Musical Metacreation: Modeling Polyphony with Neural Networks

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Outline

I. Background
II. JamBot
III. Results
IV. Conclusion

Outline

Texture

- Describes musical layers in terms of number and purpose
- Monophonic
- Polyphonic

Monophonic vs Polyphonic

Monophonic

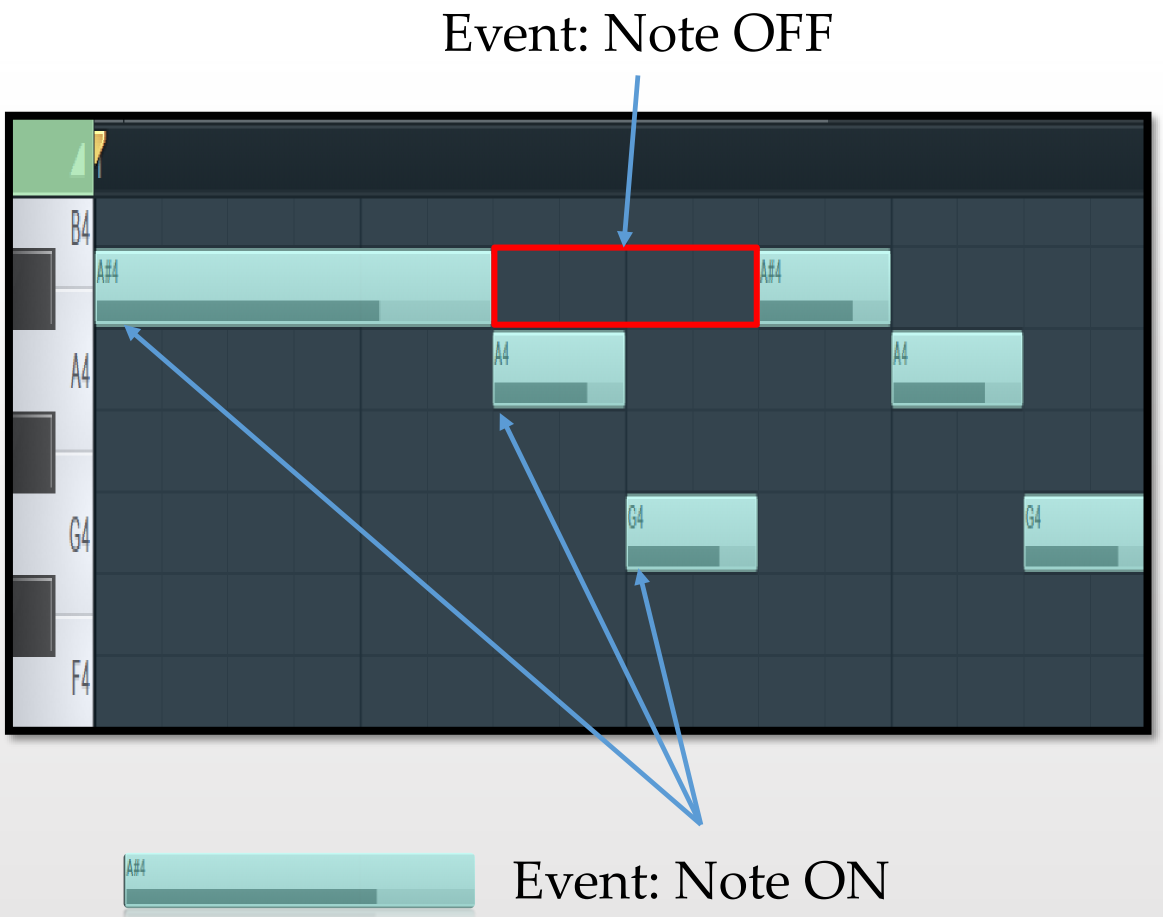
- Single layer
- One note at a time

Polyphonic

- Multiple layers
- More than one note at a time

MIDI via Piano Roll

- Musical Instrument Digital Interface
- No sound
- Carries events that represent note information

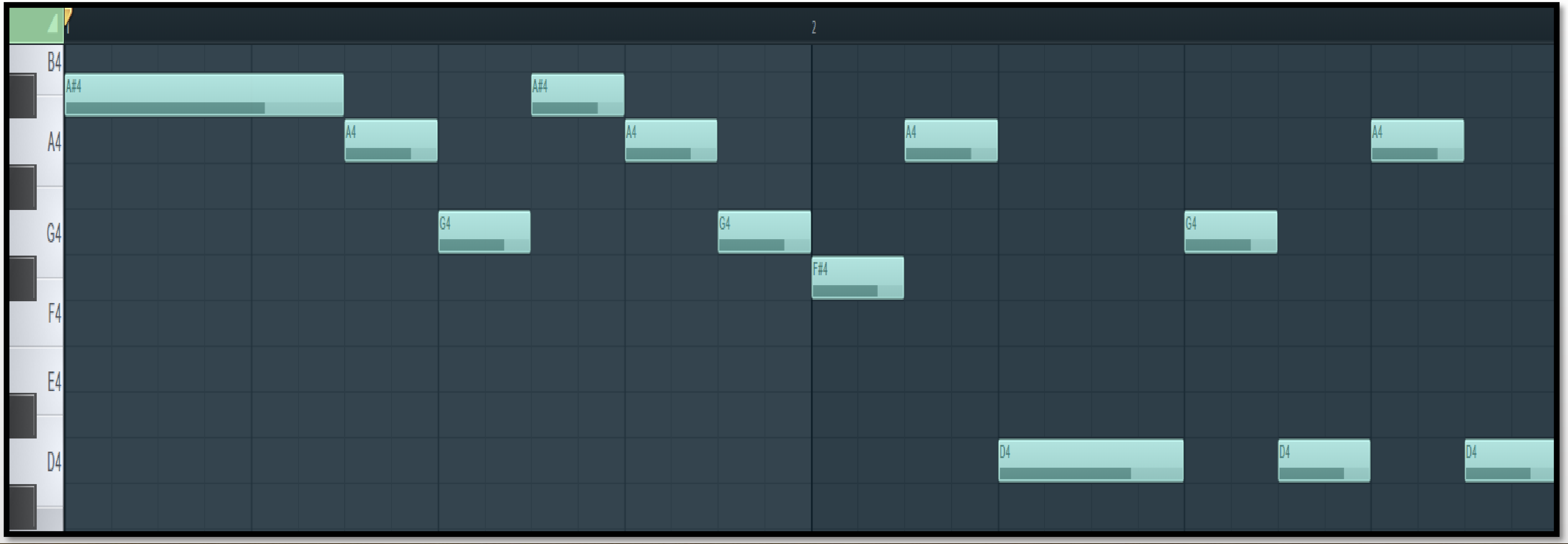


Monophonic Example

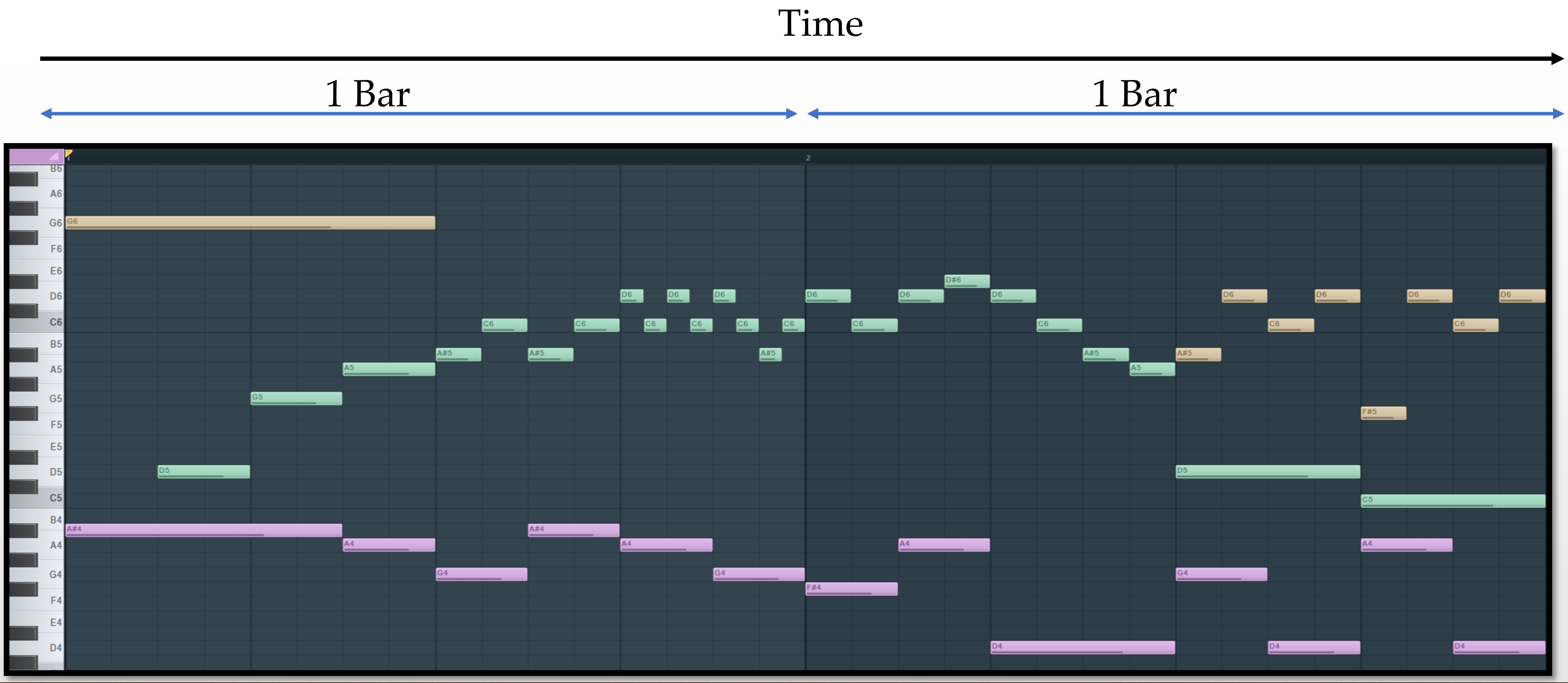
Time

1 Bar

1 Bar



Polyphonic Example



Difficulty of Modeling Polyphony

- Music is sequential
- Maintaining coherence
- Coincidences of notes

Outline

I. Background
  - Texture
  - What is a neural network?

II. JamBot

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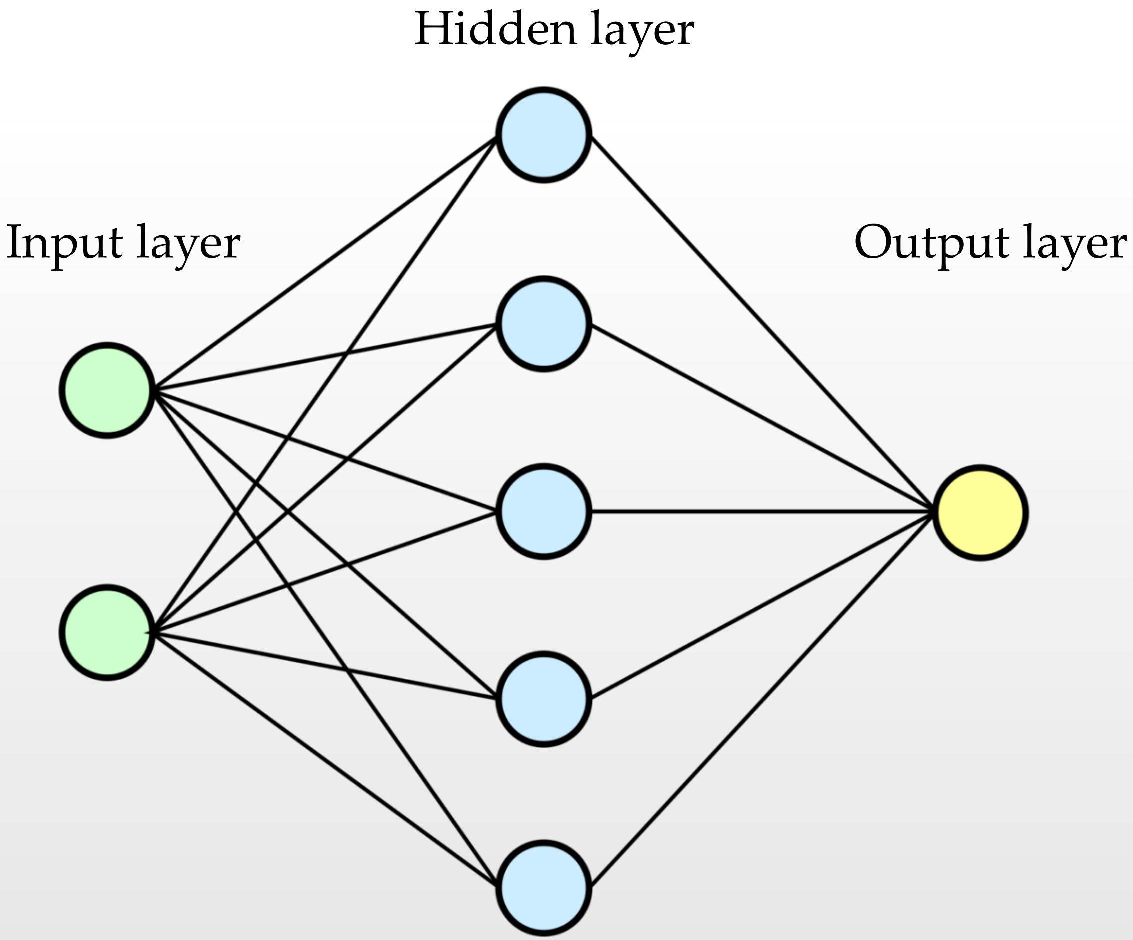
Overview

- Framework modeled loosely after the human brain
- Designed to recognize patterns in data
- Learn to perform tasks by considering examples, generally without being programmed

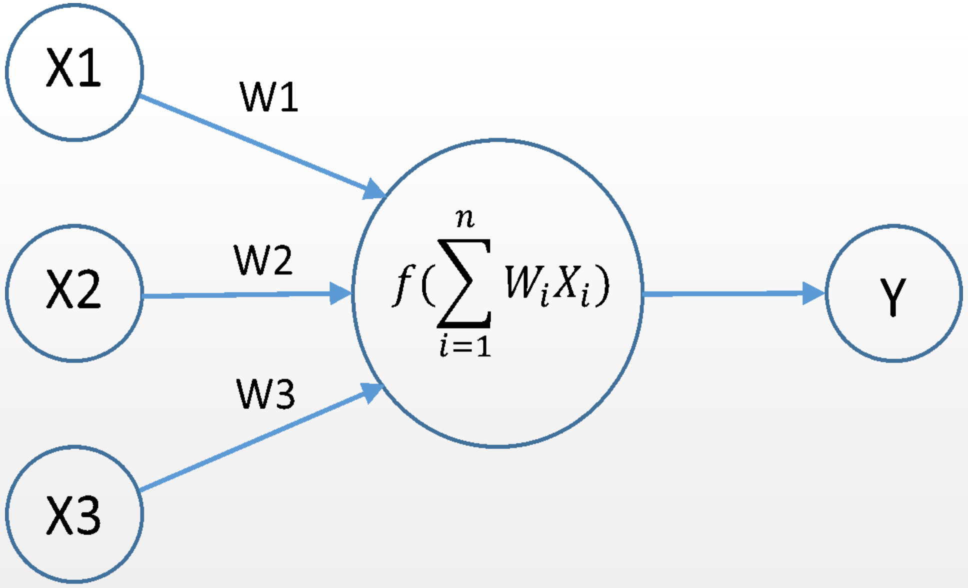
Network Structure

- Input layer
- Hidden layer(s)
- Output layer



Node Structure

- Inputs X1, X2, X3
- Weights W1, W2, W3
- Activation function *f*(x)
- Output Y



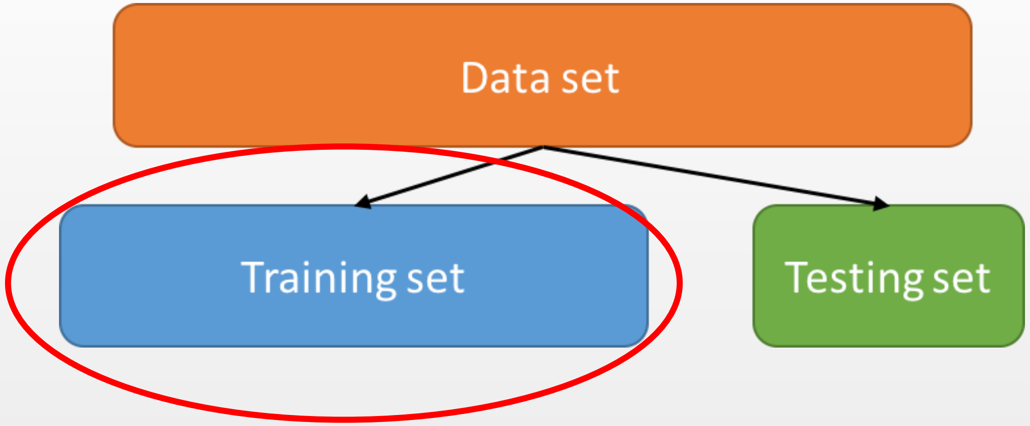
$$f(x) = tanh(x) = \frac{2}{1+e^{-2x}} - 1$$

Training

- Process of improving networks ability of making predictions
- Supervised – each dataset sample has an expected output
- Purpose is to adjust weights so the predicted output is reasonably close to expected output

Training

- Dataset is split into training and testing sets
- Weights are initialized randomly
- Training set is run through the network



Training

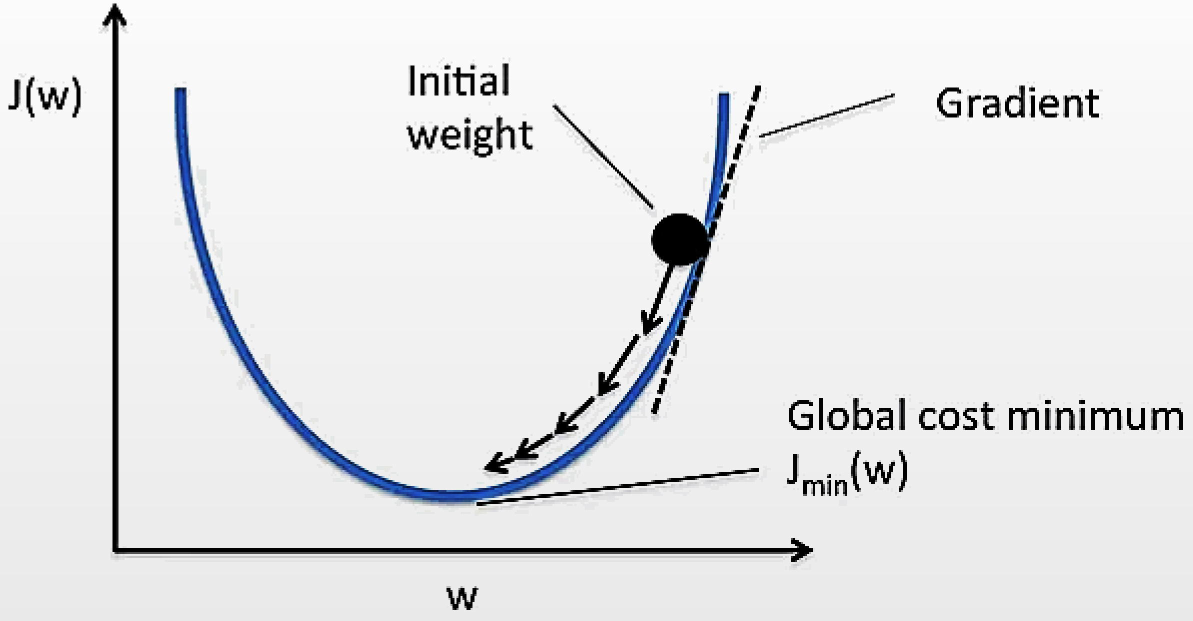
- Loss function determines how close predicted output is to expected output
- Lower value = higher accuracy
- Higher value = lower accuracy
- We want to minimize loss function

Training

- Gradient – direction and size of each loss function

- Backpropagation calculates gradients

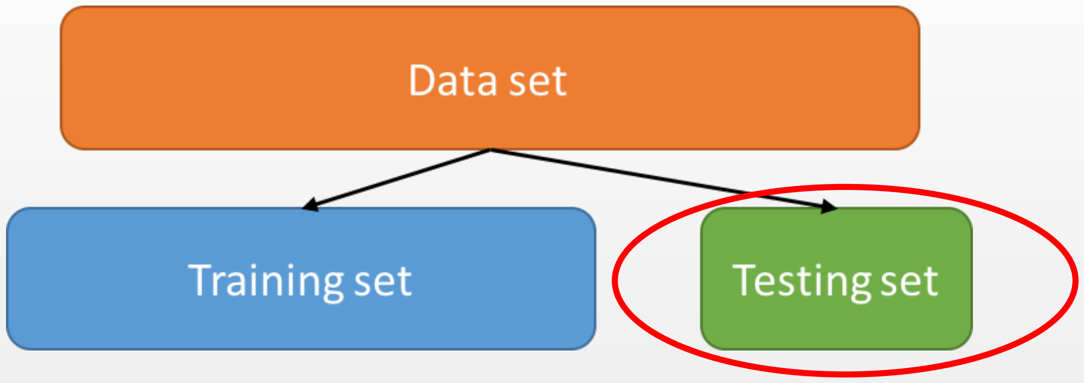
- Gradient descent uses gradients to update weights accordingly



Training

- Process is repeated until predicted output is reasonably close to the expected output

- Testing set is used to evaluate the network



Training Difficulties

- Vanishing gradient – size of gradients decrease exponentially as they are distributed back through network layers

- Network is unable to learn or learns extremely slow

Training Difficulties

- Exploding gradients – size of gradients increases exponentially causing an unstable network

- Weights are unable to be updated

Training Difficulties

- Overfitting – network learns training data too well
- Network performs well on training set but poorly on testing set
- Unable to generalize on new data

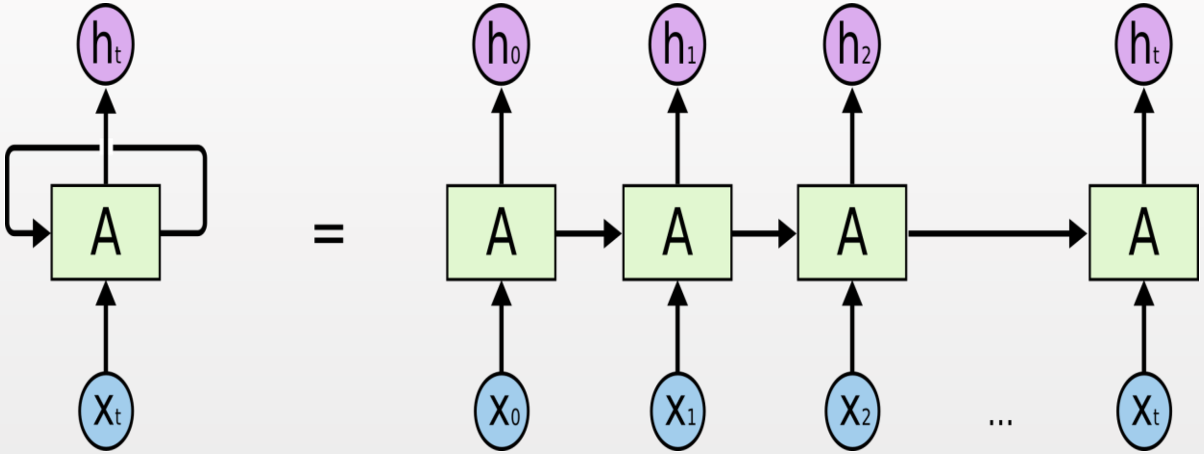
Outline

Remember

- Music is sequential
- Must know what has been played to determine what could be played next

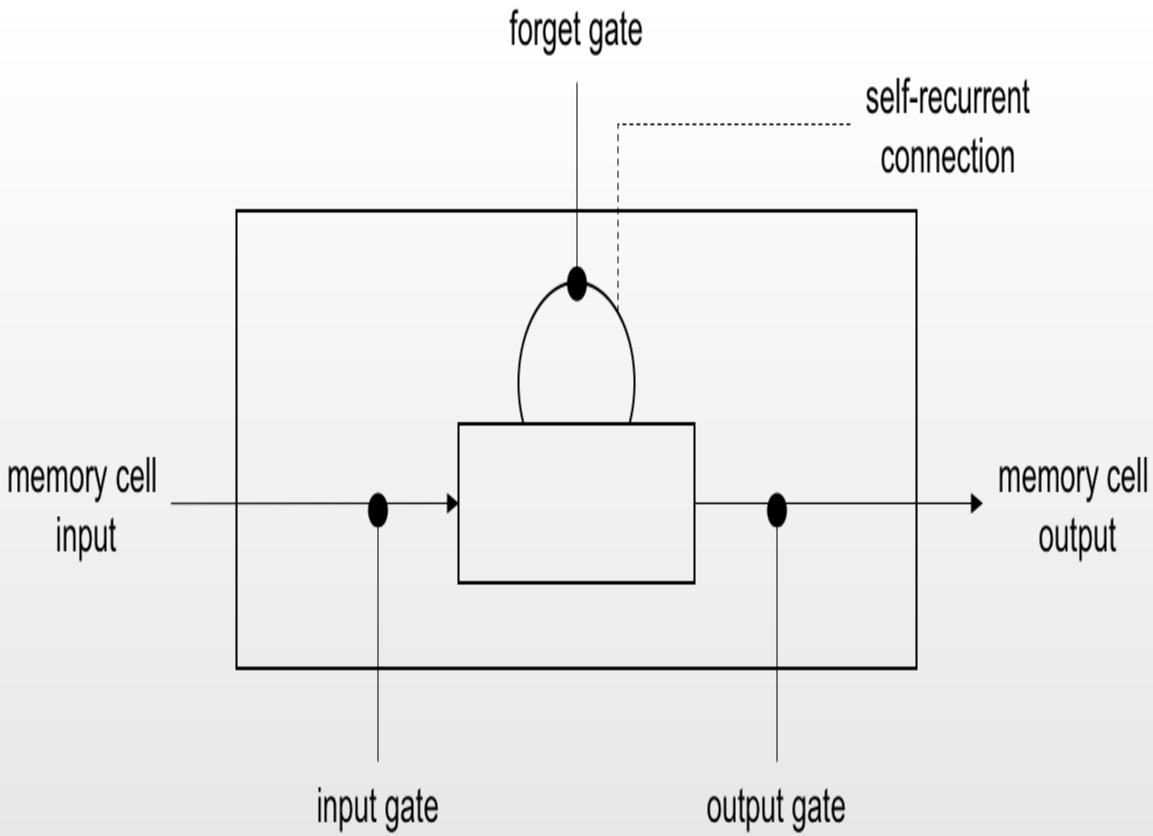
Recurrent Neural Network

- Information cycles through a loop
- Ability to `remember' previous input
- Useful for modeling sequences
- Limited to looking back a couple of timesteps



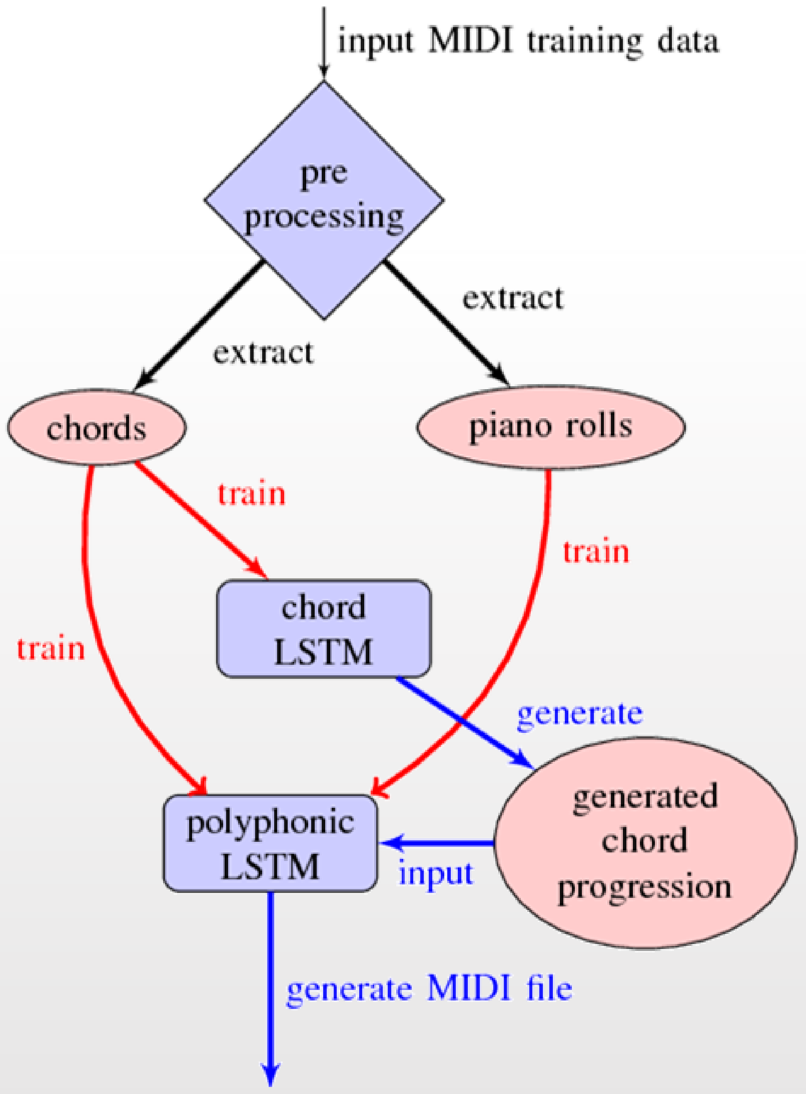
LSTM Network

- Introduces memory cells with gating architecture
- Gates decide whether cells should keep or forget previous states in each loop
- Allow modeling of long term sequences



JamBot Overview

- Composed of Chord LSTM and Polyphony LSTM
- Chord LSTM outputs probabilities of every chord to be played in next bar
- Polyphonic LSTM outputs probabilities of every note to be played in next timestep

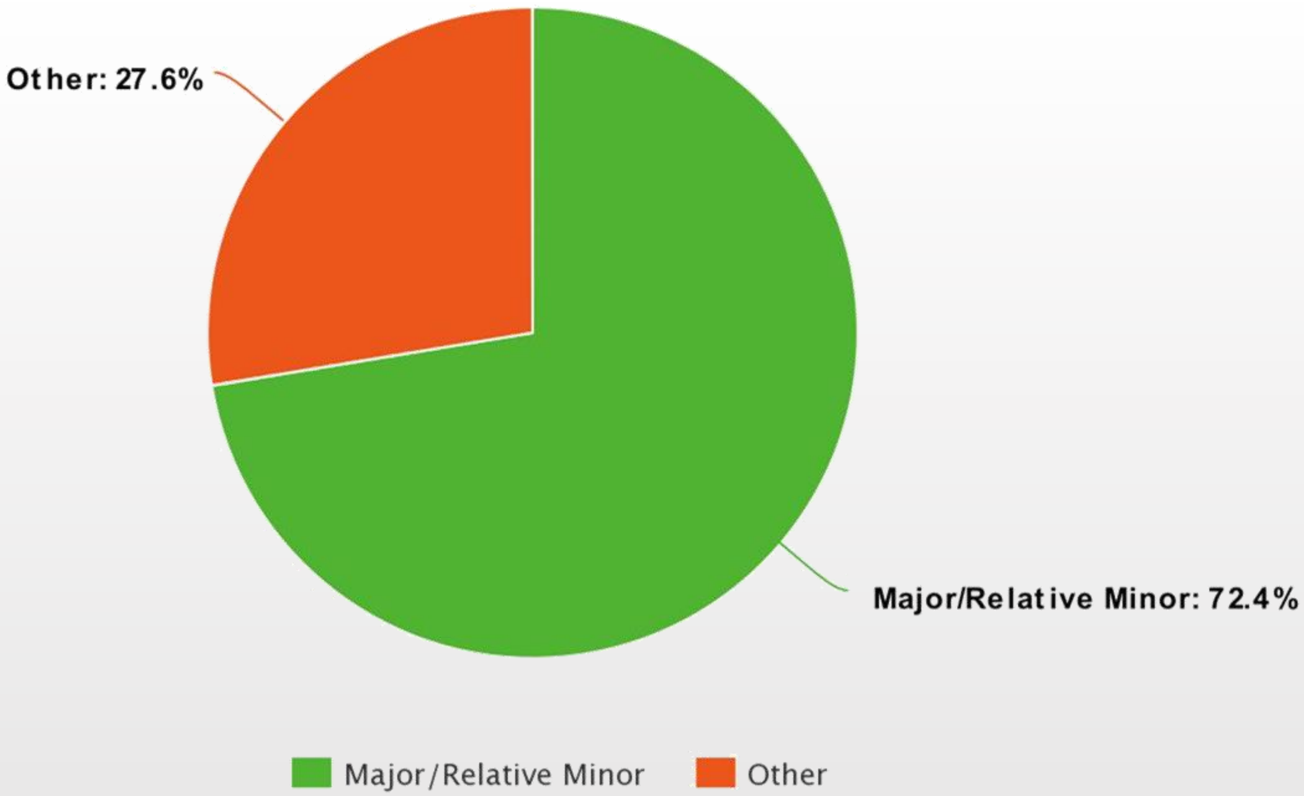


Outline

Training Data

- Subset of Lakh MIDI dataset consisting of 86,000 MIDI files
- All MIDI data is in Major/relative Minor scale
- Transposed to same key

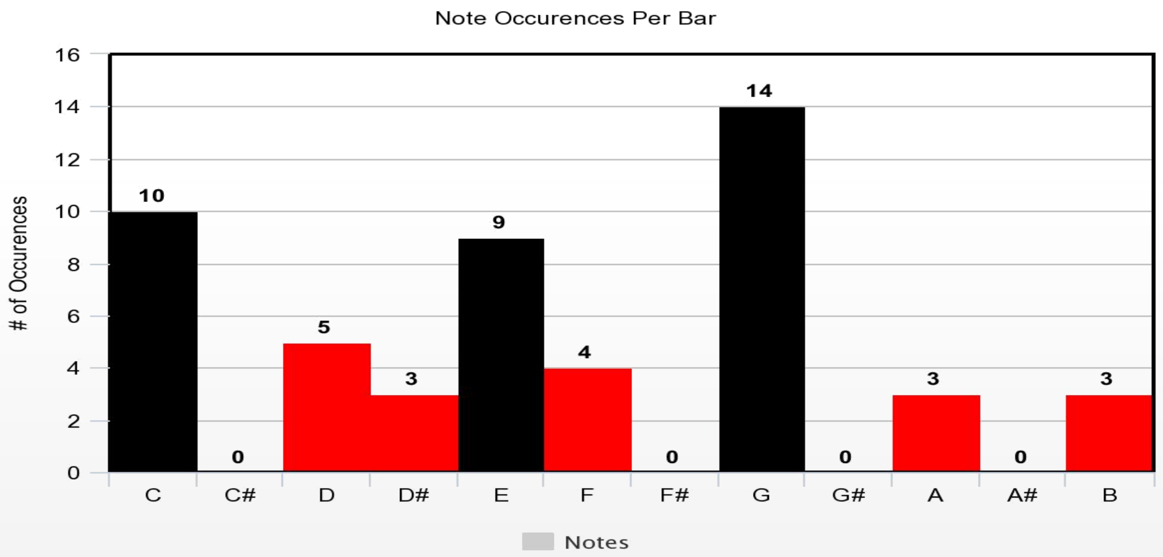
Lakh MIDI Dataset Scales

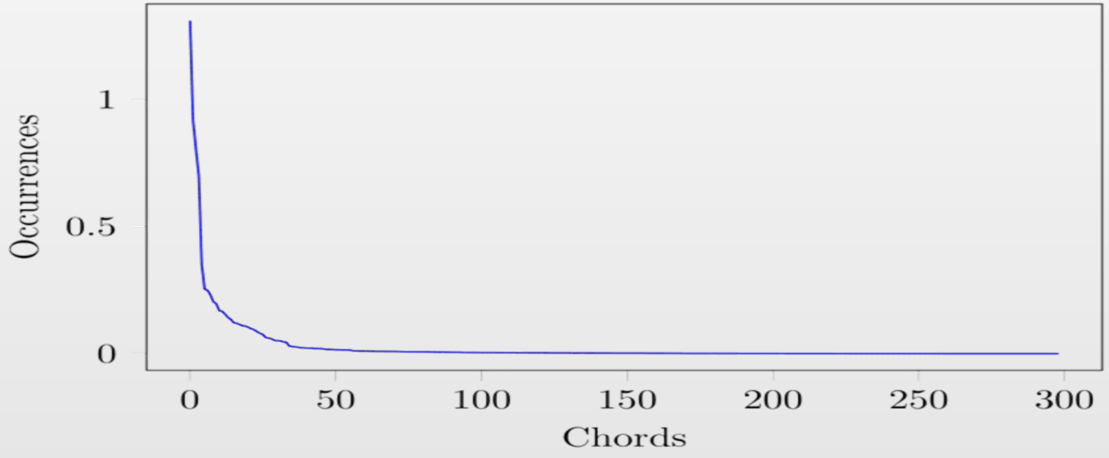


Outline

Chord LSTM

- 3 most occurring notes in every bar form a chord
- 50 most occurring chords replaced with IDs
- Chord/ID pair stored in dictionary
- Encoded as vectors X_{chord}





Chord LSTM

- Embedding matrix W_{embed} used to capture relationships between chords
- $X_{chord} \cdot W_{embed} = X_{embed}$
- X_{embed} used as input

10-Dimensional Chord Embedding X_{embed}

$$11 \longrightarrow \begin{pmatrix} \vdots \\ 1.76 \\ -2.19 \\ 0.37 \\ \vdots \end{pmatrix}$$

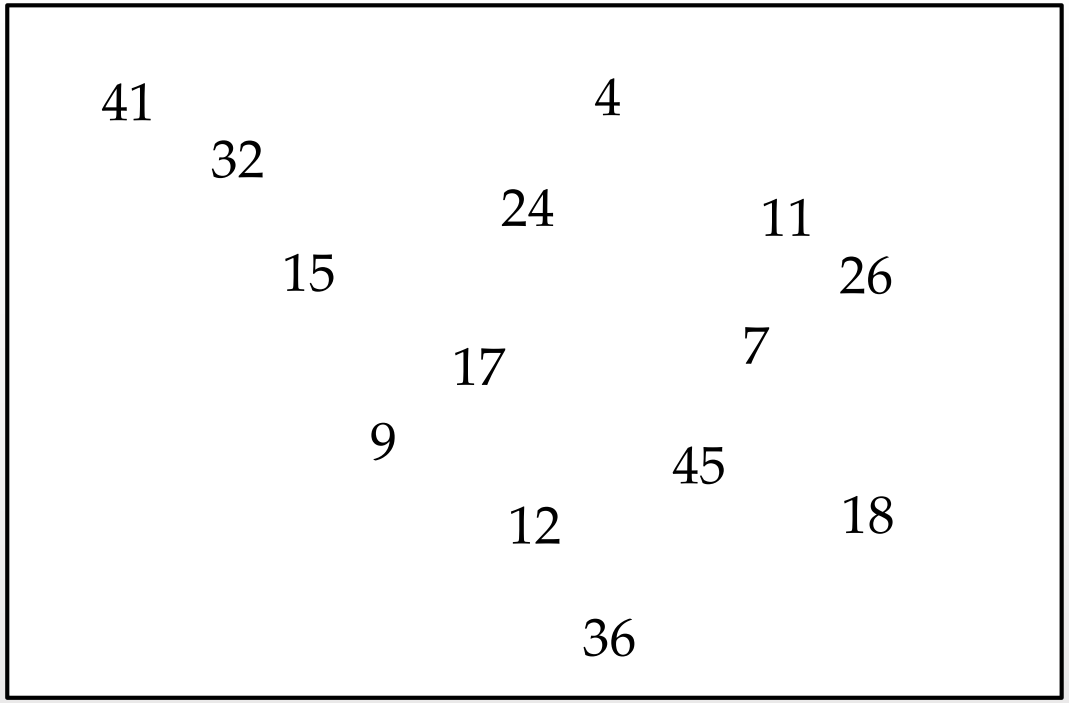
Chord ID

Chord LSTM

- Goal is to learn meaningful representation of chords

- Outputs vectors that contain probabilities for all chords to be played next

Chord IDs in Embedding Space



Prediction

- Feed seed of variable length into network

- Next chord predicted by sampling output probability with hyper-parameter temperature

Prediction

- Temperature = 0
- No variation in prediction

- Temperature = 1
- Lots of variation in prediction

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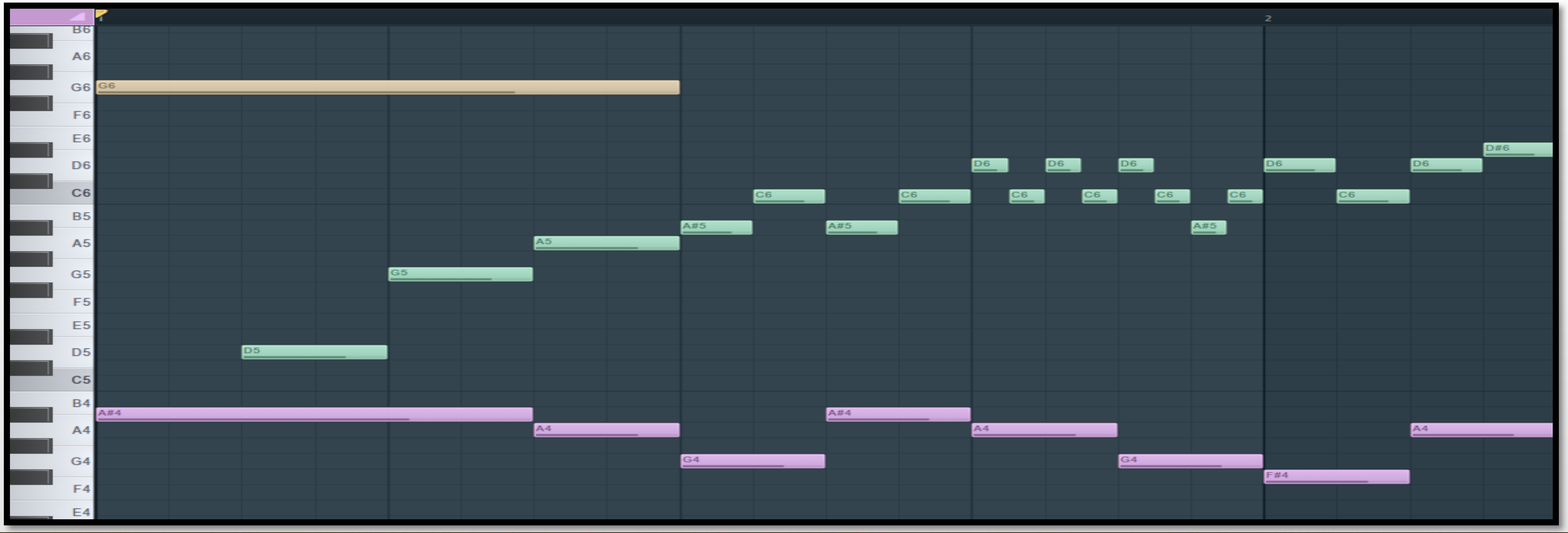
Polyphonic LSTM

- Piano roll data is extracted from dataset



Polyphonic LSTM

- Notes played at each timestep represented as vectors
- Entry = 1 if note is played
- Entry = 0 if not is not played

$$\begin{array}{cc} & \text{time} \longrightarrow \\ \text{Notes} \uparrow & \begin{pmatrix} \vdots & \vdots & & \vdots & \vdots \\ 1 & 0 & & 1 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ 0 & 0 & & 1 & 1 \\ \vdots & \vdots & & \vdots & \vdots \end{pmatrix} \end{array}$$

Polyphonic LSTM

- Piano roll vector
- Embedded chord of next timestep
- Embedded chord which follows chord of next timestep
- Binary counter

$$x^{t}_{poly} = \begin{pmatrix} \left.\begin{matrix} 0 \\ \vdots \end{matrix}\right\} \text{Piano roll} \\ \left.\begin{matrix} 3.579 \\ \vdots \end{matrix}\right\} \text{Chord} \\ \left.\begin{matrix} 0.256 \\ \vdots \end{matrix}\right\} \text{Next Chord} \\ \left.\begin{matrix} 1 \\ \vdots \end{matrix}\right\} \text{Counter} \end{pmatrix}$$

Polyphonic LSTM

- Input vectors fed to network

- Output of LSTM at time t $= y^{t}_{poly}$

- Outputs vector with same number of entries as there are notes

- Every entry is probability of the corresponding note to be played at next time step conditioned on all inputs of the timesteps before

$$\mathbf{y}^{\mathbf{t}}_{\mathbf{poly}} = \begin{pmatrix} P(n_0 = 1 | x^0_{poly}, \cdots, x^{t-1}_{poly}) \\ \vdots \\ P(n_N = 1 | x^0_{poly}, \cdots, x^{t-1}_{poly}) \end{pmatrix}$$

Prediction

- Feed seed consisting of piano roll and corresponding chords
- Notes which are played at next time step are sampled from output vector y^t_{poly}
- Notes are sampled independently

$$\mathbf{y}^{\mathbf{t}}_{\mathbf{poly}} = \begin{pmatrix} P(n_0 = 1 | x^0_{poly}, \cdots, x^{t-1}_{poly}) \\ \vdots \\ P(n_N = 1 | x^0_{poly}, \cdots, x^{t-1}_{poly}) \end{pmatrix}$$

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Results

- JamBot Generation - Song 2 , Tempo 140 BPM, Instrument Electric Guitar (Jazz)
- JamBot Generation - Song 3, Tempo 160 BPM, Instrument Bright Acoustic Piano
- JamBot Generation - Song 4, Tempo 100 BPM, Instrument Orchestral Harp

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Conclusion

- Generated music has long term structure
- Coherence is present and music is pleasing
- Learned meaningful embeddings where related chords are closer together in embedding space
- Missing emotional build

Acknowledgements

Thank you for your time!

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Questions?

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