Neural Turing Machines

and memory-augmented techniques

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Agenda

all about Neural Turing Machines (NTMs)

- Motivation
- How NTMs work
- Experiments
- Discussion

Motivation

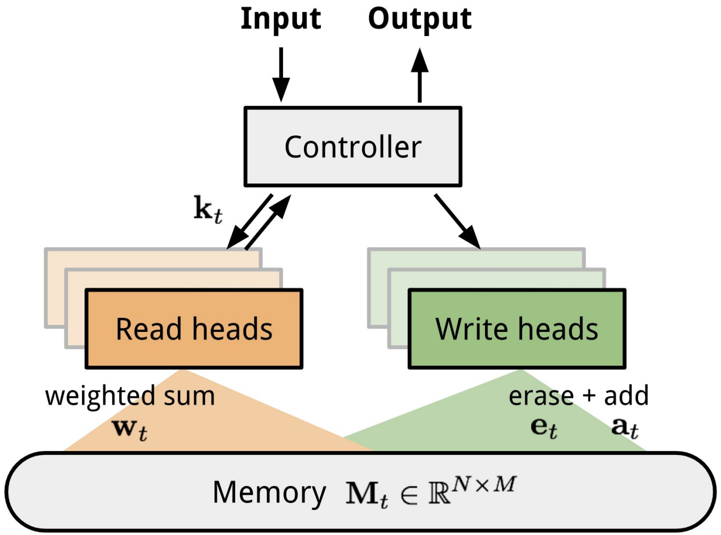
- Neuroscience angle: "working memory" is limited
    - Cognitive system with limited capacity for **temporarily** storing and manipulating information
    - Short term memory cannot manipulate the information
- For a hard mathematical problem/memorizing many numbers, ~~we~~ most of us (except Ananth) would need to **offload some computation to pen and paper**
- Like computer programs
- Learn how to manage memory to solve a problem: sort of "learning to program"
    - NTM learns its own basic algorithms for tasks such as copying, sorting, and associative recall

NTM

- Entire structure is differentiable
- Part of broader trend to "**differentiable programming**"
  - incorporation of **classic data structures** (e.g. RAM, stacks, queues) into **gradient-based learning systems**
  - Increasing memory capacity in NTM is easier than in pure LSTM networks.
- Possibility of combining the best of program induction and deep learning
  - Structured representations – *objects, forces, agents, causality, compositionality* – help explain important facets of human learning and thinking
  - Deep learning systems not shown to work with these representations, but shown surprising effectiveness of gradient descent in large models

Neural Turing Machine (NTM)

- Neural network *controller* (e.g. feed forward or RNN)
  - also outputs "heads" that parameterize reads and writes to/from the...
- Memory bank! (stores processed information)



NTM unfolded

- Controller accepts input x and read vector r, outputs read and write heads

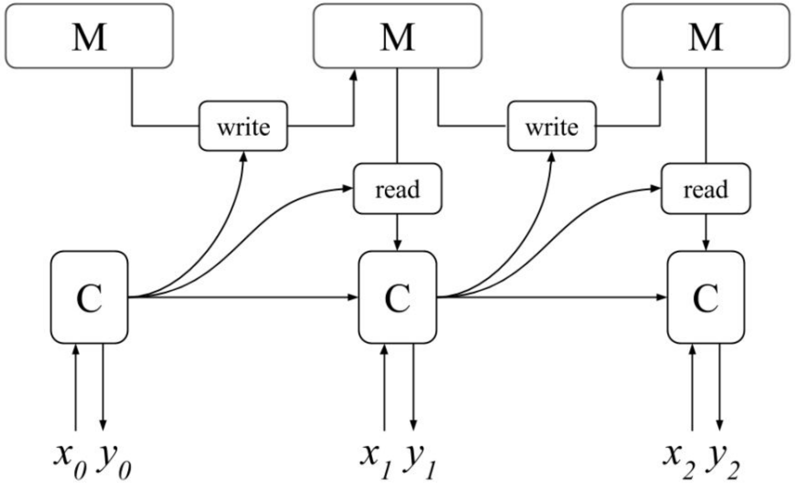


FIGURE 2.13: The neural Turing machine unrolled through time (Olah and Carter, 2016).

Reading

- At time **t**, normalized weight vector $\mathbf{w_t}$ controls how much attention to give to different memory locations

$$\sum_i w_t(i) = 1, \qquad 0 \le w_t(i) \le 1, \forall i.$$

- Read vector $\mathbf{r_t}$ is simply a sum weighted by attention intensity

$$\mathbf{r}_t \longleftarrow \sum_i w_t(i)\mathbf{M}_t(i)$$

- Differentiable with respect to both the weight and the memory bank
- A form of attention implemented as memory addressing

Writing

- Inspired by input and forget gates in LSTM
- Given weight vector $\mathbf{w_t}$ emitted by a write head at time **t**, we
    - **erase** with $\mathbf{e_t}$

$$\tilde{\mathbf{M}}_t(i) \longleftarrow \mathbf{M}_{t-1}(i)\left[\mathbf{1} - w_t(i)\mathbf{e}_t\right]$$

    - **add** with $\mathbf{a_t}$

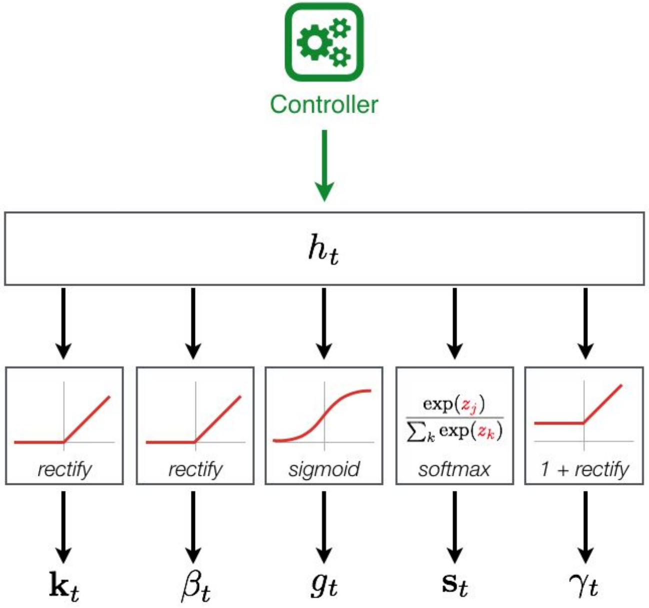
$$\mathbf{M}_t(i) \longleftarrow \tilde{\mathbf{M}}_t(i) + w_t(i)\,\mathbf{a}_t$$

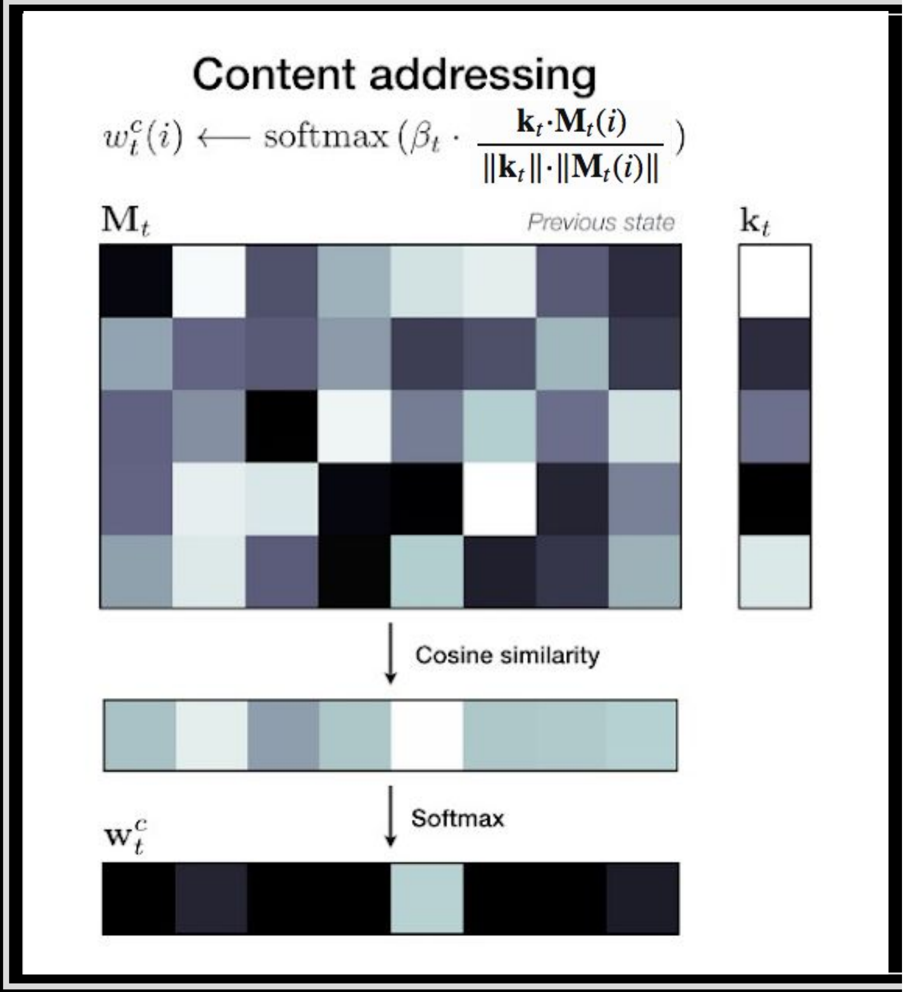
Addressing mechanisms

- How is $\mathbf{w_t}$ produced?
- $\mathbf{w_t}$ is updated through a series of four intermediate smooth operations
    - *content addressing*
    - *interpolation*
    - *convolutional shift*
    - *sharpening*
- Operations depend on parameters from the controller
    - functions of hidden state $\mathbf{h_t}$ emitted by the controller.

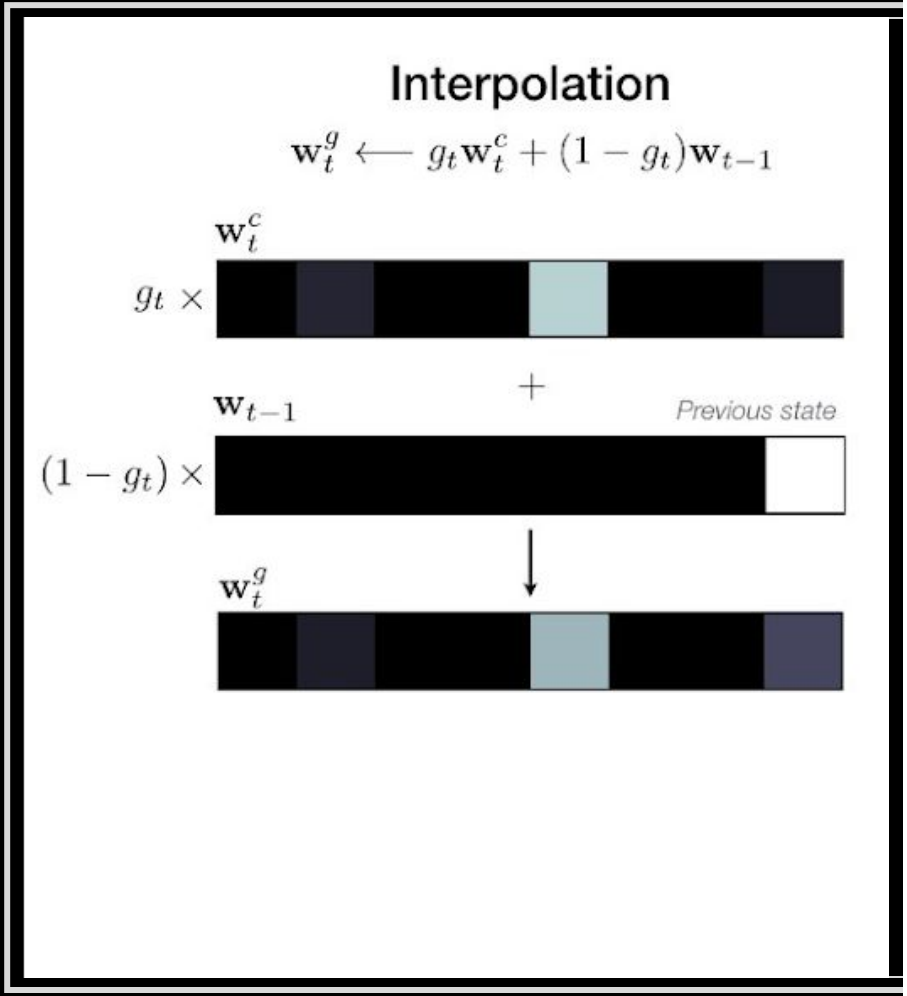
Parameters for weight ($\mathbf{w}_t$) updates

- 5 parameters specific to each read/write head
- Each box is a 1-layer neural network with some activation function

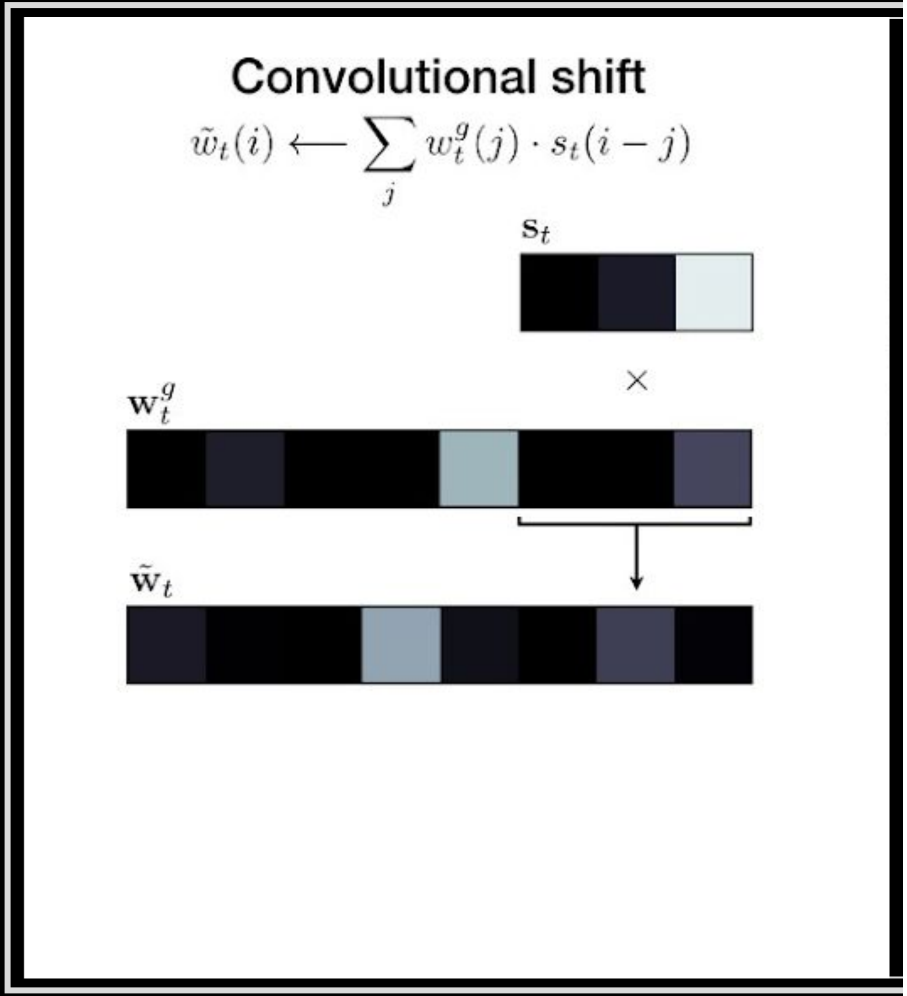




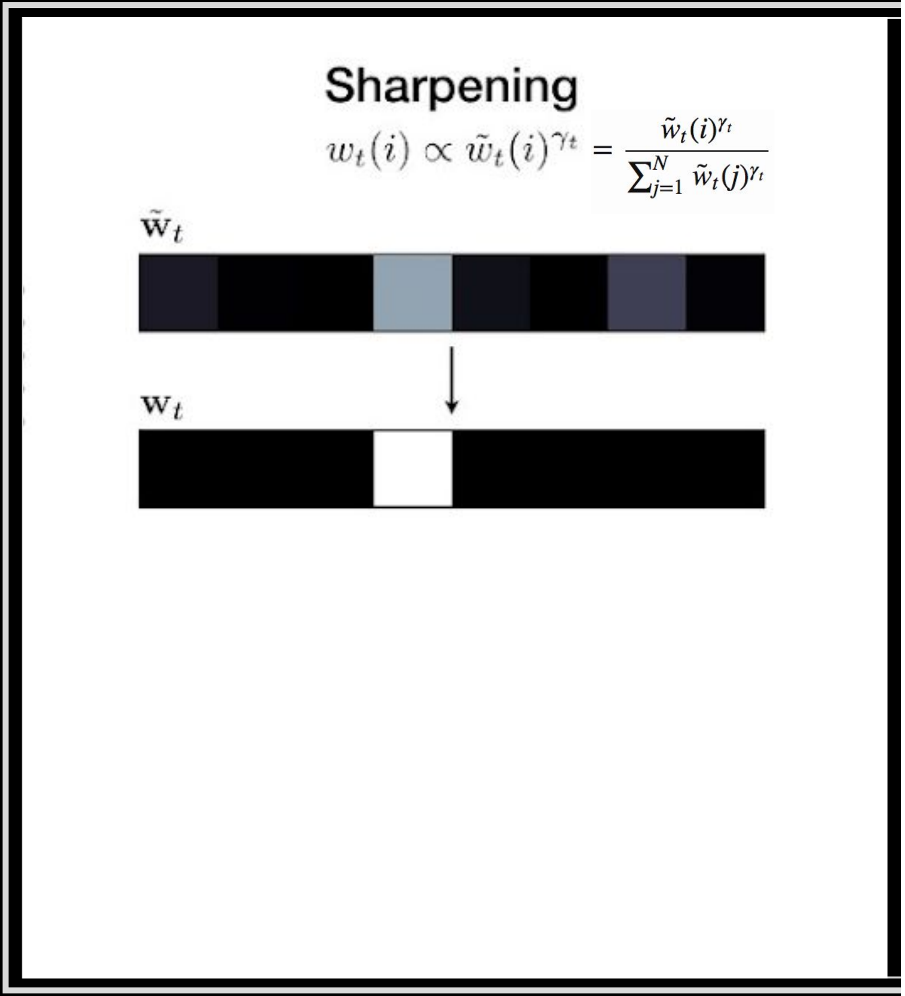
- retrieve specific informations in memory
- compute cosine similarity between key vector $\mathbf{k_t}$ extracted by controller from input and memory
- then normalized by softmax
  - with strength multiplier $\boldsymbol{\beta}_\mathbf{t}$ to amplify or attenuate the focus of the distribution



- interpolation gate scalar $\mathbf{g_t}$ blends newly-generated content-based weight vector $\mathbf{w^c}_\mathbf{t}$ with weight vector from previous time step $\mathbf{w_{t-1}}$



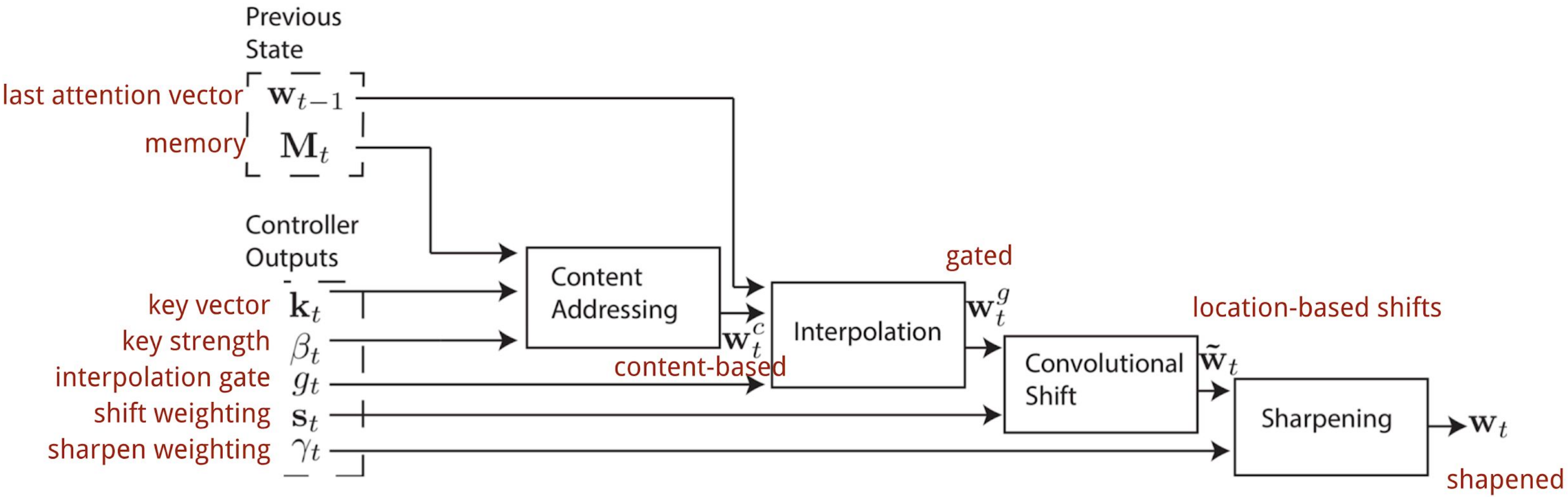
- location-based addressing done by 1-d convolution of $\mathbf{w^g_t}$ with kernel $\mathbf{s_t(.)}$, a function of the position offset $\mathbf{i - j}$



- shifted attention vector is sharpened with a sharpening scalar $\gamma_t \geq 1$

Flow diagram of addressing mechanisms

- Complete process of generating the attention vector $\mathbf{w_t}$



Controller Network Architecture

Feed forward vs recurrent:

- LSTM has its own internal memory complementary to **M**
- Feed forward has better transparency

Analogy:

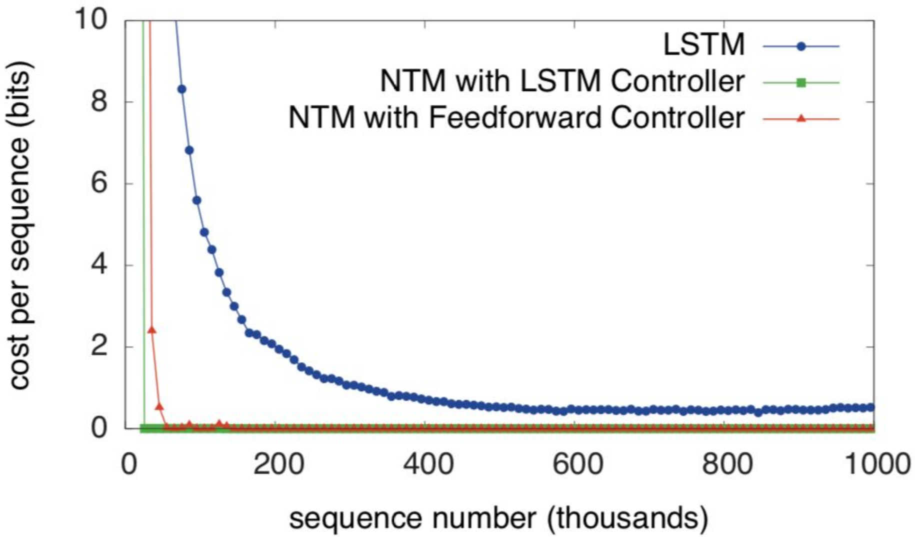
– Controller ⇔ CPU

– Memory Matrix ⇔ RAM

– Hidden Activations of LSTM ⇔ Registers in Processor

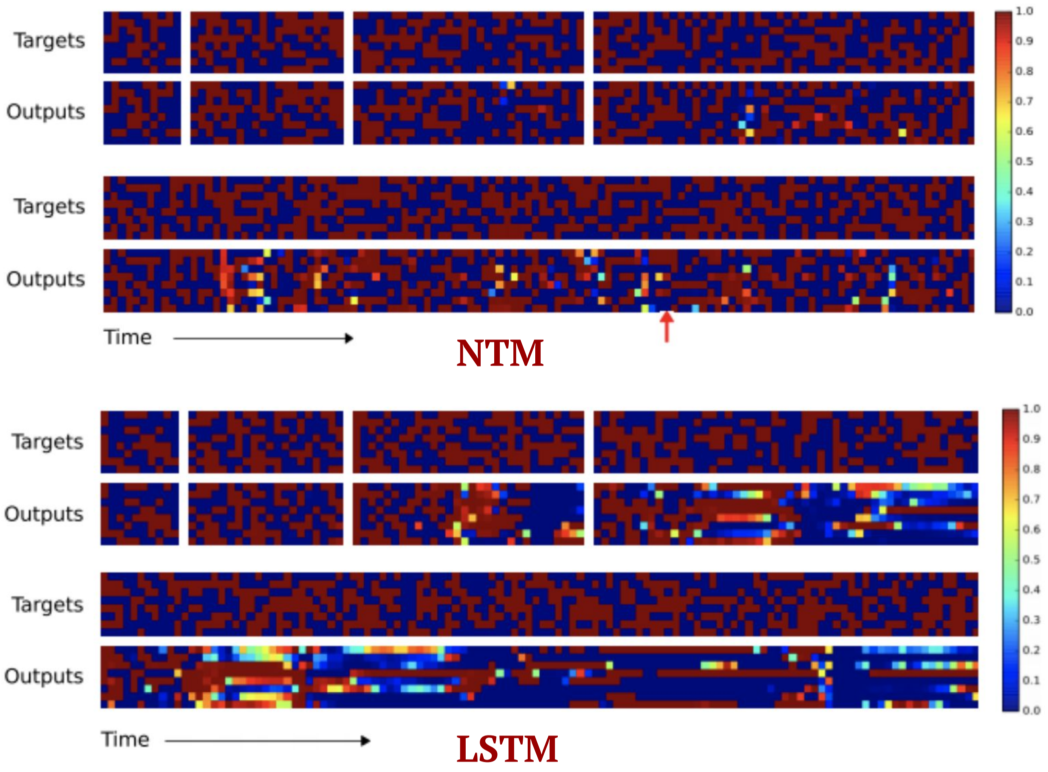
Experiments: Copy

- RNNs have struggled to remember information over long periods
- Given *n* random eight bit vectors followed by a delimiter flag, repeat it
- "Cost per sequence": number of bits incorrectly recalled over a sequence



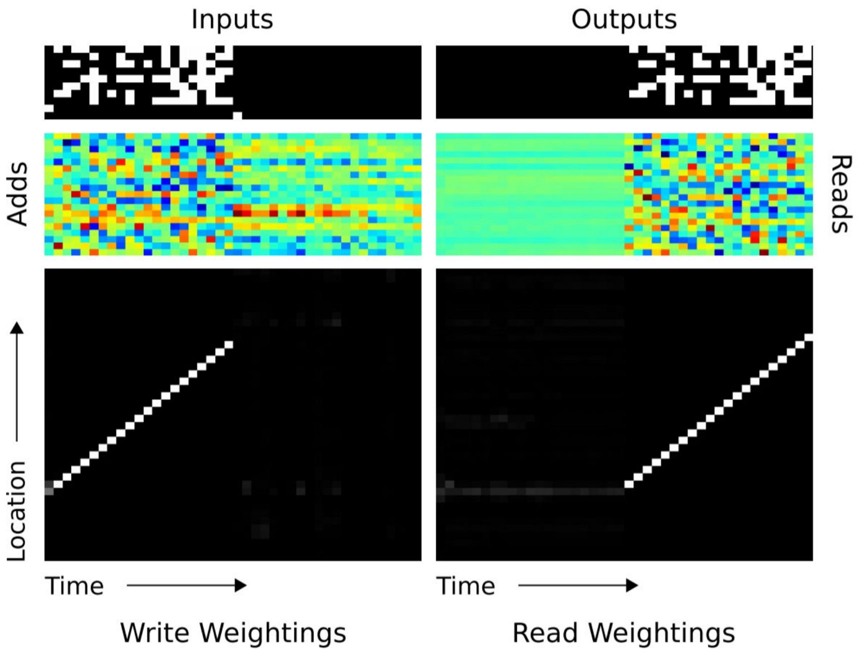
Experiments: Copy

- **Training** sequences of lengths 1 to 20
- **Test** with lengths 10, 20, 30, 50, 120
- [blue, red] -> [0, 1]
- NTM far fewer errors on longer sequences; scales better



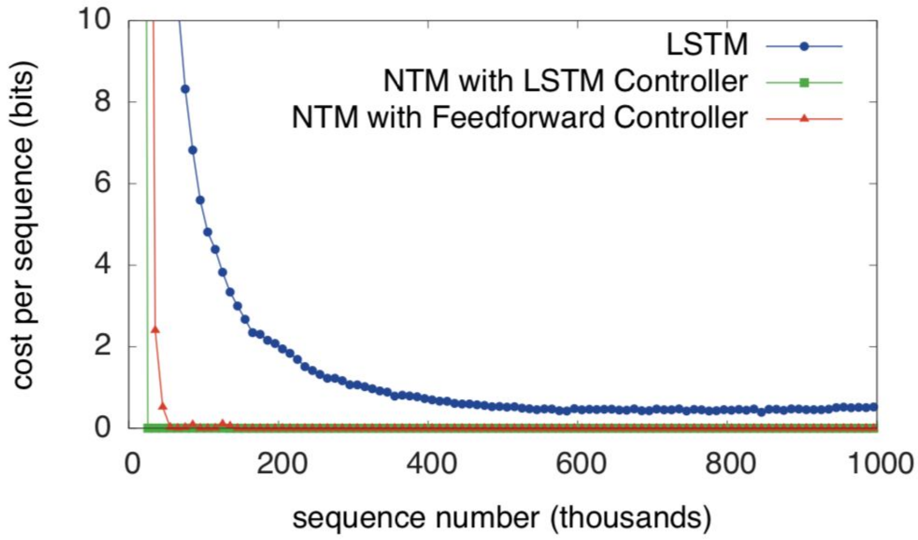
Experiments: Copy

- Visualize how the NTM reads from and writes to **M**



Experiments: Repeat Copy

- Like a **nested for loop:** repeatedly **copy** sequence some ***x* number of times**
- Training input: random-length sequence of 8-bit binary vectors + scalar *x* from 1-10



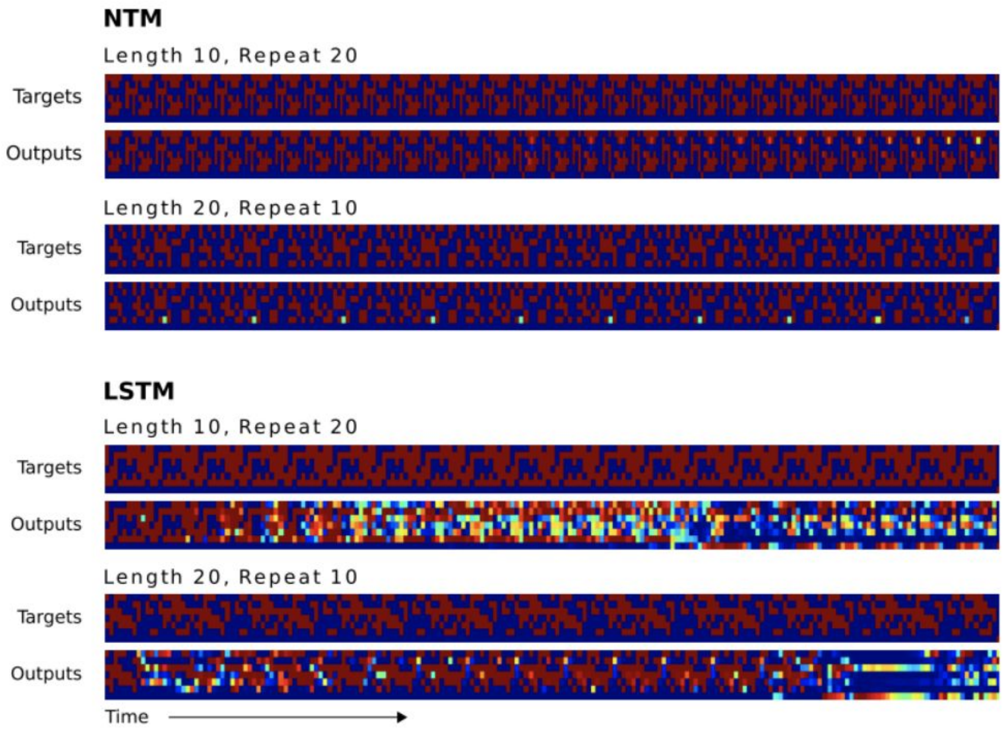
Experiments: Repeat Copy

Increased # repeats:

- NTM much better, but still keeps falsely predicting end of sequence (emits delimiter flag after every repetition beyond the 11th)

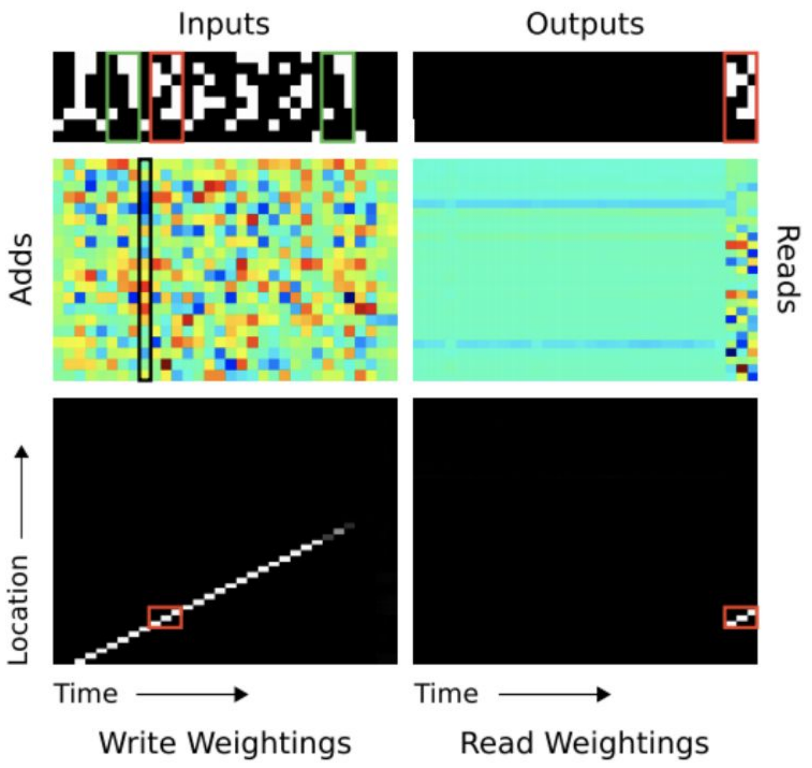
Increased length:

- NTM generalizes much better



Experiment: Associative recall

- Can NTMs can learn "indirection" i.e. one data item pointing to another?
- **input:**
  - list of items
  - query of one of the items (green)
- **output:**
  - next item in the list (red)
- at delimiter flag, NTM forms compressed representation (black box in “Adds”) of each item



Experiment: Associative recall

- **Feed forward**-controller NTM **outperforms LSTM**-controller NTM
  - suggests that NTM's memory is a superior data storage system than LSTM's internal state

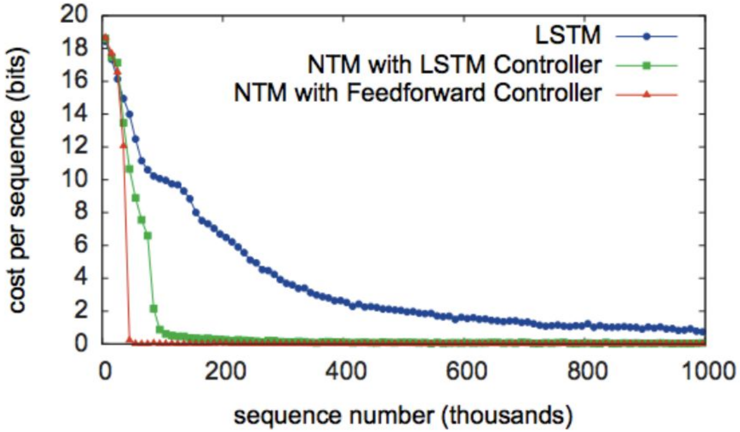


Figure 10: Associative Recall Learning Curves for NTM and LSTM.

Segue to code

Experiment: Dynamic n-grams

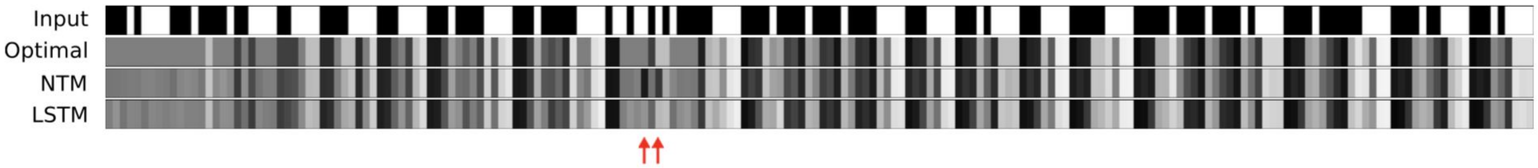
- Whether NTMs could learn posterior predictive distributions
- N-grams (sequences of N items), which given previous items in the sequence, determine some probability distribution over the next item in the sequence
- Optimal estimator:

$$P(B = 1|N_1, N_0, \mathbf{c}) = \frac{N_1 + \frac{1}{2}}{N_1 + N_0 + 1}$$

- **B** is the next bit, **c** is the previous 5-bit context, and **N0** and **N1** are the number of zeros and ones observed after **c**
- NTM achieves small, but significant performance advantage over LSTM, but never quite reaches optimum cost

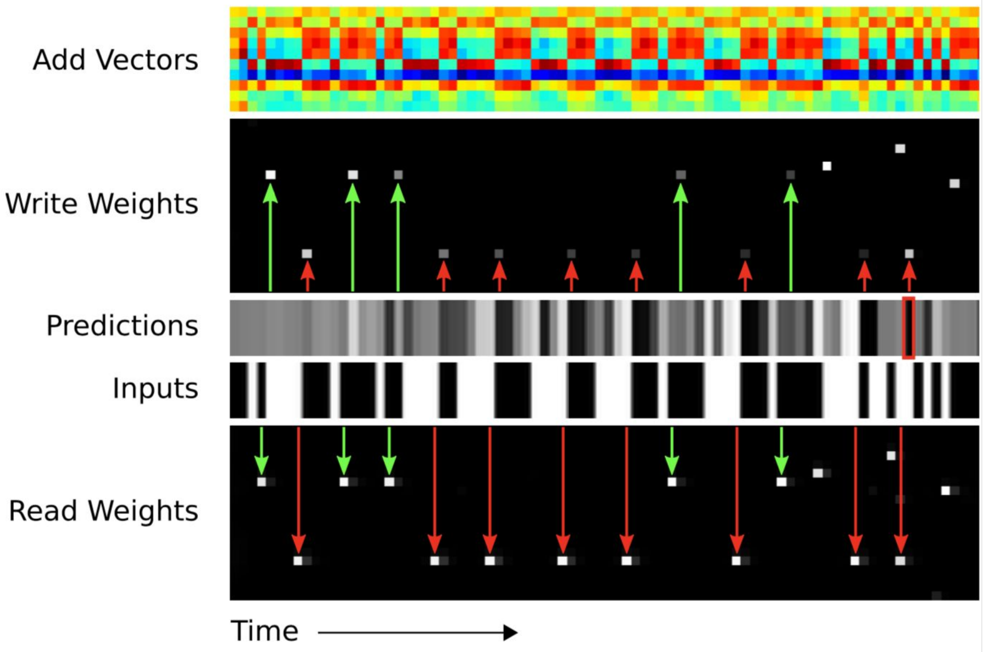
Experiment: Dynamic n-grams

- Top row: test sequence
- Rows below: predictive distributions by optimal estimator, NTM, and LSTM
- NTM predictions mostly indistinguishable from optimal (although some clear mistakes e.g. red arrows)
- LSTM good but appears to diverge further as sequence progresses
  - speculate that LSTM "forgets" observations at start



Experiment: Dynamic n-grams

- red and green arrows where same context is observed (“00010” for green, “01111” for red)
- same location read then written to
- Network uses writes to keep count of the fraction of ones and zeros following each context in the sequence so far
- Add vectors clearly anti-correlated at 0s and 1s, suggesting a distributed “counter.”



Experiment: Priority sort

Whether the NTM can sort data—an important elementary algorithm

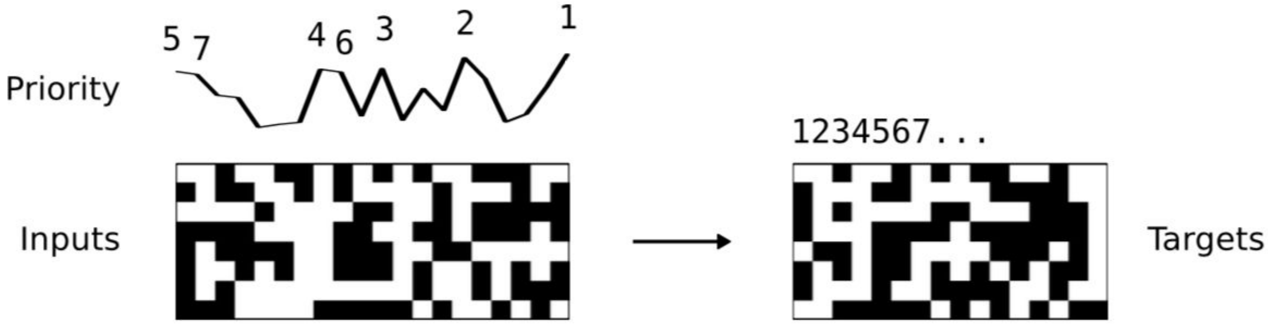
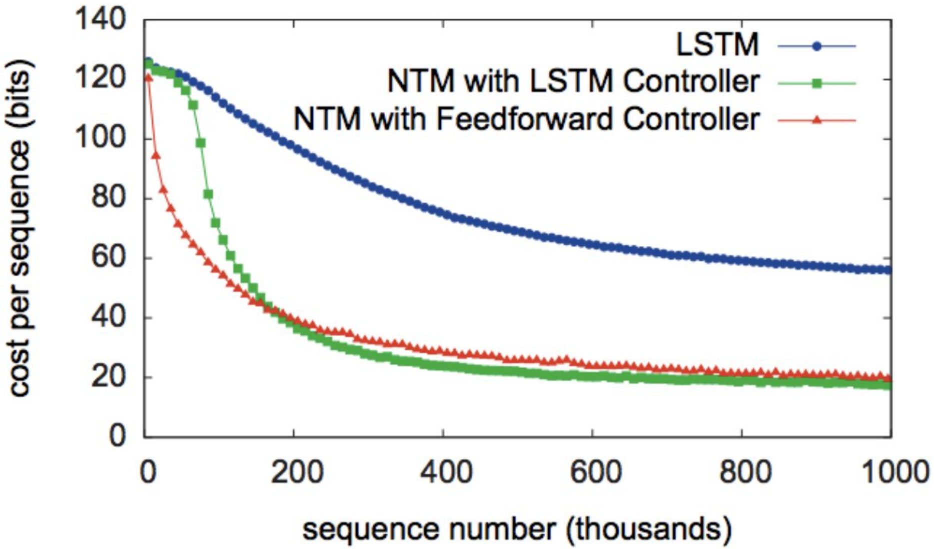


Figure 16: Example Input and Target Sequence for the Priority Sort Task. The input sequence contains random binary vectors and random scalar priorities. The target sequence is a subset of the input vectors sorted by the priorities.

Experiment: Priority sort

Again, NTMs > LSTM



Implementational Checkpoint

- Took 4 years to find a stable implementation
- Paper just on implementing NTMs

arXiv.org > cs > arXiv:1807.08518

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Implementing Neural Turing Machines

Mark Collier, Joeran Beel

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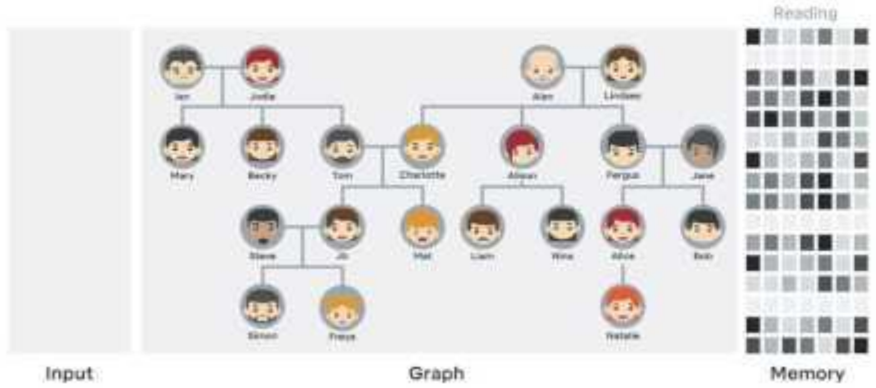
Neural Turing Machines (NTMs) are an instance of Memory Augmented Neural Networks, a new class of recurrent neural networks which decouple computation from memory by introducing an external memory unit. NTMs have demonstrated superior performance over Long Short-Term Memory Cells in several sequence learning tasks. A number of open source implementations of NTMs exist but are unstable during training and/or fail to replicate the reported performance of NTMs. This paper presents the details of our successful implementation of a NTM. Our implementation learns to solve three sequential learning tasks from the original NTM paper. We find that the choice of memory contents initialization scheme is crucial in successfully implementing a NTM. Networks with memory contents initialized to small constant values converge on average 2 times faster than the next best memory contents initialization scheme.

Differentiable Neural Computer (DNC)

- Successor of NTMs; more generalizable network structure
- Wide range of tasks including natural language understanding, basic inference, planning, etc.
    - E.g. Solving block puzzles
    - E.g. Finding paths between nodes in a graph after memorizing the graph
- Has ability to **free** and **allocate** memory, i.e. to reuse memory locations
- Using **temporal links**, can search by time of writes

DNC



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