INTERNATIONAL AUDIO LABORATORIES ERLANGEN
A joint institution of Fraunhofer IIS and Universität Erlangen-Nürnberg

AUDIO LABS

Wie gut können Computer hören? – Über die Anwendung musiktheoretischer Konzepte auf Audiodaten

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12.12.2018

FAU FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

Fraunhofer IIS

Christof Weiß

- 2006: Abitur, Max-Reger-Gymnasium Amberg

- 2006-2012: Studium **Physik** Diplom, Universität Würzburg

- 2006-2011: Studium **Komposition**, HfM Würzburg (Prof. Heinz Winbeck)

- 2011-2012: Fortbildungsklasse Komposition (Tobias Schneid)

- 2012-2015: **Promotion** Fraunhofer Institut für Digitale Medientechnologie (IDMT), Ilmenau, Thüringen, gefördert von Stiftung der Dt. Wirtschaft (sdw)
  Computational Methods for Tonality-Based Style Analysis of Classical Music Audio Recordings

- Seit 09/2015: AudioLabs Erlangen / freischaffender Komponist

- 2018: KlarText-Preis für Wissenschaftskommunikation

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International Audio Laboratories Erlangen

AudioLabs - FAU

- **Prof. Dr. Jürgen Herre**
  Audio Coding

- **Prof. Dr. Bernd Edler**
  Audio Signal Analysis

- **Prof. Dr. Meinard Müller**
  Semantic Audio Processing

- **Prof. Dr. Emanuël Habets**
  Spatial Audio Signal Processing

- **Prof. Dr. Frank Wefers**
  Virtual Reality

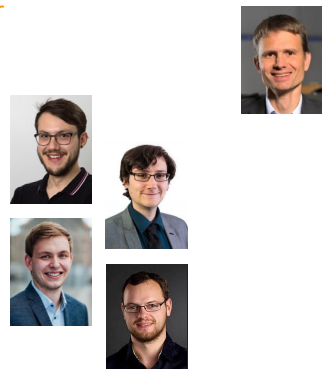- **Dr. Stefan Turowski**
  Coordinator AudioLabs-FAU

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International Audio Laboratories Erlangen

Audio Coding

3D Audio

Audio

Psychoacoustics
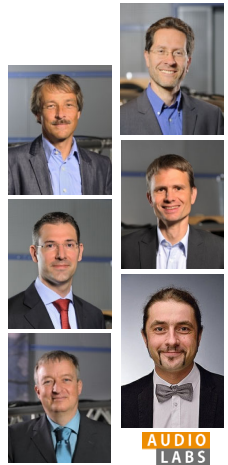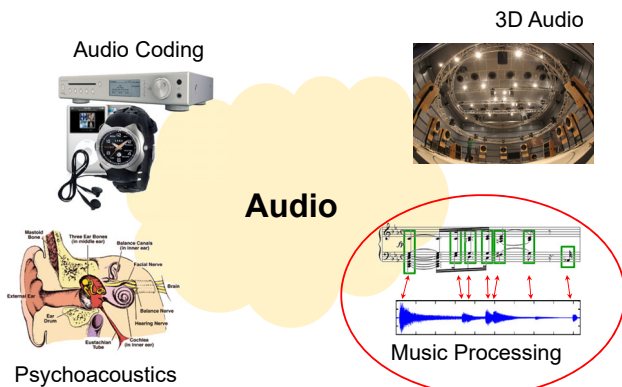
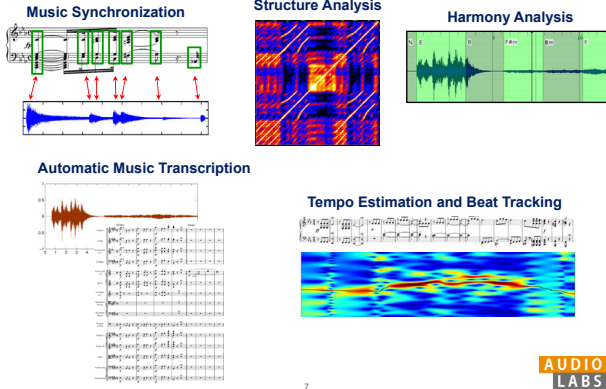Music Processing

5

Group Prof. Meinard Müller

- Patricio López-Serrano

- Frank Zalkow

- Sebastian Rosenzweig

- Christof Weiß

6

Music Processing / Music Information Retrieval (MIR)

Music Synchronization

Structure Analysis

Harmony Analysis

Automatic Music Transcription

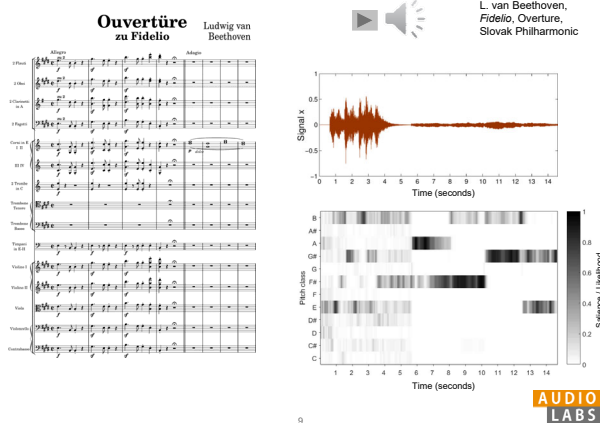**Tempo Estimation and Beat Tracking**

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Outline

1. Spectral Analysis and Chroma Features

2. Local Tonality Analysis

3. Cross-Version Analysis of Wagner's *Ring*

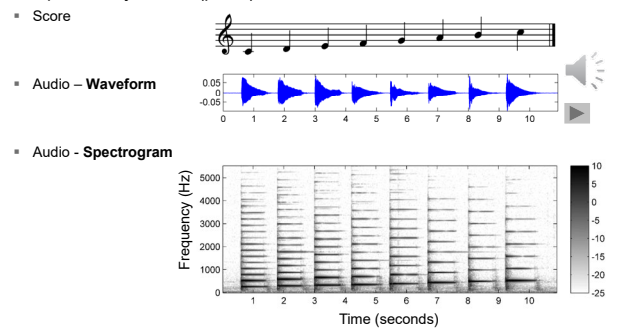4. Analyzing and Classifying Composer Styles
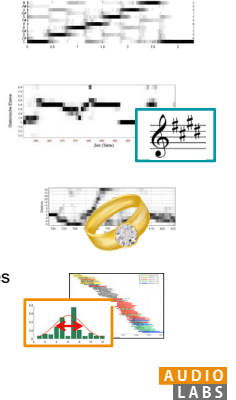
8

Chroma Representations

Ouvertüre
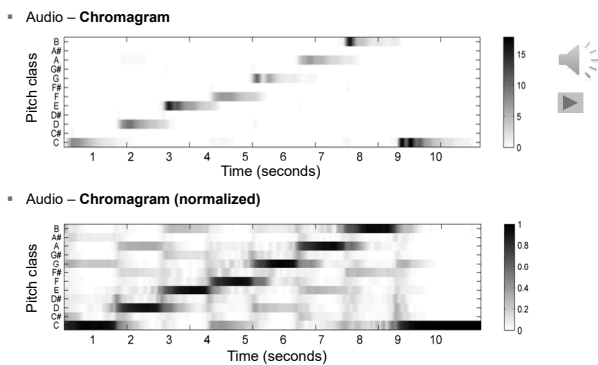**zu Fidelio**
Ludwig van Beethoven

L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic

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Chroma Representations

▪ Example: C-major scale (piano)

 ▪ Score

 ▪ Audio – **Waveform**

 ▪ Audio - **Spectrogram**

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Chroma Representations

▪ Example: C-major scale (piano)

 ▪ Audio – **Chromagram**

 ▪ Audio – **Chromagram (normalized)**

Chroma Representations

L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic

Spectrogram: Time – Frequency

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Chroma Representations

L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic
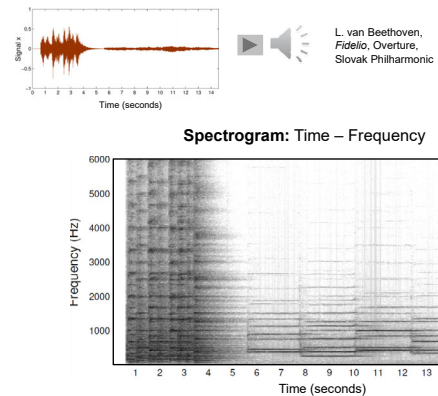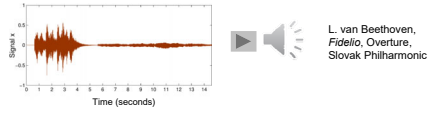
Log-Frequency-Spectrogram: Time – Pitch

Chroma Representations
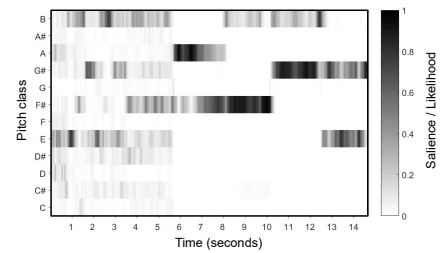

L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic
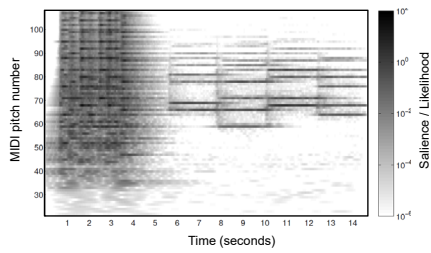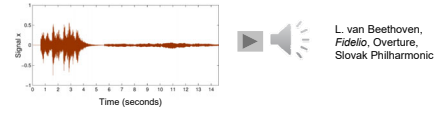
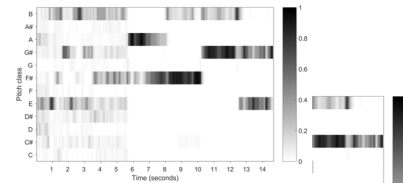**Chromagram:** Time – Pitch class
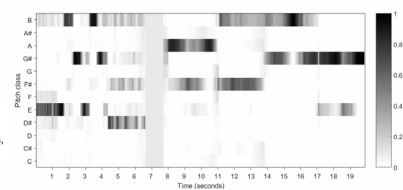

Chroma Representations

- Orchestra

L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic

- Piano

Fidelio, Overture,
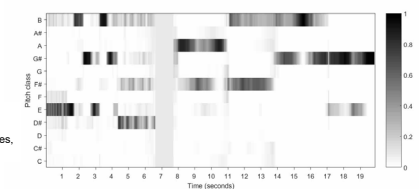arr. Alexander Zemlinsky
M. Namekawa, D.R. Davies,
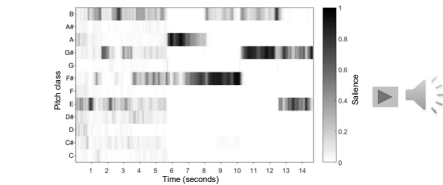piano four hands

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Chroma Representations

- Piano

Fidelio, Overture,
arr. Alexander Zemlinsky
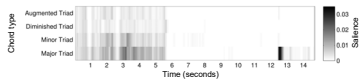M. Namekawa, D.R. Davies,
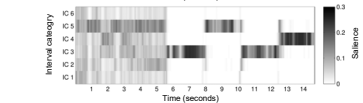piano four hands

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Chroma Representations

- Chromagram

- Chord types

- Interval categories
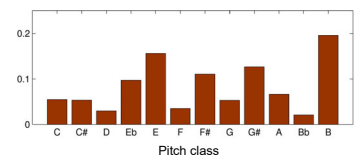

→ transposition-invariant descriptors!

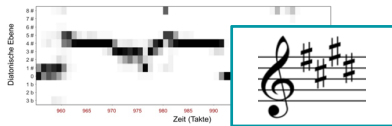# Chroma Representations

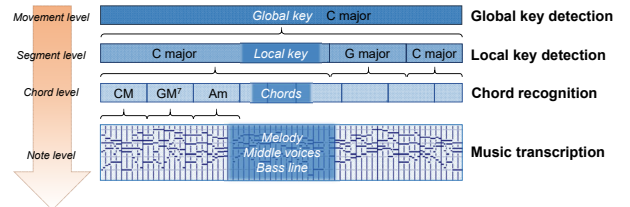- Chromagram: Full piece

- Chroma statistics:

2. Local Tonality Analysis Based on Diatonic Scales

Motivation
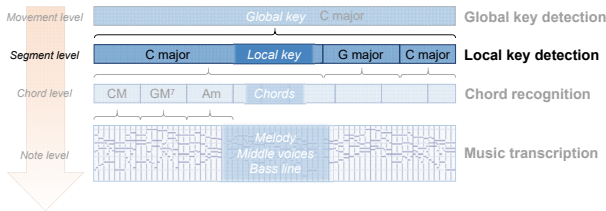
- **Harmony analysis** of music:
  - Different concepts
  - Concepts relate to different **temporal granularity**

Movement level	Global key C major	Global key detection
Segment level	C major Local key G major C major	Local key detection
Chord level	CM GM⁷ Am Chords	Chord recognition
Note level	Melody / Middle voices / Bass line	Music transcription

---

Motivation

- **Harmony analysis** of music:
  - Different concepts
  - Concepts relate to different **temporal granularity**

Movement level	Global key C major	Global key detection
Segment level	C major Local key G major C major	Local key detection
Chord level	CM GM⁷ Am Chords	Chord recognition
Note level	Melody / Middle voices / Bass line	Music transcription

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Musicological Foundations

- Method: estimate **diatonic scales – 7** fifth-related pitches

- Relationship of diatonic scales:
  - Fifth-neighbouring scales share 6 of 7 notes
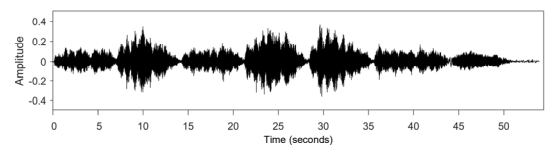 - Ordering of scales according to the **circle of fifths**:

-1 Diatonik   D +2 Diatonik

Visualization of Diatonic Scales

- Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)
- **Score** – Piano reduction
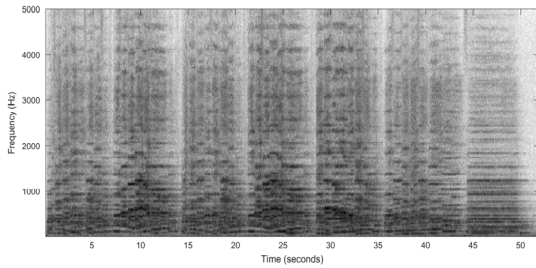

Visualization of Diatonic Scales

- Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)
- **Audio** – Waveform (Scholars Baroque Ensemble, Naxos 1994)

Visualization of Diatonic Scales

- Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)
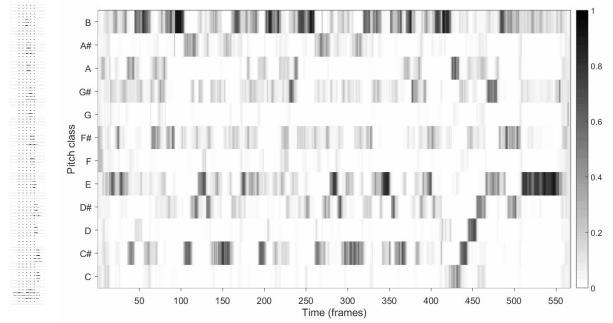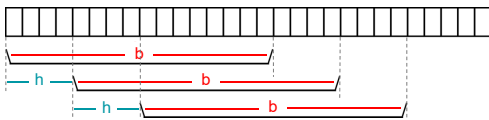- **Audio** – Spectrogram (Scholars Baroque Ensemble, Naxos 1994)

Visualization of Diatonic Scales

- Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)
- **Audio** – Chroma features (Scholars Baroque Ensemble, Naxos 1994)

Visualization of Diatonic Scales

- Summarize pitch classes over a certain time

  - **Chroma smoothing**
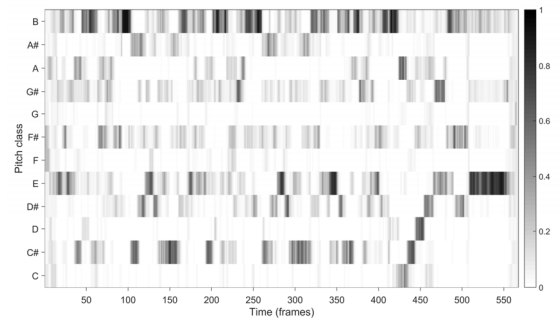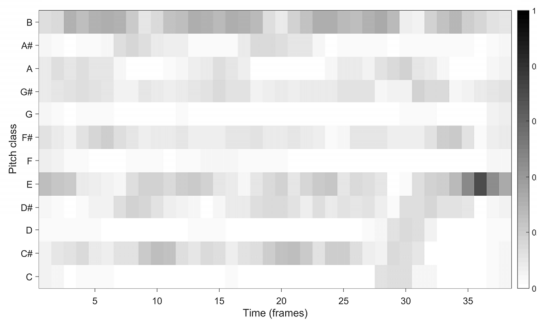 - Parameters: blocksize b and hopsize h

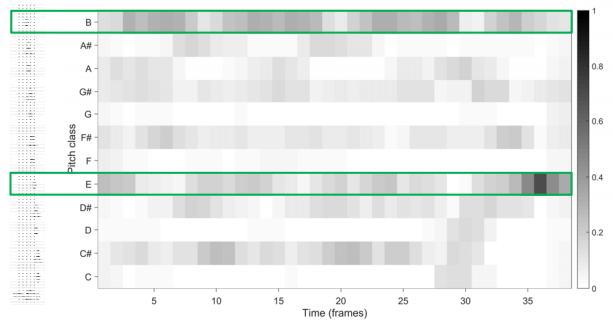## Visualization of Diatonic Scales

- Choral (Bach)

Visualization of Diatonic Scales

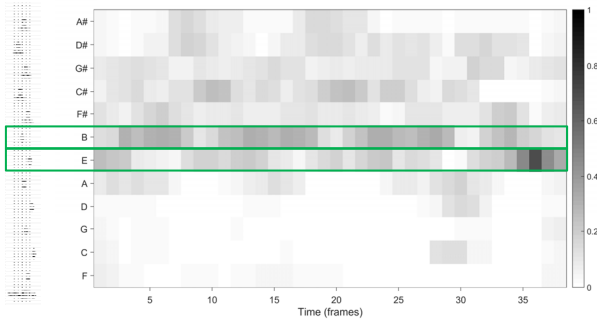- Choral (Bach) — smoothed with b = 42   and   h = 15

Visualization of Diatonic Scales

- Choral (Bach) — Re-ordering to **perfect fifth** series

Visualization of Diatonic Scales

- Choral (Bach) — Re-ordering to **perfect fifth** series

Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation (7 fifths)

Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation (7 fifths)

Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation: Multiply chroma values

Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation: Multiply chroma values

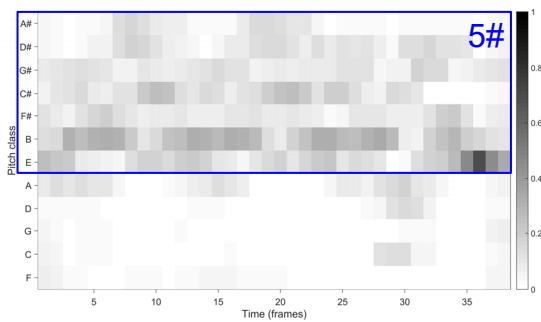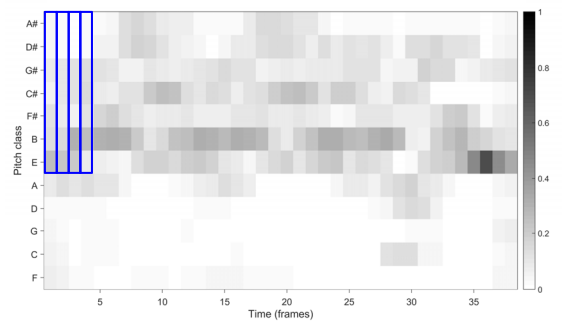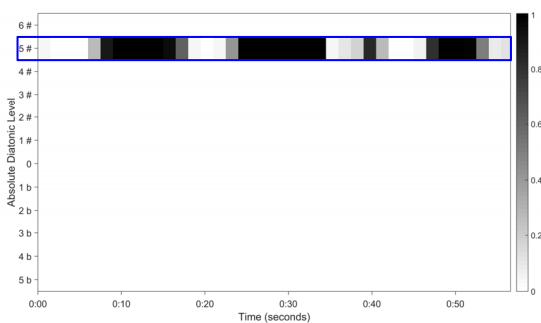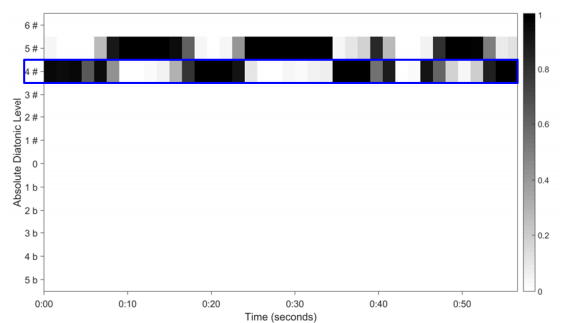## Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation

Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation

Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation: Shift to **global key**
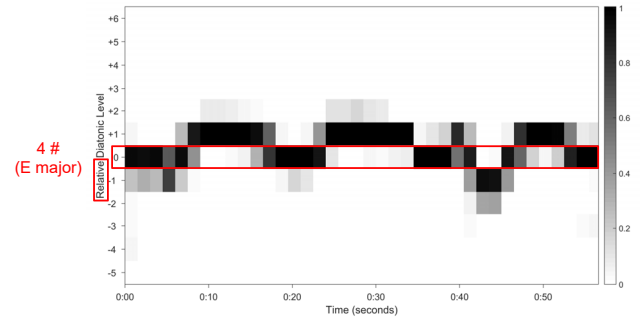
Visualization of Diatonic Scales

- Choral (Bach) — 0 ≜ 4#

C. Weiß, J. Habryka, "Chroma-Based Scale Matching for Audio Tonality Analysis" In: *Proceedings of the 9th Conference on Interdisciplinary Musicology*, Berlin 2014.
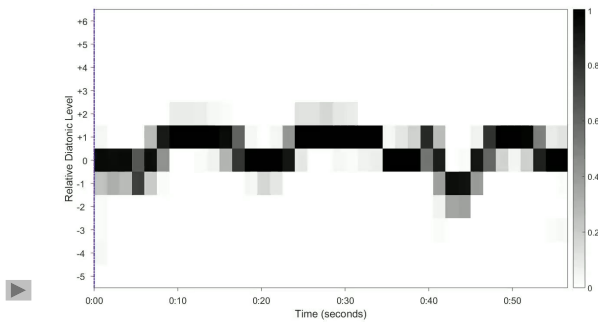
Visualization of Diatonic Scales

- L. v. Beethoven – Sonata No. 10 op. 14 Nr. 2, 1. Allegro — 0 ≜ 1
  (Barenboim, EMI 1998)
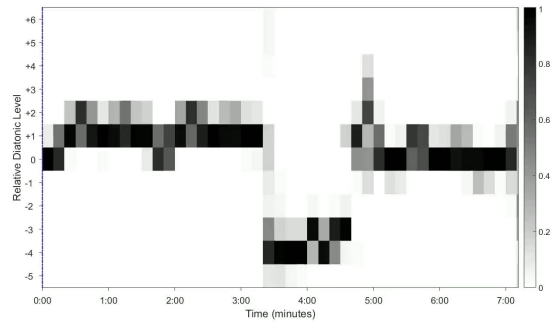
Visualization of Diatonic Scales

- R. Wagner, *Die Meistersinger von Nürnberg*, Vorspiel — 0 ≜ 0
  (Polish National Radio Symphony Orchestra, J. Wildner, Naxos 1993)
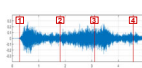
3. Cross-Version Tonality Analysis of the *Ring*

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Cross-Version Analysis

- Up to 18 versions
- 3 versions manually annotated

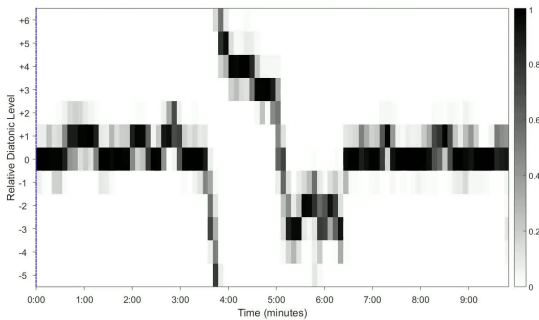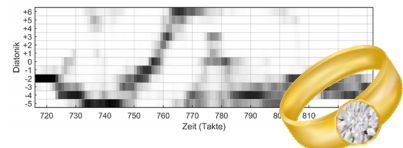| No.	Conductor	Recording	hh:mm:ss
1	Barenboim	1991–92	14:54:55
2	Boulez	1980–81	13:44:38
3	Böhm	1967–71	13:39:28
4	Furtwängler	1953	15:04:22
5	Haitink	1988–91	14:27:10
6	Janowski	1980–83	14:08:34
7	Karajan	1967–70	14:58:08
8	Keilberth/Furtwängler	1952–54	14:19:56
9	Krauss	1953	14:12:27
10	Levine	1987–89	15:21:52
11	Neuhold	1993–95	14:04:35
12	Sawallisch	1989	14:06:50
13	Solti	1958–65	14:36:58
14	Swarowsky	1968	14:56:34
15	Thielemann	2011	14:31:13
16	Weigle	2010–12	14:48:46

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Cross-Version Analysis

- Idea: Use analysis results based on different interpretations (versions)
- Tonal characteristics should not depend on interpretation
- → Test reliability of the method

- Visualize consistency with gray scheme

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Die Walküre WWV 86 B
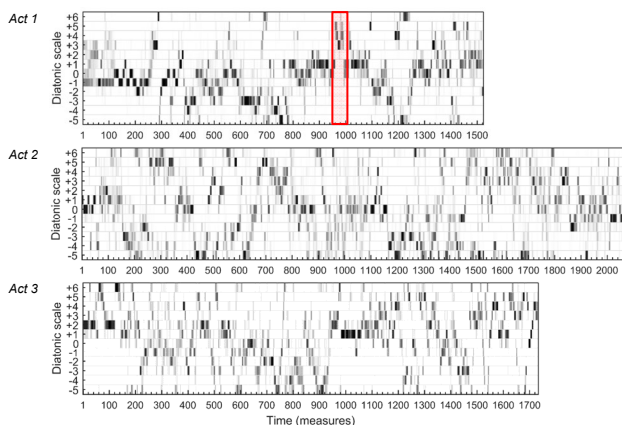
Die Walküre WWV 86 B

- Act 1, measures 955–1012
- Sieglinde´s narration
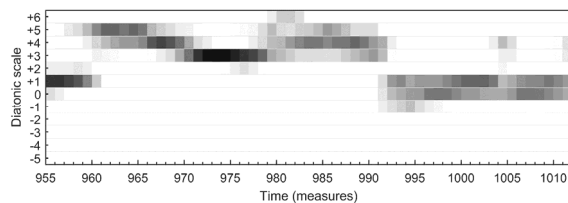
46

Die Walküre WWV 86 B

- Act 1, measures 955–1012
- Sieglinde´s narration

47

Die Walküre WWV 86 B

Die Walküre WWV 86 B

- Act 3, measures 724–789
- Wotan´s punishment
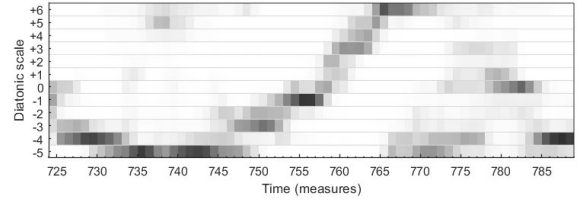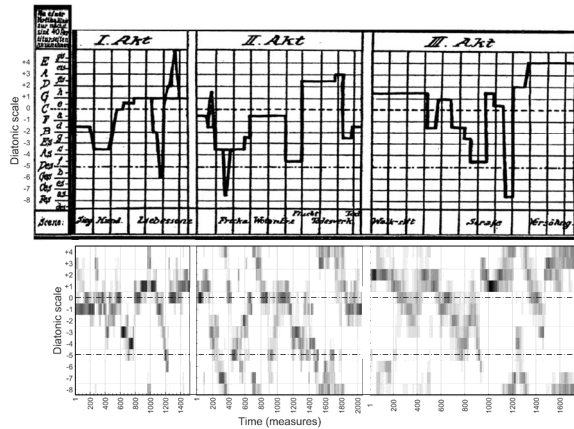
Die Walküre WWV 86 B

Exploring Tonal-Dramatic Relationships

- Histograms of Analysis over time

Das Rheingold WWV 86 A 3897 measures	Die Walküre WWV 86 B 5322 measures	Siegfried WWV 86 C 6682 measures	Götterdämmerung WWV 86 D 6040 measures
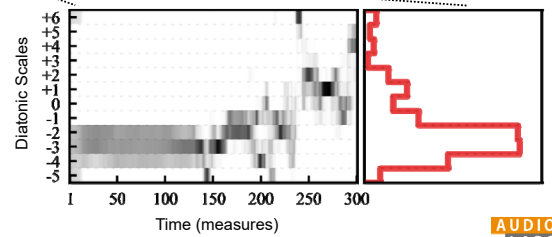
Exploring Tonal-Dramatic Relationships

Sword motif – *Die Walküre*
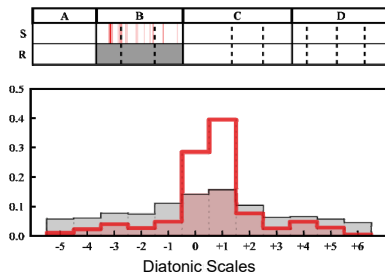
Exploring Tonal-Dramatic Relationships

Sword motif – *Siegfried*

Slide 55
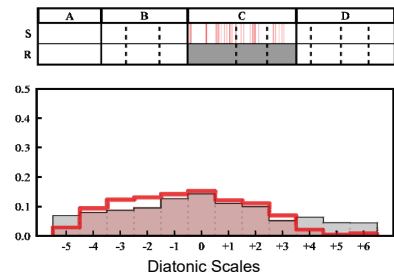
Exploring Tonal-Dramatic Relationships

Valhalla motif – *Das Rheingold*

Chords

Slide 56
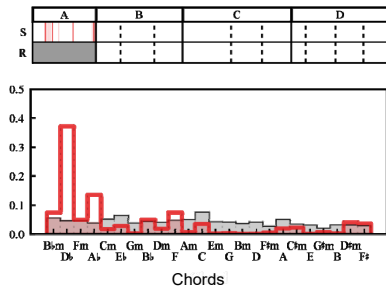
Exploring Tonal-Dramatic Relationships

Valhalla motif – *Die Walküre*

Chords

Slide 57
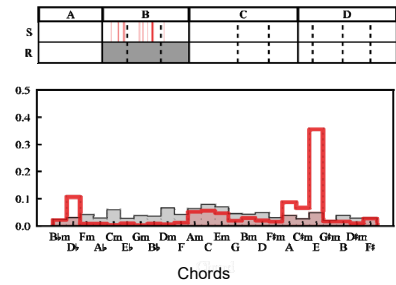
4. Computational Methods for Analyzing Composer Styles

Slide 58
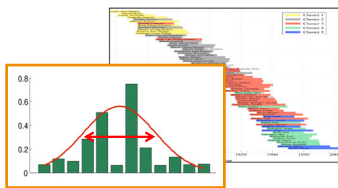
Tonal Complexity

- Global chroma statistics (audio)
- **1783** – W. A. Mozart, „Linz" symphony KV 425, 1. Adagio / Allegro (C major)

Circle of fifths →

Slide 59
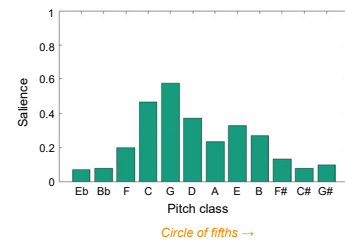
Tonal Complexity

- Global chroma statistics (audio)
- **1883** – J. Brahms, Symphony No. 3, 1. Allegro con brio (F major)

Circle of fifths →

Slide 60
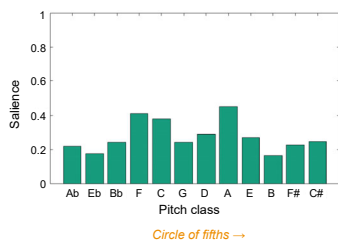
Tonal Complexity

- Global chroma statistics (audio)
- **1940** – A. Webern, Variations for Orchestra op. 30
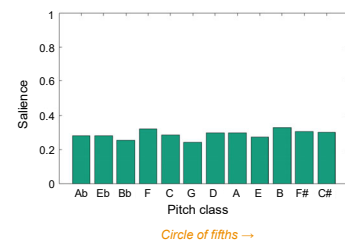
Circle of fifths →

Tonal Complexity

- Realization of complexity measure Γ
  - Entropy / Flatness measures
  - Distribution over *Circle of Fifths*

$\Gamma = 0$ $\Gamma = 1$ $0 < \Gamma < 1$

length r

$$\Gamma = \sqrt{1 - r}$$
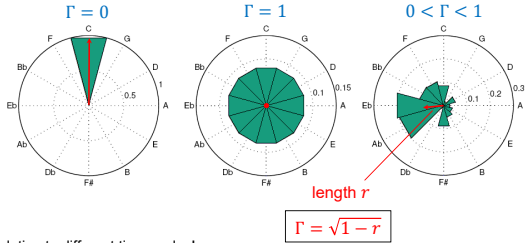
- Relating to different time scales!

Tonal Complexity – Chords
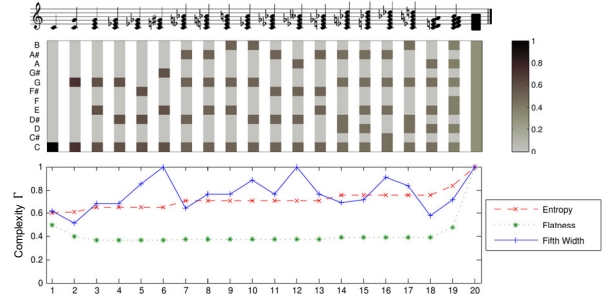
[8] Weiss / Müller, *Quantifying and Visualizing Tonal Complexity*, CIM 2014

Tonal Complexity – Beethoven's Sonatas
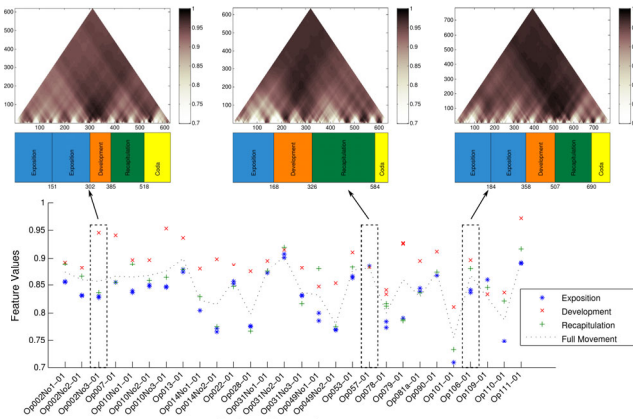
Analyzing Composer Styles

- 2000 pieces
- Piano and Orchestra music

Analyzing Composer Styles

Haydn, Joseph
1732 – 1809
100 works in dataset
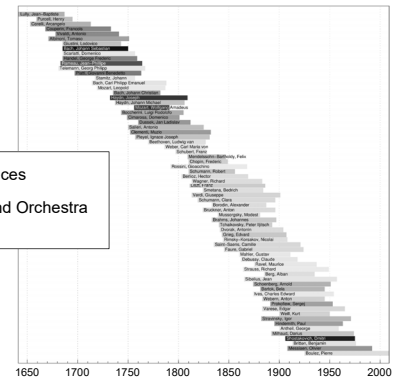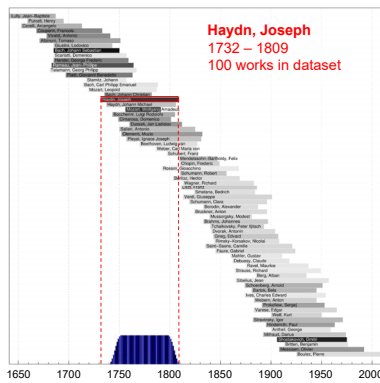
Analyzing Composer Styles
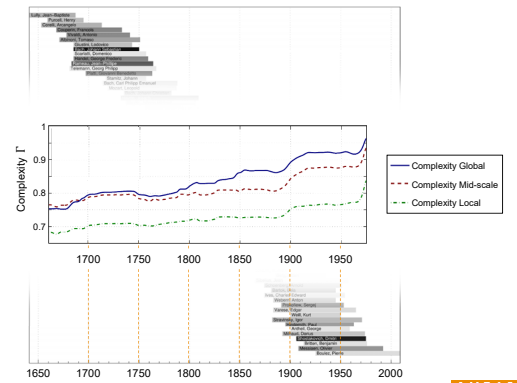
Clustering Composition Years
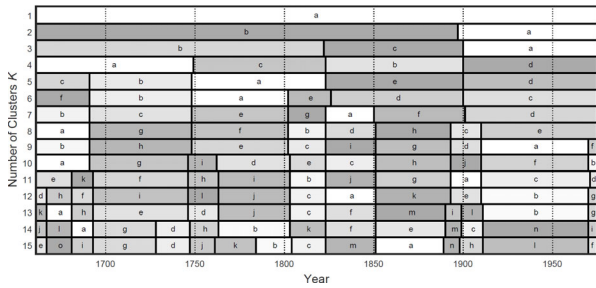
Clustering Individual Pieces
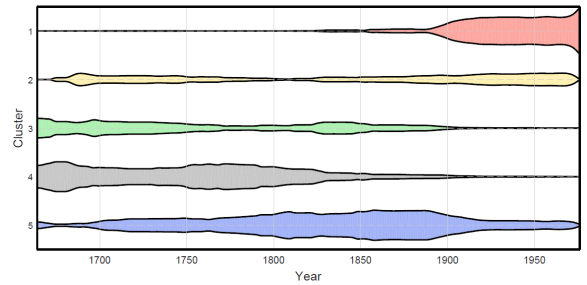
Clustering Composers
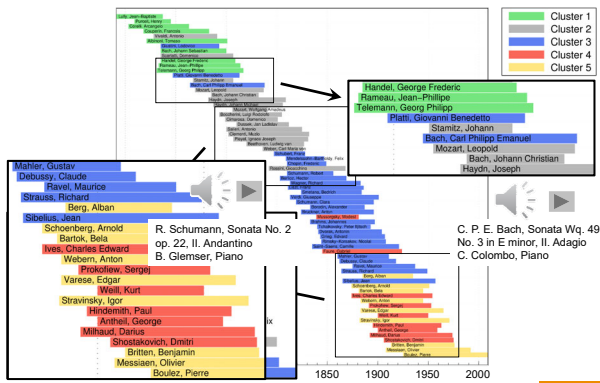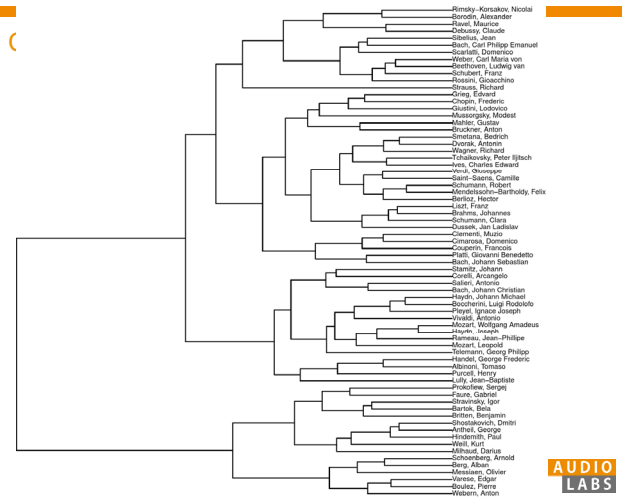
Tonal Complexity: Jazz Solos
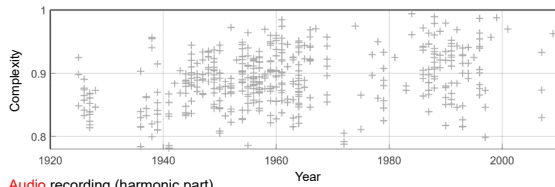
- Symbolic transcription
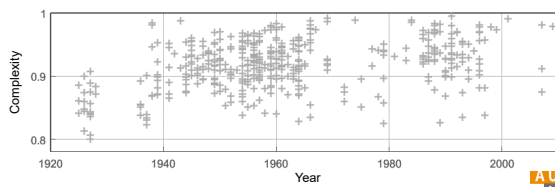
- Audio recording (harmonic part)

Tonal Complexity: Jazz Solos

- Symbolic transcription
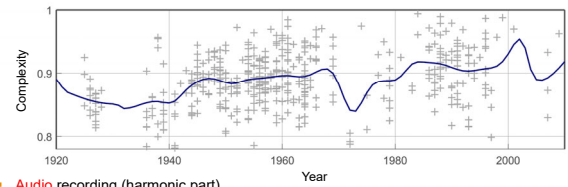
- Audio recording (harmonic part)
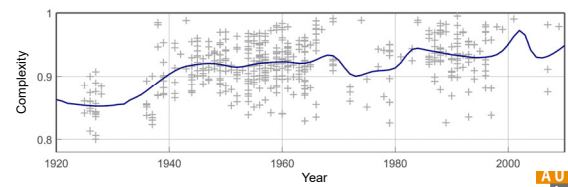
Music Genre Classification

world music *JAZZ*

HipHop **pop** **Rock**

"classical"

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

world music *JAZZ*

HipHop **pop** **Rock**

("classical")

Subgenre Categories:

Period / Era: Baroque   Classical   Romantic   Modern

Sub-era: Pre-Classical   Early Rom.   Late Rom.

Composer: Schubert   Mendelssohn
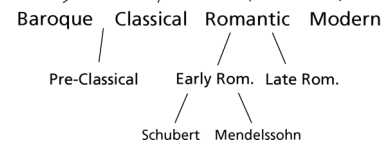
Music Genre Classification

- Typical approach: Supervised machine learning

Training set → Feature extraction → Dimensionality reduction → Classifier training

Test set → Feature extraction → Dimensionality reduction → Classification

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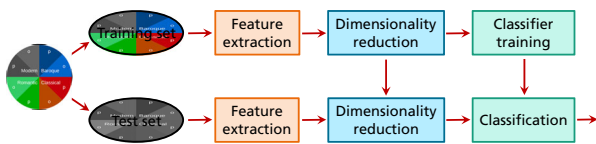
Music Genre Classification

- 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

- Distribution of classes balanced for all folds

training   test

Baroque
Classical
Romantic
Modern
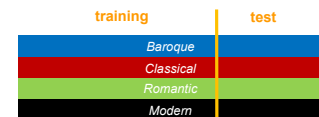
Classification Scenario

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

o   p   o   Modern   Baroque   Romantic   Classical   o   p   p   o

---

Classification Scenario

Lully, Jean-Baptiste
Purcell, Henry
Corelli, Arcangelo
Couperin, Francois
Vivaldi, Antonio
Albinoni, Tomaso
Giustini, Lodovico
Bach, Johann Sebastian
Handel, George Frederic
Rameau, Jean-Philippe
Platti, Giovanni Benedetto
Bach, Johann Christian
Haydn, Johann Michael
Mozart, Wolfgang Amadeus
Boccherini, Luigi Roberto
Dussek, Jan Ladislav
Salieri, Antonio
Clementi, Muzio
Pleyel, Ignace Joseph
Mendelssohn–Bartholdy, Felix
Chopin, Frederic
Schumann, Robert
Berlioz, Hector
Wagner, Richard
Liszt, Franz
Smetana, Bedrich

Dussek, Jan Ladislav
Salieri, Antonio
Clementi, Muzio
Pleyel, Ignace Joseph
Mendelssohn–Bartholdy, Felix
Chopin, Frederic
Schumann, Robert
Berlioz, Hector

1650   1700   1750   1800   1850   1900   1950   2000

1809

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 (prevent **curse of dimensionality**)
- Maximize separation of classes with **Linear Discriminant Analysis (LDA)**
- Using **standard features** (MFCC, spectral envelope, …)
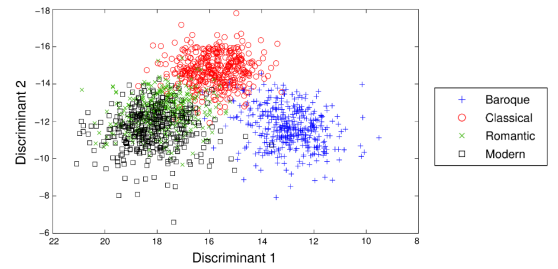
Dimensionality Reduction

- 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)
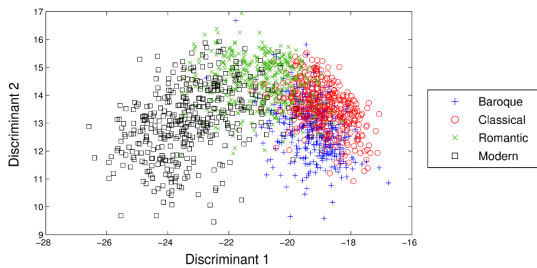
Dimensionality Reduction

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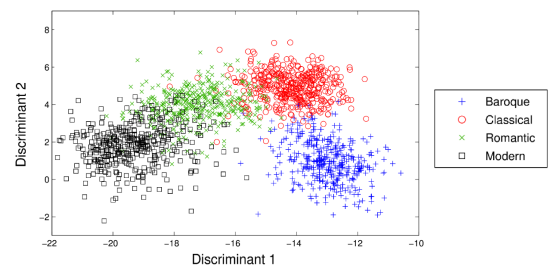
Classification methods

- Gaussian Mixture Models (GMM)

$$f(\mathbf{x}) = \sum_{g=1}^{G} w_g \cdot p(\mathbf{x}|\mu_g \Sigma_g)$$

Slides:
Christian Dittmar

Classification methods

- Gaussian Mixture Models (GMM)

Gauss components

Slides:
Christian Dittmar

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

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

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Overfitting???

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

Classification Results

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training | test

Baroque
Classical
Romantic
Modern

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**

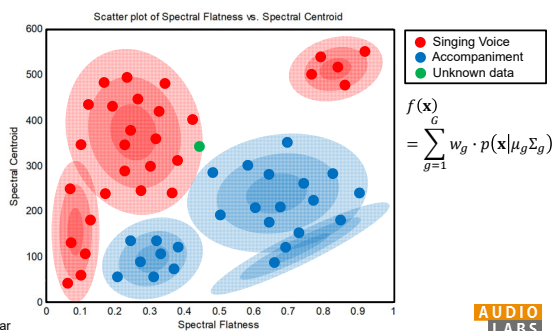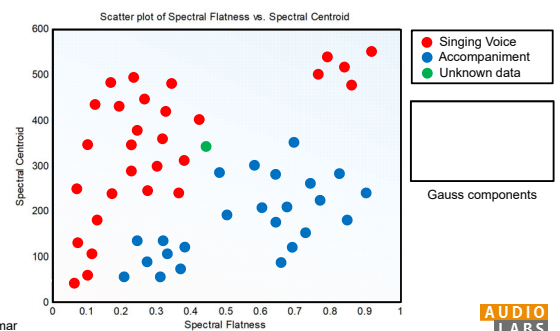|	Full Dataset	Piano	Orchestra
Standard features	87 %	88 %	85 %
Tonal features	84 %	84 %	86 %
Combined	92 %	86 %	80 %

- **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

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

	Full Dataset	Piano	Orchestra
Standard features	87 %	88 %	85 %
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Weiss / Müller, *Tonal Complexity Features for Style Classification of Classical Music*, ICASSP 2015

Classification Results

- What is actually learned?
- Pay attention to:
  - Overfitting
  - „Curse of dimensionality" – use dimensionality reduction techniques
  - Artist / album effects
- Evaluation: „Figures of merit":
  - Confusion matrix
  - Error examples: Consistently misclassified items
  - Listening tests
- Evaluation on unseen data (no cross validation)

Bob Sturm, *Classification Accuracy is not enough*, Journal of Intelligent Information Systems, 2013

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 %**

Era (correct) \ Era (classified)	Baroque	Classical	Romantic	Modern
Baroque	65.2	23.2	10.9	0.6
Classical	17.0	74.9	8.1	0.0
Romantic	6.5	5.0	77.7	10.8
Modern	1.7	0.9	16.8	80.6

AUDIO
LABS

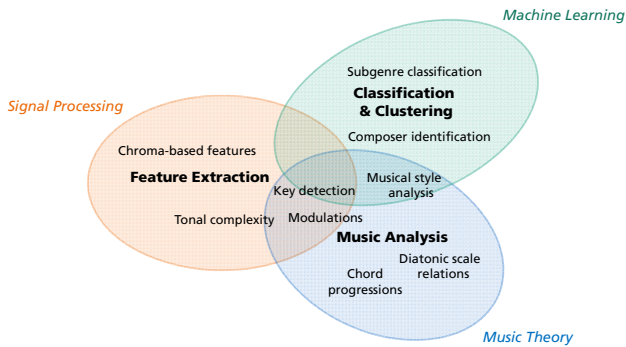---

Classification Results: Error Examples

- 80 tonal features, GMM with 1 Gaussian, LDA
- Look at **consistently** and **persistently** misclassified items

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

UDIO
LABS

Conclusions

Signal Processing · *Machine Learning* · *Music Theory*

Subgenre classification
Classification & Clustering
Composer identification
Chroma-based features
Feature Extraction
Musical style analysis
Key detection
Tonal complexity · Modulations
Music Analysis
Diatonic scale relations
Chord progressions

AUDIO
LABS