- Introduction to generative models of language
  - » What are they?
  - » Why they' re important
  - » Issues for counting words
  - » Statistics of natural language
  - » **Unsmoothed n-gram models**

Models of word sequences

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

» walk	very reasonable
» break	quite reasonable
» shower	less reasonable

  - – Compute conditional probability P (walk| let' s go…take a)

Probability of a word sequence

- $P\ (w_1\ w_2\ \ldots\ w_{n-1}\ w_n)$

$$P(w_1^n) = P(w_1)\ P(w_2|w_1)\ P(w_3|w_1^2)\ \ldots P(w_n|w_1^{n-1})$$

$$= \prod_{k=1}^n P(w_k|w_1^{k-1})$$

- Problem?
- Solution: *approximate* the probability of a word given all the previous words…

N-gram approximations

- Bigram model

$$P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-1})$$

$$P(w_1^n) \approx \prod_{k=1}^n\ P(w_k|w_{k-1})$$

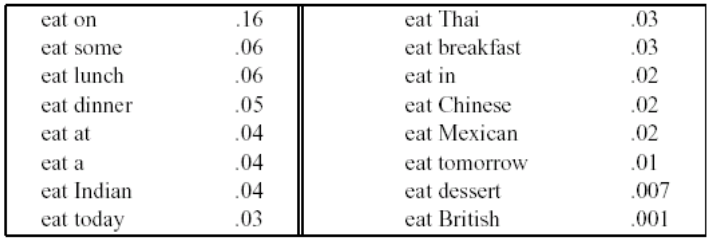
- Trigram model
  - – Conditions on the two preceding words
- N-gram approximation

$$P(w_1^n) \approx \prod_{k=1}^n\ P(w_k|w_{k-N+1}^{k-1})$$

- 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

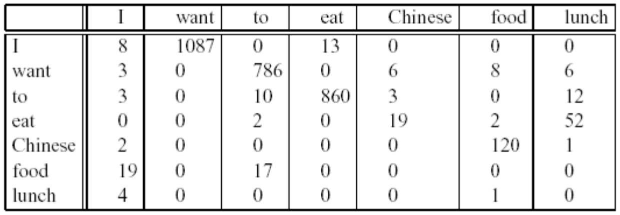
$$P(w_n \mid w_{n-1}) = \frac{C(w_{n-1}w_n)}{C(w_{n-1})}$$

  - General case

$$P(w_n \mid w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1}w_n)}{C(w_{n-N+1}^{n-1})}$$

  - 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

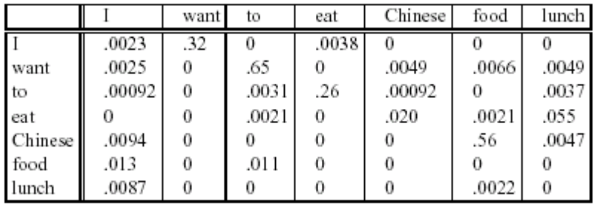


	I	want	to	eat	Chinese	food	lunch
I	8	1087	0	13	0	0	0
want	3	0	786	0	6	8	6
to	3	0	10	860	3	0	12
eat	0	0	2	0	19	2	52
Chinese	2	0	0	0	0	120	1
food	19	0	17	0	0	0	0
lunch	4	0	0	0	0	1	0

- Note the number of 0's…

Bigram probabilities

- Problem for the maximum likelihood estimates: sparse data



	I	want	to	eat	Chinese	food	lunch
I	.0023	.32	0	.0038	0	0	0
want	.0025	0	.65	0	.0049	.0066	.0049
to	.00092	0	.0031	.26	.00092	0	.0037
eat	0	0	.0021	0	.020	.0021	.055
Chinese	.0094	0	0	0	0	.56	.0047
food	.013	0	.011	0	0	0	0
lunch	.0087	0	0	0	0	.0022	0

Accuracy of N-gram models

- Accuracy increases as N increases
  - Train various N-gram models 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 these news of price. Therefore the sadness of parting, as they 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*