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Subject: Springboard Capstone 2 Final Report
Last Updated: 04/20/2019
Project Location: https://github.com/harajlim/MusicGeneration

Problem Statement:

Given a data set of “music”, we investigate learning what constitutes music (using Deep Learning tools), and generating new unheard music. More specifically, we limit the scope to solo piano pieces (no other instrument).

Project Importance:

This project is a great way of getting exposed to and familiar with various neural network architectures (LSTM, ConvNet, GAN net, etc.). Furthermore, the project presents an opportunity in dealing with a problem that does not clearly fall within either of supervised or unsupervised learning. Quantifying performance is consequently complex and requires some thought (which I think separates it from the typical data science project where accuracy and F1 scores reign supreme). Finally, the project (subjectively) has a certain “cool” factor that I as an amateur musician am attracted to: a computer is creating music!

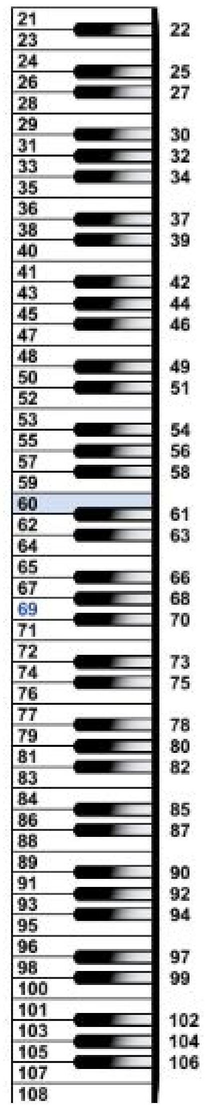
The Data:

We obtain piano midi tracks from this link. We use music21 to parse this data and obtain a representation of each midi file. This representation is called a stream, and is basically a list of music21 objects (either a note, chord or other event like an instrument definition). We concentrate on note and chord objects and list some of their relevant attributes:

- An offset: the time the note/chord started relative to the start of the stream (the start of the stream has offset 0).
- A duration, the time the note/chord lasts for.
- The pitch of the note (or pitch of each note in a chord) played. This indicates what key/keys on the piano is/are being played. Pitches are represented by a number from 1 to 127. The pitch number of each key in a piano is shown in figure 1 (note that a piano covers pitches from 21 to 108).
- A velocity: how hard the piano key is hit to play this note/chord.

We note that there are different types of music21 objects that we are not discussing. These objects enrich a musical piece and help define certain dynamic properties (like tempo of a song, time signature, and velocity); however we ignore them for simplification. With this simplification, all songs have the same tempo (which slows some and speeds others), and all notes have the same volume (no key is played softer/harder than any other).

Figure 1: MIDI pitch representation on a piano



<u>Exploratory Data Analysis:</u>

In this section we take a closer look at the chord and note events occurring for all the piano pieces in our dataset. The goal of this analysis is to understand how the attributes of notes and chords are distributed, and which ones play an important role in explaining what makes music sound as it sounds. This ultimately should help in the encoding of the midi files into a format that can be used to train deep neural nets (that will ultimately generate music). All code for this section can be found in the jupyter notebook named: *Milestone1Report.ipynb.*

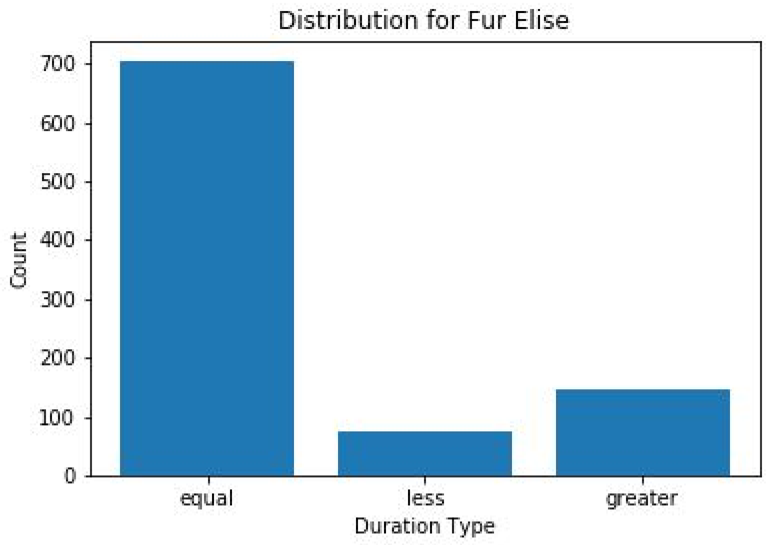
Since each note has an offset and a duration, one would think that one of the two attributes is redundant (the duration of the note could be obtained by subtracting the note's offset from the next event's offset, assuming both duration and offset have the same unit of time). That is in fact not true. There are two scenarios where this fails:

1. A note is played, then stopped. A rest (i.e. no sound) occurs for a short while, before a new note is played. This would give a duration that is smaller than the difference of offsets.
2. A note is played and held, and a new note is played as the note is still being held. This would cause the duration of the first note played to be larger than the difference of offsets.

We begin by observing the distribution of note duration types, where the the three types are: duration equal to the offset difference, duration less that the offset difference, and duration greater than the offset difference. We first look at how this distribution varies for different select songs, before obtaining the distribution over the entire dataset. In figures 2 3 and 4, the x-axis denotes whether the duration of the note is “equal” to, “less” than, or “greater” than the offset difference.

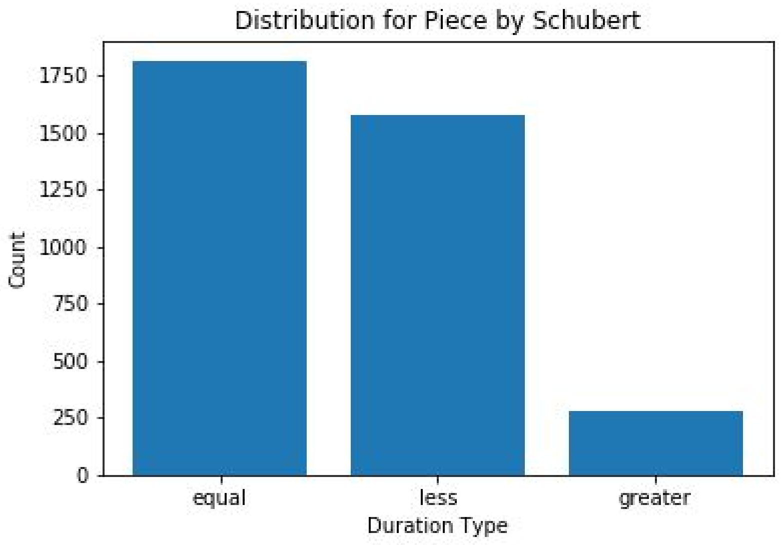
We begin by looking at Beethoven's Fur Elise. We get the following distribution:

Figure 2: Note duration types for Beethoven's Fur Elise



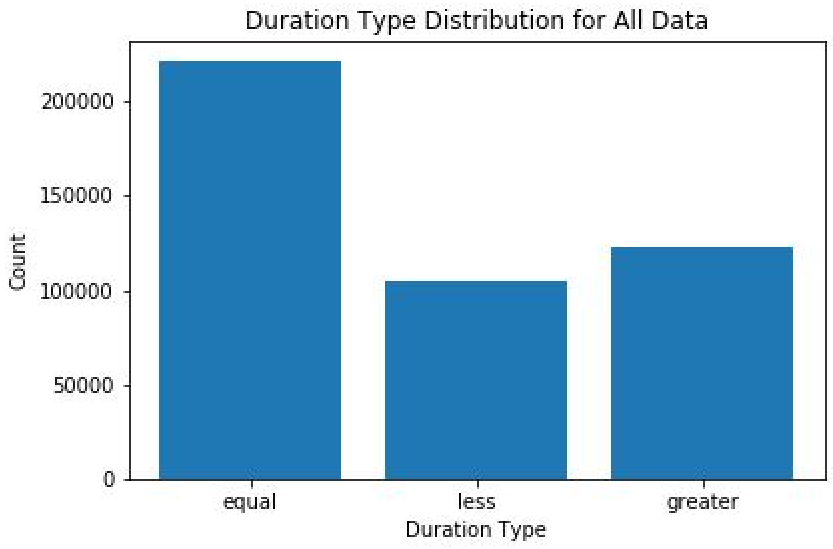
Next we look at a piano piece by Schubert:

Figure 3: Note duration types for piano piece by Schubert



As can be seen, the distribution varies between the songs. In Figure 4 we show the distribution over all the songs in our dataset.

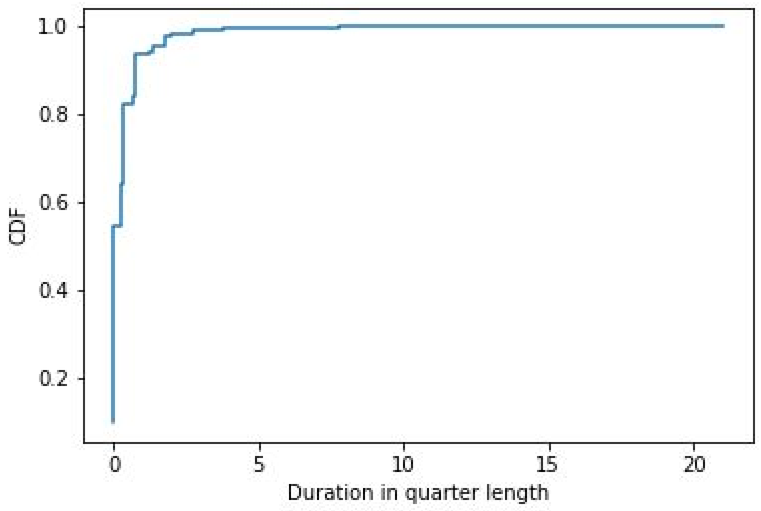
Figure 4: Note duration types for entire dataset



When looking at the entire dataset, we see that in fact the most common type of duration is that which is equal to the offset difference.

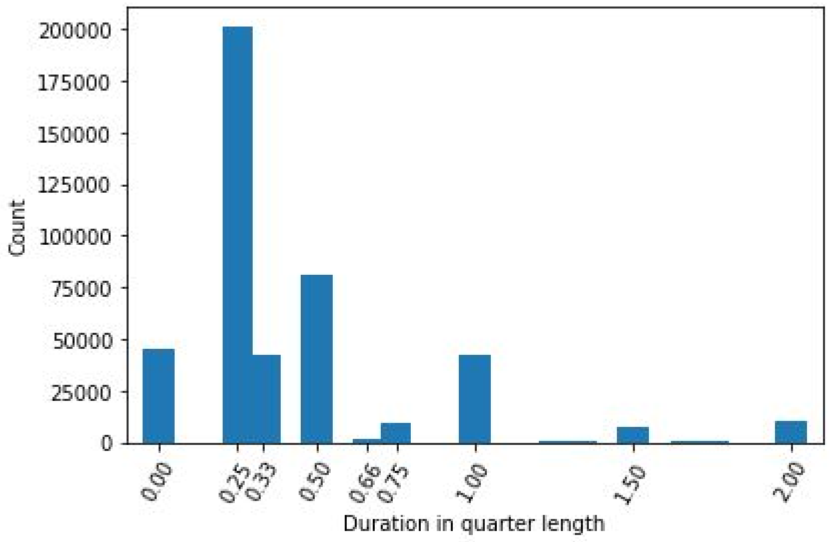
We next look at the distribution of note/chord durations. While we could use seconds (or any measure of absolute time) as a measure of duration, it is more useful to think of duration in terms of quarter notes. Quarter notes themselves are loosely defined temporally and depend on the beats per minute the songs utilizes. It it is more useful to think about duration relative to a song's inherent beat than in seconds. Below we show the cumulative distribution function of duration over all the dataset. The cumulative distribution is shown first (as opposed to the histogram), since it better handles the sparse space of occuring values.

Figure 5: Note duration types for entire dataset



From above, we see that the majority of notes/chords have durations less than 4 quarter lengths. Taking a closer look, Figure 6 shows a histogram for durations up to 2 quarter lengths.

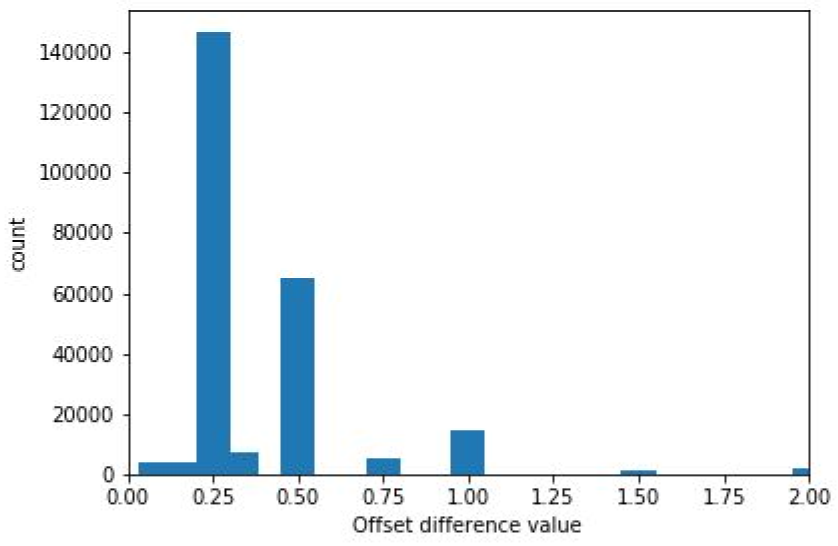
Figure 6: Histogram of durations for durations up to 2 quarter lengths



We can see from the above that most note are 0.25 quarter lengths (i.e. a sixteenth note). We also see the presence of notes of 0.33 quarter lengths (these are called triplets since we get 3 notes per beat).

Next we check the distribution of offset differences. In other words we obtain the distribution of the difference between an offset and the next event's offset. We note that more than one event may share an offset. Figure 7 shows the histogram of offset differences up to 2 seconds.

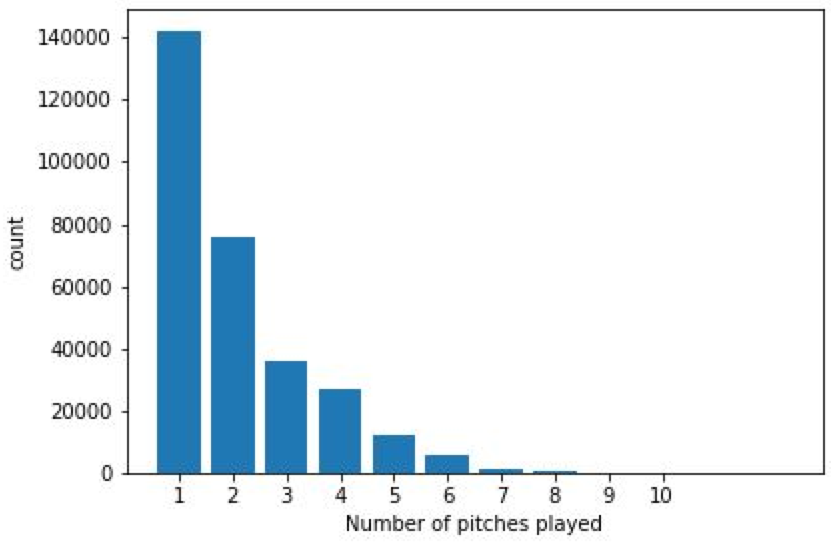
Figure 7: Histogram of offset differences up to 2 quarter lengths differences



We next check the distribution of the total number of pitches played at any given offset. We recall that a chord is a group of pitches played together. We also recall that more than one event can share the same offset. We thus obtain all the events for a given offset and count all the pitches played. Since all the music is piano music, and humans have 10 fingers, we expect that at most 10 fingers are used at any given offset and that most offsets involve events that use less than 10 pitches.

Figure 8 shows the distribution of pitches played at each offset.

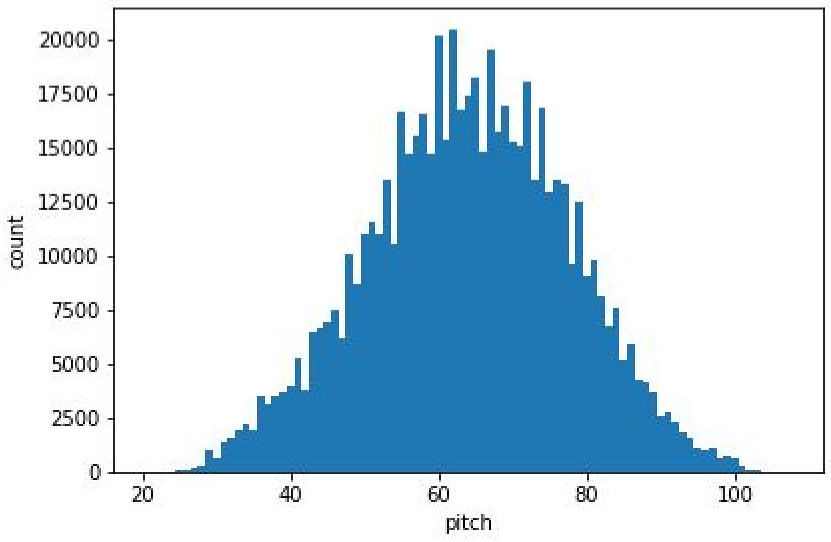
Figure 8: Histogram of number of pitches played at each offset



As can be seen in figure 8, the majority of offsets have one pitch being played.

Finally, we show the distribution of pitches used for the entire dataset. This will help us see if we can drop some unused keys when representing music, which could help us reduce the dimensionality of our feature space.

Figure 9: Histogram of pitches played



We can see from the above that the majority of the notes are centered about pitch 60 (which is called the middle C, also highlighted in figure 1). More so, we calculate that the 99% of the notes are between pitches 31 and 97.

Encoding Music:

In this section we discuss how to represent each song. We recall from the proposal that music should be expressed as a sequence of events. That way we can train a recurrent neural network to predict the next event. Since the majority of durations can be inferred from the offsets, we decide to drop durations from our representation and only encode offsets. This will change the music slightly but keep the general melody. Moreover we drop chords from the representation, since these can be expressed by note events sharing the same offset. With that the encoded sequence should have the following properties:

1. Be a sequence of events.
2. Each event should be a note event or a “goforward” event. Go forward events indicate the end of an offset and the start of a new one. A go forward event should have some indication how far forward to go (one quarter length, a quarter of a quarter length, etc.)
3. No more than 10 note events should occur between two goforward events.
4. No goforward event should be followed by another goforward event.

With the above, Beethoven’s Fur Elise become represented as follows:

[‘76’, 'gf0.25', ’75’, 'gf0.25', ‘76’, 'gf0.25', ‘75’, 'gf0.25', ‘76’, 'gf0.25', ‘71’, 'gf0.25', ‘74’, 'gf0.25', ‘72’, 'gf0.25', ‘45’, ‘69’...]

Above we highlighted the goforwards events to show where time jumps occur. We note that element that follow each other in the sequence above are not necessarily played after each other. In fact that is only the case if there is at least on “gf” event between them.

A couple of observations:

- The gf0.25 indicated a jump in time, where the jump is a quarter of a quarter length.
- More than one note can be played at a certain time, for example the 45,69 at the end of the shown list above.
- We only got goforwards (gf) events of duration 0.25. This is by chance, we will show below the encoding for other songs and see how there can be various gf events.
- When more than one note is played at one time offset, the notes are listed in increasing order. This might help as sequences have a more ordered structure.

We show the encoding for a song by Debussy:

['65', '68', 'gf0.5', '77', '80', 'gf2.0', '73', '77', 'gf1.5', '66', '69', 'gf0.5', '72', '75', 'gf0.5', '73', '77' ...]

In the jupyter notebook Milestone1Report, two functions: encode_song() and decode_song() encode and decode songs. The encode_song() function takes as input a midi and returns a list as shown above, while the decode songs takes in a list and a filename, and saves a new midi file in the location specified by filename.

We encode and decode Beethoven's Fur Elise and listen to it to make sure that the melody is still there after the encoding and decoding process. The midi file from that can be found in the samples folder in the midi file called: encoded_decoded_fur_elise.mid. As can be heard, the melody is intact albeit a bit sped up. This can be fixed by changing the tempo of the stream if necessary.

In the notebook prepareData.ipynb, we encode all the songs in our database and save them in a pandas dataframe.

Music Generation:

With each song encoded as a sequence of events (gf or note event), we look into training a model to predict the 51st event given the previous 50 events. There is no particular reason for picking 50. However a number too small would not provide the model with enough information to predict the next note, while a number too big might be overkill to the model. With that 50 seems like a reasonable number.

We will see how to use this trained model to generate music in the coming few sections. First we look into how to train such a model, and what model to chose.

Preparation of Inputs and Outputs:

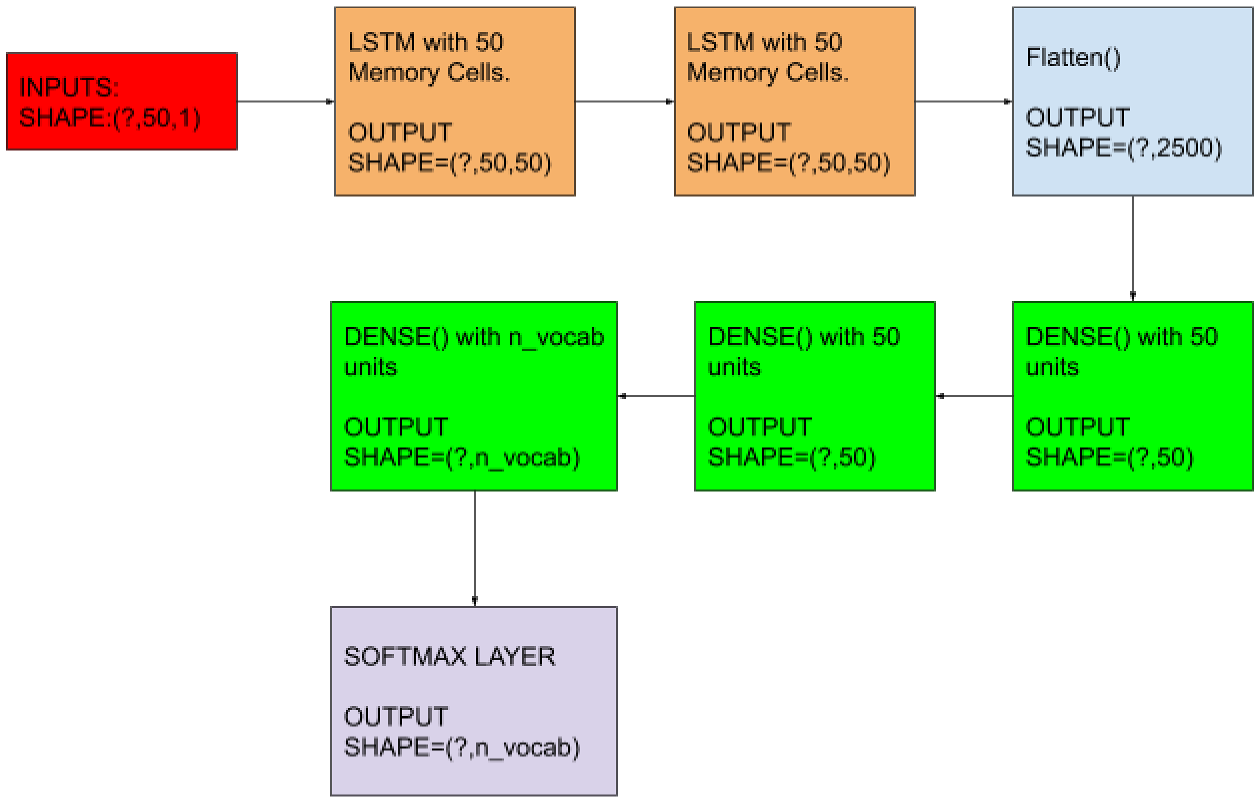
Previously (in the prepareData.ipynb jupyter notebook) we encoded all the songs in our database and ordered them in a dataframe (that can be found in encodings/information.pickle). The code pertinent to this section (for preparing, training a model and using it for generation can be found in TrainModel_andGenerate.ipynb). In order to train a neural network, the encoded stream should be transformed into a stream of numbers rather than a stream of strings (integer encoding). We do this by first obtaining the set of unique events occuring in all the representations (i.e. obtaining the vocabulary), and then defining transformations from strings to integers and vice versa (see the EventToNumber and NumberToEvent dictionaries in the jupyter notebook). We note that the integers obtained after integer encoding were normalized by dividing by the number of words in the vocab. This provided more stability in the trainin process.

Now having the appropriate inputs for a neural network we prepare the sequences of inputs and their corresponding output. Taking a close look, every input sequence will have 50 integer elements, and one event as an output. For the output, we opt to one-hot-encode the output rather than integer encode. This would entail having an output layer for the network that has as many nodes as words in the vocabulary (with softmax activation).

The preparation of the inputs and outputs can be found in the function prepare_inputs which takes as input the dataframe including the encoding of the songs, the number of words in the vocabulary, and the EventToNumber transformation.

Neural Network Architecture:

In this report, we investigate the use of a LSTM neural network. Specifically, we opt for the following architecture, and build it using KERAS.



Training the Network and Results:

To speed the process of training we use CuDNNLSTM instead of LSTM. CuDNNLSTM is a fast LSTM implementation using CuDNN. CuDNNLSTM requires GPUs however, consequently the notebook was run on an aws p2.xlarge server.

To simplify training and analysis of results, we limit the training data to one artist, namely Mendelssohn. Mendelssohn has 15 songs in the set we have. This translates to 29240 input sequences (not so small of a dataset). We take 14 of these songs for training, and keep one to see how the model performs in guessing the next note for the unseen song. We note the test train split is small here, however with the intention of music generation that should be fine.

The neural network is trained for 500 epochs (with a batch size of 1000). The training takes around 12.5 minutes achieving a loss of 0.0788. The accuracy score over the training data is about 98%. Checkpoints are set so as to save the Keras model in the SavedModels folder.

Looking at the unseen song, the model performs with an accuracy of 16.25 percent. To make sure this result is not due to the model simply guessing one very likely event many times, we plot the distribution of predicted events for the testing data (see figure 10). As can be seen the distribution seems to be reasonable. Events like gf0.5 are very likely and happen the most. Note events are also predicted relatively frequently with the distribution being pretty uniform over the notes.

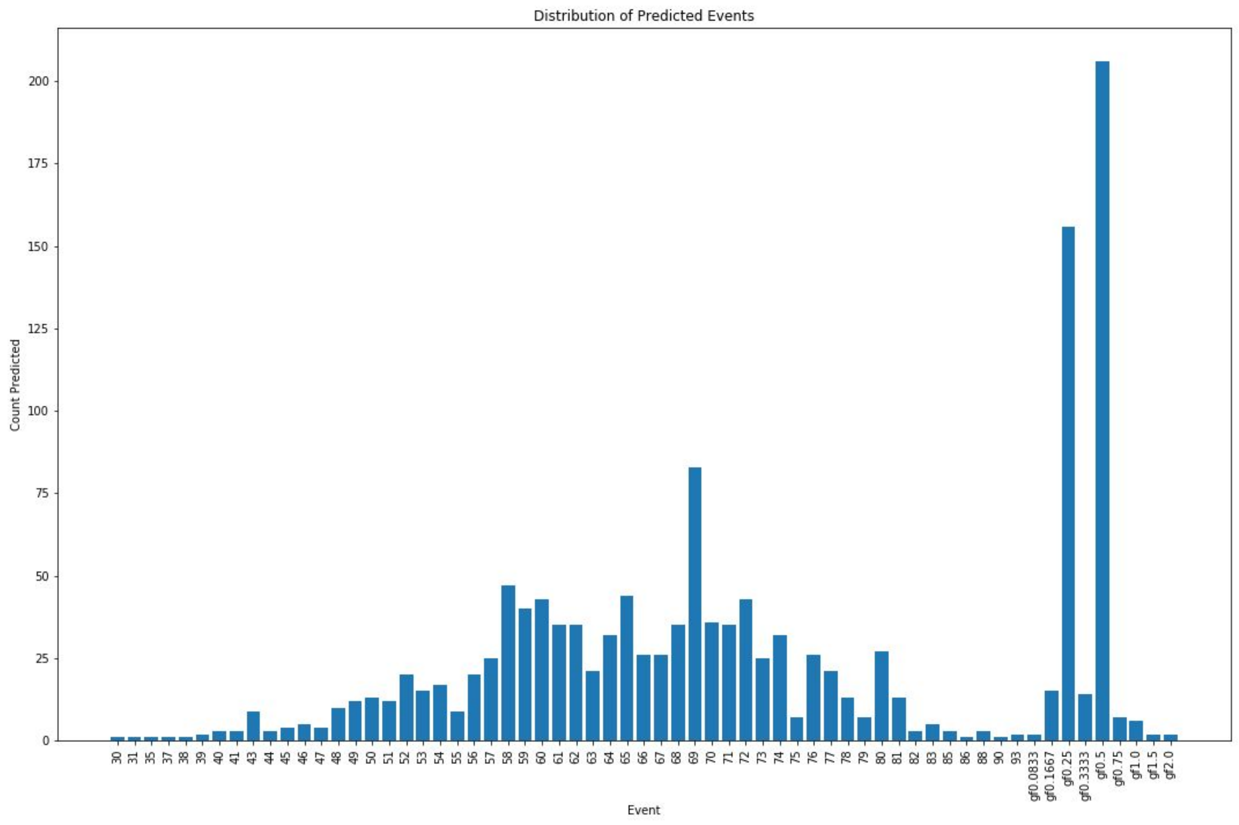


Figure 10: Distribution of Predicted Events for Unseen Input Sequence

<u>**Generating Music with the Trained Network:**</u>

Having a trained network, we now:

1. Feed the network a sequence of 50 events.
2. Let the network predict the 51st event.
3. Repeat with the last 50 events in the sequence until we obtain a sequence of desired length.

The function generate_music does the above.

We generate many samples using input sequences that the model saw during training (these sample can be found in the Samples folder with the name Mendehlsson_TrainingDataSampleX.mid) as well as with input sequences the model never saw during training (these sample can be found with the name Mendehlsson_TestingDataSampleX.mid)

Conclusions:

The generated songs actually do show some form of structure. Those generated from input seen in training are actually quite pleasant, and differ a little from the original music (but do not differ much). Those generated from unseen input tend to start rough but get better as the sequence progresses (possibly becoming more similar to something in the training set).

To get an idea of the generated songs listen to:

Mendehlsson_TrainingDataSample23: This is generated from a sequence the model has seen during training. The generated music sounds very good. It is most probably repeating a song it saw during learning.

Mendehlsson_TestingDataSample9: The music starts good (that is the input sequence), and then completely loses any sense of musicality.

Mendehlsson_TestingDataSample10: Despite the sequence never being seen by the model, the music it generates sounds pleasant. We do see that after second 35 it starts getting worse.

Future work should include finding a metric to quantify how similar a generated song is to a song seen in the training of the model. This could be done by comparing a portion of the generated song (say 5 events) to all 5 event sequences in the training data, and then see if the majority of the 5 event sequences in the generated song are similar to those in a song of training set.

Navigating The Code:

All the data and code can be found in this github repository.

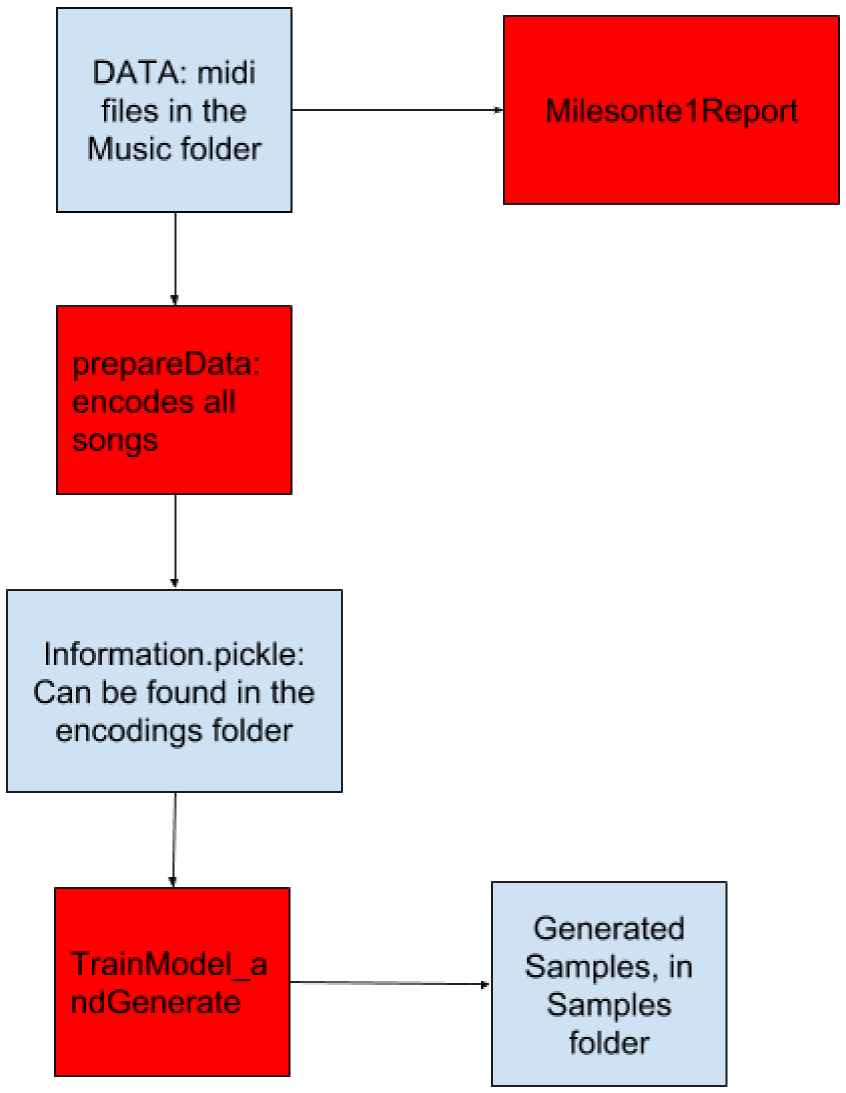
In the Music folder (which should be unzipped before running any code), we have all the data sorted by artist. The notebooks listed below reference this folder to train a model and generate music.

Milestone1Report.ipynb: This notebook is simply for exploring and visualizing the data. It does not serve any training or generating purpose.

prepareData.ipynb: This notebook encodes all the midi files in the Music folder and saves them in a dataframe where each row is a song. Each row has a column indicating the artist's name, along with the encoded song as a list in another column. The notebook also pickles this dataframe for future use.

TrainModel_andGenerate.ipynb: This notebook allows the user to pick an artist (or more by proving a list of artists) the model is to train from (it is set in the first cell and defaulted to Mendehlsson). The notebook then loads the pickled DF from prepareData, and prepares inputs, outputs, and the LSTM model, which it then trains. The jupyter notebook can then generate music using the defined generate_music() function.

This can be described in the diagram below. Each red rectangles represents code used in this project.


DATA: midi files in the Music folder
Milesonte1Report
prepareData: encodes all songs
Information.pickle: Can be found in the encodings folder
TrainModel_andGenerate
Generated Samples, in Samples folder