Modeling Complexity, Style and Representation in Language

Measurement From Text

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New York University

July 12, 2019

1. The Temptation of Unsupervised Learning

Recall

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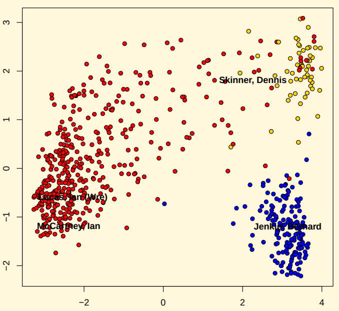

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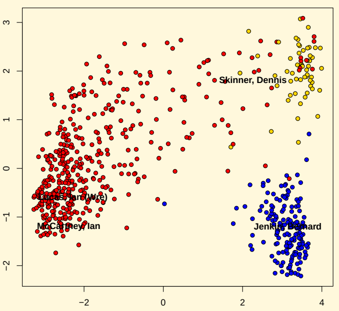

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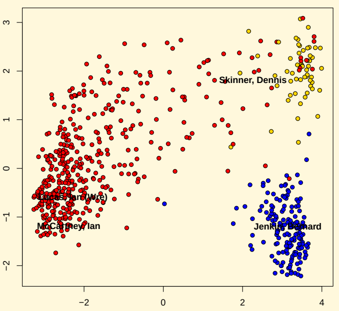

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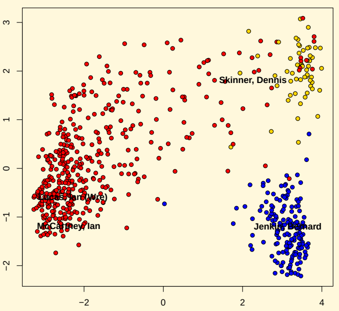

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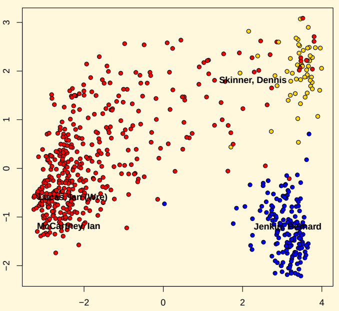

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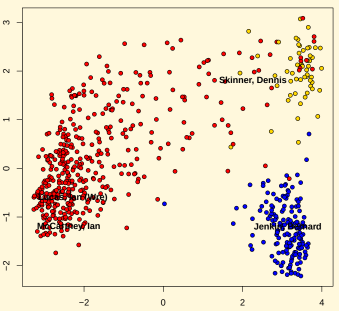

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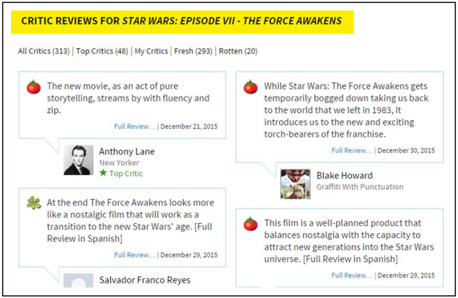

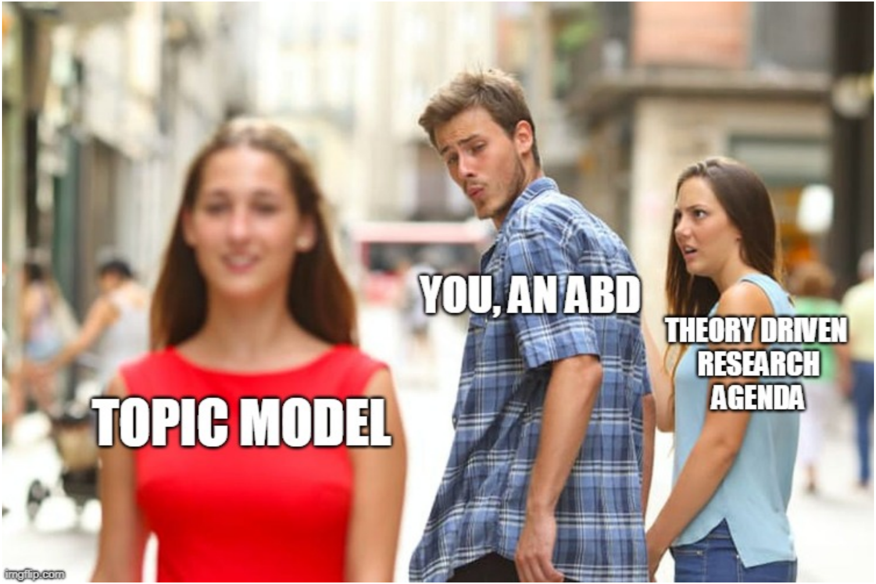
TOPIC MODEL
YOU, AN ABD
THEORY DRIVEN RESEARCH AGENDA
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Statistical properties rarely discussed in measurement sense (today)

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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

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

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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

MORE ON: ISIS

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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

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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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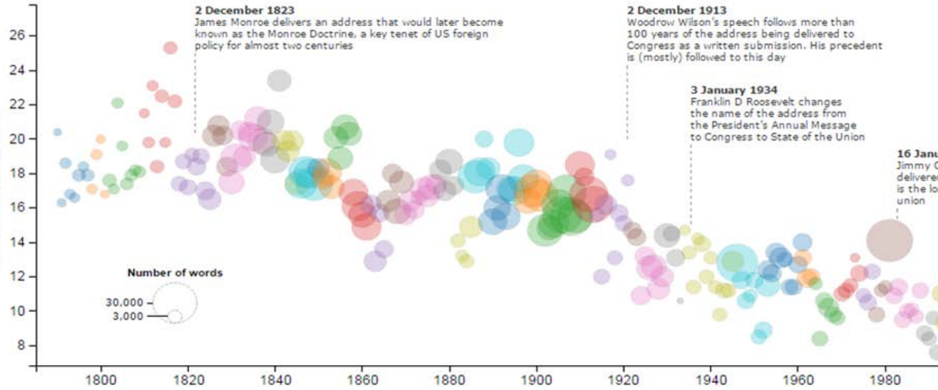
The state of our union is ... dumber:

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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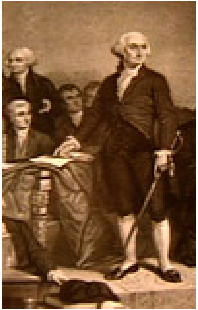

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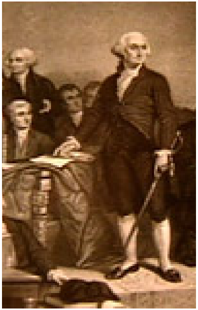

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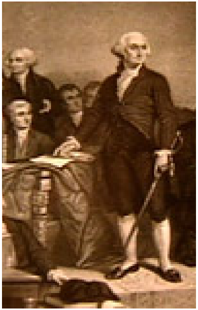

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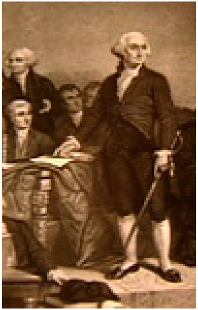

The FRE of SOTU speeches is increasing. Why might it be difficult to make readability comparisons over time? (hint: when were the reading ease measures invented? are topics of speeches constant? were addresses always delivered the same way?)

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

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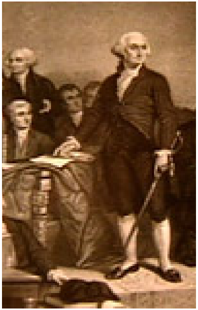

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The Great Sentence Length Shift (Benoit, Munger & Spirling)

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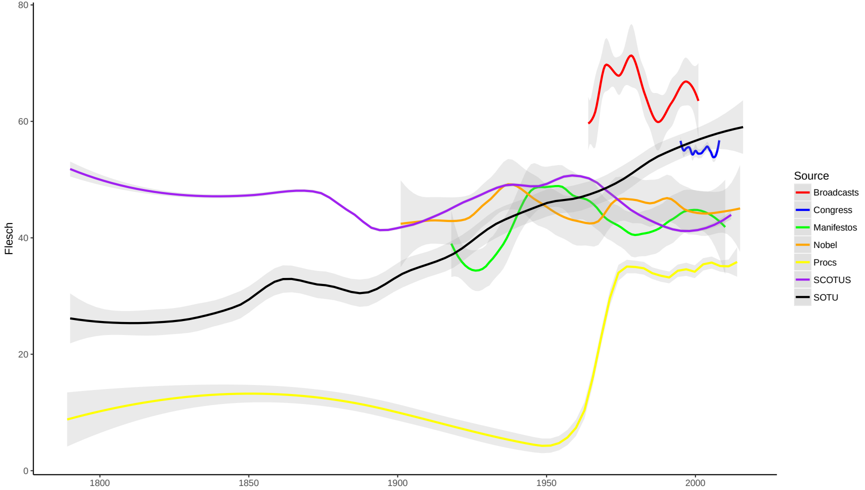

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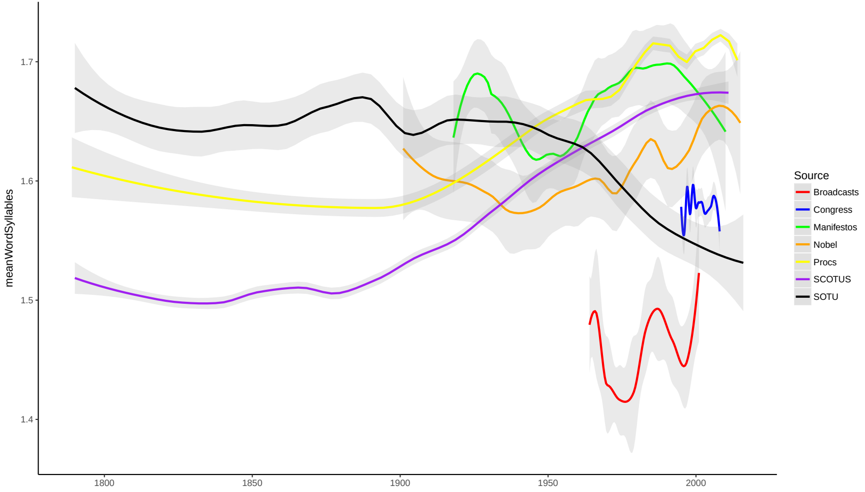

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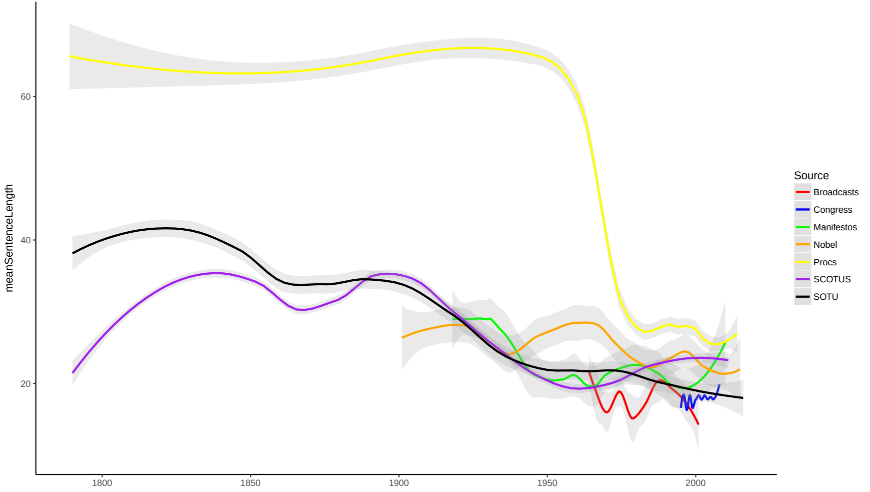

3. Doing Better

Can we do better?

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

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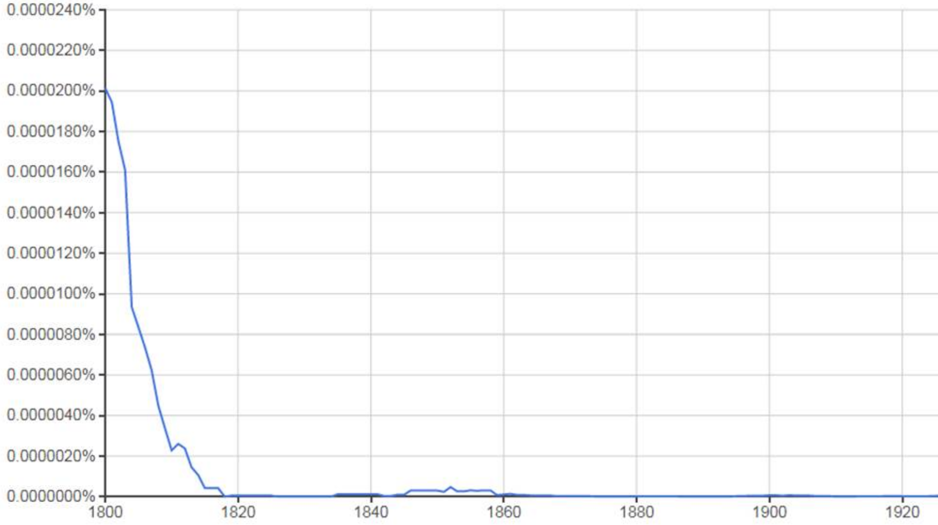
Two variables: *minimum* rarity of word in a snippet (highest when rarest word in snippet is common in corpus); *mean* rarity (lowest when average rarity is low—i.e. words in snippet are common in corpus)

Cleaning: On the incidence of `ftupid`



Performance Compared

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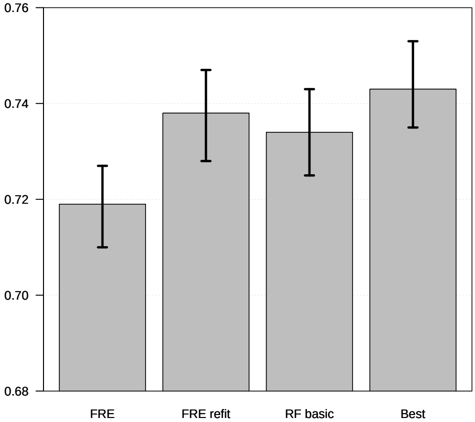

Our best model is preferred, and offers a ‘real’ improvement over FRE.

Why We Beat FRE

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I speak to you not just as a President, but as a father, when I say that responsibility for our children's education must begin at home.

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

4. Style and Stylometrics

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use Bayes' theorem to determine the posterior probability that Hamilton (Madison) wrote a particular disputed essay for all such essays

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
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must	our	there	which
and	do	his	my
things	who	any	down
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are	even	in	not
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More Details

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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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Estimation/fitting generally fast.

Validation

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

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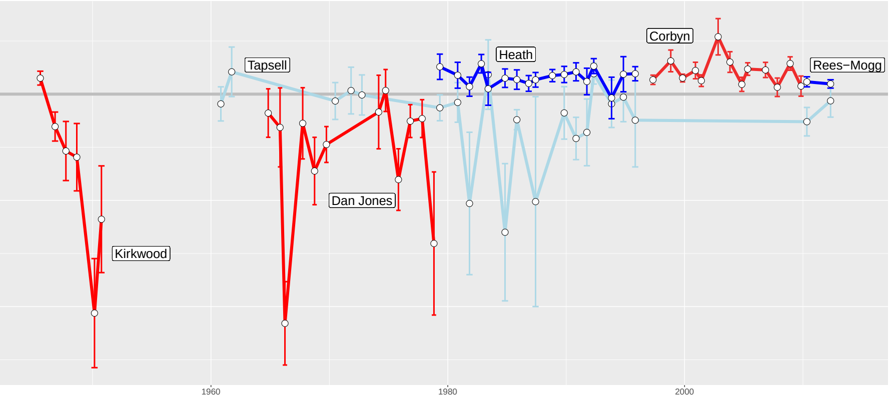
Usual Suspects (Z normalization)



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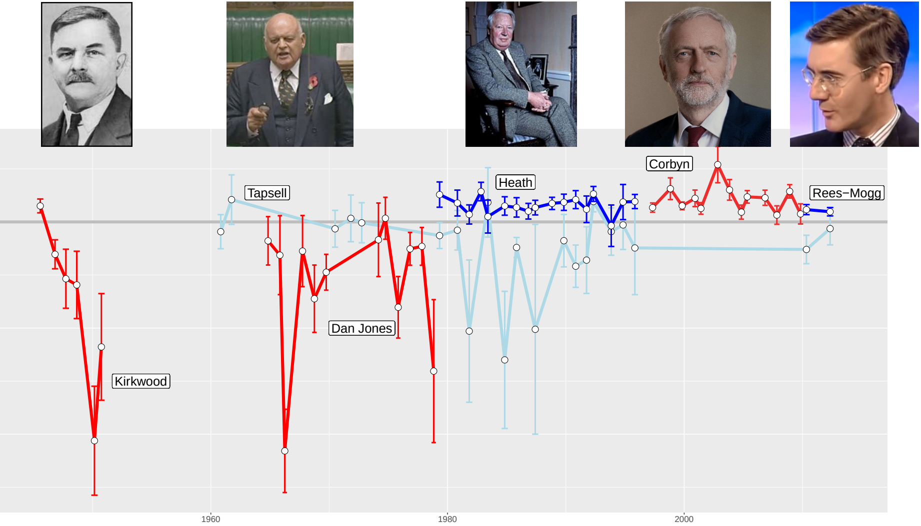

Average Level of Boringness is Constant!

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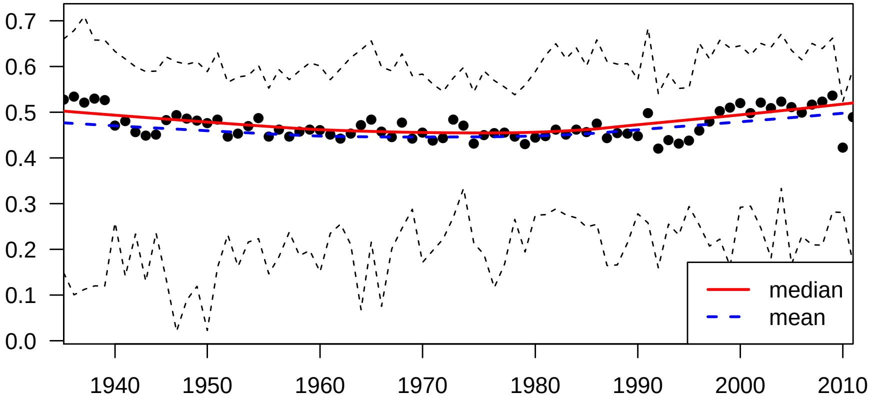
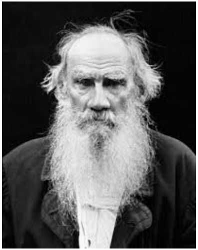


6. Thinking about Uncertainty

Partner Exercise

Partner Exercise



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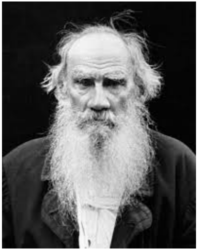

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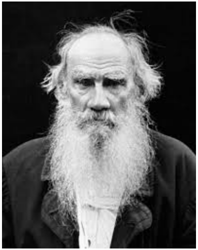
Partner Exercise



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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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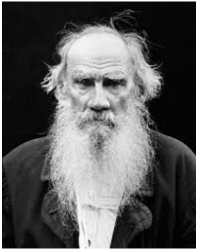

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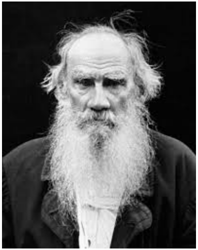

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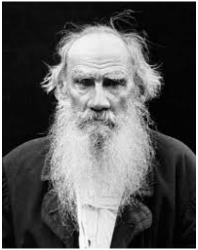

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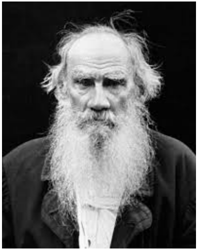

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$\rightarrow$ think a little more systematically about the sampling distribution of a statistic.

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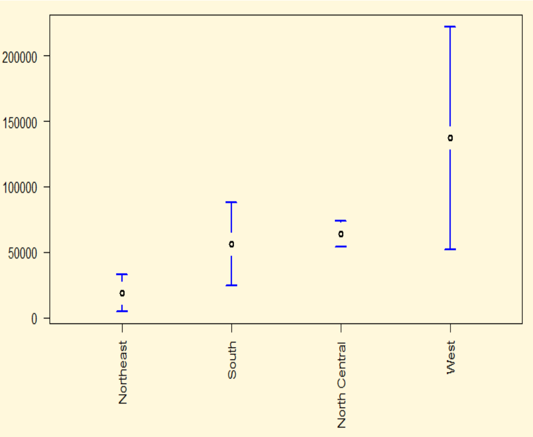

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$\rightarrow$ difficult to know how we should calculate the sampling distribution and thus the standard error.

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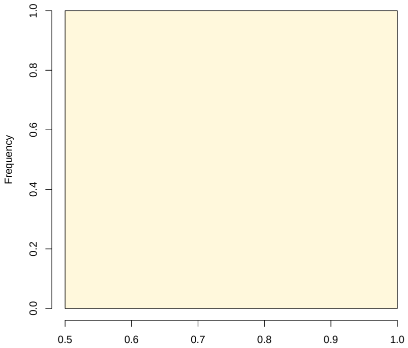

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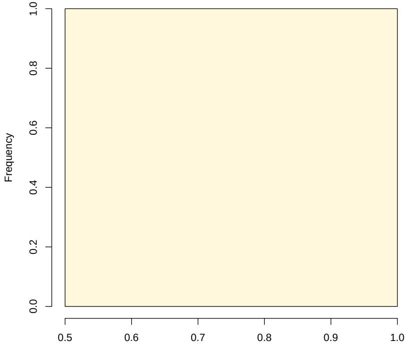

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btw long texts give rise to smaller SEs than short ones, which makes sense!

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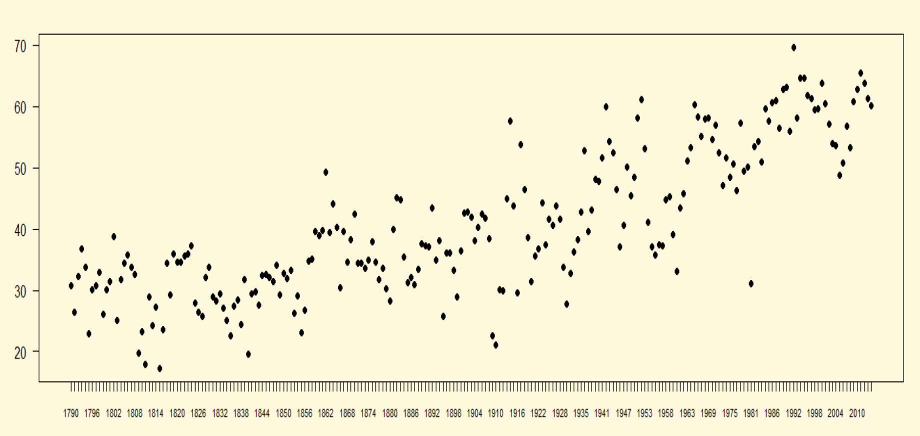

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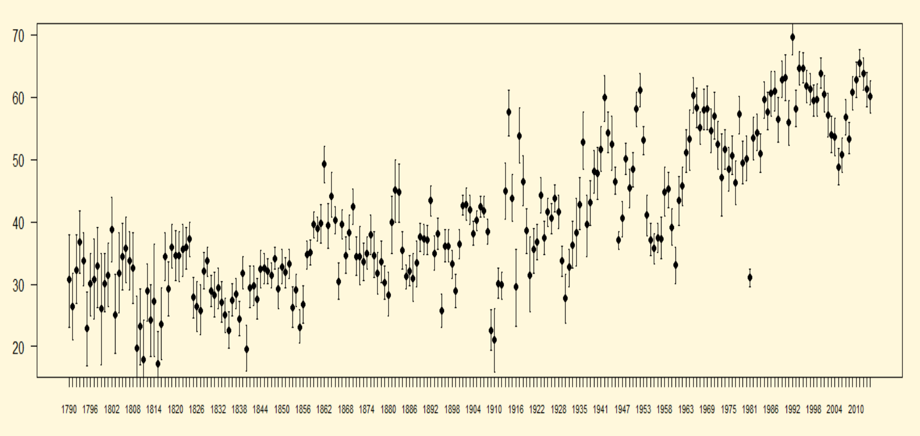

7. Embeddings: What Works and What Doesn't?

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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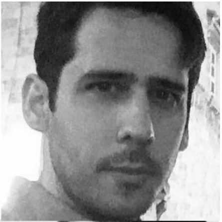
Pretrained embeddings work about as well as anything else. ✓

Thank you!




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

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

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