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Mood detection analyzing lyrics and audio signal based on deep learning architectures

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Introduction

The terms music and mood are two concepts strongly connected.

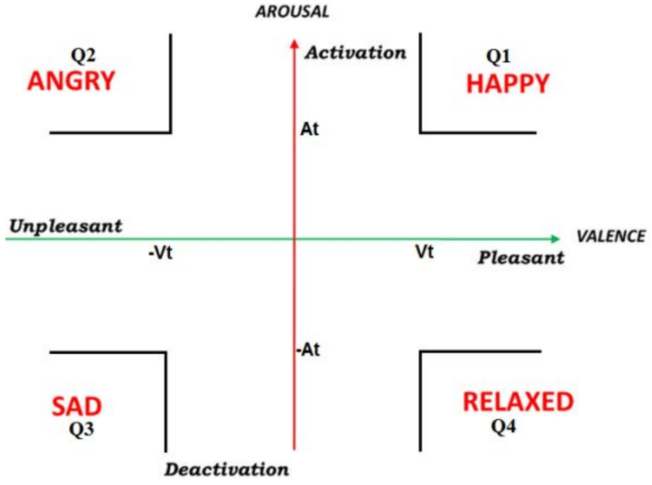
In our paper we investigate how to detect the mood of a music track applying Deep Learning techniques.

What was our approach?

- A Lyric analysis model
- An Audio analysis model
- A Multichannel model
- Compare the results

The Emotional Model

- Rusel's Circumplex is the emotional model we used in our work
- According to Circumplex all human emotions are distributed in a two-dimensional space with axes of valence and arousal
- Each quadrum represents a mood class



Valence (V) and arousal (A) values	Mood
$A > A_t$ and $V > V_t$	Happy
$A > A_t$ and $V < -V_t$	Angry
$A < -A_t$ and $V < -V_t$	Sad
$A < -A_t$ and $V > V_t$	Relaxed

From Audio to Mood

Association between structural features of music and emotion

Structural Feature	Definition	Associated Emotion
Tempo	The speed or pace of a musical piece	Fast tempo:happiness, excitement, anger. Slow tempo: sadness, serenity.
Mode	The type of scale	Major tonality: happiness, joy. Minor tonality: sadness.
Loudness	The physical strength and amplitude of a sound	Intensity, power, or anger
Melody	The linear succession of musical tones that the listener perceives as a single entity	Complementing harmonies: happiness, relaxation, serenity. Clashing harmonies: excitement, anger, unpleasantness.
Rhythm	The regularly recurring pattern or beat of a song	Smooth/consistent rhythm: happiness, peace. Rough/irregular rhythm: amusement, uneasiness. Varied rhythm: joy.

Features extracted from audio that we experimented with:

- Spectogram
- Mel Spectogram
- Log-Mel Spectogram
- MFCCs
- Chroma features
- Centroid tonal features
- Spectral contrast

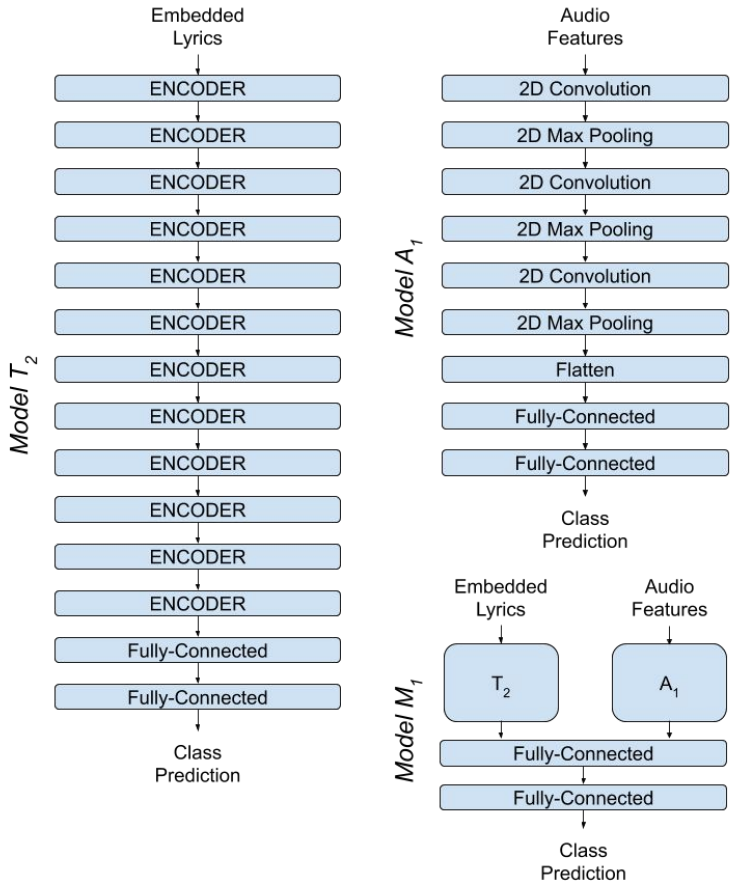
From Lyrics to Mood

- Each world in lyrics is attributed to pair of valence and arousal values
- The set of values is computed with the help of dictionaries which contain emotional information
- A general pair of valence and arousal values is computed for each song

Data Preparation

- The dataset we used is the MoodyLyrics Dataset
- 2.000 song titles with their corresponding mood label
- Mood labels = {happy, angry, sad, relaxed}
- Audio data
  - Collect audio files from web
  - Augment samples (37.989 audio samples)
  - Extract audio features
- Lyrics data
  - Collect lyrics from web
  - Augment samples (18.115 lyrics samples)
  - Compute BERT Embeddings

System Architecture



How the multichannel system (M_1) is developed?

- Train BERT-base uncased model (T_2) on lyrics
- Train CNN model (A_1) on audio signal
- System M_1 is implemented as the fusion of A_1 and T_2 with a common classifier of two fully connected layers

Results

- <u>Lyric Analysis Subsystem</u>
  We trained BERT model (T_2) and compared its results with several text analysis techniques

Model	Embedding Method	Loss	Accuracy %
T_1'	BoW	1.287	65.49
T_1'	TF-IDF	1.381	67.98
T_1	Word2Vec	1.262	41.66
T_1	GloVe	1.064	53.33
T_2	Bert	1.353	69.11

Results

- Audio Analysis Subsystem
  We trained CNN model (A_1) and experimented with different possible feature combinations

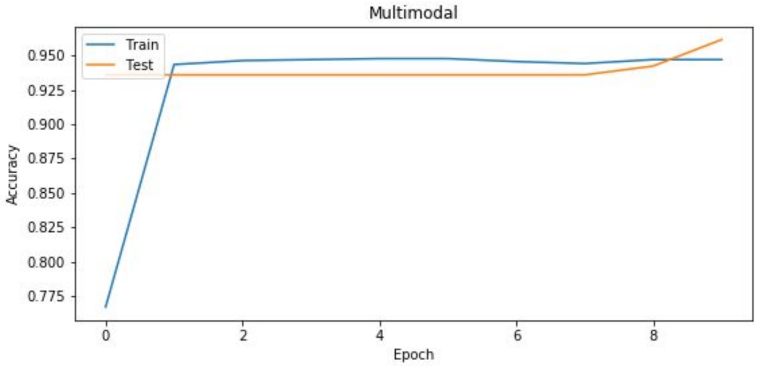
Feature Combination	Accuracy %
Mel	64.97
Mel, Log-Mel	68.38
Mel, Chroma, Tonnetz, Spectral Contrast	60.86
Log-Mel, Chroma, Tonnetz, Spectral Contrast	58.96
MFCC, Chroma, Tonnetz, Spectral Contrast	65.36
Mel, Log-Mel, MFCC, Chroma, Tonnetz	69.77
Mel, Log-Mel, MFCC, Chroma, Tonnetz, Spectral Contrast	70.34

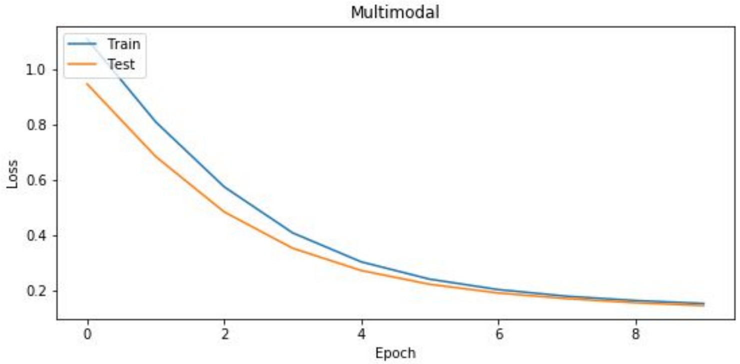
Results

- <u>Fuse Analysis System</u>
  We used the already trained subsytems to train our multichannel model (M_1)
  And compared its results with the previous models

Model	Loss	Accuracy %	Computational Time
$T_1^{'}$	1.381	67.98	0m 25.391s
T_2	1.353	69.11	18m 12.444s
A_1	0.743	70.51	80m 13.064s
M_1	0.156	94.58	3m 38.551s

Results


Multimodal
Train
Test
Accuracy
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0
2
4
6
8
Epoch


Multimodal
Train
Test
Loss
1.0
0.8
0.6
0.4
0.2
0
2
4
6
8
Epoch

Conclusion

- BERT outperforms simple text analysis techniques
- The combination of all six audio features has the best performance on the task
- Fusing the two subsystem into one complex system achieves huge improvement in performance and outperforms single channel systems