Natural Language Processing

Language modeling

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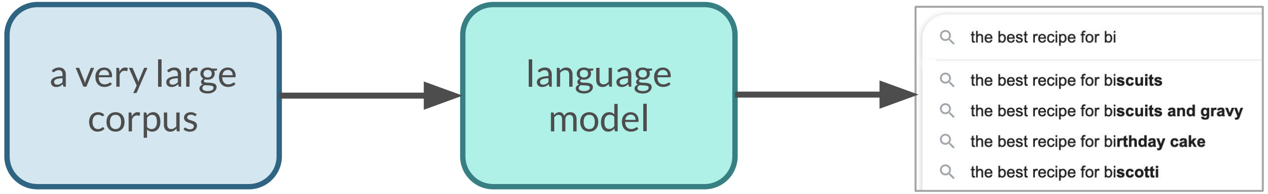
OF COMPUTER SCIENCE & ENGINEERING

Announcements

- Quiz 2
- OH tomorrow 10-11 am specifically for the write-up problems. Leroy will walk you through the two theoretical problems and will try to answer any questions. It will be recorded in case people can't make it

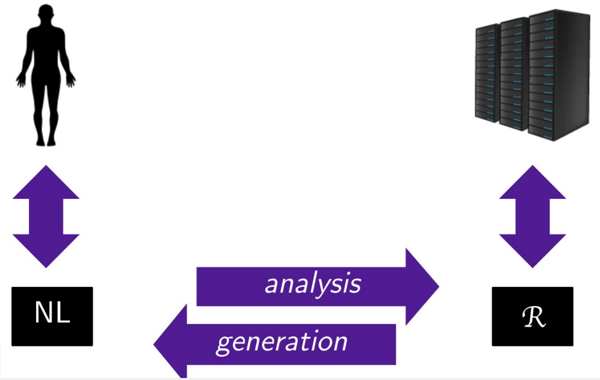
Language modeling

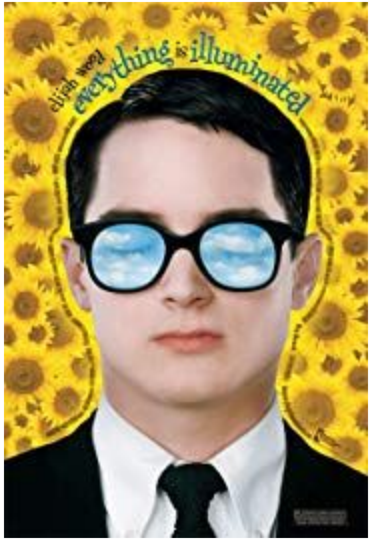


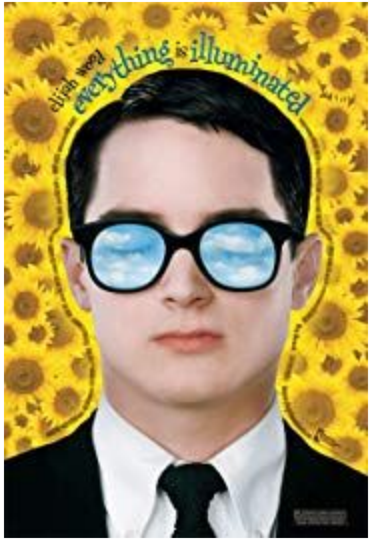
What is Natural Language Processing (NLP)?

- NL $\in$ {Mandarin Chinese, Hindi, Spanish, Arabic, English, … Inuktitut, Njerep}

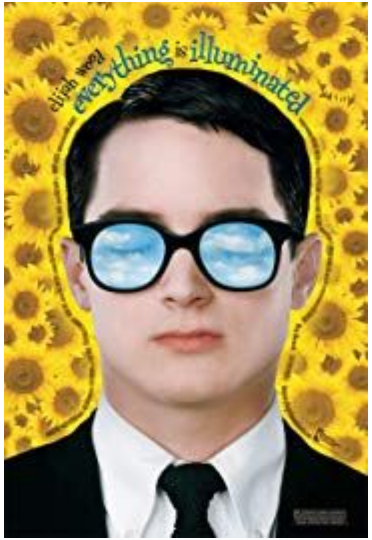
- Automation of NLs:
  - analysis of (“understanding”) what a text means, to some extent (NL $\rightarrow \mathcal{R}$)
  - generation of fluent, meaningful, context-appropriate text ($\mathcal{R} \rightarrow$ NL)
  - acquisition of $\mathcal{R}$ from knowledge and data




elijah wood
everything is illuminated



My legal name is Alexander Perchov.



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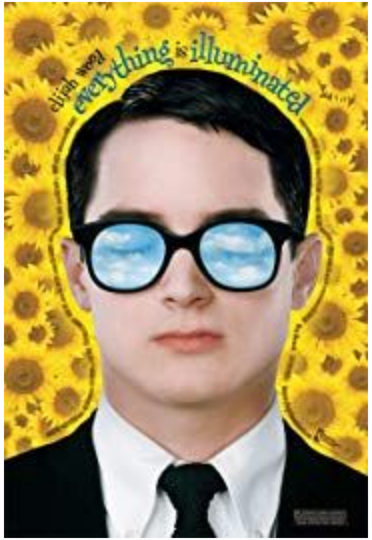

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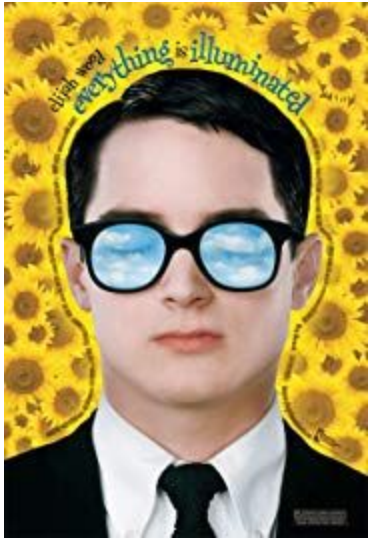

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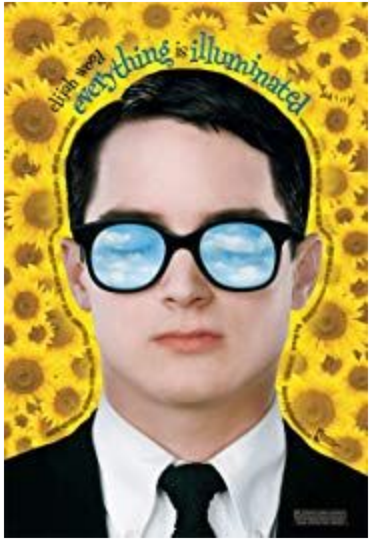

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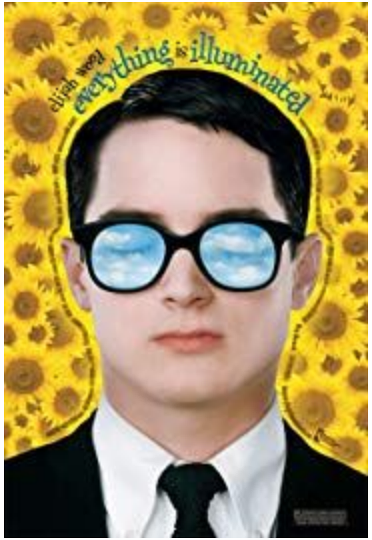

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spleening her. If you want to know why I am always spleening her, it is because I am always elsewhere with friends, and disseminating so much currency, and performing so many things that can spleen a mother. Father used to dub me Shapka, for the fur hat I would don even in the summer month. He ceased dubbing me that because I ordered him to cease dubbing me that. It sounded boyish to me, and I have always thought of myself as very potent and generative.

Language models play the role of ...

- a judge of grammaticality
- a judge of semantic plausibility
- an enforcer of stylistic consistency
- a repository of knowledge (?)

The Language Modeling problem

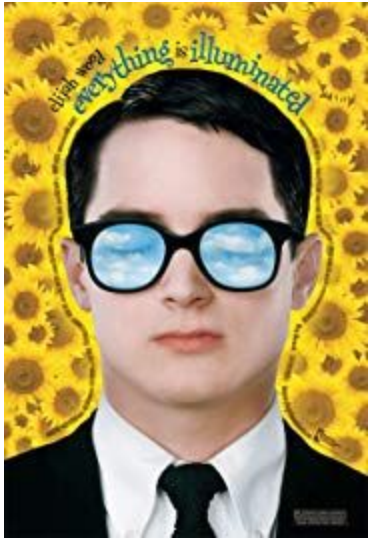
- Assign a probability to every sentence (or any string of words)
  - finite vocabulary (e.g. words or characters) *{the, a, telescope, …}*
  - infinite set of sequences
    - *a telescope STOP*
    - *a STOP*
    - *the the the STOP*
    - *I saw a woman with a telescope STOP*
    - *STOP*
    - *...*

The Language Modeling problem

- Assign a probability to every sentence (or any string of words)
  - finite vocabulary (e.g. words or characters)
  - infinite set of sequences

$$\sum_{\mathbf{e}\in\Sigma^*} p_{\mathrm{LM}}(\mathbf{e}) = 1$$

$$p_{\mathrm{LM}}(\mathbf{e}) \geq 0 \quad \forall \mathbf{e} \in \Sigma^*$$

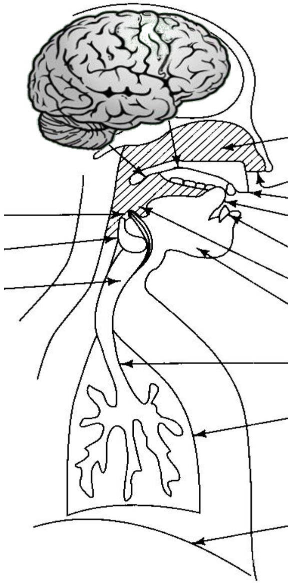


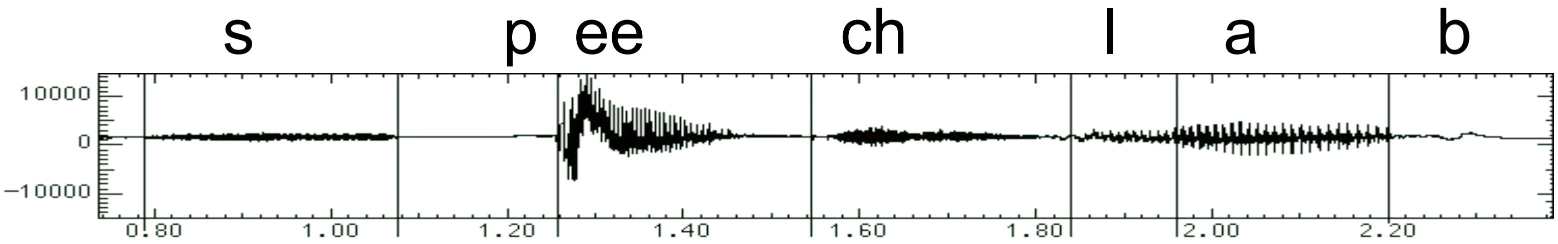
p(*disseminating so much currency STOP*) = 10^{-15}

p(*spending a lot of money STOP*) = 10^{-9}

Motivation

- Speech recognition: we want to predict a sentence given acoustics





Motivation

- Speech recognition: we want to predict a sentence given acoustics

the station signs are indeed in english	-14725
the station signs are in deep in english	-14732
the stations signs are in deep in english	-14735
the station signs are in deep into english	-14739
the station 's signs are in deep in english	-14740
the station signs are in deep in the english	-14741
the station 's signs are indeed in english	-14760
the station signs are indians in english	-14790
the station signs are indian in english	-14799
the stations signs are indians in english	-14807
the stations signs are indians and english	-14815

Motivation

- Machine translation
  - p(*strong winds*) > p(*large winds*)

- Spelling correction
  - The office is about fifteen minuets from my house
  - p(*about fifteen minutes from*) > p(*about fifteen minuets from*)

- Speech recognition
  - p(*I saw a van*) >> p(*eyes awe of an*)

- Summarization, question-answering, handwriting recognition, OCR, etc.

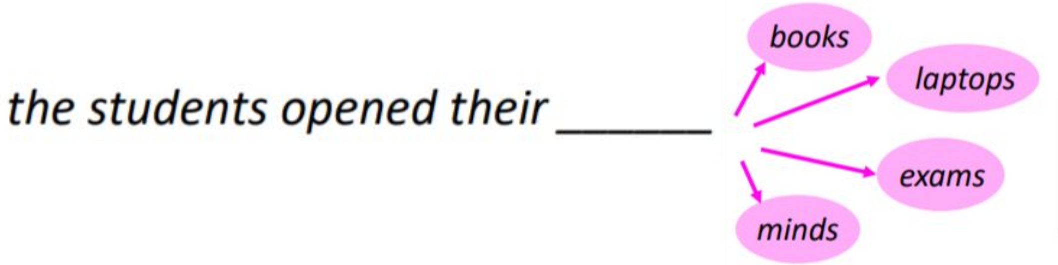
Equivalent definition

- **Language Modeling** is the task of predicting what word comes next

the students opened their ______

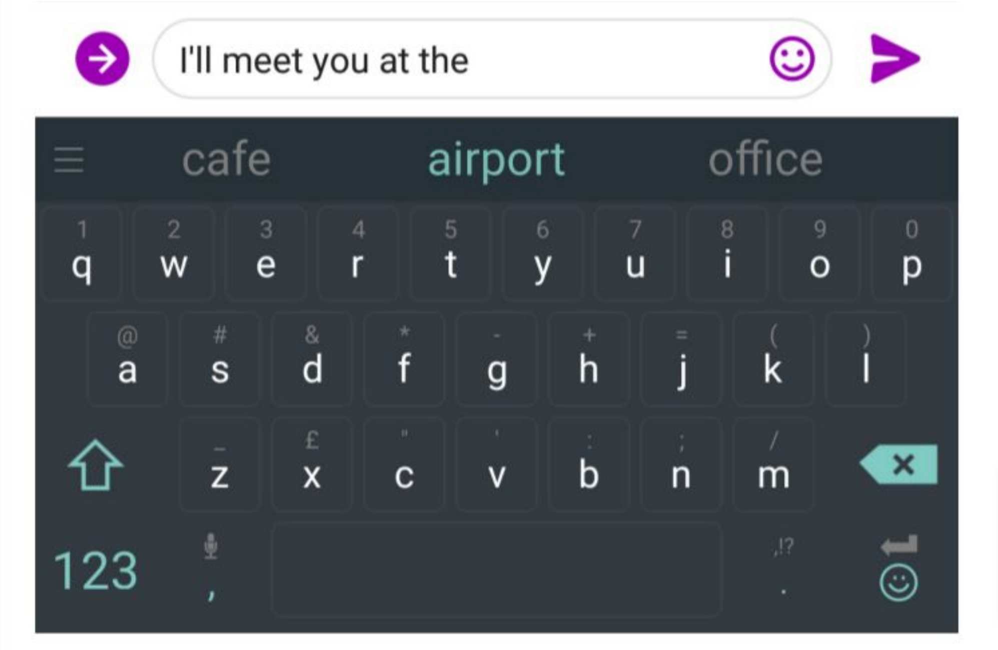
Equivalent definition

- **Language Modeling** is the task of predicting what word comes next



- More formally: given a sequence of words $x^{(1)}, x^{(2)}, \ldots x^{(t)}$
  compute the probability distribution of the next word $x^{(t+1)}$
  Where $x^{(t+1)}$ can be any word in the vocabulary $V=\{ w_1, w_2, \ldots w_{|V|}\}$

We use Language Models every day



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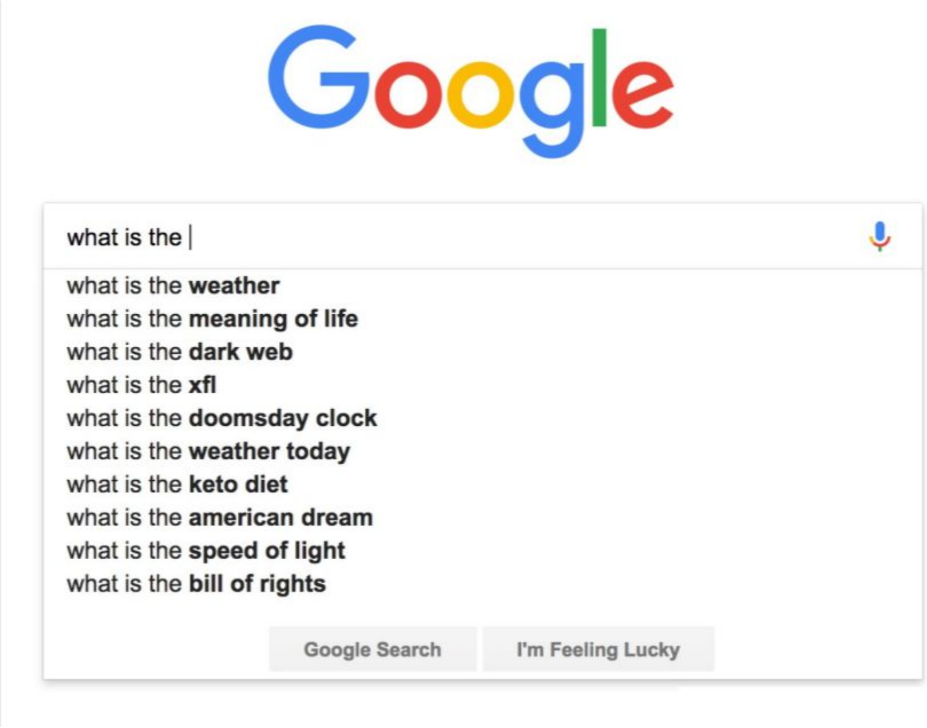

Language Modeling

- If we have some text, then the probability of this text (according to the Language Model) is:

$$P(\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}) = P(\boldsymbol{x}^{(1)}) \times P(\boldsymbol{x}^{(2)} | \, \boldsymbol{x}^{(1)}) \times \cdots \times P(\boldsymbol{x}^{(T)} | \, \boldsymbol{x}^{(T-1)}, \ldots, \boldsymbol{x}^{(1)})$$
$$= \prod_{t=1}^{T} \underbrace{P(\boldsymbol{x}^{(t)} | \, \boldsymbol{x}^{(t-1)}, \ldots, \boldsymbol{x}^{(1)})}_{\text{This is what our LM provides}}$$

n-gram Language Models

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- Question: How to learn a Language Model?

A trivial model

- Assume we have n training sentences
- Let $x_1, x_2, \ldots, x_n$ be a sentence, and $c(x_1, x_2, \ldots, x_n)$ be the number of times it appeared in the training data.
- Define a language model:

$$p(x_1, \ldots, x_n) = \frac{c(x_1, \ldots, x_n)}{N}$$

- No generalization!

n-gram Language Models

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- Question: How to learn a Language Model?
- Answer (pre- Deep Learning): learn an *n-gram* Language Model!

n-gram Language Models

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- Definition: An n-gram is a chunk of n consecutive words.

n-gram Language Models

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  - unigrams: {I, have, a, dog, whose, name, is, Lucy, two, cats, they, like, playing, with}

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  - bigrams: {I have, have a, a dog, dog whose, … , with Lucy}
  - trigrams: {I have a, have a dog, a dog whose, … , playing with Lucy}
  - four-grams: {I have a dog, … , like playing with Lucy}
  - …

n-gram Language Models

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- w_1 – a unigram
- $w_1\ w_2$ – a bigram
- $w_1\ w_2\ w_3$ – a trigram
- $w_1 w_2 \ldots w_n$ – an n-gram

n-gram Language Models

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- Question: How to learn a Language Model?
- Answer (pre- Deep Learning): learn an *n-gram* Language Model!

- Idea: Collect statistics about how frequent different n-grams are and use these to predict next word

unigram probability

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- corpus size m = 17
- P(Lucy) = 2/17; P(cats) = 1/17

- Unigram probability: $P(w) = \frac{\text{count}(w)}{m} = \frac{C(w)}{m}$

bigram probability

“I have a dog whose name is Lucy. I have two cats, they like playing with Lucy.”

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$

$$P(\text{have} \mid \text{I}) = \frac{P(\text{I have})}{P(\text{I})} = \frac{2}{2} = 1$$

$$P(\text{two} \mid \text{have}) = \frac{P(\text{have two})}{P(\text{have})} = \frac{1}{2} = 0.5$$

$$P(\text{eating} \mid \text{have}) = \frac{P(\text{have eating})}{P(\text{have})} = \frac{0}{2} = 0$$

$$P(w_2|w_1) = \frac{C(w_1,w_2)}{\sum_w C(w_1,w)} = \frac{C(w_1,w_2)}{C(w_1)}$$

trigram probability

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$

$$P(a \mid I\ have) = \frac{C(I\ have\ a)}{C(I\ have)} = \frac{1}{2} = 0.5$$

$$P(w_3 | w_1\ w_2) = \frac{C(w_1,w_2,w_3)}{\Sigma_w\ C(w_1,w_2,w)} = \frac{C(w_1,w_2,w_3)}{C(w_1,w_2)}$$

$$P(several \mid I\ have) = \frac{C(I\ have\ several)}{C(I\ have)} = \frac{0}{2} = 0$$

n-gram probability

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$

$$P(w_i \mid w_1, w_2, \ldots, w_{i-1}) = \frac{C(w_1, w_2, \ldots, w_{i-1}, w_i)}{C(w_1, w_2, \ldots, w_{i-1})}$$

Sentence/paragraph/book probability

$$P(\boldsymbol{x}^{(1)},\ldots,\boldsymbol{x}^{(T)}) = P(\boldsymbol{x}^{(1)}) \times P(\boldsymbol{x}^{(2)}|\,\boldsymbol{x}^{(1)}) \times \cdots \times P(\boldsymbol{x}^{(T)}|\,\boldsymbol{x}^{(T-1)},\ldots,\boldsymbol{x}^{(1)})$$
$$= \prod_{t=1}^{T} P(\boldsymbol{x}^{(t)}|\,\boldsymbol{x}^{(t-1)},\ldots,\boldsymbol{x}^{(1)})$$

P(its water is so transparent that the) =

P(its) ×
P(water | its) ×
P(is | its water) ×
P(so | its water is) ×
P(transparent | its water is so) ×
… ×

P(the | its water is so transparent that) → How to estimate?

Markov assumption

Andrei Markov

- We make the Markov assumption: $x^{(t+1)}$ depends only on the preceding $n-1$ words
  - Markov chain is a "*…stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event.*"

$$P(\boldsymbol{x}^{(t+1)}|\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(1)}) = P(\boldsymbol{x}^{(t+1)}|\underbrace{\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)}}_{\text{n-1 words}})$$

assumption

Markov assumption

Andrei Markov

$$P(\text{the} \mid \text{its water is so transparent that}) \approx P(\text{the} \mid \text{transparent that})$$

or maybe even

$$P(\text{the} \mid \text{its water is so transparent that}) \approx P(\text{the} \mid \text{that})$$

First-order Markov process

Chain rule

$$p(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) =$$
$$p(X_1 = x_1) \prod_{i=2}^{n} p(X_i = x_i \mid X_1 = x_1, \ldots, X_{i-1} = x_{i-1})$$

First-order Markov process

Chain rule

$$p(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) =$$

$$p(X_1 = x_1) \prod_{i=2}^{n} p(X_i = x_i \mid X_1 = x_1, \ldots, X_{i-1} = x_{i-1})$$

Markov assumption

$$= \quad P(X_1 = x_1) \prod_{i=2}^{n} P(X_i = x_i | X_{i-1} = x_{i-1})$$

Second-order Markov process:

- Relax independence assumption:

$$p(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) =$$
$$p(X_1 = x_1) \times p(X_2 = x_2 \mid X_1 = x_1)$$
$$\times \prod_{i=3}^{n} p(X_i = x_i \mid X_{i-2} = x_{i-2}, X_{i-1} = x_{i-1})$$

Second-order Markov process:

- Relax independence assumption:

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$$\times \prod_{i=3}^{n} p(X_i = x_i \mid X_{i-2} = x_{i-2}, X_{i-1} = x_{i-1})$$

- Simplify notation:

$$x_0 = *, x_{-1} = *$$

3-gram LMs

- A trigram language model contains
  - a vocabulary V
  - a non negative parameters q(*w*|*u*,*v*) for every trigram, such that

$$w \in \mathcal{V} \cup \{\text{STOP}\},\ u, v \in \mathcal{V} \cup \{*\}$$

  - the probability of a sentence $x_1, \ldots, x_n$, where x_n=STOP is

$$p(x_1, \ldots, x_n) = \prod_{i=1}^{n} q(x_i \mid x_{i-1}, x_{i-2})$$

Example

$$p(\text{the dog barks STOP}) =$$

Example

$$p(\text{the dog barks STOP}) = q(\mathit{the} \mid *, *) \times$$

Example

$$
\begin{aligned}
p(\text{the dog barks STOP}) = &q(the \mid *, *)\times \\
&q(dog \mid *, the)\times \\
&q(barks \mid the, dog)\times \\
&q(STOP \mid dog, barks)\times
\end{aligned}
$$

Berkeley restaurant project sentences

- can you tell me about any good cantonese restaurants close by
- mid priced that food is what i’m looking for
- tell me about chez pansies
- can you give me a listing of the kinds of food that are available
- i’m looking for a good place to eat breakfast
- when is caffe venezia open during the day

Raw bigram counts (~1000 sentences)

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Bigram probabilities

$$P(w_i \mid w_{i-1}) = \frac{C(w_{i-1}, w_i)}{C(w_{i-1})}$$

$$P(w_1, w_2, \dots, w_n) \approxeq \prod_i P(w_i \mid w_{i-1})$$

i	want	to	eat	chinese	food	lunch	spend
2533	927	2417	746	158	1093	341	278

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
to	0.00083	0	0.0017	0.28	0.00083	0	0.0025	0.087
eat	0	0	0.0027	0	0.021	0.0027	0.056	0
chinese	0.0063	0	0	0	0	0.52	0.0063	0
food	0.014	0	0.014	0	0.00092	0.0037	0	0
lunch	0.0059	0	0	0	0	0.0029	0	0
spend	0.0036	0	0.0036	0	0	0	0	0

Bigram estimates of sentence probability

$$P(w_i \mid w_{i-1}) = \frac{C(w_{i-1}, w_i)}{C(w_{i-1})}$$

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

P(<s> i want chinese food </s>) =

P(i|<s>)

× P(want|i)

× P(chinese|want)

× P(food|chinese)

× P(</s>|food)

= …

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
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lunch	0.0059	0	0	0	0	0.0029	0	0
spend	0.0036	0	0.0036	0	0	0	0	0

What can we learn from bigram estimates?

```
P(to|want)        = 0.66
P(chinese|want)    = 0.0065
P(eat|to)         = 0.28
P (i|<s>)         = 0.25
P(food|to)        = 0.0
P(want|spend)  = 0.0
```

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
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lunch	0.0059	0	0	0	0	0.0029	0	0
spend	0.0036	0	0.0036	0	0	0	0	0

Sampling from a language model

1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives

Sampling from a language model

1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives
2 gram	Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her

Sampling from a language model

1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives
2 gram	Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her
3 gram	They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

Sampling from a language model

1 gram	–To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have –Hill he late speaks; or! a more to leg less first you enter
2 gram	–Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow. –What means, sir. I confess she? then all sorts, he is trim, captain.
3 gram	–Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, ’tis done. –This shall forbid it should be branded, if renown made it empty.
4 gram	–King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv’d in; –It cannot be but so.

Practical issues

- Multiplying very small numbers results in numerical underflow
  - we do every operation in log space
  - (also adding is faster than multiplying)

Markovian assumption is false

He is from France, so it makes sense that his first language is…

- We would want to model longer dependencies

Sparsity

- Maximum likelihood for estimating q
  - Let $c(w_1, \ldots, w_n)$ be the number of times that *n*-gram appears in a corpus

$$q(w_i \mid w_{i-2}, w_{i-1}) = \frac{c(w_{i-2}, w_{i-1}, w_i)}{c(w_{i-2}, w_{i-1})}$$

  - If vocabulary has 20,000 words ⇒ Number of parameters is 8×10^{12}!

Bias-variance tradeoff

- Given a corpus of length M

Trigram model:

$$q(w_i \mid w_{i-2}, w_{i-1}) = \frac{c(w_{i-2}, w_{i-1}, w_i)}{c(w_{i-1}, w_i)}$$

Bigram model:

$$q(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

Unigram model:

$$q(w_i) = \frac{c(w_i)}{M}$$

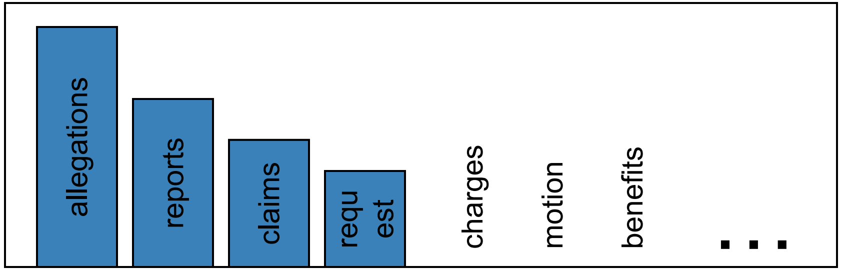
Dealing with sparsity

- For most N-grams, we have few observations
- General approach: modify observed counts to improve estimates
  - Back-off:
    - use trigram if you have good evidence;
    - otherwise bigram, otherwise unigram
  - Interpolation: approximate counts of N-gram using combination of estimates from related denser histories
  - Discounting: allocate probability mass for unobserved events by discounting counts for observed events

Discounting/smoothing methods

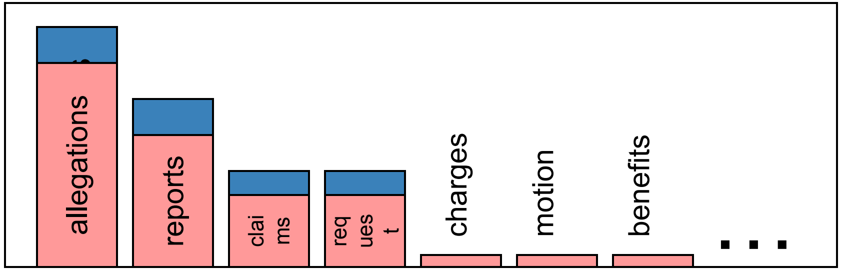
- We often want to make estimates from sparse statistics:

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



- Smoothing flattens spiky distributions so they generalize better:

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



Linear interpolation

- Combine the three models to get all benefits

$$
\begin{aligned}
q_{LI}(w_i \mid w_{i-2}, w_{i-1}) = \lambda_1 \times q(w_i \mid w_{i-2}, w_{i-1}) \\
+ \lambda_2 \times q(w_i \mid w_{i-1}) \\
+ \lambda_3 \times q(w_i)
\end{aligned}
$$

$$\lambda_i \geq 0, \;\; \lambda_1 + \lambda_2 + \lambda_3 = 1$$

Dealing with Out-of-vocabulary terms

- Define a special OOV or "unknown" symbol `<unk>`. Transform some (or all) rare words in the training data to `<unk>`
  - You cannot fairly compare two language models that apply different <unk> treatments
- Build a language model at the character level

Unigram

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
Are where exeunt and sighs have rise excellency took of.. Sleep knave we. near; vile like

Bigram

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?

Trigram

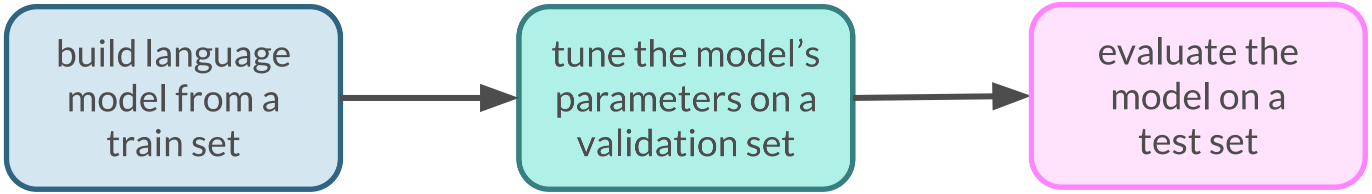
Sweet prince, Falstaff shall die. Harry of Monmouth's grave.
This shall forbid it should be branded, if renown made it empty.
Indeed the duke; and had a very good friend.
Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, 'tis done.

Quadrigram

King Henry.What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv'd in;
Will you not tell me who I am?
It cannot be but so.
Indeed the short and the long. Marry, 'tis a noble Lepidus.

Evaluation

- Extrinsic evaluation: build a new language model, use it for some task (MT, ASR, etc.)
- Intrinsic: measure how good we are at modeling language



Extrinsic evaluation of N-gram models

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

Difficulty of extrinsic (in-vivo) evaluation of N-gram models

- Extrinsic evaluation
    - Time-consuming; can take days or weeks

So

- Sometimes use intrinsic evaluation: perplexity
    - Bad approximation
        - unless the test data looks just like the training data
    - So generally only useful in pilot experiments
    - But is helpful to think about

Intrinsic evaluation: perplexity

- Test data: $S = \{s_1, s_2, \ldots, s_{sent}\}$
  - parameters are estimated on training data

$$p(\mathcal{S}) = \prod_{i=1}^{sent} p(s_i)$$

  - *sent* is the number of sentences in the test data

Evaluation: perplexity

- Test data: $S = \{s_1, s_2, \ldots, s_{sent}\}$
  - parameters are estimated on training data

$$p(\mathcal{S}) = \prod_{i=1}^{sent} p(s_i)$$

$$\begin{aligned} p(\text{the dog barks STOP}) = & q(the \mid *, *)\times \\ & q(dog \mid *, the)\times \\ & q(barks \mid the, dog)\times \\ & q(STOP \mid dog, barks)\times \end{aligned}$$

  - *sent* is the number of sentences in the test data

Evaluation: perplexity

- Test data: S = {s_1, s_2, …, s_{sent}}
  - parameters are estimated on training data

$$p(\mathcal{S}) = \prod_{i=1}^{sent} p(s_i)$$

$$\log_2 p(\mathcal{S}) = \sum_{i=1}^{sent} \log_2 p(s_i)$$

  - *sent* is the number of sentences in the test data

Evaluation: perplexity

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$$\text{perplexity} = 2^{-l}, \; l = \frac{1}{M} \sum_{i=1}^{sent} \log_2 p(s_i)$$

  - *sent* is the number of sentences in the test data
  - M is the number of words in the test corpus

Evaluation: perplexity

- Test data: $S = \{s_1, s_2, \ldots, s_{sent}\}$
  - parameters are estimated on training data

$$p(\mathcal{S}) = \prod_{i=1}^{sent} p(s_i)$$

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$$\text{perplexity} = 2^{-l}, \; l = \frac{1}{M} \sum_{i=1}^{sent} \log_2 p(s_i)$$

  - *sent* is the number of sentences in the test data
  - M is the number of words in the test corpus
  - A good language model has high p(S) and low perplexity

Language models

- Language models are distributions over sentences

$$P(w_1 \dots w_n)$$

- N-gram models are built from local conditional probabilities

$$P(w_1 \dots w_n) = \prod_i P(w_i | w_{i-k} \dots w_{i-1})$$

- The methods we've seen are backed by corpus n-gram counts

$$\hat{P}(w_i | w_{i-1}, w_{i-2}) = \frac{c(w_{i-2}, w_{i-1}, w_i)}{c(w_{i-2}, w_{i-1})}$$