N-gram Language Models

COMP90042

Natural Language Processing

Lecture 3

Semester 1 2022 Week 2
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Language Models

- One NLP application is about *explaining language*
  - Why some sentences are more **fluent** than others
- E.g. in speech recognition:
  - *recognise speech* > *wreck a nice beach*
- We measure ‘goodness’ using **probabilities** estimated by language models
- Language model can also be used for **generation**

InferKit DEMO

7497 / 10000
weekly free characters

Sign In

Generate Options

Learn more in the docs.

Length to generate

500

Start at beginning

Advanced Settings »

Donald Trump decides to become a vegan.

That's according to the diet of the President of the United States, who revealed his new eating habits Monday at a Mississippi campaign rally for Sen. Cindy Hyde-Smith, whom he endorsed over Democrat Mike Espy.

Trump, 71, spoke to the crowd at the Tupelo Regional Airport about his years of eating "perfectly healthy," including steaks and other meats.

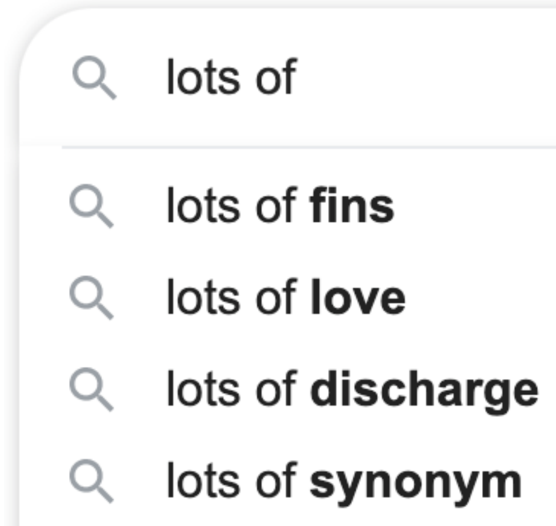
But now he's turned over a new leaf. "I'm not a fan of meat."

Trump told the crowd he now eats "mostly fish, like quite a bit of fish," and

Generate Text

Language Models

- Useful for
  - Query completion
  - Optical character recog.
- Other generation tasks
  - Machine translation
  - Summarisation
  - Dialogue systems
- Nowadays pretrained language models are the backbone of modern NLP systems



Outline

- Deriving *n*-gram language models
- Smoothing to deal with sparsity

Probabilities: Joint to Conditional

Our goal is to get a probability for an arbitrary sequence of *m* words

$$P(w_1, w_2, \ldots, w_m)$$

First step is to apply the chain rule to convert joint probabilities to conditional ones

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

The Markov Assumption

Still intractable, so make a simplifying assumption:

$$P(w_i \mid w_1 \ldots w_{i-1}) \approx P(w_i \mid w_{i-n+1} \ldots w_{i-1})$$

For some small *n*

When *n* = 1, a unigram model

$$P(w_1, w_2, .. w_m) = \prod_{i=1}^{m} P(w_i)$$

w_i
the dog barks

When *n* = 2, a bigram model

$$P(w_1, w_2, .. w_m) = \prod_{i=1}^{m} P(w_i \mid w_{i-1})$$

w_i
the dog barks

When *n* = 3, a trigram model

$$P(w_1, w_2, .. w_m) = \prod_{i=1}^{m} P(w_i \mid w_{i-2} w_{i-1})$$

w_i
the dog barks

Maximum Likelihood Estimation

How do we calculate the probabilities? Estimate based on counts in our corpus:

For unigram models,

$$P(w_i) = \frac{C(w_i)}{M}$$

$$\frac{C(\text{barks})}{M}$$

For bigram models,

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

$$\frac{C(\text{dog barks})}{C(\text{dog})}$$

For n-gram models generally,

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

Book-ending Sequences

- Special tags used to denote start and end of sequence
  - <s> = sentence start
  - </s> = sentence end

Trigram example

Corpus:

yes no no no no yes
no no no yes yes yes no

What is the probability of

yes no no yes

under a trigram language model?

P(yes no no yes) =

P(*yes* | *<s> <s>*) ×

P(*no* | *<s> yes*) ×

P(*no* | *yes no*) ×

P(*yes* | *no no*) ×

P(*</s>* | *no yes*)

Need to predict </s> because it's the end of sentence!

Corpus:

<s> <s> *yes no no no no yes* </s>
<s> <s> *no no no yes yes yes no* </s>

Compute: P(*yes no no yes*)

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

Corpus:

<s> <s> yes no no no no yes </s>
<s> <s> no no no yes yes yes no </s>

Compute: P(*yes no no yes*)

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

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*

Corpus:

<s> <s> *yes no no no no yes* </s>
<s> <s> *no no no yes yes yes no* </s>

Compute: P(*yes no no yes*)

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

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*
P(*no* | <s> *yes*)	1/1	<s> *yes no*

Corpus:

<s> <s> *yes no no no no yes* </s>
<s> <s> *no no no yes yes yes no* </s>

Compute: P(*yes no no yes*)

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

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*
P(*no* | <s> *yes*)	1/1	<s> *yes no*
P(*no* | *yes no*)	1/2	*yes no no* *yes no* </s>

Corpus:

<s> <s> yes no no no no yes </s>
<s> <s> no no no yes yes yes no </s>

Compute: P(*yes no no yes*)

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

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*
P(*no* | <s> *yes*)	1/1	<s> *yes no*
P(*no* | *yes no*)	1/2	*yes no no* *yes no* </s>
P(*yes* | *no no*)	?	

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Corpus:

<s> <s> *yes no no no no yes* </s>
<s> <s> *no no no yes yes yes no* </s>

Compute: P(*yes no no yes*)

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

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*
P(*no* | <s> *yes*)	1/1	<s> *yes no*
P(*no* | *yes no*)	1/2	*yes no no* *yes no* </s>
P(*yes* | *no no*)	2/5	no no no no no no no no yes no no no no no yes

Corpus:

<s> <s> *yes no no no no yes* </s>
<s> <s> *no no no yes yes yes no* </s>

Compute: P(*yes no no yes*)

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

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*
P(*no* | <s> *yes*)	1/1	<s> *yes no*
P(*no* | *yes no*)	1/2	*yes no no* *yes no* </s>
P(*yes* | *no no*)	2/5	no no no no no no no no yes no no no no no yes
P(</s> | *no yes*)	1/2	no yes </s> no yes yes

Corpus:

<s> <s> *yes no no no no yes* </s>
<s> <s> *no no no yes yes yes no* </s>

Compute: P(*yes no no yes*) = ½ × 1 × ½ × ⅖ × ½ = 0.05

P(*yes* | <s> <s>)	1/2	<s> <s> *yes* <s> <s> *no*
P(*no* | <s> *yes*)	1/1	<s> *yes no*
P(*no* | *yes no*)	1/2	*yes no no* *yes no* </s>
P(*yes* | *no no*)	2/5	no no no no no no no no yes no no no no no yes
P(</s> | *no yes*)	1/2	no yes </s> yes no </s>

Several Problems

- Language has long distance effects — need large *n*
  - *The lecture/s that took place last week was/were on preprocessing.*
- Resulting probabilities are often very small
  - Use log probability to avoid numerical underflow
- What about unseen *n*-grams?
  - $P(w_1, w_2, \ldots, w_m) = P(w_1 \mid <s>) \times \underbrace{P(w_2 \mid w_1)}_{\text{whole term = 0 if } P(w_2|w_1) = 0} \ldots$
  - Need to smooth the LM!

Smoothing

Smoothing

- Basic idea: give events you've never seen before some probability
- Must be the case that P(everything) = 1
- Many different kinds of smoothing
  - Laplacian (add-one) smoothing
  - Add-k smoothing
  - Absolute discounting
  - Kneser-Ney
  - And others…

Laplacian (Add-one) Smoothing

- Simple idea: pretend we've seen each *n*-gram once more than we did.

For unigram models (**V**= the vocabulary),

$$P_{add1}(w_i) = \frac{C(w_i) + 1}{M + |V|}$$

For bigram models,

$$P_{add1}(w_i | w_{i-1}) = \frac{C\left(w_{i-1}w_i\right) + 1}{C\left(w_{i-1}\right) + |V|}$$

Add-one Example

<s> *the rat ate the cheese* </s>

What's the bigram probability *P(ate* | *rat*) under add-one smoothing?

$$= \frac{C(rat\ ate) + 1}{C(rat) + |V|} = \frac{2}{6}$$

V = { the, rat, ate, cheese, </s> }

What's the bigram probability *P(ate* | *cheese*) under add-one smoothing?

$$= \frac{C\left(cheese\ ate\right) + 1}{C\left(cheese\right) + |V|} = \frac{1}{6}$$

<s> is not part of vocabulary because we never need to infer its conditional probability (e.g. P(<s> | …))

Recall: P(yes no no yes) =
P(*yes* | *<s> <s>*) × P(*no* | *<s> yes*) ×
P(*no* | *yes no*) × P(*yes* | *no no*) ×
P(*</s>* | *no yes*)

Add-*k* Smoothing

- Adding one is often too much
- Instead, add a fraction *k*
- AKA Lidstone Smoothing, or Add-α Smoothing

$$P_{addk}(w_i \mid w_{i-1}, w_{i-2}) = \frac{C\left(w_{i-2},\ w_{i-1}, w_i\right) + k}{C\left(w_{i-2}, w_{i-1}\right) + k \mid V \mid}$$

- Have to choose *k*

Lidstone Smoothing

Context = *alleged*

- 5 observed bi-grams
- 2 unobserved bi-grams

	counts	unsmoothed probability	Lidstone smoothing, $\alpha = 0.1$ effective counts	smoothed probability
impropriety	8	0.4	7.826	0.391
offense	5	0.25	4.928	0.246
damage	4	0.2	3.961	0.198
deficiencies	2	0.1	2.029	0.101
outbreak	1	0.05	1.063	0.053
infirmity	0	0	0.097	0.005
alleged	0	0	0.097	0.005
	20	1.0	20	1.0

0.391 x 20

(8 + 0.1) / (20 + 7 x 0.1)

(0 + 0.1) / (20 + 7 x 0.1)

Absolute Discounting

- ‘Borrows’ a **fixed** probability mass from observed n-gram counts
- Redistributes it to unseen n-grams

Absolute Discounting

Context = *alleged*

- 5 observed bi-grams
- 2 unobserved bi-grams

	counts	unsmoothed probability	Lidstone smoothing, $\alpha = 0.1$ effective counts	Lidstone smoothing, $\alpha = 0.1$ smoothed probability	Discounting, $d = 0.1$ effective counts	Discounting, $d = 0.1$ smoothed probability
impropriety	8	0.4	7.826	0.391	7.9	0.395
offense	5	0.25	4.928	0.246	4.9	0.245
damage	4	0.2	3.961	0.198	3.9	0.195
deficiencies	2	0.1	2.029	0.101	1.9	0.095
outbreak	1	0.05	1.063	0.053	0.9	0.045
infirmity	0	0	0.097	0.005	0.25	0.013
alleged	0	0	0.097	0.005	0.25	0.013
	20	1.0	20	1.0	20	1.0

(0.1 x 5) / 2

8 - 0.1

0.25 / 20

Backoff

- Absolute discounting redistributes the probability mass **equally** for all unseen n-grams
- Katz Backoff: redistributes the mass based on a **lower order** model (e.g. unigram)

$$P_{katz}(w_i|w_{i-1}) = \begin{cases} \frac{C(w_{i-1},w_i)-D}{C(w_{i-1})}, & \text{if } C(w_{i-1}, w_i) > 0 \\ \alpha(w_{i-1}) \times \frac{P(w_i)}{\sum_{w_j:C(w_{i-1},w_j)=0} P(w_j)}, & \text{otherwise} \end{cases}$$

unigram probability for w_i
e.g. P(infirmity)

sum unigram probabilities for all words that do not co-occur with context w_{i-1}
e.g. P(infirmity) + P(alleged)

the amount of probability mass that has been discounted for context w_{i-1}
((0.1 x 5) / 20 in previous slide)

Issues with Katz Backoff

$$P_{katz}(w_i|w_{i-1}) = \begin{cases} \frac{C(w_{i-1},w_i)-D}{C(w_{i-1})}, & \text{if } C(w_{i-1}, w_i) > 0 \\ \alpha(w_{i-1}) \times \frac{P(w_i)}{\sum_{w_j:C(w_{i-1},w_j)=0} P(w_j)}, & \text{otherwise} \end{cases}$$

- *I can't see without my reading ___*
- C(*reading*, *glasses*) = C(*reading*, *Francisco*) = 0
- C(*Fransciso*) > C(*glasses*)
- Katz backoff will give higher probability to *Francisco*

Kneser-Ney Smoothing

- Redistribute probability mass based on the **versatility** of the lower order n-gram
- AKA “continuation probability”
- What is versatility?
  - High versatility -> co-occurs with a lot of unique words, e.g. glasses
    - men’s glasses, black glasses, buy glasses, etc
  - Low versatility -> co-occurs with few unique words, e.g. francisco
    - san francisco

Kneser-Ney Smoothing

$$P_{KN}(w_i \mid w_{i-1}) = \begin{cases} \dfrac{C(w_{i-1}, w_i) - D}{C(w_{i-1})}, & \text{if } C(w_{i-1}, w_i) > 0 \\ \beta(w_{i-1}) P_{cont}(w_i), & \text{otherwise} \end{cases}$$

the amount of probability mass that has been discounted for context w_{i-1}

$$P_{cont}(w_i) = \frac{|\{w_{i-1} : C(w_{i-1}, w_i) > 0\}|}{\sum_{w_j} |\{w_{j-1} : C(w_{j-1}, w_j) > 0\}|}$$

- Intuitively the numerator of P_{cont} counts the number of unique w_{i-1} that co-occurs with w_i
- High continuation counts for glasses
- Low continuation counts for Franciso

Interpolation

- A better way to combine different orders of *n*-gram models
- Interpolated trigram model:

$$
\begin{aligned}
P_{IN}(w_i \mid w_{i-1}, wi-2) = {} & \lambda_3 P_3(w_i \mid w_{i-2}, w_{i-1}) \\
& + \lambda_2 P_2(w_i \mid w_{i-1}) \\
& + \lambda_1 P_1(w_i)
\end{aligned}
$$

Learned based on held out data

$$\lambda_1 + \lambda_2 + \lambda_3 = 1$$

A Final Word

- *N*-gram language models are a simple but effective way to capture the predictability of language
- Can be trained in an unsupervised fashion, scalable to large corpora
- Require smoothing to be effective
- Modern language models uses neural networks (lecture 8)

Reading

- E18 Chapter 6 (skip 6.3)

Events Confirmed	Week	Date, Time, Location
Summerfest Welcome Back Expo	1	1-Mar-22, 2-5pm 2-Mar-22, 2-5pm 3-Mar-22, 2-5pm 4-Mar-22, 2-5pm
Welcome event with DSSS & HackMelbourne	2	7-Mar-22, 11:30am
Google Career Discussion	2	8-Mar-22, 5 - 6:30pm
Spaghetti Bridge Building Comp Collab	2	11-Mar-22, 3-5:30pm
Robogals collab industry week	3	this whole week
Google Women in Tech clubs session	3	16-Mar-22, 5-5:45pm
Macquarie Grad Program Event	3	TBD

Events planned (wk4 onwards):

- Annual Hackathon
- Workshops for CV and job seeking
- High Tea networking
- Industry Panels
- Free lunch on campus
- Study sessions
- Tech-related clubs collaboration
- SWOT cake
- ...

Other opportunities:

- Weekly job posts
- Tech-related events/competitions
- Volunteering opportunities
- ...

WOMEN IN TECH

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