

Recurrent neural networks

Slides by Hugo Larochelle - Google Brain,
lightly edited by Aaron Courville

NEURAL NETWORK LANGUAGE MODEL

Topics: neural network language model

- Solution: model the conditional

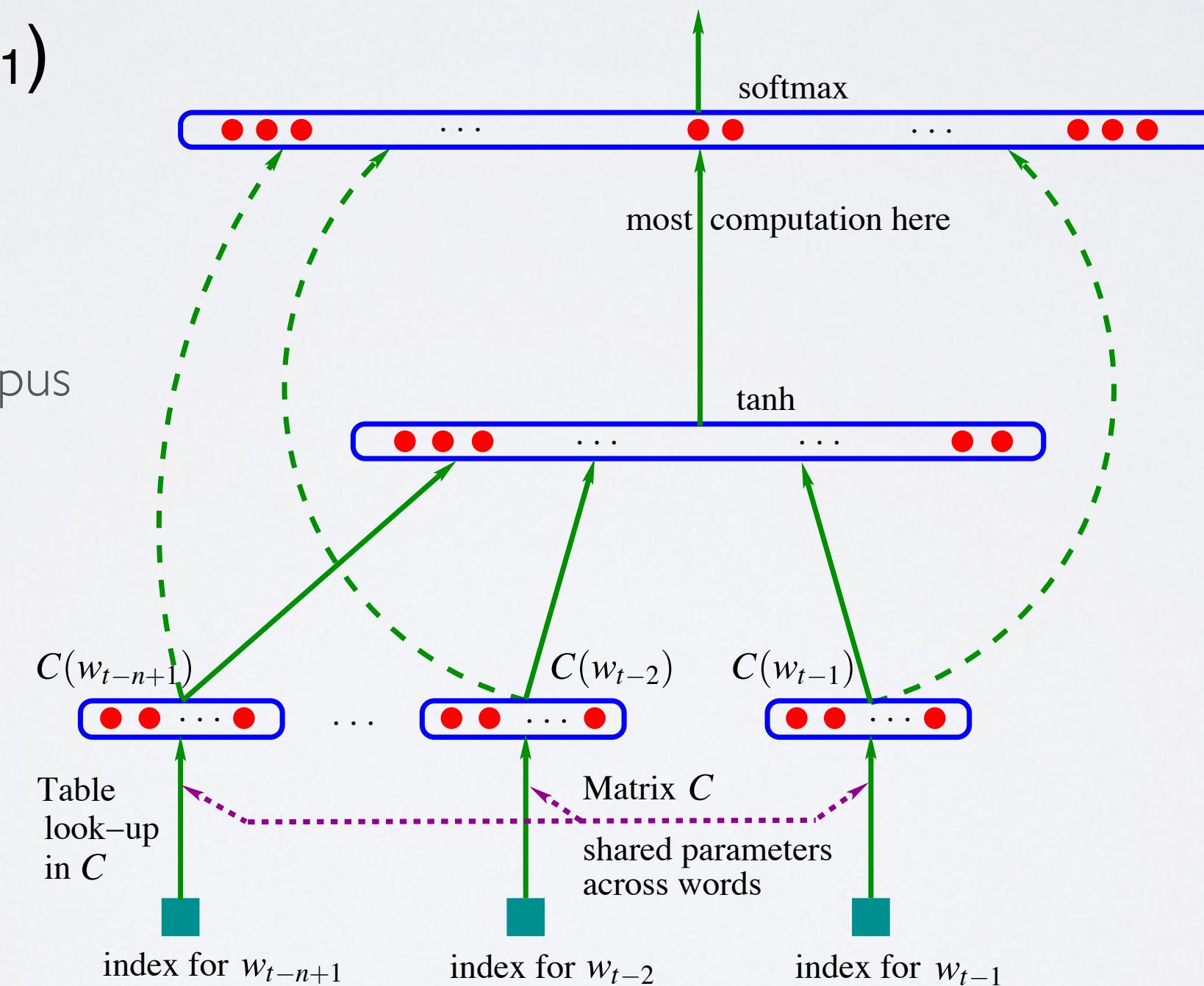
$$p(w_t | w_{t-(n-1)}, \dots, w_{t-1})$$

with a neural network

- learn word representations to allow transfer to n -grams not observed in training corpus

Bengio, Ducharme,
Vincent and Jauvin, 2003

$$i\text{-th output} = P(w_t = i | \text{context})$$



LANGUAGE MODELING

Topics: language modeling

- An assumption frequently made is the n^{th} order Markov assumption

$$p(w_1, \dots, w_T) = \prod_{t=1}^T p(w_t | w_{t-(n-1)}, \dots, w_{t-1})$$

- ▶ the t^{th} word was generated based only on the $n-1$ previous words
- ▶ we will refer to $w_{t-(n-1)}, \dots, w_{t-1}$ as the context

Could we have a neural network that depends on the full previous context, i.e. that would model?

$$p(w_1, \dots, w_T) = \prod_{t=1}^T p(w_t | w_1, \dots, w_{t-1})$$

RECURRENT NEURAL NETWORK (RNN)

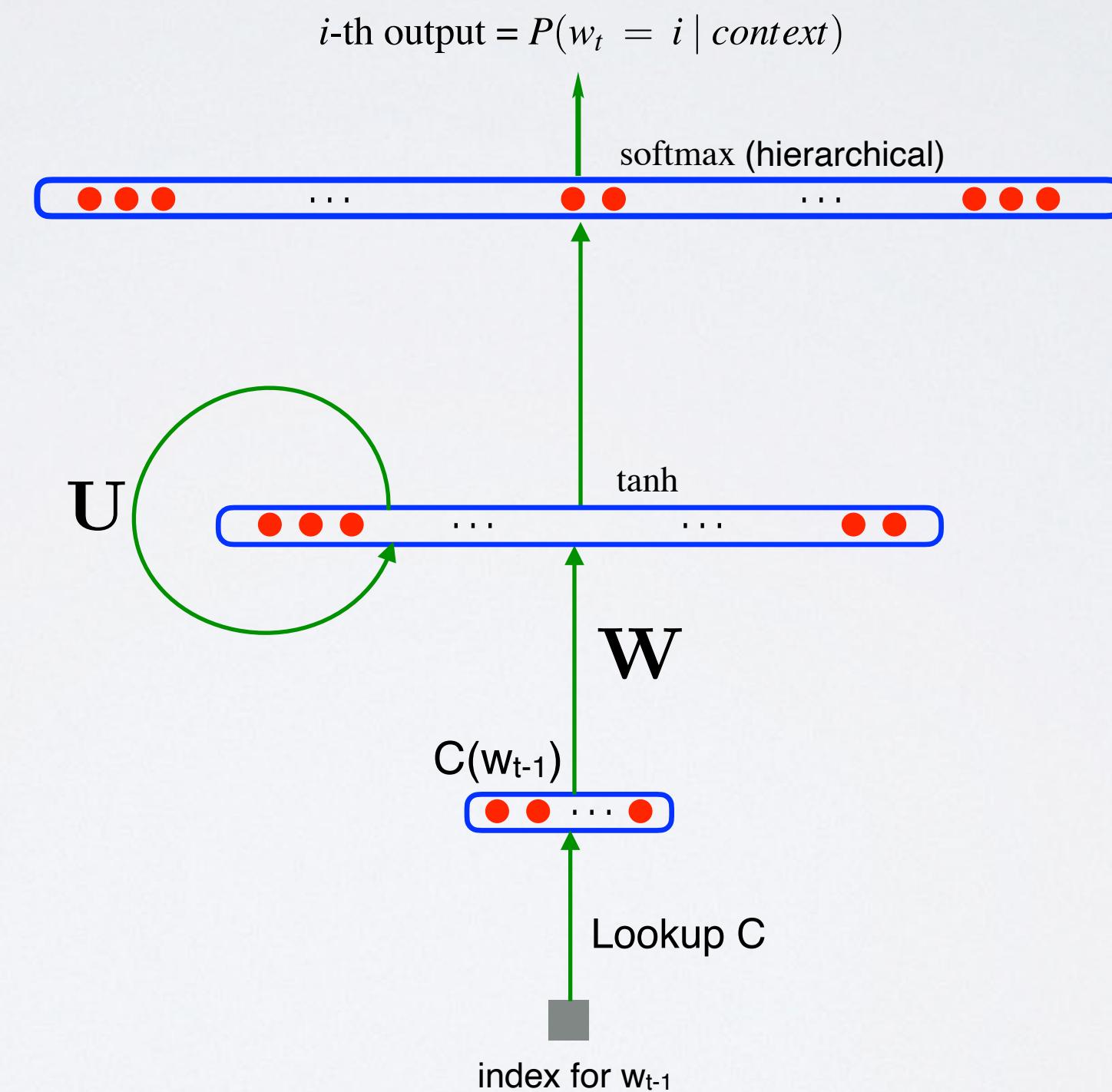
Topics: RNN language model

- Solution: recursively update a persistent hidden layer

$$\mathbf{h}_t = \tanh(\mathbf{b} + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{W}C(w_t))$$

- To compute
- $$p(w_t | \underbrace{w_1, \dots, w_{t-1}}_{\text{context}})$$

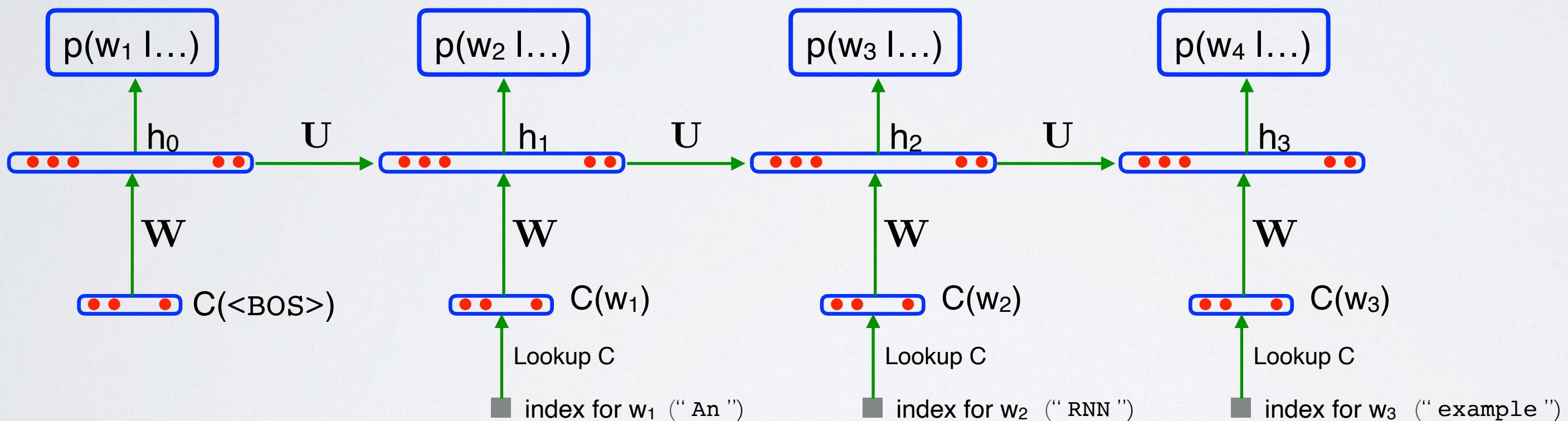
we use hidden layer \mathbf{h}_{t-1}



RECURRENT NEURAL NETWORK (RNN)

Topics: unrolled RNN

- View of RNN unrolled through time
 - example: $w = ["\text{An}", "\text{RNN}", "\text{example}", "\text{.}"]$ ($T = 4$)

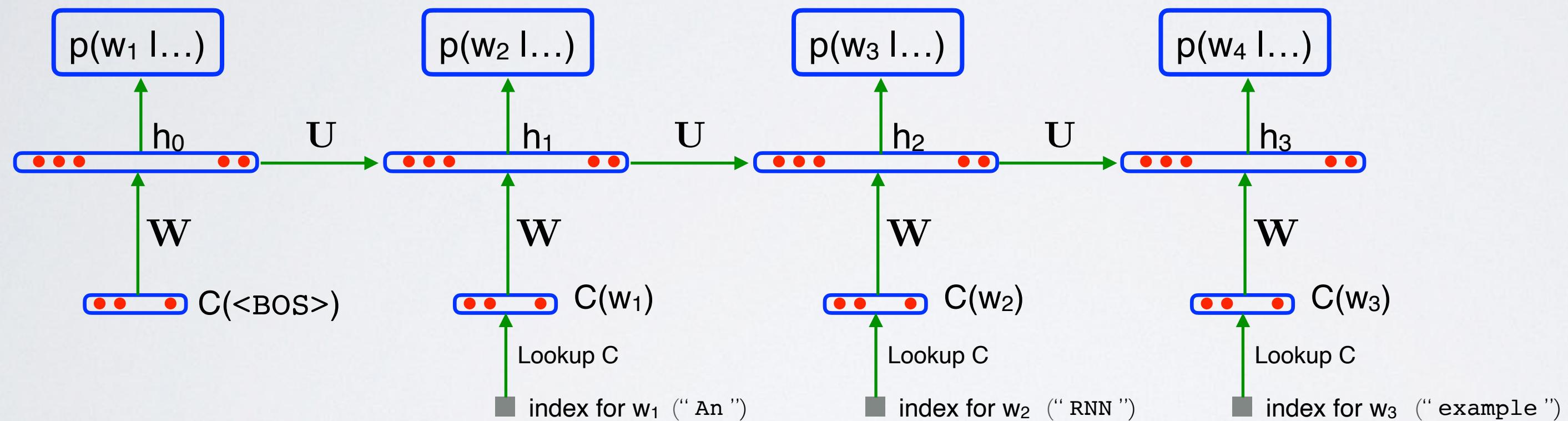


- symbol “.” serves as an end of sentence symbol
- $h_0 = \tanh(b + WC(<\text{BOS}>))$, where $C(<\text{BOS}>)$ is a unique embedding for the beginning of sentence position (<BOS> not included as possible output!)

DEEP RECURRENT NEURAL NETWORK

Topics: Deep RNN

- Straightforward to make deep
 - example: $w = ["\text{An}", "\text{RNN}", "\text{example}", "\text{.}"]$ ($T = 4$)

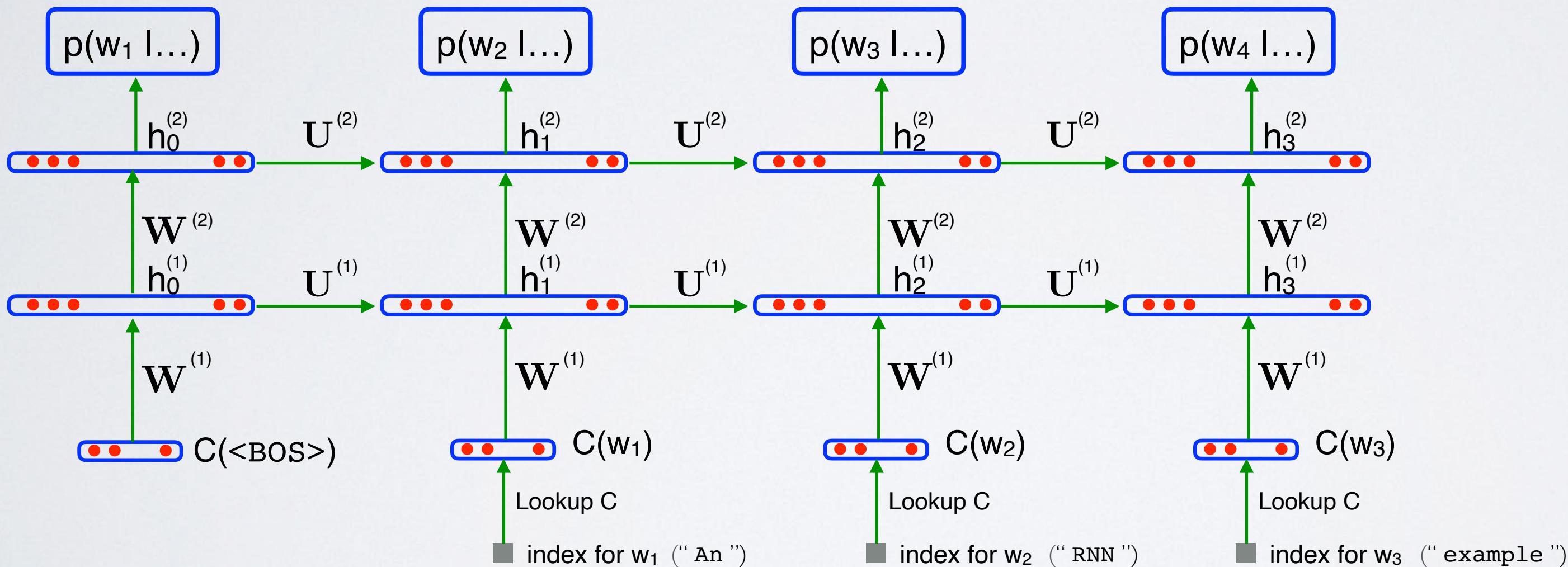


DEEP RECURRENT NEURAL NETWORK

Topics: Deep RNN

- Straightforward to make deep

► example: $w = ["\text{An}", "\text{RNN}", "\text{example}", "\text{.}"]$ ($T = 4$)



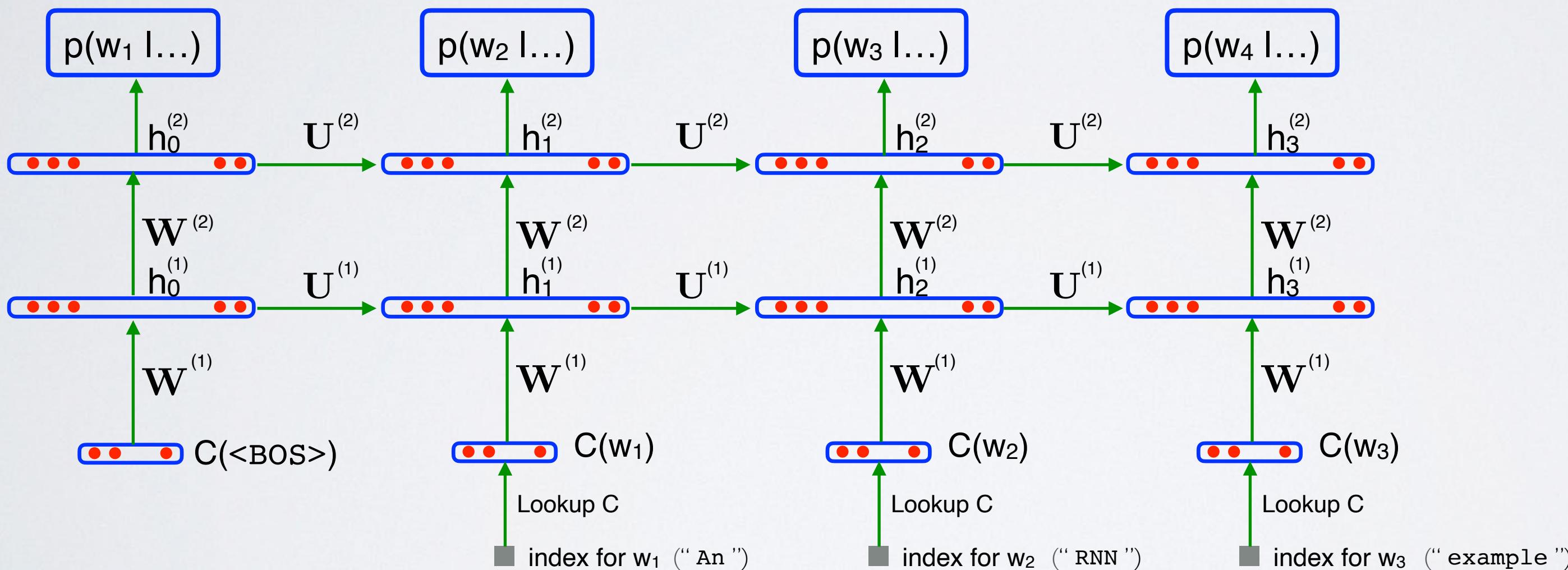
$$\begin{aligned}\mathbf{h}_t^{(1)} &= \tanh(\mathbf{b}^{(1)} + \mathbf{U}^{(1)}\mathbf{h}_{t-1}^{(1)} + \mathbf{W}^{(1)}C(w_t)) \\ \mathbf{h}_t^{(2)} &= \tanh(\mathbf{b}^{(2)} + \mathbf{U}^{(2)}\mathbf{h}_{t-1}^{(2)} + \mathbf{W}^{(2)}\mathbf{h}_t^{(1)})\end{aligned}$$

DEEP RECURRENT NEURAL NETWORK

Topics: Deep RNN

- Useful beyond language modeling

► word tagging (e.g. part-of-speech tagging, named entity recognition)



$$\mathbf{h}_t^{(1)} = \tanh(\mathbf{b}^{(1)} + \mathbf{U}^{(1)}\mathbf{h}_{t-1}^{(1)} + \mathbf{W}^{(1)}C(w_t))$$

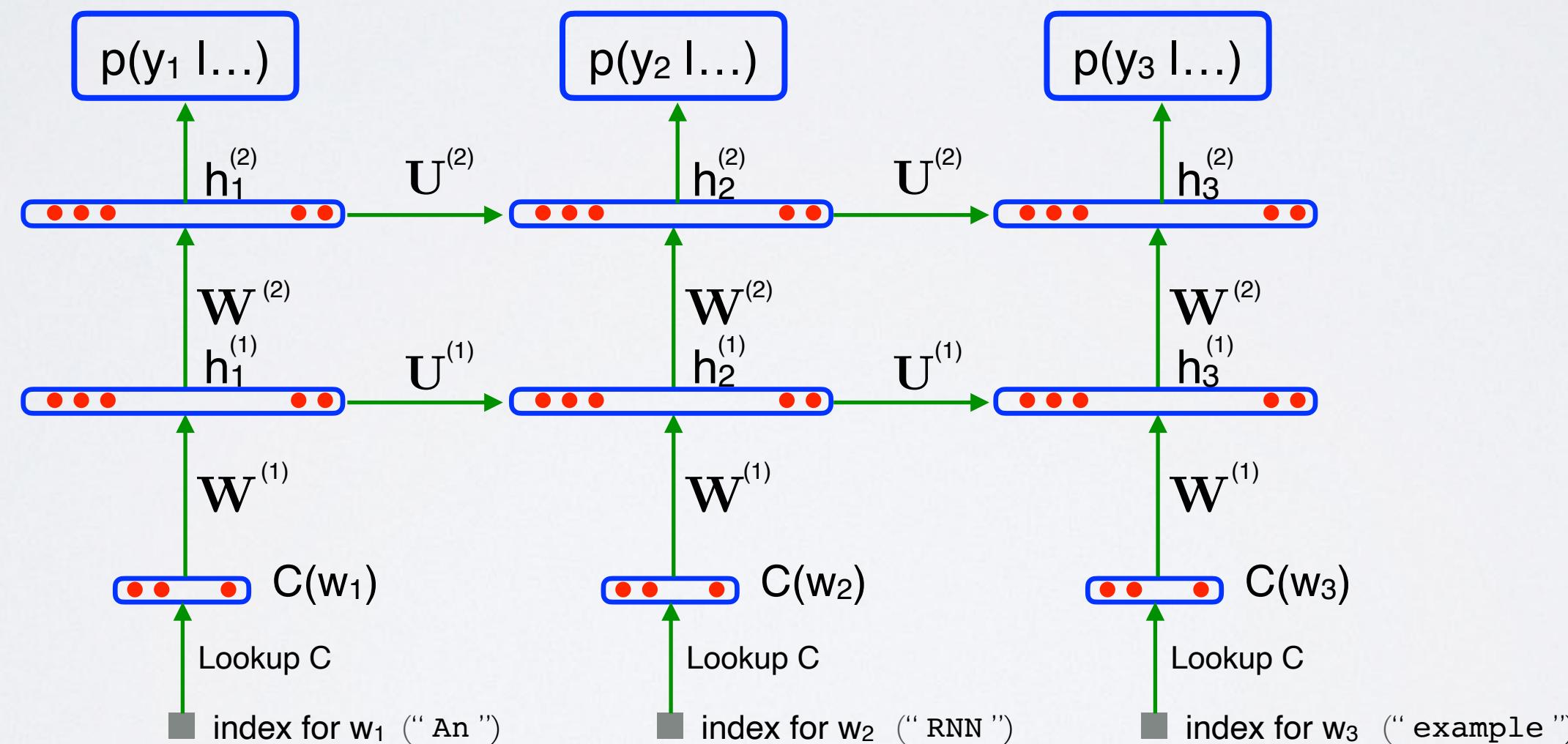
$$\mathbf{h}_t^{(2)} = \tanh(\mathbf{b}^{(2)} + \mathbf{U}^{(2)}\mathbf{h}_{t-1}^{(2)} + \mathbf{W}^{(2)}\mathbf{h}_t^{(1)})$$

DEEP RECURRENT NEURAL NETWORK

Topics: Deep RNN

- Useful beyond language modeling

- ▶ word tagging (e.g. part-of-speech tagging, named entity recognition)



$$\mathbf{h}_t^{(1)} = \tanh(\mathbf{b}^{(1)} + \mathbf{U}^{(1)}\mathbf{h}_{t-1}^{(1)} + \mathbf{W}^{(1)}C(w_t))$$

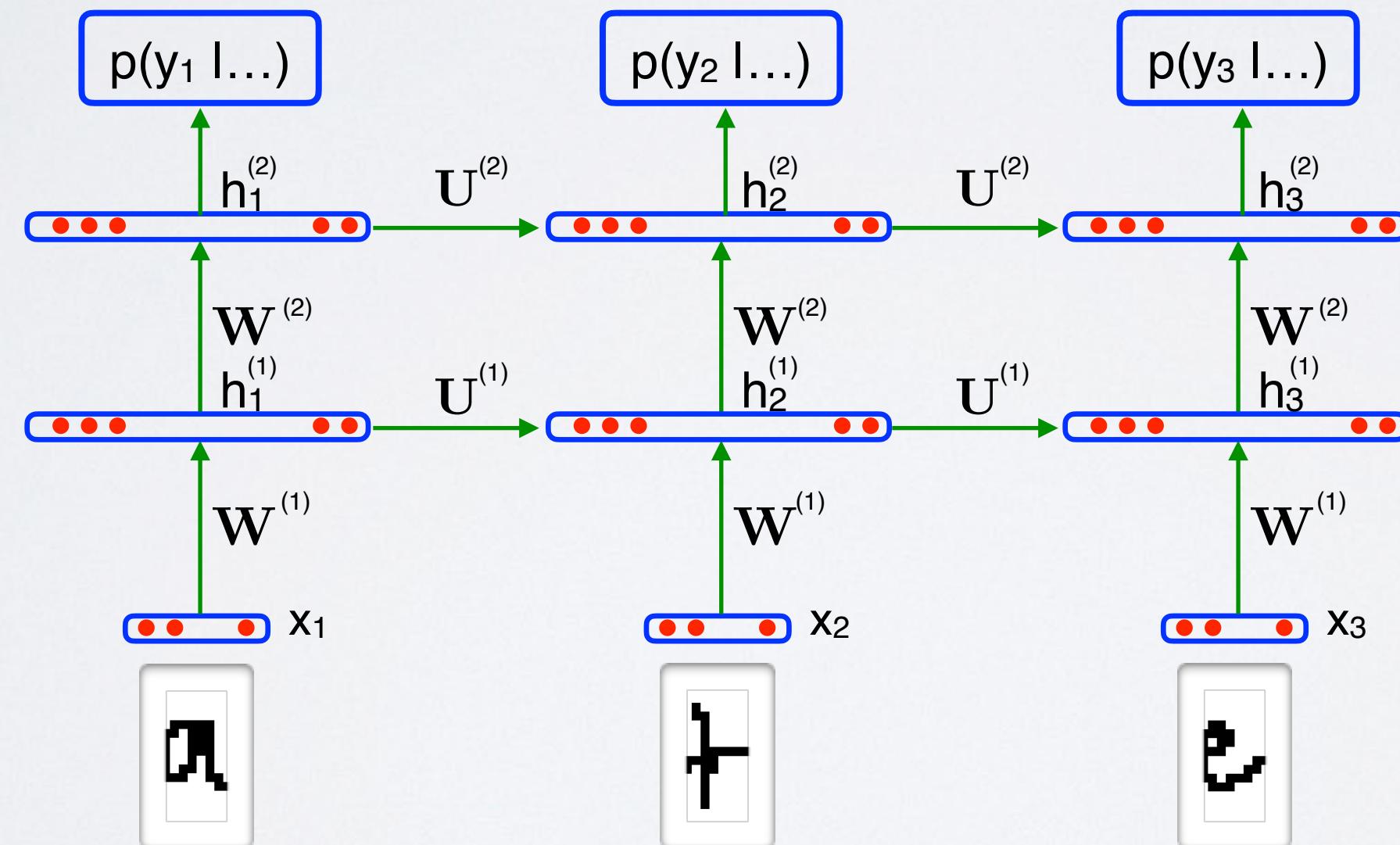
$$\mathbf{h}_t^{(2)} = \tanh(\mathbf{b}^{(2)} + \mathbf{U}^{(2)}\mathbf{h}_{t-1}^{(2)} + \mathbf{W}^{(2)}\mathbf{h}_t^{(1)})$$

DEEP RECURRENT NEURAL NETWORK

Topics: Deep RNN

- Useful beyond language modeling

- ▶ sequence labeling in general (e.g. character recognition)



$$\mathbf{h}_t^{(1)} = \tanh(\mathbf{b}^{(1)} + \mathbf{U}^{(1)}\mathbf{h}_{t-1}^{(1)} + \mathbf{W}^{(1)}C(w_t))$$

$$\mathbf{h}_t^{(2)} = \tanh(\mathbf{b}^{(2)} + \mathbf{U}^{(2)}\mathbf{h}_{t-1}^{(2)} + \mathbf{W}^{(2)}\mathbf{h}_t^{(1)})$$

Recurrent neural networks

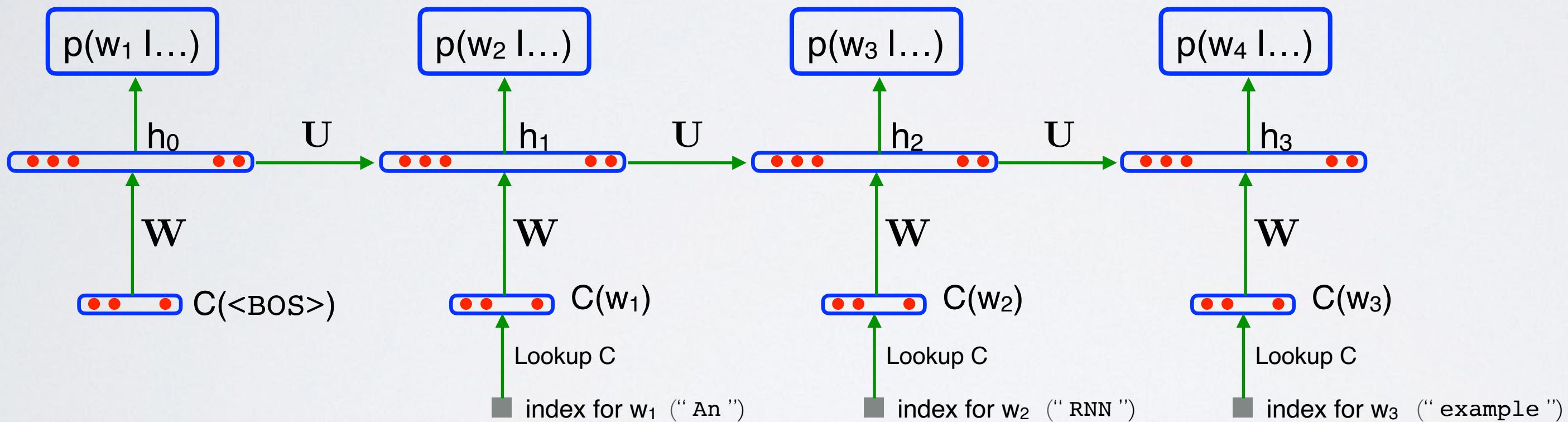
Backpropagation through time

RECURRENT NEURAL NETWORK (RNN)

REMINDER

Topics: unrolled RNN

- View of RNN unrolled through time
 - ▶ example: $w = ["\text{An}", "\text{RNN}", "\text{example}", "\text{.}"]$ ($T = 4$)

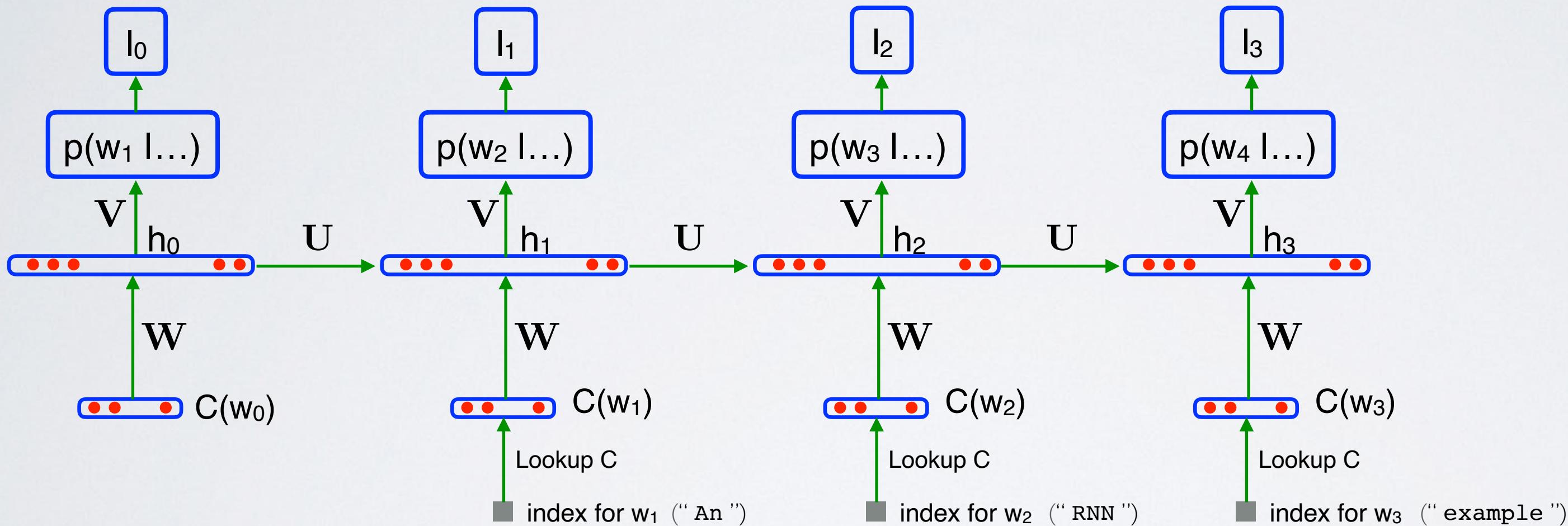


- ▶ symbol “.” serves as an end of sentence symbol
- ▶ alternative model for h_0 is to set w_0 to a unique beginning of sentence symbol, with its own embedding $C(w_0)$ (but not included as possible output!)

BACKPROPAGATION THROUGH TIME

Topics: backpropagation through time (BPTT)

- Gradients obtained by applying chain rule on unrolled graph

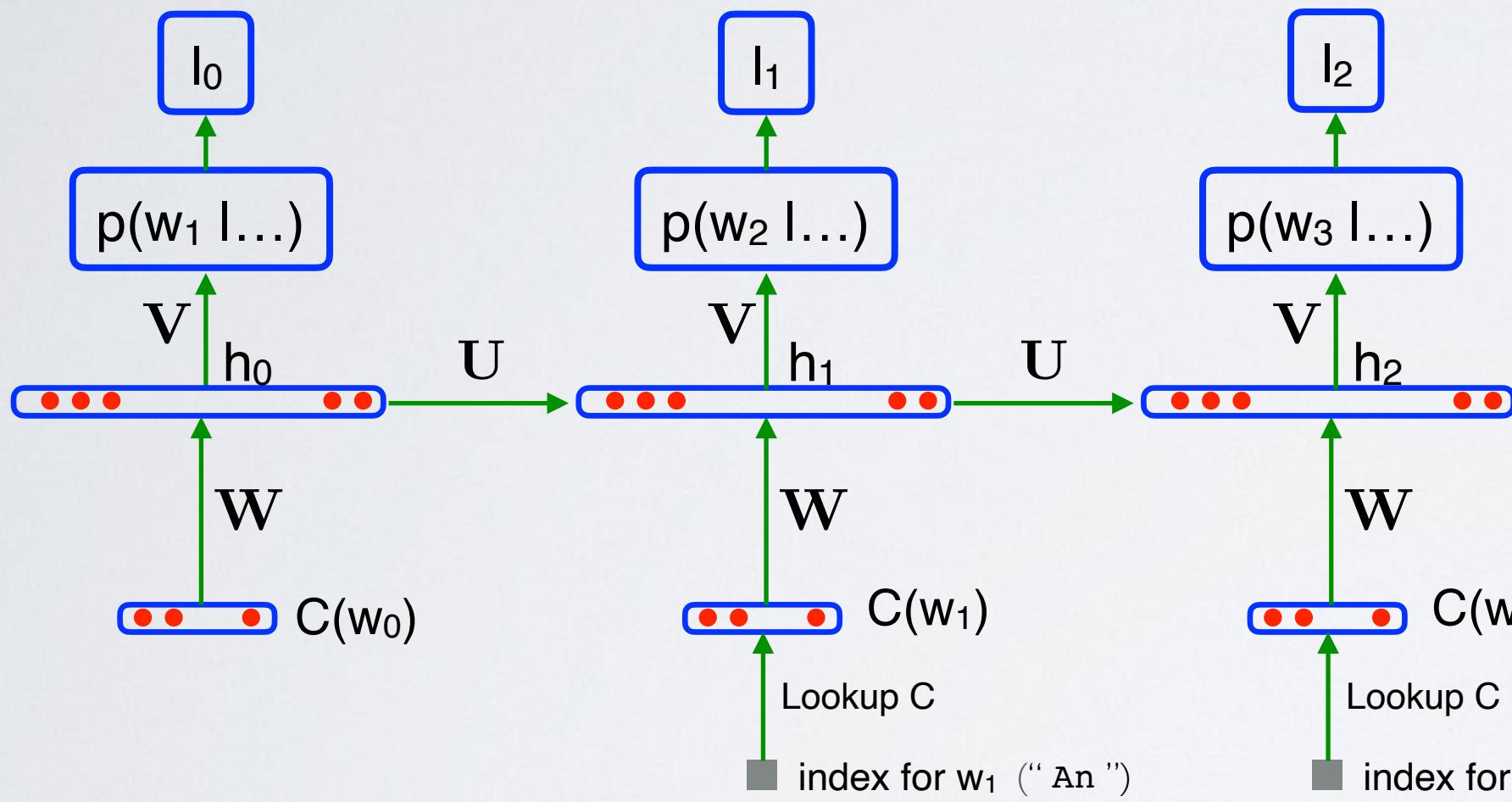


- ▶ want to minimize sum of per step loss $l = \sum_{t=0}^{T-1} l_t$
- ▶ for language modeling, $l_t = -\log p(w_{t+1} | \dots)$

BACKPROPAGATION THROUGH TIME

Topics: backpropagation through time (BPTT)

- Gradients obtained by applying chain rule



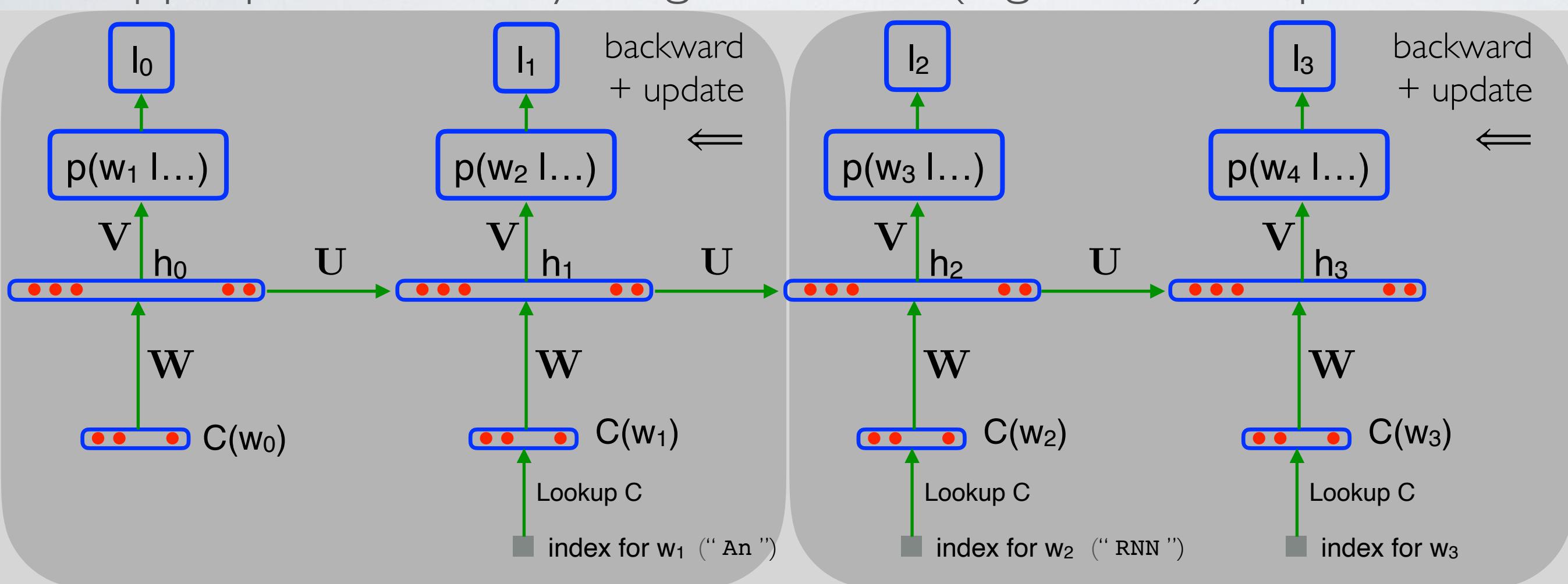
- **forward propagation:** computation follows arrows in flow graph (forward in time)

- initialize gradients
 - $\nabla_{\mathbf{V}} l \leftarrow 0, \nabla_{\mathbf{W}} l \leftarrow 0, \nabla_{\mathbf{U}} l \leftarrow 0$
 - $\nabla_{\mathbf{h}_{T-1}} l \leftarrow 0$
- for t from $T-1$ to 0
 - $\nabla_{\mathbf{V}} l += \nabla_{\mathbf{V}} l_t$
 - $\nabla_{\mathbf{h}_t} l += \nabla_{\mathbf{h}_t} l_t$
 - $\nabla_{\mathbf{a}_t} l \leftarrow (1 - \mathbf{h}_t^2) \odot \nabla_{\mathbf{h}_t} l$
 - $\nabla_{\mathbf{W}} l += (\nabla_{\mathbf{a}_t} l) C(w_t)^\top$
 - $\nabla_{\mathbf{U}} l += (\nabla_{\mathbf{a}_t} l) \mathbf{h}_{t-1}^\top$
 - $\nabla_{\mathbf{h}_{t-1}} l \leftarrow \mathbf{U}^\top \nabla_{\mathbf{a}_t} l$

TRUNCATER BPTT

Topics: truncated BPTT

- Inappropriate for very long or infinite (e.g. online) sequences



Example with
 $k_1=k_2=2$

Computed from
“pre-update” h_1

Stop BPTT at $t=2$

- Truncated BPTT:** approximate BPTT by

- performing forward pass k_1 steps at a time
- running BPTT only k_2 steps backward and update (assuming earlier steps are fixed)

Recurrent neural networks

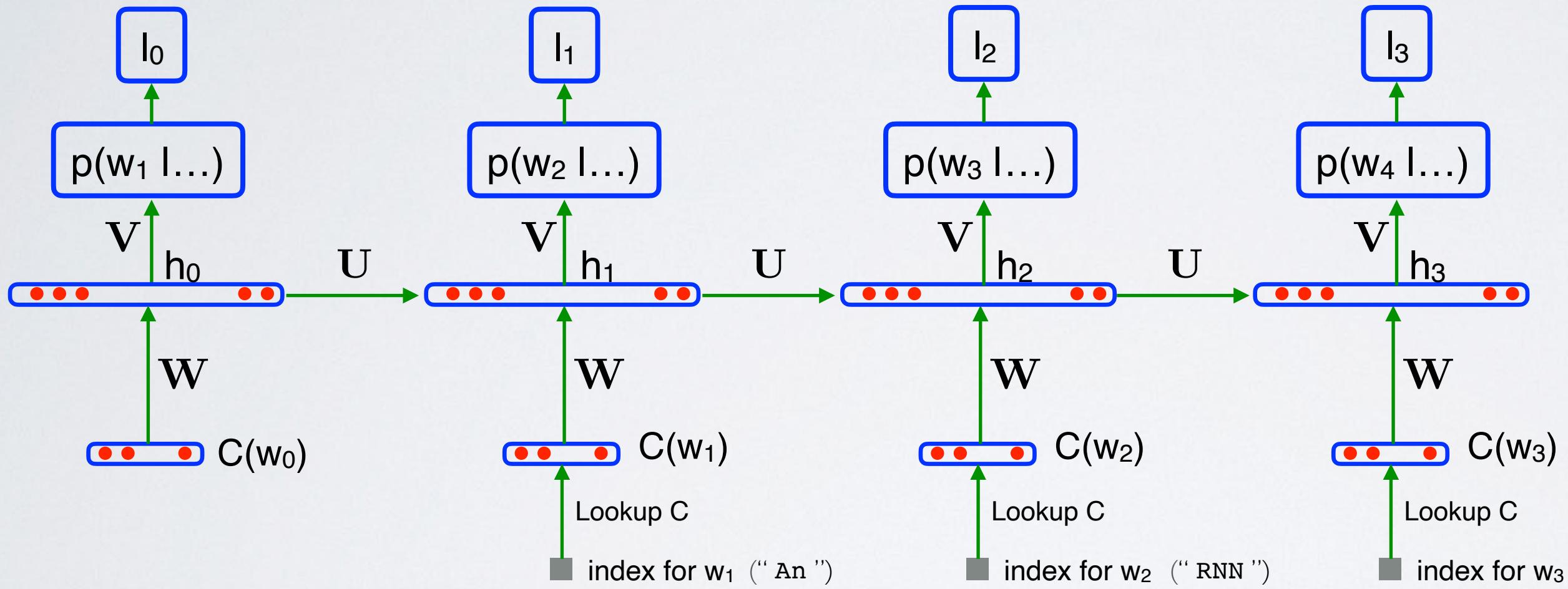
Exploding/vanishing gradient problem

BACKPROPAGATION THROUGH TIME

REMINDER

Topics: backpropagation through time (BPTT)

- Gradients obtained by applying chain rule on unrolled graph

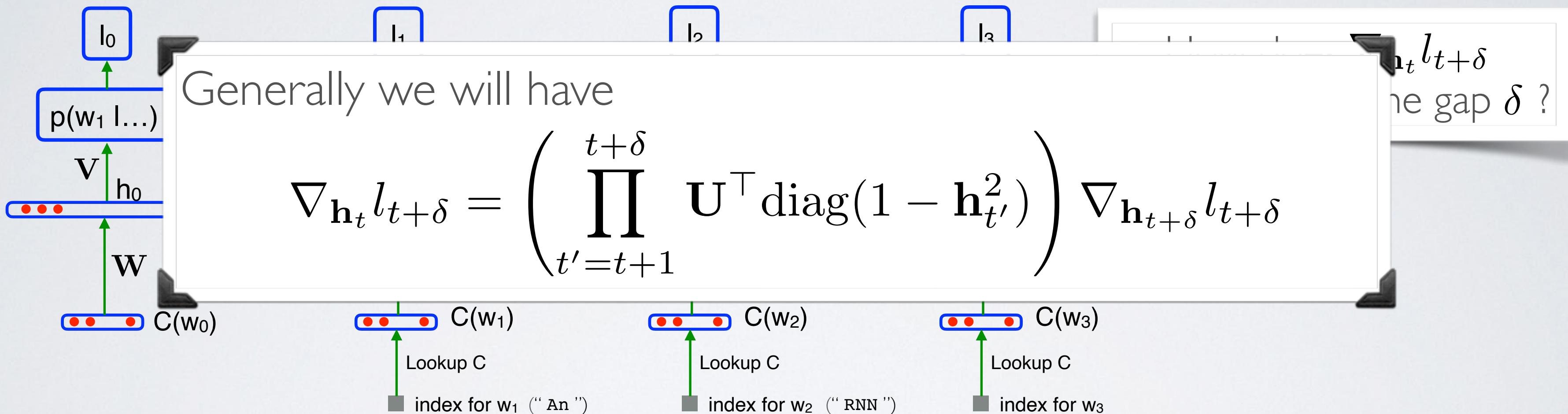


- **forward propagation:** computation follows arrows in flow graph (forward in time)

BACKPROPAGATION THROUGH TIME

Topics: backpropagation through time (BPTT)

- Gradients obtained by applying chain rule on unrolled graph



- Consider the gradient with respect to \mathbf{h}_t : $\nabla_{\mathbf{h}_t} l = \sum_{\delta=0}^{T-\delta-1} \nabla_{\mathbf{h}_t} l_{t+\delta}$

BACKPROPAGATION THROUGH TIME

Topics: exploding gradient

Generally we will have

$$\nabla_{\mathbf{h}_t} l_{t+\delta} = \left(\prod_{t'=t+1}^{t+\delta} \mathbf{U}^\top \text{diag}(1 - \mathbf{h}_{t'}^2) \right) \nabla_{\mathbf{h}_{t+\delta}} l_{t+\delta}$$

- What could go wrong, as δ increases?
 - if \mathbf{U} is “large”, then as δ grows, $\nabla_{\mathbf{h}_t} l_{t+\delta}$ will grow too (exponentially!)
 - if $\nabla_{\mathbf{h}_t} l_{t+\delta}$ is large, then so will the gradients on \mathbf{W} and ... \mathbf{U} !
 - this is known as the **exploding gradient problem**

BACKPROPAGATION THROUGH TIME

Topics: gradient clipping

Generally we will have

$$\nabla_{\mathbf{h}_t} l_{t+\delta} = \left(\prod_{t'=t+1}^{t+\delta} \mathbf{U}^\top \text{diag}(1 - \mathbf{h}_{t'}^2) \right) \nabla_{\mathbf{h}_{t+\delta}} l_{t+\delta}$$

- Solution: **gradient clipping**

- let θ be any of parameter matrix/vector of the model (e.g. \mathbf{W} , \mathbf{U} or \mathbf{V})
- before update, if the norm of $\nabla_\theta l$ is larger than some threshold C , rescale

$$\nabla_\theta l \leftarrow C \times \frac{\nabla_\theta l}{\|\nabla_\theta l\|}$$

- often applied where θ is the concatenation of *all* parameters of the model

BACKPROPAGATION THROUGH TIME

Topics: vanishing gradient

Generally we will have

$$\nabla_{\mathbf{h}_t} l_{t+\delta} = \left(\prod_{t'=t+1}^{t+\delta} \mathbf{U}^\top \text{diag}(1 - \mathbf{h}_{t'}^2) \right) \nabla_{\mathbf{h}_{t+\delta}} l_{t+\delta}$$

- What could go wrong, as δ increases?
 - if \mathbf{U} is “small” or hidden units $\mathbf{h}_{t'}$ are saturated, then $\nabla_{\mathbf{h}_t} l_{t+\delta}$ will shrink (exponentially!)
 - if $\nabla_{\mathbf{h}_t} l_{t+\delta}$ is small, then ***can't learn long term dependencies***
 - this is known as the **vanishing gradient problem**

BACKPROPAGATION THROUGH TIME

Topics: orthogonal initialization

Generally we will have

$$\nabla_{\mathbf{h}_t} l_{t+\delta} = \left(\prod_{t'=t+1}^{t+\delta} \mathbf{U}^\top \text{diag}(1 - \mathbf{h}_{t'}^2) \right) \nabla_{\mathbf{h}_{t+\delta}} l_{t+\delta}$$

- Solution: **orthogonal initialization**

- initialize \mathbf{U} as a random orthogonal matrix (i.e. $\mathbf{U}^\top \mathbf{U} = \mathbf{U} \mathbf{U}^\top = \mathbf{I}$)
 - then multiplying with \mathbf{U}^\top doesn't change the norm, since $(\mathbf{U}^\top \mathbf{v})^\top (\mathbf{U}^\top \mathbf{v}) = \mathbf{v}^\top \mathbf{U} \mathbf{U}^\top \mathbf{v} = \mathbf{v}^\top \mathbf{v}$
- initialize as usual \mathbf{W} (small random entries)
 - then $\text{diag}(1 - \mathbf{h}_{t'}^2)$ is close to \mathbf{I}
- also useful to avoid exploding gradient (at least initially)

Recurrent neural networks

Long short-term memory network

BACKPROPAGATION THROUGH TIME

Topics: vanishing gradient

REMINDER

Generally we will have

$$\nabla_{\mathbf{h}_t} l_{t+\delta} = \left(\prod_{t'=t+1}^{t+\delta} \mathbf{U}^\top \text{diag}(1 - \mathbf{h}_{t'}^2) \right) \nabla_{\mathbf{h}_{t+\delta}} l_{t+\delta}$$

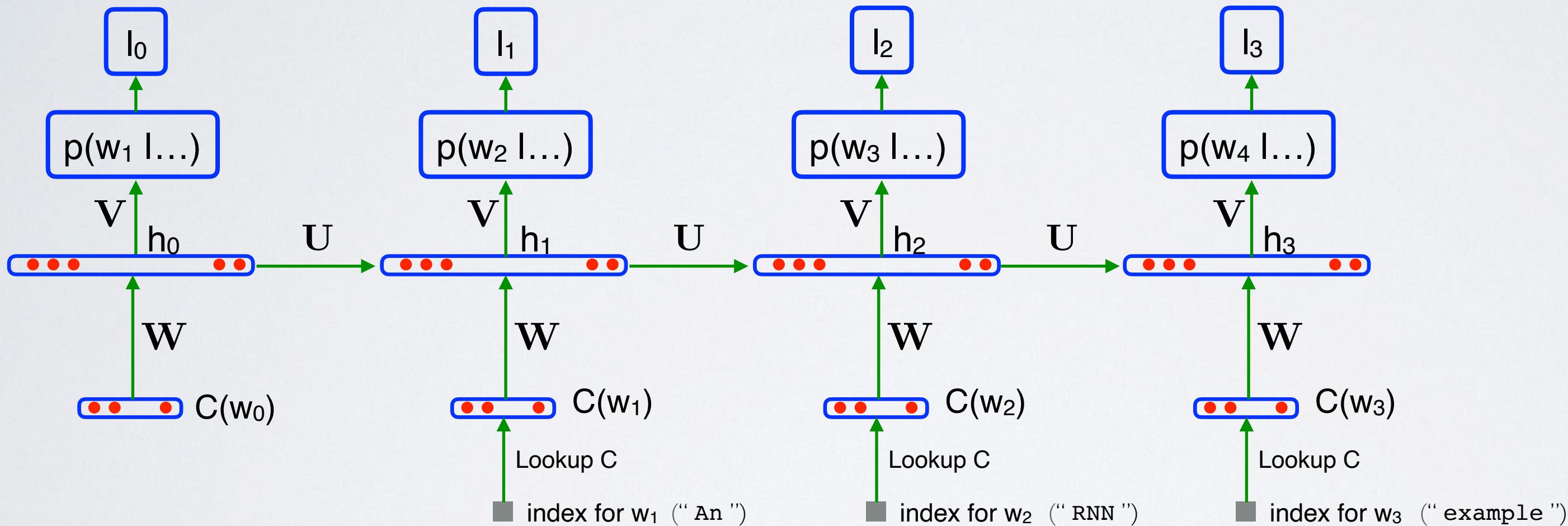
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BACKPROPAGATION THROUGH TIME

REMINDER

Topics: backpropagation through time (BPTT)

- Gradients obtained by applying chain rule on unrolled graph

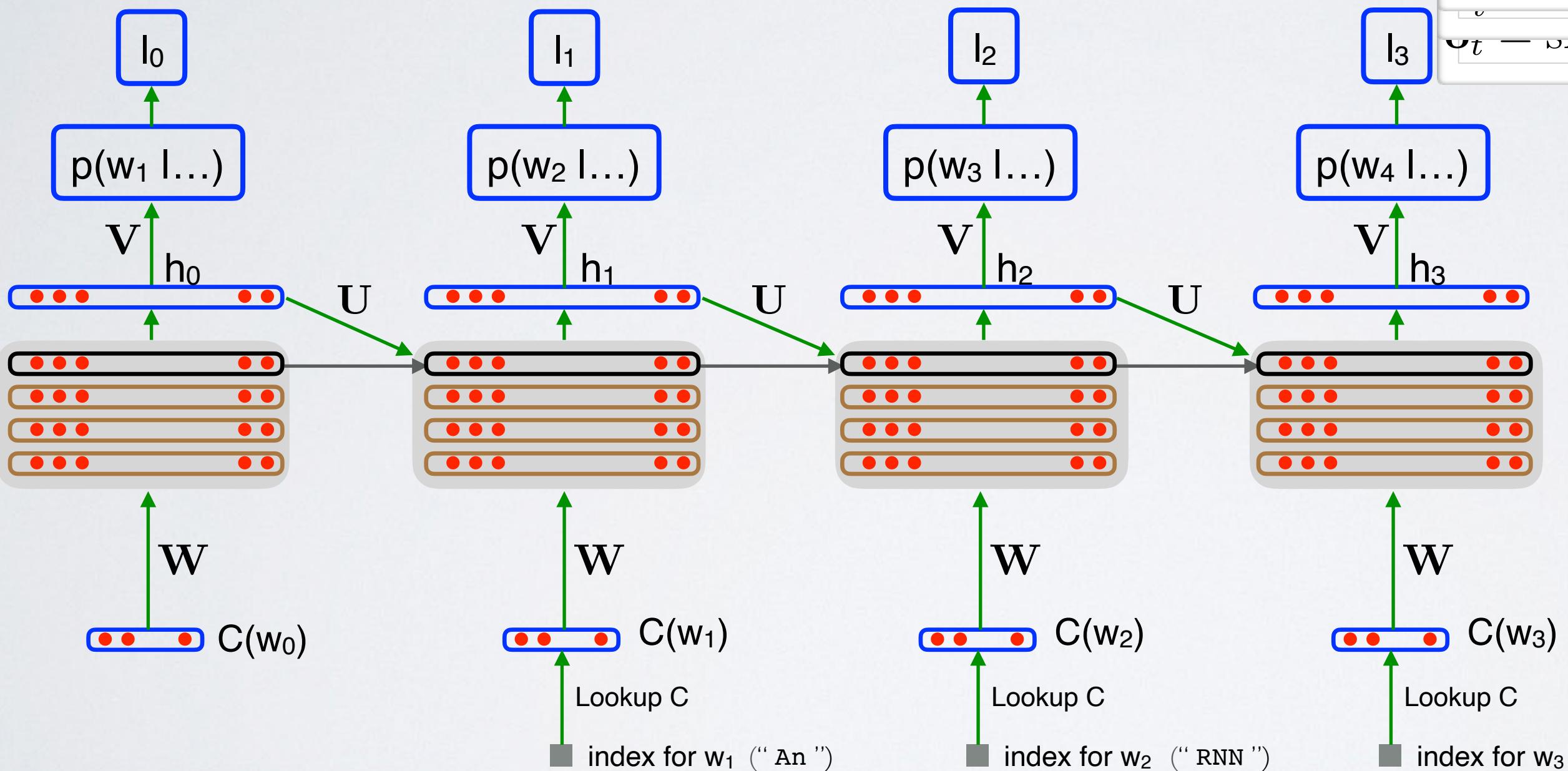


- ▶ want to minimize sum of per step loss $l = \sum_{t=0}^{T-1} l_t$
- ▶ for language modeling, $l_t = -\log p(w_{t+1} | \dots)$

LONG SHORT-TERM MEMORY NETWORK

Topics: long short-term memory (LSTM) network

- Layer h_t is a function of **memory cells**



Input, forget, output gates:

Hidden layer:

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

$$o_t = \sigma_{\text{sigm}}(w_o^T h_{t-1} + b_o)$$

Hochreiter, Schmidhuber
1995

LONG SHORT-TERM MEMORY NETWORK

Topics: long short-term memory (LSTM) network

- To sum up:

Input, forget, output gates:

$$\mathbf{i}_t = \text{sigm}(\mathbf{b}_{[i]} + \mathbf{U}_{[i]}\mathbf{h}_{t-1} + \mathbf{W}_{[i]}C(w_t))$$

$$\mathbf{f}_t = \text{sigm}(\mathbf{b}_{[f]} + \mathbf{U}_{[f]}\mathbf{h}_{t-1} + \mathbf{W}_{[f]}C(w_t))$$

$$\mathbf{o}_t = \text{sigm}(\mathbf{b}_{[o]} + \mathbf{U}_{[o]}\mathbf{h}_{t-1} + \mathbf{W}_{[o]}C(w_t))$$

Cell state:

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{b}_{[c]} + \mathbf{U}_{[c]}\mathbf{h}_{t-1} + \mathbf{W}_{[c]}C(w_t))$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

Hidden layer:

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

The **gates** control the flow of information in ($\mathbf{i}_t, \mathbf{f}_t$) and out (\mathbf{o}_t) of the cell

The **cell state** maintains information on the input

The **hidden layer** sees what passes through the output gate

LONG SHORT-TERM MEMORY NETWORK

Topics: long short-term memory (LSTM) network

- To sum up:

Input, forget, output gates:

$$i_t = \text{sigm}(\mathbf{b}_{[i]} + \mathbf{U}_{[i]}\mathbf{h}_{t-1} + \mathbf{W}_{[i]}C(w_t))$$

$$f_t = \text{sigm}(\mathbf{b}_{[f]} + \mathbf{U}_{[f]}\mathbf{h}_{t-1} + \mathbf{W}_{[f]}C(w_t))$$

$$o_t = \text{sigm}(\mathbf{b}_{[o]} + \mathbf{U}_{[o]}\mathbf{h}_{t-1} + \mathbf{W}_{[o]}C(w_t))$$

Cell state:

$$\tilde{c}_t = \tanh(\mathbf{b}_{[c]} + \mathbf{U}_{[c]}\mathbf{h}_{t-1} + \mathbf{W}_{[c]}C(w_t))$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

Hidden layer:

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

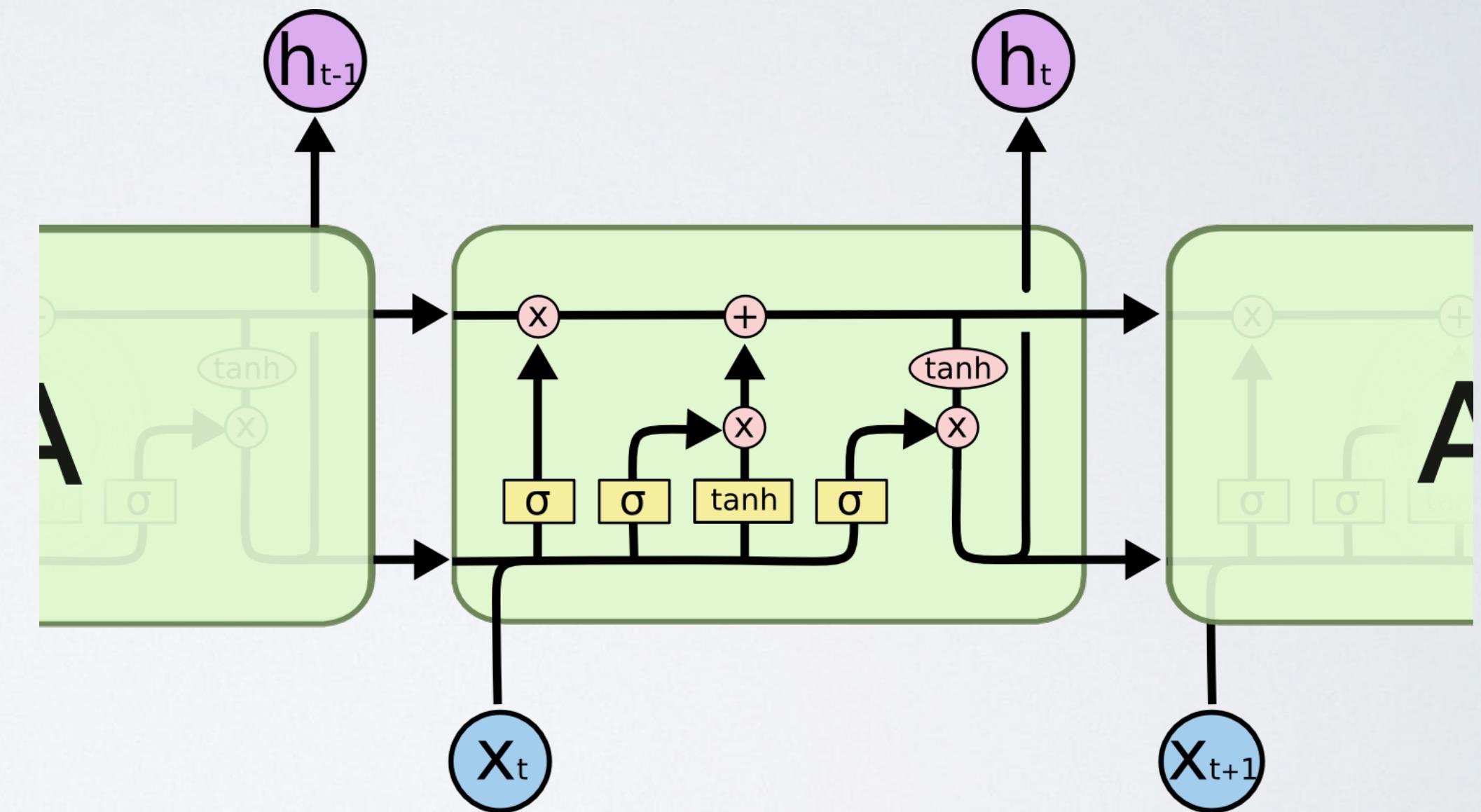


Image from Chris Olah's Blog post on Understanding LSTMs

LONG SHORT-TERM MEMORY NETWORK

Topics: long-term dependencies, forget bias initialization

- Why is it better at learning long-term dependencies?

$$\mathbf{c}_t = \sum_{t'=0}^t \mathbf{f}_{t'} \mathbf{f}_{t'-1} \odot \mathbf{i}_{t'} \mathbf{f}_{t'-1} + \mathbf{i}_t \mathbf{f}_t \mathbf{i}_t \odot \mathbf{i}_t \mathbf{f}_t \odot \tilde{\mathbf{c}}_{t-1}$$

- As long as forget gates are open (close to 1), gradient may pass into $\tilde{\mathbf{c}}_t$ over long time gaps
 - ▶ saturation of forget gates doesn't stop gradient flow
 - ▶ suggests that a better initialization of forget gate bias $b_{[f]}$ is $\gg 0$ (e.g. 1)
- Learning with BPTT more effective
 - ▶ easy to compute gradients with automatic differentiation

LONG SHORT-TERM MEMORY NETWORK

Topics: LSTM variations

- Can add “peephole connections” to the gates

$$\mathbf{i}_t = \text{sigm}(\mathbf{b}_{[i]} + \mathbf{U}_{[i]}\mathbf{h}_{t-1} + \mathbf{W}_{[i]\phi}\mathbf{c}_t C(w_t))$$

$$\mathbf{f}_t = \text{sigm}(\mathbf{b}_{[f]} + \mathbf{U}_{[f]}\mathbf{h}_{t-1} + \mathbf{W}_{[f]\phi}\mathbf{c}_t C(w_t))$$

$$\mathbf{o}_t = \text{sigm}(\mathbf{b}_{[o]} + \mathbf{U}_{[o]}\mathbf{h}_{t-1} + \mathbf{W}_{[o]\phi}\mathbf{c}_t C(w_t))$$

- For historical perspective and empirical ablation analysis

LSTM: A Search Space Odyssey

Greff, Srivastava, Koutník, Steunebrink, Schmidhuber

2015

- ▶ forget gate are crucial, as well as output gates if cell state unbounded
- ▶ coupling the input and forget gate ($\mathbf{f}_t = 1 - \mathbf{i}_t$) can also work well

Recurrent neural networks

Gated recurrent units network

LONG SHORT-TERM MEMORY NETWORK

REMINDER

Topics: long short-term memory (LSTM) network

- To sum up:

Input, forget, output gates:

$$\mathbf{i}_t = \text{sigm}(\mathbf{b}_{[i]} + \mathbf{U}_{[i]}\mathbf{h}_{t-1} + \mathbf{W}_{[i]}C(w_t))$$

$$\mathbf{f}_t = \text{sigm}(\mathbf{b}_{[f]} + \mathbf{U}_{[f]}\mathbf{h}_{t-1} + \mathbf{W}_{[f]}C(w_t))$$

$$\mathbf{o}_t = \text{sigm}(\mathbf{b}_{[o]} + \mathbf{U}_{[o]}\mathbf{h}_{t-1} + \mathbf{W}_{[o]}C(w_t))$$

Cell state:

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{b}_{[c]} + \mathbf{U}_{[c]}\mathbf{h}_{t-1} + \mathbf{W}_{[c]}C(w_t))$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

Hidden layer:

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

GATED RECURRENT UNITS NETWORK

Topics: gated recurrent units (GRU) network

Cho, Merrienboer, Bahdanau, Bengio
2014

LSTM

Input, forget, output gates:

$$\mathbf{i}_t = \text{sigm}(\mathbf{b}_{[i]} + \mathbf{U}_{[i]}\mathbf{h}_{t-1} + \mathbf{W}_{[i]}C(w_t))$$

$$\mathbf{f}_t = \text{sigm}(\mathbf{b}_{[f]} + \mathbf{U}_{[f]}\mathbf{h}_{t-1} + \mathbf{W}_{[f]}C(w_t))$$

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Cell state:

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{b}_{[c]} + \mathbf{U}_{[c]}\mathbf{h}_{t-1} + \mathbf{W}_{[c]}C(w_t))$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

Hidden layer:

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

GRU

Update, reset gates:

$$\mathbf{z}_t = \text{sigm}(\mathbf{b}_{[z]} + \mathbf{U}_{[z]}\mathbf{h}_{t-1} + \mathbf{W}_{[z]}C(w_t))$$

$$\mathbf{r}_t = \text{sigm}(\mathbf{b}_{[r]} + \mathbf{U}_{[r]}\mathbf{h}_{t-1} + \mathbf{W}_{[r]}C(w_t))$$

Cell state:

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{b}_{[c]} + \mathbf{U}_{[c]}(\mathbf{r}_t \odot \mathbf{h}_{t-1}) + \mathbf{W}_{[c]}C(w_t))$$

$$\mathbf{c}_t = (1 - \mathbf{z}_t) \odot \mathbf{c}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{c}}_t$$

Hidden layer:

$$\mathbf{h}_t = \mathbf{c}_t$$

GATED RECURRENT UNITS NETWORK

Topics: gated recurrent units (GRU) network

Cho, Merrienboer, Bahdanau, Bengio
2014

- To sum up:

Update, reset gates:

$$\mathbf{z}_t = \text{sigm}(\mathbf{b}_{[z]} + \mathbf{U}_{[z]}\mathbf{h}_{t-1} + \mathbf{W}_{[z]}C(w_t))$$

$$\mathbf{r}_t = \text{sigm}(\mathbf{b}_{[r]} + \mathbf{U}_{[r]}\mathbf{h}_{t-1} + \mathbf{W}_{[r]}C(w_t))$$

} Fewer **gates**, thus fewer parameters and computations

Cell state:

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{b}_{[c]} + \mathbf{U}_{[c]}(\mathbf{r}_t \odot \mathbf{h}_{t-1}) + \mathbf{W}_{[c]}C(w_t))$$

$$\mathbf{c}_t = (1 - \mathbf{z}_t) \odot \mathbf{c}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{c}}_t$$

} Update gate within **cell update**
Coupling of forget and input gates

Hidden layer:

$$\mathbf{h}_t = \mathbf{c}_t$$

} **Hidden layer** is the cell state,
so fewer computations there too

Recurrent neural networks

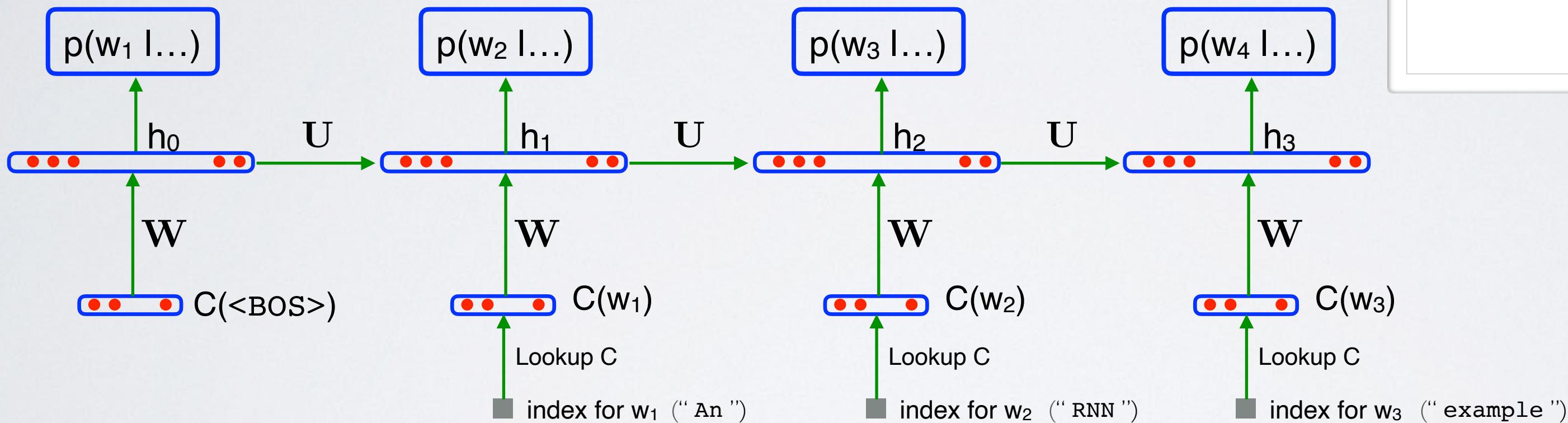
Sequence to sequence learning

RNN LANGUAGE MODEL

REMINDER

Topics: unrolled RNN

- View of RNN unrolled through time
 - example: $w = ["\text{An}", "\text{RNN}", "\text{example}", "\text{.}"]$ ($T = 4$)



$$\begin{aligned} p(w) &= p(w_1) \times p(w_2 | w_1) \\ &\quad \times p(w_3 | w_1, w_2) \\ &\quad \times p(w_4 | w_1, w_2, w_3) \end{aligned}$$

- symbol “.” serves as an end of sentence symbol
- $h_0 = \tanh(b + WC(<\text{BOS}>))$, where $C(<\text{BOS}>)$ is a unique embedding for the beginning of sentence position ($<\text{BOS}>$ not included as possible output!)

SEQUENCE TO SEQUENCE LEARNING

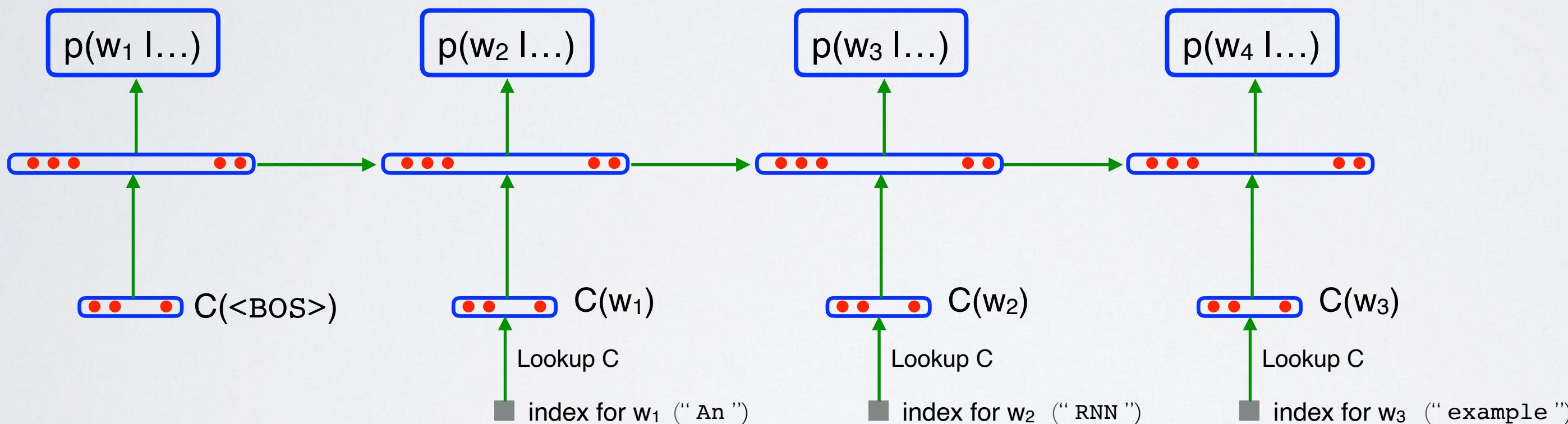
Topics: sequence to sequence (Seq2Seq) learning

- An RNN (LSTM or GRU) gives us good models over a target sequence space **w**
- What if we wanted to predict the target sequence **w** from some input sequence **x**
 - ▶ example application: machine translation
 - ▶ can't assume that **w** has same size as **x** or are aligned, so could not treat as a simpler tagging problem
- Referred to as **sequence to sequence (Seq2Seq)** learning
 - ▶ RNNs can be used to construct a model for Seq2Seq

SEQUENCE TO SEQUENCE LEARNING

Topics: sequence to sequence (Seq2Seq) learning

- View of RNN unrolled through time
 - example: $w = ["\text{An}", "\text{RNN}", "\text{example}", "\text{.}"]$ ($T = 4$)



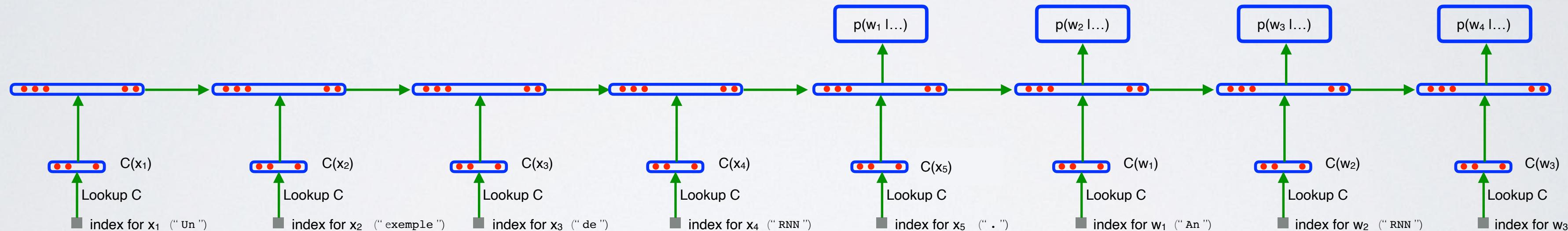
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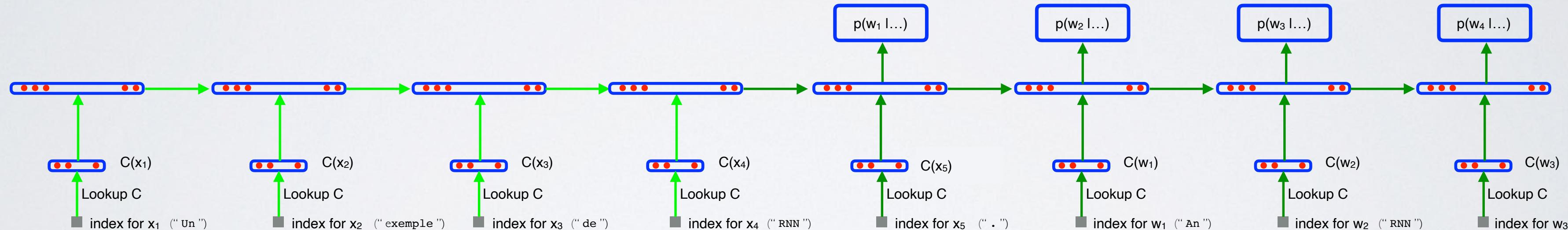
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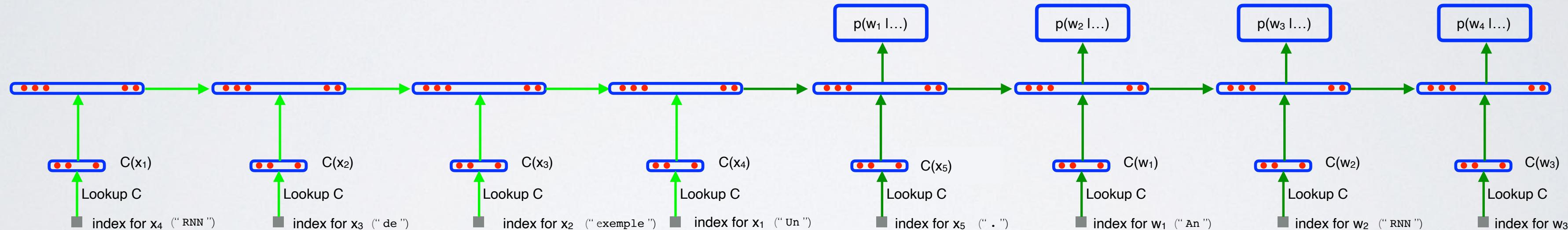
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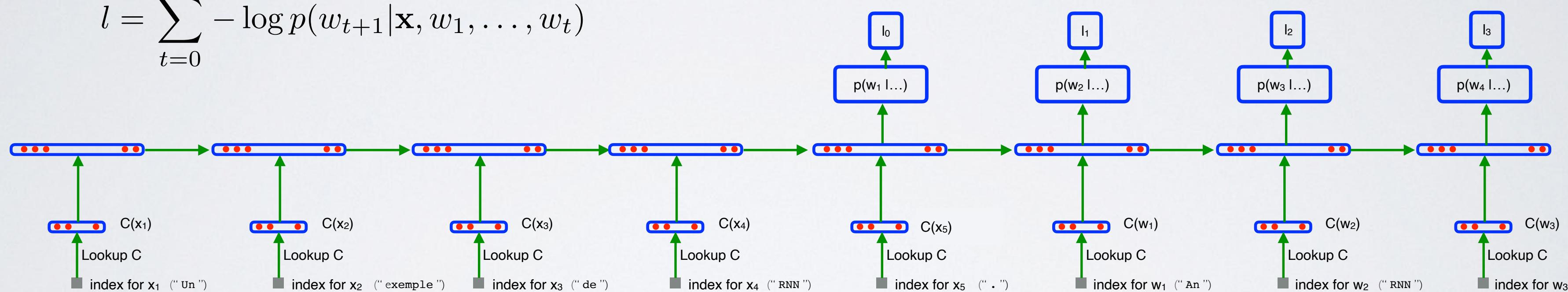
- ▶ may work better by using different RNN parameters to process \mathbf{x}
- ▶ may work better by processing sequence \mathbf{x} in reverse order

SEQUENCE TO SEQUENCE LEARNING

Topics: training

- Provides a model for $p(w|x)$
 - trained with BPTT and gradient descent on loss:

$$l = \sum_{t=0}^{T-1} -\log p(w_{t+1} | \mathbf{x}, w_1, \dots, w_t)$$

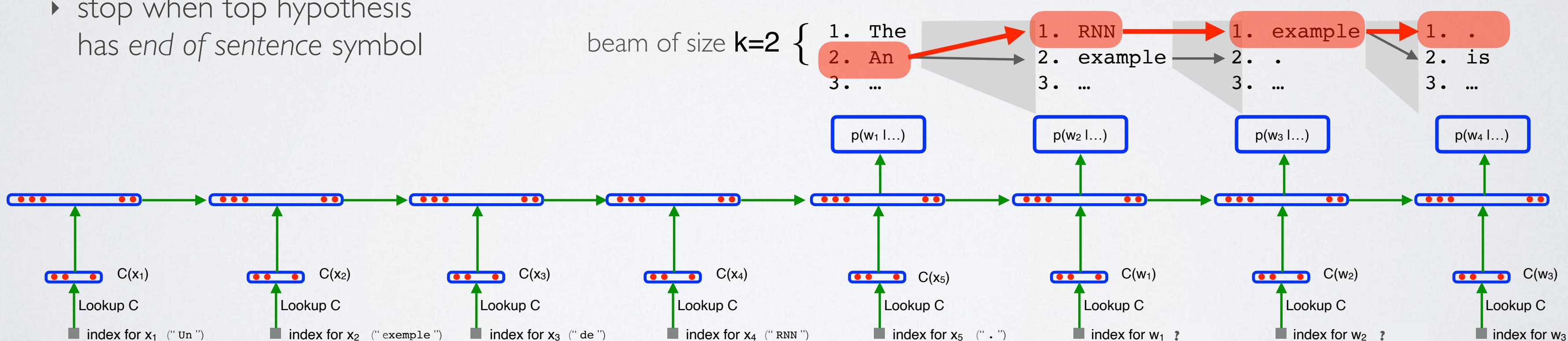


- in practice, group examples into mini-batches of sequences with similar sizes

SEQUENCE TO SEQUENCE LEARNING

Topics: beam search

- At test time, must find $\text{argmax } p(\mathbf{w}|\mathbf{x}) = \text{argmax } \sum_{t=0}^{T-1} \log p(w_{t+1}|\mathbf{x}, w_1, \dots, w_t)$
- Use beam search as approximation
 - ▶ maintain k best sequences ("hypotheses")
 - ▶ hypotheses ranked based on subsequence log-probability
 - ▶ stop when top hypothesis has end of sentence symbol



SEQUENCE CLASSIFICATION

Topics: sequence classification

- Sequence classification can be seen as special case of Seq2Seq
 - ▶ corresponds to case where target sequence has only one word $w=w_1$
 - ▶ w_1 corresponds to the input sequence's label
- RNN models allow us to represent sequences into fixed size sequences

Recurrent neural networks

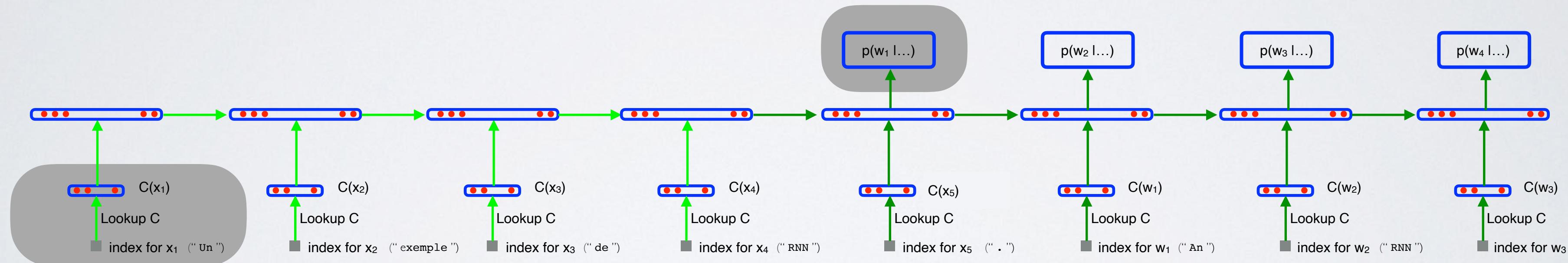
Bidirectional RNN

SEQUENCE TO SEQUENCE LEARNING

REMINDER

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Capturing long-term dependencies is crucial

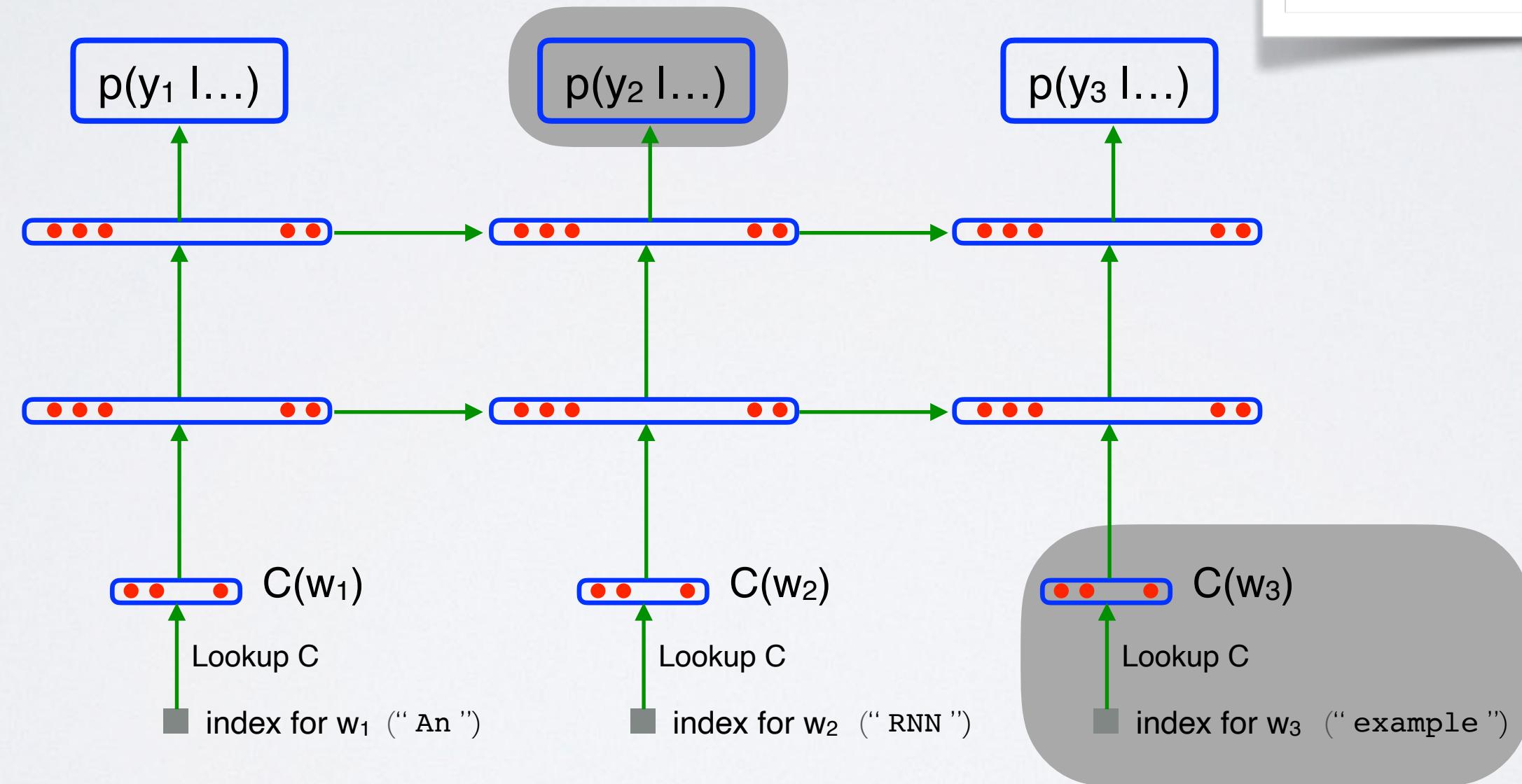
DEEP RECURRENT NEURAL NETWORK

REMINDER

Topics: Deep RNN

- Useful beyond language modeling
 - ▶ word tagging (e.g. part-of-speech tagging, named entity recognition)

Cannot use information
at following time steps



BIDIRECTIONAL RNNs

Topics: bidirectional RNNs

- When conditioning on a full input sequence, no obligation to only traverse left-to-right
- Bidirectional RNNs exploit this observation
 - ▶ have one RNNs traverse the sequence left-to-right
 - ▶ have another RNN traverse the sequence right-to-left
 - ▶ use concatenation of hidden layers as representation

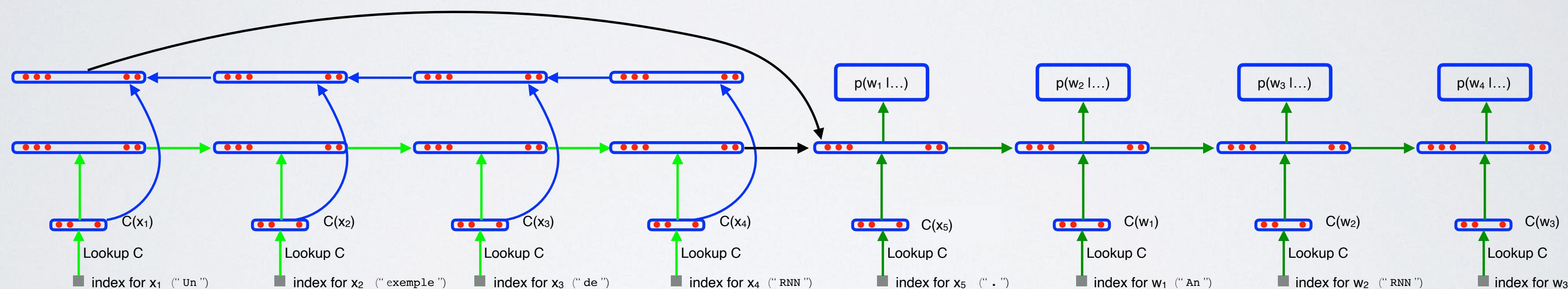
SEQUENCE TO SEQUENCE LEARNING

Topics: bidirectional Seq2Seq

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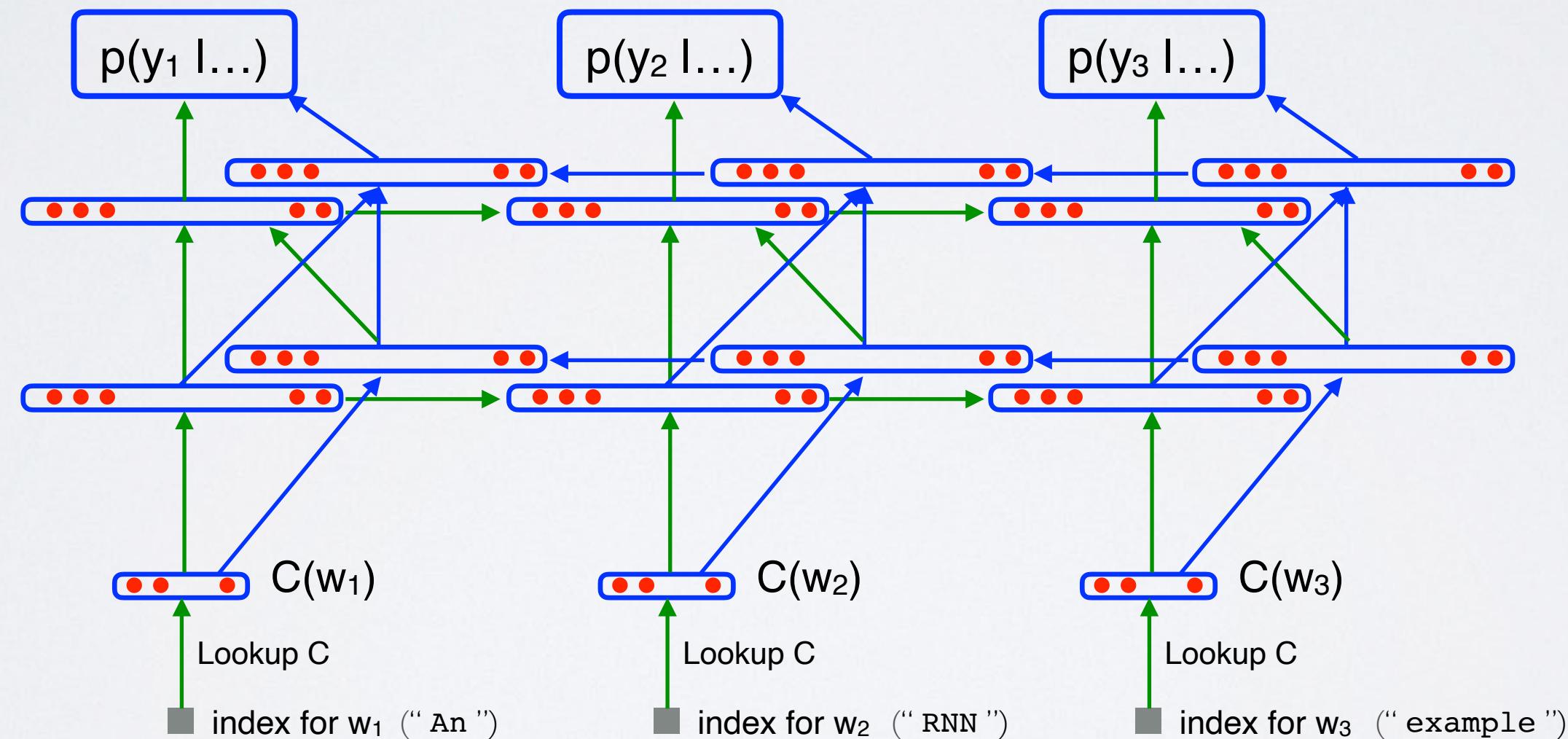
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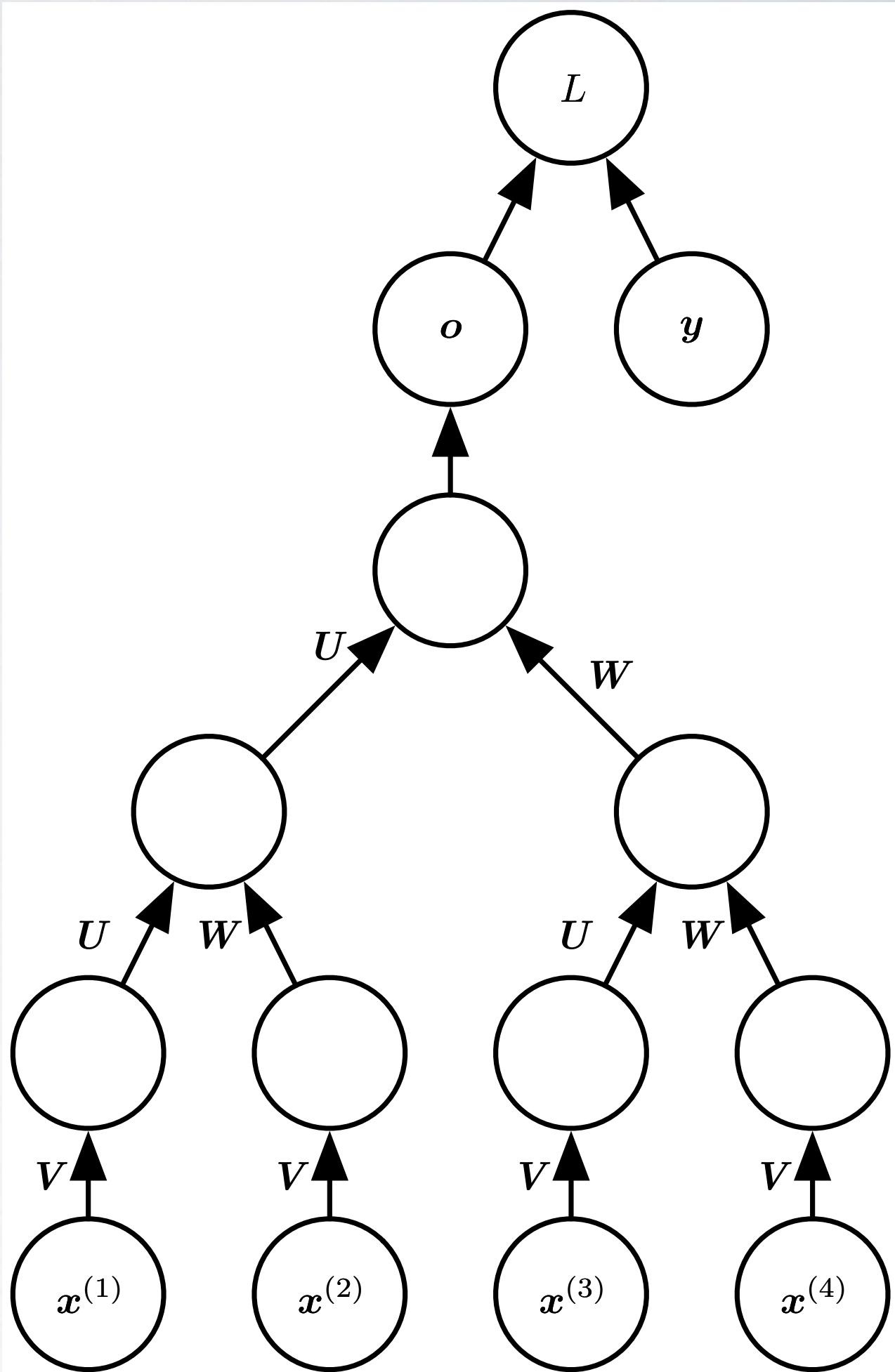


RECURSIVE NEURAL NETWORKS

Topics: Recursive NN (Socher, Manning and Ng, ICML 2011)

- Alternative to RNN and convolutional NN for sequence modeling.
- Repeating left/right branching structure:
Parameters are shared across layers
- Network depth depends on the length of the sequence.

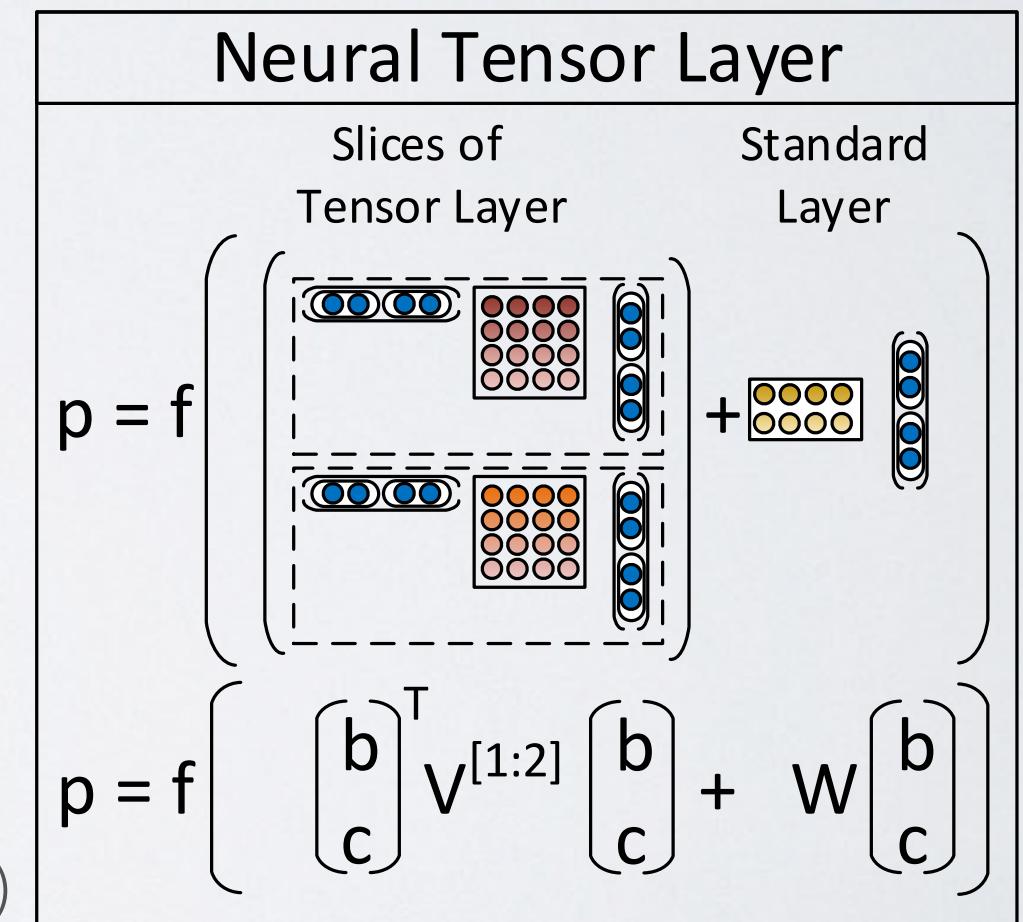
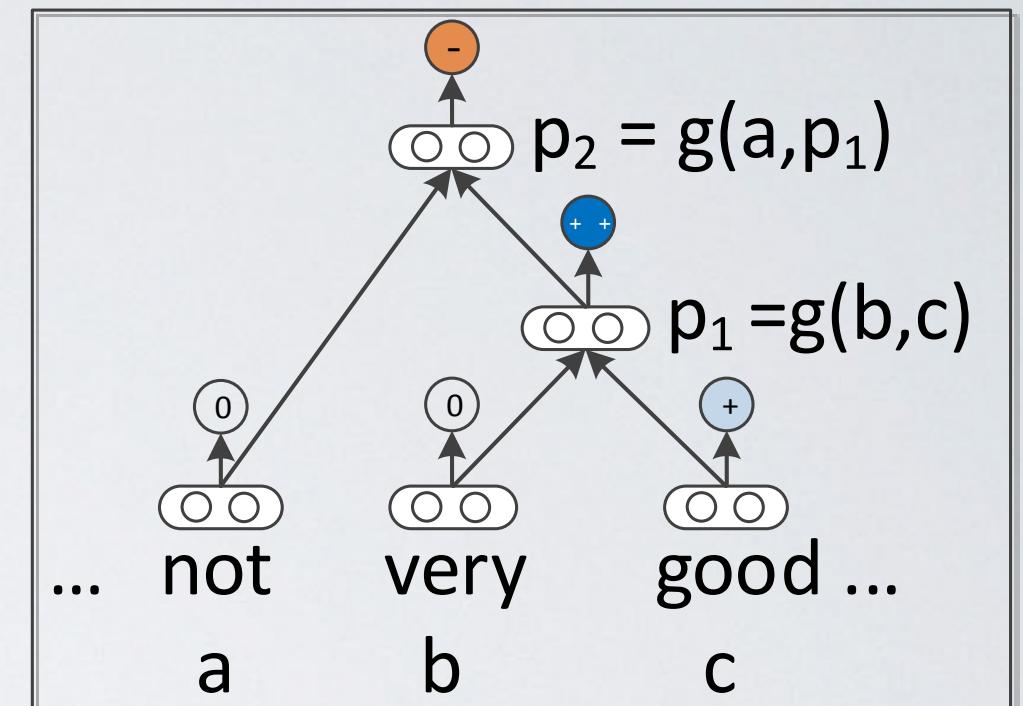
Image from Goodfellow et al. (2016)



RECURSIVE NETWORKS FOR SENTIMENT ANALYSIS

Topics: Recursive NN

- Application of Recursive NN to movie review sentiment analysis (Socher et al. EMNLP 2013).
 - Stanford Parser is used to recover the tree structure (Klein and Manning, 2003)
 - Trained with supervised (sub)phrase sentiment labels.
 - Generalize pair-wise interactions to Recursive Neural Tensor Networks (RNTNs).



RECURSIVE NETWORKS FOR SENTIMENT ANALYSIS

Image from Socher et al. (2013)

