A MULTIMODAL APPROACH TOWARDS EMOTION RECOGNITION OF MUSIC USING AUDIO AND LYRICAL CONTENT

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ABSTRACT

We propose MoodNet-A Deep Convolutional Neural Network based architecture to effectively predict the emotion associated with a piece of music given its audio and lyrical content. We evaluate different architectures consisting of varying number of two-dimensional convolutional and subsampling layers, followed by dense layers. We use Mel-Spectrograms to represent the audio content and word embeddings—specifically 100 dimensional word vectors, to represent the textual content represented by the lyrics. We feed input data from both modalities to our MoodNet architecture. The output from both the modalities are then fused as a fully connected layer and softmax classifier is used to predict the category of emotion. Using F1-score as our metric, our results show excellent performance of MoodNet over the two datasets we experimented on—The MIREX Multimodal dataset and the Million Song Dataset. Our experiments reflect the hypothesis that more complex models perform better with more training data. We also observe that lyrics outperform audio as a better expressed modality and conclude that combining and using features from multiple modalities for prediction tasks result in superior performance in comparison to using a single modality as input.

1. INTRODUCTION

With the ever-increasing amount of digital music online, there arises a need of effective organisation and retrieval of such amount of data. Although traditionally, the most common search and retrieval categories like artist and genre have received greater attention in music information retrieval (MIR) research, emotion based retrieval techniques too have been proven to be an effective criterion for MIR [8] receiving greater attention [7, 26]. Generally, Music Emotion Recognition (MER) has relied on audio features like Mel-frequency cepstral coefficients (MFCCs) or mid-level features like chord [22], rhythmic patterns [22] etc for emotion recognition.

Lyrical features being semantically rich have also been widely used for emotion recognition, as their meanings convey emotions more clearly and are composed in accordance to the music signals.

For lyrical content analysis, mostly statistical natural language processing (NLP) techniques like bag of words [24] and probabilistic latent semantic models [9] have been used to extract textual features.

With recent evolution of powerful computational hardware like GPUs, Deep Neural Networks have been used successfully in audio content analysis and retrieval, with exceptional accuracy in tasks like speech recognition [23] and computer vision [12].

In computer vision, deep convolutional neural networks (Deep CNNs) simulate the behaviour of the human vision system and learn hierarchical features, allowing object local invariance and robustness to translation and distortion in the model [14]. They have shown state-of-the-art performance in speech recognition [23] and music related tasks like music segmentation [25].

Likewise, vector space representations have also proved to be an effective method of representing words [4, 20, 27]. Using such representations along with Deep CNNs have shown great results in various NLP tasks like sentence classification [28] and sentiment analysis [6, 29].

In this paper, we propose we propose MoodNet—a deep convolutional neural network based architecture, that combines the features obtained from both audio and lyrical modalities for classification of music based on mood. We use mel-spectrograms as input for the audio modality. For the corresponding lyrical content, we use the vector representation of words present in the lyrical content as input to the network. Both of these representations are used as inputs to the Deep CNNs which output a single feature vector (for each modality). The two vectors are combined and are classified using a softmax classifier.

We discuss CNNs for audio content and textual content analysis in Section 2 and Section 3 respectively. The MoodNet architecture is introduced in Section 4 followed by experiments and results in Section 5. We end our paper with a conclusion and the scope for future work in Section 6.

2. CNNS IN AUDIO CONTENT ANALYSIS

2.1 Motivation

CNNs are motivated by our perception of vision where neurons capture local information and higher level information is obtained [14]. CNNs are therefore designed to provide a way of learning robust features that respond to certain visual objects with translational and distortion invariance. These advantages often work well with audio signals too. Deep CNNs learn features hierarchically, learning lower level features at the shallow end and hierarchically
learning complex and higher-level features at the deeper ends [14].

Audio analysis tasks uses CNNs with the underlying assumption that auditory events are detectable by observing their time-frequency representation. As emotion of a song represents a high-level feature as compared to beat, chords, tempo as mid-level features, this hierarchical nature aligns with the motivations behind the architecture of Deep CNNs.

2.2 Representation

Mel-spectrograms have been one of the most widespread features used for various audio analysis tasks like music auto-tagging and latent feature learning. The use of the mel-scale is supported by domain knowledge about the human auditory system [19] and has been empirically proven by impressive performance gains in various tasks [5].

The visual representation of audio mel-spectrogram is used as input to the MoodNet architecture (Figure 1).

2.3 Convolutions

A convolution layer of size lb,d learns d features of lb, where l refers to the height and b refers to the width of the learned kernel. The kernel size also represents the maximum span of a component it can capture. If the kernel size is too small, the corresponding convolutional layer would fail to learn a proper representation of the distribution of the data. For this reason, relatively larger dimensional kernels are often preferred [10].

The convolution axes are an important aspect of convolution layers. 2D convolutions generally perform better than 1D convolutions as the former can learn both temporal and spectral structures and have been used in tasks like boundary detection [25] and chord recognition [10].

2.4 Pooling

The pooling operation results in reduction of the feature map size with an operation, usually a max function. It is widely used in most of the modern CNN architectures. Pooling applies subsampling to reduce the size of feature map. While doing so, instead of preserving information about the whole input, it only tries to preserve the information of an activation in the region. The non-linear behaviour of subsampling also provides distortion and translation invariances. For smaller pooling sizes, the network cannot have enough distortion invariance. On the other hand, if it is too large, many feature locations may be left out when needed. Normally, the pooling axes should match the convolution axes.

3. CNNs In Lyrical Content Analysis

3.1 Motivation

3.1.1 Word Embeddings

Semantic representation of words is a challenging task in natural language processing. With the recent development of neural word representations models [13, 17, 18], word embeddings have provided a broad scope for distributional semantic models. For the first time, distributed representations of words make it possible to capture semantics of words; including even the shift in meaning of words over time [16]. Such capability explains the recent successful switch in the field of natural language processing from linear models over sparse inputs, e.g., support vectors machines (SVMs) and logistic regression, to non-linear neural-network models over dense inputs. As a result, models that rely on word embedding have been very successful in recent years, across a large spectrum of language processing tasks [15]. Word embeddings based on neural networks are prediction-based models. For a network to learn distributed representations for words, it learns its parameters by predicting the correct word (or its context) in a suitable text window over the training corpus. While the main objective of training the entire network is to learn superior parameters, word vector representations are based upon the idea that similar words are closer together. In linguistics, this is known as Distributional Hypothesis. This very idea is beneficial for extracting features from text represented in a ‘natural’ way; especially for understanding the context of word use in mood prediction. Since this notion is viable for any natural language, we take advantage of that and apply it to musical lyrics.

3.2 Representation

Each word in the lyrics of a song is a vector. So all the words in a sentence are vectors which, when concatenated represent a two-dimensional matrix. Similarly, multiple...
lines of sentences when concatenated represent a three-dimensional matrix.

The resultant input is similar to that of an image with multiple channels and thus serves as input to our Deep CNN architecture. The representation is shown in Figure 2.

4. MOODNET ARCHITECTURE

Figure 2 shows one of the proposed architectures, a 4-layer MoodNet architecture which consists of 4 convolutional layers and 4 max-pooling layers. For the audio content, this network takes a log-amplitude mel-spectrogram sized 96 × 1366 as input.

For all architectures, the MIREX Multimodal dataset [21] (Dataset I) and the resultant input is similar to that of an image with multiple channels and thus serves as input to our Deep CNN architecture. The representation is shown in Figure 2.

| Architecture   | Mel-spectrogram (input: 96 × 1366 × 1) |
|----------------|----------------------------------------|
| MoodNet-3      | Conv 3 × 3 × 128                        |
|                | MP (2, 4) (output: 48 × 341 × 128)     |
|                | Conv 3 × 3 × 256                        |
|                | MP (2, 4) (output: 24 × 85 × 256)      |
|                | Conv 3 × 3 × 512                        |
|                | MP (2, 4) (output: 12 × 21 × 512)      |
|                | *Conv 3 × 3 × 1024                      |
|                | *MP (3, 5) (output: 4 × 4 × 1024)      |
|                | **Conv 3 × 3 × 2048                     |
|                | **MP (4, 4) (output: 1 × 1 × 2048)     |
| Flattened 2048 × 1 |

Table 1. The configurations of 3, 4, and 5-layer architectures for the audio modality. The darker layers show the additional layers for 4 and 5-layer architectures.

| Architecture   | Mel-spectrogram (input: 100 × 10 × 20) |
|----------------|----------------------------------------|
| MoodNet-3      | Conv 3 × 3 × 6                          |
|                | MP (2, 2) (output: 49 × 5 × 120)       |
|                | Conv 3 × 3 × 256                        |
|                | MP (2, 2) (output: 24 × 4 × 256)       |
|                | Conv 3 × 3 × 512                        |
|                | MP (2, 2) (output: 12 × 2 × 512)       |
|                | *Conv 3 × 3 × 1024                      |
|                | *MP (3, 2) (output: 4 × 1 × 1024)      |
|                | **Conv 3 × 3 × 2048                     |
|                | **MP (4, 4) (output: 1 × 1 × 2048)     |
| Flattened 2048 × 1 |

Table 2. The configurations of 3, 4, and 5-layer architectures for the text modality. The darker layers show the additional layers for 4 and 5-layer architectures. Note that zero padding has been used whenever required to avoid dimensionality reaching zero.

Similarly, for the lyrical content, the entire corpus is first searched for the line with maximum length. This shall be the width of the three-dimensional matrix input. For all

5. EXPERIMENTS AND RESULTS

5.1 Overview

We used two datasets to evaluate our MoodNet architecture, the MIREX Multimodal dataset [21] (Dataset I) and
the Million Song Dataset [2](Dataset II).

We test three architectures (MoodNet-3,4,5) in both Dataset I and Dataset II. In both datasets, the audio was trimmed as 29.0 clips (the shortest signal in the dataset) and downsampled to 12 kHz. The hop size was set to 256 samples (21 ms) during time-frequency transformation, resulting in an output of 1,366 frames in total.

For the lyrics, Dataset I already contains the lyrics. For Dataset II, we selected a subset of the song names and scraped their corresponding lyrics from lyrics.wikia.com if they were available, else removed them from the dataset.

As each word represents a 100 dimensional vector, each sentence in the lyrics represented a matrix (by concatenating the vectors vertically). Again, a number of such sentences, when concatenated, would represent a 3-dimensional matrix. Of course, we take necessary steps to handle problems like variable length of sentences for a song, or variable number of lines for different songs.

The audio and textual components are used as inputs to the MoodNet architecture.

We used ADAM adaptive optimisation [11] on Keras [3] and Theano [1] framework during the experiments. Categorical cross-entropy function has been used since it results in faster convergence than distance-based functions such as mean squared error and mean absolute error.

5.2 Dataset I: MIREX Multimodal

The MIREX Multimodal dataset has a total of 903 30-second clips, each of which belongs to one of the five clusters (as shown in Table 3). Each cluster contains different numbers of clips, say, 170 clips in cluster I, 164 clips in cluster II, 215 clips in cluster III, 191 clips in cluster IV, and 163 clips in cluster V. The distribution has been represented in Figure 5.

![Figure 5](image)

Figure 5. The distribution of samples among the five clusters in the subset of the Million Song Dataset that we obtained.

We used F1 score as the accuracy metric for our experiment, as it considers both the precision ‘p’ and the recall ‘r’ value to compute the score. The results obtained by our architecture are summarized in Table 4.

| Architecture | F-measure |
|--------------|-----------|
| MoodNet-3    | 72.3      |
| MoodNet-4    | 76.34     |
| MoodNet-5    | 75.68     |

5.3 Dataset II: Million Song Dataset

We also evaluated our MoodNet architecture using the Million Song Dataset (MSD) with last.fm tags. We select the top 50 tags and extracted the mood based tags only. Among the variety of tags present, we clustered the tags according to Table 3. We selected subset of 50,000 samples from MSD and searched for the corresponding lyrics from lyrics.wikia. We removed the songs whose lyrics were not found. Our labels for each song was made by clustering the obtained tags and grouping them into one of the five clusters as described in Table 3. Thus, the total dataset was reduced to 48,476 (40,476 for training and

Table 3. Emotion Categories and their defined clusters used in MIREX Multimodal Dataset

| Cluster | Mood               |
|---------|--------------------|
| I       | passionate, rousing, confident, boisterous |
| II      | cheerful, fun, sweet, amiable |
| III     | poignant, wistful, bittersweet, autumnal |
| IV      | humorous, silly, campy, quirky, witty |
| V       | aggressive, fiery, intense, volatile |

Table 4. F-score obtained by various MoodNet architectures on the MIREX Multimodal dataset
The distribution of samples across the dataset has been represented by Figure 5.

We used F-1 score as the accuracy metric in our experiment with MSD. The results obtained are summarized in Table 5.

| Architecture  | F-measure |
|---------------|-----------|
| MoodNet-3     | 66.28     |
| MoodNet-4     | 69.73     |
| MoodNet-5     | 71.29     |

Table 5. F-score obtained by various MoodNet architectures on the Million Song Dataset

5.4 Modalities and Performance

We also experimented with different modalities as inputs. We supplied only audio as input, only text (lyric content) and both audio and lyrical modalities.

From the results we obtained, as shown in Table 6, it is clear that when considering single modality as input, lyrics outperform audio. This result is expected as lyrics convey meaning and emotion more explicitly, than Mel-spectrograms of audio. It is also observed that when both audio and text modalities are combined, they outperform the results obtained from a single modality input. This leads us to conclude that combining audio and text modalities leads to an increase in accuracy in emotion detection.

| Dataset       | Audio | Lyrics | Audio+Lyrics |
|---------------|-------|--------|--------------|
| MIREX Multimodal | 56.46 | 62.39  | 66.28        |
| MSD           | 58.34 | 64.79  | 69.73        |

Table 6. F-score obtained by MoodNet-4 architecture for audio and text modalities as inputs, both individually and combined.

6. CONCLUSION AND FUTURE WORK

We presented MoodNet - an emotion detection model based on Deep Convolutional Neural Networks. It was shown that our MoodNet architecture, based on Deep Convolutional Neural Networks with 2D convolutions can be effectively used for emotion detection. We tested our hypothesis on two datasets. In both datasets, we tested our architectures with both audio and text input, individually and combined. For audio, we used mel-spectrograms as input. For the text modality, we used word embeddings as input.

Our results show that lyrics as a single modality input outperforms audio. Also, combining both the modalities gave a better performance in both our datasets. Thus, we conclude that a combination of various modalities as input results in a better representation of a song as a whole.

It is to be noted that we didn’t use Long Short-Term Memory (LSTM) based Recurrent Neural Networks (RNNs) as our task involved detecting the emotion of an entire piece of music as a whole. In the future, we also plan to build an architecture capable of showing dynamic temporal behaviour. RNNs may be useful in that regard.

As future work, we also plan to explore video as an additional input modality. Also, mood-based song recommender systems based on our architecture, should effectively help users discover new music and tackle the cold-start problem associated with collaborative filtering, used in most current recommender systems.

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