



Using Deep Learning to Estimate Multiple Song Tempos

**ONE SONG
CAN HAVE
MORE THAN
ONE TEMPO**

**EVEN IF THE
TEMPO
DOESN'T
CHANGE
DURING THE
SONG**

Jackson 5

“I Want You Back”

100 Beats per Minute 🎵

Good for typical walking pace



Jackson 5

“I Want You Back”

200 Beats per Minute 🎵

Good for brisk running pace



**AUTOMATIC
TEMPO
ESTIMATION
METHODS**

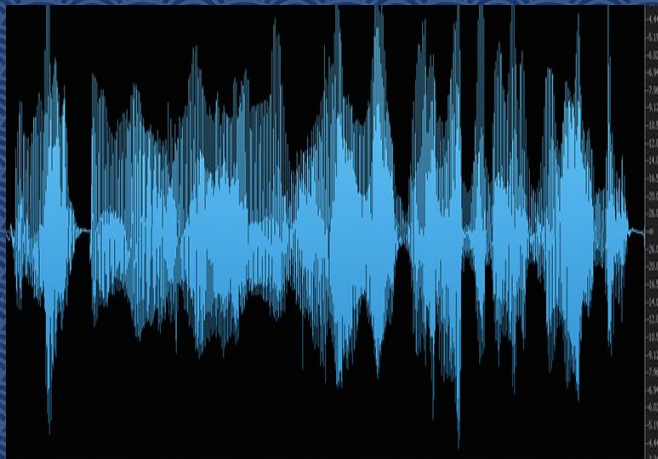
- ◎ Sometimes unreliable.
- ◎ Generally produce only one answer.

*Try to devise one that will be more reliable
and can give more than one answer when
appropriate*



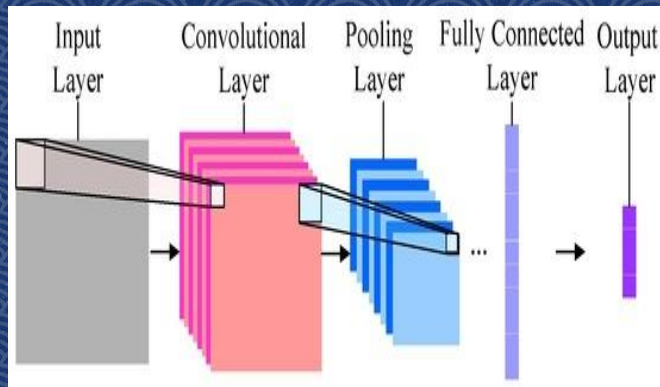
The Data

My MP3 collection:
about 150 audio files, one song each,
hand-labelled with 1, 2, or 3 tempos each



The Methods

- Mel Spectrogram computed by LibROSA
- Convolutional Neural Network



CHALLENGES

- ◎ Not enough data
- ◎ What loss function to use for multiple tempos?
- ◎ Some songs change tempo
- ◎ How to represent data to generate features

DEALING WITH TEMPO CHANGES

- ◎ Cut off beginning and end of each song (since many have tempo changes there).
- ◎ Drop songs with tempo changes in the middle.

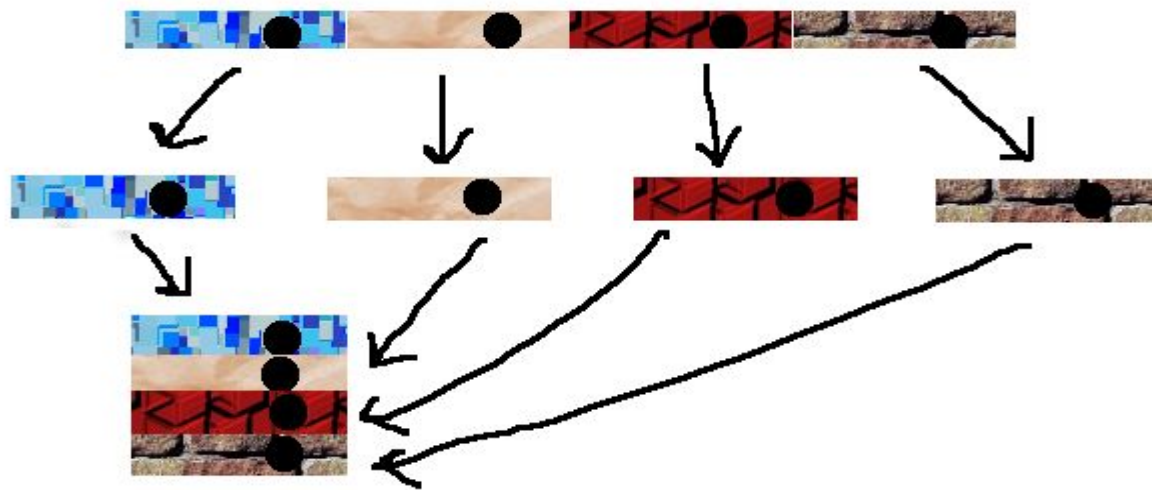
MAKING TRAINING DATA

- ◎ Create training examples by taking multiple random samples from each song. few->many
- ◎ Use peaks of LibROSA tempogram() function as “candidate tempos”
- ◎ Each sample gets assigned a candidate tempo (randomly chosen from those peaks)
- ◎ Simple binary loss: Is candidate tempo close to one of the hand-labeled tempos?

HOW TO REPRESENT THE DATA

Divide clip
into one
section for
each beat at
candidate
tempo, and
stack the
sections

Making Time 2-Dimensional

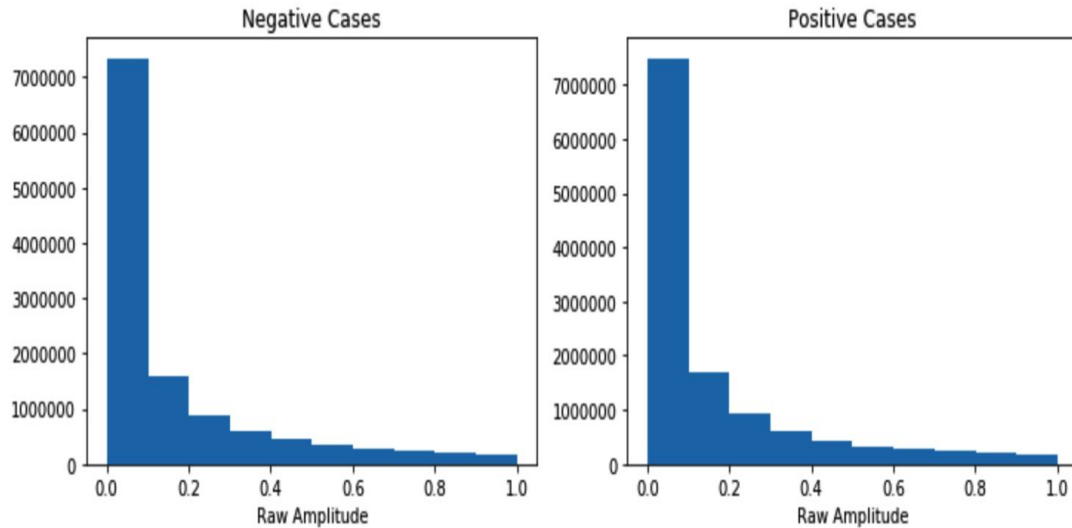


**THEN USE THE
STACKED DATA AS
INPUT TO A
2-DIMENSIONAL
CONVOLUTIONAL
NEURAL NETWORK**

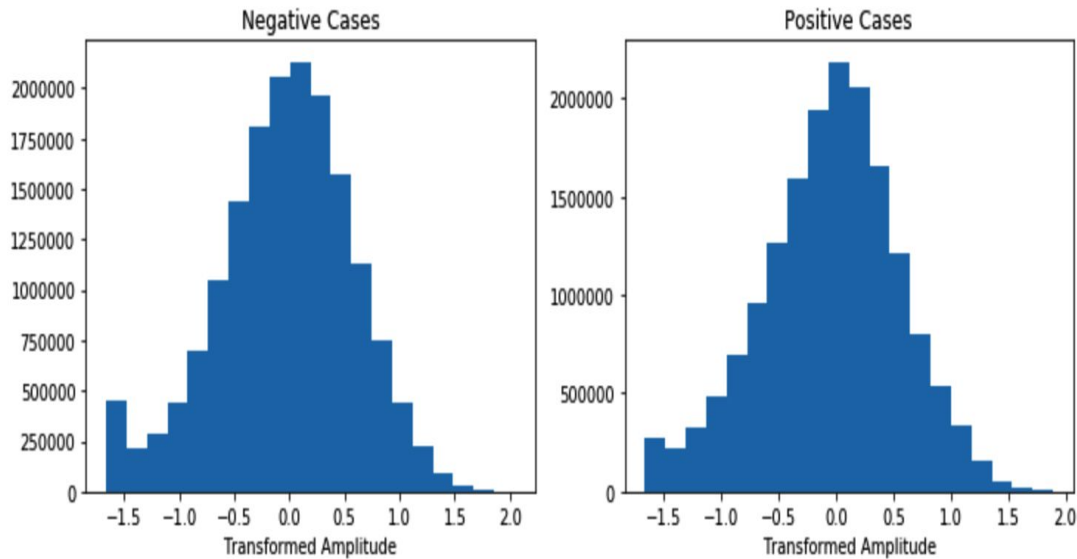
The background of the slide is a solid blue color with a repeating white wave pattern, resembling a traditional Japanese 'nami' pattern. The waves are arranged in a grid-like fashion, creating a textured effect.

How the data look

Distribution of Raw Data

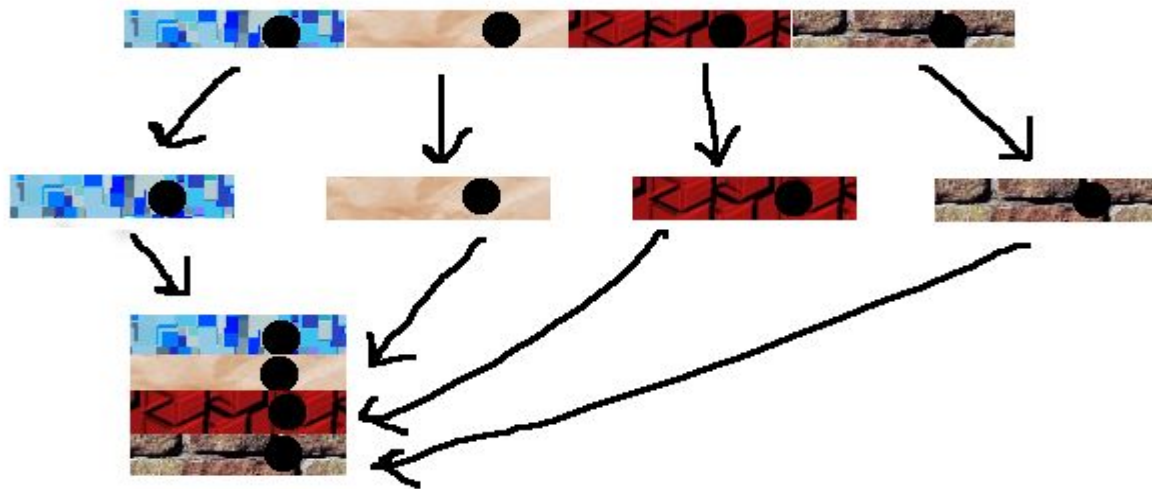


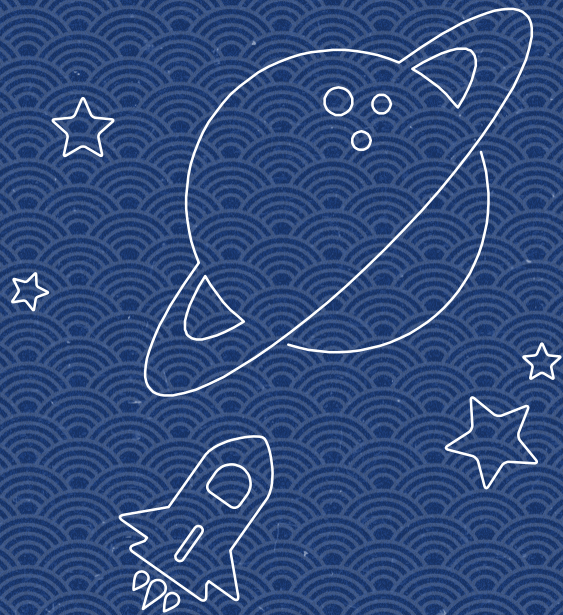
Transformed Data



**FOR
POSITIVE
(CORRECT)
CASES,
EACH BLOCK
OF DATA
SHOULD
HAVE A
CONSISTENT
VERTICAL
PATTERN, AS
BEATS GET
REPEATED**

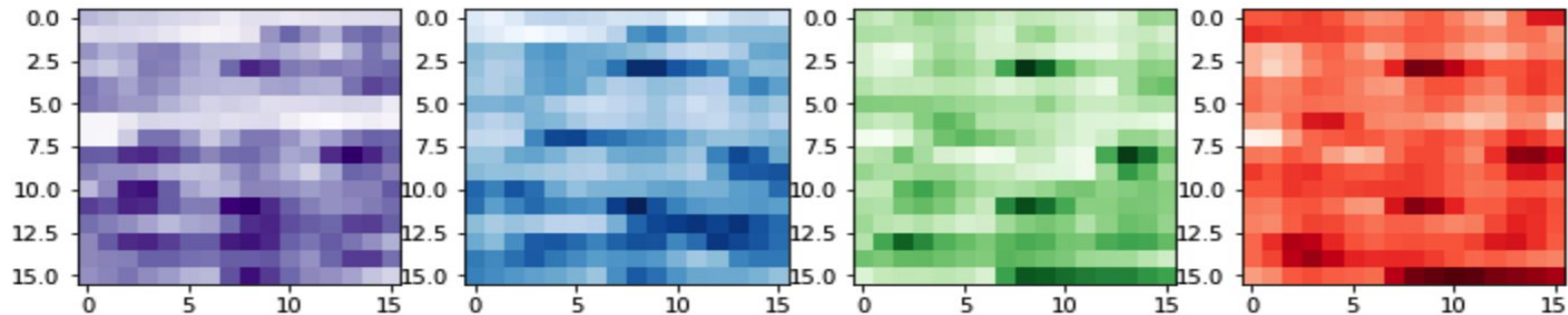
Making Time 2-Dimensional



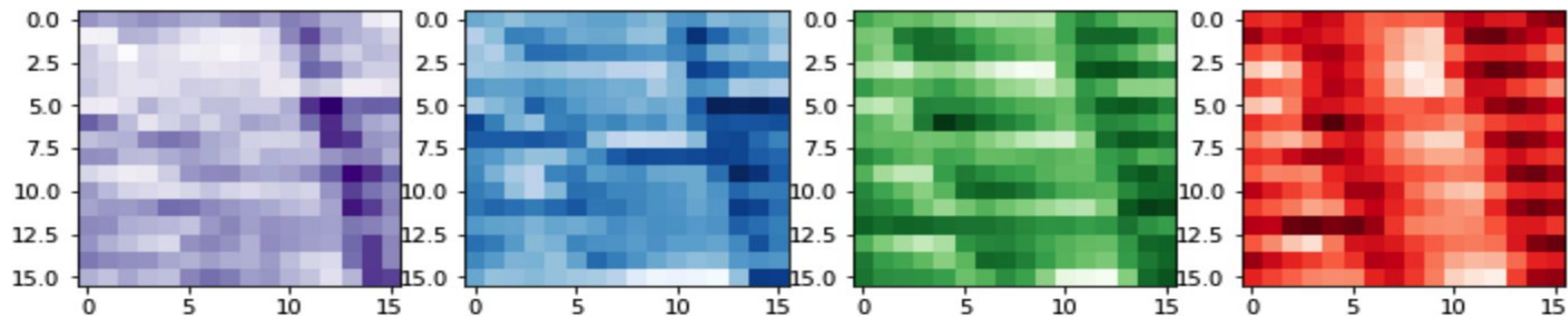


What do we actually see?

Negative case, preprocessed:



Positive case, preprocessed:



Here the spectrogram is divided into 4 sections, with the lowest pitches in purple and the highest in red. These cases are fairly typical. In the negative case, as expected, there are no clear patterns. In the positive case, there are almost-vertical patterns, but they are downward-sloping.

**STATISTICS
TO REPRESENT
VERTICAL
PATTERNS**

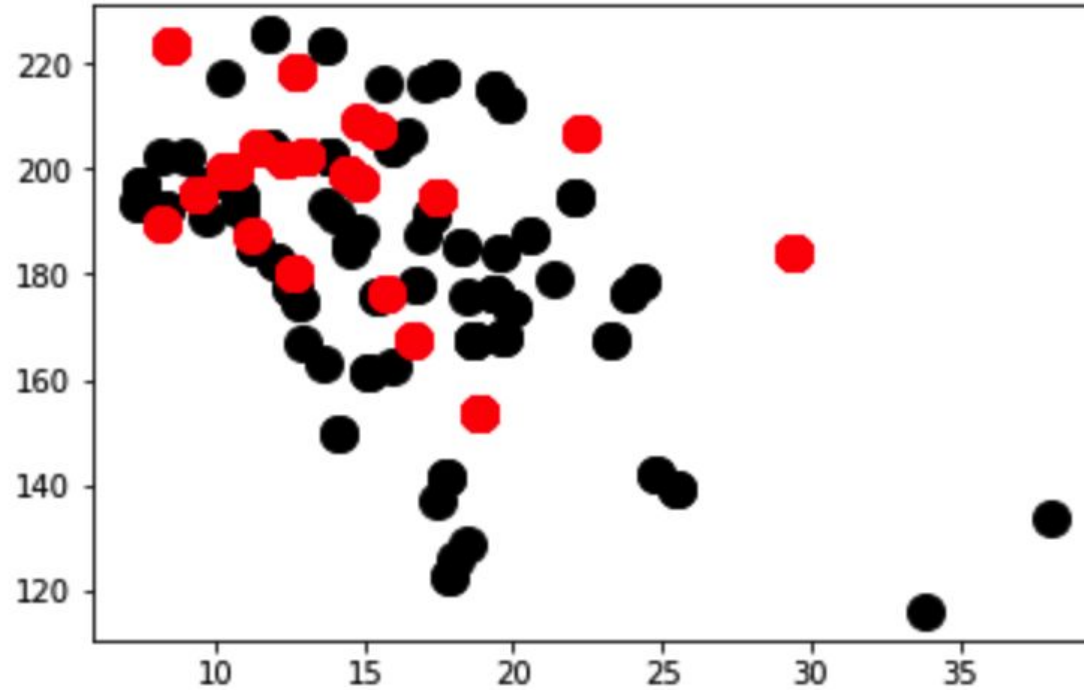
Average variance along
vertical dimension

Should be low for
positive cases

Average correlation
between successive
rows

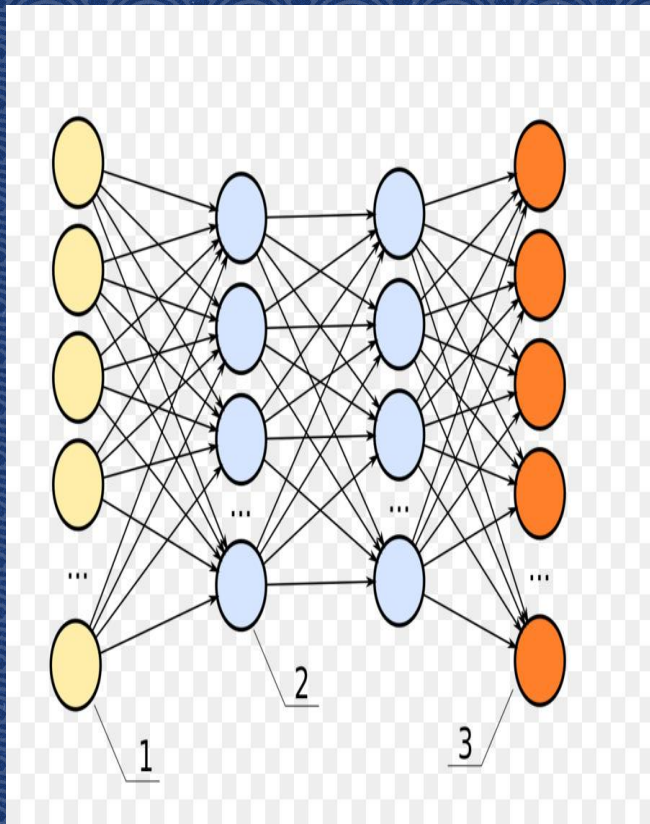
Should be high for
positive cases

**average
correlation**



average variance

The positive (red) cases, as expected, tend to have high average correlation and low average variance. The negative (black) cases are more broadly distributed, but they are more common elsewhere.



The Neural Network

STRUCTURE

Output: Sigmoid
Dense(20)
Dropout(.8)
1x4 Convolution, 3 filters
Batch Norm
4x6 Convolution, 25 filters
Dropout(.3)
1x4 Convolution, 12 filters
Batch Norm
1x1 Convolution, 32 filters
Dropout(.1)
1x1 Convolution, 64 filters
Input: 16x16, 128 channels

SALIENT FEATURES

- ◎ Narrow convolutions (1x4 and 4x6) instead of square convolutions
- ◎ Alternating batch normalization and dropout between successive convolutions
- ◎ Very high dropout before top layer

RESULTS

- ◎ Validation accuracy 0.91 (after 60 epochs using final version of model)
- ◎ This is quite good, considering that many cases are ambiguous

EXAMPLE RESULTS

- **53rdAnd3rdMP 45**
Predicted: 0.00090704486 Actual: False
- **AHardRainsAGonnaFall 56**
Predicted: 0.021726133 Actual: False
- **AHardRainsAGonnaFall 62**
Predicted: 0.017301498 Actual: True
- **InTheHillsOfShiloh 64**
Predicted: 0.13423629 Actual: False
- **CaliforniaDreamin2MP 112**
Predicted: 0.93683857 Actual: True

NEXT STEPS

So, so many: for example

- ◎ Look at results per song. Subjectively, how does model do at getting correct paces? Are typical failures legitimately ambiguous cases, or is the model really missing something?
- ◎ Get data from other human labelers.
- ◎
- ◎ Get more data for underrepresented genres (and time signatures). And a greater variety of artists.

....and so on

See <https://github.com/andyharless/paces/blob/master/README.md>



THANKS!

github.com/andyharless