Graves 2013, "Generating Sequences with Recurrent Neural Networks"

Johannes Bausch and Jack Kamm

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Outline

1. RNN and LSTM
2. Generating text
3. Generating handwriting

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RNN

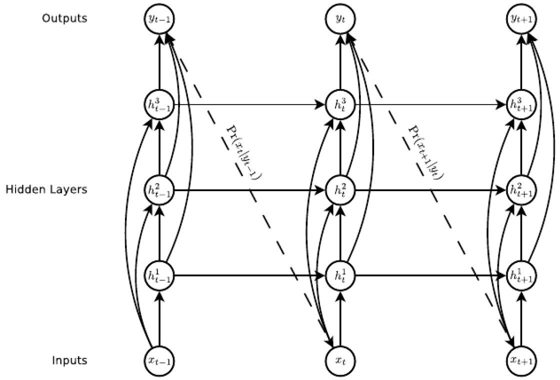


Figure 1: **Deep recurrent neural network prediction architecture.** The circles represent network layers, the solid lines represent weighted connections and the dashed lines represent predictions.

$$h_t^1 = \mathcal{H}(W_{ih^1} x_t + W_{h^1 h^1} h_{t-1}^1 + b_h^1)$$
$$h_t^n = \mathcal{H}(W_{ih^n} x_t + W_{h^{n-1} h^n} h_t^{n-1} + W_{h^n h^n} h_{t-1}^n + b_h^n)$$
$$\hat{y}_t = b_y + \sum_{i=1}^{N} W_{h^n y} h_t^n$$
$$y_t = \mathcal{Y}(\hat{y}_t)$$

Likelihood of input, loss function:

$$\mathbb{P}(\mathbf{x}) = \prod_{t=1}^{T} \mathbb{P}(x_{t+1} \mid y_t)$$
$$\mathcal{L}(\mathbf{x}) = -\sum_{t=1}^{T} \log \mathbb{P}(x_{t+1} \mid y_t)$$

LSTM

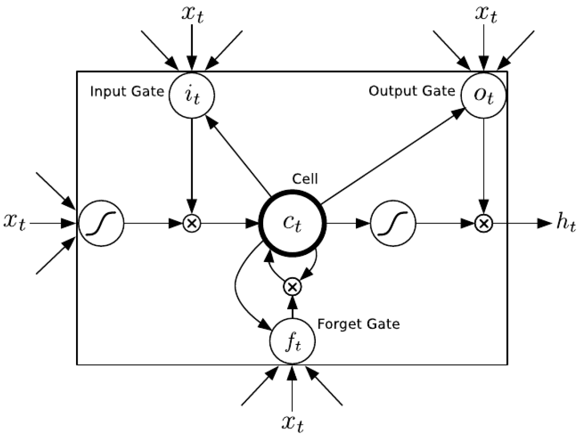


Figure 2: **Long Short-term Memory Cell**

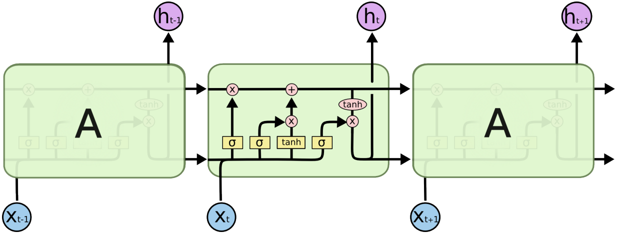
Instead of

$$h_t^n = \mathcal{H}(W_{ih^n} x_t + W_{h^{n-1}h^n} h_t^{n-1} + W_{h^n h^n} h_{t-1}^n + b_h^n)$$

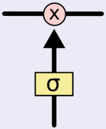
do we have instead the following?

$$h_t^n, c_t^n = \mathcal{H}(x_t, c_t^{n-1}, h_t^{n-1}, h_{t-1}^n)$$

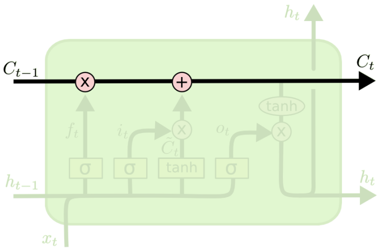
For a really nice explanation of LSTM see:
`colah.github.io/posts/2015-08-Understanding-LSTMs`



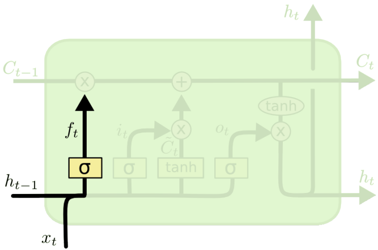
Gate=sigmoid + multiplication



0='nothing thru'
1='all thru'

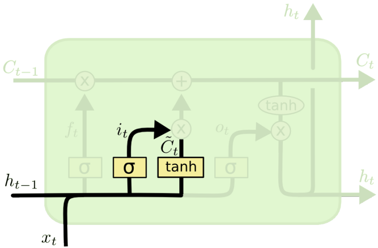


Information flows along cell state



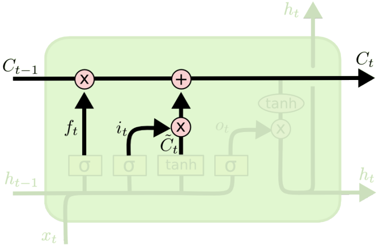
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Forget gate controls what to keep from previous



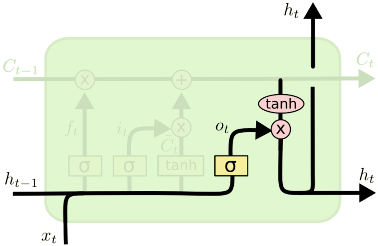
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Input gate controls what to add from input



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

Update cell state from forget and input gates



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

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

Output gate controls what to output from cell state

Backpropagation thru time

- Train with "backpropagation thru time"
  - Turn head sideways and do backpropagation
  - i.e. reverse-mode automatic differentiation
- Truncated backpropagation thru time
  - Improve numerical stability by truncating gradients if they get too big as we go backwards thru the sequence

Reference other papers?

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Text Prediction

Basic framework for text prediction
$y_t = \mathbb{P}(x_{t+1})$
Per-character vs per-word prediction

Penn Treebank Test Set

Penn Treebank
Perplexity? BPC?
Regularization schemes

Wikipedia Experiments

- Wikipedia experiments
- `karpathy.github.io/2015/05/21/rnn-effectiveness` has some nice visualizations for understanding what's going on, e.g. what the inner neurons represent

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Handwriting experiments

- Handwriting experiments
- Mixture density outputs
  - Basic framework for real valued outputs
- Figure 10 is cool

Handwriting Synthesis

- Handwriting synthesis
- Input, output sequences have different lengths
- Biased vs unbiased vs primed sampling