are able to communicate discrete emotions to listeners.

It has been highlighted that communication of emotions may reach an accuracy well above the accuracy that would be expected by chance alone in both vocal expression and music performance. This stands true for at least the broad emotion categories corresponding to basic emotions like anger, sadness, happiness, fear and love.

One cannot leave emotions unaddressed as a crucial part of the context of close relationships among people or populations is missed. The central concerns of systems theory can help us bring emotions into the picture. As stated by [8] Systems Theory has a focus on wholeness, the organization of elements in that wholeness, the process of communication and the circular feedback loops that characterize such communication. This focus on process, whether it concerns inner experience or interactions with a partner, seems to be part of a larger general shift where process forms of explanation seem to be replacing more static structural views of personality and psychological functioning. It has thus been argued that the fastest and most direct way to create change in relationships may be to change this music and actively evoke the emotions that elicit caring, compassion and contact.

B. Paradoxical cases

Though there are strong links between music listening behaviour and emotions, the relation can be paradoxical in certain cases. The paradox of why people engage with "sad music" if sadness is inherently a negative emotion has been studied in [9]. Using an online survey, they obtained responses from a large internet sample. Results point out an extensive confluence between the uses of sad music in everyday life and experiences of reward derived from music-evoked sadness. For example, the use of sad music to regulate negative emotions and moods corresponds to the reward of emotion regulation, while the consolatory use is related to the reward of empathy. Their findings suggest that the principal motivation for listening to sad music is to evoke and influence emotions and moods [10-11].

Transient sadness is a basic emotion that can be observed in people, independent of cultural background [12]. Sadness is characterized by low physical activity, tiredness, reduced interest in the outer world, low mood, rumination, decreased verbal communication, and a withdrawal from social settings [9]. The data were obtained from 772 individuals. Their results indicate that situation-related factors play a significant role in the engagement with sad music. Surprisingly, nostalgia, and not sadness, was indicated as the most frequent emotion evoked by sad music. Moreover, participants also reported experiencing positive emotions, such as peacefulness, tenderness, and wonder. For "happy music" the participants marked the categories entertainment, celebration, background, and mood maintenance received majority nominations, indicating that participants are especially likely to engage with happy music when they are with friends or at social gatherings, to experience enjoyment and maintain a positive mood or emotional state. Interestingly, the categories arousal and motor received second majority of nominations, indicating that another important use of happy music is to raise or synchronize positive energy levels, for settings such as morning routine or while physical exercise.

III. Emotion Representation

The psychologist Gabrielsson in his work [13] made a distinction between perceived and felt (induced) emotions. In the case of the perceived emotions, we can perceive emotional expression in music without necessarily being affected ourselves, while in felt emotions, we have an actual emotional response to the music. The work in [14] has elaborated on the premise that perceived emotion is the emotion recognized in the music, and induced emotion is the emotion experienced by the listener. Perceived and felt emotions are two alternatives that were the focus of psychology papers, such as those by [15] and [16]. The popular methods of representing emotions are stated below.

A. Dimensional Approach

The two-dimensional circumplex model of emotion, which uses the two dimensions of arousal and valence, was presented by Russell in [14, 17] Arousal could be high or low and valence positive or negative. In this model, all emotions can be understood as changing values of valence and arousal. Fig. 2 shows Russell’s valence-arousal plane with various pointed marked with emotions for reference.

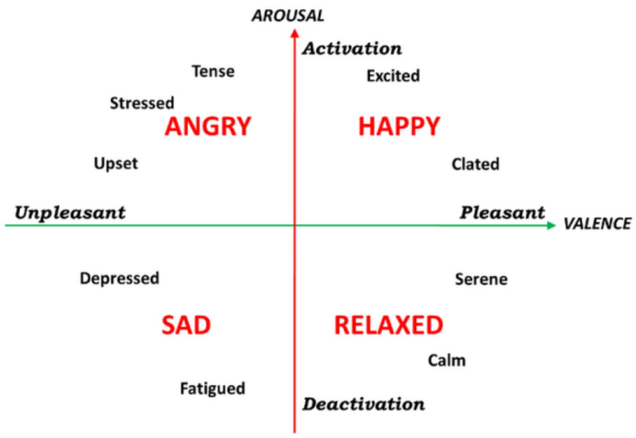

Figure 1. Russell’s valence arousal model circumplex model [14, 17]

B. Categorical Approach

In the categorical approach, emotions are described with a discrete number of classes, affective adjectives, and in the second emotions are identified by axes. In the categorical approach, there are many principles behind class quantity and grouping methods. One of the first psychology papers that focused on finding and grouping terms pertaining to emotions was by Hevner [18]. As a result of the conducted experiment, here was a list of 66 adjectives arranged into eight groups distributed on a circle [14].

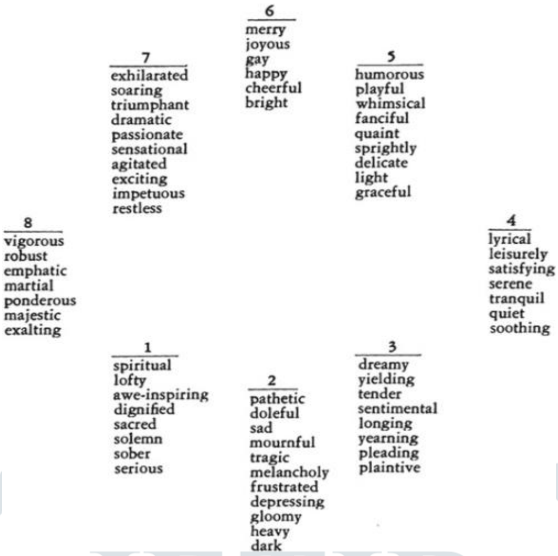

Figure 2. Hevner's adjectives arranged in eight groups [14, 18]

IV. Modelling Emotions in a System

This section will illustrate how emotions are practically modelled for experiments for computational purposes. Two studies [19-20] have clearly investigated the relation between music listening and the affect (influence on the listener) with good sample sizes.

An experiment conducted by Gabriela Ilie, et. al. [19] from University of Toronto compared the affective consequences of manipulation intensity, rate, and pitch height in music and speech. This is one of the first study involving a direct comparison of the affective consequences of manipulating acoustic features in music and speech. Participants ranging in age from 18 to 27 years participated in the study (20 females and 7 males) and rated 64 music pieces. They had an average of 3.4 years of formal music lessons They conducted Analysis of variance (ANOVA) with repeated measures on domain (music or speech), intensity, rate, and pitch height. ANOVA was conducted for rating valence, energy arousal, and tension arousal. Manipulations of intensity, rate, and pitch height had affective consequences in music and speech, influencing judgments of valence, energetic arousal, and tension arousal. Across various conditions, music was assigned higher ratings of valence and energetic arousal than speech stimuli; suggesting broad differences in the affective consequences of listening to both. The finding is consistent with the observation that people often listen to music for pleasure and to modify energetic states.

A different study by Emery Schubert in 2004, [20] investigated the relationship between musical features and affect using a continuous response from user during the duration of the musical piece, and then conducted time-series analysis. Sixty-seven volunteers participated in the study, with a wide range of ages; $\text{mean} = 30.6$ and $\text{s.d.} = 12.3$. The participants were trained to ensure that they understood what was meant by the two dimensions (valence and arousal) of the interface, and to ensure that they became comfortable with moving the mouse around the screen while listening to the music. A linear regression type model using the ordinary least square approach was employed in which the musical feature variables were used as predictors of perceived emotions for second by second response. Two sets of univariate models were developed, for arousal and valence. The results demonstrate a logical emergence of emotional response after a musical event. Rhythmic events presented strong evidence of a causal relationship. In general, there is a 1- to 3-s lag between significant musical events and proportional response. With sudden changes in loudness, response times reduced from a typical 2 or 3s lag to a 0 or 1s lag.

V. Gamification of Data Collection

A huge and diverse dataset is required for music based UMR, therefore a system for proper data collection will require a very rich and minimalistic interface. One way of achieving this would be to gamify this problem. A very good example of effective gratified data collection is MoodSwings [21], which is a collaborative, two-player game that incorporates each listener's subjective judgements of the mood of music into the gameplay. At the start of a match two players are partnered anonymously across the internet. The goal of the game is for the players to dynamically and continuously reach agreement on the mood of 5 short music clips of 30s, drawn from a database of popular music.

The MoodSwings' game board interface is a representation of the valence-arousal space discussed before [17]. During interaction the players listen to identical short music clips simultaneously. Each player positions their cursor on the game board, indicating their instantaneous assessment of the mood of the music. A player's position is sampled once per second. The primary score calculation is based upon the amount of overlap between the player's cursor and that of their partner; this is designed to encourage agreement in the mood assessments from both parties. Players can also accumulate bonus points by "convincing" their partner to agree with a particular position. The music for MoodSwings is drawn randomly from the well-known collection of over 8000 popular music tracks, from approximately 400 artists. They observed the change in instrumentation and tempo within the segment is generally marked by players as a change in intensity in the song, as well as a slight increase in valence. They plan to use the collected data to train a mood classifier for short audio segments using a Hidden Markov Model.

VI. Methodologies in Music Emotion Recognition

This section will describe the various MER methodologies that have been adopted till date. These methodologies have also been curated based on their possible usage in music based UMR applications.

A. RBF Neural Network

Yi-Hsuan Yang, et. al. [2] developed a system for MER and ranking music based on classified music. They represent an emotion as a point in the valence and arousal plane and determine the coordinates of a song by the relative emotion of the song with respect to other songs. For ranking measure they have the subjects only make pair wise comparisons of the emotions of songs, using a music emotion tournament scheme to reduce the cognitive burden on subjects. While designing the regression model for the system they used radial basis function (RBF) neural network[22]. This is because It has been shown that the characteristics of music are often better modelled with a nonlinear function such as RBF [23-24]. They used ListNet for ranking the musical pieces and hence called the final algorithm RBF-ListNet. The model's accuracy was judged using the gamma statistic, which is defined by the number of correctly ranked pairs and the number of incorrectly ranked pairs and ignoring tied pairs. The equation for the gamma statistic is given by equation 1.

$$G = \frac{C-D}{C+D} \quad (1)$$

Therefore, G equals 1 for perfect agreement, 1 for total disagreement, and 0 if the rankings are independent. As seen in Fig 3. RBF-ListNet approaches 0.3 gamma value with 300 training pieces, and reaches a plateau after that. RBF-ListNet is superior than SVR in this case, and both can be trained with a moderate-size dataset.

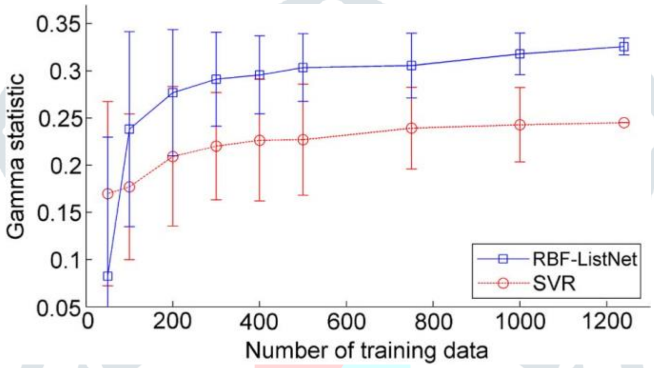

Figure 1. Gamma statistic for valence recognition of music. Error bars representing one testing data under the testing set.

This work explores the possibility of representing songs in the emotion space according to the relative mood based rankings. This will simplify both the annotation and model training processes of MER. Although, the sought out strategy of converting emotion rankings to emotion values in a linear "list-like" way may be too simplified for representing ground truth.

B. Deep Gaussian Process (Deep GP)

Sih-Huei Chen, et. al. proposed a system for detecting emotion in music that is based on a deep Gaussian process. This paper uses MIR and extracts 15 acoustical features, which are associated with five classes of features: rhythm, dynamics, timbre, pitch and tonality [3]. In this paper, the Deep Gaussian process (Deep GP) is applied for recognizing emotion in music. Deep GP is a deep belief neural network based on Gaussian process mappings[25]. The song segment's features and the emotional label of each data point are regarded as input and output respectively. The database of emotional music in this work refers to 9 classes of emotion: anger, sadness, happiness, boredom, calm, relaxation, nervousness, pleased and peace. The database was constructed by collecting music clips from two websites, and collecting 120 music clips for each class. They compared their proposed method to conventional SVM and standard GP. Their deep GP-based MER system performed better (71.3% overall accuracy) at capturing relationships compared to the conventional SVM (63.0% overall accuracy) and standard GP (67.4% overall accuracy).

C. Deep BLSTM

Xinxing Li, et. al. in 2016 [4] designed a system which fused Deep Bidirectional Long Short-Term Memory (DBLSTM) and Extreme Learning Machine (ELM) models to predict the valence arousal values in music. BLSTM model has the ability to capture both the previous and future contexts over a long period of time; though the information obtained by using BLSTM is still limited by the length of the sequence. Therefore they proposed a multiscale fusion approach based on ELM to promote the performance of the BLSTM Model.

BLSTM is a combination of LSTM and Bidirectional RNNs (BRNN) [26]. Thus the BLSTM not only exploits context for long periods of time, but also can have access to the context in both previous and future directions. ELM is a learning algorithm for single-hidden layer feedforward neural networks (SLFN) [27]. The input weights and hidden layer biases of SLFNs are randomly assigned, and the output weights are analytically determined. The results on the validation of the DBLSTM model suggests that the regression accuracy of DBLSTM was related to the sequence length. The multi-scale fusion results show that average output and ELM performed better overall than predictions given by a single scale.

VII. Methodologies in User Mood Recognition

There have been very few studies linking music and person's pre-existing, long-term emotional state computationally. Yi-Hsuan Yang, et. al. conducted a quantitative study [5] in which they developed a number of computational models to evaluate the accuracy of different content or context cues in predicting emotional state. They used 40,000 pieces of music listening records collected from a social blogging website. They quantitatively evaluated the association between user's mood and music listening behaviour using user mood tags, considered as ground truth labels, placed on the valence-arousal plane, for the corresponding music titles. These tags are characterized by audio and text features extracted from the music signals and lyrics, respectively. For classifier training they adopted the linear-kernel SVM. To offer a qualitative comparison between music-based UMR and context-based UMR, they extracted text features for the blog posts in the same way as for the song lyrics, and trained binary classifiers for each user mood class.

Furthermore, for MER-Based UMR They applied the resultant MER models to predict the emotion of the music titles. Instead of assigning binary labels, they used the Platt scaling [28] to compute probability estimates of class membership, thereby representing a track by a 190-D vector consisting of probability estimates. Based on this feature, they trained an MER-based UMR model with the same setting as the previous UMR models. Additionally, they also studied the correlation between the MER probability scores and the ground truth user mood labels to gain more insights, specifically considering the 43 music emotion tags and 22 user mood tags and computed the Pearson's correlation coefficient between every pair of music emotion and user mood. They found that Generally, people listen to mood-congruent music when being in a positive mood, but tend to listen to mood-incongruent music when being in a negative mood. Such tendency is in line with the intuition that people prefer "feeling good" [9]. In addition, people also enjoy listening to sad music when feeling bad. The study also identified tri-partite association among user mood, music emotion, and individual's personality traits. These findings, as a whole, suggest that the social functions of music can be well explored from a real-life user interaction data.

VIII. CONCLUSION

In this paper we have highlighted the various concepts and techniques, or "building blocks", that make up one branch of achieving music based UMR. numerous past research work and studies have been discussed to show the efforts being undertaken in MER and music based UMR.

The relation between humans' emotions and the qualitative information in music we listen to has been explained in detail. This marks the clear correlation between the two. The role of emotions communicated through music and vocal expression has been elaborated on [6]. As well as why we need to consider emotions while studying interpersonal relations and what role music plays in it [8]. The paradoxical case of "sad music" has also been discussed to show the complexity of the domain [9]. The purpose of energetic songs for modulating mood has also been discussed. The popular methods of emotion representation and their modelling have been explained.

Researchers have computerized the relation between music and emotion by developing regressors and classifiers. Methodologies for performing MER using machine learning techniques such as RBF neural network, Deep Gaussian Process, Deep BLSTM and ELM have been adopted in the past [2-4]. There has been a lot of work done in MER, especially by tagging musical clips or segments with mood labels or valence-arousal coordinates. The work done in music based UMR, although fewer in number, relies heavily on MER and indirectly recognizing user's mood tags. Music based UMR has also relied on sentiment analysis using text mining of blog post [5]. There is a dearth of research where user's sentiments, and not transient mood, are recognized using music listening music behaviour.

This paper acts as a precursor to a full-fledged cloud based system for music based User Mood Recognition, which is currently under development. The system takes the concepts mentioned in this paper and improves upon them for an integrated mood recognition service, serviced through a fully scalable mobile application. The application records user's music listening behaviour which along with the features of the songs they listen to act as the input for the mood recognition system.

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