605.744: Information Retrieval
Emotion Extraction From Lyrics

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Contents

Abstract

Mood classification in music has become more prevalent with the growing streaming industry. Categorizing songs based on the perceived emotions allow music streaming services to improve their recommendation systems and automatic playlist generation. Services such as Spotify use audio features such as duration, energy, tempo, etc. and other combinations of audio features such as danceability and instrumentalness to group similar tracks. These classifications focus solely on the audio production of the songs while ignoring the lyrical content. Emotion extraction from text can be a difficult task, due to the subjectivity in quantifying or discretely categorizing emotions. In this project, 2 of the popular models of emotions, the Plutchik's Wheel and the VAD model, have been used to attempt emotion extraction.

1 Introduction

This paper discusses the methods used to

2 Background

2.1 Natural Language Processing on Lyrics

Natural language processing on English song lyrics assume additional restrictions. There are no standards set for preprocessing lyrics, but the following lists the exceptions address for this project:

- Songs may be entirely composed of stopwords.
- Repetition is considered significant.
- Lyrics may contain songwriting directions, such as "[gang vocals]", "[instrumental]", "[hook]", "[Speaker A]", etc.
- Lyrics may contain adlibs. For this project, adlibs are not considered part of the dictionary.

2.2 Sentiment Analysis

Sentiment scores are evaluated as the ratios of weights of the relatively positive and negative terms in a document. Context is typically emphasized to increase the accuracy of the perceived sentiment. This is achieved by using long n-grams. This project tokenizes the documents as 1-grams, and therefore loses contexts. The sentiment scores are instead evaluated as the ratio of the positive and negative terms over the total number of terms. Terms are labeled positive or negative if they are found in their corresponding datasets.

$$S = \frac{|p| - |n|}{N} \tag{1}$$

If a document contains more negative terms, then the sentiment score will naturally be negative as well, and vice versa for a positive score.

2.3 Emotion Classification

2.3.1 Plutchik's Wheel of Emotions Model

Psychologist Robert Plutchik proposed a model composed of eight primary emotions: anger, fear, sadness, disgust, surprise, anticipation, trust, and joy [1]. The model, pictured in Figure 1, consists of several concentric circles, with the outer circles being combinations of emotions from the inner circles.

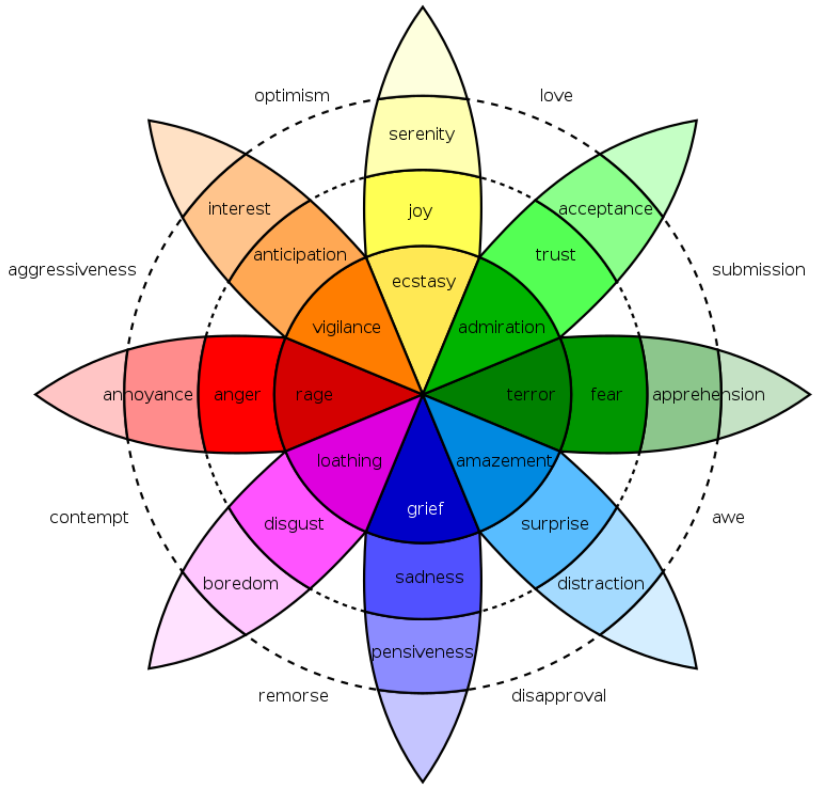

Figure 1: Plutchik's Wheel of Emotions Model

Several categories described by the model do not translate well over text. For example, a human reviewer may find it difficult to extract emotions of *trust* or *anticipation* from a document without explicit usages of synonyms of such emotions.

2.3.2 VAD Emotional State Model

The VAD (Valence-Arousal-Dominance) Emotional State Model was proposed by psychologist Albert Mehrabian. The model plots emotional states across these 3 dimensions of emotion. Valence measures how pleasant or unpleasant an emotion is, arousal determines the energy of the emotion, and dominance refers to the sense of control over the particular emotion. The model, pictured in 2, implies a more granular approach to categorizing emotions.

The third dimension of the model can be disregarded to describe the more popular Valence-Arousal Emotional State Model (also known as the Circumplex Model), developed by psychologist James A. Russell. The two dimensions of this model allows for emotions to be categorized into quadrants which are sufficient in determining the general sentiment of the emotion. The four quadrants can be labeled as:

- **Quadrant I**: High-arousal/positive-valence, "joy"

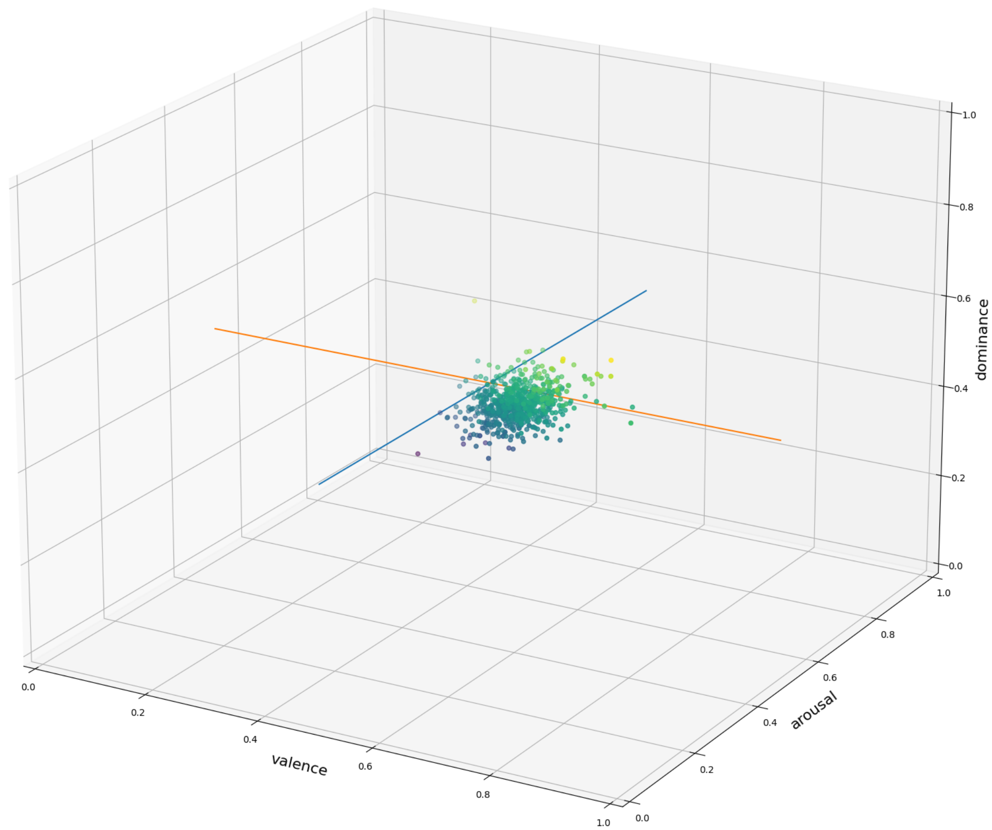

Figure 2: VAD Emotional State Model

- **Quadrant II**: High-arousal/negative-valence, “anger”
- **Quadrant III**: Low-arousal/negative-valence, “sadness”
- **Quadrant IV**: Low-arousal/positive-valence, “calm”

2.3.3 Emotion Categories

3 Technical Background

All of the source code is in Python 3.10. The program is split into several modules and follows an object oriented structure.

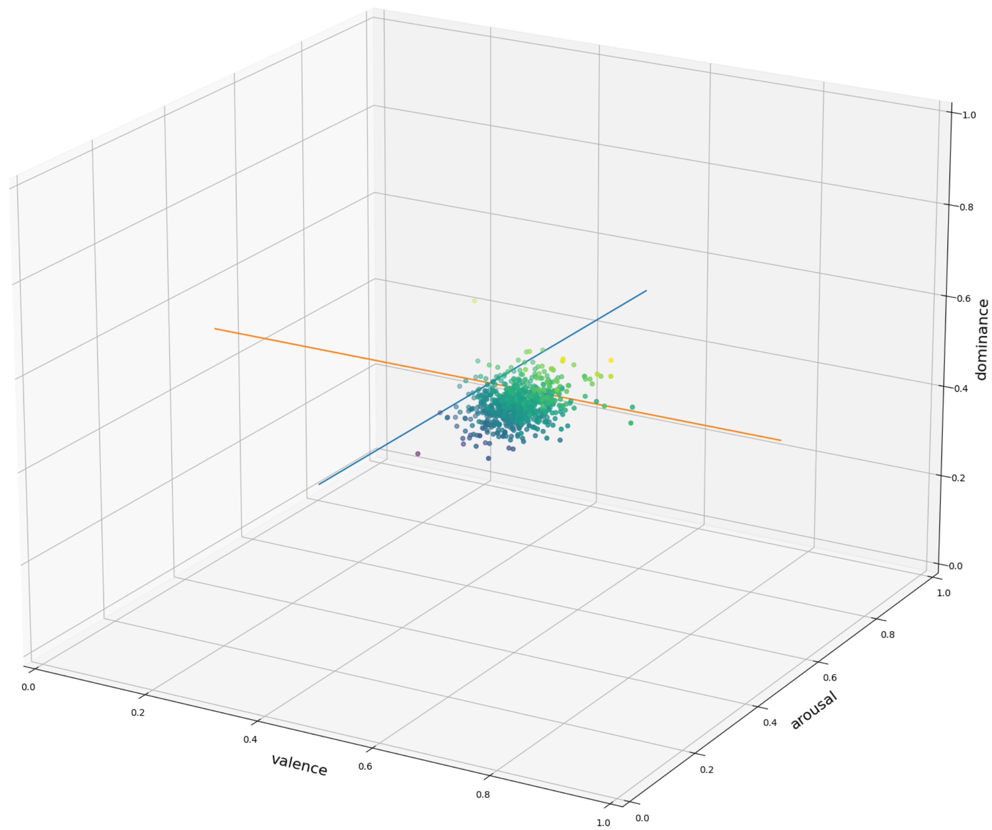

Figure 3: VAD Emotional State Model

3.1 Emotion Playlist

$$acc = \frac{\sum_{p \in E^+} \frac{\sum_i [p_i > 0]}{|p|} + \sum_{n \in E^-} \frac{\sum_i [n_i < 0]}{|n|}}{|E|} \tag{2}$$

Table 1: ratio

Metric	Tracks Categorized	Accuracy
25%	747	0.544
50%	747	0.643
75%	730	0.747
mean	747	0.673

Table 2: ratio

Metric	Tracks Categorized	Accuracy
25%	626	0.572
50%	626	0.719
75%	603	0.820
mean	626	0.713

Table 3: No transform

Emotion	mean	median	mean	median	mean	median
anticipation	1.730709	1.5940	3.719128	2.8350	1.730709	1.5940
disgust	1.069293	0.7200	2.601124	1.1640	1.069293	0.7200
anger	1.648021	1.2190	3.986169	1.8750	1.648021	1.2190
trust	2.476561	2.1790	6.776188	4.9530	2.476284	2.1790
sadness	1.790973	1.5090	3.842015	2.6960	1.701007	1.4210
joy	2.392433	2.2070	6.319867	4.4240	2.392433	2.2070
fear	1.888261	1.5315	3.869922	2.4785	1.888261	1.5315
surprise	0.851107	0.7420	1.840037	1.0710	0.851107	0.7420

Table 4: ratio

Emotion	mean	median	max
joy_ratio	0.216300	0.218978	0.668980
trust_ratio	0.186233	0.187097	0.638021
sadness_ratio	0.121942	0.114320	0.457091
surprise_ratio	0.057528	0.052510	0.407974
anticipation_ratio	0.138459	0.138032	0.456406
anger_ratio	0.101198	0.090794	0.694792
disgust_ratio	0.065279	0.057565	0.316643
fear_ratio	0.113061	0.106388	0.409779

Table 5: ratio

wheel_playlist	count
fear	490
disgust	474
anger	470
sadness	470
anticipation	469
trust	461
surprise	458
joy	444

References

[1] R. Plutchik, "The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice," *American Scientist*, vol. 89, no. 4, pp. 344–350, 2001.