Neural networks with dynamic external memory

Differentiable neural computer

Maciej Żelaszczyk

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PhD Student in Computer Science
Division of Artificial Intelligence and Computational Methods
Faculty of Mathematics and Information Science

m.zelaszczyk@mini.pw.edu.pl

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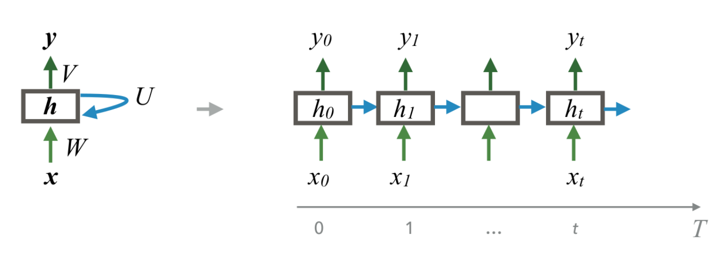
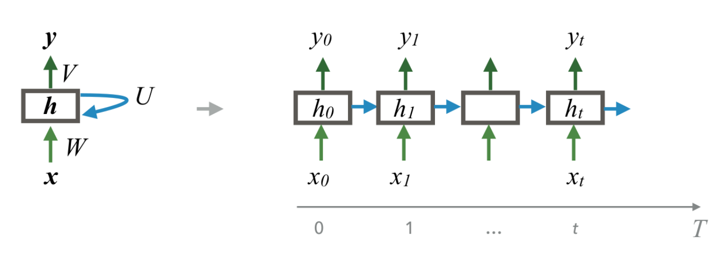


Source: Gakhov, A., *Recurrent Neural Networks. Part 1: Theory*

Vanilla RNNs

- Classic RNN architecture.

$$\mathbf{h_t} = \tanh\left(\begin{bmatrix}\mathbf{U} & \mathbf{W}\end{bmatrix}\begin{bmatrix}\mathbf{h_{t-1}} \\ \mathbf{x_t}\end{bmatrix}\right)$$



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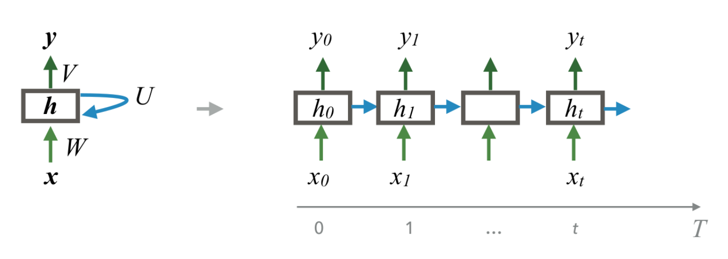

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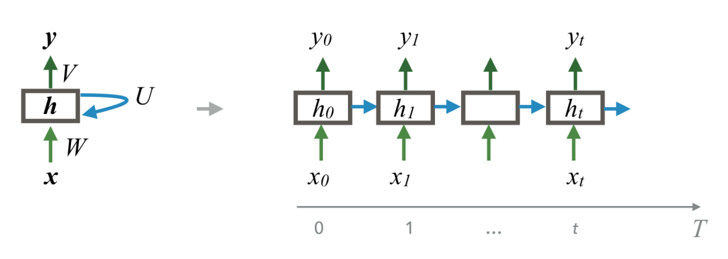

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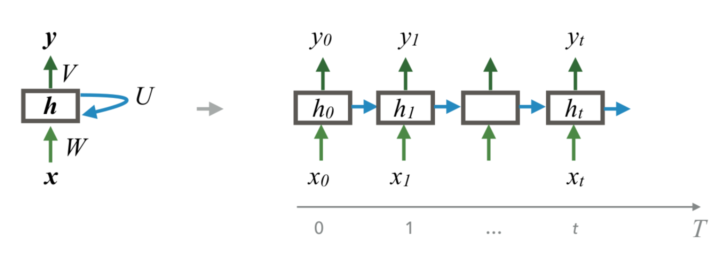
- Gradient either vanishes or explodes during training.



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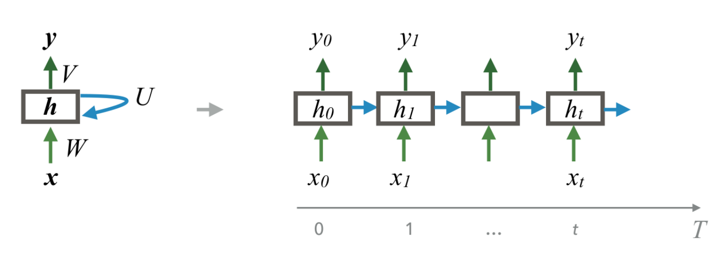

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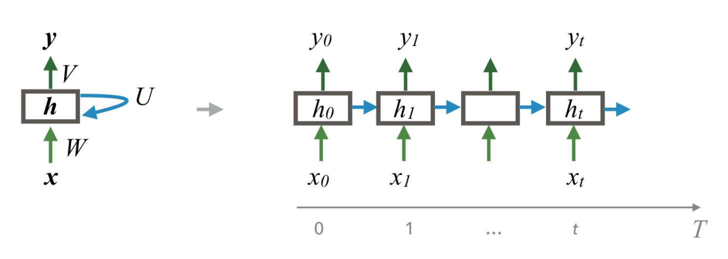

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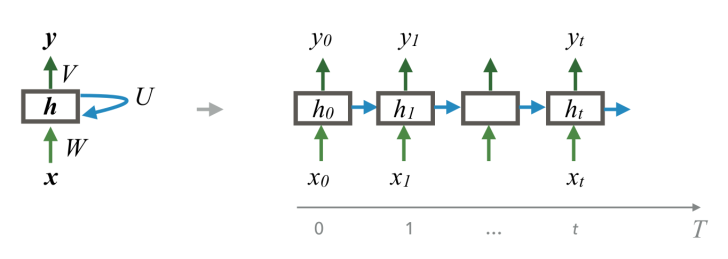

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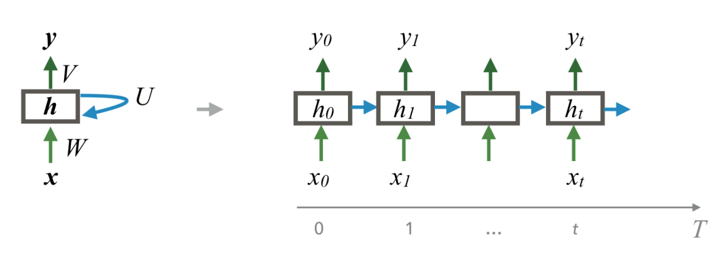

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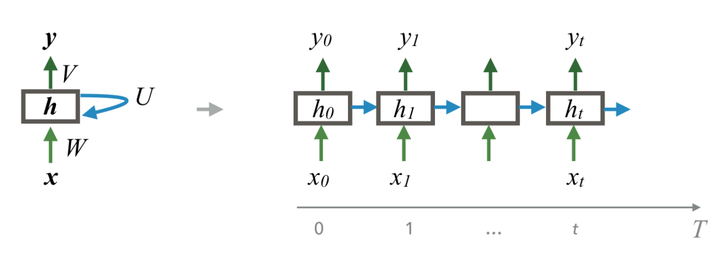
- Memory is limited to < 10 steps.



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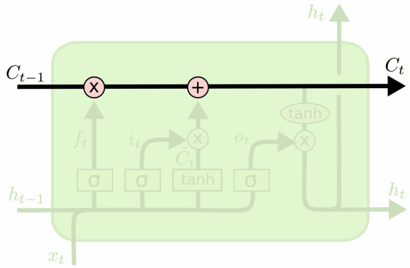

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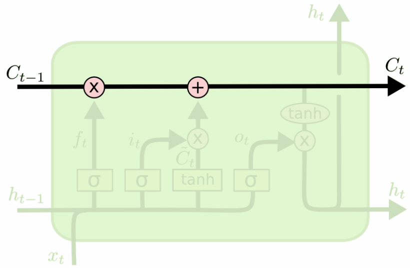

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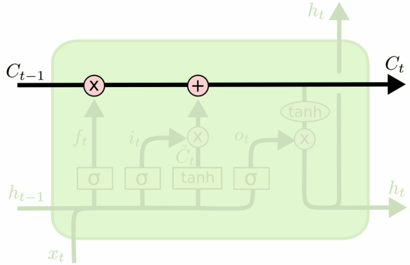

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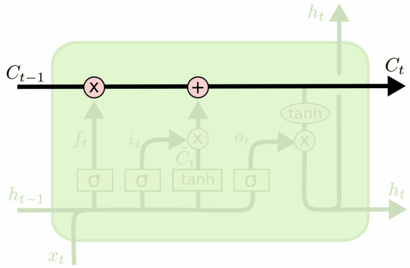
- State cell was not designed as memory in traditional sense.



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3. Increasing the size of memory is equivalent to expanding the vector $\mathbf{h_t}$ and the whole network. No. of weights grows at least linearly with required memory.
4. Memory might become "hard-coded." Specific parts of the network might be used to detect given features. Location and content are intertwined.

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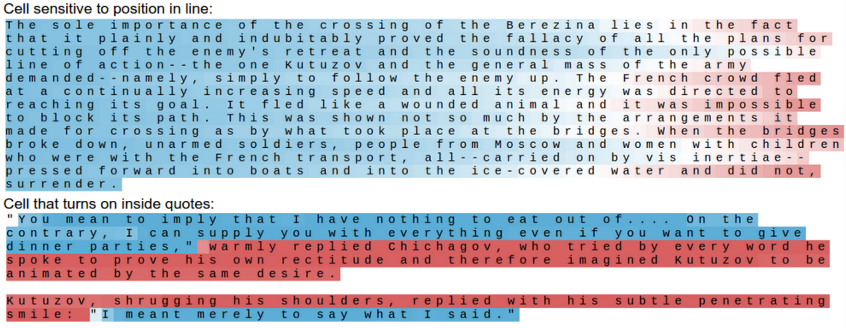
Memory/location entaglement



Source: Karpathy, A., *The Unreasonable Effectiveness of Recurrent Neural Networks*

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3. Content is separated out from location. Computation separated from memory.
4. Easier to deal with variables, linked lists, etc. Abstraction comes in handy.

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(d) Memory usage vector and temporal link matrix.

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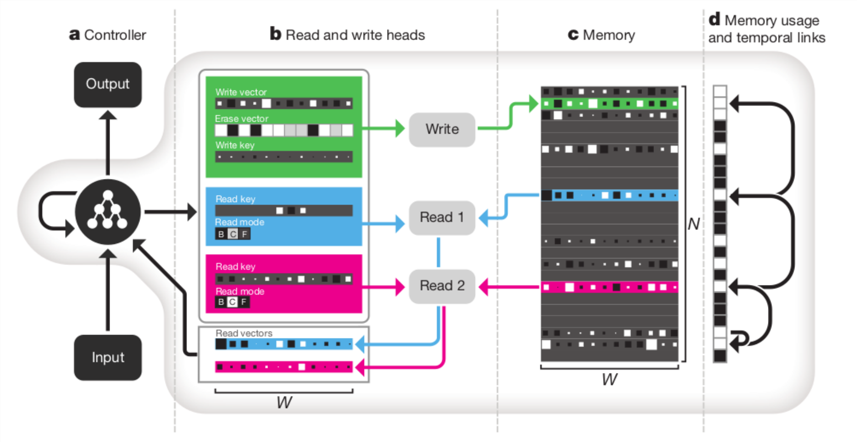

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Neural network $\mathcal{N}$. Let's use a deep LSTM architecture, which carries a hidden state vector $\begin{bmatrix} \mathbf{h}_t^1 & \dots & \mathbf{h}_t^L \end{bmatrix}$.

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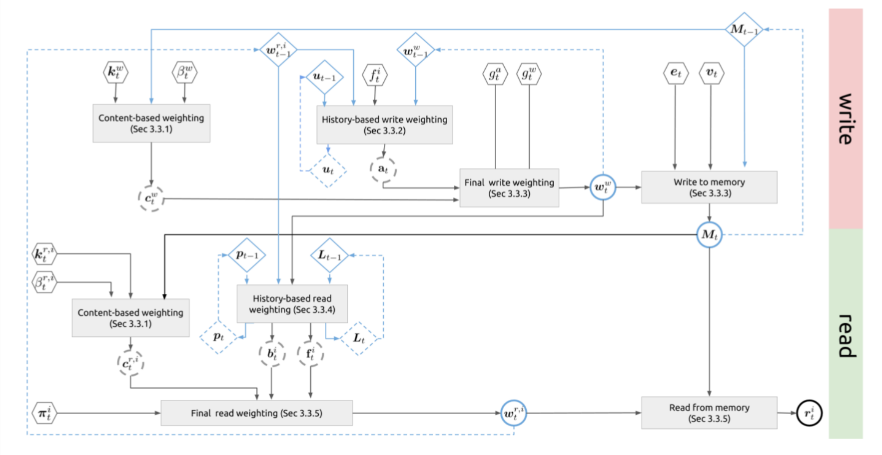
- Interface vector after processing $\xi_{\mathbf{t}} = \left[\mathbf{k}_t^{r,1} \dots \mathbf{k}_t^{r,R}; \beta_t^{r,1} \dots \beta_t^{r,R}; \mathbf{k}_t^{w}; \beta_t^{w}; \mathbf{e}_t; \mathbf{v}_t; f_t^1 \dots f_t^R; g_t^a; g_t^w; \pi_t^1 \dots \pi_t^R\right]$

Interacting with memory



Source: Hsin, C., *Implementation and Optimization of Differentiable Neural Computers*

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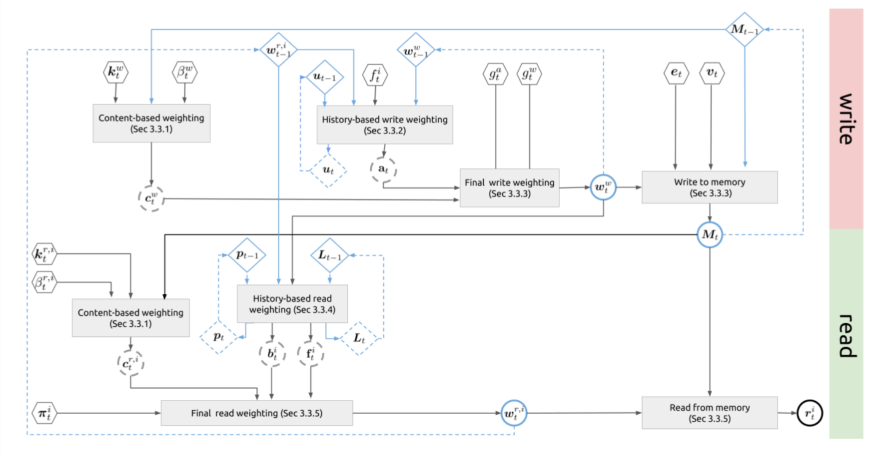
4. Actual write operation: $M_t = M_{t-1} \circ (E - \mathbf{w}_t^w \mathbf{e}_t^T) + \mathbf{w}_t^w \mathbf{v}_t^T$

Interacting with memory



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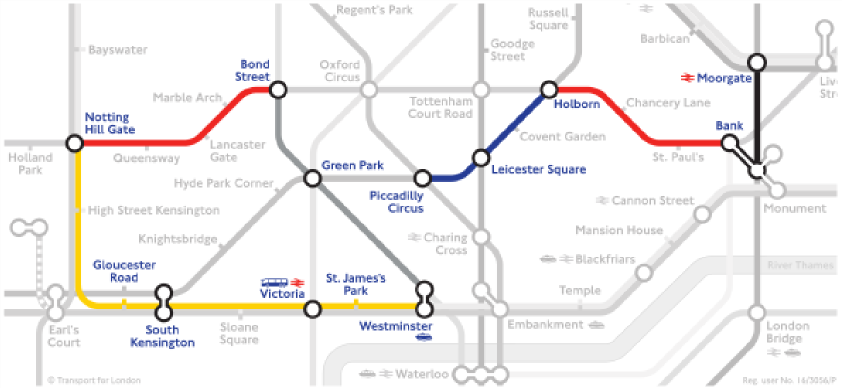
Traversing London Underground



Source: [Graves et al., 2016]

Traversing London Underground

- London Underground as a graph.

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- Explicit vector representation of an edge:
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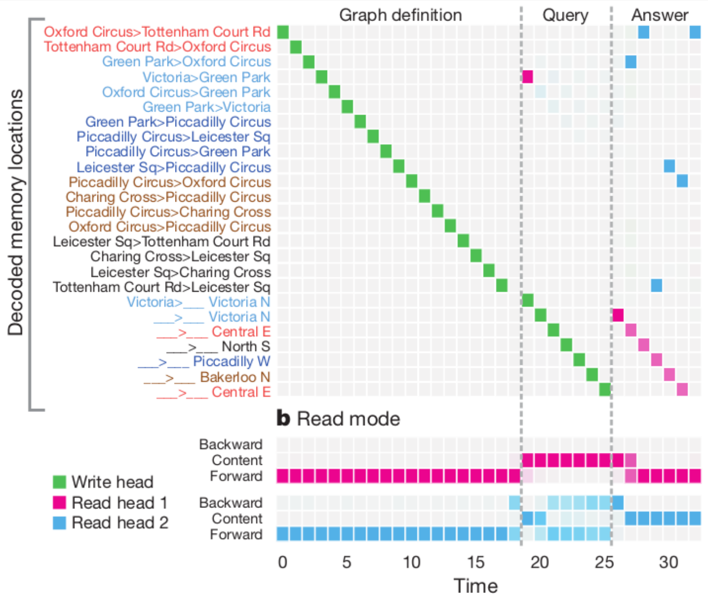
Traversal/shortest path

Traversal	Shortest-path
Traversal question: (BondSt, _, Central), (_, _, Circle), (_, _, Circle), (_, _, Circle), (_, _, Circle), (_, _, Jubilee), (_, _, Jubilee),	**Shortest-path question:** (Moorgate, PiccadillyCircus, _)
Answer: (BondSt, NottingHillGate, Central) (NottingHillGate, GloucesterRd, Circle) ⋮ (Westminster, GreenPark, Jubilee) (GreenPark, BondSt, Jubilee)	**Answer:** (Moorgate, Bank, Northern) (Bank, Holborn, Central) (Holborn, LeicesterSq, Piccadilly) (LeicesterSq, PiccadillyCircus, Piccadilly)

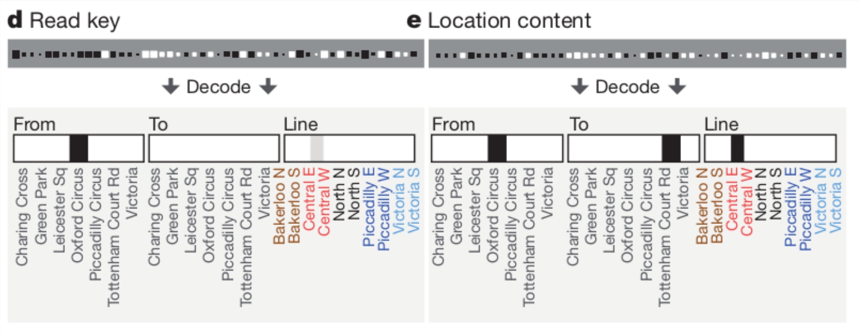
Source: [Graves et al., 2016]

Traversal



Graph definition
Query
Answer
Decoded memory locations
Oxford Circus>Tottenham Court Rd
Tottenham Court Rd>Oxford Circus
Green Park>Oxford Circus
Victoria>Green Park
Oxford Circus>Green Park
Green Park>Victoria
Green Park>Piccadilly Circus
Piccadilly Circus>Leicester Sq
Piccadilly Circus>Green Park
Leicester Sq>Piccadilly Circus
Piccadilly Circus>Oxford Circus
Charing Cross>Piccadilly Circus
Piccadilly Circus>Charing Cross
Oxford Circus>Piccadilly Circus
Leicester Sq>Tottenham Court Rd
Charing Cross>Leicester Sq
Leicester Sq>Charing Cross
Tottenham Court Rd>Leicester Sq
Victoria>___ Victoria N
___>___ Victoria N
___>___ Central E
___>___ North S
___>___ Piccadilly W
___>___ Bakerloo N
___>___ Central E
b Read mode
Write head
Read head 1
Read head 2
Backward
Content
Forward
Backward
Content
Forward
0
5
10
15
20
25
30
Time

Traversal



Source: [Graves et al., 2016]

Further research

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- DNC with other types of neural networks.
- Scale up.

Further research

- Synthetic gradients [Jaderberg et al., 2016].
- Speed up training.
- DNC with other types of neural networks.
- Scale up.
- Tasks beyond graphs.

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