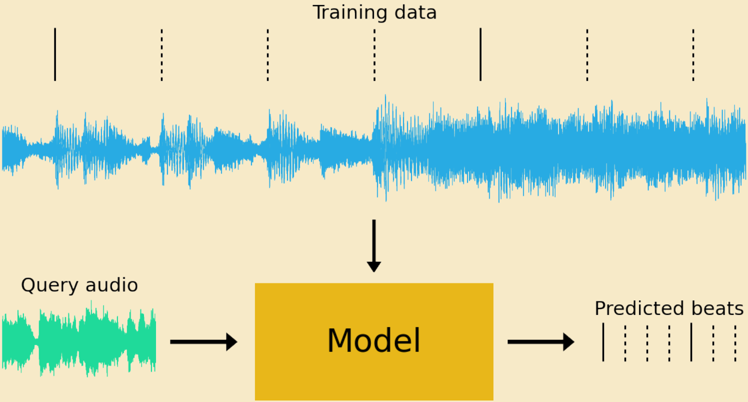
Using Convolutional Networks (with Attention) for Orders-of-Magnitude Speedup of DTW-Based Sequence Retrieval

Colin Raffel

Spotify Machine Learning Seminar

September 11, 2015

Music Information Retrieval Pipeline



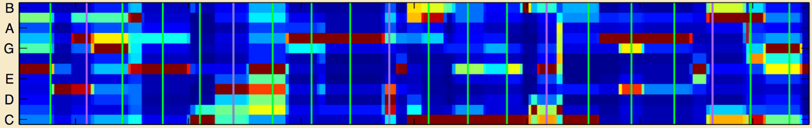
The Million Song Dataset

```
         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
```

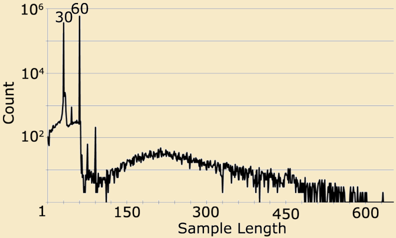
```
12 hello        6 here          3 is
11 i            6 us            3 with
10 a            6 entertain     3 oh
 9 and          4 the           3 out
 7 it           4 feel          3 an
 6 are          4 yeah          3 light
 6 we           3 to            3 less
 6 now          3 my         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



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

Audio Available from 7digital

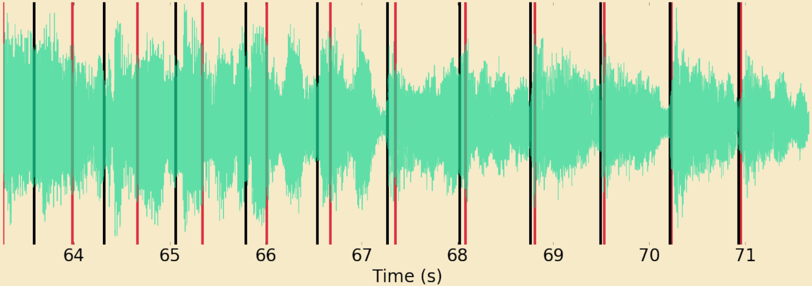
↓



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%

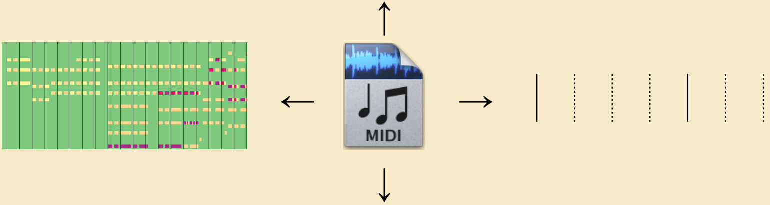
Schindler et al. *"Facilitating Comprehensive Benchmarking Experiments on the Million Song Dataset"*

Ground Truth?



Ground Truth from MIDI

0.0s: F major, 53.2s: D minor, ...



0.0s: 110 bpm, 22.2s: 103 bpm, ...

```
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())
# Get tempo changes and their times
times, tempi = midi_data.get_tempo_change_times()
# Synthesize the resulting MIDI data at 22 kHz using fluidsynth
audio_data = midi_data.fluidsynth(fs=22050)
```

Matching

```
     artist: 'Tori Amos'
    release: 'LIVE AT MONTREUX'
      title: 'Smells Like Teen Spirit'
         id: 'TRKUYPW128F92E1FC0'
   duration: 216.4502
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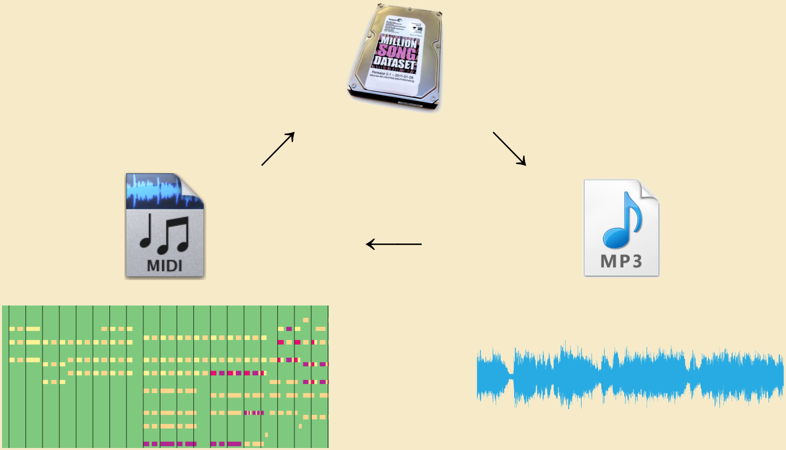
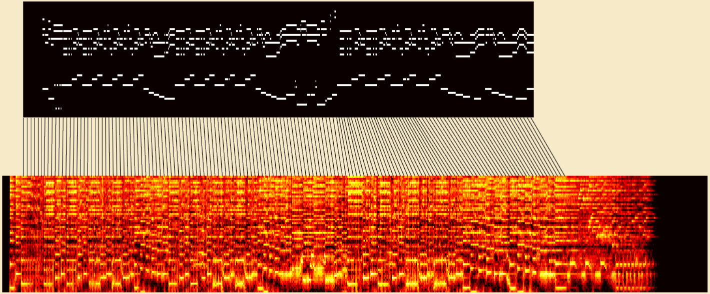


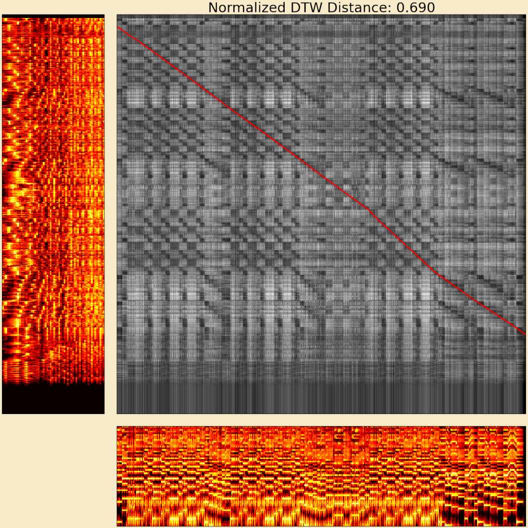
Matching by Metadata Won't Work

```
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
```

Aligning

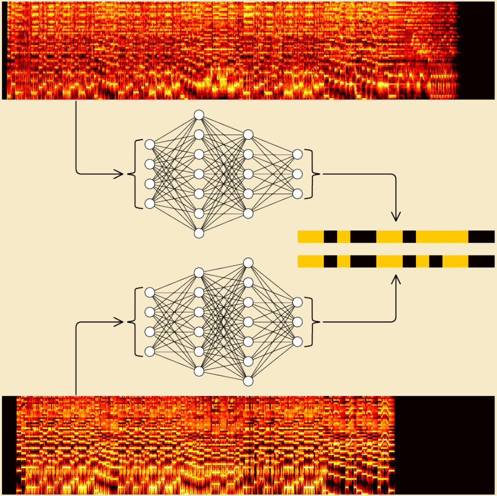


DTW: Natural, and Too Slow



Hu et al., *"Polyphonic Audio Matching and Alignment for Music Retrieval"*

Similarity-Preserving Hashing



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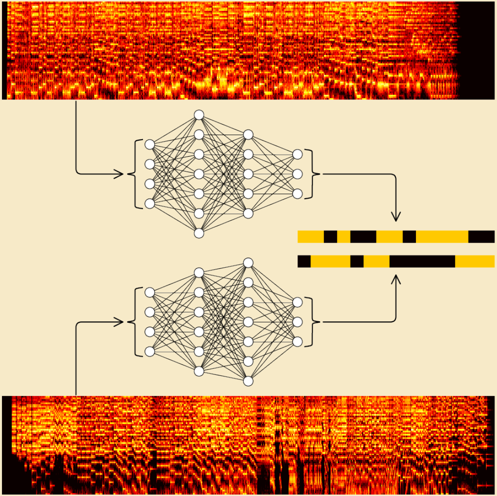
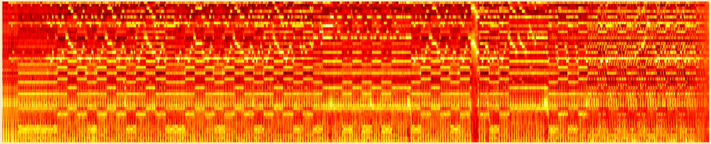


Hash Sequences



$$\downarrow$$

$$\texttt{distance}[m, n] = \texttt{bits\_set}[x[m] \oplus y[n]]$$

Training Data: Find 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
```

Training Data: Cleaning Metadata

```
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
```

```
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
```

25,000 $\rightarrow$ 17,000 (10,000)

Training Data: Text Matching

```
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,
TRLMFJ024KJ42K215E
TRFBTK0128F426441E
tlc/Crazy_Sexy_Cool/02-Creep.mp3
The Beatles - Help!.mp3
```

17,000 (9,000) $\rightarrow$ 26,000 (5,000)

Training Data: Alignment

1. Compute beat-synchronized CQTs of audio and synthesized MIDI

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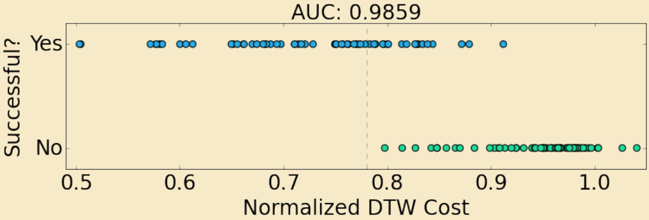
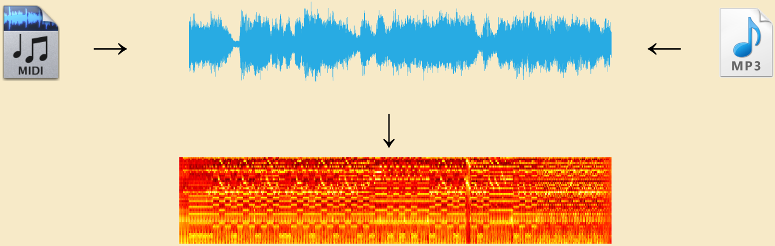
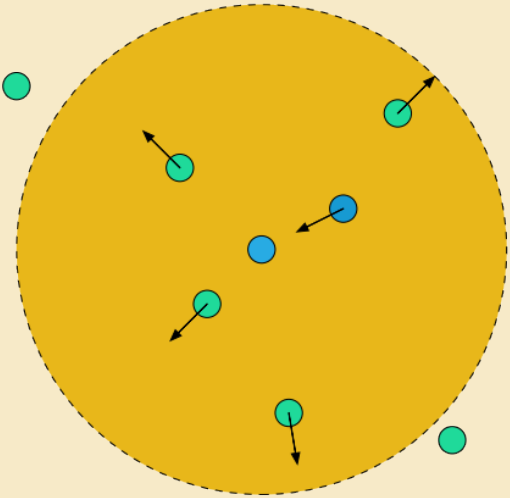


Input Features




```python
import librosa
# We could also obtain audio data from pretty_midi's fluidsynth method
audio, fs = librosa.load('audio_file.mp3')
# Compute a CQT with 48 notes, 12 bins per octave, starting from C3
cqt = np.abs(librosa.cqt(audio, fmin=librosa.midi_to_hz(36), n_bins=48))
# Compute onset envelope from CQT (for speed)
onset_envelope = librosa.onset.onset_strength(S=cqt, aggregate=np.median)
# Perform beat tracking using CQT-based onset strength
bpm, beats = librosa.beat.beat_track(onset_envelope=onset_envelope)
# Synchronize the CQT to the beats
sync_cqt = librosa.feature.sync(cqt, beats)
# Compute log amplitude
sync_cqt = librosa.logamplitude(sync_cqt, ref_power=sync_cqt.max())
# L2 normalize
sync_gram = librosa.util.normalize(sync_cqt, norm=2.)
```

Loss function



Training details

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- Objective: Bhattacharyya distance of positive/negative examples distance distributions

Network Structure

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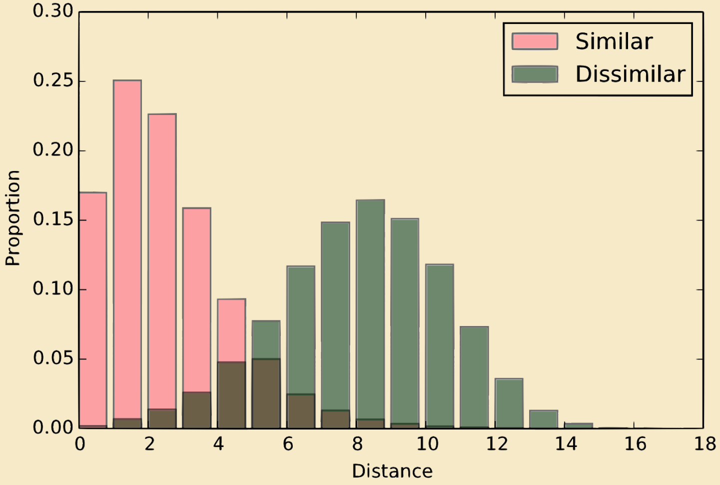
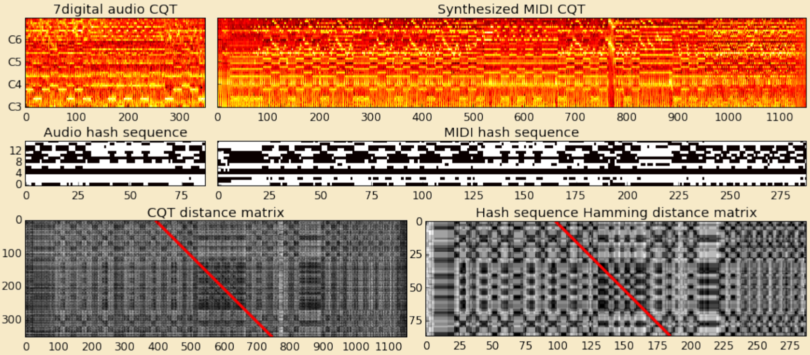
- Network made out of `lasagne`

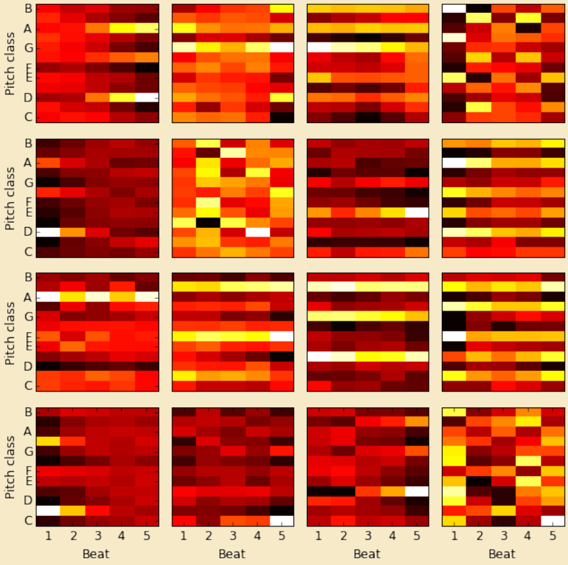
Validation Distance Distribution



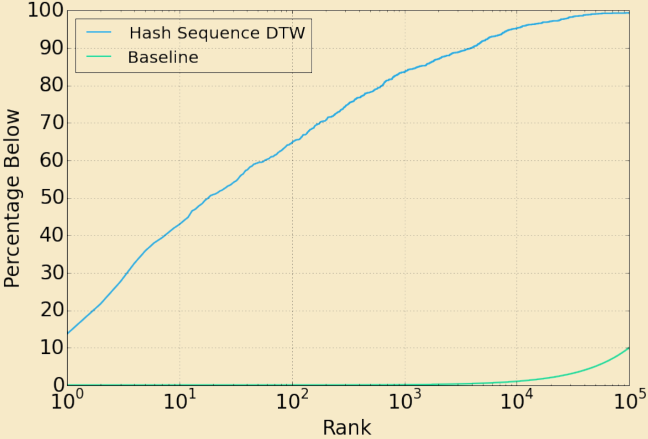
Example Sequence



First Layer Filters



Test: MIDI-to-MSD Matching



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- Discard 99% of the MSD in 1% of the time

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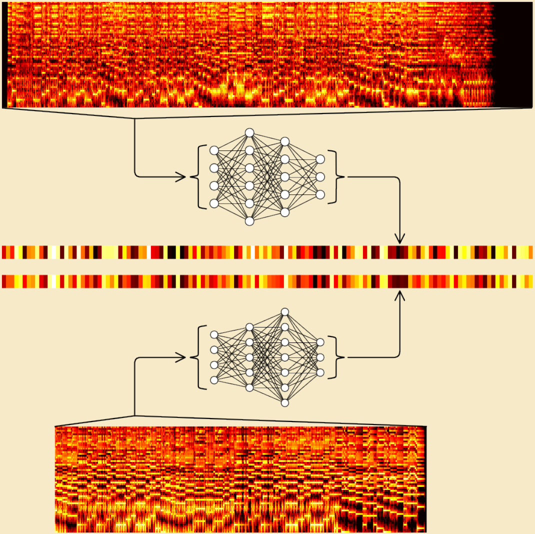
Sequence Embedding



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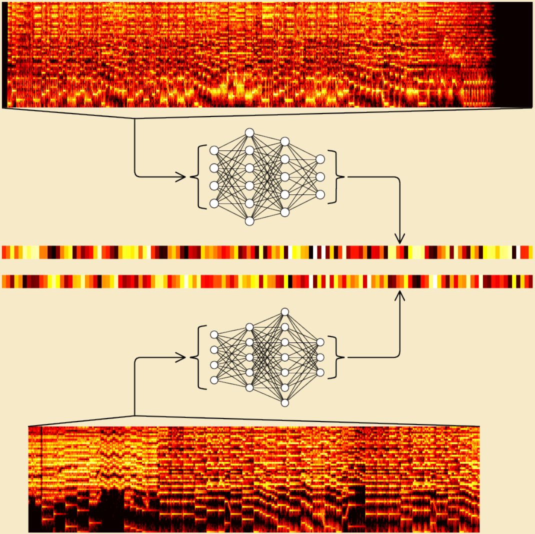
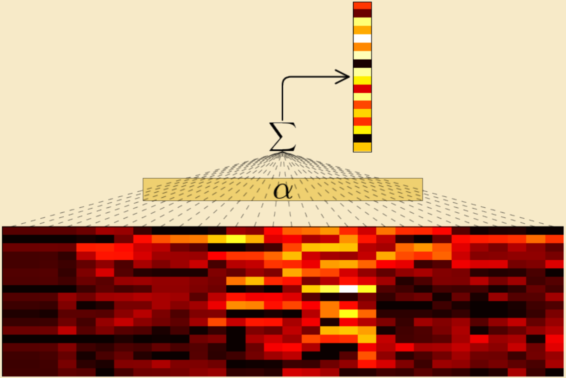


Attention



$$\alpha = \mathrm{softmax}(wx + b)$$

$$w \in \mathbb{R}^{\texttt{n\_features}},\ b \in \mathbb{R},\ \alpha \in \mathbb{R}^{\texttt{n\_steps}}$$

Other Differences

- Batches of entire (cropped) sequences

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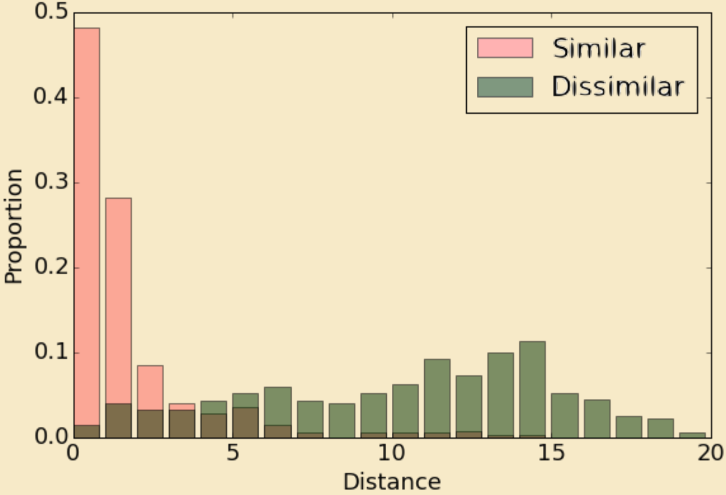
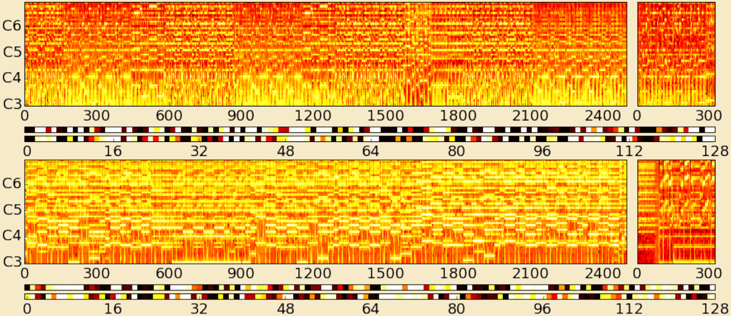
- Higher "correct alignment" threshold
- Re-tune hyperparameters with `simple_spearmint`
- Output is now $[-1, 1]^{128}$

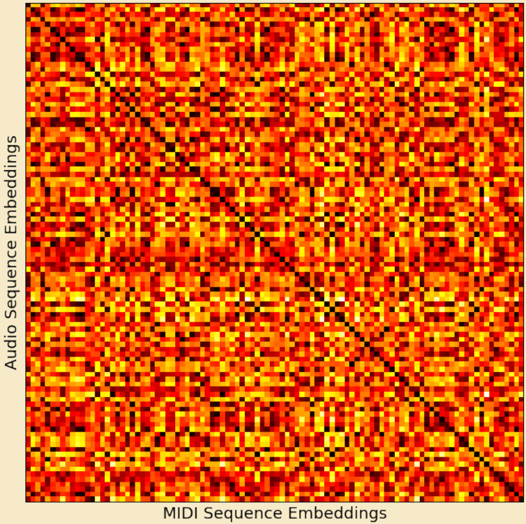
Validation Distance Distribution



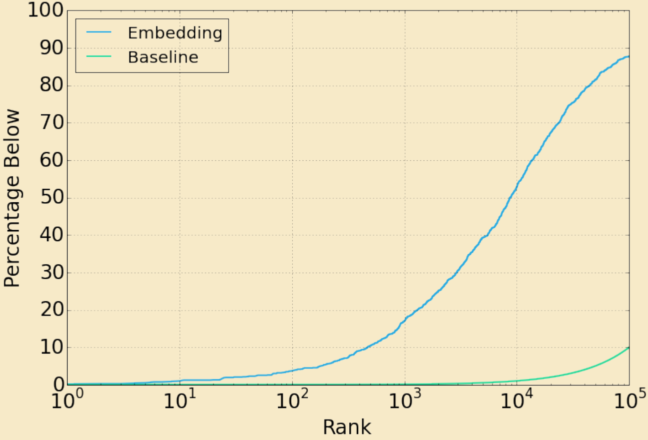
Example Embeddings



Embedding Distance Matrix



MIDI-to-MSD Matching



Related Work

Thanks!

http://github.com/craffel/midi-dataset
http://github.com/craffel/sequence-embedding
http://github.com/bmcfee/librosa
http://github.com/Lasagne/Lasagne
http://github.com/craffel/pretty-midi
http://github.com/craffel/simple_spearmint

craffel@gmail.com