CMPT 413 / 825: Natural Language Processing

Recurrent Neural Networks

How to model sequences using neural networks?

Fall 2020
2020-10-16

Adapted from slides from Anoop Sarkar, Danqi Chen, Karthik Narasimhan, and Justin Johnson

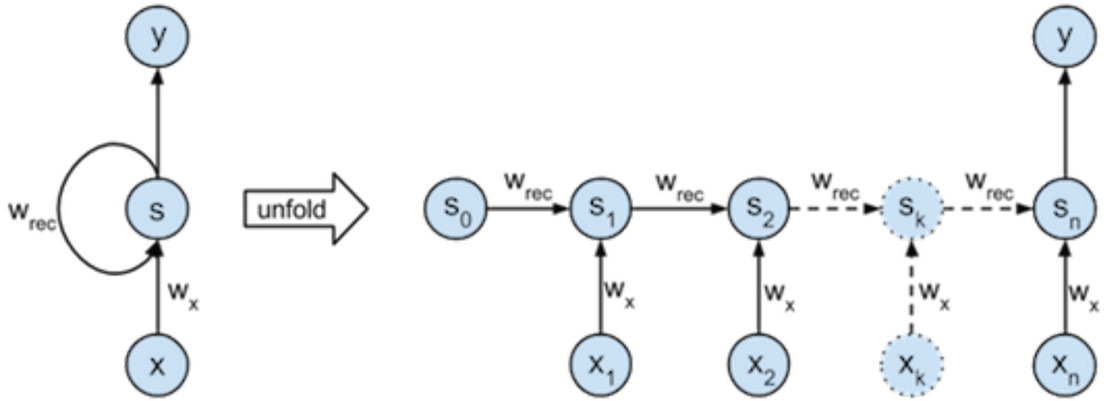
(Some slides adapted from Chris Manning, Abigail See, Andrej Karpathy)

Overview

- What is a recurrent neural network (RNN)?
- Simple RNNs
- Backpropagation through time
- Long short-term memory networks (LSTMs)
- Applications
- Variants: Stacked RNNs, Bidirectional RNNs

Recurrent neural networks (RNNs)

A class of neural networks allowing to handle **variable length inputs**



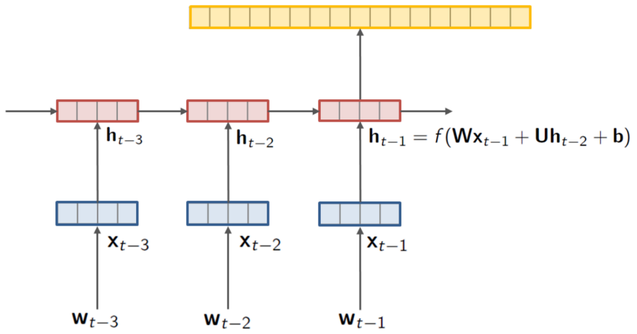
A function: $y = \text{RNN}(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n) \in \mathbb{R}^d$

where $\mathbf{x}_1, \ldots, \mathbf{x}_n \in \mathbb{R}^{d_{in}}$

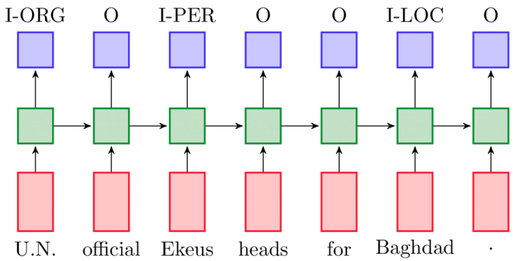
Recurrent neural networks (RNNs)

Proven to be an highly effective approach to **language modeling**, **sequence tagging** as well as **text classification** tasks:

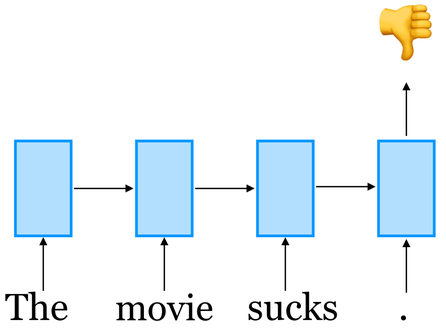
Language modeling



Sequence tagging

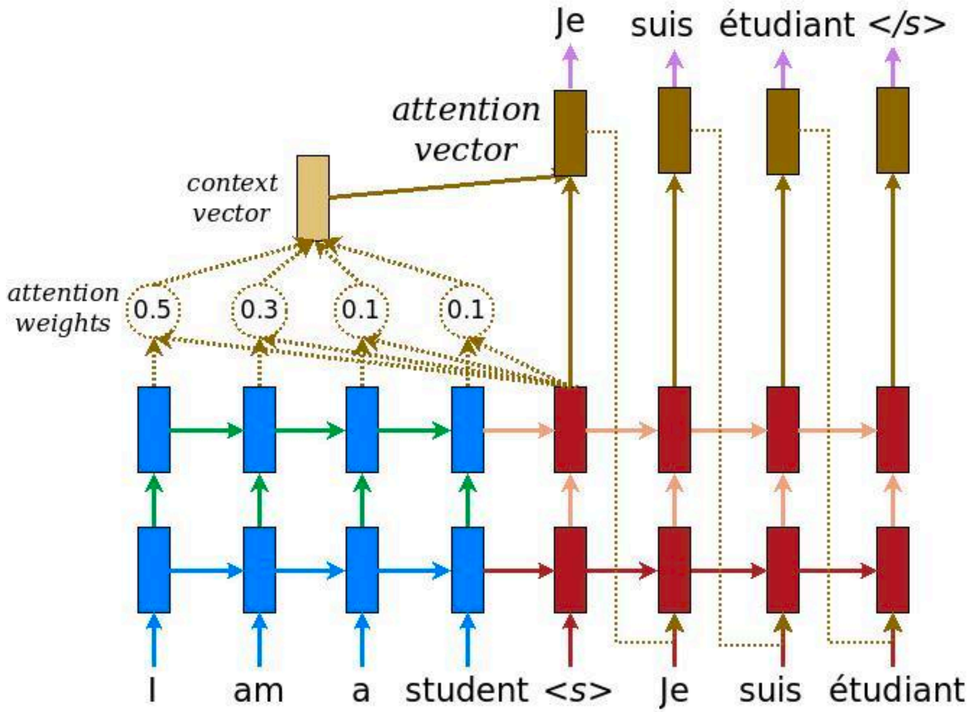


Text classification



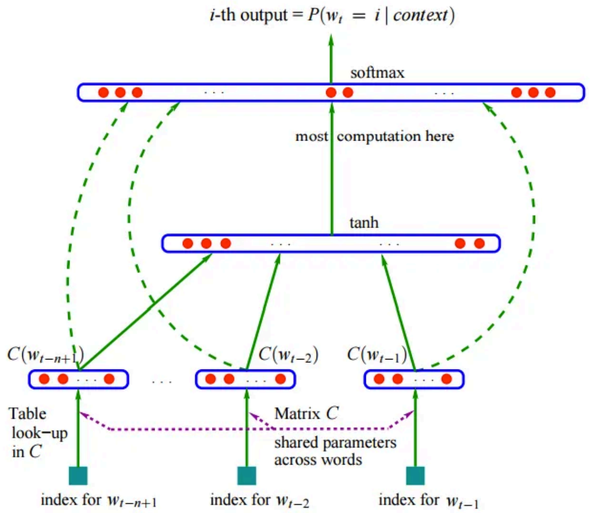
Recurrent neural networks (RNNs)

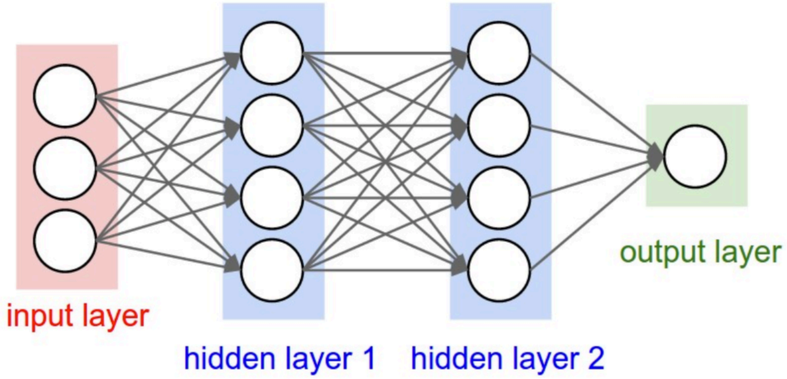
Form the basis for the modern approaches to **machine translation**, **question answering** and **dialogue**:



Why variable-length?

Recall the feedfoward neural LMs we learned:





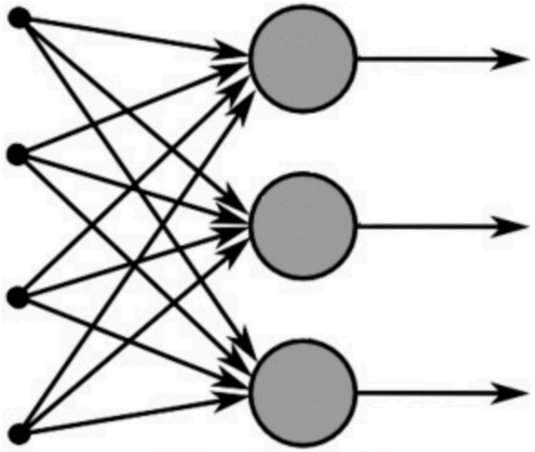
The dogs are <u>barking</u>

$$\mathbf{x} = [\mathbf{e}_{\text{the}}, \mathbf{e}_{\text{dogs}}, \mathbf{e}_{\text{are}}] \in \mathbb{R}^{3d}$$

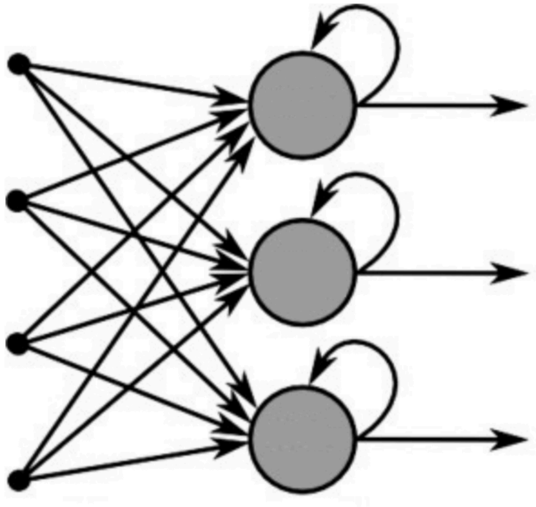
(fixed-window size = 3)

the dogs in the neighborhood are ____

RNNs vs Feedforward NNs



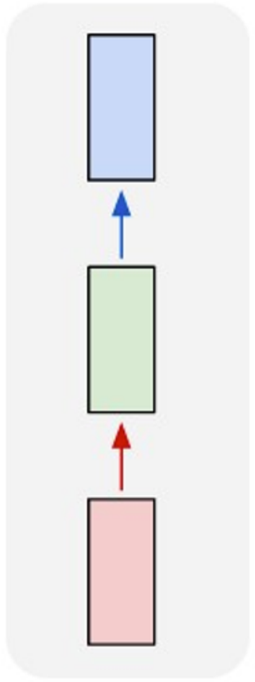
Feed-Forward Neural Network



Recurrent Neural Network

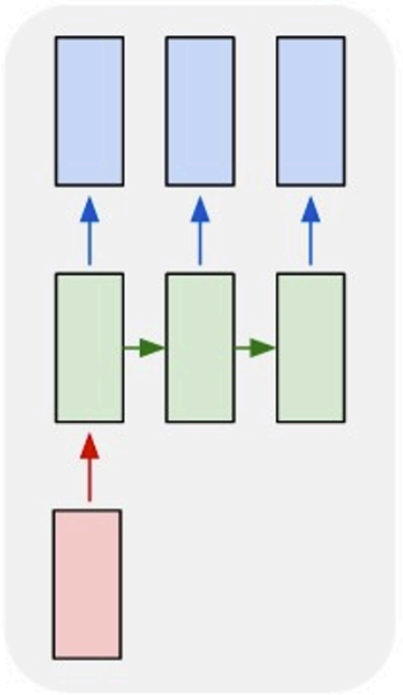
RNNs for sequence processing

one to one



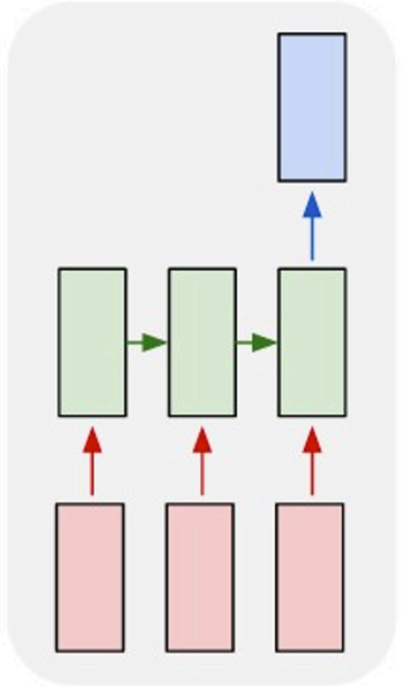
Vanilla Neural Networks

one to many



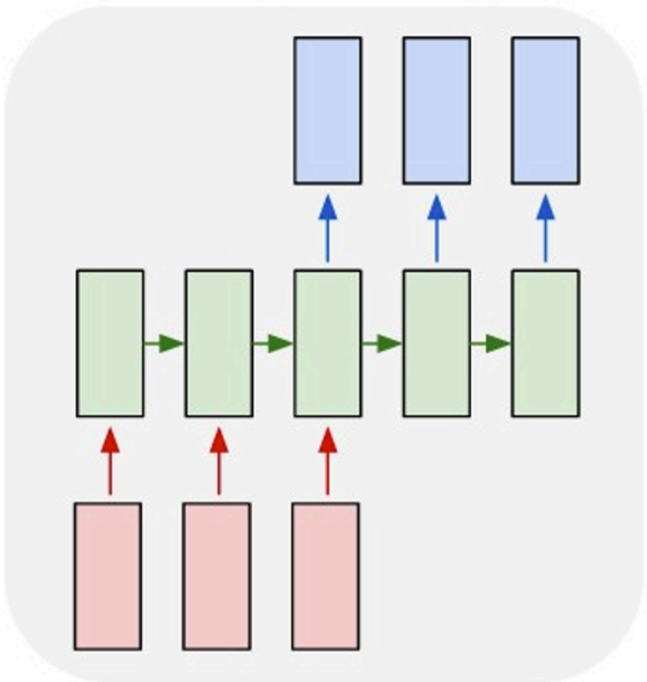
Text Generation

many to one



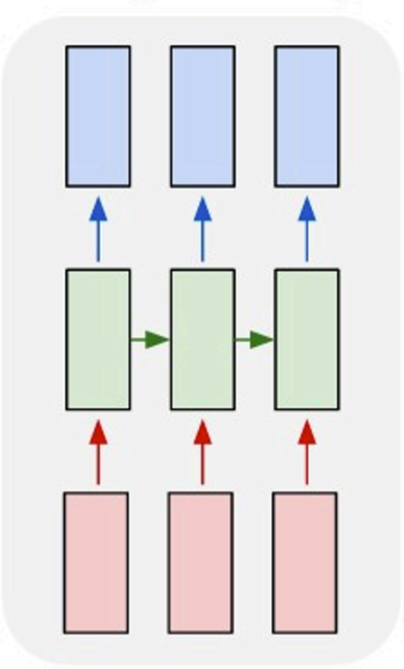
Text Classification

many to many



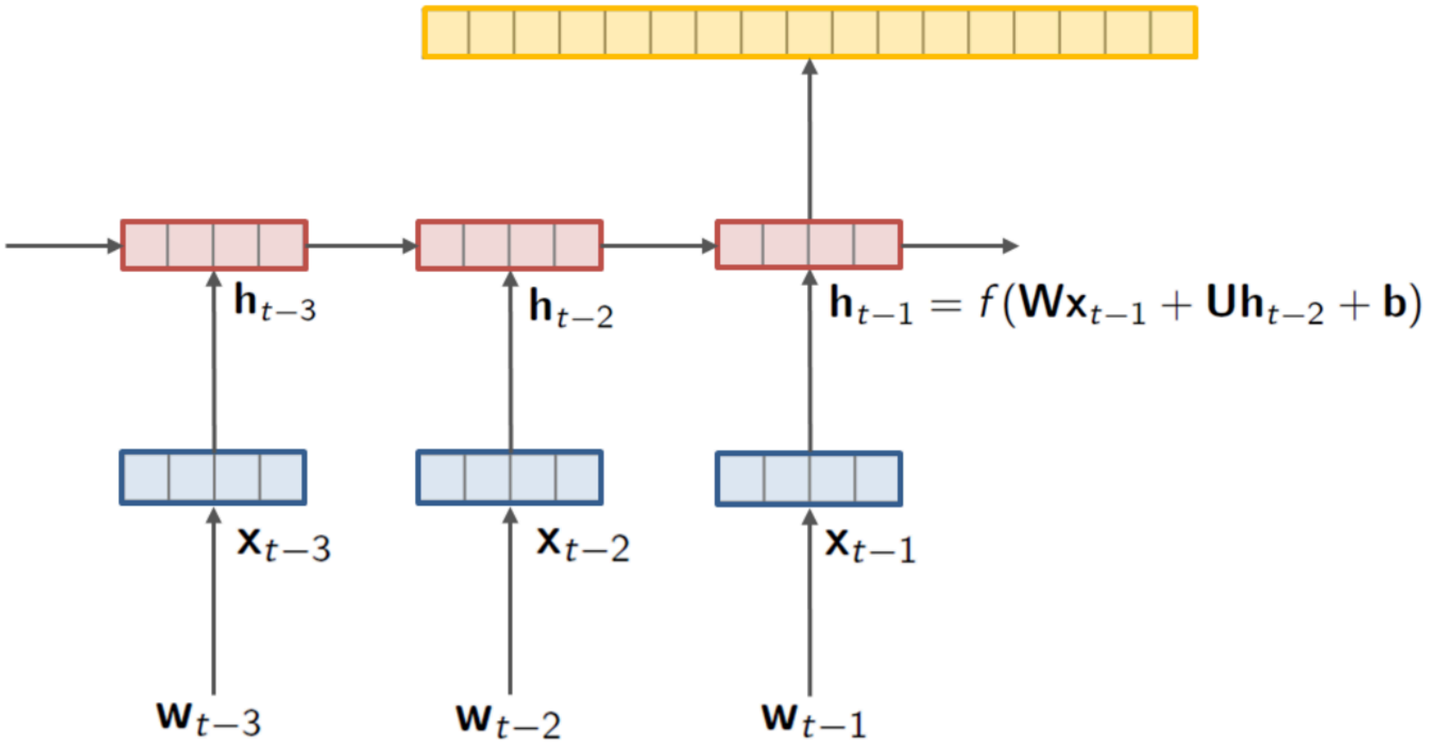
Neural Machine Translation

many to many



Sequence Tagging

Recurrent Neural Language Models



Language Modeling

Predict probability of sequence of words

$$P(s) = P(w_1, \ldots, w_T) = \prod_{t=1}^{T} P(w_t | w_{<t})$$

with n-grams

$$P(w_t | w_{<t}) \approx P(w_t | w_{t-n+1,t-1})$$

with HMMs

$$P(w_t | w_{<t}) \approx P(w_t | h_t) P(h_t | h_{t-n+1,t-1})$$

with neural networks

$$p(w_t \mid w_{<t}) \approx p(w_t \mid \phi(w_1, \ldots, w_{t-1}))$$

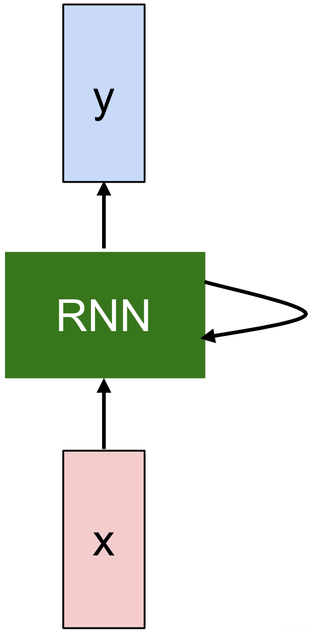
with fixed window

$$P(w_t | w_{<t}) \approx P(w_t | \phi(w_{t-n+1,t-1}))$$

with RNNs

$$P(w_t | w_{<t}) \approx P(w_t | \mathbf{h}_t), \mathbf{h}_t = f(\mathbf{h}_{t-1}, w_{t-1})$$

Simple (vanilla) RNNs



$\mathbf{h}_0 \in \mathbb{R}^d$ is an initial state

function with weights W

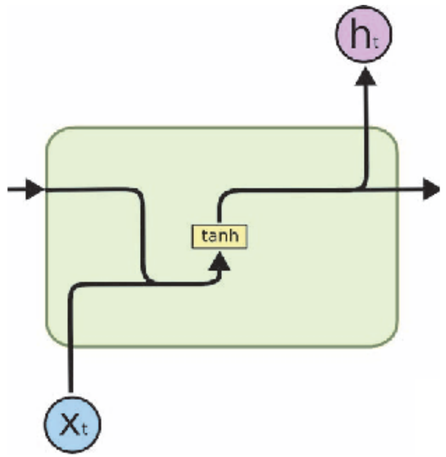
$$\mathbf{h}_t = f_{\mathbf{W}}(\mathbf{h}_{t-1}, \mathbf{x}_t) \in \mathbb{R}^d$$

new state old state input at time t

$\mathbf{h}_t$: hidden states which store information from $\mathbf{x}_1$ to $\mathbf{x}_t$

Output label for each time step: Denote $\hat{\mathbf{y}}_t = \text{softmax}(\mathbf{W}_o \mathbf{h}_t)$, $\mathbf{W}_o \in \mathbb{R}^{|V| \times d}$

Simple (vanilla) RNNs:



$$\mathbf{h}_t = g(\mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{U}\mathbf{x}_t + \mathbf{b}) \in \mathbb{R}^d$$

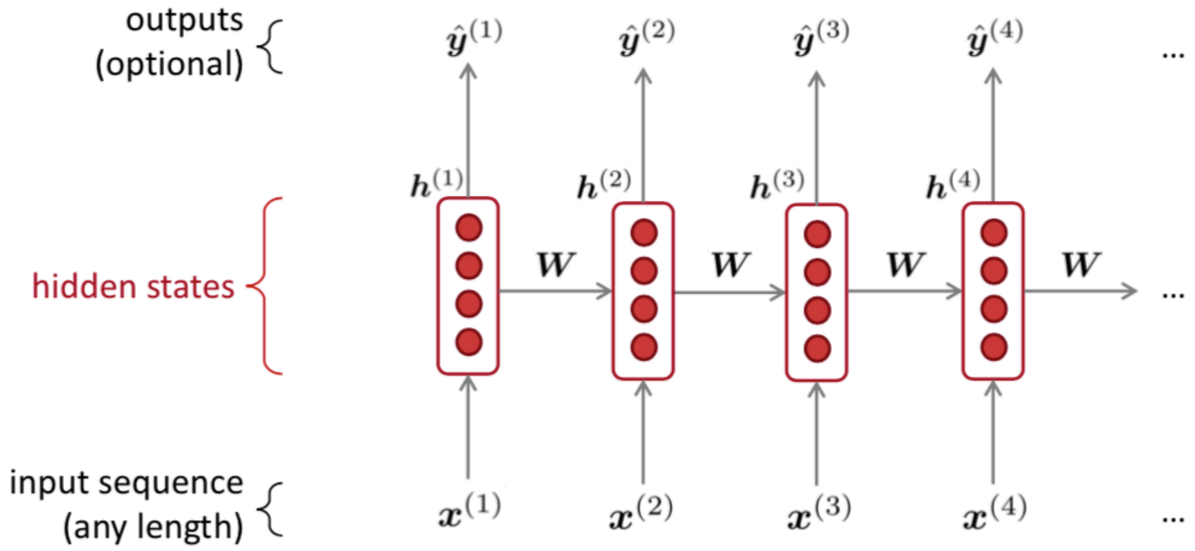
g: nonlinearity (e.g. tanh),

$\mathbf{W}_{hh} \in \mathbb{R}^{d \times d}, \mathbf{U} \in \mathbb{R}^{d \times d_{in}}, \mathbf{b} \in \mathbb{R}^d$

Simple RNNs

$$\mathbf{h}_t = g(\mathbf{W}\mathbf{h}_{t-1} + \mathbf{U}\mathbf{x}_t + \mathbf{b}) \in \mathbb{R}^d$$

Key idea: apply the same weights $\mathbf{W}$ repeatedly



Recurrent Neural Language Models (RNNLMs)

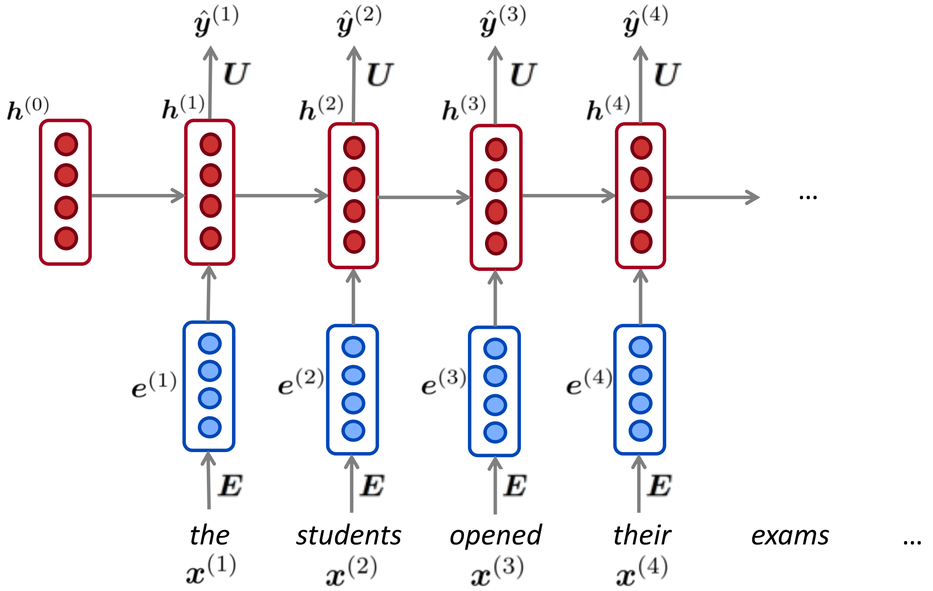
$$P(w_1, w_2, \ldots, w_n) = P(w_1) \times P(w_2 \mid w_1) \times P(w_3 \mid w_1, w_2) \times \ldots \times P(w_n \mid w_1, w_2, \ldots, w_{n-1})$$

$$= P(w_1 \mid \mathbf{h}_0) \times P(w_2 \mid \mathbf{h}_1) \times P(w_3 \mid \mathbf{h}_2) \times \ldots \times P(w_n \mid \mathbf{h}_{n-1})$$

- Denote $\hat{\mathbf{y}}_t = \text{softmax}(\mathbf{W}_o \mathbf{h}_t)$, $\mathbf{W}_o \in \mathbb{R}^{|V| \times d}$
- Cross-entropy loss:

$$L(\theta) = -\frac{1}{n} \sum_{t=1}^{n} \log \hat{\mathbf{y}}_{t-1}(w_t)$$

$$\theta = \{\mathbf{W}, \mathbf{U}, \mathbf{b}, \mathbf{W}_o, \mathbf{E}\}$$



Progress on language models

On the Penn Treebank (PTB) dataset

Metric: perplexity

KN5: Kneser-Ney 5-gram

Model	Individual
KN5	141.2
KN5 + cache	125.7
Feedforward NNLM	140.2
Log-bilinear NNLM	144.5
Syntactical NNLM	131.3
Recurrent NNLM	124.7
RNN-LDA LM	113.7

(Mikolov and Zweig, 2012): Context dependent recurrent neural network language model

Progress on language models

On the Penn Treebank (PTB) dataset

Metric: perplexity

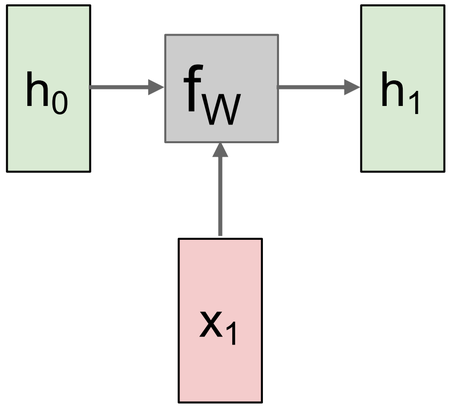
Model	#Param	Validation	Test
Mikolov & Zweig (2012) – RNN-LDA + KN-5 + cache	9M‡	-	92.0
Zaremba et al. (2014) – LSTM	20M	86.2	82.7
Gal & Ghahramani (2016) – Variational LSTM (MC)	20M	-	78.6
Kim et al. (2016) – CharCNN	19M	-	78.9
Merity et al. (2016) – Pointer Sentinel-LSTM	21M	72.4	70.9
Grave et al. (2016) – LSTM + continuous cache pointer†	-	-	72.1
Inan et al. (2016) – Tied Variational LSTM + augmented loss	24M	75.7	73.2
Zilly et al. (2016) – Variational RHN	23M	67.9	65.4
Zoph & Le (2016) – NAS Cell	25M	-	64.0
Melis et al. (2017) – 2-layer skip connection LSTM	24M	60.9	58.3
Merity et al. (2017) – AWD-LSTM w/o finetune	24M	60.7	58.8
Merity et al. (2017) – AWD-LSTM	24M	60.0	57.3
Ours – AWD-LSTM-MoS w/o finetune	22M	58.08	55.97
Ours – AWD-LSTM-MoS	22M	**56.54**	**54.44**
Merity et al. (2017) – AWD-LSTM + continuous cache pointer†	24M	53.9	52.8
Krause et al. (2017) – AWD-LSTM + dynamic evaluation†	24M	51.6	51.1
Ours – AWD-LSTM-MoS + dynamic evaluation†	22M	**48.33**	**47.69**

dropping perplexity

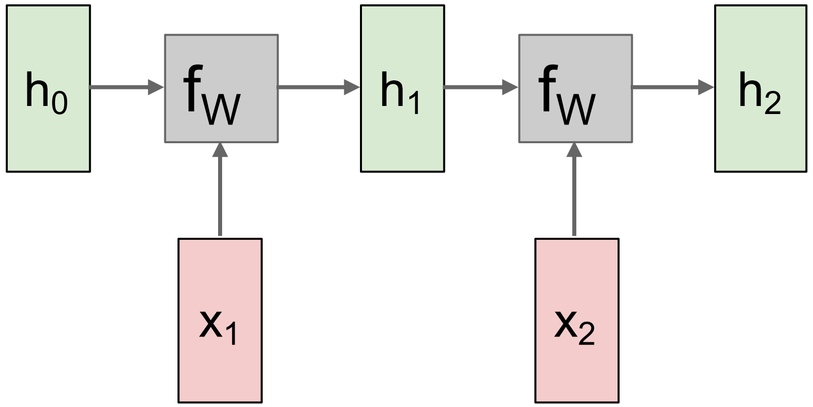
(Yang et al, 2018): Breaking the Softmax Bottleneck: A High-Rank RNN Language Model

Training the RNN

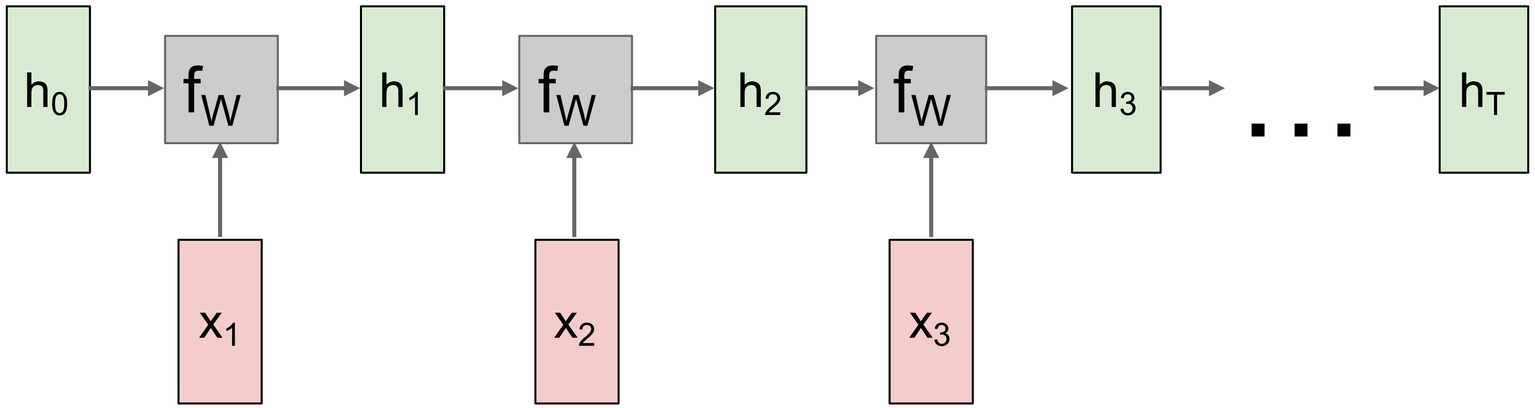
RNN Computation Graph



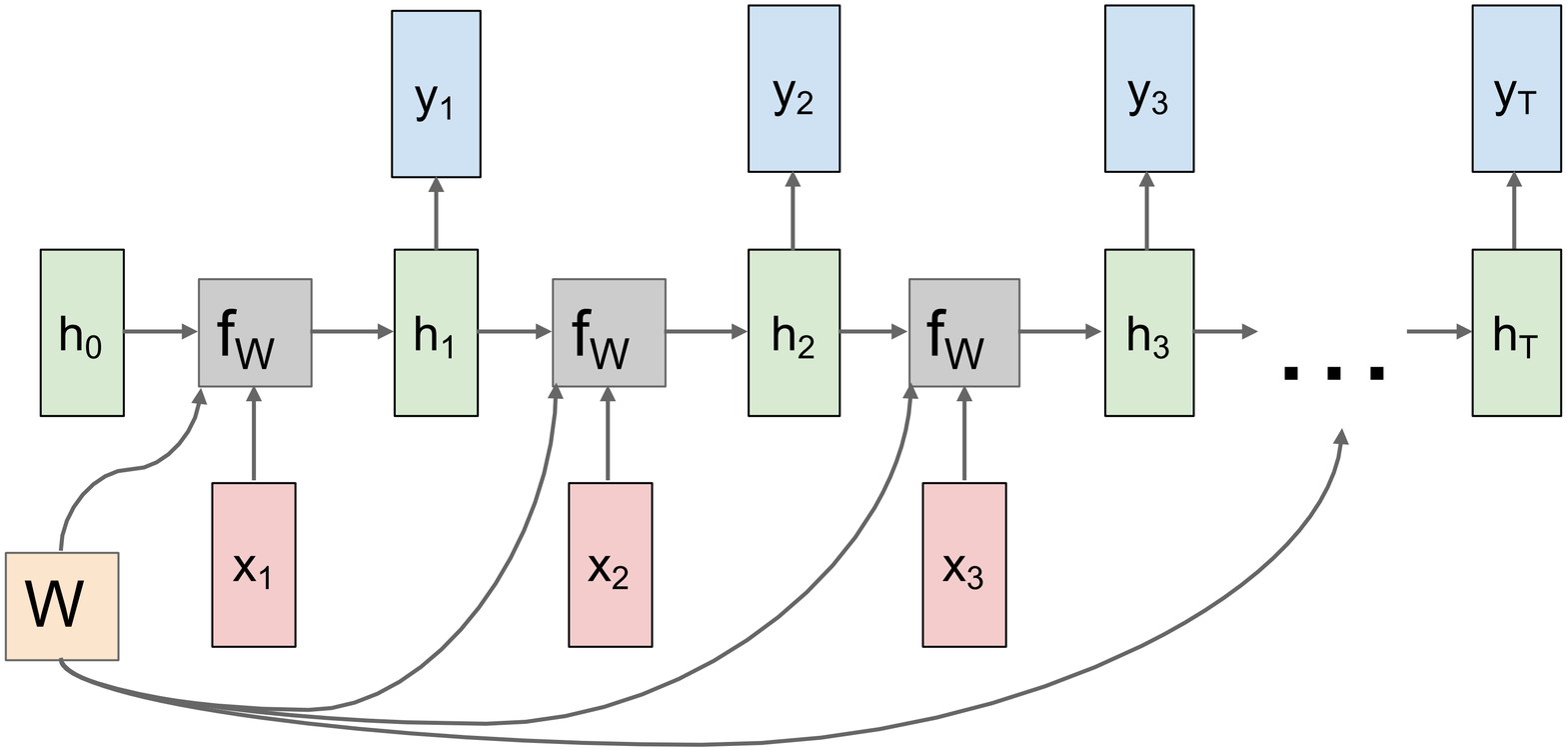
RNN Computation Graph



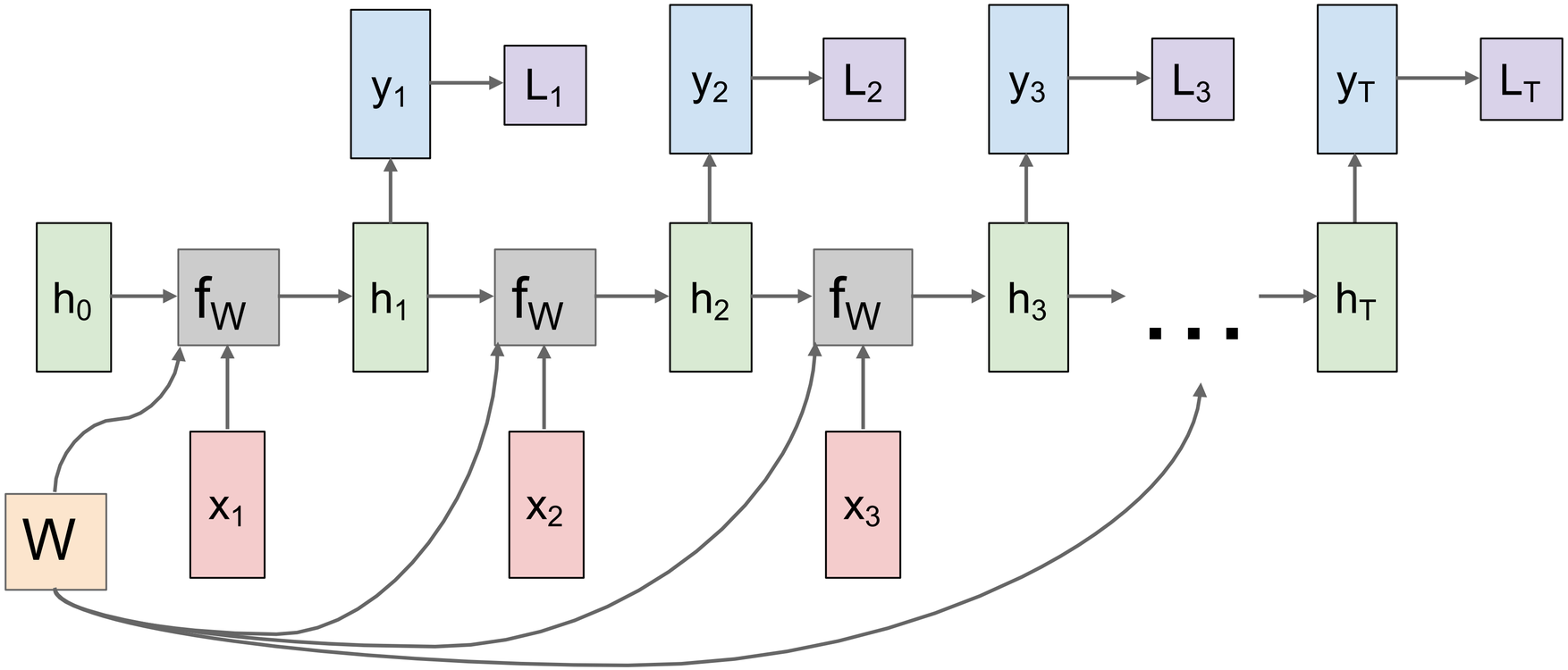
RNN Computation Graph



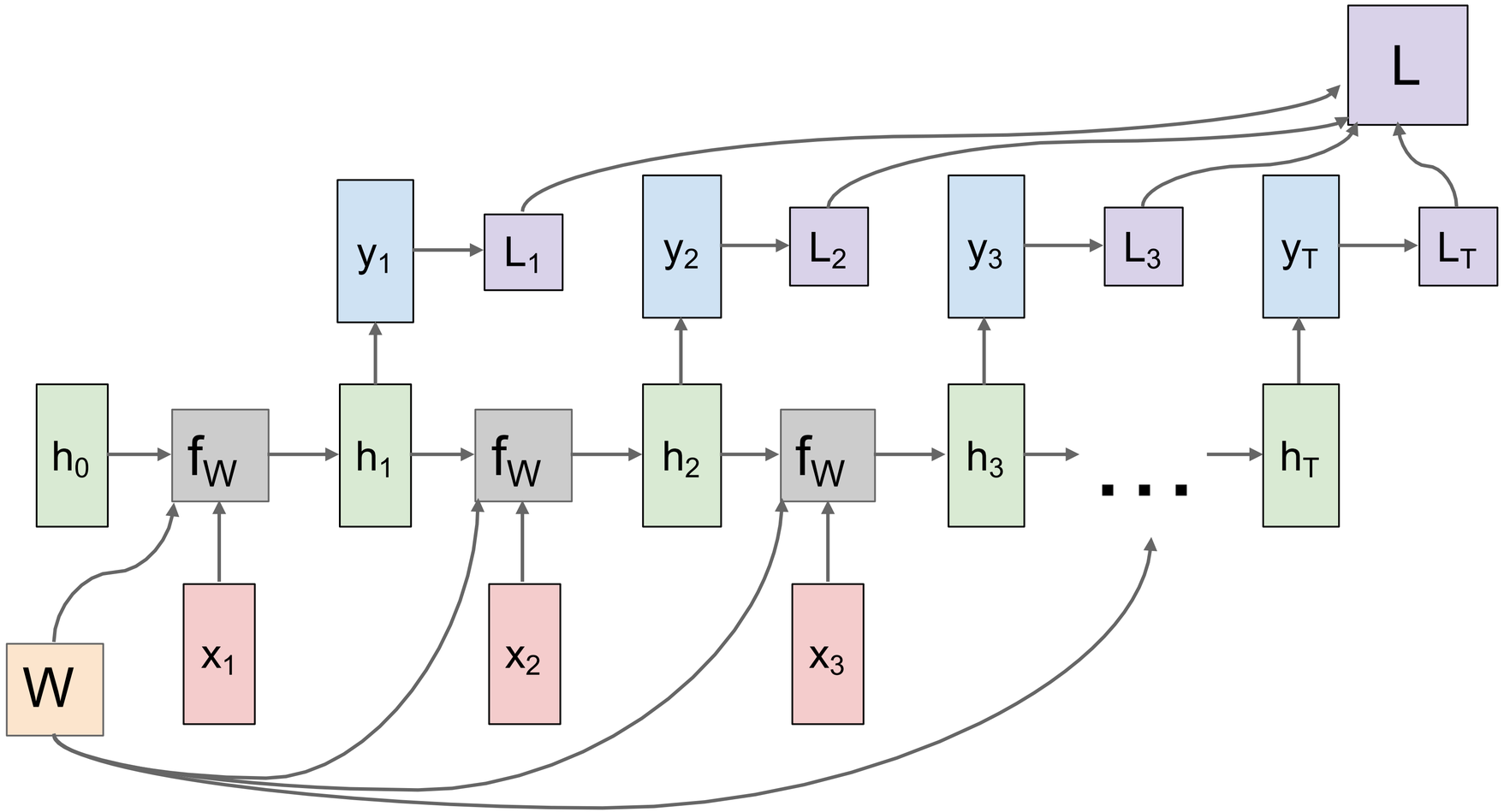
RNN Computation Graph



RNN Computation Graph

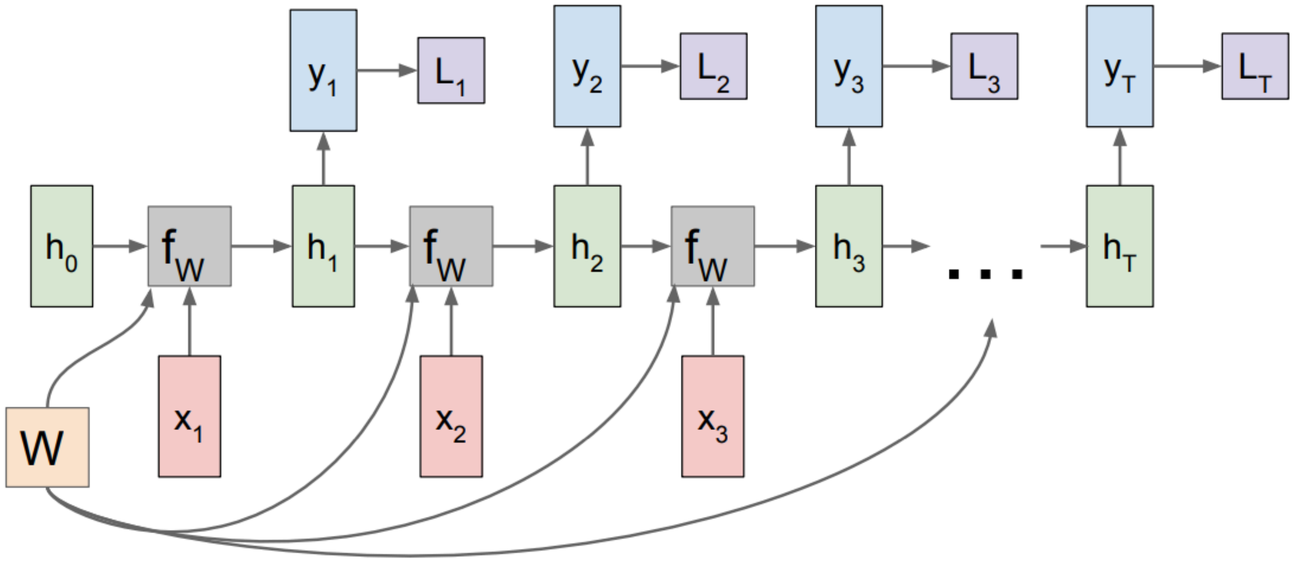


RNN Computation Graph



Training RNNLMs

- Backpropagation? Yes, but not that simple!



- The algorithm is called Backpropagation Through Time (BPTT).

Backpropagation through time

$$\mathbf{h}_1 = g(\mathbf{W}\mathbf{h}_0 + \mathbf{U}\mathbf{x}_1 + \mathbf{b})$$

$$\mathbf{h}_2 = g(\mathbf{W}\mathbf{h}_1 + \mathbf{U}\mathbf{x}_2 + \mathbf{b})$$

$$\mathbf{h}_3 = g(\mathbf{W}\mathbf{h}_2 + \mathbf{U}\mathbf{x}_3 + \mathbf{b})$$

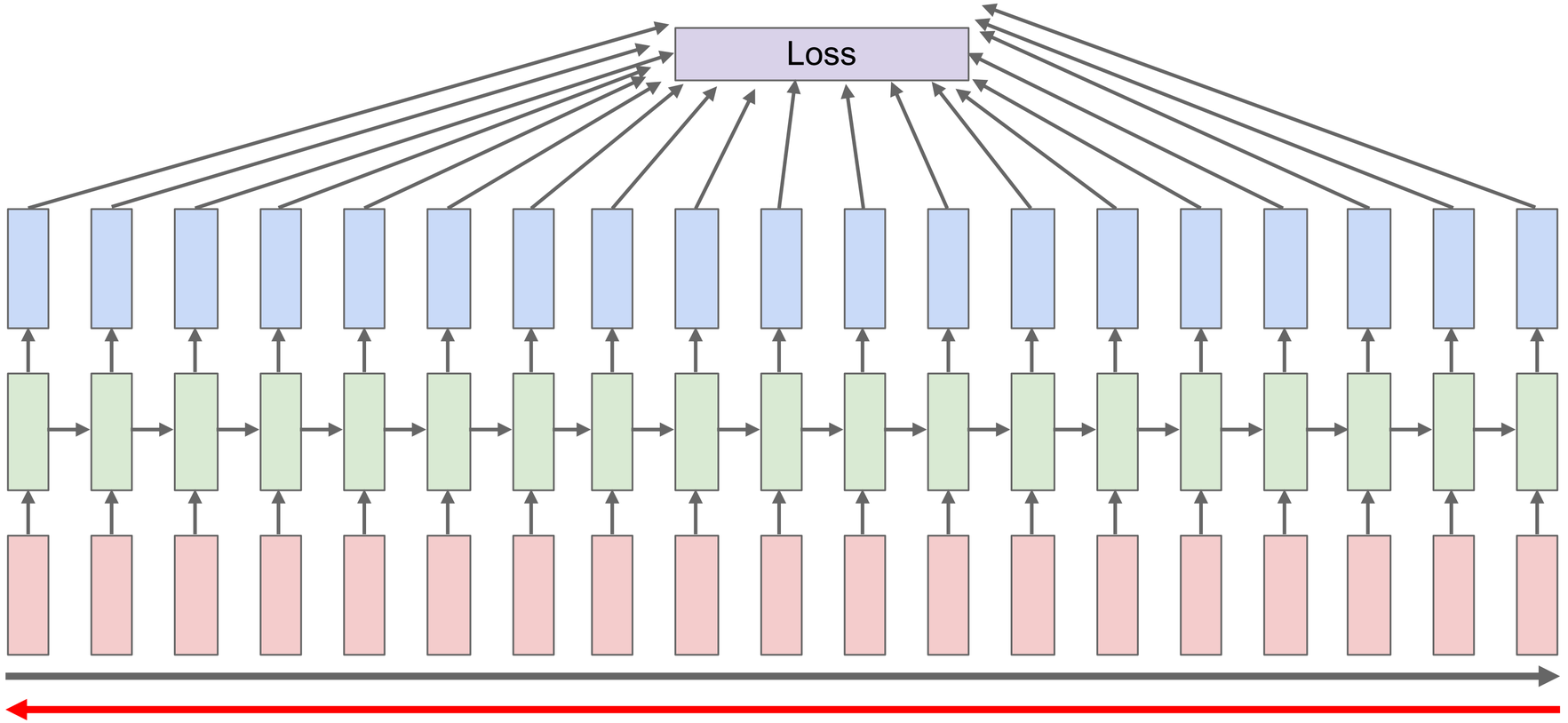
$$L_3 = -\log \hat{\mathbf{y}}_3(w_4)$$

You should know how to compute: $\frac{\partial L_3}{\partial \mathbf{h}_3}$

$$\frac{\partial L_3}{\partial \mathbf{W}} = \frac{\partial L_3}{\partial \mathbf{h}_3}\frac{\partial \mathbf{h}_3}{\partial \mathbf{W}} + \frac{\partial L_3}{\partial \mathbf{h}_3}\frac{\partial \mathbf{h}_3}{\partial \mathbf{h}_2}\frac{\partial \mathbf{h}_2}{\partial \mathbf{W}} + \frac{\partial L_3}{\partial \mathbf{h}_3}\frac{\partial \mathbf{h}_3}{\partial \mathbf{h}_2}\frac{\partial \mathbf{h}_2}{\partial \mathbf{h}_1}\frac{\partial \mathbf{h}_1}{\partial \mathbf{W}}$$

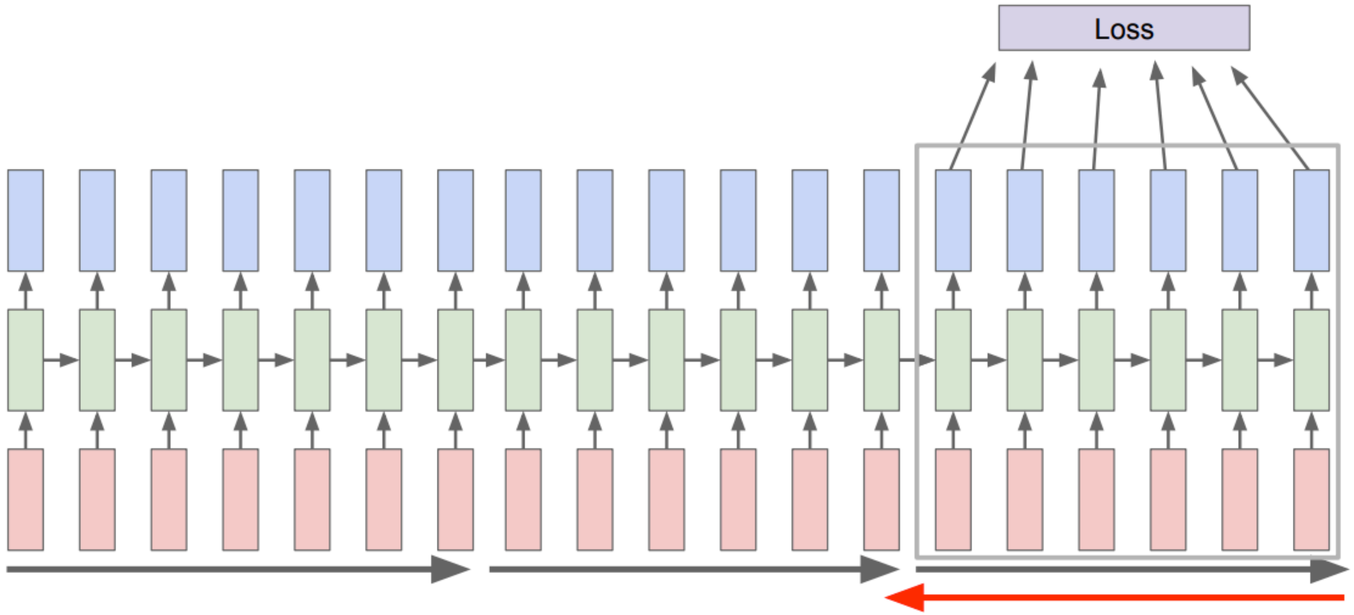
$$\boxed{\frac{\partial L}{\partial \mathbf{W}} = -\frac{1}{n}\sum_{t=1}^{n}\sum_{k=1}^{t}\frac{\partial L_t}{\partial \mathbf{h}_t}\left(\prod_{j=k+1}^{t}\frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}}\right)\frac{\partial \mathbf{h}_k}{\partial \mathbf{W}}}$$

Forward through entire sequence to compute loss, then backward through entire sequence to compute gradient



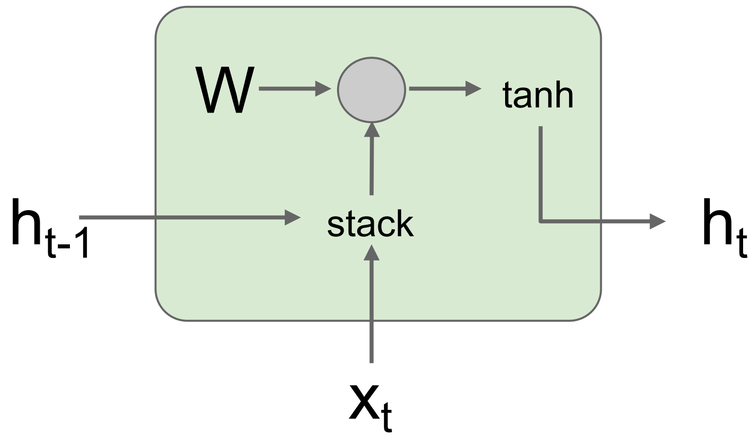
Truncated backpropagation through time

- Backpropagation is very expensive if you handle long sequences



- Run forward and backward through chunks of the sequence instead of whole sequence
- Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps

Vanishing gradients



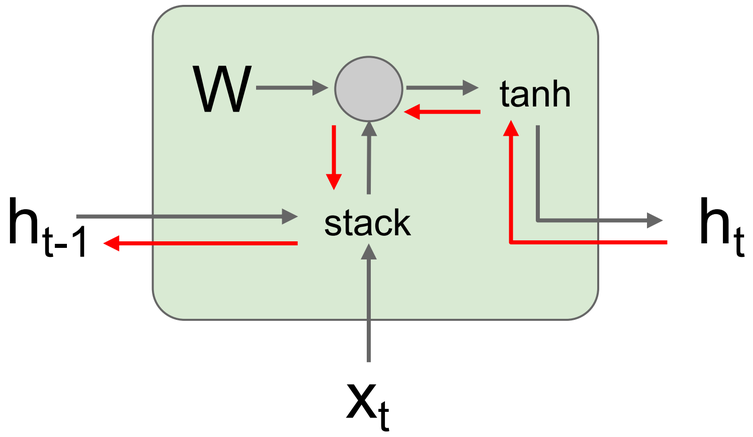
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)$$

$$= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)$$

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994

Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$= \tanh\left((W_{hh} \quad W_{hx})\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

$$= \tanh\left(W\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

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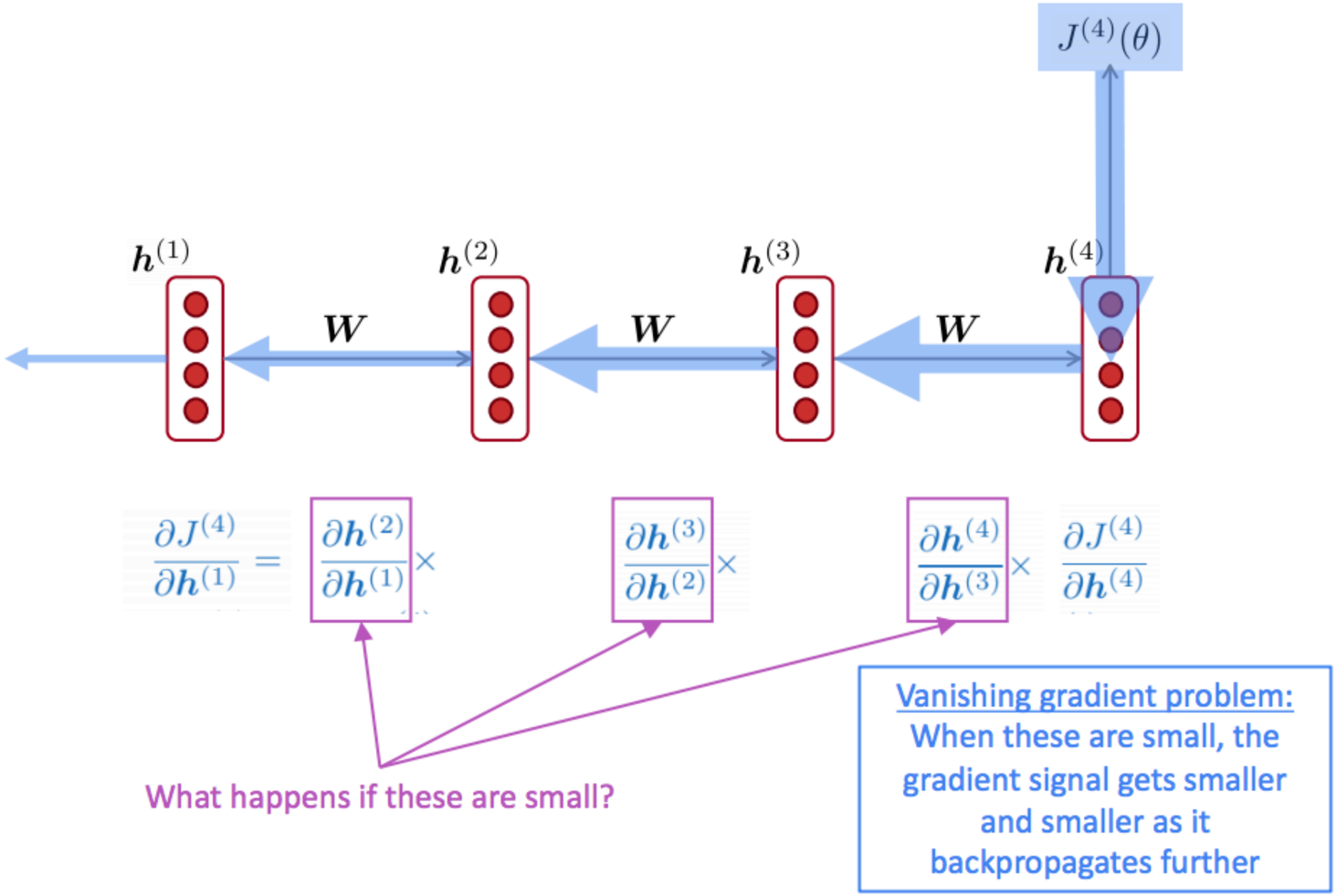
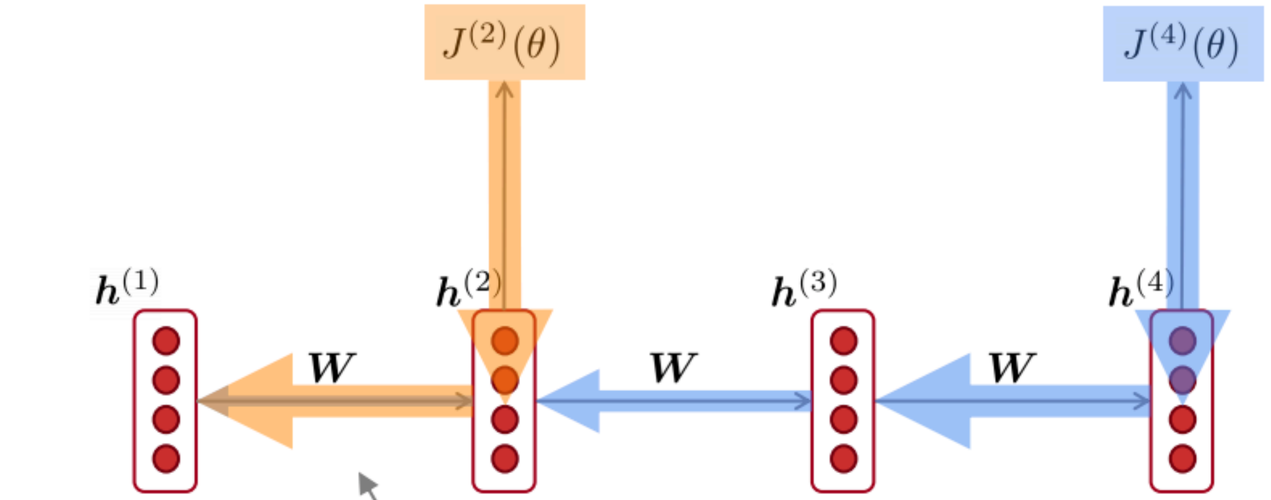
Vanishing gradients

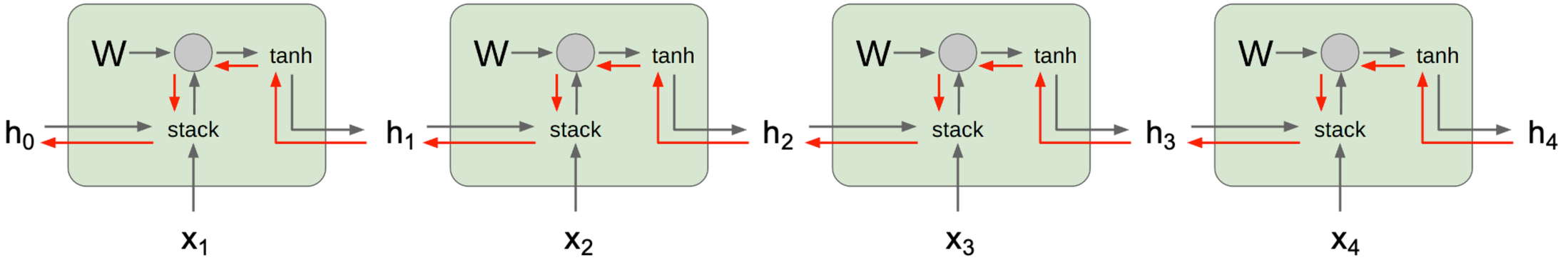


Vanishing Gradients



Gradient signal from faraway is lost because it's much smaller than gradient signal from close-by.

So model weights are updated only with respect to near effects, not long-term effects.

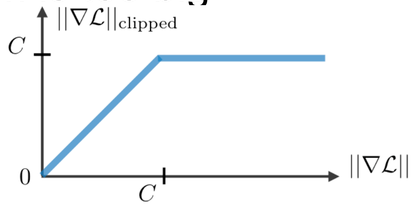


Computing gradient of h_0 involves many factors of W (and repeated tanh)

Largest singular value > 1:
Exploding gradients

Gradient clipping:
Scale gradient if its norm is too big

```
grad_norm = np.sum(grad * grad)
if grad_norm > threshold:
  grad *= (threshold / grad_norm)
```



Largest singular value < 1:
Vanishing gradients

→ Change RNN architecture

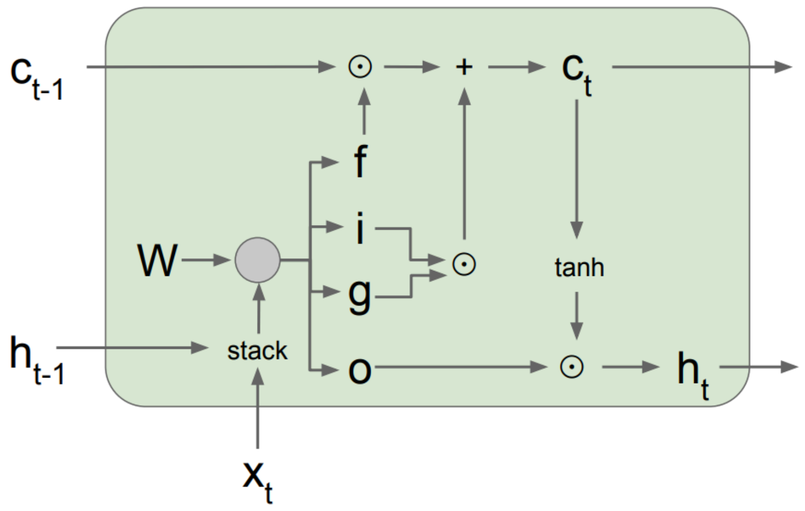
Different RNN cells

Long Short-term Memory (LSTM)

- A type of RNN proposed by Hochreiter and Schmidhuber in 1997 as a solution to the vanishing gradients problem
- Work extremely well in practice
- **Basic idea**: turning multiplication into addition
- Use "gates" to control how much information to add/erase

$$\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t) \in \mathbb{R}^d$$

- At each timestep, there is a hidden state $\mathbf{h}_t \in \mathbb{R}^d$ and also a cell state $\mathbf{c}_t \in \mathbb{R}^d$
  - $\mathbf{c}_t$ stores **long-term information**
  - We write/erase $\mathbf{c}_t$ after each step
  - We read $\mathbf{h}_t$ from $\mathbf{c}_t$



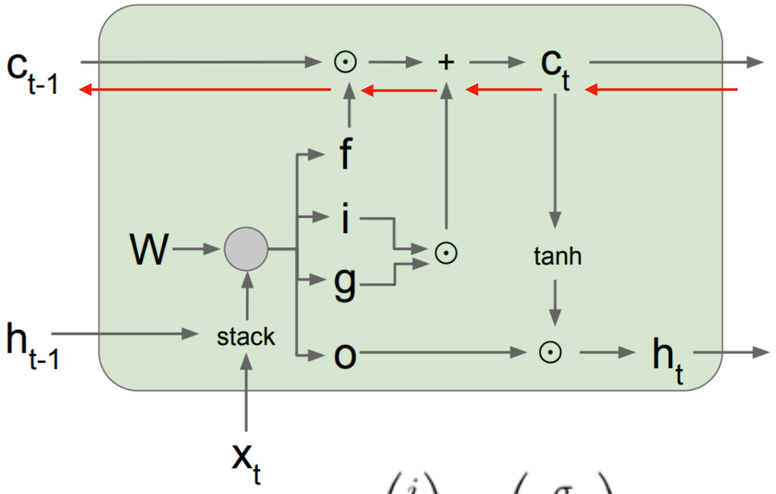
Long Short-term Memory (LSTM)

There are 4 gates:

- Input gate (how much to write):
  $\mathbf{i}_t = \sigma(\mathbf{W}^{(i)}\mathbf{h}_{t-1} + \mathbf{U}^{(i)}\mathbf{x}_t + \mathbf{b}^{(i)}) \in \mathbb{R}^d$
- Forget gate (how much to erase):
  $\mathbf{f}_t = \sigma(\mathbf{W}^{(f)}\mathbf{h}_{t-1} + \mathbf{U}^{(f)}\mathbf{x}_t + \mathbf{b}^{(f)}) \in \mathbb{R}^d$
- Output gate (how much to reveal):
  $\mathbf{o}_t = \sigma(\mathbf{W}^{(o)}\mathbf{h}_{t-1} + \mathbf{U}^{(o)}\mathbf{x}_t + \mathbf{b}^{(o)}) \in \mathbb{R}^d$
- New memory cell (what to write):
  $\mathbf{g}_t = \tanh(\mathbf{W}^{(c)}\mathbf{h}_{t-1} + \mathbf{U}^{(c)}\mathbf{x}_t + \mathbf{b}^{(c)}) \in \mathbb{R}^d$
- Final memory cell: $\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{g}_t$
- Final hidden cell: $\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$

element-wise product

Backpropagation from c_t to c_{t-1} only element wise multiplication by f, no matrix multiply by W



$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

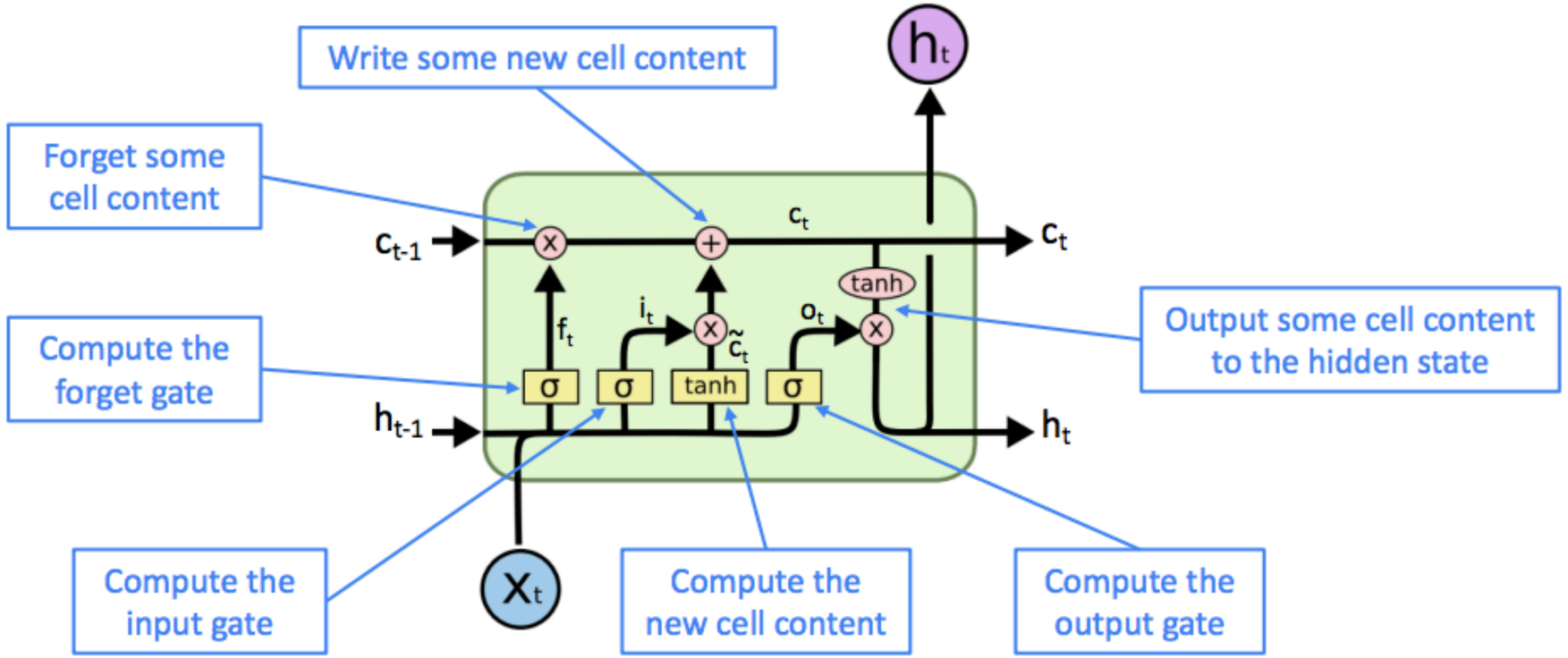
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

How many parameters in total?

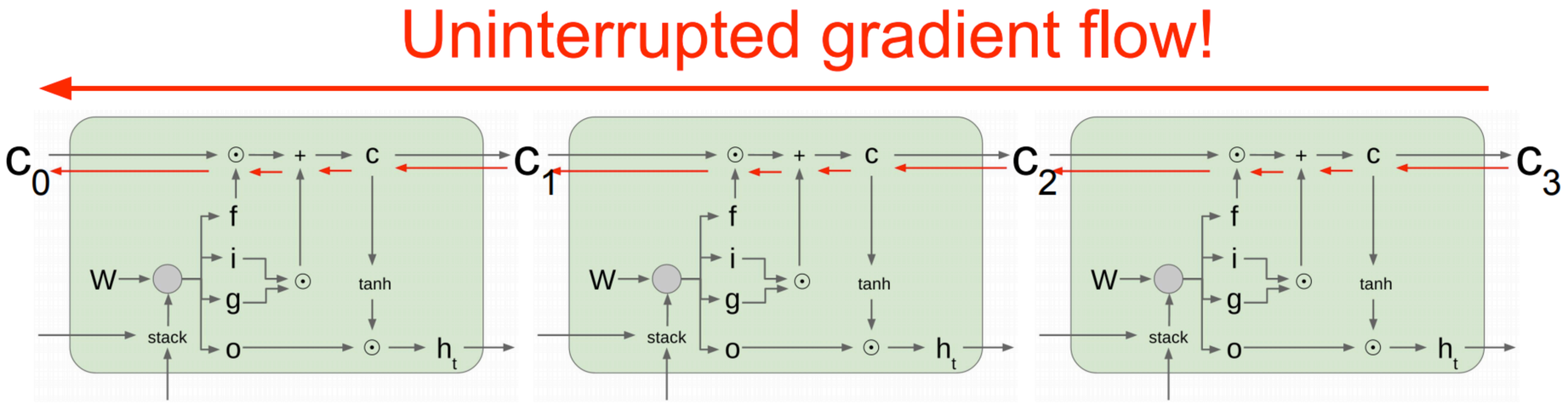
LSTM cell intuitively

You can think of the LSTM equations visually like this:



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short-term Memory (LSTM)



- LSTM doesn't guarantee that there is no vanishing/exploding gradient, but it does provide an easier way for the model to learn long-distance dependencies

- LSTMs were invented in 1997 but finally got working from 2013-2015.

Is the LSTM architecture optimal?

MUT1:

$$
\begin{aligned}
z &= \text{sigm}(W_{\text{xz}} x_t + b_{\text{z}}) \\
r &= \text{sigm}(W_{\text{xr}} x_t + W_{\text{hr}} h_t + b_{\text{r}}) \\
h_{t+1} &= \tanh(W_{\text{hh}}(r \odot h_t) + \tanh(x_t) + b_{\text{h}}) \odot z \\
&+ h_t \odot (1 - z)
\end{aligned}
$$

MUT2:

$$
\begin{aligned}
z &= \text{sigm}(W_{\text{xz}} x_t + W_{\text{hz}} h_t + b_{\text{z}}) \\
r &= \text{sigm}(x_t + W_{\text{hr}} h_t + b_{\text{r}}) \\
h_{t+1} &= \tanh(W_{\text{hh}}(r \odot h_t) + W_{xh} x_t + b_{\text{h}}) \odot z \\
&+ h_t \odot (1 - z)
\end{aligned}
$$

MUT3:

$$
\begin{aligned}
z &= \text{sigm}(W_{\text{xz}} x_t + W_{\text{hz}} \tanh(h_t) + b_{\text{z}}) \\
r &= \text{sigm}(W_{\text{xr}} x_t + W_{\text{hr}} h_t + b_{\text{r}}) \\
h_{t+1} &= \tanh(W_{\text{hh}}(r \odot h_t) + W_{xh} x_t + b_{\text{h}}) \odot z \\
&+ h_t \odot (1 - z)
\end{aligned}
$$

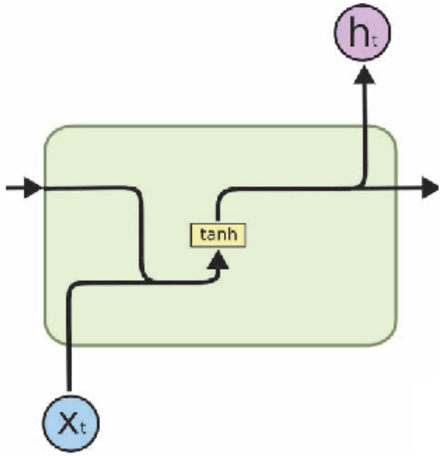
Arch.	Arith.	XML	PTB
Tanh	0.29493	0.32050	0.08782
LSTM	0.89228	0.42470	0.08912
LSTM-f	0.29292	0.23356	0.08808
LSTM-i	0.75109	0.41371	0.08662
LSTM-o	0.86747	0.42117	0.08933
LSTM-b	0.90163	0.44434	0.08952
GRU	0.89565	0.45963	0.09069
MUT1	**0.92135**	**0.47483**	0.08968
MUT2	0.89735	**0.47324**	0.09036
MUT3	0.90728	0.46478	**0.09161**

Arch.	5M-tst	10M-v	20M-v	20M-tst
Tanh	4.811	4.729	4.635	4.582 (97.7)
LSTM	4.699	4.511	4.437	4.399 (81.4)
LSTM-f	4.785	4.752	4.658	4.606 (100.8)
LSTM-i	4.755	4.558	4.480	4.444 (85.1)
LSTM-o	4.708	4.496	4.447	4.411 (82.3)
LSTM-b	4.698	4.437	4.423	**4.380 (79.83)**
GRU	4.684	4.554	4.559	4.519 (91.7)
MUT1	4.699	4.605	4.594	4.550 (94.6)
MUT2	4.707	4.539	4.538	4.503 (90.2)
MUT3	4.692	4.523	4.530	4.494 (89.47)

(Jozefowicz et al, 2015): An Empirical Exploration of Recurrent Network Architectures

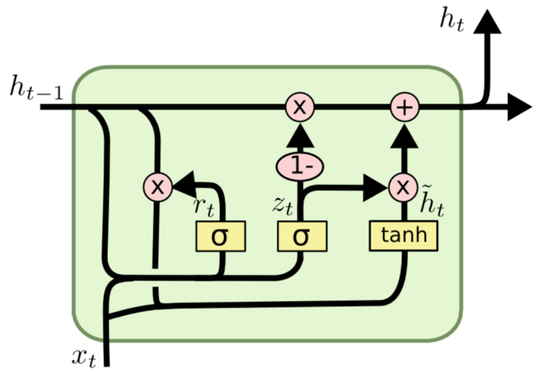
Simple RNN vs GRU vs LSTM

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$



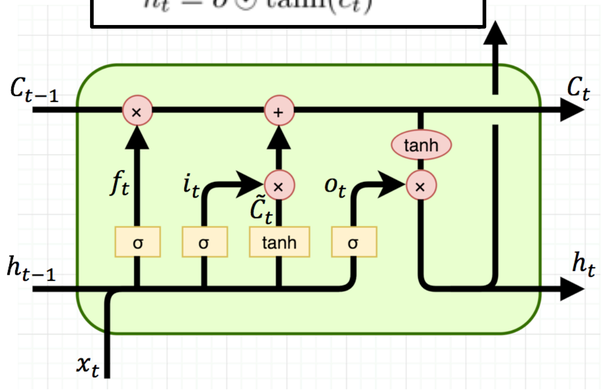
Simple RNN

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)$$
$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)$$
$$\tilde{h}_t = \tanh(W_{xh}x_t + W_{hh}(r_t \odot h_{t-1}) + b_h)$$
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t$$



GRU

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$
$$c_t = f \odot c_{t-1} + i \odot g$$
$$h_t = o \odot \tanh(c_t)$$

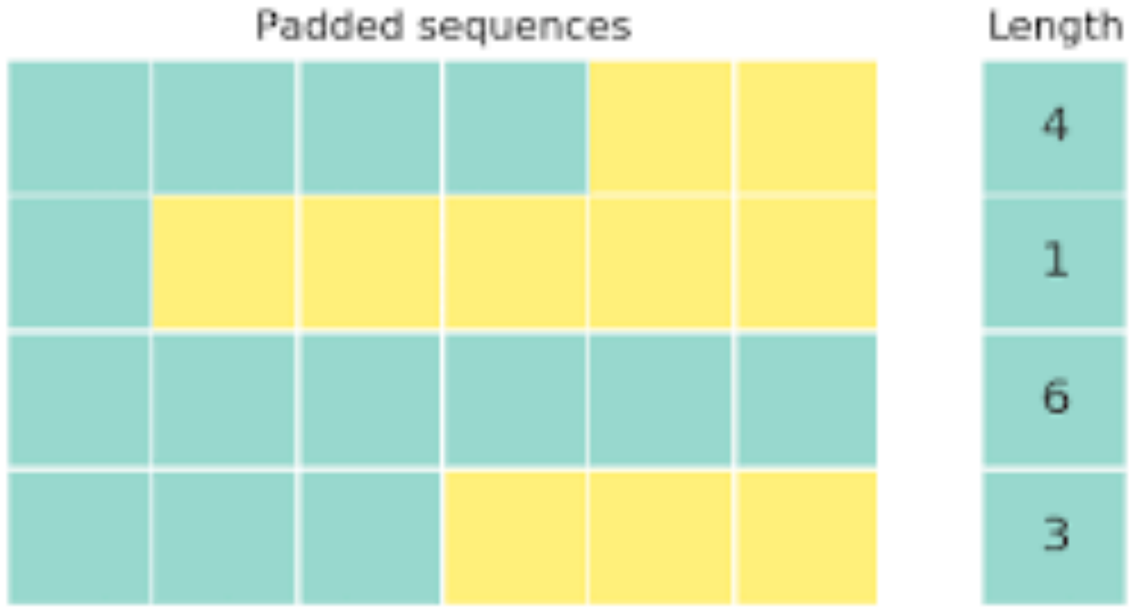


LSTM

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

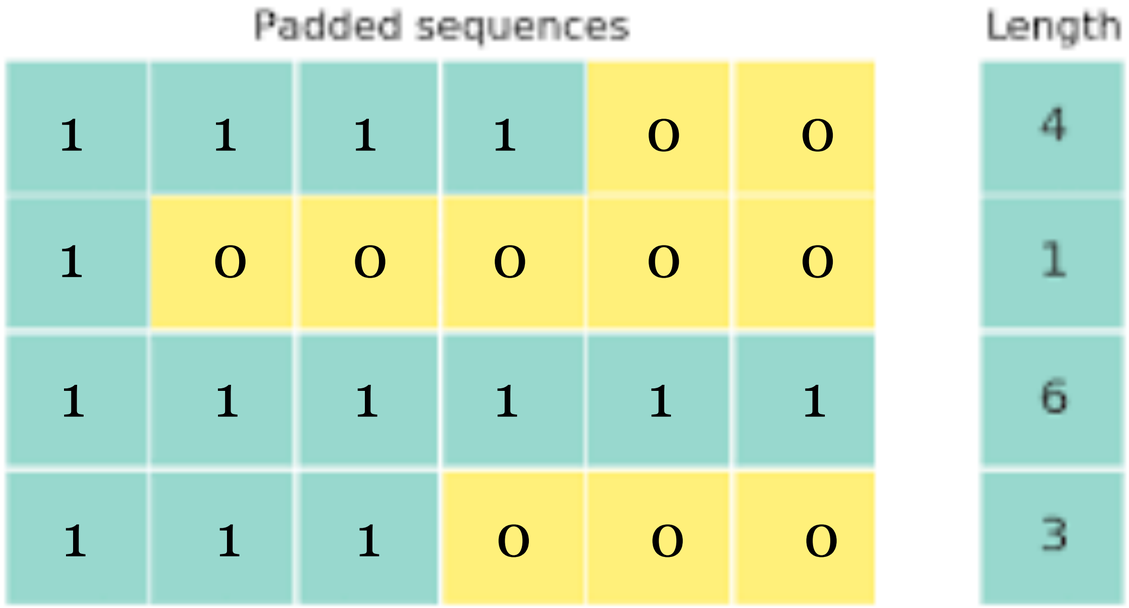
Batching

- Apply RNNs to batches of sequences
- Present data as 3D tensor of $(T \times B \times F)$



Batching

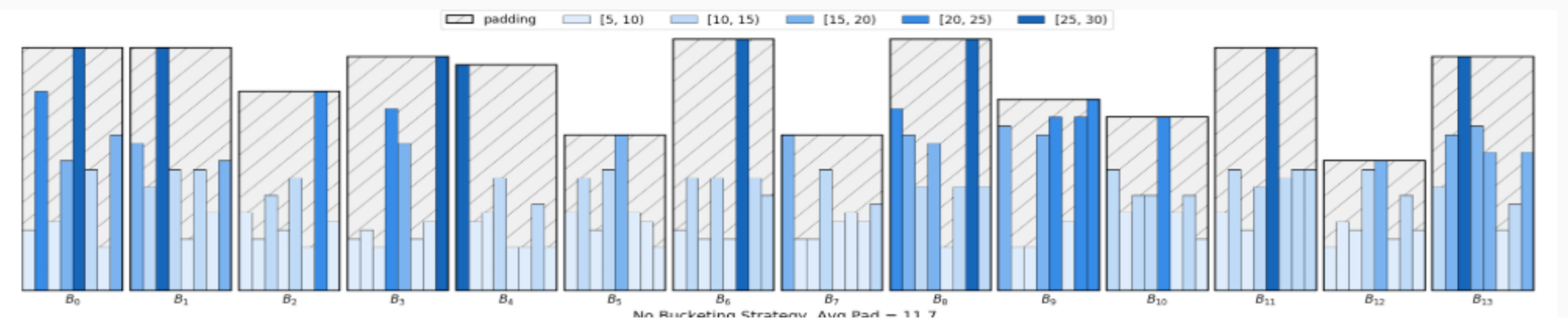
- Use mask matrix to aid with computations that ignore padded zeros



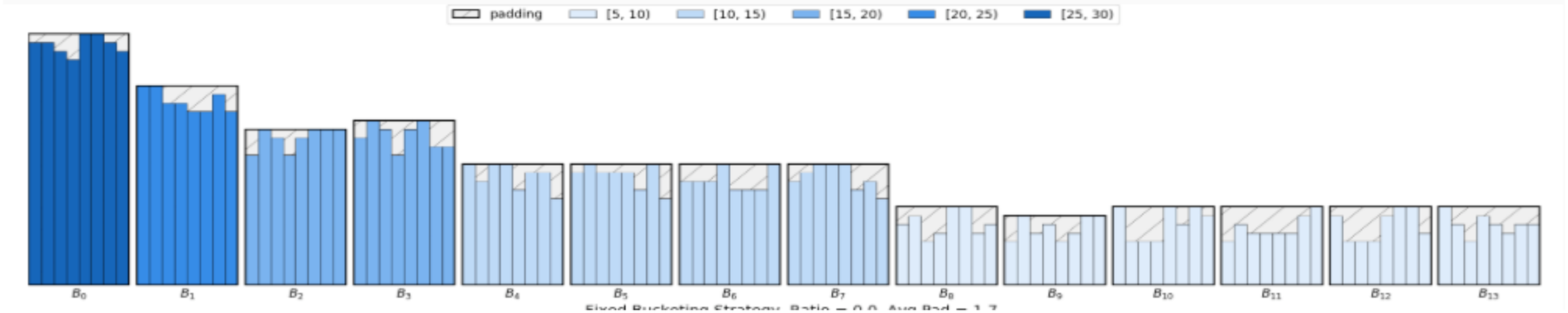
Batching

- Sorting (partially) can help to create more efficient mini-batches
- However, the input is less randomized

Unsorted



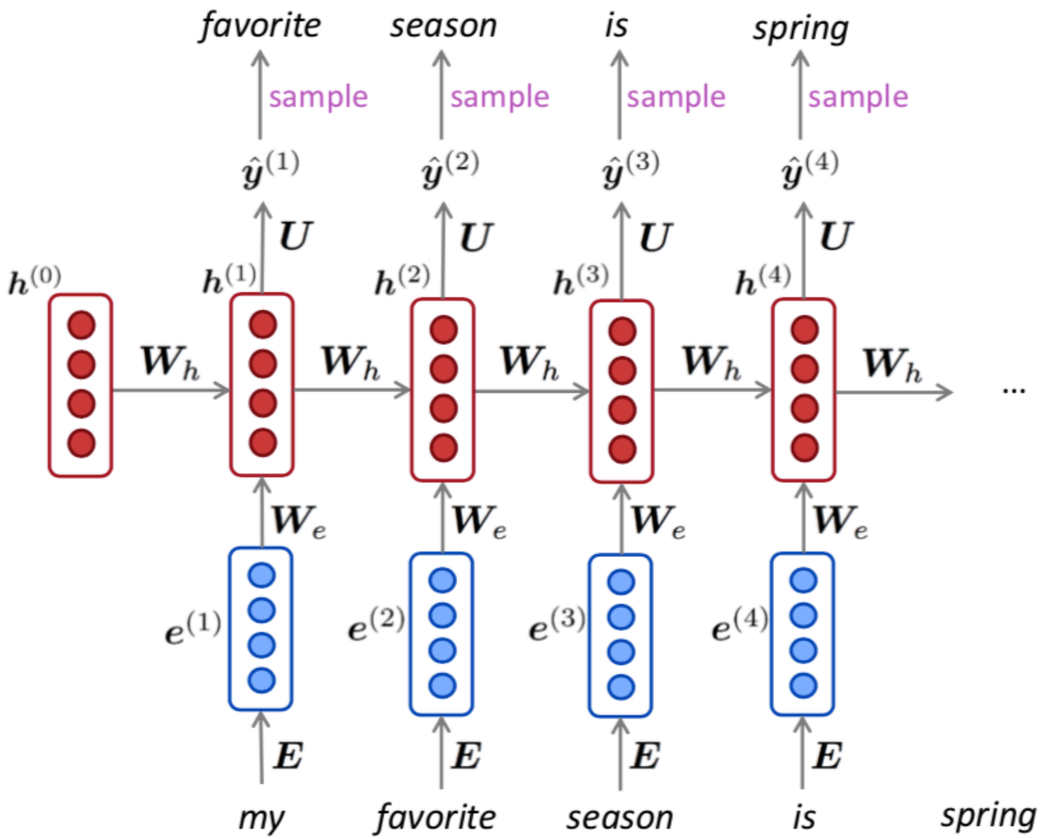
Sorted



Overview

- What is a recurrent neural network (RNN)?
- Simple RNNs
- Backpropagation through time
- Long short-term memory networks (LSTMs)
- Applications
- Variants: Stacked RNNs, Bidirectional RNNs

Application: Text Generation



You can generate text by **repeated sampling.**

Sampled output is next step's input.

Fun with RNNs

Obama speeches

Good afternoon. God bless you.

The United States will step up to the cost of a new challenges of the American people that will share the fact that we created the problem. They were attacked and so that they have to say that all the task of the final days of war that I will not be able to get this done. The promise of the men and women who were still going to take out the fact that the American people have fought to make sure that they have to be able to protect our part. It was a chance to stand together to completely look for the commitment to borrow from the American people. And the fact is the men and women in uniform and the millions of our country with the law system that we should be a strong stretcks of the forces that we can afford to increase our spirit of the American people and the leadership of our country who are on the Internet of American lives.

Thank you very much. God bless you, and God bless the United States of America.

Latex generation

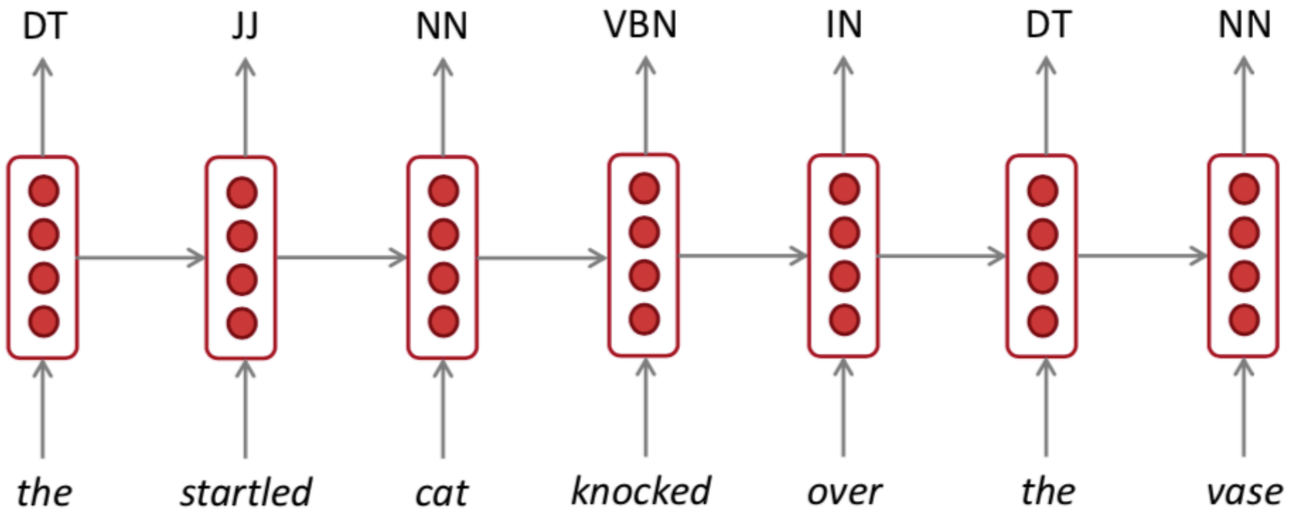
```
\begin{proof}
We may assume that $\mathcal{I}$ is an abelian sheaf on $\mathcal{C}$.
\item Given a morphism $\Delta : \mathcal{F} \to \mathcal{I}$
is an injective and let $\mathfrak q$ be an abelian sheaf on $X$.
Let $\mathcal{F}$ be a fibered complex. Let $\mathcal{F}$ be a category.
\begin{enumerate}
\item \hyperref[setain-construction-phantom]{Lemma}
\label{lemma-characterize-quasi-finite}
Let $\mathcal{F}$ be an abelian quasi-coherent sheaf on $\mathcal{C}$.
Let $\mathcal{F}$ be a coherent $\mathcal{O}_X$-module. Then
$\mathcal{F}$ is an abelian catenary over $\mathcal{C}$.
\item The following are equivalent
\begin{enumerate}
\item $\mathcal{F}$ is an $\mathcal{O}_X$-module.
\end{lemma}
```

Andrej Karpathy “The Unreasonable Effectiveness of Recurrent Neural Networks”

Application: Sequence Tagging

Input: a sentence of n words: $x_1, \ldots, x_n$

Output: $y_1, \ldots, y_n, y_i \in \{1, \ldots C\}$



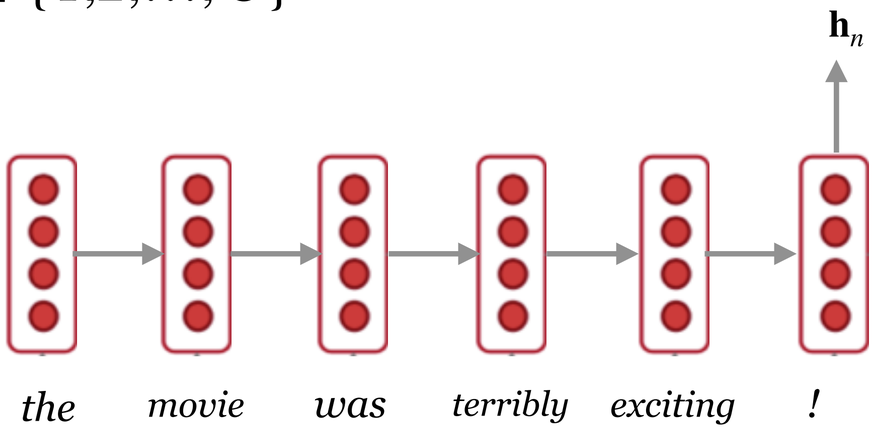
$$P(y_i = k) = softmax_k(\mathbf{W}_o \mathbf{h}_i) \quad \mathbf{W}_o \in \mathbb{R}^{C \times d}$$

$$L = -\frac{1}{n} \sum_{i=1}^{n} \log P(y_i = k)$$

Application: Text Classification

Input: a sentence of n words

Output: $y \in \{1,2,\ldots,C\}$

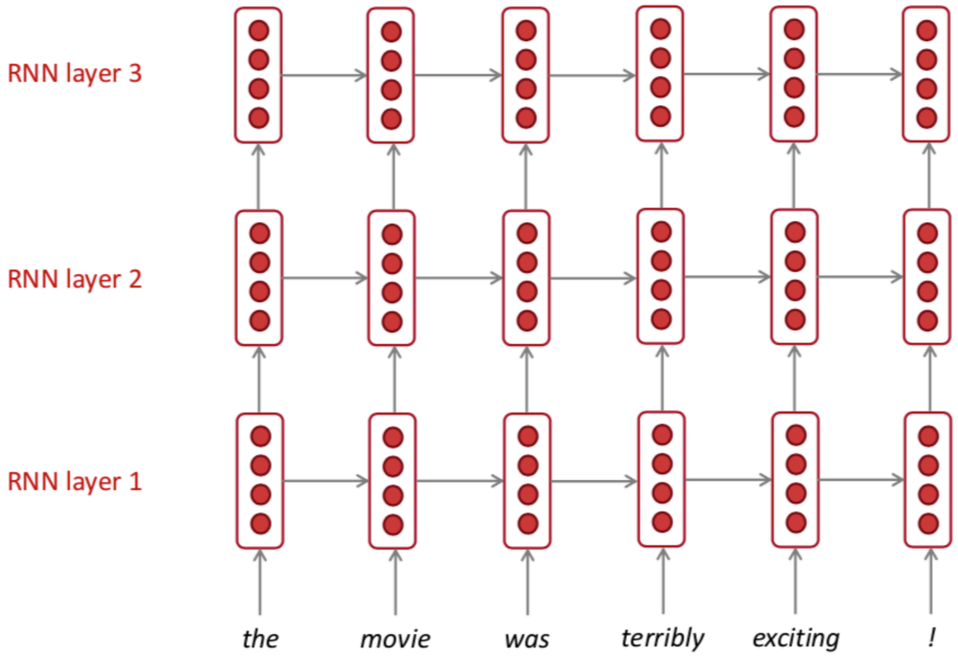


$$P(y = k) = softmax_k(\mathbf{W}_o\mathbf{h}_n) \qquad \mathbf{W}_o \in \mathbb{R}^{C \times d}$$

Multi-layer RNNs

- RNNs are already “deep” on one dimension (unroll over time steps)
- We can also make them “deep” in another dimension by applying multiple RNNs
- Multi-layer RNNs are also called stacked RNNs.

Multi-layer RNNs

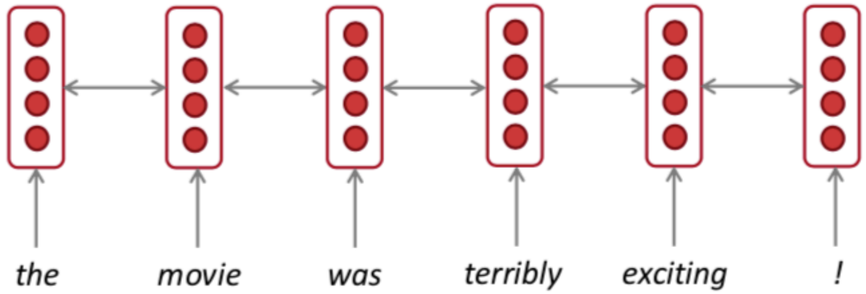


The hidden states from RNN layer i are the inputs to RNN layer $i + 1$

- In practice, using 2 to 4 layers is common (usually better than 1 layer)
- Transformer-based networks can be up to 24 layers with lots of skip-connections.

Bidirectional RNNs

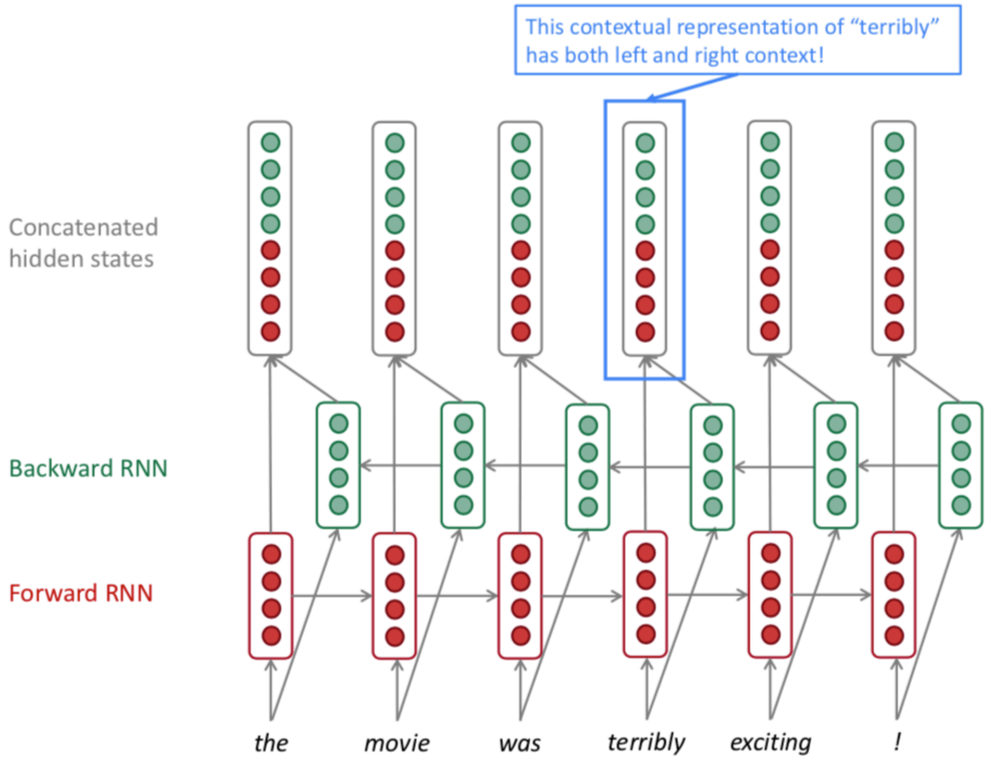
- Bidirectionality is important in language representations:



terribly:

- left context “the movie was”
- right context “exciting !”

Bidirectional RNNs



$$\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t) \in \mathbb{R}^d$$

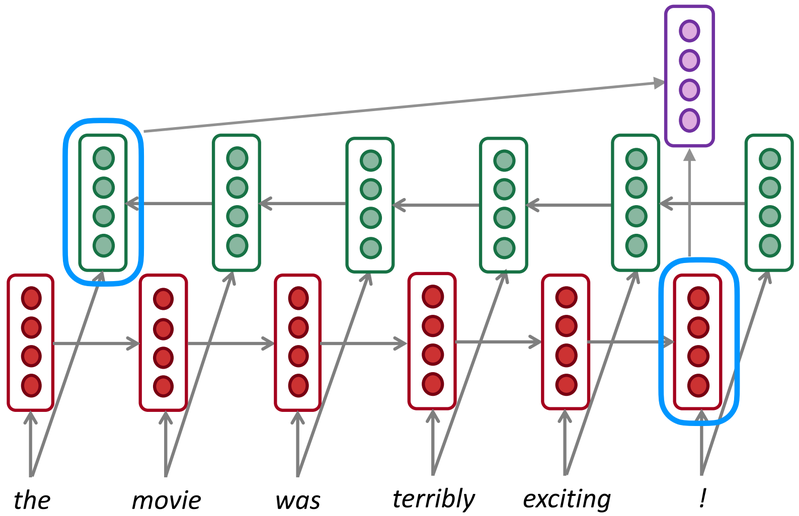
$$\overrightarrow{\mathbf{h}}_t = f_1(\overrightarrow{\mathbf{h}}_{t-1}, \mathbf{x}_t), t = 1,2,\ldots n$$

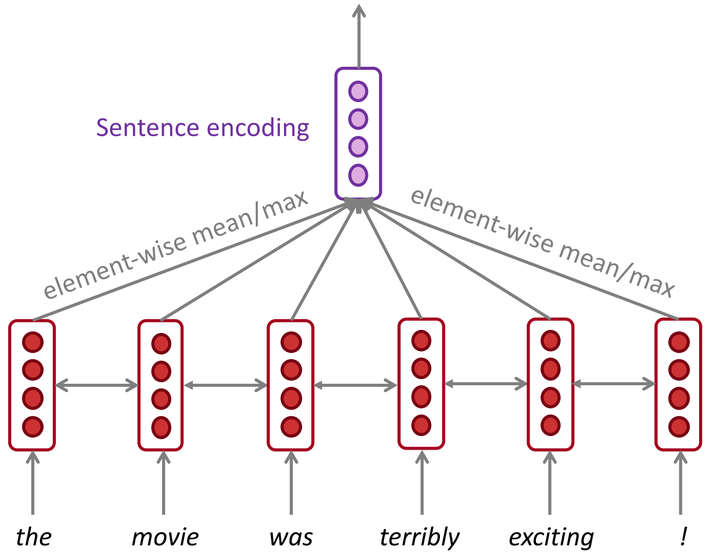
$$\overleftarrow{\mathbf{h}}_t = f_2(\overleftarrow{\mathbf{h}}_{t+1}, \mathbf{x}_t), t = n, n-1,\ldots 1$$

$$\mathbf{h}_t = [\overleftarrow{\mathbf{h}}_t, \overrightarrow{\mathbf{h}}_t] \in \mathbb{R}^{2d}$$

Bidirectional RNNs

- Sequence tagging: Yes!
- Text classification: Yes! With slight modifications.





- Text generation: No. Why?