CS674 Natural Language Processing

- Last class
 - Introduction to generative models of language
 - » What are they?
 - » Why they're important
 - » Issues for counting words
- Today
 - Introduction to generative models of language
 - » Statistics of natural language
 - » Unsmoothed N-grams

How many words are there in English?

- Option 1: count the word entries in a dictionary
 - OED: 600,000
 - American Heritages (3rd edition): 200,000
 - Actually counting lemmas not wordforms
- Option 2: estimate from a corpus
 - Switchboard (2.4 million wordform tokens): 20,000 wordform types
 - Shakespeare's complete works: 884,647 wordform tokens; 29,066 wordform types
 - Brown corpus (1 million tokens): 61.805 wordform types → 37, 851 lemma types
 - Brown et al. 1992: 583 million wordform tokens, 293,181 wordform types

How are they distributed? function words frequency content words rare words rank in frequency list

How are they distributed?

- There are stable, language-independent patterns in how people use natural language
 - A few words occur very frequently; most occur rarely
 - In general

most common words from *Tom Sawyer*» Top 2 words ~ 10-15% of all

tokens

» Top 6 words ~ 20% of all tokens

» Top 50 words ~ 50% of all tokens

The 3332 2972 word And Α 1775 1725 То 1440 Of Tom 679 14 With preposition

Statistical Properties of Text

- The most frequent words in one corpus may be rare words in another corpus
 - Example: "computer" in CACM vs. National Geographic
- Each corpus has a different, fairly small "working vocabulary"

These properties hold in a wide range of languages

Zipf's Law

- Zipf's Law relates a term's frequency to its rank
 - frequency 1/rank
 - There is a constant k such that freq * rank = k
 - Rank the terms in a vocabulary by frequency, in descending order

 f_r : frequency of term at rank r

N: total number of word occurrences

 $p_r = f_r / N$ and

Empirical observation∑p_r ≠ A ½ r, A 0.1

– Hence:

$$p_r = \frac{f_r}{N} = \frac{A}{r} \rightarrow r f_r = AN$$
 k $\,$ N/10 for English

Zipf's Law

Word	Frequency	$r \times p_r$	Word	Frequency	$r \times p_r$
the	1,130,021	0.059	by	118.863	0.081
of	547,311	0.058	as	109,135	0.080
to	516,635	0.082	at	101,779	0.080
a	464,736	0.098	mr	101,679	0.086
in	390,819	0.103	with	101,210	0.091
and	387,703	0.122	from	96,900	0.092
that	204,351	0.075	he	94,585	0.095
for	199,340	0.084	million	93,515	0.098
is	152,483	0.072	year	90,104	0.100
said	148,302	0.078	its	86,774	0.100
it	134,323	0.078	be	85,588	0.104
on	121,173	0.077	was	83,398	0.105

WSJ87 collection (46,449 articles, 19 million term occurrences, 132 MB)

Zipf's Law

- Useful as a rough description of the frequency distribution of words in human languages
- Behavior occurs in a surprising variety of situations
 - English verb polysemy
 - References to scientific papers
 - Web page in-degrees, out-degrees
 - Royalties to pop-music composers
- Zipf postulated a general law regarding human behavior: "principle of least effort"
 - Speaker: small vocabulary is best
 - Hearer: large vocabulary of unambiguous words best
 - Maximally economical compromise solution (Mandelbrot 1954): reciprocal relationship between frequency and rank

Topics for today

- Statistics of natural language
- Unsmoothed N-grams

Models of word sequences

- Simplest model
 - Let any word follow any other word
 - » P (word1 follows word2) = 1/# words in English
- Probability distribution at least obeys actual relative word frequencies
 - » P (word1 follows word2) = occurrences of word1 / # words in English
- Pay attention to the preceding words
 - "Let's go outside and take a []"
 - » walk ver
 - very reasonable quite reasonable

- Compute conditional probability P (walk| let's go...)

- » break quite
- » lion less reasonable

Probability of a word sequence

- $P(w_1, w_2, ..., w_{n-1}, w_n)$
- Problem?
- Solution: approximate the probability of a word given all the previous words...

N-gram approximations

- Bigram model
- Trigram model
- N-gram approximation
- Markov assumption: probability of some future event (next word) depends only on a limited history of preceding events (previous words)

Bigram grammar fragment

Berkeley Restaurant Project

eat on	.16	eat Thai	.03
eat some	.06	eat breakfast	.03
eat lunch	.06	eat in	.02
eat dinner	.05	eat Chinese	.02
eat at	.04	eat Mexican	.02
eat a	.04	eat tomorrow	.01
eat Indian	.04	eat dessert	.007
eat today	.03	eat British	.001

- Can compute the probability of a complete string
 - P (I want to eat British food) = P(I|<s>) P(want|I)
 P(to|want) P(eat|to) P(British|eat) P(food|British)

Training N-gram models

- N-gram models can be trained by counting and normalizing
 - Bigrams
 - General case
 - An example of Maximum Likelihood Estimation (MLE)
 - » Resulting parameter set is one in which the likelihood of the training set T given the model M (i.e. P(T|M)) is maximized.

Bigram counts

	I	want	to	eat	Chinese	food	lunch
1	- 8	1087	- 0	13	0	0	0
want	3	0	786	0	6	- 8	6
to	- 3	0	10	860	3	0	12
eat	-0	0	2	0	19	2	52
Chinese	2	0	0	0	0	120	1
food	19	0	17	0	0	0	0
lunch	- 4	0	0	-0	0	1	0

- Note the number of 0's...
- Will look soon at improvements to MLE for dealing with this sparse data problem.

Accuracy of N-gram models

- Accuracy increases as N increases
 - Train various N-grams and then use each to generate random sentences.
 - Corpus: Complete works of Shakespeare
 - » Unigram: Will rash been and by I the me loves gentle me not slavish page, the and hour; ill let
 - » Bigram: What means, sir. I confess she? Then all sorts, he is trim, captain.
 - » Trigram: Fly, and will rid me thesenews of price. Therefore the sadness of parting, as the say, 'tis done.
 - » Quadrigram: They say all lovers swear more performance than they are wont to keep obliged faith unforfeited!

Strong dependency on training data

- Trigram model from WSJ corpus
 - 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