Language acquisition

http://www.youtube.com/watch?v=RE4ce4mexrU
(4:30)

LANGUAGE MODELING: SMOOTHING

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CS159 – Spring 2019

some slides adapted from Jason Eisner

Admin

Assignment 2 out
- bigram language modeling
- Java
- Can work with partners
  - Anyone looking for a partner?
- 2a: Due this Friday
- 2b: Due next Friday
- Style/commenting (JavaDoc)
- Some advice
  - Start now!
  - Spend 1-2 hours working out an example by hand (you can check your answers with me)
  - HashMap

Admin

Our first quiz (when?)
- In-class (~30 min.)
- Topics
  - corpus analysis
  - regular expressions
  - probability
  - language modeling
- Open book/notes
  - we'll try it out for this one
  - better to assume closed book (30 minutes goes by fast!)
- 10% of your grade

Admin

Lab next class

Meet in Edmunds 105

Today

Today

Take home ideas:

- Key idea of smoothing is to redistribute the probability to handle less seen (or never seen) events
  - Still must always maintain a true probability distribution
- Lots of ways of smoothing data
- Should take into account features in your data!

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!

Smoothing

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

…

These probability estimates may be inaccurate. Smoothing can help reduce some of the noise.

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.

add $\lambda = 0.01$ to all counts

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?

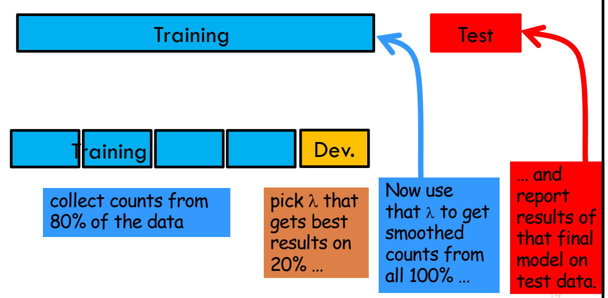
see the abacus	1	1/3	1.01	1.01/203
see the abbot	0	0/3	0.01	0.01/203
see the abduct	0	0/3	0.01	0.01/203
see the above	2	2/3	2.01	2.01/203
see the Abram	0	0/3	0.01	0.01/203
…			0.01	0.01/203
see the zygote	0	0/3	0.01	0.01/203
Total	3	3/3	203	

Setting smoothing parameters

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

Is this fair/appropriate?

Setting smoothing parameters



problems? ideas?

Vocabulary

n-gram language modeling assumes we have a fixed vocabulary
- why?

Probability distributions are over finite events!

What happens when we encounter a word not in our vocabulary (Out Of Vocabulary)?
- If we don't do anything, prob = 0
- Smoothing doesn't really help us with this!

Vocabulary

To make this explicit, smoothing helps us with…

all entries in our vocabulary

see the abacus	1	1.01
see the abbot	0	0.01
see the abduct	0	0.01
see the above	2	2.01
see the Abram	0	0.01
…		0.01
see the zygote	0	0.01

Vocabulary

and…

Vocabulary	Counts	Smoothed counts
a	10	10.01
able	1	1.01
about	2	2.01
account	0	0.01
acid	0	0.01
across	3	3.01
…	…	…
young	1	1.01
zebra	0	0.01

How can we have words in our vocabulary we've never seen before?

Vocabulary

Choosing a vocabulary: ideas?

- Grab a list of English words from somewhere
- Use all of the words in your training data
- Use some of the words in your training data
  - for example, all those the occur more than k times

Benefits/drawbacks?

- Ideally your vocabulary should represents words you're likely to see
- Too many words: end up washing out your probability estimates (and getting poor estimates)
- Too few: lots of out of vocabulary

Vocabulary

No matter how you chose your vocabulary, you're still going to have out of vocabulary (OOV) words

How can we deal with this?

- Ignore words we've never seen before
  - Somewhat unsatisfying, though can work depending on the application
  - Probability is then dependent on how many in vocabulary words are seen in a sentence/text
- Use a special symbol for OOV words and estimate the probability of out of vocabulary

Out of vocabulary

Add an extra word in your vocabulary to denote OOV (<OOV>, <UNK>)

Replace all words in your training corpus not in the vocabulary with <UNK>

- You'll get bigrams, trigrams, etc with <UNK>
  - p(<UNK> | "I am")
  - p(fast | "I <UNK>")

During testing, similarly replace all OOV with <UNK>

Choosing a vocabulary

A common approach (and the one we'll use for the assignment):

- Replace the first occurrence of each word by <UNK> in a data set
- Estimate probabilities normally

Vocabulary then is all words that occurred two or more times

This also discounts all word counts by 1 and gives that probability mass to <UNK>

Storing the table

How are we storing this table?
Should we store all entries?

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	

Storing the table

Hashtable (e.g. HashMap)

- fast retrieval
- fairly good memory usage

Only store those entries of things we've seen

- for example, we don't store $|V|^3$ trigrams

For trigrams we can:

- Store one hashtable with bigrams as keys
- Store a hashtable of hashtables (I'm recommending this)

Storing the table: add-lambda smoothing

For those we've seen before:

Unsmoothed (MLE)

$$P(c \mid ab) = \frac{C(abc)}{C(ab)}$$

add-lambda smoothing

$$P(c \mid ab) = \frac{C(abc) + \lambda}{C(ab) + ?}$$

What value do we need here to make sure it stays a probability distribution?

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	

Storing the table: add-lambda smoothing

For those we've seen before:

Unsmoothed (MLE)

$$P(c \mid ab) = \frac{C(abc)}{C(ab)}$$

add-lambda smoothing

$$P(c \mid ab) = \frac{C(abc) + \lambda}{C(ab) + \lambda V}$$

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	

For each word in the vocabulary, we pretend we've seen it λ times more (V = vocabulary size).

Storing the table: add-lambda smoothing

For those we've seen before:

$$P(c \mid ab) = \frac{C(abc) + \lambda}{C(ab) + \lambda V}$$

Unseen n-grams: p(z | ab) = ?

$$P(z \mid ab) = \frac{\lambda}{C(ab) + \lambda V}$$

Problems with frequency based smoothing

The following bigrams have never been seen:

p(X | San) p(X | ate)

Which would add-lambda pick as most likely?

Which would you pick?

Witten-Bell Discounting

Some words are more likely to be followed by new words

San: Diego, Francisco, Luis, Jose, Marcos

ate: food, apples, bananas, hamburgers, a lot, for two, grapes, …

Witten-Bell Discounting

Probability mass is shifted around, depending on the context of words

If $P(w_i \mid w_{i-1},\ldots,w_{i-m}) = 0$, then the smoothed probability $P_{WB}(w_i \mid w_{i-1},\ldots,w_{i-m})$ is higher if the sequence $w_{i-1},\ldots,w_{i-m}$ occurs with many different words w_k

Problems with frequency based smoothing

The following trigrams have never been seen:

p(car | see the)

p(zygote | see the)

p(cumquat | see the)

Which would add-lambda pick as most likely? Witten-Bell?

Which would you pick?

Better smoothing approaches

Utilize information in lower-order models

Interpolation

- Combine probabilities of lower-order models in some linear combination

Backoff

$$P(z \mid xy) = \begin{cases} \frac{C^*(xyz)}{C(xy)} & \text{if } C(xyz) > k \\ \alpha(xy)P(z \mid y) & \text{otherwise} \end{cases}$$

- Often k = 0 (or 1)
- Combine the probabilities by "backing off" to lower models only when we don't have enough information

Smoothing: simple interpolation

$$P(z \mid xy) \approx \lambda \frac{C(xyz)}{C(xy)} + \mu \frac{C(yz)}{C(y)} + (1-\lambda-\mu)\frac{C(z)}{C(\bullet)}$$

Trigram is very context specific, very noisy

Unigram is context-independent, smooth

Interpolate Trigram, Bigram, Unigram for best combination

How should we determine λ and μ?

Smoothing: finding parameter values

Just like we talked about before, split training data into training and development

Try lots of different values for λ, μ on heldout data, pick best

Two approaches for finding these efficiently
- EM (expectation maximization)
- "Powell search" – see Numerical Recipes in C

Backoff models: absolute discounting

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & if\ C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & otherwise \end{cases}$$

Subtract some absolute number from each of the counts (e.g. 0.75)
- How will this affect rare words?
- How will this affect common words?

Backoff models: absolute discounting

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & if\ C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & otherwise \end{cases}$$

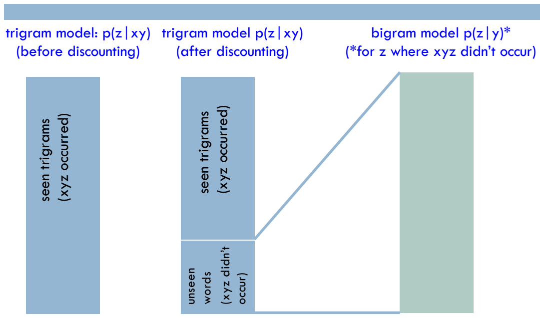
Subtract some absolute number from each of the counts (e.g. 0.75)
- will have a large effect on low counts (rare words)
- will have a small effect on large counts (common words)

Backoff models: absolute discounting

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & if\ C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & otherwise \end{cases}$$

What is $\alpha(xy)$?

Backoff models: absolute discounting



$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & \text{if } C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & \text{otherwise} \end{cases}$$

Backoff models: absolute discounting

see the dog	1
see the cat	2
see the banana	4
see the man	1
see the woman	1
see the car	1

p(cat | see the) = ?

p(puppy | see the) = ?

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & \text{if } C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & \text{otherwise} \end{cases}$$

Backoff models: absolute discounting

see the dog	1
see the cat	2
see the banana	4
see the man	1
see the woman	1
see the car	1

p(cat | see the) = ?

$$\frac{2 - D}{10} = \frac{2 - 0.75}{10} = .125$$

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & \text{if } C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & \text{otherwise} \end{cases}$$

Backoff models: absolute discounting

see the dog	1
see the cat	2
see the banana	4
see the man	1
see the woman	1
see the car	1

p(puppy | see the) = ?

α(see the) = ?

How much probability mass did we reserve/discount for the bigram model?

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & \text{if } C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & \text{otherwise} \end{cases}$$

Backoff models: absolute discounting

see the dog	1
see the cat	2
see the banana	4
see the man	1
see the woman	1
see the car	1

p(puppy | see the) = ?

α(see the) = ?

$$\frac{\text{\# of } types \text{ starting with "see the" * D}}{\text{count("see the")}}$$

For each of the unique trigrams, we subtracted D/count("see the") from the probability distribution

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & if\ C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & otherwise \end{cases}$$

Backoff models: absolute discounting

see the dog	1
see the cat	2
see the banana	4
see the man	1
see the woman	1
see the car	1

p(puppy | see the) = ?

α(see the) = ?

$$\frac{\text{\# of } types \text{ starting with "see the" * D}}{\text{count("see the")}}$$

$$reserved\_mass(\text{see the}) = \frac{6 * D}{10} = \frac{6 * 0.75}{10} = 0.45$$

distribute this probability mass to all bigrams that we are backing off to

$$P_{absolute}(z \mid xy) = \begin{cases} \frac{C(xyz) - D}{C(xy)} & if\ C(xyz) > 0 \\ \alpha(xy) P_{absolute}(z \mid y) & otherwise \end{cases}$$

Calculating α

We have some number of bigrams we're going to backoff to, i.e. those X where C(see the X) = 0, that is unseen trigrams starting with "see the"

When we backoff, for each of these, we'll be including their probability in the model: P(X | the)

α is the normalizing constant so that the sum of these probabilities equals the reserved probability mass

$$\alpha(see\ the) * \sum_{X: C(\text{see the X}) == 0} p(\text{X} \mid \text{the}) = reserved\_mass(\text{see the})$$

Calculating α

We can calculate α two ways

- Based on those we haven't seen:

$$\alpha(\text{see the}) = \frac{reserved\_mass(\text{see the})}{\sum_{X: C(\text{see the X}) = 0} p(\text{X} \mid \text{the})}$$

- Or, more often, based on those we do see:

$$\alpha(\text{see the}) = \frac{reserved\_mass(\text{see the})}{1 - \sum_{X: C(\text{see the X}) > 0} p(\text{X} \mid \text{the})}$$

Calculating α in general: trigrams

p(C | A B)

Calculate the reserved mass

$$\text{reserved\_mass(bigram--A B)} = \frac{\text{\# of } \textit{types} \text{ starting with bigram * D}}{\text{count(bigram)}}$$

Calculate the sum of the backed off probability. For bigram "A B":

$$1 - \sum_{X:C(\text{A B X}) > 0} p(\text{X} \mid \text{B})$$ either is fine, in practice the left is easier $$\sum_{X:C(\text{A B X}) = 0} p(\text{X} \mid \text{B})$$

Calculate α

$$\alpha(\text{A B}) = \frac{reserved\_mass(\text{A B})}{1 - \sum_{X:C(\text{A B X}) > 0} p(\text{X} \mid \text{B})}$$

1 – the sum of the bigram probabilities of those trigrams that we saw starting with bigram A B

Calculating α in general: bigrams

p(B | A)

Calculate the reserved mass

$$\text{reserved\_mass(unigram--A)} = \frac{\text{\# of } \textit{types} \text{ starting with unigram * D}}{\text{count(unigram)}}$$

Calculate the sum of the backed off probability. For bigram "A B":

$$1 - \sum_{X:C(\text{A X}) > 0} p(\text{X})$$ either is fine in practice, the left is easier $$\sum_{X:C(\text{A X}) = 0} p(\text{X})$$

Calculate α

$$\alpha(\text{A}) = \frac{reserved\_mass(\text{A})}{1 - \sum_{X:C(\text{A X}) > 0} p(\text{X})}$$

1 – the sum of the unigram probabilities of those bigrams that we saw starting with word A

Calculating backoff models in practice

Store the αs in another table

- If it's a trigram backed off to a bigram, it's a table keyed by the bigrams
- If it's a bigram backed off to a unigram, it's a table keyed by the unigrams

Compute the αs during training

- After calculating all of the probabilities of seen unigrams/bigrams/trigrams
- Go back through and calculate the αs (you should have all of the information you need)

During testing, it should then be easy to apply the backoff model with the αs pre-calculated

Backoff models: absolute discounting

the Dow Jones	10
the Dow rose	5
the Dow fell	5

p(jumped | the Dow) = ?

What is the reserved mass?

$$\frac{\text{\# of } \textit{types} \text{ starting with "the Dow" * D}}{\text{count("the Dow")}}$$

$$reserved\_mass(\text{the Dow}) = \frac{3*D}{20} = \frac{3*0.75}{20} = 0.115$$

$$\alpha(\text{the Dow}) = \frac{reserved\_mass(\text{see the})}{1 - \sum_{X:C(\text{the Dow X}) > 0} p(\text{X} \mid \text{the})}$$

Backoff models: absolute discounting

$$\text{reserved\_mass} = \frac{\#\text{ of } \textit{types} \text{ starting with bigram} * D}{\text{count(bigram)}}$$

Two nice attributes:

- decreases if we've seen more bigrams
  - should be more confident that the unseen trigram is no good
- increases if the bigram tends to be followed by lots of other words
  - will be more likely to see an unseen trigram