Music Composer Identification

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Outline

Who is the composer of this music sheet?

Problem

How to identify the composer of a music sheet?

Source: commons.wikimedia.org

Who is the composer of this music sheet?

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How to identify the composer of a music sheet?

Solution

- The composer can be identified by their "fingerprints" – style marker
- A style can be seen as a recurring arrangement of features
- Try to solve with a recognition algorithm

Previous Approaches

1. Theme recognition using HMM and N-Grams by Pollastri and Simoncelli
    - Recognize only the monophonic themes
    - Recognition rate: 42%
2. Style recognition system using neural networks by Buzzanca
    - Recognition rate: 97%
    - Use highly prepared data
    - Drawback: Cannot be used to explain the behavior of the recognition process and the result

N-Gram-based Approach

Basic Idea

For an unknown music sheet:

- Extract the profile (features) from the music sheet by using N-Grams
- Compare with existing profile based on the training data

Assumption

- The order of notes plays a role to distinguish the composer

Based on the research of Wolkowicz, Kulka and Kešelj [Wołkowicz et al., 2008]

Outline

Music Data Representation

Type of possible data source:

1. *Raw audio* – Recorded sound e.g WAV
2. *Symbolic representation* – Stored score notation e.g MIDI
3. *Metadata* – Stored meta information for example: year/period, title, genre

Remark

N-Gram-based approach focuses on the symbolic music data represented as *MIDI files*

MIDI Corpus

Example of the training and testing sets that are used

MIDI corpus properties

	Composer	Training Set	Testing Set
1	J.S.Bach	99 items, 890 kB	10 items, 73 kB
2	L.van Beethoven	34 items, 1029 kB	10 items, 370 kB
3	F.Chopin	48 items, 870 kB	10 items, 182 kB
4	W.A.Mozart	15 items, 357 kB	2 items, 91 kB
5	F.Schubert	18 items, 863 kB	5 items, 253 kB

Features

The features consist of:

1. *Melodic*
   - The pitch (melodic) in MIDI is represented by **MIDI key number**
   - For example: A4 (440 Hz) $\rightarrow$ 69
2. *Rhythmic*
   - Musicians express tempo as "the amount of quarter notes in every minute **(BPM)**"
   - The duration in MIDI is calculated in terms of "the amount of time (in microseconds) per quarter note"
   - A conversion from ms to BPM needs to be done
3. *Melodic and rhythmic combined*
   - The third feature can be build by concatenating the first two features

Constraints

Several constraints that are applied:

- Only piano works are selected as the data input for better compatibility
- Each channel on the MIDI correspond to one staff (hand)
- To solve parallelism problem within one channel, only the highest currently played notes are taken

Source : [Wołkowicz et al., 2008]

Pitch & Duration Extraction - 1

Problem

Key and tempo of the music pieces will not give any information about the composer identity

- The pitch needs to be flat and normalized
- The note duration should be independent from the tempo of the pieces

Solution

Consider only the relative pitch and relative duration

Pitch & Duration Extraction - 2

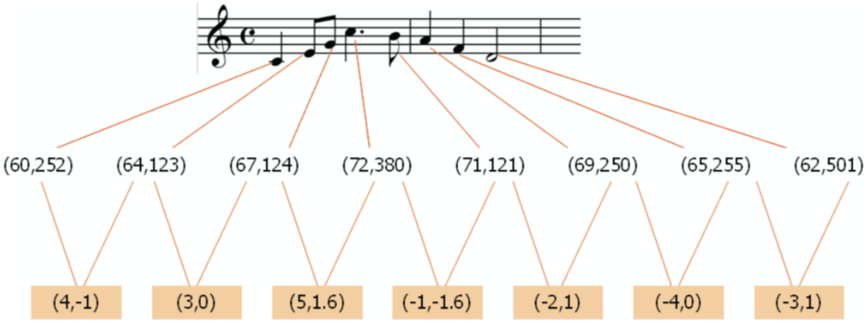
The relative pitch and relative duration calculation:

$$(P_i, T_i) = \left(p_{i+1} - p_i, round\left(\log_2\left(\frac{t_{i+1}}{t_i}\right)\right)\right), \tag{1}$$

where p_i denotes the i-th note pitch, t_i denotes the i-th note duration and (P_i, T_i) is the resulting tuple.

Unigram Extraction

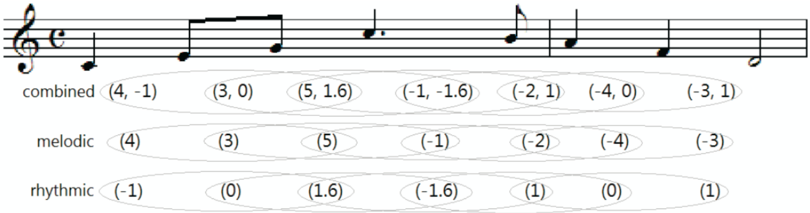
Extract unigram based on the pitch and duration



Source : [Wołkowicz et al., 2008]

Building Profiles

Using the unigram to build N-Gram composer profile (for example N=3)



melodic		rhythmic		combined	
(4,3,5)	- 1	(-1,0,1.6)	- 1	(4,3,5,-1,0,1.6)	- 1
(3,5,-1)	- 1	(0,1.6,-1.6)	- 1	(3,5,-1,0,1.6,-1.6)	- 1
(5,-1,-2)	- 1	(1.6,-1.6,1)	- 1	(5,-1,-2,1.6,-1.6,1)	- 1
(-1,-2,-4)	- 1	(-1.6,1,0)	- 1	(-1,-2,-4,-1.6,1,0)	- 1
(-2,-4,-3)	- 1	(1,0,1)	- 1	(-2,-4,-3,1,0,1)	- 1

Source : [Wołkowicz et al., 2008]

Composer Recognition Task - 1

Similarity Equation

The similarity score of the N-Gram profile between known composer (x) and the unknown composer of the piece (y) can be calculated by:

$$Sim\,(x, y) = \sum_i \left(4 - \left(\frac{2 \cdot (x_i - y_i)}{x_i + y_i}\right)^2\right), \tag{2}$$

Composer Recognition Task - 2

Find the most probable composer

For each known composer profile:

1. Calculate 3 similarity scores with the corresponding profile of the piece.
2. Sum up all the similarity scores for each composer profile.
3. Sort all sums descending.
4. Take a composer with the highest sum as a result.

Result - Proper Judgement

The example result using N-Gram-based approach:

Evaluation of the Frederic Chopin prelude Op. 28 No. 22

		Profiles			Total	Verdict
		melodic	rhythmic	combined		
Composer	Beethoven	43.2	17.2	11.0	71	3
	Mozart	49.2	11.4	6.4	67	4
	Bach	62.4	8.2	6.4	77	2
	Schubert	19,3	13.2	5.9	38	5
	Chopin	86.8	25.1	10.9	122	1

Result - Poor Judgement

The example result using N-Gram-based approach with poor judgement:

Evaluation of the Ludwig van Beethoven Sonata Op. 49 No. 2

		Profiles			Total	Verdict
		melodic	rhythmic	combined		
Composer	Beethoven	303.7	208.8	109.7	622	4
	Mozart	319.2	201.7	124.4	645	2
	Bach	366.1	263.0	83.7	712	1
	Schubert	315.6	201.8	119.1	636	3
	Chopin	296.5	127.3	79.0	502	5

Experiment

Result based on the experiment on the degrees of freedoms (profile size and length of N-Gram):

Results of the algorithm.

n \ profile size	100	250	500	1000	2500	5000	10000
2	0.41	0.38	0.38	0.35	0.32	0.43	0.43
3	0.46	0.54	0.59	0.62	0.59	0.51	0.43
4	0.62	0.70	0.65	0.73	0.73	0.78	0.86
5	0.54	0.62	0.70	0.78	0.78	0.81	0.81
6	0.54	0.59	0.68	0.68	0.84	0.78	0.84
7	0.46	0.49	0.68	0.68	0.68	0.70	0.84
9	0.46	0.57	0.49	0.51	0.57	0.68	0.76
12	0.41	0.46	0.41	0.41	0.41	0.46	0.49

Outline

Conclusion

- The analysis shows that N-gram can be used for composer recognition
- Similarity score based on the N-Gram profiles can be used to find the most probable composer
- Additional weight based on the composer era can be added to increase the recognition rate
- The algorithm might not reach 100% accuracy because some pieces written by the same composer but in different styles are difficult to be classified.

References

Buzzanca, G. (2002).
A supervised learning approach to musical style recognition.
In *Music and Artificial Intelligence. Additional Proceedings of the Second International Conference, ICMAI*, volume 2002, page 167. Citeseer.

Pollastri, E. and Simoncelli, G. (2001).
Classification of melodies by composer with hidden markov models.
In *Web Delivering of Music, 2001. Proceedings. First International Conference on*, pages 88–95. IEEE.

Wołkowicz, J., Kulka, Z., and Kešelj, V. (2008).
N-gram-based approach to composer recognition.
Archives of Acoustics, 33(1):43–55.