



Meisterklasse HfM Karlsruhe

Music Information Retrieval

Classification & Clustering

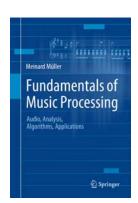
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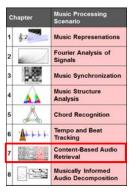
Book: Fundamentals of Music Processing



Meinard Müller Fundamentals of Music Processing Audio, Analysis, Algorithms, Applications 483 p., 249 illus., hardcover ISBN: 978-3-319-21944-8 Springer, 2015

Accompanying website: www.music-processing.de

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Dissertation: Tonality-Based Style Analysis

Christof Weiß

Computational Methods for Tonality-Based Style Analysis of Classical Music Audio Recordings Dissertation, Technical University of Ilmenau 2017 to appear

Chapter 7: Clustering and Analysis of Musical Styles

Chapter 8: Subgenre Classification for Western Classical Music

Music Genre Classification



Music Genre Classification

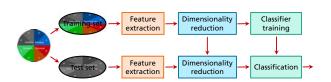


Music Genre Classification

- Standard approach (content-based)
 - Supervised machine learning
 - Based on spectral / timbral features
- $\blacksquare \ \ \, \text{In classical music} \to \text{Instrumentation} \\$
- Better categories?
 - Musical style
 - Independent from instrumentation
 - → Tonality / Harmony

Music Genre Classification

Typical approach: Supervised machine learning



Music Genre Classification

- Experimental design: Evaluation with Cross Validation (CV)
- Separate data into different parts (folds)



Distribution of classes balanced for all folds

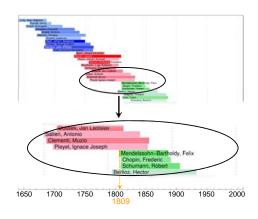


Classification Scenario

- Dataset: CrossEraDB (Historical Periods)
 - Balanced Piano (p) Orchestra (o)
 - Each 200 pieces → 1600 in total



Classification Scenario

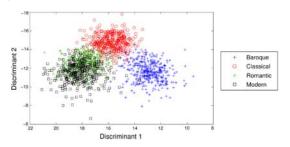


Classification Features

Standard			
MFCC	16	Interval cat.	6 x 4
OSC	14	Triad types	4 x 4
ZCR	1	Complexity	7 x 4
ASE	16	Chord progr.	11 x 5
SFM	16		
SCF	16		
SC	16		
LogLoud	12		
NormLoud	12		
Sum	119	Sum	123
Mean & Std	x 2	Mean & Std	x 2
Total	238	Total	246

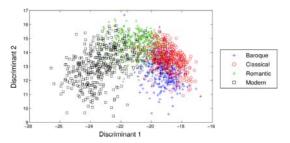
Dimensionality Reduction

- Reduce feature space to few dimensions
- Maximize separation of classes with Linear Discriminant Analysis (LDA)
- Using standard features (MFCC, spectral envelope, ...)



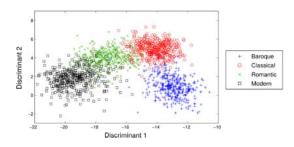
Dimensionality Reduction

- Reduce feature space to few dimensions
- Maximize separation of classes with Linear Discriminant Analysis (LDA)
- Using tonal features (interval, triad types, tonal complexity, ... 4 time scales)



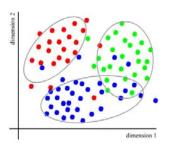
Dimensionality Reduction

- Reduce feature space to few dimensions
- Maximize separation of classes with Linear Discriminant Analysis (LDA)
- Using tonal & standard features



Classifier

- Train Machine Learning Classifier
- Gaussian Mixture Model (GMM)
- Using Gaussian distributions to model data points in feature space



Classification Results

Gaussian Mixture Model (GMM) classifier, LDA reduction, 3-fold cross validation

	Full Dataset	Piano	Orchestra
Standard features	87 %	88 %	85 %
Tonal features	84 %	84 %	86 %
Combined	92 %	86 %	80 %

Weiss / Mauch / Dixon, Timbre-Invariant Audio Features for Style Analysis of Classical Music, ICMC / SMC 2014

Classification Results

GMM classifier, LDA reduction, 3-fold cross validation

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Flexer, A Closer Look on Artist Filters for Musical Genre Classification. ISMIR 2007

Classification Results

- GMM classifier, LDA reduction, 3-fold cross validation
- No composer filter

omposer mer	Full Dataset	Piano	Orchestra
Standard features	87 %	88 %	85 %
Tonal features	84 %	84 %	86 %
Combined	92 %	86 %	80 %

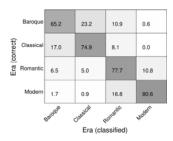
Using composer filter

.g composer mis.	Full Dataset	Piano	Orchestra
Standard features	54 %	36 %	70 %
Tonal features	73 %	70 %	78 %
Combined	68 %	44 %	68 %

Weiss / Müller, Tonal Complexity Features for Style Classification of Classical Music, ICASSP 2015

Classification Results - Confusion Matrix

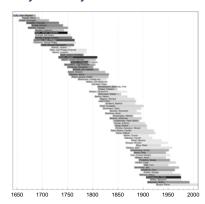
- 80 tonal features, GMM with 1 Gaussian, LDA, composer filtering
- Full dataset
- Mean accuracy: 75 %
- Inter-class standard deviation: 6.7 %



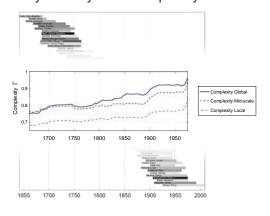
Classification Results - Summary

- Different types of tonal features
- Combination of time scales
- Classifiers (SVM, Random Forest)
- State-of-the-art
 - Few studies on audio
 - Good separation of tonal-vs.-atonal (91 %):
 Izmirli, Tonal-Atonal Classification of Music Audio Using Diffusion Maps, ISMIR 2009
- Composer Identification
 - Up to 78 % for 11 composers
 Hamel, Pooled Features Classification, MIREX 2011
 - Dataset balanced?

Musical Style Analysis

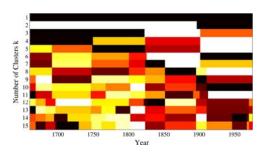


Musical Style Analysis - Complexity



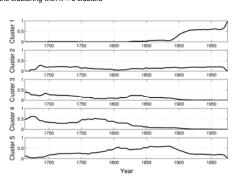
Clustering: Years

- Features: Interval, complexity, chord progressions
- Dimensional reduction with Principal Component Analysis (PCA)
- k-means clustering with different number of clusters k

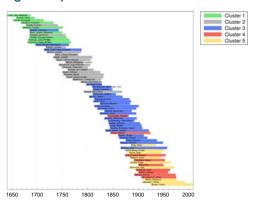


Clustering: Pieces

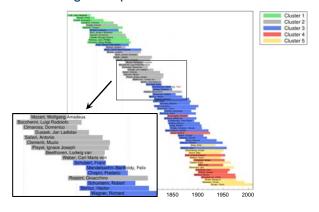
• k-means clustering with k = 5 clusters



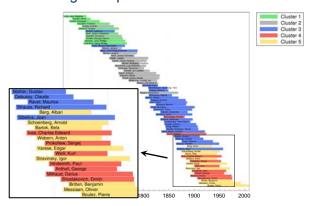
Clustering: Composers



Clustering: Composers



Clustering: Composers



Clustering: Composers

