Deep Learning

How Data Scientists become magicians

Sequence Data

Data that includes an order representation of its components is called *sequence data*.

Denver is nicer than Boulder.

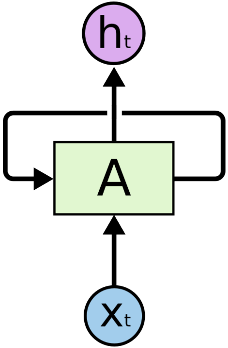
Boulder is nicer than Denver.

Sequence Data

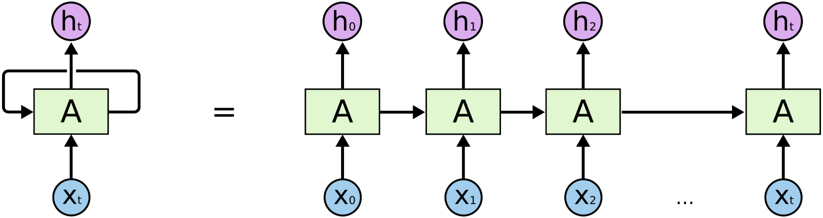
With a vocabulary of ”ATCG”, we can represent a string ”AACG” as,

$$x_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, x_2 \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, x_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, x_4 \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}.$$

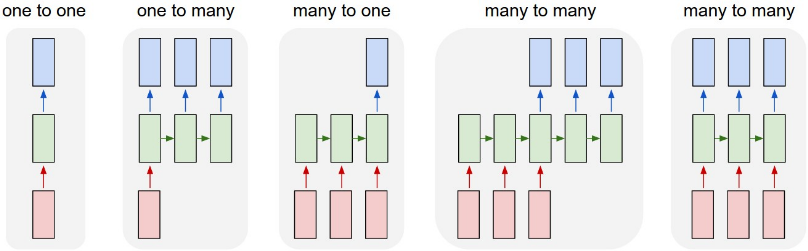
Recurrent Neural Networks



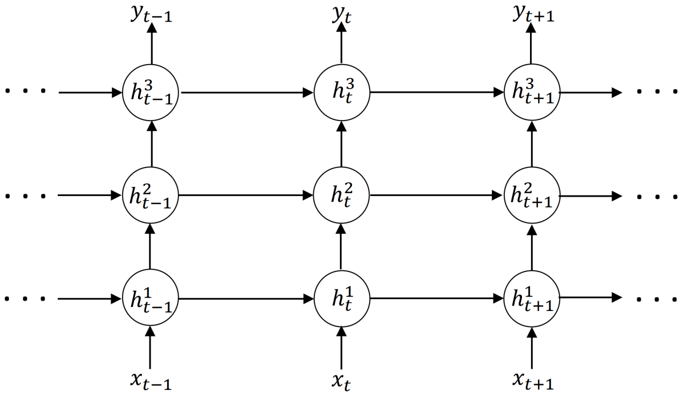
Recurrent Neural Networks



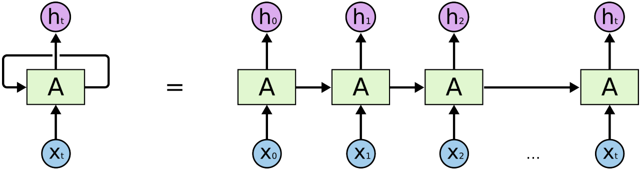
Types of Recurrent Neural Networks



Deep Recurrent Neural Networks



Recurrent Neural Network - Calculations

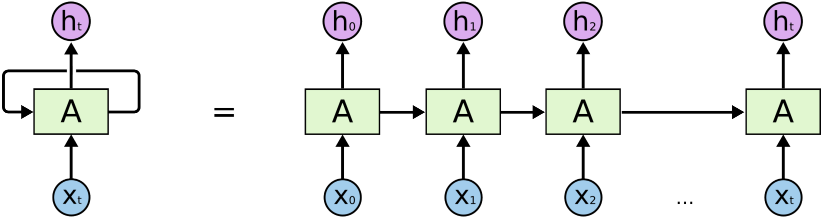


$$
\begin{aligned}
\mathbf{a}_t &= f(\mathbf{W}_{ax}\mathbf{x}_t + \mathbf{W}_{aa}\mathbf{a}_{t-1} + \mathbf{b}_a), \\
\mathbf{h}_t &= f(\mathbf{W}_{ha}\mathbf{a}_t + \mathbf{b}_h).
\end{aligned}
$$

Vanishing Gradient Problem

Deeper networks result in minimal changes in layers closer to input layer.

Vanishing Gradient Problem



Gated Recurrent Units

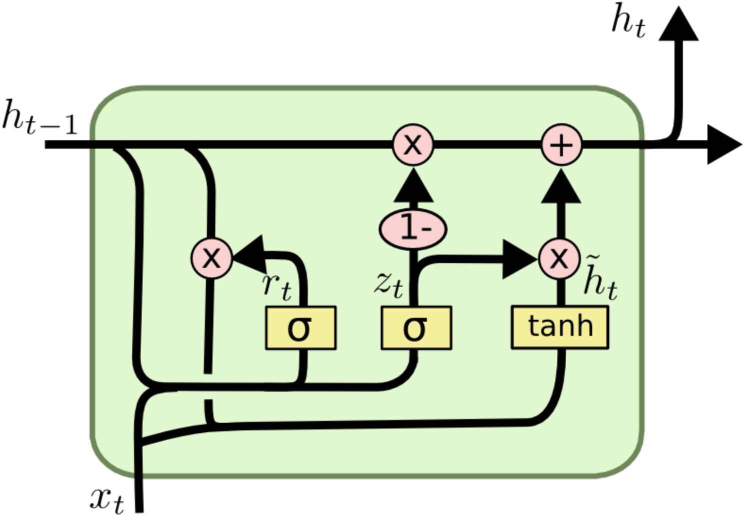
- Update gate - controls how much to update the passed through values
- Reset gate - how to reset the passed through value based on the current input

$$\mathbf{z}_t = f(\mathbf{W}_{zh}\mathbf{h}_{t-1} + \mathbf{W}_{zx}\mathbf{x}_t + \mathbf{b}_z),$$
$$\mathbf{r_t} = f(\mathbf{W}_{rh}\mathbf{h}_{t-1} + \mathbf{W}_{rx}\mathbf{x}_t + \mathbf{b}_r).$$

Gated Recurrent Units

$$\tilde{\mathbf{h}}_t = g(\mathbf{W}_{hh}(\mathbf{r}_t * \mathbf{h}_{t-1}) + \mathbf{W}_{hx}\mathbf{x}_t + \mathbf{b}_h)$$
$$\mathbf{h}_t = (1 - \mathbf{z}_t) * \mathbf{h}_{t-1} + \mathbf{z}_t * \tilde{\mathbf{h}}_t$$

Gated Recurrent Units



Long Short Term Memory Cells

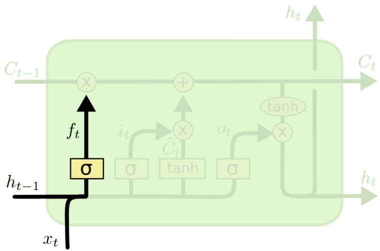
- Forget gate - controls how much to forget from past memory
- Input gate - controls how much to update future memory based on current input
- Output gate - controls how to update the cell output

$$
\begin{aligned}
\mathbf{f}_t &= f(\mathbf{W}_{fh}\mathbf{h}_{t-1} + \mathbf{W}_{fx}\mathbf{x}_t + \mathbf{b}_f), \\
\mathbf{i}_t &= f(\mathbf{W}_{ih}\mathbf{h}_{t-1} + \mathbf{W}_{ix}\mathbf{x}_t + \mathbf{b}_i), \\
\mathbf{o}_t &= f(\mathbf{W}_{oh}\mathbf{h}_{t-1} + \mathbf{W}_{ox}\mathbf{x}_t + \mathbf{b}_o).
\end{aligned}
$$

Long Short Term Memory Cells

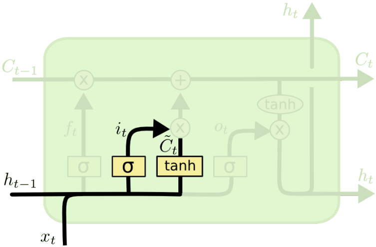
$$
\begin{aligned}
\tilde{\mathbf{c}}_t &= g(\mathbf{W}_{ah}(\mathbf{h}_{t-1}) + \mathbf{W}_{ax}\mathbf{x}_t + \mathbf{b}_a),\\
\mathbf{c}_t &= \mathbf{f}_t * \mathbf{c}_{t-1} + \mathbf{i}_t * \tilde{\mathbf{c}}_t,\\
\mathbf{h}_t &= \mathbf{o}_t * g(\mathbf{c}_t).
\end{aligned}
$$

LSTM - Forget Gate



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

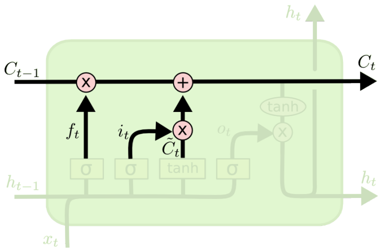
LSTM - Input Gate



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

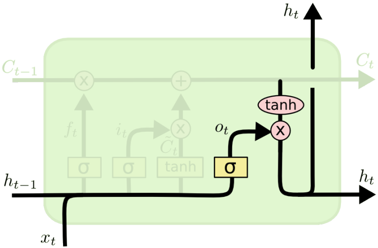
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

LSTM - Cell Memory Update



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

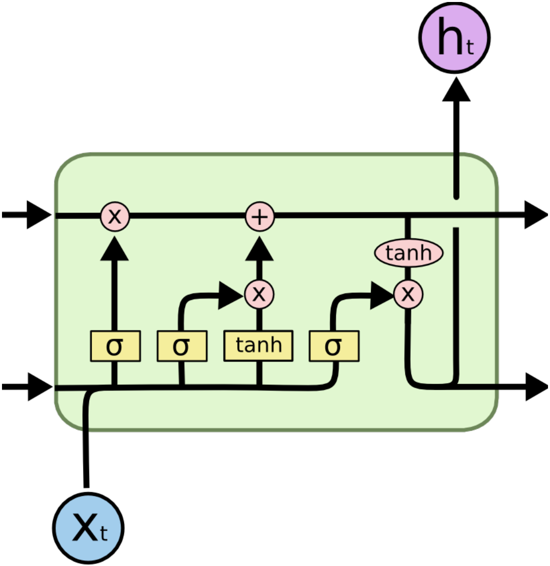
LSTM - Output Gate



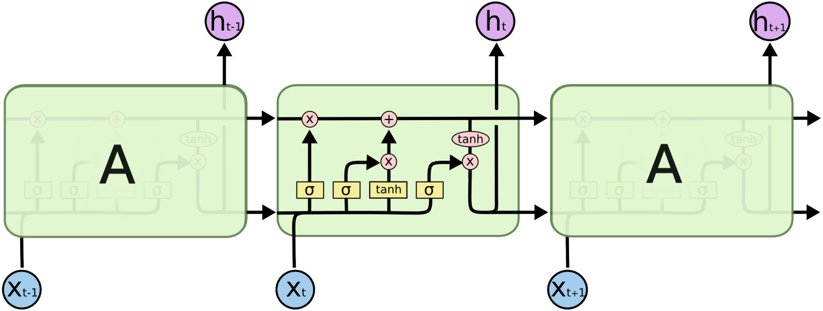
$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

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

LSTM



LSTM



Bidirectional RNNs

Send values forwards and backwards to previous cells.

- In text, allows us to extract more context based on words before and after the current one.
- Requires the full text to be available

Questions

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