Progress Report for CSS 586 Course Project: Modeling Latent Patterns to Generate Symbolic Music

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ABSTRACT

This report explores recent research in symbolic music modeling with deep learning and provides a progress report on a course project to train and evaluate generative models of classical and popular music.

KEYWORDS

generative modeling, midi, music, recurrent neural networks, sequence learning, symbolic music, deep learning

1 INTRODUCTION

Machine learning models of music have interesting applications in music information retrieval and creative tools for musical artists and educators. Generative models can create accompaniments for music, transfer styles between clips of music, and even generate entirely new music. Music is challenging to model because it exhibits a complex hierarchy of recurring patterns and long-range temporal dependencies, and because both musical scores and performances have multiple possible digital representations.

Depending on the task, machine learning models of music may be trained on the audio signal itself, either in a time domain or a frequency domain representation, or they may be trained on a digital symbolic representation of music, the most common of which is MIDI (Musical Instrument Digital Interface) notation. MIDI is an encoding of music as streams of bytes in one or more tracks or channels, each representing a sequence of 128 possible pitch values (where 0 is the lowest and 127 is the highest), along with timing, pressure and instrument identifier values. A music transcription model may transcribe an audio signal as a MIDI score, which can easily be converted into other symbolic representations such as sheet music for human performers to read from, while a synthesizer model can convert MIDI representations into audio signals. A generative music model can be trained either to generate raw audio, or to produce a symbolic score that must be played by a synthesizer or by humans to produce an audio music performance. This project focuses on the latter type of modeling: generative modeling of symbolic (MIDI) music to compose original musical scores.

2 RELATED WORK

The state of the art in music generation has a long way to go before it can consistently generate music scores or performances that would be enjoyable and popular for humans to listen to, but a number of recent research projects have shown promising progress in this area.

Google's Magenta is an umbrella project for music deep learning research and development of software tools to expose these models for use by creative artists and students.

MusicVAE, part of the Magenta project, is a variational Long Short-Term Memory (LSTM) autoencoder for MIDI that incorporates a novel hierarchical structure using a "conductor" recurrent layer in its decoder model to better capture structure at multiple levels and avoid the problem of "posterior/mode collapse" whereby a generative model learns to ignore its latent code and rely on autoregression [11]. This model is trained on 16-bar paragraphs of music and is capable of generating new melodies that blend two given melodies via latent space interpolation.

Another Magenta model called Music Transformer is a generative model that borrows its approach from the Natural Language Processing (NLP) domain, using a self-attention network to model MIDI music as a sequence of discrete tokens with relative positional dependencies [4]. The focus of this model is on learning long-term dependencies in music to produce longer clips of music with coherent structure. Music Transformer was trained on a dataset of Piano-e-competition performances [3] and its generated piano music received favorable qualitative (Likert scale) ratings from human listeners for its resemblance to human-composed music [4].

MuseGAN [2] is an application of Generative Adversarial Networks (GAN) to polyphonic MIDI music generation, trained on four-bar phrases of a multi-track pianoroll representation of rock songs from the Lakh Midi Dataset [9]. Like MusicVAE, MuseGAN includes a two-level generator that first samples latent codes at the phrase or bar level, then generates notes within the bars, to produce longer-term structural patterns.

A major advantage of working with the symbolic representation of music is that it is of far lower dimensionality than the raw audio waveforms of a recorded performance, which makes it less computationally expensive. However, there are many stylistic aspects of musical performance that are not captured by a symbolic representation, and may be specific to a particular performer, so the expressiveness of symbolic generative models is limited in comparison [5].

Other research has focused on modeling raw audio waveforms directly. WaveNet is a causal convolutional neural network for generating raw audio waveforms, developed by Google DeepMind, which achieves state of the art performance in generating natural sounding speech from text, but is also capable of generating short, realistic snippets of audio music [7]. Another model named SampleRNN generates raw audio waveforms using a three-tier hierarchy of gated recurrent units (GRU) to model recurrent structure at multiple temporal resolutions [6].

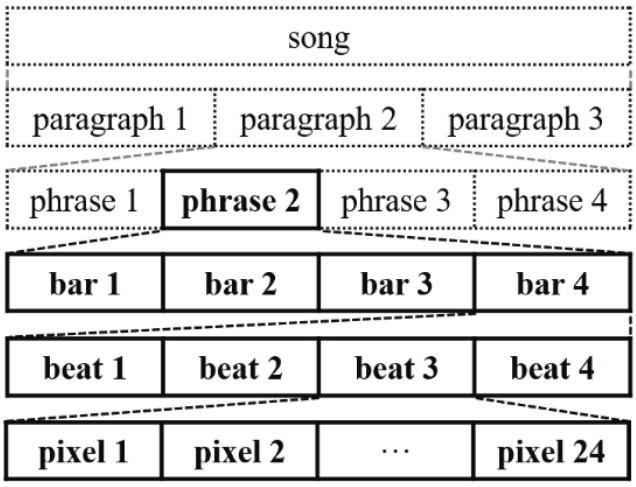

Figure 1: Diagram of the hierarchical structure of a musical composition, from the MuseGAN paper [2].

Prior work points out that the division between symbolic music notes and music performances, is analogous to the division between symbolic language and utterances in speech, which may inspire ideas for combining the two approaches [3]. A paper from Boston University describes an effort to combine the symbolic and waveform approaches to music modeling, by training an LSTM to learn melodic structure of different styles of music, then providing generations from this model as conditioning inputs to a WaveNet-based raw audio generator [5].

3 PLANNED METHODS

This research project will focus on the generative modeling of symbolic music using MIDI data as inputs, because of the advantages of symbolic music models in representing long-range patterns in musical compositions to produce generations with coherent structure and use of repetition over long time scales.

3.1 Datasets

Two primary datasets will be used for this research project: MusicNet, which is a collection of 330 freely licensed European classical music recordings with aligned MIDI scores [12], and the Lakh MIDI Dataset, which includes a collection of 45,129 Creative Commons licensed MIDI files of popular music songs that have been matched and aligned to MP3 recordings, and of which I plan to use a subset for model training and evaluation [9]. Including this second dataset may help to generalize the modeling approach beyond European classical music to include other popular genres and associated instruments.

3.2 Data Preprocessing

Several choices must be made in how to preprocess binary MIDI files into training examples for a neural network. There are multiple open-source Python packages that assist with the process of reading MIDI files from their binary on-disk representations into Python objects, such as pretty_midi [10] and Pypianoroll [1].

In order to accommodate polyphonic music, I will convert each MIDI file into a pianoroll representation, as visualized in Figure 2, wherein each instrument track is a sparse matrix that multi-hot encodes the velocity values for each of 128 possible pitch levels at each timestep. To reduce dimensionality, I will clip the note pitch values to a narrower range, excluding the rarely used notes in the extreme high and low octaves, and encode chords (combinations of notes played simultaneously on the same instrument) as distinct tokens, so that they can be one-hot encoded

Because songs are typically at least a few minutes long and of varying length, it will not be feasible to train with entire songs as examples, so we will crop songs into phrases of equal numbers of measures to use as training data.

The result of this preprocessing is that each training example will be a 3D tensor of shape (tracks x ticks x pitches) and stacking the training examples will produce a 4D tensor.

While I plan to model music with multiple instrument tracks, I anticipate the need to model only a fixed selection of instrument parts, similar to how MusicVAE models three-part (drum, bass and melody) [11] and MuseGAN models five-part (drum, bass, guitar, string, piano) arrangements.

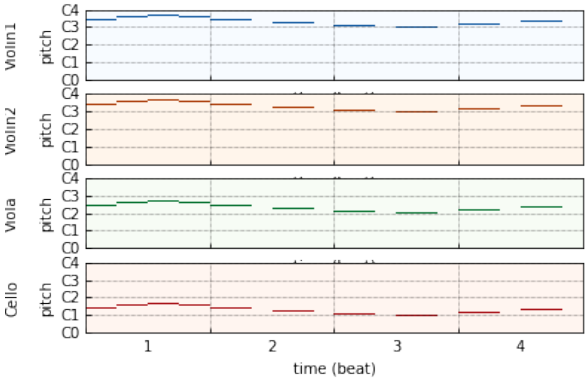

Figure 2: Pianoroll visualization of the first measure of Beethoven's Serioso String Quartet

Data augmentation is also possible and I plan to test its impact on the results–the literature suggests augmentation via pitch shifting each training example up or down by up to six semitones, and increasing or reducing the speed by up to 10% in order to create additional training examples and reduce overfitting [8].

3.3 Model Design

I plan to utilize recurrent neural networks with LSTM or GRU cells to model the sequential structure of music, stacking multiple layers to allow the network to learn at multiple levels of abstraction.

There are two general methods of generating sequences from a model: sliding window prediction, where a model is trained on a fixed length sequence and then used to predict the next item in the sequence repeatedly; and latent space interpolation, where a model learns random distributions of latent code embeddings for the sequences and draws from the distributions to generate new

samples. I plan to attempt both of these approaches and compare the results.

3.4 Model Evaluation

Evaluation of generative models is challenging because there is no equivalent of an accuracy metric like what is used in supervised learning. For autoencoder models we can measure how accurately the model can reconstruct its own inputs, but this does not tell us the quality of the interpolated examples. Generative models are typically evaluated using a combination of qualitative metrics whereby human judges rate the quality of the generated examples (essentially a Turing test), and quantitative metrics that assess the differences in the parametric distributions of generated and real examples. Yang and Lerch (2020) proposes a set of metrics informed by music theory, for probabilistically evaluating how similar the generations are to known sample distributions of real music [13]. These metrics include counts, ranges, histograms and transition matrices of pitches and note lengths, then the Kullback-Leibler divergence and overlapping area of the probability density functions are used to compare against known reference distributions per musical genre [13]. Due to the cost and time requirements associated with designing a human subjects experiment, I plan to utilize this quantitative approach to the quality assessment of generated samples.

4 PROGRESS AND REMAINING WORK

At this stage, I have decided on MIDI generation as the modeling problem, downloaded several MIDI datasets, and begun exploring them to learn how to interpret, process, and visualize them. Due to the complexity of the MIDI format and the multiple options for representing it in memory, data representation has been a time-consuming portion of the work in this project.

So far I have implemented in Python several pianoroll data processing functions that crop sections of MIDI files into fixed-length training examples consisting of multi-track note sequences in symbolic time (beats) at a given time resolution. I have also started implementing a training data processing pipeline that will read MIDI files from disk and transform them into the pianoroll-style tensor representation, providing batches of training examples to Keras model layers for fitting.

I have begun designing a simple LSTM autoencoder to model short (e.g. 16 beats or 4 bars) clips of monophonic (single instrument track) music, in order to learn the basics of sequence model architecture and determine how complex the model must be in order to be capable of reconstructing music note sequences. I will create a sequence predictor model with a similar structure and compare its generative capability to that of the autoencoder. Next I will add support for polyphonic music with 3-5 instrument tracks. Once polyphonic music generation is working well, I plan to increase the length of the sequences and make adjustments to the model architecture to permit it to model longer phrases and paragraphs of music. I aim to improve upon the hierarchical decoding approach taken in the MusicVAE [11] and MuseGAN [2] papers, possibly adding more than two recurrent layers in the decoder and providing even longer training examples, to address a key challenge in generative music modeling: the ability to learn from the layered patterns in music to produce compositions with convincing long-term structure. A stretch goal that would significantly differentiate my work is to produce the first model capable of generating not just separate phrases of symbolic music, but a coherent song from beginning to end.

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