

Composing like a human:

Adapting generative networks to few-shot learning in the musical domain

Tudor Paisa | 2019551 | 315146
Tilburg University, March 21 2019

Introduction

Deep Learning as a Problem

New ways to tackle ML problems and advance AI research

Discover rich hierarchical models over various applications

Most developments in discriminative models

- **Input:** High Dimensional Data → **Output:** Class label

Introduction

Recent Developments:

Generative Models

Few-Shot Learning

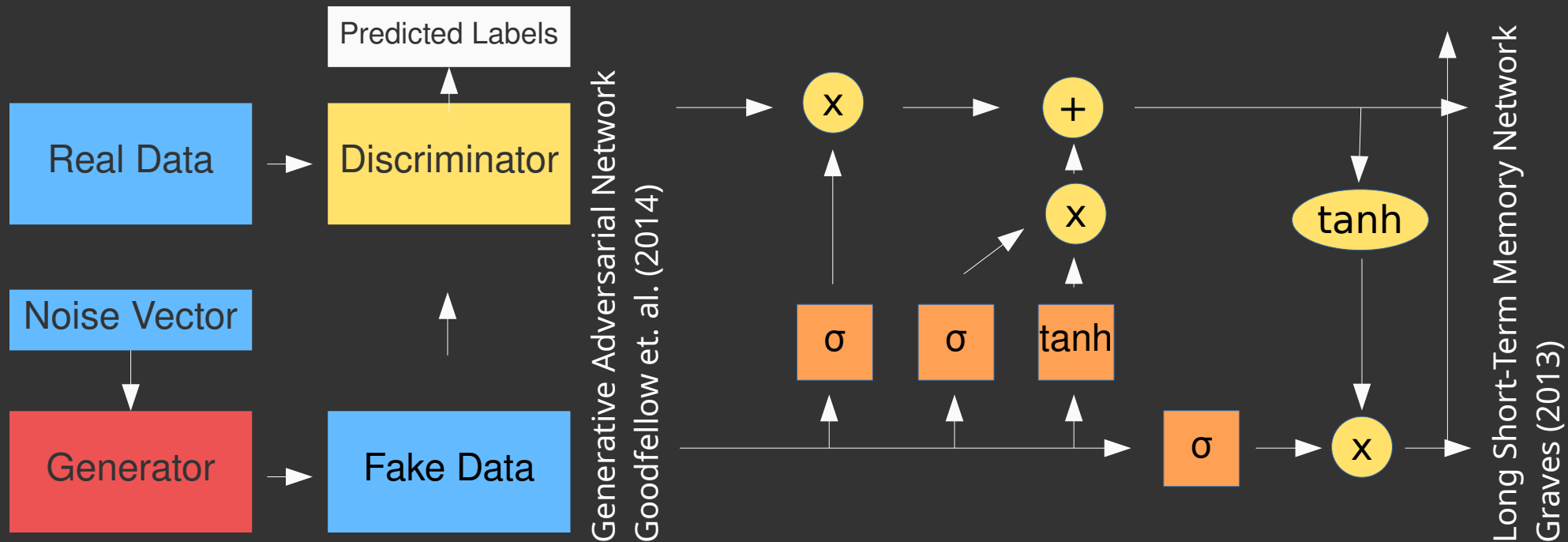
Generative Models

NN that generates output similar to the input

Learn the true data distribution to generate new data points

Scarce developments...

Generative Models



Generative Models



the young men are playing volleyball in the ball .

a lady wearing a blue white shirt is laughing



♪ ♪ ♪ ???

Few-Shot Learning

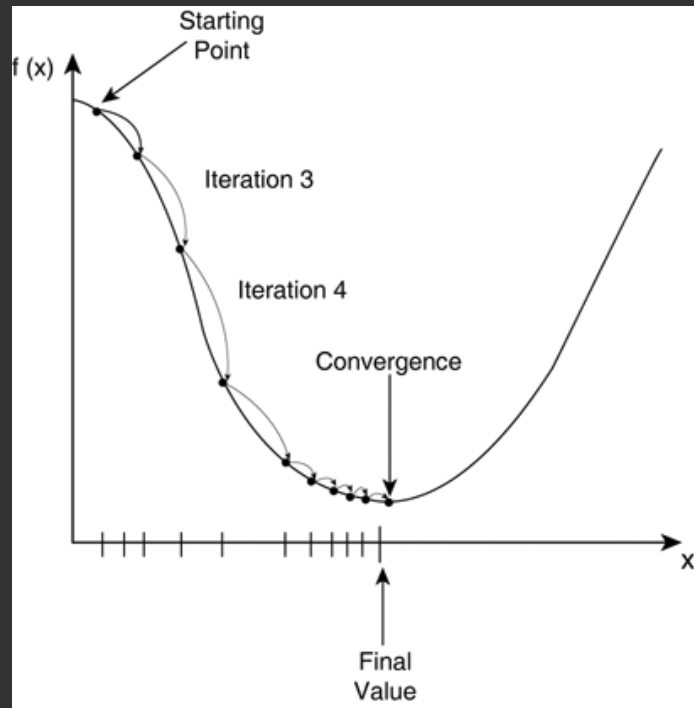


Few-Shot Learning

Solving this would make DL models easier to train

Generalize like humans

Few-Shot Learning (in short):
Learning a new function from only a few input/output pairs using prior data from similar tasks



Few-Shot Learning

Reptile (Nichol et. al., 2018): the few-shot solution

Algorithm 1: Reptile (serial version)

Initialize ϕ , the vector of initial parameters

for $iteration = 1, 2, \dots$ **do**

 Sample task τ , corresponding to loss L_τ on weight vectors $\tilde{\phi}$

 Compute $\tilde{\phi} = U_\tau^k(\phi)$, denoting k steps of SGD or Adam

 Update $\phi \leftarrow \phi + \epsilon(\tilde{\phi} - \phi)$

end

Few-Shot Generative Models (same story)



the young men are playing volleyball in the ball .

a lady wearing a blue white shirt is laughing



♪ ♪ ♪ ???

Research

Generative Models + Few-Shot Learning + Music = ???

Research Questions:

- To what extent is the music created by a few-shot generative model comparable to the music of a generative model that is trained on a larger dataset?
- To what extent is the music created by a few-shot generative model comparable to real music?

Research

Adapt 2 Generative Networks to Reptile:

1. C-RNN-GAN (GAN, 2 LSTM layers, 350 units; Mogren, 2016)
2. Performance RNN (3 LSTM layers 500 units; Oore et. al., 2018)

Baseline: 1 LSTM layer 200 hidden units trained on the whole dataset

Dataset

MAESTRO dataset (Hawthorne et. al., 2018):

- 1,184 piano expert performances recorded as MIDI
- 430 individual compositions
- 6.18 million notes
- 172 hours of playback

Evaluation

- Negative Log Likelihood (*standard*)
- Number of Statistically Different Bins (recommended by Richardson & Weiss, 2018)
- Domain-specific (adapted from Mogren, 2016):
 - Polyphony
 - Scale Consistency
 - Repetitions
 - Tone span

Milestones

Task	Deadline
Develop one-hot encoder/decoder for data	March 15th
Develop domain-specific evaluation tools	March 22nd
Create Keras implementation of PerformanceRNN	March 24th
Create baseline	March 24th
Create Keras implementation of C-RNN-GAN	March 29th
Augment models with Reptile	April 5th
Train Models	April 5th - 19th
Evaluate Models	April 26th
Write thesis	May 12th

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