MACHINE LEARNING METHODS FOR MUSIC TRANSCRIPTION

CMPE 492 FINAL REPORT

Student Name: Onur Orhan

Student ID: 2014400099

Advisor: Ali Taylan Cemgil

Boğaziçi University

Department of Computer Engineering

Fall 2018

Table of Contents

1. Introduction

1.1. What is Music Transcription

Music transcription is the transformation of a musical signal into either a human-readable, or a machine-readable form. Some trained people could achieve this task, with the help of their education and the human intuition. But it is very challenging to develop an automated transcriber, because we need to teach a machine to. We do not realize it often, but there is great mathematical harmony in music. So if we could figure out the aspects of this mathematics, it would be help us develop new technologies for the analysis and synthesis of music.

1.2. Main Attributes of Sound Events

In order to work on a sound event, there are four main qualities which need to be analyzed. These are namely the sound event's *pitch*, *loudness*, *duration* and *timbre* [1]. Here are some brief explanations of these four attributes.

a. **Pitch** refers to the perception of highness or lowness of the sound. In physical terms, this corresponds to the *fundamental frequency* in the signal. Usually integer multiples of the fundamental frequency (f_0) could also be observed, which together form the harmonics of f_0. In Western music, going an octave up means doubling the frequency. And this octave is logarithmically quantized as 12 notes (semitones). Which means that the kth semitone after f_0 has the frequency: $f_k = f_0 \times 2^{k/12}$

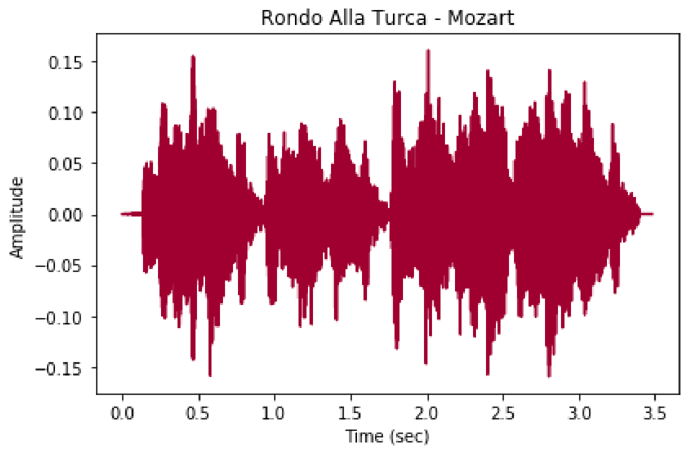
b. **Loudness** is the perception of the level of sound pressure in the ear [2]. This attribute depends on how quiet or loud the signal is.

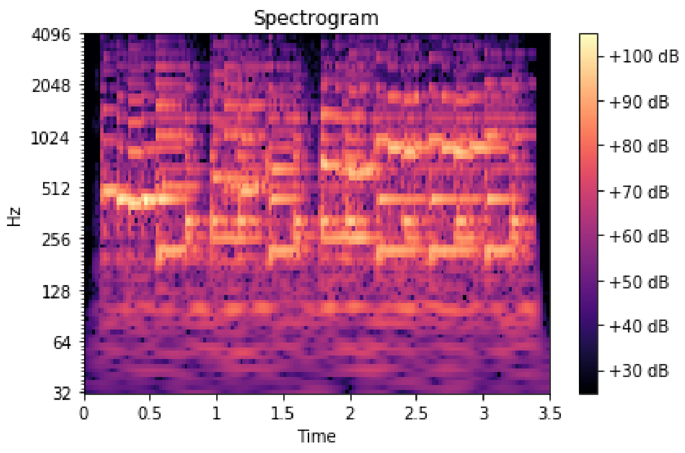
c. The interval between the onset and the offset of a sound event is called the **duration**.

d. **Timbre** of the sound depends on the source. For instance knocking on a door or playing the guitar creates different colors of sound. And although two sources could create sound signals with the same pitch, loudness and duration, they might be easily distinguished by their timbres.

Relating to these attributes of sounds, there are particular problems in music transcription. For example: beat tracking, pitch detection etc.

Let's analyze a musical excerpt from Mozart's *Rondo alla Turca*. Below, we see the sound intensity (loudness) versus time representation of a 3.5 seconds excerpt from Mozart. The note onsets are clearly visible as sharp spikes. But the peaks in the graph are indistinguishable in terms of their pitch values. After this, the musical excerpt is analyzed over a spectrogram on the right hand side. The sound signal is divided into different frequency values in every time frame. As the frequency gets higher, we hear higher tones. Per time frame and frequency value, the power output of the signal is represented by a color, ranging from purple to yellow in this case. We could observe the main melody between the frequencies 400-1000 Hz, and the accompanying chords between 200-400 Hz.





Samples: 76800

Sample Rate: 22050 Hz

Frequency Bins: 84

Spectrogram Frames: 151

2. Recent Research

2.1. Onsets and Frames: Dual Objective Piano Transcription

This is a newly released research by Google's *Magenta* team. Magenta focuses on machine learning methods for analyzing and synthesizing music. In this paper, they try to address the problem of polyphonic transcription for piano music using deep neural networks. They use *CNNs* (Convolutional Neural Networks) and *LSTMs* (Long Short Term Memory networks) during this process [4].

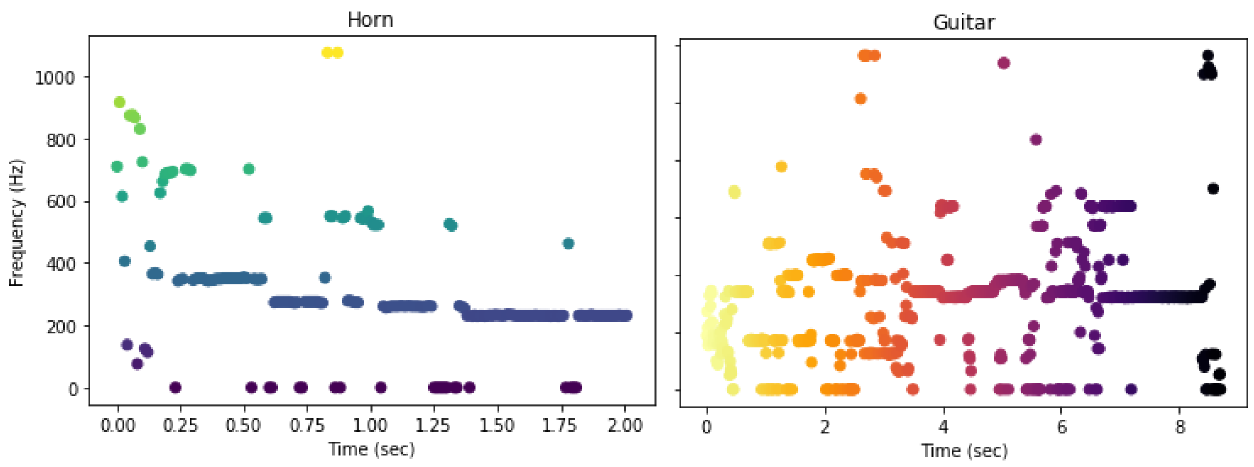
They utilize the MAPS dataset, which contains piano pieces both software synthesized and real time recorded. The synthesized pieces are used in training, whereas piano recordings form the test set. The onsets and frames model was trained using TensorFlow on the dataset.

Magenta divides the piano transcription problem into two: onset detection and framewise detection. The framewise detector is allowed to accept a note only if the onset for that pitch has been detected. Notes are more easily identifiable at the beginning, so onset detection is crucial in this model. The team actually experimented with removing the onset detection, but it turned out to be a bad idea. The onset and frame detectors first run a convolutional layer. This is followed by bidirectional LSTMs and fully connected sigmoid layers for both. At the same time, onset predictions are fed into the frame detection process as input.

2.2. Crepe: A Convolutional Representation for Pitch Estimation

CREPE is a data-driven pitch tracking algorithm for monophonic sound signals, producing state-of-the-art results. It stands for "Convolutional Representation for Pitch Estimation". CREPE works directly on time-domain and is based on a deep convolutional neural network [6].

The architecture composes of six convolutional layers with inputs of 1024-sample excerpts with a 16 kHz sampling rate. The output of the convolutional layers passes through a sigmoid activation layer, and the result is a 360-dimensional vector ŷ y^. The 360 nodes of this vector represents 360 pitch values. The vector covers six octaves with 20 cent intervals.



(100 cents equal to one semitone and 1200 cents equal to an octave) Each value in the vector shows the likelihood of the corresponding pitch value.

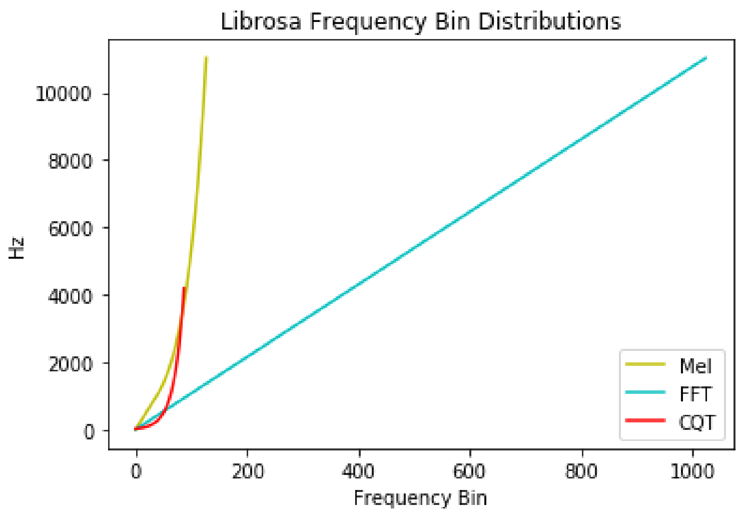
In the first plot above, there is a pitch analysis result of CREPE for an excerpt from Tchaikovsky's *Piano Concerto No. 1* which is played by a horn here. The four notes could be clearly observed as four lines in the graph. They correspond to the frequencies 350, 275, 261 and 231 Hz, slowly descending in pitch. Due of the timbre of the sound and the quality of the recording, we also see other frequency values in the graph. Some of them values are nearly integer multiples of the fundamental frequencies. So these frequencies could as well be analyzed as part of the musical signal, instead of being treated as noise.

The second plot is the CREPE pitch detection result for the beginning of the song *Paint it Black*, a guitar recording. We see that there are many frequencies apart from the main melody, although the sample music is mostly monophonic.

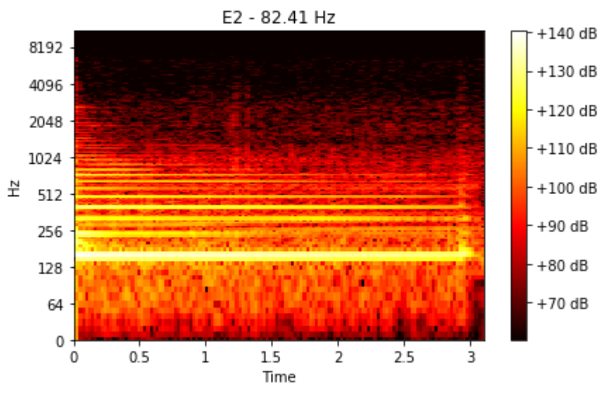
3. Implementation

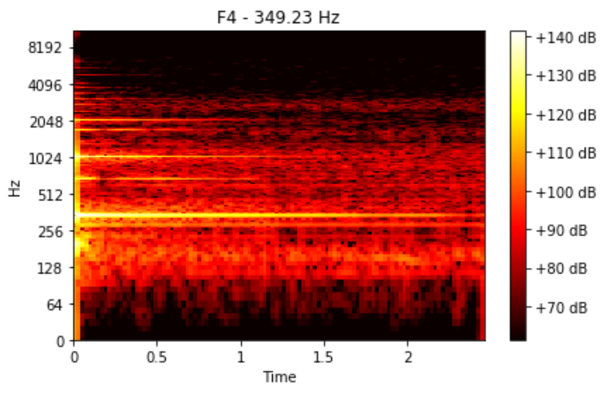
3.1. Frequency Bin Distributions

When the spectrograms are calculated from time domain signals, the frequency domain is quantized. There are various methods for spectrogram calculation, which apply different types of frequency scales. Major methods are namely Short Time Fourier Transform (STFT), Constant-Q Transform (CQT) and Mel-Frequency Cepstrum. In the Librosa library, FFT and Mel methods both cover the range of 1Hz-11KHz. But the CQT method covers lower frequencies much better, and the number of frequencies could also be adjusted. CQT has a very suitable frequency distribution between 1Hz and 4KHz, mapping frequency bins to a logarithmic scale. But why this interval? Because human ears are the most sensitive here. [8] Likewise, musical instruments chiefly span this frequency range. In my implementation, I applied the CQT method with 88 frequency bins (corresponding to 88 notes in the piano keyboard, from A0 to C8) with 12 bins per octave (12 semitones).



3.2. Musical Data





I collected Piano MIDI files from [d] and modified them as monophonic MIDI files. If there were multiple notes playing at the same time, I selected the note with the highest pitch and removed the rest. If there were any overlapping notes, I cropped them. Thus, I got monophonic MIDI files from polyphonic ones. I used the Pretty_MIDI Python library for this task. I also created text files and wrote down all the necessary information (frequency, onset, offset). Later when processing the audio files, I would use these information. For trying two-note polyphony, I repeated these steps for two simultaneous notes. (leaving out only two notes at any given instance, and cropping any interference)

After this, I synthesized WAV files from these monophonic MIDI files. I achieved this by using TiMidity++, which has inherent instrument libraries. But because WAV files take up too much space, I converted these into MP3 files, by using FFmpeg.

3.3. Input and Output

Because there are 88 notes in the piano, I calculated the 88-bin CQT spectrograms of the MP3 files. Then, I found the corresponding pitch frequency for each time frame. (This information is present in the text files) And for the ground truth, I created a probability vector of length 88 for each time frame. The probability distribution is Gaussian, with STD = 25 cents (cents are logarithmic and 1200 cents = 1 octave), and the correct frequency bin has the probability 1. To sum up, the input of the model is a 88-element vector, representing the frequency spectrum of a single time frame. And the output of the model is a probability vector of length 88. According to these probabilities, I will try to predict which note is being played at the given time.

3.4. Neural Network Model

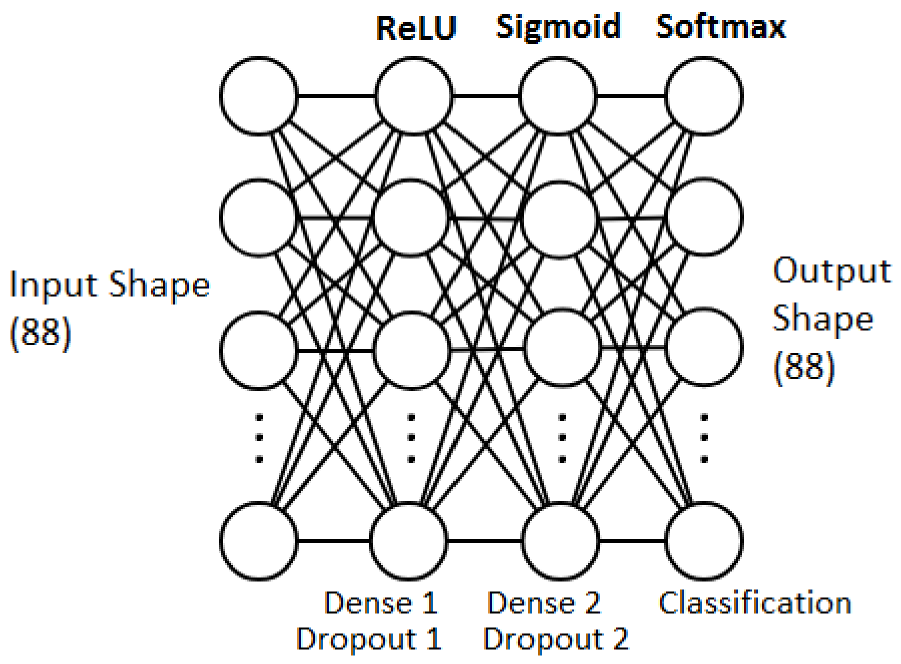
My neural network aims to transcribe monophonic piano music. It takes spectrogram data as input and provides pitch probabilities as output. The model model starts with an Input layer which takes 88-element vectors as input. This corresponds to the 88 notes in the piano. So each vector input represents the frequency spectrum of a single time frame. Higher values mean greater energy for the particular frequency during that particular time frame.

Following the Input layer, there is a Dense layer with ReLU activation. In a Dense layer, each input neuron is connected to all the output neurons. So there are 88 x 440 = 38,720 parameters to train, plus 440 bias parameters which add up to 39,160. This layer is followed by a Dropout layer with a ratio of 0.15, to avoid overfitting. ReLU (Rectified Linear Unit) is a non-linear function which outputs identity for positive input and outputs zero for others.

After the first Dense layer, there is another layer followed by a Sigmoid activation function. And finally there is a third Dense layer with Softmax activation. The reason for using the Softmax activation function is that it applies exponential normalization to the output. This is a classification problem and each element in the output vector represents a probability. So the Softmax function is suitable for this task, squeezing all the values so that they sum up to 1. On the other hand, the Sigmoid function maps input values individually to the range of 0-1, without doing any normalization.

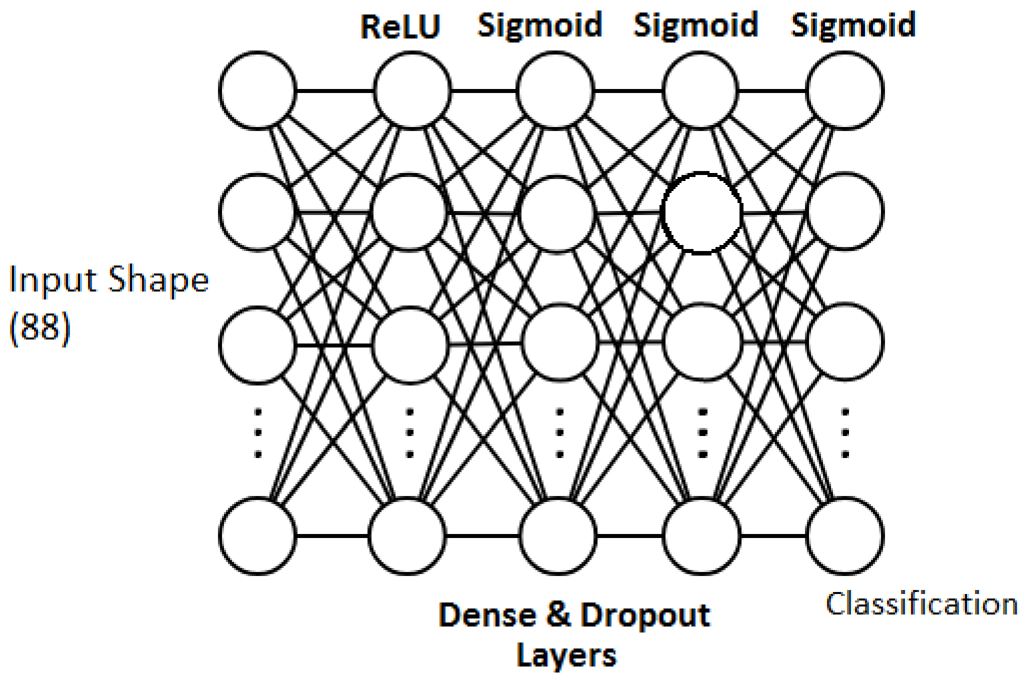
Finally, after making the necessary calculations for all the three layers, the total number of trainable parameters would add up to 177,846. When compiling the models, I selected the Adam (adaptive momentum estimation) optimizer and the binary cross-entropy loss function which is suitable for categorization problems.

Apart from the monophonic model, I also implemented and tested a polyphonic neural network model which could detect two notes playing at the same time. This new neural network has 4 layers, which includes 3 hidden layers. The first hidden layer is followed by a ReLU activation function whereas the following 3 layers have Sigmoids. The reason I did not use the Softmax function is that in the case of two simultaneous notes, the sum of the output vector would equal more than 1. That is why the Softmax function would not apply in this case. Actually, this model could be trained for even more simultaneous notes. Though I could not achieve acceptable results when I tried three-note polyphony. Thus, I adjusted the training and validation data so that they do not contain more than two simultaneous notes.



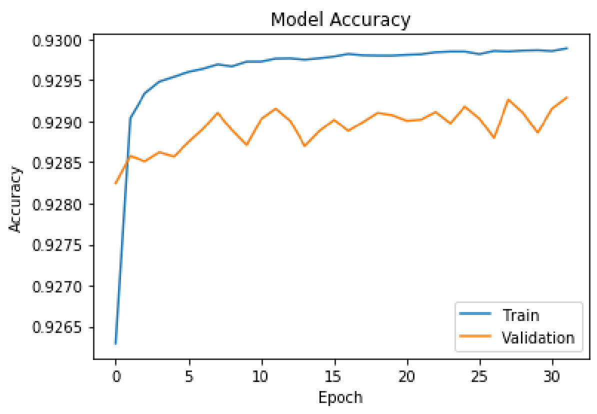
Above is a visualization of my neural network for monophonic music transcription. All three dense layers are followed by dropout layers and non-linear activation functions.

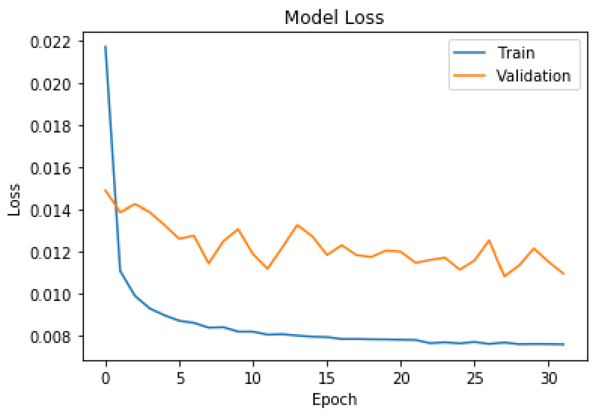
(Graph drawn at [10])



The above neural network model is for polyphonic (2-note) music transcription. This time, there is an additional hidden layer and the final activation function is sigmoid instead of softmax.

4. Results





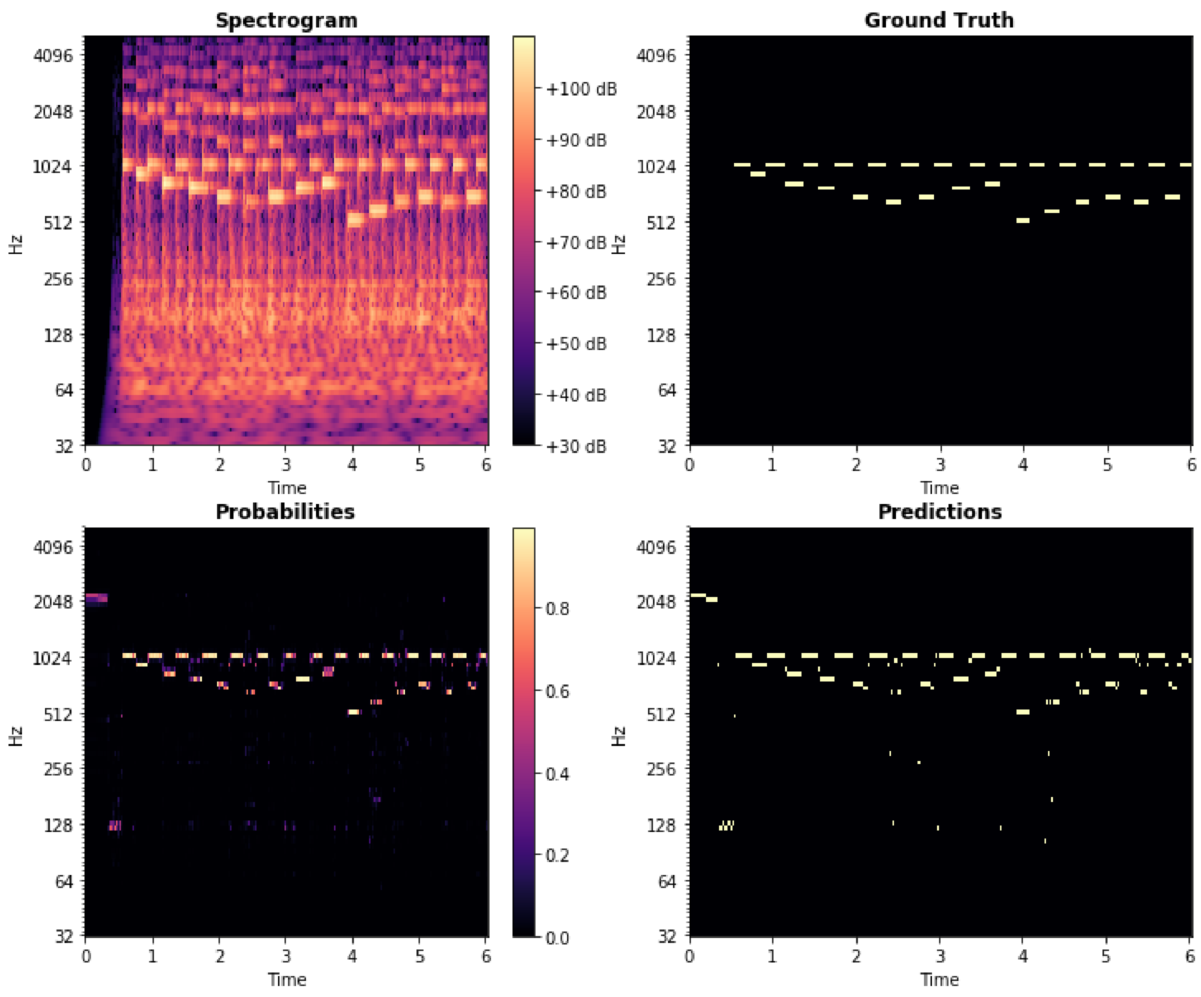
Above are the accuracy and loss plots, showing 32 epochs of training for the monophonic transcription model, with batch size 32.

For monophonic music, my neural network model achieved around 80% accuracy per time frame. Placing a hidden markov model after this showed less accurate results, but this is probably because of an implementation error. On the other hand, calculating the onsets and the offsets helped a lot for smoothing the output. Though I did not put these results in my report, because this method is too ad-hoc, and not systematic. Finally for polyphonic music, I did not get very good results, but I will still show a few results.

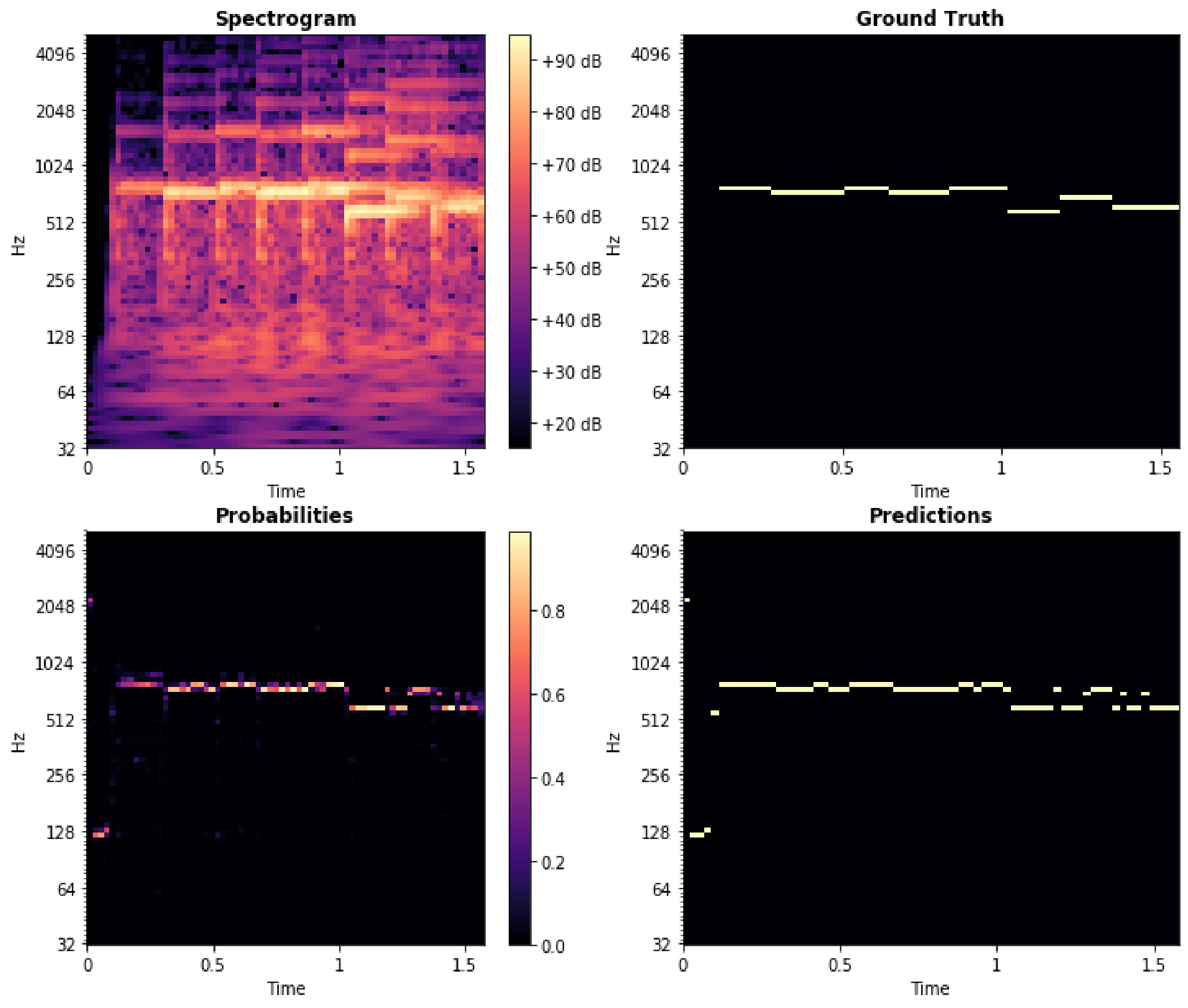
4.1. Transcription Examples

Here are some pitch predictions for four musical samples. The first two are monophonic piano music. These are samples namely from *Toccata and Fugue in D Minor - Bach* (sample recorded by me), and *Fur Elise - Beethoven* (samples taken from [e]). Following these monophonic ones, there are two polyphonic samples. Both have two-note chords, but one of them is a synthetic signal. These could be easily differentiated, because the synthetic signal would produce more accurate pitch predictions. This is actually not surprising, because the model itself was trained with synthetic piano data.

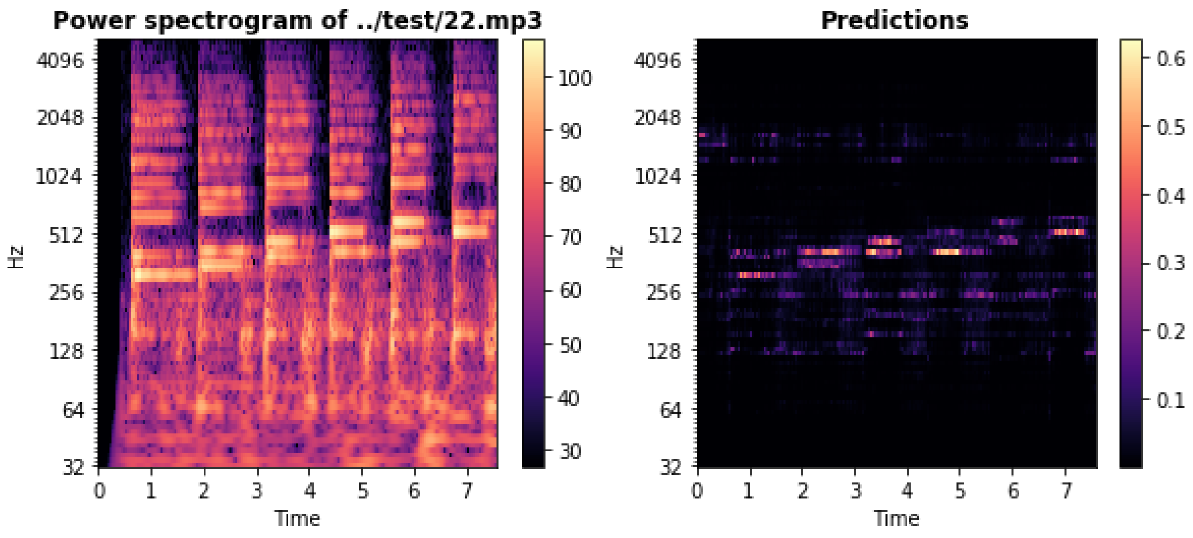
In the figures below, the spectogram is plotted on top-left, together with ground truth pitch values to its right. Next, the pitch probabilities are plotted on the bottom rows. The most probable pitch is selected for each time frame and predictions are displayed on the bottom right.



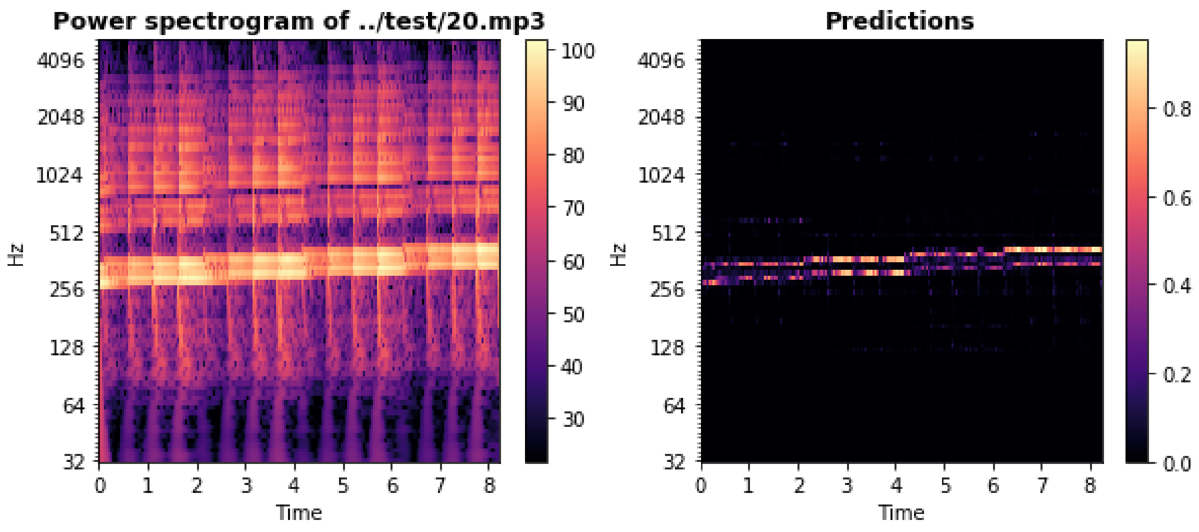
Toccata and Fugue in D Minor - Bach (monophonic recording)



Fur Elise - Beethoven (monophonic recording)



2-note chords (polyphonic recording)

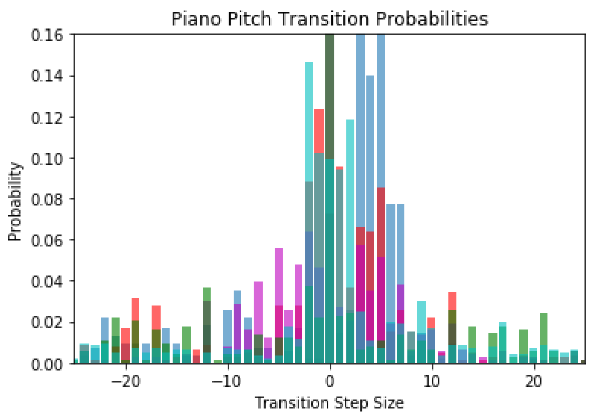


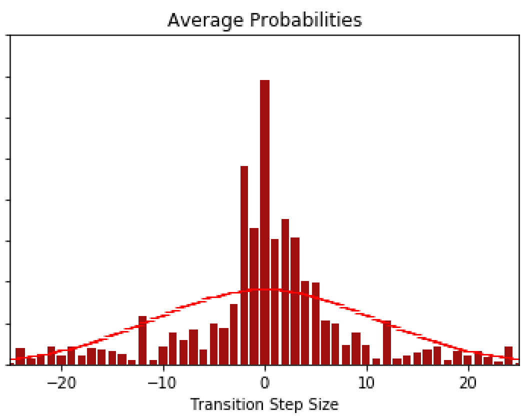
2-note chords (polyphonic and synthetic)

5. Hidden Markov Models

Hidden Markov Models (HMM) are used extensively for language processing since they are *sequence models* [7]. As language is made up of sequences of phonemes and words, music is made up of note sequences. So because of the similarity, HMMs could reasonably be used for musical transcription as well. Practically, we could collect statistics from musical sequences and then make inferences about unencountered music.

The only thing we know for certain are out observations, but we would like to reach information that is unknown to us. In a Hidden Markov Model, hidden states are the unknown information and they probabilistically make transitions to other states. The observations in the model are also produced probabilistically from hidden states. For pitch detection, HMMs could play a supporting role since we could analyze ground truth from musical data. And we could probabilistically represent note transitions and observations.

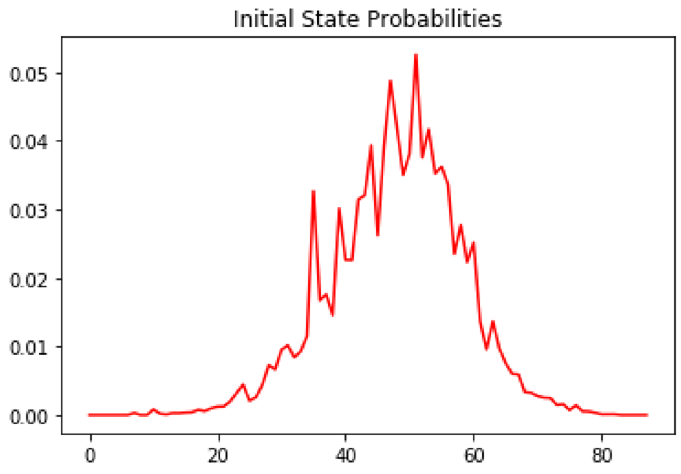




Above, sample guitar MIDI files [a] are analyzed for pitch transitions. Pitch intervals are logarithmic, and each transition is represented in terms of logarithmic steps. Transition probabilities are normalized for every midi file and then their average is calculated for the final plot. We could fit the average probabilities on a normal distribution by calculating the mean and the deviation. Although we could find a formulation for this phenomenon, preserving the irregularities could be helpful. Apparently, the probability distribution has larger values at small step sizes. But there are also irregular trends and spikes due to issues of musical harmony. Some transitions are more pleasant to our ears, thus preferred more often.

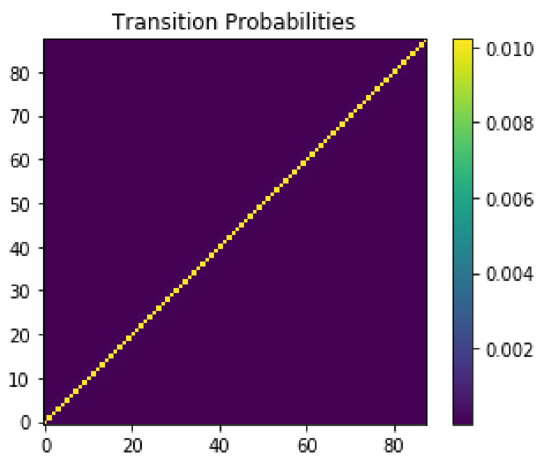
5.1. Viterbi Algorithm

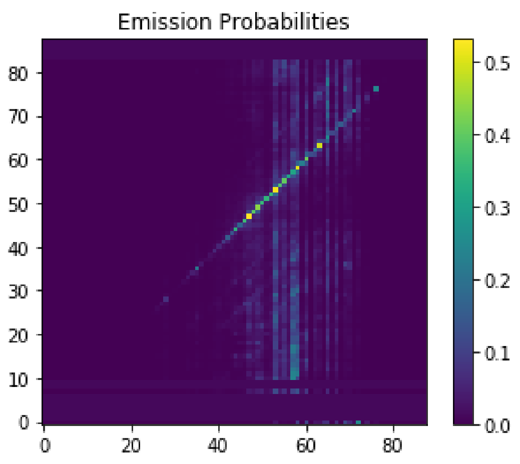
The Viterbi Algorithm is a method for finding the most probable hidden state sequence in a Hidden Markov Model, given the probability values and the observations. First, the initial probability distribution finds us a candidate state. Here, we also consider the emission probabilities which affect our initial observations. After selecting our initial hidden state, the algorithm enters a recursive phase where we continue level by level. When we complete this recursion, we backtrack and record the most probable state sequence.



If we analyze the case of music transcription, the initial state probabilities are actually how frequent each note occurs. From the plot on the left, we see that notes which are closer to the center keyboard are played much more frequently than the others. I calculated this data from MIDI files which I collected from the Internet.

The two plots below show the transition and emission probabilities of notes. Note transitions occur very frequently on the main diagonal, because this plot shows frame-wise probabilities. Once a note starts to play, it would stay for at least a few fractions of a second. The main diagonal is also visible for emission probabilities, because every note would most probably be observed as the same note. But due to errors in my neural network model, some notes could be observed incorrectly. (seen as vertical lines on the bottom-right plot) I actually implemented the Viterbi algorithm on top of my neural network model for monophonic transcription, but it surprisingly did not improve the overall transcription accuracy.





6. References

1. Klapuri, Anssi, and Manuel Davy. Signal Processing Methods for Music Transcription. Springer, 2006.

2. “Sound.” Wikiwand, https://www.wikiwand.com/en/Sound#/Sound_wave_properties_and_characteristics.

3. Goodfellow, Ian, et al. Deep Learning. MIT Press, 2016.

4. Hawthorne, et al. Onsets and Frames: Dual-Objective Piano Transcription. 30 Oct. 2017, https://arxiv.org/abs/1710.11153.

5. Olah, Christopher. “Understanding LSTM Networks.” Colah's Blog, 27 Aug. 2015, https://colah.github.io/posts/2015-08-Understanding-LSTMs/.

6. Kim, Jong Wook, et al. Crepe: A Convolutional Representation for Pitch Estimation. New York University, Feb. 2018.

7. “Hidden Markov Models.” Speech and Language Processing, by Dan Jurafsky and James H. Martin, 2016.

8. “How Does a Guitar Work?” How a Guitar Works, https://newt.phys.unsw.edu.au/music/guitar/guitarintro.html.

9. Neural Network Foundations, Explained: Activation Function, https://www.kdnuggets.com/2017/09/neural-network-foundations-explained-activation-function.html.

10. CS Academy, https://csacademy.com/app/graph_editor/.

6.1. Data

a. Classical Guitar Midi Archives, https://www.classicalguitarmidi.com.

b. Simple Pitch Detector, https://www.kaggle.com/asparago/simple-pitch-detector.

c. guitar-tuner-notes, https://soundcloud.com/guitar-tuner-notes.

d. Classical MIDI Files, https://www.mfiles.co.uk/classical-midi.htm.

e. Fur Elise (Piano Version), https://www.youtube.com/watch?v=_mVW8tgGY_w.