AUDIO CLASSICAL COMPOSER IDENTIFICATION IN MIREX 2015: SUBMISSION BASED ON STRUCTURAL ANALYSIS OF MUSIC

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ABSTRACT

Based on musicological fundamentals of classical composers and the structural analysis primary ideas, in this work I study some compositive features to train a neural network using author recognition techniques applied to the task of Audio Classical Composer Identification in MIREX 2015.

1. INTRODUCTION

I propose a model based on some of the high level features that the humans use to identify a composer in an audio or a score: musical structure and harmonic analysis. These features are parallel to the features that is usual to look for in a text, as POS tagging, n-grams, different kind of element counts (number of punctuation marks, hyphens, number of paragraphs, etc.) or the general structure of the text (introduction, development of the text, conclusion, etc.).

These features are susceptible to having errors. However, as shown in the PAN contest for author identification [1] and author profiling [2] the previous features discriminate the different authors with a similar accuracy that the state of the art of the Audio Classical Composer Identification task [3].

1.1 Key Mode

The Vamp Plugin "Key Mode" calculates the major or minor mode of the estimated key in windows of 10 chroma frames. After calculate them, I use the count of the changes between minor and major as a feature. Major is written as 0 and minor as 1.

1.2 Segmentation

This is also feature from a Vamp Plugin from Queen Mary which divides the audio channel into 10 segments based on chroma and MFCC. Also, it labels similar segments, which gives us a structural analysis of the sample based on tonality. As key mode, I also use the count of the segments that appear at the segment.

$$argmax_{k \in Keys} \sum_{w_1=1}^{n_{win}} w_k \sum_{w_{10}=2}^{n_{win}} w_k * ((1-w)_{(k+7)\%12}) * pond$$

Figure 1. Formula to obtain a ponderated key using perfect cadences and key strength

1.3 Tonality

The main work has been done in these following high level features based on the key of the sample and the detected chords. First of all, I obtain through the key strength Vamp plugin the value between -1 and 1 of every key (from C, C#, and so on, to B minor and major) of every window of 1 chroma frame. Then, I select the most strong key of every window (in the figure, the most red value of a column) obtaining a vector of keys.

From this keys vector, I created a script in Python that obtains the key of the sample using a weighted sum of the number of perfect cadences found at the key strength using 1 chroma and the values of key strength plugin using 10 chroma. In the mathematical notation, keys are sorted by 12 Major tones and then 12 minor tones, the ponderation in the implementation is 12 after some tests and the w is the 1 and 10 chroma window through the algorithm iterates. This obtained key is used as a feature.

1.4 Harmonic analysis

The previous key vector, then, need to be transposed to convert this incontextual chords into a functional chords to get a functional harmonic analysis of the sample. To transpose, I use the previous obtained key of the sample.

From the previous feature we can obtain the number of functional units in the sample (tonic, dominant, subdominant, etc.), the number of most used cadences (perfect authentic cadence, plagal cadence, half-cadence, etc.) and even a set of most used progressions of three chords (like IV-V-I). As a parallelism of the POS tagging in text, is interesting to analyze the impact of this features because it's known that discriminate the composers [7].

1.5 MFCC means

At last, I included the means of the MFCC (Vamp Plugin) from the sample, using 20 coefficients and including

C0, also to compare this timbral feature with the structural ones.

2. CLASSIFICATION

In the proposed systems, I used a Multi Layer Perceptron (Feedforward Backpropagation Neural Network or simply NN) in one system and a Deep Belief Network (DBN) in another one as a classifiers. The features are normalized with z-score to remove outlayers and after that I normalized between 0 and 1 before using the neural network because of artificial neural network input restriction by design. The networks are configured with 44 neurons at the hidden layer, 300 epochs, a batch size based on a divisor of the number of dataset samples, sigmoid activation function and softmax function at the output layer. I tested the system with a homemade database of FLAC files, extracted from my own CD's of the authors of the task.

3. ACKNOWLEDGEMENTS

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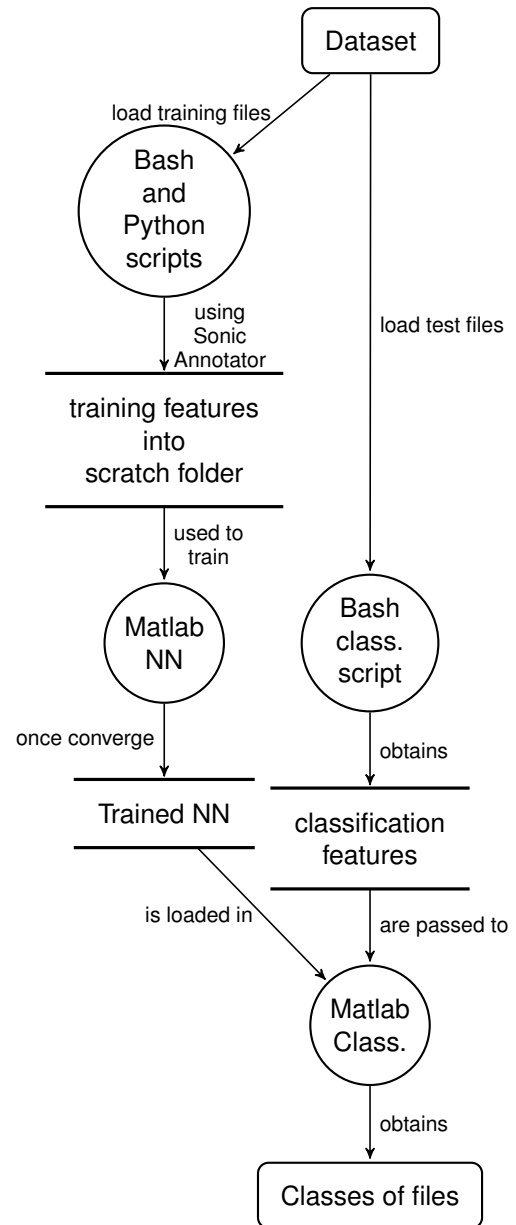
Figure 2. Workflow of the proposed system