TEXT AS DATA: WEEK 9

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GOALS FOR TODAY

GOALS

- Scaling Models with Wordscores
- Scaling Models with Wordfish

WORDSCORES

WORDSCORES

Wordscores compares the word frequencies of texts at hand to the word frequencies of so called reference texts with known (or assumed) positions and assigns document scores based on the similarity of these references.

- Highly automated, (nearly) no language knowledge needed

WORDSCORES CONCEPT

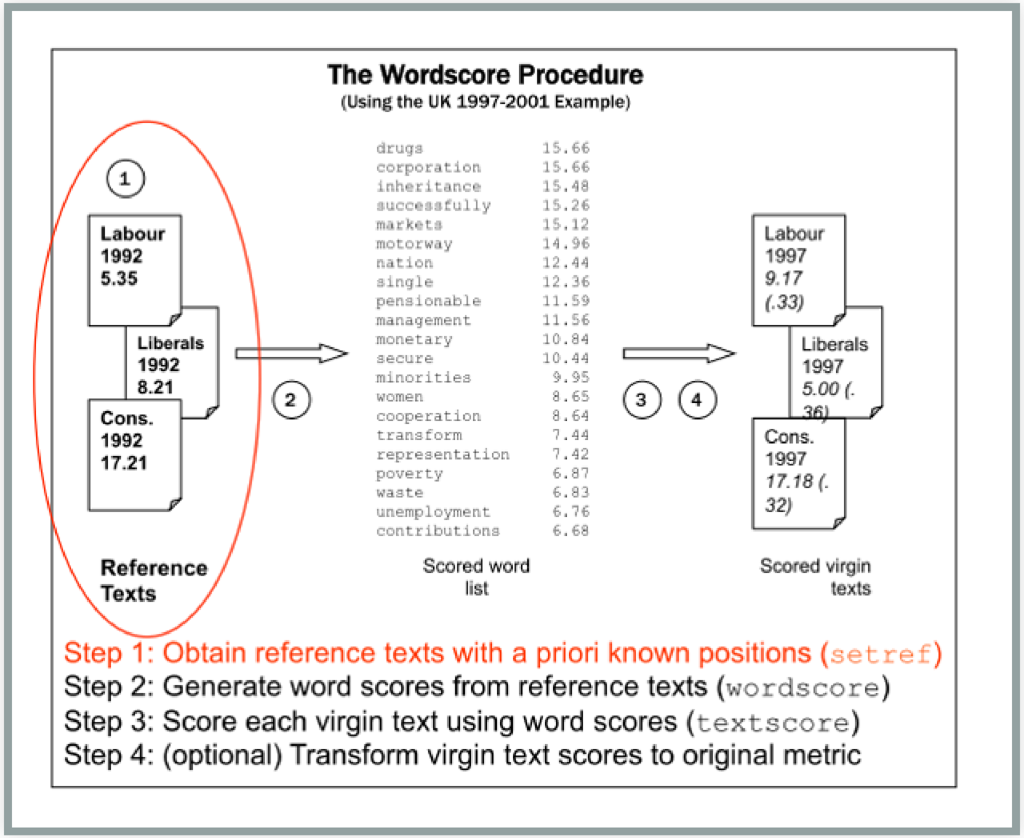
The idea

- Each word has a policy position (word score)
- Some reference document positions are known
- Document positions are average of its words' positions
- 1st step: Derive wordscores from reference texts
- 2nd step: Apply wordscores to virgin texts

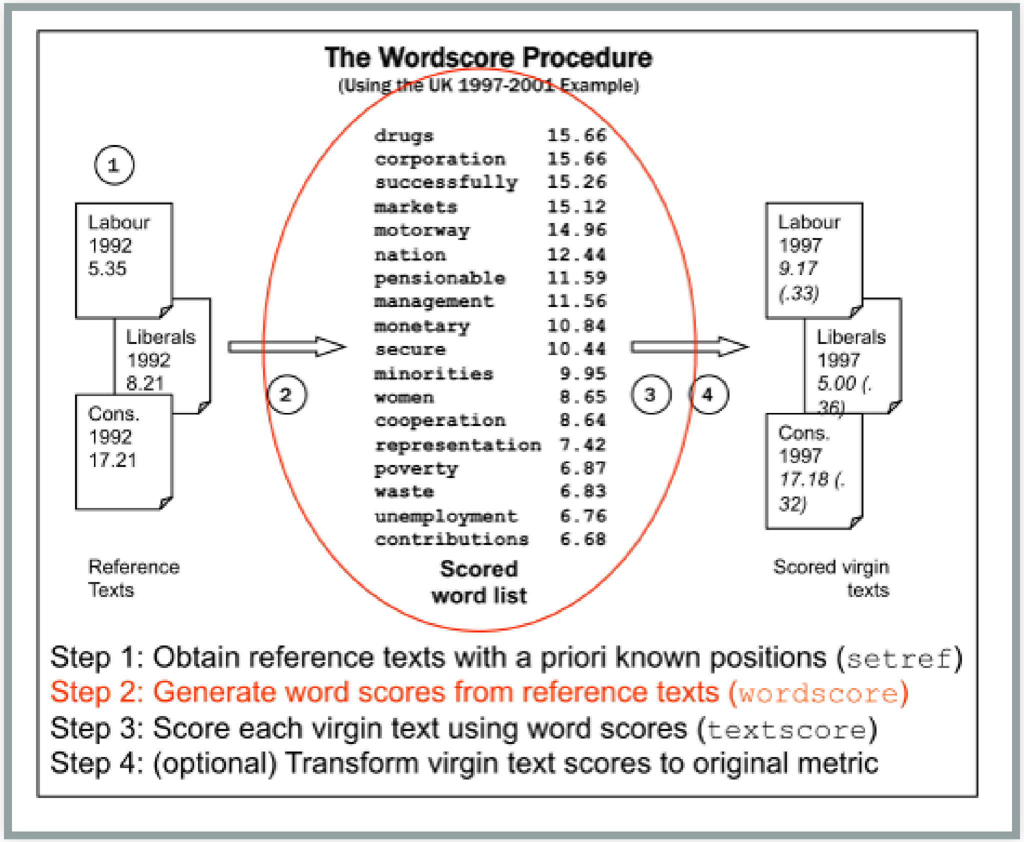
WORDSCORES: ILLUSTRATIVE EXAMPLE

- Consider two reference texts A and B
- The word “choice” is used 10 times per 10,000 words in text A and 30 times per 10,000 words in text B
- Conditional on observing the “choice”, we are reading text A with probability 0.25 and text B with 0.75
- We can compute a “word score” once we assign reference values to the reference texts
- Suppose reference text A has position -1, and text B position +1
- then the score of word “choice” is:
- $0.25(-1.0) + 0.75(1.0) = -0.25 + 0.75 = 0.5$

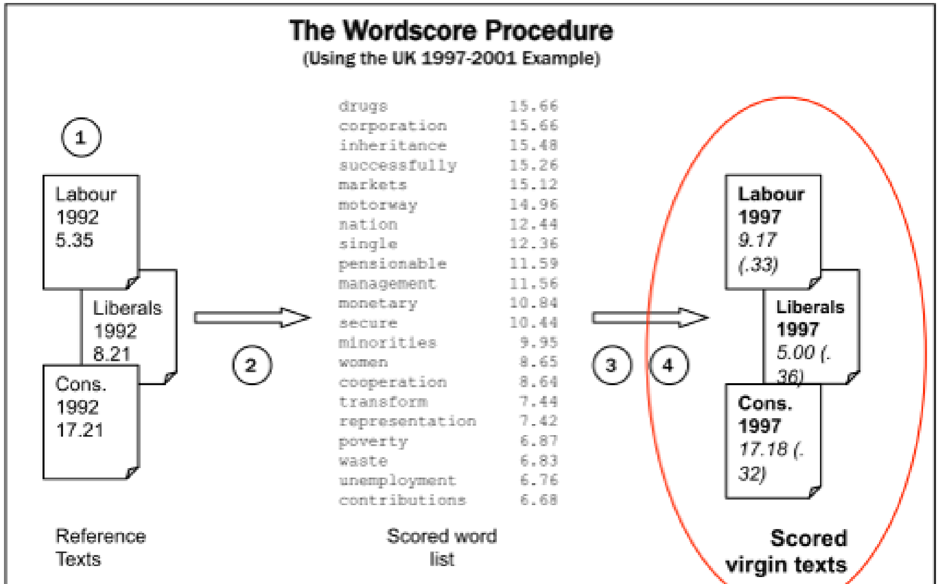
WORDSCORES PROCEDURE



WORDSCORES PROCEDURE



WORDSCORES PROCEDURE



Step 1: Obtain reference texts with a priori known positions (`setref`)
Step 2: Generate word scores from reference texts (`wordscore`)
Step 3: Score each virgin text using word scores (`textscore`)
Step 4: (optional) Transform virgin text scores to original metric

Laver & Garry

- Goal: Generating party positions for British and Irish manifestos
- Coding scheme similar to the CMP's
  - More hierachical, larger number of categories
  - Each category has a pro-, con- and neutral variant

ESTIMATING POLICY POSITIONS FROM POLITICAL TEXTS

Assumptions:

1. Manifesto content is related to party policy positions
2. Word usage is realted to policy positions
3. Word usage is contant over time
4. All relevant words are coverered in the reference texts

1st step: Training set

- Manifestos of Labour and Cons (UK) in 1992
  - Pool of ‘keywords’
  - $N_L \geq 2N_R$ => Dictionary element left
  - $N_R \geq 2N_L$ => Dictionary element right
- Allocate selected words to the coding scheme’s categories

2nd step: Count occurence of elements in the dictionary in manifestos

- Britain (1992 & 1997)
- Ireland (1992 & 1997)
- Left-right-scaling: $\frac{R-L}{R+L}$
  - $Econ_{LR}$
  - Soc_{LR}

Test-Set: Crossvalidation

- Expert Surveys
- CMP Coding/Revised CMP Coding

TABLE 3 **Pearson Correlations between Alternative Estimates of Economic Left-Right Scale Positions, Britain and Ireland 1992–97**

	Computer Codings	Revised Expert Codings	Original MRG Codings	Expert Surveys
1992				
Computer codings	1.00			
Revised expert codings	0.85	1.00		
Original MRG codings	0.72	0.94	1.00	
Expert surveys	0.75	0.95	0.99	1.00
1997				
Computer codings	1.00			
Revised expert codings	0.94	1.00		
Expert surveys	0.91	0.95	n.a	1.00

WORDSCORES AND DICTIONARIES

- Conceptually, the two steps do the same in both approaches:
  - 1st step derives a position of a word from texts with known properties
  - 2nd step weighs the words in the unknown texts with this information
- Information in dictionary is often binary, wordscores in wordscore are scale

SELECTING REFERENCE TEXTS

- Reference texts should use the same vocabulary in the same context
- Reference texts need to span the full dimension
- Set of reference text should contain as many words as possible
- Estimates of the positions (reference scores) need to be well grounded and/or very conservative

1ST STEP - OBTAINING WORDSCORES

- Start out from the observed word frequencies in reference texts:
- F_{wr}: Relative frequency of word w in reference-text r
- Conditional probabilities: Given we are observing word w, what is the probability that we are reading text r?
- $P_{wr} = \frac{F_{wr}}{\sum_r F_{wr}}$
- $S_w = \sum_r (P_{wr} * A_r)$
  - A_r is the a priori score for reference text r
  - S_w is the actual wordscore for word w

2ND STEP – APPLYING THE WORDSCORES

- $S_v = \sum_w (F_{wv} * S_w)$
  - F_{wv} is analogous to F_{wr}
  - S_v is the weighted mean score of the words in text v
- Variance is the basis for calculating uncertainty
  - Summary for the consensus of the scores of each word in the virgin text
  - Higher consensus -> lower variance -> less uncertainty

WORDSCORES – PRACTICAL CONSIDERATIONS

- What about scaling things other than manifestos?
- E.g. speeches:
  - Use reference texts from other context (e.g. manifesto)?
  - What scores to use?
  - Length of the reference texts?

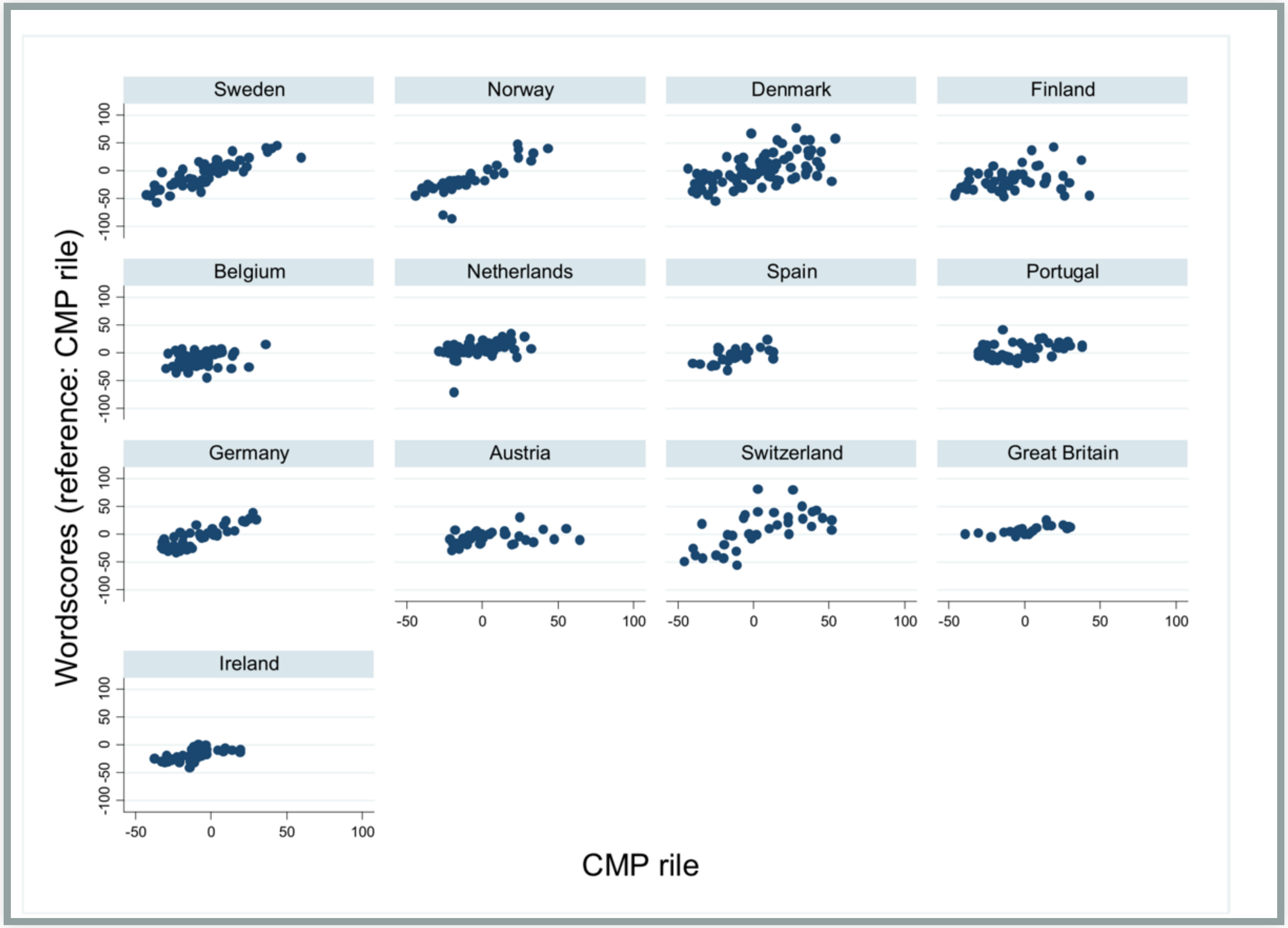
COMPARING WORDSCORES AND CMP

- Laver, Garry & Benoit use Irish and British manifestos to demonstrate/validate
- CMP data offers information for many countries and over long periods
- How do wordscores results compare across countries?

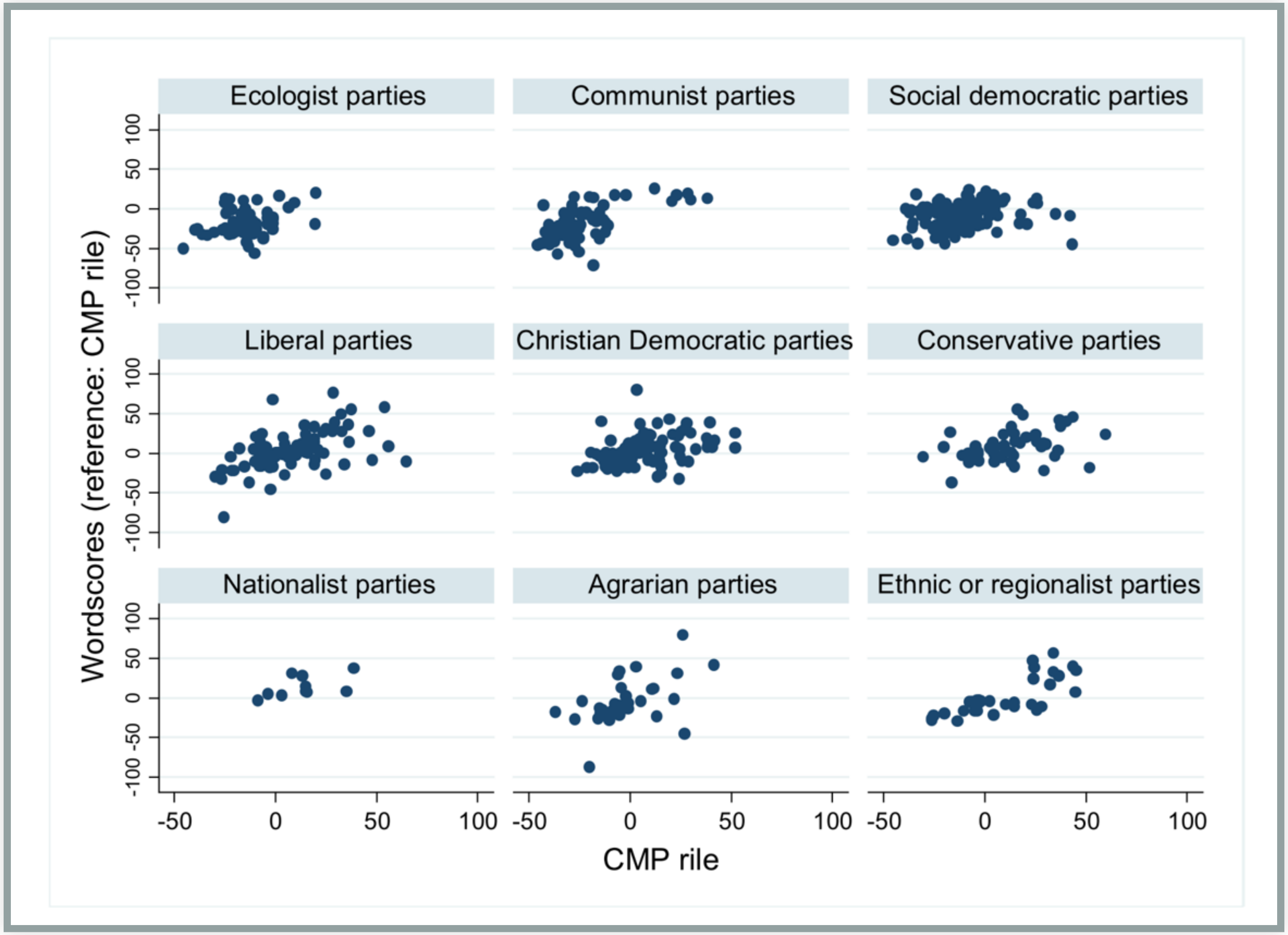
COMPARING WORDSCORES AND CMP

- Bräuninger, Debus & Müller (2013) compare wordscores results for 13 countries between 1980 and 2000
- Reference texts are the manifestos in the latest elections
- Reference scores are the Rile scores from CMP
- Essentially ‘replicate’ CMP scores using wordscores

COMPARING WORDSCORES AND CMP



COMPARING WORDSCORES AND CMP



COMPARING WORDSCORES AND CMP

- Wordscores replicates CMP better whew
  - reference texts cover the full range of a dimension
  - the percentage of scored words is high
- Cross-check results from wordscores before using them in an analysis

WORDSCORES EXERCISE: LOAD DATA AND CREATE CORPUS

In the wordscores exercise we'll be looking at annual budget speeches held in the Irish Parliament from 2008 - 2012. Let's load the data, tokenize it and create a dfm.

```
library(quanteda.textmodels)
data(data_corpus_irishbudget2010, package = "quanteda.textmodels")
budget_dfm <- dfm(tokens(data_corpus_irishbudget2010))
```

WORDSCORES EXERCISE: LOAD DATA AND CREATE CORPUS

As we just learned wordscores requires us to assign a set of known scores to so called reference texts to identify the positions of new documents. Let's create some reference scores for the 5th and 6th document.

```
refscores <- c(rep(NA, 4), 1, -1, rep(NA, 8))
```

WORDSCORES EXERCISE: PREDICT WORD POSITIONS

We can use the `textmodel_wordscores()` function from the `quanteda.textmodels` package to estimate the document positions based on the positions of the reference texts.

```
ws <- textmodel_wordscores(budget_dfm, y = refscores, smooth = 1)
head(coef(ws))
```

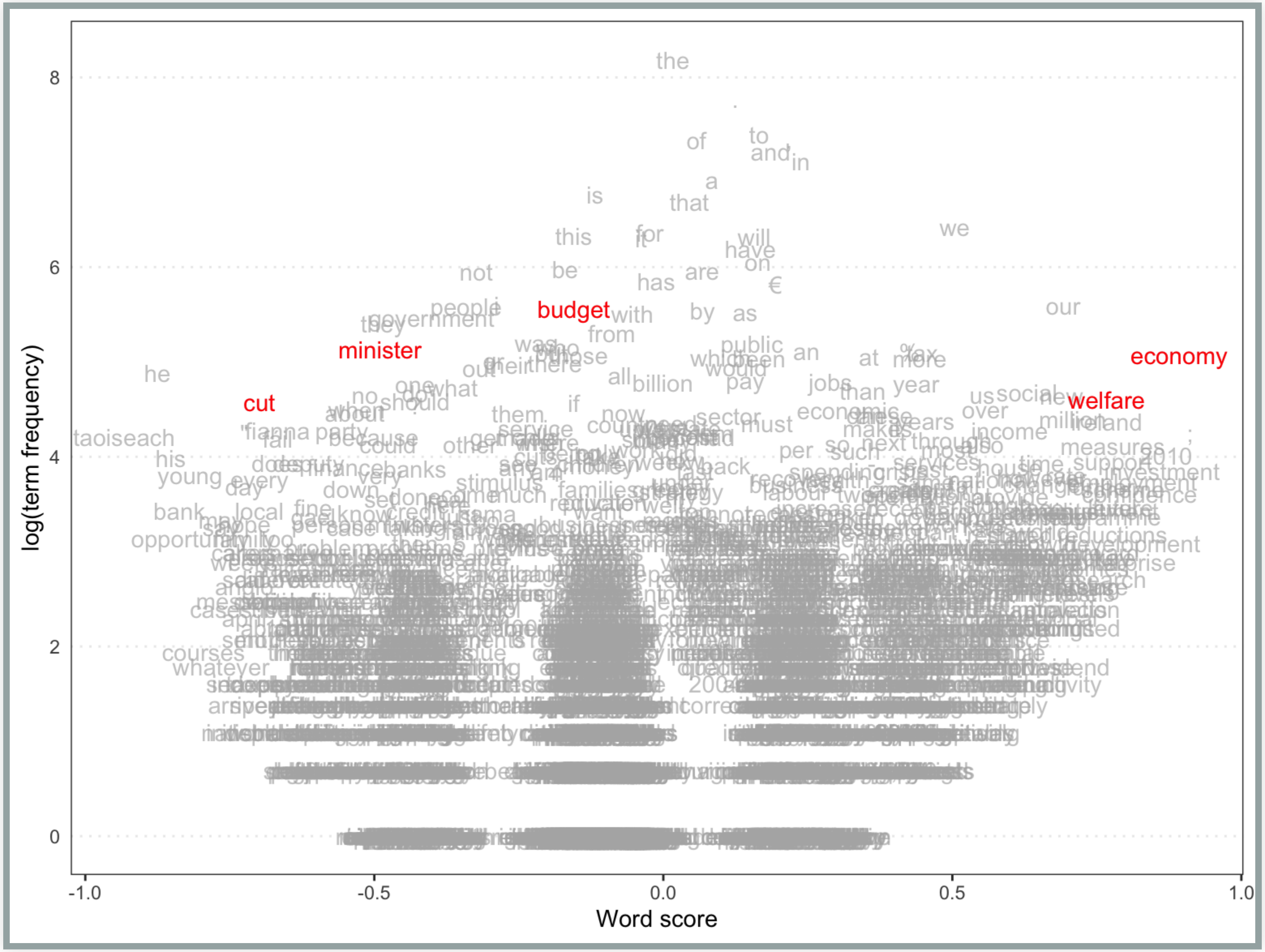
```
##          when             i     presented           the supplementary
##   -0.53014011   -0.28805749   -0.42939762    0.01670114   -0.42939762
##        budget
##   -0.15483456
```

WORDSCORES EXERCISE: PLOT WORD POSITIONS

We can use the `textplot_scale1d()` function from the `quanteda.textplots` package to plot word positions.

```
library(quanteda.textplots)
textplot_scale1d(ws,
                 highlighted = c("cut", "minister", "welfare",
        "economy", "budget"),
                 highlighted_color = "red")
```

WORDSCORES EXERCISE: PLOT WORD POSITIONS



WORDSCORES EXERCISE: PREDICT DOCUMENT POSITIONS

We can extract the estimated speaker positions using the `precict()` function as if this were a regular fitted regression model.

```
ws_pred <- predict(ws, interval = "confidence")
ws_pred
```

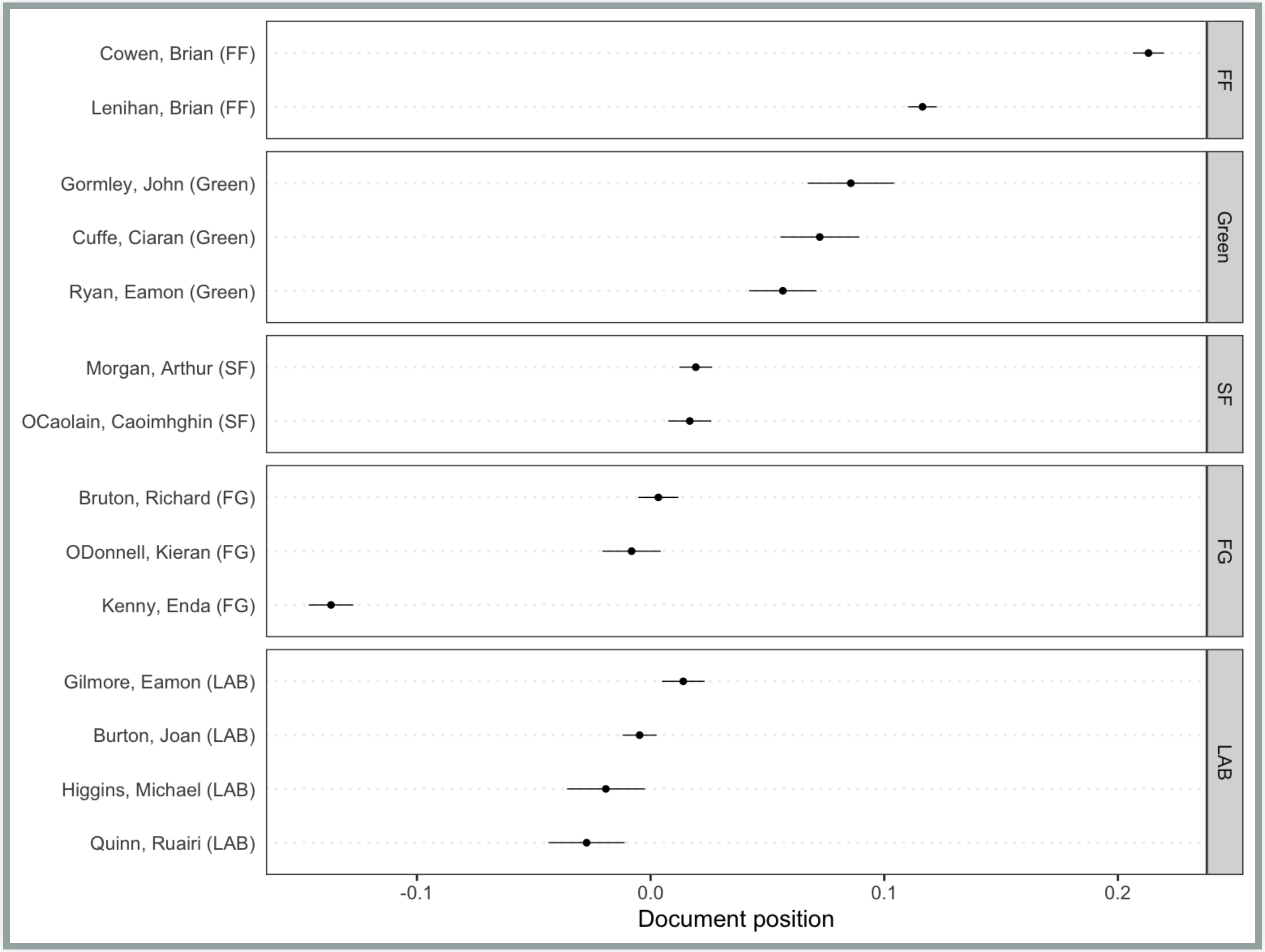
```
## $fit
##                                    fit          lwr          upr
## Lenihan, Brian (FF)         0.116362873  0.110173633  0.122552114
## Bruton, Richard (FG)        0.003318195 -0.005228996  0.011865387
## Burton, Joan (LAB)         -0.004696791 -0.011996402  0.002602821
## Morgan, Arthur (SF)         0.019334198  0.012308623  0.026359774
## Cowen, Brian (FF)           0.213090960  0.206424497  0.219757423
## Kenny, Enda (FG)           -0.136776116 -0.146311207 -0.127241025
## ODonnell, Kieran (FG)      -0.008132150 -0.020643605  0.004379306
## Gilmore, Eamon (LAB)        0.013988095  0.004862201  0.023113990
## Higgins, Michael (LAB)     -0.019145477 -0.035788594 -0.002502360
## Quinn, Ruairi (LAB)        -0.027387712 -0.043704917 -0.011070506
## Gormley, John (Green)       0.085698169  0.067187907  0.104208431
## Ryan, Eamon (Green)         0.056610204  0.042201917  0.071018490
## Cuffe, Ciaran (Green)       0.072391730  0.055483988  0.089299472
## OCaolain, Caoimhghin (SF)   0.016769698  0.007557775  0.025981621
```

WORDSCORES EXERCISE: PLOT SPEAKER POSITIONS

And then plot the results using the same `textplot_scale1d()` function and grouping by party.

```
textplot_scale1d(ws_pred, margin = "documents",
                 groups = docvars(data_corpus_irishbudget2010,
         "party"))
```

WORDSCORES EXERCISE: PLOT SPEAKER POSITIONS



WORDFISH

WORDSCORES VS. WORDFISH

- Wordscores derives and ‘transfers’ known properties of words, i.e. the wordscores between texts.
- Wordfish builds a statistical model that explains the occurence of each word: Poisson regression

WORDSCORES VS. WORDFISH

- Advantages from a practical perspective
  - No reference texts needed; Anchor points instead
  - Statistically models all words in a text
  - Absolute minimum of input from the user; Versatile and well suited for smaller projects
- The statistical model replaces the need for reference texts
  - Mathematical complexity of the model

POISSON MODEL

- Dependent variables of interest may be counts, e.g.
  - Occurence of conflict/wars, casualties in conflicts; Number of bills brought forward in a term; Number of hospitalizations, sicknesses etc.
  - **Word count in a document**
- A dependent count variable y
  - bound between 0 and ∞
  - takes only discrete values (0,1,2,3,…)

POISSON MODEL

Poisson distribution

$$\gamma_i = Possion(\lambda_i)$$

- Poisson distribution: Repeated Bernoulli-Experiments (0/1)
- Generally used in count data (poisson regression)
- Has only one parameter: ‘Event occurrence rate’
- No contagion effects; the event rate remains constant

WORDFISH MODEL

$$\gamma_{ij} \sim Poisson(\lambda_{ij})$$
$$\lambda_{ij} = exp(\alpha_i + \psi_j + \beta_j * \omega_i)$$

- i = document (e.g. party manifesto)
- j = unique word
- α_i = document fixed effect
- ψ_j = word fixed effect
- β_j = word specific weight (sign representing the ideological direction)
- ω_i = document position

WORDFISH ESTIMATION

- Regression without independent variables
  - Solution: Maximum Likelihood Estimation

1. Estimate party parameters conditional on the expectation for the word parameters (in first iteration the starting values)
2. Estimate word parameters conditional on party parameters obtained in previous step
3. Go back and forth until a convergence criterion is met and the likelihoods do not change anymore

WORDFISH ESTIMATION

Likelihood function

$$\sum_{j}^{m} \sum_{i}^{n} -exp(\alpha_i + \psi_j + \beta_j * \omega_i) + ln(exp(\alpha_{it} + \psi_j + \beta_j * \omega_i)$$

Without fixing some parameters, there are infinite combinations of ω and β, which could provide the same likelihood.

- Document positions: mean of all positions ω across all elections is set to 0, and standard deviation to 1.
- Set directionality (e.g. document A always has a smaller valuer than document B).
- Set document fixed effect: first document α is set to 0.

Set document fixed effect: first document α is set to 0.

WORDFISH ESTIMATION

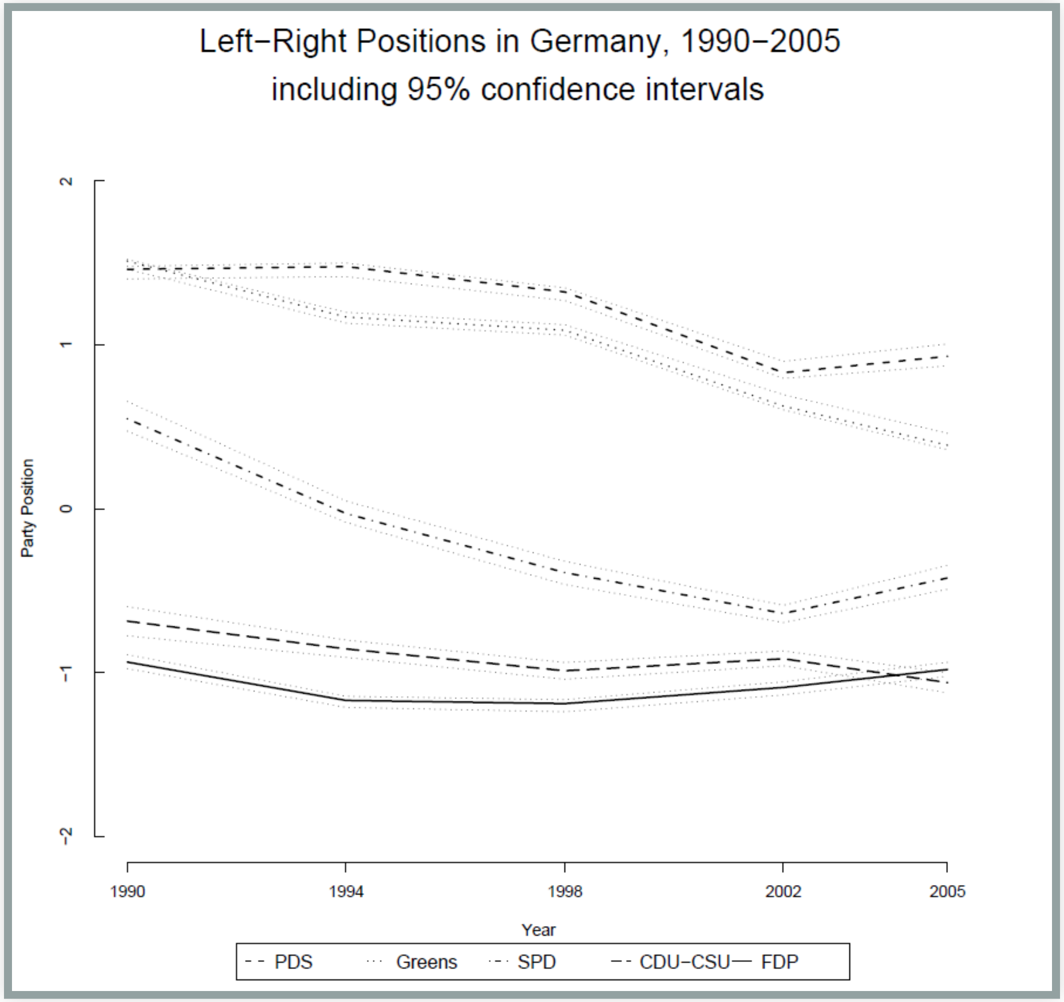
This means that you **cannot directly compare estimates ACROSS different estimations** (for example, in secondary analysis). This is the case for ALL scaling models (e.g. Nominate), and also for Wordscores.

- Think to what extent position estimates are actually comparable…
  - … across countries
  - … over time
  - … between documents

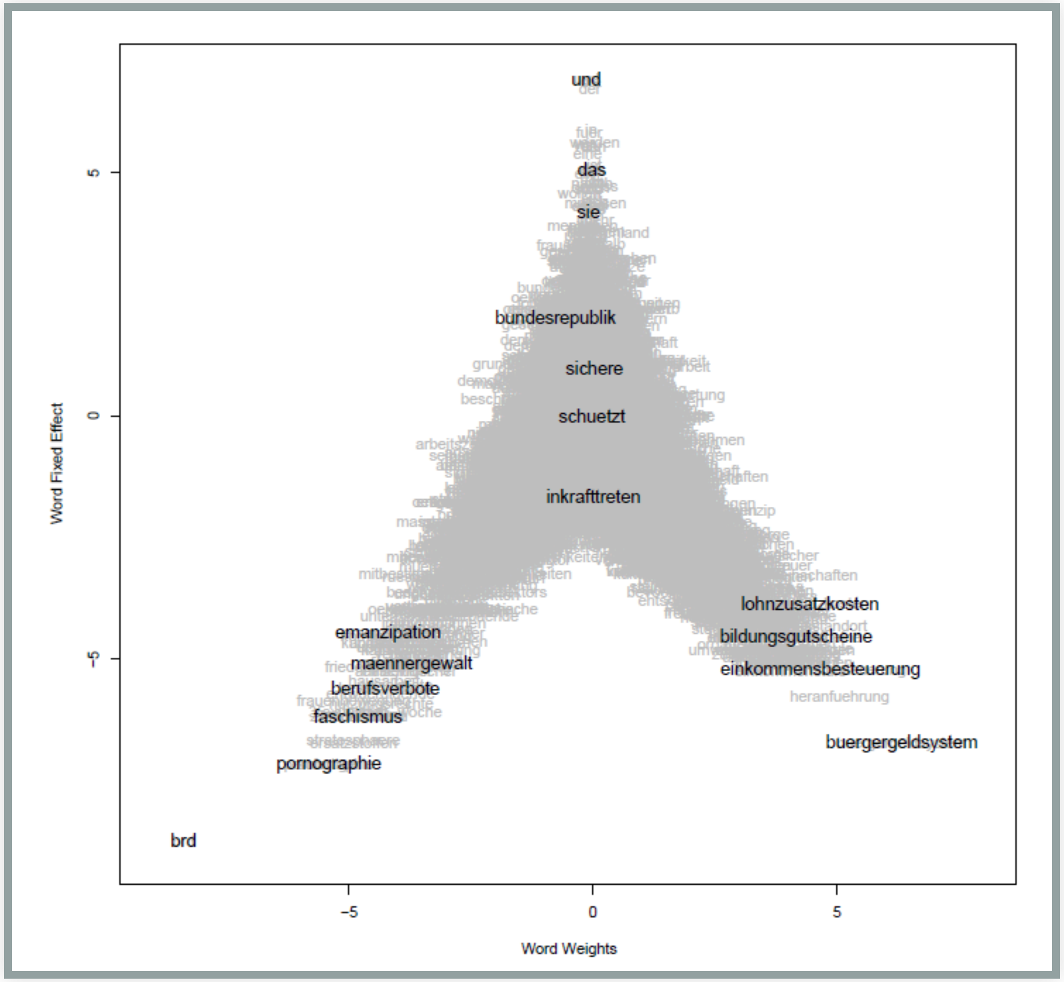
WORDFISH ESTIMATION

- Dimension of the scaling is created ex post (as compared to Wordscores)
  - What is the dimension identified?
  - More validation required
  - Creation of alternative dimensions via subsetting texts only

WORDFISH OUTPUT



WORDFISH OUTPUT

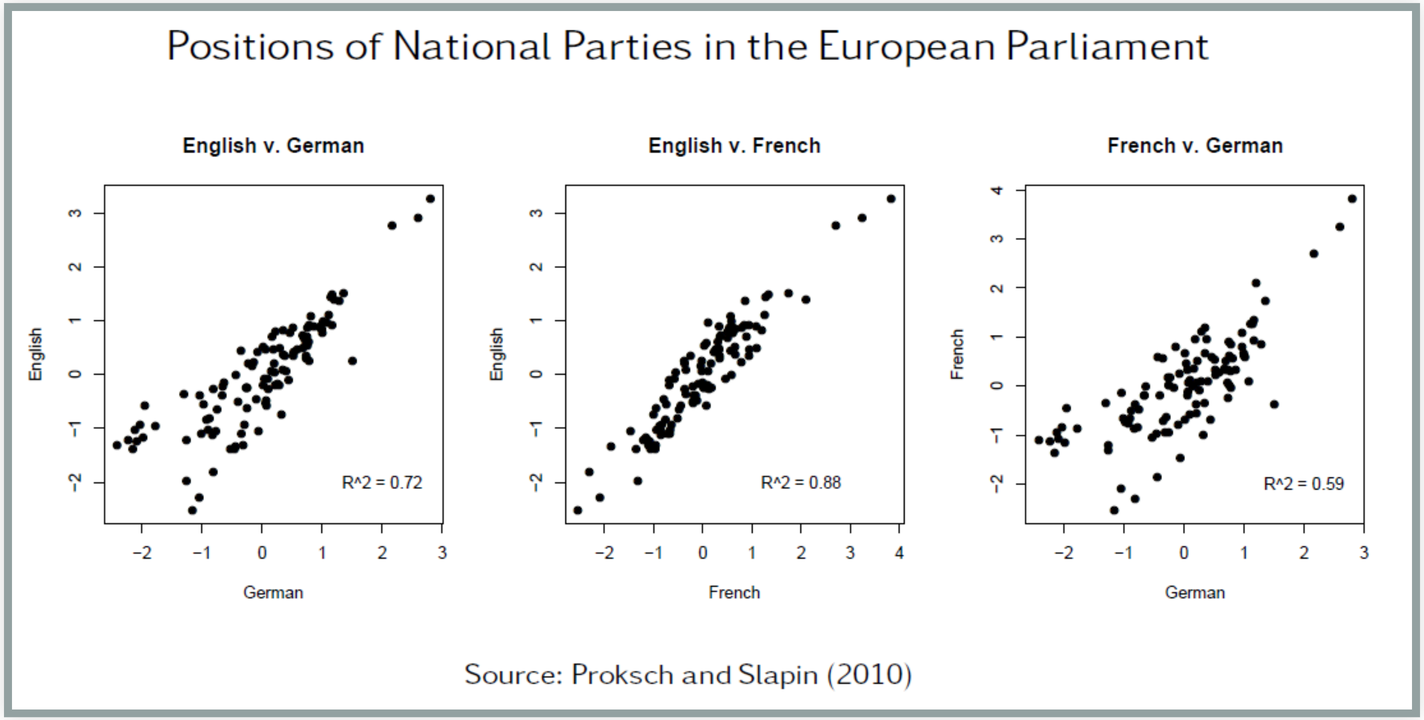


WORDFISH: MULTILINGUAL?

Does it work in different languages? What are some reasons for doubting it?

- Ideal case: get the exact same political texts in high quality translations
- Estimate Wordfish and compare across different languages
- This is possible: European Parliament speeches (translated into all official languages)

WORDFISH: SPEECHES IN EU PARLIAMENT



(IN)STABILITY OF THE POLITICAL LEXICON

- What if the political lexicon is unstable over time?
  - New issues appear, old issues disappear
- If this happens frequently, then scaling algorithms will pick up shifts in the policy agenda – rather than shifts in party positions.
- In fact, this is one assumption: that word usage reflects ideology.
  - For example, it becomes seriously problematic when all parties start talking about the “issue” of the day. Then we can distinguish between elections, but not very well between parties

POLICY DIMENSIONALITY

- In the original Wordscores article, the authors assumed the policy dimensions can be chosen by using different reference scores from known policy scales (expert surveys)
  - “Economic policy” and a “social policy” for the UK in 1997
  - Reference texts: 3 manifestos from 1992 (same for BOTH dimensions)

Reference Scores	Lib Dems	Labour	Cons.
Economic Policy	8.21	5.35	17.21
Social Policy	6.87	6.53	15.34

POLICY DIMENSIONALITY

- This means that estimates across dimensions vary only because different expert evaluations are used to anchor the texts, not because the text input varies according to the policy area of interest
    - This is not a necessary assumption. There is no reason why one cannot run analysis of sort of a policy dictionary.
    - One possibility is to preserve as much of the context as possible and parse the sections of manifestos into policy areas and then estimate positions on those sections only (Proksch and Slapin 2006, Slapin and Proksch 2008)

WORDFISH EXERCISE: LOAD DATA

We will take a look at the US Senate debate on partial birth abortion.

First let's load the data into R and take a look at the corpus:

```
library(quanteda)
load("data/corpus_us_debate_speaker.rda")
summary(corpus_us_debate_speaker)
```

```
## Corpus consisting of 23 documents, showing 23 documents:
##
##        Text Types Tokens Sentences party    speaker
##      ALLARD   400   1165        53     R     ALLARD
##        BOND   129    232         9     R       BOND
##       BOXER  2231  18527       886     D      BOXER
##   BROWNBACK   646   2884       168     R  BROWNBACK
##     BUNNING   281    593        32     R    BUNNING
##    CANTWELL   395   1114        55     D   CANTWELL
##      DeWINE   463   1438        75     R     DeWINE
##    DOMENICI   203    479        27     R   DOMENICI
##      DURBIN   520   1874        89     D     DURBIN
##      ENSIGN   410   1235        66     R     ENSIGN
##    FEINGOLD   213    414        19     D   FEINGOLD
##   FEINSTEIN  1348   6112       284     D  FEINSTEIN
```

```
##   FEINSTEIN  1348   6112         284      D  FEINSTEIN
##      FRIST   222    501          25      R      FRIST
##     HARKIN   655   2612         145      D     HARKIN
##      HATCH   451   1173          60      R      HATCH
```

WORDFISH EXERCISE: TOKENIZE AND DFM

Now we'll tokenize the text and create a document term matrix.

```
stops <- c(setdiff(stopwords(),
                   c("her", "she", "hers", "he", "his", "him")),
           "bill", "can")

toks <- tokens(corpus_us_debate_speaker,
               remove_punct = TRUE,
               remove_symbols = TRUE,
               remove_numbers = TRUE) |>
  tokens_remove(stops) |>
  tokens_tolower()

senate_dfm <- dfm(toks)
```

WORDFISH EXERCISE: RUN THE WORDFISH MODEL

Let's run the one-dimensional scaling model known as wordfish using the `textmodel_wordfish` function from the `quanteda.textmodels` package.

```
library(quanteda.textmodels)
wf <- textmodel_wordfish(senate_dfm, dir = c(3, 21))
```

We use the `dir` argument to set the polar opposites of the scale. In this case we assume that that the 3rd speaker Barbara Boxer, is to the left of the 21st speaker Rick Santorum.

WORDFISH EXERCISE: INVESTIGATE THE OUTPUT

Let's take a look at the components of the fitted model.

```
wf_coef <- coef(wf)
names(wf_coef)
```

```
## [1] "documents" "features"
```

```
head(wf_coef$documents)
```

```
##                  theta       alpha
## ALLARD      0.02165274  0.21348639
## BOND       -0.08693357 -1.29227632
## BOXER      -1.05777079  2.76206193
## BROWNBACK   2.38269597  0.12975044
## BUNNING     0.81776695 -0.48868033
## CANTWELL   -1.25634814 -0.07911048
```

```
head(wf_coef$features)
```

```
##                    beta        psi
## mr           0.06468449  0.8700898
```

```
## president      0.05462191  1.5038171

## commend       -0.02595502 -2.0448676
## senator        0.06740927  1.8584309
## pennsylvania -0.13413832 -0.6192956
## santorum       0.12538330 -0.4688482
```

WORDFISH EXERCISE: INVESTIGATE THE OUTPUT

```
head(wf_coef$features)
```

```
##                    beta        psi
## mr           0.06468449  0.8700898
## president    0.05462191  1.5038171
## commend     -0.02595502 -2.0448676
## senator      0.06740927  1.8584309
## pennsylvania -0.13413832 -0.6192956
## santorum     0.12538330 -0.4688482
```

WORDFISH EXERCISE: ESTIMATE SPEAKER POSITIONS

We can extract the estimated speaker positions using the `precict()` function just as with wordscores.

```
preds  <- predict(wf, interval = "confidence")
preds
```

```
## $fit
##                    fit         lwr        upr
## ALLARD      0.02165274 -0.10190180  0.1452073
## BOND       -0.08693357 -0.34076934  0.1669022
## BOXER      -1.05777079 -1.07929641 -1.0362452
## BROWNBACK   2.38269597  2.28117382  2.4842181
## BUNNING     0.81776695  0.62356627  1.0119676
## CANTWELL   -1.25634814 -1.33174776 -1.1809485
## DeWINE      1.38728909  1.25204737  1.5225308
## DOMENICI    0.32865152  0.12357508  0.5337280
## DURBIN     -0.25969664 -0.35154658 -0.1678467
## ENSIGN      0.83658945  0.68738863  0.9857903
## FEINGOLD   -1.20437761 -1.32919832 -1.0795569
## FEINSTEIN  -1.59354288 -1.61938317 -1.5677026
## FRIST       0.83880779  0.61988997  1.0577256
## HARKIN     -0.79094571 -0.85650252 -0.7253889
## HATCH       0.97739715  0.83244576  1.1223485
## LAUTENBERG -0.65712119 -0.73253786 -0.5817045
```

WORDFISH EXERCISE: CREATE A NICE DATA FRAME

If we want to we can extract the estimated speaker positions into a data frame and merge in the docvars.

```
speaker_pos <- data.frame(preds$fit,
                          speaker = row.names(preds$fit)) %>%
  dplyr::left_join(docvars(senate_dfm)) %>%
  dplyr::arrange(fit)
head(speaker_pos)
```

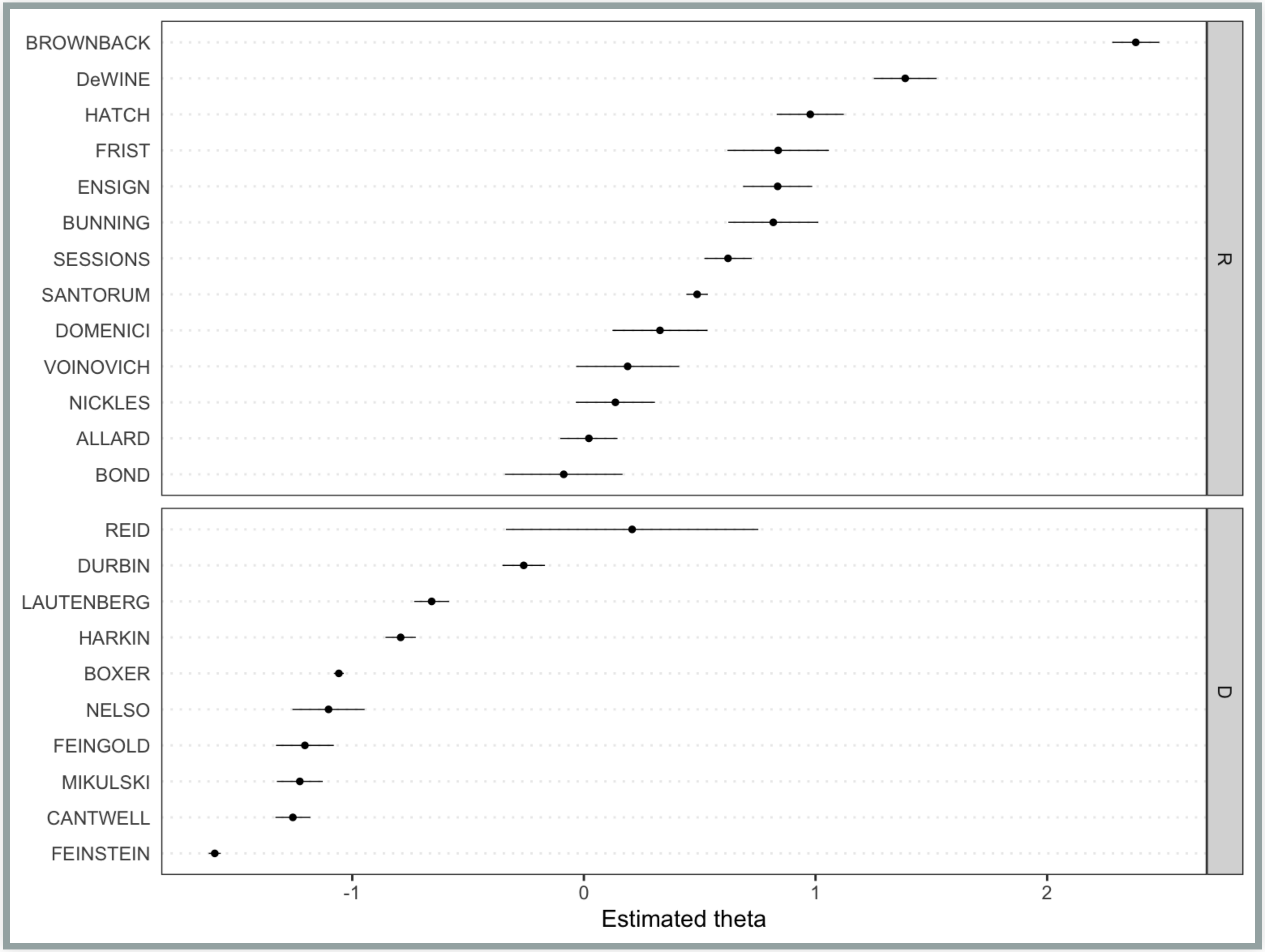
```
##          fit       lwr        upr   speaker party
## 1 -1.593543 -1.619383 -1.5677026 FEINSTEIN     D
## 2 -1.256348 -1.331748 -1.1809485  CANTWELL     D
## 3 -1.226258 -1.325300 -1.1272152  MIKULSKI     D
## 4 -1.204378 -1.329198 -1.0795569  FEINGOLD     D
## 5 -1.102293 -1.258032 -0.9465541     NELSO     D
## 6 -1.057771 -1.079296 -1.0362452     BOXER     D
```

WORDFISH EXERCISE: LET'S PLOT THE SPEAKER POSITIONS

We can use the `textplot_scale1d()` function from the `quanteda.textplots` package to plot speaker positions.

```
library(quanteda.textplots)
textplot_scale1d(wf, groups = corpus_us_debate_speaker$party)
```

WORDFISH EXERCISE: LET'S PLOT THE SPEAKER POSITIONS

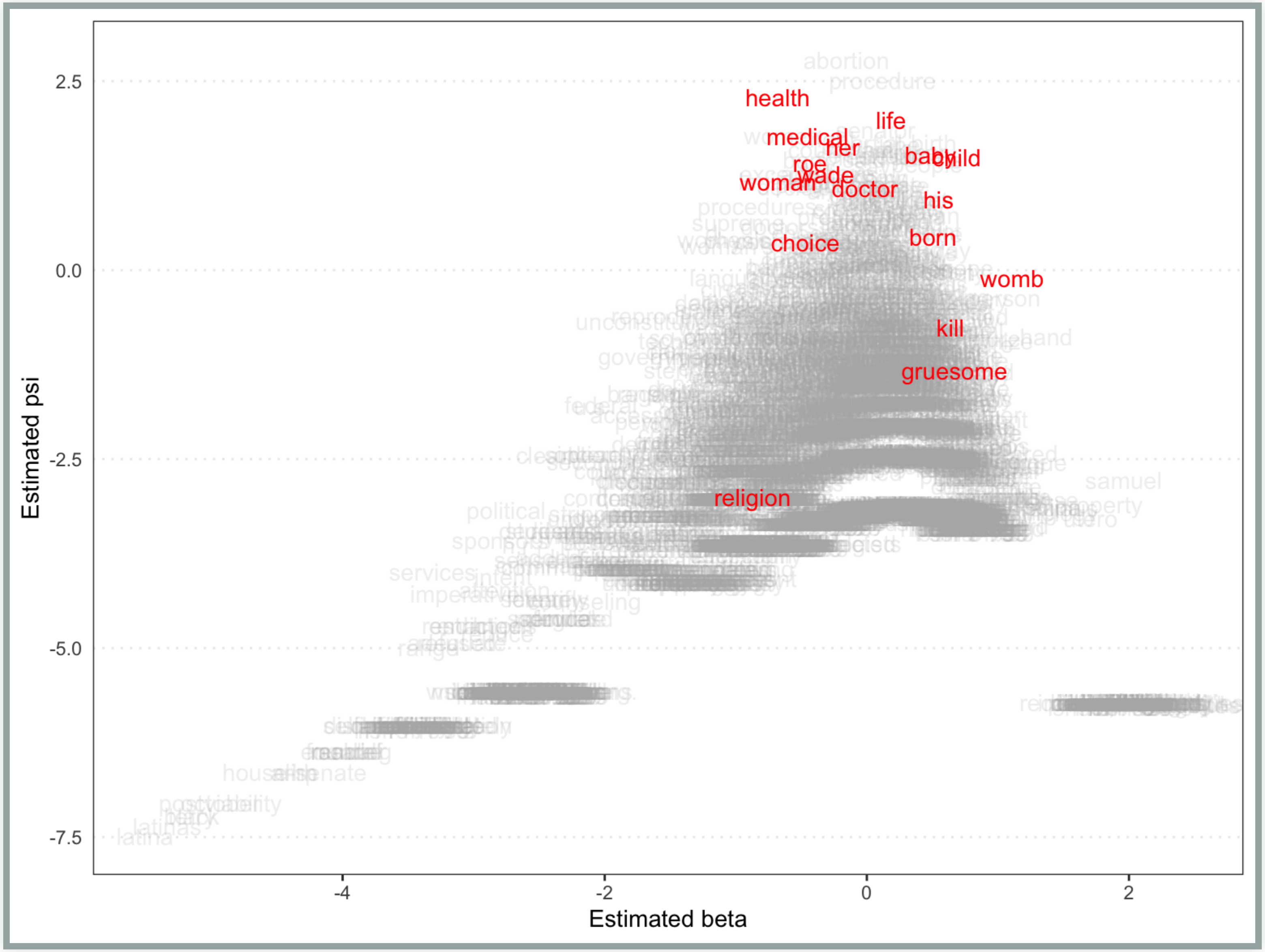


WORDFISH EXERCISE: LET'S PLOT THE WORD POSITIONS

Similarly, we can use the same function to plot the estimated positions of each word.

```
textplot_scale1d(wf, margin = "features",  alpha = 0.2,
                 highlighted = c("life", "choice", "womb", "her",
         "woman", "health",
                                 "born", "baby", "gruesome", "kill",
         "roe", "wade",
                                 "medical", "her", "his", "child",
         "religion","doctor"),
                 highlighted_color = "red")
```

WORDFISH EXERCISE: LET'S PLOT THE WORD POSITIONS

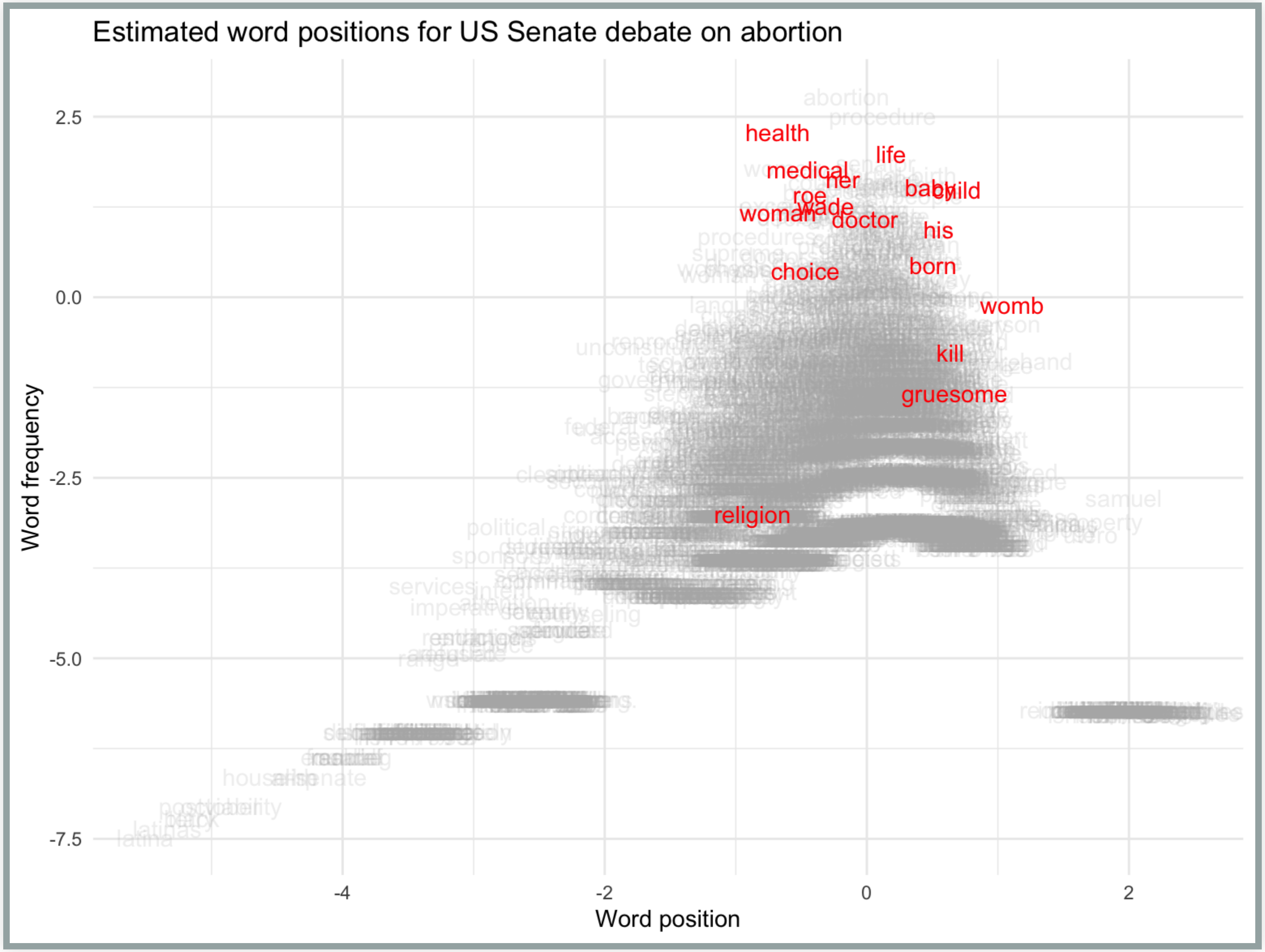


WORDFISH EXERCISE: LET'S PLOT THE WORD POSITIONS

We can also use our ggplot syntax to make the plot a bit nicer.

```
textplot_scale1d(wf, margin = "features",  alpha = 0.2,
                 highlighted = c("life", "choice", "womb", "her",
        "woman", "health",
                                "born", "baby", "gruesome", "kill",
        "roe", "wade",
                                "medical", "her", "his", "child",
        "religion","doctor"),
                 highlighted_color = "red") +
  labs(x = "Word position", y = "Word frequency") +
  ggtitle("Estimated word positions for use senate debate on abortion")
        +
  theme_minimal()
```

WORDFISH EXERCISE: LET'S PLOT THE WORD POSITIONS



HOMEWORK

Create a corpus from a number of documents of your own choosing and use either the wordscores or the wordfish approach to estimate the document positions. Plot your results and share them in class next week.

WRAPPING UP

QUESTIONS?

OUTLOOK FOR OUR NEXT SESSION

Next week we will look at different ways of generating topics from text.

THAT'S IT FOR TODAY

Thanks for your attention!