Deep Learning Project

D7047E, Advanced Deep Learning

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Scope of presentation

- Introduction
- Goals
- What others have done
- Datasets
 - Maestro (piano music)
 - Lakhnes (video game music)
- Models
- Implementation
 - PyTorch
 - Model structure
 - Two GRU (maestro dataset)
 - RNN (lakhnes dataset)
- Results
- Learning outcomes/conclusion

Introduction

Generating music with DL? How? Why?

- **Explore Artificial creativity**
- Most people listen to music

Music is similar to language

- Context
- Rhythm
- Predictable

Train on music data

Music data

Neural Network

To generate music data

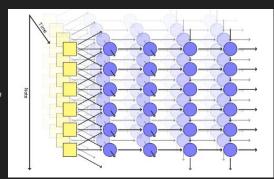
Music data

Goals of this project

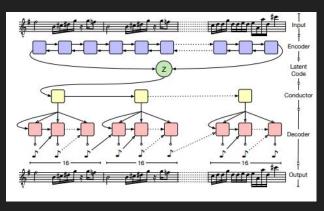
- Make (Good) music with AI
- Learn pyTorch
- Implement RNNs in pyTorch
- Loading and pre-process datasets
- Construct a baseline for experiments
- Post-process output to appropriate file-format

What others have done

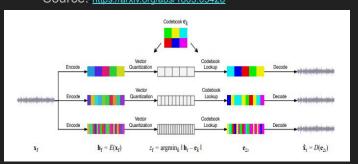
- Magenta
 - Variational Autoencoders with RNNs
- openAl
 - Jukebox
 - Vector Quantization VAE (VQ-VAE)
- Daniel Johnson
 - Biaxial LSTM
- LakhNES
 - https://chrisdonahue.com/LakhNES/
- "a first look at music composition using lstm recurrent neural networks"
 J. Schmidhuber 2002
- Many more...



Biaxial LSTM Source: http://www.hexahedria.com/2015/08/03/composing-music-with-recurrent-neural-networks/



Magenta paper Source: https://arxiv.org/abs/1803.05428



Jukebox paper Source: https://arxiv.org/abs/2005.00341

MIDI - Datasets

NES-MDB



https://github.com/chrisdonahue/LakhNES

Maestro



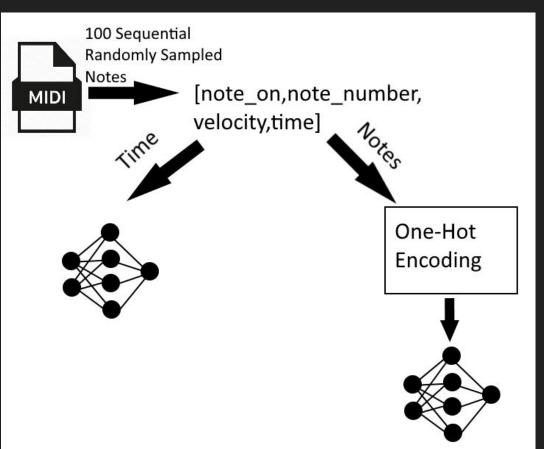
https://magenta.tensorflow.org/datasets/maestro

Midi message: [track = 0, type = note_on, note = 64, velocity = 100, time = 384]

Implementation

MAESTRO:

• 2 separate Neural networks

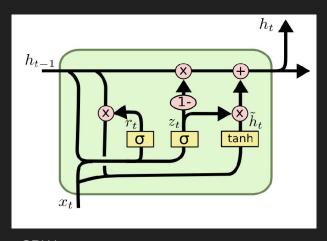


Model Structure MAESTRO

Note Input (batch_size, seq_len, 216)

Time Input (batch_size, seq_len, 1)

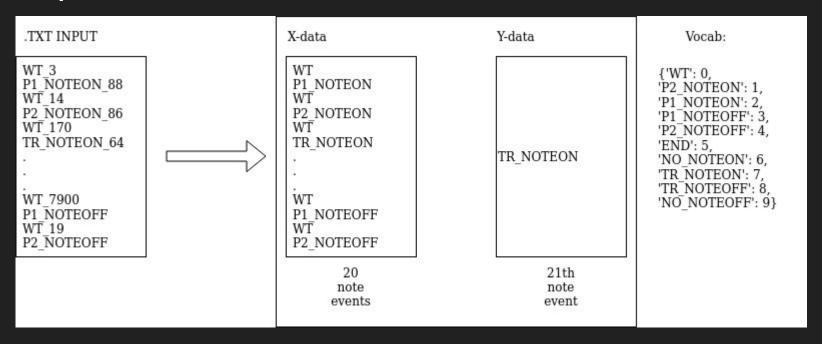
- GRU Layer (256)
- Dropout Layer (0.3)
- GRU Layer (128)
- Dropout Layer (0.3)
- FC Layer (128)
- Dropout Layer (0.3)
- FC Layer (Input_size)



GRU layer, Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

RMSprop optimizer. MSE loss function for the time net, and CCE for the note net

Implementation Lakhnes



Structure

Model 1

- LSTM (64)
- Dropout (0.2)
- FC Layer

Model 2

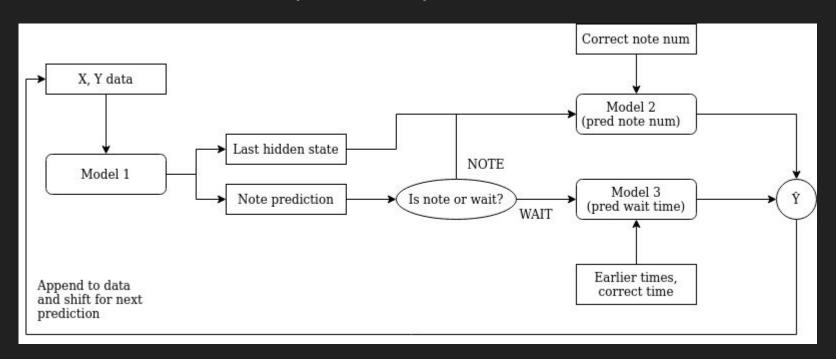
- FC Layer (162)
- Dropout(0.2)
- FC Layer

Model 3

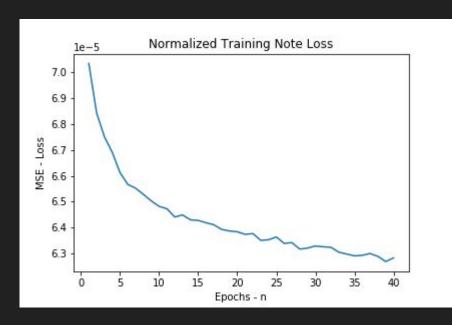
- FC Layer (128)
- Dropout(0.2)
- FC Layer

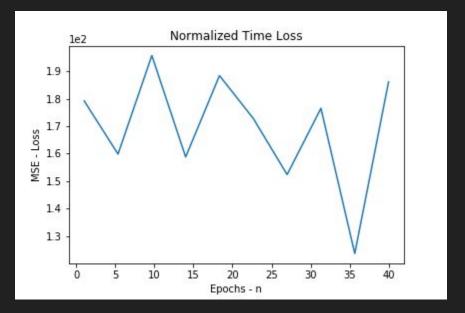
ADAM on models. MSE for model 3 (wait time) and CCE for other two.

Model structure (Laknes)



Losses MAESTRO model

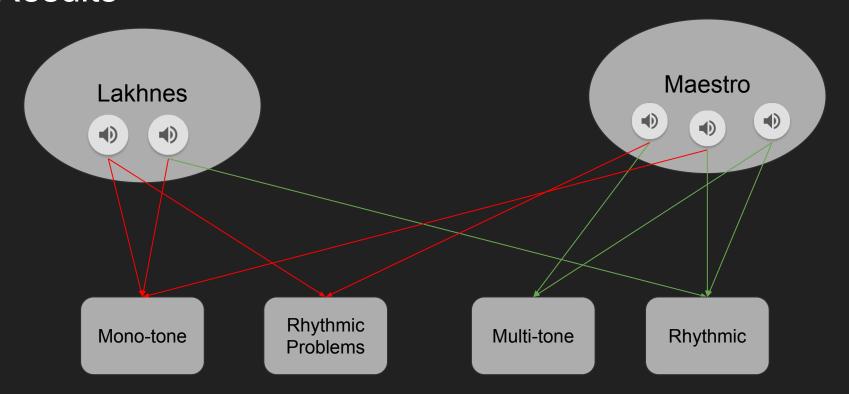




Losses Lakhnes

Dessa ser lite skumma ut, kommer typ inte säga så mycket om dem. Mer intressant att titta på.

Results



Comparison of output, lakhnes

<u>Predicted sequence (further)</u>

P1 NOTEON 66 WT 523 TR NOTEON 44 WT 710 TR NOTEOFF WT 639 TR NOTEON 44 WT 581 TR NOTEON 44 WT 591 TR NOTEOFF WT 567 P1 NOTEON 66 WT 530

P1 NOTEON 66

WT 629

TR_NOTEOFF
WT_633
P1_NOTEON_66
WT_592
P1_NOTEON_66
WT_761
NO_NOTEOFF
WT_721
P1_NOTEON_66

Predicted start (after green)

P2 NOTEON 90 WT 2212 P1 NOTEON 94 WT 2208 P1 NOTEON 86 WT 31 WT 35 P2 NOTEON 86 P2 NOTEON 94 WT 2159 WT 24 P1 NOTEON 66 TR NOTEON 46 WT 438 WT 2136 P1 NOTEON 66 P2 NOTEON 86 WT 510 WT 2208 TR NOTEOFF P1 NOTEON 82 WT 661 WT 31 TR NOTEOFF P2 NOTEON 90 WT 588 WT 2164 TR NOTEON 44 P2 NOTEON 82 WT 720 TR NOTEON 44 WT 603

Analysis

Models tried: Many RNN/LSTM variants, VAE, seq2seq, seq2one

Not good! But not a complete failure

Time network: Common subdivision

Note network: Tends to stick to primed key

Things to try: Custom loss function, multidimensional LSTM, fix the VAE

Learning outcomes / conclusion

Ability to implement RNN/LSTM on other problems

Finding and implementing datasets is possible

Improved python skills

Generating good music using RNN/LSTM is harder then expected

Getting an output of some sort is not as hard

Generating music will give you a laugh.

Thank you for listening!