Learning from few examples

One-shot learning with memory-augmented neural networks

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- Sometimes the net is not as important as the data.

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- Possibly inefficient with respect to data.

Different learning paradigm

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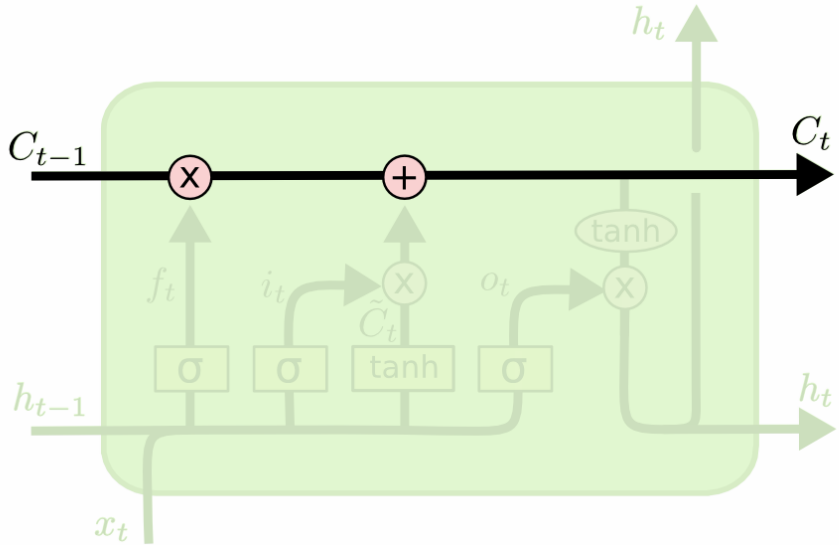
- General premise - learning occurs on two levels:
  1. Within a task, e.g. bind input data to class in a particular dataset.
  2. Across tasks - how task structure varies across target domains.
- Several neural net structures seem fit to meta-learn.

Long-short term memory

- Introduced to circumvent the vanishing gradient problem [Hochreiter and Schmidhuber, 1997].



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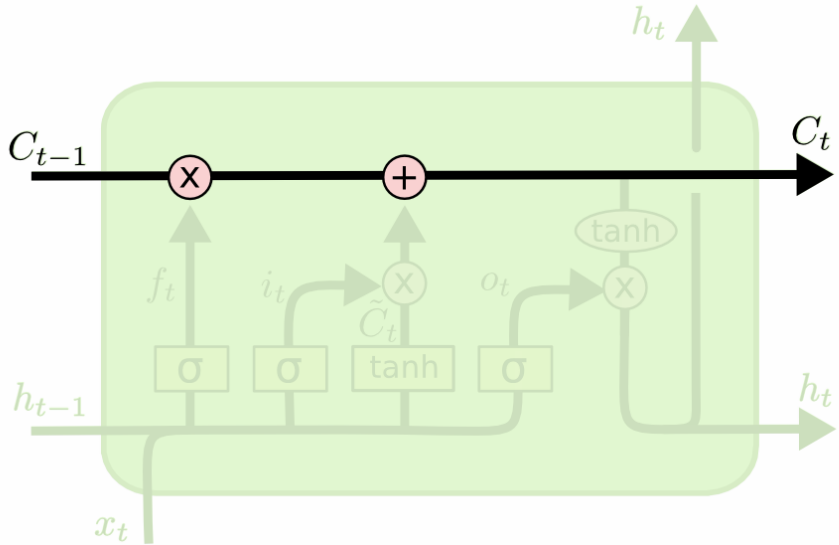

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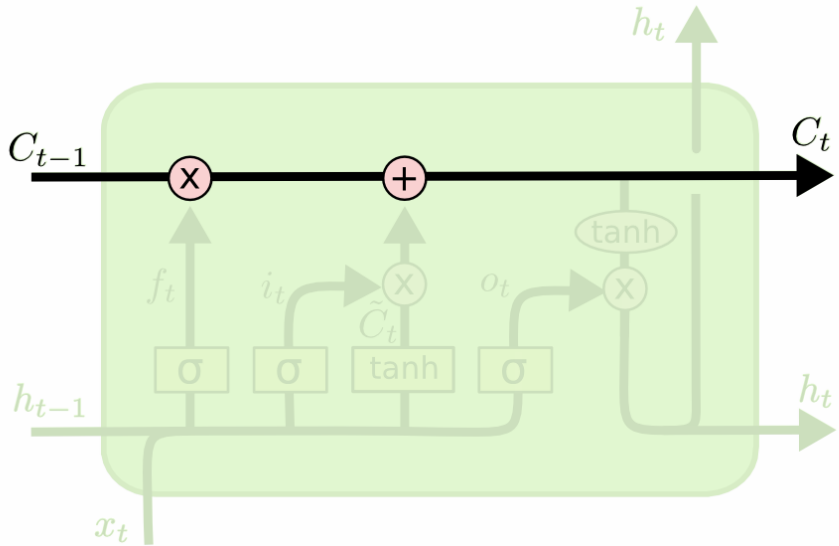

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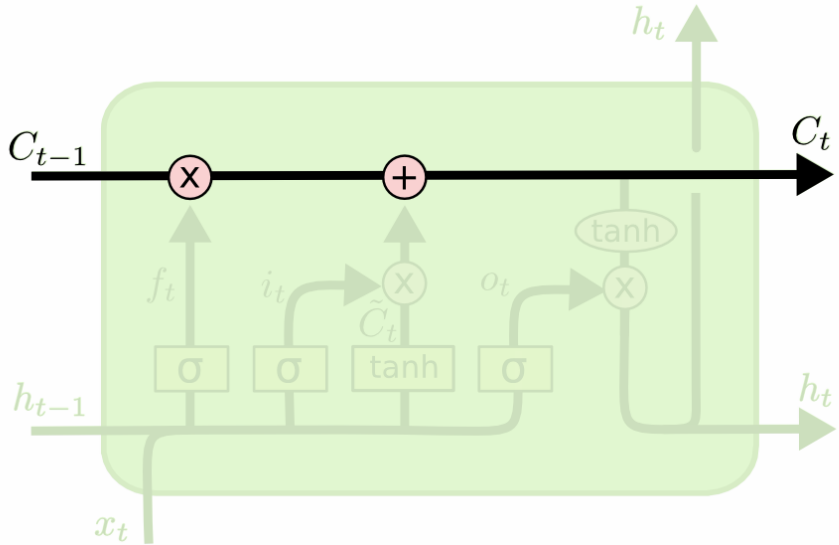

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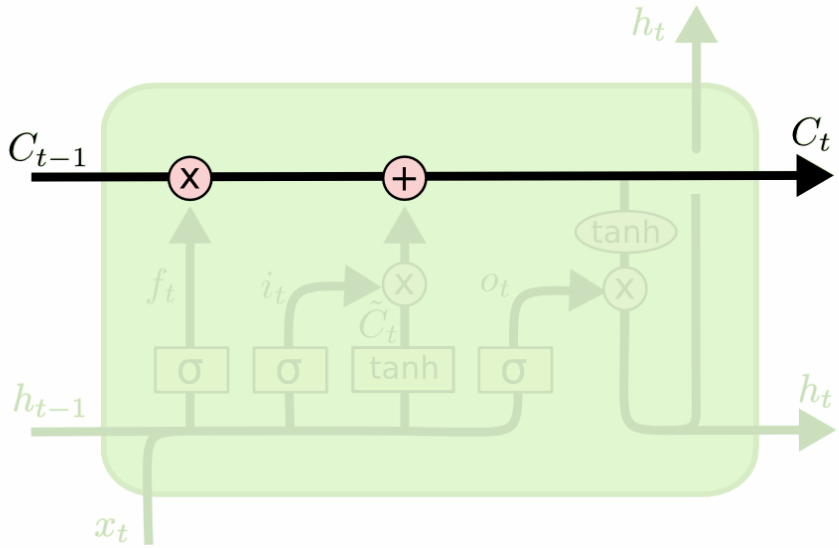

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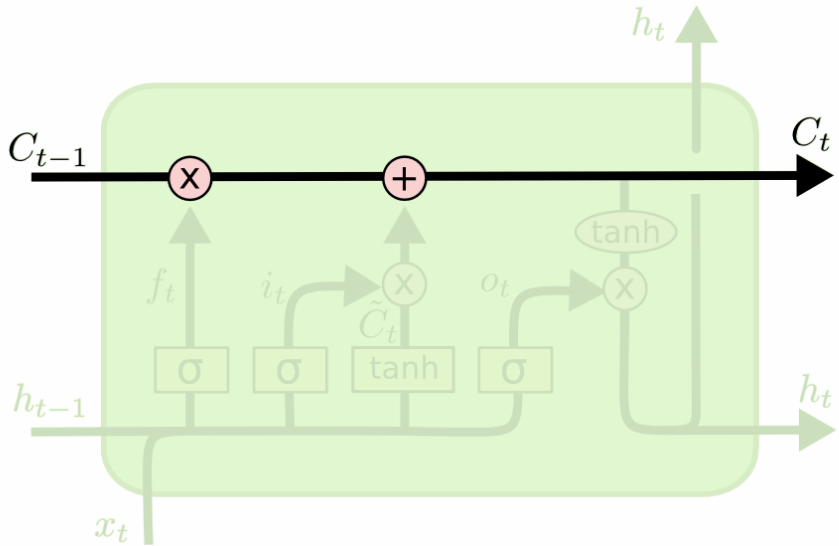

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Long-short term memory

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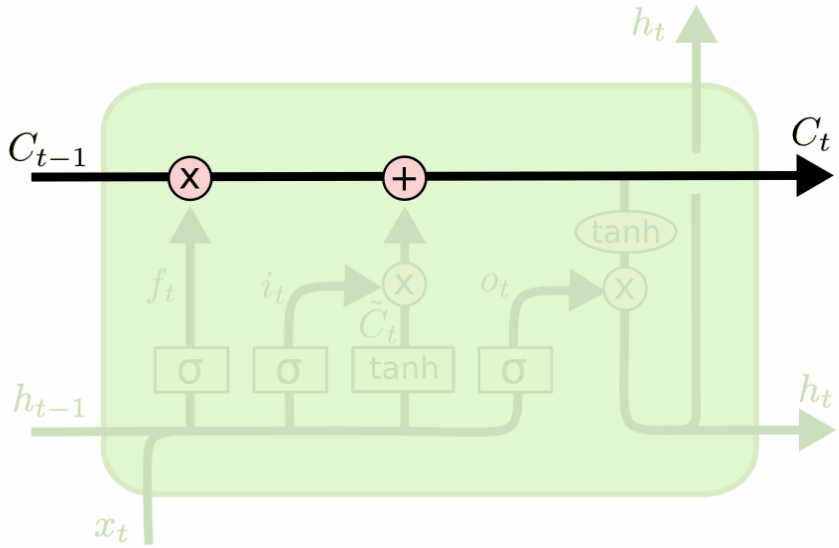
- Learns never-before-seen quadratic functions with low number of data samples [Hochreiter et al., 2001].



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3. No. of parameters independent of size of memory.

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3. Location and content are intertwined. Not easy to extract content.

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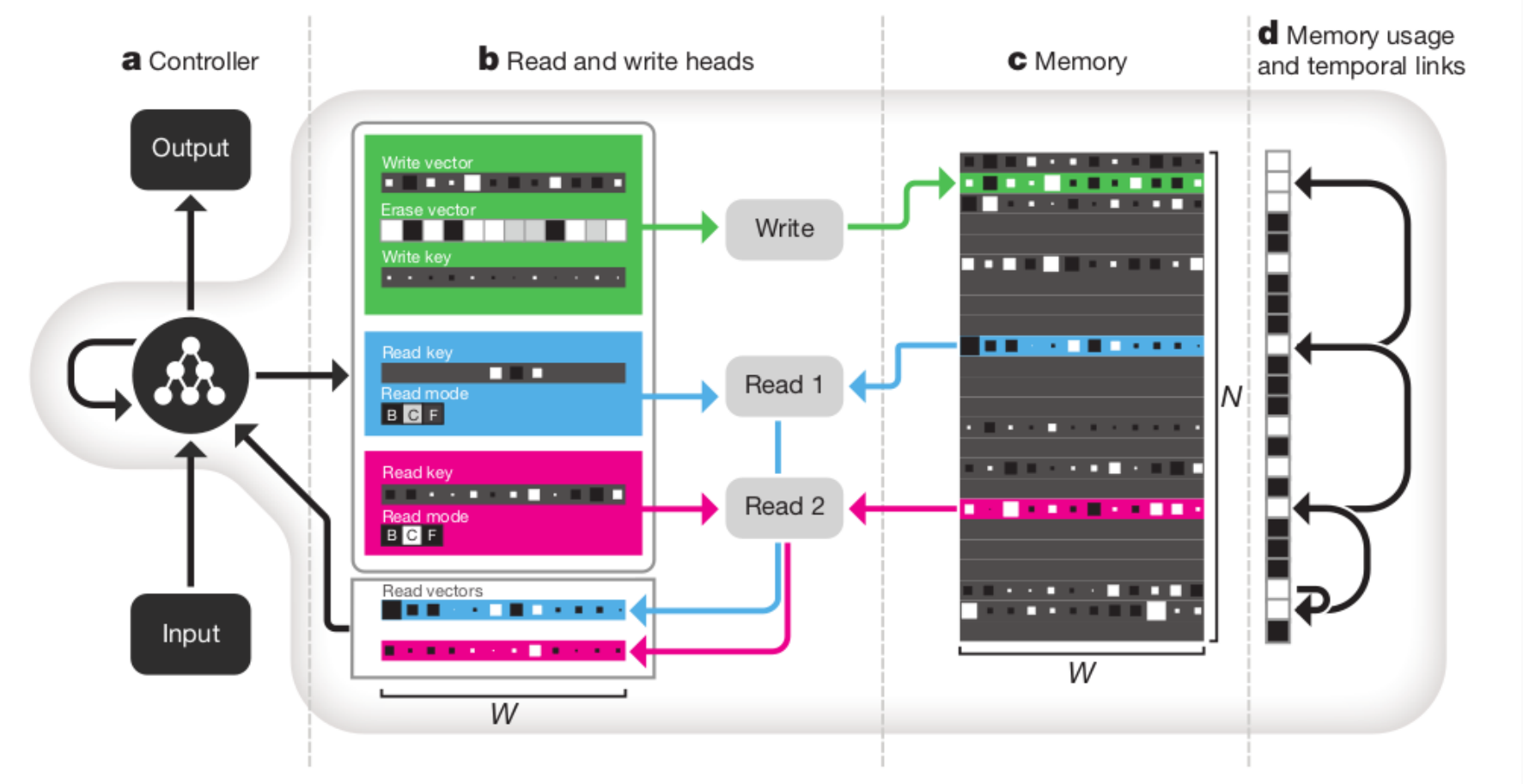
Differentiable neural computer



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- Weight updates allow us to extract representations of data, memory enables rapid binding of information.

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- There is exploitable structure: a meta-learning model would learn to bind input to appropriate class regardless of particular input data or label.

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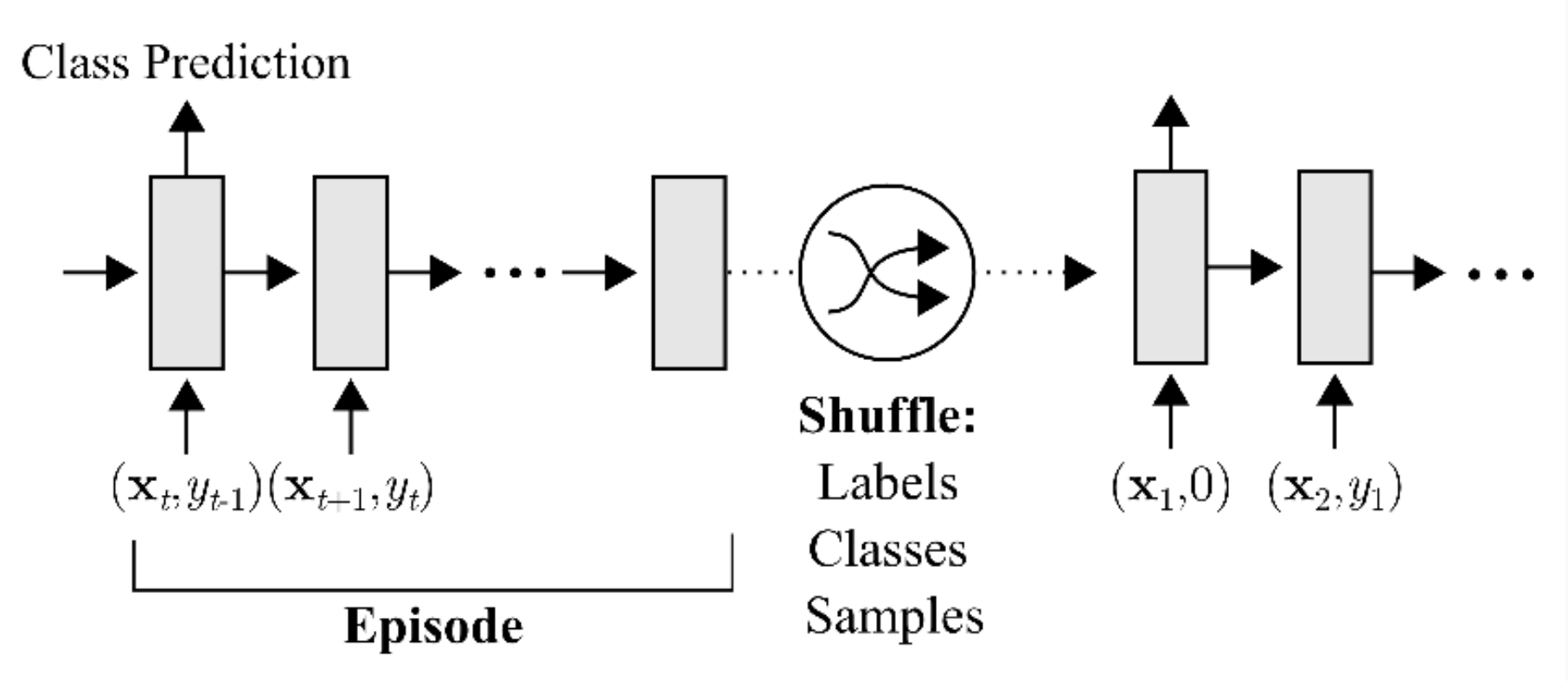

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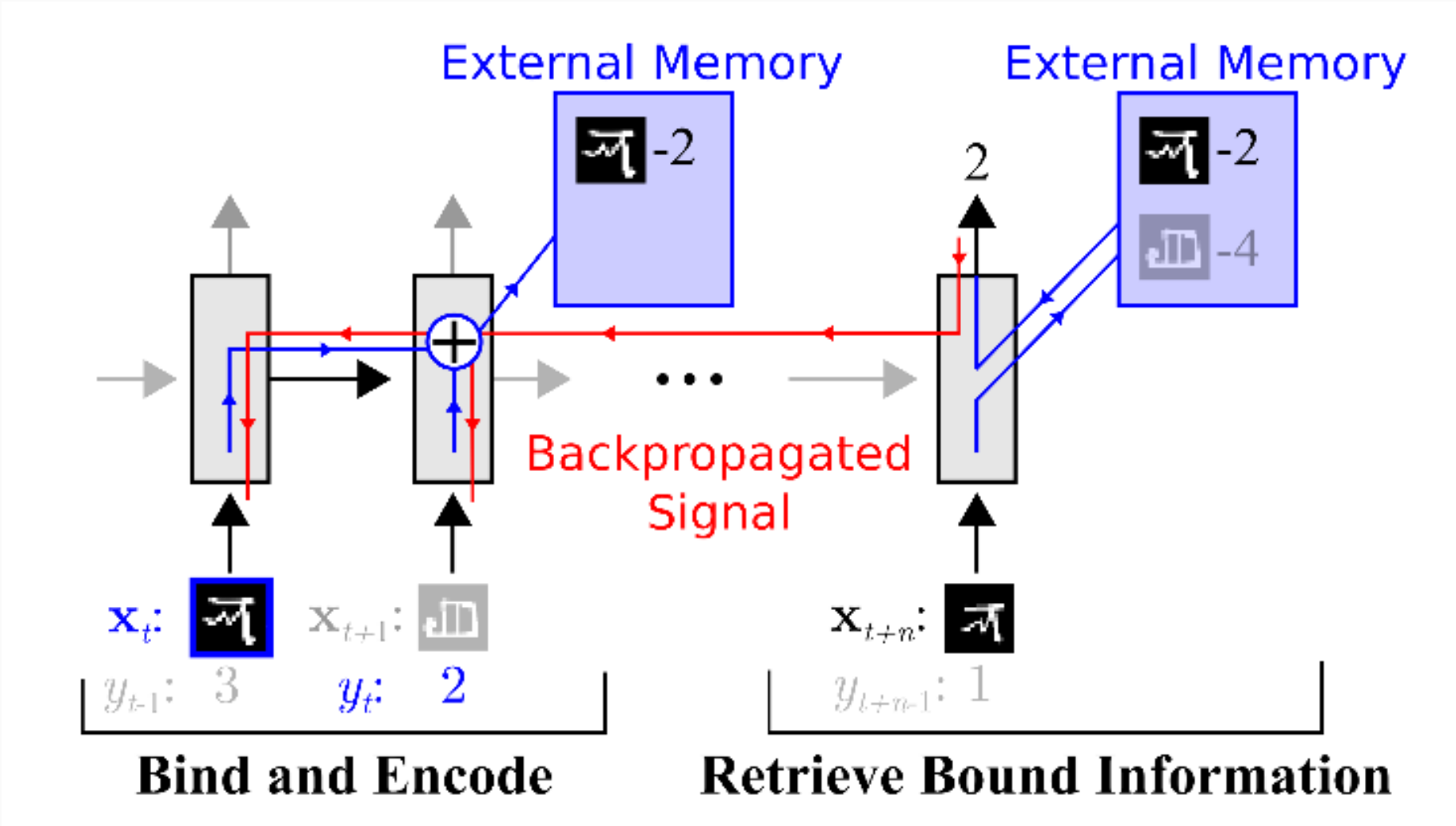

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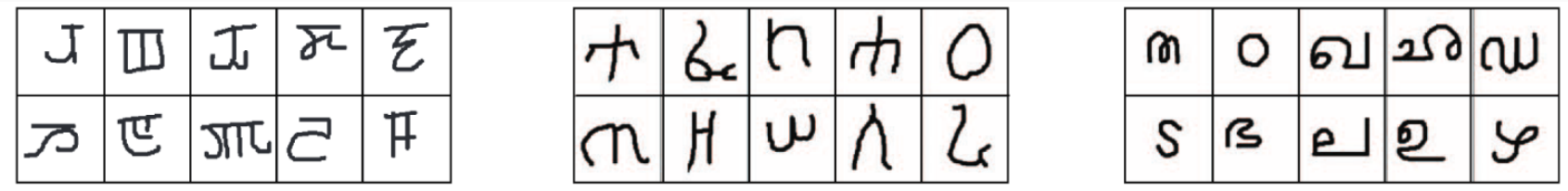

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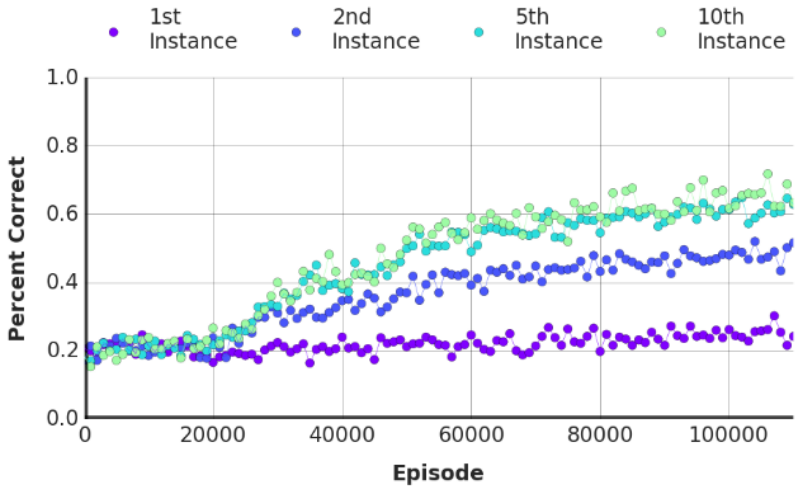
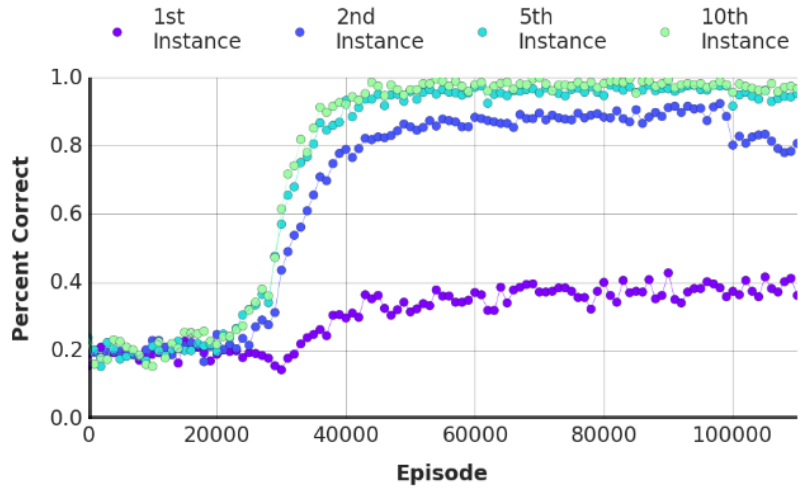
- For one-hot labels, episode loss is

$$\mathcal{L}(\theta) = -\sum_t \mathbf{y_t^T} \log \mathbf{p_t}$$

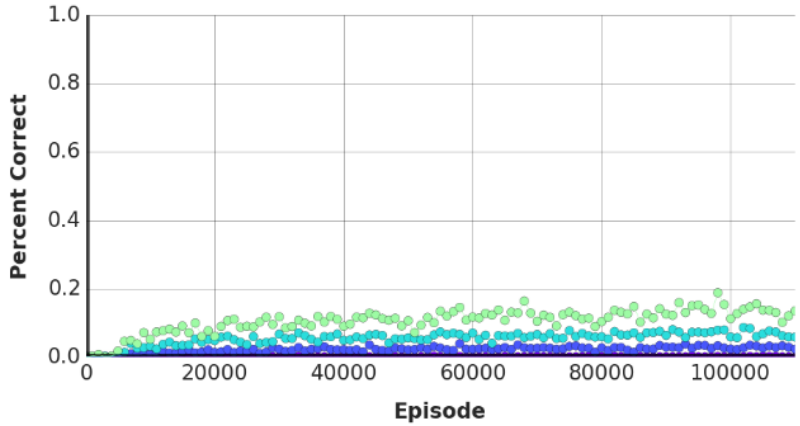
Experimental results



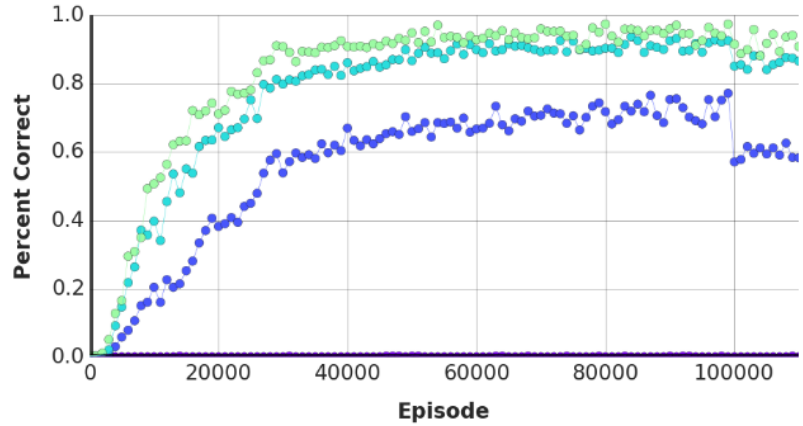
(a) LSTM, five random classes/episode, one-hot vector labels



(b) MANN, five random classes/episode, one-hot vector labels



(c) LSTM, fifteen classes/episode, five-character string labels



(d) MANN, fifteen classes/episode, five-character string labels

Source: [Santoro et al., 2016]

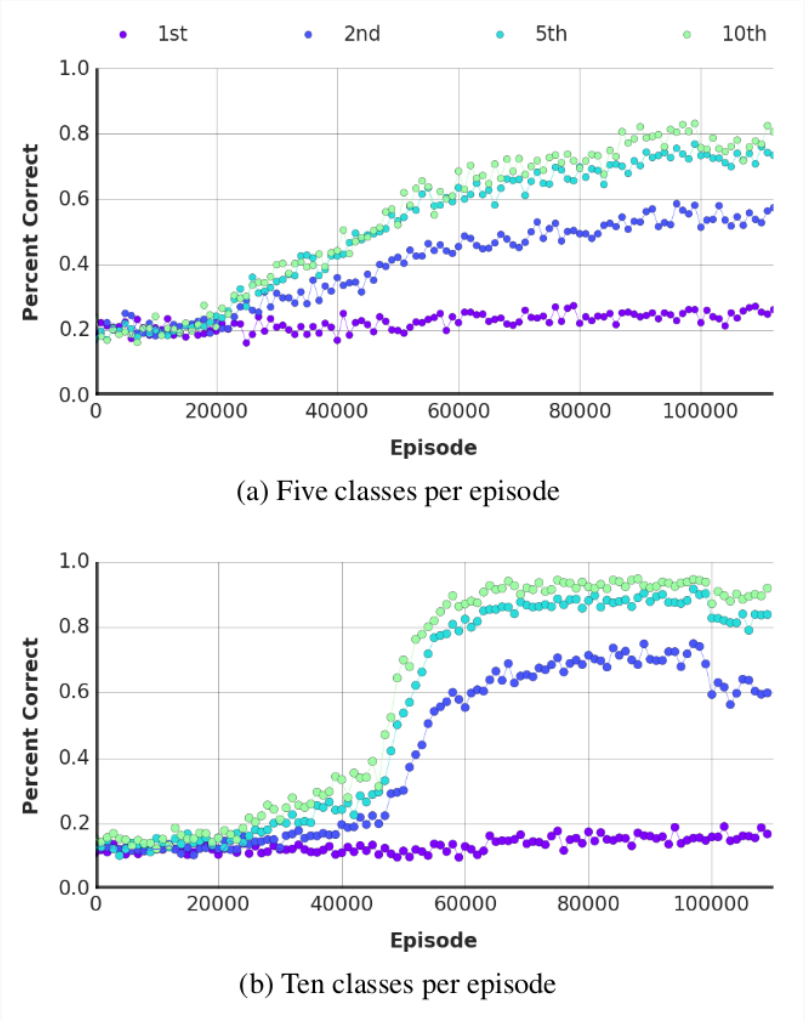
Experimental results

Model	Instance (% Correct)					
	1st	2nd	3rd	4th	5th	10th
Human	34.5	57.3	70.1	71.8	81.4	92.4
Feedforward	24.4	19.6	21.1	19.9	22.8	19.5
LSTM	24.4	49.5	55.3	61.0	63.6	62.5
MANN	**36.4**	**82.8**	**91.0**	**92.6**	**94.9**	**98.1**

Source: [Santoro et al., 2016]

Experimental results

- Persistent memory interference.



(a) Five classes per episode

(b) Ten classes per episode

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Experimental results

Model	Controller	# of Classes	Instance (% Correct)					
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kNN (raw pixels)	–	5	4.0	36.7	41.9	45.7	48.1	57.0
kNN (deep features)	–	5	4.0	51.9	61.0	66.3	69.3	77.5
Feedforward	–	5	0.0	0.2	0.0	0.2	0.0	0.0
LSTM	–	5	0.0	9.0	14.2	16.9	21.8	25.5
MANN	Feedforward	5	0.0	8.0	16.2	25.2	30.9	46.8
MANN	LSTM	5	0.0	**69.5**	**80.4**	**87.9**	**88.4**	**93.1**
kNN (raw pixels)	–	15	0.5	18.7	23.3	26.5	29.1	37.0
kNN (deep features)	–	15	0.4	32.7	41.2	47.1	50.6	60.0
Feedforward	–	15	0.0	0.1	0.0	0.0	0.0	0.0
LSTM	–	15	0.0	2.2	2.9	4.3	5.6	12.7
MANN (LRUA)	Feedforward	15	0.1	12.8	22.3	28.8	32.2	43.4
MANN (LRUA)	LSTM	15	0.1	**62.6**	**79.3**	**86.6**	**88.7**	**95.3**
MANN (NTM)	LSTM	15	0.0	35.4	61.2	71.7	77.7	88.4

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- Another type of problem where DNCs are advantageous.

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Future work

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