University of Tokyo: Text-as-Data
Day 1, Part II

Arthur Spirling

June 3, 2017

Where Are We?

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Icebay of Forochel
Carn Dûm
Angmar
Here was of old
the Witch-realm
of Angmar
The Lost Realm of
ARNOR
ERED LUIN
EMYN UIAL
Nenuial
(Lake Evendim)
North Downs
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Hoarwell
Trollshaws
Last Bridge
Bruinen
(Loudwater)
Forlindon
Forlond
Mithlond
(Grey Havens)
Gulf of Lhûn
Lhûn (Lune)
Tower Hills
Harlond
Harlindon
(Blue Mountains)
ERIADOR
ARTHEDAIN
THE SHIRE
Hobbiton
Brandywine Bridge
Old Forest
Bree
East-West Road
Midgewater
South Downs
CARDOLAN
Sarn Ford
(Brandywine)
Baranduin
Mitheithel
Nîn-in-Eilph
(Swanfleet)
Tharbad
Glanduin
Moria Gate
MINHIRIATH
Eryn Vorn
Gwathló (Greyflood)
Lond Daer
ENEDWAITH
Dunland
North-South Road
Isengard
FANGORN
RO
Angren (Isen)
Fords of Isen
Adorn
WESTFOLD
Helm's Deep
Edoras
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Lefnui
GO
N
The Realm Of
MIDDLE EARTH
Miles
50
100
150
200

:)

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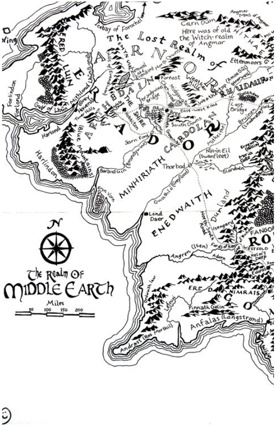

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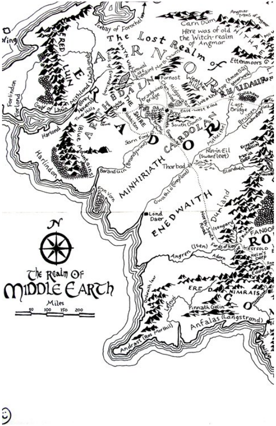

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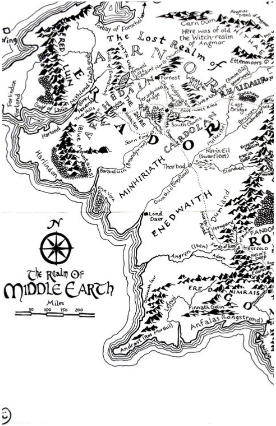

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e.g. stemmed word like ‘`treasuri`’, which doesn’t appear in the document itself.

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and	28826
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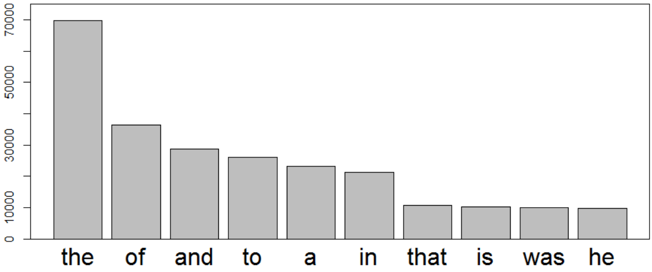

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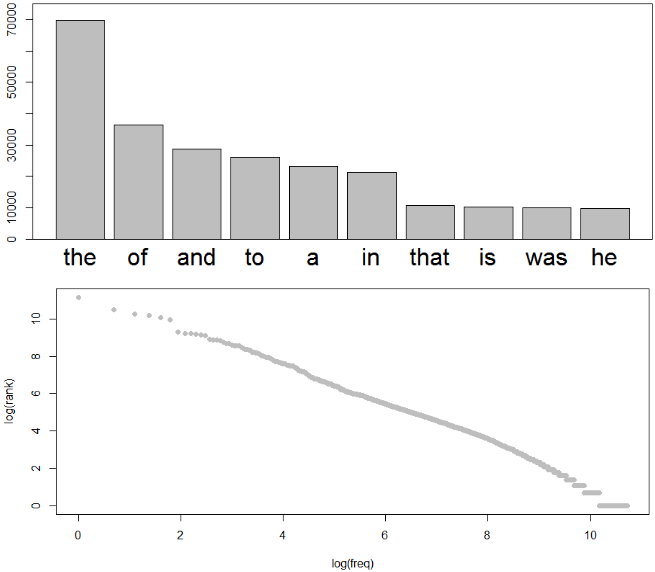

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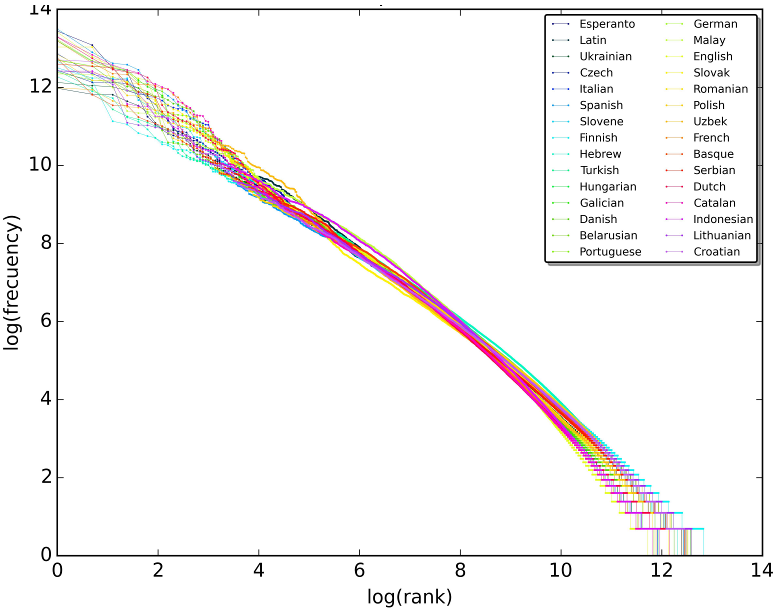

Distance Metrics and Measures

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e.g. principal components analysis operates on distance matrix.

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larger distances imply lower similarity.

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   $[50, 40, 30]$
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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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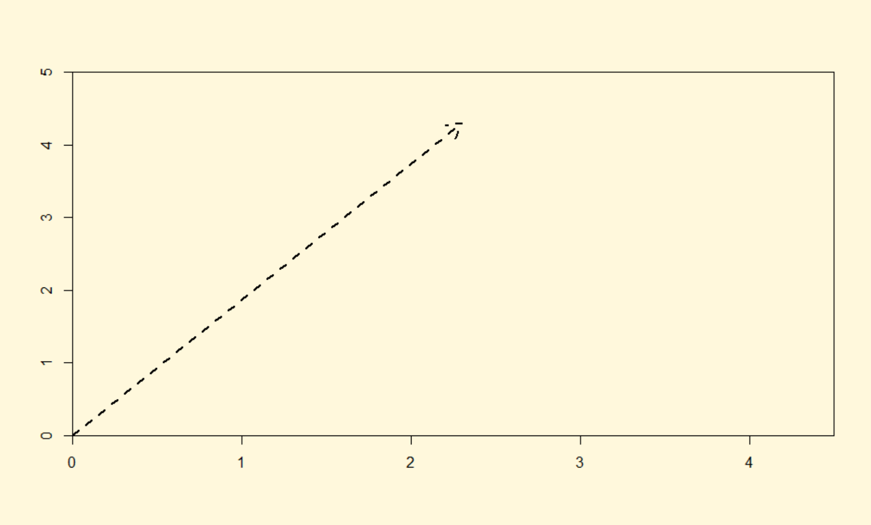

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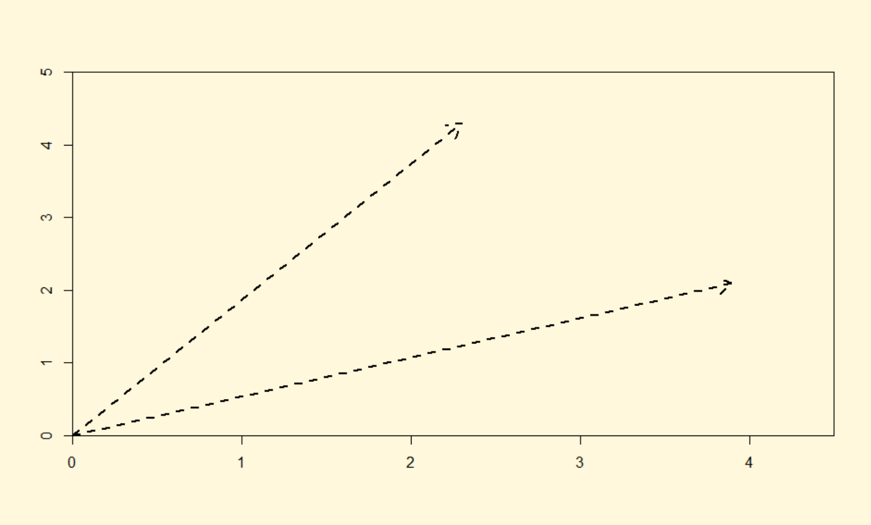

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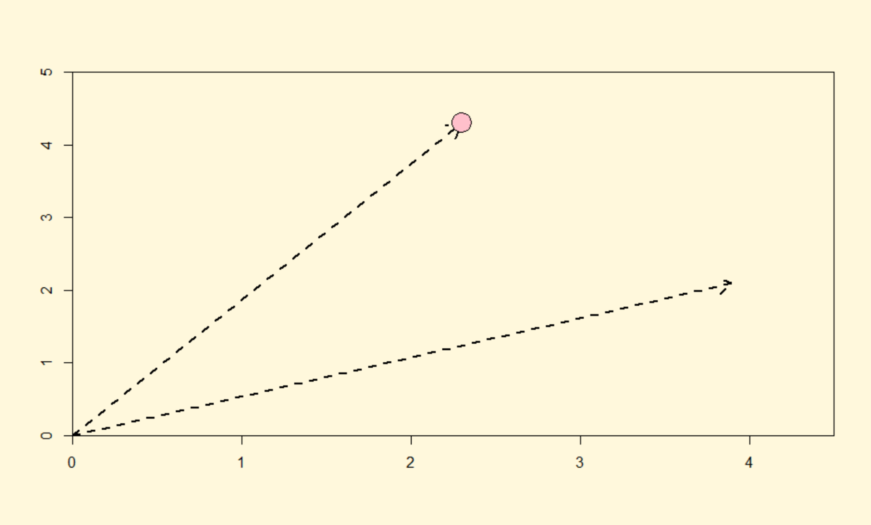

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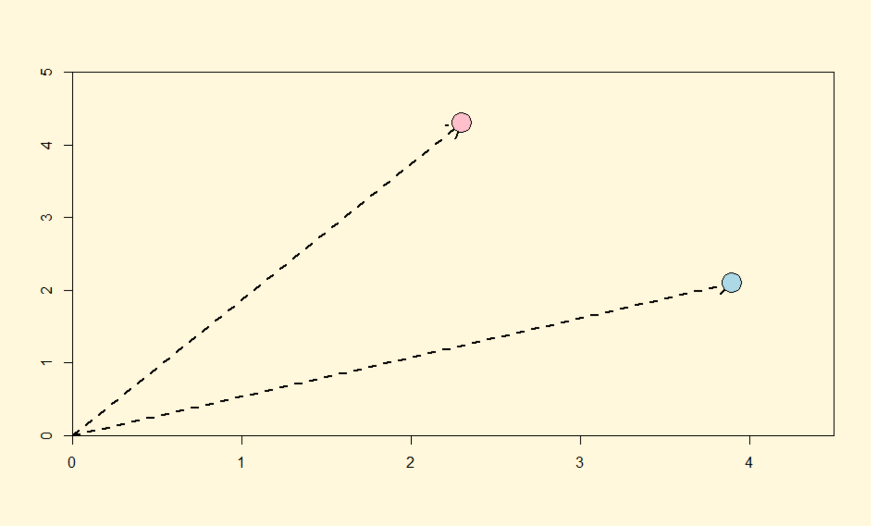

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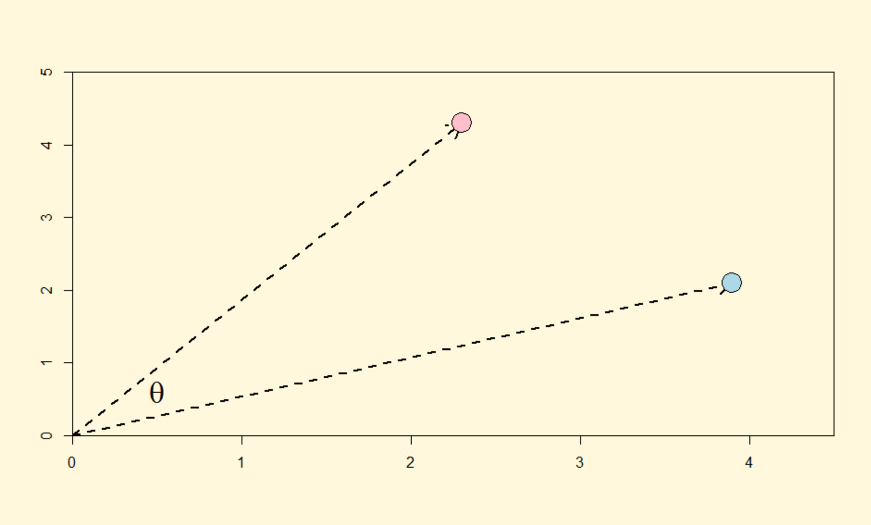

Algebra

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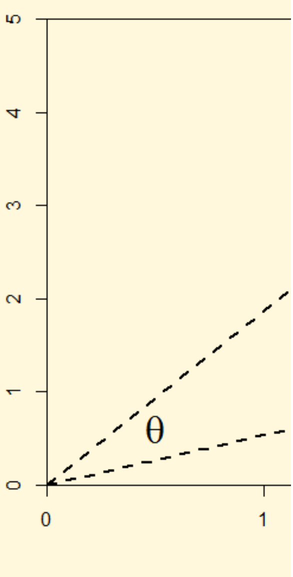

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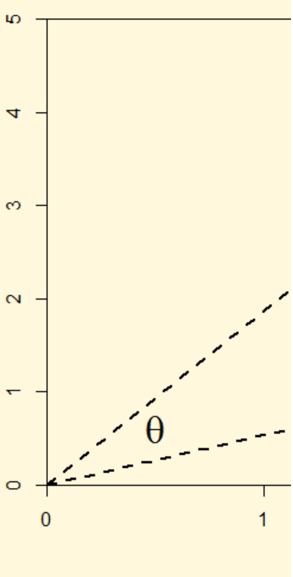

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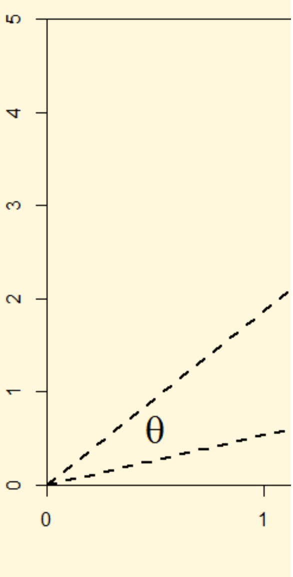

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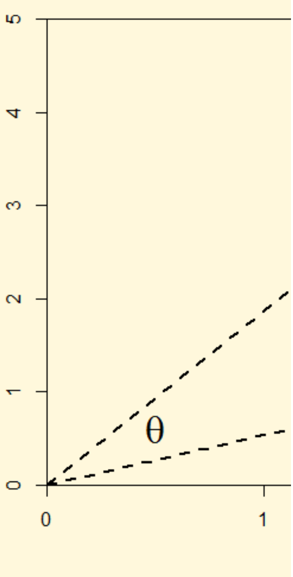

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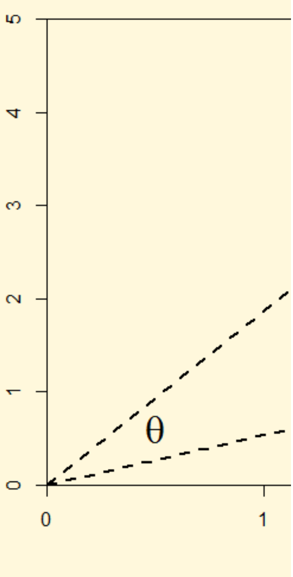

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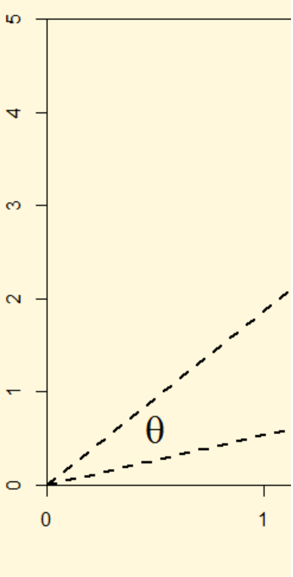

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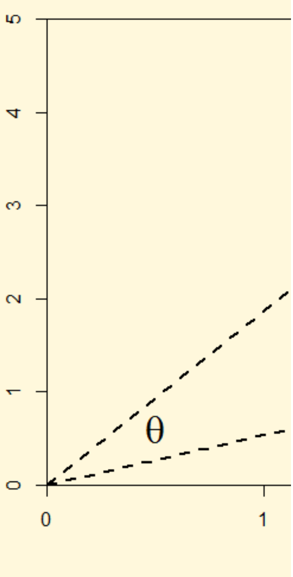

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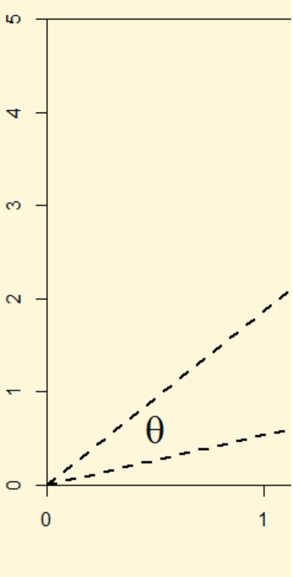

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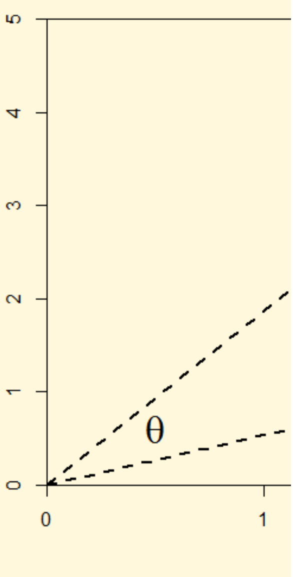

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Looks about right.

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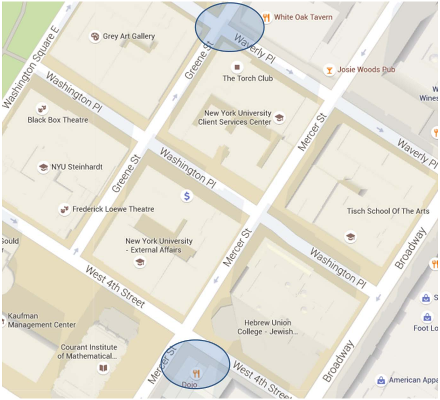

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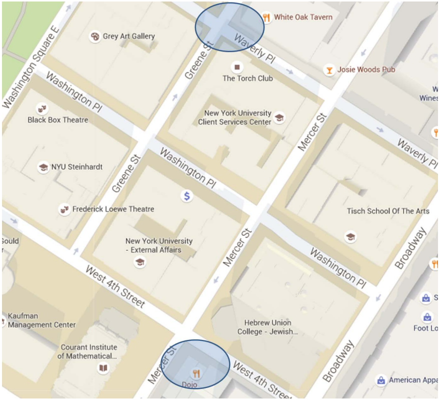

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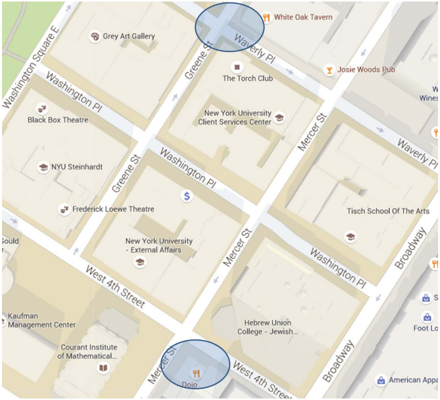

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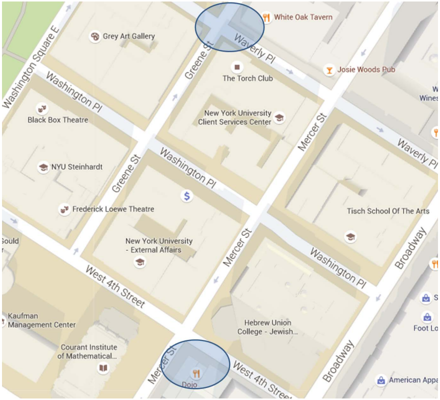

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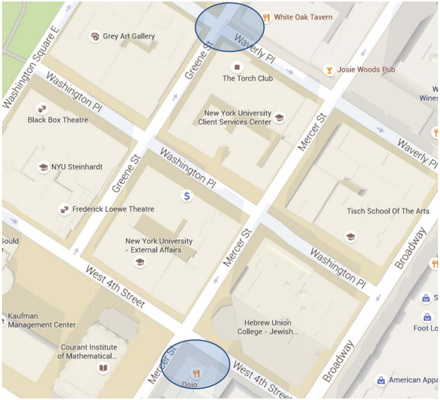

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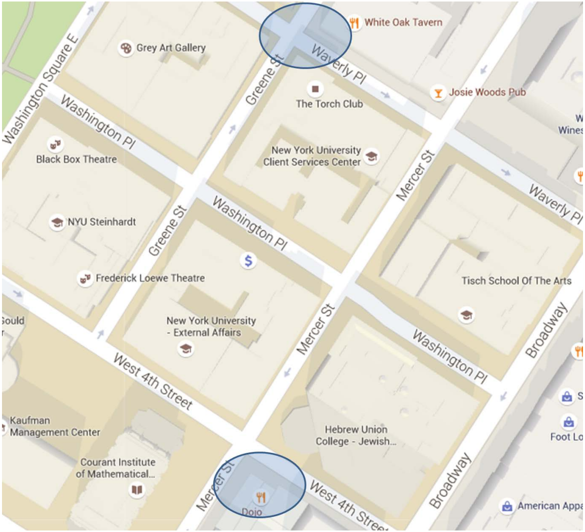

White Oak Tavern
Grey Art Gallery
Washington Square E
Waverly Pl
Greene St
The Torch Club
Josie Woods Pub
Washington Pl
Black Box Theatre
New York University
Client Services Center
Mercer St
Waverly Pl
NYU Steinhardt
Greene St
Washington Pl
Frederick Loewe Theatre
Tisch School Of The Arts
New York University
- External Affairs
Mercer St
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Washington Pl
West 4th Street
Kaufman
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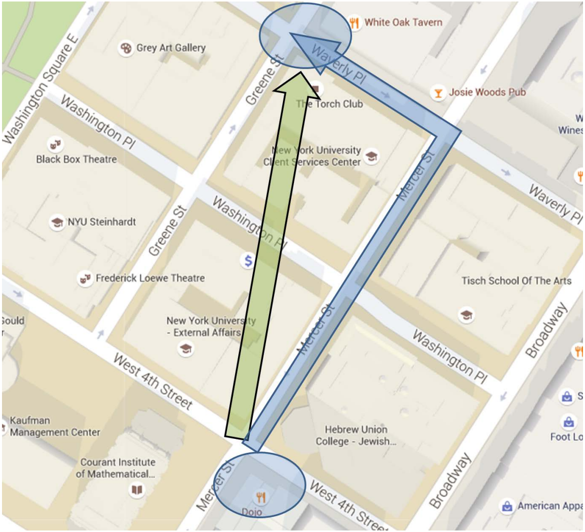

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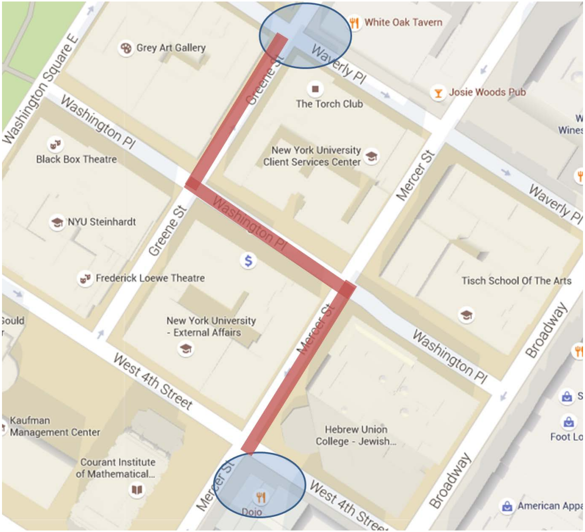

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Descriptive Statistics: Key Words in Context

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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

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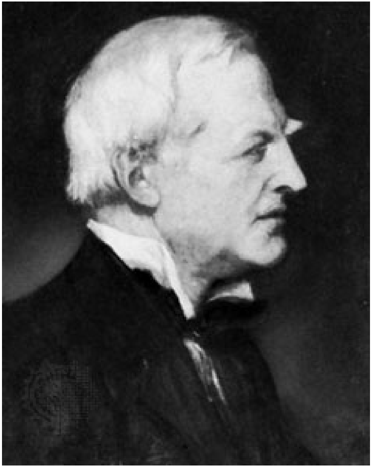

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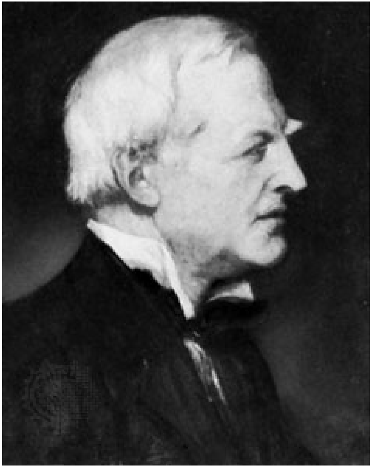

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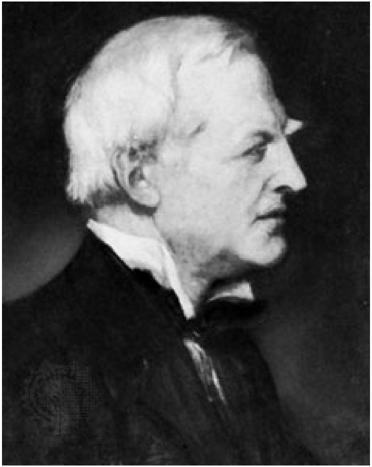

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In accordance with the democratic principle the army would demand to elect their own officers, and there would be endless change in the Constitution arising out of the present Bill, which, so far from being an end to our evils, is only the first step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

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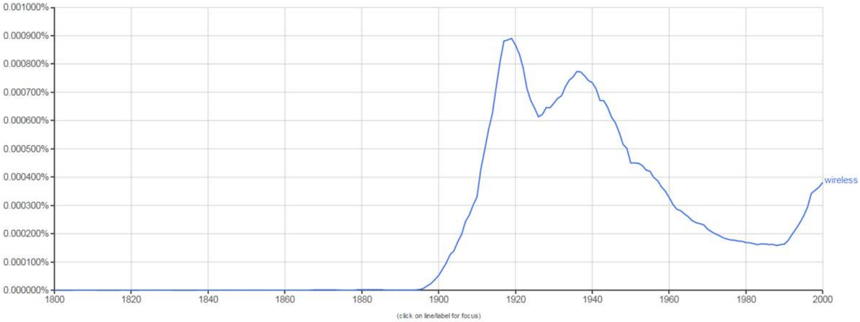
Give an example of a political key word that might appear in a different *context* if we study the US vs some other country.

Use of ‘Wireless’



Descriptive Statistics: Diversity and Complexity

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e.g. authors with limited vocabularies will have a low lexical diversity.

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NEW YORK POST

NEWS

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By Associated Press

December 28, 2015 | 6:34am | Updated

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Photo: Getty Images

MORE ON: ISIS

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MIDDLE EAST

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By FALIH HASSAN and SEWELL CHAN DEC. 28, 2015

Iraqi soldiers at the Anbar police headquarters in Ramadi, Iraq, on Monday, after seizing a government complex from the Islamic State. Ahmad Al-Rubaye/Agence France-Presse — Getty Images

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Share

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Score	Education	Description	Clve % US popn
0–30	college graduates	very difficult	28
31–50		difficult	72
51–60		fairly difficult	85
61–70	9th grade	standard	–
71–80		fairly easy	–
81–90		easy	–
91–100	4th grade	very easy	–

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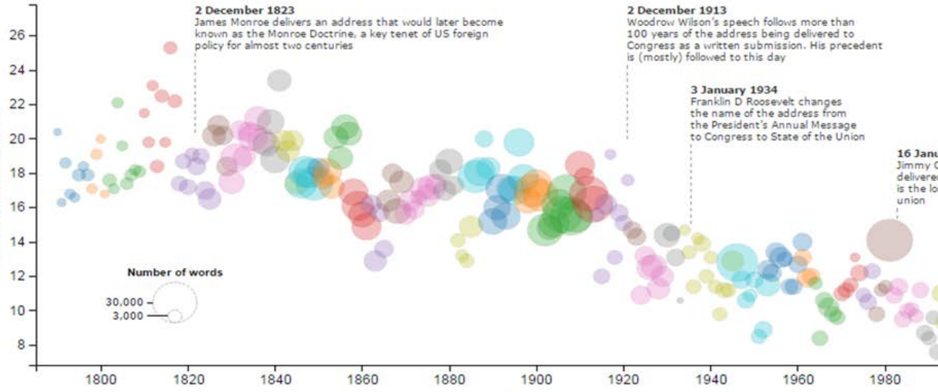
The state of our union is ... dumber:

How the linguistic standard of the presidential address has declined

Using the Flesch-Kincaid readability test the Guardian has tracked the reading level of every State of the Union



Leaders and their incentives

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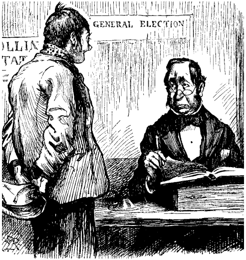

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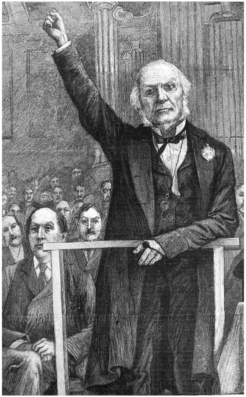

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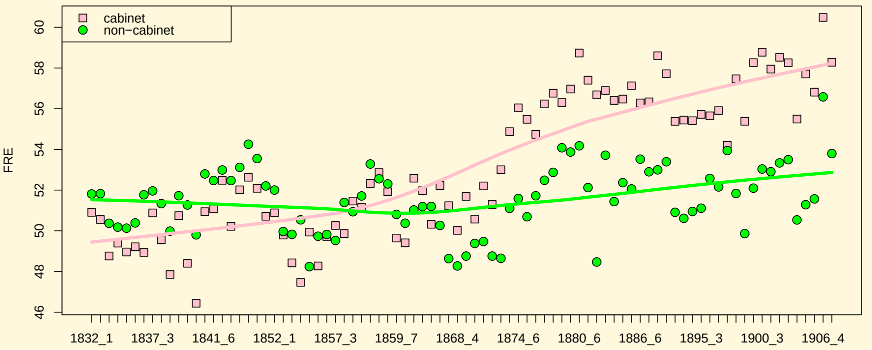
Flesch overtime plot



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e.g. `about`, `back`, `call`, etc.

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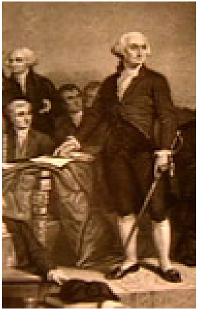

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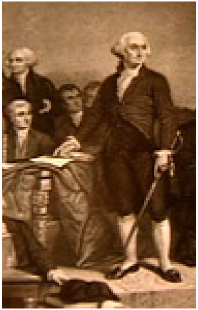

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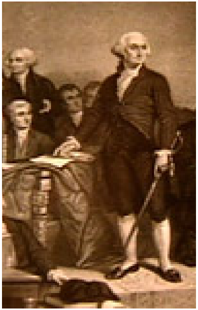

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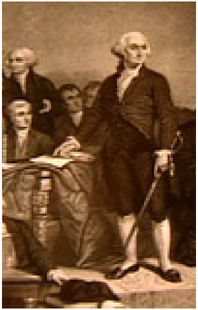

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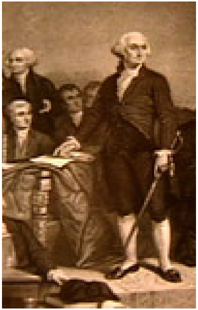

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Descriptive Statistics: Stylometrics

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i.e. they ask "if rates of function word usage are constant within authors for these documents, which author was most likely to have written essay x given the observed function word usage of these authors on the other documents?"

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but	has	may	only
their	what	also	by
have	more	or	then
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must	our	there	which
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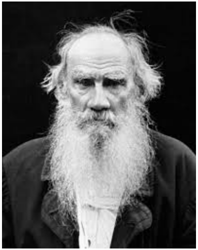

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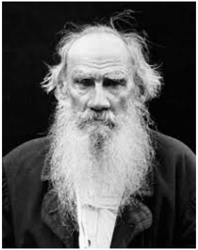

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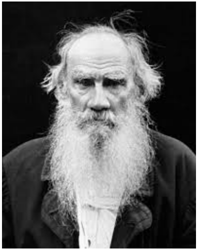

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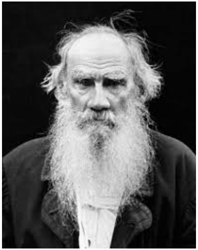

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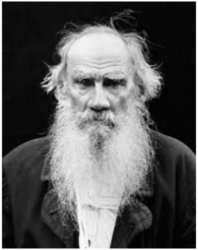

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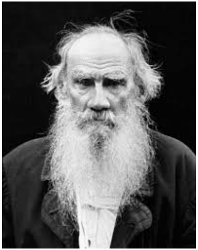

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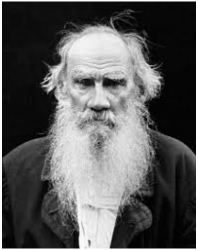

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→ think a little more systematically about the sampling distribution of a statistic.

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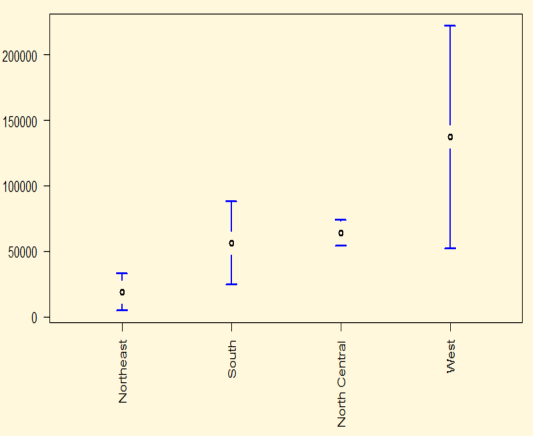

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$\rightarrow$ difficult to know how we should calculate the sampling distribution and thus the standard error.

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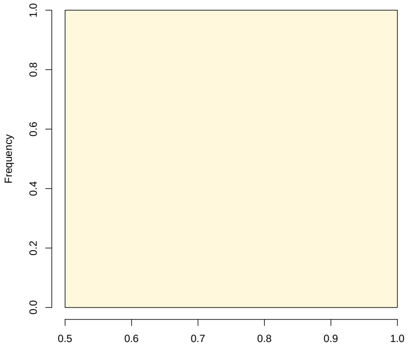

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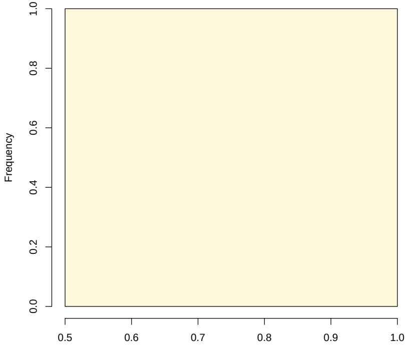

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btw long texts give rise to smaller SEs than short ones, which makes sense!

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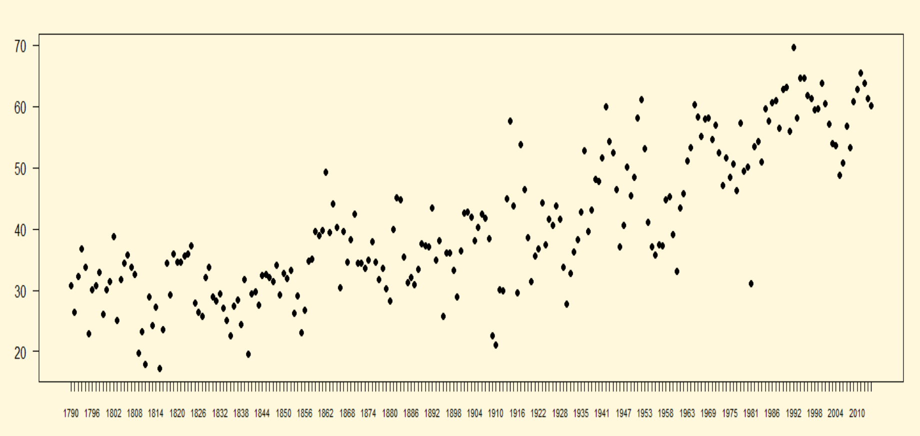

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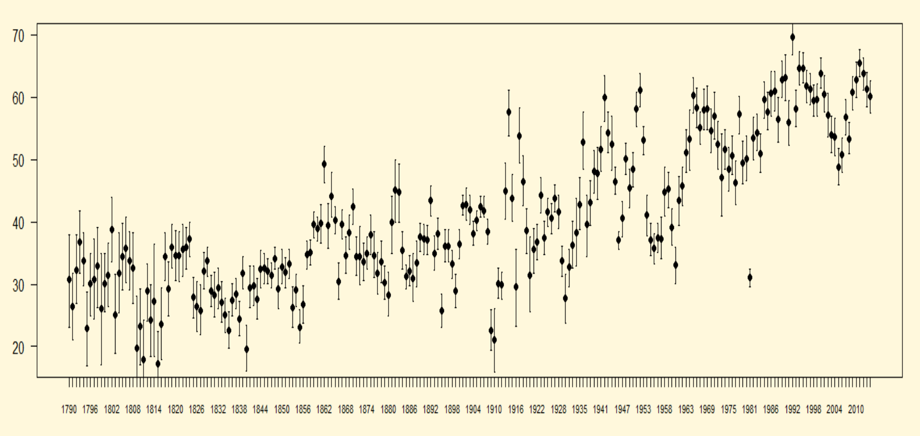

Descriptive Statistics: Burstiness

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Idea is to model arrival times of words.

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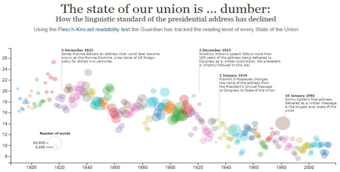

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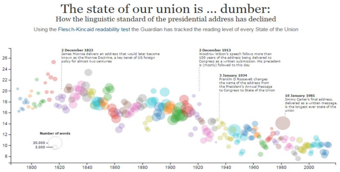

word	burst
gentlemen	1790–1800
british	1809–1814
slaves	1859–1863
japanese	1942–1945
health	1992–1994
help	1998–

Burstiness: more details

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3. How do models of the burstiness of words differ from 'topic models'? Which would you use to study changing subjects of debate over time? Which would you use to study conceptual change?

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