Progress Report for CSS 586: Modeling Latent Patterns in Music

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ABSTRACT

This report explores recent research in modeling music with deep learning and provides a progress report on a project to train a generative model of classical music on the MusicNet dataset.

KEYWORDS

deep learning, neural networks, music

1 INTRODUCTION

Machine learning models of music have interesting applications in music information retrieval and creative tools for musical artists and educators. Music is complex and challenging to model because it exhibits a hierarchy of recurring patterns.

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, along with timing, pressure and instrument values. A music transcription model may convert an audio signal into MIDI, which can easily be converted into other symbolic representations such as sheet music, while a synthesizer model can convert MIDI representations into audio signals.

2 RELATED WORK

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 is a variational LSTM autoencoder for MIDI that incorporates a novel hierarchical structure using a "composer" recurrent layer in its encoder model to better capture structure at multiple levels [7].

Music Transformer is a generative model that borrows its approach from the Natural Language Processing (NLP) domain, using an attention network to model MIDI music as a sequence of discrete tokens with relative positional dependencies [3].

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 aspects of musical performance that are not captured by a symbolic representation, so the expressiveness of symbolic generative models is constrained [4].

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 [6].

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 [5].

Jukebox by OpenAI utilizes a vector-quantized variational autoencoder (VQ-VAE) to compress raw audio into a sequence of discrete codes and models these sequences using autoregressive transformers to generate music [1].

Audio data can also be modeled in the frequency domain through the use of Fourier analysis. The recent MelNet model is trained on spectrograms and can learn musical structures such as melody and harmony and variations in volume, timbre and rhythm [8].

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 [4].

Prior work points out that the division between symbolic music notes and the sounds of music is analogous to the division between symbolic language and utterances in speech [2].

3 PLANNED METHODS

4 PROGRESS

5 FUTURE WORK

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