Differentiable Neural Computers

Hybrid Computing using a neural network with dynamic external memory (Graves et al. 2016)

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Logic and Computation

Overview: Probabilistic Programming

Cross-domain

- Data Flow Programming
- Bayesian Reasoning
- Machine Learning
- Functional Programming

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Program	Model
Discrete	Continuous
Deterministic	Stochastic
Static	Adaptive

Overview: DNC

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A recurrent neural network coupled with an external memory.

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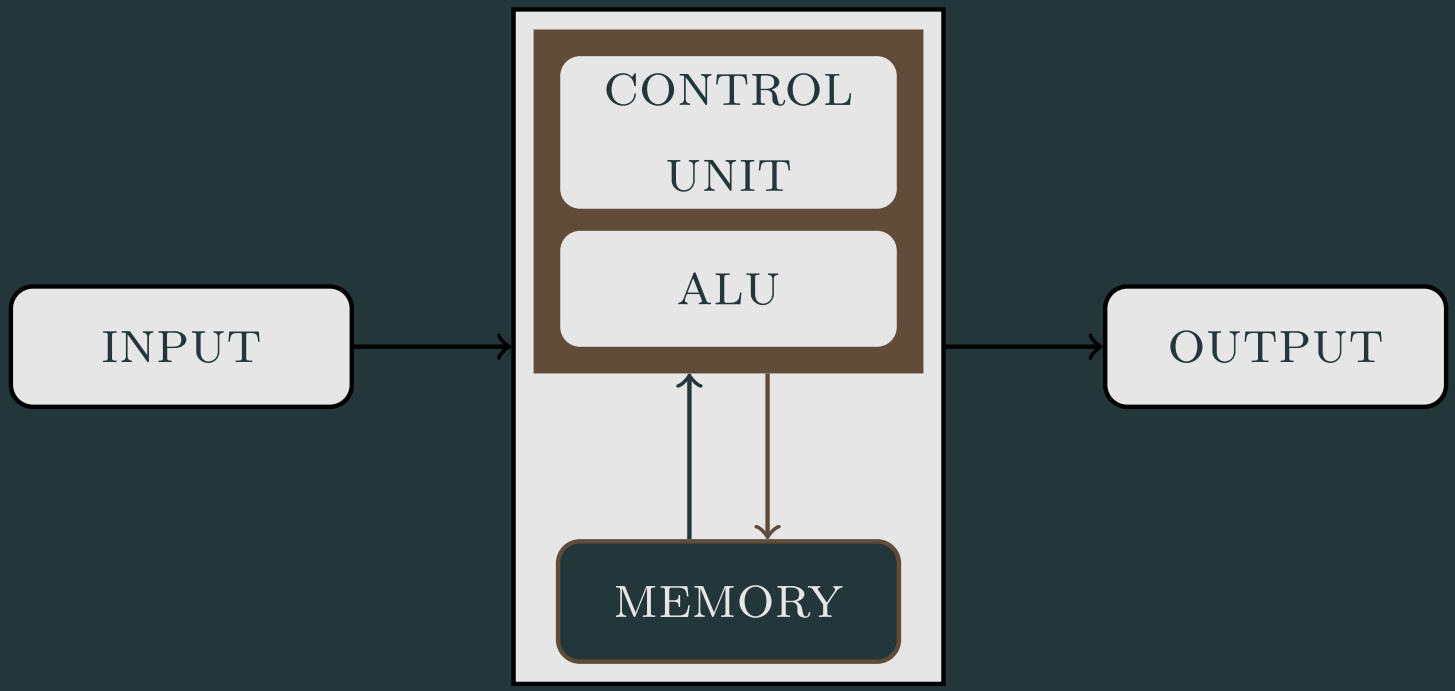
- Extension of NTMs
  - End-to-end differentiable
  - Auto-associative memory
  - Turing complete
  - \+ Memory attention mechanisms
- Mimic mammalian biological memory
- Employ classical concepts of computation

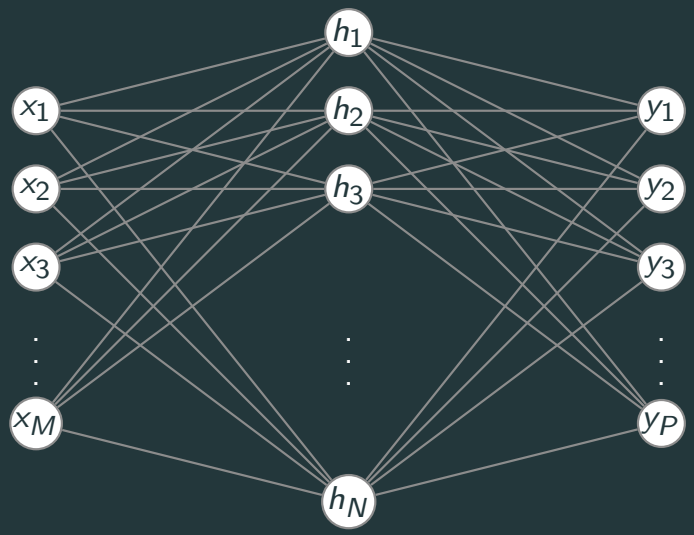
Introduction: Classic Computation

Von Neumann architecture



Introduction: RNNs

Simple Neural Net



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No memory

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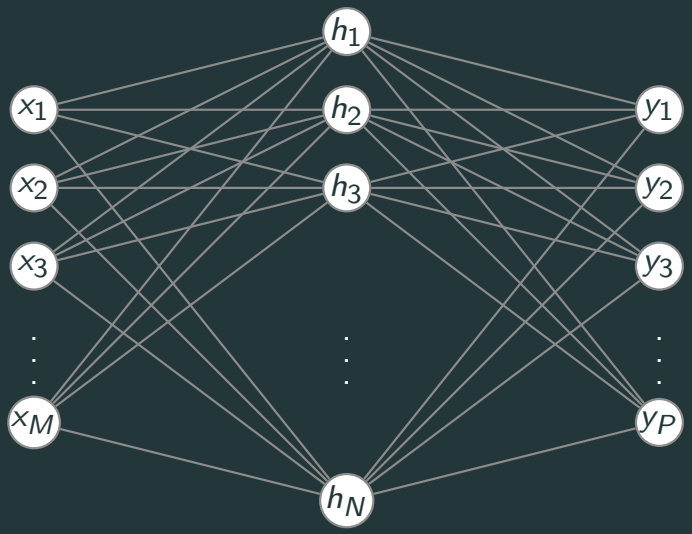

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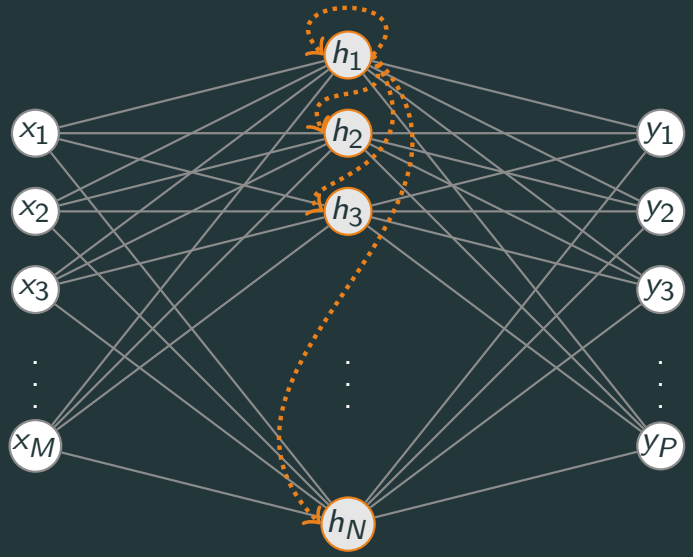
Simple Recurrent Net



$$h(t) = f([x(t); h(t-1)])$$

Finite, non-contiguous memory

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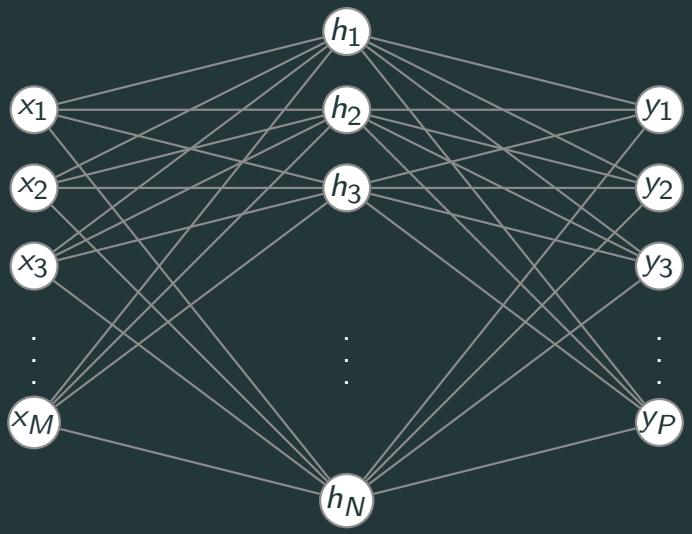

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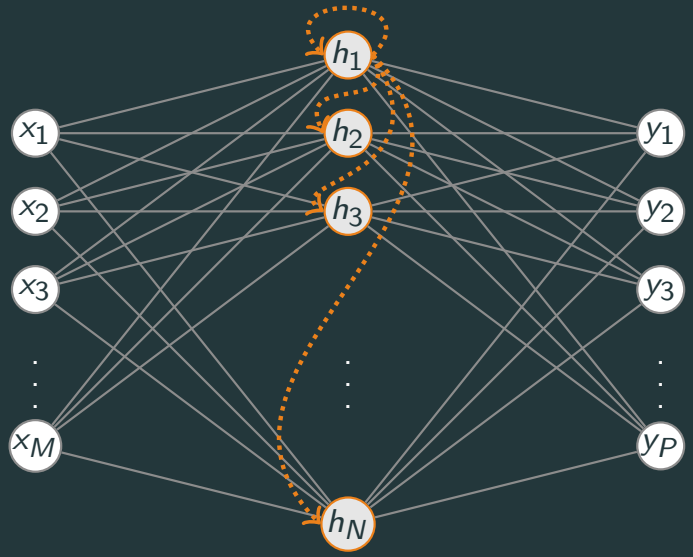

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"If training vanilla neural nets is optimization over functions, training recurrent nets is optimization over programs."

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3. Dynamic Allocation
   - Mark memory locations with $\{0,1\}$ to signal usage
   - Manipulate signals during R/W operations to enable reallocation
   - Generalization to unbounded memory

Controller

A deep long short-term memory network receiving input:

$$\boldsymbol{\chi}_t = [\boldsymbol{x}_t; \boldsymbol{r}_{t-1}^1; \ldots; \boldsymbol{r}_{t-1}^R]$$

and producing output:

$$(\boldsymbol{v}_t, \boldsymbol{\xi}_t) = \mathcal{N}([\boldsymbol{\chi}_1; \ldots; \boldsymbol{\chi}_T]; \vartheta)$$

where $\mathcal{N}$ a set of state equations and ϑ their trainable parameters.

Controller: State Equations

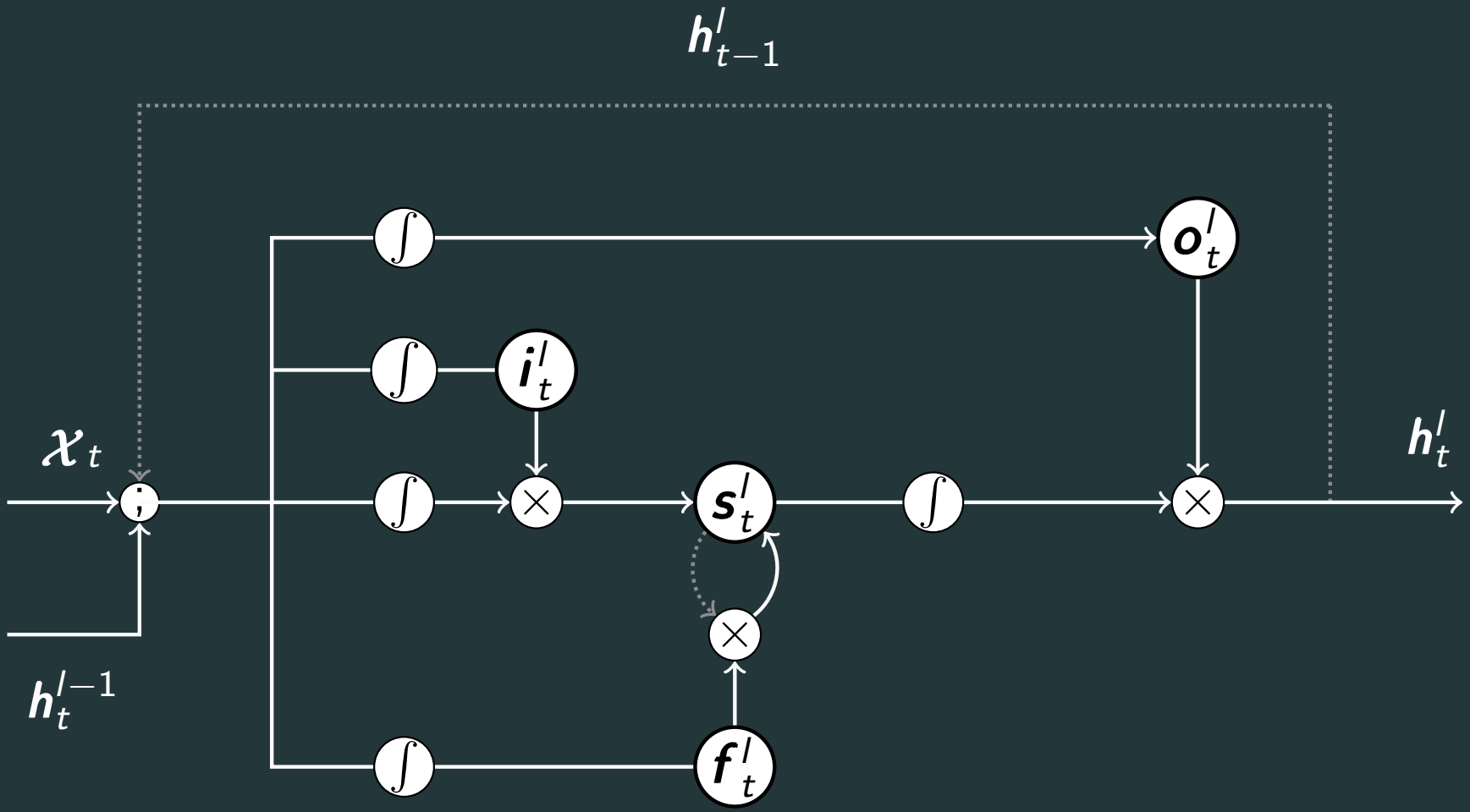
A more detailed look into $\mathcal{N}$:

$$
\begin{aligned}
\boldsymbol{i}_t^l &= \sigma(W_i^l[\boldsymbol{\mathcal{X}}_t; \boldsymbol{h}_{t-1}^l; \boldsymbol{h}_t^{l-1}] + \boldsymbol{b}_i^l) && \text{(input gate)} \\
\boldsymbol{f}_t^l &= \sigma(W_f^l[\boldsymbol{\mathcal{X}}_t; \boldsymbol{h}_{t-1}^l; \boldsymbol{h}_t^{l-1}] + \boldsymbol{b}_f^l) && \text{(forget gate)} \\
\boldsymbol{s}_t^l &= \boldsymbol{f}_t^l \boldsymbol{s}_{t-1}^l + \boldsymbol{i}_t^l tanh(W_s^l[\boldsymbol{\mathcal{X}}_t; \boldsymbol{h}_{t_1}^l; \boldsymbol{h}_t^{l-1}] + \boldsymbol{b}_s^l) && \text{(state)} \\
\boldsymbol{o}_t^l &= \sigma(W_o^l[\boldsymbol{\mathcal{X}}_t; \boldsymbol{h}_{t-1}^l; \boldsymbol{h}_t^{l-1}] + \boldsymbol{b}_o^l) && \text{(output gate)} \\
\boldsymbol{h}_t^l &= \boldsymbol{o}_t^l tanh(\boldsymbol{s}_t^l) && \text{(hidden)}
\end{aligned}
$$

$$
\begin{aligned}
\boldsymbol{v}_t &= W_y[\boldsymbol{h}_t^1; \ldots; \boldsymbol{h}_t^L] && \text{(output vector)} \\
\boldsymbol{\xi}_t &= W_\xi[\boldsymbol{h}_t^1; \ldots; \boldsymbol{h}_t^L] && \text{(interface vector)}
\end{aligned}
$$

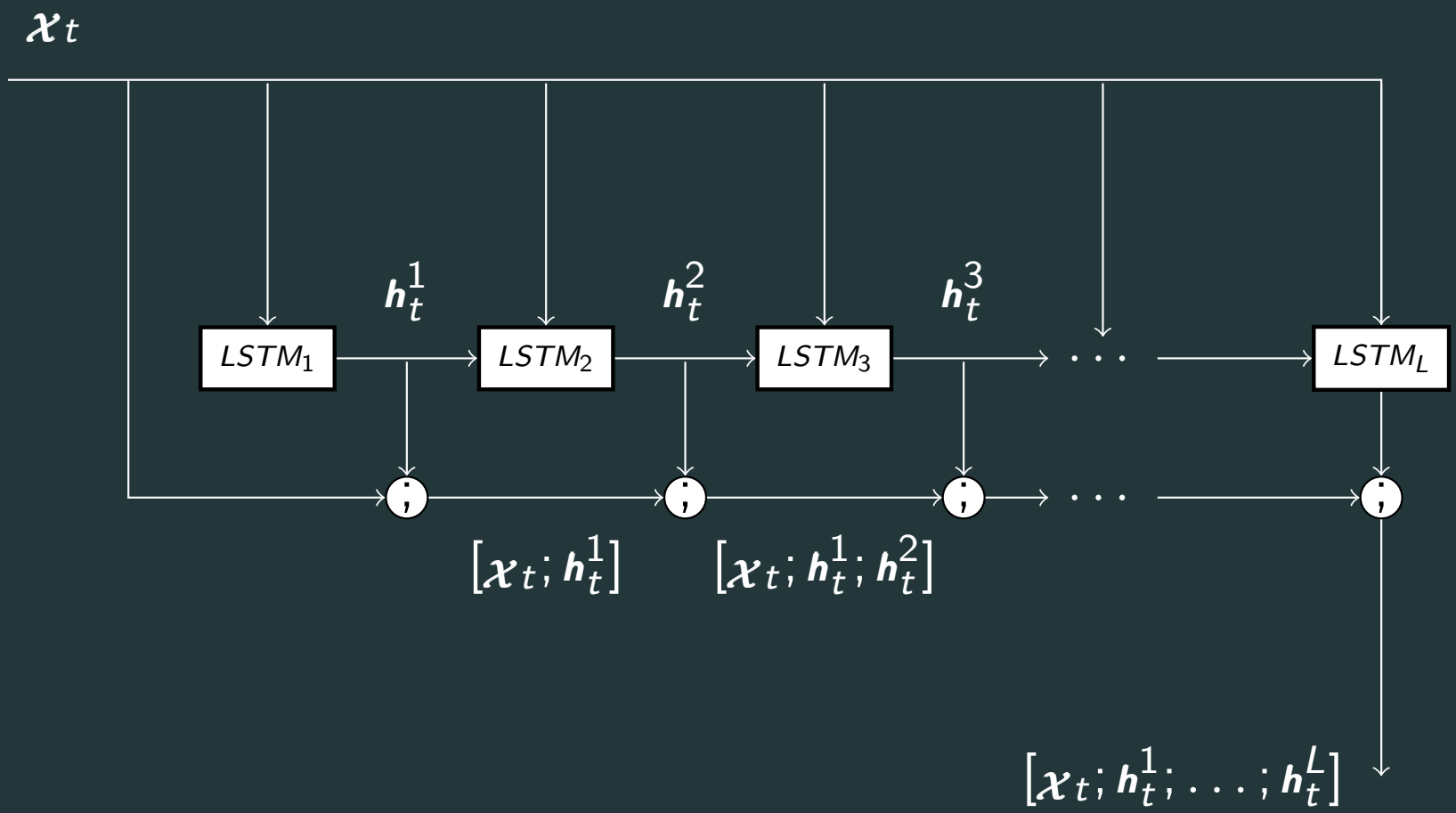
Controller: Signal-Flow

Single LSTM layer



Controller: Full View

LSTM Network (multiple layers)



Controller: Outputs

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Intermediate output $\boldsymbol{v}_t$

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Interface vector $\boldsymbol{\xi}_t$

- Read keys
- Read strengths
- Write key
- Write strength
- Erase vector
- Write vector
- Free gates
- Allocation gate
- Write gate
- Read modes

Memory Adressing: RW

Read operations

$$\boldsymbol{r}_t^i = M_t^T \boldsymbol{w}_t^{r,i}$$

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Read operations

$$\boldsymbol{r}_t^i = M_t^T \boldsymbol{w}_t^{r,i}$$

Write operations

$$M_t = M_{t-1} \circ (\mathbf{1} - \boldsymbol{w}_t^T \boldsymbol{e}_t^T) + \boldsymbol{w}_t^W \boldsymbol{v}_t^T$$

Further Reading

- Neural Turing Machines (Graves, Wayne, Danihelka)
- Entity Networks (Henaff, Weston, Szlam, Bordes, LeCun)
- Principles of Probabilistic Programming Languages (Goodman)
- Backprop as a Functor (Fong, Spivak, Tuyras)
- Formal Methods for Probabilistic Programming (Selsam, Liang, Dill)