An Introduction to Analyzing Political Texts Part I

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Boring but important sanity check

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https://github.com/ArthurSpirling/yale_text_course

Overview

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since
stand
responsibility
parents
live
law
together
matter
south

Overview

- Descriptive inference:

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- Descriptive inference: how to characterize text, vector space model,

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- Basic supervised techniques: sentiment, scaling.
- Basic unsupervised techniques: topics.

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author ‘what does this Senator prioritize?’, ‘where is this party in ideological space?’

doc ‘does this treaty represent a fair deal for American Indians?’, ‘how did the discussion of lasers change over time?’

both ‘how does the way Japanese politicians talk about national defence change in response to electoral system shift?’

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→ comparing, testing, validating.

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Order. The Minister must be allowed to reply without interruption.

I am grateful to my hon. Friend for her question. I pay tribute to her work with the International Myeloma Foundation...

My constituent, Brian Jago, was fortunate enough to receive a course of Velcade, as a result of which he does not have to...

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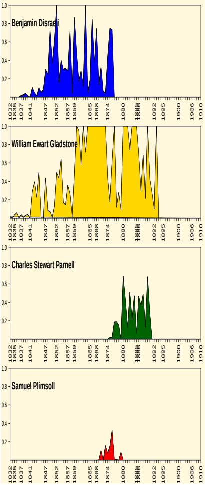

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Random error may not be the only concern: corpus should be representative in some well defined sense for inferences to be meaningful.

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

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e.g. “`Brown vs Board of Education`” may not be usefully tokenized as ‘`Brown`’, ‘`vs`’, ‘`Board`’, ‘`of`’, ‘`Education`’

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am	an	and	any	are	aren't	as
at	be	because	been	before	being	below
between	both	but	by	can't	cannot	could
couldn't	did	didn't	do	does	doesn't	doing
don't	down	during	each	few	for	from
further	had	hadn't	has	hasn't	have	haven't
having	he	he'd	he'll	he's	her	here
here's	hers	herself	him	himself	his	how
how's	i	i'd	i'll	i'm	i've	if
in	into	is	isn't	it	it's	its
itself	let's	me	more	most	mustn't	my
myself	no	nor	not	of	off	on
once	only	or	other	ought	our	ours
ourselves	out	over	own	same	shan't	she
she'd	she'll	she's	should	shouldn't	so	some
such	than	that	that's	the	their	theirs
them	themselves	then	there	there's	these	they
they'd	they'll	they're	they've	this	those	through
to	too	under	until	up	very	was
wasn't	we	we'd	we'll	we're	we've	were
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e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions: one corresponds to how '`Bob`'-ish it is, one corresponds to how '`goes`'-ish it is, one corresponds to how '`home`'-ish it is.

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docs	american	expect	induct	presid	will
	features				
1933-Roosevelt	2	1	1	1	12
1937-Roosevelt	4	0	0	2	16
1941-Roosevelt	4	0	0	1	4
1945-Roosevelt	1	0	0	1	7

→ could re-weight in various ways, but will leave as raw counts for now.

partial TDM from Roosevelt's Inaugural Addresses

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```
          docs
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1. `The mountains are beautiful in Ore. and Wash.`
2. `http://www.wsj.com/articles/son-of-saul-not-about-the-survivors-1449590175`
3. `I can't go with him to Beijing.`

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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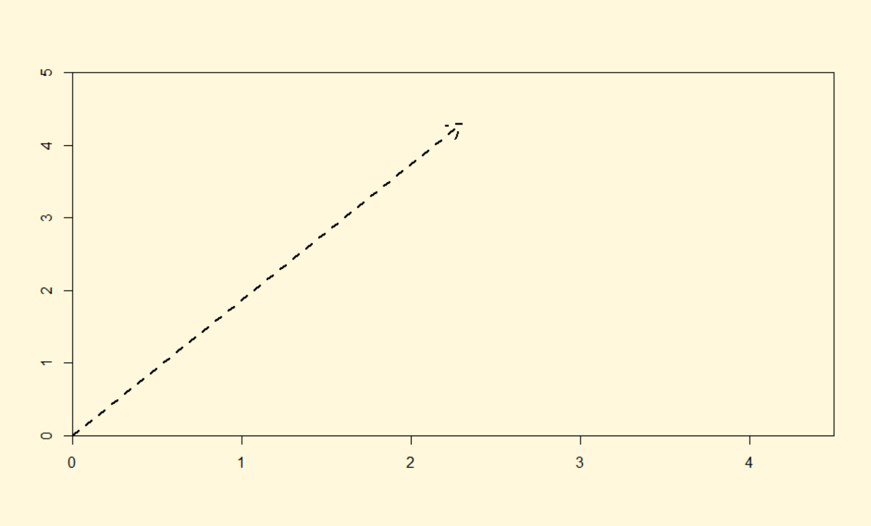

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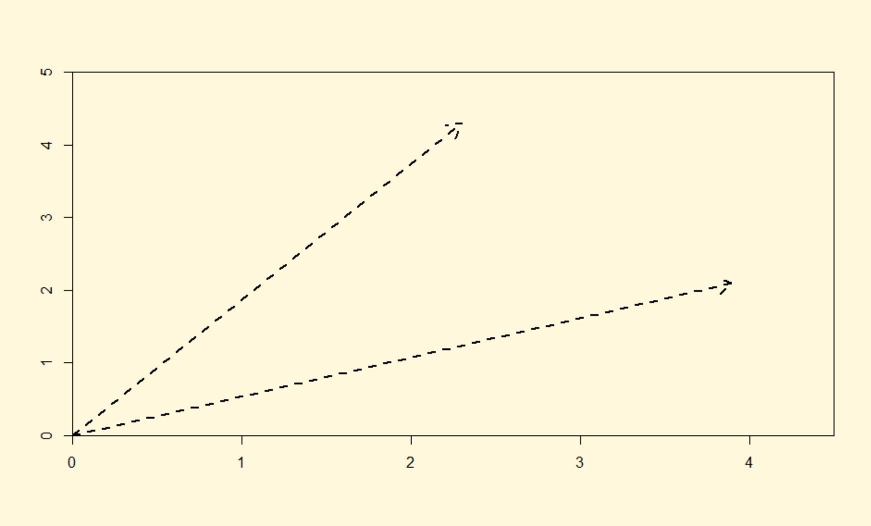

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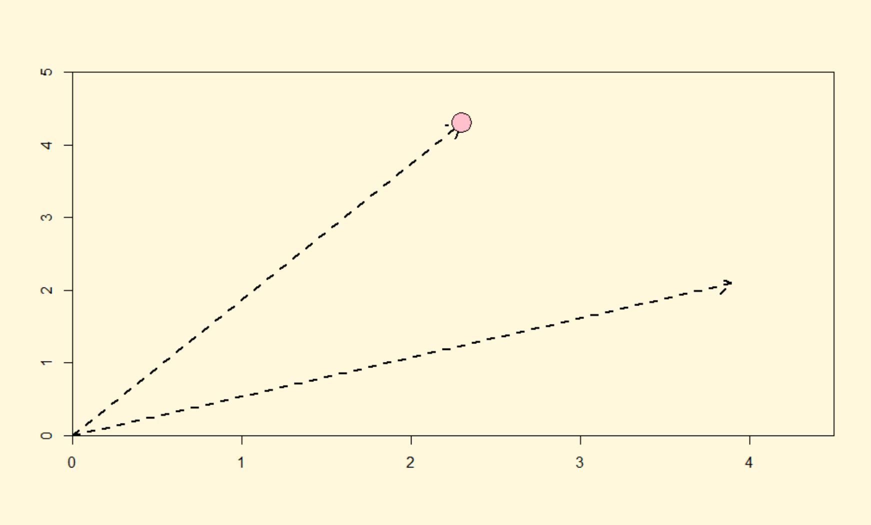

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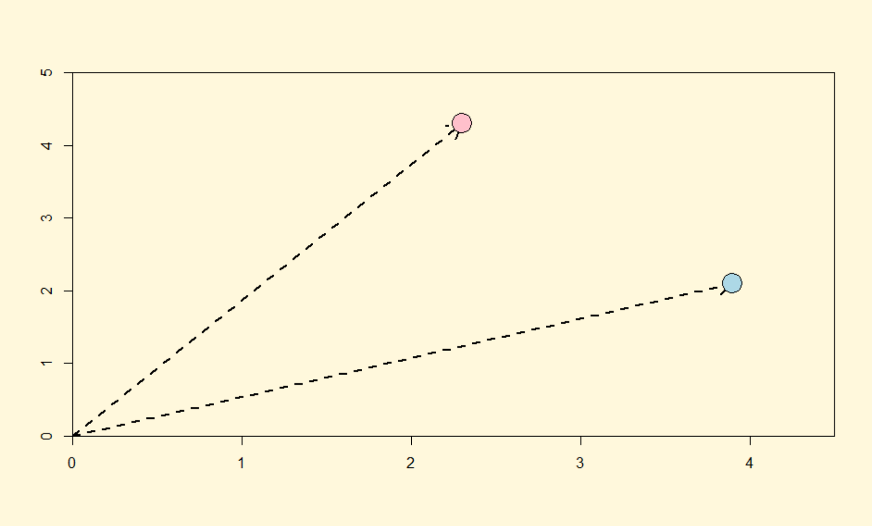

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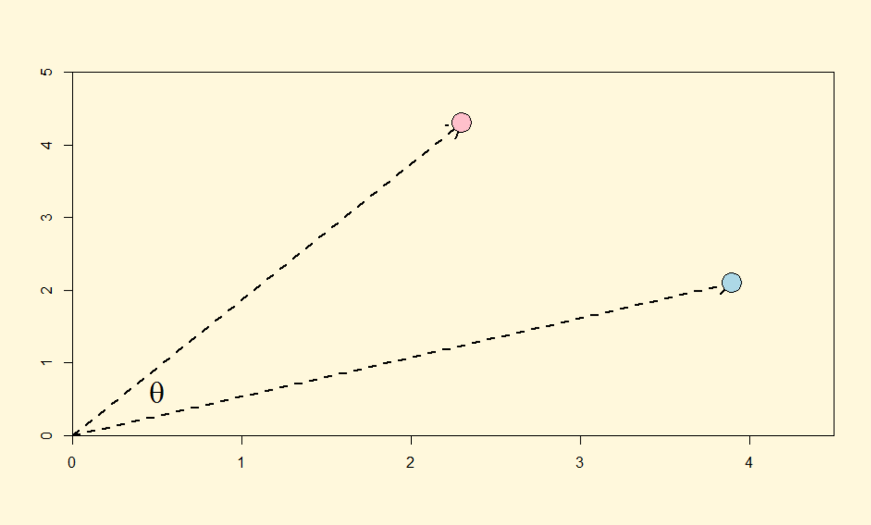

Algebra

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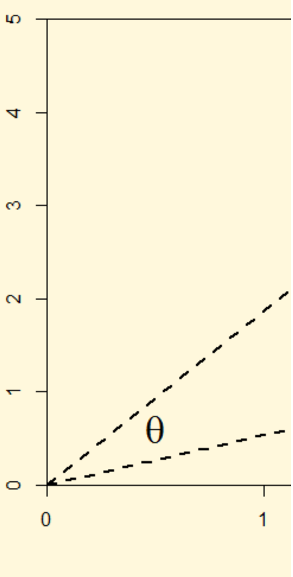

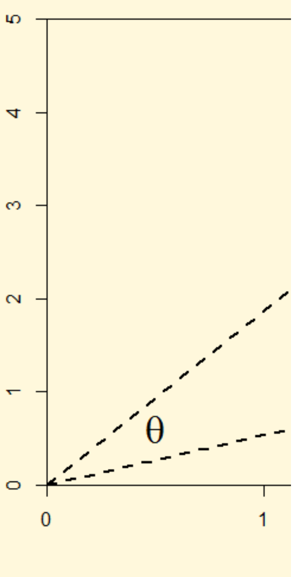

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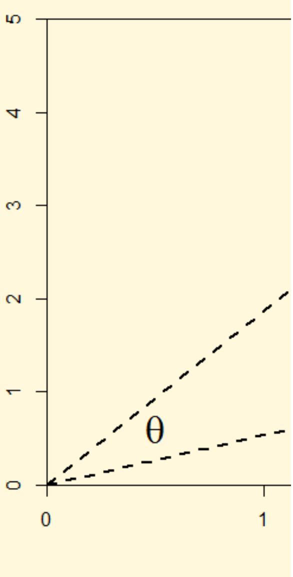

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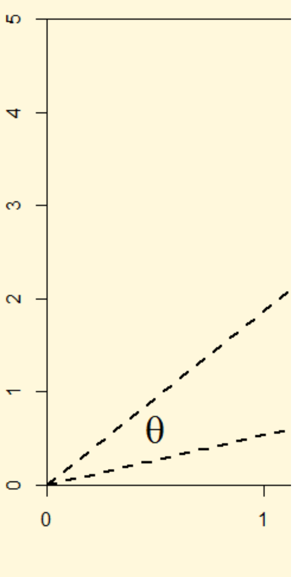

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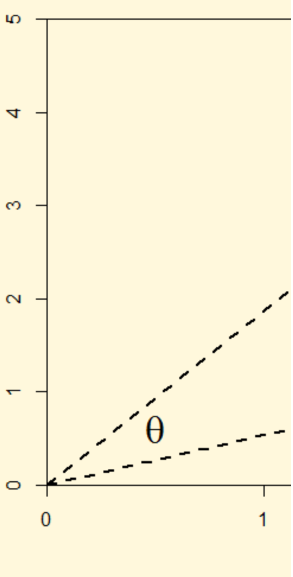

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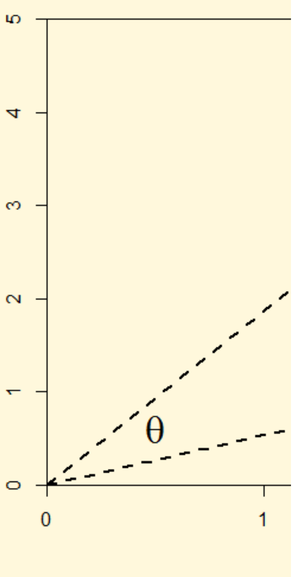

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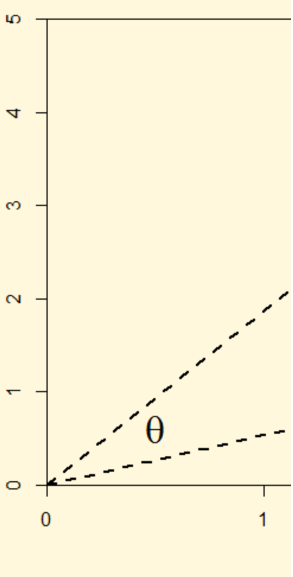

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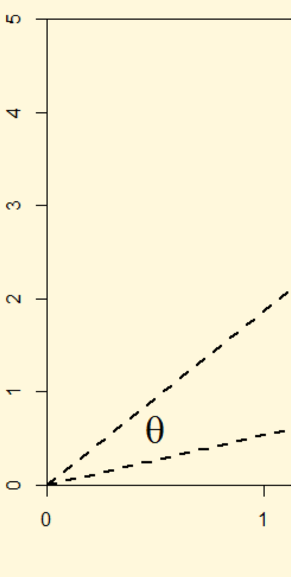
Algebra



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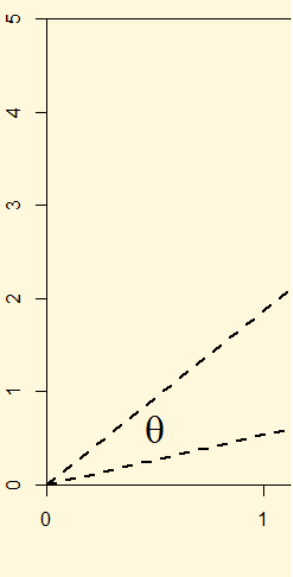

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Looks about right.

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Descriptive Statistics: Key Words

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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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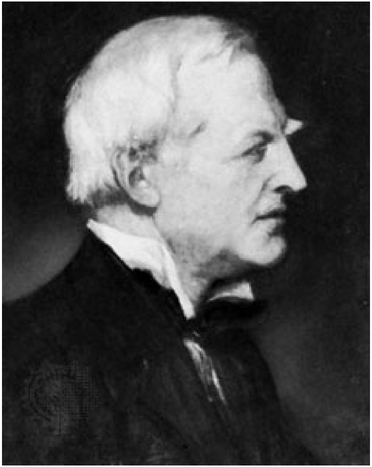

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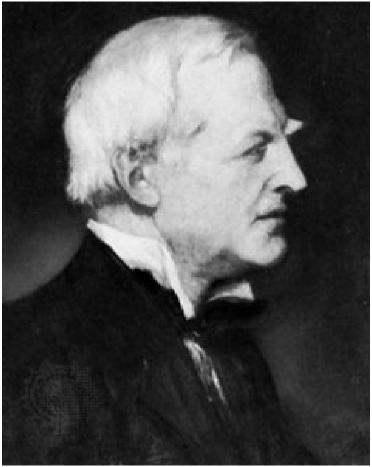

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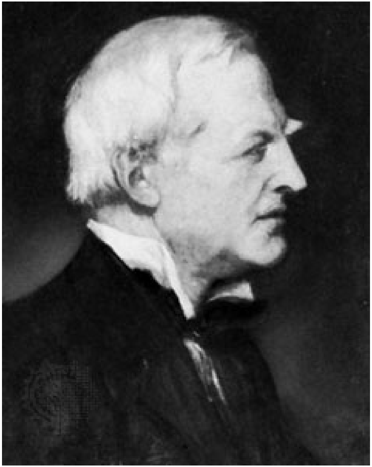

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In accordance with the democratic principle the army would demand to elect their own officers, and there would be endless change in the Constitution arising out of the present Bill, which, so far from being an end to our evils, is only the first step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

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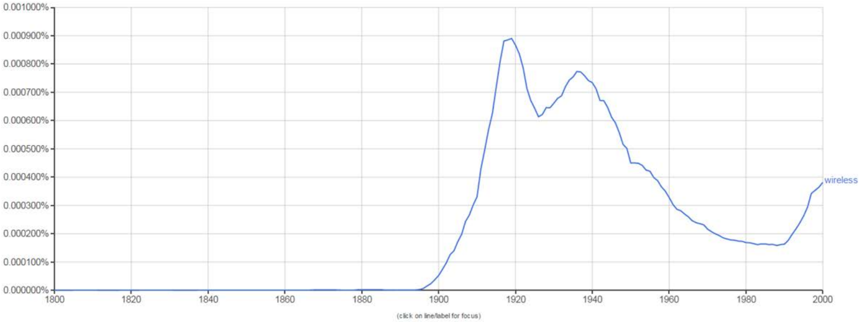
Suppose you were studying the history of entertainment technology. Consider the key word '`wireless`'. How has the frequency of this term changed over time? How has the context changed?

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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Restoration of national income, which shows continuing gains for the third successive year, supports the normal and logical policies under which agriculture and industry are returning to full activity. Under these policies we approach a balance of the national budget. National income increases; tax receipts, based on that income, increase without the levying of new taxes.

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- Kincaid et al later translate to US School grade level that would be (on average) required to comprehend text.

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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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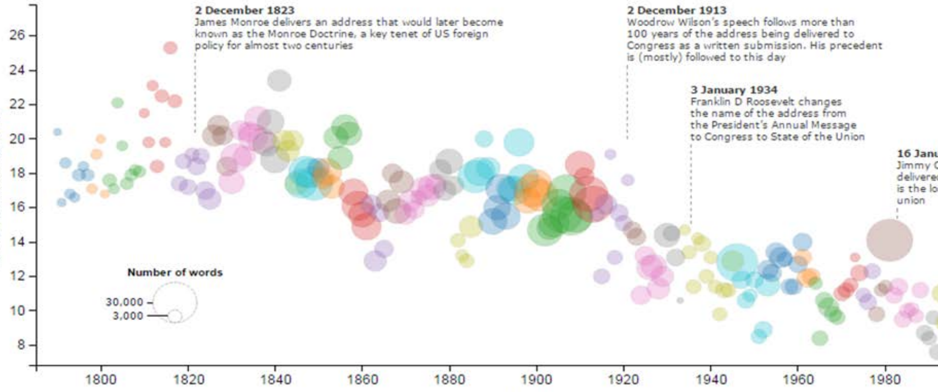
90	death row inmate last statements (TX)
100	this entry right here.

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



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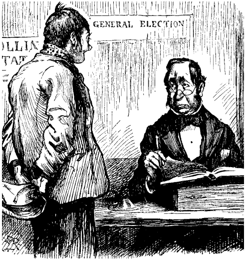

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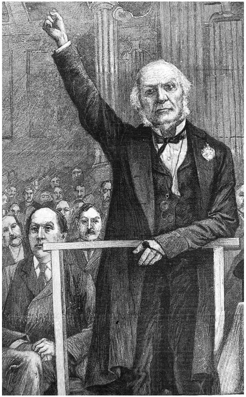

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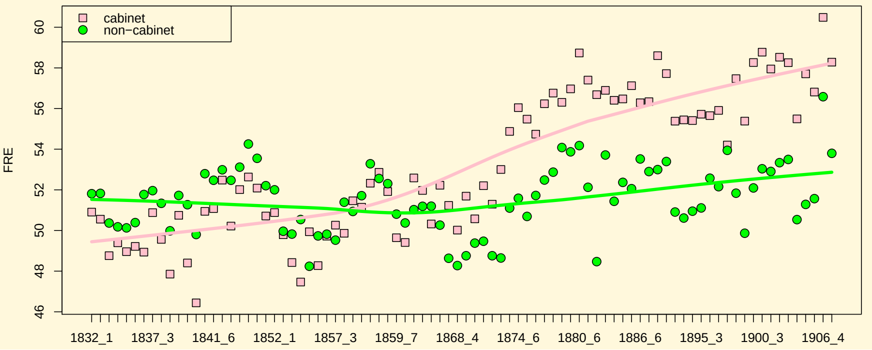
Flesch overtime plot



Partner Exercise

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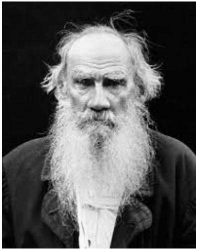

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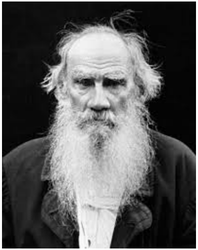

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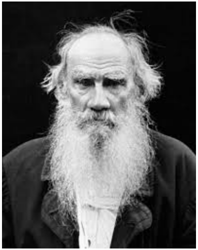

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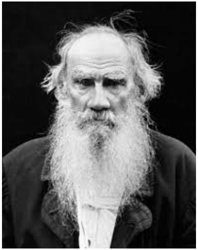

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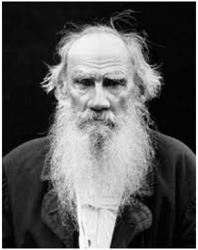

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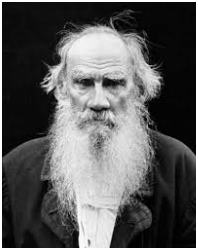

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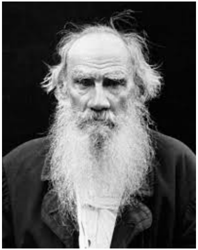

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→ think a little more systematically about the sampling distribution of a statistic.

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

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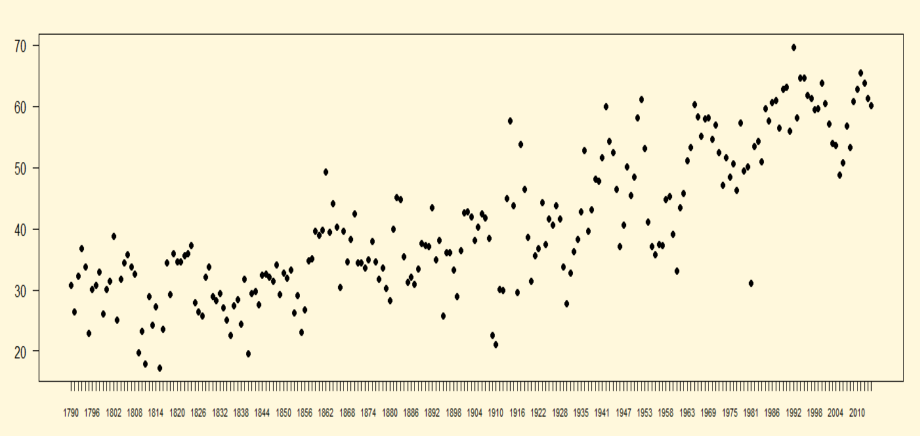

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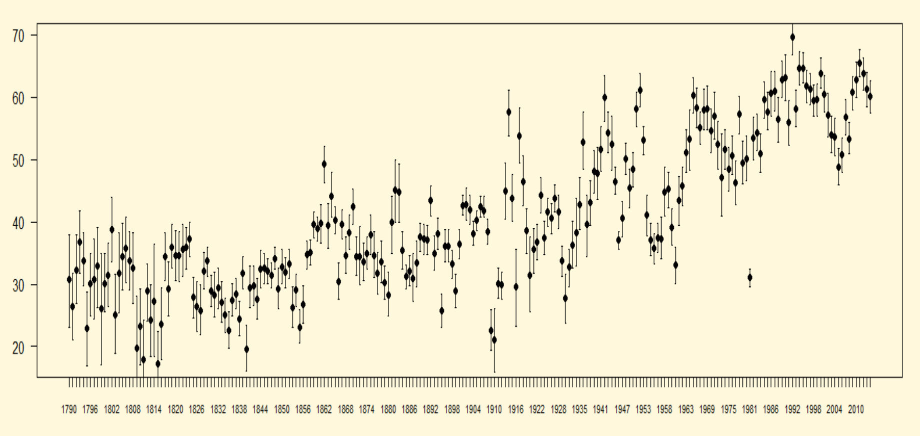

Descriptive Statistics: Stylometrics & Burstiness

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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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their	what	also	by
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Methods allow one to see which words and phrases have dramatic shifts in usage over time—oftentimes this corresponds to substance but sometimes style.

Idea is to model arrival times of words. As 'gaps' between use of same word become shorter, infer that term is 'bursty'.

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Applying to SOTU, 1790–2002

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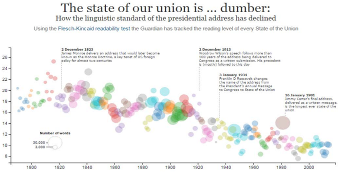

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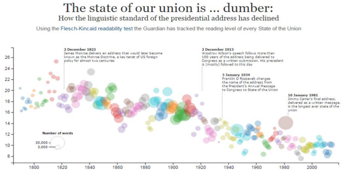

word	burst
gentlemen	1790–1800
british	1809–1814
slaves	1859–1863
japanese	1942–1945
health	1992–1994
help	1998–