Woche der Forschung 2019:
Digitalisierung der Wissenschaften

Computergestützte Analyse von Musikaufnahmen – ein Beispiel für interdisziplinäre Forschung

Dr. Christof Weiß
International Audio Laboratories Erlangen

26.02.2019 | 12.30 Uhr | Raum WE5/02.005

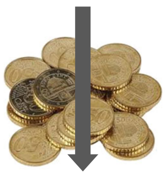
Christof Weiß

- 2006: Abitur, Max-Reger-Gymnasium Amberg
- 2006-2012: Studium **Physik** Diplom, Universität Würzburg
- 2006-2011: Studium **Komposition**, HfM Würzburg
- 2011-2012: Fortbildungsklasse Komposition
- 2012-2015: **Promotion**
  Fraunhofer Institut für Digitale Medientechnologie, Ilmenau
  gefördert von Stiftung der Deutschen 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

International Audio Laboratories Erlangen

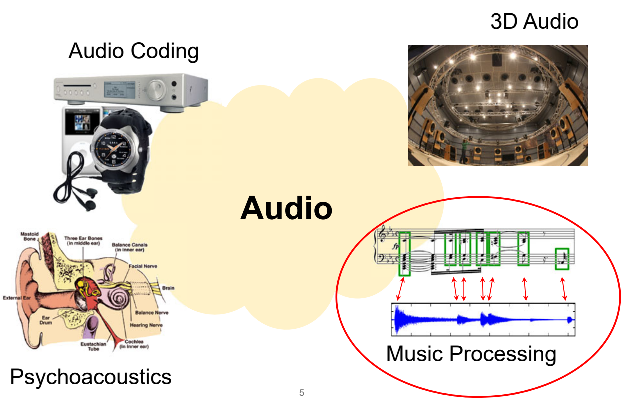


AUDIO LABS

AudioLabs - FAU

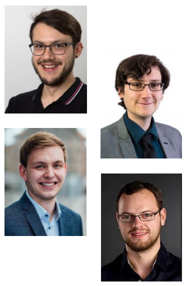
- Prof. Dr. Jürgen Herre
  Audio Coding
- Prof. Dr. Bernd Edler
  Audio Signal Analysis
- Prof. Dr. Meinard Müller
  Semantic Audio Processing
- Prof. Dr. Emanuël Habets
  Spatial Audio Signal Processing
- Prof. Dr. Frank Wefers
  Virtual Reality
- Dr. Stefan Turowski
  Coordinator AudioLabs-FAU

International Audio Laboratories Erlangen



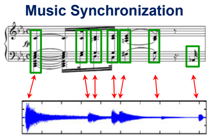
Group Prof. Meinard Müller

- Patricio López-Serrano
- Frank Zalkow
- Sebastian Rosenzweig
- Christof Weiß

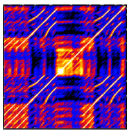


Music Processing / Music Information Retrieval (MIR)

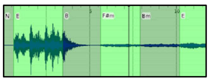
Music Synchronization



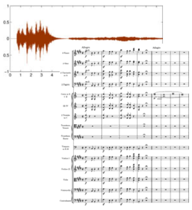
Structure Analysis



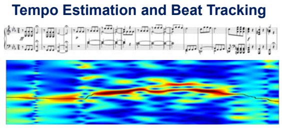
Harmony Analysis



Automatic Music Transcription



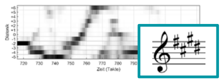
Tempo Estimation and Beat Tracking



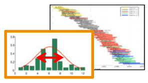
Outline

1. Measure Annotations in Wagner's *Ring*

2. Cross-Version Analysis of Harmonic Structures: Local Keys and Chords



3. Machine Learning and Corpus Analyses in Classical Music and Jazz



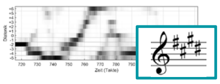
Outline

1. Measure Annotations in Wagner's *Ring*

→ *Software example: Sonic Visualizer*

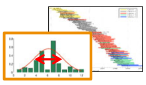
2. Cross-Version Analysis of Harmonic Structures: Local Keys and Chords

→ *Programming example: Python and Jupyter Notebooks*



3. Machine Learning and Corpus Analyses in Classical Music and Jazz

→ *Discussion: Chances and Challenges of Interdisciplinary Research*



Material

- Workshop website with resources:

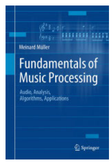
www.audiolabs-erlangen.de/resources/MIR/2019_WorkshopMIR_UniBamberg

- Book: M. Müller, *Fundamentals of Music Processing*

www.audiolabs-erlangen.de/fau/professor/mueller/bookFMP

- Jupyter Notebooks in Python:

www.audiolabs-erlangen.de/FMP

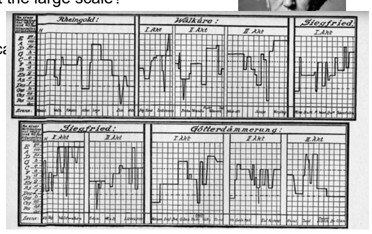


1. A Typical Scenario – Measure Annotations in Wagner's *Ring*

DFG-funded Project: Computational Analysis of Harmonic Structures

- With Prof. Rainer Kleinertz, Musicology, Uni Saarland

- Richard Wagner, *Der Ring des Nibelungen*
  - Four operas, up to 15 hours of music
  - How is harmony organized at the large scale?
  - Analyses by A. Lorenz 1924
  - Hypothesis of „Poetico-musica



Music Scenario

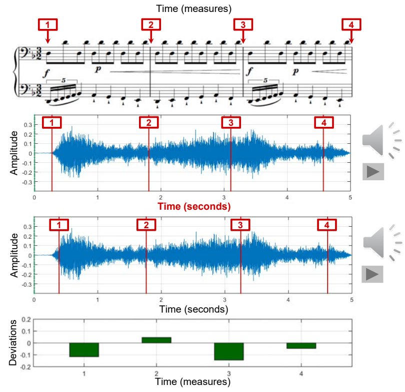
- Richard Wagner, *Die Walküre* (opera)
  - Long work (1st act: 67 minutes)
  - No interruptions of acts
- Different data types
  - Libretto (**text**)
  - Score / piano reduction (**sheet music**)
  - Recorded performance (**audio**)

Music Scenario

Score:

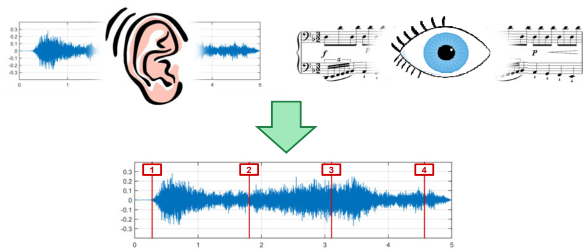
Performance (Karajan 1966):

- Annotation 1
- Annotation 2
- Deviations



Manual Measure Annotations

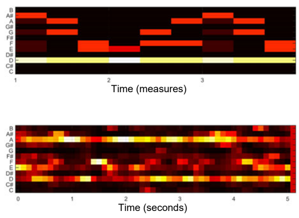
- 5 students with musical background
- Procedure: Listening while reading the vocal score
- Tool: *Sonic Visualiser*



→ Software example: Measure Annotations in Sonic Visualizer

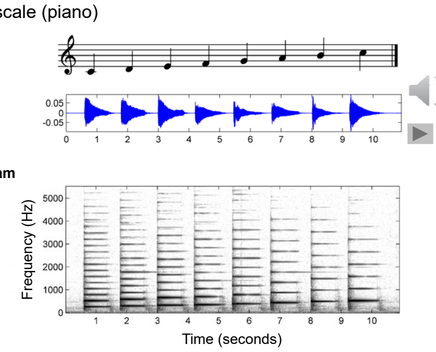
Computed Measure Annotations

- Synchronization (score-to-audio alignment)
- Based on *chroma features*



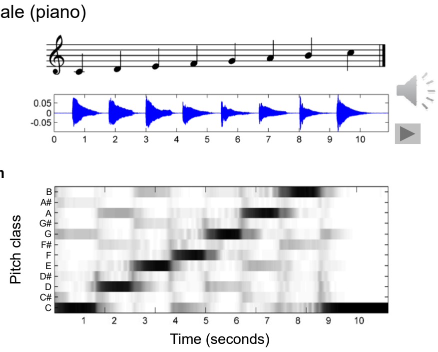
Excursus: Chroma Features

- Example: C-major scale (piano)
  - Score
  - Audio – **Waveform**
  - Audio - **Spectrogram**



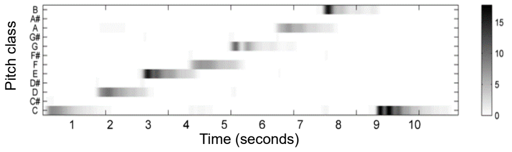
Excursus: Chroma Features

- Example: C-major scale (piano)
  - Score
  - Audio – **Waveform**
  - Audio - **Chromagram**

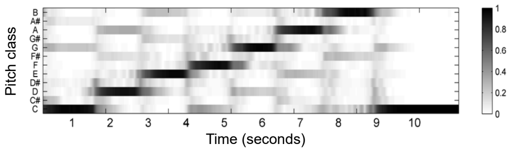


Chroma Features

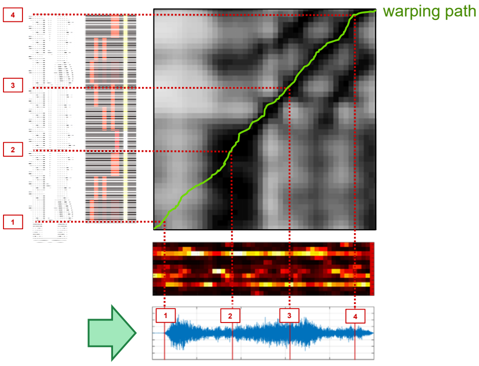
- Example: C-major scale (piano)
  - Audio – **Chromagram**



  - Audio – **Chromagram (normalized)**

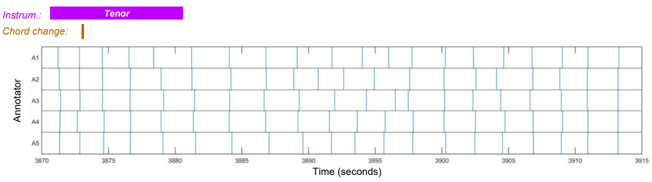


Computed Measure Annotations



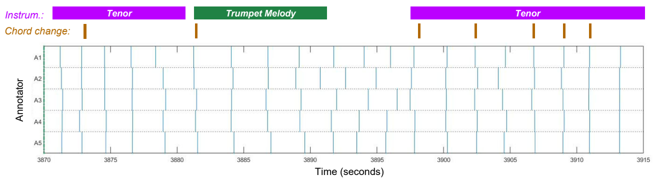
Analysis of Manual Annotations

- Compare 5 different annotators
- Questions:
  - Accuracy?
  - Typical errors?
  - Systematic offsets?
- Example passage (Karajan 1966)

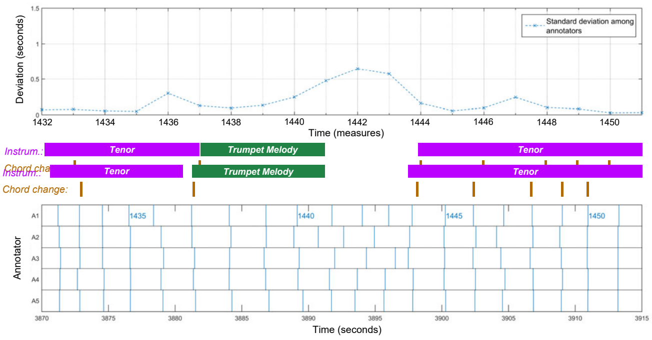


Analysis of Manual Annotations

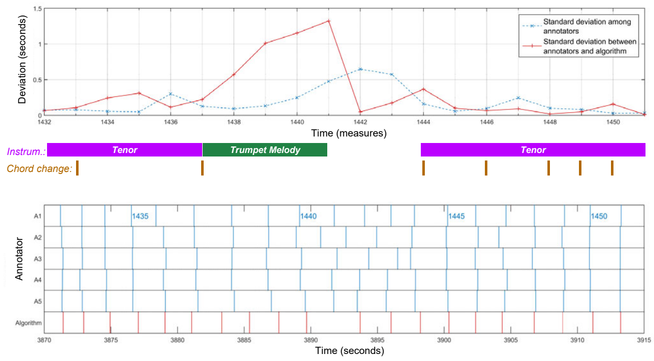
- Compare 5 different annotators
- Questions:
  - Accuracy?
  - Typical errors?
  - Systematic offsets?
- Example passage (Karajan 1966)



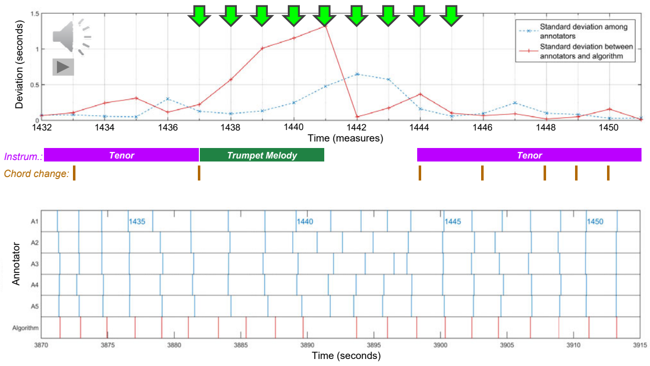
Analysis of Manual Annotations



Analysis of Computed Annotations



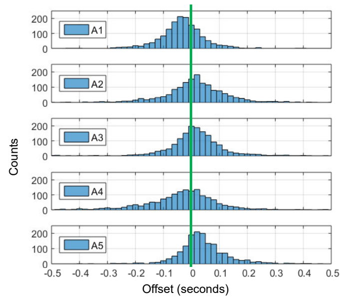
Analysis of Computed Annotations



AUDIO LABS

Analysis of Manual Annotations

Dataset: Full act (*67 minutes*, *1523 measures*)

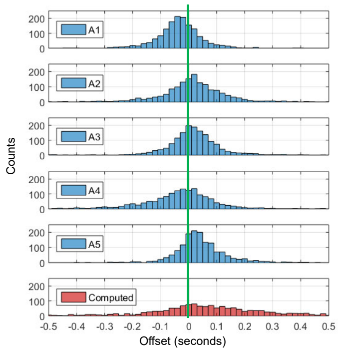


0 s = mean position of A1 … A5

AUDIO LABS

Analysis of Computed Annotations

Dataset: Full act (*67 minutes*, *1523 measures*)



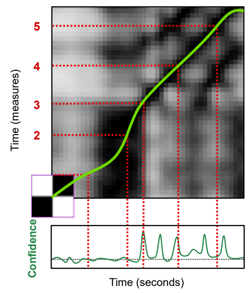
0 s = mean position of A1 … A5

AUDIO LABS

Confidences for Computed Annotations

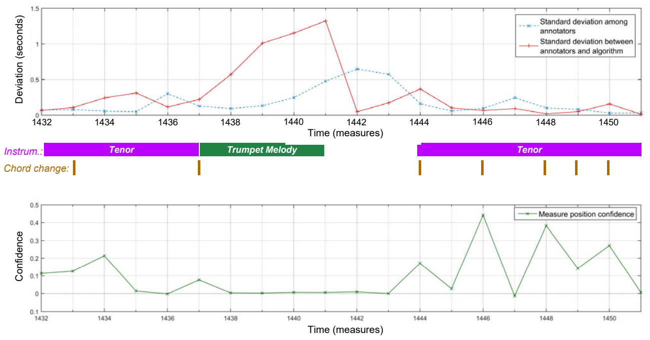
- Use information from **similarity matrix**
- Shift checkerboard kernel **along the warping path**

J. Foote (2000):
Shift checkerboard kernel
along the main diagonal
of a self-similarity matrix



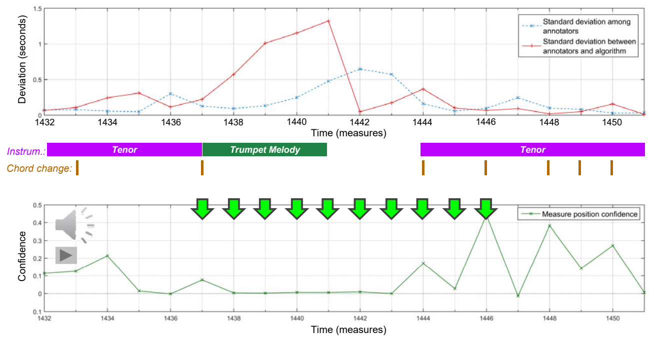
AUDIO LABS

Confidences for Computed Annotations



AUDIO LABS

Confidences for Computed Annotations



AUDIO LABS

Towards Confidence-based Measure Annotations

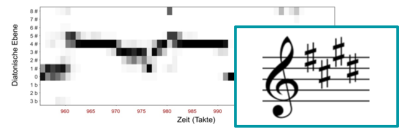
High confidence implies high reliability (quantitative evaluation, full act)

Future work:

- Reliable measures → anchor points
- → improve computed annotations
- Other types of features

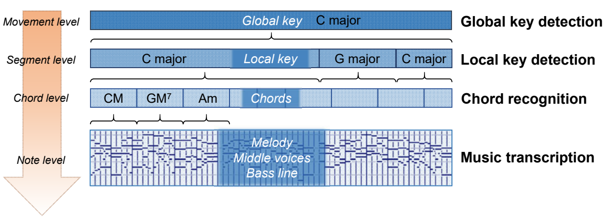
C. Weiß, V. Arifi-Müller, T. Prätzlich, R. Kleinertz, M. Müller
"Analyzing Measure Annotations for Western Classical Music Recordings"
In: *Proceedings of the 17th International Society for Music Information Retrieval Conference (ISMIR)*, New York, USA 2016.

2. Cross-Version Analysis of Harmonic Structures: Local Keys and Chords



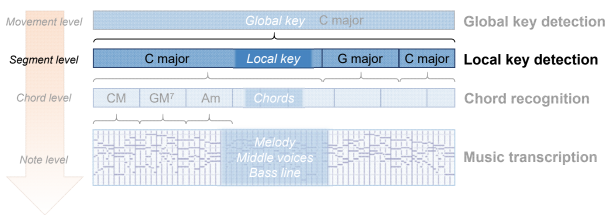
Motivation

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



Motivation

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



Musicological Foundations

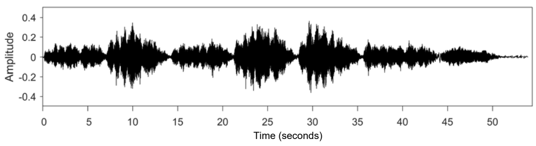
- Method: estimate **diatonic scales – 7** fifth-related pitches
- Relationship of diatonic scales:
  - Fifth-neighbouring scales share 6 of 7 notes
  - Ordering of scales according to the **circle of fifths:**

Visualization of Diatonic Scales

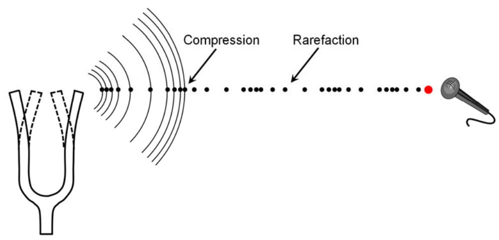
- Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)
- **Score** – Piano reduction

Visualization of Diatonic Scales

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

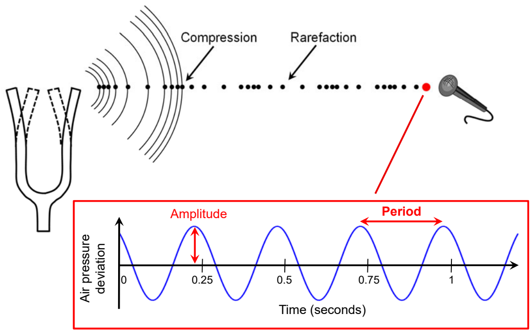


Excursus: Waveform



Slides:
Meinard Müller

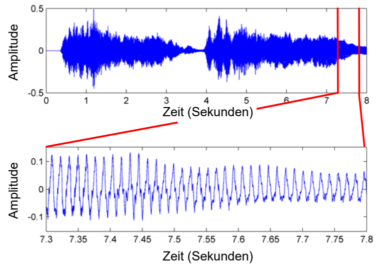
Excursus: Waveform



Frequency: 1/Period
Unit: Hertz (Oscillations per second)

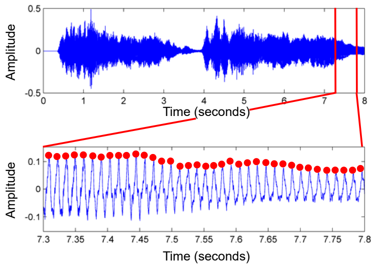
Excursus: Waveform

D2 (73.4 Hz)



Excursus: Waveform

D2 (73.4 Hz)

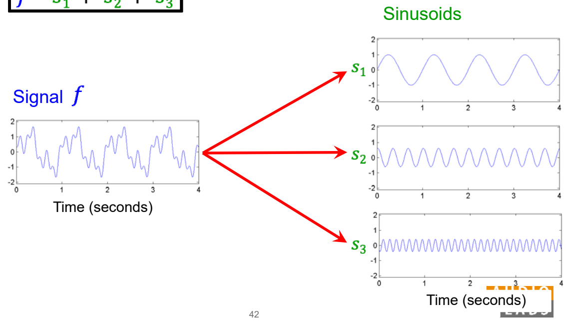


37 Periods
in 500 ms

Excursus: Fourier Transform

Idea: Decompose a given signal into a superposition of sinusoids (elementary signals).

$$\boxed{f = s_1 + s_2 + s_3}$$



Excursus: Fourier Transform

Each sinusoid has a physical meaning and can be described by three parameters:

$$\boxed{s_{(A,\omega,\varphi)}(t) = A \cdot \sin(2\pi(\omega t - \varphi))}$$

ω = frequency
A = amplitude
φ = phase

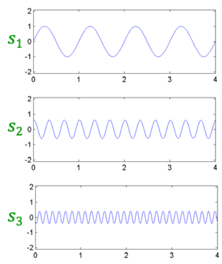
Interpretation:
The amplitude A reflects the intensity at which the sinusoidal of frequency ω appears in f.
The phase φ reflects how the sinusoidal has to be shifted to best correlate with f.

Sinusoids

$A_1 = 1$, $\omega_1 = 1$, $\varphi_1 = 0$

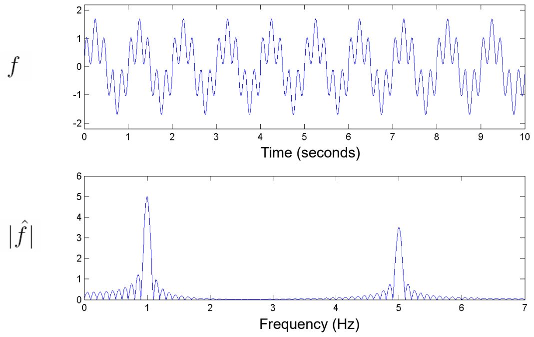
$A_2 = 0.6$, $\omega_2 = 3$, $\varphi_2 = -0.2$

$A_3 = 0.4$, $\omega_3 = 7$, $\varphi_3 = 0.4$



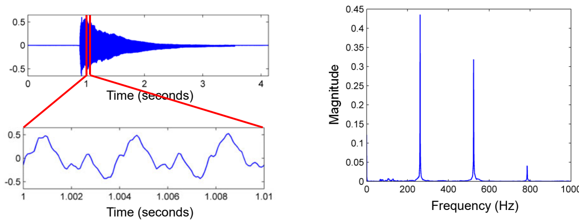
Excursus: Fourier Transform

Example: Superposition of two sinusoids



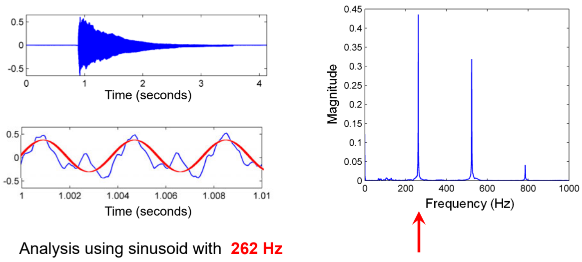
Excursus: Fourier Transform

Example: Piano tone (C4, 261.6 Hz)



Excursus: Fourier Transform

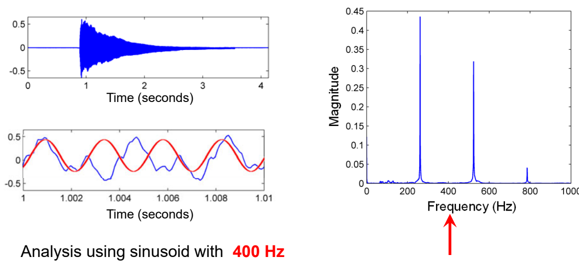
Example: Piano tone (C4, 261.6 Hz)



Analysis using sinusoid with **262 Hz**
→ high correlation
→ large Fourier coefficient

Excursus: Fourier Transform

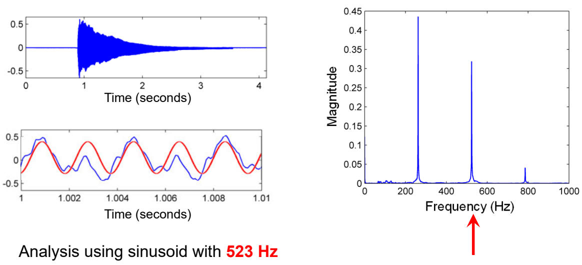
Example: Piano tone (C4, 261.6 Hz)



Analysis using sinusoid with **400 Hz**
→ low correlation
→ small Fourier coefficient

Excursus: Fourier Transform

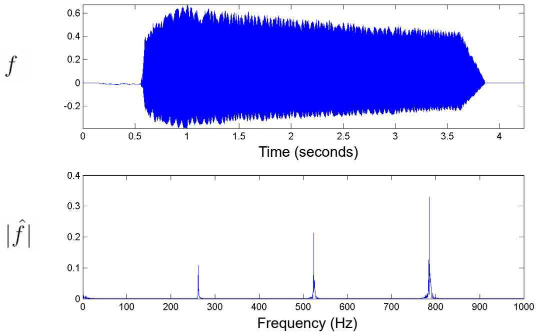
Example: Piano tone (C4, 261.6 Hz)



Analysis using sinusoid with **523 Hz**
→ high correlation
→ large Fourier coefficient

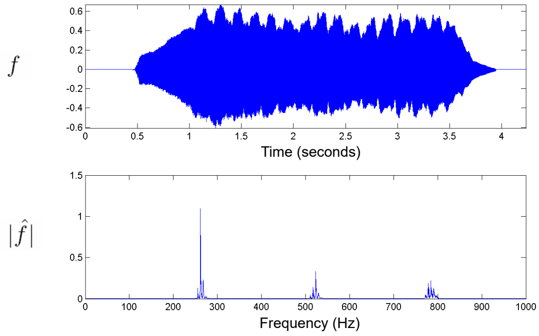
Excursus: Fourier Transform

Example: C4 played by trumpet



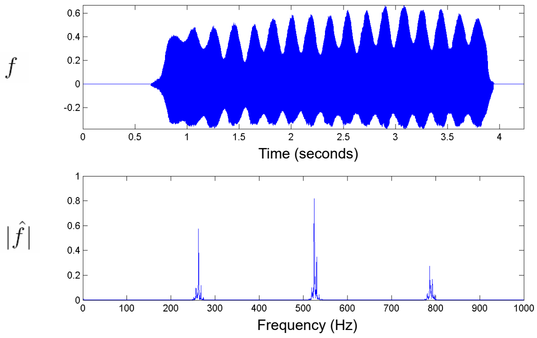
Excursus: Fourier Transform

Example: C4 played by violine



Excursus: Fourier Transform

Example: C4 played by flute



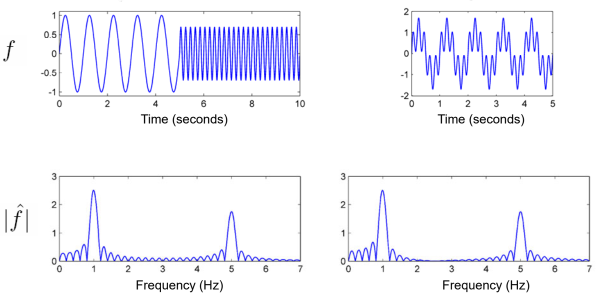
Excursus: Fourier Transform

Signal $\quad f:\mathbb{R}\to\mathbb{R}$

Fourier representation $\quad f(t) = \int_{\omega\in\mathbb{R}} c_\omega \exp(2\pi i\omega t)\,d\omega$

Fourier transform $\quad c_\omega = \hat{f}(\omega) = \int_{t\in\mathbb{R}} f(t)\exp(-2\pi i\omega t)\,dt$

Excursus: Fourier Transform



Excursus: Short Time Fourier Transform

Idea (Dennis Gabor, 1946):

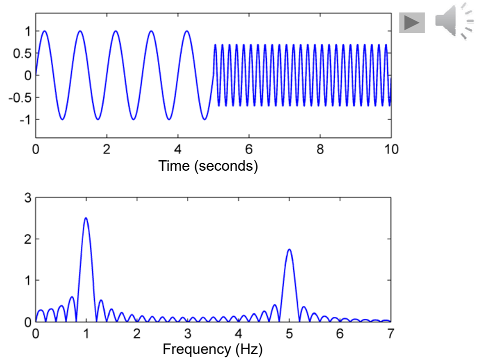
- Consider only a small section of the signal for the spectral analysis

  → recovery of time information

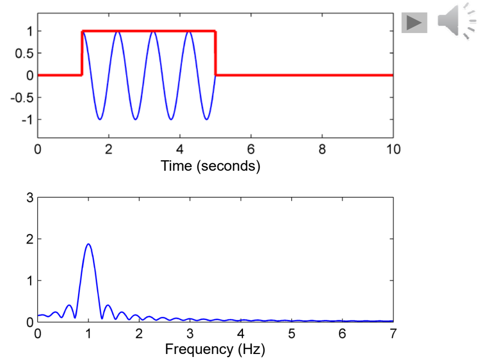
- Short Time Fourier Transform (STFT)

- Section is determined by pointwise multiplication of the signal with a localizing window function

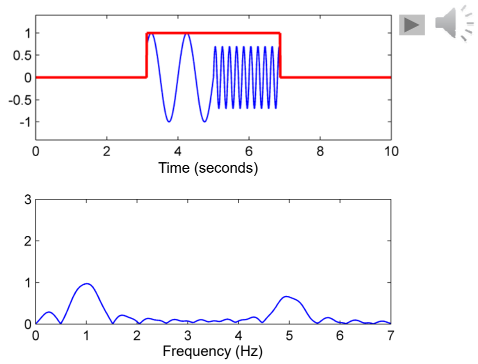
Excursus: Short Time Fourier Transform



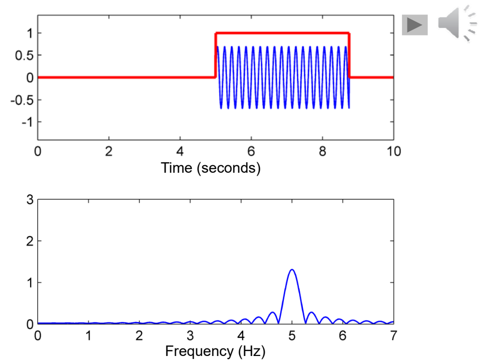
Excursus: Short Time Fourier Transform



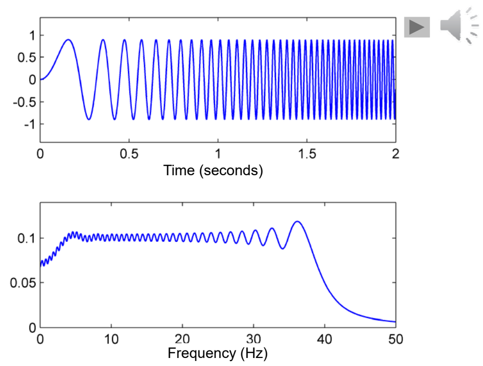
Excursus: Short Time Fourier Transform



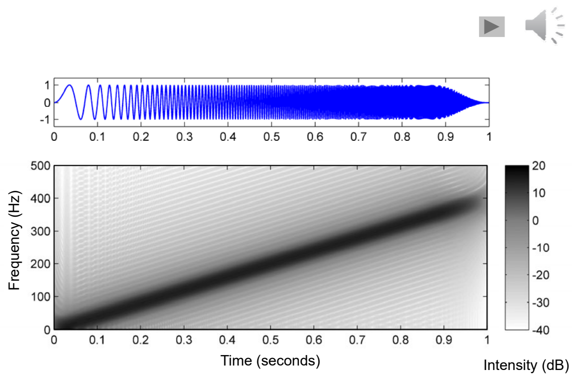
Excursus: Short Time Fourier Transform



Excursus: Short Time Fourier Transform

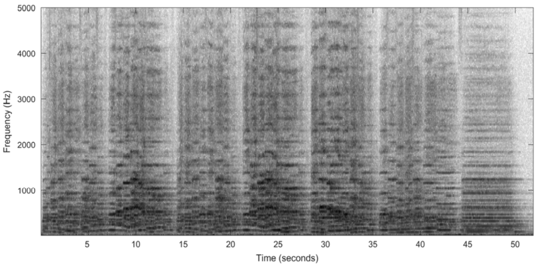


Excursus: Spectrogram



Visualization of Diatonic Scales

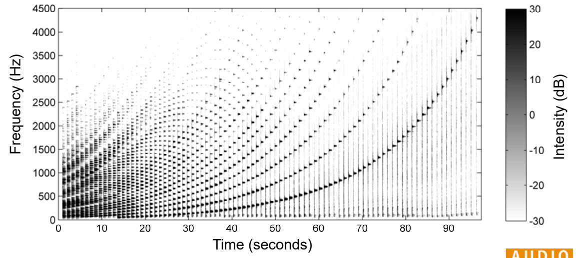
- Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)
- **Audio** – Spectrogram (Scholars Baroque Ensemble, Naxos 1994)



Excursus: Spectrogram

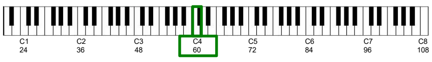
Example: Chromatic scale

Spectrogram

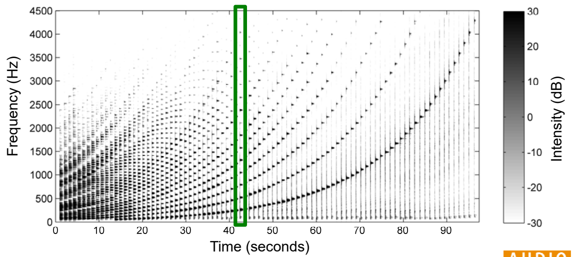


Excursus: Spectrogram

Example: Chromatic scale

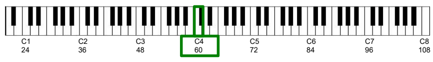


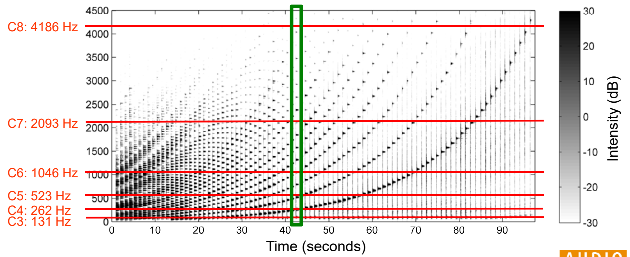
Spectrogram



Excursus: Spectrogram

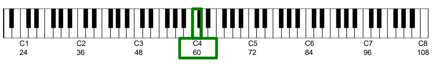
Example: Chromatic scale

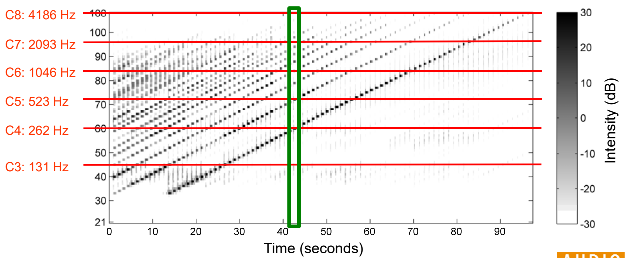




Excursus: Log-Frequency Spectrogram

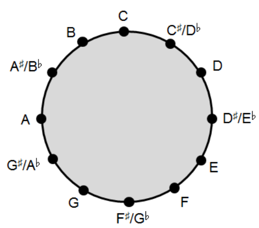
Example: Chromatic scale



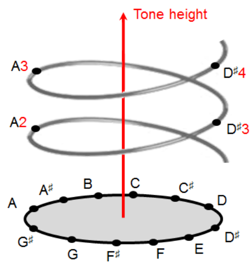


Excursus: Chroma Features

Chromatic circle

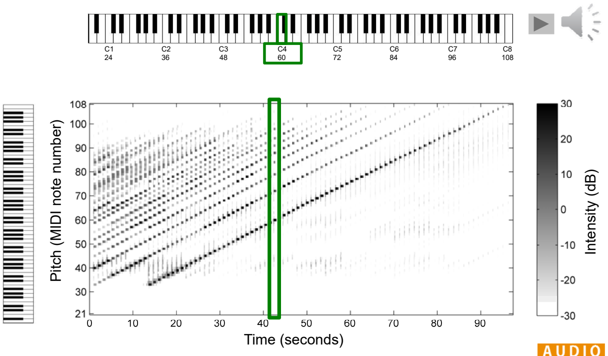


Shepard's helix of pitch



Excursus: Chroma Features

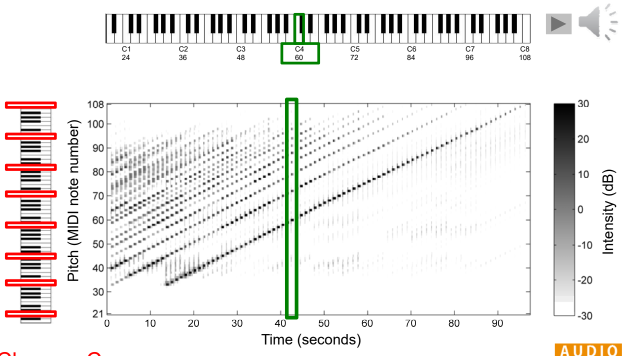
Example: Chromatic scale



AUDIO LABS

Excursus: Chroma Features

Example: Chromatic scale

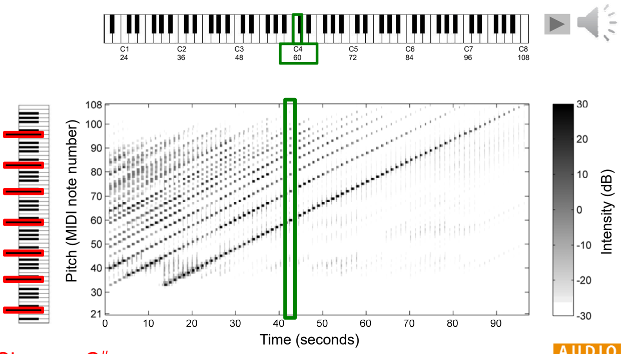


Chroma C

AUDIO LABS

Excursus – Chroma Features

Example: Chromatic scale

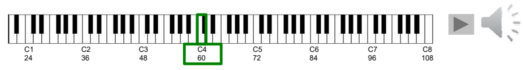


Chroma $C^{\#}$

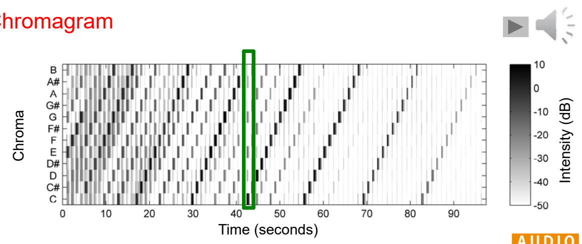
AUDIO LABS

Excursus: Chroma Features

Example: Chromatic scale



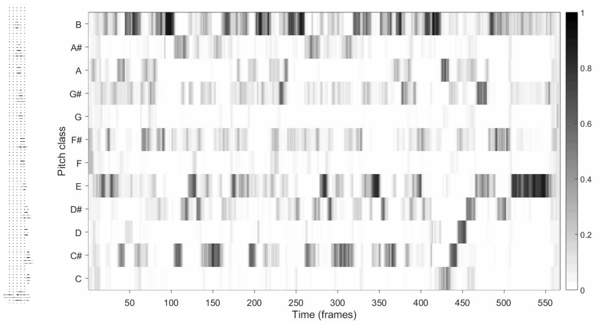
Chromagram



AUDIO LABS

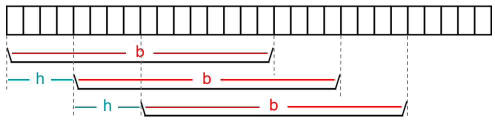
Visualization of Diatonic Scales

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



Visualization of Diatonic Scales

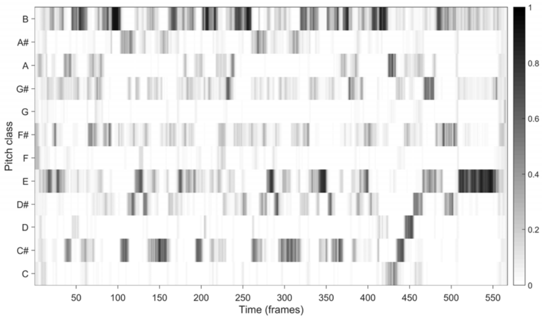
- Summarize pitch classes over a certain time
  - **Chroma smoothing**
  - Parameters: blocksize b and hopsize h



AUDIO LABS

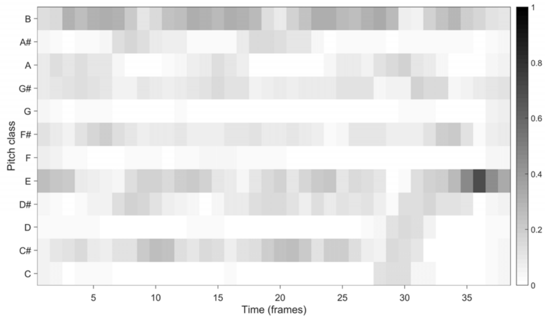
Visualization of Diatonic Scales

- Choral (Bach)



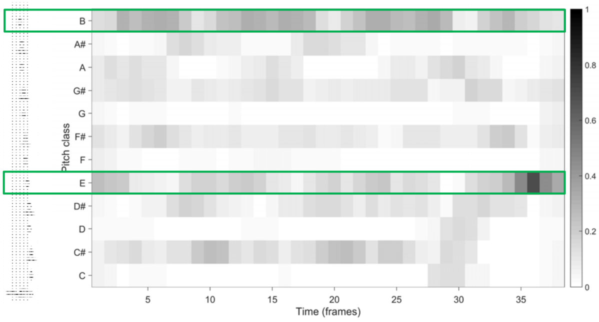
Visualization of Diatonic Scales

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



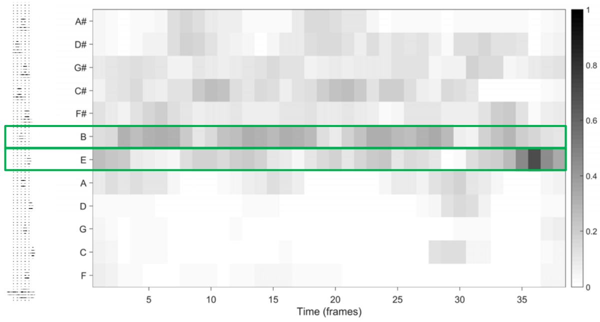
Visualization of Diatonic Scales

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



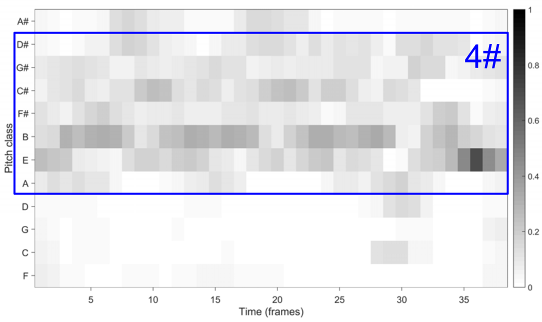
Visualization of Diatonic Scales

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



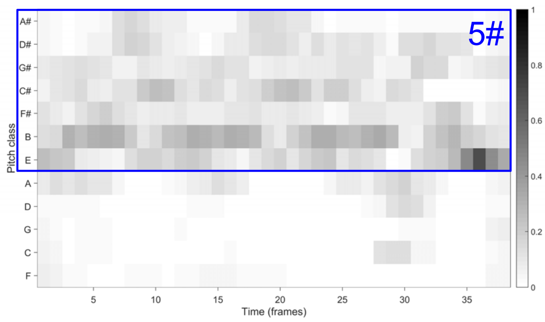
Visualization of Diatonic Scales

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



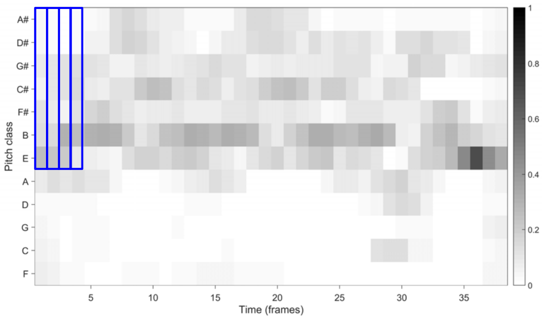
Visualization of Diatonic Scales

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



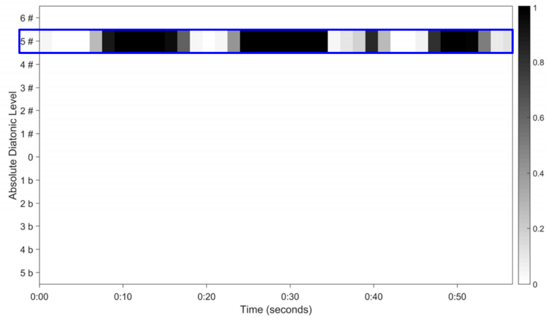
Visualization of Diatonic Scales

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



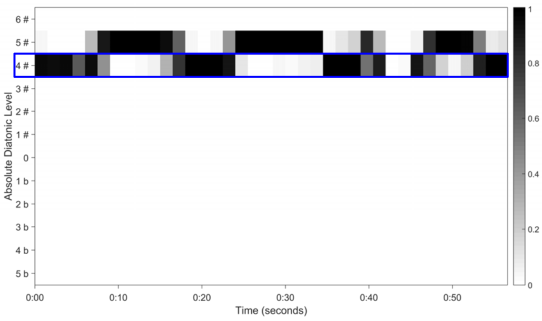
Visualization of Diatonic Scales

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



Visualization of Diatonic Scales

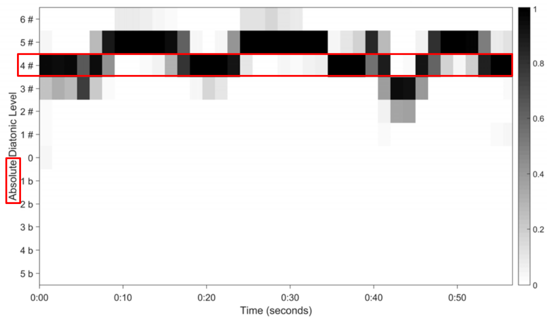
- Choral (Bach) — Diatonic Scale Estimation



Visualization of Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation

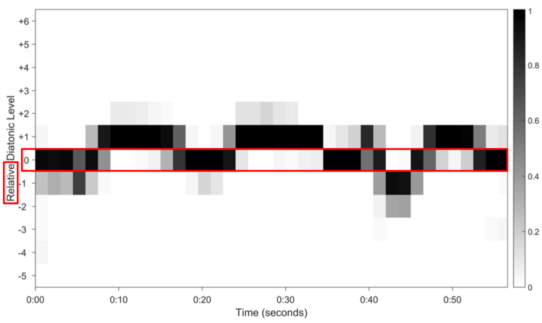
4 #
(E major)



Visualization of Diatonic Scales

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

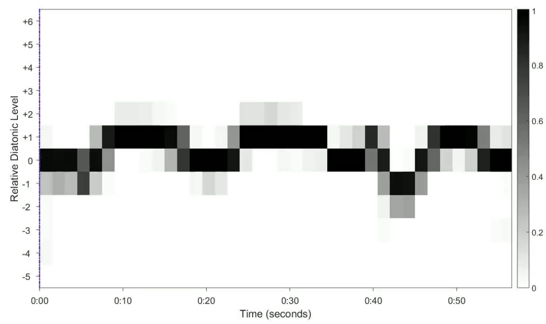
4 #
(E major)



Visualization of Diatonic Scales

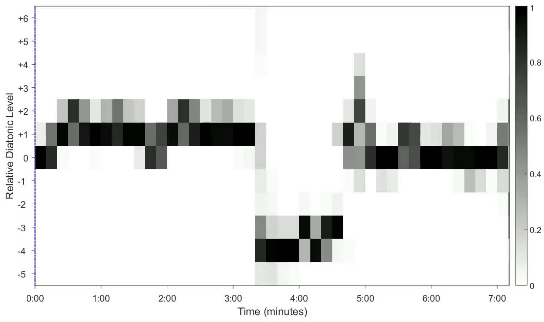
- Choral (Bach) — 0 ≙ 4#

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



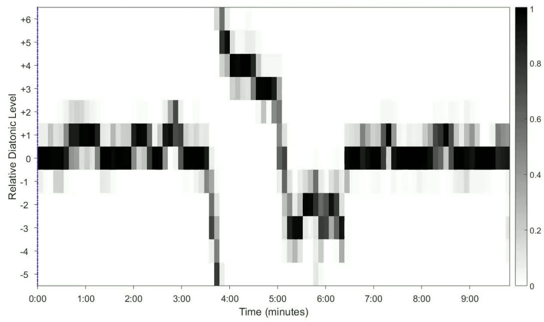
Visualization of Diatonic Scales

- L. v. Beethoven – Sonata No. 10 op. 14 Nr. 2, 1. Allegro — 0 ≙ 1
(Barenboim, EMI 1998)



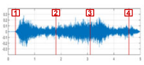
Visualization of Diatonic Scales

- R. Wagner, *Die Meistersinger von Nürnberg*, Vorspiel — 0 ≙ 0
(Polish National Radio Symphony Orchestra, J. Wildner, Naxos 1993)



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

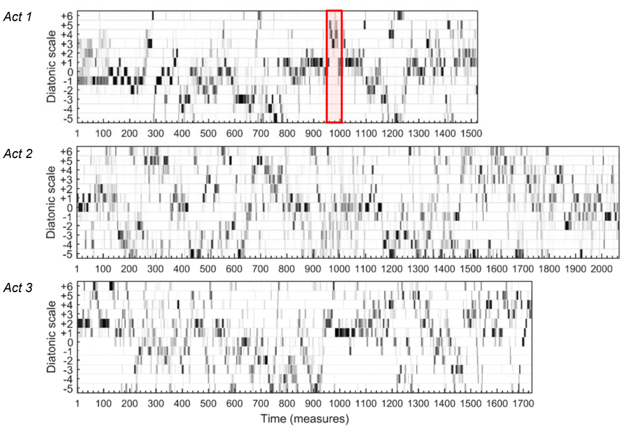
Cross-Version Analysis

- Idea: Use analysis results based on different interpretations (versions)
- Tonal characteristics should not depend on interpretation

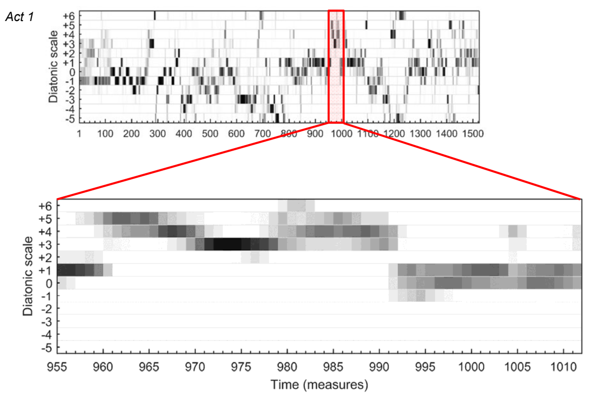
→ Test reliability of the method

- Visualize consistency with gray scheme

Die Walküre WWV 86 B

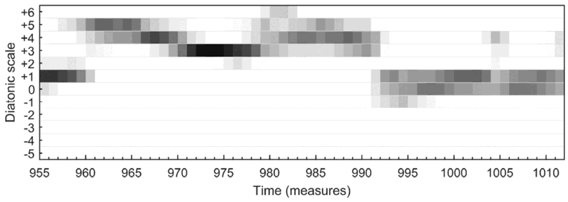


Die Walküre WWV 86 B



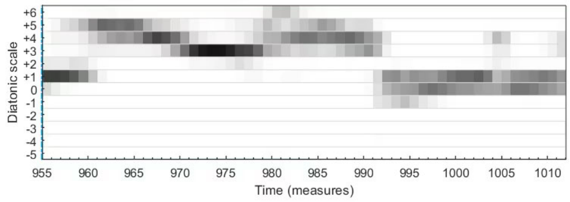
Die Walküre WWV 86 B

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

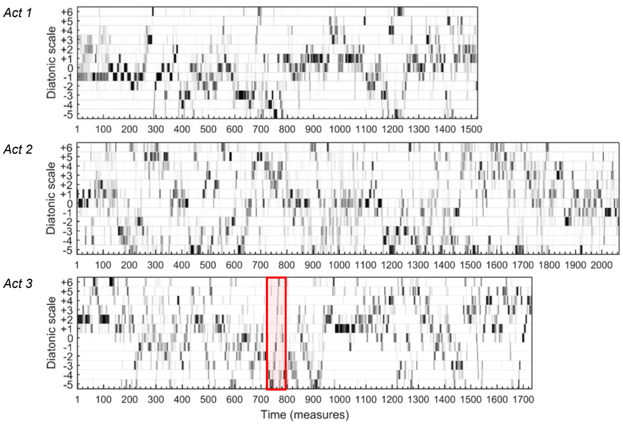


Die Walküre WWV 86 B

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

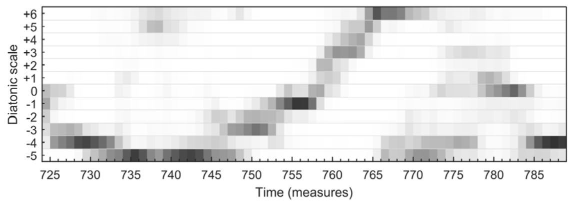


Die Walküre WWV 86 B



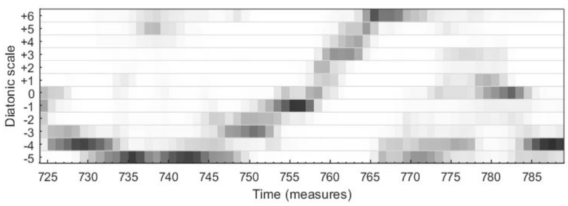
Die Walküre WWV 86 B

- Act 3, measures 724–789
- Wotan´s punishment

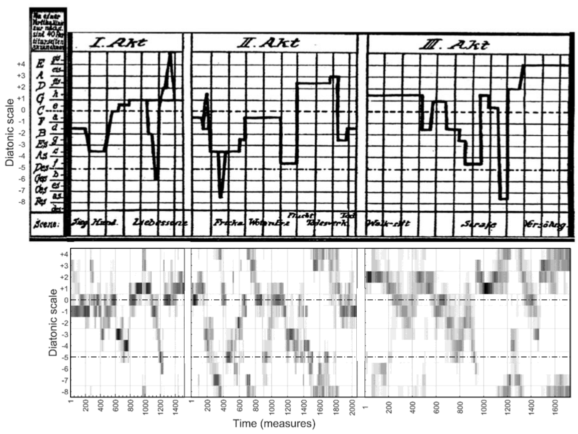


Die Walküre WWV 86 B

- Act 3, measures 724–789
- Wotan´s punishment

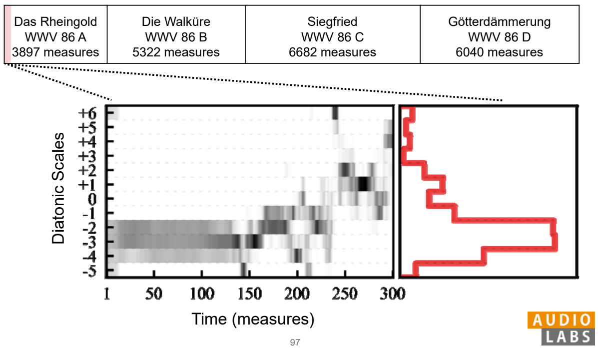


Die Walküre WWV 86 B



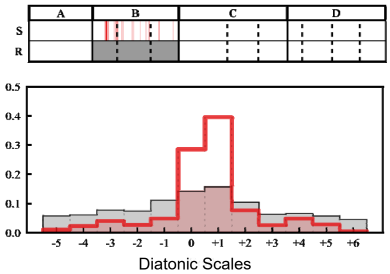
Exploring Tonal-Dramatic Relationships

- Histograms of Analysis over time



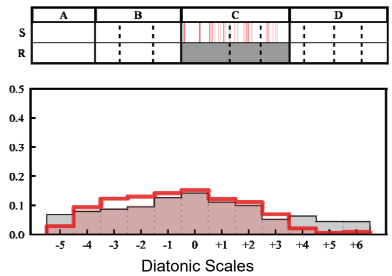
Exploring Tonal-Dramatic Relationships

Sword motif – *Die Walküre*



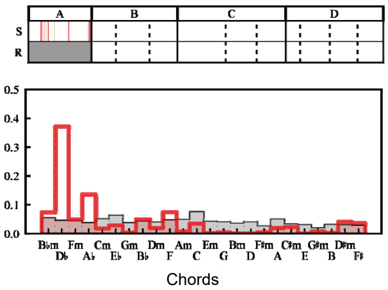
Exploring Tonal-Dramatic Relationships

Sword motif – *Siegfried*



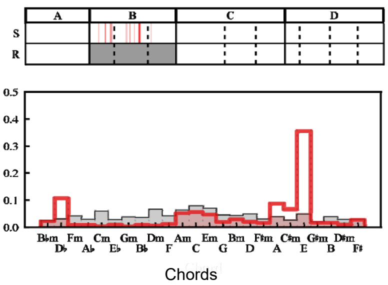
Exploring Tonal-Dramatic Relationships

Valhalla motif – *Das Rheingold*

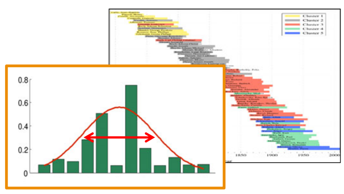


Exploring Tonal-Dramatic Relationships

Valhalla motif – *Die Walküre*

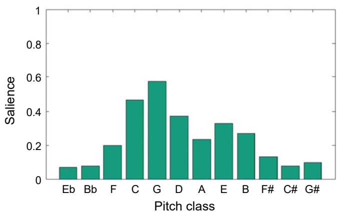


3. Machine Learning and Corpus Analyses in Classical Music and Jazz



Tonal Complexity

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

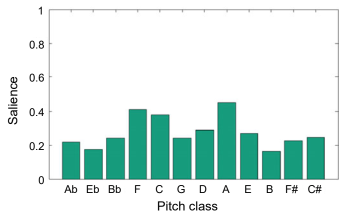


Circle of fifths →

AUDIO LABS

Tonal Complexity

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

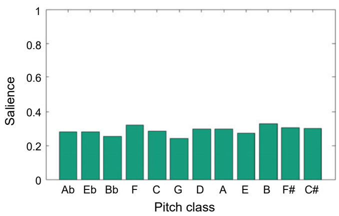


Circle of fifths →

AUDIO LABS

Tonal Complexity

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

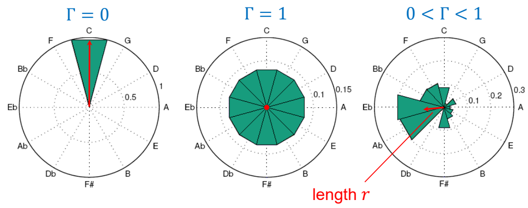


Circle of fifths →

AUDIO LABS

Tonal Complexity

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

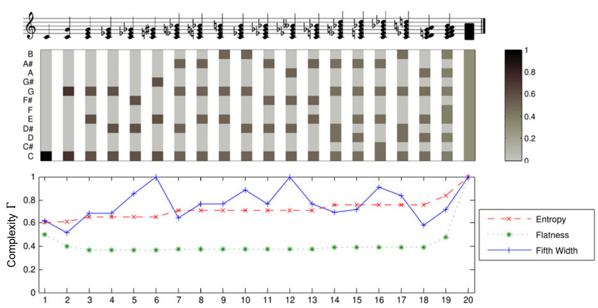


$$\Gamma = \sqrt{1 - r}$$

- Relating to different time scales!

AUDIO LABS

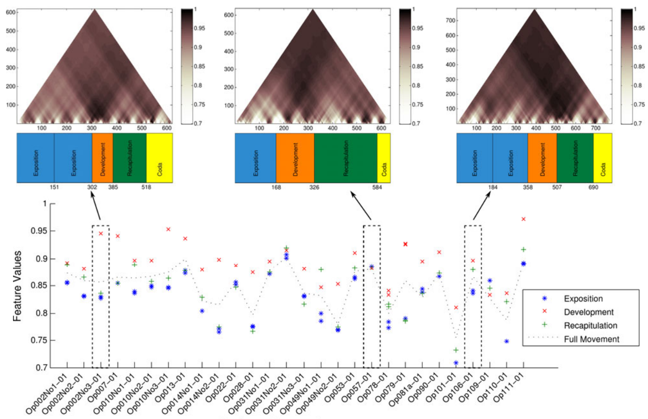
Tonal Complexity – Chords



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

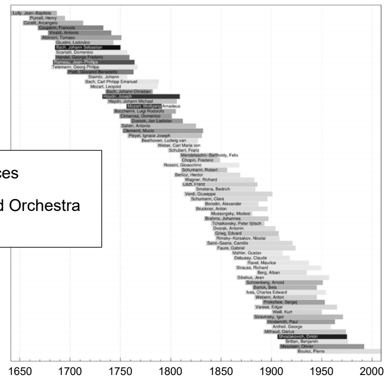
AUDIO LABS

Tonal Complexity – Beethoven's Sonatas



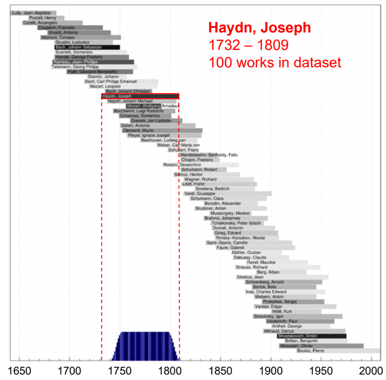
AUDIO LABS

Analyzing Composer Styles

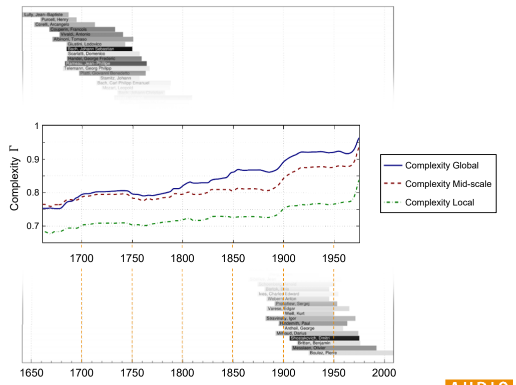


- 2000 pieces
- Piano and Orchestra music

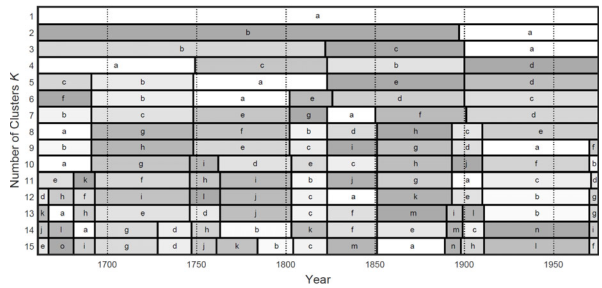
Analyzing Composer Styles



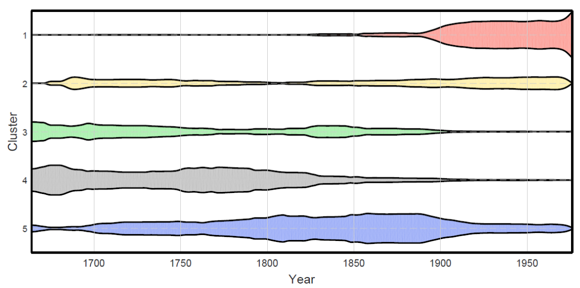
Analyzing Composer Styles



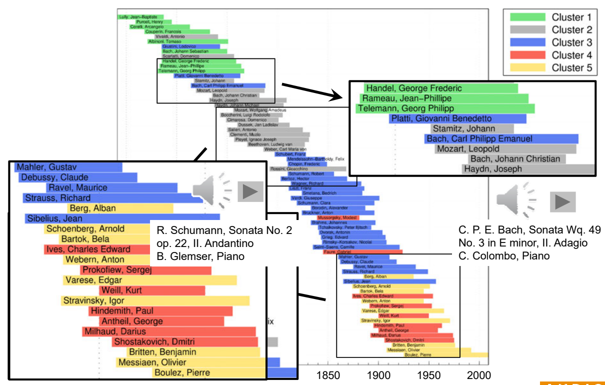
Clustering Composition Years



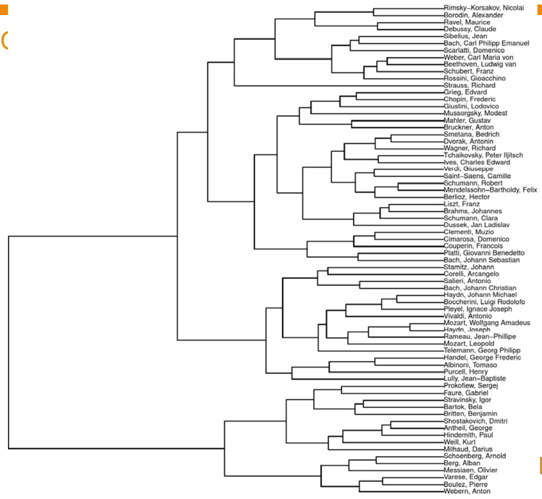
Clustering Individual Pieces



Clustering Composers



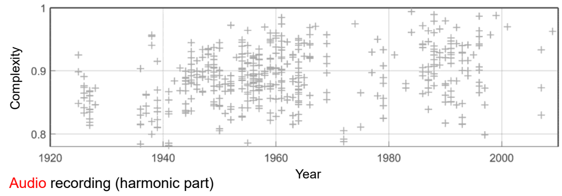
(



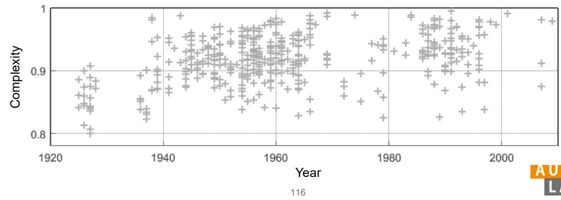
AUDIO LABS

Tonal Complexity: Jazz Solos

- Symbolic transcription



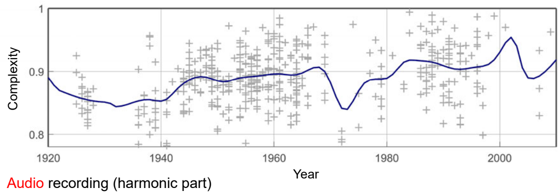
- Audio recording (harmonic part)



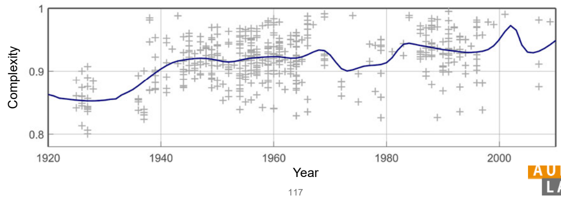
AUDIO LABS

Tonal Complexity: Jazz Solos

- Symbolic transcription



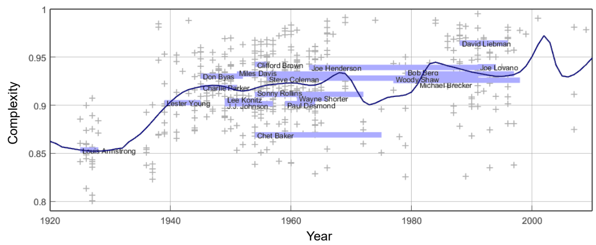
- Audio recording (harmonic part)



AUDIO LABS

Tonal Complexity: Jazz Solos

- Audio recording (harmonic part)



AUDIO LABS

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

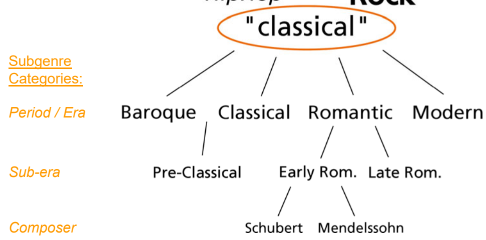
A. Webern, Variations for Orchestra op. 30 Ulster Orchestra

AUDIO LABS

Music Genre Classification

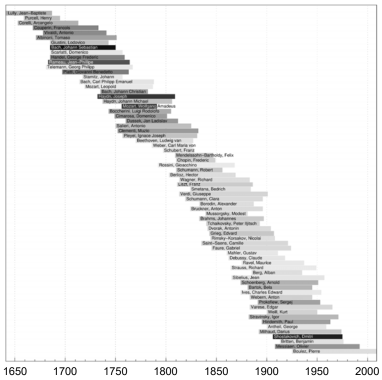
world music JAZZ

HipHop pop Rock

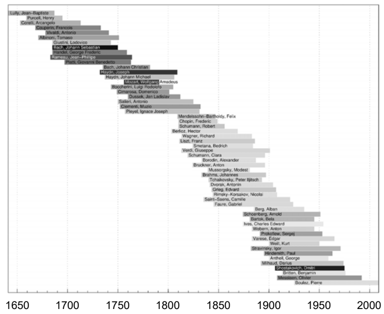


AUDIO LABS

Music Genre Classification: Dataset

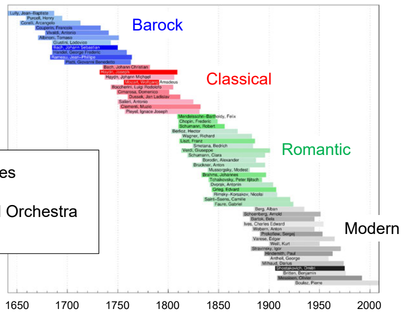


Music Genre Classification: Dataset



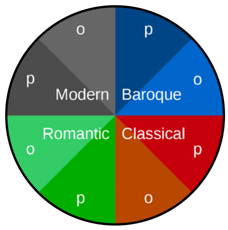
Music Genre Classification: Dataset

- 1600 pieces
- Piano and Orchestra music



Music Genre Classification: Dataset

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

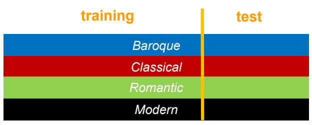


Music Genre Classification: Dataset

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

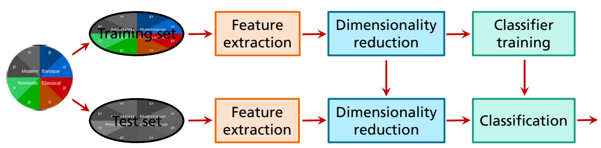
	Fold 1	*Fold 2*	*Fold 3*
Round 1	Training fold	Training fold	Test fold
Round 2	Training fold	Test fold	Training fold
Round 3	Test fold	Training fold	Training fold

- Distribution of classes balanced for all folds

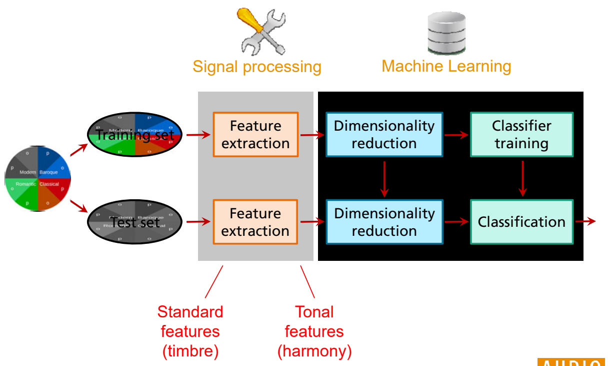


Classification Pipeline

- Typical approach: Supervised machine learning



Classification Pipeline

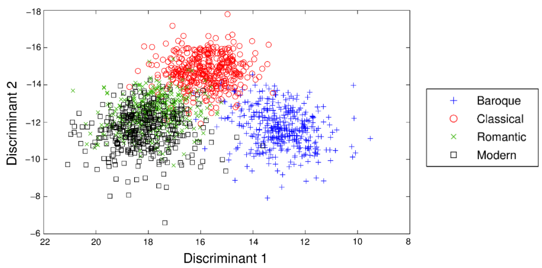


Classification Features

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**

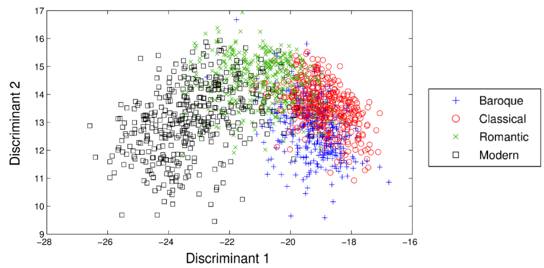
Dimensionality Reduction

- 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, …)



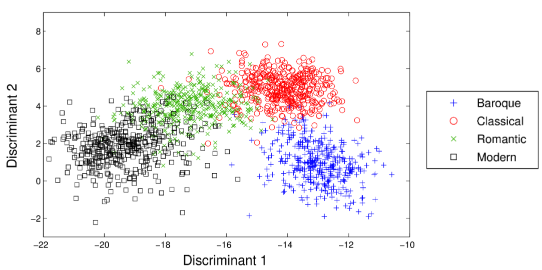
Dimensionality Reduction

- 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)



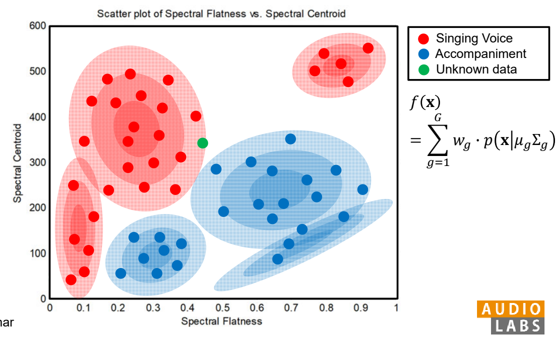
Dimensionality Reduction

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



Classifier

- Gaussian Mixture Models (GMM)

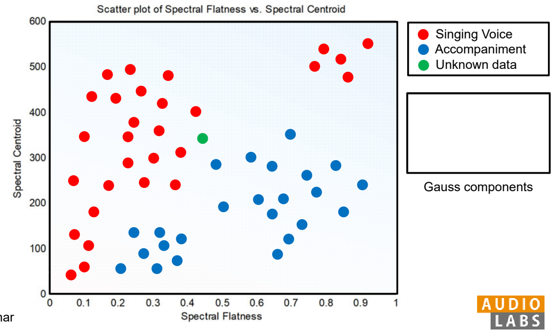


$$f(\mathbf{x}) = \sum_{g=1}^{G} w_g \cdot p(\mathbf{x}|\mu_g \Sigma_g)$$

Slides:
Christian Dittmar

Classifier

- Gaussian Mixture Models (GMM)



Slides:
Christian Dittmar

AUDIO LABS

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

AUDIO LABS

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 %**

Overfitting???

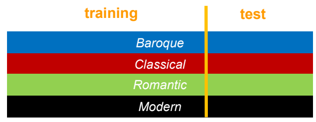
Weiss / Mauch / Dixon, *Timbre-Invariant Audio Features for Style Analysis of Classical Music*, ICMC / SMC 2014

AUDIO LABS

Classification Results

- 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 %**



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

AUDIO LABS

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

AUDIO LABS

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

AUDIO LABS

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

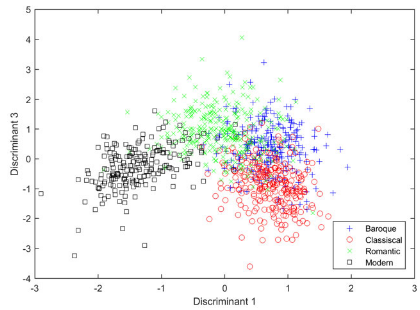
Classification Results: Error Examples

- 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

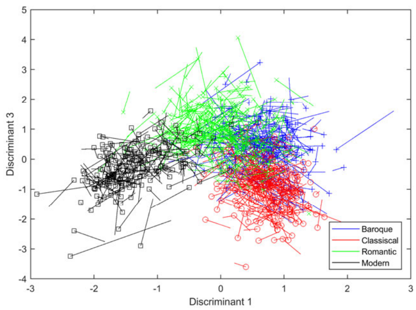
Classification Results: Cross-Version Analysis

- Dimensionality reduction: *Cross-Era* dataset



Classification Results: Cross-Version Analysis

- Dimensionality reduction: *Cross-Era – Cross-Era Mirror* dataset



Conclusions