NTM

Atef Chaudhury and Chris Cremer
Motivation
Memory is good

Working memory is key to many tasks
- Humans use it everyday
- Essential to computers (core to Von Neumann architecture/Turing Machine)

Why not incorporate it into NNs which would let us do cool things
What about RNNs?

Shown to be Turing-Complete

Practically not always the case hence there are ways to improve
- (e.g. attention for translation)

https://distill.pub/2016/augmented-rnns/
Core idea

Similar to attention, external memory could help for some tasks
- e.g. copy sequences with lengths longer than seen at training

One module does not have to both store data and learn logic (the architecture introduces a bias towards separation of tasks)
- hope is that one module learns generic logic while other tracks values
Architecture
Overview

Memory is an array of vectors.

Network A writes and reads from this memory each step.

https://distill.pub/2016/augmented-rnns/
Soft-attention reading

The RNN gives an attention distribution which describe how we spread out the amount we care about different memory positions.

The read result is a weighted sum.

\[ r \leftarrow \sum_i a_i M_i \]

https://distill.pub/2016/augmented-rnns/
Soft-attention writing

Instead of writing to one location, we write everywhere, just to different extents.

The RNN gives an attention distribution, describing how much we should change each memory position towards the write value.

\[ M_i \leftarrow a_i w + (1-a_i)M_i \]
Addressing

Content-based
- (cosine similarity + softmax between key vector and memory)

Location based
- Interpolation with last weight vector + shift operation
Results
Copying

Feed an input sequence of binary vectors, and then expected result is same sequence (output after the entire sequence has been fed in)
What’s going on?
Other tasks

Repeated copy (for-loop), Adjacent elements in sequence (associative memory), Dynamic N-grams (counting), Sorting

Memory accesses work as you would expect indicating that algorithms are being learned

Generalizes to longer sequences when the LSTM on its own does not
  - All with less parameters as well
Final notes

Influenced several models: Neural Stacks/Queues, MemNets, MANNs

Extensions
- Neural GPU to reduce sequential memory access
- DNC for more efficient memory usage
Discrete Read/Write

Sample distribution over memory addresses instead of weighted sum

Why?

- Constant time addressing
- Sharp retrieval

Unifying Discrete Models

**RL:**
\[ x \xrightarrow{\pi(a|x)} a \xrightarrow{Env} R \]
\[ \nabla_\pi E_\pi[R] = E_\pi[R \nabla_\pi \log \pi(a|x)] \]

**Discrete VAE:**
\[ x \xrightarrow{q(z|x)} z \xrightarrow{p(x|z)} R \]
\[ \nabla_q E_q[R] = E_q[R \nabla_q \log q(z|x)] \]

**MANN read:**
\[ x \xrightarrow{p(address|x)} address \xrightarrow{controller} R \]
\[ \nabla_p E_p[R] = E_p[R \nabla_p \log p(address|x)] \]
Unifying Discrete Models

Sample

RL: \( x \xrightarrow{\pi(a|x)} a \xrightarrow{\text{Env}} R \)

Gradient

\( \nabla_{\pi} E_{\pi}[R] = E_{\pi}[R \nabla_{\pi} \log \pi(a|x)] \)

Discrete VAE: \( x \xrightarrow{q(z|x)} z \xrightarrow{p(x|z)} R \)

\( \nabla_{q} E_{q}[R] = E_{q}[R \nabla_{q} \log q(z|x)] \)

MANN read: \( x \xrightarrow{p(\text{address}|x)} \text{controller} \xrightarrow{R} \)

\( \nabla_{p} E_{p}[R] = E_{p}[R \nabla_{p} \log p(\text{address}|x)] \)

MANN write: \( x \xrightarrow{p(\text{address}|x)} \text{address} \xrightarrow{\text{write}} \text{controller} \xrightarrow{R} \)

\( \nabla_{p} E_{p}[R] = E_{p}[R \nabla_{p} \log p(\text{address}|x)] \)
RL-NTM

Variance Reduction
- future rewards back-propagation
- online baseline prediction
- offline baseline prediction

Curriculum learning

Direct access controller
RL-NTM - Variance Reduction

Future rewards back-propagation

- Use sum of rewards starting from the current time step
  \[ R_t = \sum_{i=t}^{T} r_i \]

- Instead of the sum of rewards over the entire episode
  \[ R_t = \sum_{i=1}^{T} r_i \]
RL-NTM - Variance Reduction

Online baseline prediction

\[ R_t = \sum_{i=t}^{T} r_i - b_i \]

where \( b_t = E[R_t] \)
RL-NTM - Variance Reduction

Offline baseline prediction

- Use baseline LSTM to minimize \((r_i - b_i)^2\)
- Biased

\[
R_t = \sum_{i=t}^{T} r_i - b_i - b_i(a_{1:T})
\]
RL-NTM - Direct Access

- All the tasks considered involved rearranging the input symbols in some way
  - For example: reverse a sequence, copy a sequence

- Controller benefits from a built-in mechanism that can directly copy an input to memory or to the output

- Drawback: domain specific
Difficulty Curriculum

RL–NTM unable to solve tasks when trained on difficult problem instances

- Complexity of problem instance measured by the maximal length of the desired output

To succeed, it required a curriculum of tasks of increasing complexity

- During training, maintain a distribution over the task complexity
- Shift the distribution over the task complexities whenever the performance of the RL–NTM exceeds a threshold
RL-NTM - Results

Table 4: Success of training on various task for a given controller.
Dynamic-NTM
Dynamic-NTM

Transition from soft/continuous to hard/discrete addressing

- For each minibatch, the controller stochastically decides to choose either to use the discrete or continuous weights
- Have hyperparameter determine the probability of discrete vs continuous
- Hyperparameter is annealed during training

\[ w_t = \pi_n \bar{w}_t + (1 - \pi_n) \tilde{w}_t \]
D-NTM

Variance Reduction

- Global baseline + variance normalization

\[
\tilde{R}(x) = \frac{R(x) - b}{\sqrt{\sigma^2 + \epsilon}}
\]

where \( b \) is the running average and \( \sigma \) is the standard deviation of \( R \)

- Input-dependent baseline

\[
\bar{R}(x) = \tilde{R}(x) - b(x).
\]
bAbI Question answering - reads a sequence of factual sentences followed by a question, all of which are given as natural language sentences.

### LSTM controller

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<th>Task</th>
<th>LSTM</th>
<th>MemN2N</th>
<th>DMN+</th>
<th>1-step LBA* NTM</th>
<th>1-step CBA NTM</th>
<th>1-step Soft D-NTM</th>
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### FF controller

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Learning Curves

The discrete attention D-NTM converges faster than the continuous-attention model.
- Difficulty of learning continuous-attention is due to the fact that learning to write with soft addressing can be challenging.
TARDIS (2017)

Wormhole-Connections help with vanishing gradient

Uses Gumbel-Softmax

Improved results
Takeaways

Learning memory-augmented models with discrete addressing is challenging

Especially writing to memory

Improved variance reduction techniques are required
Thanks