2. Descriptive Inference I

DS-GA 1015, Text as Data
Arthur Spirling

Feb 16, 2020

Where Are We?

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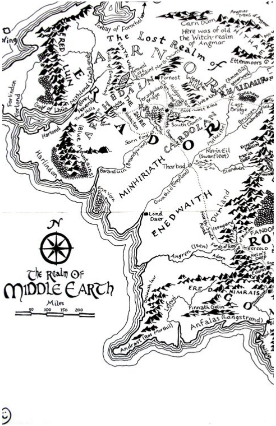
The Lost Realm of
ARNOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Ettenmoors
Weather Hills
Fornost
Bree
East-West Road
THE SHIRE
South Downs
Last Bridge
Sarn Ford
CARDOLAN
Tharbad
MINHIRIATH
ENEDWAITH
Dunland
Isengard
Lond Daer
Gulf of Lhûn
Forlindon
Forlond
Harlond
Harlindon
Blue Mountains
ERIADOR
Helm's Deep
Pinnath Gelin
Anfalas (Langstrand)
N
The Realm Of
MIDDLE EARTH
Miles
50 100 150 200

Where Are We?



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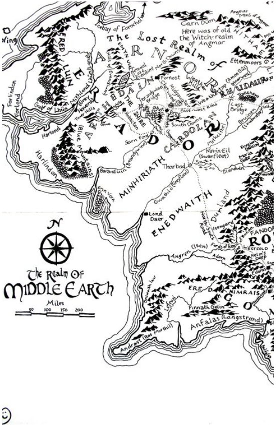

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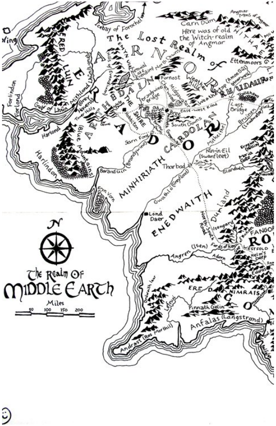

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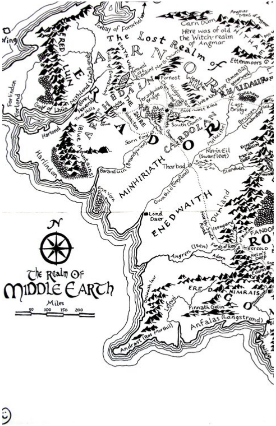

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e.g. stemmed word like '`treasuri`', which doesn't appear in the document itself.

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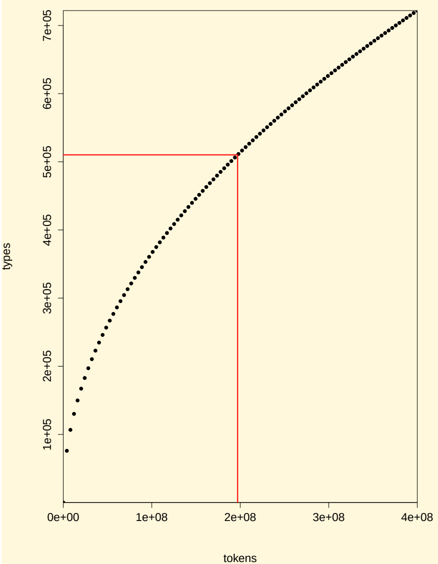

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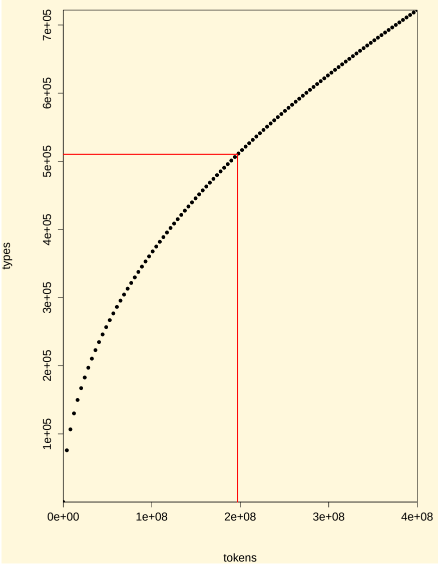
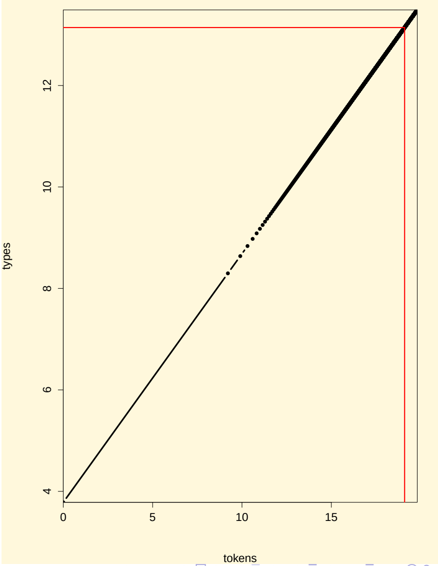


RCV1, log-log.



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the	69836
of	36365
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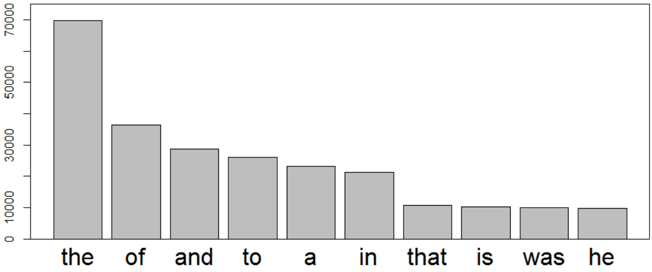

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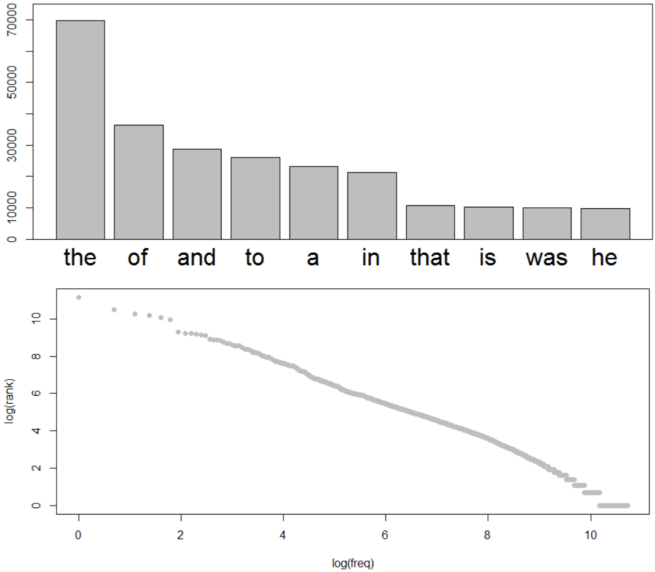

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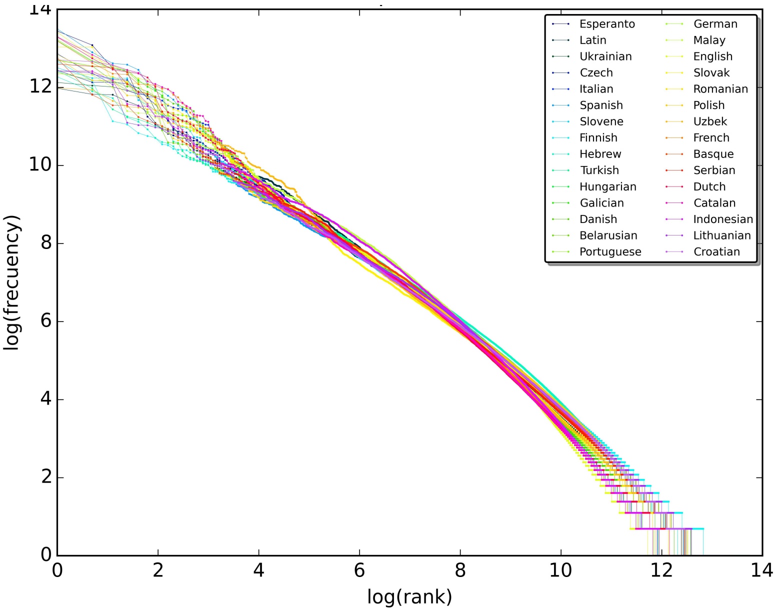

City Populations in US (Gabaix, 1999)

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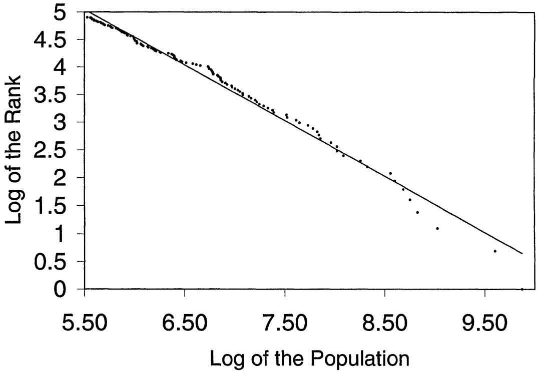

FIGURE I
Log Size versus Log Rank of the 135 largest U. S. Metropolitan Areas in 1991
Source: Statistical Abstract of the United States [1993].

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larger distances imply lower similarity.

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so when the document has generally high term frequencies (because it is longer), w^2 will be larger, which makes $||\mathbf{y}_i||$ larger.

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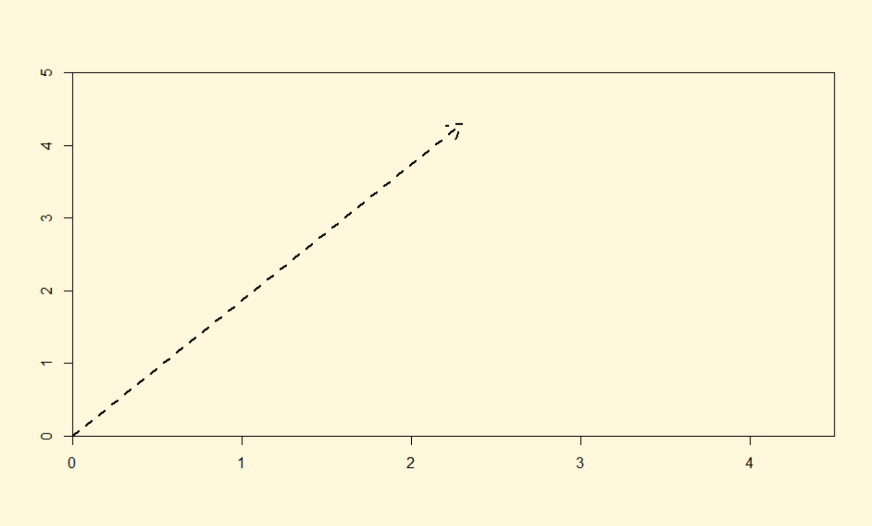

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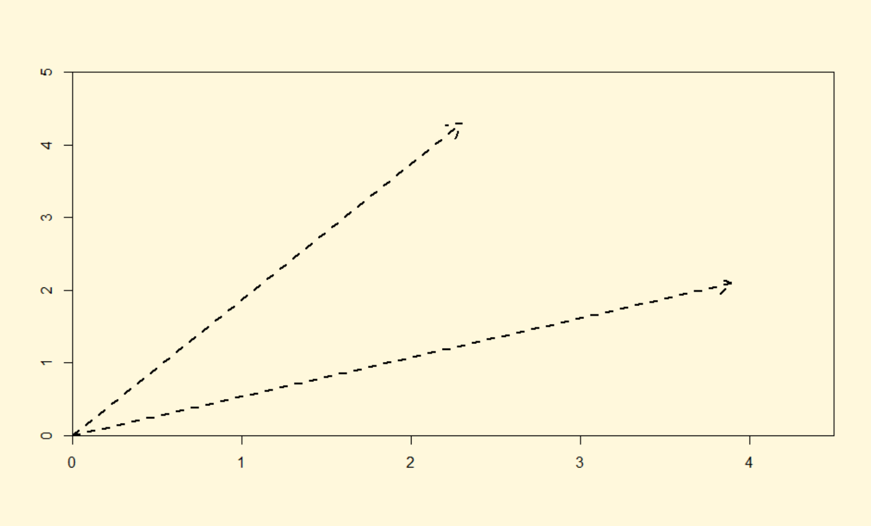

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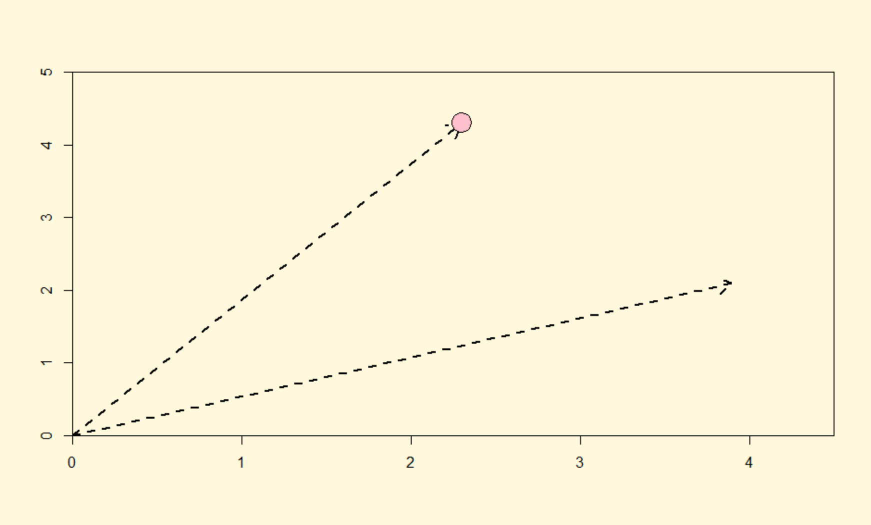

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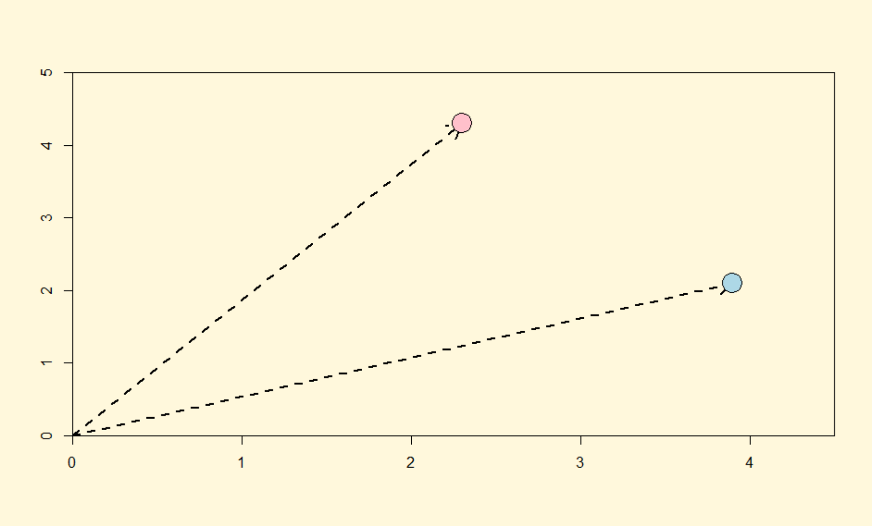

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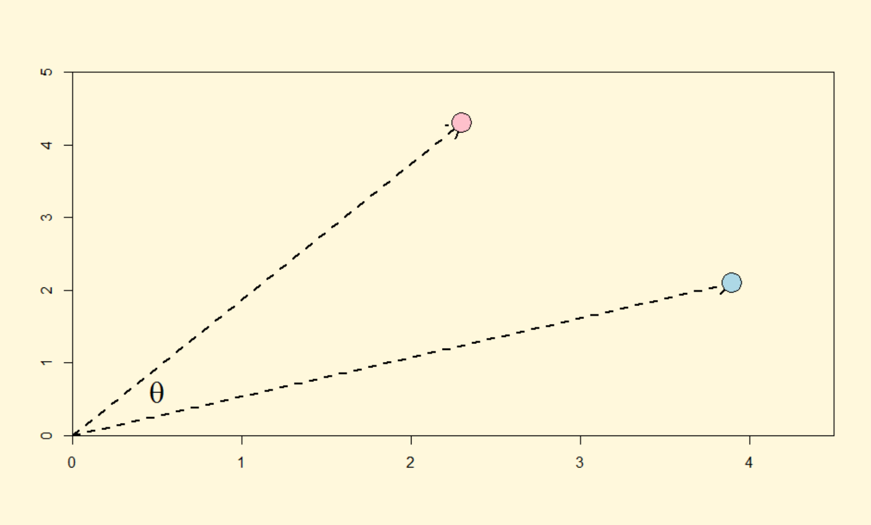
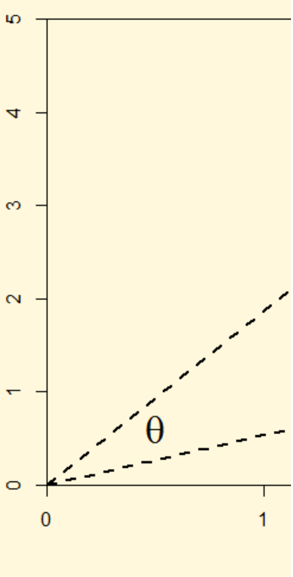


Algebra


θ
0
1
2
3
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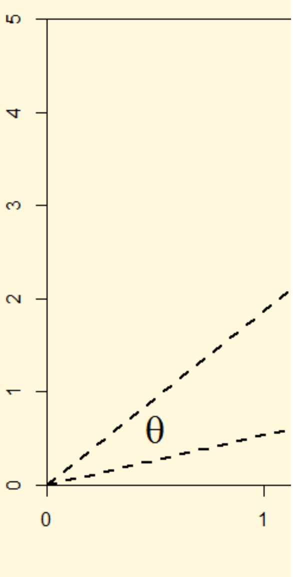

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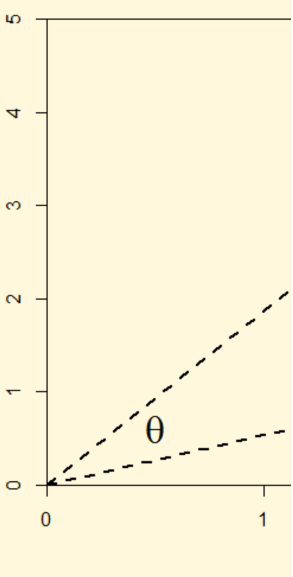

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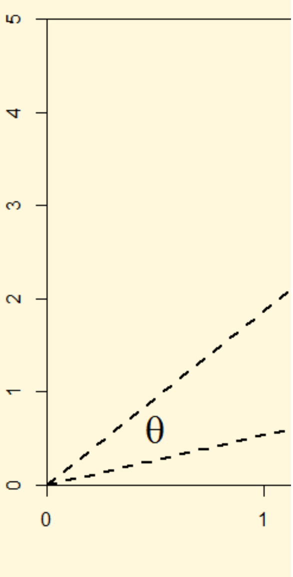

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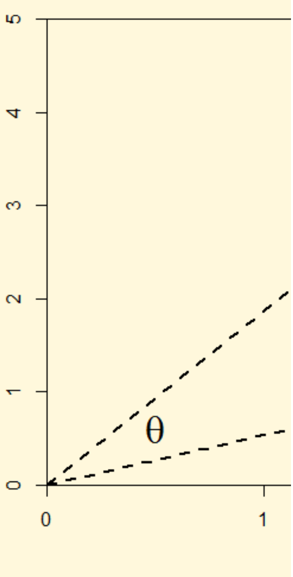

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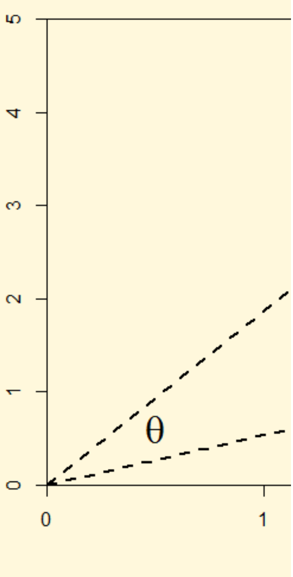

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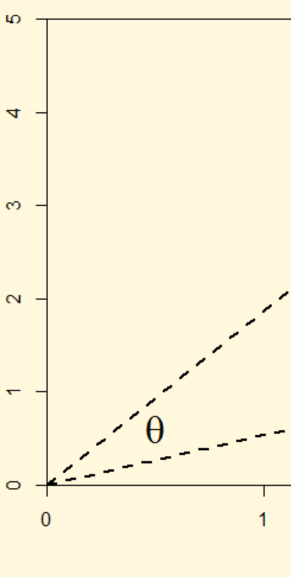

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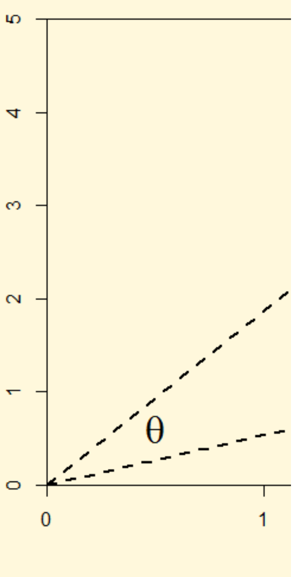

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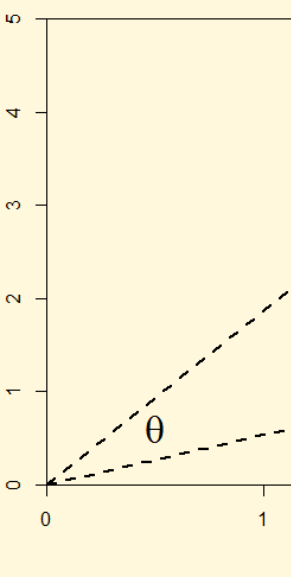

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Looks about right.

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$$\boxed{c_{ij} \approx 0.70}$$

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We may want to know how much different rules in different agencies at different times change in response to consultation: look at *edit distance*.

see Rashin (2019) for more elaborate ideas

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The smallest number of operations taking us from s_1 to s_2 is the **Levenshtein distance** between those strings.

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How many operations? $4 + 1$

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How many operations? $4 + 1 + 3$

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How many operations? $4 + 1 + 3 = 8$.

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Different types of edit distances allow different types of operations.

Collocations, phrasemes and co-occurrence

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15494	to	be
13899	in	a
13689	of	a
13361	by	the
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How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

frequency	w_1	w_2
80871	of	the
58841	in	the
26430	to	the
21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

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pattern	example
A N	Prime Minister
N N	surface area
A A N	little green men
A N N	real estate agent
N A N	home sweet home
N N N	term document matrix
N P N	Secretary of State

Reanalyzing NYT corpus: top ranked bi-grams

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frequency	$w_1\,w_2$	
11487	New York	A N
7261	United States	A N
5412	Los Angeles	N N
3301	last year	A N
3191	Saudi Arabia	N N
2699	last week	A N
2514	vice president	A N
2378	Persian Gulf	A N
2161	San Francisco	N N
2106	President Bush	N N
2001	Middle East	A N
1942	Saddam Hussein	N N
1867	Soviet Union	A N
1850	White House	A N
1633	United Nations	A N
1337	York City	N N
1328	oil prices	N N
1210	next year	A N
1074	chief executive	A N
1073	real estate	A N

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can construct 2×2 table, and consider expected vs observed frequency. . .

2×2 table

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Second Word

First Word

	w_2	$\neg w_2$	total
w_1	O_{11}	O_{12}	$O_{11}+O_{12}$
$\neg w_1$	O_{21}	O_{22}	$O_{21}+O_{22}$
total	$O_{11}+O_{21}$	$O_{12}+O_{22}$	N

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First Word \ Second Word	York	¬ York	total
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→ 'york' doesn't occur often in the corpus, but when it does, it's almost always proceeded by 'new'

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$\Rightarrow$ reject the null hypothesis of independence: this word is a good choice as a collocation.

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Bigger the λ and z-score push up the ranking of MWEs of interest (and can be interpreted in "usual" way relative to null).

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$\rightarrow$ small numbers here, so λ and zs small.

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3. location code —document details.

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q What role did ‘democratic’ play in the debate?

Some KWIC from the debates: `kwic()` in quanteda

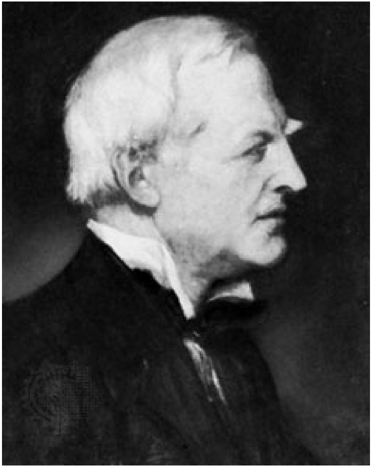
	preword	word	postword
⋮	⋮	⋮	⋮
[s267549.txt, 994]	evil that attends a purely	democratic	form of Government. There could be
[s267549.txt, 1015]	here, not possibly towards a	democratic	form of government, but in
[s267738.txt, 1492]	swept away in some further	democratic	change. And it is for
[s267738.txt, 1560]	throne. When you get a	democratic	basis for your institutions, you
[s267738.txt, 1952]	differences between ourselves and other	democratic	legislatures? Where is the democratic
[s267738.txt, 1957]	democratic legislatures? Where is the	democratic	legislature which enjoys the powers
[s267738.txt, 2243]	almost utterly useless against a	democratic	Chamber, and the question to
[s267738.txt, 2286]	to the violence of the	democratic	Chamber you are creating, and,
[s267738.txt, 2294]	are creating, and, as the	democratic	principle brooks no rival, this
[s267738.txt, 2374]	spirit of democracy that the	democratic	Chamber itself would become an
[s267738.txt, 2678]	power is given to the	democratic	majority, that majority does not
[s267738.txt, 2767]	job? In accordance with the	democratic	principle the army would demand
[s267744.txt, 204]	Conservative patronage, of the most	democratic	Reform Bill ever brought in.

Detail: s267738.txt

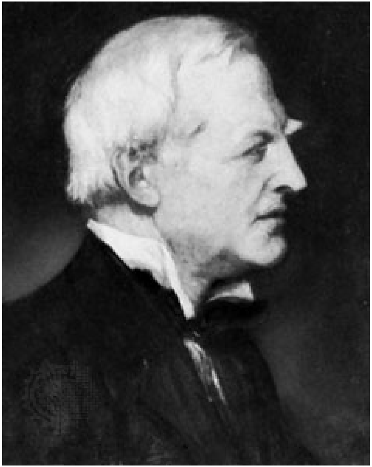
Detail: s267738.txt

preword	word	postword
swept away in some further	democratic	change. And it is for
throne. When you get a	democratic	basis for your institutions, you
differences between ourselves and other	democratic	legislatures? Where is the democratic
democratic legislatures? Where is the	democratic	legislature which enjoys the powers
almost utterly useless against a	democratic	Chamber, and the question to
to the violence of the	democratic	Chamber you are creating, and,
are creating, and, as the	democratic	principle brooks no rival, this
spirit of democracy that the	democratic	Chamber itself would become an
power is given to the	democratic	majority, that majority does not
job? In accordance with the	democratic	principle the army would demand

The Original Speaker and Speech



The Original Speaker and Speech



You cannot trust to a majority elected by men just above the status of paupers. The experiment has been tried; it has answered nowhere; it has failed in America, and it will not answer here.

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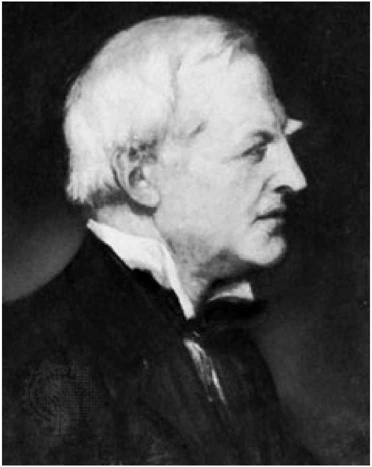

You cannot trust to a majority elected by men just above the status of paupers. The experiment has been tried; it has answered nowhere; it has failed in America, and it will not answer here.

In accordance with the democratic principle the army would demand to elect their own officers, and there would be endless change in the Constitution arising out of the present Bill, which, so far from being an end to our evils, is only the first step to them.

Use of 'Wireless'