2024 edition

Deep Learning for Music Analysis and Generation

Miscellaneous Topics

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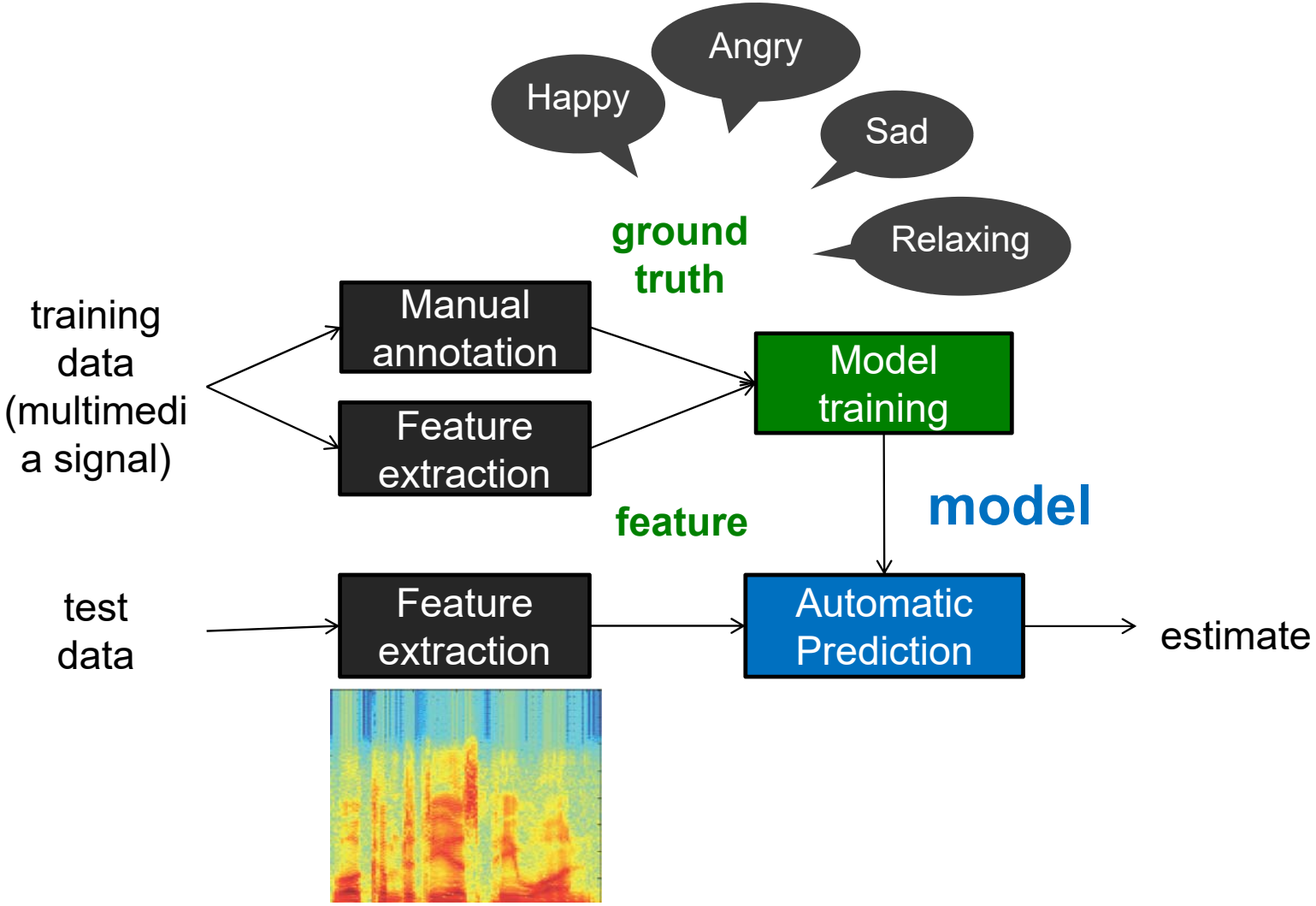
Outline

- **Music emotion**
- Structure/form analysis
- Alignment
- Rhythm & beat tracking

Music & Emotion (Episode 1: Around 2006)

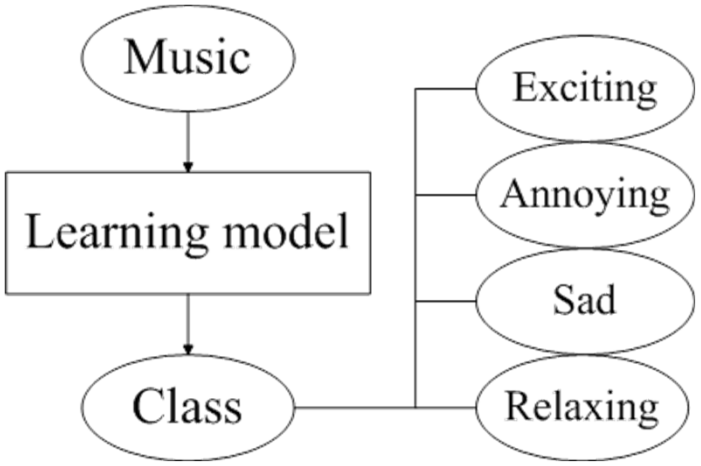
- Yang et al, “Music emotion classification: A fuzzy approach,” *ACM Multimedia*, short paper, **2006** [CIEEE Undergraduate Research Award]
- Yang et al, “A regression approach to music emotion recognition,” *IEEE Transactions on Audio, Speech and Language Processing*, Feb **2008** [IEEE Signal Processing Society Young Author Best Paper Award]

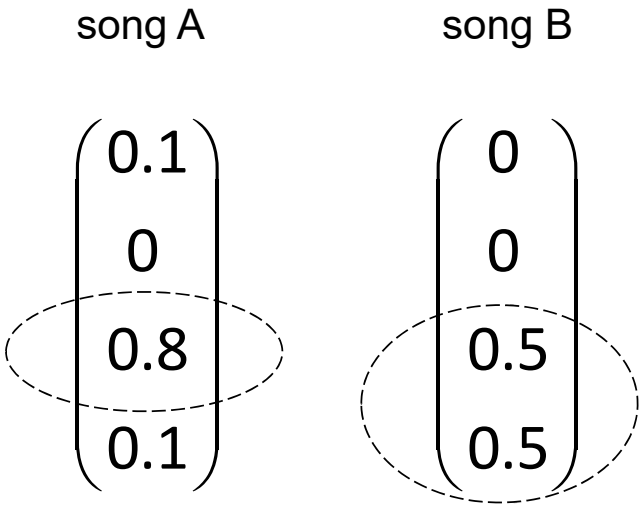
Automatic Music Emotion Classification



Subjectivity in Emotion Perception & the Fuzzy Approach

- Traditional classifiers
  → **provide an answer** *(hard)*
  - NN, k-NN, SVM
- Fuzzy classifiers
  → provide a **fuzzy vector** *(soft)*
  - fuzzy k-NN, Nearest-Mean



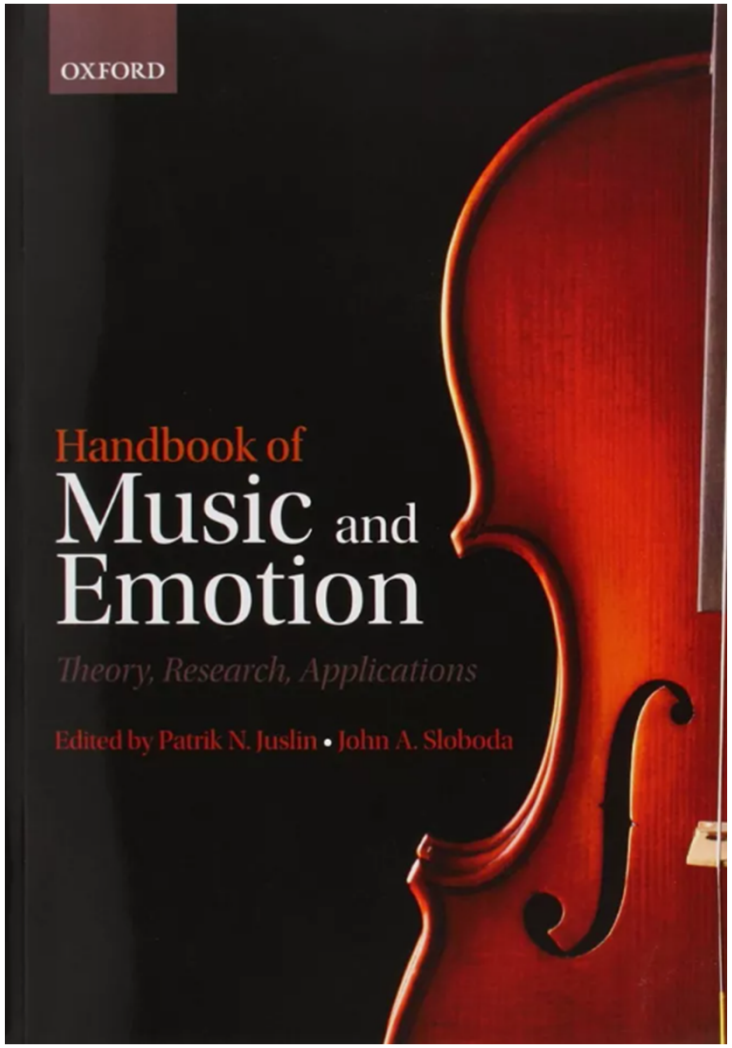


Ref: Yang et al., "Music emotion classification: A fuzzy approach," ACM Multimedia, short paper, 2006

Ambiguity & Granularity of Emotion Taxonomy

Work	#	Emotion description
Katayose et al [icpr98]	4	Gloomy, urbane, pathetic, serious
Feng et al [sigir03]	4	Happy, angry, fear, sad
Li et al [ismir03], Wieczorkowska et al [imtci04]	13	Happy, light, graceful, dreamy, longing, dark, sacred, dramatic, agitated, frustrated, mysterious, passionate, bluesy
Wang et al [icsp04]	6	Joyous, robust, restless, lyrical, sober, gloomy
Tolos et al [ccnc05]	3	Happy, aggressive, melancholic+calm
Lu et al [taslp06]	4	Exuberant, anxious/frantic, depressed, content
Yang et al [mm06]	4	Happy, angry, sad, relaxed
Skowronek et al [ismir07]	12	Arousing, angry, calming, carefree, cheerful, emotional, loving, peaceful, powerful, sad, restless, tender
Wu et al [mmm08]	8	Happy, light, easy, touching, sad, sublime, grand, exciting
Hu et al [ismir08]	5	Passionate, cheerful, bittersweet, witty, aggressive
Trohidis et al [ismir08]	6	Surprised, happy, relaxed, quiet, sad, angry

Inspirations from Music Psychology Literature



BOOK

Handbook of Music and Emotion: Theory, Research, Applications

Get access >

Patrik N. Juslin

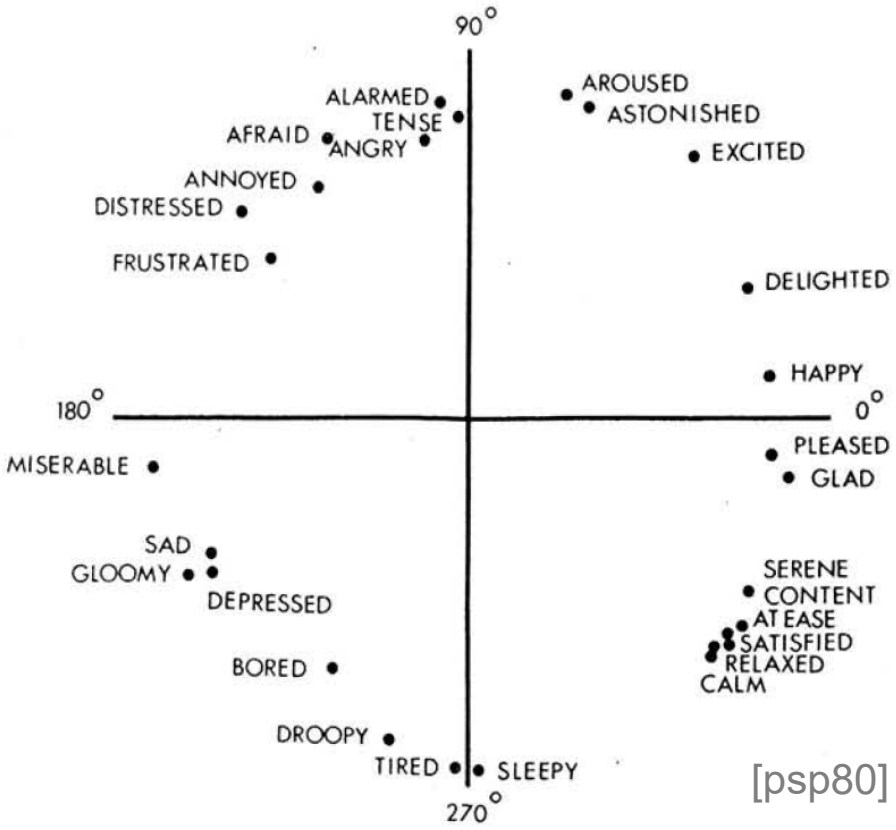
Published online: 22 March 2012

Published in print: 1 January 2010

Dimensional Model

Arousal

- Activation, activity
- Energy and stimulation level



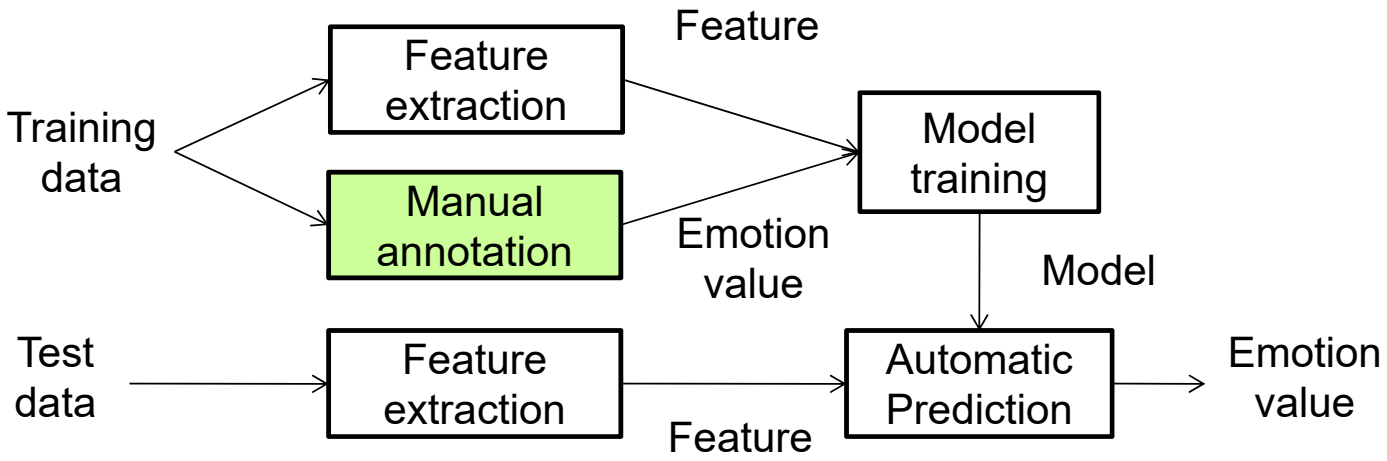
[psp80]

Valence

- Pleasantness
- Positive and negative affective states

Rating instead of Labeling/Classifying

- Manual annotation
  - Rates the VA values of each song
    - Ordinal rating scale ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
    - Scroll bar 

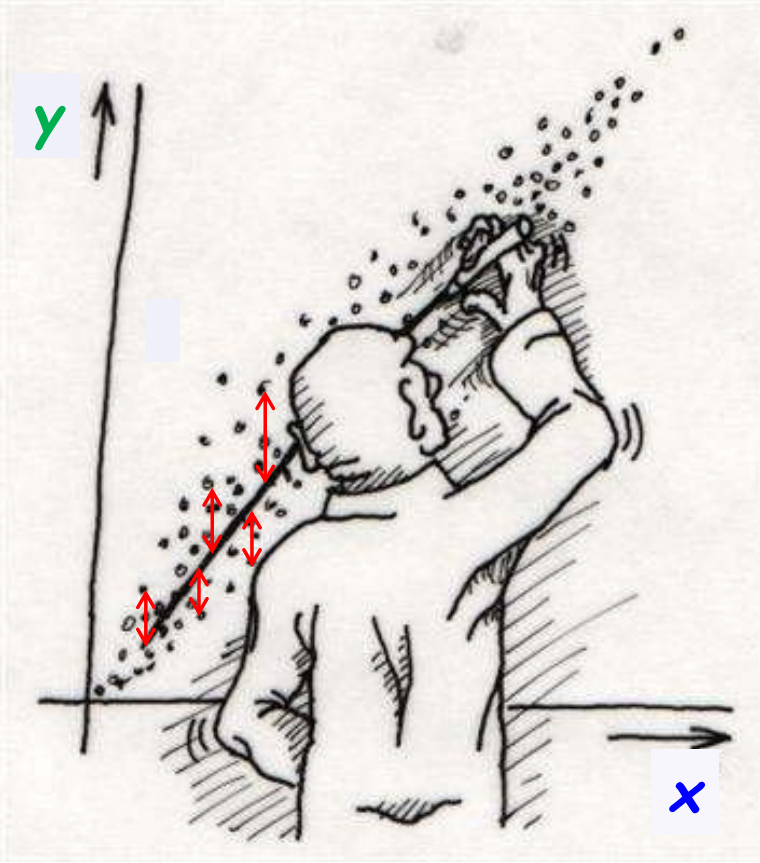


Regression instead of Classification

- Regression
  - Given features, predict a numerical value

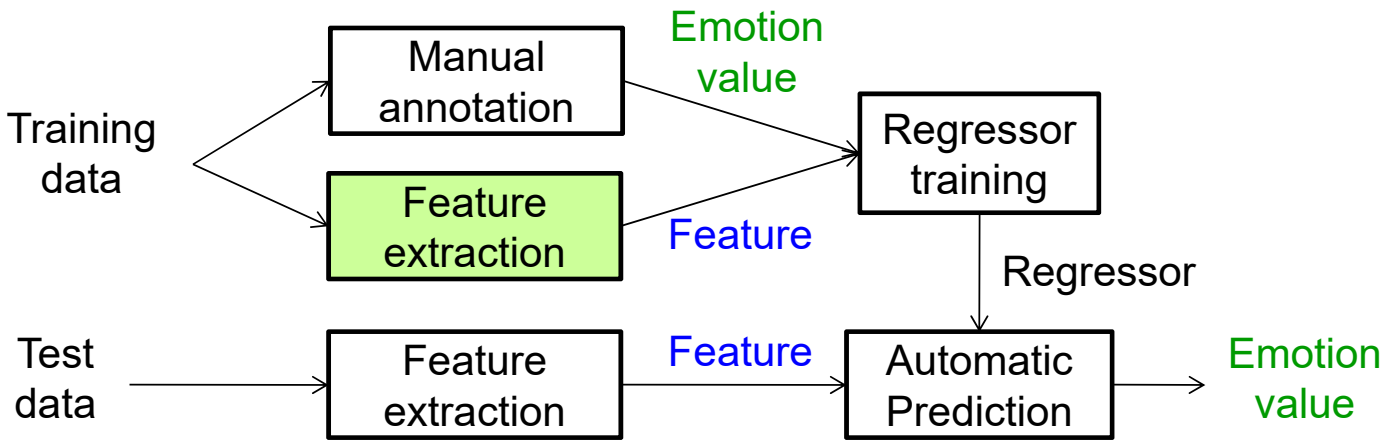
Given N inputs (x_i, y_i), $1 \le i \le N$, where x_i is feature and y_i is the numerical value to be predicted, train a regression model $R(.)$ such that the following mean squared error (MSE) is minimized

$$\min_f \frac{1}{N} \sum_{i=1}^{N} (y_i - f(\boldsymbol{x}_i))^2$$

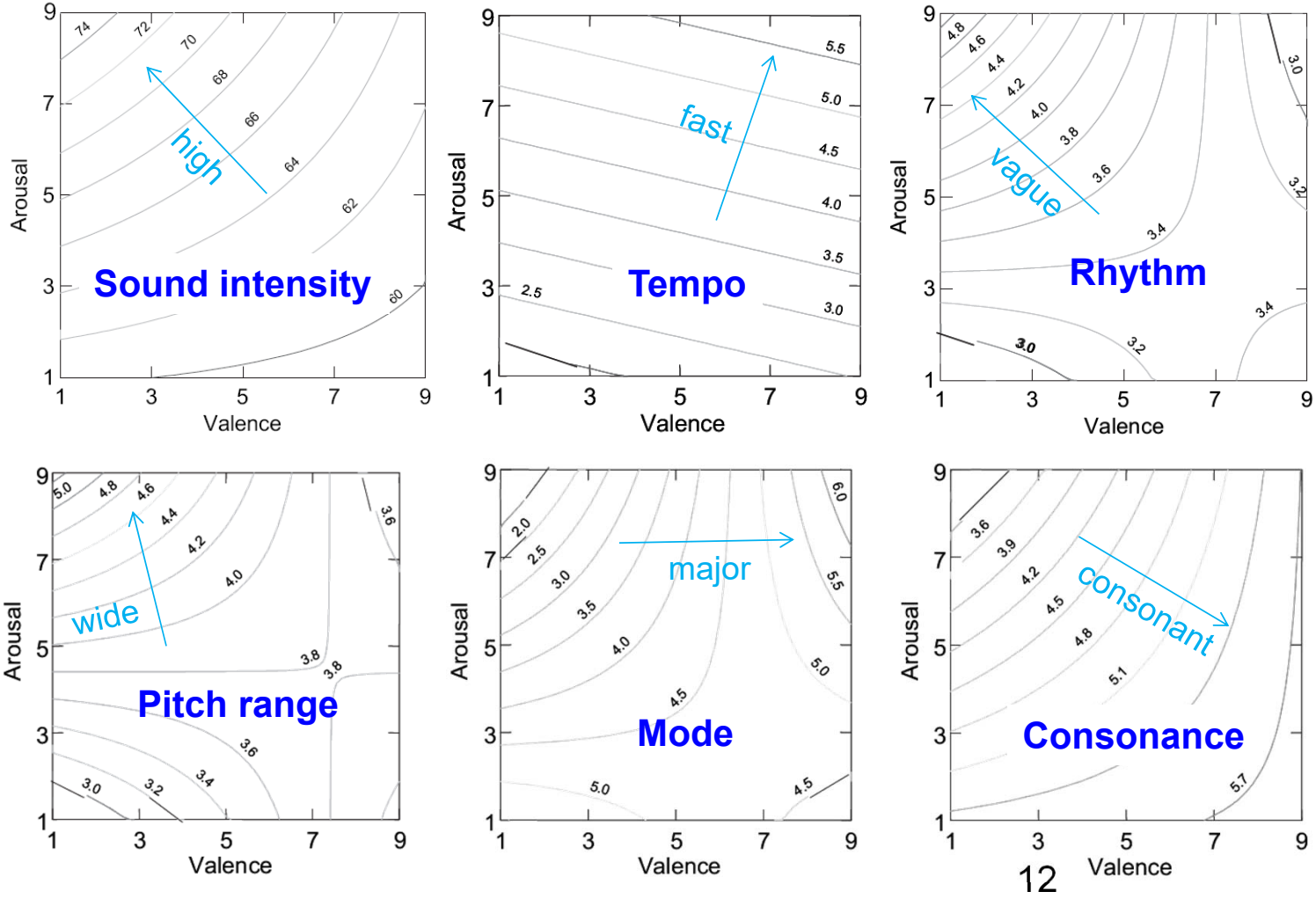


Computational Framework

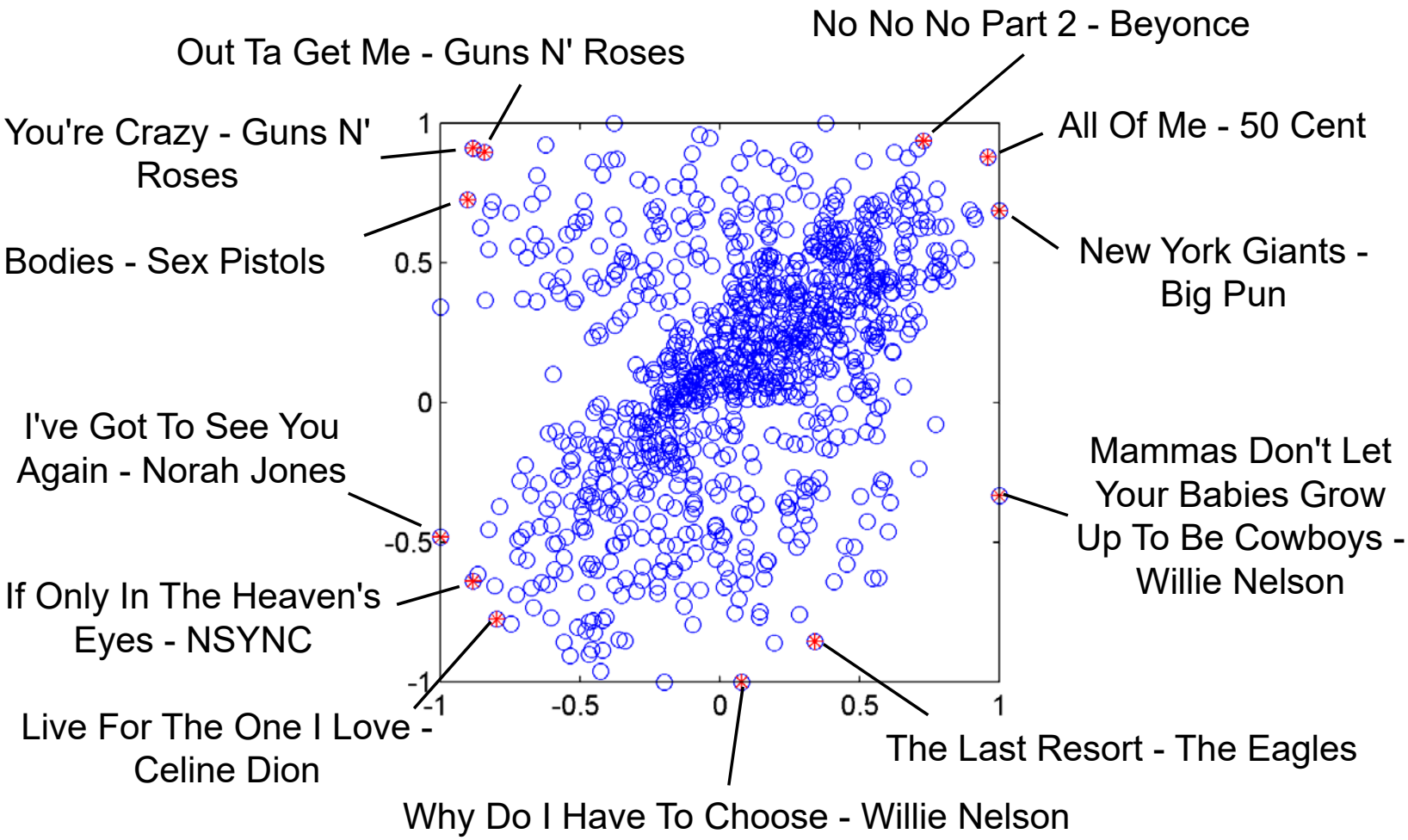
- Feature extraction
  - Arousal
    - **Pitch**: high/low
    - **Tempo**: fast/slow
    - **Timbre**: bright/soft
  - Valence
    - Harmony: consonant/dissonant
    - Mode: major/minor
    - Tonality: tonal/atonal



Extracting Relevant Audio Features



Mapping Music to the Emotion Space

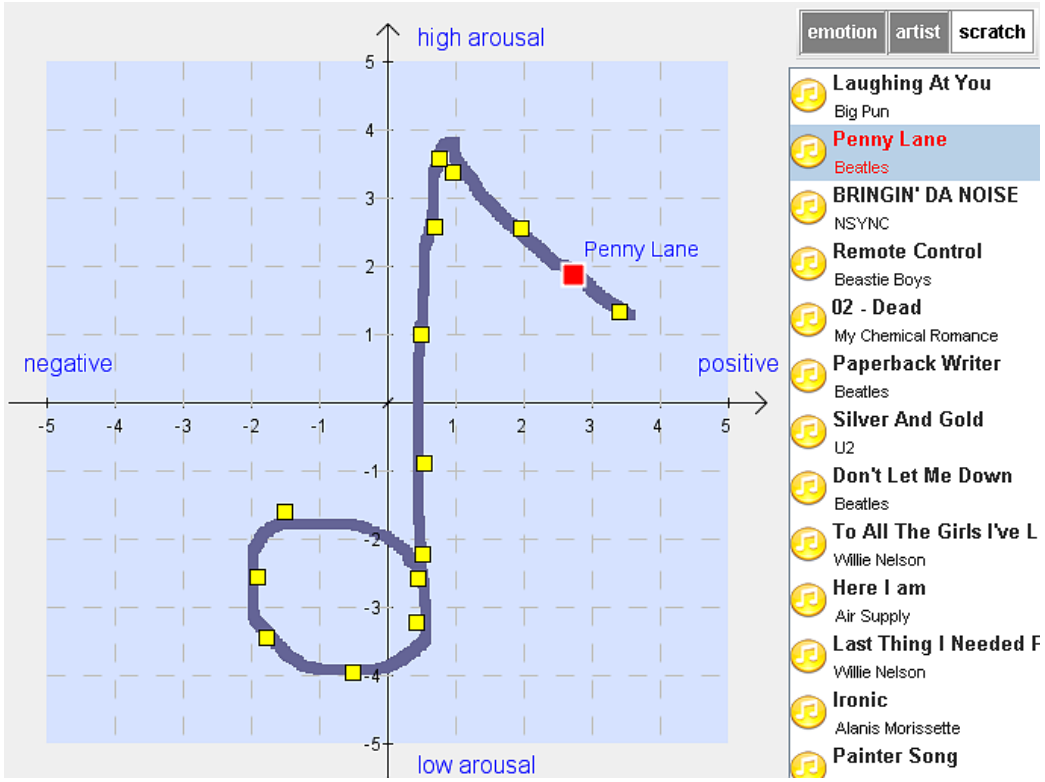


Music Retrieval in the Emotion Space

https://www.youtube.com/watch?v=ra55xO20UHU

activation energy level

valence positive or negative



- Simple 2D user interface
- Useful for mobile devices

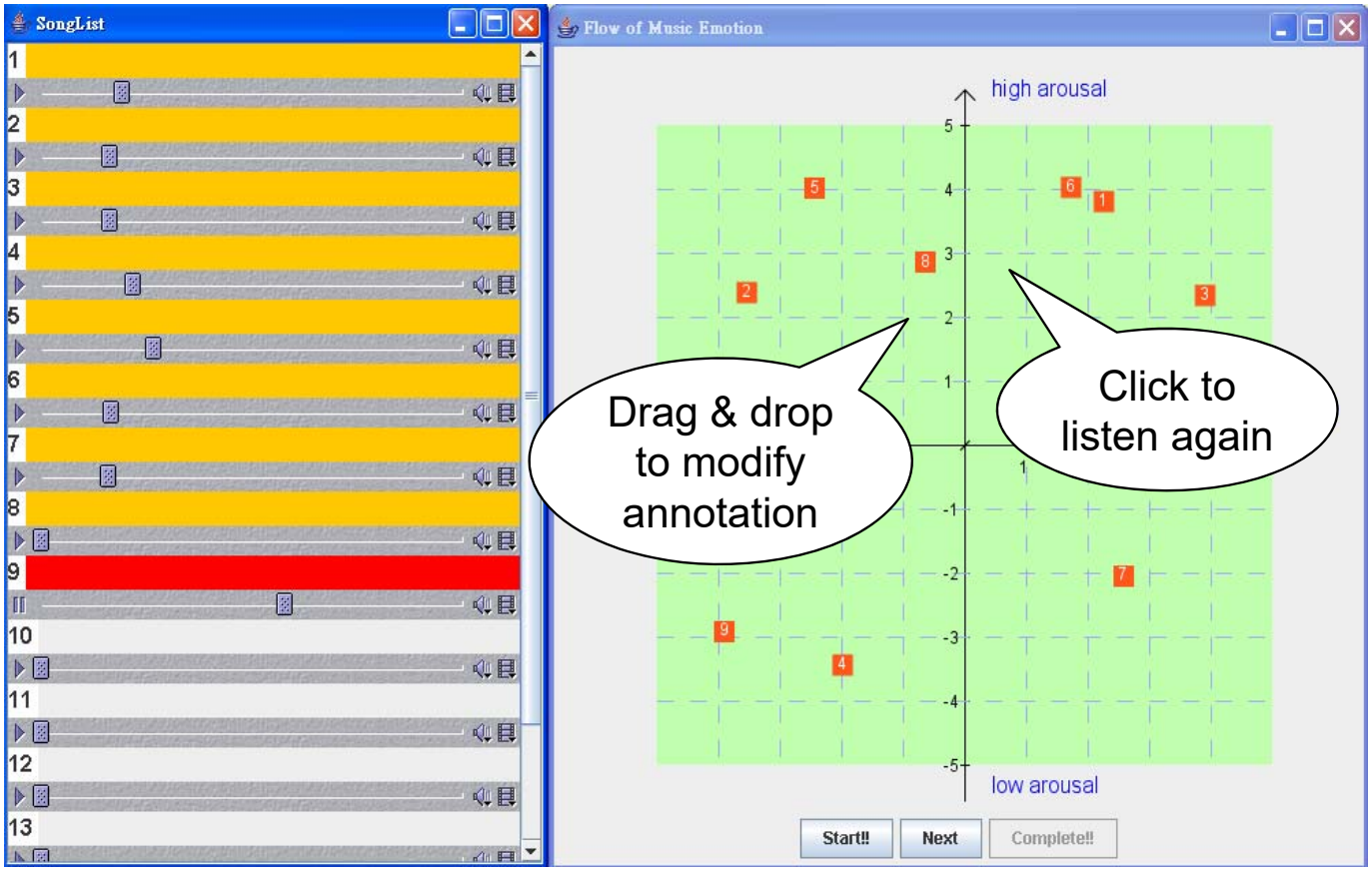
Difficulty of Emotion Annotation

- Rating emotion in a continuum is difficult
  - User fatigue
  - Less reliable ground truth
  - Small-scale dataset

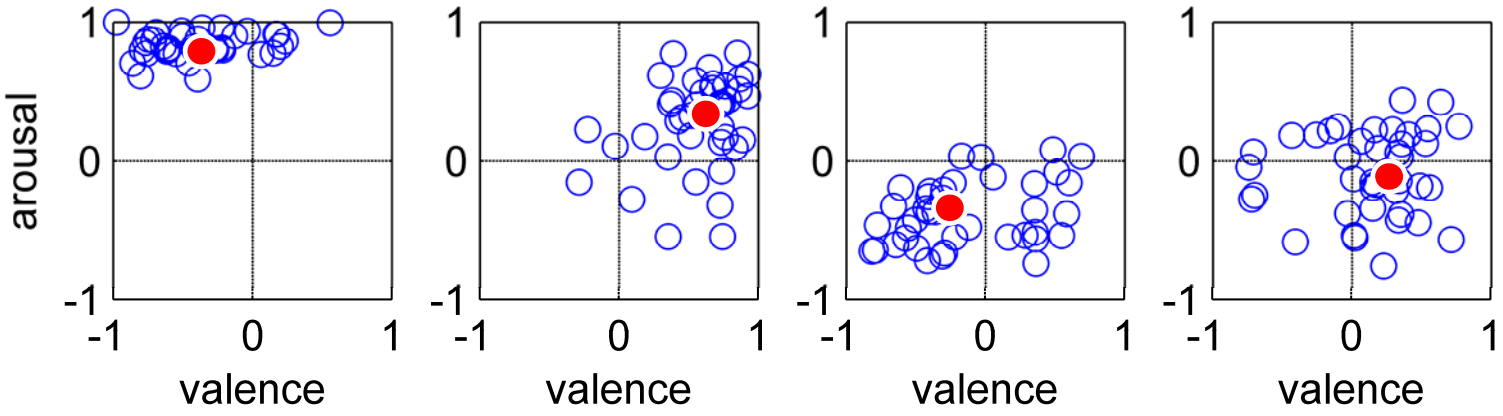
	user A	user B
1	10	10
2	10	8
3	10	8
4	10	10
5	0	0
6	0	0
7	5	10
8	5	5
9	0	0
10	0	2
11	0	3
12	0	0

AnnoEmo: GUI for Emotion Rating

- Encourages differentiation



Subjectivity Issue



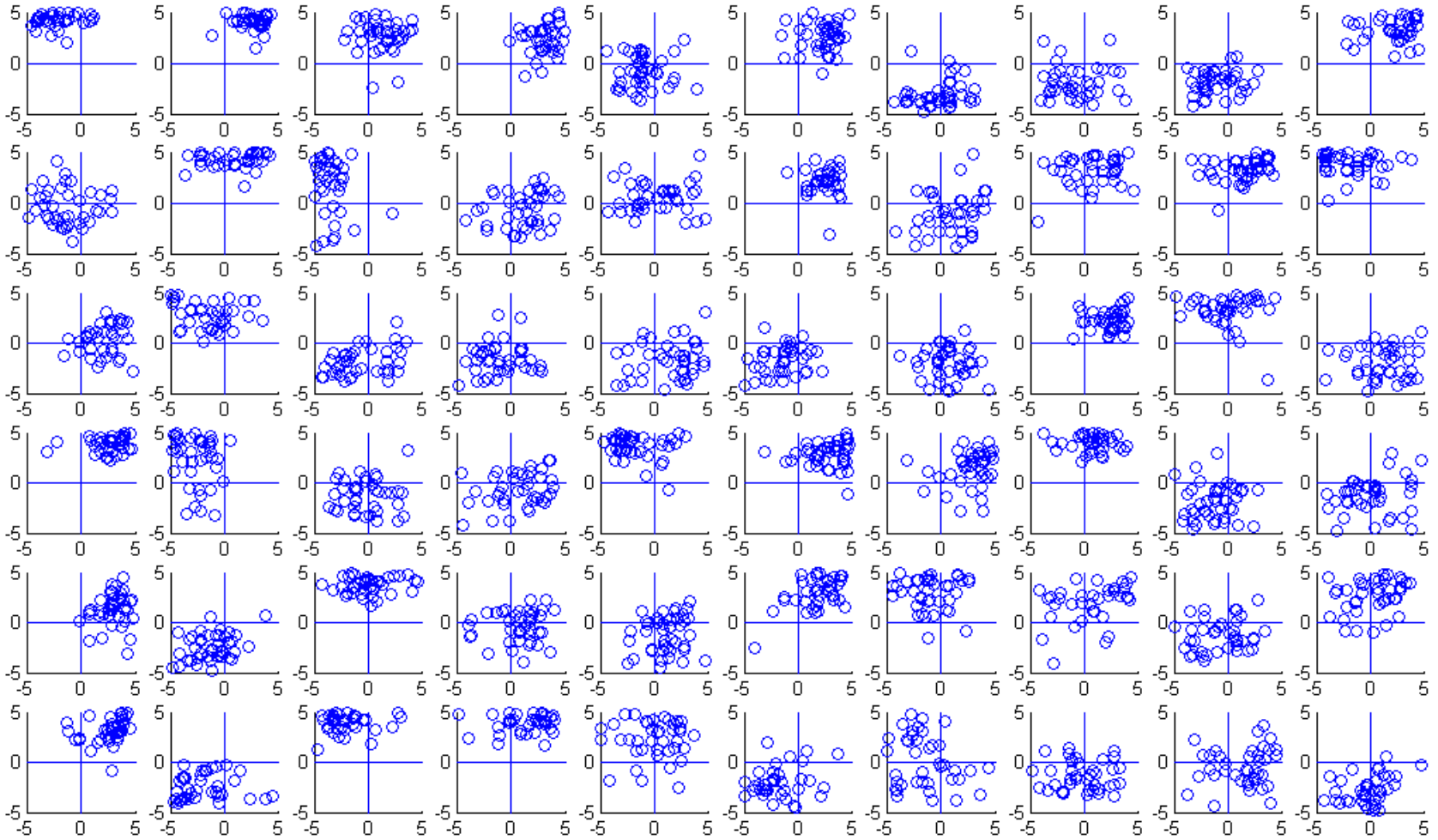
(a) Smells Like Teen Spirit [–0.38, 0.82]

(b) A Whole New World [0.53, 0.28]

(c) The Rose [–0.12, –0.36]

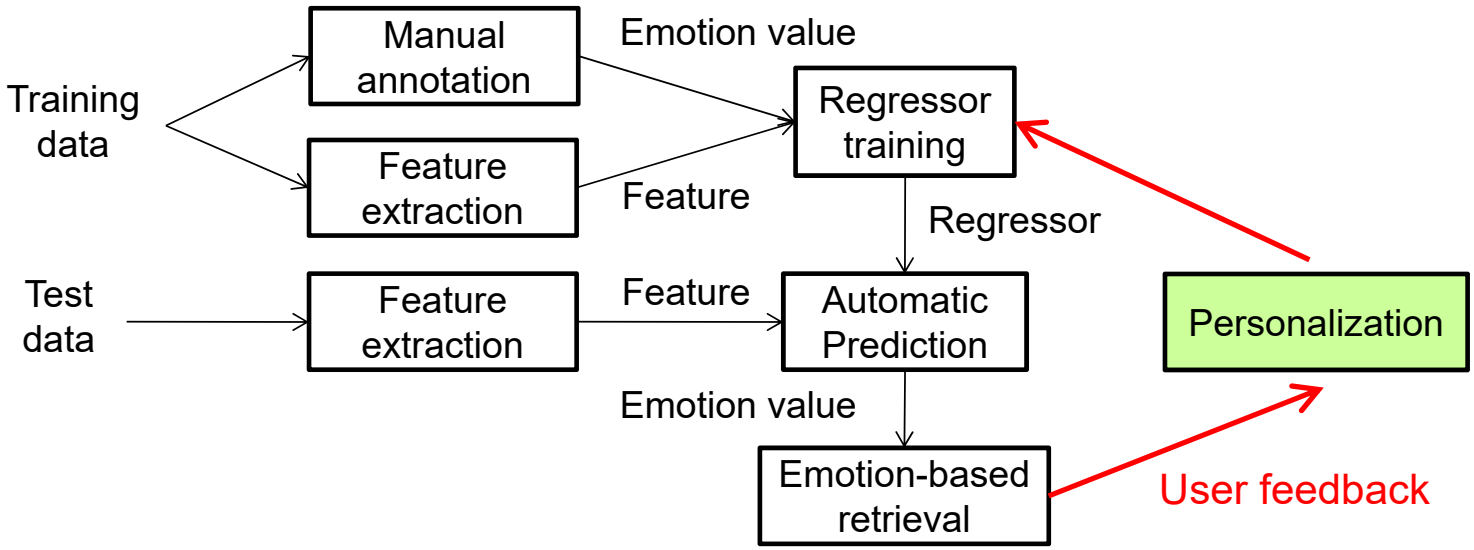
(d) Tell Laura I Love Her [0.13, –0.08]

Subjectivity Issue



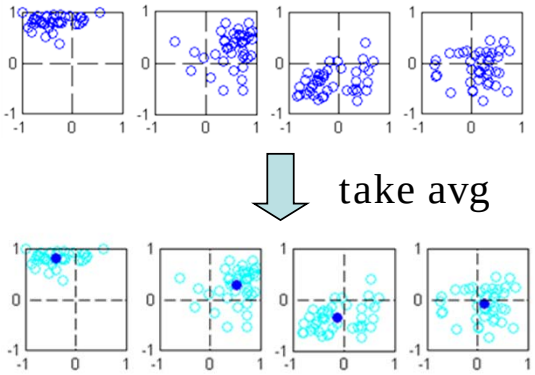
Personalized Music Emotion Recognition

- From $P(e|d)$ to $P(e|d,u)$
  - General regressor → personal regressor
  - Utilize user feedback



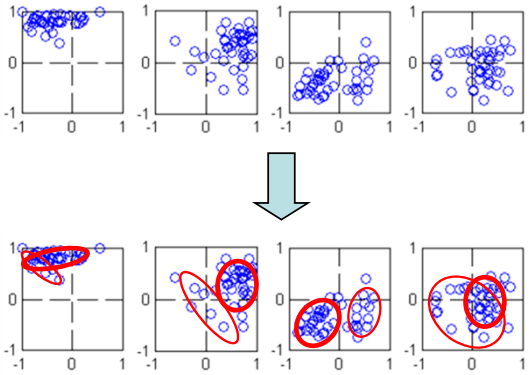
Addressing the Subjectivity Issue

Single point



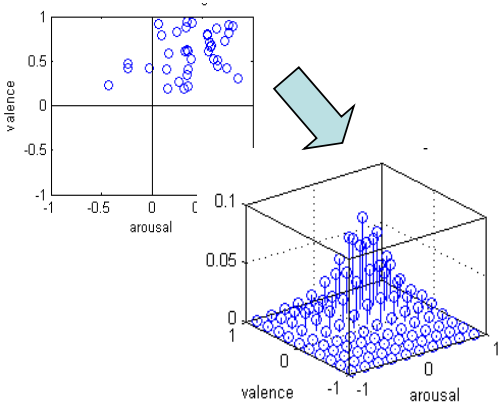
- {valence, arousal}
- Two regressors
- Simply representing a song as a point is not enough

Gaussian mixture



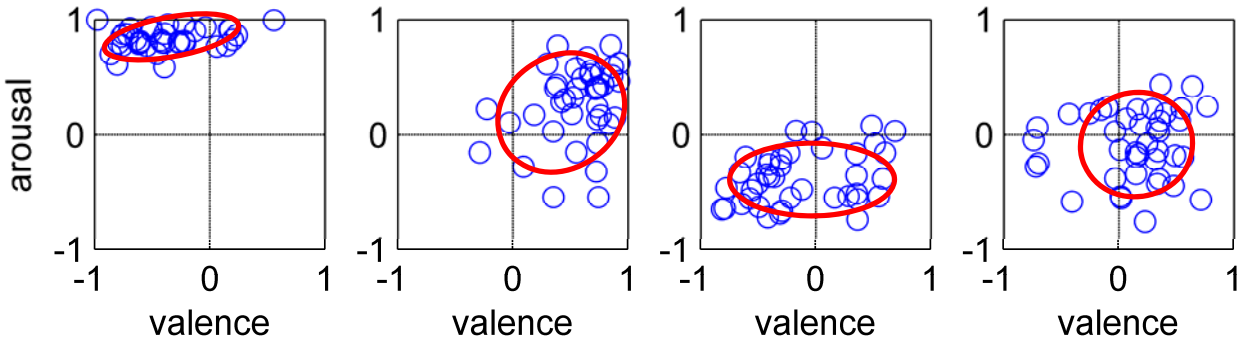
- \sum $w_i\, N(\mu_i,\sigma_i)$
- Multiple regressors
- Hard to determine the number of components
- May be **ill-posed** (multiple GMMs fit a distribution well)

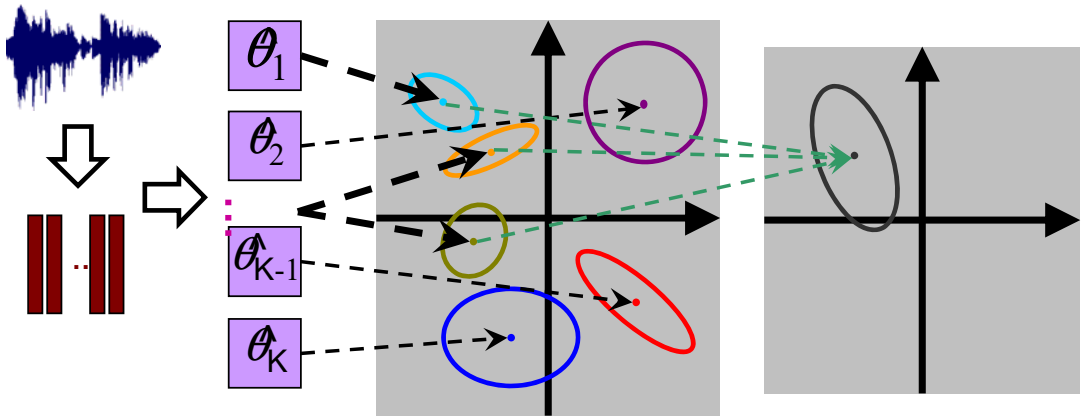
Probabilistic distribution



- Predict the *emotion mass* at every point in the emotion plane
- Using a 10x10 grid → 100 regressors
- Predict $\boldsymbol{P(e^{ij}|d)}$

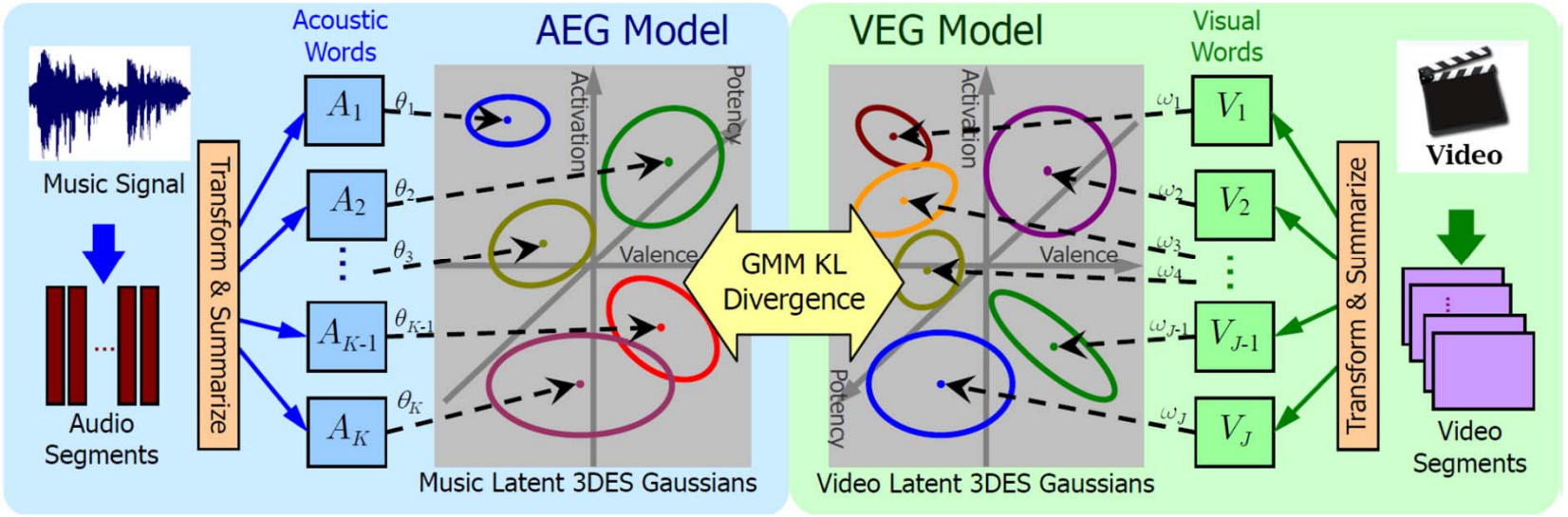
Probabilistic Framework for Music Emotion Recognition





Ref: Wang et al., "The Acoustic Emotion Gaussians model for emotion-based music annotation and retrieval," ACM Multimedia 2012

Emotion-Based MV Composition

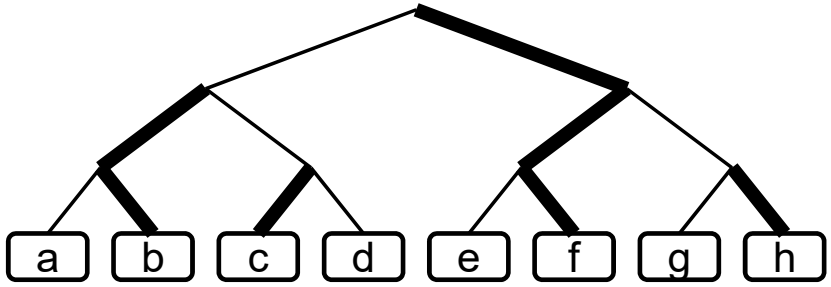


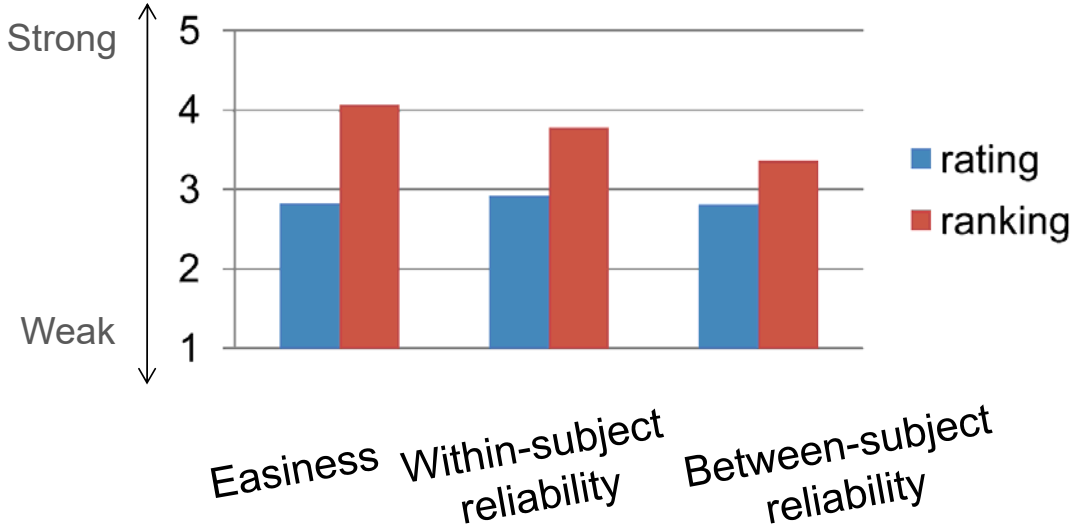
- Audio
  - Sound energy
  - Tempo and beat strength
  - Rhythm regularity
  - Pitch
- Video
  - Lighting key
  - Shot change rate
  - Motion Intensity
  - Color (saturation, color energy)

Ref: Wang et al., "The Acousticvisual Emotion Gaussians model for automatic generation of music video," ACM MM Grand Challenge 2012 [ACM MM Multimedia Grand Challenge First Prize]

Alternatives: Ranking-Based Emotion Annotation

- Emotion tournament
  - Which song is more positive?
- *Ranking* is easier than *rating*



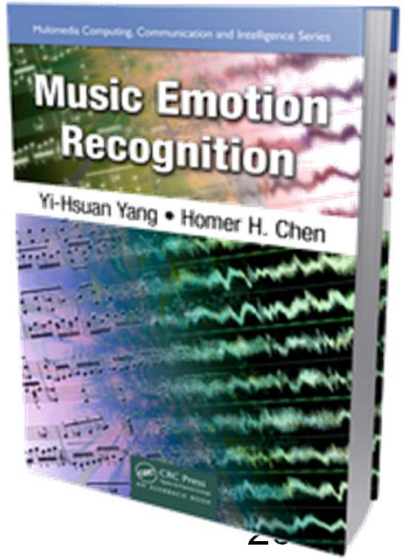


Ranking-Based Emotion Recognition

- Determine the position of a song
  - By the relative ranking with respect to other songs (*learning-to-rank*)
  - Rather than by the exact emotion values

Music & Emotion (Episode 2: 2006-2010)

- Yang & Chen, “Ranking-based emotion recognition for music organization and retrieval,” *IEEE Transactions on Audio, Speech and Language Processing*, May **2011**
- Yang & Chen, “Prediction of the distribution of perceived music emotions using discrete samples,” *IEEE Transactions on Audio, Speech and Language Processing*, Sept **2011**
- Yang & Chen, *Music Emotion Recognition*, CRC Taylor & Francis Books, Feb **2011**
- Yang & Chen, “Machine recognition of music emotion: A review,” *ACM Transactions on Intelligent Systems and Technology*, May **2012**



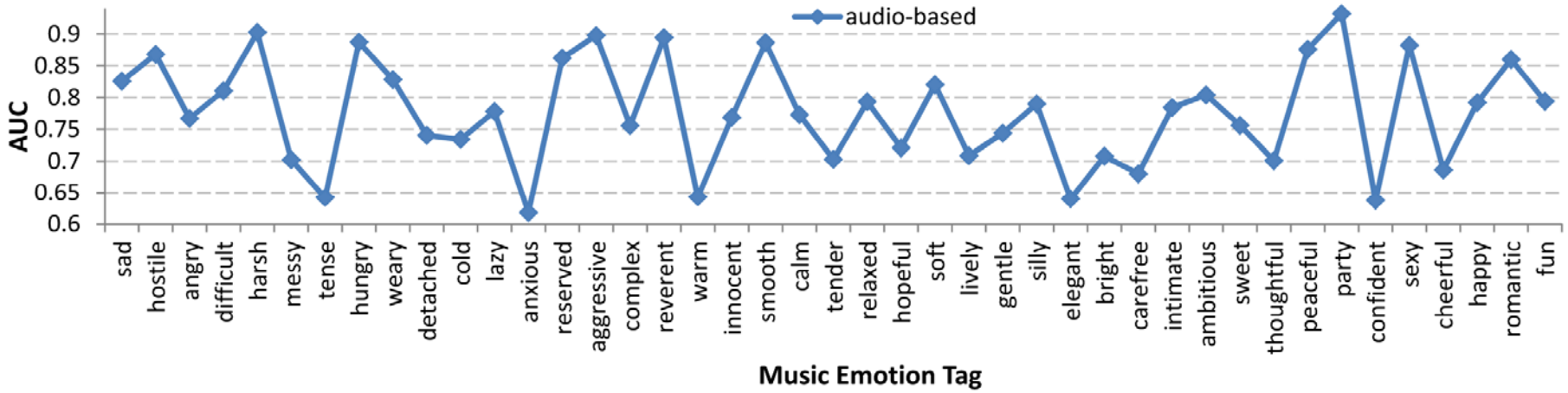
Music & Emotion (Episode 3: 2011—)

- Yang & Liu, “Quantitative study of music listening behavior in a social and affective context,” *IEEE Transactions on Multimedia*, 2013
- Yang & Teng, “Quantitative study of music listening behavior in a smartphone context,” *ACM Transactions on Interactive Intelligent Systems*, 2015

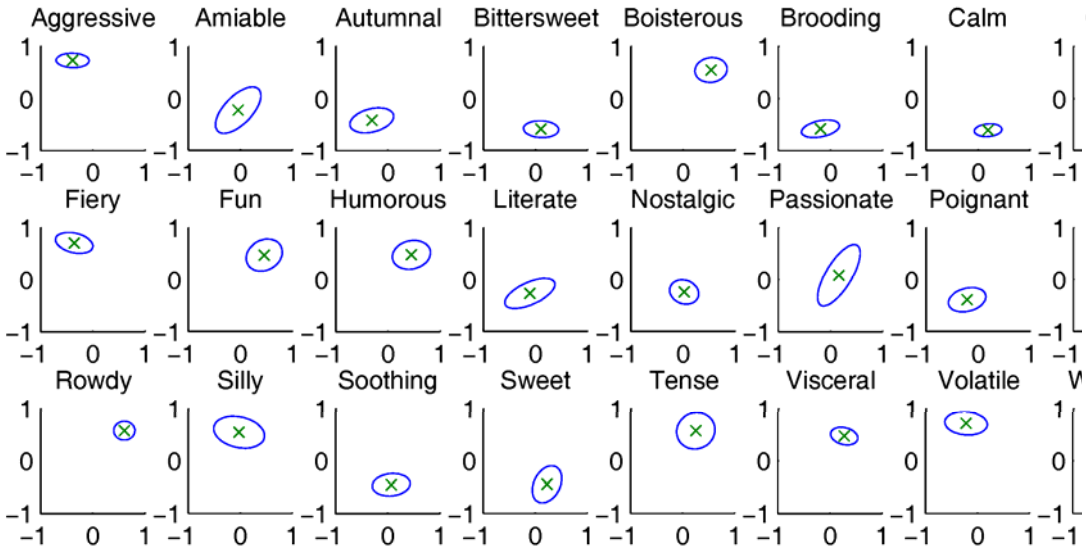
Extension 1: Modeling More Emotion Tags

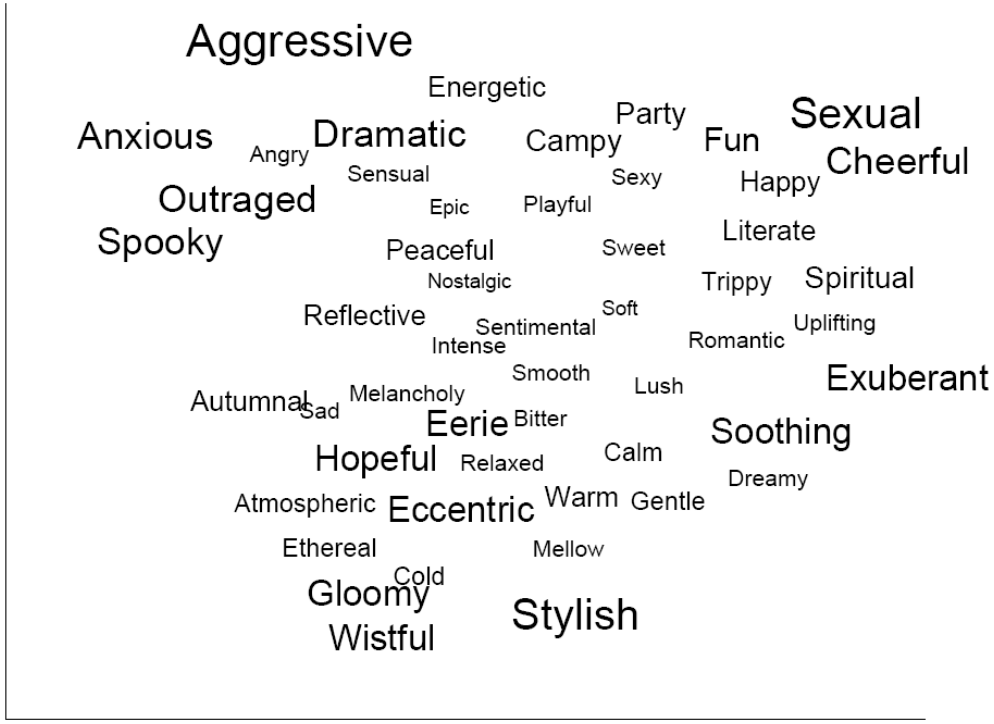
- Use Allmusic tags (selected by music editors) to consider 190 emotion classes
- Crawl 31k songs from last.fm for training/test

Modality		Feature	Dim	AUC	NDCG
Random		—	—	0.4999	0.2806
Music	Audio	Energy	24	0.6969	0.3292
		Rhythm	5	0.6229	0.3049
		Timbre	176	0.7432	0.3789
		Tonal	38	0.7060	0.3374
		Late fusion	—	0.7614	0.3913



Mapping Mood Tags to the 2D Emotion Space



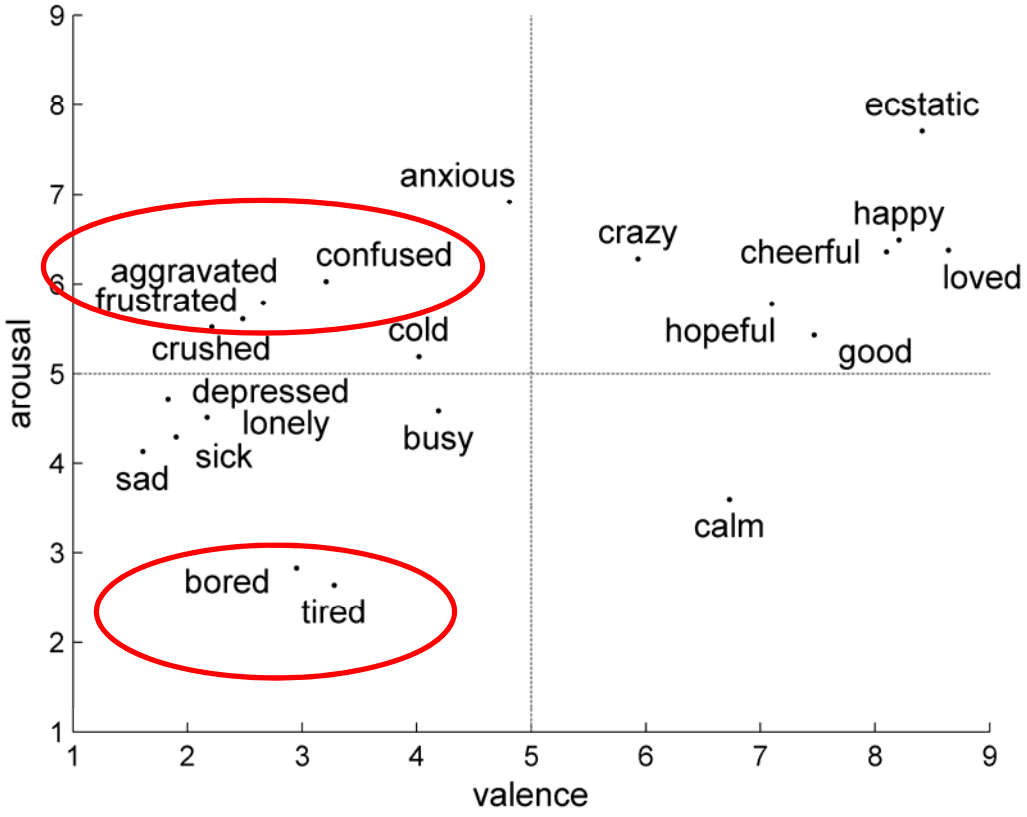


- Data driven: the mapping is directly learned from data with audio feature

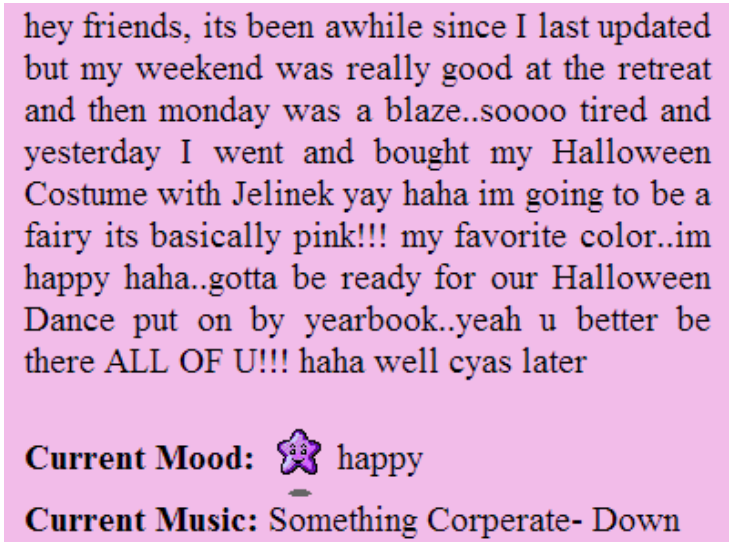
Ref: Wang et al., "Exploring the relationship between categorical and dimensional emotion semantics of music," ACM MM Workshop 2012

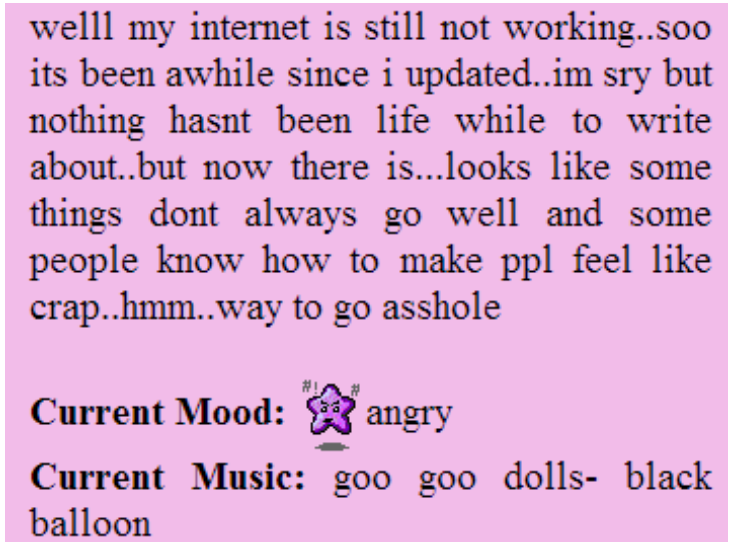
Extension 2: User Mood vs. Music Emotion

- Everyday emotion vs. aesthetic emotion



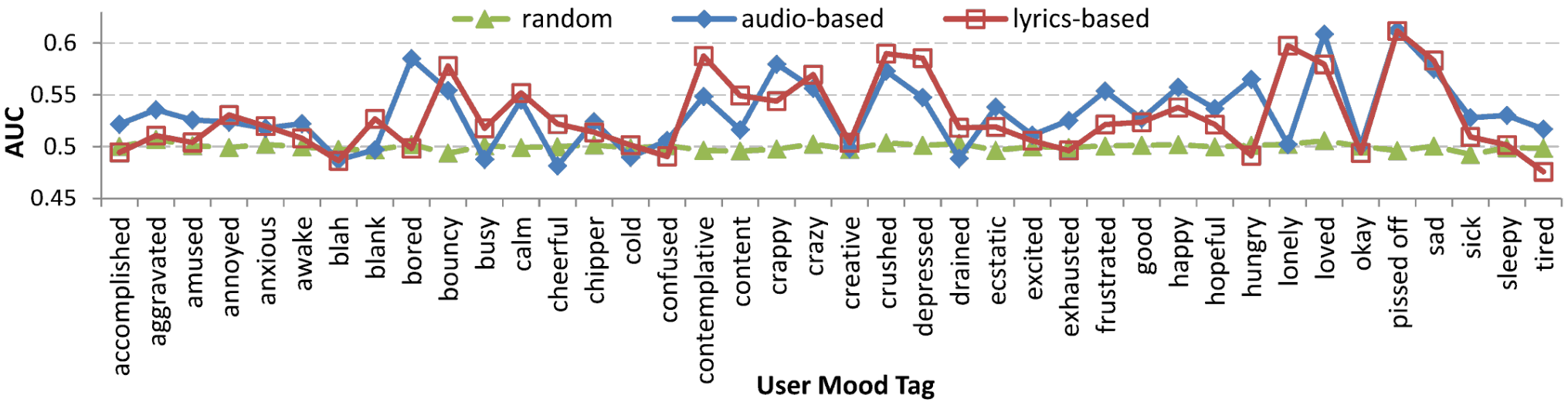
LiveJournal: A Large-Scale, In-Situ Dataset





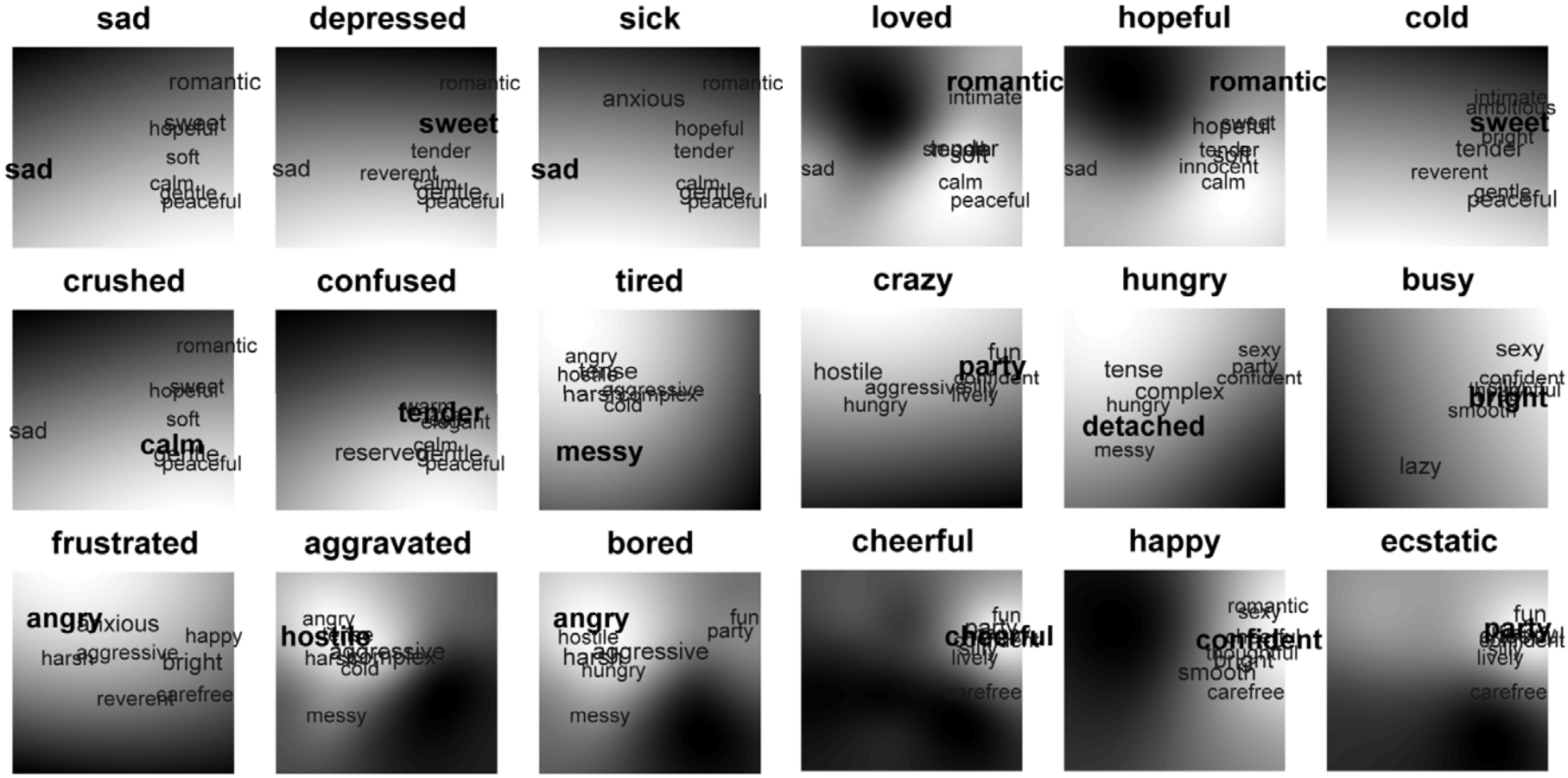
- In addition to blog writing, users
  - enter an emotion tag (user mood)
  - enter a song title & artist name (music emotion)

Predicting User's Emotional State from the Music Listening Behavior



- Audio-based model perform better for "aggravated," "awake," "contemplative," "drained," and "tired"
- Lyrics-based model is good for "crazy," "creative," "crushed," and "pissed-off"
- Both are poor for "blah," "blank," and "okay"

Mood-Congruent or -Incongruent



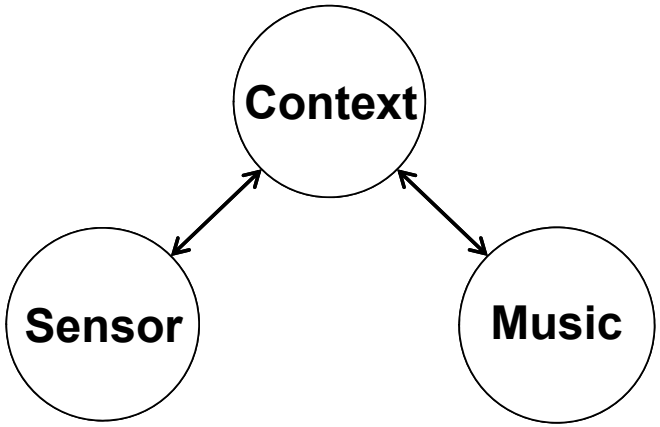
Yang & Liu, "Quantitative study of music listening behavior in a social and affective context," IEEE Transactions on Multimedia, 2013

The Role of Personality

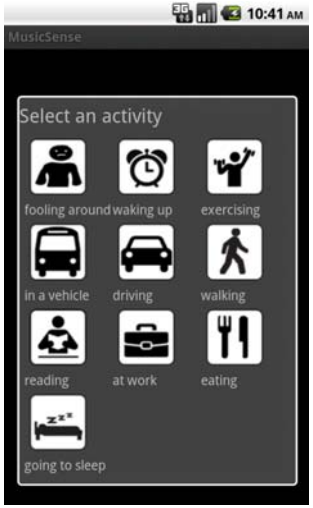
- Estimate from writing styles (linguistic features) by *Personality Recognizer* developed by MIT
- Use two-sample, one-tailed t-test for testing hypothesis

Personality	User mood	Music emotion
High in Extraversion	loved	more party music
High in Extraversion	sick	more party music
Low in Extraversion	anxious	less angry music
Low in Extraversion	awake	less angry music
Low in Extraversion	blank	less party music
Low in Extraversion	bored	less angry music
Low in Extraversion	bored	more peaceful music
Low in Extraversion	cheerful	less angry music
Low in Extraversion	drained	less angry music
Low in Extraversion	drained	more peaceful music

Understanding Users: from Smartphones



Accelerometer	Microphone
Ambient light	Proximity
Compass	Running apps
Dual cameras	Time
GPS	Wifi
Gyroscope	



Yang & Teng, "Quantitative study of music listening behavior in a smartphone context," ACM Transactions on Interactive Intelligent Systems, 2015

Affect-Based Music Recommendation

Sensor data

Accelerometer
Ambient light
Ambient sound
Compass
Dual cameras
GPS
Gyroscope
Microphone
Proximity
Running apps
Time
Wifi

User data

Age 22, Male, Live in Taipei
Easy-going, inventive, friendly
Love Classic songs; can play piano

Music listening profile

2012/7/25 15:02:23 song A
2012/7/25 15:20:08 song B
2012/7/26 08:42:30 song C
2012/7/26 20:11:07 song D
2012/7/27 08:35:51 song C

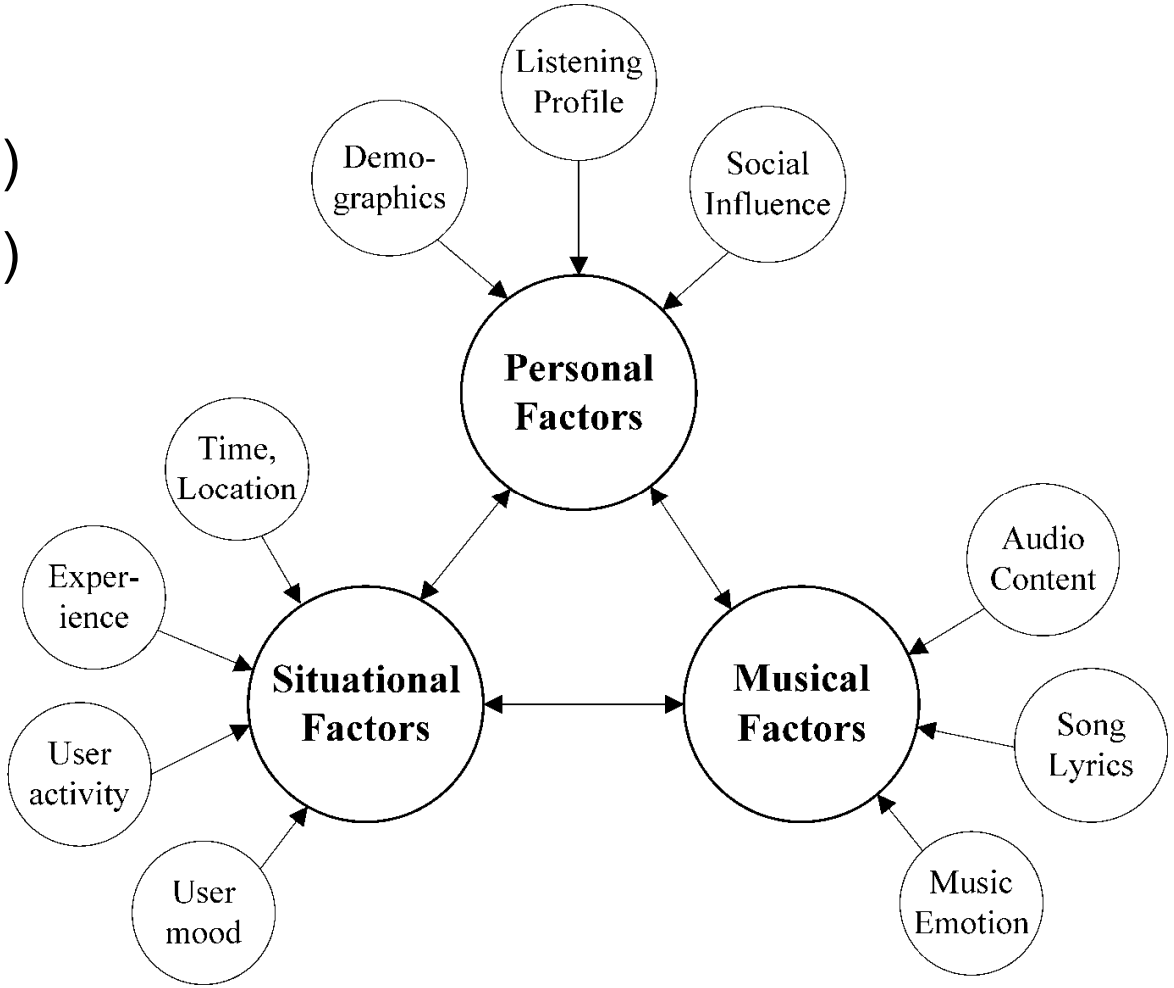
Semantic labels

Activity
Mood
Location

Personal, Situational, and Musical Factors

Blogs (LiveJournal)

Smartphones (HTC)



Context of Music Listening

Experienced emotion = structural features × performance features × listener features × context features

Where

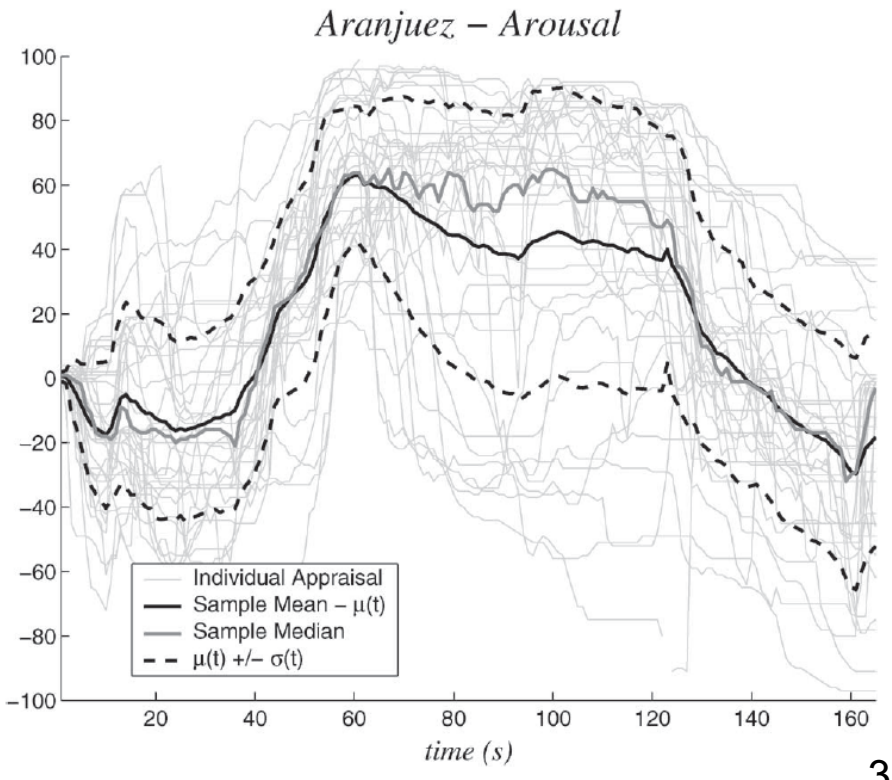
Structural features = β_1 (segmental features) × β_2 (suprasegmental features)
Performance features = β_3 (performer skills) × β_4 (performer state)
Listener features = β_5 (musical expertise) × β_6 (stable dispositions) × β_7 (mood state)
Context features = β_8 (location) × β_9 (sound acoustics) × β_{10} (event)

Adapted from Scherer and Zentner (2001). β represents a variable.

- Listening mood/context
- Familiarity/associated memory
- Preference of the singer/performer/song
- Social relationship

Less Studied: Temporal Context of Music

- "Sweet anticipation"
  - Music's most expressive qualities probably relate to structural changes across time
- Music emotion can also vary within an excerpt



Outline

- Music emotion
- **Structure/form analysis**
- Alignment
- Rhythm & beat tracking

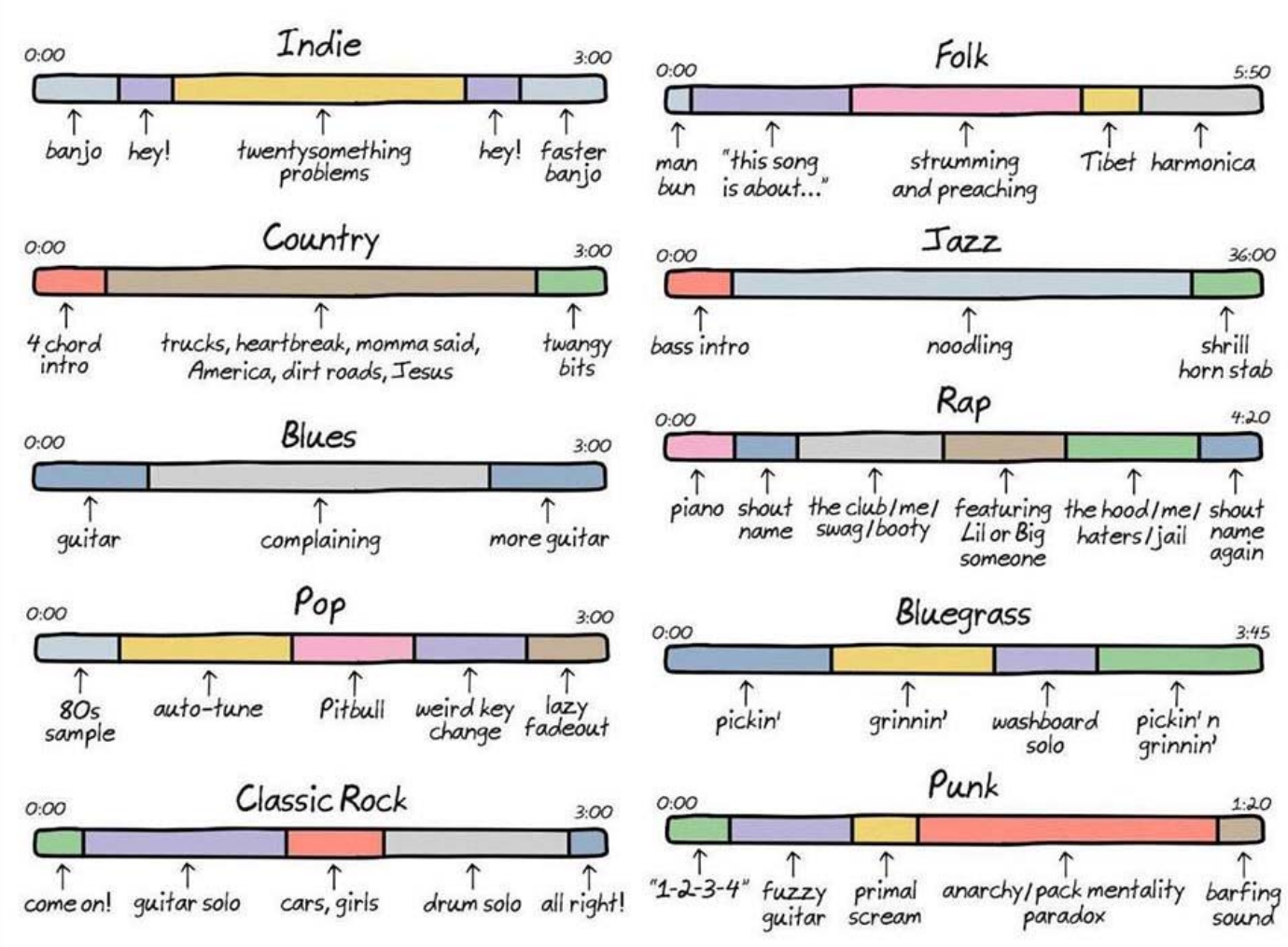
Reference: FMP Notebook

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4.html

Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
B	Basics	Basic information on Python, Jupyter notebooks, Anaconda package management system, Python environments, visualizations, and other topics	[html]	[ipynb]
0	Overview	Overview of the notebooks (https://www.audiolabs-erlangen.de/FMP)	[html]	[ipynb]
1	Music Representations	Music notation, MIDI, audio signal, waveform, pitch, loudness, timbre	[html]	[ipynb]
2	Fourier Analysis of Signals	Discrete/analog signal, sinusoid, exponential, Fourier transform, Fourier representation, DFT, FFT, STFT	[html]	[ipynb]
3	Music Synchronization	Chroma feature, dynamic programming, dynamic time warping (DTW), alignment, user interface	[html]	[ipynb]

Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
4	Music Structure Analysis	Similarity matrix, repetition, thumbnail, homogeneity, novelty, evaluation, precision, recall, F-measure, visualization, scape plot	[html]	[ipynb]
5	Chord Recognition	Harmony, music theory, chords, scales, templates, hidden Markov model (HMM), evaluation	[html]	[ipynb]
6	Tempo and Beat Tracking	Onset, novelty, tempo, tempogram, beat, periodicity, Fourier analysis, autocorrelation	[html]	[ipynb]
7	Content-Based Audio Retrieval	Identification, fingerprint, indexing, inverted list, matching, version, cover song	[html]	[ipynb]
8	Musically Informed Audio Decomposition	Harmonic/percussive separation, signal reconstruction, instantaneous frequency, fundamental frequency (F0), trajectory, nonnegative matrix factorization (NMF)	[html]	[ipynb]

Music Structure / Form



(Image from the Internet)

Hungarian Dance No. 5 by Johannes Brahms (Ormandy)

MIR tasks

1. Alignment
2. Transcription
3. Instrument recognition
4. Tempo estimation
5. Key detection
6. Dynamics
7. Emotion

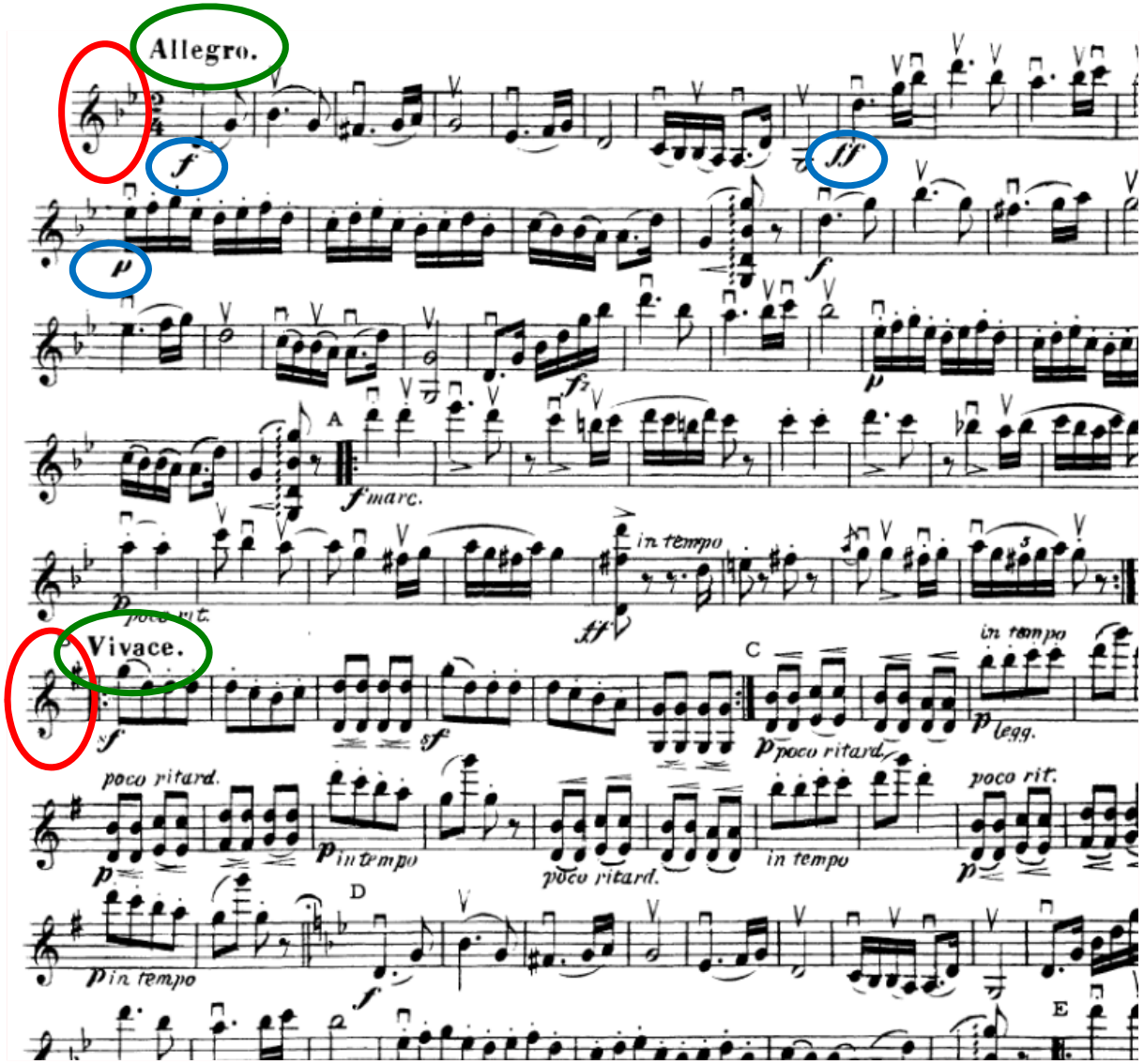
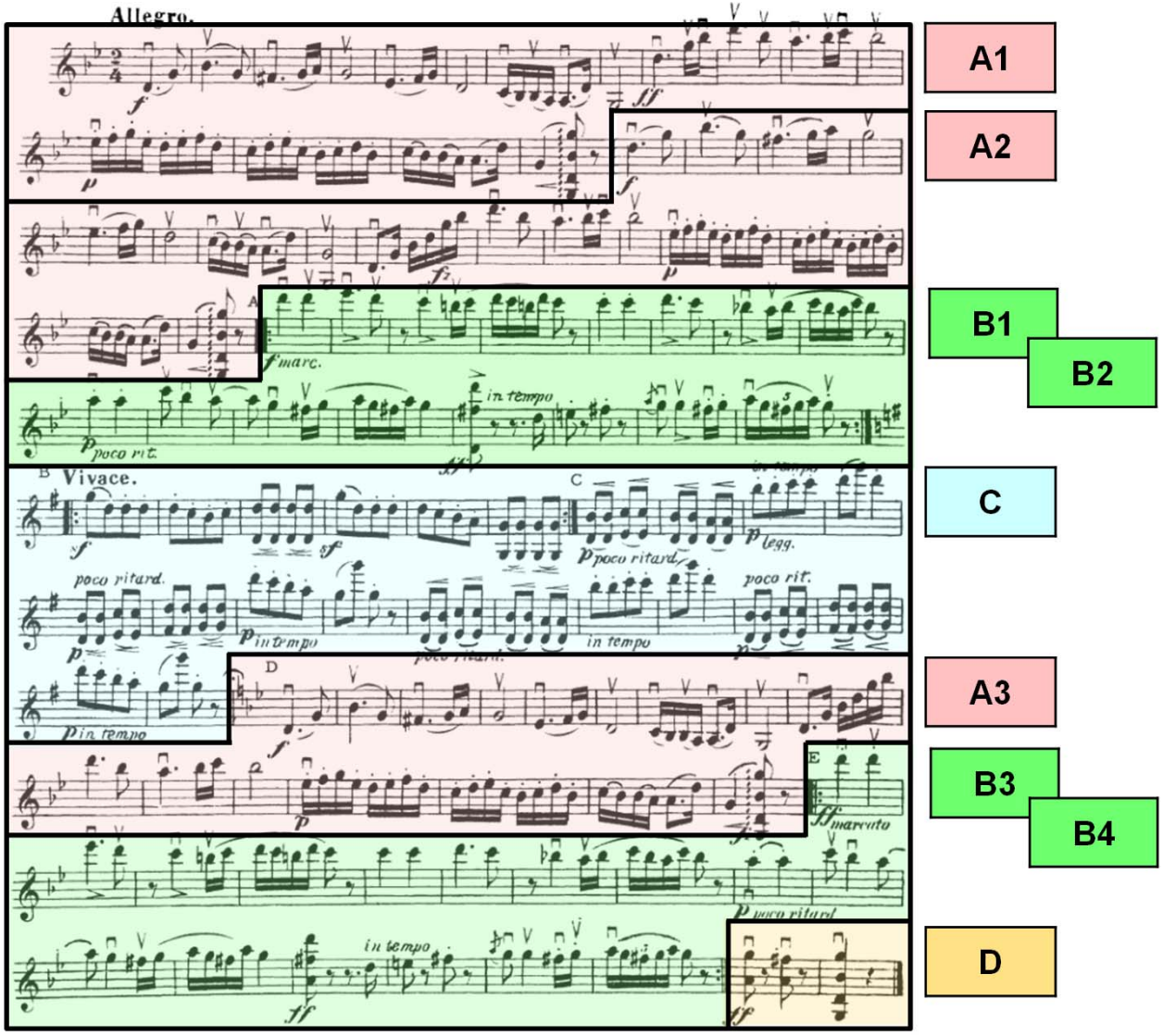


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Hungarian Dance No. 5 by Johannes Brahms (Ormandy)

8. Structure

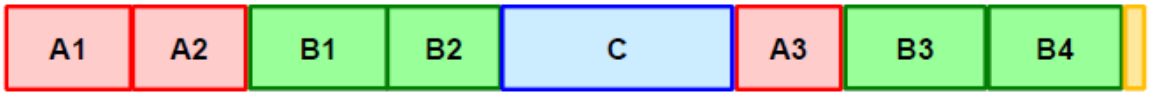


https://www.youtube.com/watch?v=QAMxkietiik

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Music Structure Analysis

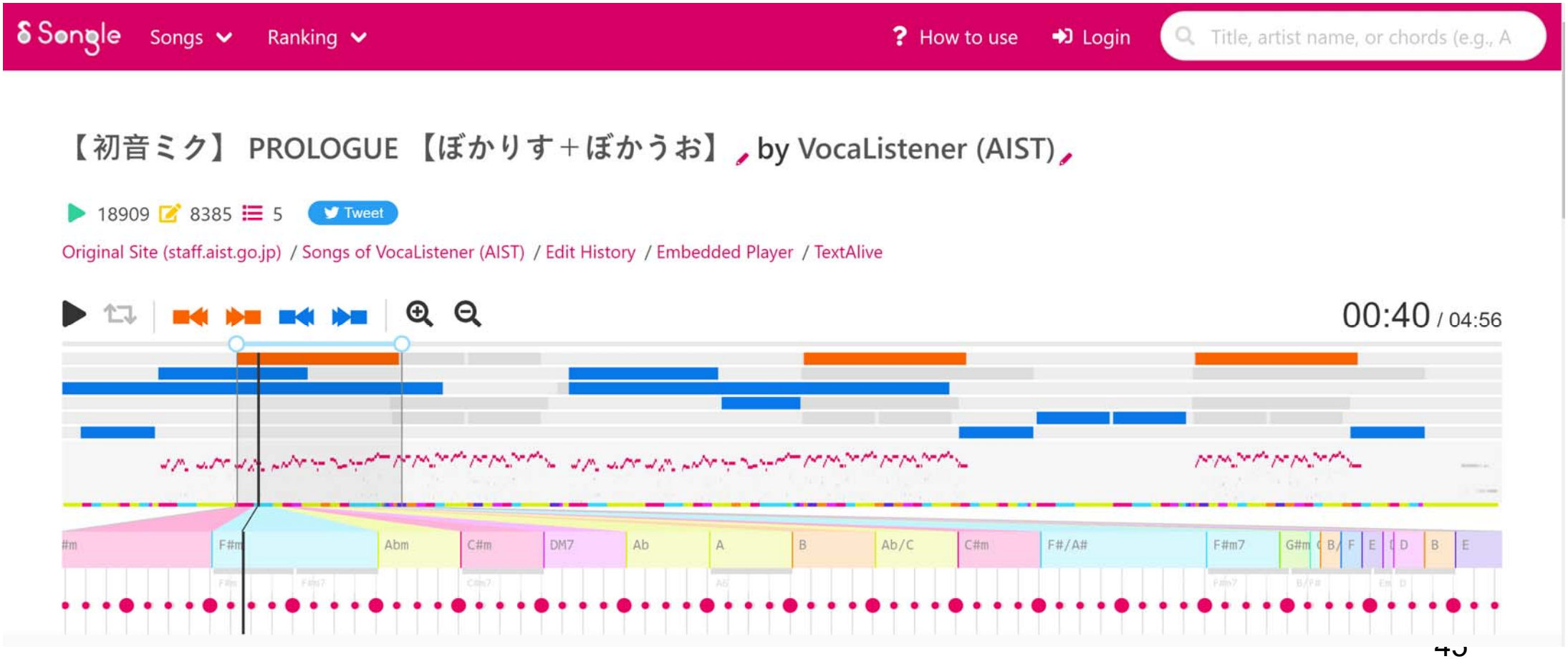
- General goal:
  1. **Segmentation:** **Divide** an audio recording into temporal segments corresponding to musical parts
  2. **Grouping**: **Cluster** or **label** these segments into musically meaningful categories



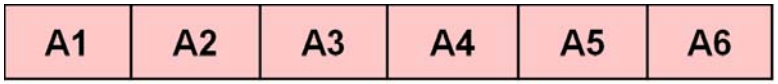
- Examples
  - *Intro, verse, chorus, bridge, outro* of a pop song
  - *Exposition, development, recapitulation, coda* of a sonata

Demonstration: Songle

https://songle.jp/



Music Structure / Form



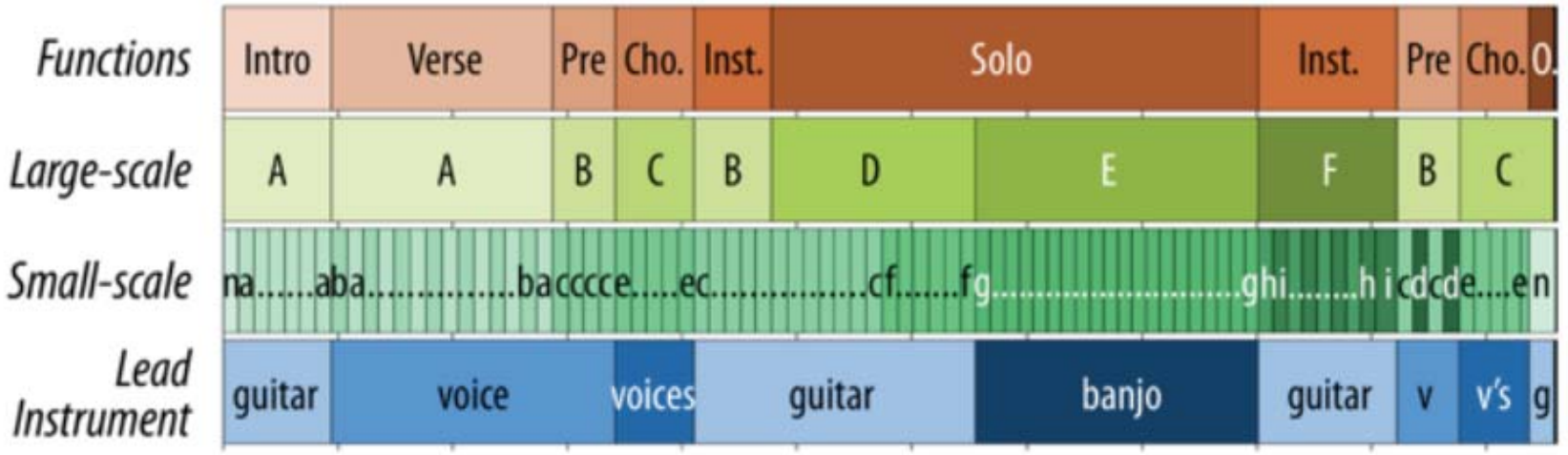
- Strophic form
- Chain form
- Rondo form

- Sonata form
- “Tell Me Why” by Beatles
- “Yesterday” by Beatles

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Ambiguity in Structure Analysis

- "Musical structure naturally exhibits a **hierarchical** organization where a variety of cues can trigger boundaries between segments of different length, depending on the time scale at which they are observed"



Ref 1: Buisson et al, "Learning multi-level representations for hierarchical music structure analysis," ISMIR 2022

Ref 2: Smith et al, "Design and creation of a large-scale database of structural annotations," ISMIR 2011

General Principles of Music Structure Analysis

1) Novelty, 2) Homogeneity, 3) Repetition

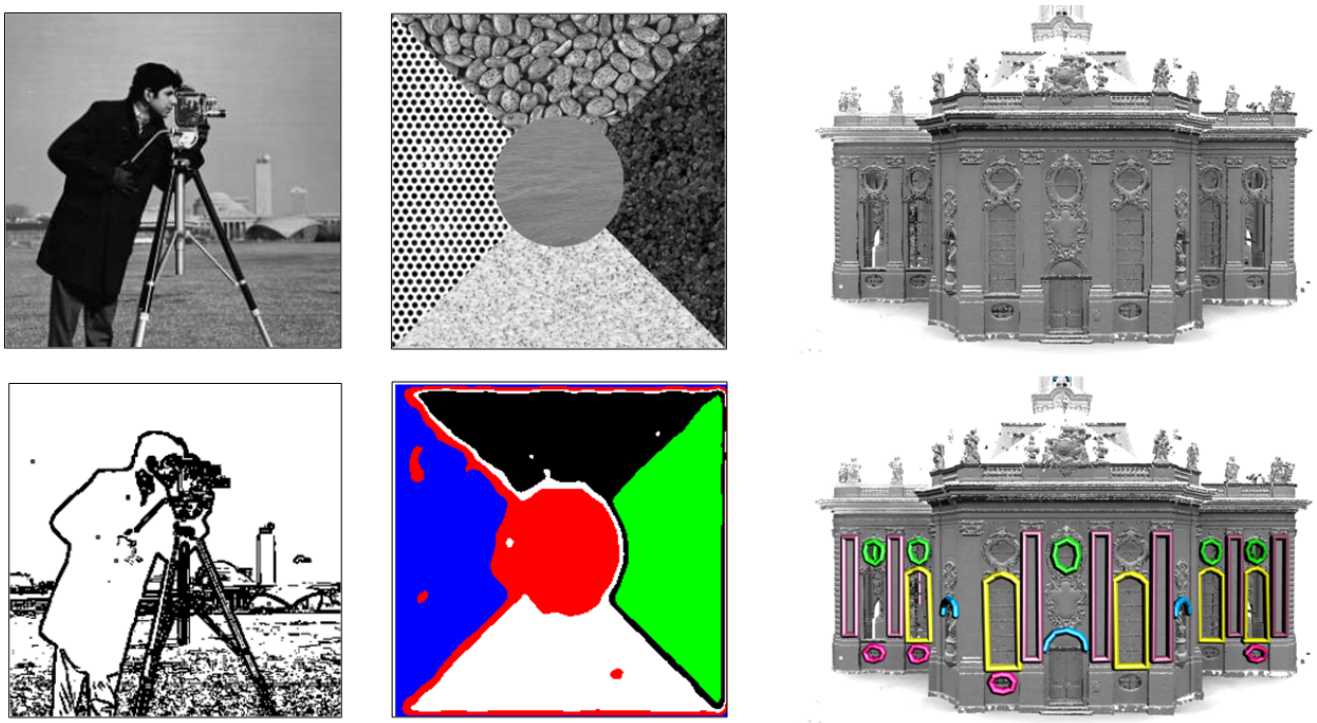
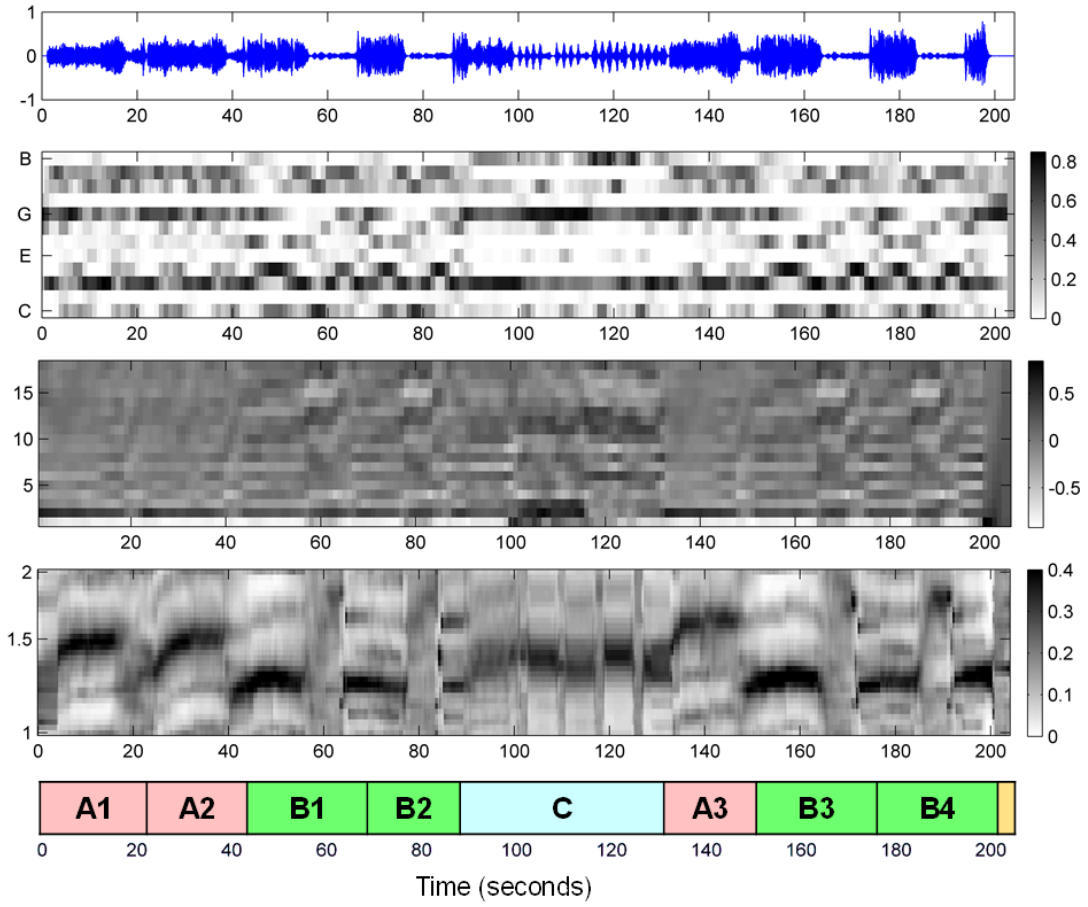


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Acoustic Features Cues

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S1_MusicStructureGeneral.html

- Wav
- Chromagram
- MFCC
- Tempogram
- Groundtruth



Feature Representation

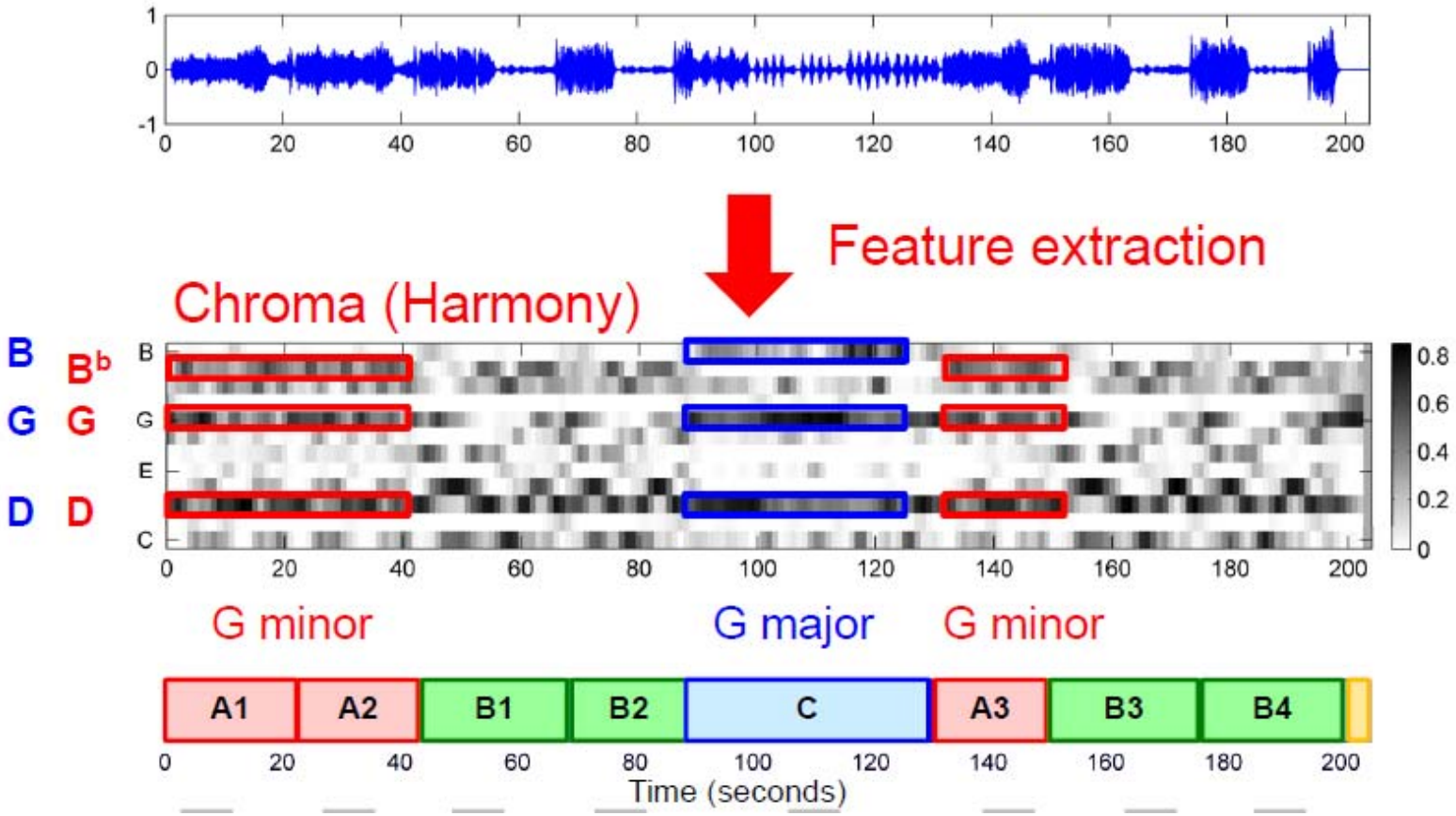


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Self-Similarity Matrices (SSM)

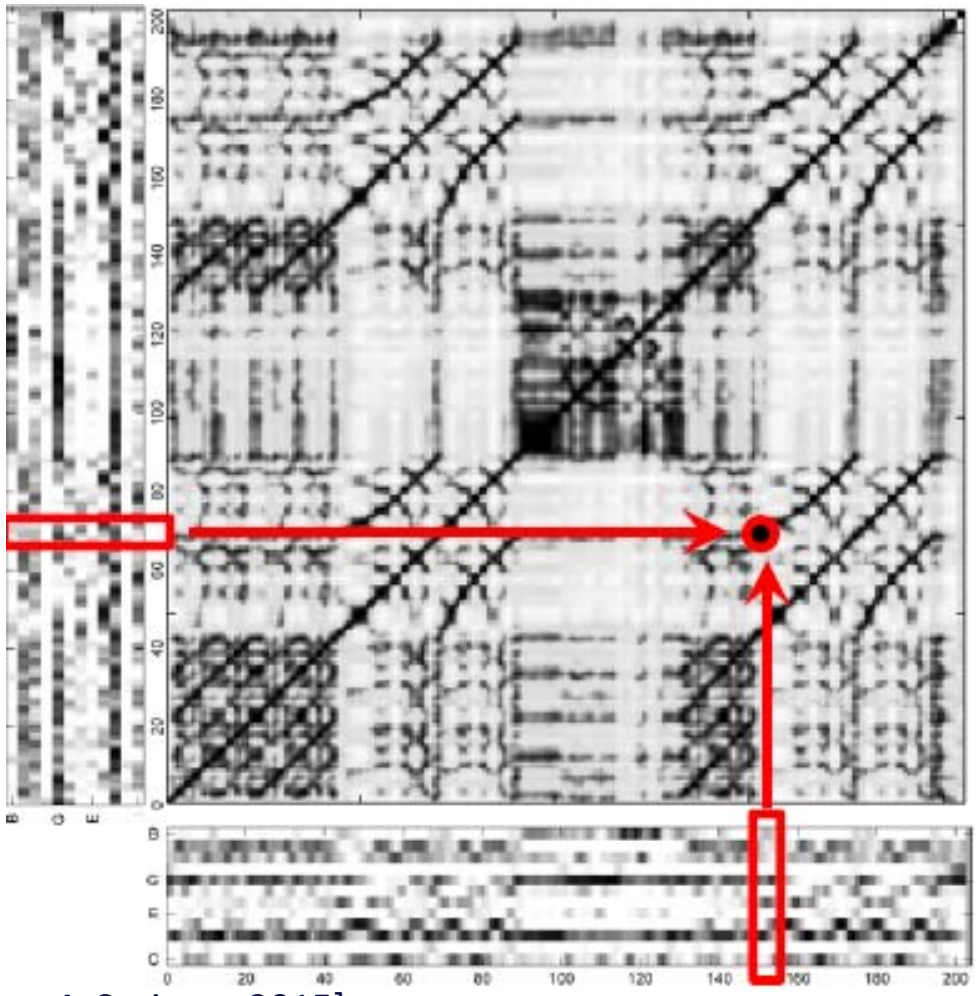


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Blocks → Homogeneity

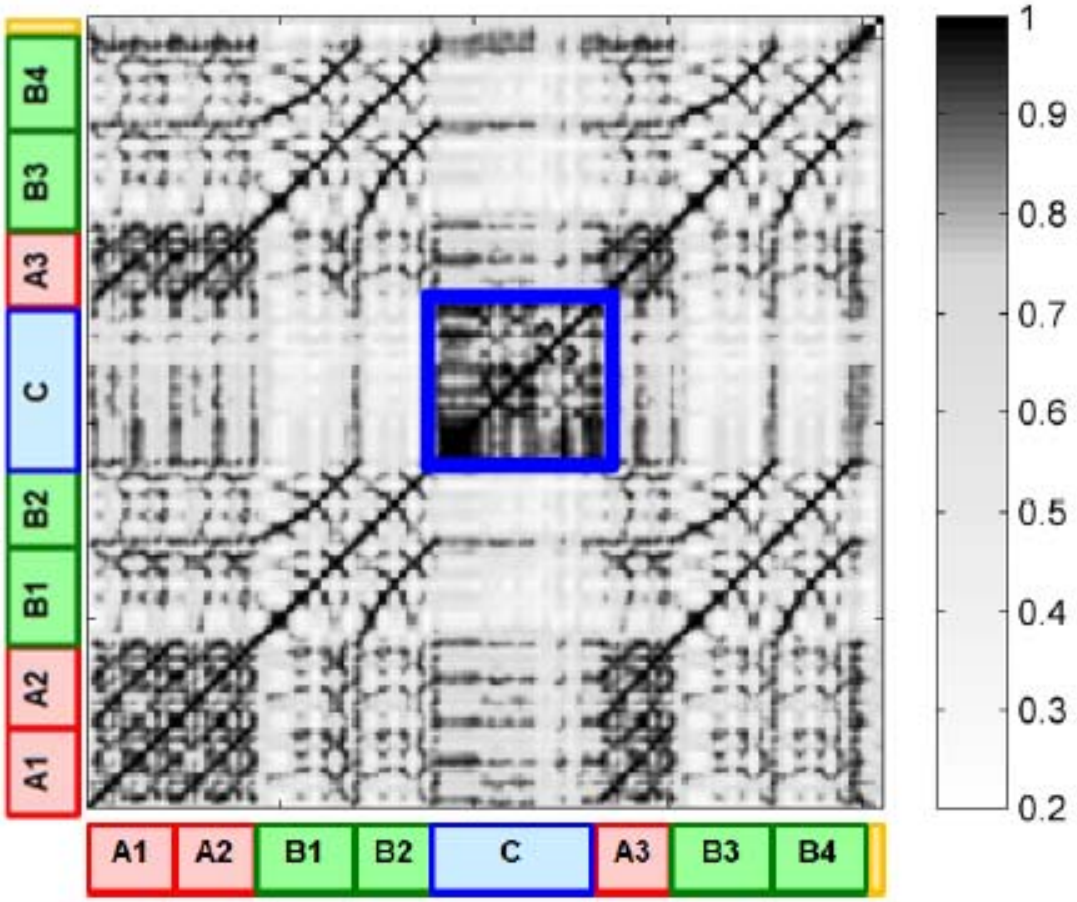


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Paths → Repetition

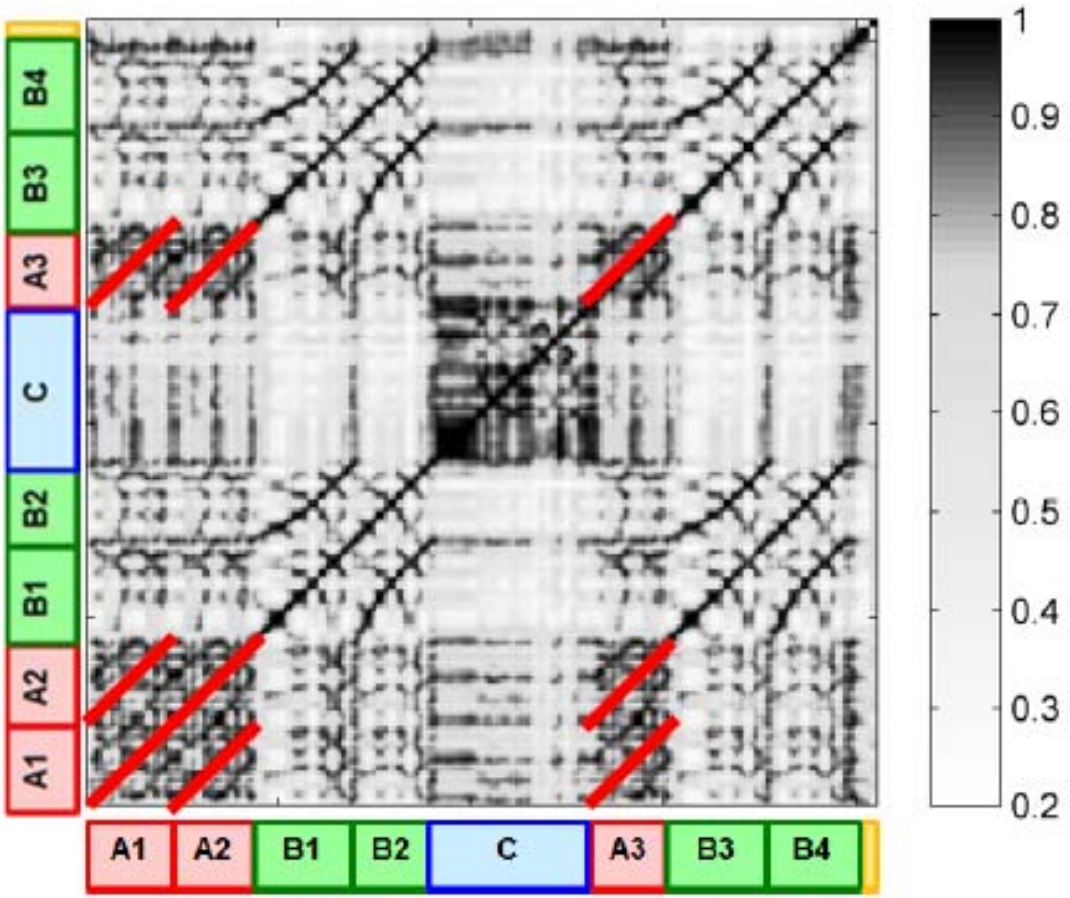


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Paths → Repetition

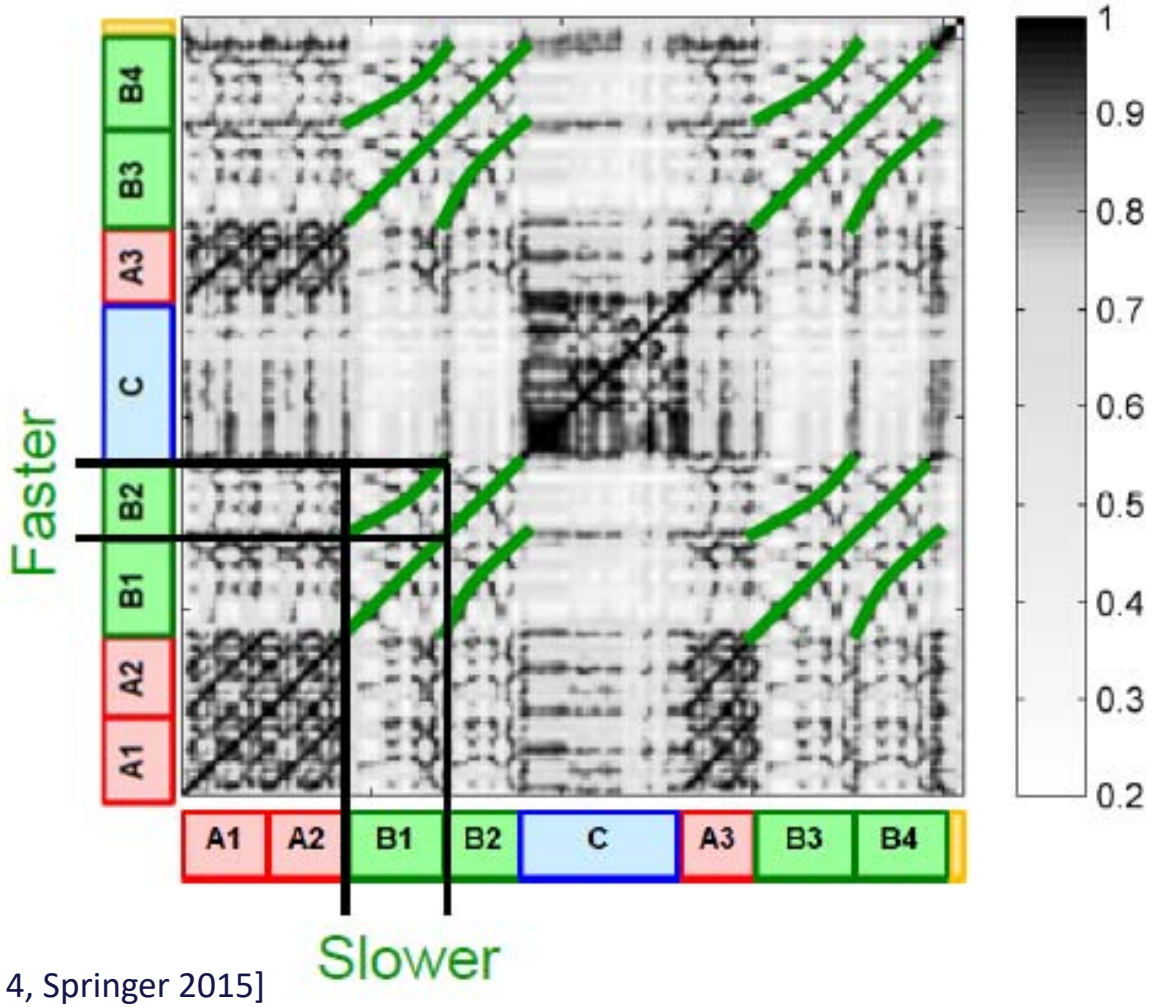


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Self-Similarity Matrices (SSM)

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S2_SSM.html

Blocks: Homogeneity

Paths: Repetition

Corners: Novelty

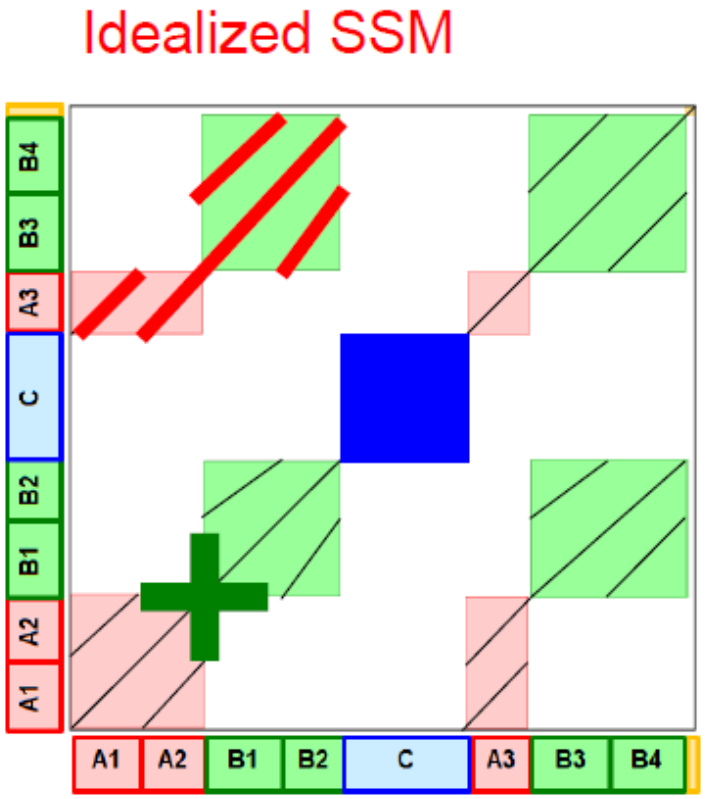
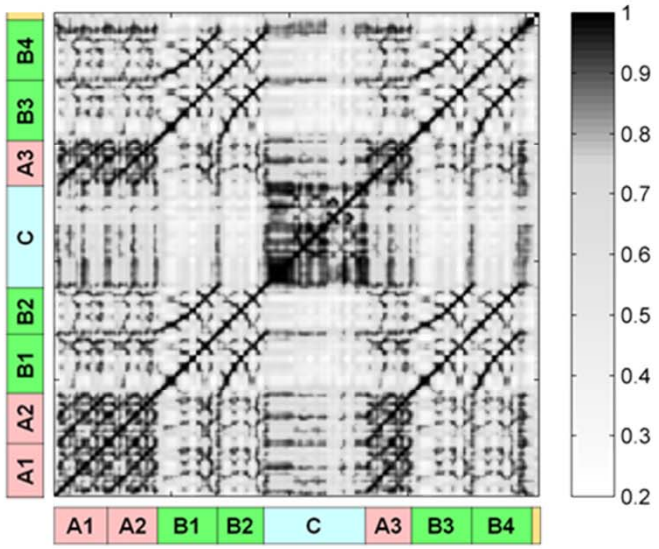


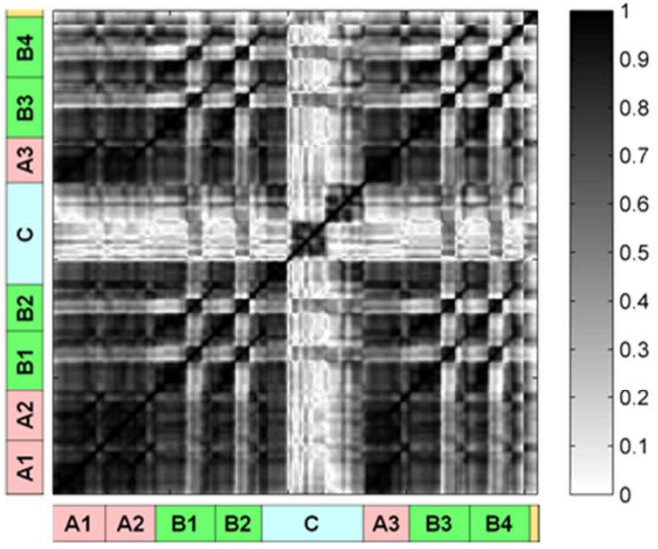
Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Self-Similarity Matrices (SSM)

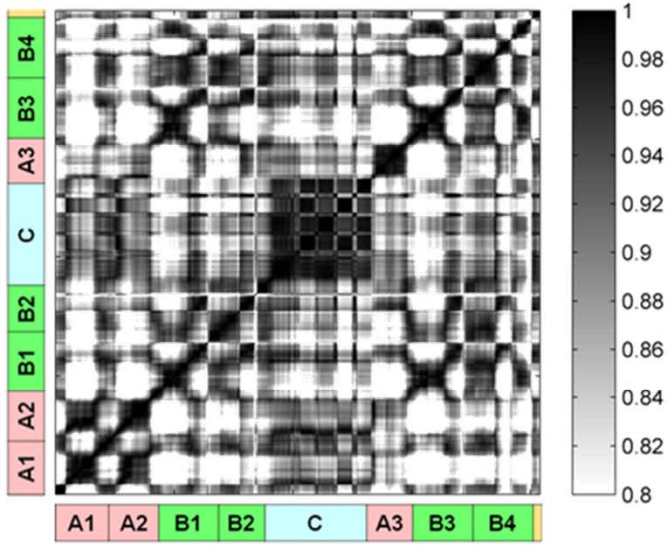
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S2_SSM.html



SSM from chromagram



SSM from MFCC



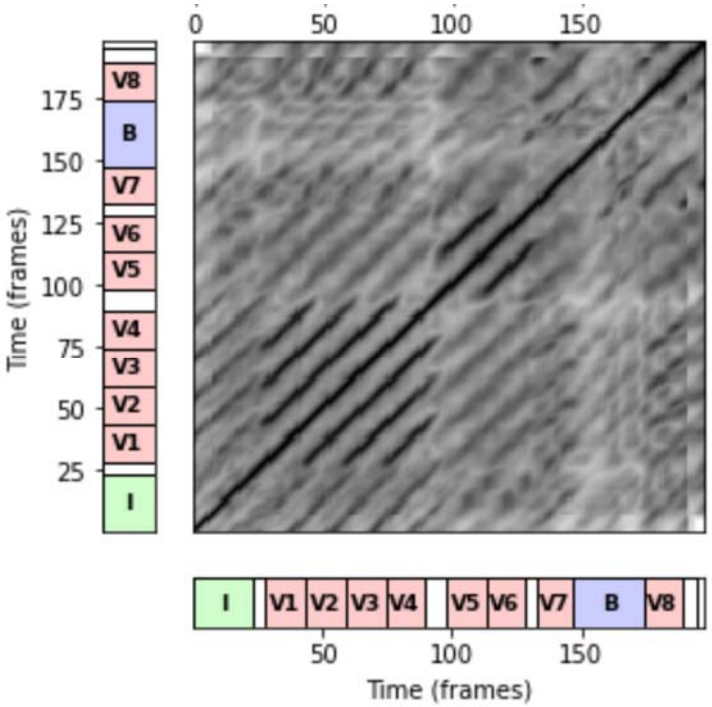
SSM from tempogram

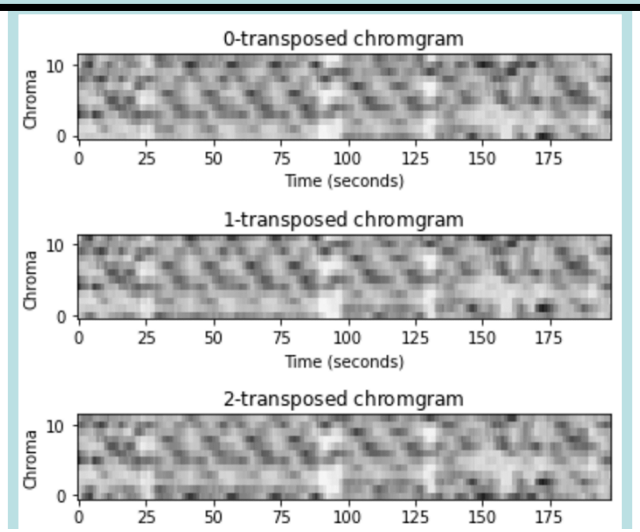
Figure from [Mueller, FPM, Chapter 4, Springer 2015]

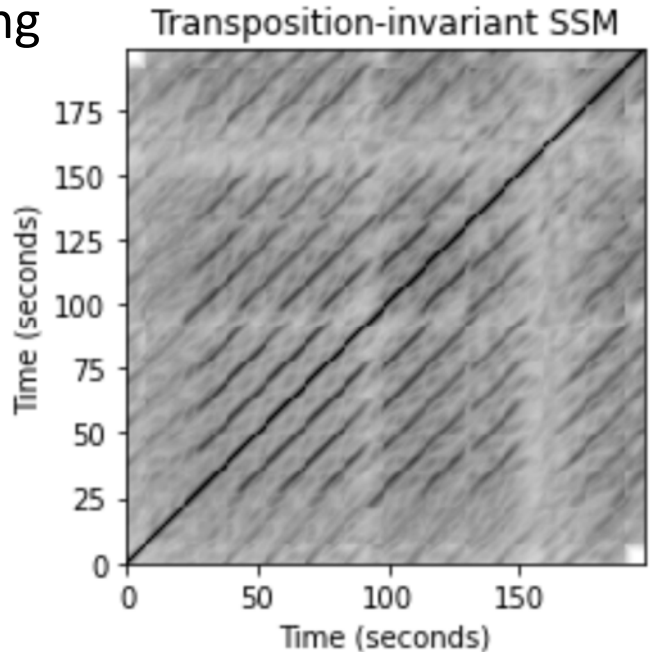
Transposition-Invariant SSM

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S2_SSM-TranspositionInvariance.html

1. **Cyclic shift** the chromagram
2. Compare the original recording with the transposed ones
3. Cell-wise **max** over 12 shifts

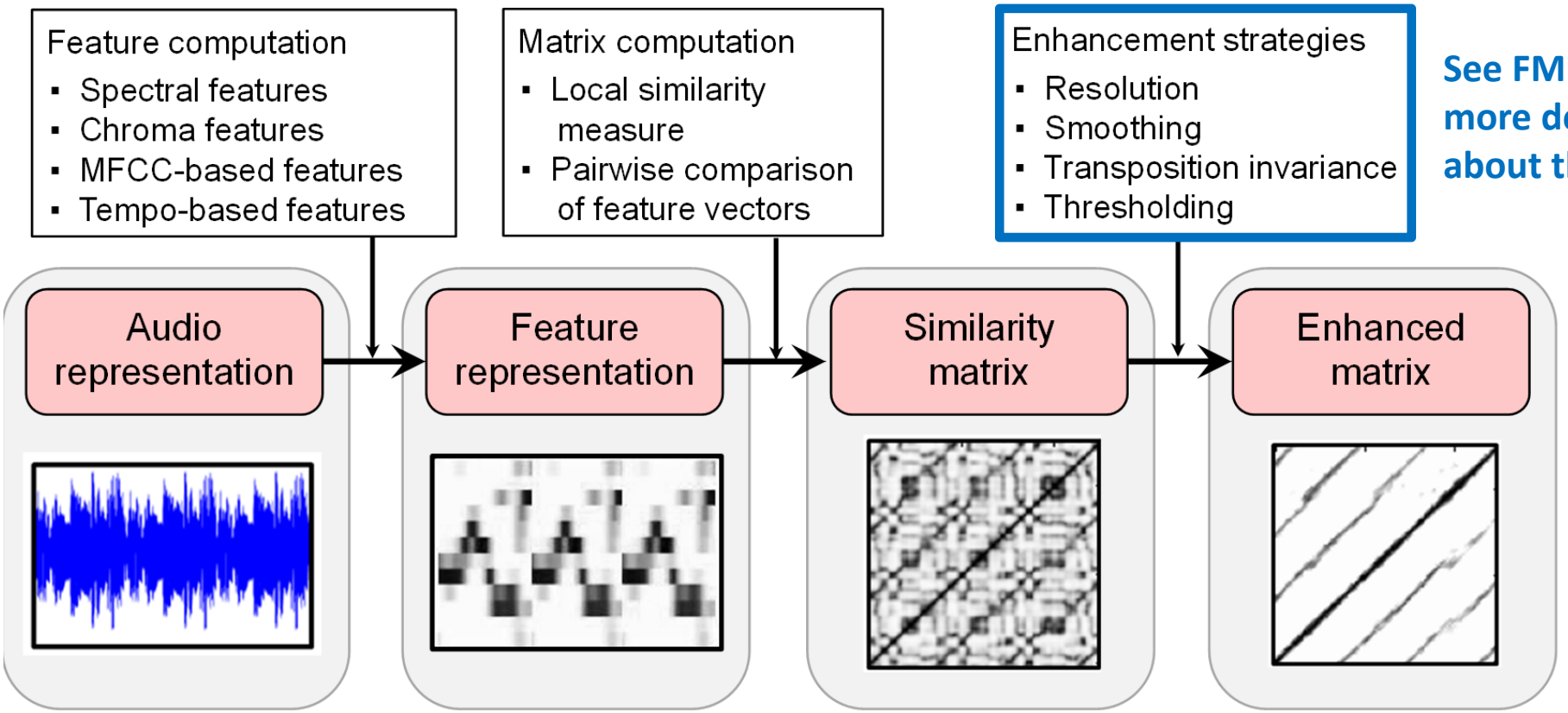






Procedure

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S1_MusicStructureGeneral.html



See FMP for more details about this part

Novelty-based Segmentation

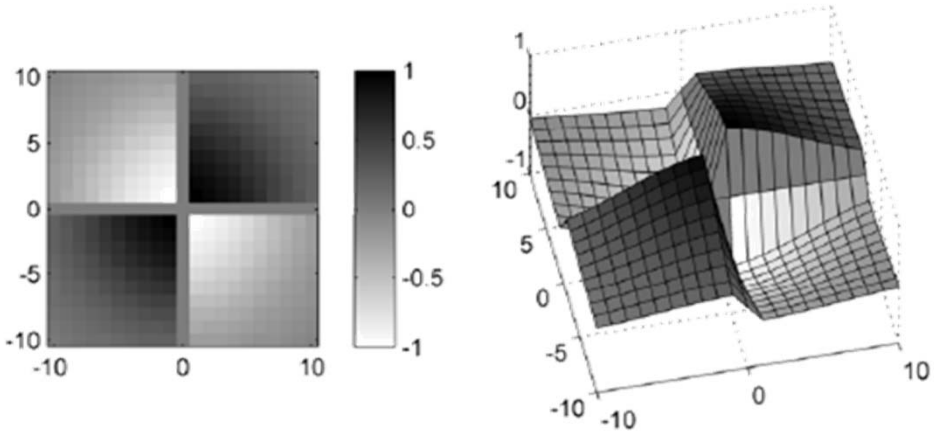
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S4_NoveltySegmentation.html

General goals:

- Find instances where musical changes occur.
- Find transition between subsequent musical parts.

Idea (Foote):

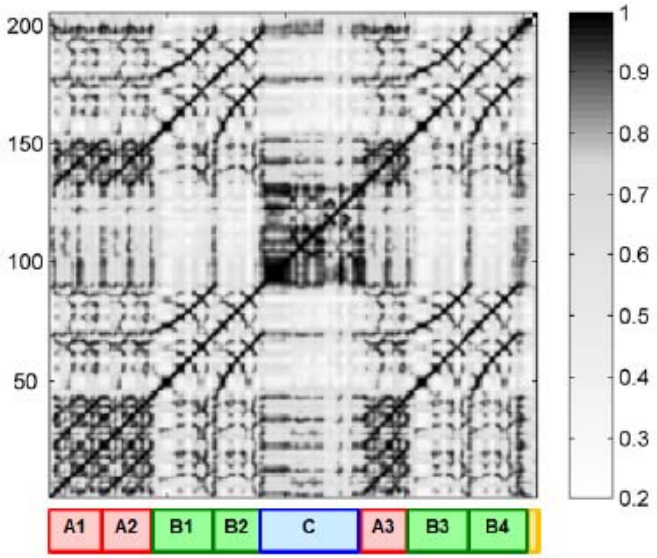
Use checkerboard-like kernel function to detect corner points on main diagonal of SSM.



Gaussian checkerboard kernel

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Novelty-based Segmentation



Idea (Foote):

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Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Novelty-based Segmentation

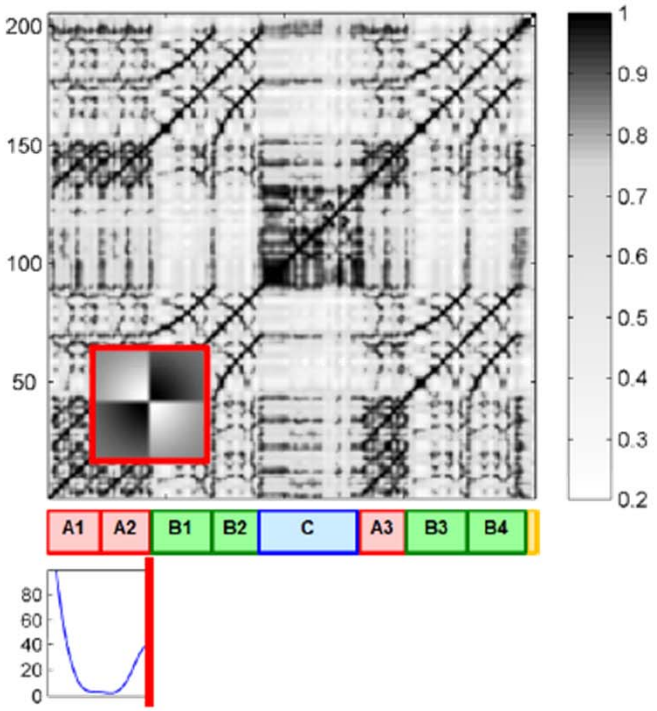

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Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Novelty-based Segmentation

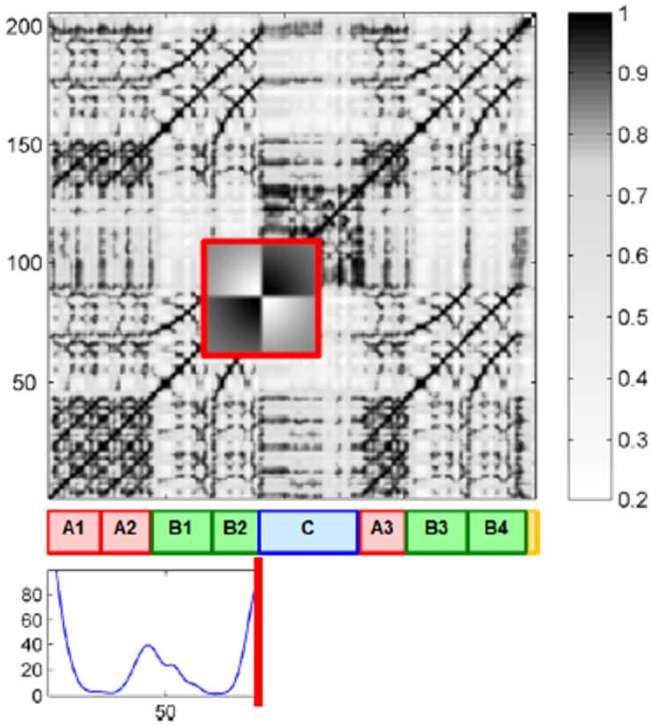

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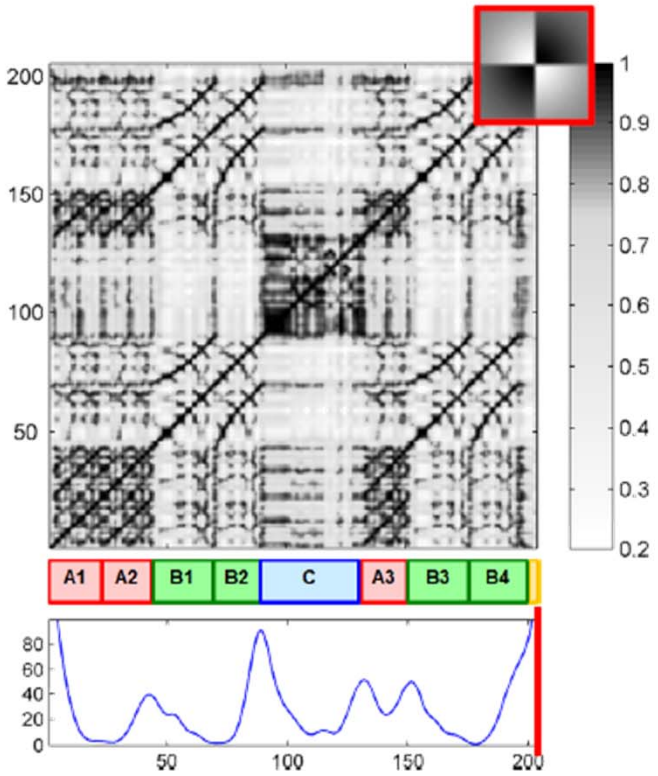
Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Novelty-based Segmentation



Idea (Foote):

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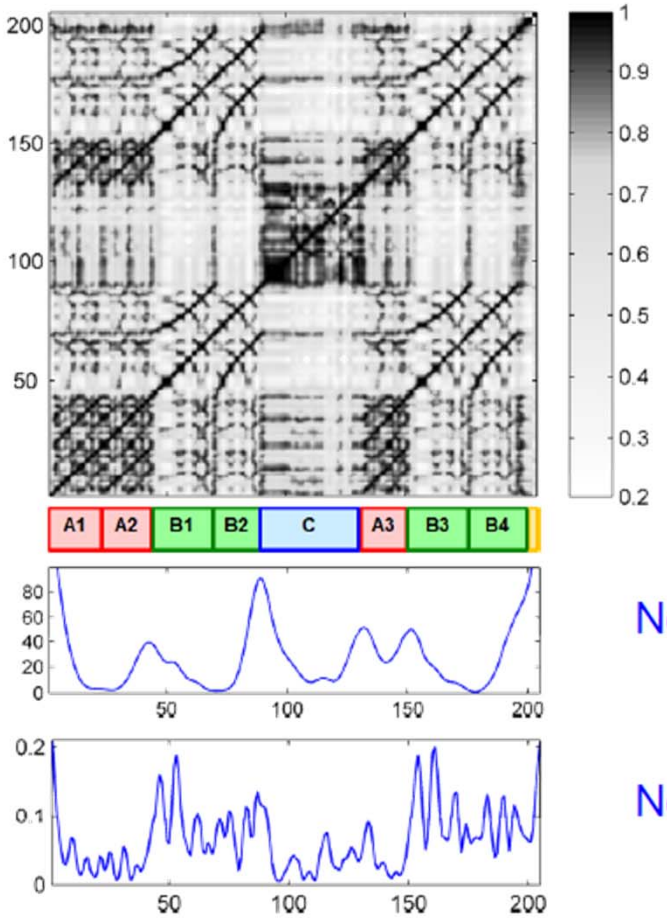
Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Novelty-based Segmentation



Idea (Foote):

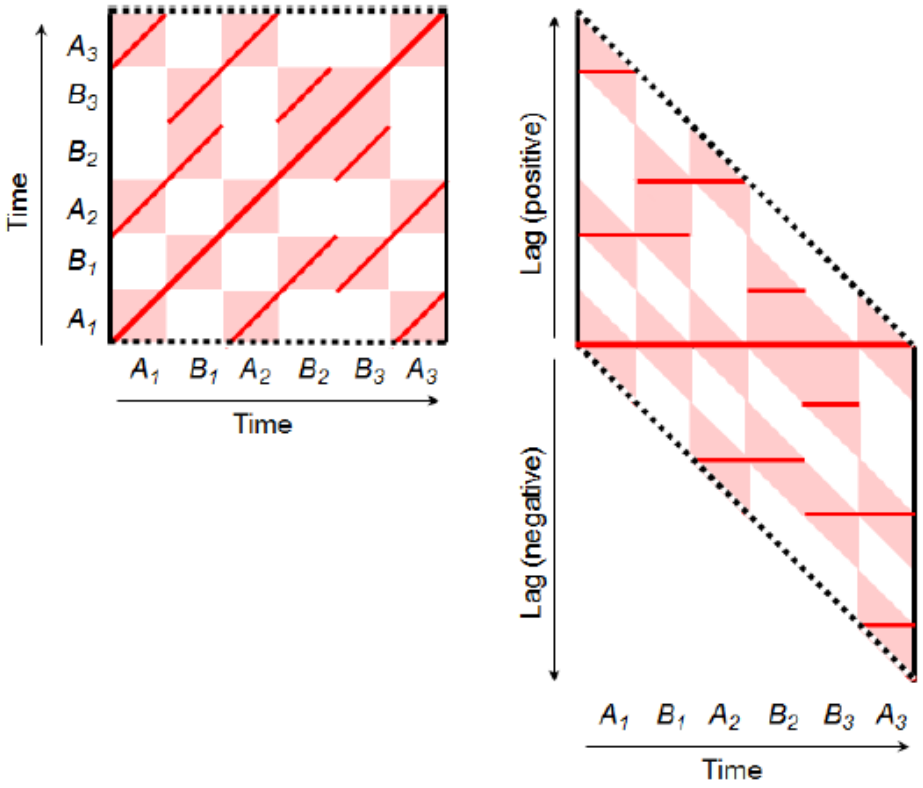
Use checkerboard-like kernel function to detect corner points on main diagonal of SSM.

Novelty function using 

Novelty function using 

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Structure Feature-based Segmentation

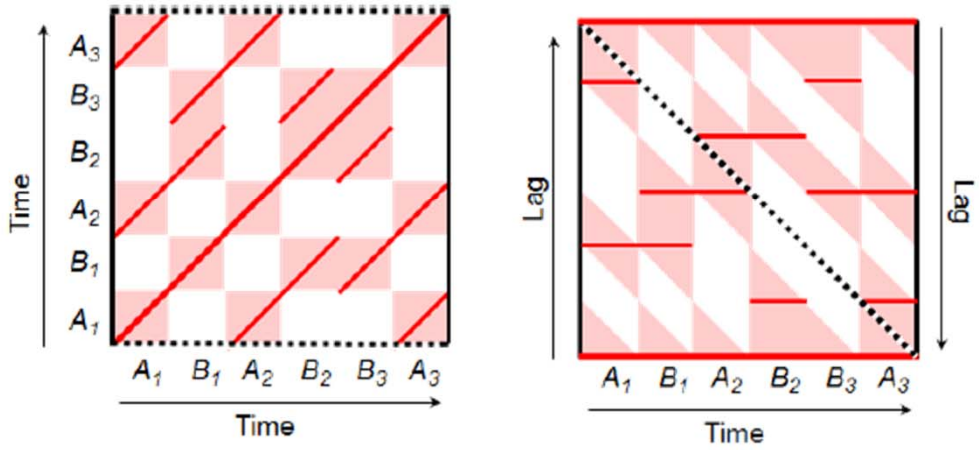


Structure features

- Enhanced SSM
- Time-lag SSM

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Structure Feature-based Segmentation



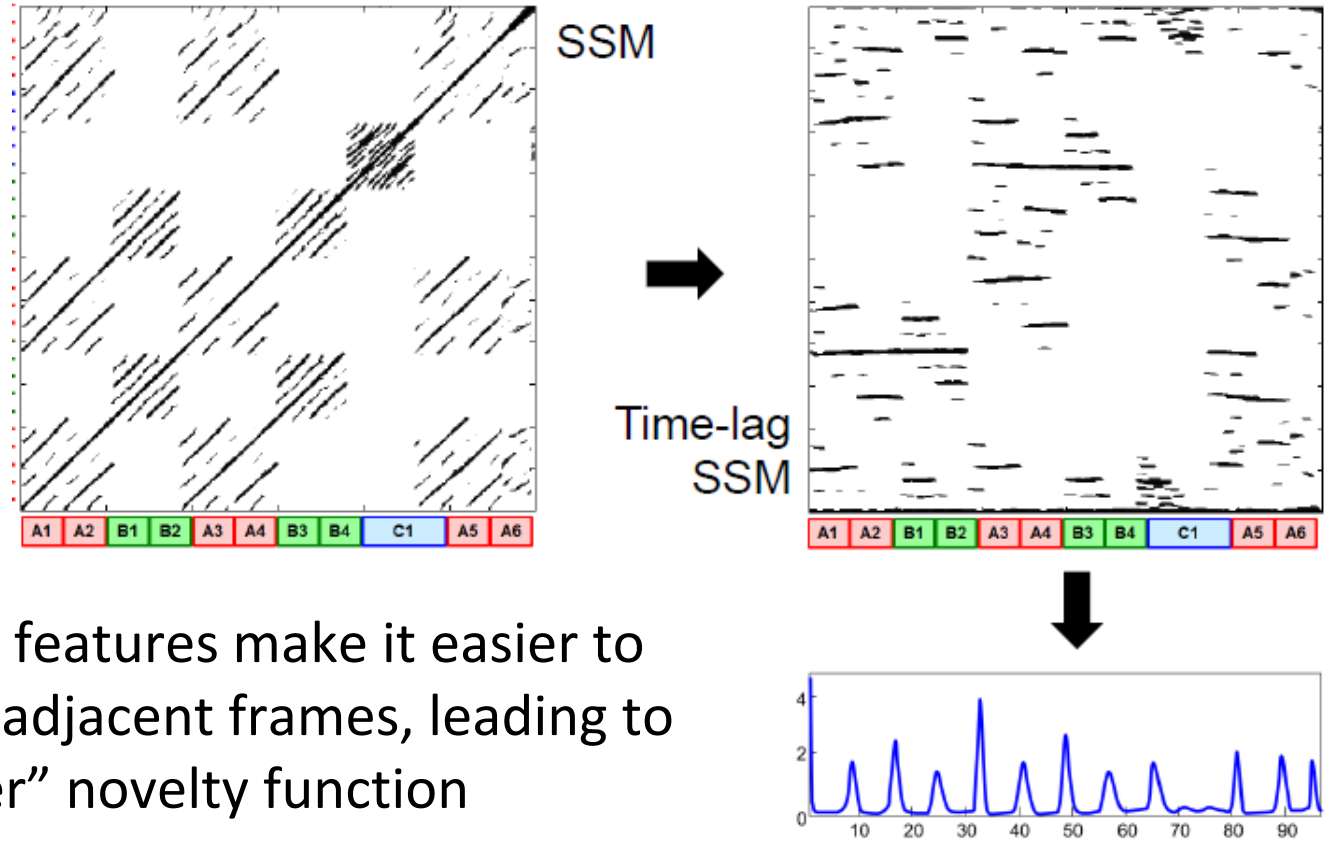
Structure features

- Enhanced SSM
- Time-lag SSM
- Cyclic time-lag SSM

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Structure Feature-based Segmentation

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S4_StructureFeature.html

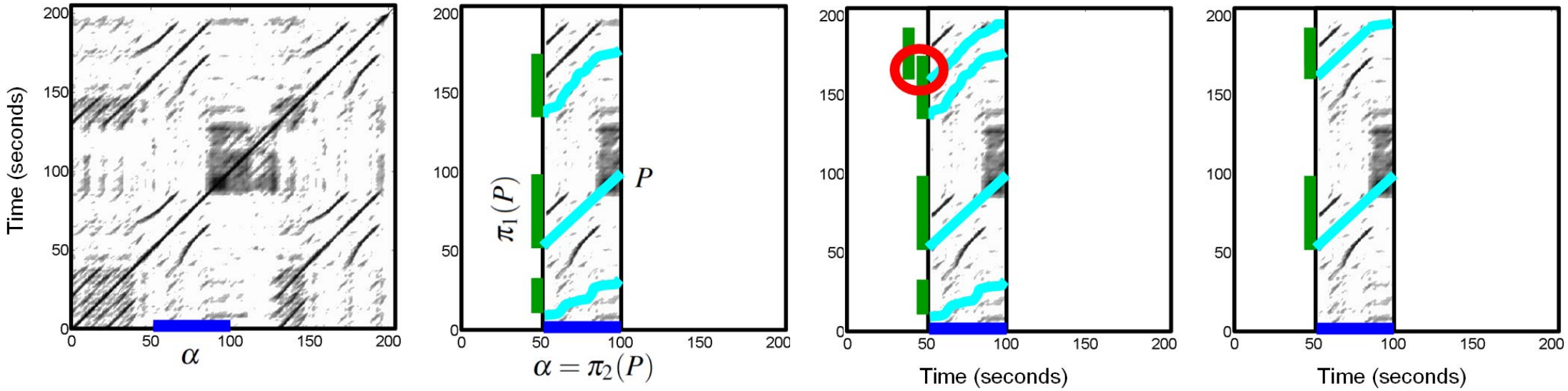


- Structure features make it easier to compare adjacent frames, leading to a “sharper” novelty function

Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Application of SSM: Thumbnailing

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S3_AudioThumbnailing.html

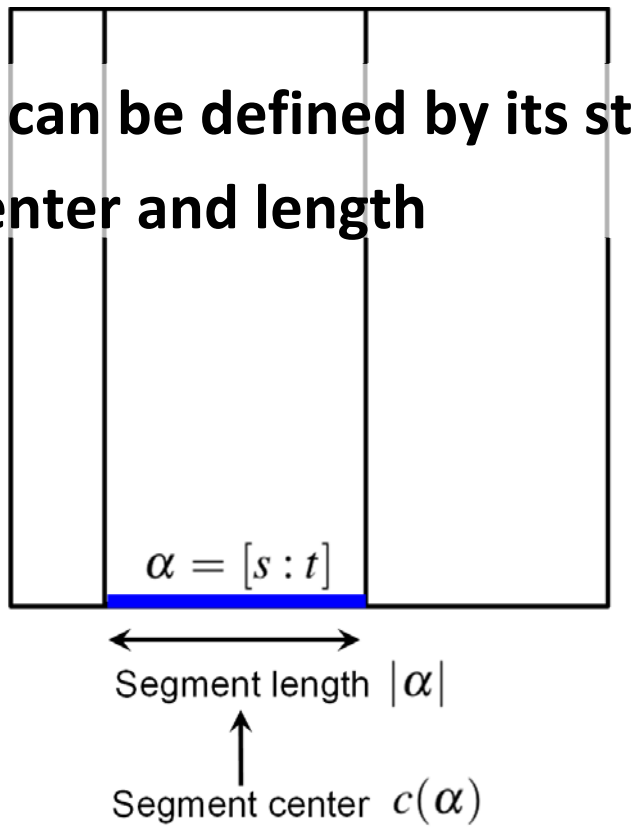


- **Fitness**: how well a given segment explains other related segments (by **DTW**) & how much of the overall music recording is covered by all these related segments (considering **non-overlapping** segments with **certain similarity**)
- **Audio thumbnail:** the segment of maximal fitness

Application: Scape Plot Representation

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S3_ScapePlot.html

- **A segment can be defined by its starting and end points**
- **Or by its center and length**



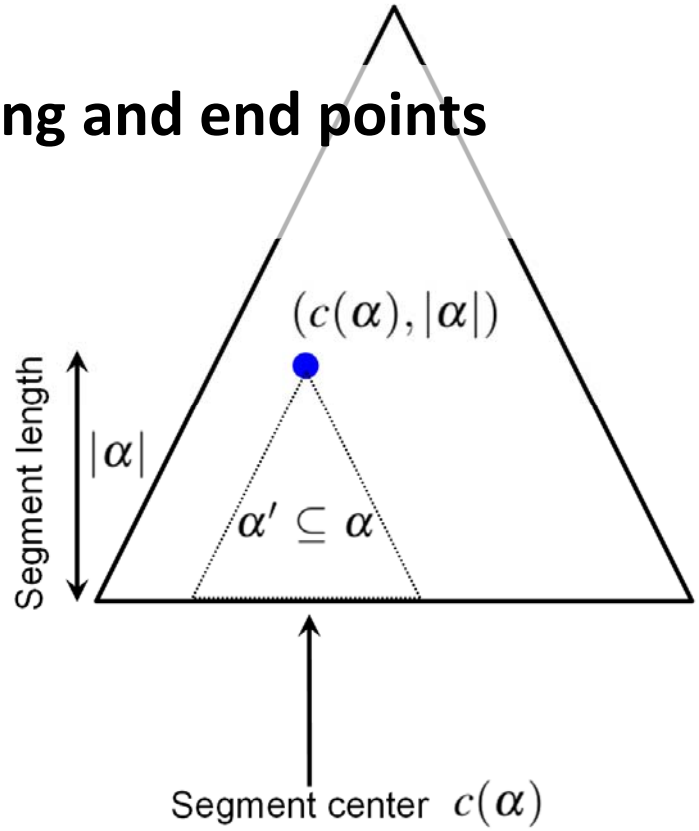


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Application: Scape Plot Representation

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S3_ScapePlot.html

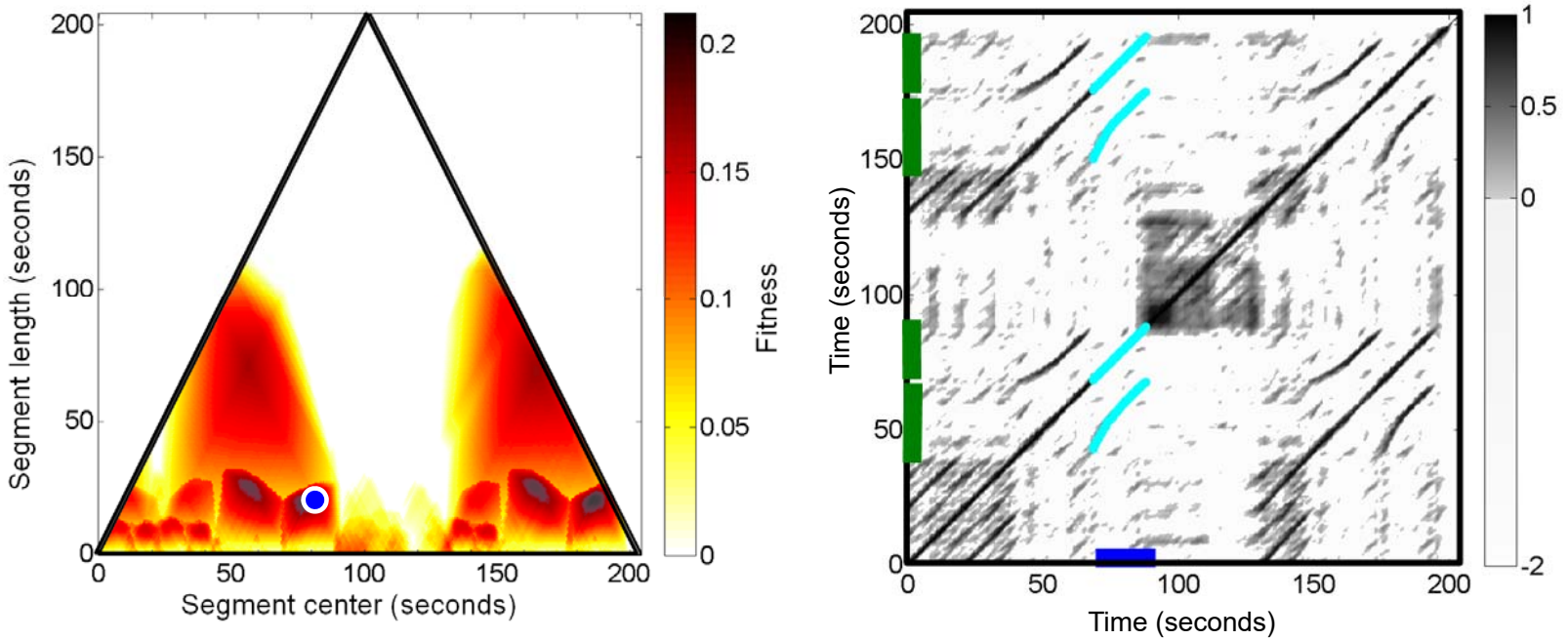


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Application: Scape Plot Representation

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C4/C4S3_ScapePlot.html

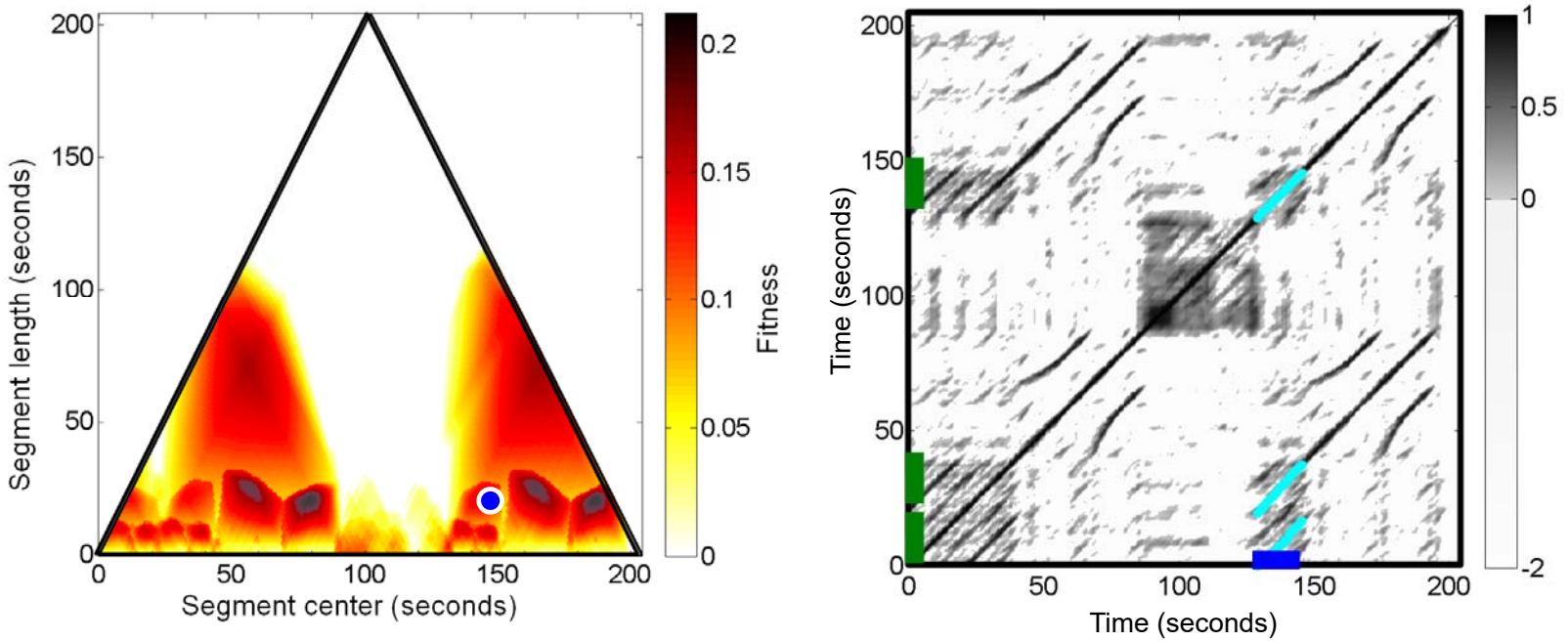


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Application: Scape Plot Representation

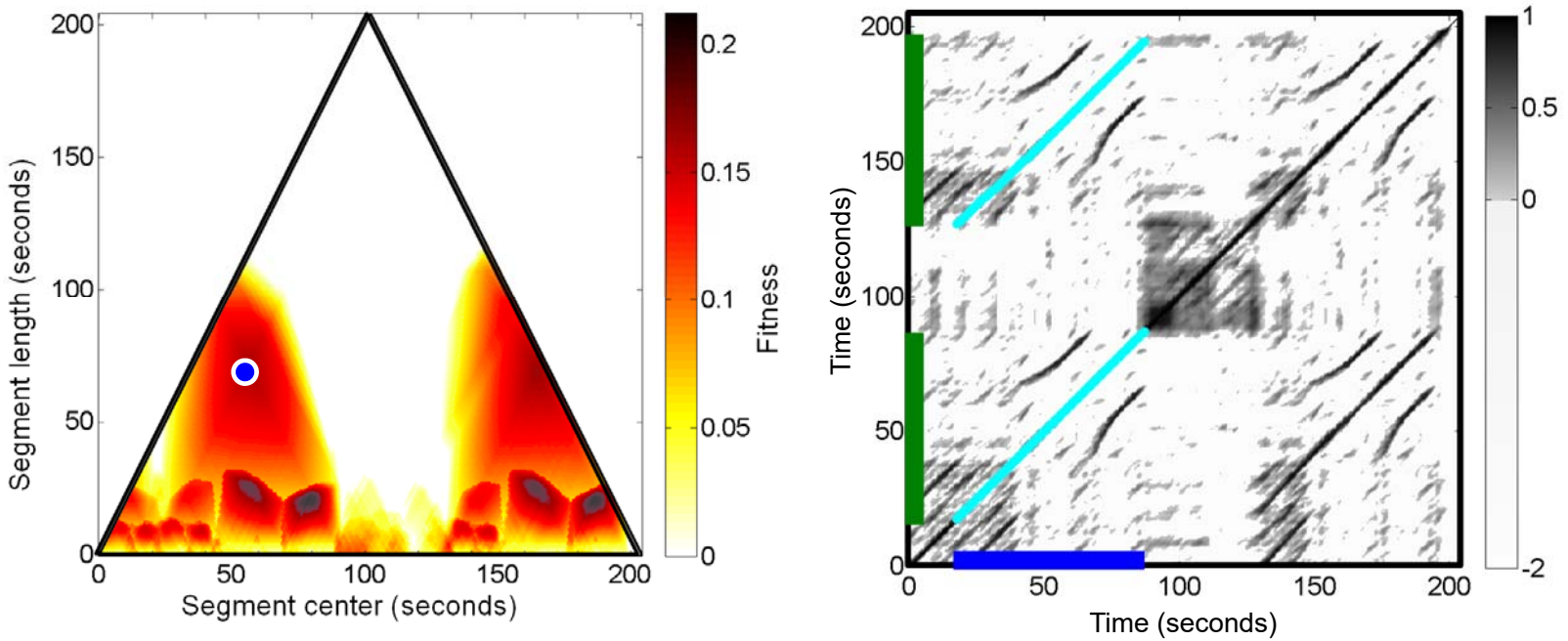


Figure from [Mueller, FPM, Chapter 4, Springer 2015]

Library: Librosa

https://librosa.org/doc/latest/segment.html

Temporal segmentation

Recurrence and self-similarity

`recurrence_matrix` (data[, k, width, metric, ...])	Compute a recurrence matrix from a
`recurrence_to_lag` (rec[, pad, axis])	Convert a recurrence matrix into a l
`lag_to_recurrence` (lag[, axis])	Convert a lag matrix into a recurren
`timelag_filter` (function[, pad, index])	Filtering in the time-lag domain.

Temporal clustering

`agglomerative` (data, k[, clusterer, axis])	Bottom-up temporal segmentation.
`subsegment` (data, frames[, n_segments, axis])	Sub-divide a segmentation by featu

Library: MSAF

https://github.com/urinieto/msaf

Boundary Algorithms

- Improved C-NMF (Nieto & Jehan 2013)
- Checkerboard-like Kernel (Foote 2000)
- OLDA (McFee & Ellis 2014) (original source code from here)
- Spectral Clustering (McFee & Ellis 2014) (original source code from here)
- Structural Features (Serrà et al. 2012)

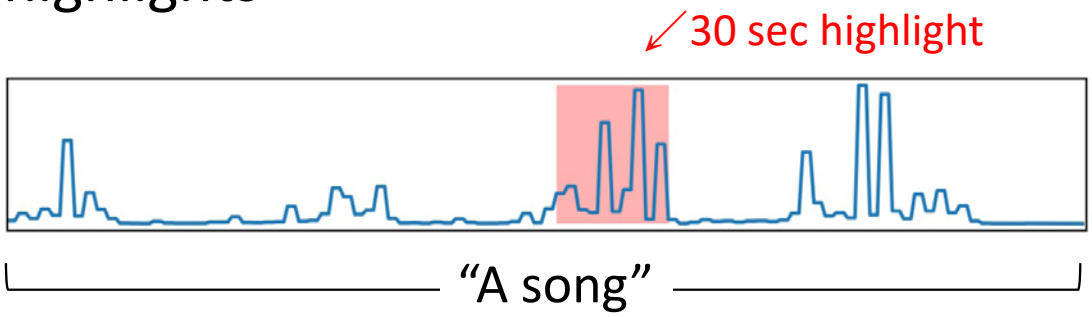
Labeling Algorithms

- Improved C-NMF (Nieto & Jehan 2013)
- 2D Fourier Magnitude Coefficients (Nieto & Bello 2014)
- Spectral Clustering (McFee & Ellis 2014) (original source code from here)

Extension 1: Music Thumbnailing (Highlight Dectection)

https://remyhuang.github.io/music_thumbnailing/

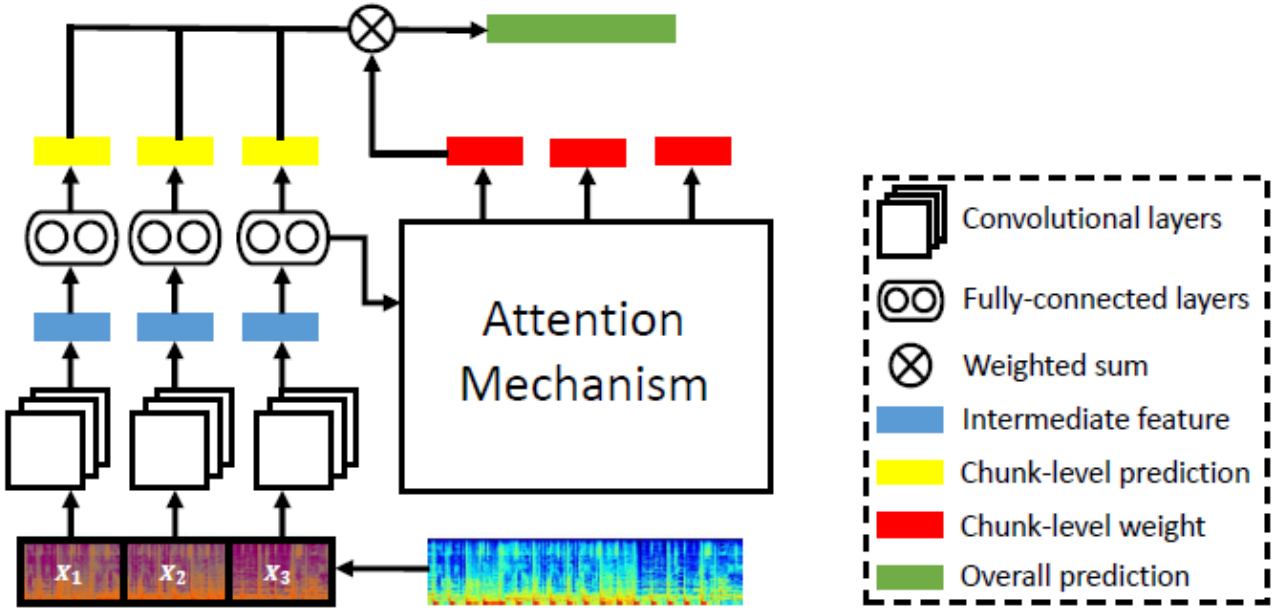
- Extract music highlights



- Application
  - music browsing
  - ringtone generation
  - song representation

Extension 1: Music Thumbnailing (Highlight Dectection)

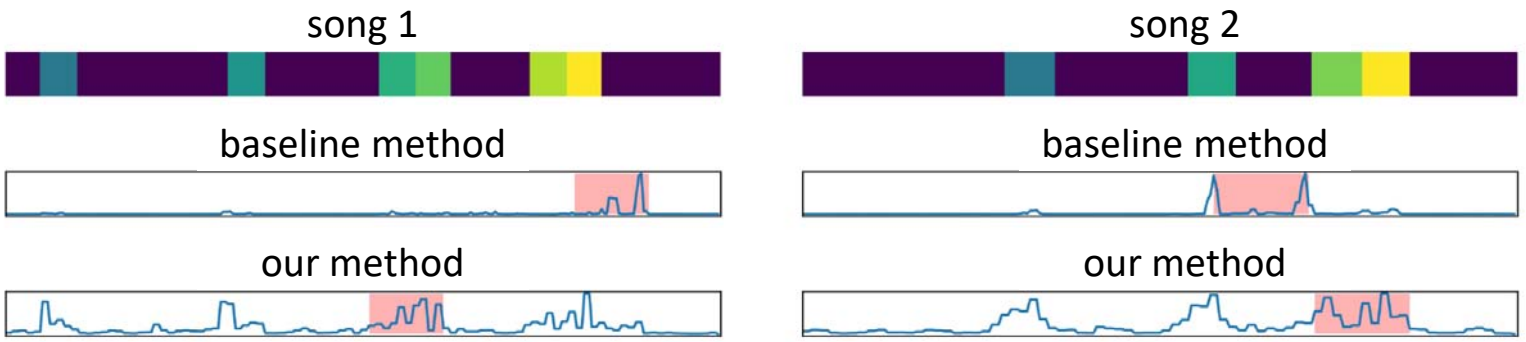
- CNN for **emotion prediction** + **attention** (predicting weights of different parts of a song)
- *Transfer learning*: no need of structural (chorus) labels



Ref: Huang et al., "Pop music highlighter: Marking the emotion keypoints," TISMIR 2018

Extension 1: Music Thumbnailing (Highlight Dectection)

- Performance of different music highlight extraction methods on “chorus detection”
  - Training data: MER31K (emotion labels)
  - Test data: RWC-Pop100 (chorus labels)
  - The baseline method is based on spectral energy



Ref: Huang et al., “Pop music highlighter: Marking the emotion keypoints,” TISMIR 2018

Extension 2: Music Sequencing

https://www.youtube.com/watch?v=yE5DiniY45w

- Find an ordering of music pieces within a music playlist
- Or “medley” (mashup) generation (ref: “Pop Danthology”)

Daniel Kim

@canadankim · 1.06M subscribers · 76 videos

Content creator most known for making "Pop Danthology" ...more

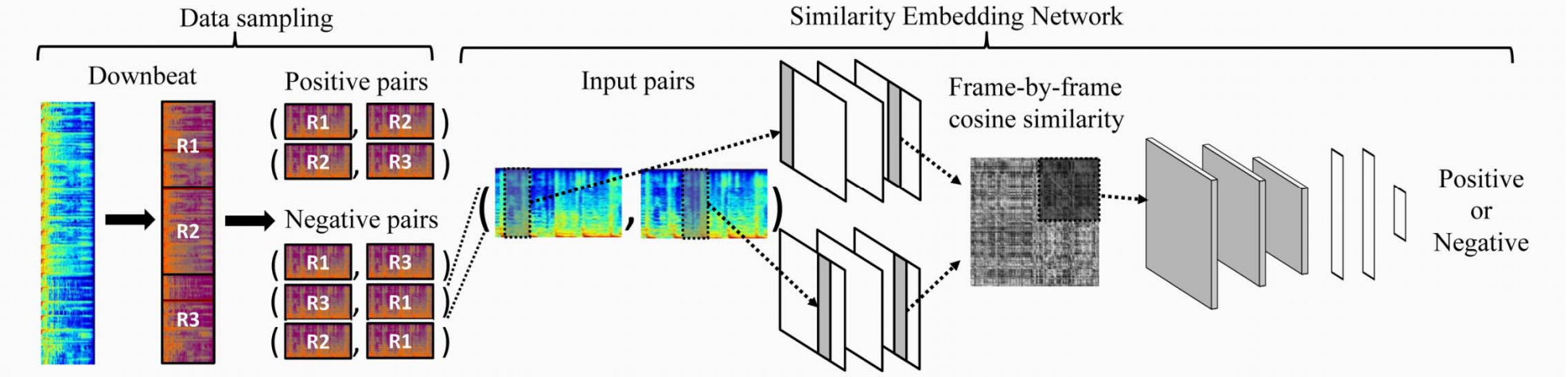
facebook.com/canadankim and 3 more links

Subscribe

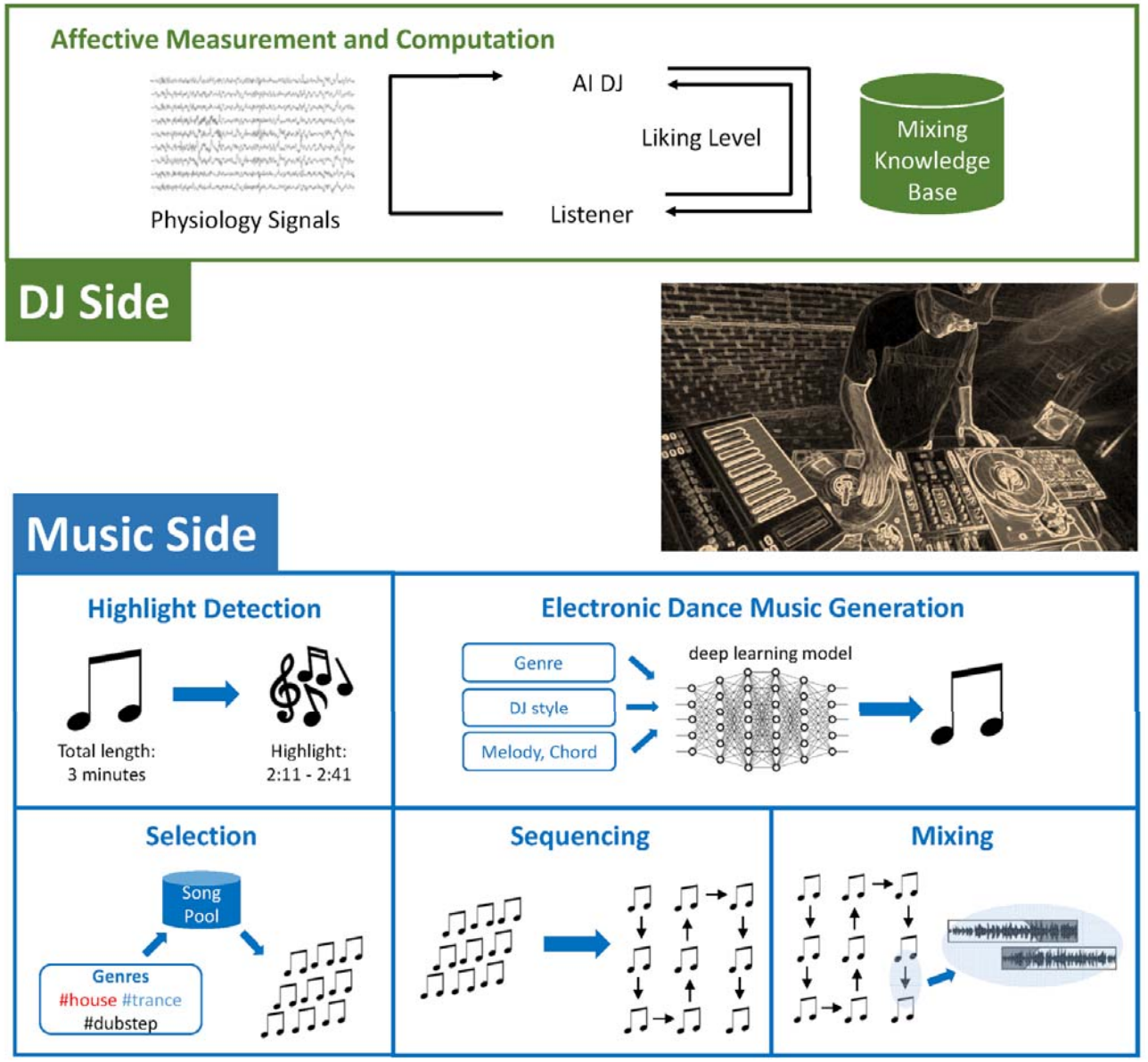
Extension 2: Sequencing via Solving the Music Puzzle Game

https://remyhuang.github.io/music_puzzle_game/

- Divide a song into non-overlapping chunks
- Learn to order them by contrastive learning
  - Positive pair: R1R2, R2R3
  - Negative pair: R2R1, R3R2, R1R3, R3R1



AI DJ


Affective Measurement and Computation
Physiology Signals
AI DJ
Liking Level
Listener
Mixing Knowledge Base
DJ Side
Music Side
Highlight Detection
Total length: 3 minutes
Highlight: 2:11 - 2:41
Electronic Dance Music Generation
Genre
DJ style
Melody, Chord
deep learning model
Selection
Song Pool
Genres
#house #trance #dubstep
Sequencing
Mixing

Outline

- Music emotion
- Structure/form analysis
- **Alignment**
- Rhythm & beat tracking

FMP Notebook

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C3/C3.html

Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
B	Basics	Basic information on Python, Jupyter notebooks, Anaconda package management system, Python environments, visualizations, and other topics	[html]	[ipynb]
0	Overview	Overview of the notebooks (https://www.audiolabs-erlangen.de/FMP)	[html]	[ipynb]
1	Music Representations	Music notation, MIDI, audio signal, waveform, pitch, loudness, timbre	[html]	[ipynb]
2	Fourier Analysis of Signals	Discrete/analog signal, sinusoid, exponential, Fourier transform, Fourier representation, DFT, FFT, STFT	[html]	[ipynb]
3	Music Synchronization	Chroma feature, dynamic programming, dynamic time warping (DTW), alignment, user interface	[html]	[ipynb]

Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
4	Music Structure Analysis	Similarity matrix, repetition, thumbnail, homogeneity, novelty, evaluation, precision, recall, F-measure, visualization, scape plot	[html]	[ipynb]
5	Chord Recognition	Harmony, music theory, chords, scales, templates, hidden Markov model (HMM), evaluation	[html]	[ipynb]
6	Tempo and Beat Tracking	Onset, novelty, tempo, tempogram, beat, periodicity, Fourier analysis, autocorrelation	[html]	[ipynb]
7	Content-Based Audio Retrieval	Identification, fingerprint, indexing, inverted list, matching, version, cover song	[html]	[ipynb]
8	Musically Informed Audio Decomposition	Harmonic/percussive separation, signal reconstruction, instantaneous frequency, fundamental frequency (F0), trajectory, nonnegative matrix factorization (NMF)	[html]	[ipynb]

Audio-to-Audio Synchronization: Intro

- Two interpretations – Tchaikovsky Violin Concerto

Jascha Heifetz

https://youtu.be/kFaq9kTIcaY?t=39s

David Oistrakh

https://youtu.be/fNCeYKfAOZI?si=0dGo2LBEPRHgfadl&t=108

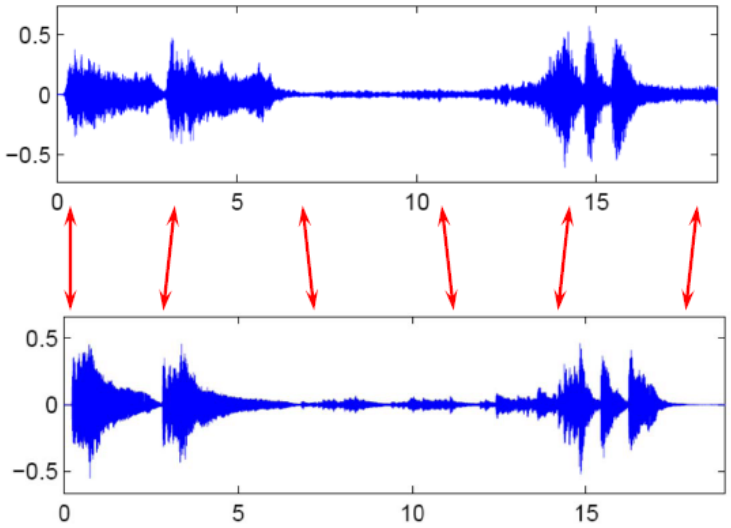
Audio-to-Audio Synchronization: Intro

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C3/C3_MusicSynchronization.html

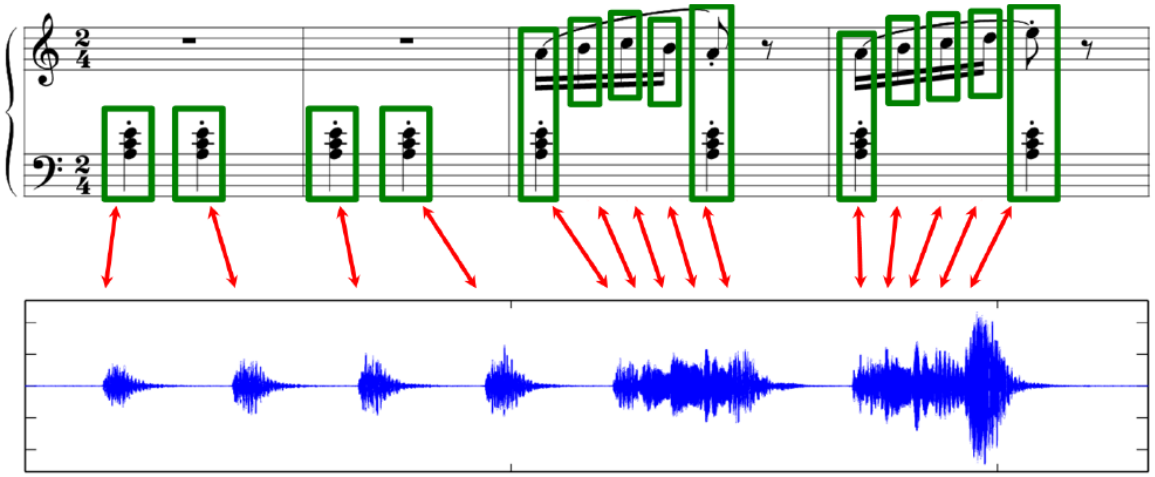
Beethoven's Fifth

Karajan

Scherbakov



Audio-to-Score Synchronization: Intro



- Need to take into account tempo variations

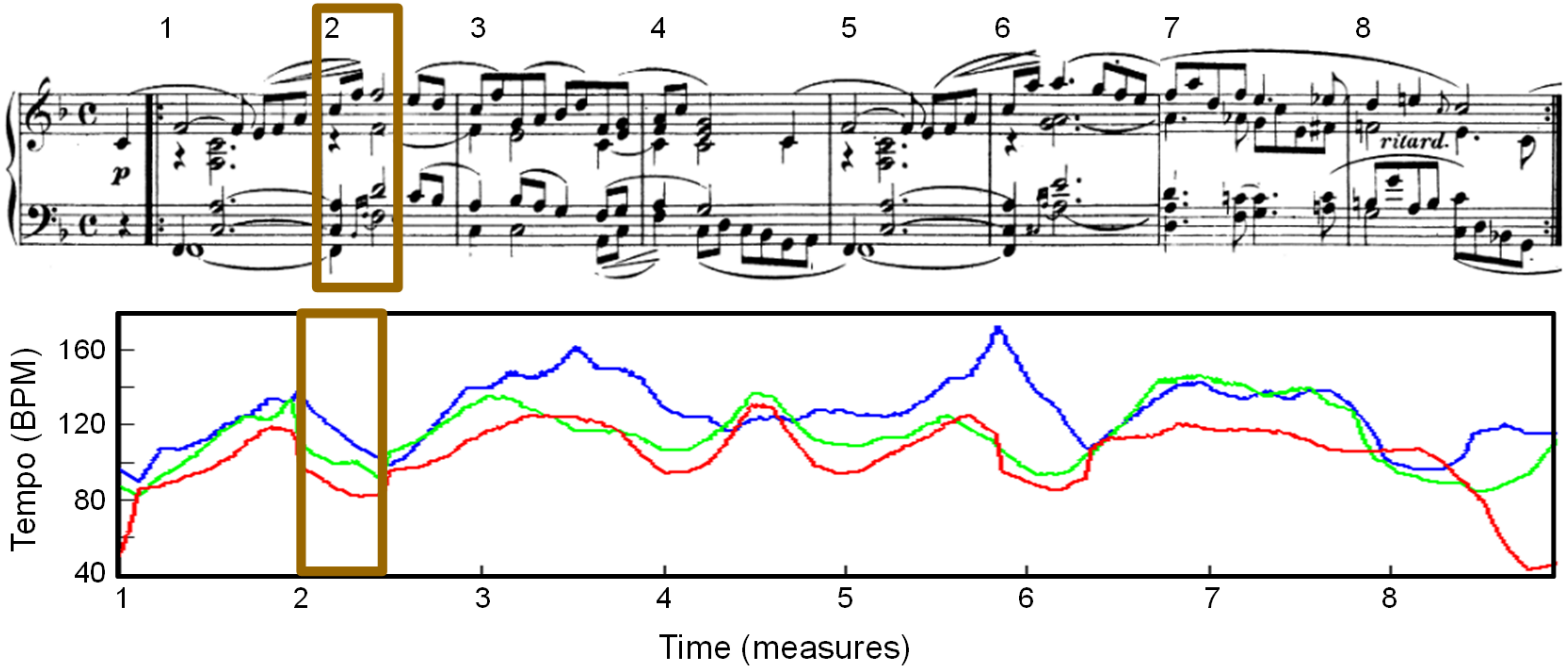
Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Audio-to-Score Synchronization: Intro

- **Goal**: given the score of a music piece and an audio recording of it, align them in time
- **Offline**
  - the whole audio recording is given
  - application: *performance analysis, feature extraction*
- **Online**
  - the alignment is done on-the-fly progressively while the recording is being played
  - a.k.a. score following
  - constraint: cannot "look into the future" (i.e. has to be *causal*)
  - application: *automatic accompaniment, page turner*
  - **harder** due to the causal and low-latency constraint

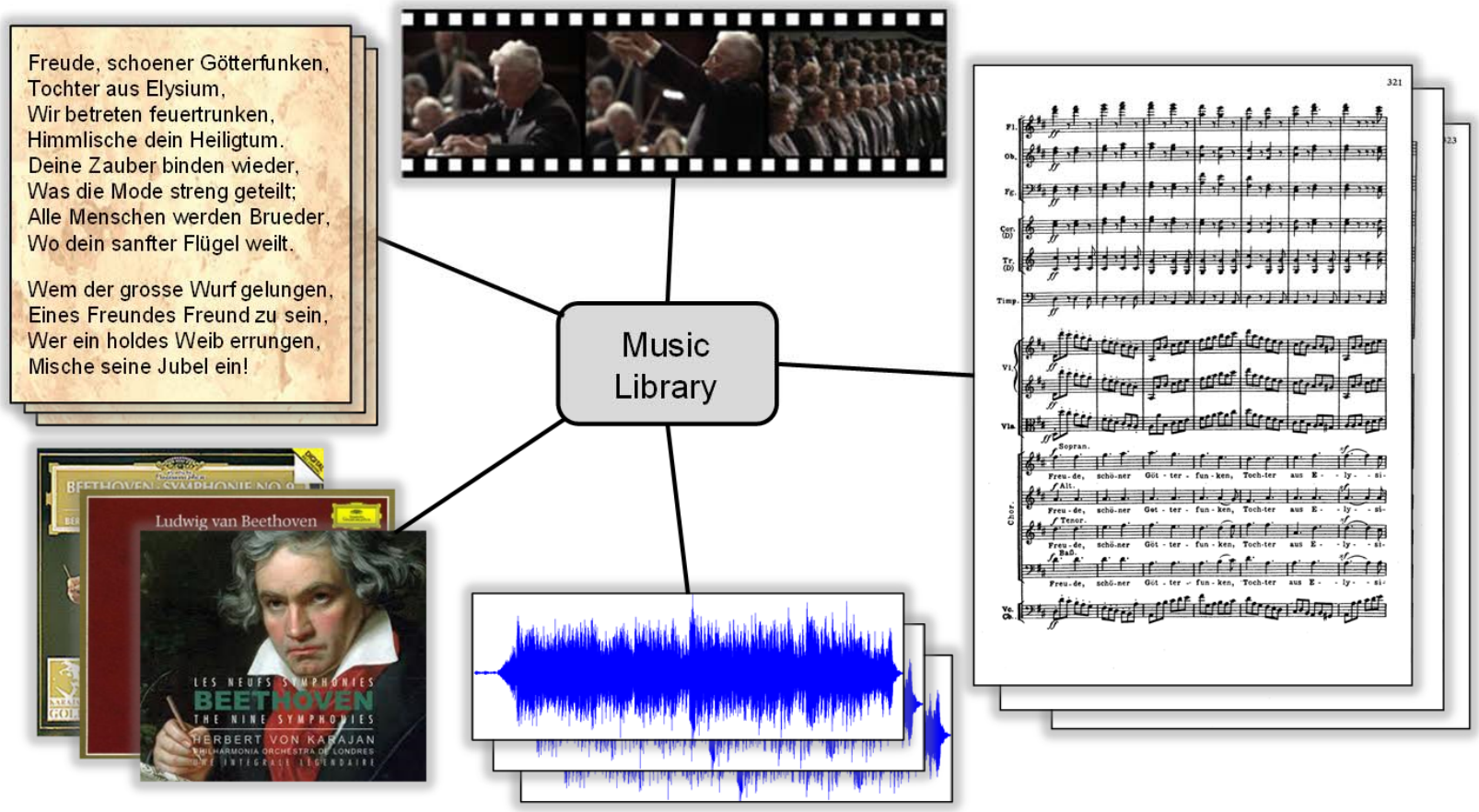
Offline Application: Performance Analysis

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C3/C3S3_MusicAppTempoCurve.html



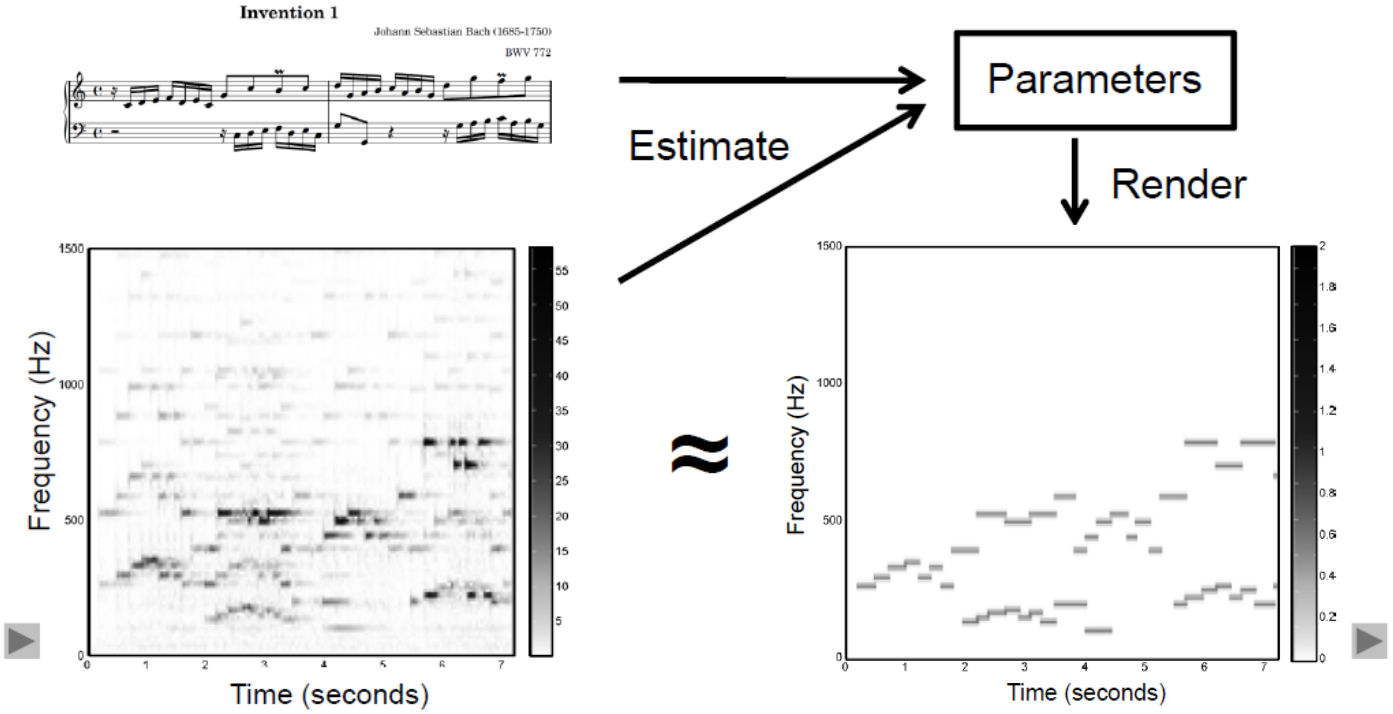
Offline Application: Feature Extraction

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C3/C3S3_MusicAppNav.html



Offline Application: Score-Informed Source Separation

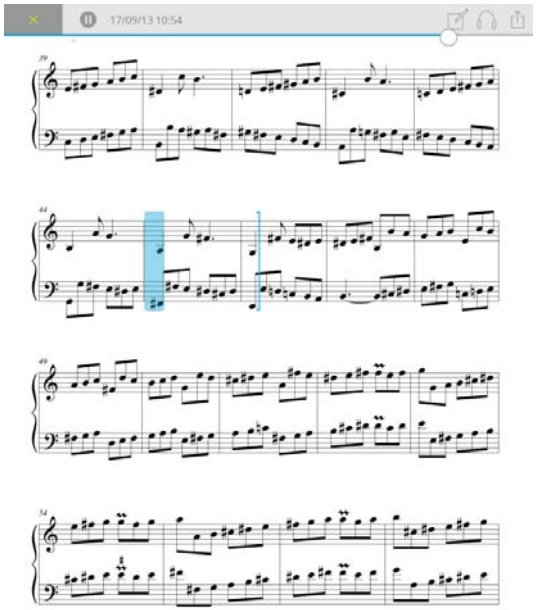
Goal: approximate spectrogram using a parametric model exploiting the score (requires *offline* synchronization)



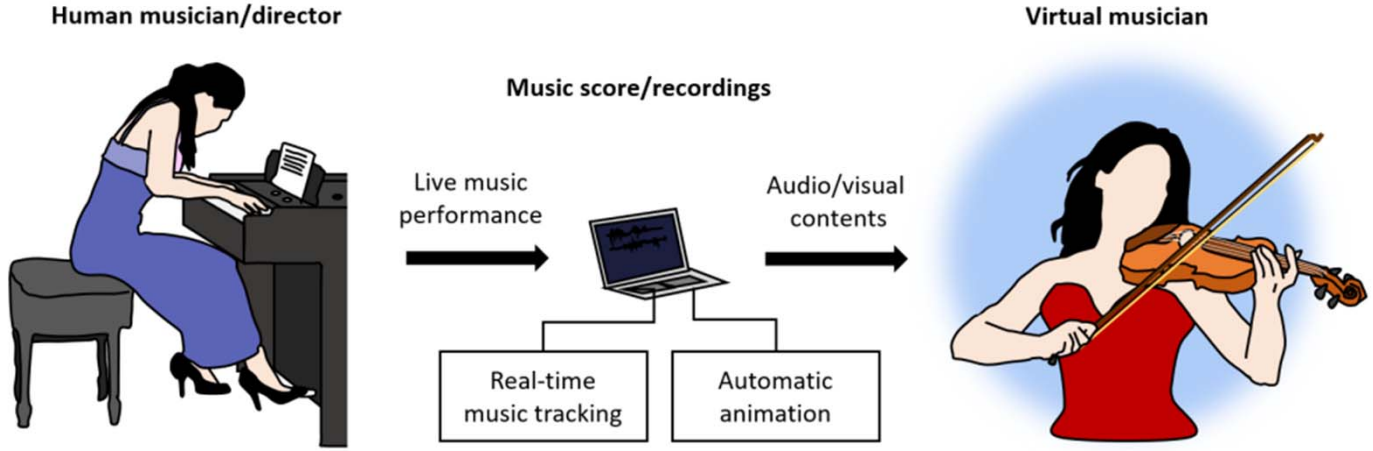
Online Application: Page Turner

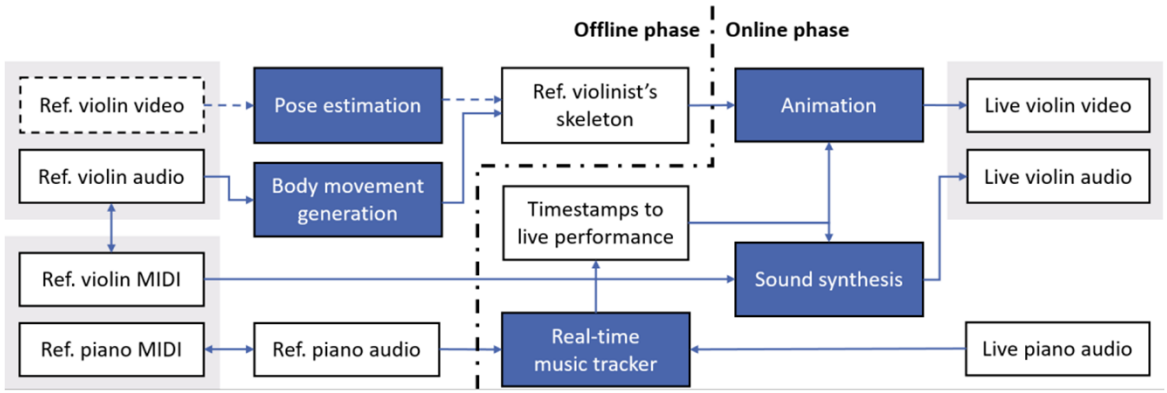
https://www.youtube.com/watch?v=HBXJZKTOcpw&t=25s

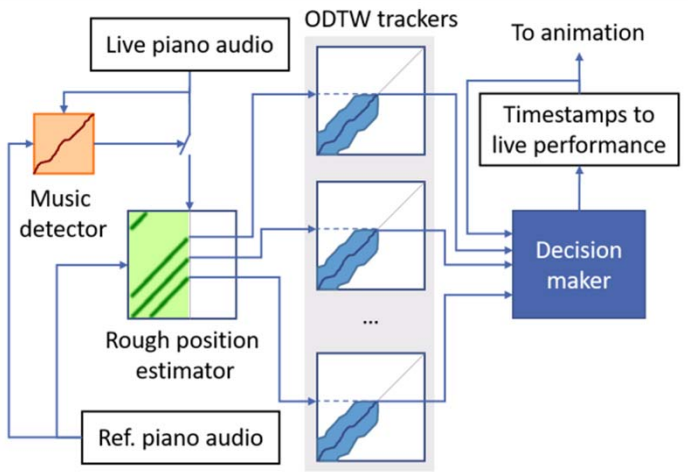
- **Goal**: a computer listens to the music and knows “when” to turn the pages (requires *online* synchronization)



Online Application: Automatic Accompaniment





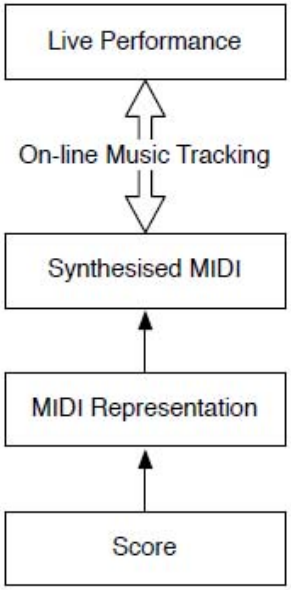


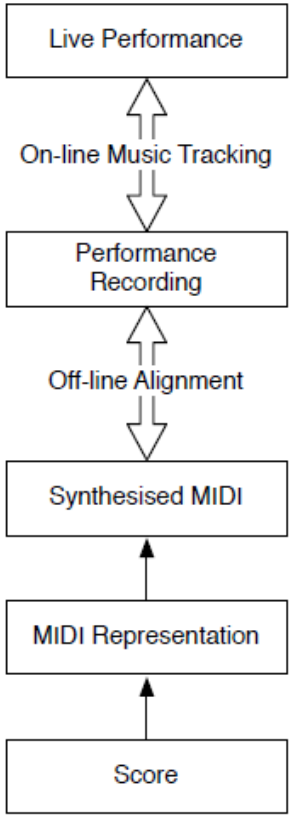
Ref: Lin et al, "A human-computer duet system for music performance," ACM Multimedia 2020

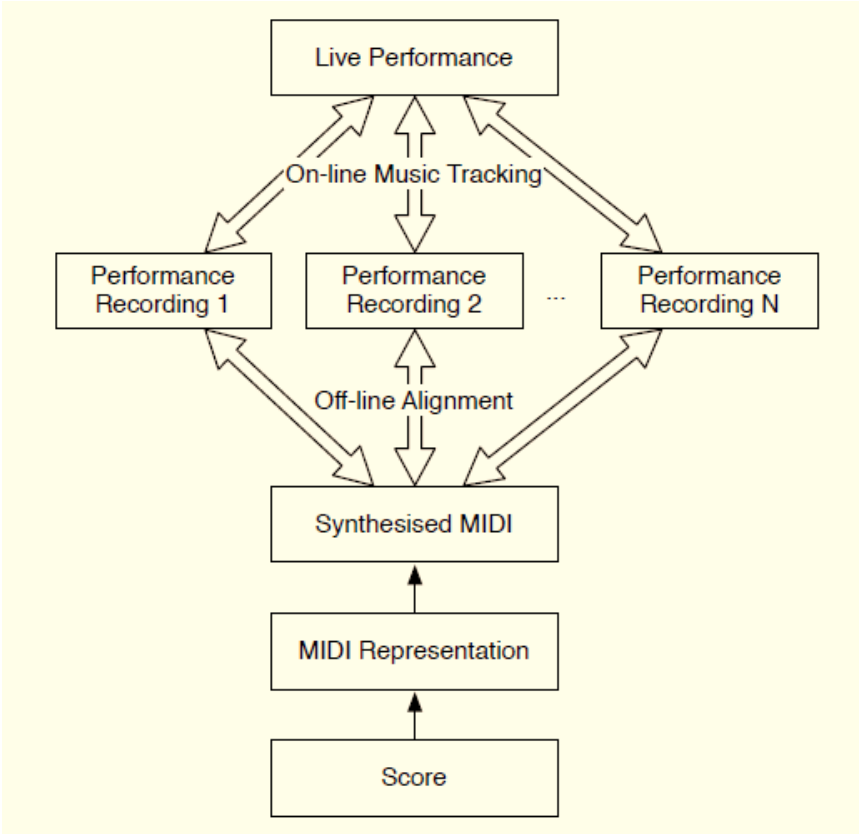
Audio-to-Score Synchronization: Approach

- **Approach 1**
  - use MIDI synthesizers (e.g. fluidsynth) to convert a score representation into a sound file
  - then treat it as an audio-to-audio synchronization problem
  - advantage
    - easy to implement
    - applicable for both offline and online scenario
  - drawback
    - low quality/deadpan/mechanical
    - a performance implicitly encodes a lot of information that is missing in the symbolic score

- **Approach 2**
  - use different performances of the piece as reference







Ref: Arzt et al, "Real-time music tracking using multiple performances as a reference," ISMIR 2015

Recap

- Many music synchronization problems **can be viewed as** an **audio-to-audio** synchronization problem

- **Question**: how to compare two audio sequences and find musically corresponding time positions
  1. Feature representation
  2. Alignment technique, offline and online

- First research dates back to 1984

Ref 1: “The synthetic performer in the context of live performance,” ICMC 1984

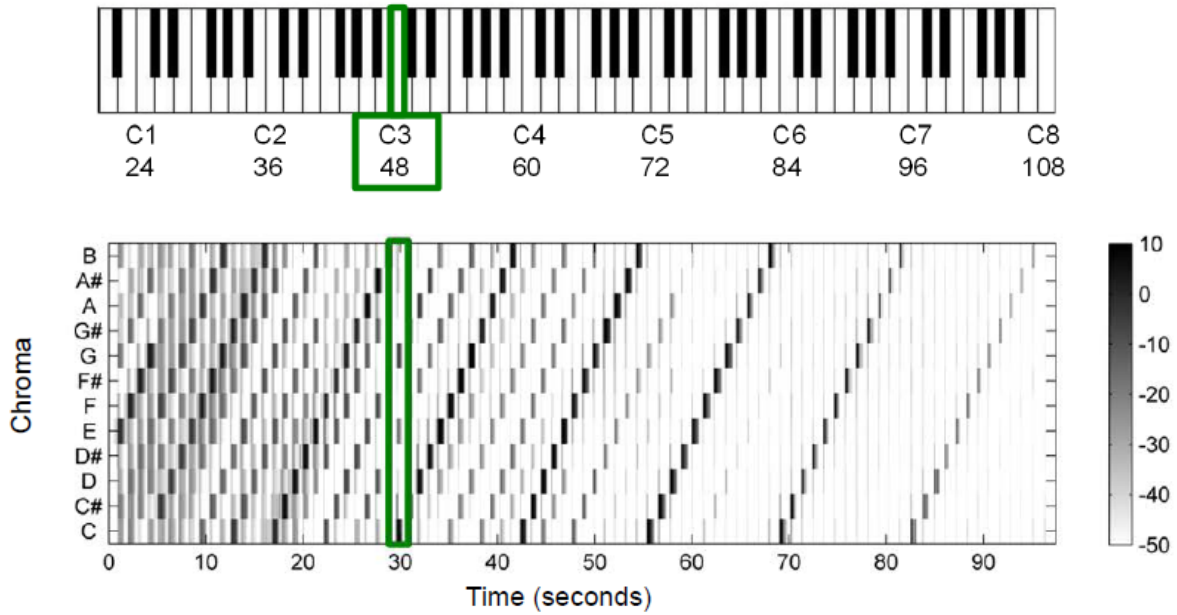
Ref 2: “An on-line algorithm for real-time accompaniment,” ICMC 1984

Two Main Components of Synchronization

1. **Feature representation**
   - robust but discriminative
   - robust to variations in instrumentation, timbre, and dynamics
   - correlate to harmonic progression

2. **Alignment technique**
   - deals with local and global tempo variations
   - needs to be efficient

Chroma Features (Chromagrams)

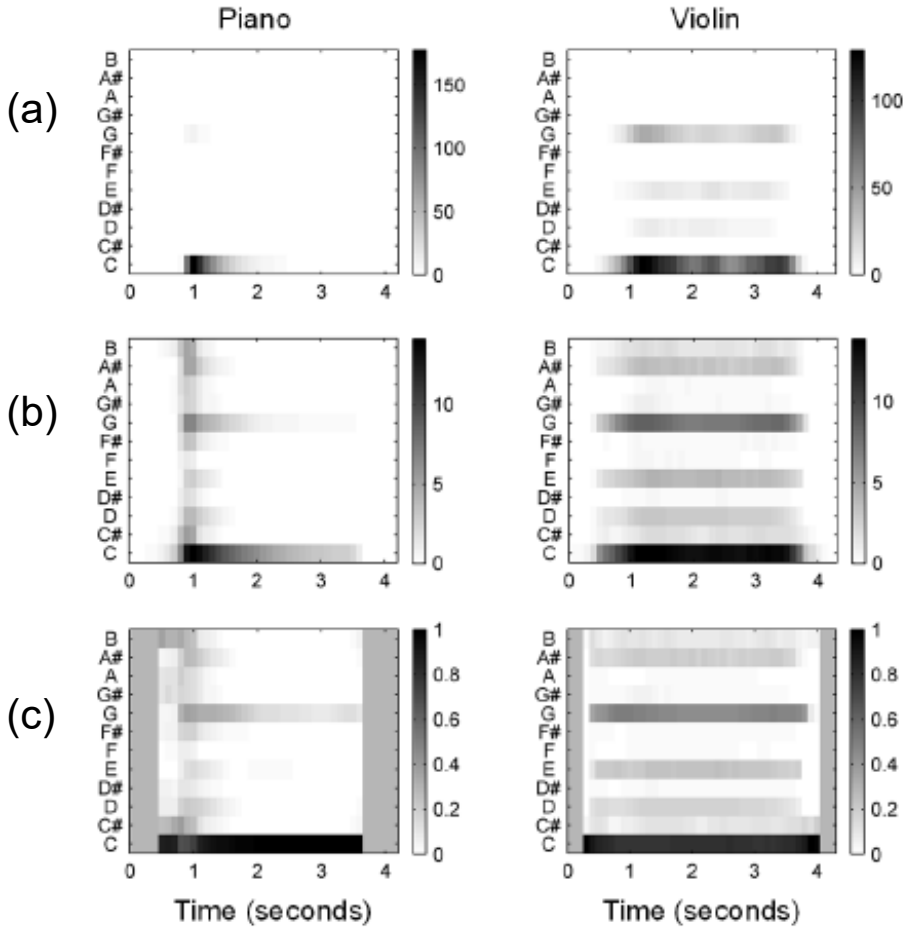


- **Timbre-invariant**: 1st, 2nd, 4th, 8th harmonics are in the same chroma band (similarly for 3rd, 6th, 12th harmonics)
- Correlate to harmonic progression

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Chroma Features

- **Timbre-invariant**: frame-wise normalization reduces differences in energy decay

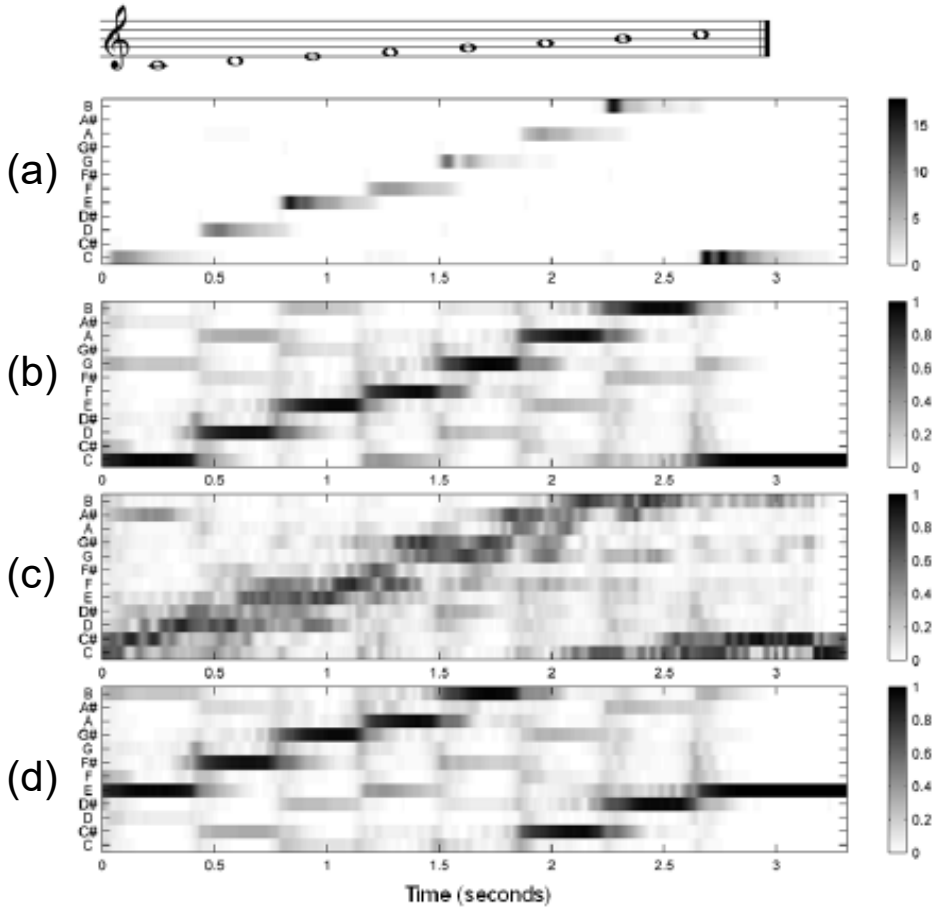


a. original chroma
b. log compression
c. frame-wise normalization

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Chroma Features

- **Tuning**: global frequency deviation



a. original chroma

b. log compression + frame-wise normalization

c. chroma of a piano tuned 40 cents upwards

d. chroma after correcting for tuning

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Chromagrams for Two Performances

- Compressed and normalized chromagram

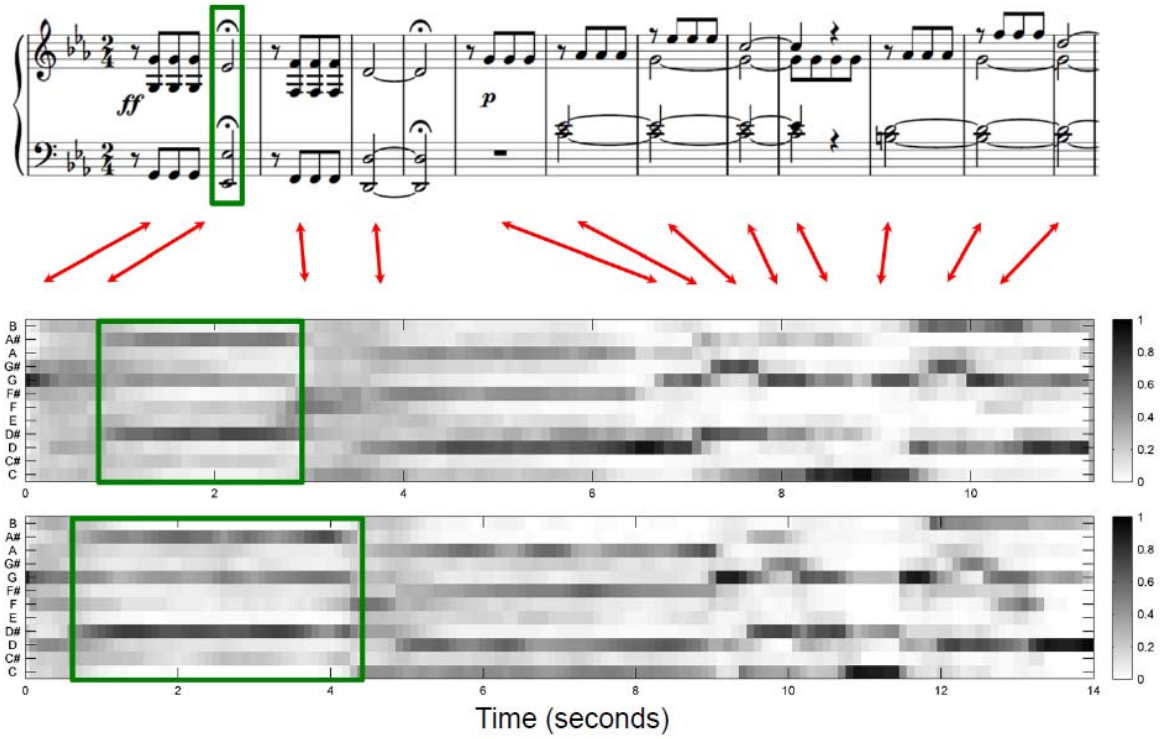


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Chromagrams for Two Performances

- Further enhanced chromagram (by quantization and smoothing)

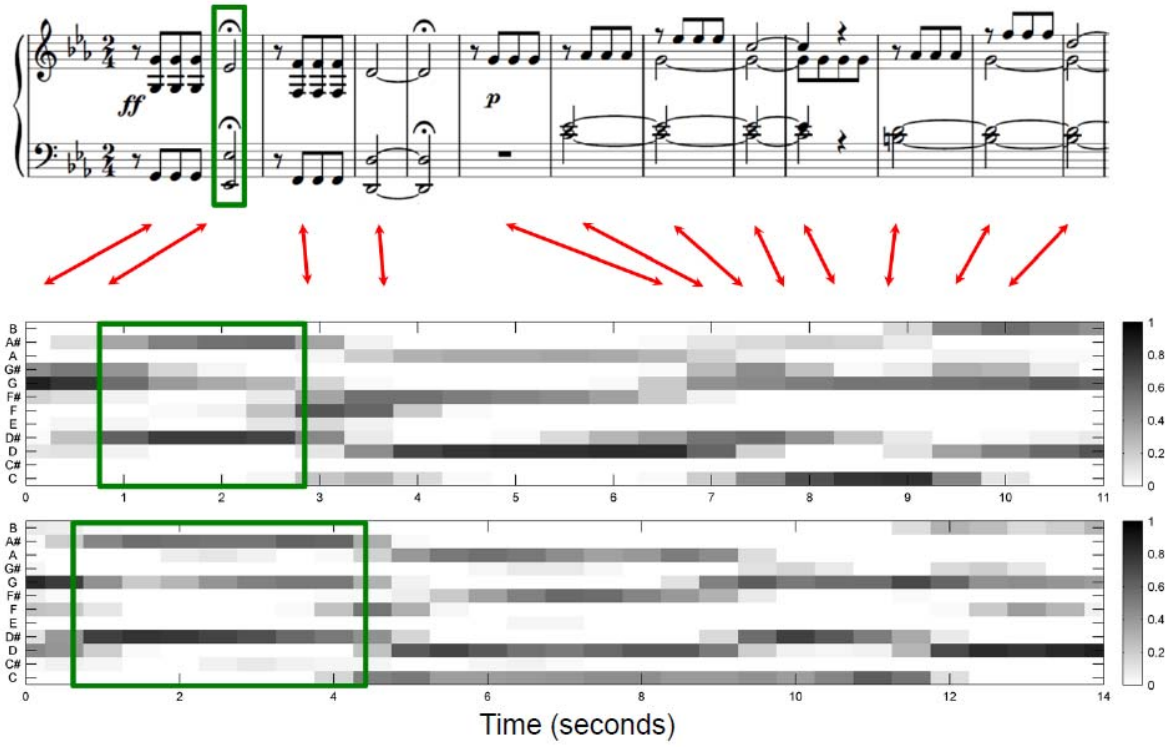
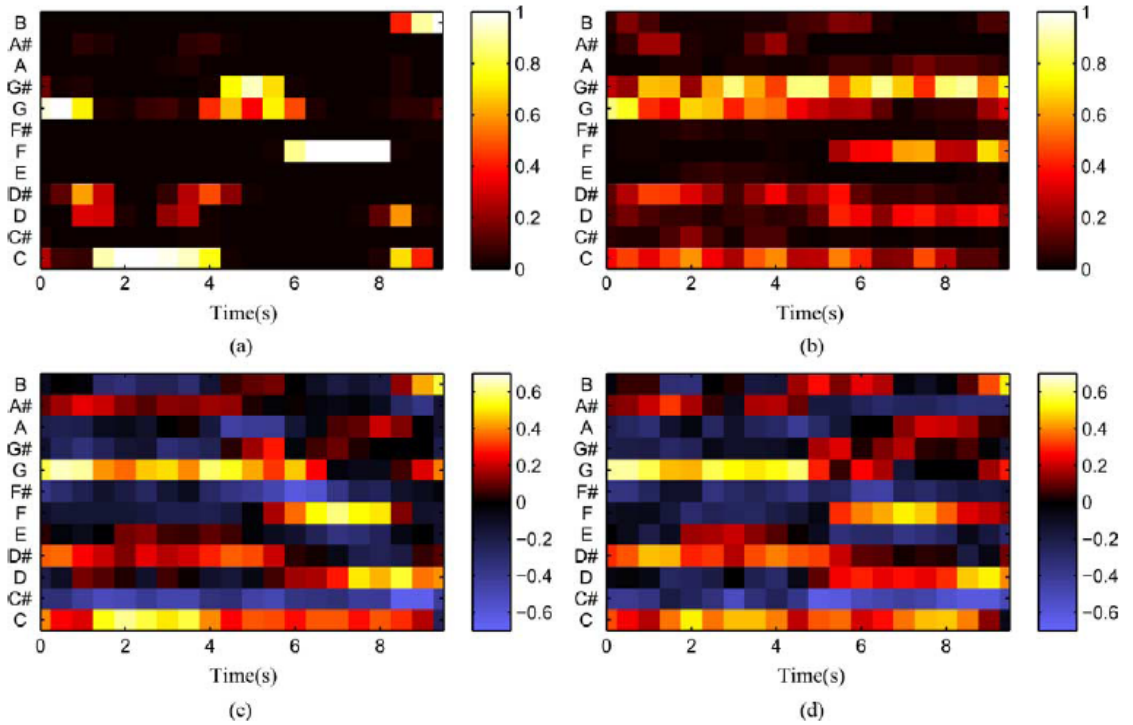


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Chroma Toolbox (in Matlab)

https://www.audiolabs-erlangen.de/resources/MIR/chromatoolbox/

clarinet
(woodwind)



trombone
(brass)

Figure from the chromatoolbox paper

Fig. 4. Various chromagrams of the passages E_1 (clarinet) and E_3 (trombone) in the Yablonsky recording of the Shostakovich Waltz. (a)/(b) Conventional chromagram of E_1/E_3. (c)/(d) CRP(55) chromagram of E_1/E_3. All chroma vectors are normalized w.r.t. the Euclidean norm.

Music Synchronization: Audio-to-Audio

- Two chromagrams

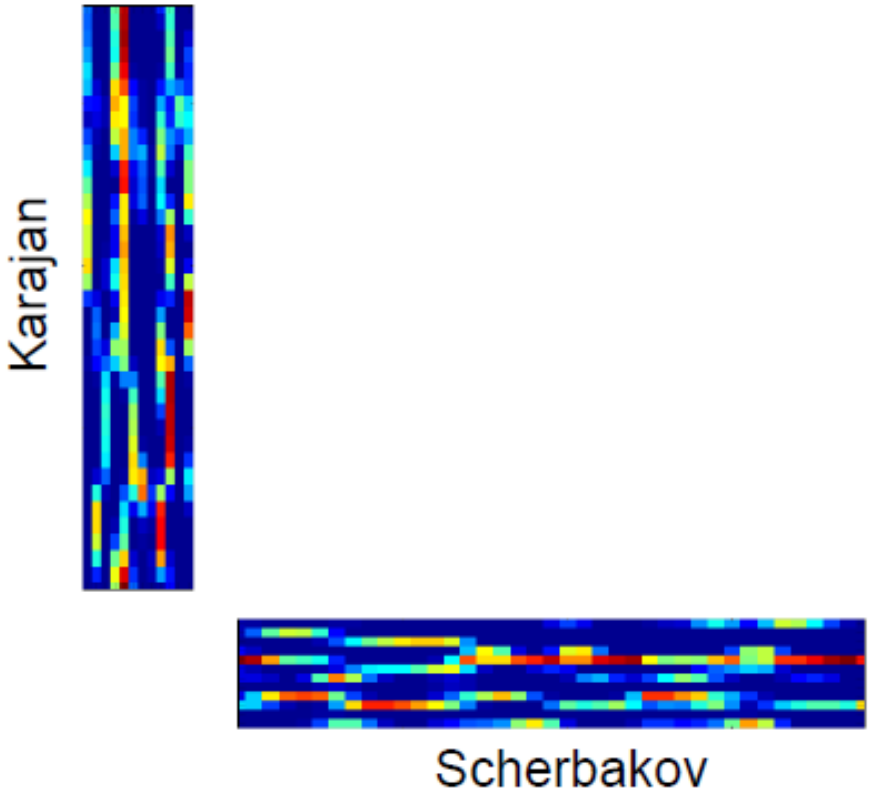
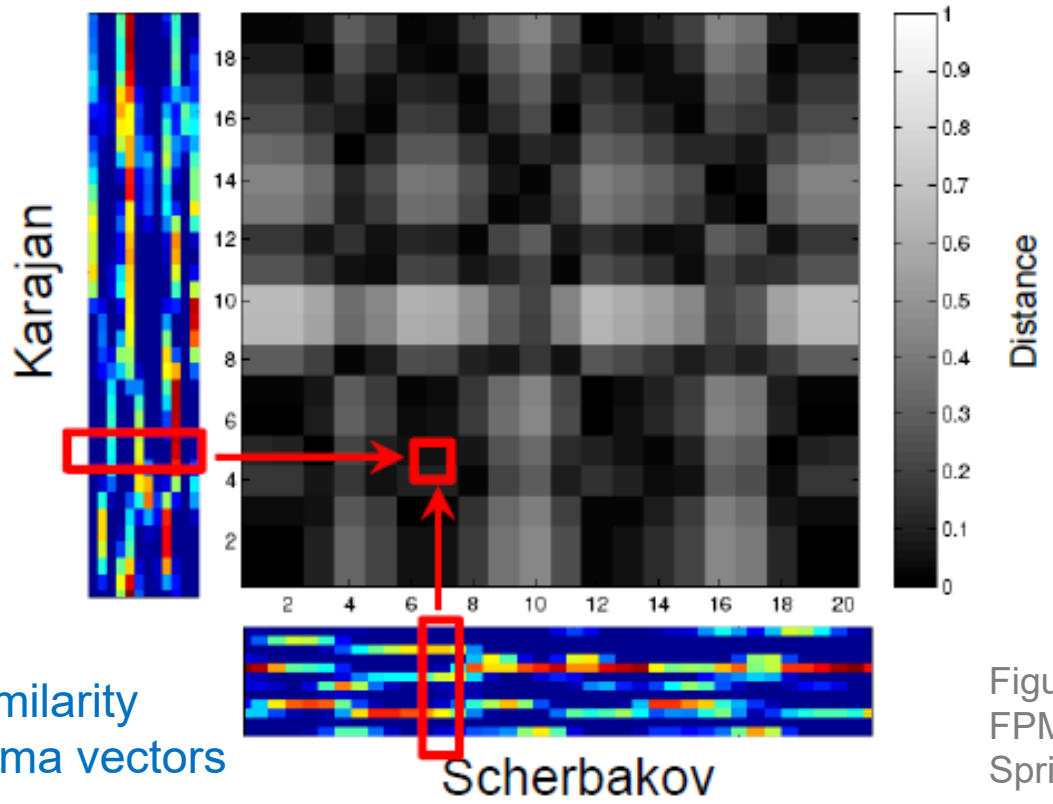


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Music Synchronization: Audio-to-Audio

- Compute the frame-by-frame **cost matrix**



e.g. cosine similarity between chroma vectors

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Music Synchronization: Audio-to-Audio

- **Cost minimizing alignment path**

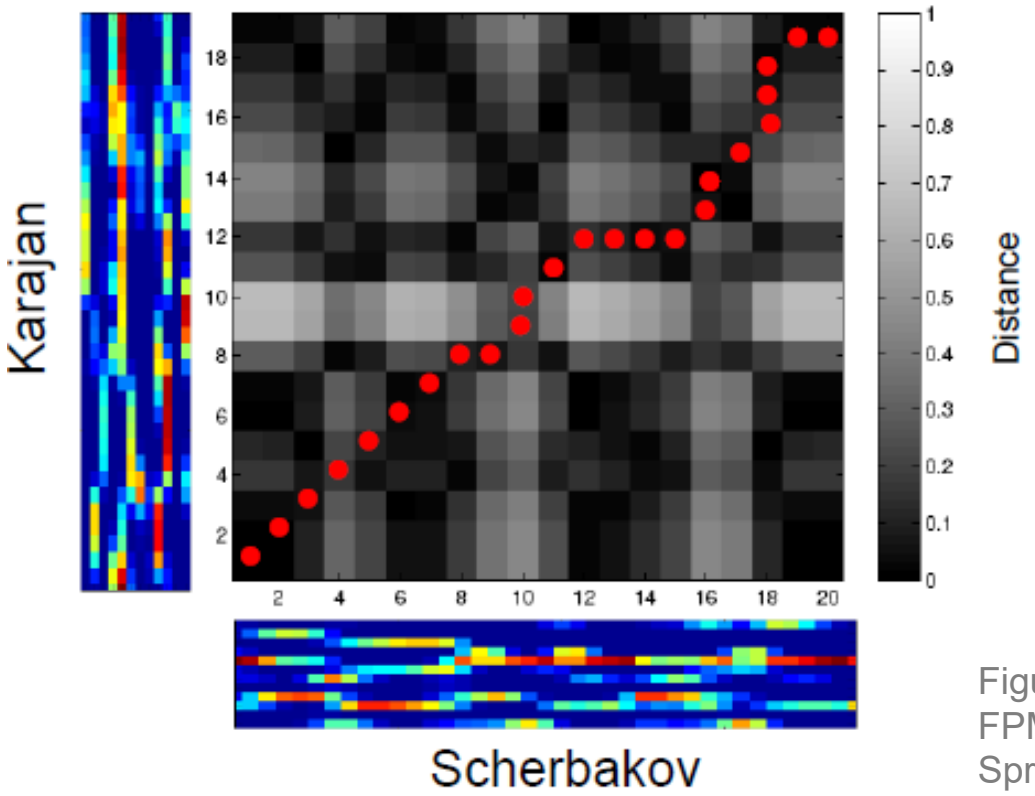


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Music Synchronization: Audio-to-Audio

- **Cost minimizing alignment path**

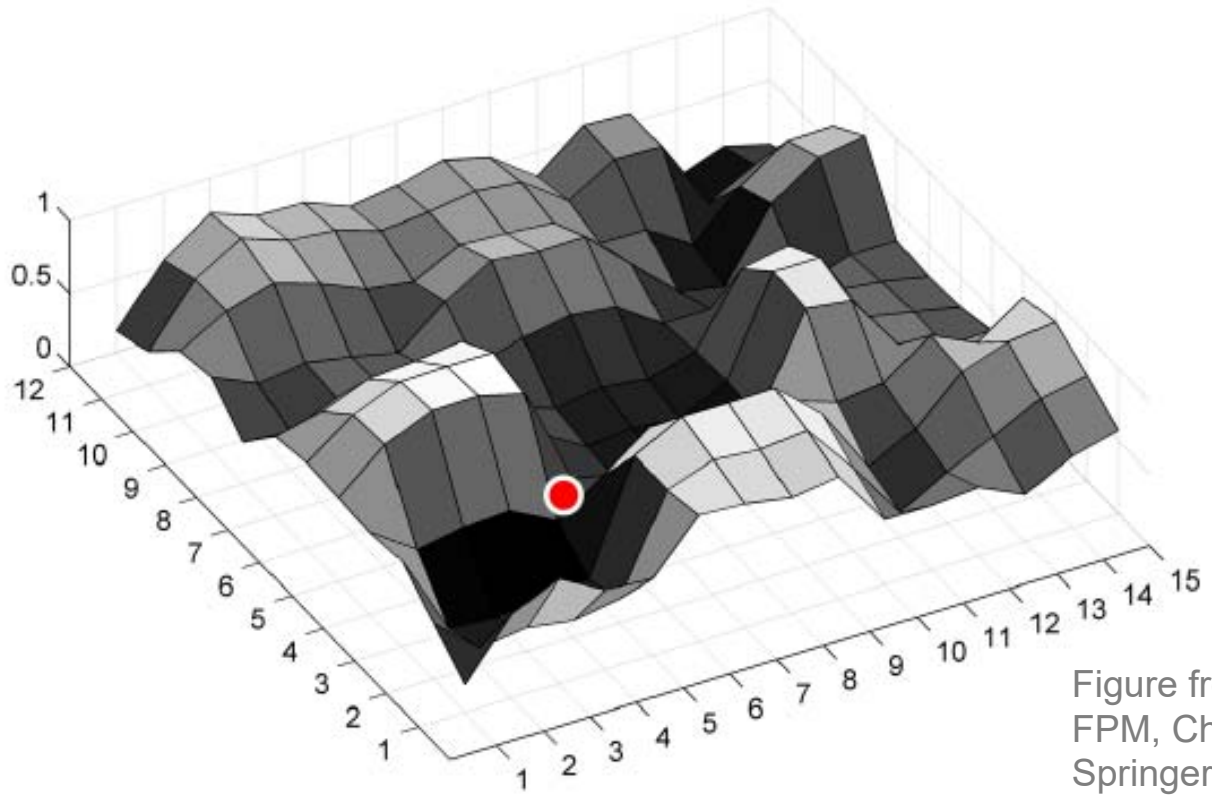


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Two Main Components of Synchronization

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   - robust but discriminative
   - robust to variations in instrumentation, timbre, and dynamics
   - correlate to harmonic progression

2. **Alignment technique**
   - deals with local and global tempo variations
   - needs to be efficient

How to Compute the Alignment?

- Cost matrix
- Constraints
  - boundary condition
  - monotonically increase
  - step size condition
- Problem formulation
  - given two sequences $X = (x_1, x_2, \ldots, x_N)$ and $Y = (y_1, y_2, \ldots, y_M)$
  - find a warping path $p = (p_1, p_2, \ldots, p_L)$ with $p_l = (n_l, ml) \in [1:N]$ x $[1:M]$

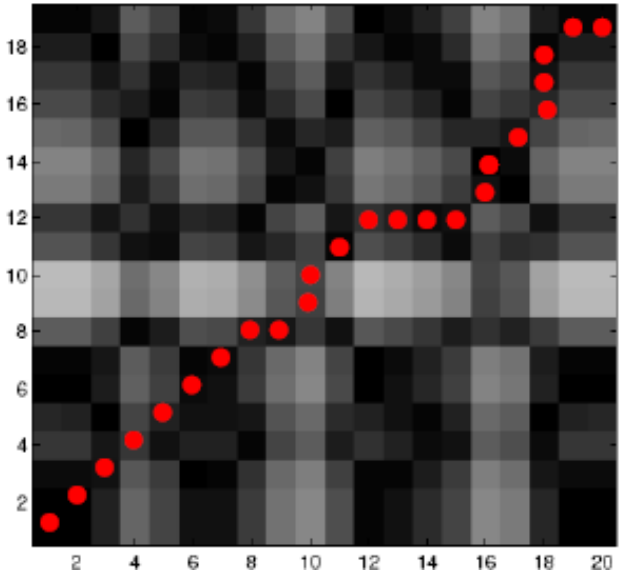
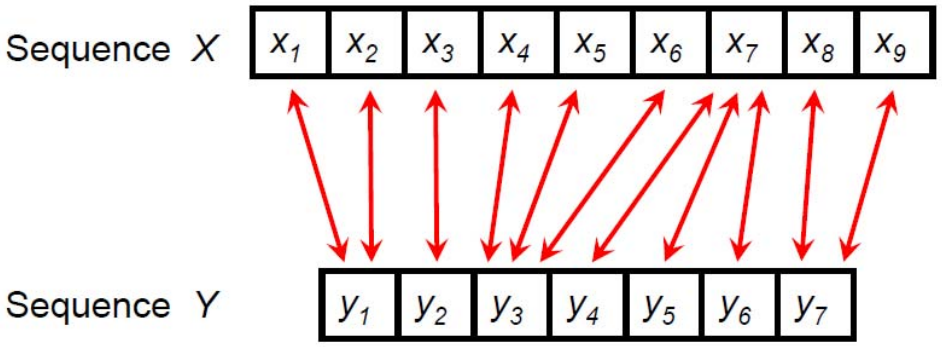
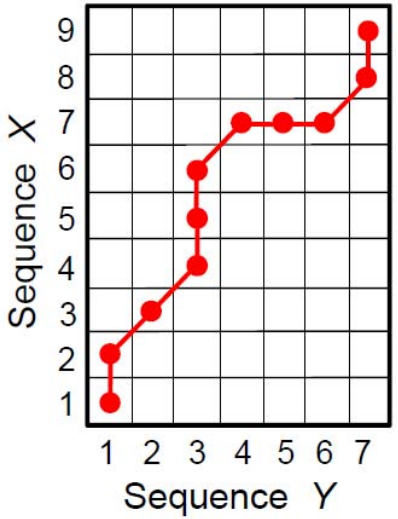


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Alignment



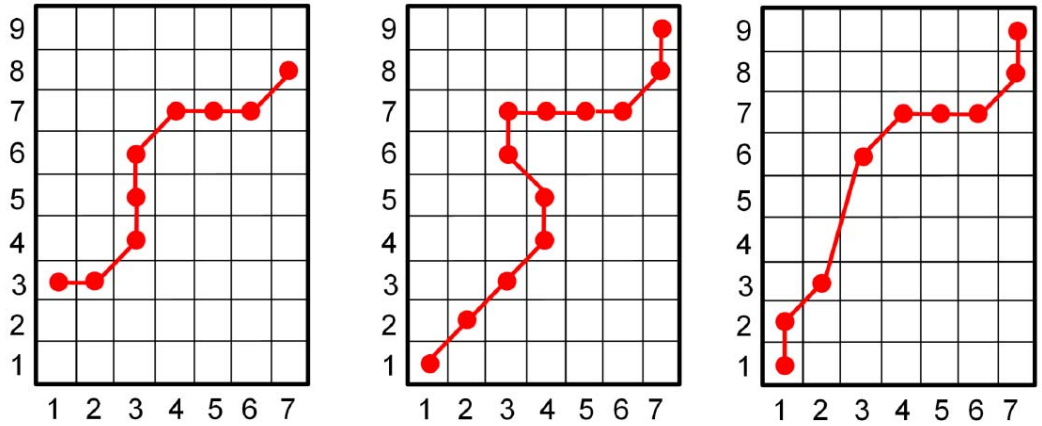


- Boundary condition: $p_1 = (1,1)$ and $p_L = (N,M)$
- Monotonicity condition: $n_1 \leq n_2 \leq \ldots \leq n_L$ and $m_1 \leq m_2 \leq \ldots \leq m_L$
- Step size condition: $p_{\ell+1} - p_\ell \in \{(1,0),(0,1),(1,1)\}$ for $\ell \in [1 : L-1]$

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Alignment

- Invalid alignments



- Boundary condition: $p_1 = (1,1)$ and $p_L = (N,M)$
- Monotonicity condition: $n_1 \leq n_2 \leq \ldots \leq n_L$ and $m_1 \leq m_2 \leq \ldots \leq m_L$
- Step size condition: $p_{\ell+1} - p_\ell \in \{(1,0),(0,1),(1,1)\}$ for $\ell \in [1 : L-1]$

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping

- Dynamic programming
  - optimal sub-structure
  - overlapping sub-problems
- Complexity
  O(NM)
- Trace back

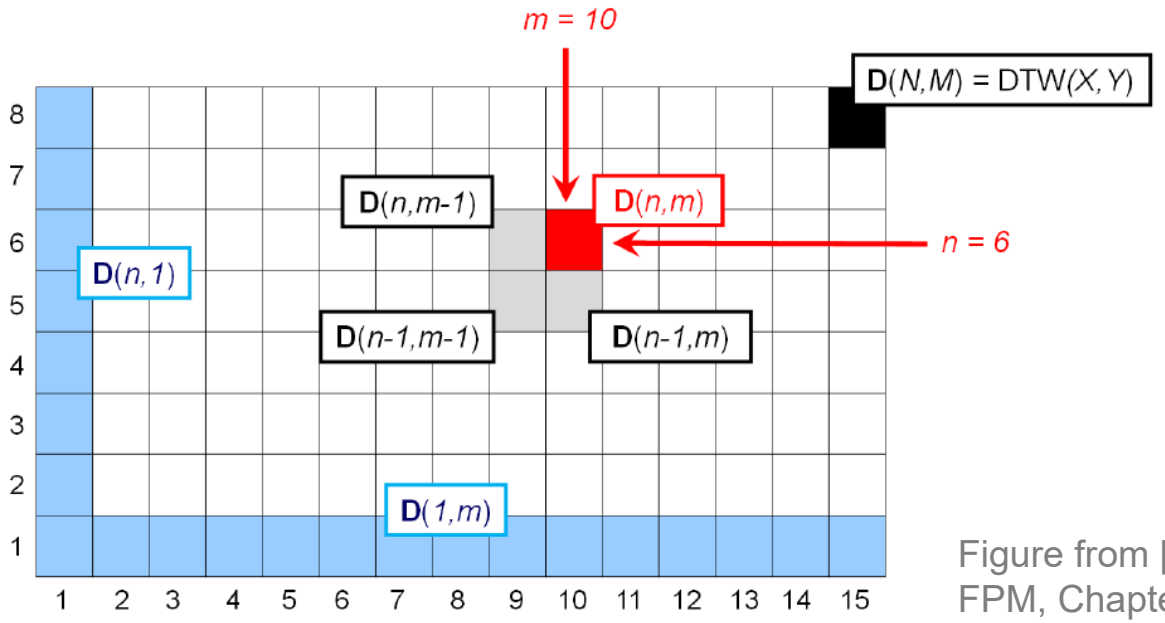
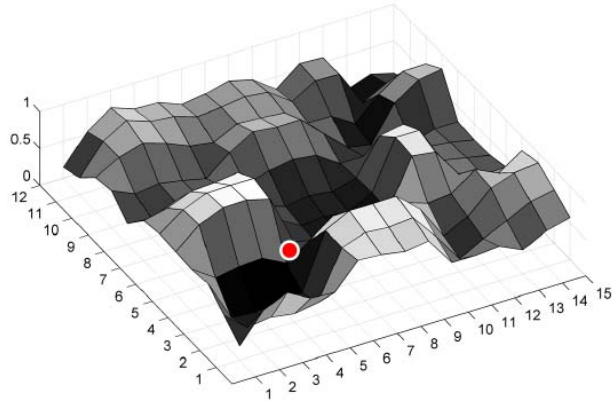


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping

$$
\begin{array}{lll}
(i) & D(N,M) = \mathrm{DTW}(X,Y) \\
(ii) & D(1,1) = C(1,1) \\
(iii) & D(n,1) = \sum_{k=1}^{n} C(k,1) \\
 & D(1,m) = \sum_{k=1}^{m} C(1,k)
\end{array}
$$



$$
(iv) \quad D(n,m) = \min \begin{pmatrix} D(n-1,m-1) \\ D(n-1,m) \\ D(n,m-1) \end{pmatrix} + C(n,m)
$$

for $n > 1, m > 1$

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping

Algorithm: DTW

Input: Cost matrix $\mathbf{C}$ of size $N \times M$
Output: Accumulated cost matrix $\mathbf{D}$
Optimal warping path P^*

Procedure: Initialize $(N \times M)$ matrix $\mathbf{D}$ by $\mathbf{D}(n,1) = \sum_{k=1}^{n} \mathbf{C}(k,1)$ for $n \in [1:N]$ and $\mathbf{D}(1,m) = \sum_{k=1}^{m} \mathbf{C}(1,k)$ for $m \in [1:M]$. Then compute in a nested loop for $n = 2,\ldots,N$ and $m = 2,\ldots,M$:

$$\mathbf{D}(n,m) = \mathbf{C}(n,m) + \min\{\mathbf{D}(n-1,m-1), \mathbf{D}(n-1,m), \mathbf{D}(n,m-1)\}.$$

Set $\ell = 1$ and $q_\ell = (N,M)$. Then repeat the following steps until $q_\ell = (1,1)$:

Increase ℓ by one and let $(n,m) = q_{\ell-1}$.
If $n = 1$, then $q_\ell = (1,m-1)$,
else if $m = 1$, then $q_\ell = (n-1,m)$,
else $q_\ell = \text{argmin}\{\mathbf{D}(n-1,m-1), \mathbf{D}(n-1,m), \mathbf{D}(n,m-1)\}$.
(If 'argmin' is not unique, take lexicographically smallest cell.)

Set $L = \ell$ and return $P^* = (q_L, q_{L-1}, \ldots, q_1)$ as well as $\mathbf{D}$.

From [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping: Example

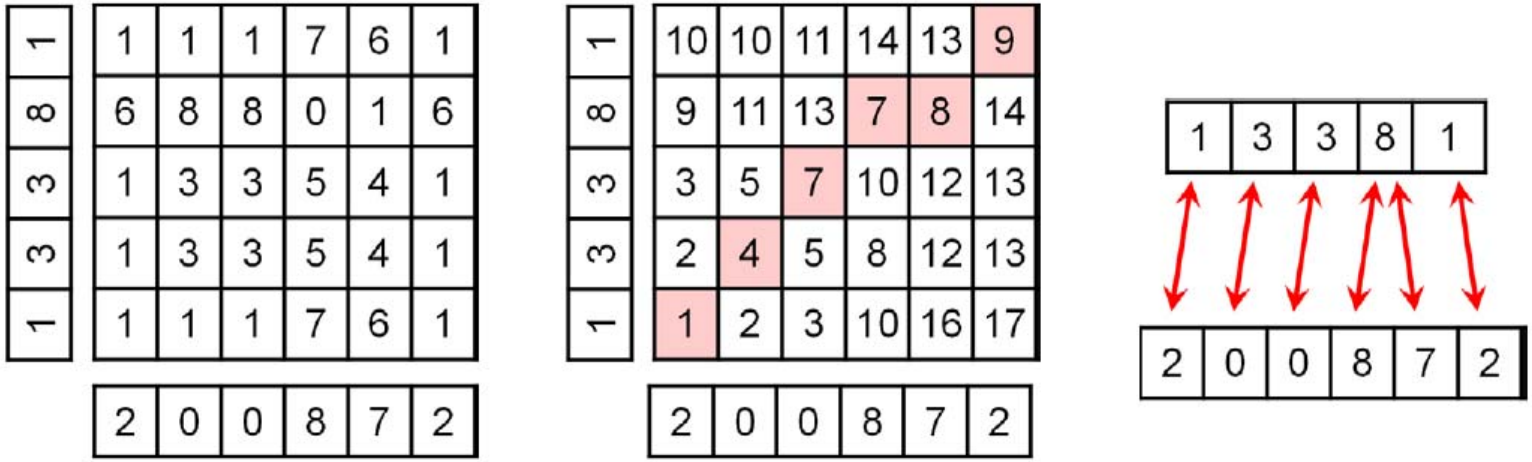
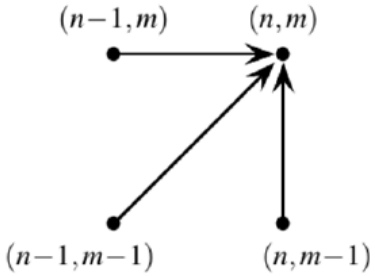
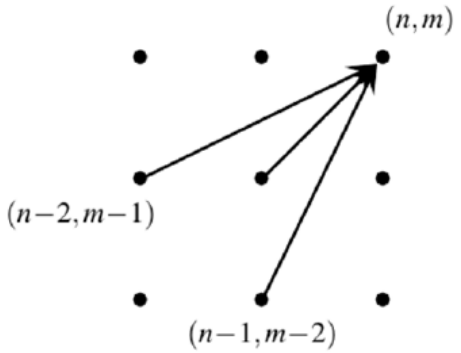
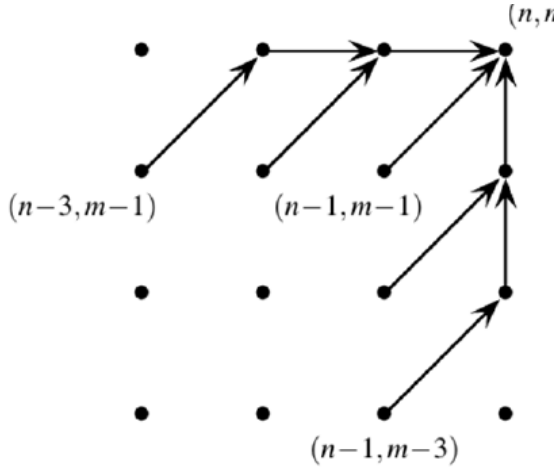


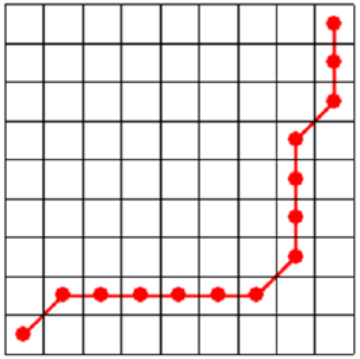
Figure from [Mueller, FPM, Chapter 3, Springer 2015]

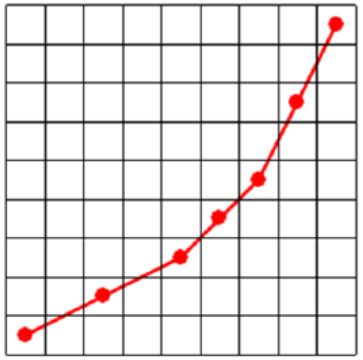
Dynamic Time Warping: Step Size











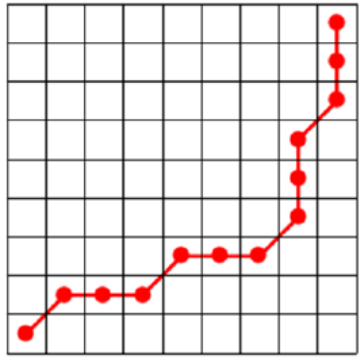
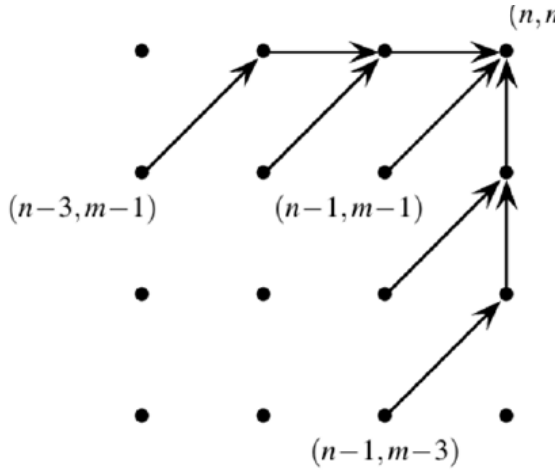


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping: Step Size

$$D(n,m) = C(n,m) + \min \begin{pmatrix} D(n-1,m-1) \\ D(n-2,m-1) + C(n-1,m) \\ D(n-1,m-2) + C(n,m-1) \\ D(n-3,m-1) + C(n-2,m) + C(n-1,m) \\ D(n-1,m-3) + C(n,m-2) + C(n,m-1) \end{pmatrix}$$



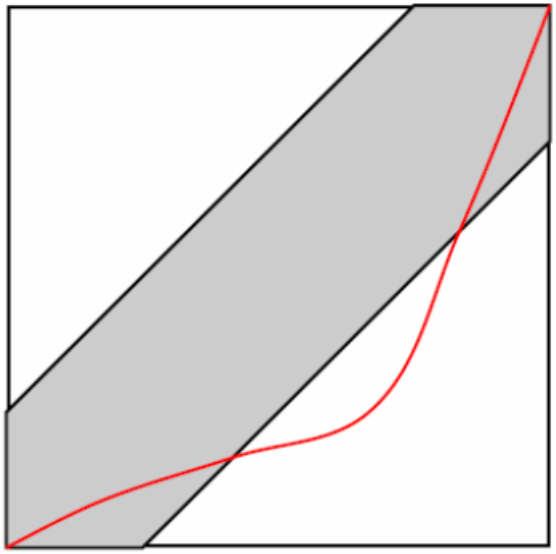
- Another variant (e.g. $w_d = 2$, $w_v = w_h = 1$):

$$D(n,m) = \min \begin{pmatrix} D(n-1,m-1) + w_d\, C(n,m) \\ D(n-1,m) + w_v\, C(n,m) \\ D(n,m-1) + w_h\, C(n,m) \end{pmatrix}$$

Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping: Global Constraint

Sakoe-Chiba band



Itakura parallelogram

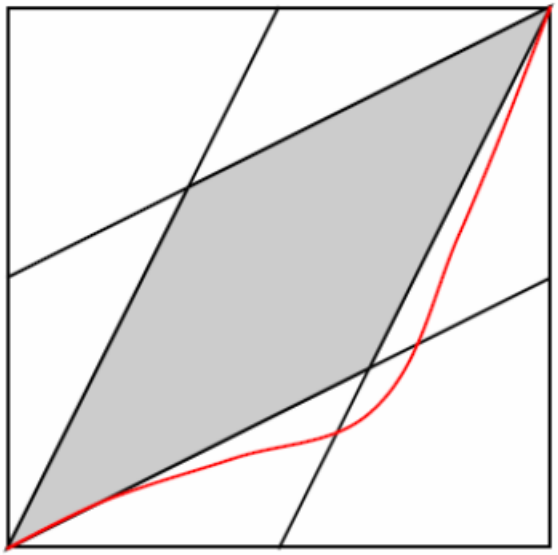


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Dynamic Time Warping: Multi-resolution

- Coarse → fine

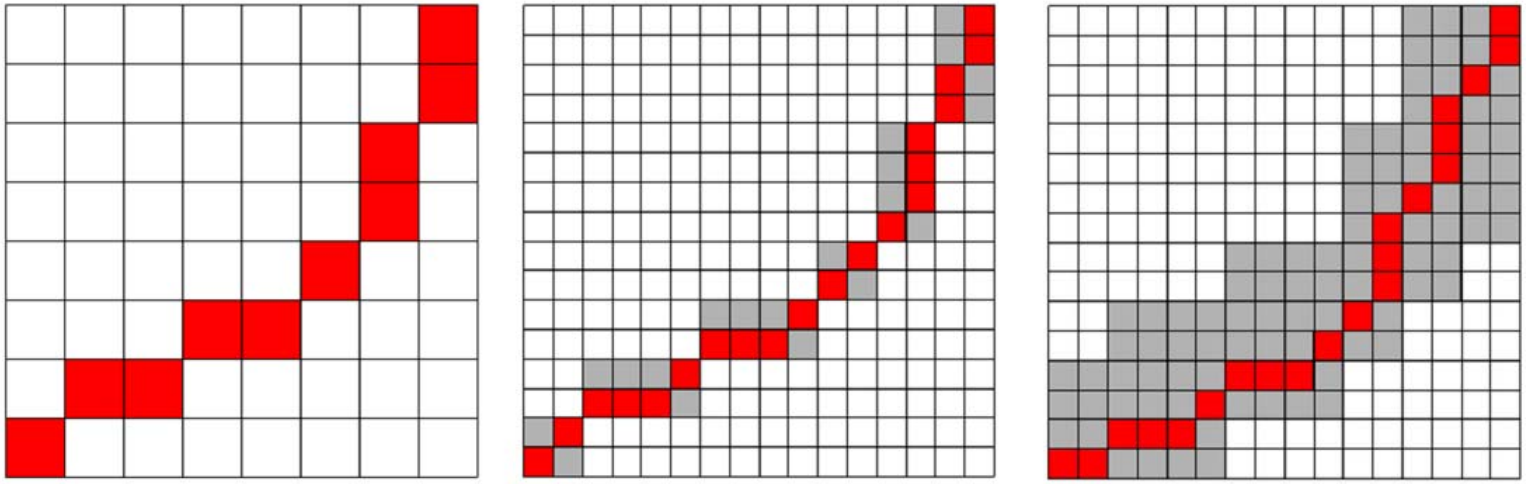


Figure from [Mueller, FPM, Chapter 3, Springer 2015]

Score Following: Model the Tempo Variation

- Dynamical system
  - Position:

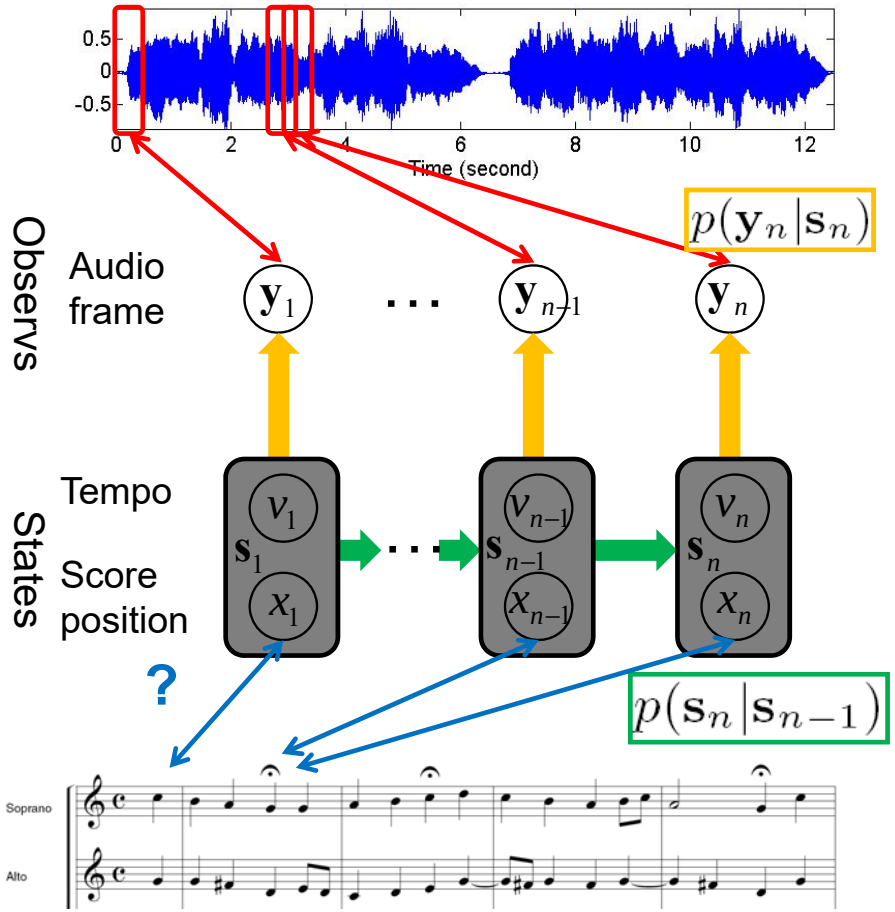
$$x_n = x_{n-1} + l \cdot v_{n-1}$$

  - Tempo:

$$v_n = \begin{cases} v_{n-1} + n_v \\ v_{n-1} \end{cases}$$

where

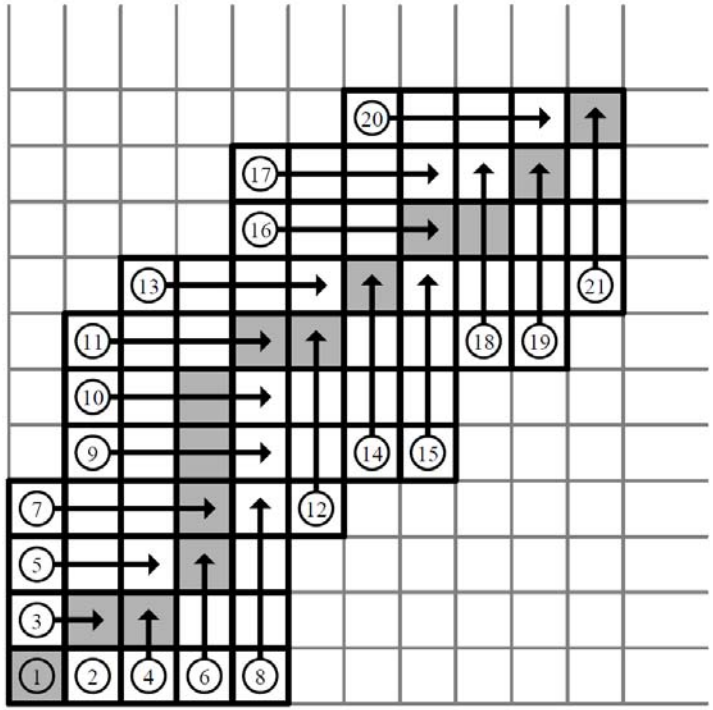
$$n_v \sim \mathcal{N}(0, \sigma_v^2)$$



Ref: Duan et al, "Soundprism: An online system for score-informed source separation of music audio," JSTSP 2011

Score Following: Online DTW

- Key changes
  - compute the path incrementally
  - reduce the complexity to being linear w.r.t. length of the input
  - reconsider past decisions to increase robustness

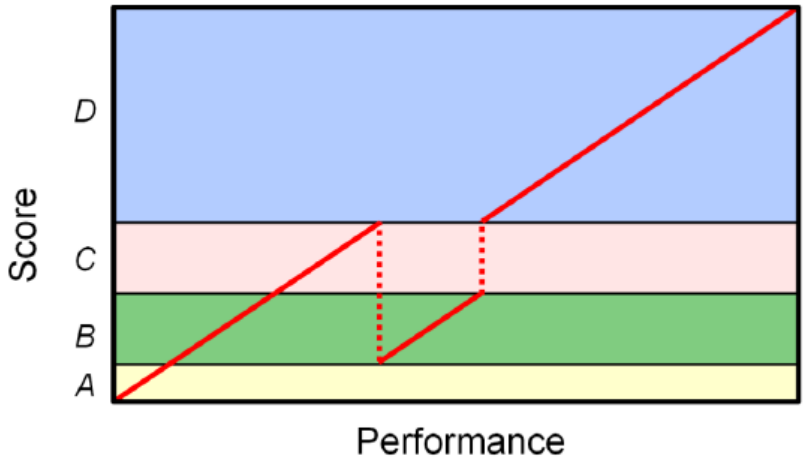


Ref 1: Dixon, “Live tracking of musical performances using on-line time warping,” DAFx 2005

Ref 2: Arzt et al, “Automatic page turning for musicians via real-time machine listening,” ECAI 2008

Score Following: Advanced Issues

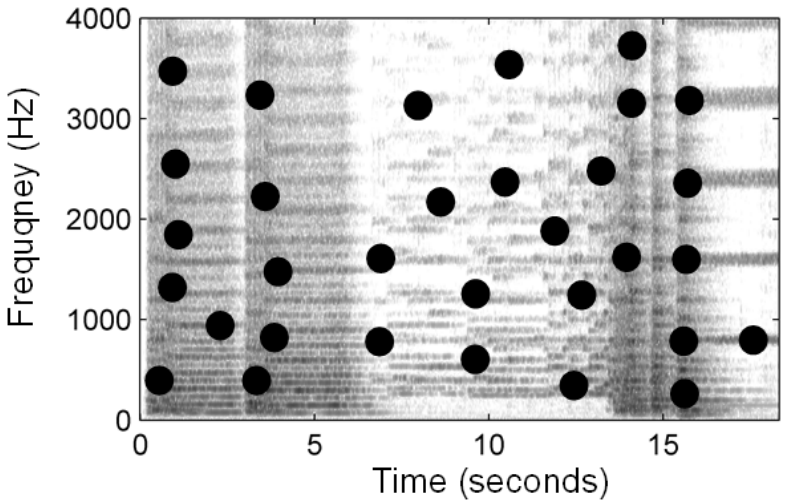
- Errors, repeats, skips
- Structure difference between the score and the performance (i.e. repeated sections)
- Multiple instruments

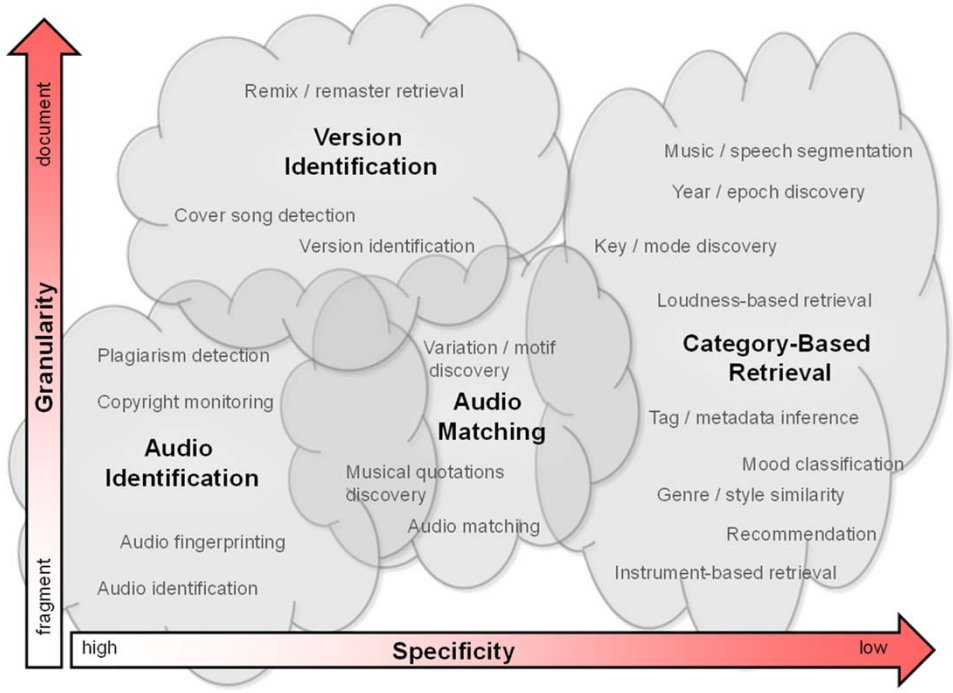


Ref 1: Fremerey et al, “Handling repeats and jumps in score performance synchronization,” ISMIR 2010
Ref 2: Grachten et al, “Automatic alignment of music performances with structural differences,” ISMIR 2013

Extension: Query-by-humming and Friends

- **Query-by-humming**: monophonic
- **Audio fingerprinting**: polyphonic, possibly noisy
- **Cover song identification**





Outline

- Music emotion
- Structure/form analysis
- Alignment
- **Rhythm & beat tracking**

Reference 1: FMP Notebook

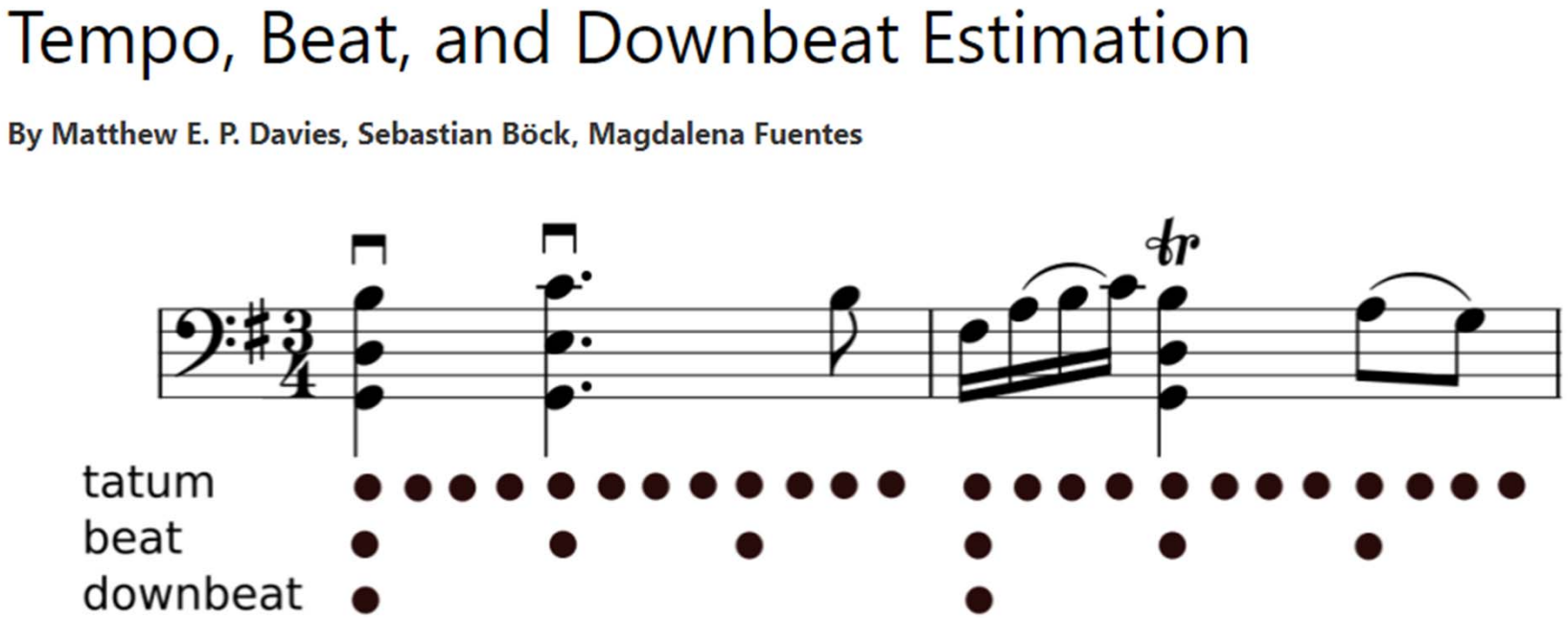
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C6/C6.html

Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
B	Basics	Basic information on Python, Jupyter notebooks, Anaconda package management system, Python environments, visualizations, and other topics	[html]	[ipynb]
0	Overview	Overview of the notebooks (https://www.audiolabs-erlangen.de/FMP)	[html]	[ipynb]
1	Music Representations	Music notation, MIDI, audio signal, waveform, pitch, loudness, timbre	[html]	[ipynb]
2	Fourier Analysis of Signals	Discrete/analog signal, sinusoid, exponential, Fourier transform, Fourier representation, DFT, FFT, STFT	[html]	[ipynb]
3	Music Synchronization	Chroma feature, dynamic programming, dynamic time warping (DTW), alignment, user interface	[html]	[ipynb]

Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
4	Music Structure Analysis	Similarity matrix, repetition, thumbnail, homogeneity, novelty, evaluation, precision, recall, F-measure, visualization, scape plot	[html]	[ipynb]
5	Chord Recognition	Harmony, music theory, chords, scales, templates, hidden Markov model (HMM), evaluation	[html]	[ipynb]
6	Tempo and Beat Tracking	Onset, novelty, tempo, tempogram, beat, periodicity, Fourier analysis, autocorrelation	[html]	[ipynb]
7	Content-Based Audio Retrieval	Identification, fingerprint, indexing, inverted list, matching, version, cover song	[html]	[ipynb]
8	Musically Informed Audio Decomposition	Harmonic/percussive separation, signal reconstruction, instantaneous frequency, fundamental frequency (F0), trajectory, nonnegative matrix factorization (NMF)	[html]	[ipynb]

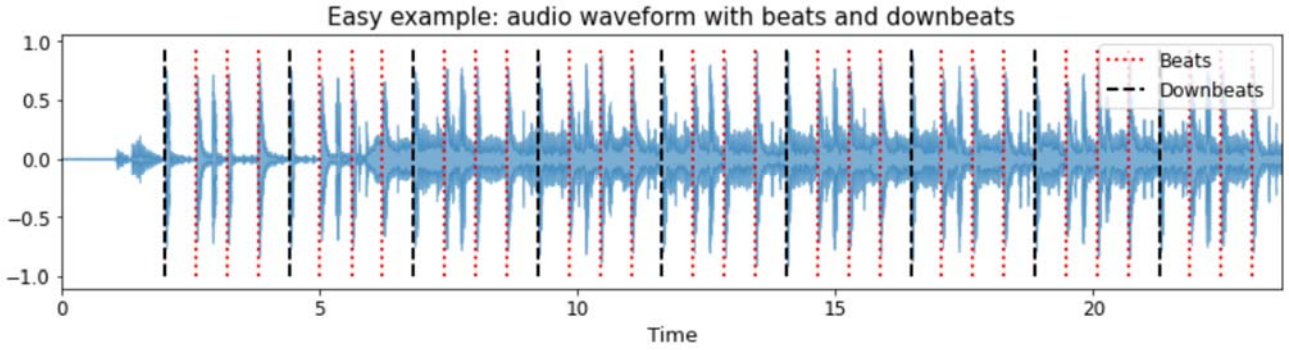
Reference 2: ISMIR 2021 Tutorial

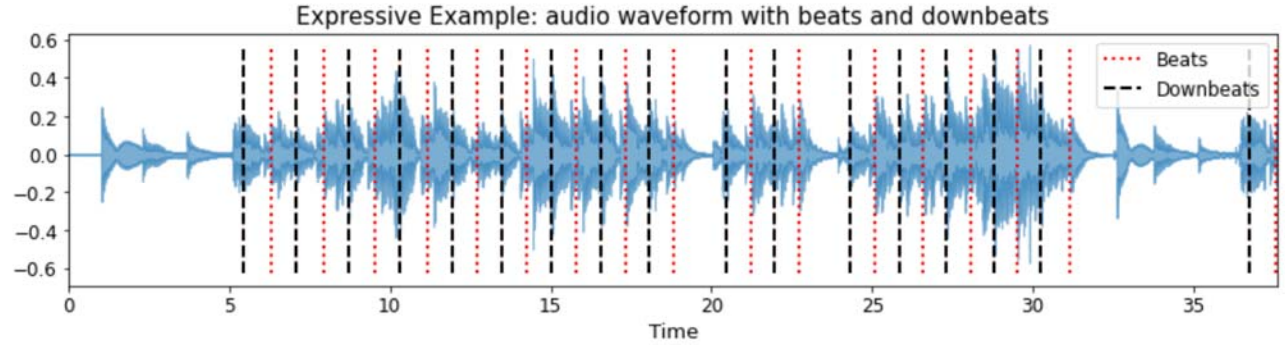
https://tempobeatdownbeat.github.io/tutorial/intro.html



What is Beat/Downbeat Tracking?

https://tempobeatdownbeat.github.io/tutorial/ch2_basics/definition.html





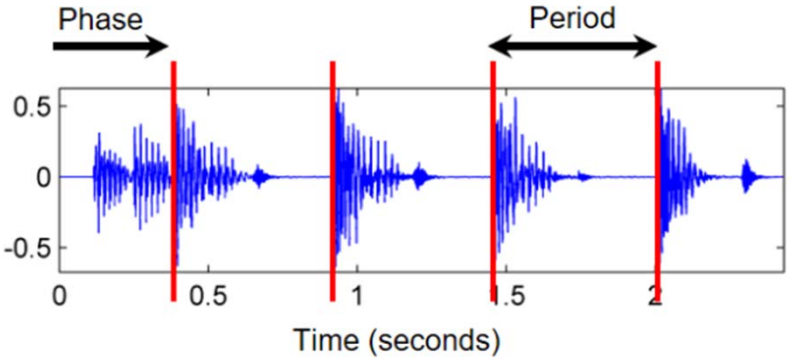
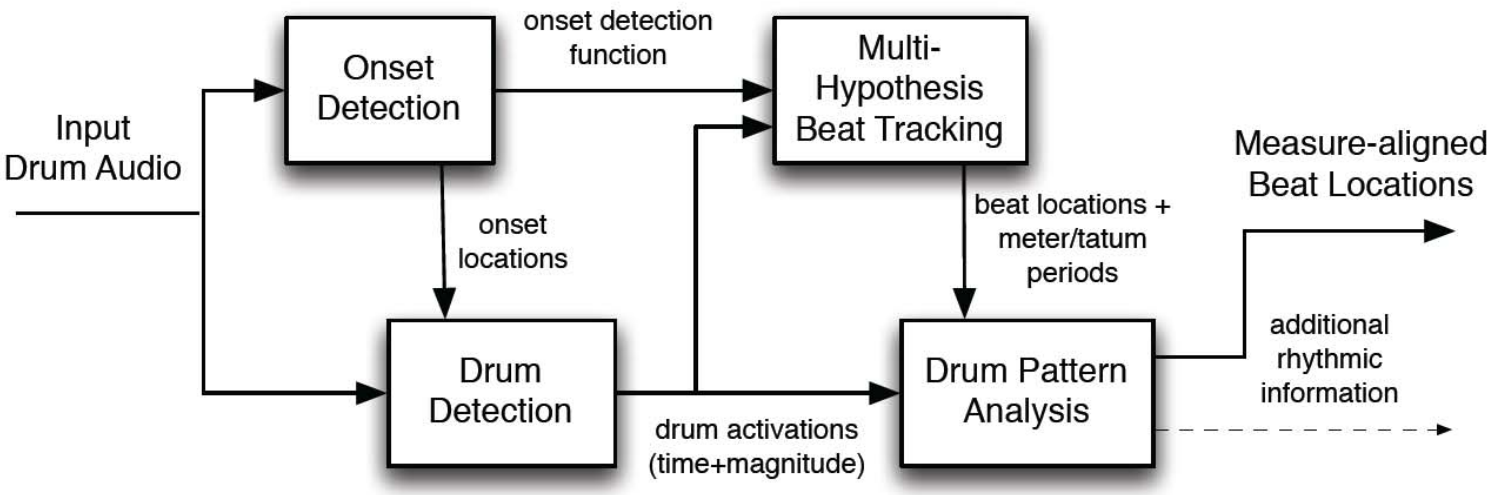


Figure 6.1 from [Müller, FMP, Springer 2015]

Motivation: Beat, Tempo, Rhythmic Pattern

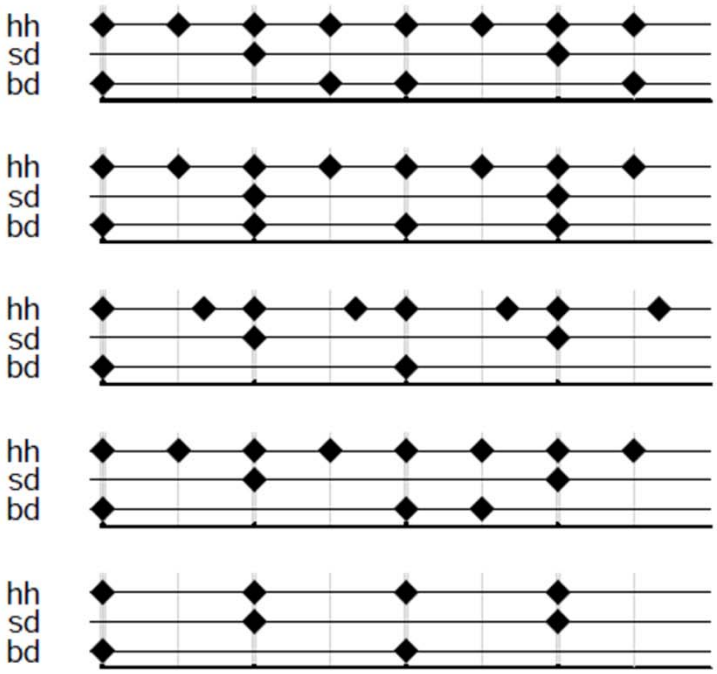
- The drum track in popular music conveys information about tempo, rhythm, style, and possibly the structure of a song

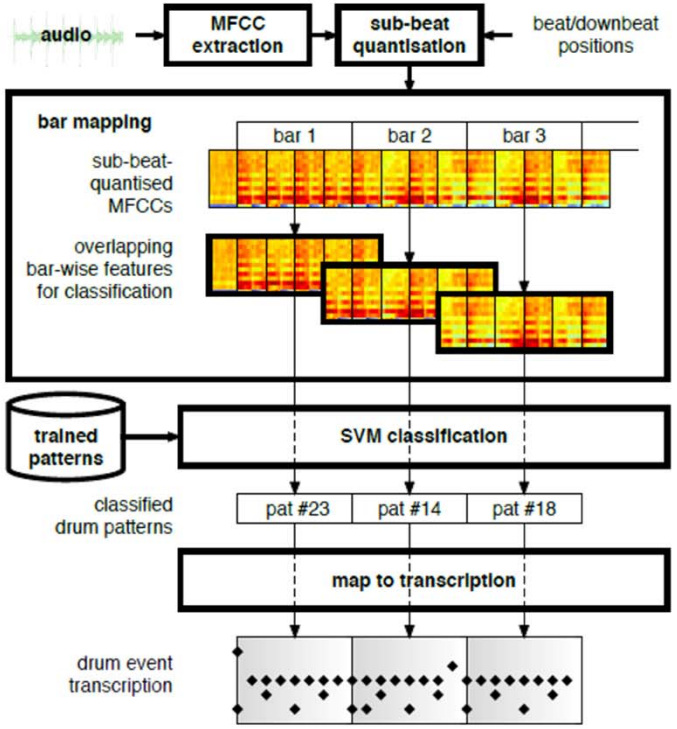


Ref: Battenberg, “Techniques for machine understanding of live drum performances,” PhD Thesis, UC Berkeley, 2012

Motivation: Drum Pattern Analysis

https://youtu.be/lm_oz7P8TWE?t=12m28s



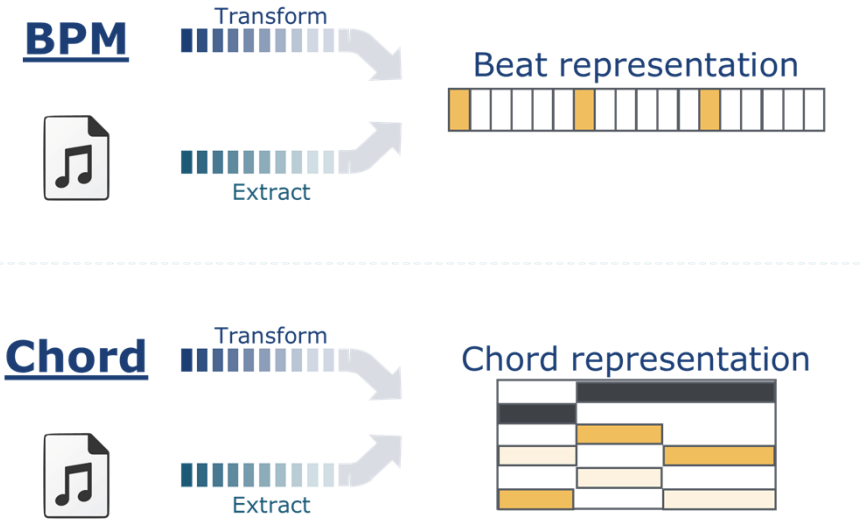


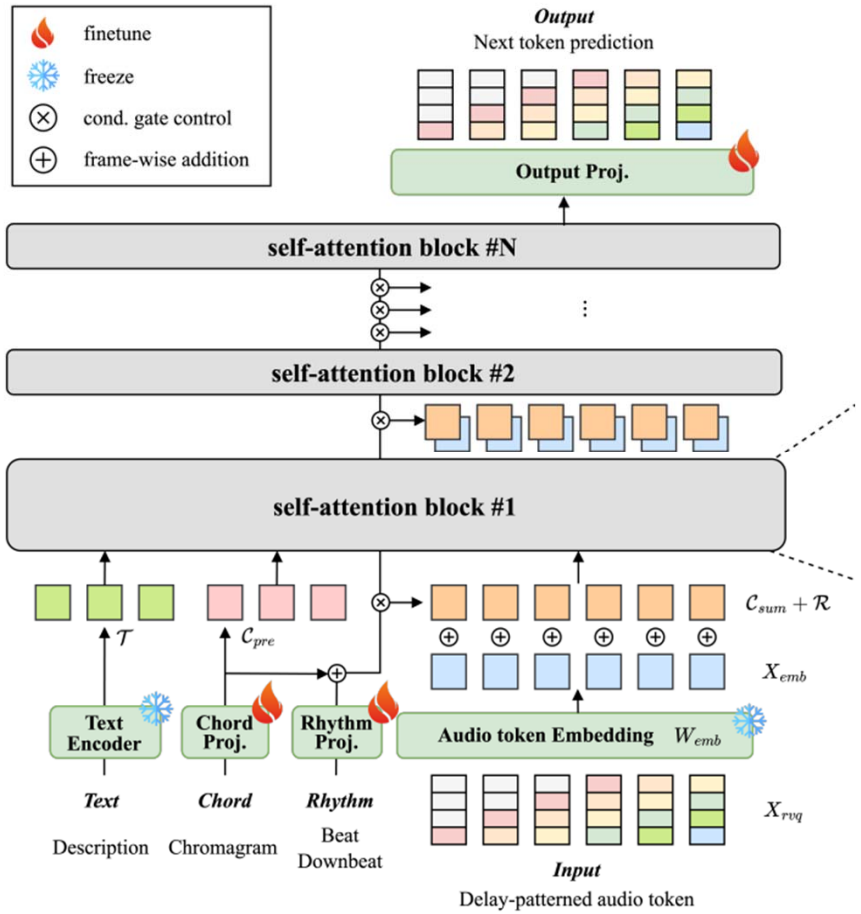
Ref 1: Mauch & Dixon, “A corpus-based study of rhythm patterns,” ISMIR 2012

Ref 2: Thompson et al, “Drum transcription via classification of bar-level rhythmic patterns,” ISMIR 2014

Motivation: Backing Track Generation

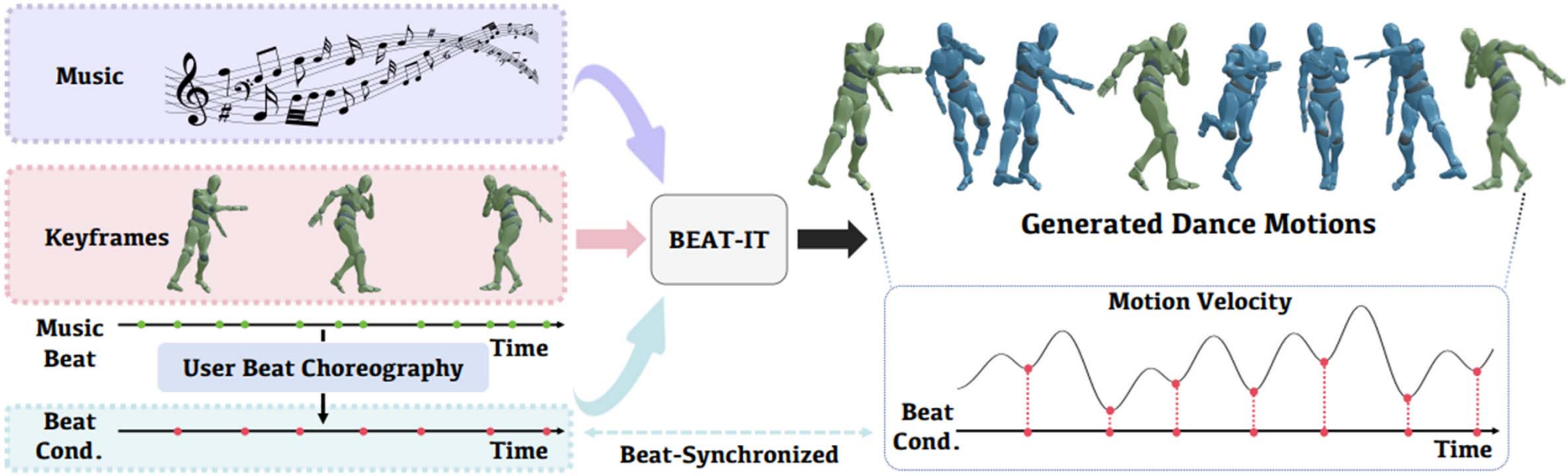
https://musicongen.github.io/musicongen_demo/





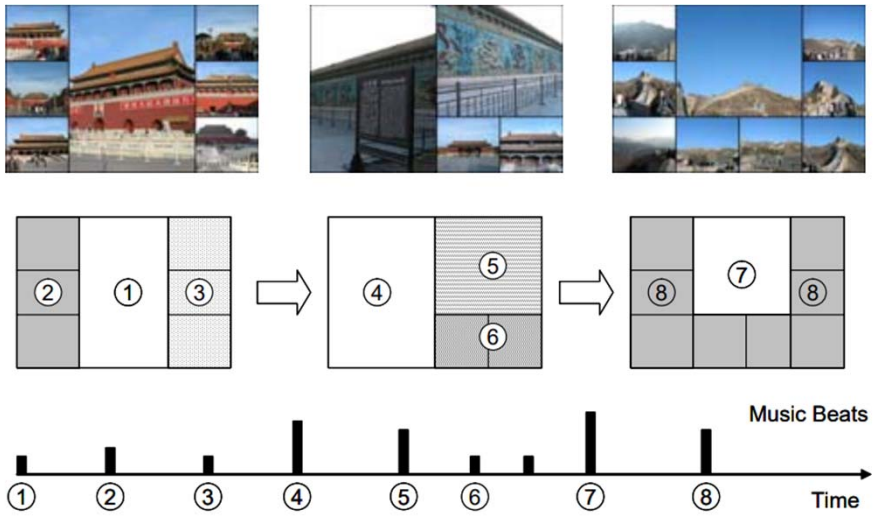
Ref: Lan et al, “MusiConGen: Rhythm and chord control for transformer-based text-to-music generation,” ISMIR 2024

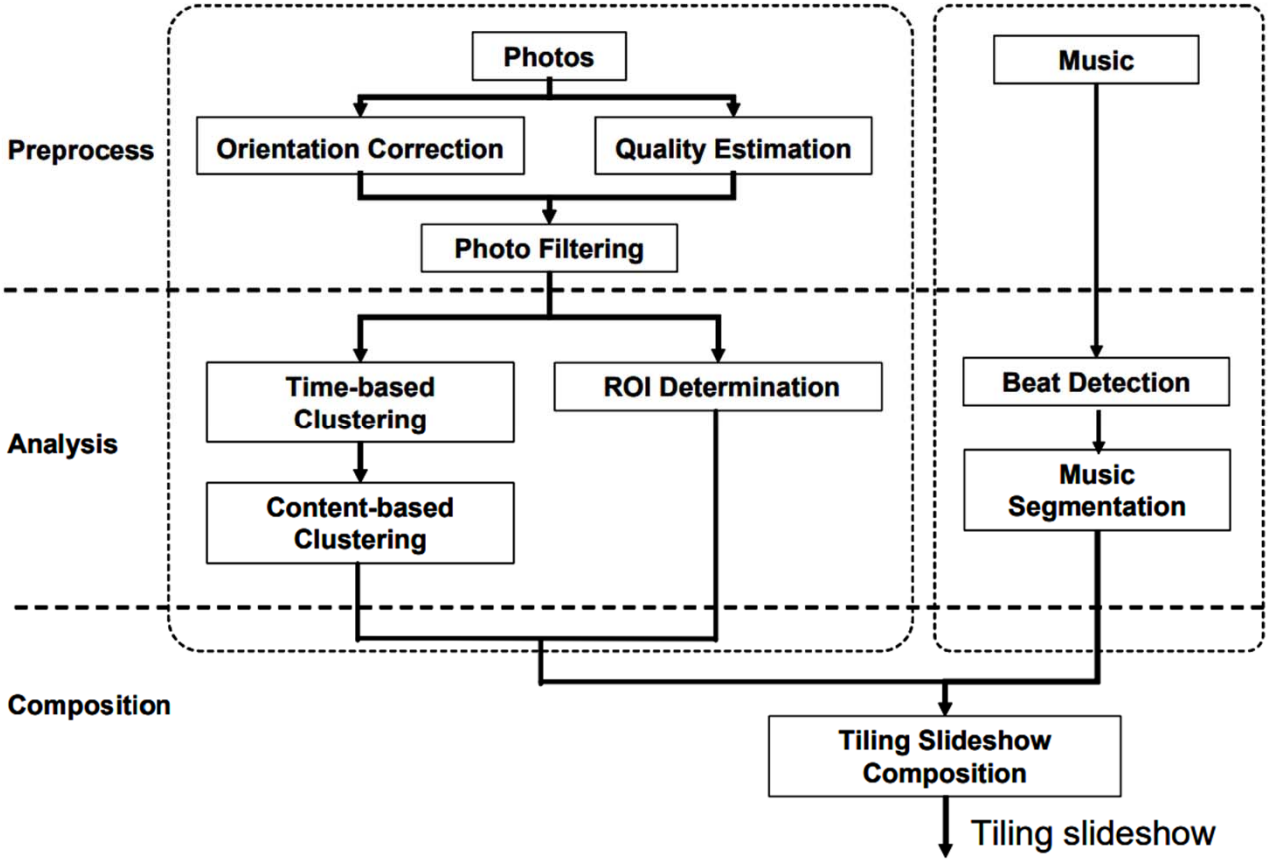
Motivation: Dance Generation



Ref: Huang et al, "Beat-It: Beat-synchronized multi-condition 3d dance generation," ECCV 2024

Motivation: Music Video/Slideshow Generation





Ref: Chen et al, "Tiling slideshow," ACM Multimedia 2006

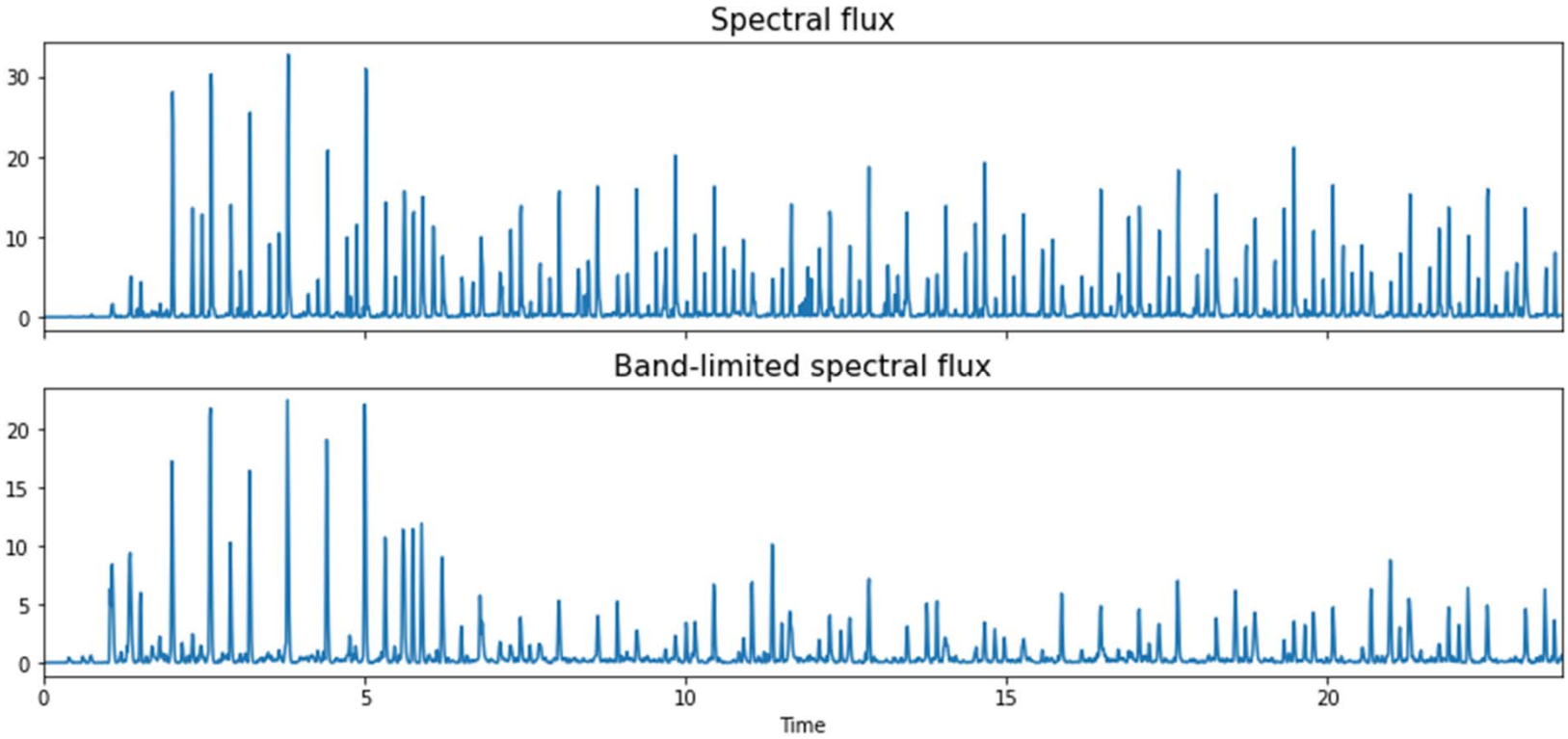
Beat/Downbeat Annotation

https://tempobeatdownbeat.github.io/tutorial/ch2_basics/annotation.html

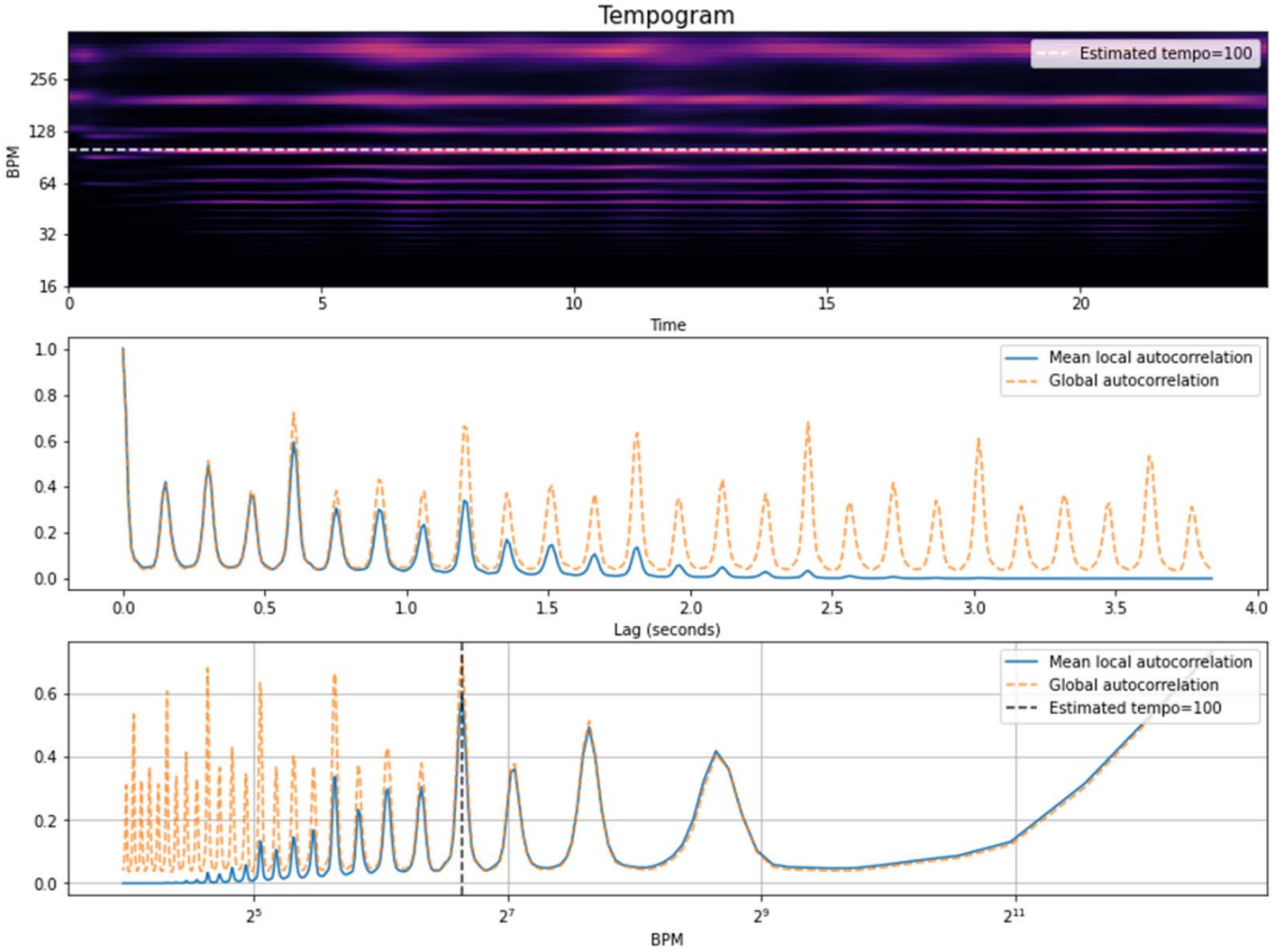
- Annotation is hard!
- It takes a long time, and the more challenging the material to annotate the greater the likelihood of this being helpful for learning.
- On the plus side, annotation is a fantastic way to learn about the task of beat and downbeat estimation so it's a really great excercise.
- We always need more data, so do consider doing some annotating!
- As hard as we try, annotation "mistakes" are made, so they made need correcting.
- This makes comparative evaluation more challenging, so it's always worthwile to ensure you are using the most up to date version of any annotations.

Baseline Approach

https://tempobeatdownbeat.github.io/tutorial/ch2_basics/baseline.html



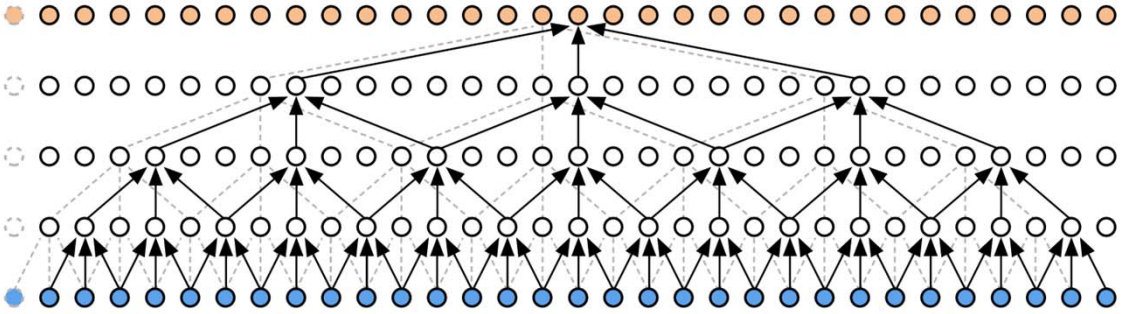
Baseline Approach



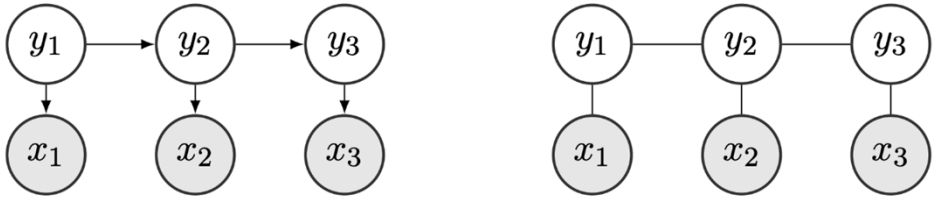
Deep Learning Approaches

https://tempobeatdownbeat.github.io/tutorial/ch3_going_deep/overview.html

https://tempobeatdownbeat.github.io/tutorial/ch3_going_deep/dnns.html



https://tempobeatdownbeat.github.io/tutorial/ch3_going_deep/postprocessing.html



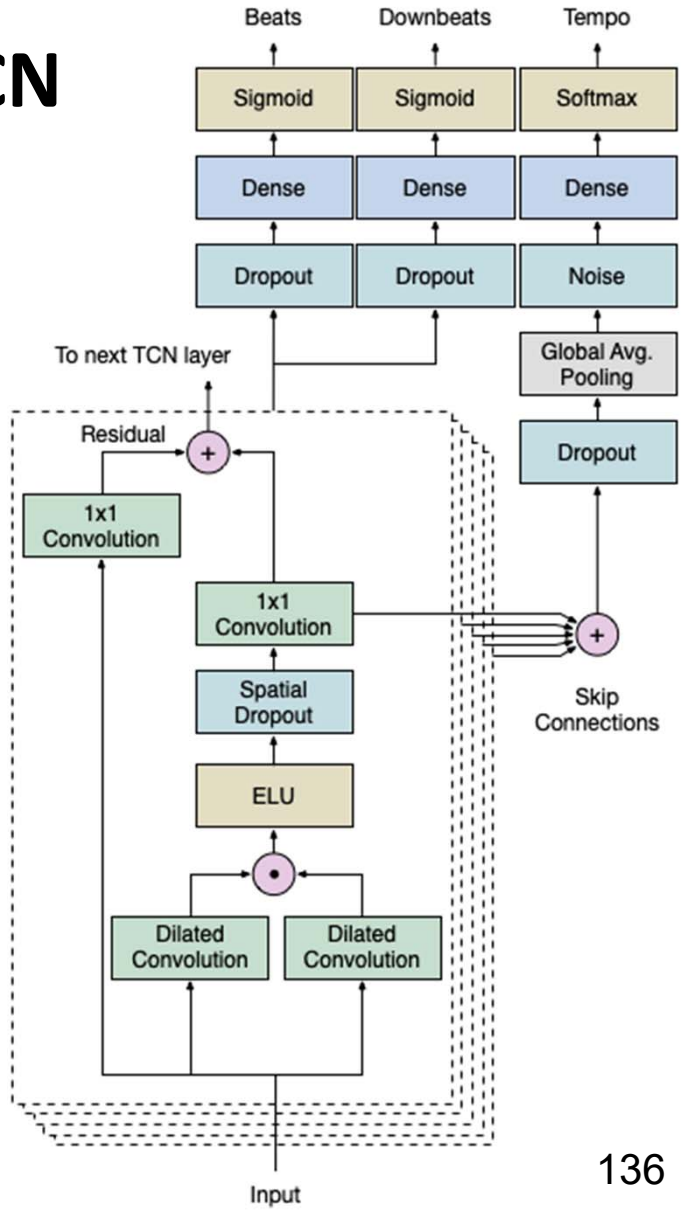
Hands on!

https://colab.research.google.com/drive/1tuOqNyO9gdMmYJsj33fP_QOfpRsm2tmt?usp=sharing

Ref: Böck & Davies, “Deconstruct, analyse, reconstruct: How to improve tempo, beat, and downbeat estimation,” ISMIR 2020

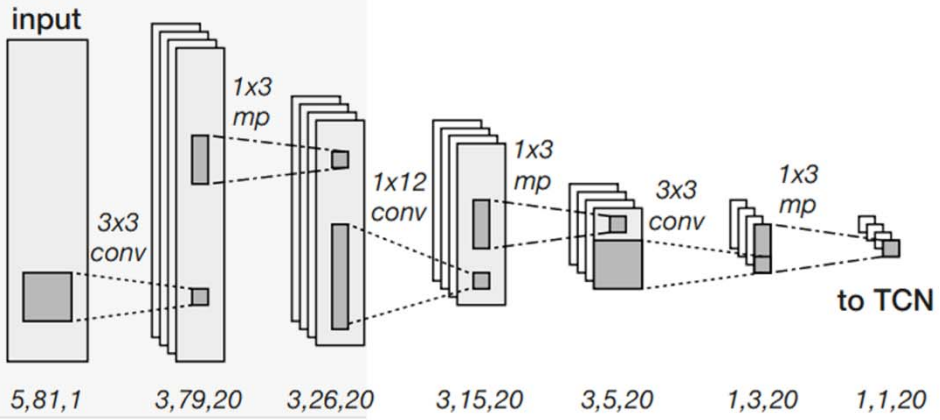
Main Architecture - TCN

```
def residual_block(x, i, activation, num_filters, kernel_size, padding, dropout_rate=0, name=''):
    # name of the layer
    name = name + '_dilation_%d' % i
    # 1x1 conv. of input (so it can be added as residual)
    res_x = Conv1D(num_filters, 1, padding='same', name=name + '_1x1_conv_residual')(x)
    # two dilated convolutions, with dilation rates of i and 2i
    conv_1 = Conv1D(
        filters=num_filters,
        kernel_size=kernel_size,
        dilation_rate=i,
        padding=padding,
        name=name + '_dilated_conv_1',
    )(x)
    conv_2 = Conv1D(
        filters=num_filters,
        kernel_size=kernel_size,
        dilation_rate=i * 2,
        padding=padding,
        name=name + '_dilated_conv_2',
    )(x)
    # concatenate the output of the two dilations
    concat = keras.layers.concatenate([conv_1, conv_2], name=name + '_concat')
    # apply activation function
    x = Activation(activation, name=name + '_activation')(concat)
    # apply spatial dropout
    x = SpatialDropout1D(dropout_rate, name=name + '_spatial_dropout_%f' % dropout_rate)(x)
    # 1x1 conv. to obtain a representation with the same size as the residual
    x = Conv1D(num_filters, 1, padding='same', name=name + '_1x1_conv')(x)
```



PreNet

```
def create_model(input_shape, num_filters=20, num_dilations=11, kernel_size=5, activation='elu', dropout_rate=0.15):
    # input layer
    input_layer = Input(shape=input_shape)

    # stack of 3 conv layers, each conv, activation, max. pooling & dropout
    conv_1 = Conv2D(num_filters, (3, 3), padding='valid', name='conv_1_conv')(input_layer)
    conv_1 = Activation(activation, name='conv_1_activation')(conv_1)
    conv_1 = MaxPooling2D((1, 3), name='conv_1_max_pooling')(conv_1)
    conv_1 = Dropout(dropout_rate, name='conv_1_dropout')(conv_1)

    conv_2 = Conv2D(num_filters, (1, 10), padding='valid', name='conv_2_conv')(conv_1)
    conv_2 = Activation(activation, name='conv_2_activation')(conv_2)
    conv_2 = MaxPooling2D((1, 3), name='conv_2_max_pooling')(conv_2)
    conv_2 = Dropout(dropout_rate, name='conv_2_dropout')(conv_2)

    conv_3 = Conv2D(num_filters, (3, 3), padding='valid', name='conv_3_conv')(conv_2)
    conv_3 = Activation(activation, name='conv_3_activation')(conv_3)
    conv_3 = MaxPooling2D((1, 3), name='conv_3_max_pooling')(conv_3)
    conv_3 = Dropout(dropout_rate, name='conv_3_dropout')(conv_3)

    # reshape layer to reduce dimensions
    x = Reshape((-1, num_filters), name='tcn_input_reshape')(conv_3)

    # TCN layers
    dilations = [2 ** i for i in range(num_dilations)]
    tcn, skip = TCN(
        num_filters=[num_filters] * len(dilations),
        kernel_size=kernel_size,
        dilations=dilations,
```



Data Sequence Handling & Target Widening

```python
# infer (global) tempo from beats
def infer_tempo(beats, hist_smooth=15, fps=FPS, no_tempo=MASK_VALUE):
    ibis = np.diff(beats) * fps
    bins = np.bincount(np.round(ibis).astype(int))
    # if no beats are present, there is no tempo
    if not bins.any():
        return NO_TEMPO
    intervals = np.arange(len(bins))
    # smooth histogram bins
    if hist_smooth > 0:
        bins = madmom.audio.signal.smooth(bins, hist_smooth)
    # create interpolation function
    interpolation_fn = interp1d(intervals, bins, 'quadratic')
    # generate new intervals with 1000x the resolution
    intervals = np.arange(intervals[0], intervals[-1], 0.001)
    tempi = 60.0 * fps / intervals
    # apply quadratic interpolation
    bins = interpolation_fn(intervals)
    peaks = argrelmax(bins, mode='wrap')[0]
    if len(peaks) == 0:
        # no peaks, no tempo
        return no_tempo
    else:
        # report only the strongest tempo
        sorted_peaks = peaks[np.argsort(bins[peaks])[::-1]]
        return tempi[sorted_peaks][0]
```

```python
# pad features
def cnn_pad(data, pad_frames):
    """Pad the data by repeating the first and last frame N times."""
    pad_start = np.repeat(data[:1], pad_frames, axis=0)
    pad_stop = np.repeat(data[-1:], pad_frames, axis=0)
    return np.concatenate((pad_start, data, pad_stop))
```

```python
def widen_beat_targets(self, size=3, value=0.5):
    for y in self.beats.values():
        # skip masked beat targets
        if np.allclose(y, MASK_VALUE):
            continue
        np.maximum(y, maximum_filter1d(y, size=size) * value, out=y)

def widen_downbeat_targets(self, size=3, value=0.5):
    for y in self.downbeats.values():
        # skip masked downbeat targets
        if np.allclose(y, MASK_VALUE):
            continue
        np.maximum(y, maximum_filter1d(y, size=size) * value, out=y)

def widen_tempo_targets(self, size=3, value=0.5):
    for y in self.tempo.values():
        # skip masked tempo targets
        if np.allclose(y, MASK_VALUE):
            continue
        np.maximum(y, maximum_filter1d(y, size=size) * value, out=y)
```

Data Augmentation

- "We use a simple approach of adding the same training examples with **changed hop-size when computing the STFT**. This results in the same song being represented with a different numbers of frames. This way the **beat positions are "stretched" or "squeezed"** and the tempo changes accordingly."

```
[ ] for fps in [95, 97.5, 102.5, 105]:
        ds = DataSequence(
            tracks={f'{k}_{fps}': v for k, v in tracks.items() if k in train_files},
            pre_processor=PreProcessor(fps=fps),
            pad_frames=pad_frames,
        )
        ds.widen_beat_targets()
        ds.widen_downbeat_targets()
        ds.widen_tempo_targets(3, 0.5)
        ds.widen_tempo_targets(3, 0.5)
        train.append(ds)
```

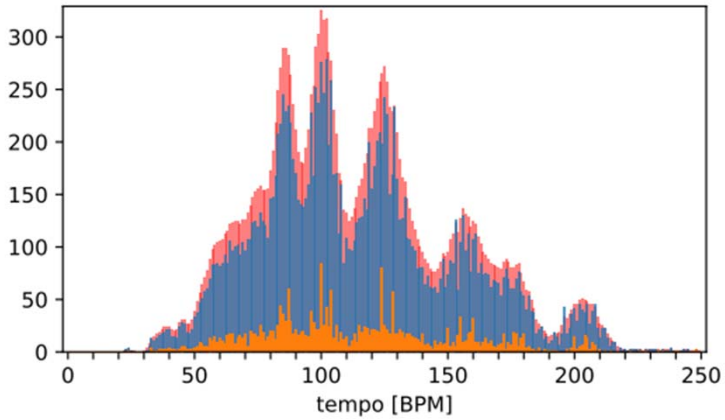


Figure 2: Tempo distribution of original tempo annotations (orange, foreground), after data augmentation (blue) and target widening (red, background).

Post-processing

```
[ ]  # track beats with a DBN
     beat_tracker = madmom.features.beats.DBNBeatTrackingProcessor(
            min_bpm=55.0, max_bpm=215.0, fps=FPS, transition_lambda=100, threshold=0.05
     )

     # track downbeats with a DBN
     # as input, use a combined beat & downbeat activation function
     downbeat_tracker = madmom.features.downbeats.DBNDownBeatTrackingProcessor(
            beats_per_bar=[3, 4], min_bpm=55.0, max_bpm=215.0, fps=FPS, transition_lambda=100
     )

     # track bars, i.e. first track the beats and then infer the downbeat positions
     bar_tracker = madmom.features.downbeats.DBNBarTrackingProcessor(
            beats_per_bar=(3, 4), meter_change_prob=1e-3, observation_weight=4
```

```
def detect_tempo(bins, hist_smooth=11, min_bpm=10):
        min_bpm = int(np.floor(min_bpm))
        tempi = np.arange(min_bpm, len(bins))
        bins = bins[min_bpm:]
        # smooth histogram bins
        if hist_smooth > 0:
                bins = madmom.audio.signal.smooth(bins, hist_smooth)
        # create interpolation function
        interpolation_fn = interp1d(tempi, bins, 'quadratic')
        # generate new intervals with 1000x the resolution
        tempi = np.arange(tempi[0], tempi[-1], 0.001)
        # apply quadratic interpolation
        bins = interpolation_fn(tempi)
        peaks = argrelmax(bins, mode='wrap')[0]
        if len(peaks) == 0:
                # no peaks, no tempo
                tempi = np.array([], ndmin=2)
        elif len(peaks) == 1:
                # report only the strongest tempo
                ret = np.array([tempi[peaks[0]], 1.0])
                tempi = np.array([tempi[peaks[0]], 1.0])
        else:
                # sort the peaks in descending order of bin heights
                sorted_peaks = peaks[np.argsort(bins[peaks])[::-1]]
                # normalize their strengths
                strengths = bins[sorted_peaks]
                strengths /= np.sum(strengths)
```

Libraries

- Madmom
  https://github.com/CPJKU/madmom

madmom.features

- madmom.features.beats
- madmom.features.beats_crf
- madmom.features.beats_hmm
- madmom.features.chords
- madmom.features.downbeats
- madmom.features.key
- madmom.features.notes
- madmom.features.notes_hmm
- madmom.features.onsets
- madmom.features.tempo

- BeatNet
  https://github.com/mjhydri/BeatNet

BeatNet is state-of-the-art (Real-Time) and Offline joint music beat, downbeat, tempo, and meter tracking system using CRNN and particle filtering. (ISMIR 2021's paper implementation).