Logistics

- Office hours
  - Prof. Lu Wang, Thursdays 1:30pm - 2:30pm, or by appointment, Rm 2211, 177 Huntington Ave
  - To attend OH at 177 Huntington Ave., you’ll need to put down your name on Piazza beforehand (by 2pm each Monday), and then bring a photo ID (e.g. husky card) with you and check in at the front desk.
  - TA Akshay Vasant Dangare (email: dangare.a@husky.neu.edu), Mondays and Wednesdays, 4pm-5pm, 162 WVH (exception: on April 8th, the OH will be in the 1st floor lab at WWH)

Project proposal (due Jan 28)

- In general, we want to see that you have a clear goal in the project. The technical details can be described in a rough manner, but in principle, you need to show what problem you want to study, and what is novel of your project.
- **Introduction:** the problem has to be well-defined. What are the input and output. Why this is an important problem to study.
- **Related work:** put your work in context. Describe what has been done in previous work on the same or related subject. And why what you propose to do here is novel and different.
- **Datasets:** what data do you want to use? What is the size of it? What information is contained? Why is it suitable for your task?
- **Methodology:** what models do you want to use? You may change the model as the project goes, but you may want to indicate some type of models that might be suitable for your problem. Is it a supervised/learning problem or unsupervised? What classifiers can you start with? Are you making improvements? You don’t have to be crystal clear on this section, but it can be used to indicate the direction that your project goes to.
- **Evaluation:** what metrics do you want to use for evaluating your models?
- **Length:** 1 page (or more if necessary). Single space if MS word is used. Or you can choose latex templates, e.g. https://www.acm.org/publications/proceedings-template.
- Grading: based on each section described above, 20 points per section. But as you can tell, they’re related to each other.
- Each group just needs to submit one copy on blackboard with all group member names indicated.

Outline

- Probabilistic language model and n-grams
- Estimating n-gram probabilities
- Language model evaluation and perplexity
- Generalization and zeros
- Smoothing: add-one
- Interpolation, backoff, and web-scale LMs
- Smoothing: Kneser-Ney Smoothing

Probabilistic Language Models

- Assign a probability to a sentence
Probabilistic Language Models

• Assign a probability to a sentence
• Machine Translation:
  • \( P(\text{high winds tonight}) > P(\text{large winds tonight}) \)
• Spell Correction
  • \( P(\text{about fifteen minutes from}) > P(\text{about fifteen minuets from}) \)
• Speech Recognition
  • \( P(\text{saw a van}) >> P(\text{eyes awe of an}) \)
• Text Generation in general:
  • Summarization, question-answering ...

Probabilistic Language Modeling

• Goal: compute the probability of a sentence or sequence of words:
  \( P(W) = P(w_1, w_2, w_3, w_4, w_5, \ldots) \)
• Related task: probability of an upcoming word:
  \( P(w | w_1, w_2, w_3) \)
• A model that computes either of these:
  \( P(W) \) or \( P(w_n | w_1, w_2, \ldots, w_{n-1}) \) 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

Quick Review: Probability

• Recall the definition of conditional probabilities
  \( p(B | A) = \frac{P(A,B)}{P(A)} \)
  Rewriting: \( P(A,B) = P(A)p(B | A) \)
• More variables:
  \( p(A,B,C,D) = \frac{P(A,B,C,D)}{P(A,B)}p(C | A,B) \)
• The Chain Rule in General
  \( P(x_1, x_2, x_3, \ldots, x_n) = P(x_1)p(x_2 | x_1)p(x_3 | x_1, x_2) \ldots P(x_n | x_1, \ldots, x_{n-1}) \)

The Chain Rule applied to compute joint probability of words in sentence

\[
P(w_1, w_2, \ldots, w_n) = \prod P(w_j | w_{j-1})
\]
The Chain Rule applied to compute joint probability of words in sentence

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

\[ P(\text{"its water is so transparent"}) = P(\text{its}) \times P(\text{water | its}) \times P(\text{is | its water}) \times P(\text{so | its water is}) \times P(\text{transparent | its water is so}) \]

How to estimate these probabilities

• Could we just count and divide?

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

• No! Too many possible sentences!

• We’ll never see enough data for estimating these

Markov Assumption

• Simplifying assumption:

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

• Or maybe

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

Simplest case: Unigram model

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

In other words, we approximate each component in the product

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

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:

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

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(s) which I had just put into the machine room on the fifth floor is (are) crashing.”
• But we can often get away with N-gram models

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• Language model evaluation and perplexity
• Generalization and zeros
• Smoothing: add-one
• Interpolation, backoff, and web-scale LMs
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Estimating bigram probabilities

• The Maximum Likelihood Estimate for bigram probability

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

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

An example

\( \langle s \rangle \) I am Sam \( \langle /s \rangle \)
\( \langle s \rangle \) Sam I am \( \langle /s \rangle \)
\( \langle s \rangle \) I do not like green eggs and ham \( \langle /s \rangle \)
An example

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

\[ P(\text{I am Sam} | \text{I am}) = 0.5 \]

\[ P(\text{I do not like green eggs and ham} | \text{I am}) = 0.33 \]

\[ P(\text{Sam} | \text{I am}) = 0.5 \]

\[ P(\text{I am}) = 0.33 \]

\[ P(\text{I do not like green eggs and ham}) = 0.67 \]

\[ P(\text{Sam} | \text{I am}) = 0.5 \]

\[ P(\text{I am}) = 0.33 \]

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>
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Raw bigram probabilities

• Normalize by unigrams:

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<tr>
<th></th>
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<th>want</th>
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<td>0</td>
<td>0</td>
<td>0</td>
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</table>

Bigram estimates of sentence probabilities

\[ P(\text{I want english food} | \text{I}) = \frac{P(\text{I want}) \times P(\text{english} | \text{want}) \times P(\text{food} | \text{english}) \times P(\text{I})}{P(\text{I})} \]

\[ P(\text{I want}) = 0.0011 \]

\[ P(\text{english} | \text{want}) = 0.0065 \]

\[ P(\text{to} | \text{want}) = 0.66 \]

\[ P(\text{eat} | \text{to}) = 0.28 \]

\[ P(\text{food} | \text{to}) = 0 \]

\[ P(\text{I}) = 0.25 \]

Knowledge

• \[ P(\text{english} | \text{I}) = 0.0011 \]
• \[ P(\text{chinese} | \text{I}) = 0.0065 \]
• \[ P(\text{to} | \text{I}) = 0.66 \]
• \[ P(\text{eat} | \text{to}) = 0.28 \]
• \[ P(\text{food} | \text{to}) = 0 \]
• \[ P(\text{I}) = 0.25 \]
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/

• Neural language models (will be discussed later)
  • Word2vec
  • Glove
  • Elmo and BERT

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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!

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 evaluation of N-gram models
• Extrinsic evaluation
  • Time-consuming; can take days or weeks
• So
  • Sometimes use intrinsic evaluation: perplexity

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
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:

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

Chain rule:

$$PP(W) = \frac{1}{\prod_{w=1}^{N} P(w_i|w_{i-1})}$$

For bigrams:

$$PP(W) = \frac{1}{\prod_{w=1}^{N-1} P(w_i|w_{i-1})}$$

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?

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>
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<tbody>
<tr>
<td>Perplexity</td>
<td>962</td>
<td>170</td>
<td>109</td>
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</table>
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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!

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

In training set, we see
  ... denied the allegations
  ... denied the reports
  ... denied the claims
  ... denied the request

But in 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!)

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The intuition of smoothing (from Dan Klein)

- When we have sparse statistics:
  - Steal probability mass to generalize better

**P(w | denied the)***

<table>
<thead>
<tr>
<th>Allegations</th>
<th>Reports</th>
<th>Claims</th>
<th>Requests</th>
<th>Total</th>
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</table>

**P(w | denied the)***

<table>
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<td>7</td>
</tr>
</tbody>
</table>

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! *Instead of taking away counts*

**MLE estimate:**

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

**Add-1 estimate:**

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

Berkeley Restaurant Corpus: Laplace smoothed bigram counts

<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>
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</thead>
<tbody>
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<td>1</td>
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Laplace-smoothed bigrams

\[
P'(w_i | w_{i-1}) = \frac{C(w_{i-1} w_i) + 1}{C(w_{i-1}) + V}
\]

Add-1 estimation is a blunt instrument

- So add-1 isn’t used for N-grams:
  - We’ll see better methods.
  - Nowadays, neural LM becomes popular, will discuss later.
- But add-1 is used to smooth other NLP models
  - For text classification (coming soon!) in domains where the number of zeros isn’t so huge.
  - Add-1 can be extended to add-k (k can be any positive real number, sometimes also called add-alpha)
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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 (e.g. the trigram is observed in training)
  - otherwise bigram
  - otherwise unigram
- Interpolation:
  - mix unigram, bigram, trigram
- In general, interpolation works better

Linear Interpolation

- Simple interpolation
  \[ \hat{P}(w_n | w_{n-1}, \ldots, w_{n-k}) = \lambda_1 P(w_n | w_{n-1}) + \lambda_2 P(w_n | w_{n-2}, \ldots, w_{n-k-1}) + \lambda_3 P(w_n) \sum \lambda_i = 1 \]

How to set the lambdas?

- Use a held-out corpus
- Choose \( \lambda \) to maximize the probability of held-out data:
  - Fix the N-gram probabilities (on the training data)
  - Then search for \( \lambda \) that give largest probability to held-out set:
  \[ \log P(w_1, \ldots, w_n | M(\lambda_{\text{best}})) = \sum \log P_{M(\lambda_{\text{best}})}(w_i | w_{i-1}) \]
  An assignment of \( \lambda \)

A Common Method – Grid Search

- Take a list of possible values, e.g. [0.1, 0.2, ... , 0.9]
- Try all combinations

Linear Interpolation

- Simple interpolation
  \[ \hat{P}(w_n | w_{n-1}, \ldots, w_{n-k}) = \lambda_1 P(w_n | w_{n-1}) + \lambda_2 P(w_n | w_{n-2}, \ldots, w_{n-k-1}) + \lambda_3 P(w_n) \sum \lambda_i = 1 \]

- Lambdas conditional on context:
  \[ \hat{P}(w_n | w_{n-1}, \ldots, w_{n-k}) = \lambda_1 (w_{n-1}^{o-1}) P(w_n | w_{n-1}) + \lambda_2 (w_{n-2}^{o-1}) P(w_n | w_{n-2}, \ldots, w_{n-k-1}) + \lambda_3 P(w_n) \]
  (Short notation for \( w_{n-1} \))
Linear Interpolation

- Simple interpolation
  \[ P(w_n | w_{n-k}, ... , w_{n-1}) = \lambda_0 P(w_n | w_{n-k}, ... , w_{n-1}) + \lambda_1 P(w_n | w_{n-k}) + \lambda_2 P(w_n | w_{n-1}) \]
  \[ \sum \lambda_i = 1 \]

- Lambda conditional on context:
  \[ \hat{P}(w_n | w_{n-k}, ... , w_{n-1}) = \lambda_0 \frac{P(w_n | w_{n-k}, ... , w_{n-1})}{\sum_{i=0}^{2} \lambda_i P(w_i)} \]

Unknown words: Open versus closed vocabulary tasks

- If we know all the words in advance
  - 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 <UNK>
    - Training of <UNK> probabilities
    - Create a fixed lexicon L of size V (e.g. selecting high frequency words)
    - At text normalization phase, any training word not in L changed to <UNK>
    - At test time
      - Use UNK probabilities for any word not in training

Smoothing for Web-scale N-grams

- "Stupid backoff" (Brants et al. 2007)
  - No discounting, just use relative frequencies
    \[ S(w_i | w_{i-k}) = \begin{cases} \text{count}(w_i | w_{i-k}) & \text{if } \text{count}(w_i | w_{i-k}) > 0 \\ 0.4 \times S(w_{i-1} | w_{i-k}) & \text{otherwise} \end{cases} \]
    \[ S(w_i) = \frac{\text{count}(w_i)}{N} \] until unigram probability

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!
    - It sure looks like \( c^* = (- .75) \)

Today’s Outline

- Probabilistic language model and n-grams
- Estimating n-gram probabilities
- Language model evaluation and perplexity
- Generalization and zeros
- Smoothing: add-one
- Interpolation, backoff, and web-scale LMs
- Smoothing: Kneser-Ney Smoothing
Absolute Discounting Interpolation

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

\[
P_{\text{Absolute Discounting}}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i) - d}{c(w_{i-1})} + \lambda(w_{i-1}) P(w_i)
\]

- 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” 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”
- \( P_{\text{continuation}}(w) \): “How likely is \( w \) to appear as a novel continuation (unique bigrams)?
  - For each word, count the number of unique bigrams it completes
  - Every unique bigram was a novel continuation the first time it was seen

\[
P_{\text{continuation}}(w) = \frac{\# \{\text{unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}{\# \{\text{all unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}
\]

Kneser-Ney Smoothing II

- How many times does \( w \) appear as a novel continuation (unique bigrams):
  - \( P_{\text{continuation}}(w) \) vs \([w_{i-1} \cap c(w_{i-1}, w) > 0]\)
  - Normalized by the total number of word bigram types

\[
P_{\text{continuation}}(w) = \frac{\# \{\text{unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}{\# \{\text{all unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}
\]

Kneser-Ney Smoothing III

- Alternative metaphor: The number of # of unique words seen to precede \( w \)
  - \( \# \{\text{unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0) \)
  - normalized by the # of (unique) words preceding all words:

\[
P_{\text{continuation}}(w) = \frac{\# \{\text{unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}{\# \{\text{all unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}
\]

- A frequent word (Francisco) occurring in only one context (San) will have a low continuation probability

Kneser-Ney Smoothing IV (not required)

- Better estimate for probabilities of lower-order unigrams!
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\]

- A frequent word (Francisco) occurring in only one context (San) will have a low continuation probability

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

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

\[
\lambda(w_{i-1}) = \frac{d}{c(w_{i-1})} \left( \frac{\# \{\text{unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)}{\# \{\text{all unique } w \} \cap (w_{i-1} : c(w_{i-1}, w) > 0)} \right)
\]

- The number of word types that can follow \( w \)
  - \# of word types we discounted
  - \# of times we applied normalized discount

Shannon game: Francisco is more common than glasses

\[
P(w) = \frac{1}{N-1} \sum_{i=1}^{N} \left( \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \right)
\]

The unigram is useful exactly when we haven’t seen this bigram!
<table>
<thead>
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<th>Language Modeling</th>
</tr>
</thead>
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</tr>
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</tr>
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<td>• Start thinking about course project and find a team</td>
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<td>• Project proposal due Jan 28th.</td>
</tr>
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</tr>
</tbody>
</table>