CS 1671/2071
Human Language Technologies

Session 13: Neural networks, part 2

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February 24, 2025

University of Pittsburgh | School of Computing and Information

Course logistics: homework

- Thanks for your Homework 2 submissions
- Kaggle results on private leaderboard

BridgetBrinkman	0.672
Abe	0.672
César Guerra-Solano	0.663
braynguyen	0.663
Stephen Gwon	0.655
Jeremy Luu	0.646
Jal355	0.620
Benjup	0.586

Course logistics: project

- Project proposal due **this Fri Feb 28**
- Set of 8 questions to answer with a PDF report
- Think about how you would apply approaches we have covered so far (n-gram feature extraction, logistic regression, n-gram language modeling) to your task
- Feel free to email or book office hours with Michael to discuss
- Peer review where you will rate your own performance and the performance of other group members
  - Not used for grading, just to identify and address any issues

Course logistics

- This Wed Feb 26, Norah Almousa will be giving the lecture
  - Michael will be at a workshop downtown (feel free to still email me, etc)

Structure of this course

MODULE 1	Prerequisite skills for NLP	text normalization, linear alg., prob., machine learning	
	Approaches	**How text is represented**	**NLP tasks**
MODULE 2	statistical machine learning	n-grams	language modeling text classification
MODULE 3	neural networks	static word vectors	language modeling text classification
MODULE 4			
MODULE 5	NLP applications and ethics	machine translation, chatbots, information retrieval, bias	

A brief history of NLP

Sentences in Russian are punched into standard cards for feeding into the electronic data processing machine for translation into English

The Georgetown-IBM Experiment.
Credit: John Hutchins

- 1950s: **foundations**
  - Turing Test ("Computing Machinery and Intelligence" paper)
  - Georgetown-IBM Experiment translating Russian to English
- 1960s-1980s: **symbolic reasoning**
  - Processing language with hand-built rules
- 1990s-2010s: **statistical NLP**
  - Learn patterns from large corpora (feature-based machine learning)
- 2000s-today: **neural NLP**
  - Powerful models of language from "deep" layers of neural networks trained on tons of text

Lecture overview: neural networks, part 1

- Word embeddings as input to neural networks
- Training neural networks
- Recurrent neural networks (RNNs)
- Review activity
- (If time allows) project work time

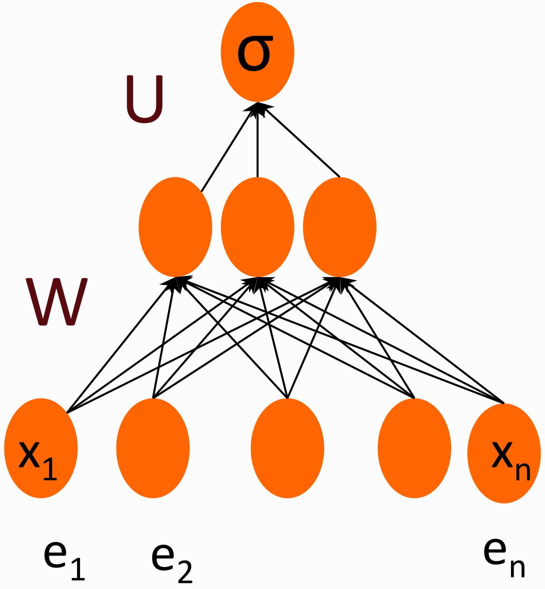
Feedforward neural networks with word embedding input

Even better: representation learning

The real power of deep learning comes from the ability to **learn** features from the data

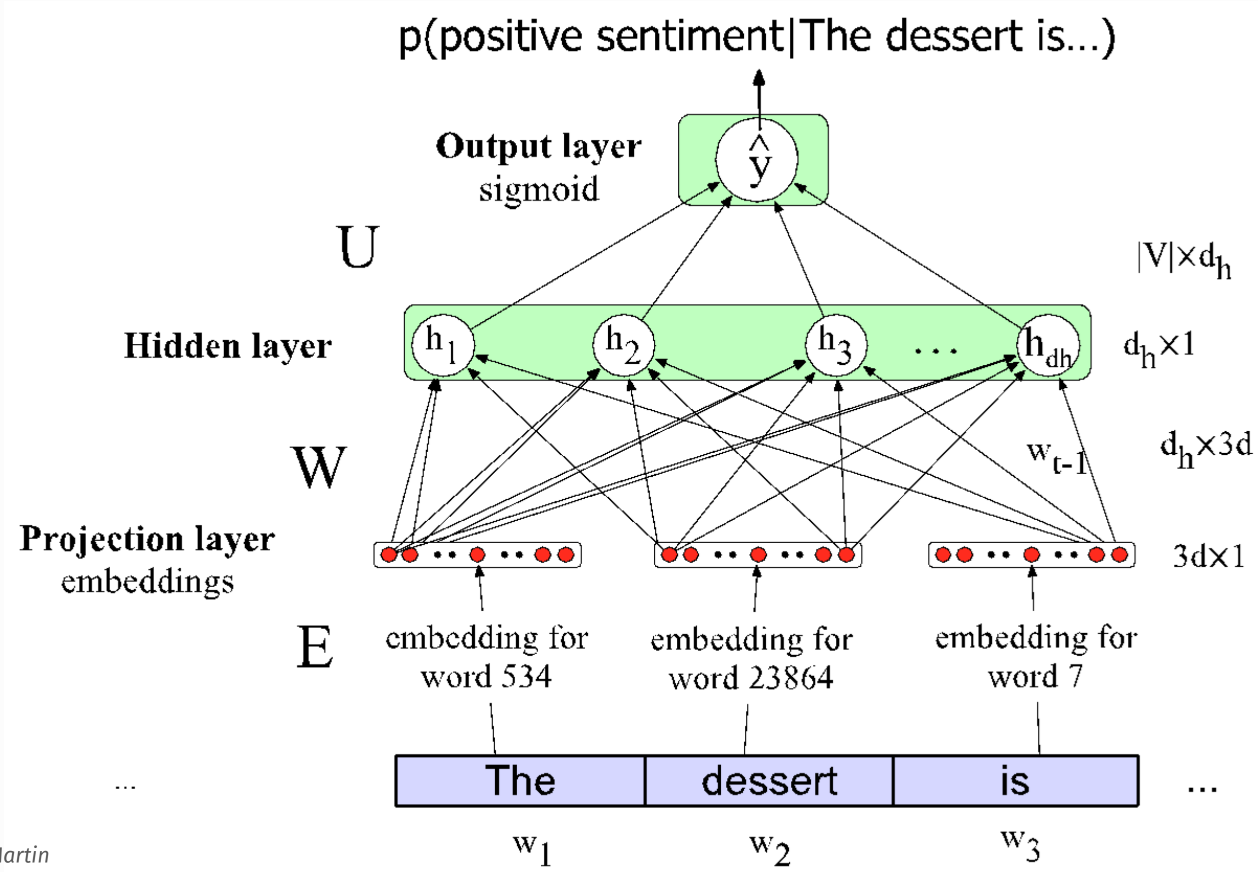
Instead of using hand-built human-engineered features for classification

Use learned representations like embeddings!



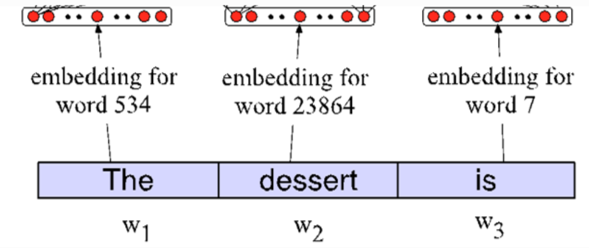
Slide adapted from Jurafsky & Martin

Neural net classification with embeddings as input features!



Slide adapted from Jurafsky & Martin

Issue: texts come in different sizes



This assumes a fixed size length (3)!
Kind of unrealistic.
Some simple solutions:

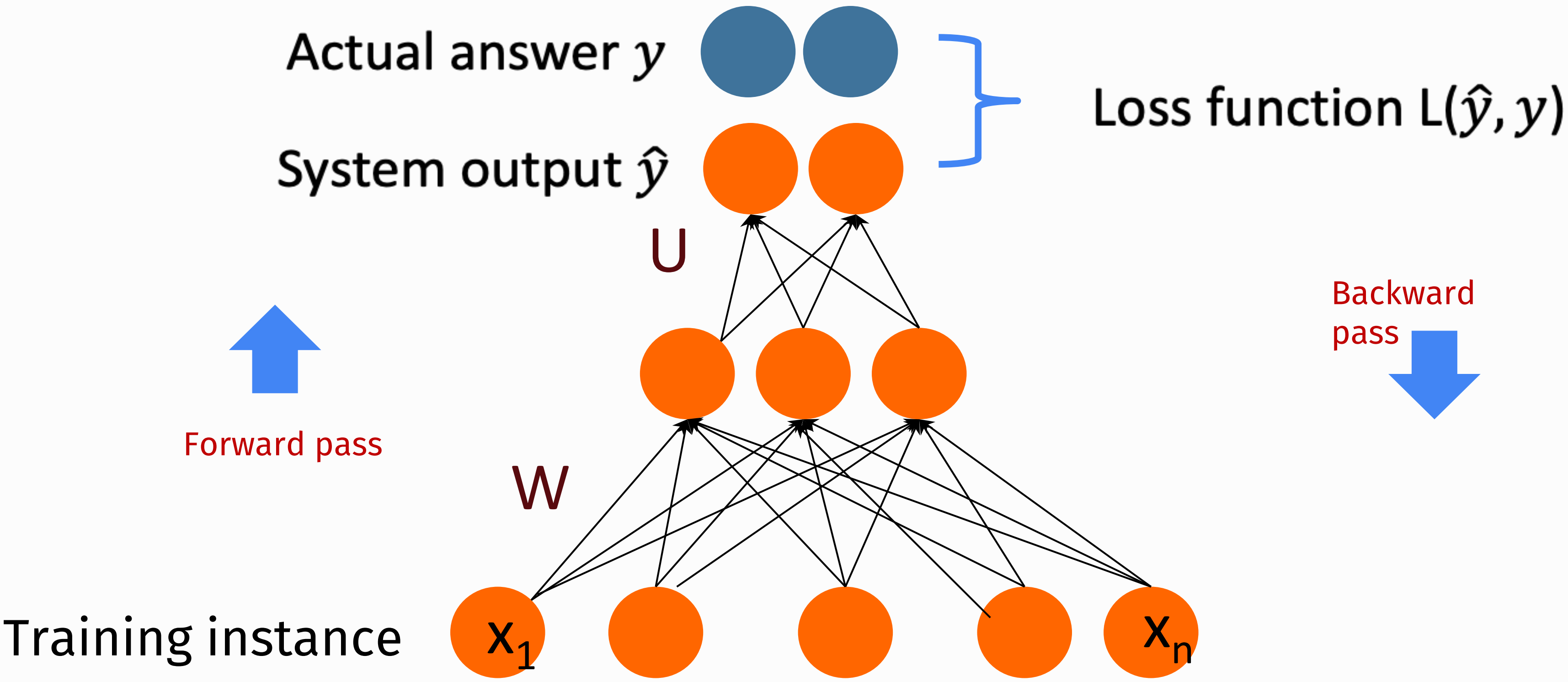
1. Make the input the length of the longest review
    - If shorter then pad with zero embeddings
    - Truncate if you get longer reviews at test time

2. Create a single "sentence embedding" (the same dimensionality as a word) to represent all the words
    - Take the mean of all the word embeddings
    - Take the element-wise max of all the word embeddings
        - For each dimension, pick the max value from all words

Slide adapted from Jurafsky & Martin

Training feedforward neural networks

Intuition: training a 2-layer Network



Slide adapted from Jurafsky & Martin

Remember stochastic gradient descent from the logistic regression lecture—find gradient and optimize

Slide credit: David Mortensen

The Intuition Behind Training a 2-Layer Network

For every training tuple (x, y)

1. Run **forward** computation to find the estimate $\hat{y}$
2. Run **backward** computation to update weights
    - For every output node
        - Compute the loss L between true y and estimated $\hat{y}$
        - For every weight w from the hidden layer to the output layer: update the weights
    - For every hidden node
        - Assess how much blame it deserves for the current answer
        - From every weight w from the input layer to the hidden layer
        - Update the weight

Slide credit: David Mortensen

Computing the gradient requires finding the derivative of the loss with respect to each weight in every layer of the network. **Error backpropagation through computation graphs.**

Slide credit: David Mortensen

Reminder: gradient descent for weight updates

Use the derivative of the loss function with respect to weights $\frac{d}{dw}L(f(x;w),y)$

To tell us how to adjust weights for each training item

- Move them in the opposite direction of the gradient

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \eta \frac{d}{dw} L_{CE}(f(\mathbf{x};\mathbf{w}),y)$$

- For logistic regression

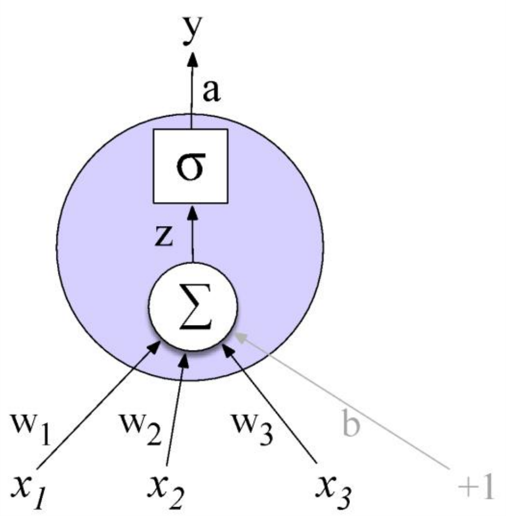
$$\frac{\partial L_{\mathrm{CE}}(\hat{y},y)}{\partial w_j} = [\sigma(w \cdot x + b) - y]x_j$$

Slide adapted from Jurafsky & Martin

Where did that derivative come from?

Using the chain rule of derivates! $f(x) = u(v(x))$

$$\frac{df}{dx} = \frac{du}{dv} \cdot \frac{dv}{dx}$$



Derivative of the weighted sum

Derivative of the Activation

Derivative of the Loss

$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial z} \frac{\partial z}{\partial w_i}$$

Slide adapted from Jurafsky & Martin

How can I find that gradient for every weight in the network?

These derivatives on the prior slide only give the updates for one weight layer: the last one!

What about deeper networks? For training, we need the derivative of the loss with respect to each weight in every layer of the network

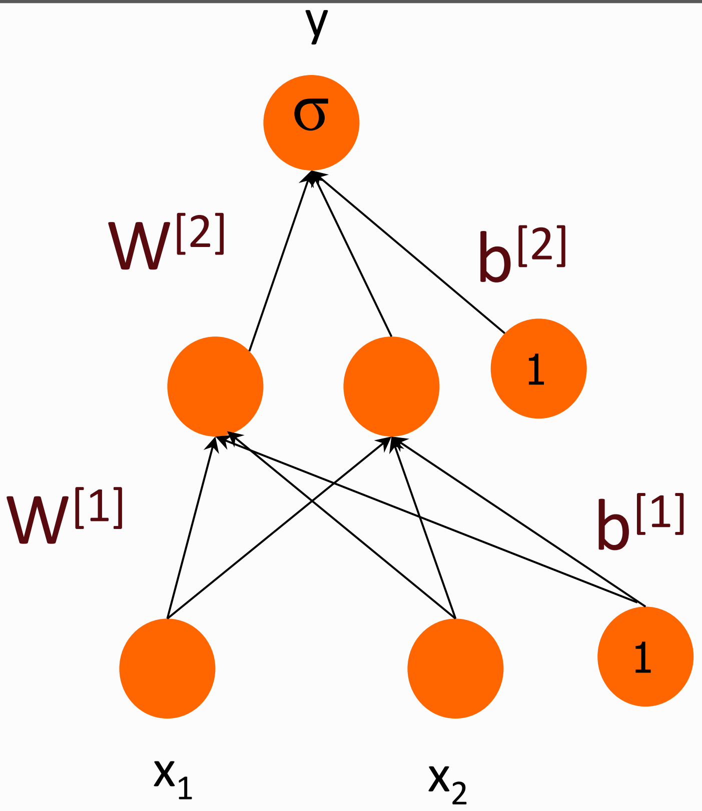
- Lots of layers, different activation functions?
- But the loss is computed only at the very end of the network!

Solution:

- Even more use of the chain rule!!
- This process is called **error backpropagation** (Rumelhart, Hinton, Williams, 1986)

Slide adapted from Jurafsky & Martin

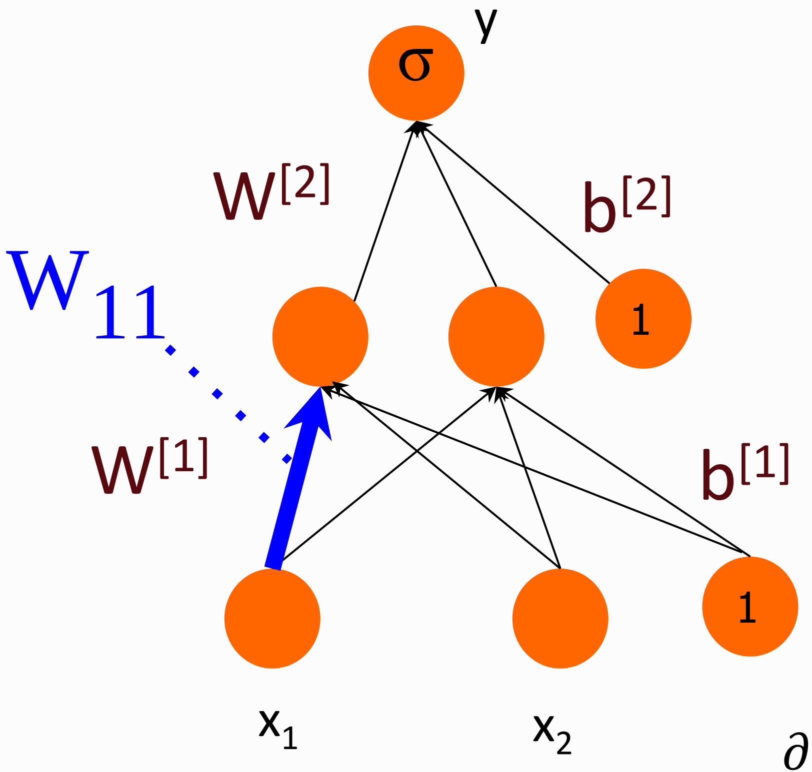
Backward differentiation on a two layer network



$$
\begin{aligned}
z^{[1]} &= W^{[1]}\mathbf{x} + b^{[1]} \\
a^{[1]} &= \mathrm{ReLU}(z^{[1]}) \\
z^{[2]} &= W^{[2]}a^{[1]} + b^{[2]} \\
a^{[2]} &= \sigma(z^{[2]}) \\
\hat{y} &= a^{[2]}
\end{aligned}
$$

Slide adapted from Jurafsky & Martin

Backward differentiation on a two layer network



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\hat{y} &= a^{[2]}
\end{aligned}
$$

$$\frac{\partial L}{\partial W_{11}} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial a^{[1]}} \cdot \frac{\partial a^{[1]}}{\partial z^{[1]}} \cdot \frac{\partial z^{[1]}}{\partial W_{11}^{[1]}}$$

Slide adapted from Jurafsky & Martin

Summary

For training, we need the derivative of the loss with respect to weights in early layers of the network

- But loss is computed only at the very end of the network!

Solution: **backpropagation**

Given the derivatives of all the functions in it we can automatically compute the derivative of the loss with respect to these early weights.

Recurrent neural networks (RNNs)

FFNNs take an input of fixed dimensions—a fixed number of features, a fixed number of tokens

Slide credit: David Mortensen

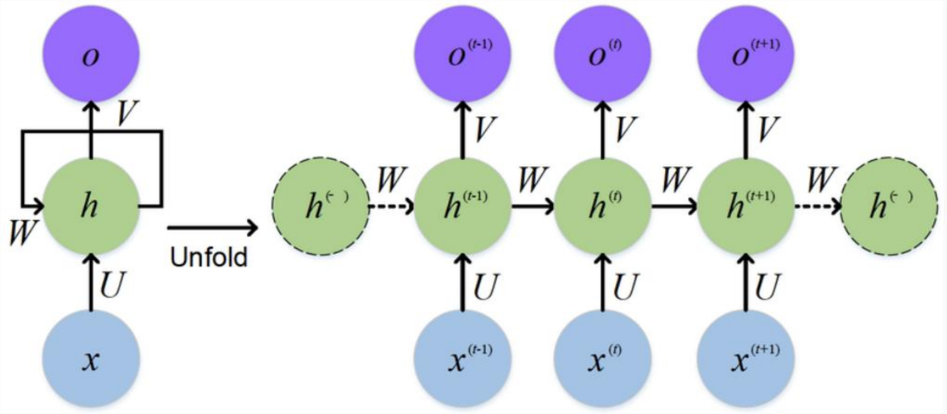
The number tokens in a text—even a sentence—can be **arbitrarily large** (or short)

Slide credit: David Mortensen

RNNs help us address this issue

The architecture of an RNN

- Special kind of multilayer neural network for modeling sequences
- Hidden layers between the input and output receive input not just form the input layer, **but also from the hidden layer at a preceding timestep**
- RNNs can "remember" information from earlier on



Slide credit: David Mortensen

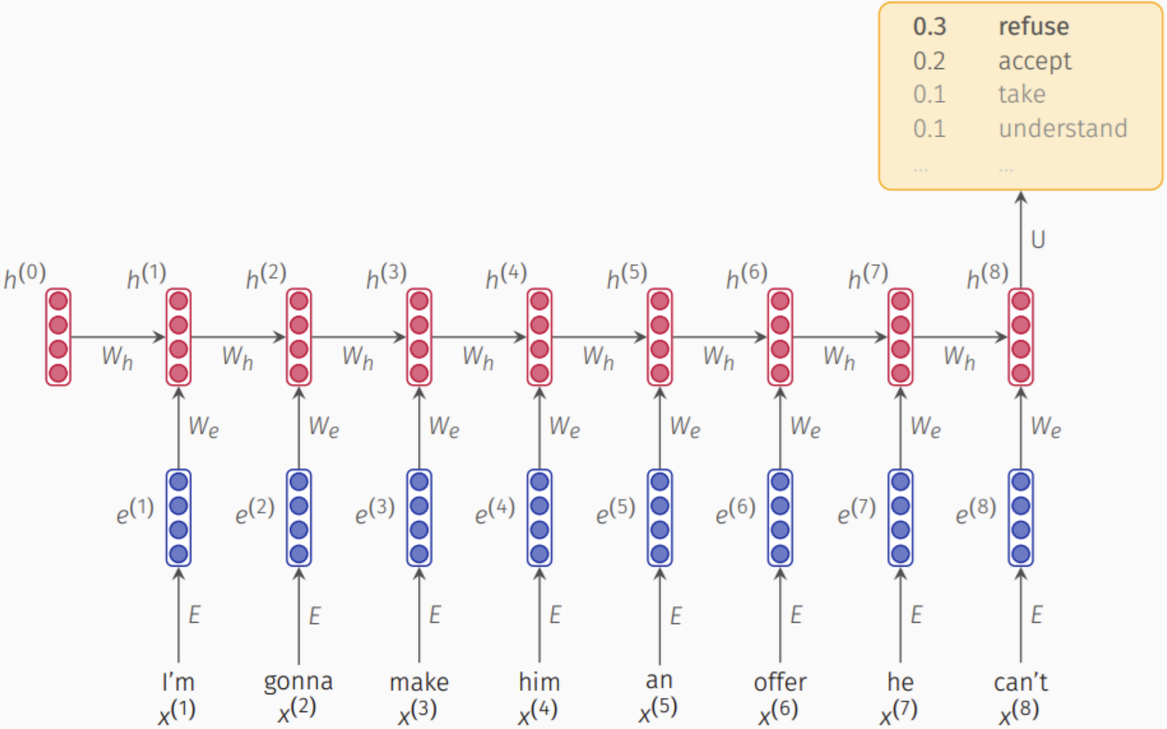
An RNN Language Model

output distribution
$\hat{y}^{(t)} = \text{softmax}(Uh^{(t)} + b_2) \in \mathbb{R}^{|V|}$

hidden states
$h^{(t)} = \sigma(W_h h^{(t-1)} + W_e e^{(t)} + b_1)$
$h^{(0)}$ is the initial hidden state

word embeddings
$e^{(t)} = Ex^{(t)}$

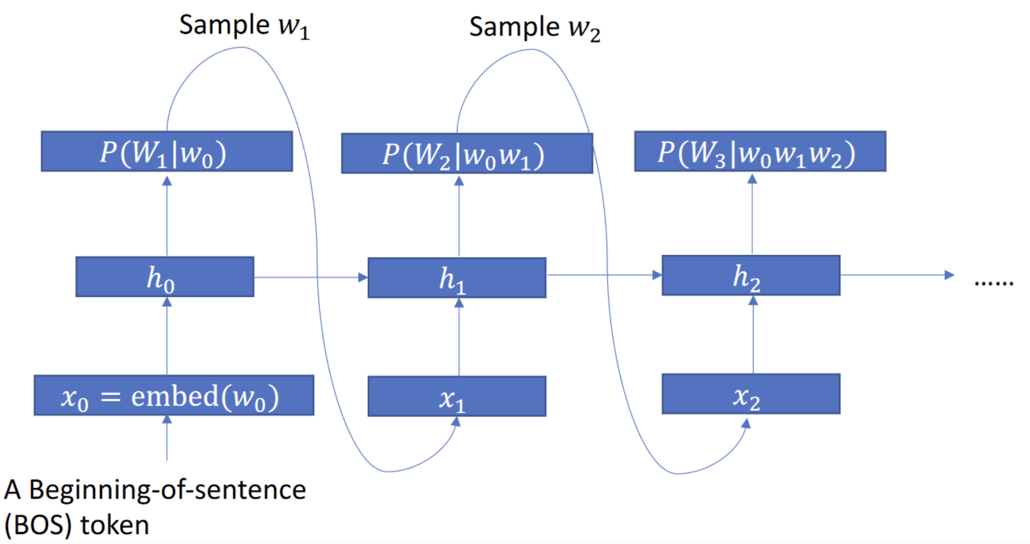
one-hot vectors
$x^{(t)} \in \mathbb{R}^{|V|}$



Slide credit: David Mortensen

Generation with RNN LMs

- At each time step t, we sample w_t from $P(W_t| \dots)$, and feed it to the next timestep!
- LM with this kind of generation process is called autoregressive LM



Slide adapted from Tianxing He

Training an RNN Language Model

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

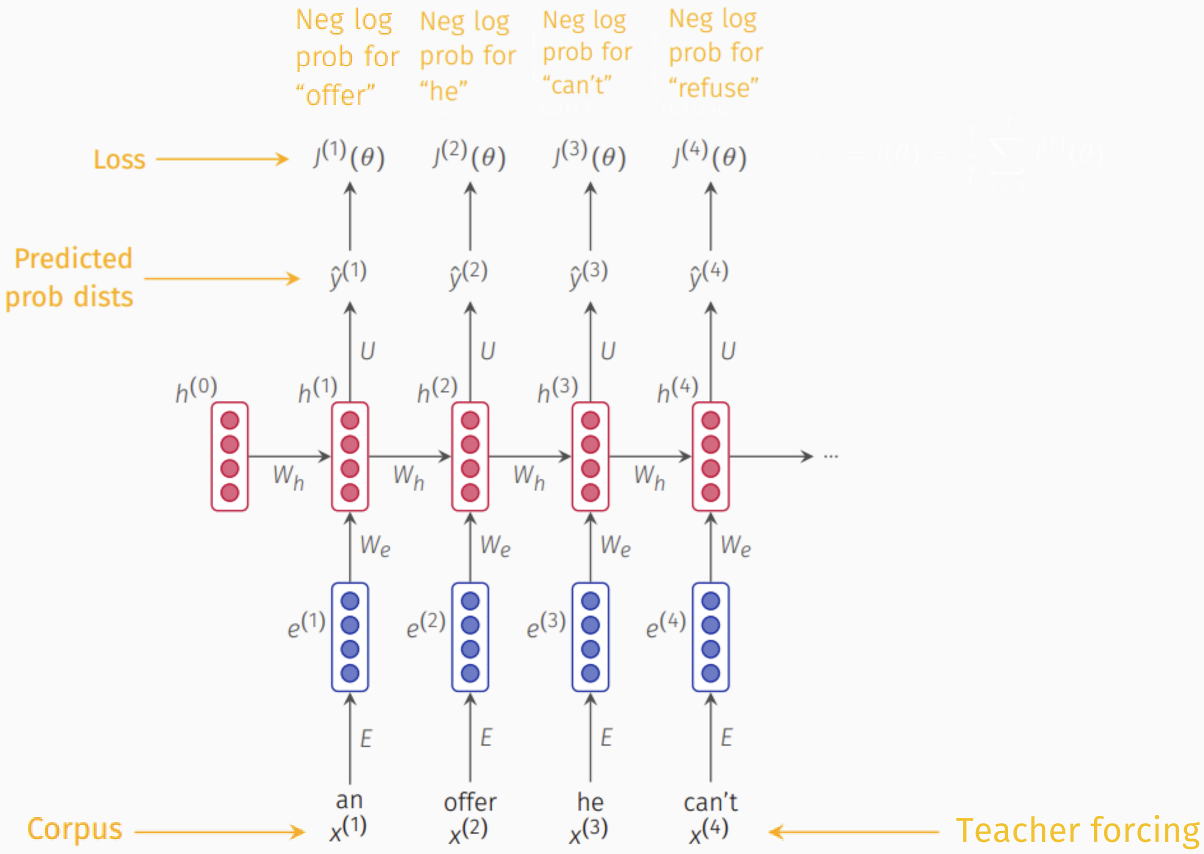
$$J^{(t)}(\theta) = CE(\mathbf{y}^{(t)}, \hat{\mathbf{y}}^{(t)}) = -\sum_{w \in V} \mathbf{y}_w^{(t)} \log \hat{\mathbf{y}}_w^{(t)} = -\log \hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)}$$

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

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

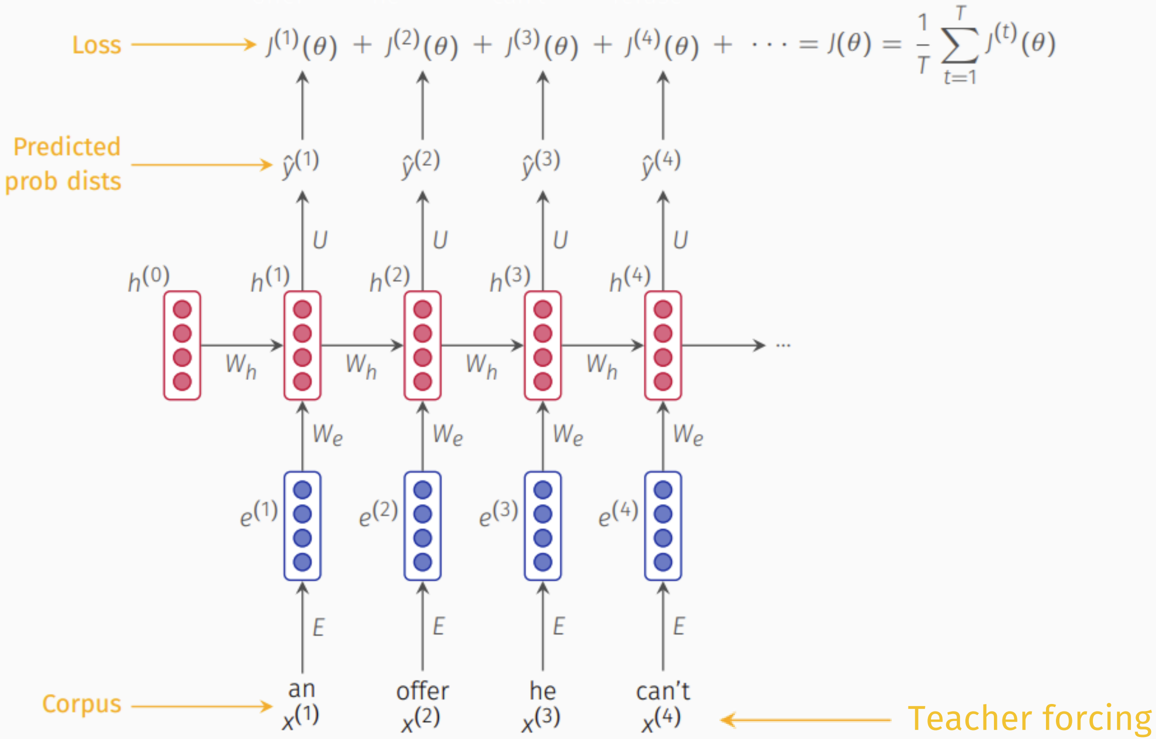
Slide credit: David Mortensen

Training an RNN Language Model



Slide credit: David Mortensen

Training an RNN Language Model



Slide credit: David Mortensen

Computing Loss and Gradients in Practice

- In principle, we could compute loss and gradients across the whole corpus $(x^{(1)}, \ldots, x^{(T)})$ but that would be incredibly expensive!

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

- Instead, we usually treat $x^{(1)}, \ldots, x^{(T)}$ as a document, or even a sentence
- This works much better with **Stochastic Gradient Descent**, which lets us compute loss and gradients for little chunks and update as we go.
- Actually, we do this in batches: compute $J(\theta)$ for a batch of sentences; update weights; repeat.

Slide credit: David Mortensen

We Will Skip the Details of Backpropogation in RNNs for Now

- The fact that training RNNs involves backpropagation over timesteps, summing as you go, means that it (the **backpropagation through time** algorithm) is a bit more complicated than backpropagation in feedforward neural networks.
- We will skip these details for now, but you will want to learn them if you are doing serious work with RNNs.

Slide credit: David Mortensen

Review activity

These concepts are confusing!

I don’t expect you to understand the intuition of backpropagation or RNNs the first time around. With a group, decide which concept you are most comfortable with and which you find most confusing:

1. Neural network training and backpropagation
2. RNNs

Make a list of questions you have about the concept you are most confused about. Then find a group that is comfortable with the concept you find confusing. Maybe they can answer your questions! I am also available to answer questions.

Project work time