3. Descriptive Inference II

DS-GA 3001, Text as Data
Arthur Spirling

February 13, 2018

Housekeeping

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3. Next week, AS will lecture Tues and Thurs.

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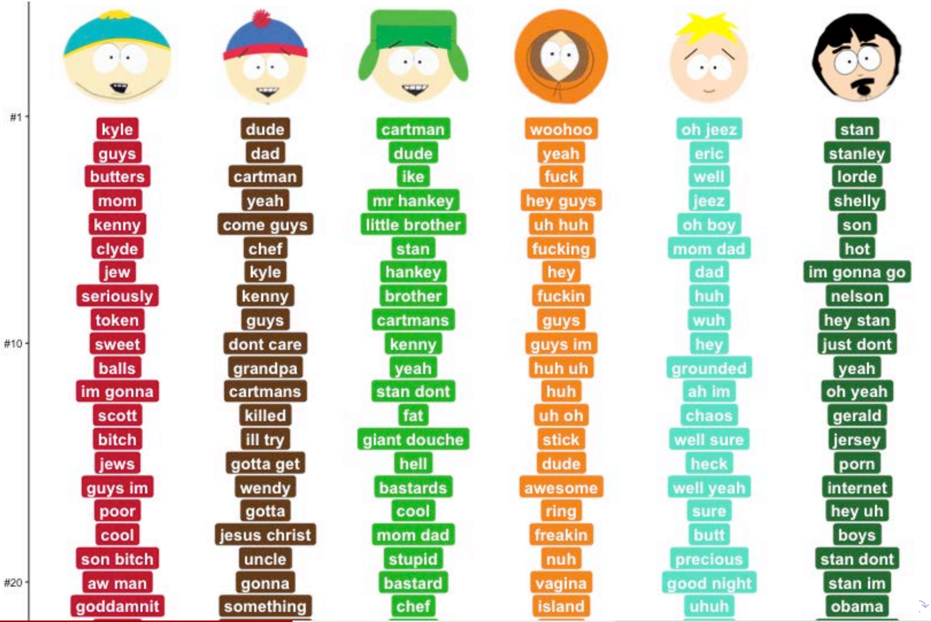
kaylinwalker.com/text-mining-south-park/



Where Are We?

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The Realm Of
Middle Earth
Miles
50 100 150 200
The Lost Realm of
ARNOR
Here was of old
the Witch-realm
of Angmar
Carn Dûm
Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop
RHUDAUR
Last Bridge
Bree
East-West Road
South Downs
THE SHIRE
Hobbiton
Sarn Ford
CARDOLAN
Tharbad
Nîn-in-Eilph
(Swanfleet)
Mitheithel
Glanduin
MINHIRIATH
Gulf of Lhûn
Grey Havens
Tower Hills
Harlond
Harlindon
Forlindon
Forlond
Blue Mountains
Baranduin
Eryn Vorn
Lond Daer
ENEDWAITH
Dunland
Isengard
FANGORN
Fords of Isen
(Isen)
Adorn
Angren
Helm's Deep
WESTFOLD
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
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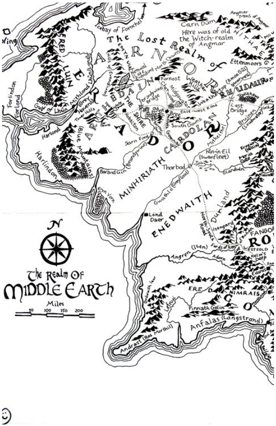

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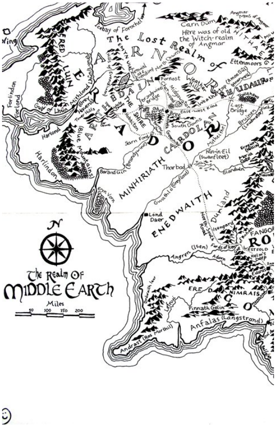

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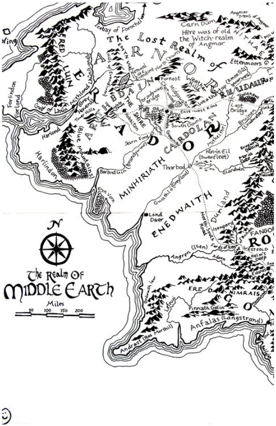

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e.g. authors with limited vocabularies will have a low lexical diversity.

Tabloid vs Broadsheet

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RCH NEW YORK POST

NEWS

Iraqi troops retake key government complex in Ramadi

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

Iraqi Forces Retake Center of Ramadi From ISIS

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

Email

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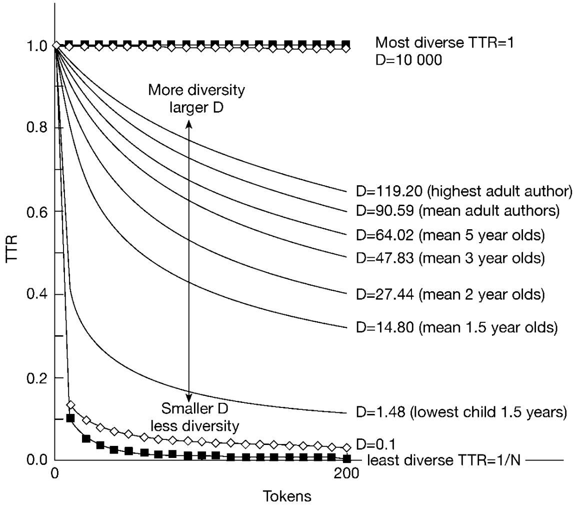

Figure 1: Model TTR plotted against samples of increasing length for different values of D

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$\rightarrow$ if text is highly diverse, be able to maintain given threshold for longer (on average) and thus mean number of words will be higher.

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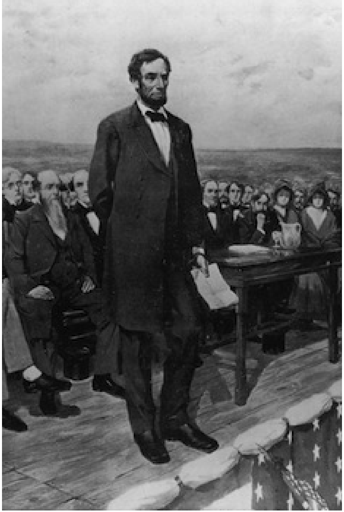

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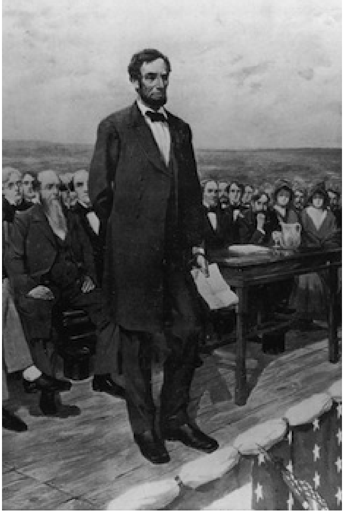

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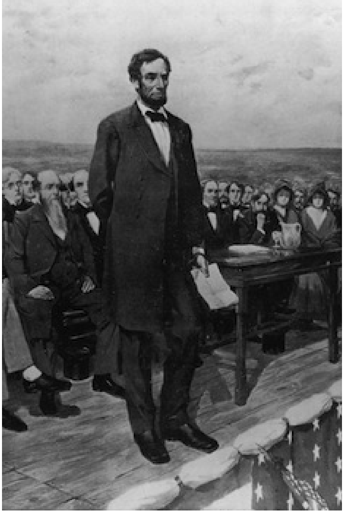

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0–30	college graduates	very difficult	28
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51–60		fairly difficult	85
61–70	9th grade	standard	–
71–80		fairly easy	–
81–90		easy	–
91–100	4th grade	very easy	–

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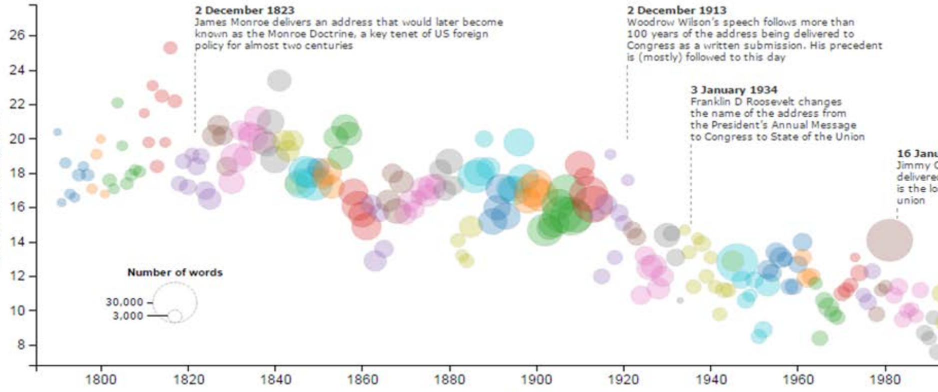
- $\pm$ rules for special endings and use of consonents (e.g. `hassle` vs `mule`)

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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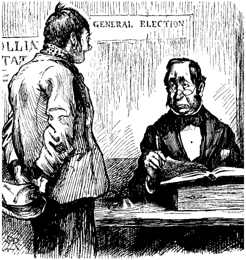

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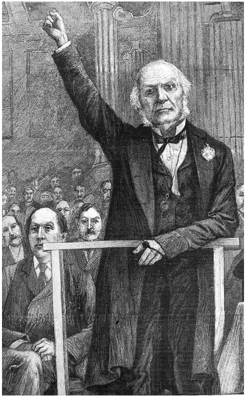

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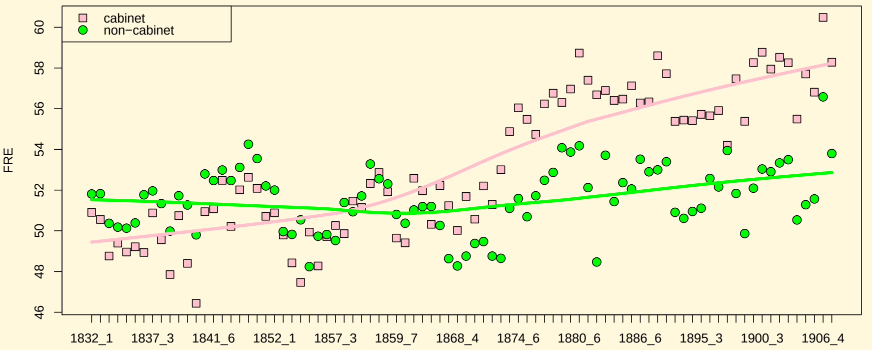
Flesch overtime plot



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

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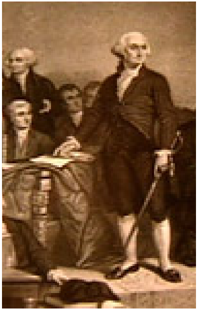

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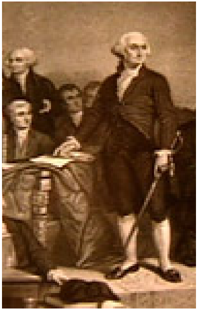

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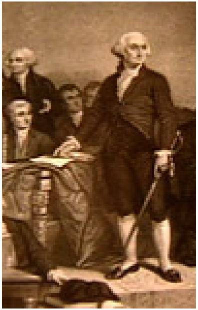

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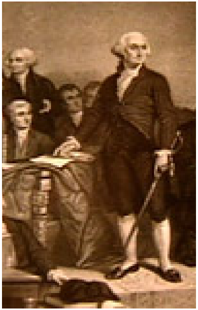

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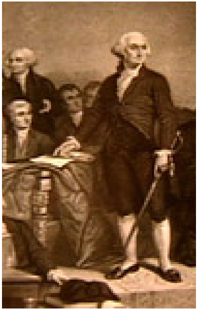

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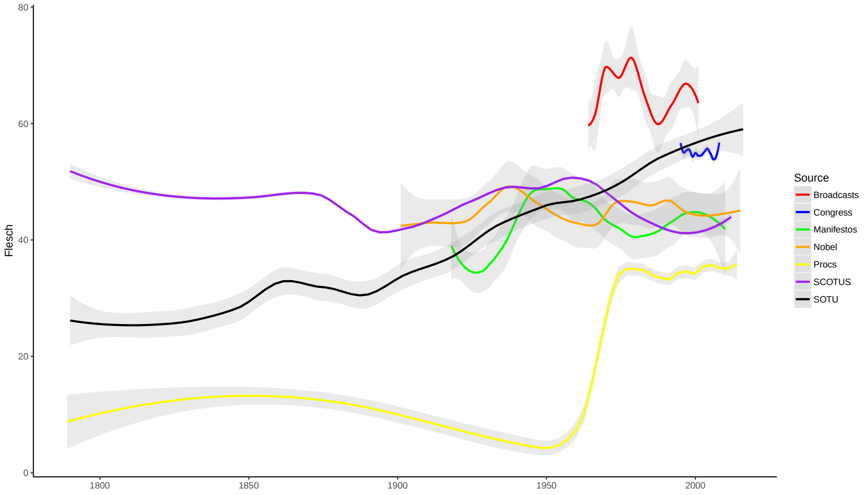

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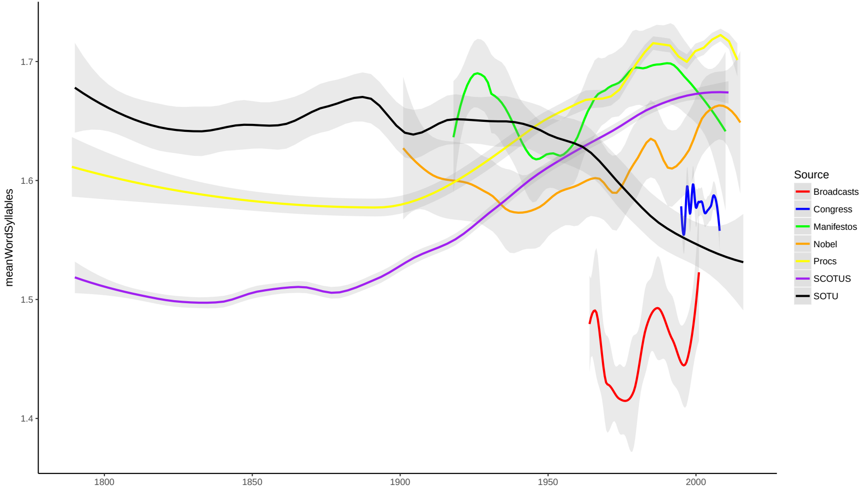

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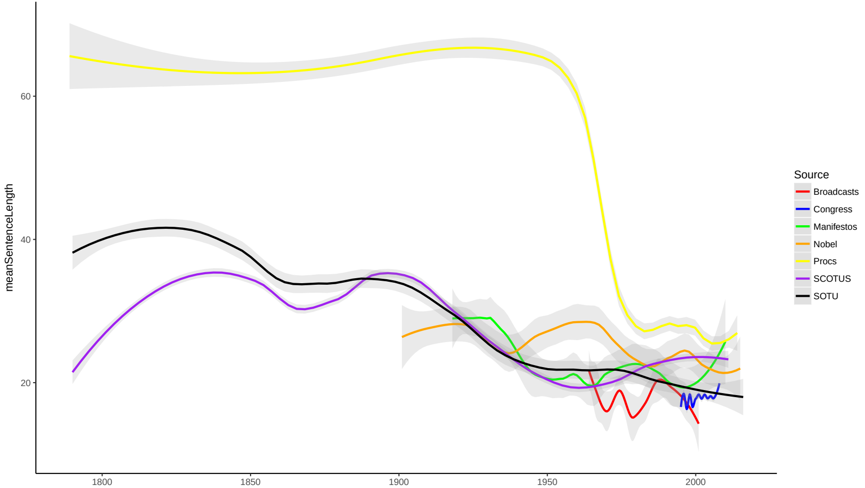

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Paper and Software

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Measuring and Explaining Political Sophistication Through Textual Complexity

42 Pages • Posted: 1 Nov 2017

Kenneth Benoit
London School of Economics & Political Science (LSE); Trinity College Dublin

Kevin Munger
New York University (NYU)

Arthur Spirling
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Date Written: October 30, 2017

Abstract

The sophistication of political communication has been measured using "readability" scores developed from other contexts, but their application out of domain is problematic. We systematically review the shortcomings of previous measures, before developing a new approach, with software, better suited to the task. We use the crowd to perform thousands of pairwise comparisons of text snippets and incorporate these results into a statistical model of comprehension. We include previously excluded features such as parts of speech, and a

Paper and Software

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Code for use in measuring the sophistication of political text

"Measuring and Explaining Political Sophistication Through Textual Complexity" by Kenneth Benoit, Kevin Munger, and Arthur Spirling. This package is built on quanteda.

How to install

Using the **devtools** package:

```
devtools::install_github("kbenoit/sophistication")
```

Included Data

new name	original name	description
`data_corpus_fifthgrade`	`fifthCorpus`	Fifth-grade reading texts
`data_corpus_crimson`	`crimsonCorpus`	Editorials from the Harvard *Crimson*
`data_corpus_partybroadcast`	`partybcastCorpus`	UK political party broadcasts
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Style and 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?"

More Details

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one	the	were	all
but	has	may	only
their	what	also	by
have	more	or	then
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must	our	there	which
and	do	his	my
things	who	any	down
if	no	so	this
are	even	in	not
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→ wrong, but models relying on these assns discriminate well (see Peng & Hengartner on e.g. Austin v Shakespeare)

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and Negative Binomial (which adds a gamma distributed random effect, δ):

$$NB(X_w = x|\Theta_w = (\omega, \mu, \delta)) = \frac{\gamma(x+k)}{x!\gamma(k)}(\omega\delta)^x(1+\omega\delta)^{-(x+k)}$$

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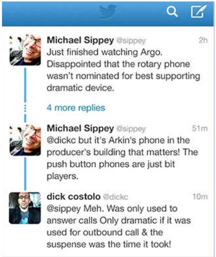

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Eisenstein ("Rhetorical Patterns in Legislative Speech") models discourse relations—conceptual links between units of text, like 'so', 'however'—as function of covariates (e.g. ideology of member)

Partner Exercise

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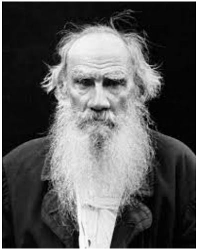

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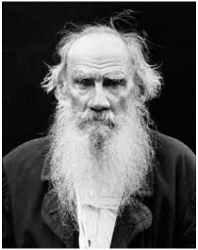

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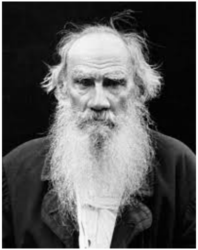

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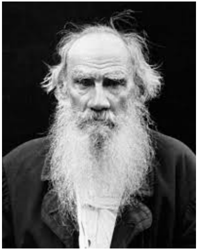

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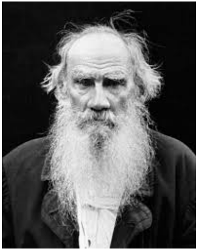

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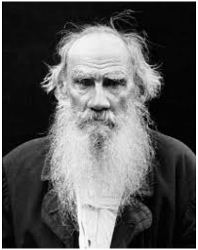

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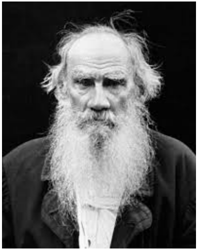

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→ think a little more systematically about the sampling distribution of a statistic.

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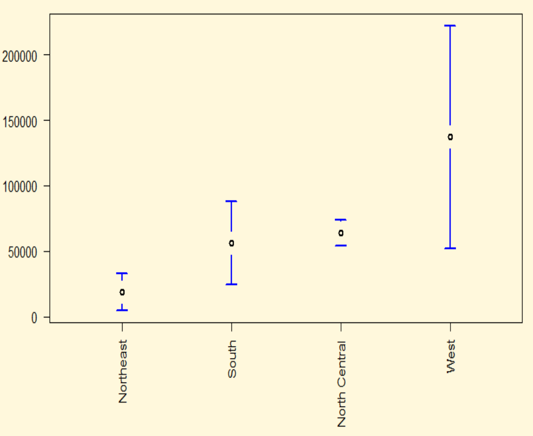

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$\rightarrow$ difficult to know how we should calculate the sampling distribution and thus the standard error.

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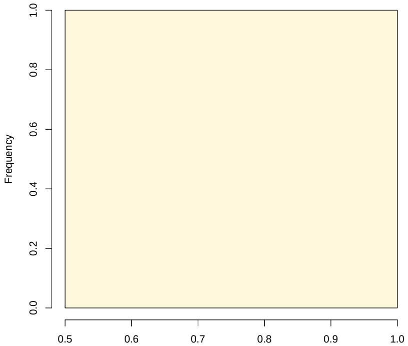

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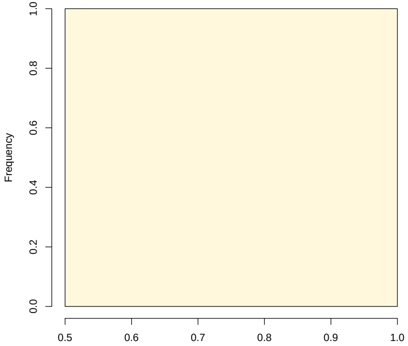

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btw long texts give rise to smaller SEs than short ones, which makes sense!

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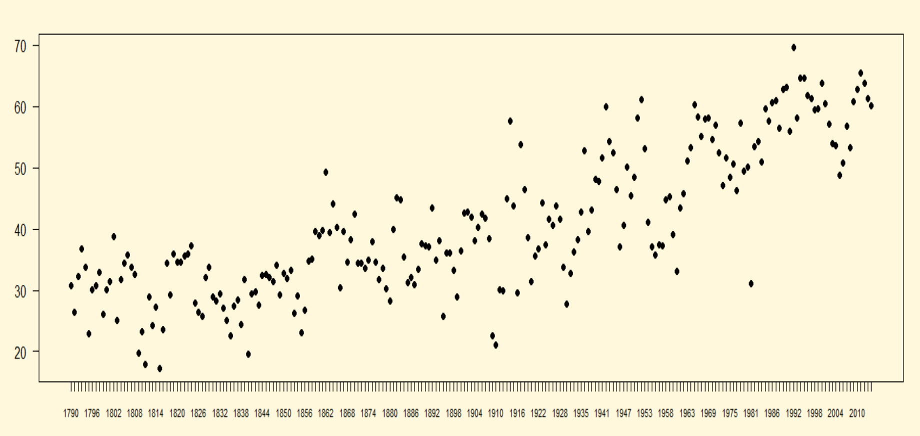

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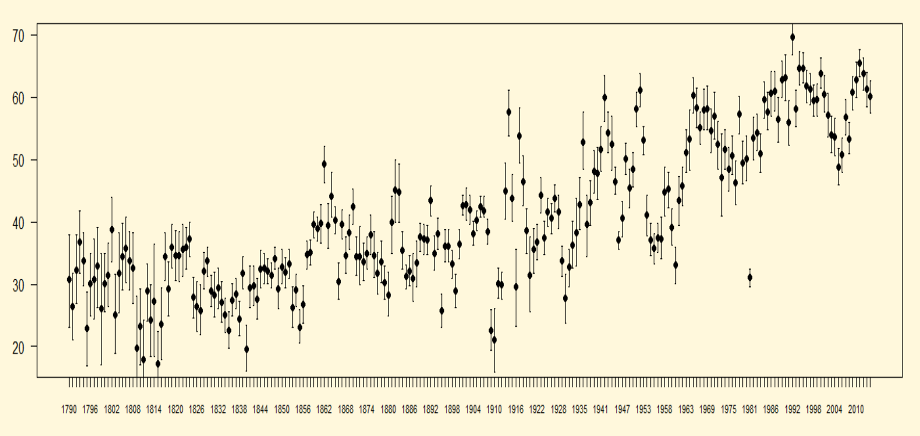

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$\rightarrow$ SIMEX (simulation-extrapolation) or MO (multiple overimputation) might be called for.

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2. What if the goal is prediction of the expected value of Y only?