Language & Technology

Lecture 4: More Word-Based Models

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Previously on "Language & Technology"...

- Counting words!

string = "The sun shone, having no alternative, on the nothing new."

tokens ["the", "sun", "shone", "having", "no", "alternative", "on", "the", "nothing", "new"]

- More technically: for each word type we count its word tokens.

word type a word of a given language

word token instance of the word in a text

Previously on "Language & Technology"...

Steps of Word Counting Model

1. collect corpus
2. tokenize strings
3. count tokens for each type

Counting words is surprisingly useful:

- Culturomics
- Stylistic analysis

But there's more!

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Application 3: Authorship Attribution

- Computational stylistic analysis isn't just good at predicting success of novels.
- Word counts pick up on **statistical tendencies in writing** of individual authors
- This means that potential authors can be inferred from word frequencies!

Example: Auditing the Bard's Oeuvre

- Several works of Shakespeare have supposedly been (partially) authored by somebody else:
  - *Edward III*
    co-authored with Thomas Kyd
  - *The Comedy of Errors*,
    Love's Labour Lost,
    The Tempest
    co-authored with Francis Bacon
- These are **fringe ideas** in literary circles.
- But there are word counting models that **support these claims**.

Another Example: Harry Potter's Mum

- New book: *The Cuckoo's Calling* by Robert Galbraith
- *Sunday Times* suspected that to be a pseudonym for J. K. Rowling.
- Evidence from word-based model:
  - 100 most common words
  - average word length
  - word pairs
    (discussed in next lecture)
  - character 4-grams
    (discussed in next lecture)

A Friendly Pointer

Article on LanguageLog:
`http://languagelog.ldc.upenn.edu/nll/?p=5315`

Evaluation

- As with culturomics, it is unclear what to make of the findings.
  - J.K. Rowling: success!
  - Shakespeare: success?
- One can get vastly different results depending on:
  - absolute size of test corpus
  - relative size (e.g. ratio of Shakespeare to Bacon)
  - whether certain words are ignored
  - whether one pays attention to rare words or frequent words
- Many of these studies feel backwards:
  - They start with a specific hypothesis and then present one specific model that supports this hypothesis.
  - But why is this model better than all of the alternatives?

Moral of the Story

- Authorship attribution models still ill-understood
- In the future, these models might answer long-standing questions or pose new ones.
- Maybe you can try it in an English class.

Application 4: Word Meanings

- For some tasks, the word types are not that important, what matters is their **meaning**:
  - web search
  - Google *Ad Sense* (automatic ad placement)
- But what is a word meaning?

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Example: Dictionary Approach

dog

- is a **mammal**,
- descended from **wolf**,
- is commonly a **pet**,
- subtypes are **poodle**, **bulldog**, ...
- has **fur**,
- ...

Why the Dictionary Approach is Problematic

- Such dictionaries have been tried for computers.
  e.g. WordNet
- They must be created by hand, which is a big problem:
  - expensive
  - only available for some languages
  - many new words missing
- We need dictionaries that can be generated automatically.

Meaning as Word Use

- The philosopher **Ludwig Wittgenstein** said that a word's meaning is its use.

Computational Counterpart

A word's meaning is given by how often it occurs together with other words.

Counting Tokens for Word Meaning

Step 1: Record in how many sentences words **occur together**

Example

The dog barked at the cat. The cat ran away. The dog ran after the cat. The dog kept barking. He also kept running.

	dog	cat	bark	run
dog	-			
cat		-		
bark			-	
run				-

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dog	-	2		
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bark			-	
run				-

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bark			-	
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cat	2	-	1	2
bark	2	1	-	0
run				-

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From Vector to Vector Spaces

Step 2: Construct an n-dimensional vector space.

n is given by the number of word types in the text

2-Dimensional Vector Space with *dog* and *cat*

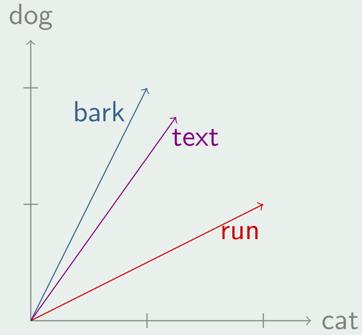
	dog	cat	bark	run
dog	-	2	2	1
cat	2	-	1	2
bark	2	1	-	0
run	1	2	0	-

- *bark* more closely related to *dog*
- *run* more closely related to *cat*

From Word Meaning to Text Meaning

Step 3: construct vector for whole text from word vectors

Meaning for *He either barks or runs and barks*



Is that Realistic?

- **Possible Concerns**
  - Is word meaning really just a bunch of numbers?
  - In a real-word model, the vector space will have thousands of dimensions.
- But this might actually be what you have stored in your brain!

Psycholinguistic Experiment

- Word association task
- The more similar the meaning vectors of two words, the faster test subjects recognize them as related.
- Also: Masked priming effects

Usage for Web Search and Ad Sense

- **Web Search**
  - construct meaning vector for every website
  - convert search string to vector
  - rank websites by vector similarity
- **Ad Sense**
  - construct meaning vector for every website
  - associate every ad with a vector
  - pick ad that most closely matches website vector

Bells and Whistles

- weigh words in search string by linear order
  aliens conspiracy $\neq$ conspiracy aliens
- prioritize certain words in text
- compress vector space for efficiency

Evaluation

- For word meaning, the approach seems to work.
- But it is bad for sentence/text meaning.

Example

The following two sentences receive the same vector:

(1) a. Dog bites man!
    b. Man bites dog!

A Friendly Pointer

How meaning actually works: **LIN 346 Language and Meaning**

An Observation on Frequencies: Zipf's Law

- Word models care about word frequency.
- But there is a problem...

Zipf's Law

The frequency of a type is inversely proportional to its rank.

In Plain English

The most frequent word is

- 2 times as common as the 2nd most frequent word,
- 3 times as common as the 3rd most frequent word,
- and so on.

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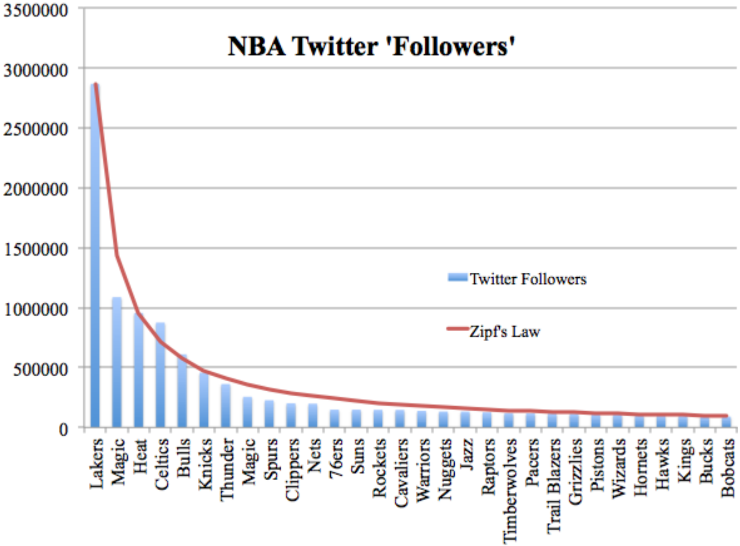
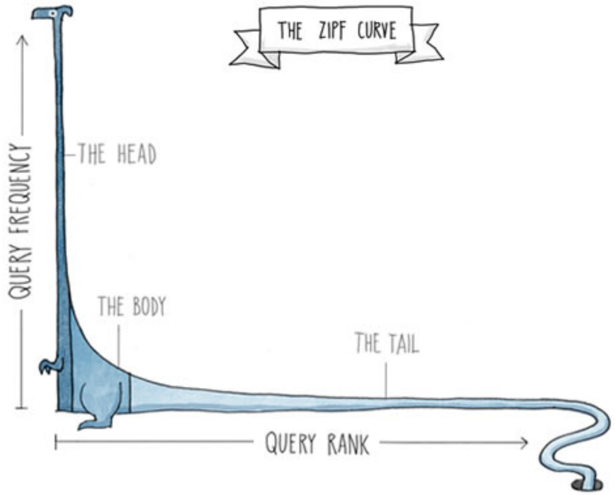
An Example from. . . the NBA?



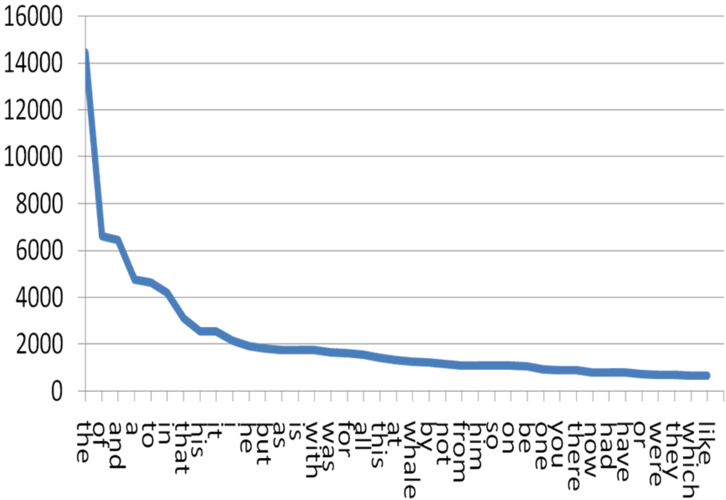
Visualizing Zipf Distributions



Zipf's Law is Everywhere...

- A distribution is probably Zipfian if
  - there is a **long neck**:
    a few types make up the majority of tokens,
  - there is a **long tail**:
    most types only have 1 token (**hapax legomenon**)
- Surprisingly, Zipf's Law shows up in tons of places:
  - size of large cities in a country
  - citations for academic papers
  - frequencies of last names
  - frequencies of weekdays in text

. . . Even in Language!



Stop Words

- About 150 words make up 50% of all English texts:
  the, *of*, *and*, *a*, . . .
- These are called **stop words**.
- Stop words are not very informative for many applications.
- So they are usually discarded after the tokenization step.
- Failure to do so can greatly reduce the model's performance.

Steps of Word Counting Model (Revised)

1. collect corpus
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Example: A Text Without (Non)-Stop Words

- Stop words are much less informative than non-stop words.
- Just check the example below.

Stop Words only

The having no on the

Example: A Text Without (Non)-Stop Words

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- Just check the example below.

Stop Words and Non-Stop Words

The sun shone having no alternative on the nothing new

Example: A Text Without (Non)-Stop Words

- Stop words are much less informative than non-stop words.
- Just check the example below.

Non-Stop Words only

sun shone alternative nothing new

An Important Consequence of Zipf's Law

- Texts mostly consist of stop words.
- Hence it can be difficult to get representative counts for non-stop words.

Sparse Data Problem

- Most of the data is not informative.
- You need tons of data to have enough useful data.

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- You need tons of data to have enough useful data.

Example

- Most models require corpora with at least a few million sentences.
- Really good models (e.g. Google translate) use billions of data points.

Summary

- Unigram (= word-based) models are surprisingly useful.
  - culturomics
  - stylistic analysis
  - authorship attribution
  - word meaning
  - web search
  - ad sense
  - and much more
- They just count words and do some number crunching with the frequencies.
- These models are everywhere, but they are also very simplistic.
- Quality depends largely on how much data is available.