Melody Classifier with Stacked-LSTM

You Li\textsuperscript{1} and Zhuowen Lin\textsuperscript{2}

\textsuperscript{1} Steinhardt School of Culture, Education, and Human Development, New York University, New York City, United States
\textsuperscript{2} School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, United States

Abstract. Attempts to use neural network models for music generation have been common in recent years, and some of them have achieved good results. However, the research on the evaluation system of machine-generated music is still at a relatively early stage. This paper proposes a stacked-LSTM binary classifier based on a language model, which can distinguish the human composer’s work from the machine-generated melody by learning the MIDI file’s pitch, position, and duration.

Keywords: Melody Classification

1 Introduction

Significant progress in the realm of music generative models has been made in the last few years. To capture the salient characteristics of music data and to generate new music samples that are indistinguishable from the true data are two main goals of generative modeling. Several deep neural network architectures for music generation have been proposed, like WaveNet\textsuperscript{5}, MuseGAN\textsuperscript{2}, and Jukebox\textsuperscript{4}, and has brought exciting innovations.

However, the development of music generative models blurs the borderline between human music and artificial intelligence (AI) generated music. Legal issues may arise in music industry when high-accuracy generative models are utilized intentionally to conduct music plagiarism. Therefore, a model that can be used to do classification on human-composed music and AI-composed music is of great importance.

In this paper, as part of the AI Composition Recognition Competition held by Conference on Sound and Music Technology, we introduce the implementation details of the competition, including dataset preparation and the stacked-LSTM model we used to distinguish AI-generated music from human-composed music.

2 Implementation Details

2.1 Dataset Preparation

To unify the terminology of datasets in this paper, the development dataset provided by the committee would be named as fake data (because it only contains
MIDI files generated by AI algorithms); the dataset collected and modified by ourselves would be called as real data (because it entirely consists of melodies written by human musicians). Fake data and real data are used collectively to train our neural network model. The evaluation dataset provided by the committee would be used as test data to test our trained model and generate final results.

In order to use our LSTM model, which is a supervised learning model, we used the dataset crawled, collected, and posted on a Reddit post by the user "midi_man" [4] to form our real data. It was posted five years ago and are still available and free to use by the date of submission of this paper.

The fake data are monophonic melodies with the length of 8 bars each, so we cut pieces in real data manually in Digital Audio Workstation (DAW) to let them have the same structure, and further, quantized them to make the MIDI events on the grid. Because the MIDI events in fake data and test data are all off the grid, in order to eliminate the possibility that the neural network model would learn to classify the test data purely with beats of MIDI events, we wrote a function in our MIDI parser to stretch or quantize the fake and test data according to their BPMs.

The final composition of training dataset is 6000 pieces of fake data and 1000 pieces of real data, covering several genres including classical, pop, and electronic.

2.2 Features and Representation

Usually, MIDI files contain massive information, including but not limited to notes and MIDI control change messages. And for notes, the most critical features are pitch, position, duration, and velocity. Unfortunately, in many MIDI files, the velocity value is set fixed, so we cannot use it effectively.

The features we chose are the pitch and duration of notes extracted from the melody and their corresponding position (beat) in each bar. The following figure shows the feature map within a single bar, in which the first column represents the pitch, and the rest are position and duration, respectively. It is worth noting that the position ‘0.0’ refers to the first downbeat of a measure in music theory, and ‘1.0’ represents the duration of a quarter note.

\[
\text{mapping} = \begin{bmatrix}
    'C4', '0.0', '1.0' \\
    'E4', '1.0', '0.5' \\
    'G4', '1.5', '0.5' \\
    'C5', '2.0', '2.0'
\end{bmatrix}
\]

Fig. 1. Feature mapping in a bar.

To meet the LSTM input requirements, we performed one-hot encoding on the three features separately and stacked them along the 0-axis to form a sparse matrix. In this way, the weights of the features could be updated at the same
time. Also, LSTM requires the input sequence to have a fixed length, so we padded the input sequence according to the length of the most extended sequence in the training set.

2.3 Model

As for the model, we chose to use a stacked-LSTM model. A similar structure was first introduced by Graves et al. in 2013. Their speech recognition experiments found that deeper recurrent neural networks can significantly improve the model’s performance in dealing with sequence inputs.

Our model contains two LSTM layers. The first one has 64 units. Each time step has a hidden state output for every single LSTM unit in this layer, which would be used as the second LSTM layer input. The second LSTM layer has eight units. In this layer, we only took the final output of the sequence. Finally, we used a fully connected layer to obtain the final classification results. We added two dropout layers between the LSTM layers and the fully connected layer to prevent overfitting, with a dropout rate of 0.4. This model’s advantage is that it uses a deeper neural network and can better learn more abstract and global features from the sequence. The following figure shows the detailed structure of our model.

We also tried out bidirectional LSTMs, the model’s performance on the validation set did not improve significantly, but we still included the prediction in the final results.
3 Conclusion and Further Work

We proposed and trained a stacked-LSTM neural network model to do classification on human-composed music and AI-composed music. It is submitted along with the classification result to the competition committee to evaluate its performance.

Future work can be done in finding a faster way to increase the amount and diversity of real data suitable for model training.

References

1. Dhariwal, P., Jun, H., Payne, C., Kim, J.W., Radford, A., Sutskever, I.: Jukebox: A generative model for music. arXiv preprint arXiv:2005.00341 (2020)
2. Dong, H.W., Hsiao, W.Y., Yang, L.C., Yang, Y.H.: Musegan: Multi-track sequential generative adversarial networks for symbolic music generation and accompaniment. arXiv preprint arXiv:1709.06298 (2017)
3. Graves, A., Mohamed, A.r., Hinton, G.: Speech recognition with deep recurrent neural networks. In: 2013 IEEE international conference on acoustics, speech and signal processing, pp. 6645–6649. IEEE (2013)
4. midi_man: The largest midi collection on the internet, collected and sorted diligently by yours truly. (2015). URL https://www.reddit.com/r/WeAreTheMusicMakers/comments/3ajwe4/the_largest_midi_collection_on_the_internet/ [Online; accessed 7-August-2020]
5. Oord, A.v.d., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., Kavukcuoglu, K.: Wavenet: A generative model for raw audio. arXiv preprint arXiv:1609.03499 (2016)