ECE365: Introduction to NLP

Spring 2021

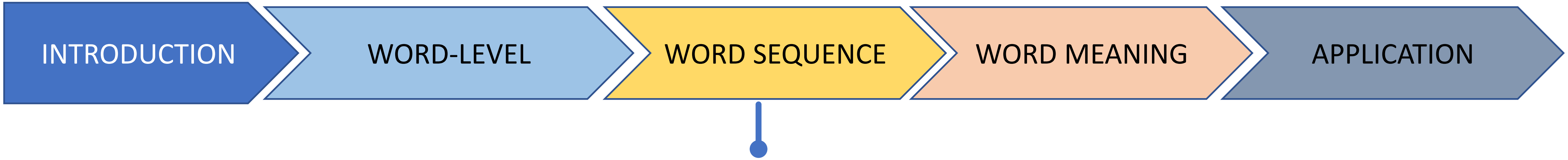
Lecture 4: Words in a sequence – Language modeling

[Reading J&M Chapter 3 (sections 3.1, 3.2)]

Logistics

- Quiz 1 today, material lectures 1, 2 & 3
- Quiz 1 solution will appear on course page later in the week
- Lab 3 will be up 04/20 due 4/28

Course Progress



WEEK 3

What is the nature of understanding we can get considering words as sequences?

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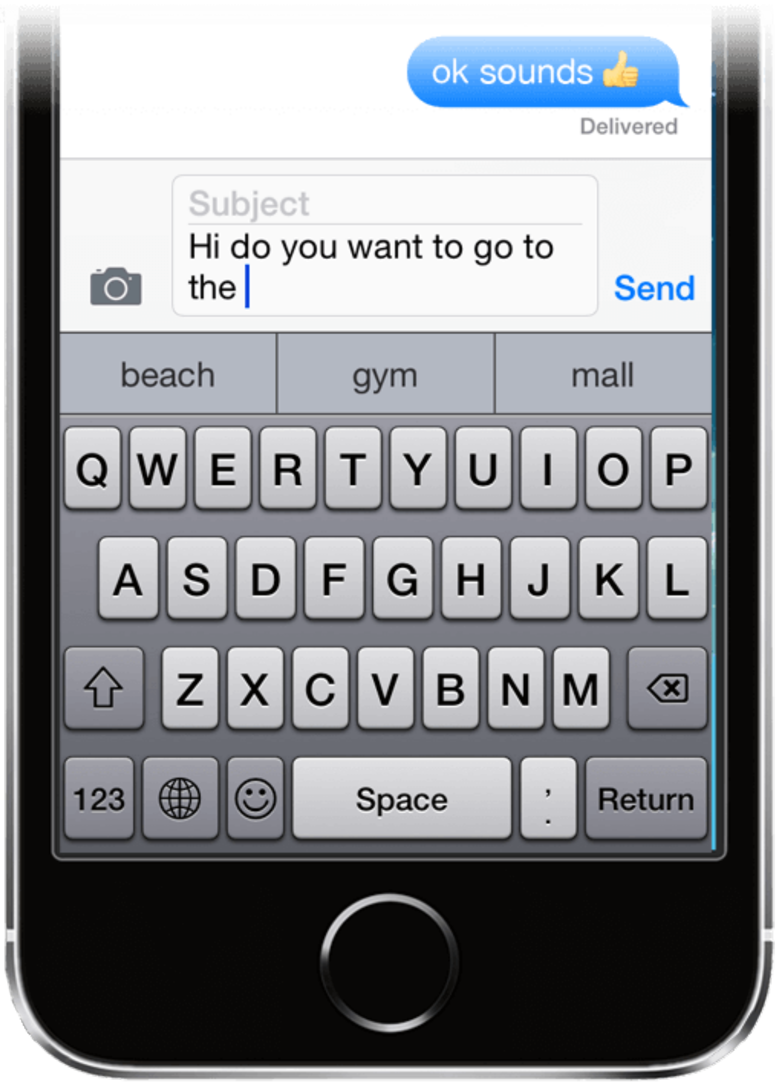
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Return

What do we see?

The next word is being predicted

Consider the following instances

- Iryna went to the museum.
- Iryna the museum to went.
- Iryna went museum.

Consider System Outputs

I ate a cherry

Eye eight uh Jerry

Machine translation (Zh-> En)

他向记者介绍了发言的主要内容

- He briefed to reporters on the chief contents of the statement
- He briefed reporters on the chief contents of the statement
- He briefed to reporters on the main contents of the statement
- He briefed reporters on the main contents of the statement

Applications

- Deciding which word/phrase to choose

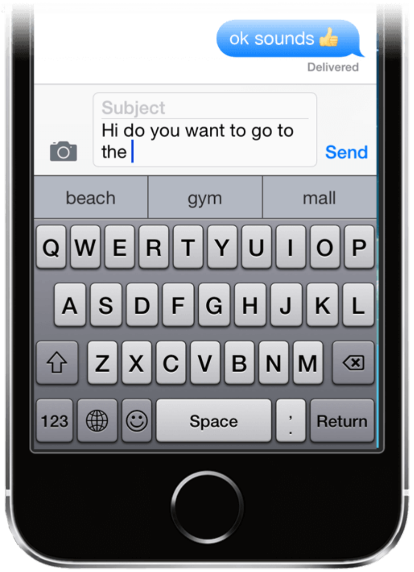
  Spelling checking/correction or Speech recognition:

  P(high school **principal**) > P(high school **principle**)

  Machine translation:

  P(How to make <u>strong</u> tea) > P(How to make <u>powerful</u> tea)

Problem



I ate a cherry

Eye eight uh Jerry

Sentence is not a bag of words. Use order of words permitted by language (grammar) to solve the problem.

Language model

What is a language model?

- A model that permit computing the probability of a sequence of words
  - How likely is a given word/phrase/sentence?

- P(X = *the*) be the probability that the random variable X takes the value “the”

- Let the joint probability of each word in a sequence (i.e., a sentence) having a particular value is

  $P(X_1 = w_1, X_2 = w_2, \ldots, X_n = w_n)$ *denoted by* $P(w_1, w_2, \ldots, w_n)$

Learning the language model

- *Chain rule*

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

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

P(the cow jumped over the moon) =

Learning the language model

- *Use a large corpus of the language*
  - Estimate the probability of word/phrase/sentence

  - By counting, i.e., using MLE

Estimating the Probabilities

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

Use a large corpus of English (e.g. Wikipedia) to get MLE

$$P(\mathrm{the}) = \frac{count(the)}{total\ words}$$

$$P(\mathrm{cow}|\mathrm{the}) = \frac{count(the\ cow)}{count(the)}$$

Markov Assumption

- Use only the recent past to predict the next word
- Definition: A sequence of n words is an n-gram
  - The cow jumped over the moon
  - unigram
  - bigram

Markov Assumption

- An n-gram language model considers only the most recent n-1 words
  - bigram model:

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

$$P(w_1 w_2 \ldots w_n) \approx \prod_i P(w_i \mid w_{i-k} \ldots w_{i-1})$$

K+1 gram model

Markov Assumption

- Use only the recent past to predict the next word

  - unigram LM

  $P(\texttt{moon}|\texttt{the cow jumped over the}) \approx$

  - Bigram LM

  $P(\texttt{moon}|\texttt{the cow jumped over the}) \approx$

N-gram models

Larger the N, more accurate and better the language model (but also higher costs)

1 trillion words from public web pages

Google AI Blog

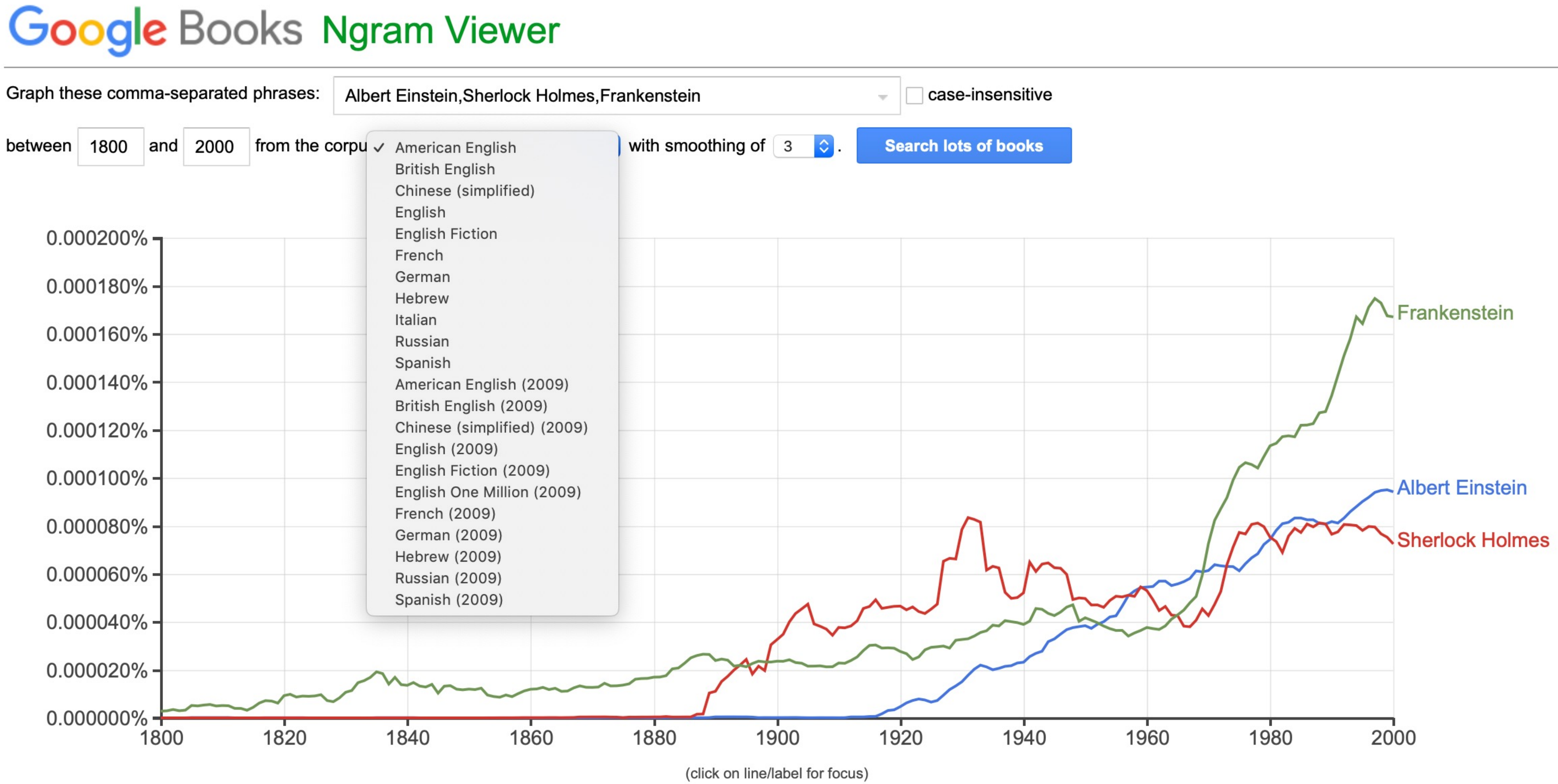
The latest news from Google AI

All Our N-gram are Belong to You

Thursday, August 3, 2006

Posted by Alex Franz and Thorsten Brants, Google Machine Translation Team

N-grams


Google Books Ngram Viewer
Graph these comma-separated phrases:
Albert Einstein,Sherlock Holmes,Frankenstein
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and
2000
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British English
Chinese (simplified)
English
English Fiction
French
German
Hebrew
Italian
Russian
Spanish
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British English (2009)
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Frankenstein
Albert Einstein
Sherlock Holmes
(click on line/label for focus)

Generalization of n-grams

- Not all n-grams will be observed in training data

- Long tail of infrequent words in finite-sized corpora
  - Zipf's law

- Test might have unseen words in training corpus
  - Training data: Google news
  - Test set: Shakespeare

  Since arm from arm that voice doth us affray,

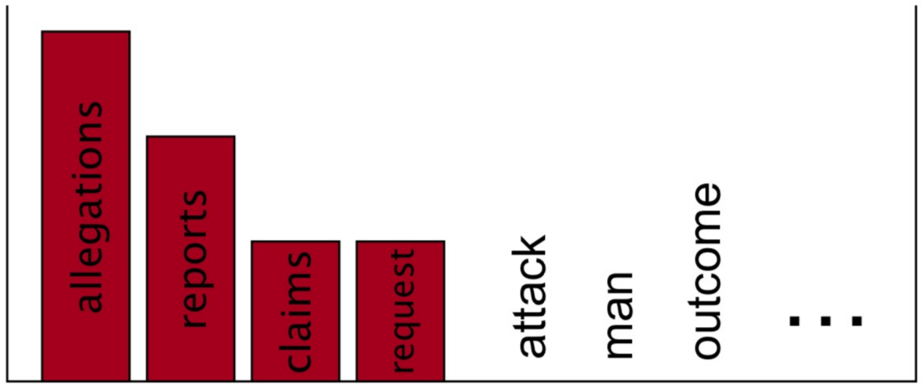
    - P (affray | voice doth us) = ?

Smoothing intuition

When we have sparse statistics:

P(w | denied the)
3 allegations
2 reports
1 claims
1 request

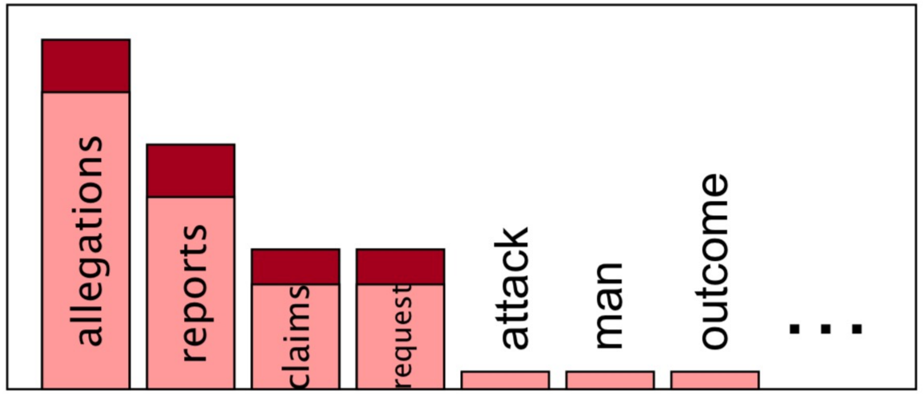
7 total



Steal probability mass to generalize better

P(w | denied the)
2.5 allegations
1.5 reports
0.5 claims
0.5 request
2 other

7 total



Smoothing

- Handle sparsity by making sure all probabilities are non-zero in our model
  - Additive: Add a small amount to all probabilities
  - Discounting: Redistribute probability mass from observed n- grams to unobserved ones
  - Back-off: Use lower order n-grams if higher ones are too sparse
  - Interpolation: Use a combination of different granularities of n-grams

Evaluating Language Models

- A good language model should assign higher probability to typical, grammatically correct sentences

Process

- on a suitable training corpus
  - Assumption: observed sentences ~ good sentences
- on *different, unseen* corpus
  Training on any part of test set not acceptable!

Evaluating Language Models

- Best evaluation for comparing LMs A and B
  - Put each model in a task
    - spelling corrector, speech recognizer, MT system
  - Run the task, get performance for A and for B
    - How many misspelled words corrected properly
    - How many words translated correctly
  - Compare A and B

  - Extrinsic evaluation, expensive

Evaluating language models

- Intrinsic evaluation
- Need a number that says how good my model is for a test set
  - Given by
  - If a model assigns higher   to a test set, it more   predicts the test set
- For a test sentence W given by $w_1w_2...w_N$

Practical Issues

- Computation using log
  - Probabilities can be very small

- <s> I am Sam </s>
- <s> Sam I am </s>
- <s> I do not like green eggs and ham </s>

Limitations

- In general this is an insufficient model of language
  - Because language has **long-distance dependencies**
  - "The computers, which I had just put into the machine room on the fifth floor, are crashing."
- But we can often get away with N-gram models
- State-of-the-art (for the curious): https://openai.com/blog/better-language-models/

Summary

- Text has an intrinsic structure and language model is a way to mathematically represent this structure
- Useful in a variety of tasks (decide the next word, or to judge the quality of a sentence)
- N-gram language models offer one way of doing this
- Smoothing as a way to prevent unseen words getting zero probability
- Evaluated using Perplexity (instrinsic), or in a specific task (extrinsic)