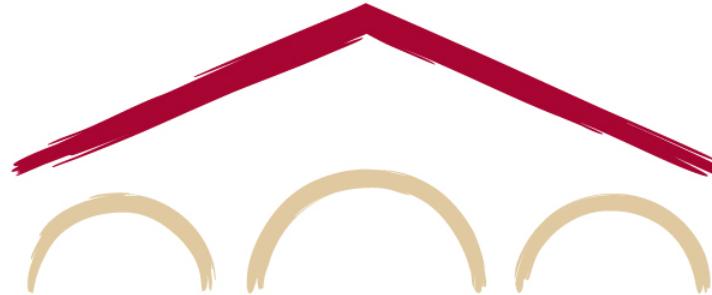


Natural Language Processing with Deep Learning

CS224N/Ling284



Christopher Manning

Lecture 6: Simple and LSTM Recurrent Neural Networks

Lecture Plan

1. RNN Language Models (25 mins)
2. Other uses of RNNs (8 mins)
3. Exploding and vanishing gradients (15 mins)
4. LSTMs (20 mins)
5. Bidirectional and multi-layer RNNs (12 mins)



- Projects
 - Next Thursday: a lecture about choosing final projects
 - It's fine to delay thinking about projects until next week
 - But if you're already thinking about projects, you can view some info/inspiration on the website. It's still last year's information at present!
 - It's great if you can line up your own mentor; we also lining up some mentors

Overview

- Last lecture we learned:
 - Language models, n-gram language models, and Recurrent Neural Networks (RNNs)
- Today we'll learn how to get RNNs to work for you
 - Training RNNs
 - Uses of RNNs
 - Problems with RNNs (exploding and vanishing gradients) and how to fix them
 - These problems motivate a more sophisticated RNN architecture: LSTMs
 - And other more complex RNN options: bidirectional RNNs and multi-layer RNNs
- Next lecture we'll learn:
 - How we can do Neural Machine Translation (NMT) using an RNN-based architecture called sequence-to-sequence with attention

1. The Simple RNN Language Model

output distribution

$$\hat{y}^{(t)} = \text{softmax}(\mathbf{U}\mathbf{h}^{(t)} + \mathbf{b}_2) \in \mathbb{R}^{|V|}$$

hidden states

$$\mathbf{h}^{(t)} = \sigma(\mathbf{W}_h \mathbf{h}^{(t-1)} + \mathbf{W}_e \mathbf{e}^{(t)} + \mathbf{b}_1)$$

$\mathbf{h}^{(0)}$ is the initial hidden state

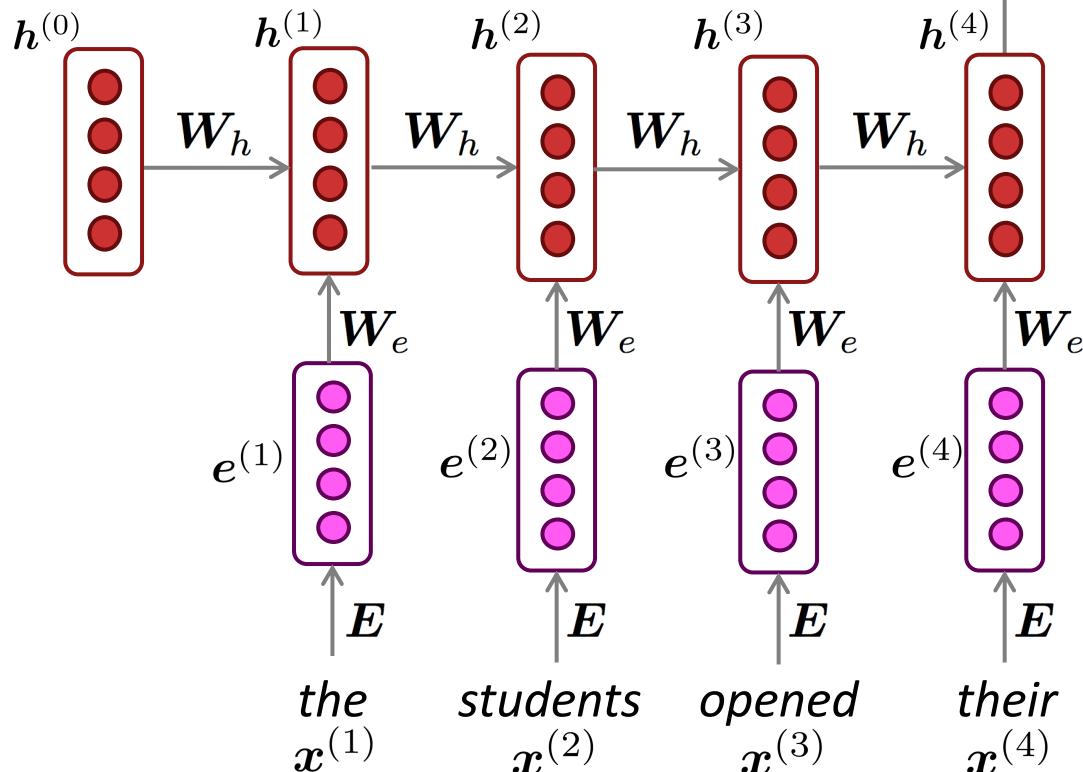
word embeddings

$$\mathbf{e}^{(t)} = \mathbf{E}\mathbf{x}^{(t)}$$

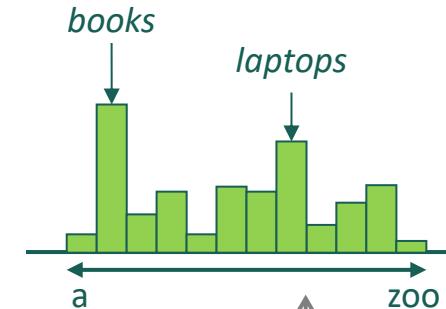
words / one-hot vectors

$$\mathbf{x}^{(t)} \in \mathbb{R}^{|V|}$$

Note: this input sequence could be much longer now!



$$\hat{y}^{(4)} = P(\mathbf{x}^{(5)} | \text{the students opened their})$$



Training an RNN Language Model

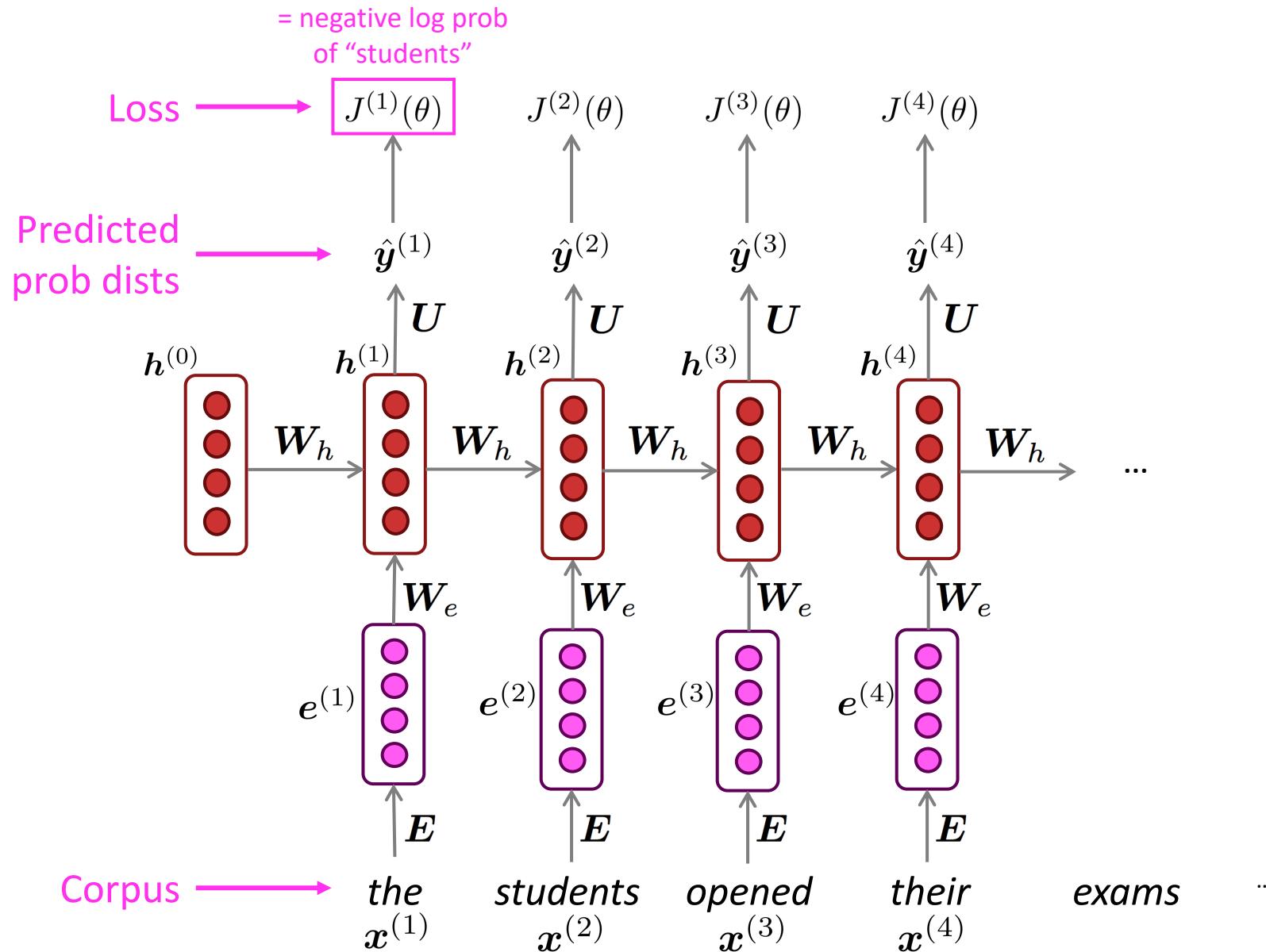
- Get a **big corpus of text** which is a sequence of words $\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(T)}$
- Feed into RNN-LM; compute output distribution $\hat{\mathbf{y}}^{(t)}$ **for every step t .**
 - i.e., predict probability dist of *every word*, given words so far
- **Loss function** on step t is **cross-entropy** between predicted probability distribution $\hat{\mathbf{y}}^{(t)}$, and the true next word $\mathbf{y}^{(t)}$ (one-hot for $\mathbf{x}^{(t+1)}$):

$$J^{(t)}(\theta) = CE(\mathbf{y}^{(t)}, \hat{\mathbf{y}}^{(t)}) = - \sum_{w \in V} \mathbf{y}_w^{(t)} \log \hat{\mathbf{y}}_w^{(t)} = - \log \hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)}$$

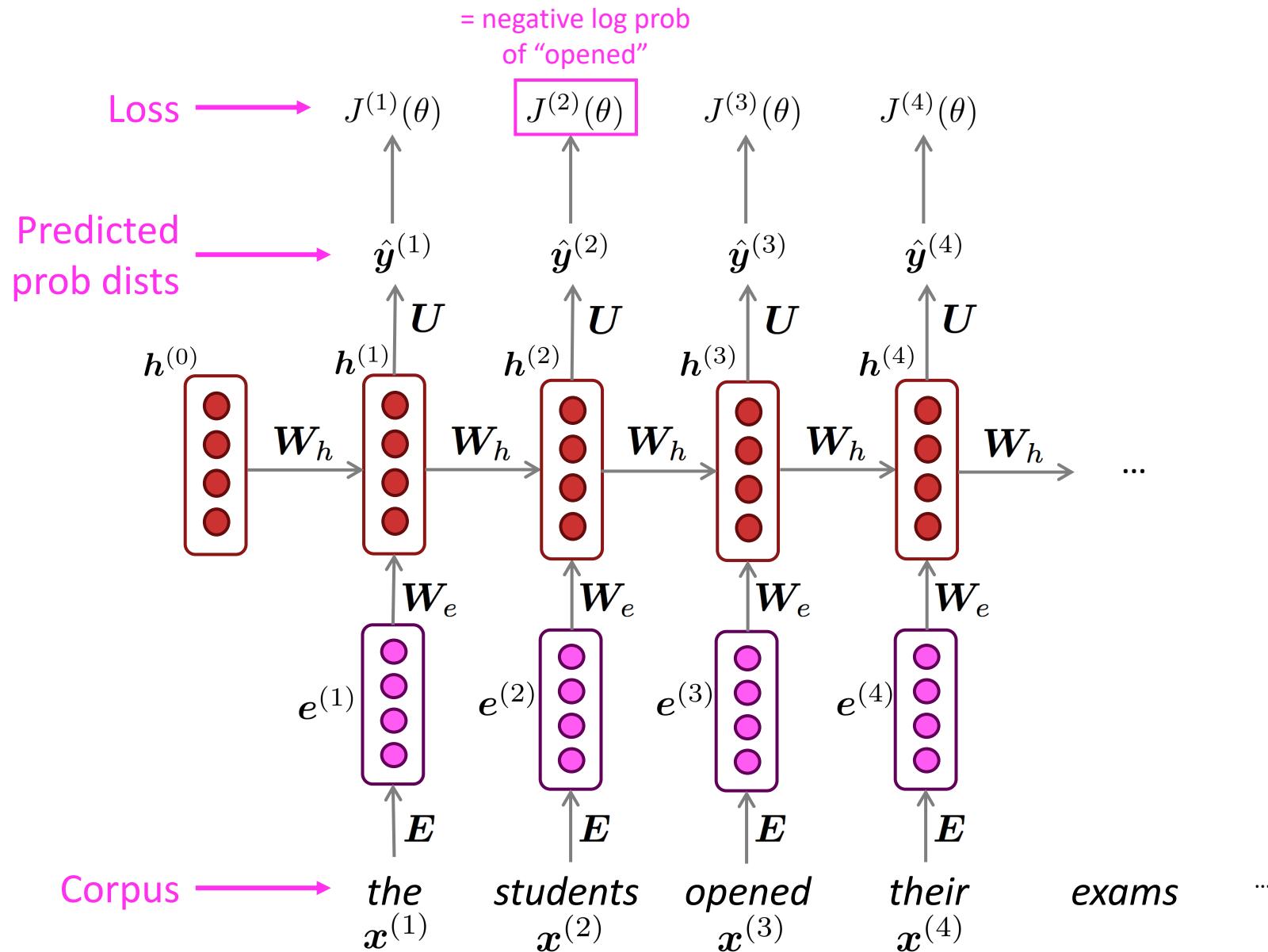
- Average this to get **overall loss** for entire training set:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T J^{(t)}(\theta) = \frac{1}{T} \sum_{t=1}^T - \log \hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)}$$

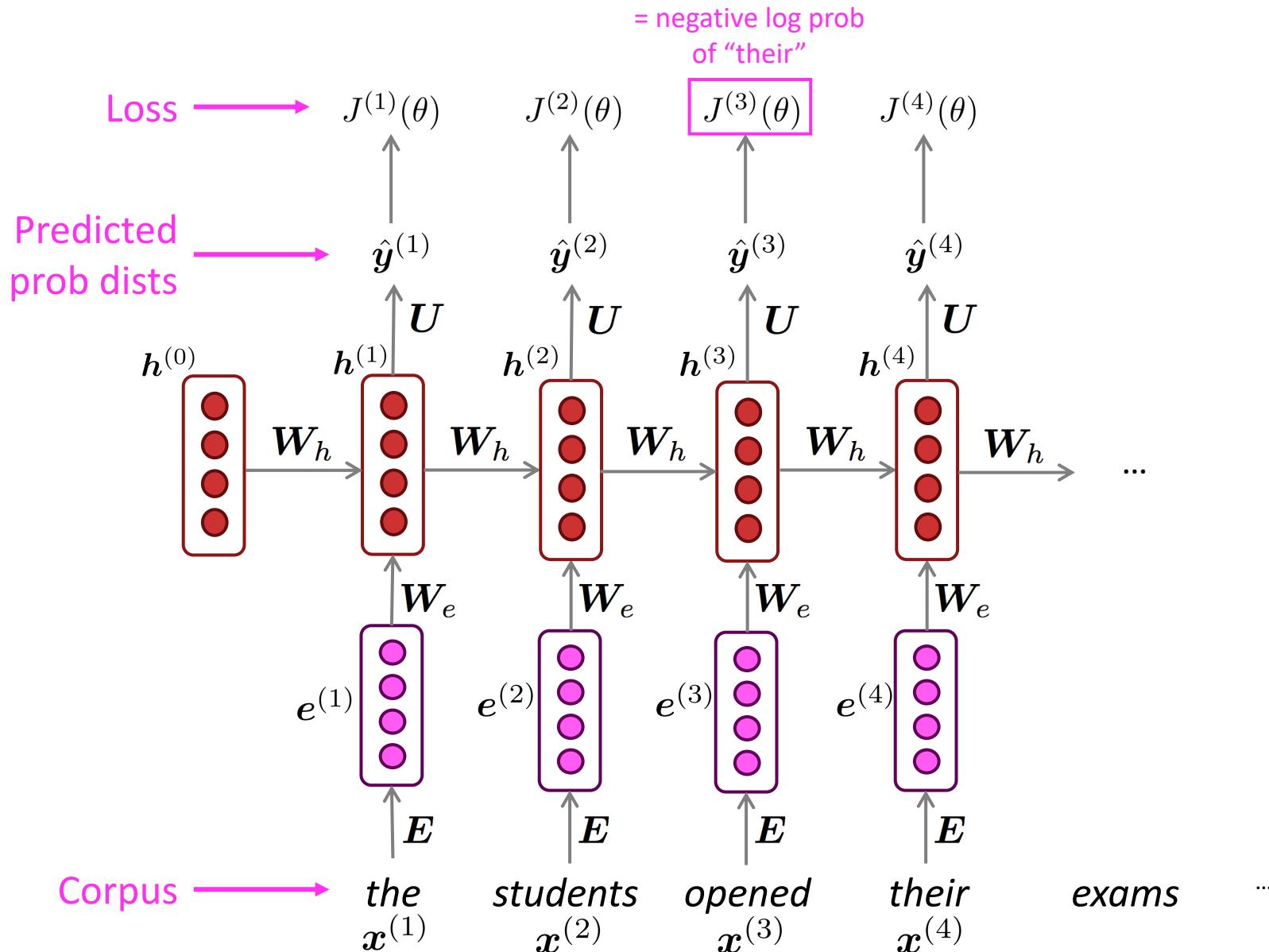
Training an RNN Language Model



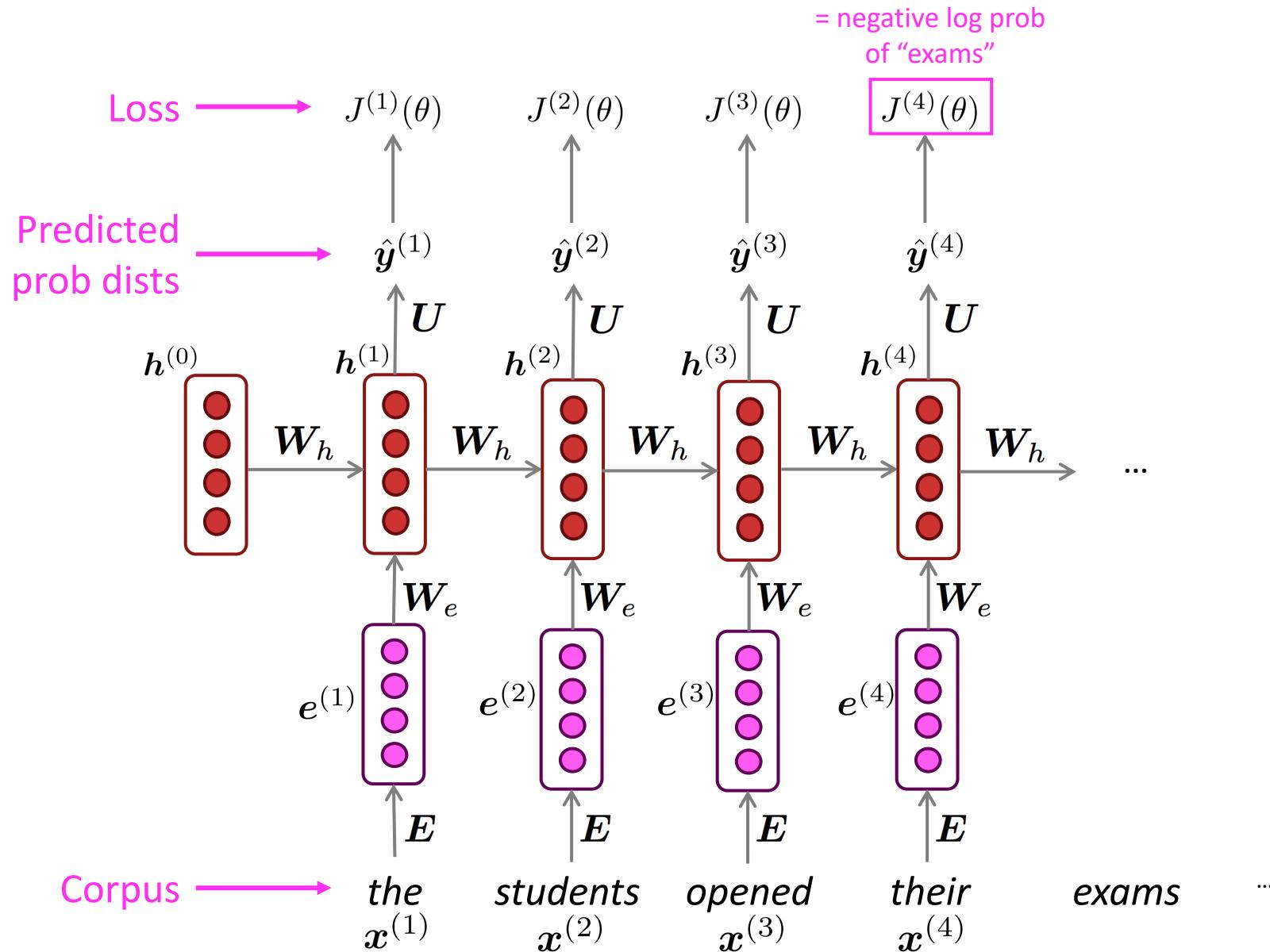
Training an RNN Language Model



Training an RNN Language Model

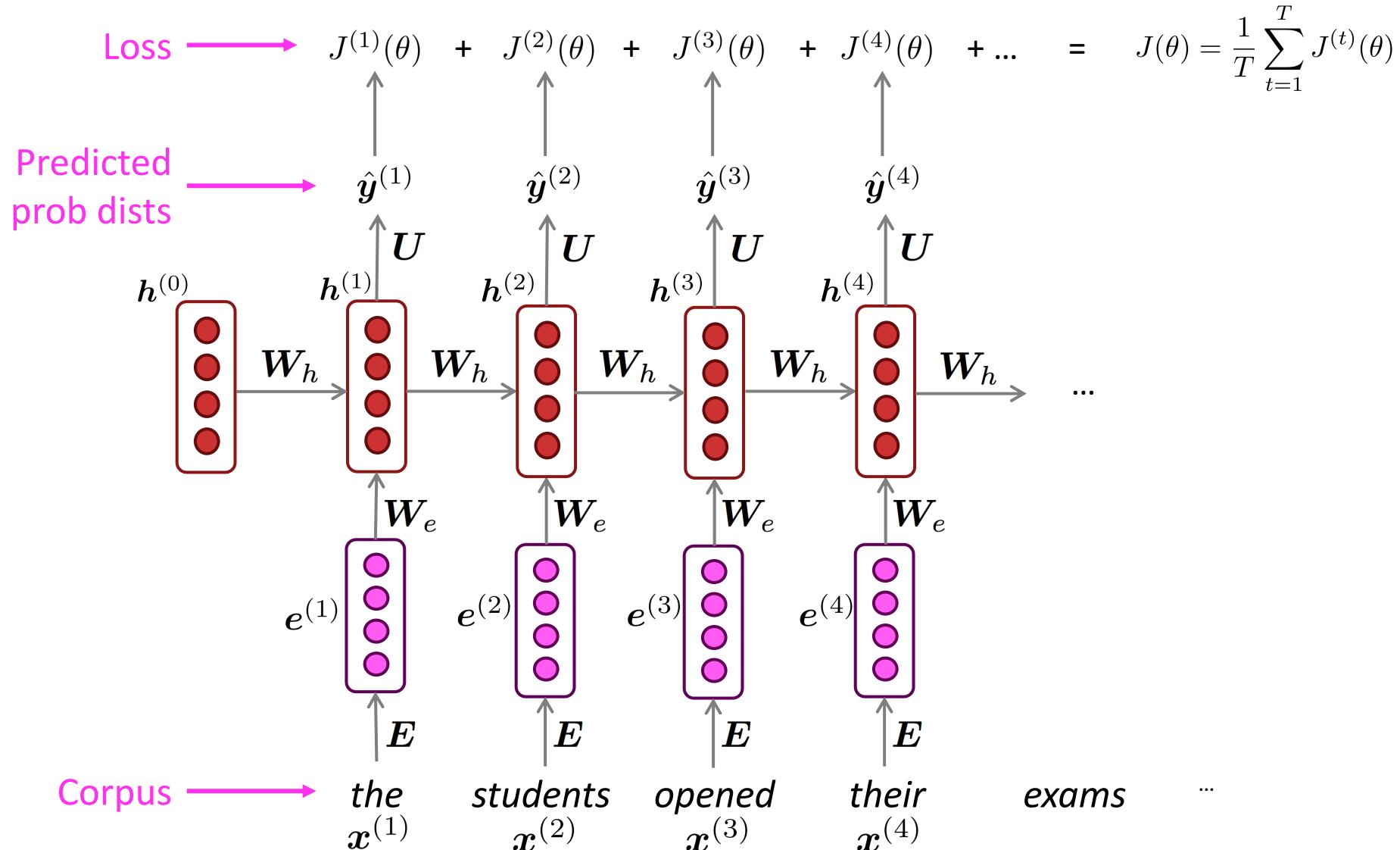


Training an RNN Language Model



Training an RNN Language Model

“Teacher forcing”



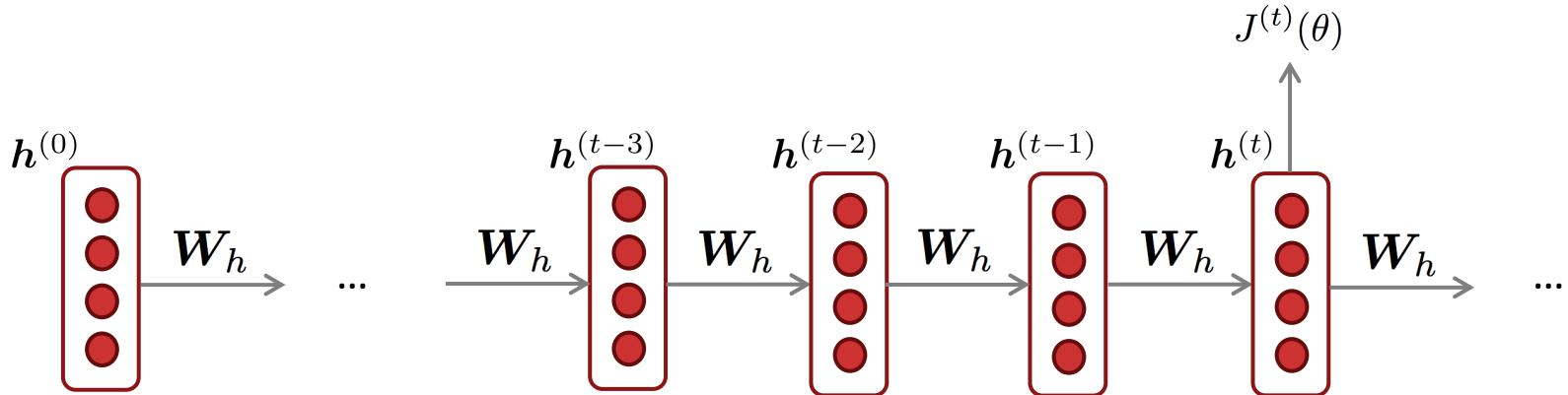
Training a RNN Language Model

- However: Computing loss and gradients across **entire corpus** $x^{(1)}, \dots, x^{(T)}$ is **too expensive!**

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T J^{(t)}(\theta)$$

- In practice, consider $x^{(1)}, \dots, x^{(T)}$ as a **sentence** (or a **document**)
- Recall: **Stochastic Gradient Descent** allows us to compute loss and gradients for small chunk of data, and update.
- Compute loss $J(\theta)$ for a sentence (actually, a batch of sentences), compute gradients and update weights. Repeat.

Training the parameters of RNNs: Backpropagation for RNNs



Question: What's the derivative of $J^{(t)}(\theta)$ w.r.t. the **repeated** weight matrix W_h ?

Answer:
$$\frac{\partial J^{(t)}}{\partial W_h} = \sum_{i=1}^t \frac{\partial J^{(t)}}{\partial W_h} \Big|_{(i)}$$

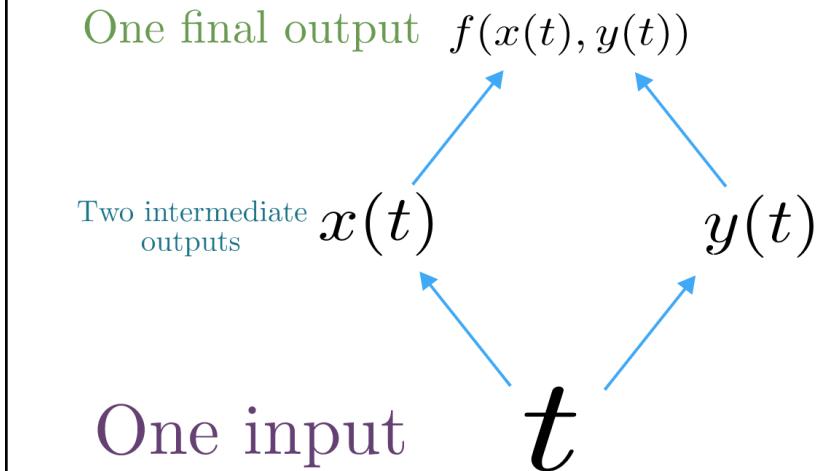
“The gradient w.r.t. a repeated weight
is the sum of the gradient
w.r.t. each time it appears”

Why?

Multivariable Chain Rule

- Given a multivariable function $f(x, y)$, and two single variable functions $x(t)$ and $y(t)$, here's what the multivariable chain rule says:

$$\underbrace{\frac{d}{dt} f(\textcolor{teal}{x}(t), \textcolor{red}{y}(t))}_{\text{Derivative of composition function}} = \frac{\partial f}{\partial \textcolor{teal}{x}} \frac{d\textcolor{teal}{x}}{dt} + \frac{\partial f}{\partial \textcolor{red}{y}} \frac{d\textcolor{red}{y}}{dt}$$



Gradients sum at
outward branches!
(lecture 3)

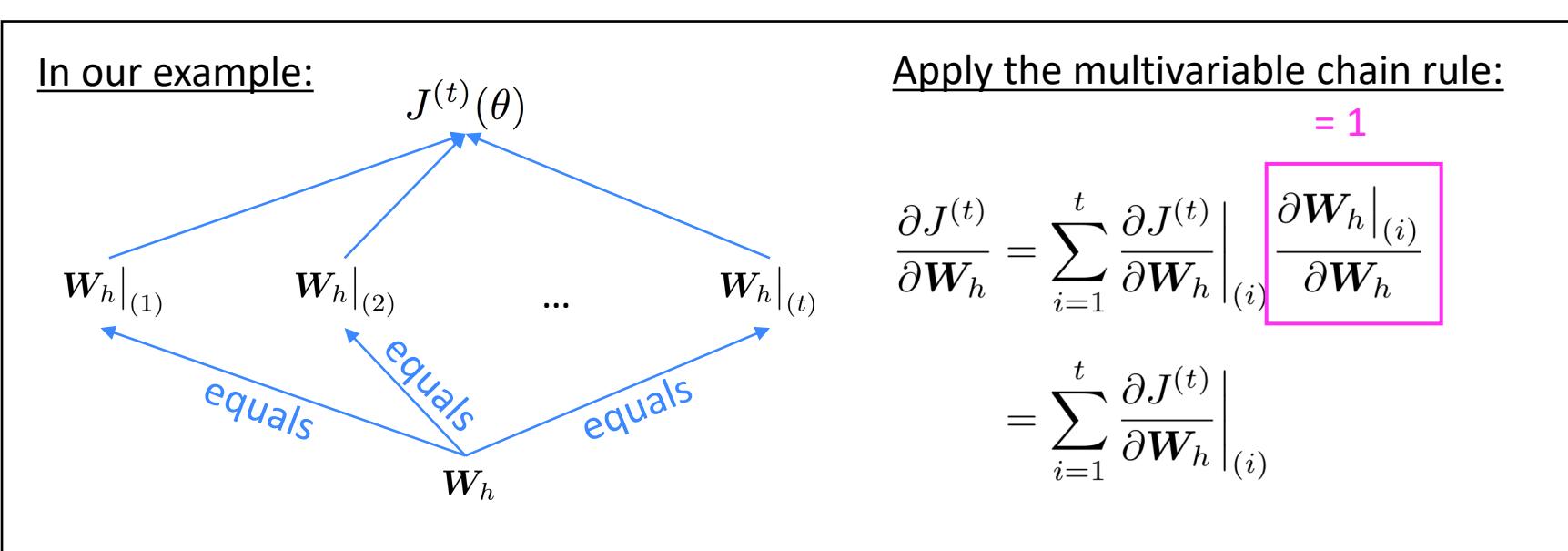
Source:

<https://www.khanacademy.org/math/multivariable-calculus/multivariable-derivatives/differentiating-vector-valued-functions/a/multivariable-chain-rule-simple-version>

Backpropagation for RNNs: Proof sketch

- Given a multivariable function $f(x, y)$, and two single variable functions $x(t)$ and $y(t)$, here's what the multivariable chain rule says:

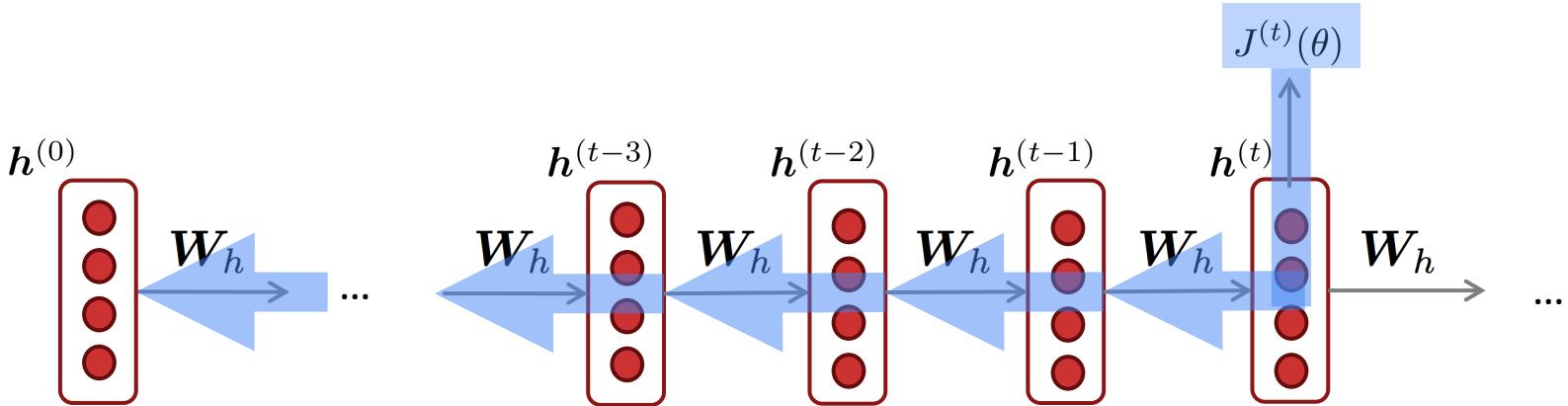
$$\underbrace{\frac{d}{dt} f(\textcolor{teal}{x}(t), \textcolor{red}{y}(t))}_{\text{Derivative of composition function}} = \frac{\partial f}{\partial \textcolor{teal}{x}} \frac{d\textcolor{teal}{x}}{dt} + \frac{\partial f}{\partial \textcolor{red}{y}} \frac{d\textcolor{red}{y}}{dt}$$



Source:

<https://www.khanacademy.org/math/multivariable-calculus/multivariable-derivatives/differentiating-vector-valued-functions/a/multivariable-chain-rule-simple-version>

Backpropagation for RNNs



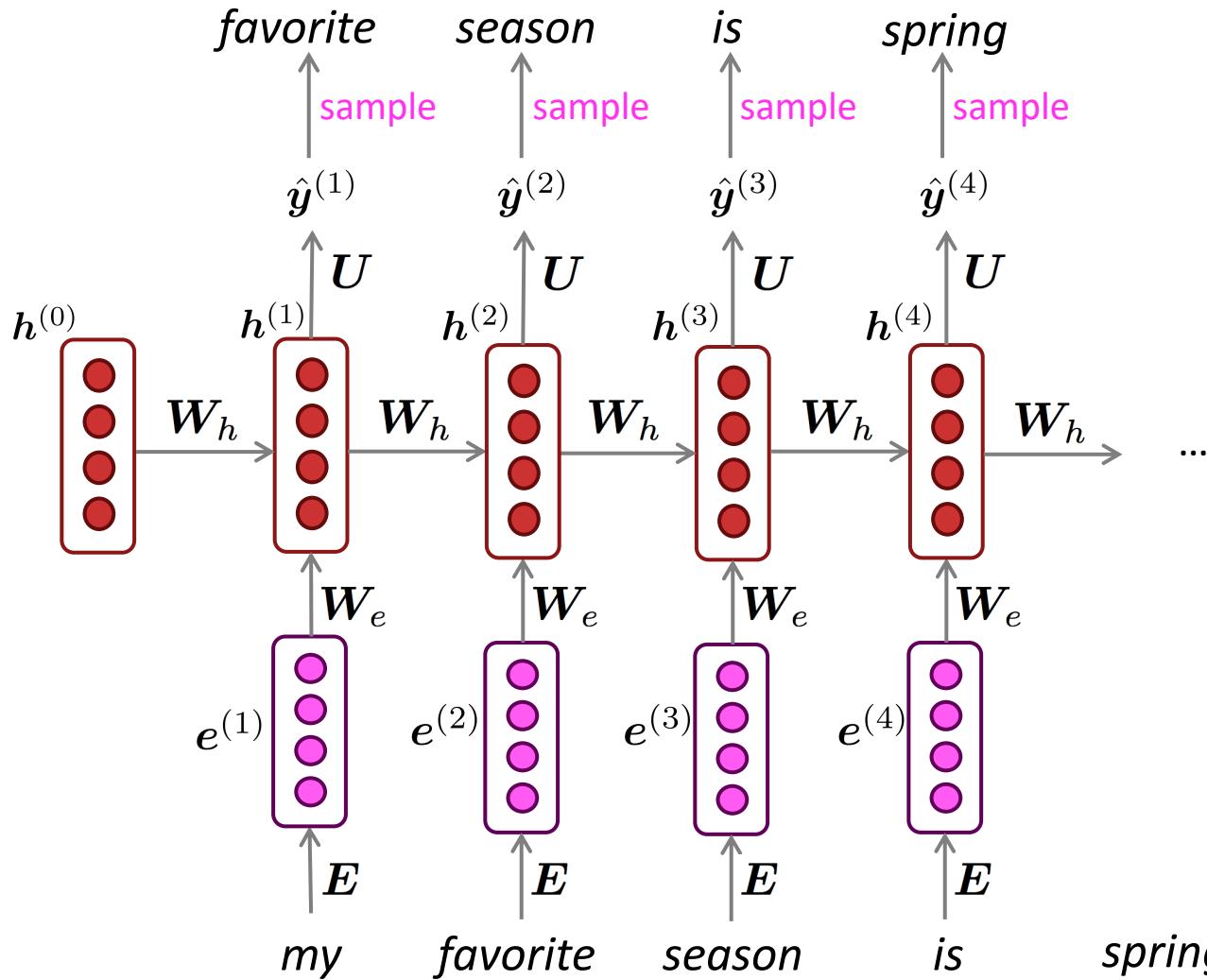
$$\frac{\partial J^{(t)}}{\partial W_h} = \boxed{\sum_{i=1}^t \frac{\partial J^{(t)}}{\partial W_h} \Big|_{(i)}}$$

Question: How do we calculate this?

Answer: Backpropagate over timesteps $i=t, \dots, 0$, summing gradients as you go.
This algorithm is called “**backpropagation through time**” [Werbos, P.G., 1988, *Neural Networks 1*, and others]

Generating text with a RNN Language Model

Just like a n-gram Language Model, you can use an RNN Language Model to generate text by **repeated sampling**. Sampled output becomes next step's input.



Generating text with an RNN Language Model

Let's have some fun!

- You can train an RNN-LM on any kind of text, then generate text in that style.
- RNN-LM trained on *Harry Potter*:



“Sorry,” Harry shouted, panicking—“I’ll leave those brooms in London, are they?”

“No idea,” said Nearly Headless Nick, casting low close by Cedric, carrying the last bit of treacle Charms, from Harry’s shoulder, and to answer him the common room perched upon it, four arms held a shining knob from when the spider hadn’t felt it seemed. He reached the teams too.

Source: <https://medium.com/deep-writing/harry-potter-written-by-artificial-intelligence-8a9431803da6>

Generating text with an RNN Language Model

Let's have some fun!

- You can train an RNN-LM on any kind of text, then generate text in that style.
- RNN-LM trained on **recipes**:

Title: CHOCOLATE RANCH BARBECUE
Categories: Game, Casseroles, Cookies, Cookies
Yield: 6 Servings

2 tb Parmesan cheese -- chopped
1 c Coconut milk
3 Eggs, beaten

Place each pasta over layers of lumps. Shape mixture into the moderate oven and simmer until firm. Serve hot in bodied fresh, mustard, orange and cheese.

Combine the cheese and salt together the dough in a large skillet; add the ingredients and stir in the chocolate and pepper.



Source: <https://gist.github.com/nylki/1efbaa36635956d35bcc>

Evaluating Language Models

- The standard **evaluation metric** for Language Models is **perplexity**.

$$\text{perplexity} = \prod_{t=1}^T \left(\frac{1}{P_{\text{LM}}(\mathbf{x}^{(t+1)} | \mathbf{x}^{(t)}, \dots, \mathbf{x}^{(1)})} \right)^{1/T}$$



Normalized by
number of words

- This is equal to the exponential of the cross-entropy loss $J(\theta)$:

$$= \prod_{t=1}^T \left(\frac{1}{\hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)}} \right)^{1/T} = \exp \left(\frac{1}{T} \sum_{t=1}^T -\log \hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)} \right) = \exp(J(\theta))$$

Lower perplexity is better!

RNNs have greatly improved perplexity

n-gram model →

Increasingly complex RNNs ↓

Model	Perplexity
Interpolated Kneser-Ney 5-gram (Chelba et al., 2013)	67.6
RNN-1024 + MaxEnt 9-gram (Chelba et al., 2013)	51.3
RNN-2048 + BlackOut sampling (Ji et al., 2015)	68.3
Sparse Non-negative Matrix factorization (Shazeer et al., 2015)	52.9
LSTM-2048 (Jozefowicz et al., 2016)	43.7
2-layer LSTM-8192 (Jozefowicz et al., 2016)	30
Ours small (LSTM-2048)	43.9
Ours large (2-layer LSTM-2048)	39.8

Perplexity improves
(lower is better) ↓

Source: <https://research.fb.com/building-an-efficient-neural-language-model-over-a-billion-words/>

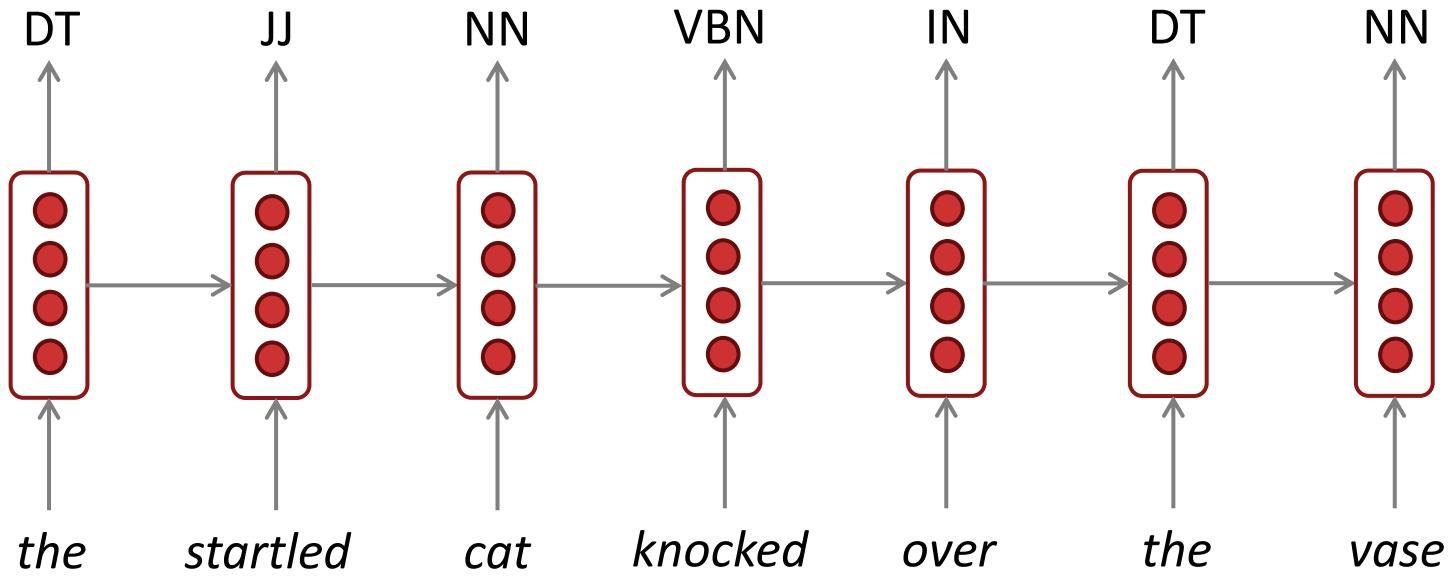
Why should we care about Language Modeling?

- Language Modeling is a **benchmark task** that helps us **measure our progress** on understanding language
- Language Modeling is a **subcomponent** of **many** NLP tasks, especially those involving **generating text** or **estimating the probability of text**:
 - Predictive typing
 - Speech recognition
 - Handwriting recognition
 - Spelling/grammar correction
 - Authorship identification
 - Machine translation
 - Summarization
 - Dialogue
 - etc.

Recap

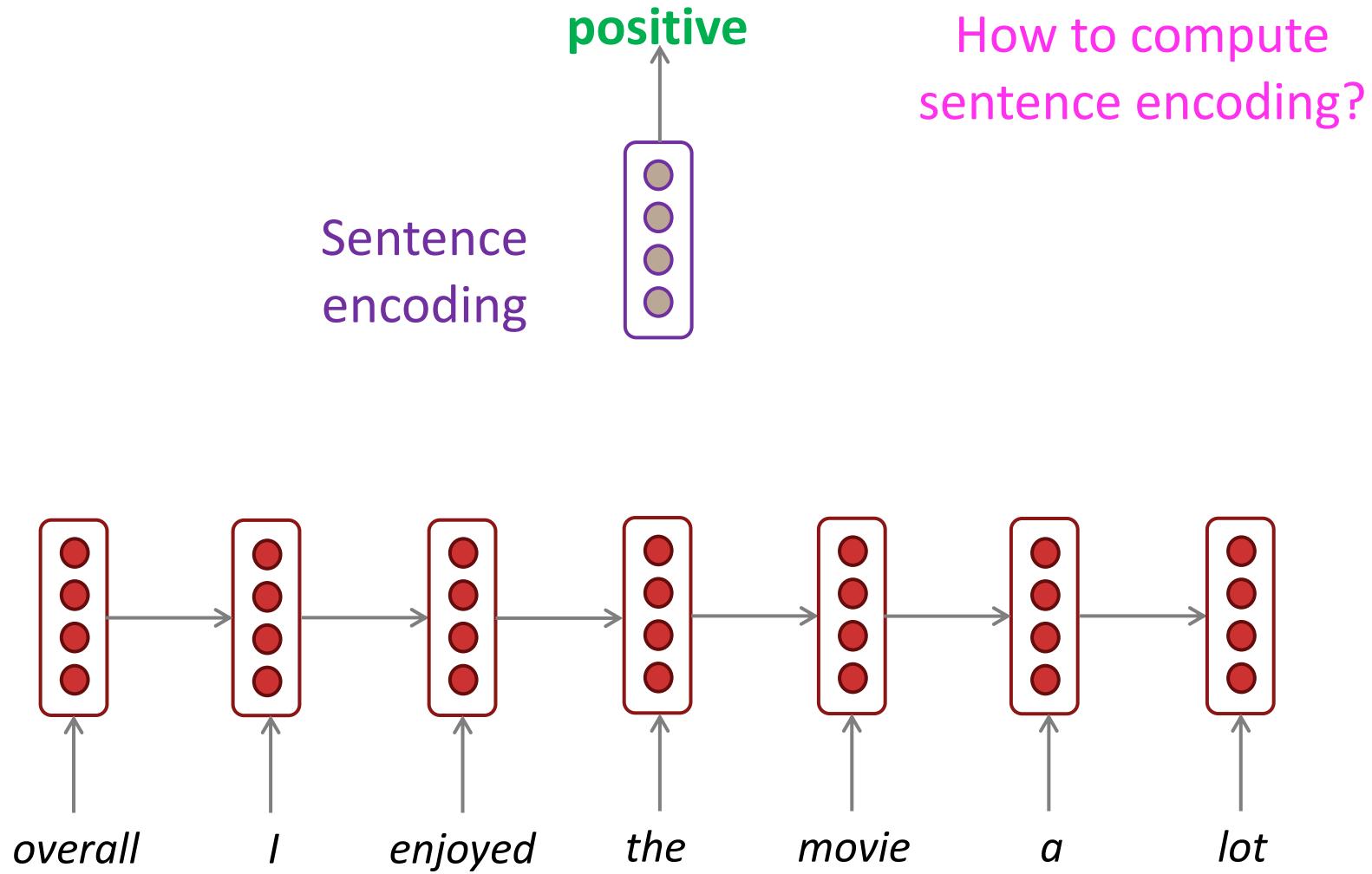
- **Language Model**: A system that predicts the next word
- **Recurrent Neural Network**: A family of neural networks that:
 - Take sequential input of any length
 - Apply the same weights on each step
 - Can optionally produce output on each step
- Recurrent Neural Network \neq Language Model
- We've shown that RNNs are a great way to build a LM
- But RNNs are useful for much more!

2. Other RNN uses: RNNs can be used for sequence tagging e.g., part-of-speech tagging, named entity recognition



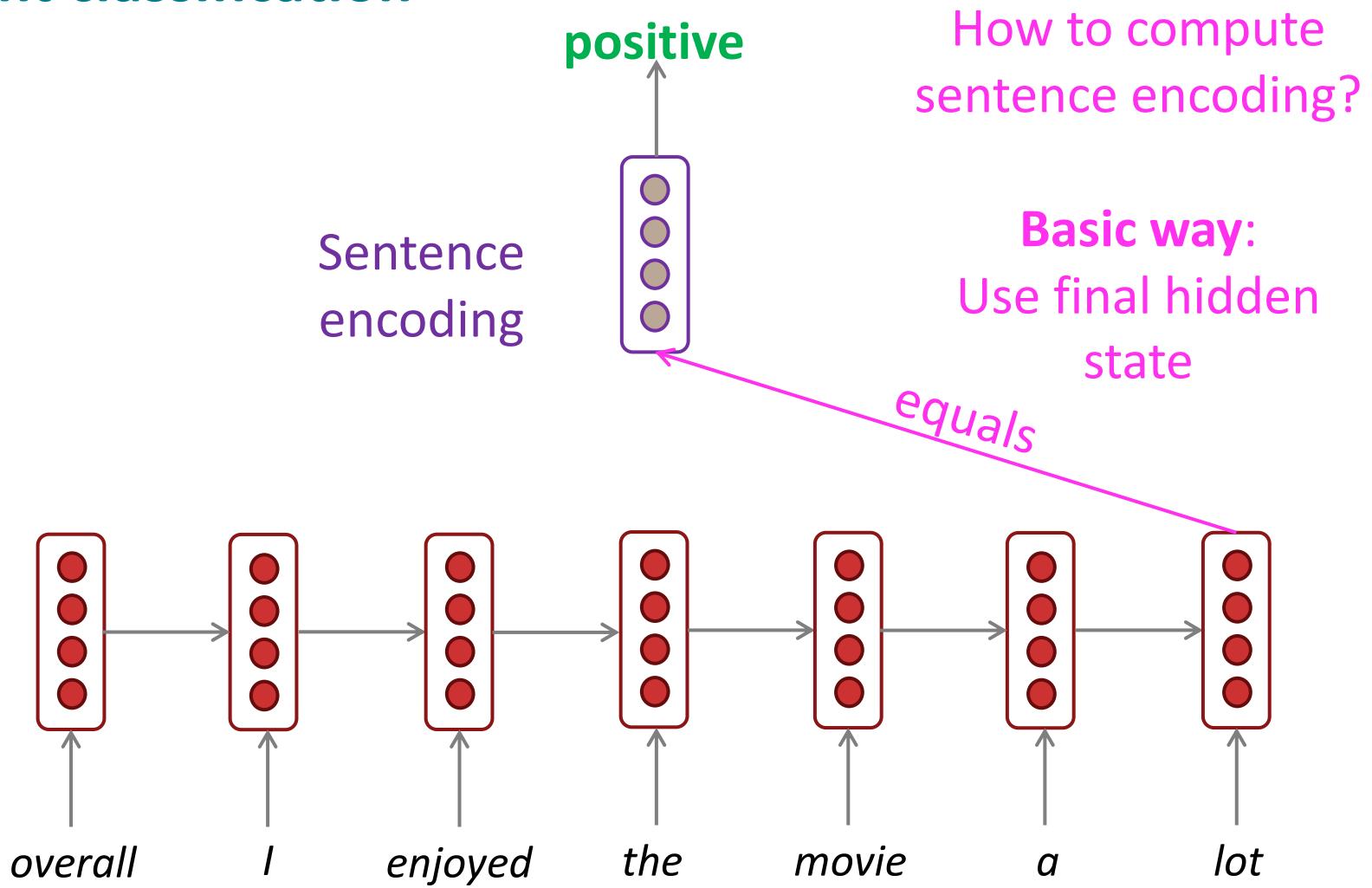
RNNs can be used for sentence classification

e.g., sentiment classification



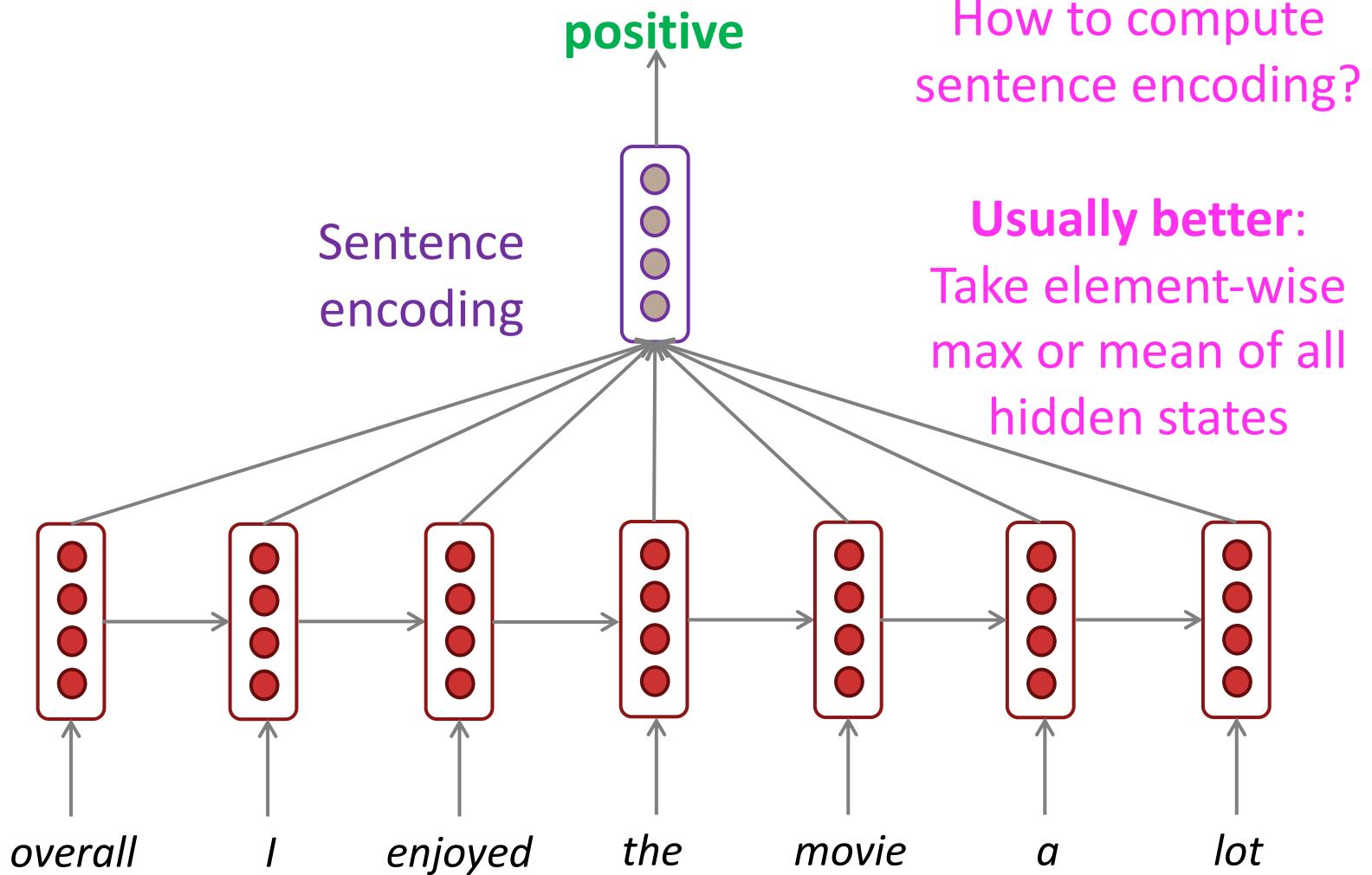
RNNs can be used for sentence classification

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RNNs can be used for sentence classification

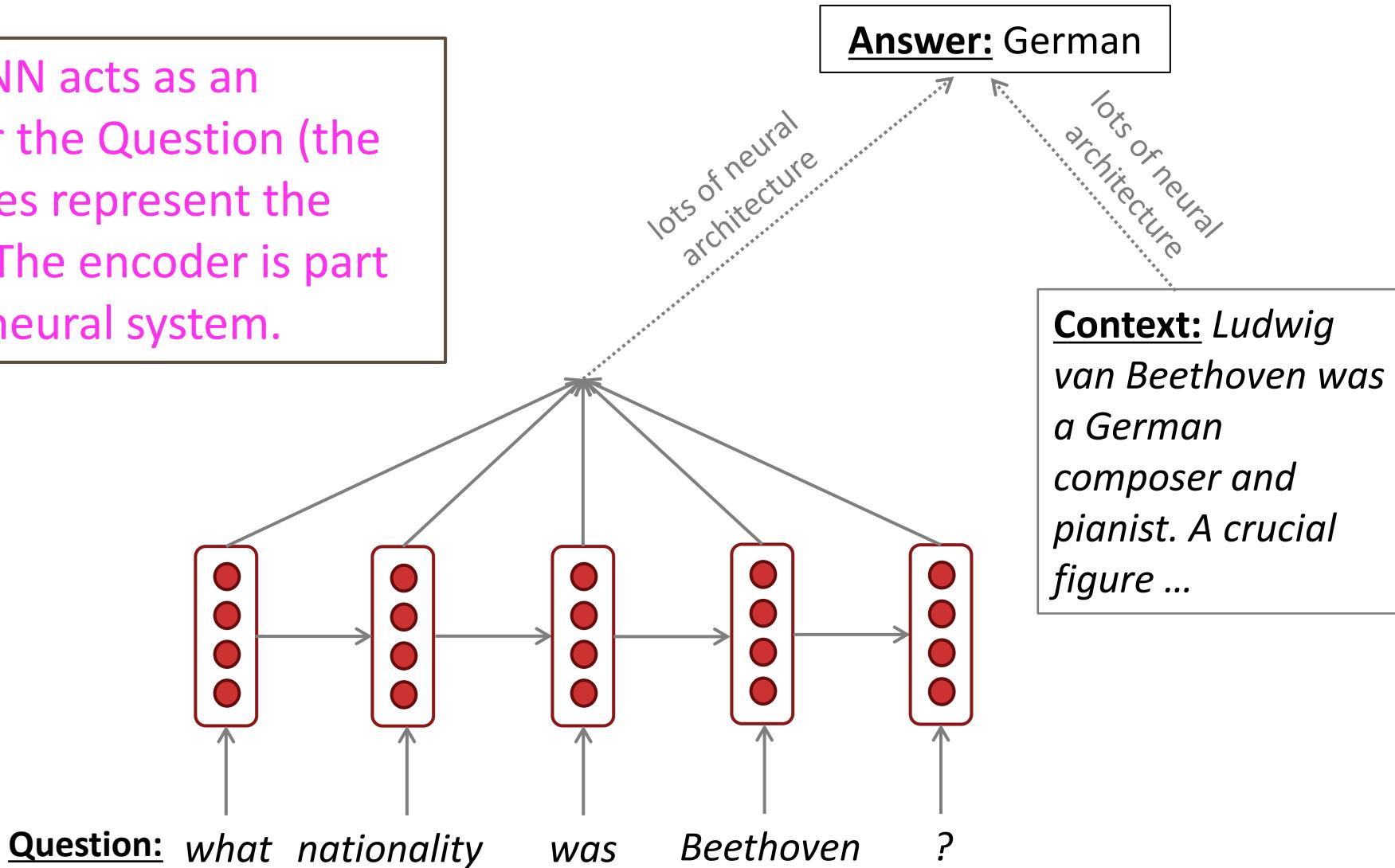
e.g., sentiment classification



RNNs can be used as a language encoder module

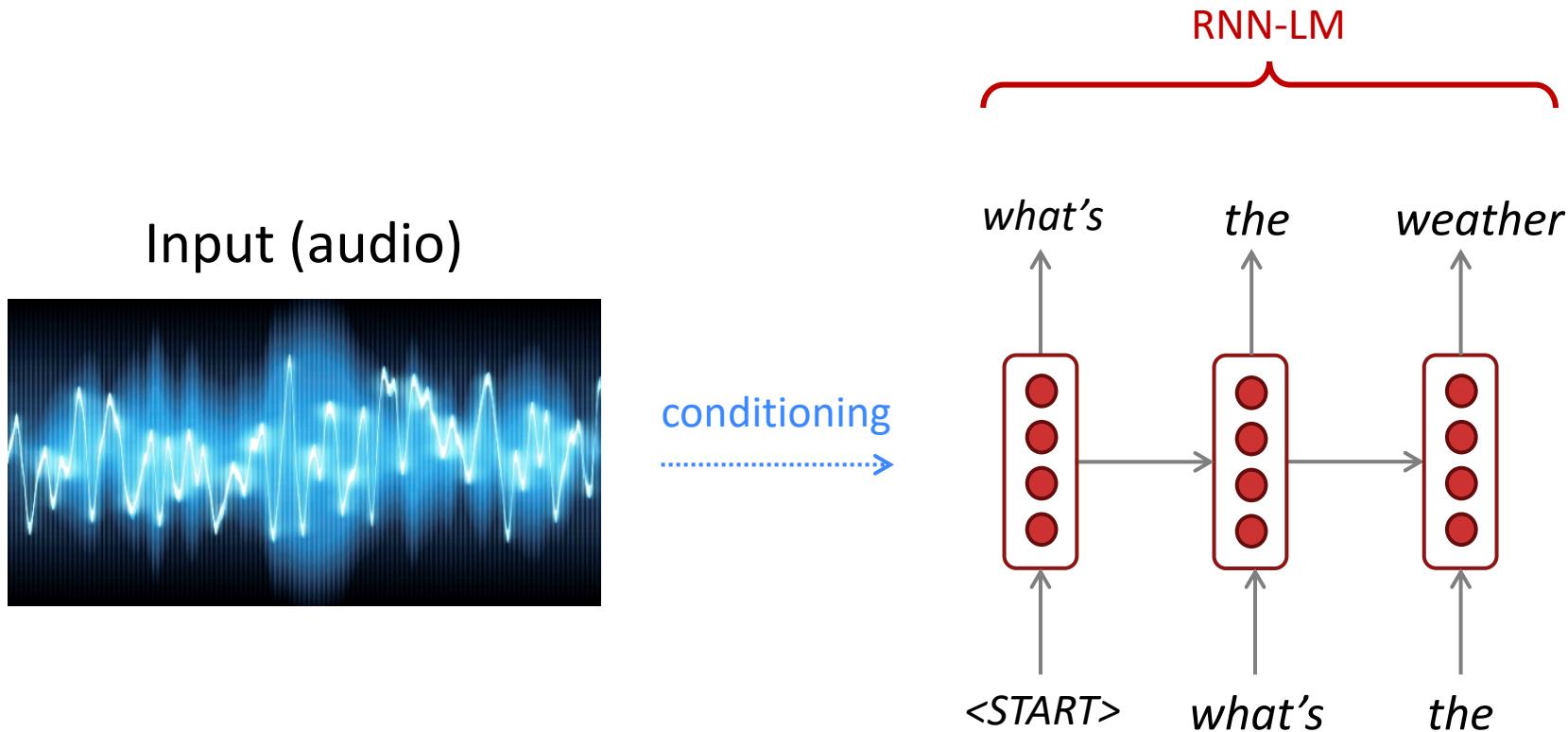
e.g., question answering, machine translation, *many other tasks!*

Here the RNN acts as an **encoder** for the Question (the hidden states represent the Question). The encoder is part of a larger neural system.



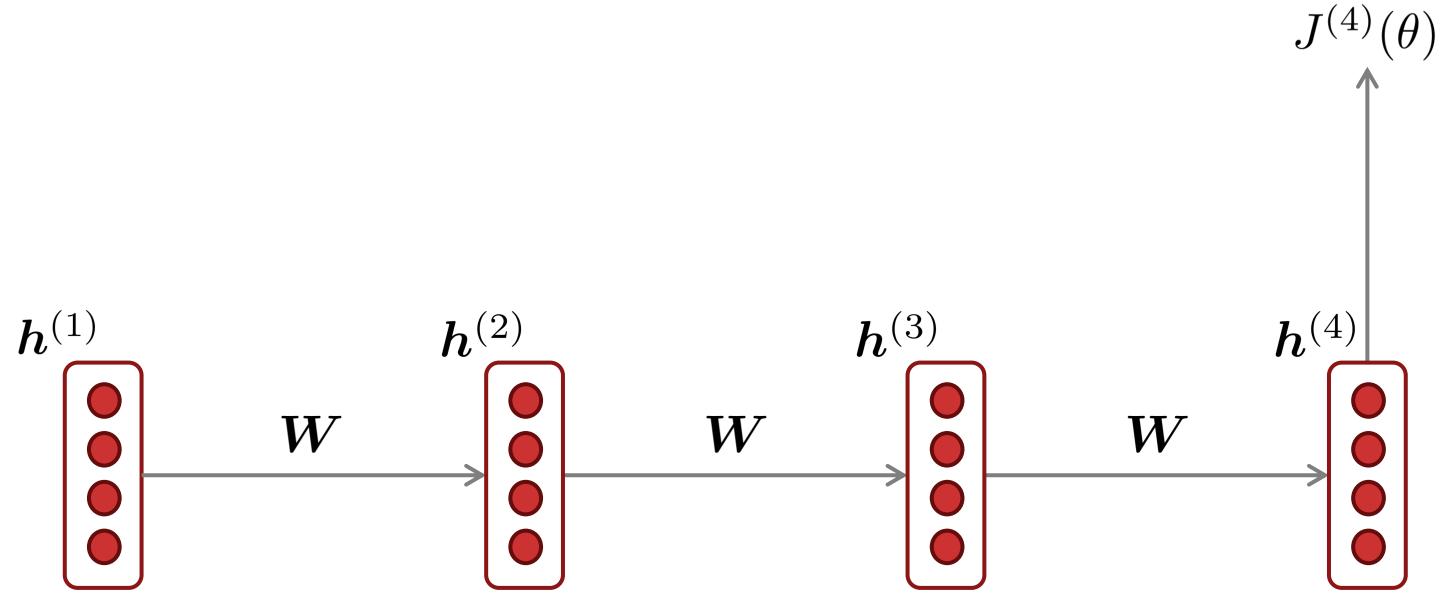
RNN-LMs can be used to generate text

e.g., speech recognition, machine translation, summarization

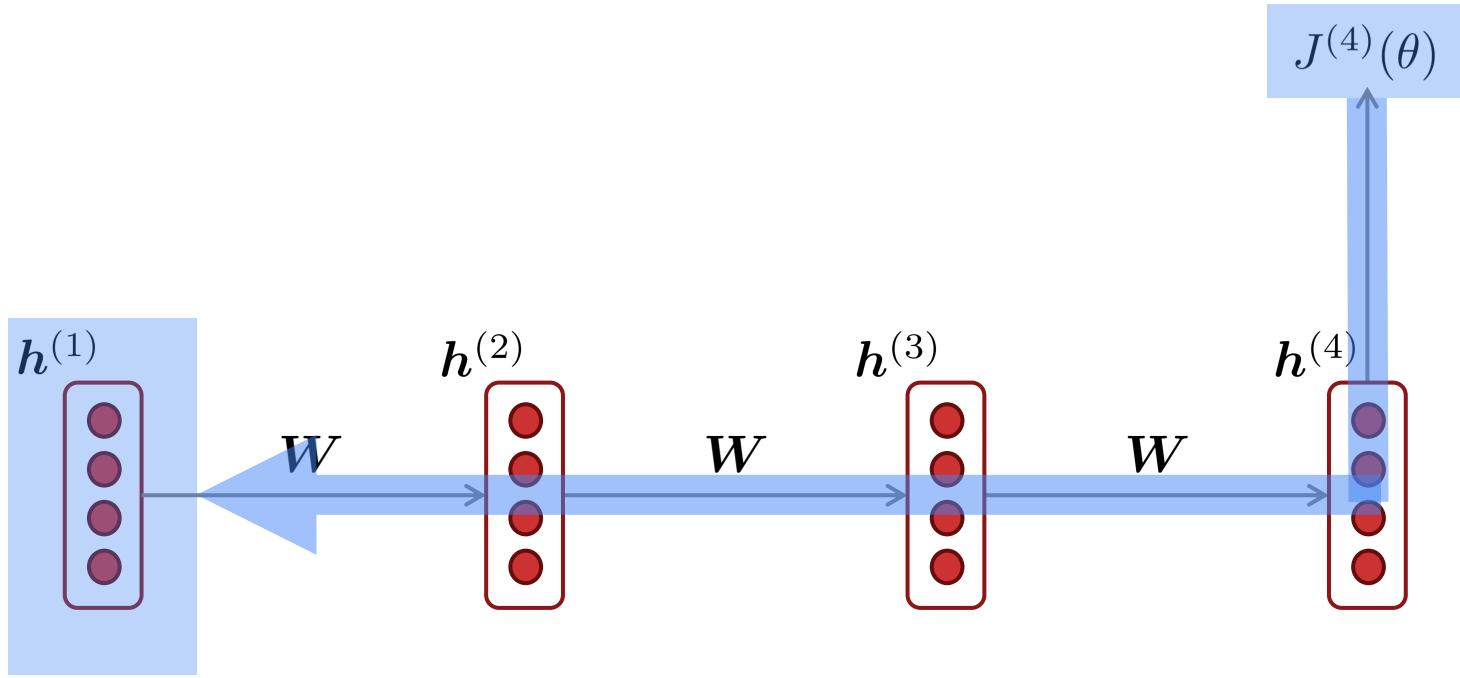


This is an example of a *conditional language model*.
We'll see Machine Translation in much more detail next class.

3. Problems with Vanishing and Exploding Gradients

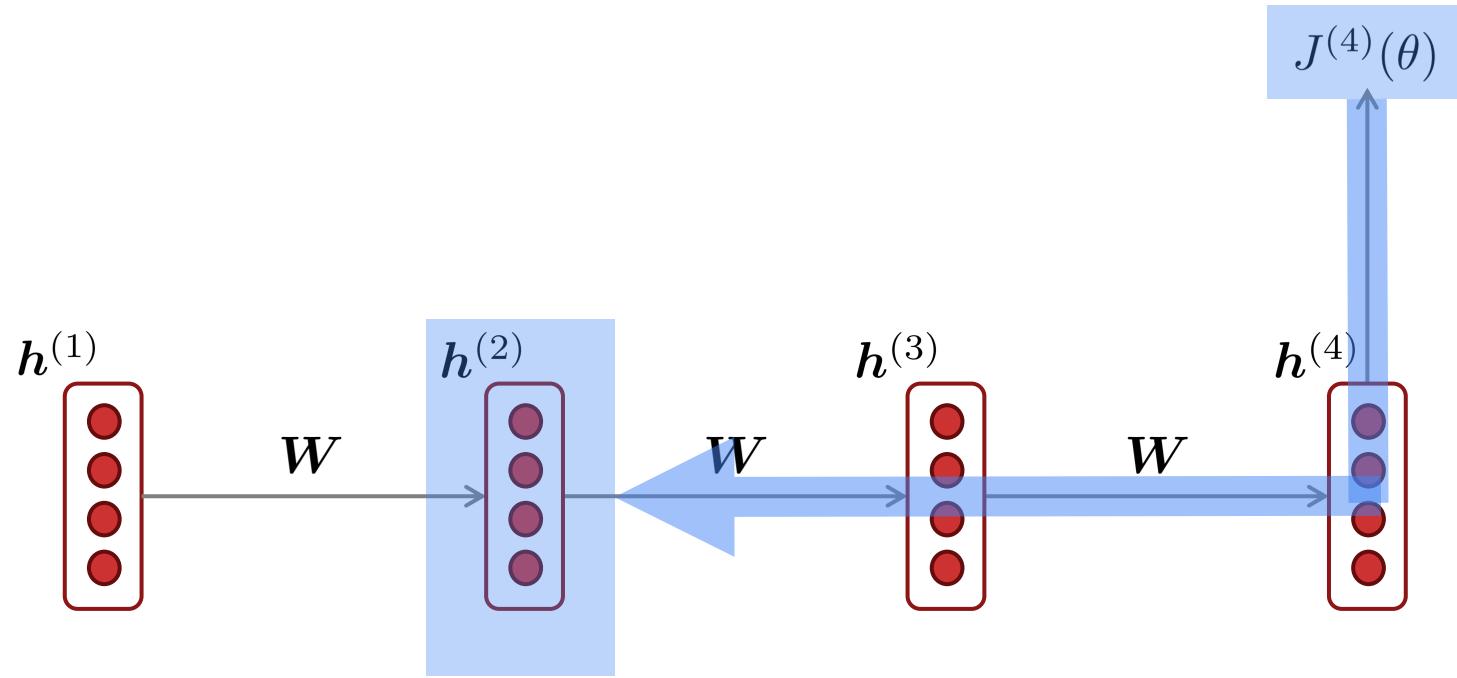


Vanishing gradient intuition



$$\frac{\partial J^{(4)}}{\partial h^{(1)}} = ?$$

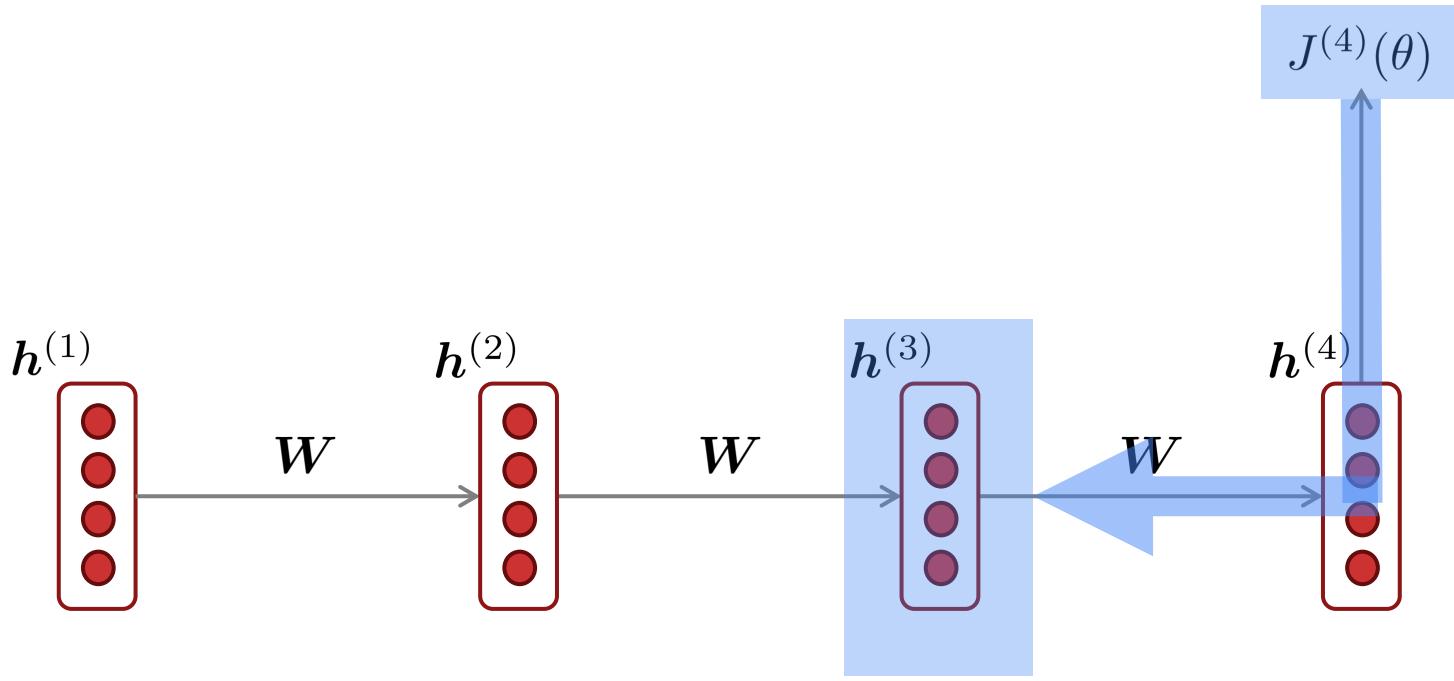
Vanishing gradient intuition



$$\frac{\partial J^{(4)}}{\partial \mathbf{h}^{(1)}} = \frac{\partial \mathbf{h}^{(2)}}{\partial \mathbf{h}^{(1)}} \times \frac{\partial J^{(4)}}{\partial \mathbf{h}^{(2)}}$$

chain rule!

Vanishing gradient intuition

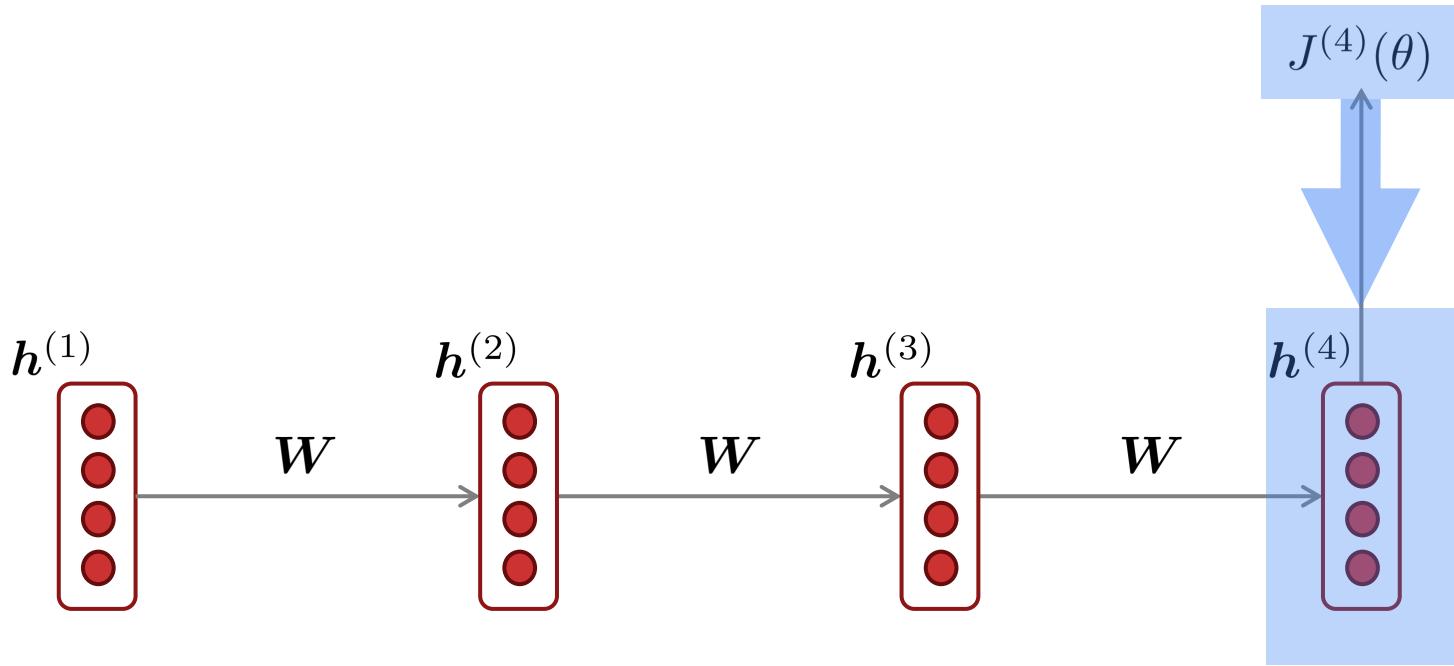


$$\frac{\partial J^{(4)}}{\partial \mathbf{h}^{(1)}} = \frac{\partial \mathbf{h}^{(2)}}{\partial \mathbf{h}^{(1)}} \times$$

$$\frac{\partial \mathbf{h}^{(3)}}{\partial \mathbf{h}^{(2)}} \times \frac{\partial J^{(4)}}{\partial \mathbf{h}^{(3)}}$$

chain rule!

Vanishing gradient intuition



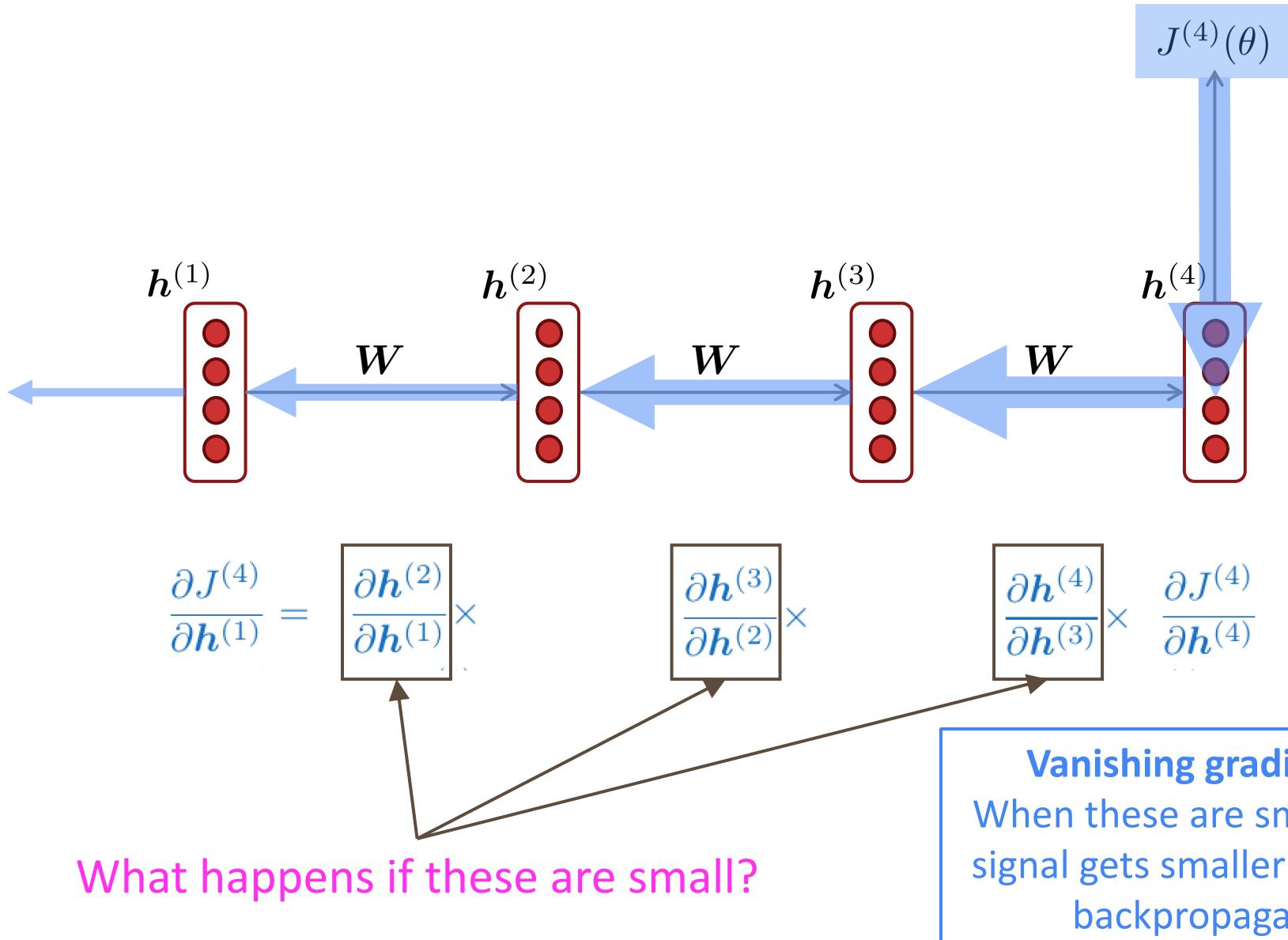
$$\frac{\partial J^{(4)}}{\partial \mathbf{h}^{(1)}} = \frac{\partial \mathbf{h}^{(2)}}{\partial \mathbf{h}^{(1)}} \times$$

$$\frac{\partial \mathbf{h}^{(3)}}{\partial \mathbf{h}^{(2)}} \times$$

$$\frac{\partial \mathbf{h}^{(4)}}{\partial \mathbf{h}^{(3)}} \times \frac{\partial J^{(4)}}{\partial \mathbf{h}^{(4)}}$$

chain rule!

Vanishing gradient intuition



Vanishing gradient proof sketch (linear case)

- Recall: $\mathbf{h}^{(t)} = \sigma(\mathbf{W}_h \mathbf{h}^{(t-1)} + \mathbf{W}_x \mathbf{x}^{(t)} + \mathbf{b}_1)$
- What if σ were the identity function, $\sigma(x) = x$?

$$\begin{aligned}\frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(t-1)}} &= \text{diag}\left(\sigma'\left(\mathbf{W}_h \mathbf{h}^{(t-1)} + \mathbf{W}_x \mathbf{x}^{(t)} + \mathbf{b}_1\right)\right) \mathbf{W}_h && \text{(chain rule)} \\ &= \mathbf{I} \quad \mathbf{W}_h = \mathbf{W}_h\end{aligned}$$

- Consider the gradient of the loss $J^{(i)}(\theta)$ on step i , with respect to the hidden state $\mathbf{h}^{(j)}$ on some previous step j . Let $\ell = i - j$

$$\frac{\partial J^{(i)}(\theta)}{\partial \mathbf{h}^{(j)}} = \frac{\partial J^{(i)}(\theta)}{\partial \mathbf{h}^{(i)}} \prod_{j < t \leq i} \frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(t-1)}} \quad \text{(chain rule)}$$

$$= \frac{\partial J^{(i)}(\theta)}{\partial \mathbf{h}^{(i)}} \prod_{j < t \leq i} \mathbf{W}_h = \frac{\partial J^{(i)}(\theta)}{\partial \mathbf{h}^{(i)}} \boxed{\mathbf{W}_h^\ell}$$

↑
(value of $\frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(t-1)}}$)

If \mathbf{W}_h is “small”, then this term gets exponentially problematic as ℓ becomes large

Vanishing gradient proof sketch (linear case)

- What's wrong with W_h^ℓ ?
- Consider if the eigenvalues of W_h are all less than 1:
sufficient but
not necessary

$$\lambda_1, \lambda_2, \dots, \lambda_n < 1$$
$$q_1, q_2, \dots, q_n \text{ (eigenvectors)}$$

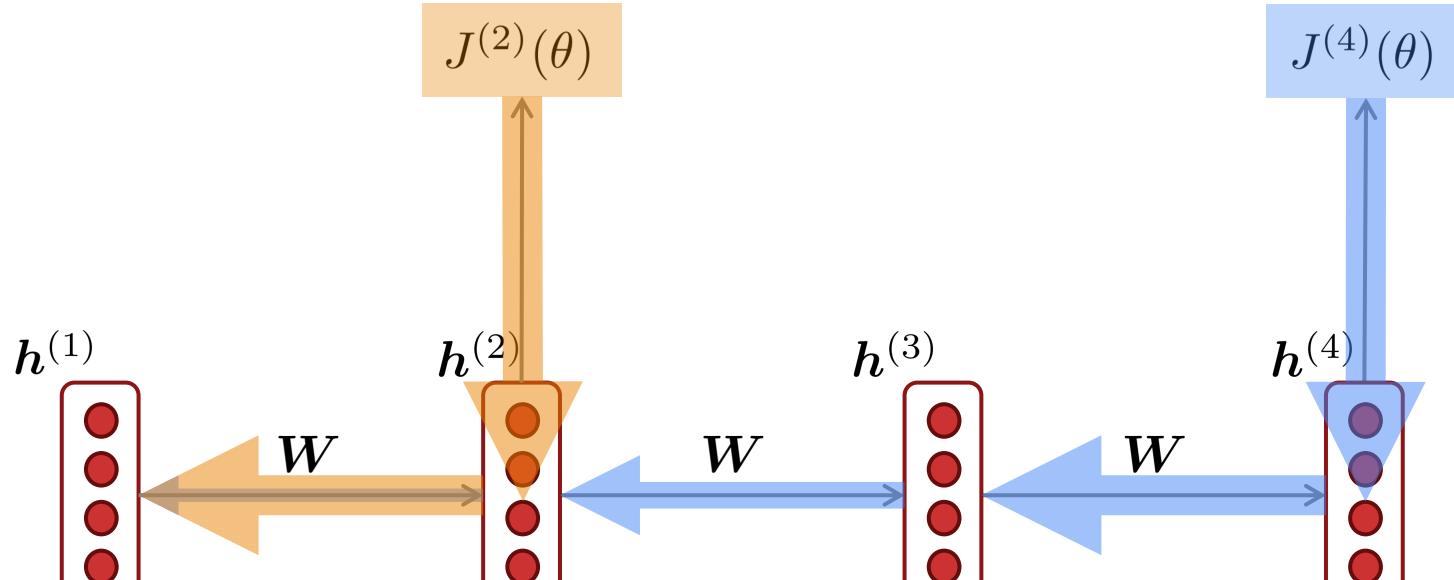
- We can write $\frac{\partial J^{(i)}(\theta)}{\partial h^{(i)}} W_h^\ell$ using the eigenvectors of W_h as a basis:

$$\frac{\partial J^{(i)}(\theta)}{\partial h^{(i)}} W_h^\ell = \sum_{i=1}^n c_i \boxed{\lambda_i^\ell} q_i \approx \mathbf{0} \text{ (for large } \ell\text{)}$$

Approaches 0 as ℓ grows, so gradient vanishes

- What about nonlinear activations σ (i.e., what we use?)
 - Pretty much the same thing, except the proof requires $\lambda_i < \gamma$ for some γ dependent on dimensionality and σ

Why is vanishing gradient a problem?



Gradient signal from far away 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.

Effect of vanishing gradient on RNN-LM

- **LM task:** *When she tried to print her tickets, she found that the printer was out of toner. She went to the stationery store to buy more toner. It was very overpriced. After installing the toner into the printer, she finally printed her _____*
- To learn from this training example, the RNN-LM needs to **model the dependency** between “*tickets*” on the 7th step and the target word “*tickets*” at the end.
- But if gradient is small, the model **can't learn this dependency**
 - So, the model is **unable to predict similar long-distance dependencies** at test time

Why is exploding gradient a problem?

- If the gradient becomes too big, then the SGD update step becomes too big:

$$\theta^{new} = \theta^{old} - \underbrace{\alpha \nabla_{\theta} J(\theta)}_{\text{gradient}}$$

learning rate

- This can cause **bad updates**: we take too large a step and reach a weird and bad parameter configuration (with large loss)
 - You think you've found a hill to climb, but suddenly you're in Iowa
- In the worst case, this will result in **Inf** or **NaN** in your network
(then you have to restart training from an earlier checkpoint)

Gradient clipping: solution for exploding gradient

- **Gradient clipping**: if the norm of the gradient is greater than some threshold, scale it down before applying SGD update

Algorithm 1 Pseudo-code for norm clipping

```
 $\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$ 
if  $\|\hat{\mathbf{g}}\| \geq \text{threshold}$  then
     $\hat{\mathbf{g}} \leftarrow \frac{\text{threshold}}{\|\hat{\mathbf{g}}\|} \hat{\mathbf{g}}$ 
end if
```

- **Intuition**: take a step in the same direction, but a smaller step
- In practice, remembering to clip gradients is important, but exploding gradients are an easy problem to solve

How to fix the vanishing gradient problem?

- The main problem is that *it's too difficult for the RNN to learn to preserve information over many timesteps.*
- In a vanilla RNN, the hidden state is constantly being **rewritten**

$$\mathbf{h}^{(t)} = \sigma \left(\mathbf{W}_h \mathbf{h}^{(t-1)} + \mathbf{W}_x \mathbf{x}^{(t)} + \mathbf{b} \right)$$

- How about a RNN with separate **memory**?

4. Long Short-Term Memory RNNs (LSTMs)

- A type of RNN proposed by Hochreiter and Schmidhuber in 1997 as a solution to the vanishing gradients problem.
 - Everyone cites that paper but really a crucial part of the modern LSTM is from Gers et al. (2000) 
- On step t , there is a hidden state $\mathbf{h}^{(t)}$ and a cell state $\mathbf{c}^{(t)}$
 - Both are vectors length n
 - The cell stores long-term information
 - The LSTM can read, erase, and write information from the cell
 - The cell becomes conceptually rather like RAM in a computer
- The selection of which information is erased/written/read is controlled by three corresponding gates
 - The gates are also vectors length n
 - On each timestep, each element of the gates can be open (1), closed (0), or somewhere in-between
 - The gates are dynamic: their value is computed based on the current context

“Long short-term memory”, Hochreiter and Schmidhuber, 1997. <https://www.bioinf.jku.at/publications/older/2604.pdf>

“Learning to Forget: Continual Prediction with LSTM”, Gers, Schmidhuber, and Cummins, 2000. <https://dl.acm.org/doi/10.1162/089976600300015015>

Long Short-Term Memory (LSTM)

We have a sequence of inputs $x^{(t)}$, and we will compute a sequence of hidden states $h^{(t)}$ and cell states $c^{(t)}$. On timestep t :

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

Input gate: controls what parts of the new cell content are written to cell

Output gate: controls what parts of cell are output to hidden state

Sigmoid function: all gate values are between 0 and 1

$$\begin{aligned} f^{(t)} &= \sigma \left(\mathbf{W}_f h^{(t-1)} + \mathbf{U}_f x^{(t)} + \mathbf{b}_f \right) \\ i^{(t)} &= \sigma \left(\mathbf{W}_i h^{(t-1)} + \mathbf{U}_i x^{(t)} + \mathbf{b}_i \right) \\ o^{(t)} &= \sigma \left(\mathbf{W}_o h^{(t-1)} + \mathbf{U}_o x^{(t)} + \mathbf{b}_o \right) \end{aligned}$$

New cell content: this is the new content to be written to the cell

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

Hidden state: read (“output”) some content from the cell

$$\tilde{c}^{(t)} = \tanh \left(\mathbf{W}_c h^{(t-1)} + \mathbf{U}_c x^{(t)} + \mathbf{b}_c \right)$$

$$c^{(t)} = f^{(t)} \circ c^{(t-1)} + i^{(t)} \circ \tilde{c}^{(t)}$$

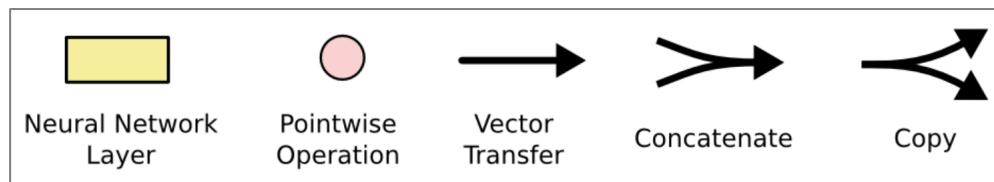
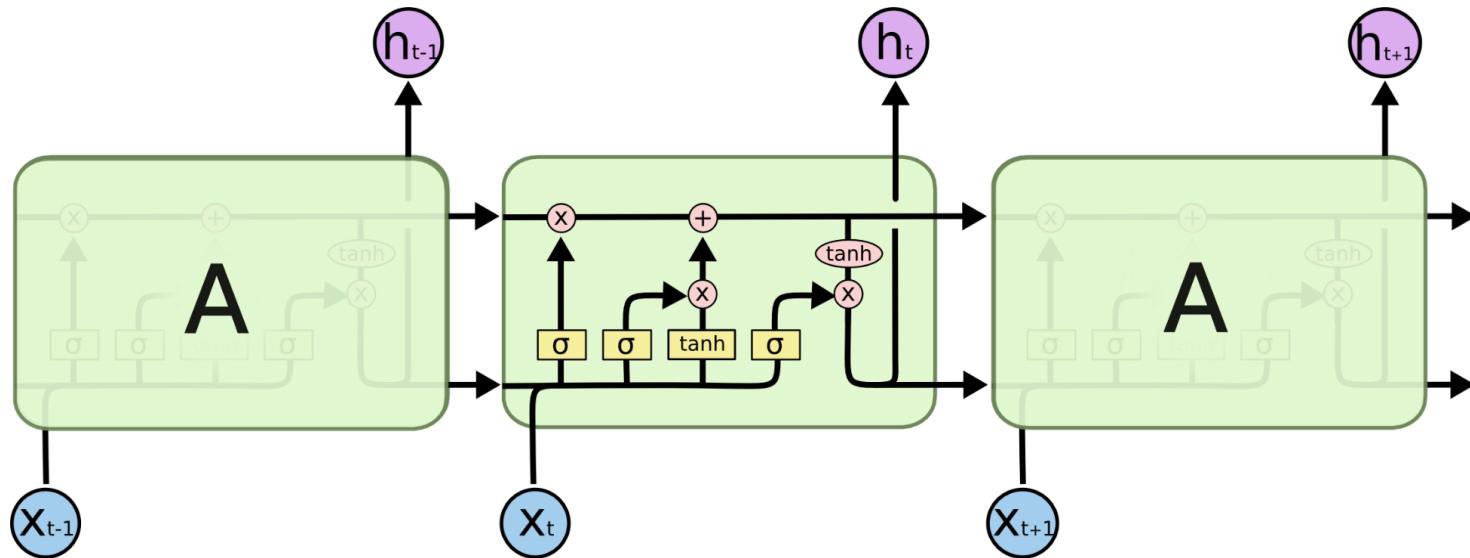
$$h^{(t)} = o^{(t)} \circ \tanh c^{(t)}$$

All these are vectors of same length n

Gates are applied using element-wise (or Hadamard) product: \odot

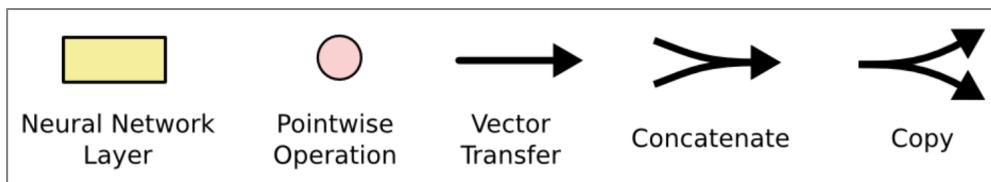
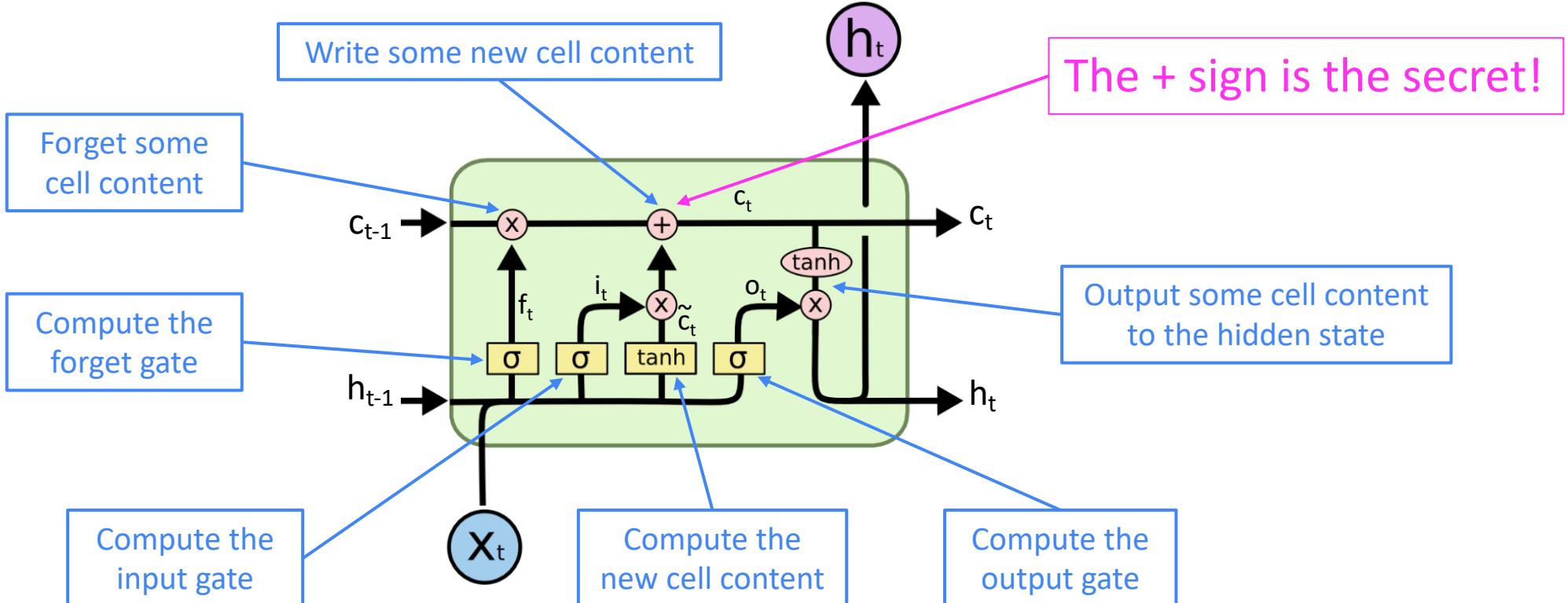
Long Short-Term Memory (LSTM)

You can think of the LSTM equations visually like this:



Long Short-Term Memory (LSTM)

You can think of the LSTM equations visually like this:



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

How does LSTM solve vanishing gradients?

- The LSTM architecture makes it easier for the RNN to preserve information over many timesteps
 - e.g., if the forget gate is set to 1 for a cell dimension and the input gate set to 0, then the information of that cell is preserved indefinitely.
 - In contrast, it's harder for a vanilla RNN to learn a recurrent weight matrix W_h that preserves info in the hidden state
 - In practice, you get about 100 timesteps rather than about 7
- 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

RNN: Short Short Term Memory

LSTMs: real-world success

- In 2013–2015, LSTMs started achieving state-of-the-art results
 - Successful tasks include handwriting recognition, speech recognition, machine translation, parsing, and image captioning, as well as language models
 - LSTMs became the dominant approach for most NLP tasks
- Now (2021), other approaches (e.g., Transformers) have become dominant for many tasks
 - For example, in WMT (a Machine Translation conference + competition):
 - In WMT 2016, the summary report contains “RNN” 44 times
 - In WMT 2019: “RNN” 7 times, “Transformer” 105 times

Source: "Findings of the 2016 Conference on Machine Translation (WMT16)", Bojar et al. 2016, <http://www.statmt.org/wmt16/pdf/W16-2301.pdf>

Source: "Findings of the 2018 Conference on Machine Translation (WMT18)", Bojar et al. 2018, <http://www.statmt.org/wmt18/pdf/WMT028.pdf>

Source: "Findings of the 2019Conference on Machine Translation (WMT19)", Barrault et al. 2019, <http://www.statmt.org/wmt18/pdf/WMT028.pdf>

Is vanishing/exploding gradient just a RNN problem?

- No! It can be a problem for all neural architectures (including **feed-forward** and **convolutional**), especially **very deep** ones.
 - Due to chain rule / choice of nonlinearity function, gradient can become vanishingly small as it backpropagates
 - Thus, lower layers are learned very slowly (hard to train)
- Solution: lots of new deep feedforward/convolutional architectures that **add more direct connections** (thus allowing the gradient to flow)

For example:

- **Residual connections** aka “ResNet”
- Also known as **skip-connections**
- The **identity connection** **preserves information** by default
- This makes **deep** networks much **easier to train**

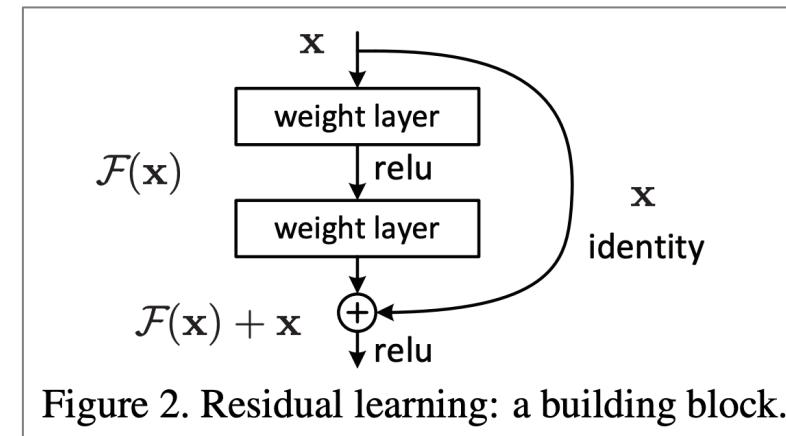


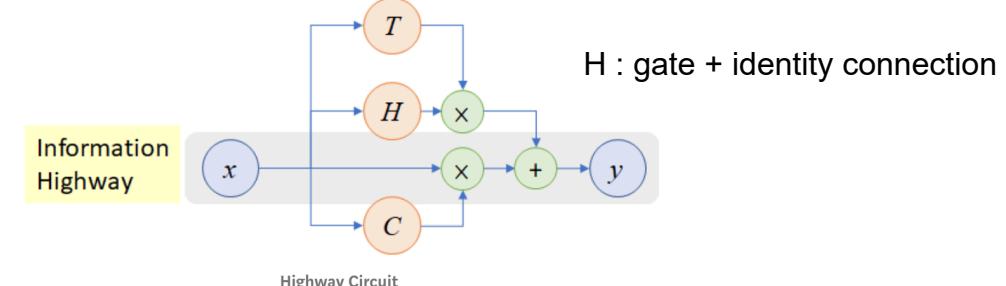
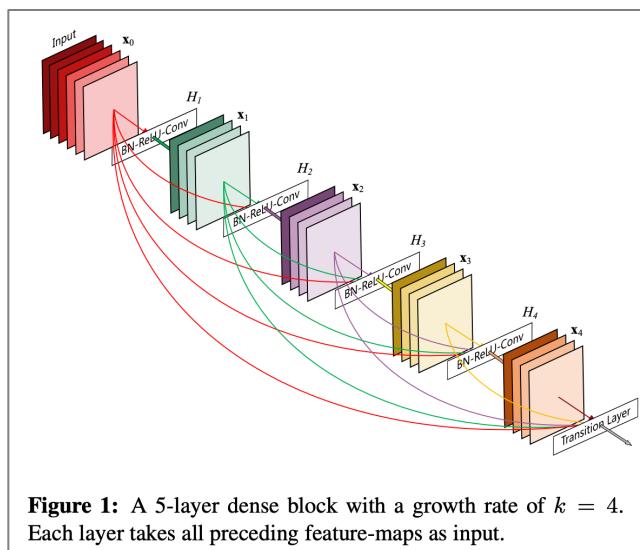
Figure 2. Residual learning: a building block.

Is vanishing/exploding gradient just a RNN problem?

- Solution: lots of new deep feedforward/convolutional architectures that **add more direct connections** (thus allowing the gradient to flow)

Other methods:

- Dense connections** aka “DenseNet”
- Directly connect each layer to all future layers!
- Highway connections** aka “HighwayNet”
- Similar to residual connections, but the identity connection vs the transformation layer is controlled by a **dynamic gate**
- Inspired by LSTMs, but applied to deep feedforward/convolutional networks

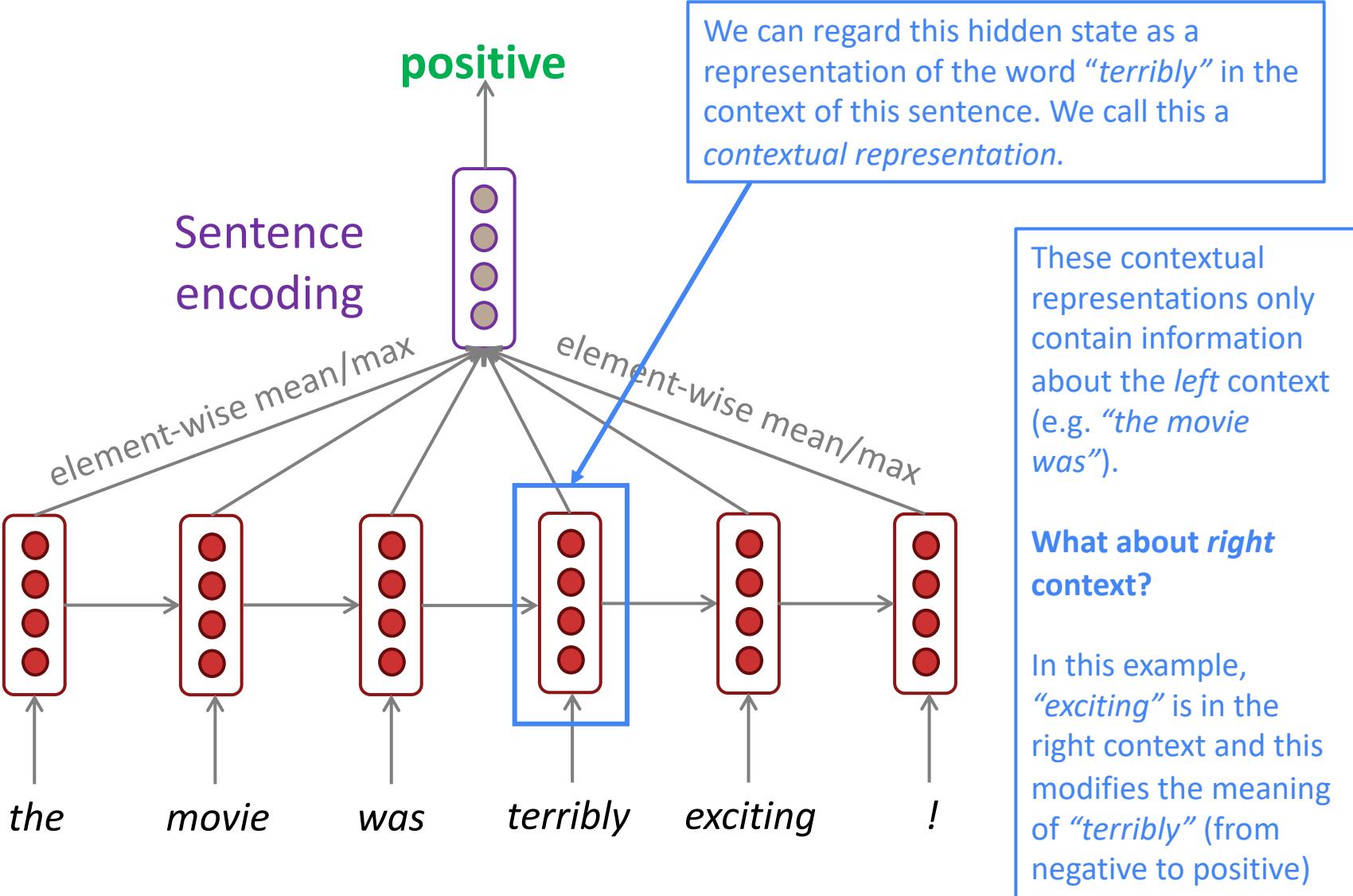


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- **Conclusion:** Though vanishing/exploding gradients are a general problem, **RNNs are particularly unstable** due to the repeated multiplication by the **same** weight matrix [Bengio et al, 1994]

5. Bidirectional and Multi-layer RNNs: motivation

Task: Sentiment Classification



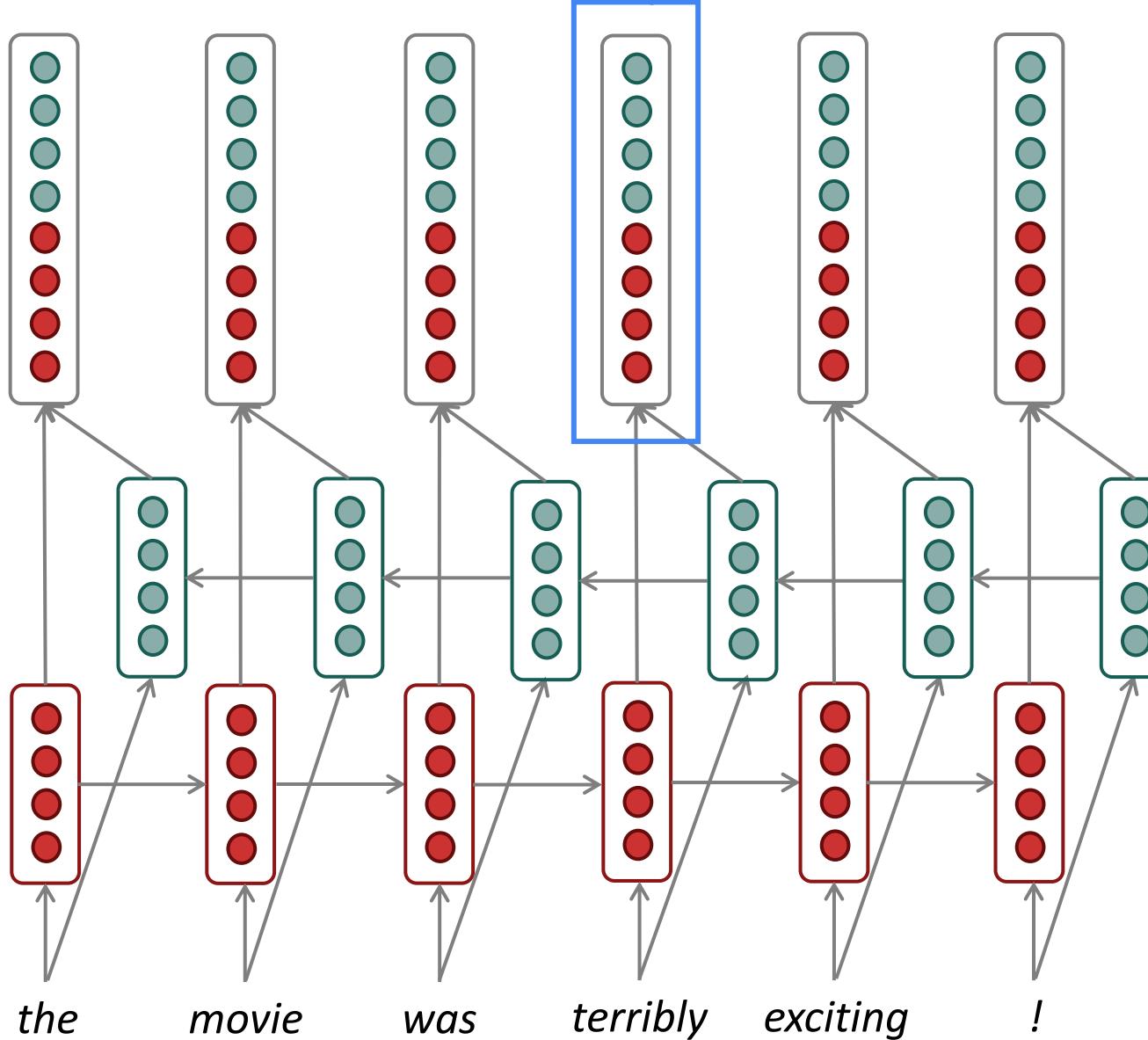
Bidirectional RNNs

Concatenated
hidden states

Backward RNN

Forward RNN

This contextual representation of “terribly”
has both left and right context!



Bidirectional RNNs

On timestep t :

This is a general notation to mean “compute one forward step of the RNN” – it could be a vanilla, LSTM or GRU computation.

Forward RNN $\vec{h}^{(t)} = \text{RNN}_{\text{FW}}(\vec{h}^{(t-1)}, \mathbf{x}^{(t)})$

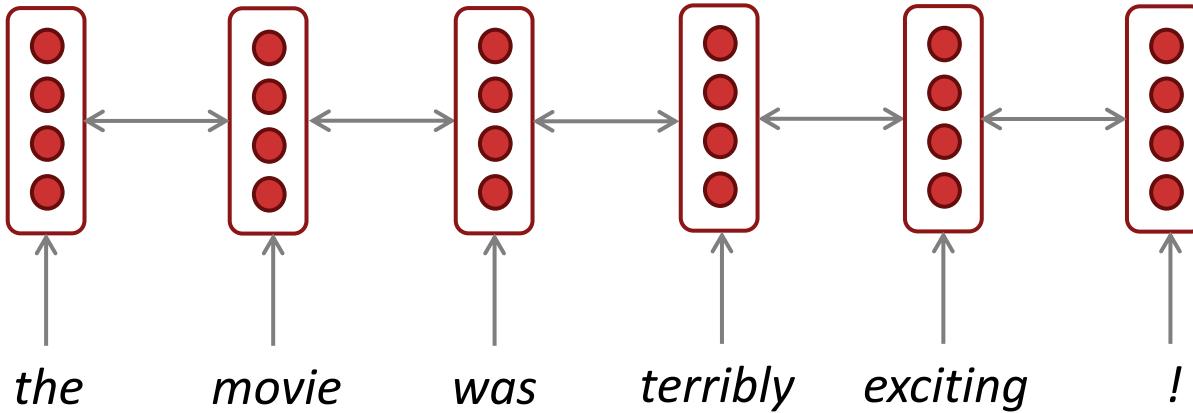
Backward RNN $\overleftarrow{h}^{(t)} = \text{RNN}_{\text{BW}}(\overleftarrow{h}^{(t+1)}, \mathbf{x}^{(t)})$

Concatenated hidden states $\boxed{\mathbf{h}^{(t)}} = [\vec{h}^{(t)}; \overleftarrow{h}^{(t)}]$

Generally, these two RNNs have separate weights

We regard this as “the hidden state” of a bidirectional RNN. This is what we pass on to the next parts of the network.

Bidirectional RNNs: simplified diagram



The two-way arrows indicate bidirectionality and the depicted hidden states are assumed to be the concatenated forwards+backwards states

Bidirectional RNNs

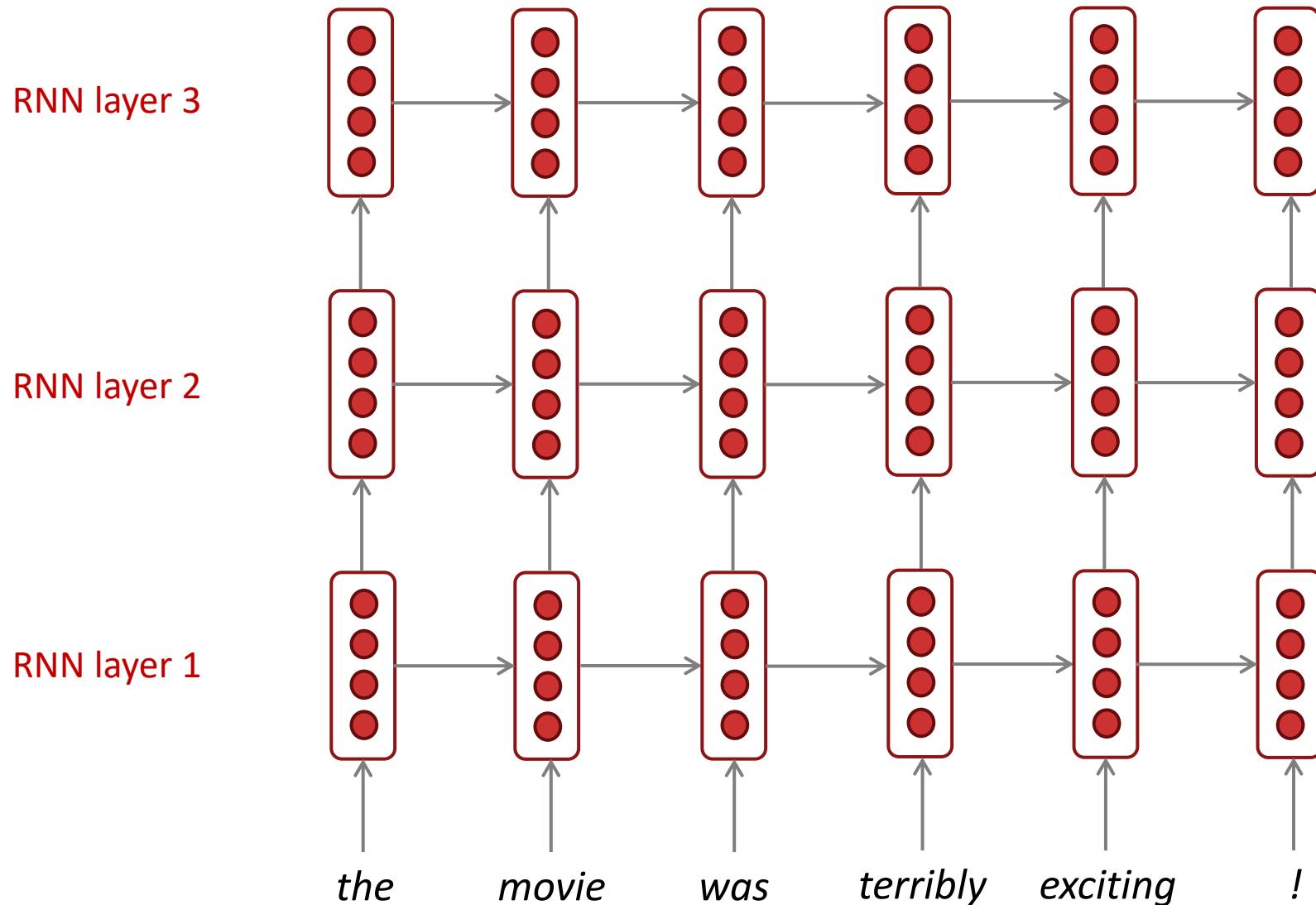
- Note: bidirectional RNNs are only applicable if you have access to the **entire input sequence**
 - They are **not** applicable to Language Modeling, because in LM you *only* have left context available.
- If you do have entire input sequence (e.g., any kind of encoding), **bidirectionality is powerful** (you should use it by default).
- For example, **BERT** (**Bidirectional** Encoder Representations from Transformers) is a powerful pretrained contextual representation system **built on bidirectionality**.
 - You will learn more about **transformers** include BERT in a couple of weeks!

Multi-layer RNNs

- RNNs are already “deep” on one dimension (they unroll over many timesteps)
- We can also make them “deep” in another dimension by applying multiple RNNs – this is a multi-layer RNN.
- This allows the network to compute more complex representations
 - The lower RNNs should compute lower-level features and the higher RNNs should compute higher-level features.
- Multi-layer RNNs are also called *stacked RNNs*.

Multi-layer RNNs

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

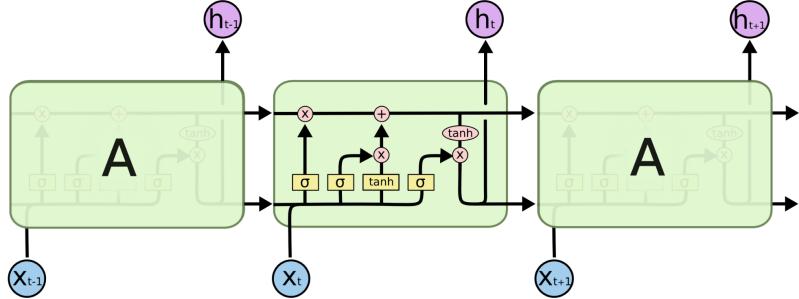


Multi-layer RNNs in practice

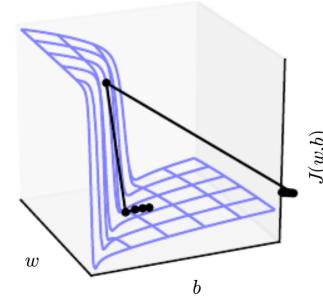
- High-performing RNNs are often multi-layer (but aren't as deep as convolutional or feed-forward networks)
- For example: In a 2017 paper, Britz et al find that for Neural Machine Translation, 2 to 4 layers is best for the encoder RNN, and 4 layers is best for the decoder RNN
 - Usually, skip-connections/dense-connections are needed to train deeper RNNs (e.g., 8 layers)
- Transformer-based networks (e.g., BERT) are usually deeper, like 12 or 24 layers.
 - You will learn about Transformers later; they have a lot of skipping-like connections

In summary

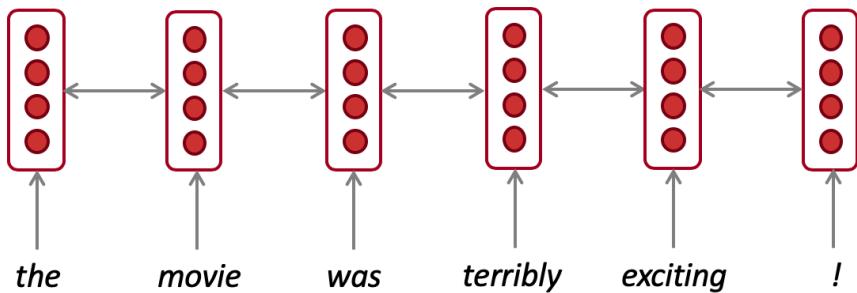
Lots of new information today! What are some of the [practical takeaways](#)?



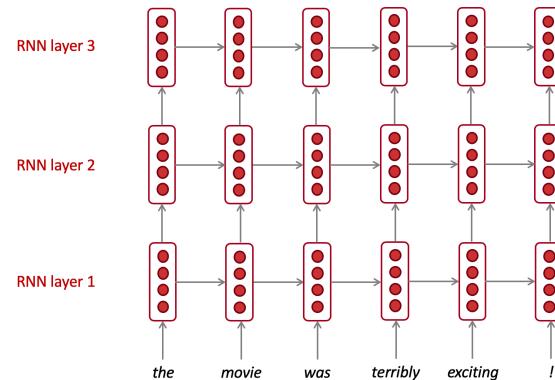
1. LSTMs are powerful



2. Clip your gradients



3. Use bidirectionality when possible



4. Multi-layer RNNs are more powerful, but you might need skip connections if it's deep