Language Modeling

Introduction to N-grams
Probabilistic Language Models

• Today’s goal: assign a probability to a sentence
  • Machine Translation:
    • $P(\text{high winds tonite}) > P(\text{large winds tonite})$
  • Spell Correction
    • The office is about fifteen minuets from my house
      • $P(\text{about fifteen minutes from}) > P(\text{about fifteen minuets from})$
  • Speech Recognition
    • $P(\text{I saw a van}) >> P(\text{eyes awe of an})$
  • + Summarization, question-answering, etc., etc.!!
Probabilistic Language Modeling

• Goal: compute the probability of a sentence or sequence of words:

\[ P(W) = P(w_1,w_2,w_3,w_4,w_5...w_n) \]

• Related task: probability of an upcoming word:

\[ P(w_5|w_1,w_2,w_3,w_4) \]

• A model that computes either of these:

\[ P(W) \quad \text{or} \quad P(w_n|w_1,w_2...w_{n-1}) \]

is called a language model.

• Better: the grammar    But language model or LM is standard
How to compute $P(W)$

- How to compute this joint probability:
  - $P(\text{its, water, is, so, transparent, that})$

- Intuition: let’s rely on the Chain Rule of Probability
Reminder: The Chain Rule

- Recall the definition of conditional probabilities
  \[ p(B \mid A) = \frac{P(A,B)}{P(A)} \]  
  Rewriting:  \[ P(A,B) = P(A)P(B \mid A) \]

- More variables:
  \[ P(A,B,C,D) = P(A)P(B \mid A)P(C \mid A,B)P(D \mid A,B,C) \]

- The Chain Rule in General
  \[ P(x_1,x_2,x_3,...,x_n) = P(x_1)P(x_2 \mid x_1)P(x_3 \mid x_1,x_2)...P(x_n \mid x_1,...,x_{n-1}) \]
The Chain Rule applied to compute joint probability of words in sentence

\[ P(w_1w_2\ldots w_n) = \prod_i P(w_i \mid w_1w_2\ldots w_{i-1}) \]

\[ P(\text{“its water is so transparent”}) = P(\text{its}) \times P(\text{water} \mid \text{its}) \times P(\text{is} \mid \text{its water}) \]
\[ \times P(\text{so} \mid \text{its water is}) \times P(\text{transparent} \mid \text{its water is so}) \]
How to estimate these probabilities

- Could we just count and divide?

\[ P(\text{its water is so transparent that the}) = \frac{\text{Count}(\text{its water is so transparent that the})}{\text{Count}(\text{its water is so transparent that})} \]

- No! Too many possible sentences!

- We’ll never see enough data for estimating these
Markov Assumption

• Simplifying assumption:

\[ P(\text{the | its water is so transparent that}) \approx P(\text{the | that}) \]

• Or maybe

\[ P(\text{the | its water is so transparent that}) \approx P(\text{the | transparent that}) \]
Markov Assumption

\[ P(w_1w_2\ldots w_n) \approx \prod_i P(w_i | w_{i-k} \ldots w_{i-1}) \]

- In other words, we approximate each component in the product

\[ P(w_i | w_1w_2\ldots w_{i-1}) \approx P(w_i | w_{i-k} \ldots w_{i-1}) \]
Simplest case: Unigram model

\[ P(w_1w_2 \ldots w_n) \approx \prod_i P(w_i) \]

Some automatically generated sentences from a unigram model

fifth, an, of, futures, the, an, incorporated, a, a, the, inflation, most, dollars, quarter, in, is, mass

thrift, did, eighty, said, hard, 'm, july, bullish

that, or, limited, the
Bigram model

- Condition on the previous word:

\[ P(w_i \mid w_1 w_2 \ldots w_{i-1}) \approx P(w_i \mid w_{i-1}) \]

texaco, rose, one, in, this, issue, is, pursuing, growth, in, a, boiler, house, said, mr., gurria, mexico, 's, motion, control, proposal, without, permission, from, five, hundred, fifty, five, yen

outside, new, car, parking, lot, of, the, agreement, reached

this, would, be, a, record, november
N-gram models

• We can extend to trigrams, 4-grams, 5-grams
• In general this is an insufficient model of language
  • because language has long-distance dependencies:
    “The computer which I had just put into the machine room on the fifth floor crashed.”
• But we can often get away with N-gram models
Language Modeling

Introduction to N-grams
Language Modeling

Estimating N-gram Probabilities
Estimating bigram probabilities

- The Maximum Likelihood Estimate

\[ P(w_i | w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i)}{\text{count}(w_{i-1})} \]

\[ P(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \]
An example

\[
P(w_i \mid w_{i-1}) = \frac{c(w_{i-1},w_i)}{c(w_{i-1})}
\]

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

\[
P(I \mid <s>) = \frac{2}{3} = .67 \quad P(Sam \mid <s>) = \frac{1}{3} = .33 \quad P(am \mid I) = \frac{2}{3} = .67
\]

\[
P(<s> \mid Sam) = \frac{1}{2} = 0.5 \quad P(Sam \mid am) = \frac{1}{2} = .5 \quad P(do \mid I) = \frac{1}{3} = .33
\]
More examples:
Berkeley Restaurant Project sentences

• can you tell me about any good cantonese restaurants close by
• mid priced thai food is what i’m looking for
• tell me about chez panisse
• 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

- Out of 9222 sentences

<table>
<thead>
<tr>
<th></th>
<th>i</th>
<th>want</th>
<th>to</th>
<th>eat</th>
<th>chinese</th>
<th>food</th>
<th>lunch</th>
<th>spend</th>
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</thead>
<tbody>
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<td>15</td>
<td>0</td>
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<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
# Raw bigram probabilities

- Normalize by unigrams:

<table>
<thead>
<tr>
<th></th>
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<th>food</th>
<th>lunch</th>
<th>spend</th>
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<td>746</td>
<td>158</td>
<td>1093</td>
<td>341</td>
<td>278</td>
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</table>

- Result:

<table>
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<tr>
<th></th>
<th>i</th>
<th>want</th>
<th>to</th>
<th>eat</th>
<th>chinese</th>
<th>food</th>
<th>lunch</th>
<th>spend</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
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<td>0</td>
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<td>0</td>
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<td>0</td>
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<td>0.0065</td>
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<tr>
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<td>0.0027</td>
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<td>0.0037</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
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<td>lunch</td>
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<td>0</td>
<td>0.0036</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>spend</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Bigram estimates of sentence probabilities

\[
P(<s> \text{ I want english food } </s>) = \\
\quad P(I|<s>) \\
\quad \times P(\text{want}|I) \\
\quad \times P(\text{english}|\text{want}) \\
\quad \times P(\text{food}|\text{english}) \\
\quad \times P(</s>|\text{food}) \\
\quad = .000031
\]
What kinds of knowledge?

- $P(\text{english} \mid \text{want}) = 0.0011$
- $P(\text{chinese} \mid \text{want}) = 0.0065$
- $P(\text{to} \mid \text{want}) = 0.66$
- $P(\text{eat} \mid \text{to}) = 0.28$
- $P(\text{food} \mid \text{to}) = 0$
- $P(\text{want} \mid \text{spend}) = 0$
- $P(i \mid <s>) = 0.25$
Practical Issues

• We do everything in log space
  • Avoid underflow
  • (also adding is faster than multiplying)

\[ \log(p_1 \times p_2 \times p_3 \times p_4) = \log p_1 + \log p_2 + \log p_3 + \log p_4 \]
Language Modeling Toolkits

• SRILM
  • http://www.speech.sri.com/projects/srilm/

• KenLM
  • https://kheafield.com/code/kenlm/
All Our N-gram are Belong to You

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

Here at Google Research we have been using word n-gram models for a variety of R&D projects, ...

That’s why we decided to share this enormous dataset with everyone. We processed 1,024,908,267,229 words of running text and are publishing the counts for all 1,176,470,663 five-word sequences that appear at least 40 times. There are 13,588,391 unique words, after discarding words that appear less than 200 times.
Google N-Gram Release

- serve as the incoming 92
- serve as the incubator 99
- serve as the independent 794
- serve as the index 223
- serve as the indication 72
- serve as the indicator 120
- serve as the indicators 45
- serve as the indispensable 111
- serve as the indispensible 40
- serve as the individual 234

http://googleresearch.blogspot.com/2006/08/all-our-n-gram-are-belong-to-you.html
Google Book N-grams

• http://ngrams.googlelabs.com/
Language Modeling

Estimating N-gram Probabilities
Language Modeling

Evaluation and Perplexity
Evaluation: How good is our model?

- Does our language model prefer good sentences to bad ones?
  - Assign higher probability to “real” or “frequently observed” sentences
    - Than “ungrammatical” or “rarely observed” sentences?
- We train parameters of our model on a **training set**.
- We test the model’s performance on data we haven’t seen.
  - A **test set** is an unseen dataset that is different from our training set, totally unused.
  - An **evaluation metric** tells us how well our model does on the test set.
Training on the test set

• We can’t allow test sentences into the training set
• We will assign it an artificially high probability when we set it in the test set
• “Training on the test set”
• Bad science!
• And violates the honor code
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.
Intuition of Perplexity

• The Shannon Game:
  • How well can we predict the next word?
    
    I always order pizza with cheese and ____
    
    The 33rd President of the US was ____
    
    I saw a ____

  • Unigrams are terrible at this game. (Why?)

• A better model of a text
  • is one which assigns a higher probability to the word that actually occurs

mushrooms 0.1
pepperoni 0.1
anchovies 0.01
....
fried rice 0.0001
....
and 1e-100
Perplexity

The best language model is one that best predicts an unseen test set

- Gives the highest $P(\text{sentence})$

Perplexity is the inverse probability of the test set, normalized by the number of words:

$$PP(W) = \frac{1}{N} \sqrt[1][N]{\frac{1}{P(w_1w_2...w_N)}}$$

Chain rule:

For bigrams:

$$PP(W) = \frac{1}{N} \sqrt[1][N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1...w_{i-1})}}$$

Minimizing perplexity is the same as maximizing probability
Perplexity as branching factor

- Let’s suppose a sentence consisting of random digits
- What is the perplexity of this sentence according to a model that assign $P=1/10$ to each digit?

$$PP(W) = P(w_1w_2\ldots w_N)^{-\frac{1}{N}}$$

$$= \left(\frac{1}{10}\right)^{-\frac{1}{N}}$$

$$= 1^{-1}$$

$$= \frac{1}{10}$$

$$= 10$$
Lower perplexity = better model

- Training 38 million words, test 1.5 million words, WSJ

<table>
<thead>
<tr>
<th>N-gram Order</th>
<th>Unigram</th>
<th>Bigram</th>
<th>Trigram</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perplexity</td>
<td>962</td>
<td>170</td>
<td>109</td>
</tr>
</tbody>
</table>
Language Modeling

Evaluation and Perplexity
Language Modeling

Generalization and zeros
The Shannon Visualization Method

- Choose a random bigram $\langle s, w \rangle$ according to its probability
- Now choose a random bigram $(w, x)$ according to its probability
- And so on until we choose $\langle s \rangle$
- Then string the words together

$s$ I
   I want
      want to
         to eat
            eat Chinese
               Chinese food
                  food $\langle s \rangle$

I want to eat Chinese food
### Approximating Shakespeare

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

- $N=884,647$ tokens, $V=29,066$
- Shakespeare produced 300,000 bigram types out of $V^2=844$ million possible bigrams.
  - So 99.96% of the possible bigrams were never seen (have zero entries in the table)
- Quadrigrams worse: What's coming out looks like Shakespeare because it *is* Shakespeare
The wall street journal is not shakespeare (no offense)

<table>
<thead>
<tr>
<th>1 gram</th>
<th>Months the my and issue of year foreign new exchange’s september were recession exchange new endorsed a acquire to six executives</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 gram</td>
<td>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</td>
</tr>
<tr>
<td>3 gram</td>
<td>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</td>
</tr>
</tbody>
</table>
Can you guess the author of these random 3-gram sentences?

• 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 gram Brazil on market conditions
• This shall forbid it should be branded, if renown made it empty.
• “You are uniformly charming!” cried he, with a smile of associating and now and then I bowed and they perceived a chaise and four to wish for.
The perils of overfitting

- N-grams only work well for word prediction if the test corpus looks like the training corpus
  - In real life, it often doesn’t
- We need to train robust models that generalize!
  - One kind of generalization: Zeros!
    - Things that don’t ever occur in the training set
      - But occur in the test set
Zeros

• Training set:
  ... denied the allegations
  ... denied the reports
  ... denied the claims
  ... denied the request

• Test set
  ... denied the offer
  ... denied the loan

P(“offer” | denied the) = 0
Zero probability bigrams

• Bigrams with zero probability
  • mean that we will assign 0 probability to the test set!
• And hence we cannot compute perplexity (can’t divide by 0)!
Generalization and zeros
Language Modeling

Smoothing: Add-one (Laplace) smoothing
The intuition of smoothing (from Dan Klein)

- When we have sparse statistics:
  \[ P(w \mid \text{denied the}) \]
  - 3 allegations
  - 2 reports
  - 1 claim
  - 1 request
  - 7 total

- Steal probability mass to generalize better
  \[ P(w \mid \text{denied the}) \]
  - 2.5 allegations
  - 1.5 reports
  - 0.5 claim
  - 0.5 request
  - 2 other
  - 7 total
Add-one estimation

- Also called Laplace smoothing
- Pretend we saw each word one more time than we did
- Just add one to all the counts!

\[
P_{MLE}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}
\]

\[
P_{Add-1}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i) + 1}{c(w_{i-1}) + V}
\]
Maximum Likelihood Estimates

• The maximum likelihood estimate
  • of some parameter of a model M from a training set T
  • maximizes the likelihood of the training set T given the model M
• Suppose the word “bagel” occurs 400 times in a corpus of a million words
• What is the probability that a random word from some other text will be “bagel”? 
  • MLE estimate is $\frac{400}{1,000,000} = 0.0004$
• This may be a bad estimate for some other corpus
  • But it is the estimate that makes it most likely that “bagel” will occur 400 times in a million word corpus.
<table>
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<tr>
<th></th>
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<th>lunch</th>
<th>spend</th>
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</thead>
<tbody>
<tr>
<td>i</td>
<td>6</td>
<td>828</td>
<td>1</td>
<td>10</td>
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<td>1</td>
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<td>1</td>
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Laplace-smoothed bigrams

\[ P^*(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n) + 1}{C(w_{n-1}) + V} \]

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<thead>
<tr>
<th></th>
<th>i</th>
<th>want</th>
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<th>eat</th>
<th>chinese</th>
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Reconstituted counts

\[ c^*(w_{n-1}w_n) = \frac{[C(w_{n-1}w_n) + 1] \times C(w_{n-1})}{C(w_{n-1}) + V} \]

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Compare with raw bigram counts

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Add-1 estimation is a blunt instrument

• So add-1 isn’t used for N-grams:
  • We’ll see better methods
• But add-1 is used to smooth other NLP models
  • For text classification
  • In domains where the number of zeros isn’t so huge.
Language Modeling

Smoothing: Add-one (Laplace) smoothing
Language Modeling

Interpolation, Backoff, and Web-Scale LMs
Backoff and Interpolation

• Sometimes it helps to use **less** context
  • Condition on less context for contexts you haven’t learned much about

• **Backoff:**
  • use trigram if you have good evidence,
  • otherwise bigram, otherwise unigram

• **Interpolation:**
  • mix unigram, bigram, trigram

• Interpolation works better
### Linear Interpolation

- **Simple interpolation**

  \[
  \hat{P}(w_n|w_{n-2}w_{n-1}) = \lambda_1 P(w_n|w_{n-2}w_{n-1}) + \lambda_2 P(w_n|w_{n-1}) + \lambda_3 P(w_n)
  \]

  \[
  \sum_{i} \lambda_i = 1
  \]

- **Lambdas conditional on context:**

  \[
  \hat{P}(w_n|w_{n-2}w_{n-1}) = \lambda_1 (w_{n-2}^{n-1}) P(w_n|w_{n-2}w_{n-1}) + \lambda_2 (w_{n-2}^{n-1}) P(w_n|w_{n-1}) + \lambda_3 (w_{n-2}^{n-1}) P(w_n)
  \]
How to set the lambdas?

- Use a **held-out** corpus

![Diagram with Training Data, Held-Out Data, and Test Data]

- Choose λs to maximize the probability of held-out data:
  - Fix the N-gram probabilities (on the training data)
  - Then search for λs that give largest probability to held-out set:

\[
\log P(w_1...w_n \mid M(\lambda_1...\lambda_k)) = \sum_i \log P_{M(\lambda_1...\lambda_k)}(w_i \mid w_{i-1})
\]
Unknown words: Open versus closed vocabulary tasks

• If we know all the words in advanced
  • Vocabulary $V$ is fixed
  • Closed vocabulary task

• Often we don’t know this
  • Out Of Vocabulary = OOV words
  • Open vocabulary task

• Instead: create an unknown word token \(<\text{UNK}>\)
  • Training of \(<\text{UNK}>\) probabilities
    • Create a fixed lexicon $L$ of size $V$
    • At text normalization phase, any training word not in $L$ changed to \(<\text{UNK}>\)
    • Now we train its probabilities like a normal word
  • At decoding time
    • If text input: Use UNK probabilities for any word not in training
Huge web-scale n-grams

• How to deal with, e.g., Google N-gram corpus
• Pruning
  • Only store N-grams with count > threshold.
    • Remove singletons of higher-order n-grams
  • Entropy-based pruning
• Efficiency
  • Efficient data structures like tries
  • Bloom filters: approximate language models
  • Store words as indexes, not strings
    • Use Huffman coding to fit large numbers of words into two bytes
  • Quantize probabilities (4-8 bits instead of 8-byte float)
Smoothing for Web-scale N-grams

- “Stupid backoff” (Brants et al. 2007)
- No discounting, just use relative frequencies

\[
S(w_i | w_{i-k+1}^{i-1}) = \begin{cases} 
\frac{\text{count}(w_{i-k+1}^i)}{\text{count}(w_{i-k+1}^{i-1})} & \text{if } \text{count}(w_{i-k+1}^i) > 0 \\
0.4S(w_i | w_{i-k+2}^{i-1}) & \text{otherwise}
\end{cases}
\]

\[
S(w_i) = \frac{\text{count}(w_i)}{N}
\]
N-gram Smoothing Summary

• Add-1 smoothing:
  • OK for text categorization, not for language modeling
• The most commonly used method:
  • Extended Interpolated Kneser-Ney
• For very large N-grams like the Web:
  • Stupid backoff
Advanced Language Modeling

• Discriminative models:
  • choose n-gram weights to improve a task, not to fit the training set
• Parsing-based models
• Caching Models
  • Recently used words are more likely to appear

\[ P_{\text{CACHE}}(w \mid \text{history}) = \lambda P(w_i \mid w_{i-2}w_{i-1}) + (1 - \lambda) \frac{c(w \in \text{history})}{|\text{history}|} \]

• These perform very poorly for speech recognition (why?)
Language Modeling

Interpolation, Backoff, and Web-Scale LMs
Language Modeling

Advanced: Kneser-Ney Smoothing
Absolute discounting: just subtract a little from each count

- Suppose we wanted to subtract a little from a count of 4 to save probability mass for the zeros
- How much to subtract?
- Church and Gale (1991)’s clever idea
- Divide up 22 million words of AP Newswire
  - Training and held-out set
  - for each bigram in the training set
  - see the actual count in the held-out set!
Absolute Discounting Interpolation

• Save ourselves some time and just subtract 0.75 (or some d)!

\[ P_{\text{AbsoluteDiscounting}}(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i) - d}{c(w_{i-1})} + \lambda(w_{i-1})P(w) \]

• (Maybe keeping a couple extra values of d for counts 1 and 2)

• But should we really just use the regular unigram \( P(w) \)?
Kneser-Ney Smoothing I

• Better estimate for probabilities of lower-order unigrams!
  
  • Shannon game: *I can’t see without my reading* Francisco?  
  • “Francisco” is more common than “glasses”  
  • ... but “Francisco” always follows “San”  

• The unigram is useful exactly when we haven’t seen this bigram!  

• Instead of $P(w)$: “How likely is $w$”  

• $P_{continuation}(w)$: “How likely is $w$ to appear as a novel continuation?“  
  
  • For each word, count the number of bigram types it completes  
  • Every bigram type was a novel continuation the first time it was seen

\[
P_{continuation}(w) \propto \left| \{ w_{i-1} : c(w_{i-1}, w) > 0 \} \right|
\]
Kneser-Ney Smoothing II

• How many times does \( w \) appear as a novel continuation:

\[
P_{\text{continuation}}(w) \propto \left\{ w_{i-1} : c(w_{i-1}, w) > 0 \right\}
\]

• Normalized by the total number of word bigram types

\[
\left| \left\{ (w_{j-1}, w_j) : c(w_{j-1}, w_j) > 0 \right\} \right|
\]

\[
P_{\text{continuation}}(w) = \frac{\left\{ w_{i-1} : c(w_{i-1}, w) > 0 \right\}}{\left\{ (w_{j-1}, w_j) : c(w_{j-1}, w_j) > 0 \right\}}
\]
Kneser-Ney Smoothing III

• Alternative metaphor: The number of # of word types seen to precede w

  \[ | \{ w_{i-1} : c(w_{i-1}, w) > 0 \} | \]

• normalized by the # of words preceding all words:

  \[ P_{\text{CONTINUATION}}(w) = \frac{| \{ w_{i-1} : c(w_{i-1}, w) > 0 \} |}{\sum_{w'} | \{ w'_{i-1} : c(w'_{i-1}, w') > 0 \} |} \]

• A frequent word (Francisco) occurring in only one context (San) will have a low continuation probability
Kneser-Ney Smoothing IV

\[ P_{KN}(w_i \mid w_{i-1}) = \frac{\max(c(w_{i-1}, w_i) - d, 0)}{c(w_{i-1})} + \lambda(w_{i-1})P_{CONTINUATION}(w_i) \]

\( \lambda \) is a normalizing constant; the probability mass we’ve discounted

\[ \lambda(w_{i-1}) = \frac{d}{c(w_{i-1})} \left| \{w : c(w_{i-1}, w) > 0\} \right| \]

The number of word types that can follow \( w_{i-1} \)

= # of word types we discounted

= # of times we applied normalized discount
Kneser-Ney Smoothing: Recursive formulation

\[ P_{KN}(w_i | w^{i-1}_{i-n+1}) = \frac{\max(c_{KN}(w^{i}_{i-n+1}) - d, 0)}{c_{KN}(w^{i-1}_{i-n+1})} + \lambda(w^{i-1}_{i-n+1})P_{KN}(w_i | w^{i-1}_{i-n+2}) \]

\[ c_{KN}(\bullet) = \begin{cases} 
\text{count}(\bullet) & \text{for the highest order} \\
\text{continuationcount}(\bullet) & \text{for lower order}
\end{cases} \]

Continuation count = Number of unique single word contexts for •
Language Modeling

Advanced:
Kneser-Ney Smoothing