Lecture 10: Topic Modeling, Word2Vec

LING-351 Language Technology and LLMs

Instructor: Hakyung Sung

September 25, 2025

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Review

Python tutorial so far

- Tokenization
- Lemmatization
- Frequency calculation
- Concordance
- (Collocation)

Word distributions

Word distributions

Examining word distributions is the first and most important step in corpus/text analysis.

Zipf's power law (1932)

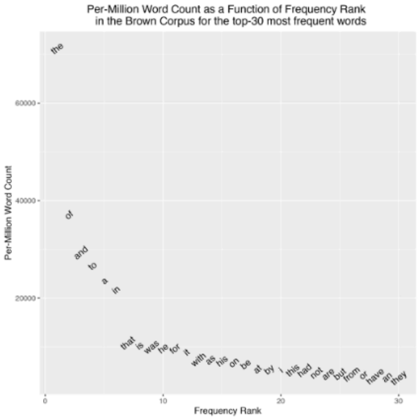

Figure 4.3: Per-million-word frequency of words in the Brown Corpus as a function of their frequency rank (ordered from left to right as the first most frequent word, the second most frequent, and so on).

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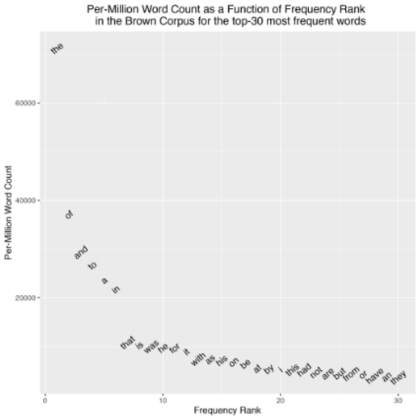

Figure 4.3: Per-million-word frequency of words in the Brown Corpus as a function of their frequency rank (ordered from left to right as the first most frequent word, the second most frequent, and so on).

Implication: Few words are very frequent; many are rare ⇒ long tail.

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- e.g., Brown corpus: *the* $\approx$ 6% tokens; *of* $\approx$ 3%; *and* $\approx$ 2.6%.

Zipf's brevity law

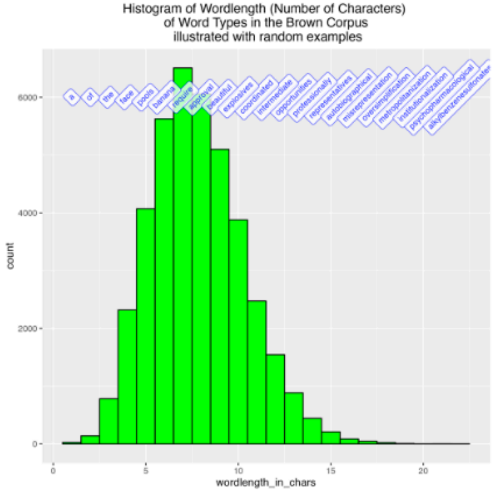

Figure 4.4: Histogram of the length (number of characters) of all word types in the Brown Corpus.

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- Efficiency pressure: frequent items economize articulatory/processing effort.
- Most frequent Brown words: monosyllabic, $\leq$3 letters (*the, of, and, a, in, to, is, was, I, for*).

Heaps' law

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Why it matters?

- Estimate how much data you need before vocabulary "stabilizes"
- Reminds us that growth is **sublinear**

Topic modeling

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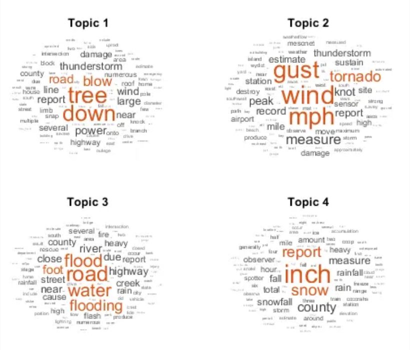

Sourced from *https://medium.com/analytics-vidhya/*

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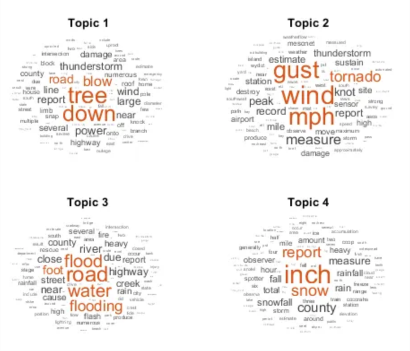

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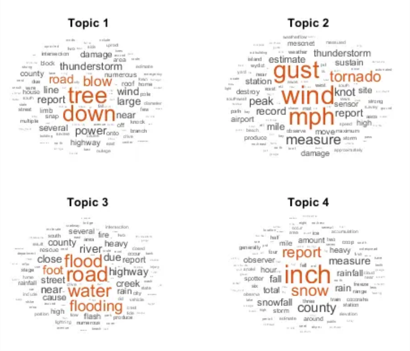
- Classic model: LDA (Blei et al., 2003).



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LDA: minimal workflow

Key idea: (1) Each document is a *mixture of topics*. (2) Each topic is a *distribution over words*. (3) Given only the words, LDA uses Bayesian inference to approximate the hidden topic structure.

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5. We'll do some hands-on practice with topic modeling.

Word vectors

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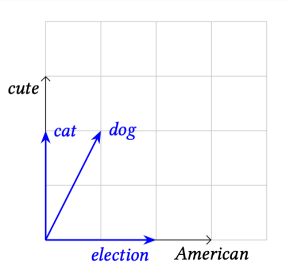
    - *vector*: an ordered list of numbers (e.g., [0.1, 0.3, -0.5])

Word vectors

- If two words often occur near the same neighbors (e.g., *dog* and *cat* near *cute*), their vectors will be similar.



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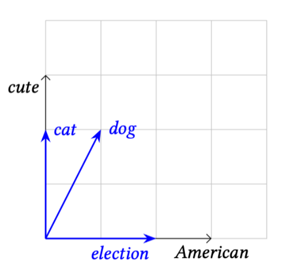
- *How*? Algorithms can automatically learn these vectors from corpus data



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- (*more on this in the NLP class*!)

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- *Word2Vec* (Mikolov et al. 2013):

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- *Word2Vec* (Mikolov et al. 2013):

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- We'll also explore *Word2Vec*.

Submission/Grading Guidelines

- **Text/Docx file** (either *`.txt`* or *`.docx`*): Submit your output from the corpus exploration on Tuesday. (If you missed class, complete it individually and submit.) (10 points)
- **Notebook file** (*`.ipynb`*): Submit your work from today's session.
  - Topic Modeling (5 points)
    - + 5 extra points, if you experiment this code on another corpus
  - Word2Vec (5 points)
- **Optional:** Please complete the *Collocation* Tutorial for extra credit (+3 points above max)
  - Guidelines/Code are on the last week's section (course website)
- PLEASE run all the codes, so the grader can seamlessly check your outputs!