RNN and LSTM

(Oct 12, 2016)

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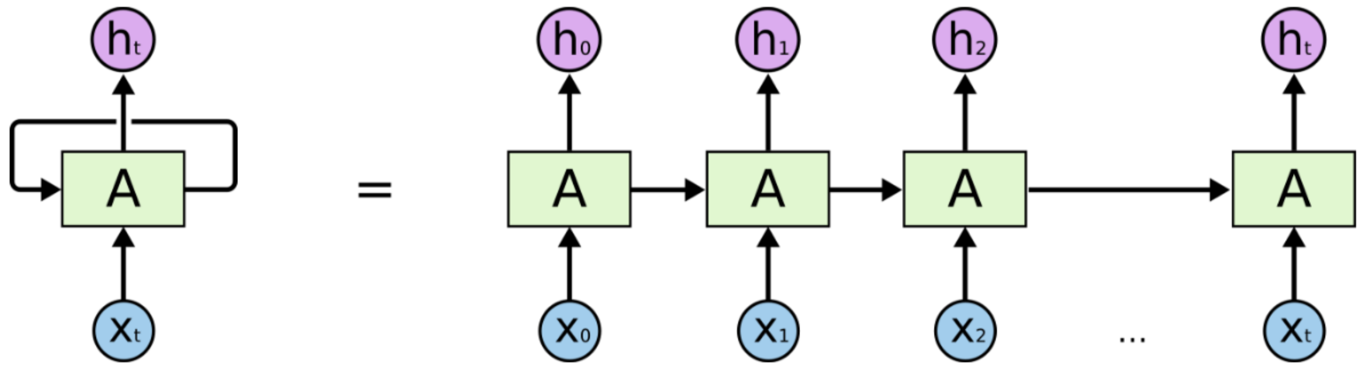
Outline

- I. Vanilla RNN
- II. LSTM
- III. GRU and Other Structures

• **I. Vanilla RNN**

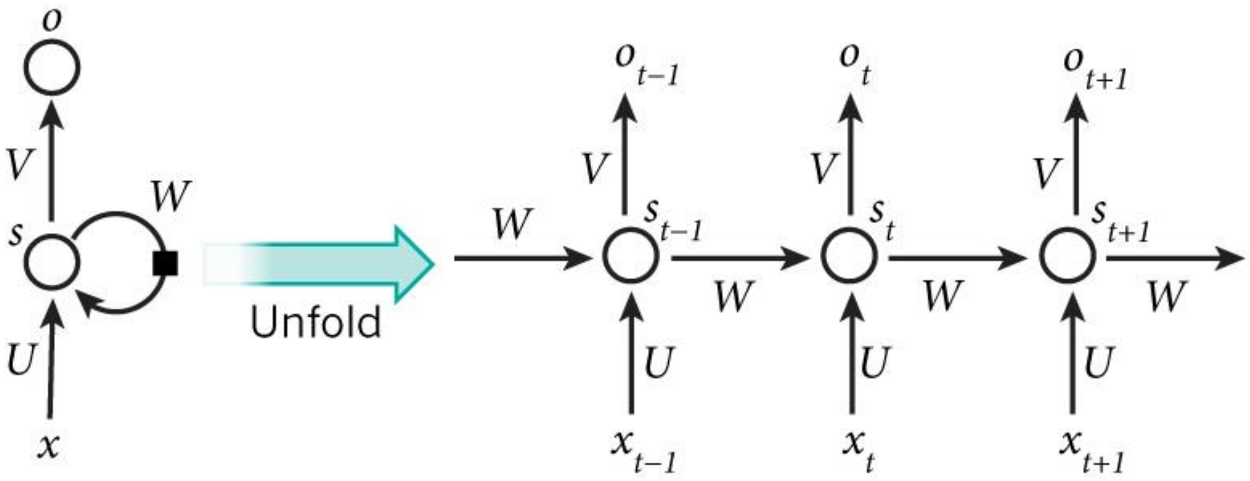
GREAT Intro: Understanding LSTM Networks



An unrolled recurrent neural network.

In theory, RNNs are absolutely capable of handling such "long-term dependencies." A human could carefully pick parameters for them to solve toy problems of this form. Sadly, **in practice**, RNNs don't seem to be able to **learn** them.

• I. Vanilla RNN



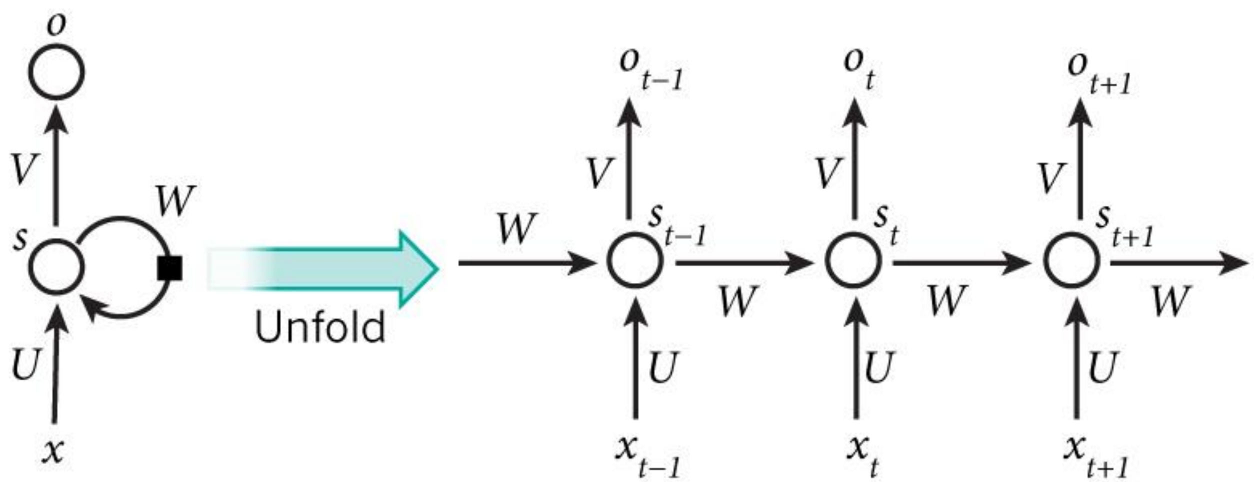
$$s_t = \tanh(Ux_t + Ws_{t-1})$$

$$\hat{y}_t = \mathrm{softmax}(Vs_t)$$

WILDML has a series of articles to introduce RNN (4 articles, 2 GitHub repos).

• I. Vanilla RNN

- **Back Prop Through Time (BPTT)**



$$\begin{aligned}\frac{\partial E_3}{\partial V} &= \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial V} \\ &= \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial z_3}\frac{\partial z_3}{\partial V} \\ &= (\hat{y}_3 - y_3) \otimes s_3\end{aligned}$$

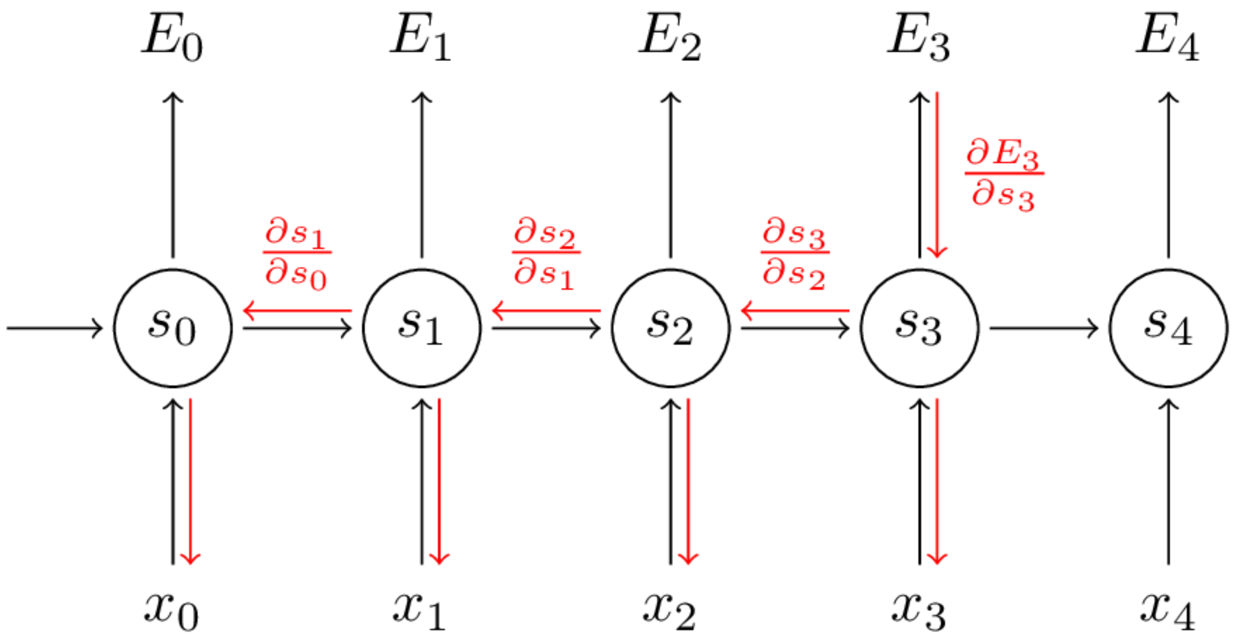
$$\frac{\partial E_3}{\partial W} = \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial s_3}\frac{\partial s_3}{\partial W}$$

$$s_3 = \tanh(Ux_t + Ws_2)$$

$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial s_3}\frac{\partial s_3}{\partial s_k}\frac{\partial s_k}{\partial W}$$

• I. Vanilla RNN

• Back Prop Through Time (BPTT)



$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \frac{\partial s_3}{\partial s_k} \frac{\partial s_k}{\partial W}$$

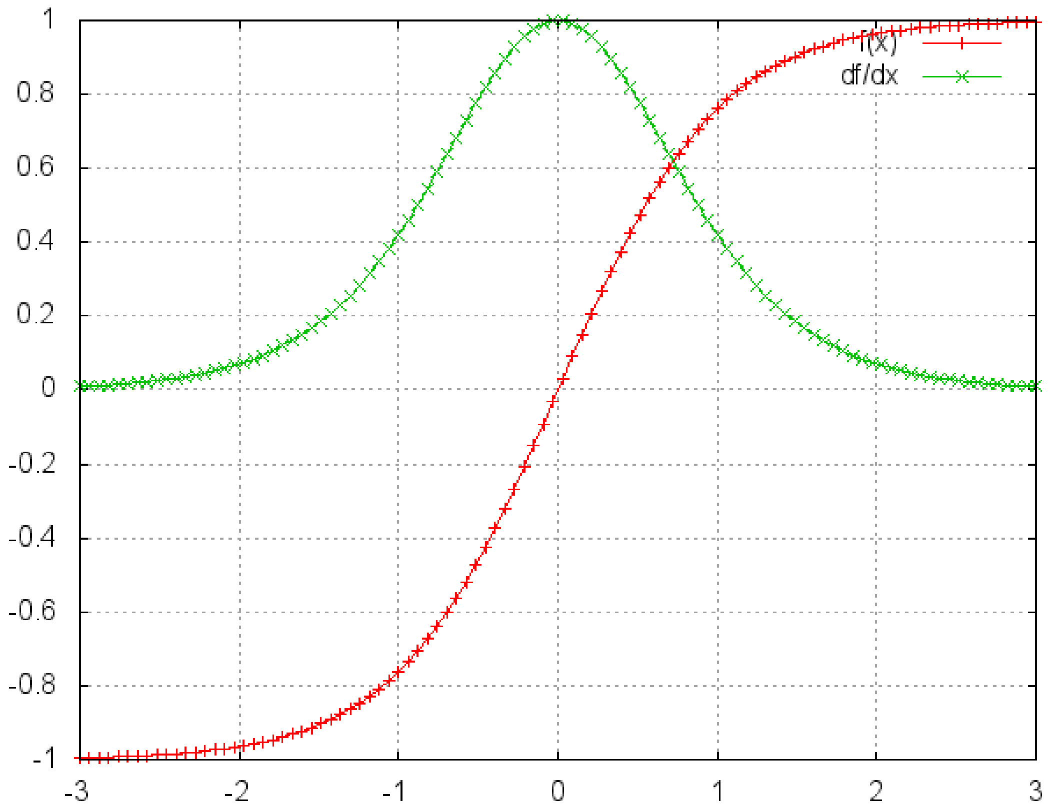
$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \left(\prod_{j=k+1}^{3} \frac{\partial s_j}{\partial s_{j-1}} \right) \frac{\partial s_k}{\partial W}$$

• I. Vanilla RNN

- **Gradient Vanishing Problem**

RNNs tend to be very deep

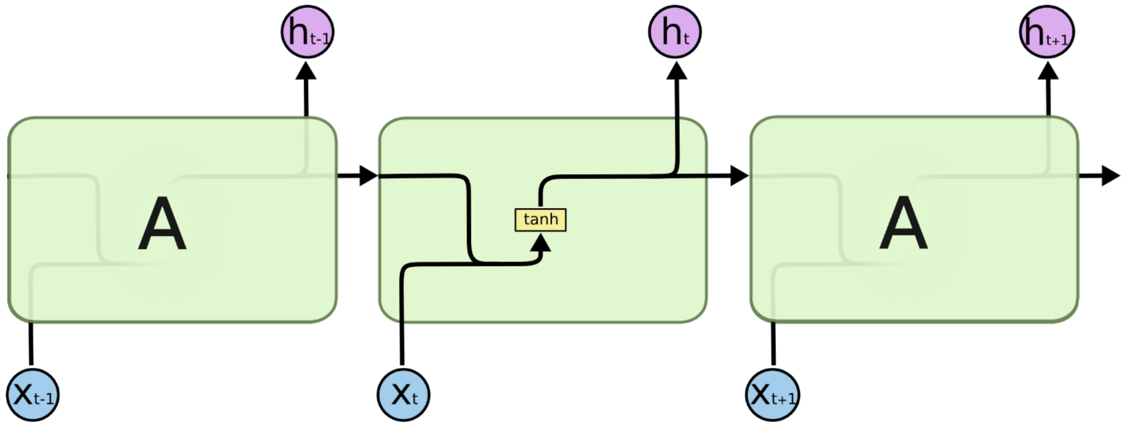
$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \left(\prod_{j=k+1}^{3} \frac{\partial s_j}{\partial s_{j-1}} \right) \frac{\partial s_k}{\partial W}$$



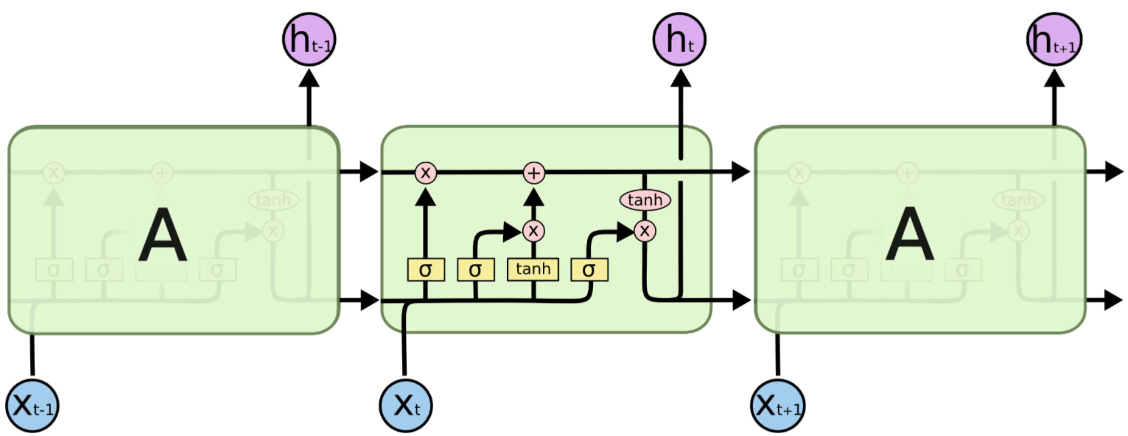
tanh and derivative. Source: http://nn.readthedocs.org/en/rtd/transfer/

• II. LSTM

- **Differences of LSTM and Vanilla RNN**



The repeating module in a standard RNN contains a single layer.

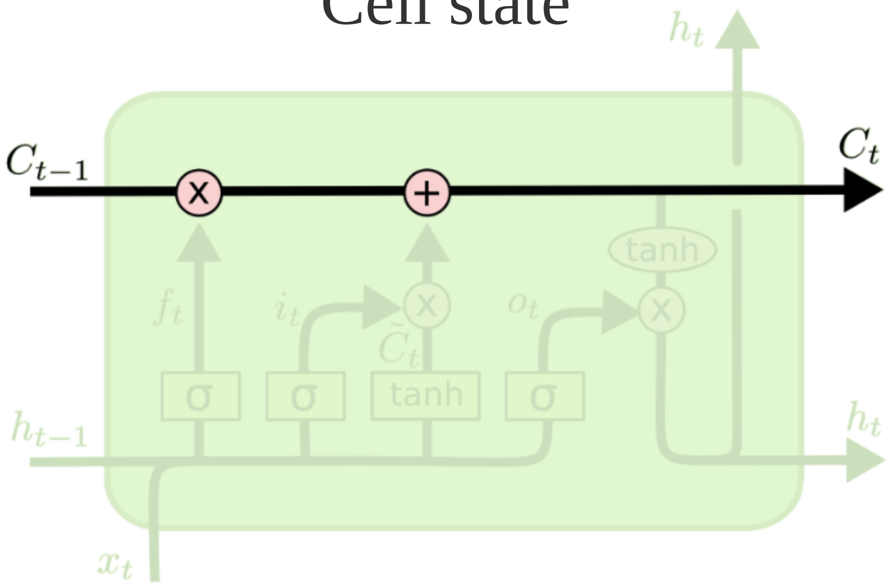


The repeating module in an LSTM contains four interacting layers.

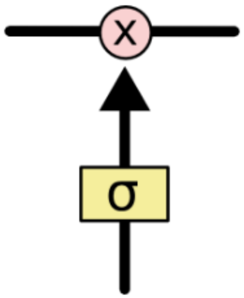
• II. LSTM

- **Core Idea Behind LSTMs**

Cell state

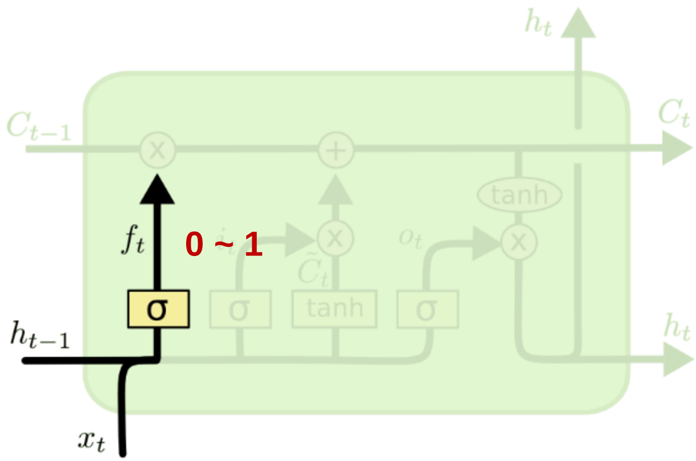


Gates

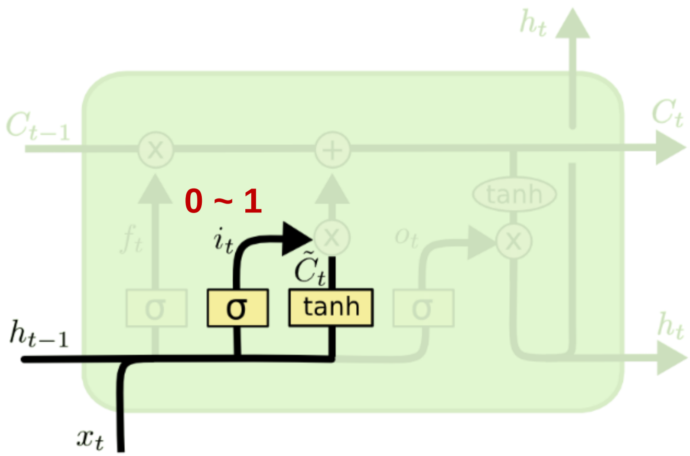


• II. LSTM

- **Step-by-Step Walk Through**



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

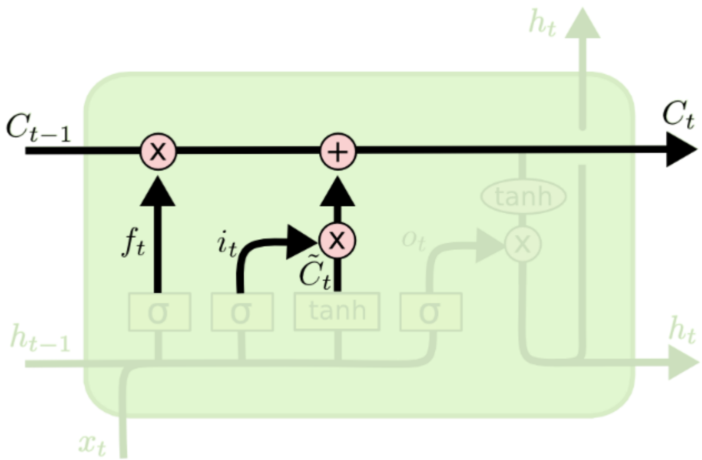


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

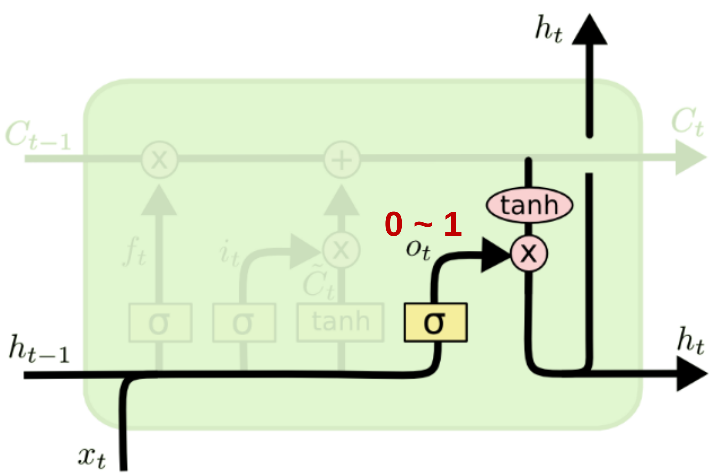
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

• II. LSTM

- **Step-by-Step Walk Through**



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

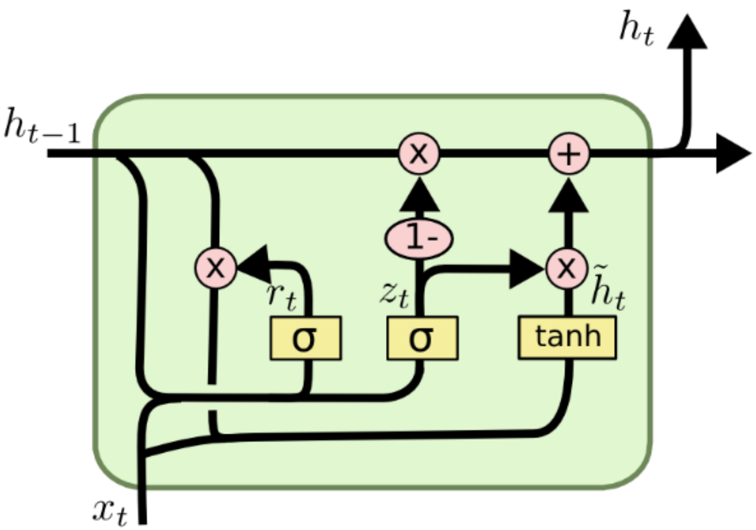


$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

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

• III. GRU and other structures

- **Gated Recurrent Unit (GRU)**



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

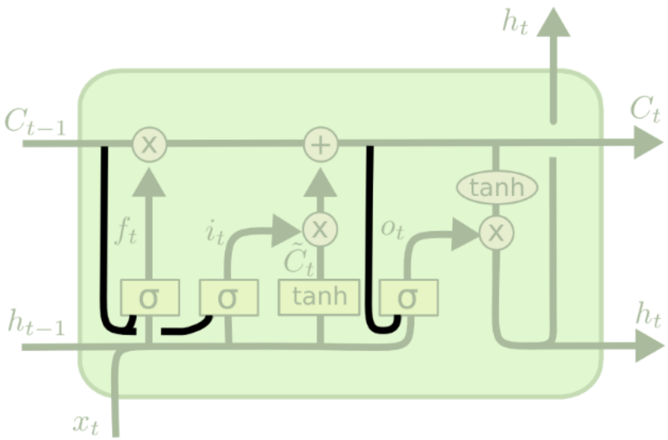
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

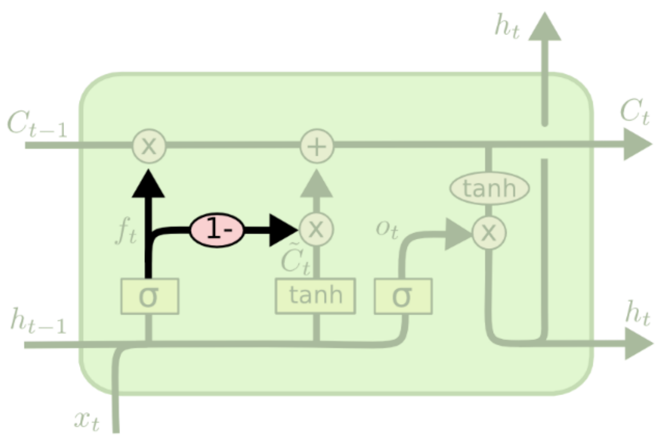
- Combines the forget and input gates into a single “update gate.”
- Merges the cell state and hidden state
- Other changes

• III. GRU and other structures

- **Variants on Long Short Term Memory**



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$



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

Greff, et al. (2015) do a nice comparison of popular variants, finding that they're all about the same.

Bibliography

- [1] Understanding LSTM Networks
- [2] Back Propagation Through Time and Vanishing Gradients

Thanks for listening!