Topic 11

Score-Informed Source Separation

(chroma slides adapted from Meinard Mueller)

Why Score-informed Source Separation?

- Audio source separation is useful
  - Music transcription, remixing, search

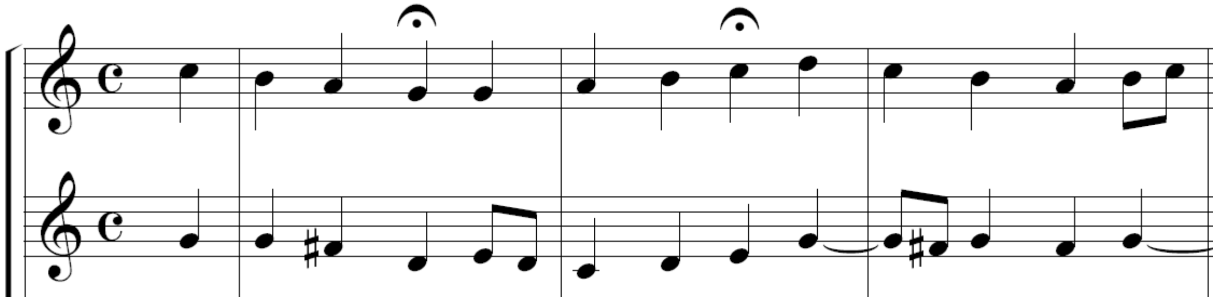
- Non-satisfying results if only using audio

- Score provides some info that one can use
  - E.g., conductor, learn to sing in a choir

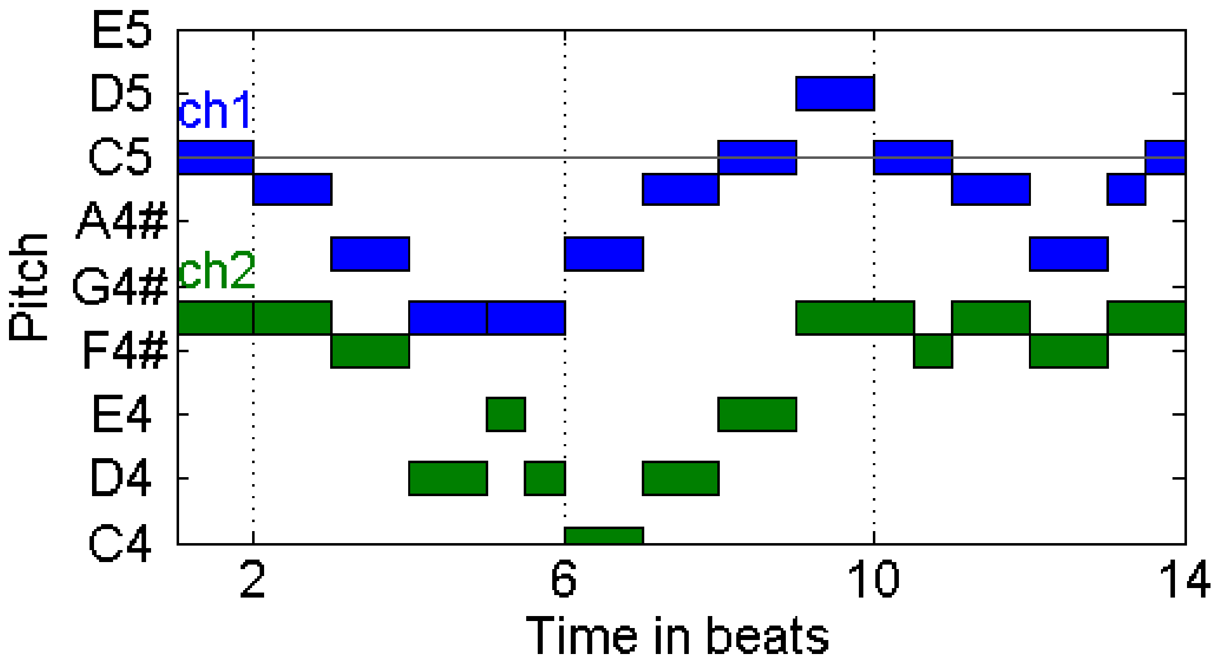
- Lots of scores are out there

Musical Score in MIDI

score sheet



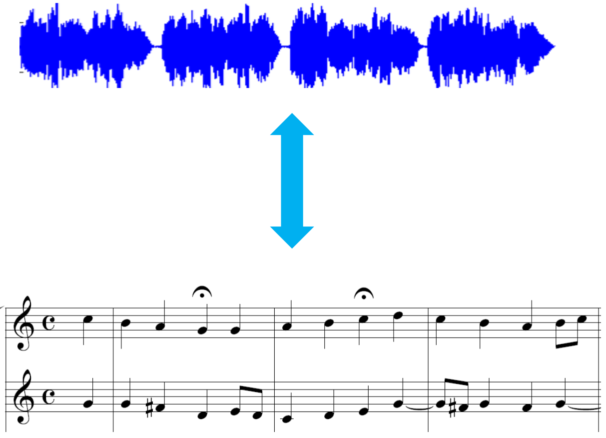
MIDI score



Would it be trivial?

instantiation

abstraction



- Is map-informed tourism trivial (for machine)?

Remaining Tasks

- Score tells us what musical objects to look for, but not where to look nor what they sound like.

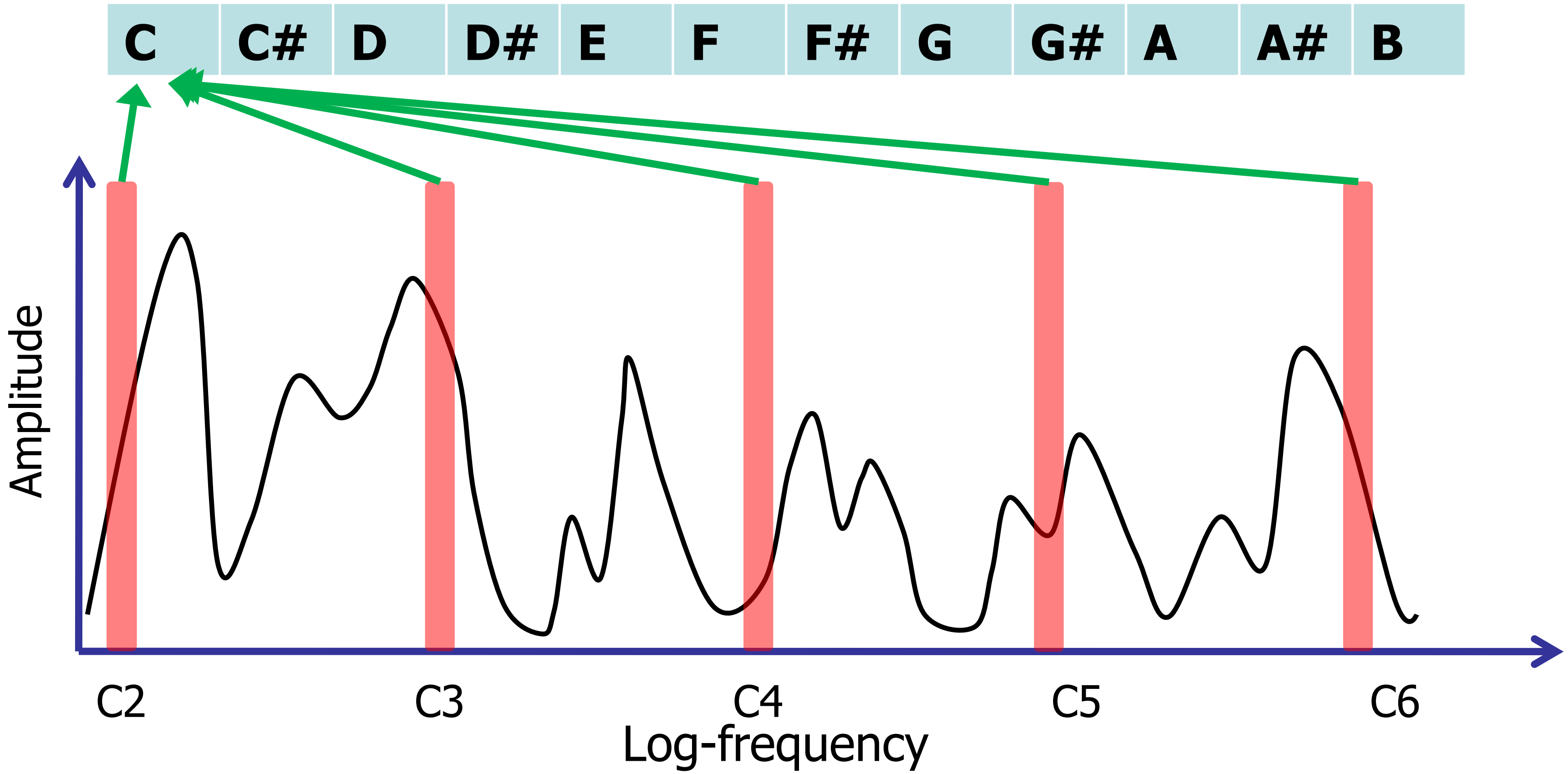
- Problems
  - How to align audio with score?
    - How to represent them?
  - How to separate the signal?

Audio/Score representations for alignment

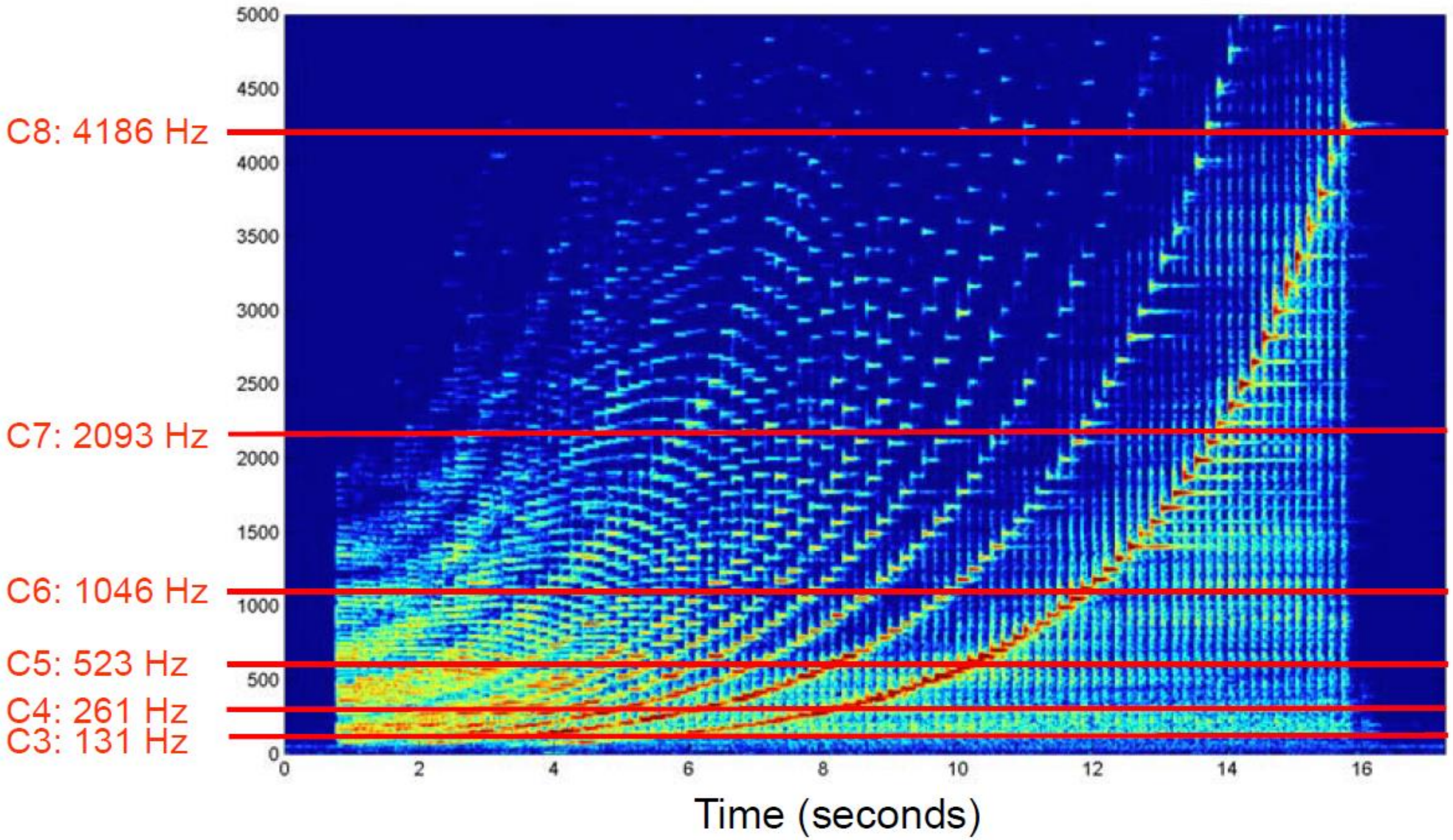
- Represent in the same way
  - Spectrum
    - Only good for monophonic music
  - Chroma feature
    - Good for polyphonic music
  - Pitch info
    - Ideal for both monophonic and polyphonic music
    - Relies on good multi-pitch estimation techniques

Chroma Feature

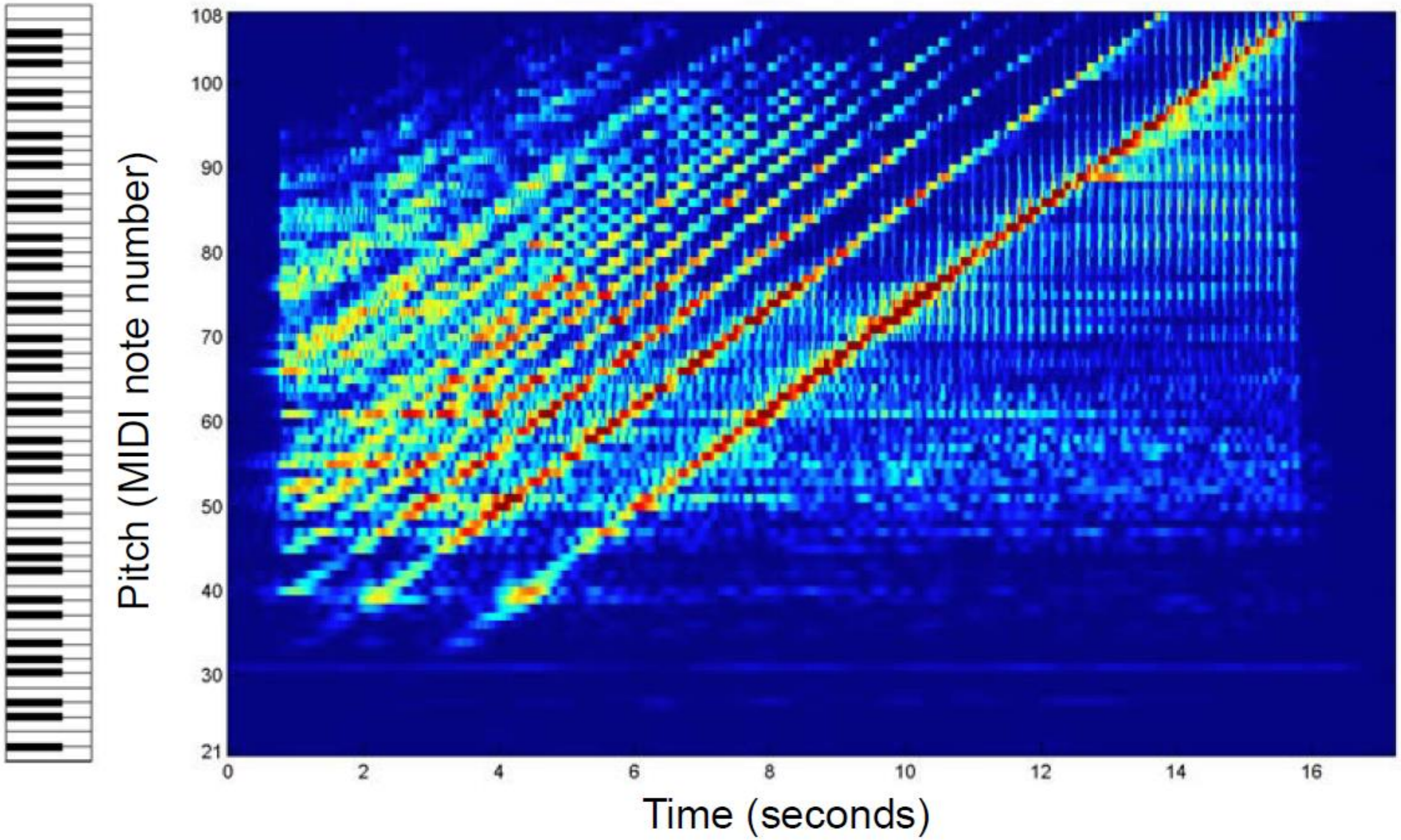
- Spectral energy of the 12 pitch classes
  - 12-d vector



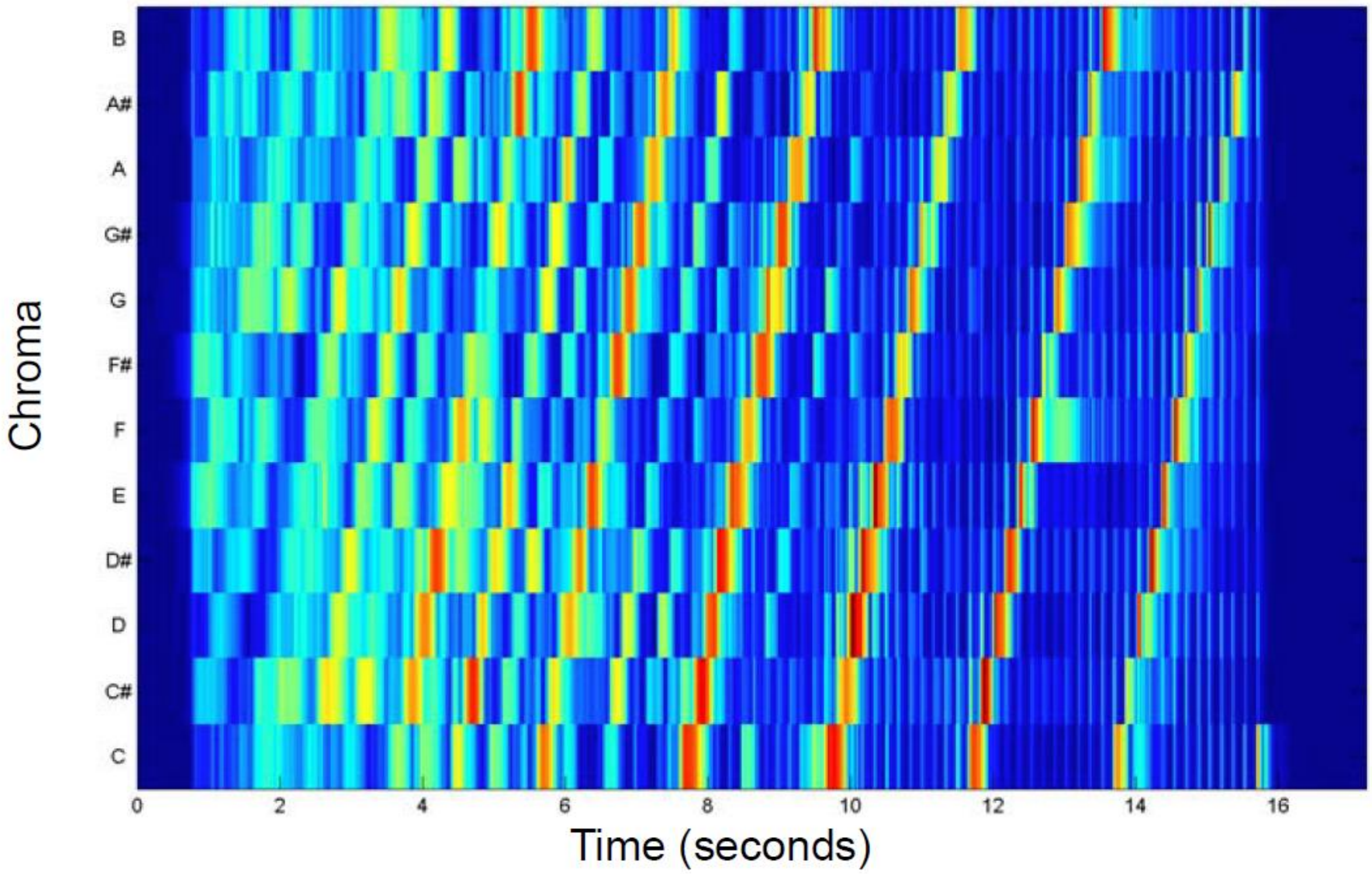
Spectrogram



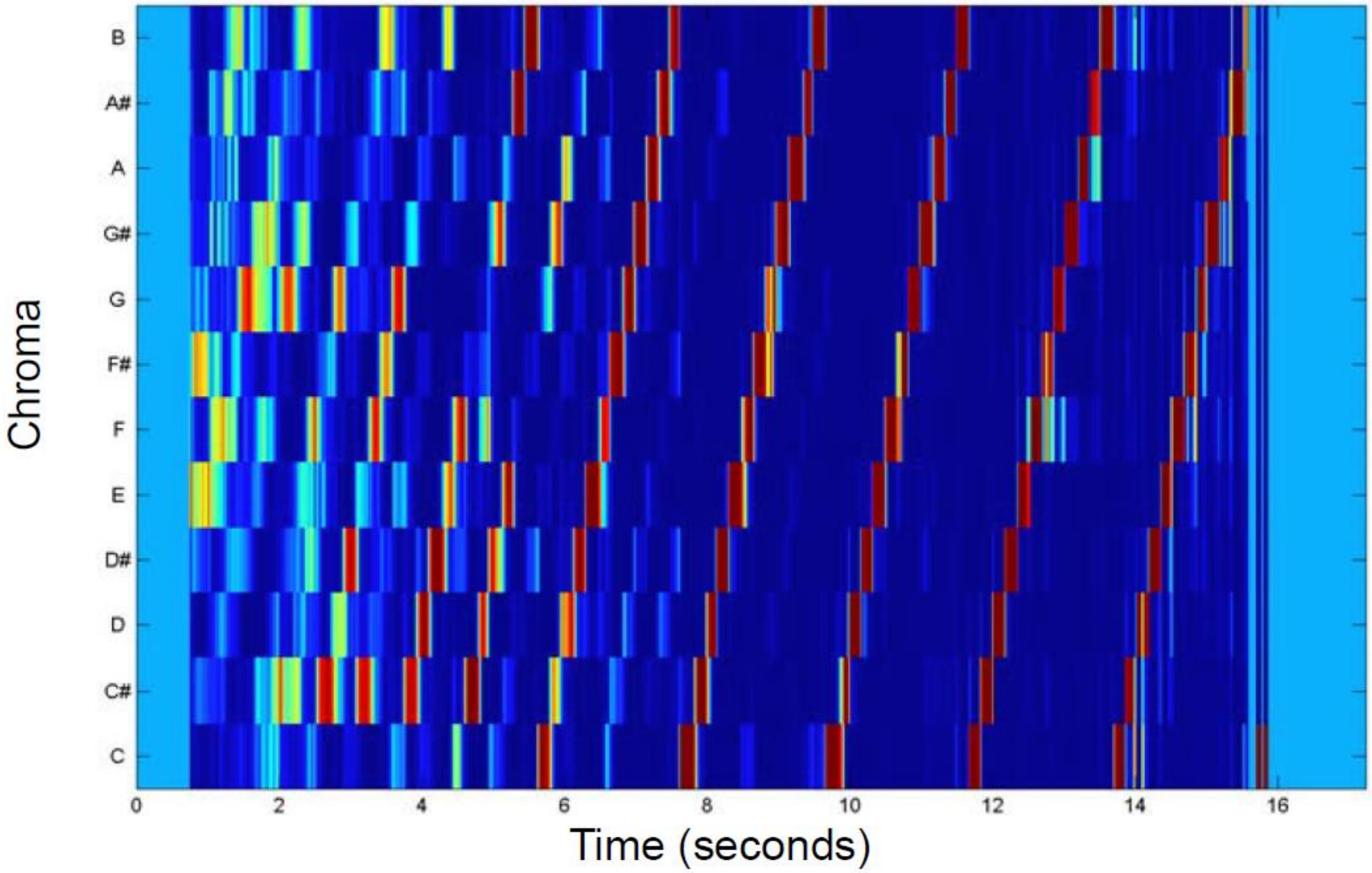
Log-frequency Spectrogram



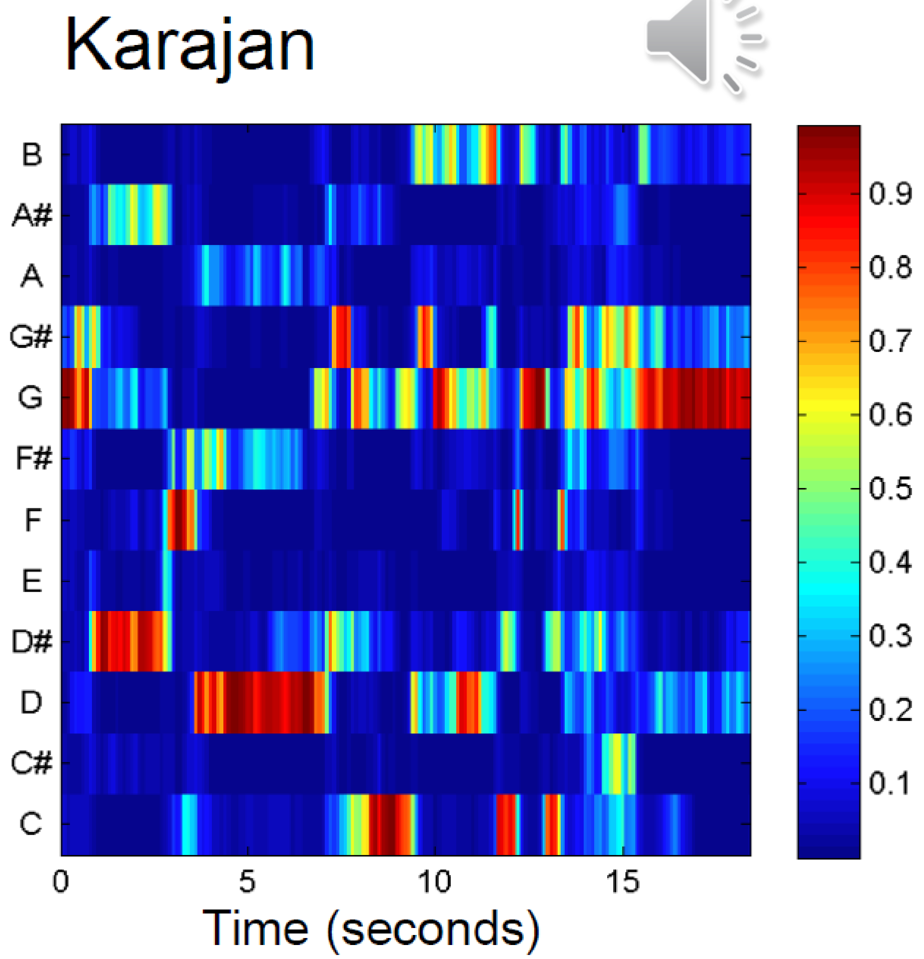
Chromagram

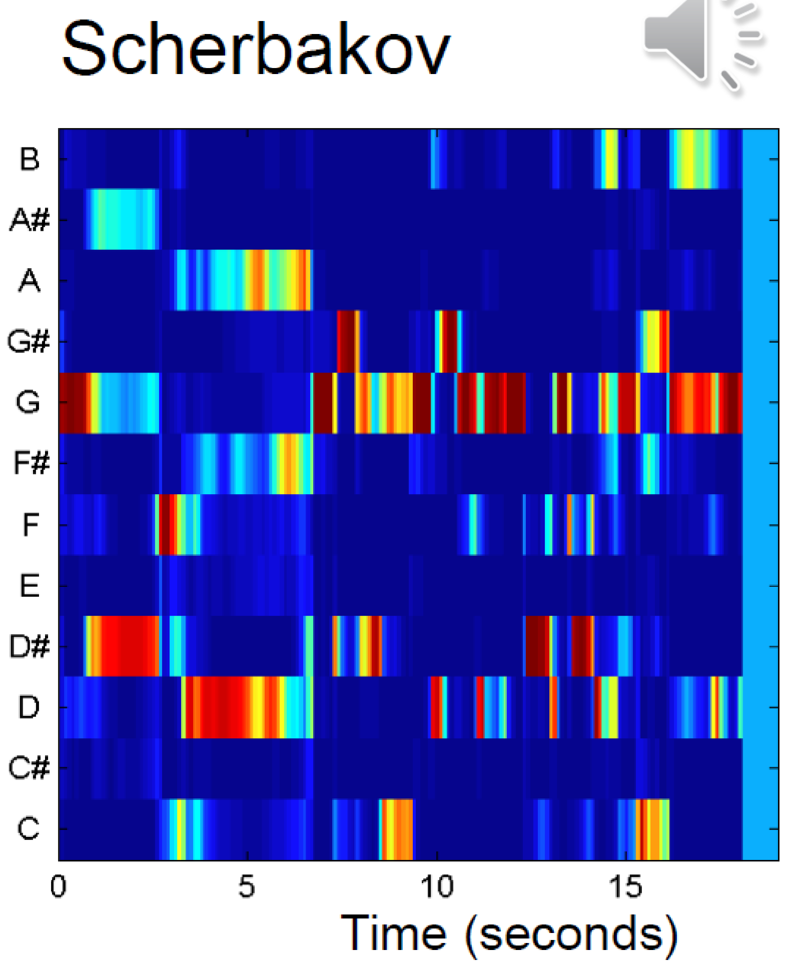


Normalized Chromagram



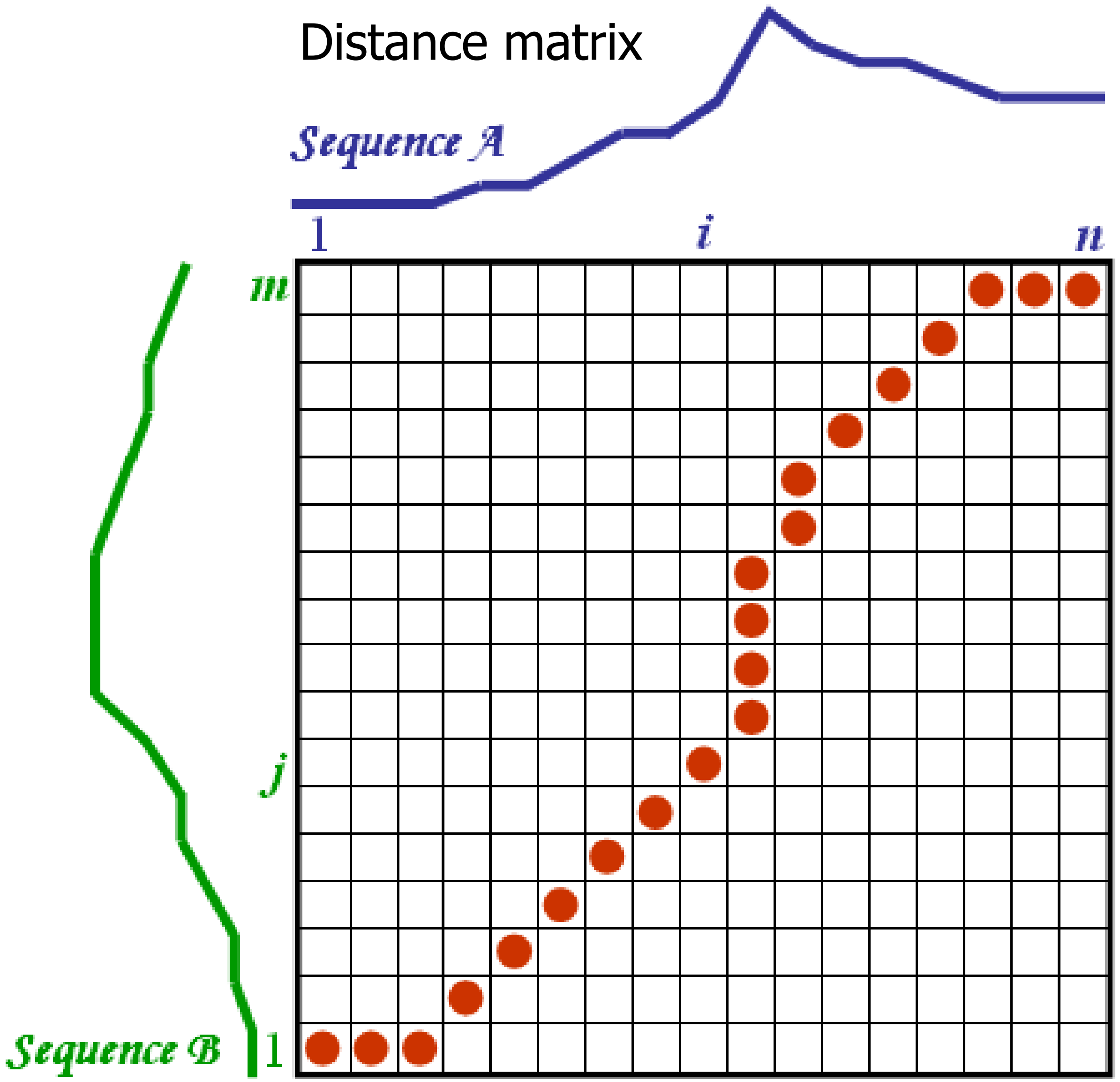
Chromagram of Polyphonic Music





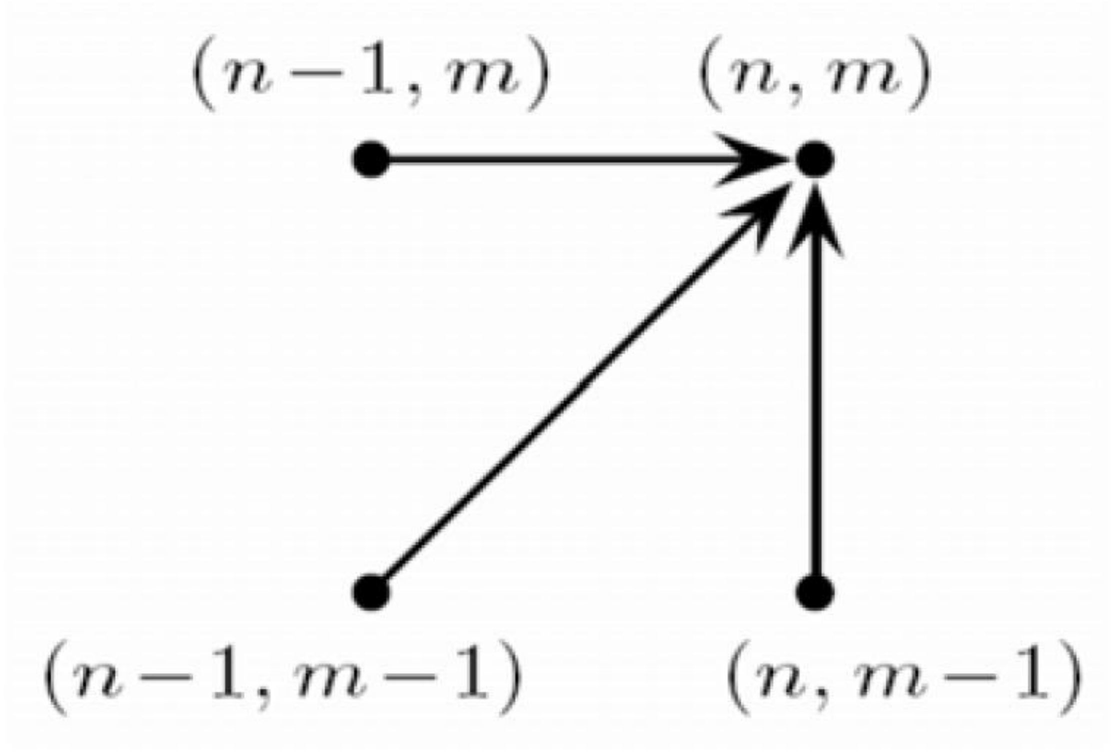
Dynamic Time Warping

- Find the path with lowest cost
- A path should
  - Monotonic
  - Step size 1
  - From (1,1) to (n,m)
- How many possible paths?



Possible Progression

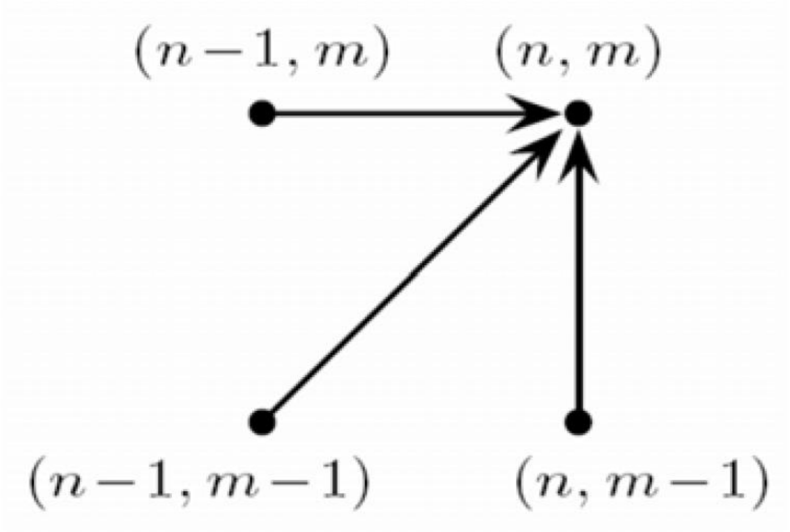
- Three ways for a path to get to (n,m) in one step



A Nice Property

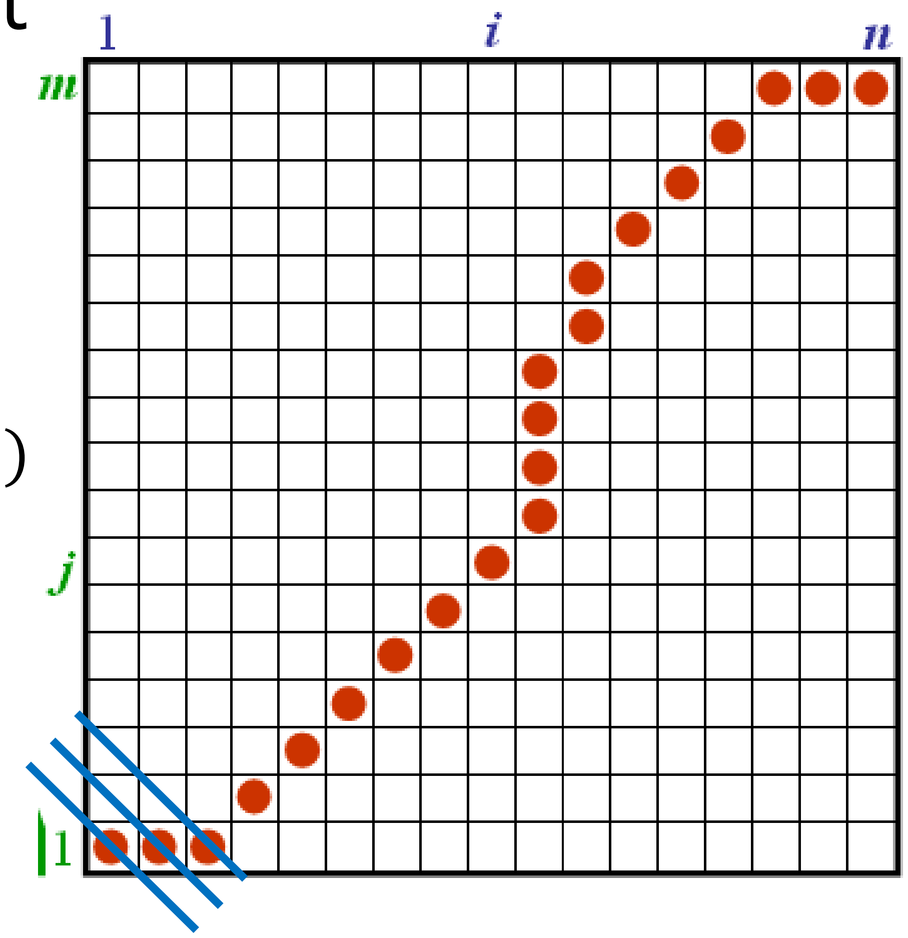
- Let $d(i,j)$ be the distance matrix
- Let $C(n,m)$ be the lowest cost from (1,1) to (n,m)
  - Then $C(1,1) = d(1,1)$

$$C(n,m) = \min \begin{cases} C(n-1,m) + d(n,m) \\ C(n-1,m-1) + d(n,m) \\ C(n,m-1) + d(n,m) \end{cases}$$



Dynamic Programming!

- Calculate the lowest cost matrix $C(i,j)$
  - Starting from $C(1,1)$
  - Then calculate $C(1,2), C(2,1)$
  - Then $C(1,3), C(2,2), \mathrm{C}(3,1)$
  - ……
  - Finally, calculate $C(n,m)$
- Remember how you calculated, and trace back to get the path



Two SISS Systems for Polyphonic Music

- Score-informed NMF
  - Chroma feature to represent audio
  - Dynamic time warping for alignment
  - NMF-based separation
  - Offline

[Ewert et al., 2009]
[Ewert & Muller, 2012]

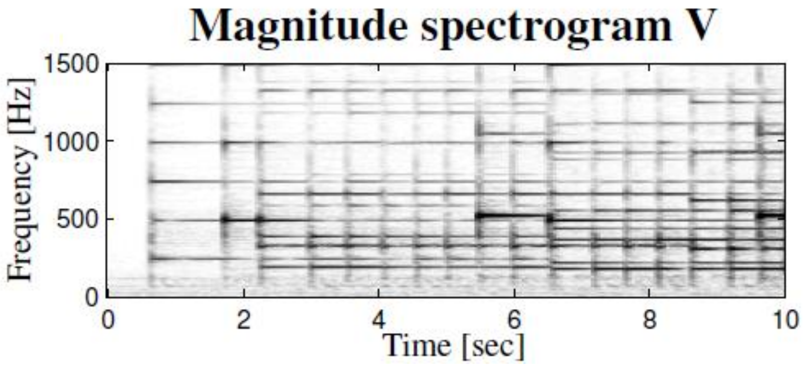
- Soundprism
  - Multi-pitch info of audio
  - Particle filtering for alignment
  - Pitch-based separation
  - Online

[Duan & Pardo, 2011]

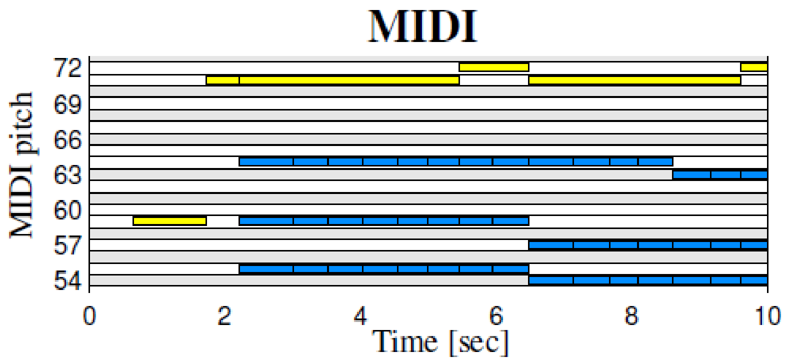
Score-informed NMF

[Ewert & Muller, 2012]

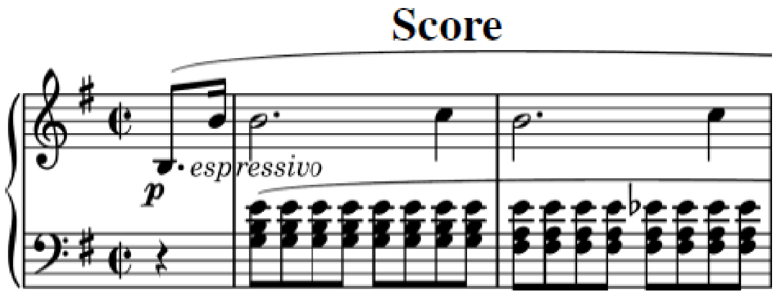
Polyphonic audio



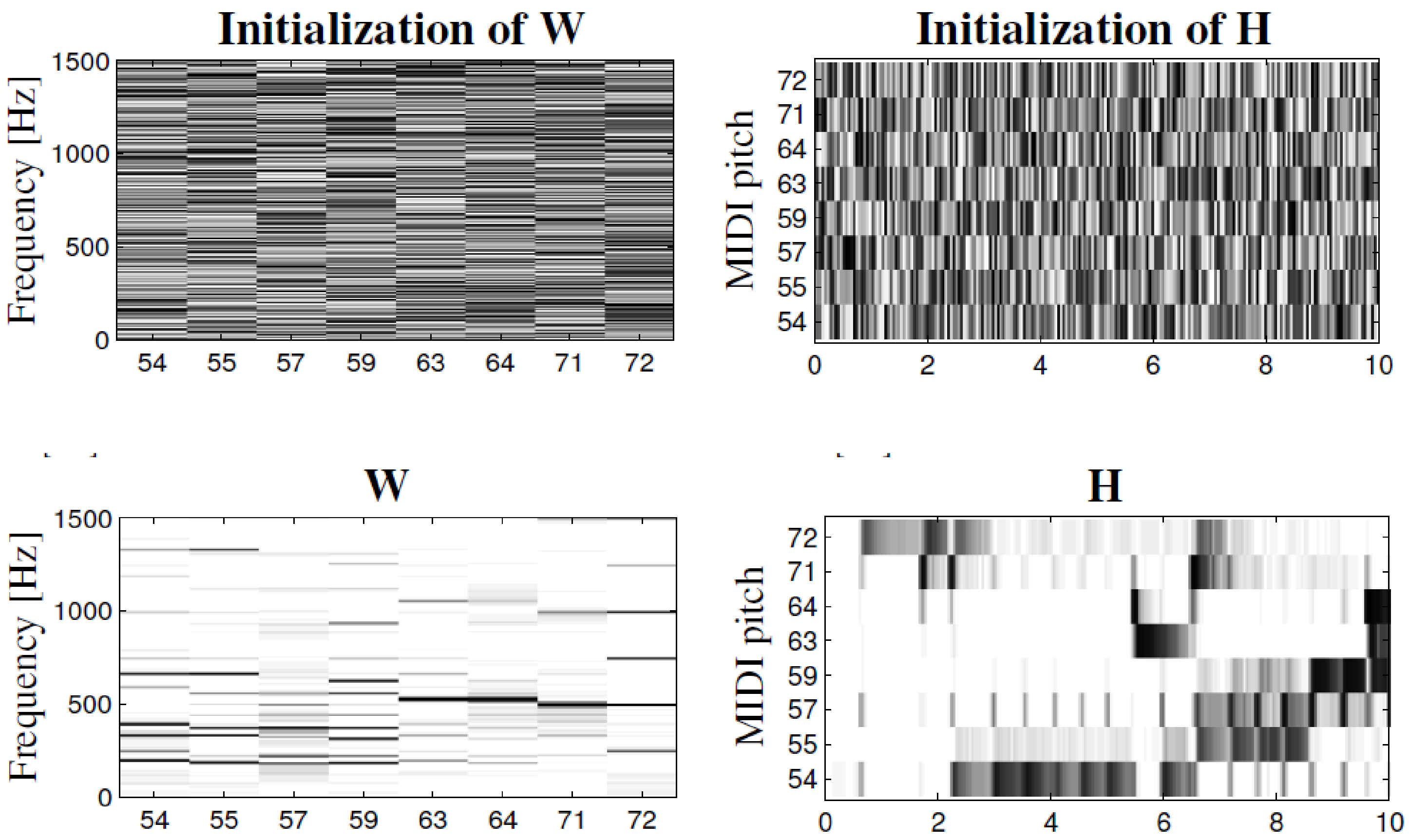
Aligned MIDI score



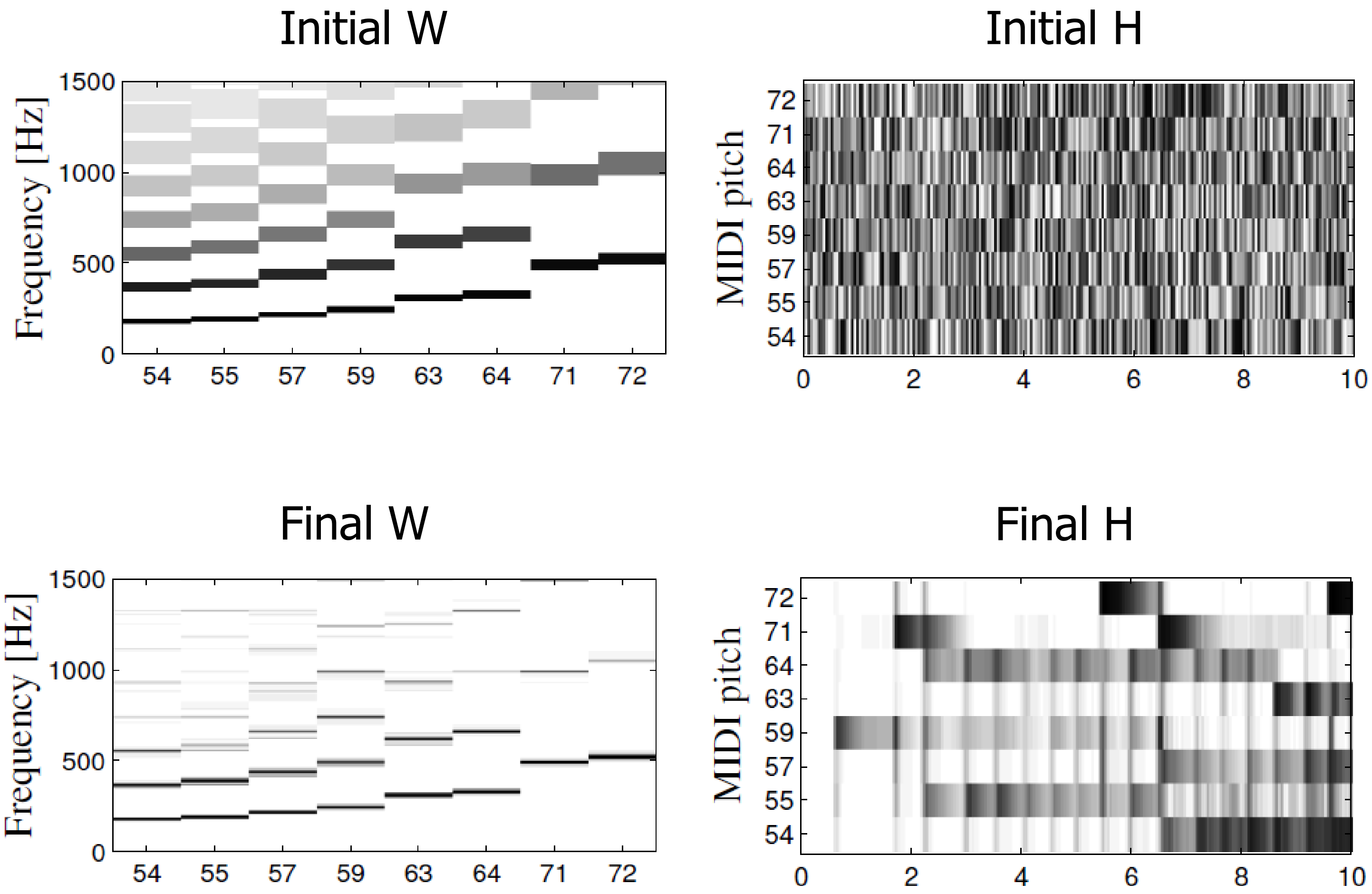
Sheet music



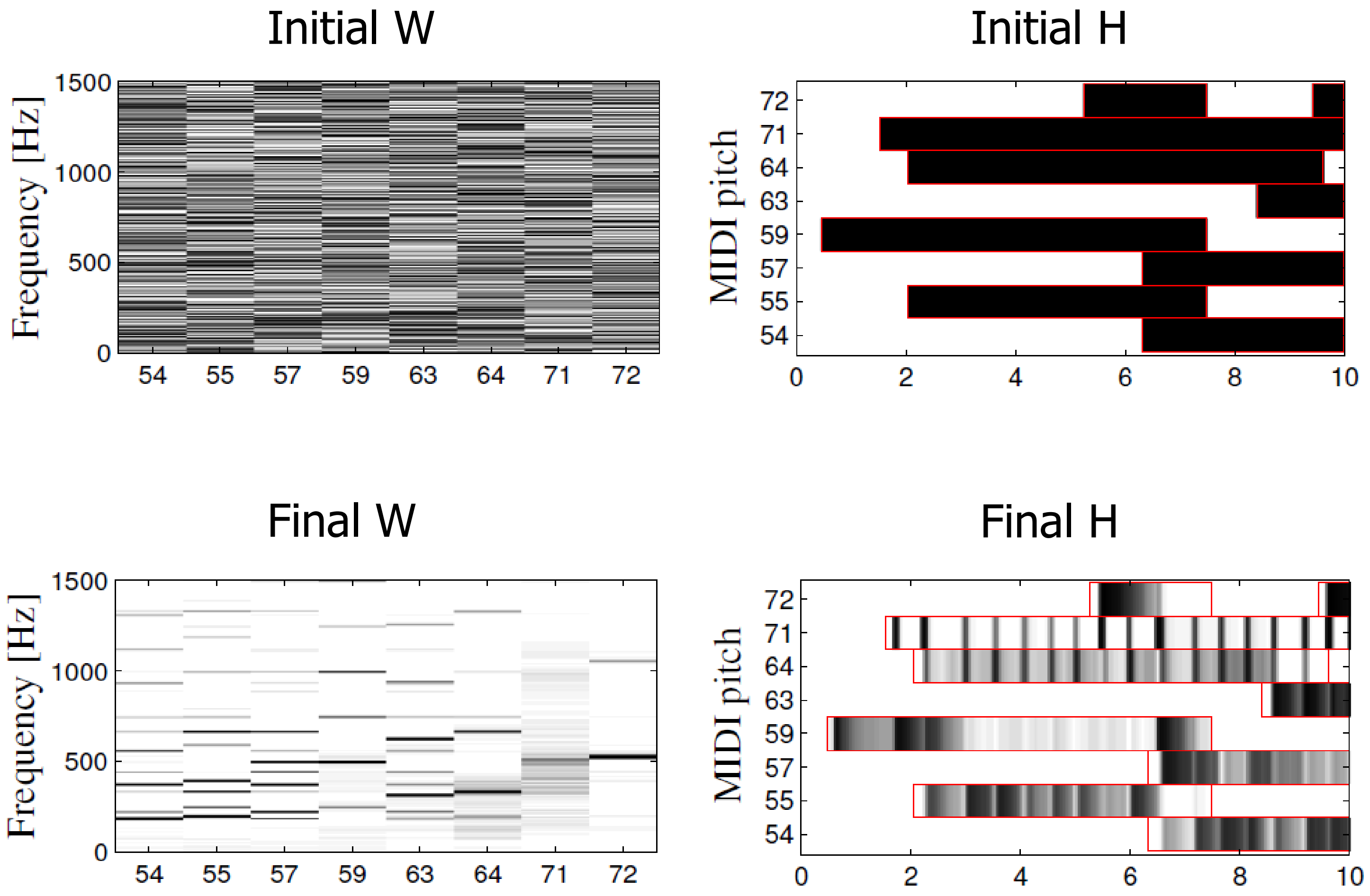
When score info is not used



When dictionary is initialized by score notes

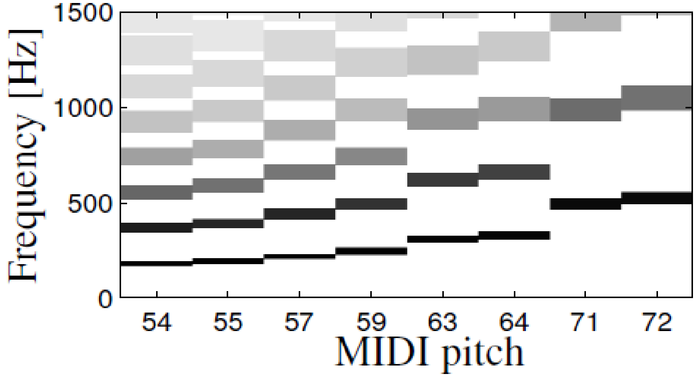


When activation is initialized by score notes

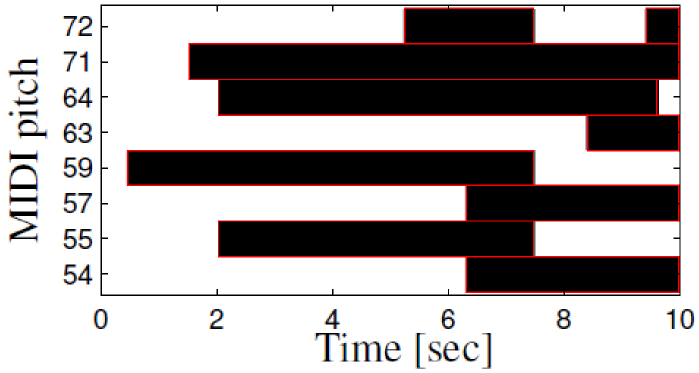


When both W and H are initialized

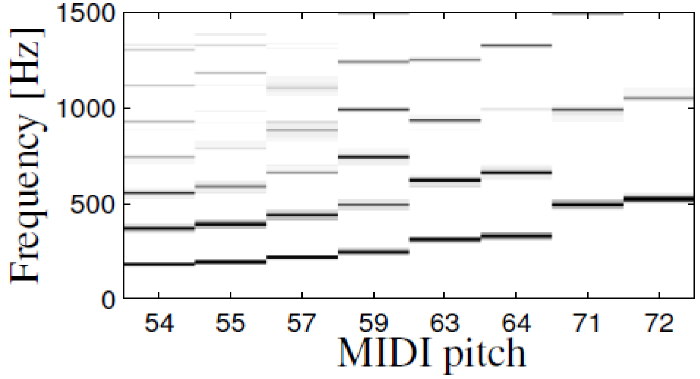
Initial W



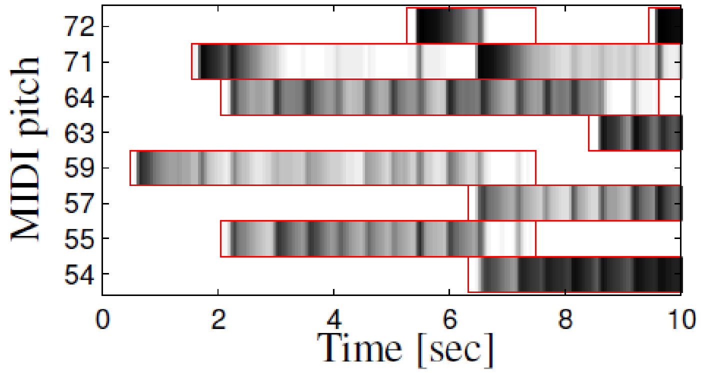
Initial H



Final W

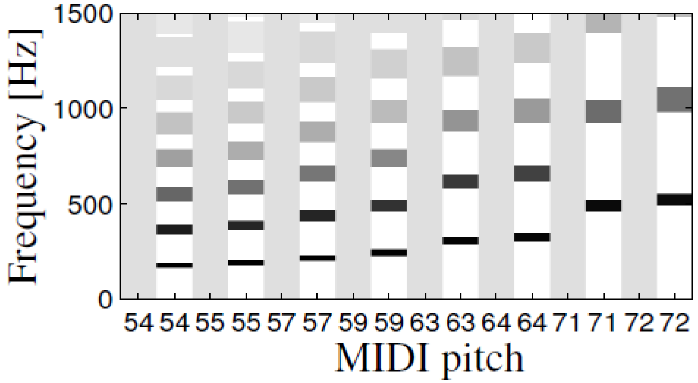


Final H

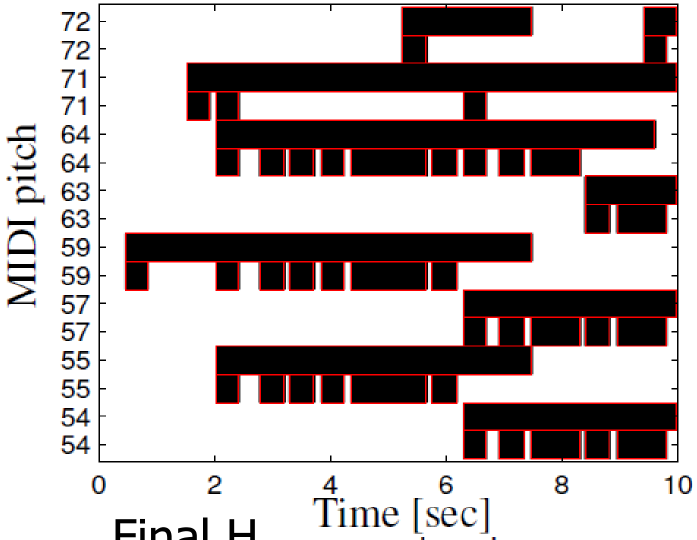


Also Considering Onset Models

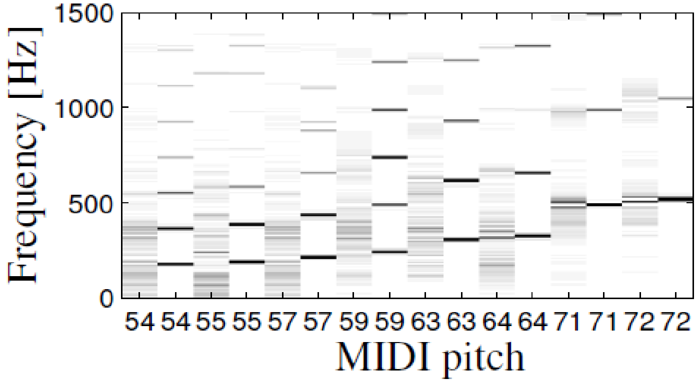
Initial W



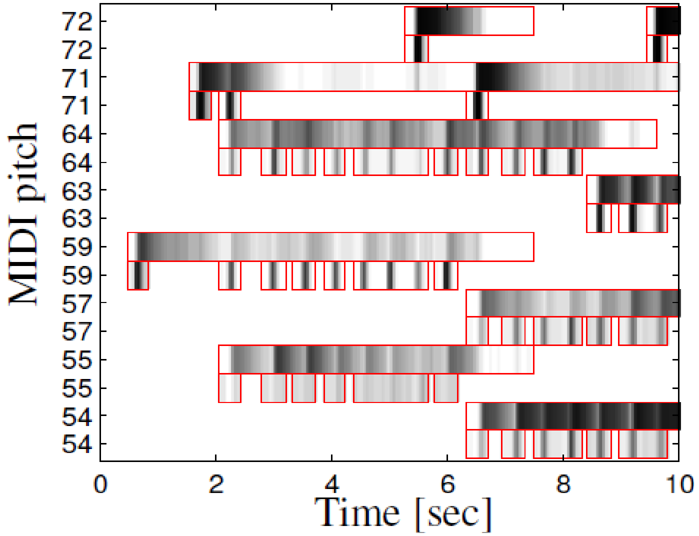
Initial H



Final W

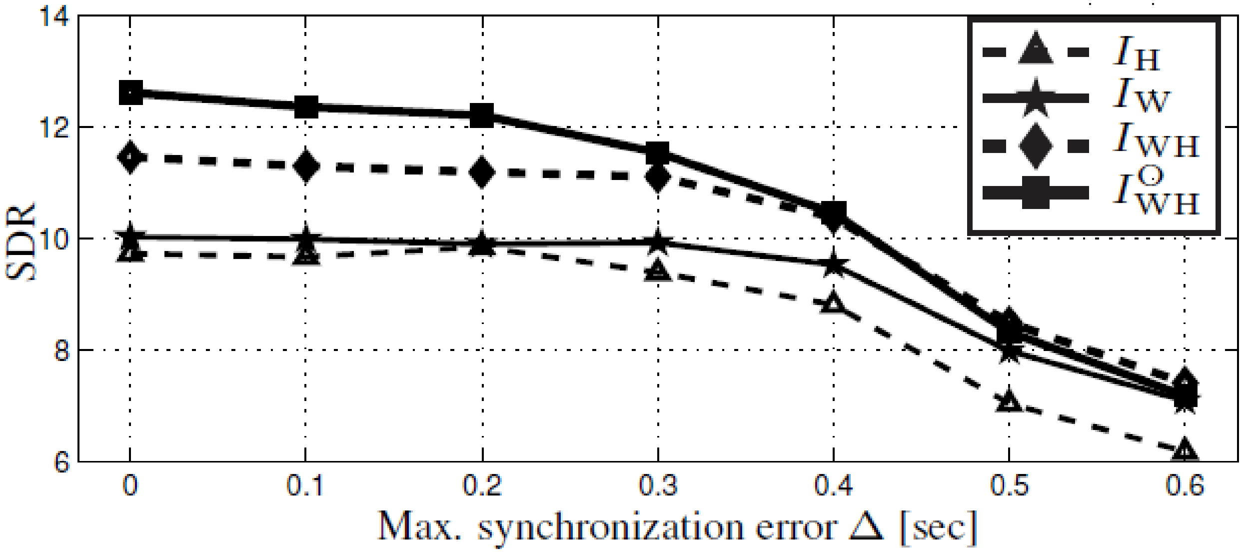


Final H



Experiments

- MIDI-synthesized piano music with randomly imposed alignment errors
  - Audio has accurate pitch, simple timbre
- Separate left/right hand notes



Discussions

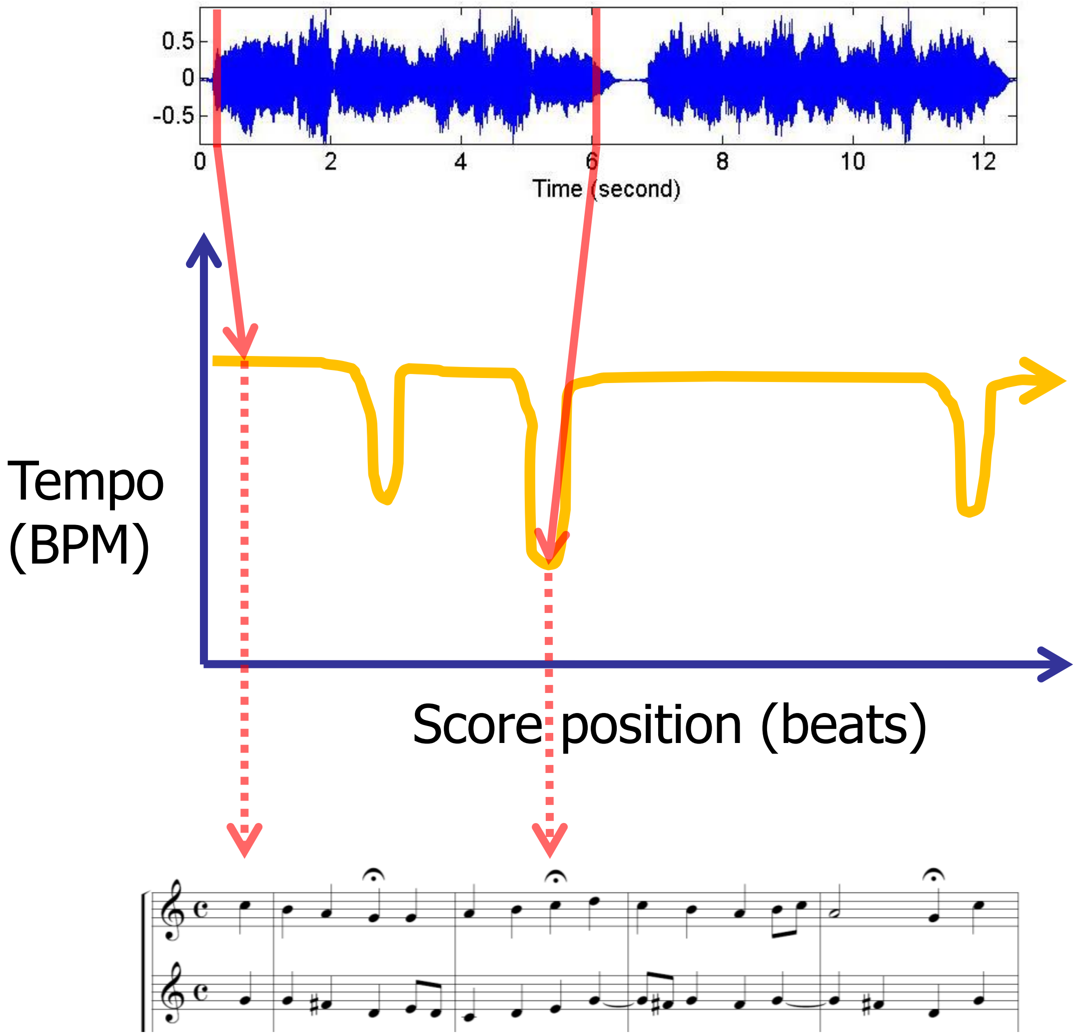
- Pros
  - “smart initialization” of W and H
  - Detailed timbre model using NMF
  - Onset modeling

- Cons
  - May be hard to deal with multi-instrument polyphonic audio
  - The same note can have different pitch and timbre
  - How many dictionary elements do we need then?

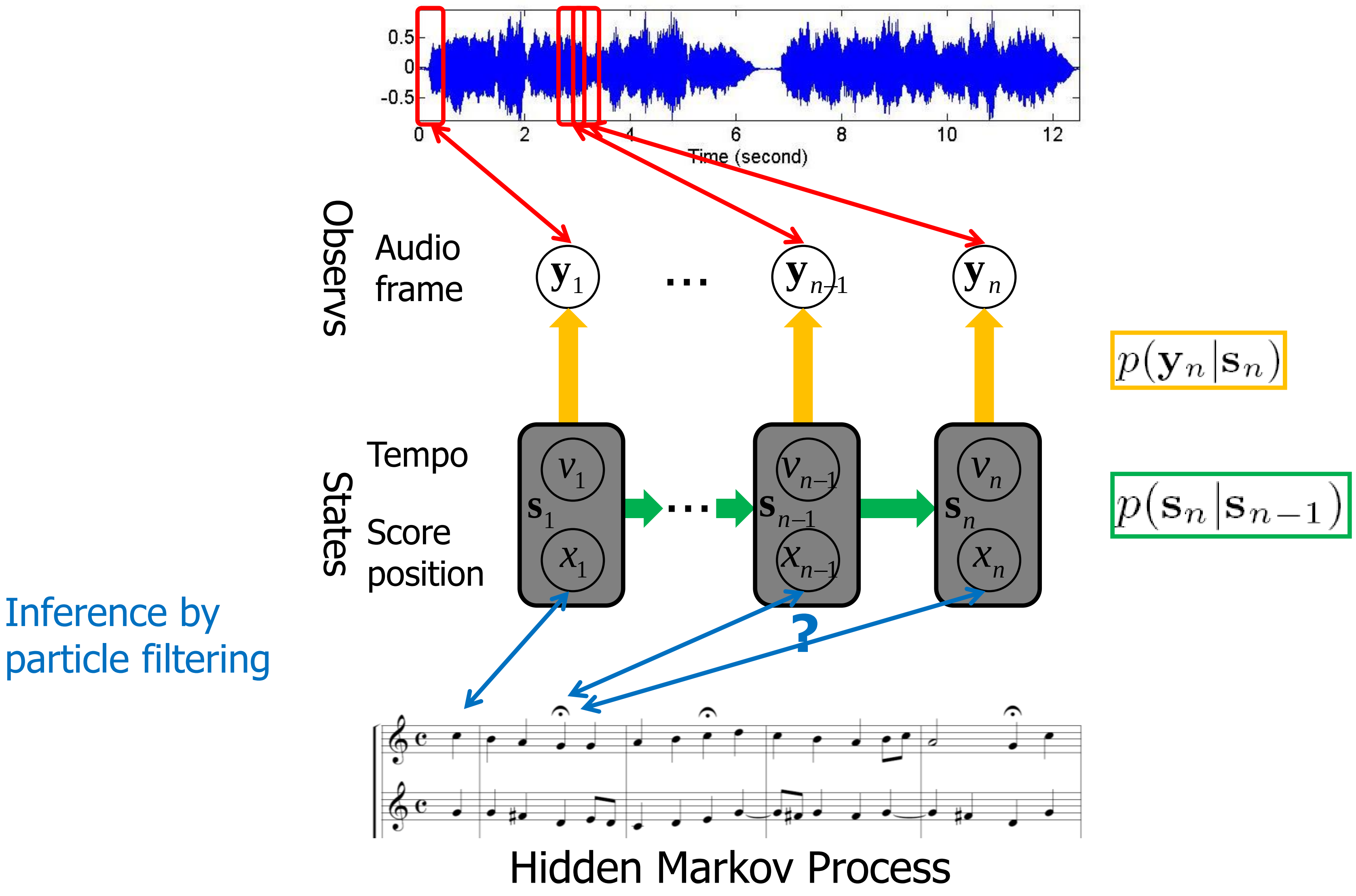
Soundprism

- Multi-pitch info of audio [Duan & Pardo, 2011]
- Particle filtering for alignment
- Pitch-based separation
- Online

Align Audio with Score

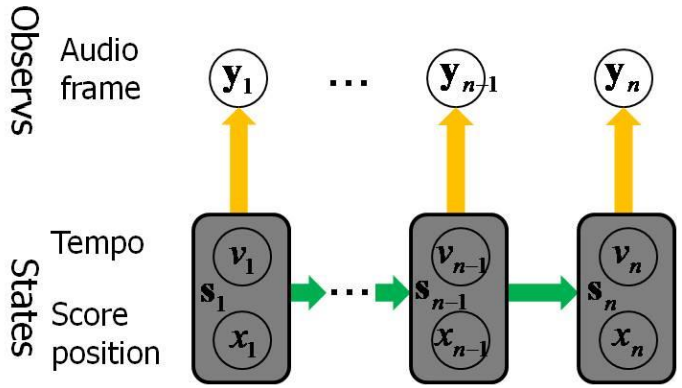


A State Space Model



Transition Model

$$\boxed{p(\mathbf{s}_n | \mathbf{s}_{n-1})}$$



- Dynamical system
  - Position: $$x_n = x_{n-1} + l \cdot v_{n-1}$$
  - Tempo: $$v_n = \begin{cases} v_{n-1} + n_v \\ v_{n-1} \end{cases}$$

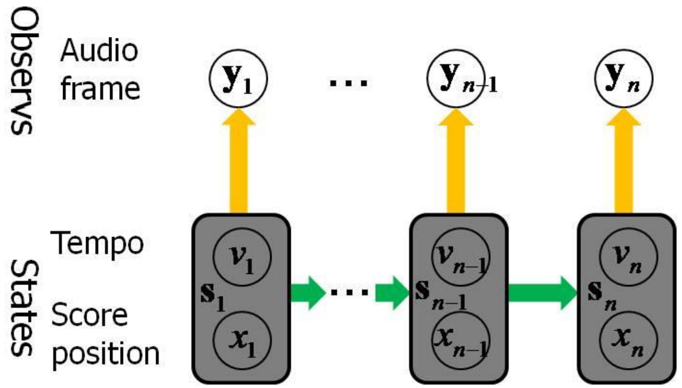
If the score position x_n just passed a score note onset

otherwise

where $$n_v \sim \mathcal{N}(0, \sigma_v^2)$$

Observation Model

$\boxed{p(\mathbf{y}_n|\mathbf{s}_n)}$



Deterministic

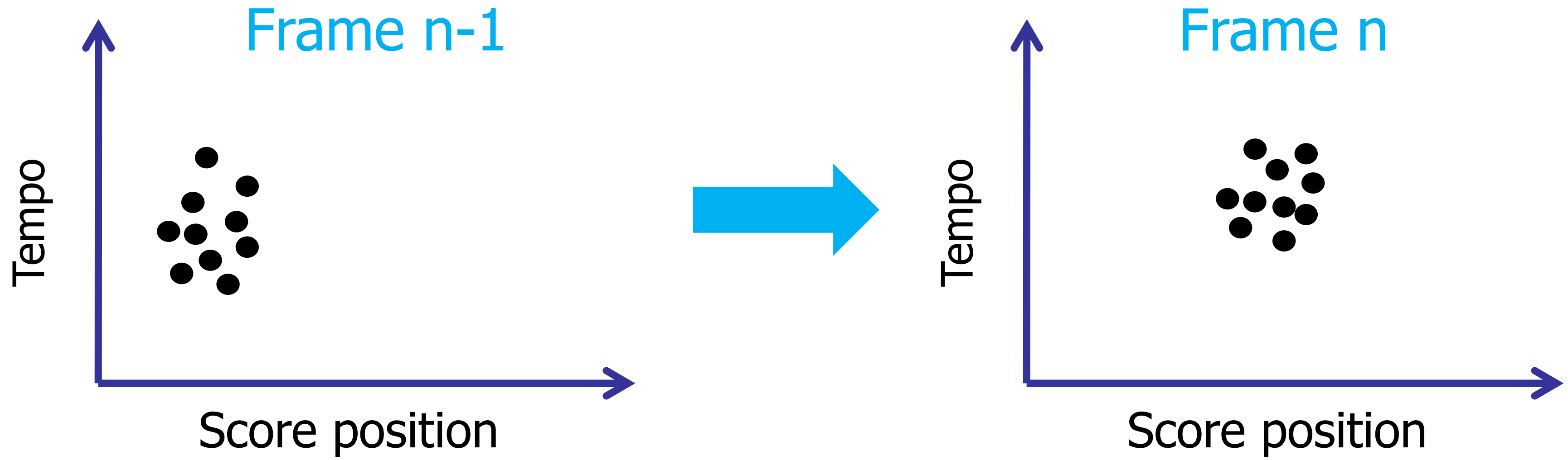
Probabilistic
$p(\boldsymbol{y}_n|\boldsymbol{\theta}_n)$

$$\begin{pmatrix} \text{tempo } v_n \\ \text{score position } x_n \end{pmatrix} \Rightarrow \text{score pitches } \boldsymbol{\theta}_n \Rightarrow \text{audio frame } \mathbf{y}_n$$

- $p(\boldsymbol{y}_n|\boldsymbol{\theta}_n)$ is the multi-pitch estimation model trained from thousands of random chords

Online Inference by Particle Filtering

- In n-th frame, estimate posterior $p(\boldsymbol{s}_n|\boldsymbol{Y}_{1:n})$ from past observations $\boldsymbol{Y}_{1:n} = (\boldsymbol{y}_1, \dots, \boldsymbol{y}_n)$
- Update $p(\boldsymbol{s}_n|\boldsymbol{Y}_{1:n})$ from $p(\boldsymbol{s}_{n-1}|\boldsymbol{Y}_{1:n-1})$ with a fixed number of particles
  - Move by $p(\boldsymbol{s}_n|\boldsymbol{s}_{n-1})$ (i.e., the dynamic equations), resample by $p(\boldsymbol{y}_n|\boldsymbol{s}_n)$

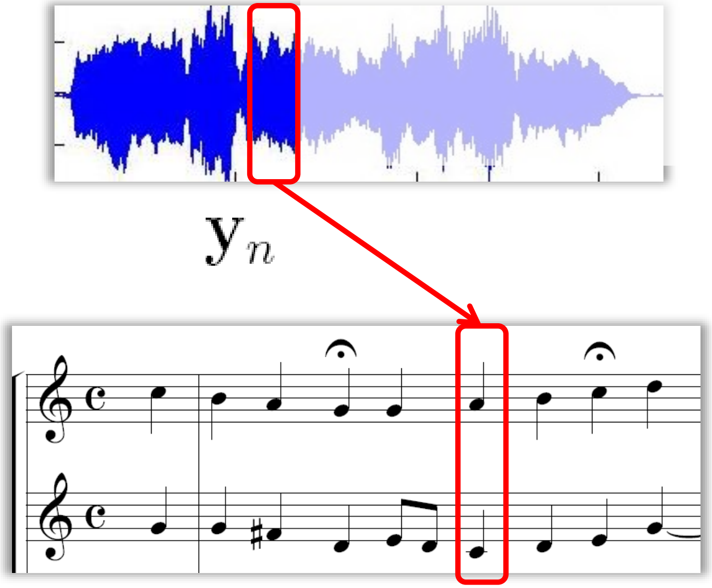


Source Separation

- 1. Accurately estimate performed pitches $\hat{\theta}_n$
  - Around score pitches $\boldsymbol{\theta}_n$

$$\hat{\theta}_n = \arg\max p(\mathbf{y}_n \mid \theta)$$

$$\text{s.t. } \theta \in [\theta_n - 50\text{cents}, \theta_n + 50\text{cents}]$$

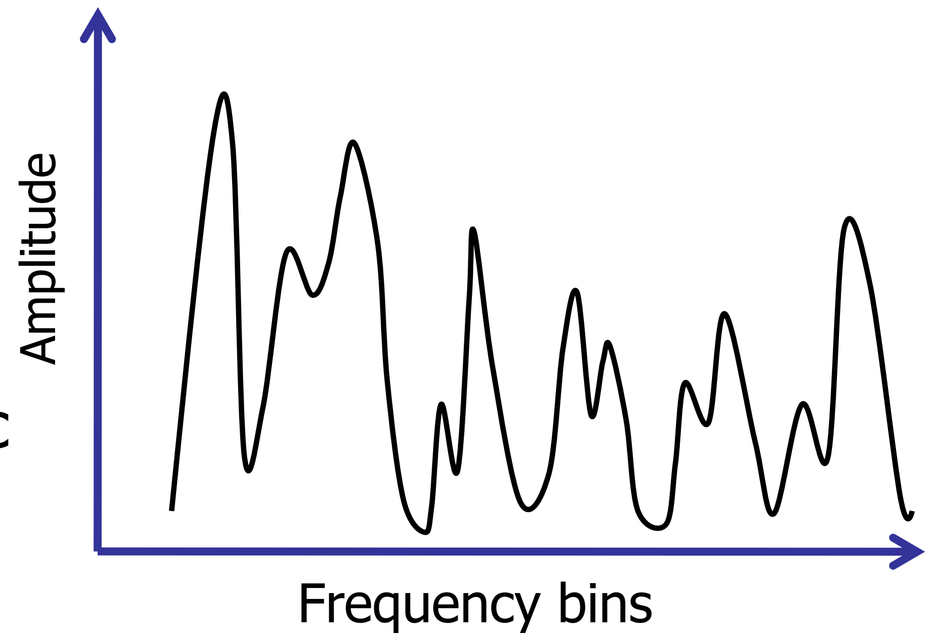


$\mathbf{y}_n$

$\boldsymbol{\theta}_n$

Reconstruct Source Signals

- 2. Allocate mixture's spectral energy
  - Non-harmonic bins
    - To all sources, evenly
  - Non-overlapping harmonic bins
    - To the active source, solely
  - Overlapping harmonic bins
    - To active sources, in inverse proportion to the square of harmonic numbers



Harmonic positions for Source 1	0	1	0	1	0	1	0	1	0	1
Harmonic positions for Source 2	0	0	1	0	0	1	0	0	1	0

- 3. IFFT with mixture's phase to go back to time domain

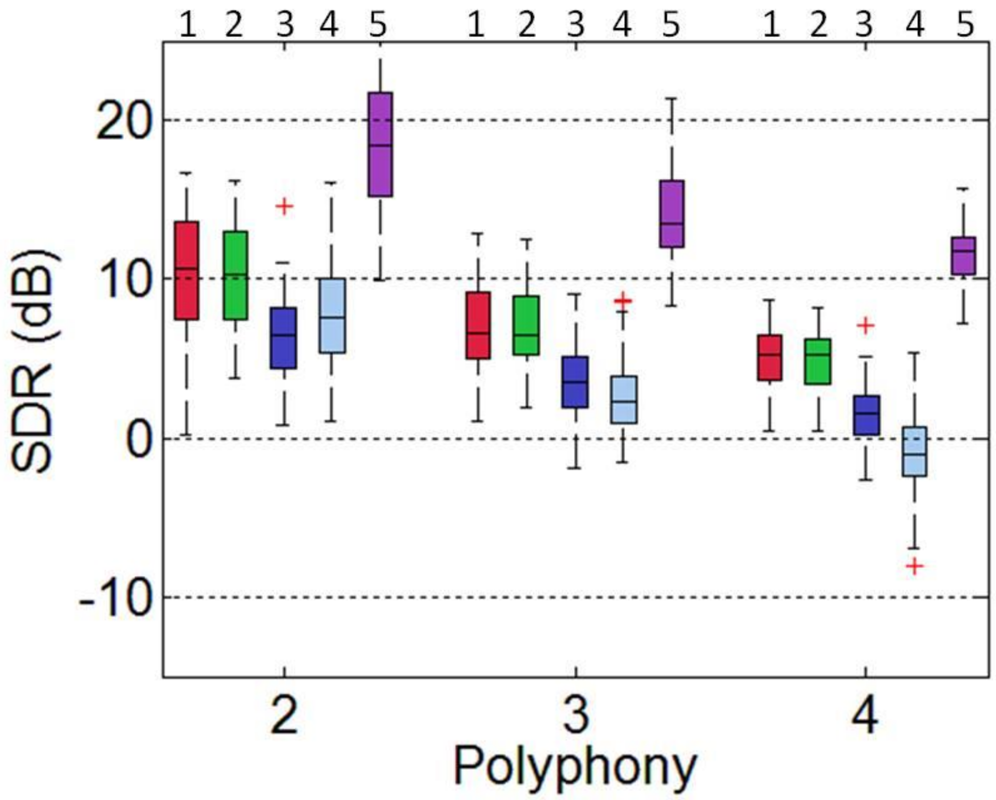
Experiments

- 10 pieces of J.S. Bach 4-part chorales
- Audio played by violin, clarinet, saxophone and bassoon, separately recorded and then mixed.
- MIDI score downloaded
- Ground-truth alignment manually annotated

- 150 combinations = 40 solos + 60 duets + 40 trios + 10 quartets

Source Separation Results

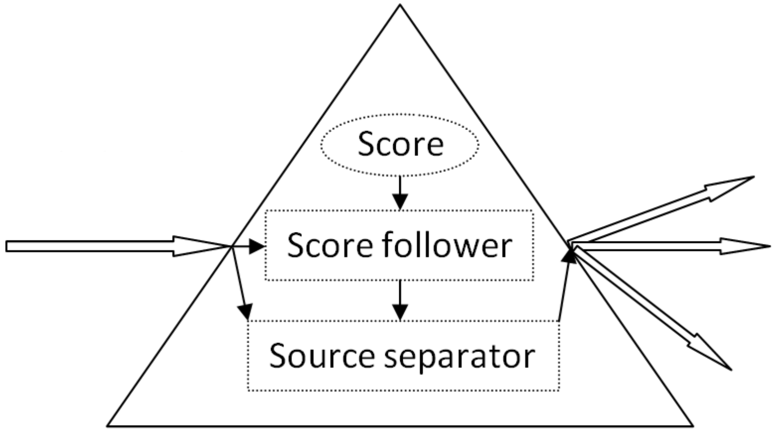
- 1. Proposed
- 2. Ideally-aligned
- 3. Ganseman et al'10 (offline algorithm)
- 4. Multi-pitch estimation & streaming-based separation (without score)
- 5. Oracle



Average input SDR	0dB	-3dB	-4.78dB

Soundprism

Single-channel polyphonic music



Source 1
Source 2
…
Source N

J. Brahms, Clarinet Quintet in B minor, op.115. 3rd movement

Interactive Music Editing

Demo…

Discussions

- Advantages
  - Online system, potential for real-time applications
  - Can deal with multi-instrument polyphonic audio
  - Multi-pitch info is used

- Disadvantages
  - Multi-pitch model cannot distinguish different parts of a note
  - No onset modeling, alignment not precise
  - No timbre modeling in separation