Deep Learning for Computer Vision

LSTMs and GRUs

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Review: Questions

Question

- How to tackle the vanishing gradient problem in RNNs with solutions that don't change the architecture?

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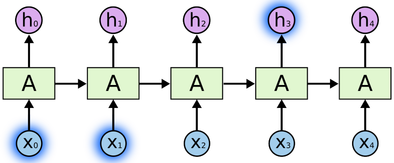
- How to tackle the vanishing gradient problem in RNNs with solutions that don't change the architecture? **Use ReLU; Regularization; Better initialization of weights; Use only short time sequences**

Long-Term Dependencies: The Problem

- RNNs connect previous information to present task which:
  - may be enough for predicting the next word for "*the clouds are in the sky*"



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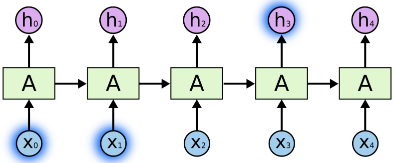
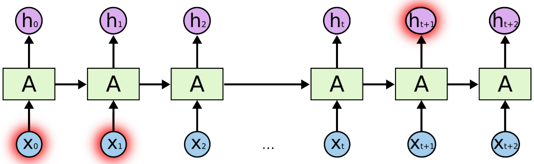


  - may not be enough when more context is needed: "*I grew up in France ... I speak fluent French*"



Credit: Christopher Olah

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- How to overcome by changes in RNN architecture?
  - **LSTMs** (1997)
  - **GRUs** (2014)

Long Short-Term Memory (LSTM)[1]

- A type of RNN proposed by Hochreiter and Schmidhuber in 1997 as a solution to the long-term dependency problem

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  - The gates are dynamic, their value is computed based on current context

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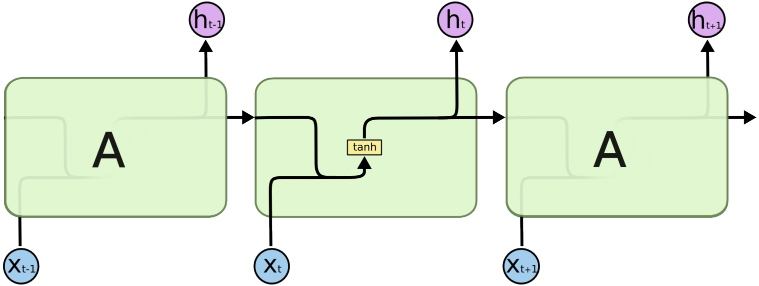
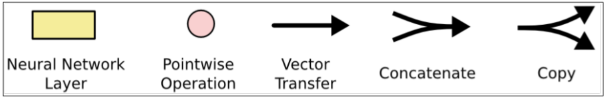
LSTMs

- All RNNs have the form of a **chain of repeating modules** of neural network
- Repeating module in a vanilla RNN is a single layer with `tanh` activation





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LSTMs

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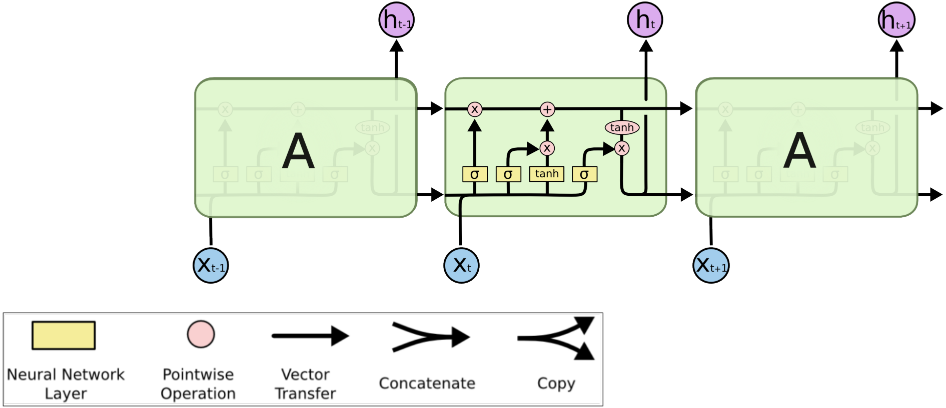
- Repeating module in an **LSTM** contains four interacting layers



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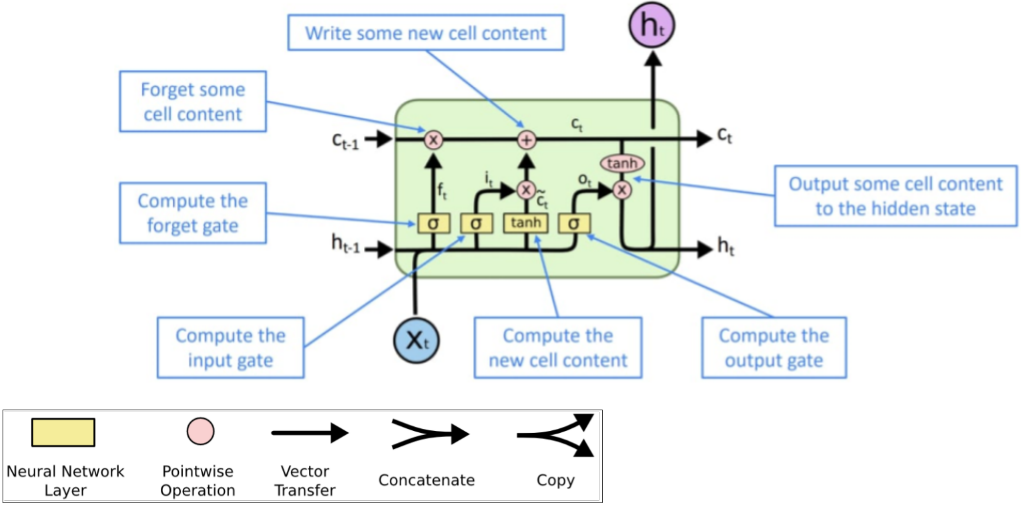

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LSTMs Explained

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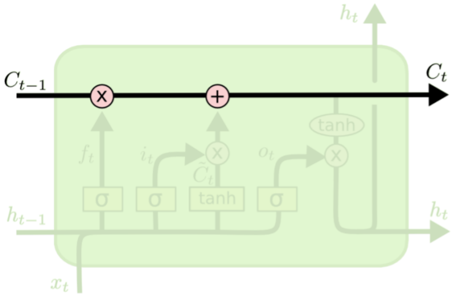

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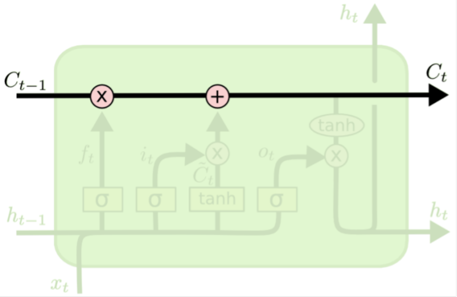

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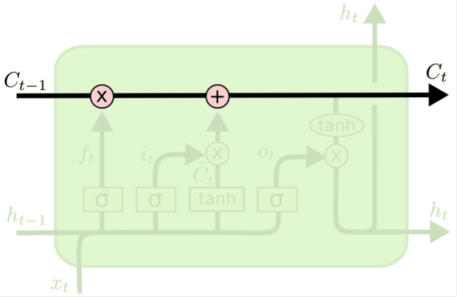

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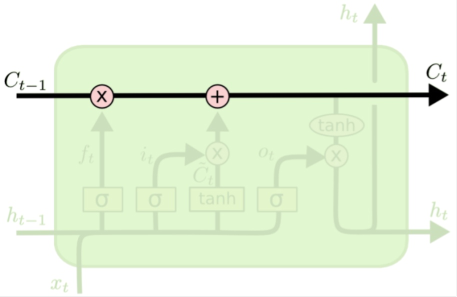

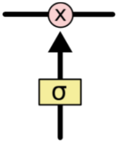

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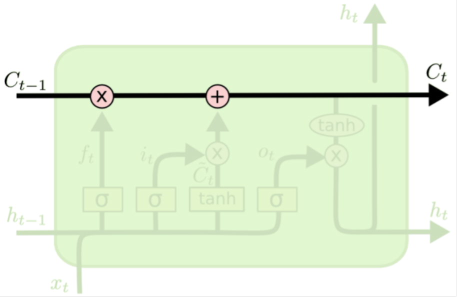

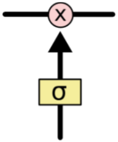

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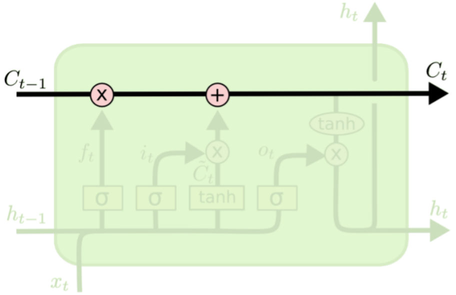
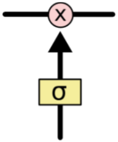
  - Sigmoid layer outputs numbers between zero and one, describing how much of each component should be let through





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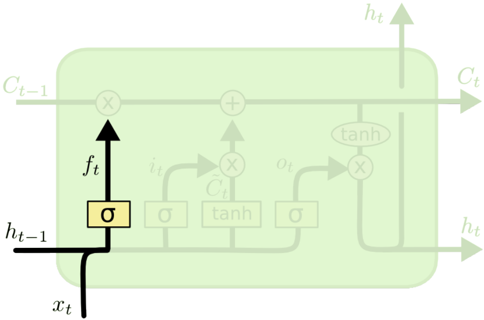
LSTMs Explained

Forget gate: controls what is kept vs what is forgotten, from previous cell state



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

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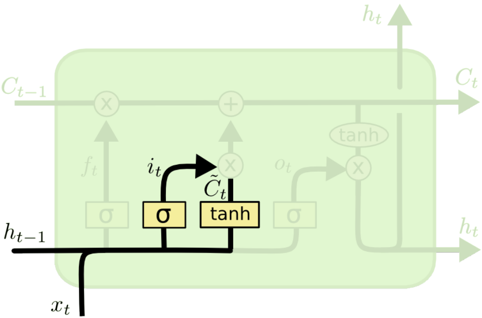
LSTMs Explained

Input gate: decides what information to throw away from the cell state
Cell content: new content to be written to cell



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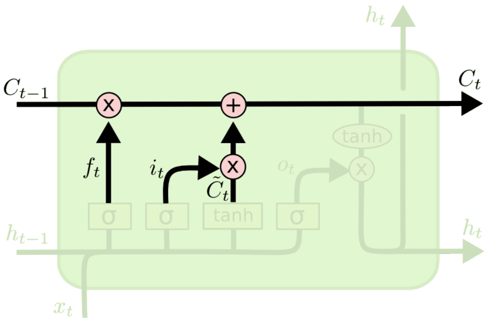
LSTMs Explained

Cell state: erase ("forget") some content from last cell state, and write ("input") some new cell content



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

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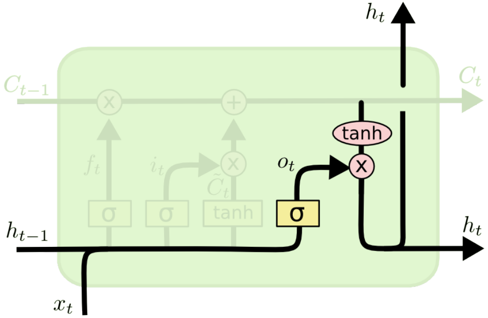
LSTMs Explained

Output gate: controls what parts of cell are output to hidden state
Hidden state: read ("output") some content from cell



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LSTMs Explained

Sigmoid function: all gate values are between 0 and 1

Forget gate: controls what is kept vs forgotten, from previous cell state

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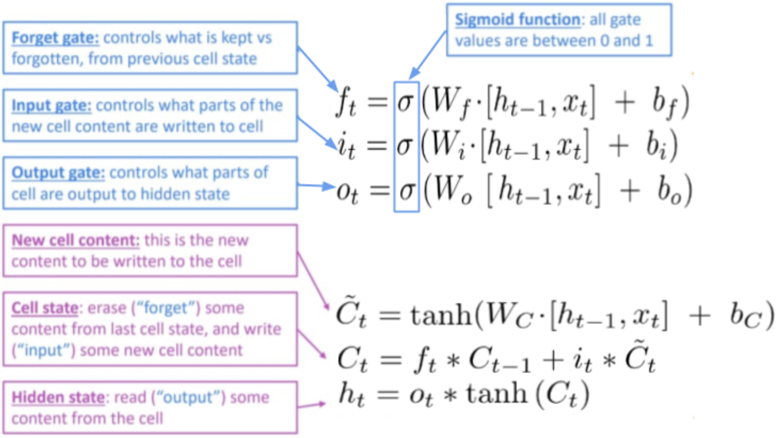

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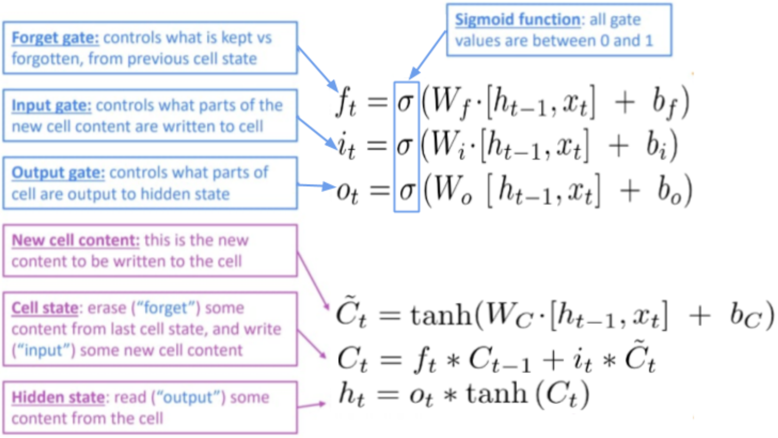

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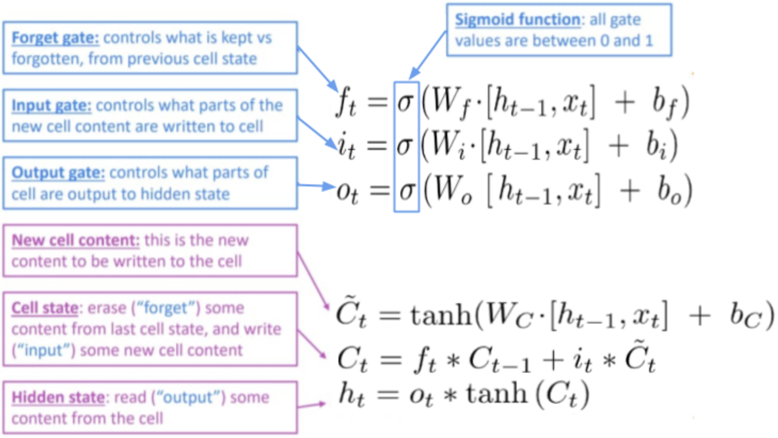

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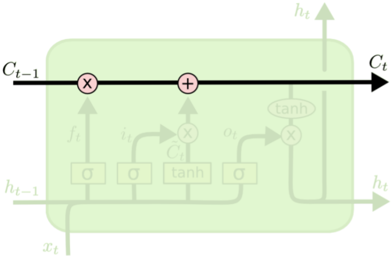
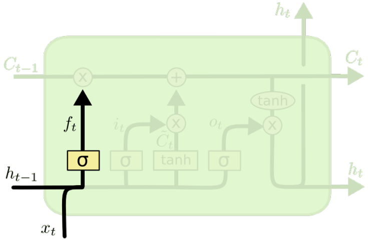
  - **Tanh** added here

Credit: Christopher Olah; Christopher Manning, Stanford University

LSTM: How does it solve the vanishing gradient problem?





- Gradient "highway"

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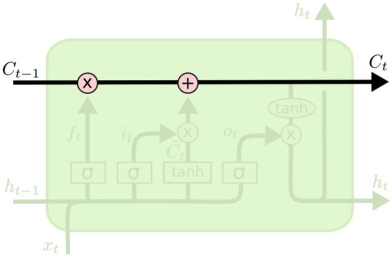

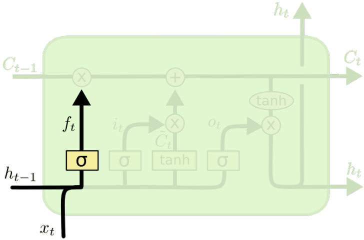

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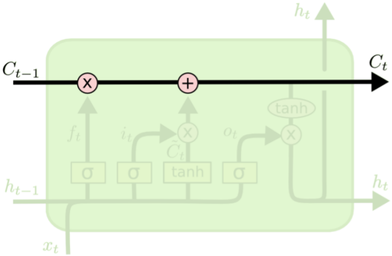

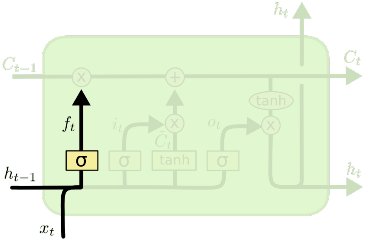

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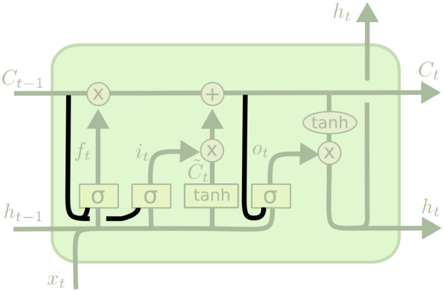
- Forget gate is part of the design, it reduces the gradient where it should, does not ameliorate the gradient otherwise!

Variants of LSTM

- **LSTM with peephole connections**[2]



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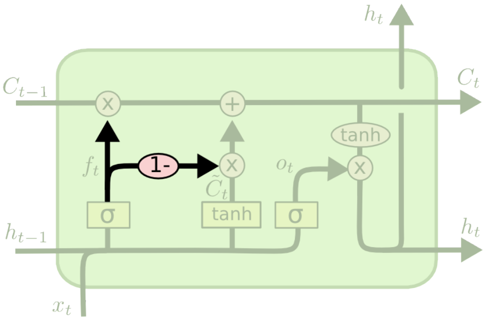
[2] Gers and Schmidhuber, Recurrent nets that time and count, IJCNN 2000

Variants of LSTM

- **Coupled forget and input gates**
  - Instead of separately deciding what to **forget** and what to **add**, make decisions together



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History of LSTMs

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- **2005 – Vanilla LSTM (as we know today) – Used BPTT**
  - Graves and Schmidhuber, Framewise phoneme classification with bidirectional LSTM and other neural network architectures, Neural Networks, 2005

LSTMs: Real-world success

- **2013-2015**: LSTMs started achieving **state-of-the-art results**
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  - Successful tasks include: handwriting recognition, speech recognition, machine translation, parsing, image captioning
- **Now (2020)**, other approaches (e.g. **Transformers**) have become more dominant for certain tasks
  - Transformers use the idea of self-attention
  - In **WMT 2019** ((a MT conference + competition), summary report contains "RNN" 7 times, "Transformer" 105 times

Credit: Christopher Manning, Stanford University

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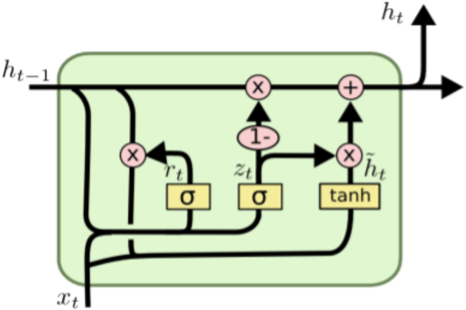

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Gated Recurrent Unit (GRU)[2]

Update gate: controls what parts of hidden state are updated vs preserved

Reset gate: controls what parts of previous hidden state are used to compute new content

New hidden state content: reset gate selects useful parts of prev hidden state. Use this and current input to compute new hidden content.

Hidden state: update gate simultaneously controls what is kept from previous hidden state, and what is updated to new hidden state content

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

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

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

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

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- What happens if reset gate is set to all 1s and update gate to all 0s?

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- Input and forget gates of LSTMs are coupled by an update gate in GRUs; reset gate (GRUs) is applied directly to previous hidden state
- GRU has two gates, an LSTM has three gates; what does this tell you? **Lesser parameters to learn!**
- In GRUs:
  - No internal memory (c_t) different from exposed hidden state
  - No output gate as in LSTMs
- LSTM a good default choice (especially if data has long-range dependencies, or if training data is large); Switch to GRUs for speed and fewer parameters

Homework

Readings

- Deep Learning book: Sections 10.1-10.7, 10.10-10.11
- Understanding LSTM Networks
- Illustrated Guide to LSTMs and GRUs: A step by step explanation
- (Optional) Recurrent Neural Network Tutorial– Implementing a GRU/LSTM RNN with Python and Theano
- (Optional) Training LSTMs using BPTT: Alex Graves' book on RNN (Sec 4.6, pg 36-38)

Questions

- How does GRU address vanishing gradients?

References

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