CS 540 Introduction to Artificial Intelligence
Natural Language Processing (before LLMs)

University of Wisconsin-Madison
Spring 2025

Announcements

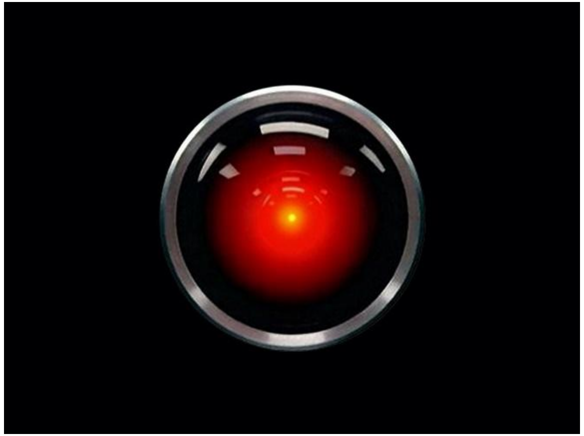
- **HW 2 online**:
  - Deadline **today 11:59PM**
- **HW 3**:
  - Deadline **Thursday Feb 13th at 11:59PM**
  - PCA
- Class roadmap:

NLP
Machine Learning: Introduction
Machine Learning: Unsupervised Learning I, II
Machine Learning: Linear regression

What is **NLP**?

Combining computing with human language. Want to:

- Answer questions
- Summarize or extract information
- Translate between languages
- Generate dialogue/language
- Write stories automatically



Why is it **hard**?

Many reasons:

- Ambiguity: *"Mary saw the duck with the telescope in the park".* Several meanings.
- Understanding of the world
  - "Bob and Joe are fathers".
  - "Bob and Joe are brothers".

Approaches to NLP

A brief history

- Symbolic NLP: 50’s to 90’s
- Statistical/Probabilistic: 90’s to present
  - Neural nets: 2010’s to present
  - Large Language Model (LLM): GPT etc.

Lots of progress!

Lots more to work to do

ELIZA program

Outline

- Introduction to language models
  - n-grams, training, evaluation, generation
- Word representations
  - One-hot, word embeddings, transformer-based

Language Models

- Basic idea: use probabilistic models to **assign a probability to a sentence W**

$$P(W) = P(w_1, w_2, \ldots, w_n) \text{ or } P(w_{\mathrm{next}} | w_1, w_2 \ldots)$$

- Goes back to Shannon
  - Information theory: letters

Zero-order approximation	XFOML RXKHRJFFJUJ ALPWXFWJXYJ FFJEYVJCQSGHYD QPAAMKBZAACIBZLKJQD
First-order approximation	OCRO HLO RGWR NMIELWIS EU LL NBNESEBYA TH EEI ALHENHTTPA OOBTTVA NAH BRL
Second-order approximation	ON IE ANTSOUTINYS ARE T INCTORE ST BE S DEAMY ACHIN D ILONASIVE TUCOOWE AT TEASONARE FUSO TIZIN ANDY TOBE SEACE CTISBE
Third-order approximation	IN NO IST LAT WHEY CRATICT FROURE BIRS GROCID PONDENOME OF DEMONSTURES OF THE REPTAGIN IS REGOACTIONA OF CRE
First-order word approximation	REPRESENTING AND SPEEDILY IS AN GOOD APT OR COME CAN DIFFERENT NATURAL HERE HE THE A IN CAME THE TO OF TO EXPERT GRAY COME TO FURNISHES THE LINE MESSAGE HAD BE THESE

Training The Model

Recall the chain rule of probability:

$$P(w_1, w_2, \ldots, w_n) = P(w_1)P(w_2|w_1)\ldots P(w_n|w_{n-1}\ldots w_1)$$

- How do we estimate these probabilities?
  - I.e., “training” in machine learning.
- From data (text corpus)
  - Can’t estimate reliably for long histories.

Training: Make Assumptions

- Markov assumption with shorter history:

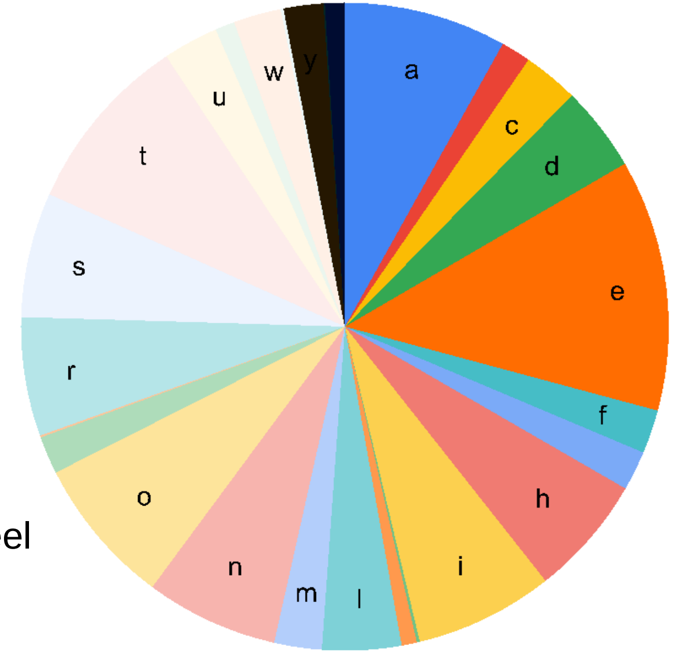
$$P(w_i|w_{i-1}w_{i-2}\ldots w_1) = P(w_i|w_{i-1}w_{i-2}\ldots w_{i-k})$$

- Present doesn’t depend on whole past
  - Just recent past, i.e., *context*.
  - What’s ***k=0?***

k=0: **Uni**gram Model

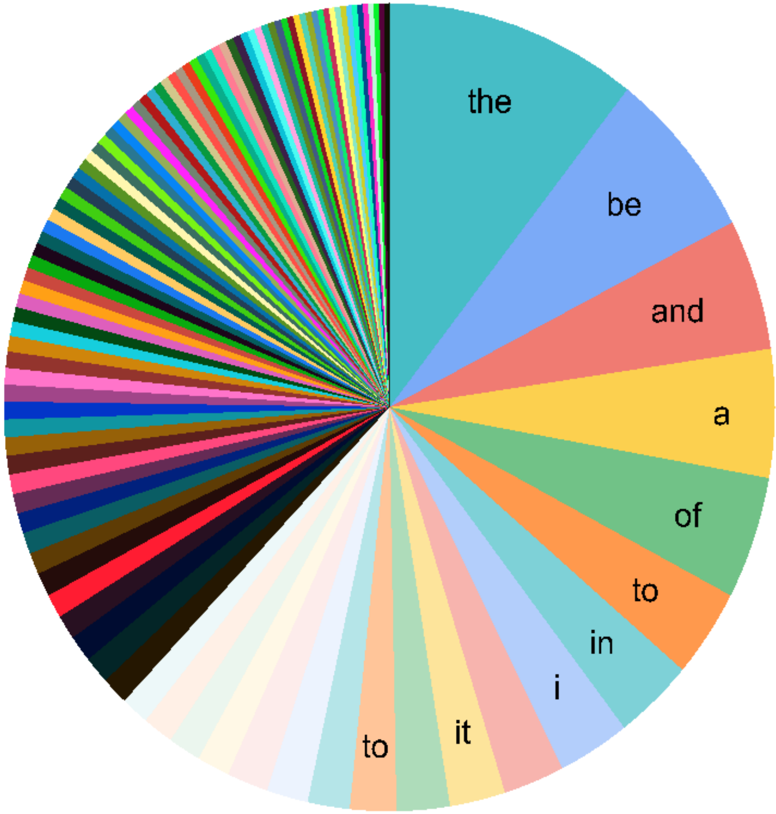
- Full independence assumption:
  - (Present doesn't depend on the past)

$$P(w_1, w_2, \ldots, w_n) = P(w_1)P(w_2)\ldots P(w_n)$$



The English letter frequency wheel

Unigram word model



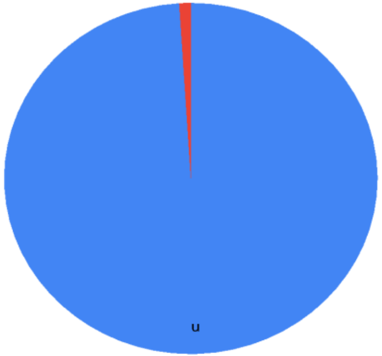
Example (from Dan Jurafsky's notes)

```
fifth, an, of, futures, the, an, incorporated, a,
a, the, inflation, most, dollars, quarter, in, is,
mass thrift, did, eighty, said, hard, 'm, july,
bullish that, or, limited, the
```

k=1: **Bi**gram Model

- Markov Assumption:
  - (Present depends on immediate past)

$$P(w_1, w_2, \ldots, w_n) = P(w_1)P(w_2|w_1)P(w_3|w_2)\ldots P(w_n|w_{n-1})$$



$p(.|q)$: the "after q" wheel

$p(.|j)$: the "after j" wheel

```
texaco, rose, one, in, this, issue,
is, pursuing, growth, in, a, boiler,
house, said, mr., gurria, mexico, 's,
motion, control, proposal, without,
permission, from, five, hundred,
fifty, five, yen outside, new, car,
parking, lot, of, the, agreement,
reached this, would, be, a, record,
november
```

k=n-1: **n-**gram Model

Can do trigrams, 4-grams, and so on

- More expressive as *n* goes up
- Harder to estimate

Training: just count? I.e, for bigram:

$$P(w_i|w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i)}{\text{count}(w_{i-1})}$$

Simple "generative AI" from letter bigram (Markov Chain)

Writing = sampling

- Say we start with q
- Sample from $P(\,\cdot \mid q)$: spin the "after q" wheel  , we get u
- Sample from $P(\,\cdot \mid u)$: spin the "after u" wheel, say we get e
- Sample from $P(\,\cdot \mid e)$: spin the "after e" wheel, say we get r
- ...

Sampling Shakespeare unigram LM

- To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have
- Every enter now severally so, let
- Hill he late speaks; or! a more to leg less first you enter
- Will rash been and by I the me loves gentle me not slavish page, the and hour; ill let
- Are where exeunt and sighs have rise excellency took of .. sleep knave we. near; vile like

Jurafsky & Martin, Speech and language processing, Prentice Hall, 2000.

Sampling Shakespeare bigram LM

- What means, sir. I confess she? then all sorts, he is trim, captain.
- Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow.
- What we, hath got so she that I rest and sent to scold and nature bankrupt, nor the first gentleman?
- Enter Menenius, if it so many good direction found'st thou art a strong upon command of fear not a liberal largess given away, Falstaff! Exeunt

Jurafsky & Martin, Speech and language processing, Prentice Hall, 2000.

Sampling Shakespeare trigram LM

- Sweet prince, Falstaff shall die. Harry of Monmouth's grave.
- This shall forbid it should be branded, if renown made it empty.
- What ist that cried?
- Indeed the duke; and had a very good friend.

Jurafsky & Martin, Speech and language processing, Prentice Hall, 2000.

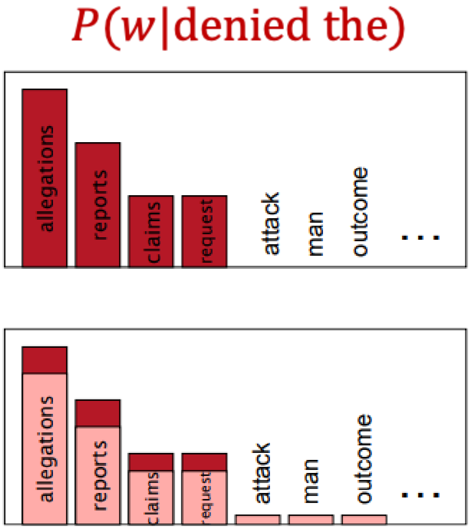
n-gram Training

Issues:

$$P(w_i|w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i)}{\text{count}(w_{i-1})}$$

- **1**. Multiply tiny numbers?
  - **Solution**: use logs; add instead of multiply
- **2.** n-grams with zero probability?
  - **Solution**: smoothing

$$P(w_i|w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i) + 1}{\text{count}(w_{i-1}) + V}$$



Dan Klein

Break & Quiz

Q 1.1: Which of the below are bigrams from the sentence "It is cold outside today".

- A. It is
- B. cold today
- C. is cold
- D. A & C

Break & Quiz

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- **D. A & C**

Break & Quiz

Q 1.2: Smoothing is increasingly useful for n-grams when

- A. n gets larger
- B. n gets smaller
- C. always the same
- D. n larger than 10

Break & Quiz

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Evaluating Language Models

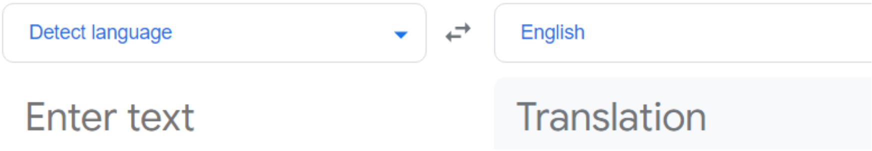
How do we know we've done a good job?

- Observation
- Train/test on separate data & measure metrics
- **Metrics**:
  - 1. Extrinsic evaluation
  - 2. Perplexity

Extrinsic Evaluation

How do we know we've done a good job?

- **Pick a task** and use the model to do the task
- For two models, M_1, M_2, compare the accuracy for each task
  - **Ex**: Q/A system: how many questions right. Translation: how many words translated correctly
- Downside: slow; may change relatively



Intrinsic Evaluation: Perplexity

Perplexity is a **measure of uncertainty**

$$\mathrm{PP}(W) = P(w_1, w_2, \ldots, w_n)^{-\frac{1}{n}}$$

Compute average PP(W) for all W from a dataset

Lower is better! Examples:

- WSJ corpus; 40 million words for training:
  - Unigram: 962, Bigram 170, Trigram 109

Further NLP Tasks

Language modeling is **not the only NLP task:**

- Part-of-speech tagging, parsing, etc.
- Question-answering, translation, summarization, classification (e.g., sentiment analysis), generation, etc.

Break & Quiz

Q 2.1: What is the perplexity for a sequence of *n* digits 0-9? All occur independently with equal probability.

$$\mathrm{PP}(W) = P(w_1, w_2, \ldots, w_n)^{-\frac{1}{n}}$$

- A. 10
- B. 1/10
- C. 10^n
- D. 0

Break & Quiz

Q 2.1: What is the perplexity for a sequence of *n* digits 0-9? All occur independently with equal probability.

- **A. 10**
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$$\mathrm{PP}(W) = P(w_1, w_2, \ldots, w_n)^{-\frac{1}{n}}$$

$(P(w_1)*P(w_2)\ldots*P(w_{10}))^{(-1/10)} = ((1/10)*(1/10)*\ldots.(1/10))^{(-1/10)} = 10$

Representing Words

Remember value of random variables **(RVs)**

- Easier to work with than objects like ‘dog’

Traditional representation: **one-hot vectors**

$$\text{dog} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

- Dimension: # of words in vocabulary
- Relationships between words?

Smarter Representations

Distributional semantics: account for relationships

- Reps should be close/similar to other words that appear in a similar context

Dense vectors:

$$\text{dog} = \begin{bmatrix} 0.13 & 0.87 & -0.23 & 0.46 & 0.87 & -0.31 \end{bmatrix}^T$$

$$\text{cat} = \begin{bmatrix} 0.07 & 1.03 & -0.43 & -0.21 & 1.11 & -0.34 \end{bmatrix}^T$$

AKA **word embeddings**

Training Word Embeddings

Many approaches (super popular 2010-present)

- Word2vec: a famous approach
- What's our likelihood?

Windows of length 2a

$$L(\theta) = \prod_{t=1}^{T} \prod_{-a \leq j \leq a} P(w_{t+j} | w_t, \theta)$$

Our word vectors

All positions

Training Word Embeddings

Word2vec likelihood

$$L(\theta) = \prod_{t=1}^{T} \prod_{-a \le j \le a} P(w_{t+j} | w_t, \theta)$$

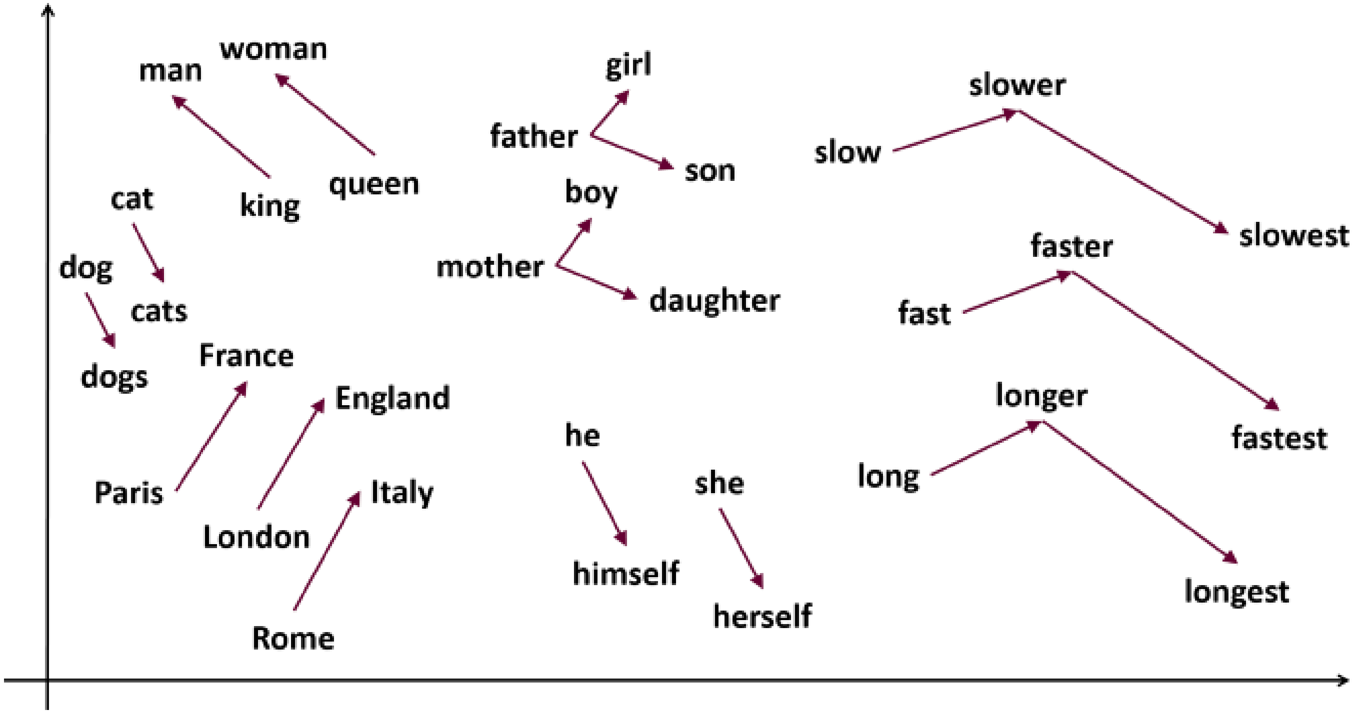
- Maximize this; what's the probability?
  - Two vectors per word. v_w, u_w for center/context

(o is context word, c is center)

Similarity

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

Word Embeddings

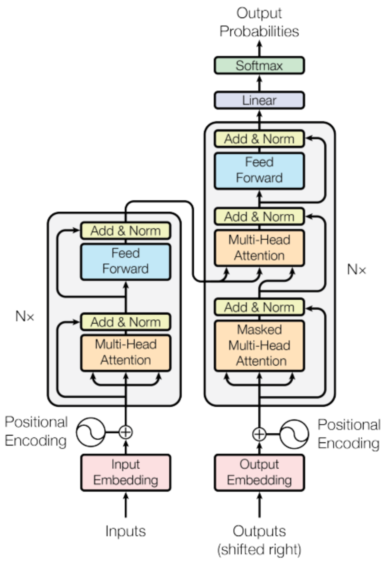


[Saurabh Pal – Implementing Word2Vec in Tensorflow]

Beyond "Shallow" Embeddings

- Transformers: special model architectures based on **attention**
  - Sophisticated types of neural networks
- Pretrained models
  - Based on transformers: BERT, GPT
  - Include context!

- **Fine-tune** for desired task



Vaswani et al. 17

Reading

- Natural Language and Statistics, Notes by Zhu. https://pages.cs.wisc.edu/~jerryzhu/cs540/handouts/NLP.pdf