3. Descriptive Inference II (Flipped)

DS-GA 1015, Text as Data
Arthur Spirling

Feb 23, 2021

Housekeeping

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HW 1 out tonight (deadline: two weeks). Turn in an RMarkdown book. Note the academic honesty policy!

Where Are We?

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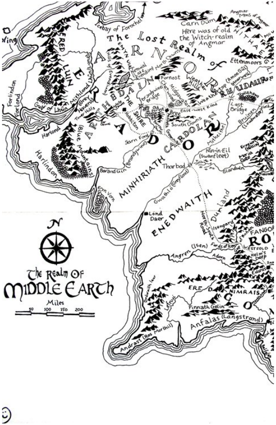
The Lost Realm of
ARNOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop
RHUDAUR
Last Bridge
Bree
East-West Road
South Downs
THE SHIRE
Hobbiton
Sarn Ford
CARDOLAN
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
MINHIRIATH
ENEDWAITH
Lond Daer
Dunland
Isengard
FANGORN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

Where Are We?



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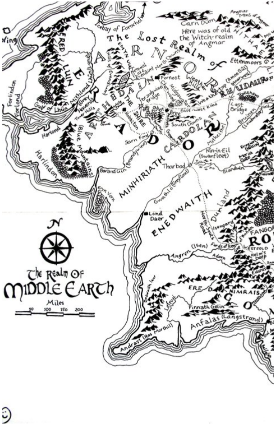

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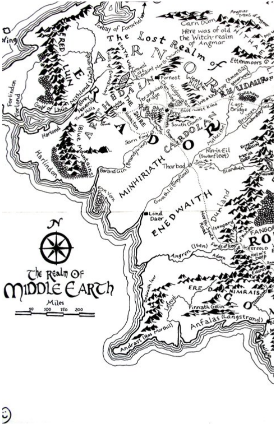

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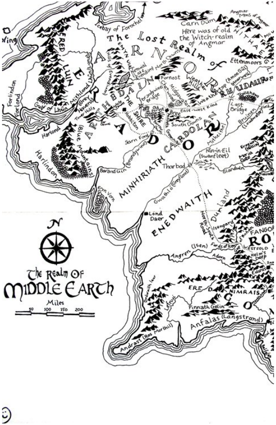

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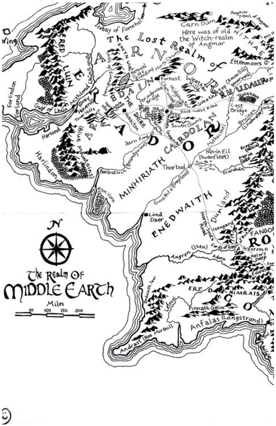

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and think seriously about the nature of the sampling process that produces the texts we see, and what to do about it.

Distinctive terms (χ^2): Democratic Debates

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Laura Bronner
@laurabronner

Some of the more distinctive words and phrases this #DemDebate

docs	turn_the_page	billionaires	diverse	mr_trump	zero	busted_my_neck
BIDEN	0	1	0	0	1	1
BUTTIGIEG	5	0	0	0	0	0
KLOBUCHAR	0	0	0	0	0	0
SANDERS	0	4	0	1	0	0
STEYER	0	0	5	8	0	0
WARREN	0	6	0	0	0	0
YANG	0	0	0	0	7	0

>

11:04 PM · Feb 7, 2020 · Twitter Web App

Recap

Recap

What is the TTR? What does it tell us?

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There is some evidence that it (initially) *falls* as babies learn to speak. Why?

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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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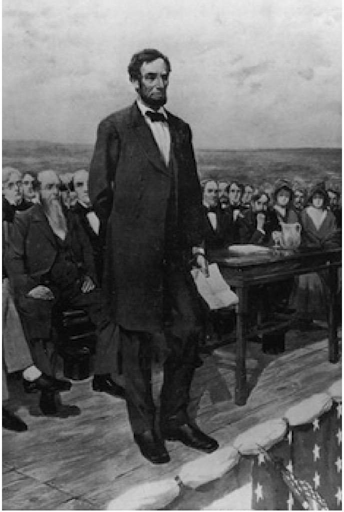

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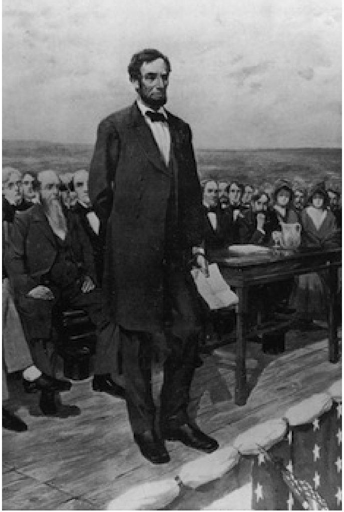

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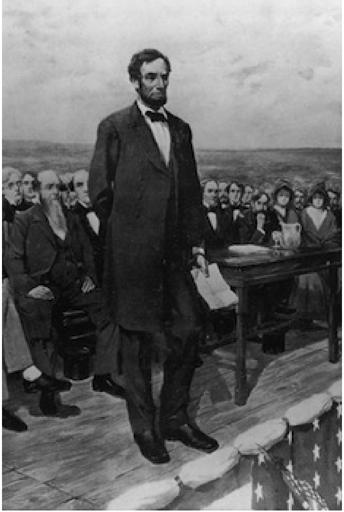

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“`The reporter who the senator attacked admitted the error`” is harder than “`The reporter who attacked the senator admitted the error`” because less obvious to whom ‘who’ refers.

Exercise

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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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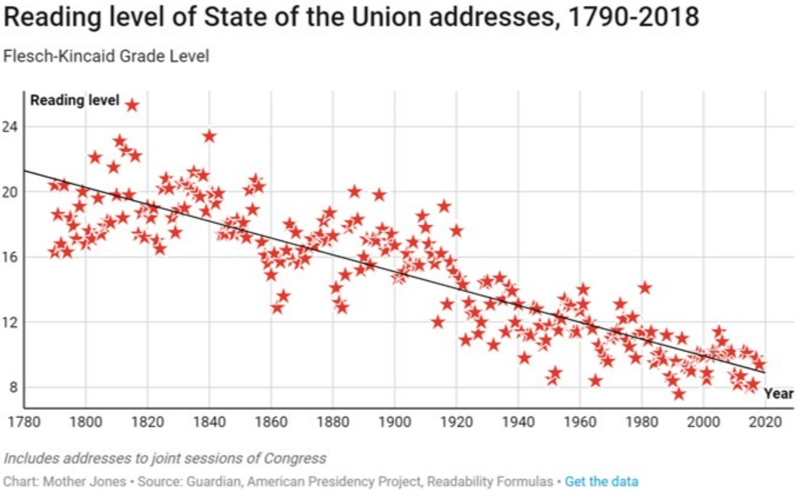
What's 'wrong' with this measurement approach?


Reading level of State of the Union addresses, 1790-2018
Flesch-Kincaid Grade Level
Reading level
24
20
16
12
8
Year
1780
1800
1820
1840
1860
1880
1900
1920
1940
1960
1980
2000
2020
Includes addresses to joint sessions of Congress
Chart: Mother Jones • Source: Guardian, American Presidency Project, Readability Formulas • Get the data

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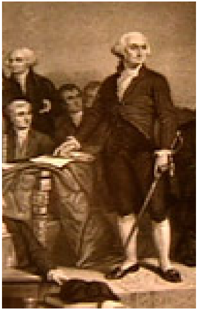

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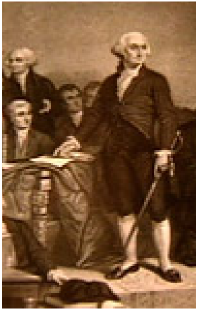

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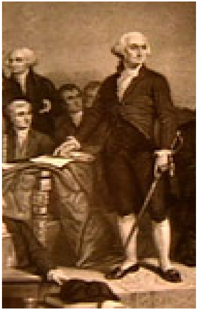

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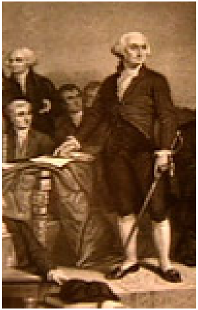

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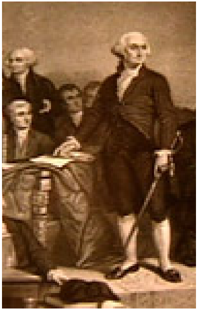

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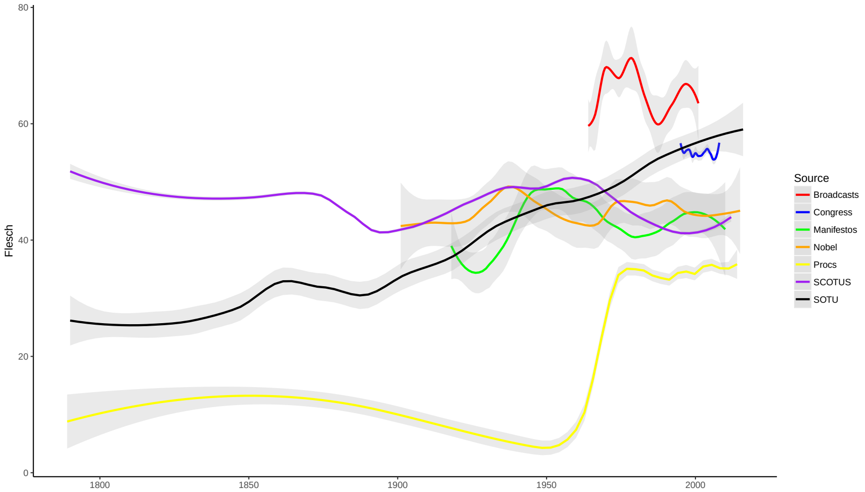

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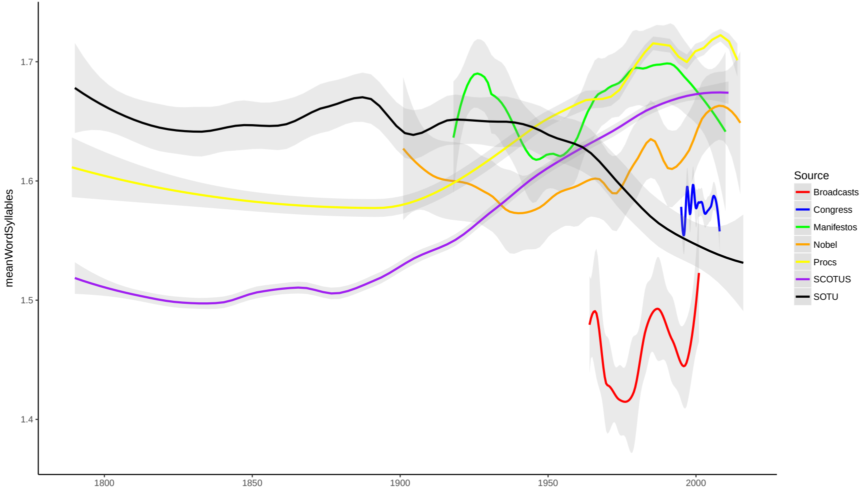

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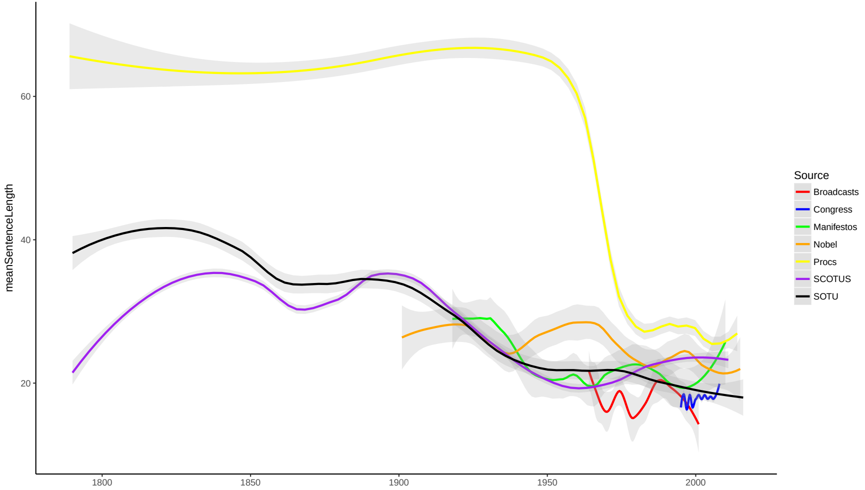

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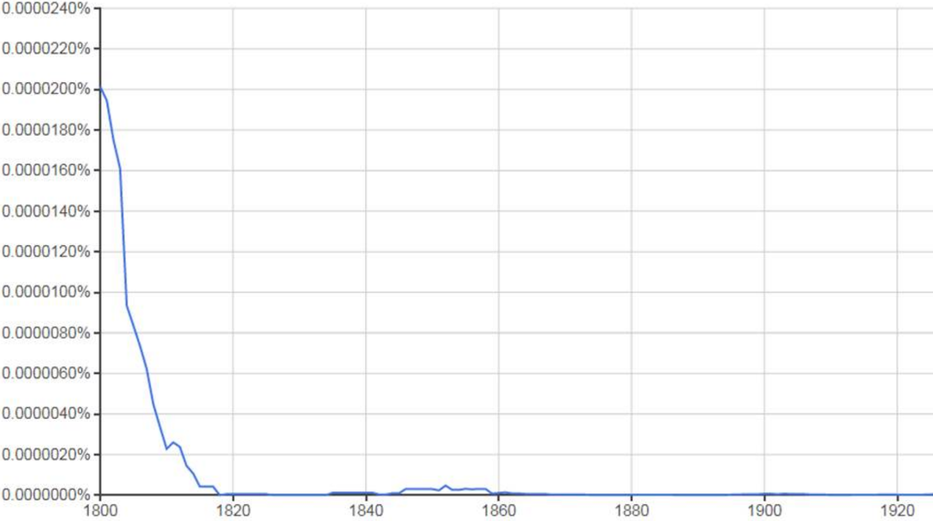
4. Provide meaningful uncertainty inference estimates via bootstrapping of document-level estimates.

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

Cleaning `ftupid`: What Could Possibly Go Wrong?



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Q why use function words? what is the motivation?

A More General Model: The Backbencher's Dilemma...

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Related: unclear how seniority affects this.

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Generalize: two directions, across all speeches, across all speakers, take average pairwise differences.

Formally. . .

Formally...

Consider posterior log-odds of authorship for speech i for speaker t vs s ($\sim$ M&W):

$$\sum_{v \in V} x_{iv} \log \left\{ \frac{\Pr(v|t)}{\Pr(v|s)} \right\}$$

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Then, think about average log-odds per token (let n_i be tokens in speech i)

$$\sum_{v \in V} (x_{iv}/n_i) \log \left\{ \frac{\Pr(v|t)}{\Pr(v|s)} \right\}$$

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where x_{iv} is the incidence of token v in speech i.

Then, think about average log-odds per token (let n_i be tokens in speech i)

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Estimation/fitting generally fast.

Average Level of Boringness is Constant!

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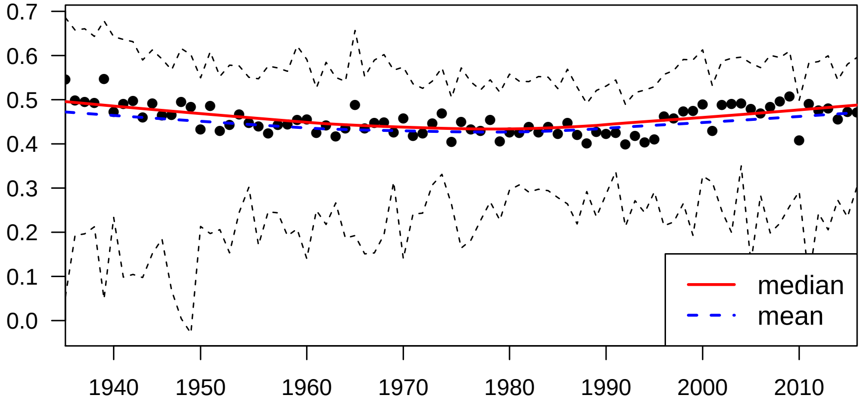

Software etc



Paper:
`http://nyu.edu/projects/spirling/documents/VeryBoring.pdf`

Software:
`https://github.com/leslie-huang/stylest`

Vignette:
`https://leslie-huang.github.io/stylest/`

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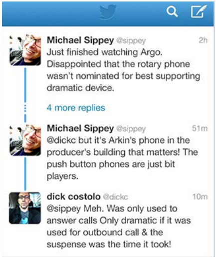

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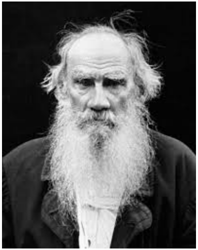

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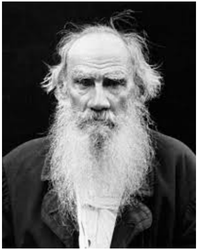

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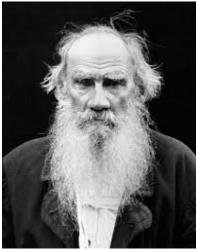

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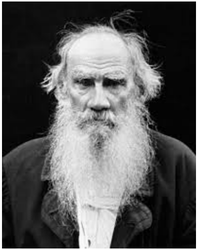

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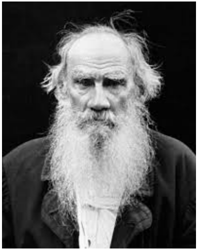

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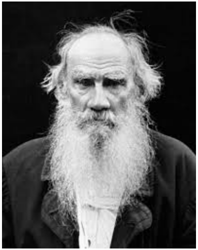

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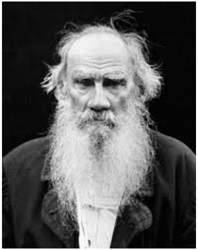

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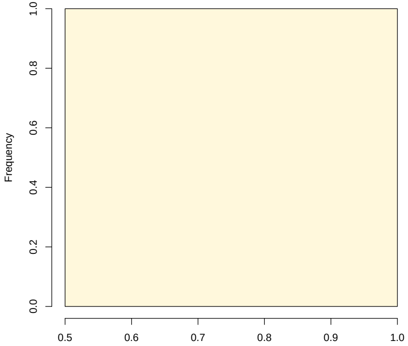
Bootstrap Example

Have simple linear model, $n = 20$ of form $y_i = \beta_0 + \beta_1 X_1 + \beta X_2 + \epsilon_i$

Want to know distribution of R^2, via bootstrap

so resample data ($n = 20$ every time), and record R^2—then plot...



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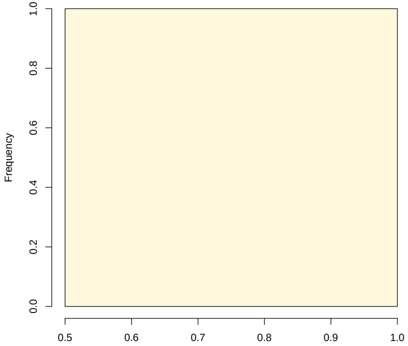

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