Text as Data

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Ideological Scaling

1) Task
   - Measure political actors' position in policy space
   - Low dimensional representation of beliefs
2) Objective function
   - Linear Discriminant Analysis (ish)$\rightsquigarrow$ Wordscores (today)
   - Item Response Theory $\rightsquigarrow$ Wordfish
   - Item Response Theory + Roll Call Votes $\rightsquigarrow$ Issue-specific ideal points (12/2)
3) Optimization
   - Wordscores$\rightsquigarrow$ straightforward, based on training texts
   - Wordfish$\rightsquigarrow$ EM, MCMC methods
4) Validation
   - What is the goal of embedding?
   - What is the gold standard?

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Scaling$\rightsquigarrow$ placing actors in low-dimensional space (like principal components!)

Estimating Ideal Points: Roll Call Data and the US Congress

US Congress and Roll Call

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  - Extensible: insight of IRT allows model to be embedded in many forms
  - Widely used: hard to write a paper on American political institutions with ideal points

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   - Bonica (2013, 2014) $\rightsquigarrow$ estimate ideology from donations (but not everyone donates)

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Healthy skepticism!

Our plan

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2) Wordfish $\rightsquigarrow$ single dimension

Wordscores $\rightsquigarrow$ Big in Europe

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$\boldsymbol{x}_i \rightsquigarrow$ aggregation across documents.

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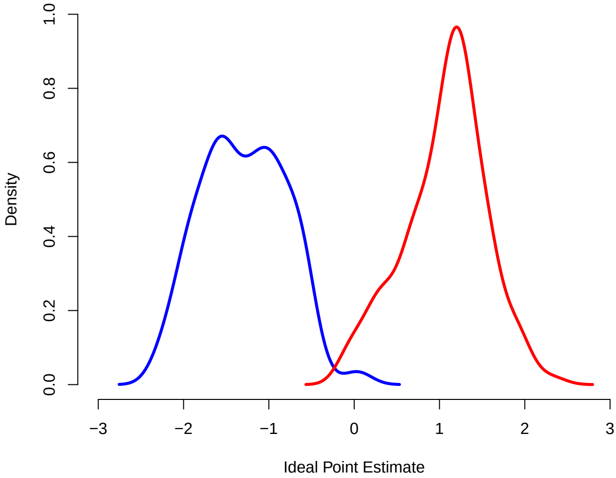
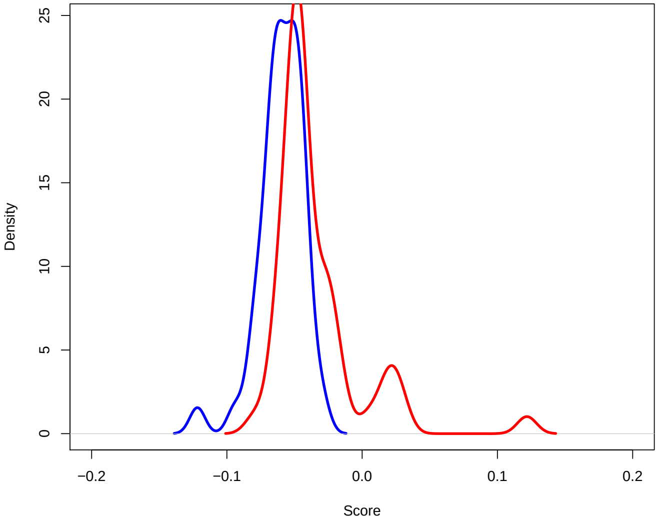
Applied to the Senate Press Releases

$L =$ Ted Kennedy
$C =$ Tom Coburn
Apply to other senators.

Applying to Senate Press Releases $\rightsquigarrow$ Gold Standard Scaling from NOMINATE



Applying to Senate Press Releases⇝ WordScores



Supervised Scaling

Wordscores is one example of supervised embedding:

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- Sensitive to who is chosen
- False prediction problem $\rightsquigarrow$ speech accomplishes many goals, only some of which are ideological

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To be fair: fast, nonparametric, and novel [trailblazing] method for scoring documents (starts conversation)

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Simplest model: Principal Components

Application of Principal Components in R

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`prcomp(dtm)` applies principal components

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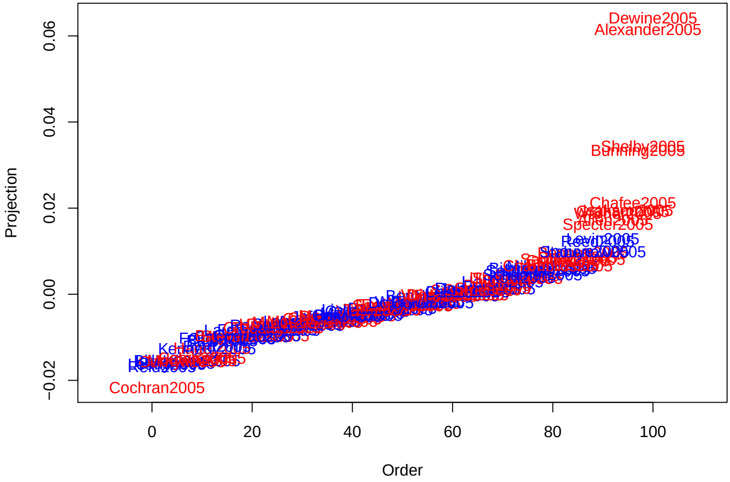

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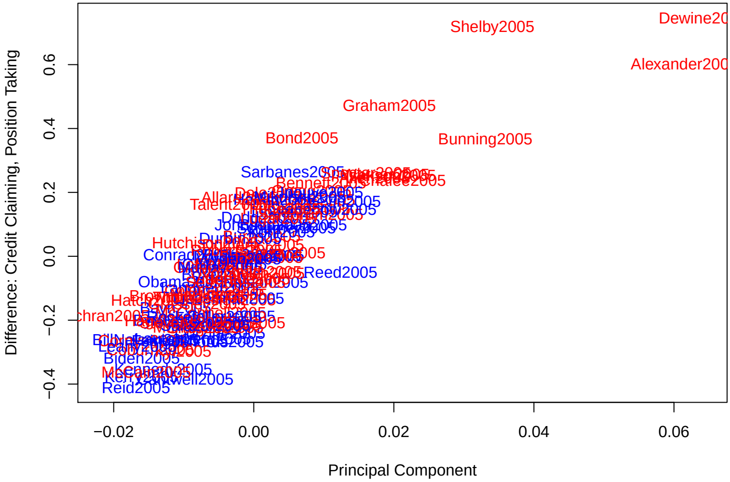

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Item Response Theory (IRT)

- Origins: educational testing
- Jackman (2002), Clinton, Jackman, and Rivers (2004) apply to roll call voting

Probabilistic Unsupervised Embeddings

Principal components is powerful $\rightsquigarrow$ statistical model for unsupervised scaling

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Monroe and Maeda (2005) and Slopkin and Proksch (2008) develop similar algorithms

WordFish Objective Function

Suppose we have legislator i.

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"Regression" of x_{ij} on ideal points θ_i, where we have to learn θ_i

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Implies the following posterior distribution:

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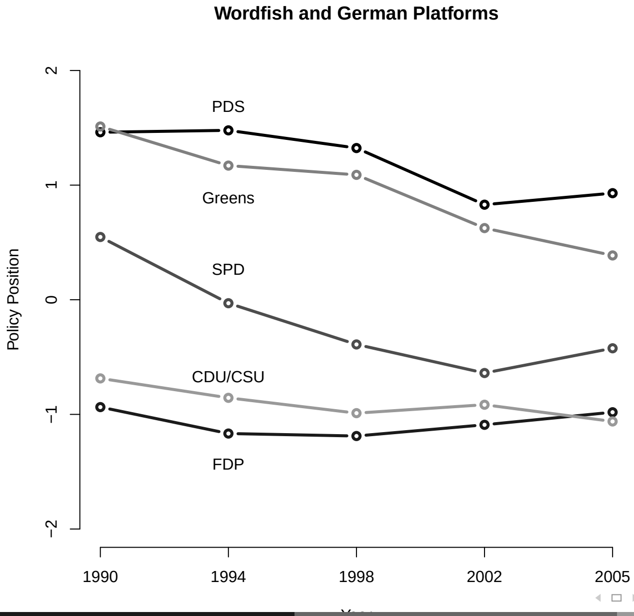
`Wordfish` package in `R`

Applications: German Party Manifestos



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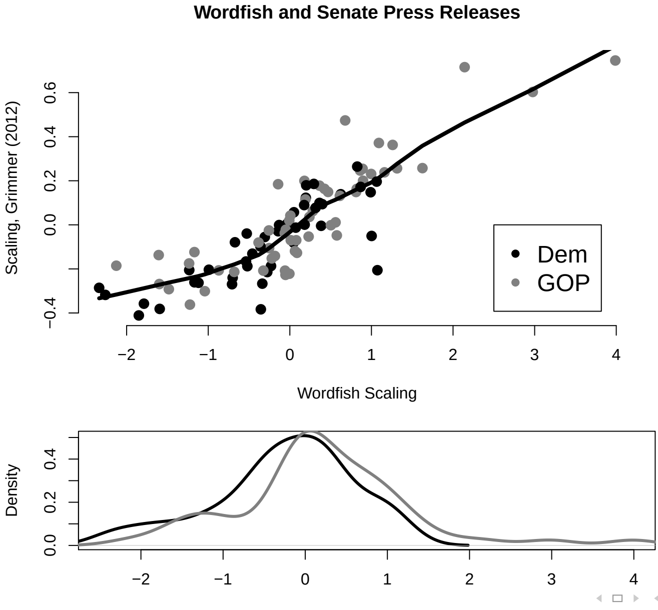

The Problem with Text-Based Scaling

What does validation mean?

1) Replicate NOMINATE, DIME, or other gold standards?
2) Agreement with experts
3) Prediction of other behavior

Must answer this to make progress on pure text scaling