Long Short-Term Memory (LSTM)

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"Time moves in one direction, memory in another" – William Gibson

Examples

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- However, if you had observed the past you could easily say whether the person was on the way down or the way up

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- Feed-forward neural networks cannot be used when the data originates from a dynamical system. For example, a CNN cannot produce the correct output on seeing the image of the person squatting. Why?
- We thus turn our attention to neural networks that can *store* the past and that respond based on the present input as well as what occurred in the past

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  - Tapped-delay line – store the past inputs explicitly
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  - Fully recurrent networks allowing connections between arbitrary neurons
  - The idea is to concentrate information in time

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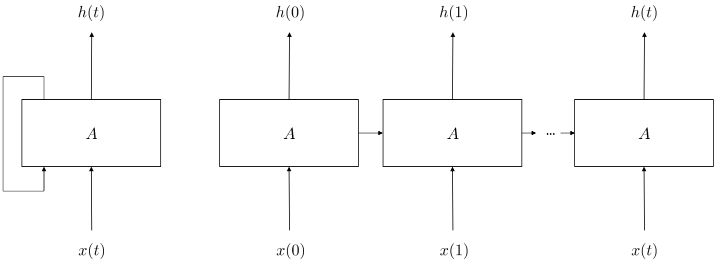
    - There are issues of convergence with fully recurrent networks. Why?
    - Most recurrent networks thus unfold time i.e. allow the feedback signal to persist for a limited time and then use standard back-propagation (gradient descent) to train the network

Unfolding Time



$$
\begin{aligned}
h(t) &= f\left[W_t x(t) + G_t h(t-1)\right] \\
&= f\left[W_t x(t) + G_t\left(f(W_{t-1}x(t-1) + G_{t-1}x(t-2))\right)\right] \\
\ldots &= \ldots
\end{aligned}
\tag{1}
$$

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- The gradient vanishes after a few terms!

Elements of LSTM - Cell State

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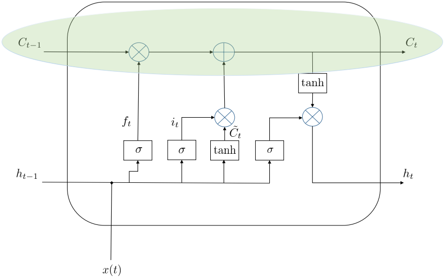
- LSTM's introduce the notion of a cell-state. Each cell has the ability to add to or remove from the cell state using gating mechanisms



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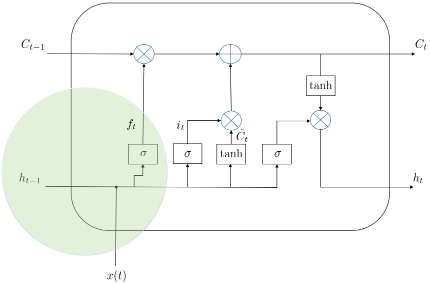

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

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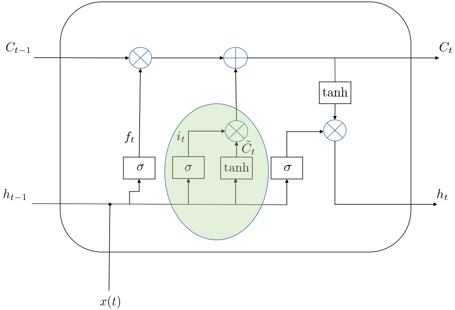

$$
\begin{aligned}
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
\tilde{C}_t &= \tanh(W_C[h_{t-1}, x_t] + b_C) \\
C_t &= f_t * C_{t-1} + i_t * \tilde{C}_{t-1}
\end{aligned} \tag{4}
$$

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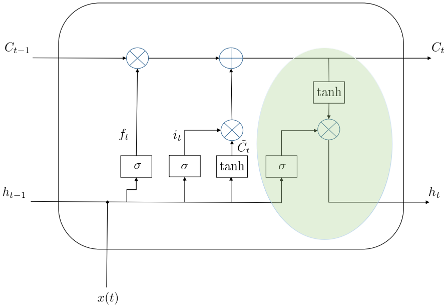

$$
\begin{aligned}
o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\
\tilde{C}_t &= \tanh(W_C[h_{t-1}, x_t] + b_C) \\
h_t &= o_t * \tanh(C_t) \qquad (5)
\end{aligned}
$$

Demo

Hand-writing demo:
http://www.cs.toronto.edu/~graves/handwriting.html
Music composition: http://www.hexahedria.com/2015/08/03/composing-music-with-recurrent-neural-networks/
Image captioning:
http://karpathy.github.io/2015/05/21/rnn-effectiveness/