Generating Sequences with Recurrent Neural Networks

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Why Generate Sequences?

• To improve classification?
• To create synthetic training data?
• Practical tasks like speech synthesis?
• To simulate situations?
• To understand the data
Generation and Prediction

• Obvious way to generate a sequence: repeatedly predict what will happen next

\[ \Pr(x) = \prod_{t} \Pr(x_t | x_{1:t-1}) \]

• Best to split into smallest chunks possible: more flexible, fewer parameters, avoids ‘blurred edges’
The Role of Memory

- Need to remember the past to predict the future
- Having a longer memory has several advantages:
  - can store and generate longer range patterns
  - especially ‘disconnected’ patterns like balanced quotes and brackets
  - more robust to ‘mistakes’
**Long Short-Term Memory**

- **LSTM** is an RNN architecture designed to have a better memory. It uses linear memory cells surrounded by multiplicative gate units to store read, write and reset information.

- **Input gate:** scales input to cell (write)
- **Output gate:** scales output from cell (read)
- **Forget gate:** scales old cell value (reset)

- S. Hochreiter and J. Schmidhuber, “Long Short-term Memory” Neural Computation 1997
Basic Architecture

• Deep recurrent LSTM net with skip connections

• Inputs arrive one at a time, outputs determine predictive distribution over next input

• Train by minimising log-loss:

\[
\sum_{t=1}^{T} - \log \Pr(x_t | x_{1:t-1})
\]

• Generate by sampling from output distribution and feeding into input
Text Generation

- Task: generate text sequences one character at a time
- Data: raw wikipedia markup from Hutter challenge (100 MB)
- 205 inputs (unicode bytes), 205 way softmax output layer, 5 hidden layers of 700 LSTM cells, ~21M weights
- Split into length 100 sequences, no resets in between
- Trained with SGD, learn rate 0.0001, momentum 0.9
- Took forever!
## Compression Results

| Method       | Bits per Character |
|--------------|--------------------|
| bzip2        | 2.32               |
| M-RNN        | 1.6 (text only)    |
| **deep LSTM**| **1.42** (1.33 validation) |
| PAQ-8        | 1.28               |

1. Sutskever et al. “Generating Text with Recurrent Neural Networks” ICML, 2011
2. M. Mahoney, “Adaptive Weighing of Context Models for Lossless Data Compression”, Florida Tech. CS-2005-16, 2005
Handwriting Generation

• Task: generate pen trajectories by predicting one \((x,y)\) point at a time

• Data: IAM online handwriting, 10K training sequences, many writers, unconstrained style, captured from whiteboard

So you say to your neighbour,
would find the bus safe and sound
would be the vineyards

• First problem: how to predict real-valued coordinates?
Recurrent Mixture Density Networks

• Can model continuous sequences with RMDNs

• Suitably squashed output units parameterise a mixture distribution (usually Gaussian)

• Not just fitting Gaussians to data: every output distribution conditioned on all inputs so far

\[
\Pr(o_t) = \sum_i w_i(x_{1:t})N(o_t | \sigma_i(x_{1:t}), \Sigma_i(x_{1:t}))
\]

• For prediction, number of components is number of choices for what comes next

• M. Schuster, “Better Generative Models for Sequential Data Problems: Bidirectional Recurrent Mixture Density Networks”, NIPS 1999
Network Details

- 3 inputs: $\Delta x, \Delta y, \text{pen up/down}$
- 121 output units
  - 20 two dimensional Gaussians for $x, y = 40 \text{ means (linear)} + 40 \text{ std. devs (exp)} + 20 \text{ correlations (tanh)} + 20 \text{ weights (softmax)}$
  - 1 sigmoid for up/down
- 3 hidden Layers, 400 LSTM cells in each
- 3.6M weights total
- Trained with RMSprop, learn rate 0.0001, momentum 0.9
- Error clipped during backward pass (lots of numerical problems)
- Trained overnight on fast multicore CPU
Samples
Samples

carry an undetained. Fared late male
night that hypoge. made luscious. hi.

Theophile she will. I far from
Persiliness. Write Duffy of width insl
sweats a block shaw shit weapons
Handwriting Synthesis

• Want to tell the network what to write without losing the distribution over how it writes

• Can do this by conditioning the predictions on a text sequence

• Problem: alignment between text and writing unknown

• Solution: before each prediction, let the network decide where it is in the text sequence
Soft Windows

window vector (input to net)

\[ v^{t+1} = \sum_{i=1}^{S} w_i^t s_i \]

kernel weights (net outputs for a,b,c)

\[ w_i^t = \sum_{k=1}^{K} a_k^t \exp \left( -b_k^t [c_k^t - i]^2 \right) \]

input vectors (text)

\((s_1, \ldots, s_S)\)
Thought that the muster from
Which is Real?

that a doctor should be a doctor should be that a doctor should be that a doctor should be that a doctor should be
Which is Real?

dr. present in being in remembering
of present reality in remembering
of present reality in remembering
of present reality in remembering
of present reality in remembering
Which is Real?

was an occasion worthy of his
was an occasion worthy of his
was an occasion worthy of his
was an occasion worthy of his
was an occasion worthy of his
was an occasion worthy of his
was an occasion worthy of his
Unbiased Sampling

These sequences were generated by picking samples at every star every line is a different style.

Yes, real people write this badly.
Biased Sampling

when the samples are biased towards move probable sequences
they get easier to read
but less interesting to look at.
Primed Sampling

when the sample started with real data

(pension welfare Officer complement)

it continues in the same style

(He dismissed the idea)
Synthesis Output Density
Prediction Output Density
# Some Numbers

| Network                                | $\Delta$ Nats |
|----------------------------------------|---------------|
| 3 layer tanh prediction                | +1139(!)      |
| 1 layer prediction                     | +15           |
| 3 layer prediction (baseline)          | 0             |
| 3 layer synthesis                      | -56           |
| 3 layer synthesis + var. Bayes         | -86           |
| 3 layer synthesis + text               | -25           |
Where Next?

- Speech synthesis
- Better understanding of internal representation
- Learn high level features (strokes, letters, words...) rather than adding them manually
Thank You!