CS 540 Introduction to Artificial Intelligence
Natural Language Processing

University of Wisconsin-Madison

Spring 2023

Announcements

- **Homeworks**:
  - HW2 just due; HW3 released soon (due next Thursday).
- Class roadmap (now shifted back a lecture):

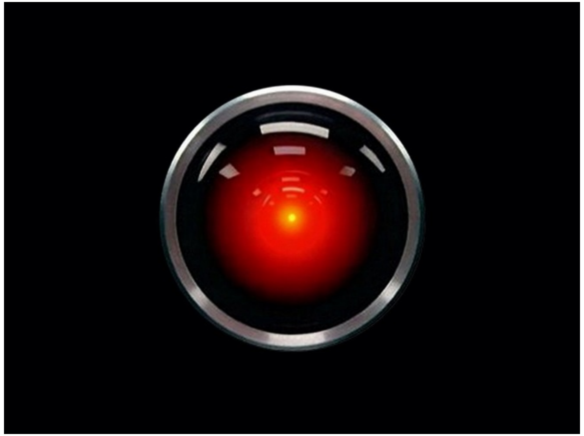
Thursday, Feb. 9	**NLP**
Tuesday, Feb. 14	NLP
Thursday, Feb. 16	ML Intro
Tuesday, Feb. 21	ML Unsupervised I
Thursday, Feb. 23	ML Unsupervised II

Machine Learning

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: “*We saw her duck”.* Several meanings.
- Non-standard use of language
- Reference challenges:
  - “The president told the senate leader that he disagreed with his position.”
- Understanding of the world
  - “Bob and Joe are fathers”.
  - “Bob and Joe are brothers”.

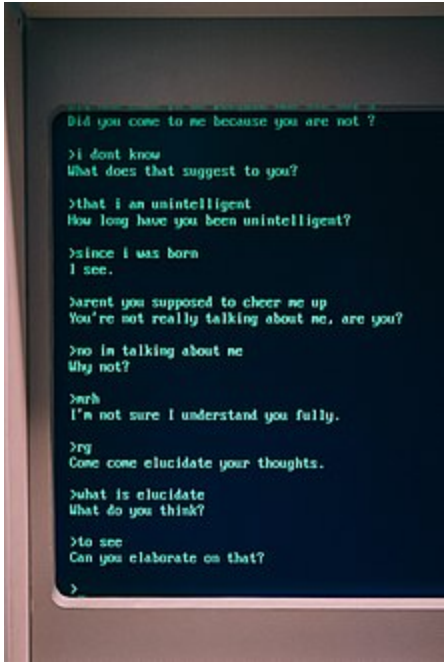
Approaches to NLP

A brief history

- Symbolic NLP: 50’s to 90’s
- Statistical/Probabilistic: 90’s to present
  - Neural: 2010’s to present

Lots of progress!

Lots more to work to do



ELIZA program

Outline

- Introduction to language models
  - n-grams, training, improving issues, evaluation
- Classic NLP tasks
  - Part-of-speech tagging, parsing, dependencies
- Word representations
  - One-hot, word embeddings, transformer-based

Language Models

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

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

- Goes back to Claude Shannon
  - "Father of Information Theory"
  - 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

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?
  - Yes, recall estimating probabilities from statistics review.
  - But can’t estimate directly: too many sentences.
  - Can’t estimate reliably.

Training: Make Assumptions

- Markov-type assumptions:

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

- Present doesn't depend on whole past
  - Just recent past, i.e., *context*.
  - Markov chains have *k=1.* **(Present only depends on immediate past).**
  - What's ***k=0?***

k=0: **Uni**gram Model

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

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

- 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)

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

- Example:

```
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 conditional word probabilities.

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

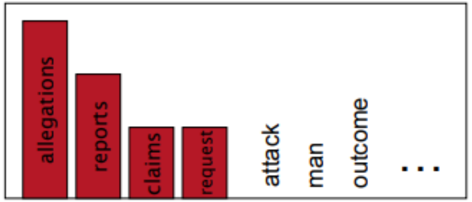
$$P(w_i|w_{i-1}) = \frac{\mathrm{count}(w_{i-1}, w_i)}{\mathrm{count}(w_{i-1})}$$

n-gram Training

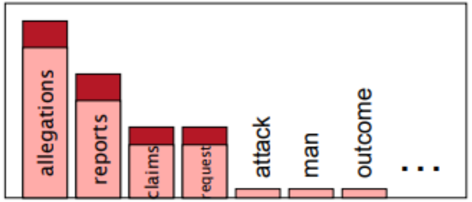
$$P(w_i|w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i)}{\text{count}(w_{i-1})}$$

Issues:

- **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

Other Solutions: Backoff & Interpolation

For **issue 2**, back-off methods

- Use n-gram where there is lots of information, r-gram (with r << *n*) elsewhere. (trigrams / bigrams)

Interpolation

- Mix different models: (tri- + bi- + unigrams)

$$\hat{P}(w_i|w_{i-1}, w_{i-2}) = \lambda_1 P(w_i|w_{i-1}, w_{i-2}) + \lambda_2 P(w_i|w_{i-1}) + \lambda_3 P(w_i)$$

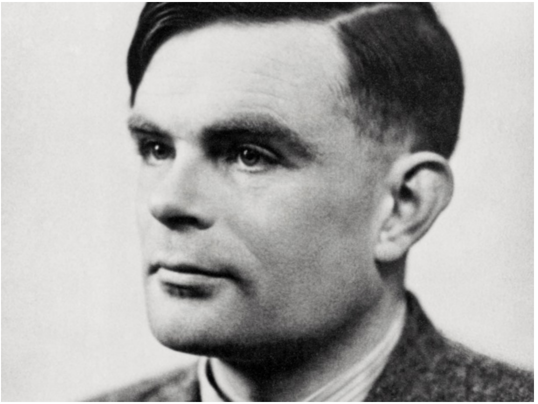
n-gram Training Issues

Issues:

- **1**. Multiply tiny numbers?
  - **Solution**: use logs; add instead of multiply
- **2.** Sparse n-grams
  - **Solution**: smoothing, backoff, interpolation
- **3.** Vocabulary: open vs closed
  - **Solution**: use <UNK> unknown word token

Vocabulary: open vs closed

- Possible to estimate size of unknown vocabulary
  - **Good-Turing** estimator
- Originally developed to crack the Enigma machine



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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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

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

Evaluating Language Models

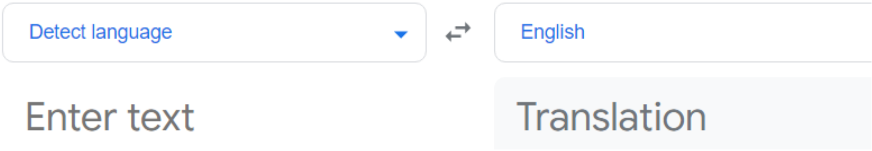
How do we know we've done a good job?

- 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**

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

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 task. Two further types:

1. **Auxilliary** tasks:
   - Part-of-speech tagging, parsing, etc.
2. **Direct** tasks:
   - Question-answering, translation, summarization, classification (e.g., sentiment analysis)

Part-of-speech Tagging

Tag words as nouns, verbs, adjectives, etc.

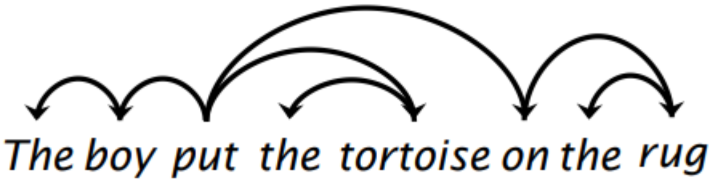
- Tough part: ambiguous, even for people.
- Needs:
  - Getting neighboring word parts right
  - Knowledge of words (“man” is used as a noun, rarely as verb)

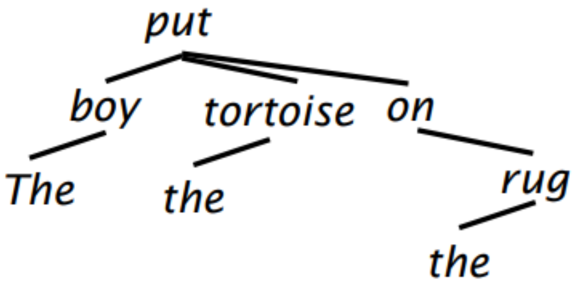
Model	Features	Token	Unknown	Sentence
Baseline	56,805	**93.69%**	82.61%	26.74%
3Words	239,767	**96.57%**	86.78%	48.27%

Chris Manning

Parsing

Get the grammatical structure of sentences





Chris Manning

- Which words depend on each other? Note: input a sentence, output a tree (dependency parsing)

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

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Representing Words

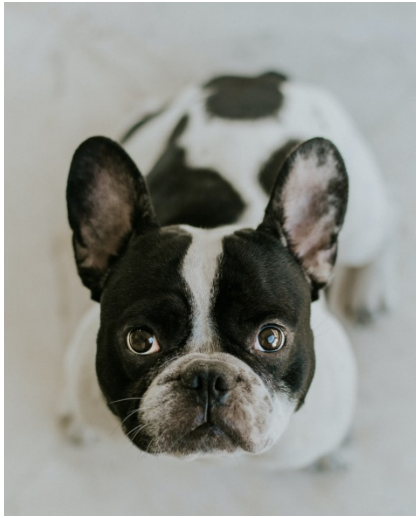
Remember value of random variables **(RVs)**

- 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

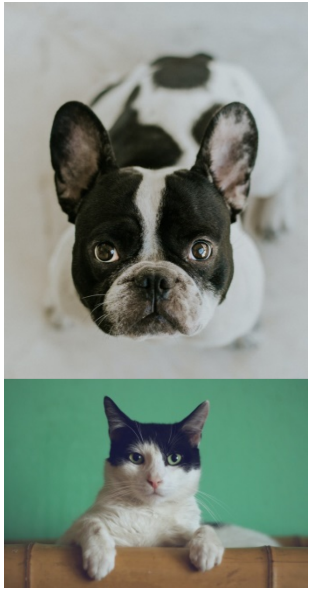
- Reps should be close/similar to other words that appear in a similar context

Dense vectors:

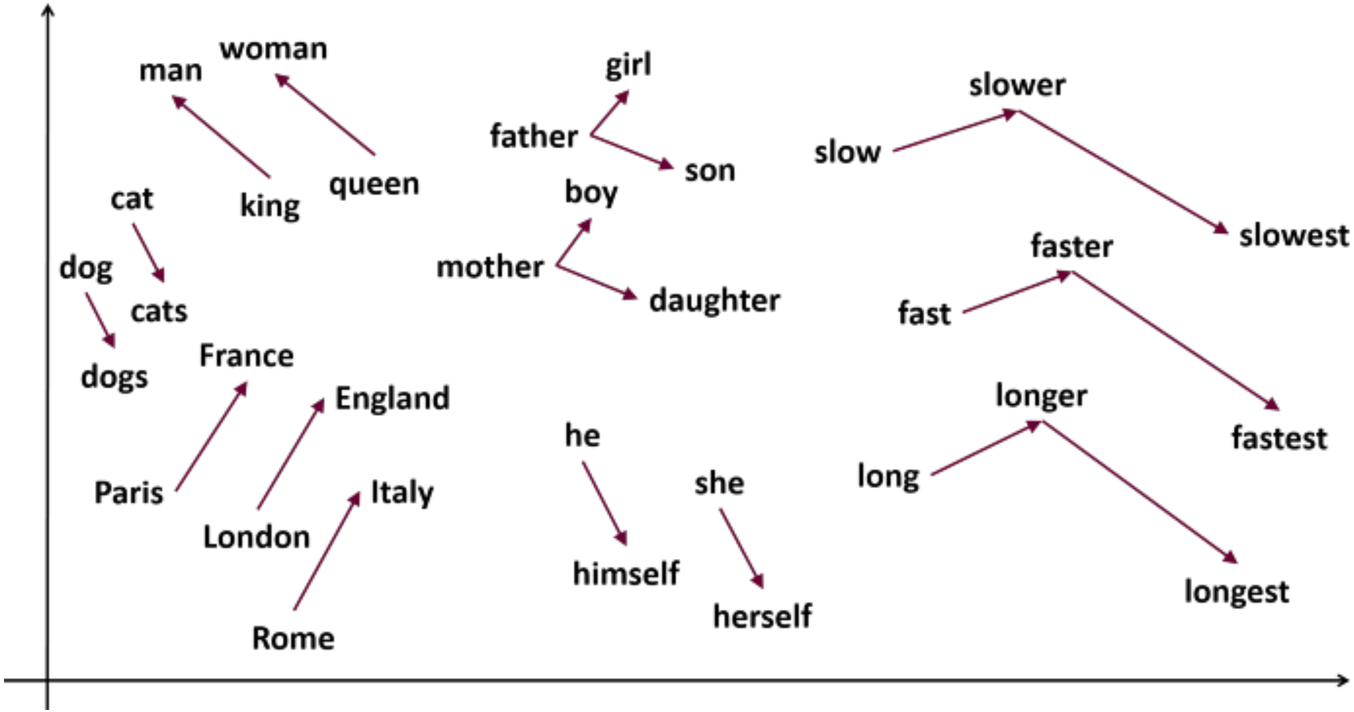
$$\text{dog} = \begin{bmatrix}0.13 & 0.87 & -0.23 & 0.46 & 0.87 & -0.31\end{bmatrix}^T$$

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

AKA **word embeddings**



Word Embeddings



[Saurabh Pal – Implementing Word2Vec in Tensorflow]

Training Word Embeddings

Many approaches (super popular 2010-present)

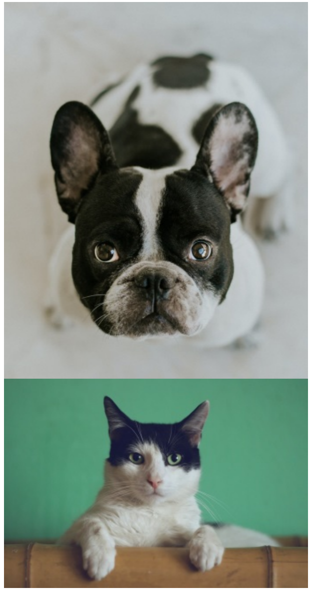
- Word2vec: a famous approach
- What's our likelihood?

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 (variables/ hypotheses)

All positions



Training Word Embeddings

Word2vec likelihood

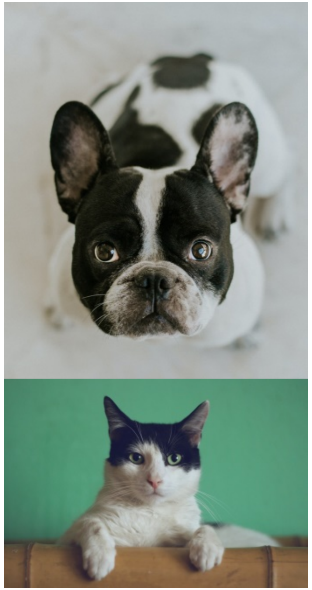
$$L(\theta) = \prod_{t=1}^{T} \prod_{-a \leq j \leq a} P(w_{t+j} | w_t, \theta)$$

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

(o is context word, c is center)

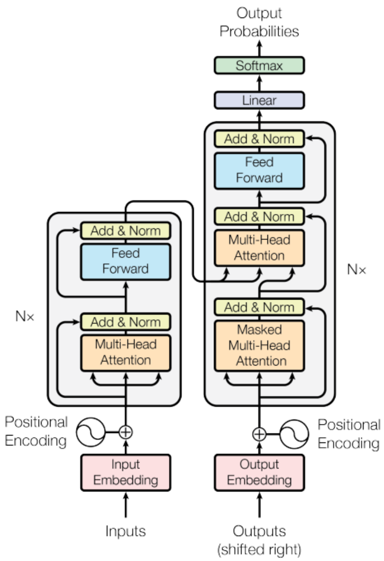
Similarity

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



Beyond "Shallow" Embeddings

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