NLP & Linguistics

Natural Language Processing
CS 4120/6120—Spring 2017
Northeastern University

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some slides from
Jason Eisner, Chris Manning & Roger Levy
Engineering vs. Science?

• One story
  • NLP took formal language theory and generative linguistics (same source?),
  • Built small AI systems for a while,
  • Then added statistics/machine learning (from speech recognition).

• What now?
  • Shouldn’t AI tell us about natural intelligence?
  • Are all NLP models lousy linguistics?
Zipf’s Law

The Roots of Quantitative Linguistics
Zipf’s Law

• Distribution of word frequencies is very skewed
  – a few words occur very often, many words hardly ever occur
  – e.g., two most common words (“the”, “of”) make up about 10% of all word occurrences in text documents

• Zipf’s “law” (more generally, a “power law”):
  – observation that rank ($r$) of a word times its frequency ($f$) is approximately a constant ($k$)
    • assuming words are ranked in order of decreasing frequency
  – i.e., $r.f \approx k$ or $r.P_r \approx c$, where $P_r$ is probability of word occurrence and $c \approx 0.1$ for English
Zipf’s Law
## News Collection (AP89) Statistics

- Total documents: 84,678
- Total word occurrences: 39,749,179
- Vocabulary size: 198,763
- Words occurring > 1000 times: 4,169
- Words occurring once: 70,064

<table>
<thead>
<tr>
<th>Word</th>
<th>Freq.</th>
<th>r</th>
<th>Pr(%)</th>
<th>r.Pr</th>
</tr>
</thead>
<tbody>
<tr>
<td>assistant</td>
<td>5,095</td>
<td>1,021</td>
<td>.013</td>
<td>0.13</td>
</tr>
<tr>
<td>sewers</td>
<td>100</td>
<td>17,110</td>
<td>2.56 × 10⁻⁴</td>
<td>0.04</td>
</tr>
<tr>
<td>toothbrush</td>
<td>10</td>
<td>51,555</td>
<td>2.56 × 10⁻⁵</td>
<td>0.01</td>
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<tr>
<td>hazmat</td>
<td>1</td>
<td>166,945</td>
<td>2.56 × 10⁻⁶</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Top 50 Words from AP89

<table>
<thead>
<tr>
<th>Word</th>
<th>Freq.</th>
<th>r</th>
<th>$P_r$ (%)</th>
<th>$r.P_r$</th>
<th>Word</th>
<th>Freq.</th>
<th>r</th>
<th>$P_r$ (%)</th>
<th>$r.P_r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>the</td>
<td>2,420,778</td>
<td>1</td>
<td>6.49</td>
<td>0.065</td>
<td>has</td>
<td>136,007</td>
<td>26</td>
<td>0.37</td>
<td>0.095</td>
</tr>
<tr>
<td>of</td>
<td>1,045,733</td>
<td>2</td>
<td>2.80</td>
<td>0.056</td>
<td>are</td>
<td>130,322</td>
<td>27</td>
<td>0.35</td>
<td>0.094</td>
</tr>
<tr>
<td>to</td>
<td>968,882</td>
<td>3</td>
<td>2.60</td>
<td>0.078</td>
<td>not</td>
<td>127,493</td>
<td>28</td>
<td>0.34</td>
<td>0.096</td>
</tr>
<tr>
<td>a</td>
<td>892,429</td>
<td>4</td>
<td>2.39</td>
<td>0.096</td>
<td>who</td>
<td>116,364</td>
<td>29</td>
<td>0.31</td>
<td>0.090</td>
</tr>
<tr>
<td>and</td>
<td>865,644</td>
<td>5</td>
<td>2.32</td>
<td>0.120</td>
<td>they</td>
<td>111,024</td>
<td>30</td>
<td>0.30</td>
<td>0.089</td>
</tr>
<tr>
<td>in</td>
<td>847,825</td>
<td>6</td>
<td>2.27</td>
<td>0.140</td>
<td>its</td>
<td>111,021</td>
<td>31</td>
<td>0.30</td>
<td>0.092</td>
</tr>
<tr>
<td>said</td>
<td>504,593</td>
<td>7</td>
<td>1.35</td>
<td>0.095</td>
<td>had</td>
<td>103,943</td>
<td>32</td>
<td>0.28</td>
<td>0.089</td>
</tr>
<tr>
<td>for</td>
<td>363,865</td>
<td>8</td>
<td>0.98</td>
<td>0.078</td>
<td>will</td>
<td>102,949</td>
<td>33</td>
<td>0.28</td>
<td>0.091</td>
</tr>
<tr>
<td>that</td>
<td>347,072</td>
<td>9</td>
<td>0.93</td>
<td>0.084</td>
<td>would</td>
<td>99,503</td>
<td>34</td>
<td>0.27</td>
<td>0.091</td>
</tr>
<tr>
<td>was</td>
<td>293,027</td>
<td>10</td>
<td>0.79</td>
<td>0.079</td>
<td>about</td>
<td>92,983</td>
<td>35</td>
<td>0.25</td>
<td>0.087</td>
</tr>
<tr>
<td>on</td>
<td>291,947</td>
<td>11</td>
<td>0.78</td>
<td>0.086</td>
<td>i</td>
<td>92,005</td>
<td>36</td>
<td>0.25</td>
<td>0.089</td>
</tr>
<tr>
<td>he</td>
<td>250,919</td>
<td>12</td>
<td>0.67</td>
<td>0.081</td>
<td>been</td>
<td>88,786</td>
<td>37</td>
<td>0.24</td>
<td>0.088</td>
</tr>
<tr>
<td>is</td>
<td>245,843</td>
<td>13</td>
<td>0.65</td>
<td>0.086</td>
<td>this</td>
<td>87,286</td>
<td>38</td>
<td>0.23</td>
<td>0.089</td>
</tr>
<tr>
<td>with</td>
<td>223,846</td>
<td>14</td>
<td>0.60</td>
<td>0.084</td>
<td>their</td>
<td>84,638</td>
<td>39</td>
<td>0.23</td>
<td>0.089</td>
</tr>
<tr>
<td>at</td>
<td>210,064</td>
<td>15</td>
<td>0.56</td>
<td>0.085</td>
<td>new</td>
<td>83,449</td>
<td>40</td>
<td>0.22</td>
<td>0.090</td>
</tr>
<tr>
<td>by</td>
<td>209,586</td>
<td>16</td>
<td>0.56</td>
<td>0.090</td>
<td>or</td>
<td>81,796</td>
<td>41</td>
<td>0.22</td>
<td>0.090</td>
</tr>
<tr>
<td>it</td>
<td>195,621</td>
<td>17</td>
<td>0.52</td>
<td>0.089</td>
<td>which</td>
<td>80,385</td>
<td>42</td>
<td>0.22</td>
<td>0.091</td>
</tr>
<tr>
<td>from</td>
<td>189,451</td>
<td>18</td>
<td>0.51</td>
<td>0.091</td>
<td>we</td>
<td>80,245</td>
<td>43</td>
<td>0.22</td>
<td>0.093</td>
</tr>
<tr>
<td>as</td>
<td>181,714</td>
<td>19</td>
<td>0.49</td>
<td>0.093</td>
<td>more</td>
<td>76,388</td>
<td>44</td>
<td>0.21</td>
<td>0.090</td>
</tr>
<tr>
<td>be</td>
<td>157,300</td>
<td>20</td>
<td>0.42</td>
<td>0.084</td>
<td>after</td>
<td>75,165</td>
<td>45</td>
<td>0.20</td>
<td>0.091</td>
</tr>
<tr>
<td>were</td>
<td>153,913</td>
<td>21</td>
<td>0.41</td>
<td>0.087</td>
<td>us</td>
<td>72,045</td>
<td>46</td>
<td>0.19</td>
<td>0.089</td>
</tr>
<tr>
<td>an</td>
<td>152,576</td>
<td>22</td>
<td>0.41</td>
<td>0.090</td>
<td>percent</td>
<td>71,956</td>
<td>47</td>
<td>0.19</td>
<td>0.091</td>
</tr>
<tr>
<td>have</td>
<td>149,749</td>
<td>23</td>
<td>0.40</td>
<td>0.092</td>
<td>up</td>
<td>71,082</td>
<td>48</td>
<td>0.19</td>
<td>0.092</td>
</tr>
<tr>
<td>his</td>
<td>142,285</td>
<td>24</td>
<td>0.38</td>
<td>0.092</td>
<td>one</td>
<td>70,266</td>
<td>49</td>
<td>0.19</td>
<td>0.092</td>
</tr>
<tr>
<td>but</td>
<td>140,880</td>
<td>25</td>
<td>0.38</td>
<td>0.094</td>
<td>people</td>
<td>68,988</td>
<td>50</td>
<td>0.19</td>
<td>0.093</td>
</tr>
</tbody>
</table>
Zipf’s Law for AP89

- Log-log plot: Note problems at high and low frequencies
Zipf’s Law

• What is the proportion of words with a given frequency?
  – Word that occurs \( n \) times has rank \( r_n = k/n \)
  – Number of words with frequency \( n \) is
    • \( r_n - r_{n+1} = k/n - k/(n + 1) = k/n(n + 1) \)
  – Proportion found by dividing by total number of words = highest rank = \( k \)
  – So, proportion with frequency \( n \) is \( 1/n(n+1) \)
Zipf’s Law

• Example word frequency ranking

<table>
<thead>
<tr>
<th>Rank</th>
<th>Word</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>concern</td>
<td>5,100</td>
</tr>
<tr>
<td>1001</td>
<td>spoke</td>
<td>5,100</td>
</tr>
<tr>
<td>1002</td>
<td>summit</td>
<td>5,100</td>
</tr>
<tr>
<td>1003</td>
<td>bring</td>
<td>5,099</td>
</tr>
<tr>
<td>1004</td>
<td>star</td>
<td>5,099</td>
</tr>
<tr>
<td>1005</td>
<td>immediate</td>
<td>5,099</td>
</tr>
<tr>
<td>1006</td>
<td>chemical</td>
<td>5,099</td>
</tr>
<tr>
<td>1007</td>
<td>african</td>
<td>5,098</td>
</tr>
</tbody>
</table>

• To compute number of words with frequency 5,099 – rank of “chemical” minus the rank of “summit” – 1006 − 1002 = 4
Example

<table>
<thead>
<tr>
<th>Number of Occurrences ((n))</th>
<th>Predicted Proportion ((1/n(n+1)))</th>
<th>Actual Proportion</th>
<th>Actual Number of Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.500</td>
<td>.402</td>
<td>204,357</td>
</tr>
<tr>
<td>2</td>
<td>.167</td>
<td>.132</td>
<td>67,082</td>
</tr>
<tr>
<td>3</td>
<td>.083</td>
<td>.069</td>
<td>35,083</td>
</tr>
<tr>
<td>4</td>
<td>.050</td>
<td>.046</td>
<td>23,271</td>
</tr>
<tr>
<td>5</td>
<td>.033</td>
<td>.032</td>
<td>16,332</td>
</tr>
<tr>
<td>6</td>
<td>.024</td>
<td>.024</td>
<td>12,421</td>
</tr>
<tr>
<td>7</td>
<td>.018</td>
<td>.019</td>
<td>9,766</td>
</tr>
<tr>
<td>8</td>
<td>.014</td>
<td>.016</td>
<td>8,200</td>
</tr>
<tr>
<td>9</td>
<td>.011</td>
<td>.014</td>
<td>6,907</td>
</tr>
<tr>
<td>10</td>
<td>.009</td>
<td>.012</td>
<td>5,893</td>
</tr>
</tbody>
</table>

- Proportions of words occurring \(n\) times in 336,310 TREC documents
- Vocabulary size is 508,209
Vocabulary Growth

• As corpus grows, so does vocabulary size
  – Fewer new words when corpus is already large

• Observed relationship (Heaps’ Law):

  \[ v = k \cdot n^\beta \]

  where \( v \) is vocabulary size (number of unique words), \( n \) is the number of words in corpus,

  \( k, \beta \) are parameters that vary for each corpus (typical values given are \( 10 \leq k \leq 100 \) and \( \beta \approx 0.5 \))
AP89 Example

Words in Vocabulary vs. Words in Collection graph.
Heaps’ Law Predictions

• Predictions for TREC collections are accurate for large numbers of words
  – e.g., first 10,879,522 words of the AP89 collection scanned
  – prediction is 100,151 unique words
  – actual number is 100,024

• Predictions for small numbers of words (i.e. < 1000) are much worse
GOV2 (Web) Example
Ever Upwards

• Heaps’ Law works with very large corpora
  – new words occurring even after seeing 30 million!
  – parameter values different than typical TREC values

• New words come from a variety of sources
  • spelling errors, invented words (e.g. product, company names), code, other languages, email addresses, etc.

• Language models (and other NLP and IR systems) need to handle open, growing vocabulary
Power-Law Distributions

• For discrete data (Clauset et al., 2009):

\[ p(x) = \Pr(X = x) = C x^{-\alpha} \]

• which diverges at 0, thus requiring a lower bound \( x_{\text{min}} > 0 \)

• which normalizes to \( p(x) = \frac{x^{-\alpha}}{\zeta(\alpha, x_{\text{min}})} \)

• with Hurwitz zeta \( \zeta(\alpha, x_{\text{min}}) = \sum_{n=0}^{\infty} (n + x_{\text{min}})^{-\alpha} \)
Power Laws Everywhere!

Fig. 6.1. The cumulative distribution functions $P(x)$ and their maximum likelihood power-law fits for the first twelve of our twenty-four empirical data sets. (a) The frequency of occurrence of unique words in the novel Moby Dick by Herman Melville. (b) The degree distribution of proteins in the protein interaction network of the yeast S. cerevisiae. (c) The degree distribution of metabolites in the metabolic network of the bacterium E. coli. (d) The degree distribution of autonomous systems on the Internet. (e) The number of calls received by US customers of the long-distance telephone carrier AT&T. (f) The intensity of wars from 1816–1980 measured as the number of battle deaths per 10,000 of the combined populations of the warring nations. (g) The severity of terrorist attacks worldwide from February 1968 to June 2006, measured by number of deaths. (h) The number of bytes of data received in response to HTTP (web) requests from computers at a large research laboratory. (i) The number of species per genus of mammals during the late Quaternary period. (j) The frequency of sightings of bird species in the United States. (k) The number of customers affected by electrical blackouts in the United States. (l) The sales volume of bestselling books in the United States.

(Clauset et al., 2009)
Power Laws Everywhere!

Fig. 6.2. The cumulative distribution functions $P(x)$ and their maximum likelihood power-law fits for the second twelve of our twenty-four empirical data sets. (m) The populations of cities in the United States. (n) The sizes of email address books at a university. (o) The number of acres burned in California forest fires. (p) The intensities of solar flares. (q) The intensities of earthquakes. (r) The numbers of adherents of religious sects. (s) The frequencies of surnames in the United States. (t) The net worth in US dollars of the richest people in America. (u) The numbers of citations received by published academic papers. (v) The numbers of papers authored by mathematicians. (w) The numbers of hits on web sites from AOL users. (x) The numbers of hyperlinks to web sites.

For reference, the first column repeats the $p$-values given in Table 6.1. Based on the results of our tests, we summarize in the final column of the table how convincing the fits are for these alternatives we tested using the likelihood ratio test, implying that these data sets are not well-characterized by any of the functional forms considered here.)

Tables 6.2 and 6.3 show the results of likelihood ratio tests comparing the best fit power laws for each of our data sets to the alternative distributions given in Table 2.1. (Clauset et al., 2009)
# Power Laws Everywhere?

Power-law distributions in empirical data

<table>
<thead>
<tr>
<th>data set</th>
<th>Poisson p</th>
<th>log-normal p</th>
<th>exponential p</th>
<th>stretched exp. p</th>
<th>power law + cut-off p</th>
<th>support for power law</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet</td>
<td>0.29</td>
<td>-0.807 0.42</td>
<td>6.49 0.00</td>
<td>0.493 0.62</td>
<td>-1.97 0.05</td>
<td>with cut-off</td>
</tr>
<tr>
<td>calls</td>
<td>0.63</td>
<td>-2.03 0.04</td>
<td>35.0 0.00</td>
<td>14.3 0.00</td>
<td>-30.2 0.00</td>
<td>with cut-off</td>
</tr>
<tr>
<td>citations</td>
<td>0.20</td>
<td>-0.141 0.89</td>
<td>5.91 0.00</td>
<td>1.72 0.09</td>
<td>-0.007 0.91</td>
<td>moderate</td>
</tr>
<tr>
<td>email</td>
<td>0.16</td>
<td>-1.10 0.27</td>
<td>0.639 0.52</td>
<td>-1.13 0.26</td>
<td>-1.89 0.05</td>
<td>with cut-off</td>
</tr>
<tr>
<td>metabolic</td>
<td>0.00</td>
<td>-1.05 0.29</td>
<td>5.59 0.00</td>
<td>3.66 0.00</td>
<td>0.000 1.00</td>
<td>none</td>
</tr>
<tr>
<td>papers</td>
<td>0.90</td>
<td>-0.091 0.93</td>
<td>3.08 0.00</td>
<td>0.709 0.48</td>
<td>-0.016 0.86</td>
<td>moderate</td>
</tr>
<tr>
<td>proteins</td>
<td>0.31</td>
<td>-0.456 0.65</td>
<td>2.21 0.03</td>
<td>0.055 0.96</td>
<td>-0.414 0.36</td>
<td>moderate</td>
</tr>
<tr>
<td>species</td>
<td>0.10</td>
<td>-1.63 0.10</td>
<td>2.39 0.02</td>
<td>-1.59 0.11</td>
<td>-3.80 0.01</td>
<td>with cut-off</td>
</tr>
<tr>
<td>terrorism</td>
<td>0.68</td>
<td>-0.278 0.78</td>
<td>2.457 0.01</td>
<td>0.772 0.44</td>
<td>-0.077 0.70</td>
<td>moderate</td>
</tr>
<tr>
<td>words</td>
<td>0.49</td>
<td>0.395 0.69</td>
<td>9.09 0.00</td>
<td>4.13 0.00</td>
<td>-0.899 0.18</td>
<td>good</td>
</tr>
</tbody>
</table>

Table 6.3: Tests of power-law behavior in the data sets with discrete (integer) data. Statistically significant p-values are denoted in bold. Results for the continuous data sets are given in Table 6.2; see that table for a description of the individual column entries.

(Clauset et al., 2009)
Learning in the Limit
Gold’s Theorem
Observe some values of a function
Guess the whole function

\[ f(x) = 2x^2 - 6x + 6 \]
Another guess: Just as good?

Graph showing two functions, one represented by $2x^2 - 6x + 6$ and the other by $-8x^6 + 72.8x^5 - 250x^4 + 401x^3 - 297x^2 + 79.2x + 6$. The graph plots the functions against $x$ values from 0 to 3.
More data needed to decide

- $2x^2 - 6x + 6$
- $-8x^6 + 72.8x^5 - 250x^4 + 401x^3 - 297x^2 + 79.2x + 6$

Input Data

More Input Data
Poverty of the Stimulus
Poverty of the Stimulus

- Never enough input data to completely determine the polynomial …
  - Always have infinitely many possibilities

- … unless you know the order of the polynomial ahead of time.
  - 2 points determine a line
  - 3 points determine a quadratic
  - etc.

- In language learning, is it enough to know that the target language is generated by a CFG?
  - without knowing the size of the CFG?
Language learning:
Language learning:

- Children listen to language  [unsupervised]
Language learning:

- Children listen to language  [unsupervised]
- Children are corrected??  [supervised]
Language learning:

- Children listen to language  [unsupervised]
- Children are corrected??  [supervised]
- Children observe language in context
Language learning:

- Children listen to language [unsupervised]
- Children are corrected?? [supervised]
- Children observe language in context
- Children observe frequencies of language
Language learning:

- Children listen to language [unsupervised]
- Children are corrected?? [supervised]
- Children observe language in context
- Children observe frequencies of language
Language learning:

- Children listen to language [unsupervised]
- Children are corrected?? [supervised]
- Children observe language in context
- Children observe frequencies of language

Remember: Language = set of strings
Poverty of the Stimulus (1957)

- Children listen to language
- Children are corrected??
- Children observe language in context
- Children observe frequencies of language
Poverty of the Stimulus (1957)

Chomsky: Just like polynomials: never enough data unless you know something in advance. So kids must be born knowing what to expect in language.

- Children listen to language
- Children are corrected??
- Children observe language in context
- Children observe frequencies of language
Gold’s Theorem (1967)

a simple negative result along these lines: kids (or computers) can’t learn much without supervision, inborn knowledge, or statistics

- Children listen to language
- Children are corrected??
- Children observe language in context
- Children observe frequencies of language
The Idealized Situation
The Idealized Situation

- Mom talks
The Idealized Situation

- Mom talks
- Baby listens
The Idealized Situation

- Mom talks
- Baby listens
The Idealized Situation

- Mom talks
- Baby listens

- 1. Mom outputs a sentence
The Idealized Situation

- Mom talks
- Baby listens

1. Mom outputs a sentence
2. Baby hypothesizes what the language is (given all sentences so far)
The Idealized Situation

- Mom talks
- Baby listens

1. Mom outputs a sentence
2. Baby hypothesizes what the language is (given all sentences so far)
3. Goto step 1
The Idealized Situation

- Mom talks
- Baby listens

1. Mom outputs a sentence
2. Baby hypothesizes what the language is (given all sentences so far)
3. Goto step 1
The Idealized Situation

- Mom talks
- Baby listens

1. Mom outputs a sentence
2. Baby hypothesizes what the language is (given all sentences so far)
3. Goto step 1

 Guarantee: Mom’s language is in the set of hypotheses that Baby is choosing among
The Idealized Situation

- Mom talks
- Baby listens

1. Mom outputs a sentence
2. Baby hypothesizes what the language is (given all sentences so far)
3. Goto step 1

**Guarantee:** Mom’s language *is* in the set of hypotheses that Baby is choosing among

**Guarantee:** Any sentence of Mom’s language is *eventually* uttered by Mom (even if infinitely many)
The Idealized Situation

- Mom talks
- Baby listens

1. Mom outputs a sentence
2. Baby hypothesizes what the language is (given all sentences so far)
3. Goto step 1

**Guarantee:** Mom’s language is in the set of hypotheses that Baby is choosing among

**Guarantee:** Any sentence of Mom’s language is eventually uttered by Mom (even if infinitely many)

**Assumption:** Vocabulary (or alphabet) is finite.
Can Baby learn under these conditions?
Can Baby learn under these conditions?

- Learning in the limit:
  - There is some point at which Baby’s hypothesis is correct and never changes again. Baby has converged!
  - Baby doesn’t have to know that it’s reached this point – it can keep an open mind about new evidence – but if its hypothesis is right, no such new evidence will ever come along.
Can Baby learn under these conditions?

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- A class C of languages is **learnable in the limit** if one could construct a perfect C-Baby that can learn any language \( L \in C \) in the limit from a Mom who speaks L.
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- Is there a perfect finite-state Baby?
- Is there a perfect context-free Baby?
Languages vs. Grammars

- Does Baby have to get the right grammar?
  (E.g., does VP have to be called VP?)

- Assumption: Finite vocabulary.
Conservative Strategy

- Baby’s hypothesis should always be smallest language consistent with the data

- Works for finite languages? Let’s try it …
  - Language 1: \{aa,ab,ac\}
  - Language 2: \{aa,ab,ac,ad,ae\}
  - Language 3: \{aa,ac\}
  - Language 4: \{ab\}

Mom
Baby
Conservative Strategy

- Baby’s hypothesis should always be smallest language consistent with the data

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Mom aa
Baby
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Mom       aa
Baby       L3
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Mom     aa     ab
Baby    L3
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Mom    |    aa    |    ab   | Baby    |    L3    |    L1   |
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Mom       aa     ab     ac     ab
Baby      L3     L1     L1     L1
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Mom
Baby
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Mom      aa
Baby
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Mom  aa
Baby  L3
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Mom  aa  ab
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Mom  aa  ab
Baby  L3  L1
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Baby   L3    L1    L1
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Mom  aa  ab  ac  ab  ab  aa
Baby  L3  L1  L1  L1  L1
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Mom  aa  ab  ac  ab  ab  aa
Baby L3 L1 L1 L1 L1 L1
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Mom       aa       ab       ac       ab       aa       …
Baby  L3       L1       L1       L1       L1       L1
Evil Mom

- To find out whether Baby is perfect, we have to see whether it gets 100% even in the most adversarial conditions
- Assume Mom is trying to fool Baby
  - although she must speak only sentences from L
  - and she must eventually speak each such sentence
- Does Baby’s strategy work?
An Unlearnable Class

- Class of languages:
  - Let $L_n = \text{set of all strings of length } < n$
  - What is $L_0$?
  - What is $L_1$?
  - What is $L_\infty$?
    - If the true language is $L_\infty$, can Mom really follow rules?
    - Must eventually speak every sentence of $L_\infty$. Possible?
      - Yes: $\varepsilon$; a, b; aa, ab, ba, bb; aaa, aab, aba, abb, baa, …
  - Our class is $C = \{L_0, L_1, \ldots, L_\infty\}$
An Unlearnable Class
An Unlearnable Class

- Let $L_n$ = set of all strings of length < $n$
  - What is $L_0$?
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- Let $L_n =$ set of all strings of length $< n$
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- A perfect C-baby will distinguish among all of these depending on the input.
An Unlearnable Class

- Let $L_n =$ set of all strings of length $< n$
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- Our class is $C = \{L_0, L_1, \ldots L_\infty\}$

- A perfect C-baby will distinguish among all of these depending on the input.
- But there is no perfect C-baby …
An Unlearnable Class
Our class is $C = \{L_0, L_1, \ldots L_\infty\}$
An Unlearnable Class

- Our class is $C = \{L_0, L_1, \ldots L_{\infty}\}$
- Suppose Baby adopts conservative strategy, always picking smallest possible language in $C$. 
An Unlearnable Class

- Our class is $C = \{L_0, L_1, \ldots L_\infty\}$
- Suppose Baby adopts conservative strategy, always picking smallest possible language in $C$.
- So if Mom’s longest sentence so far has 75 words, baby’s hypothesis is $L_{76}$. 
An Unlearnable Class

- Our class is $C = \{L_0, L_1, \ldots L_\infty\}$
- Suppose Baby adopts conservative strategy, always picking smallest possible language in $C$.
- So if Mom’s longest sentence so far has 75 words, baby’s hypothesis is $L_{76}$.
- This won’t always work: What language can’t a conservative Baby learn?
An Unlearnable Class
An Unlearnable Class

- Our class is $C = \{L_0, L_1, \ldots, L_\infty\}$
An Unlearnable Class

- Our class is $C = \{L_0, L_1, \ldots L_\infty\}$
- Could a non-conservative baby be a perfect C-Baby, and eventually converge to any of these?
An Unlearnable Class

- Our class is \( C = \{L_0, L_1, \ldots L_\infty\} \)
- Could a non-conservative baby be a perfect C-Baby, and eventually converge to any of these?
- **Claim:** *Any* perfect C-Baby must be “quasi-conservative”:
An Unlearnable Class

- Our class is $C = \{L_0, L_1, \ldots, L_\infty\}$
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- **Claim:** *Any* perfect C-Baby must be “quasi-conservative”:
  - If true language is $L_{76}$, and baby posits something else, baby must still eventually come back and guess $L_{76}$ (since it’s perfect).
An Unlearnable Class

- Our class is \( C = \{L_0, L_1, \ldots L_\infty\} \)
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  - So if longest sentence so far is 75 words, and Mom keeps talking from \( L_{76} \), then eventually baby must actually return to the conservative guess \( L_{76} \).
An Unlearnable Class

- Our class is \( C = \{L_0, L_1, \ldots L_\infty\} \)
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- So if longest sentence so far is 75 words, and Mom keeps talking from \( L_{76} \), then eventually baby must actually return to the conservative guess \( L_{76} \).

Agreed?
**Mom’s Revenge**

If longest sentence so far is 75 words, and Mom keeps talking from $L_{76}$, then eventually a perfect C-baby must actually return to the conservative guess $L_{76}$.

- Suppose true language is $L_{\infty}$.
- Evil Mom can prevent our supposedly perfect C-Baby from converging to it.
- If Baby ever guesses $L_{\infty}$, say when the longest sentence is 75 words:
  - Then Evil Mom keeps talking from $L_{76}$ until Baby capitulates and revises her guess to $L_{76}$ – as any perfect C-Baby must.
  - So Baby has *not* stayed at $L_{\infty}$ as required.
- Then Mom can go ahead with longer sentences. If Baby ever guesses $L_{\infty}$ again, she plays the same trick again.
Mom’s Revenge

If longest sentence so far is 75 words, and Mom keeps talking from $L_{76}$, then eventually a perfect C-baby must actually return to the conservative guess $L_{76}$.

- Suppose true language is $L_\infty$.
- Evil Mom can prevent our supposedly perfect C-Baby from converging to it.
- If Baby ever guesses $L_\infty$, say when the longest sentence is 75 words:
  - Then Evil Mom keeps talking from $L_{76}$ until Baby capitulates and revises her guess to $L_{76}$ – as any perfect C-Baby must.
  - So Baby has not stayed at $L_\infty$ as required.

**Conclusion:** There’s no perfect Baby that is guaranteed to converge to $L_0$, $L_1$, … or $L_\infty$ as appropriate. If it always succeeds on finite languages, Evil Mom can trick it on infinite language.
Implications
Implications

- We found that $C = \{L_0, L_1, \ldots L_\infty\}$ isn’t learnable in the limit.
Implications

- We found that \( C = \{L_0, L_1, \ldots, L_\infty\} \) isn’t learnable in the limit.
Implications

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- How about class of finite-state languages?
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- How about class of finite-state languages?
  - Not unless you limit it further (e.g., # of states)
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  - After all, it includes all languages in $C$, and more, so learner has harder choice
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- How about class of finite-state languages?
  - Not unless you limit it further (e.g., # of states)
  - After all, it includes all languages in \( C \), and more, so learner has harder choice

- How about class of context-free languages?
  - Not unless you limit it further (e.g., # of rules)
Punchline

- But class of \textit{probabilistic} context-free languages \textit{is} learnable in the limit!! \textit{(Horning, 1969)}

- If Mom has to output sentences randomly \textbf{with the appropriate probabilities},
  - she’s unable to be too evil
  - there are then perfect Babies that are guaranteed to converge to an appropriate probabilistic CFG

- I.e., from hearing a finite number of sentences, Baby can correctly converge on a grammar that predicts an infinite number of sentences.
  - Baby is generalizing! Just like real babies!
Perfect fit to perfect, incomplete data

- $f(x) = 2x^2 - 6x + 6$
- $f(x) = -8x^6 + 72.8x^5 - 250x^4 + 401x^3 - 297x^2 + 79.2x + 6$
- More Input Data
Imperfect fit to noisy data

\[ f(x) = -8x^6 + 72.8x^5 - 250x^4 + 401x^3 - 297x^2 + 79.2x + 6 \]

\[ f(x) = 2x^2 - 6x + 6 \]

Input Data

More Input Data
Imperfect fit to noisy data

Will an ungrammatical sentence ruin baby forever?
Imperfect fit to noisy data

Will an ungrammatical sentence ruin baby forever? (yes, under the conservative strategy ... )
Imperfect fit to noisy data

Will an ungrammatical sentence ruin baby forever? (yes, under the conservative strategy ...)
Or can baby figure out which data to (partly) ignore?
Imperfect fit to noisy data

Will an ungrammatical sentence ruin baby forever? (yes, under the conservative strategy ...)
Or can baby figure out which data to (partly) ignore?
Statistics can help again ... how?
Frequencies and Probabilities in Natural Languages

Chris Manning and others
Models for language

- Human languages are the prototypical example of a symbolic system
- From the beginning, logics and logical reasoning were invented for handling natural language understanding
- Logics and formal languages have a language-like form that draws from and meshes well with natural languages
- Where are the numbers?
Dominant answer in linguistic theory: Nowhere

Chomsky again (1969: 57; also 1956, 1957, etc.):

- “It must be recognized that the notion ‘probability of a sentence’ is an entirely useless one, under any known interpretation of this term.”

Probabilistic models wrongly mix in world knowledge

- New York vs. Dayton, Ohio

They don’t model grammaticality [also, Tesnière 1959]

- Colorless green ideas sleep furiously
- Furiously sleep ideas green colorless
- [But see Pereira 2005]
Categorical linguistic theories (GB, Minimalism, LFG, HPSG, CG, ...)

- Systems of variously rules, principles, and representations is used to describe an infinite set of grammatical sentences of the language
- Other sentences are deemed ungrammatical
- Word strings are given a (hidden) structure
The need for frequencies / probability distributions

The motivation comes from two sides:

- Categorical linguistic theories claim too much:
  - They place a hard categorical boundary of grammaticality, where really there is a fuzzy edge, determined by many conflicting constraints and issues of conventionality vs. human creativity

- Categorical linguistic theories explain too little:
  - They say nothing at all about the soft constraints which explain how people choose to say things
  - Something that language educators, computational NLP people – and historical linguists and sociolinguists dealing with real language – usually want to know about
1. The hard constraints of categorical grammars

- Sentences must satisfy all the rules of the grammar
- One group specifies the arguments that different verbs take – lexical subcategorization information
  - Some verbs must take objects: *Kim devoured
    [ * means ungrammatical]
  - Others do not: *Kim’s lip quivered the straw
  - Others take various forms of sentential complements
- In NLP systems, ungrammatical sentences don’t parse
- But the problem with this model was noticed early on:
  - “All grammars leak.” (Sapir 1921: 38)
Example: verbal clausal subcategorization frames

• Some verbs take various types of sentential complements, given as subcategorization frames:
  • regard: __ NP[acc] as {NP, AdjP}
  • consider: __ NP[acc] {AdjP, NP, VP[inf]}
  • think: __ CP[that]; __ NP[acc] NP

• Problem: in context, language is used more flexibly than this model suggests
  • Most such subcategorization ‘facts’ are wrong
The Conductor of this train is responsible to ensure that your trip is both safe and enjoyable.

…responsible for ensuring…

…responsible that it be ensured that …
Standard subcategorization rules (Pollard and Sag 1994)

- We consider Kim to be an acceptable candidate
- We consider Kim an acceptable candidate
- We consider Kim quite acceptable
- We consider Kim among the most acceptable candidates
- *We consider Kim as an acceptable candidate
- *We consider Kim as quite acceptable
- *We consider Kim as among the most acceptable candidates
- ??*We consider Kim as being among the most acceptable candidates
Subcategorization facts from The New York Times

Consider as:

- The boys consider her as family and she participates in everything we do.
- Greenspan said, “I don't consider it as something that gives me great concern.
- “We consider that as part of the job,” Keep said.
- Although the Raiders missed the playoffs for the second time in the past three seasons, he said he considers them as having championship potential.
- Culturally, the Croats consider themselves as belonging to the “civilized” West, ...
More subcategorization facts: regard

Pollard and Sag (1994):
- *We regard Kim to be an acceptable candidate
- We regard Kim as an acceptable candidate

The New York Times:
- As 70 to 80 percent of the cost of blood tests, like prescriptions, is paid for by the state, neither physicians nor patients regard expense to be a consideration.
- Conservatives argue that the Bible regards homosexuality to be a sin.
More subcategorization facts: turn out and end up

Pollard and Sag (1994):
- Kim turned out political
- *Kim turned out doing all the work

The New York Times:
- But it turned out having a greater impact than any of us dreamed.

Pollard and Sag (1994):
- Kim ended up political
- *Kim ended up sent more and more leaflets

The New York Times:
- On the big night, Horatio ended up flattened on the ground like a fried egg with the yolk broken.
Probability mass functions: subcategorization of regard
Leakage leads to change

- People continually stretch the ‘rules’ of grammar to meet new communicative needs, to better align grammar and meaning, etc.
- As a result language slowly changes
  - **while**: used to be only a noun (That takes a while); now mainly used as a subordinate clause introducer (While you were out)
  - **e-mail**: started as a mass noun like mail (most junk e-mail is annoying); it’s moving to be a count noun (filling the role of e-letter): I just got an interesting email about that.
An example of blurring in syntactic category during linguistic change is so-called ‘marginal prepositions’ in English, which are moving from being participles to prepositions. Some still clearly maintain a verbal existence, like following, concerning, considering; for some it is marginal, like according, excepting; for others their verbal character is completely lost, such as during [cf. endure], pending, notwithstanding.
Verb (VBG)  📚 Preposition IN

As verbal participle, understood subject agrees with noun:
- They moved slowly, toward the main gate, following the wall
- Repeat the instructions following the asterisk

A temporal use with a controlling noun becomes common:
- This continued most of the week following that ill-starred trip to church

Prep. uses (meaning is after, no controlling noun) appear
- He bled profusely following circumcision
- Following a telephone call, a little earlier, Winter had said ...
Mapping the recent change of following: participle → prep.

- Fowler (1926): “there is a continual change going on by which certain participles or adjectives acquire the character of prepositions or adverbs, no longer needing the prop of a noun to cling to ... [we see] a development caught in the act”
- Fowler (1926) -- no mention of following in particular
- Fowler [Gowers] (1948): “Following is not a preposition. It is the participle of the verb follow and must have a noun to agree with”
- Fowler [Gowers] (1954): generally condemns temporal usage, but says it can be justified in certain circumstances
2. Explaining more:
What do people say?

- What people do say has two parts:
  - Contingent facts about the world
    - People in Minnesota have talked a lot about snow falling, not stocks falling, lately
  - The way speakers choose to express ideas using the resources of their language
    - People don’t often put that-clauses pre-verbally:
      - That we will have to revise this program is almost certain

- The latter is properly part of people’s Knowledge of Language—i.e., part of linguistics.
What do people say?

- Simply delimiting a set of grammatical sentences provides only a very weak description of a language, and of the ways people choose to express ideas in it.

- Probability densities over sentences and sentence structures can give a much richer view of language structure and use.

- In particular, we find that the same soft generalizations and tendencies of one language often appear as (apparently) categorical constraints in other languages.

- A syntactic theory should be able to uniformly capture these constraints, rather than only recognizing them when they are categorical.
Example: Bresnan, Dingare & Manning

- Project modeling English diathesis alternations (active/passive, locative inversion, etc.)
- In some languages passives are categorically restricted by person considerations:
  - In Lummi (Salishan, Washington state), 1/2 person must be the subject if other argument is 3rd person. There is variation if both arguments are 3rd person. (Jelinek and Demers 1983)  [cf. also Navajo, etc.]
  - *That example was provided by me
  - *He likes me
  - ?I am liked by him
In English, there is no such categorical constraint, but we can still see it at work as a soft constraint.

Collected data from verbs with an agent and patient argument (canonical transitives) from treebanked portions of the Switchboard corpus of conversational American English, analyzing for person and act/pass

<table>
<thead>
<tr>
<th></th>
<th>Active</th>
<th>Passive</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/2 Ag, 1/2 Pt</td>
<td>158</td>
<td>0 (0.0%)</td>
</tr>
<tr>
<td>1/2 Ag, 3 Pt</td>
<td>5120</td>
<td>1 (0.0%)</td>
</tr>
<tr>
<td>3 Ag, 1/2 Pt</td>
<td>552</td>
<td>16 (2.8%)</td>
</tr>
<tr>
<td>3 Ag, 3 Pt</td>
<td>3307</td>
<td>46 (1.4%)</td>
</tr>
</tbody>
</table>
While person is only a small part of the picture in determining the choice of active/passive in English (information structure, genre, etc. is more important), there is nonetheless a highly significant ($\chi^2 p < 0.0001$) effect of person on active/passive choice.

- The exact same hard constraint of Lummi appears as a soft constraint in English.
- This behavior is predicted by the universal hierarchies within a stochastic OT model (which extends existing OT approaches to valence – Aissen 1999, Lødrup 1999).
- Conversely linguistic model predicts that no “anti-English” [which is just the opposite] exists.
Syntactic Matching

Roger Levy
Conclusions

• There are many phenomena in language that cry out for non-categorical and probabilistic modeling and explanation
• Probabilistic models can be applied on top of one’s favorite sophisticated linguistic representations!
• Frequency evidence can enrich linguistic theory by revealing soft constraints at work in language use
What Next?

- Courses you could take
  - Machine Learning
  - Information Retrieval
  - Data Mining
  - Special Topics
What Next?

• People you could talk to
  • Lu Wang
  • Byron Wallace
  • Jay Aslam
  • Tim Bickmore

• People in network science, the social sciences, the humanities, and linguistics working on language data
nothing but the events, unless the accounts from many quarters as to General Schenck's instructions are utterly belied, the New American Ambassador will bring us quite reasonable, though not perhaps wholly admissible demands,—demands which we certainly ought to consider most gravely, and of which we should do well to yield frankly and freely all that we should ourselves feel called upon, in the same circumstances, to press. If we do so, General Schenck's mission may make England safer and stronger than she has ever been since the close of the Civil War in 1865, and will give her a reputation for moderation and candour as well.

ENGLISH PUBLIC OPINION ON THE WAR.

Some of the philosophers should turn their attention from the subject of spectroscopic investigations and the invention of electrometers, galvanometers, hygrometers, and so forth, to the far more difficult problem of inventing a mode of measuring the intensity and diffusion of political wishes and convictions. No task at present is more difficult for a Statesman than this. There are, indeed, all sorts of shades of difference between the character of really prevalent and preponderant public opinions, of which no man, however acute, ever forms more than a purely conjectural impression, and of which, nevertheless, any respectably-accurate measure would be a matter of the highest political importance. For instance, there is at times a public opinion on one side of a question which is very widely diffused, but of very slight intensity,—which, in fact, amounts to nothing more than a wish in a particular direction without a will, and still more without any intention of submitting to a considerable sacrifice rather than not carry out the will into action. Again, there is such a thing as