CS489/698: Intro to ML

Lecture 14: RNNs

focal Systems

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Outline

- Motivation
- Intro to RNNs
- Bidirectional RNN
- LSTM
- Applications

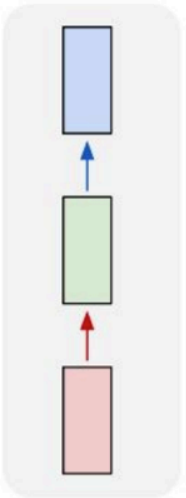
Motivation

- Introducing bias for modeling sequences
- Multiple inputs into a model

Intro to RNNs

“Vanilla” Neural Network

one to one

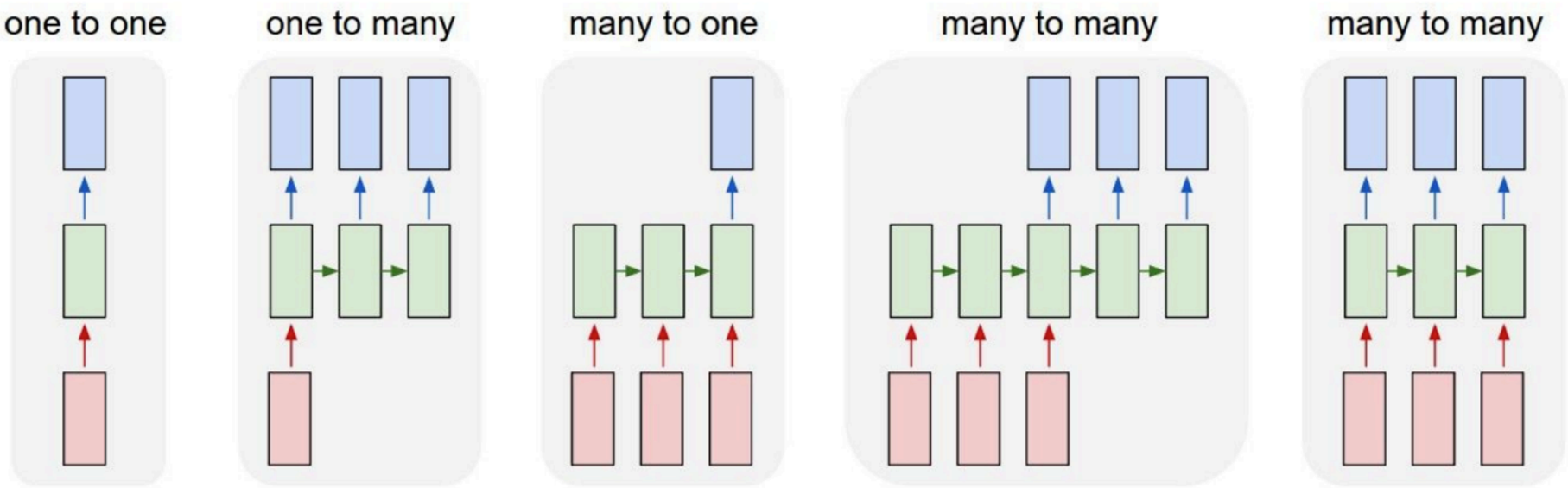


Vanilla Neural Networks

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

Intro to RNNs

Recurrent Neural Networks: Process Sequences



e.g. **Image Captioning**
image -> sequence of words

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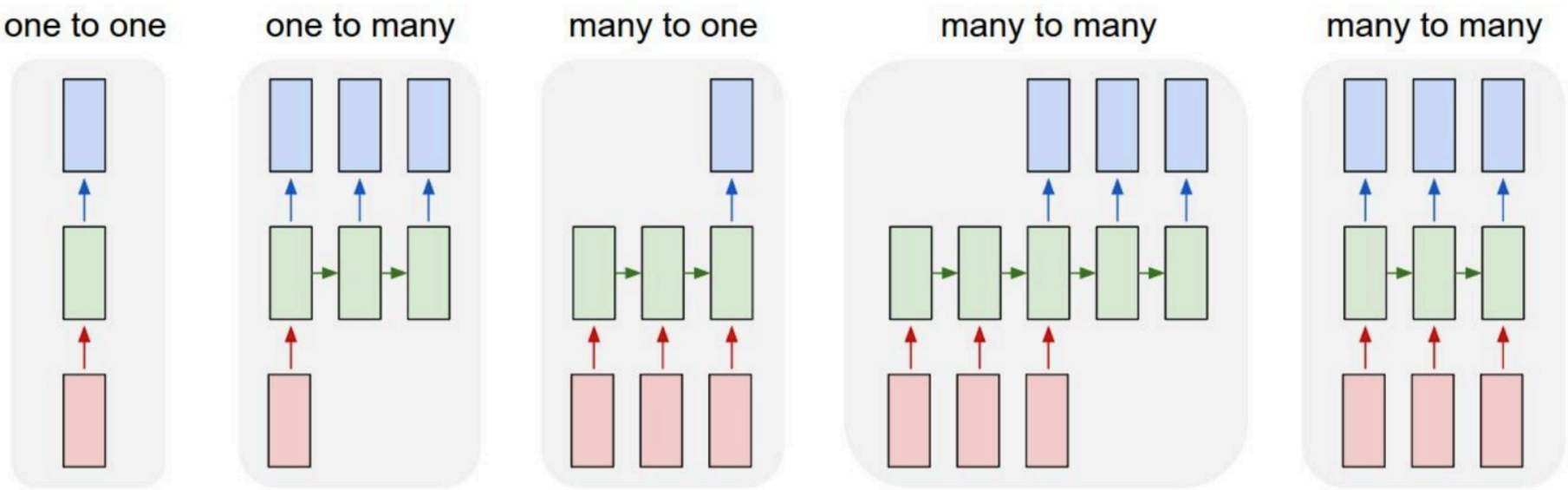
Intro to RNNs

Recurrent Neural Networks: Process Sequences



e.g. **Sentiment Classification**
sequence of words -> sentiment

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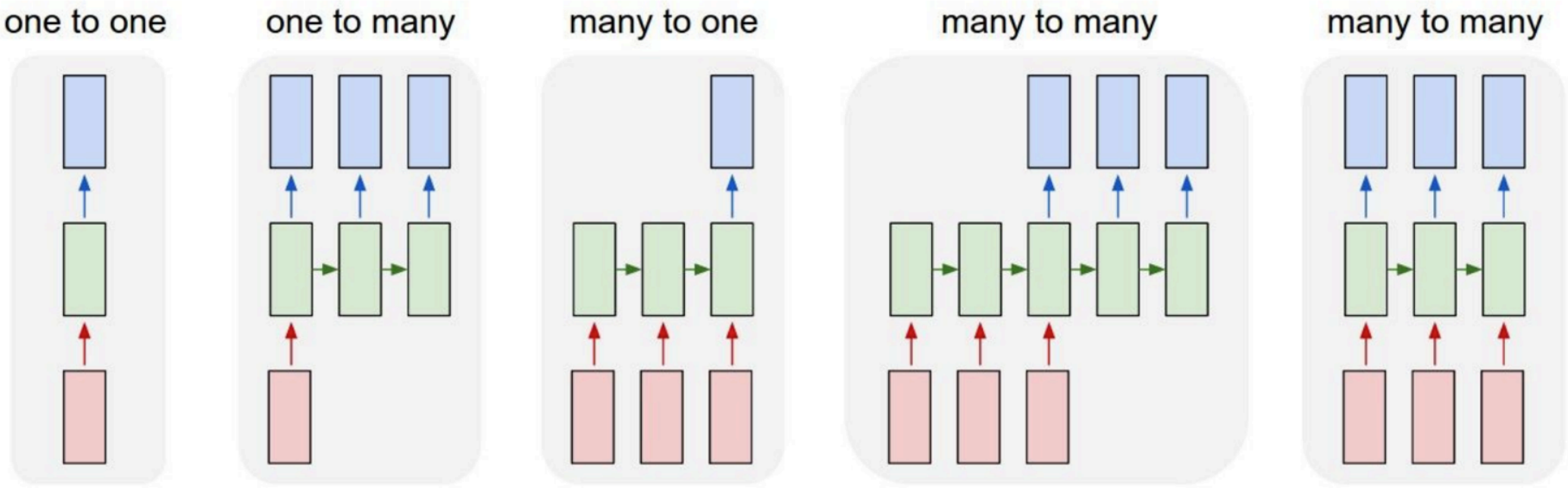
Intro to RNNs

Recurrent Neural Networks: Process Sequences



e.g. **Machine Translation**
seq of words -> seq of words

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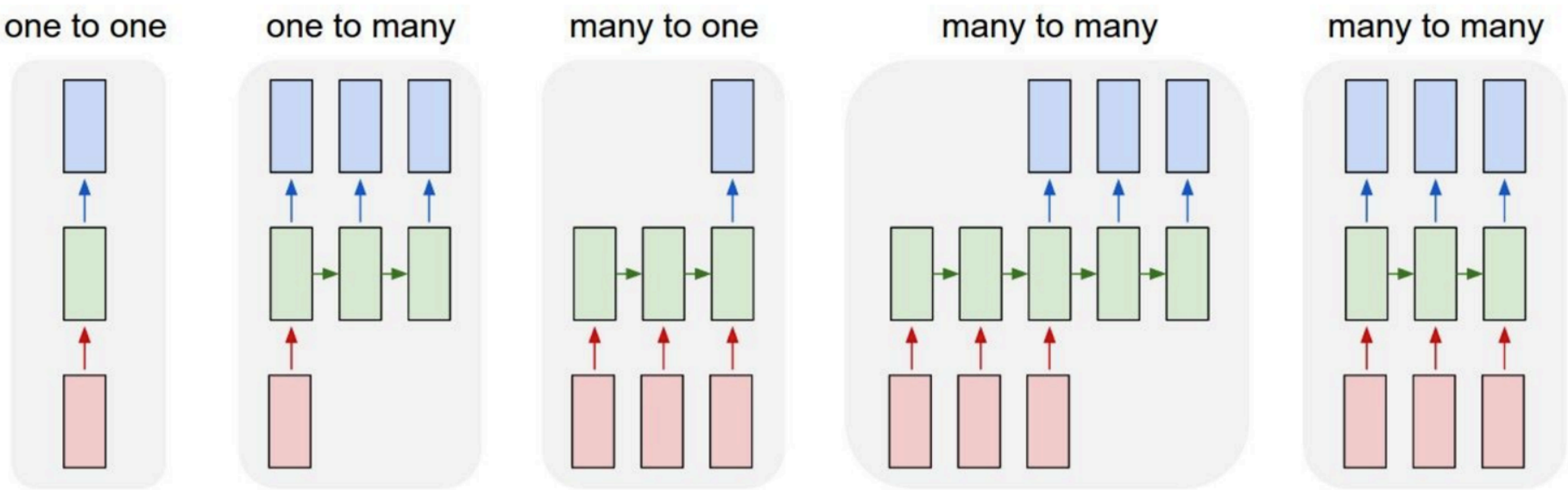
Intro to RNNs

Recurrent Neural Networks: Process Sequences



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Unfolding a computation Graph

Unfolding Computation Graphs

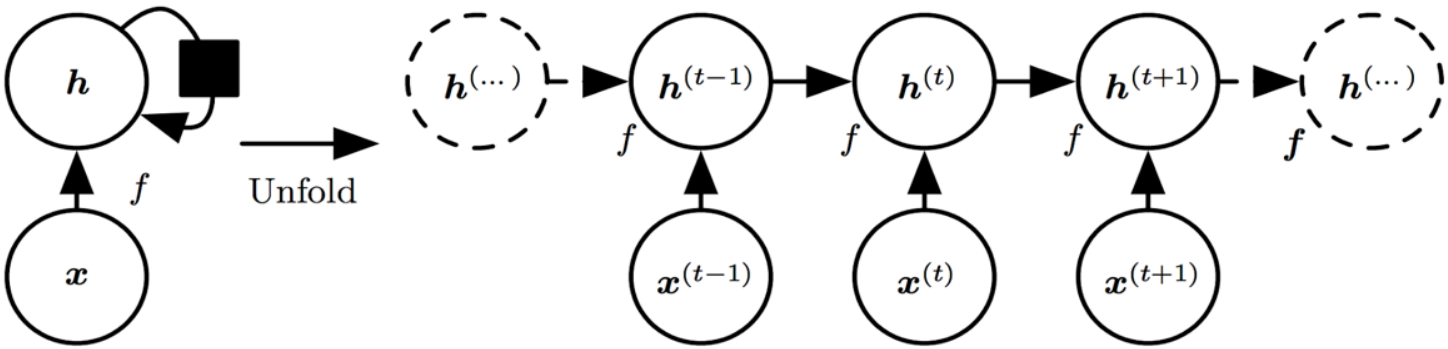

Figure 10.2

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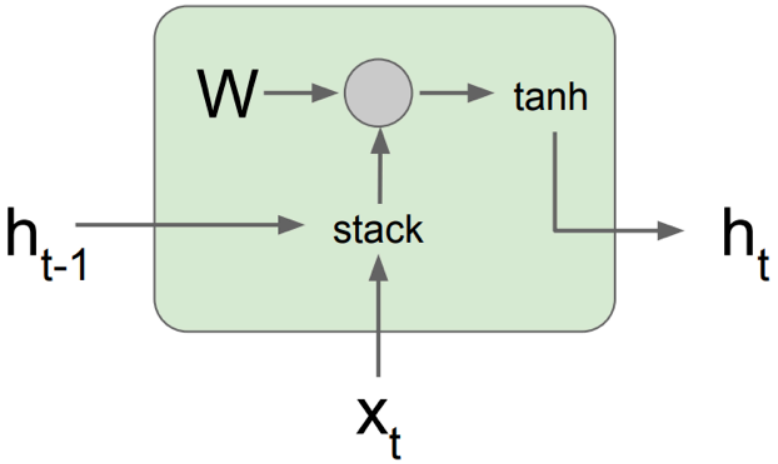
Vanilla RNN



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

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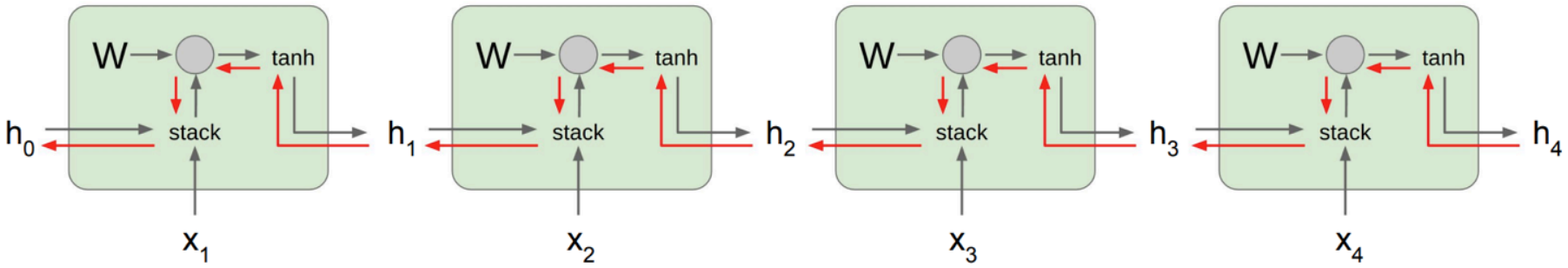
Vanilla RNN



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

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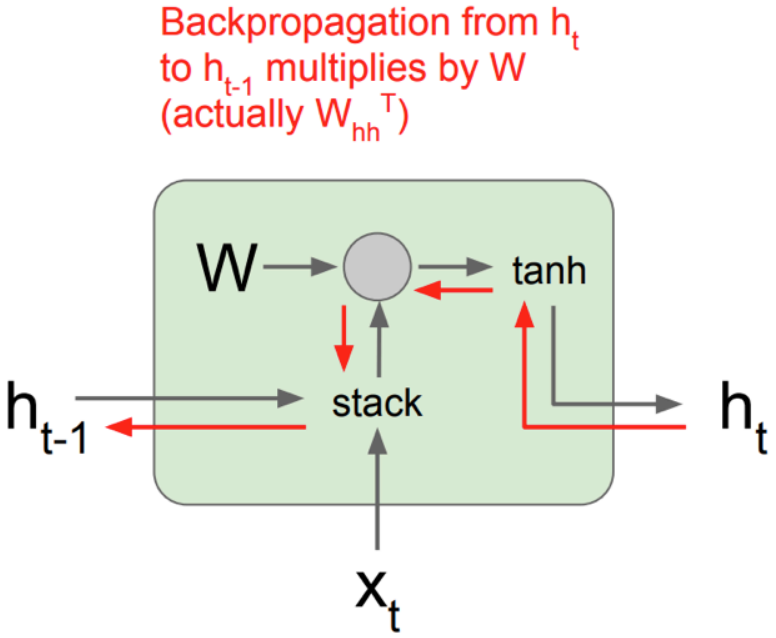
Vanilla RNN

The gradient either vanishes or exploded



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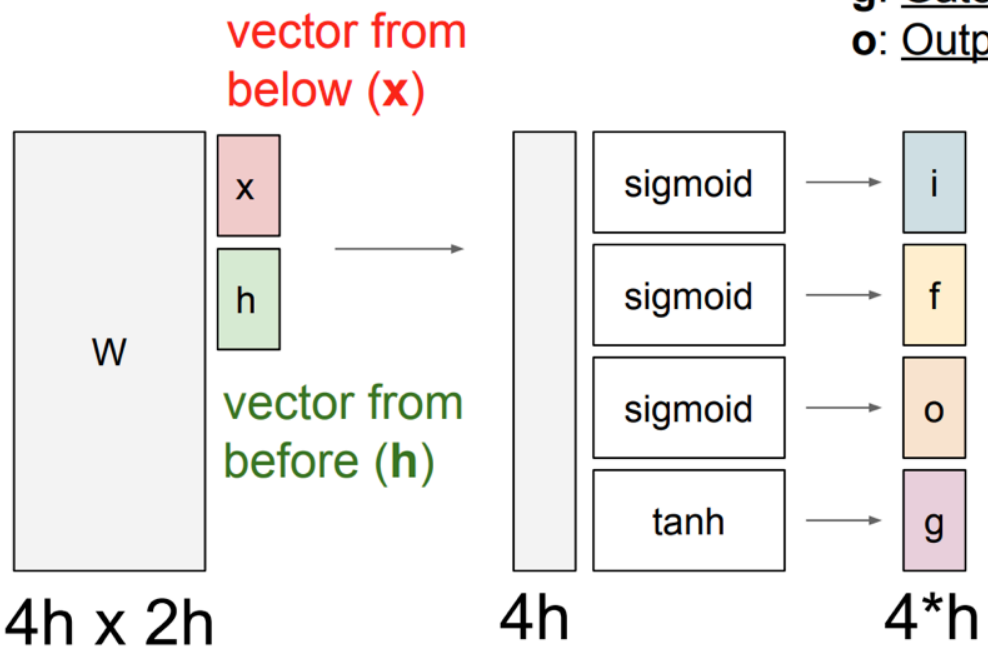
LSTM

[Hochreiter et al., 1997]

f: Forget gate, Whether to erase cell
i: Input gate, whether to write to cell
g: Gate gate (?), How much to write to cell
o: Output gate, How much to reveal cell



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

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

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

LSTMs are explicitly designed to avoid the long-term dependency problem.

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Vanilla RNN vs Long Short Term Memory

Vanilla RNN

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

LSTM

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

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

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

f(forget gate): A 1 represents “completely keep this” while a 0 represents “completely get rid of this.

i and g gate: The next step is to decide what new information we’re going to store in the cell state. This has two parts. First, a sigmoid layer called the “input gate layer” decides which values we’ll update. Next, a tanh layer creates a vector of new candidate values, C̃ tC~t, that could be added to the state. In the next step, we’ll combine these two to create an update to the state

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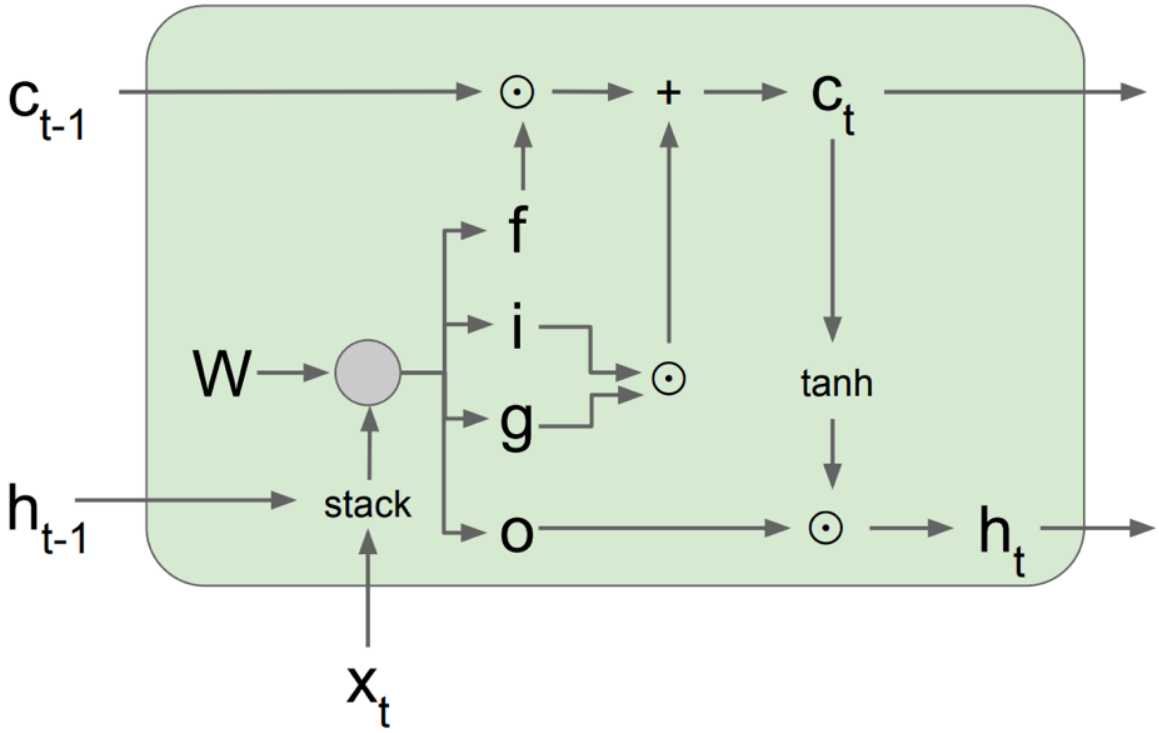
LSTM Backprop

[Hochreiter et al., 1997]

f: decides how much we want to forget about the previous info
i & g: decides how much we much to add the current info to C
o: how much we want to out put the current info



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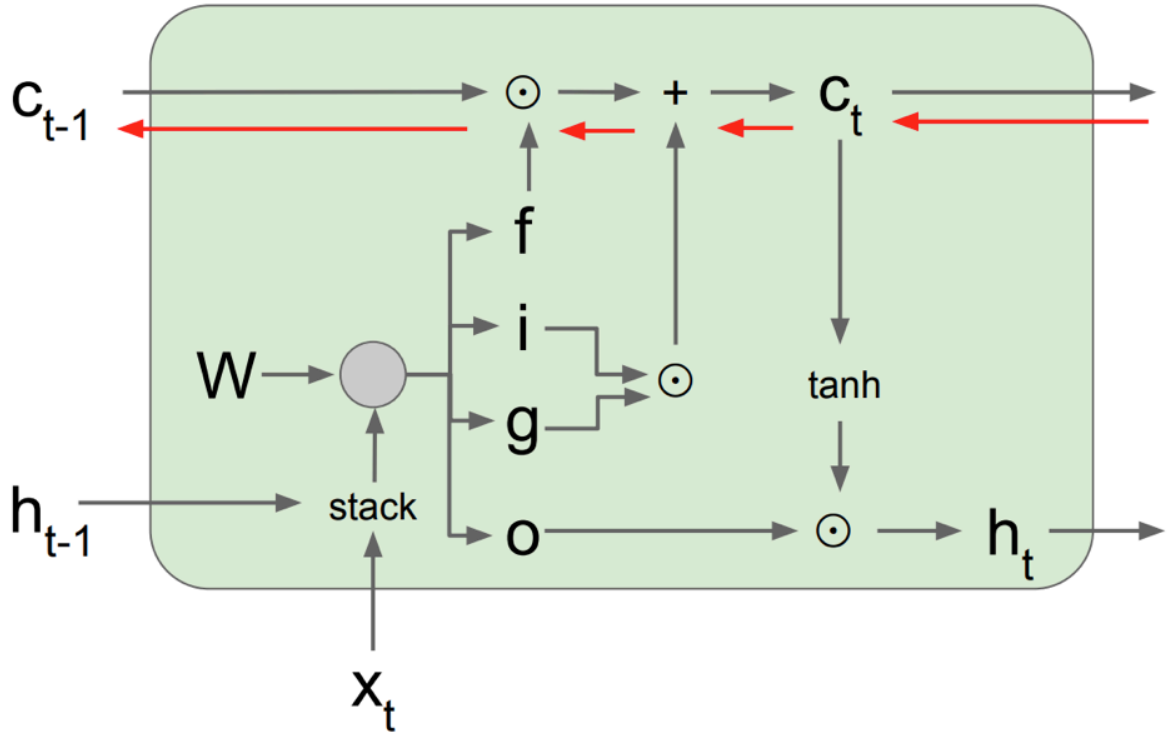
LSTM Backprop

[Hochreiter et al., 1997]



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

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

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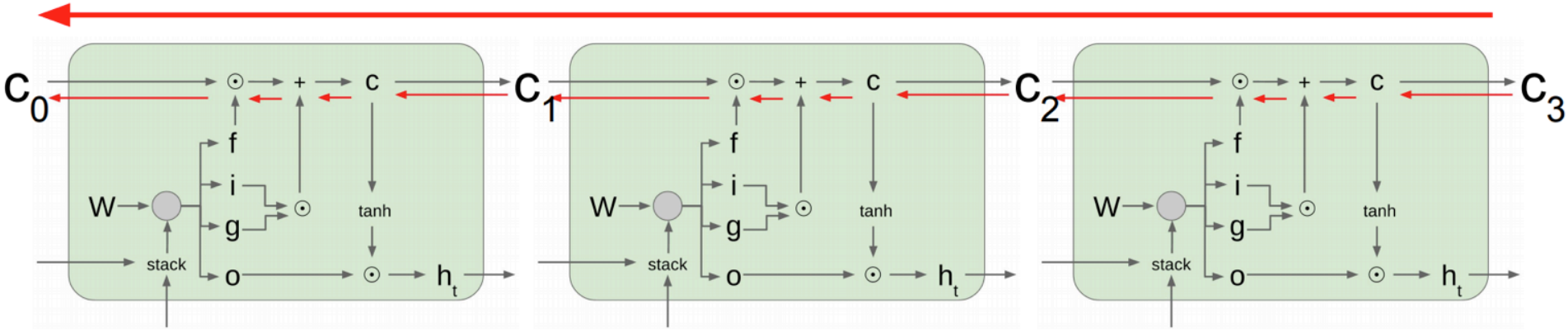
LSTM backprop

[Hochreiter et al., 1997]

Uninterrupted gradient flow!



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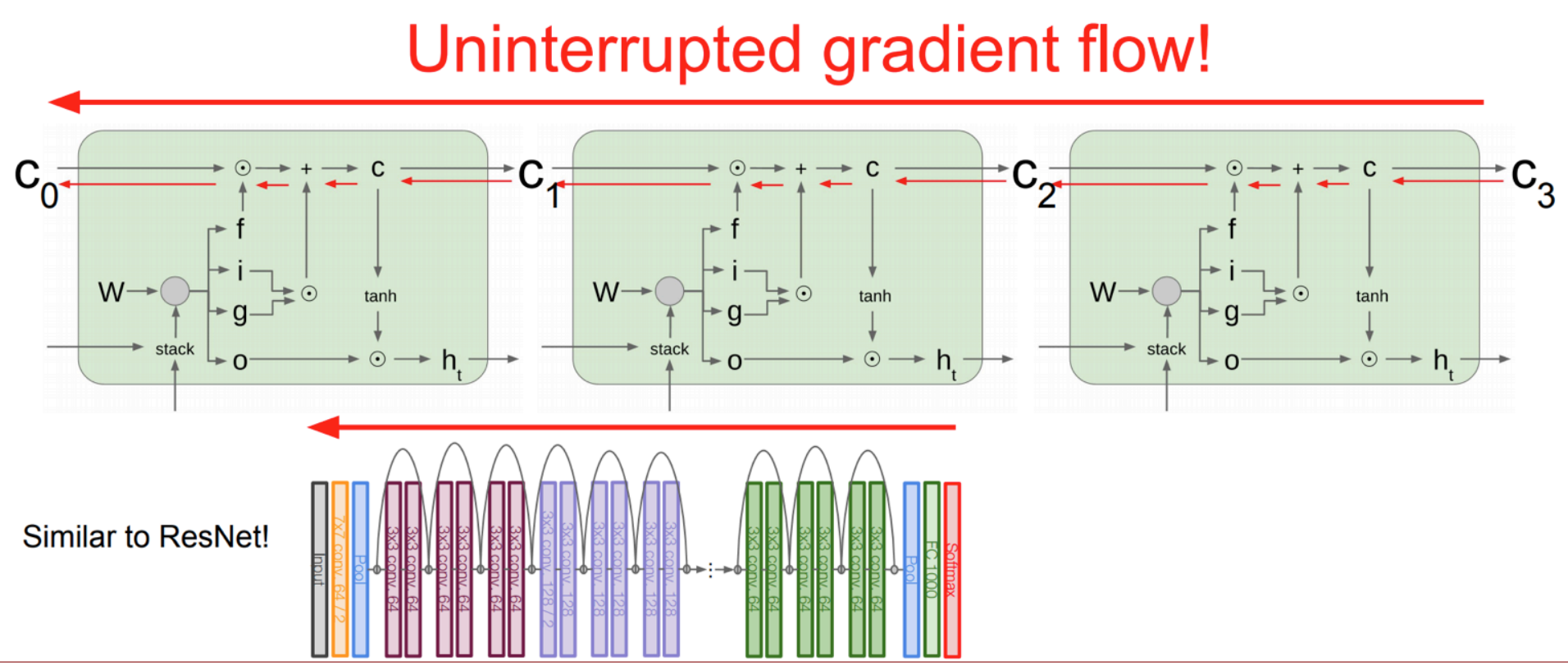
LSTM vs ResNet



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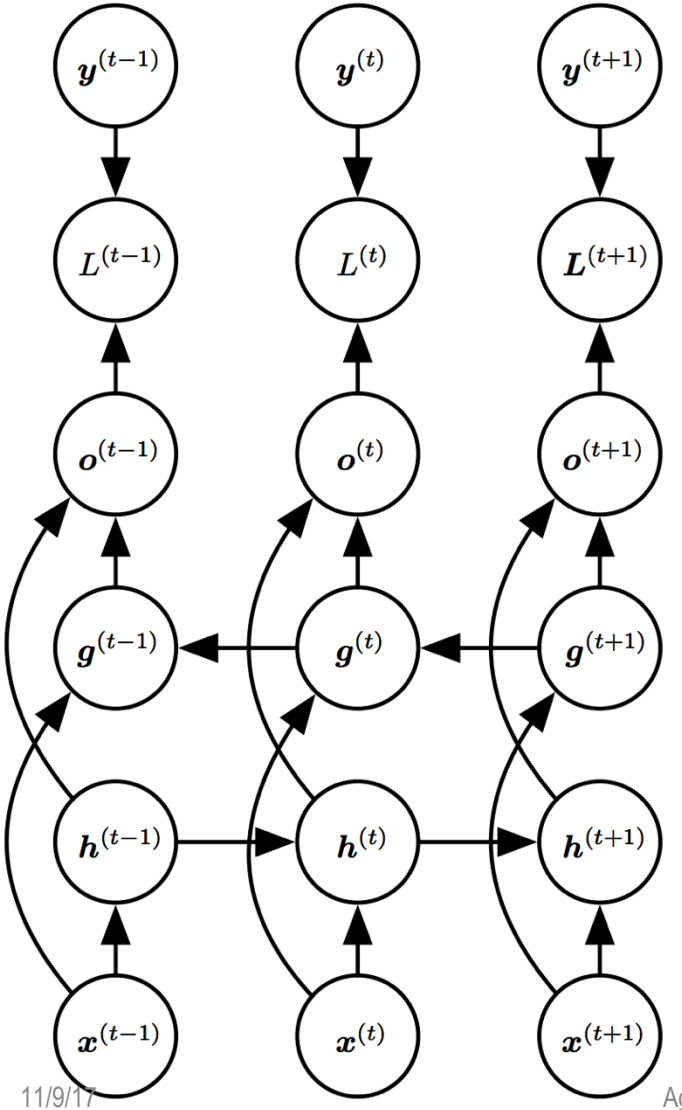
Bi-Directional RNN



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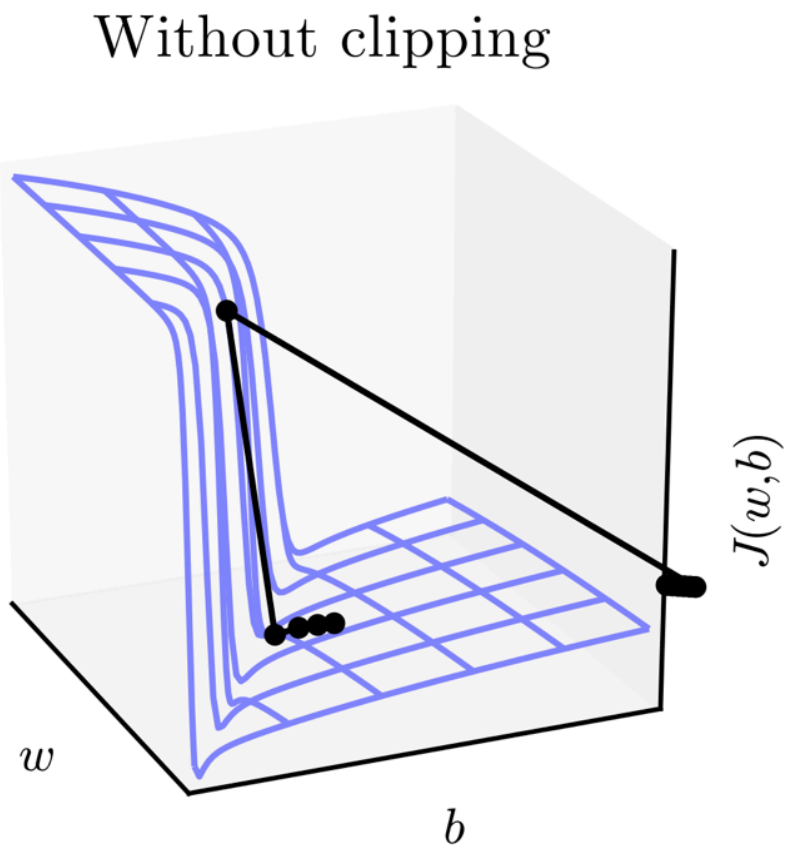
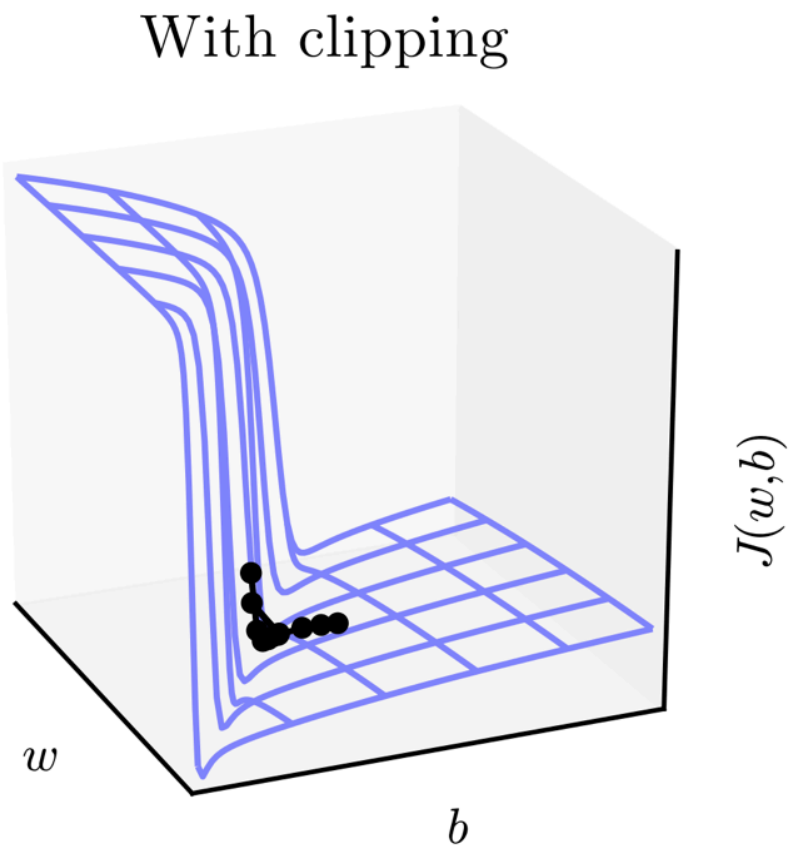
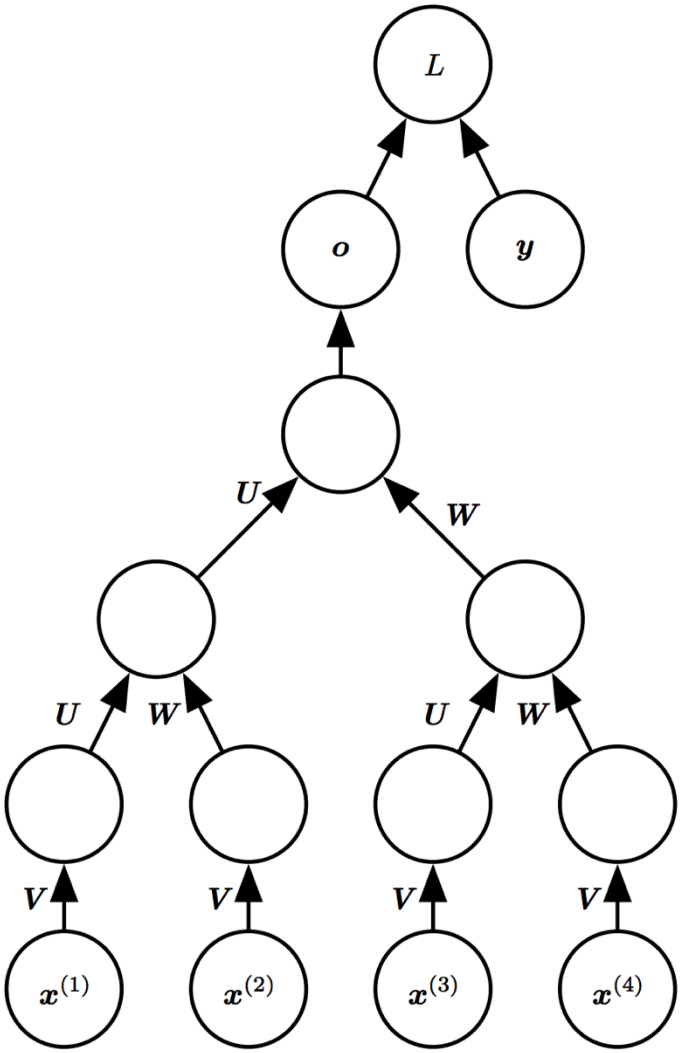
Gradient Clipping





Recursive Networks

- Superset of Recurrent
- Recurrent means processed in sequential order
- Recursive means processed in any order



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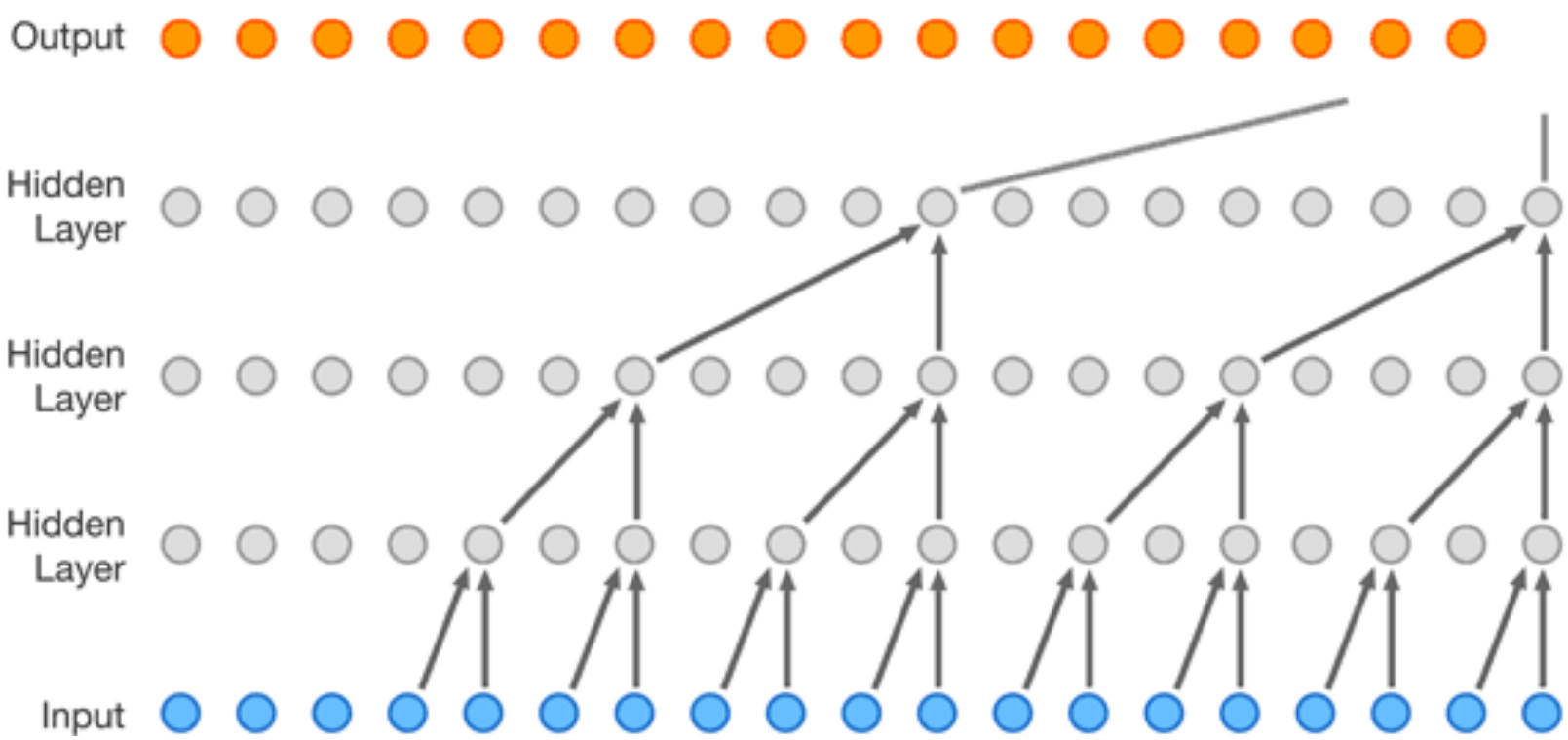
WaveNet

- Audio Generation



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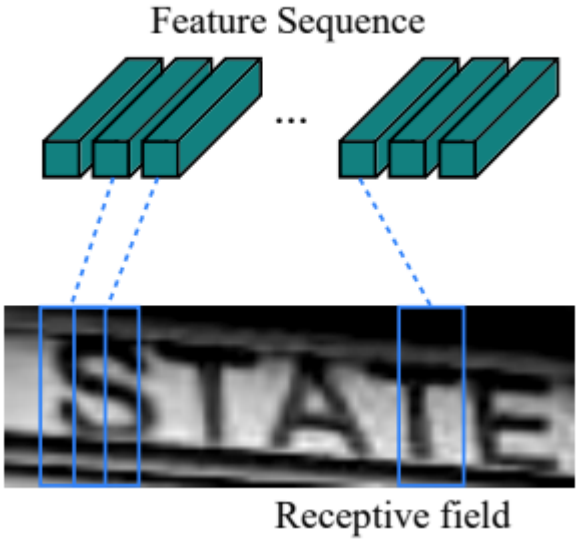
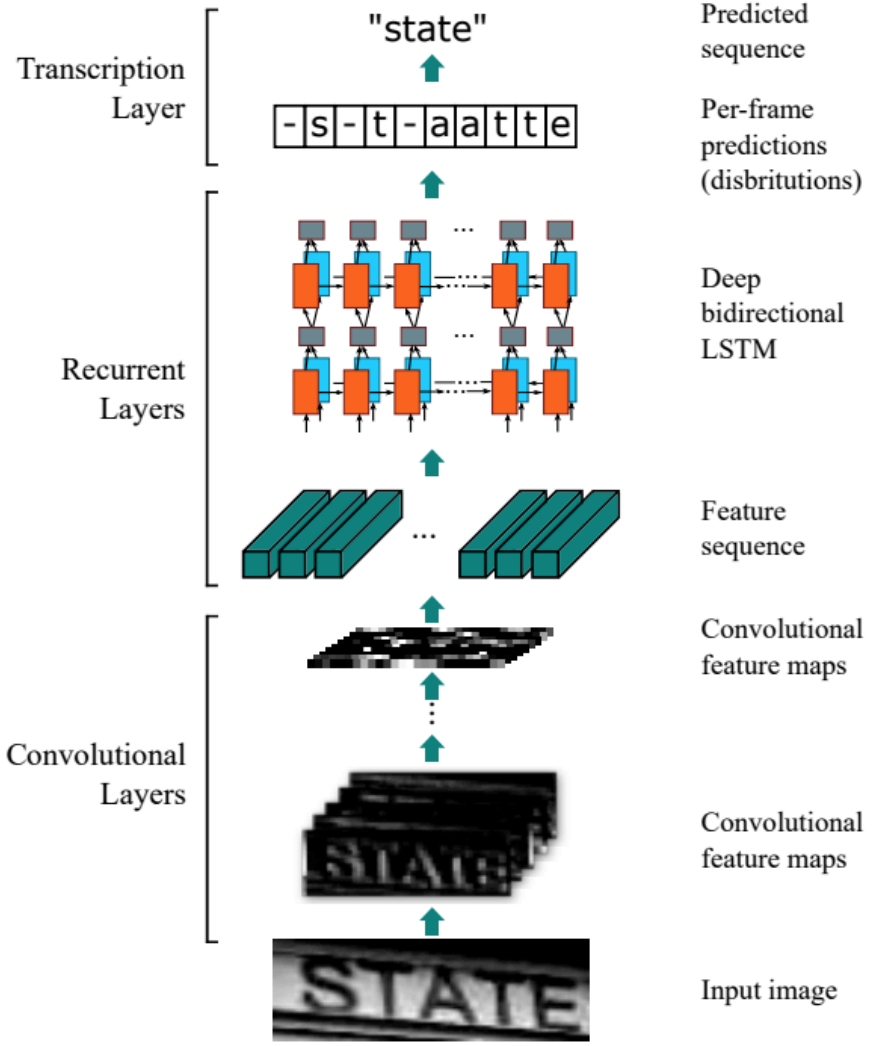
Convolutional Recurrent Neural Network

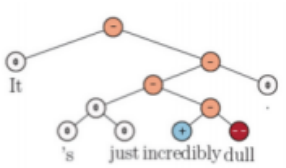
- Object Character Recognition in the wild

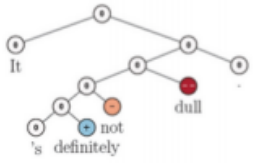


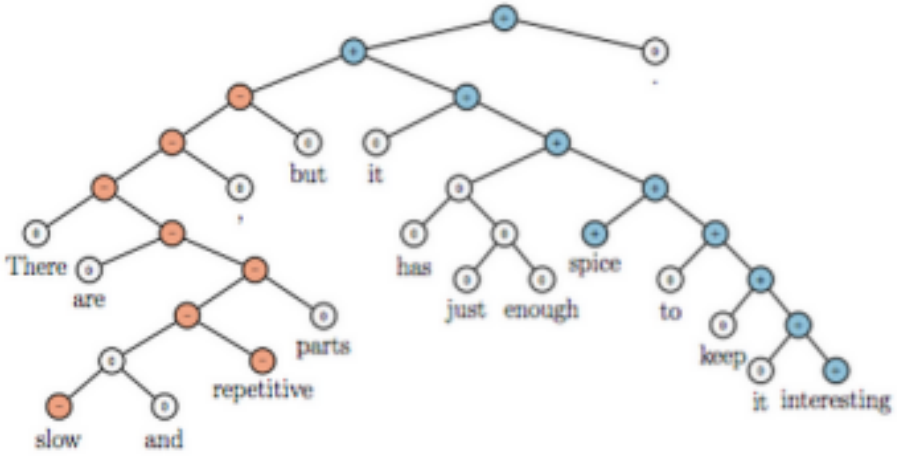


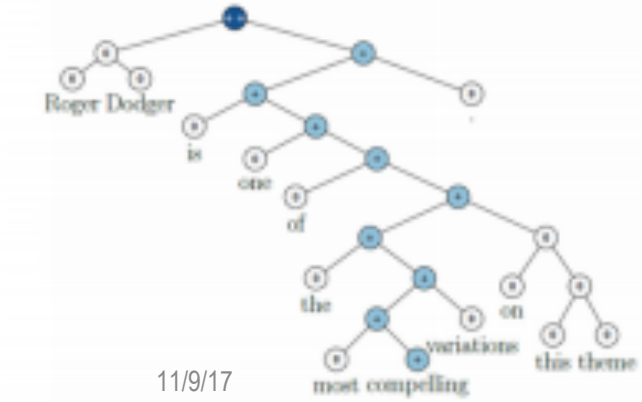
Sentiment analysis - RNTN

Recursive Networks









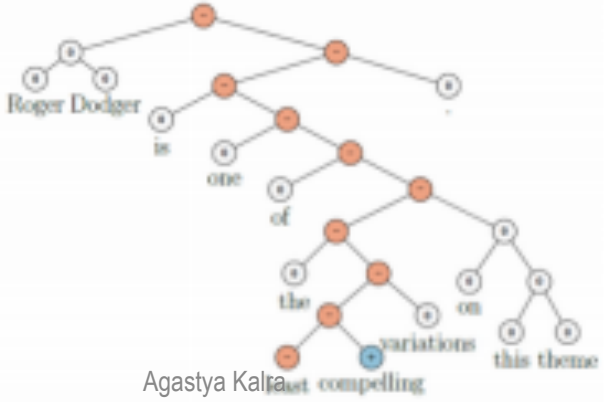


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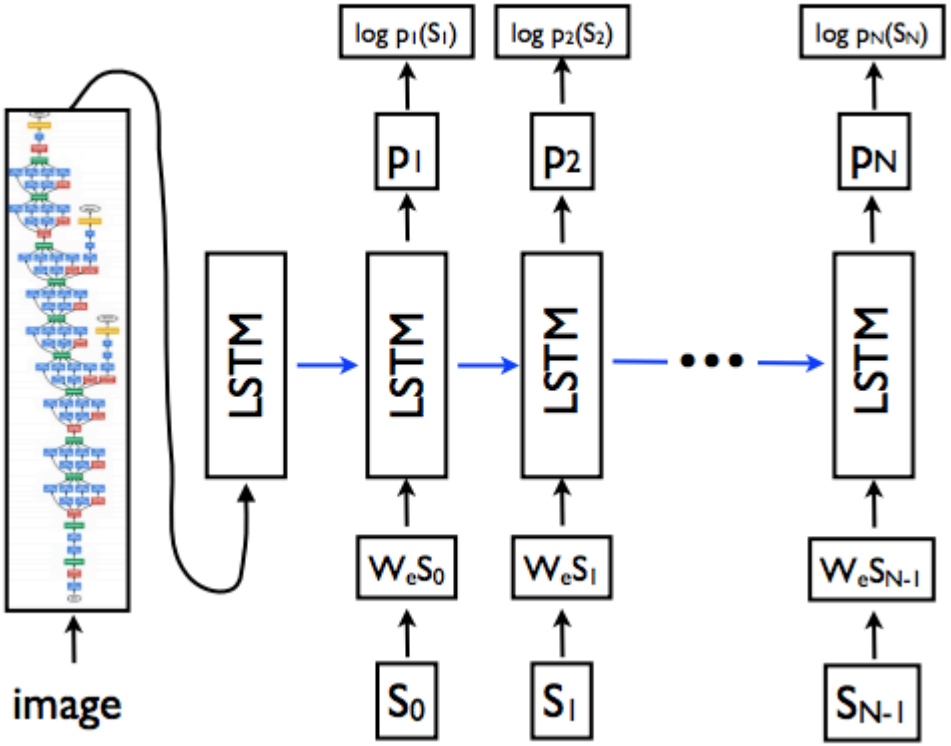
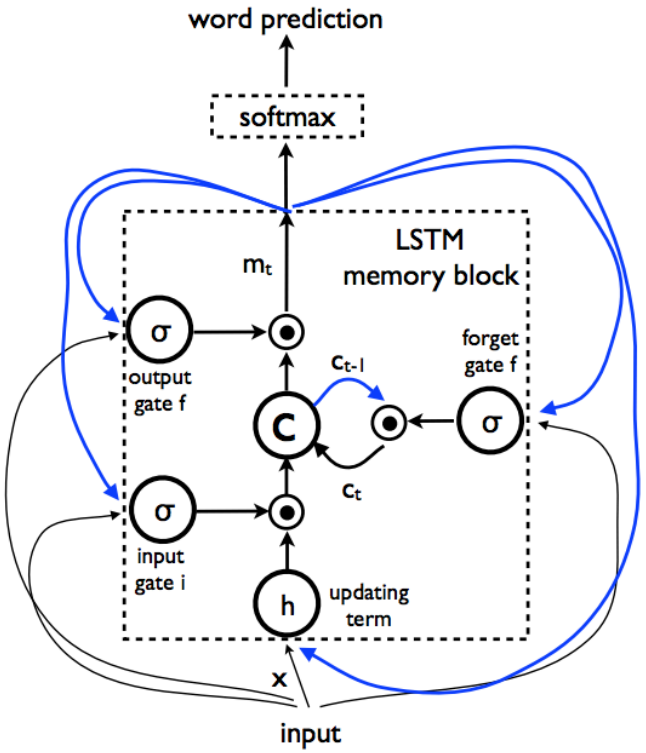
Image Captioning





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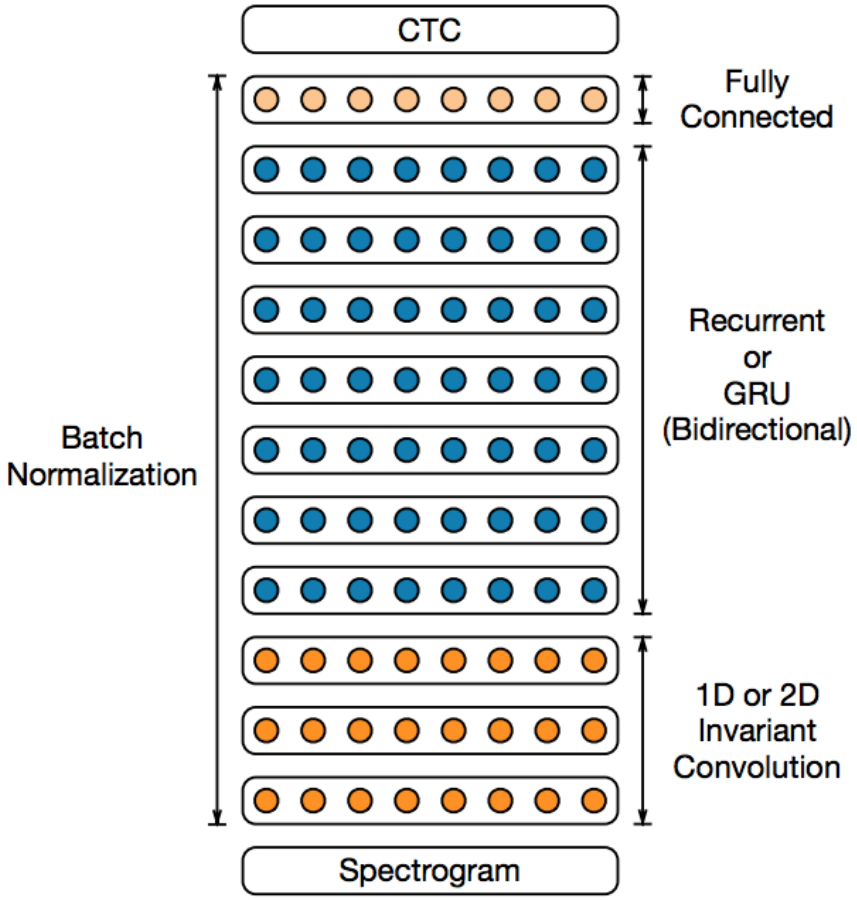
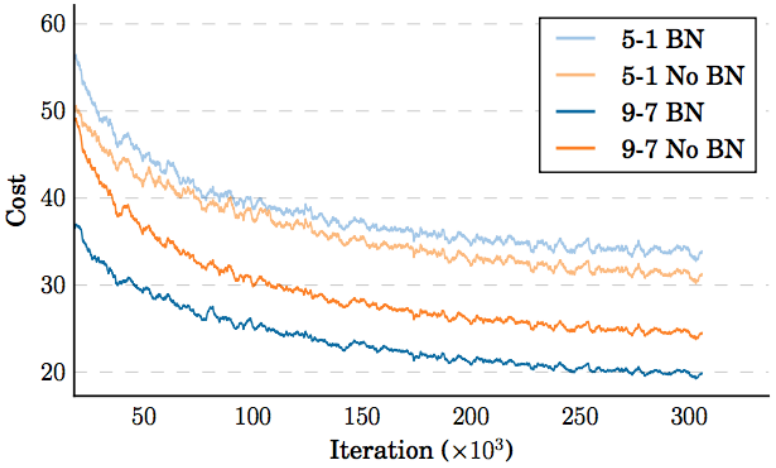
Speech Recognition





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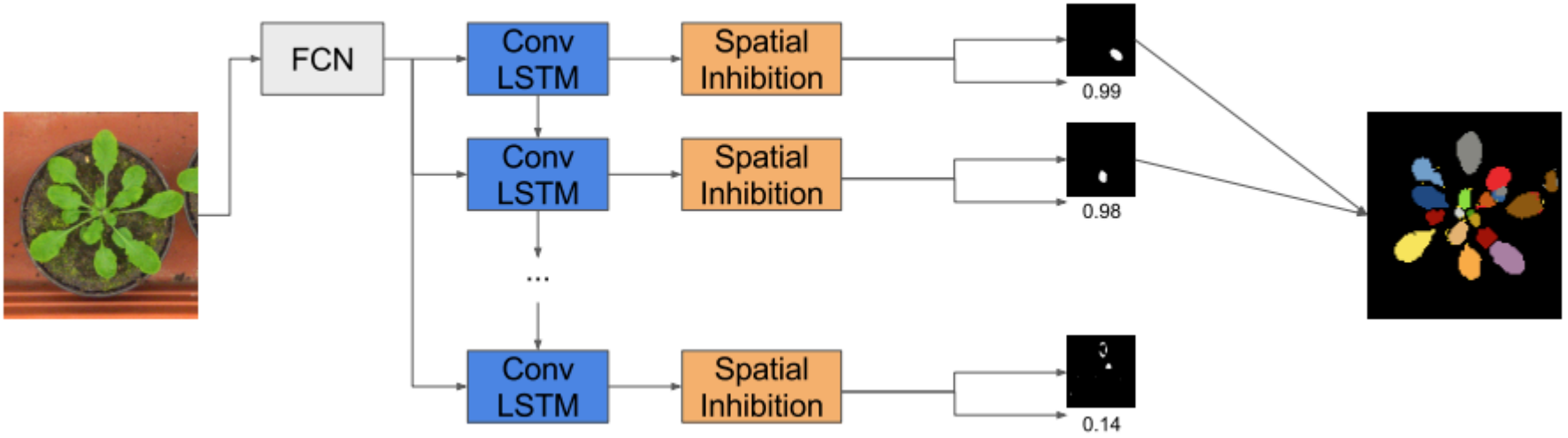
Recurrent Instance Segmentation



Deep Learning for Retail