INTERNATIONAL AUDIO LABORATORIES ERLANGEN

Workshop HfM Karlsruhe

Music Information Retrieval

Harmony Analysis

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FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

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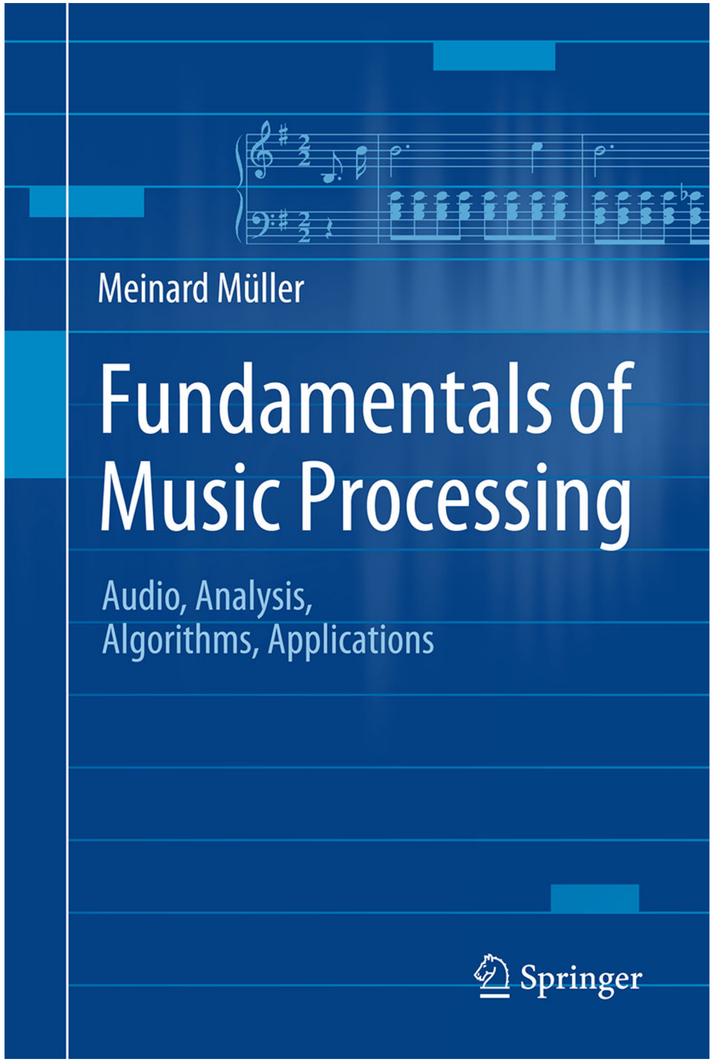
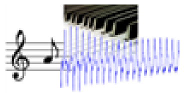
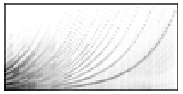
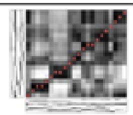
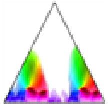
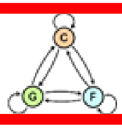
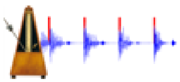
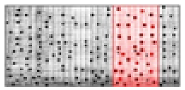
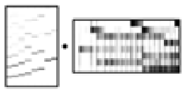
Book: Fundamentals of Music Processing



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

Accompanying website:
www.music-processing.de

Book: Fundamentals of Music Processing

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

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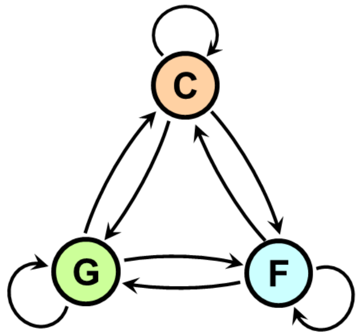
Chapter 5: Chord Recognition



In Chapter 5, we consider the problem of analyzing harmonic properties of a piece of music by determining a descriptive progression of chords from a given audio recording. We take this opportunity to first discuss some basic theory of harmony including concepts such as intervals, chords, and scales. Then, motivated by the automated chord recognition scenario, we introduce template-based matching procedures and hidden Markov models—a concept of central importance for the analysis of temporal patterns in time-dependent data streams including speech, gestures, and music.

Dissertation: Tonality-Based Style Analysis

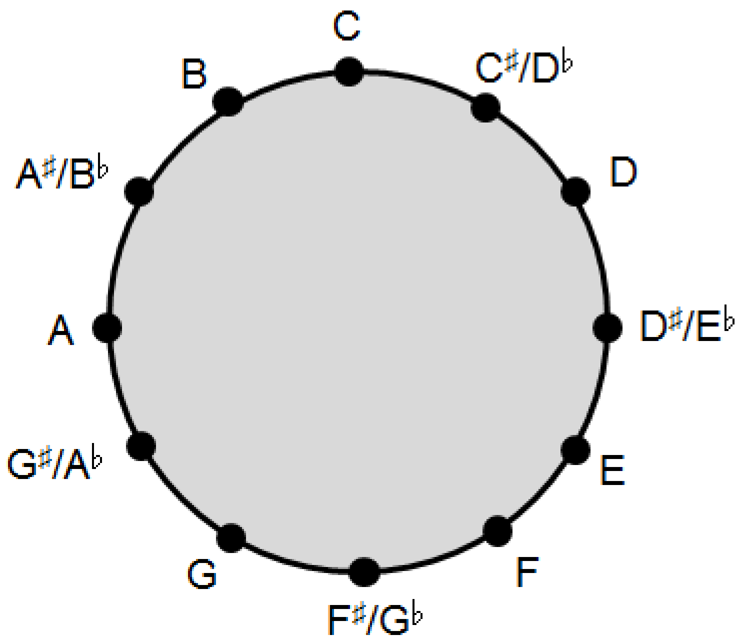
Christof Weiß
Computational Methods for Tonality-Based Style Analysis of Classical Music Audio Recordings
Dissertation, Ilmenau University of Technology, 2017

Chapter 5: Analysis Methods for Key and Scale Structures
Chapter 6: Design of Tonal Features

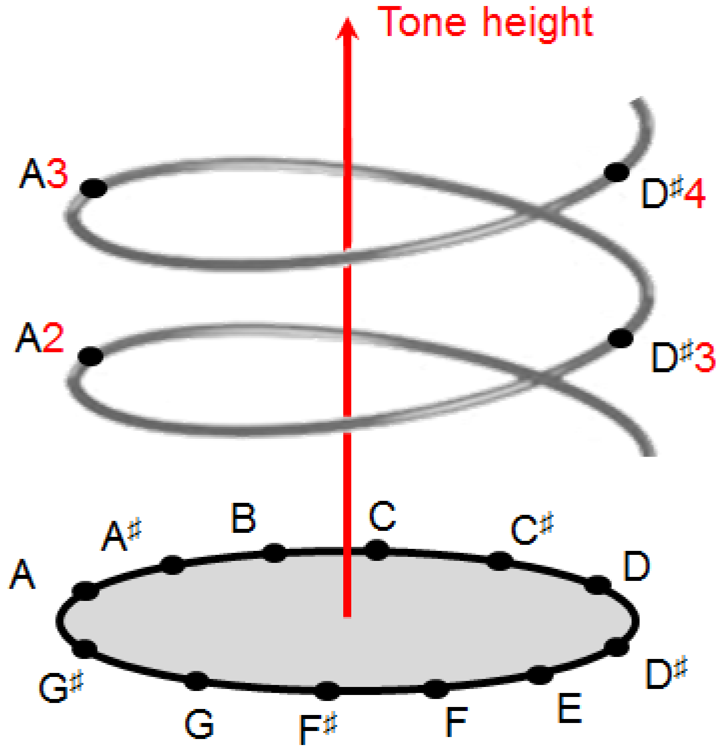
Recall: Chroma Features

- Human perception of pitch is periodic
- Two components: tone height (octave) and chroma (pitch class)

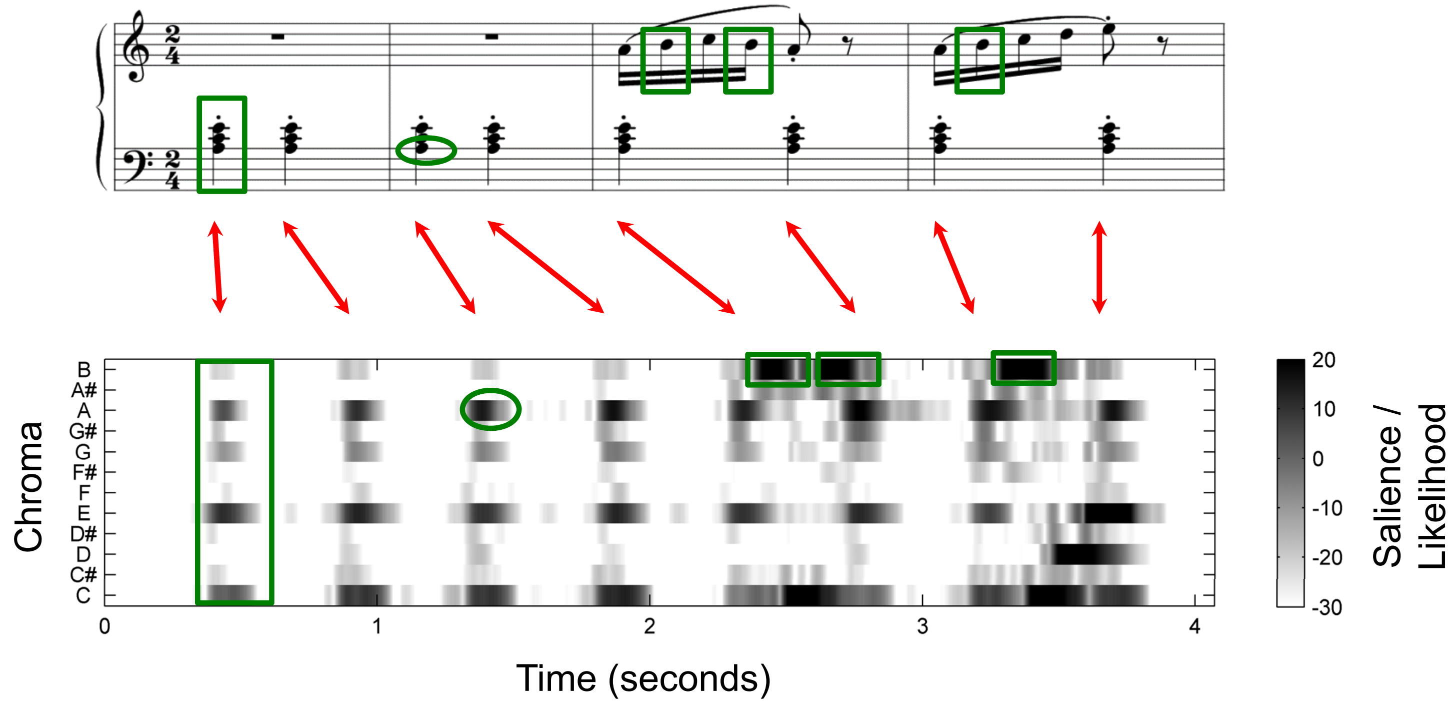
Chromatic circle



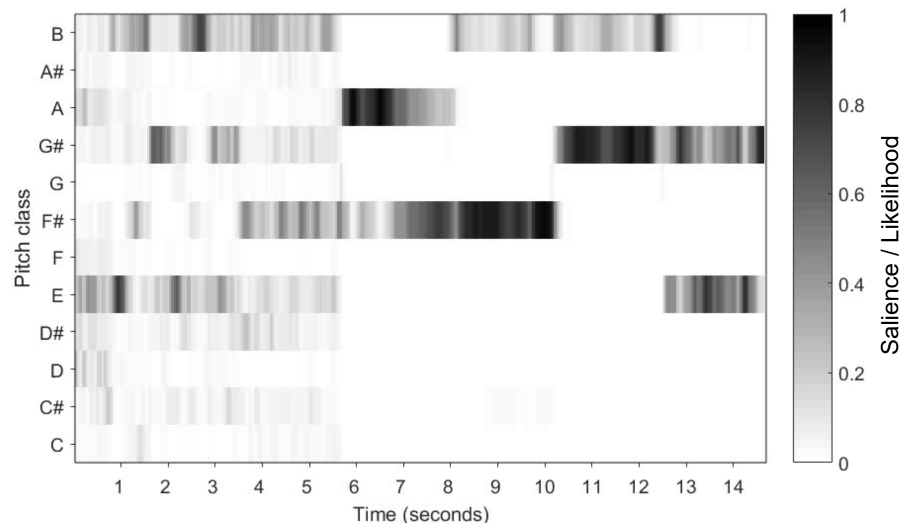
Shepard's helix of pitch



Recall: Chroma Features



Recall: Chroma Representations

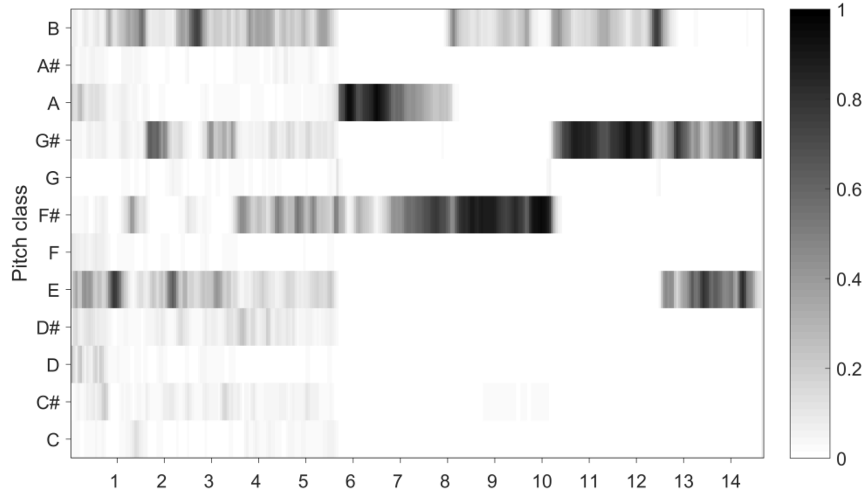


L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic

Recall: Chroma Representations

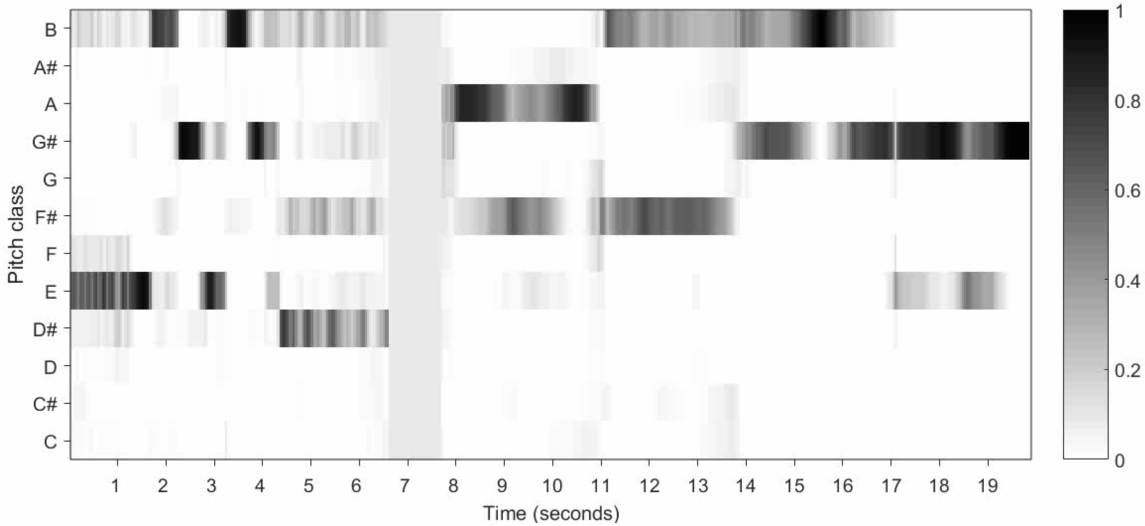
- Orchestra

L. van Beethoven,
Fidelio, Overture,
Slovak Philharmonic



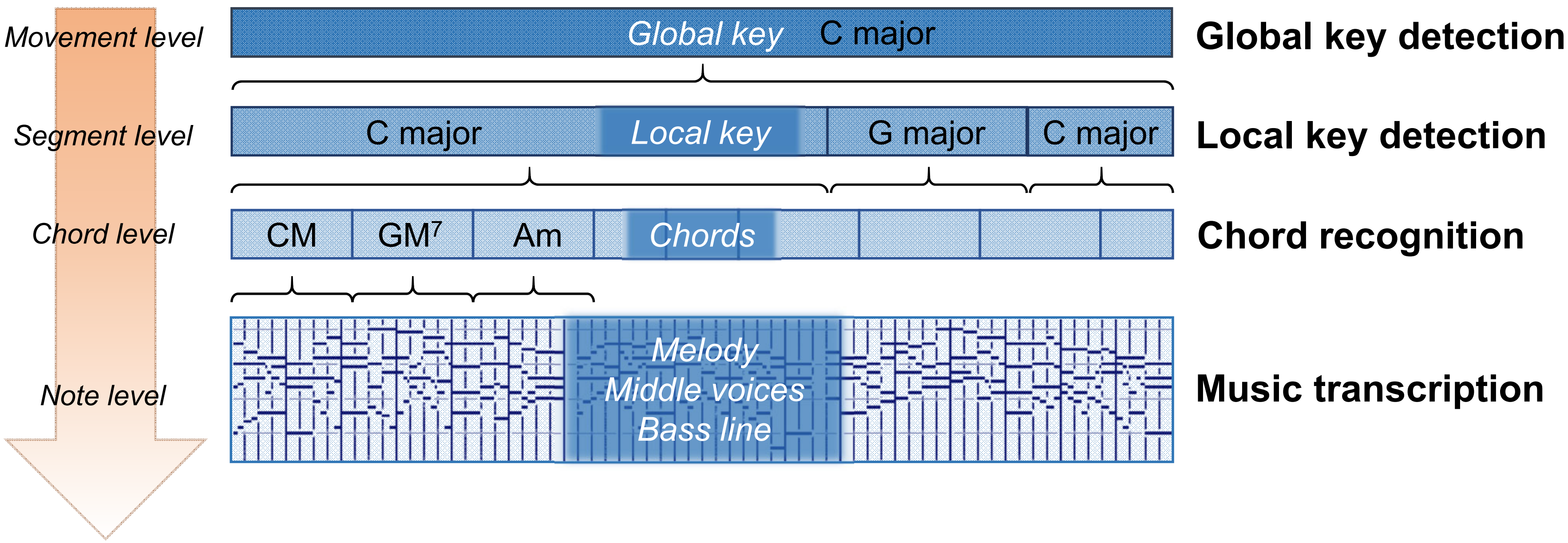
- Piano

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



Tonal Structures

- Western music (and most other music): Different aspects of harmony
- Referring to different time scales



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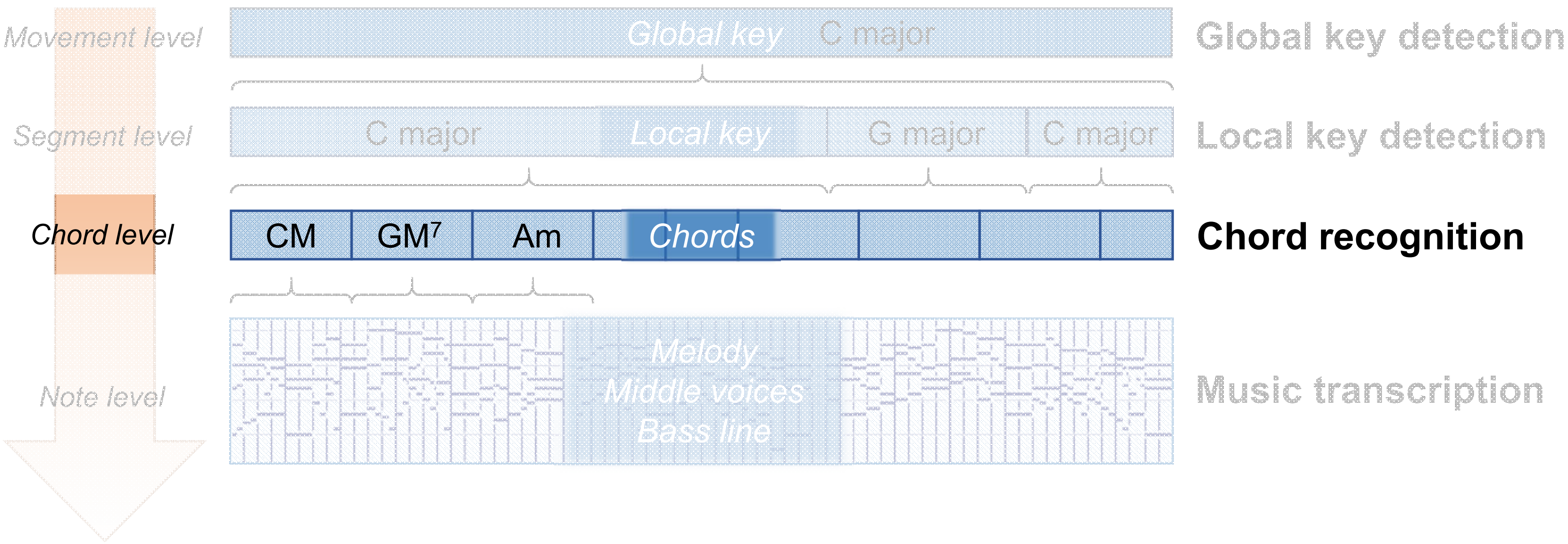
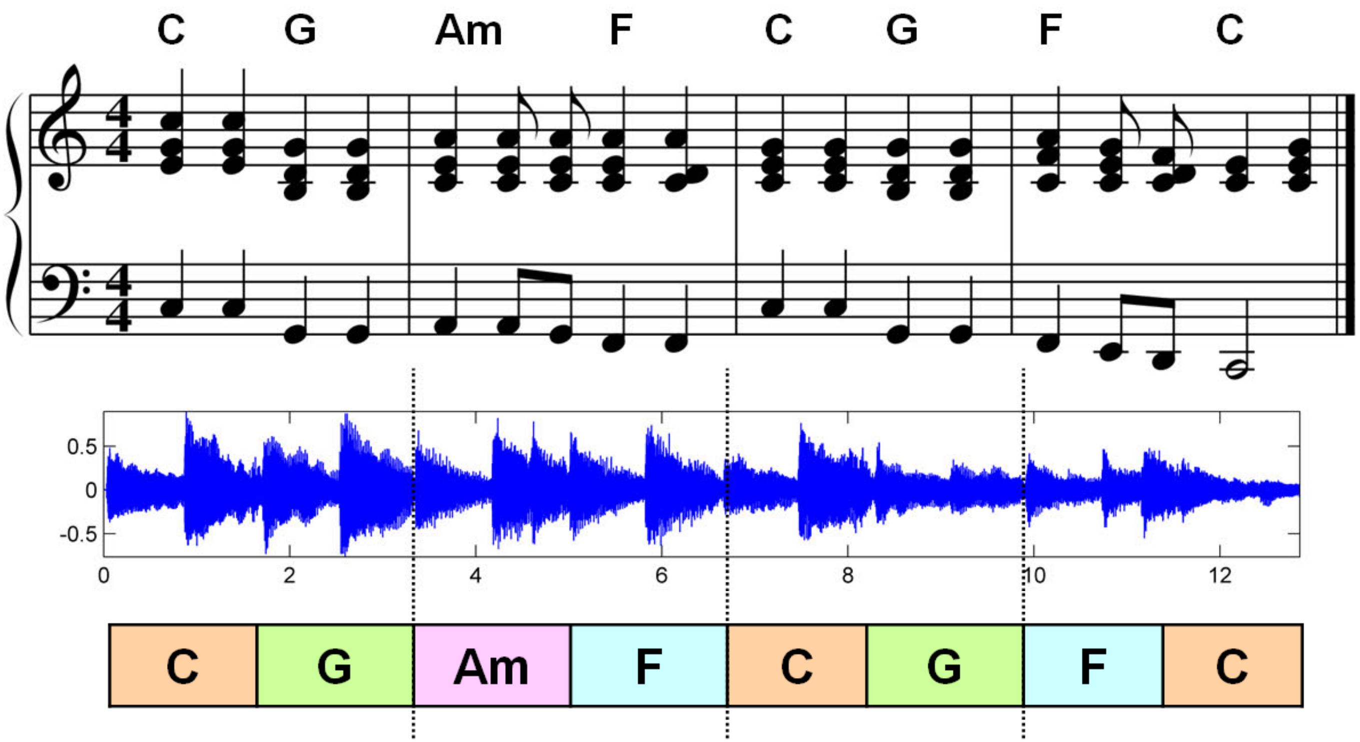


Chord Recognition

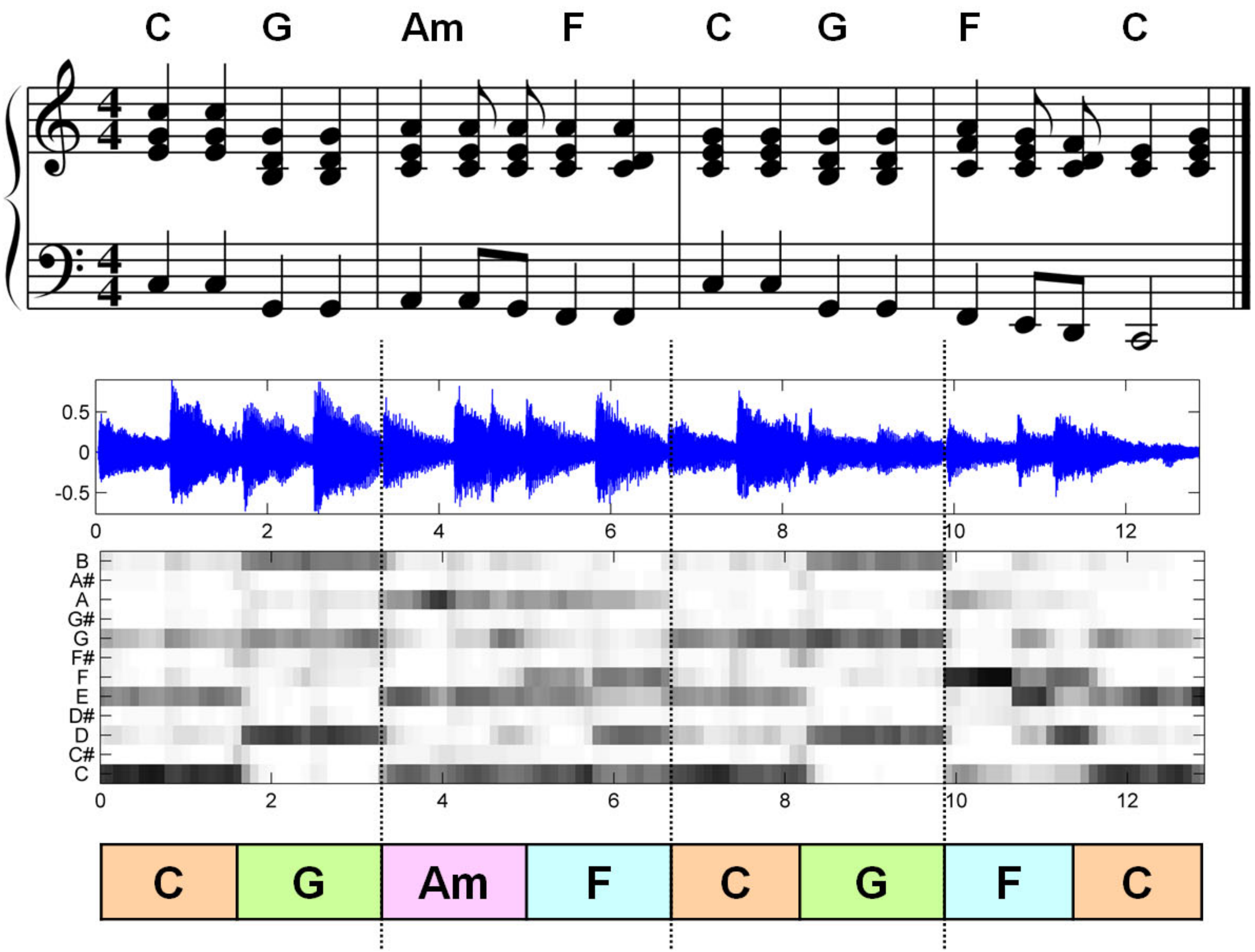
```
Let It Be chords
The Beatles 1970  (Let It Be)

[Intro]

C G Am F C G
F C Dm C

[Verse 1]

       C              G                 Am          F
When I find myself in times of trouble, Mother Mary comes to me
C                 G              F C Dm C
Speaking words of wisdom, let it be

    C             G                 Am                F
And in my hour of darkness, she is standing right in front of me
C                 G              F C Dm C
Speaking words of wisdom, let it be

[Chorus]

C      Am         G          F          C
Let it be, let it be, let it be, let it be
C                G              F C Dm C
Whisper words of wisdom, let it be
```

Source: www.ultimate-guitar.com

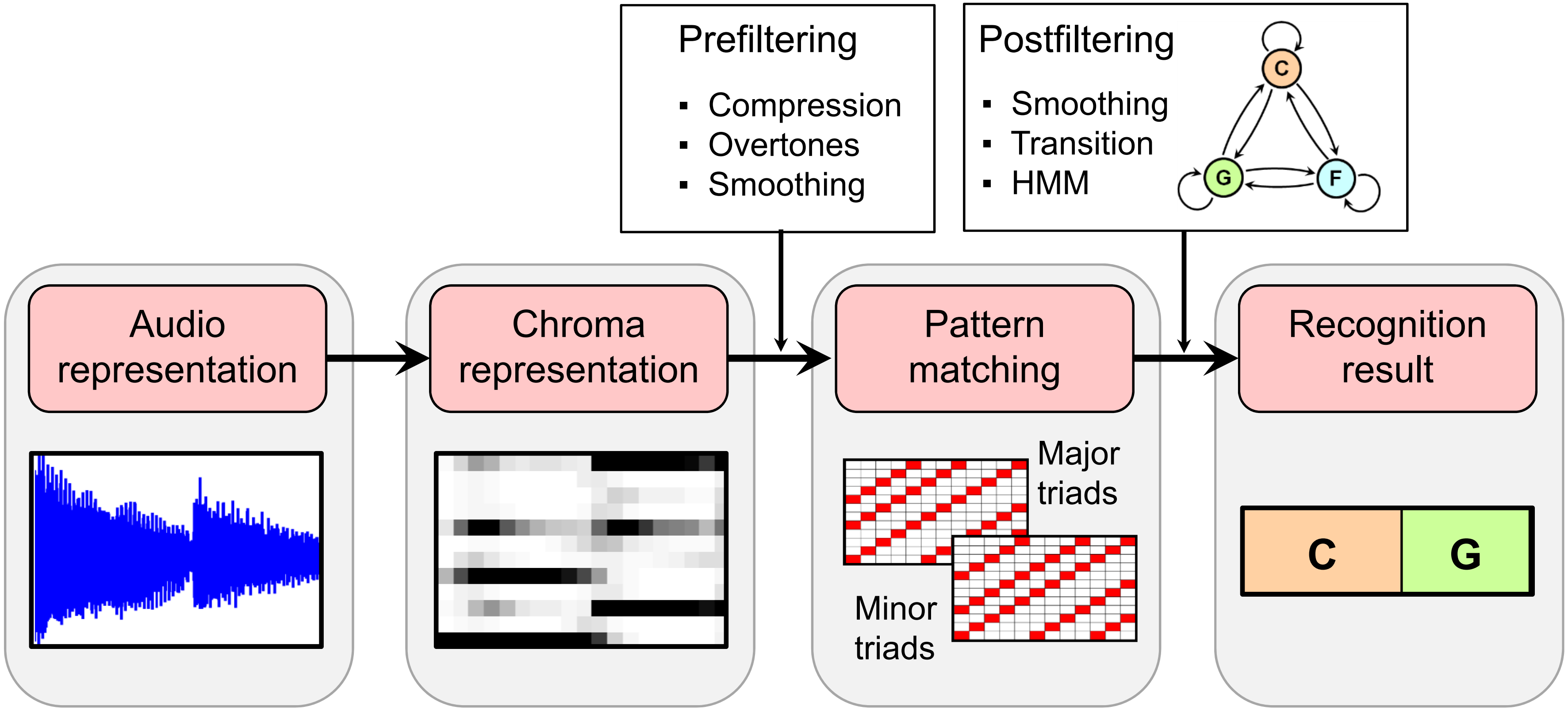
Chord Recognition



Chord Recognition

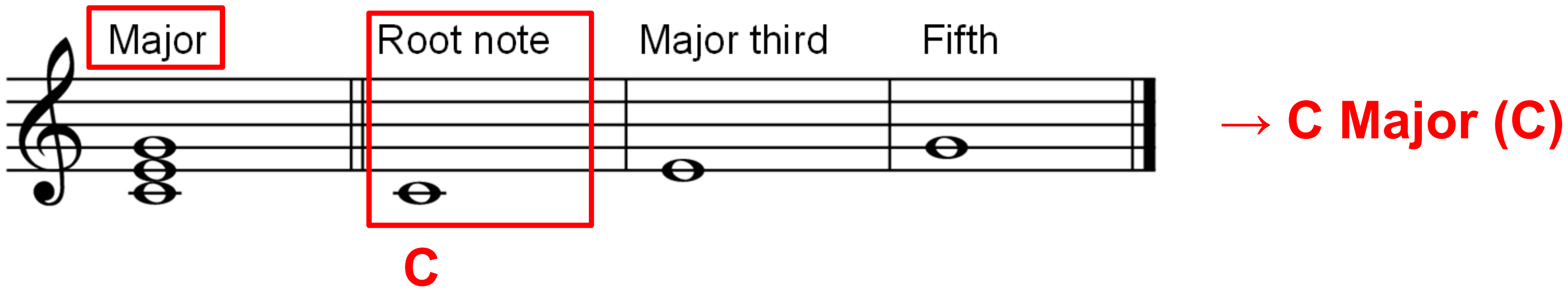


Chord Recognition



Chord Recognition: Basics

- Musical chord: Group of three or more notes
- Combination of three or more tones which sound simultaneously
- Types: triads (major, minor, diminished, augmented), seventh chords…
- Here: focus on major and minor triads



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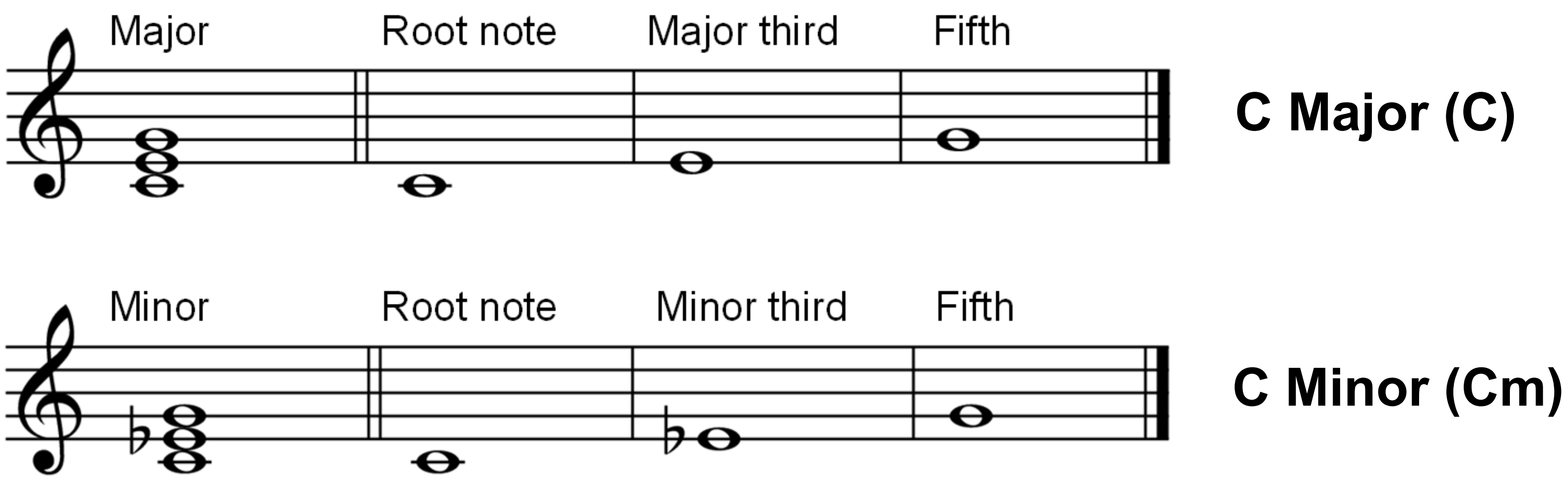
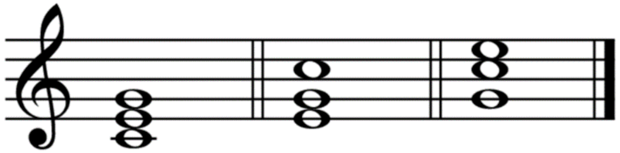


- Enharmonic equivalence: 12 different root notes possible → **24 chords**

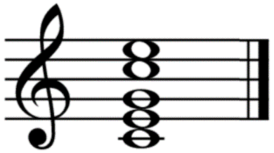
Chord Recognition: Basics

Chords appear in different forms:

- Inversions



- Different voicings

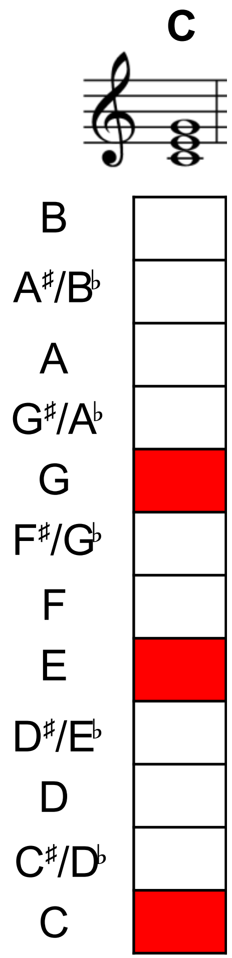


- Harmonic figuration: Broken chords (arpeggio)

- Melodic figuration: Different melody note (suspension, passing tone, …)
- Further: Additional notes, incomplete chords

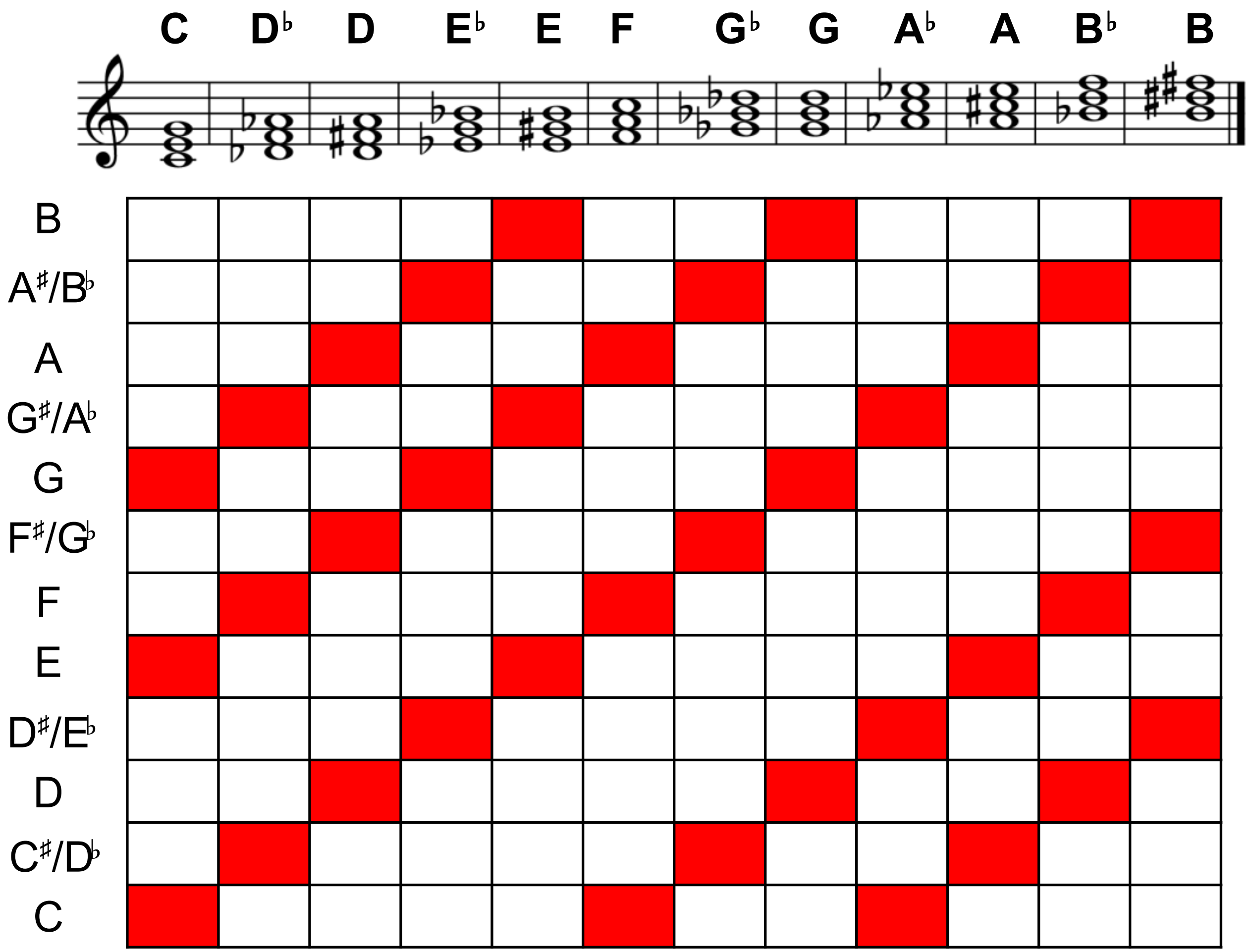
Chord Recognition: Basics

- Templates: **Major Triads**



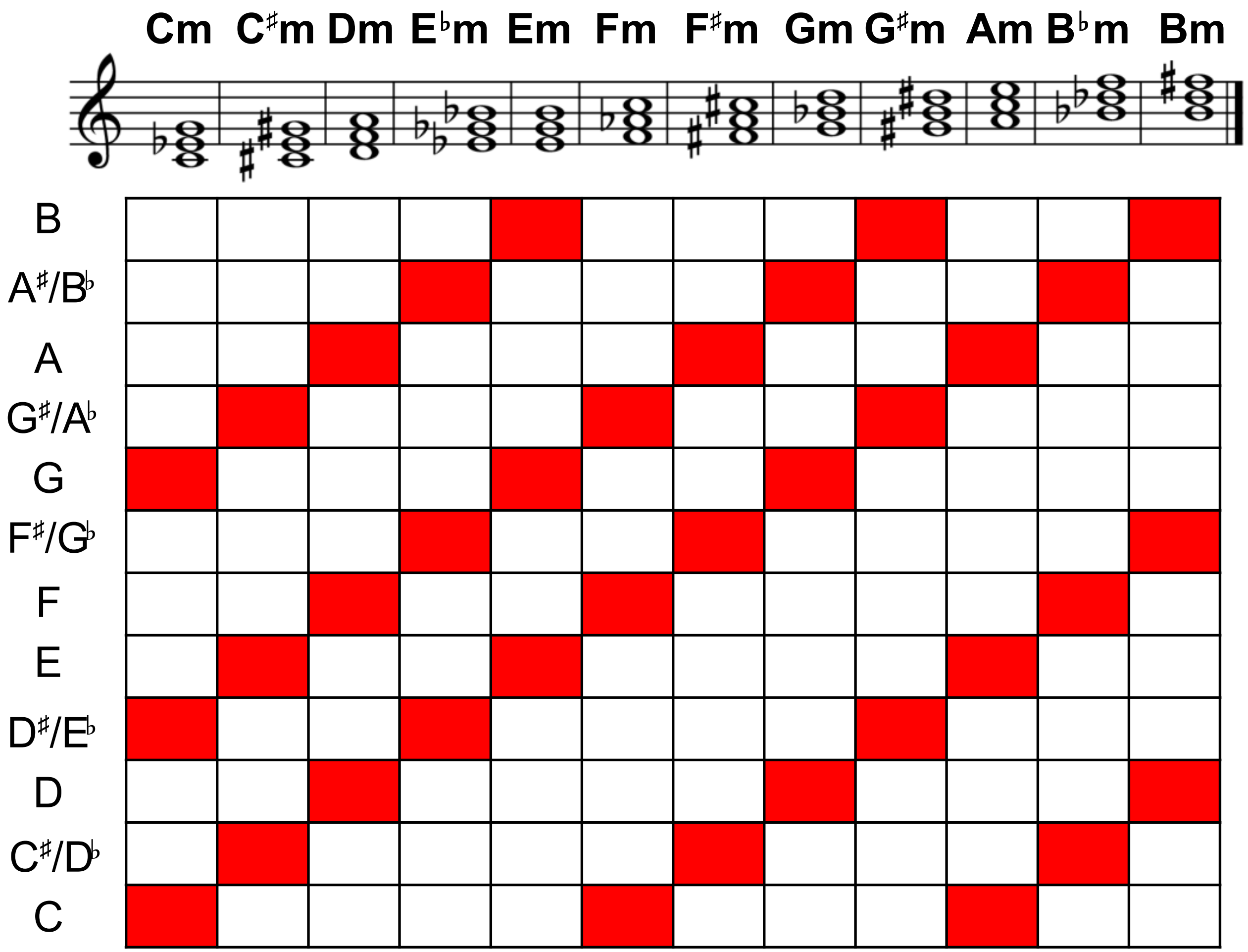
Chord Recognition: Basics

- Templates: **Major Triads**

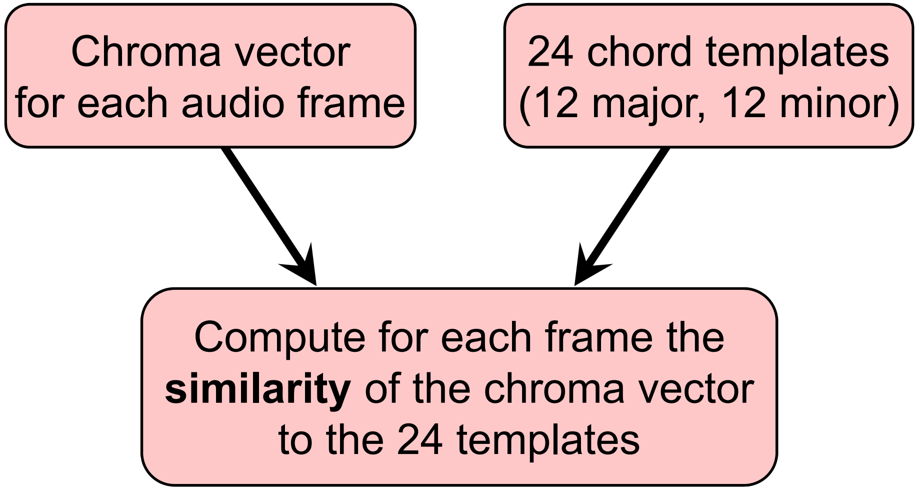


Chord Recognition: Basics

- Templates: **Minor Triads**



Chord Recognition: Template Matching



	C	**C♯**	**D**	**…**	**Cm**	**C♯m**	**Dm**	**…**
B	0	0	0	…	0	0	0	…
A♯	0	0	0	…	0	0	0	…
A	0	0	1	…	0	0	1	…
G♯	0	1	0	…	0	1	0	…
G	1	0	0	…	1	0	0	…
F♯	0	0	1	…	0	0	0	…
F	0	1	0	…	0	0	1	…
E	1	0	0	…	0	1	0	…
D♯	0	0	0	…	1	0	0	…
D	0	0	1	…	0	0	1	…
C♯	0	1	0	…	0	1	0	…
C	1	0	0	…	1	0	0	…

Chord Recognition: Template Matching

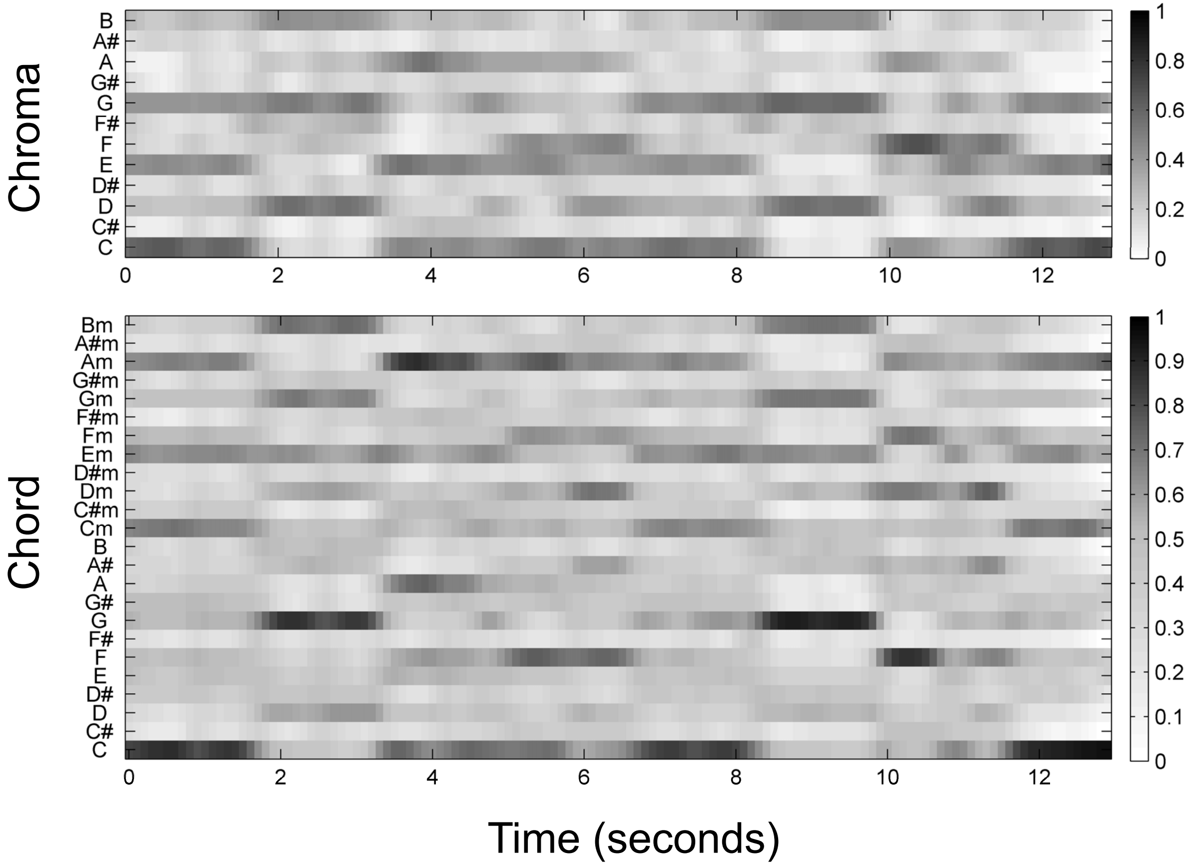
- Similarity measure: Cosine similarity (inner product of normalized vectors)

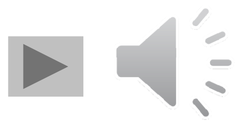
Chord template: $\boldsymbol{t} \in \mathbb{R}^{12}$

Chroma vector: $\boldsymbol{c} \in \mathbb{R}^{12}$

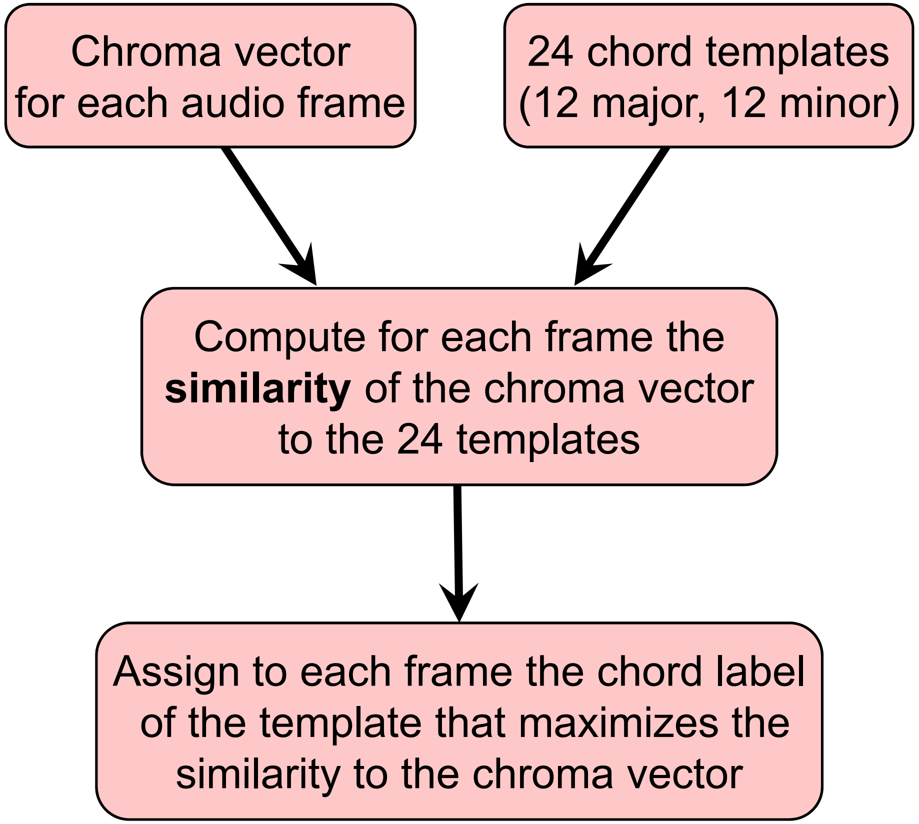
Similarity measure: $$s(\boldsymbol{t}, \boldsymbol{c}) = \frac{\langle \boldsymbol{t} | \boldsymbol{c} \rangle}{||\boldsymbol{t}|| \cdot ||\boldsymbol{c}||}$$

Chord Recognition: Template Matching



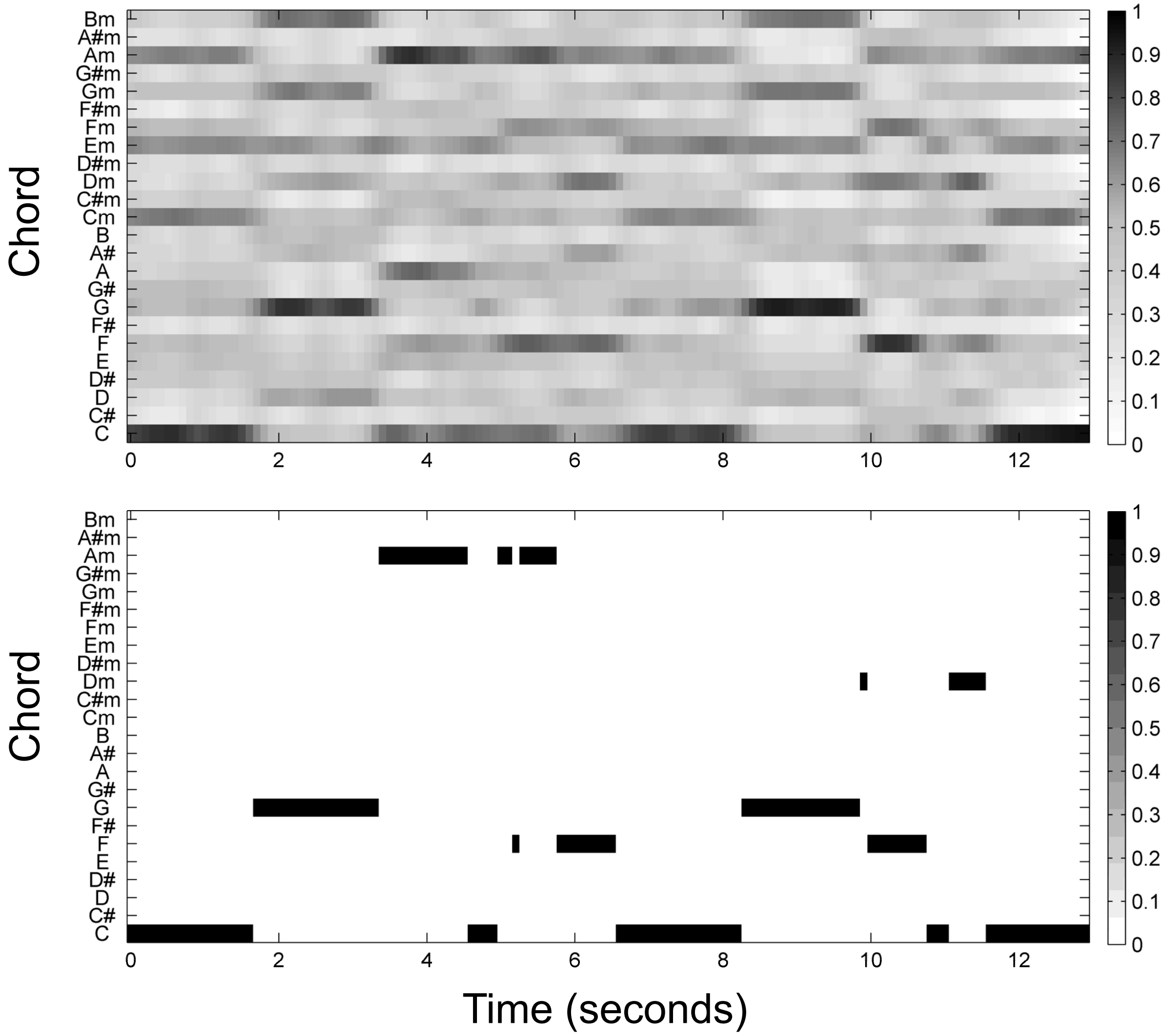


Chord Recognition: Label Assignment

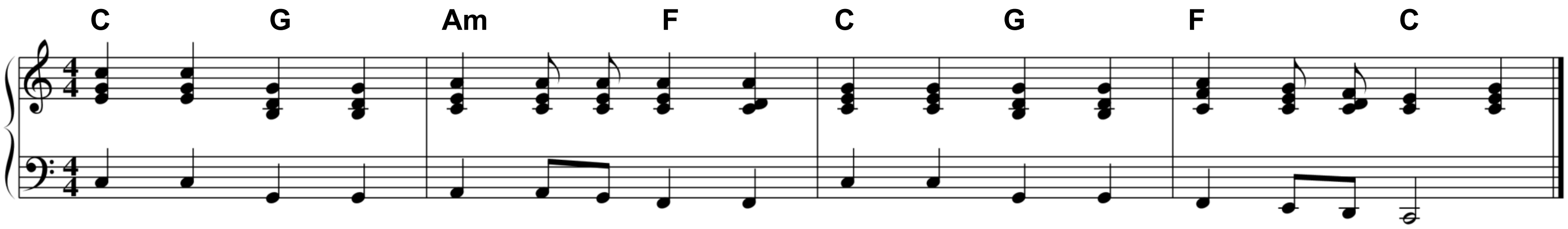


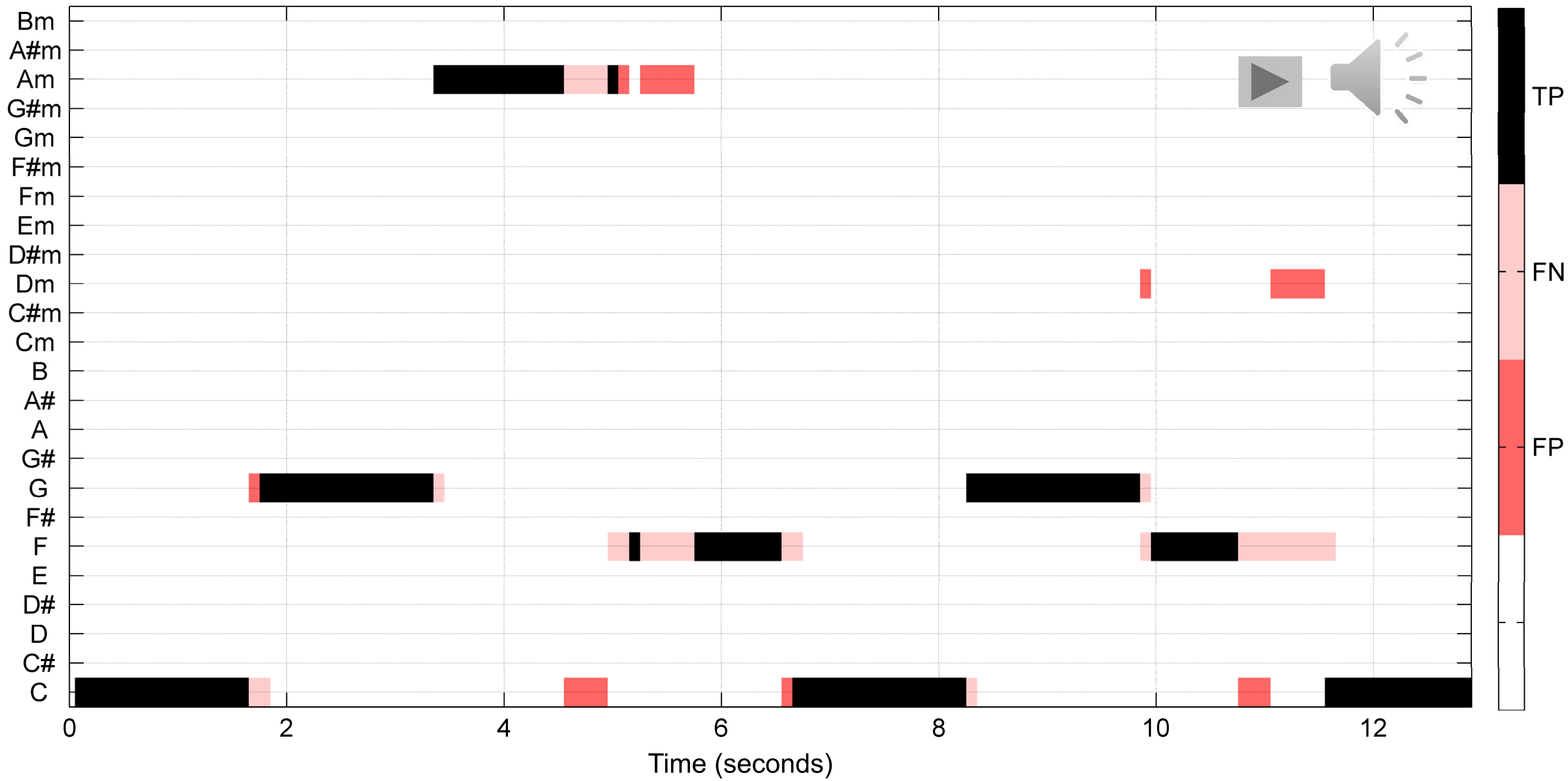
	C	$C^\sharp$	D	…	Cm	$C^\sharp$m	Dm	…
B	0	0	0	…	0	0	0	…
$A^\sharp$	0	0	0	…	0	0	0	…
A	0	0	1	…	0	0	1	…
$G^\sharp$	0	1	0	…	0	1	0	…
G	1	0	0	…	1	0	0	…
$F^\sharp$	0	0	1	…	0	0	0	…
F	0	1	0	…	0	0	1	…
E	1	0	0	…	0	1	0	…
$D^\sharp$	0	0	0	…	1	0	0	…
D	0	0	1	…	0	0	1	…
$C^\sharp$	0	1	0	…	0	1	0	…
C	1	0	0	…	1	0	0	…

Chord Recognition: Label Assignment



Chord Recognition: Evaluation





Chord Recognition: Evaluation

- "No-Chord" annotations: not every frame labeled

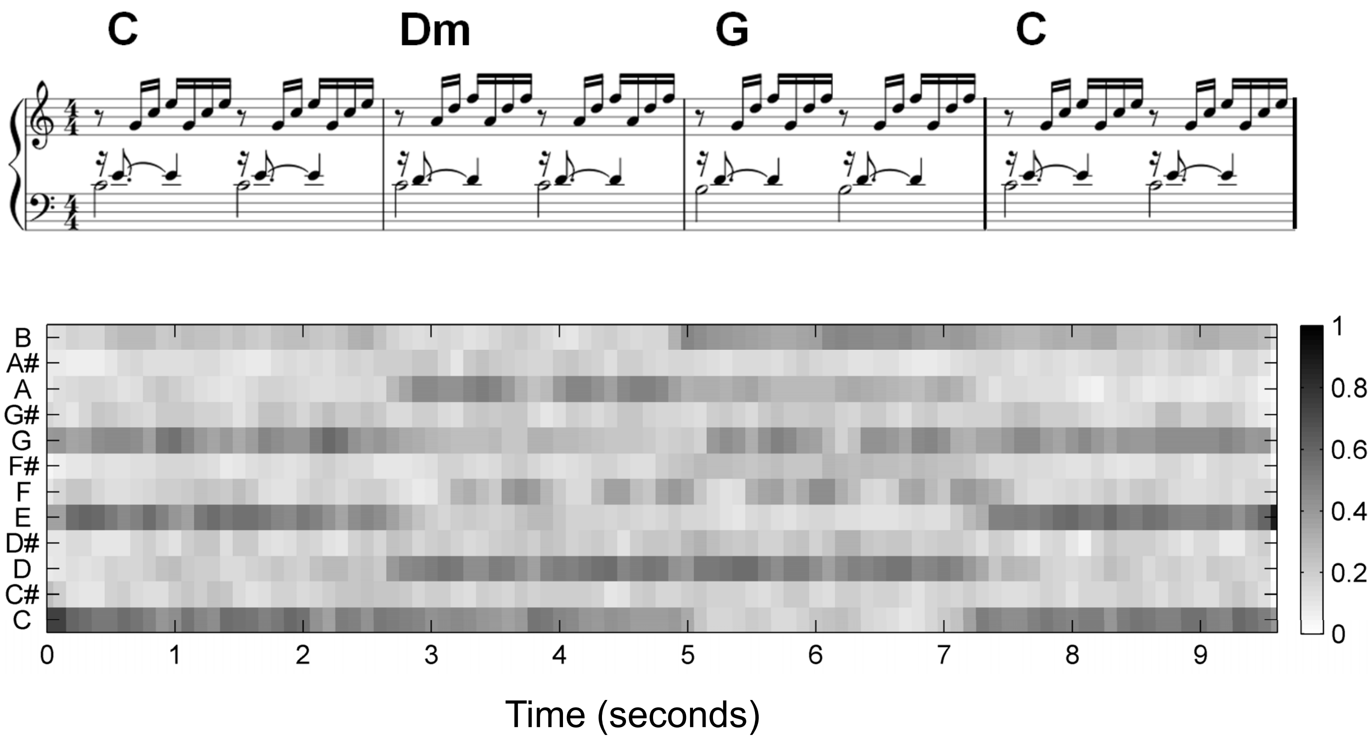
- Different evaluation measures:
  - Precision: $$P = \frac{\#\mathrm{TP}}{\#\mathrm{TP} + \#\mathrm{FP}}$$
  - Recall: $$R = \frac{\#\mathrm{TP}}{\#\mathrm{TP} + \#\mathrm{FN}}$$
  - F-Measure (balances precision and recall):

$$F = \frac{2 \cdot P \cdot R}{P + R}$$

- Without "No-Chord" label: $P = R = F$

Chord Recognition: Smoothing

- Apply average filter of length $L \in \mathbb{N}$:



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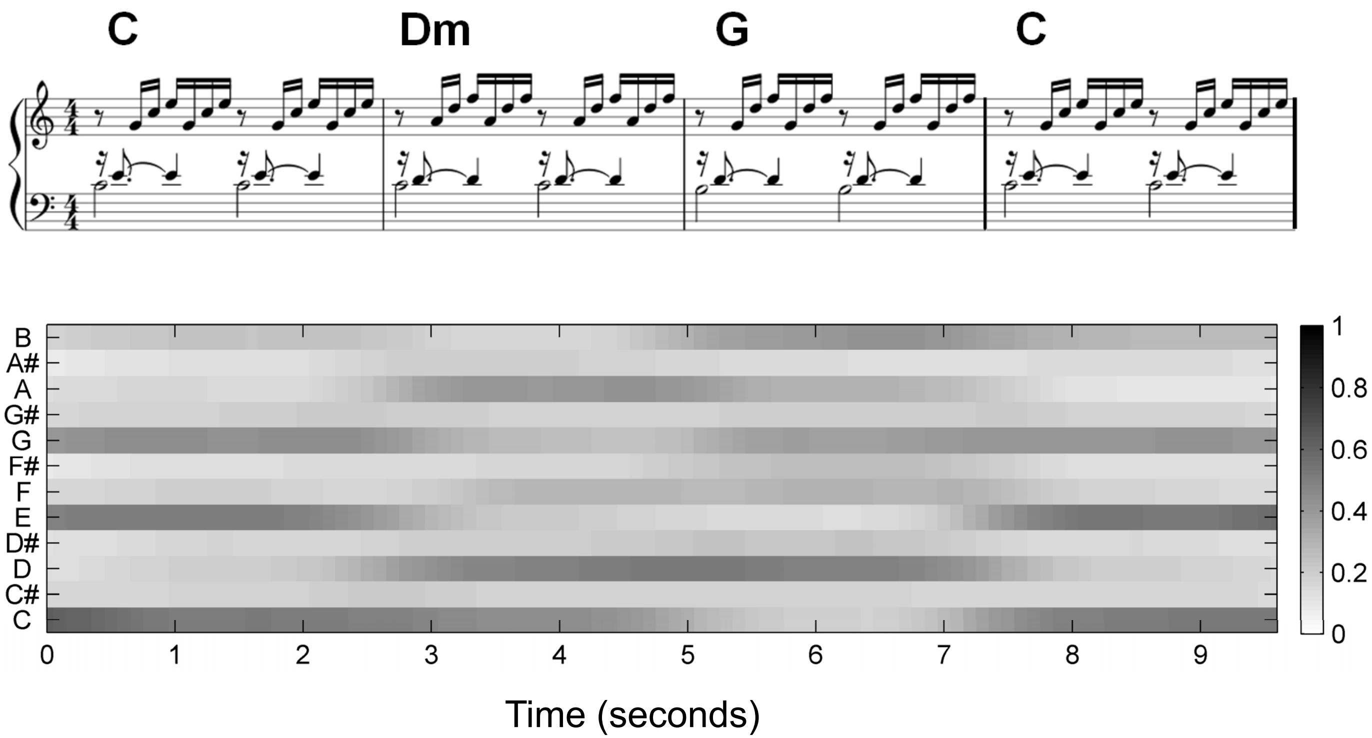
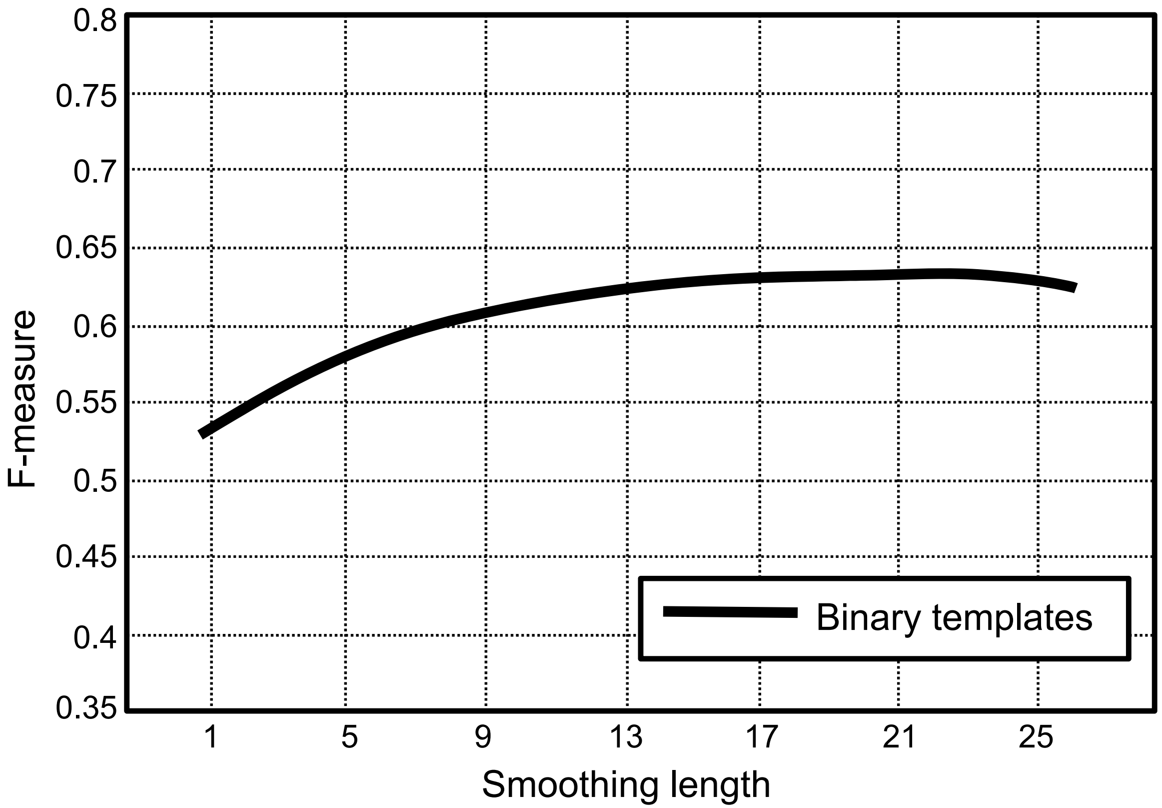


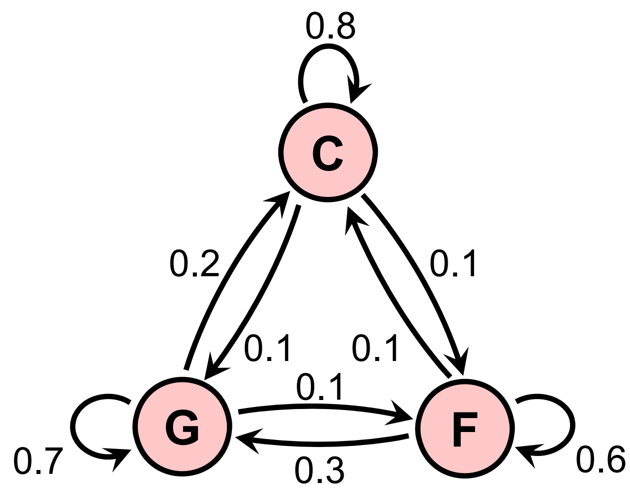
Chord Recognition: Smoothing

- Evaluation on all Beatles songs



Markov Chains

- Probabilistic model for sequential data
- Markov property: Next state only depends on current state (no “memory”)
- Consist of:
  - Set of states (hidden)
  - State transition probabilities
  - *Initial state probabilities*



Markov Chains

Notation:

States α_i for $i \in [1:I]$

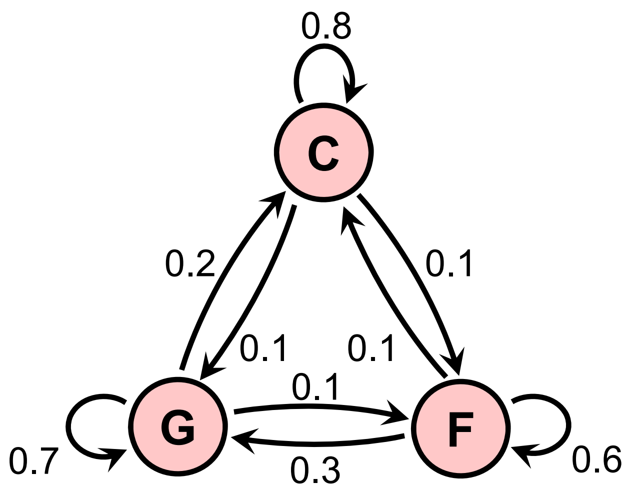
State transition probabilities a_{ij}

A	α_1	α_2	α_3
α_1	a_{11}	a_{12}	a_{13}
α_2	a_{21}	a_{22}	a_{23}
α_3	a_{31}	a_{32}	a_{33}

Initial state probabilities c_i

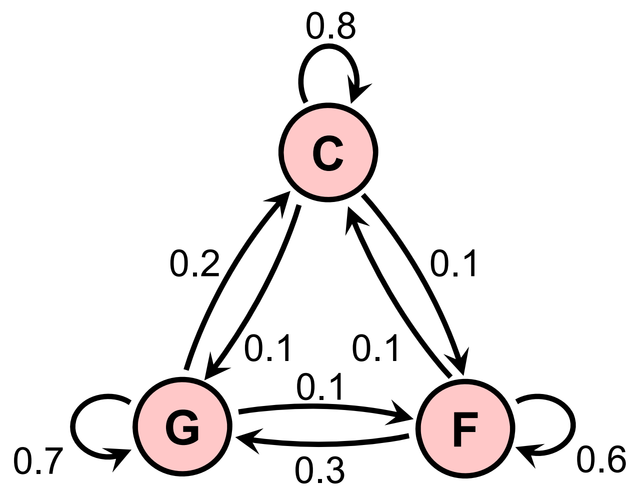
C	α_1	α_2	α_3
	c_1	c_2	c_3

β_k for $k \in [1:K]$



Markov Chains

- Application examples:
  - Compute probability of a sequence using given a model (evaluation)
  - Compare two sequences using a given model
  - Evaluate a sequence with two different models (classification)



Hidden Markov Models

- States as **hidden** variables

- Consist of:
  - Set of states (hidden)
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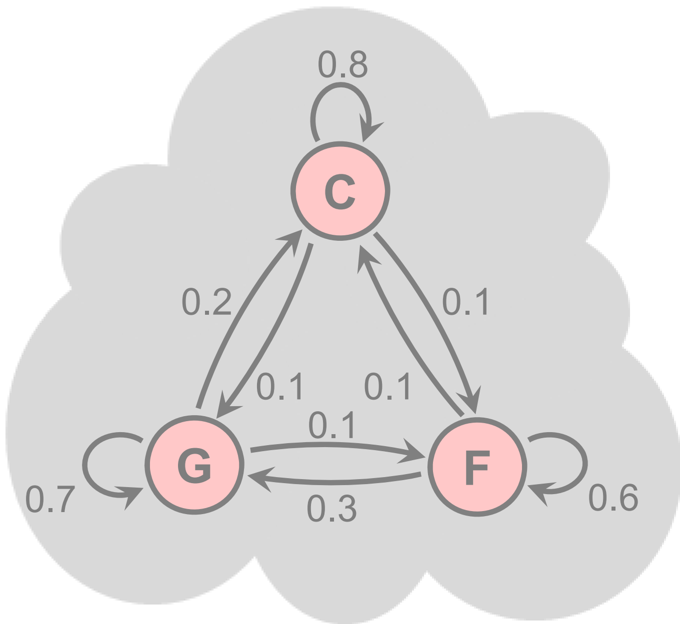

Hidden Markov Models

- States as **hidden** variables
- Consist of:
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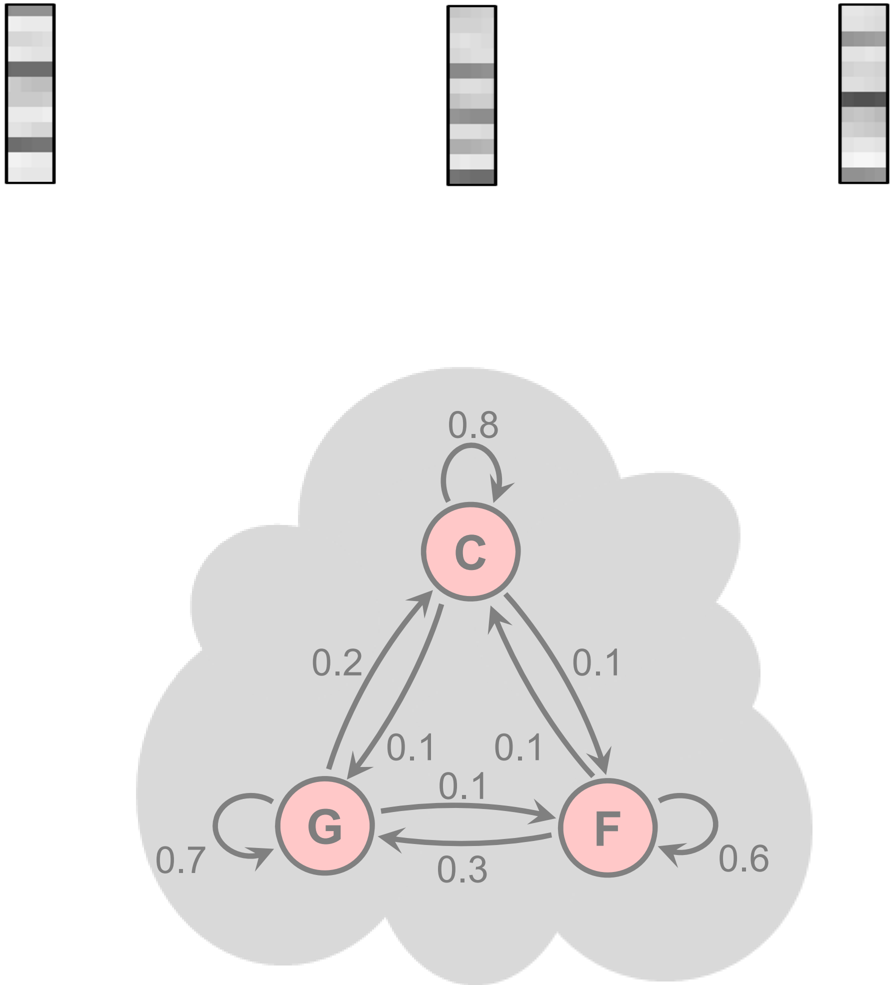
  - State transition probabilities
  - *Initial state probabilities*
  - Observations (visible)



Hidden Markov Models

- States as **hidden** variables
- Consist of:
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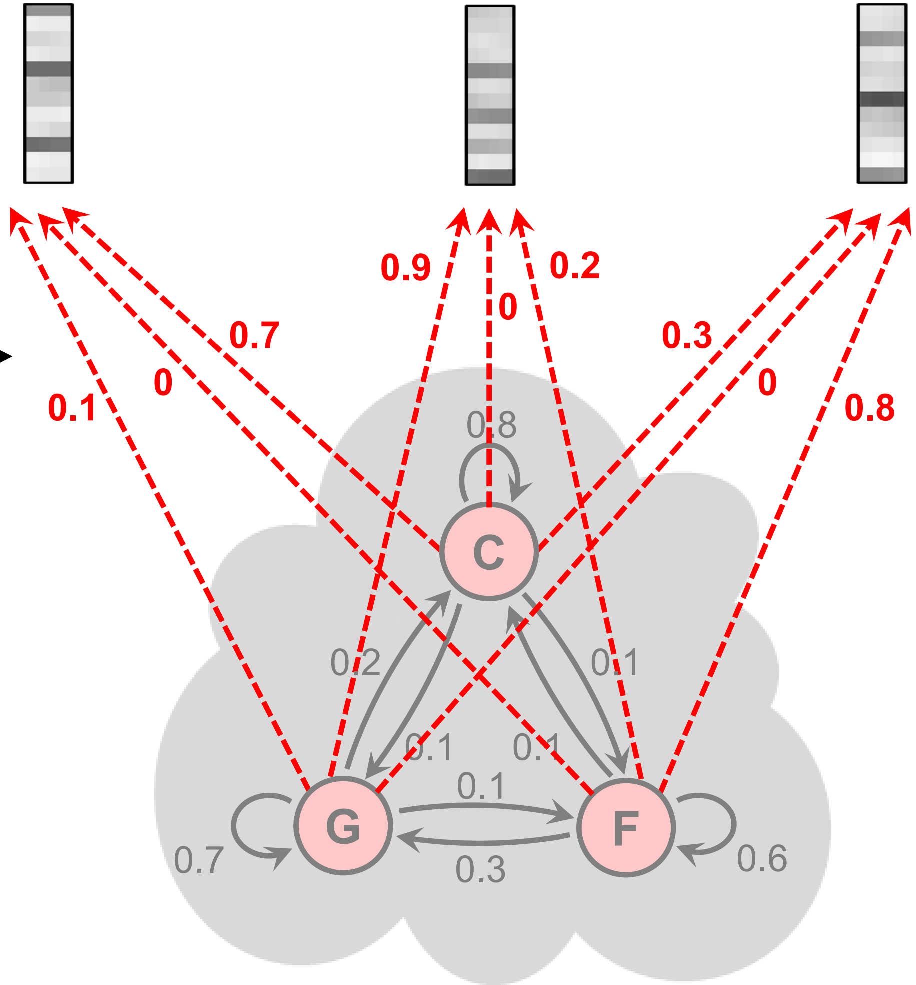
  - State transition probabilities
  - *Initial state probabilities*
  - Observations (visible)
  - Emission probabilities



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α2	a_{21}	a_{22}	a_{23}
α3	a_{31}	a_{32}	a_{33}

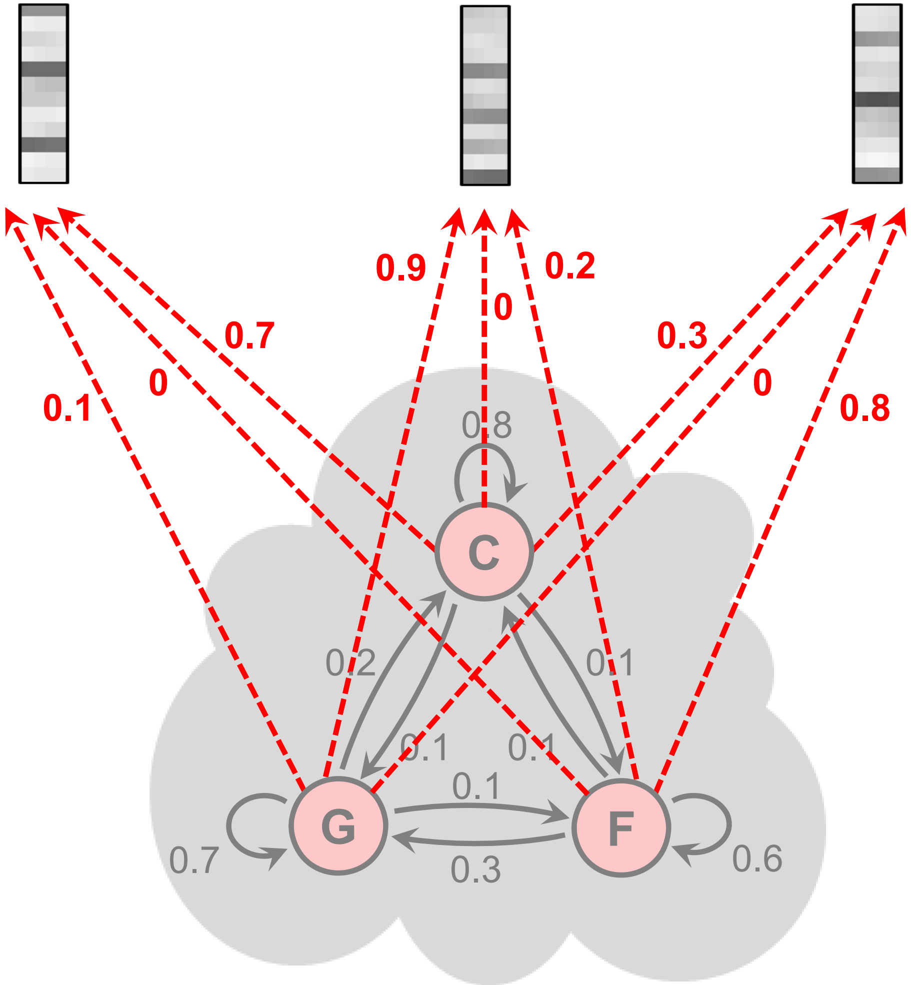
Initial state probabilities c_i

C	α1	α2	α3
	c_1	c_2	c_3

Observation symbols β_k for $k \in [1:K]$

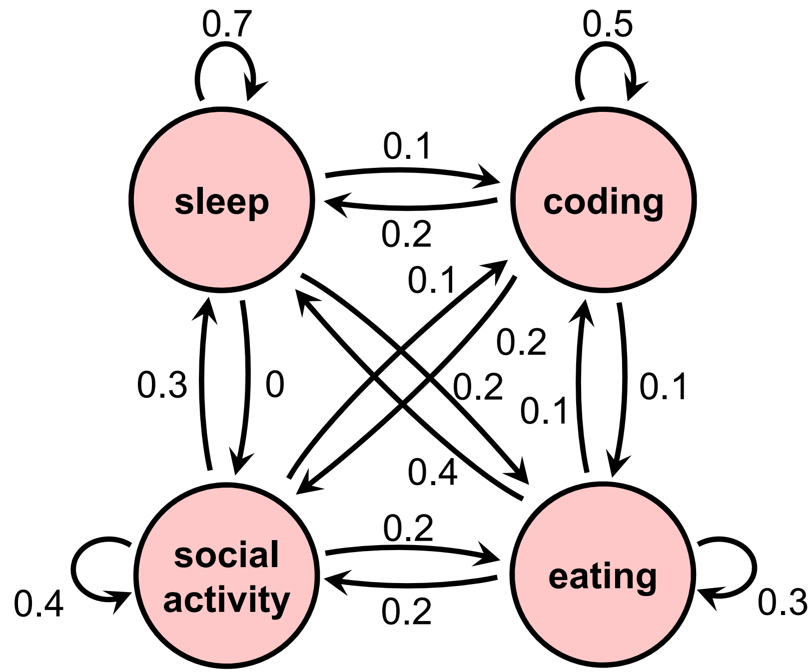
Emission probabilities b_{ik}

B	β1	β2	β3
α1	b_{11}	b_{12}	b_{13}
α2	b_{21}	b_{22}	b_{23}
α3	b_{31}	b_{32}	b_{33}



Markov Chains

- Analogon: the student's life
- Consists of:
  - Set of states (hidden)
  - State transition probabilities
  - *Initial state probabilities*



Hidden Markov Models

- Analogon: the student‘s life
- Consists of:
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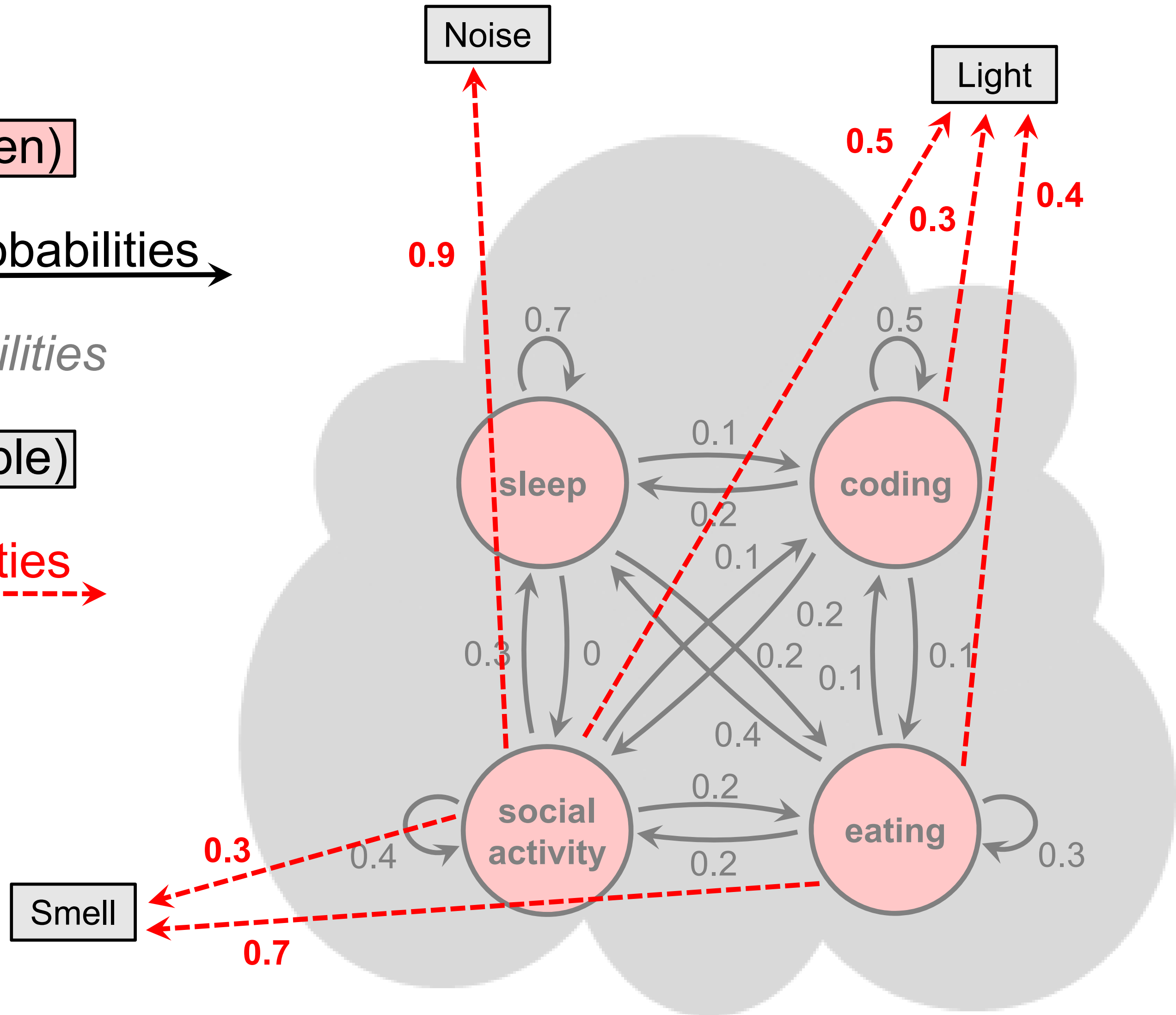
  - State transition probabilities
  - *Initial state probabilities*
  - Observations (visible)
  - Emission probabilities



Hidden Markov Models

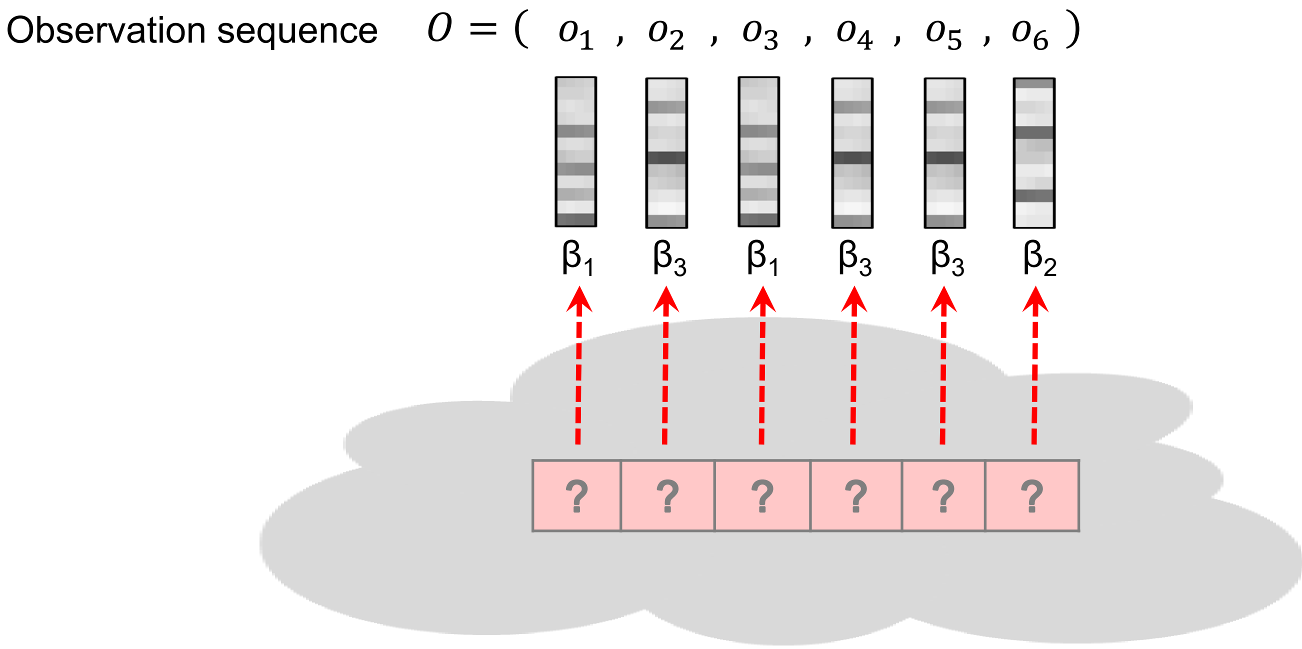
- Only observation sequence is visible!

Different algorithmic problems:

- **Evaluation problem**
  - Given: observation sequence and model
  - Calculate how well the model matches the sequence
- **Uncovering problem:**
  - Given: observation sequence and model
  - Find: optimal hidden state sequence
- **Estimation problem** („training“ the HMM):
  - Given: observation sequence
  - Find: model parameters
  - Baum-Welch algorithm (Expectation-Maximization)

Uncovering problem

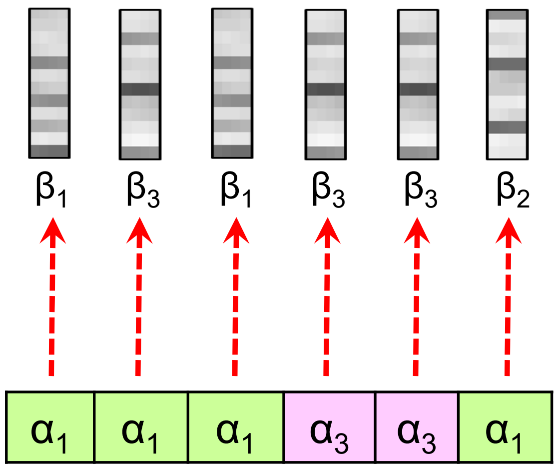
- Given: observation sequence $O = (o_1, \ldots, o_N)$ of length $N \in \mathbb{N}$ and HMM Θ (model parameters)
- Find: optimal hidden state sequence $S^* = (s_1^*, \ldots, s_N^*)$
- Corresponds to chord estimation task!



Uncovering problem

- Given: observation sequence $O = (o_1, \ldots, o_N)$ of length $N \in \mathbb{N}$ and HMM Θ (model parameters)
- Find: optimal hidden state sequence
- Corresponds to chord estimation task!

Observation sequence $O = (o_1 , o_2 , o_3 , o_4 , o_5 , o_6)$

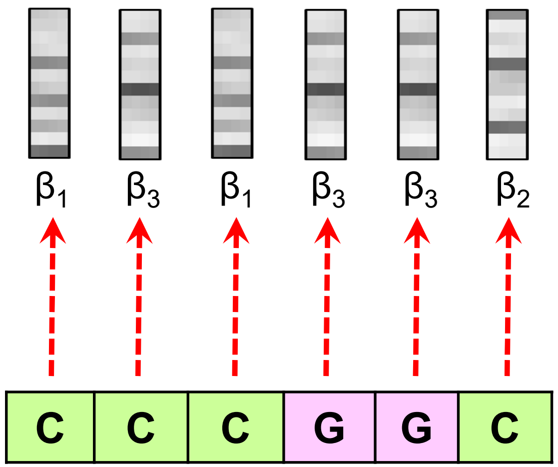


Hidden state sequence $S^* = (s_1^* , s_2^* , s_3^* , s_4^* , s_5^* , s_6^*)$

Uncovering problem

- Given: observation sequence $O = (o_1, \ldots, o_N)$ of length $N \in \mathbb{N}$ and HMM Θ (model parameters)
- Find: optimal hidden state sequence
- Corresponds to chord estimation task!

Observation sequence $O = (o_1 , o_2 , o_3 , o_4 , o_5 , o_6)$



Hidden state sequence $S^* = (s_1^* , s_2^* , s_3^* , s_4^* , s_5^* , s_6^*)$

Uncovering problem

- **Optimal** hidden state sequence?
  - “Best explains” given observation sequence O
  - Maximizes probability $P[O, S \mid \Theta]$

$$\mathrm{Prob}^* = \max_S P[O, S \mid \Theta]$$

$$S^* = \operatorname*{argmax}_S P[O, S \mid \Theta]$$

- Straight-forward computation (naive approach):
  - Compute probability for each possible sequence S
  - Number of possible sequences of length N (I = number of states):

$$\underbrace{I \cdot I \cdot \ldots \cdot I}_{N \text{ factors}} = I^N$$

computationally infeasible!

Viterbi Algorithm

- Based on dynamic programming (similar to DTW)
- Idea: Recursive computation from subproblems
- Use truncated versions of observation sequence

$$O(1{:}n) := (o_1, \ldots, o_n), \text{ length } n \in [1{:}N]$$

- Define $\mathbf{D}(i,n)$ as the highest probability along a single state sequence $(s_1, \ldots, s_n)$ that ends in state $s_n = \alpha_i$

$$\mathbf{D}(i,n) = \max_{(s_1,\ldots,s_n)} P[O(1{:}n), (s_1, \ldots, s_{n-1}, s_n = \alpha_i) \mid \Theta]$$

- Then, our solution is the state sequence yielding

$$\mathrm{Prob}^* = \max_{i \in [1:I]} \mathbf{D}(i,N)$$

Viterbi Algorithm

- $\mathbf{D}$: matrix of size $I \times N$
- Recursive computation of $\mathbf{D}(i, n)$ along the column index n
- Initialization:
  - $n = 1$
  - Truncated observation sequence: $O(1) = (o_1)$
  - Current observation: $o_1 = \beta_{k_1}$

$\mathbf{D}(i, 1) = c_i \cdot b_{ik_1}$ for some $i \in [1:I]$

Viterbi Algorithm

- $\mathbf{D}$: matrix of size $I \times N$
- Recursive computation of $\mathbf{D}(i,n)$ along the column index n
- Recursion:
  - $n \in [2:N]$
  - Truncated observation sequence: $O(1:n) = (o_1, \dots, o_n)$
  - Last observation: $o_n = \beta_{k_n}$

$$\mathbf{D}(i,n) = b_{ik_n} \cdot a_{j^*i} \cdot \underbrace{P\big[O(1:n-1), (s_1, \dots, s_{n-1} = \alpha_{j^*}) \,\big|\, \Theta\big]}_{\text{must be maximal!}} \qquad \text{for } i \in [1:I]$$

$$\mathbf{D}(i,n) = b_{ik_n} \cdot a_{j^*i} \cdot \mathbf{D}(j^*, n-1)$$

Viterbi Algorithm

- $\mathbf{D}$: matrix of size $I \times N$
- Recursive computation of $\mathbf{D}(i,n)$ along the column index n
- Recursion:
  - $n \in [2:N]$
  - Truncated observation sequence: $O(1:n) = (o_1, \ldots, o_n)$
  - Last observation: $o_n = \beta_{k_n}$

$$\mathbf{D}(i,n) = b_{ik_n} \cdot a_{j^*i} \cdot \underbrace{P\left[O(1:n-1), (s_1, \ldots, s_{n-1} = \alpha_{j^*}) \,\middle|\, \Theta\right]}_{\text{must be maximal!}} \qquad \text{for } i \in [1:I]$$

$$\mathbf{D}(i,n) = b_{ik_n} \cdot \underbrace{a_{j^*i} \cdot \mathbf{D}(j^*, n-1)}_{\text{must be maximal (best index } j^*\text{)}}$$

$$\mathbf{D}(i,n) = b_{ik_n} \cdot \max_{j \in [1:I]} \left(a_{ji} \cdot \mathbf{D}(j, n-1) \right)$$

Viterbi Algorithm

- $\mathbf{D}$ given – find optimal state sequence $S^* = (s_1^*, \dots, s_N^*) := (\alpha_{i_1}, \dots, \alpha_{i_N})$
- Backtracking procedure (reverse order)
- Last element:
  - $n = N$
  - Optimal state: α_{i_N}

$$i_N = \underset{j \in [1:I]}{\operatorname{argmax}} \, \mathbf{D}(j, N)$$

Viterbi Algorithm

- $\mathbf{D}$ given – find optimal state sequence $S^* = (s_1^*, \dots, s_N^*) := \left(\alpha_{i_1}, \dots, \alpha_{i_N}\right)$
- Backtracking procedure (reverse order)
- Further elements:
  - $n = N-1, N-2, \dots, 1$
  - Optimal state: α_{i_n}

$$i_n = \underset{j \in [1:I]}{\operatorname{argmax}} \left(a_{j i_{n+1}} \cdot \mathbf{D}(i, n) \right)$$

Viterbi Algorithm

- $\mathbf{D}$ given – find optimal state sequence $S^* = (s_1^*, \dots, s_N^*) := \left(\alpha_{i_1}, \dots, \alpha_{i_N}\right)$
- Backtracking procedure (reverse order)
- Further elements:
  - $n = N-1, N-2, \dots, 1$
  - Optimal state: α_{i_n}

$$i_n = \underset{j \in [1:I]}{\operatorname{argmax}} \left(a_{j i_{n+1}} \cdot \mathbf{D}(i, n)\right)$$

- Simplification of backtracking: Keep track of maximizing index j in

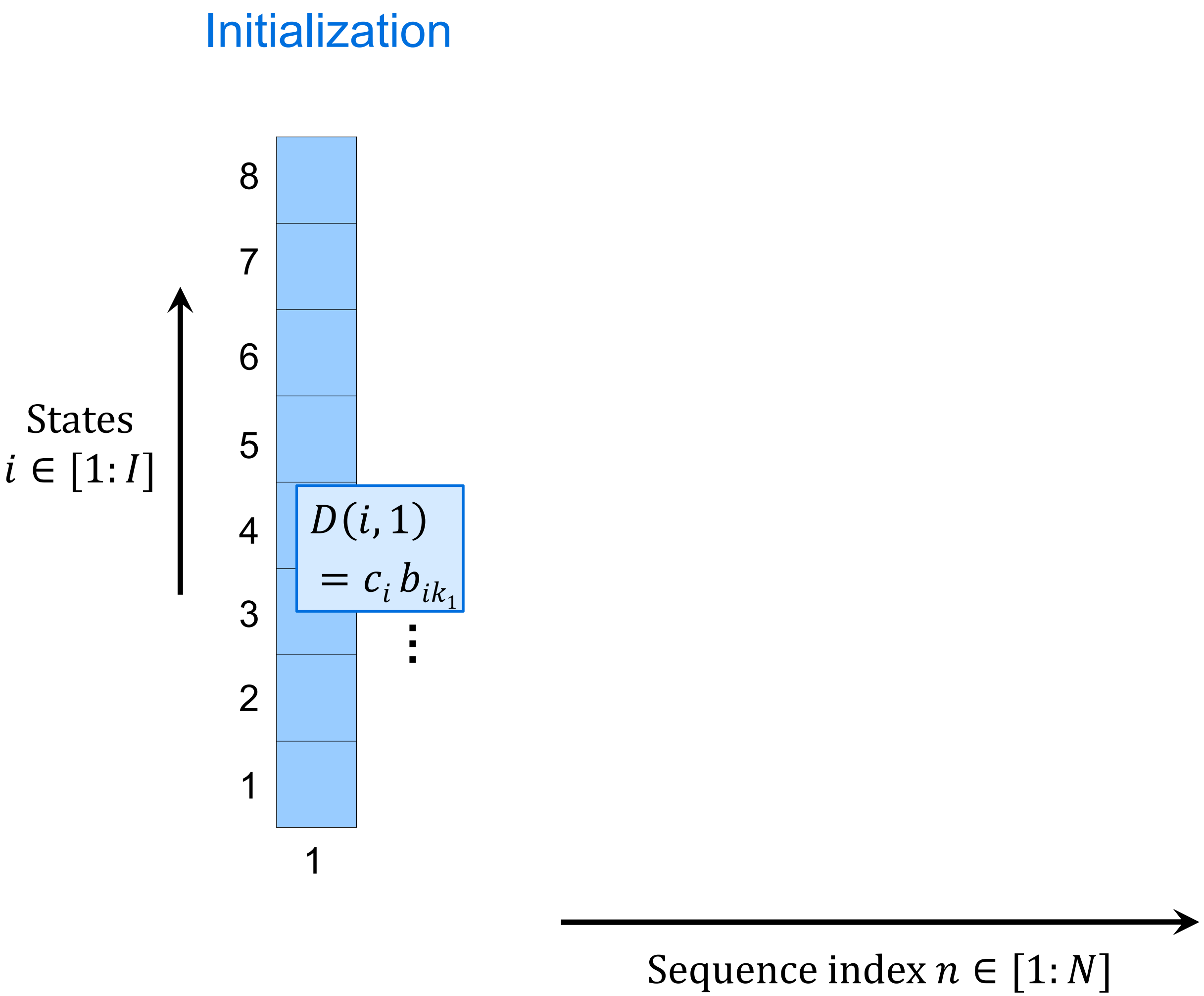
$$\mathbf{D}(i, n) = b_{i k_n} \cdot \max_{j \in [1:I]} \left(a_{ji} \cdot \mathbf{D}(j, n-1)\right)$$

- Define $I \times (N-1)$ matrix $\mathbf{E}$:

$$\mathbf{E}(i, n-1) = \underset{j \in [1:I]}{\operatorname{argmax}} \left(a_{ji} \cdot \mathbf{D}(j, n-1)\right)$$

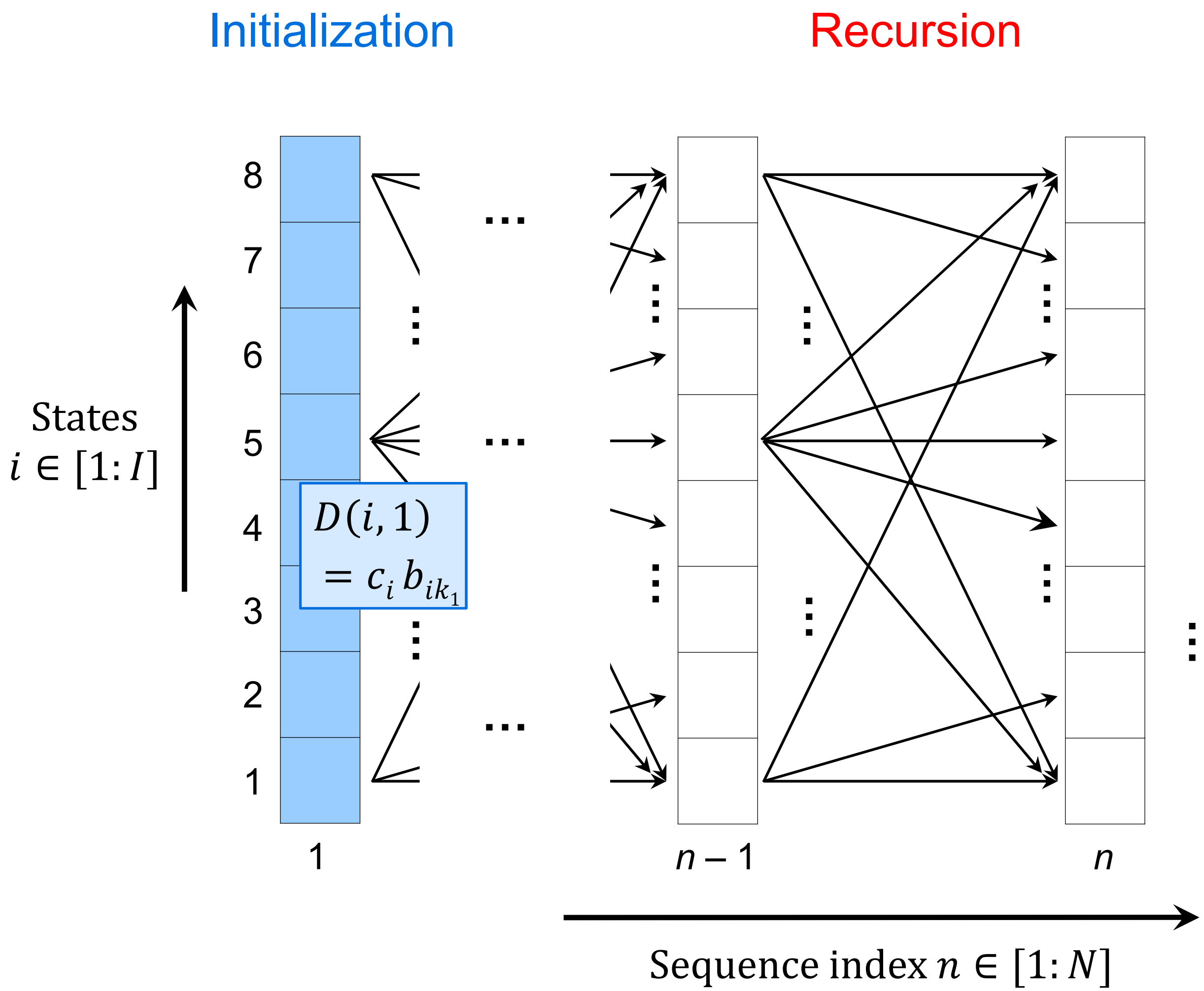
Viterbi Algorithm

Summary



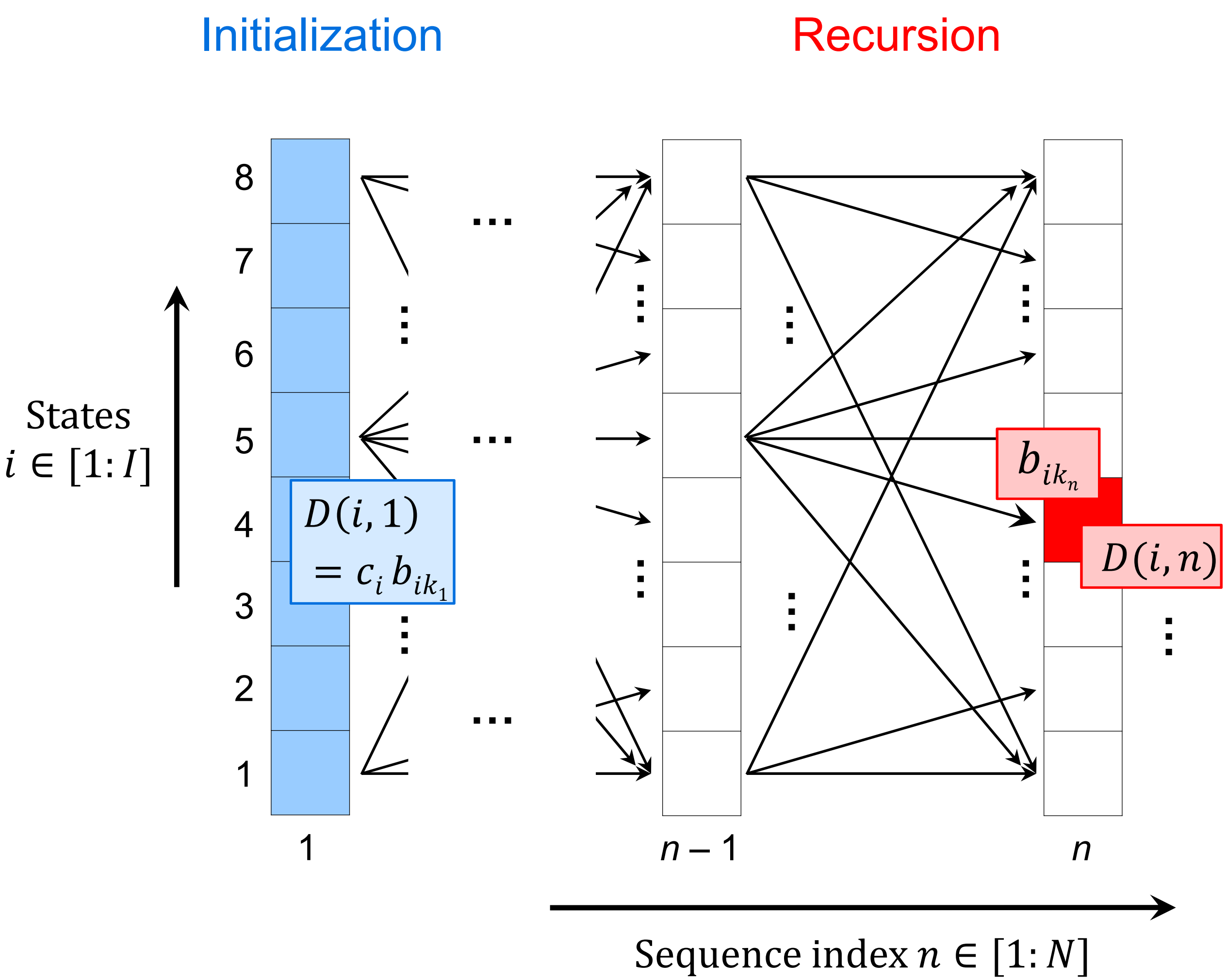
Viterbi Algorithm

Summary



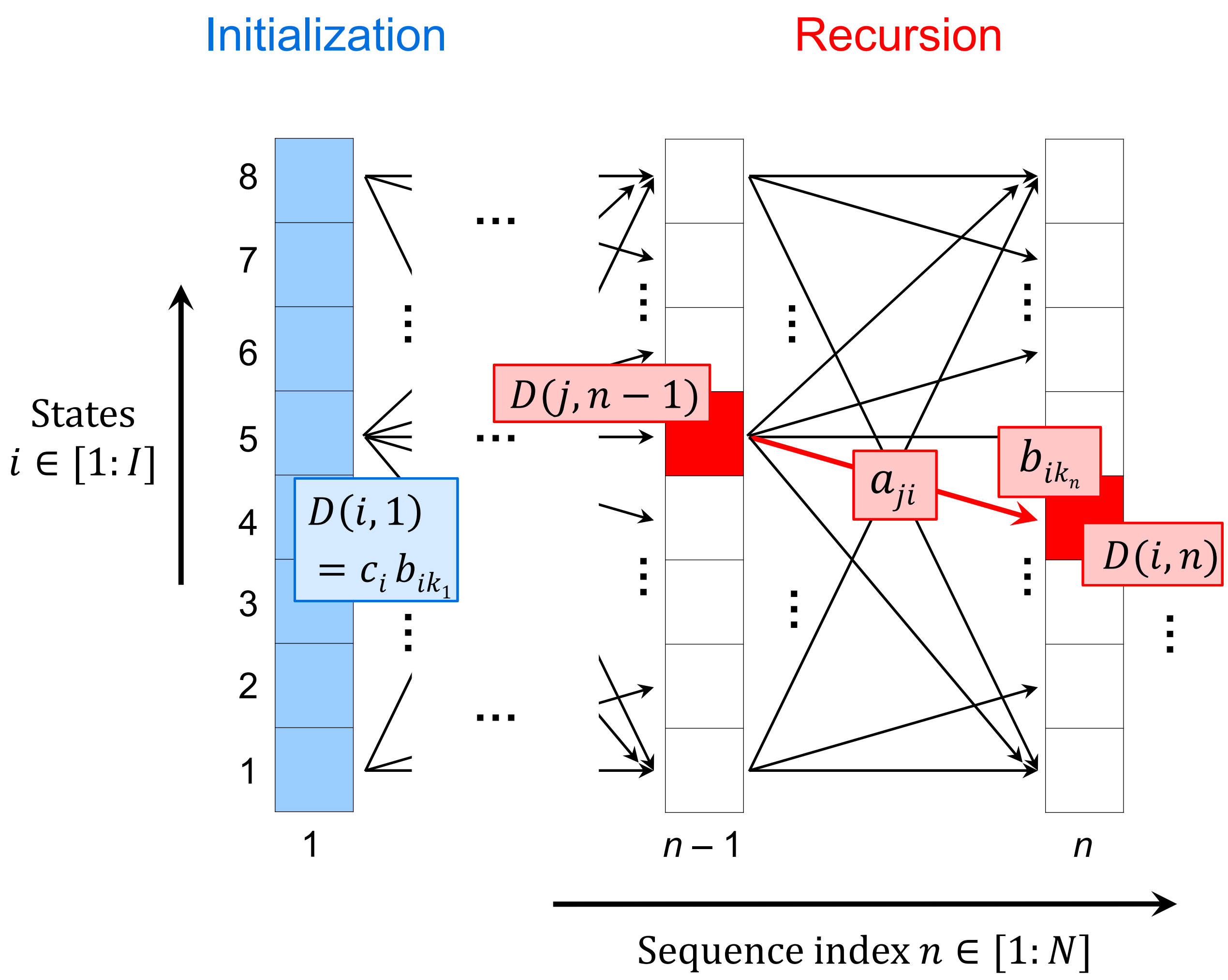
Viterbi Algorithm

Summary



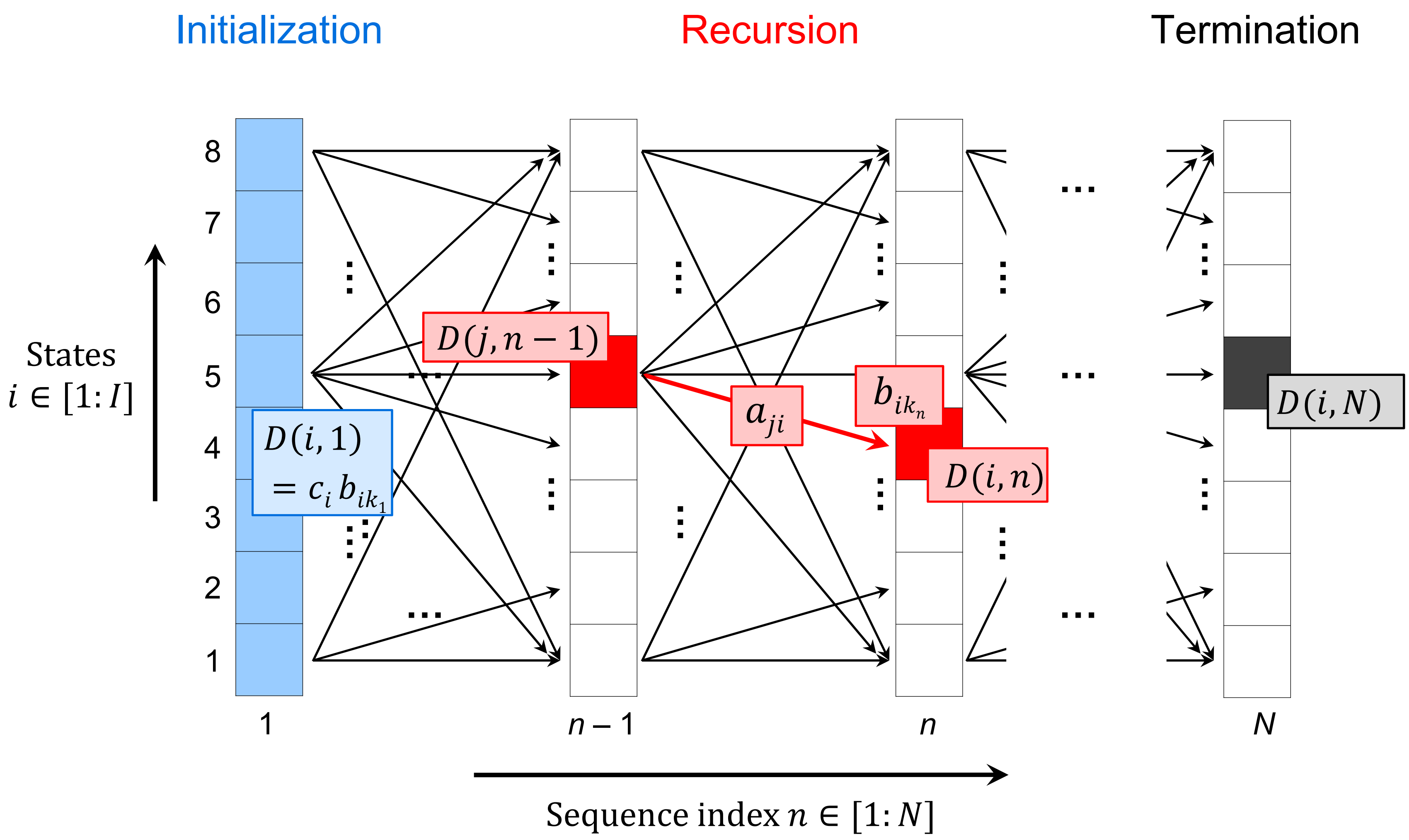
Viterbi Algorithm

Summary



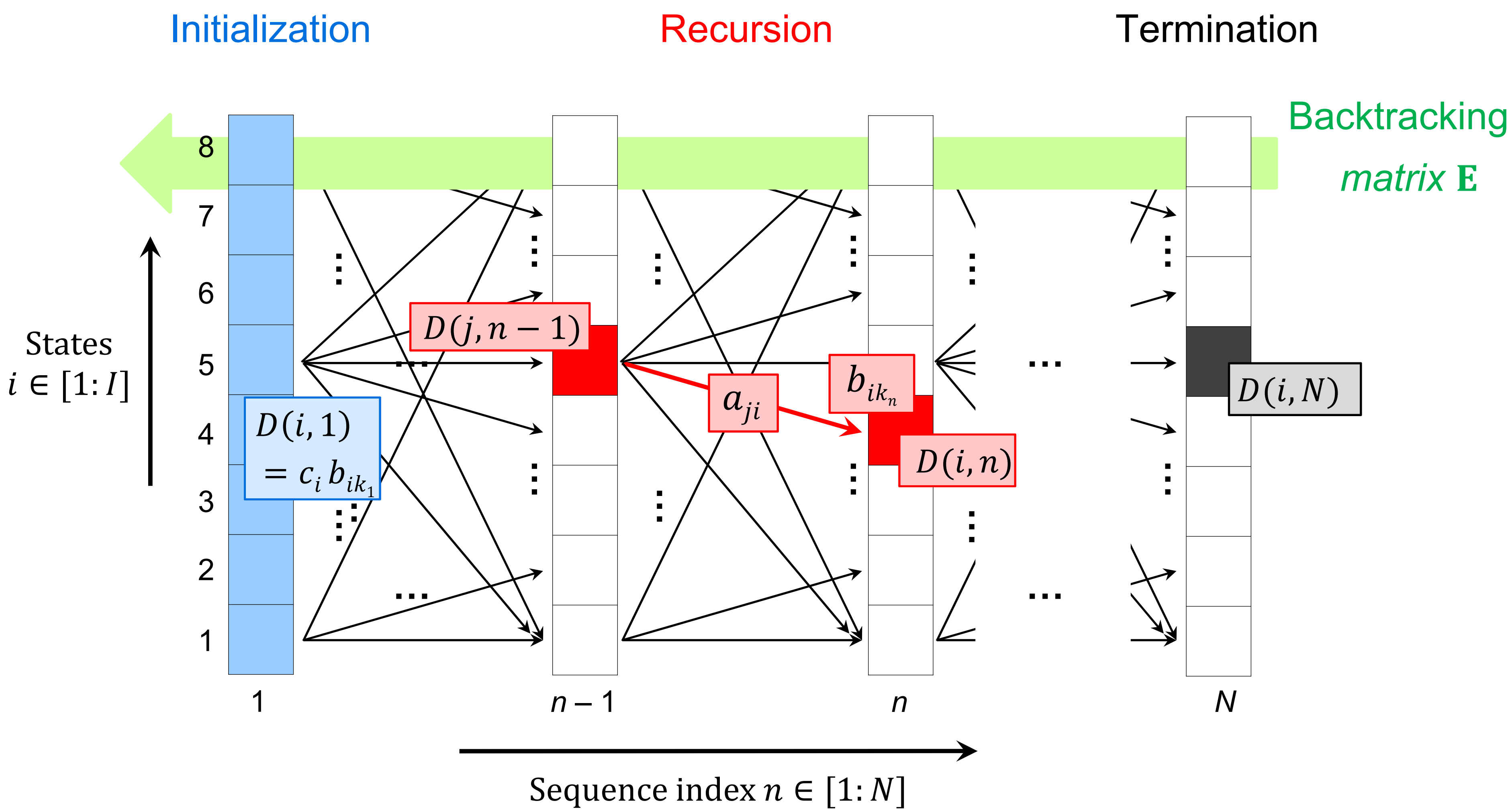
Viterbi Algorithm

Summary



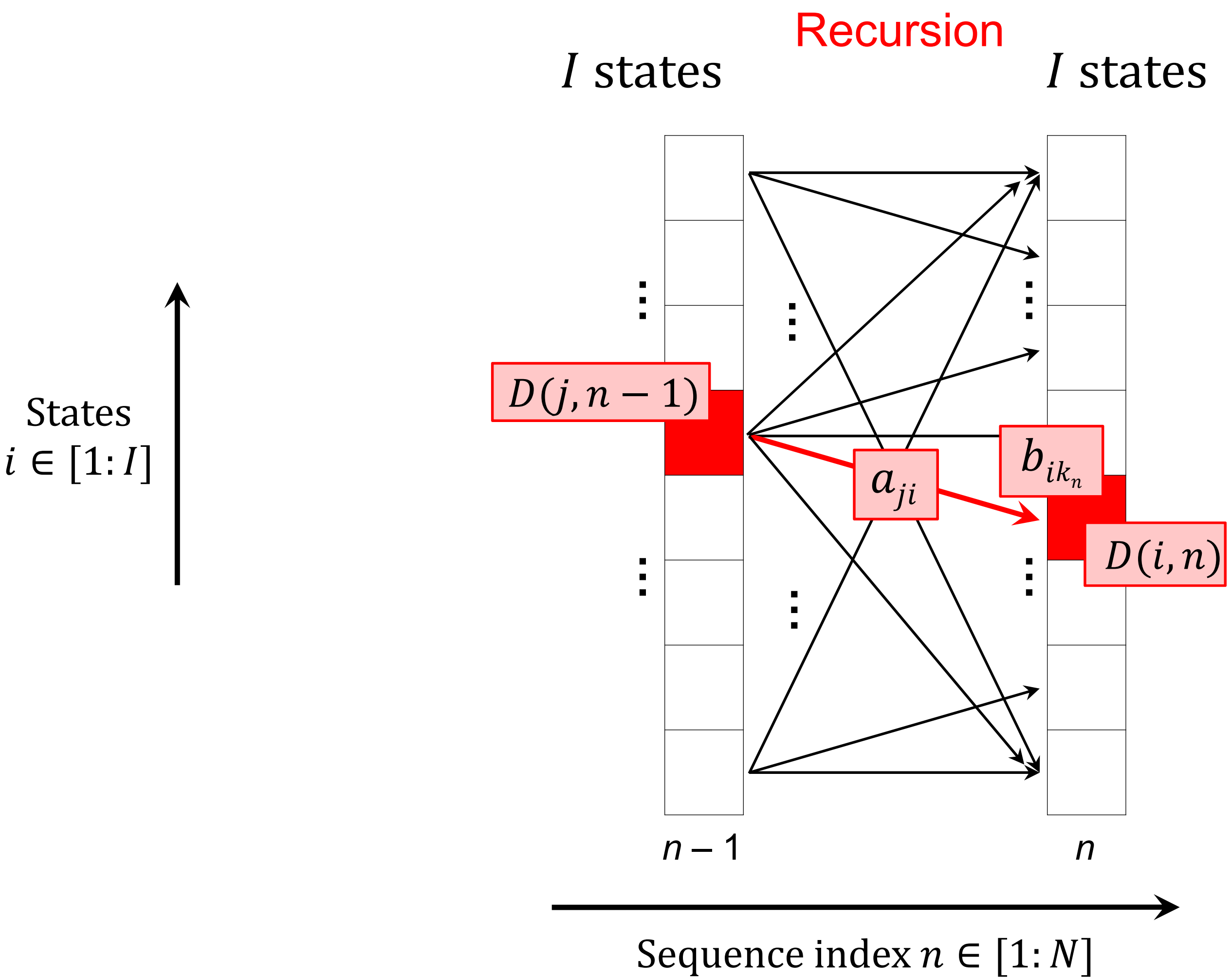
Viterbi Algorithm

Summary



Viterbi Algorithm

Computational Complexity



Per recursion step:
$I \cdot I$

Total recursion:
$I^2 \cdot N$

Viterbi Algorithm

Summary

Algorithm: VITERBI

Input: HMM specified by $\Theta = (\mathcal{A}, A, C, \mathcal{B}, B)$
Observation sequence $O = (o_1 = \beta_{k_1}, o_2 = \beta_{k_2}, \ldots, o_N = \beta_{k_N})$
Output: Optimal state sequence $S^* = (s_1^*, s_2^*, \ldots, s_N^*)$

Procedure: Initialize the $(I \times N)$ matrix $\mathbf{D}$ by $\mathbf{D}(i,1) = c_i b_{ik_1}$ for $i \in [1:I]$. Then compute in a nested loop for $n = 2, \ldots, N$ and $i = 1, \ldots, I$:

$$\begin{aligned}
\mathbf{D}(i,n) &= \max_{j \in [1:I]} \left(a_{ji} \cdot \mathbf{D}(j, n-1) \right) \cdot b_{ik_n} \\
\mathbf{E}(i,n-1) &= \operatorname{argmax}_{j \in [1:I]} \left(a_{ji} \cdot \mathbf{D}(j, n-1) \right)
\end{aligned}$$

Set $i_N = \operatorname{argmax}_{j \in [1:I]} \mathbf{D}(j,N)$ and compute for decreasing $n = N-1, \ldots, 1$ the maximizing indices

$$i_n = \operatorname{argmax}_{j \in [1:I]} \left(a_{ji_{n+1}} \cdot \mathbf{D}(j,n) \right) = \mathbf{E}(i_{n+1}, n).$$

The optimal state sequence $S^* = (s_1^*, \ldots, s_N^*)$ is defined by $s_n^* = \alpha_{i_n}$ for $n \in [1:N]$.

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	a_{11}	a_{12}	a_{13}
α_2	a_{21}	a_{22}	a_{23}
α_3	a_{31}	a_{32}	a_{33}

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	b_{11}	b_{12}	b_{13}
α_2	b_{21}	b_{22}	b_{23}
α_3	b_{31}	b_{32}	b_{33}

Initial state probabilities

c_i

C	α_1	α_2	α_3
	c_1	c_2	c_3

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	0.8	0.1	0.1
α_2	0.2	0.7	0.1
α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	0.8	0.1	0.1
α_2	0.2	0.7	0.1
α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

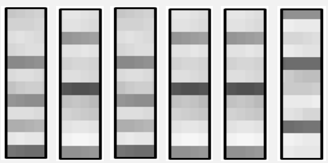
c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

Observation sequence

$O = (o_1, o_2, o_3, o_4, o_5, o_6)$



β_1 β_3 β_1 β_3 β_3 β_2

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

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α_3	0.1	0.3	0.6

Emission probabilities

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α_1	0.7	0	0.3
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α_3	0	0.2	0.8

Initial state probabilities

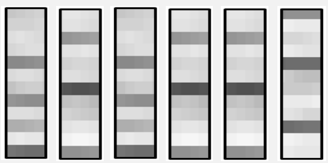
c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

Observation sequence

$O = (o_1,o_2,o_3,o_4,o_5,o_6)$



β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$	$o_6 = \beta_2$
α_1						
α_2						
α_3						

E	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$
α_1					
α_2					
α_3					

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
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Emission probabilities

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α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

o_1 o_2 o_3 o_4 o_5 o_6

β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1=\beta_1$	$o_2=\beta_3$	$o_3=\beta_1$	$o_4=\beta_3$	$o_5=\beta_3$	$o_6=\beta_2$
α_1						
α_2						
α_3						

E	$o_1=\beta_1$	$o_2=\beta_3$	$o_3=\beta_1$	$o_4=\beta_3$	$o_5=\beta_3$
α_1					
α_2					
α_3					

Initialization

$$\mathbf{D}(i,1) = c_i \cdot b_{ik_1}$$

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

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α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

o_1 o_2 o_3 o_4 o_5 o_6

β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$	$o_6 = \beta_2$
α_1	0.4200					
α_2	0.0200					
α_3	0					

E	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$
α_1					
α_2					
α_3					

Initialization

$$\mathbf{D}(i,1) = c_i \cdot b_{ik_1}$$

Recursion

$$\mathbf{D}(i,n) = b_{ik_n} \cdot \max_{j\in[1:I]} \left(a_{ji} \cdot \mathbf{D}(j,n-1)\right)$$

$$\mathbf{E}(i,n-1) = \operatorname*{argmax}_{j\in[1:I]} \left(a_{ji} \cdot \mathbf{D}(j,n-1)\right)$$

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	0.8	0.1	0.1
α_2	0.2	0.7	0.1
α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

o_1 o_2 o_3 o_4 o_5 o_6

β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$	$o_6 = \beta_2$
α_1	0.4200	0.1008				
α_2	0.0200	0				
α_3	0	0.0336				

E	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$
α_1	1				
α_2	1				
α_3	1				

Initialization

$$\mathbf{D}(i,1) = c_i \cdot b_{ik_1}$$

Recursion

$$\mathbf{D}(i,n) = b_{ik_n} \cdot \max_{j\in[1:I]} \left(a_{ji} \cdot \mathbf{D}(j,n-1) \right)$$

$$\mathbf{E}(i,n-1) = \operatorname*{argmax}_{j\in[1:I]} \left(a_{ji} \cdot \mathbf{D}(j,n-1) \right)$$

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	0.8	0.1	0.1
α_2	0.2	0.7	0.1
α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

o_1 o_2 o_3 o_4 o_5 o_6

β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$	$o_6 = \beta_2$
α_1	0.4200	0.1008	0.0564	0.0135	0.0033	0
α_2	0.0200	0	0.0010	0	0	0.0006
α_3	0	0.0336	0	0.0045	0.0022	0.0003

E	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$
α_1	1	1	1	1	1
α_2	1	1	1	1	3
α_3	1	3	1	3	3

Backtracking

$$i_N = \underset{j \in [1:I]}{\operatorname{argmax}} \mathbf{D}(i, n)$$

$$i_n = \mathbf{E}(i_{n+1}, n)$$

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	0.8	0.1	0.1
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α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

o_1 o_2 o_3 o_4 o_5 o_6

β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$	$o_6 = \beta_2$
α_1	0.4200	0.1008	0.0564	0.0135	0.0033	0
α_2	0.0200	0	0.0010	0	0	0.0006
α_3	0	0.0336	0	0.0045	0.0022	0.0003

E	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$
α_1	1	1	1	1	1
α_2	1	1	1	1	3
α_3	1	3	1	3	3

$i_6 = 2$

Backtracking

$$i_N = \operatorname*{argmax}_{j \in [1:I]} \mathbf{D}(i, n)$$

$$i_n = \mathbf{E}(i_{n+1}, n)$$

Viterbi Algorithm: Example

HMM:

States

α_i for $i \in [1:I]$

Observation symbols

β_k for $k \in [1:K]$

State transition probabilities

a_{ij}

A	α_1	α_2	α_3
α_1	0.8	0.1	0.1
α_2	0.2	0.7	0.1
α_3	0.1	0.3	0.6

Emission probabilities

b_{ik}

B	β_1	β_2	β_3
α_1	0.7	0	0.3
α_2	0.1	0.9	0
α_3	0	0.2	0.8

Initial state probabilities

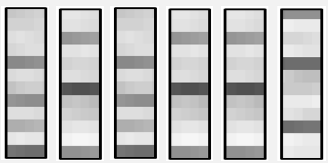
c_i

C	α_1	α_2	α_3
	0.6	0.2	0.2

Input

Observation sequence

$O = (o_1,o_2,o_3,o_4,o_5,o_6)$



β_1 β_3 β_1 β_3 β_3 β_2

Viterbi algorithm

D	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$	$o_6 = \beta_2$
α_1	0.4200	0.1008	0.0564	0.0135	0.0033	0
α_2	0.0200	0	0.0010	0	0	0.0006
α_3	0	0.0336	0	0.0045	0.0022	0.0003

E	$o_1 = \beta_1$	$o_2 = \beta_3$	$o_3 = \beta_1$	$o_4 = \beta_3$	$o_5 = \beta_3$
α_1	$\boxed{1}$	$\boxed{1}$	1	1	1
α_2	1	1	1	1	$\boxed{3}$
α_3	1	3	$\boxed{1}$	$\boxed{3}$	3

$\boxed{i_6 = 2}$

Output

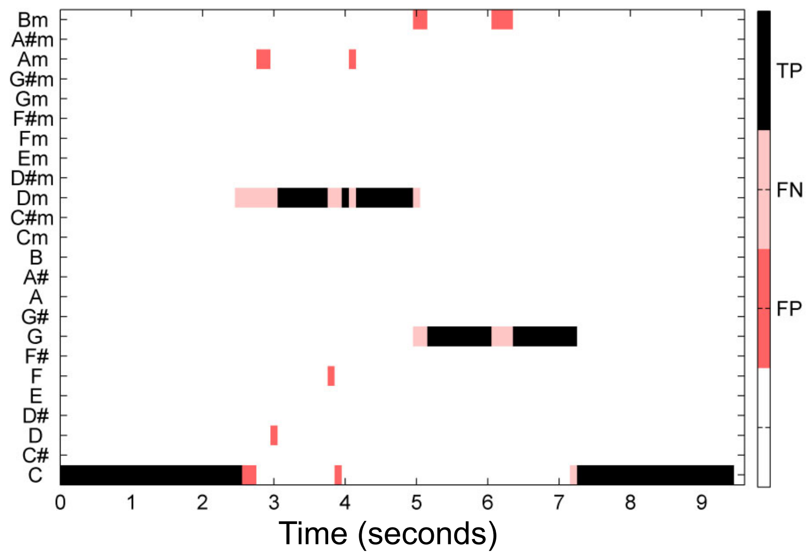
Optimal state sequence

$S^* = (\alpha_1,\alpha_1,\alpha_1,\alpha_3,\alpha_3,\alpha_2)$

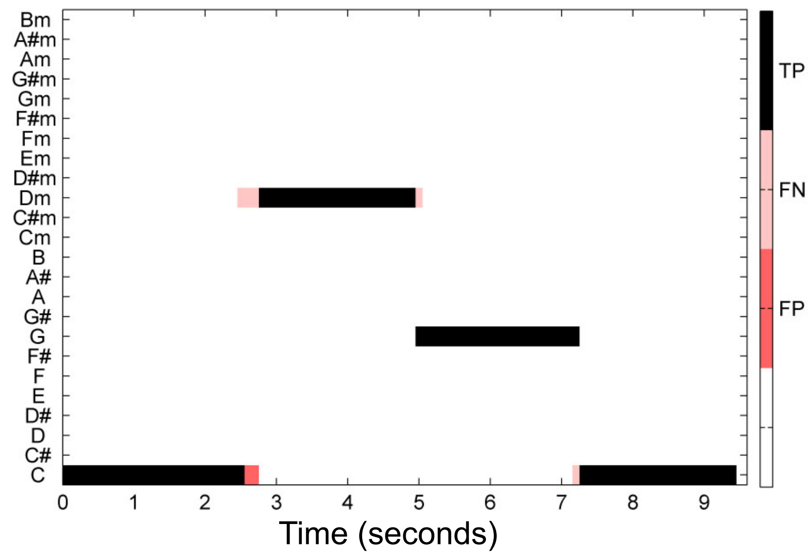
HMM: Application to Chord Recognition

- Effect of HMM-based chord estimation and smoothing:

(a) Template Matching (frame-wise)

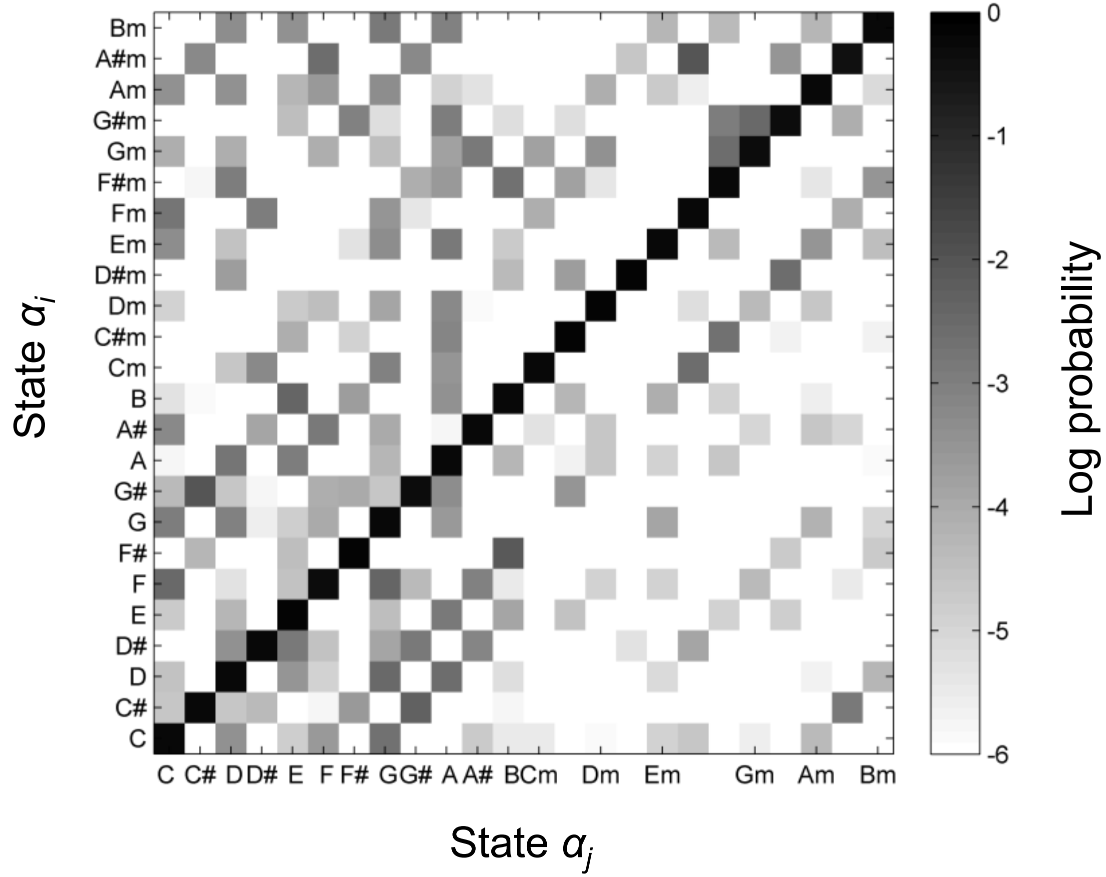


(b) HMM



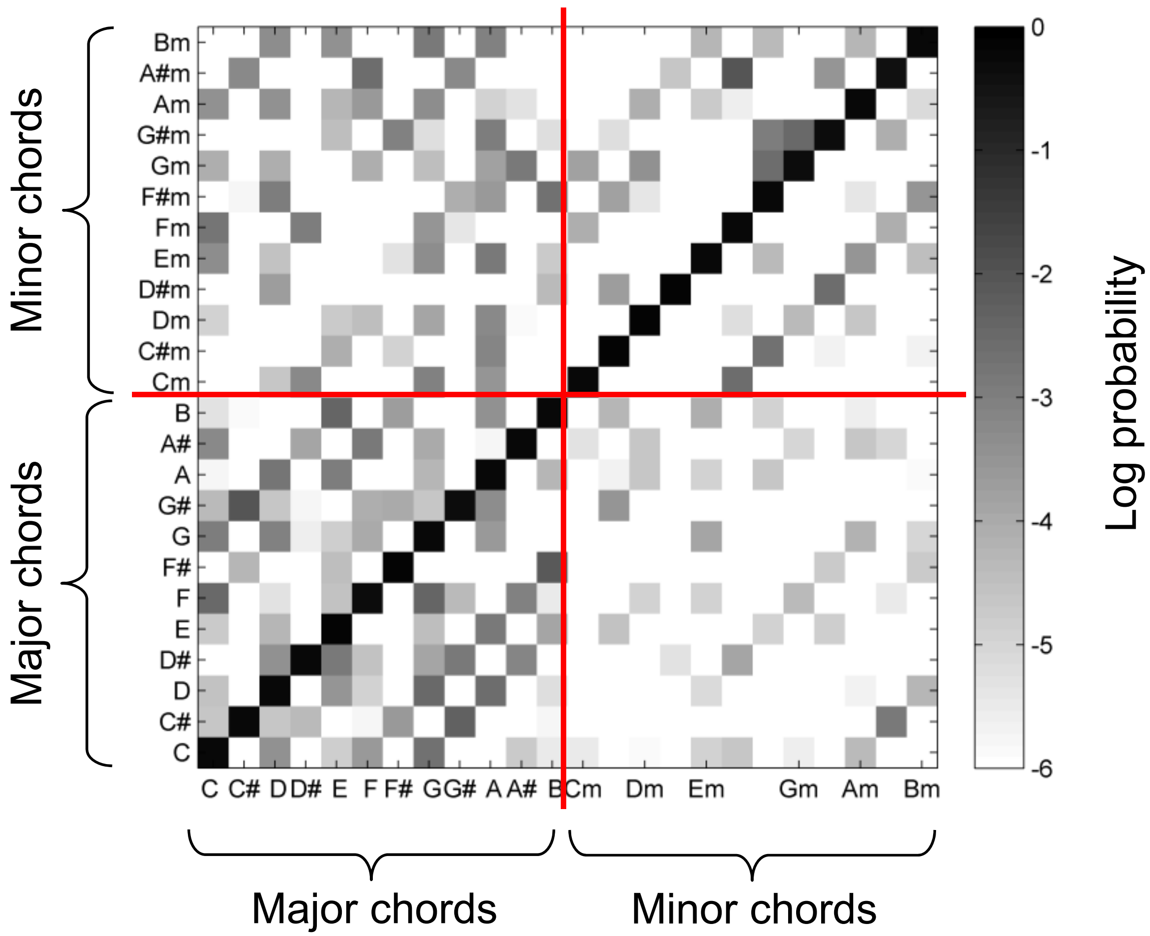
HMM: Application to Chord Recognition

- Parameters: **Transition probabilities**
- Estimated from data



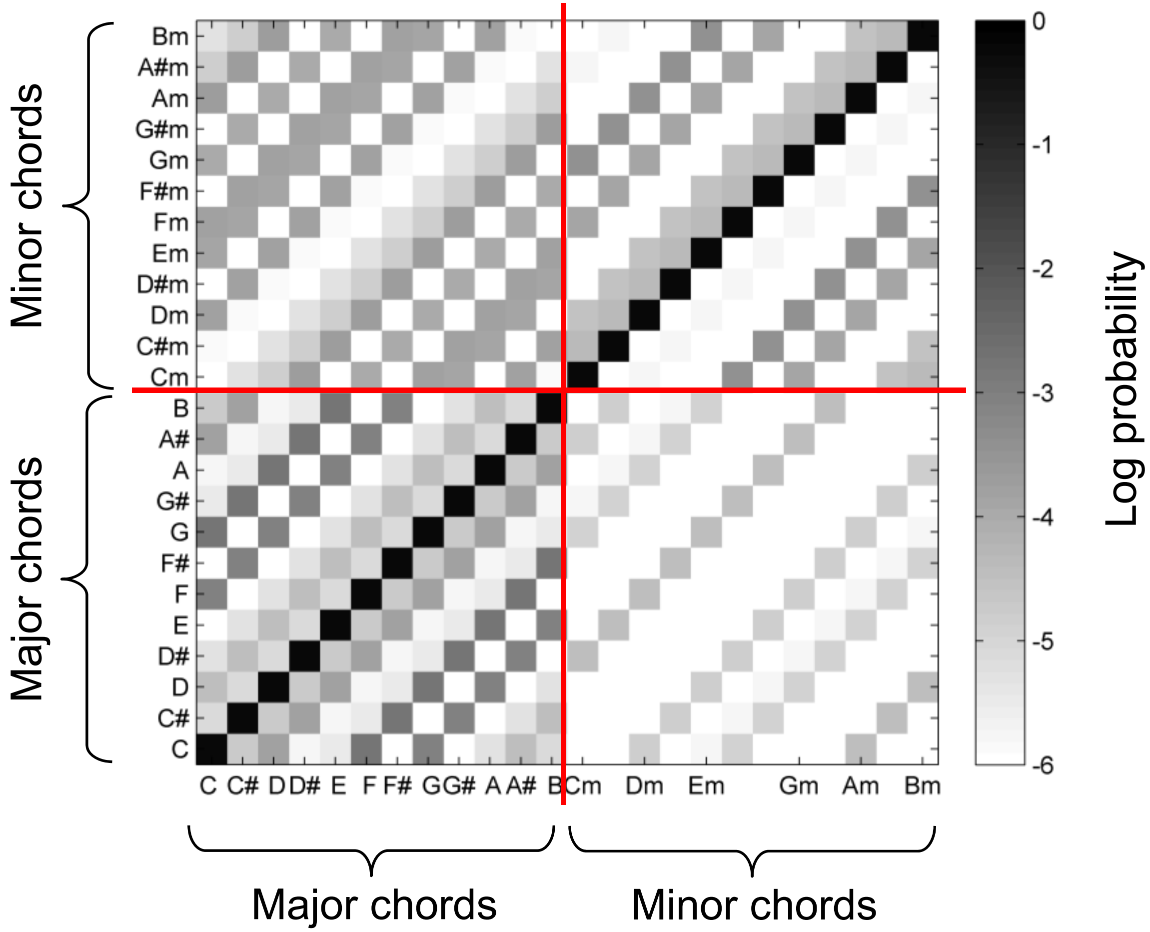
HMM: Application to Chord Recognition

- Parameters: **Transition probabilities**
- Estimated from data



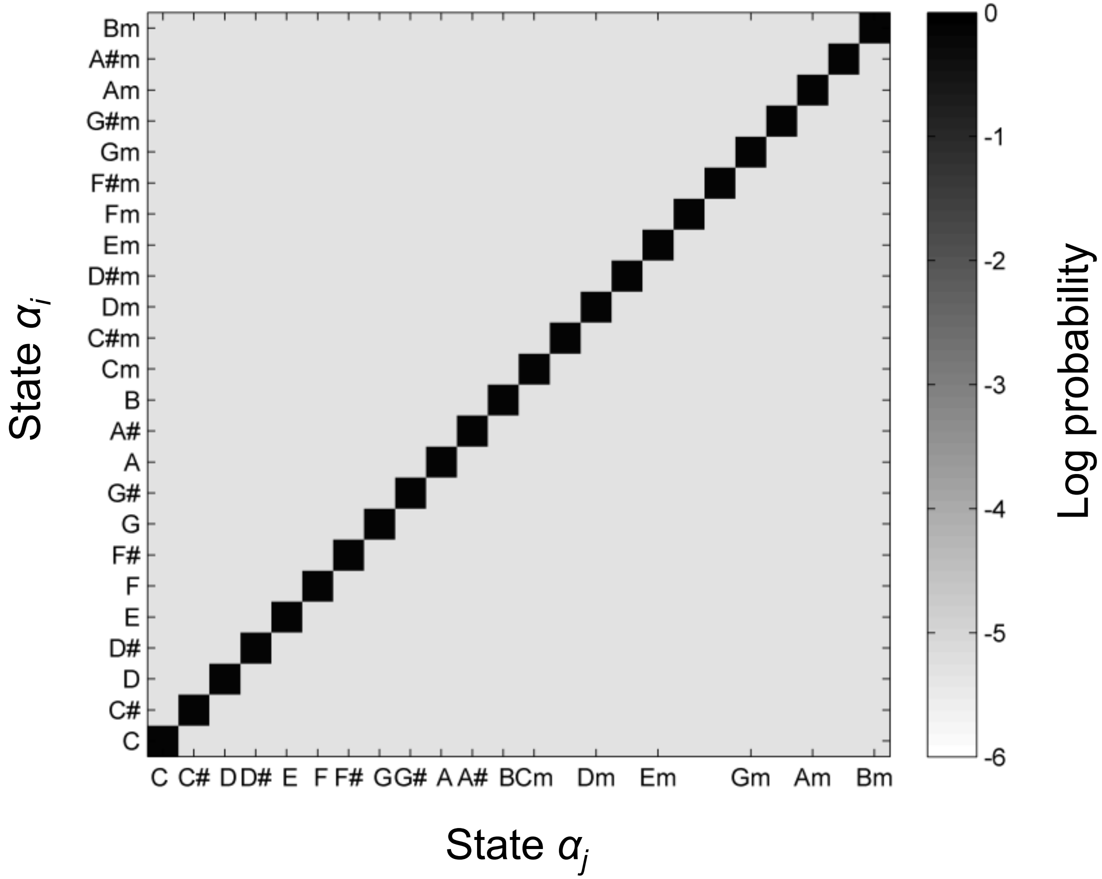
HMM: Application to Chord Recognition

- Parameters: **Transition probabilities**
- Transposition-invariant



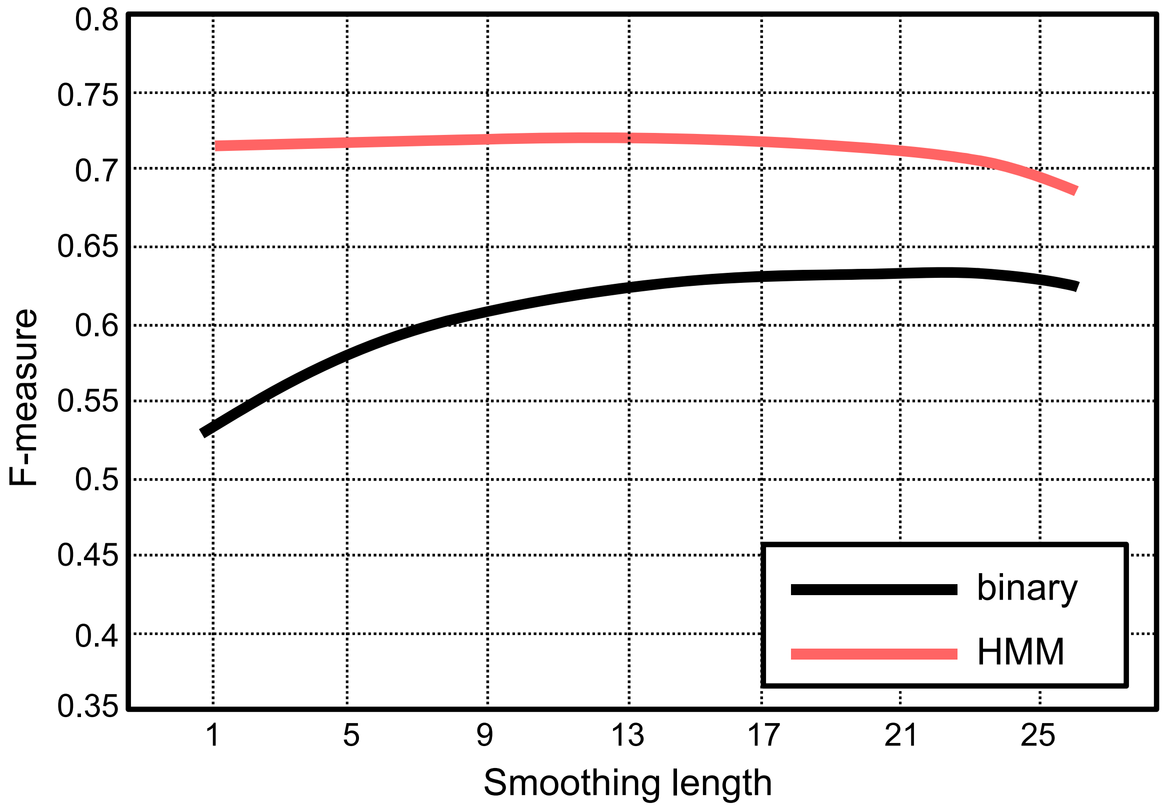
HMM: Application to Chord Recognition

- Parameters: **Transition probabilities**
- Uniform transition matrix (only smoothing)



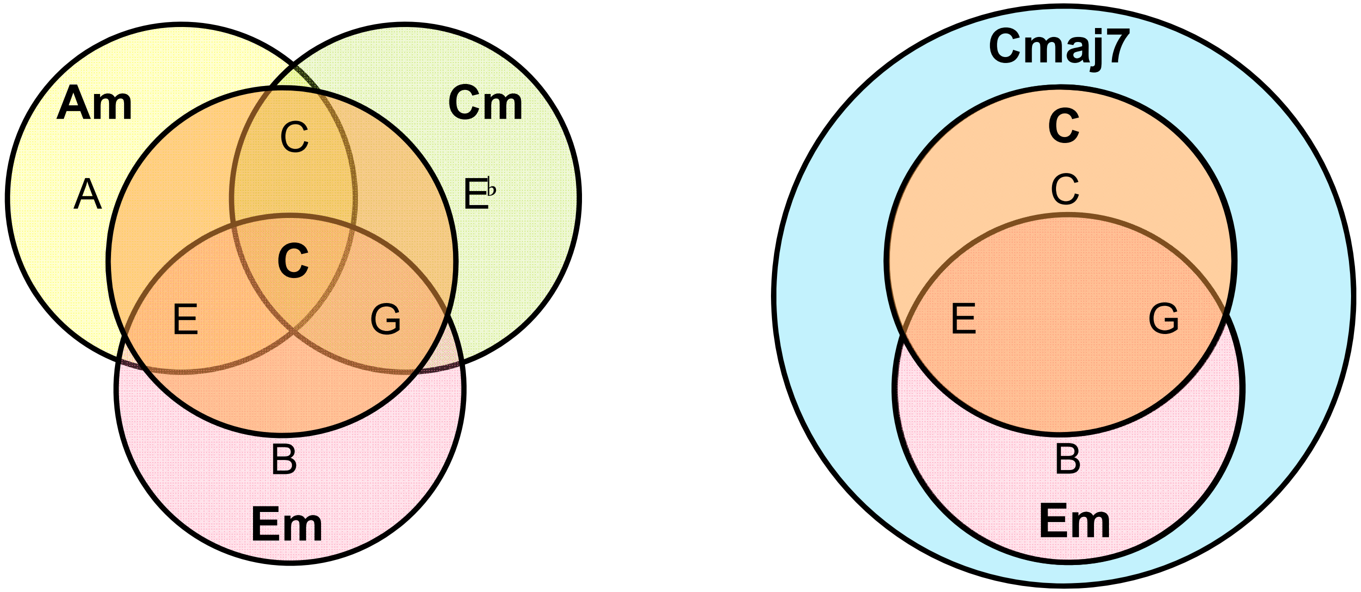
HMM: Application to Chord Recognition

- Evaluation on all Beatles songs



Chord Recognition: Further Challenges

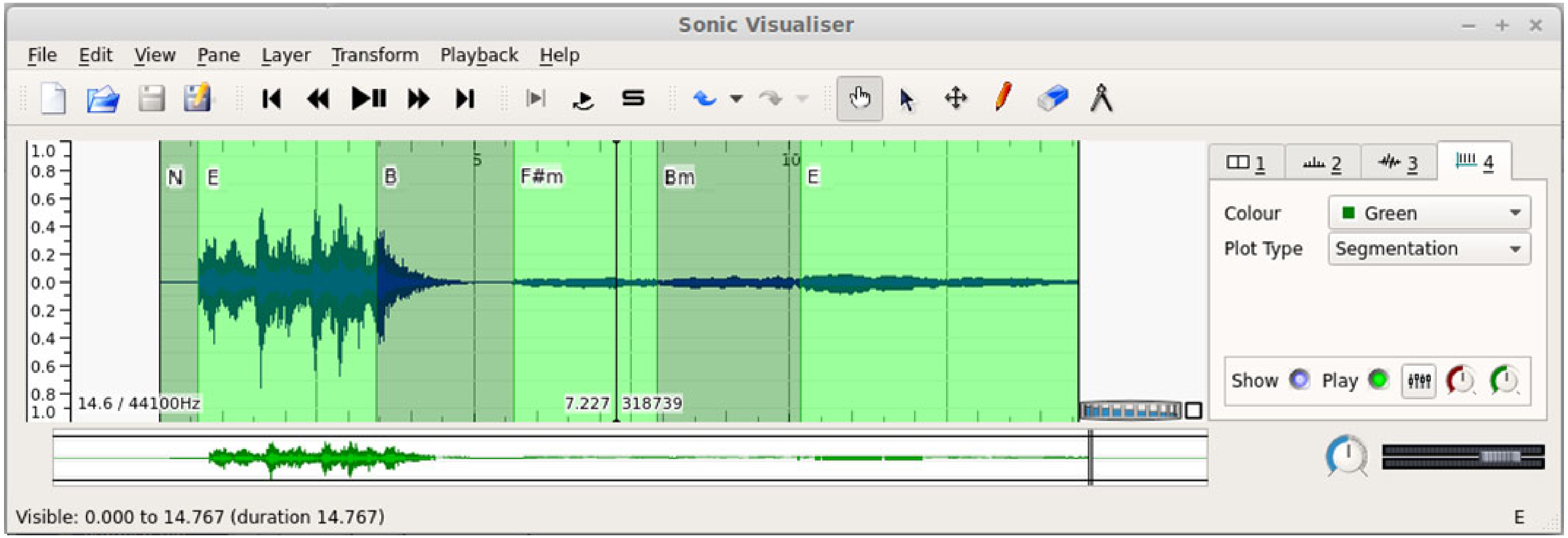
- Chord ambiguities



- Acoustic ambiguities (overtones)
  - Use advanced templates (model overtones, learned templates)
  - Enhanced chroma (logarithmic compression, overtone reduction)
- Tuning inconsistency

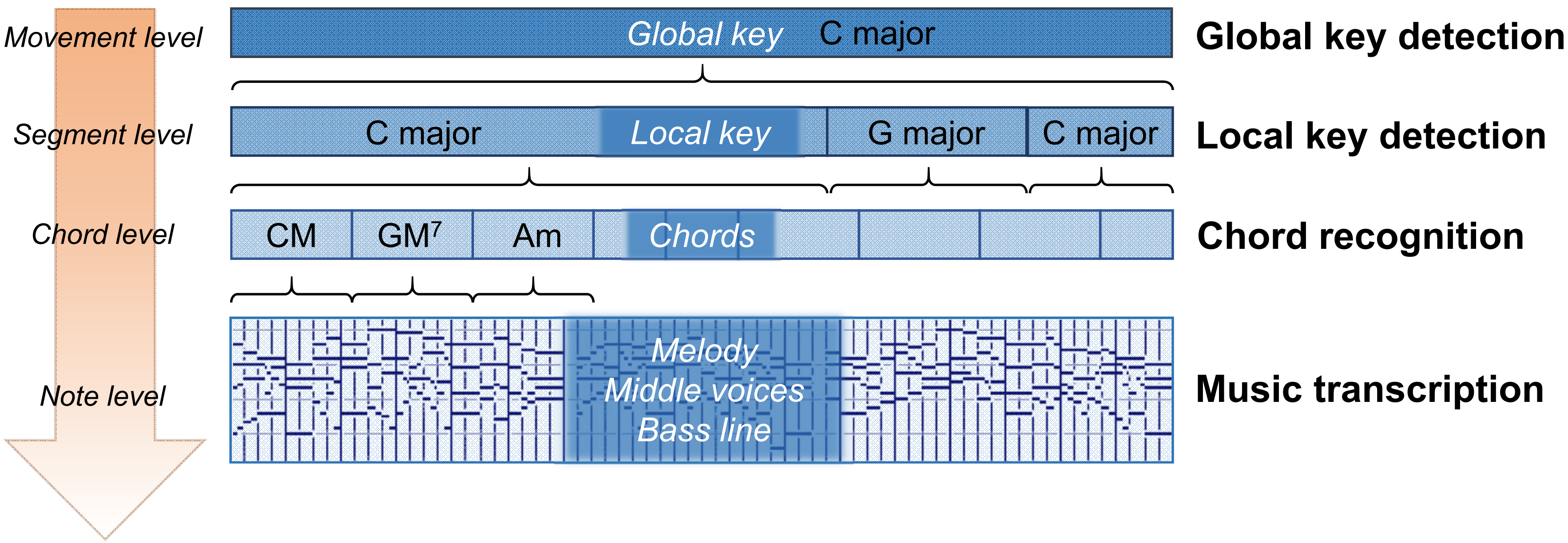
Chord Recognition: Public System

- Chord recognition
  - Typically: Feature extraction, pattern matching, filtering (HMM)
  - „Out-of-the-box“ solutions (Sonic Visualizer, Chordino plugin)

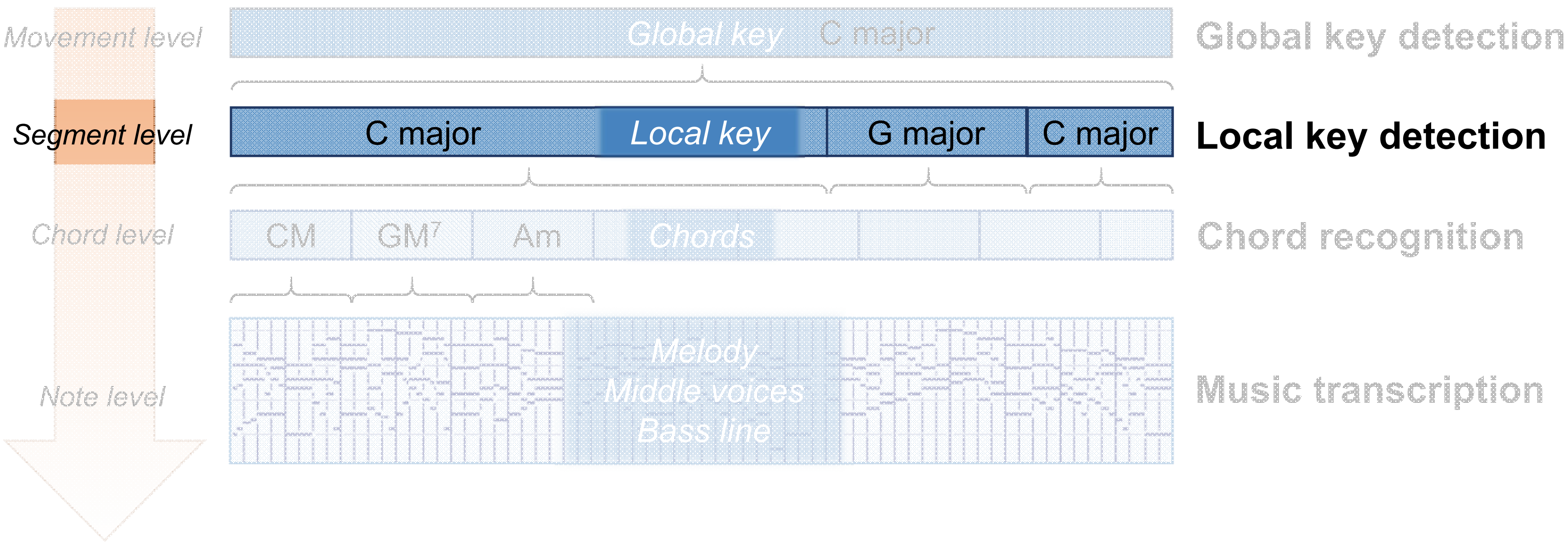


Sonic Visualizer, Chordino Vamp Plugin (Queen Mary University of London)

Tonal Structures

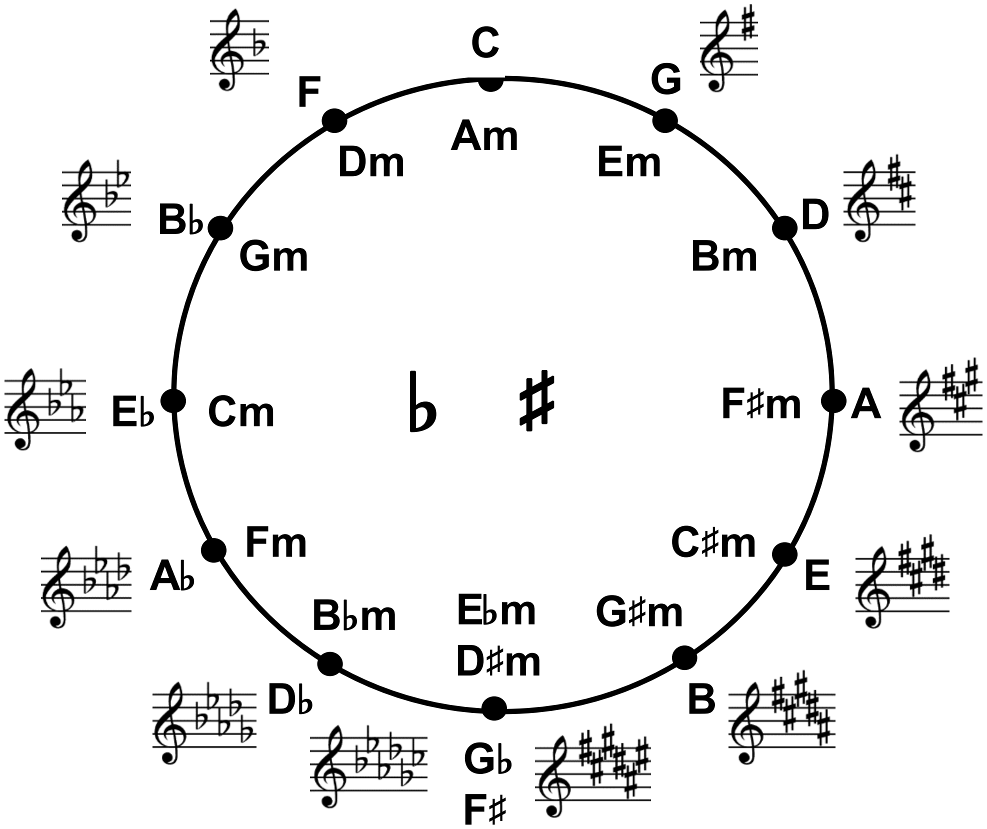


Tonal Structures



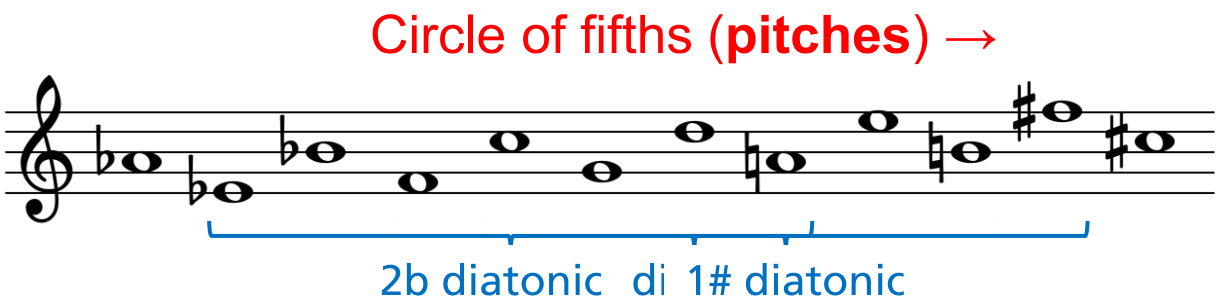
Local Key Detection

- Key as an important musical concept (*“Symphony in C major”*)
- Modulations → Local approach
- Key relations: Circle of fifth (**keys**)



Local Key Detection

- Key as an important musical concept (*“Symphony in C major”*)
- Modulations → Local approach
- Diatonic Scales
  - Simplification of keys
  - Perfect-fifth relation

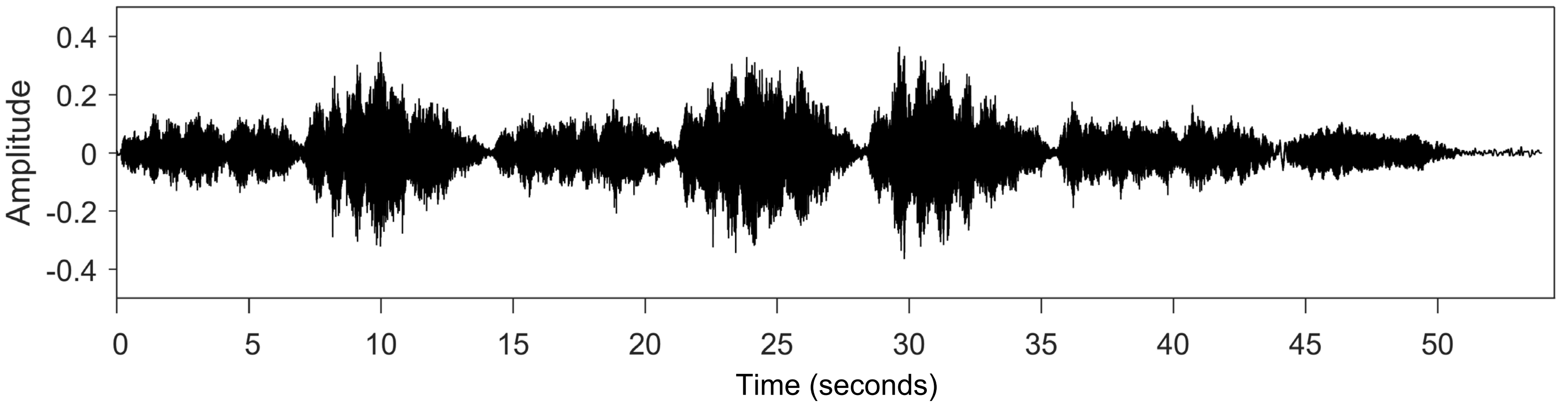


Local Key Detection

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

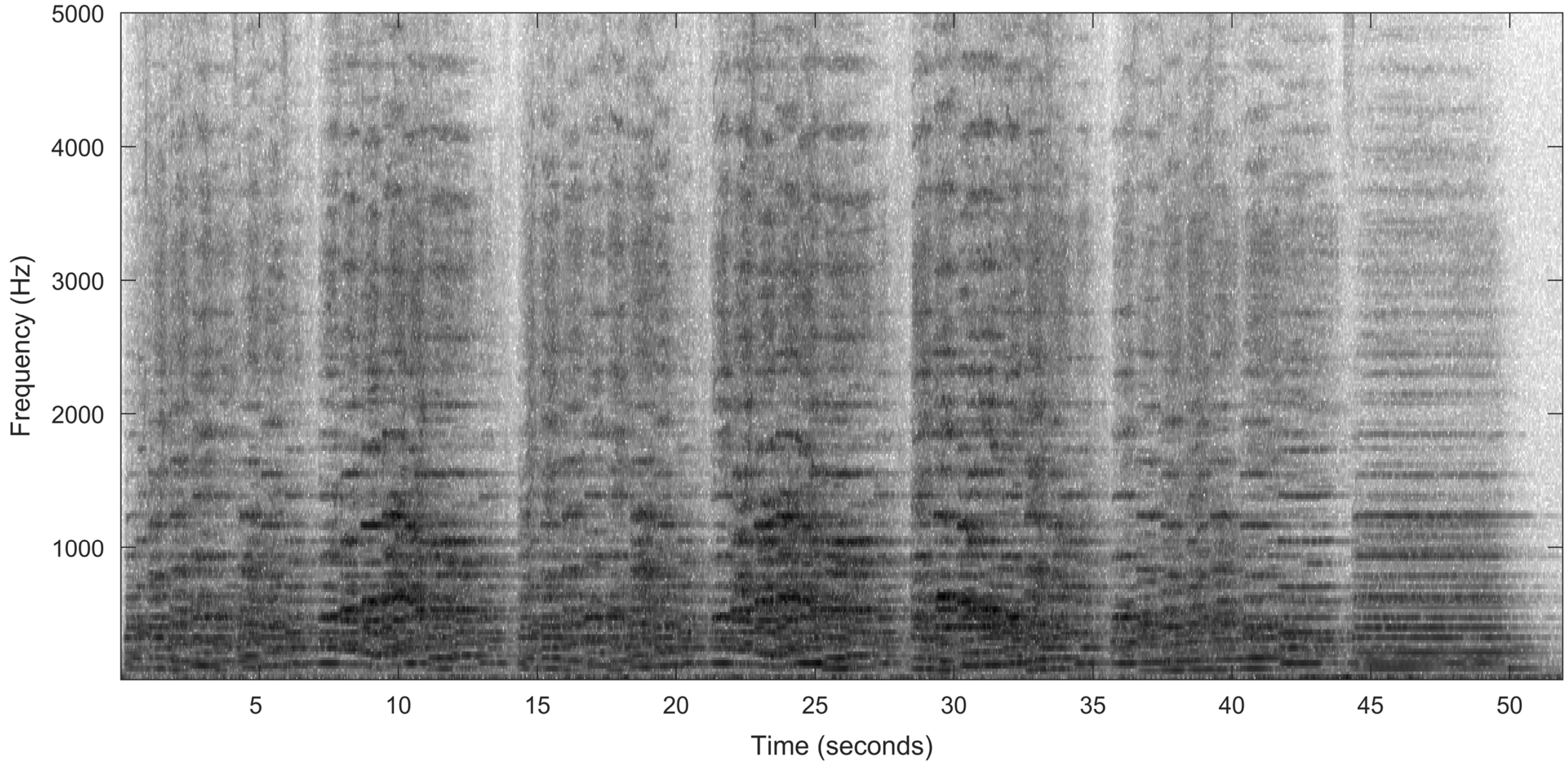
Local Key Detection

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



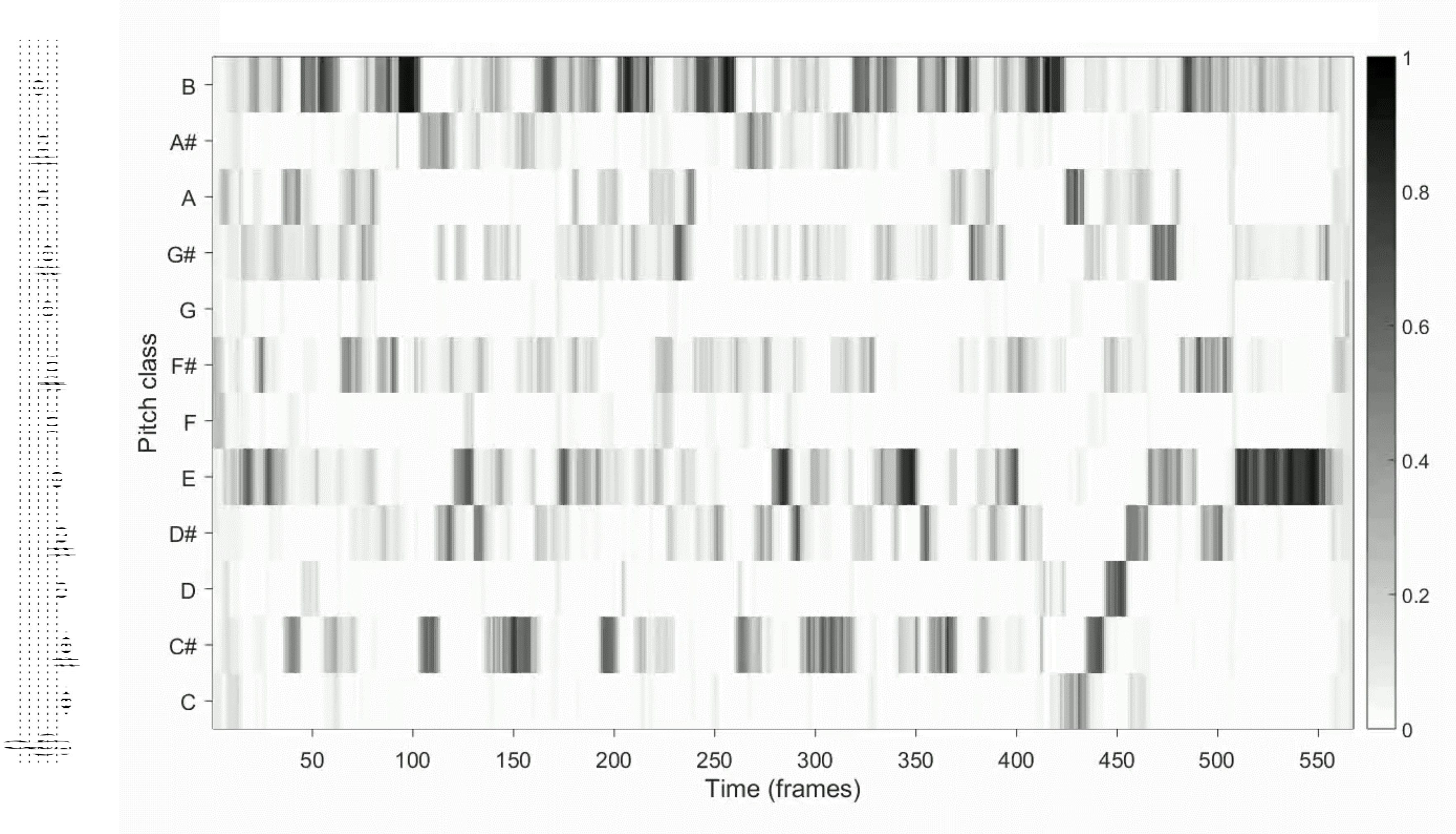
Tonal Structures: Local Diatonic Scales

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



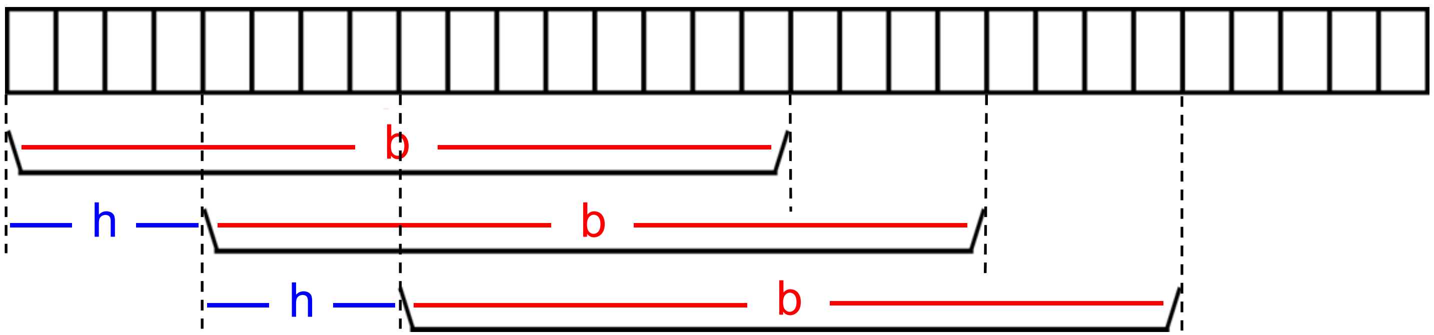
Local Key Detection: Chroma Features

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



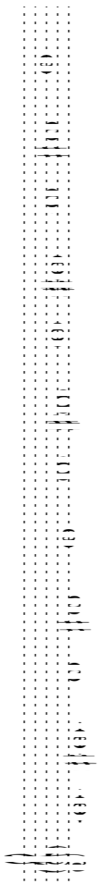
Local Key Detection: Chroma Smoothing

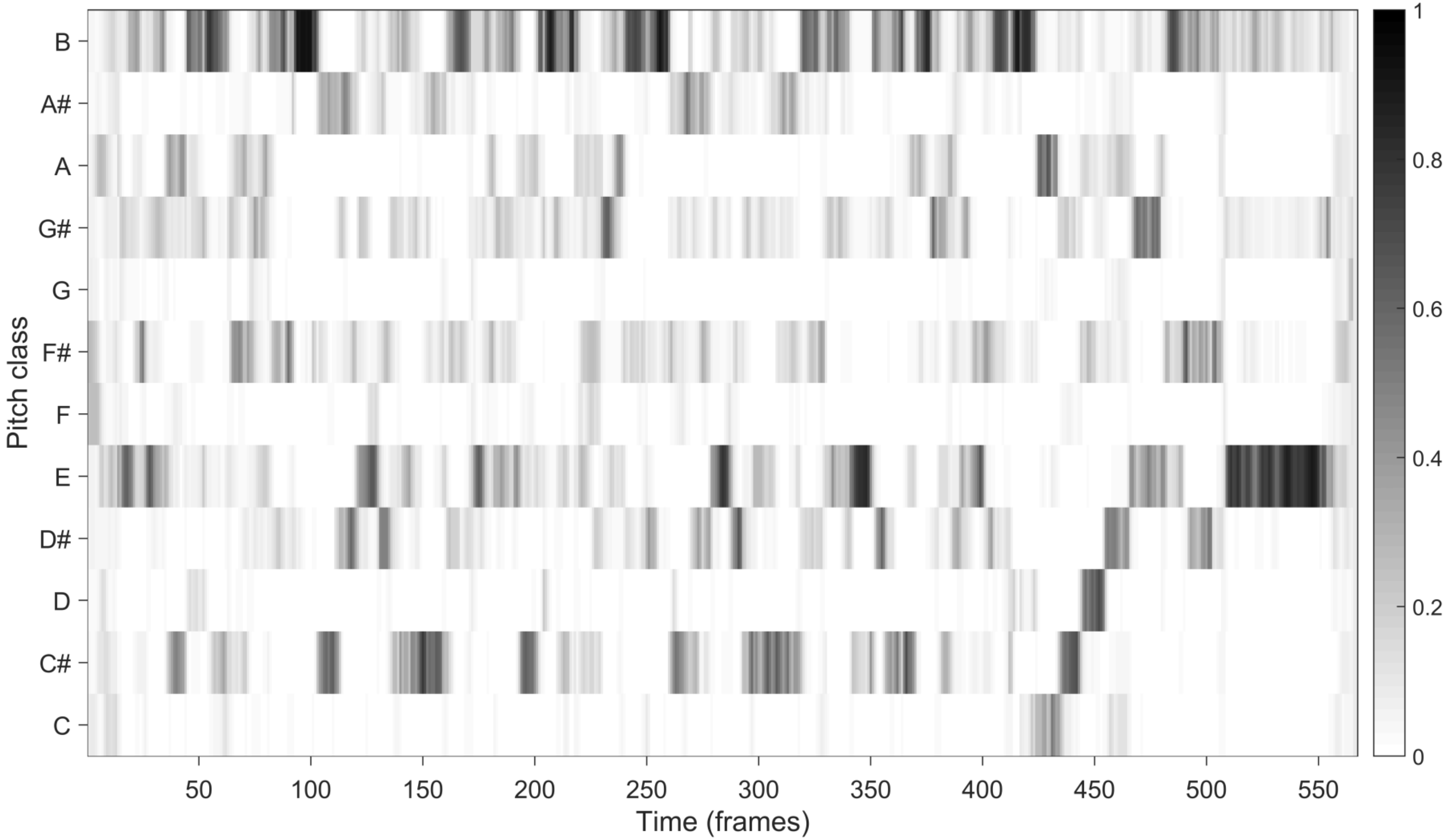
- Summarize pitch classes over a certain time
  - **Chroma smoothing**
  - Parameters: blocksize b and hopsize h



Local Key Detection: Chroma Smoothing

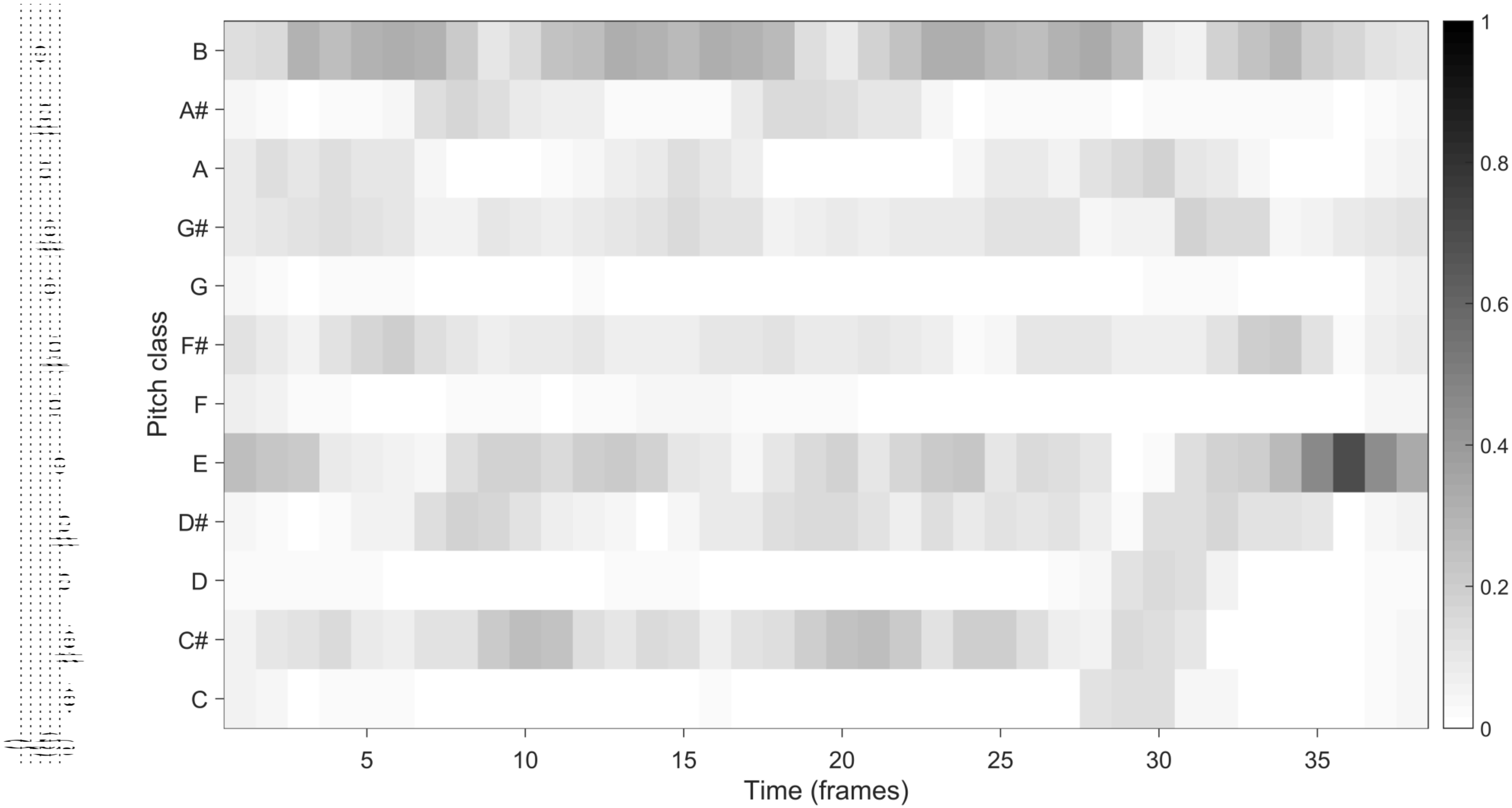
- Choral (Bach)





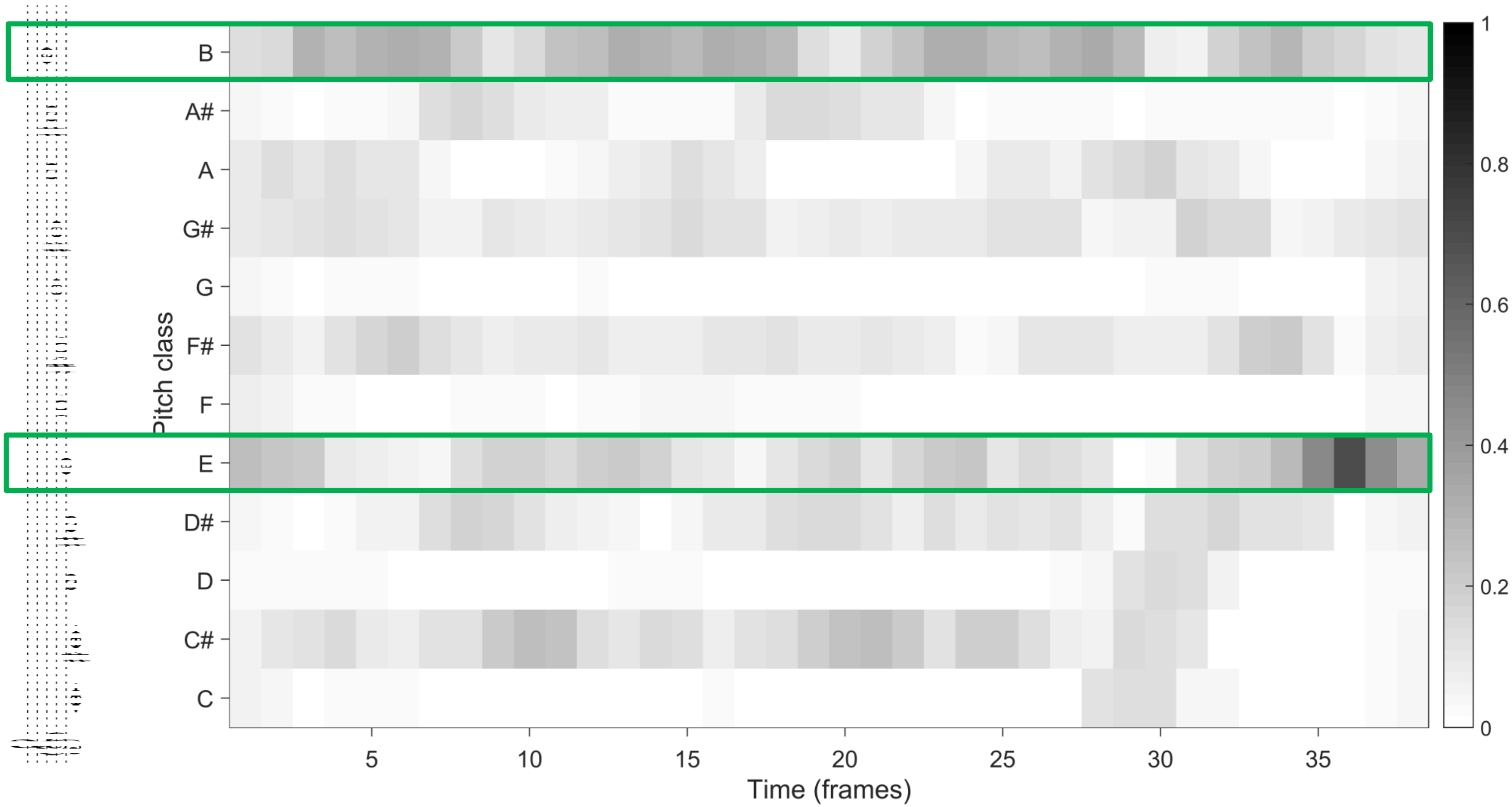
Local Key Detection: Chroma Smoothing

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



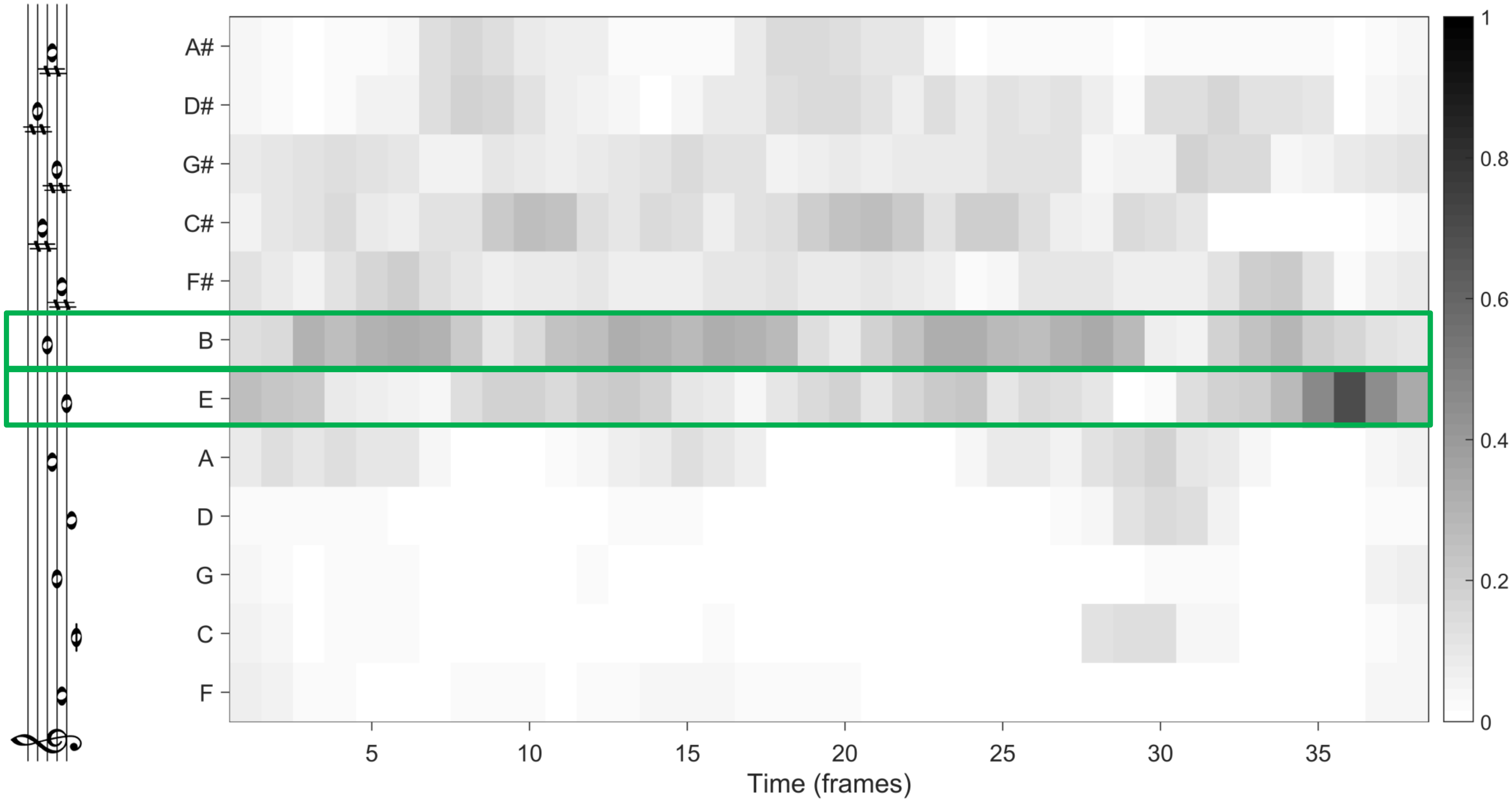
Local Key Detection: Diatonic Scales

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



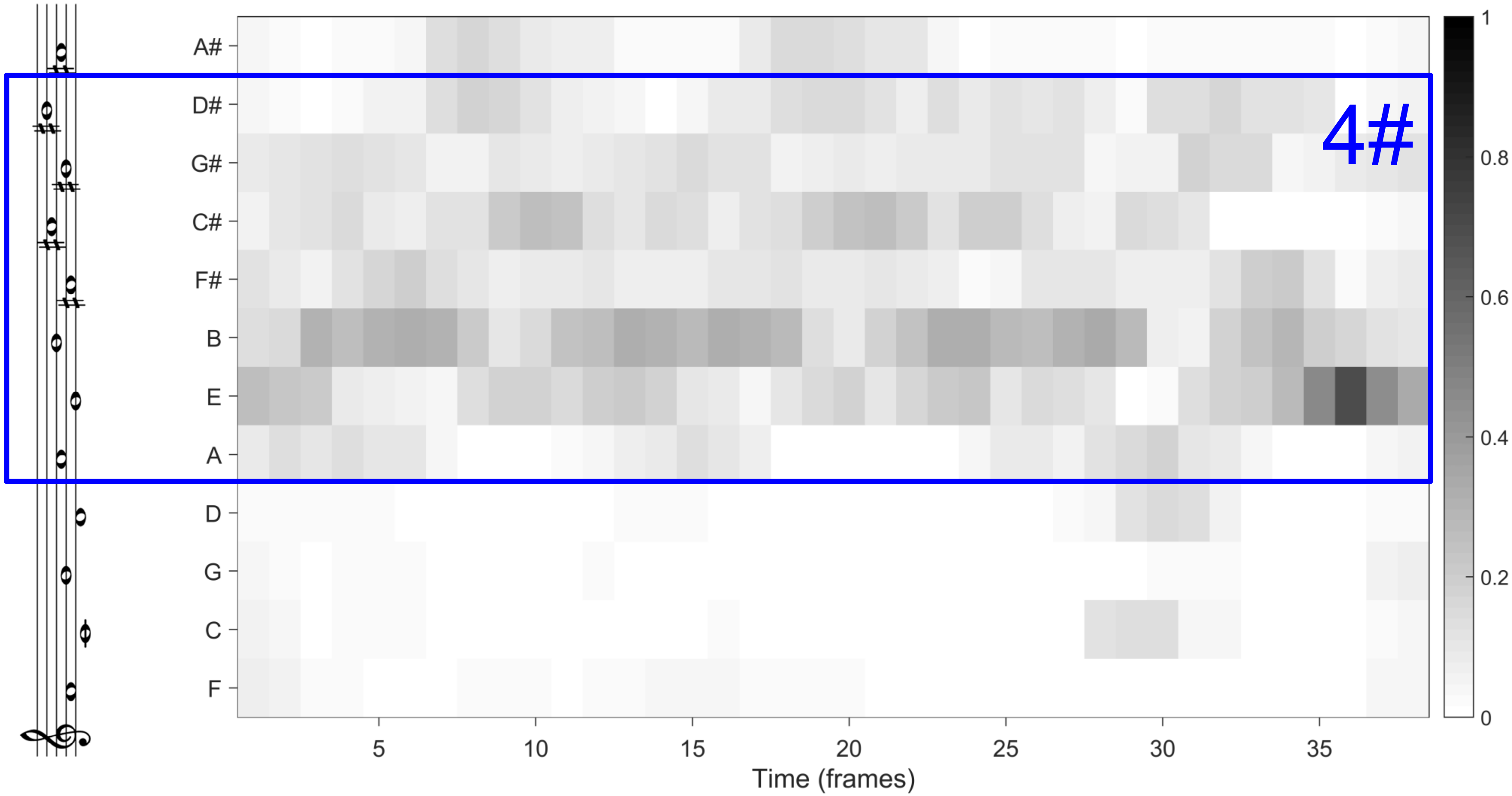
Local Key Detection: Diatonic Scales

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



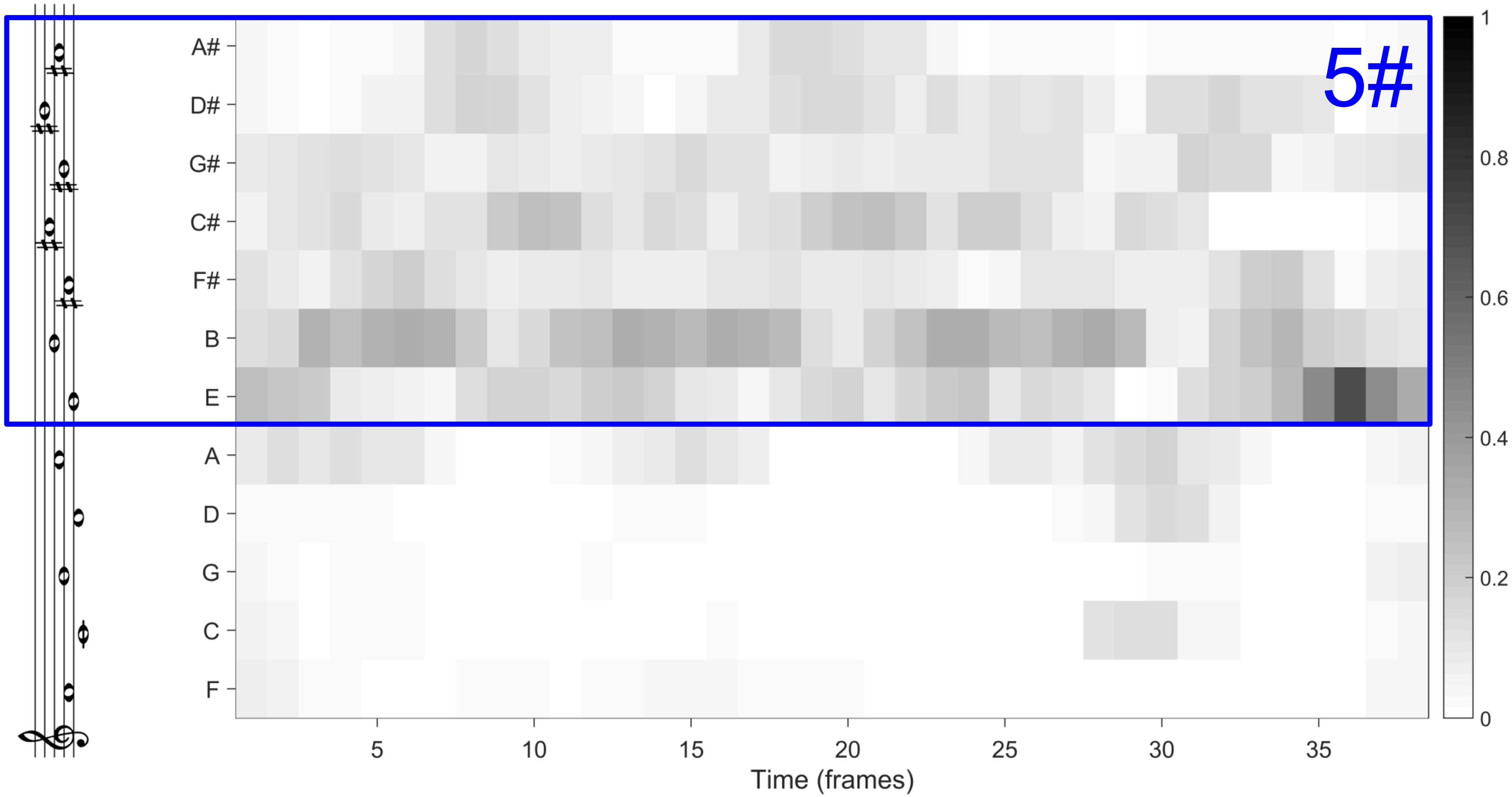
Local Key Detection: Diatonic Scales

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



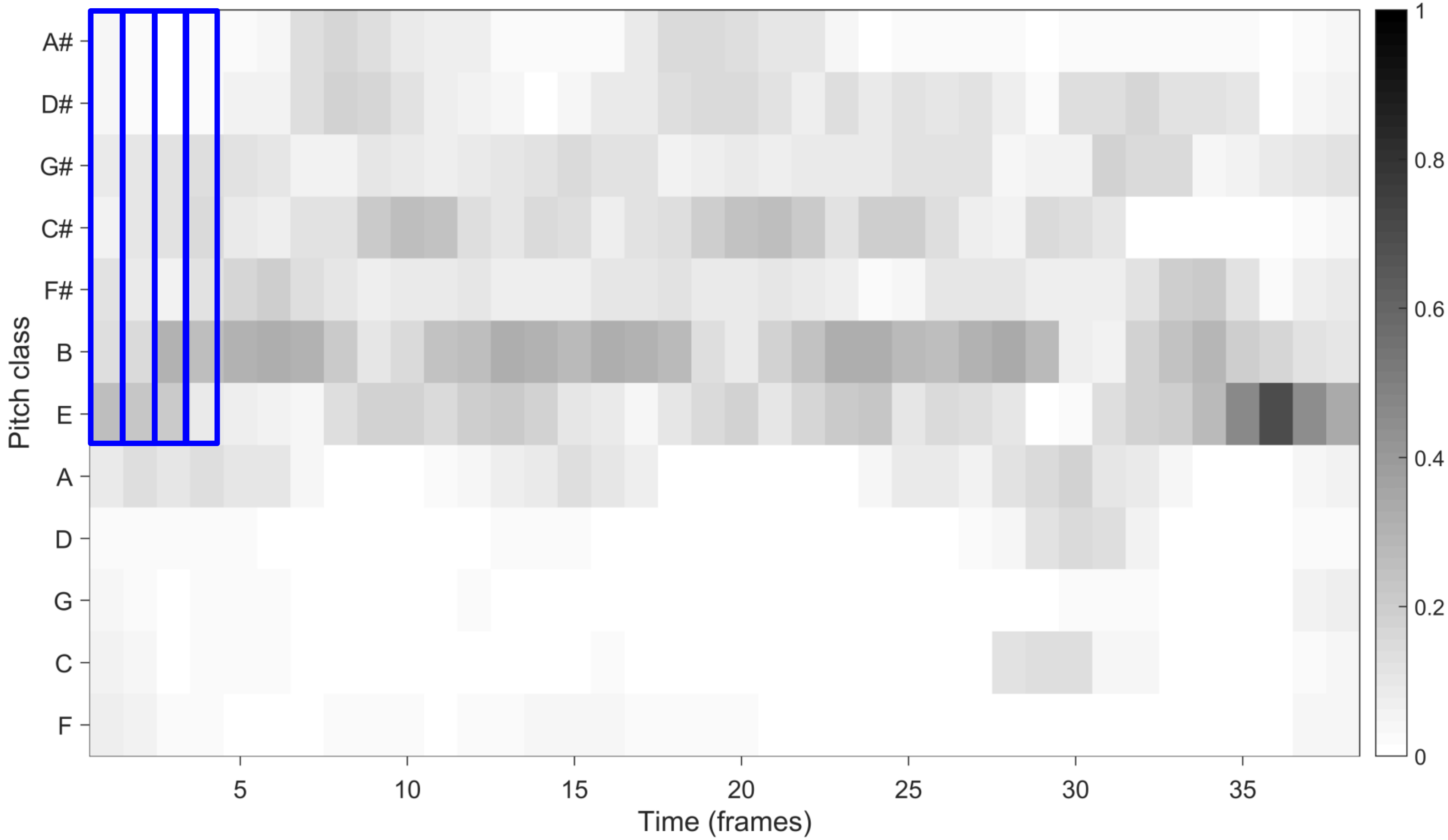
Local Key Detection: Diatonic Scales

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



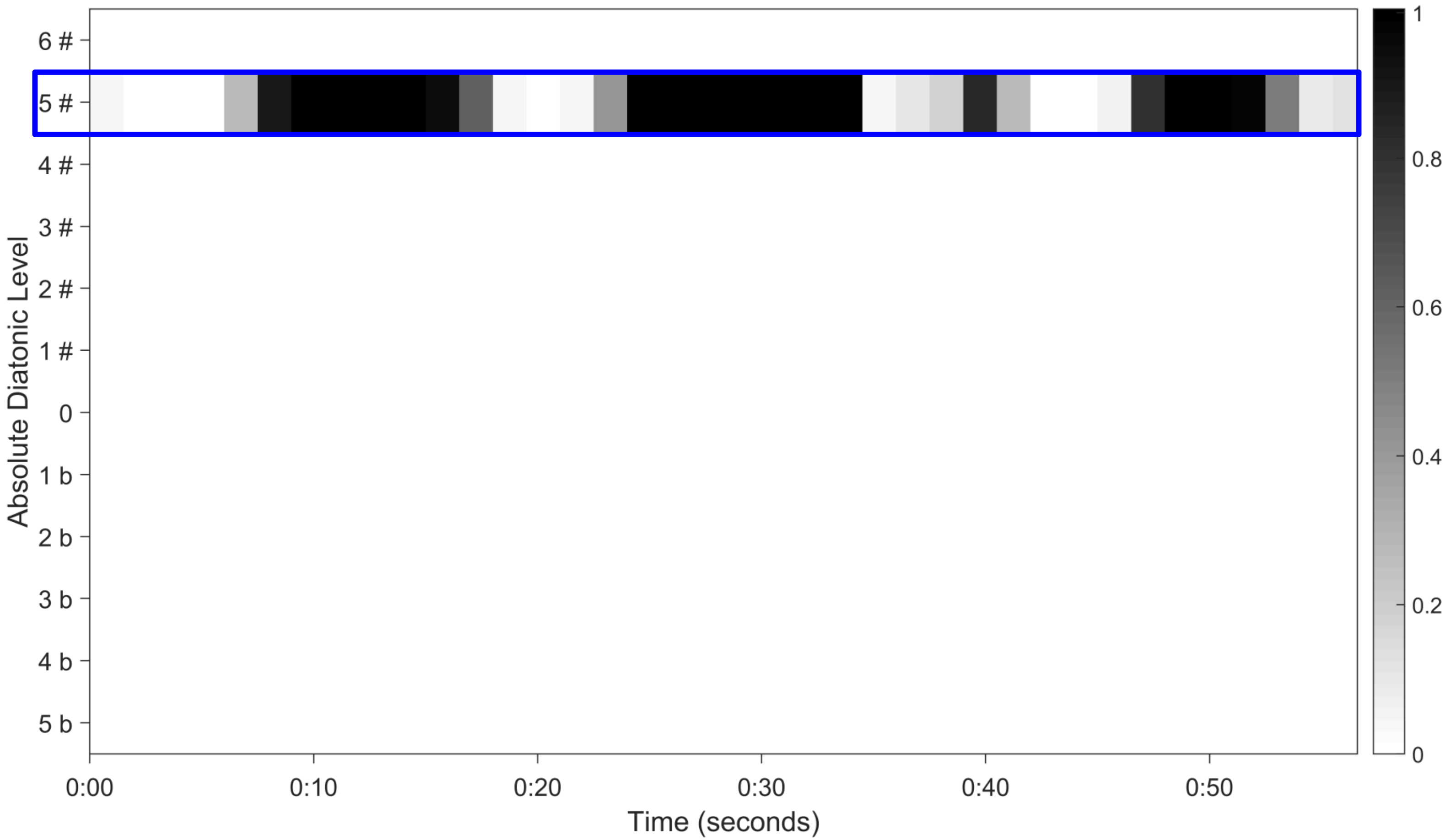
Local Key Detection: Diatonic Scales

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



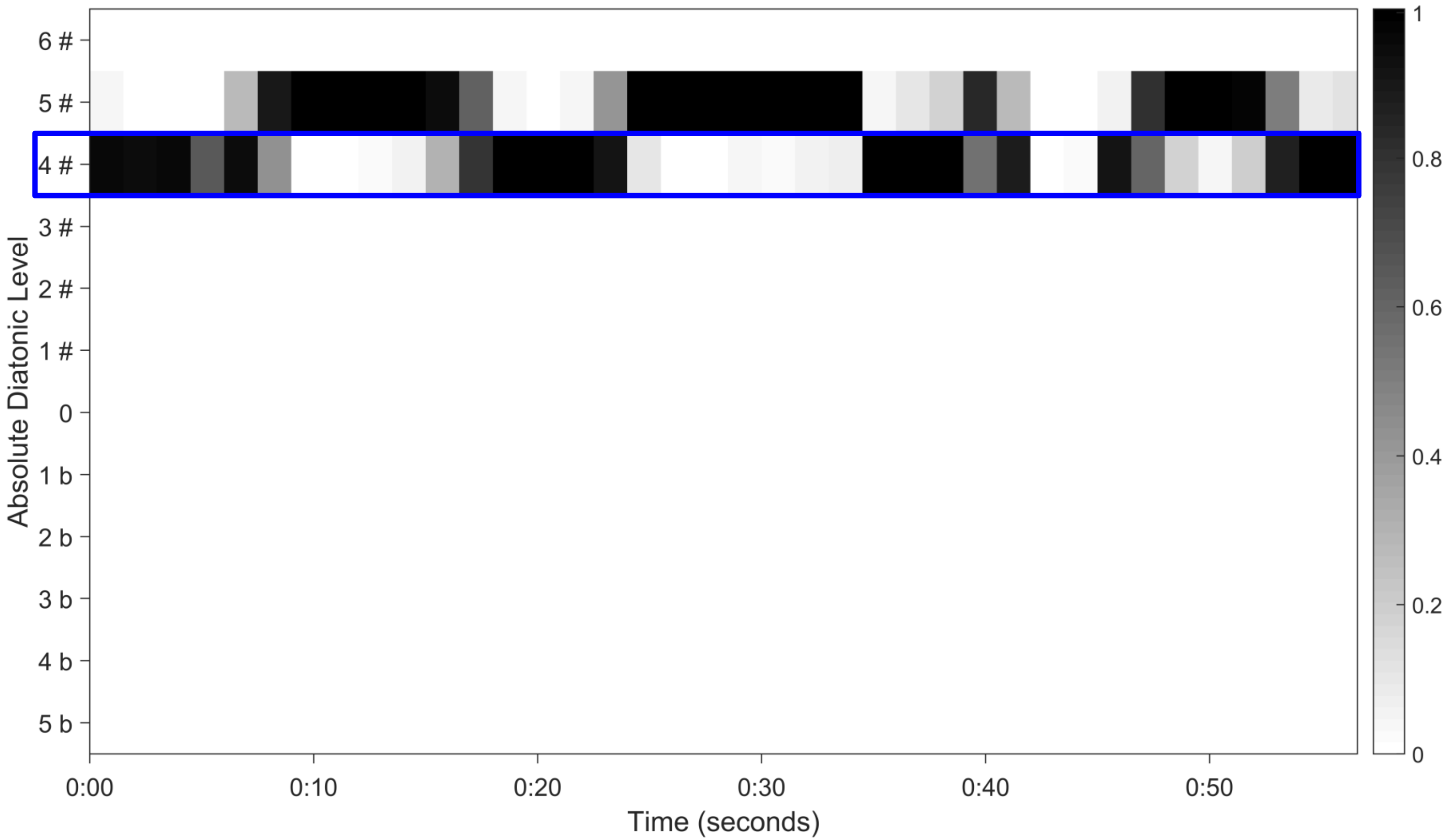
Local Key Detection: Diatonic Scales

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



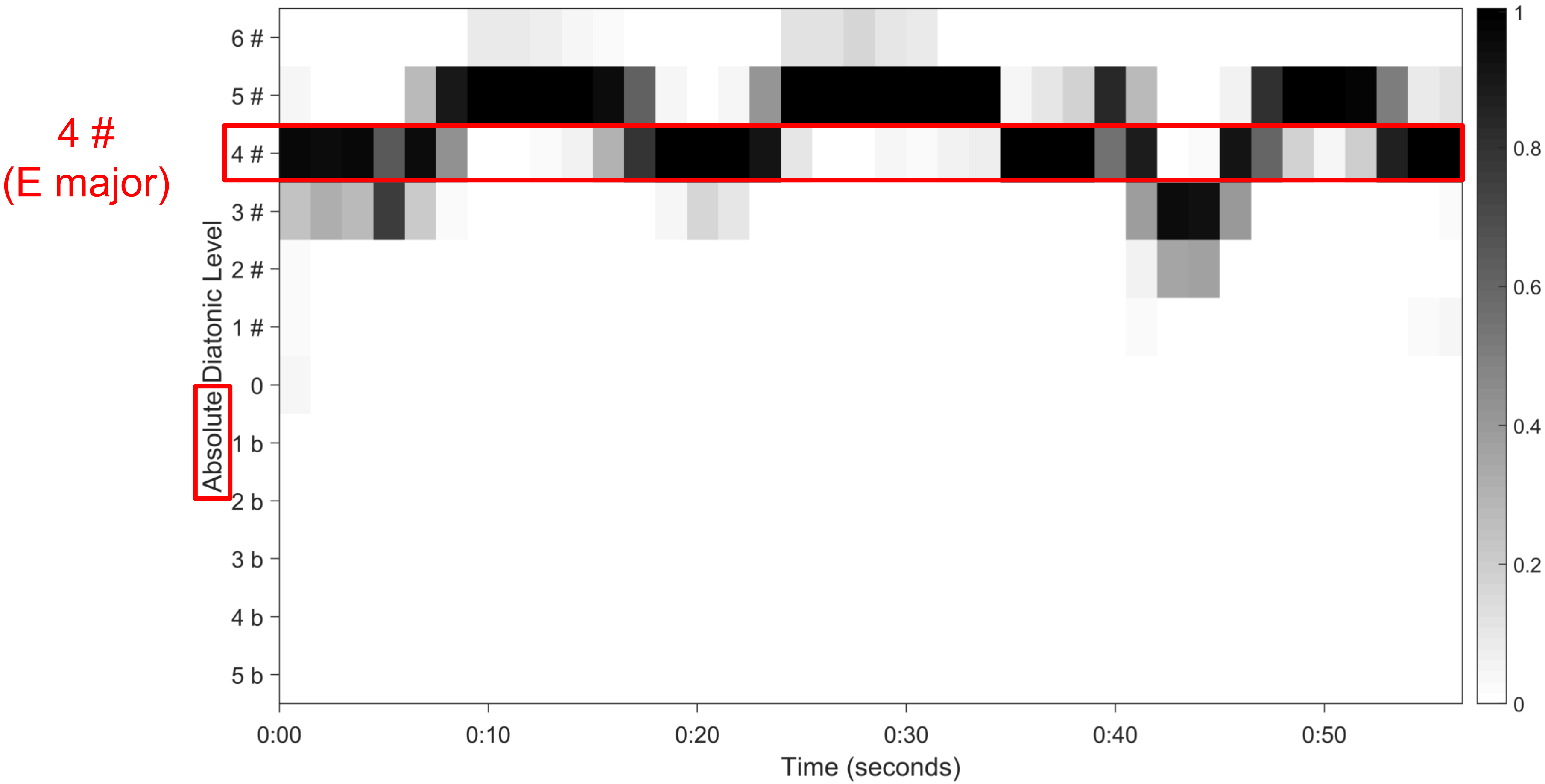
Local Key Detection: Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation



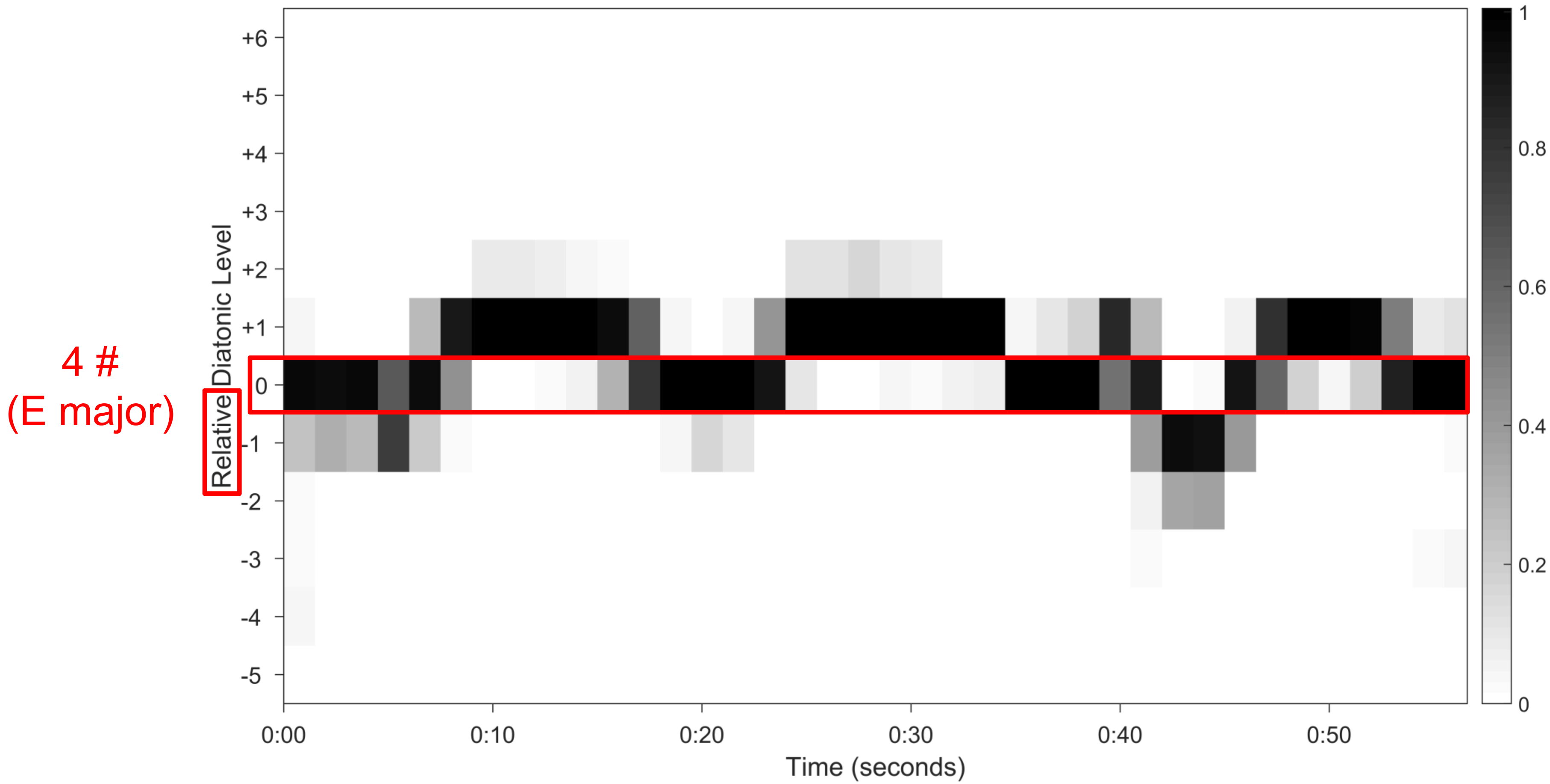
Local Key Detection: Diatonic Scales

- Choral (Bach) — Diatonic Scale Estimation



Local Key Detection: Diatonic Scales

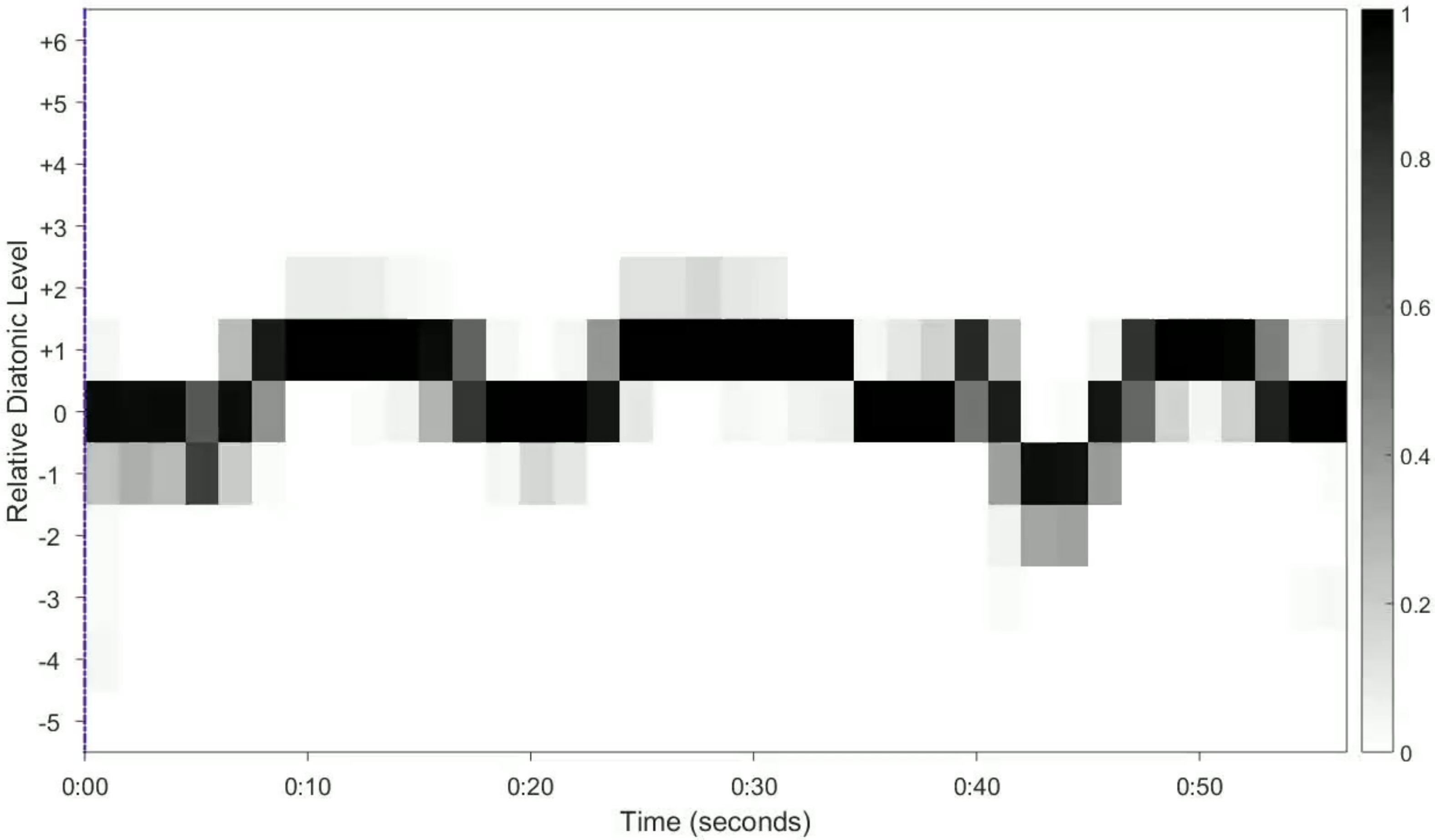
- Choral (Bach) — Diatonic Scale Estimation: Shift to **global key**



Local Key Detection: Diatonic Scales

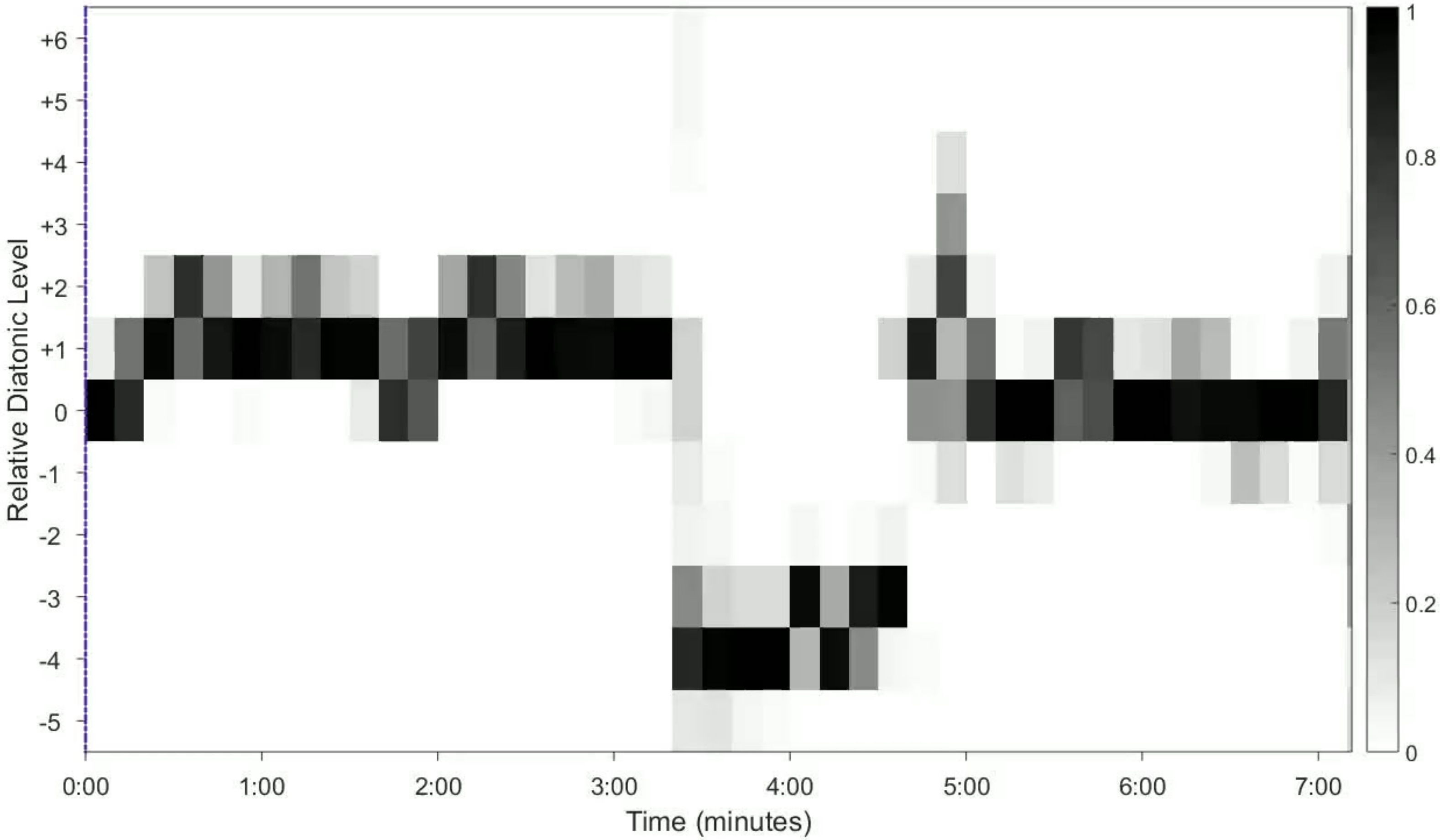
- Choral (Bach) — 0 ≙ 4#

Weiss / Habryka, *Chroma-Based Scale Matching for Audio Tonality Analysis*, CIM 2014



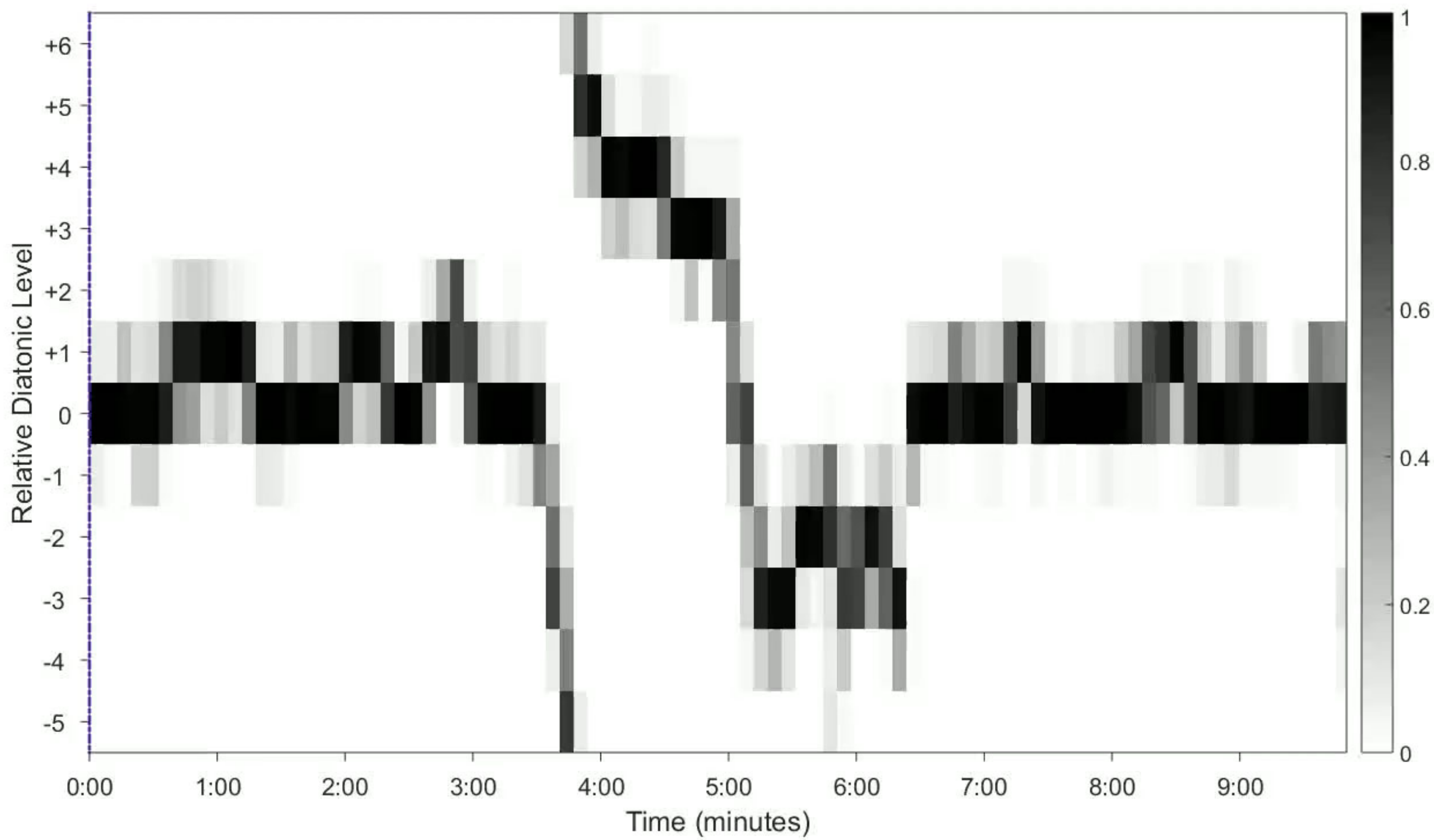
Local Key Detection: Examples

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



Local Key Detection: Examples

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



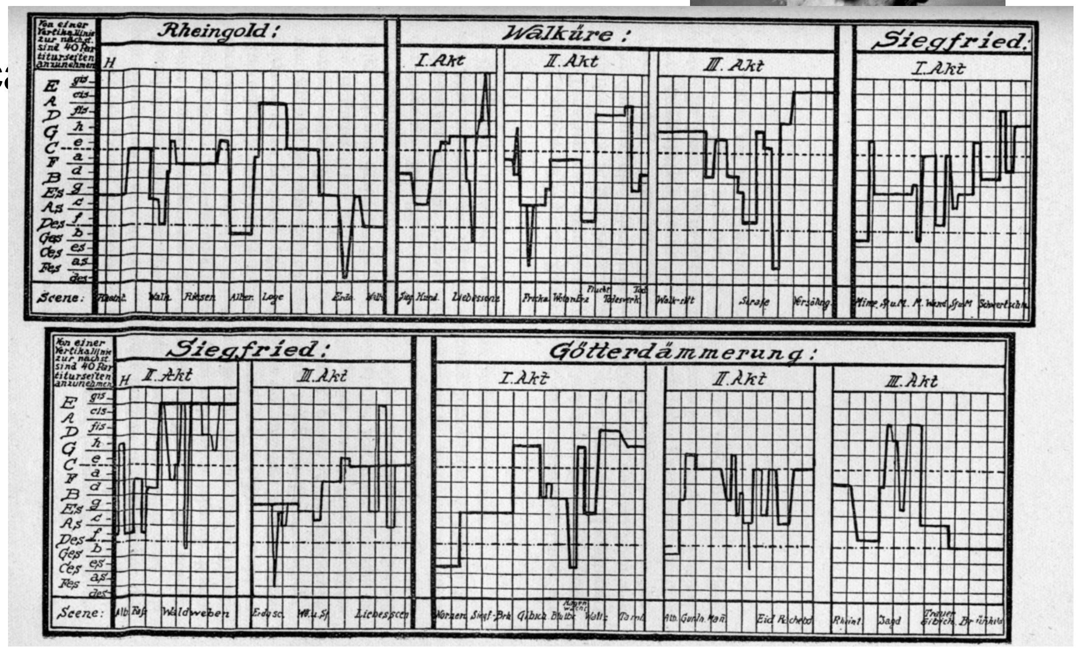
DFG-funded Project: Computational Analysis of Harmonic Structures

DFG

- With Prof. Rainer Kleinertz, Musicology, Uni Saarland

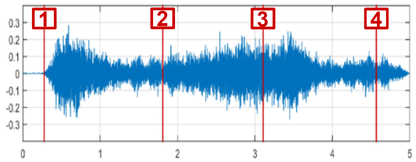
UNIVERSITÄT DES SAARLANDES

- 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



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

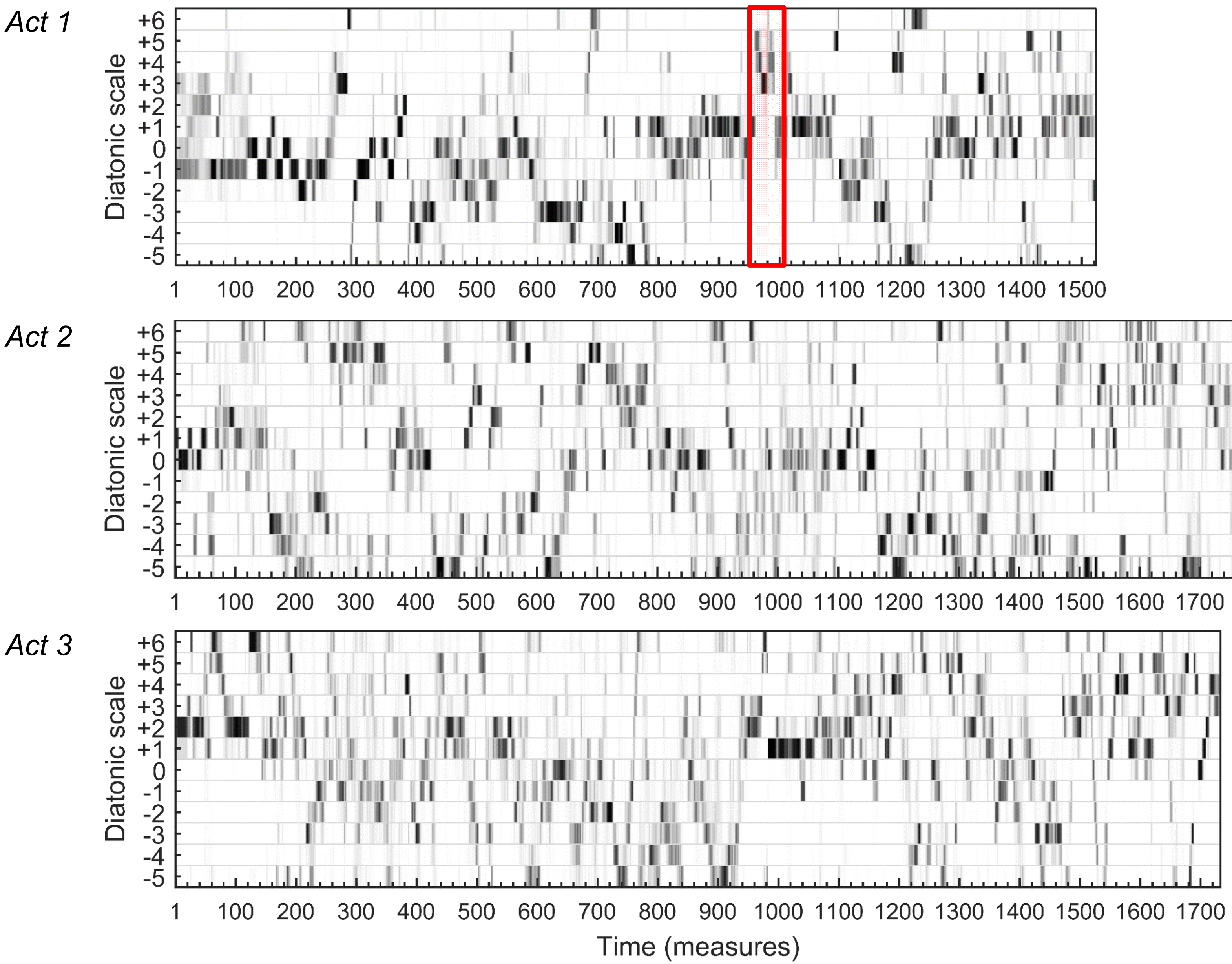
Cross-Version Analysis

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

→ Test reliability of the method

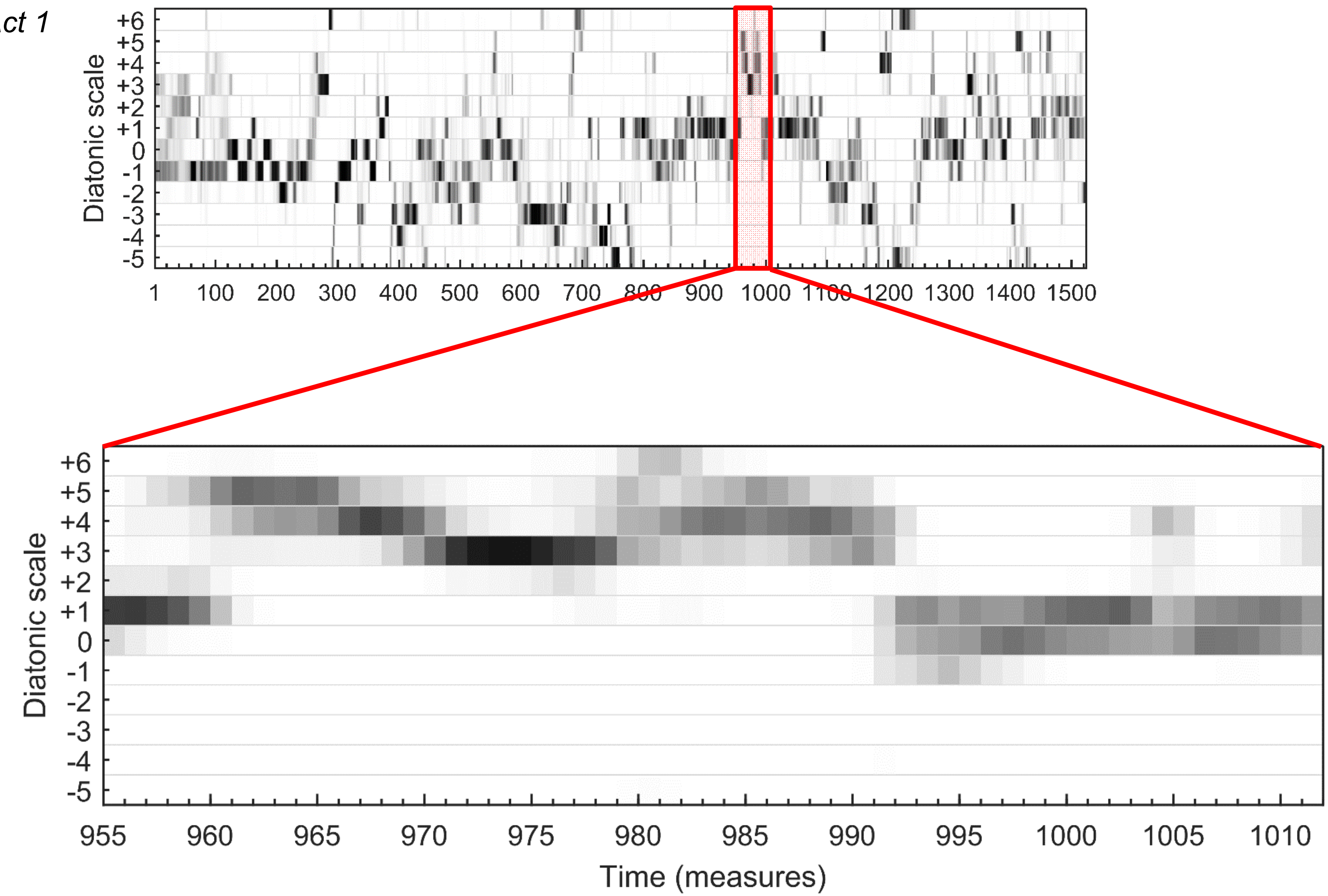
- Visualize consistency with gray scheme

Die Walküre WWV 86 B



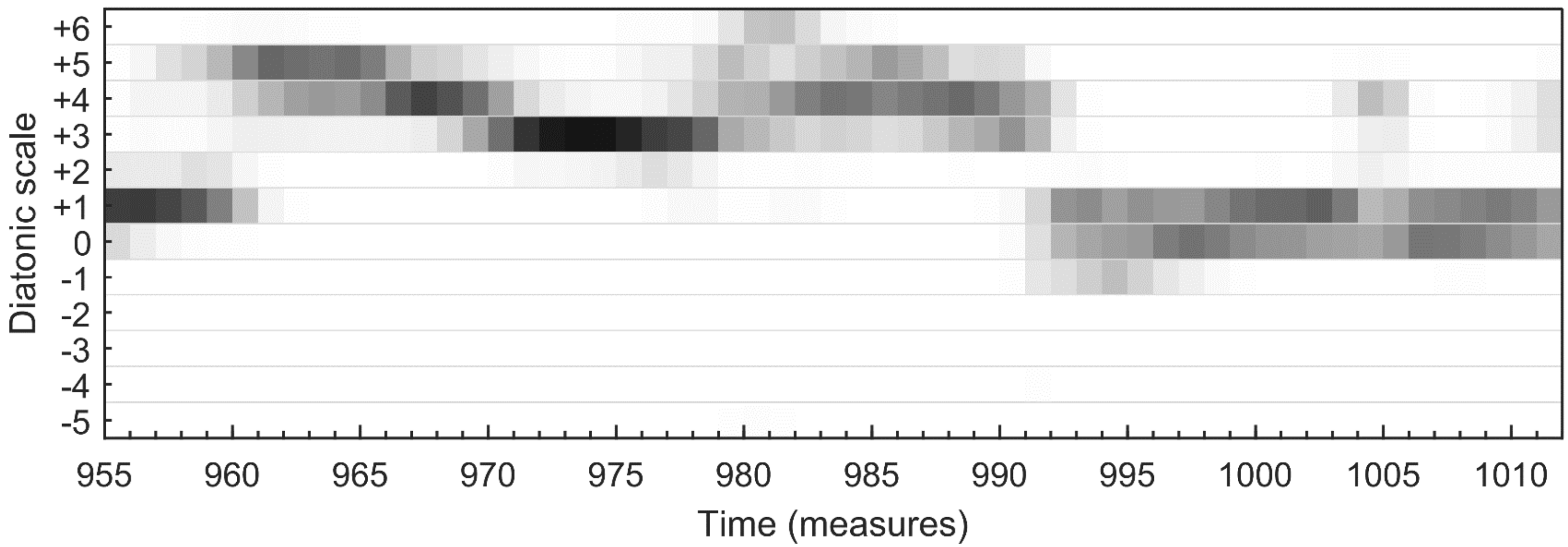
Die Walküre WWV 86 B

Act 1



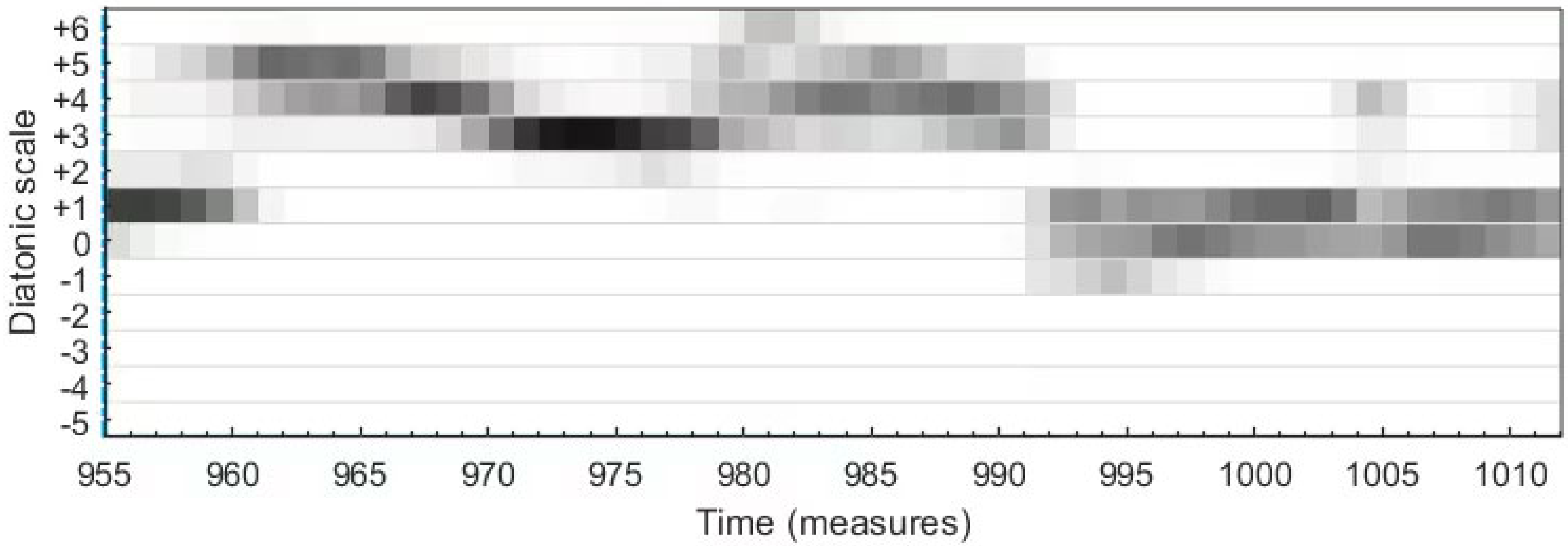
Die Walküre WWV 86 B

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

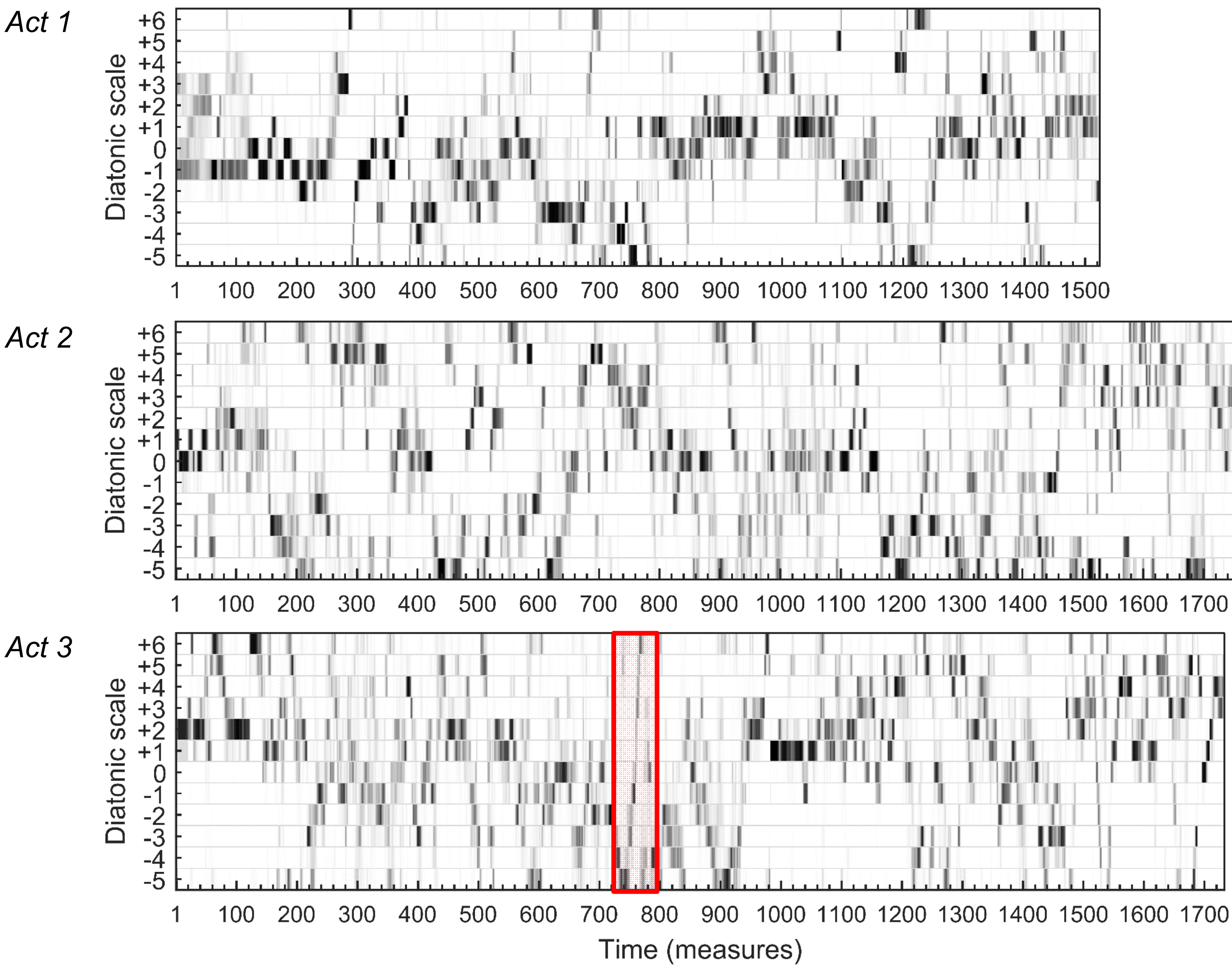


Die Walküre WWV 86 B

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

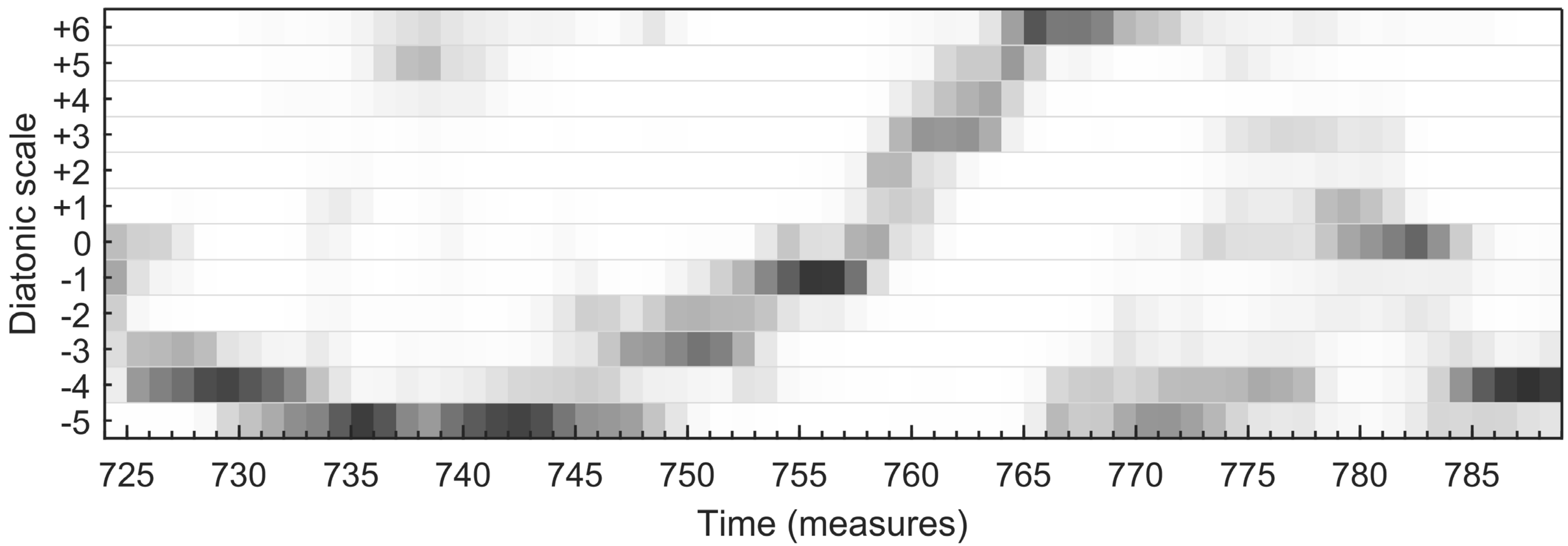


Die Walküre WWV 86 B



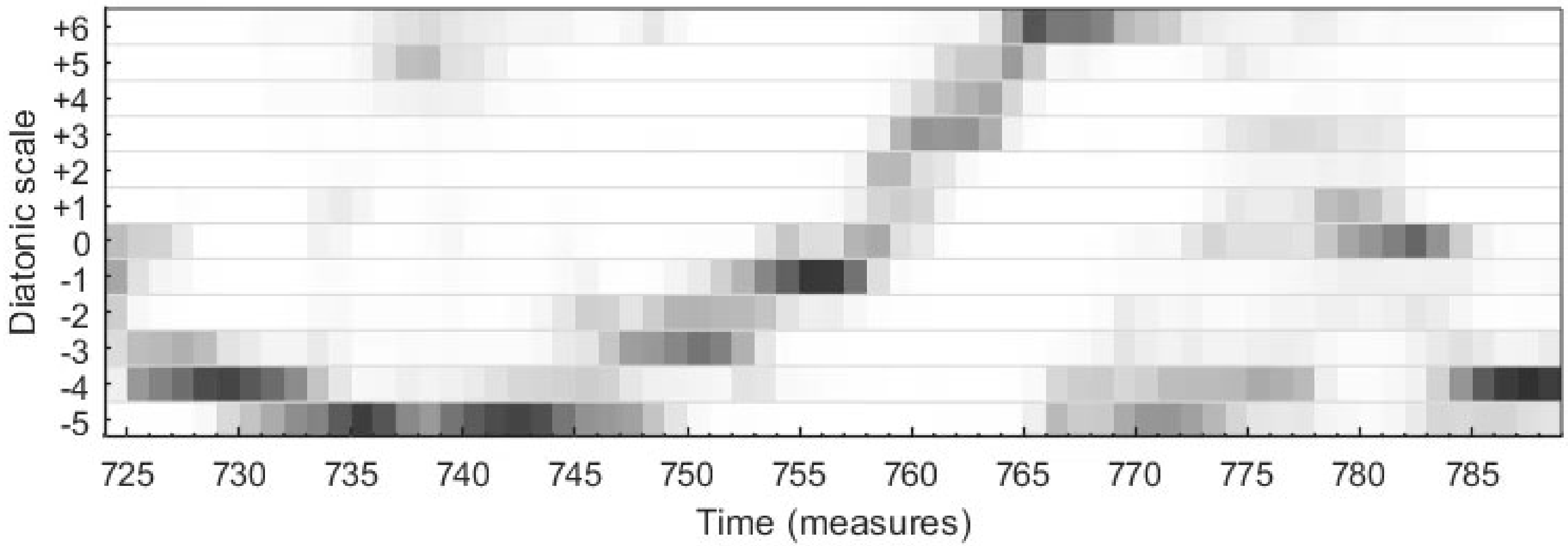
Die Walküre WWV 86 B

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

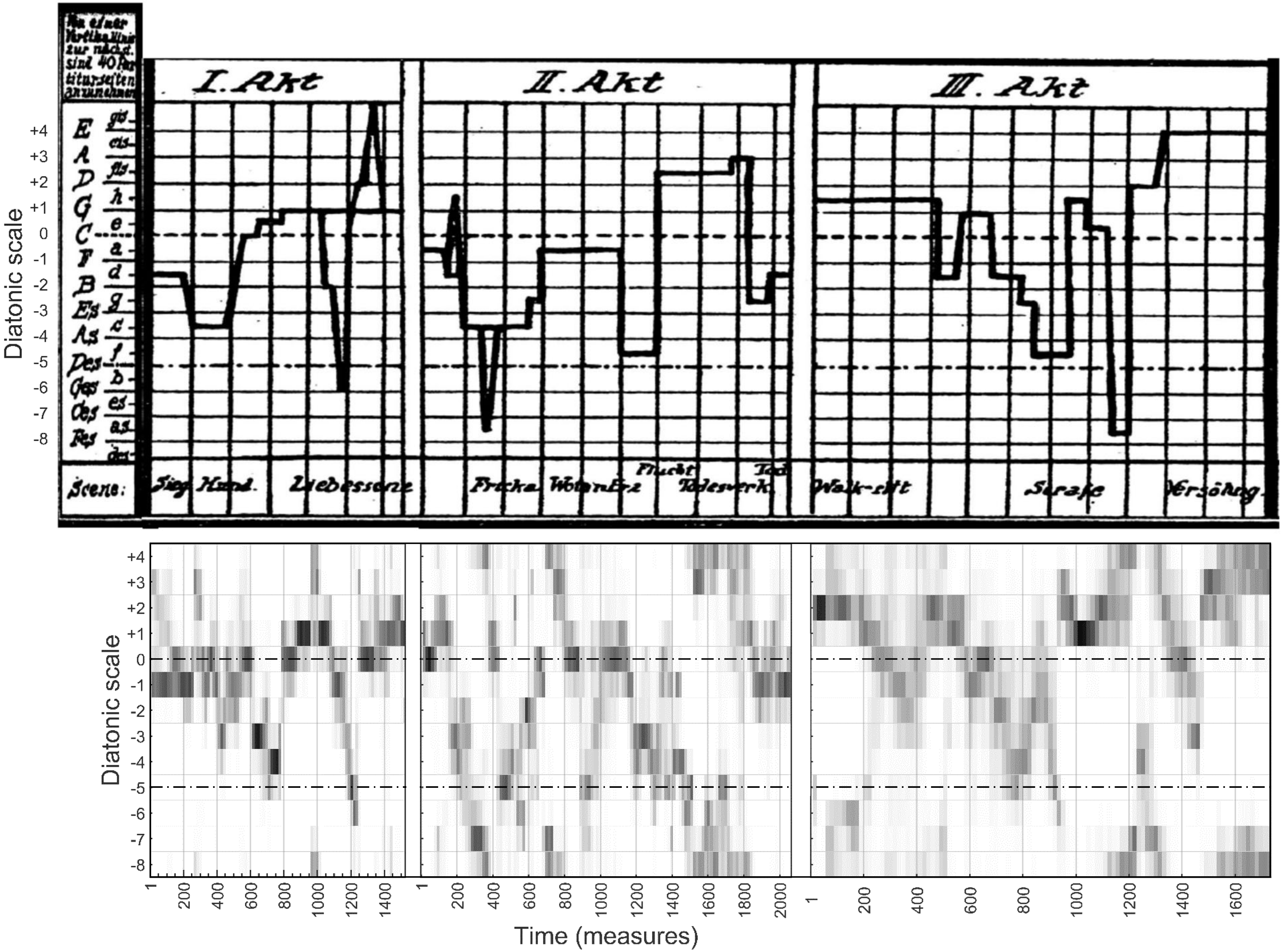


Die Walküre WWV 86 B

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



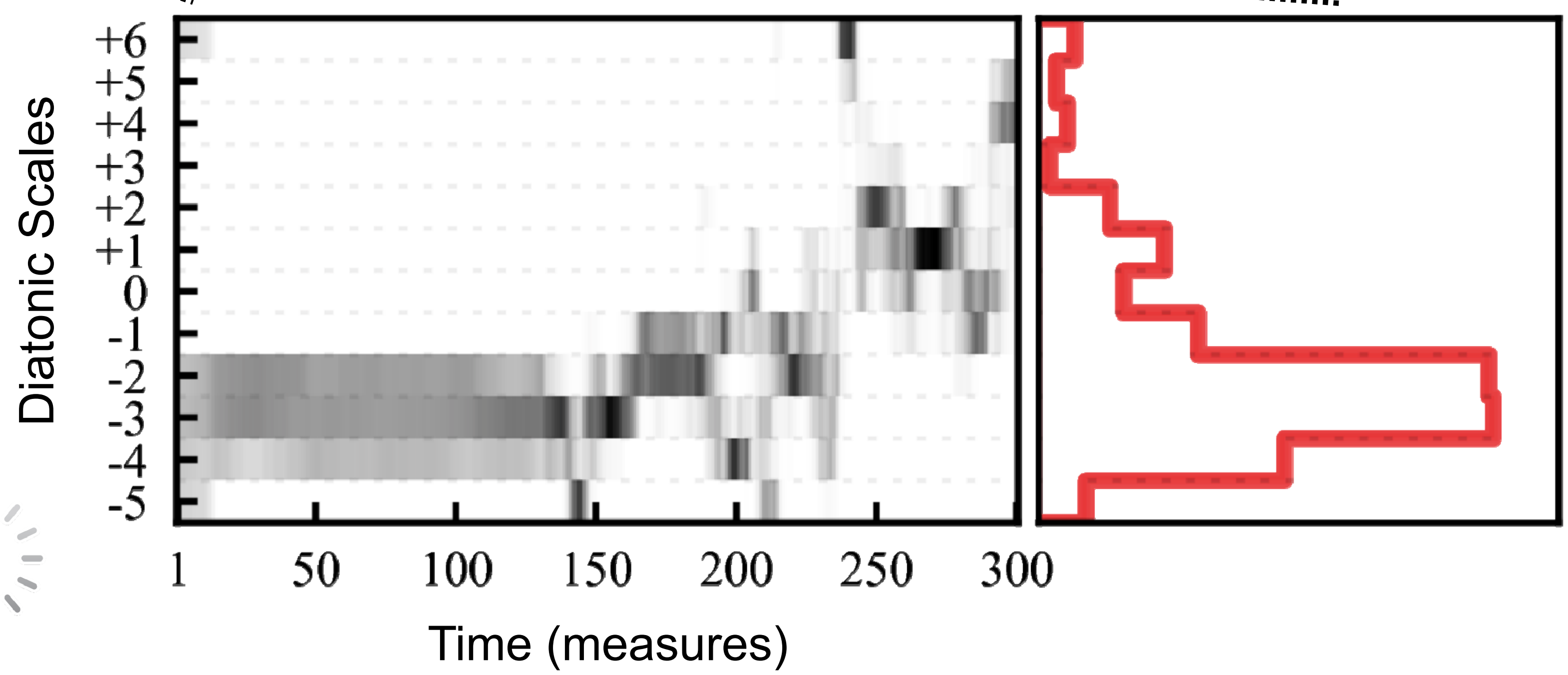
Die Walküre WWV 86 B



Exploring Tonal-Dramatic Relationships

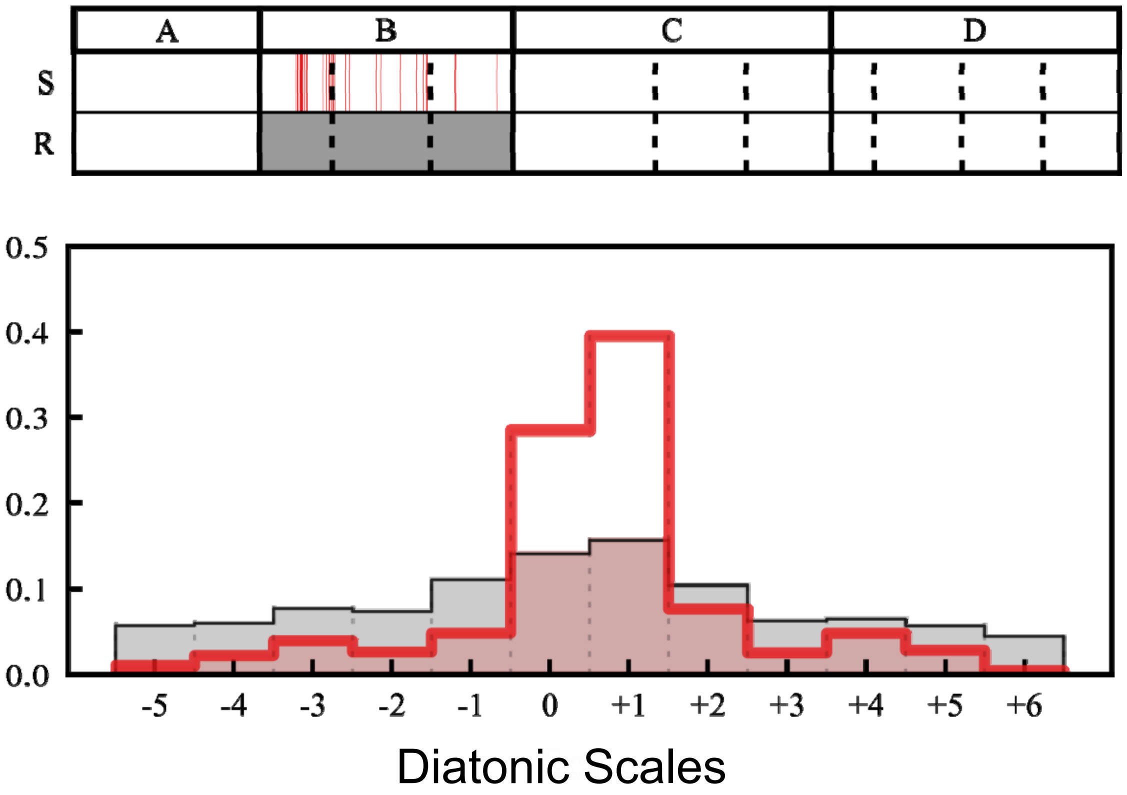
- Histograms of Analysis over time

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



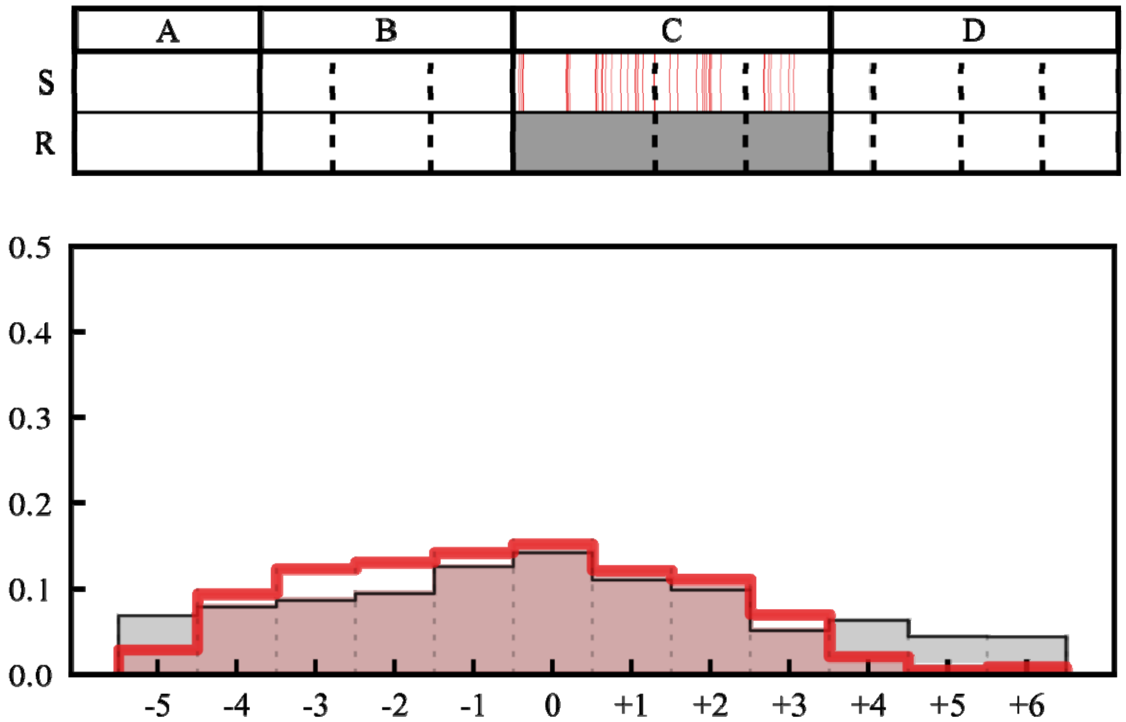
Exploring Tonal-Dramatic Relationships

Sword motif – *Die Walküre*



Exploring Tonal-Dramatic Relationships

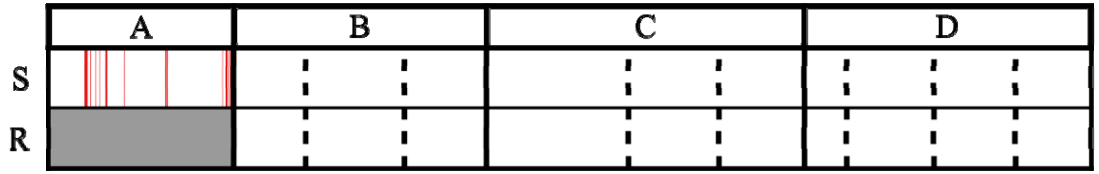
Sword motif – *Siegfried*

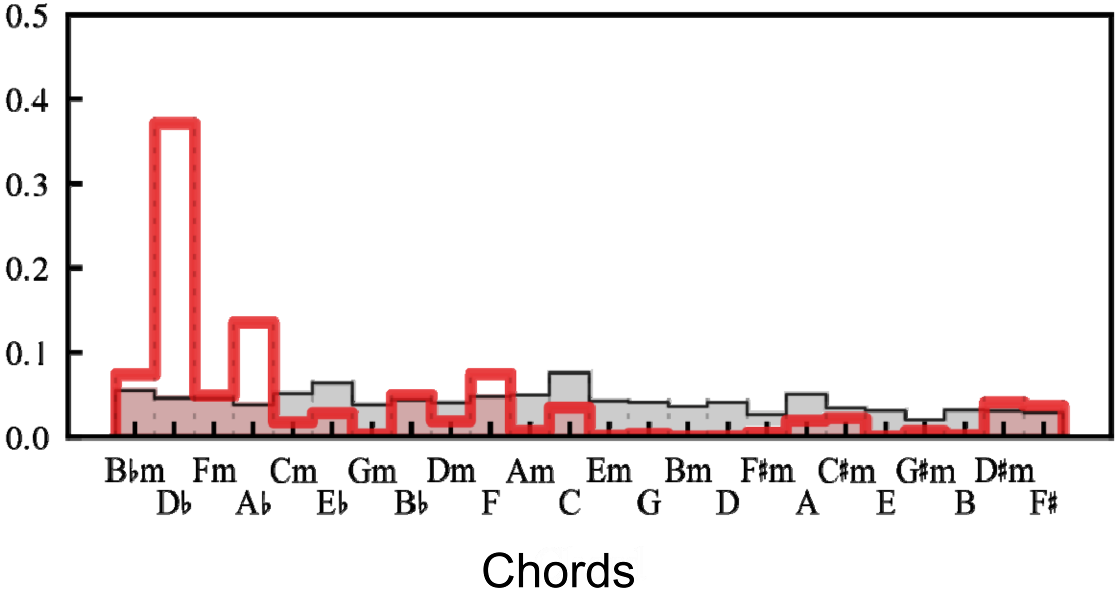


Diatonic Scales

Exploring Tonal-Dramatic Relationships

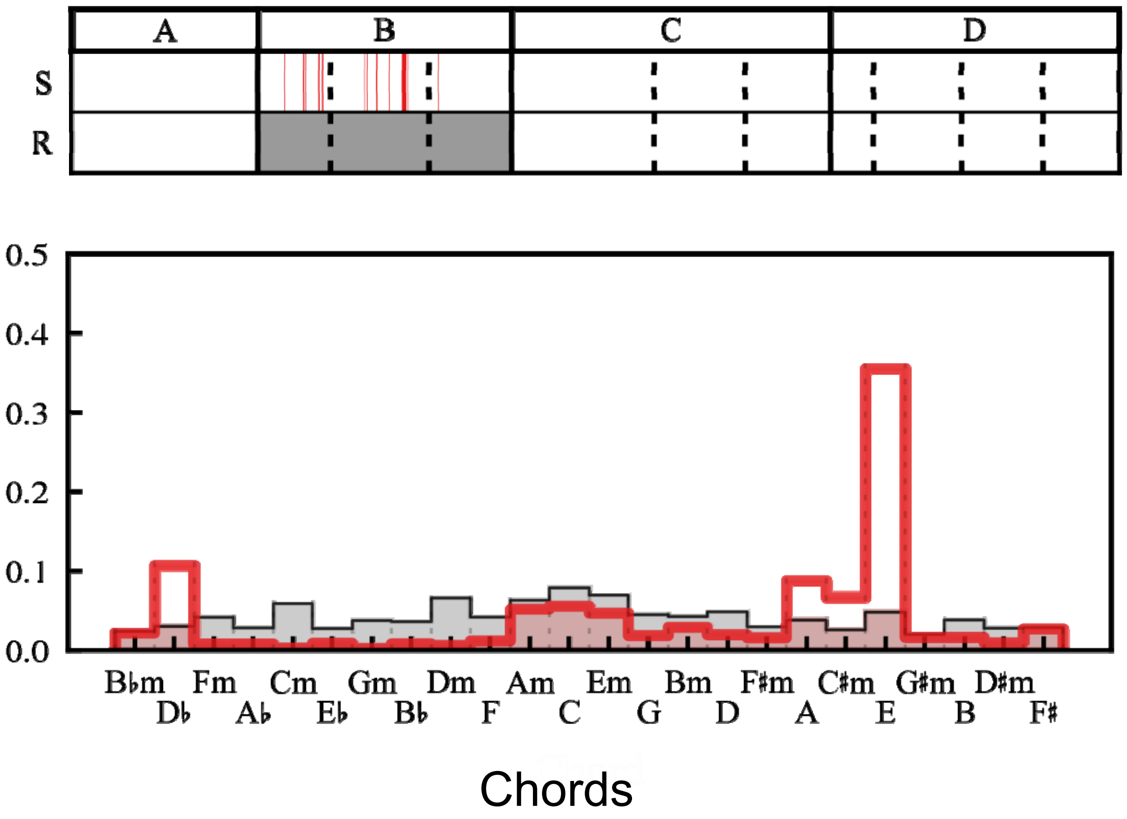
Valhalla motif – *Das Rheingold*





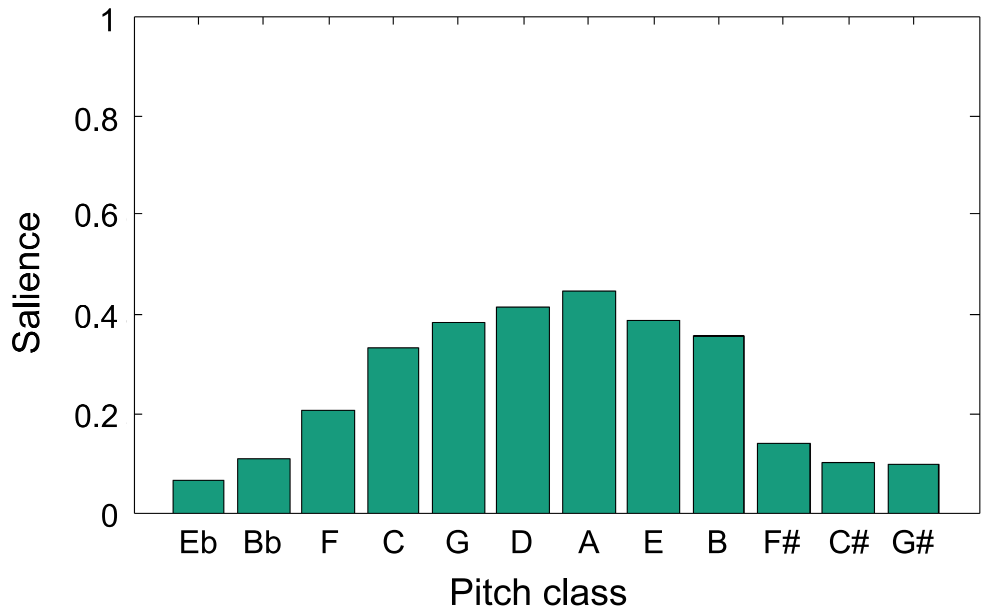
Exploring Tonal-Dramatic Relationships

Valhalla motif – *Die Walküre*



Tonal Structures: Complexity

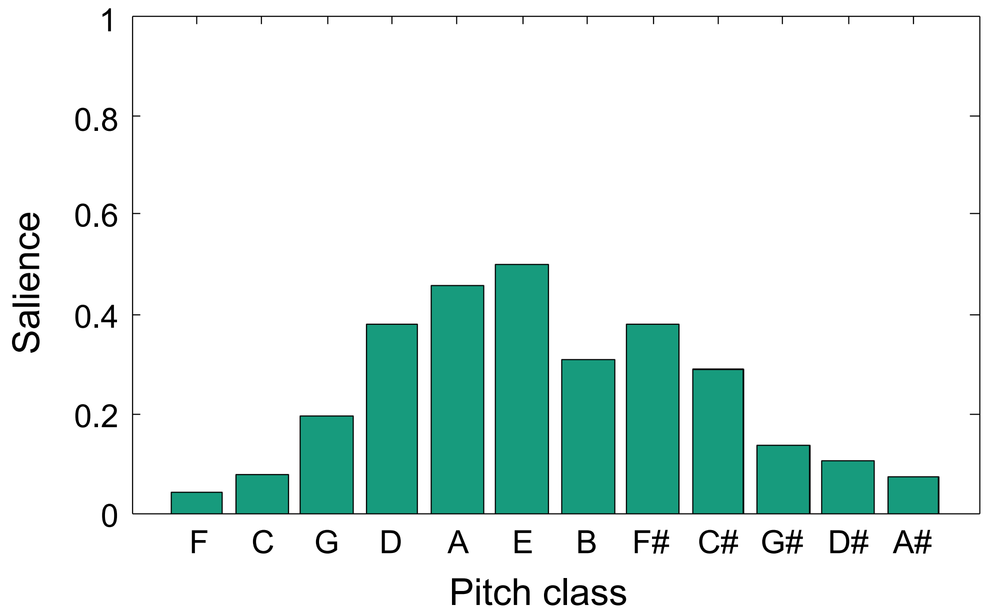
- Global chroma statistics (audio)
- **1567** – G. da Palestrina, Missa de Beata Virgine, Credo



Circle of fifths →

Tonal Structures: Complexity

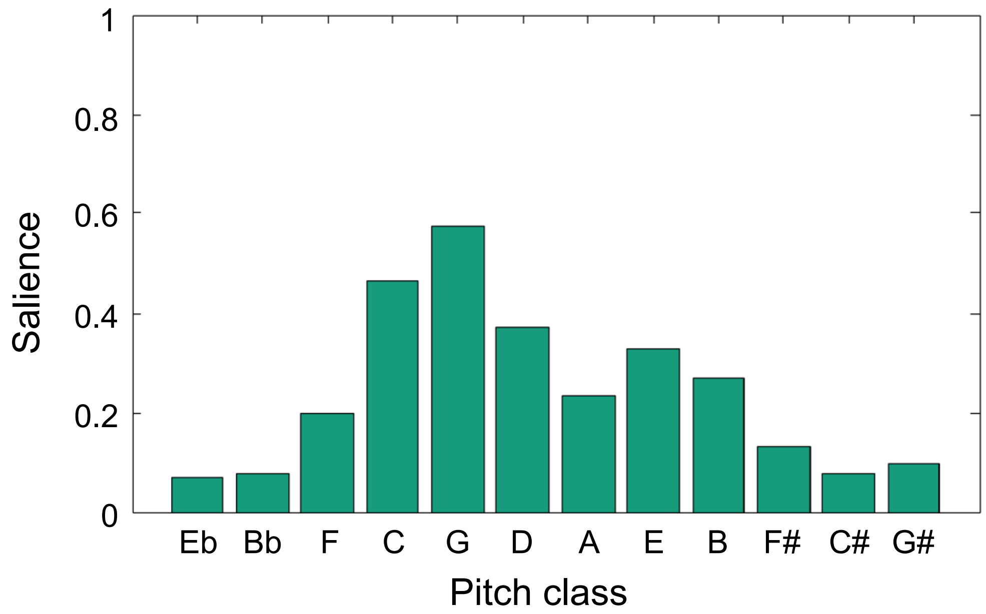
- Global chroma statistics (audio)
- **1725** – J. S. Bach, Orchestral Suite No. 4 BWV 1069, 1. Ouverture (D major)



Circle of fifths →

Tonal Structures: Complexity

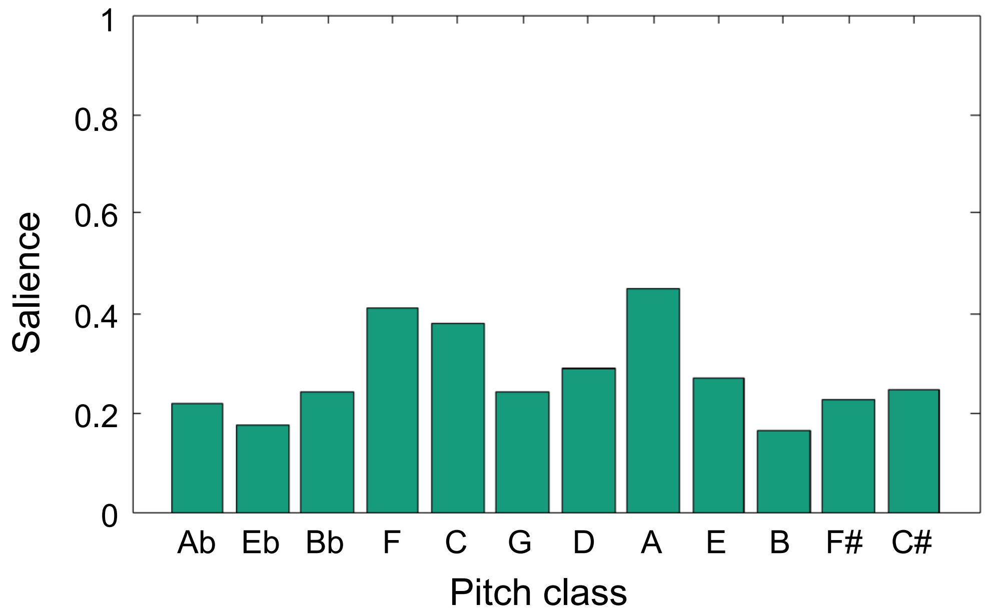
- Global chroma statistics (audio)
- **1783** – W. A. Mozart, „Linz“ symphony KV 425, 1. Adagio / Allegro (C major)



Circle of fifths →

Tonal Structures: Complexity

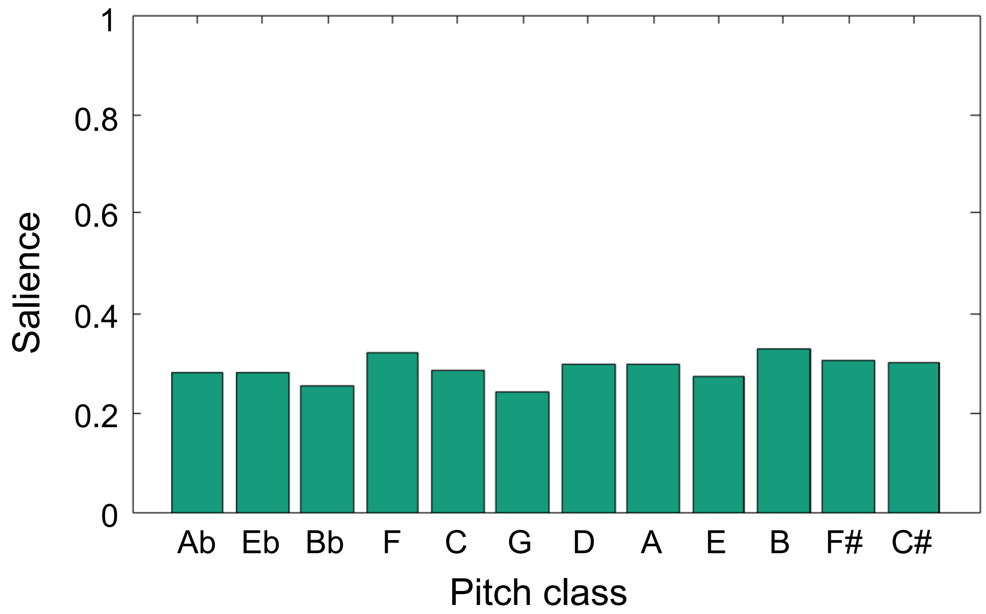
- Global chroma statistics (audio)
- **1883** – J. Brahms, Symphony No. 3, 1. Allegro con brio (F major)



Circle of fifths →

Tonal Structures: Complexity

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

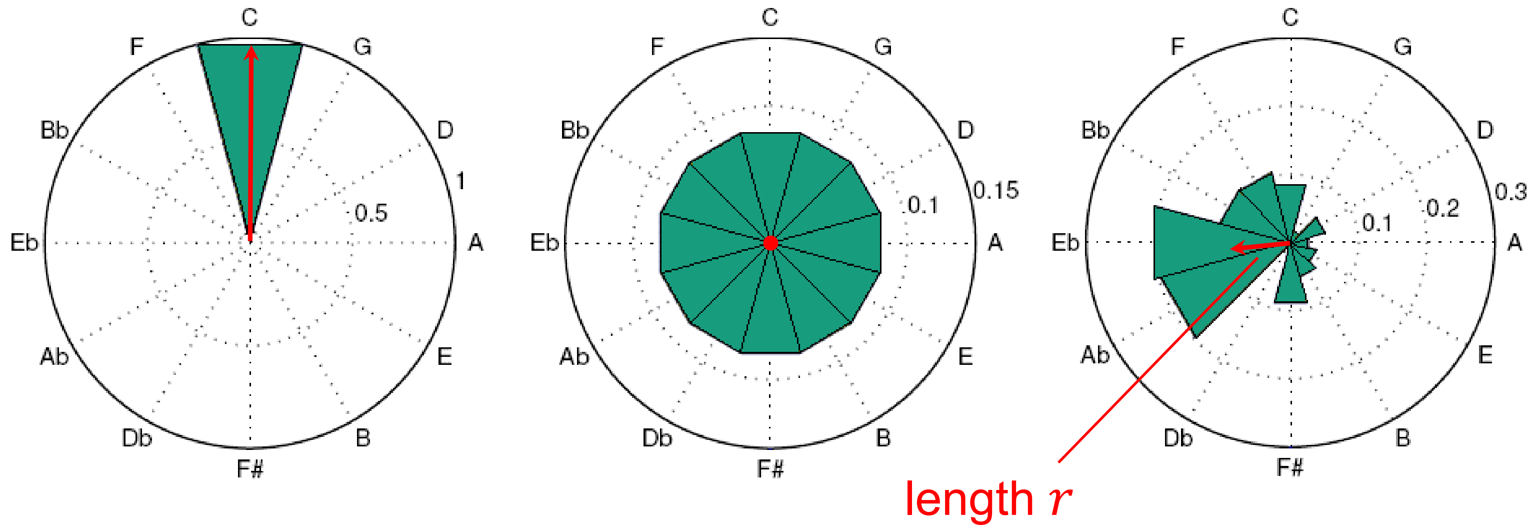


Circle of fifths →

Tonal Structures: Complexity

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

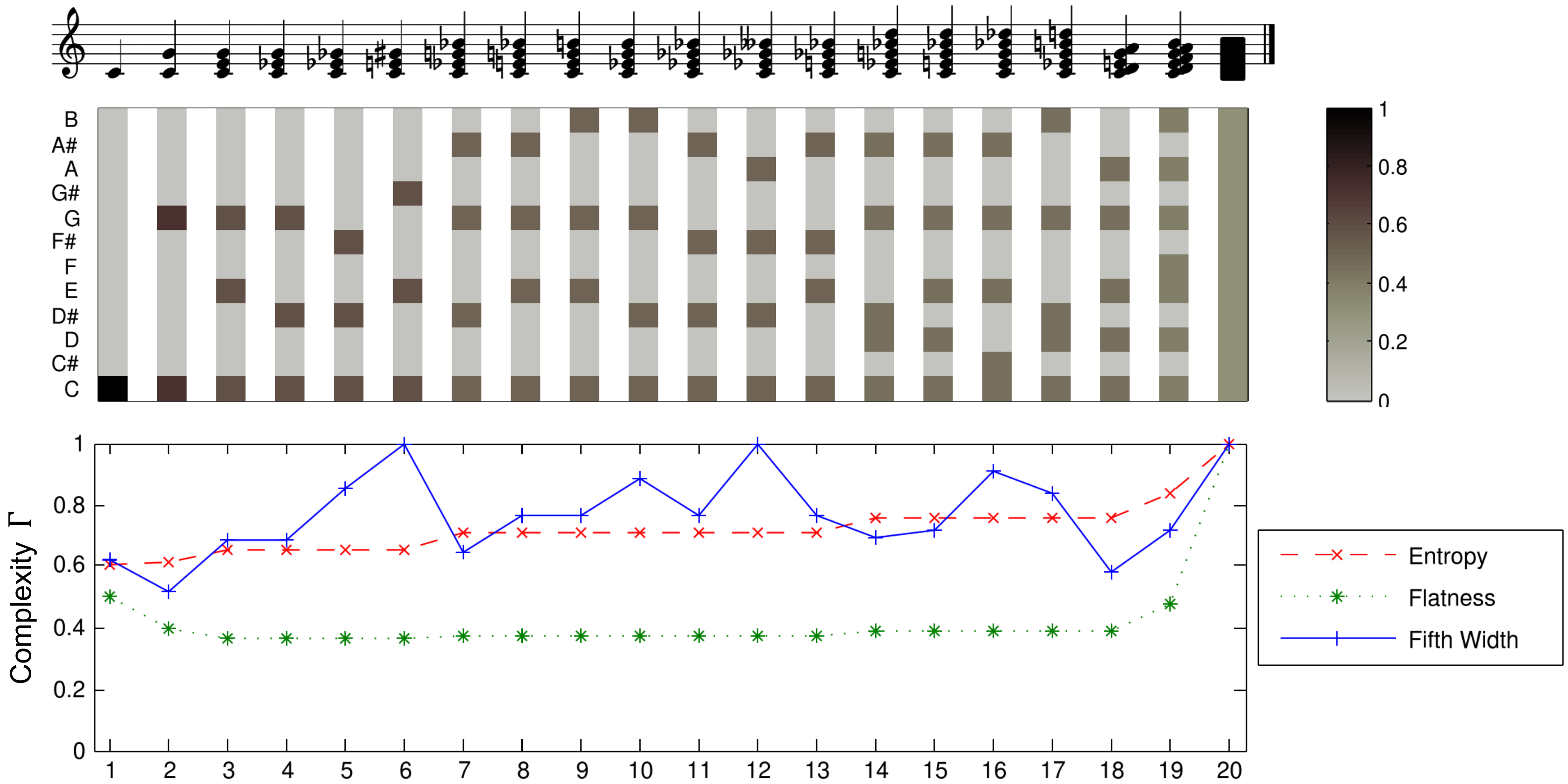
$\Gamma = 0$ $\Gamma = 1$ $0 < \Gamma < 1$



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

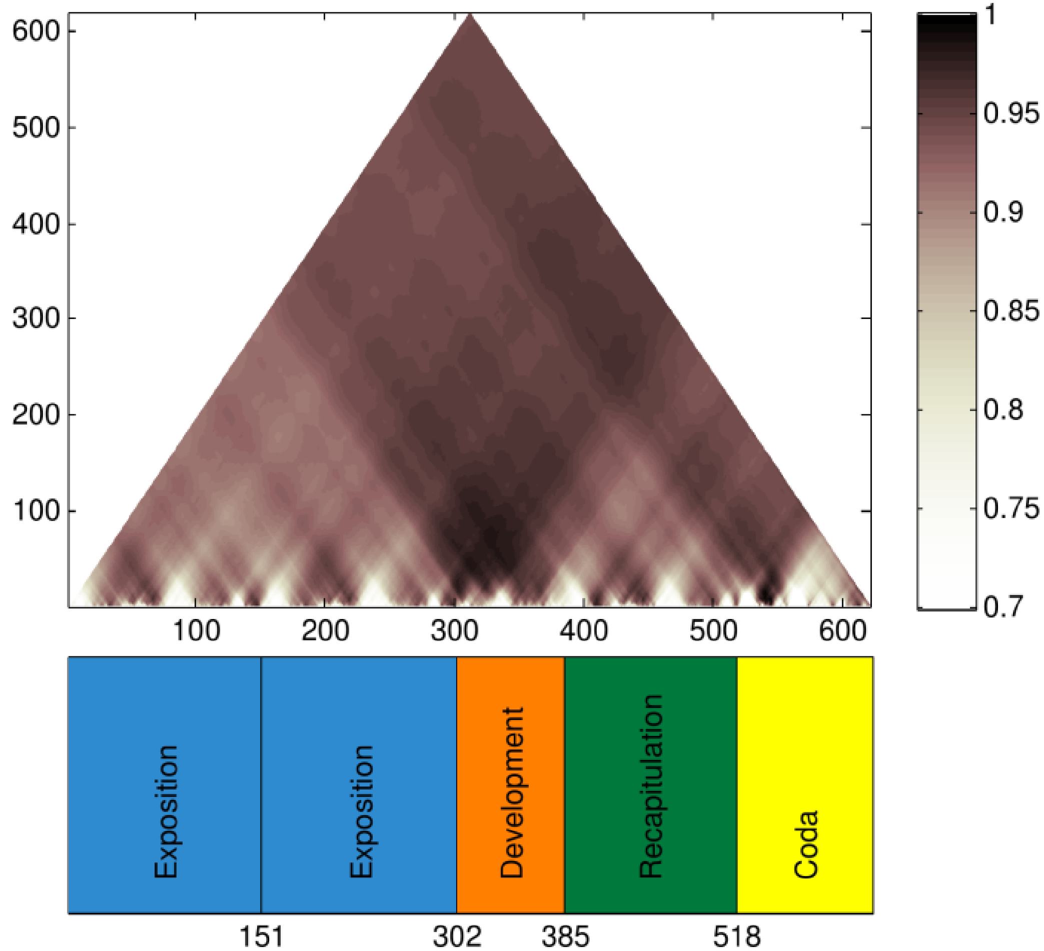
- Relating to different time scales!

Tonal Structures: Complexity



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

Tonal Structures: Complexity



L. van Beethoven
Sonata Op. 2, No. 3
1st movement

Tonal Structures: Complexity