Methods for the automatic structural analysis of music

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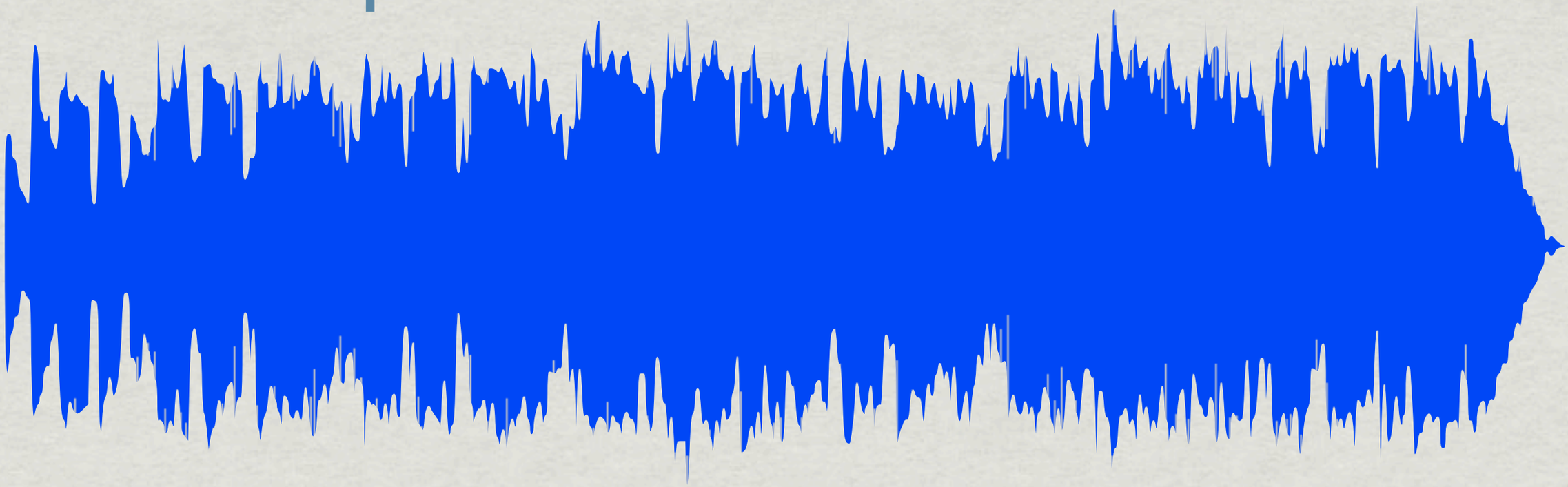
CIRMMT Workshop on Structural Analysis of Music

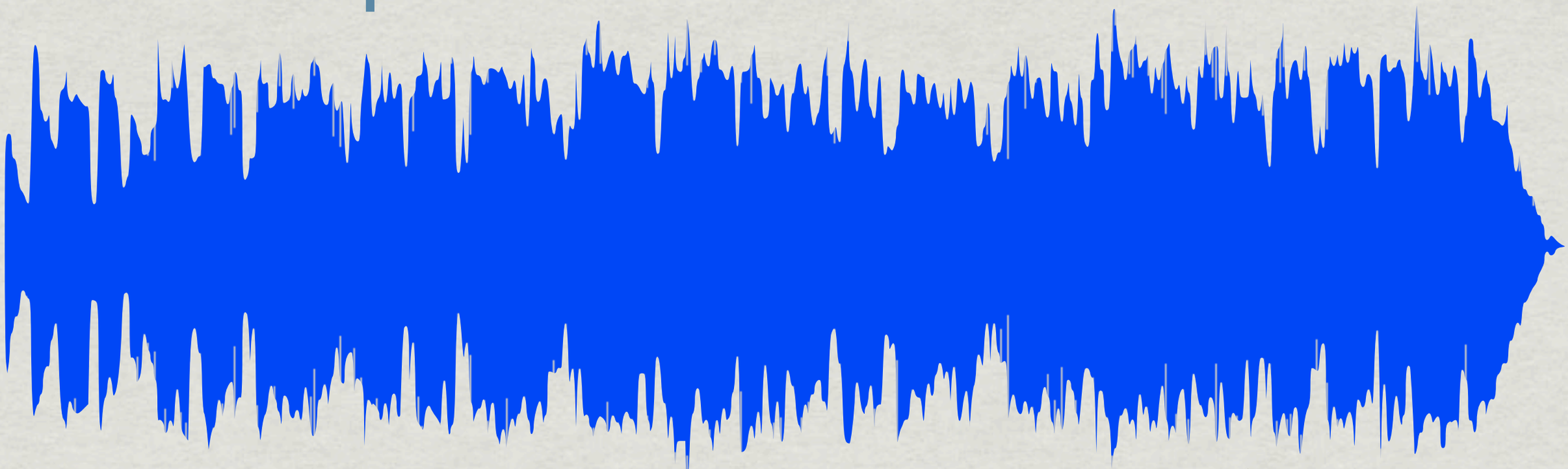
26 March 2010

The problem



- Going from sound to structure

The problem



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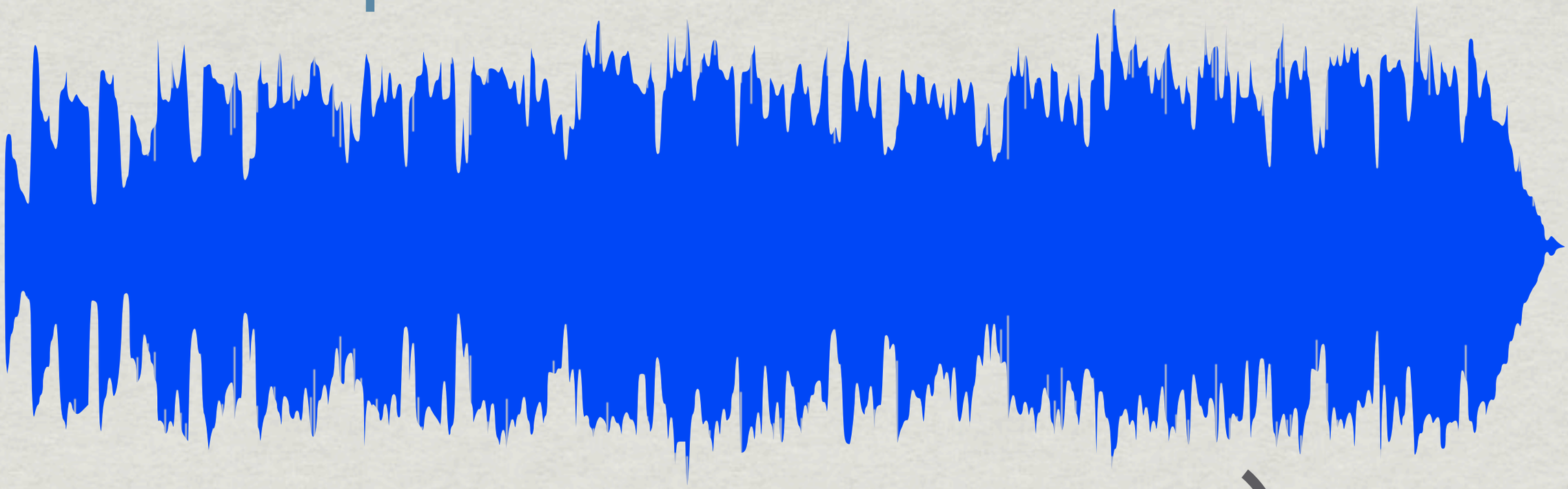
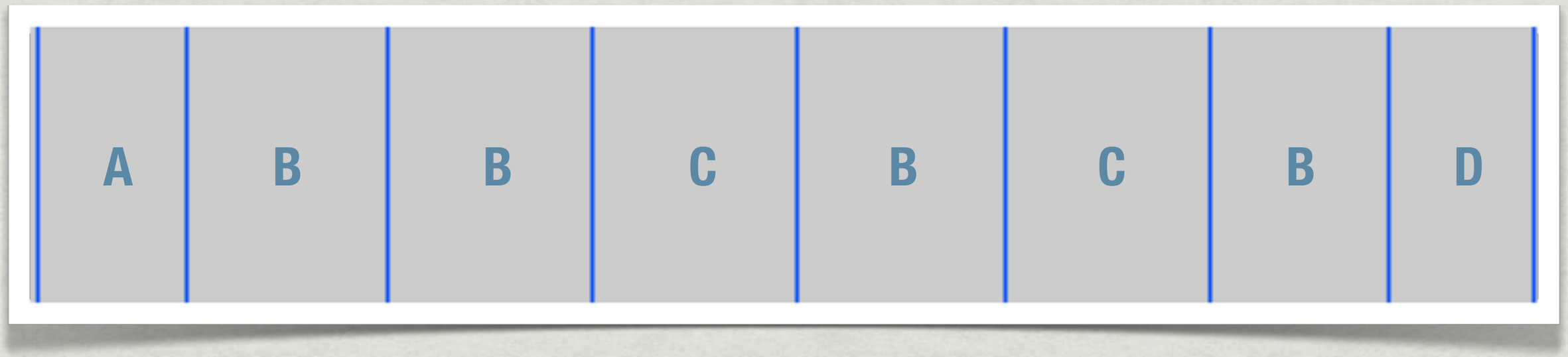


- Going from sound to structure



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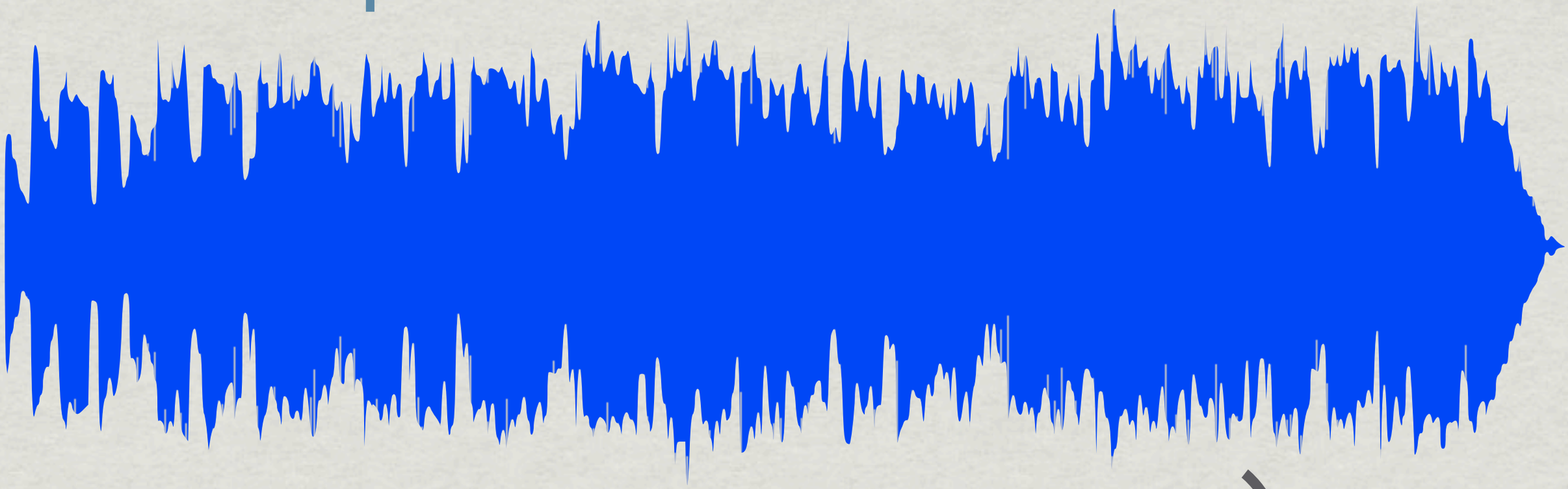

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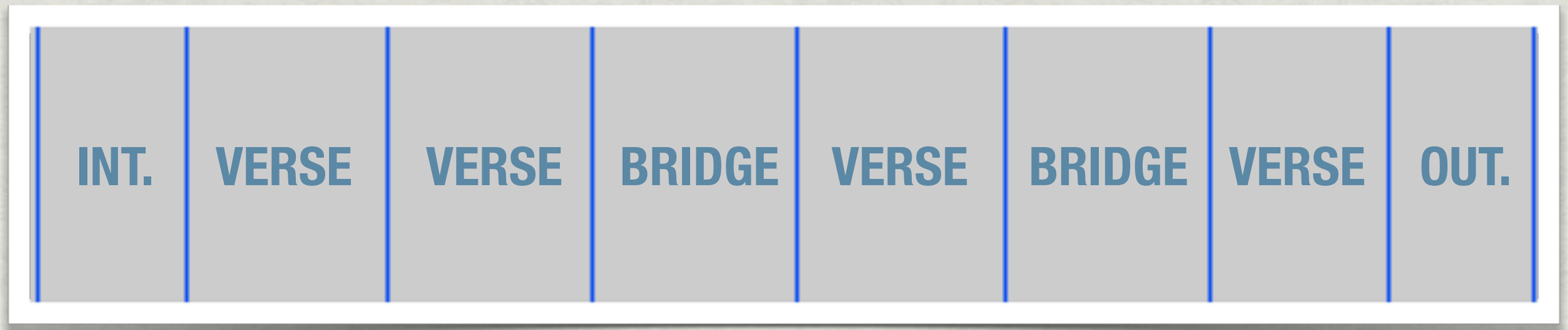


My objective today:

- To describe the variety of methods out there
- To illustrate three ways of subdividing the field

Three ways to look at the field:

- By hypotheses about what structure is → Sequences vs. states
- By hypotheses about how structure is expressed → Timbre vs. harmony (vs. rhythm vs. lyrics...)
- By techniques to do structure analysis → Similarity matrix vs. clustering

Outline

1. Two hypotheses:

- States
- Sequences

2. A word on features:

- Timbre, harmony, etc.
- Dynamic features

3. Two techniques:

- Similarity matrix
- Clustering models

Features (fast)

- Timbral features: instrumentation, vocal quality, etc.

MFCC,
MPEG-7 DESCRIPTORS

- Pitch features: what notes and chords are being played

CHROMA VECTOR,
FUNDAMENTAL FREQUENCY

- Rhythmic features: pulse periods

RHYTHMOGRAM

Features (fast)

- Timbral features: instrumentation, vocal quality, etc.

  MFCC, MPEG-7 DESCRIPTORS

- Pitch features: what notes and chords are being played

  CHROMA VECTOR, FUNDAMENTAL FREQUENCY

- Rhythmic features: pulse periods

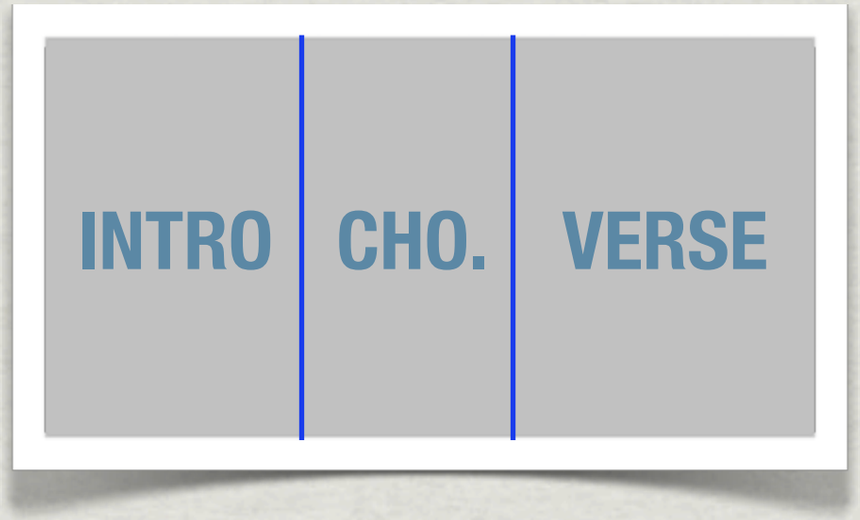
  RHYTHMOGRAM

- Lyrics

  LYRICS

Features

- What makes sections different?



PAUL SIMON: "CAN'T RUN BUT"

Features

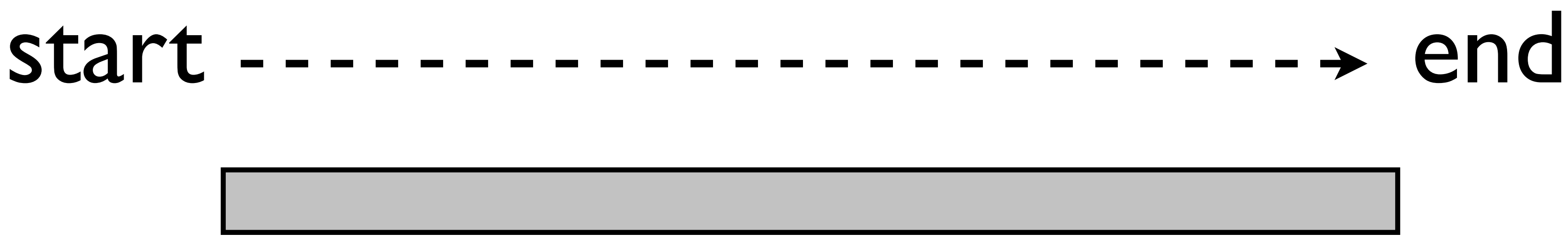
- What makes sections similar?

...

...

THE BEATLES: “BABY IT’S YOU”

Technique 1:
Similarity Matrices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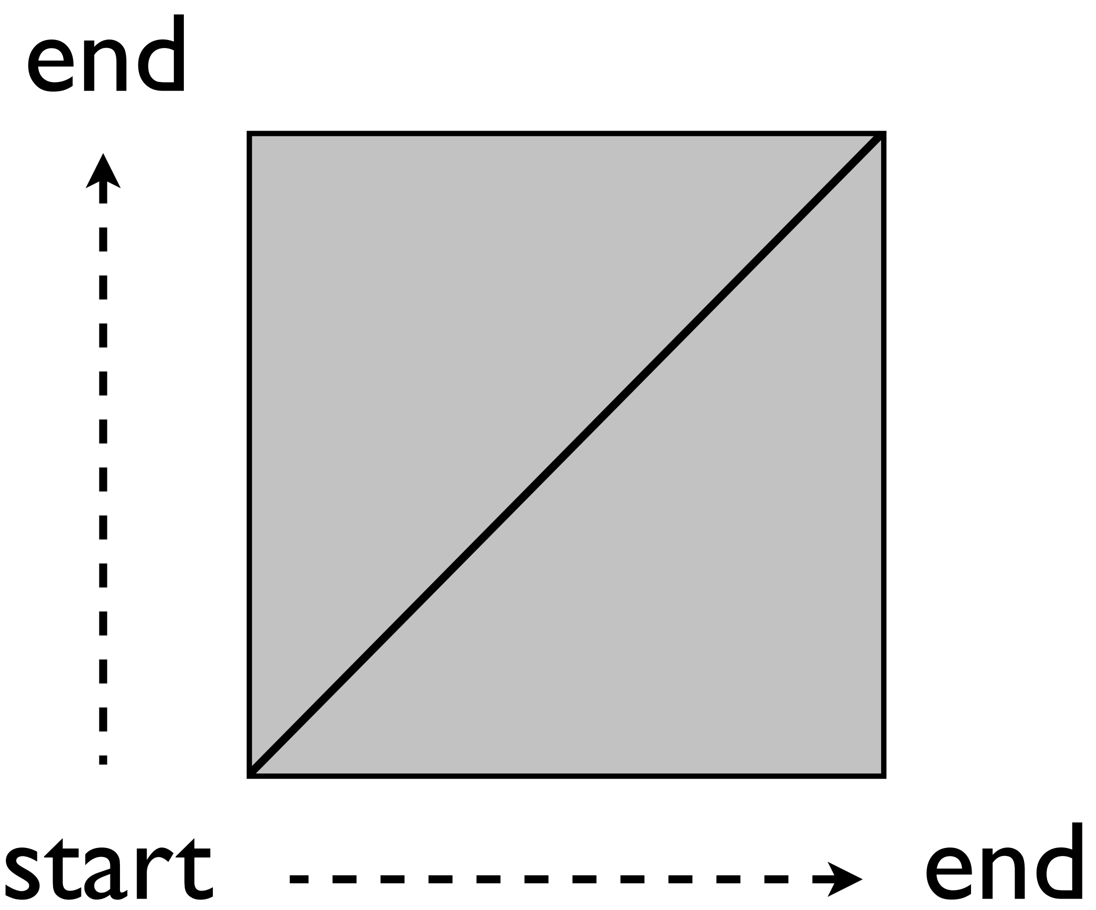
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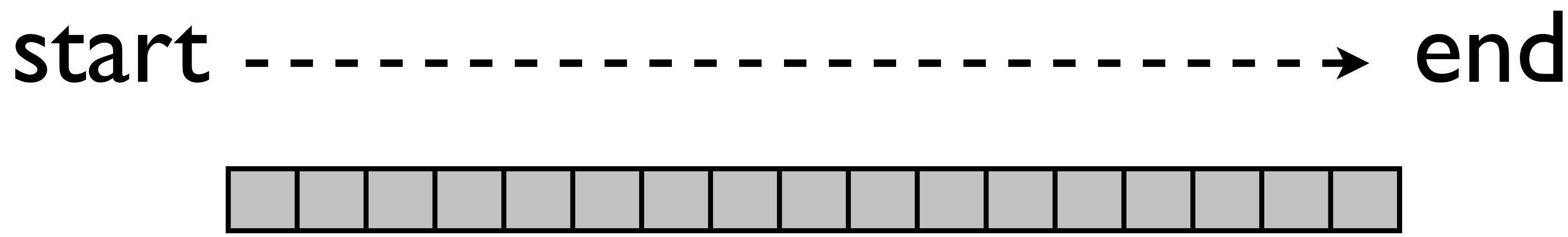
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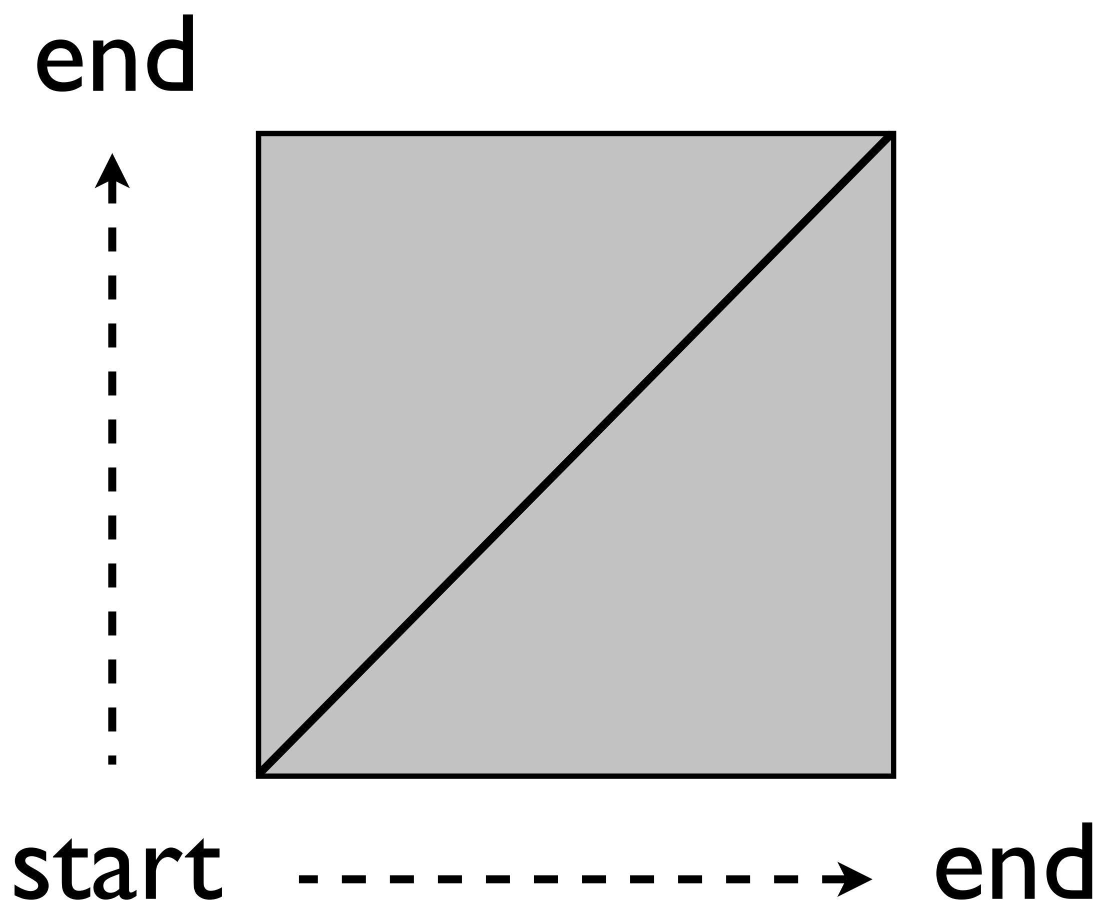
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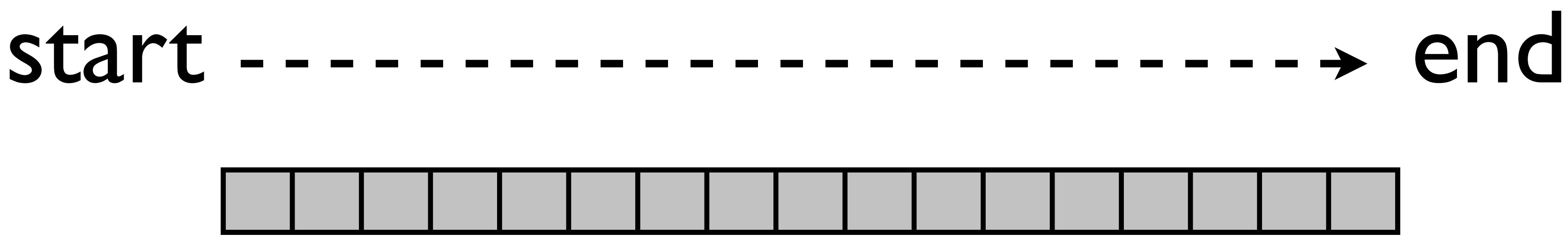
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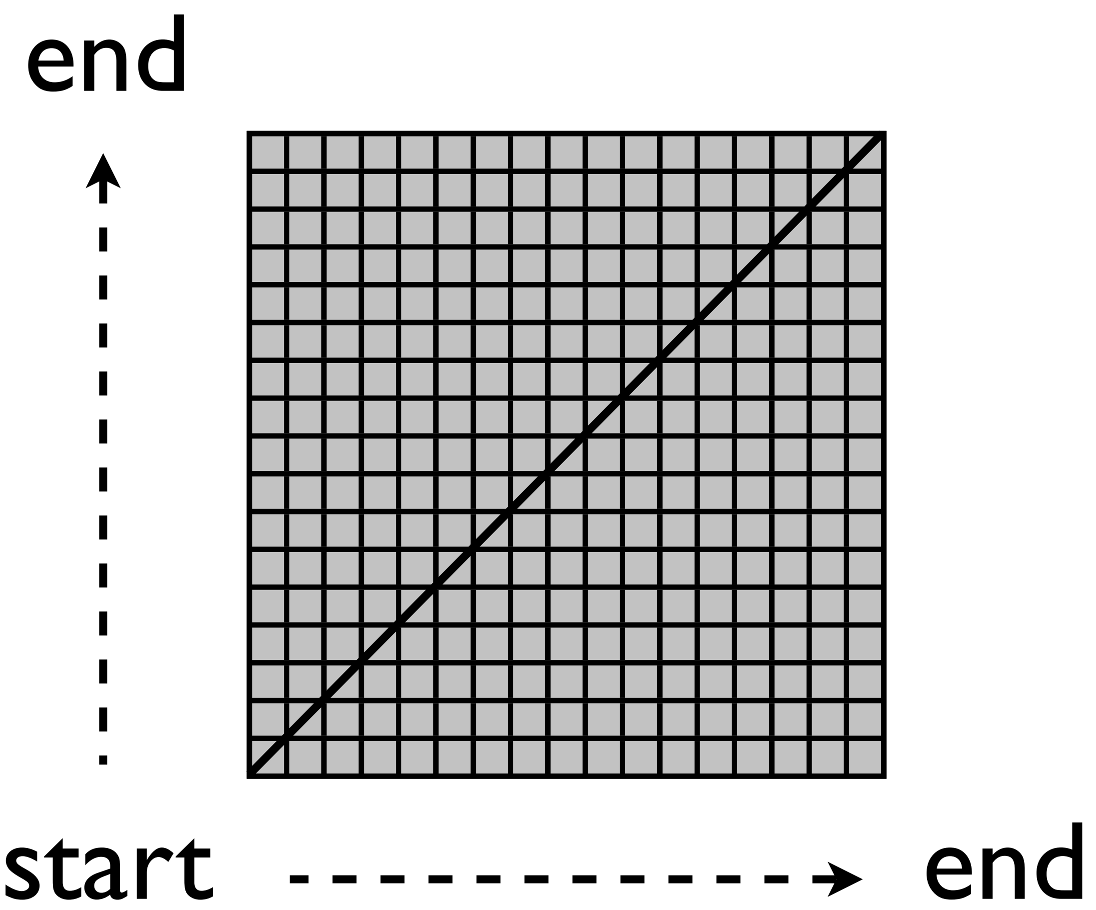
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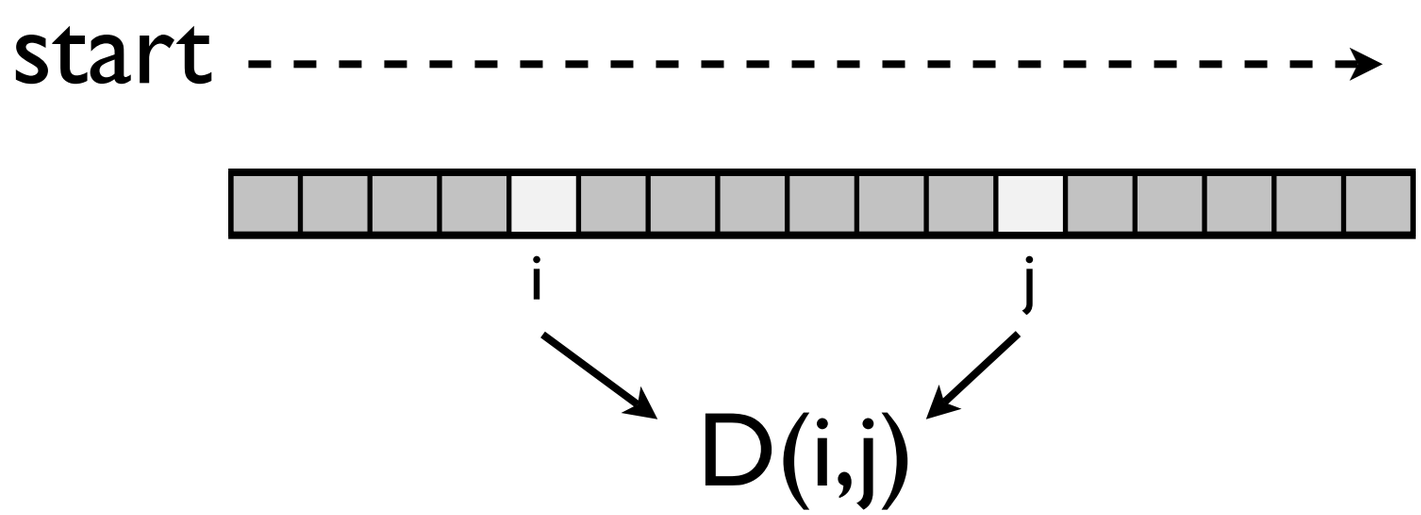
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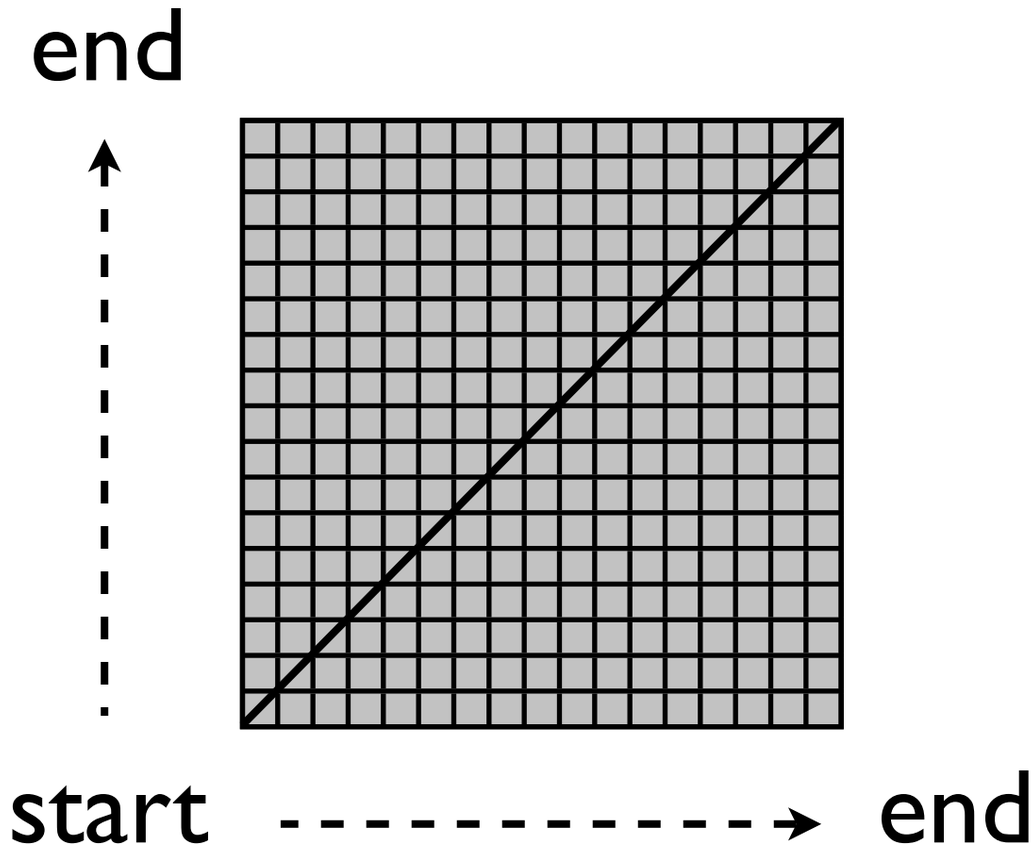
j
D(i,j)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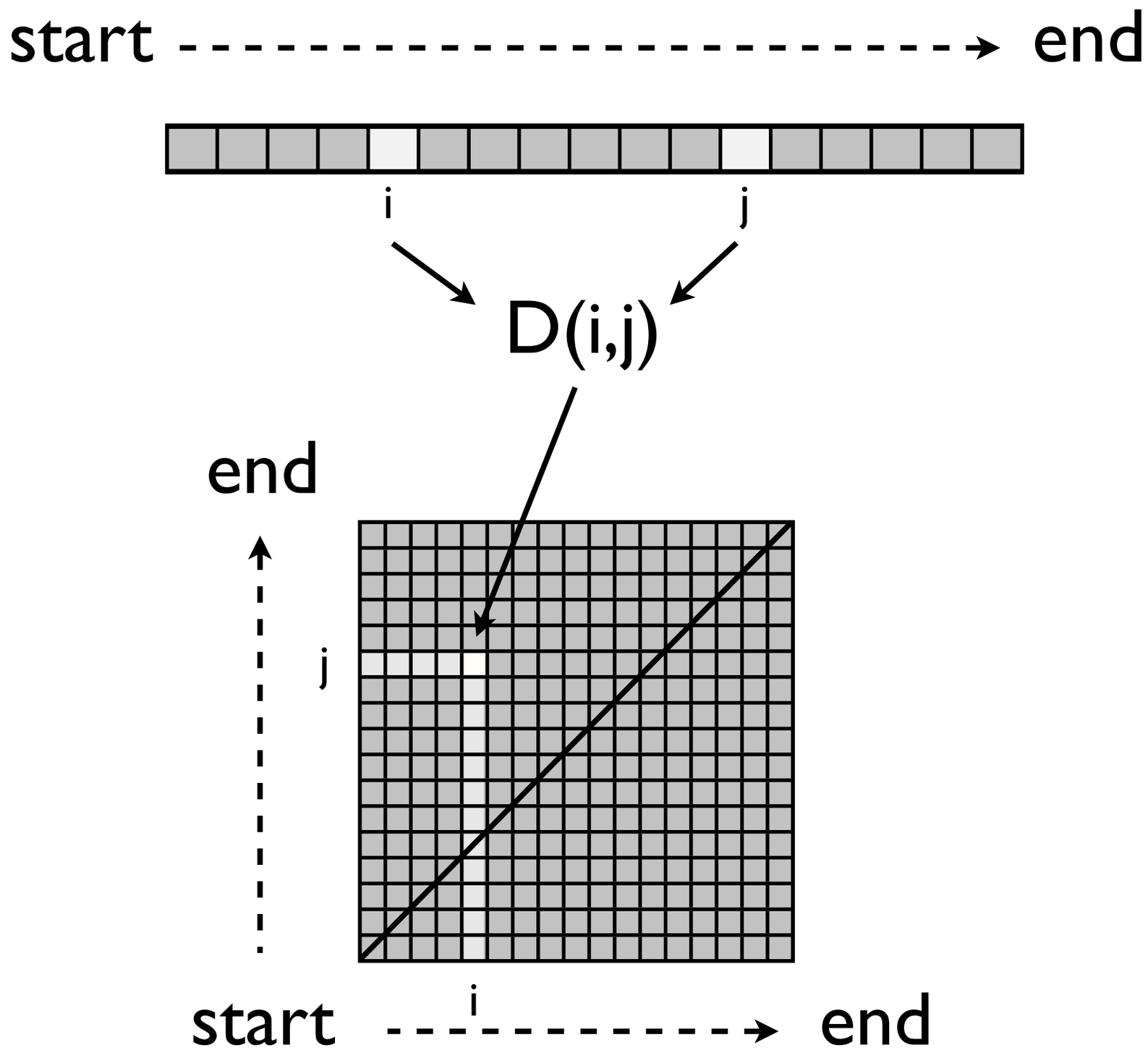
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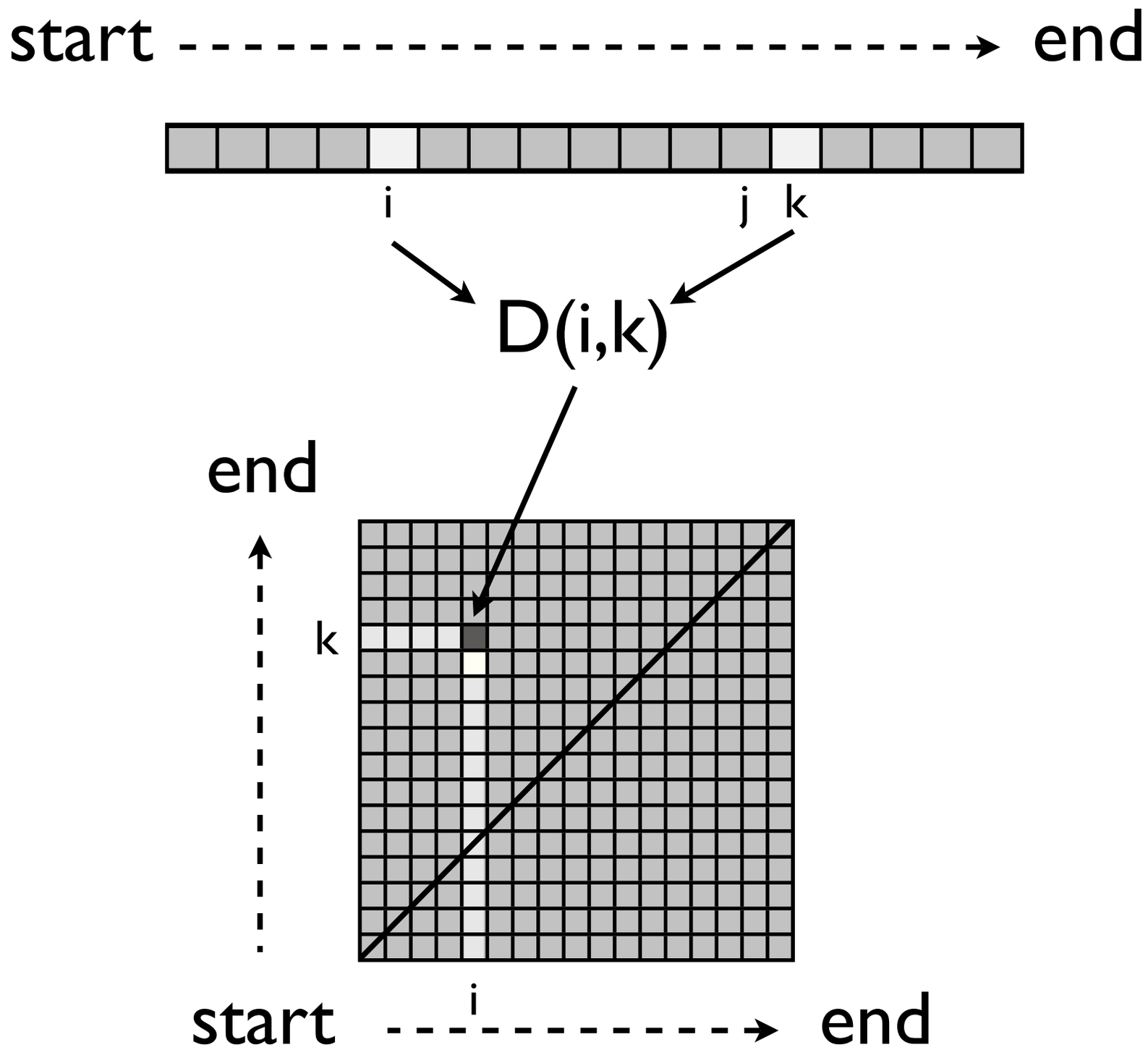
j
start
i
end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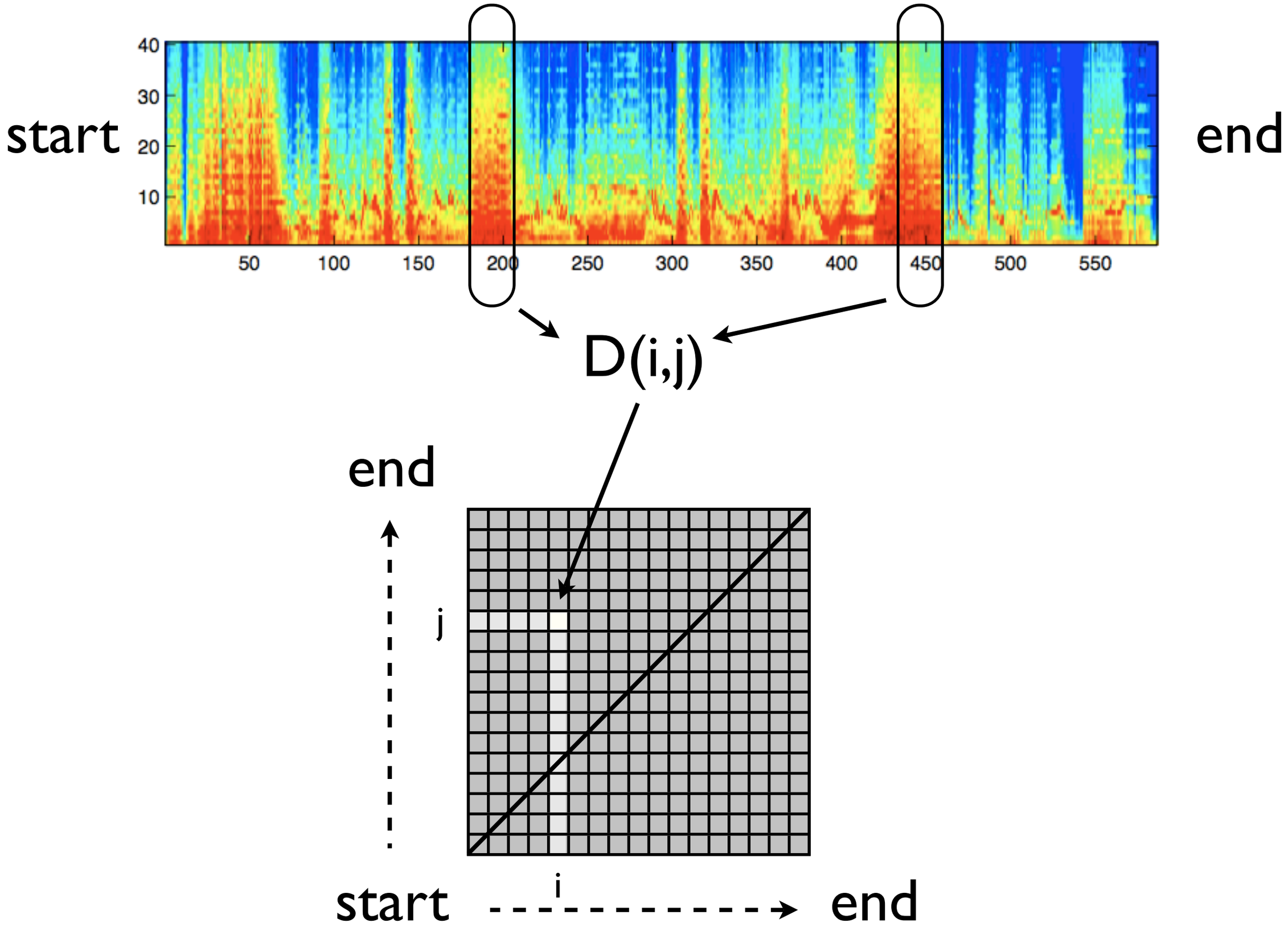
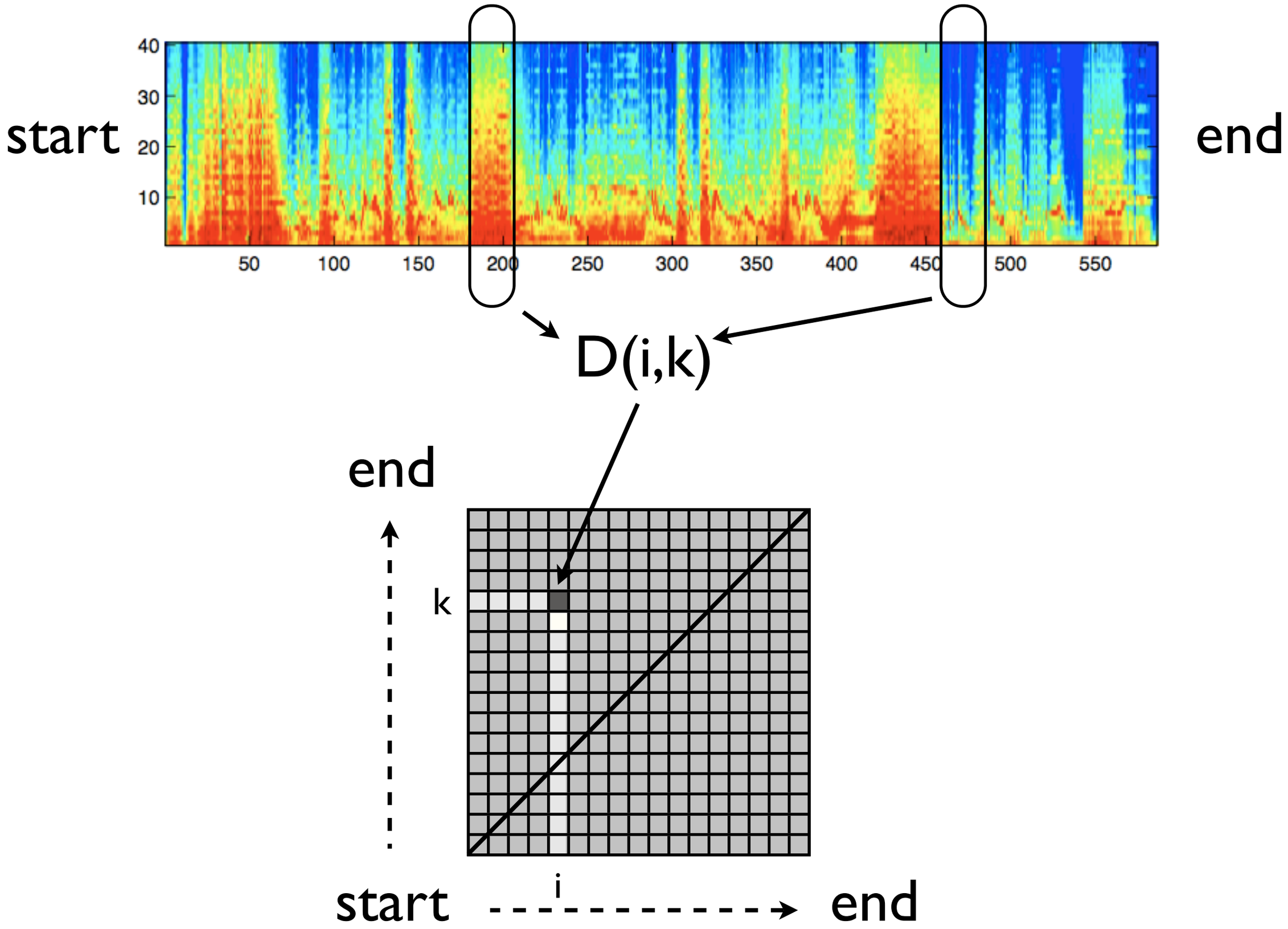


image: Foote 2000a



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Similarity Matrices

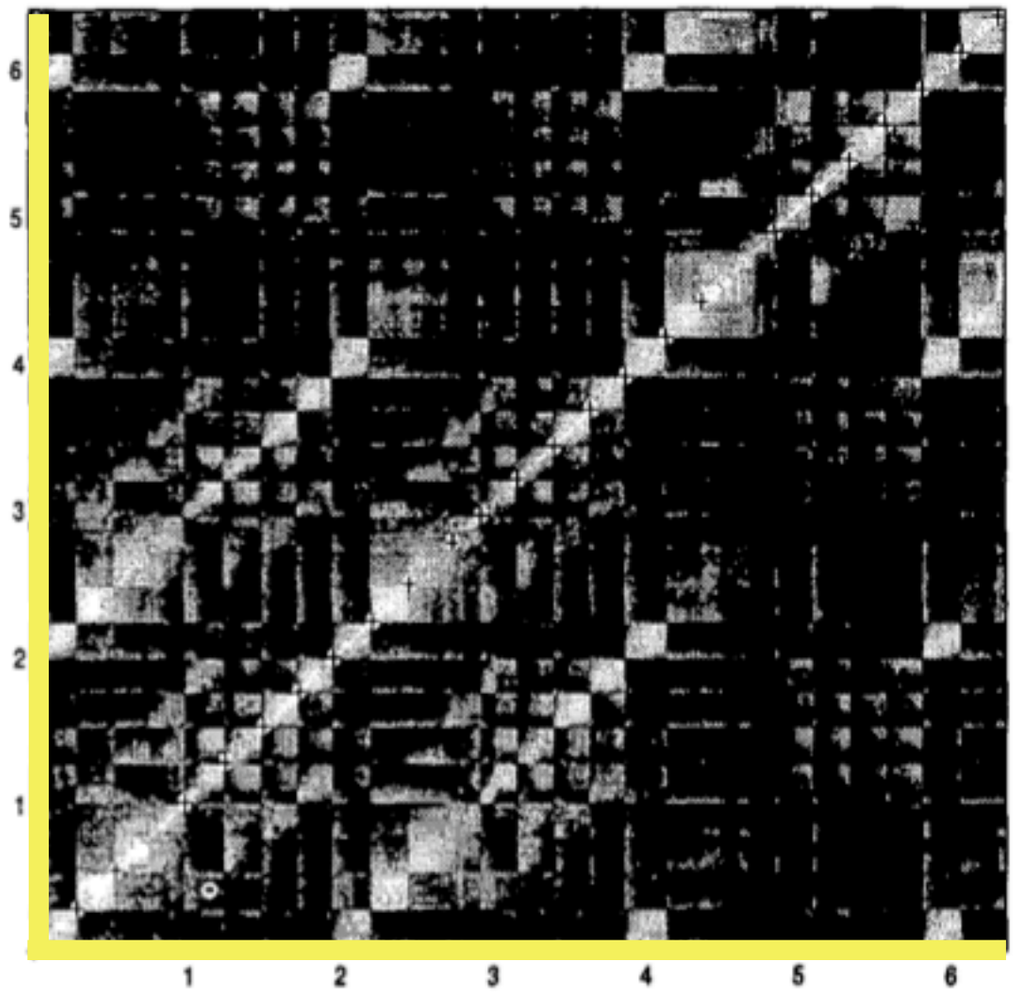


Figure 2. Gould performance showing note boundaries

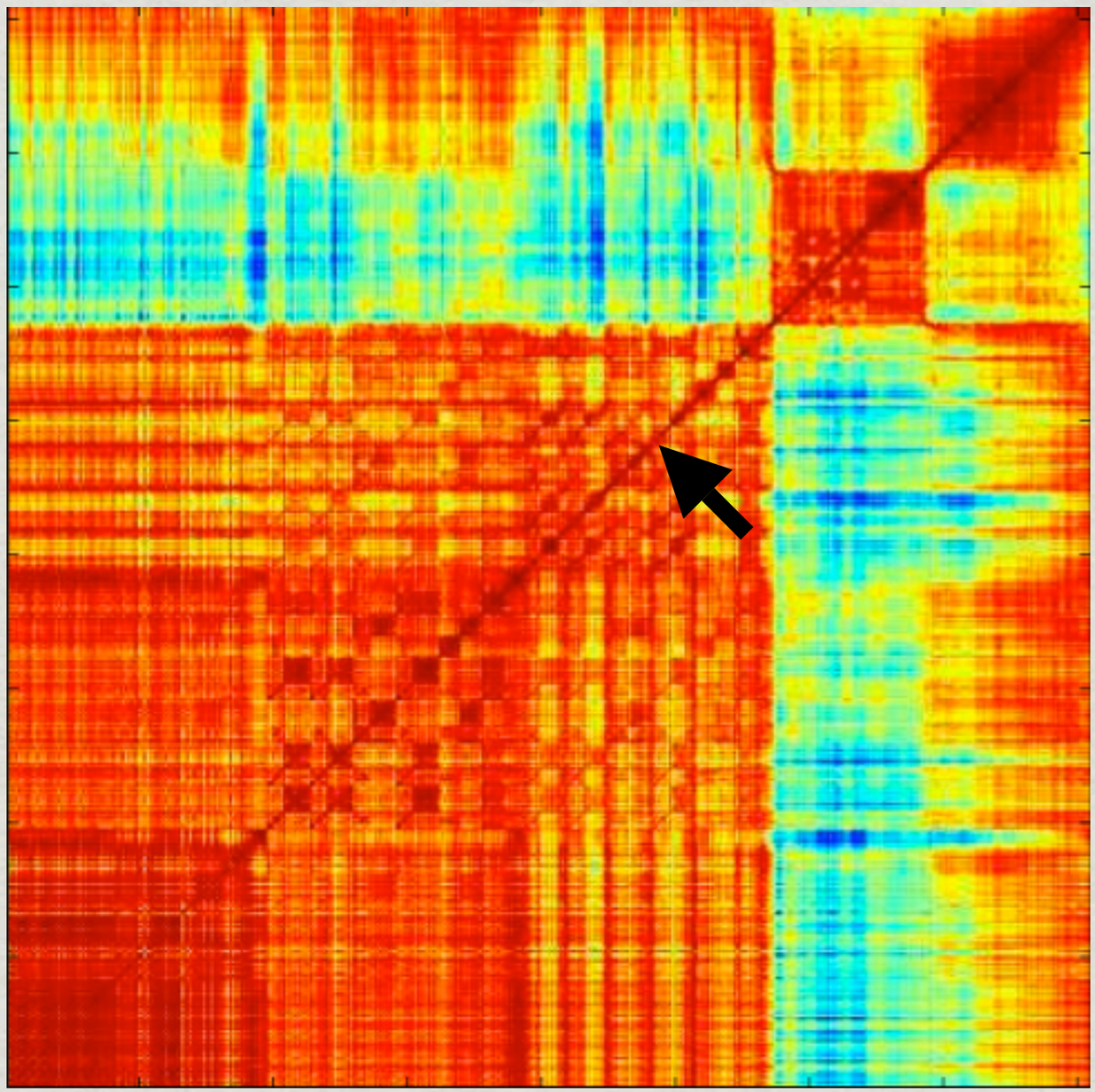
image: Foote 2000b

audio: http://youtube.com/watch?v=bOTW2VS4w5w

Similarity matrices

- They can show us stuff:

  Points of novelty



THE BEATLES: “FLYING”

Novelty detection

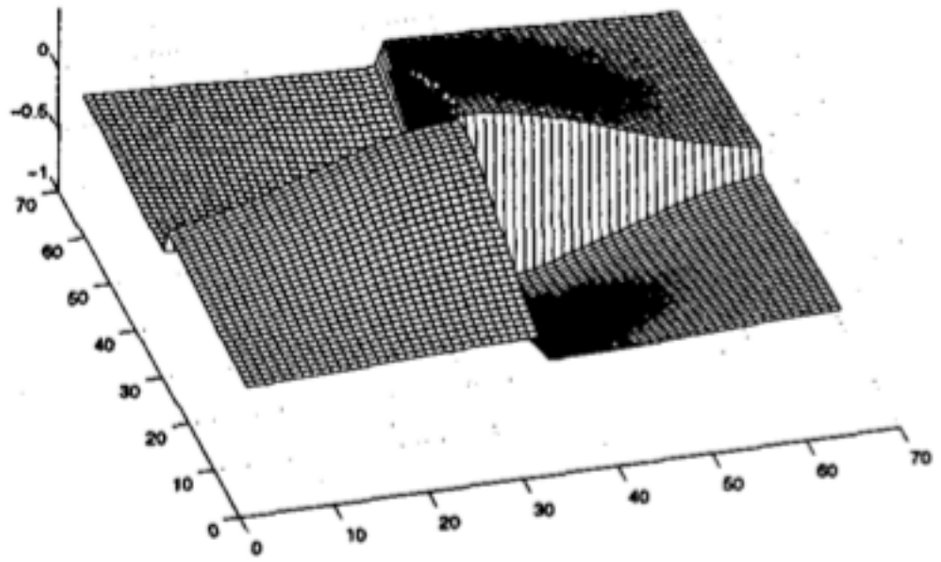
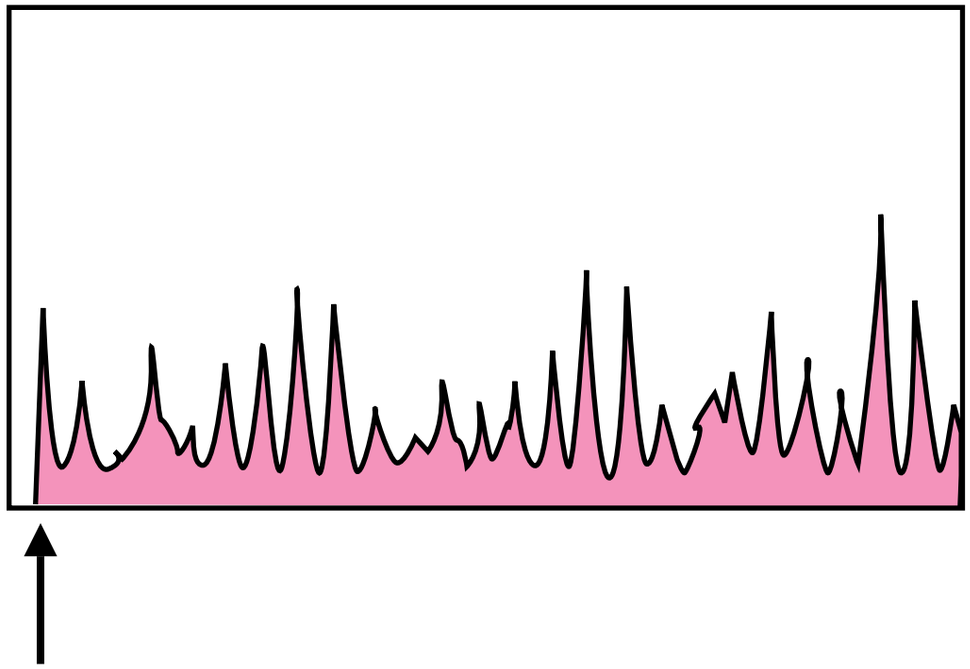


Figure 3. 64 x 64 checkerboard kernel with Gaussian taper

image: Foote 2000b

Novelty detection



Novelty scores

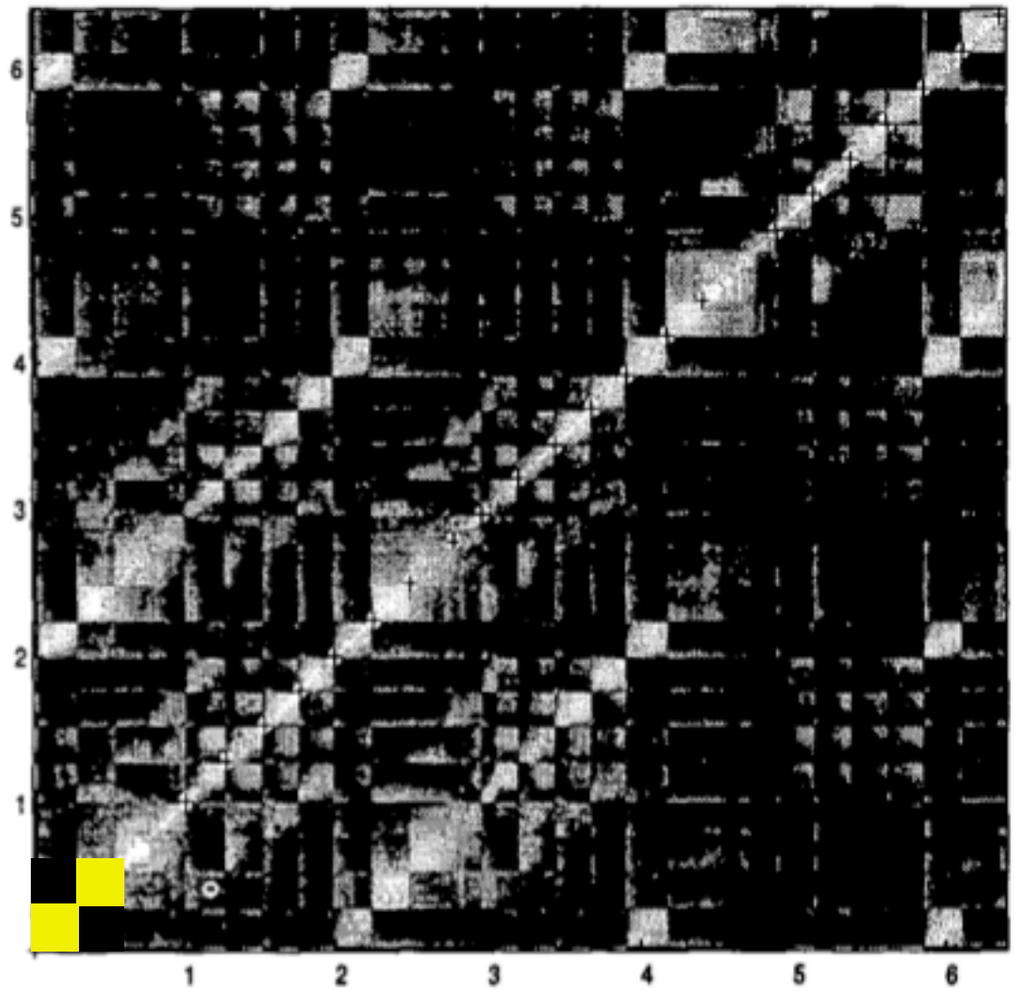


Figure 2. Gould performance showing note boundaries

images: Foote 2000b

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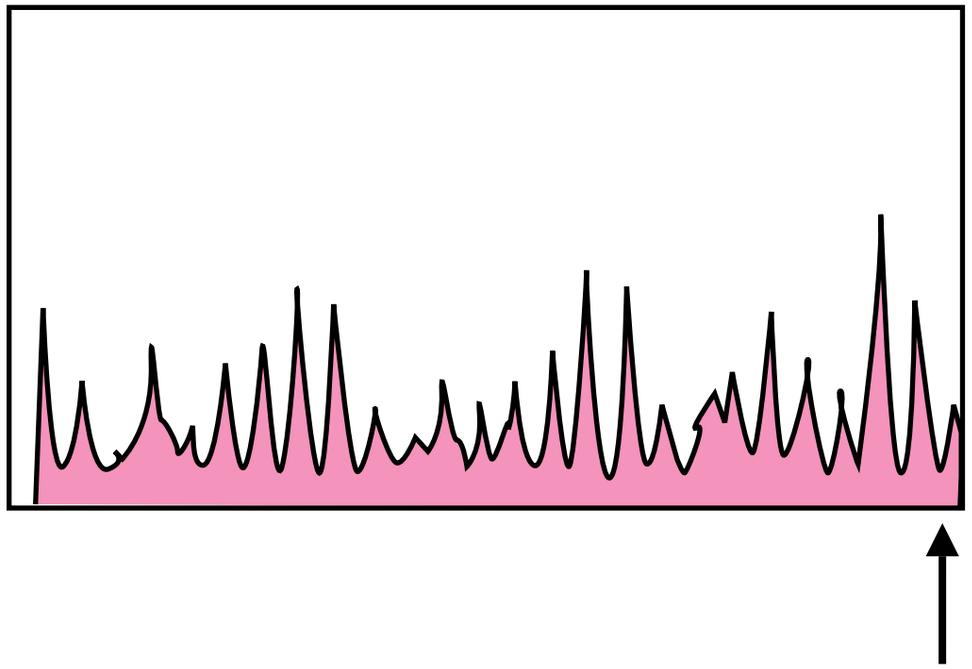
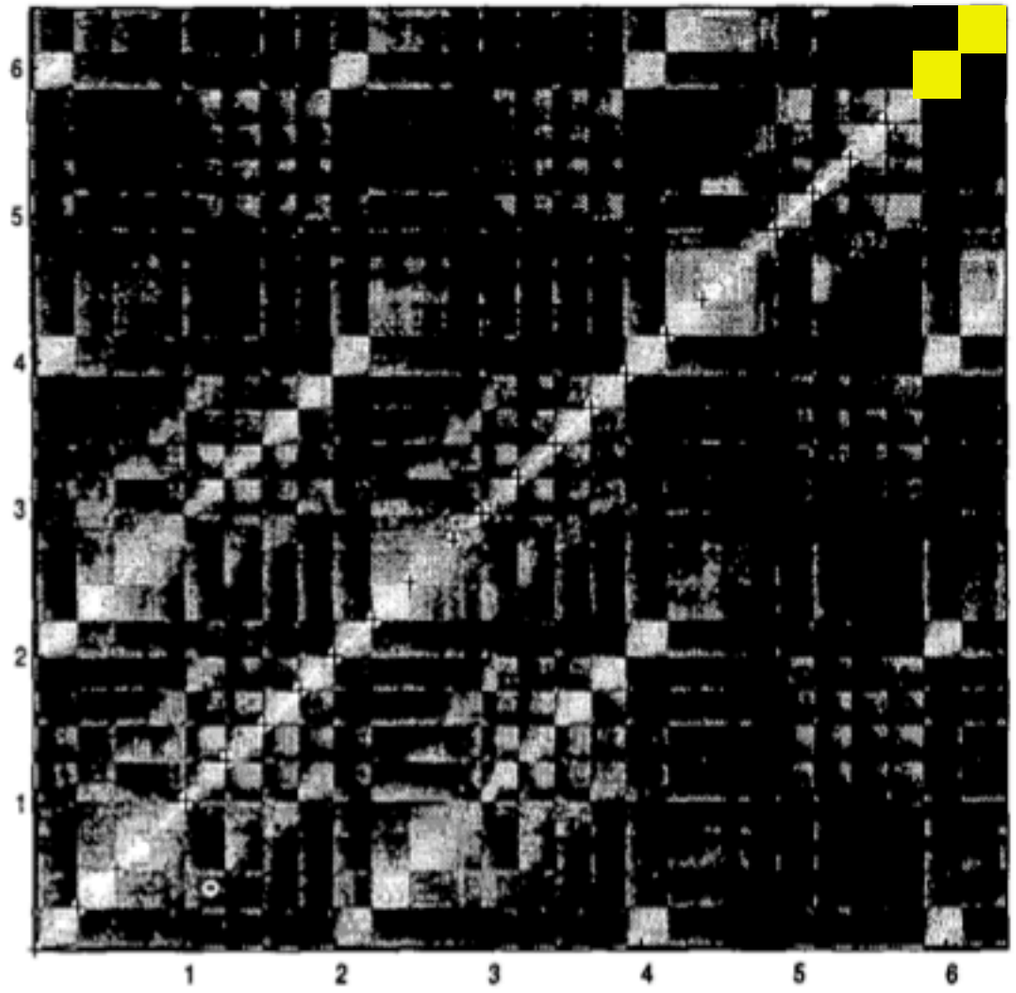


Novelty scores



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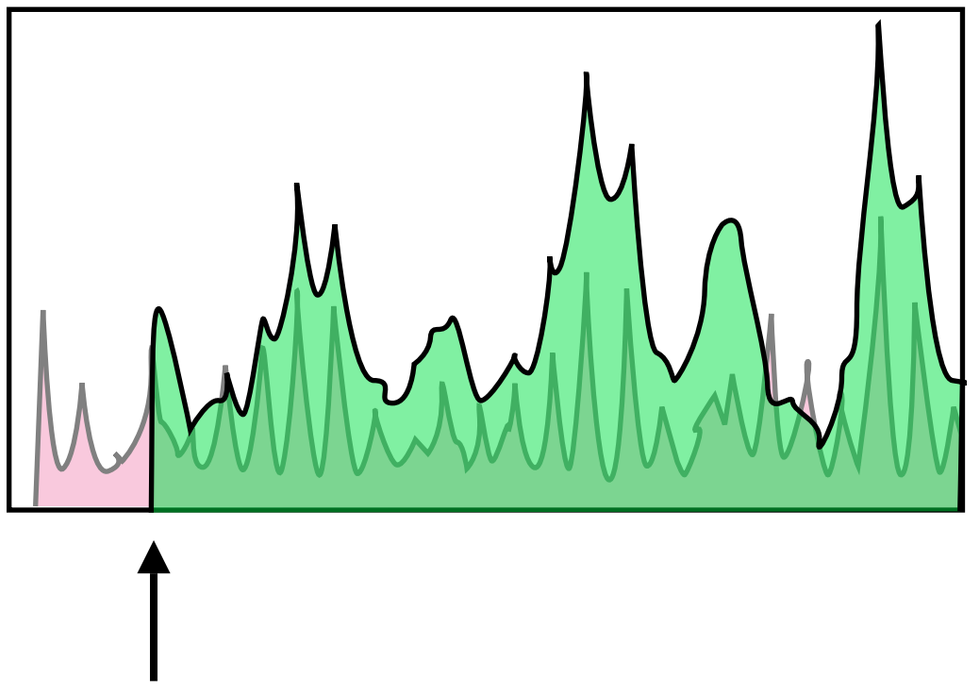

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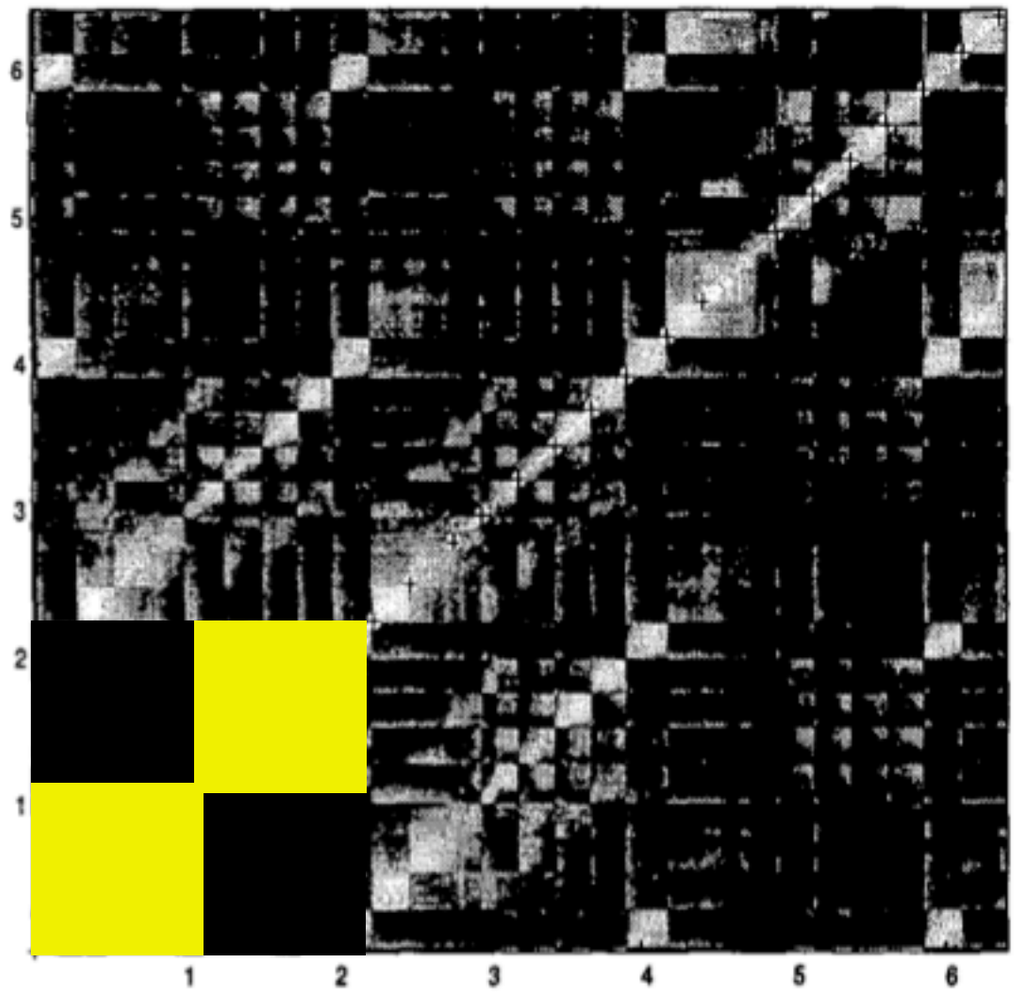

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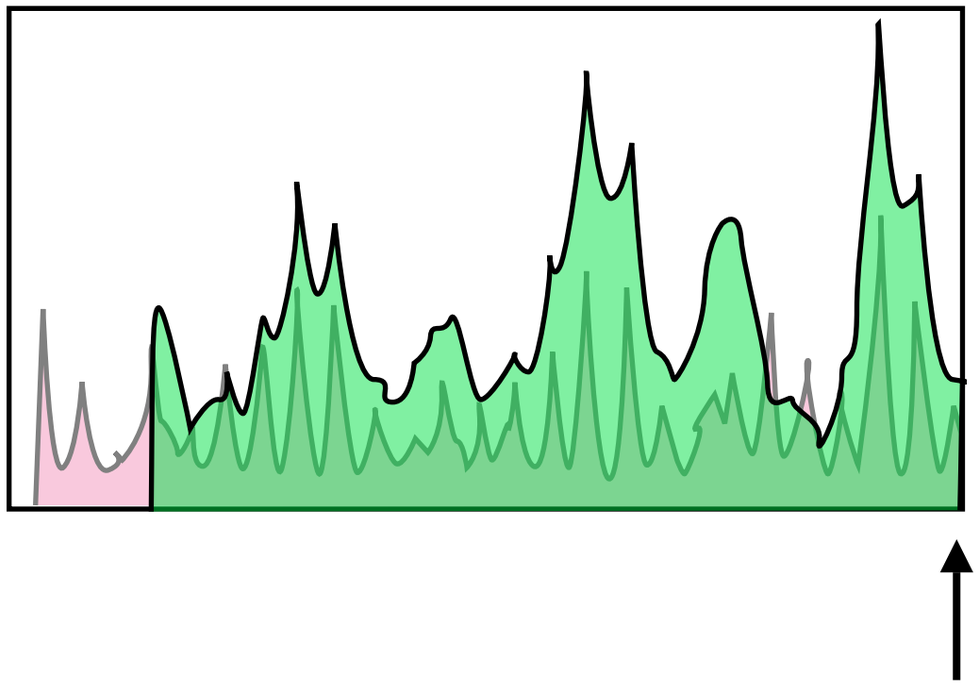
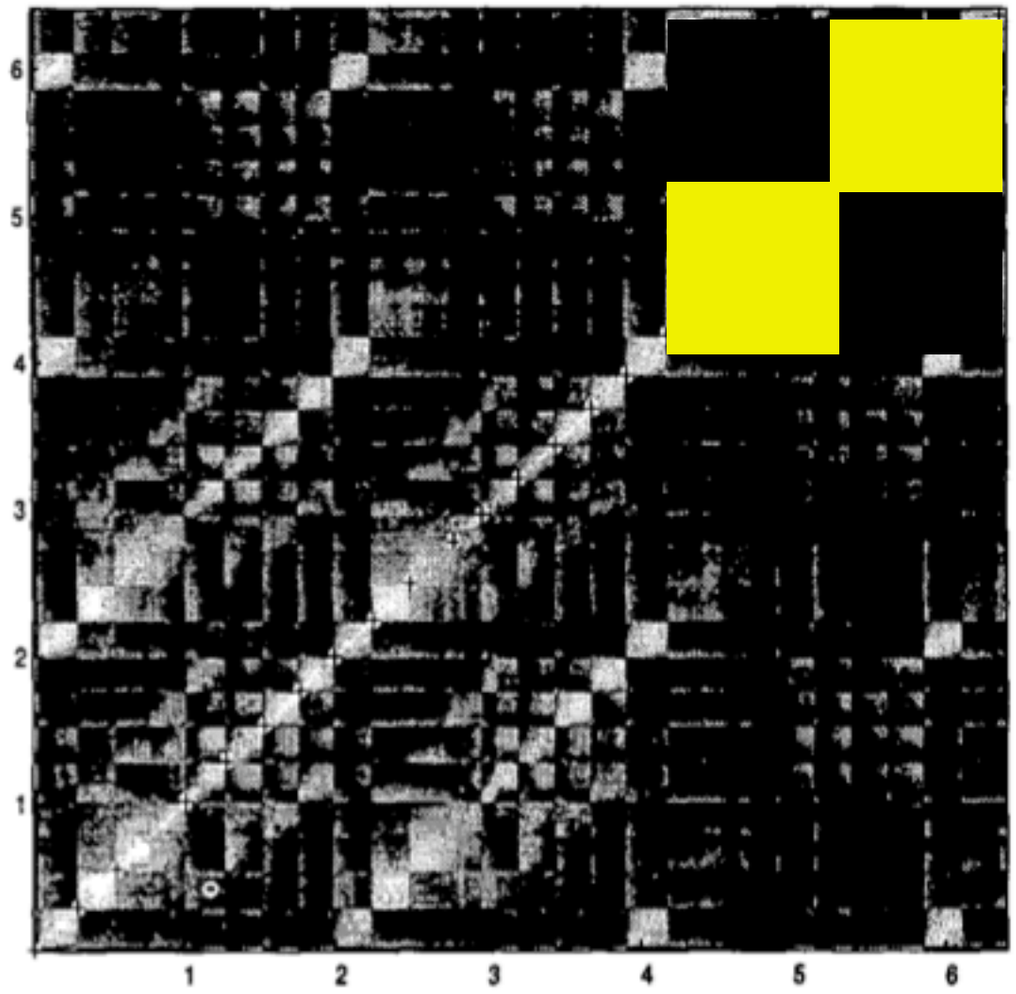


Novelty scores



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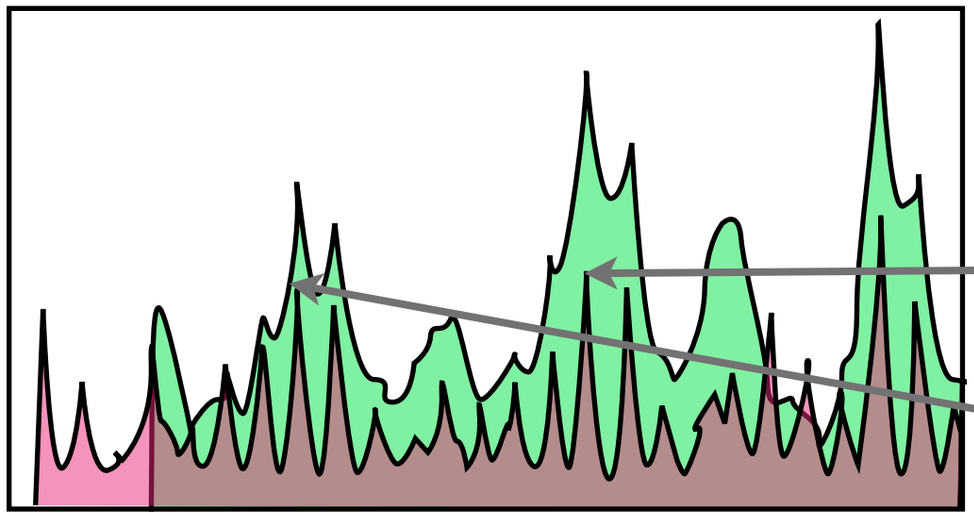

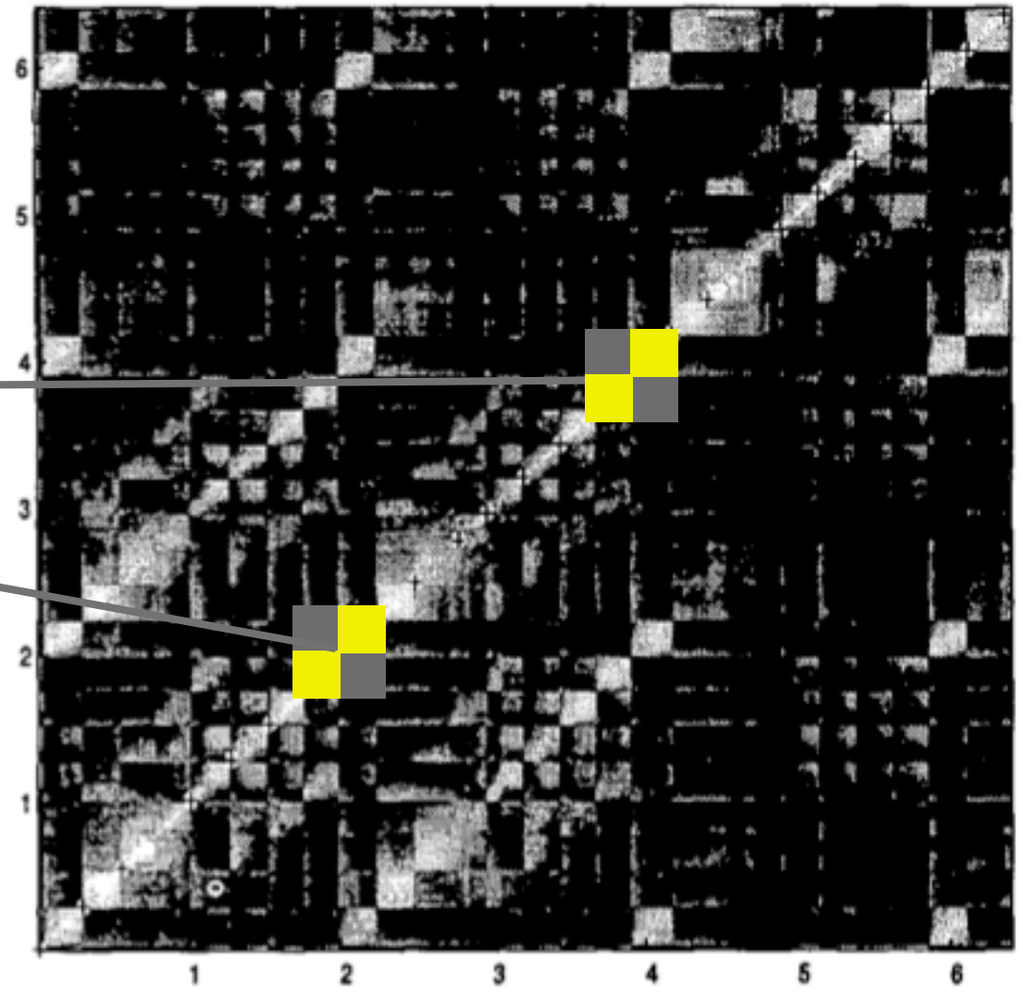

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Novelty scores

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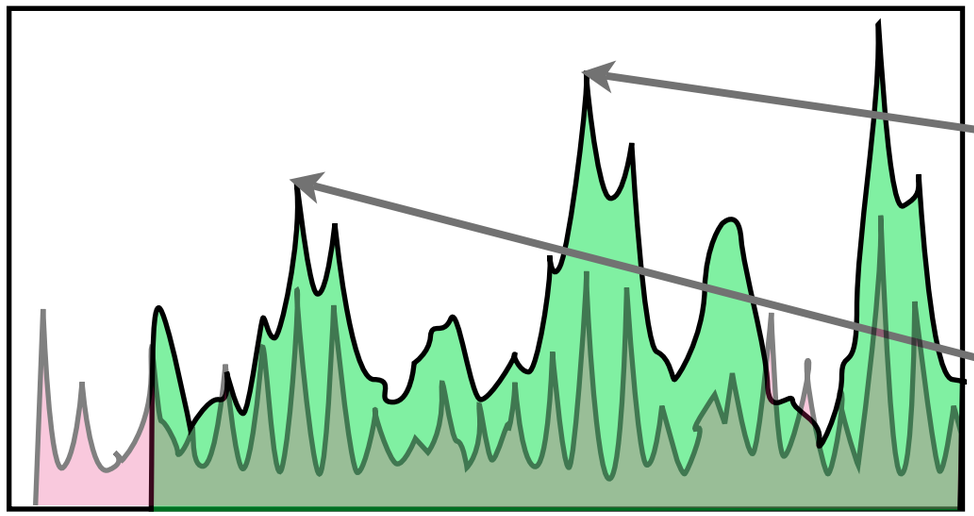

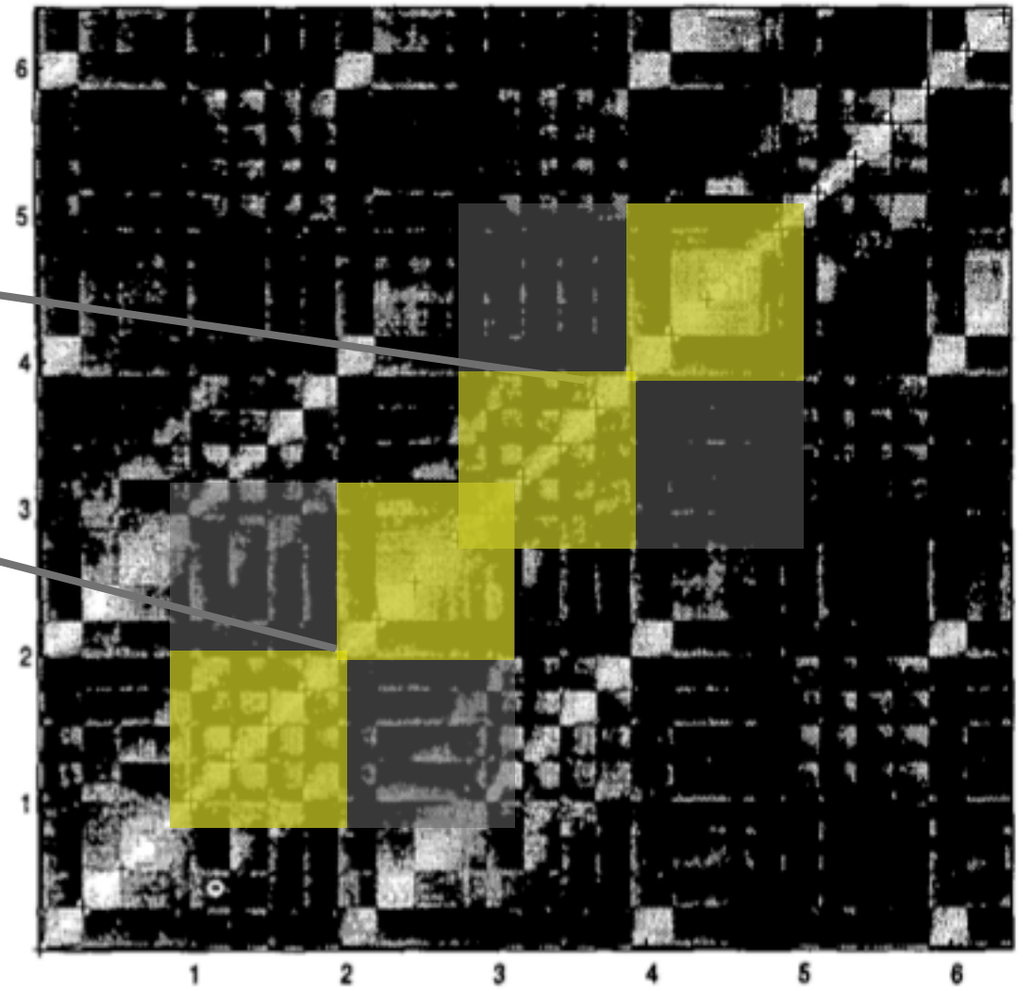

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Novelty scores

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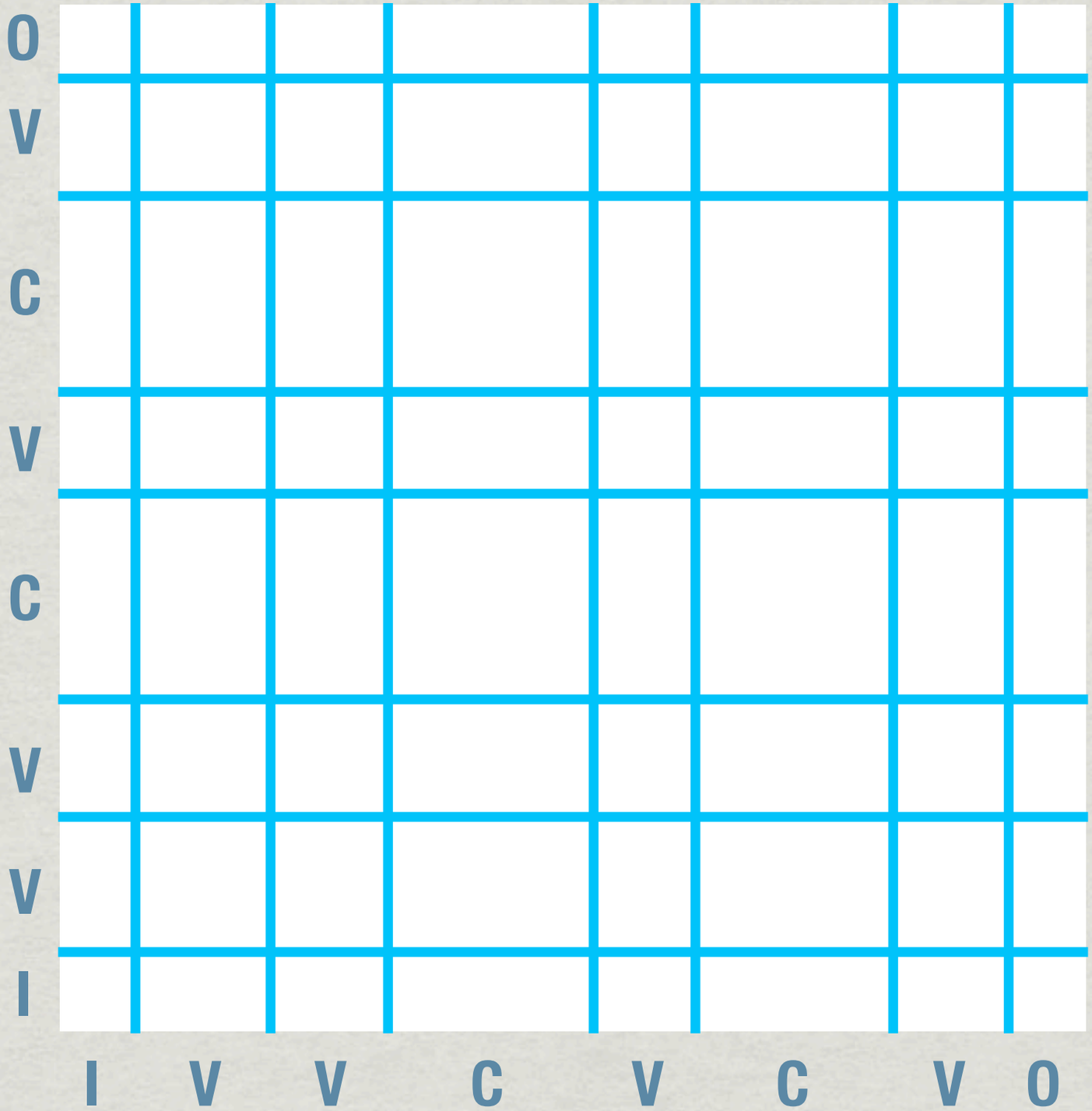
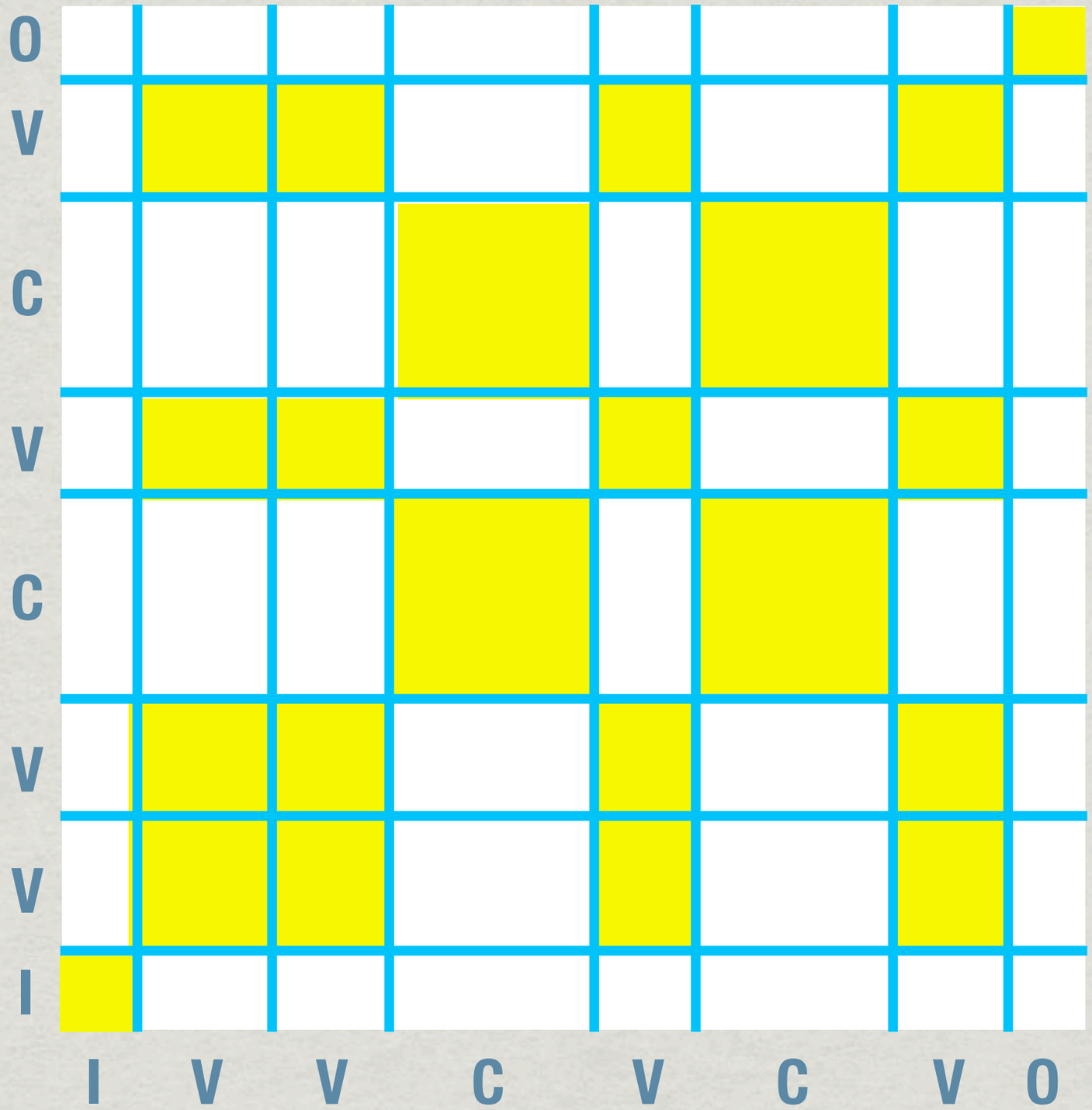
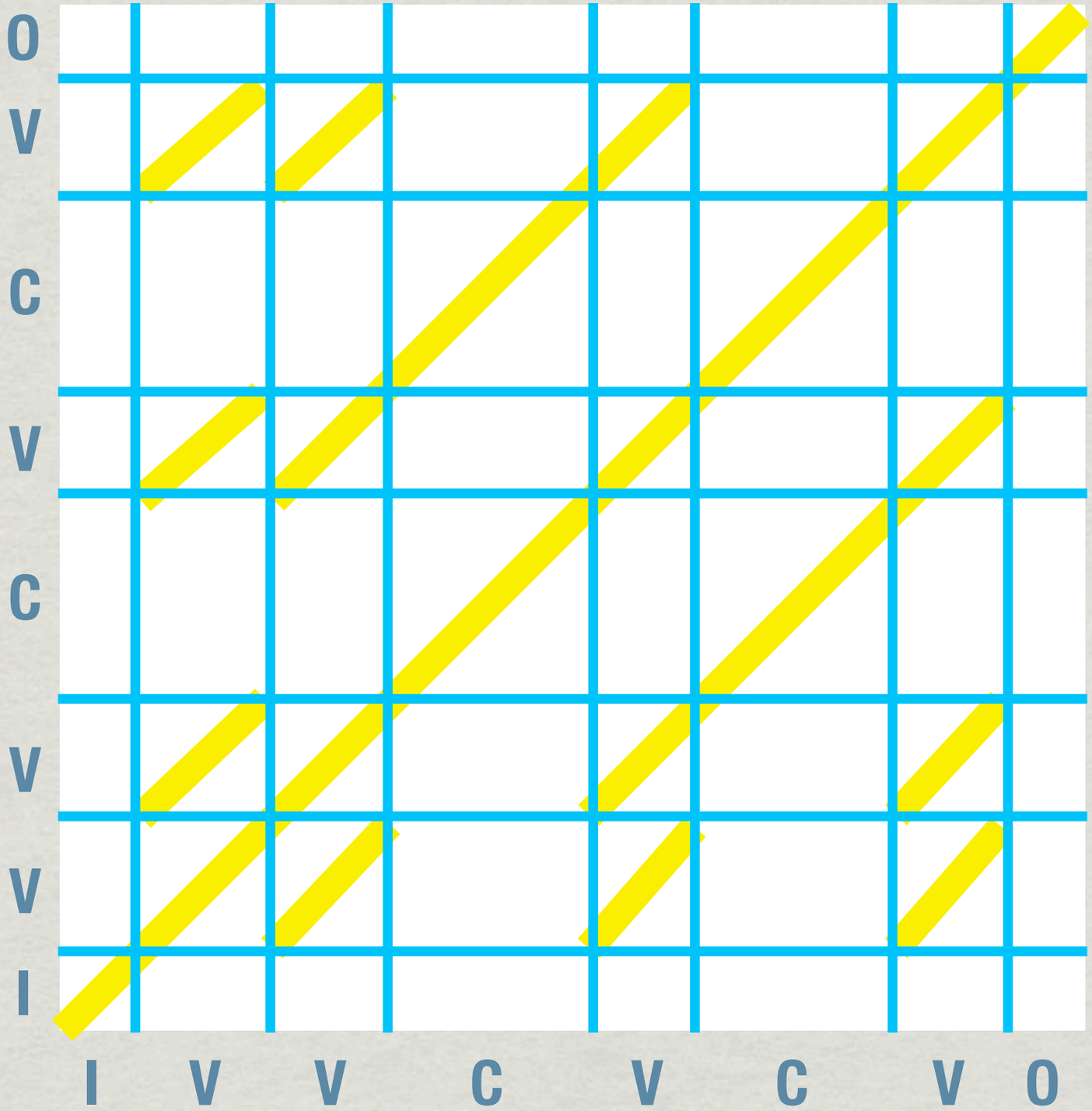
STATES OR SEQUENCES?



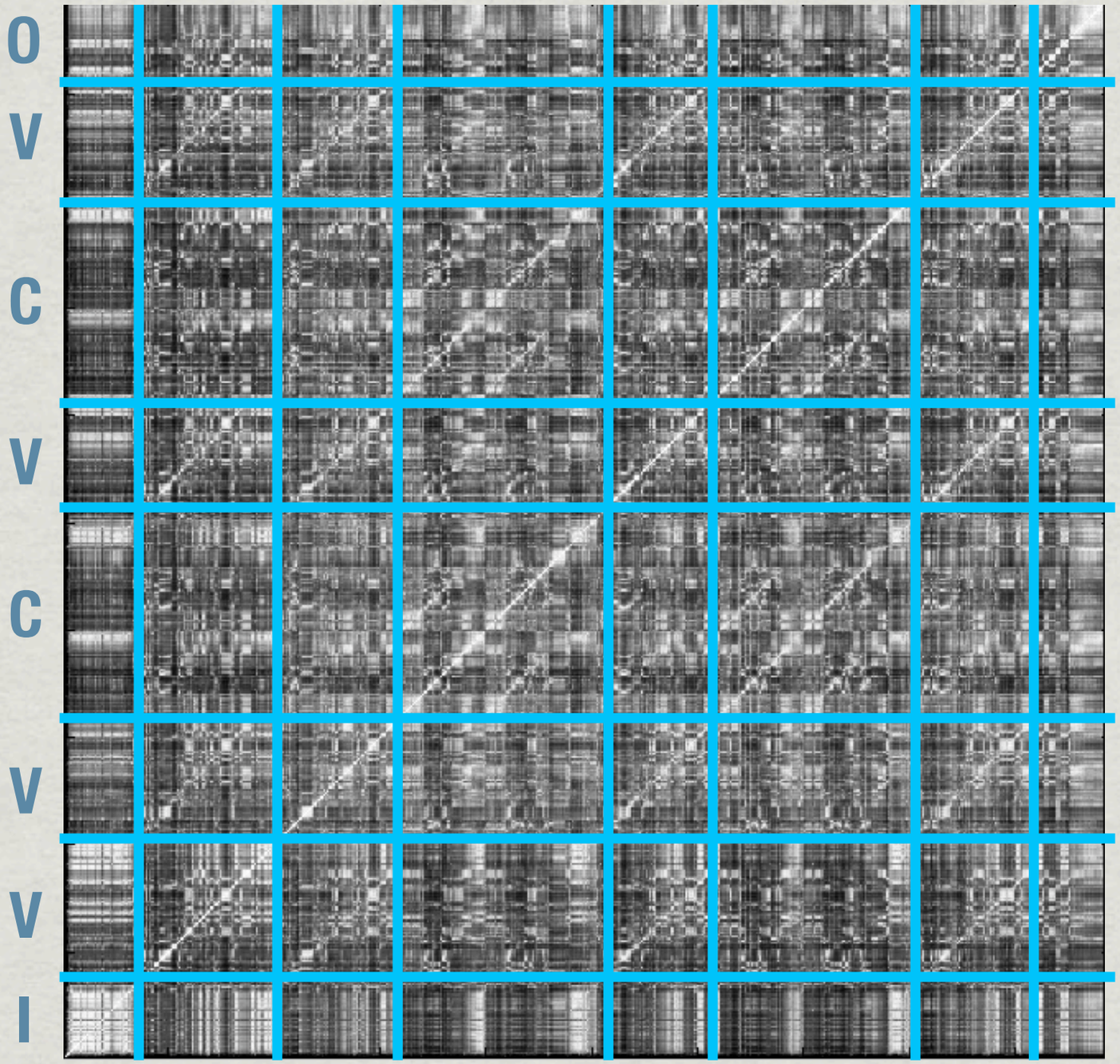
STATES VIEW



SEQUENCES VIEW



THE BEATLES: “YESTERDAY”



SEQUENCE WORKFLOW

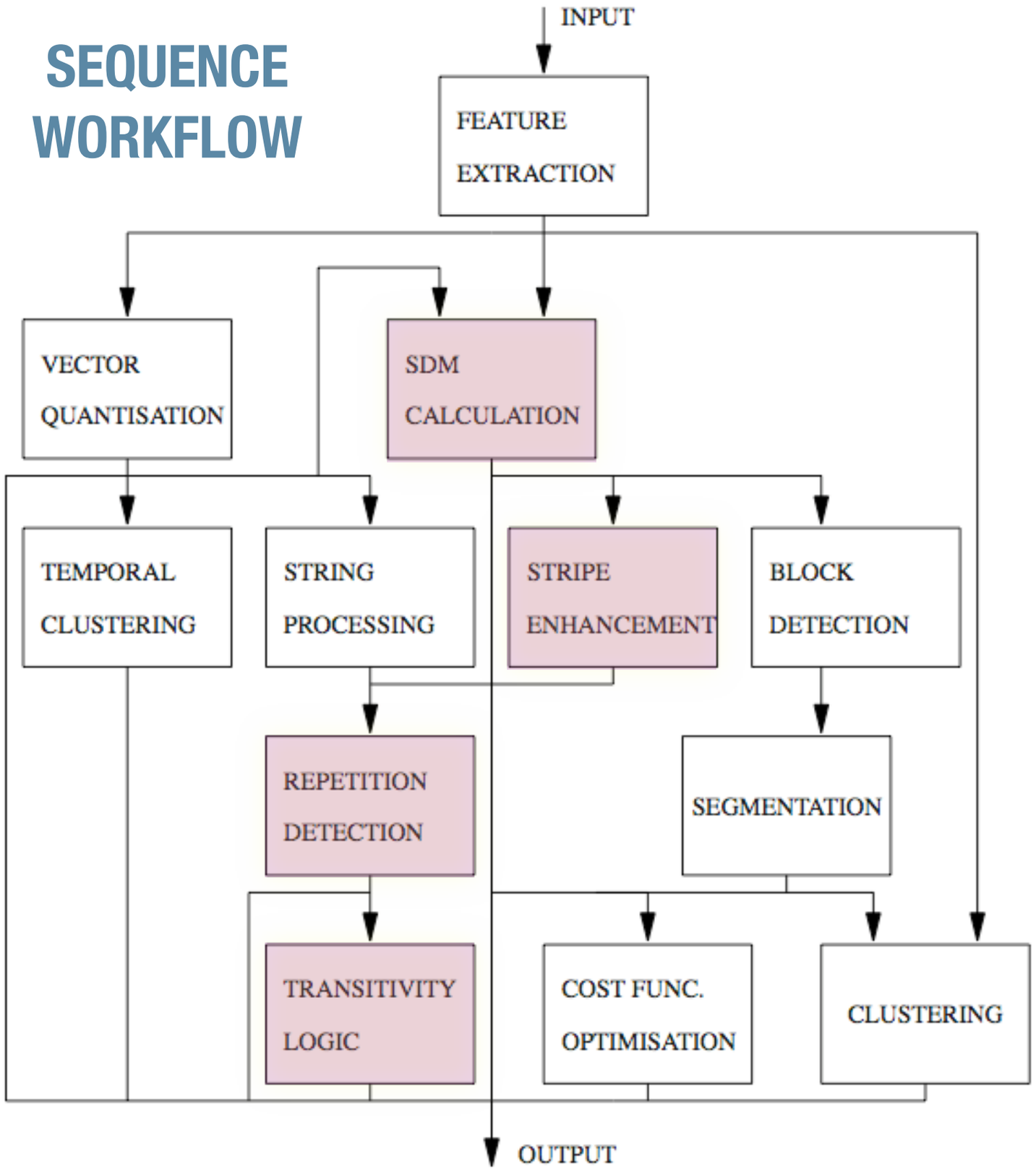


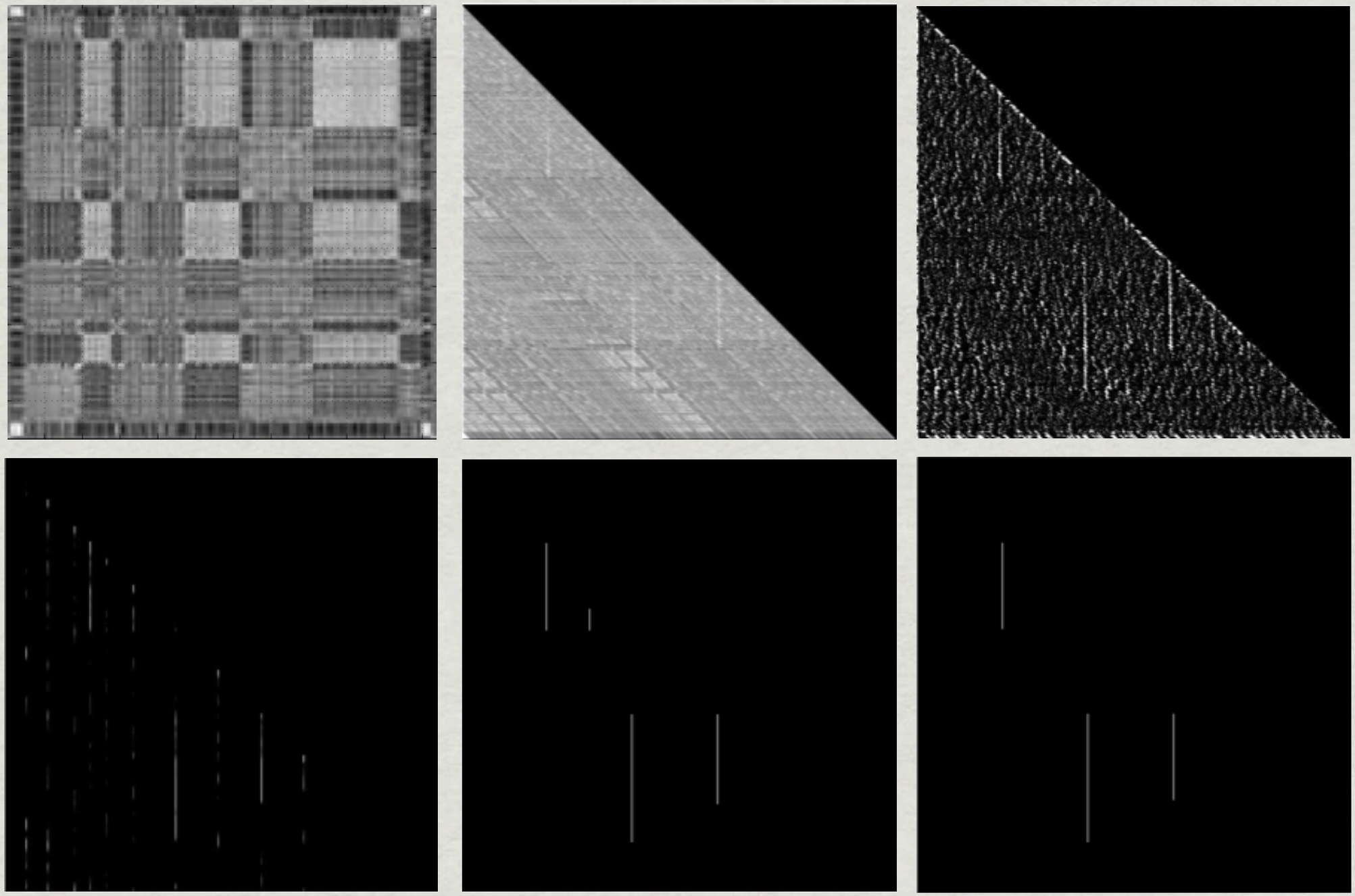
image: Paulus 2009

STRIPE SEARCH

TIME-LAG

FILTER

THRESHOLD



ERODE / DILATE

GROUND TRUTH

STATE WORKFLOW

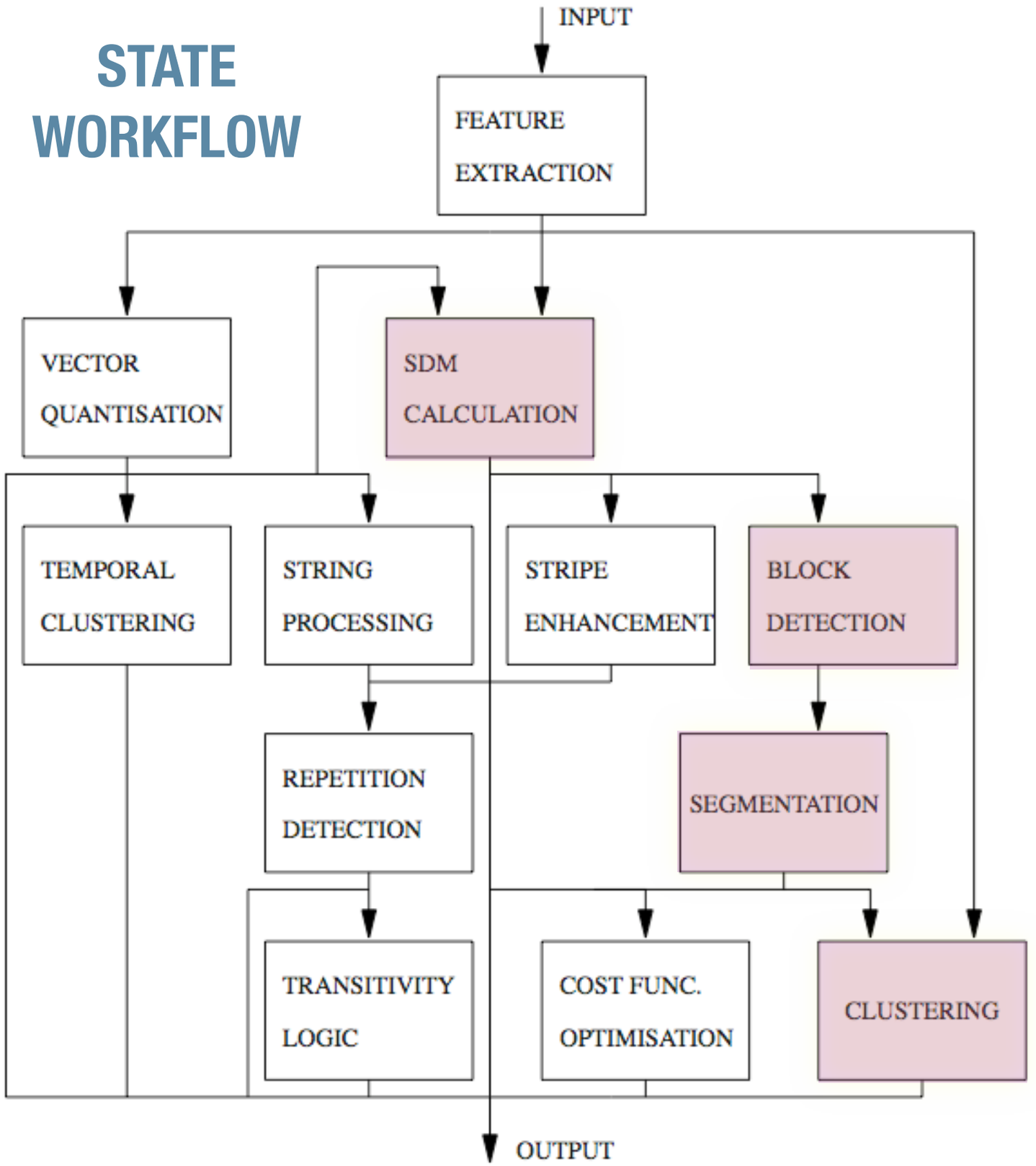
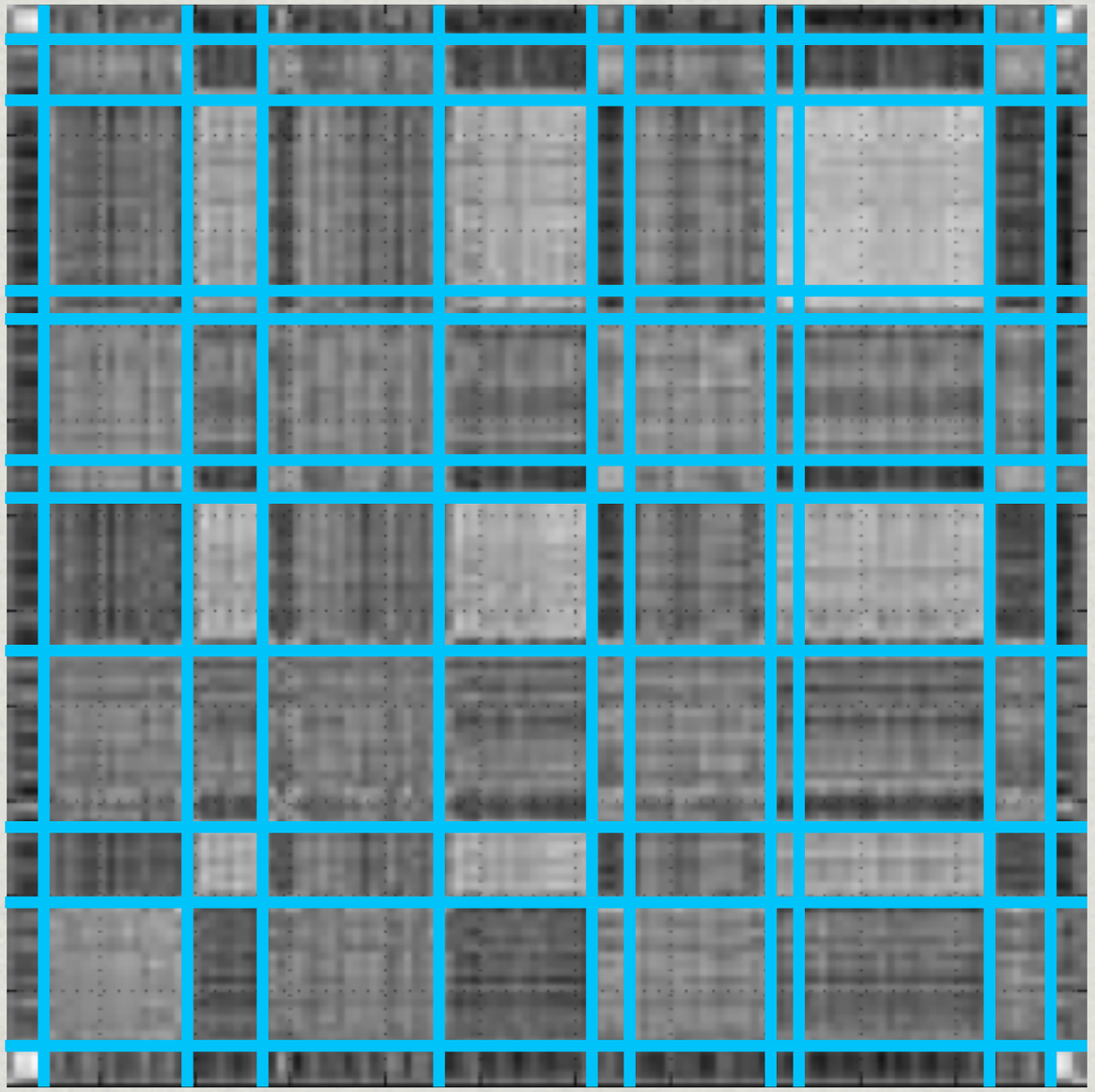
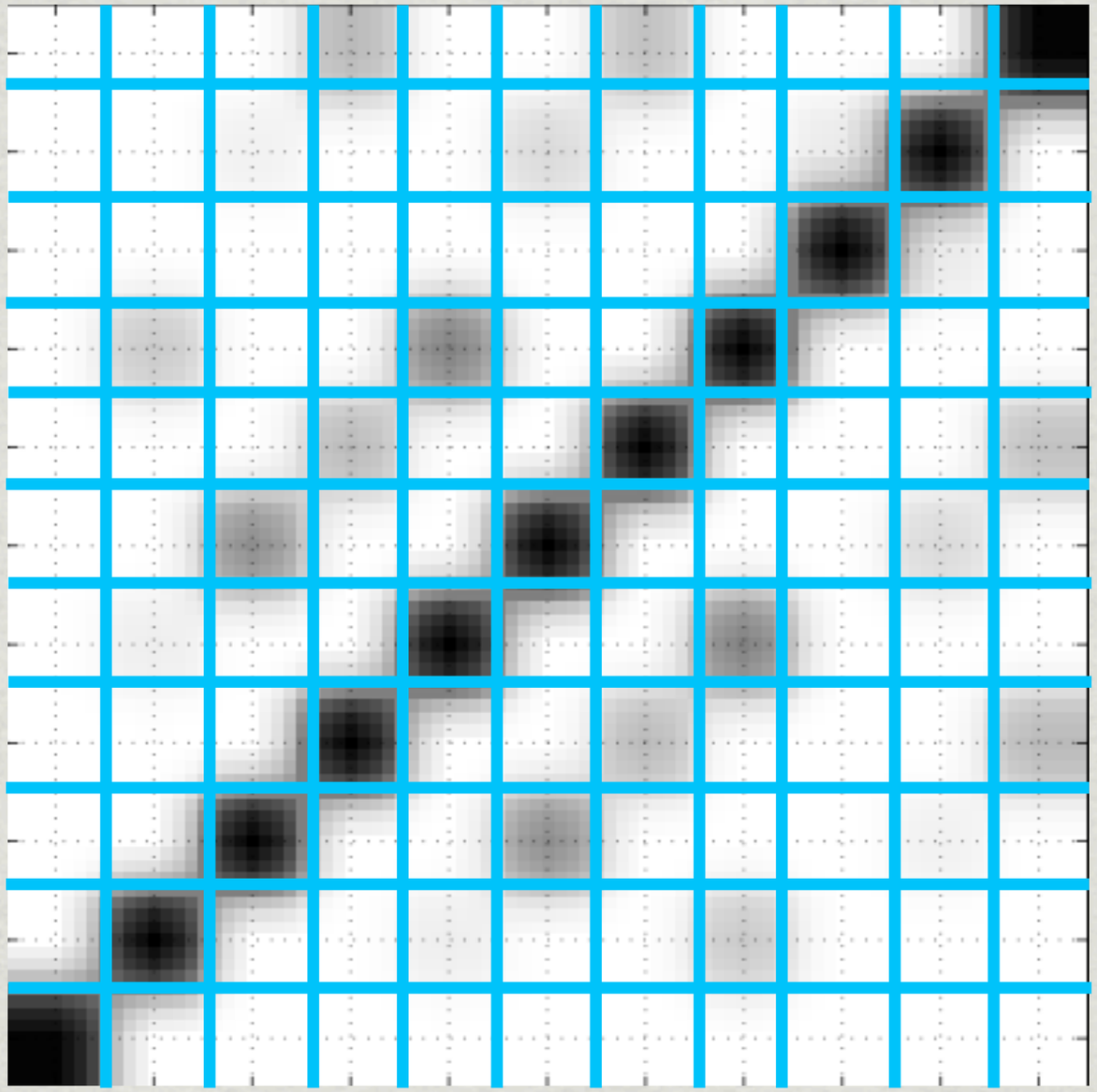


image: Paulus 2009

BLOCK SEARCH



BLOCK SEARCH



Outline

1. Two hypotheses:

- ✓ States
- ✓ Sequences

2. A word on features:

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3. Two techniques:

- ✓ Similarity matrix
- Clustering models

Technique 2:
Clustering Models

Clustering

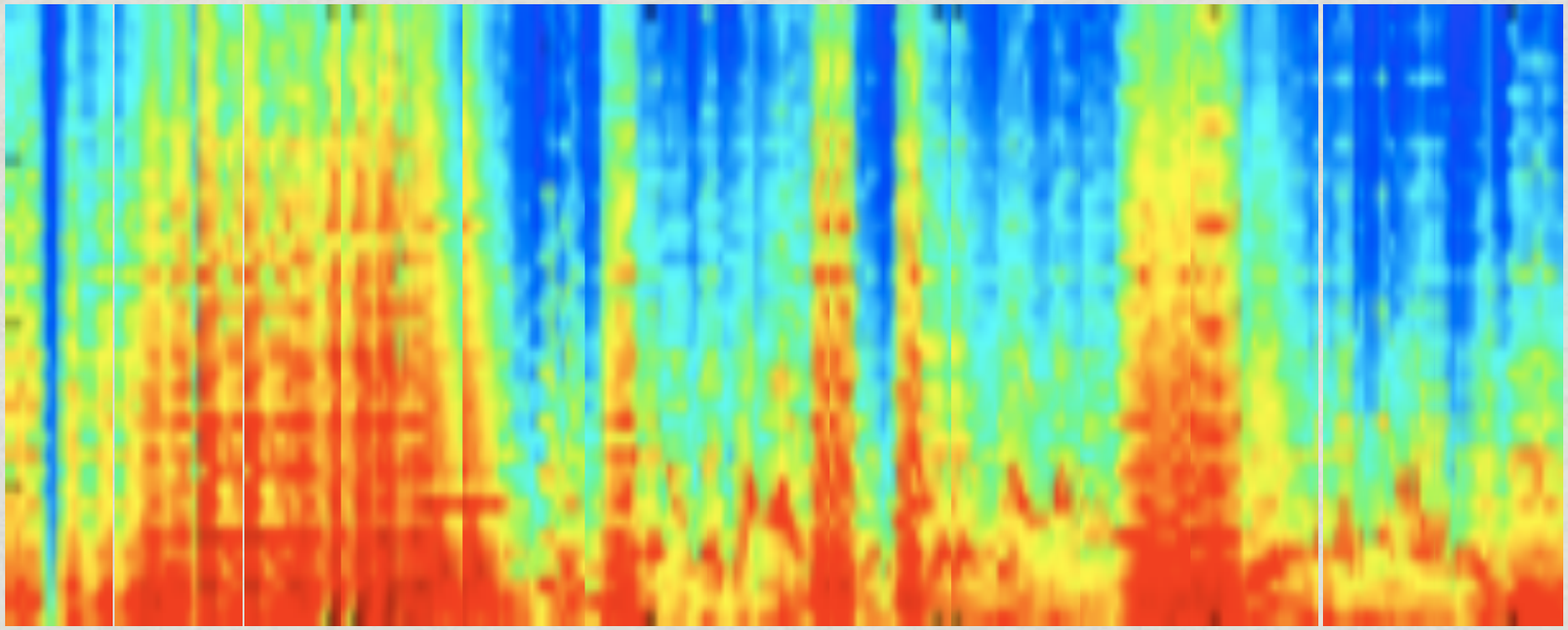


image: Foote 2000a

Clustering

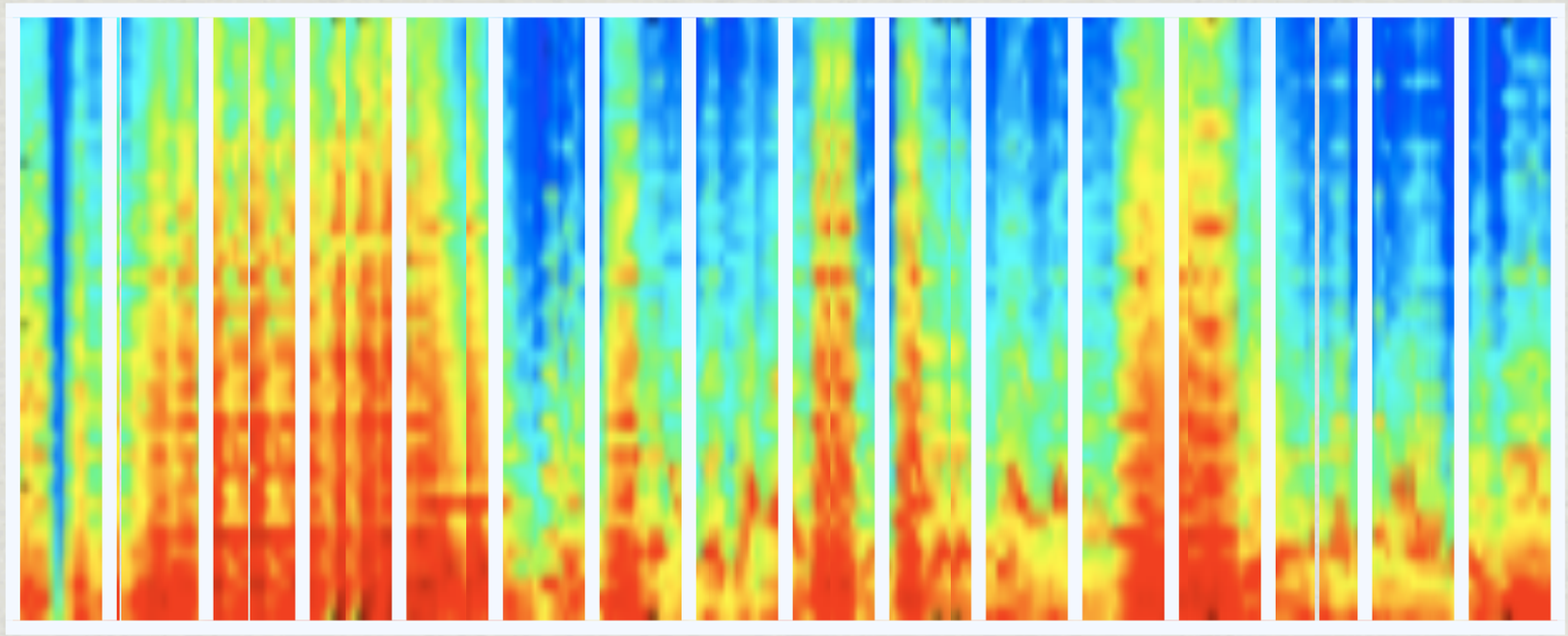
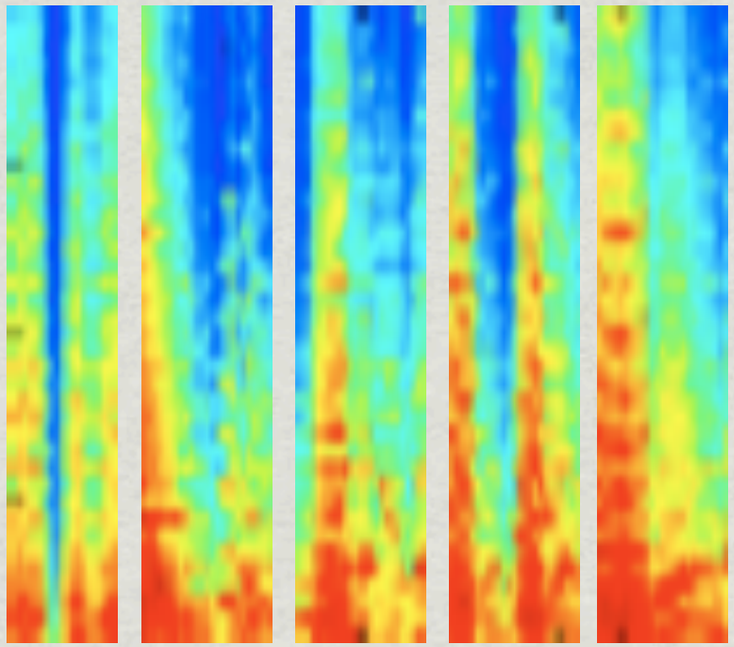
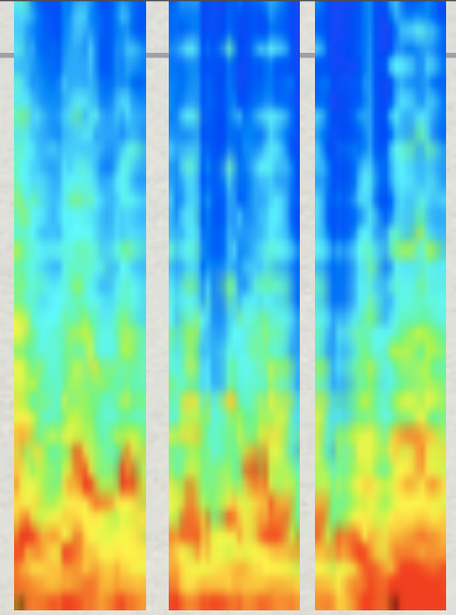
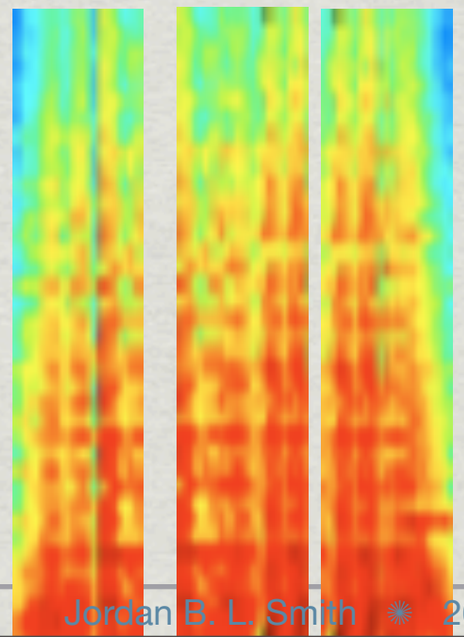


image: Foote 2000a

Clustering







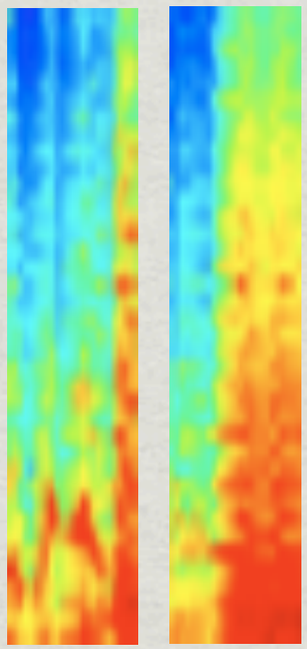
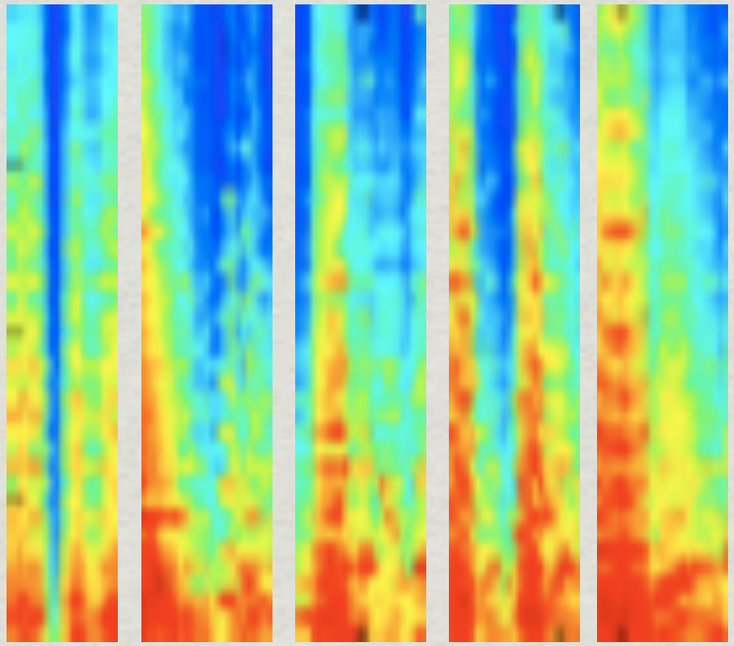
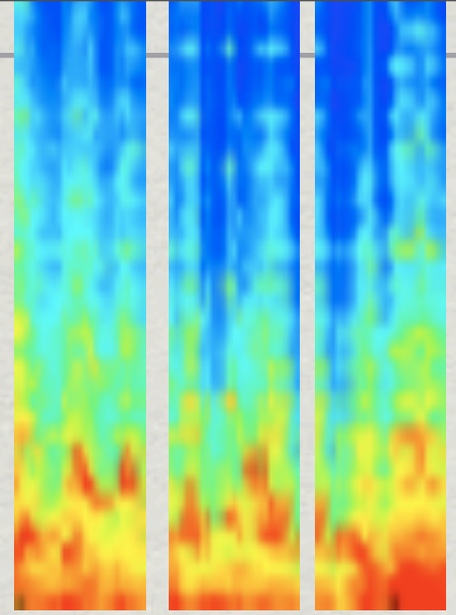


image: Foote 2000a

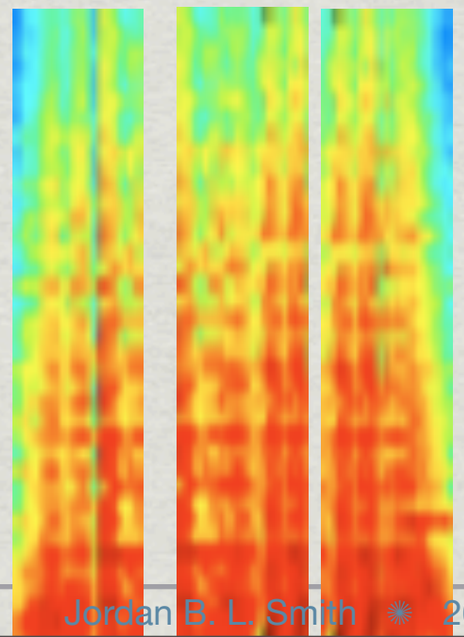
Clustering



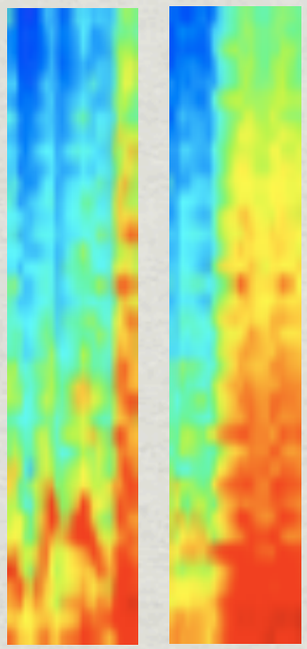
GROUP 1



GROUP 2



GROUP 3



GROUP 4

image: Foote 2000a

Clustering

1 3 3 3 1 1 4 1 2 4 1 2 2 ...

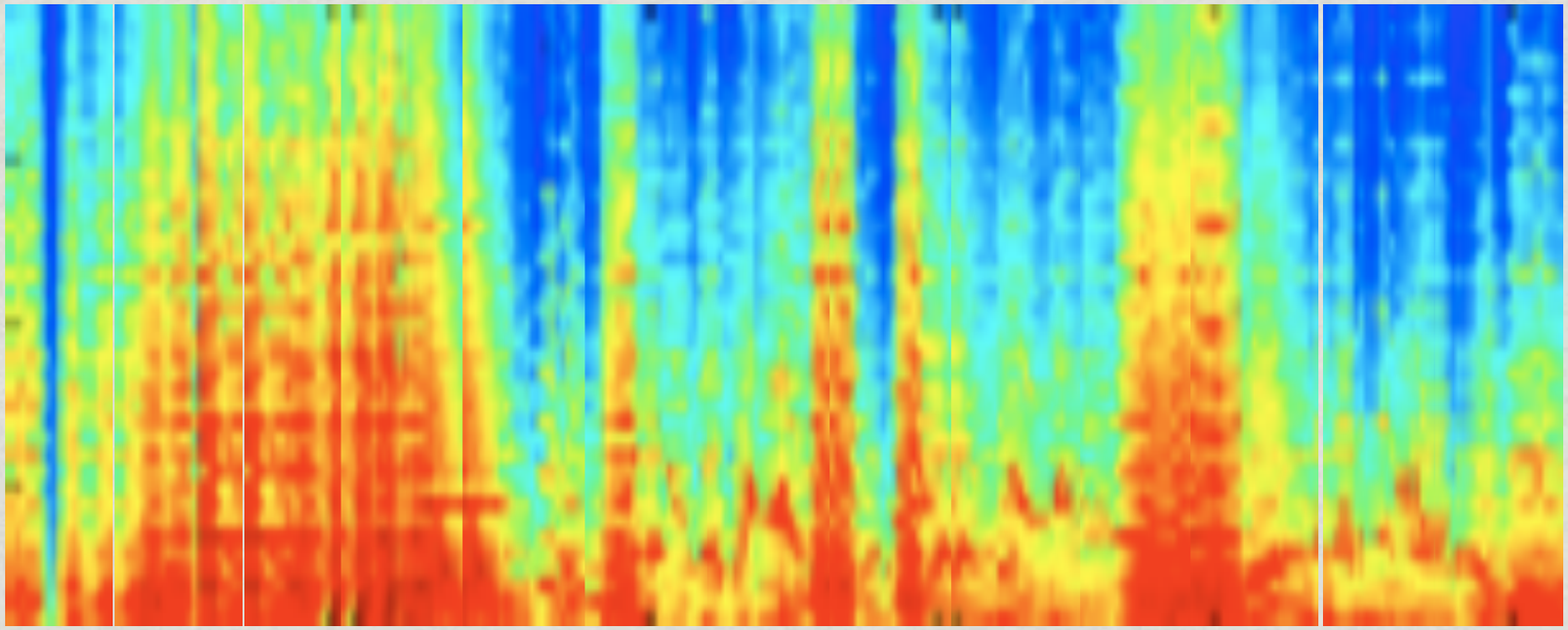


image: Foote 2000a

Clustering with HMM

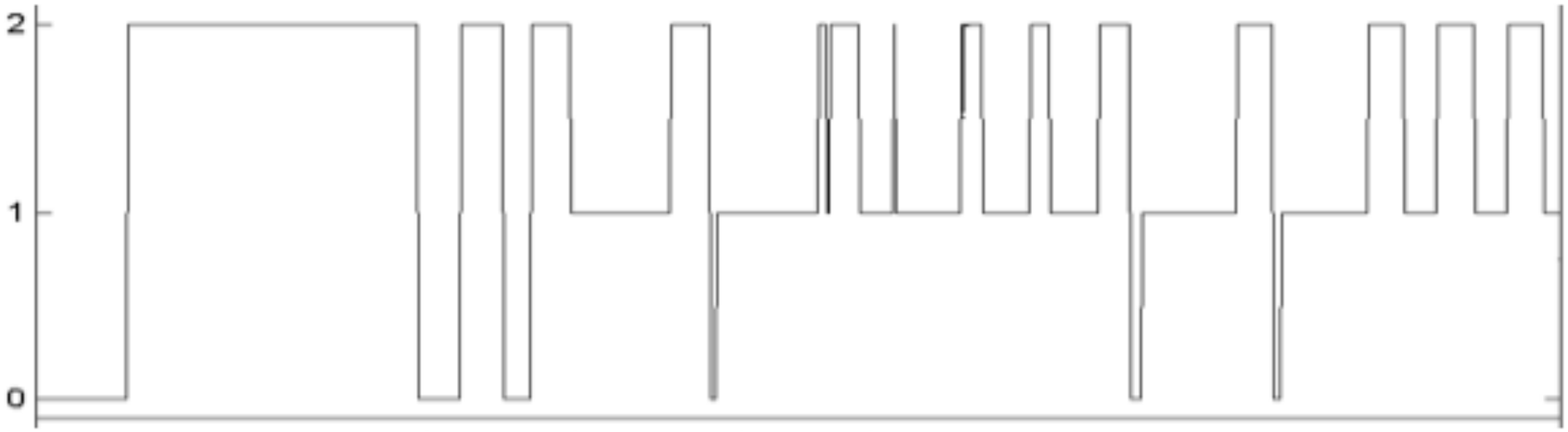
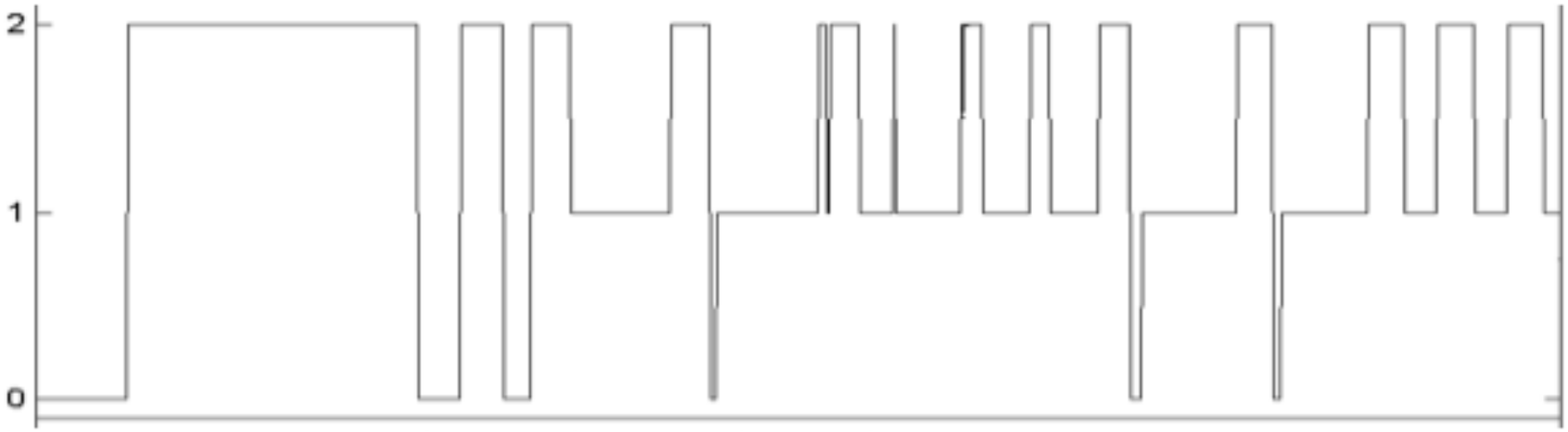


Figure 3-12: Segmentation of Bourvil's song. State 0 is {silence}, state 1 is {voice + accordion + accompaniment} and state 2 is {accordion + accompaniment}

image: Aucouturier 2001

Clustering with HMM



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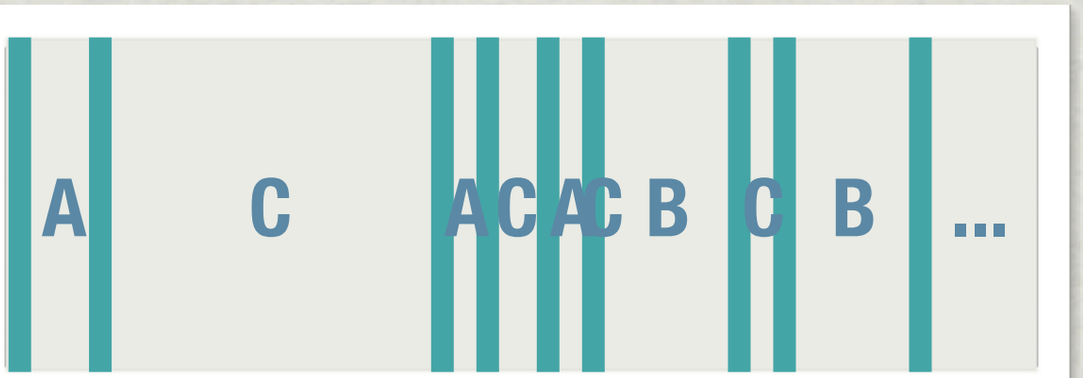


image: Aucouturier 2001

CLUSTERING

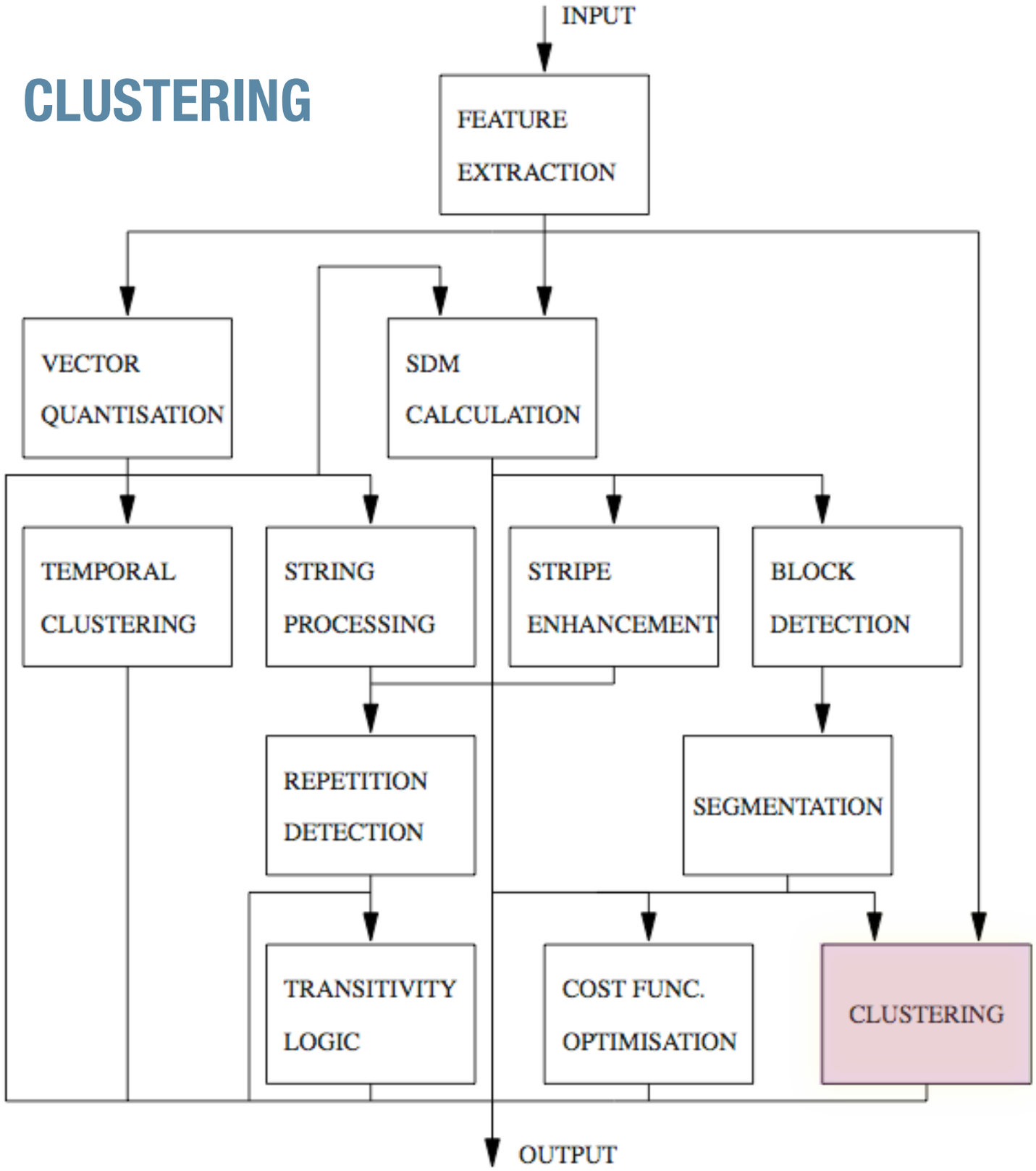


image: Paulus 2009

TEMPORAL CLUSTERING

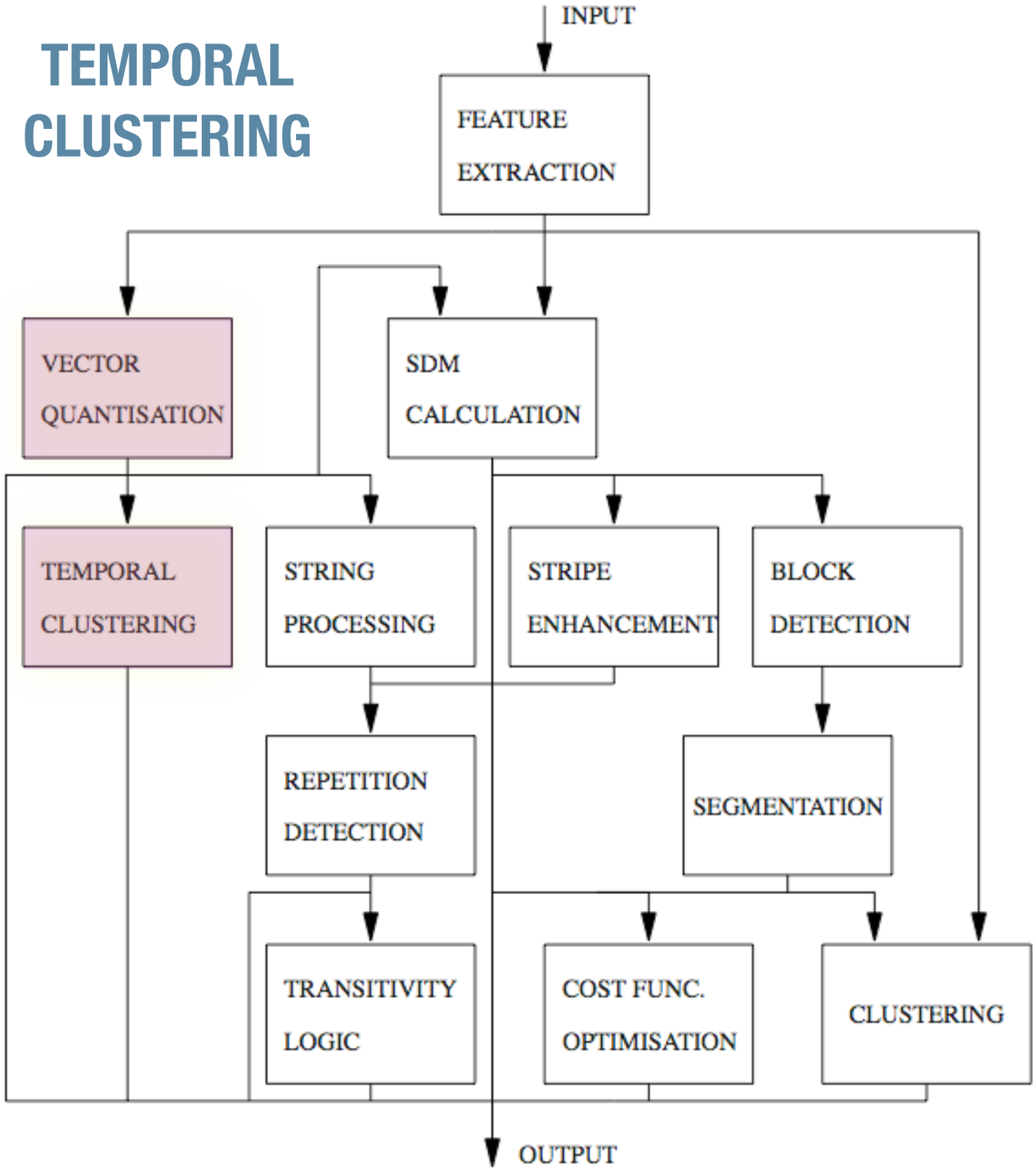
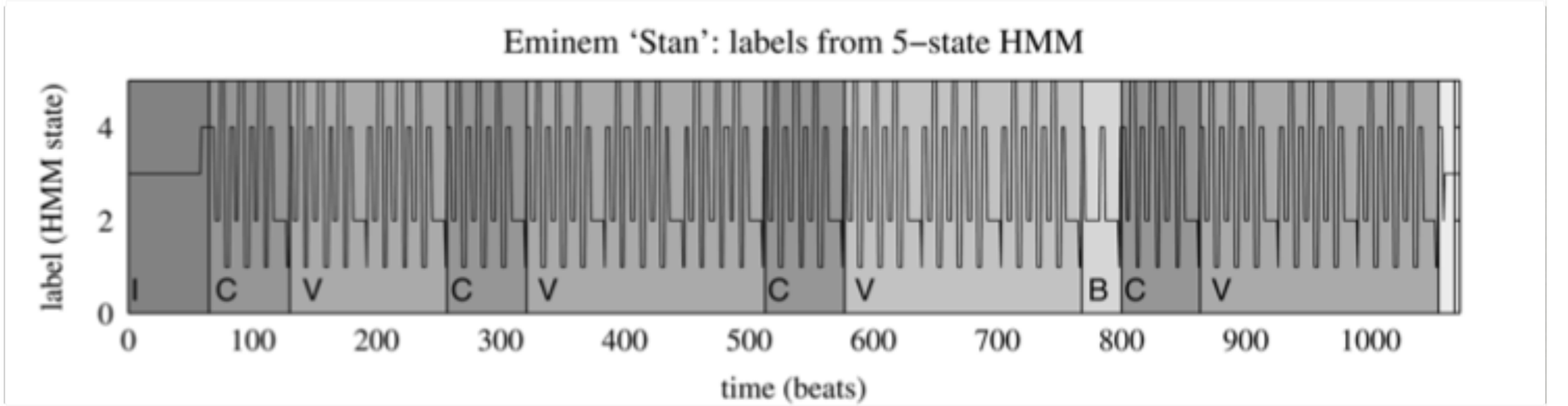
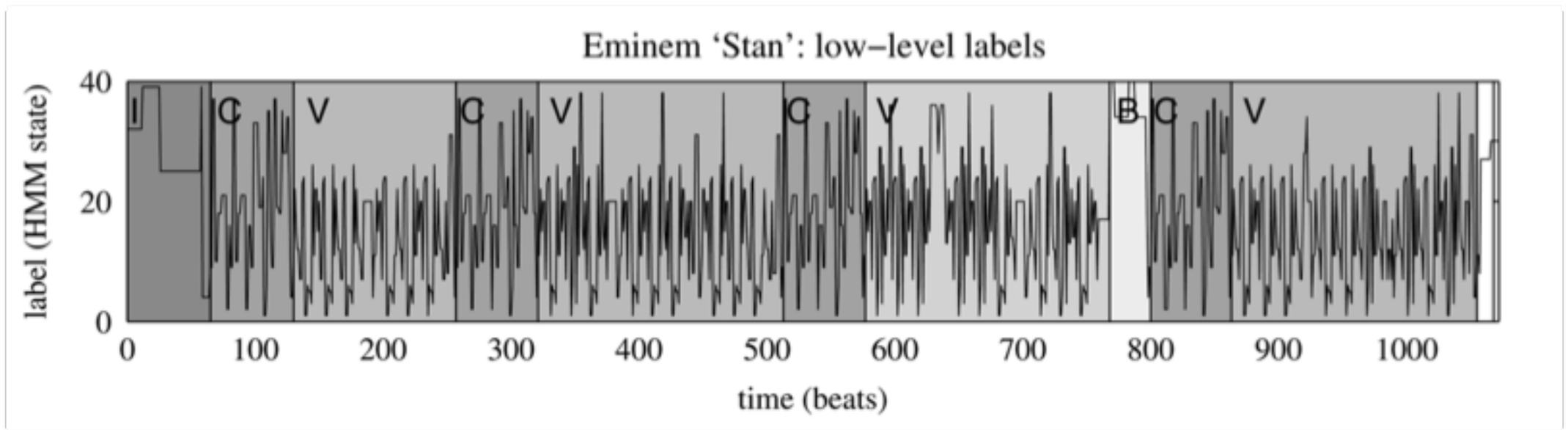


image: Paulus 2009

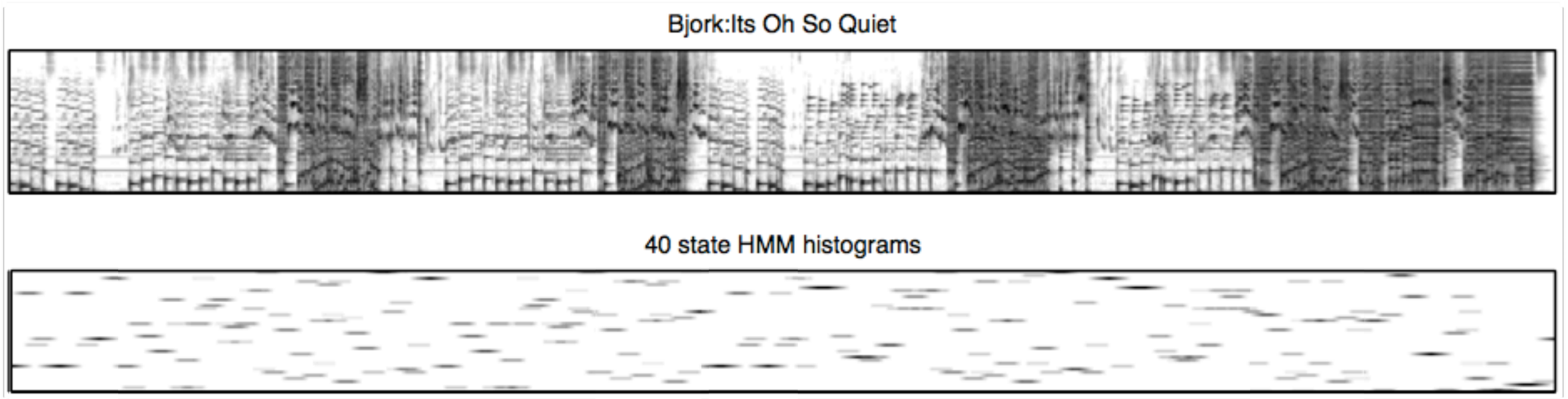
Clustering as mid-level representation

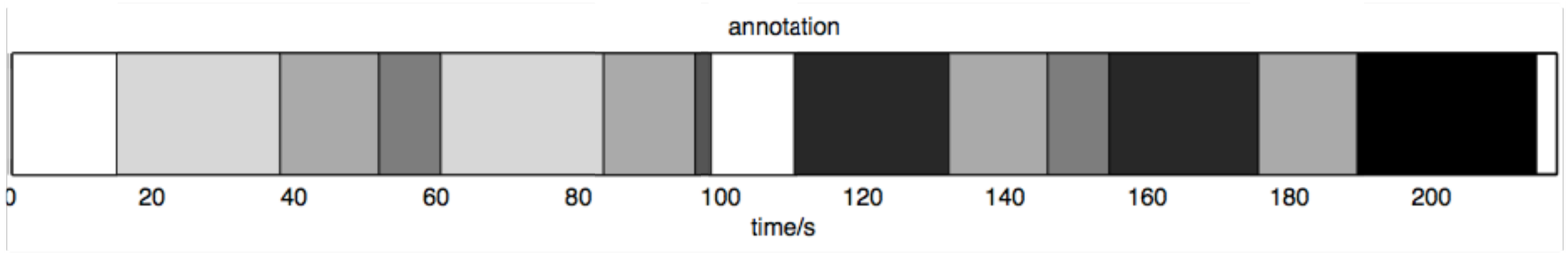




Images: Levy and Sandler 2008

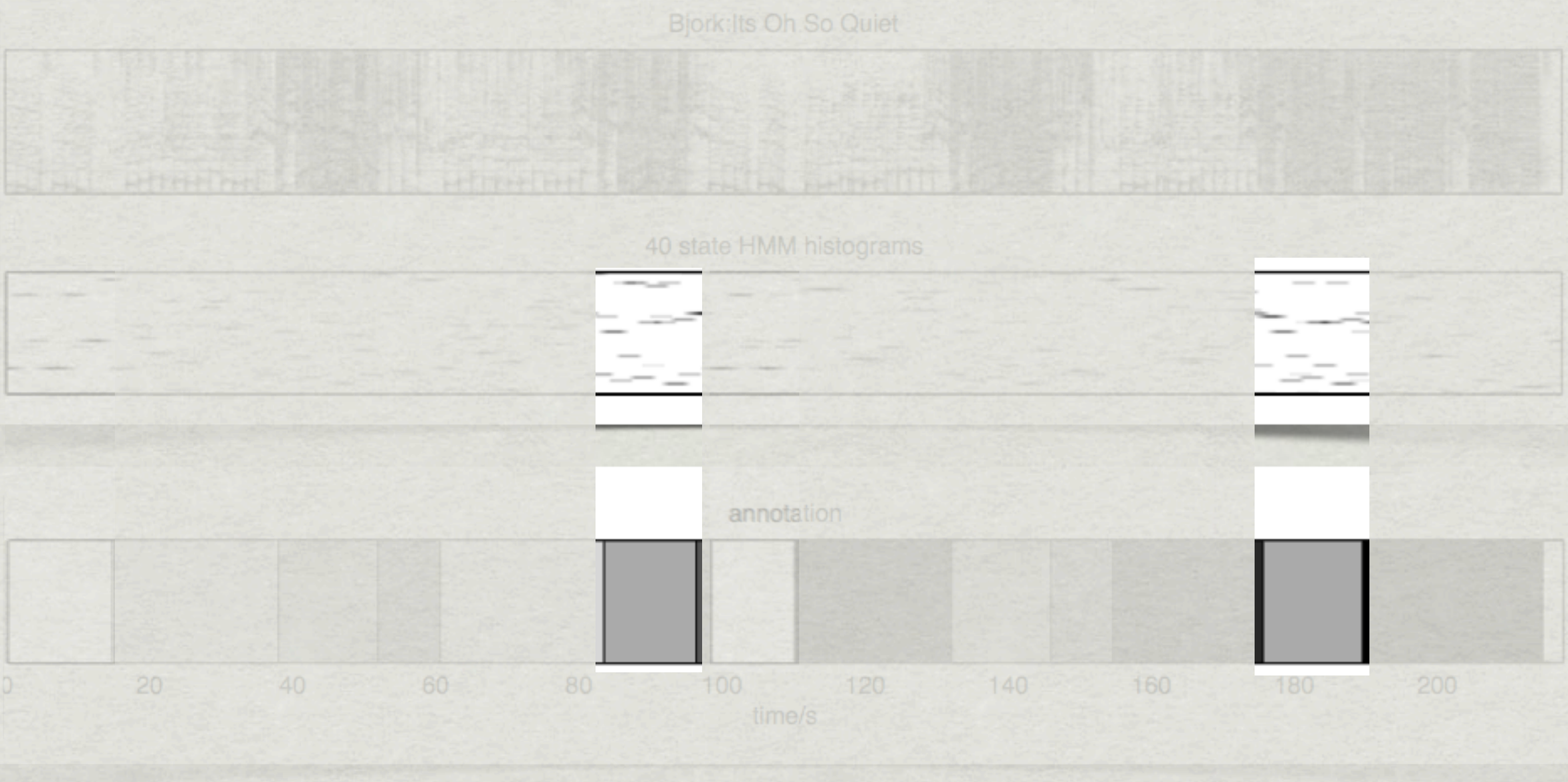
Clustering as mid-level representation





images: Abdallah et al. 2005

Clustering as mid-level representation



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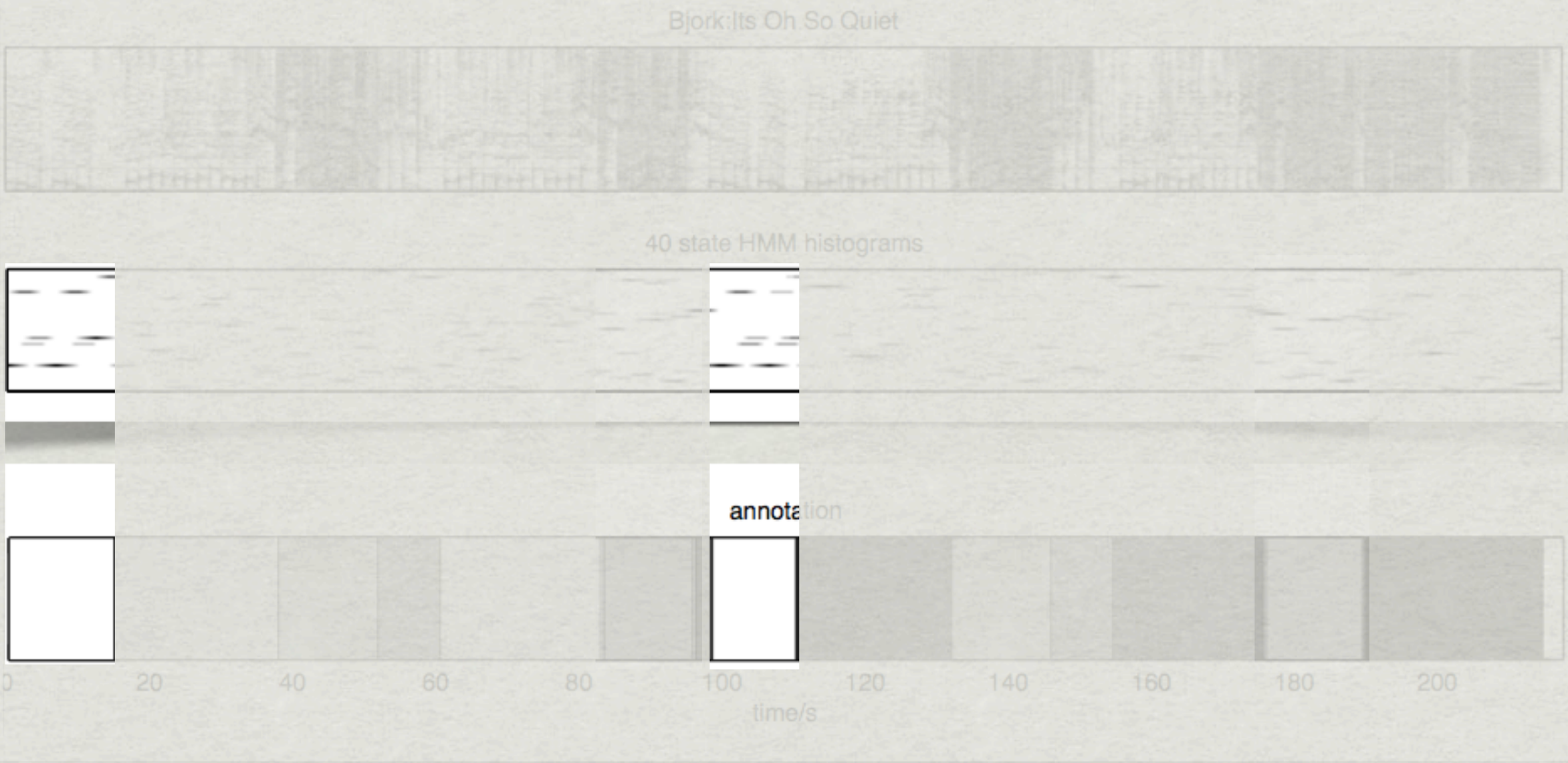
Clustering as mid-level representation



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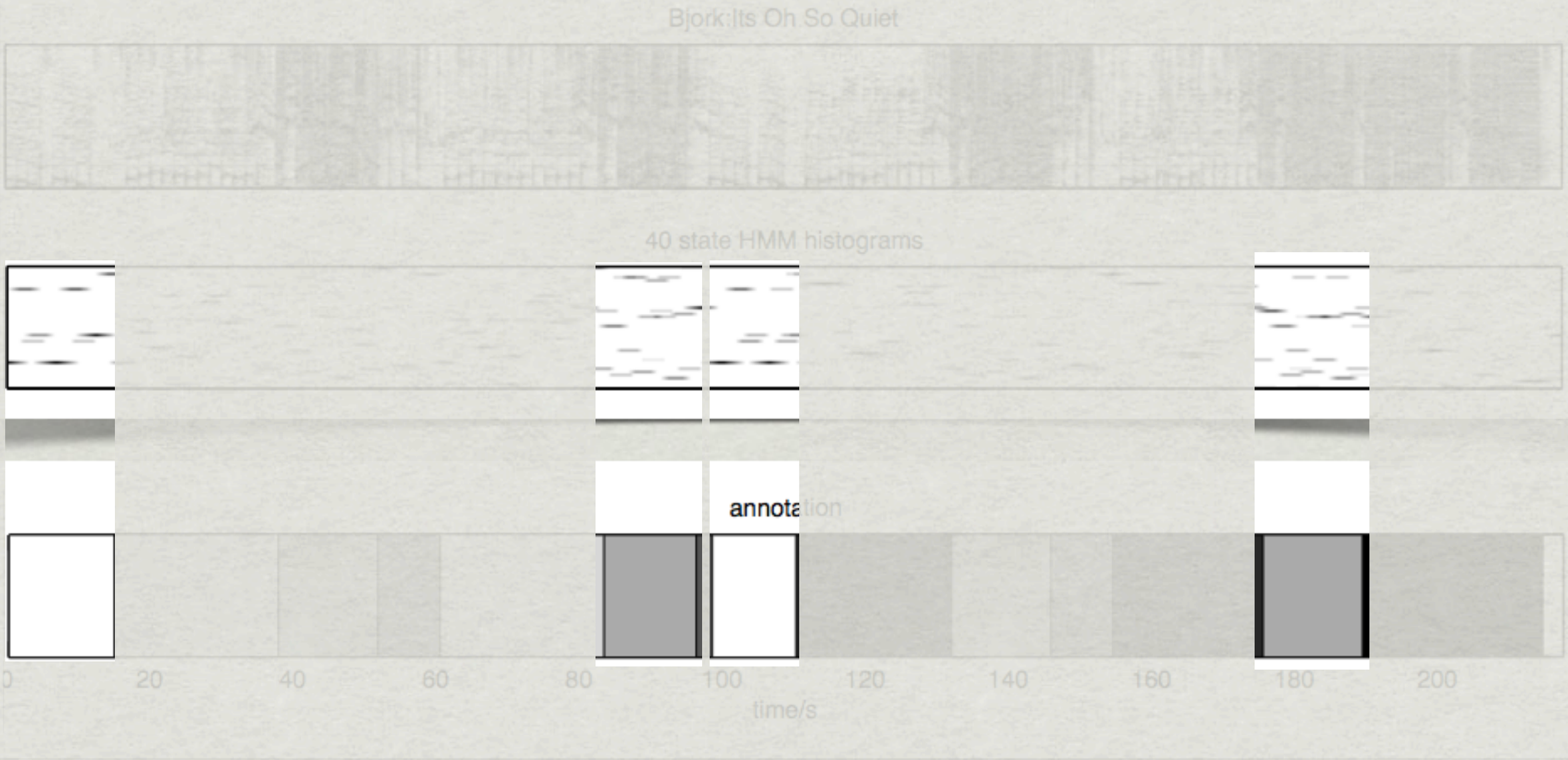

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Clustering as mid-level representation

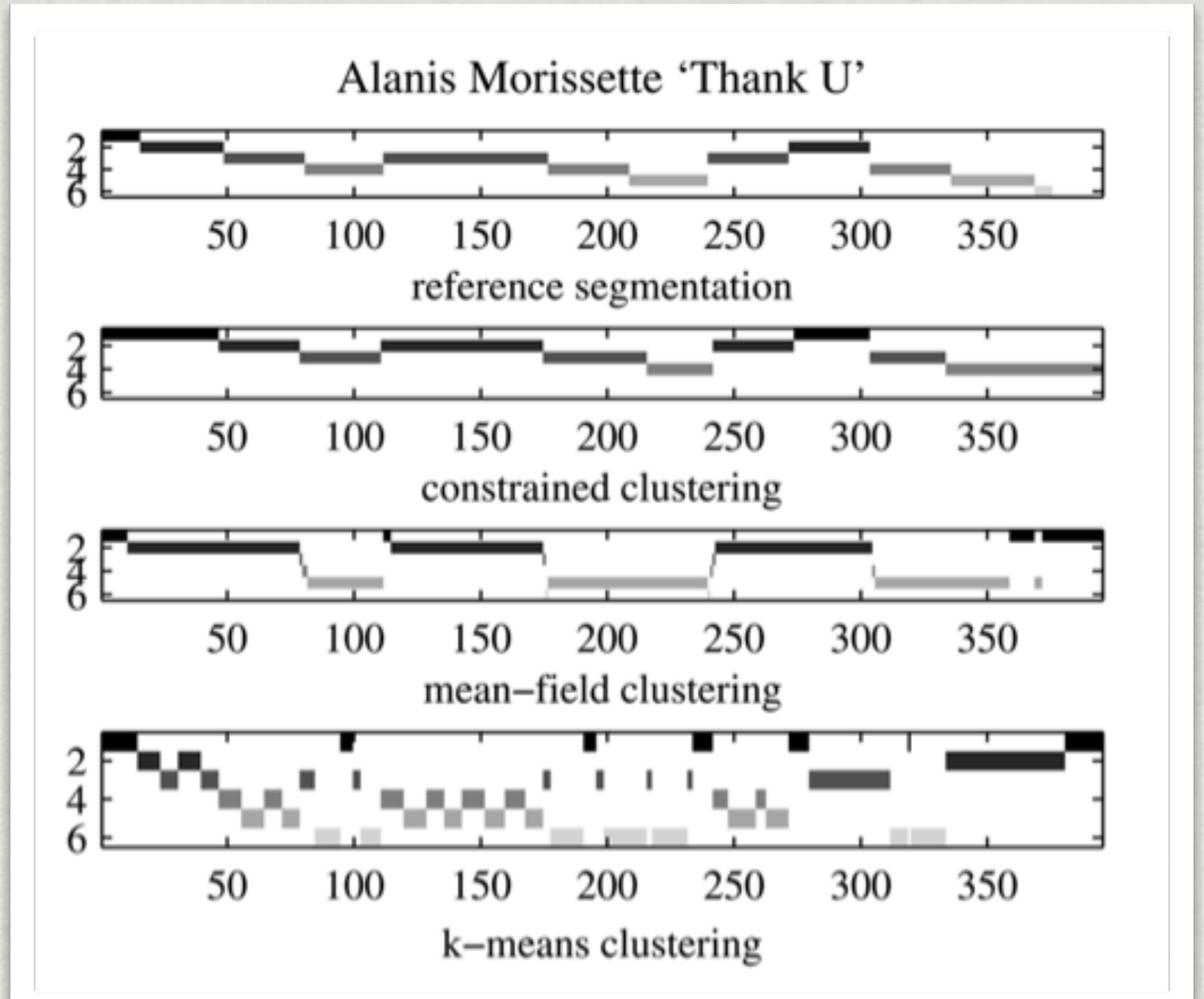

image: Levy and Sandler 2008

Features again

- Most features: static
  - each frame described by a vector
  - no information about temporal extent

- Solution: dynamic features

Dynamic features

- Information about timing or context:
  - Histograms (just saw)
  - Frame-wise derivatives (many)
  - Difference features (Turnbull et al. 2007)
  - FFTs of features (Peeters 2004)
  - Dynamic Texture Models (Barrington 2009)

~~Outline~~ Summary

1. Two hypotheses:

- ✓ States
- ✓ Sequences

2. A word on features:

- ✓ Timbre, harmony, etc.
- ✓ Dynamic features

3. Two techniques:

- ✓ Similarity matrix
- ✓ Clustering models

Discussion

- What can supervised learning do for structure analysis?
- Are either of the “states” or “sequences” hypotheses correct?
- Which of these methods can solve the Bohemian Rhapsody problem? (i.e., through-composed or ‘ABCD’ music)

Supervised learning

- Paulus & Klapuri 2010: applying semantic labels to analyses
- Turnbull et al. 2007: learning what boundaries look like

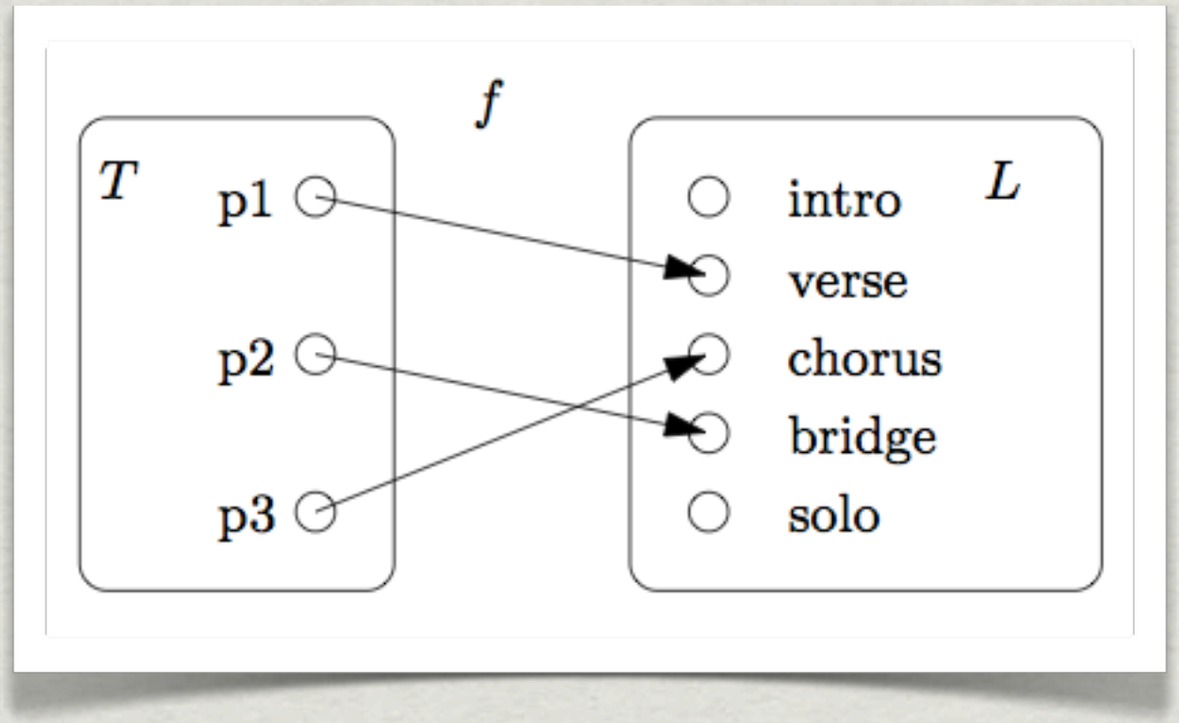

image: Paulus & Klapuri 2010

Thank you!

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École de musique Schulich

CIRMMT Centre for Interdisciplinary Research in Music Media and Technology

DDMAL

Social Sciences and Humanities Research Council of Canada

Conseil de recherches en sciences humaines du Canada

Canada

Image credits

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