LANGUAGE MODELING

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CS159 – Spring 2011

some slides adapted from Jason Eisner

Admin

- How did assignment 1 go?
  - How did you feel about not handing in code?
- Assignment 2 will be out soon on language modeling
- Readings
  - make sure you're keeping up with them
  - I will post a popular media article for next week (probably Monday) to read and discuss in class

In-class exercise

- How did it go?
  - Did you make it through all of the questions?
- Estimating probabilities
  - How accurate were your estimates for the average draw from 1-13 with 10, 50 and 100 draws?
  - How accurate were your estimates for the single card?
- Poker face
  - How probable is a royal flush? How does this compare to NLP probabilities?

In-class exercise

- Birthdays
  - Any shared birthdays?
  - Anyone's birthday that day? week?
- Monty hall
  - should you switch?
- The Coin game
  - HHH vs. THT
  - This is sort of like the language modeling task we'll look at today

Independence

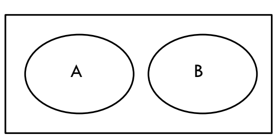
- Two variables are independent if they do not effect each other
- For two independent variables, knowing the value of one does not change the probability distribution of the other variable
  - the result of the toss of a coin is independent of a roll of a dice
  - price of tea in England is independent of the result of general election in Canada

Independent or Dependent?

- Catching a cold and enjoying reading books
- Miles per gallon and driving habits
- Height and longevity of life

Independent variables

- How does independence affect our probability equations/ properties?



- If A and B are independent (written …)
  - P(A,B) = P(A)P(B)
  - P(A|B) = P(A)
  - P(B|A) = P(B)

Conditional Independence

- Dependent events can become independent given certain other events
- Examples,
  - height and length of life
  - “correlation” studies
    - size of your lawn and length of life
- If A, B are conditionally independent of C
  - P(A,B|C) = P(A|C)P(B|C)
  - P(A|B,C) = P(A|C)
  - P(B|A,C) = P(B|C)
  - but P(A,B) ≠ P(A)P(B)

Assume independence

- Sometimes we will assume two variables are independent (or conditionally independent) even though they're not
- Why?
  - Creates a simpler model
    - p(X,Y) many more variables than just P(X) and P(Y)
  - May not be able to estimate the more complicated model

Language modeling

- What does natural language look like?
- More specifically in NLP, probabilistic model
- Two related questions:
  - p(sentence)
    - p("I like to eat pizza")
    - p("pizza like I eat")
  - p(word | previous words)
    - p("pizza" | "I like to eat")
    - p("garbage" | "I like to eat")
    - p("run" | "I like to eat")

Language modeling

- How might these models be useful?
  - Language generation tasks
    - machine translation
    - summarization
    - simplification
    - speech recognition
    - …
  - Text correction
    - spelling correction
    - grammar correction

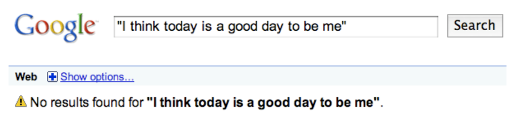
Ideas?

- p("I like to eat pizza")
- p("pizza like I eat")
- p("pizza" | "I like to eat")
- p("garbage" | "I like to eat")
- p("run" | "I like to eat")

Look at a corpus

Language modeling

I think today is a good day to be me



Language modeling is about dealing with data sparsity!

Language modeling

- Language model is really a probabilistic explanation of how the sentence was generated
- Key idea:
  - break this generation process into smaller steps
  - estimate the probabilities of these smaller steps
  - the overall probability is the combined product of the steps

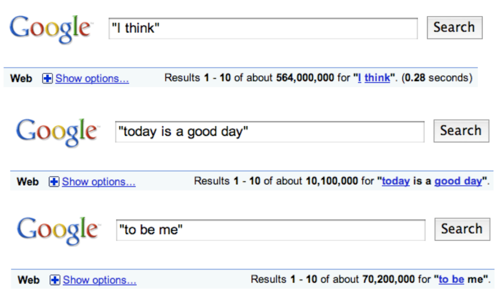
Language modeling

- Two approaches:
  - n-gram language modeling
    - Start at the beginning of the sentence
    - Generate one word at a time based on the previous words
  - syntax-based language modeling
    - Construct the syntactic tree from the top down
    - e.g. context free grammar
    - eventually at the leaves, generate the words

Pros/cons?

n-gram language modeling

I think today is a good day to be me



Our friend the chain rule

Step 1: decompose the probability

P(I think today is a good day to be me) =

P(I | <start>) x

P(think | I) x

P(today | I think) x

P(is | I think today) x

P(a | I think today is) x

P(good | I think today is a) x

…

How can we simplify these?

The n-gram approximation

Assume each word depends only on the previous n-1 words (e.g. trigram: three words total)

P(is | I think today) ≈ P(is | think today)

P(a | I think today is) ≈ P(a | today is)

P(good | I think today is a) ≈ P(good | is a)

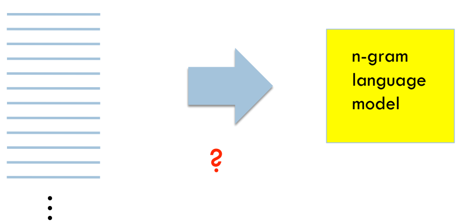
Estimating probabilities

- How do we find probabilities? P(is | think today)
- Get real text, and start counting (MLE)!

$$P(\text{is} \mid \text{think today}) = \frac{\text{count(think today is)}}{\text{count(think today)}}$$

Estimating from a corpus

Corpus of sentences
(e.g. gigaword corpus)



Estimating from a corpus

I am a happy Pomona College student .

count all of the trigrams

<start> <start> I
<start> I am
I am a
am a happy
a happy Pomona
happy Pomona College
Pomona College student
College student .
student . <end>
. <end> <end>

why do we need <start> and <end>?

Estimating from a corpus

I am a happy Pomona College student .

count all of the trigrams

<start> <start> I
<start> I am
I am a
am a happy
a happy Pomona
happy Pomona College
Pomona College student
College student .
student . <end>
. <end> <end>

Do we need to count anything else?

Estimating from a corpus

I am a happy Pomona College student .

count all of the bigrams

<start> <start>
<start> I
I am
am a
a happy
happy Pomona
Pomona College
College student
student .
. <end>

$$p(c \mid a\ b) = \frac{\text{count}(a\ b\ c)}{\text{count}(a\ b)}$$

Estimating from a corpus

- 1. Go through all sentences and count trigrams and bigrams
  - usually you store these in some kind of data structure
- 2. Now, go through all of the trigrams and use the count and the bigram count to calculate MLE probabilities
  - do we need to worry about divide by zero?

Applying a model

- Given a new sentence, we can apply the model

p(Pomona College students are the best .) = ?

p(Pomona | <start>|<start>) *

p(College| <start> Pomona) *

p(students | Pomona College) *

⋮

p(<end>| . <end>) *

Some examples

Generating examples

- We can also use a trained model to generate a random sentence
- Ideas?

<start> <start> ________

We have a distribution over all possible starting words

Draw one from this distribution

p(A | <start> <start>)

p(Apples | <start> <start>)

p(I | <start> <start>)

p(The| <start> <start>)

⋮

p(Zebras| <start> <start>)

Generating examples

<start> <start> Zebras ______

repeat!

p(are | <start> Zebras)

p(eat | <start> Zebras)

p(think | <start> Zebras)

p(and | <start> Zebras)

⋮

p(mostly | <start> Zebras)

Generation examples

- Unigram

are were that ères mammal naturally built describes jazz territory heteromyids film tenor prime live founding must on was feet negro legal gate in on beside . provincial san ; stephenson simply spaces stretched performance double-entry grove replacing station across to burma . repairing ères capital about double reached omnibus el time believed what hotels parameter jurisprudence words syndrome to ères profanity is administrators ères offices hilarius institutionalized remains writer royalty dennis , ères tyson , and objective , instructions seem timekeeper has ères valley ères " magnitudes for love on ères from allakaket , , ana central enlightened . to , ères is belongs fame they the corrected , . on in pressure %NUMBER% her flavored ères derogatory is won metcard indirectly of crop duty learn northbound ères ères dancing similarity ères named ères berkeley . . off-scale overtime . each mansfield stripes dānu traffic ossetic and at alpha popularity town

Generation examples

- Bigrams

the wikipedia county , mexico .

maurice ravel . it is require that is sparta , where functions . most widely admired .

halogens chamiali cast jason against test site .

Generation examples

- Trigrams

is widespread in north africa in june %NUMBER% %NUMBER% units were built by with .

jewish video spiritual are considered ircd , this season was an extratropical cyclone .

the british railways ' s strong and a spot .

Evaluation

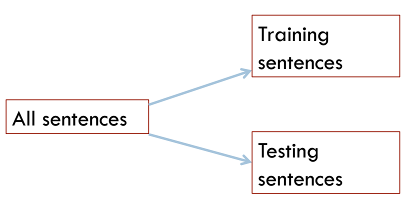
- We can train a language model on some data
- How can we tell how well we're doing?
  - for example
    - bigrams vs. trigrams
    - 100K sentence corpus vs. 100M
    - …

Evaluation

- A very good option: extrinsic evaluation
- If you're going to be using it for machine translation
  - build a system with each language model
  - compare the two based on their approach for machine translation
- Sometimes we don't know the application
- Can be time consuming

Evaluation

- Common NLP/machine learning/AI approach

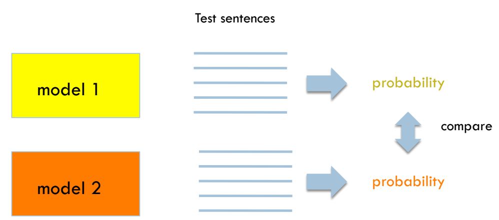


Evaluation

Ideas?

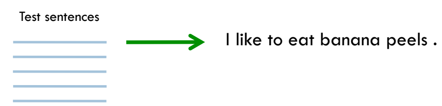
Evaluation

- A good model should do a good job of predicting actual sentences



Perplexity

- View the problem as trying to predict the test corpus one word at a time in sequence
- A perfect model would always know give the next work probability 1



Perplexity

- Perplexity is the average per-word probability

$$\sqrt[n]{\prod_{i=1}^{n} P(w_i \mid w_{1..i-1})}$$

- Sometimes is also written as

$$\sqrt[n]{\prod_{i=1}^{n} P(w_i \mid w_{1..i-1})} \cong \frac{\sum_{i=1}^{n} \log p(w_i \mid w_{1...i-1})}{n}$$

Another view of perplexity

- Weighted average branching factor
  - number of possible next words that can follow a word or phrase
  - measure of the complexity/uncertainty of text (as viewed from the language models perspective)

Smoothing

What if our test set contains the following sentence, but one of the trigrams never occurred in our training data?

P(I think today is a good day to be me) =

P(I | <start> <start>) x

P(think | <start> I) x

P(today | I think) x

P(is | think today) x

P(a | today is) x

P(good | is a) x

…

If any of these has never been seen before, prob = 0!

A better approach

- p(z | x y) = ?
- Suppose our training data includes
  - … x y a ..
  - … x y d …
  - … x y d …

  but never: xyz
- We would conclude
  - p(a | x y) = 1/3?
  - p(d | x y) = 2/3?
  - p(z | x y) = 0/3?
- Is this ok?
- Intuitively, how should we fix these?

Smoothing the estimates

- Basic idea:
  - p(a | x y) = 1/3? *reduce*
  - p(d | x y) = 2/3? *reduce*
  - p(z | x y) = 0/3? *increase*
- **Discount** the positive counts somewhat
- **Reallocate** that probability to the zeroes
- Remember, it needs to stay a probability distribution

Other situations

- p(z | x y) = ?
- Suppose our training data includes
  - … x y a … (100 times)
  - … x y d … (100 times)
  - … x y d … (100 times)

  but never: x y z
- Suppose our training data includes
  - … x y a …
  - … x y d …
  - … x y d …
  - … x y … (300 times)

  but never: x y z

Is this the same situation as before?

Smoothing the estimates

- Should we conclude
  - p(a | xy) = 1/3? *reduce*
  - p(d | xy) = 2/3? *reduce*
  - p(z | xy) = 0/3? *increase*
- Readjusting the estimate is particularly important if:
  - the denominator is small …
    - 1/3 probably too high, 100/300 probably about right
  - numerator is small …
    - 1/300 probably too high, 100/300 probably about right

Add-one (Laplacian) smoothing

xya	1	1/3	2	2/29
xyb	0	0/3	1	1/29
xyc	0	0/3	1	1/29
xyd	2	2/3	3	3/29
xye	0	0/3	1	1/29
…				
xyz	0	0/3	1	1/29
Total xy	3	3/3	29	29/29

Add-one (Laplacian) smoothing

300 observations instead of 3 – better data, less smoothing

xya	100	100/300	101	101/326
xyb	0	0/300	1	1/326
xyc	0	0/300	1	1/326
xyd	200	200/300	201	201/326
xye	0	0/300	1	1/326
…				
xyz	0	0/300	1	1/326
Total xy	300	300/300	326	326/326

Add-one (Laplacian) smoothing

What happens if we're now considering 20,000 word types?

xya	1	1/3	2	2/29
xyb	0	0/3	1	1/29
xyc	0	0/3	1	1/29
xyd	2	2/3	3	3/29
xye	0	0/3	1	1/29
…				
xyz	0	0/3	1	1/29
Total xy	3	3/3	29	29/29

Add-one (Laplacian) smoothing

20000 word types, not 26 letters

see the abacus	1	1/3	2	2/20003
see the abbot	0	0/3	1	1/20003
see the abduct	0	0/3	1	1/20003
see the above	2	2/3	3	3/20003
see the Abram	0	0/3	1	1/20003
…				
see the zygote	0	0/3	1	1/20003
Total	3	3/3	20003	20003/20003

Any problem with this?

Add-one (Laplacian) smoothing

- An "unseen event" is a 0-count event
- The probability of an unseen event is 19998/20003
  - add one smoothing thinks it is very likely to see a novel event
- The problem with add-one smoothing is it gives too much probability mass to unseen events

see the abacus	1	1/3	2	2/20003
see the abbot	0	0/3	1	1/20003
see the abduct	0	0/3	1	1/20003
see the above	2	2/3	3	3/20003
see the Abram	0	0/3	1	1/20003
…				
see the zygote	0	0/3	1	1/20003
Total	3	3/3	20003	20003/20003

The general smoothing problem

			modification	probability
see the abacus	1	1/3	?	?
see the abbot	0	0/3	?	?
see the abduct	0	0/3	?	?
see the above	2	2/3	?	?
see the Abram	0	0/3	?	?
…			?	?
see the zygote	0	0/3	?	?
Total	3	3/3	?	?

Add-lambda smoothing

- A large dictionary makes novel events too probable.
- Instead of adding 1 to all counts, add $\lambda = 0.01$?
  - This gives much less probability to novel events

see the abacus	1	1/3	1.01	1.01/203
see the abbot	0	0/3	0.01	0.01/203
see the abduct	0	0/3	0.01	0.01/203
see the above	2	2/3	2.01	2.01/203
see the Abram	0	0/3	0.01	0.01/203
…			0.01	0.01/203
see the zygote	0	0/3	0.01	0.01/203
Total	3	3/3	203	

Add-lambda smoothing

How should we pick lambda?

see the abacus	1	1/3	1.01	1.01/203
see the abbot	0	0/3	0.01	0.01/203
see the abduct	0	0/3	0.01	0.01/203
see the above	2	2/3	2.01	2.01/203
see the Abram	0	0/3	0.01	0.01/203
…			0.01	0.01/203
see the zygote	0	0/3	0.01	0.01/203
Total	3	3/3	203	

Setting smoothing parameters

- Idea 1: try many λ values & report the one that gets best results?

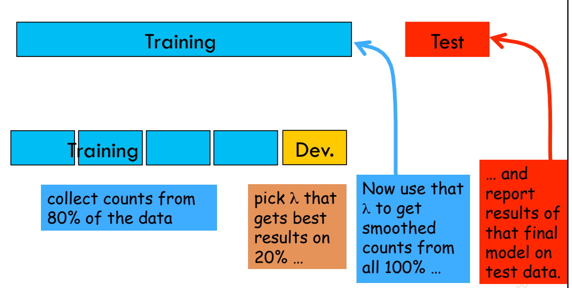
Training | Test

Is this fair/appropriate?

Correct experimentation

- General rules:
  - Test data should *only* be used for evaluation
  - No peeking! Only use it for your final results.
  - Never skew anything in your favor
- Other ideas?

Setting smoothing parameters



problems? ideas?

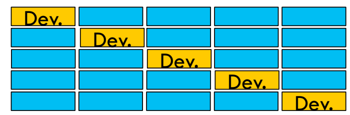
Concerns

- 20% may not be enough to reliably determine λ
- We're maximizing lambda for only 80% of our data (will not be the same as the optimal for 100%)
- We're losing 20% of our data for calculating counts

Ideas?

Cross-validation (aka "jackknifing")

- If 20% too little: try 5 training/test splits as below
  - Pick λ that gets best average performance



  - ☺ This tests on all 100% (in turn), so we can more reliably assess λ
  - ☹ Unfortunately, still picks a λ that does well on 80% training.

N-fold Cross-Validation and "Leave One Out"

(more extreme version of strategy from last slide)

- Test each sentence with smoothed model from other N-1 sentences
- ☺ Still tests on all 100% (in turn), so we can reliably assess λ
- ☺ Tests if λ is good for smoothing $(N-1)/N \approx 100\%$ of training data, which matches our actual test conditions
- ☺ Surprisingly fast: why?
  - Usually easy to change model by adding/subtracting 1 sentence's counts