Statistical NLP

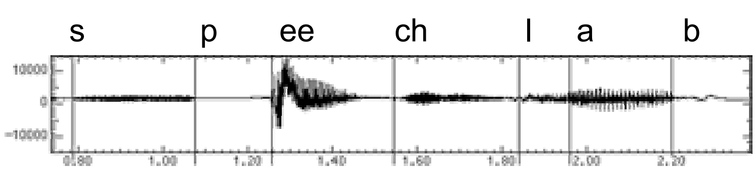
Spring 2007

Lecture 2: Language Models

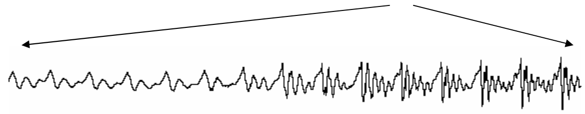
Dan Klein – UC Berkeley

Speech in a Slide (or Three)

- Speech input is an acoustic wave form



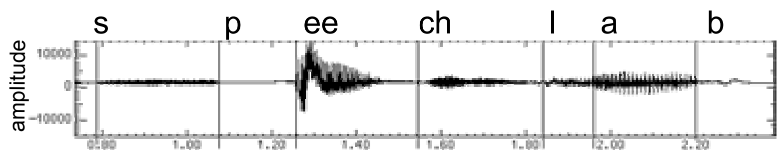
“l” to “a” transition:



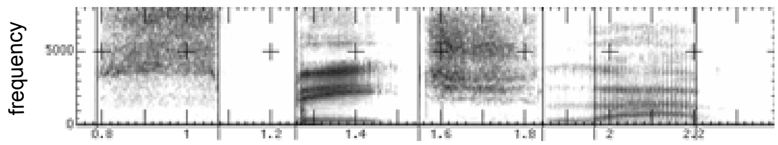
Graphs from Simon Arnfield’s web tutorial on speech, Sheffield:
http://www.psyc.leeds.ac.uk/research/cogn/speech/tutorial/
Some later bits from Joshua Goodman’s LM tutorial

Spectral Analysis

- Frequency gives pitch; amplitude gives volume
  - sampling at ~8 kHz phone, ~16 kHz mic (kHz=1000 cycles/sec)

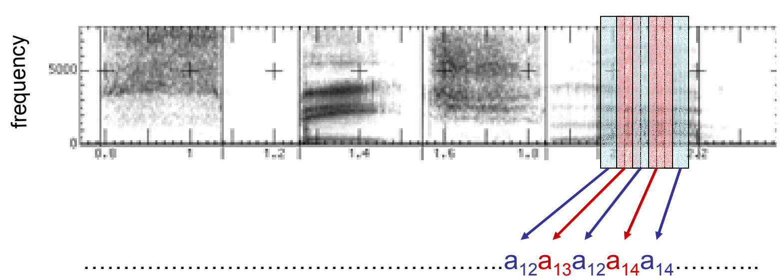


- Fourier transform of wave displayed as a spectrogram
  - darkness indicates energy at each frequency



Acoustic Feature Sequence

- Time slices are translated into acoustic feature vectors (~15 real numbers per slice, details later in the term)



- Now we have to figure out a mapping from sequences of acoustic observations to words.

The Speech Recognition Problem

- We want to predict a sentence given an acoustic sequence:

$$s^* = \arg\max_s P(s \mid a)$$

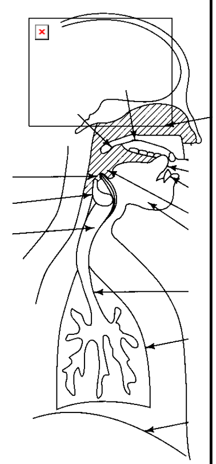
- The noisy channel approach:
  - Build a generative model of production (encoding)

$$P(a, s) = P(s) P(a \mid s)$$

  - To decode, we use Bayes' rule to write

$$\begin{aligned} s^* &= \arg\max_s P(s \mid a) \\ &= \arg\max_s P(s)P(a \mid s) / P(a) \\ &= \arg\max_s P(s)P(a \mid s) \end{aligned}$$

  - Now, we have to find a sentence maximizing this product

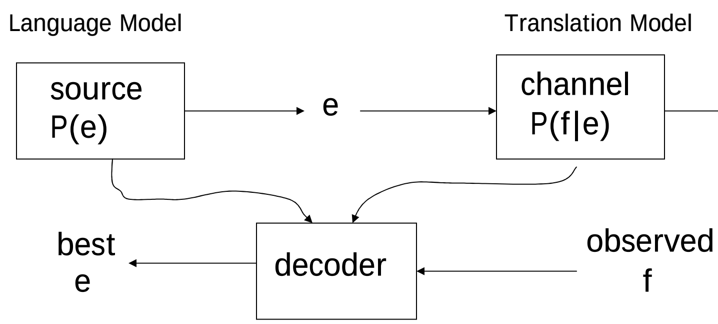


- Why is this progress?

Just a Code?

- "Also knowing nothing official about, but having guessed and inferred considerable about, the powerful new mechanized methods in cryptography—methods which I believe succeed even when one does not know what language has been coded—one naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: 'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.' "
  - Warren Weaver (1955:18, quoting a letter he wrote in 1947)

MT System Components



$$\underset{e}{\operatorname{argmax}}\ P(e|f) = \underset{e}{\operatorname{argmax}}\ P(f|e)P(e)$$

Other Noisy-Channel Processes

- Handwriting recognition

  $$P(text \mid strokes) \propto P(text)P(strokes \mid text)$$

- OCR

  $$P(text \mid pixels) \propto P(text)P(pixels \mid text)$$

- Spelling Correction

  $$P(text \mid typos) \propto P(text)P(typos \mid text)$$

- Translation

  $$P(english \mid french) \propto P(english)P(french \mid english)$$

Probabilistic Language Models

- Want to build models which assign scores to sentences.
  - P(I saw a van) >> P(eyes awe of an)
  - Not really grammaticality: P(artichokes intimidate zippers) ≈ 0
- One option: empirical distribution over sentences?
  - Problem: doesn't generalize (at all)
- Two ways of generalizing
  - Decomposition: sentences generated in small steps which can be recombined in other ways
  - Smoothing: allow for the possibility of unseen events

N-Gram Language Models

- No loss of generality to break sentence probability down with the chain rule

$$P(w_1 w_2 \dots w_n) = \prod_i P(w_i \mid w_1 w_2 \dots w_{i-1})$$

- Too many histories!
  - P(??? | No loss of generality to break sentence) ?
  - P(??? | the water is so transparent that) ?
- N-gram solution: assume each word depends only on a short linear history

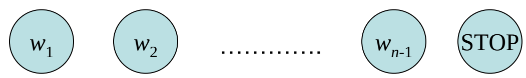
$$P(w_1 w_2 \dots w_n) = \prod_i P(w_i \mid w_{i-k} \dots w_{i-1})$$

Unigram Models

- Simplest case: unigrams

$$P(w_1 w_2 \ldots w_n) = \prod_i P(w_i)$$

- Generative process: pick a word, pick a word, …
- As a graphical model:

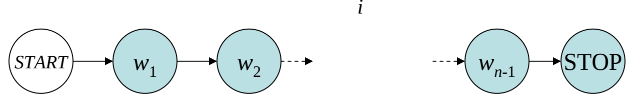


- To make this a proper distribution over sentences, we have to generate a special STOP symbol last. (Why?)
- Examples:
  - [fifth, an, of, futures, the, an, incorporated, a, a, the, inflation, most, dollars, quarter, in, is, mass.]
  - [thrift, did, eighty, said, hard, 'm, july, bullish]
  - [that, or, limited, the]
  - []
  - [after, any, on, consistently, hospital, lake, of, of, other, and, factors, raised, analyst, too, allowed, mexico, never, consider, fall, bungled, davison, that, obtain, price, lines, the, to, sass, the, the, further, board, a, details, machinists, the, companies, which, rivals, an, because, longer, oakes, percent, a, they, three, edward, it, currier, an, within, in, three, wrote, is, you, s., longer, institute, dentistry, pay, however, said, possible, to, rooms, hiding, eggs, approximate, financial, canada, the, so, workers, advancers, half, between, nasdaq]

Bigram Models

- Big problem with unigrams: P(the the the the) >> P(I like ice cream)!
- Condition on previous word:

$$P(w_1 w_2 \ldots w_n) = \prod_i P(w_i \mid w_{i-1})$$



- Any better?
  - [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]
  - [although, common, shares, rose, forty, six, point, four, hundred, dollars, from, thirty, seconds, at, the, greatest, play, disingenuous, to, be, reset, annually, the, buy, out, of, american, brands, vying, for, mr., womack, currently, sharedata, incorporated, believe, chemical, prices, undoubtedly, will, be, as, much, is, scheduled, to, conscientious, teaching]
  - [this, would, be, a, record, november]

More N-Gram Examples

Unigram	• To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have • Every enter now severally so, let • Hill he late speaks; or! a more to leg less first you enter • Are where exeunt and sighs have rise excellency took of.. Sleep knave we. near; vile like
Bigram	• What means, sir. I confess she? then all sorts, he is trim, captain. •Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow. •What we, hath got so she that I rest and sent to scold and nature bankrupt, nor the first gentleman? •Enter Menenius, if it so many good direction found'st thou art a strong upon command of fear not a liberal largess given away, Falstaff! Exeunt
Trigram	• Sweet prince, Falstaff shall die. Harry of Monmouth's grave. • This shall forbid it should be branded, if renown made it empty. • Indeed the duke; and had a very good friend. • Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, 'tis done.
Quadrigram	• King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv'd in; • Will you not tell me who I am? • It cannot be but so. • Indeed the short and the long. Marry, 'tis a noble Lepidus.

Regular Languages?

- N-gram models are (weighted) regular processes
  - Why can't we model language like this?
    - Linguists have many arguments why language can't be merely regular.
    - Long-distance effects:
      "The computer which I had just put into the machine room on the fifth floor crashed."
  - Why CAN we often get away with n-gram models?

- PCFG LM (later):
  - [This, quarter, 's, surprisingly, independent, attack, paid, off, the, risk, involving, IRS, leaders, and, transportation, prices, .]
  - [It, could, be, announced, sometime, .]
  - [Mr., Toseland, believes, the, average, defense, economy, is, drafted, from, slightly, more, than, 12, stocks, .]

Is This Working?

- The game isn't to pound out fake sentences!
- What we really want to know is:
  - Will our model prefer good sentences to bad ones?
  - Bad ≠ ungrammatical!
  - Bad ≈ unlikely
  - Bad = sentences that our acoustic model really likes but aren't the correct answer

Measuring Model Quality

- Word Error Rate (WER)

$$\frac{\text{insertions} + \text{deletions} + \text{substitutions}}{\text{true sentence size}}$$

Correct answer: Andy saw a part of the movie

Recognizer output: And he saw apart of the movie

WER: 4/7
= 57%

- The "right" measure:
  - Task error driven
  - For speech recognition
  - For a specific recognizer!
- For general evaluation, we want a measure which references only good text, not mistake text

Measuring Model Quality

- The Shannon Game:
  - How well can we predict the next word?

    When I order pizza, I wipe off the ____

    Many children are allergic to ____

    I saw a ____

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

grease 0.5
sauce 0.4
dust 0.05
….
mice 0.0001
….
the 1e-100

- The "Entropy" Measure
  - Really: average cross-entropy of a text according to a model

$$H(S \mid M) = \frac{\log_2 P_M(S)}{|S|} = \frac{\sum_i \log_2 P_M(s_i)}{\sum_i |s_i|}$$

$$\sum_j \log_2 P_M(w_j \mid w_{j-1})$$

Measuring Model Quality

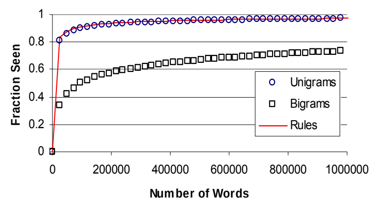
- Problem with entropy:
  - 0.1 bits of improvement doesn't sound so good
  - Solution: perplexity

$$P(S \mid M) = 2^{H(S|M)} = \sqrt[n]{\frac{1}{\prod_{i=1}^{n} P_M(w_i \mid h)}}$$

  - Note that even though our models require a stop step, people typically don't count it as a symbol when taking these averages.

Sparsity

- Problems with n-gram models:
  - New words appear all the time:
    - Synaptitute
    - 132,701.03
    - fuzzificational
  - New bigrams: even more often
  - Trigrams or more – still worse!

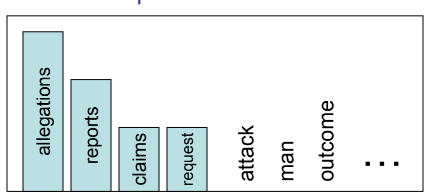


- Zipf's Law
  - Types (words) vs. tokens (word occurences)
  - Broadly: most word types are rare ones
  - Specifically:
    - Rank word types by token frequency
    - Frequency inversely proportional to rank
  - Not special to language: randomly generated character strings have this property (try it!)

Smoothing

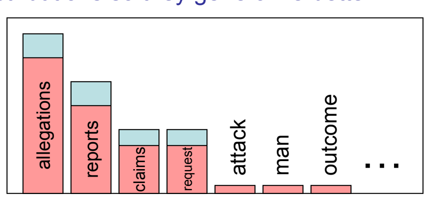
- We often want to make estimates from sparse statistics:

P(w | denied the)
3 allegations
2 reports
1 claims
1 request
7 total



- Smoothing flattens spiky distributions so they generalize better

P(w | denied the)
2.5 allegations
1.5 reports
0.5 claims
0.5 request
2 other
7 total



- Very important all over NLP, but easy to do badly!
- We'll illustrate with bigrams today (h = previous word, could be anything).

Smoothing: Add-One, Etc.

c	number of word tokens in training data
$c(w)$	count of word w in training data
$c(w,w_{-1})$	count of word w following word w_{-1}
V	total vocabulary size (assumed known)
N_k	number of word types with count k

- One class of smoothing functions:
  - Add-one / delta: assumes a uniform prior

$$P_{ADD-\delta}(w \mid w_{-1}) = \frac{c(w, w_{-1}) + \delta(1/V)}{c(w_{-1}) + \delta}$$

  - Better to assume a unigram prior

$$P_{UNI-PRIOR}(w \mid w_{-1}) = \frac{c(w, w_{-1}) + \delta \hat{P}(w)}{c(w_{-1}) + \delta}$$

Linear Interpolation

- One way to ease the sparsity problem for n-grams is to use less-sparse n-1-gram estimates
- General linear interpolation:

$$P(w \mid w_{-1}) = [1 - \lambda(w, w_{-1})]\hat{P}(w \mid w_{-1}) + [\lambda(w, w_{-1})]P(w)$$

  - Having a single global mixing constant is generally not ideal:

$$P(w \mid w_{-1}) = [1 - \lambda]\hat{P}(w \mid w_{-1}) + [\lambda]P(w)$$

  - Solution: have different constant buckets
    - Buckets by count
    - Buckets by average count (better)

Held-Out Data

- Important tool for getting models to generalize:

  - When we have a small number of parameters that control the degree of smoothing, we set them to maximize the (log-)likelihood of held-out data

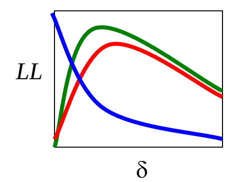
$$LL(w_1 \ldots w_n \mid M(\lambda_1 \ldots \lambda_k)) = \sum_i \log P_{M(\lambda_1 \ldots \lambda_k)}(w_i \mid w_{i-1})$$

  - Can use any optimization technique (line search or EM usually easiest)

- Examples:

$$P_{LIN(\lambda_1,\lambda_2)}(w \mid w_{-1}) = \lambda_1 \hat{P}(w \mid w_{-1}) + \lambda_2 \hat{P}(w)$$

$$P_{UNI-PRIOR(\delta)}(w \mid w_{-1}) = \frac{c(w, w_{-1}) + \delta \hat{P}(w)}{c(w_{-1}) + \delta}$$



Held-Out Reweighting

- What's wrong with unigram-prior smoothing?
- Let's look at some real bigram counts [Church and Gale 91]:

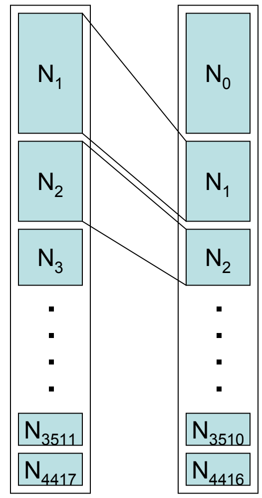
Count in 22M Words	Actual c* (Next 22M)	Add-one's c*	Add-0.0000027's c*
1	0.448	2/7e-10	~1
2	1.25	3/7e-10	~2
3	2.24	4/7e-10	~3
4	3.23	5/7e-10	~4
5	4.21	6/7e-10	~5

Mass on New	9.2%	~100%	9.2%
Ratio of 2/1	2.8	1.5	~2

- Big things to notice:
  - Add-one vastly overestimates the fraction of new bigrams
  - Add-0.0000027 still underestimates the ratio 2*/1*
- One solution: use held-out data to predict the map of c to c*

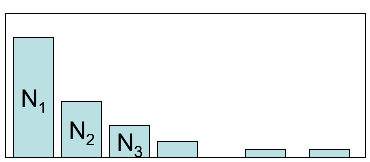
Good-Turing Reweighting I

- We'd like to not need held-out data (why?)
- Idea: leave-one-out validation
  - Take each of the c training words out in turn
  - c training sets of size c-1, held-out of size 1
  - What fraction of held-out words are unseen in training?
    - N_1/c
  - What fraction of held-out words are seen k times in training?
    - $(k+1)N_{k+1}/c$
  - So in the future we expect $(k+1)N_{k+1}/c$ of the words to be those with training count k
  - There are N_k words with training count k
  - Each should occur with probability:
    - $(k+1)N_{k+1}/c/N_k$
  - …or expected count $(k+1)N_{k+1}/N_k$

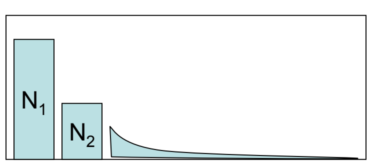


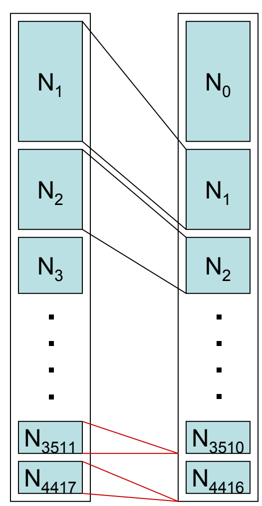
Good-Turing Reweighting II

- Problem: what about "the"? (say c=4417)
  - For small k, $N_k > N_{k+1}$
  - For large k, too jumpy, zeros wreck estimates



  - Simple Good-Turing [Gale and Sampson]: replace empirical N_k with a best-fit power law once count counts get unreliable





Good-Turing Reweighting III

- Hypothesis: counts of k should be $k^* = (k+1)N_{k+1}/N_k$

Count in 22M Words	Actual c* (Next 22M)	GT's c*
1	0.448	0.446
2	1.25	1.26
3	2.24	2.24
4	3.23	3.24
Mass on New	9.2%	9.2%

- Katz Smoothing
  - Use GT discounted *bigram* counts (roughly – Katz left large counts alone)
  - Whatever mass is left goes to empirical unigram

$$P_{KATZ}(w \mid w_{-1}) = \frac{c^*(w, w_{-1})}{\sum_w c(w, w_{-1})} + \alpha(w_{-1})\hat{P}(w)$$

Kneser-Ney Smoothing I

- Something's been very broken all this time
  - Shannon game: There was an unexpected ____?
    - delay?
    - Francisco?
  - "Francisco" is more common than "delay"
  - … but "Francisco" always follows "San"
- Solution: Kneser-Ney smoothing
  - In the back-off model, we don't want the unigram probability of w
  - Instead, probability given that we are observing a novel continuation
  - Every bigram type was a novel continuation the first time it was seen

$$P_{CONTINUATION}(w) = \frac{|\{w_{-1} : c(w, w_{-1}) > 0\}|}{|(w, w_{-1}) : c(w, w_{-1}) > 0|}$$

Kneser-Ney Smoothing II

- One more aspect to Kneser-Ney:
  - Look at the GT counts:

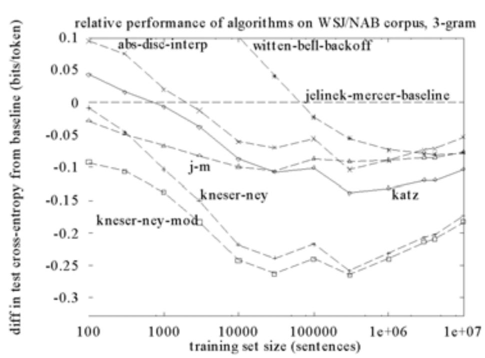
Count in 22M Words	Actual c* (Next 22M)	GT's c*
1	0.448	0.446
2	1.25	1.26
3	2.24	2.24
4	3.23	3.24

- Absolute Discounting
  - Save ourselves some time and just subtract 0.75 (or some d)
  - Maybe have a separate value of d for very low counts

$$P_{KN}(w \mid w_{-1}) = \frac{c(w, w_{-1}) - D}{\sum_{w'} c(w', w_{-1})} + \alpha(w_{-1}) P_{CONTINUATION}(w)$$

What Actually Works?

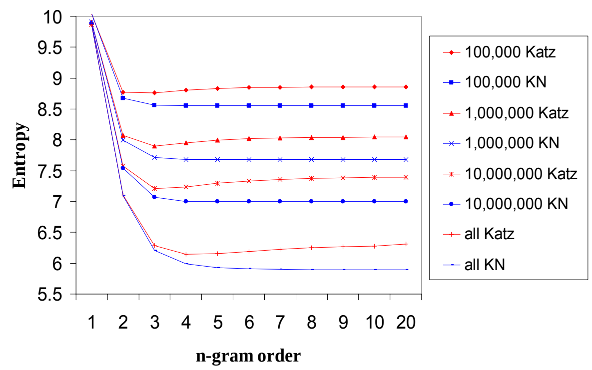
- Trigrams:
  - Unigrams, bigrams too little context
  - Trigrams much better (when there's enough data)
  - 4-, 5-grams usually not worth the cost (which is more than it seems, due to how speech recognizers are constructed)
- Good-Turing-like methods for count adjustment
  - Absolute discounting, Good-Turing, held-out estimation, Witten-Bell
- Kneser-Ney equalization for lower-order models
- See [Chen+Goodman] reading for tons of graphs!



[Graphs from Joshua Goodman]

Data >> Method?

- Having more data is always good…



- … but so is picking a better smoothing mechanism!
- N > 3 often not worth the cost (greater than you'd think)

Beyond N-Gram LMs

- Caching Models
  - Recent words more likely to appear again

$$P_{CACHE}(w \mid history) = \lambda P(w \mid w_{-1} w_{-2}) + (1-\lambda)\frac{c(w \in history)}{\mid history \mid}$$

  - Can be disastrous in practice for speech (why?)

- Skipping Models

$$P_{SKIP}(w \mid w_{-1} w_{-2}) = \lambda_1 \hat{P}(w \mid w_{-1} w_{-2}) + \lambda_2 P(w \mid w_{-1} \_\_) + \lambda_3 P(w \mid \_\_ \, w_{-2})$$

- Clustering Models: condition on word classes when words are too sparse
- Trigger Models: condition on bag of history words (e.g., maxent)
- Structured Models: use parse structure (we'll see these later)

For Next Time

- Readings: J+M 2nd Ed Ch 4, Chen & Goodman (on web page)
- Assignment 1 out soon