# 3. Descriptive Inference II

DS-GA 1015, Text as Data
Arthur Spirling

Feb 19, 2019

# Housekeeping

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Looking to push a homework out ~Feb 20:

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Looking to push a homework out ∼Feb 20: be clear about the academic honesty policy. Do not copy another student's work, or allow them to copy yours.

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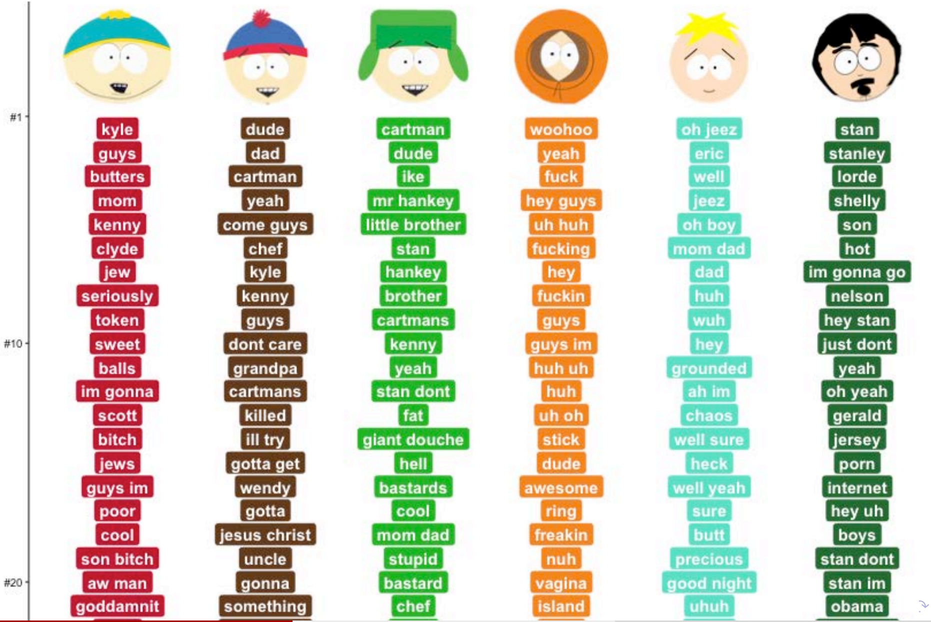
Walker considers transcripts of South Park (preprocessed), and collapses on character (treating all other characters' speeches as the corpus when estimating)...

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



# Where Are We?

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


:)

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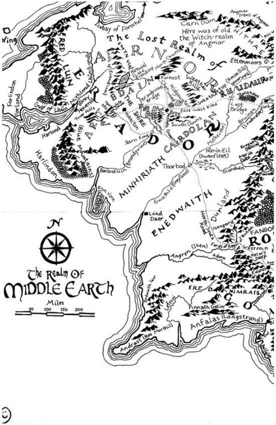


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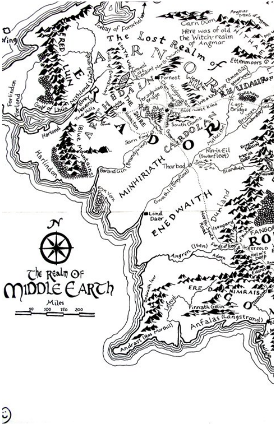


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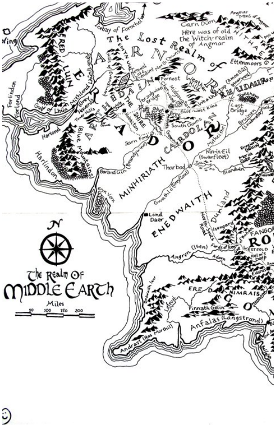


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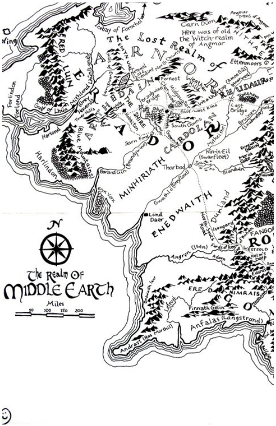


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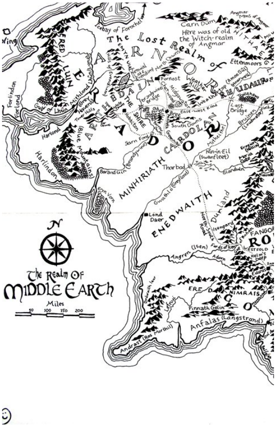


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e.g. authors with limited vocabularies will have a low lexical diversity.

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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

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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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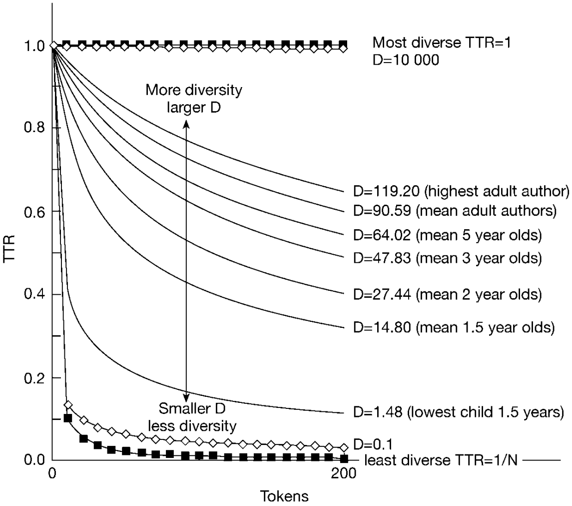


*Figure 1: Model TTR plotted against samples of increasing length for different values of* D

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→ 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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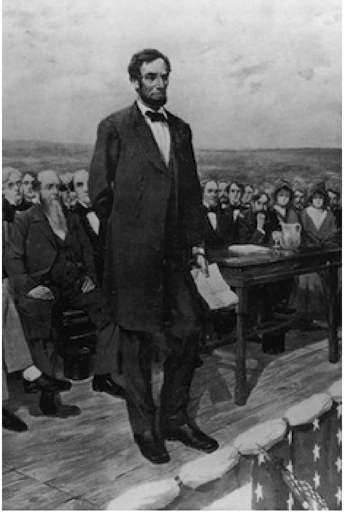

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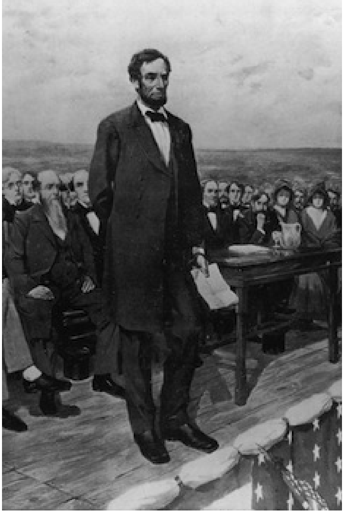

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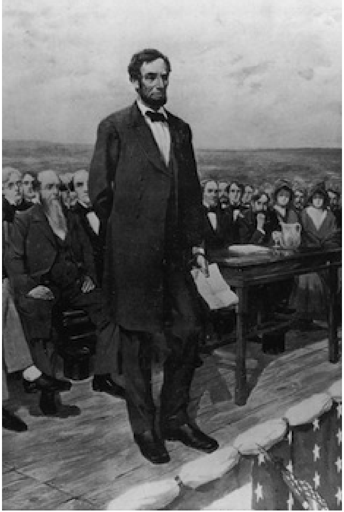

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- Kincaid et al later translate to US School grade level that would be (on average) required to comprehend text.

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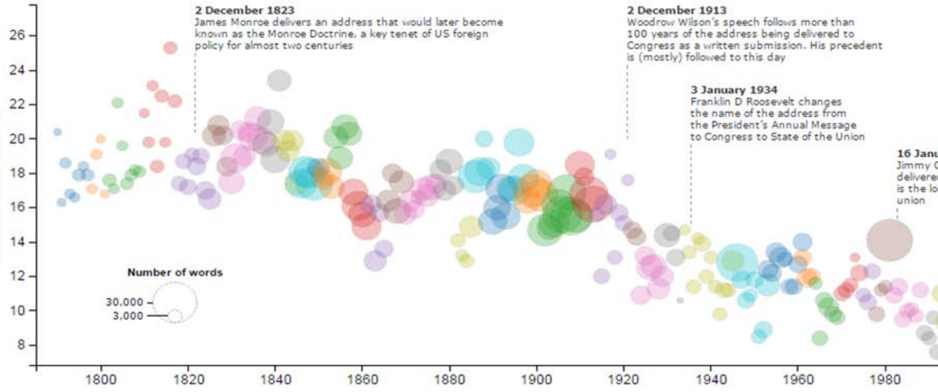
- ± rules for special endings and use of consonents (e.g. `hassle` vs `mule`)

# 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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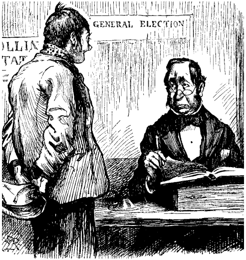

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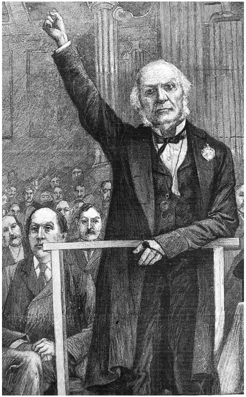

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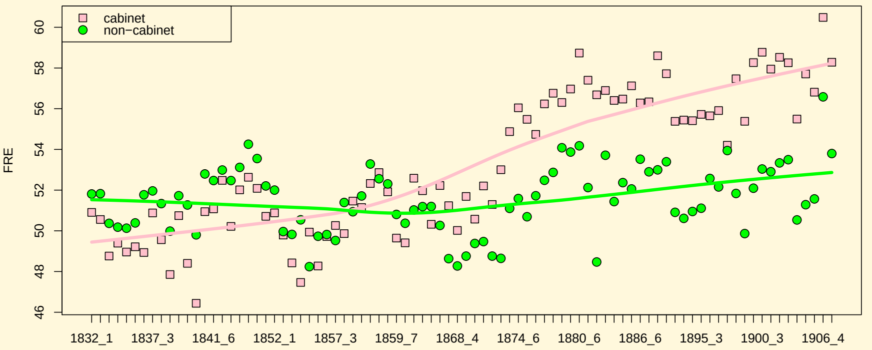

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e.g. `about`, `back`, `call`, etc.

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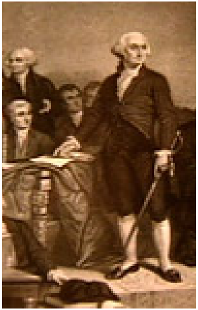

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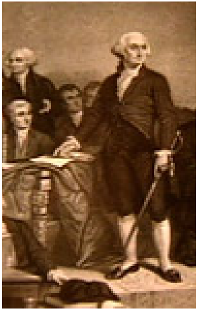

The FRE of SOTU speeches is increasing. Why might it be difficult to make readability comparisons over time?

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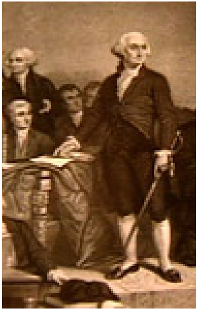

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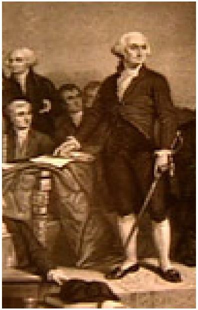

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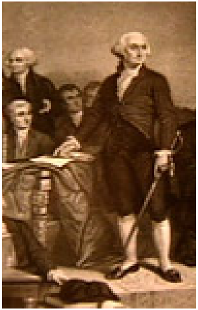

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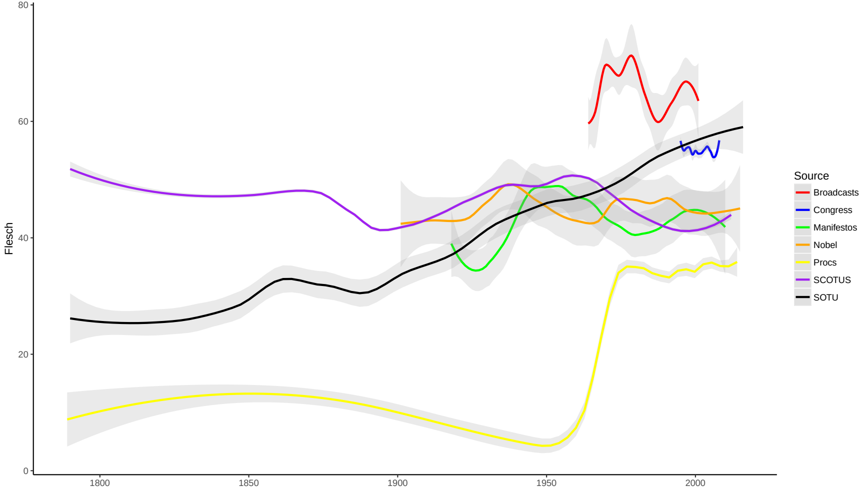

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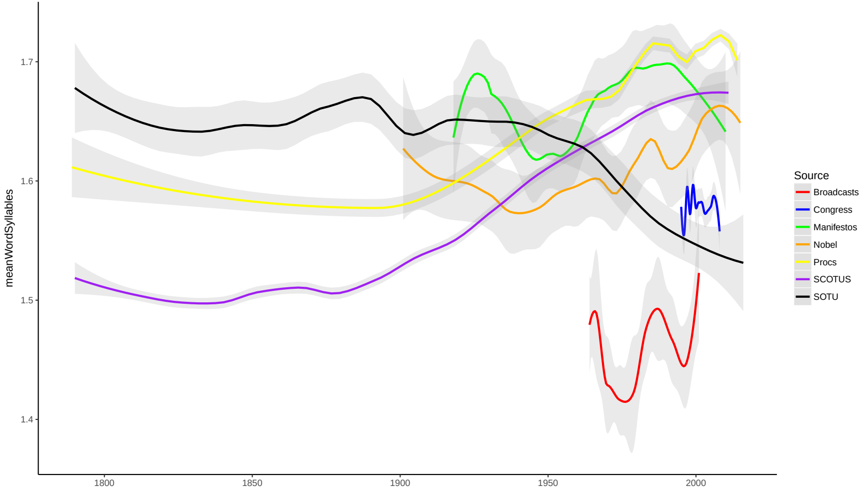

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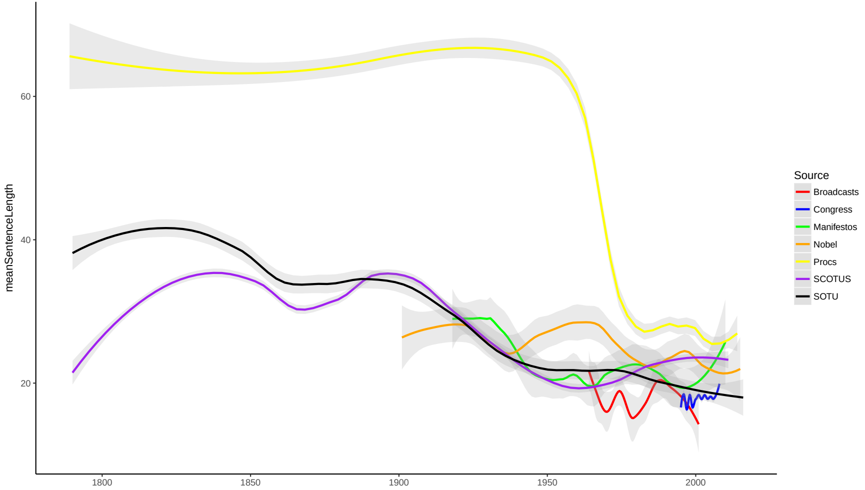

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# Paper and Software

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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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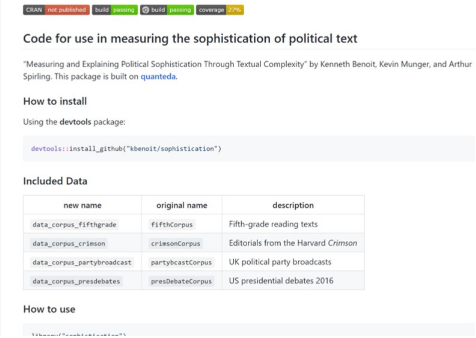

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# Style and Stylometrics

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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

# 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 |
| 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

may think that sentence length distinguishes authors

| | | | |
|---|---|---|---|
| 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

| | | | |
|---|---|---|---|
| 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 | | | |

may think that sentence length distinguishes authors, but Hamilton and Madison “practically twins” on this.

# 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 |
| 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 | | | |

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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 | | | |

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# 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 |
| 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 | | | |

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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 |
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# 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 |
| are | even | in | not |
| some | to | with | as |
| every | into | now | such |
| up | would | at | for |
| is | of | than | upon |
| your | be | from | it |
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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 |
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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 | | | |

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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 |
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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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let $X_w$ be number of times word $w$ appears in a document.

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and Negative Binomial (which adds a gamma distributed random effect, $\delta$):

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

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$+$ confirmed by many subsequent analyses (via e.g. machine learning)

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# Application: 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.

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

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Estimation/fitting generally fast.

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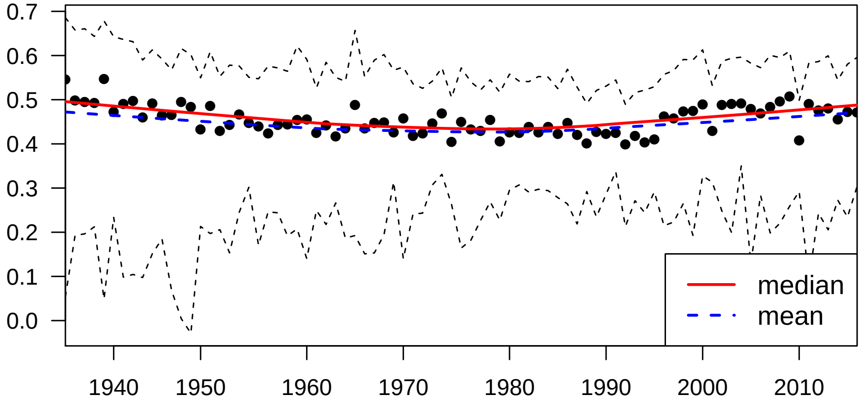

Paper:
http://nyu.edu/projects/spirling/documents/VeryBoring.pdf

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

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

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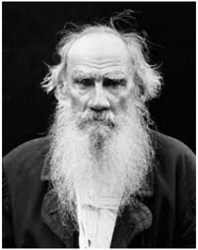

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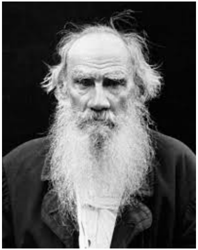

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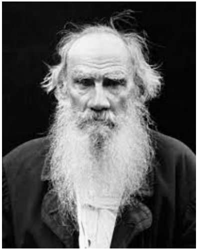

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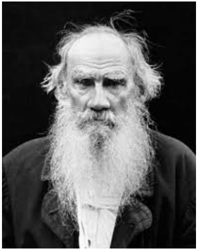

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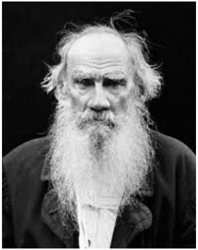

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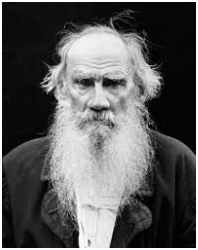

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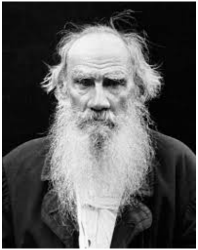

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→ think a little more systematically about the sampling distribution of a statistic.

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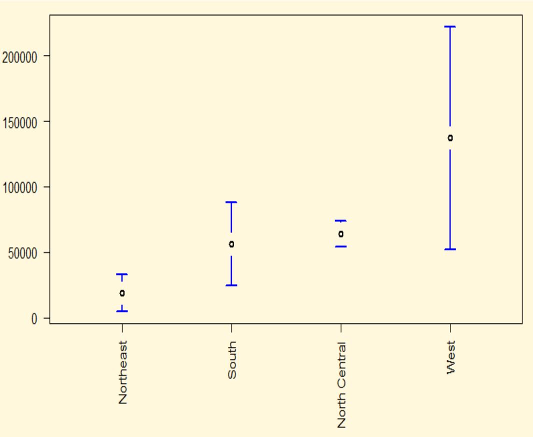

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$\rightarrow$ difficult to know how we should calculate the sampling distribution and thus the standard error.

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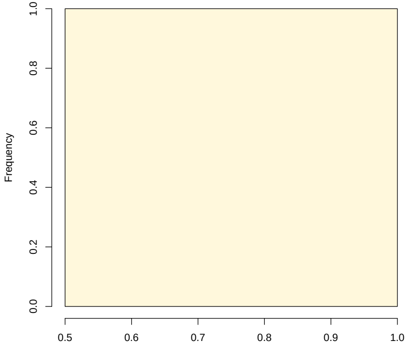

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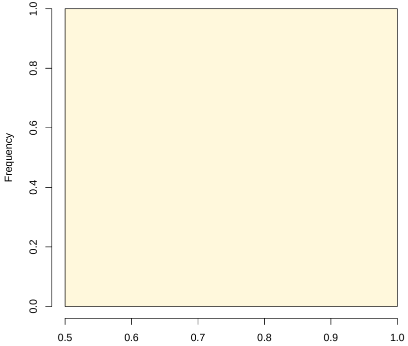

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btw long texts give rise to smaller SEs than short ones, which makes sense!

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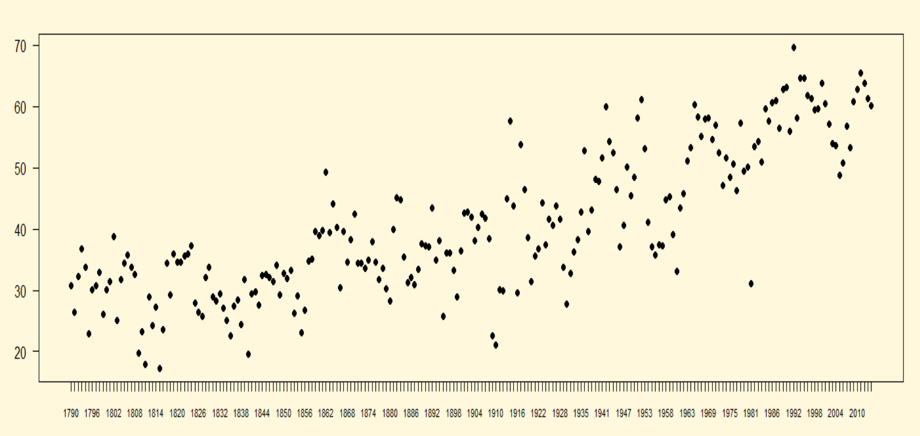

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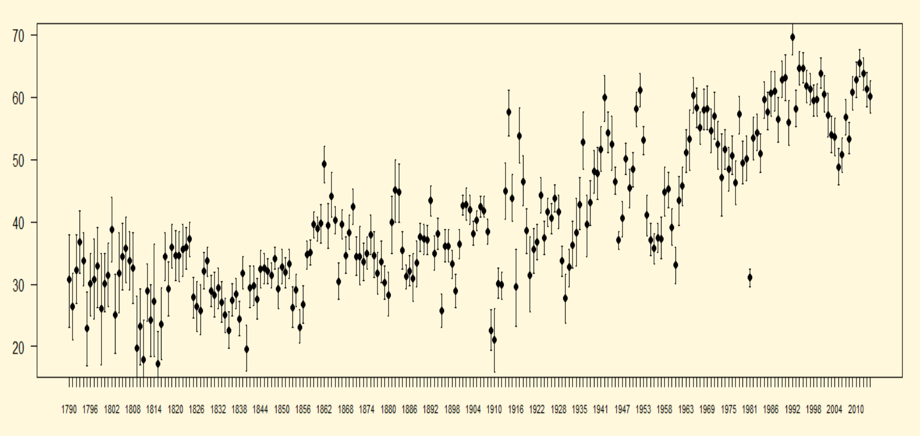

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$\rightarrow$ SIMEX (simulation-extrapolation) or MO (multiple overimputation) might be called for.

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