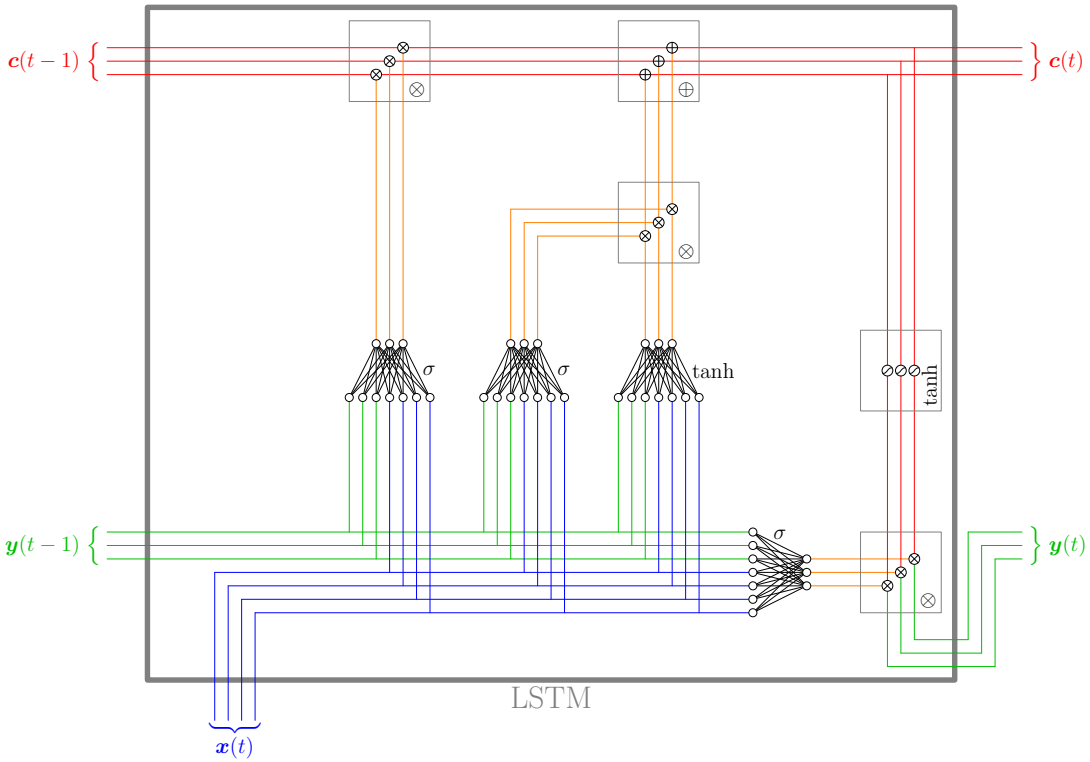
Advanced Machine Learning

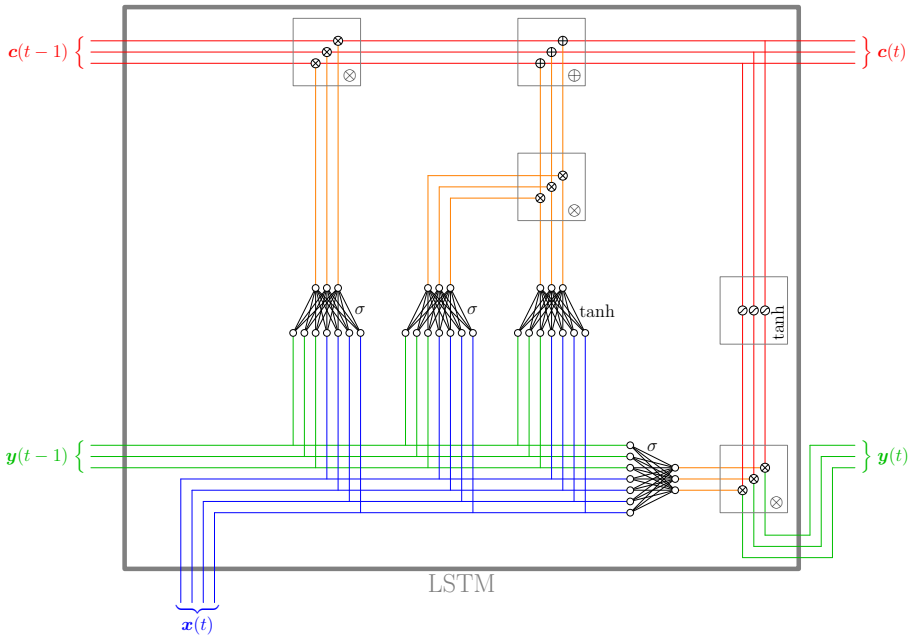
LSTM



Recurrent Neural Networks, Vanishing Gradients, LSTM

Outline

1. **More on CNNs**
2. Recurrent Networks
3. LSTM
4. Word Embedding
5. Applications



A Bit More on CNNs

- This lecture covers recurrent neural networks (RNNs)
- But, before we go there let we finish off with CNNs

Transfer Learning

- Although unsupervised pre-training of CNNs has never taken off, people use CNNs trained on other data sets (mostly imageNet)
- They will often decapitate a CNN trained on imageNet just before the dense layer
- The weights are publicly available for many classic networks (VGG, resNet, GoogLeNet)
- Often used and quite different problems (imageNet features seem to be generally useful)
- This is known as **transfer learning**

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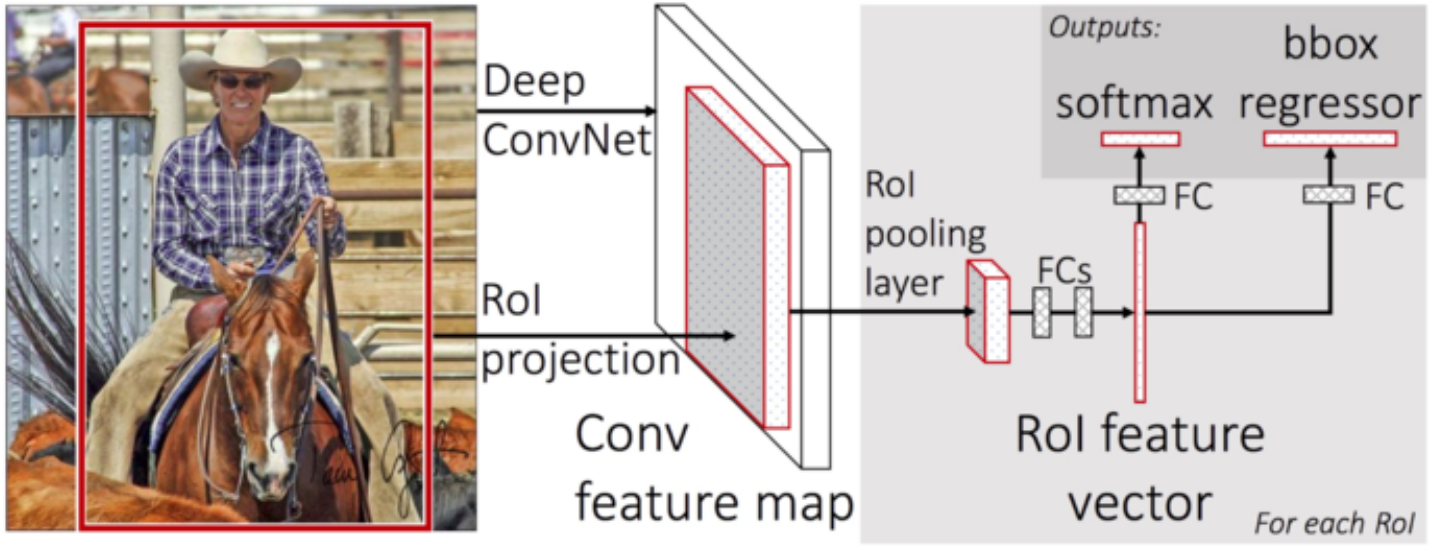
Regional CNN

- CNNs are also used for object location—putting a bounding box around subjects
- Use different data set with multiple objects—e.g. COCO
- Some of the best known networks for this are R-CNN, Fast R-CNN, Faster R-CNN and Masked R-CNN



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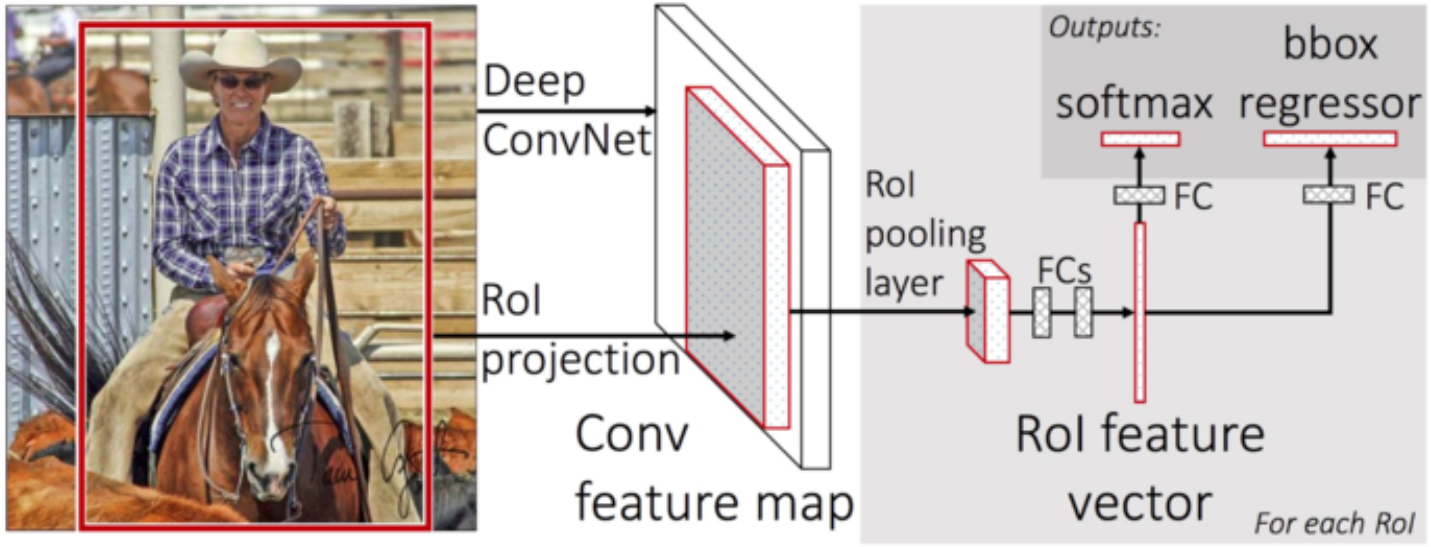

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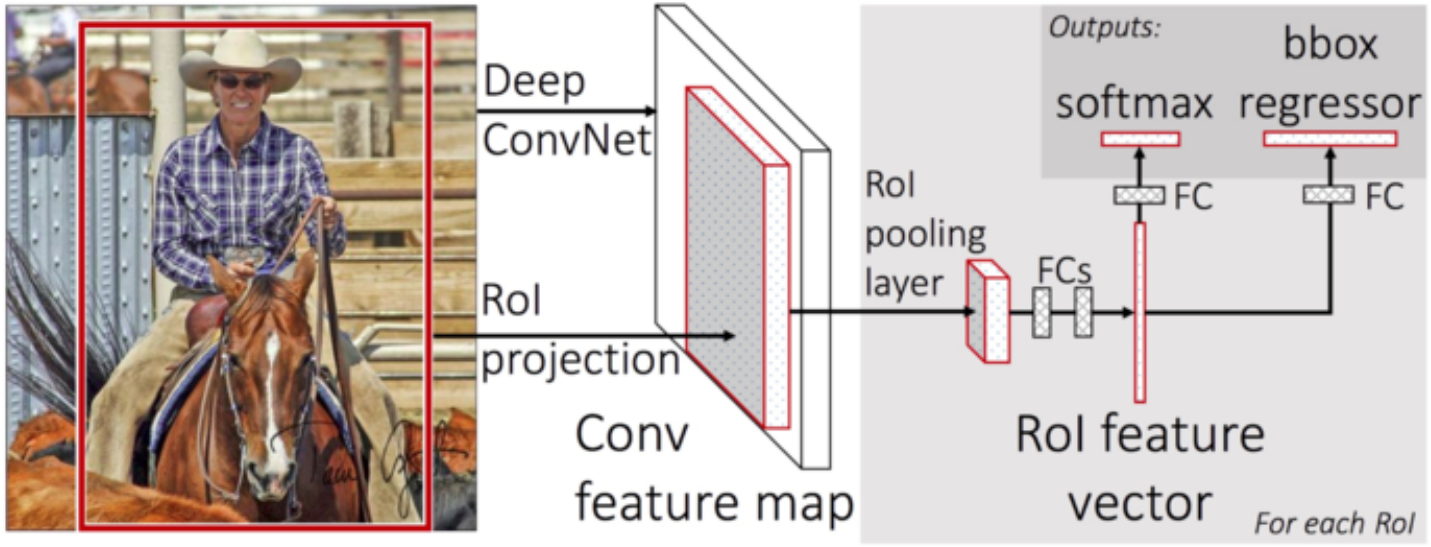

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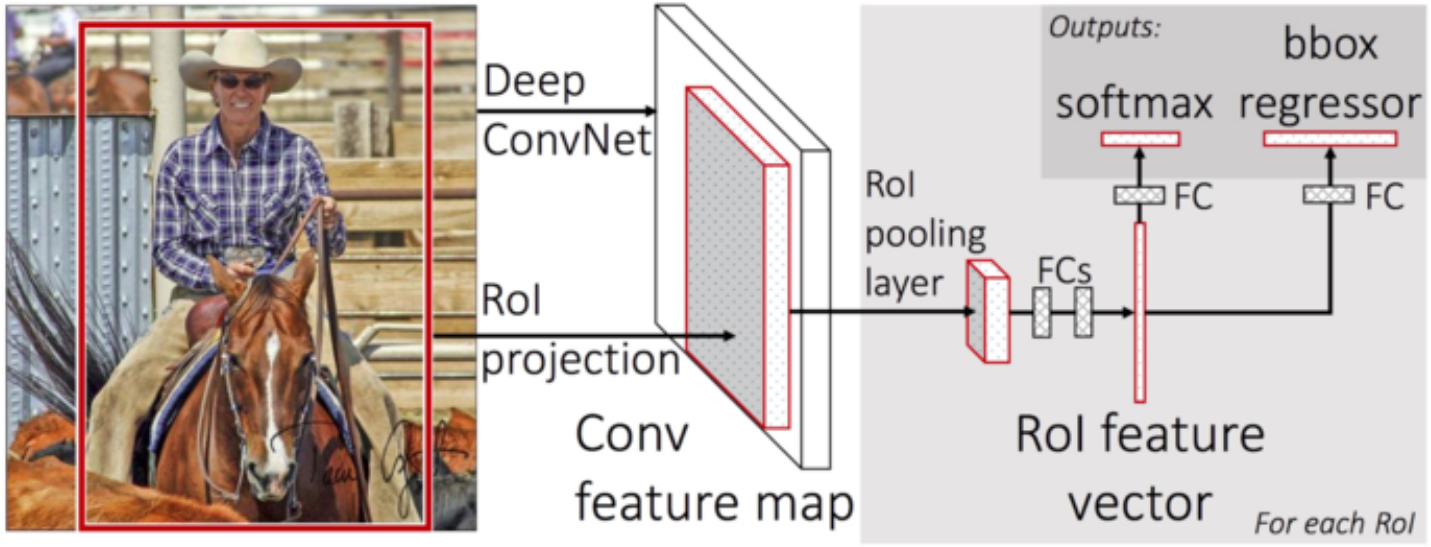
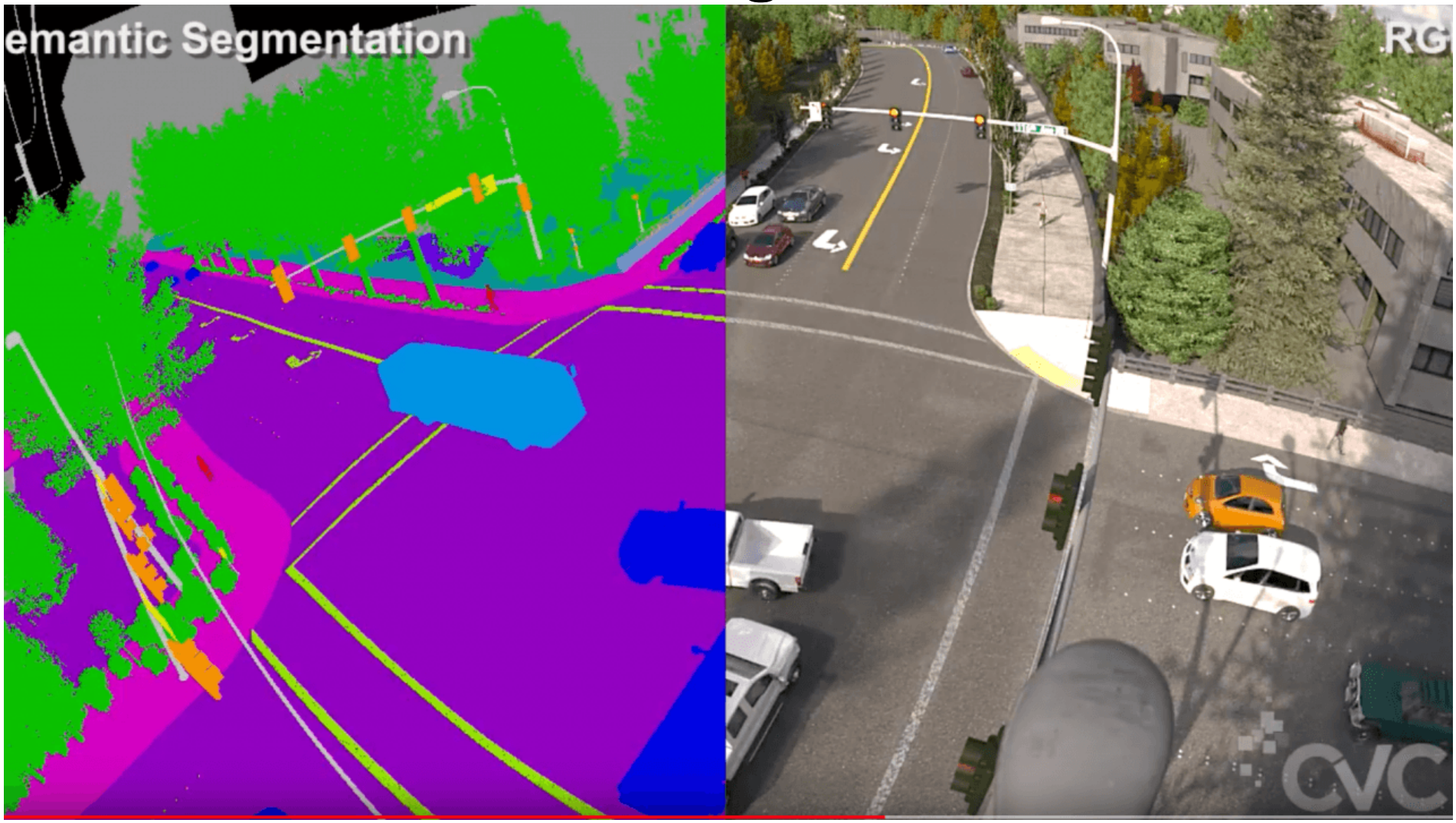
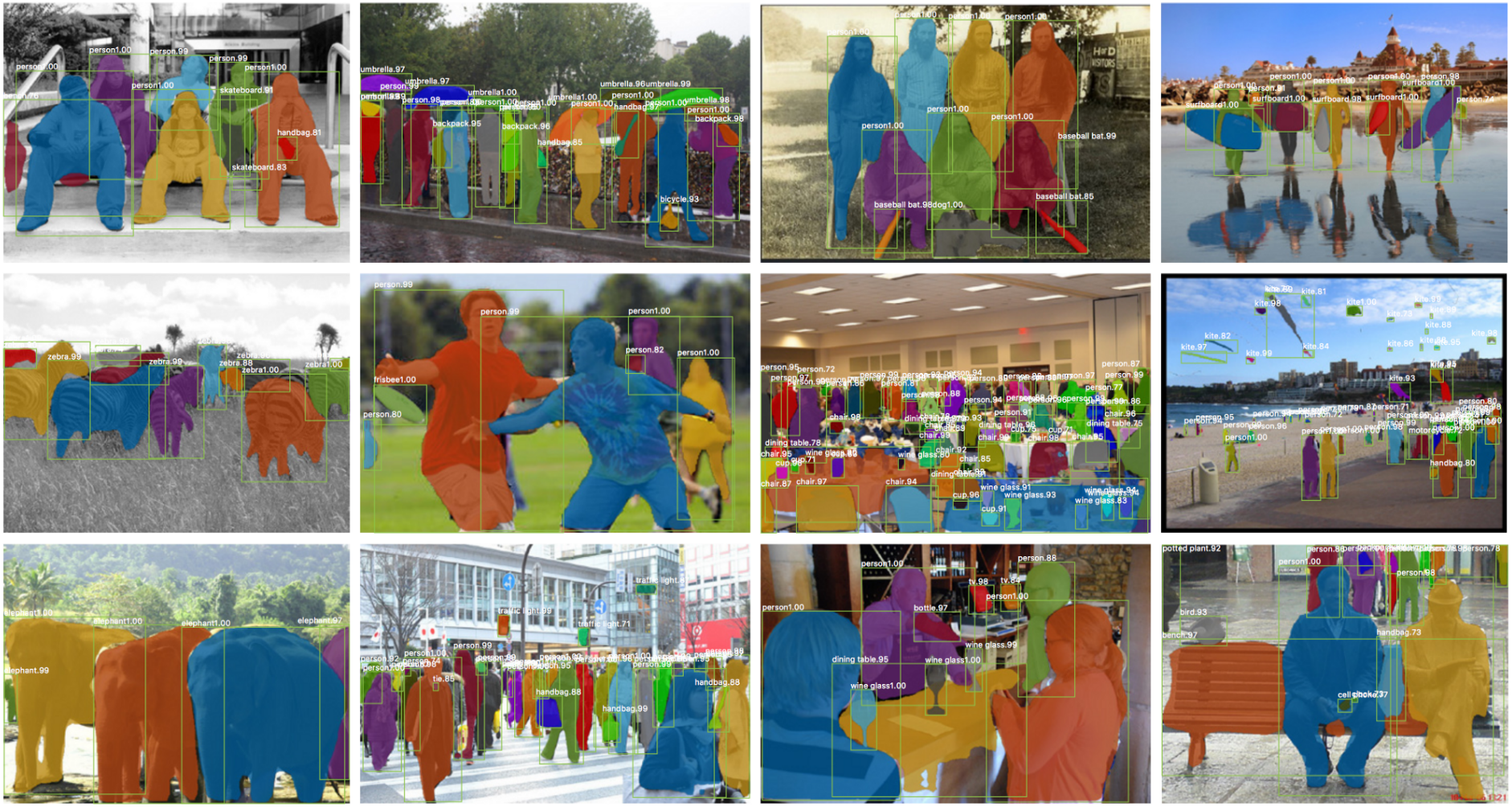


Semantic Segmentation



- Semantic segmentation is a pixel-level labelling of images

Semantic Segmentation



- Networks for achieving this include U-Net and Masked R-CNN

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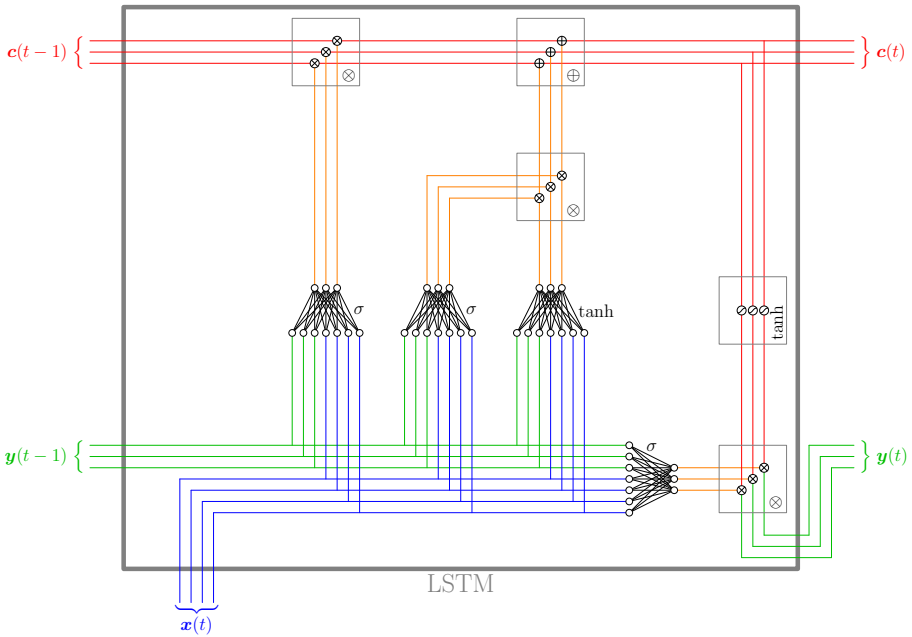

Recurrent Network

- Feed-forward networks are rather limited for some applications
- They are not particularly well matched for interpreting arbitrary length time series
- To interpret a sentence, or to predict tomorrows weather it is necessary to remember what happened in the past
- To facilitate this we would like to add a feedback loop delayed in time

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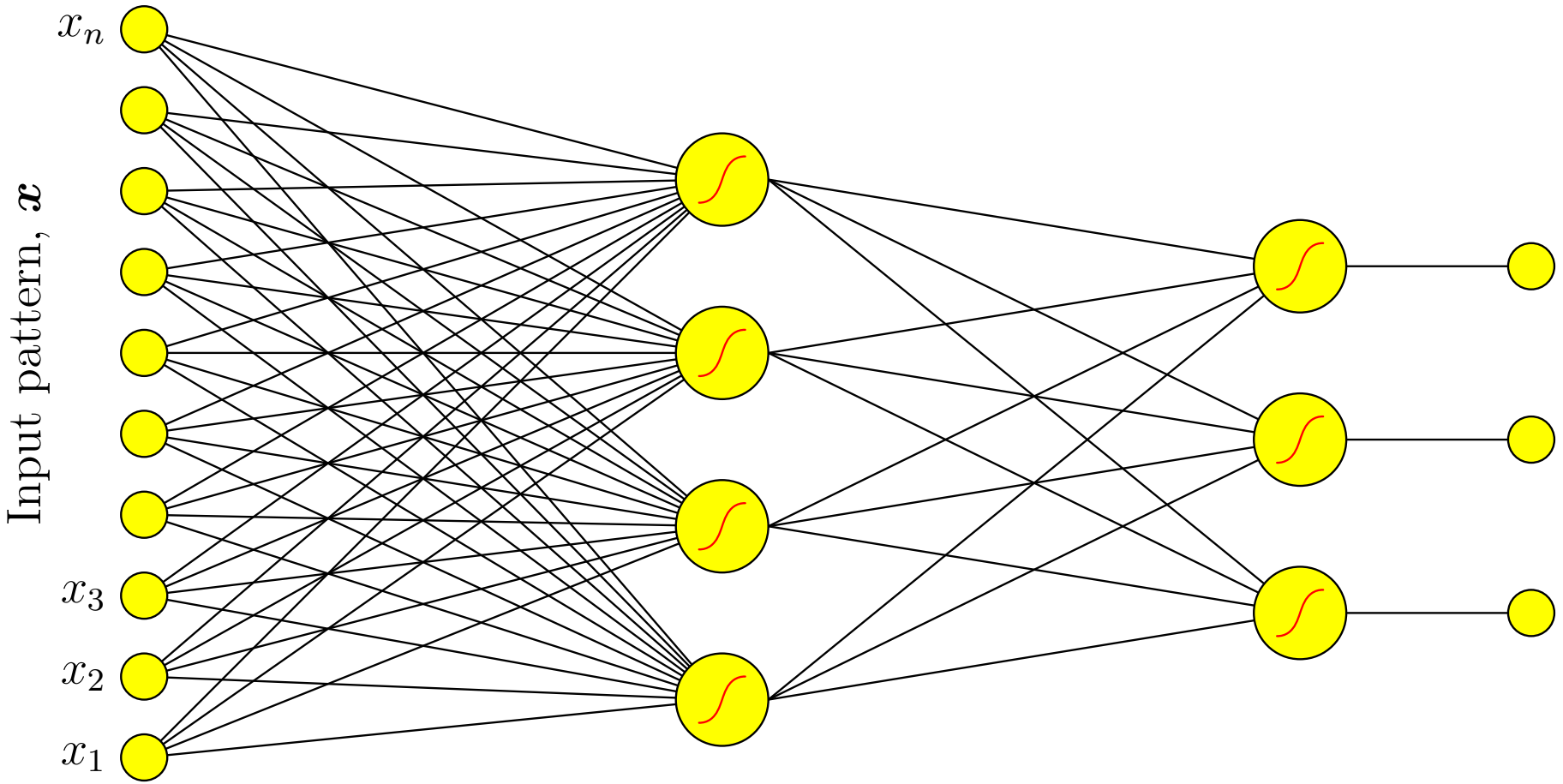

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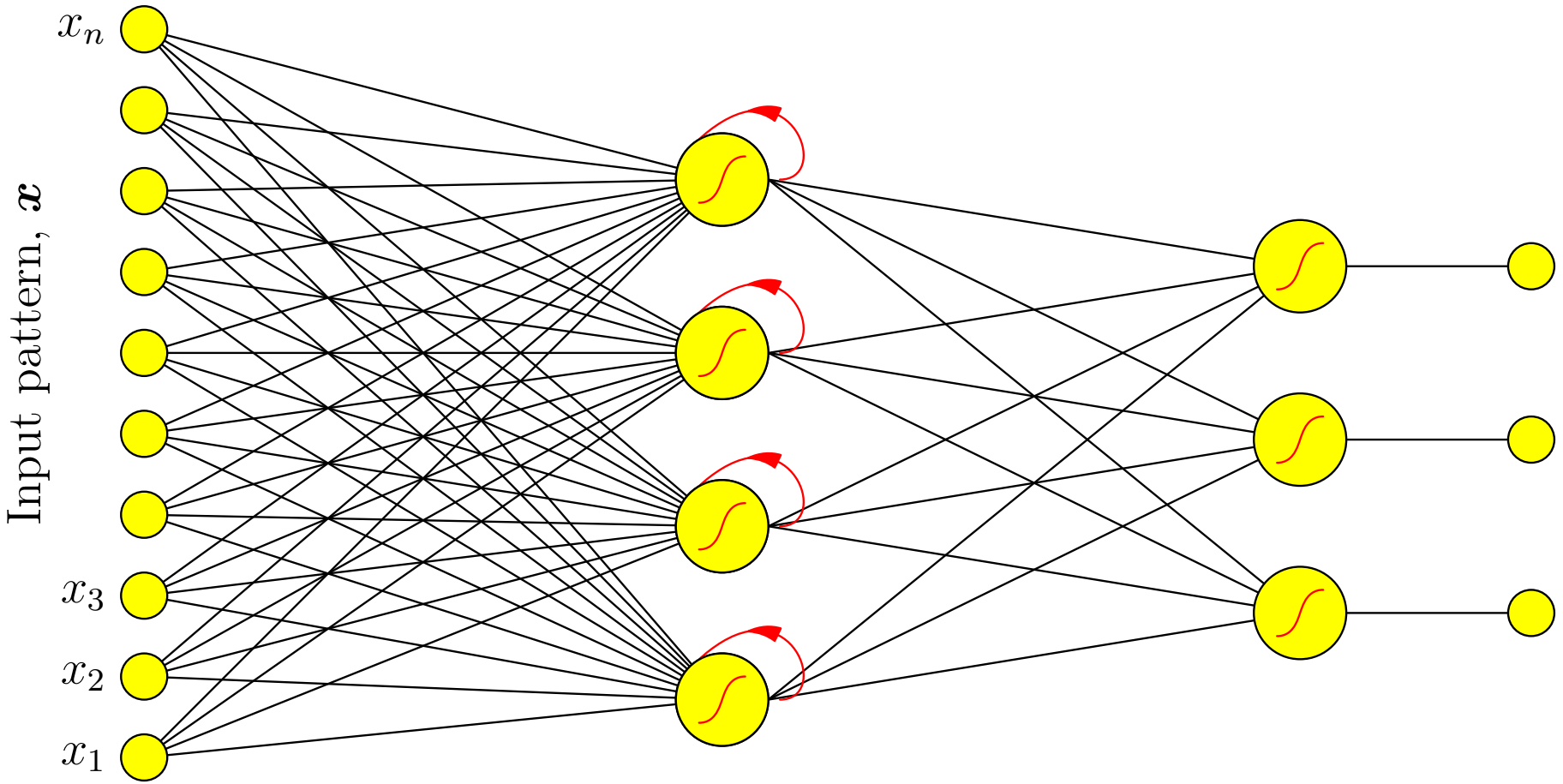

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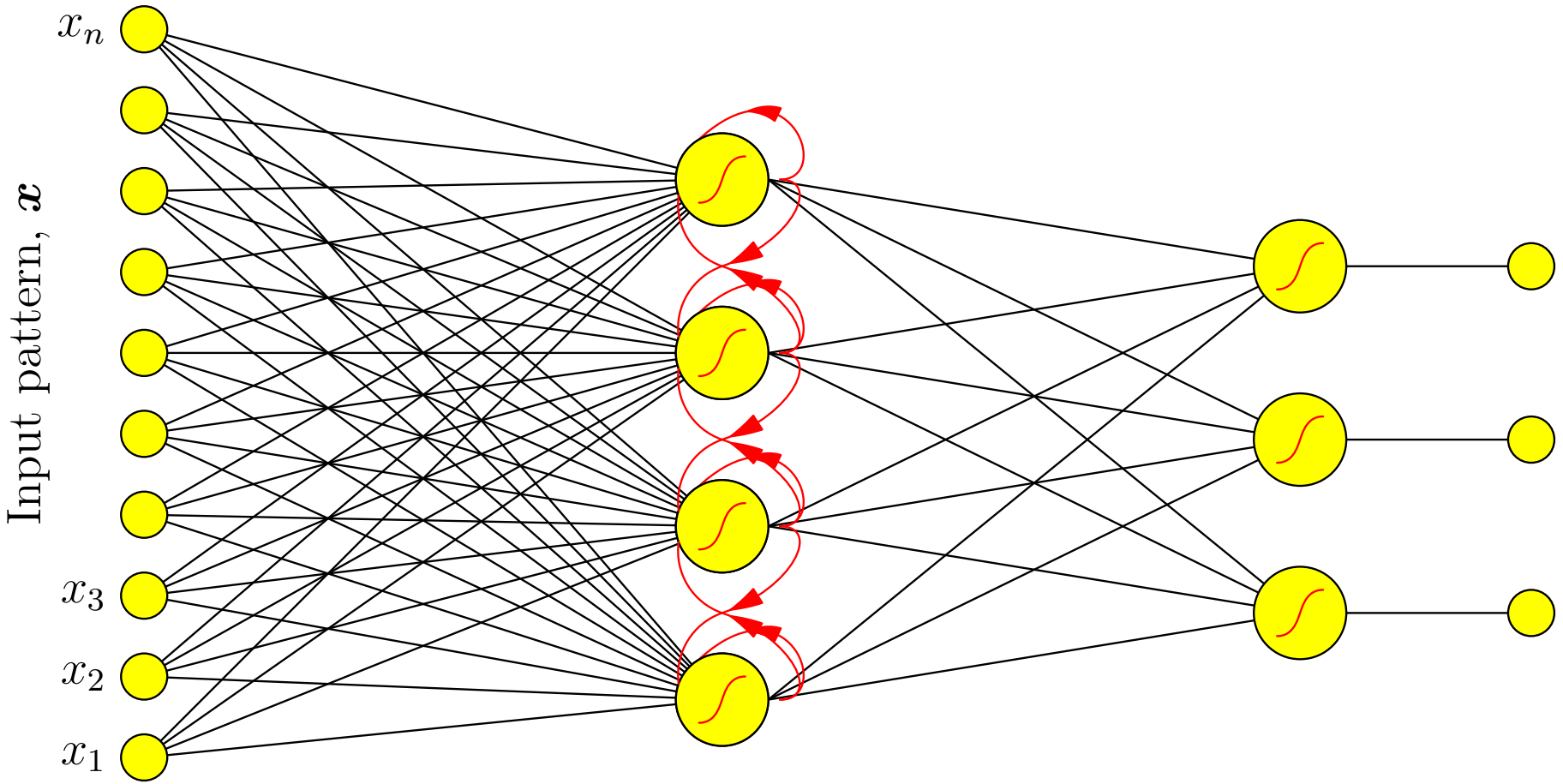

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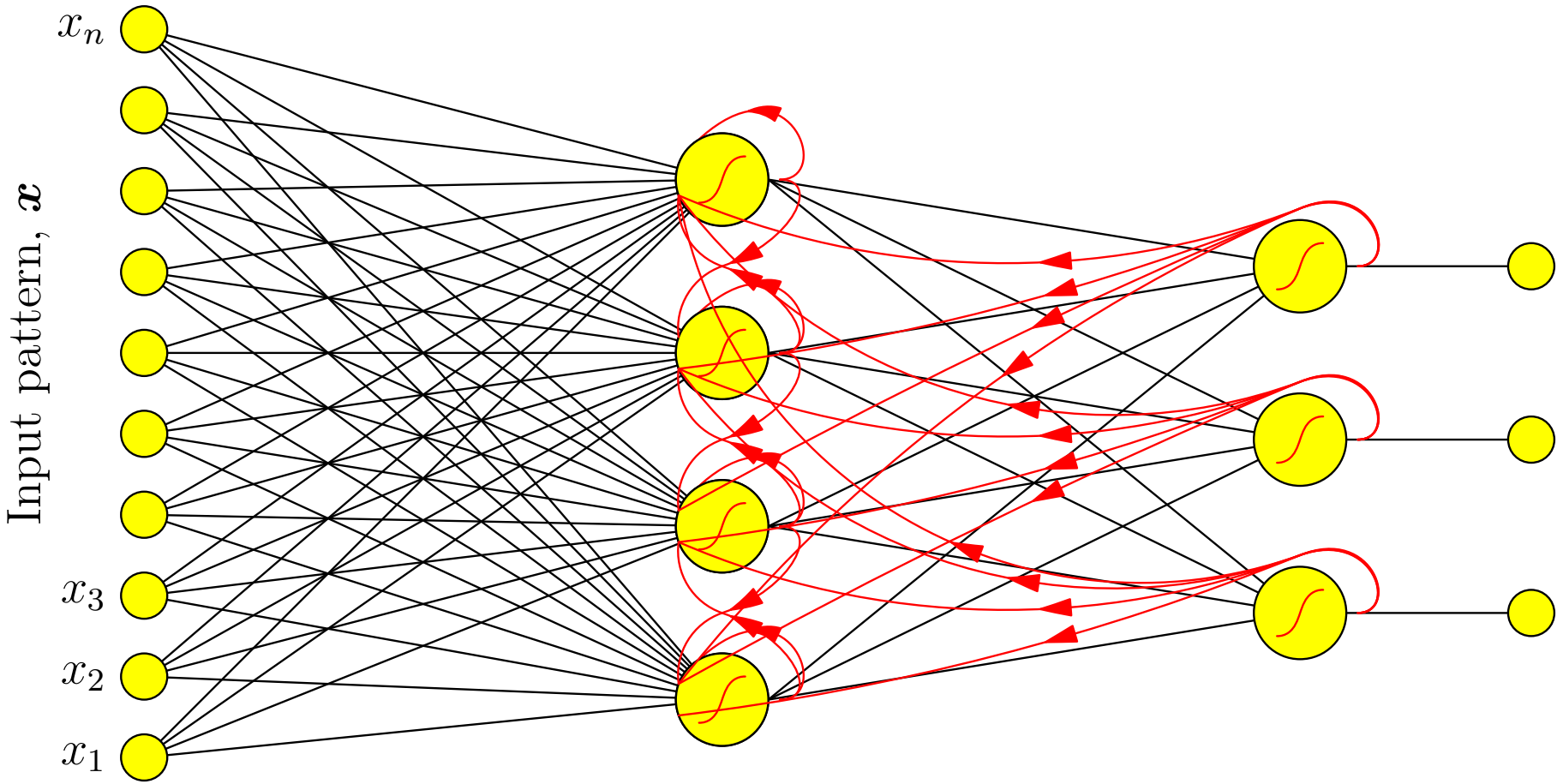
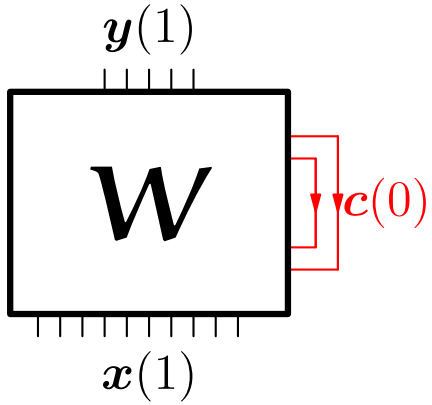


Training Recurrent Networks

- Given a set of inputs $\mathcal{D} = \left((\boldsymbol{x}(t), \boldsymbol{y}(t)) \middle| t = 1, 2, \ldots, T \right)$



- Minimise the error

$$E(\boldsymbol{W}) = \sum_{t=1}^{T} \left\| \boldsymbol{y}(t) - \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{c}(t-1) | \boldsymbol{W}) \right\|^2$$

- This is known as **back-propagation through time**

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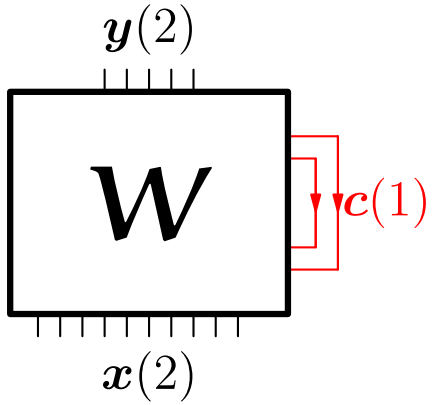

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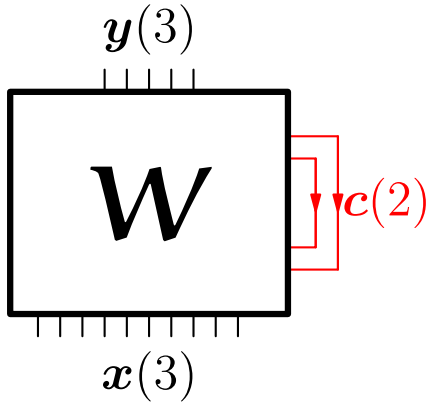

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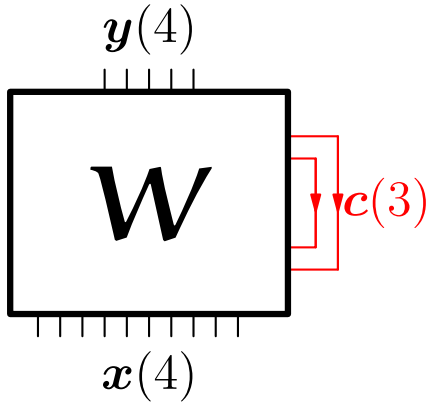

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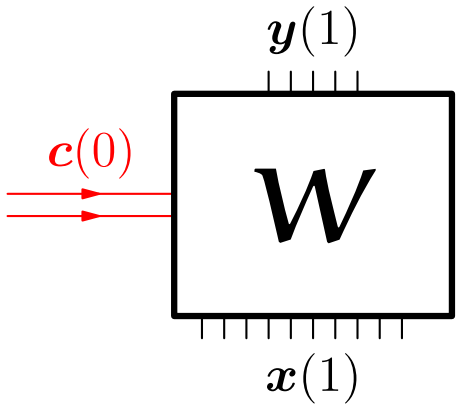

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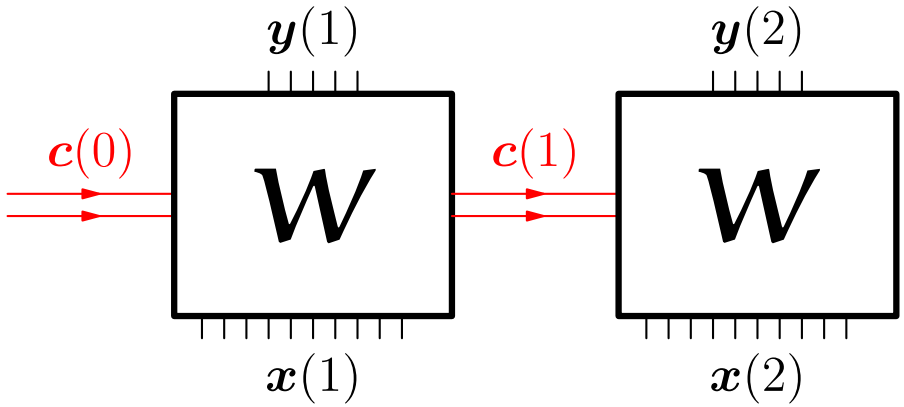

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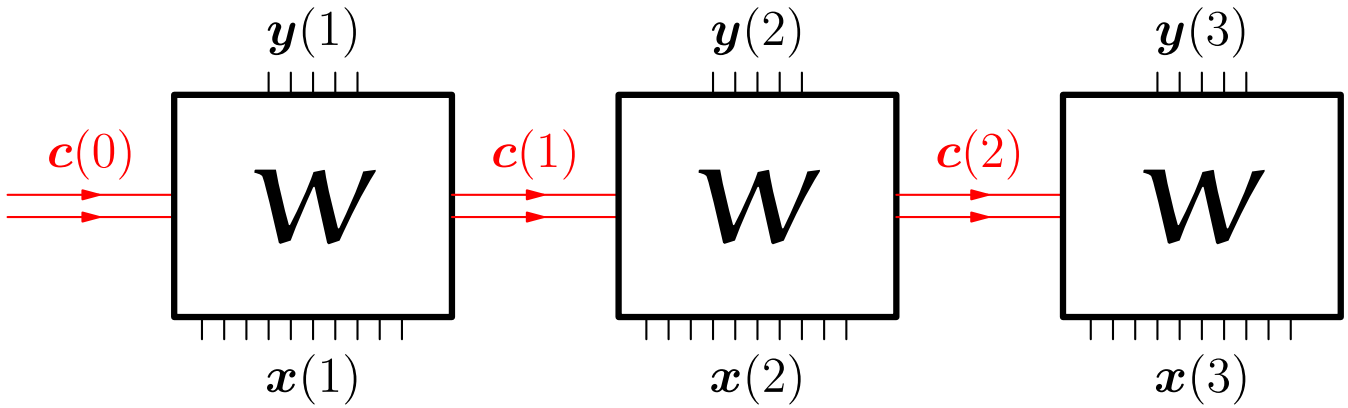

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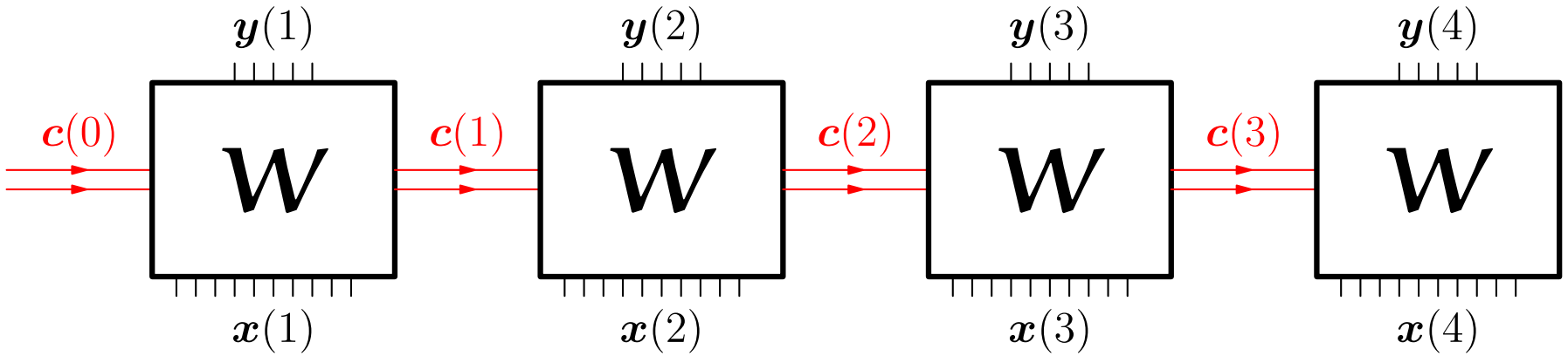

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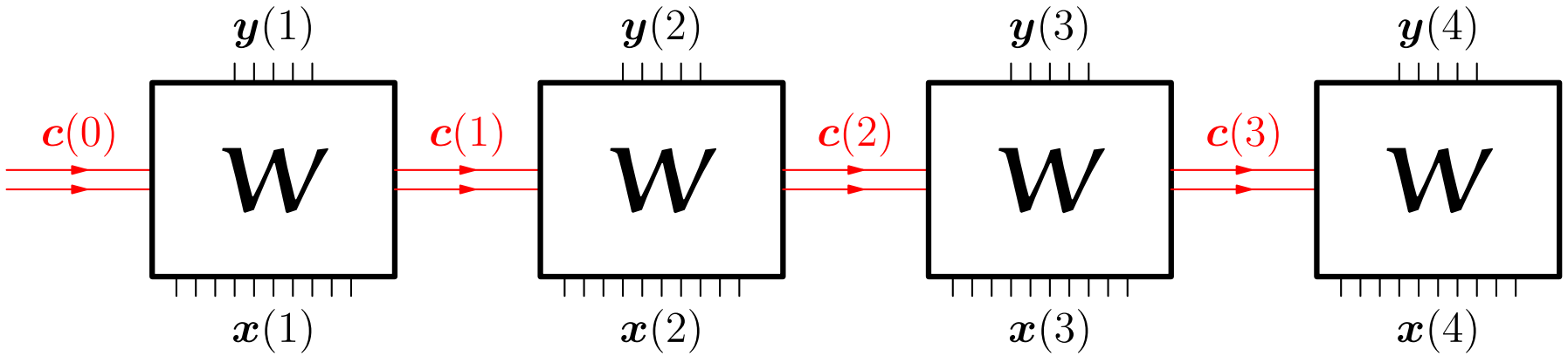

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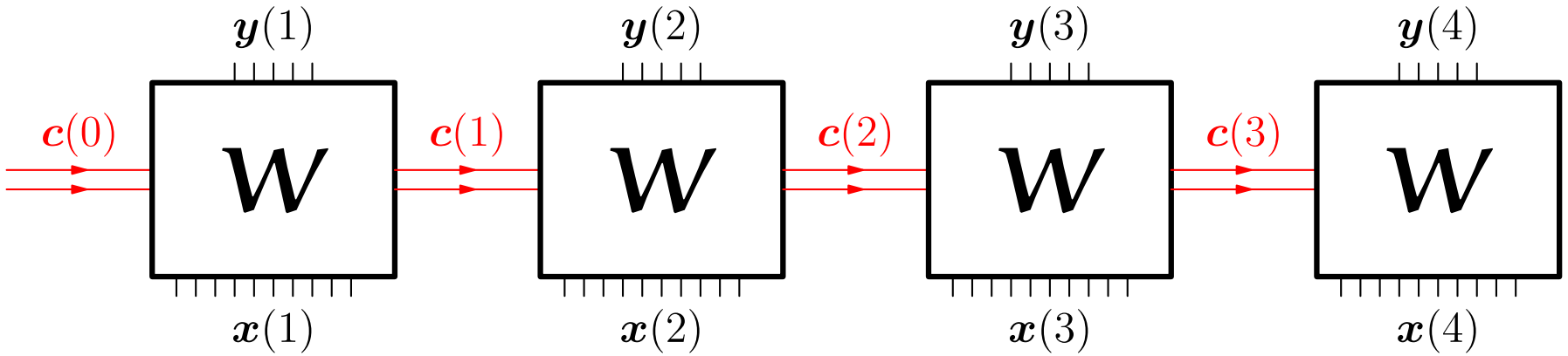

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Vanishing and Exploding Gradients

- Note that $\boldsymbol{c}(t) = \boldsymbol{f}_1(\boldsymbol{x}(t-1), \boldsymbol{c}(t-1)|\boldsymbol{W})$
- If the output $\boldsymbol{y}(t)$ depends on the input $\boldsymbol{x}(t-3)$, say then prediction will be

$$\boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{f}_1(\boldsymbol{x}(t-1), \boldsymbol{f}_1(\boldsymbol{x}(t-2), \boldsymbol{f}_1(\boldsymbol{x}(t-3)|\boldsymbol{W}), \boldsymbol{W}), \boldsymbol{W}), \boldsymbol{W})$$

- The back-propagated error will involve applying $\boldsymbol{f}_1$ multiple times
- Each time the error will get multiplied by some factor a
- If $\boldsymbol{y}(t)$ depends on the input $\boldsymbol{x}(t-\tau)$ then the back-propagated signal will be proportional to $a^{\tau-1}$
- This either vanishes or explodes when τ becomes large

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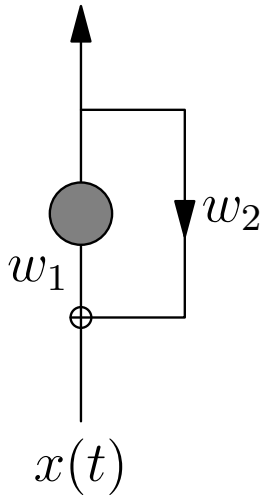
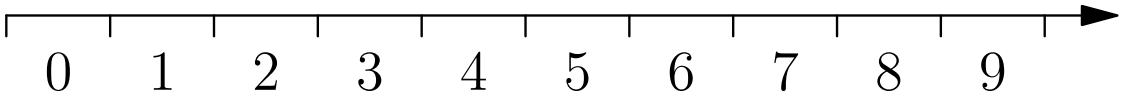
Simple Recurrent Network

$$y(t) = w_1 \left(x(t) + w_2 \, y(t-1) \right)$$





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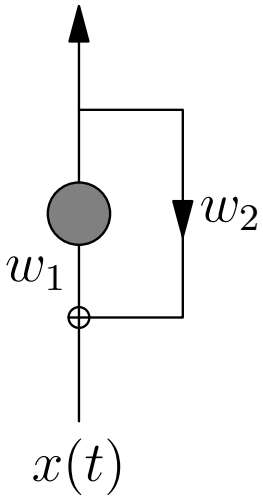
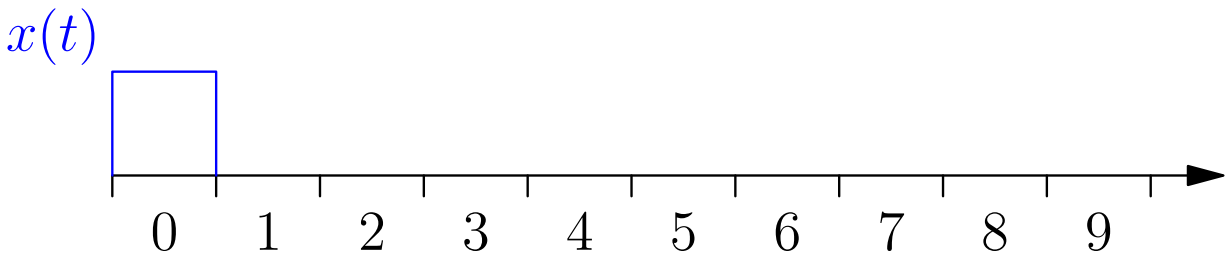


$$w_1 = w_2 = 0.9$$



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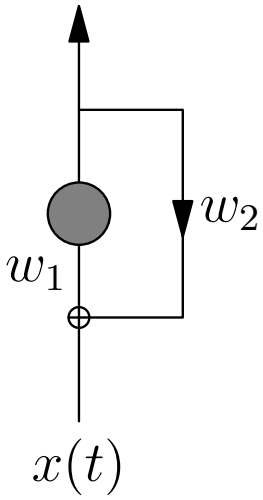

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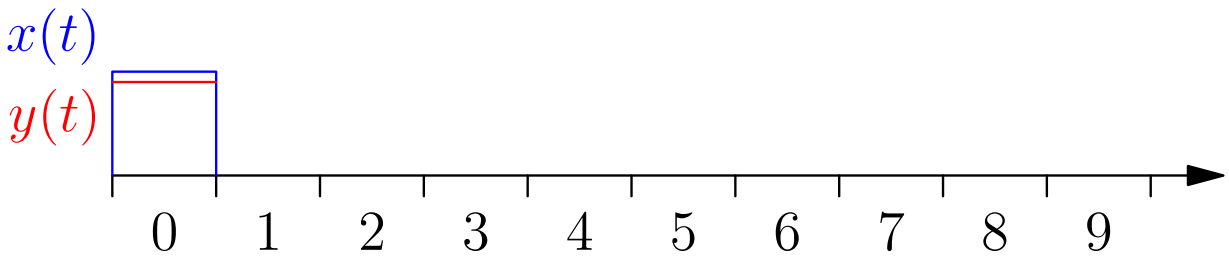

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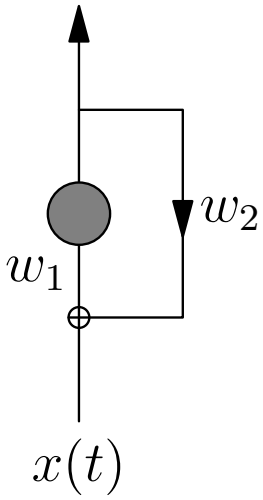

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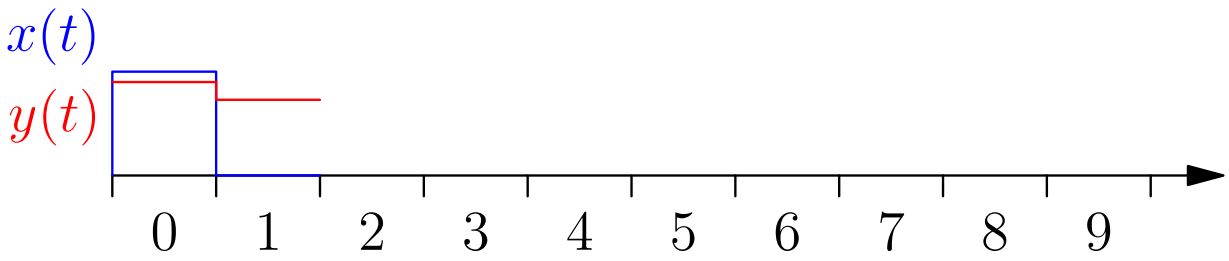

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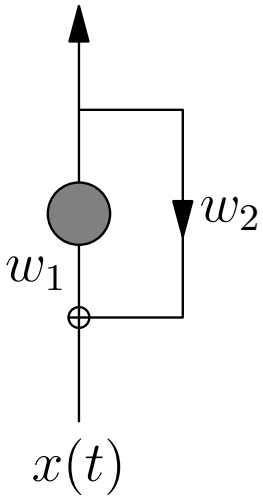

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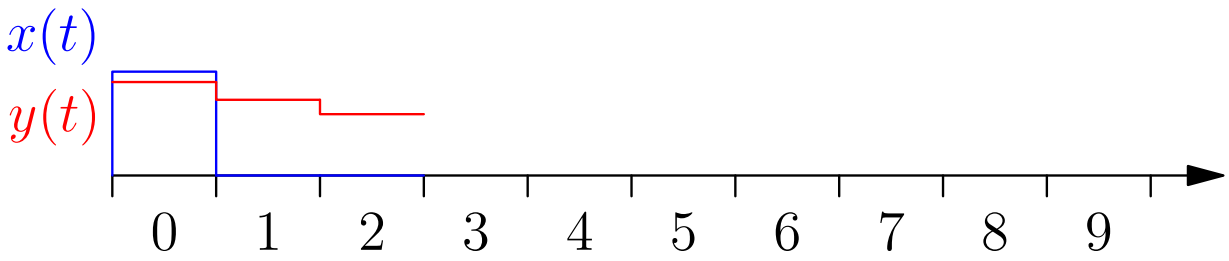

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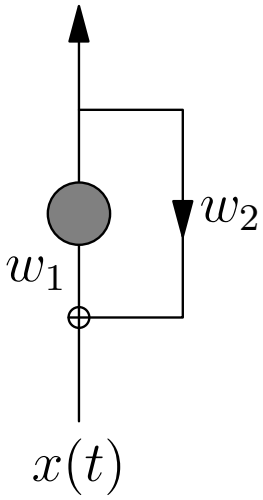

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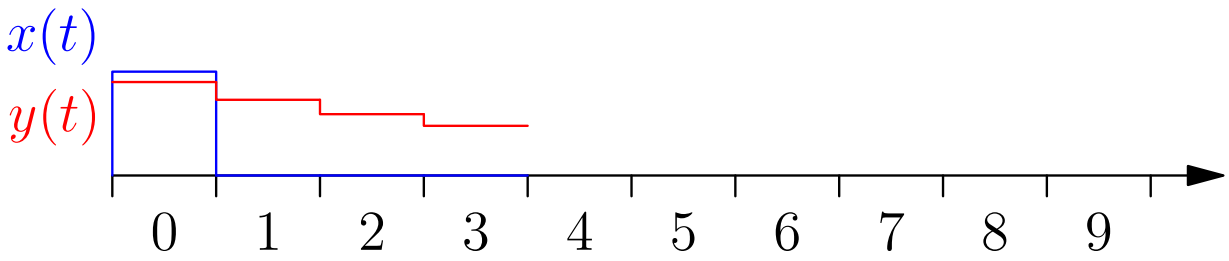

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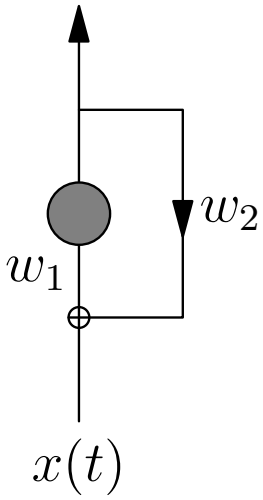

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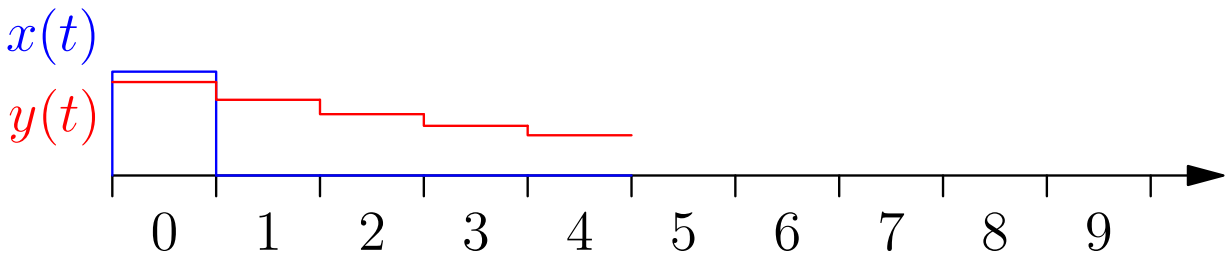

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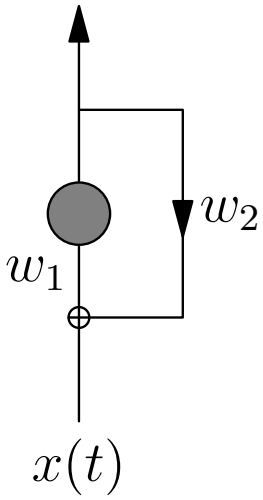

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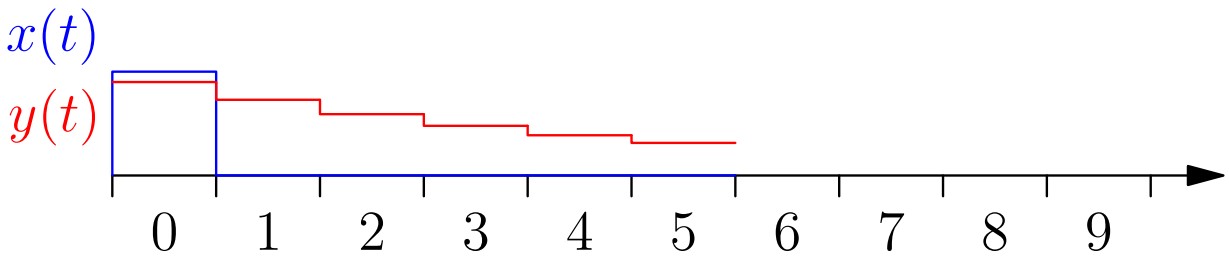

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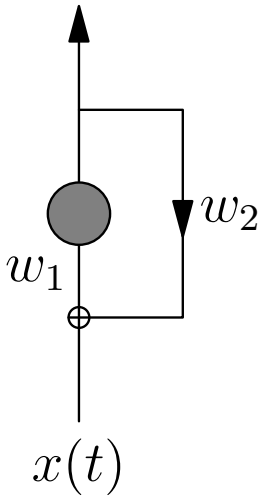

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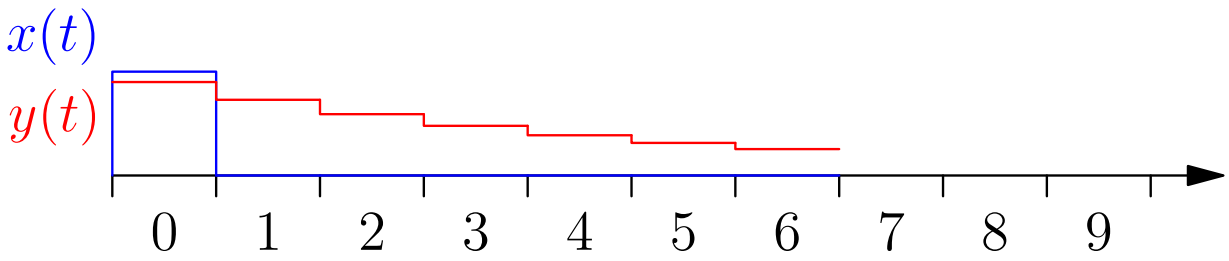

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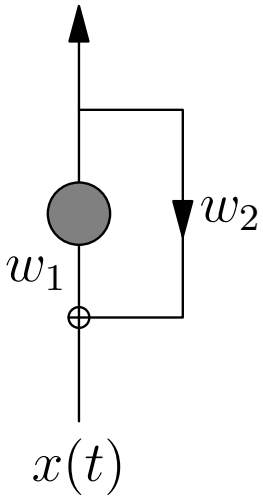

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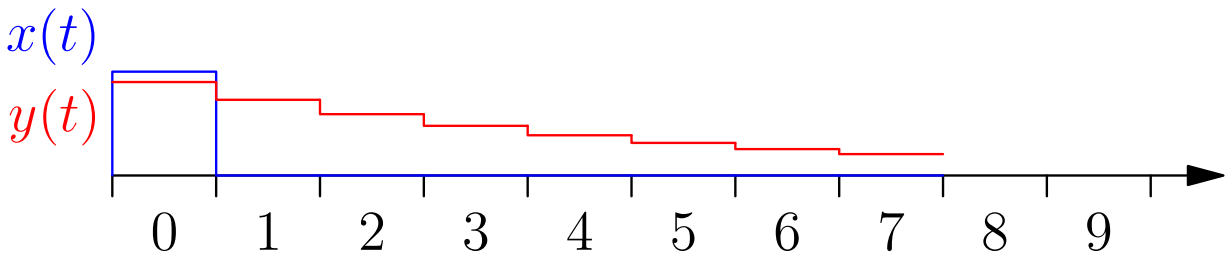

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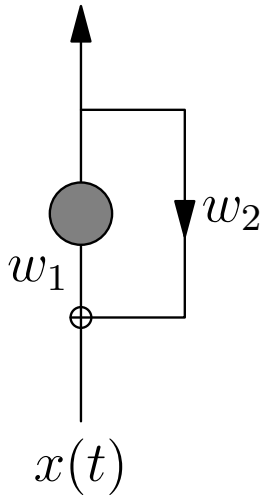

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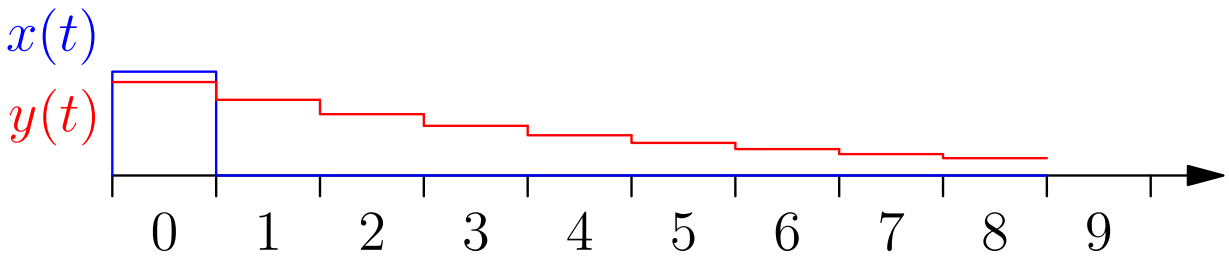

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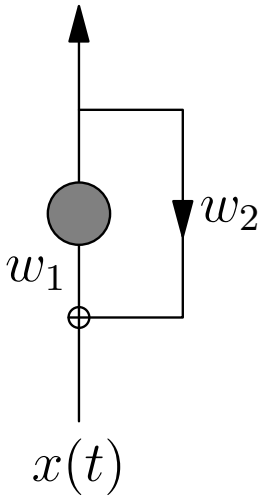

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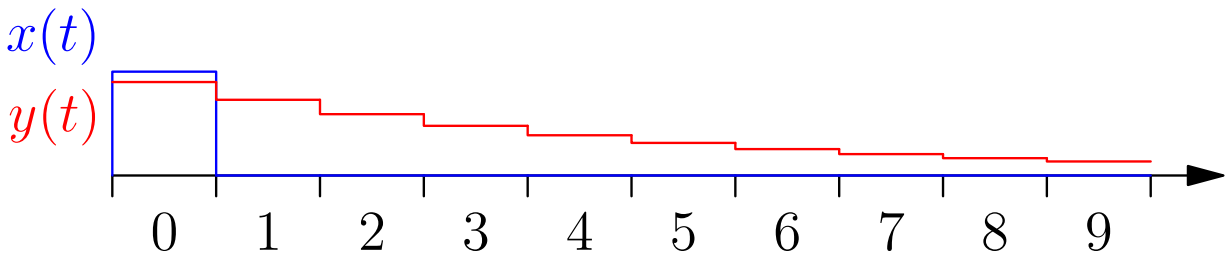

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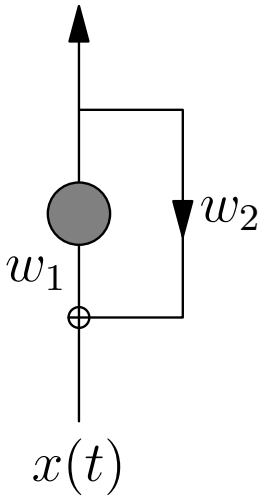

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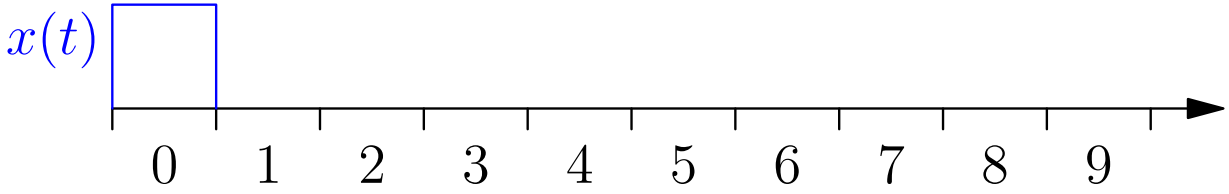

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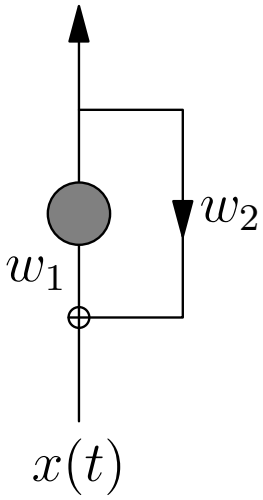

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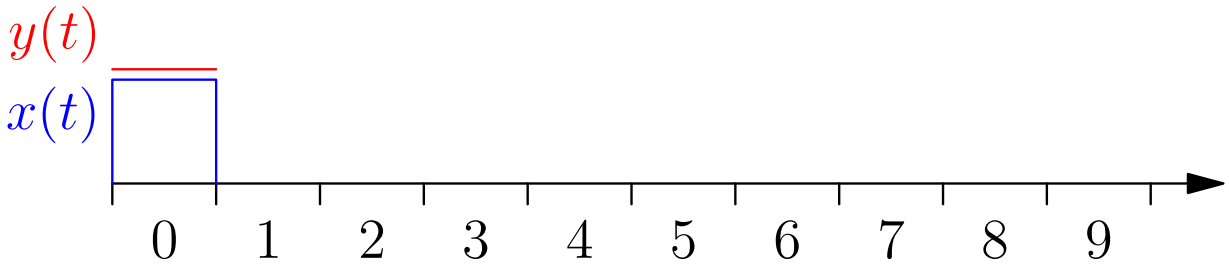

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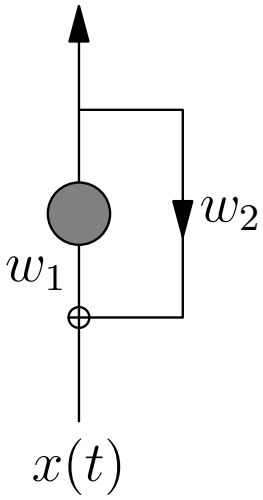

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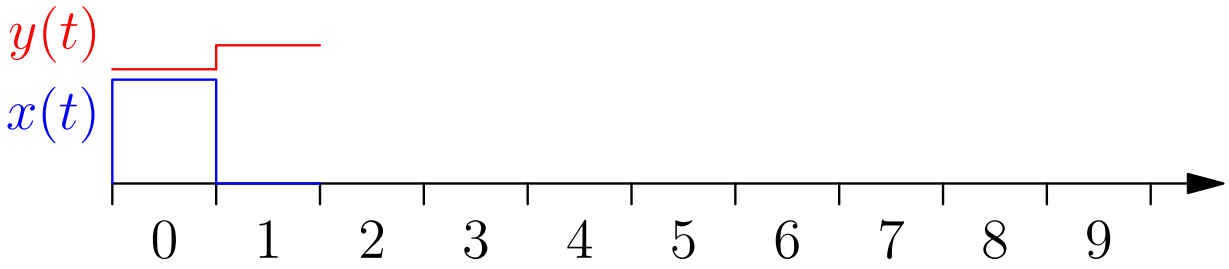

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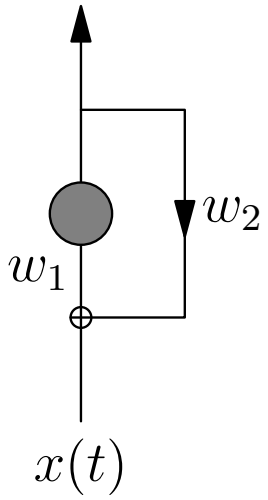

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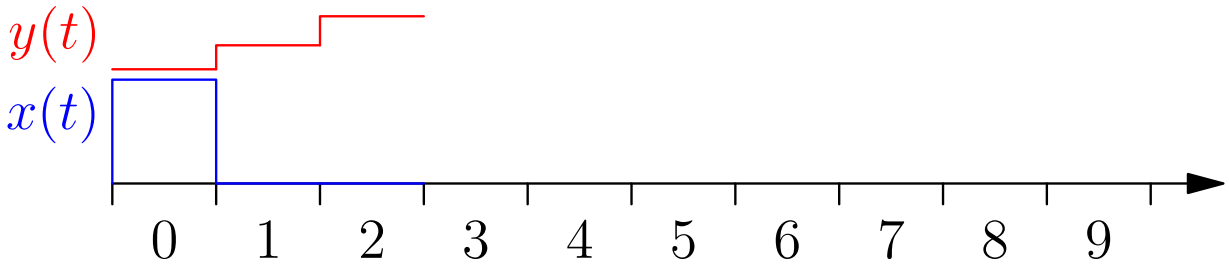

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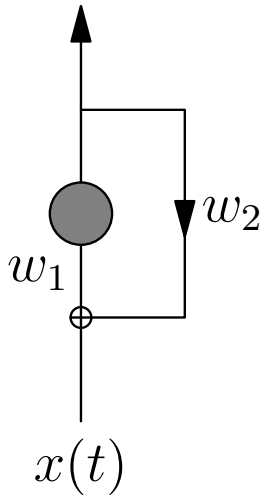

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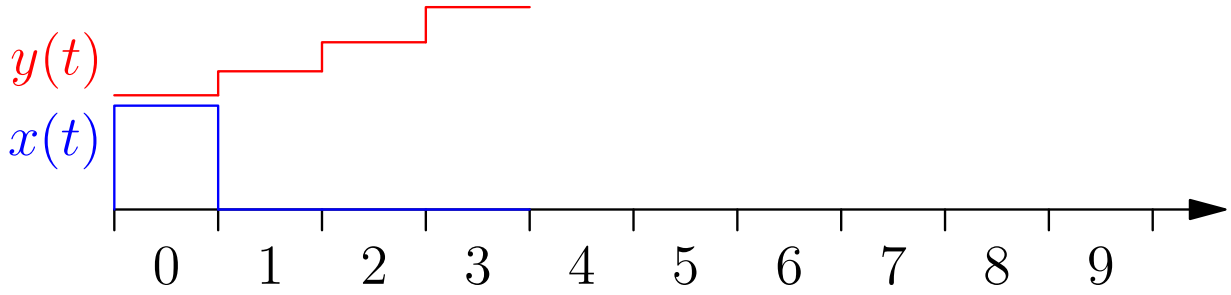

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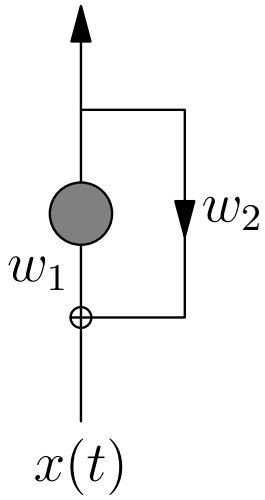

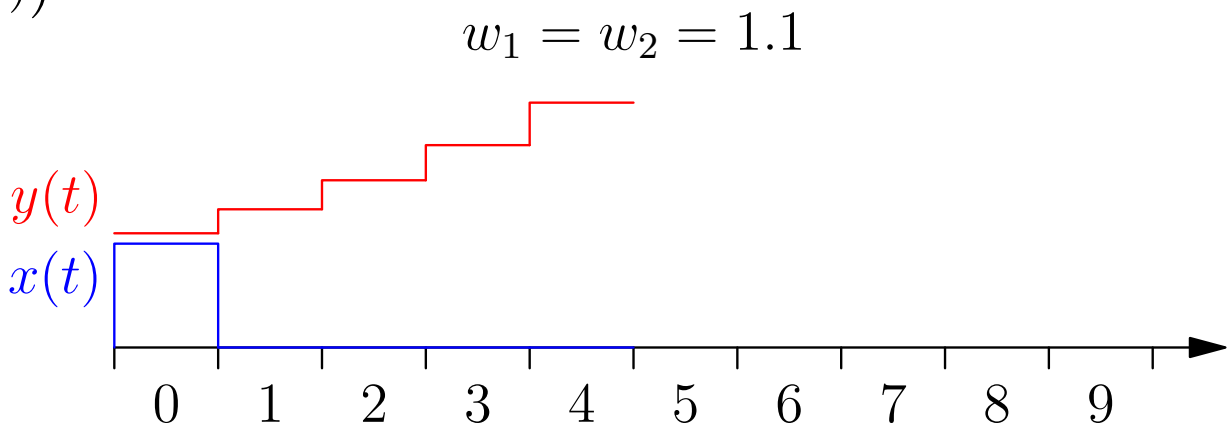

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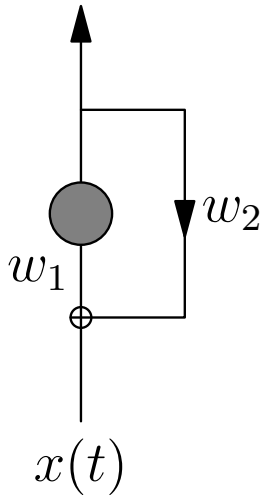

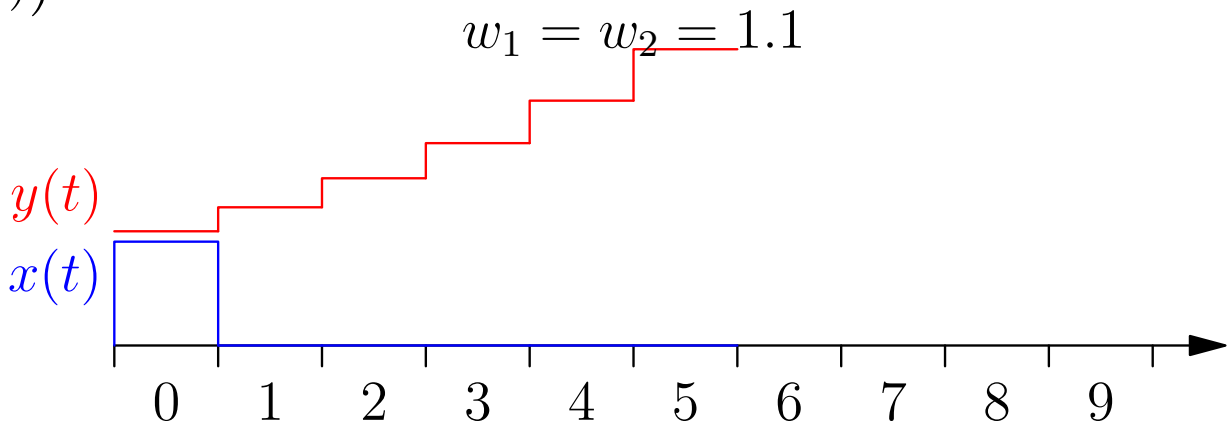

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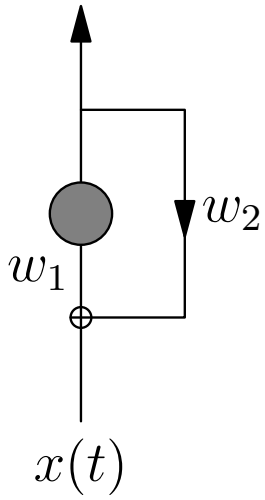
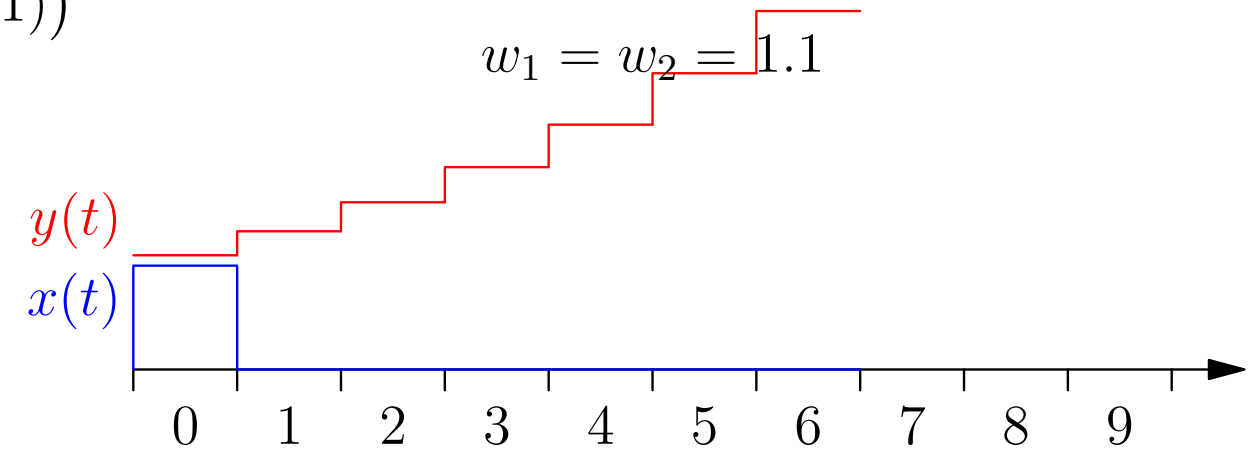
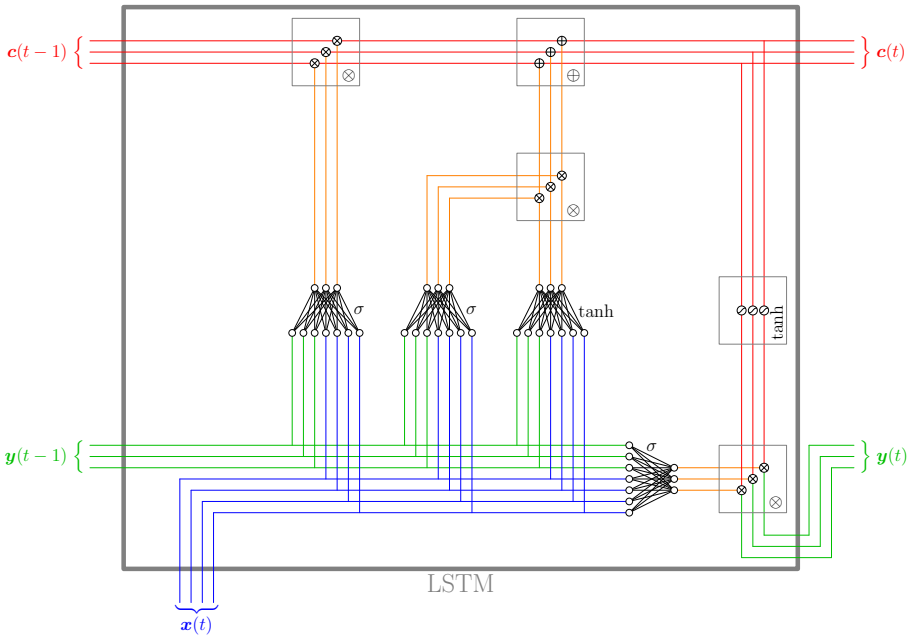




Outline

1. More on CNNs
2. Recurrent Networks
3. **LSTM**
4. Word Embedding
5. Applications



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- LSTMs (long-short term memory) was designed to solve this problem
- It recognised that to retain a long time memory requires

$$\boldsymbol{c}(t) = \boldsymbol{c}(t-1)$$

- Sometimes we have to forget and sometimes we have to change a memory
- To do this we should use gates that saturate at 0 and 1
- Sigmoid functions naturally saturate at 0 and 1

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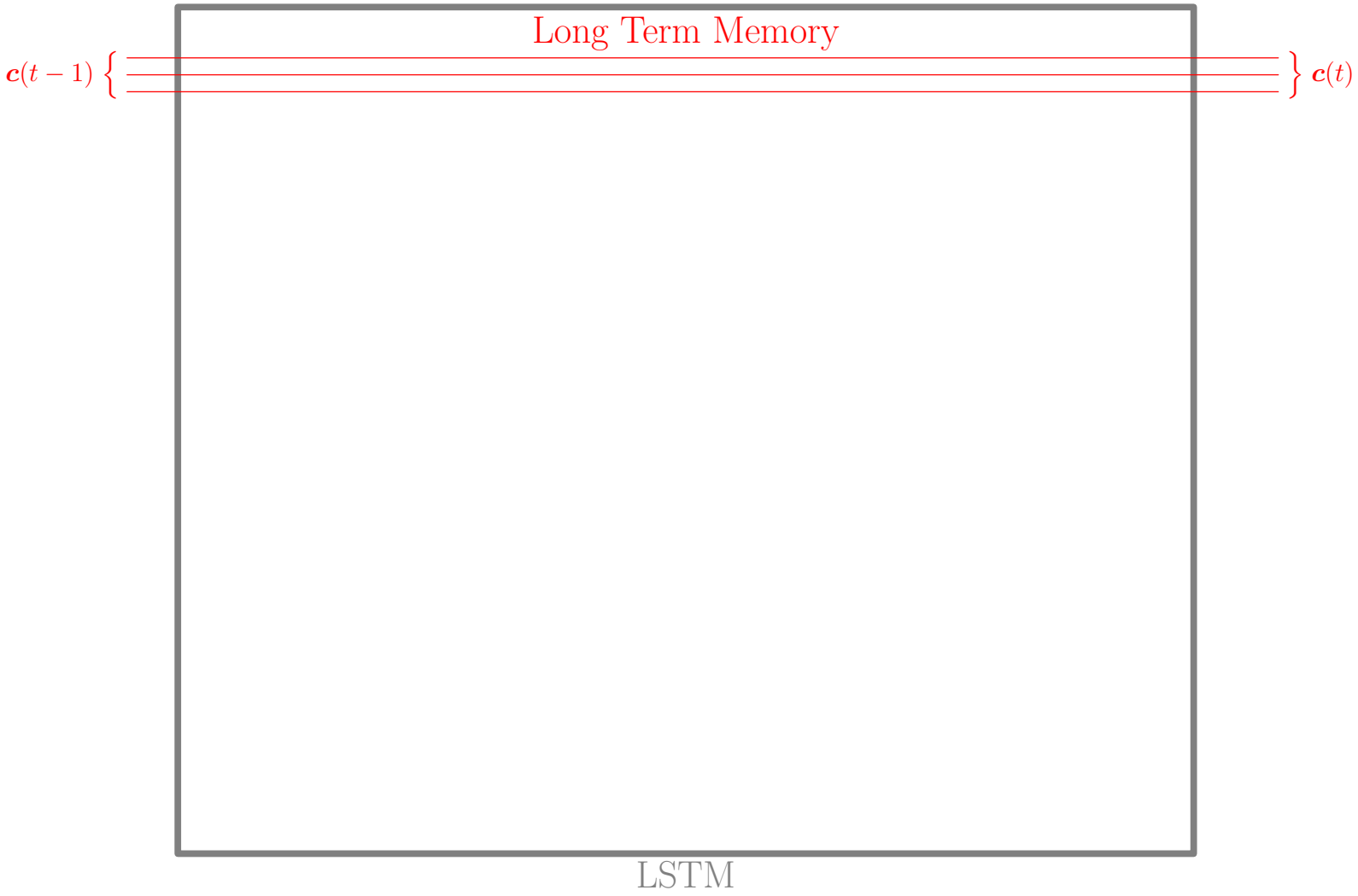

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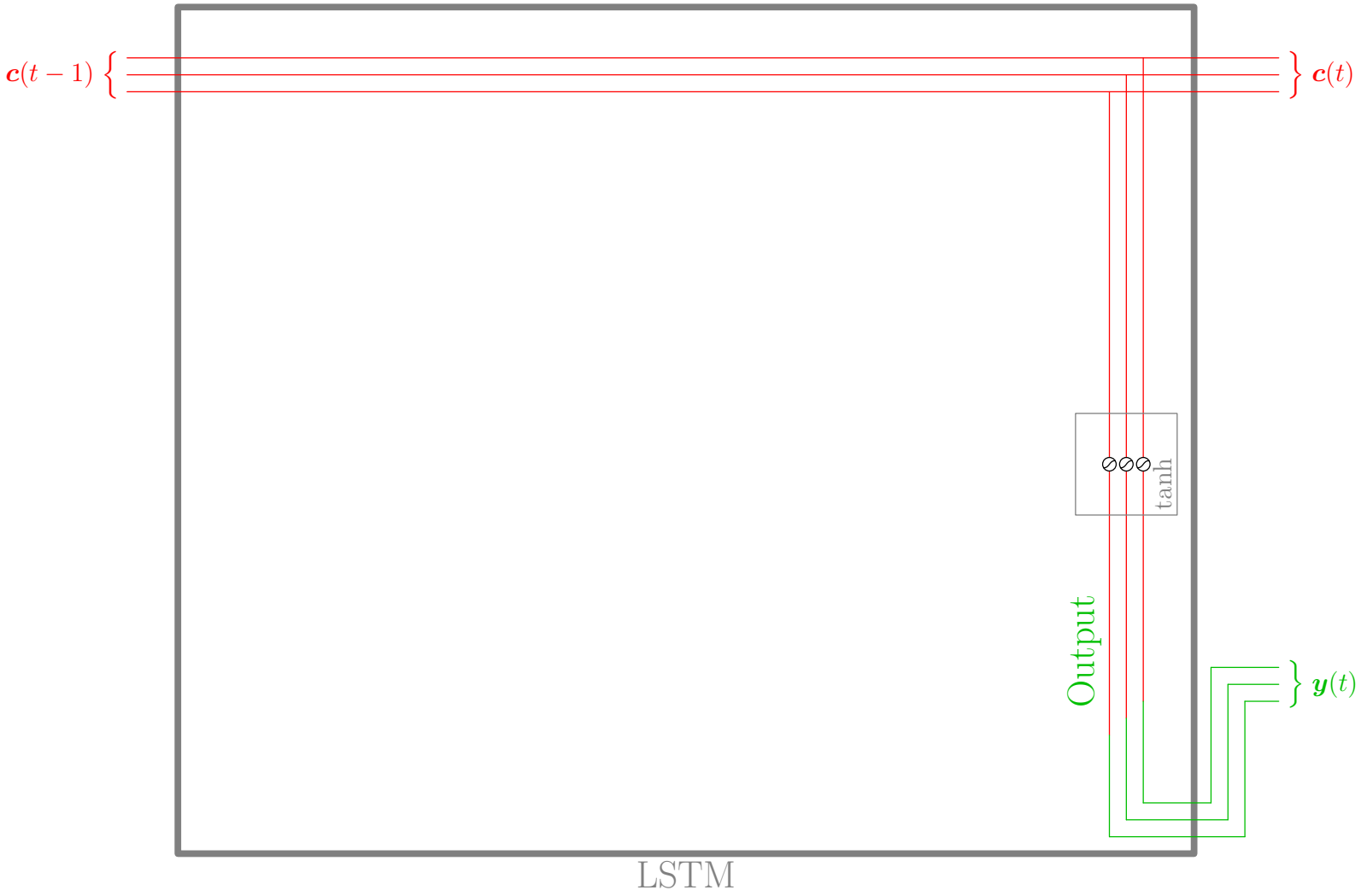

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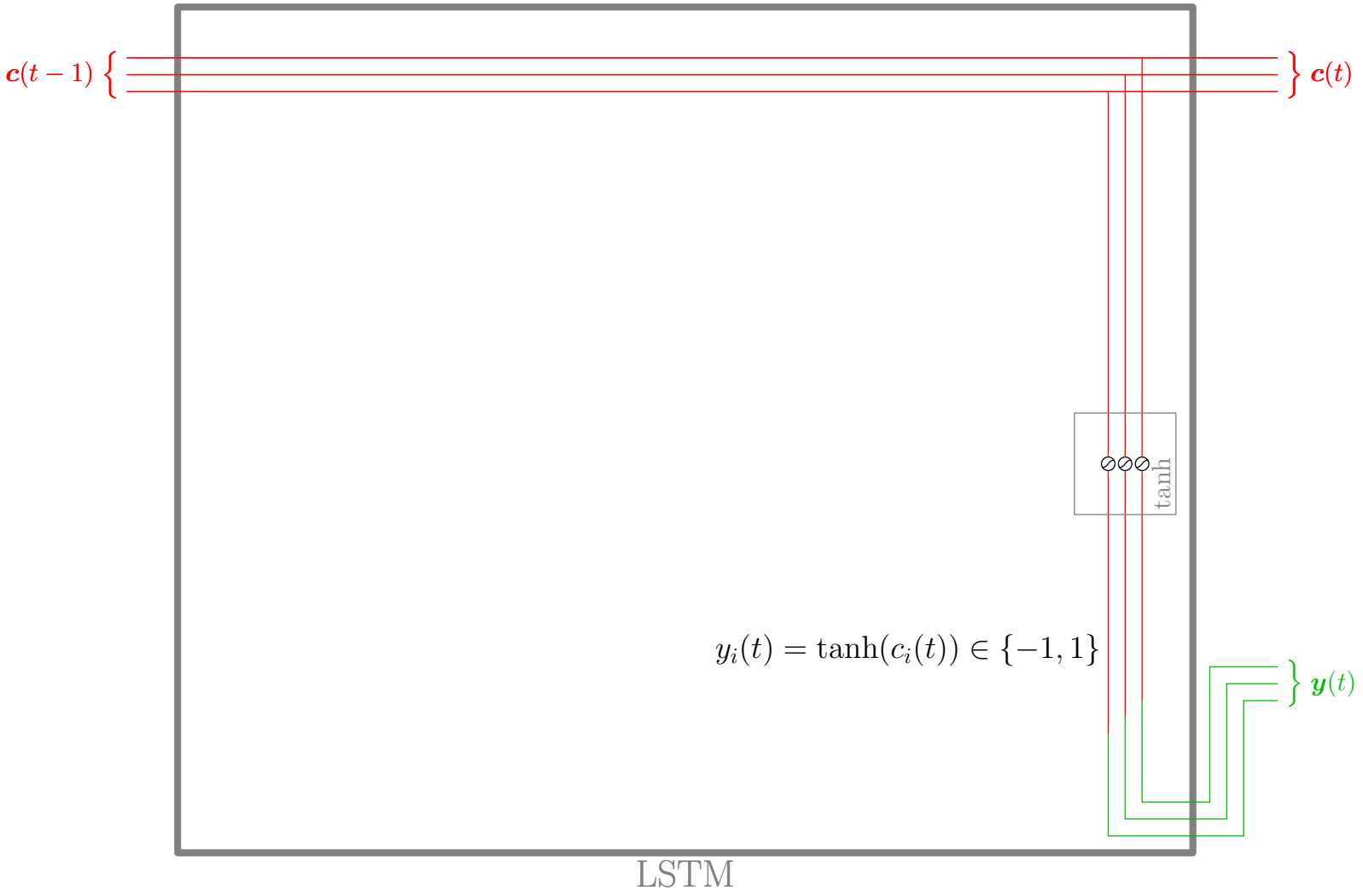

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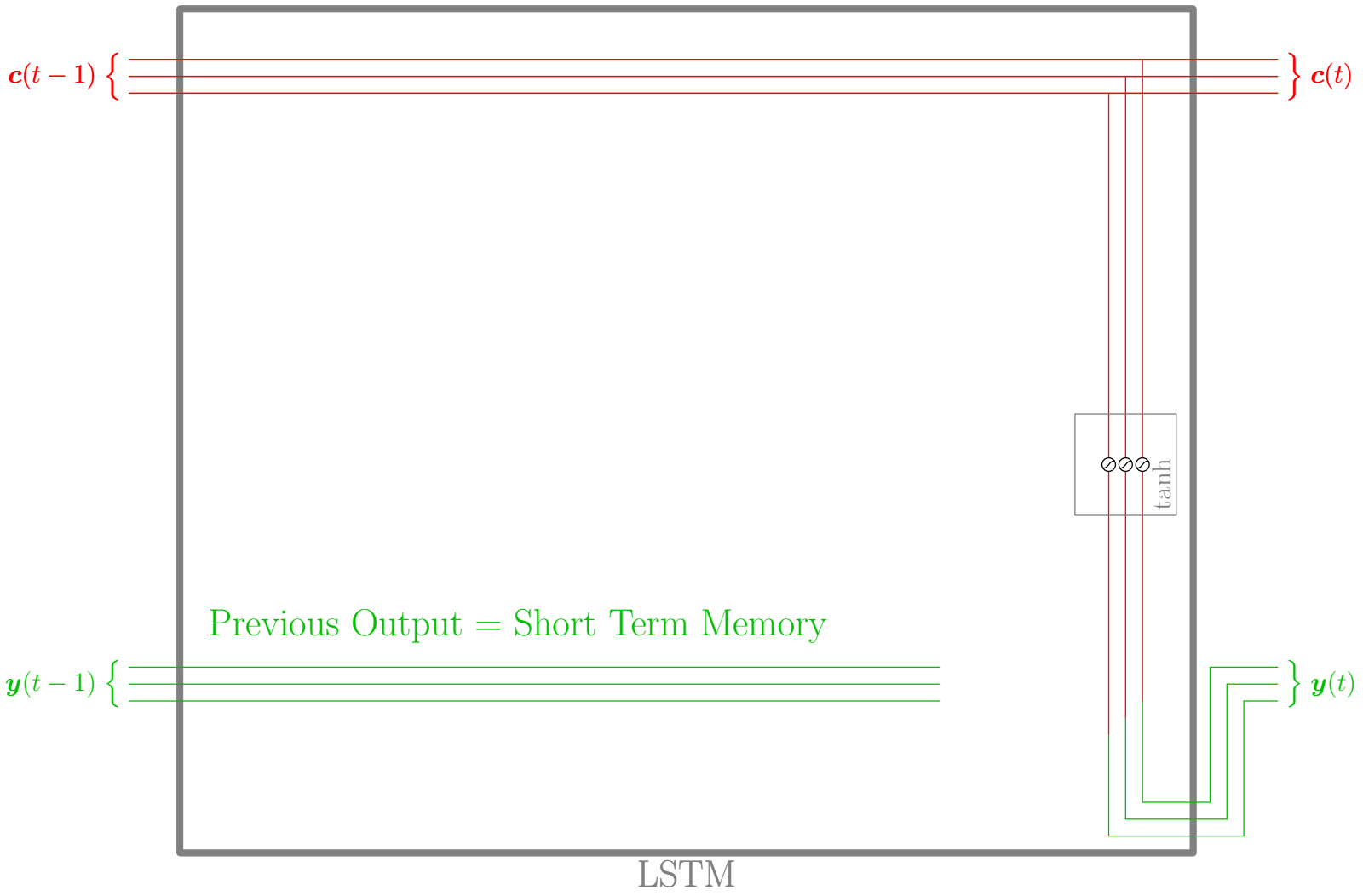

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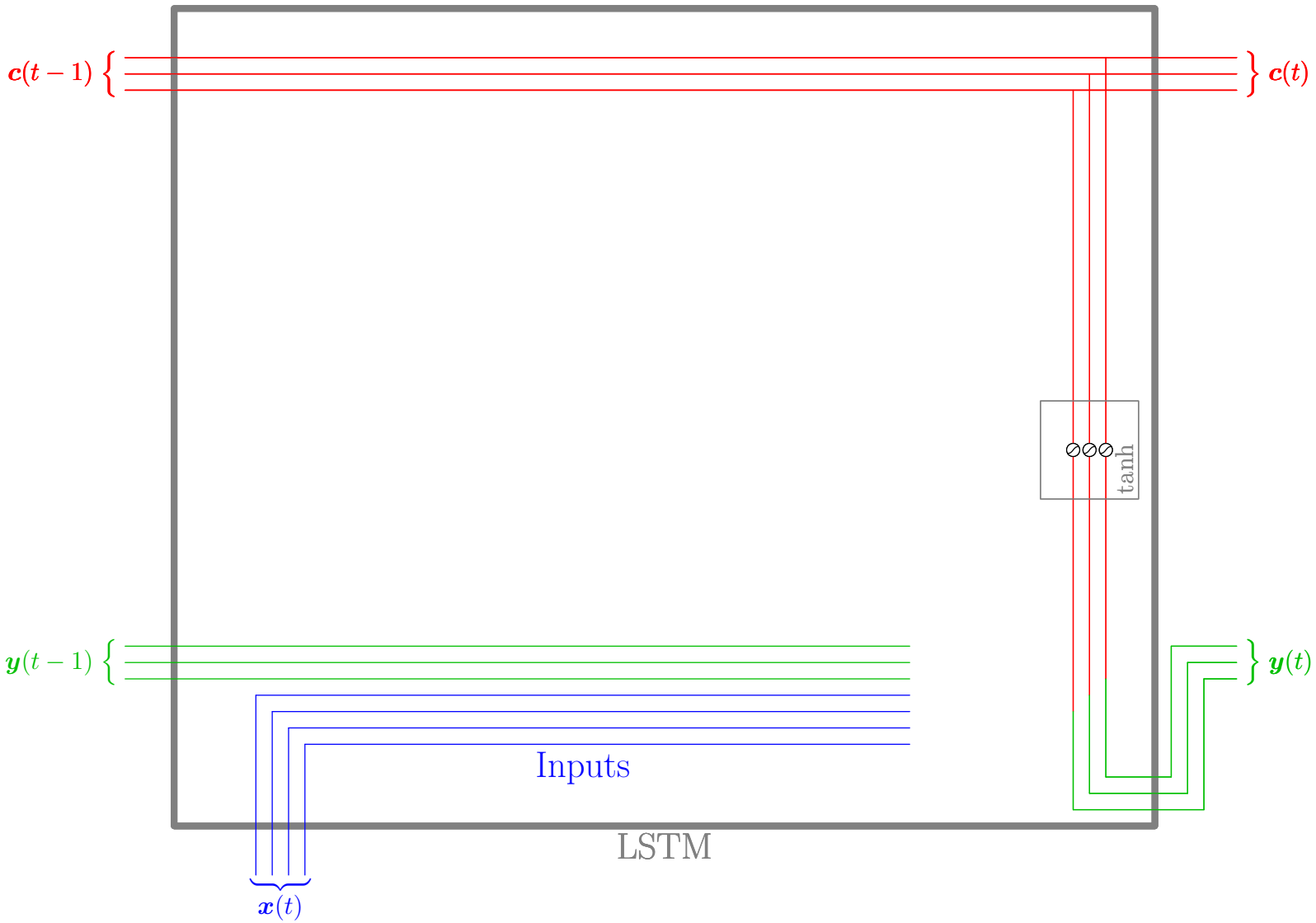

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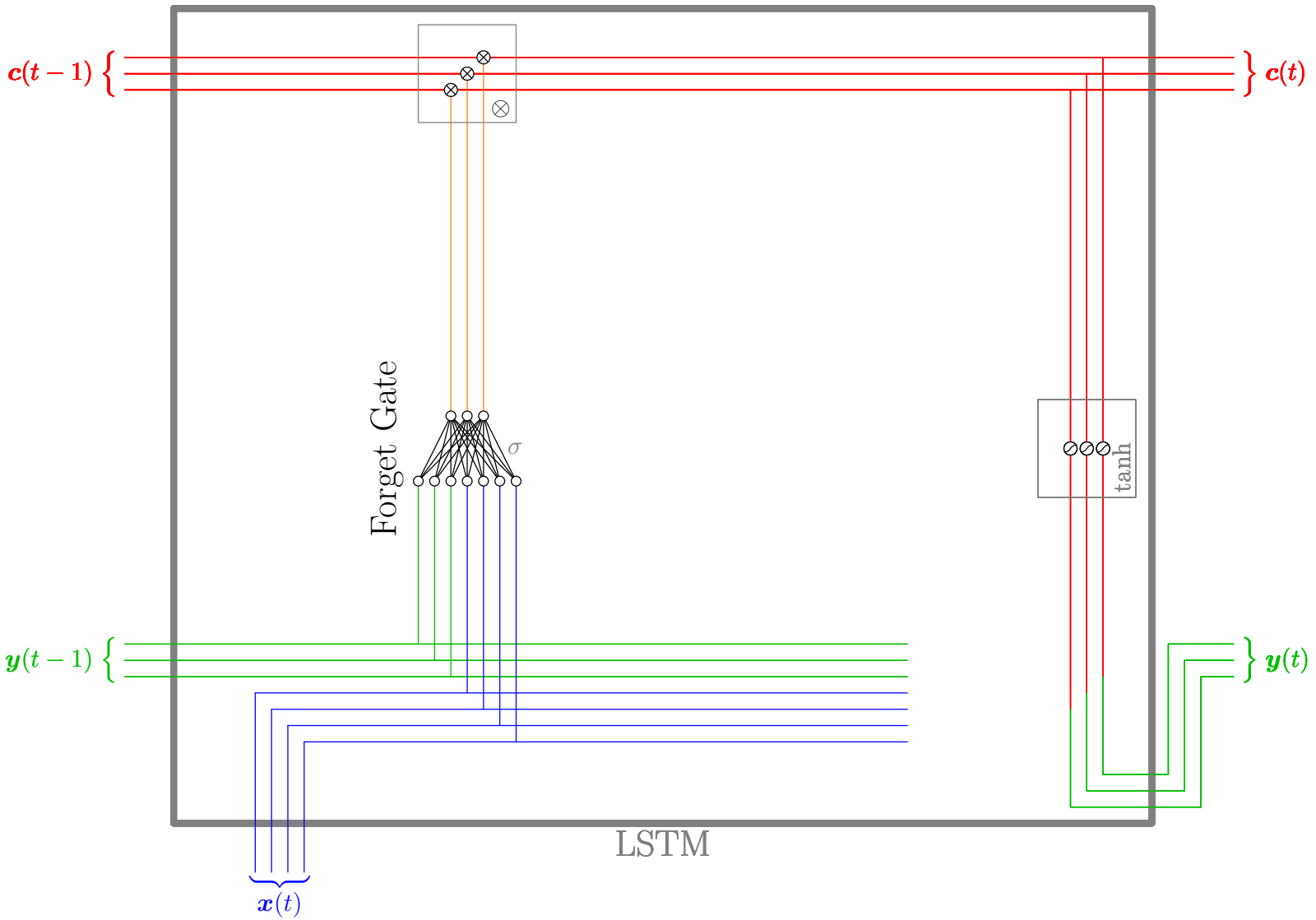

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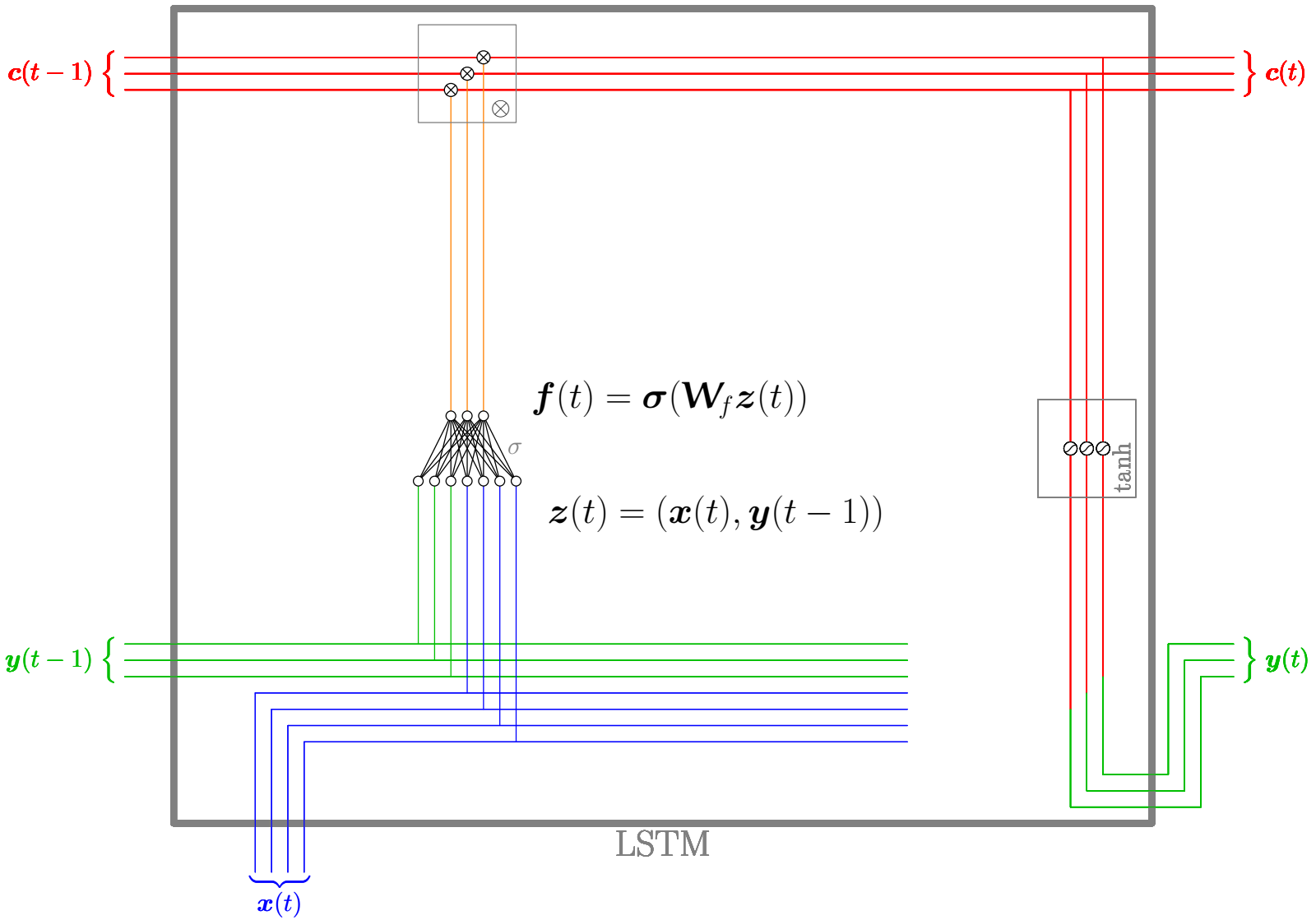

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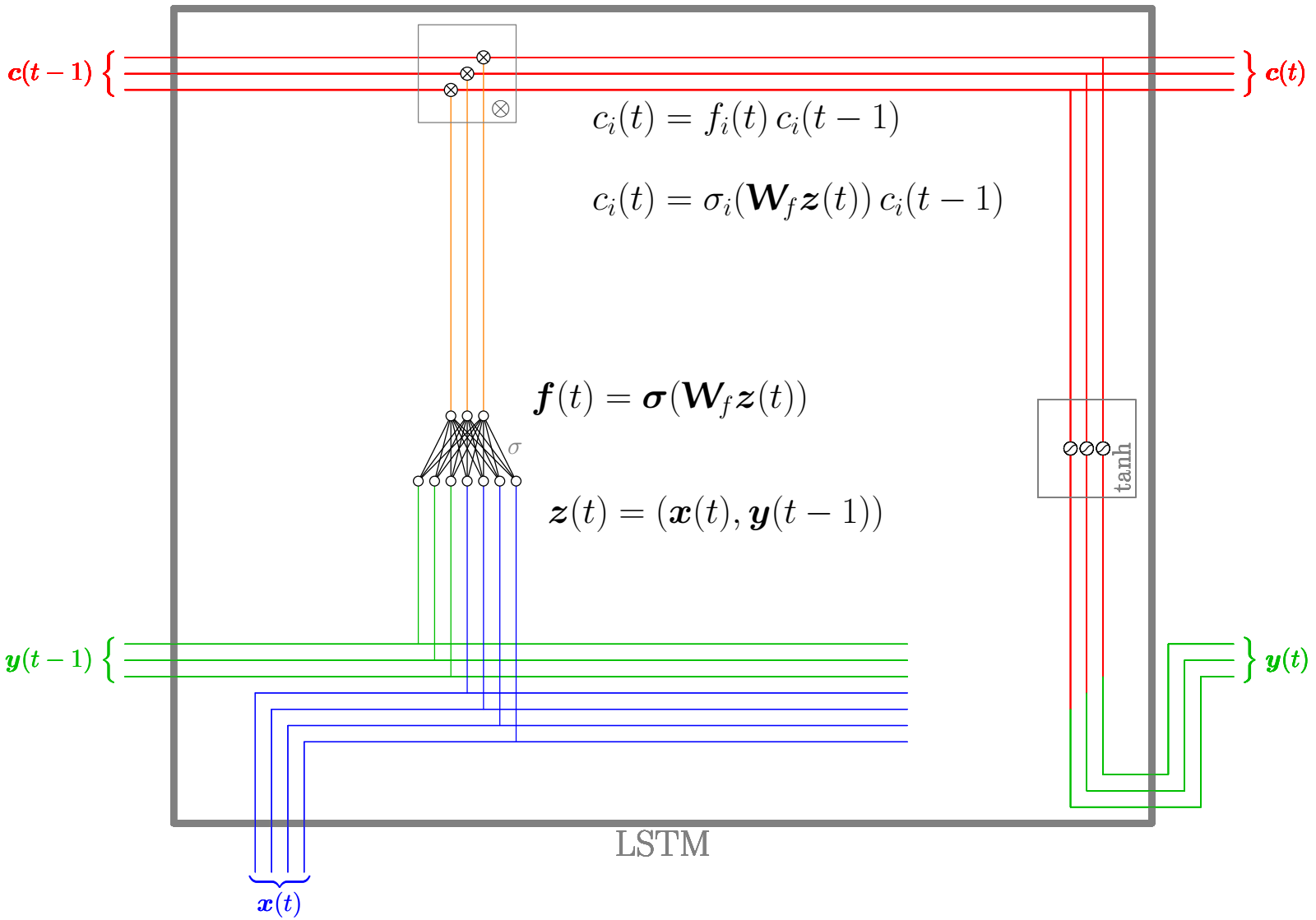

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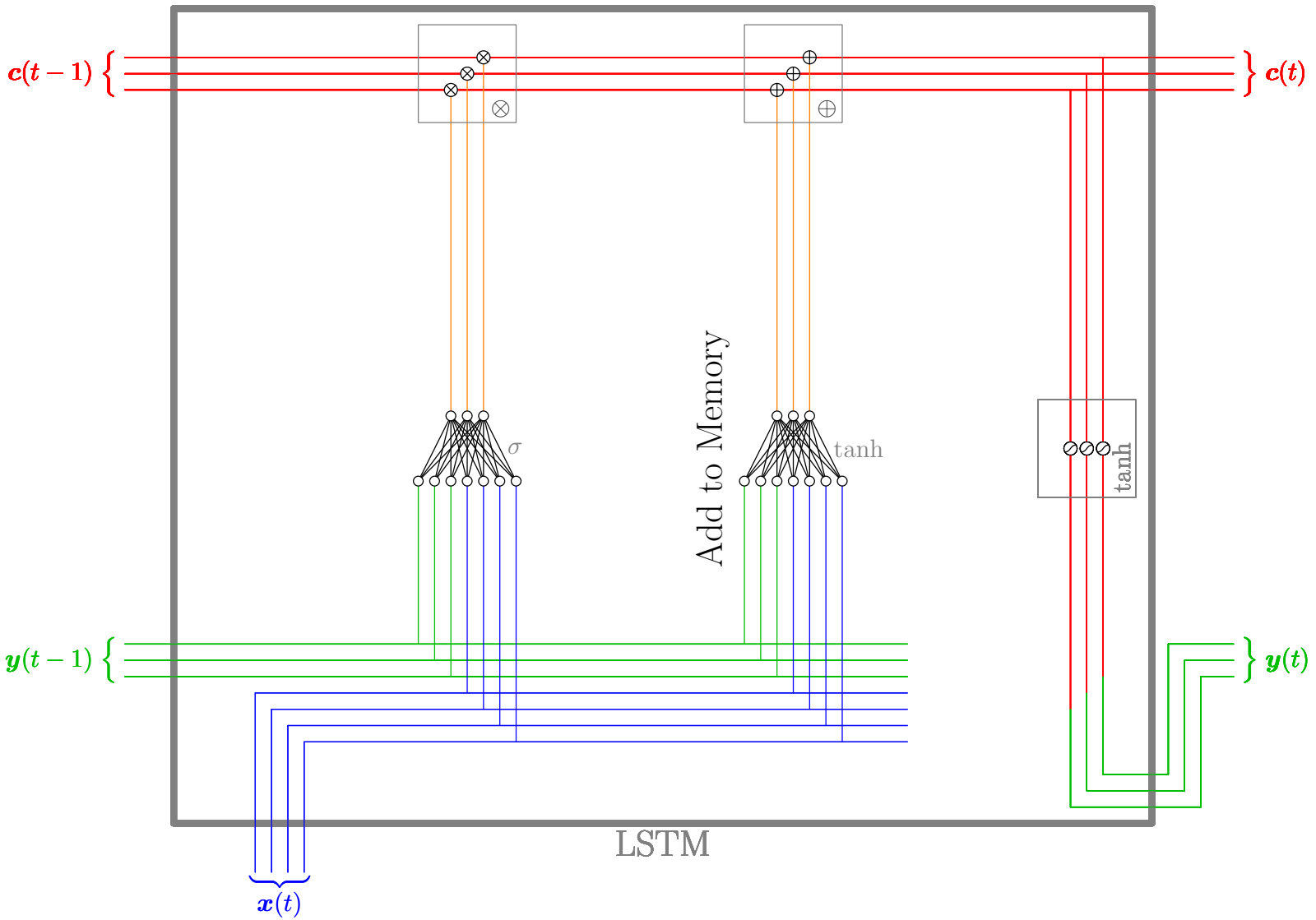

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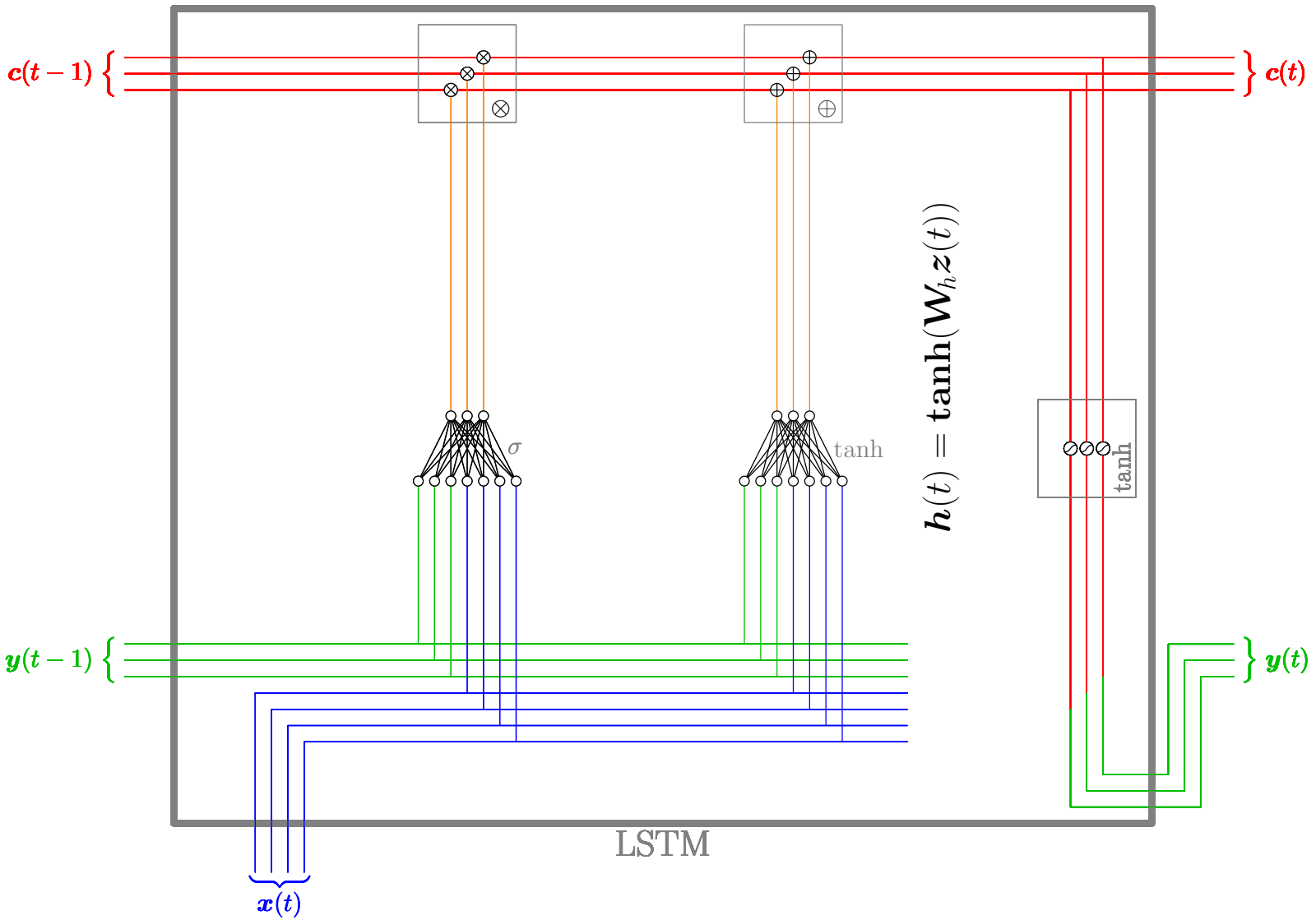

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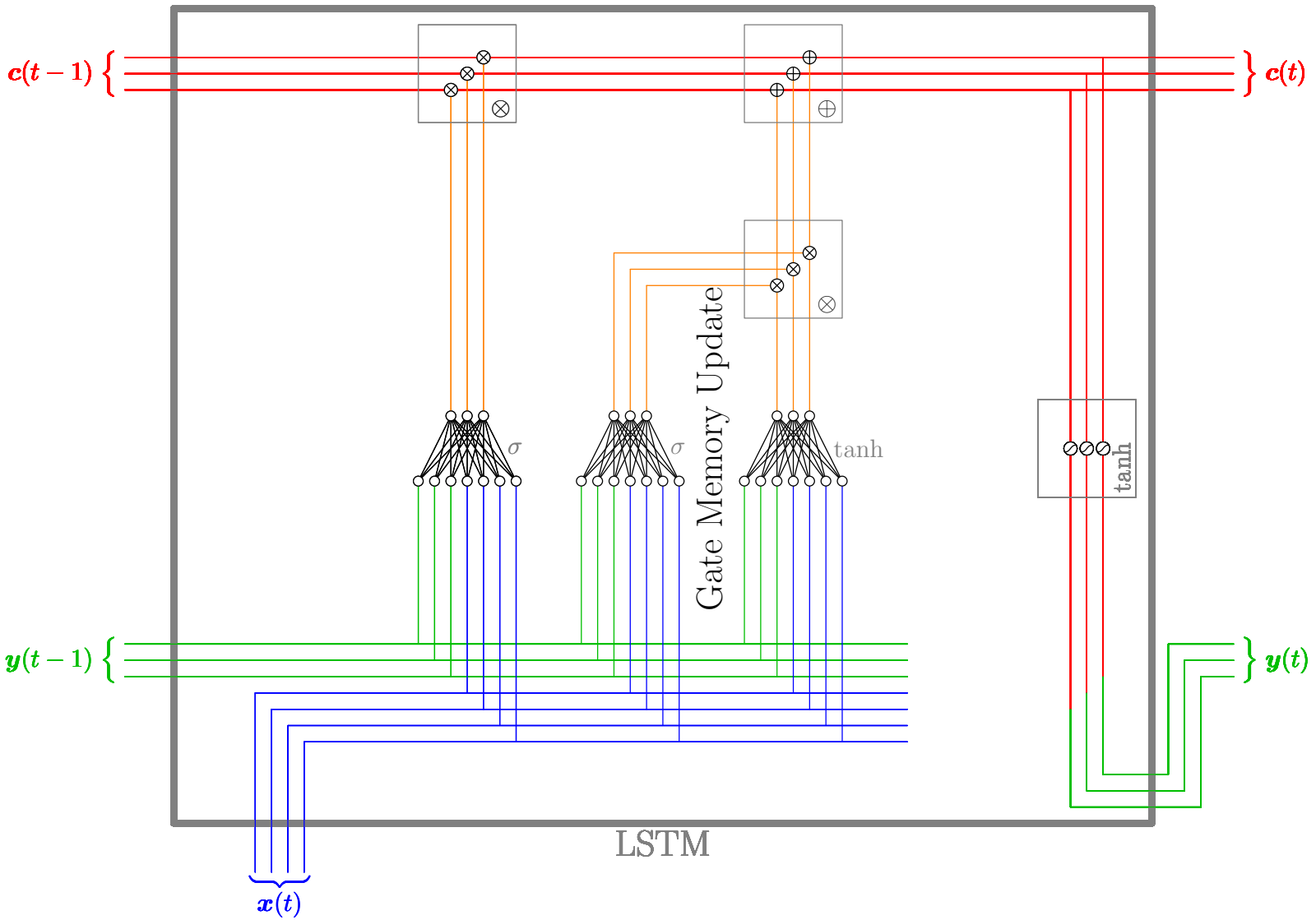

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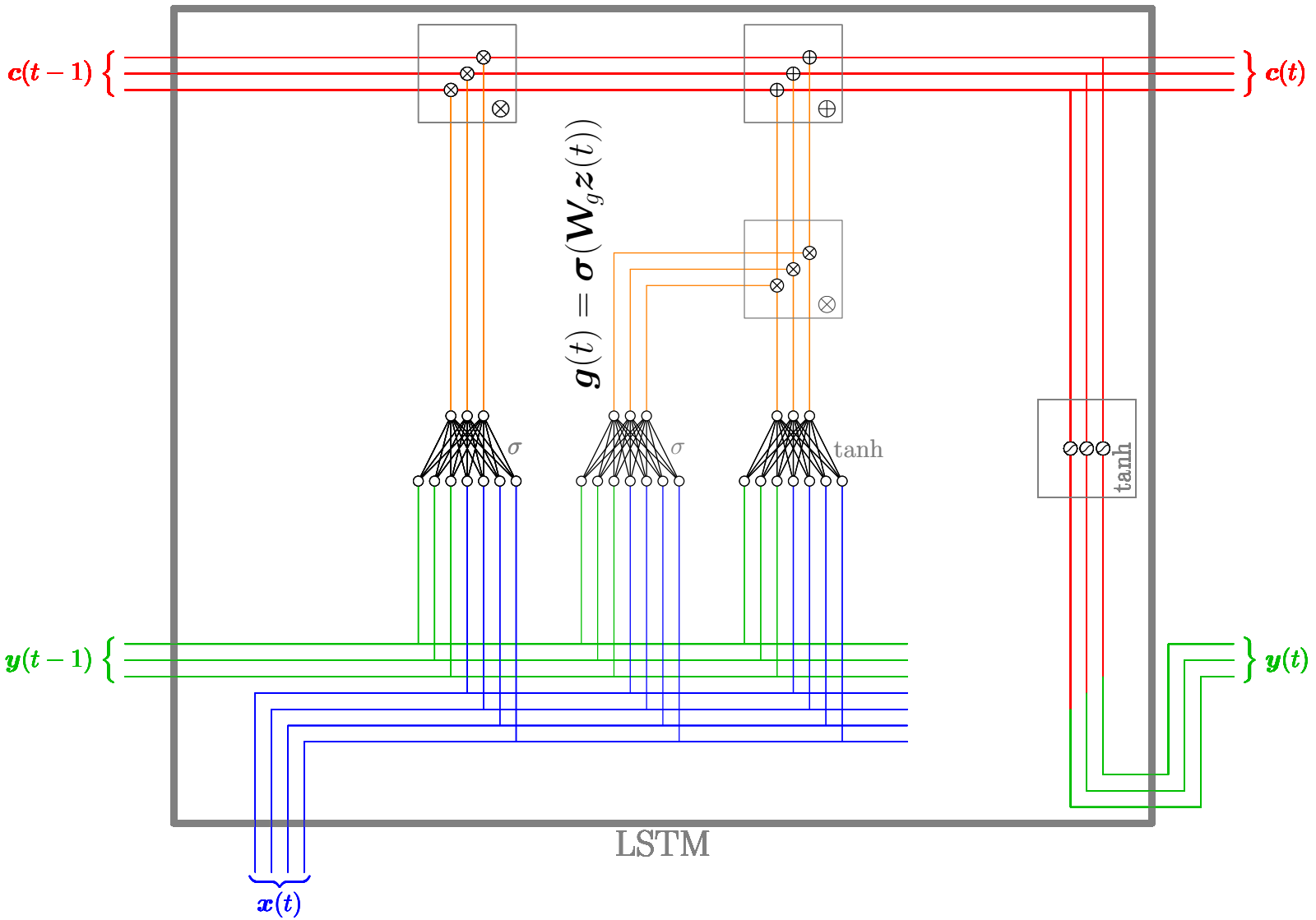
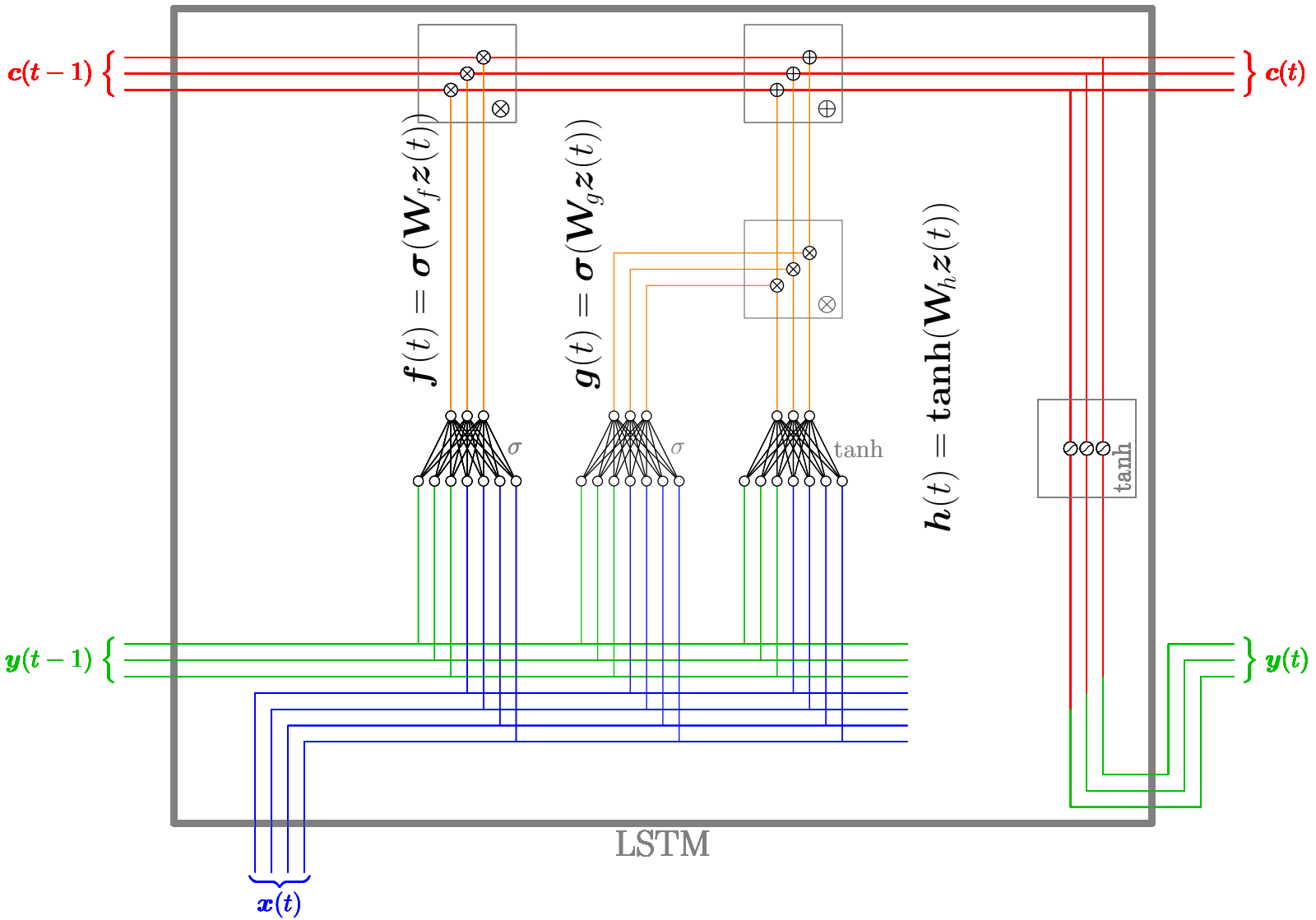


LSTM Architecture

$$c_i(t) = f_i(t)\, c_i(t-1) + g_i(t)\, h_i(t)$$



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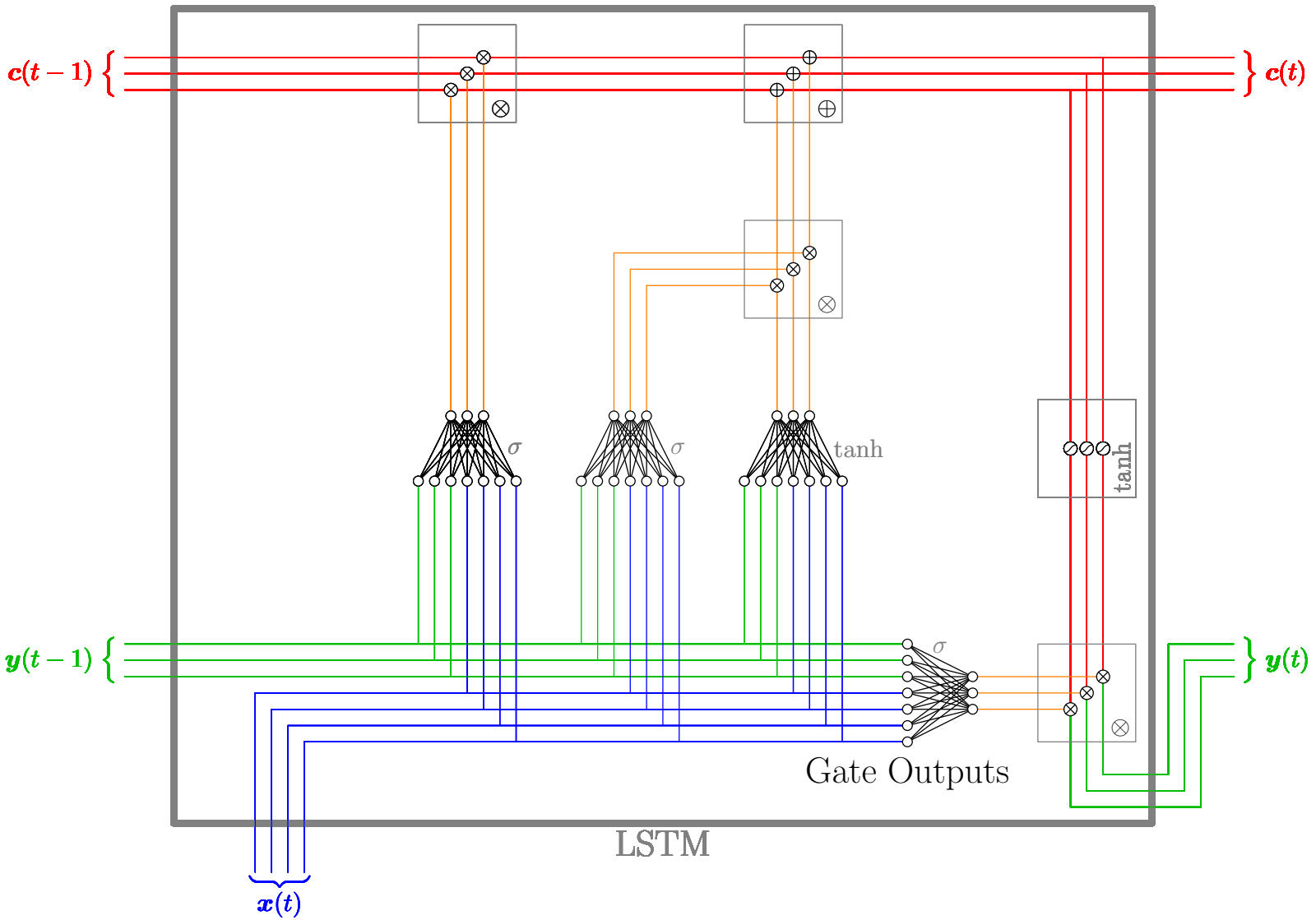

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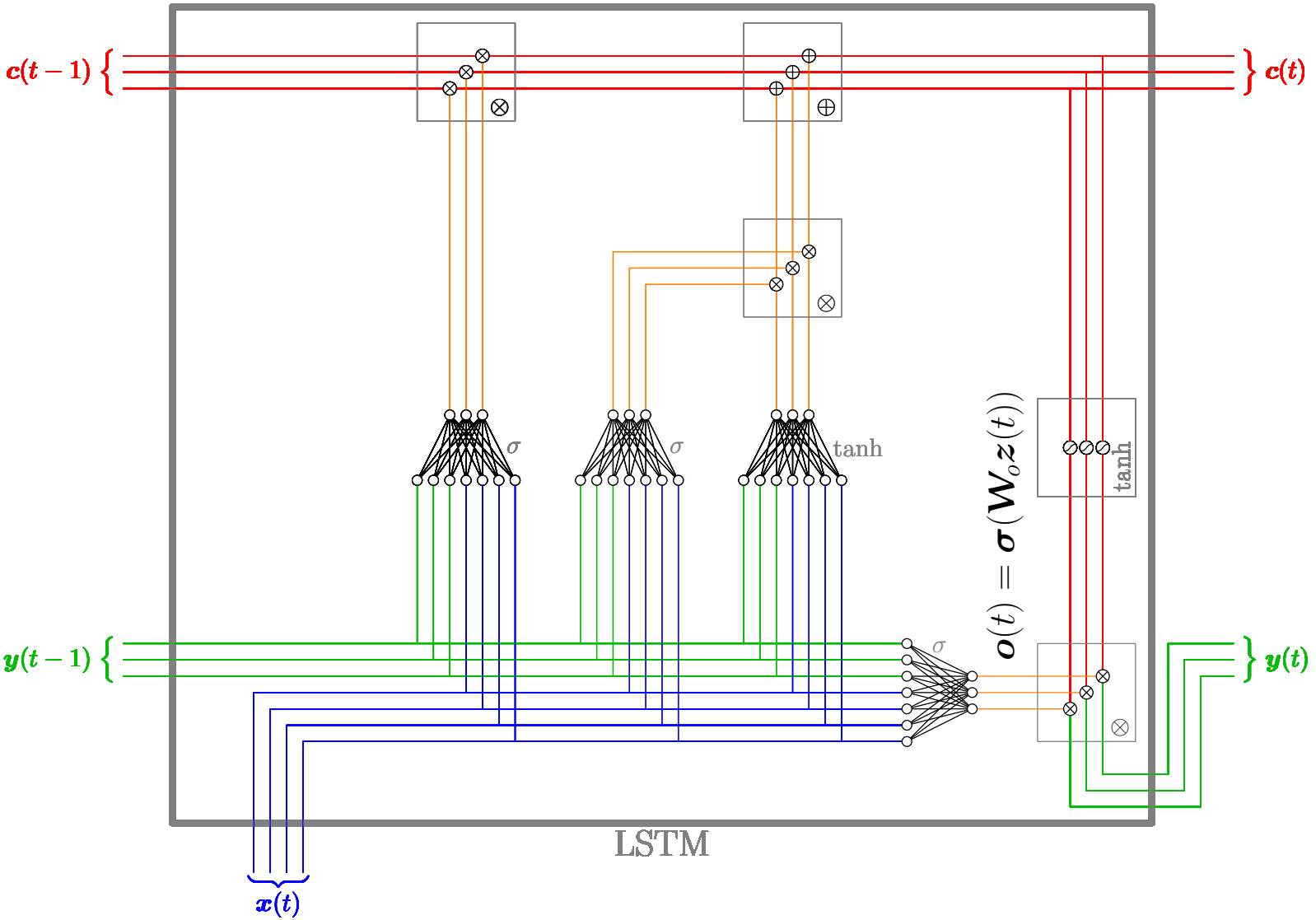

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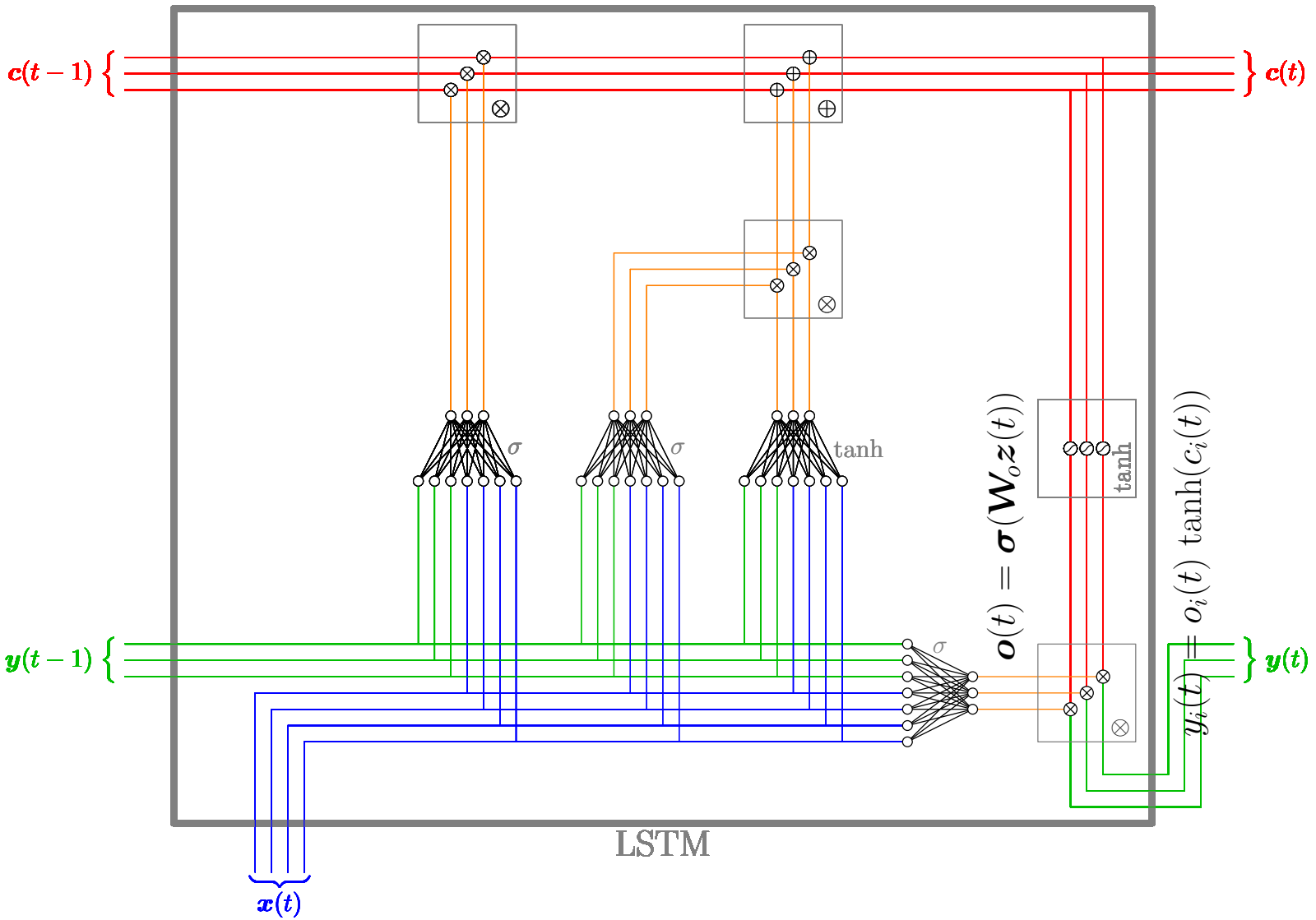

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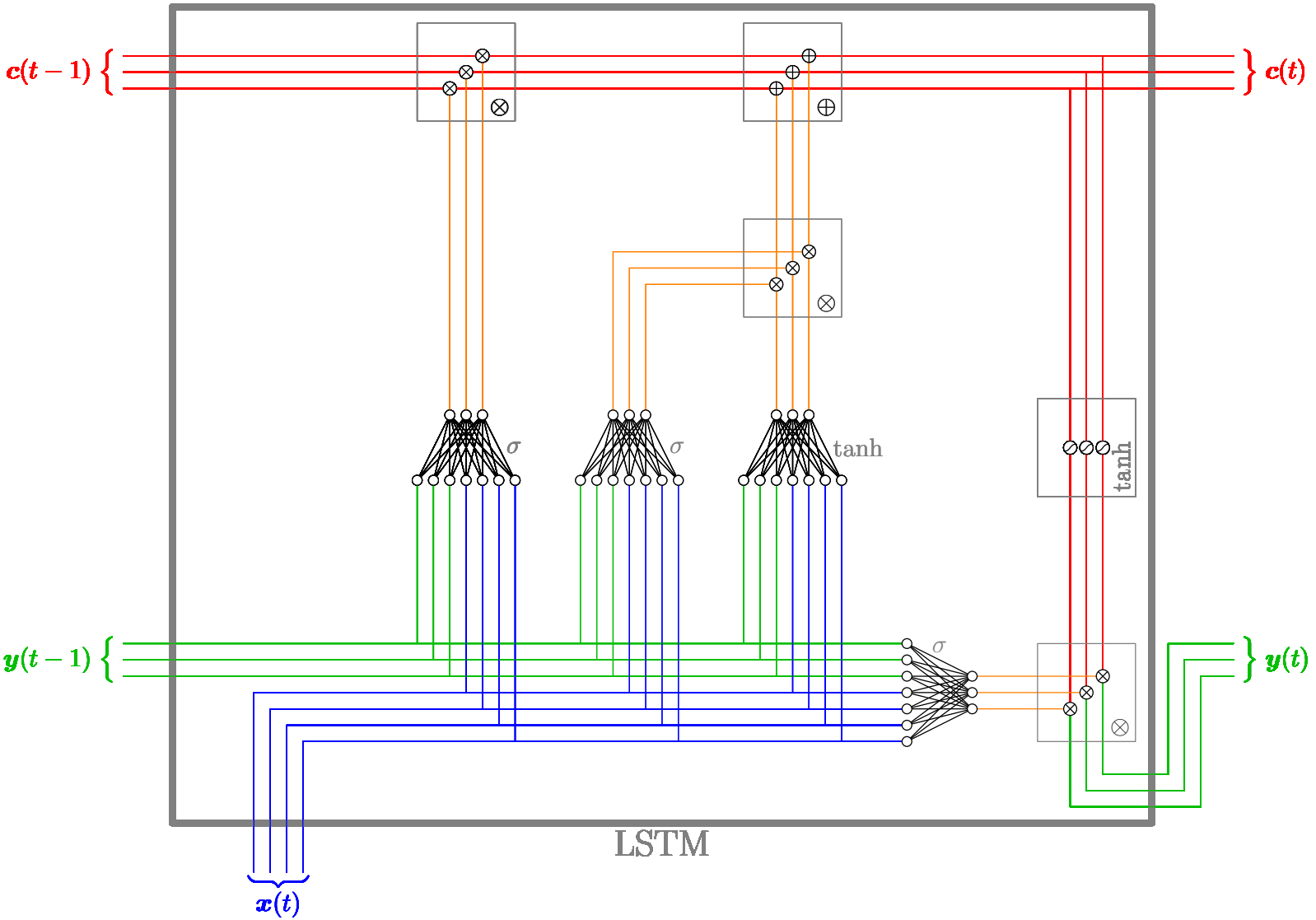

Update Equations

- Inputs $\boldsymbol{z}(t) = \big(\boldsymbol{x}(t), \boldsymbol{y}(t-1)\big)$
- Network updates ($\boldsymbol{W}_*$ are the free parameters)

$$\boldsymbol{f}(t) = \boldsymbol{\sigma}(\boldsymbol{W}_f\, \boldsymbol{z}(t)) \qquad \boldsymbol{g}(t) = \boldsymbol{\sigma}(\boldsymbol{W}_g\, \boldsymbol{z}(t))$$
$$\boldsymbol{h}(t) = \mathbf{tanh}(\boldsymbol{W}_h\, \boldsymbol{z}(t)) \qquad \boldsymbol{o}(t) = \boldsymbol{\sigma}(\boldsymbol{W}_o\, \boldsymbol{z}(t))$$

- Long-term memory update

$$\boldsymbol{c}(t) = \boldsymbol{f}(t) \otimes \boldsymbol{c}(t-1) + \boldsymbol{g}(t) \otimes \boldsymbol{h}(t)$$

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- We can train an LSTM by unwrapping it in time
- Note that it involves four dense layers with sigmoidal (or tanh) outputs
- This means that typically it is very slow to train
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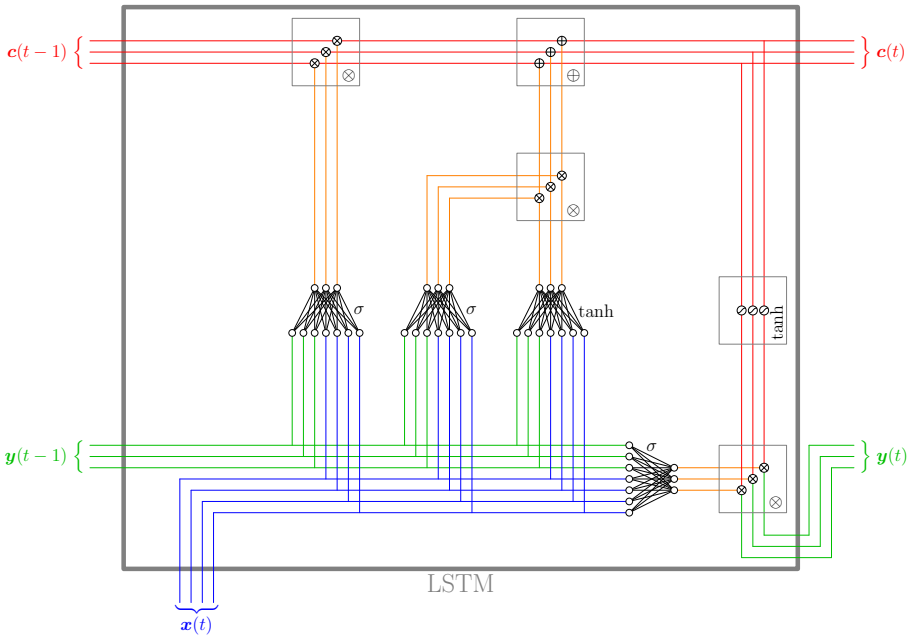
Outline

1. More on CNNs
2. Recurrent Networks
3. LSTM
4. **Word Embedding**
5. Applications



Working with Words

- Words often need some preprocessing (removing punctuation, removing stop words, stemming, etc)—depends on application
- Usually use a 1-hot vector representation of words
- Document can be represented by a **Bag of Words** representation which is a weighted sum of the 1-hot vectors
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aardvark
abacus
acrobat
Adam
...
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zebra

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Word Embeddings

- For LSTMs or GRUs we need a lower dimensional representation than the 1-hot vectors
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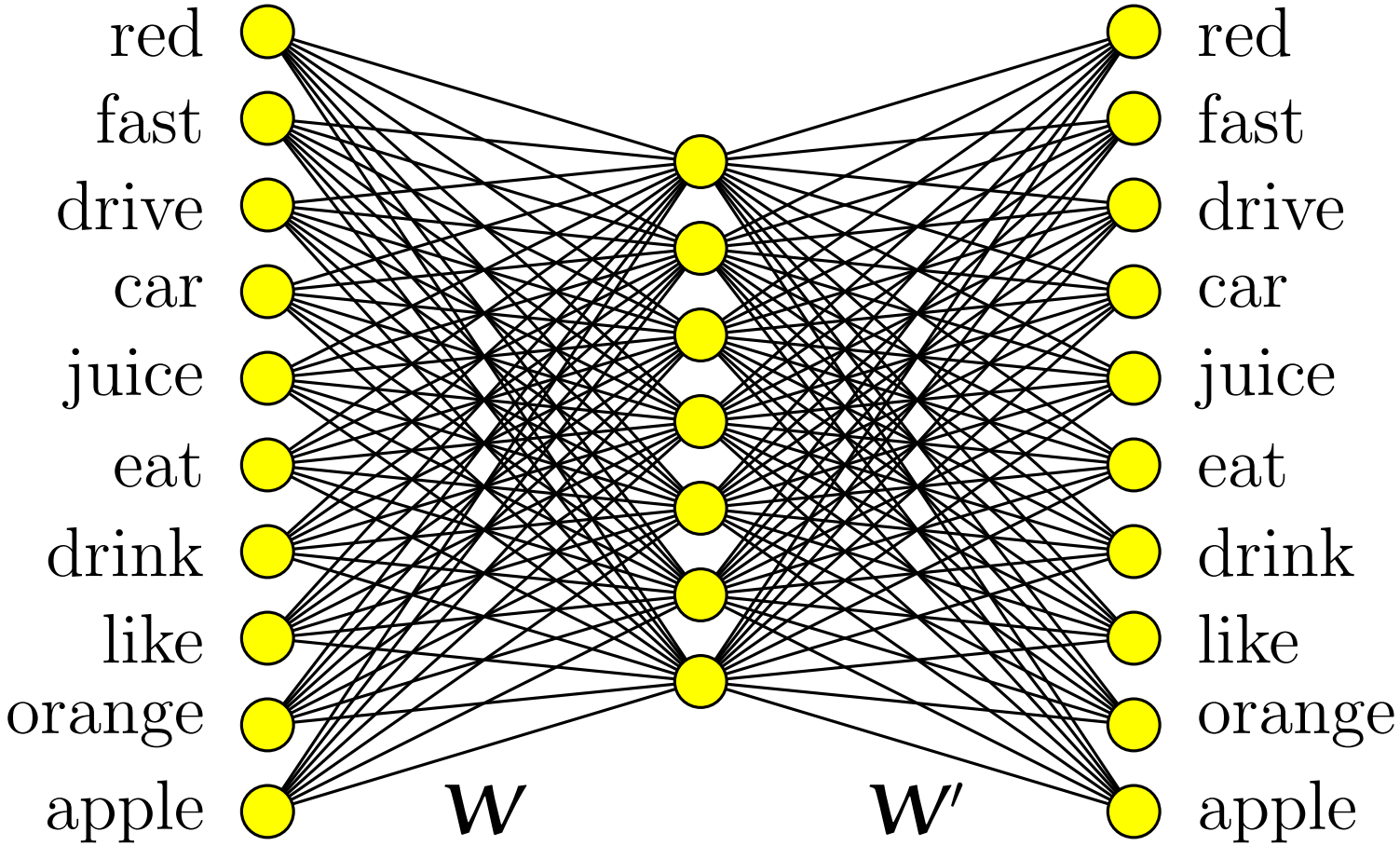
Word2Vec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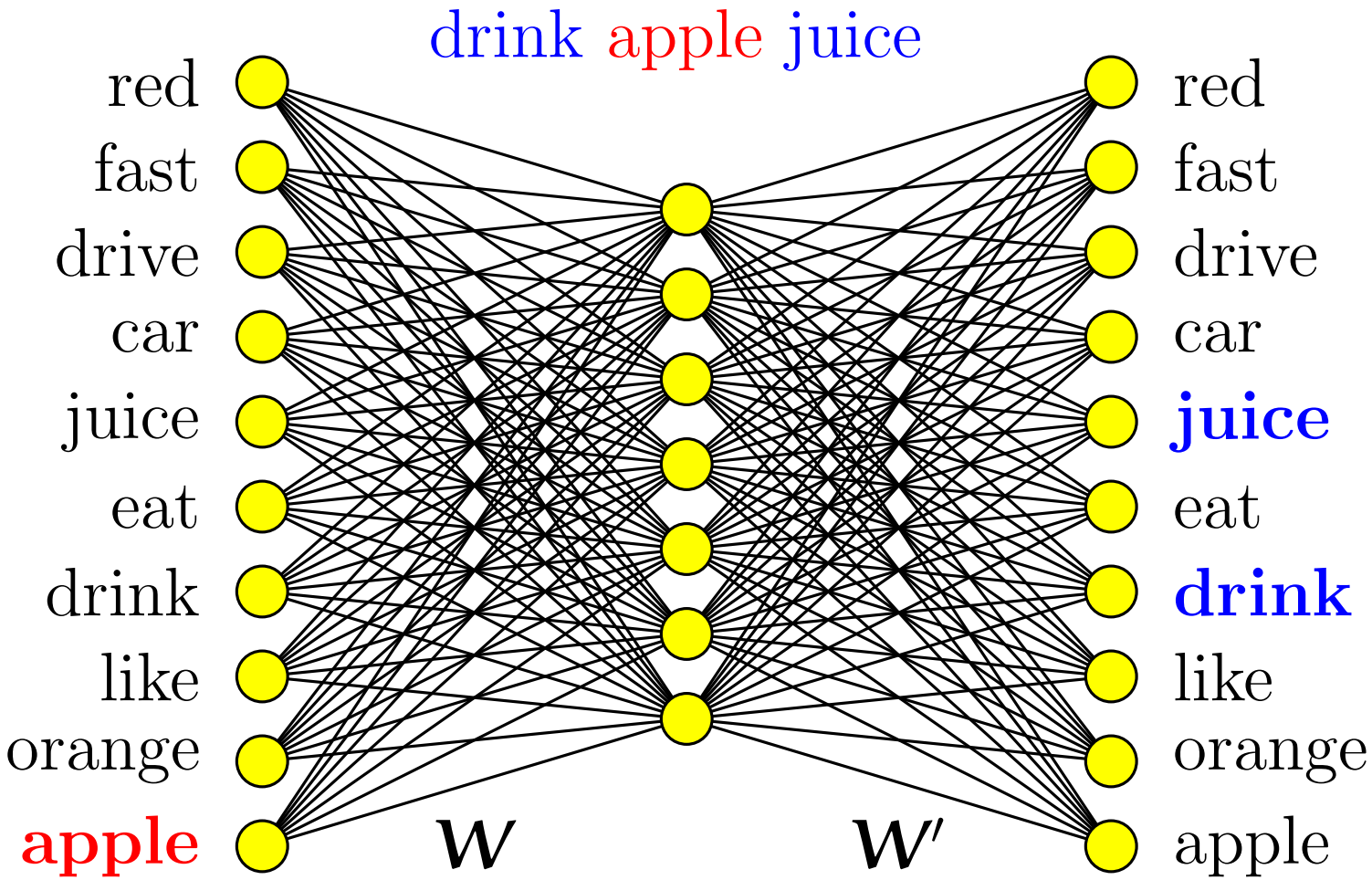
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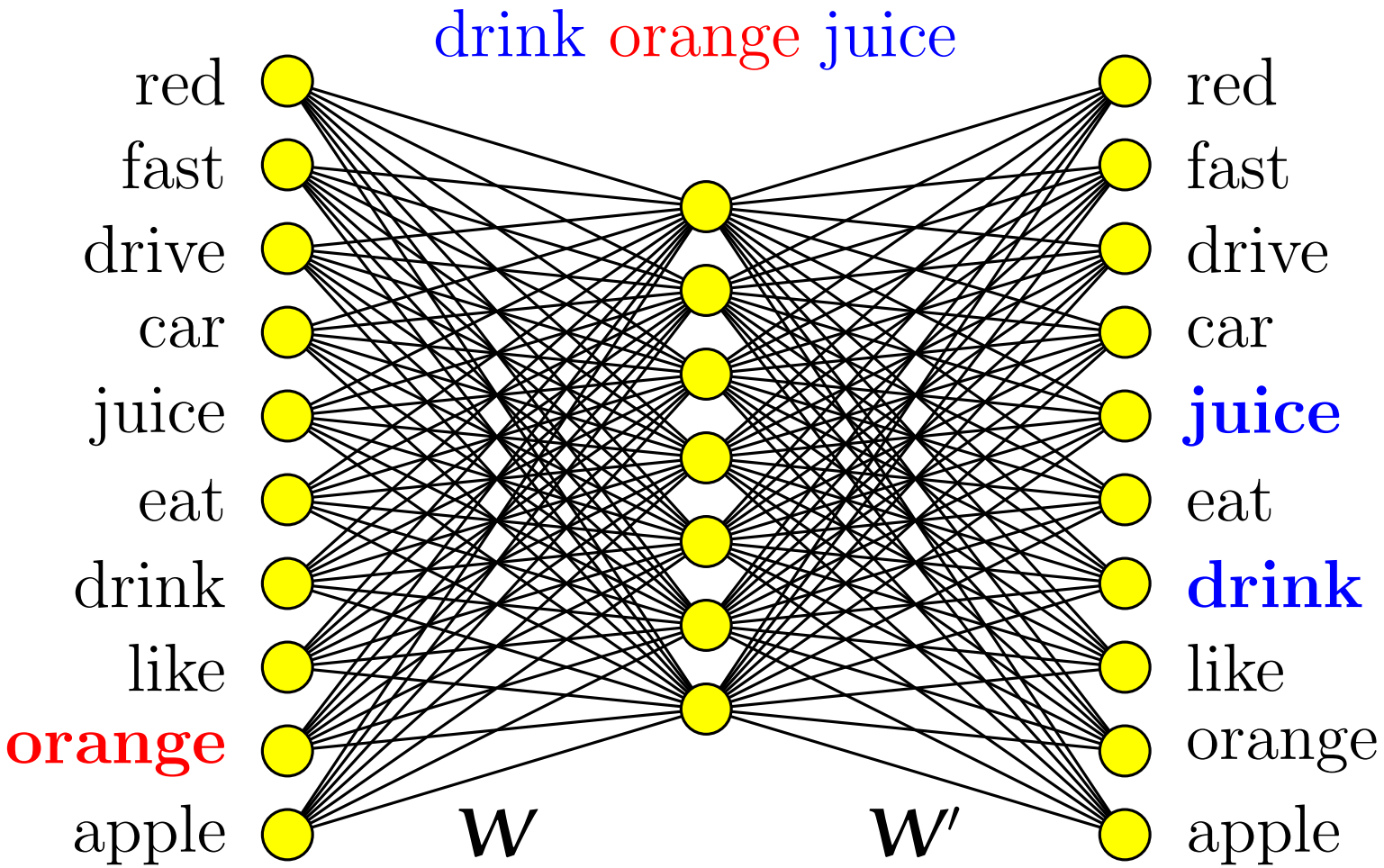
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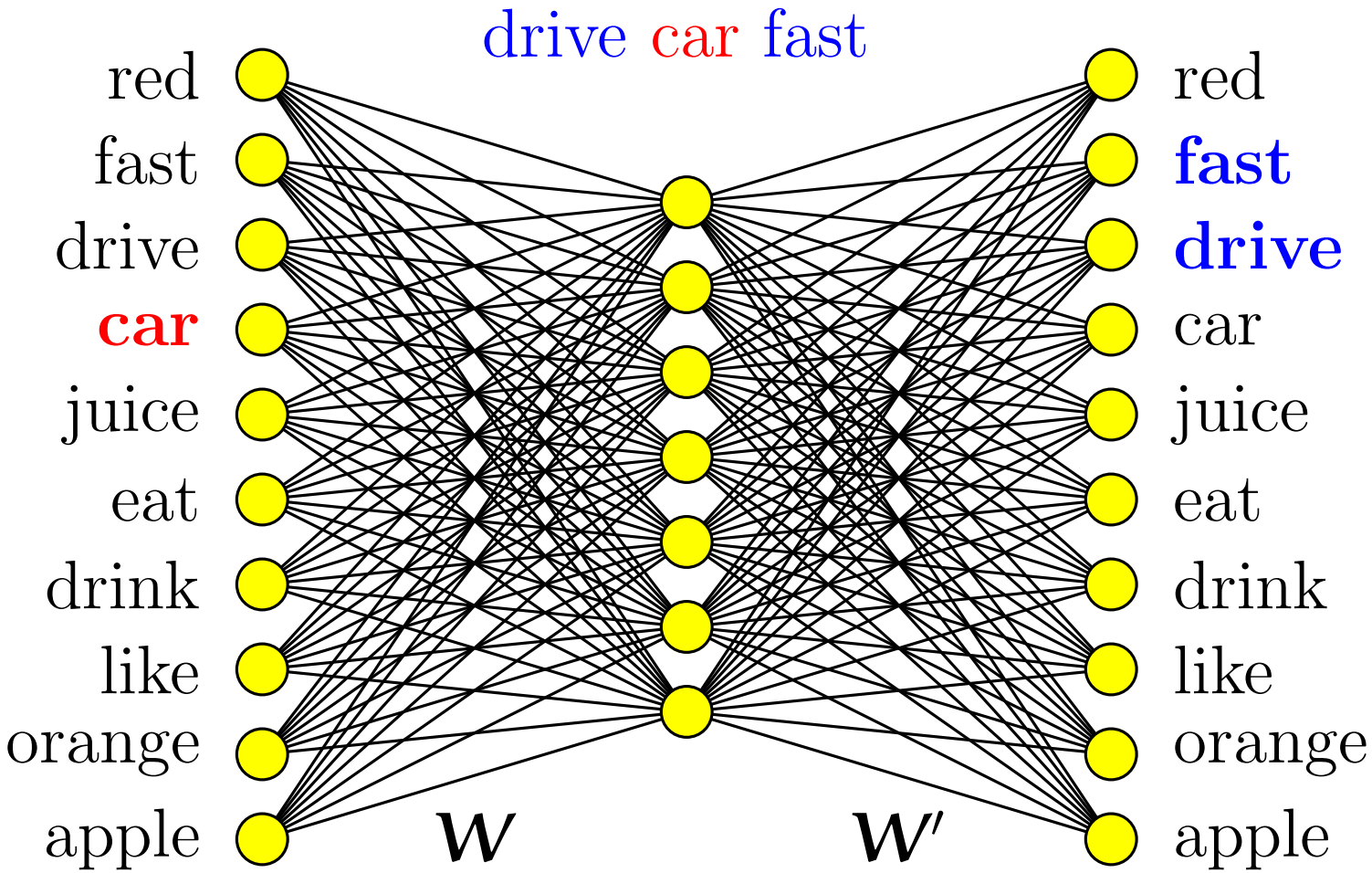
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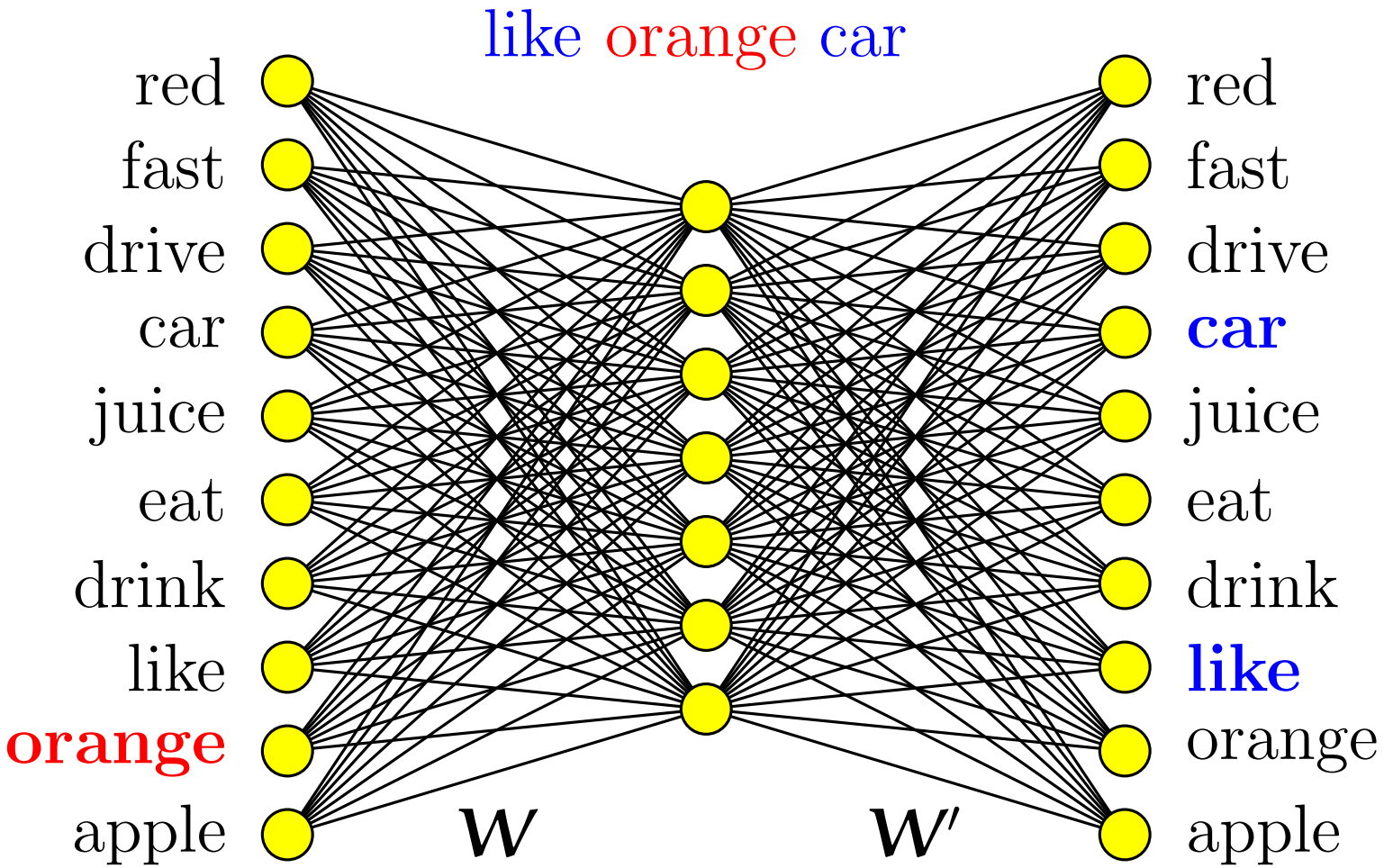
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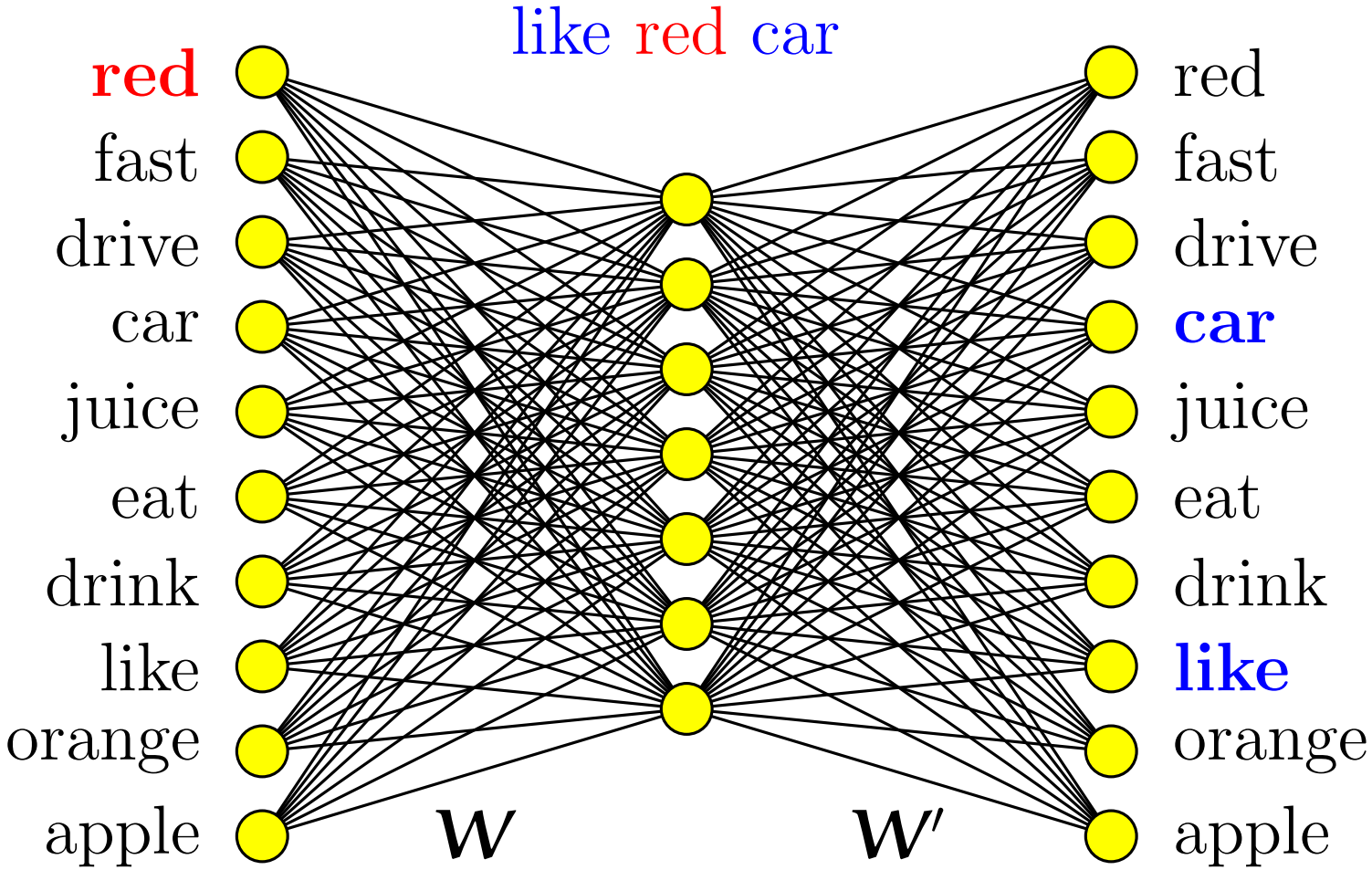
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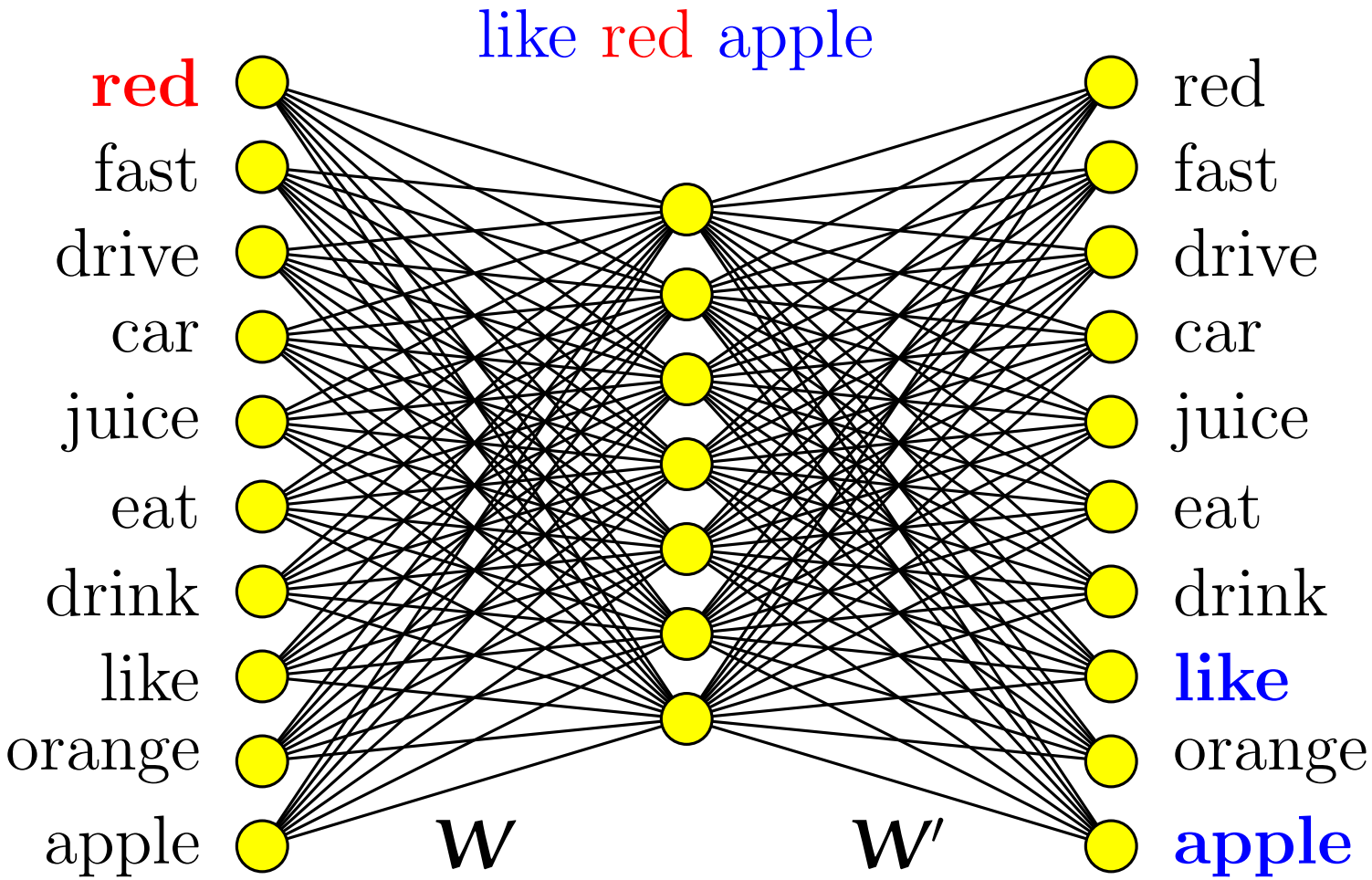
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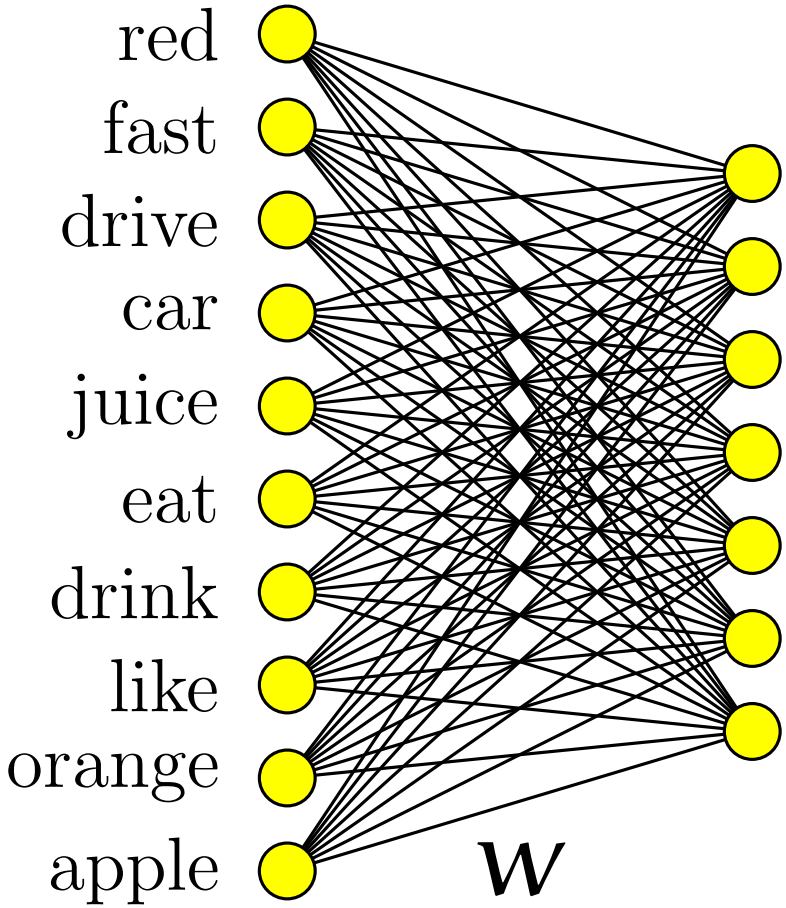
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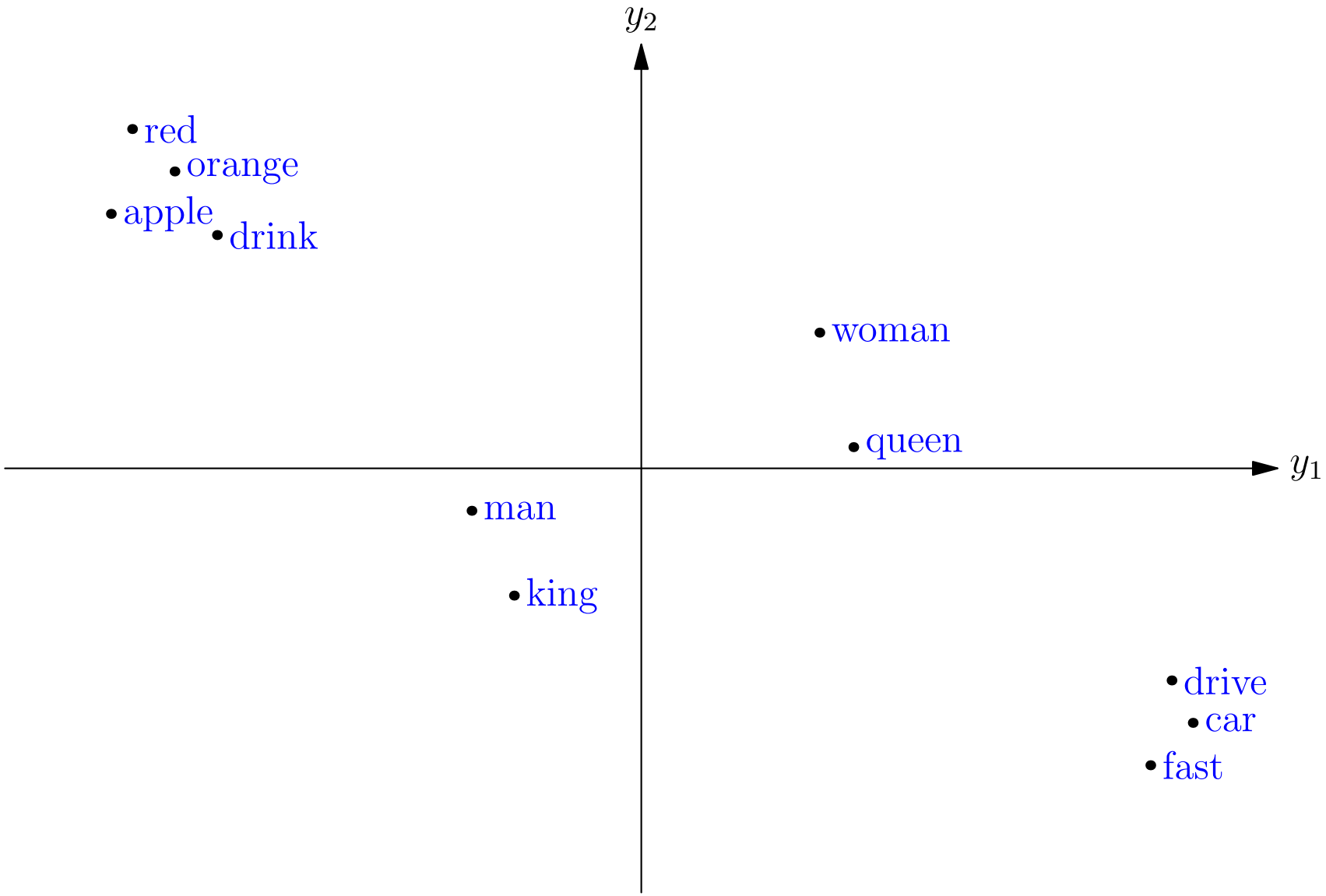

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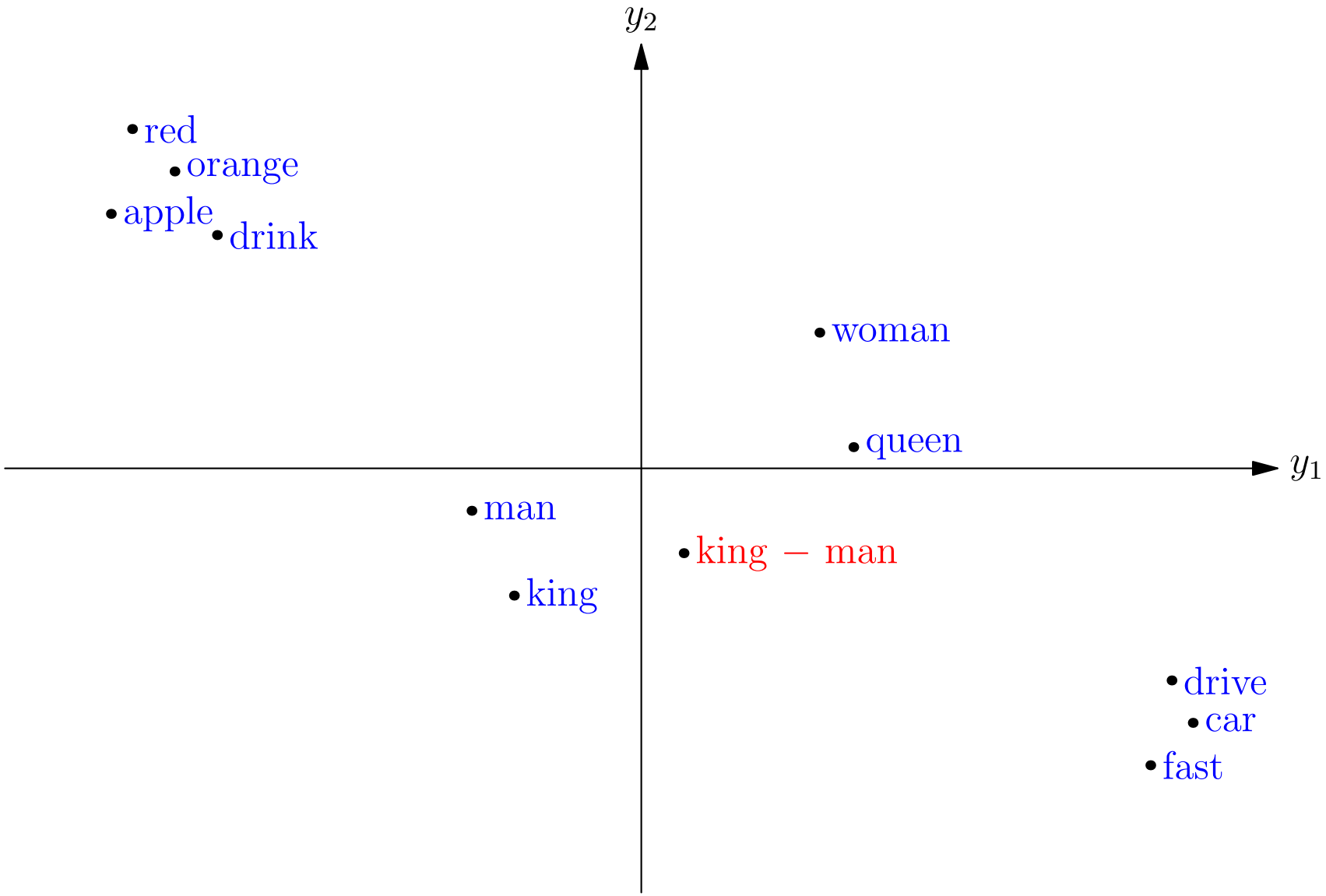

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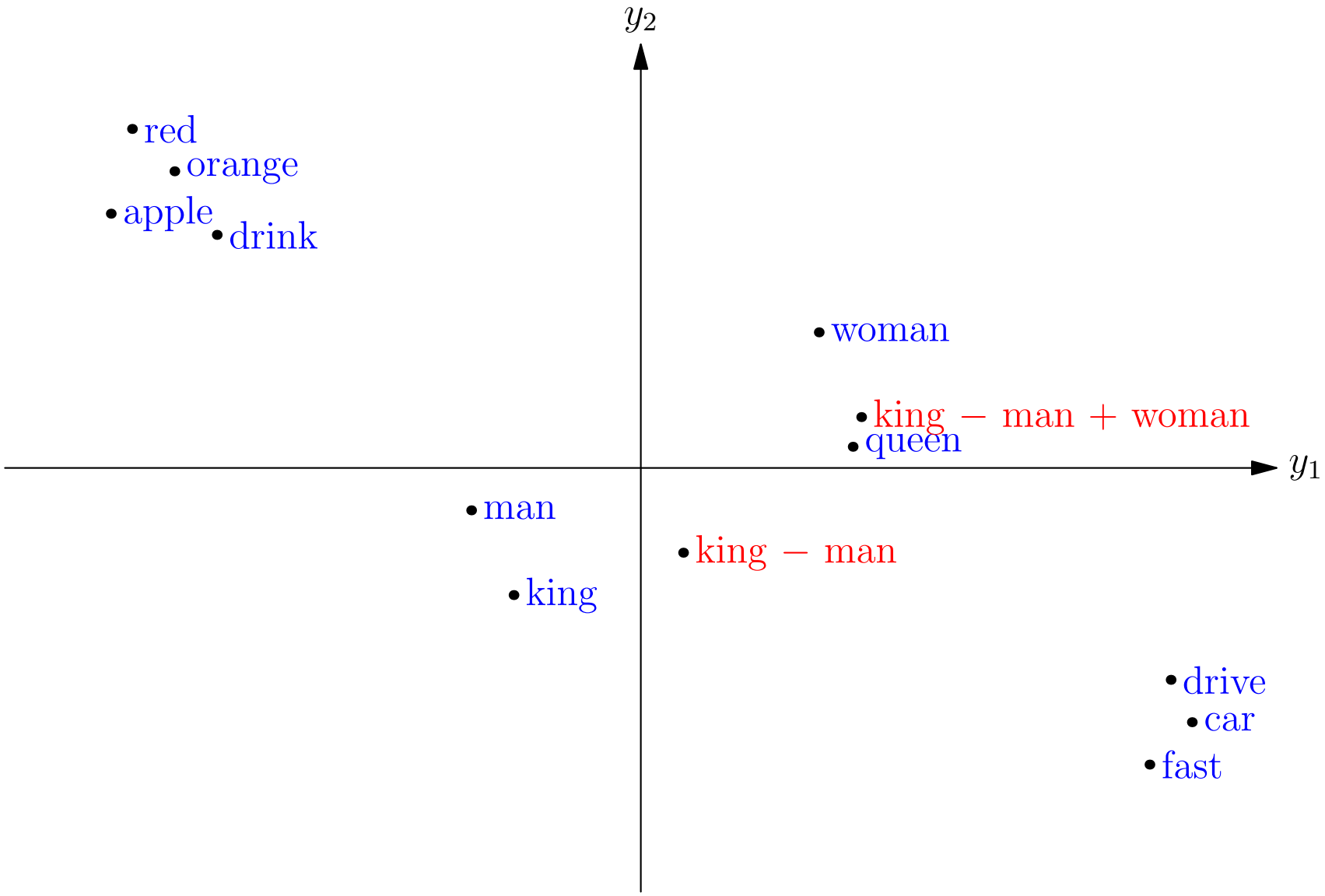

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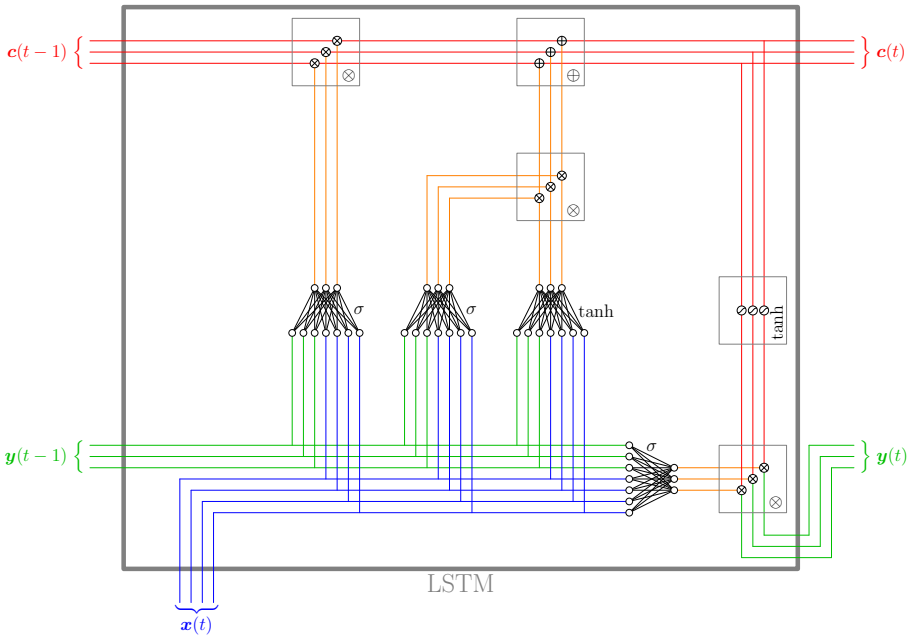

Sequence-to-Sequence

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- This has been used in various applications such as generating answers to questions, chatbots, etc.
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- Used a database with 12M sentences
- Used 160 000 English words and 80 000 French words

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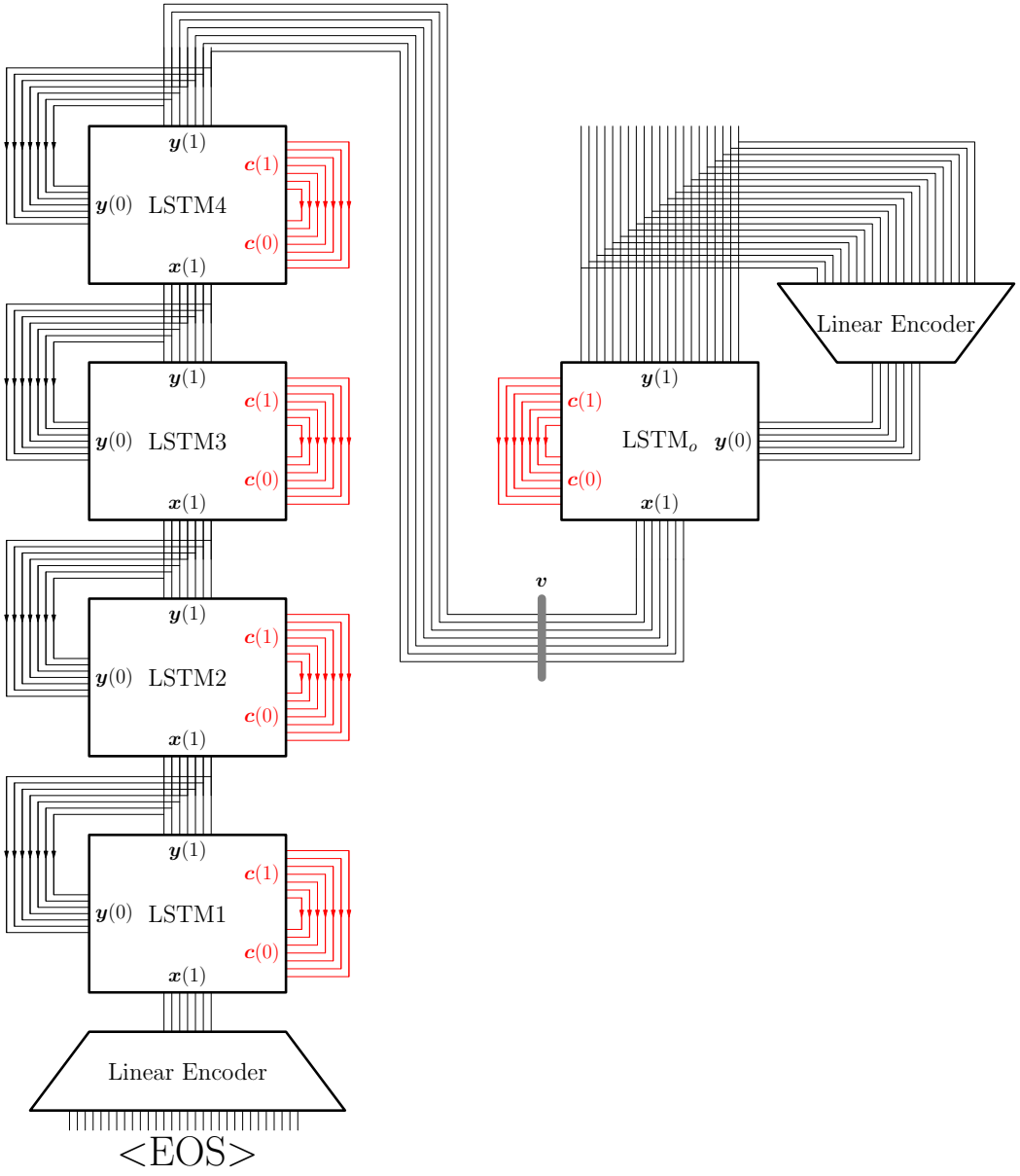
How Are You?

- Used 4 layers of LSTM
- Internal vectors are of length 1000
- English put in backwards
- <EOS> token used to mark end of sentence
- All information stored in a static vector $\boldsymbol{v}$



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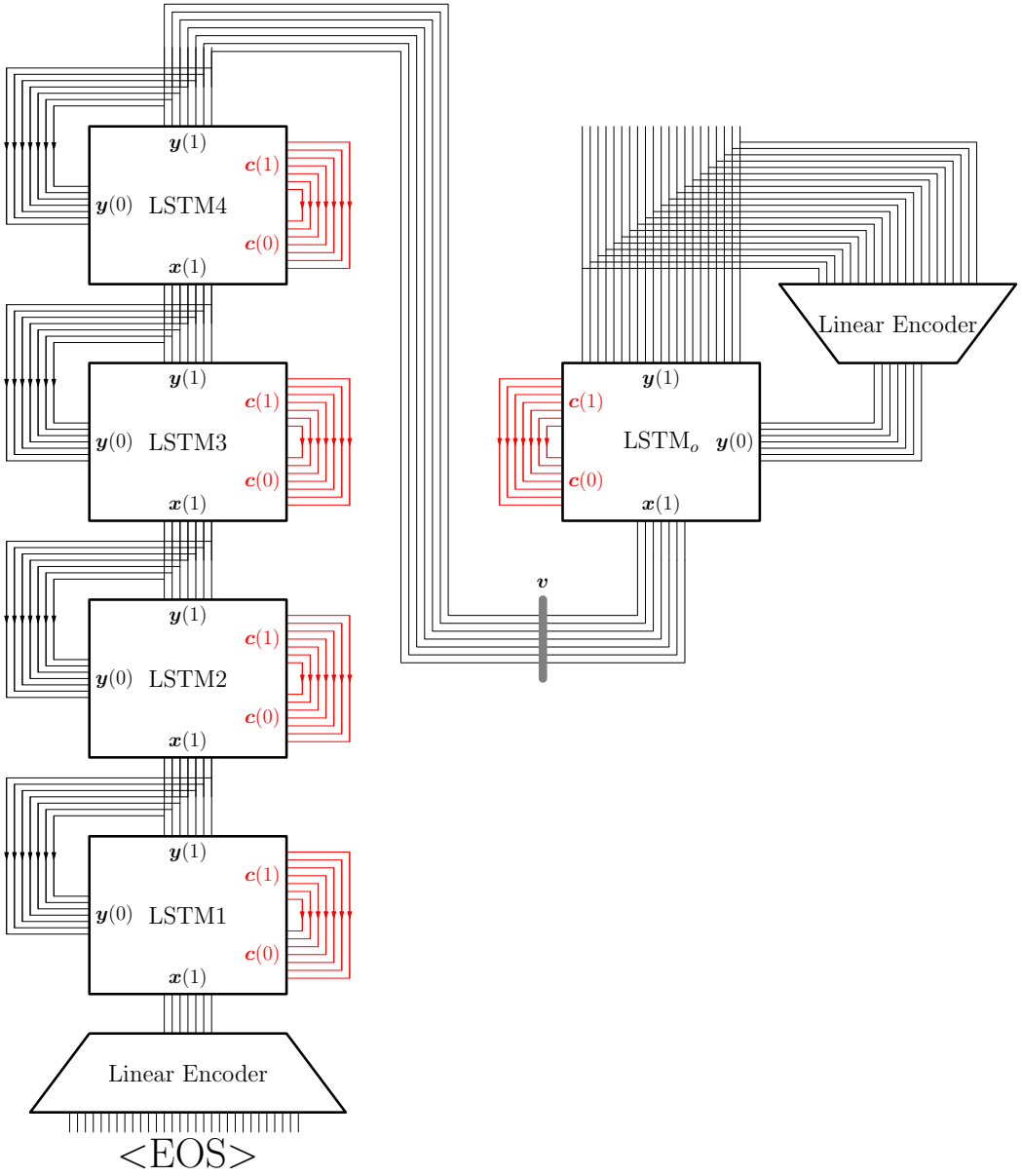

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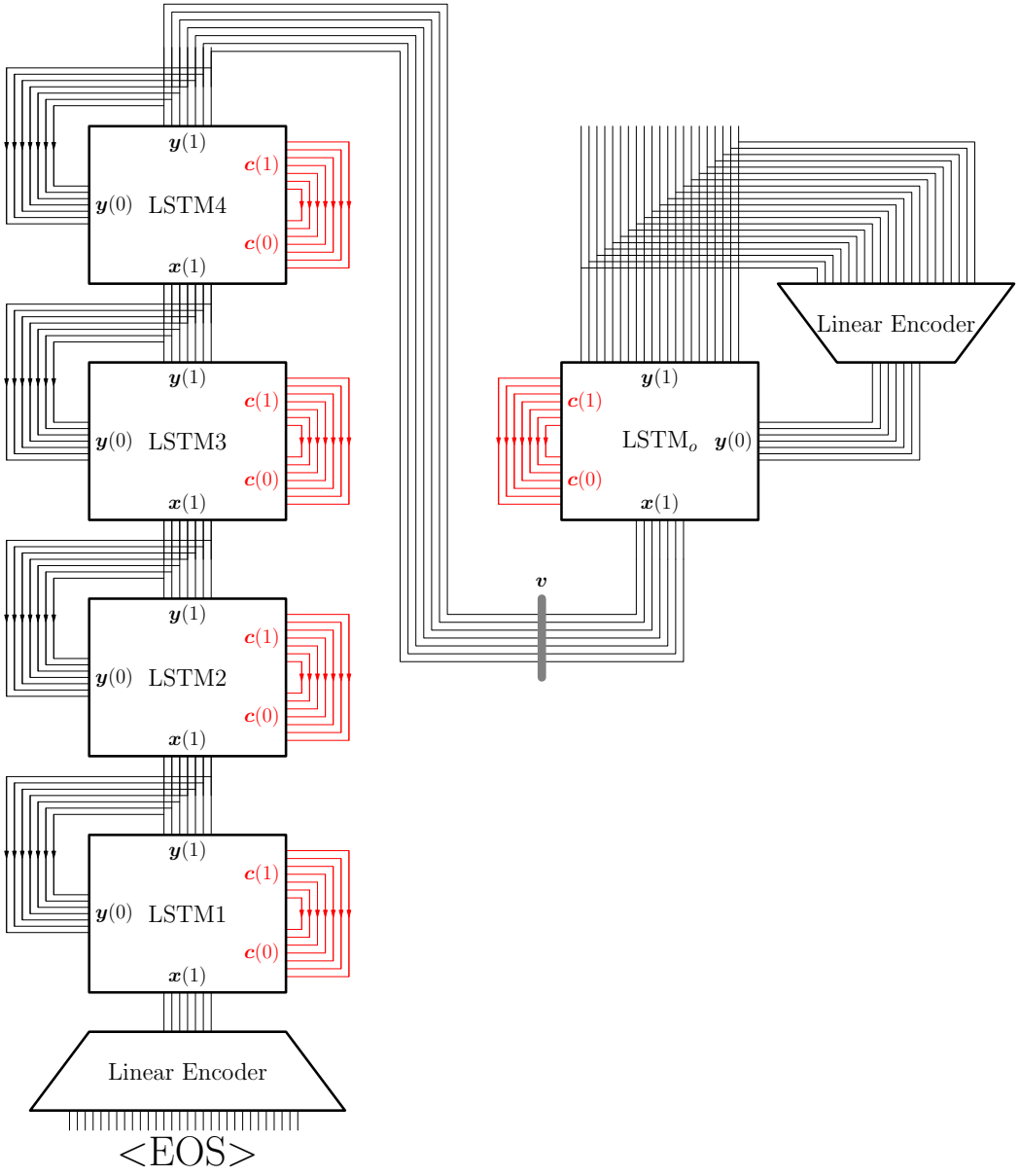

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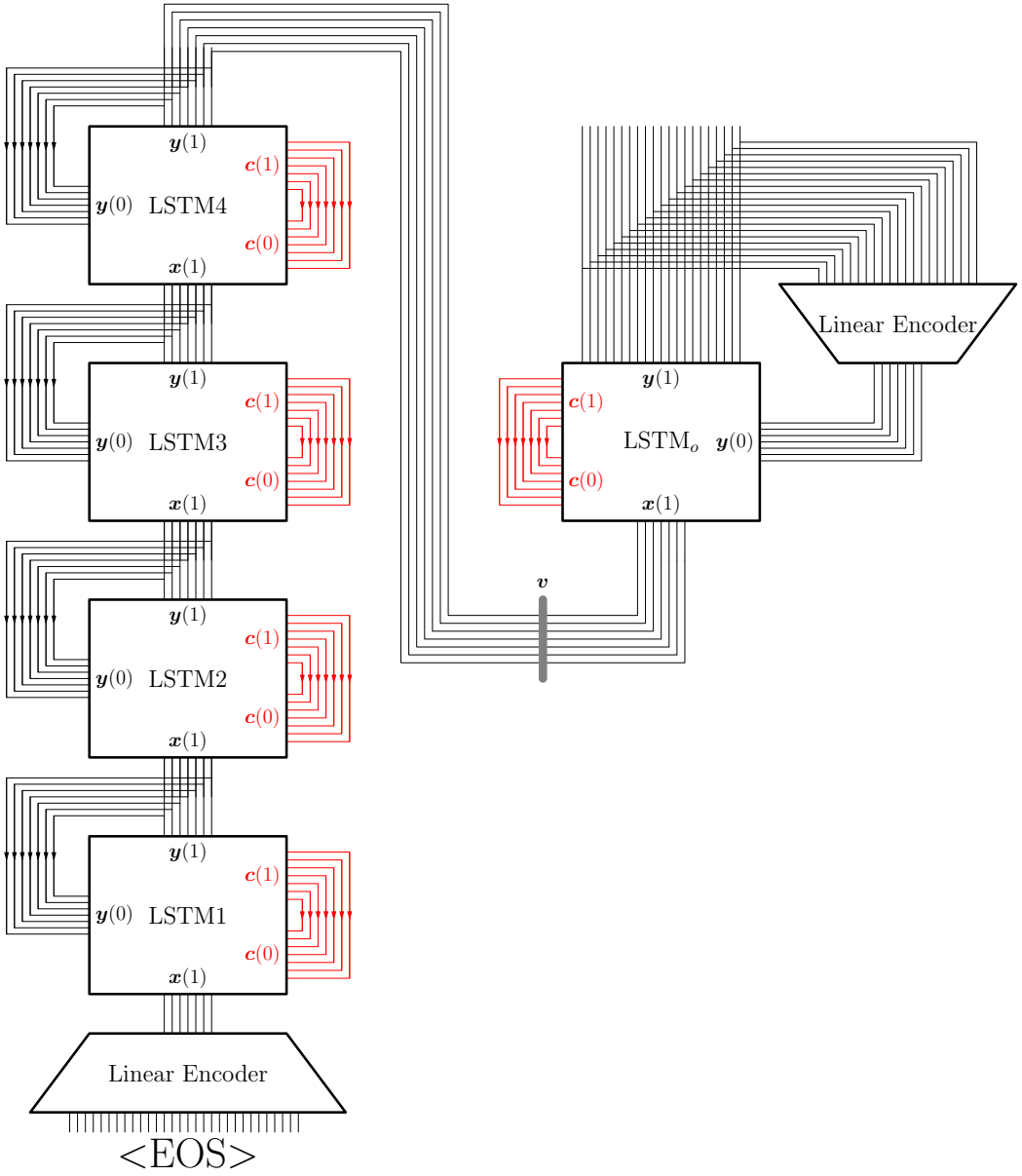

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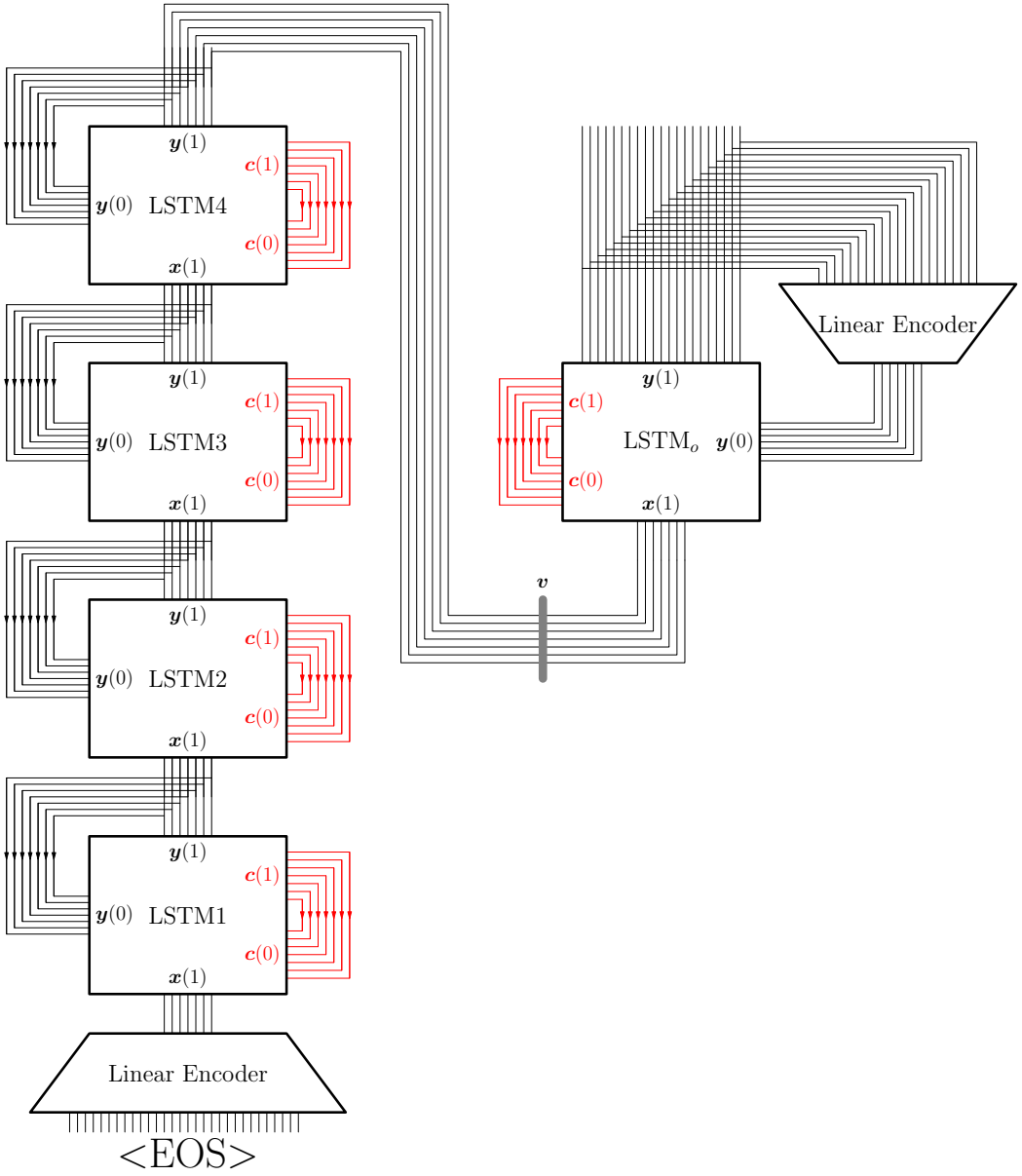

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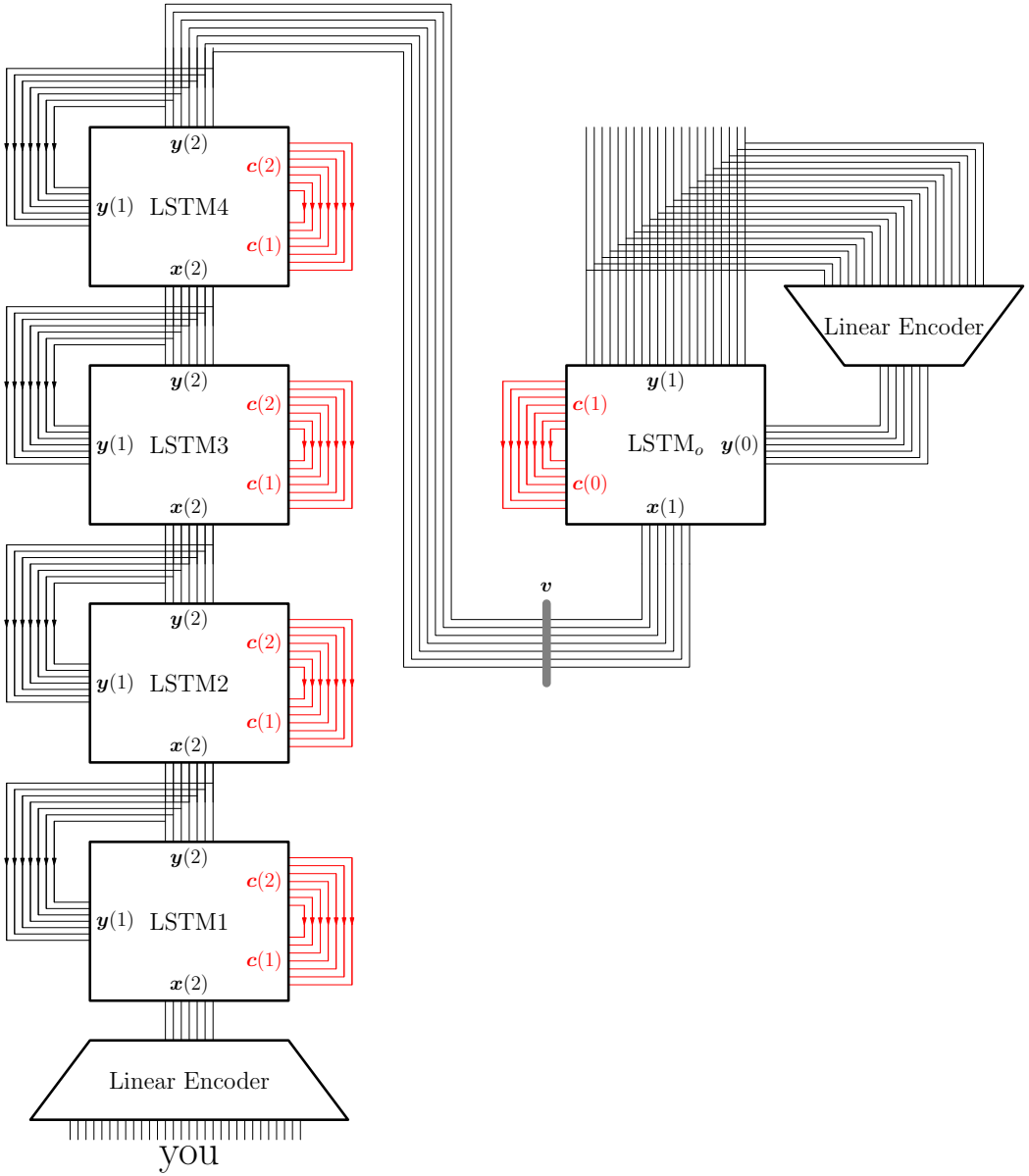

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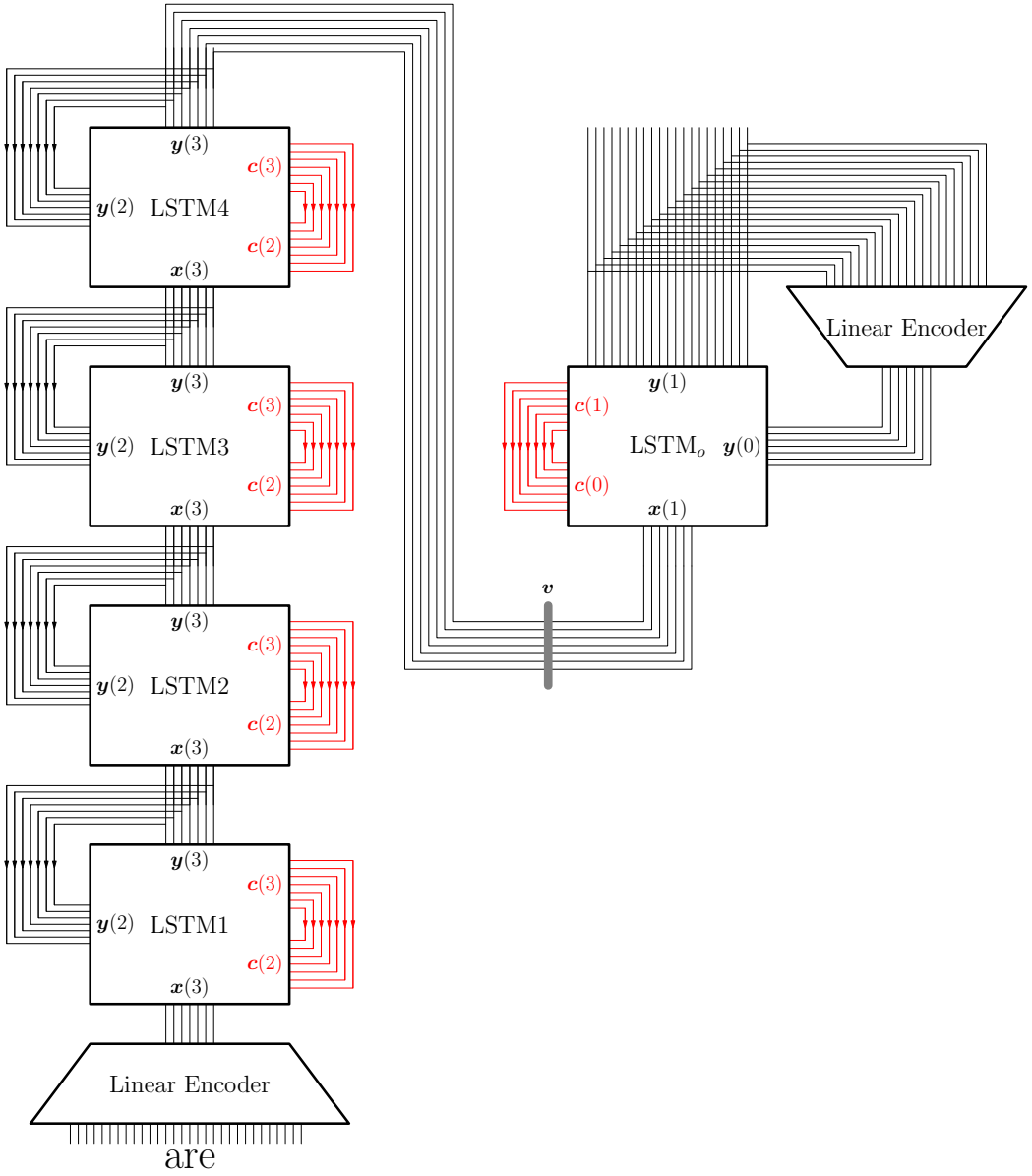

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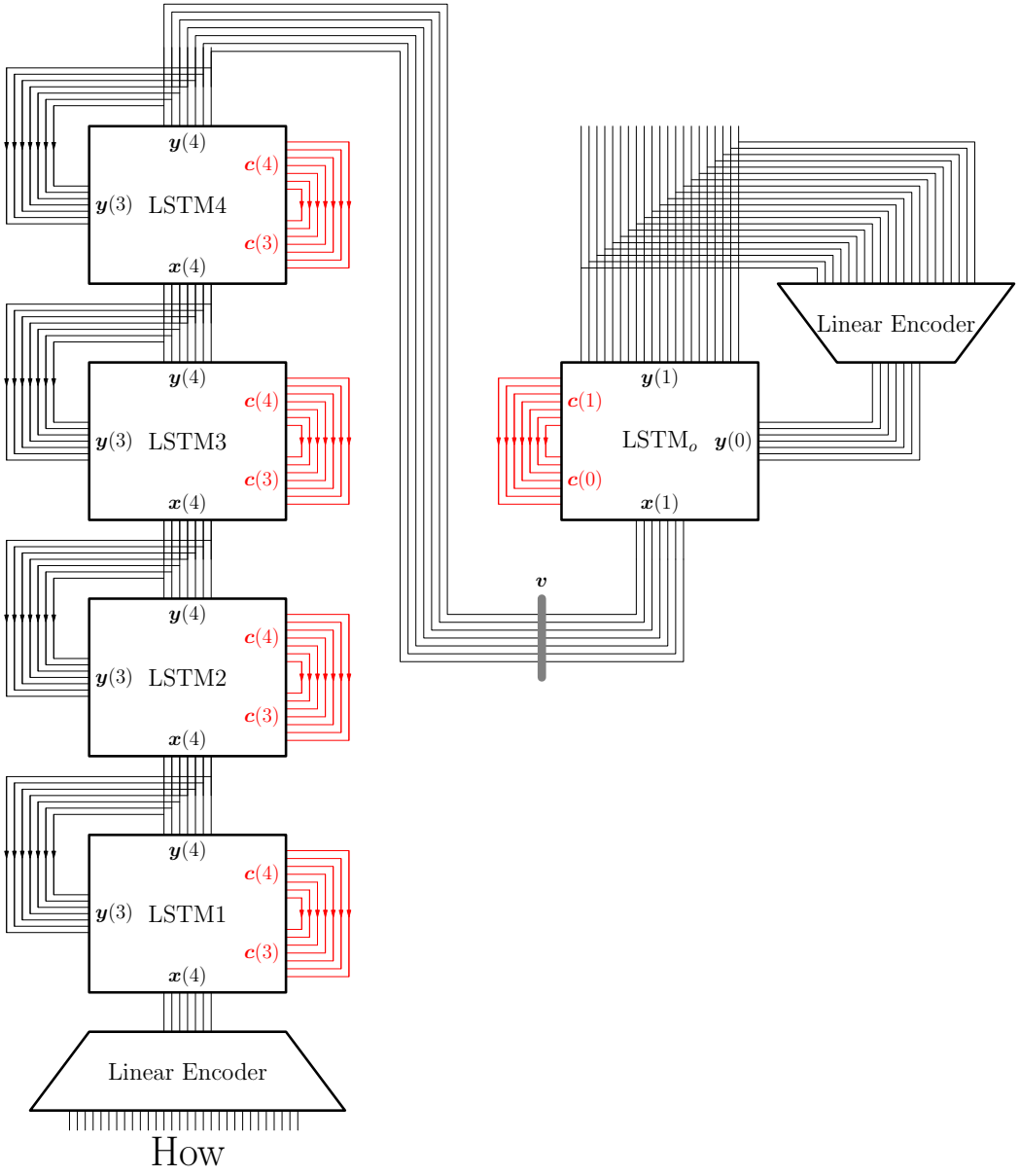

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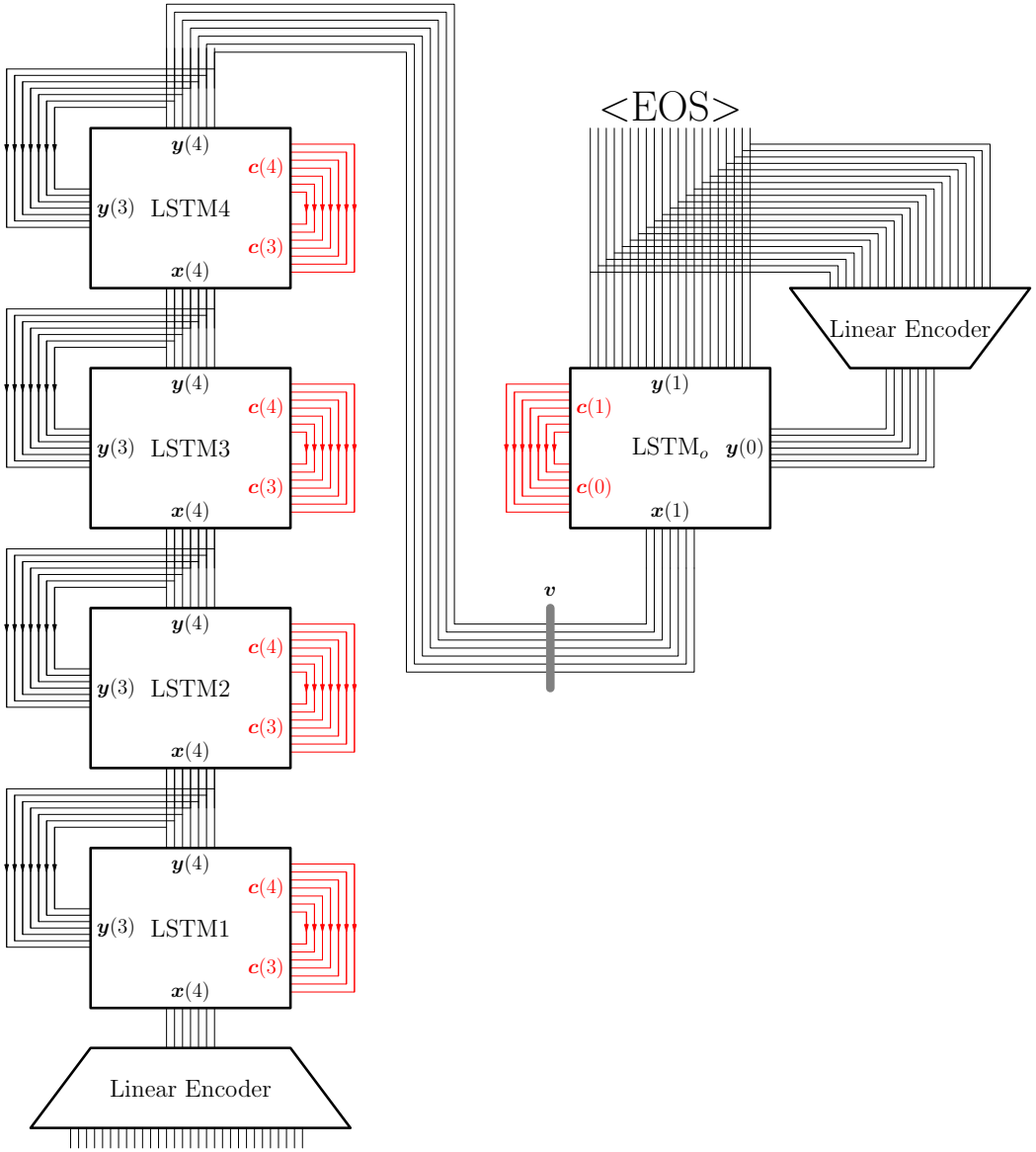

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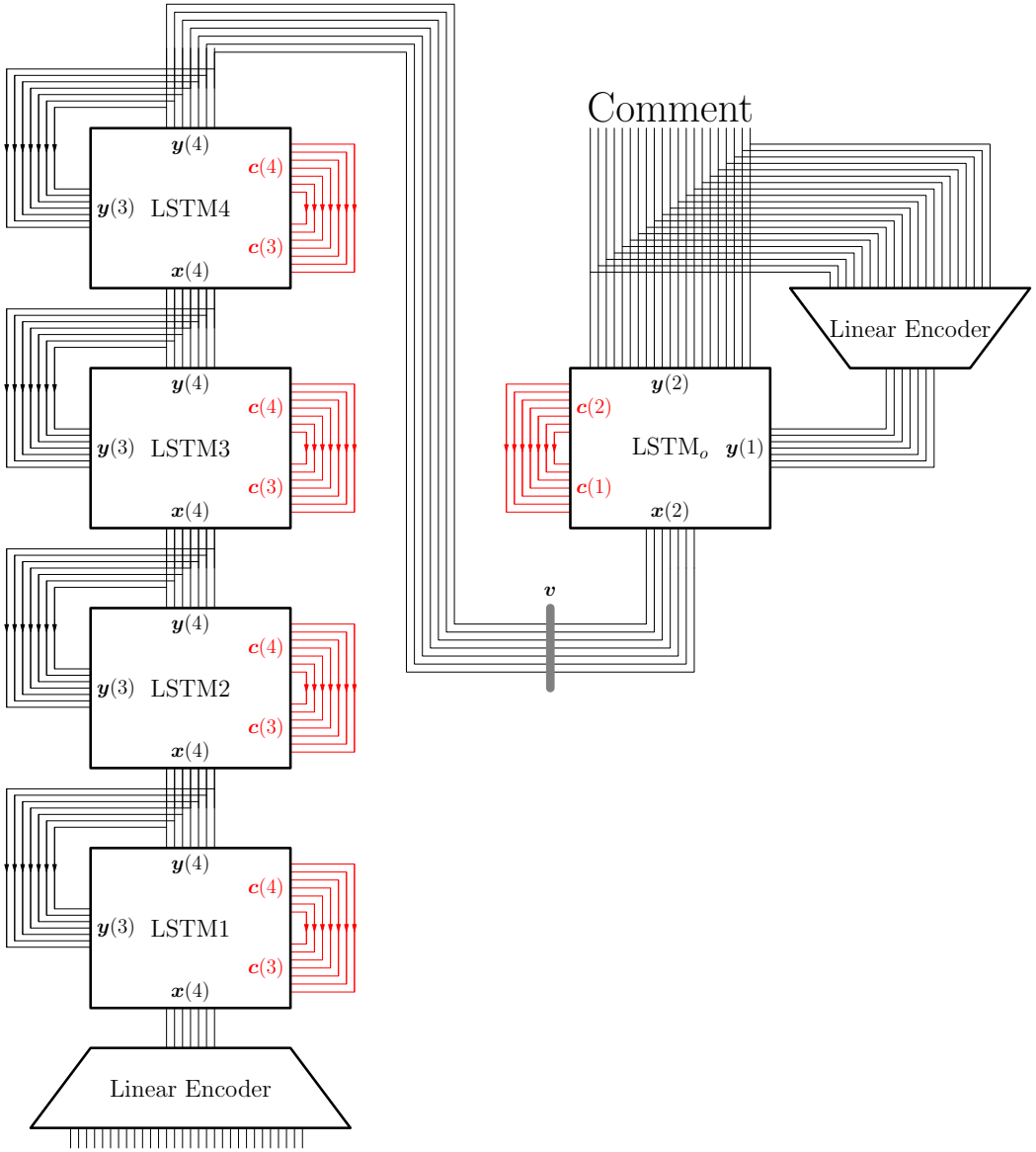

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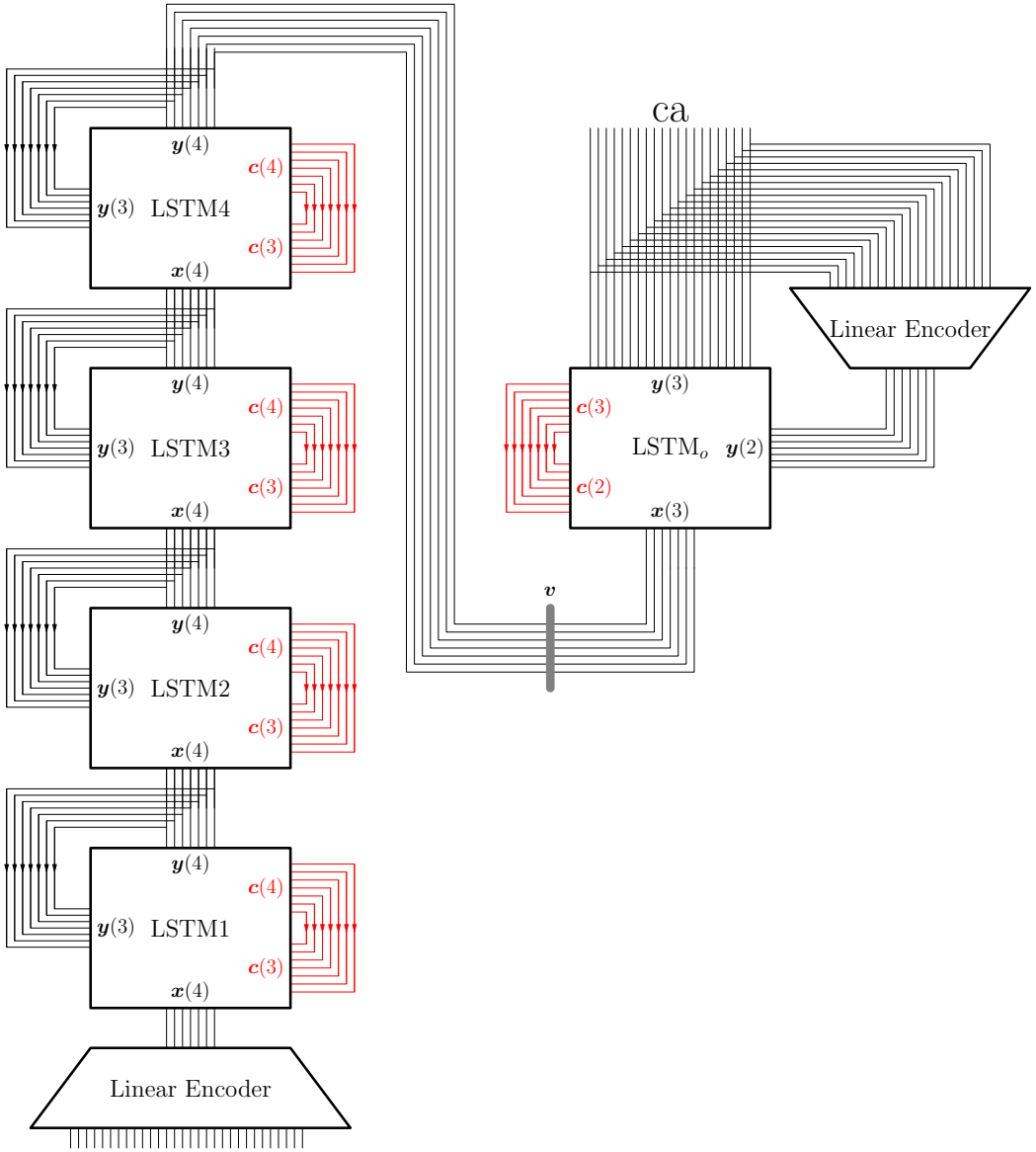

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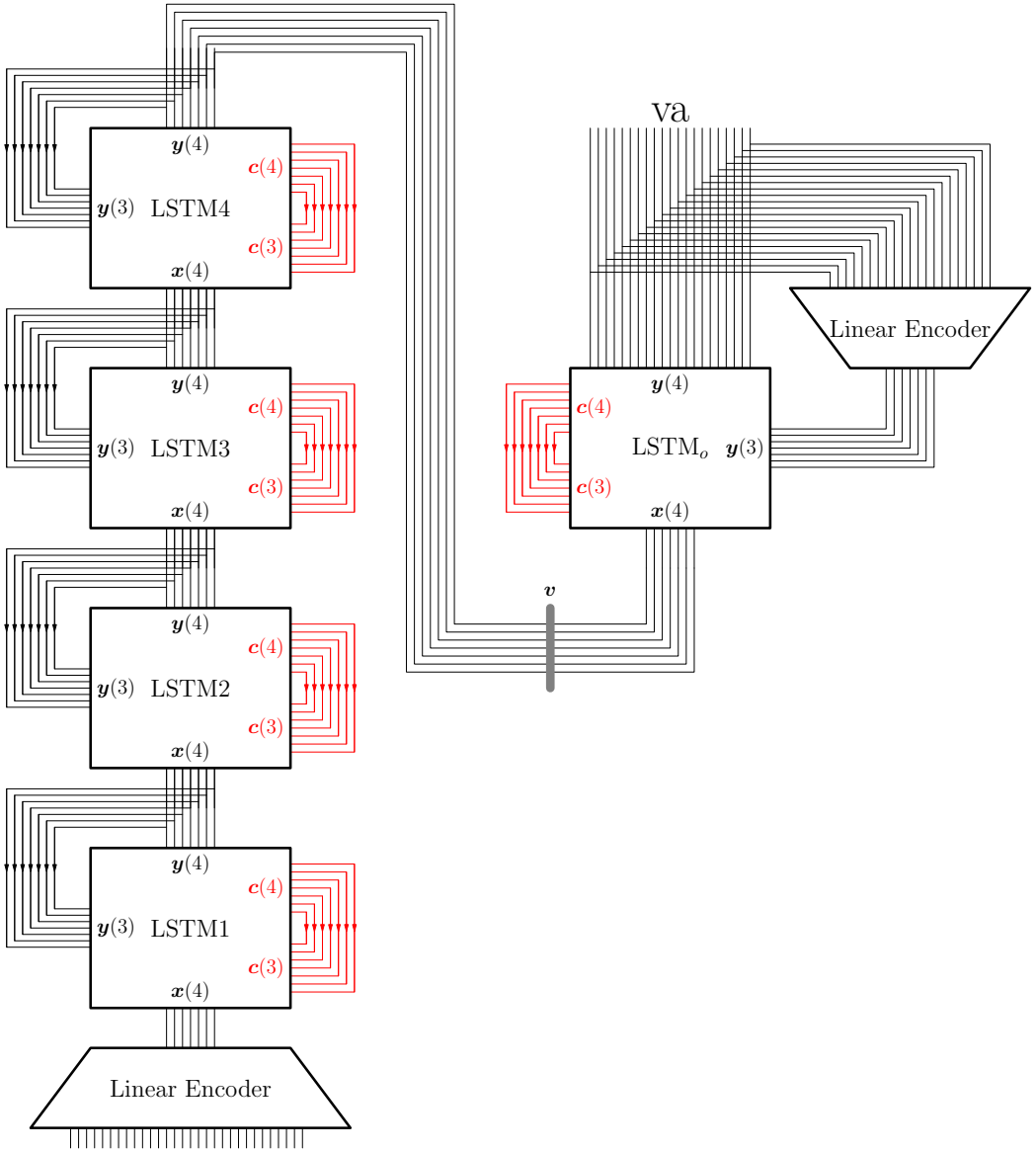

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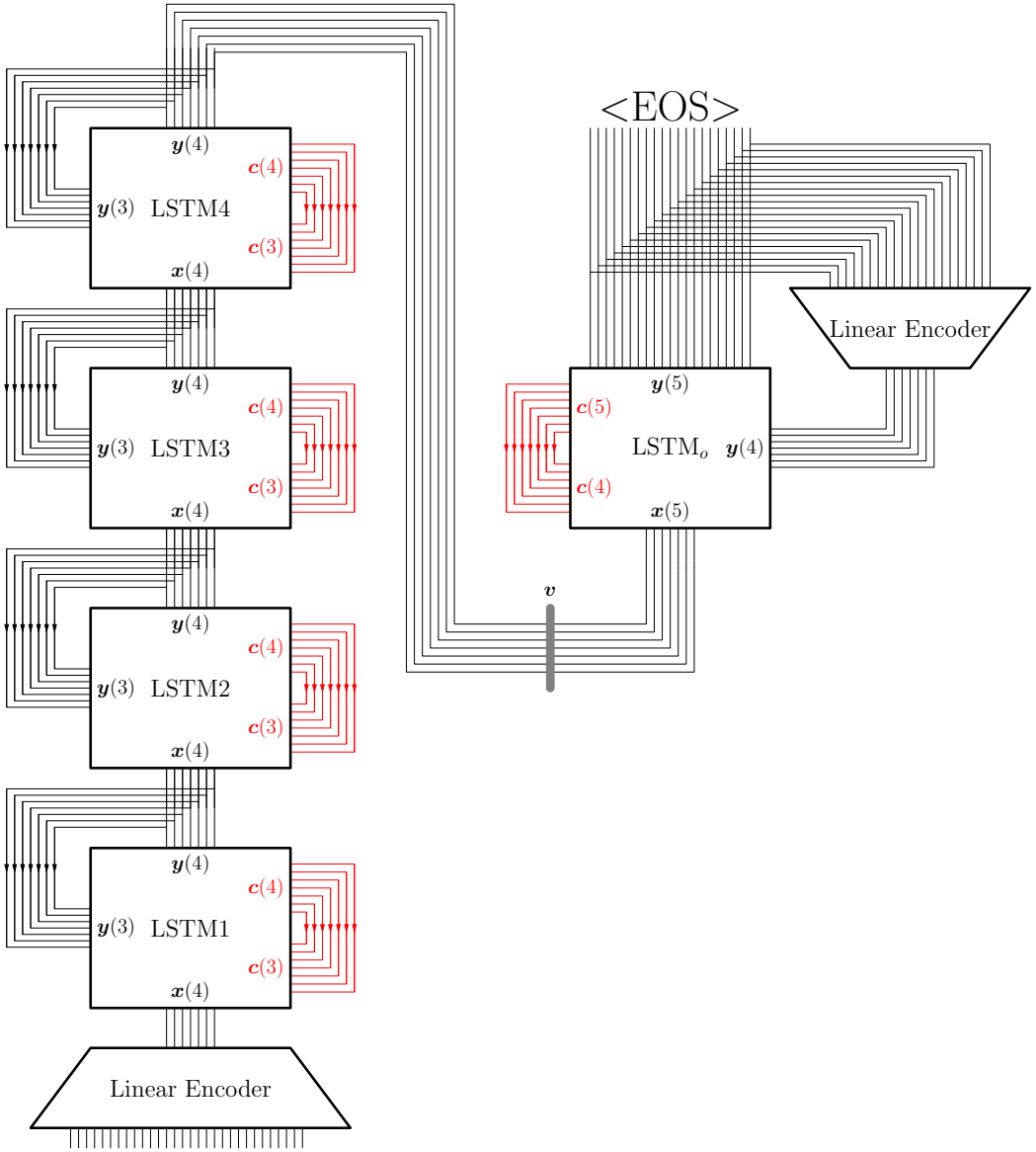

Training Deep LSTM

- The English is put in backwards so that corresponding words in English and French are next to each other
- This speeds up learning
- Nevertheless they only managed 7.5 training epochs
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- To achieve near state of art performance use an ensemble of 5 LSTMs

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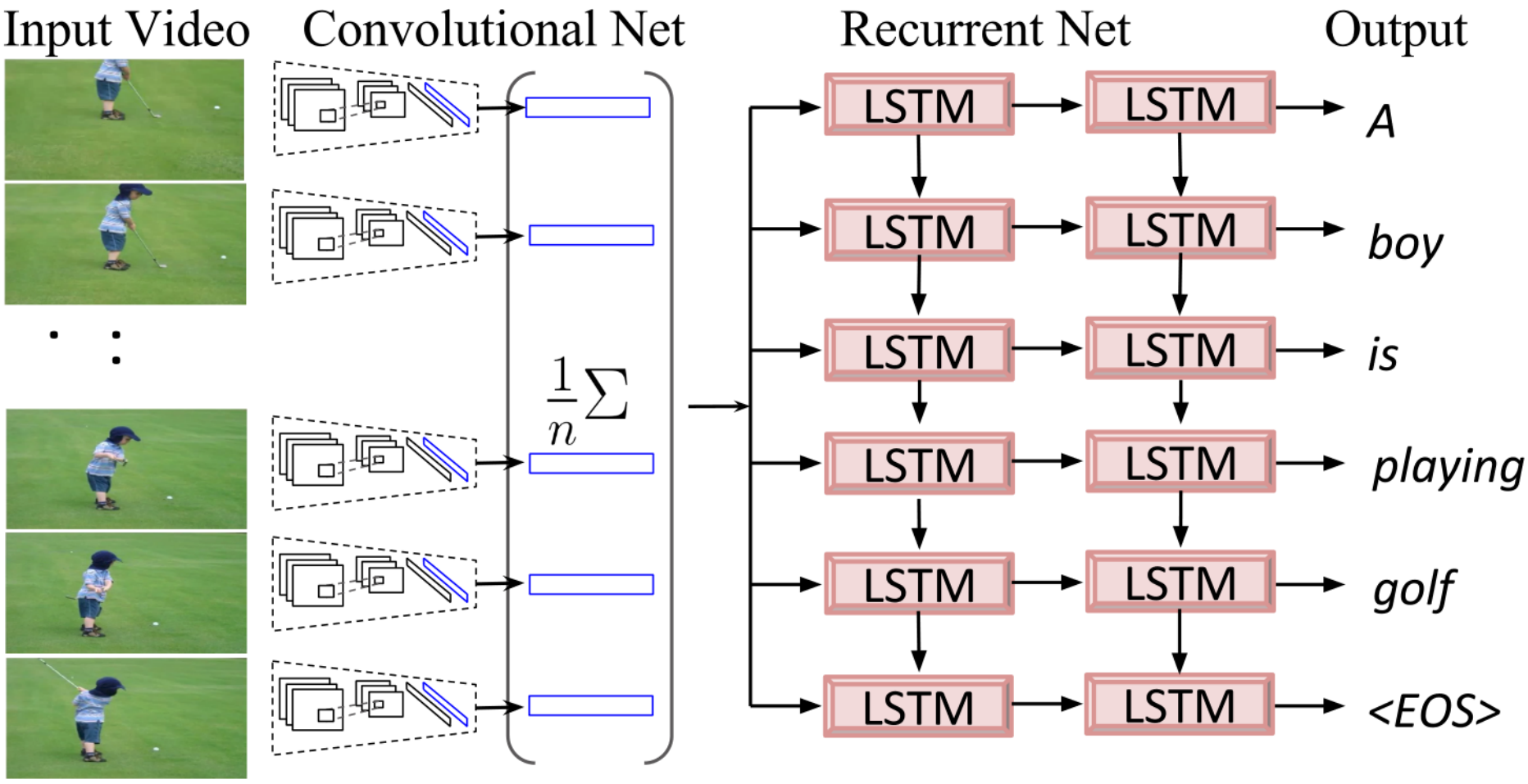
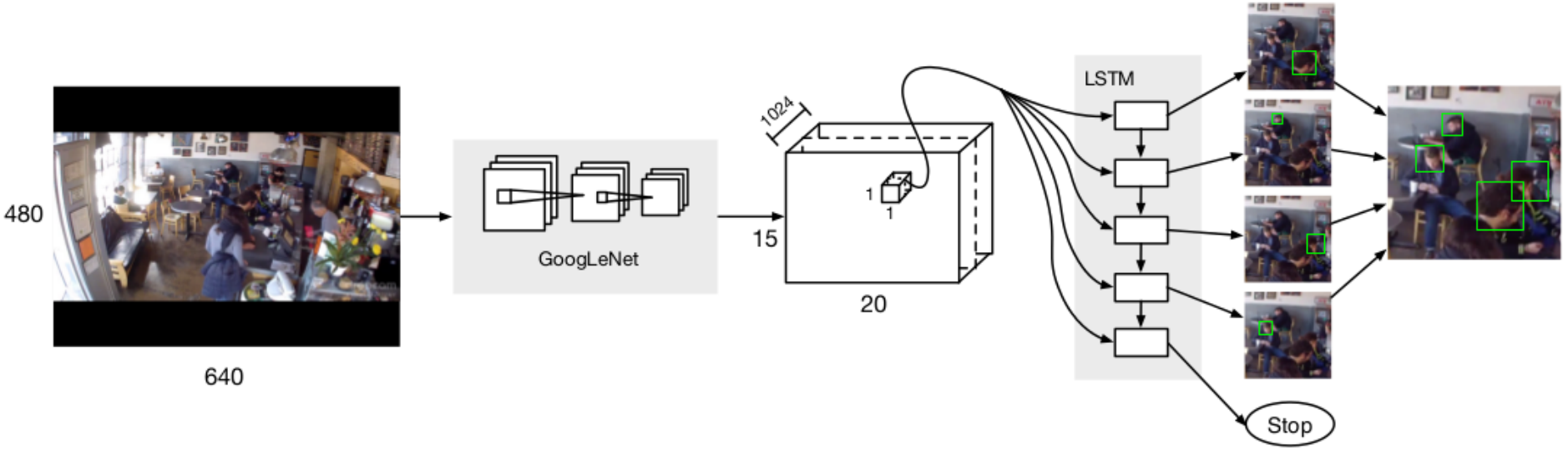
CNN and LSTM


Input Video
Convolutional Net
Recurrent Net
Output
$\frac{1}{n}\sum$
LSTM
A
boy
is
playing
golf
<EOS>

End-to-End People Detection



Conclusions

- LSTMs have become a major component of "deep" learning
- They allow a richer set of functionality than the traditional feed-forward networks
- Because the involve dense networks they are usually very slow to train
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