

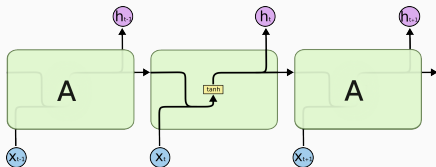
# Long Short Term Memory Networks

Recurrent Neural Networks

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# LSTM vs RNN



In an **RNN** there are multiple inputs. Inside each cell the input is processed by a tanh gate and the produced output is called a hidden state. The network is able to *remember* relationships between inputs by sharing the hidden state between cells.

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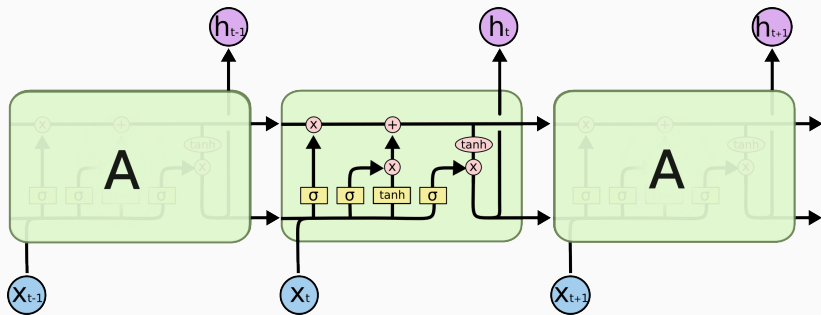
<sup>1</sup> All nice figures were taken from Christopher Olah's Understanding LSTM Networks, August, 2015.  
[http : //colah.github.io/posts/2015 - 08 - Understanding - LSTMs/](http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

## So why do we like LSTMs?

- Gradient doesn't vanish

- They have a longer term memory

# How do LSTMs work?



There are two states inside each cell that are passed on through time, the cell state and the hidden state. They are what allow long and short term memory. As opposed to RNNs, what we forget of the previous information is not completely lost we are keeping it in any of the two internal states.

## How do LSTMs work?

There are 3 internal gates that decide what information from the previous cell and the input is passed on to the next cell and outputted.

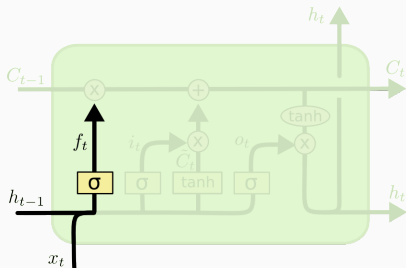
- i: input gate layer.

- f: forget gate layer.

- o: output gate layer.

# How do LSTMs work?

**Forget gate layer** This layer looks at the previous hidden state ( $h_{t-1}$ ) and the current input ( $x_t$ ) and decides whether or not keep the past cell state ( $C_{t-1}$ ). This is done by using the sigma operation, taking the output 0 to forget and 1 to remember.

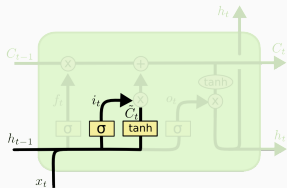


$$f_t = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f)$$

**Forget gates could lead to the gradient vanishing**, to avoid killing it too soon in the learning process their **bias is initialized positive**. Thus allowing the forget gates to be active later in the training.

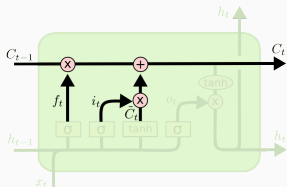
# How do LSTMs work?

**Input gate layer** This layer decides what new information  $x_t$  is important to keep in  $C_t$ , taking into account what happened before  $h_{t-1}$ .  $C_t$  is updated by using the i gate and the decision taken in the f gate.



$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

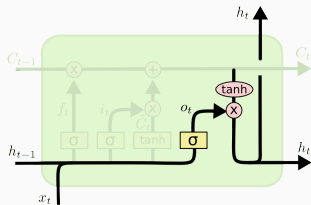


$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Why are  $\tilde{C}_t$  and  $i_t$  so similar? We are learning independently what new information we want to keep and whether or not we want to keep it.

# How do LSTMs work?

**Output gate layer** This gate coupled with  $C_t$  defines the hidden state  $h_t$  which is what is later interpreted as the networks output.



$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$