### CS 232: Artificial Intelligence

### Spring 2024

Prof. Carolyn Anderson Wellesley College

### Reminders

- Reading for Tuesday: <u>Illustrated Stable Diffusion blog</u> <u>post</u>
- Reading for Friday: Chiang (2023)
- Tensorflow version compatibility issues: check email I sent for how to downgrade Tensorflow to 2.13
  pip instal feasing formers
- My help hours today: 3:30-4:30
- My help hours Monday: 4-5:15
- Lyra's Sunday help hours: 4-6

### New Policy: Earn Bonus Late Days

You can earn bonus late days by attending a research talk. To be eligible:

- The talk must be on CS research or on research related to AI
- The talk must be live, not recorded (so you can ask questions)
- You must write a paragraph about the talk and what you learned and email it to me.

# Upcoming Talks



# **Upcoming Talks**





#### **Christine Doran**

Clockwork Language Verified email at clockworklanguage.com Corpus linguistics evaluation dialogue



Catherine Chen PhD Candidate at Brown University



Dr. Rachel Lomasky

DIRECTOR OF MACHINE LEARNING | MANIFOLD

Dr. Rachel Lomasky is Director of Machine Learning at Manifold, where she helps clients train and productionalize their machine learning algorithms.

Prior to Manifold, she was co-founder and Chief Data Officer of WEVO Conversion, a platform for digital marketers that uses AI to improve websites and search **Representation Learning** 

# How Do We Represent Text?

In the next homework assignment, you will try to improve our recipe classifier using neural networks instead of regression.

To feed text into a neural network, we need to turn it into numbers. In our regression classifier, we did this by **hand-crafting features**.



## **Representation Learning**

From now on, we're going to use neural networks to **learn representations** for us.



**Representation Learning**: a machine learning technique for extracted features (informative aspects) from data.

### Word Vectors

Idea: a word's meaning is based on its **distance** from other word meanings.

Each word = a vector (not just "good" or " $w_{45}$ ")

Similar words are "nearby in semantic space"

We build this space automatically by seeing which words are **nearby in text** 



### Word Embeddings

Which of these word pairs are most alike?

| sun    | - moon      | ſ     | Celestiol<br>bright<br>No | in the sk        | 5       |          |
|--------|-------------|-------|---------------------------|------------------|---------|----------|
| sun    | - lightbulb | 5     |                           |                  |         |          |
| sun    | - mystical  | 2     |                           |                  |         |          |
| moon   | lightbulb   | 3     |                           |                  |         |          |
| moon - | mystical    | 4     | nights =<br>twilight      | ne Mare<br>Supre | maturel | folklore |
| mystic | al lightbu  | alb 💧 |                           |                  |         |          |

# Word Embeddings

Imagine defining a large number of ways that words can be similar (*dimensions*). Maybe around 2000 ways?



### Word Embeddings

If we have good word embeddings, their geometric relationships should be meaningful:



https://www.cs.cmu.edu/~dst/WordEmbeddingDemo

Neural Networks with Word Embedding Features

#### Neural Net Classification with embeddings as input features!



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### Issue: texts come in different sizes





### Issue: texts come in different sizes

This assumes a fixed size length (3)!

Some simple solutions (more sophisticated solutions later)

•••

The

 $w_1$ 

embedding for

word 534

🌔 • • 🔴 • • 🔴 🗡

embedding for

word 23864

dessert

 $W_2$ 

embedding for

word 7

is

W<sub>3</sub>

- 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

# Solution 2: Average the word embeddings





# **Revisiting Our Classifier**



 $https://www.tiktok.com/@chelseaparlettpelleriti/video/7072586373064248622? is from_webapp = 1 \& sender_device = pc \& web_id = 7159271848050869802 \\ id = 715927184802 \\ id = 715927184802 \\ id = 71592718400 \\ id = 7$ 

# AI Tasks

Search

Uninformed Search Informed Search Adversarial Games Navigation Learning Under

Uncertainty

Classification

Regression

Sentiment Analysis

Neural Networks

**Image Classification** 

**Text Classification** 

Generation

Language Models

**Image Generation** 

Chatbots

Finetuning

**Prompt Engineering** 

We're moving into generation!

Language Modeling (Text Generation)

#### Neural Net Classification with embeddings as input features!



### Language Generation

So far we have used language models to predict the next word in a sequence and estimate the probability of a sentence.

How do we **generate** sentences?

### Language Generation

We sample words according to their estimated probabilities:

P(english | want) = .0011P(chinese | want) = .0065P(to | want) = .66 $P(eat \mid to) = .28$ P(food | to) = 0P(want | spend) = 0P(i | <s>) = .25

### Language Generation

- Start the sentence
- Sample a next word according to its probability
- 1g! jepresent beginning of sentence (s> I b) vaguess I want b) Keep going! want to to eat eat Chinese Chinese food food </s> I want to eat Chinese food