Statistical NLP

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University of California

CAL NLP

Berkeley

Lecture 2: Language Models

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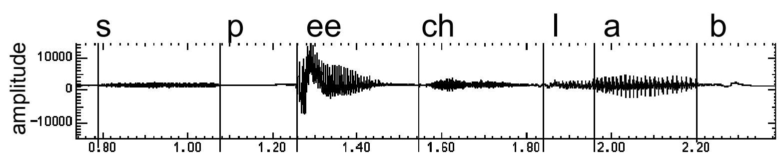
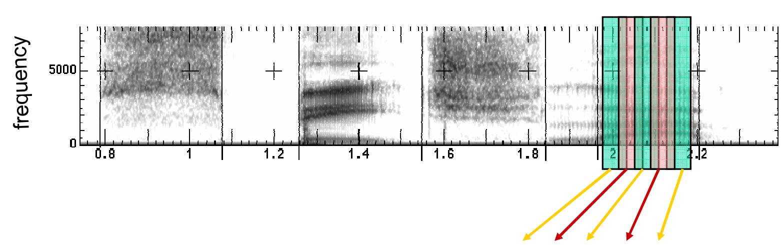
Speech in a Slide

- Frequency gives pitch; amplitude gives volume



- Frequencies at each time slice processed into observation vectors



……………………………………………..$a_{12}a_{13}a_{12}a_{14}a_{14}$………..

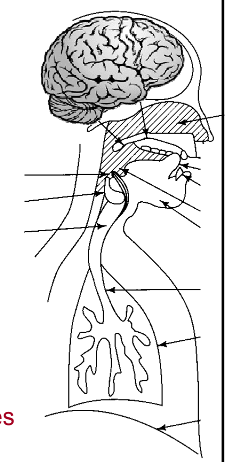
The Noisy-Channel Model

- We want to predict a sentence given acoustics:

$$w^* = \arg\max_w P(w|a)$$

- The noisy channel approach:

$$\begin{aligned} w^* &= \arg\max_w P(w|a) \\ &= \arg\max_w P(a|w)P(w)/P(a) \\ &\propto \arg\max_w P(a|w)P(w) \end{aligned}$$



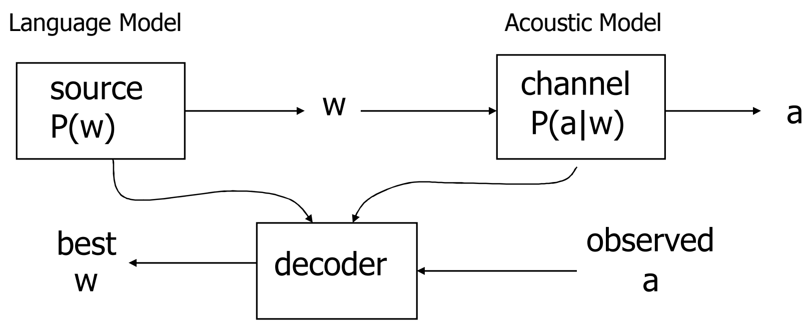
Acoustic model: HMMs over word positions with mixtures of Gaussians as emissions

Language model: Distributions over sequences of words (sentences)

Acoustically Scored Hypotheses

the station signs are in deep in english	-14732
the stations signs are in deep in english	-14735
the station signs are in deep into english	-14739
the station 's signs are in deep in english	-14740
the station signs are in deep in the english	-14741
the station signs are indeed in english	-14757
the station 's signs are indeed in english	-14760
the station signs are indians in english	-14790
the station signs are indian in english	-14799
the stations signs are indians in english	-14807
the stations signs are indians and english	-14815

ASR System Components

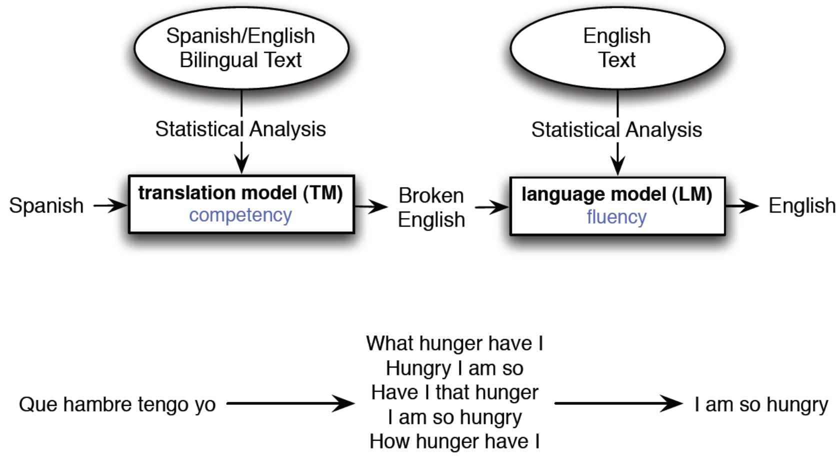


$$\arg\max_{w} P(w|a) = \arg\max_{w} P(a|w)P(w)$$

Translation: Codebreaking?

- "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 Overview



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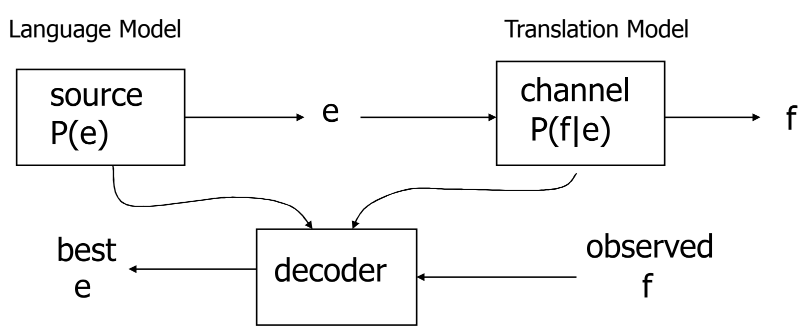
MT System Components



$$\arg\max_{e} P(e|f) = \arg\max_{e} P(f|e)P(e)$$

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

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

- More…

Probabilistic Language Models

- Goal: Assign useful probabilities P(x) to sentences x
  - Input: many observations of training sentences x
  - Output: system capable of computing P(x)
- Probabilities should broadly indicate likelihood of sentences
  - P(I saw a van) >> P(eyes awe of an)
  - *Not grammaticality*: P(artichokes intimidate zippers) $\approx$ 0
  - In principle, “likely” depends on the domain, context, speaker…
- One option: empirical distribution over training sentences?
  - Problem: doesn’t generalize (at all)
- Two ways of generalizing
  - Decomposition: break sentences into small steps which can be recombined in new ways (conditional independence)
  - Smoothing: allow for the possibility of unseen events

N-Gram Language Models

- No loss of generality: break sentence probability down

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

- Too many histories!
  - P(??? | No loss of generality : break sentence) ?
  - P(??? | the water is so transparent that) ?

- N-gram models: assume each word depends only on a short linear history

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

Unigram Models

- Simplest case: unigrams

$$P(w_1 \dots w_n) = \prod_i P(w_i)$$

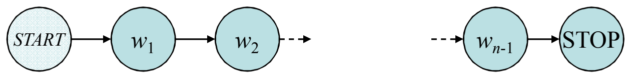
- Generative process: pick a word, pick a word, …
- As a graphical model:

- 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:

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



- Obvious that this should help – in probabilistic terms, we're using weaker conditional independence assumptions (what's the cost?)
- 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

Regular Languages?

- N-gram models are (weighted) regular languages
  - Many linguistic arguments that language isn't regular.
    - Long-distance effects: "The computer which I had just put into the machine room on the fifth floor crashed."
    - Recursive structure
  - 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, .]

Model Parameters

- The parameters of an n-gram model:
  - The conditional probability estimates, we'll call them θ
  - Obvious estimate is the *relative frequency estimate* (aka the *maximum likelihood estimate*)

$$\hat{P}(w|w_{-1}) = \frac{c(w_{-1}, w)}{\sum_{w'} c(w_{-1}, w')}$$

- General method
  - Take a training set X and a test set X'
  - Compute an estimate θ from X
  - Use it to assign probabilities to other sentences, such as X'

- Some quantities of interest
  - Training likelihood
  - Test likelihood

$$L(X|\theta) = \prod_{x \in X} P(x|\theta)$$

$$L(X'|\theta) = \prod_{x' \in X'} P(x'|\theta)$$

Is This Working?

- The game isn't to pound out fake sentences!
  - Obviously, generated sentences get "better" as we increase the model order
  - More precisely: using ML estimators, higher order is always better likelihood on train, but not test
- 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 (why?)

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

- "Entropy": really per-word test log likelihood (misnamed)

$$H(X|\theta) = -\frac{1}{\underbrace{|X|}_{\sum_{x \in X} |x|}} \underbrace{\sum_{x \in X} \log_2 P(x|\theta)}_{\sum_i \log P(x_i|x_{i-1}, \theta)}$$

Measuring Model Quality

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

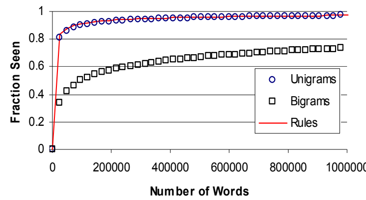
$$\mathrm{perp}(X, \theta) = 2^{H(X|\theta)}$$

  - Interpretation: average branching factor in model

- Big notes:
  - It's easy to get bogus perplexities by having bogus probabilities that sum to more than one over their event spaces. 30% of you will do this on HW1.
  - Even though our models require a stop step, averages are per actual word, not per derivation step.

Sparsity

- Problems with n-gram models:
  - New words appear all the time:
    - Synaptitute
    - 132,701.03
    - multidisciplinarization
  - 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!)

Parameter Estimation

- Maximum likelihood estimates won't get us very far

$$\hat{P}(w|w_{-1}) = \frac{c(w_{-1}, w)}{\sum_{w'} c(w_{-1}, w')}$$

- Need to *smooth* these estimates

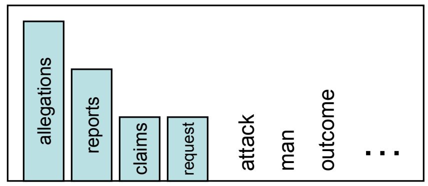
- General method (procedurally)
  - Take your empirical counts
  - Modify them in various ways to improve estimates

- General method (mathematically)
  - Often can give estimators a formal statistical interpretation
  - … but not always
  - Stuff that works not always the same as stuff we can explain (yet!)

Smoothing

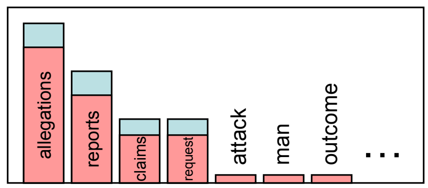
- We often want to make estimates from sparse statistics:

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).

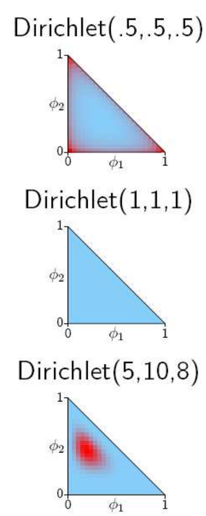
Priors on Parameters

- Most obvious formal solution: use MAP estimate instead of ML estimate for a multinomial P(X)
- Maximum likelihood estimate: max P(X|θ)

$$\theta_{\mathrm{ML}} = \frac{c(x)}{\sum_{x'} c(x')}$$

- MAP estimate: max P(θ|X)
  - Dirichlet priors are a convenient choice
    - Specified by a center θ' and strength k, Dir(θ',k) or Dir(kθ')
    - Mean is center, higher strength means lower variance
  - MAP estimate is then

$$\theta_{\mathrm{MAP}} = \frac{c(x) + k\theta_x - 1}{\sum_{x'} (c(x') + k\theta_x - 1)}$$



Smoothing: Add-One, Etc.

- With a uniform prior, get estimates of the form

$$P_{\text{add}-\delta}(x) = \frac{c(x)+\delta}{\sum_{x'}(c(x')+\delta)}$$

  - Add-one smoothing especially often talked about

- For a bigram distribution, can use a prior centered on the empirical unigram:

$$P_{dir}(w|w_{-1}) = \frac{c(w_{-1},w)+k\hat{P}(w)}{\left(\sum_{w'} c(w_{-1},w')\right)+k}$$

- Can consider hierarchical formulations in which trigram is centered on smoothed bigram estimate, etc [MacKay and Peto, 94]

- Basic idea of conjugacy is convenient: prior shape shows up as *pseudo-counts*

- Problem: works quite poorly!

Linear Interpolation

- Problem: $\hat{P}(w|w_{-1},w_{-2})$ is supported by few counts
- Classic solution: mixtures of related, denser histories, e.g.:

$$\lambda\hat{P}(w|w_{-1},w_{-2}) + \lambda'\hat{P}(w|w_{-1}) + \lambda''\hat{P}(w)$$

- The mixture approach tends to work better than the Dirichlet prior approach for several reasons
  - Can flexibly include multiple back-off contexts, not just a chain
  - Good ways of learning the mixture weights with EM (later)
  - Not entirely clear why it works so much better

- All the details you could ever want: [Chen and Goodman, 98]

Held-Out Data

- Important tool for calibrating how models generalize:

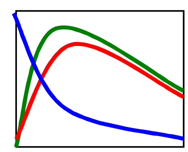
Training Data	Held-Out Data	Test Data

  - Set a small number of hyperparameters that control the degree of smoothing by maximizing the (log-)likelihood of held-out data
  - Can use any optimization technique (line search or EM usually easiest)

- Examples:

$$P_{dir}(w|w_{-1},k) = \frac{c(w_{-1},w) + k\hat{P}(w)}{\left(\sum_{w'} c(w_{-1},w')\right) + k}$$

L



k

$$P_{lin}(w|w_{-1},\lambda,\lambda',\lambda'') = \lambda\hat{P}(w|w_{-1},w_{-2}) + \lambda'\hat{P}(w|w_{-1}) + \lambda''\hat{P}(w)$$

Held-Out Reweighting

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

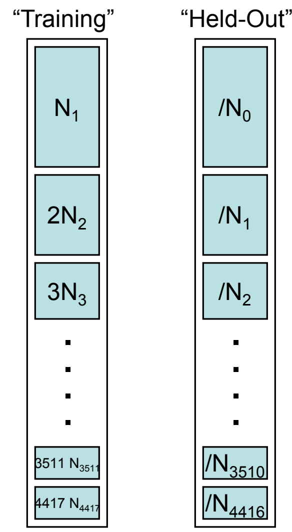
Count in 22M Words	Actual c* (Next 22M)	Add-one's c*	Add-0.0000027's c*
1	0.448	2/7e-10	~1
2	1.25	3/7e-10	~2
3	2.24	4/7e-10	~3
4	3.23	5/7e-10	~4
5	4.21	6/7e-10	~5

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 vastly underestimates the ratio 2*/1*
- One solution: use held-out data to predict the map of c to c*

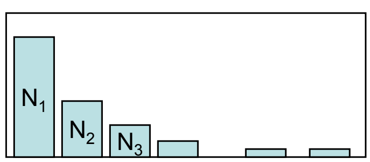
Good-Turing Reweighting I

- We'd like to not need held-out data (why?)
- Idea: leave-one-out validation
  - N_k: number of types which occur k times in the entire corpus
  - Take each of the c tokens out of corpus in turn
  - c "training" sets of size c-1, "held-out" of size 1
  - How many held-out tokens are unseen in training?
    - N_1
  - How many held-out tokens are seen k times in training?
    - $(k+1)N_{k+1}$
  - There are N_k words with training count k
  - Each should occur with expected count
    - $(k+1)N_{k+1}/N_k$
  - Each should occur with probability:
    - $(k+1)N_{k+1}/(cN_k)$

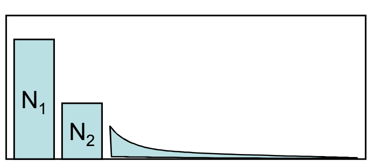


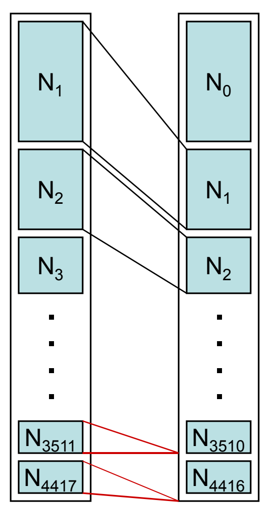
Good-Turing Reweighting II

- Problem: what about "the"? (say k=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

$$P_{\text{katz}}(w|w') = \frac{c^*(w', w)}{c(w')} + \alpha(w')\hat{P}(w)$$

Kneser-Ney: Discounting

- Kneser-Ney smoothing: very successful but slightly ad hoc estimator
- Idea: observed n-grams occur more in training than they will later:

Count in 22M Words	Avg in Next 22M	Good-Turing 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

$$P_{\text{ad}}(w|w') = \frac{c(w', w) - d}{c(w')} + \alpha(w')\hat{P}(w)$$

Kneser-Ney: Continuation

- 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 probability of w as a unigram
  - Instead, want the probability that w is *allowed in this novel context*
  - For each word, count the number of bigram types it completes

$$P_{\mathrm{C}}(w) \propto |w' : c(w', w) > 0|$$

Kneser-Ney

- Kneser-Ney smoothing combines these two ideas
  - Absolute discounting

$$P(w|w') = \frac{c(w', w) - d}{c(w')} + \alpha(w')P'(w)$$

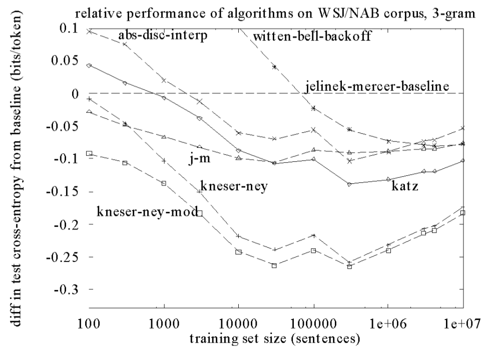
  - Lower order models take a special form

$$P_c(w) \propto |w' : c(w', w) > 0|$$

- KN smoothing repeatedly proven effective
  - But we've never been quite sure why
  - And therefore never known how to make it better
- [Teh, 2006] shows KN smoothing is a kind of approximate inference in a hierarchical Pitman-Yor process (and better approximations are superior to basic KN)

What Actually Works?

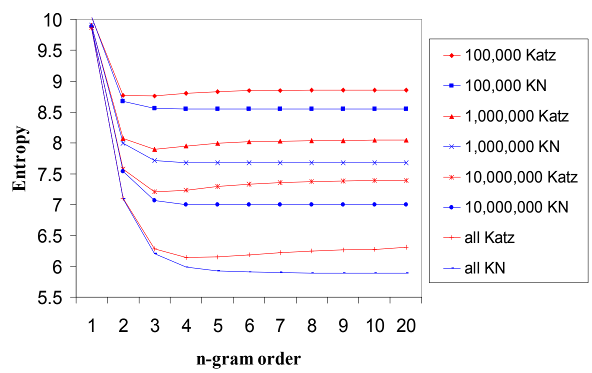
- Trigrams:
  - Unigrams, bigrams too little context
  - Trigrams much better (when there's enough data)
  - 4-, 5-grams often not worth the cost (which is more than it seems, due to how speech recognizers are constructed)
  - Note: for MT, 5+ often used!
- Good-Turing-like methods for count adjustment
  - 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 better…



- … but so is using a better model
- Another issue: N > 3 has huge costs in speech recognizers

Beyond N-Gram LMs

- Lots of ideas we won't have time to discuss:
  - Caching models: recent words more likely to appear again
  - Trigger models: recent words trigger other words
  - Topic models
- A few recent ideas
  - Syntactic models: use tree models to capture long-distance syntactic effects [Chelba and Jelinek, 98]
  - Discriminative models: set n-gram weights to improve final task accuracy rather than fit training set density [Roark, 05, for ASR; Liang et. al., 06, for MT]
  - Structural zeros: some n-grams are syntactically forbidden, keep estimates at zero [Mohri and Roark, 06]
  - Bayesian document and IR models [Daume 06]