INTERNATIONAL AUDIO LABORATORIES ERLANGEN

AUDIO LABS

Tutorial
Automatisierte Methoden der Musikverarbeitung
47. Jahrestagung der Gesellschaft für Informatik

Style Classification

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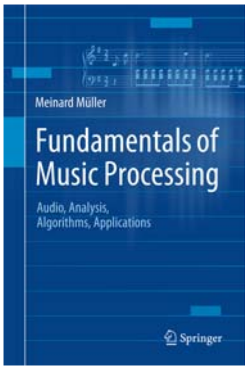
Book: Fundamentals of Music Processing



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

Book: Fundamentals of Music Processing

Chapter	Music Processing Scenario
1	Music Representations
2	Fourier Analysis of Signals
3	Music Synchronization
4	Music Structure Analysis
5	Chord Recognition
6	Tempo and Beat Tracking
7	Content-Based Audio Retrieval
8	Musically Informed Audio Decomposition

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Dissertation: Tonality-Based Style Analysis

Christof Weiß
Computational Methods for Tonality-Based Style Analysis of Classical Music Audio Recordings
PhD thesis, Technical University of Ilmenau, 2017

Chapter 7: Clustering and Analysis of Musical Styles
Chapter 8: Subgenre Classification for Western Classical Music

Music Genre Classification

Music Genre Classification

J. S. Bach, Brandenburg Concerto No. 2 in F major, I. Allegro, Cologne Chamber Orch.

L. van Beethoven, *Fidelio*, Overture, Slovak Philharm.

R. Schumann, Sonata No. 2 op. 22, II. Andantino B. Glemser, Piano

A. Webern, Variations for Orchestra op. 30 Ulster Orchestra

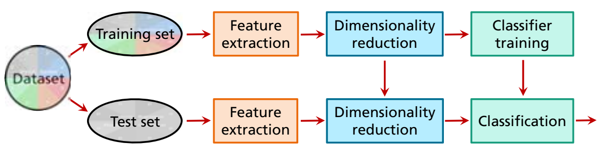
Music Genre Classification

Music Genre Classification

- Standard approach (*content-based*)
  - Supervised machine learning
  - Based on spectral / timbral features
- In classical music → Instrumentation
- Better categories?
  - *Musical style*
  - Independent from instrumentation
  - → **Tonality / Harmony**

Music Genre Classification

- Supervised machine learning



Music Genre Classification

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

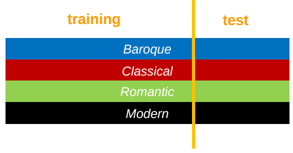
	Fold 1	*Fold 2*	*Fold 3*
Round 1	Training fold	Training fold	Test fold
Round 2	Training fold	Test fold	Training fold
Round 3	Test fold	Training fold	Training fold

Music Genre Classification

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

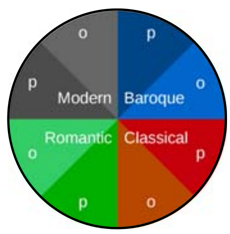
	Fold 1	*Fold 2*	*Fold 3*
Round 1	Training fold	Training fold	Test fold

- Distribution of classes balanced for all folds

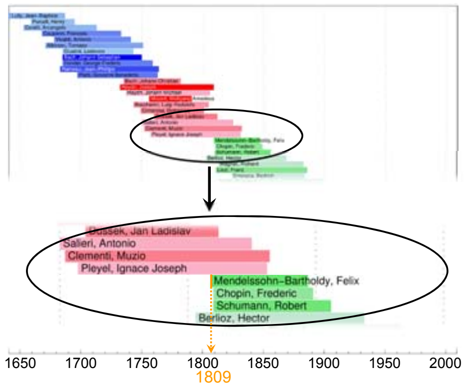


Classification Scenario

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



Classification Scenario

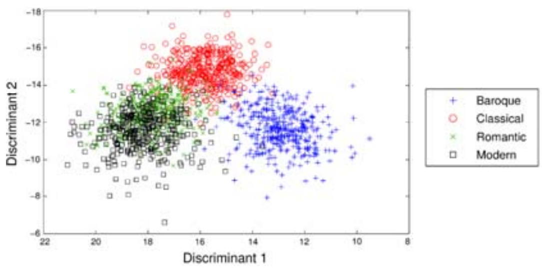


Classification Features

Standard	Dim.	Tonal	Dim.
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**

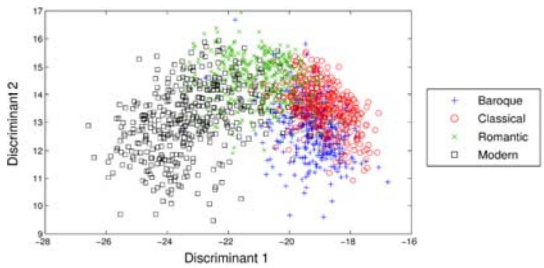
Dimensionality Reduction

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



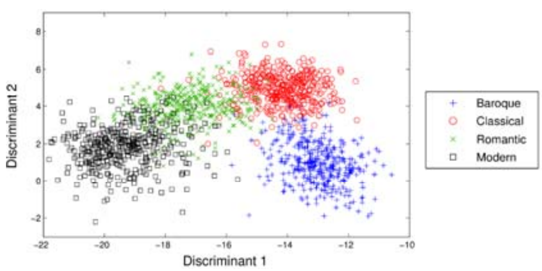
Dimensionality Reduction

- 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)



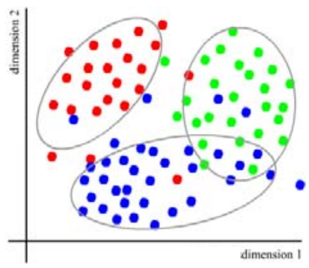
Dimensionality Reduction

- 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

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Overfitting???

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

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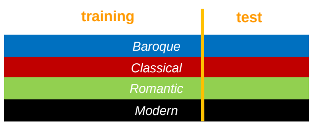


"Album effect"

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**

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

- **Using composer filter**

	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

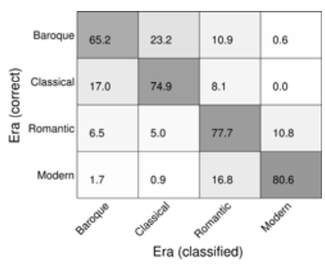
Classification Results: Error Examples

- 80 tonal features, GMM with 1 Gaussian, LDA
- Look at **consistently** and **persistently** misclassified items (B. Sturm 2012 & 2013)

Class	*Composer*	*Piece*	*Classified*
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in E♭ minor BWV 853	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in F major BWV 856	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in A minor BWV 865	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in B♭ major BWV 866	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in B♭ minor BWV 867	Romantic
Baroque	Bach, J. S.	English Suite No. 3 in G minor BWV 808, Sarabande	Romantic
Baroque	Bach, J. S.	Brandenburg Conc. No. 1 in F major BWV 1046, Adagio	Romantic
Baroque	Bach, J. S.	Overture No. 2 in B minor BWV 1067, Badinerie	Romantic
Baroque	Bach, J. S.	Overture No. 3 in D major BWV 1068, Gigue	Romantic
Baroque	Couperin, F.	27 Ordres, Huitième ordre, IX. Rondeau passacaille	Romantic
Baroque	Corelli, A.	Concerto grosso op. 6 No. 2, III. Grave – Andante largo	Romantic
Baroque	Lully, J.-B.	Ballet de Xerces LWV 12, Gavotte en rondeau	Romantic
Baroque	Purcell, H.	Opera "Dido and Aeneas" Z. 626, Overture	Romantic
Baroque	Vivaldi, A.	"The Four Seasons," RV 293 "Autumn," Adagio molto	Romantic
Romantic	Schumann, R.	Kinderszenen op. 15, "Haschemann"	Baroque
Romantic	Grieg, E.	Holberg suite op. 40, Gavotte	Baroque
Romantic	Mendelssohn, F.	Symphony No. 4 in A major, IV. Saltarello, presto	Baroque
Modern	Shostakovich, D.	Preludes & Fugues op. 87 Fugue No. 1 in C major	Baroque
Modern	Shostakovich, D.	Preludes & Fugues op. 87 Fugue No. 5 in D major	Baroque

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: Unseen Data

- 80 tonal features, GMM with 1 Gaussian, LDA

- Full dataset, 4 historical periods
- Training on piano, evaluating on orchestra → mean acurracy 65 %
- Training on orchestra, evaluating on piano → mean acurracy 64 %

- Training on full dataset
- Evaluating on a different dataset
- Mean accuracy **62.3 %**
  (Ignoring Beethoven & Schubert)

Classified Era	Baroque	Classical	Romantic	Modern
Bach	68	5	9	18
Handel	56	23	15	6
Rameau	69	22	6	3
Haydn	25	53	19	3
Mozart	28	51	7	14
Beethoven	16	37	38	9
Schubert	7	16	24	53
Mendelssohn	15	19	55	11
Brahms	6	13	69	12
Dvořak	14	17	65	4
Shostakovich	15	2	8	75

Classification Results: Summary

- Extreme influence of album effect: What is actually learned?

- Tonal features seem to be more robust

- Different tonal features, Combination of time scales beneficial

- Complex classifier does not necessarily lead to better results