Natural Language Processing

Lecture 6: Language Models

One-Slide Review of Probability Terminology

- Random variables take different values, depending on chance.
- Notation:

  $p(X = x)$ is the probability that r.v. X takes value x

  $p(x)$ is shorthand for the same

  $p(X)$ is the distribution over values X can take (a function)
- Joint probability: $p(X = x, Y = y)$
  - Independence
  - Chain rule
- Conditional probability: $p(X = x \mid Y = y)$

Unigram Model

- Every word in Σ is assigned some probability.
- Random variables W_1, W_2, … (one per word).

$$
\begin{aligned}
p(\boldsymbol{W} = \boldsymbol{w}) &= p(W_1 = w_1, W_2 = w_2, \ldots, W_{L+1} = stop) \\
&= \left(\prod_{\ell=1}^{L} p(W_\ell = w_\ell) \right) p(W_{L+1} = stop) \\
&= \left(\prod_{\ell=1}^{L} p(w_\ell) \right) p(stop)
\end{aligned}
$$

Part of A Unigram Distribution

[rank 1]

p(the) = 0.038

p(of) = 0.023

p(and) = 0.021

p(to) = 0.017

p(is) = 0.013

p(a) = 0.012

p(in) = 0.012

p(for) = 0.009

...

[rank 1001]

p(joint) = 0.00014

p(relatively) = 0.00014

p(plot) = 0.00014

p(DEL1SUBSEQ) = 0.00014

p(rule) = 0.00014

p(62.0) = 0.00014

p(9.1) = 0.00014

p(evaluated) = 0.00014

...

Unigram Model as a Generator

first, from less the This different 2004), out which goal 19.2 Model their It ~(i?1), given 0.62 these (x0; match 1 schedule. x 60 1998. under by Notice we of stated CFG 120 be 100 a location accuracy If models note 21.8 each 0 WP that the that Nov?ak. to function; to [0, to different values, model 65 cases. said - 24.94 sentences not that 2 In to clustering each K&M 100 Boldface X))] applied; In 104 S. grammar was (Section contrastive thesis, the machines table -5.66 trials: An the textual (family applications.Wehave for models 40.1 no 156 expected are neighborhood

Full History Model

- Every word in Σ is assigned some probability, *conditioned on every history*.

$$\begin{aligned}
p(\boldsymbol{W} = \boldsymbol{w}) &= p(W_1 = w_1, W_2 = w_2, \ldots, W_{L+1} = \mathit{stop}) \\
&= \left(\prod_{\ell=1}^{L} p(W_\ell = w_\ell \mid \boldsymbol{W}_{1:\ell-1} = \boldsymbol{w}_{1:\ell-1})\right) p(W_{L+1} = \mathit{stop} \mid \boldsymbol{W}_{1:L} = \boldsymbol{w}_{1:L}) \\
&= \left(\prod_{\ell=1}^{L} p(w_\ell \mid \mathit{history}_\ell)\right) p(\mathit{stop} \mid \mathit{history}_L)
\end{aligned}$$

Bill Clinton's unusually direct comment Wednesday on the possible role of race in the election was in keeping with the Clintons' bid to portray Obama, who is aiming to become the first black U.S. president, as the clear favorite, thereby lessening the potential fallout if Hillary Clinton does not win in South Carolina.

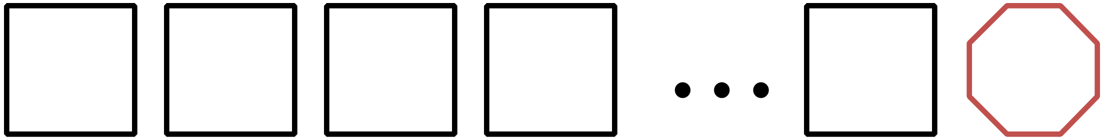
N-Gram Model

- Every word in Σ is assigned some probability, conditioned on a *fixed-length* history ($n - 1$).

$$\begin{aligned}
p(\boldsymbol{W} = \boldsymbol{w}) &= p(W_1 = w_1, W_2 = w_2, \ldots, W_{L+1} = stop) \\
&= \left(\prod_{\ell=1}^{L} p(W_\ell = w_\ell \mid \boldsymbol{W}_{\ell-n+1:\ell-1} = \boldsymbol{w}_{\ell-n+1:\ell-1}) \right) \\
&\quad \times p(W_{L+1} = stop \mid \boldsymbol{W}_{L-n+1:L} = \boldsymbol{w}_{L-n+1:L}) \\
&= \left(\prod_{\ell=1}^{L} p(w_\ell \mid history_\ell) \right) p(stop \mid history_{L+1})
\end{aligned}$$

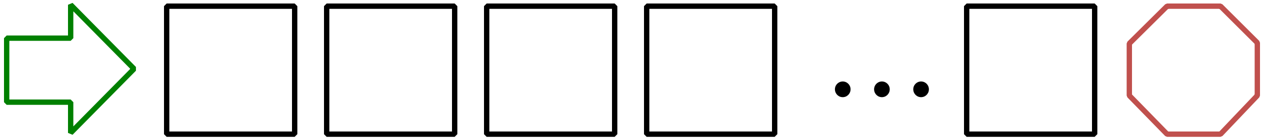
Starting and Stopping

Unigram model:



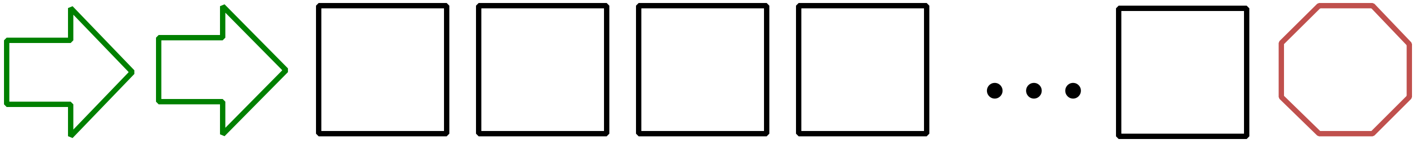
$$\prod_{i=1}^{L+1} p(w_i)$$

Bigram model:



$$\prod_{i=1}^{L+1} p(w_i \mid w_{i-1})$$

Trigram model:



$$\prod_{i=1}^{L+1} p(w_i \mid w_{i-2}, w_{i-1})$$

Bigram Model as a Generator

e. (A.33) (A.34) A.5 ModelS are also been completely surpassed in performance on drafts of online algorithms can achieve far more so while substantially improved using CE. 4.4.1 MLEasaCaseofCE 71 26.34 23.1 57.8 K&M 42.4 62.7 40.9 44 43 90.7 100.0 100.0 100.0 15.1 30.9 18.0 21.2 60.1 undirected evaluations directed DEL1 TRANS1 neighborhood. This continues, with supervised init., semisupervised MLE with the METU- SabanciTreebank 195 ADJA ADJD ADV APPR APPRART APPO APZR ART CARD FM ITJ KOUI KOUS KON KOKOM NN NN NN IN JJ NNTheir problem is y x. The evaluation offers the hypothesized link grammar with a Gaussian

Trigram Model as a Generator

top(xI ,right,B). (A.39) vine0(X, I) rconstit0(I 1, I). (A.40) vine(n). (A.41) These equations were presented in both cases; these scores u<AC>into a probability distribution is even smaller(r =0.05). This is exactly fEM. During DA, is gradually relaxed. This approach could be efficiently used in previous chapters) before training (test) K&MZeroLocalrandom models Figure4.12: Directed accuracy on all six languages. Importantly, these papers achieved state- of-the-art results on their tasks and unlabeled data and the verbs are allowed (for instance) to select the cardinality of discrete structures, like matchings on weighted graphs (McDonald et al., 1993) (35 tag types, 3.39 bits). The Bulgarian,

Evaluation

Perplexity

$$\begin{aligned}
\text{perplexity}(p(\cdot);\boldsymbol{w}) &= 2^{\left(-\frac{\log_2 p(\boldsymbol{w})}{|\boldsymbol{w}|}\right)} \\
&= p(\boldsymbol{w})^{-\frac{1}{|\boldsymbol{w}|}} \\
&= \sqrt[|\boldsymbol{w}|]{\frac{1}{p(\boldsymbol{w})}} \\
&= \sqrt[|\boldsymbol{w}|]{\frac{1}{\prod_{i=1}^{|\boldsymbol{w}|} p(w_i \mid w_{i-N+1}, \ldots, w_{i-1})}}
\end{aligned}$$

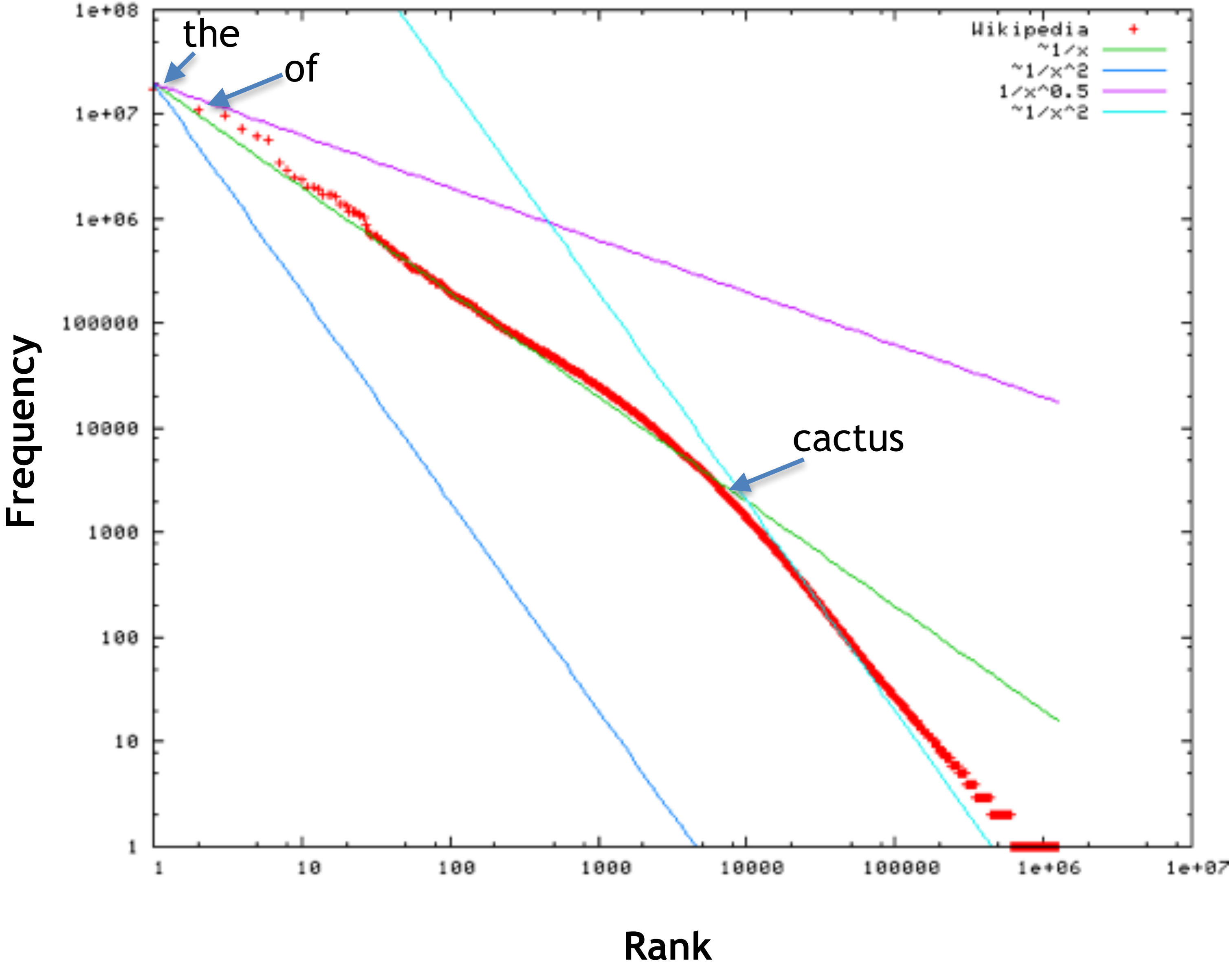
Estimating $p(w \mid \text{history})$

- Relative frequencies (count & normalize)
- Transform the counts:
  - Laplace/“add one”/“add λ”
  - Good-Turing discounting

Good-Turing’s Discounted Counts

	AP Bigrams		Berkeley Restaurants		Thesis Bigrams	
c	***N_c***	***c****	***N_c***	***c****	***N_c***	***c****
0	74,671,100,000	0.0000270	2,081,496	0.002553	*x*	38,048 / *x*
1	***2,018,046***	***0.446***	***5,315***	***0.533960***	***38,048***	***0.21147***
2	449,721	1.26	1,419	1.357294	4,032	1.05071
3	***188,933***	***2.24***	***642***	***2.373832***	***1,409***	***2.12633***
4	105,668	3.24	381	4.081365	749	2.63685
5	***68,379***	***4.22***	***311***	***3.781350***	***395***	***3.91899***
6	48,190	5.19	196	4.500000	258	4.42248

$$c^* = \frac{(c+1) \times N_{c+1}}{N_c}$$



the

of

cactus

Estimating $p(w \mid \text{history})$

- Relative frequencies (count & normalize)
- Transform the counts:
  - Laplace/“add one”/“add λ”
  - Good-Turing discounting
- Interpolate or “backoff”:
  - With Good-Turing discounting: Katz backoff
  - Absolute discounting
  - Kneser-Ney

For Thought

- Do N-Gram models “know” English?
- Unknown words?
- N-gram models and finite-state automata