Lecture 13
Neural Networks with External Memory

CMSC 35246: Deep Learning

Shubhendu Trivedi
&
Risi Kondor

University of Chicago

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Neural Networks with Explicit Memory

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- These models (such as for object recognition, machine translation) slowly absorb the examples into their weights to learn the concept over successive gradient descent iterations

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- Traditional frameworks struggle with memorizing facts and being able to manipulate information for some task of interest (such as question answering, programming need longer term memory, out of sequence accesses to information)
- Solution: Endow a Neural Network with an external memory that it can read from and write to

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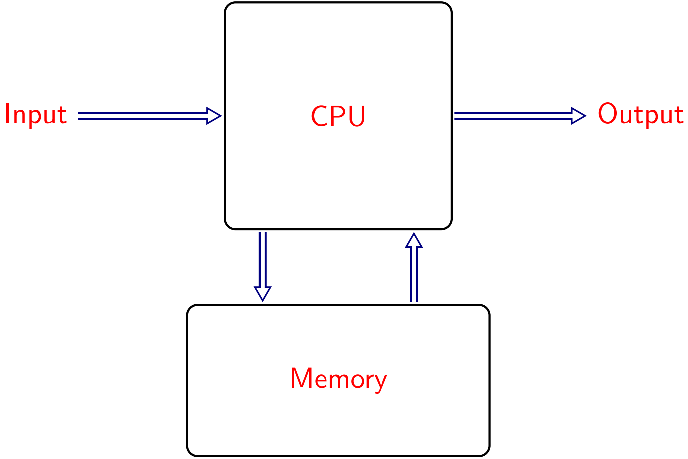
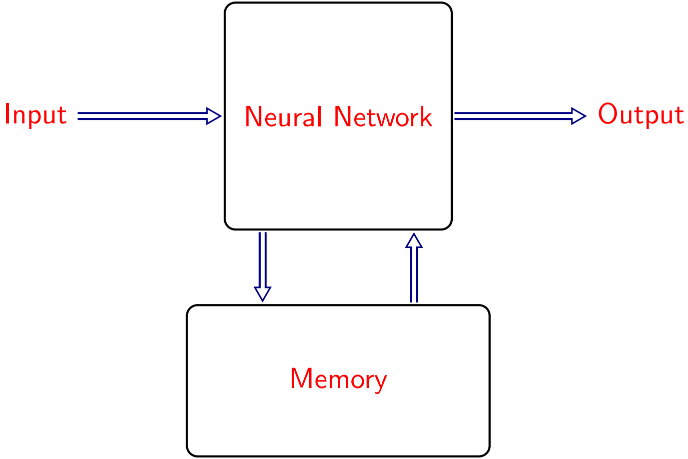
- Slightly anachronistic: Will first look at Neural Turing Machines and then Memory Networks

A Primitive Computer Model



A Neural Computer



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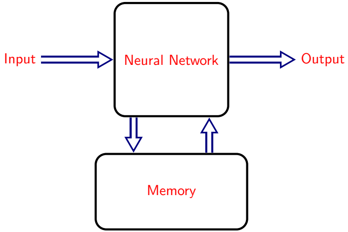

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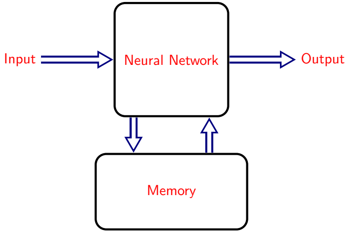
A Neural Computer



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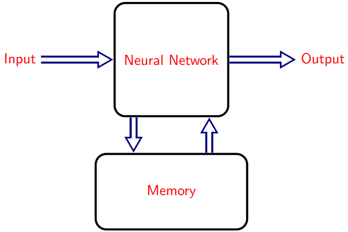

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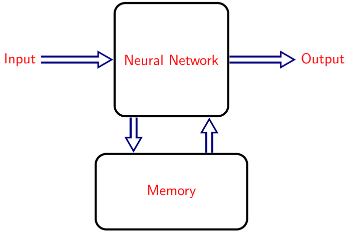

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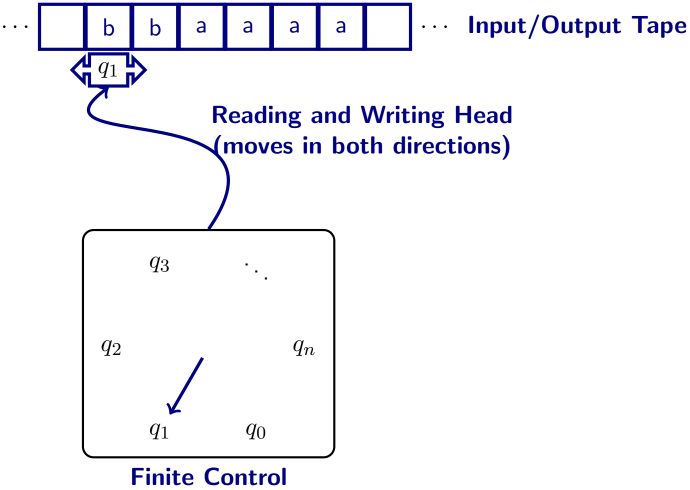
- Want the whole system to trainable by backpropagation

A Turing Machine



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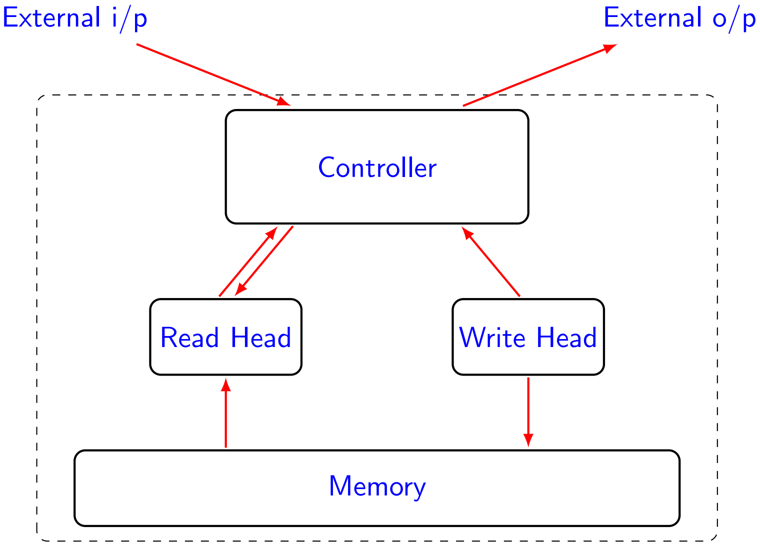
Goal: Want to mimic the working of a Turing Machine in a differentiable manner

Architecture



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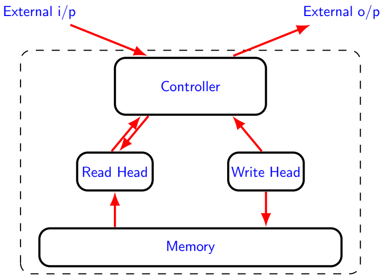

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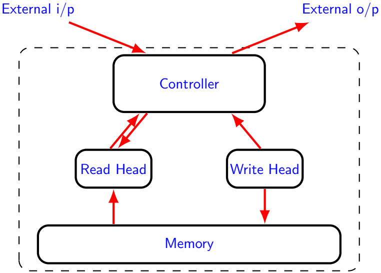

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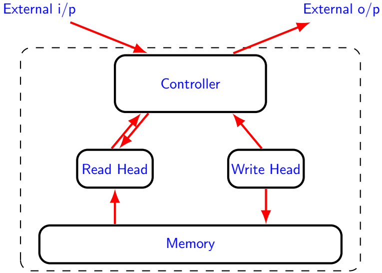

- Controller: Is a RNN or a CNN
- Receives input vectors and outputs vectors just as a normal neural network

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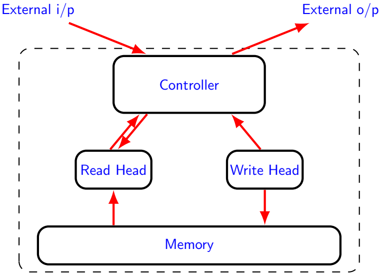

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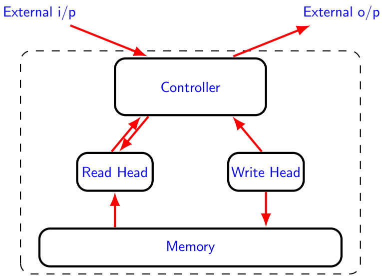

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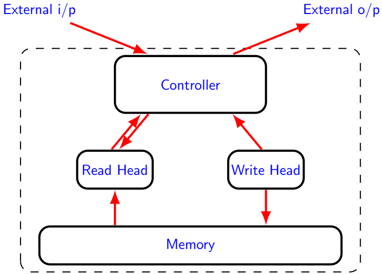

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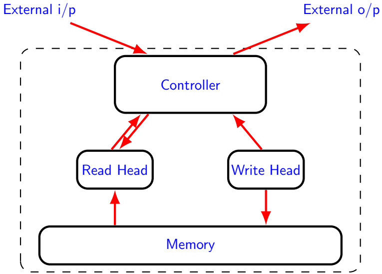

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- Main Idea: Keep everything differentiable

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- Let's see both

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$$\mathbf{w}[i] = \frac{\exp(\beta S(\mathbf{k}, M[i]))}{\sum_j \exp(\beta S(\mathbf{k}, M[j]))}$$

- Find memories close to the key

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- Gives a way to use a weighing already generated and push it up or down

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- Idea is to mimic various data structures and accessors in programming languages
- **Content key only:** Associative map
- **Content and Location:** $\mathbf{k}$ finds an array in memory, shift indexes in it
- **Location:** Only iterates from the last focus

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$$\mathbf{r} = \sum_i \mathbf{w}[i] M[i]$$

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$$M[i] \leftarrow M[i](1 - \mathbf{w}[i] \odot \mathbf{e}) + \mathbf{w}[i] \odot \mathbf{a}$$

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- Roughly: Want our NN to operate as a CPU that can read/write to an external memory
- Idea: The two together should be able to learn to program from input and output examples using backpropagation
- Separate computation from memory

Task 1: Repeat Copy

- Task: Read a vector and then reproduce the whole vector

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- Implements a simple algorithm. Time goes from left to right. Left column shows the write weighings, right columns shows the read weightings

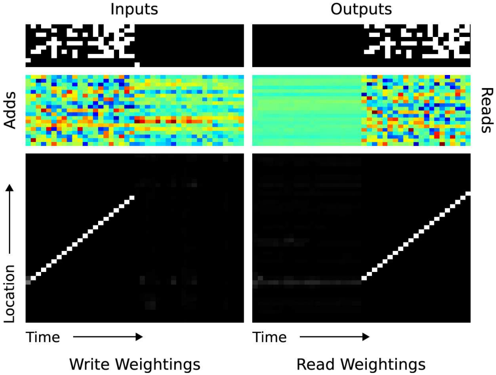

Figure: Neural Turing Machine, Graves *et al.*

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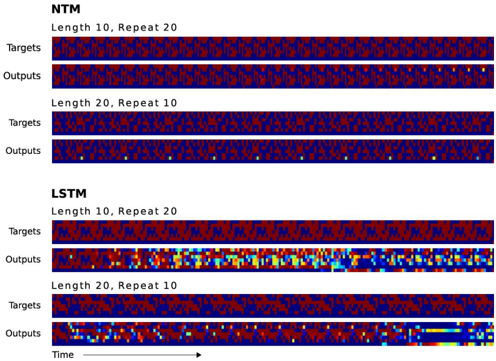

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Task 2: Copy N times

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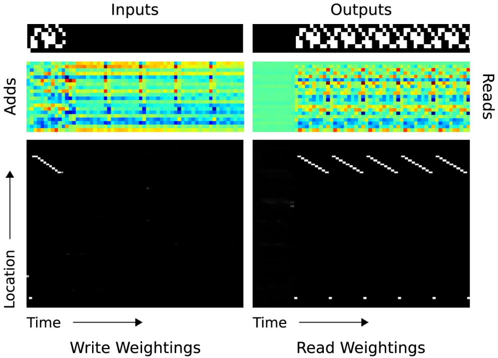

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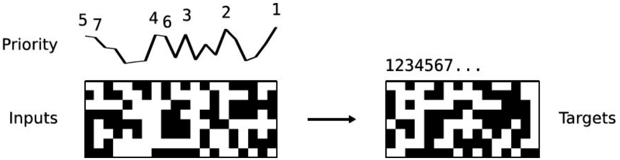
Task 3: Priority Sort



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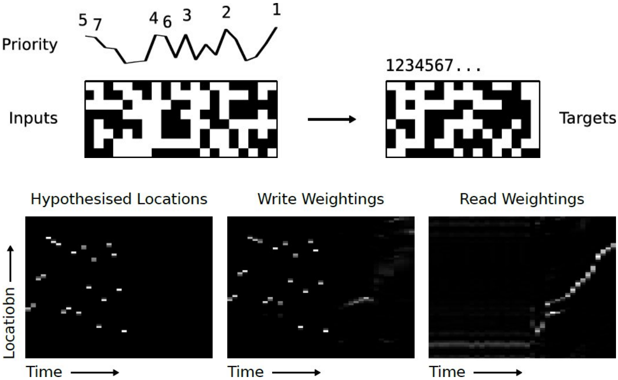

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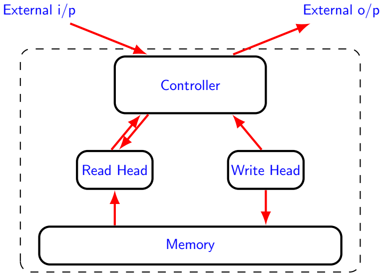
NTM v 2.0

Differentiable Neural Computers

Architecture



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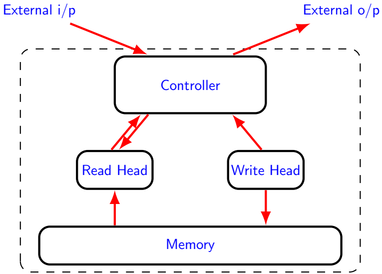

- Remember: The whole architecture is recurrent even if the controller is not recurrent.

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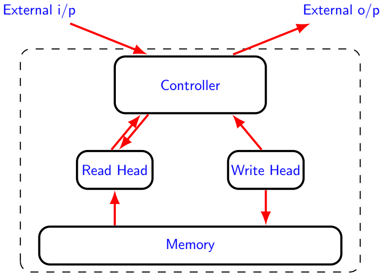

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- Let us see how far can we push this paradigm of modifying these real numbers i.e. the memory

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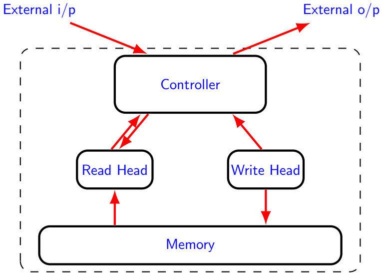

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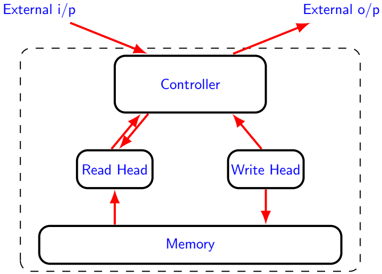

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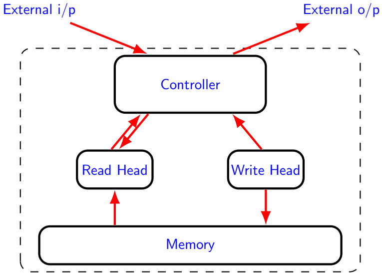

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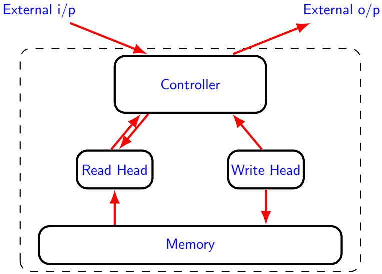

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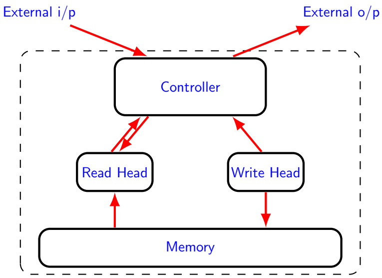
  - Based on memory allocation
  - Based on temporal order

Architecture



- We now have three attentional processes:
  - Based on content
  - Based on memory allocation
  - Based on temporal order
- Based on content, memory allocation and temporal order: The controller will interpolate between these by using scalar gates

Allocating Memory

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$$\mathbf{u}_t = (\mathbf{u}_{t-1} + \mathbf{w}_{t-1}^w - \mathbf{u}_{t-1} \odot \mathbf{w}_{t-1}^w) \odot \prod_{i=1}^{R} (\mathbf{1} - f_t^i \mathbf{w}_{t-1}^{r,i})$$

Allocating Memory: Test

- Gave a bunch of random sequences and asked the system to reproduce them without resetting the memory:

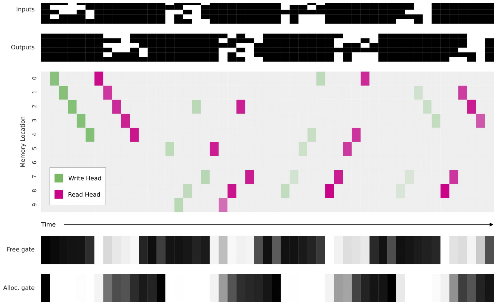

Figure: Hybrid Computing using a Neural Network with Dynamic External Memory, Graves *et al.*

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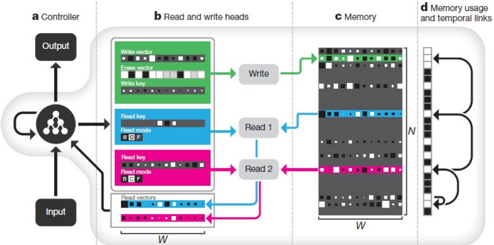
- Three way gates are used to interpolate between the forward and backward iterations as well as content

Architecture



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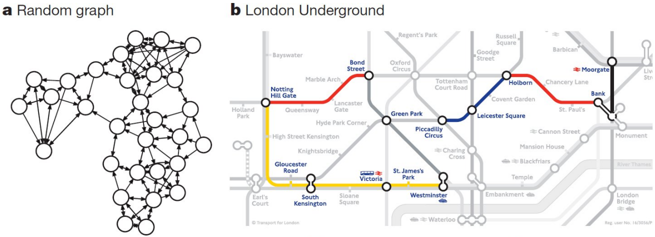
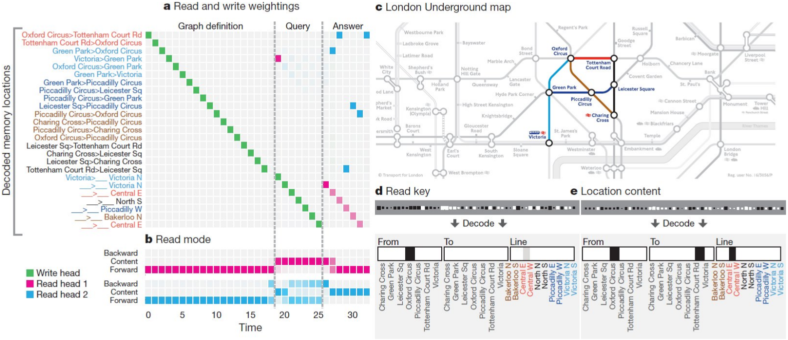
Shortest Paths



Underground input:	Traversal	Shortest-path
(OxfordCircus, TottenhamCtRd, Central) (TottenhamCtRd, OxfordCircus, Central) (BakerSt, Marylebone, Circle) (BakerSt, Marylebone, Bakerloo) (BakerSt, OxfordCircus, Bakerloo) ⋮ (LeicesterSq, CharingCross, Northern) (TottenhamCtRd, LeicesterSq, Northern) (OxfordCircus, PiccadillyCircus, Bakerloo) (OxfordCircus, NottingHillGate, Central) (OxfordCircus, Euston, Victoria) 84 edges in total	Traversal question: (BondSt, _, Central), (_, _, Circle), (_, _, Circle), (_, _, Circle), (_, _, Circle), (_, _, Jubilee), (_, _, Jubilee), Answer: (BondSt, NottingHillGate, Central) (NottingHillGate, GloucesterRd, Circle) ⋮ (Westminster, GreenPark, Jubilee) (GreenPark, BondSt, Jubilee)	Shortest-path question: (Moorgate, PiccadillyCircus, _) Answer: (Moorgate, Bank, Northern) (Bank, Holborn, Central) (Holborn, LeicesterSq, Piccadilly) (LeicesterSq, PiccadillyCircus, Piccadilly)

Figure: Hybrid Computing using a Neural Network with Dynamic External Memory, Graves *et al.*

Shortest Paths



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Family Tree

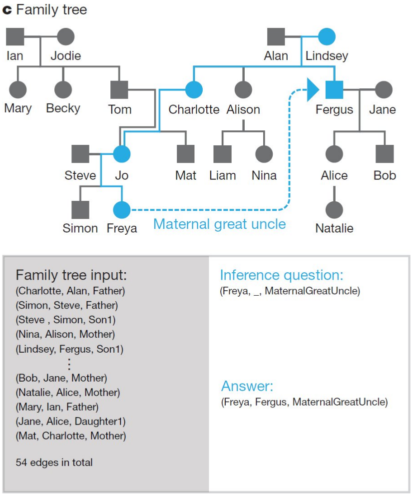

Figure: Hybrid Computing using a Neural Network with Dynamic External Memory, Graves *et al.*
https://www.youtube.com/watch?v=B9U8sI7TcMY

Question Answering (bAbi)

Sample:

Sheep are afraid of wolves
Cats are afraid of dogs
Mice are afraid of cats
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- There can be many sentences in between: long term dependencies

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- The goal again is to keep the system differentiable end-to-end