**Auxiliary Information:**

Members: Jared Frazier, Romario Nan, Ethan Lawing, Deven Kennedy

1. **Abstract**
2. **Introduction and Background**

Can the machine be a force of creativity? Can it take the very heat of music and learn from it, to create something new? These were the questions asked in the conception of this project. Our network is a generative model. It has been trained using examples, which it then attempts to make something akin to, but not identical to. The more complex and interesting original ideas can be generated by neural networks, the wider of an application they will have. If neural nets can write music, then what can’t they do? Such is our goal. We aim to train a Neural Network that writes original music.

1. **Methods**

Our examples used to train the model are music from Nintendo video games. They were then scraped and reformatted into MIDI files.

-------------------- Performance Metrics Section --------------------

We will be using an evaluation toolbox developed by Li-Chia Yang and Alexander Lerch. This toolbox has an immense array of metrics to use that can be classified as either an objective or subjective metric. The subjective metrics are specialized for comparing two sets of data (i.e. comparing generated data and test data). The most notable concepts of these metrics are the computations of the intra-set and inter-set distances, the Kullback-Leibler Divergence (KLD), and the overlapped area (OA).

In order to find the two different types of distances a “pairwise exhaustive cross-validation is performed for each feature.” I will also quote Yang and Lerch to explain what intra- and inter-set distances are: “If the cross-validation is computed within one set of data, we will refer to it as intra-set distances. If each sample of one set is compared with all samples of the other set, we call it the inter-set distances.” The KLD and OA are similarity measurements. In order to explain what they show, imagine we have sets of generated data from two models, M1 and M2, and the training data. We calculate the intra- and inter-set distances for each set of data. Then we compute the KLD and OA for the inter-set distances of the data for M1 and the training, and we do the same for M2’s data and the training data. The M1/training KLD was smaller than the M2/training KLD. The M1/training OA was larger than the M2/training OA. This implies that the generated data from M1 is more similar to the training data than the generated data from M2. If all the data were music, that means the music M1 generated is more similar to the training music than the music from M2. That could mean the music from M1 is more human-like than the music from M2.

The objective aspect of this toolbox takes advantage of the varying parts of music that make a full song. Take for example the pitch count and note count for a song. The pitch count is the total number of different pitches used in a song. If a song used the pitches C, F, and G throughout the entire song, it would have a pitch count of three (**testing will help check if it actually comes out like this)**. The note count is the total number of notes used. If that same song used C four times, F one time, and G three times, it would have a note count of eight. Now that we have these varying musical structures, we can perform the computations mentioned above on specific aspects of songs and visualize more accurately where different data sets are outperforming others, or possibly where they both struggle.

1. **Results**
2. **Discussion and Conclusion**