PLSC 597: Modern Measurement

Scaling Text

April 12, 2018

Scaling Text

Scaling, so far:

- UDS / MDS, FA/PCA, IRT
- Goal: Combine/aggregate information (data reduction)

Scaling text: Underlying assumptions...

- Individuals speaking/writing/etc. differ in systematic, measurable ways
- Those differences manifest themselves in text...
  - What they say
  - When they say it (topic selection)
  - How they say it (style, tone, etc.)
- The mapping from latent differences to text is *systematic* and observable, and
- Can be learned via analysis of the text itself

Scaling Text (continued)

IRT-type data:

```
> irt.df[1:3,1:7]
        Q1  Q2  Q3  Q4  Q5  Q6  Q7
R1       1   1   1   0   0   0   0
R2       0   0   1   1   1   0   1
R3       1   0   1   0   0   1   0
```

Intuition: Go from binary "correct / incorrect" responses to measures of latent phenomena.

A TDM:

```
> tdm.df[1:3,1:7]
                 ability able about above abroad absolutely abused
Debate2016-1.txt       2   13    78     1      3          5      1
Debate2016-2.txt       0   16   102     1      0          5      0
Debate2016-3.txt       0    6    75     0      0          5      0
```

Intuition: Go from word frequencies / co-occurrences to measures of latent phenomena.

Supervised Text Scoring

Basic idea:

1. We know some documents' / authors' locations

2. Assess which terms in those documents give it it's location (distinctive)

3. Use the resulting term-level scores to locate other documents

One example: "Wordscores" (originally for scoring legislative text: speeches, press releases, etc.)

Wordscores: Details

Suppose there are N legislators, $i \in \{1, 2, ...N\}$. For each legislator, we observe D_i documents. Define:

$$\begin{aligned} \boldsymbol{X}_i &= \sum_{\ell=1}^{D_i} \boldsymbol{X}_{i\ell} \\ &= \sum_{\ell=1}^{D_i} (X_{i\ell 1}, X_{i\ell 2}, \ldots, X_{i\ell J}) \end{aligned}$$

as the aggregation of words across documents for each legislator.

Set two legislators' scores:

- Legislator L is **liberal** $(Y_L = -1)$
- Legislator C is **conservative** $(Y_C = 1)$

Wordscores: Details (continued)

For each word j, define:

$$\begin{aligned} P_{jL} &= \text{The probability that a liberal uses word } j \\ P_{jC} &= \text{The probability that a conservative uses word } j \end{aligned}$$

The score for word j is:

$$\begin{aligned} S_j &= Y_C P_{jC} + Y_L P_{jL} \\ &= P_{jC} - P_{jL} \end{aligned}$$

Wordscores: Details (continued)

From there, we can scale the remaining legislators / documents. Define:

$$N_i = \sum_{j=1}^{J} \boldsymbol{X}_i$$

$\hat{\theta}_i$ is then:

$$\begin{aligned} \hat{\theta}_i &= \sum_{j=1}^{J} \left(\frac{X_{ij}}{N_i} \right) S_j \\ &= \frac{\boldsymbol{X}_i'}{N_i} \boldsymbol{S} \end{aligned}$$

Wordscores: Details (continued)

Similarly, define:

$$
\begin{aligned}
N_L &= \sum_{m=1}^{J} X_{mL} \\
N_C &= \sum_{m=1}^{J} X_{mC}
\end{aligned}
$$

And estimate P_{jL}, P_{jC}, and S_j:

$$
\begin{aligned}
P_{jL} &= \frac{\frac{X_{jL}}{N_L}}{\frac{X_{jL}}{N_L} + \frac{X_{jC}}{N_C}} \\
P_{jC} &= 1 - P_{jL} \\
&= \frac{\frac{X_{jC}}{N_C}}{\frac{X_{jL}}{N_L} + \frac{X_{jC}}{N_C}} \\
S_j &= P_{jC} - P_{jL}
\end{aligned}
$$

Wordscores: Things to Remember

- Document scores are (weighted) averages of the words in them, where
- ...the weighting is "according to the proportion of tokens of each word type in the reference document" (Lowe 2008, 357)
- So, words' importance are a function of their frequency in each document type.
- Word-level scores are similar...
- Estimated document scores have vastly underestimated variability
- Issues with rescaling original texts for comparability (Martin and Vanberg 2007; Benoit and Laver 2007)
- Lowe (2008): Wordscores $\leftrightarrow$ Correspondence Analysis $\leftrightarrow$ IRT

Unsupervised Text Scoring

Basic idea:

1. Assume that words $\mathbf{X}$ are generated according to some PDF $f(\cdot)$, with (latent) parameters θ for the units being scaled
2. Assess $\Pr(\theta|f(\cdot), \mathbf{X})$
3. Resulting posterior $\hat{\theta}$ are your scale scores

Characteristics:

- IRT-like...
- One example: "Wordfish" (also originally for scoring legislators)

Wordfish Details

Again begin with "legislators" indexed by i and words by j. Assume that words are generated according to:

$$\begin{aligned} X_{ij} &\sim \text{Poisson}(\lambda_{ij}) \\ \lambda_{ij} &= \exp(\alpha_i + \psi_j + \beta_j \times \theta_i) \end{aligned}$$

where

$$\begin{aligned} \lambda_{ij} &= \text{Rate individual } i \text{ uses word } j \\ \alpha_i &= \text{Individual } i\text{'s overall word usage} \\ \psi_j &= \text{Word } j\text{'s frequency} \\ \beta_j &= \text{Word } j\text{'s discrimination} \\ \theta_i &= \text{Legislator } i\text{'s latent position(s)} \end{aligned}$$

One interpretation: A "regression" of X_{ij} on ideal points θ_i, where we have to learn θ_i.

WordFish Details

The assumptions above imply the following posterior distribution for the parameters (Slapin and Prokschk 2008):

$$\Pr(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{\psi}, \boldsymbol{\beta}) \propto \Pr(\boldsymbol{\alpha}) \Pr(\boldsymbol{\beta}) \Pr(\boldsymbol{\psi}) \Pr(\boldsymbol{\theta}) \times \prod_{i=1}^{N} \prod_{j=1}^{J} \frac{\exp\left[-\left(\alpha_i + \psi_j + \beta_j \times \theta_i\right)\right] \left(\alpha_i + \psi_j + \beta_j \times \theta_i\right)^{X_{ij}}}{X_{ij}!}$$

Estimation accomplished by (choose one):

- EM
- MCMC
- Variational Approximation

WordFish...

- Yields estimates of the parameters $(\hat{\theta}, \hat{\alpha}, \hat{\psi}, \hat{\beta})$
- Also provides estimates of variability (method varies by estimation approach)
- More recently: Also estimates ideological clarity / ambiguity (Lo, Proksch and Slapin 2014 *BJPS*)

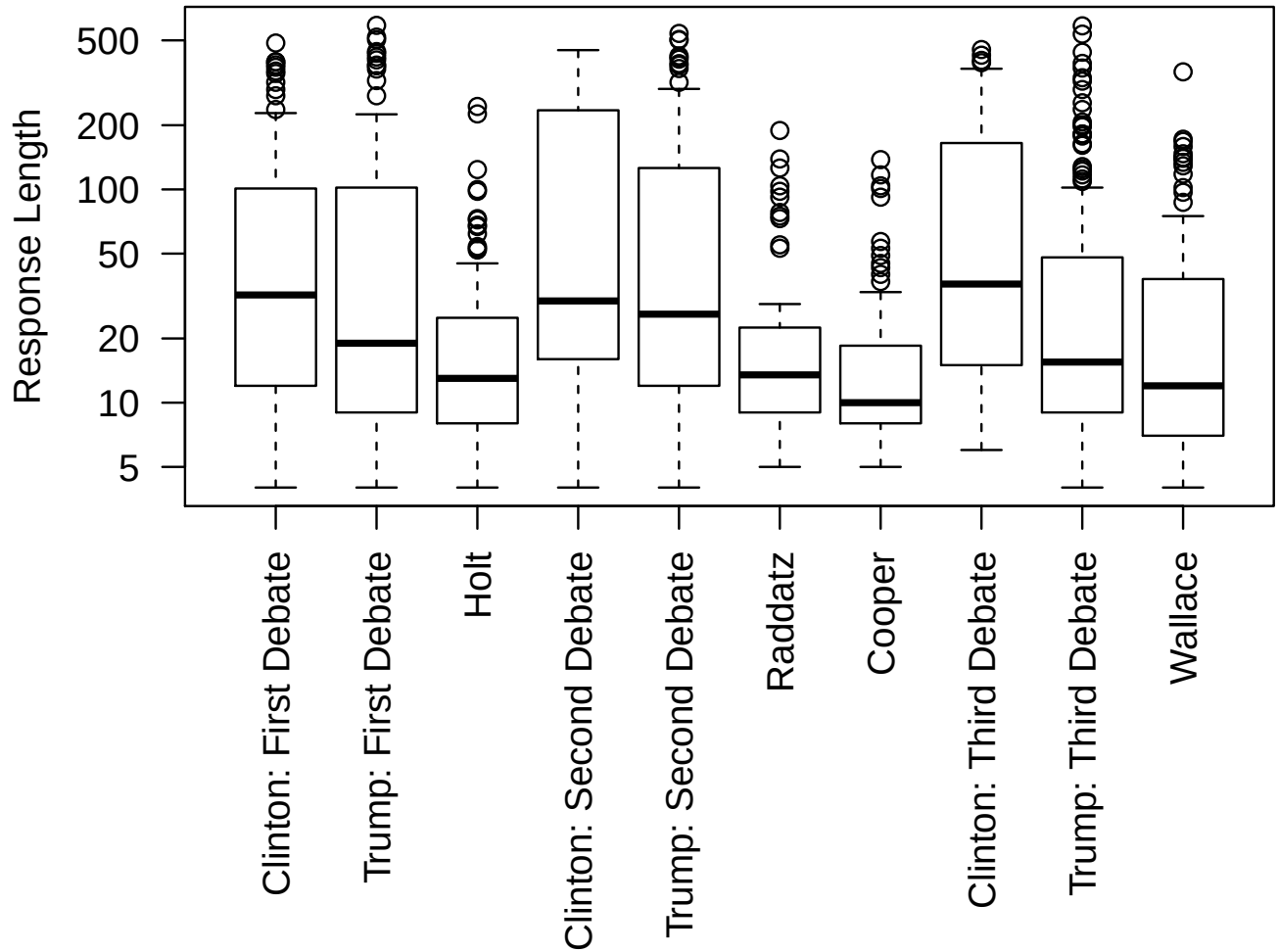
Text Scaling: Options in R

- `quanteda` (Benoit et al.)
- `austin` (Lowe)
- Various others (e.g., Slapin's `wordfish` code)

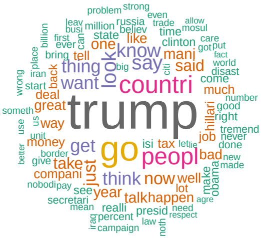
Example: The 2016 Presidential Debates

- Transcripts from all three general election (Clinton/Trump) debates
  - First Debate: 9/26/16, Hofstra University (Lester Holt moderating)
  - Second Debate: 10/9/16, Washington University (Martha Raddatz and Anderson Cooper moderating, town hall format)
  - Third Debate: 10/19/16, UNLV (Chris Wallace moderating)
- $N = 922$ "documents" (instances of one person speaking), 3986 sentences, 59256 tokens (34943 unique terms)
- Goals:
  - Scale Clinton, Trump, perhaps the moderators
  - Assess change from one debate to the next
  - ???

Length of Responses



Word Clouds!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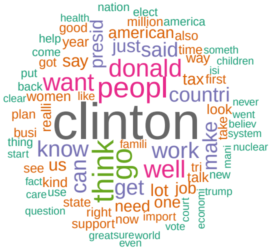
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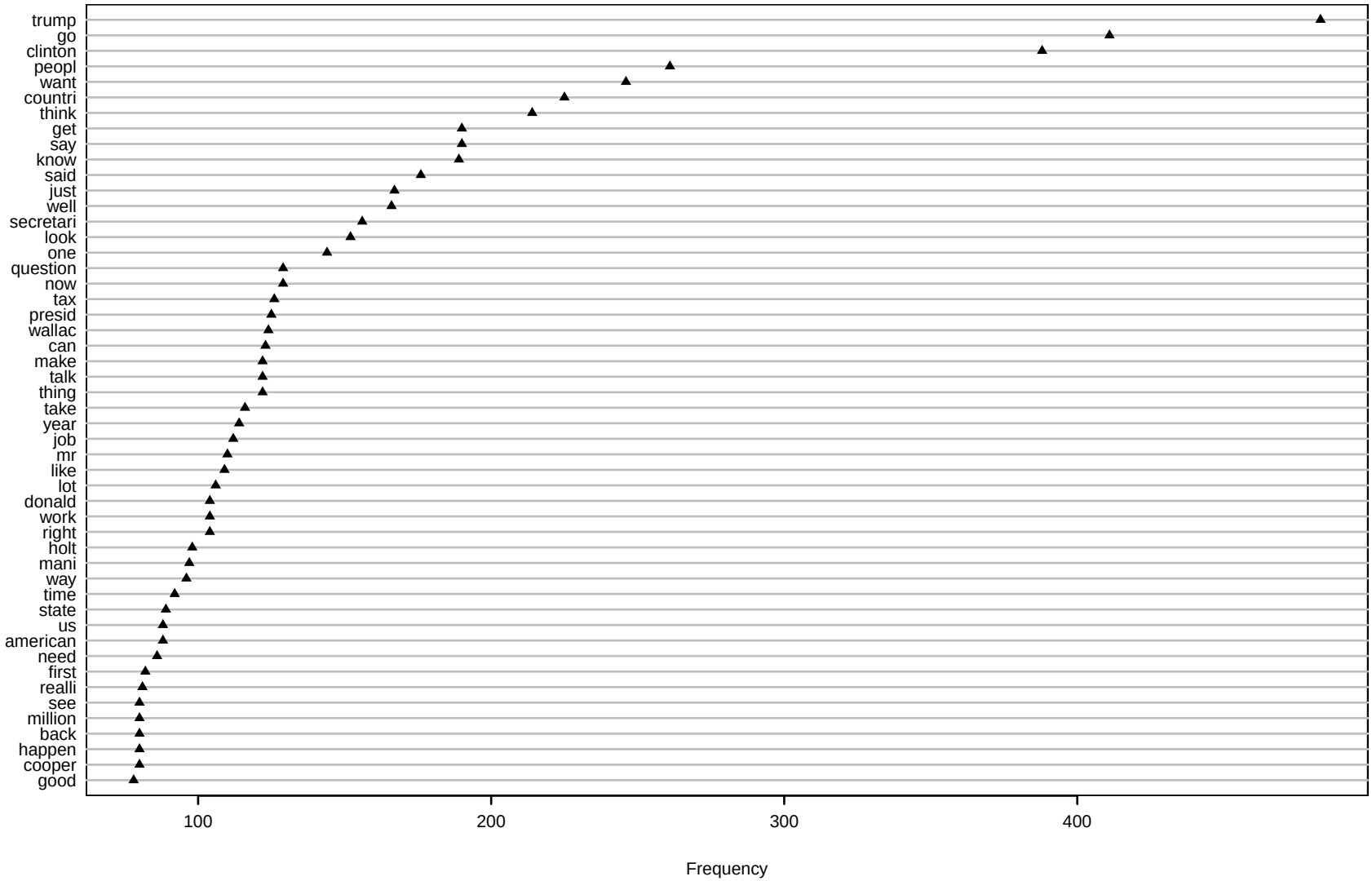
Top 50 Words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300
400
Frequency

Diversion: "Keyness"

Q: How good is a word (say, "terrorist") at *discriminating* among documents?

- Equally common (or rare) in both = not very
- Common in one, rare in the other = *very*

Intuition: a χ^2 statistic from a 2×2 frequency table:

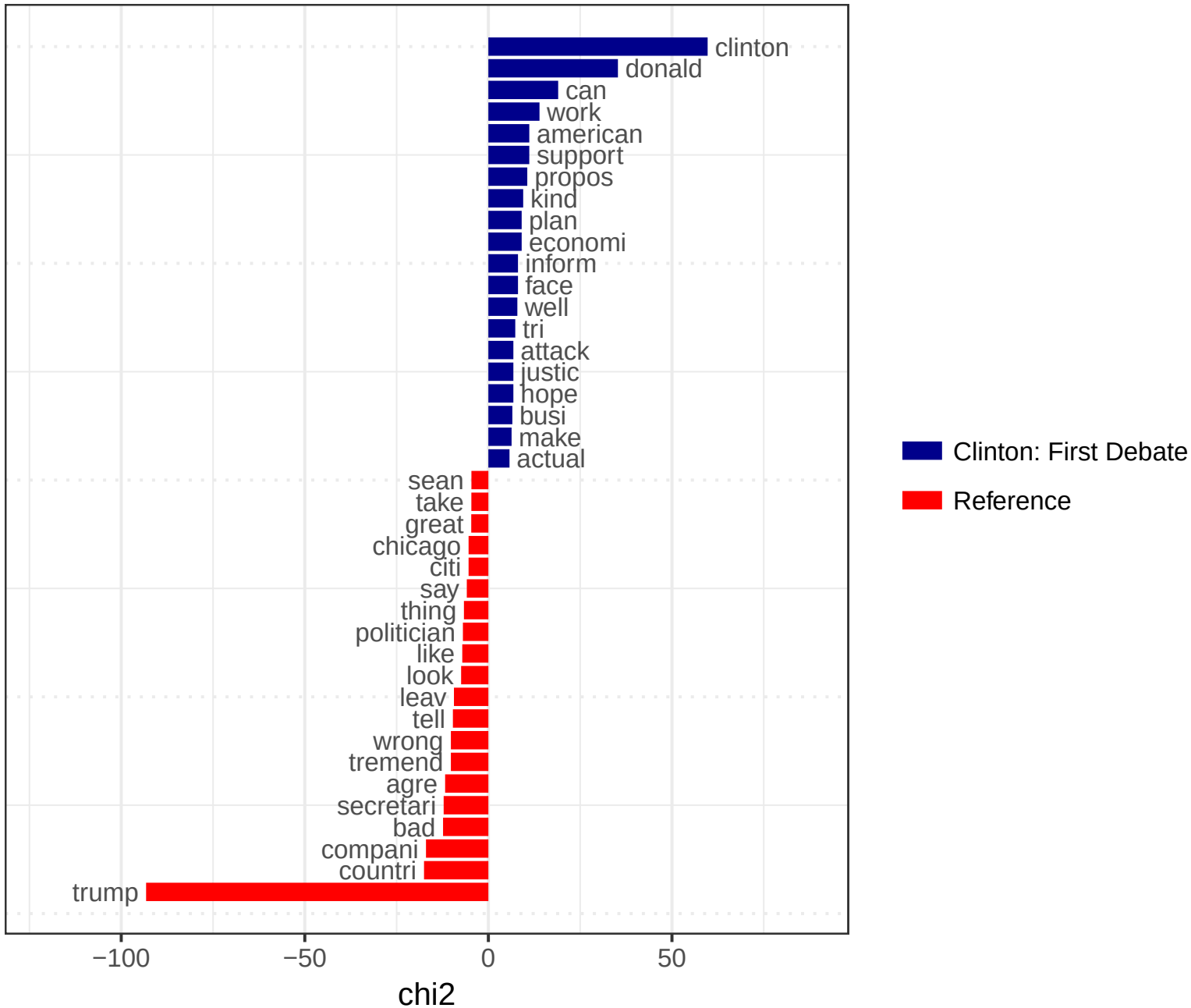
	"terrorist"	All other words	Total
Document A	N_{TA}	N_{OA}	N_A
Document B	N_{TB}	N_{OB}	N_B
Total	N_T	N_A	N

Larger values of $\chi^2 \rightarrow$ higher "keyness"

Word "Keyness": First Debate

```
> D1C2<-corpus_subset(D1C,Speaker %in% c("Clinton: First Debate",
+                                        "Trump: First Debate"))
> D1C2DFM <- dfm(D1C2,remove=stopwords("english"),stem=TRUE,
+            remove_punct=TRUE,groups="Speaker")
>
> D1Key <- textstat_keyness(D1C2DFM, target = "Clinton: First Debate")
>
> head(D1Key,12)
    feature   chi2         p n_target n_reference
1   clinton 59.722 1.088e-14       87          21
2    donald 35.291 2.840e-09       30           1
3       can 19.012 1.299e-05       30           8
4      work 13.924 1.903e-04       31          12
5   support 11.142 8.440e-04       13           2
6  american 11.142 8.440e-04       13           2
7    propos 10.600 1.131e-03       10           0
8      kind  9.480 2.078e-03       15           4
9   economi  9.064 2.607e-03       13           3
10     plan  9.064 2.607e-03       13           3
11     face  8.068 4.506e-03        8           0
12   inform  8.068 4.506e-03        8           0
```

First Debate Keyness Differentials



Wordscores: Code

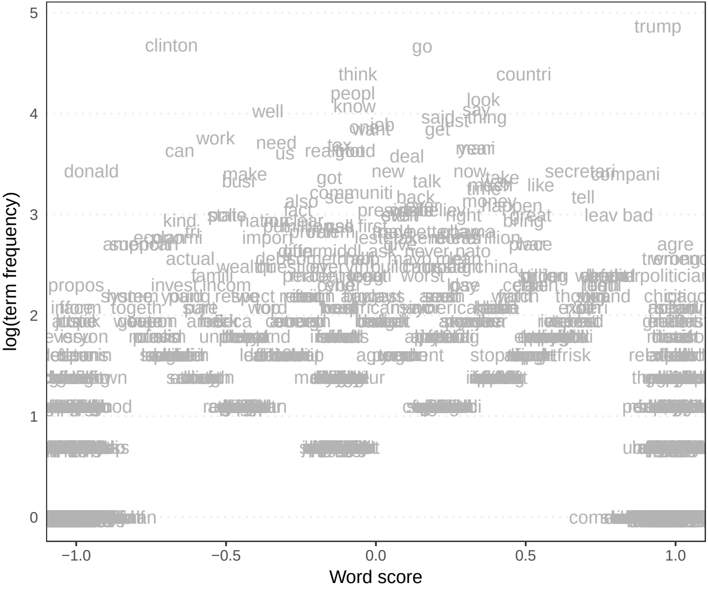
```
> # Work with the "candidates only" corpuses.
> # Set the statements made by Clinton in the first
> # debate equal to -1, and those made by Trump
> # to -1:
>
> TScores <- c(-1,1,NA)
>
> WS.train <- textmodel_wordscores(D1C2DFM,TScores,
+                                  scale="linear")
> summary(WS.train)

Call:
textmodel_wordscores.dfm(x = D1C2DFM, y = TScores, scale = "linear")

Reference Document Statistics:
                      score total min max mean median
Clinton: First Debate    -1  3030   0  87 1.89      1
Trump: First Debate       1  3866   0 127 2.42      1
Holt                     NA     0   0   0 0.00      0

Wordscores:
(showing first 30 elements)
    clinton      donald     applaus        well       thank      lester
   -0.68183    -0.94908    -0.01026    -0.36031    -0.43691     0.00383
    hofstra        host          us     central    question       elect
   -1.00000    -1.00000    -0.30346    -1.00000    -0.28219    -0.12123
     realli        kind     countri        want       futur       build
   -0.17276    -0.65426     0.49375    -0.01504    -1.00000     0.04637
     togeth       today granddaught      second    birthday       think
   -0.79862    -0.12123    -1.00000    -0.67233    -1.00000    -0.05995
         lot       first     economi        work     everyon        just
   -0.06904    -0.01026    -0.69367    -0.53446    -1.00000     0.26321
```

Word Scores...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time
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money
tell
also
fact
happen
president
right
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kind
state
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leav
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obama
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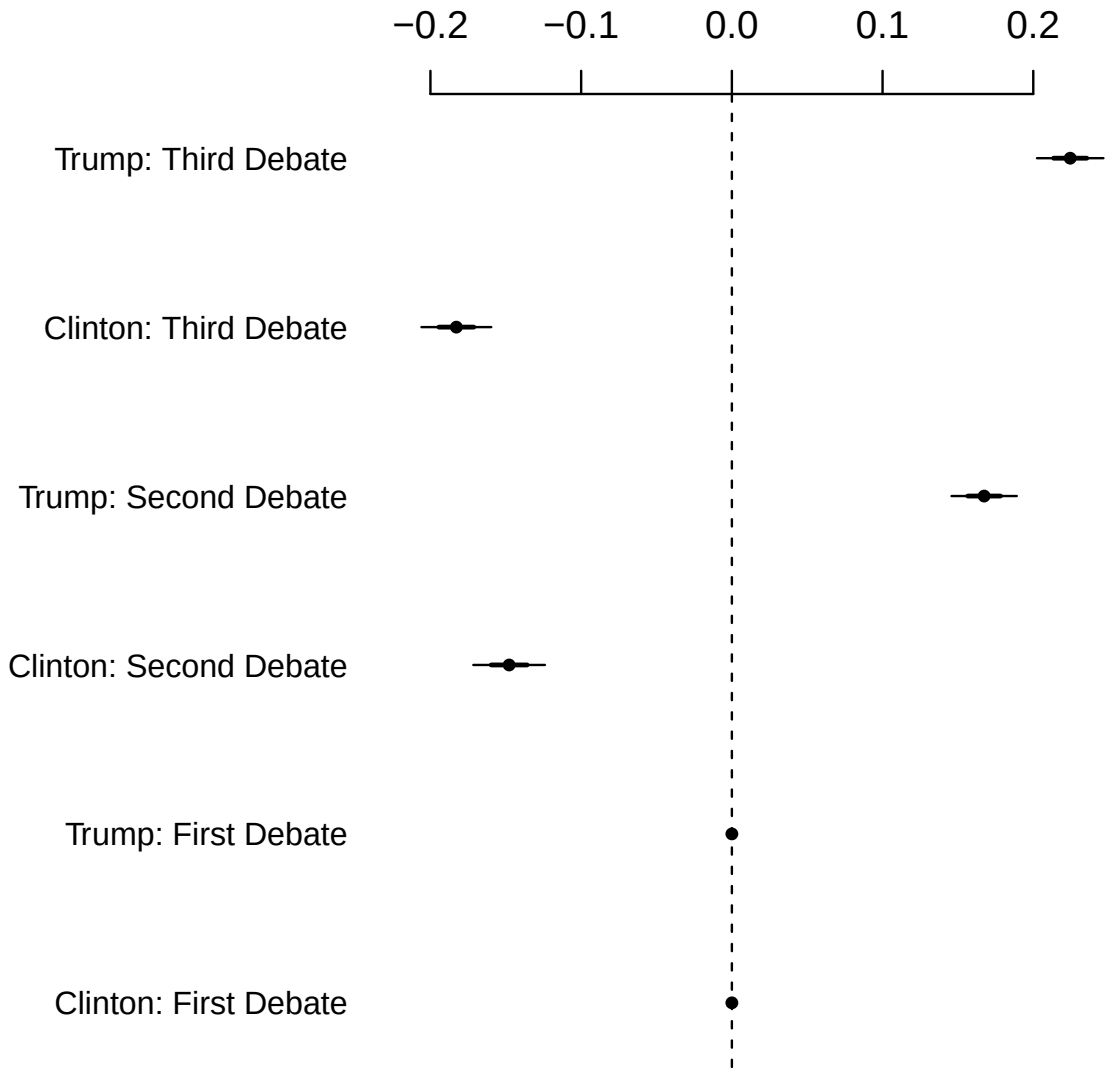
agre
actual
nato
china
famili
wealth
politician
propos
invest
incom
cyber
worst
lose
inform
togeth
america
american
stop
frisk
agreement
log(term frequency)
Word score
5
4
3
2
1
0
−1.0
−0.5
0.0
0.5
1.0

Wordscores: Predicting

```
> # Predict to the second and third debates:
>
> D23Corpus <- corpus_subset(CTonly,Speaker=="Clinton: Second Debate" |
+                            Speaker=="Clinton: Third Debate" |
+                            Speaker=="Trump: Second Debate" |
+                            Speaker=="Trump: Third Debate",
+                            select=Speaker)
> D23DFM <- dfm(D23Corpus,remove=stopwords("english"),stem=TRUE,
+               remove_punct=TRUE,groups="Speaker")
>
> WS.test <- predict(WS.train,D23DFM,se.fit=TRUE,interval="confidence")
> WS.test
$fit
                           fit   lwr   upr
Clinton: First Debate     0.00   NaN   NaN
Trump: First Debate       0.00   NaN   NaN
Holt                      0.00   NaN   NaN
Clinton: Second Debate   -0.15 -0.17 -0.12
Trump: Second Debate      0.17  0.15  0.19
Raddatz                   0.00   NaN   NaN
Cooper                    0.00   NaN   NaN
Clinton: Third Debate    -0.18 -0.21 -0.16
Trump: Third Debate       0.22  0.20  0.25
Wallace                   0.00   NaN   NaN

$se.fit
 [1]   NaN   NaN   NaN 0.012 0.011   NaN   NaN 0.012 0.011   NaN
```

Wordscores: Ladder Plot



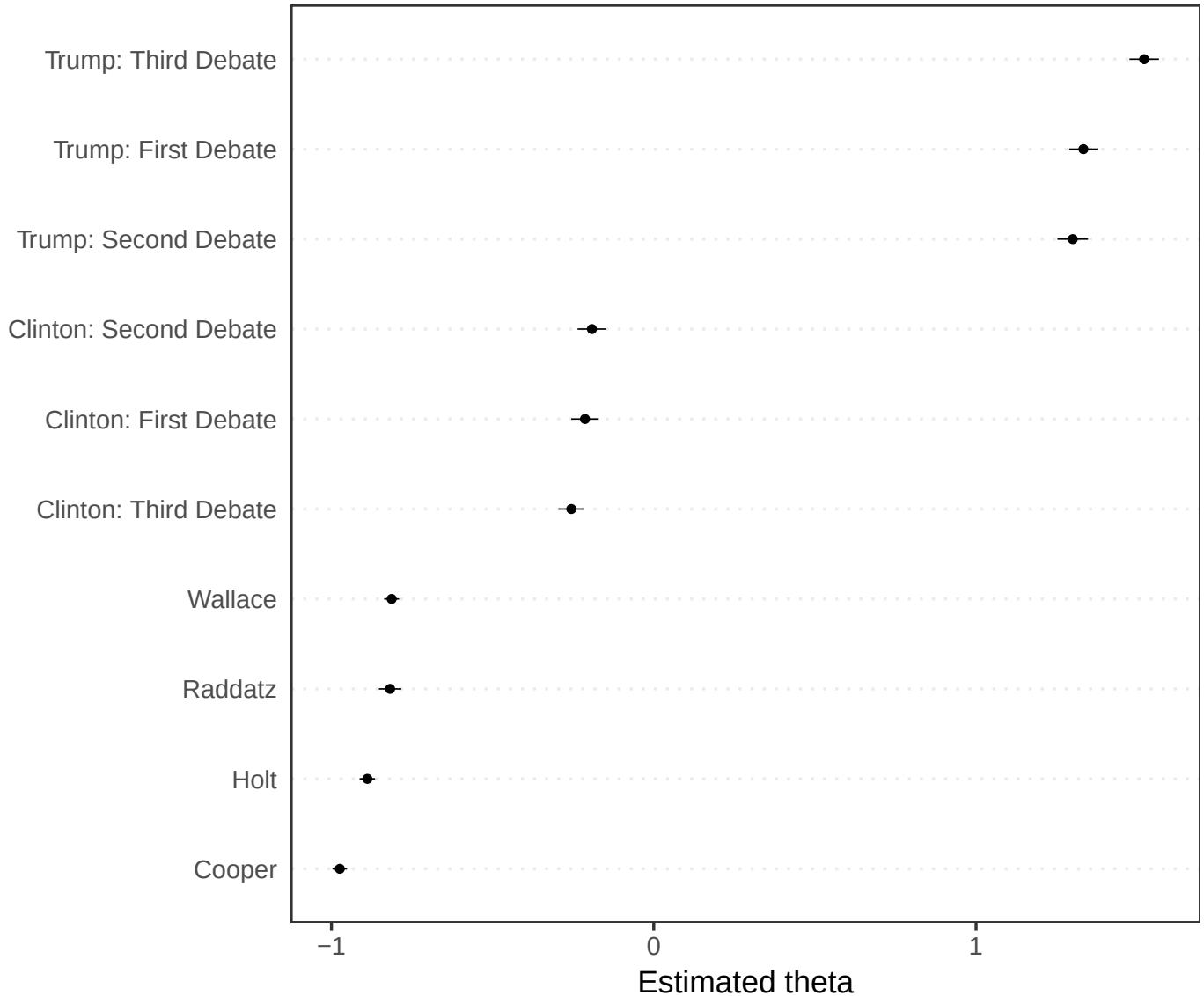
Rescaled Wordscores

```
> # Rescaled wordscores:
>
> WS.test2 <- predict(WS.train,D23DFM,se.fit=TRUE,interval="confidence",
+                     rescaling="lbg")
> WS.test2
$fit
                          fit  lwr  upr
Clinton: First Debate  -0.065  NaN  NaN
Trump: First Debate    -0.065  NaN  NaN
Holt                   -0.065  NaN  NaN
Clinton: Second Debate -1.782 -2.1 -1.5
Trump: Second Debate    1.880  1.6  2.1
Raddatz                -0.065  NaN  NaN
Cooper                 -0.065  NaN  NaN
Clinton: Third Debate  -2.189 -2.5 -1.9
Trump: Third Debate     2.544  2.3  2.8
Wallace                -0.065  NaN  NaN

$se.fit
 [1]   NaN   NaN   NaN 0.073 0.061   NaN   NaN 0.070 0.063   NaN
```

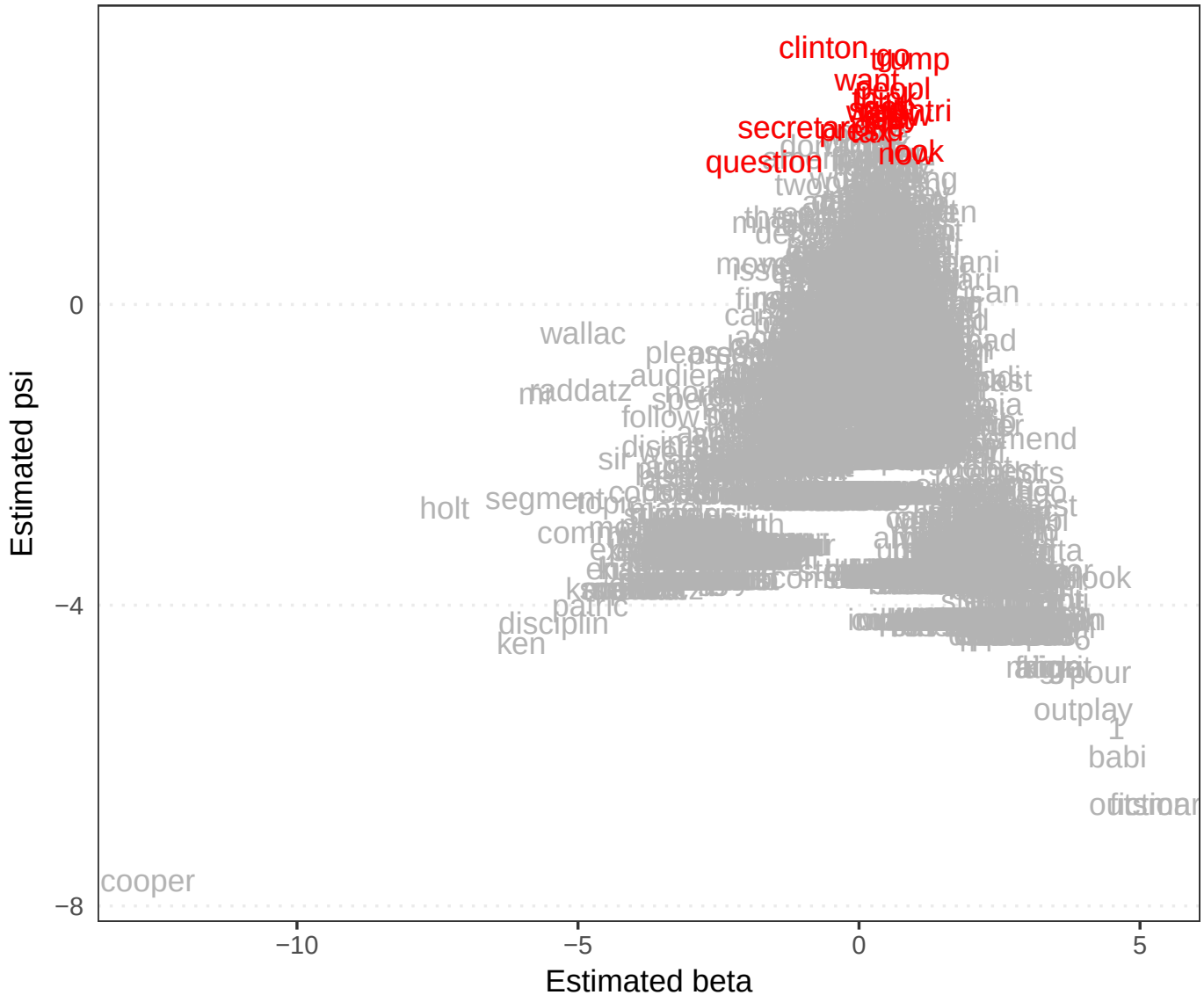
Wordfish!

```
> WF <- textmodel_wordfish(DDFM,dir=c(1,2))
> summary(WF)

Call:
textmodel_wordfish.dfm(x = DDFM, dir = c(1, 2))

Estimated Document Positions:
                         theta     se
Clinton: First Debate  -0.213 0.0218
Trump: First Debate     1.333 0.0224
Holt                   -0.889 0.0123
Clinton: Second Debate -0.192 0.0227
Trump: Second Debate    1.300 0.0243
Raddatz                -0.818 0.0177
Cooper                 -0.974 0.0115
Clinton: Third Debate  -0.256 0.0204
Trump: Third Debate     1.522 0.0233
Wallace                -0.813 0.0119

Estimated Feature Scores:
     clinton donald applaus  well thank lester hofstra   host    us central
beta  -0.626 -0.579  0.0833 0.252 -1.36  0.606   -1.43 -0.578 0.211   -1.15
psi    3.425  2.119  0.5430 2.571  1.17  0.139   -2.13 -1.427 1.948   -1.61
     question  elect realli   kind countri  want  futur build togeth  today
beta    -1.69 -0.513   0.57 -0.147   0.821 0.145 -0.561 0.679 -0.375 0.4548
psi      1.90  1.225   1.72  1.326   2.583 2.992 -0.442 0.441  0.553 0.0914
     granddaught second birthday think   lot   first economi    work
beta      -0.451  0.214   -0.451  0.46 0.383 -0.0648   -0.25 -0.0746
psi       -2.502  1.159   -2.502  2.75 2.077  1.9229    1.01  2.1613
     everyon  just
beta  -0.267 0.504
psi    0.351 2.478
```

Wordfish: Speaker Locations



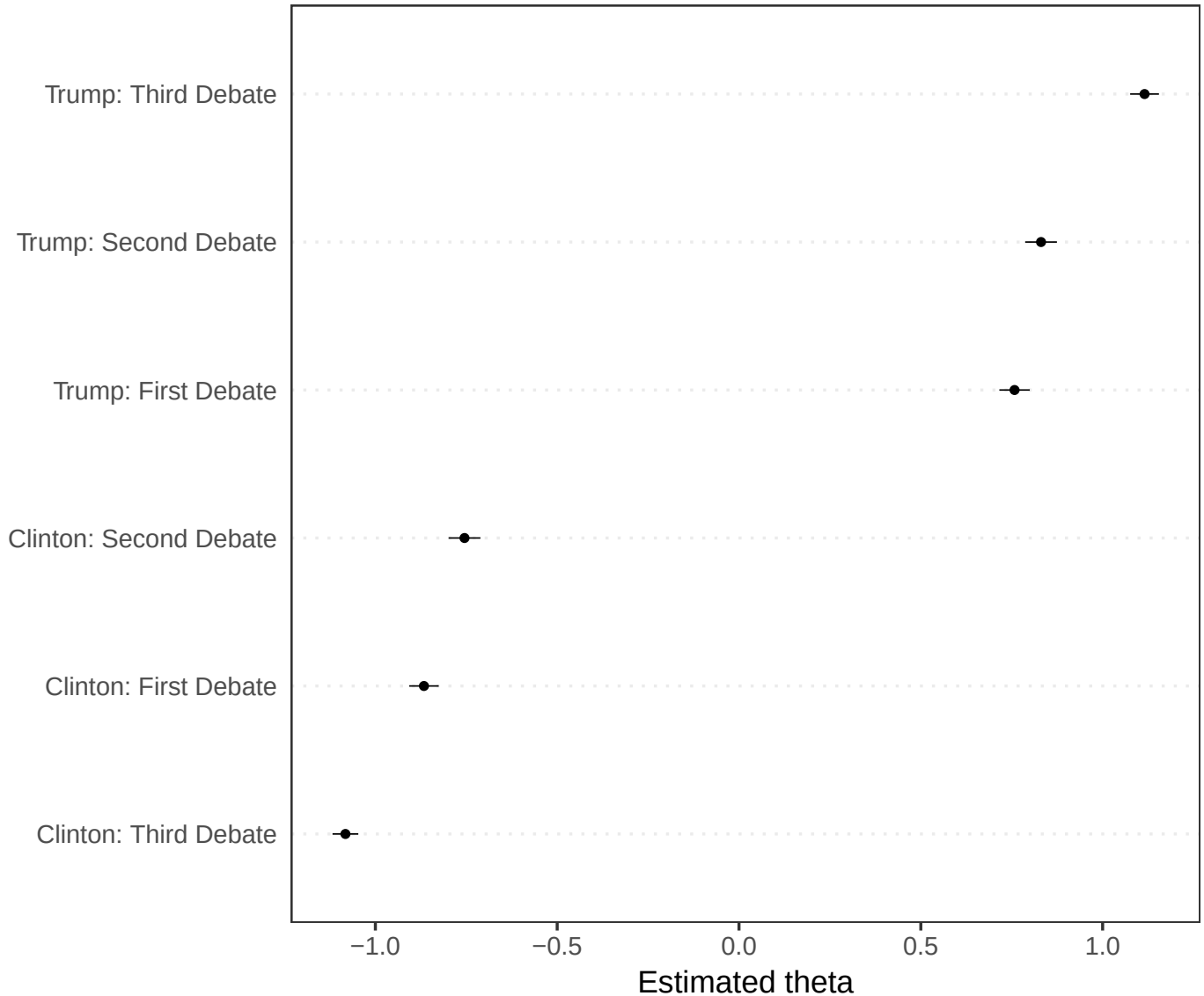
Wordfish: Word Locations



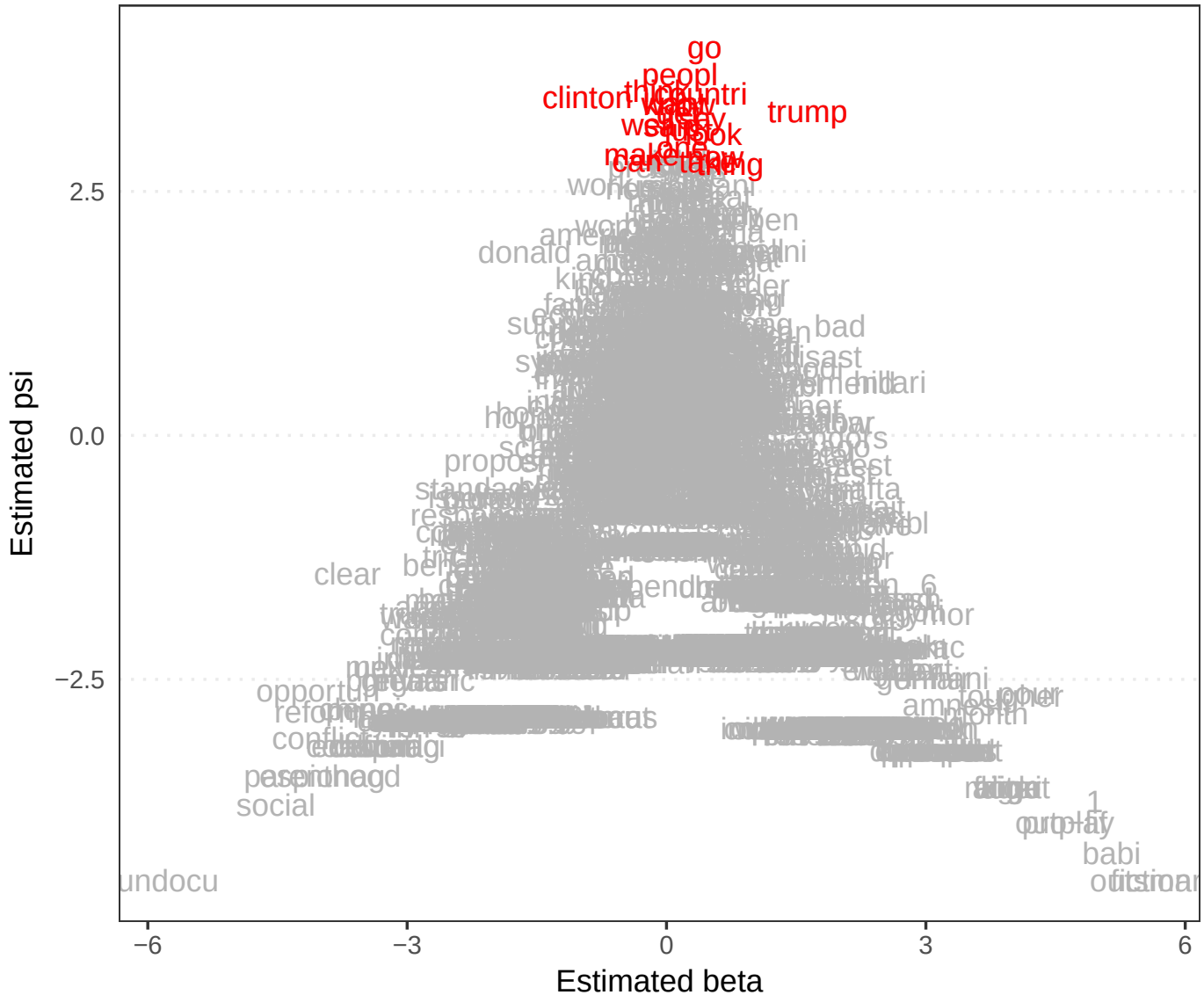
Wordfish: Candidates Only

```
> WF2 <- textmodel_wordfish(CTDFM,dir=c(1,2))
Note: removed the following zero-token documents: Holt
Note: removed the following zero-token documents: Raddatz
Note: removed the following zero-token documents: Cooper
Note: removed the following zero-token documents: Wallace

> summary(WF2)

Call:
textmodel_wordfish.dfm(x = CTDFM, dir = c(1, 2))

Estimated Document Positions:
                         theta     se
Clinton: First Debate  -0.866 0.0207
Trump: First Debate     0.758 0.0213
Clinton: Second Debate -0.755 0.0223
Trump: Second Debate    0.831 0.0223
Clinton: Third Debate  -1.082 0.0181
Trump: Third Debate     1.115 0.0202

Estimated Feature Scores:
     clinton donald applaus   well thank lester hofstra  host     us
beta  -0.916  -1.64   0.166 -0.212 0.230  0.113   -1.17 -2.41 -0.293
psi    3.466   1.88   0.834  3.188 0.895  0.971   -2.32 -2.27  2.558
     central question  elect realli  kind countri   want  futur build
beta   -1.84    -0.14 -0.874 0.0492 -0.96   0.394 0.0868 -1.905 0.181
psi    -2.17     1.77  1.317 2.5562  1.61   3.506 3.4032 -0.842 1.329
     togeth today granddaught second birthday  think     lot  first economi
beta  -1.01 0.646       -1.17  0.206    -1.17 -0.111 -0.0186 -0.118  -0.889
psi    0.74 0.463       -2.32  1.558    -2.32  3.536  2.7721  2.248   1.241
       work everyon  just
beta -0.764  -0.904 0.257
psi   2.574   0.637 3.139
```

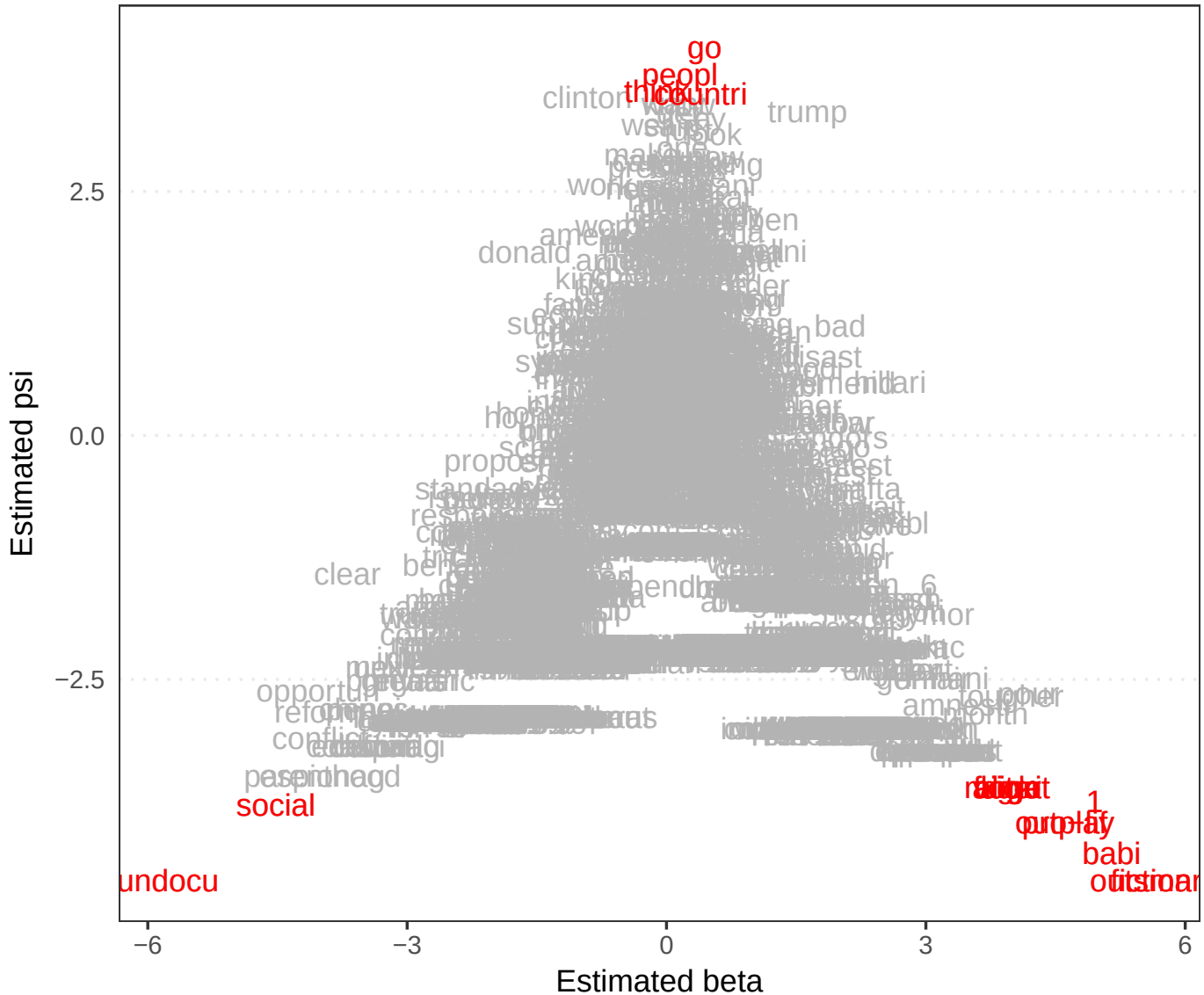
Wordfish: Speaker Locations (Candidates Only)



Wordfish: Word Locations (Frequent Words)



Wordfish: Word Locations (large $|\hat{\psi}|$)



Scaling Texts: Other Approaches...

- E.g., factor analysis / SEM, unfolding, IRT...
- The "Class Affinity Model"
  - Perry and Benoit (2017)
  - "...a text modeling framework that allows actors to take latent positions on a 'gray' spectrum between 'black' and 'white' polar opposites."
  - In `quanteda`
- They're all kinda the same.
- (Read this paper by Will Lowe: `http://dl.conjugateprior.org/preprints/all-on-the-line.pdf`)

Scaling Texts: Things to Think About

- Interpretation: What do the scales mean?
- What does it mean to "validate"?
  - Compare to human / expert coding?
  - Compare to "numerical" position estimates (D-NOMINATE / Martin-Quinn / etc.)?
  - Cross-validate?
  - Predicting other phenomena
- Propagating (measurement and estimation) uncertainty...