

Workshop HfM Karlsruhe

**Music Information Retrieval**

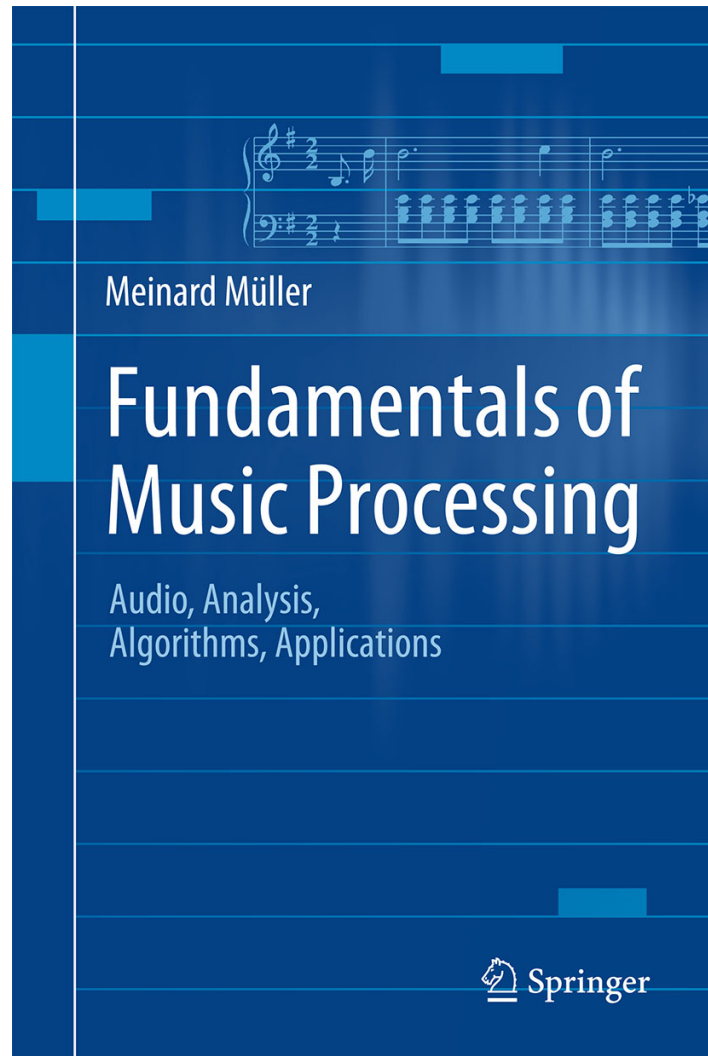
# **Classification & Clustering**

**Christof Weiß, Frank Zalkow, Christian Dittmar, Meinard Müller**

International Audio Laboratories Erlangen

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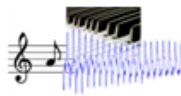

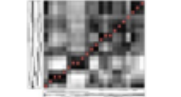


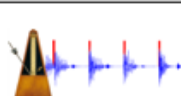
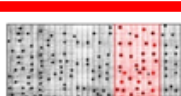

# Book: Fundamentals of Music Processing



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](http://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

Meinard Müller

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# Dissertation: Tonality-Based Style Analysis

Christof Weiß

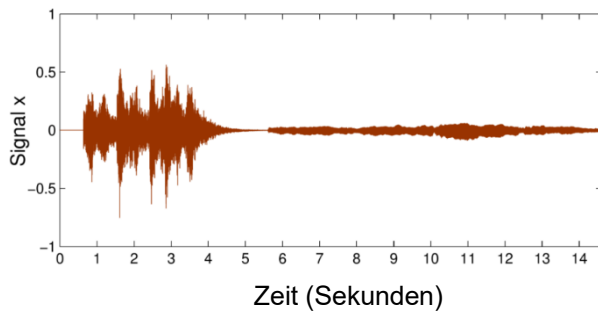
*Computational Methods for Tonality-Based Style Analysis of  
Classical Music Audio Recordings*

Dissertation, Ilmenau University of Technology, 2017

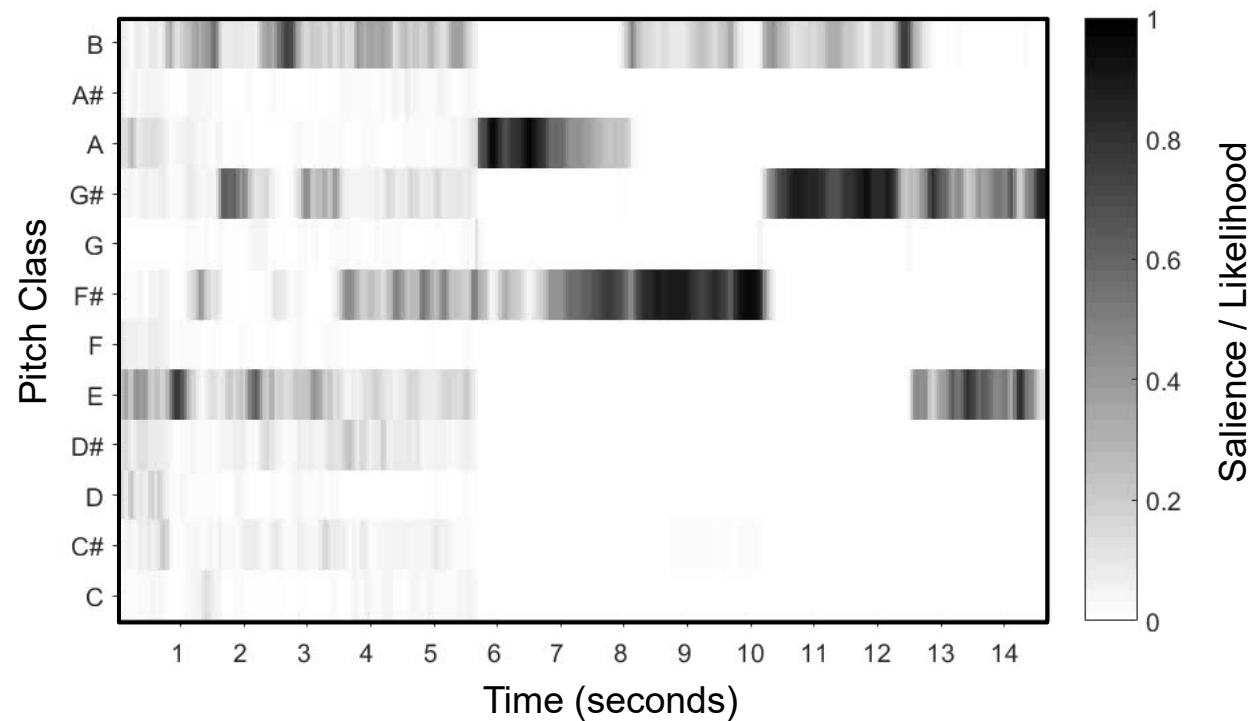
Chapter 7: Clustering and Analysis of Musical Styles

Chapter 8: Subgenre Classification for Western Classical Music

# Recall: Chroma Features



L. van Beethoven,  
*Fidelio*, Ouvertüre,  
Slovak Philharmonic

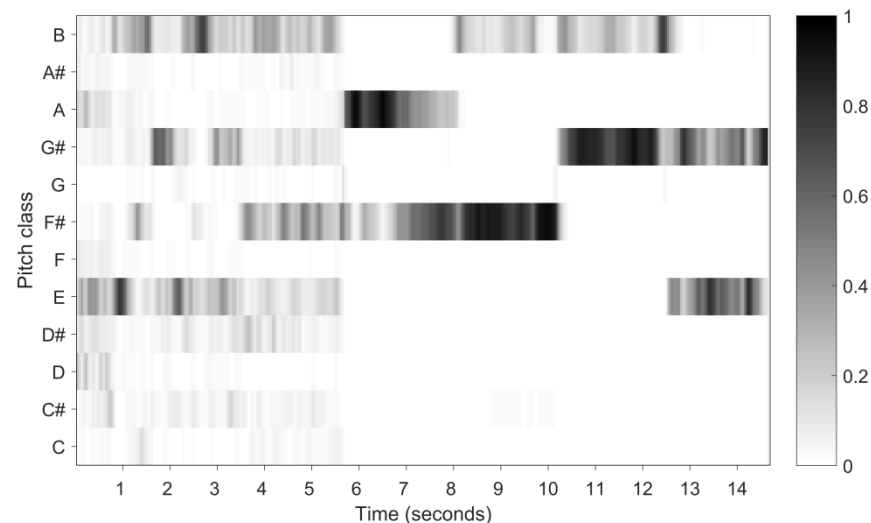


# Recall: Chroma Features

- Orchestra



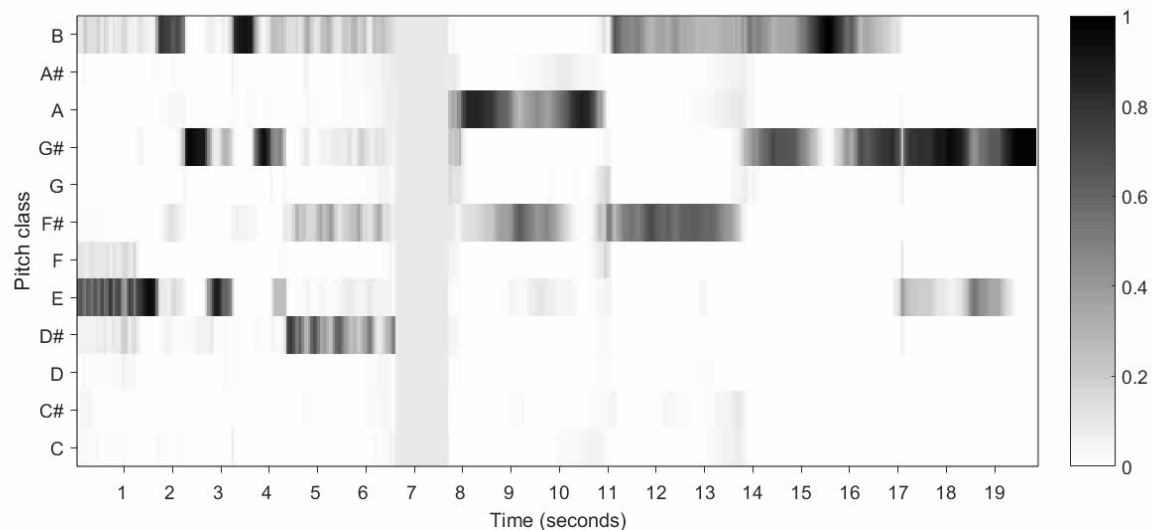
L. van Beethoven,  
*Fidelio*, Ouvertüre,  
Slovak Philharmonic



- Piano



*Fidelio*, Ouvertüre,  
arr. Alexander Zemlinsky  
M. Namekawa, D.R. Davies,  
Klavier vierhändig



# Recall: Chroma Features

Allegro Adagio

G. Orch. *f* *sf* *sf* *p dolce*

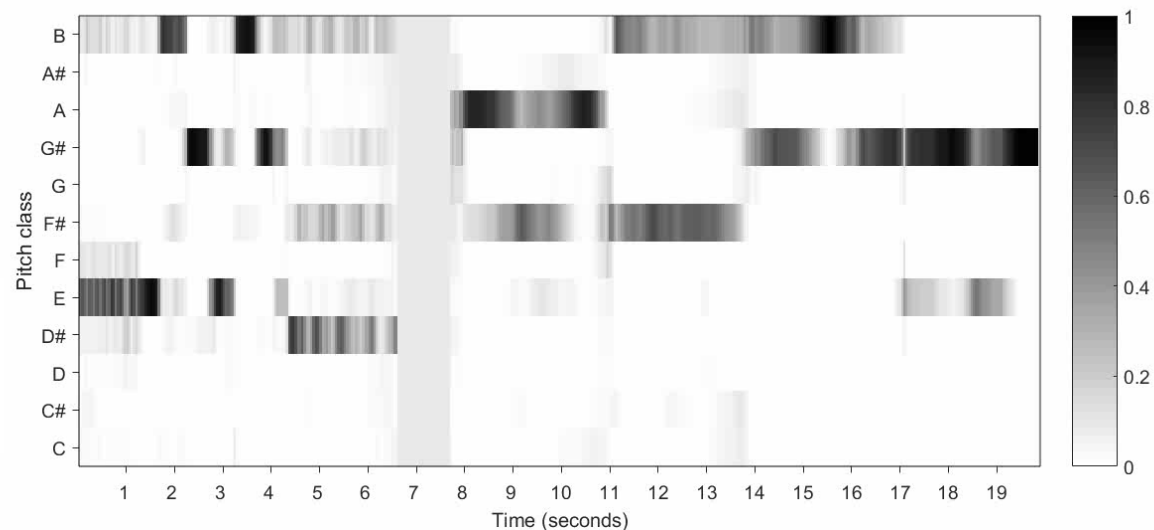
Hrn.



- Piano

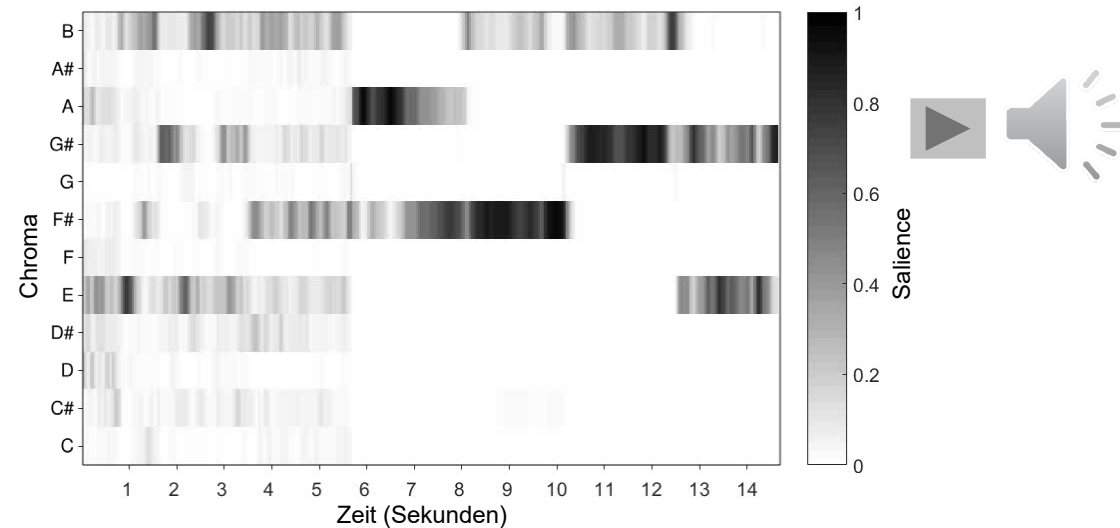


*Fidelio*, Overture,  
arr. Alexander Zemlinsky  
M. Namekawa, D.R. Davies,  
piano four hands

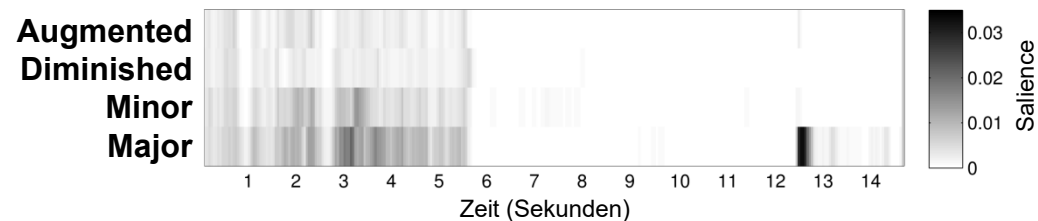


# Chroma-based Classification Features

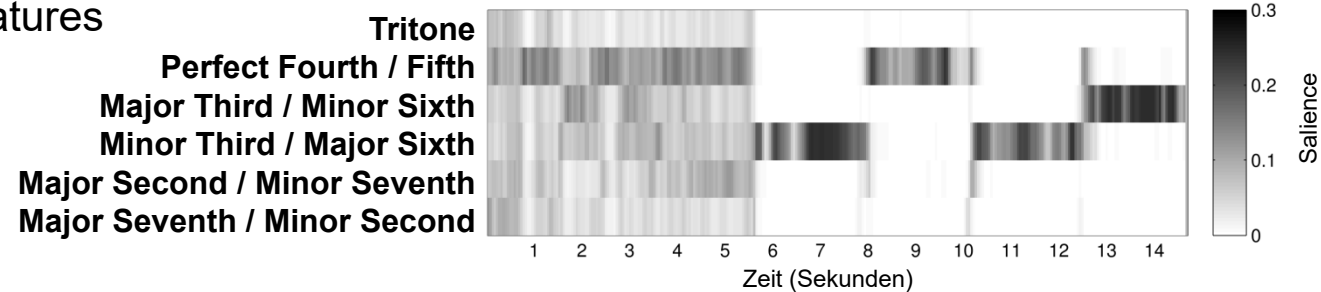
- Chromagram



- Triad features



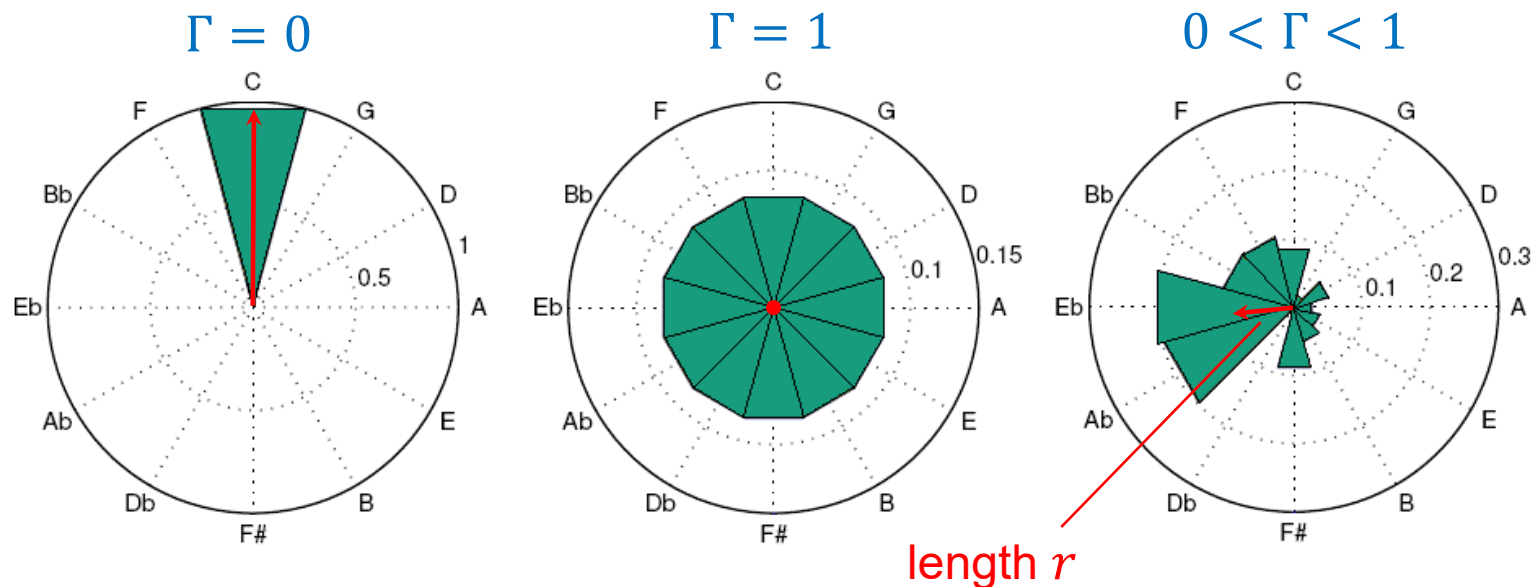
- Interval features



→ transposition-invariant

# Recall: Tonal Complexity

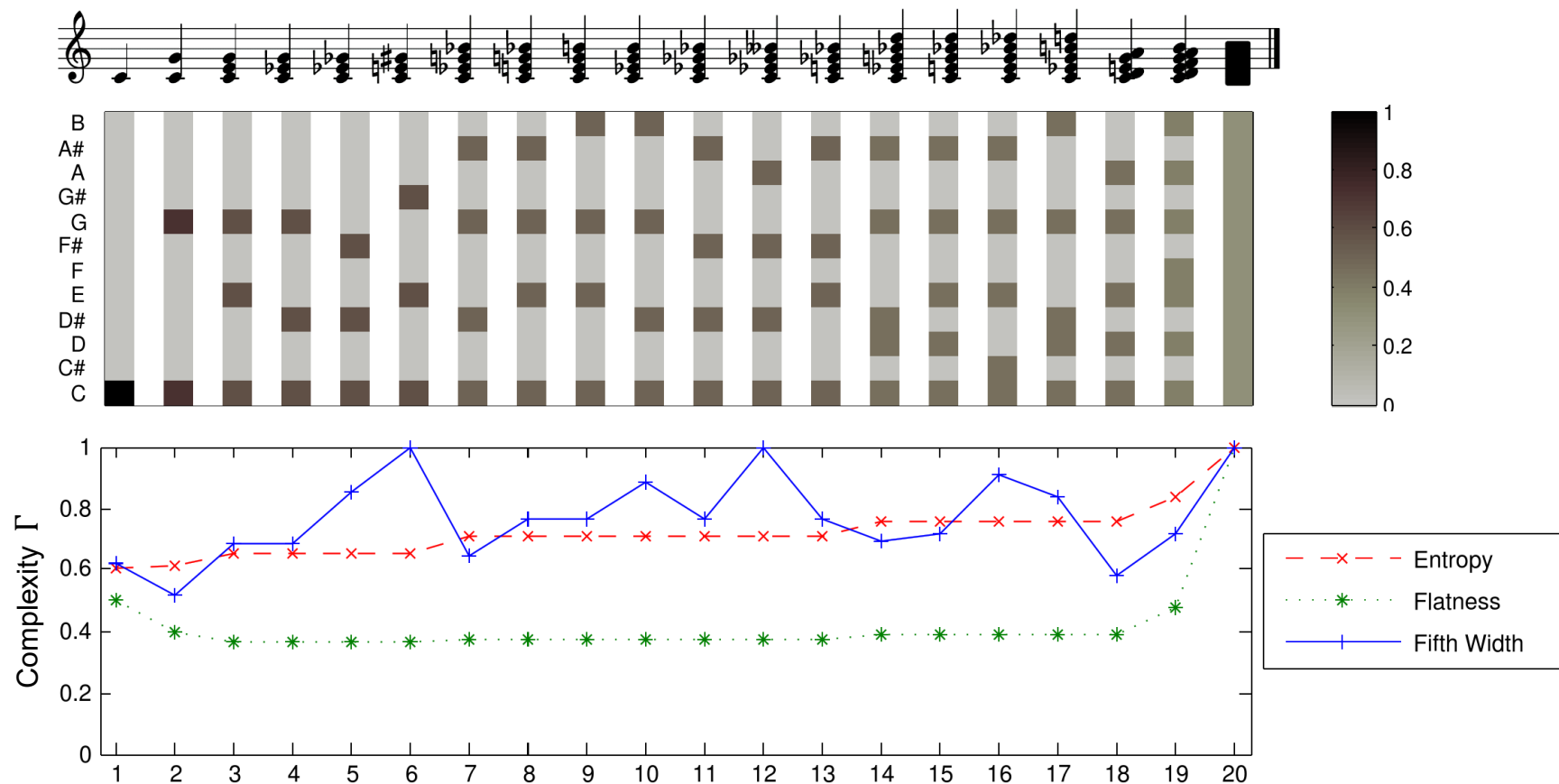
- Realization of complexity measure  $\Gamma$ 
  - Entropy / Flatness measures
  - Distribution over *Circle of Fifths*



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

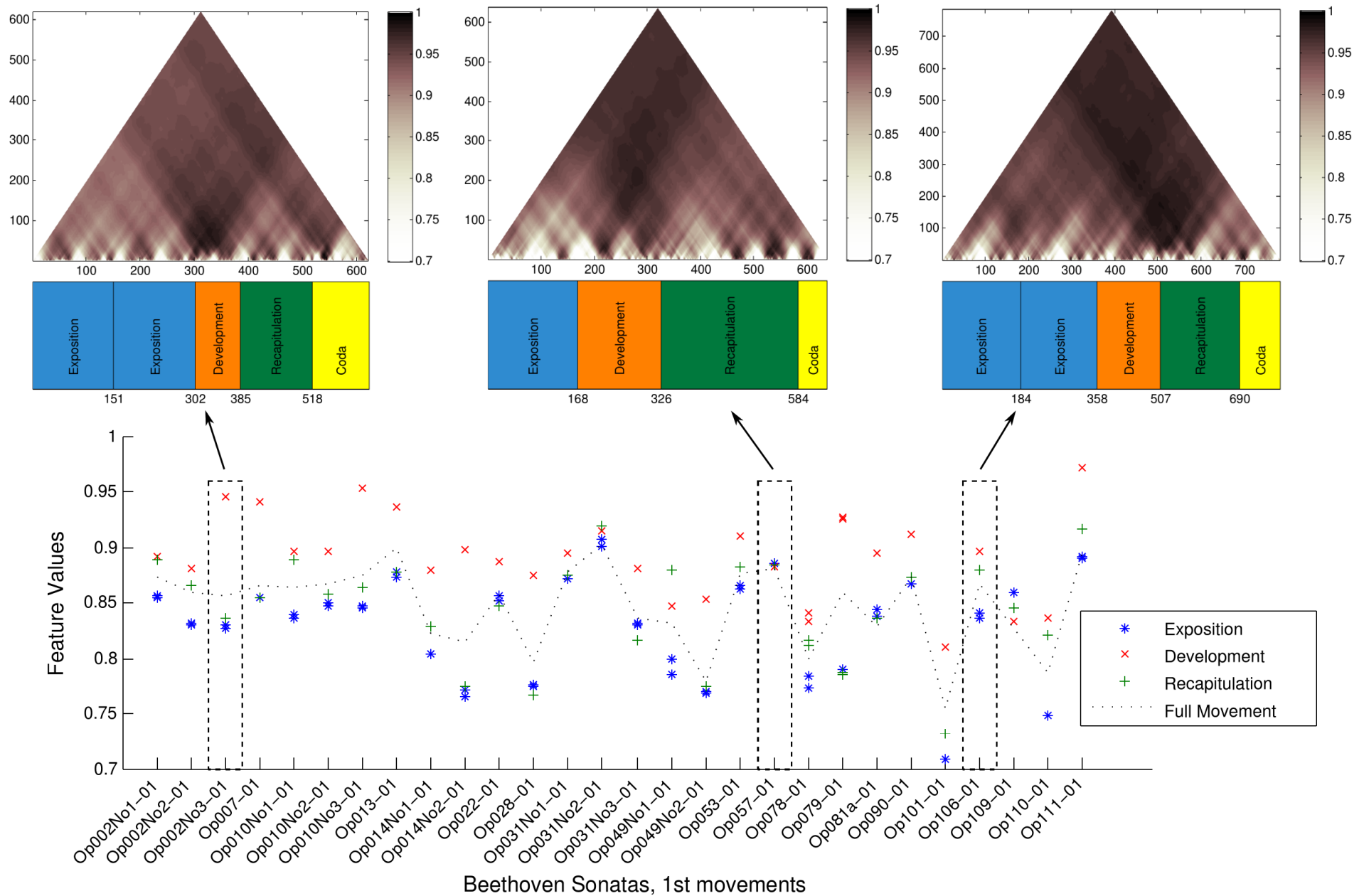
- Relating to different time scales!

# Recall: Tonal Complexity

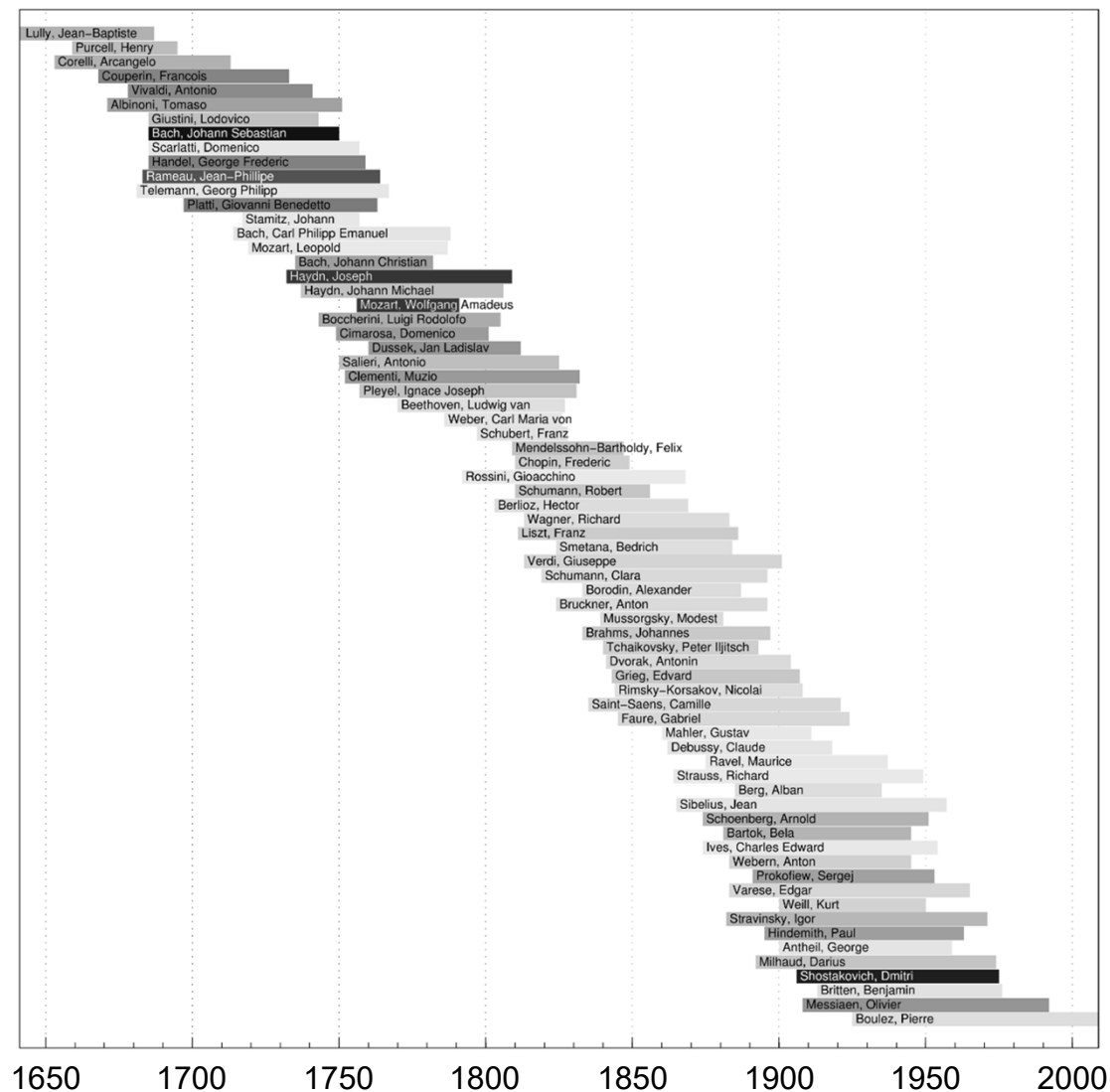


Weiss / Müller, *Quantifying and Visualizing Tonal Complexity*, CIM 2014

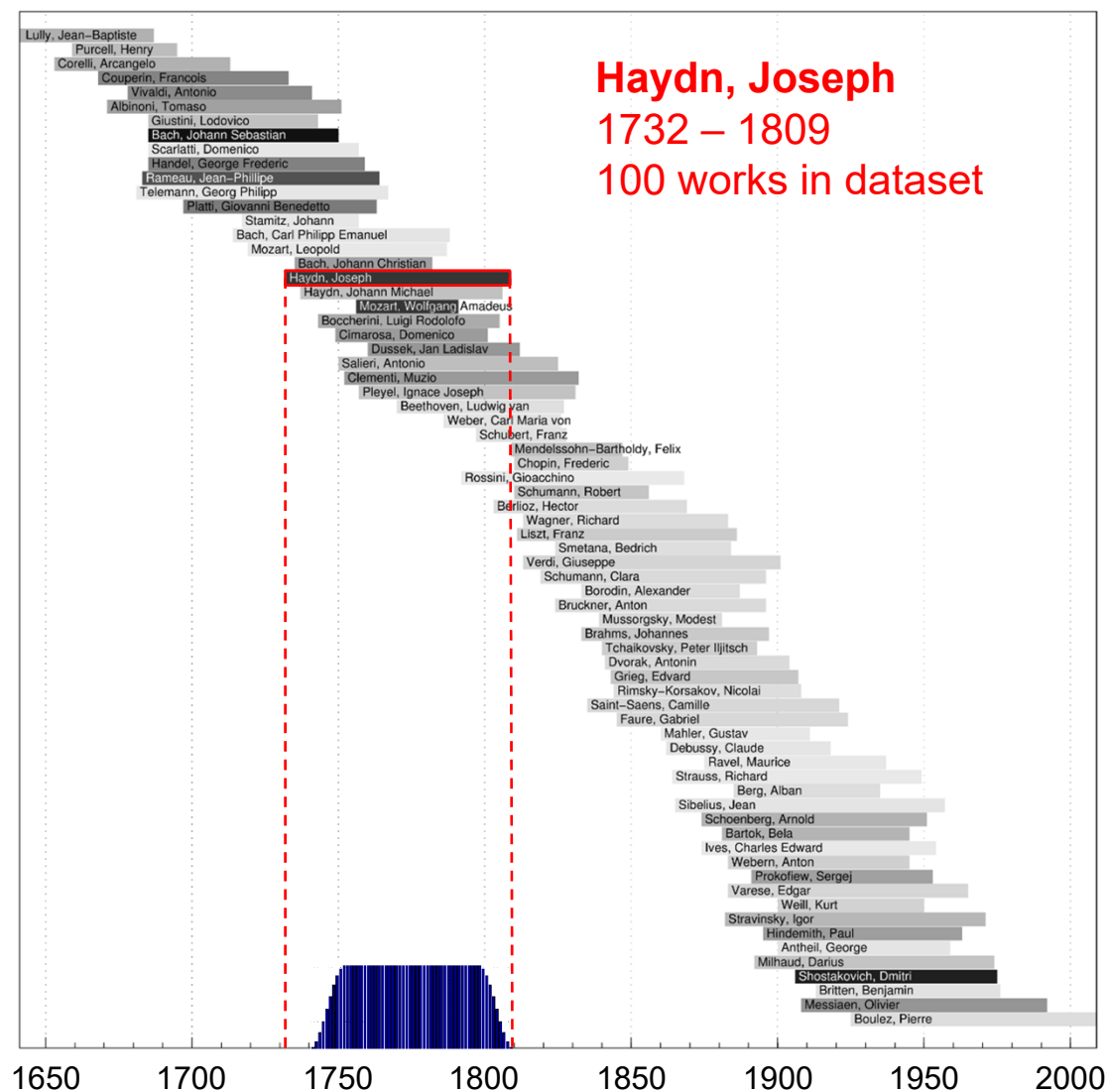
# Recall: Tonal Complexity



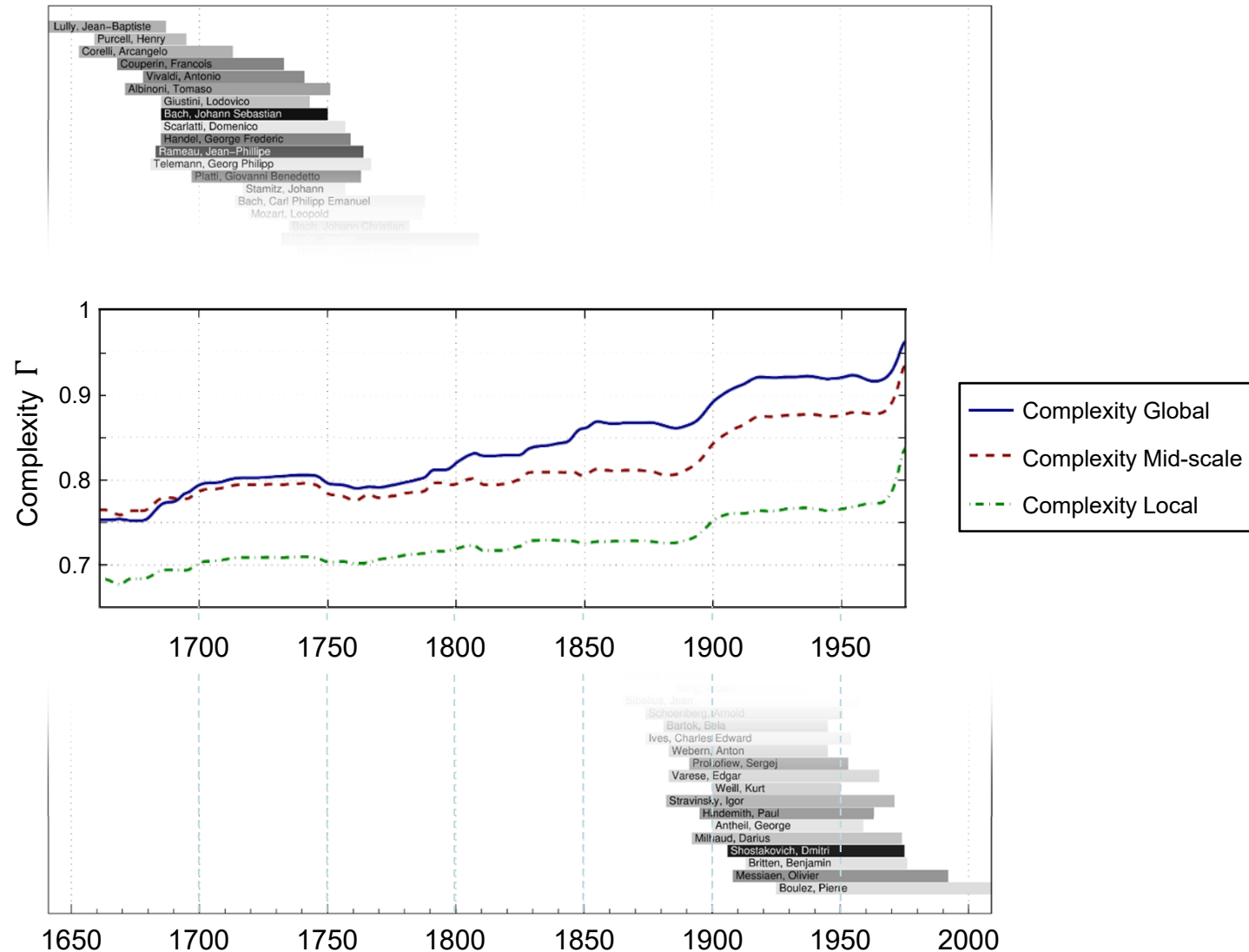
# Recall: Tonal Complexity



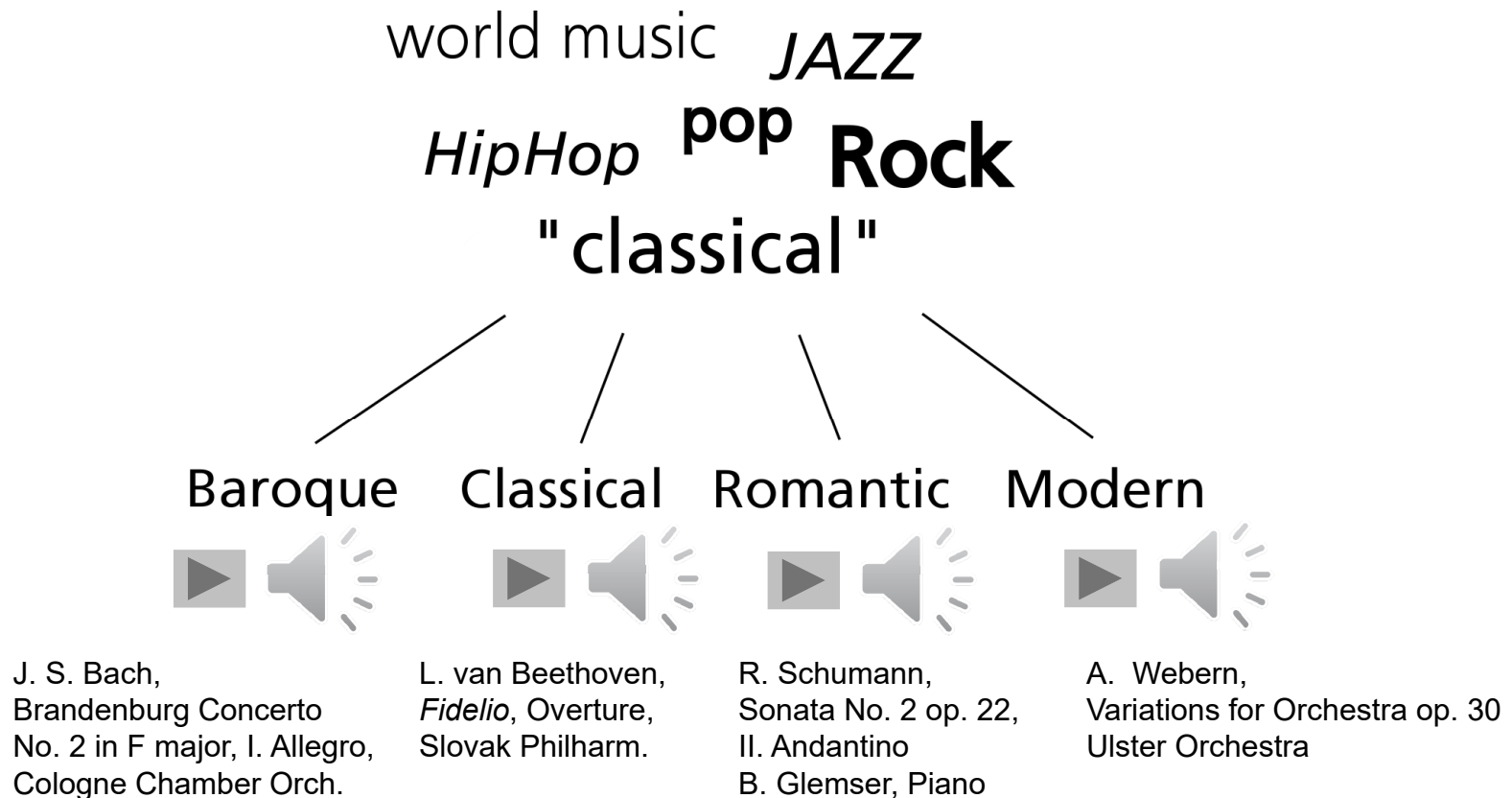
# Recall: Tonal Complexity



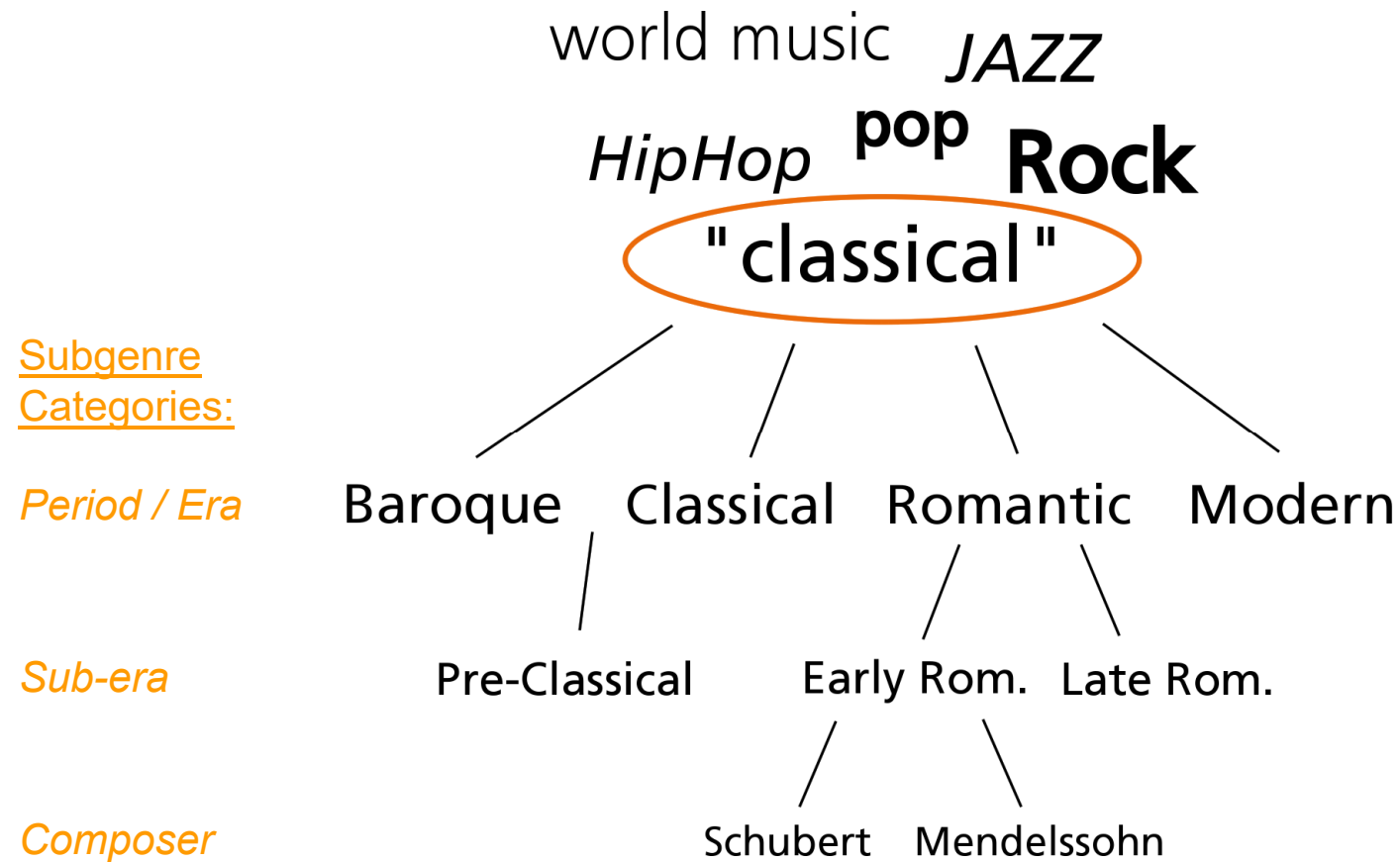
# Recall: Tonal Complexity



# Music Genre Classification



# Music Genre Classification

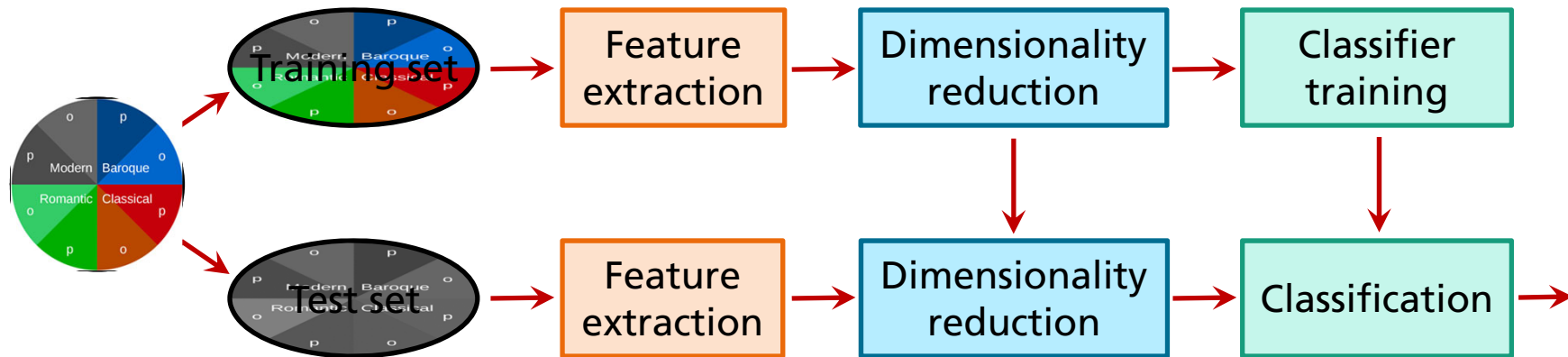


# Music Genre Classification

- 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

- Typical approach: Supervised machine learning



# Music Genre Classification

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

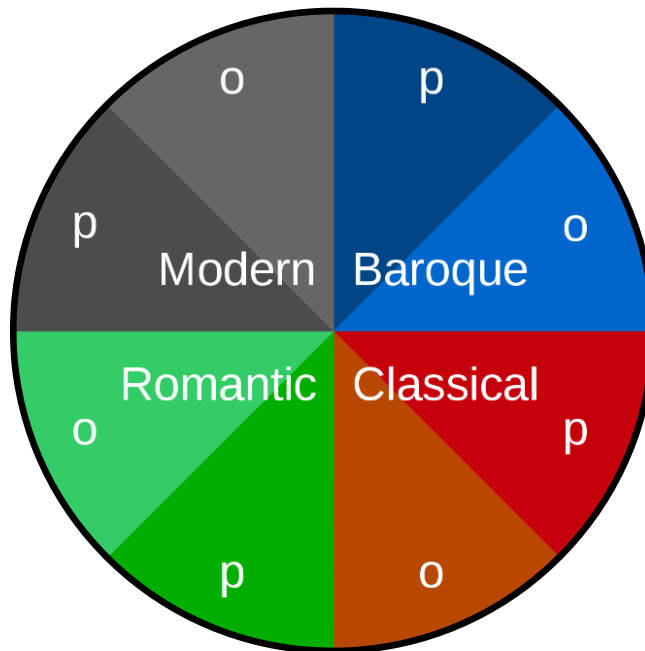
	<i>Fold 1</i>	<i>Fold 2</i>	<i>Fold 3</i>
<i>Round 1</i>	Training fold	Training fold	Test fold
<i>Round 2</i>	Training fold	Test fold	Training fold
<i>Round 3</i>	Test fold	Training fold	Training fold

- Distribution of classes balanced for all folds

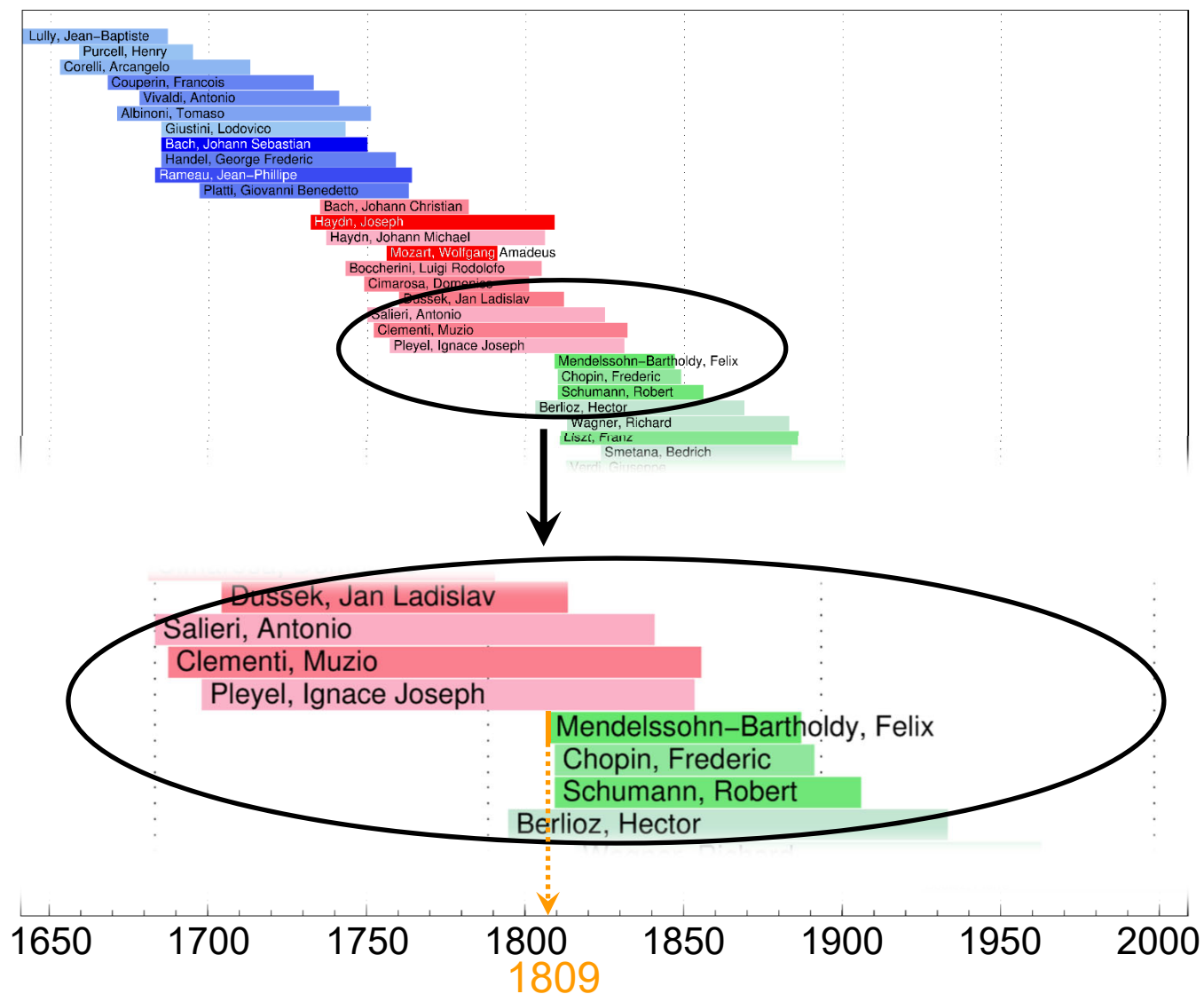
training	test
Baroque	Baroque
Classical	Classical
Romantic	Romantic
Modern	Modern

# Classification Scenario

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



# Classification Scenario

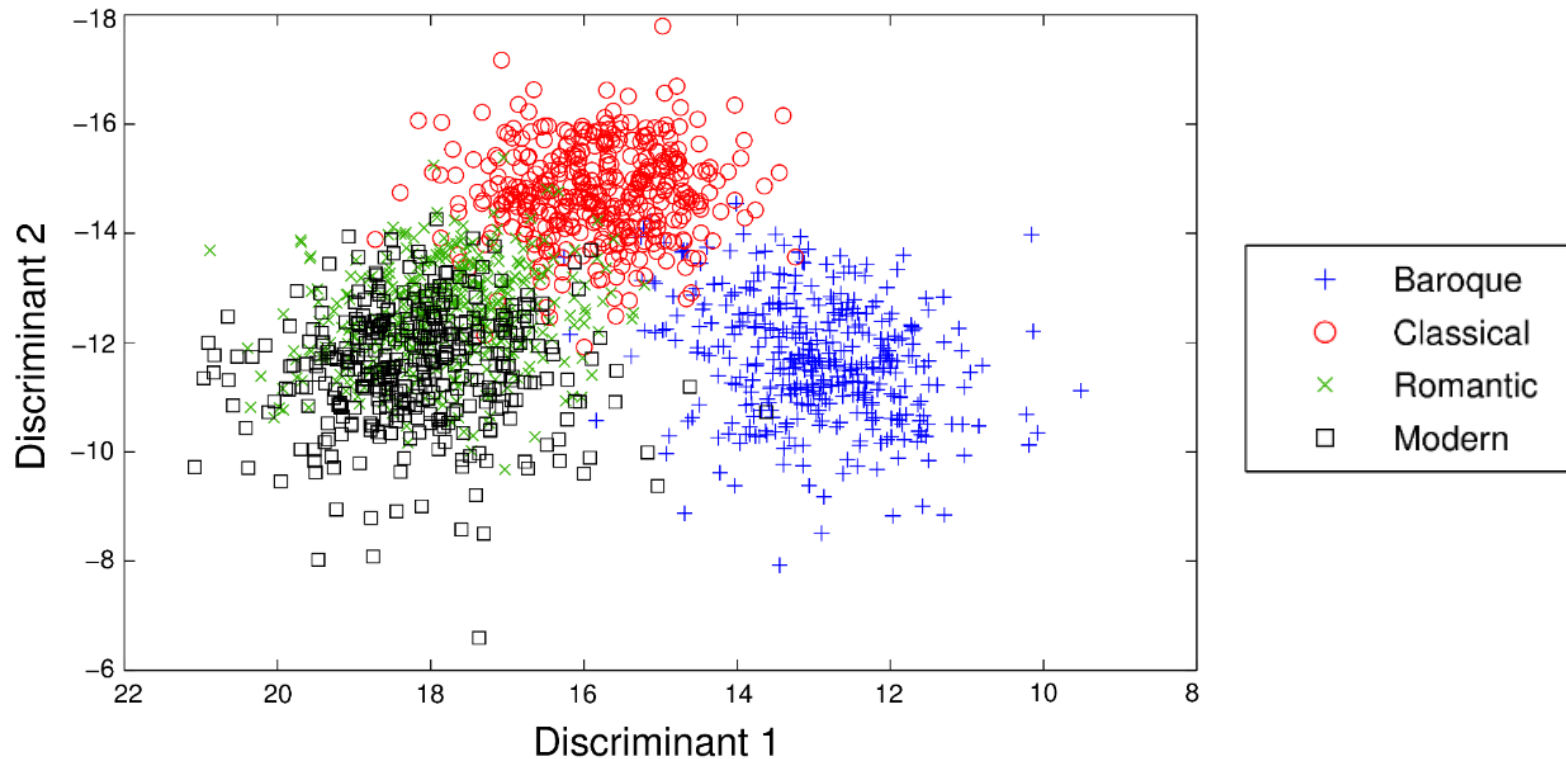


# Classification Features

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
<b>Total</b>	<b>238</b>	<b>Total</b>	<b>246</b>

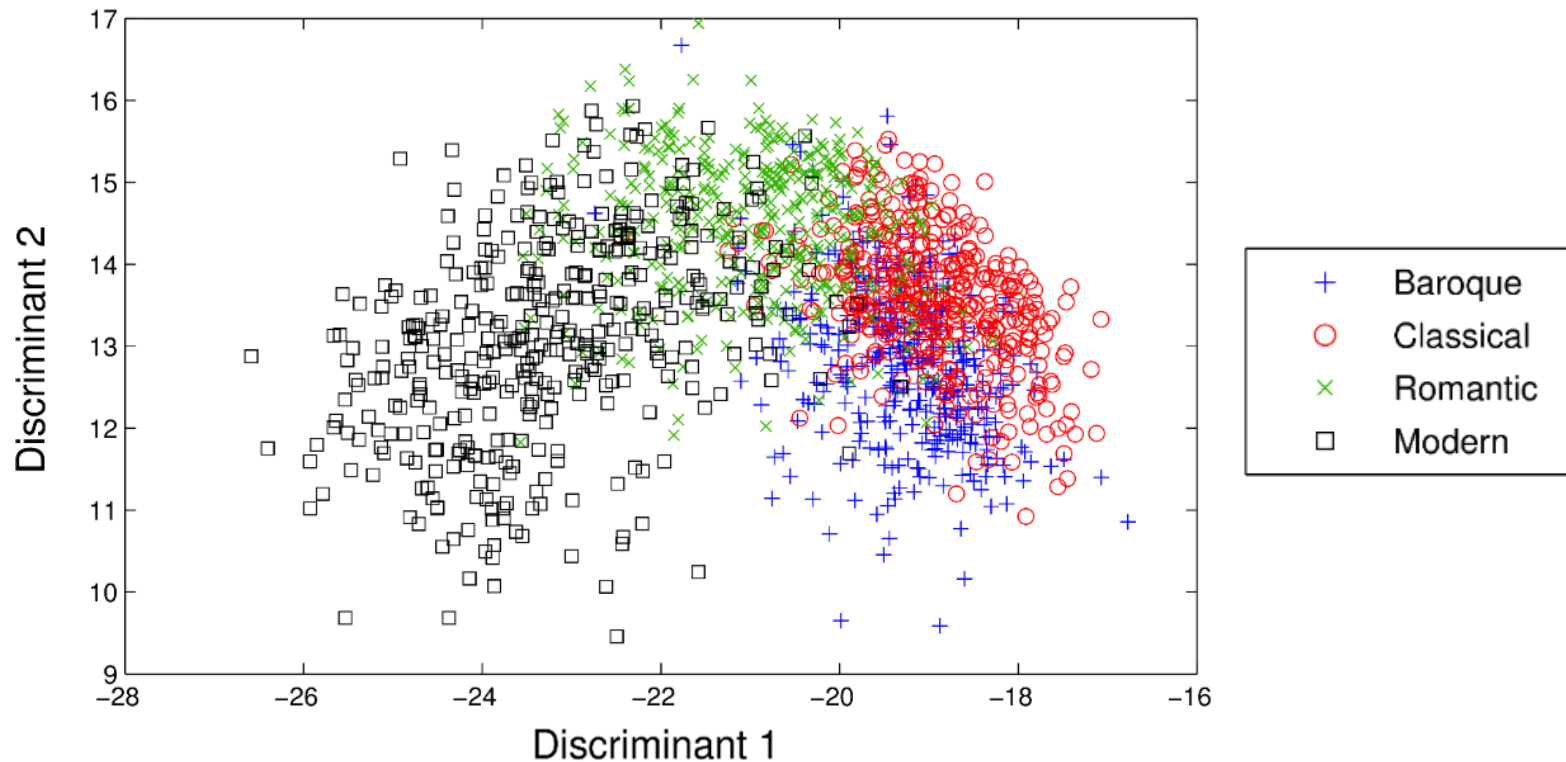
# Dimensionality Reduction

- 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, ...)



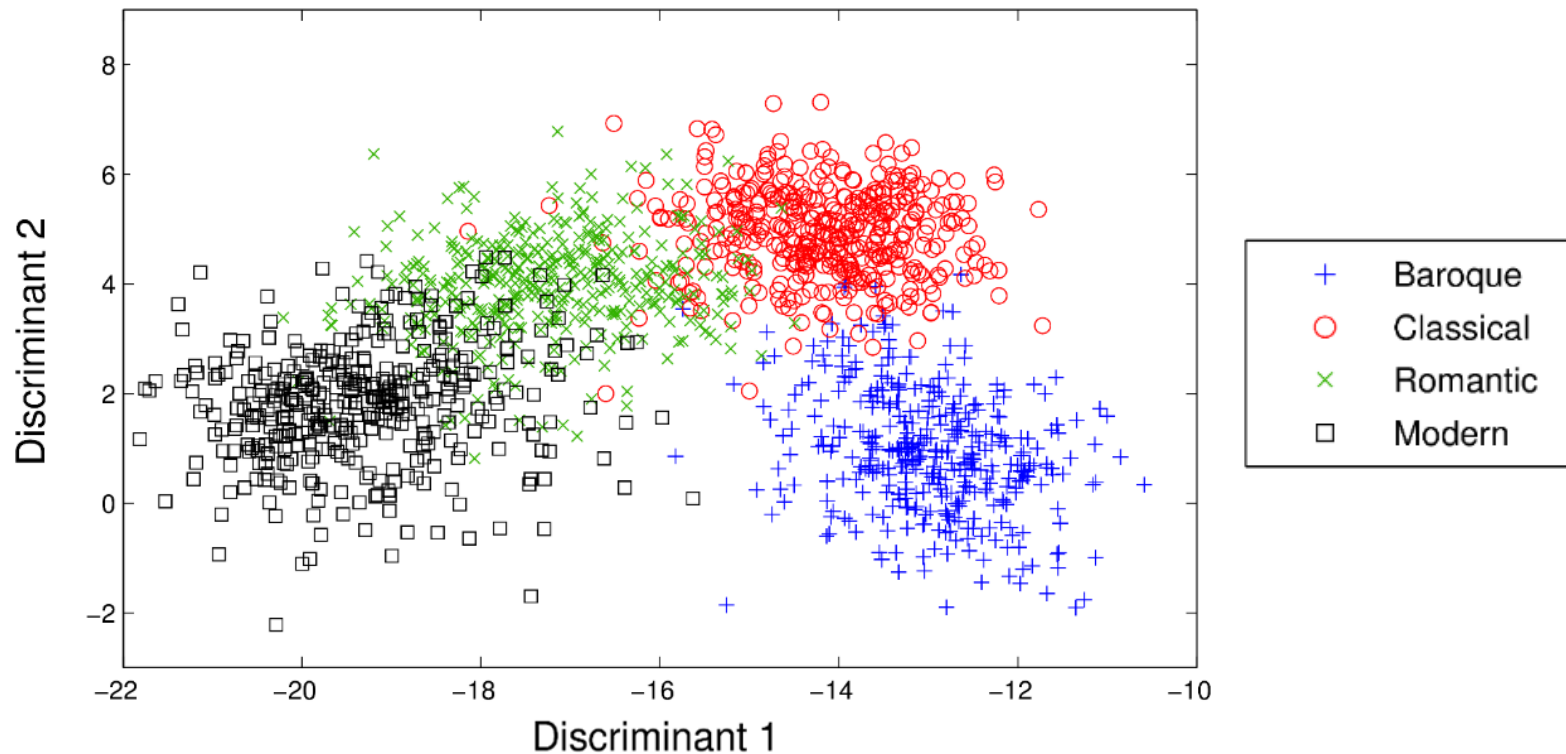
# Dimensionality Reduction

- 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**

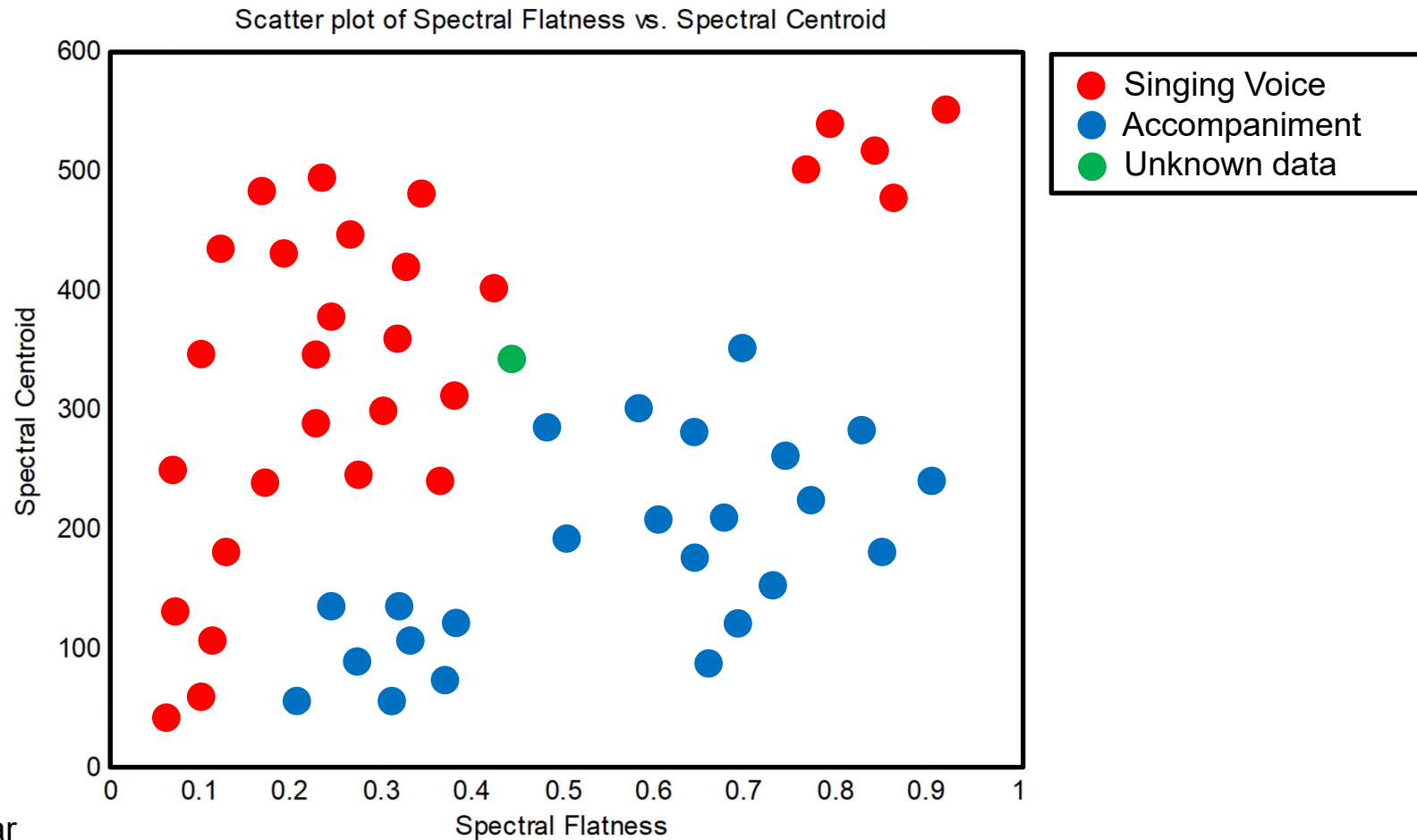


# Dimensionality Reduction

- Reduce feature space to few dimensions
- Other methods (supervised):
  - (DNN-based) Autoencoder
  - Feature selection
- Other methods (unsupervised):
  - Principal component analysis (PCA)
  - Nonnegative matrix factorization (NMF)

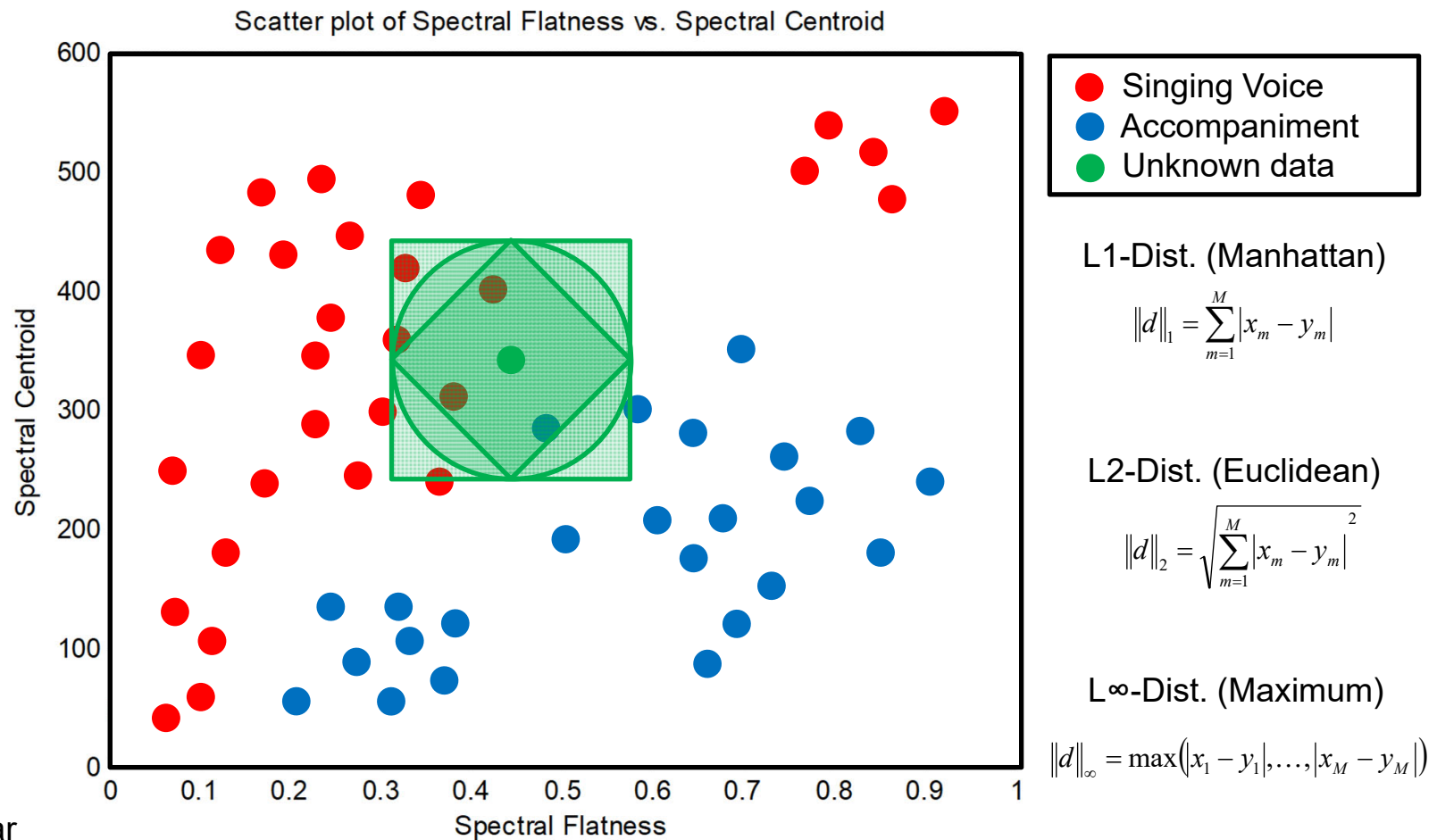
# Classification methods

- $k$  Nearest Neighbours (kNN)



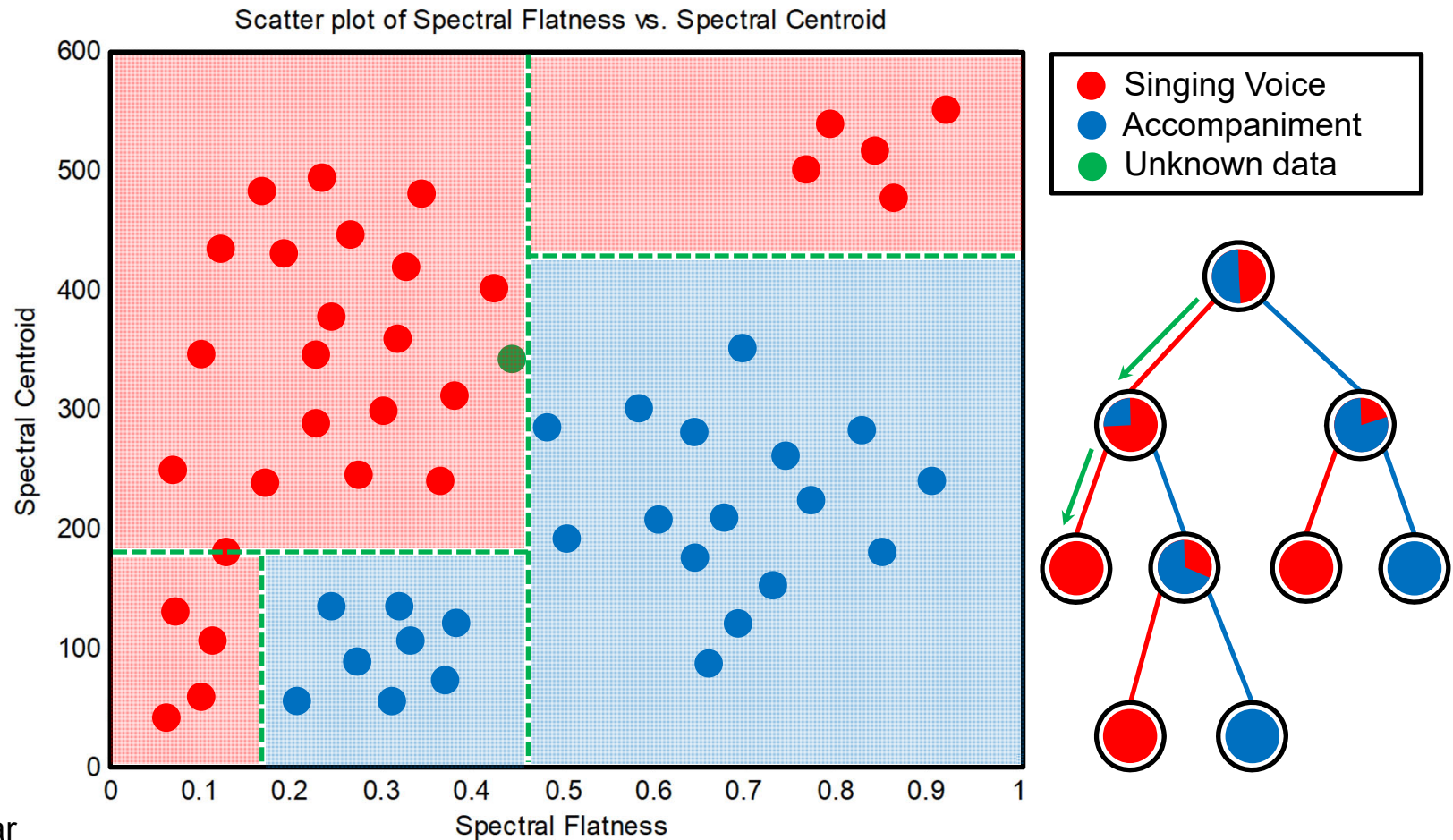
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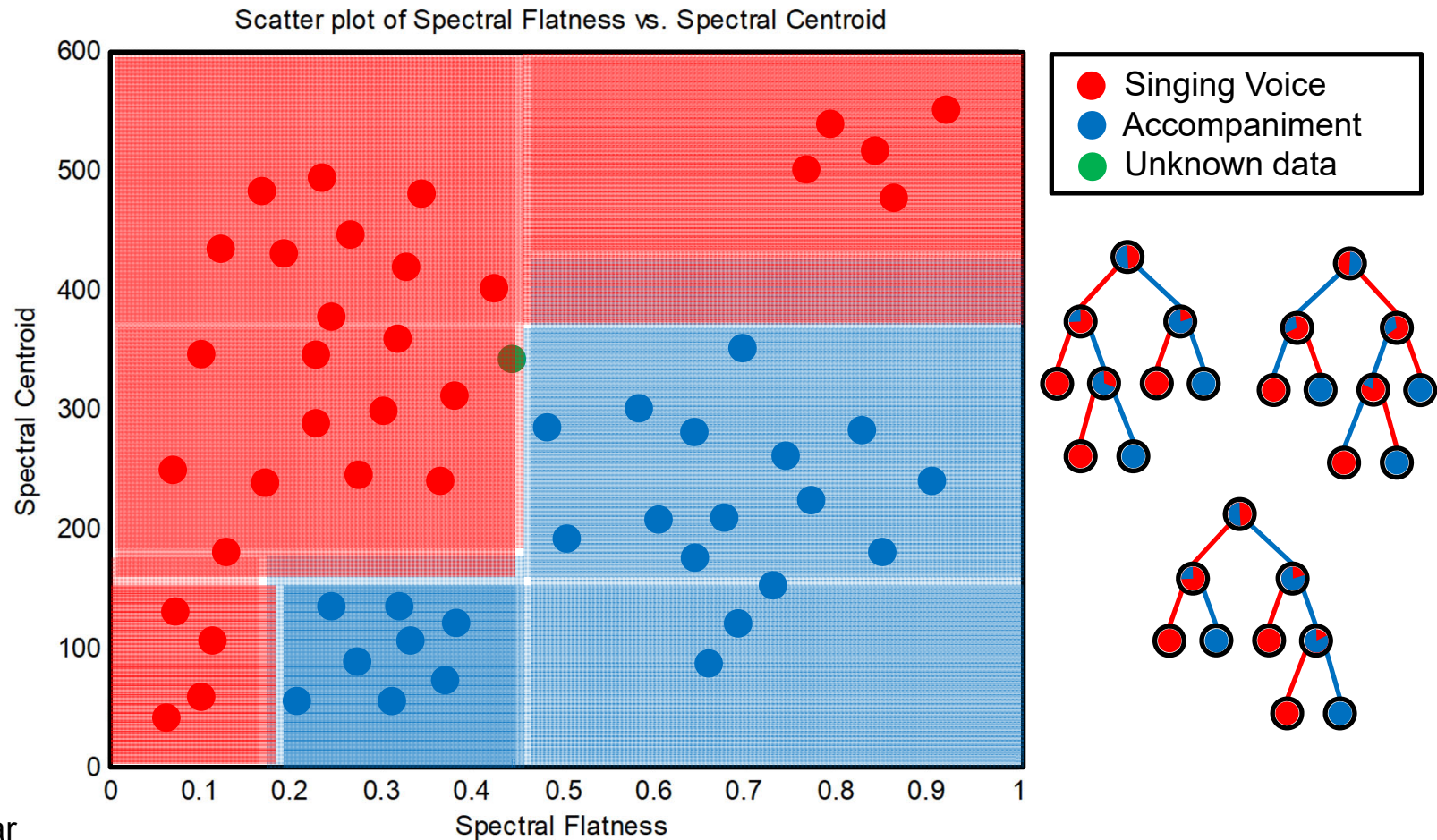
# Classification methods

- Decision Trees (DT)



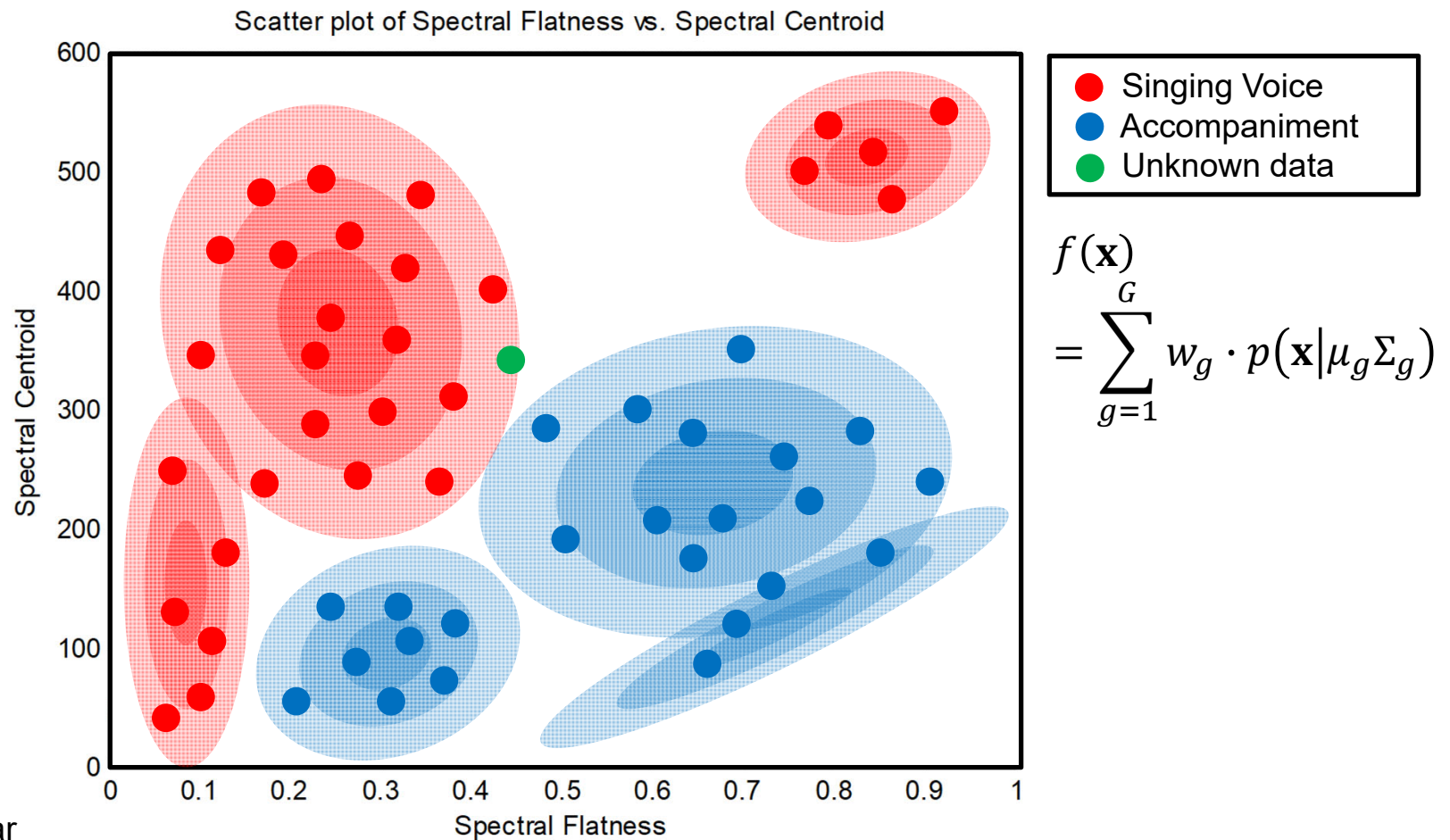
# Classification methods

- Random Forests (RF)



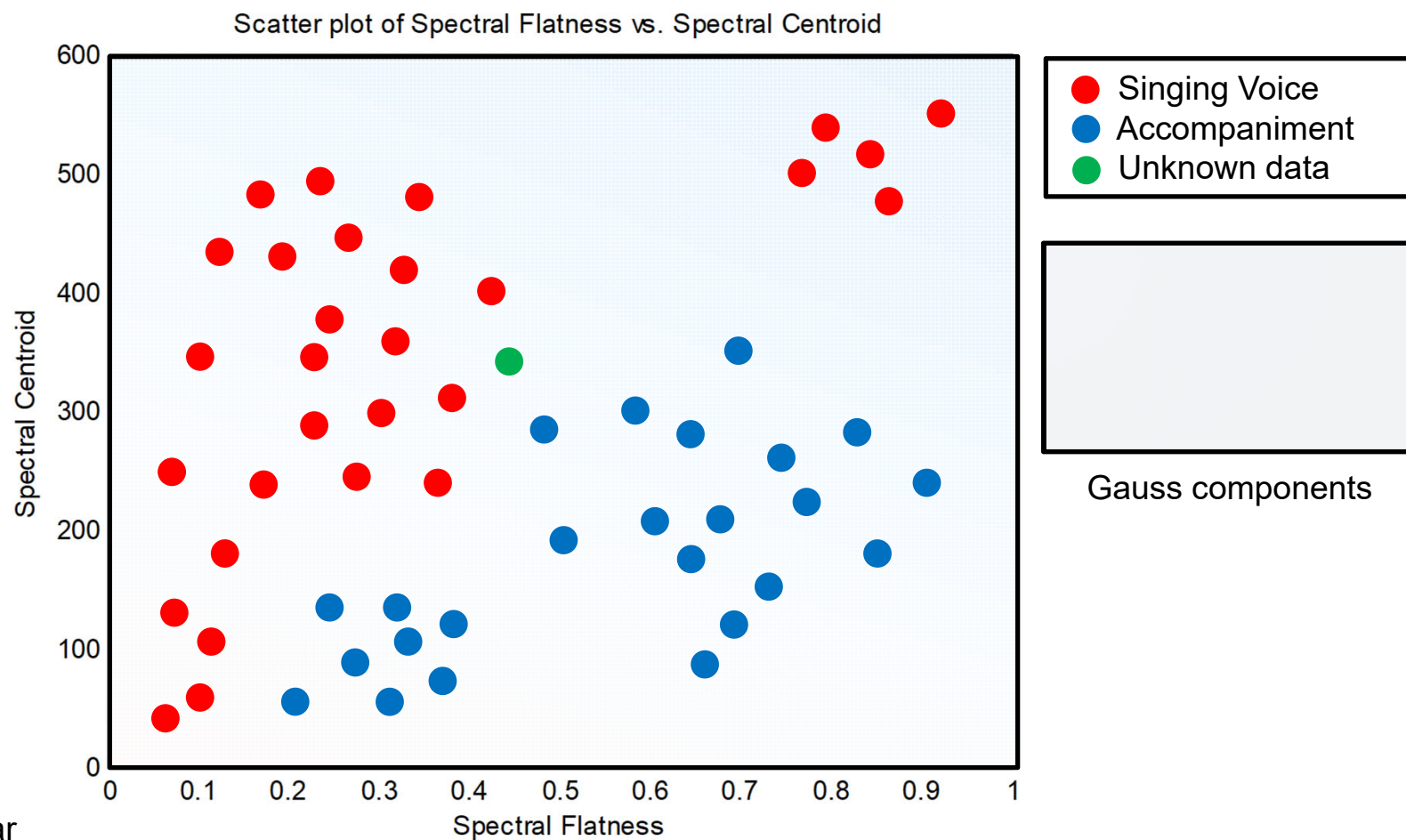
# Classification methods

- Gaussian Mixture Models (GMM)



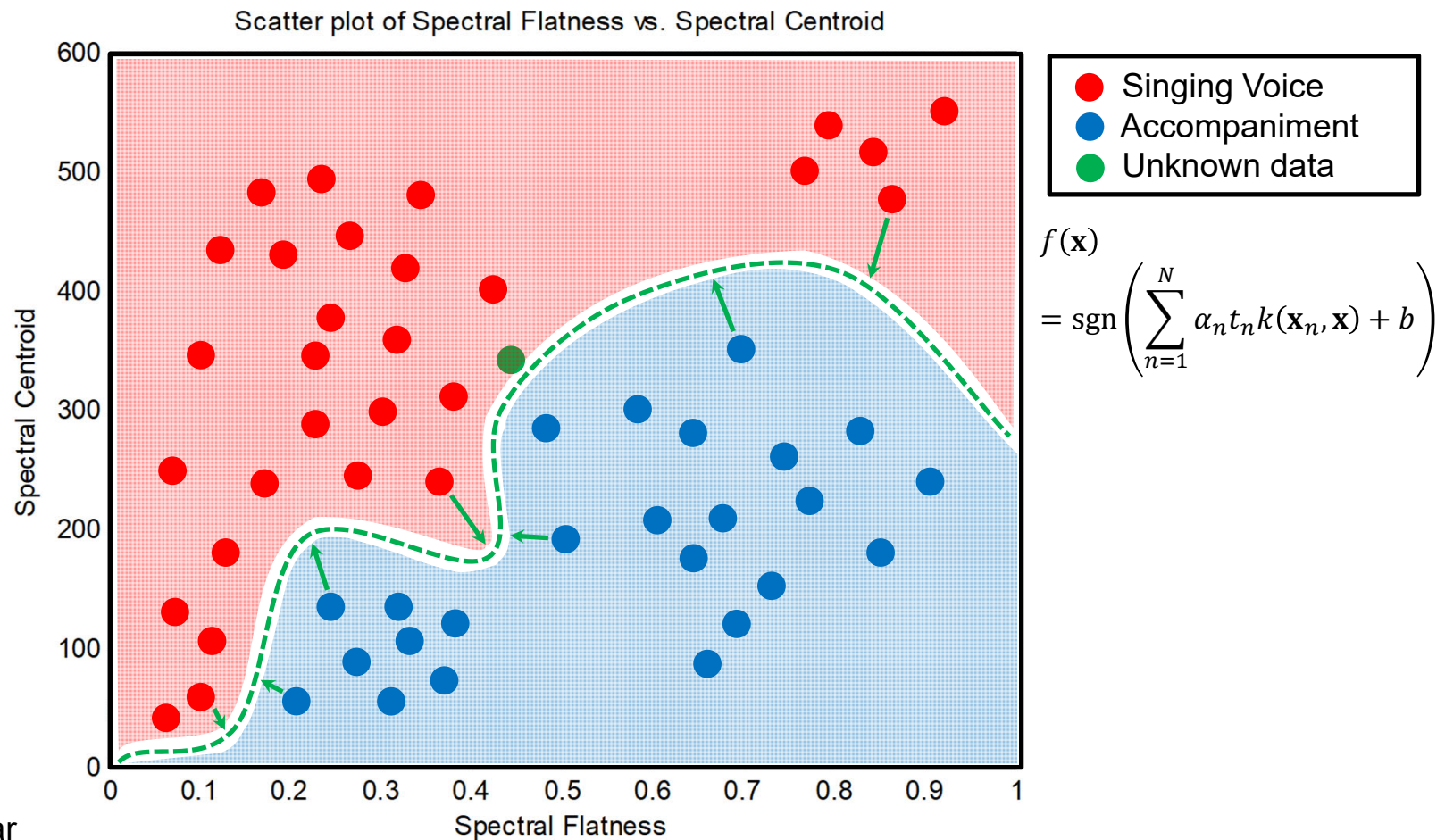
# Classification methods

- Gaussian Mixture Models (GMM)



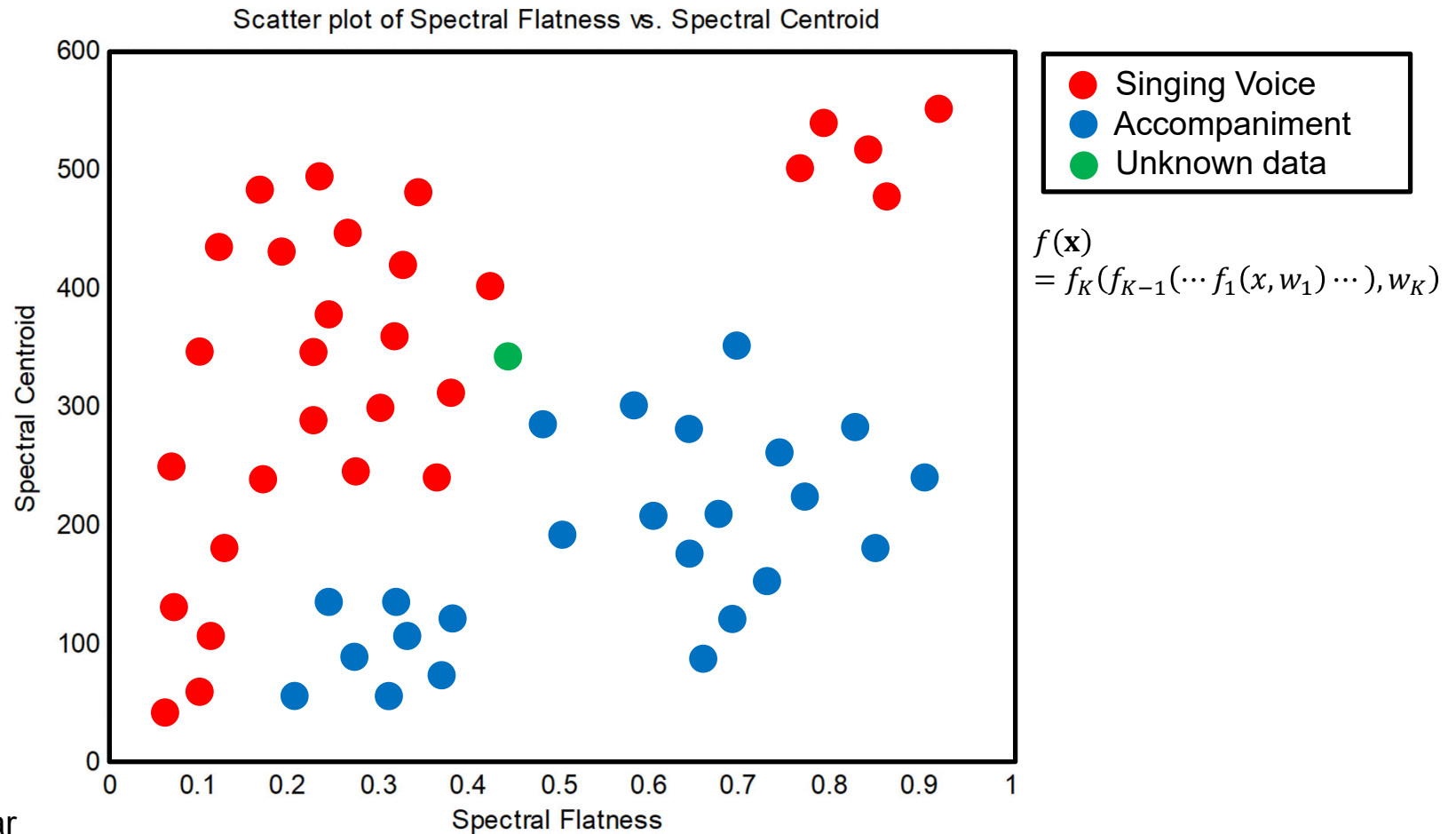
# Classification methods

- Support Vector Machines (SVM)



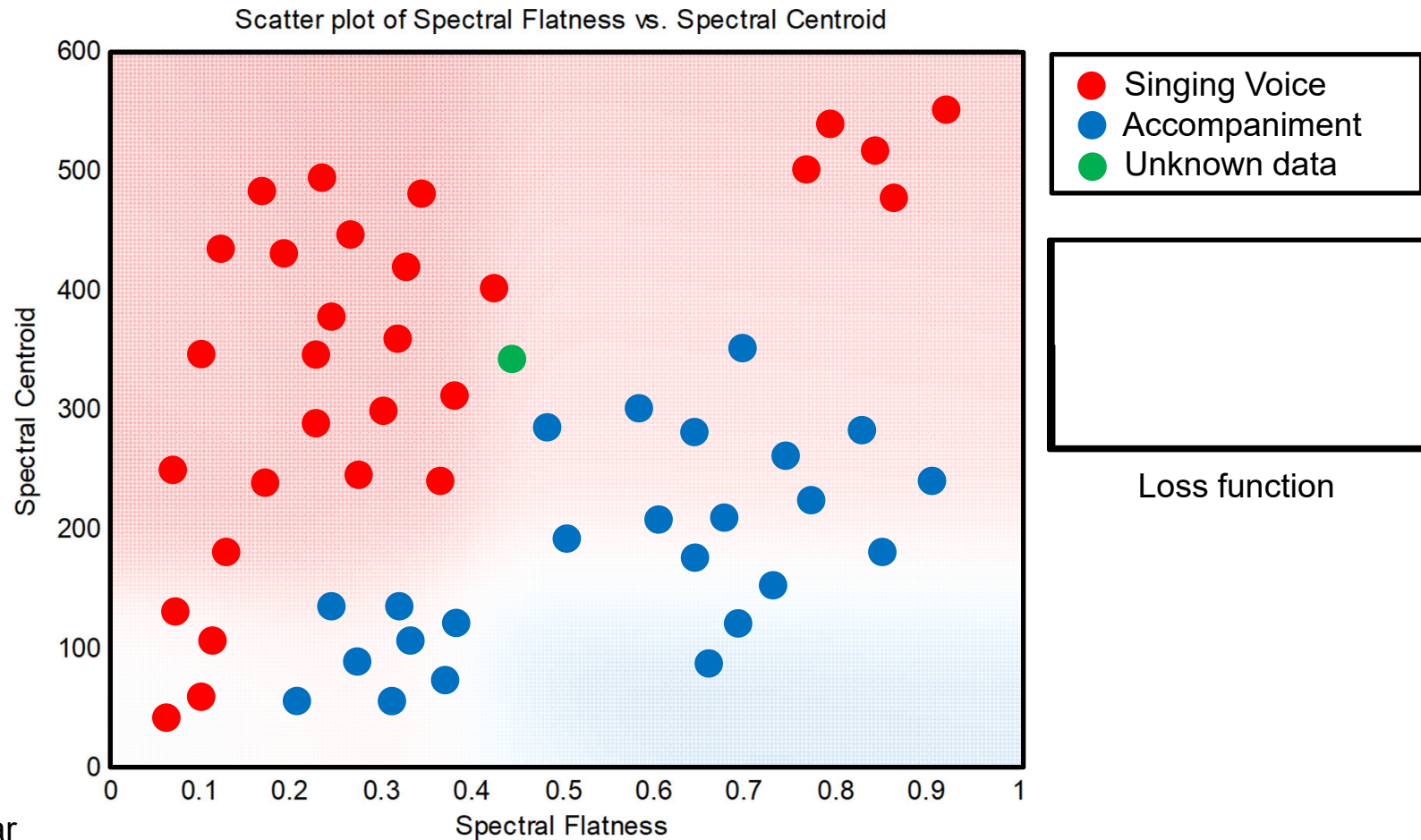
# Classification methods

- Deep Neural Networks (DNN)



# Classification methods

- Deep Neural Networks (DNN)



# Classification Results

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

	Full Dataset	Piano	Orchestra
<i>Standard features</i>	87 %	88 %	85 %
<i>Tonal features</i>	84 %	84 %	86 %
<b><i>Combined</i></b>	<b>92 %</b>	<b>86 %</b>	<b>80 %</b>

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

# Classification Results

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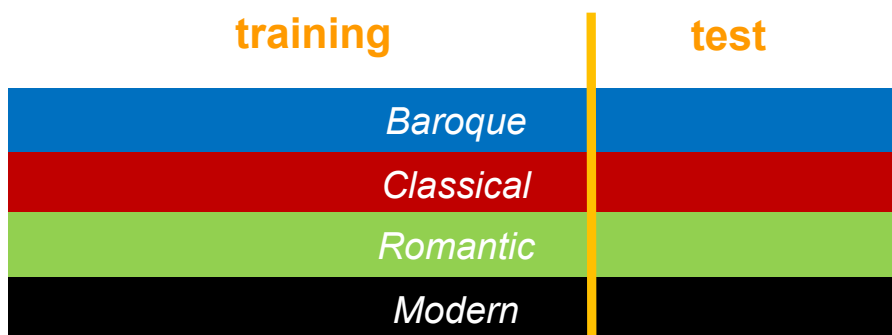
**Overfitting???**

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

# Classification Results

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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**

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- **Using composer filter**

	Full Dataset	Piano	Orchestra
<i>Standard features</i>	54 %	36 %	70 %
<i>Tonal features</i>	73 %	70 %	78 %
<b>Combined</b>	<b>68 %</b>	<b>44 %</b>	<b>68 %</b>

# Classification Results

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

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# 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)	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
Era (classified)		Baroque	Classical	Romantic	Modern

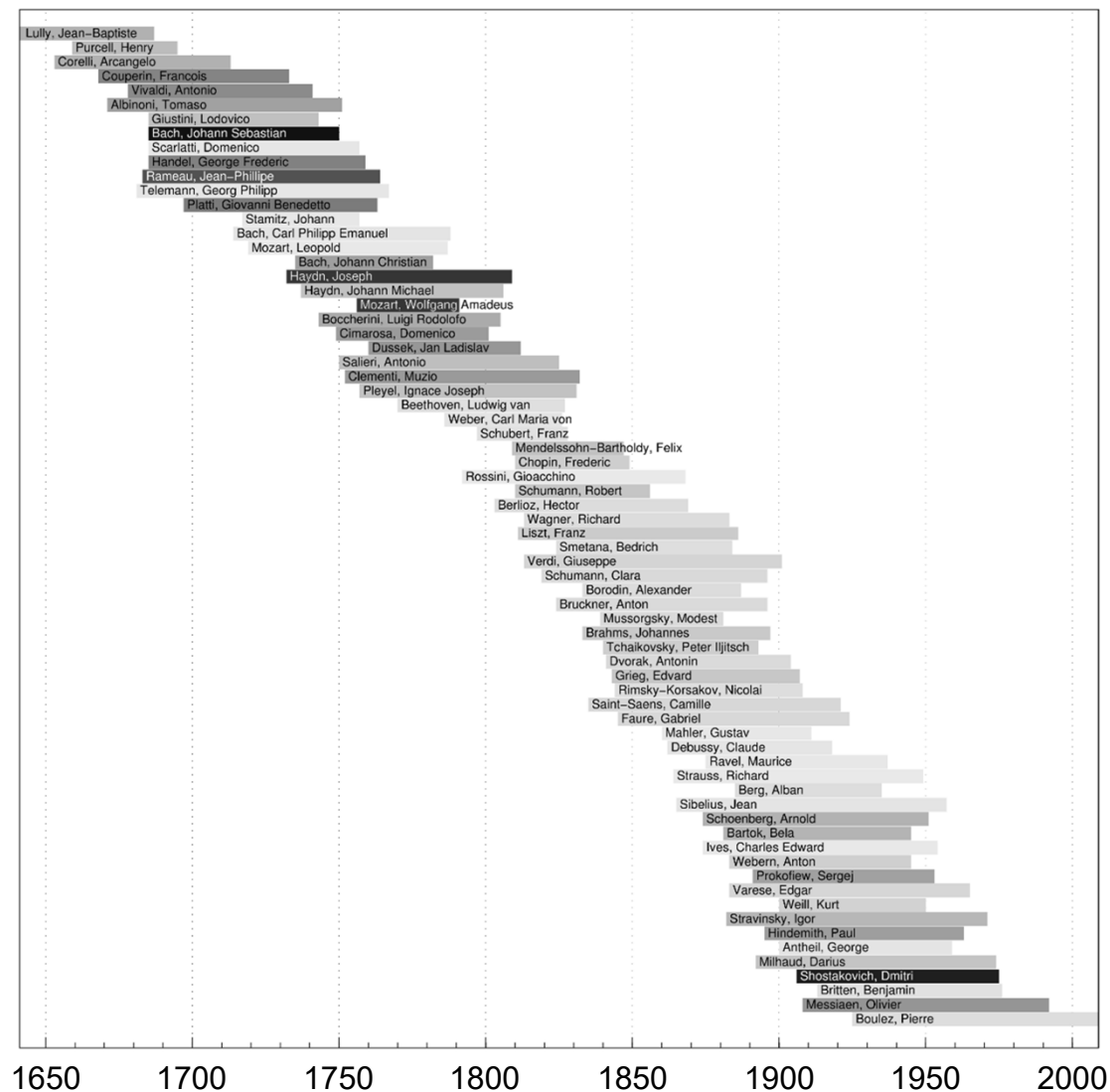
# Classification Results: Error Examples

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

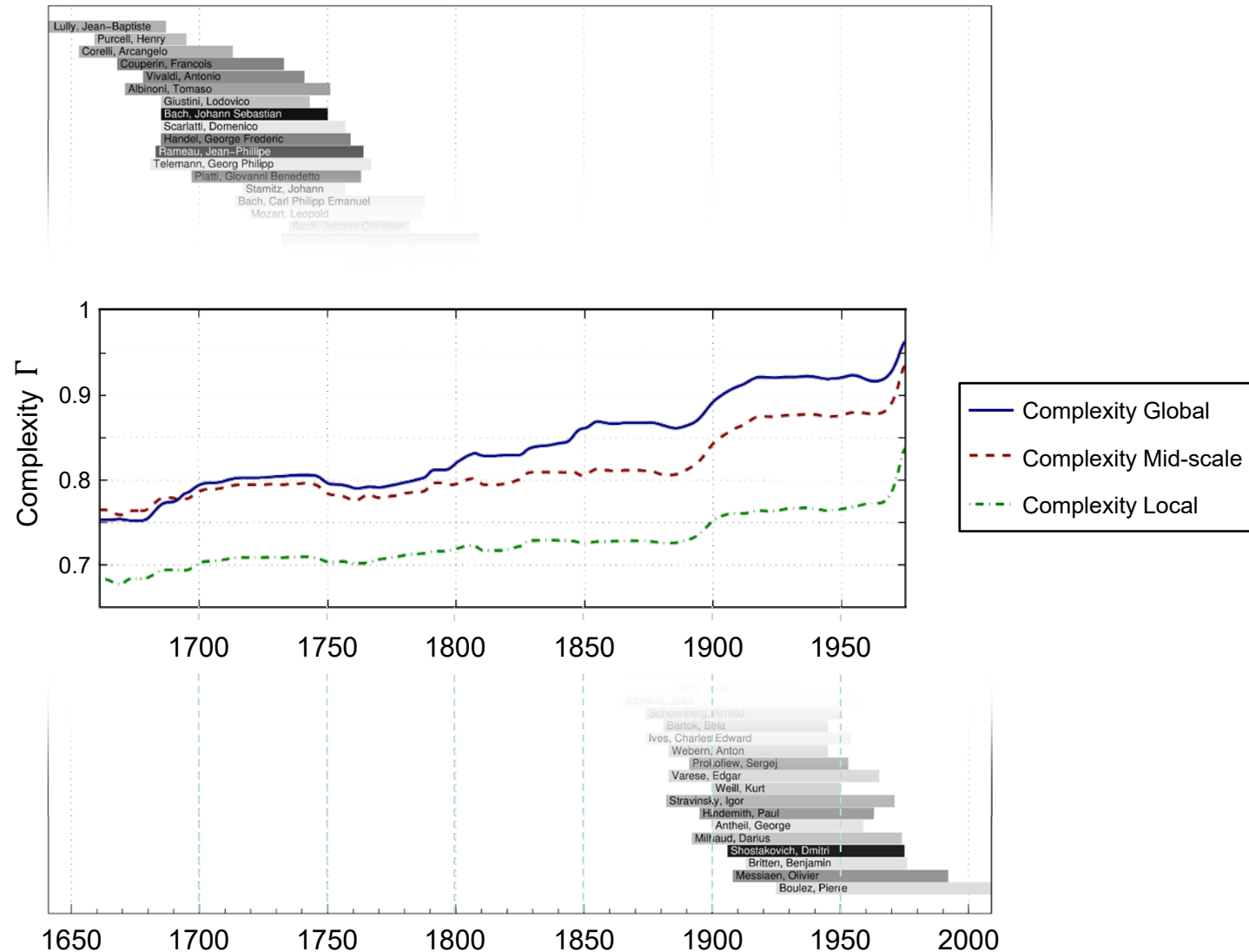
<i>Class</i>	<i>Composer</i>	<i>Piece</i>	<i>Classified</i>
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in E $\flat$ minor BWV 853	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in F major BWV 856	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in A minor BWV 865	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in B $\flat$ major BWV 866	Romantic
Baroque	Bach, J. S.	Well-Tempered Piano 1, Prelude in B $\flat$ 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



# Musical Style Analysis

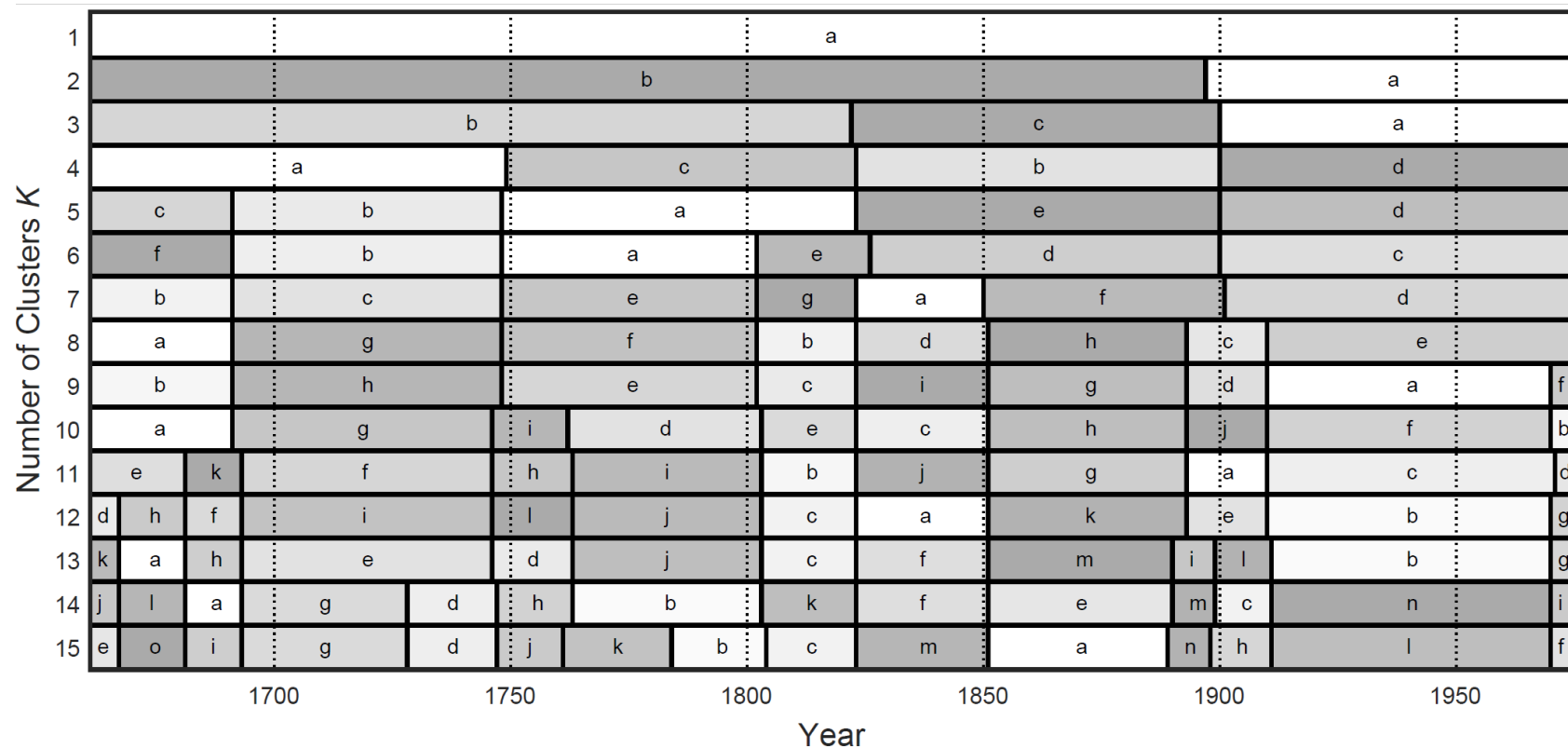


# Musical Style Analysis – Complexity



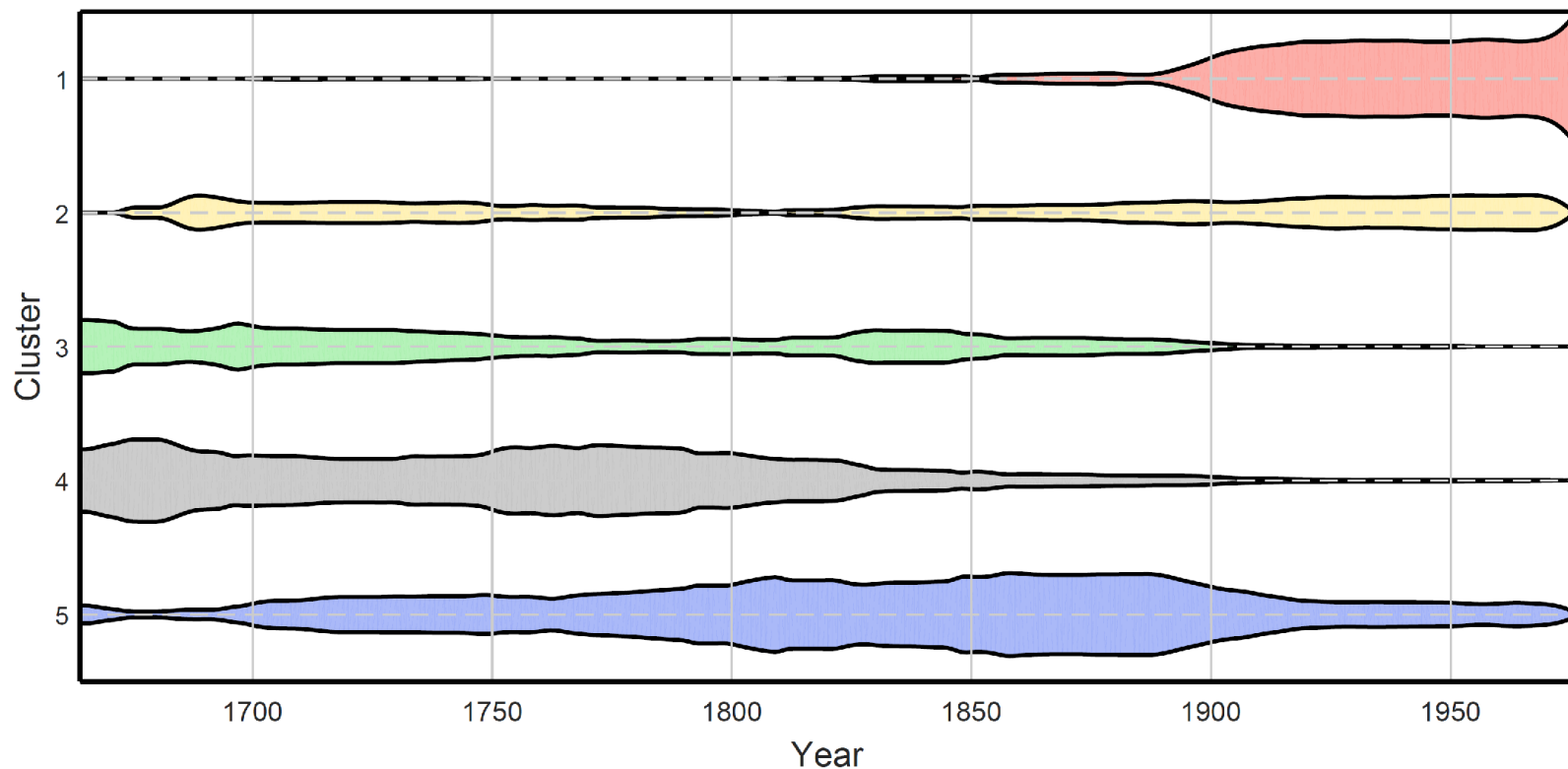
# Clustering: Years

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



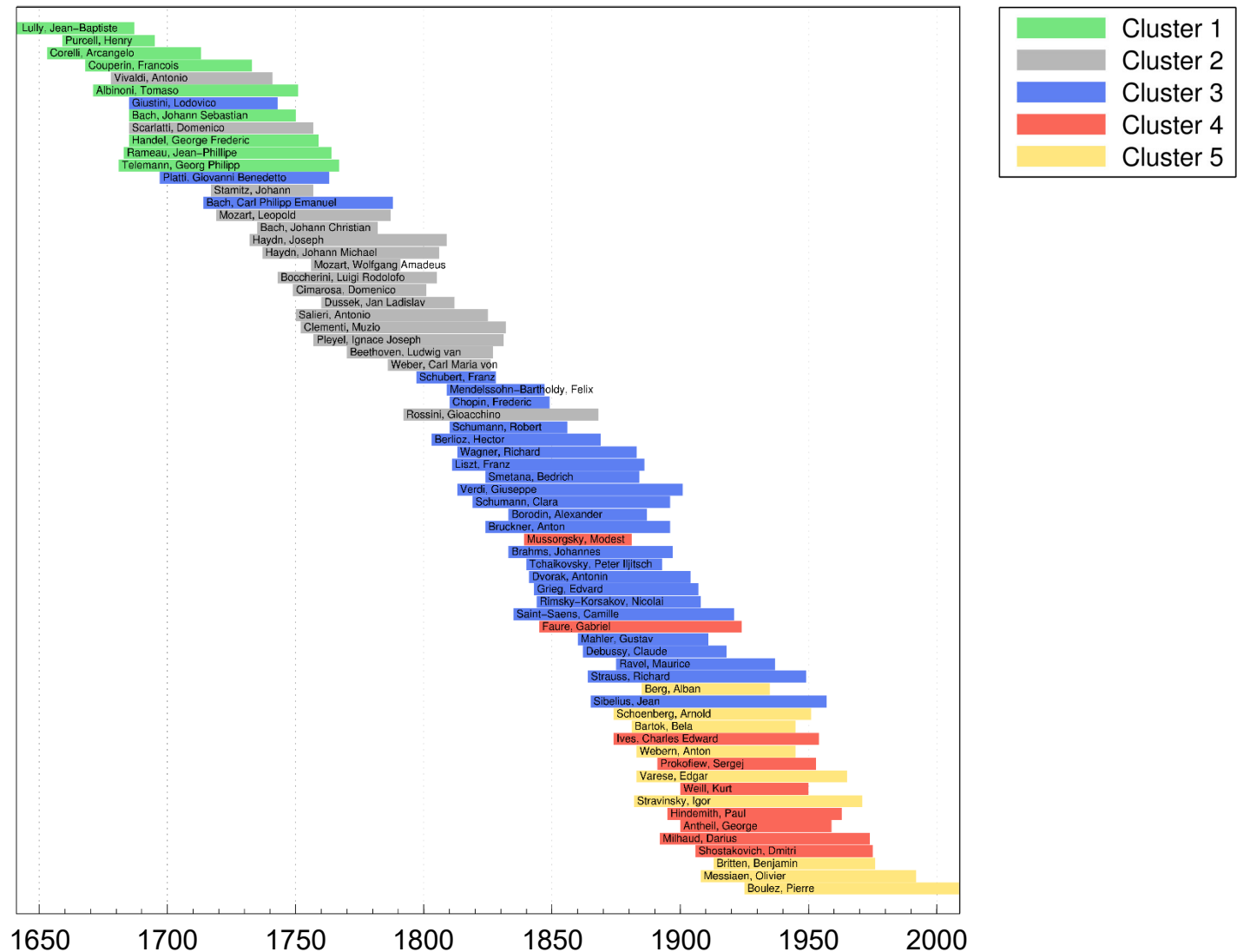
# Clustering: Pieces

- $k$ -means clustering with  $k = 5$  clusters

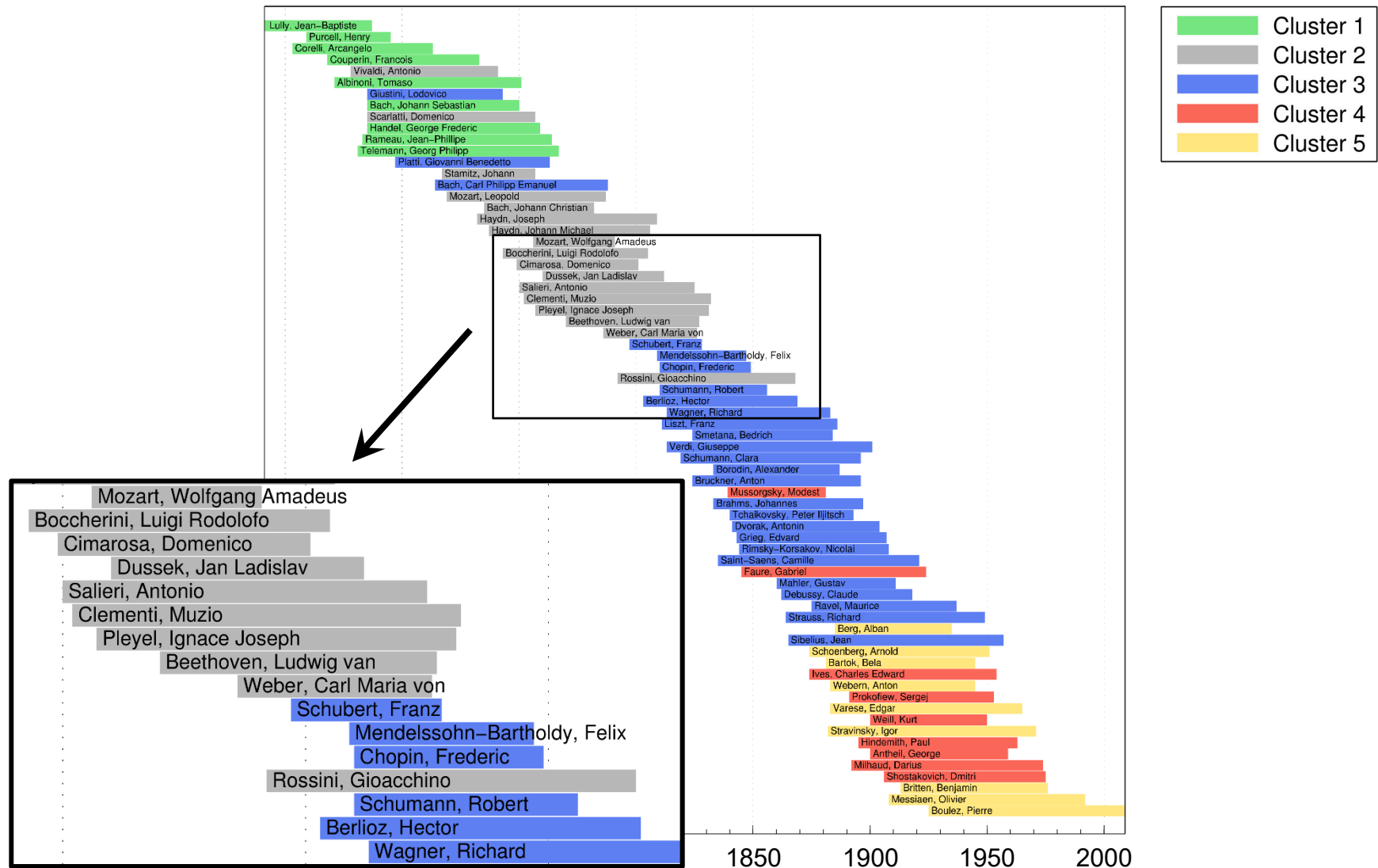


Weiss / Mauch / Dixon / Müller,  
*Investigating Style Evolution of Western  
Classical Music: A Computational Approach*  
Musicae Scientiae 2018

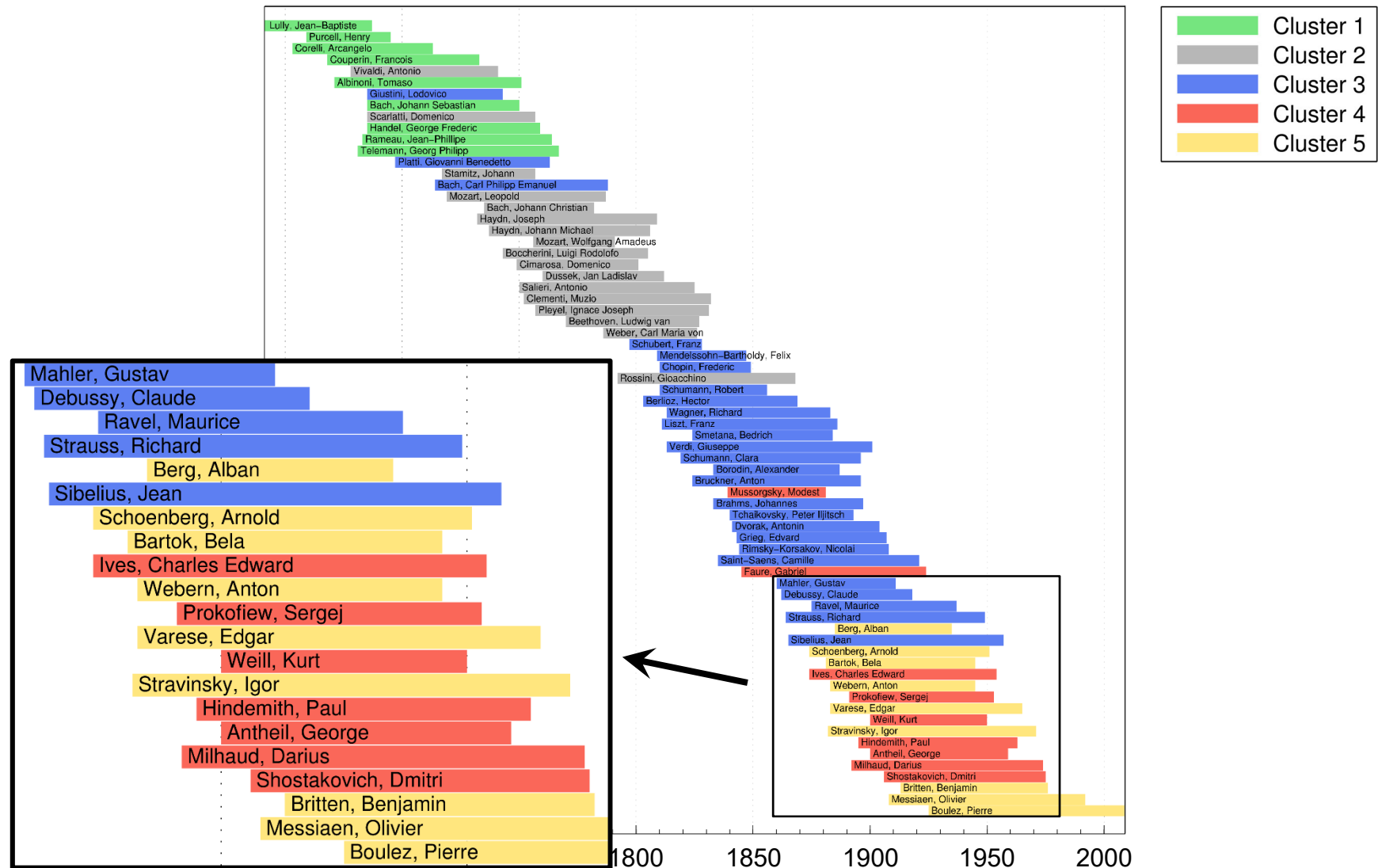
# Clustering: Composers



# Clustering: Composers



# Clustering: Composers



# Clustering: Composers

