Statistical Properties of Text

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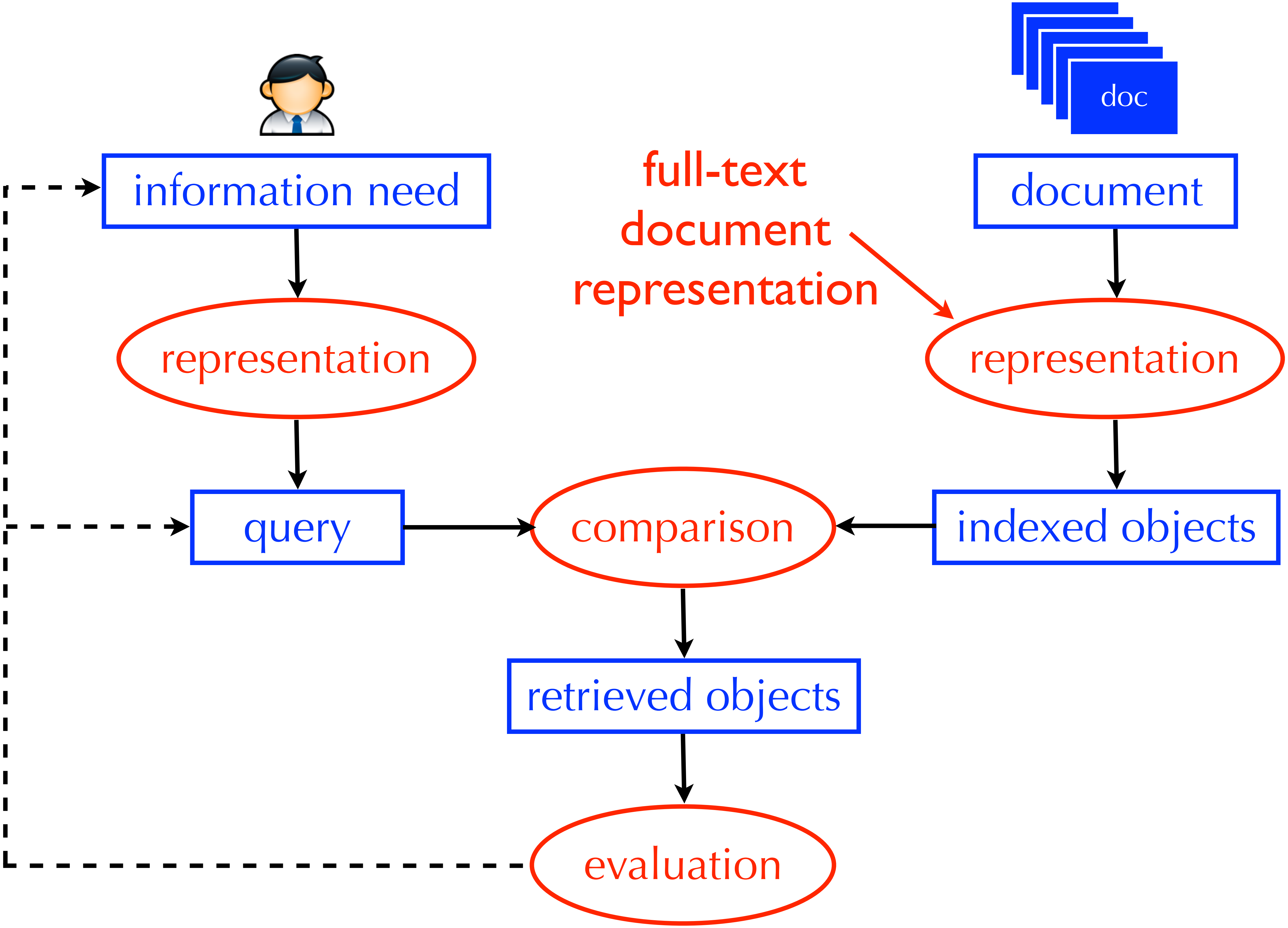
The Basic IR Process



information need

representation

query

full-text document representation

document

representation

indexed objects

comparison

retrieved objects

evaluation

Text-Processing

```
<p><b>Gerard Salton</b> (8 March 1927 in <a href="/wiki/Nuremberg"
title="Nuremberg">Nuremberg</a> - 28 August 1995), also known as
Gerry Salton, was a Professor of <a href="/wiki/Computer_Science"
title="Computer Science" class="mw-redirect">Computer Science</a> at
<a href="/wiki/Cornell_University" title="Cornell University">Cornell
University</a>. Salton was perhaps the leading computer scientist
working in the field of <a href="/wiki/Information_retrieval"
title="Information retrieval">information retrieval</a> during his time.
His group at Cornell developed the <a href="/wiki/
SMART_Information_Retrieval_System" title="SMART Information
Retrieval System">SMART Information Retrieval System</a>, which he
initiated when he was at Harvard.</p>
```

- Mark-up removal
- Down-casing
- Tokenization

Text-Processing

gerard salton 8 march 1978 in nuremberg 28 august 1995 also know as gerry salton was professor of computer science at cornell university salton was perhaps the leading computer scientist working in the field of information retrieval during his time his group at cornell developed the smart information retrieval system which he initiated when he was at harvard

- Our goal is to describe content using content
- Are all these words equally descriptive?
- What are the most descriptive words?
- How might a computer identify these?

Statistical Properties of Text

- We know that language use if varied
- There are many ways to convey the same information (which makes IR difficult)
- However, are there statistical properties of word usage that are predictable? Across languages? Across modalities? Across genres?

IMDB Corpus

internet movie database

- Each document corresponds to a movie, a plot description, and a list of artists and their roles
  - number of documents: **230,721**
  - number of term occurrences (tokens): **36,989,629**
  - number of unique terms (token-types): **424,035**

http://www.imdb.com/

IMDB Corpus

term-frequencies

rank	term	frequency	rank	term	frequency
1	the	1586358	11	year	250151
2	a	854437	12	he	242508
3	and	822091	13	movie	241551
4	to	804137	14	her	240448
5	of	657059	15	artist	236286
6	in	472059	16	character	234754
7	is	395968	17	cast	234202
8	i	390282	18	plot	234189
9	his	328877	19	for	207319
10	with	253153	20	that	197723

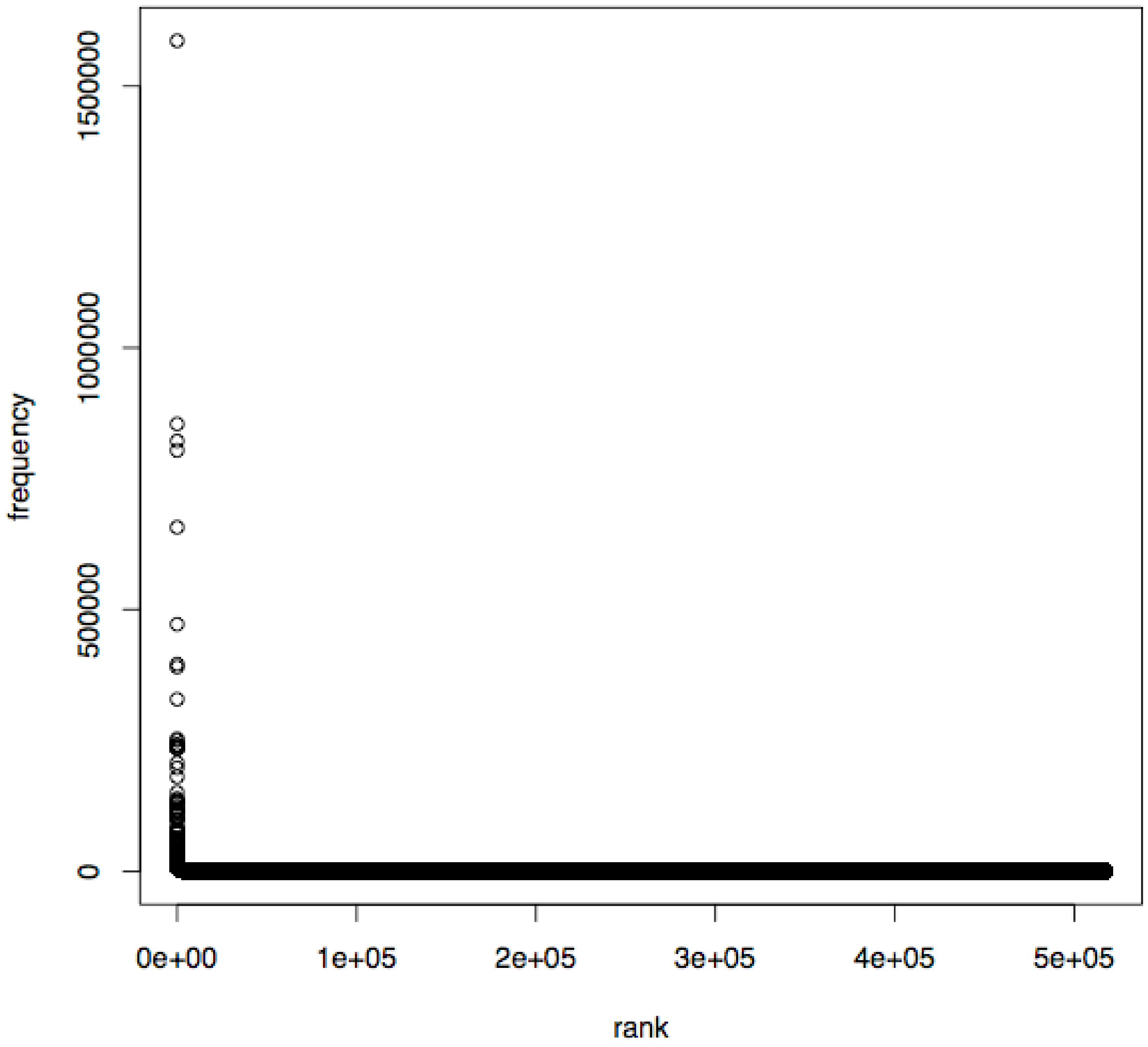
IMDB Corpus

term-frequencies

rank	term	frequency	rank	term	frequency
21	on	180760	31	their	116803
22	as	150721	32	they	116113
23	by	138580	33	has	113336
24	himself	138214	34	him	112589
25	but	134017	35	when	106723
26	she	132237	36	I	100475
27	who	132151	37	are	99544
28	an	129717	38	it	98455
29	from	122086	39	man	87115
30	at	118190	40	ii	80583

IMDB Corpus

term-frequencies



term frequency decreases rapidly as a function of rank!

George Kingsley Zipf

Zipf’s Law

- Term-frequency decreases rapidly as a function of rank
- How rapidly?
- Zipf’s Law:

$$f_t = \frac{k}{r_t}$$

- **f**$_t$ = frequency (number of times term **t** occurs)
- **r**$_t$ = frequency-based rank of term **t**
- **k** = frequency of most frequent term
- What does this mean?

Zipf's Law

$$\frac{1}{N} \times f_t = \frac{1}{N} \times \frac{k}{r_t}$$

$$P_t = \frac{c}{r_t}$$

- **P$_t$** = proportion of the collection corresponding to term **t**
- **c** = proportion of the collection associated with the most frequent term
- For English **c** = 0.1 (more or less)
- What does this mean?

Zipf's Law

$$P_t = \frac{c}{r_t} \qquad c = 0.1$$

- The most frequent term accounts for 10% of the text
- The second most frequent term accounts for 5%
- The third most frequent term accounts for about 3%
- Together, the top 10 account for about 30%
- Together, the top 20 account for about 36%
- Together, the top 50 account for about 45%
  - that's nearly half the text!
- What <u>else</u> does Zipf's law tell us?

Zipf's Law

- With some crafty manipulation, it also tells us that the faction of terms that occur **n** times is given by:

$$\frac{1}{n(n+1)}$$

- So, what fraction of the terms occur only once?

Zipf's Law

- With some crafty manipulation, it also tells us that the faction of terms that occur **n** times is given by:

$$\frac{1}{n(n+1)}$$

- About half the terms occur only once!
- About 75% of the terms occur 3 times or less!
- About 83% of the terms occur 5 times or less!
- About 90% of the terms occur 10 times or less!

Zipf's Law

- Note: the fraction of terms that occur **n** times or less is given by:

$$\sum_{i=1}^{n}\left(\frac{1}{i(i+1)}\right)$$

- That is, we have to add the fraction of terms that appear 1, 2, 3, ... up to **n** times

Verifying Zipf's Law

visualization

Zipf's Law $f = \frac{k}{r}$

... still Zipf's Law $\log(f) = \log(\frac{k}{r})$

... still Zipf's Law $\log(f) = \log(k) - \log(r)$

- So, if Zipf's law holds, what would we see if we plotted log(f) vs. log(r)?

Verifying Zipf's Law

visualization

Zipf's Law $$f = \frac{k}{r}$$

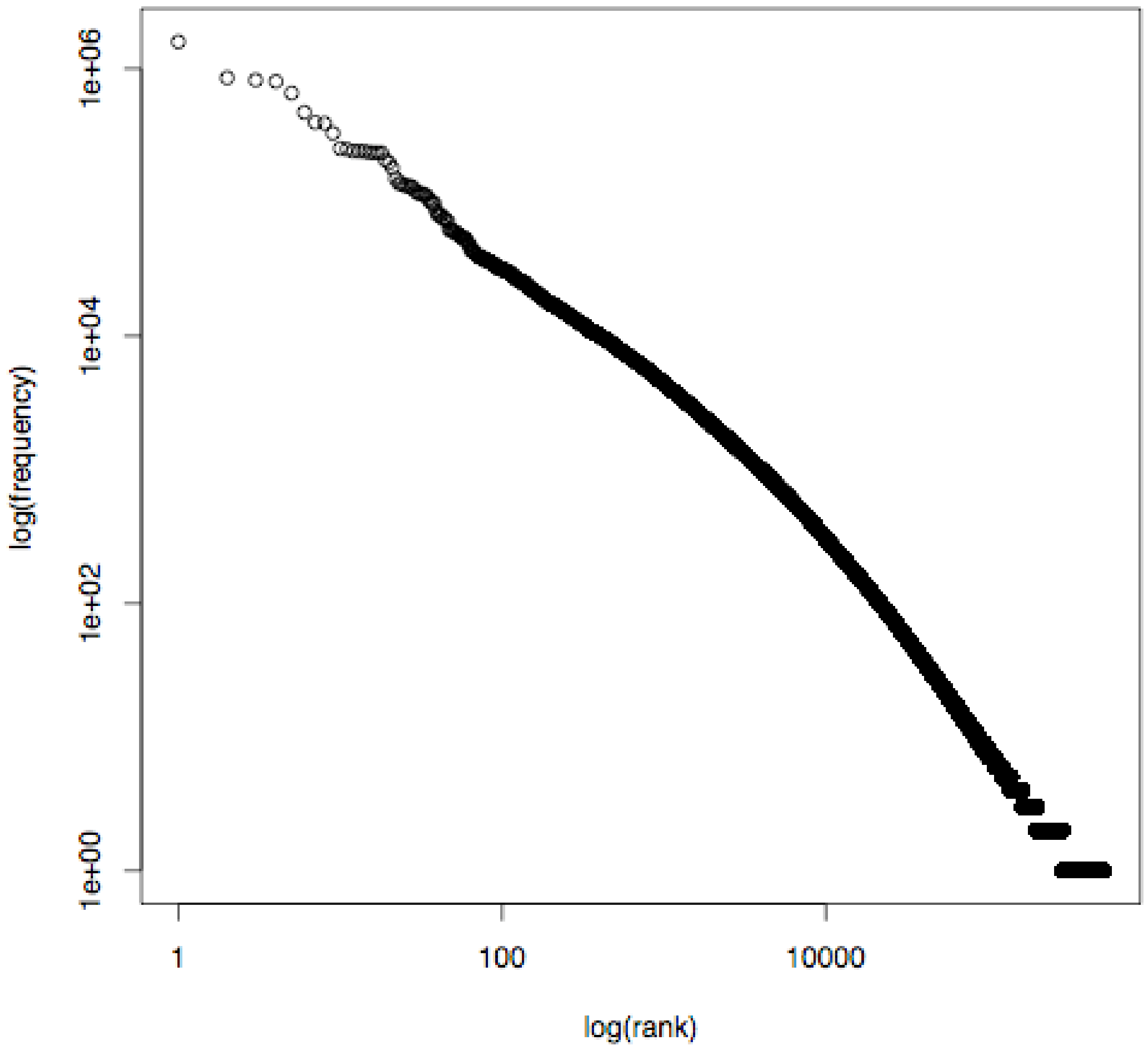
... still Zipf's Law $$\log(f) = \log(\frac{k}{r})$$

... still Zipf's Law $$\log(f) = \log(k) - \log(r)$$

- If Zipf's law holds true, we should be able to plot **log(f)** vs. **log(r)** and see a straight light with a slope of -1

Zipf's Law

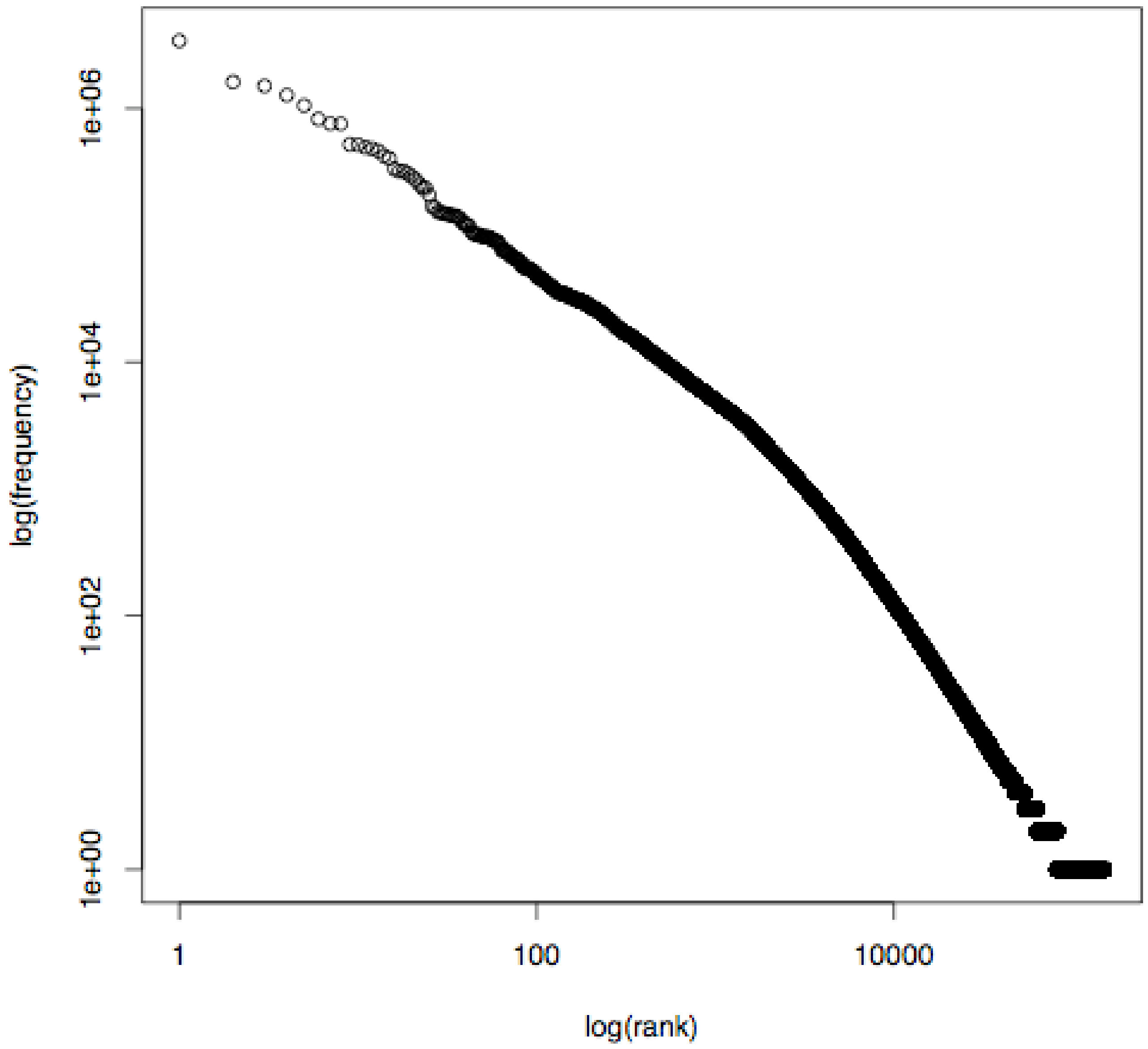
IMDB Corpus



Does Zipf's Law generalize across languages?

Zipf's Law

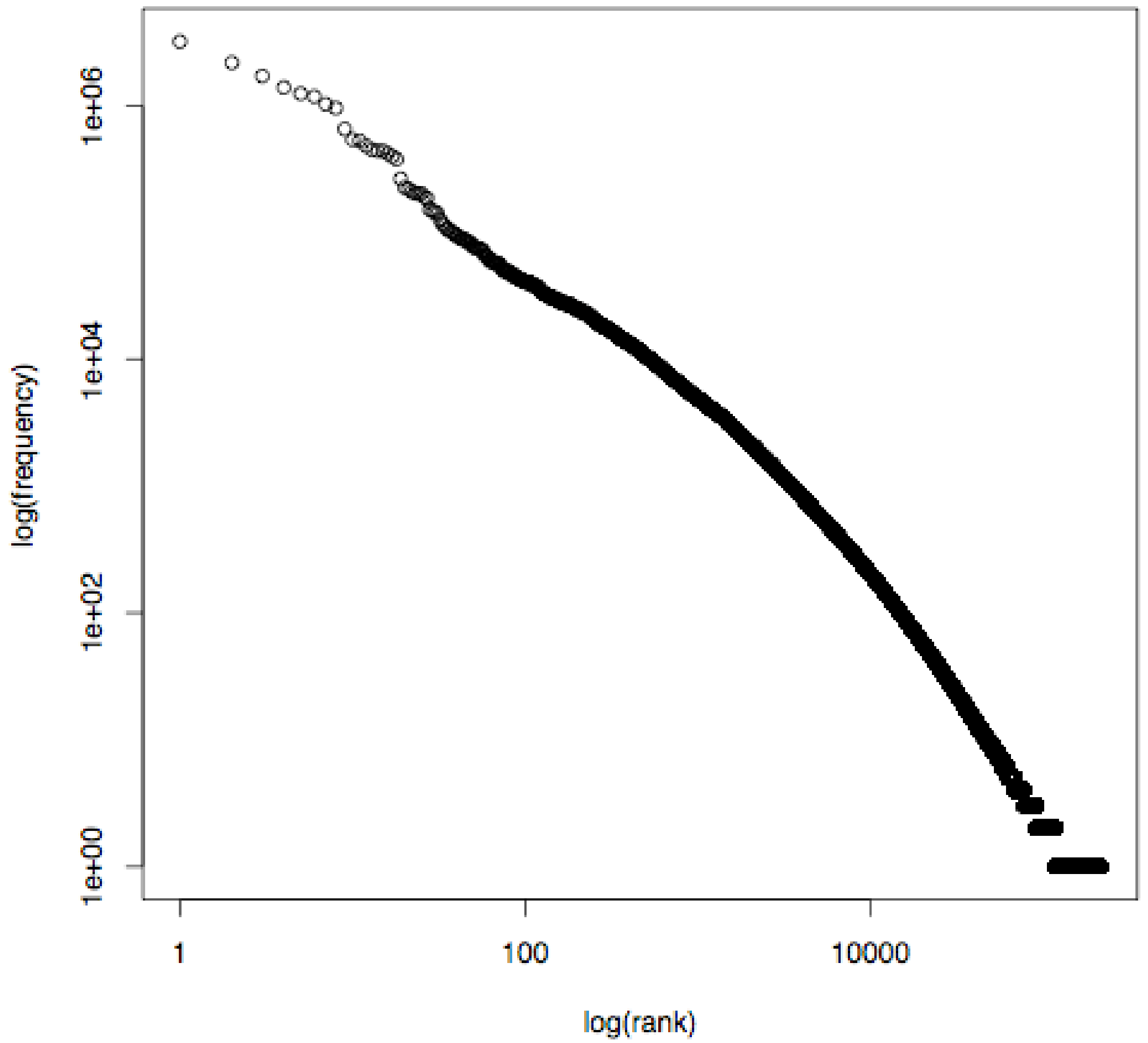
European Parliament: English

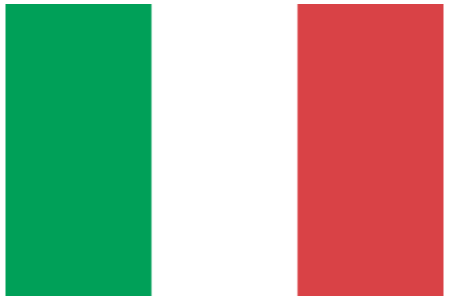


- Transcribed speech from proceedings of the European Parliament **(Koehn '05)**

Zipf's Law

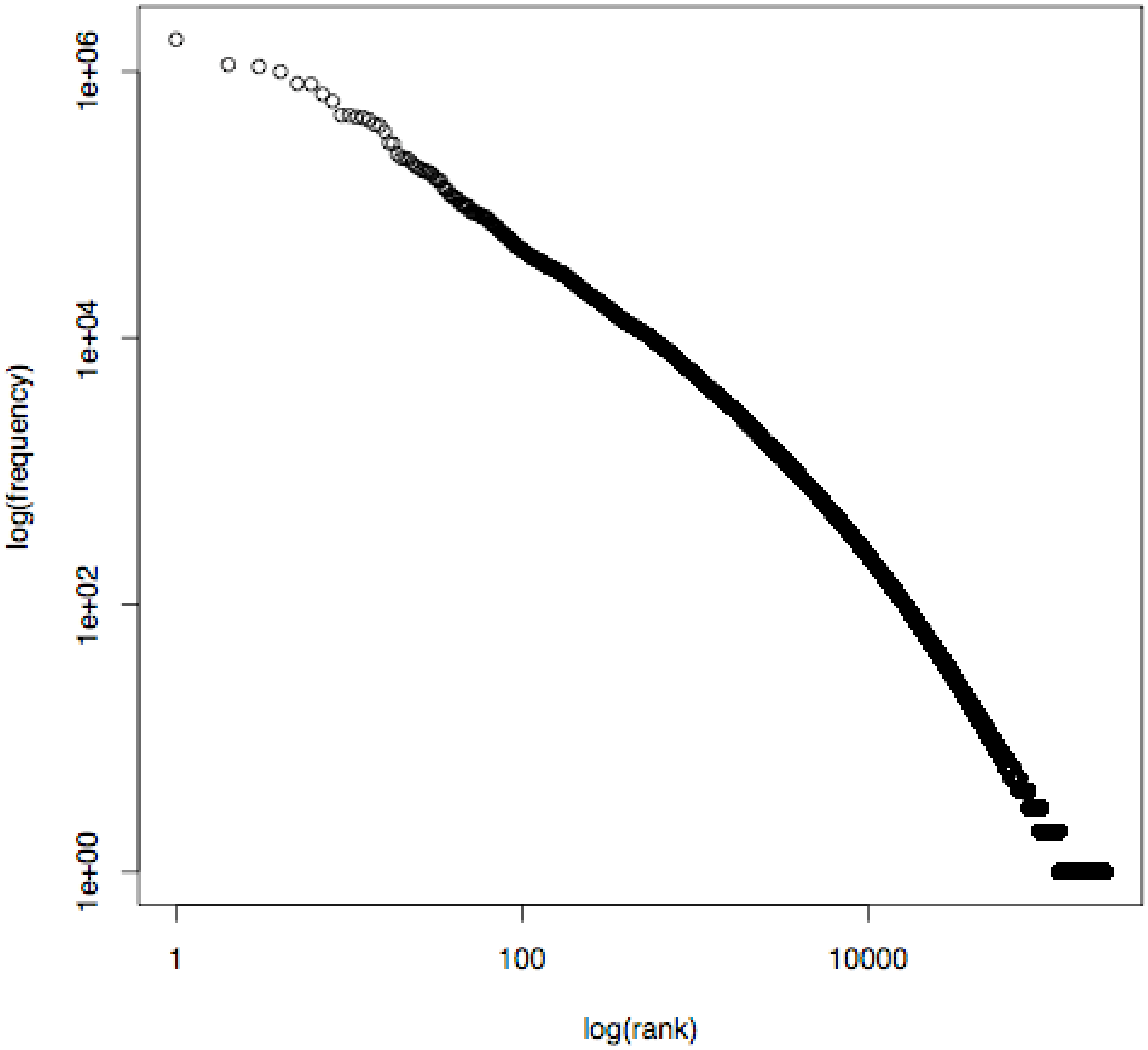
European Parliament: Spanish





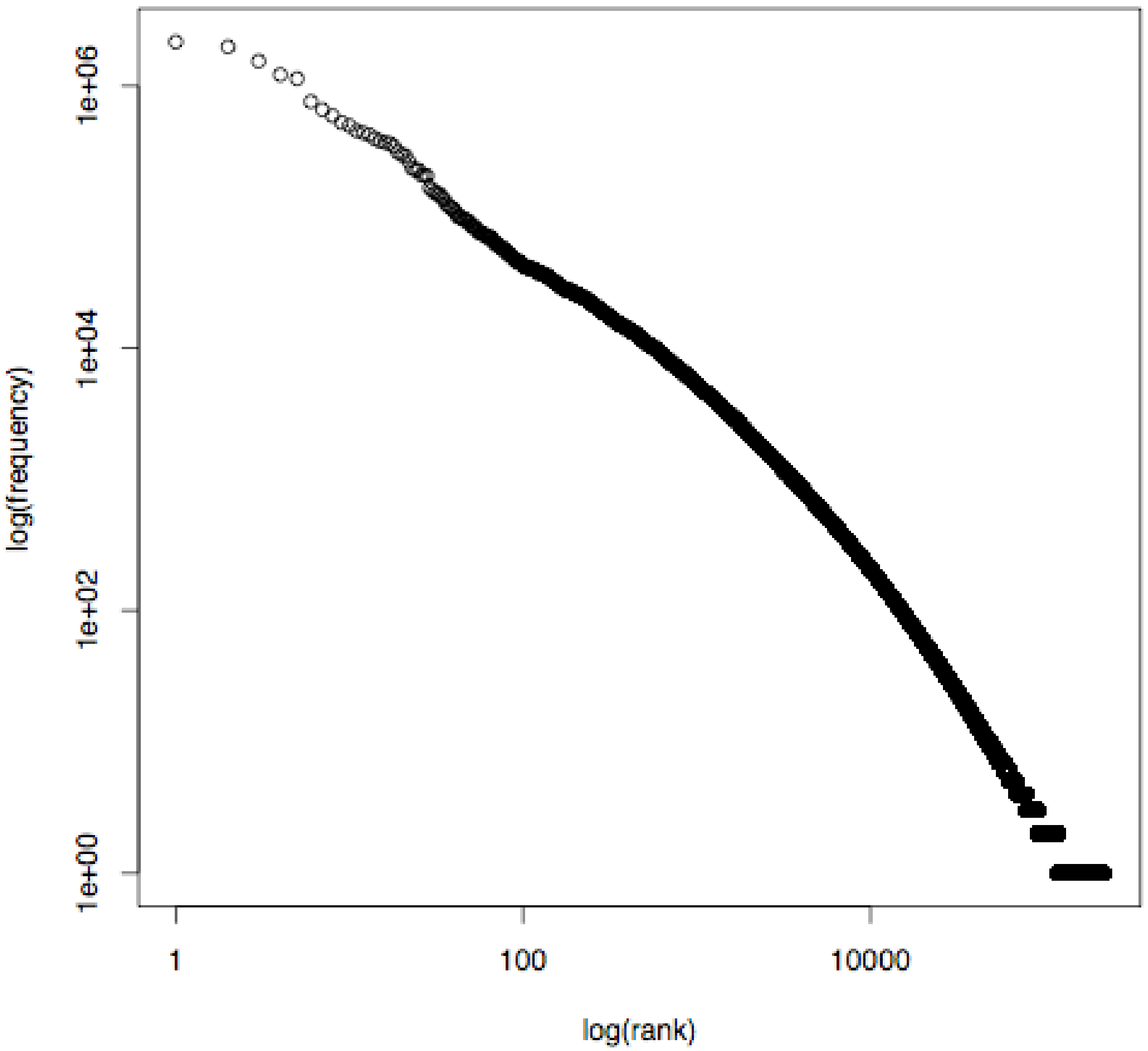
Zipf's Law

European Parliament: Italian



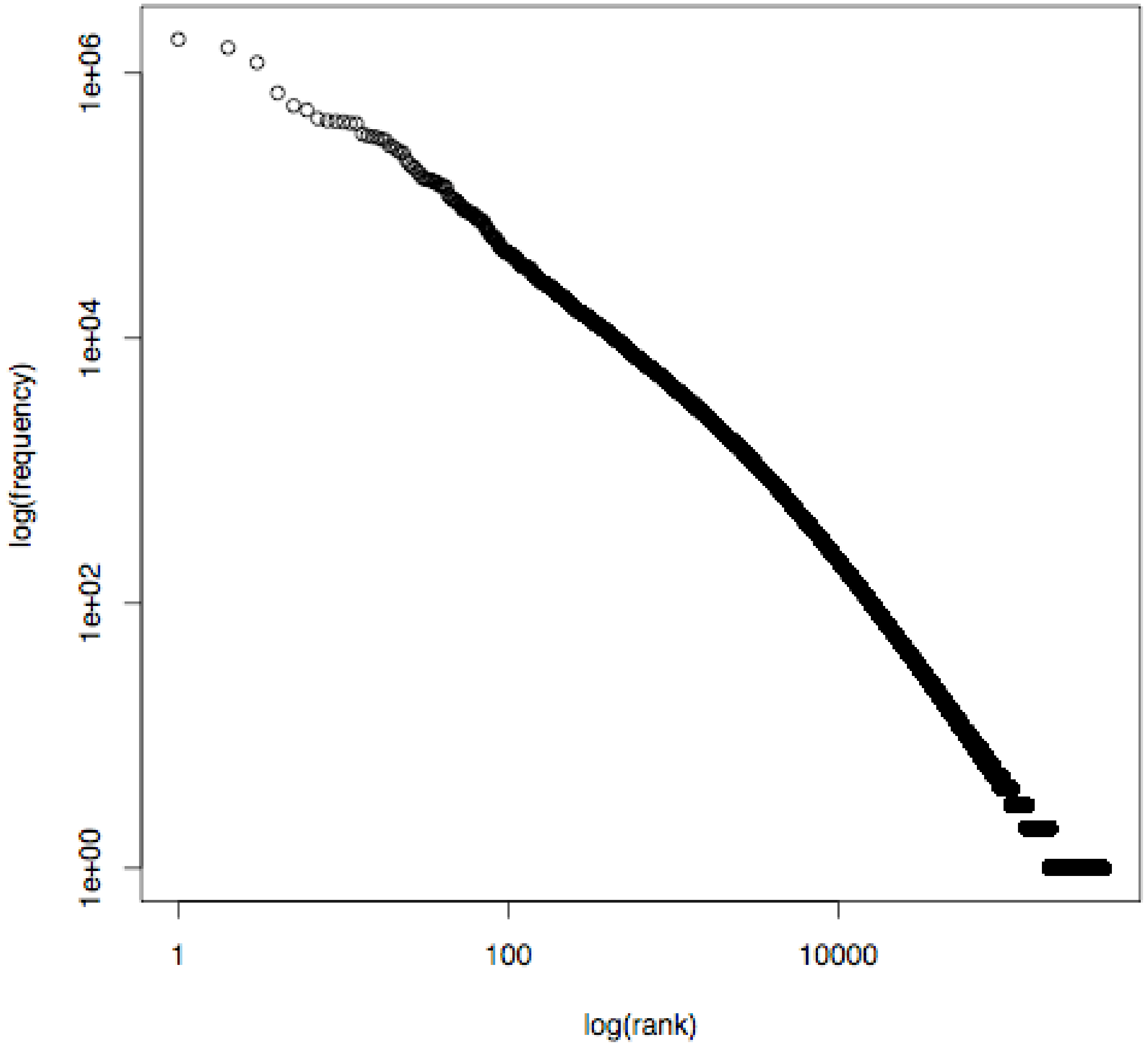
Zipf's Law

European Parliament: Portuguese



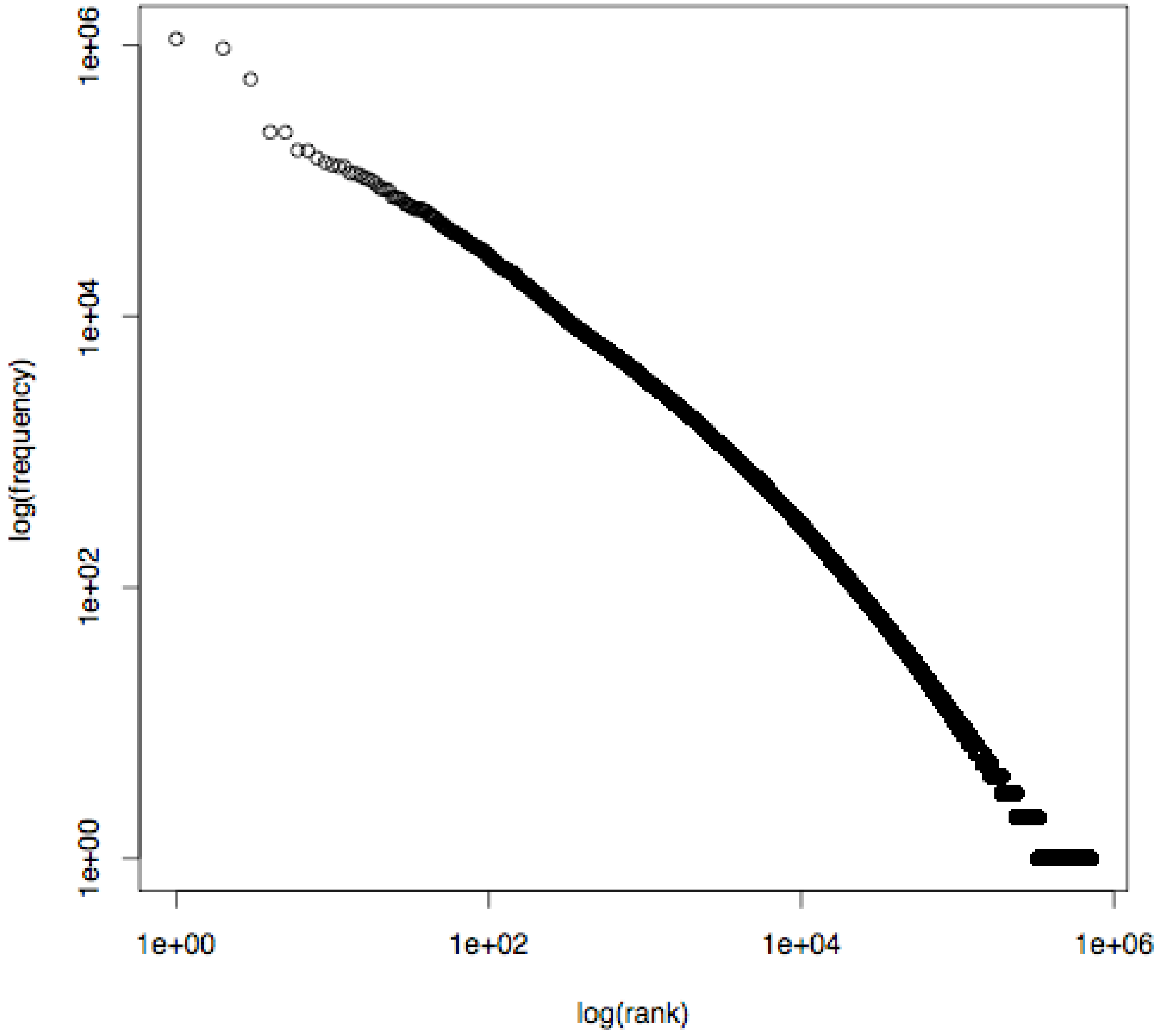
Zipf's Law

European Parliament: German



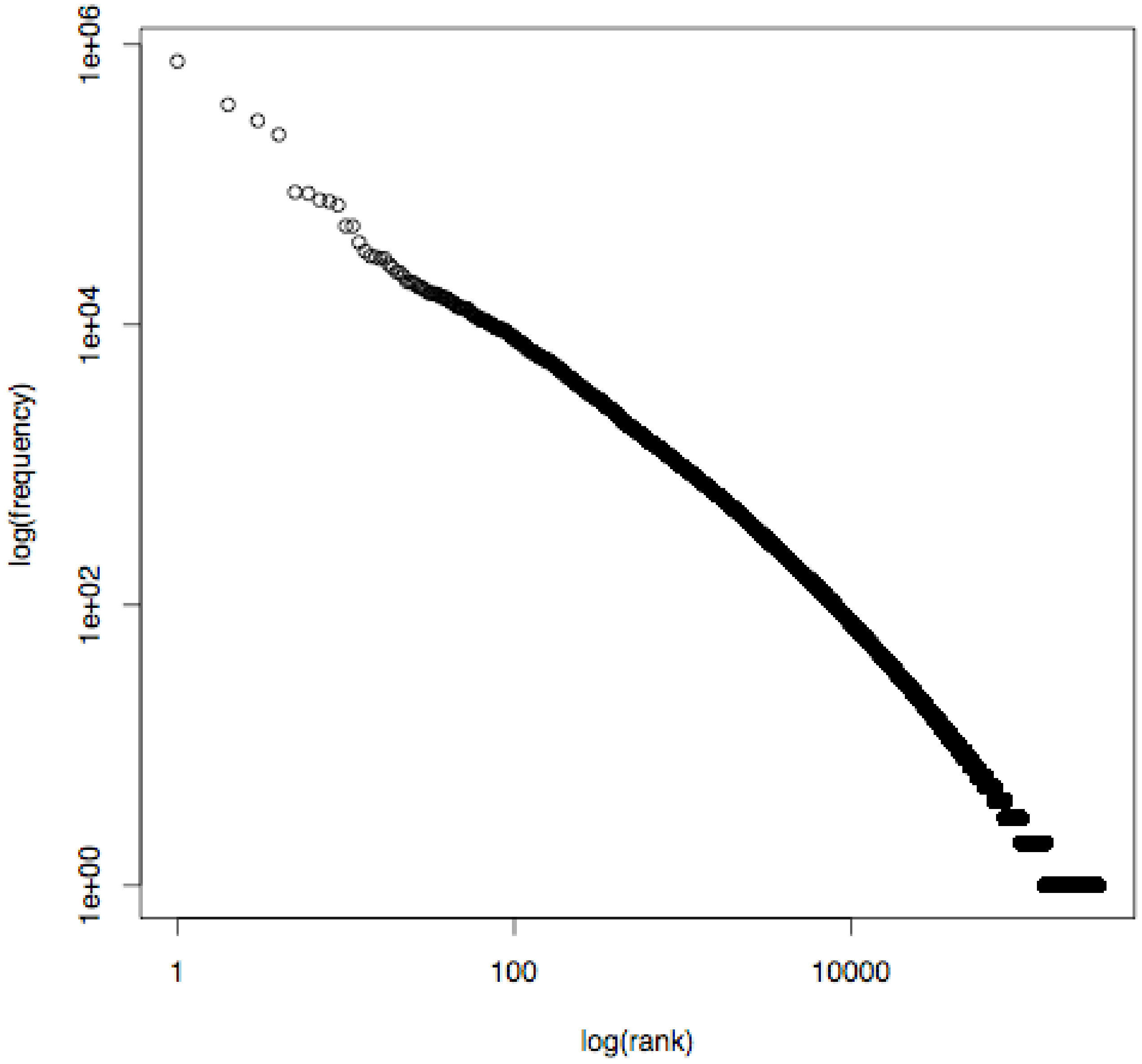
Zipf's Law

European Parliament: Finnish



Zipf's Law

European Parliament: Hungarian

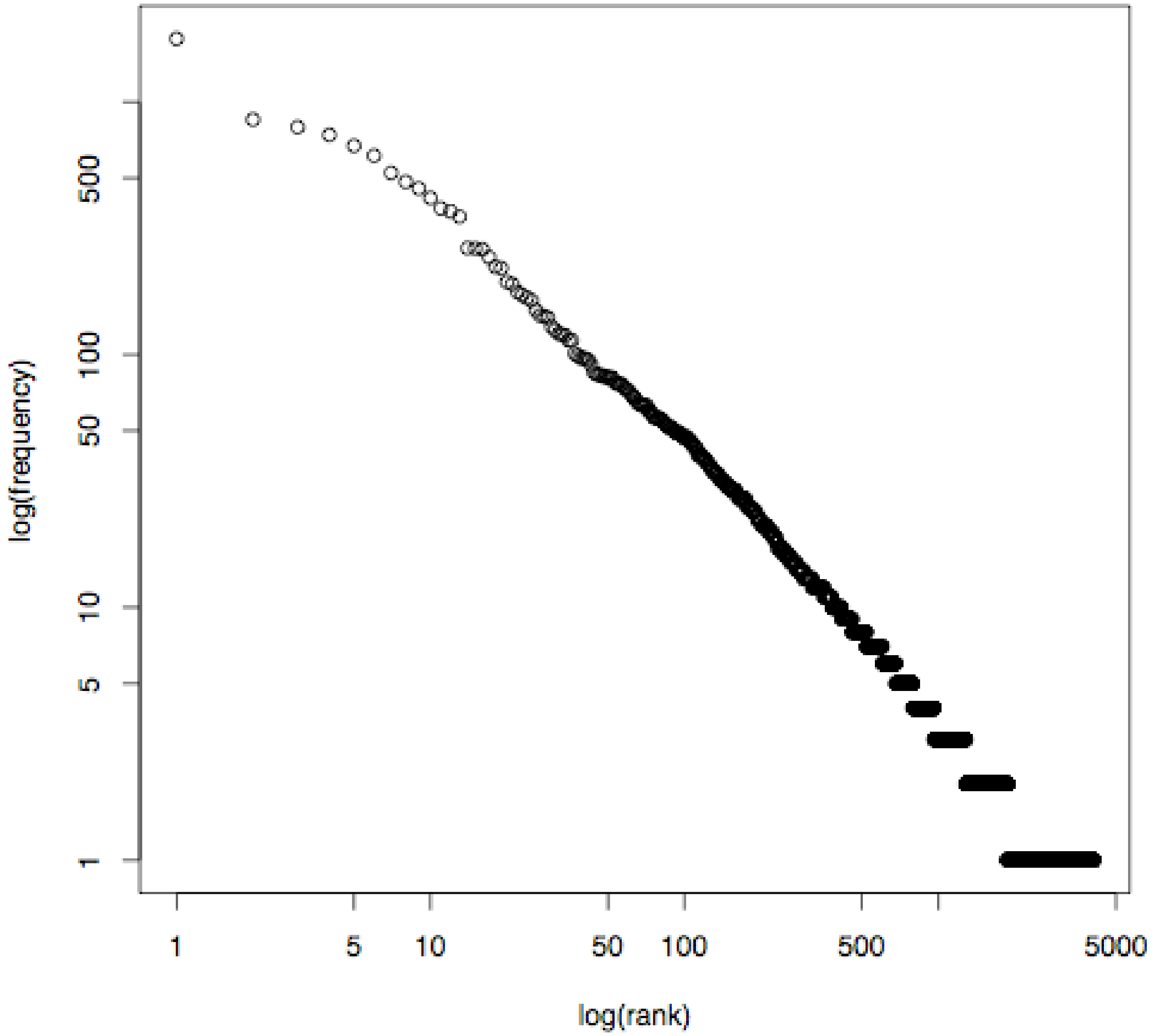


Yes, but these texts are translations of the same content!

What about different texts?
different topics?
different genres?
different sizes?
different complexity?

Zipf's Law

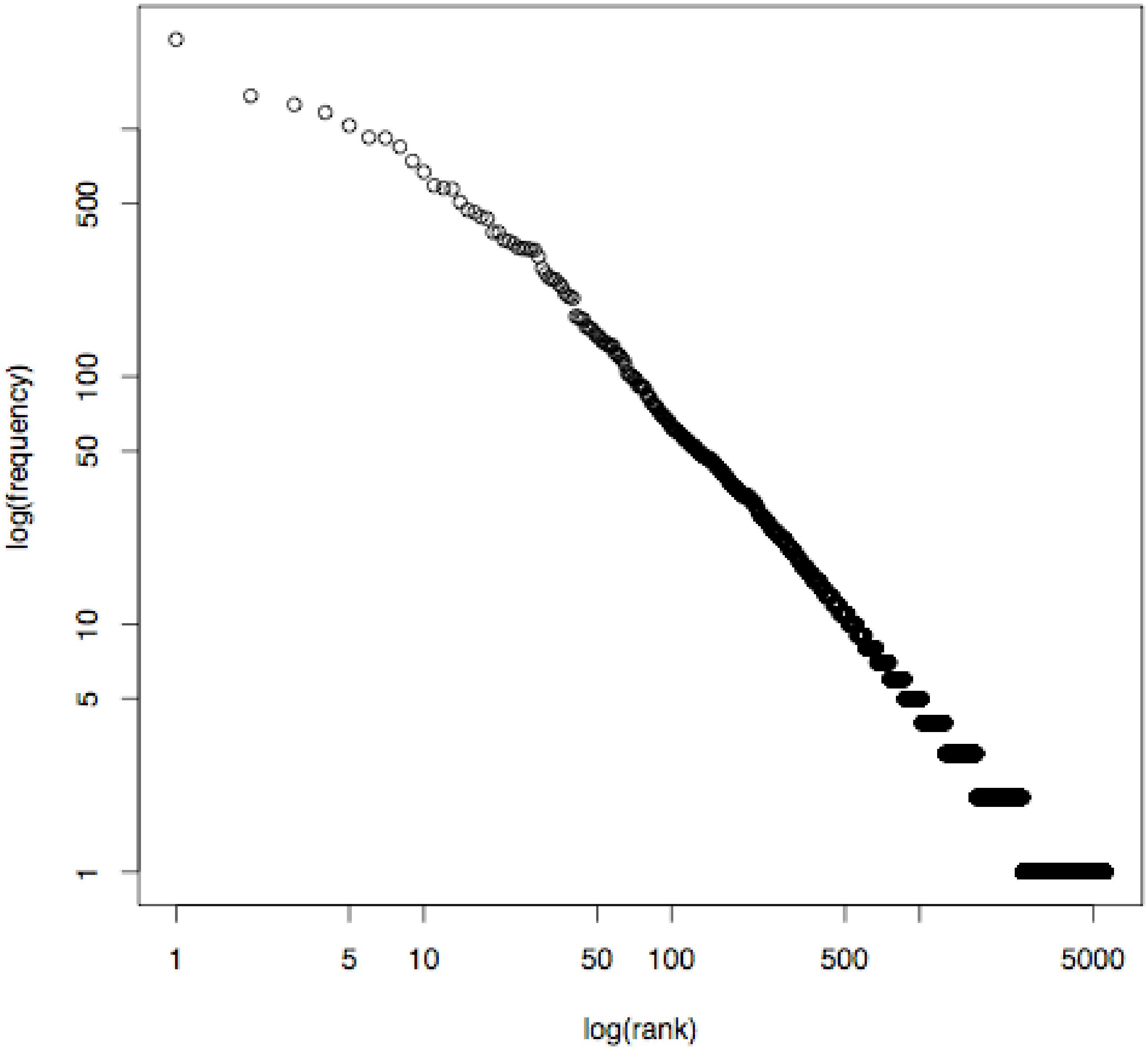
Alice in Wonderland



(text courtesy of Project Gutenberg)

Zipf's Law

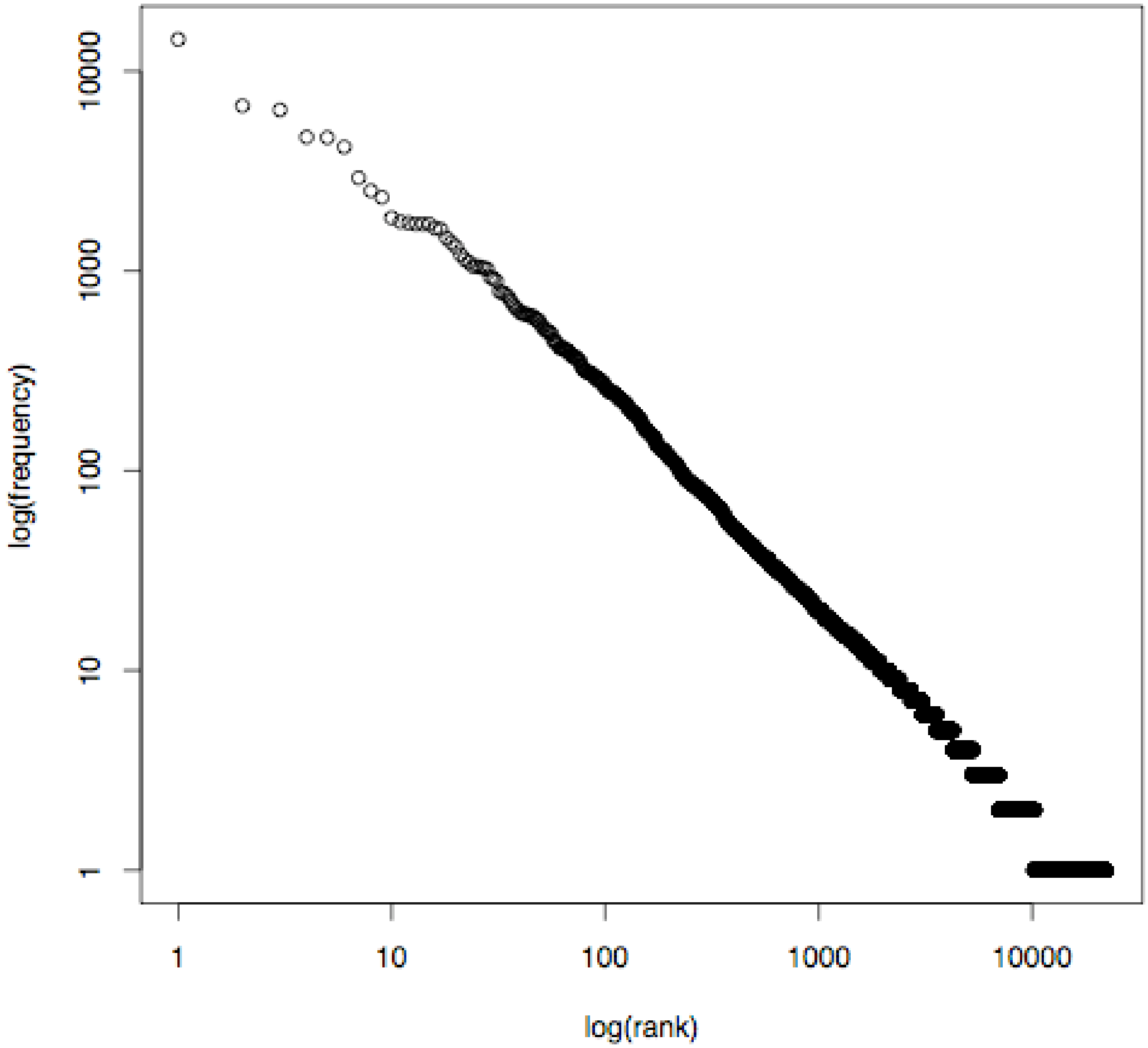
Peter Pan



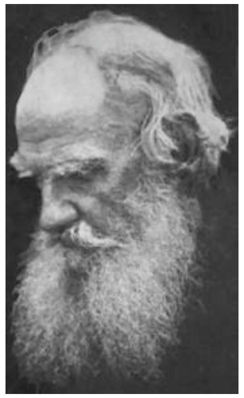
(text courtesy of Project Gutenberg)

Zipf's Law

Moby Dick

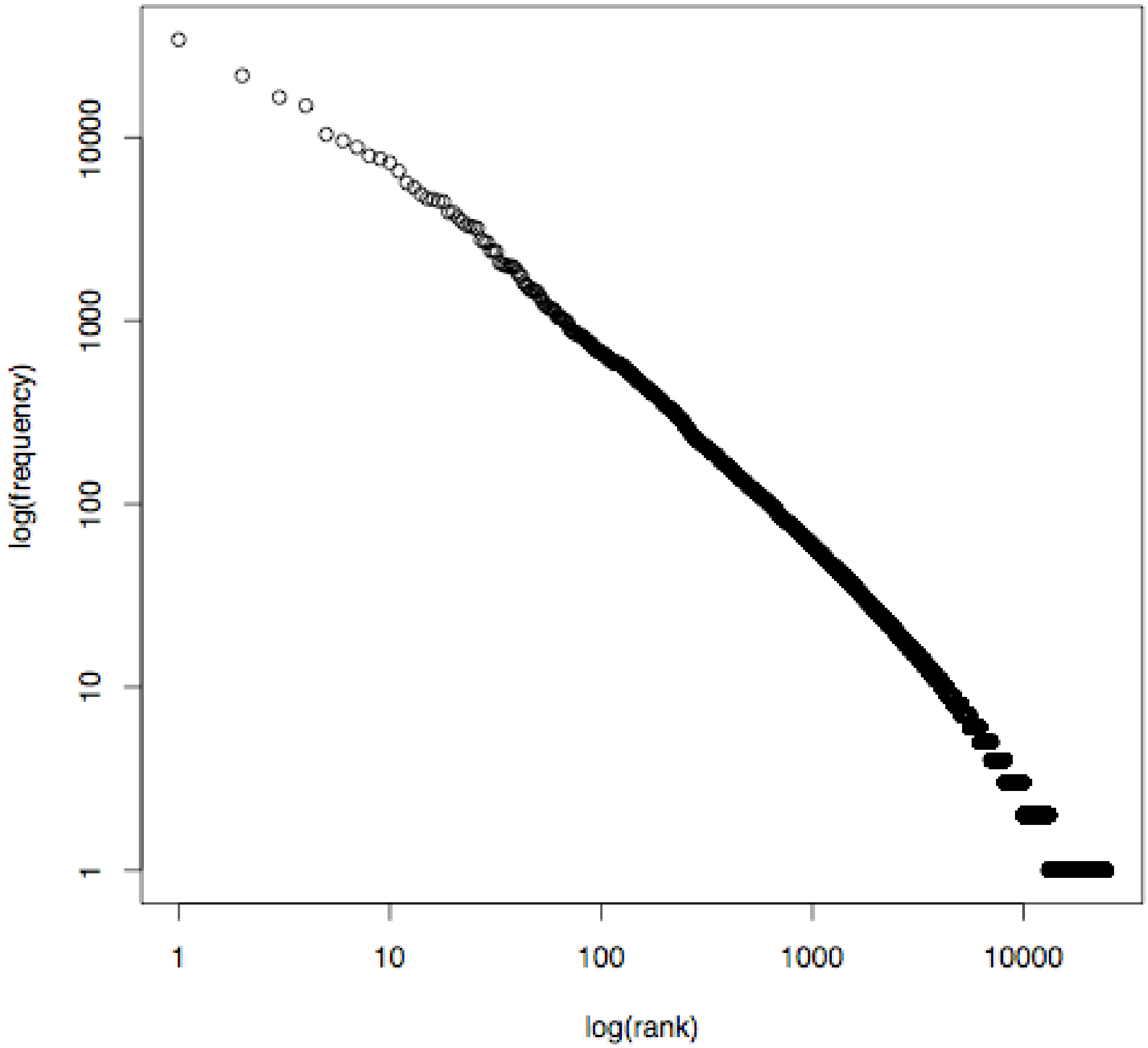


(text courtesy of Project Gutenberg)

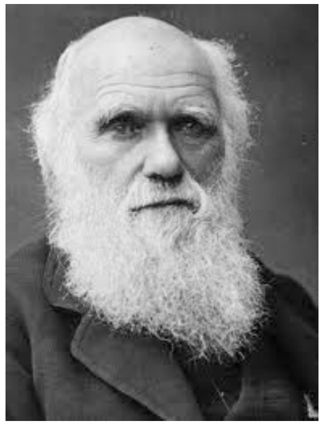


Zipf's Law

War and Peace

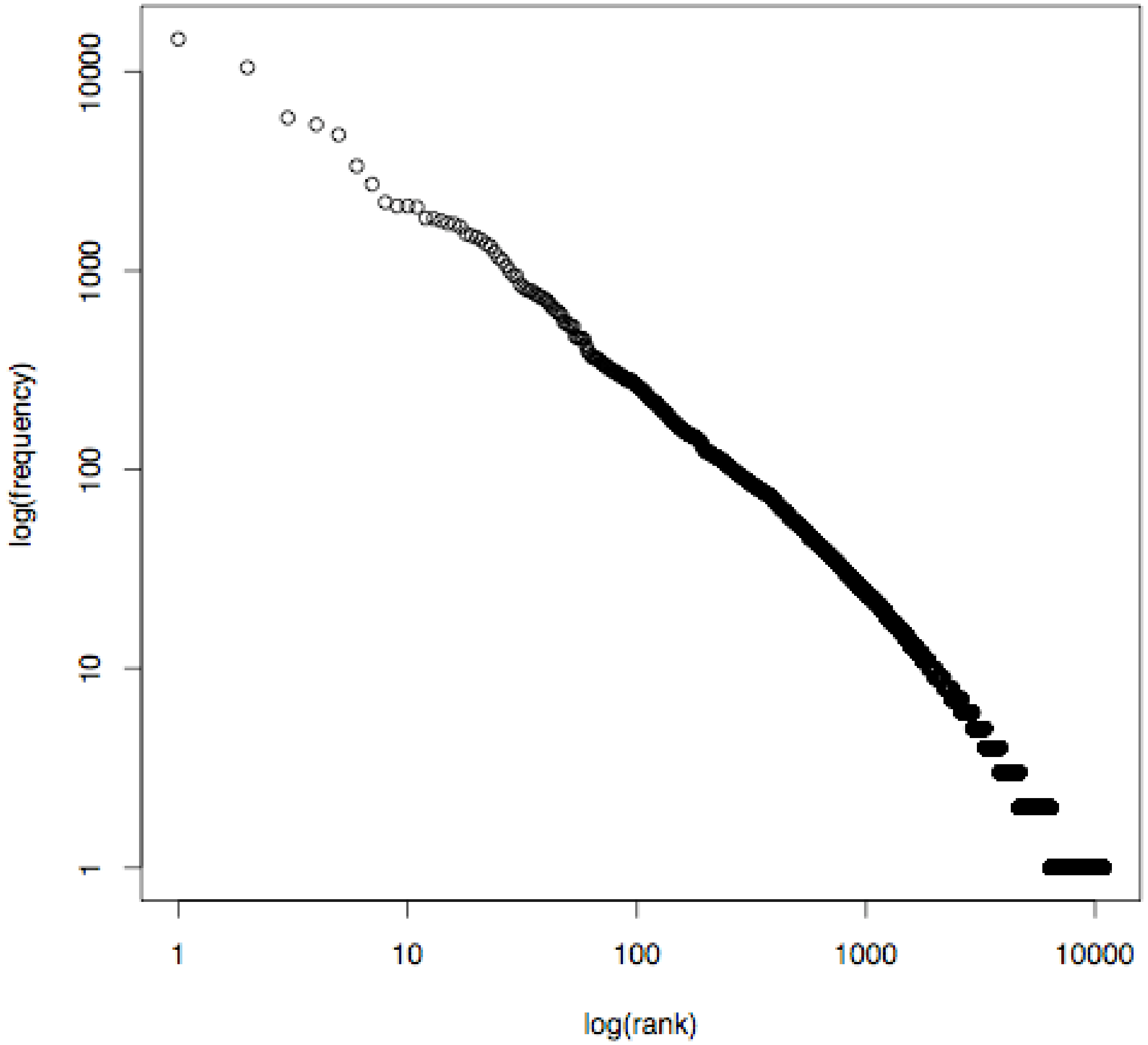


(text courtesy of Project Gutenberg)

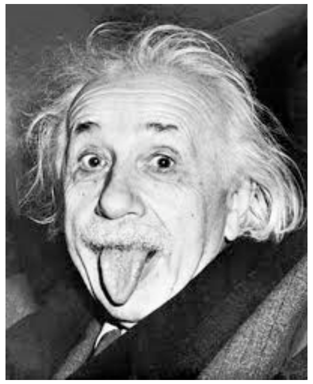


Zipf's Law

On the Origin of Species

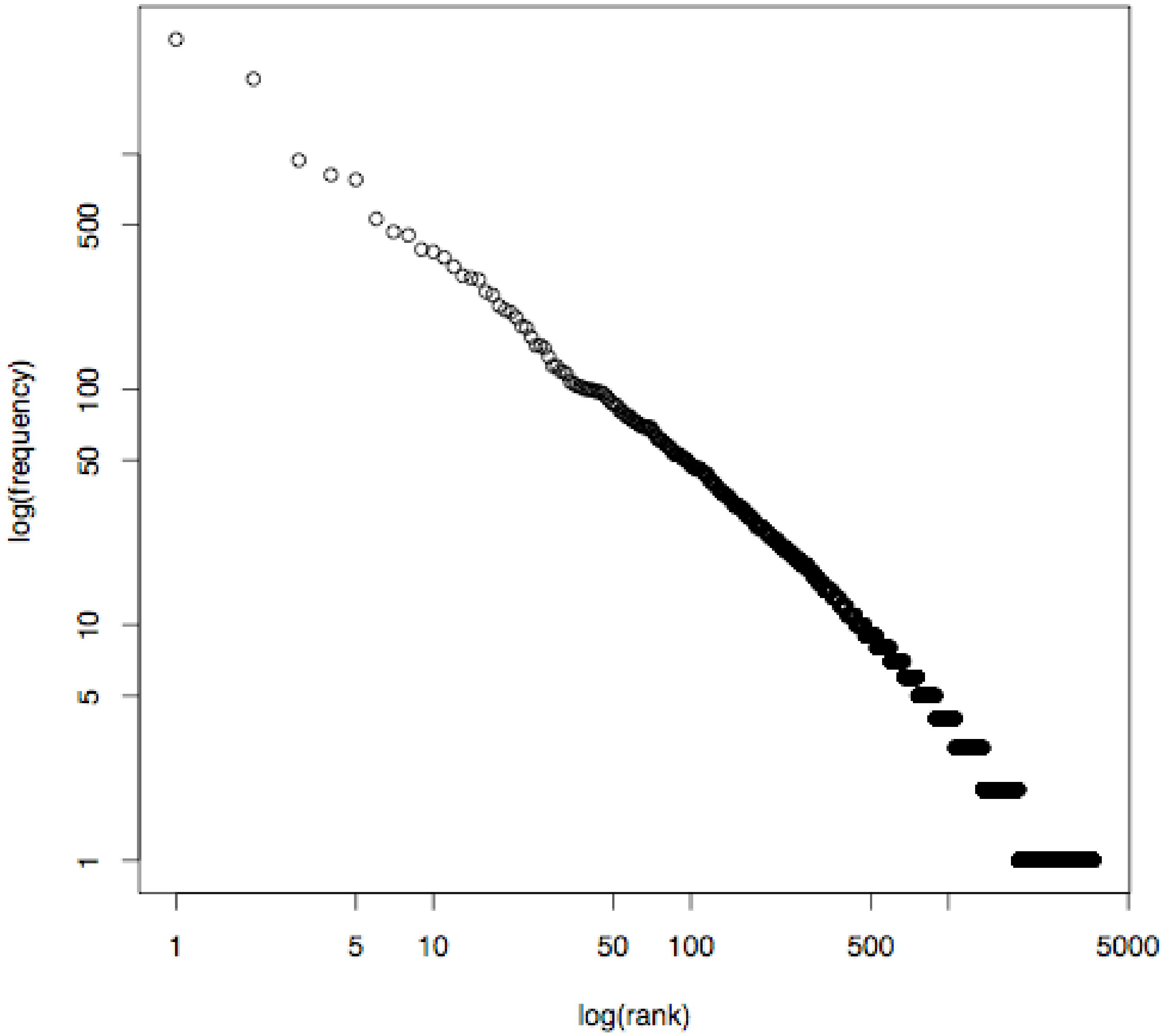


(text courtesy of Project Gutenberg)



Zipf's Law

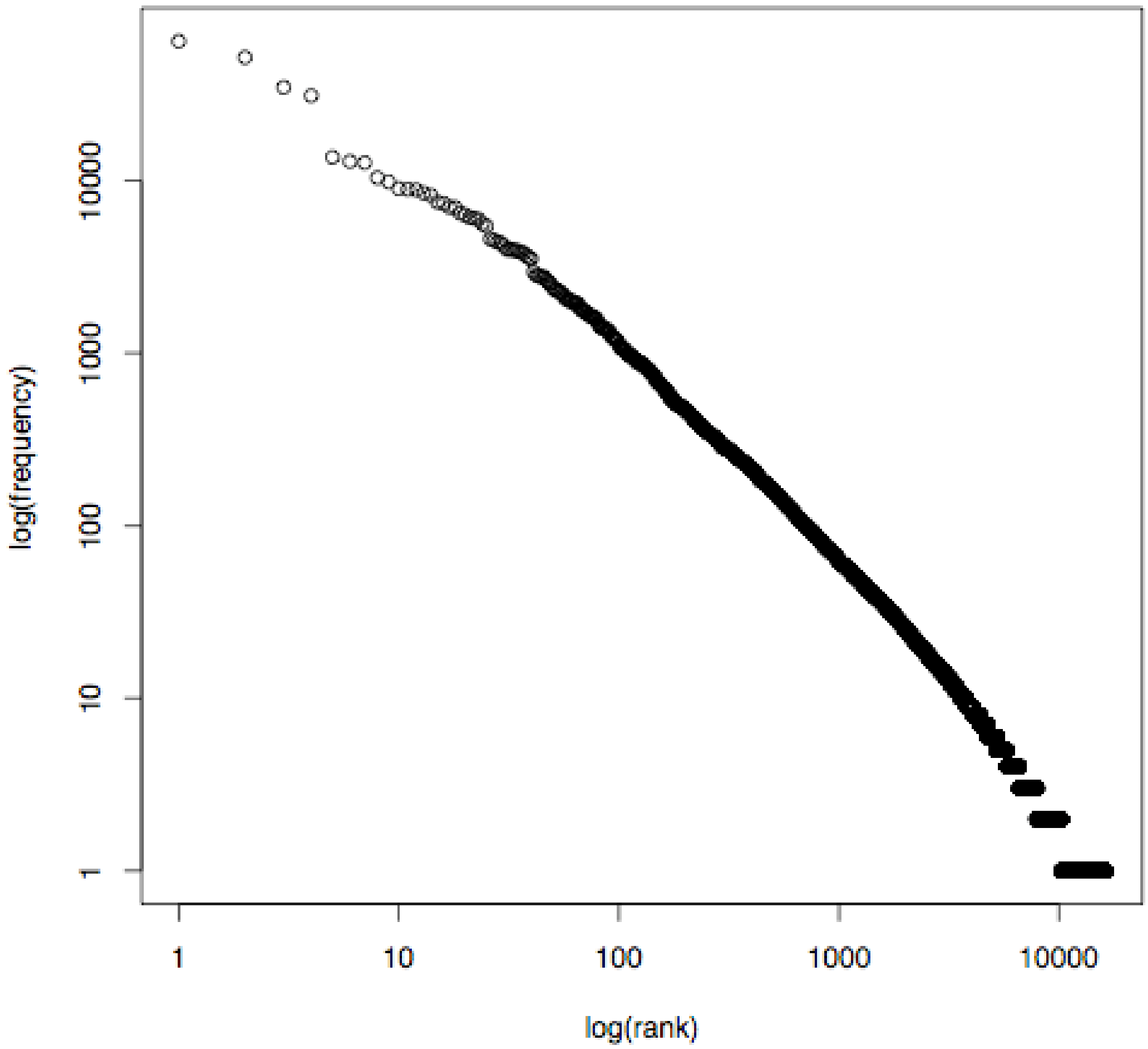
Relativity: The Special and General Theory



(text courtesy of Project Gutenberg)

Zipf's Law

The King James Bible



(text courtesy of Project Gutenberg)

Zipf's Law

- Zipf's Law holds true for:
  - different sizes of text
  - different genres
  - different topics
  - different complexity of content
  - different languages

Implications of Zipf's Law (1)

gerard salton 8 march 1978 in nuremberg 28 august 1995 also know as gerry salton was professor of computer science at cornell university salton was perhaps the leading computer scientist working in the field of information retrieval during his time his group at cornell developed the smart information retrieval system which he initiated when he was at harvard

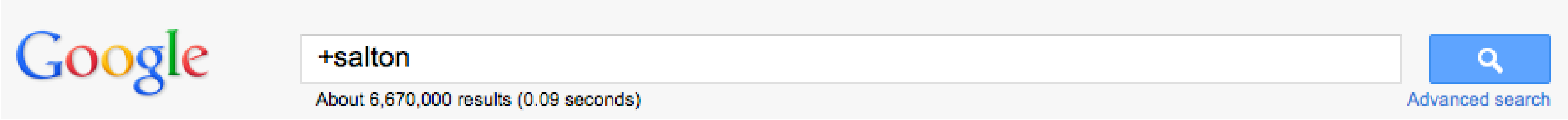
- The most descriptive words are those that do not appear in every document
- Most retrieval models exploit this idea
- Zipf's law allows us to automatically identify these non-descriptive terms and treat them differently

Implications of Zipf's Law (2)

- Ignoring the most frequent terms greatly reduces the size of the index
- The top 50 accounts for about 45% of the collection
- These have very long inverted lists
- Warning: these words can be important in combination with others (e.g., in proximity operators)
- Example queries: "to be or not to be", "the who", "state of the union", "it had to be you"

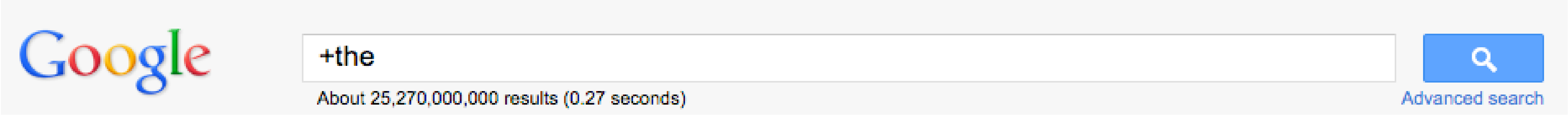
Implications of Zipf's Law (3)

- Ignoring the most frequent terms can improve retrieval efficiency (response time)
- The most frequent terms have long inverted lists
- Alternative: leave them in the index and remove them from the query, unless they occur in a proximity operator



+salton

About 6,670,000 results (0.09 seconds)



+the

About 25,270,000,000 results (0.27 seconds)

Implications of Zipf’s Law (4)

- Ignoring the most frequent terms can improve retrieval effectiveness

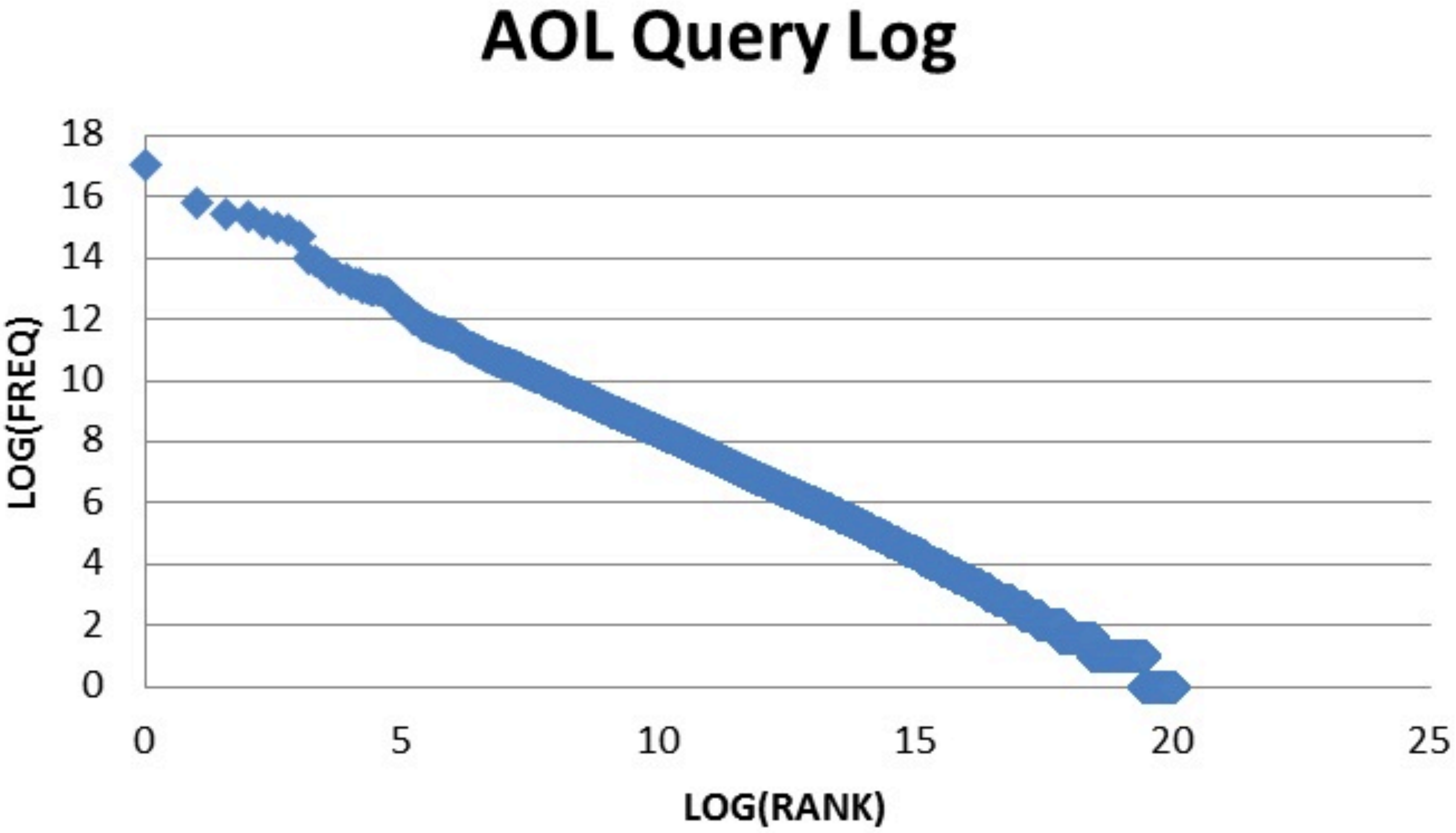
- Very frequent terms may not be related to the main content of the doc, but may be a “quirk” of the corpus

rank	term	frequency	rank	term	frequency
1	the	1586358	11	year	250151
2	a	854437	12	he	242508
3	and	822091	13	movie	241551
4	to	804137	14	her	240448
5	of	657059	15	artist	236286
6	in	472059	16	character	234754
7	is	395968	17	cast	234202
8	i	390282	18	plot	234189
9	his	328877	19	for	207319
10	with	253153	20	that	197723

Implications of Zipf's Law (5)

- We've talked about Zipf's Law in the collection
- What about Zipf's Law in queries issued to the search engine?

Implications of Zipf's Law (5)



Implications of Zipf's Law (5)

- Same trend: a few queries occur very frequently, while most occur very infrequently
- Opportunity: the system can be tweaked to do well on those queries it is likely to "see" again and again
- Curse: this is only a partial solution.
- In web search, about half the queries ever observed are unique
- How does this affect evaluation?

Implications of Zipf's Law

- Given Zipf's Law, as a collection grows, how will the size of the vocabulary grow?

Vocabulary Growth and Heaps’ Law

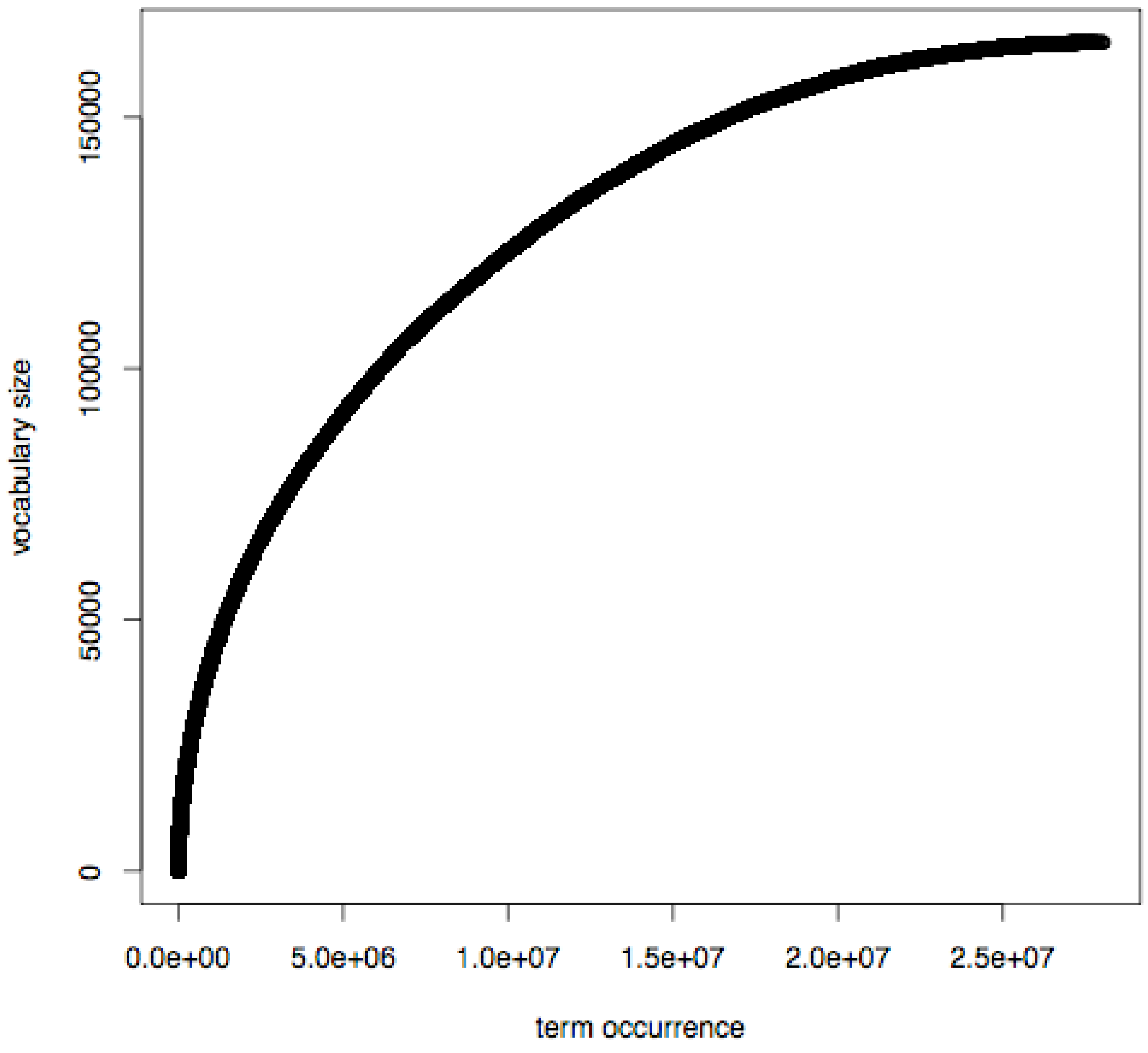
- The number of new words decreases as the size of the corpus increases
- Heaps’ Law:

$$v = k \times n^{\beta}$$

- **v** = size of the vocabulary (number of unique words)
- **n** = size of the corpus (number of word-occurrences)
- **k** = constant (10 ≤ **k** ≤ 100)
  - not the same as **k** in Zipf’s law
- **B** = constant (**B** ≈ 0.50)

Heaps’ Law

IMDB Corpus



Heaps' Law

- As the corpus grows, the number of new terms increases dramatically at first, but then increases at a slower rate
- Nevertheless, as the corpus grows, new terms will always be found (even if the corpus becomes huge)
    - there is no end to vocabulary growth
    - invented words, proper nouns (people, products), misspellings, email addresses, etc.

Implications of Heaps' Law

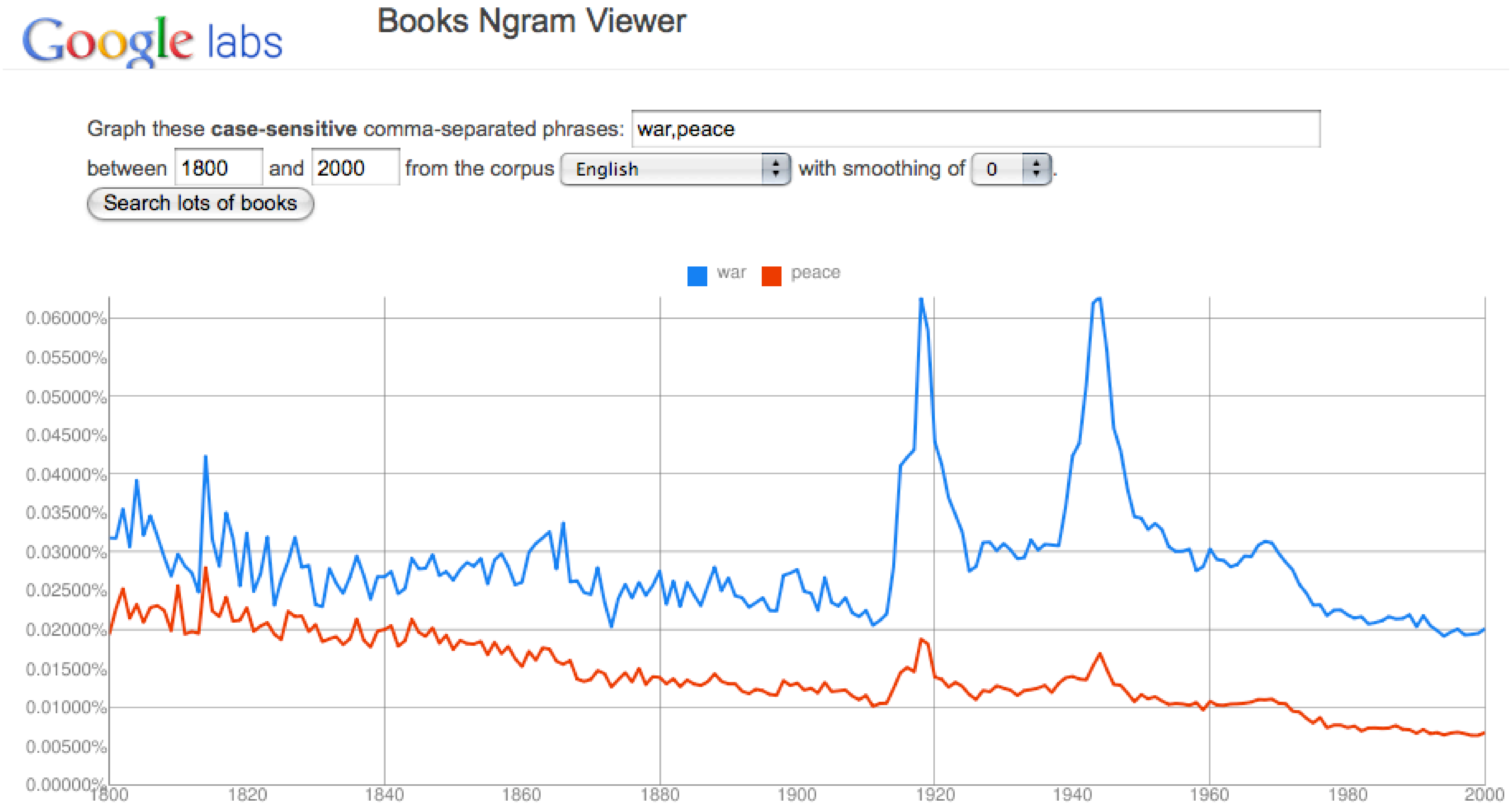
- Given a corpus and a new set of data, the number of new index terms will depend on the size of the corpus
- Given more data, new index terms will always be required
- This may also be true for controlled vocabularies (?)
  - Given a corpus and a new set of data, the requirement for new concepts will depend on the size of the corpus
  - Given more data, new concepts will always be required

Term Co-occurrence

- So far, we've talked about statistics for single terms
- What about statistics for pairs of terms?
- Term co-occurrence considers the extent to which different terms tend to appear together in text
- Does knowledge that one term appears, tell us whether another term is likely to appear?

Term Co-occurrence Example

war vs. peace



Books Ngram Viewer

Graph these **case-sensitive** comma-separated phrases: war,peace

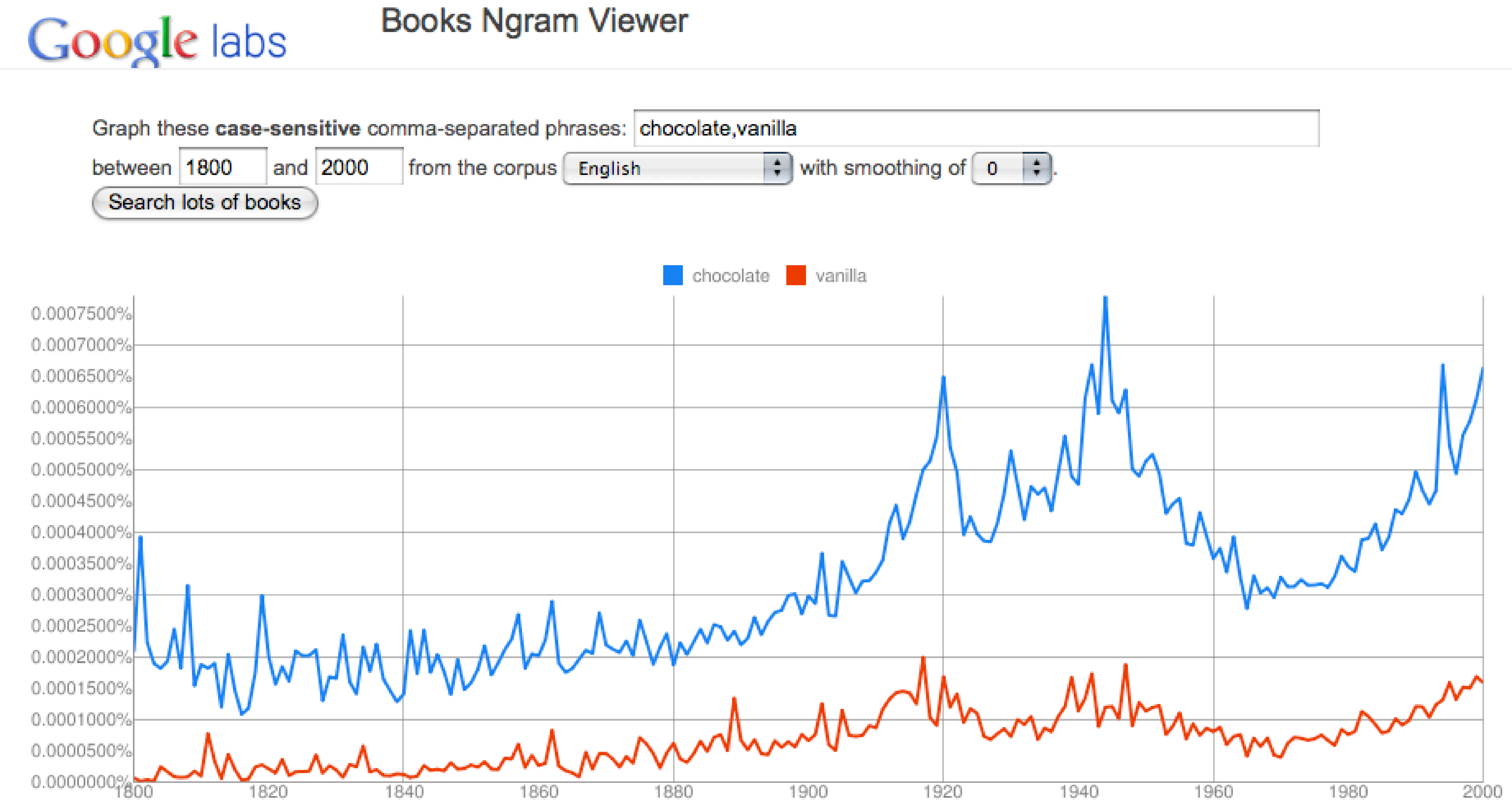
between 1800 and 2000 from the corpus English with smoothing of 0.

Search lots of books

(The Google Books N-gram Corpus)

Term Co-occurrence Example

chocolate vs. vanilla



Google labs

Books Ngram Viewer

Graph these **case-sensitive** comma-separated phrases: chocolate,vanilla

between 1800 and 2000 from the corpus English with smoothing of 0.

Search lots of books

(The Google Books N-gram Corpus)

A Few Important Concepts in Probability and Statistics

(Some material courtesy of Andrew Moore: http://www.autonlab.org/tutorials/prob.html)

Discrete Random Variable

- A is a discrete random variable if:
  - A describes an event with a finite number of possible outcomes (discrete vs. continuous)
  - A describes and event whose outcome has some degree of uncertainty (random vs. pre-determined)
- A is a boolean-valued random variable if it describes an event with two outcomes: TRUE or FALSE
- Can you name some examples of boolean-valued random variables?

Boolean-Valued Random Variables

Examples

- A = it will rain tomorrow
- A = the outcome of a coin-flip will be heads
- A = you will be win the lottery in your lifetime
- A = the word “retrieval” will occur in a document

Probabilities

- P(A=TRUE): the probability that the outcome is TRUE
  - the probability that it will rain tomorrow
  - the probability that the coin will show “heads”
  - the probability that “retrieval” appears in the doc
- P(A=FALSE): the probability that the outcome is FALSE
  - the probability that it will NOT rain tomorrow
  - the probability that the coin will show “tails”
  - the probability that “retrieval” does NOT appear in the doc

Estimating the Probability of an Outcome

- P(heads=TRUE)
- P(rain tomorrow=TRUE)
- P(you have the flu=TRUE)
- P(“retrieval” in a document=TRUE)

Statistical Estimation

- Use data to estimate the probability of an outcome
- Data = observations of previous outcomes of the event
- What is the probability that the coin will show “heads”?
- Statistical Estimation Example:

Statistical Estimation

- Use data to estimate the probability of an outcome
- Data = observations of previous outcomes of the event
- What is the probability that the coin will show “heads”?
- Statistical Estimation Example:
  - To gather data, you flip the coin 100 times
  - You observe 54 “heads” and 46 “tails”
  - What would be your estimation of P(heads=TRUE)?

Statistical Estimation

- What is the probability that it will rain tomorrow?
- Statistical Estimation Example:
  - To gather data, you keep a log of the past 365 days
  - You observe that it rained on 93 of those days
  - What would be your estimation of P(rain=TRUE)?

Statistical Estimation

- What is the probability that “retrieval” occurs in a document?
- Statistical Estimation Example:
  - To gather data, you take a sample of 1000 documents
  - You observe that “retrieval” occurs in 2 of them.
  - What would be your estimation of P(“retrieval” in a document=TRUE)?
- Usually, more data leads to a more accurate estimate!

Joint and Conditional Probability

- For simplicity, P(A=TRUE) is typically written as P(A)
- P(A,B): the probability that outcome A and B both true
- P(A|B): the probability that outcome A is true given prior knowledge that B is true

Chain Rule

- $P(A, B) = P(A|B) \times P(B)$
- Example:
  - probability that it rains today and tomorrow =
  - probability that it rains today
  - probability that it rains tomorrow given prior knowledge that it rains today

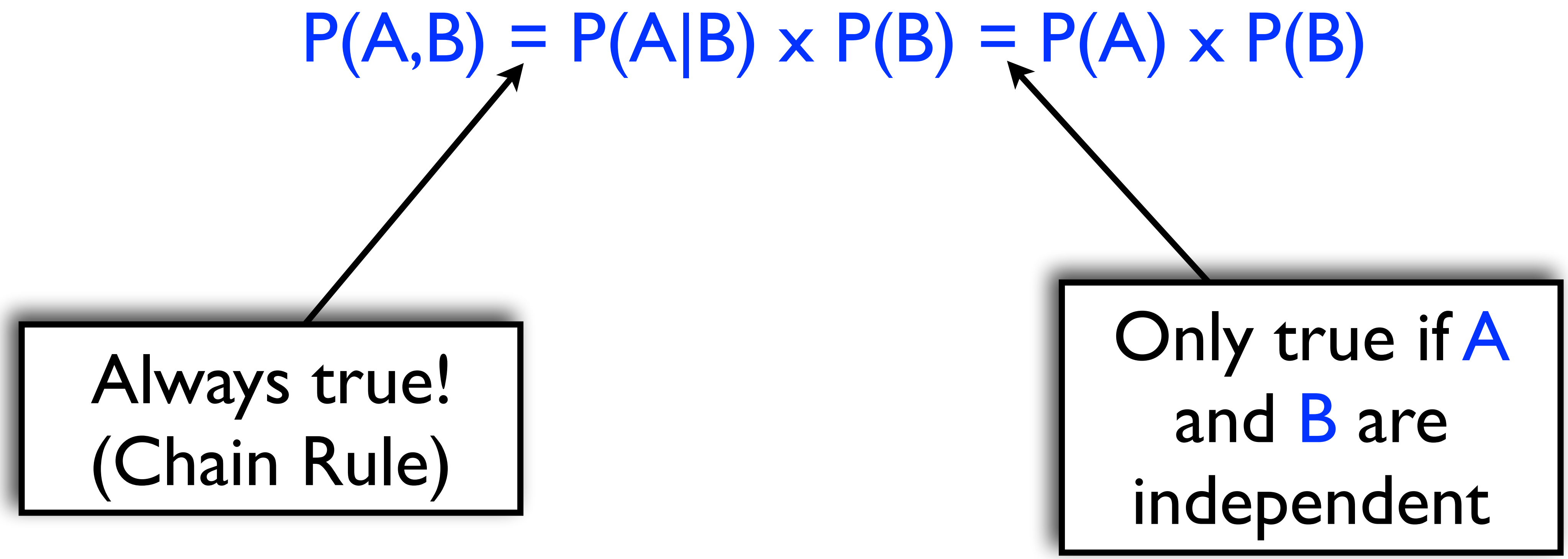
Independence

- Events A and B are independent if:

$$P(A,B) = P(A) \times P(B)$$

Independence

- Events A and B are independent if:



$$P(A,B) = P(A|B) \times P(B) = P(A) \times P(B)$$

Always true!
(Chain Rule)

Only true if A
and B are
independent

- Events A and B are independent if the outcome of A tells us nothing about the outcome of B (and vice-versa)
- Can you think of examples of two events that are (in)dependent?

Independence

- Suppose A = rain tomorrow and B = rain today
  - Are these likely to be independent?
- Suppose A = rain tomorrow and B = coin flip lands ‘tails’
  - Are these likely to be independent?

Mutual Information

$$MI(w_1, w_2) = \log \left(\frac{P(w_1, w_2)}{P(w_1)P(w_2)} \right)$$

- $P(w_1, w_2)$: probability that words w_1 and w_2 both appear in a text
- $P(w_1)$: probability that word w_1 appears in a text, with or without w_2
- $P(w_2)$: probability that word w_2 appears in a text, with or without w_1
- The definition of “a text” is up to you (e.g., a sentence, a paragraph, a document)

Mutual Information

$$MI(w_1, w_2) = \log\left(\frac{P(w_1, w_2)}{P(w_1)P(w_2)}\right)$$

- If $P(w_1, w_2) = P(w_1)\, P(w_2)$, it means that the words are independent: knowing that one appears conveys no information that the other one appears

- If $P(w_1, w_2) > P(w_1)\, P(w_2)$, it means that the words are not independent: knowing that one appears makes it more probable that the other one appears

Mutual Information

estimation (using documents as units of analysis)

	word w_1 appears	word w_1 does not appear
word w_2 appears	a	b
word w_2 does not appear	c	d

every document falls under one of these quadrants

total # of documents
$N = a + b + c + d$

$P(w_1, w_2) = ?$

$P(w_1) = ?$

$P(w_2) = ?$

Mutual Information

estimation (using documents as units of analysis)

	word w_1 appears	word w_1 does not appear
word w_2 appears	a	b
word w_2 does not appear	c	d

every document falls under one of these quadrants

total # of documents
$N = a + b + c + d$

$P(w_1, w_2) = a / N$

$P(w_1) = (a + c) / N$

$P(w_2) = (a + b) / N$

Mutual Information

IMDB Corpus

- Word-pairs with highest mutual information (1-20)

w1	w2	MI
francisco	san	6.619
angeles	los	6.282
prime	minister	5.976
united	states	5.765
9	11	5.639
winning	award	5.597
brooke	taylor	5.518
con	un	5.514
un	la	5.512
belle	nicole	5.508
dollars	million	5.437
brooke	rick	5.405
teach	lesson	5.370
canada	canadian	5.338
un	ma	5.334
nicole	roman	5.255
china	chinese	5.231
japan	japanese	5.204
belle	roman	5.202
border	mexican	5.186

Mutual Information

IMDB Corpus

- Word-pairs with highest mutual information (20-40)

w1	w2	MI	w1	w2	MI
belle	lucas	5.138	brooke	eric	4.941
nick	brooke	5.136	serial	killer	4.927
loved	ones	5.116	christmas	eve	4.911
hours	24	5.112	italy	italian	4.909
magazine	editor	5.103	un	1	4.904
e	fianc	5.088	photo	shoot	4.866
newspaper	editor	5.080	ship	aboard	4.856
donna	brooke	5.064	al	un	4.800
ed	un	5.038	plane	flight	4.792
mexican	mexico	5.025	nicole	victor	4.789

Mutual Information

IMDB Corpus

- Word-pairs with highest mutual information (1-20)

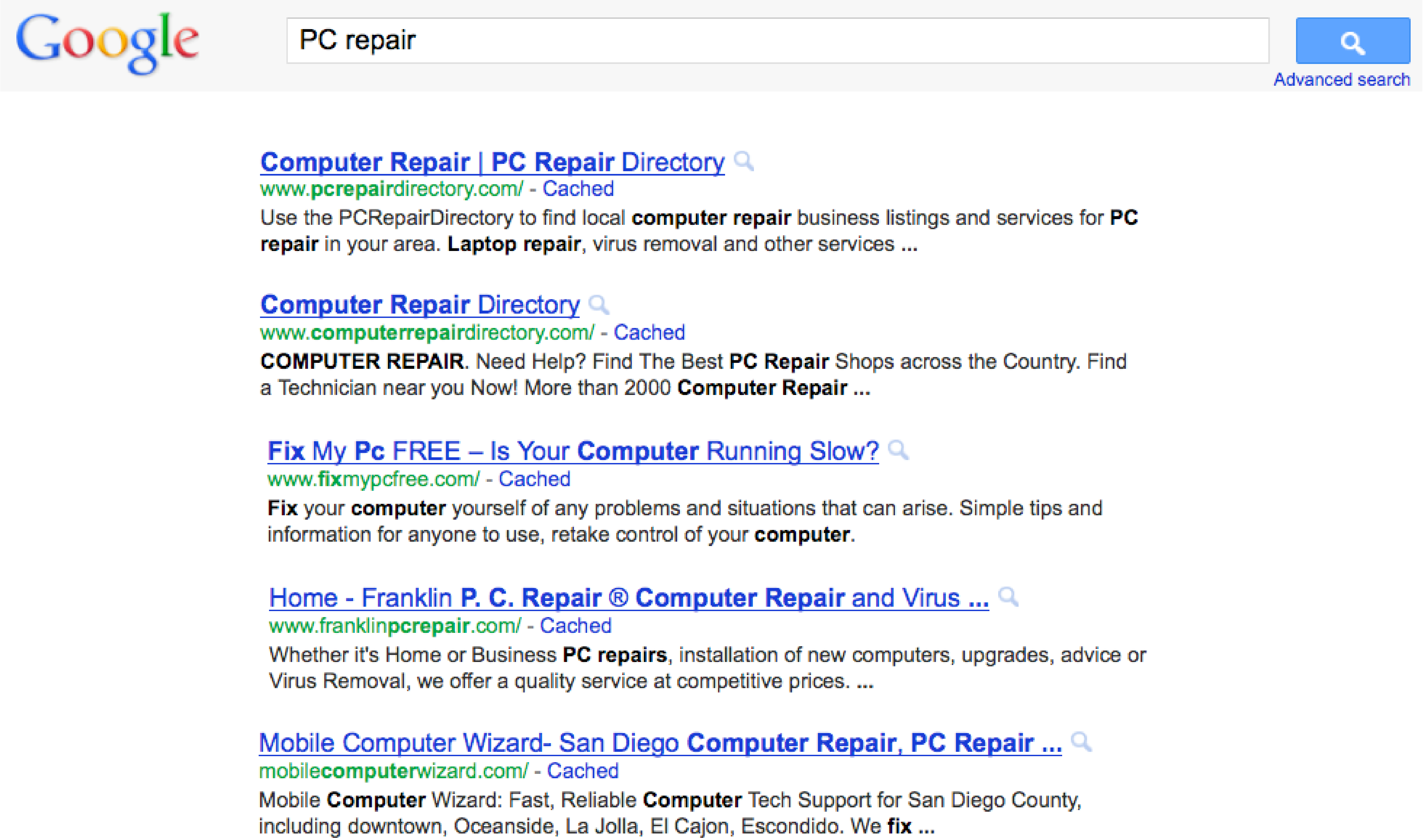
w1	w2	MI	w1	w2	MI
francisco				n	5.437
angeles					5.405
prime	m			n	5.370
united	states	[illegible]	canada	canadian	5.338
9	11	5.639	un	ma	5.334
winning	award	5.597	nicole	roman	5.255
brooke	taylor	5.518	china	chinese	5.231
con	un	5.514	japan	japanese	5.204
un	la	5.512	belle	roman	5.202
belle	nicole	5.508	border	mexican	5.186

Not a perfect metric! Subject to subtleties in the collection (these are pairs of semantically unrelated Spanish words)

Implications of Term Co-occurrence

- Potential to improve search
  - word-variants co-occur: canada, canadian
  - semantically-related terms co-occur: plane, flight
  - phrases describe important concepts: san francisco
- Multiple paths to improvement
  - document representation: conflating variants, adding related terms, indexing phrases
  - information need representation: conflating variants, adding related terms, proximity operators
  - search assistance and interactions: query suggestions

Implications of Term Co-occurrence (1)



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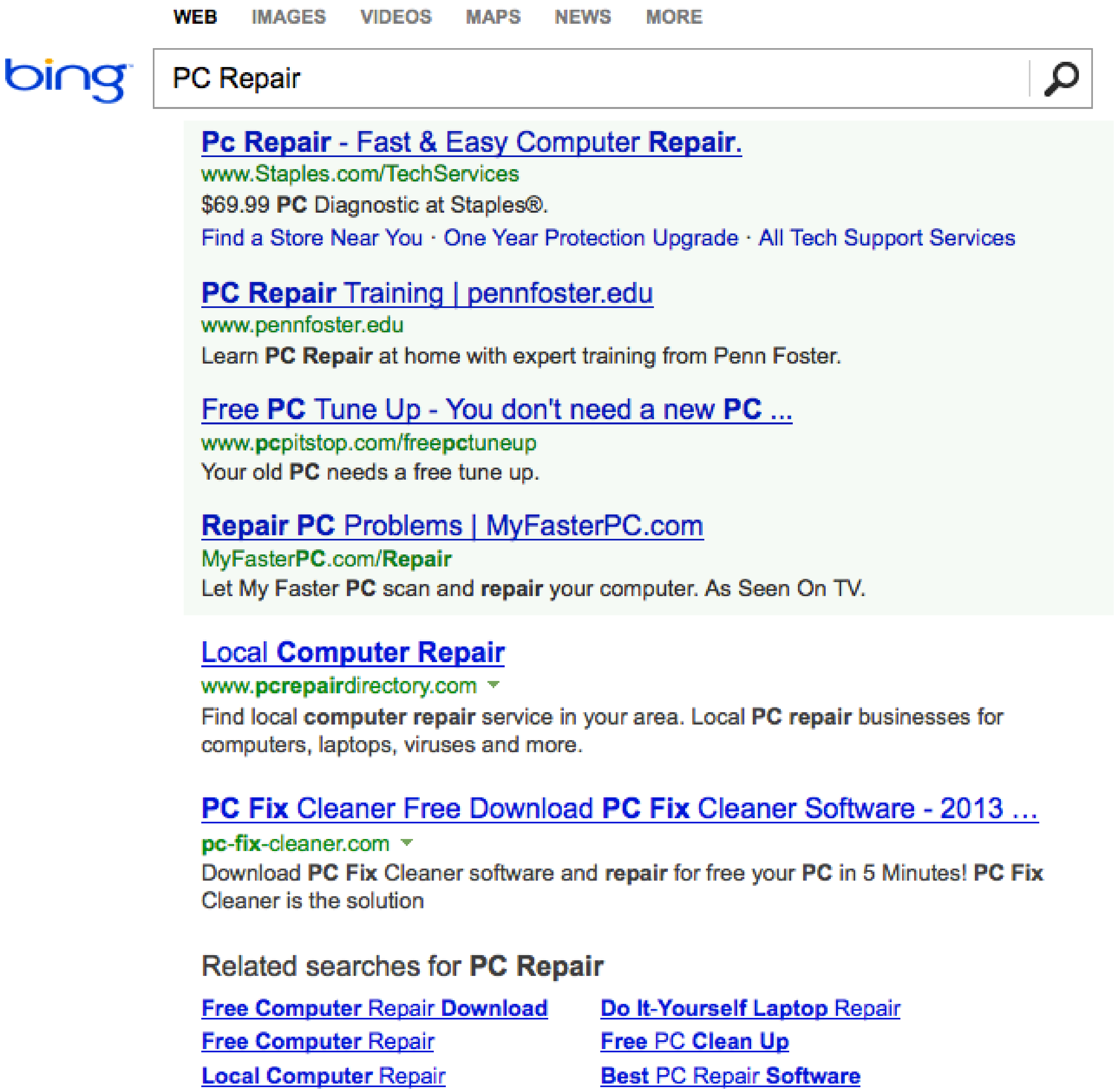
Implications of Term Co-occurrence (2)



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Take-Home Message

- Language use is highly varied
- However, there are statistical properties of language that are highly consistent across domains and languages
- A few terms occur very frequently and most terms occur very infrequently
- Term co-occurrences can be used to identify semantically related terms and phrases
- These statistical properties of text make search easier
- Learn them, love them, and use them to your advantage in doing automatic analysis of text