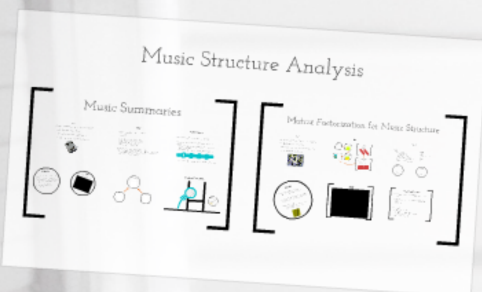
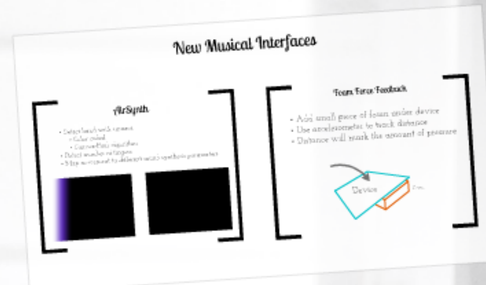
Music Structure Analysis and New Musical Interfaces





Oriol Nieto
Music and Audio Research Lab
New York University
Jan 10th 2013

MARL
NYU Music and Audio Research Laboratory

the echonest

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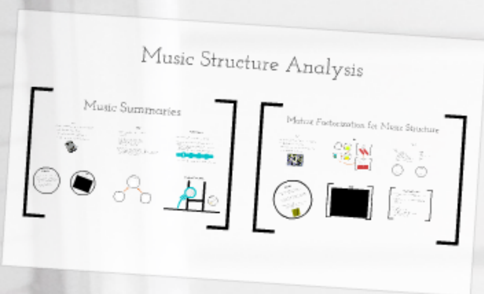

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Music Structure Analysis

Music Summaries

Matrix Factorization for Music Structure

Goal

- To generate audible summaries of music recordings that
    - optimally explain a given track
    - don't contain (much) repeated information
    - compress the entire music piece into a few seconds

Motivation

- To facilitate the navigation of massive digital music collections
- To provide an alternative to audio thumbnailing
  - all the parts of a piece are included in the summary
  - a potential buyer could get a better glimpse of the piece
- To normalize an entire music collection
  - more efficient for MIR techniques

Example

Chopin Mazurka Op. 30 No. 2
Original: A-B-C-B
Summary: A-B-C

How?

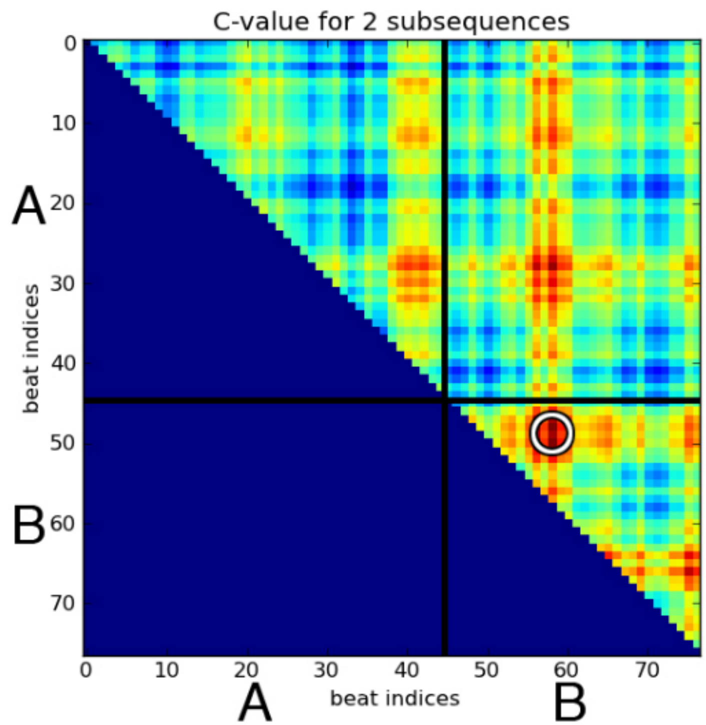
- Extract beat-synchronous harmonic features:
  - Chromas
  - Tonnetz

- Quantize the feature space using k-means
  - reduce space into a few discrete values
  - computationally advantageous
  - loose precision if k is too small

- Exhaustively search the quantized feature space for
  - Best P subsequences of N beats that can compress the entire signal
  - P subsequences of N beats that have the highest amount of disjoint information between them

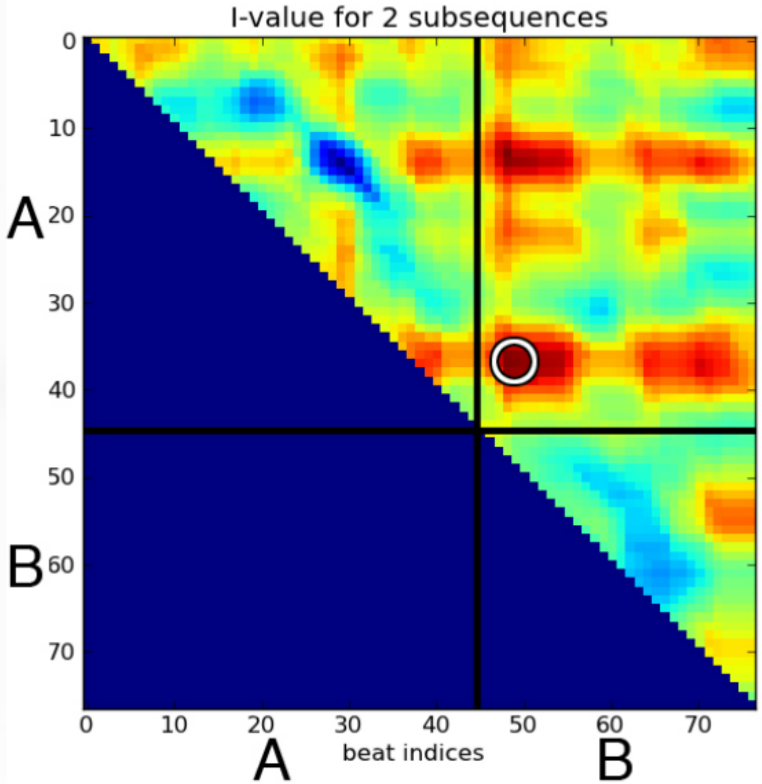
Compression

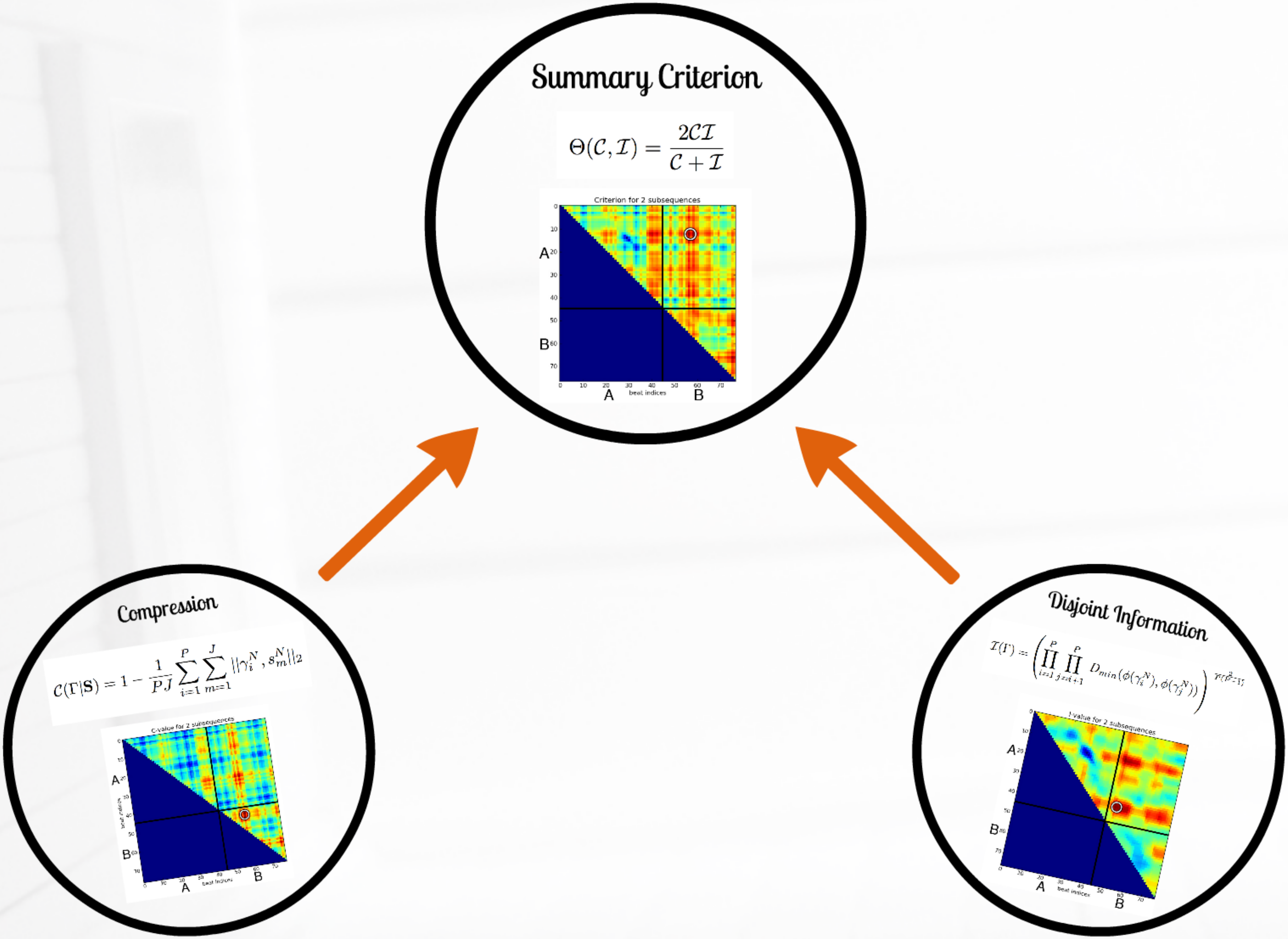
$$\mathcal{C}(\Gamma|\mathbf{S}) = 1 - \frac{1}{PJ}\sum_{i=1}^{P}\sum_{m=1}^{J}||\gamma_i^N, s_m^N||_2$$



Disjoint Information

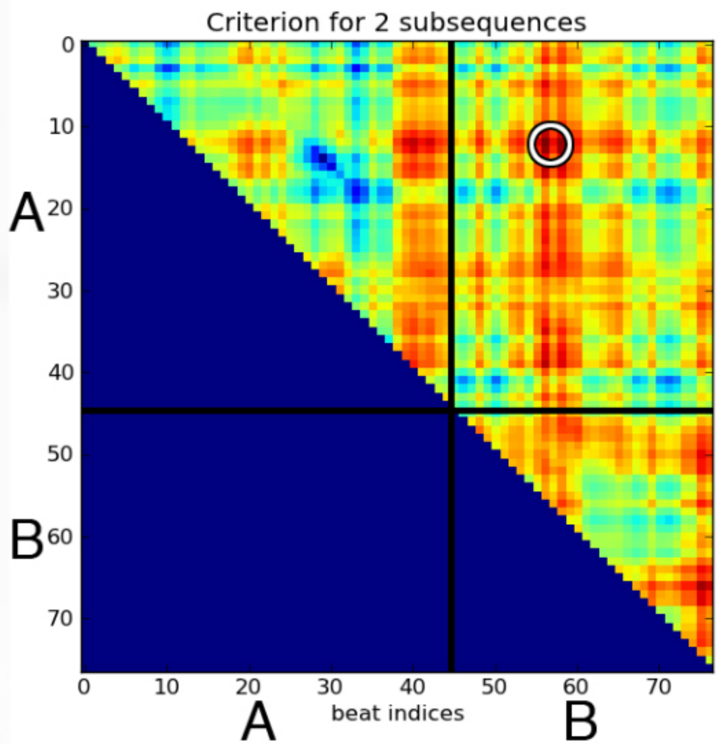
$$\mathcal{I}(\Gamma) = \left(\prod_{i=1}^{P} \prod_{j=i+1}^{P} D_{min}(\phi(\gamma_i^N), \phi(\gamma_j^N)) \right)^{\frac{2}{P(P-1)}}$$




Summary Criterion
$\Theta(\mathcal{C},\mathcal{I}) = \frac{2\mathcal{C}\mathcal{I}}{\mathcal{C}+\mathcal{I}}$
Criterion for 2 subsequences
beat indices
A
B
Compression
$\mathcal{C}(\Gamma|\mathbf{S}) = 1 - \frac{1}{PJ}\sum_{i=1}^{P}\sum_{m=1}^{J} ||\gamma_i^N, s_m^N||_2$
C-value for 2 subsequences
Disjoint Information
I-value for 2 subsequences

Summary Criterion

$$\Theta(\mathcal{C}, \mathcal{I}) = \frac{2\mathcal{C}\mathcal{I}}{\mathcal{C} + \mathcal{I}}$$



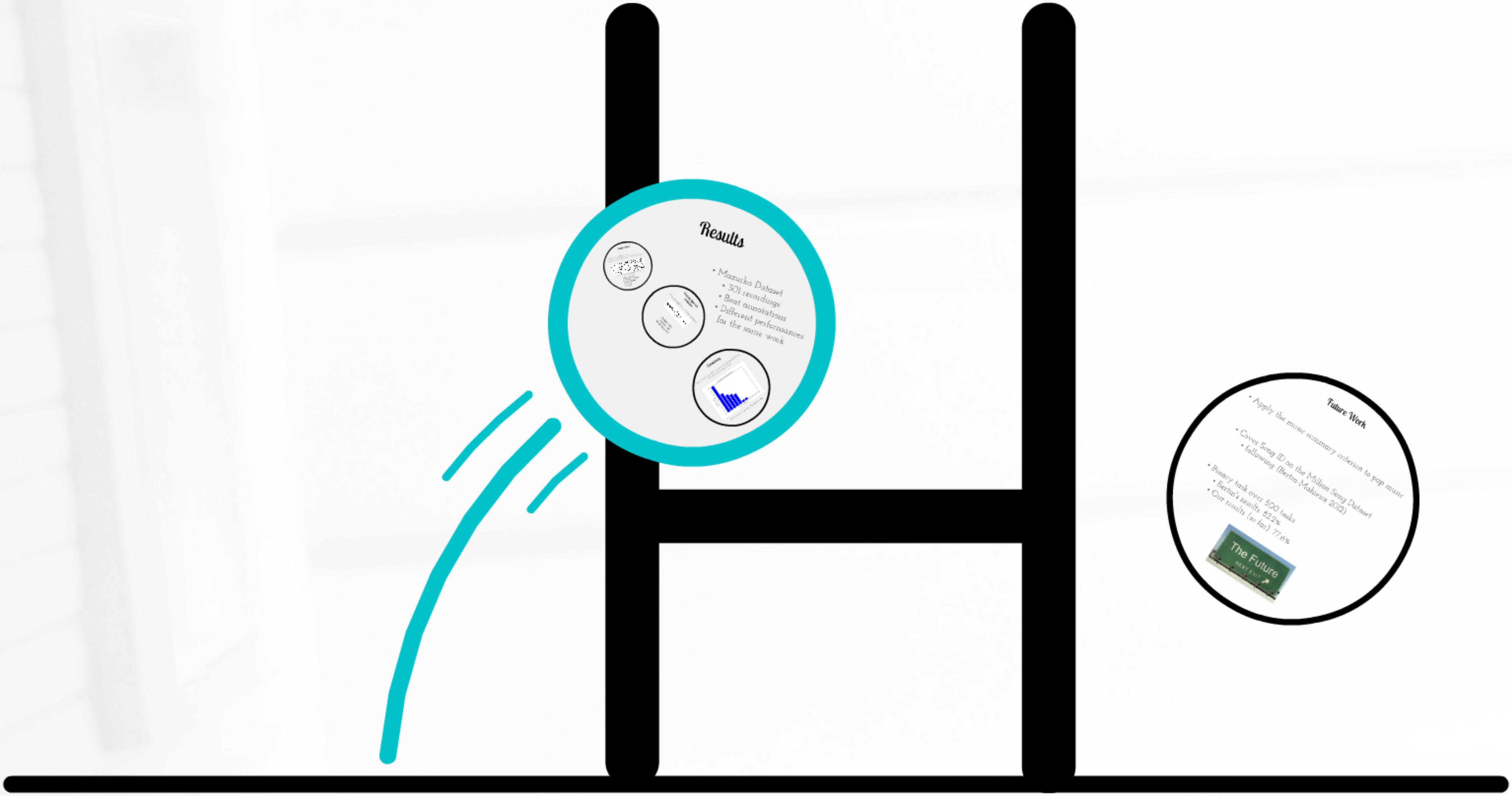
Heuristic Approach

- Brute force method is computationally expensive

- We can approximate the same results with a heuristic approach
  - Initialize P subsequences equally spaced in time across the music recording
  - Find maximum criterion one subsequence at a time

- The problem becomes linear with respect to P instead of exponential

Results and Future Work



Results

- Mazurka Dataset
  - 301 recordings
  - Beat annotations
  - Different performances for the same work

Feature Space

k	GT-C	GT-T	A-C	A-T
50	3.64	3.97	2.71	3.80
100	3.83	4.29	2.68	4.20
200	4.09	4.74	2.87	4.45

Fisher's ratio between recordings from the same work and the rest

k: Dictionary size
GT: Ground Truth Beats
A: Automatic Beats
C: Chromas
T: Tonnetz

Heuristic Approach Evaluation

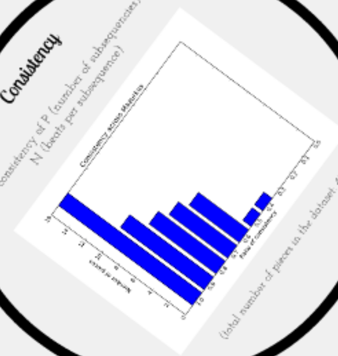
Mean Squared Error between strategies

$$MSE(\Theta) = \frac{1}{S}\sum_{i}^{S}(1 - \Theta_i)^2$$

Random: 21%
Heuristic: 1%
(Brute Force: 0%)

Consistency

Check consistency of P (number of subsequencies) and N (beats per subsequence)



(total number of pieces in the dataset: 49)

Feature Space

- Is automatic beat tracking sufficient?
- Do chroma and Tonnetz features perform equivalently?
- Does performance vary significantly as a function of codebook size?

k	GT-C	GT-T	A-C	A-T
50	3.64	3.97	2.71	3.89
100	3.84	4.29	2.68	4.20
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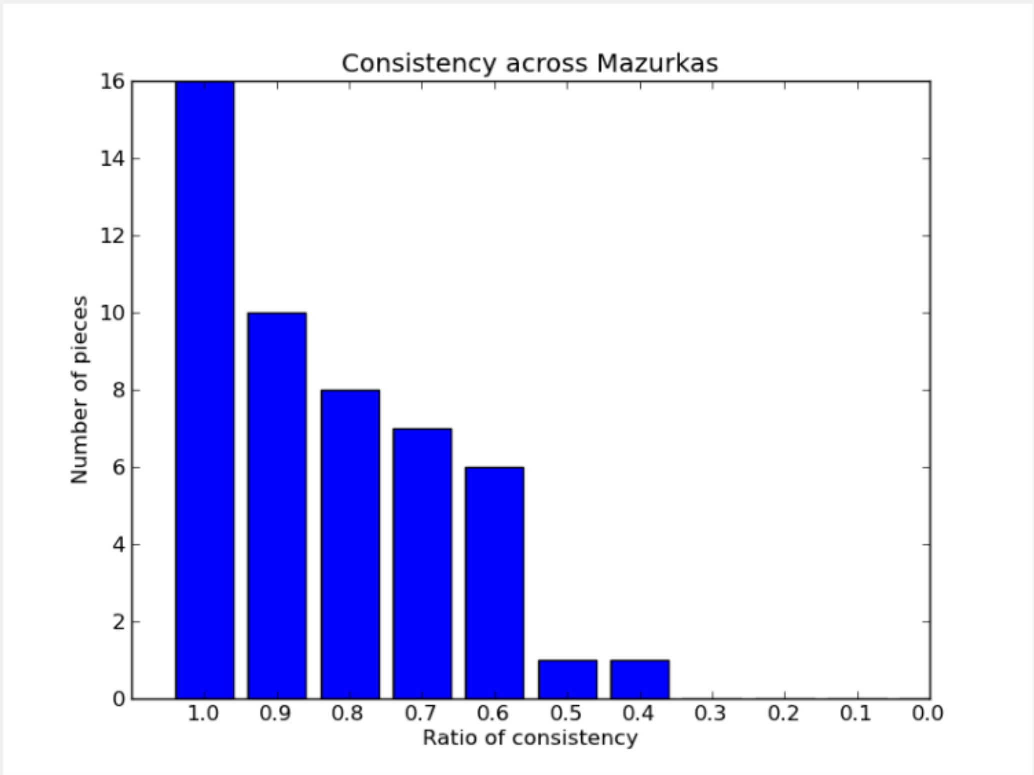

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Future Work

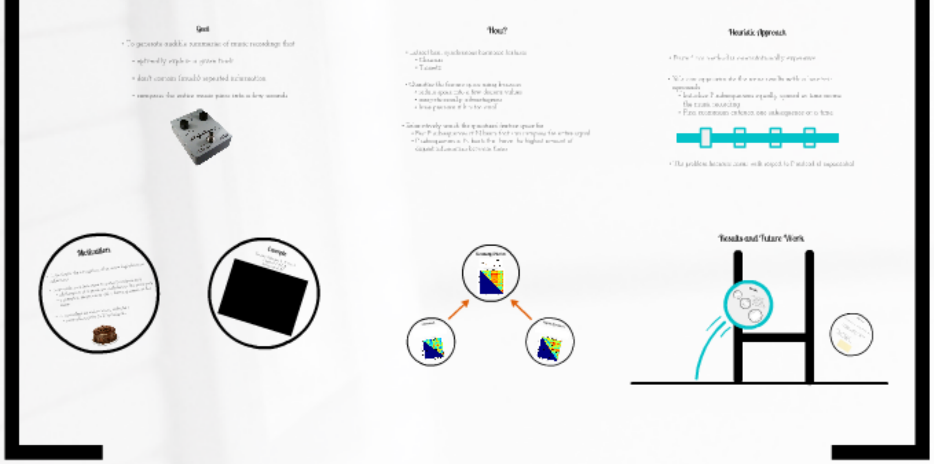
- Apply the music summary criterion to pop music

- Cover Song ID on the Million Song Dataset
    - following (Bertin-Mahieux 2012)

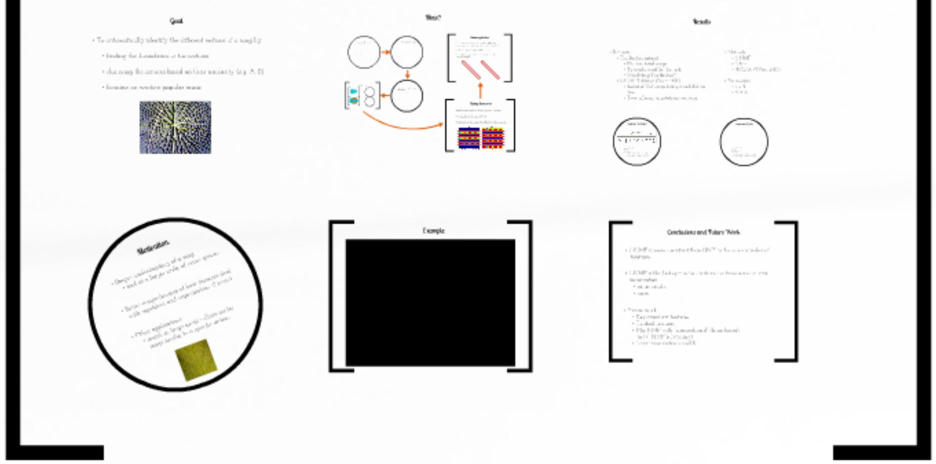
- Binary task over 500 tasks
    - Bertin's results: 82.2%
    - Our results (so far): 77.6%

Music Structure Analysis

Music Summaries



Matrix Factorization for Music Structure

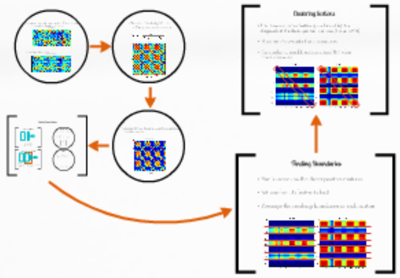


Matrix Factorization for Music Structure

Goal

- To automatically identify the different sections of a song by
  - finding the boundaries of the sections
  - clustering the sections based on their similarity (e.g. A, B)
  - focusing on western popular music

How?



Results

- Datasets:
  - The Beatles dataset
    - 176 annotated songs
    - Typically used for this task
    - Overfitting The Beatles?
  - SALAMI dataset (Smith 2011)
    - Subset of 253 songs freely available on-line
    - Two different annotations per song

- Methods:
  - C-NMF
  - NMF
  - SI-PLCA (Weiss 2010)

- Parameters:
  - r = 2
  - K = 4

Motivation

- Deeper understanding of a song
  - and at a larger scale, of music genres
- Better comprehension of how humans deal with repetition and organization of sound
- Other applications:
  - search in large music collections for songs similar to a specific section

Example

Conclusions and Future Work

- C-NMF is more consistent than NMF in the same number of iterations

- C-NMF is the best option for clustering sections using matrix factorization
  - better results
  - faster

- Future work:
  - Key-invariant features
  - Timbral features
  - Mix NMF with "checkerboard" (boundaries) and C-NMF (clustering)
  - Learn parameters r and K

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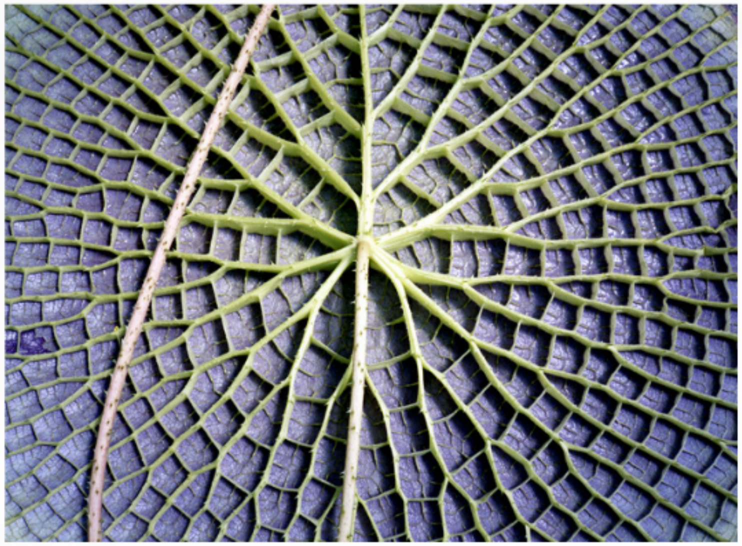

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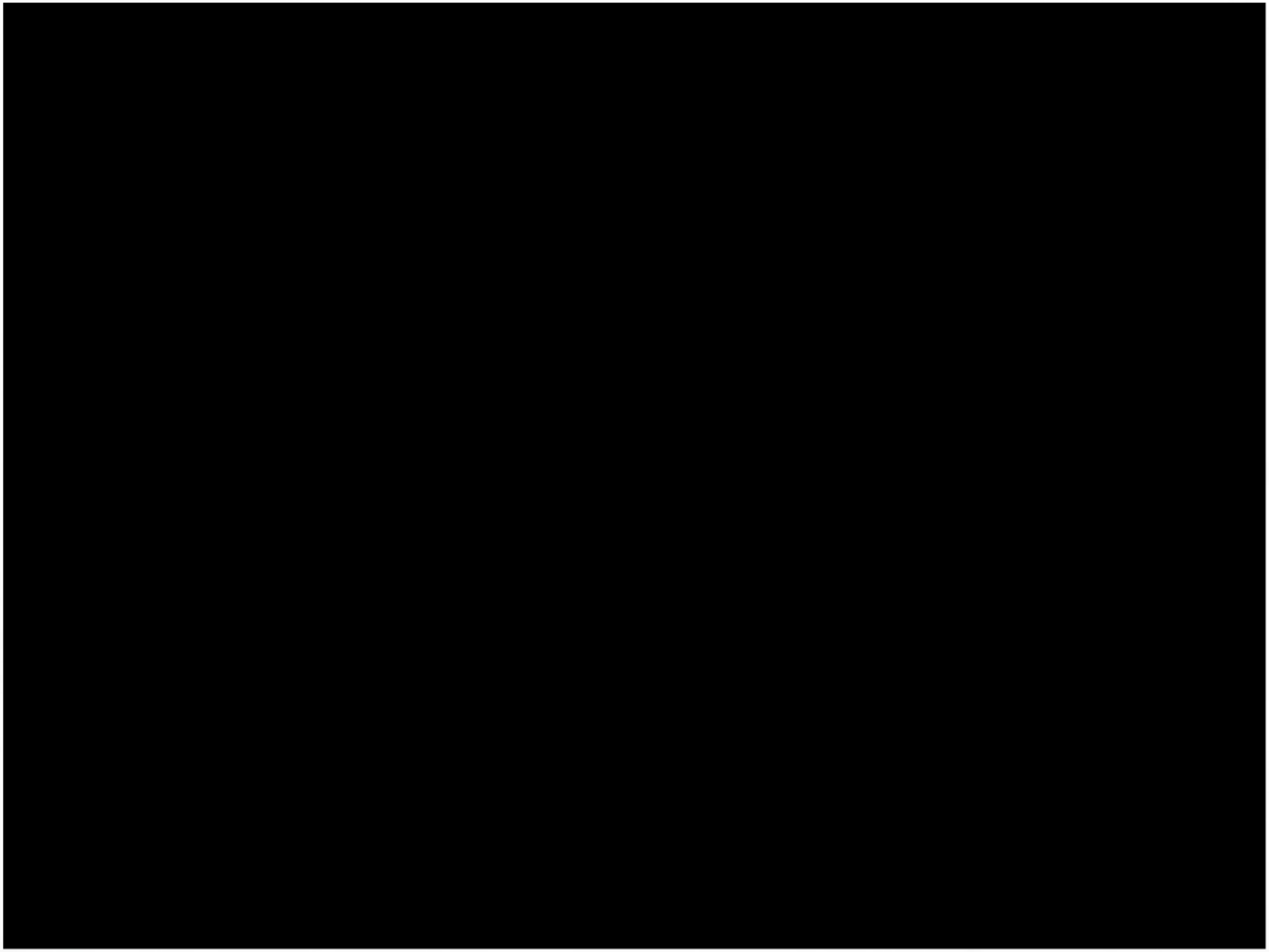

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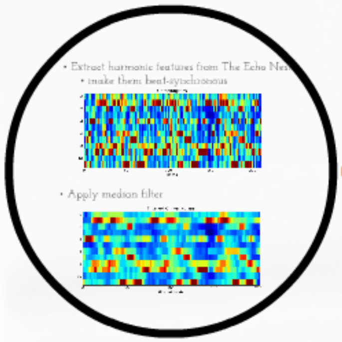
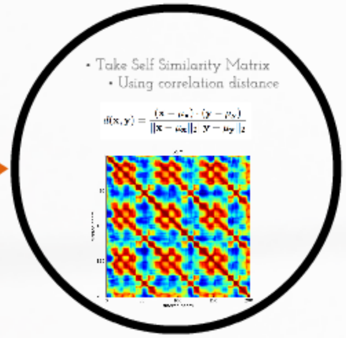
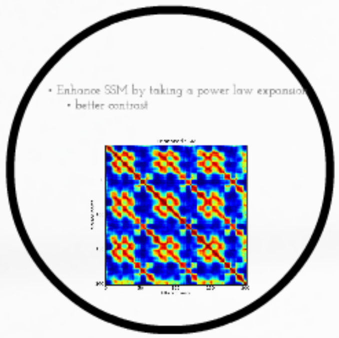
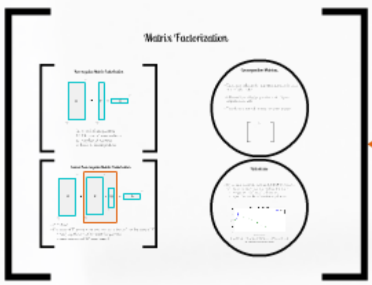


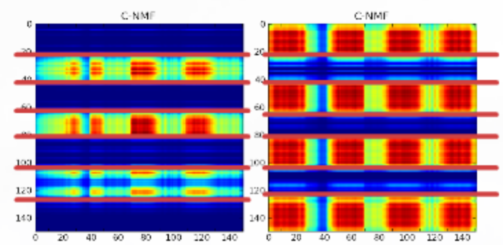






Finding Boundaries

- Run k-means on the decomposition matrices
- Set number of clusters to k=2
- Average the resulting boundaries of each matrix



Clustering Sections

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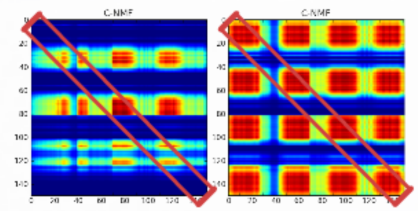
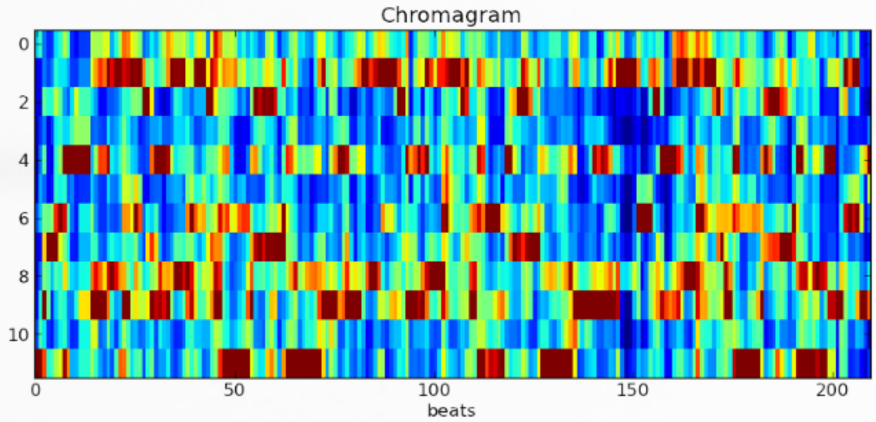
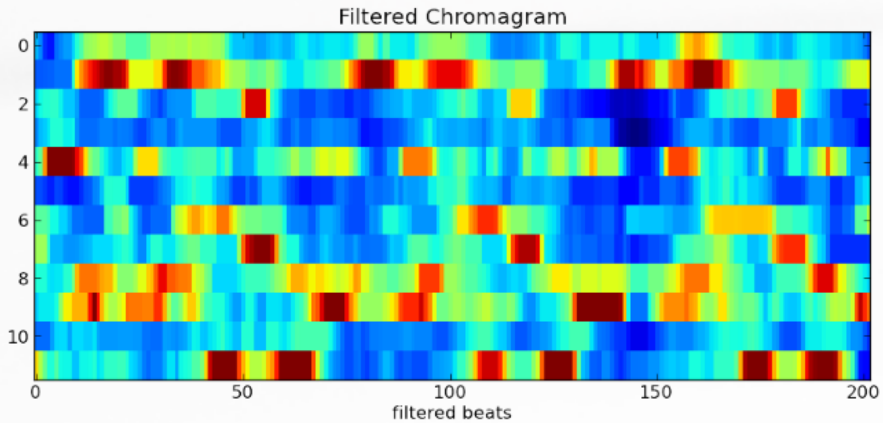
- The number of possible sections is fixed (K) when running k-means



- Extract harmonic features from The Echo Nest
  - make them beat-synchronous

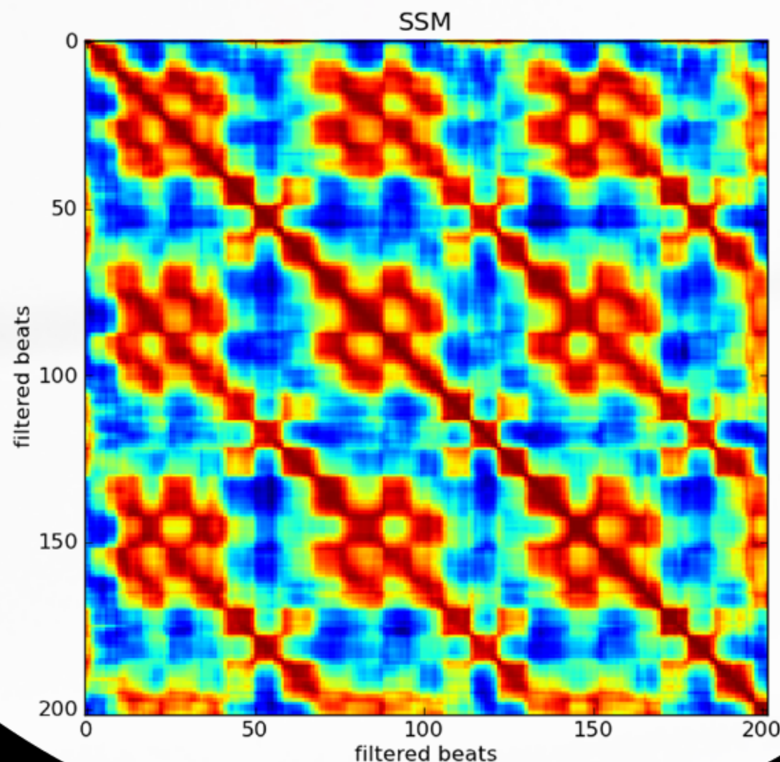


- Apply median filter

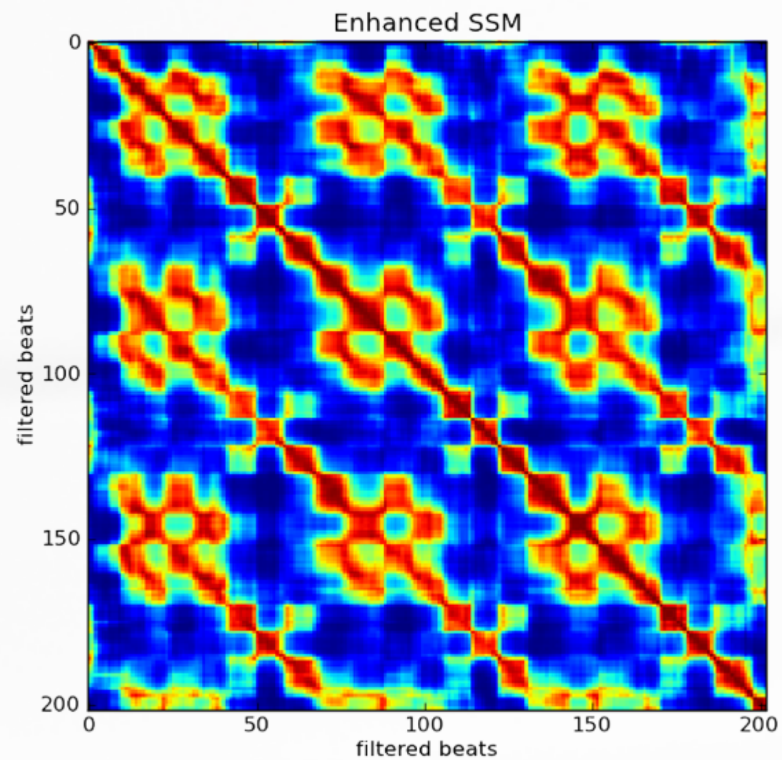


- Take Self Similarity Matrix
    - Using correlation distance

$$d(\mathbf{x}, \mathbf{y}) = \frac{(\mathbf{x} - \mu_{\mathbf{x}}) \cdot (\mathbf{y} - \mu_{\mathbf{y}})}{||\mathbf{x} - \mu_{\mathbf{x}}||_2 ||\mathbf{y} - \mu_{\mathbf{y}}||_2}$$

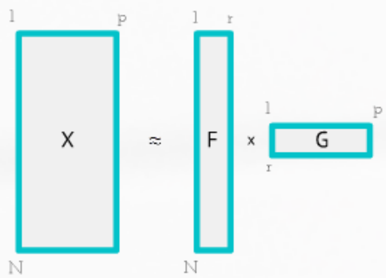


- Enhance SSM by taking a power law expansion
    - better contrast



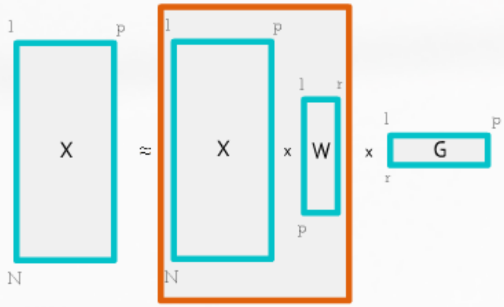
Matrix Factorization

Non-negative Matrix Factorization



X, F, and G are positive
N: Number of observations
p: Number of features
r: Rank of decomposition

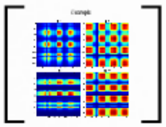
Convex Non-negative Matrix Factorization



- F = XW
- Columns of F become convex combinations of the features of X
  - Each coefficient of W must be positive
  - Each column of W must sum 1

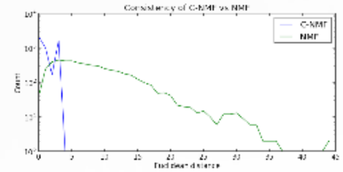
Decomposition Matrices

- There are r different decomposition matrices for each matrix factorization
- Obtained by multiplying a column of F by its respective row of G
- They have a key role in music structure analysis



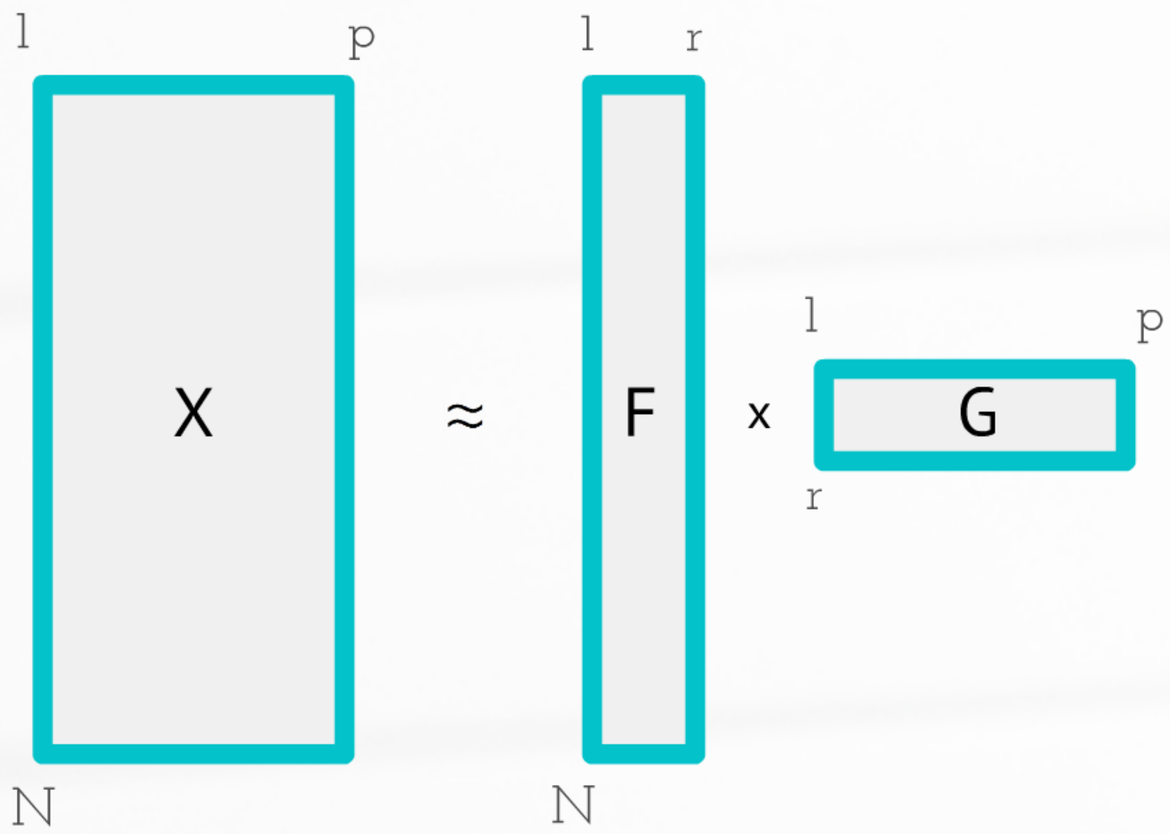
Robustness

- By adding a convex constrain to NMF we tend to find more consistent solutions in less iterations
  - Less prone to fall into local minima
  - Lower the number of iterations -> Faster



Logarithmic histogram of distances between 100 sets of decomposition matrices

Non-negative Matrix Factorization



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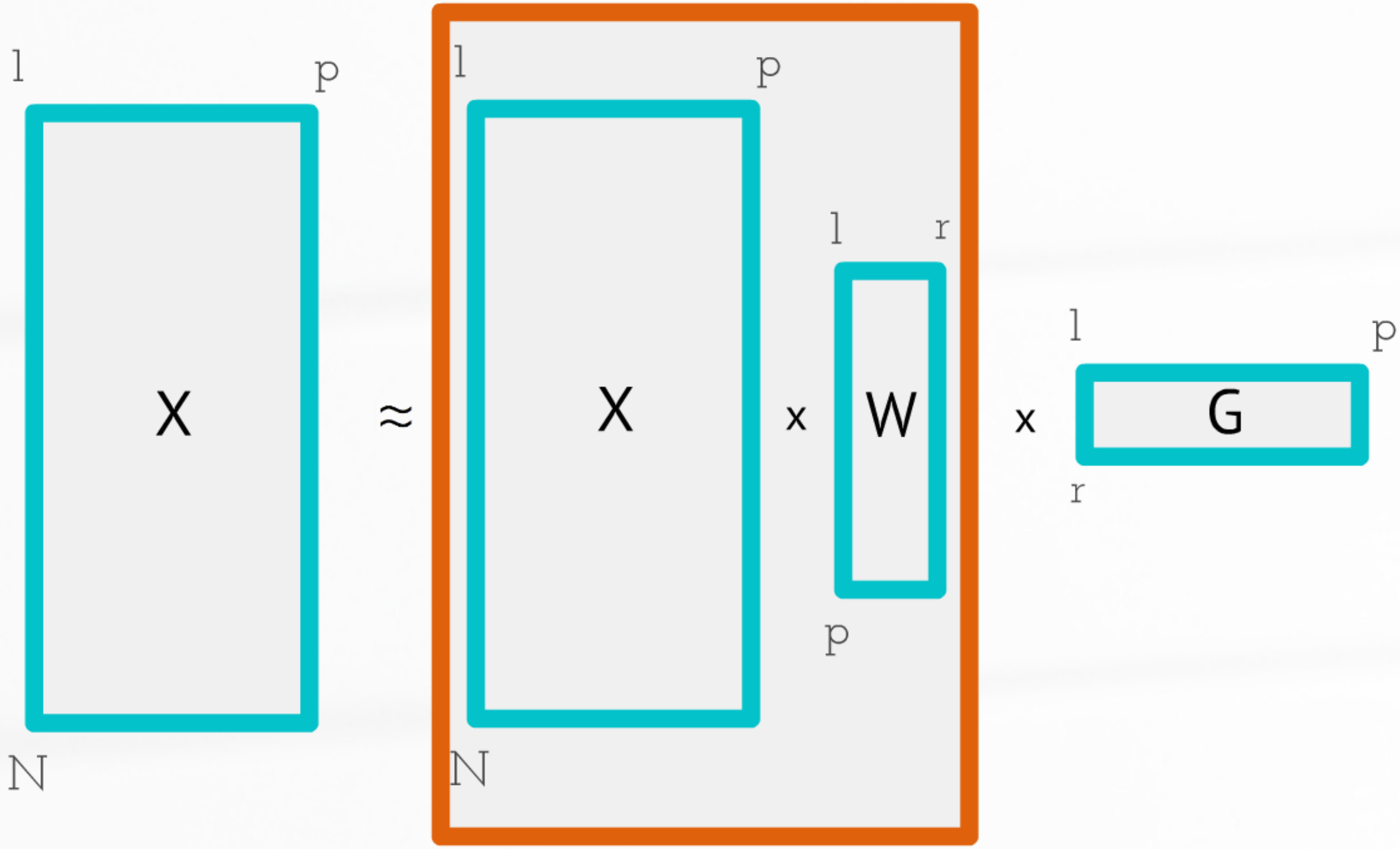

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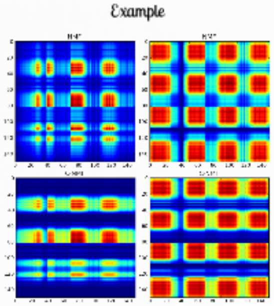

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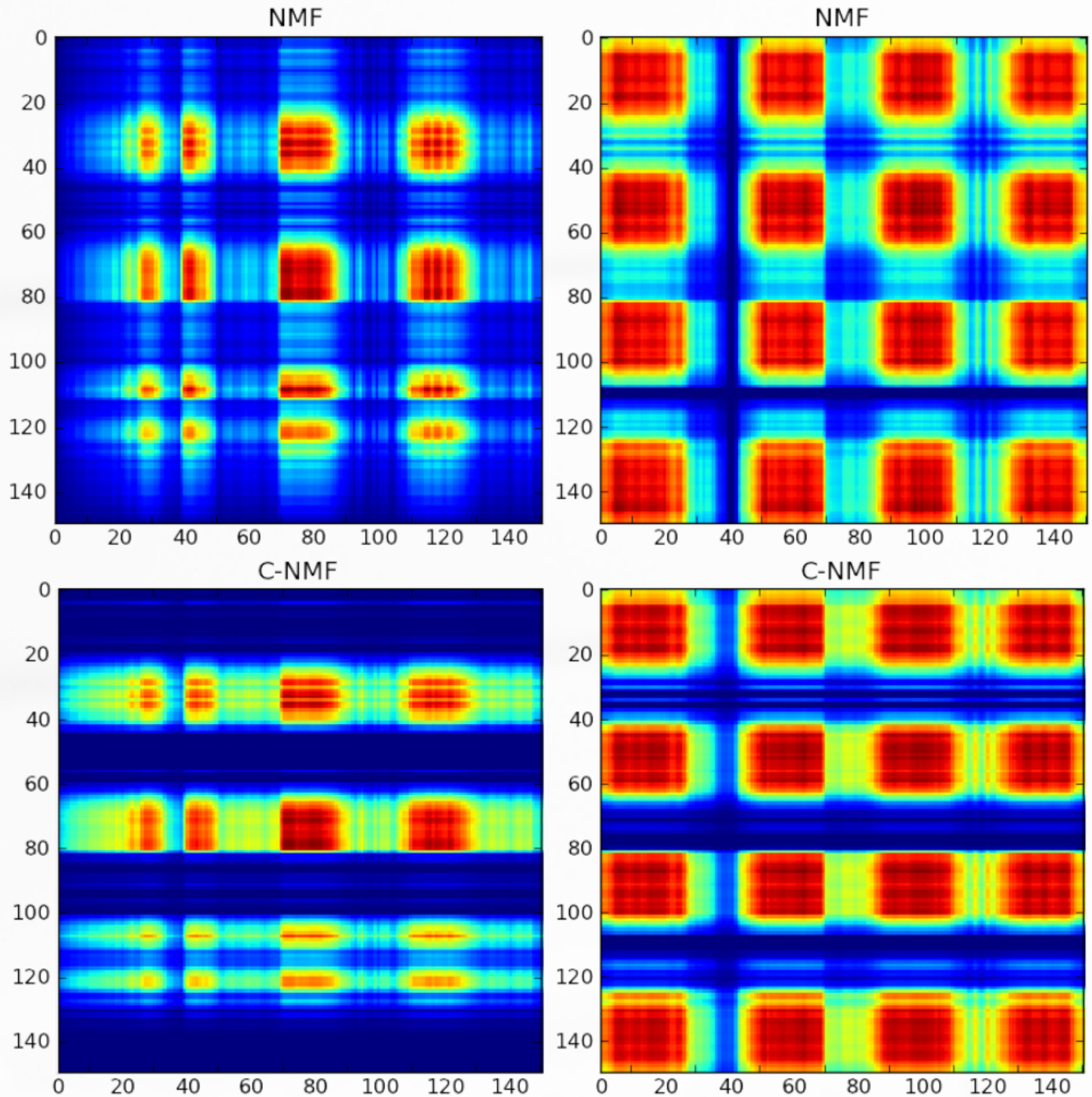

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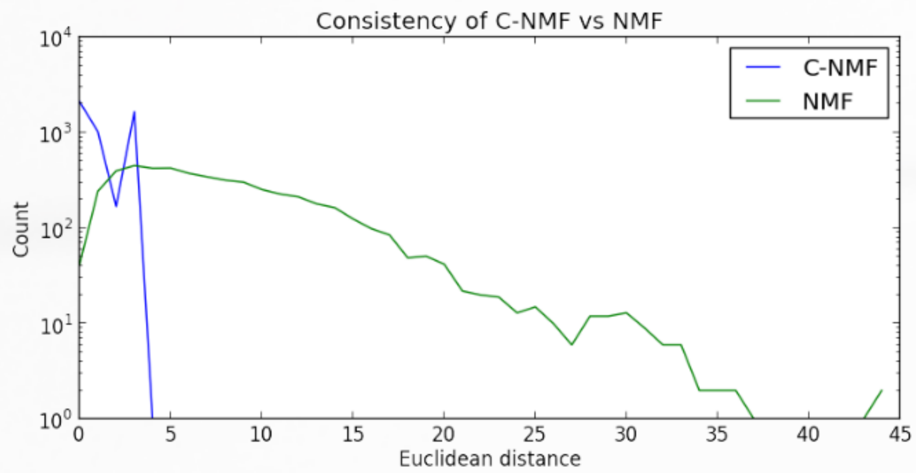

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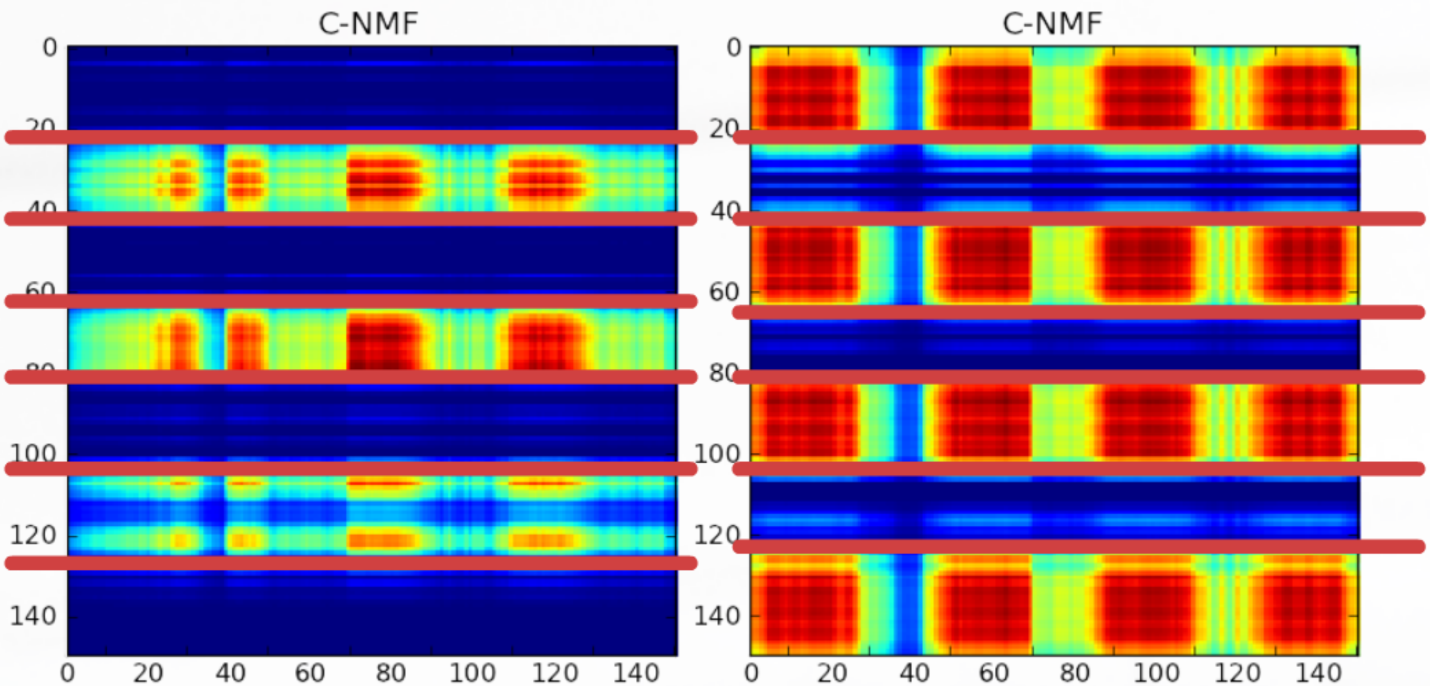

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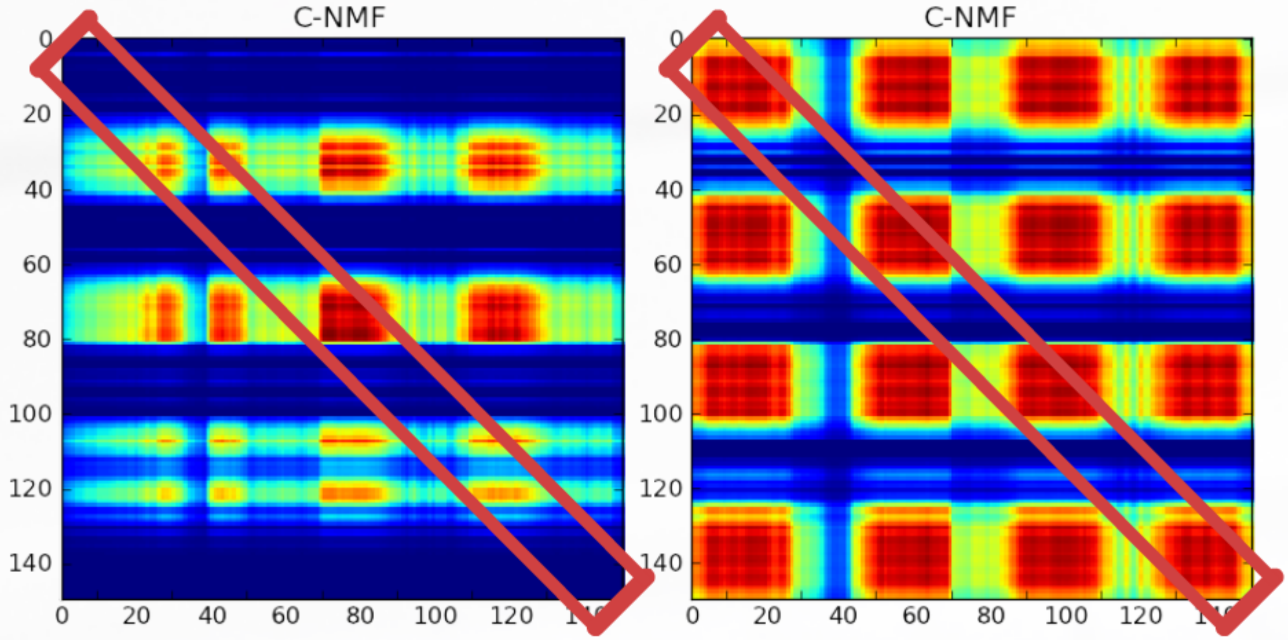

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Results on The Beatles

TUT Beatles Dataset								
	Clustering					Boundaries		
Method	F	P	R	S_o	S_u	F	P	R
C-NMF	**59.3**	48.9	83.2	49.8	47.8	57.3	54.9	64.6
NMF	56.6	48.8	77.7	43.7	49.6	**58.9**	54.7	67.7
SI-PLCA	55.8	46.3	80.7	41.0	50.6	23.2	50.9	17.2
Kaiser	60.8	61.5	64.6	–	–	50.0	46.5	52.2

F: F-measure
P: Precision
R: Recall
So: Over-Segmentation entropy
Su: Under-Segmentation entropy

Results on SALAMI

SALAMI (Internet Archive) Dataset								
	Clustering					Boundaries		
Method	F	P	R	S_o	S_u	F	P	R
C-NMF	**53.1**	**44.0**	81.0	50.6	**44.3**	45.1	43.0	52.3
NMF	51.5	42.8	77.6	37.9	45.6	**48.8**	44.0	62.7
SI-PLCA	51.3	55.8	52.1	44.2	51.4	24.8	45.1	18.4

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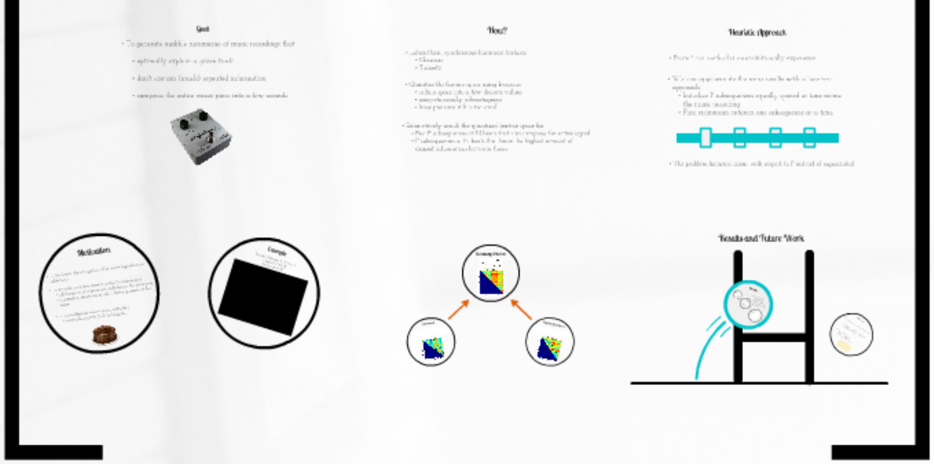

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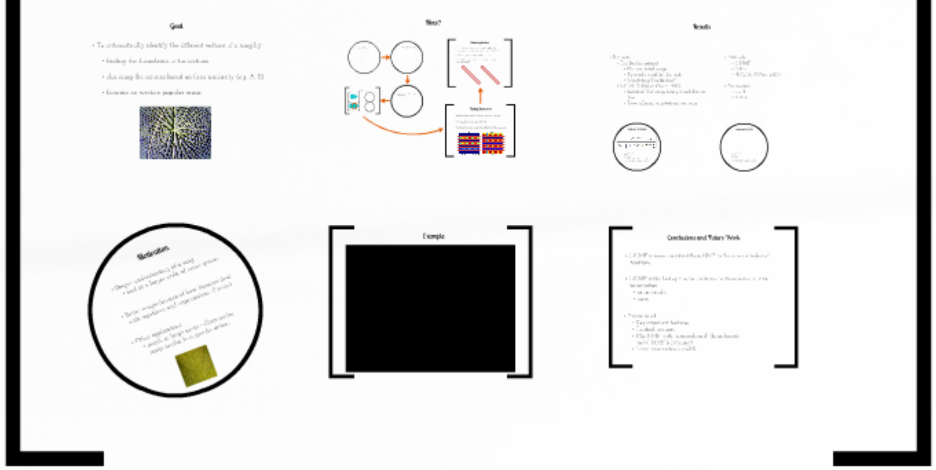
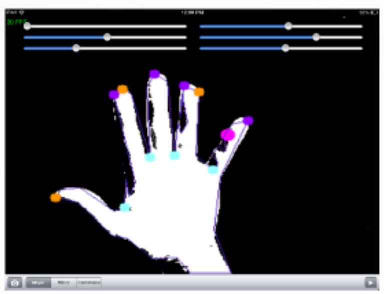
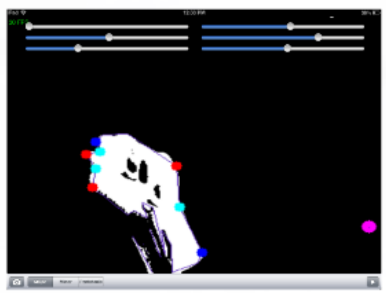


New Musical Interfaces

AirSynth

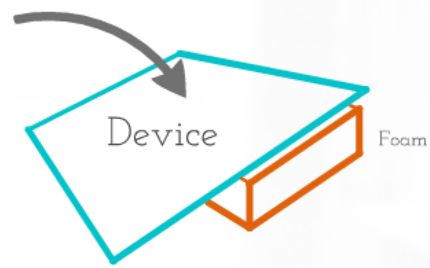
- Detect hand with camera
  - Color coded
  - Convex-Hull algorithm
- Detect number of fingers
- Map movement to different sound synthesis parameters





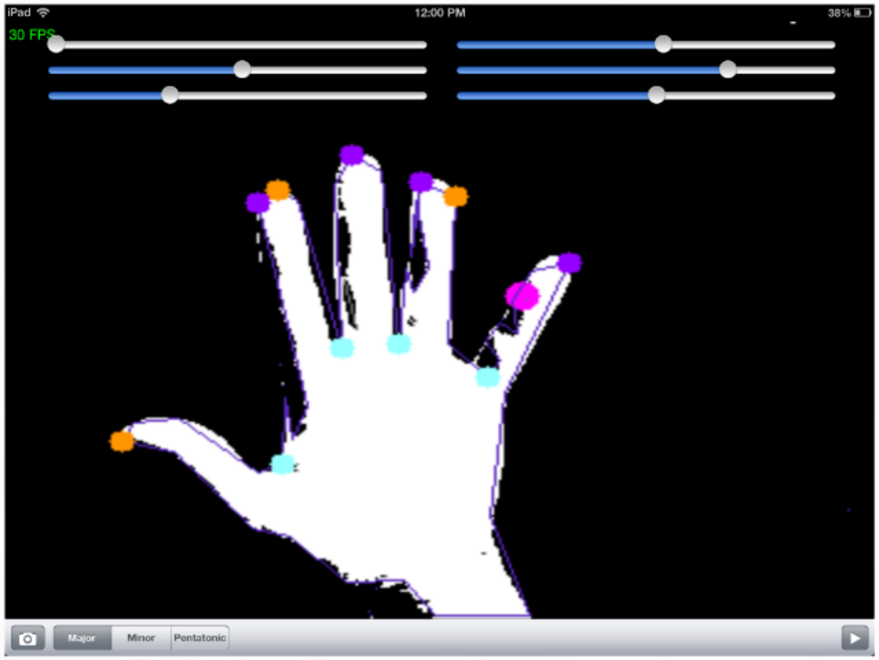
Foam Force Feedback

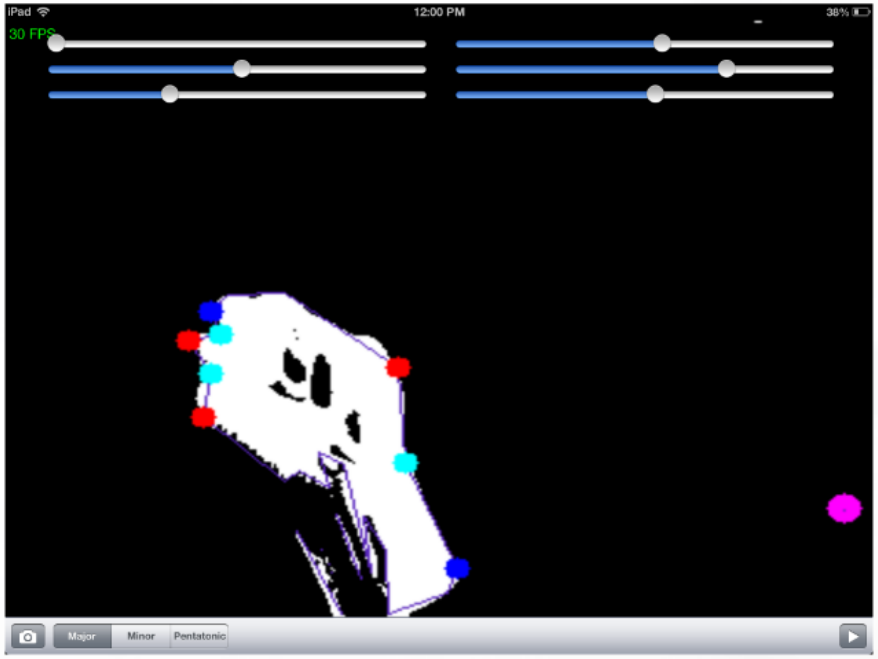
- Add small piece of foam under device
- Use accelerometer to track distance
- Distance will mark the amount of pressure



AirSynth

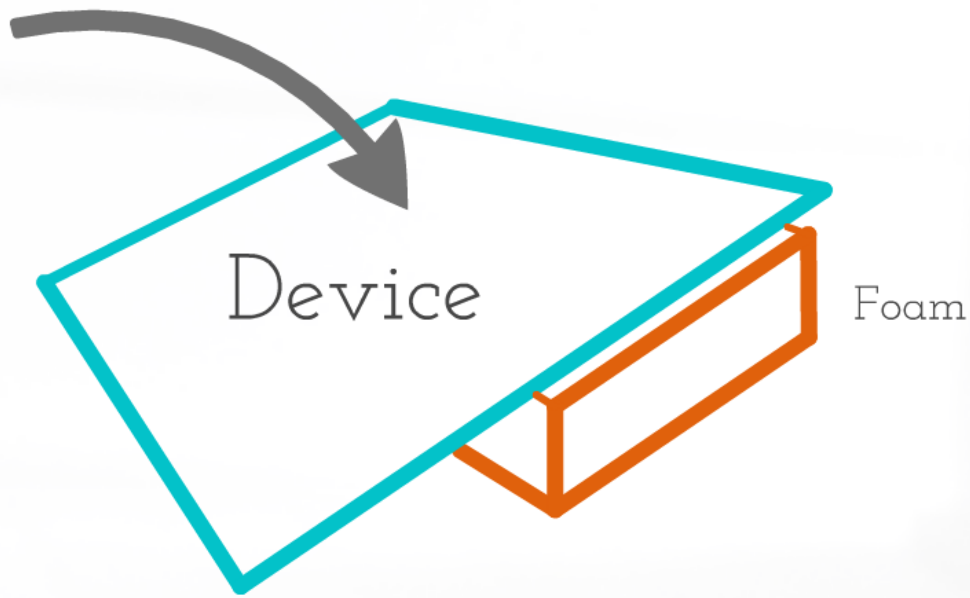
- Detect hand with camera
  - Color coded
  - Convex-Hull algorithm
- Detect number of fingers
- Map movement to different sound synthesis parameters



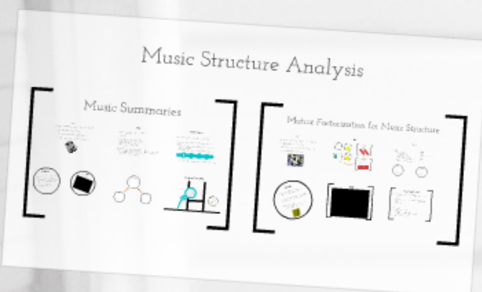


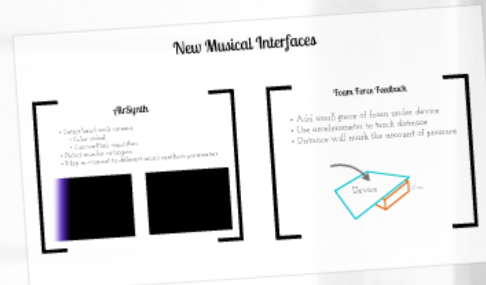
Foam Force Feedback

- Add small piece of foam under device
- Use accelerometer to track distance
- Distance will mark the amount of pressure



Music Structure Analysis and New Musical Interfaces





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