NN Language Models

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About Myself

2003-2010 RWTH AACHEN UNIVERSITY

PhD on hierarchical MT

Main author of Jane MT toolkit

2011-2013 DFKI

Researcher. More work on MT, trying to make it usable for professional translators

2013-2014 Pixformance

Lead developer

Since 2014 NUANCE

Sr. Research Scientist: Language Modelling and Natural Language Understanding

Overview

1. Introduction to Word Embeddings
2. Recurrent Neural Networks
3. LSTMs
4. A Few Notes About the Output Layer

Introduction to Word Embeddings

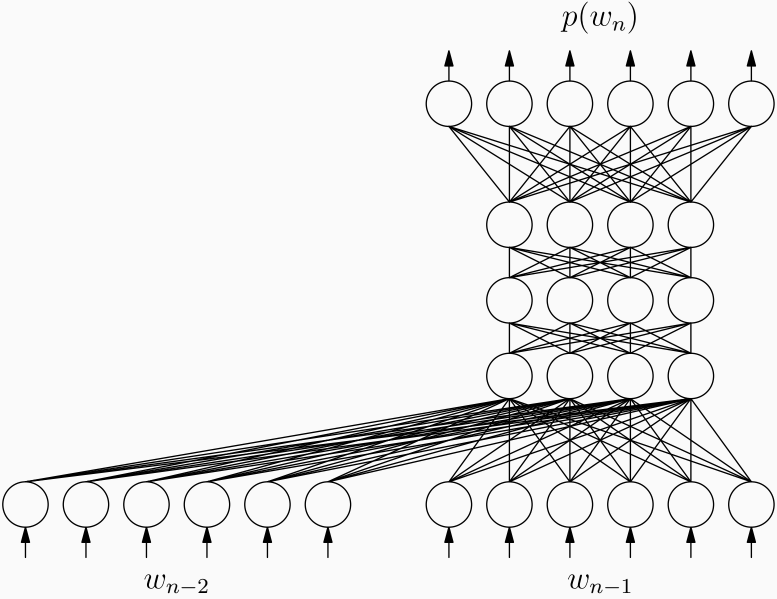
1-hot encodings

- 1-hot encoding is the "natural" way to encode symbolic information (e.g. words)
- But:
  - The encoding itself is arbitrary (e.g. first appearance of a word in the training text)
  - No useful information can be read from the vector representation
  - Example:

the green dog bites the cat

the	$(1, 0, 0, 0, 0)$
green	$(0, 1, 0, 0, 0)$
dog	$(0, 0, 1, 0, 0)$
bites	$(0, 0, 0, 1, 0)$
cat	$(0, 0, 0, 0, 1)$

Feed-forward LM

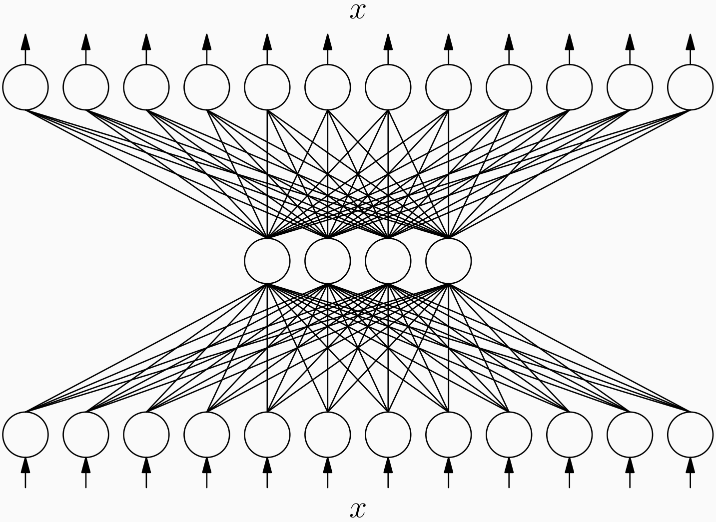


Intuition

- A NN represents a *flow* of information
- A NN can be decomposed into smaller networks
- Each of these networks transforms the information, which serves as input to the next network
- Can be seen in the recursive structure of the equations

$$y^{(l)}(x) = f(W^{(l)} y^{(l-1)}(x) + b^{(l)})$$

The most "stupid" network



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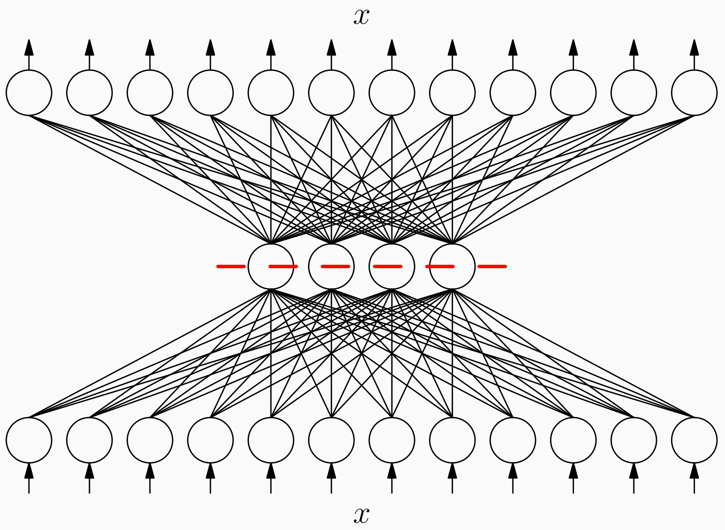

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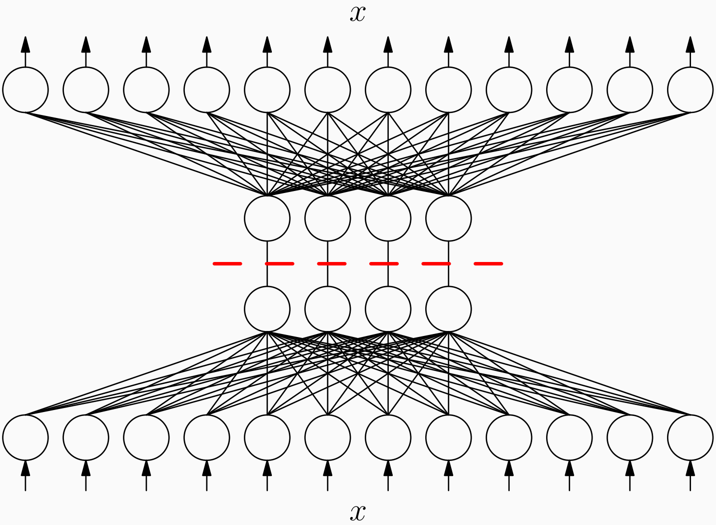

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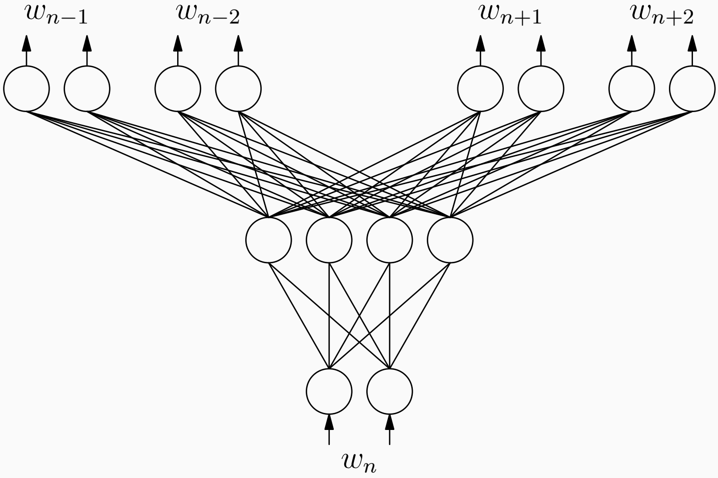
We can do better!

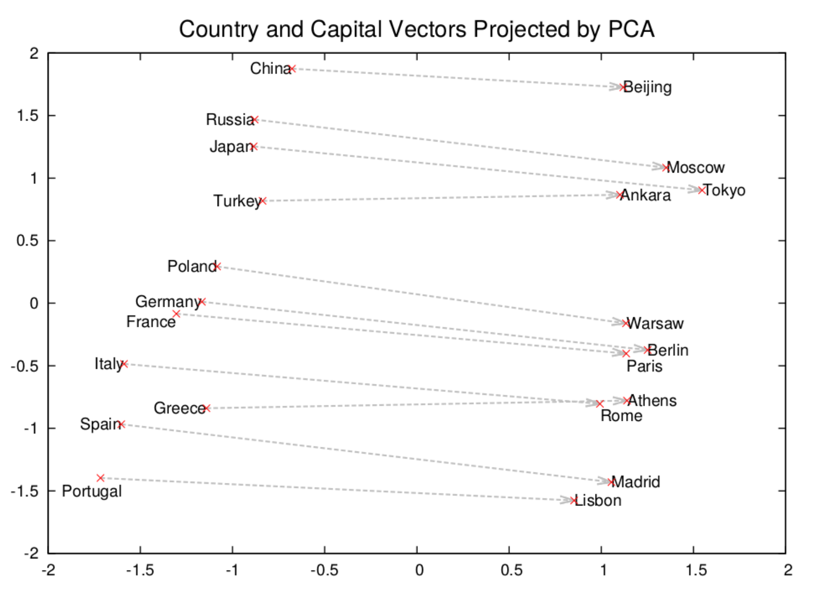
Skip-gram model



Skip-gram model

- Assumption: similar words appear in similar contexts
- Goal: similar words have similar representations (as they will predict similar contexts)
- Indeed:
    - $\text{vec}(King) - \text{vec}(Man) + \text{vec}(Woman)$ results in a vector that is closest to $Queen$
    - $\text{vec}(Madrid) - \text{vec}(Spain) + \text{vec}(France)$ results in a vector that is closest to $Paris$

Skip-gram model



- Different implementations available (many of them open source)
- (One of) The most widely used: `word2vec` by Mikolov et al.
- Efficient implementation, can deal with big datasets
- `https://code.google.com/archive/p/word2vec/`
- Normally used pre-training for embedding layer
  - May be further refined by task-specific training

Recurrent Neural Networks

Recap

- Language model

$$p(w_1^N)$$

- Chain rule (mathematical equality)

$$p(w_1^N) = \prod_{n=1}^{N} p(w_n | w_1^{n-1})$$

- k-th order Markov *assumption*: $(k+1)$-grams

$$p(w_1^N) \approx \prod_{n=1}^{N} p(w_n | w_{n-k}^{n-1})$$

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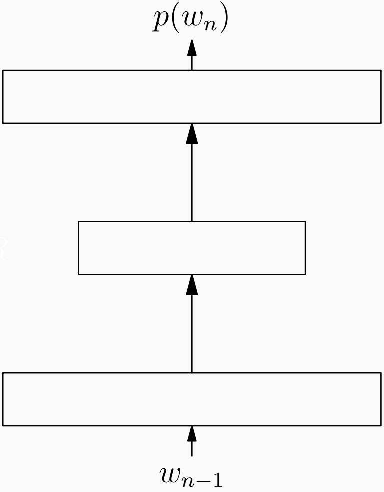
We would like to be able to take into account the *whole* history!
$\rightarrow$ Let the network remember everything it has seen!

Recurrent NNs



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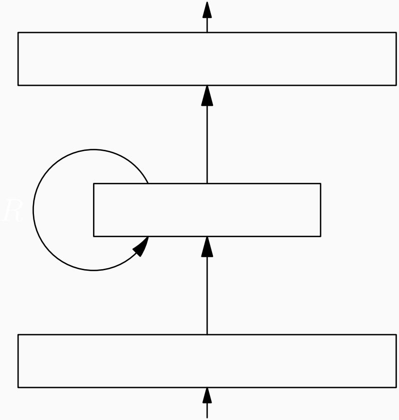

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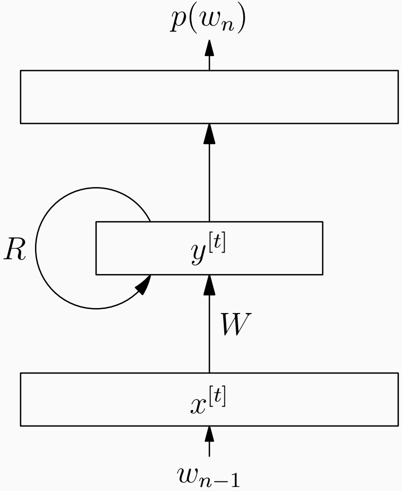
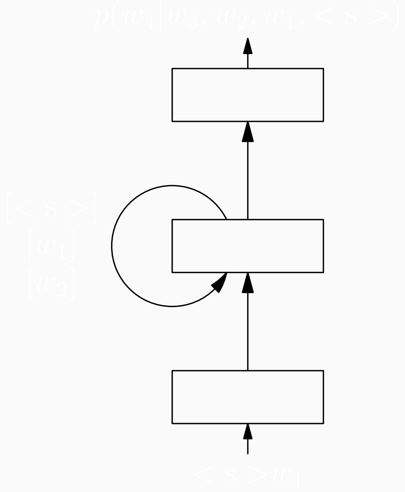


In Equations: $y^{[t]} = f(Wx^{[t]} + Ry^{[t-1]} + b)$

Recurrent NNs

$p(w_1^4) =$



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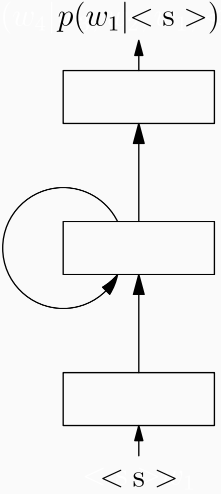

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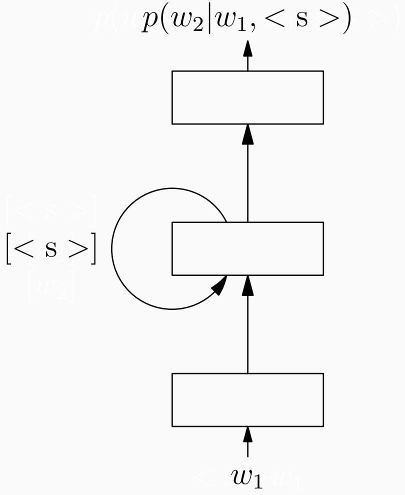

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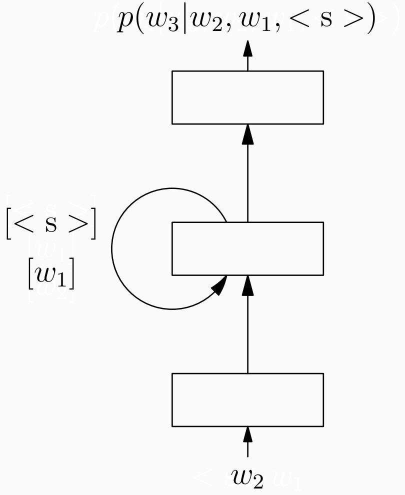

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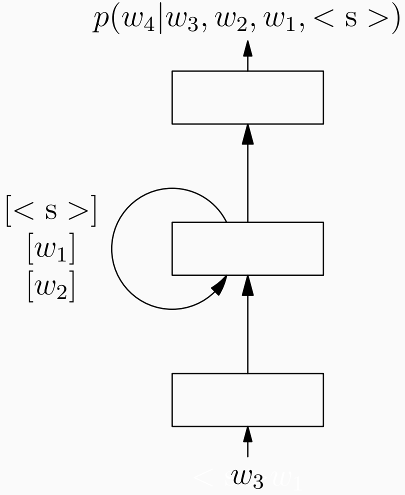

Backpropagation through time

How to train a RNN?

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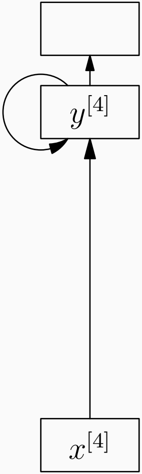
- Of course. . . with backpropagation
- Unfold recurrent connections through time
- Results in a wide network, backpropagation can be used
- Use chain rule not only for layers, but also for time steps

Backpropagation through time



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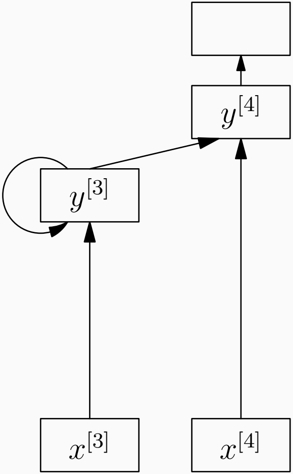

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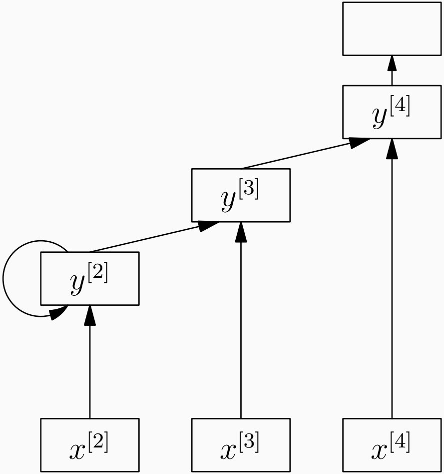

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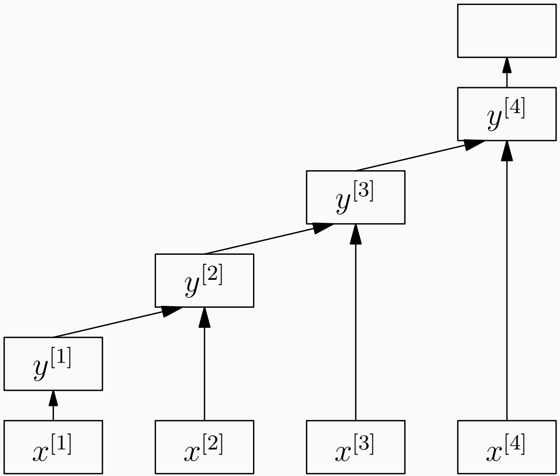
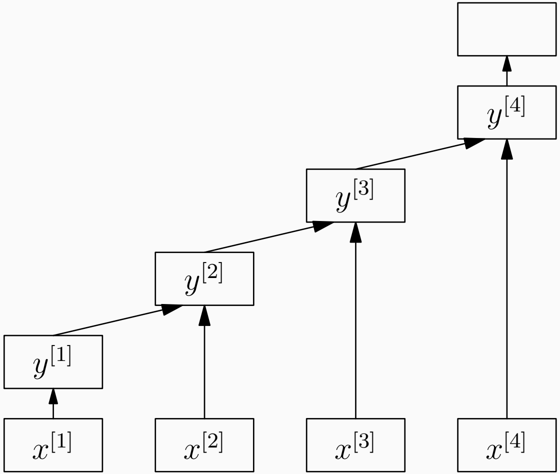


Backpropagation through time

$$\frac{\partial \mathcal{L}}{\partial \theta} =$$



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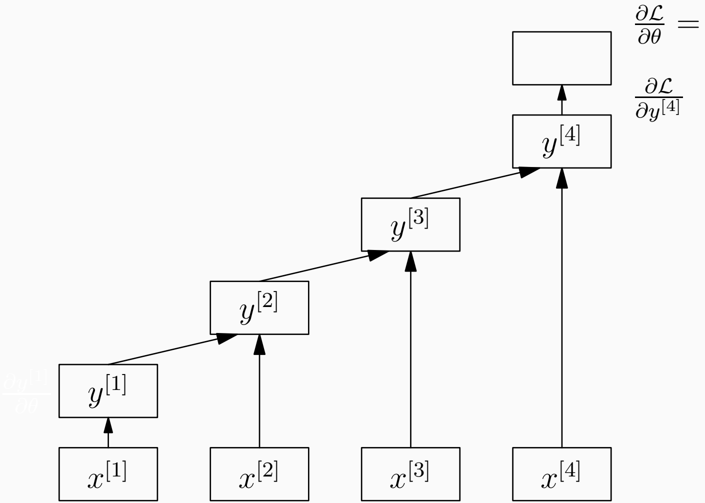

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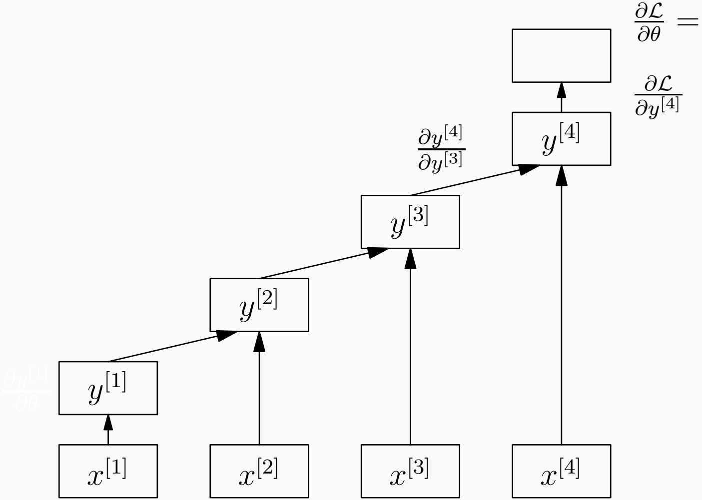

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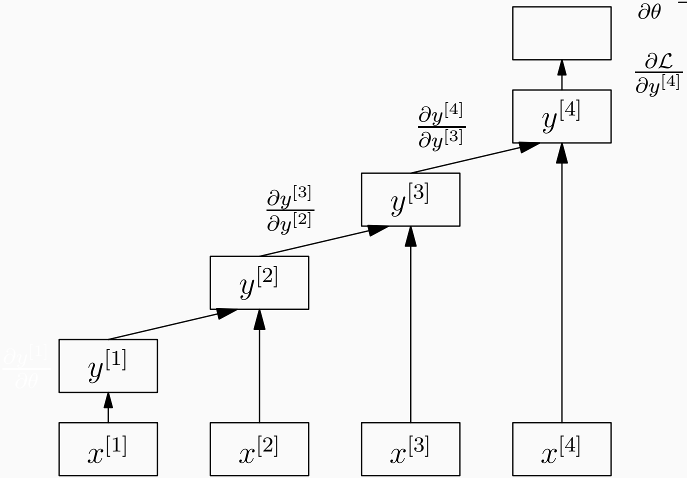

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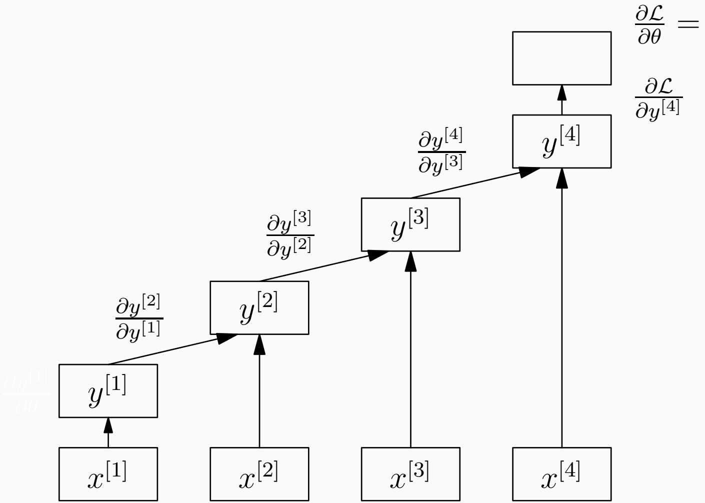

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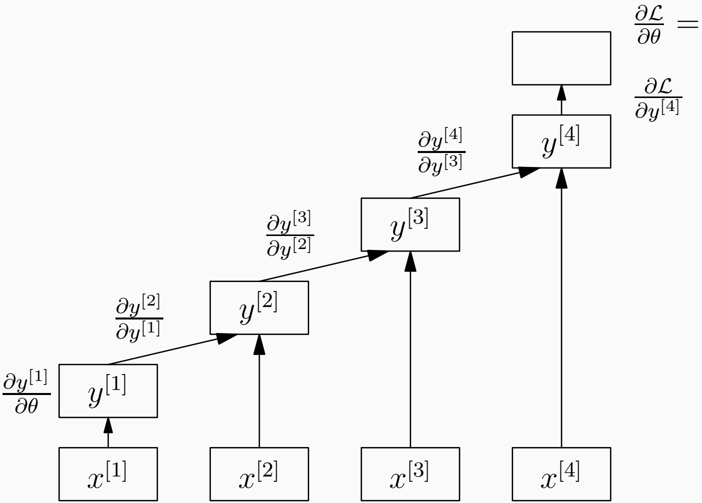

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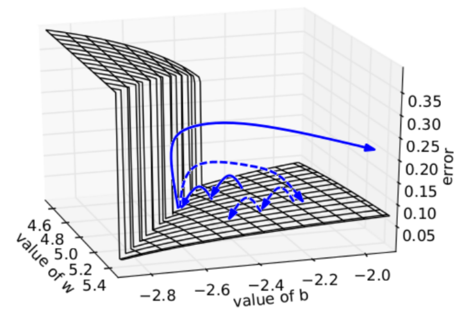

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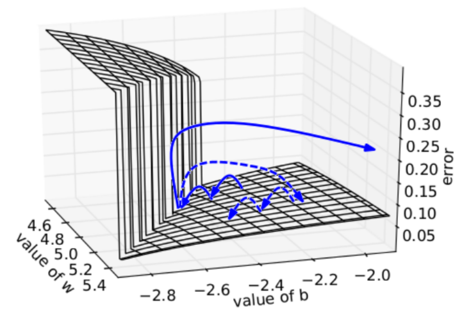

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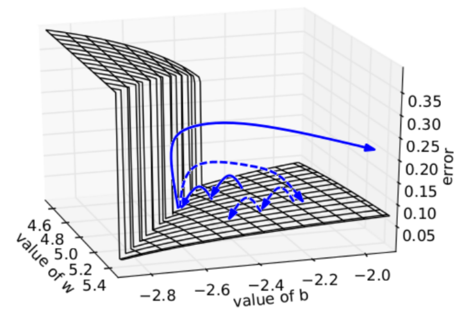

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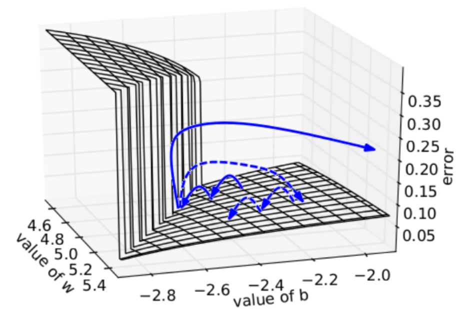

- Vanishing gradient: you have a problem!

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and for $\frac{\partial y^{[t_2]}}{\partial y^{[t_1]}}$:

$$\frac{\partial y^{[t_2]}}{\partial y^{[t_1]}} = \prod_{t_1 < t \le t_2} \frac{\partial y^{[t]}}{\partial y^{[t-1]}}$$

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Exploding and vanishing gradient

Why does this happen?

$$\left\| \frac{\partial y^{[t]}}{\partial y^{[t-1]}} \right\| \leq \|R^T\| \left\| \text{diag}\left(f'(Ry^{[t-1]} \right) \right\| \leq \gamma \sigma_{\max}$$

with

- γ a maximal bound for $f'(Ry^{[t-1]})$
  - e.g. $|\tanh'(x)| \leq 1$; $|\sigma'(x)| \leq \frac{1}{4}$
- $\sigma_{\max}$ the largest singluar value of R^T

More details: R. Pascanu, T. Mikolov, Y. Bengio *On the difficulty of training recurrent neural networks* ICML 2013
(and previous work)

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Exploding and vanishing gradient

- Vanishing gradient: you have a problem!
- We cannot distinguish if
  - There is no dependency in the data
  - We have chosen the wrong parameters

LSTMs

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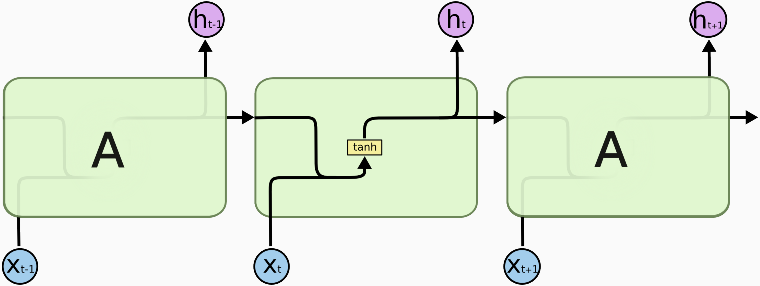
  - Ignoring the “current” output
  - Forgetting the history

RNN units



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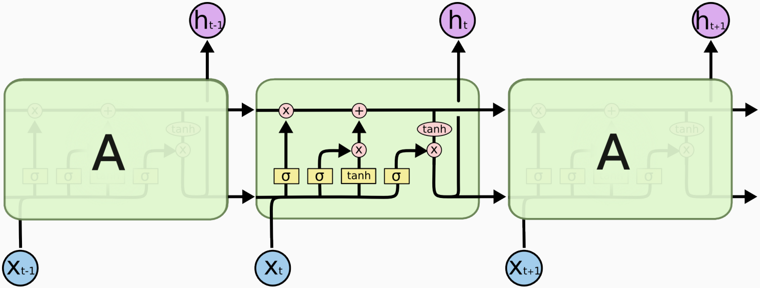

LSTM Equations

Compute a “candidate value”, similar to RNNs:

$$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

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Forget gate: control the influence of the history

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

LSTM Equations

Memory cell state: combination of new and old state

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

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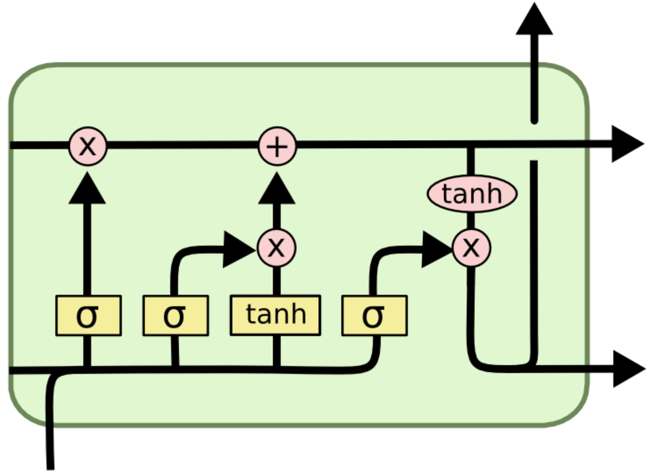
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

Output of the cell:

$$y_t = o_t \cdot \tanh(C_t)$$

LSTM Visualization



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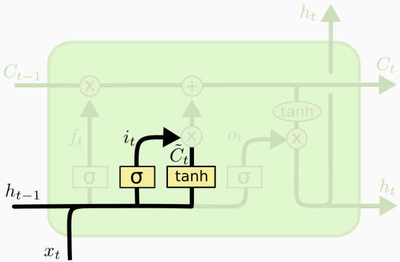

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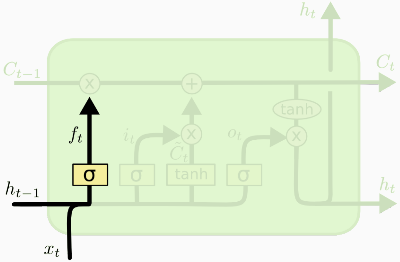

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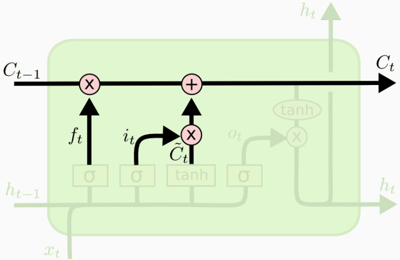

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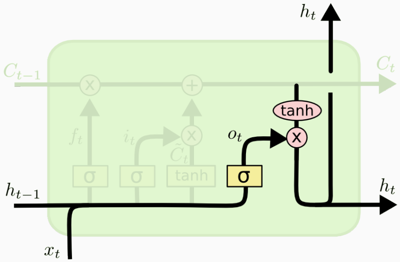

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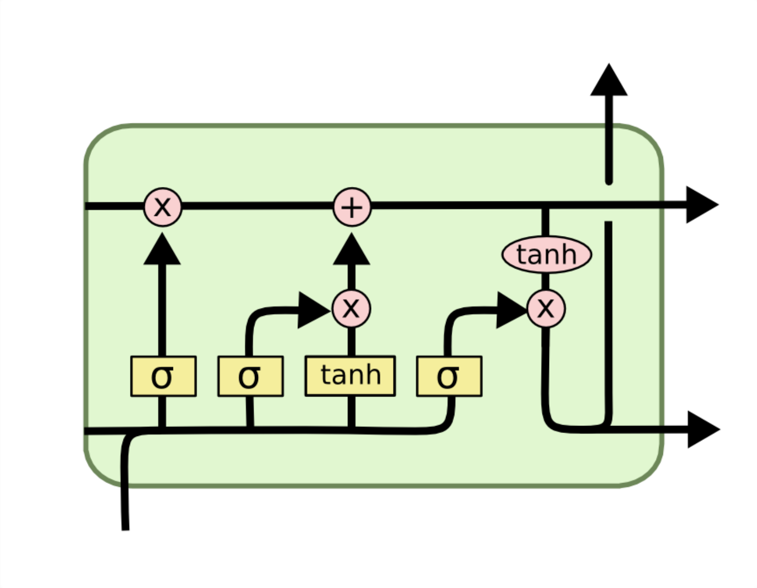
LSTM Visualization



LSTMs: additional remarks

- LSTMs solve the vanishing gradient problem, but the gradient can still explode
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  - Pay attention when reading the literature

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- LSTMs solve the vanishing gradient problem, but the gradient can still explode
    - Use gradient clipping
- Different variants of LSTMs. Basic idea is similar, but
    - Different gates
    - Different parametrization of the gates
    - Pay attention when reading the literature
- Mathematically: “Constant Error Carousel”
    - No repeated weight application in the derivative
    - “The derivative is the forget gate”

GRUs

Gated Recurrent Units:

- Combine forget and input gates into an “update gate”
- Suppress output gate
- Add a “reset gate”

Simpler than LSTMs (less parameters) and quite succesful

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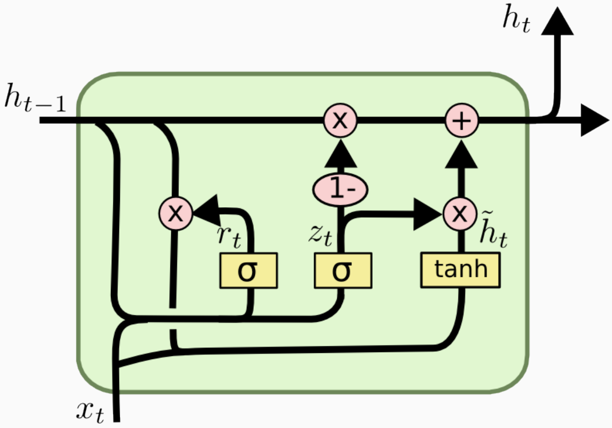
$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$$
$$\tilde{h}_t = \tanh(W x_t + U(r_t h_{t-1}) + b)$$
$$h_t = z_t \tilde{h}_t + (1 - z_t h_{t-1})$$

GRUs Visualization



Experimental Results

Results on 1B Word Benchmark

Model	Test PPL
RNN	68.3
Interpolated KN 5-gram, 1.1B N-Grams	67.6
RNN + MaxEnt 9-gram features	51.3
"Small" LSTM	54.1
"Big" LSTM with dropout	32.2
2 Layer LSTM with dropout	30.6

From R. Jozefowicz, O. Vinyals, M. Schuster, N. Shazeer, Y. Wu *Exploring the Limits of Lanugage Modelling*, 2016

A Few Notes About the Output Layer

The Output Layer

Computing a softmax is expensive
(specially for large vocabularies)

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Possible approaches:

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- Use hierarchical output
- Use self-normalizing networks (e.g. NCE training)

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NN Language Models

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