Natural Language Processing with Deep Learning

CS224N/Ling284

Lecture 8:
Recurrent Neural Networks
and Language Models

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LANGUAGE UNDERSTANDING

Topics: Natural Language Understanding

- ***It's all about telling how likely a sentence is..***

- How likely is this sentence as an answer to the question?
  - Q. "*Who is the President of the United States?*"
  - *Likely* answer: "*Obama is the President of the U.S.*"
  - *Unlikely* answer: "*Tsipras is the President of America.*"

LANGUAGE UNDERSTANDING

Topics: Natural Language Understanding

- ***It's all about telling how likely a sentence is..***

- How likely is this sentence given this view?

  - *Likely*: "*Two dolphins are diving*"
  - *Unlikely*: "*Two men are flying*"

LANGUAGE UNDERSTANDING

Topics: Natural Language Understanding

It's all about telling how likely a sentence is..

HOW LIKELY IS THIS SENTENCE?

Topics: Language Modelling

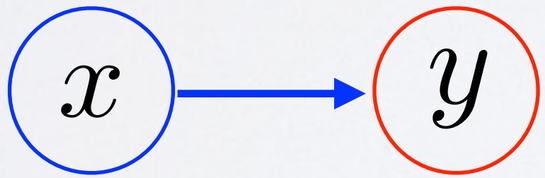
- A sentence $(x_1, x_2, \ldots, x_T)$
  - Ex) (“the”,“cat”,“is”,“eating”,“a”,“sandwich”,“on”,“a”,“couch”)
- How likely is this sentence?
- In other words, what is the probability of $(x_1, x_2, \ldots, x_T)$?
  - i.e., $p(x_1, x_2, \ldots, x_T) = ?$

HOW LIKELY IS THIS SENTENCE?

Topics: Probability 101 - Conditional Probability

- Joint probability $p(x, y)$
- Conditional probability $p(x|y)$
- Marginal probability $p(x)$ and $p(y)$

- They are related by $p(x, y) = p(x|y)p(y) = p(y|x)p(x)$



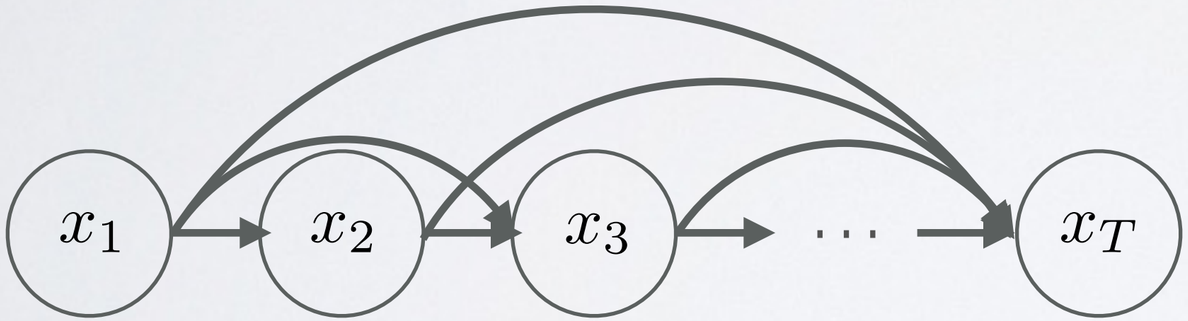
HOW LIKELY IS THIS SENTENCE?

Topics: Language Modelling as a Product of Conditionals

- Rewrite $p(x_1, x_2, \ldots, x_T)$ into

$$p(x_1, x_2, \ldots, x_T) = \prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1})$$

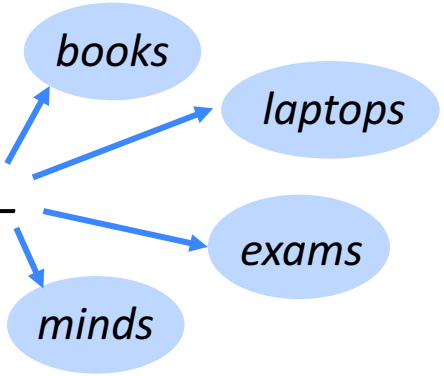
- Graphically,



Language Modeling

- **Language Modeling** is the task of predicting what word comes next.

the students opened their _____



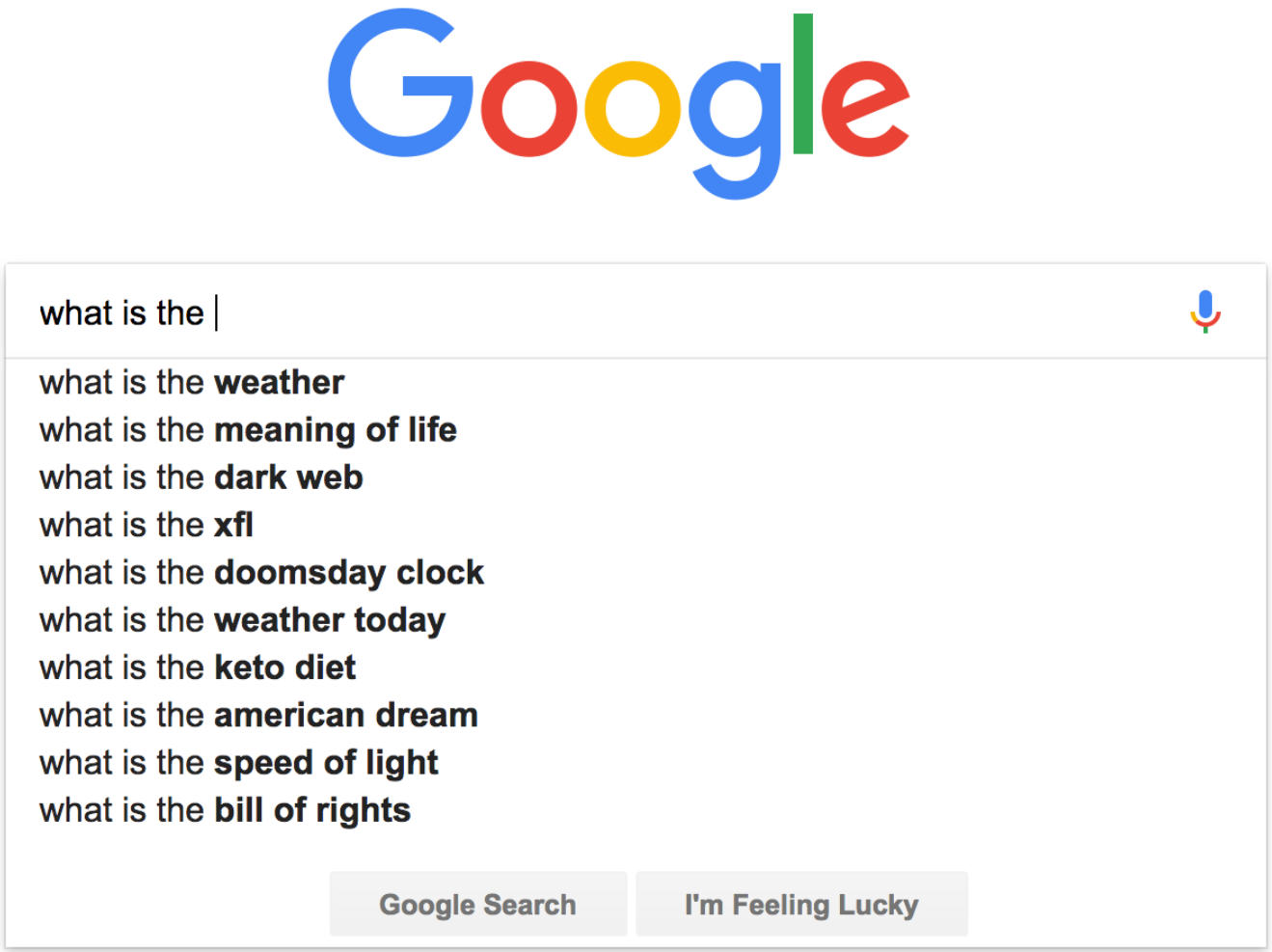
- More formally: given a sequence of words $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots, \boldsymbol{x}^{(t)}$, compute the probability distribution of the next word $\boldsymbol{x}^{(t+1)}$:

$$P(\boldsymbol{x}^{(t+1)} = \boldsymbol{w}_j \mid \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})$$

where $\boldsymbol{w}_j$ is a word in the vocabulary $V = \{\boldsymbol{w}_1, \ldots, \boldsymbol{w}_{|V|}\}$

- A system that does this is called a **Language Model**.

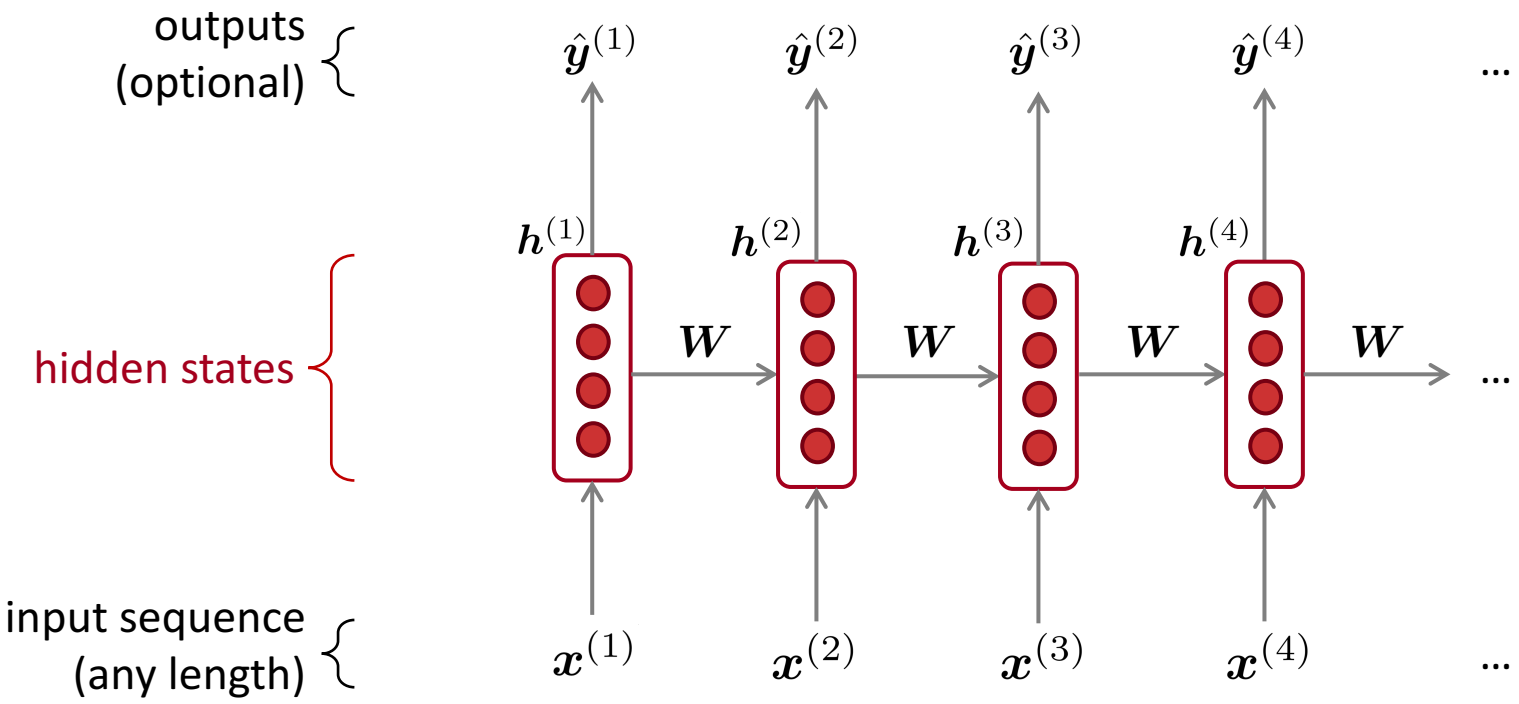
You use Language Models every day!



Recurrent Neural Networks (RNN)

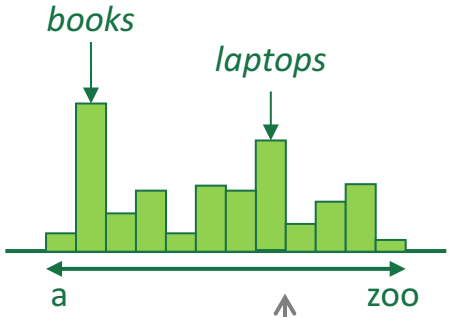
A family of neural architectures

Core idea: Apply the same weights $\boldsymbol{W}$ *repeatedly*



A RNN Language Model

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



output distribution

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

hidden states

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

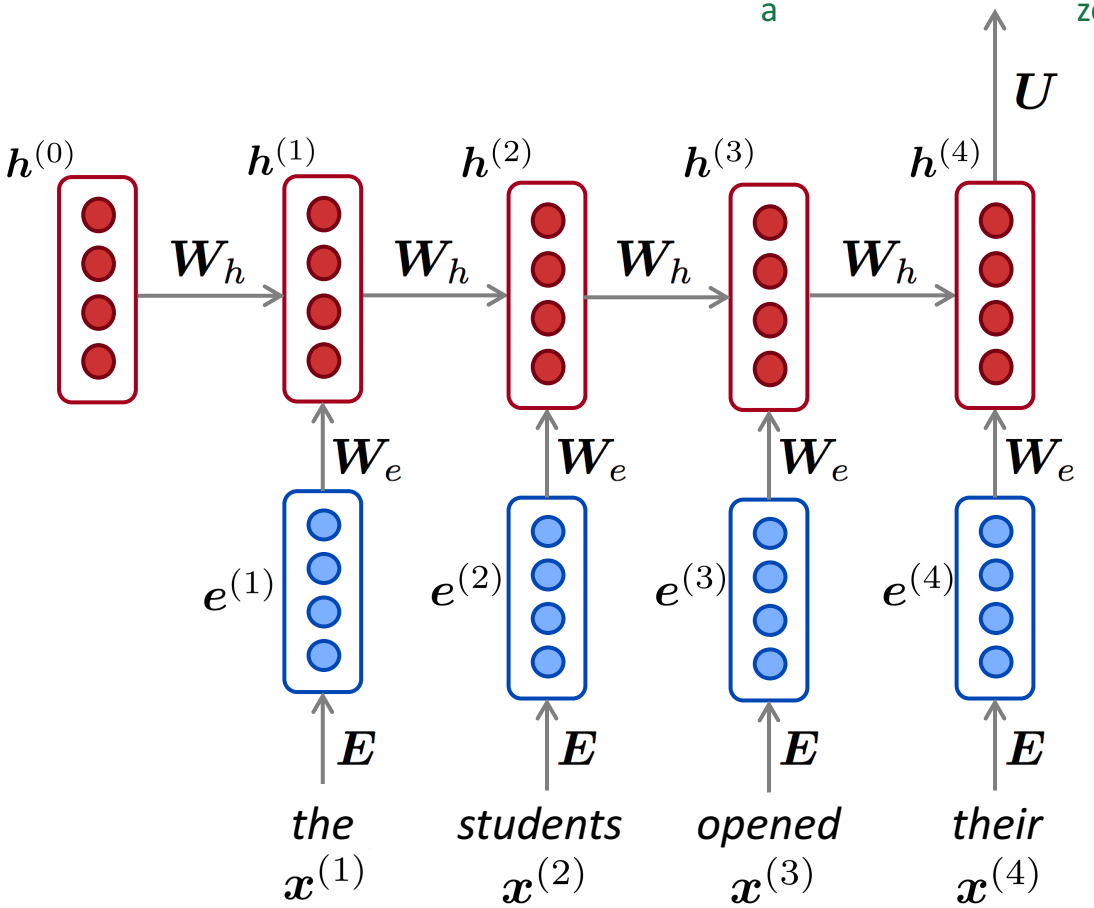
$\boldsymbol{h}^{(0)}$ is the initial hidden state

word embeddings

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

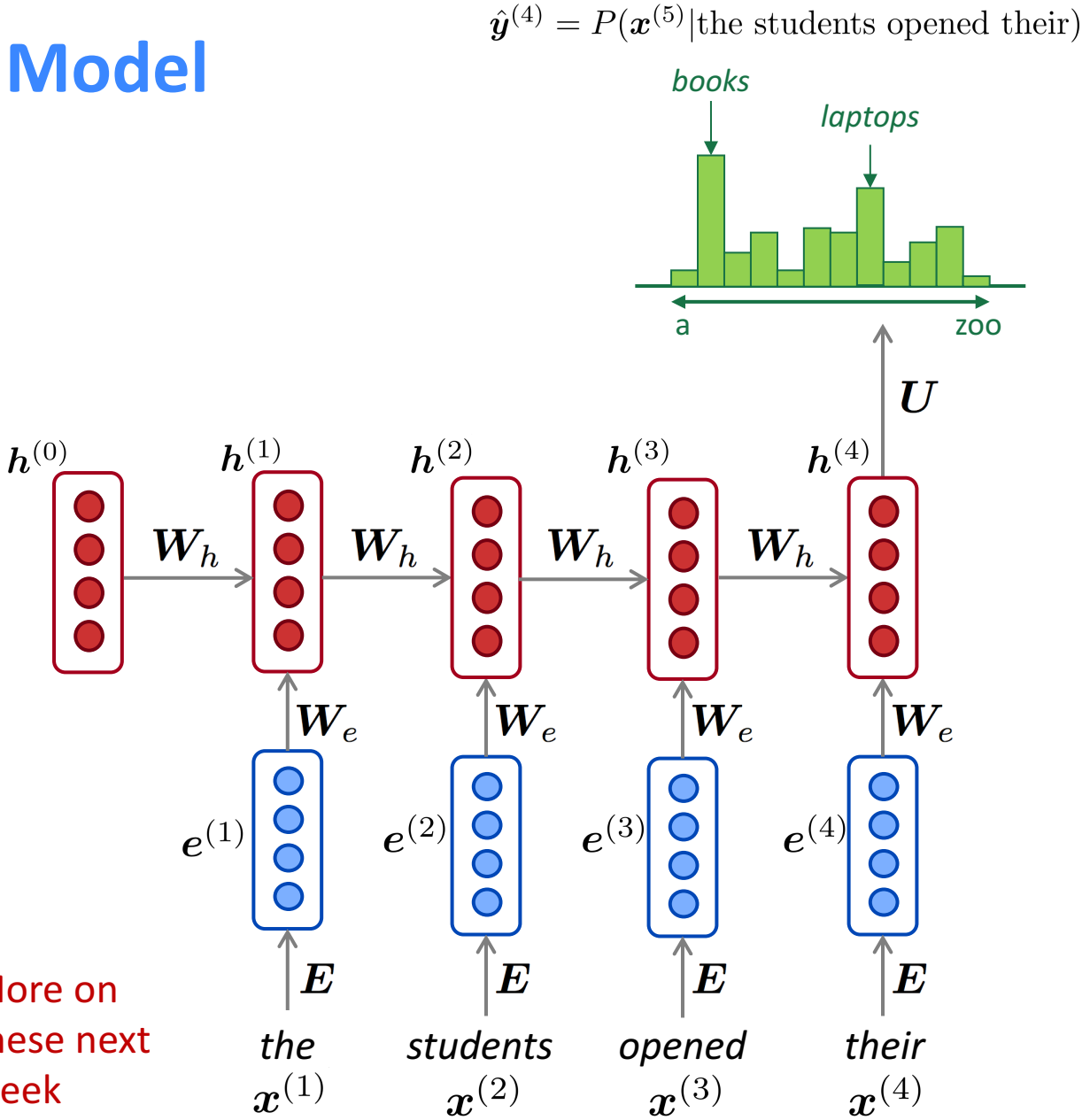
words / one-hot vectors

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



***Note**: this input sequence could be much longer, but this slide doesn't have space!*

A RNN Language Model



RNN **Advantages**:

- Can process any length input
- Model size doesn't increase for longer input
- Computation for step *t* can (in theory) use information from many steps back
- Weights are shared across timesteps → representations are shared

RNN **Disadvantages**:

- Recurrent computation is slow
- In practice, difficult to access information from many steps back

More on these next week

Training a RNN Language Model

- Get a big corpus of text which is a sequence of words $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}$
- Feed into RNN-LM; compute output distribution $\hat{\boldsymbol{y}}^{(t)}$ for *every step t*.
  - i.e. predict probability dist of *every word*, given words so far

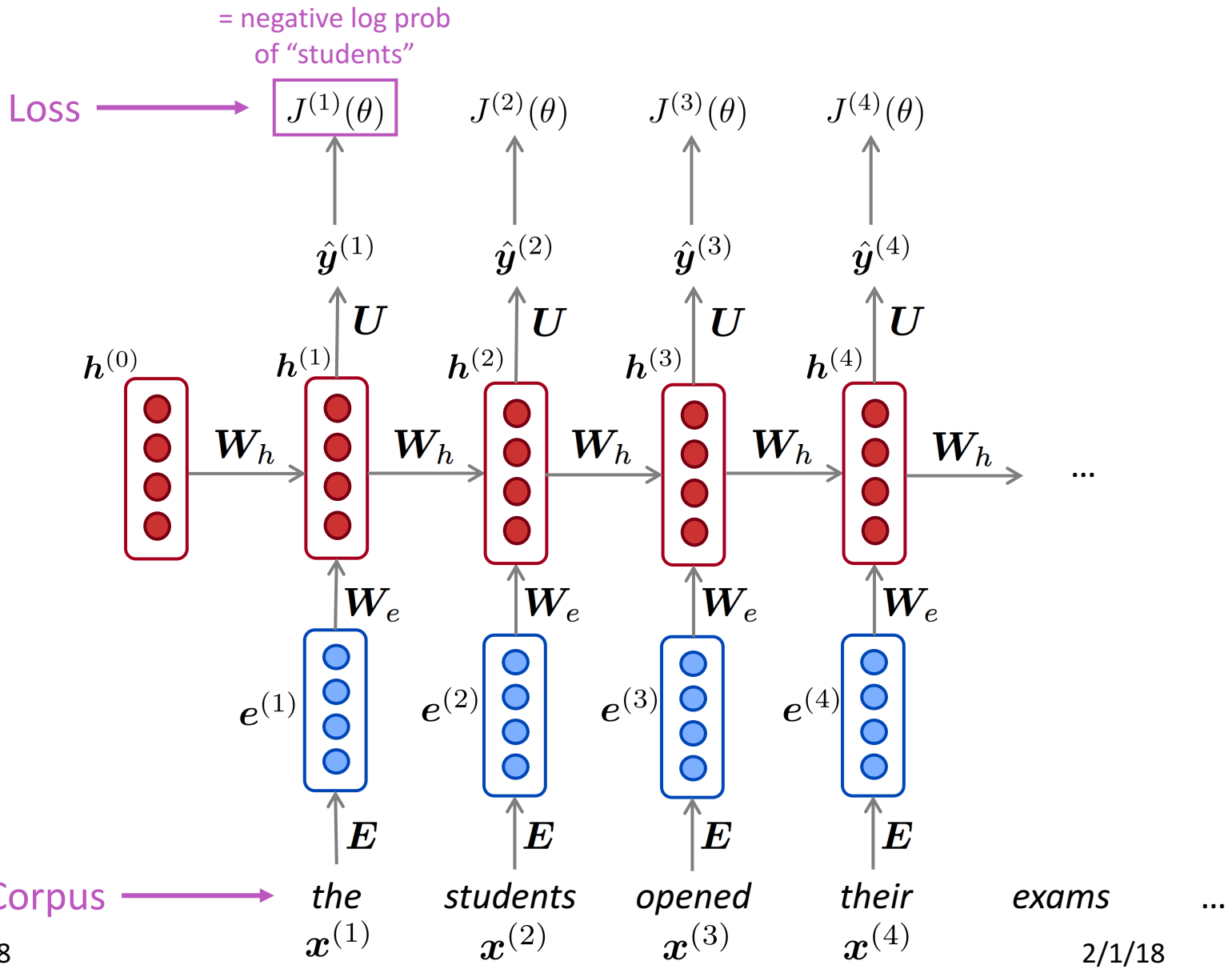
- Loss function on step *t* is usual cross-entropy between our predicted probability distribution $\hat{\boldsymbol{y}}^{(t)}$, and the true next word $\boldsymbol{y}^{(t)} = \boldsymbol{x}^{(t+1)}$:

$$J^{(t)}(\theta) = CE(\boldsymbol{y}^{(t)}, \hat{\boldsymbol{y}}^{(t)}) = -\sum_{j=1}^{|V|} y_j^{(t)} \log \hat{y}_j^{(t)}$$

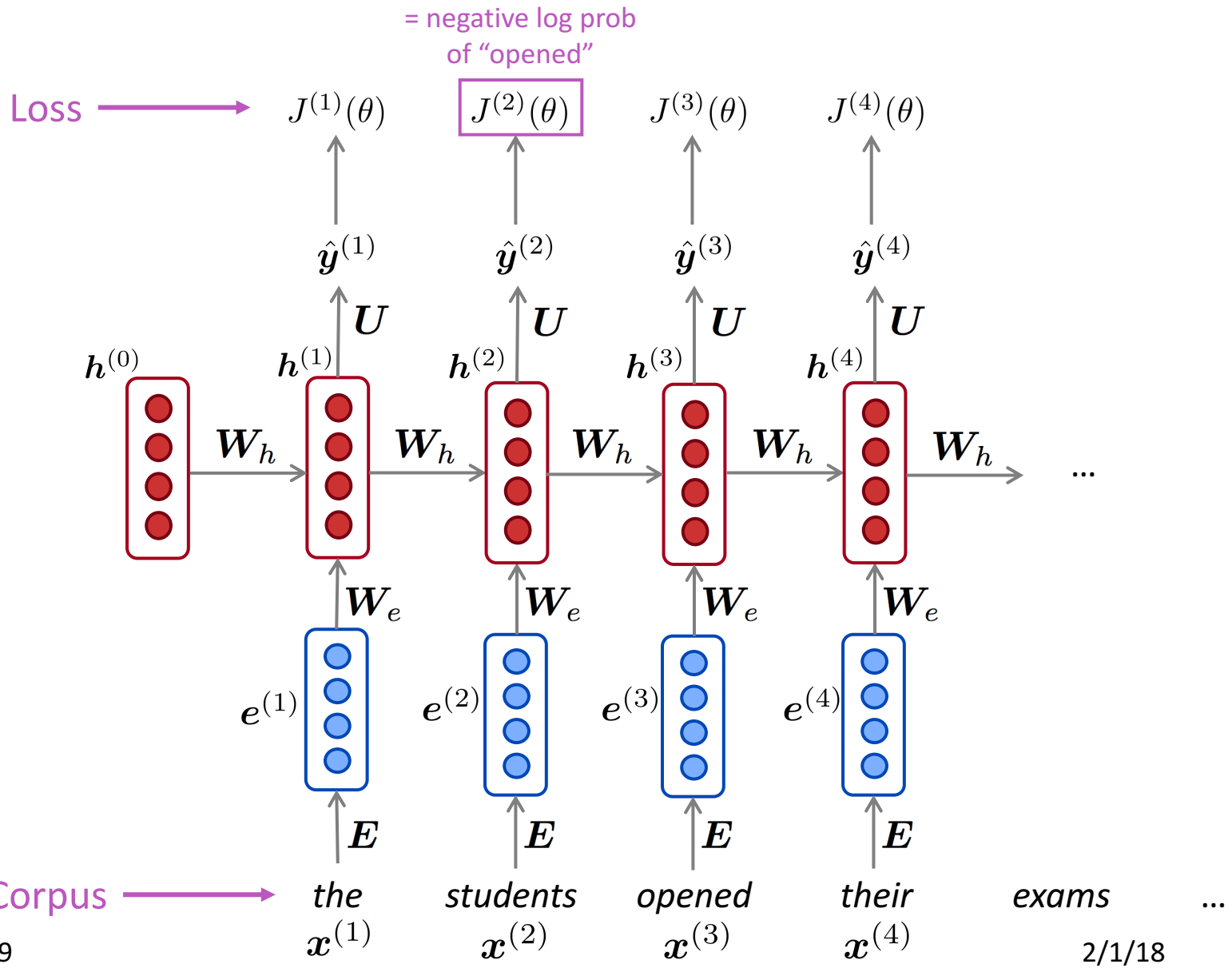
- Average this to get overall loss for entire training set:

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

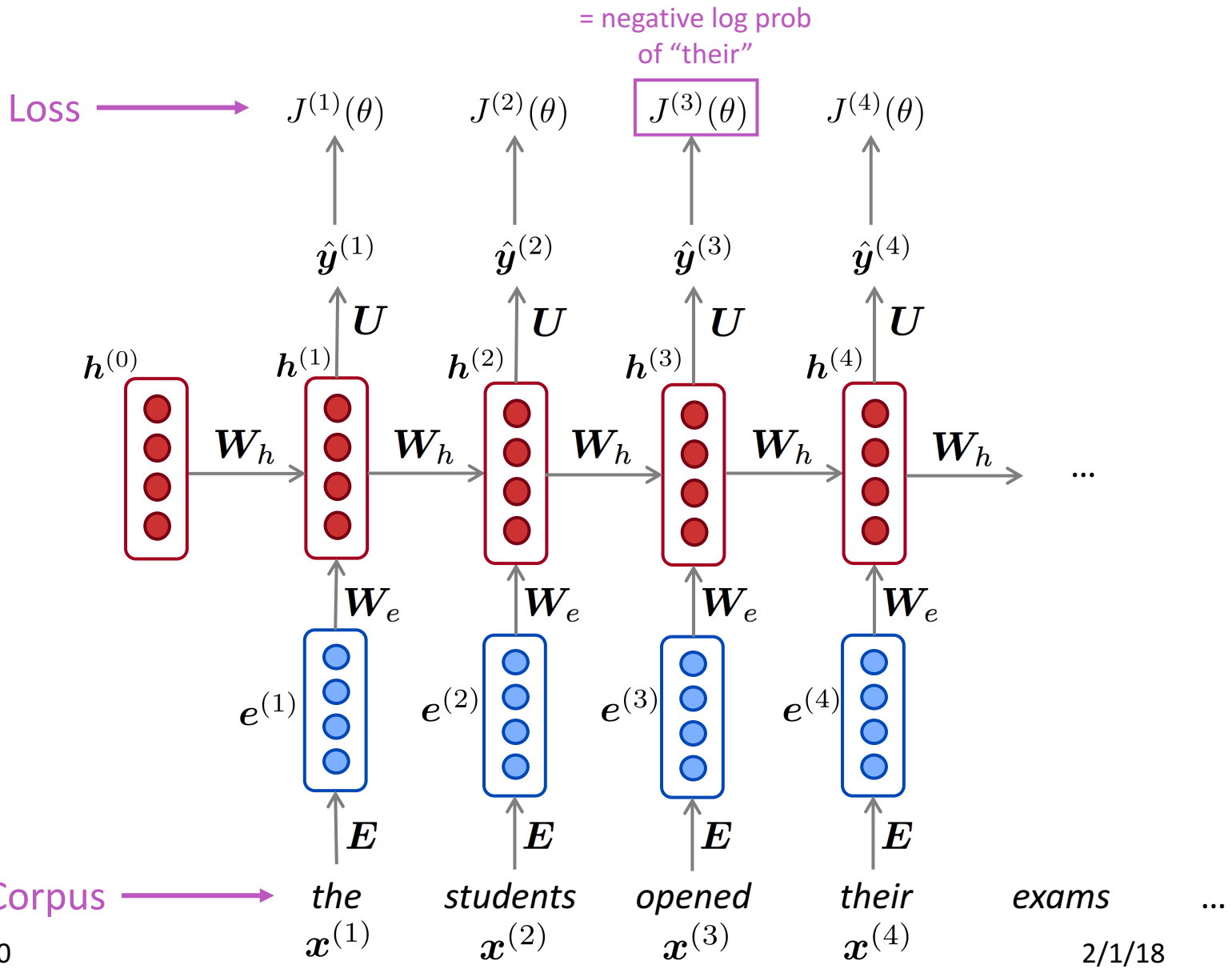
Training a RNN Language Model



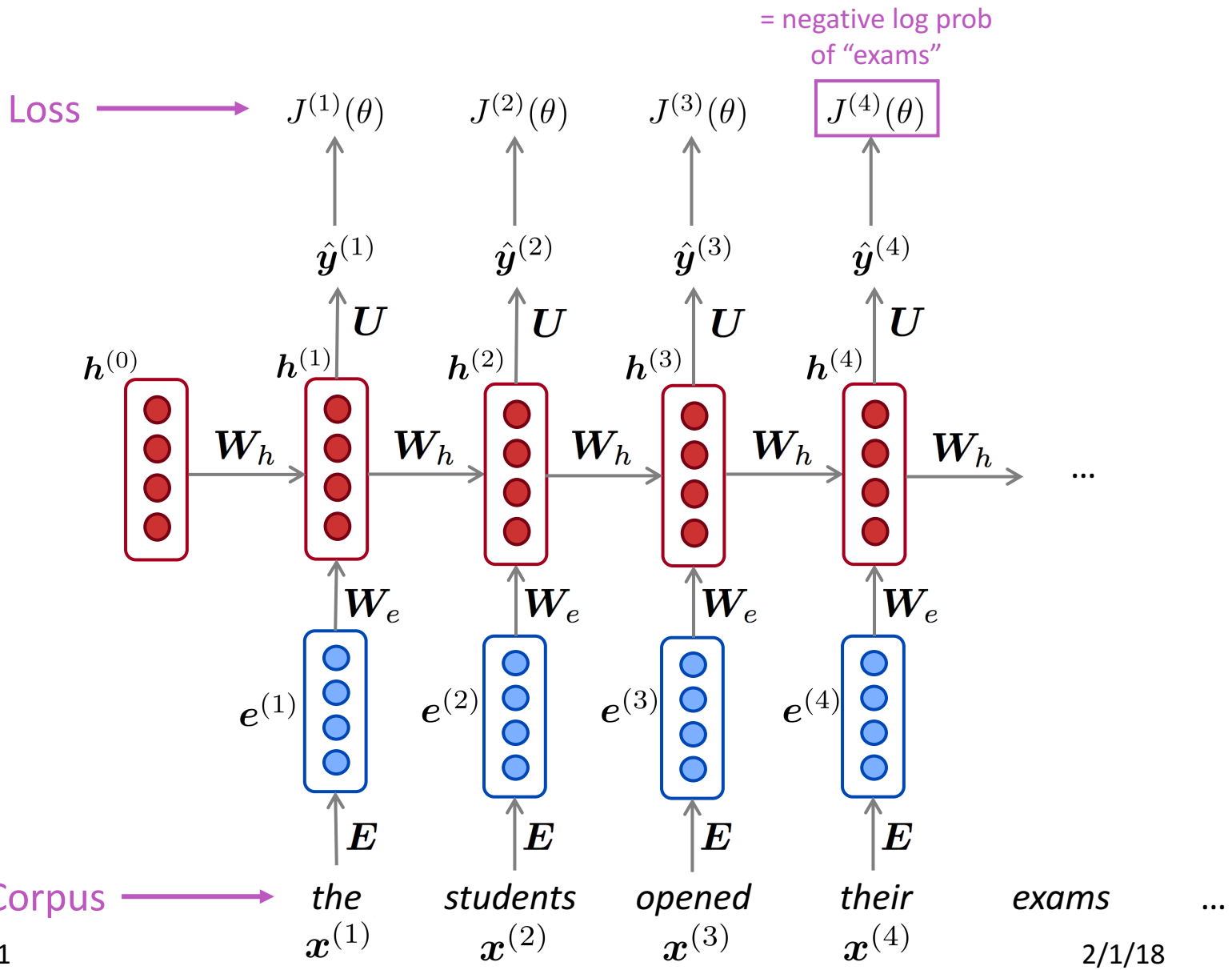
Training a RNN Language Model



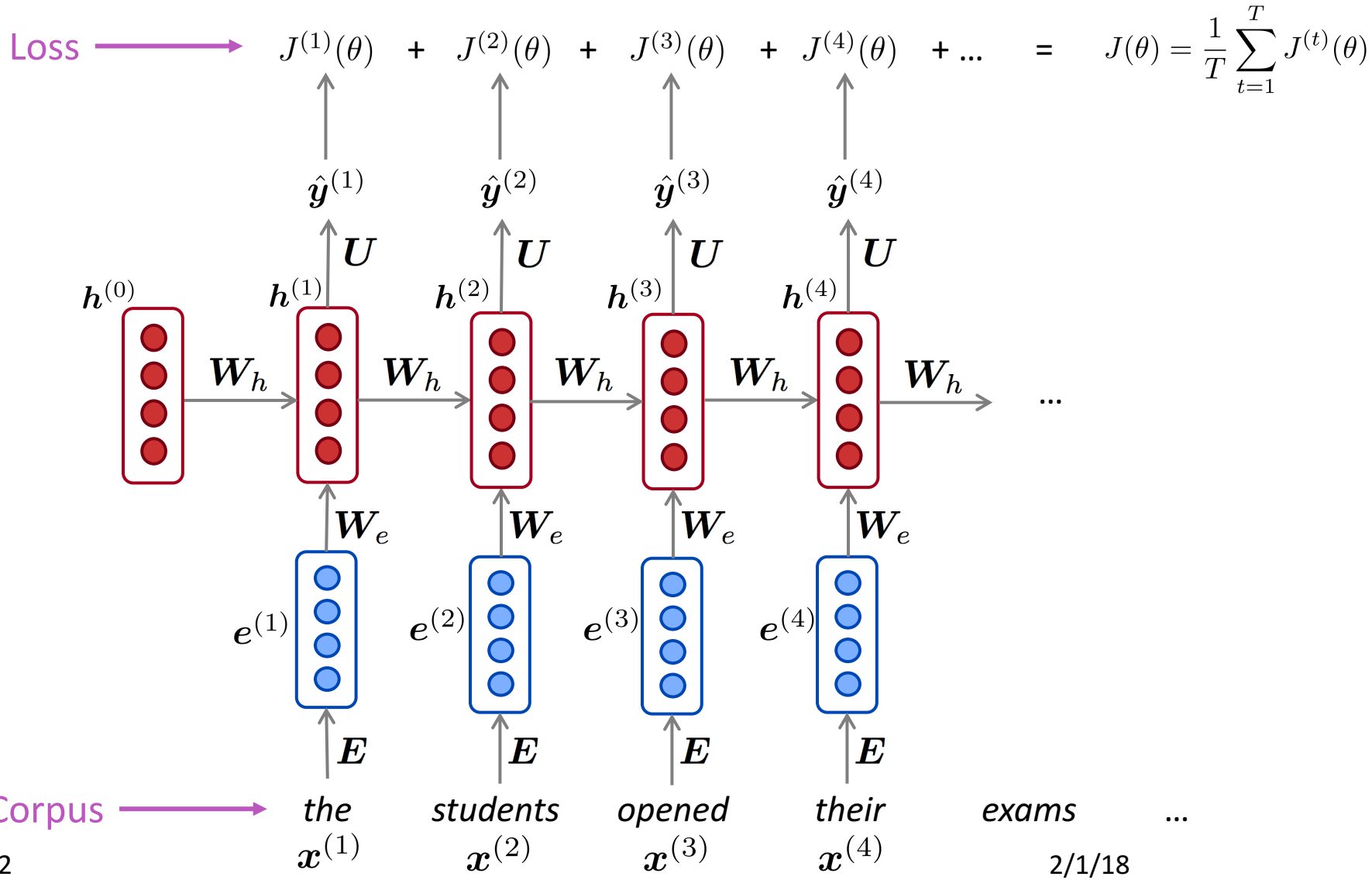
Training a RNN Language Model



Training a RNN Language Model



Training a RNN Language Model



Training a RNN Language Model

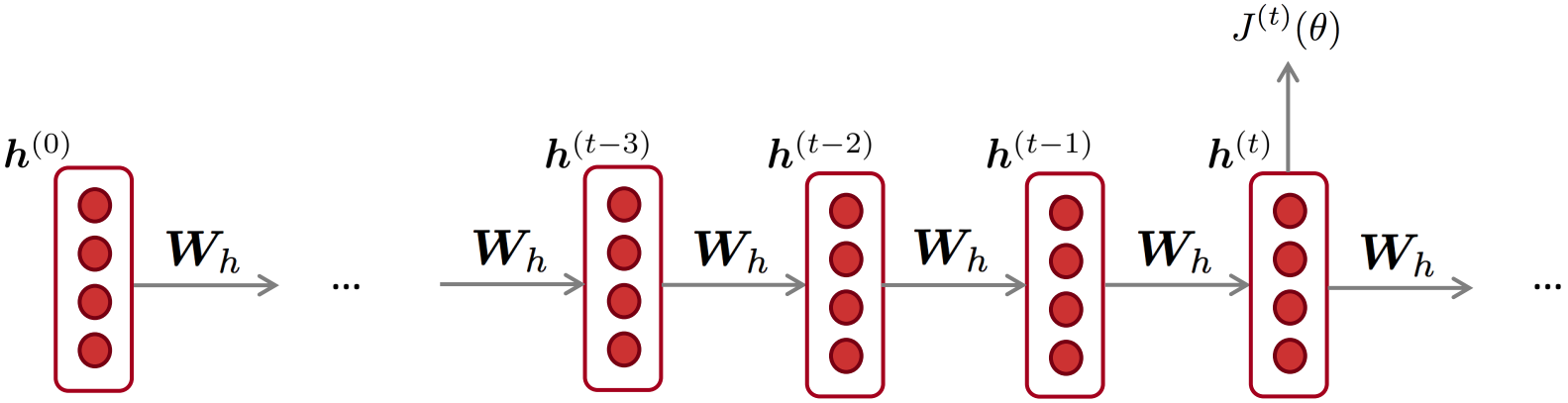
- However: Computing loss and gradients across entire corpus is too expensive!
- Recall: Stochastic Gradient Descent allows us to compute loss and gradients for small chunk of data, and update.

- → In practice, consider $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}$ as a sentence

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

- Compute loss $J(\theta)$ for a sentence (actually usually a batch of sentences), compute gradients and update weights. Repeat.

Backpropagation for RNNs



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

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

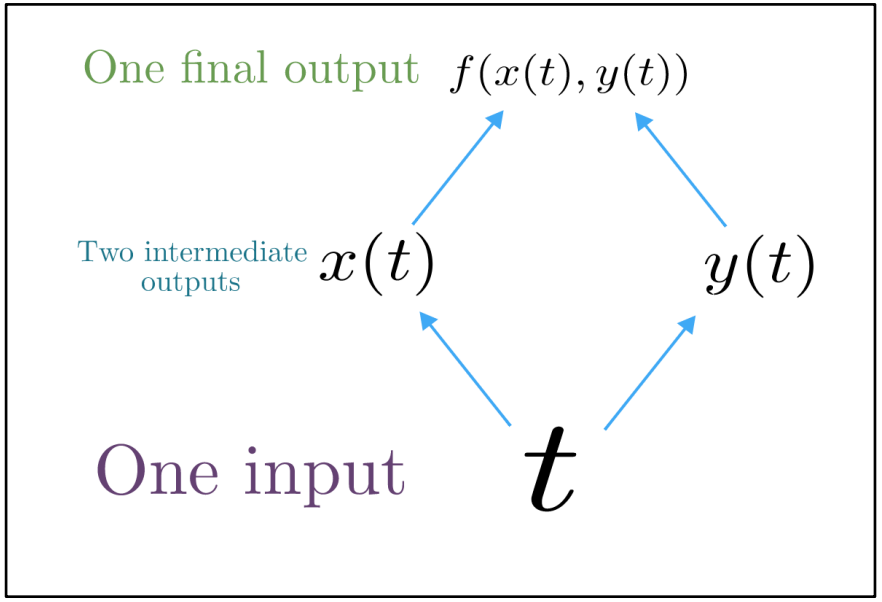
"The gradient w.r.t. a repeated weight is the sum of the gradient w.r.t. each time it appears"

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:

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



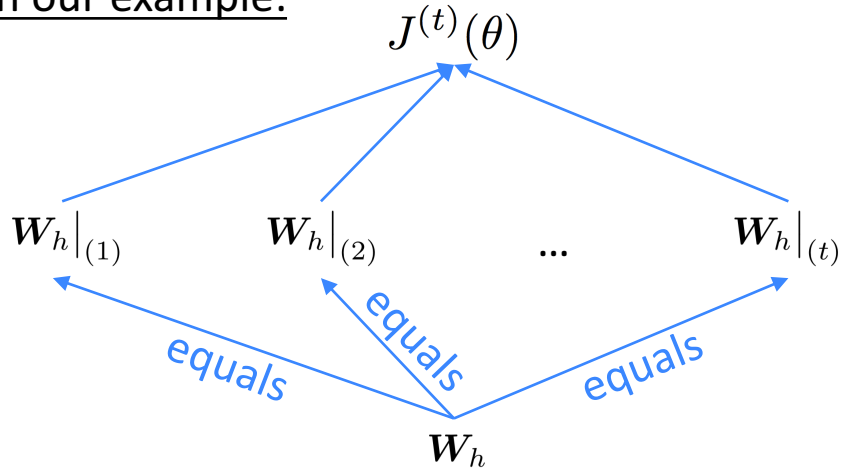
Source:
https://www.khanacademy.org/math/multivariable-calculus/multivariable-derivatives/differentiating-vector-valued-functions/a/multivariable-chain-rule-simple-version

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:

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

In our example:



Apply the multivariable chain rule:

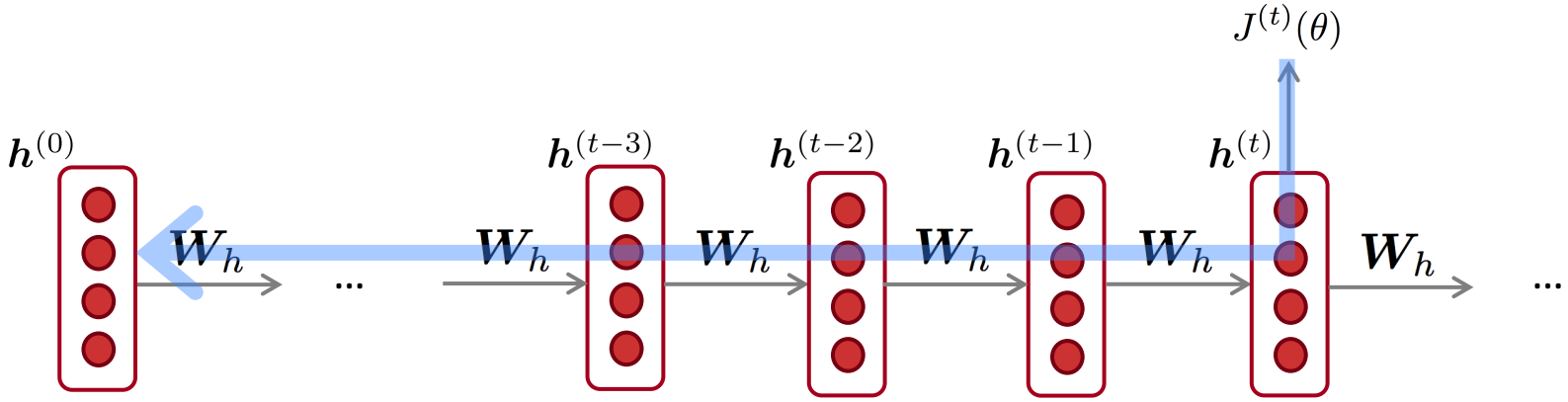
$$\frac{\partial J^{(t)}}{\partial W_h} = \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial W_h}\bigg|_{(i)} \frac{\partial W_h|_{(i)}}{\partial W_h}$$

= 1

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

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

Backpropagation for RNNs



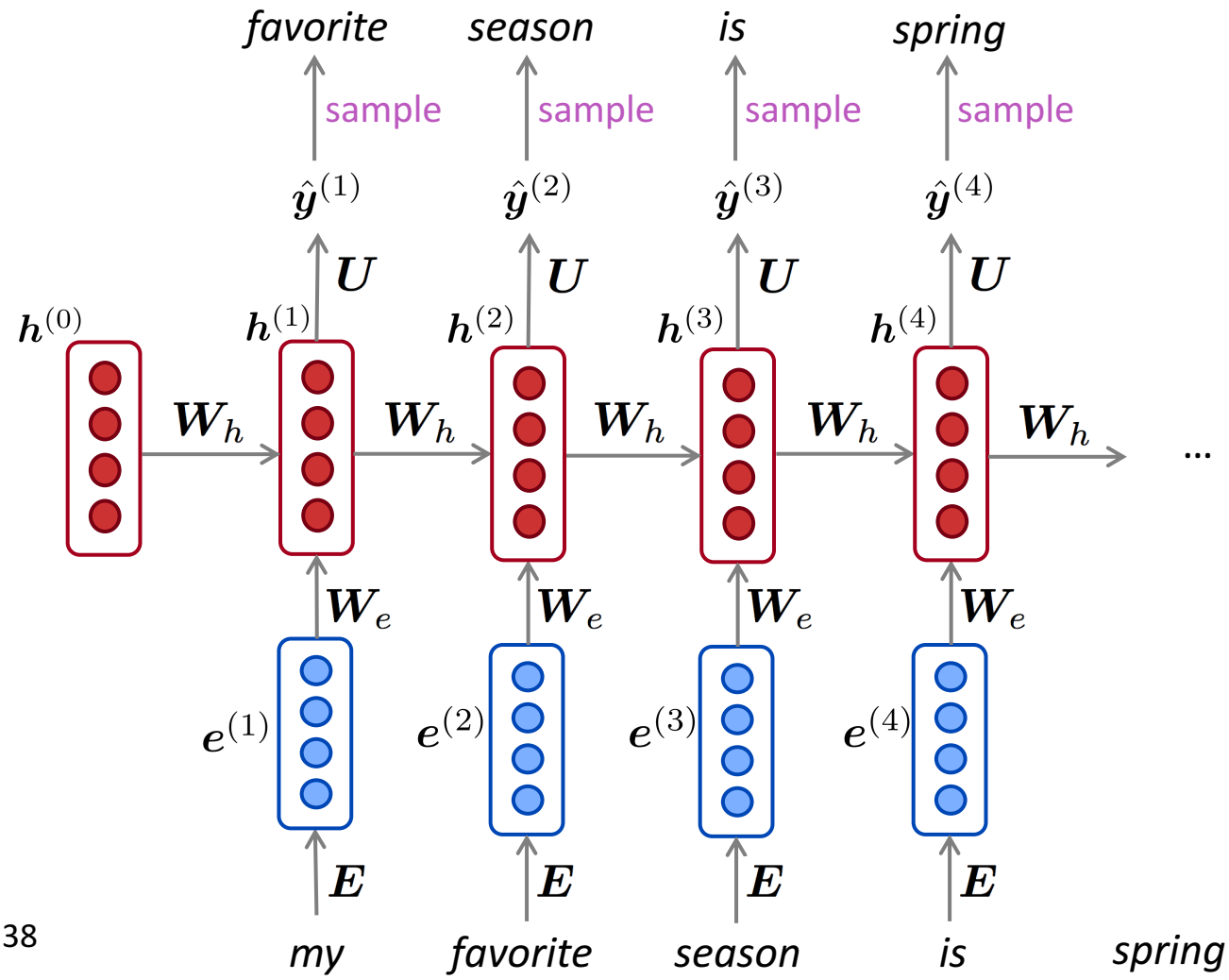
$$\frac{\partial J^{(t)}}{\partial \boldsymbol{W_h}} = \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial \boldsymbol{W_h}}\Big|_{(i)}$$

Question: How do we calculate this?

Answer: Backpropagate over timesteps *i*=*t*,…,0, summing gradients as you go.
This algorithm is called **"backpropagation through time"**

Generating text with a RNN Language Model

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



Generating text with a RNN Language Model

- Let's have some fun!
- You can train a RNN-LM on any kind of text, then generate text in that style.
- RNN-LM trained on Obama speeches:

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.

Source: https://medium.com/@samim/obama-rnn-machine-generated-political-speeches-c8abd18a2ea0

Generating text with a RNN Language Model

- Let's have some fun!
- You can train a 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

Evaluating Language Models

- The traditional evaluation metric for Language Models is perplexity.

$$\text{PP} = \underbrace{\prod_{t=1}^{T} \left(\frac{1}{\sum_{j=1}^{|V|} y_j^{(t)} \cdot \hat{y}_j^{(t)}} \right)}_{\text{Inverse probability of dataset}}^{1/T}$$

Normalized by number of words

- Lower is better!
- In Assignment 2 you will show that minimizing perplexity and minimizing the loss function are equivalent.

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 subcomponent of other NLP systems:
  - Speech recognition
    - Use a LM to generate transcription, conditioned on audio
  - Machine Translation
    - Use a LM to generate translation, conditioned on original text
  - Summarization
    - Use a LM to generate summary, conditioned on original text

These systems are called *conditional Language Models*

- Language Modeling is a benchmark task that helps us measure our progress on understanding language

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

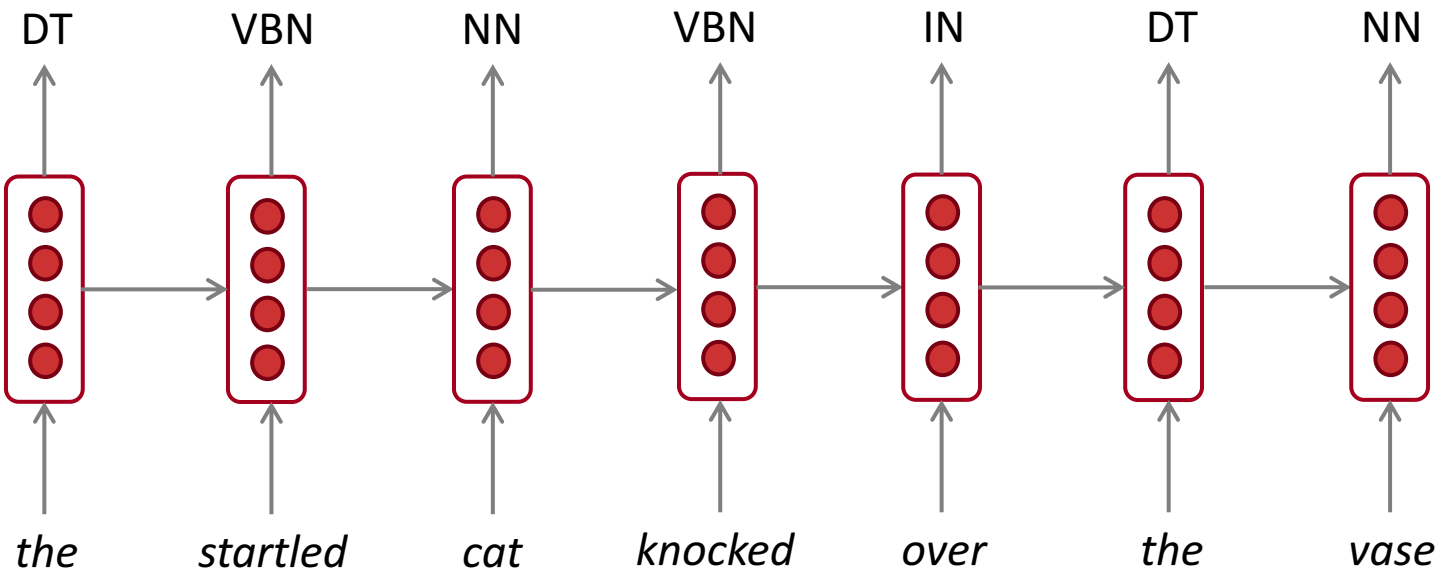
- Recurrent Neural Network ≠ Language Model

- We've shown that RNNs are a great way to build a LM.

- But RNNs are useful for much more!

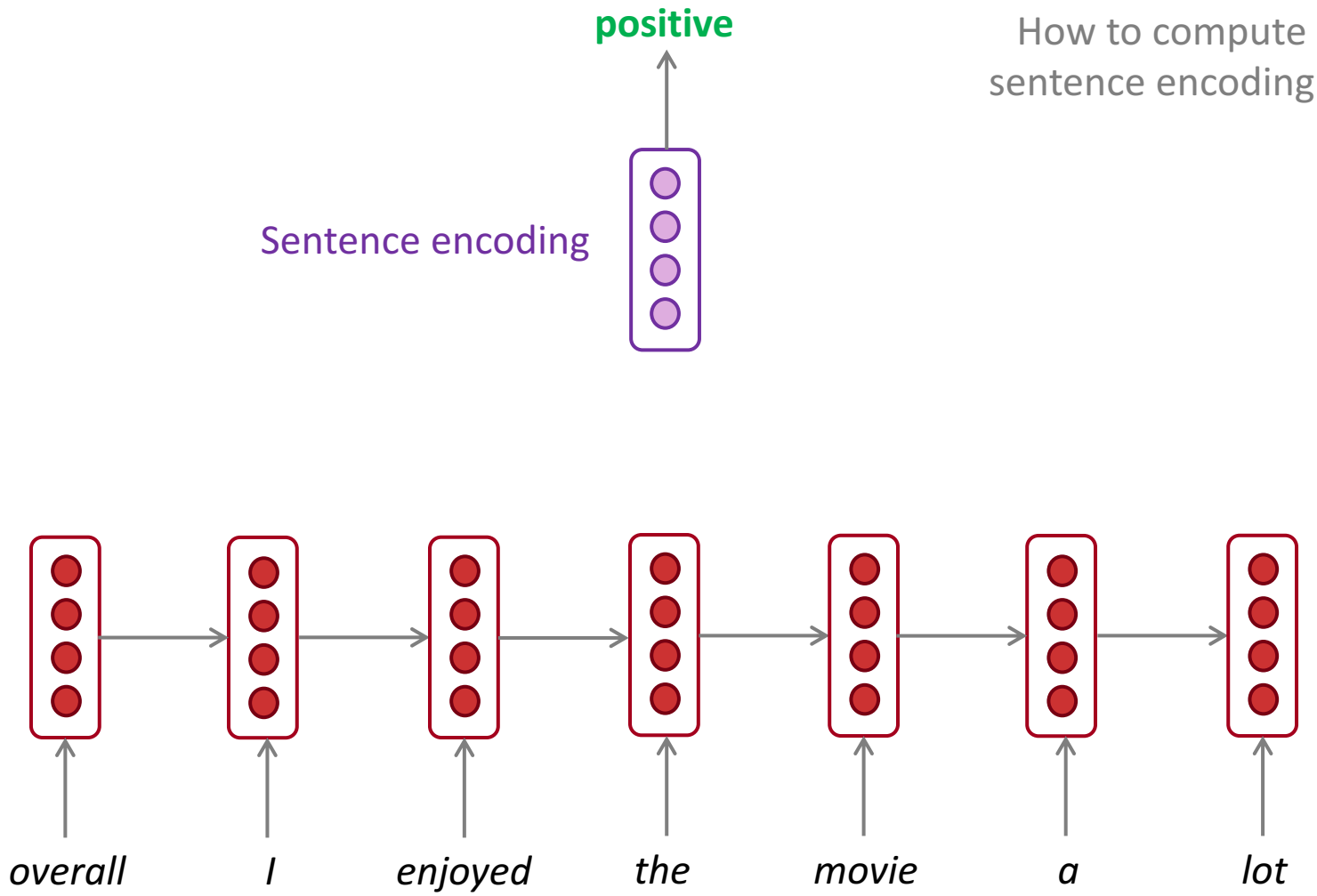
RNNs can be used for tagging

e.g. part-of-speech tagging, named entity recognition



RNNs can be used for sentence classification

e.g. sentiment classification



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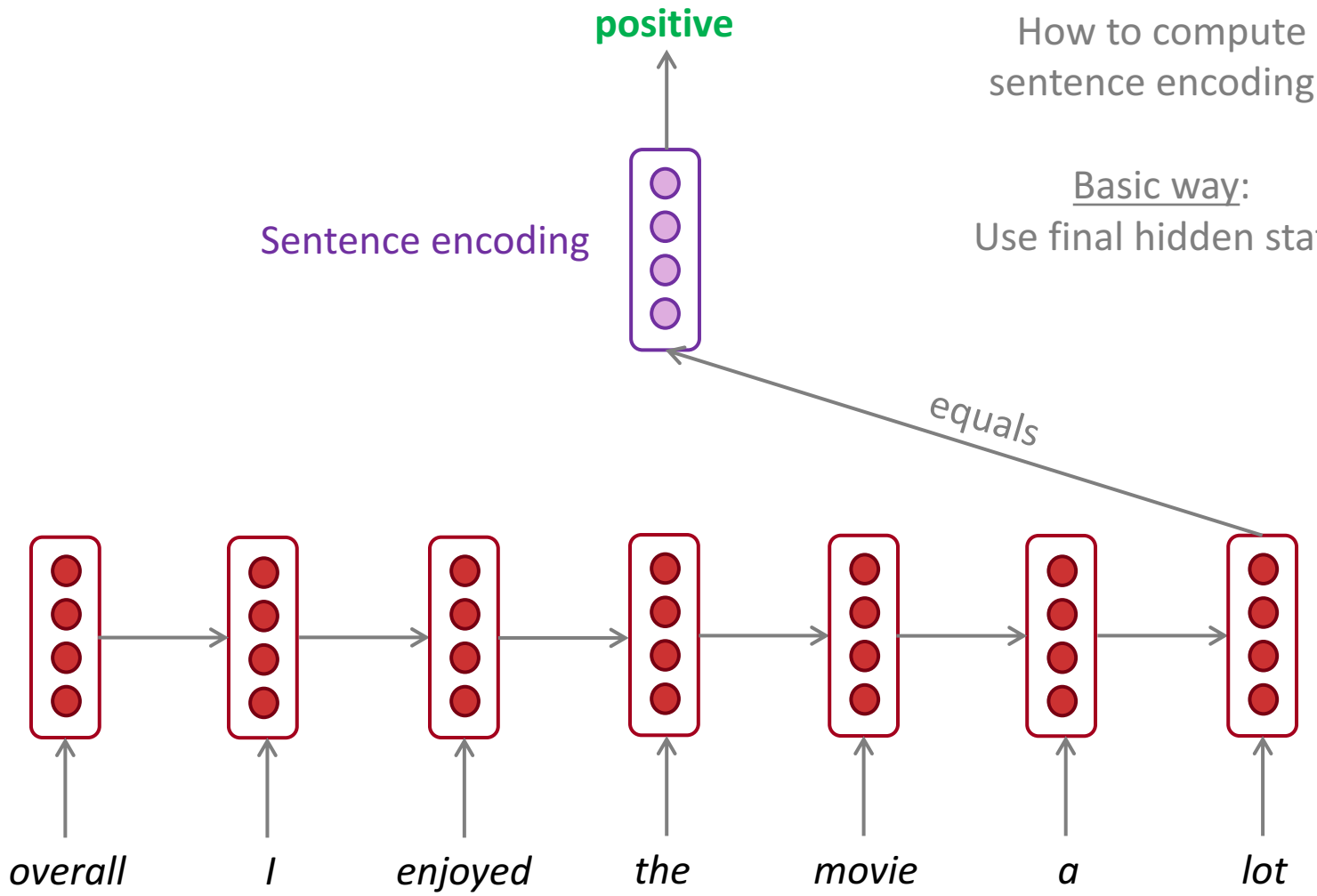

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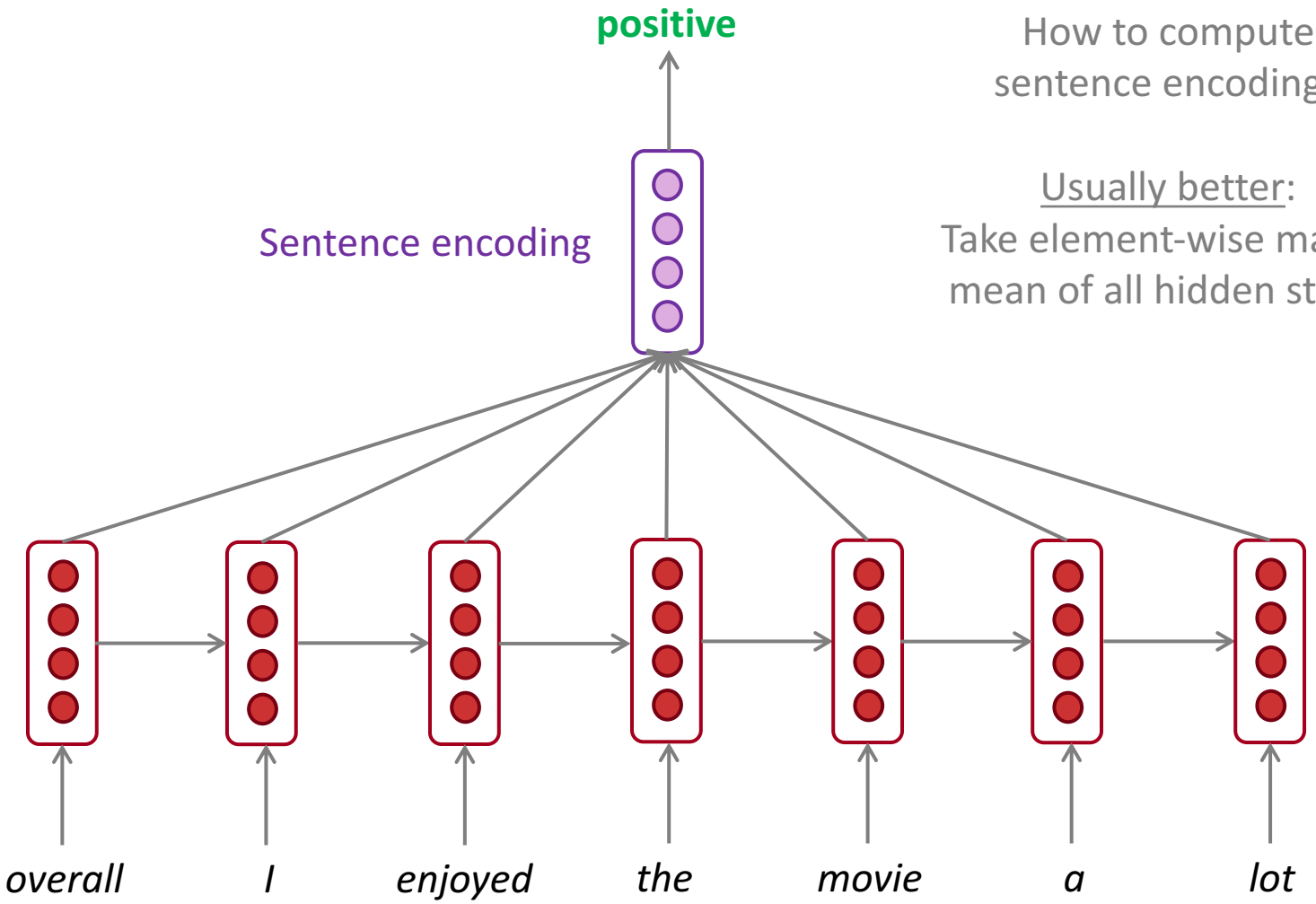
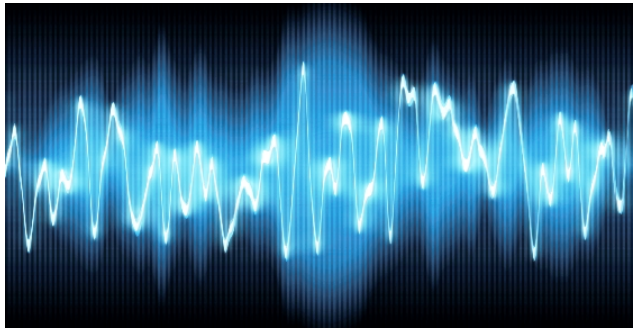
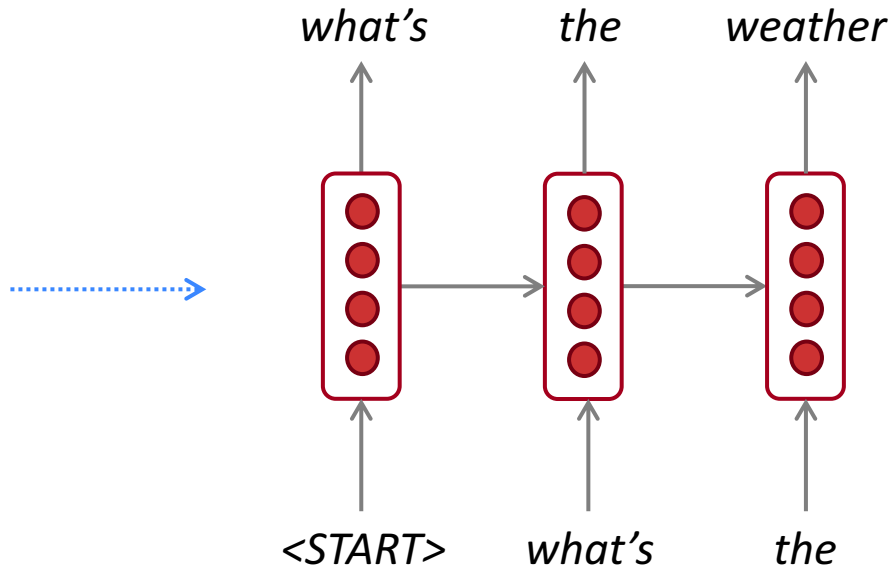
e.g. sentiment classification



RNNs can be used to generate text

e.g. speech recognition, machine translation, summarization

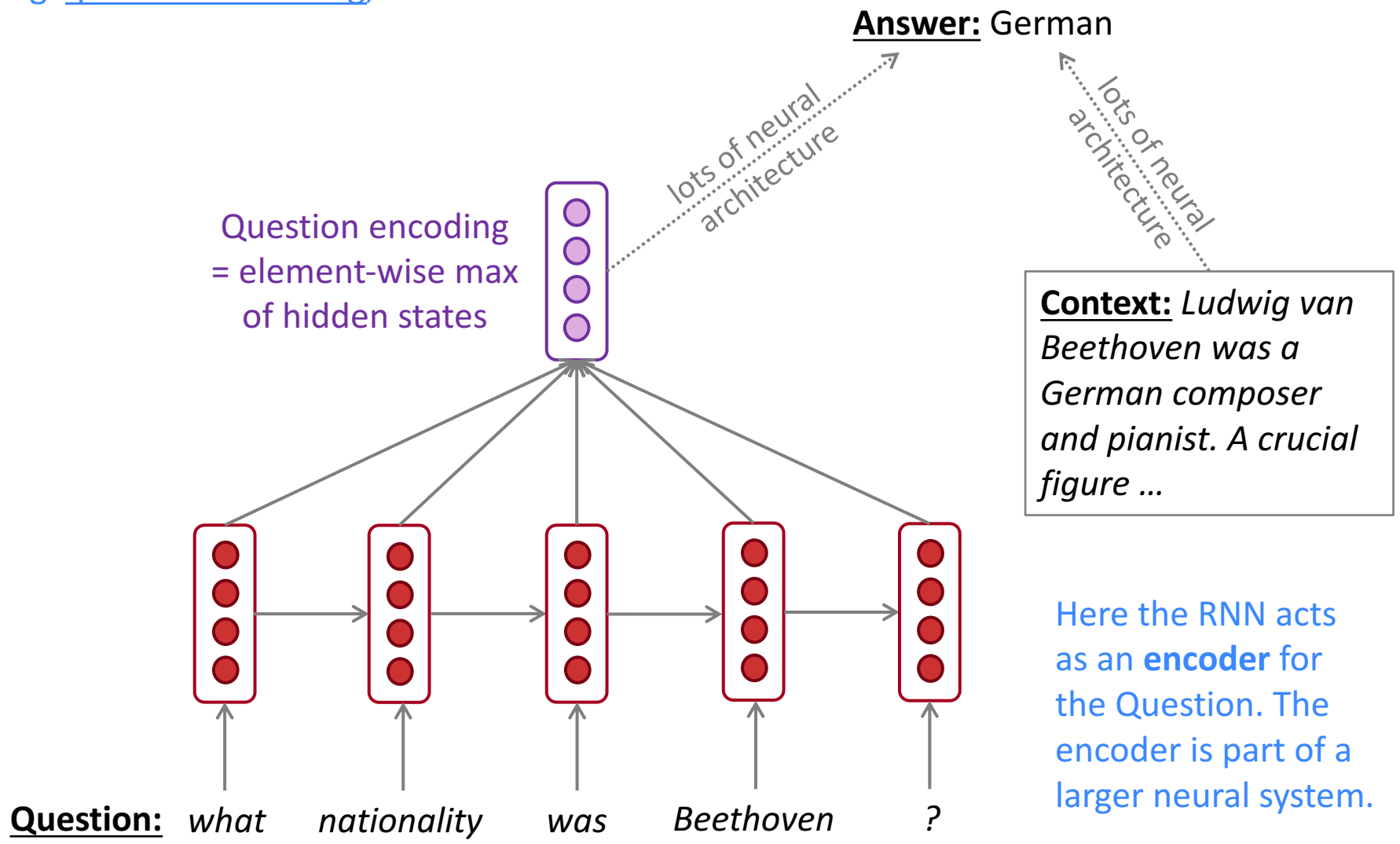




Remember: these are called "conditional language models".
We'll see Machine Translation in much more detail later.

RNNs can be used as an encoder module

e.g. question answering, machine translation



Here the RNN acts as an **encoder** for the Question. The encoder is part of a larger neural system.

A note on terminology

RNN described in this lecture = “vanilla RNN”

Next lecture: You will learn about other RNN flavors like GRU

and LSTM

and multi-layer RNNs

By the end of the course: You will understand phrases like *“stacked bidirectional LSTM with residual connections and self-attention”*

Next time

- Problems with RNNs!
  - Vanishing gradients

- Fancy RNN variants!
  - LSTM
  - GRU
  - multi-layer
  - bidirectional