MUSIC GENERATION

TEAM ALCOVE (9)

MOTIVATIONS AND KEY AIMS

- Original Goal: Generate 30-second Pop songs using Long-Short-Term-Memory (LSTM) and compare the results of our network against other music-generating nets from universities, researchers, Google, etc. to see how our network compared in various areas.
- Altered Goal: Construct a Recurrent Neural Network (RNN) and a Generative Adversarial Network (GAN) and compare the MIDI files generated by each to determine which architecture is generally capable of making better music at a basic level.
- Network Comparison: Metrics include training time, accuracy, loss, number of parameters, etc.
- Output Comparison: Although music quality is subjective, a better-trained, better-performing network will output music with some obvious trends that clearly show the network has learned the melodic and harmonic patterns present in the training data.
- Ultimately, we wanted a neural network which could output "good" music in a fast amount of time!

STRATEGY

Recurrent Neural Network

Adapt a sample architecture and processing methodology from a Keras music generation tutorial to mesh with the model architecture for RNNs from class.

Adjust hyperparameters for performance

- Number of epochs
- Batch size
- Learning rate
- Optimizers
- Positive pressure

Generative Adversarial Network

Adapt the GAN model from class and apply image-focused GAN to MIDI files. Convert midi files to piano roll images, get Generator to make piano rolls, discriminator to detect fake rolls.

Adjust hyperparameters for performance

- Number of Epochs
- Batch Size
- Learning Rate
- Dropout
- Optimizer
- Activation Functions
- Alpha (leaky RELU)

NETWORK OUTPUT

Recurrent Neural Network

- **Training time** – Averages 6.3 minutes
- **Loss** – .1668
- **Number of parameters** – Total params: 824,962
- **Song Quality** –

Generative Adversarial Network

- **Training time** – 6 to 11 minutes, averaging 8 minutes
- **Accuracy** – 50% - can vary heavily with hyperparameter tuning
- **Loss** – Both discriminator and generator hover around .64-.74 loss. Hyperparameter tuning can drastically drive values up.
- **Number of parameters** – Total - 35,106,698
  - Nontrainable Parameters – 14,529
- Song Quality –

THE TEAM & TEAM CONTRIBUTIONS

Emily Musselman – Milestone lead, GAN network lead, demo

Evan Kubick - Musician/theory analyst, GAN tester, presentation, demo

Jason Miller – GAN tester

Joseph May - Created MIDI dataset, presentation, GAN tester

Louis Lizzadro - Network pioneer (GAN & RNN), RNN lead, demo

DEMO

QUESTIONS?

- Team Alcove – Music Generation
- Emily Musselman
- Evan Kubick
- Jason Miller
- Joseph May
- Louis Lizzadro