3. Descriptive Inference II

DS-GA 1015, Text as Data
Arthur Spirling

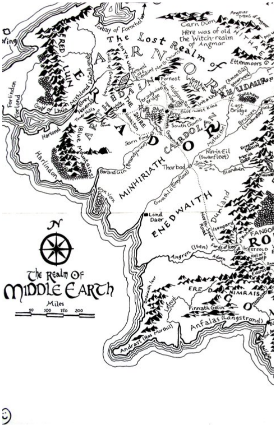
Feb 16, 2021

Where Are We?

Where Are We?

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

Where Are We?



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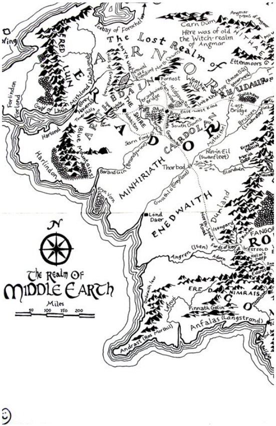

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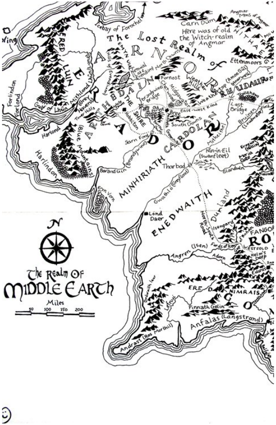

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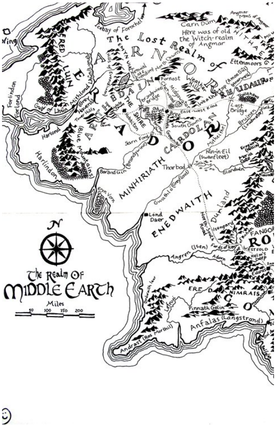

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and think seriously about the nature of the sampling process that produces the texts we see, and what to do about it.

Complexity of Text

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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:
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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

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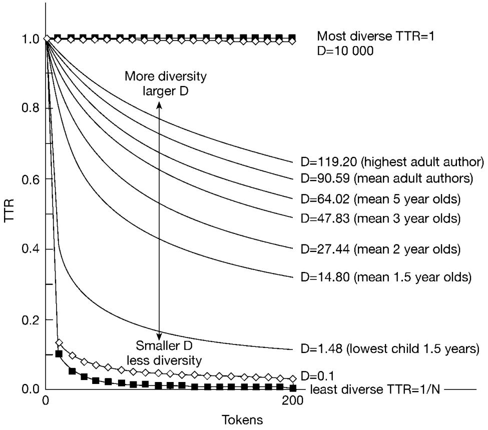

Figure 1: Model TTR plotted against samples of increasing length for different values of D

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$\rightarrow$ straightforward measurement literature...

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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.

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Surprisingly little effort to describe statistical behavior of estimator:

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Flesch scoring only uses syllable information: no input from rarity or unfamiliarity of word.

e.g. "`Indeed, the shoemaker was frightened`" would score similarly to "`Forsooth, the cordwainer was afeared`"

Widely used because it 'works', not because it is justified from first principles

One of many such indices: Gunning-Fog, Dale-Chall, Automated Readability Index, SMOG. Typically highly correlated (at text level).

Surprisingly little effort to describe statistical behavior of estimator: sampling distribution etc.

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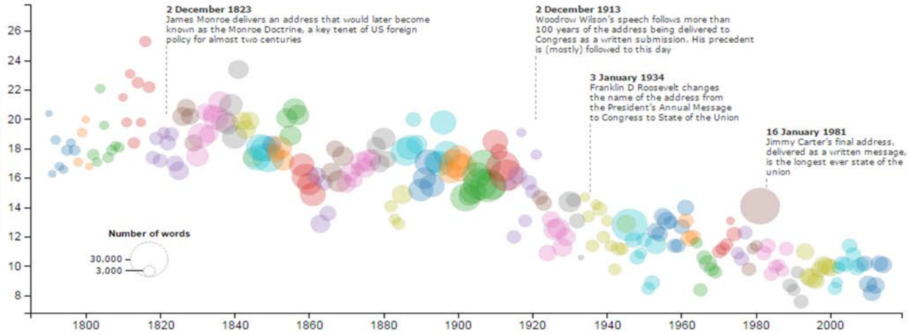
- ± rules for diphthongs and triphthongs: i.e. multiple vowels that sound like one (e.g. `book`)
- ± rules for special endings and use of consonents (e.g. `hassle` vs `mule`)

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



Leaders and their incentives

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C19th Britain is notable for fast expansion of suffrage.

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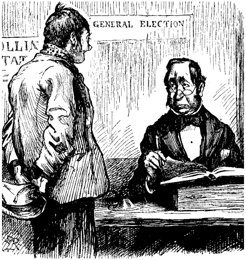

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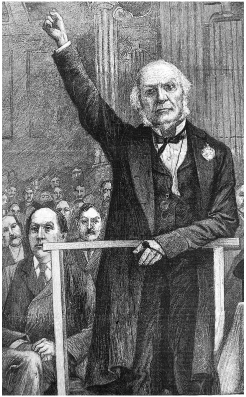
$\downarrow$ local, clientalistic appeals via bribery...

$\uparrow$ 'party orientated electorate', with national policies and national leaders



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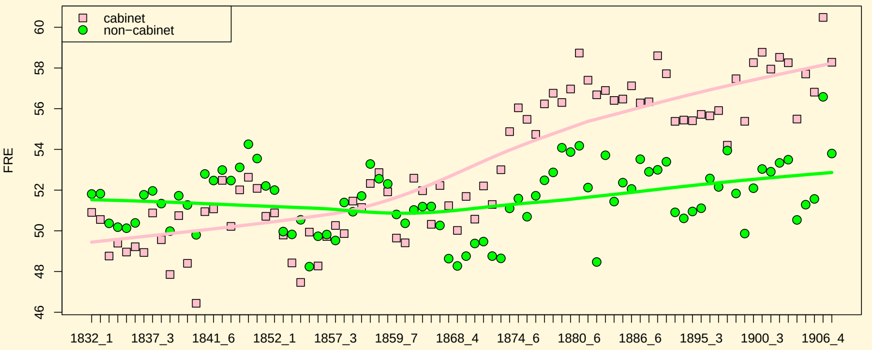
Flesch overtime plot



Dale-Chall, 1948

yields grade level of text sample.

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

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3. Designed for readers in 1940/50s, not easily updated.

Some Statistical Concerns

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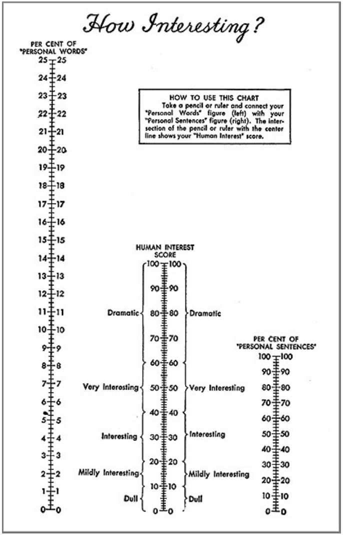

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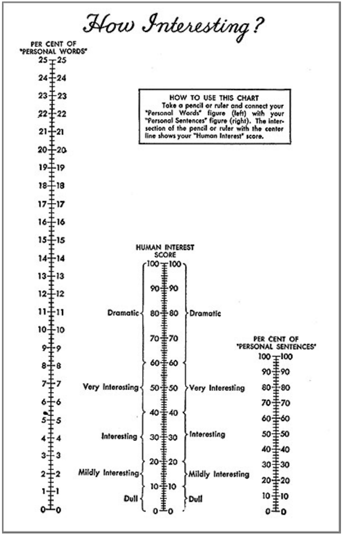

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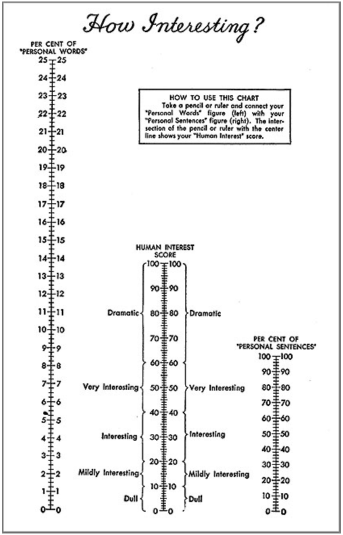

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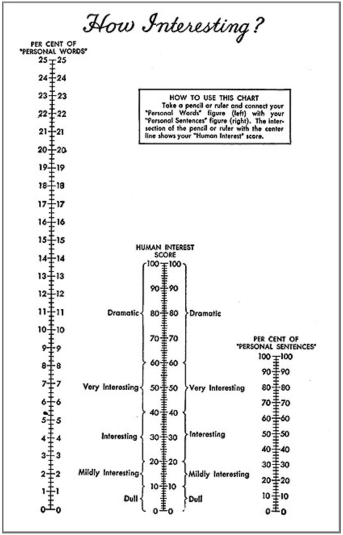

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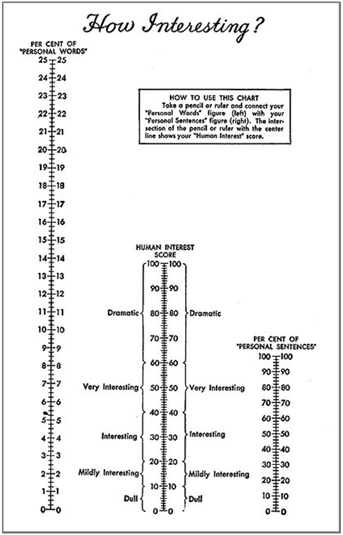

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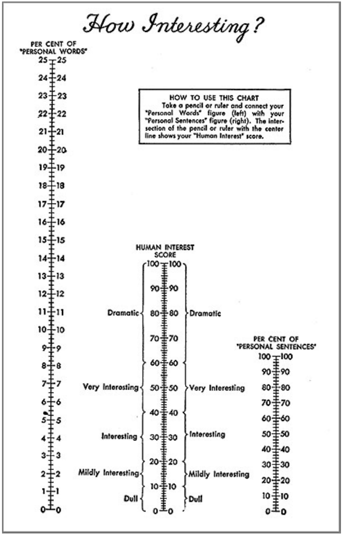

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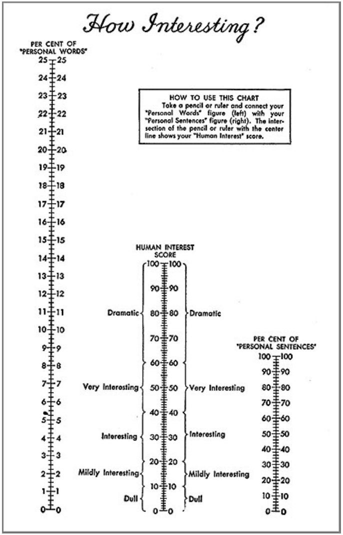

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4. Rarity of terms included in static, *ad hoc* way.

The Fix: Overview

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$\rightarrow$ *provide better measure of political sophistication*

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
New York University

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

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CRAN not published | build passing | build passing | coverage 27%

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
`data_corpus_presdebates`	`presDebateCorpus`	US presidential debates 2016

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library("sophistication")
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Paper and Software


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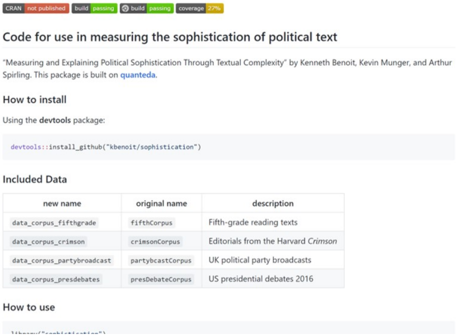
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Cleveland wins on FRE, but Obama wins in our model (penalizing for rarity).

Style and Stylometrics

Mystery of *The Federalist Papers*

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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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a	been	had	its
one	the	were	all
but	has	may	only
their	what	also	by
have	more	or	then
when	an	can	her
must	our	there	which
and	do	his	my
things	who	any	down
if	no	so	this
are	even	in	not
some	to	with	as
every	into	now	such
up	would	at	for
is	of	than	upon
your	be	from	it
on	that	was	will
should			

More Details

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must	our	there	which
and	do	his	my
things	who	any	down
if	no	so	this
are	even	in	not
some	to	with	as
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and Negative Binomial (which adds a gamma distributed random effect, δ):

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$\rightarrow$ think a little more systematically about the sampling distribution of a statistic.

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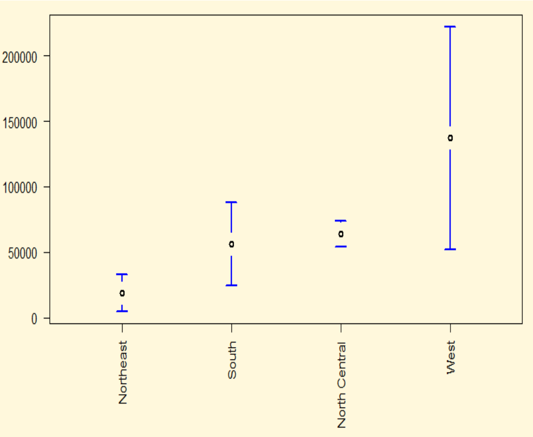

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$\rightarrow$ difficult to know how we should calculate the sampling distribution and thus the standard error.

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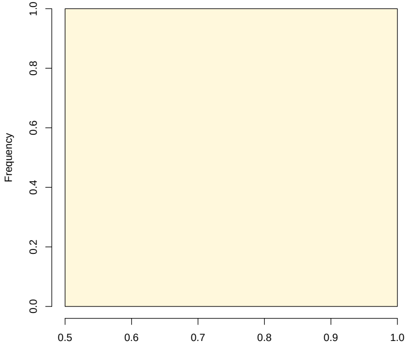

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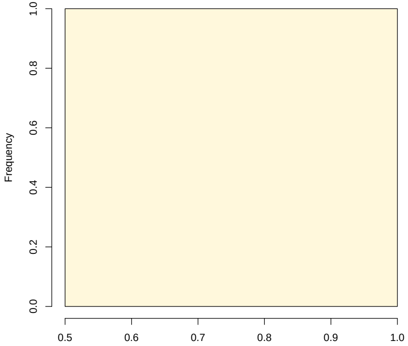

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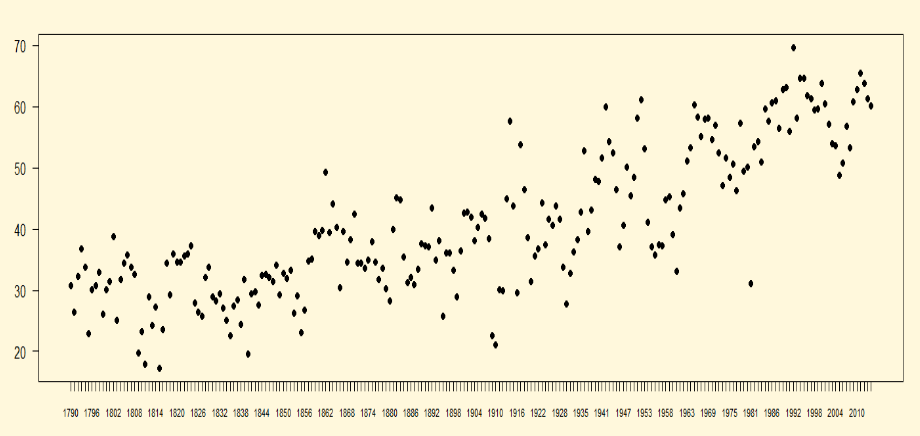
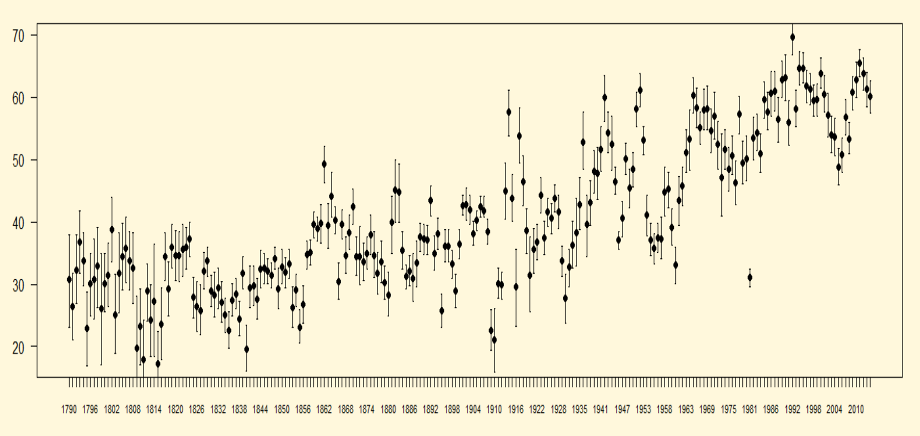


SOU: 1000 bootstrap samples



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