Composer classification using grammatical inference

Jeroen Geertzen J.GEERTZEN@UVT.NL
Menno van Zaanen MVZAANEN@UVT.NL
ILK / Dept. of Communication & Information Sciences, Tilburg University, Tilburg, The Netherlands

Abstract

We present an approach to automatic composer recognition based on learning recurring patterns in music by grammatical inference. These patterns are more flexible than, for instance, commonly used Markov chains. The induced patterns are subsequently used in a regular-expression based classifier. We show that this approach yields promising classification results and allows investigation of induced composer-typical sequential structure.

1. Introduction

Where the automatic classification of music genre has received considerable attention recently, composer classification, being a more specific task, has not.

For classifying on genre or composer, supervised machine learning is commonly used, in which an algorithm learns a classification model of how features are related to classes based on labelled training samples. In most studies the features used tend to be local, i.e. the features predominantly describe events in rather short time intervals (e.g. tempo changes). Global features are usually statistical measures of musical pieces, such as the distributions of intervals, certain harmonics, tempo, etc. (e.g. in Backer et al., 2005).

When we aim to classify music by composer, we are essentially looking for recurring patterns of features in musical data that are typical to a specific composer. In order to describe what is happening over a span of time, several researchers have used probabilistic methods, notably Markov chains. A n-th order Markov chain bases the probability for a symbol to occur on the last n symbols. Based on the occurrence of unique or frequent Markov chains, a classifier can be built. However, such models do not allow the capture of more complex sequences.

We propose an approach to automatic composer classification that is based on grammatical inference (GI). GI is a branch of unsupervised machine learning that aims to find underlying structure of symbolic sequential data. Contrary to Markov chains, the sequences that are learned may have variable length and may be non-contiguous.

2. Approach

Music has characteristics relating to several aspects, such as harmony (i.e. intervals), melody, and rhythm. In our approach, we decompose the music along the latter two dimensions.[1]

In each of the dimensions, we look for patterns that characterize the music for that particular dimension, and formulate composer classification as a similarity search in a 2-dimensional vector space. For the induction of patterns, we use GI to obtain typical phrases or patterns in an unsupervised manner. We subsequently use these patterns as features in a supervised classification algorithm to automatically classify musical pieces by composer. This approach is depicted in Figure 1.

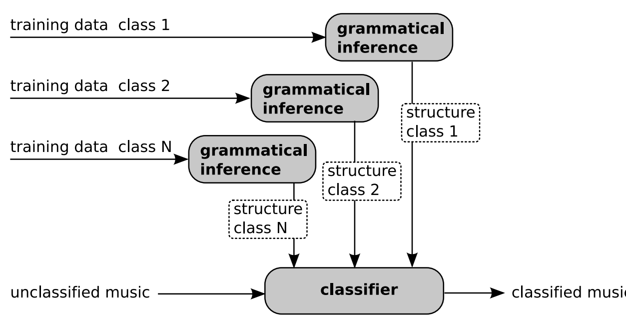

Figure 1. Overview of the GI component in classification.

The GI component in the system is realized by Alignment-Based Learning (ABL) (van Zaanen, 2002). ABL is a generic GI framework that has been successfully applied in natural language processing. It induces structure from sequences by aligning them. Based

[1]There are more dimensions that could be distinguished, but those will be included in future work.

on interchangeable subsequences, the data is generalized. For instance, given the two following melodic sequences:

```
d c d [ e f# ] g e
d c d [ d e ] g e
```

the alignment learning of ABL induces the pattern `d c d X g e`, in which `X` may be any substitutable part. In a similar way, ABL is applied to sequences, each of which representing a piece for a particular dimension.

The supervised classification algorithm determines, for each dimension, the phrases and patterns that are typical to each composer. Subsequently, these global patterns are applied as regular expressions to an unseen piece. This gives for each composer a measure of structural similarity with the piece. The composer with the highest similarity is selected.

3. Data

GI approaches are inherently symbolic and we do not want to consider stylistic aspects related to performance. Therefore, we extracted symbolic representations from music in humdrum **kern format (Huron, 1997). The melodic sequences encode relative pitch changes by means of number of semitones and the direction (upwards or downwards); the rhythmic sequences encode relative meter changes in tempo difference and direction (quicker or slower).

To look for recurring patterns of features in musical data *that is typical to a specific composer*, we compiled two datasets[2] of composers from the same musical era with the same type of musical piece: a baroque dataset with preludes from Bach (42) and Chopin (24), and a classic dataset with quartet pieces from Beethoven (70), Haydn (213), and Mozart (82).

4. Experimental results

The performance of the GI based approach was compared to that of a 2^{nd} order Markov model approach (MM-2) and evaluated using leave-one-out cross-validation.[3] The performance is measured by error rate, which is calculated by dividing the number of incorrectly classified musical pieces by the total number of pieces in the test set.

The resulting scores are given in Table 1. Classification was performed both with a similarity search in a 2-dimensional vector space (joint) and for each dimension in isolation (melody, rhythm).

Table 1. Error rate for both datasets with both approaches.

Dataset	*Dimension*	*ABL*	*MM-2*
BAROQUE	MELODY	19.8 ±0.3	29.1 ±0.4
	RHYTHM	22.5 ±0.6	32.4 ±0.7
	JOINT	19.9 ±0.2	29.0 ±3.6
CLASSIC	MELODY	23.6 ±0.7	34.8 ±2.1
	RHYTHM	28.8 ±1.2	37.2 ±5.9
	JOINT	21.3 ±1.3	35.1 ±2.8

From the table we can conclude that for both datasets, the GI based approach results in lower error rates than the MM-2 approach. Furthermore, it is interesting to see that the joint model (which learns from both melodic and rhythmic sequences) results for the GI system on the classic dataset in a lower error rate than any of the dimensions in isolation.

The discriminative sequences that are found provide ample opportunity for qualitative style analysis, which is beyond the scope of this paper. To give an idea, the following melodic pattern typically occurs in Chopin's preludes: `b♭ e♭ X b♭ b♭ X b♭ X`, where `X` matches an arbitrary number of notes.

Preliminary results in varying the level of detail of the sequences (e.g. relative pitch versus absolute pitch change) indicate that there is still a lot to gain in looking for the optimum balance between detail in data representation and data sparsity.

5. Conclusions & future work

We present a GI based approach to composer classification with promising results. It uses humanly readable patterns automatically extracted from music. Future research will address the use of other GI algorithms, a further exploration of more elaborate and finer grained feature dimensions, as well as motif extraction.

References

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[2]A specification of the datasets can be found at: `http://cosmion.net/jeroen/publications/`.

[3]Leave-one-out was used due to the small amount of training data available.