Large-Scale Content-Based Matching of Audio and MIDI Data

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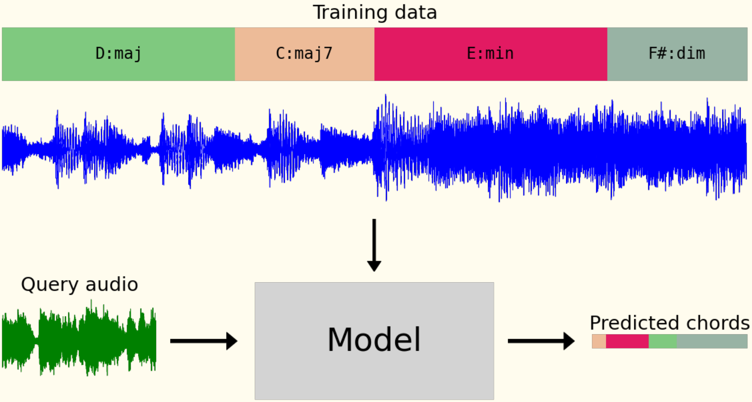
with help from Kitty Shi and Hilary Mogul

CCRMA DSP Seminar, January 13, 2015

Music Information Retrieval Pipeline



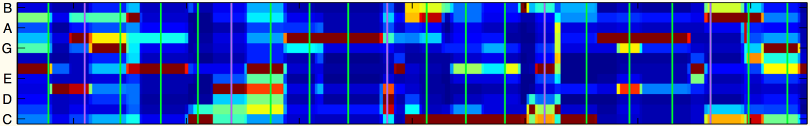
The Million Song Dataset

```
         artist: 'Tori Amos'
        release: 'LIVE AT MONTREUX'
          title: 'Smells Like Teen Spirit'
             id: 'TRKUYPW128F92E1FC0'
            key: 5
           mode: 0
       loudness: -16.6780
          tempo: 87.2330
 time_signature: 4
       duration: 216.4502
    sample_rate: 22050
      audio_md5: '8'
     7digitalid: 5764727
    familiarity: 0.8500
           year: 1992
```

100.0 — cover	5.0 — cover songs
57.0 — covers	4.0 — soft rock
43.0 — female vocalists	4.0 — nirvana cover
42.0 — piano	4.0 — Mellow
34.0 — alternative	4.0 — alternative rock
14.0 — singer-songwriter	3.0 — chick rock
11.0 — acoustic	3.0 — Ballad
8.0 — tori amos	3.0 — Awesome Covers
7.0 — beautiful	2.0 — melancholic
6.0 — rock	2.0 — k00l ch1x
6.0 — pop	2.0 — indie
6.0 — Nirvana	2.0 — female vocalistist
6.0 — female vocalist	2.0 — female
6.0 — 90s	2.0 — cover song
5.0 — out of genre covers	2.0 — american

```
%5489,4468, Smells Like Teen Spirit
TRTUOVJ128E078EE10 Nirvana
TRFZJOZ128F4263BE3 Weird Al Yankovic
TRJHCKN12903CDD274 Pleasure Beach
TRELTOJ128F42748B7 The Flying Pickets
TRJKBXL128F92F994D Rhythms Del Mundo feat. Shanade
TRIHLAW128F429BBF8 The Bad Plus
TRKUYPW128F92E1FC0 Tori Amos
```

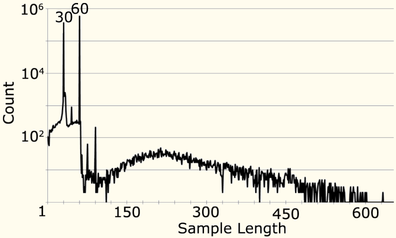
12	hello	6	here	3	is
11	i	6	us	3	with
10	a	6	entertain	3	oh
9	and	4	the	3	out
7	it	4	feel	3	an
6	are	4	yeah	3	light
6	we	3	to	3	less
6	now	3	my	3	danger



Thierry Bertin-Mahieux et al. *"The million song dataset"*

Audio? One solution:

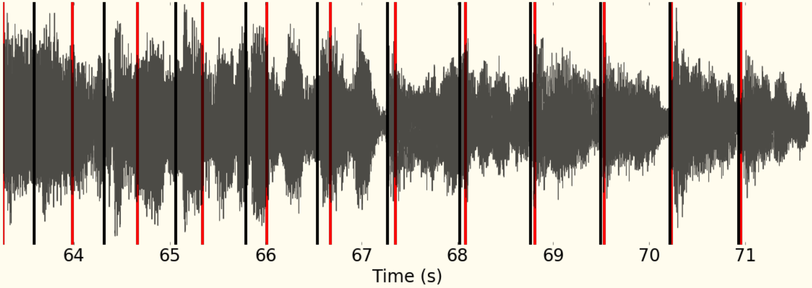
↓



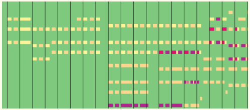
Samplerate		
22	768,710	77,26%
44	226,169	22,73%
other	81	0,01%
Bitrate		
128	646,120	64,94%
64	343,344	34,51%
other (VBR)	5,494	0,55%
Channels		
Mono	6,342	0.64%
Stereo	150,779	15.15%
Joint stereo / dual channel	837,839	84.21%

Schindler et al. *"Facilitating Comprehensive Benchmarking Experiments on the Million Song Dataset"*

Ground Truth?



Ground Truth from MIDI



←

→

↓

110 bpm

Extracting with `pretty_midi`

```python
import pretty_midi
# Load MIDI file into PrettyMIDI object
midi_data = pretty_midi.PrettyMIDI('midi_file.mid')
# Get a beat-synchronous piano roll
piano_roll = midi_data.get_piano_roll(times=midi_data.get_beats())
# Compute the relative amount of each semitone across the entire song, a proxy for key
print [sum(semitone)/sum(sum(midi_data.get_chroma())) for semitone in midi_data.get_chroma()]
# Shift all notes up by 5 semitones
for instrument in midi_data.instruments:
    # Don't want to shift drum notes
    if not instrument.is_drum:
        for note in instrument.notes:
            note.pitch += 5
# Synthesize the resulting MIDI data using sine waves
audio_data = midi_data.synthesize()
```

http://github.com/craffel/pretty-midi

MIDI + Audio + MSD

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         id: 'TRKUYPW128F92E1FC0'
   duration: 216.4502
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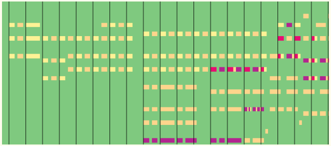
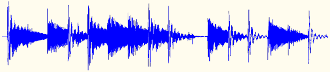
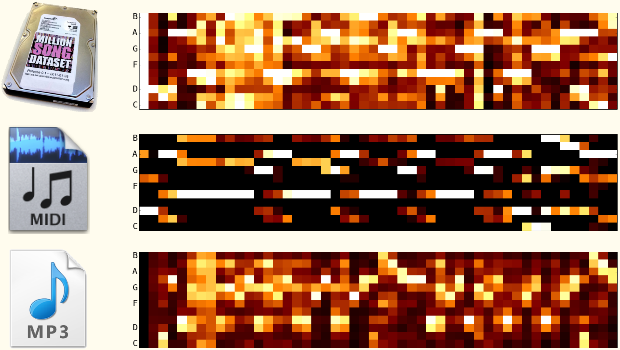




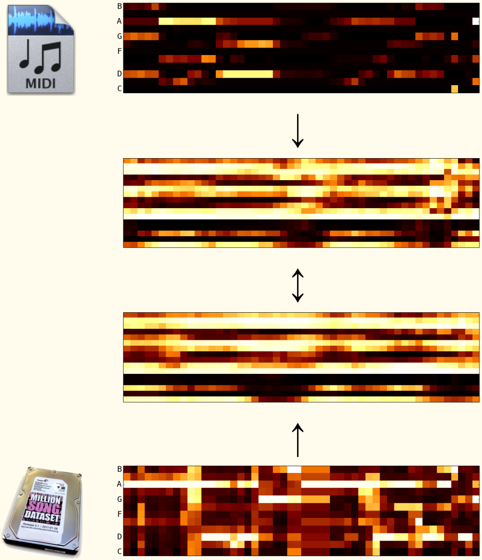
Matching by Text

```
J/Jerseygi.mid
V/VARIA18O.MID
Carpenters/WeveOnly.mid
2009 MIDI/handy_man1-D105.mid
G/Garotos Modernos - Bailanta De Fronteira.mid
Various Artists/REWINDNAS.MID
GoldenEarring/Twilight_Zone.mid
Sure.Polyphone.Midi/Poly 2268.mid
d/danza3.mid
100%sure.polyphone.midi/Fresh.mid
rogers_kenny/medley.mid
2009 MIDI/looking_out_my_backdoor3-Bb192.mid
```

Matching by Content



Idea: Map to a Common Space



The Plan

1. Obtain a large collection of MIDI files

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6. Use the mapping to **efficiently** match MIDI files without metadata to MSD entries

Unique MIDIs

500,000 $\longrightarrow$ 250,000

Finding Good Metadata

```
J/Jerseygi.mid
V/VARIA18O.MID
Carpenters/WeveOnly.mid
2009 MIDI/handy_man1-D105.mid
G/Garotos Modernos - Bailanta De Fronteira.mid
Various Artists/REWINDNAS.MID
GoldenEarring/Twilight_Zone.mid
Sure.Polyphone.Midi/Poly 2268.mid
```

↓

```
Mc Broom, Amanda/The Rose.mid
Men At Work/Down Under.mid
Beach Boys, The/Barbara Ann.mid
Star Wars/Cantina.mid
T L C/CREEP.MID
Beatles/help.mid
Idol, Billy/White Wedding.mid
```

Cleaning Metadata

`Mc Broom, Amanda/The Rose.mid`	`Amanda McBroom/The Rose.mid`
`Men At Work/Down Under.mid`	`Men At Work/Down Under.mid`
`Beach Boys, The/Barbara Ann.mid`	`The Beach Boys/Barbara Ann.mid`
`Star Wars/Cantina.mid`	
`T L C/CREEP.MID`	`TLC/Creep.mid`
`Beatles/help.mid`	`The Beatles/Help!.mid`
`Idol, Billy/White Wedding.mid`	`Billy Idol/White Wedding.mid`

25,000 → 17,000 (9,000)

Matching to Existing Collections

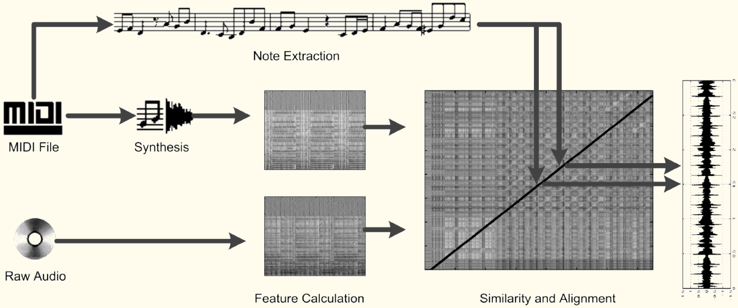
Amanda McBroom/The Rose.mid
Men At Work/Down Under.mid
The Beach Boys/Barbara Ann.mid
TLC/Creep.mid
The Beatles/Help!.mid
Billy Idol/White Wedding.mid

men_at_work/Brazil/07-Down_Under.mp3

tlc/Crazy_Sexy_Cool/02-Creep.mp3
The Beatles - Help!.mp3

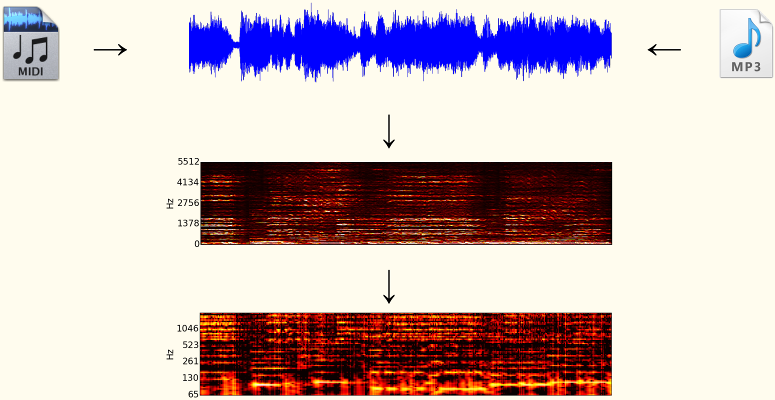
17,000 (9,000) → 5,000 (2,000)

Alignment



Turetsky and Ellis, *"Ground-Truth Transcriptions of Real Music from Force-Aligned MIDI Syntheses"*

Feature Extraction for Alignment

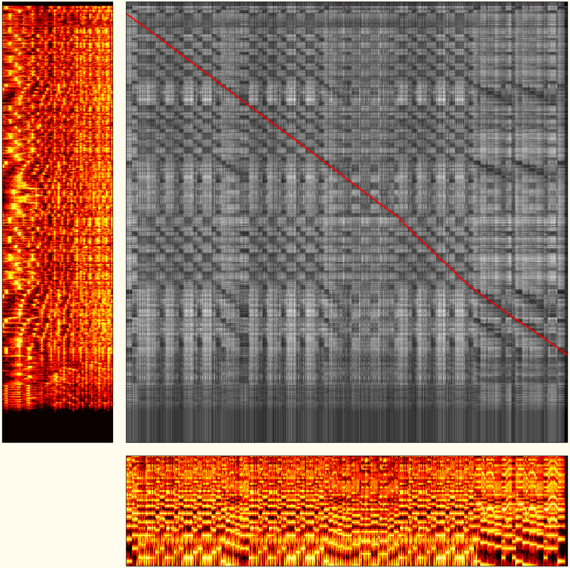


Feature Extraction with librosa

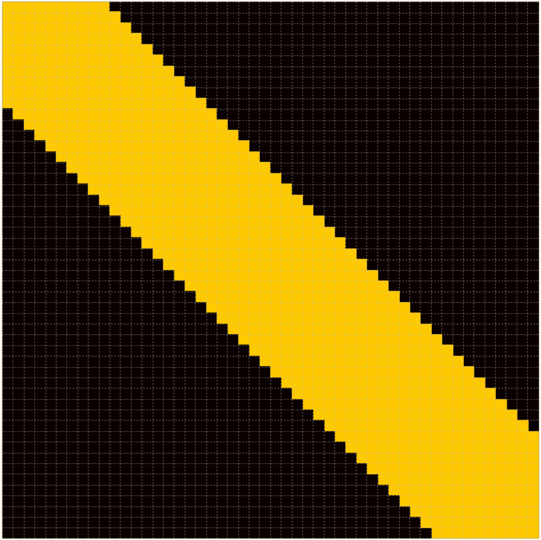
```
import librosa
# We could also obtain audio data from pretty_midi's fluidsynth method
audio, fs = librosa.load('audio_file.mp3')
# Separate harmonic and percussive components
audio_stft = librosa.stft(audio)
H, P = librosa.decompose.hpss(audio_stft)
audio_harmonic = librosa.istft(H)
# Compute log-frequency spectrogram of original audio
audio_gram = np.abs(librosa.cqt(y=audio_harmonic, sr=fs, hop_length=hop,
                                fmin=librosa.midi_to_hz(36), n_bins=60))
# Convert to decibels
log_gram = librosa.logamplitude(audio_gram, ref_power=audio_gram.max())
# Normalize the columns (each frame)
normed_gram = librosa.util.normalize(log_gram, axis=0)
```

http://www.github.com/bmcfee/librosa

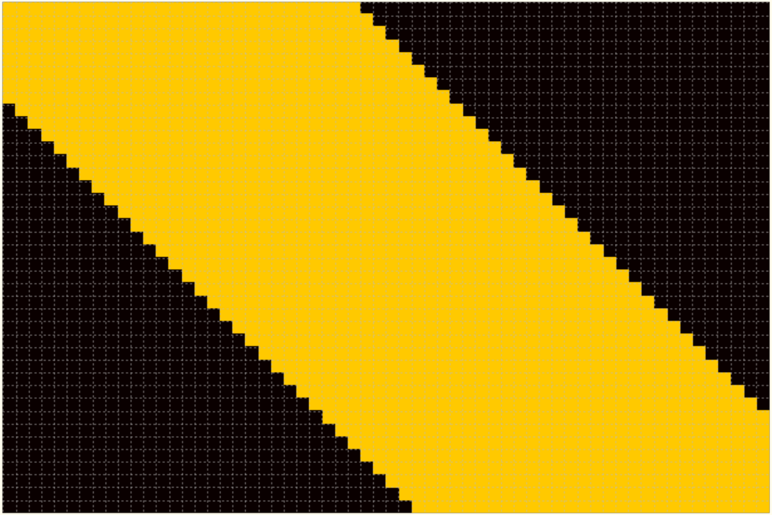
Dynamic Time Warping



Traditional DTW Constraint



Sequences of Different Length



Reporting a Confidence Score

1. Compute the total distance between aligned frames

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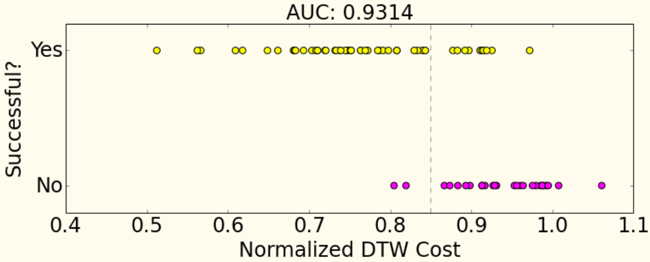
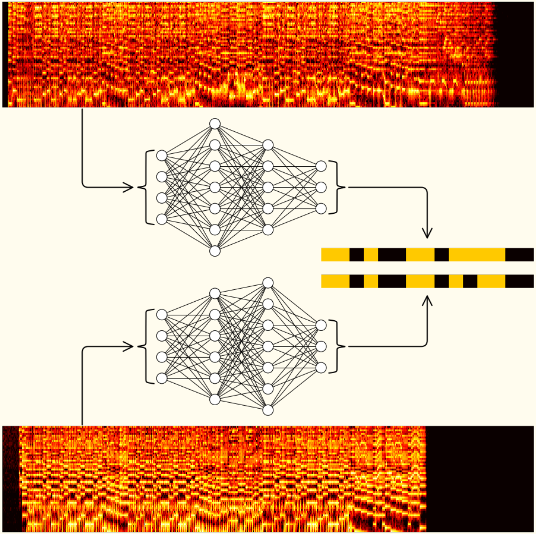


Similarity-Preserving Hashing



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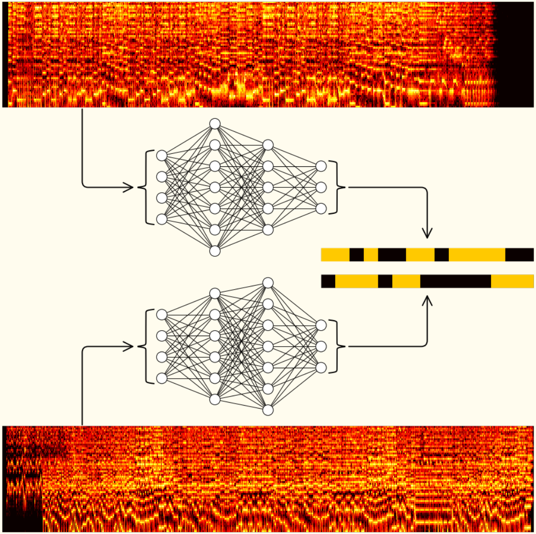
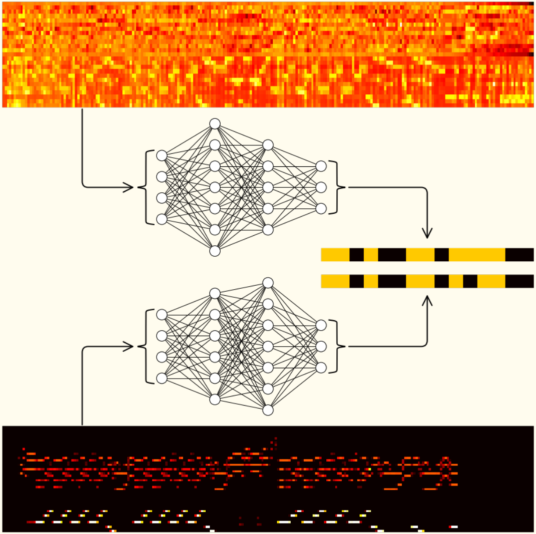
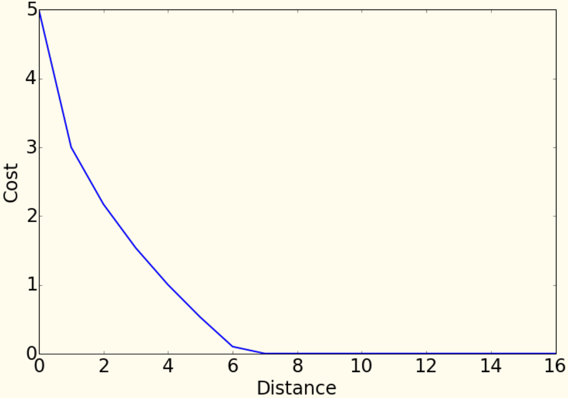


Cross-Modality Hashing



Cost Thresholding for Negatives

$$\max(0, m - \|x - y\|_2)^2$$



Neural Network Details

- $\approx$ 1.4M examples, 10% used as validation set

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- 16-bit hashes created by thresholding output

Neural Nets with `lasagne`

```python
import lasagne
layers = []
# Input layer signals end of network computations
layers.append(lasagne.layers.InputLayer(shape=(batch_size, n_features)))
# Add each hidden layer recursively
for num_units in hidden_layer_sizes:
    # A dense layer implements \sigma(Wx + b)
    layers.append(lasagne.layers.DenseLayer(layers_X[-1], num_units=num_units))
    # Dropout is implemented as a layer
    layers.append(lasagne.layers.DropoutLayer(layers[-1]))
# Add output layer
layers.append(lasagne.layers.DenseLayer(layers[-1], num_units=n_output))
# Get a list of all network parameters
params = lasagne.layers.get_all_params(layers[-1])
# Define a cost function using layers[-1].get_output(input)
# Compute updates for Nesterov's Accelerated Gradient
updates = lasagne.updates.nesterov_momentum(cost, params, learning_rate, momentum)
```

http://www.github.com/benanne/Lasagne

Why Hash?

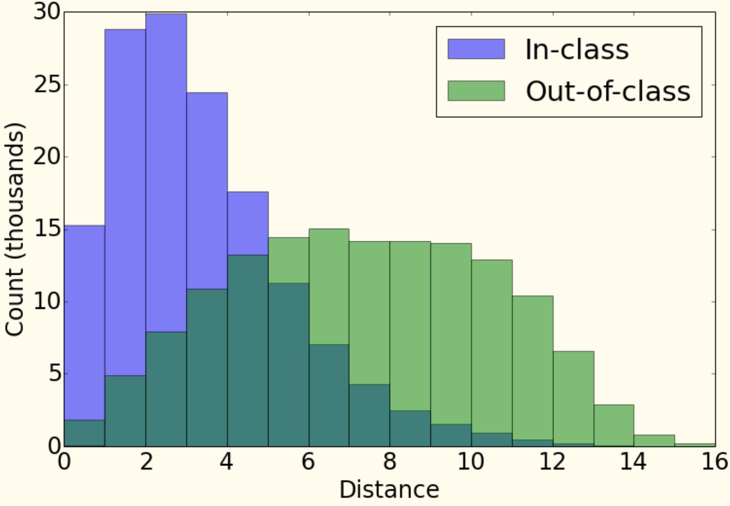
$$x \in \mathbb{R}^{M \times I}, y \in \mathbb{R}^{N \times I}$$

$$distance[m, n] = \sum_i (x[m, i] - y[n, i])^2$$

$$x \in \mathbb{R}^{M}, y \in \mathbb{R}^{N}$$

$$distance[m, n] = bits\_set[x[m]^\wedge y[n]]$$

Validation Set Distances



Content-Based Matching Pipeline

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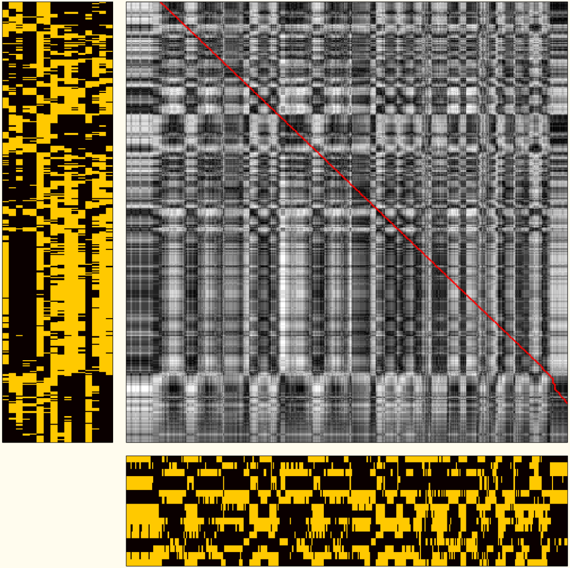
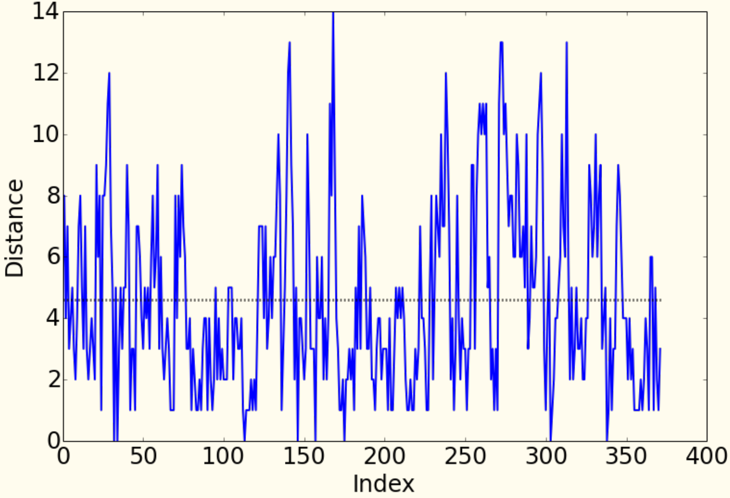
4. Select MSD hash sequences within a tolerance of MIDI file duration
5. Compute DTW distances to these sequences

Example: Hash Sequence DTW



Example: Distance Along Path



Confounding Factors

- MIDI and MSD durations aren't within chosen tolerance

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- MIDI and MSD durations aren't within chosen tolerance
- Beat tracking varies drastically
- MIDI is a poor transcription
- Hashing fails

Future Work

- Better hashing (recurrence)

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- Faster DTW

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- Better text-based matching

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- Better text-based matching
- Regular alignment after matching
- Quantitative evaluation!
- Dataset release

Related Work

Thanks!

http://github.com/craffel/midi-dataset
http://github.com/craffel/pretty-midi
http://github.com/bmcfee/librosa
http://github.com/benanne/Lasagne

craffel@gmail.com