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A MUSIC BASED MOOD REGULATION SYSTEM USING SENTIMENT ANALYSIS, RUSSELL'S CIRCUMPLEX MODEL AND VECTOR DISTANCE CALCULATION TO IMPROVE THE PRODUCTIVITY OF THE USER

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ABSTRACT

It has been recognized that music plays a significant role in altering and regulating the mood and emotion of a person. The various Music Information Retrieval models available today rarely factor in the user's current mood based constraints. Making a model that sorts music with respect to these parameters can be utilized in many applications. With this realization, we have decided to implement a model and use it to build a software application that allows users to seamlessly retrieve music suggestions based on their mood and emotional state in order to help them reach their desired positive goal state. The underlying NLP-based Interactive Agent will map the user interaction data with a sentiment analysis model developed using the Russell's Circumplex Model of Emotion developed by James Russell which suggests that emotions are distributed in a two-dimensional circular space, containing valence and arousal dimensions. This then is used as an input to the Valence-Arousal based song database we created earlier to find the best matching songs to enqueue for the user, and take them gradually to improve their mental state and reach the goal state.

KEYWORDS: Music recommendation, Emotion detection, Emotion alleviation, Russell's Circumplex Model, Valence-Arousal, Music tags.

1. INTRODUCTION

Music has been something that has transcended ages, it's a part, and even soul for many culture's. Its range of application was varied, from calming sounds for meditation, to enraging drums on warring battlefields, it is evident it plays a role to help influence a person's emotional state, which in turn can affect a person's physical wellbeing.[1]

This affective aspect of music has been drawn into the limelight, with the expanse of computer systems and internet, leading to the rise of a new era for music consumption, Streaming, and the defining of music with its respective "music mood" attributes, for better Music Information Retrieval (MIR).

Most of the current Streaming services, provides curated playlists, mainly through Collaborative Filtering, where they recommend songs based on popularity and what other users are listening to which are close to it, this method extends further to creating curated or preset playlists with a similar mood.

However, these methods fail to take into account how a user might currently feel, and how to recommend a selection of songs based upon the user's current emotional state, and recommend music, in a way that it helps improve their current emotional state, by taking them slowly into their desired positive state of mind.

So the first part of our model, the interactive agent converses with the user and assesses the user's current emotional state by assigning valence arousal values to the keywords used by the user in the conversation, via Natural Language Processing Methods.[15-17]

When the current emotional state has been established, the goal state is also established, the recommendation path is also plotted after referring to the datasets.

Once all this is done, the user gets recommended songs based on the given emotional state parameters, after a few recommendations, the agent once again asks how the user might be feeling, and determines whether to change the goal line or not.

This Model hopefully can be used not just as a tool for improving productivity, but to improve one's overall emotional wellbeing, it can also be used as part of music therapy as well.

2. RELATED WORKS

Xiao Hu[1] has explored the the connection betwixt music and emotion, specifically in the area of categorizing the "Music Mood" of a song, by referencing its attributes with social tags and cross referencing it with various psychological models of categorizing human spectrum of emotions to find a suitable model in which music can be properly attributed to for Music Information Retrieval and music psychology.

Karbauskaitė et. al[2], explored the various categorical classifications for music and was useful in our selection of Russell's Circumplex model of emotion as the core for our system.

Mohammed Elsaid Mouussa et al.[3] work on sentiment analysis using a generic lexicon-based framework was referred for better understanding and training of our Sentiment-Analysis emotion detection model.

To better understand the way services such as Spotify recommends songs or albums to their users, via Collaborative Filtering, Javier Pérez-Marcos[5] et. al explores the use of Collaborative Filtering in various services such as Netflix and Spotify, and Spotify's "Discover Weekly" services.

The Effects of the Collaborative Filtering on music recommender interfaces has been conducted and detailed by Martjin Millecamp[6] et al, with the nature of most recommender systems and the challenges faced by the user who interacts with it.

The Inner workings and processes of music therapy have been thoroughly explored starting with the work by Denise Grocke et al,[7] who has laid out what are the most common receptive methods used.

To understand how music therapy is fully effective, Leslie Bunt's et. Al[8] research into how music can greatly influence a person's mind, especially in the context such as the setting of music therapy is looked into deeply.

The Decision to employ an interactive agent as a tool to guage's the user's emotional state was made after perusing through Se Hun An[9] research into the effectiveness of Artificial Intelligence into the field of Psychology.[11-14]

Finally, to understand the scope of our work in an applicative fashion as well as the future scopes for deployment of similar technologies, reference was made into a survey conducted by Yading Song et. al[10] on future perspectives into these systems.

3. MODEL IMPLEMENTATION AND METHODS

Our model has a number of steps starting from an interactive agent, which employs Sentiment Analysis and NLP to get user's current state, then the model continues to process the information based on Russel's circumplex model of emotions, plots a line between the user's current state and the goal state and recommend songs along the line.

A. Interactive Agent

An interactive agent acts as the primary interface for the user within our model, it is where we employ NLP and Sentiment Analysis[11], the agent employs question which feels natural and authentic and reads keywords from user's conversation, these keywords helps us to categorize the user's current emotional state, with this we confirm their current emotional state and mark the plot point on the Circumplex model for the corresponding emotion.[18-21]

Specifically, the interactive agent is built on top of the VADER (Valence Aware Dictionary and Sentiment Reasoner) package and other NLTK (Natural Language Toolkit) packages.[22]

The 'NRC Valence, Arousal, and Dominance (VAD) Lexicon' or 'NRC-VAD-Lexicon' for short[12], is used in the model for our score determination. It includes a list of more than 20,000 English words and their valence, arousal, and dominance scores. The Interactive Agent then parses the retrieved user's text data and uses it in the model to output a (Valence, Arousal) score, which is used as an input to our recommendation model.

With the confirmation of the user's current emotional state, their goal state is also identified, either with their specific confirmation, or our default recommendation of a positive emotional state which can counter and remedy their current negative emotional state.[15]

B. Russell's Circumplex Model of Emotion

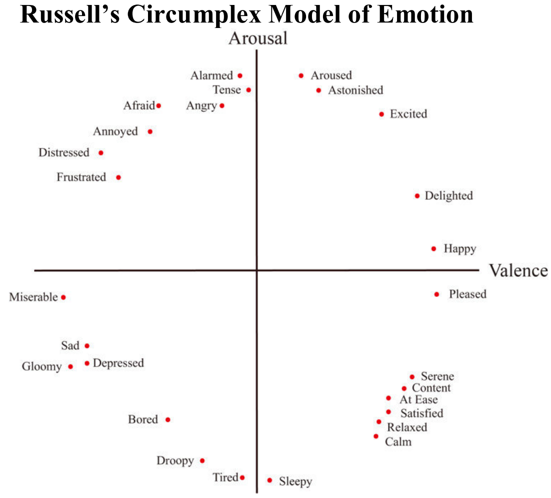

Fig 1. Russell's Circumplex Model of Emotion.

Developed by James A. Russell in 1980, in his paper[4], he has classified emotions onto a 2D plane based on the Valence and Arousal values of each emotions, which can broadly be classified into 4 types of emotions, happy, angry, sad and relaxed, which are categorized into the first, second, third and fourth quadrants respectively.

Keywords in the lexicon dictionary has their own Valence and arousal values, which helps to find the plot of the current emotional state of the user easily, Spotify also assigns attributes of Valence and Energy (Arousal) to all available songs in their database[13], this helps in recommending songs we need for the user, by filtering and selecting songs with the closest or matching Valence-Arousal attributes we are searching for.

Our model initially plots down the user's current emotional state as well as the goal state. Wherein a straight line is drawn, this acts as the baseline for the recommendation system, and recommends songs along the lines, the songs are chosen based on the shortest vector distance from the line, as well factoring in user's preferences (Such as genre)[14], gradually through the line from the current state to the goal state.

C. Data Processing

The main need for data processing in our model is mainly for vector distance calculation.

The line drawn from the current emotional state to the goal state, can be divided into n sections based on how many songs the user wants to be recommended. From each section the shortest vector distance for songs in the dataset is computed, these songs are then recommended for the user.

The equation of the goal line can be found with the coordinates of the current emotional state and the goal emotional state state. The equation for given as

$$\mathbf{y-y_1=(y_2-y_1)/(x_2-x_1)\ (x-x_1)}$$

where,
X_1 = X coordinate of the current emotional state
Y_1 = Y coordinate of the current emotional state
X_2 = X coordinate of the goal emotional state
Y_2 = Y coordinate of the goal emotional state
X = X axis constant
Y = Y axis constant

This is then converted to normal form of a line represented as:

$$\mathbf{Ax + By = C}$$

where,
A,B,C – Constants
x,y – Variables

The Vector distance between the song and the sections of the goal line or the goal line itself can be calculated using the following equation.

$$d = \frac{|ax_0 + by_0 + c|}{\sqrt{a^2 + b^2}}$$

where,
d = distance
a,b,c - non zero constants
X_0 - X coordinate of the point
Y_0 - Y coordinate of the point

The Spotify Song Attribute dataset has the values written in the range of 0 to 1, this has to be converted to a range between -1 ro 1, without losing the ratio, the range conversion equation is used.

$$\mathbf{New_{value} = \frac{(Old_{value} - Old_{min})\ X\ New_{range}}{Old_{Range} + New_{min}}}$$

where,
New_{value} = The new value
Old_{value} = The old value
Old_{min} = The minimum value of old range
New_{range} = The maximum value of new range
Old_{range} = The maximum value of old range
New_{min} = The minimum value of new range

D. Datasets

Mainly 2 datasets are required, one for the Valence-Arousal plane for quick mapping of current emotional state and goal state, and the second dataset contains a database of songs from spotify with their attributes, this is for faster recommendation of songs.

i) Valence-Arousal Plane Dataset

The Valence-Arousal Plane dataset contains the list of primary emotions, this dataset is used for the quick mapping of the user's current emotional state and goal state via referencing the dataset for both of its coordinates respectively.

Table 1: Coordinates of Main Emotional States.

Emotion	Valence	Arousal
Angry	-0.405	0.787
Afraid	-0.109	0.786
Excited	0.7	0.725
Happy	0.897	0.162
Depressed	-0.809	-0.465
Bored	-0.34	-0.792
Relaxed	0.711	-0.664
Pleased	0.881	-0.106

ii) Spotify Song Attribute Dataset

This dataset is created by crawling the spotify database with a script that is programmed to retrieve a set amount of songs over various amounts of genre within Spotify.

The Script retrieves values such as artist name, track name, track id, valence, energy, popularity, danceability, loudness, speechiness, acousticness, instrumentalness, tempo and duration. We mainly focus on the valence and energy attribute of these songs.

Table 2: Snippet of Spotify Song Attribute Dataset.

artist_name	track_name	energy	valence
Olivia Rodrigo	drivers license	0.431	0.137
The Weeknd	Blinding Lights	0.73	0.334
Glass Animals	Heat Waves	0.525	0.531
Masked Wolf	Astronaut In The Ocean	0.695	0.472
Ed Sheeran	Bad Habits	0.893	0.537
The Weeknd	Save Your Tears	0.826	0.644

Since the values are in the range 0 to 1, this is converted to a range of -1 to 1, using the equation. This resulting dataset is used.

Table 3: Snippet of Range Corrected Spotify Song Attribute Dataset.

artist_name	track_name	energy	valence
Olivia Rodrigo	drivers license	-0.138	-0.726
The Weeknd	Blinding Lights	0.460	-0.332
Glass Animals	Heat Waves	0.050	0.062
Masked Wolf	Astronaut In The Ocean	0.390	-0.056
The Weeknd	Save Your Tears	0.652	0.288

4. RESULTS AND DISCUSSION

With testing with a small user sample, we have seen our model being able to bring about change in their emotional state, in most cases alleviating them and bringing them to their desired, if not closer to their desired goal state.

First, we tested out the accuracy and functionality of the interactive agent, and answers of the user, and the Valence-Arousal scores for current emotional state and goal state.

We ask them 2 main questions to assess this:
Q1: Hi, How are you feeling today ?
Q2: Understood, What would you describe as your ideal emotional state ?

Based on this we have transcribed below the replies of a few users.

User 1:

Response	Score
I think my depression is back	-0.808, -0.498
I just would like to feel happy for a moment	0.899, 0.161

User 2:

Response	Score
I can feel my blood boiling	-0.167, 0.724
I would like to calm down and be more approachable	0.764, -0.595

User 3:

Response	Score
Things look very bleak	-0.868, -0.463
I would like to feel the light again	0.619, -0.298

Based on the score given, the current emotional state and the ideal goal state for the sample set of user's are:

User	Current State	Goal State
1	Depressed	Happy
2	Enraged	Friendly
3	Melancholic	At Ease

With these data inputted into our recommendation model, it has recommend songs based on the Valence-Arousal values of the songs, starting from the initial, the current emotional state and ending with the goal state, Songs are recommended in between based on the line that draws between the two states in the Valence-Arousal plane and the distance of the song from that line.

These songs were recommended for the sample user set:

User 1:

Artist	Title	Valence	Arousal
Kevin Kern	Fields of Gold	-0.808	-0.896
Gandalf	Never Too Far	-0.268	-0.284
Queen	I Want to Break Free	0.004	-0.172
Iron and Wine	Call it Dreaming	0.452	0.002
Martha and the Muffins	Paint by Number Heart	0.902	0.164

User 2

Artist	Title	Valence	Arousal
The Carburetors	Burnout	-0.166	0.874
Radiohead	I Might Be Wrong	0.001	0.470
The Gladiators	Soul	0.342	-0.038

	Rebel		
N.W.A	Express Yourself	0.498	0.570
Elvis Presly	Have a Happy	0.764	-0.510

User 3

Artist	**Title**	**Valence**	**Arousal**
Frances Black	Wall of Tears	-0.040	-0.690
Don McLean	Babylon	0.368	-0.640
Ken Griffin	St. Louis Blues	0.498	-0.604
Billie Holiday	Why Was I Born?	0.584	-0.612
Ed Sheeran	Gold Rush	0.778	-0.504

The time or number of songs or cycles of recommendation varied from user to user, as psychologically everyone has a different mental constitution, and their difference in taste of music as well.

Overall, our model can be considered as successful and can have scope to improve further.

5. CONCLUSION AND FUTURE SCOPE

Our recommendation model has shown promise in its effective use as well as flexibility in both recommending based on the user's needs as well as in flexibility for further improvement in the future. Increasing the accuracy of emotions detected and songs recommended can be done in the future as an update of the model, into a more specific one with more molecular classification in emotional classification.

The emotional reading perhaps can be even extended over the context of just textual conversation, into areas of verbal and facial expression based detection systems.

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