Modeling Complexity, Style and Representation in Language

Measurement From Text

Arthur Spirling

New York University

July 12, 2019

1. The Temptation of Unsupervised Learning

Recall

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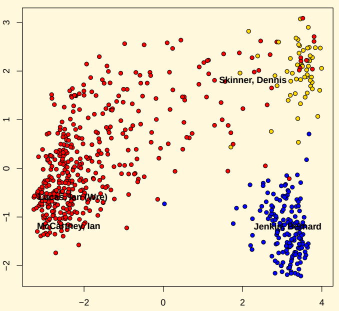

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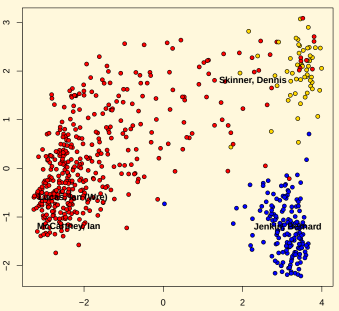

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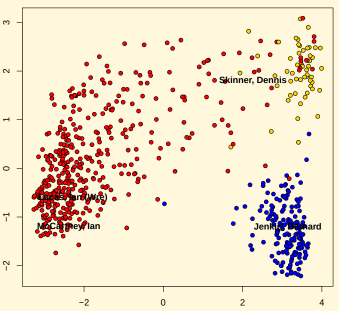

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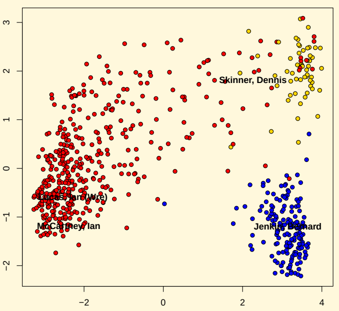

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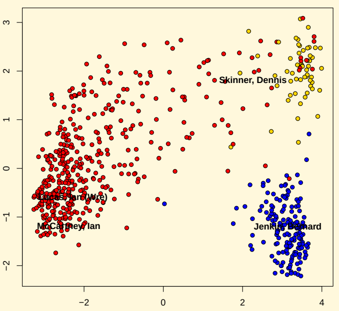

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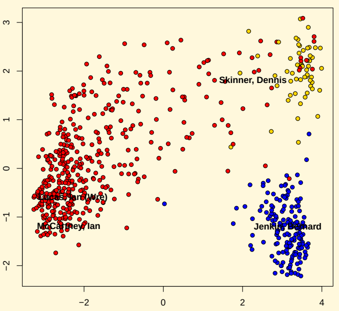

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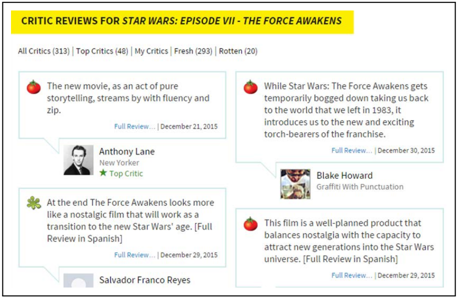

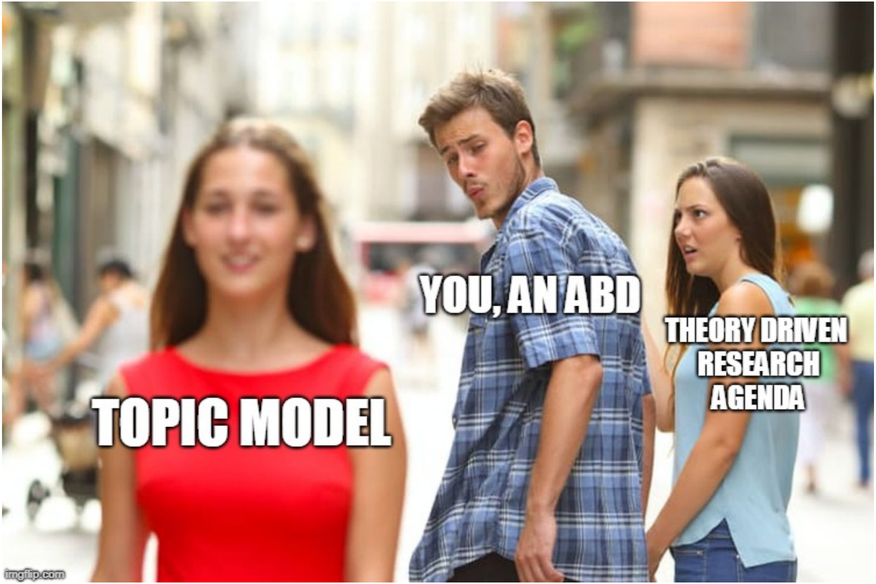
YOU, AN ABD
THEORY DRIVEN RESEARCH AGENDA
TOPIC MODEL
imgflip.com

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Statistical properties rarely discussed in measurement sense (today)

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for unsupervised problems, exists related problem (we) called **PEACH**ing: Presenting Explorations As Confirmable Hypotheses.

→ researchers (haphazardly) explore a corpus (e.g. via topic models), but then present these explorations as hypotheses to be tested

2. Complexity

Lexical Diversity

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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

Members of Iraq's elite counter-terrorism service secure a neighborhood in the city of Ramadi.

Photo: Getty Images

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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

Email

Share

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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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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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100	this entry right here.

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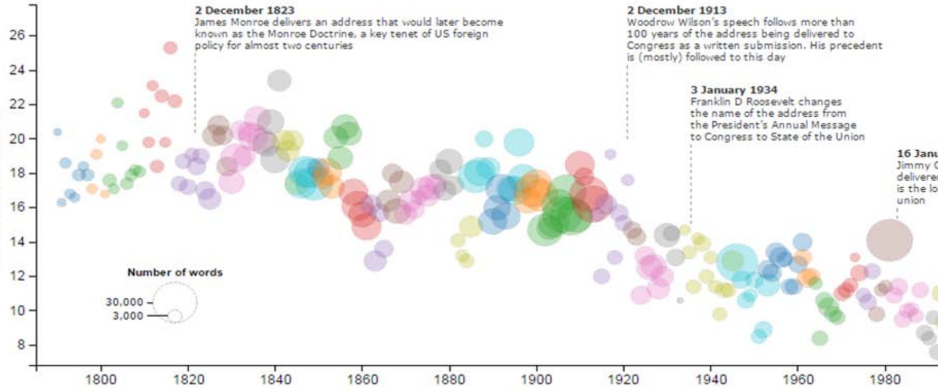
The state of our union is ... dumber:

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



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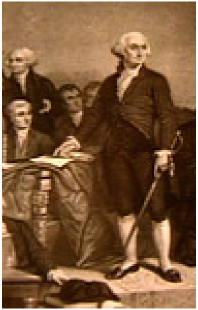

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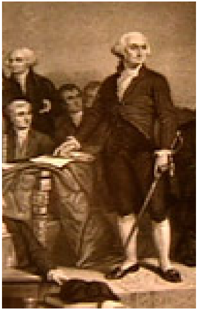

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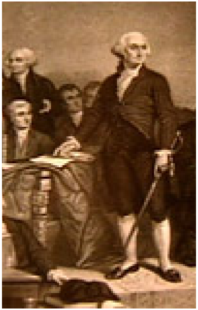

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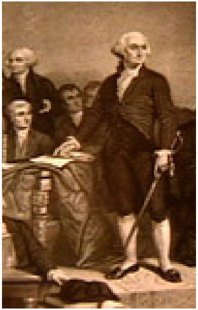

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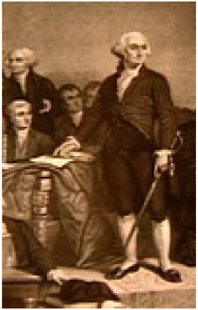
Does the nature of the decline suggest that speeches are becoming simpler for demand (i.e. voter) or supply (i.e. leader) incentive reasons?

Partner Exercise



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The Great Sentence Length Shift (Benoit, Munger & Spirling)

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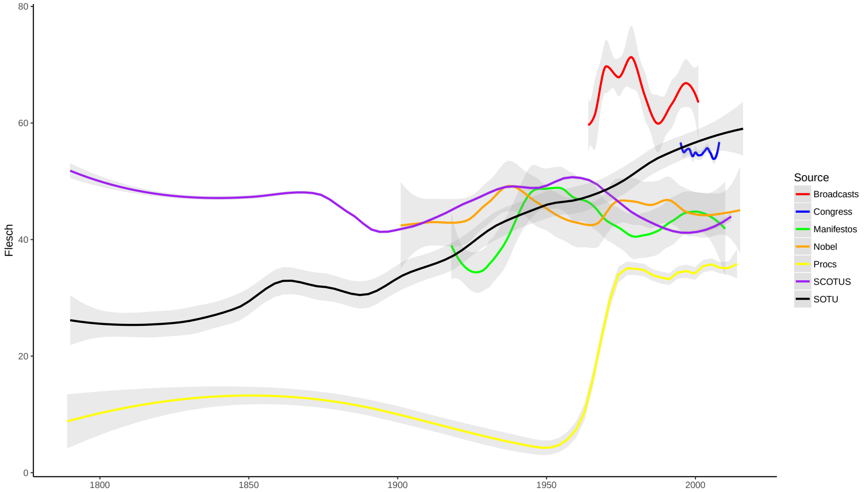

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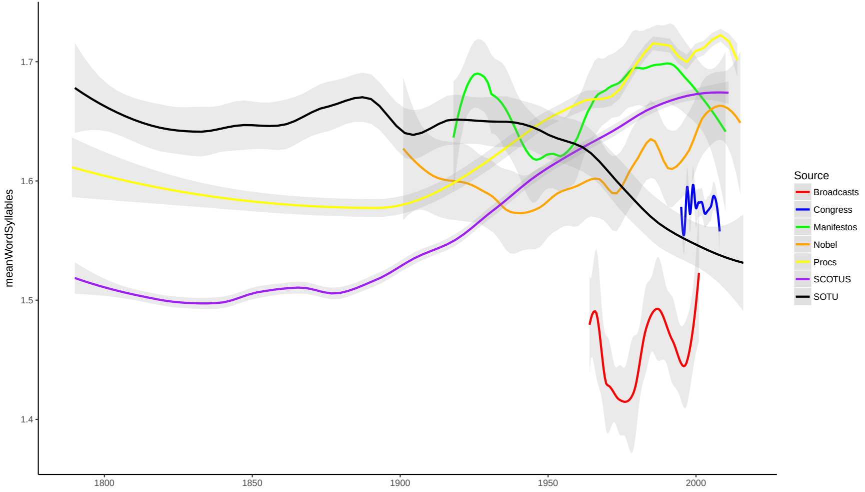

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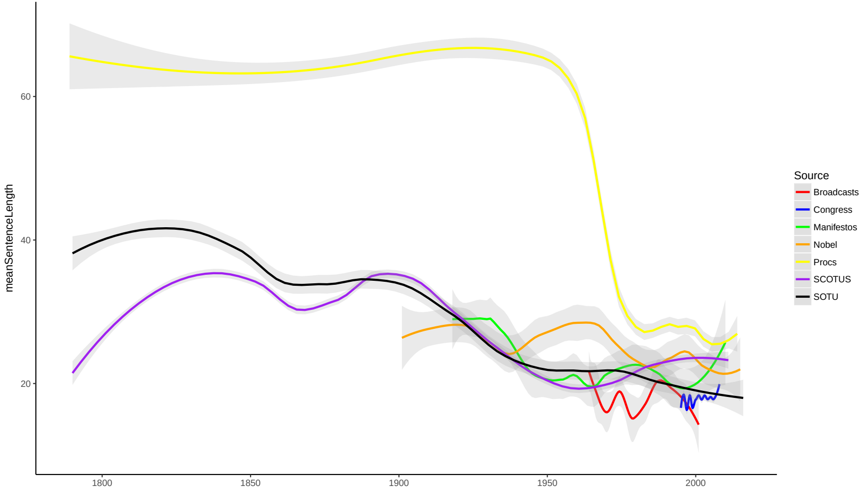

3. Doing Better

Can we do better?

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i.e. have I, personally, written a paper about this?

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Key innovation:

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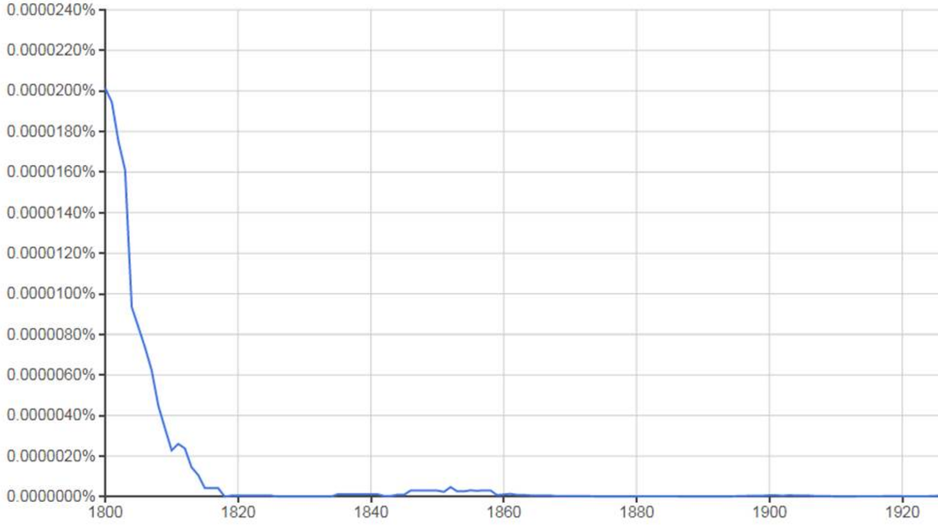
Two variables: *minimum* rarity of word in a snippet (highest when rarest word in snippet is common in corpus); *mean* rarity (lowest when average rarity is low—i.e. words in snippet are common in corpus)

Cleaning: On the incidence of `ftupid`



Performance Compared

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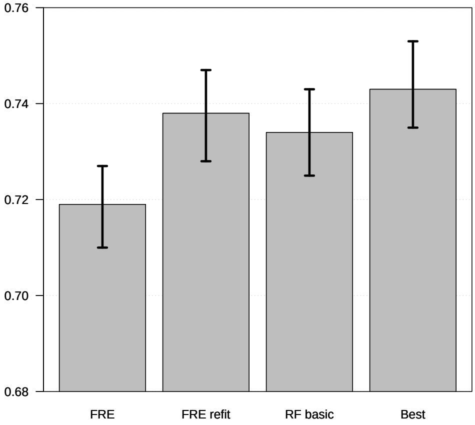

Our best model is preferred, and offers a ‘real’ improvement over FRE.

Why We Beat FRE

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

4. 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

More Details

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
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More Details

may think that sentence length distinguishes authors

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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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Data is all speeches by backbenchers in UK HoC, 1935–2018

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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)

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Estimation/fitting generally fast.

Validation

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Compare mentions in *The Guardian* (for relevant parliamentary session)

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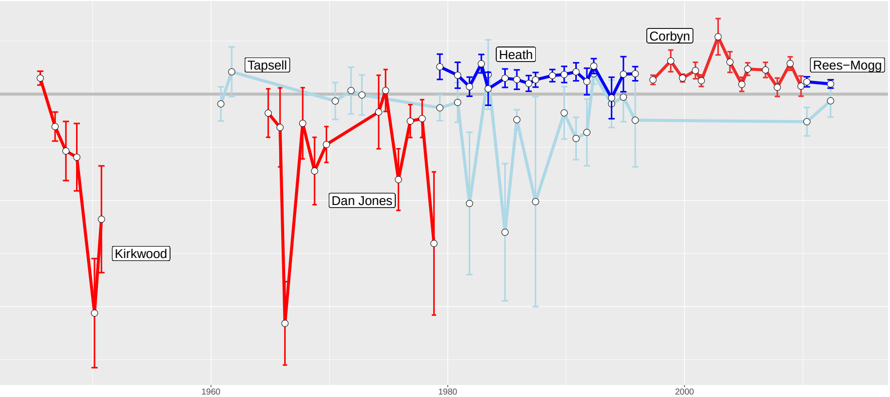

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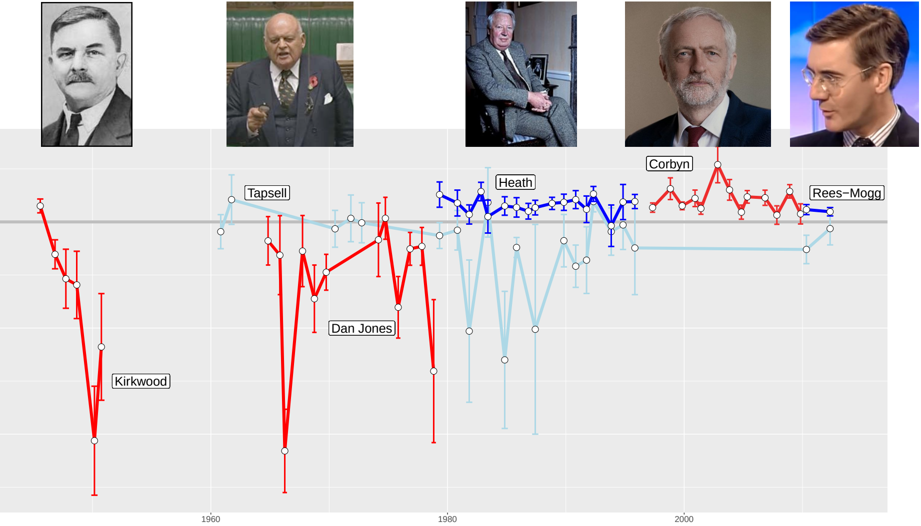

Average Level of Boringness is Constant!

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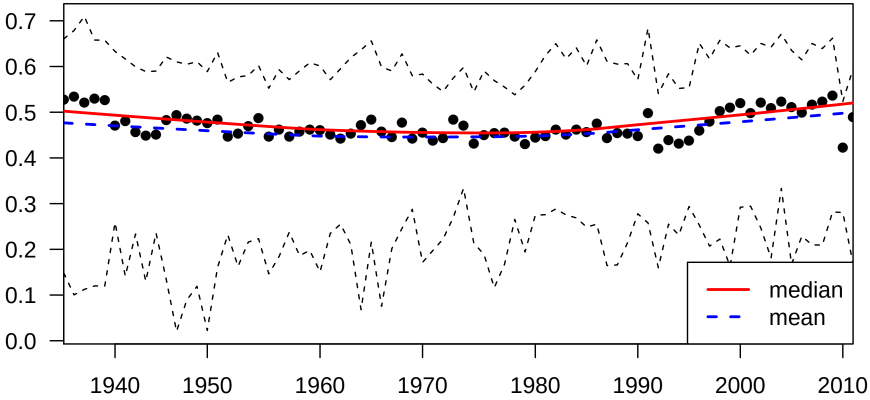
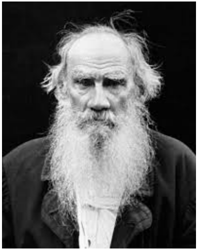


6. Thinking about Uncertainty

Partner Exercise

Partner Exercise



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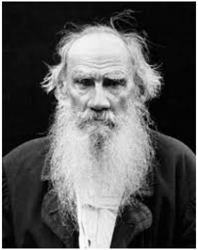

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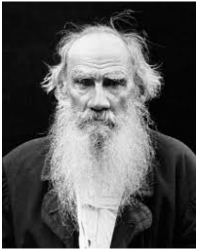
Partner Exercise



Suppose you wanted to compare the novels of Leo Tolstoy and J.D. Salinger.

1. You estimate the FRE score for *War and Peace* and compare it to the FRE of *The Catcher in the Rye*. Which estimate are you more confident in?

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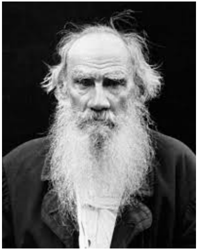

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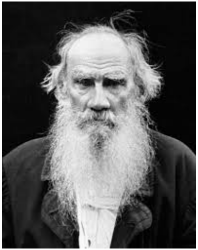

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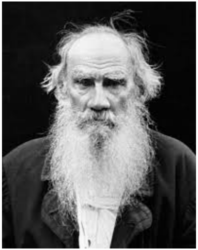

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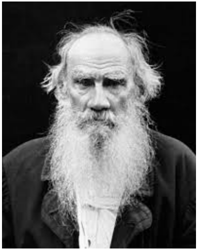

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$\rightarrow$ think a little more systematically about the sampling distribution of a statistic.

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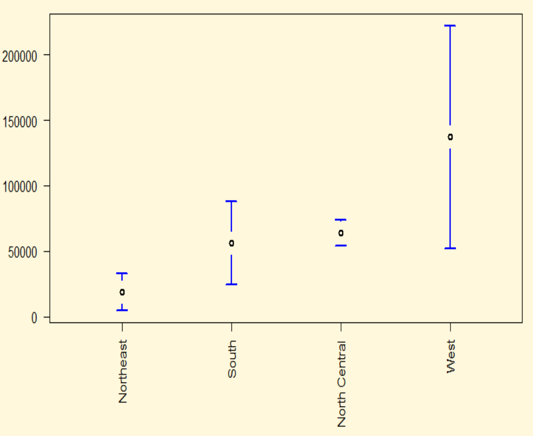

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$\rightarrow$ difficult to know how we should calculate the sampling distribution and thus the standard error.

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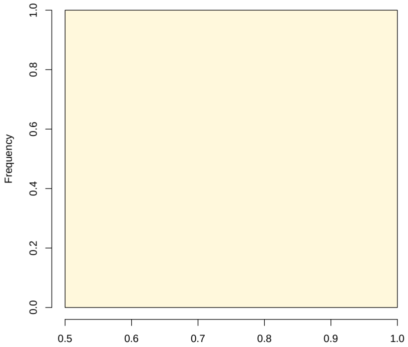

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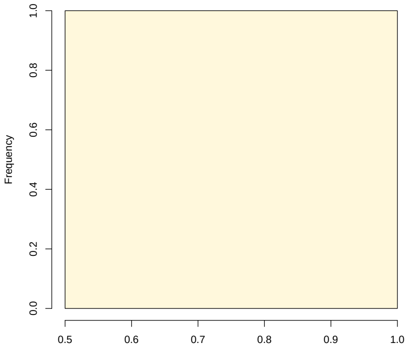

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btw long texts give rise to smaller SEs than short ones, which makes sense!

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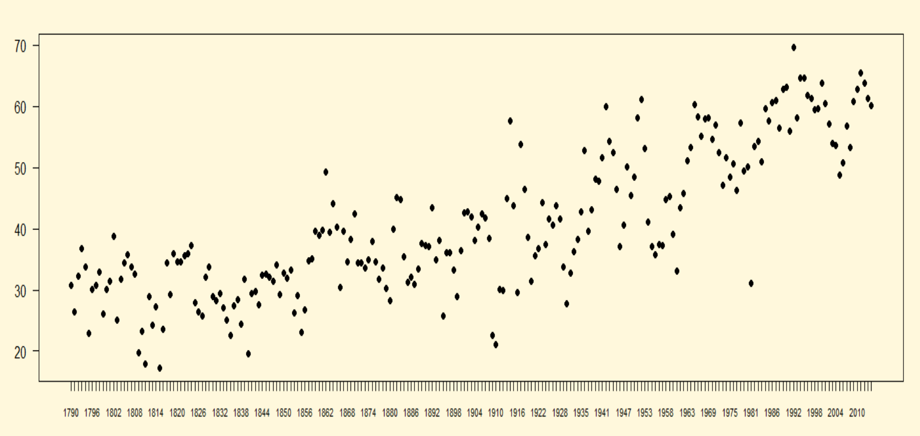

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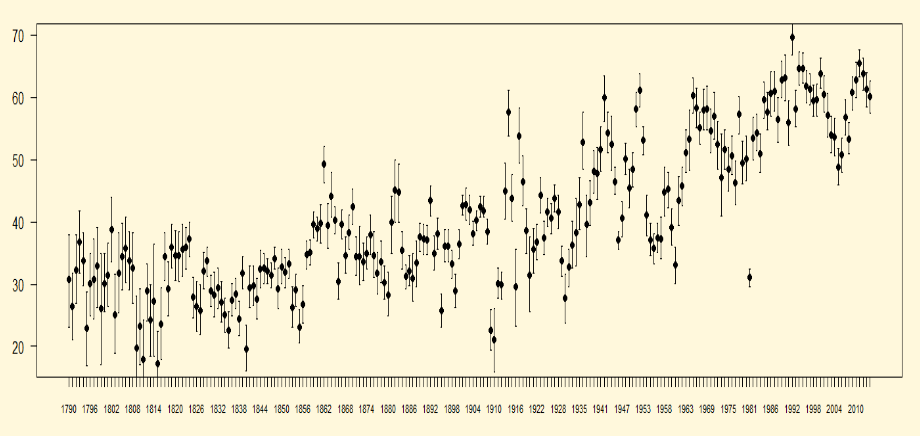

7. Embeddings: What Works and What Doesn't?

Big Picture(s)

Which one of these Rembrandts do you prefer?

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What should political scientists that want to apply embeddings do?

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We get remarkable, human-like performance from embeddings models in terms of meaning. ✓

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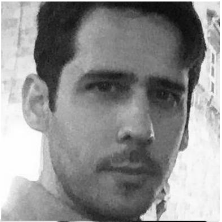
Pretrained embeddings work about as well as anything else. ✓

Thank you!



GitHub:
`http://github.com/ArthurSpirling/EmbeddingsPaper`

Paper:
`../Paper/Embeddings_SpirlingRodriguez.pdf`

FAQ:
`../Project_FAQ/faq.md`