Day 10: Text classification and scaling

ME314: Introduction to Data Science and Big Data Analytics

LSE Methods Summer Programme 2019

13 August 2019

Day 10 Outline

Overview of Supervised Learning vs. Unsupervised Learning

- Dictionary Methods
- Scaling

Text Classification

- Naive Bayes
- Regularized Regression
- Support Vector Machines

Scaling

- Wordscores
- Wordfish
- Correspondence Analysis

Overview of Machine Learning Methods for Text Analysis

Supervised machine learning

Goal: classify documents into pre existing categories.

e.g. authors of documents, sentiment of tweets, ideological position of parties based on manifestos, tone of movie reviews...

What we need:

- Hand-coded dataset (labeled), to be split into:
  - Training set: used to train the classifier
  - Validation/Test set: used to validate the classifier
- Method to extrapolate from hand coding to unlabeled documents (classifier):
  - Naive Bayes, regularized regression, SVM, K-nearest neighbors, BART, ensemble methods...
- Approach to validate classifier: cross-validation
- Performance metric to choose best classifier and avoid overfitting: confusion matrix, accuracy, precision, recall...

Creating a labeled set

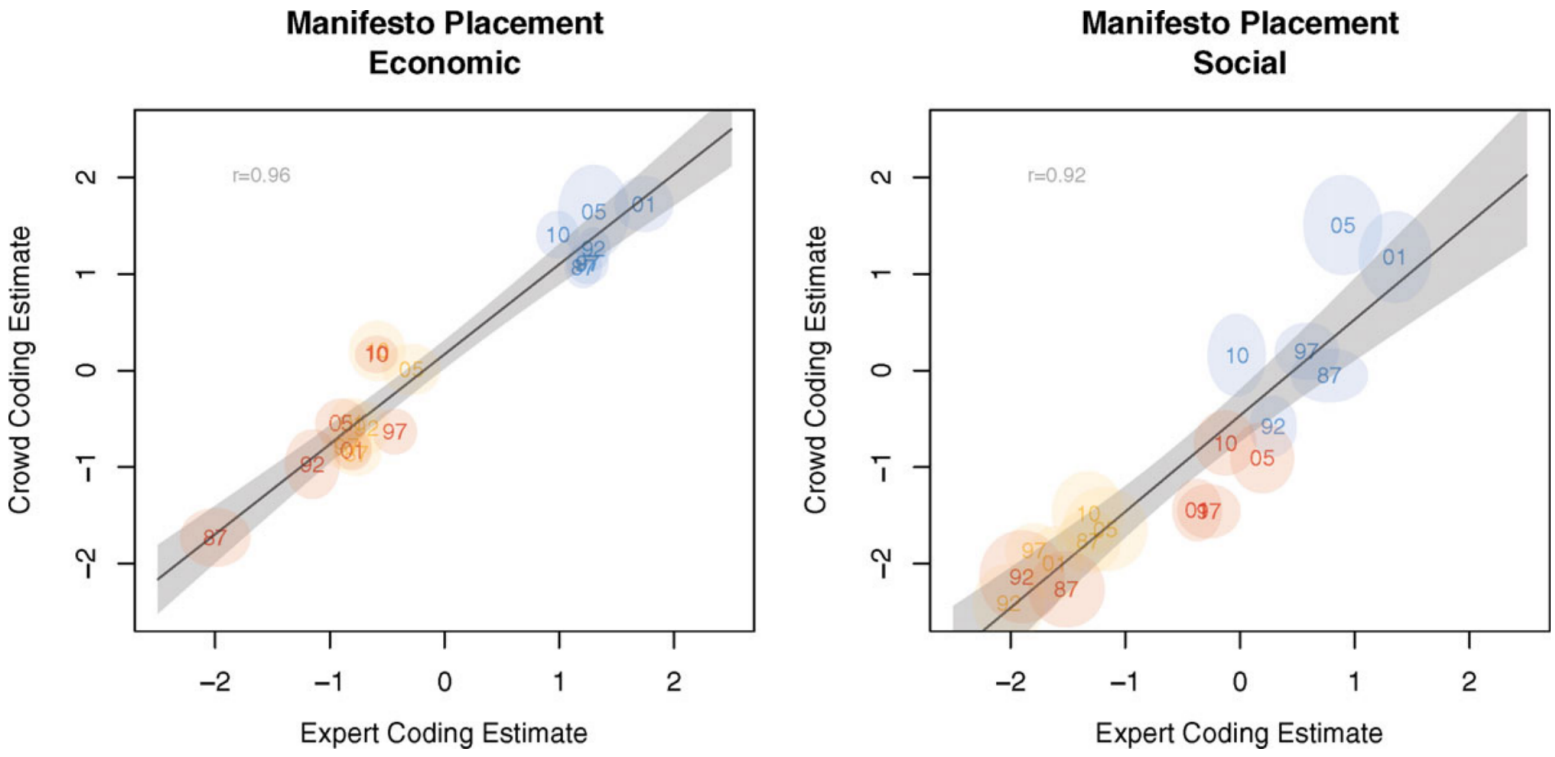
How do we obtain a **labeled set**?

- External sources of annotation
  - Disputed authorship of Federalist papers estimated based on known authors of other documents
  - Party labels for election manifestos
  - Legislative proposals by think tanks (text reuse)
- Expert annotation
  - "Canonical" dataset in Comparative Manifesto Project
  - In most projects, undergraduate students (expertise comes from training)
- Crowd-sourced coding
  - **Wisdom of crowds**: aggregated judgments of non-experts converge to judgments of experts at much lower cost (Benoit et al, 2016)
  - Easy to implement with CrowdFlower or MTurk

like active learning

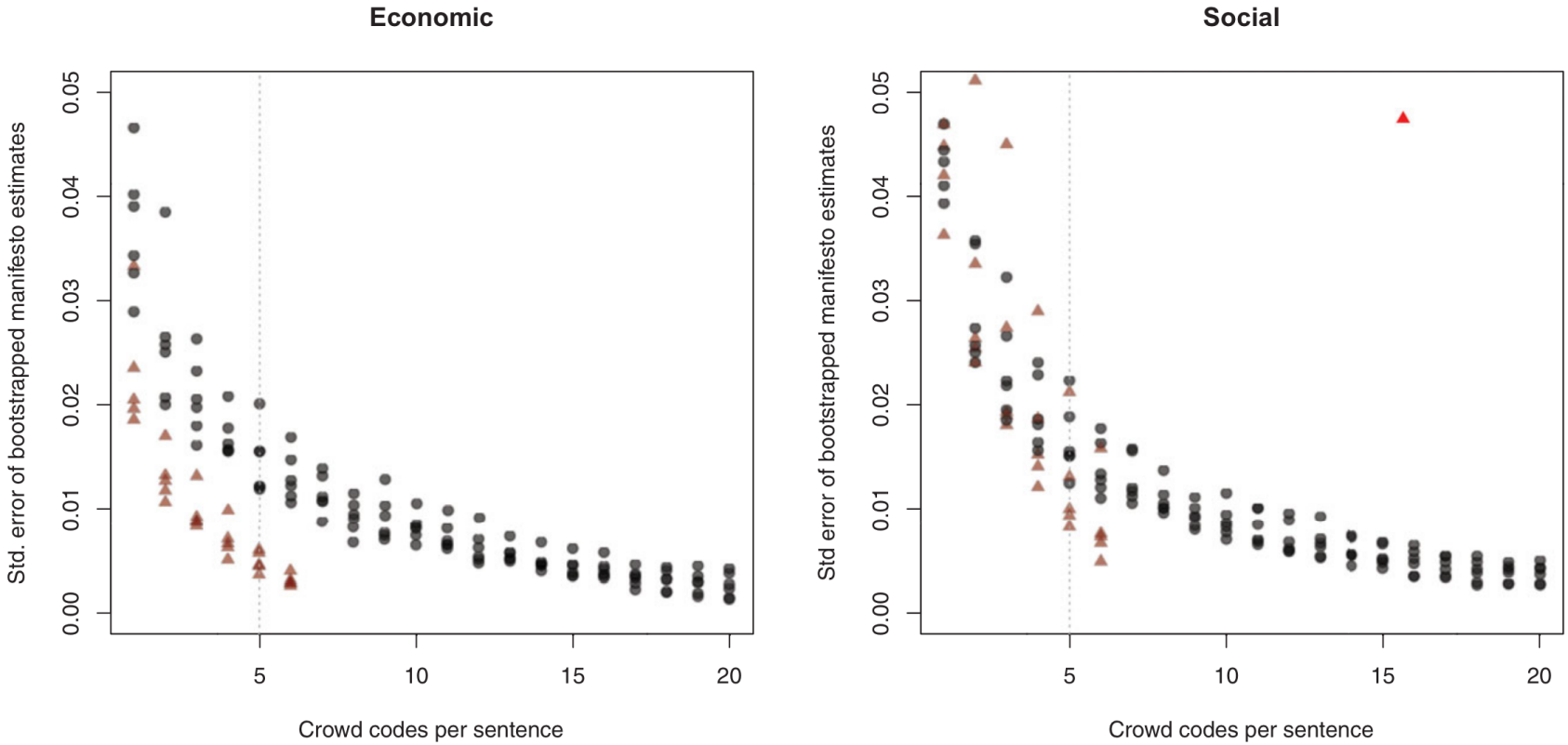
Crowd-sourced text analysis (Benoit et al, 2016 APSR)

FIGURE 3. Expert and Crowd-sourced Estimates of Economic and Social Policy Positions



Crowd-sourced text analysis (Benoit et al, 2016 APSR)

FIGURE 5. Standard Errors of Manifesto-level Policy Estimates as a Function of the Number of Workers, for the Oversampled 1987 and 1997 Manifestos



Note: Each point is the bootstrapped standard deviation of the mean of means aggregate manifesto scores, computed from sentence-level random n subsamples from the codes.

this is heteroskedastic errors. Not good

Evaluating the quality of a labeled set

Any labeled set should be tested and reported for its inter-rate reliability, at three different standards:

Type	**Test Design**	**Causes of Disagreements**	Strength
Stability	test-retest	intraobserver inconsistencies	weakest
Reproducibility	test-test	intraobserver inconsistencies + interobserver disagreements	medium
Accuracy	test-standard	intraobserver inconsistencies + interobserver disagreements + deviations from a standard	strongest

> need a formal metrics for this

Measures of agreement

- Percent agreement Very simple:

  (number of agreeing ratings) / (total ratings) * 100%

- Correlation
  - (usually) Pearson's r, aka product-moment correlation
  - Formula: $r_{AB} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{A_i - \bar{A}}{s_A} \right) \left(\frac{B_i - \bar{B}}{s_B} \right)$ diff between this and co-variance formula?
  - May also be ordinal, such as Spearman's rho or Kendall's tau-b
  - Range is [0,1]
- Agreement measures
  - Take into account not only observed agreement, but also *agreement that would have occured by chance*
  - Cohen's κ is most common this is the most basic test
  - Krippendorf's α is a generalization of Cohen's κ
  - Both range from [0,1]

Reliability data matrixes

Example here used binary data (from Krippendorff)

Article:	1	2	3	4	5	6	7	8	9	10
Coder A	1	1	0	0	0	0	0	0	0	0
Coder B	0	1	1	0	0	1	0	1	0	0

- A and B agree on 60% of the articles: 60% agreement
- Correlation is (approximately) 0.10
- Observed *dis*agreement: 4
- Expected *dis*agreement (by chance): 4.4211
- Krippendorff's $\alpha = 1 - \frac{D_o}{D_e} = 1 - \frac{4}{4.4211} = 0.095$
- Cohen's κ (nearly) identical

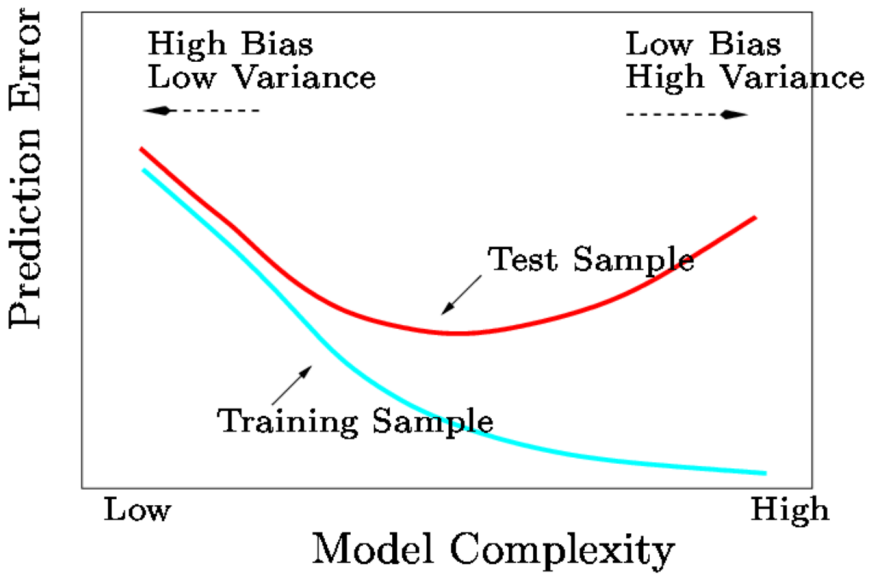
Basic principles of supervised learning

this is why CV is important

- Generalization: A classifier or a regression algorithm learns to correctly predict output from given inputs not only in previously seen samples but also in previously unseen samples
- Overfitting: A classifier or a regression algorithm learns to correctly predict output from given inputs in previously seen samples but fails to do so in previously unseen samples. This causes poor prediction/generalization.
- Goal is to maximize the frontier of precise identification of true condition with accurate recall

Measuring performance

- Classifier is trained to maximize in-sample performance
- But generally we want to apply method to new data
- Danger: overfitting



- Model is too complex, describes noise rather than signal (Bias-Variance trade-off)
- Focus on features that perform well in labeled data but may not generalize (e.g. "inflation" in 1980s)
- In-sample performance better than out-of-sample performance

- Solutions?
  - Randomly split dataset into training and test set
  - Cross-validation

Supervised v. unsupervised methods compared

- The goal (in text analysis) is to differentiate *documents* from one another, treating them as "bags of words"
- Different approaches:
  - *Supervised methods* require a training set that exemplify contrasting classes, identified by the researcher
  - *Unsupervised methods* scale documents based on patterns of similarity from the term-document matrix, without requiring a training step
- Relative advantage of supervised methods:

  You already know the dimension being scaled, because you set it in the training stage
- Relative disadvantage of supervised methods:

  You *must* already know the dimension being scaled, because you have to feed it good sample documents in the training stage

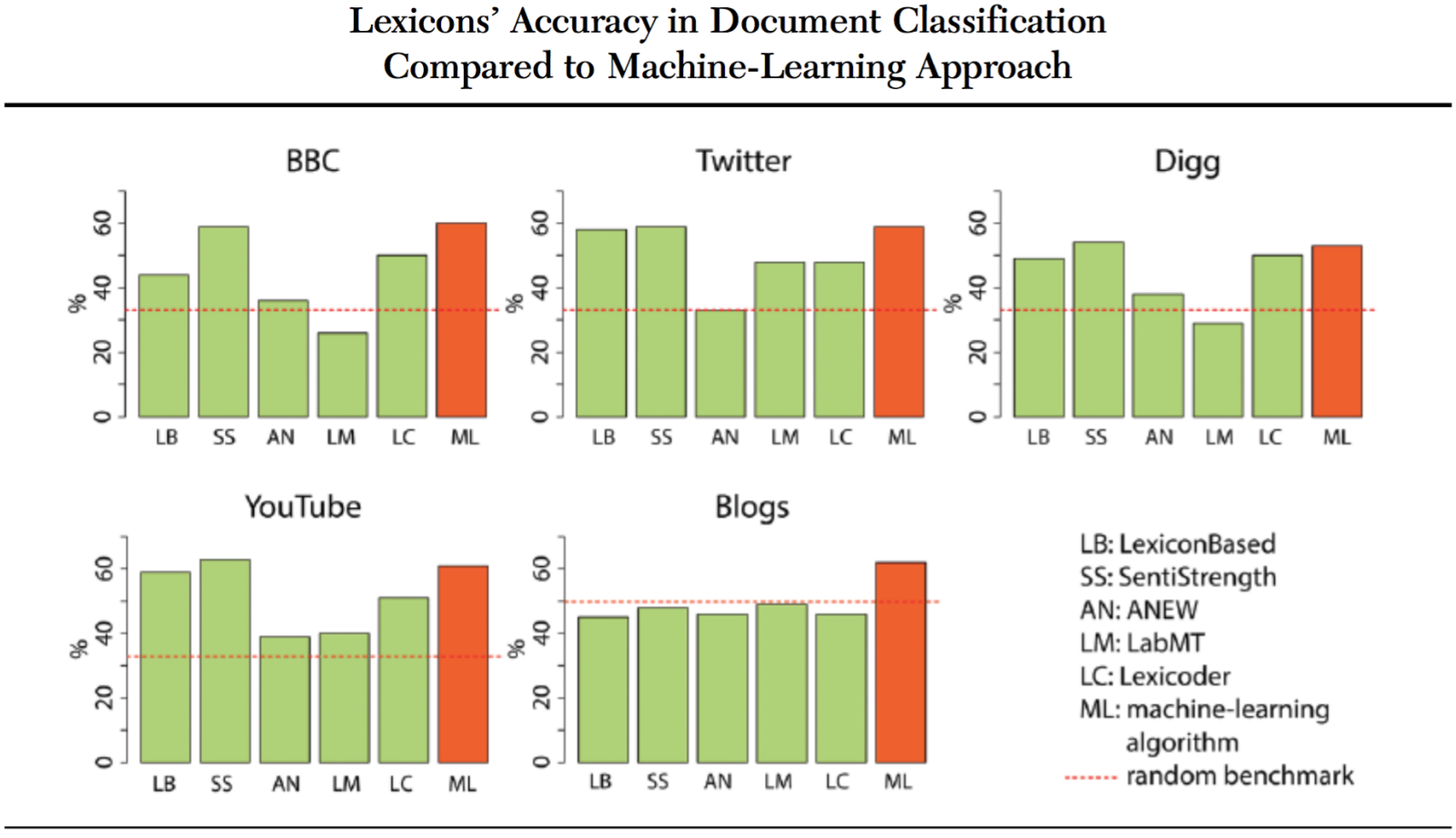
Supervised v. unsupervised methods: Examples

- General examples:
  - Supervised: Naive Bayes, regularized regression, Support Vector Machines (SVM)
  - Unsupervised: topic models, IRT models, correspondence analysis, factor analytic approaches
- Political science applications
  - Supervised: Wordscores (LBG 2003); SVMs (Yu, Kaufman and Diermeier 2008); Naive Bayes (Evans et al 2007)
  - Unsupervised: Structural topic model (Roberts et al 2014); "Wordfish" (Slapin and Proksch 2008); two-dimensional IRT (Monroe and Maeda 2004)

Supervised learning v. dictionary methods

- Dictionary methods:
  - Advantage: not corpus-specific, cost to apply to a new corpus is trivial
  - Disadvantage: not corpus-specific, so performance on a new corpus is unknown (domain shift)
- Supervised learning can be conceptualized as a generalization of dictionary methods, where features associated with each categories (and their relative weight) are learned from the data
- By construction, they will outperform dictionary methods in classification tasks, as long as training sample is large enough

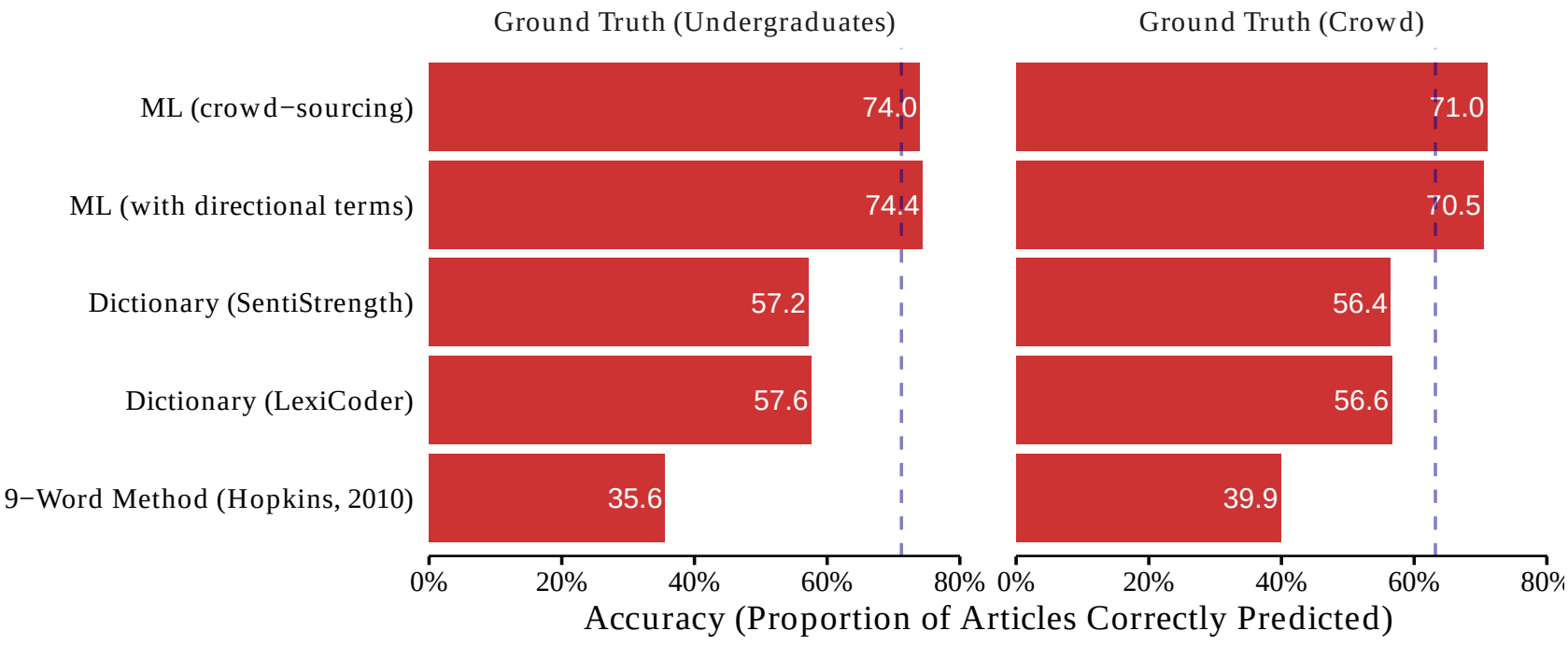
Dictionaries vs supervised learning



Source: González-Bailón and Paltoglou (2015)

Dictionaries vs supervised learning

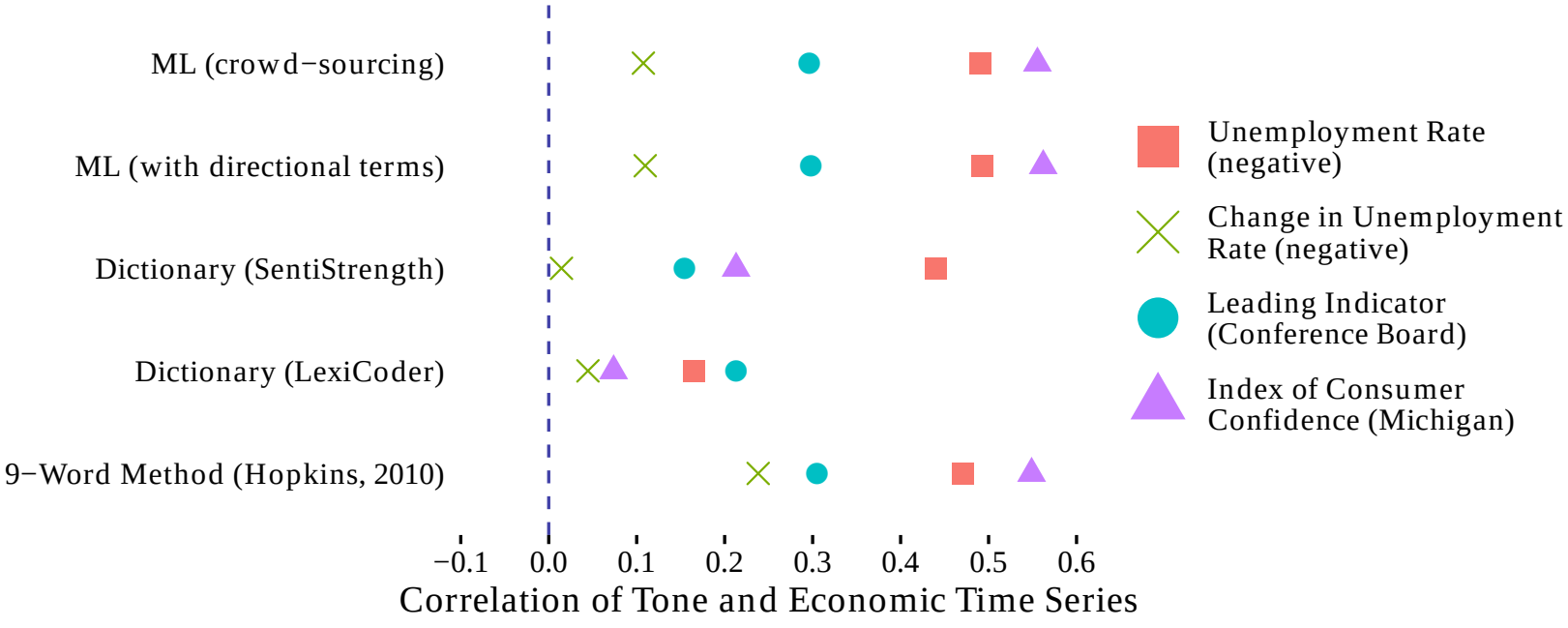
Application: sentiment analysis of NYTimes articles



Source: Barberá et al (2017)

Dictionaries vs supervised learning

Application: sentiment analysis of NYTimes articles



Source: Barberá et al (2017)

Classification v. scaling methods compared

- Machine learning focuses on identifying classes (classification), while social science is typically interested in locating things on latent traits (scaling)
- But the two methods overlap and can be adapted – will demonstrate later using the Naive Bayes classifier
- Applying lessons from machine learning to supervised scaling, we can
  - Apply classification methods to scaling
  - Improve it using lessons from machine learning

Text Classification

Types of classifiers

General thoughts:

- Trade-off between accuracy and interpretability
- Parameters need to be cross-validated

Frequently used classifiers:

- Naive Bayes
- Regularized regression
- SVM
- Others: k-nearest neighbors, tree-based methods, etc.
- Ensemble methods

Multinomial Bayes model of Class given a Word

Consider J word types distributed across N documents, each assigned one of K classes.

At the word level, Bayes Theorem tells us that:

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j)}$$

For two classes, this can be expressed as

$$= \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})} \tag{1}$$

Multinomial Bayes model of Class given a Word

Class-conditional word likelihoods

P(A | B) = [P(B | A) * P(A)]
———————
[P(B)]

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

what's the probability of C being about abortion given that C is seen? (e.g. C = "clinic")

- The word likelihood within class
- The maximum likelihood estimate is simply the proportion of times that word j occurs in class k, but it is more common to use Laplace smoothing by adding 1 to each oberved count within class

Multinomial Bayes model of Class given a Word
Word probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j)}$$

- This represents the word probability from the training corpus
- Usually uninteresting, since it is constant for the training data, but needed to compute posteriors on a probability scale

Multinomial Bayes model of Class given a Word
Class prior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the class prior probability
- Machine learning typically takes this as the document frequency in the training set

Multinomial Bayes model of Class given a Word
Class posterior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the posterior probability of membership in class k for word j
- Key for the classifier: in new documents, we only observe word distributions and want to predict class

Moving to the document level

- The "Naive" Bayes model of a joint document-level class posterior assumes conditional independence, to multiply the word likelihoods from a "test" document, to produce:

$$P(c|d) = P(c) \prod_j \frac{P(w_j|c)}{P(w_j)}$$

$$P(c|d) \propto P(c) \prod_j P(w_j|c)$$

- This is why we call it "naive": because it (wrongly) assumes:
  - *conditional independence* of word counts
  - *positional independence* of word counts

Naive Bayes Classification Example

(From Manning, Raghavan and Schütze, *Introduction to Information Retrieval*)

▶ **Table 13.1** Data for parameter estimation examples.

	docID	words in document	in $c = China$?
training set	1	Chinese Beijing Chinese	yes
	2	Chinese Chinese Shanghai	yes
	3	Chinese Macao	yes
	4	Tokyo Japan Chinese	no
test set	5	Chinese Chinese Chinese Tokyo Japan	?

Naive Bayes Classification Example

Example 13.1: For the example in Table 13.1, the multinomial parameters we need to classify the test document are the priors $\hat{P}(c) = 3/4$ and $\hat{P}(\overline{c}) = 1/4$ and the following conditional probabilities:

+1 because of laplace smoothing

$$\begin{aligned}
\hat{P}(\text{Chinese}|c) &= (5+1)/(8+6) = 6/14 = 3/7 \\
\hat{P}(\text{Tokyo}|c) = \hat{P}(\text{Japan}|c) &= (0+1)/(8+6) = 1/14 \\
\hat{P}(\text{Chinese}|\overline{c}) &= (1+1)/(3+6) = 2/9 \\
\hat{P}(\text{Tokyo}|\overline{c}) = \hat{P}(\text{Japan}|\overline{c}) &= (1+1)/(3+6) = 2/9
\end{aligned}$$

The denominators are $(8+6)$ and $(3+6)$ because the lengths of $text_c$ and $text_{\overline{c}}$ are 8 and 3, respectively, and because the constant B in Equation (13.7) is 6 as the vocabulary consists of six terms.

We then get:

$$\begin{aligned}
\hat{P}(c|d_5) &\propto 3/4 \cdot (3/7)^3 \cdot 1/14 \cdot 1/14 \approx 0.0003. \\
\hat{P}(\overline{c}|d_5) &\propto 1/4 \cdot (2/9)^3 \cdot 2/9 \cdot 2/9 \approx 0.0001.
\end{aligned}$$

Thus, the classifier assigns the test document to $c = \textit{China}$. The reason for this classification decision is that the three occurrences of the positive indicator Chinese in d_5 outweigh the occurrences of the two negative indicators Japan and Tokyo.

Regularized regression

Assume we have:

- $i = 1, 2, \ldots, N$ documents
- Each document i is in class $y_i = 0$ or $y_i = 1$
- $j = 1, 2, \ldots, J$ unique features
- And x_{ij} as the count of feature j in document i

We could build a linear regression model as a classifier, using the values of β_0, β_1, ..., β_J that minimize:

$$RSS = \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2$$

But can we?

- If $J > N$, OLS does not have a unique solution
- Even with $N > J$, OLS has low bias/high variance (overfitting)

Regularized regression

What can we do? Add a penalty for model complexity, such that we now minimize:

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{J}\beta_j^2 \rightarrow \text{ridge regression}$$

or

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{J}|\beta_j| \rightarrow \text{lasso regression}$$

where λ is the **penalty parameter** (to be estimated)

Regularized regression

Why the penalty (shrinkage)?

- Reduces the variance
- Identifies the model if J $>$ N
- Some coefficients become zero (feature selection)

The penalty can take different forms:

- Ridge regression: $\lambda \sum_{j=1}^{J} \beta_j^2$ with $\lambda > 0$; and when $\lambda = 0$ becomes OLS
- Lasso $\lambda \sum_{j=1}^{J} |\beta_j|$ where some coefficients become zero.
- Elastic Net: $\lambda_1 \sum_{j=1}^{J} \beta_j^2 + \lambda_2 \sum_{j=1}^{J} |\beta_j|$ (best of both worlds?)

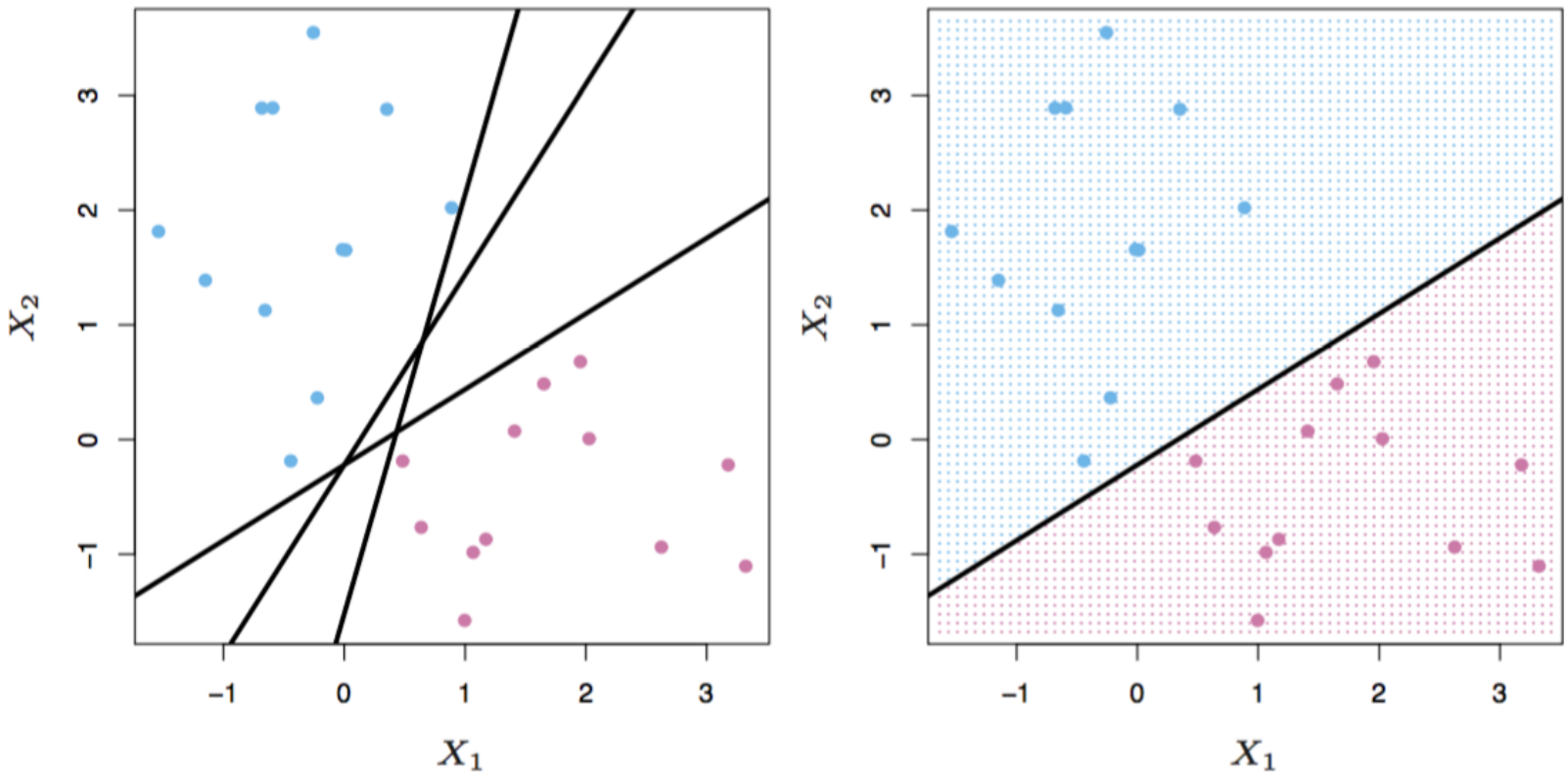
like a diamond shape

like a circle

How to find best value of λ? Cross-validation.
Evaluation: regularized regression is easy to interpret, but often outperformed by more complex methods.

SVM

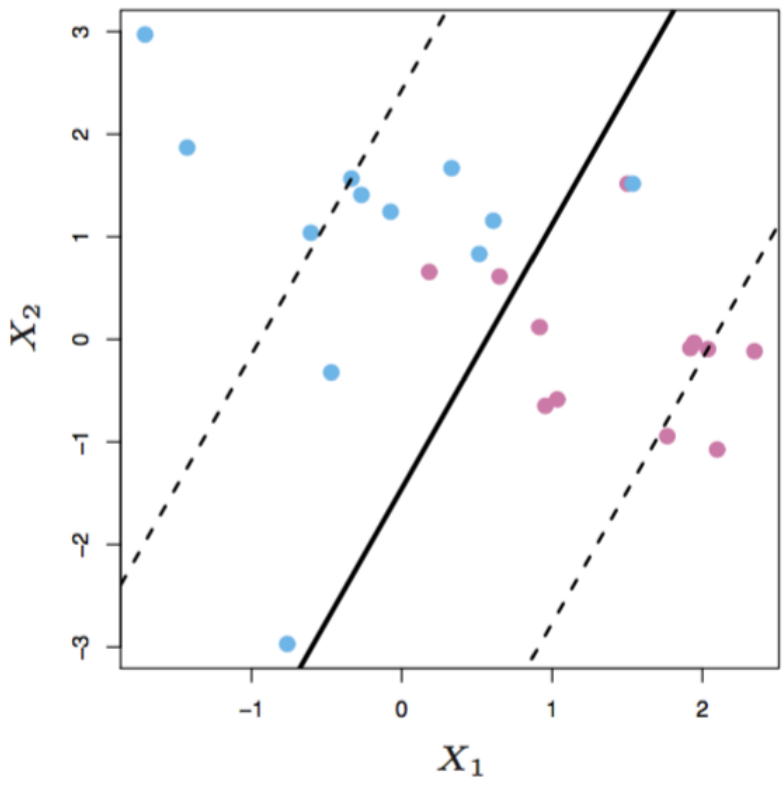
Intuition: finding classification boundary that best separates observations of different classes.

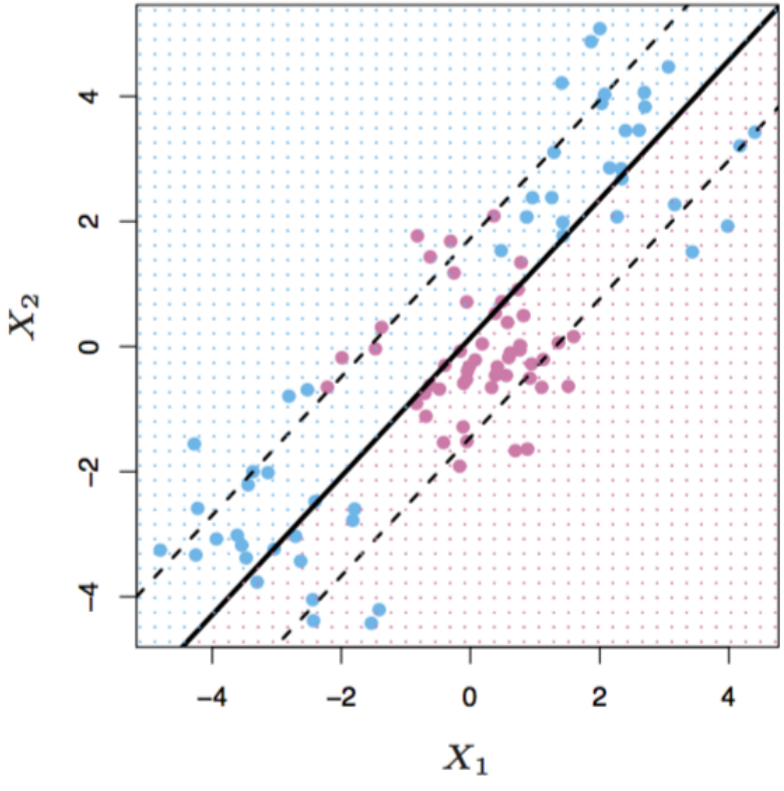


Harder to visualize in more than two dimensions (hyperplanes)

Support Vector Machines

With no perfect separation, goal is to minimize distances to marginal points, conditioning on a tuning parameter C that indicates tolerance to errors (controls bias-variance trade-off)

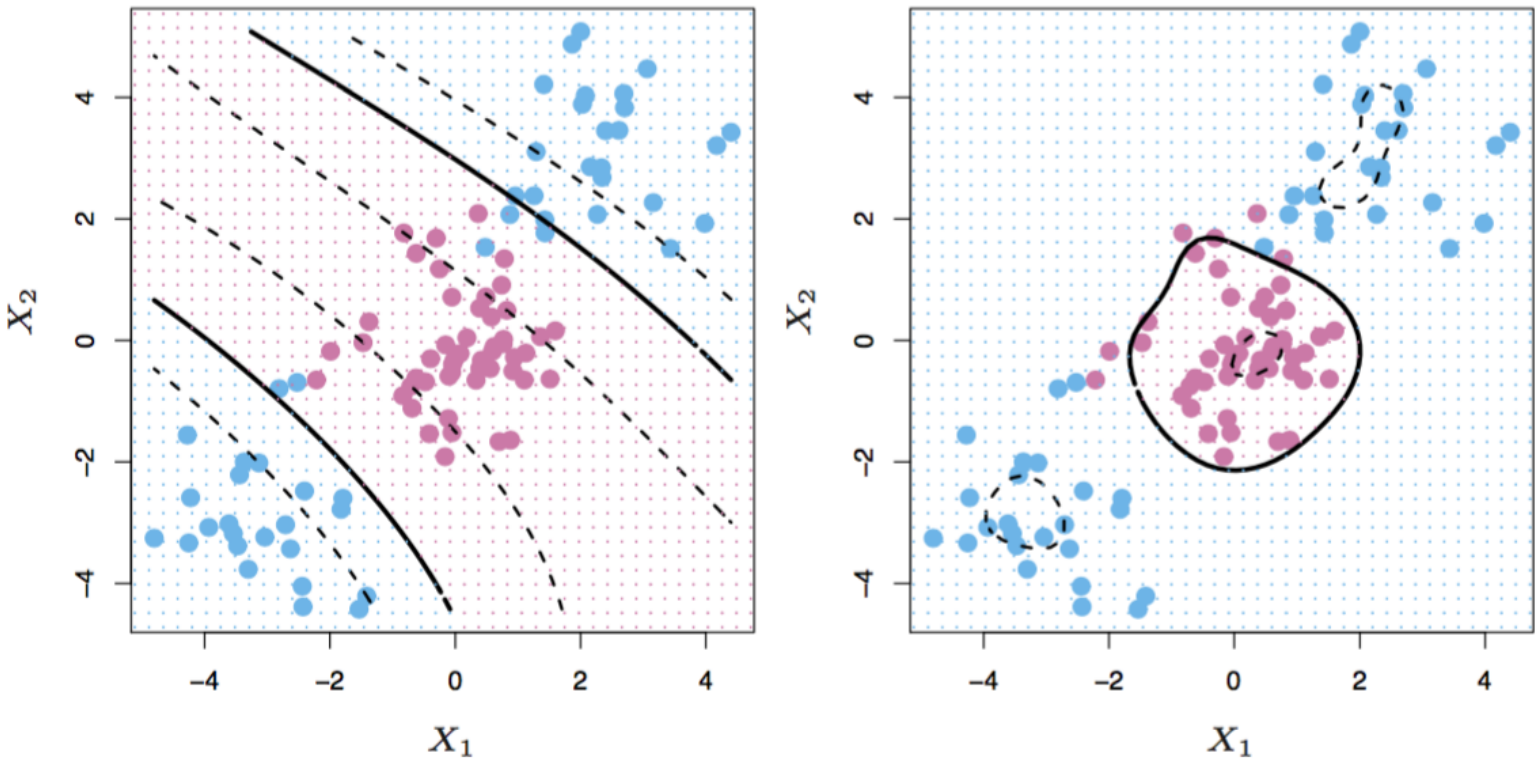




also like maximizing the distance between points with the boundary on both sides.

SVM

In previous examples, vectors were linear; but we can try different kernels (polynomial, radial):



And of course we can have multiple vectors within same classifier.

Ensemble methods

Intuition:

- Fit multiple classifiers, different types
- Test how well they perform in test set
- For new observations, produce prediction aggregating predictions of individual classifiers
- How to aggregate predictions?
  - Pick best classifier
  - Average of predicted probabilities
  - Weighted average (weights proportional to classification error)
- Implement in `SuperLearner` package in R

there is stg called `caret.ensemble` also for this.

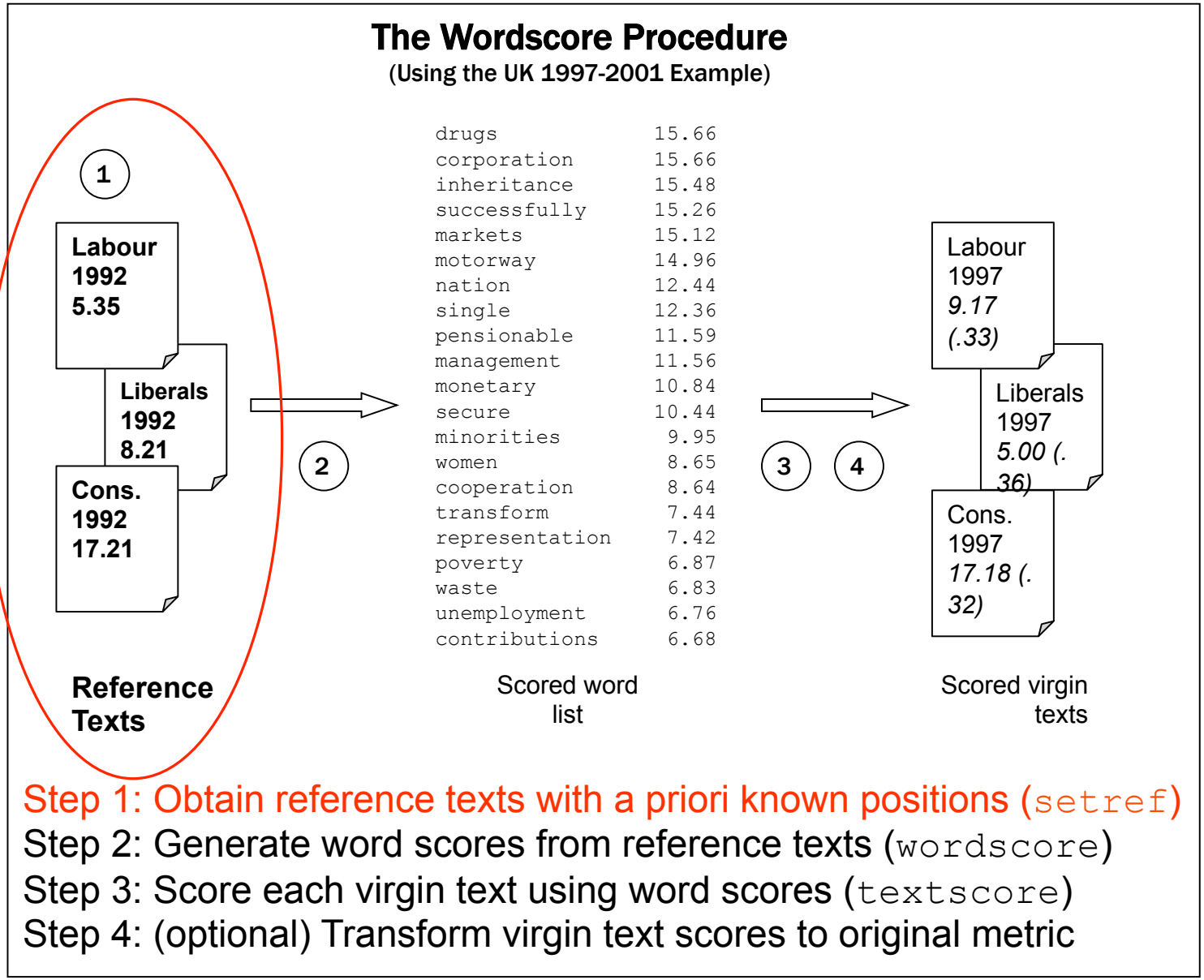
Scaling

Supervised scaling methods

Wordscores method (Laver, Benoit & Garry, 2003):

- Two sets of texts
  - Reference texts: texts about which we know something (a scalar dimensional score)
  - Virgin texts: texts about which we know nothing (but whose dimensional score we'd like to know)
- These are analogous to a "training set" and a "test set" in classification
- Basic procedure:
  1. Analyze reference texts to obtain word scores
  2. Use word scores to score virgin texts

Wordscores Procedure



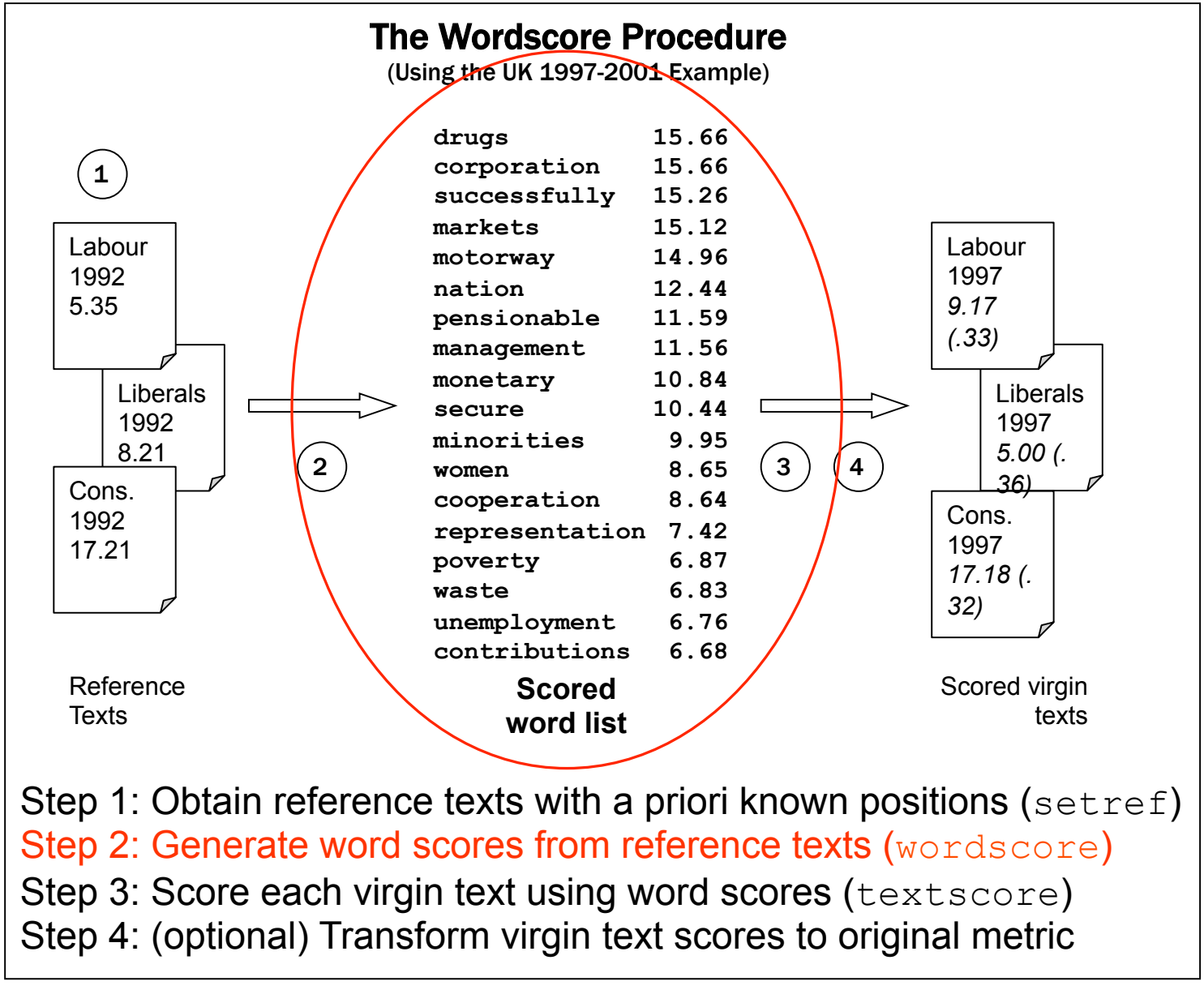
Step 1: Obtain reference texts with a priori known positions (`setref`)

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

Wordscores Procedure



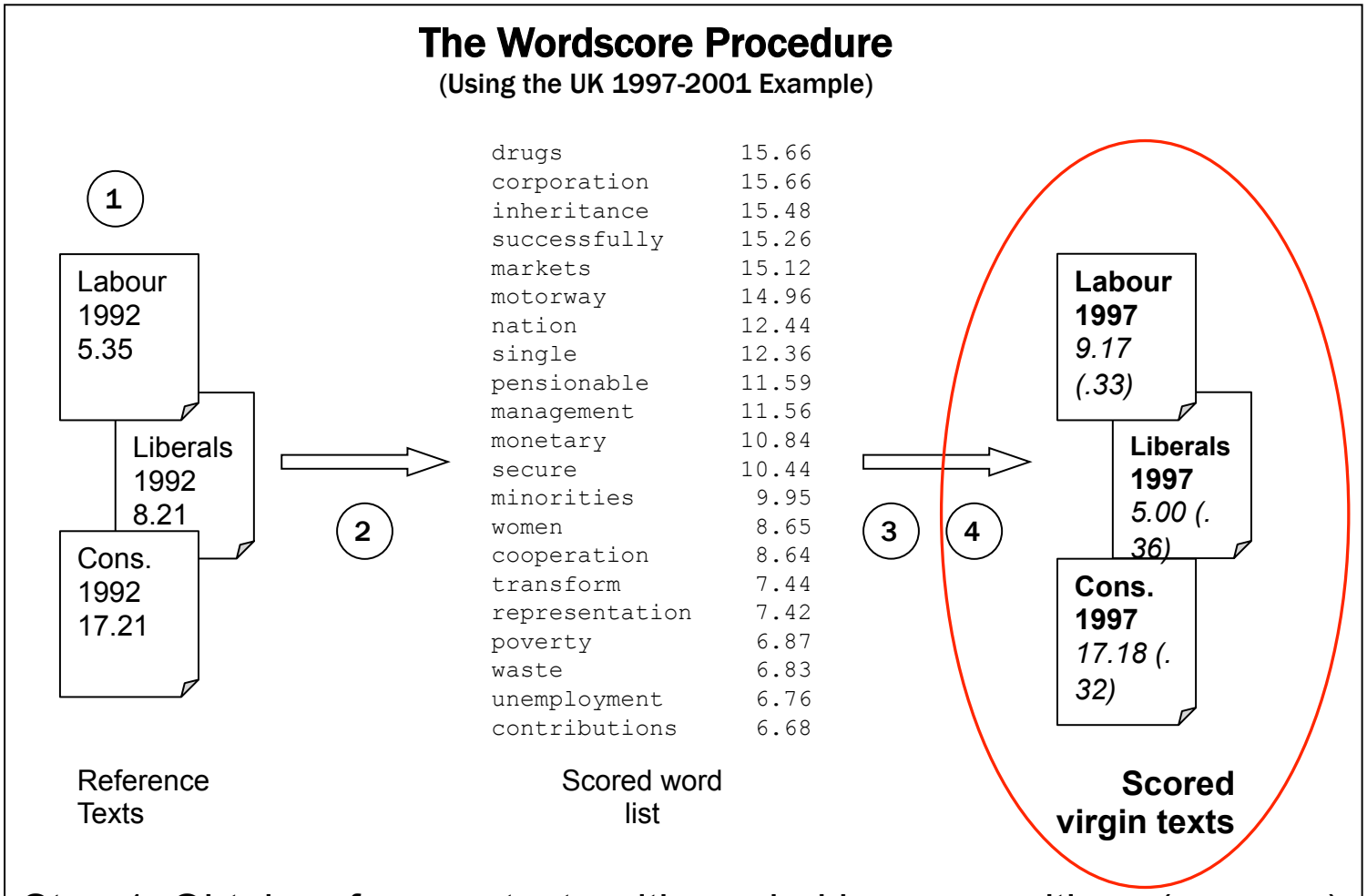
Step 1: Obtain reference texts with a priori known positions (`setref`)

Step 2: Generate word scores from reference texts (`wordscore`)

Step 3: Score each virgin text using word scores (`textscore`)

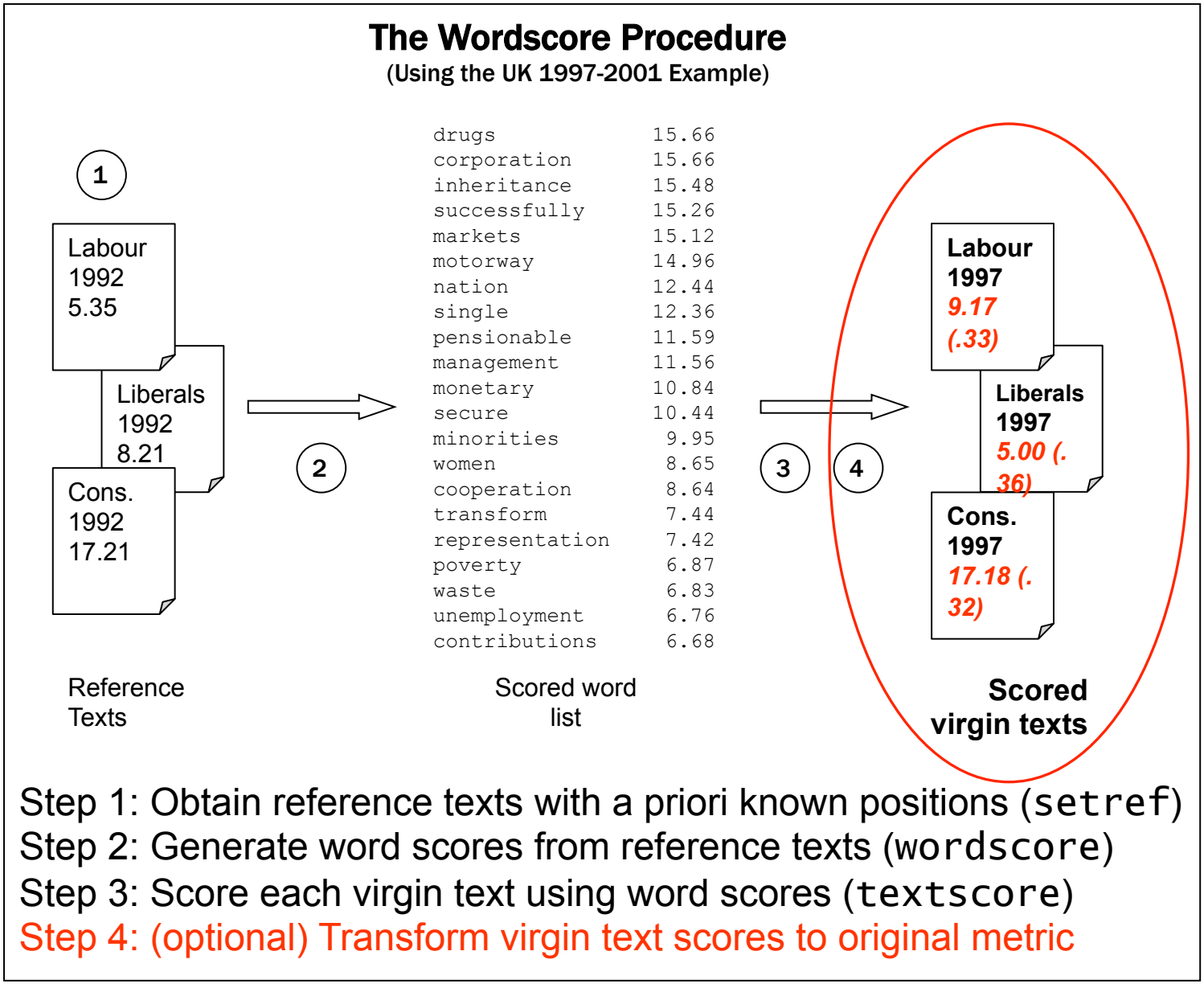
Step 4: (optional) Transform virgin text scores to original metric

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

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

Wordscores mathematically: Reference texts

- Start with a set of I *reference* texts, represented by an $I \times J$ document-feature matrix C_{ij}, where i indexes the document and j indexes the J total word types
- Each text will have an associated "score" a_i, which is a single number locating this text on a single dimension of difference
  - This can be on a scale metric, such as 1–20
  - Can use arbitrary endpoints, such as -1, 1
- We *normalize* the document-feature matrix within each document by converting C_{ij} into a *relative* document-feature matrix (within document), by dividing C_{ij} by its word total marginals:

$$F_{ij} = \frac{C_{ij}}{C_{i\cdot}} \tag{2}$$

where $C_{i\cdot} = \sum_{j=1}^{J} C_{ij}$

Wordscores mathematically: Word scores

- Compute an $I \times J$ matrix of relative document probabilities P_{ij} for each word in each reference text, as

$$P_{ij} = \frac{F_{ij}}{\sum_{i=1}^{I} F_{ij}} \tag{3}$$

- This tells us the probability that given the observation of a specific word j, that we are reading a text of a certain reference document i

Wordscores mathematically: Word scores (example)

- Assume we have two reference texts, A and B
- The word "choice" is used 10 times per 1,000 words in Text A and 30 times per 1,000 words in Text B
- So $F_{i\ \text{"choice"}} = \{.010, .030\}$
- If we know only that we are reading the word choice in one of the two reference texts, then probability is 0.25 that we are reading Text A, and 0.75 that we are reading Text B

$$P_{A\ \text{"choice"}} = \frac{.010}{(.010 + .030)} = 0.25 \tag{4}$$

$$P_{B\ \text{"choice"}} = \frac{.030}{(.010 + .030)} = 0.75 \tag{5}$$

Wordscores mathematically: Word scores

- Compute a J-length "score" vector S for each word j as the average of each document i's scores a_i, weighted by each word's P_{ij}:

$$S_j = \sum_{i=1}^{I} a_i P_{ij} \tag{6}$$

- In matrix algebra, $\underset{1\times J}{S} = \underset{1\times I}{a} \cdot \underset{I\times J}{P}$
- This procedure will yield a single "score" for every word that reflects the balance of the scores of the reference documents, weighted by the relative document frequency of its normalized term frequency

Wordscores mathematically: Word scores

- Continuing with our example:
  - We "know" (from independent sources) that Reference Text A has a position of -1.0, and Reference Text B has a position of $+1.0$
  - The score of the word "choice" is then $0.25(-1.0) + 0.75(1.0) = -0.25 + 0.75 = +0.50$

Wordscores mathematically: Scoring "virgin" texts

- Here the objective is to obtain a single score for any new text, relative to the reference texts
- We do this by taking the mean of the scores of its words, weighted by their term frequency
- So the score v_k of a virgin document k consisting of the j word types is:

$$v_k = \sum_j (F_{kj} \cdot s_j) \tag{7}$$

where $F_{kj} = \frac{C_{kj}}{C_{k.}}$ as in the reference document relative word frequencies

- Note that new words outside of the set J may appear in the K virgin documents — these are simply ignored (because we have no information on their scores) ***a.k.a. you'll lose this data
- Note also that nothing prohibits reference documents from also being scored as virgin documents *** meaning nothing prevents you from doing this

Wordscores mathematically: Rescaling raw text scores

- Because of overlapping or non-discriminating words, the raw text scores will be dragged to the interior of the reference scores (we will see this shortly in the results)
- Some procedures can be applied to rescale them, either to a unit normal metric or to a more "natural" metric
- Martin and Vanberg (2008) have proposed alternatives to the LBG (2003) rescaling

***meaning you lose intrepretation; go into arbitrarily

Computing confidence intervals

- The score v_k of any text represents a weighted mean
- LBG (2003) used this logic to develop a standard error of this mean using a *weighted variance* of the scores in the virgin text
- Given some assumptions about the scores being fixed (and the words being conditionally independent), this yields approximately normally distributed errors for each v_k
- An alternative would be to bootstrap the textual data prior to constructing C_{ij} and C_{kj} — see Lowe and Benoit (2012)

Pros and Cons of the Wordscores approach

Pros:
1. language-agnostic Good!

- Estimates unknown positions on a priori scales – hence no inductive scaling with a posteriori interpretation of unknown policy space
- Very dependent on correct identification of:
  - appropriate reference texts
  - appropriate reference scores

Suggestions for choosing reference texts

- Texts need to contain information representing a clearly dimensional position
- Dimension must be known a priori. Sources might include:
  - Survey scores or manifesto scores
  - Arbitrarily defined scales (e.g. -1.0 and 1.0)
- Should be as discriminating as possible: extreme texts on the dimension of interest, to provide reference anchors -- meaning need outliers
- Need to be from the same lexical universe as virgin texts
- Should contain lots of words

Suggestions for choosing reference values

- Must be "known" through some trusted external source
- For any pair of reference values, all scores are simply linear rescalings, so might as well use (-1, 1)
- The "middle point" will not be the midpoint, however, since this will depend on the relative word frequency of the reference documents
- Reference texts if scored as virgin texts will have document scores more extreme than other virgin texts
- With three or more reference values, the mid-point is mapped onto a multi-dimensional simplex. The values now matter but only in relative terms (we are still investigating this fully)

Multinomial Bayes model of Class given a Word
Class posterior probabilities

$$P(c_k|w_j) = \frac{P(w_j|c_k)P(c_k)}{P(w_j|c_k)P(c_k) + P(w_j|c_{\neg k})P(c_{\neg k})}$$

- This represents the posterior probability of membership in class k for word j
- Under *certain conditions*, this is identical to what LBG (2003) called P_{wr}
- Under those conditions, the LBG "wordscore" is the linear difference between $P(c_k|w_j)$ and $P(c_{\neg k}|w_j)$

"Certain conditions"

- The LBG approach required the identification not only of texts for each training class, but also "reference" scores attached to each training class
- Consider two "reference" scores s_1 and s_2 attached to two classes $k = 1$ and $k = 2$. Taking P_1 as the posterior $P(k = 1|w = j)$ and P_2 as $P(k = 2|w = j)$, A generalised score s_j^* for the word j is then

$$\begin{aligned} s_j^* &= s_1 P_1 + s_2 P_2 \\ &= s_1 P_1 + s_2(1 - P_1) \\ &= s_1 P_1 + s_2 - s_2 P_1 \\ &= P_1(s_1 - s_2) + s_2 \end{aligned}$$

"Certain conditions": More than two reference classes

- For more than two reference classes, if the reference scores are ordered such that $s_1 < s_2 < \cdots < s_K$, then

$$
\begin{aligned}
s_j^* &= s_1 P_1 + s_2 P_2 + \cdots + s_K P_K \\
&= s_1 P_1 + s_2 P_2 + \cdots + s_K (1 - \sum_{k=1}^{K-1} P_k) \\
&= \sum_{k=1}^{K-1} P_i (s_k - s_K) + s_I
\end{aligned}
$$

A simpler formulation:
Use reference scores such that $s_1 = -1.0, s_K = 1.0$

- From above equations, it should be clear that any set of reference scores can be linearly rescaled to endpoints of $-1.0, 1.0$
- This simplifies the "simple word score"

$$s_j^* = (1 - 2P_1) + \sum_{k=2}^{K-1} P_k(s_k - 1)$$

- which simplifies with just two reference classes to:

$$s_j^* = 1 - 2P_1$$

Implications

- LBG's "word scores" come from a linear combination of class posterior probabilities from a Bayesian model of class conditional on words
- We might as well always anchor reference scores at $-1.0, 1.0$
- There is a special role for reference classes in between $-1.0, 1.0$, as they balance between "pure" classes — more in a moment
- There are alternative scaling models, such that used in Beauchamp's (2012) "Bayesscore", which is simply the difference in logged class posteriors at the word level. For $s_1 = -1.0$, $s_2 = 1.0$,

$$\begin{aligned} s_j^B &= -\log P_1 + \log P_2 \\ &= \log \frac{1 - P_1}{P_1} \end{aligned}$$

Moving to the document level

- The "Naive" Bayes model of a joint document-level class posterior assumes conditional independence, to multiply the word likelihoods from a "test" document, to produce:

$$P(c|d) = P(c) \frac{\prod_j P(w_j|c)}{P(w_j)}$$

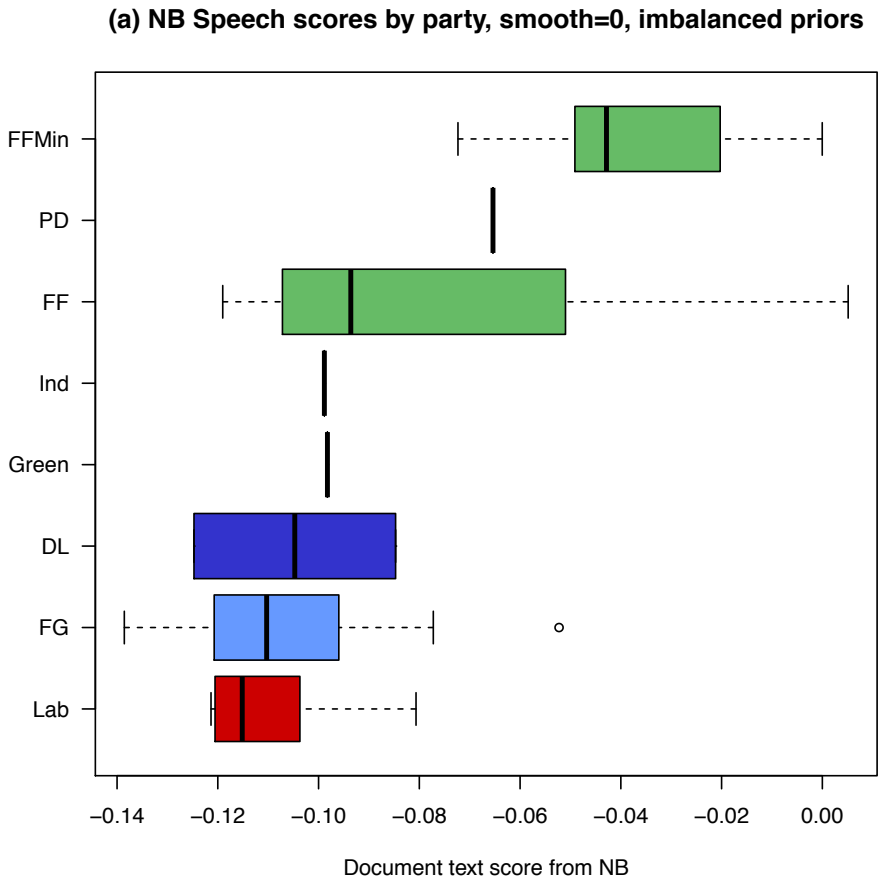
- So we *could* consider a document-level relative score, e.g. $1 - 2P(c_1|d)$ (for a two-class problem)
- But this turns out to be *useless*, since the predictions of class are highly separated

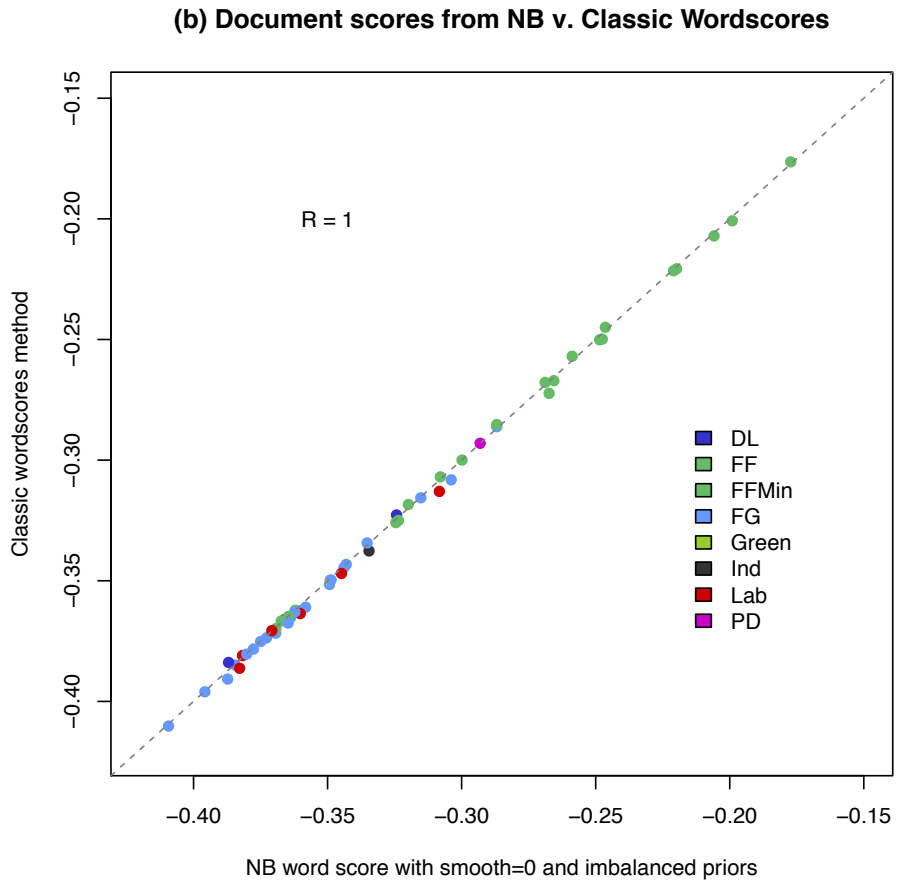
Moving to the document level

- A better solution is to score a test document as the arithmetic mean of the scores of its words
- This is exactly the solution proposed by LBG (2003)
- Beauchamp (2012) proposes a "Bayesscore" which is the arithmetic mean of the log difference word scores in a document – which yields extremely similar results

And now for some demonstrations with data...

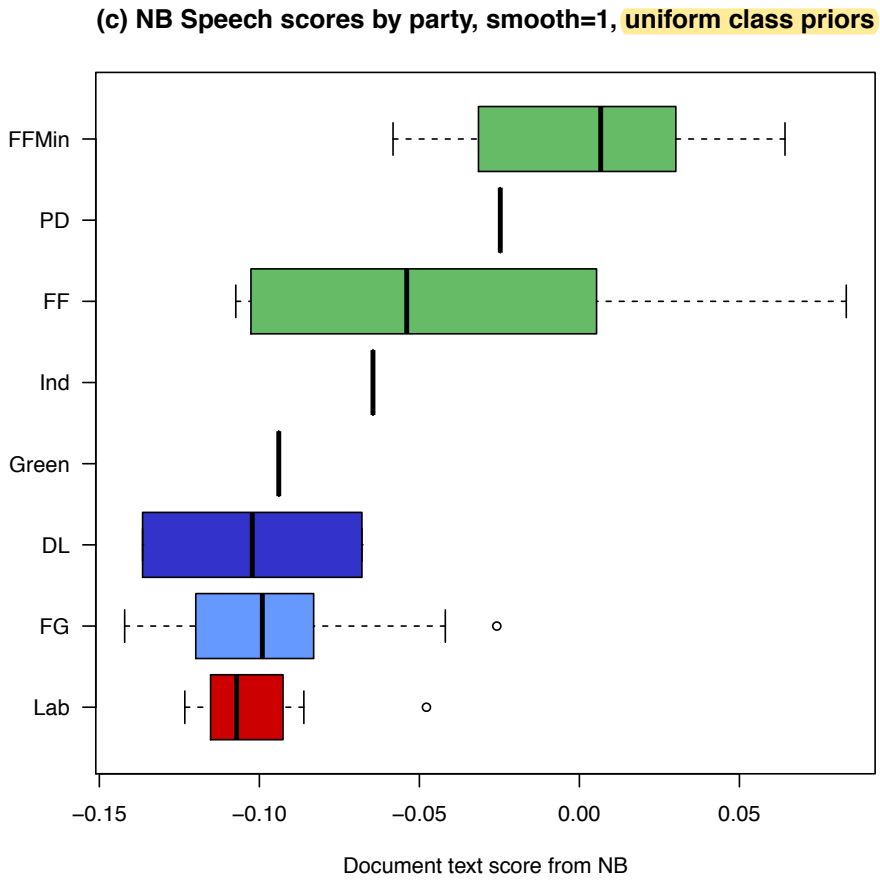
Application 1: Dail speeches from LBG (2003)

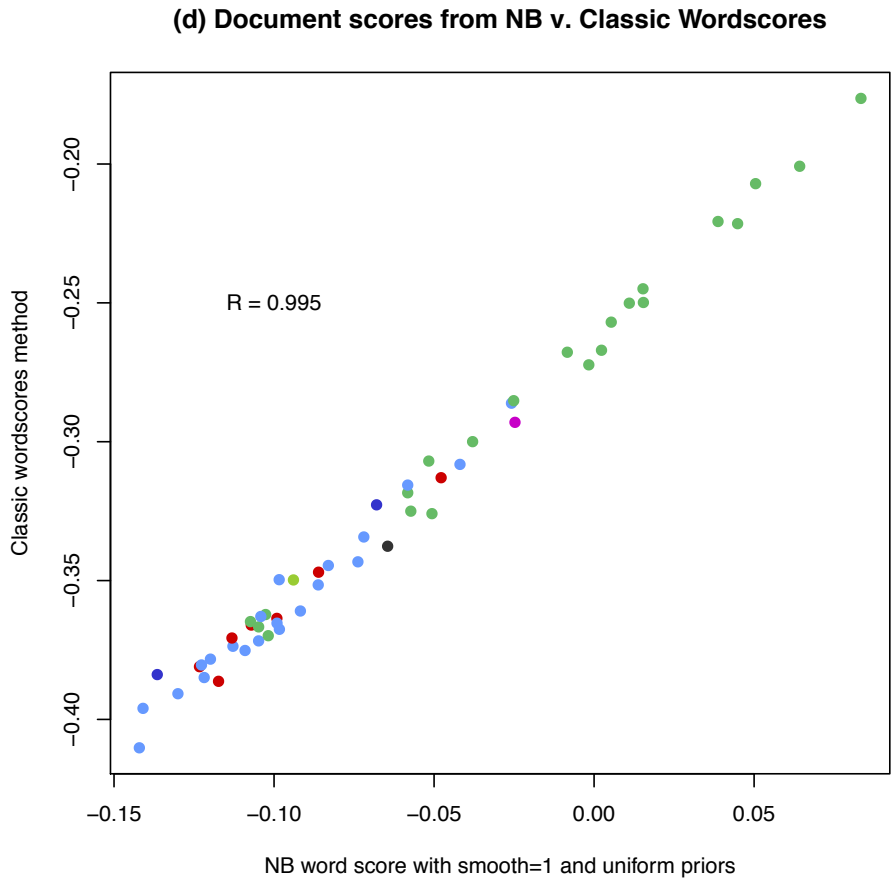




- three reference classes (Opposition, Opposition, Government) at {-1, -1, 1}
- no smoothing

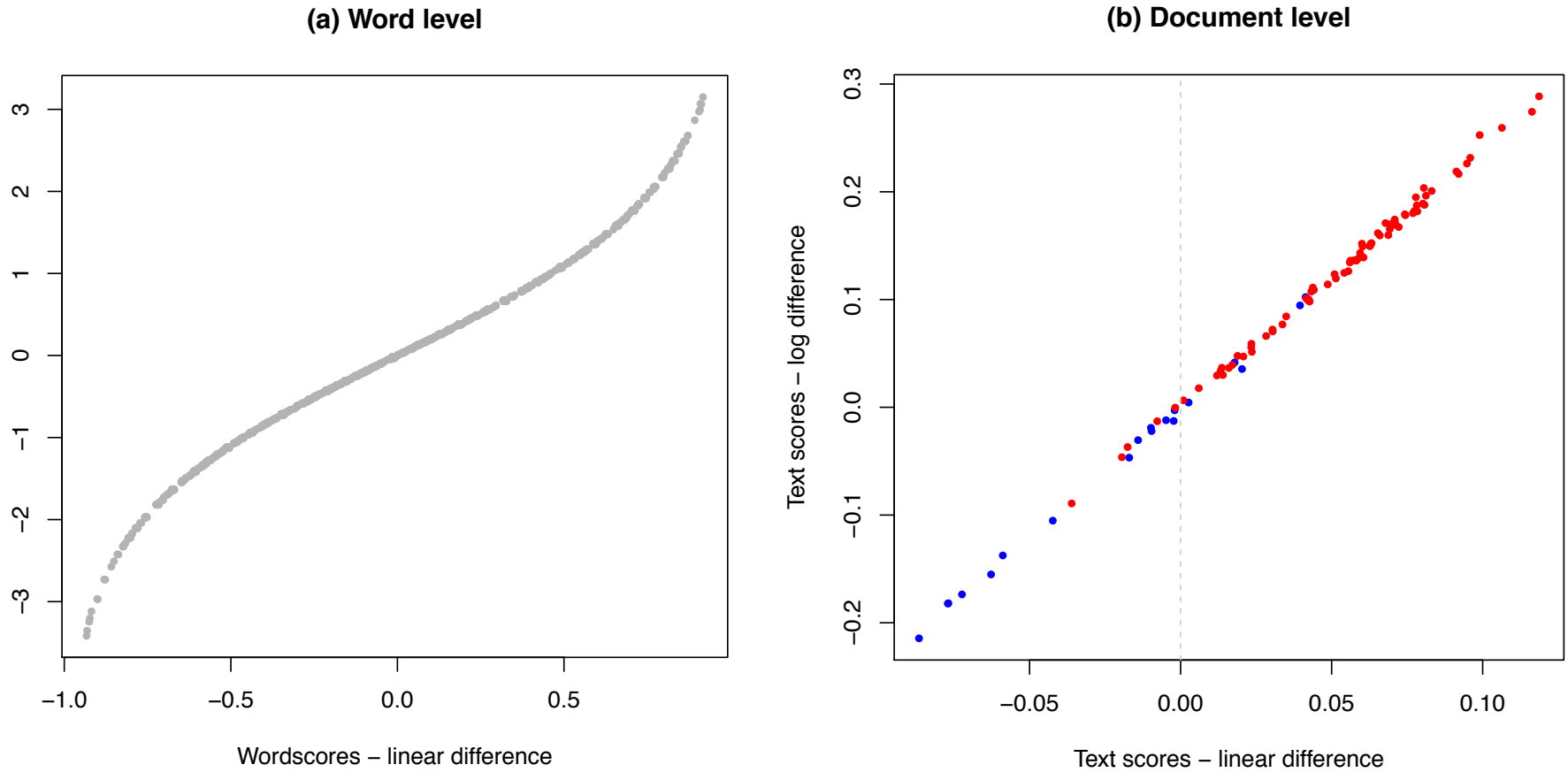
Application 1: Dail speeches from LBG (2003)





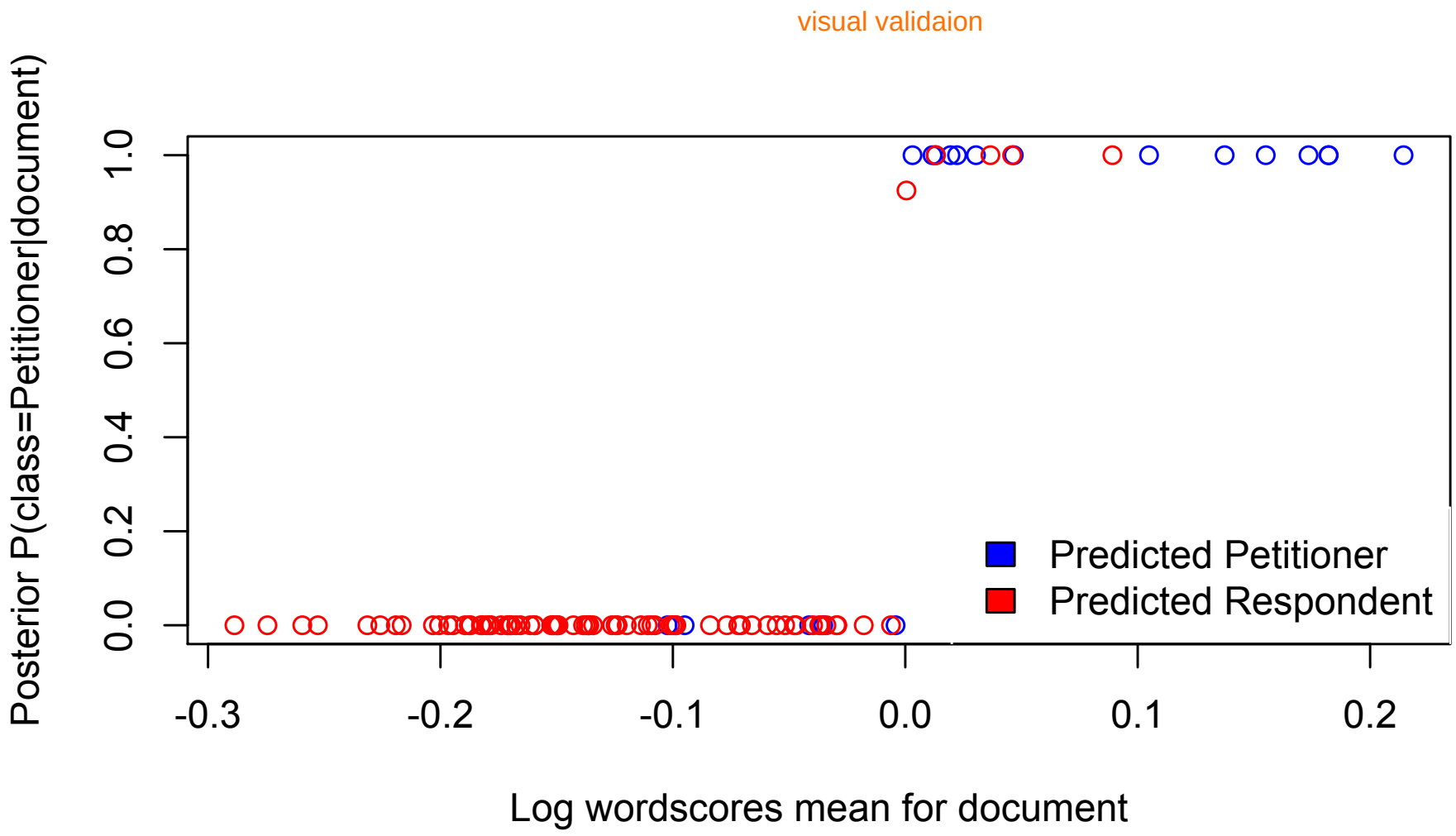
- two reference classes (Opposition+Opposition, Government) at {-1, 1}
- Laplace smoothing

Application 2: Classifying legal briefs (Evans et al 2007) Wordscores v. Bayesscore

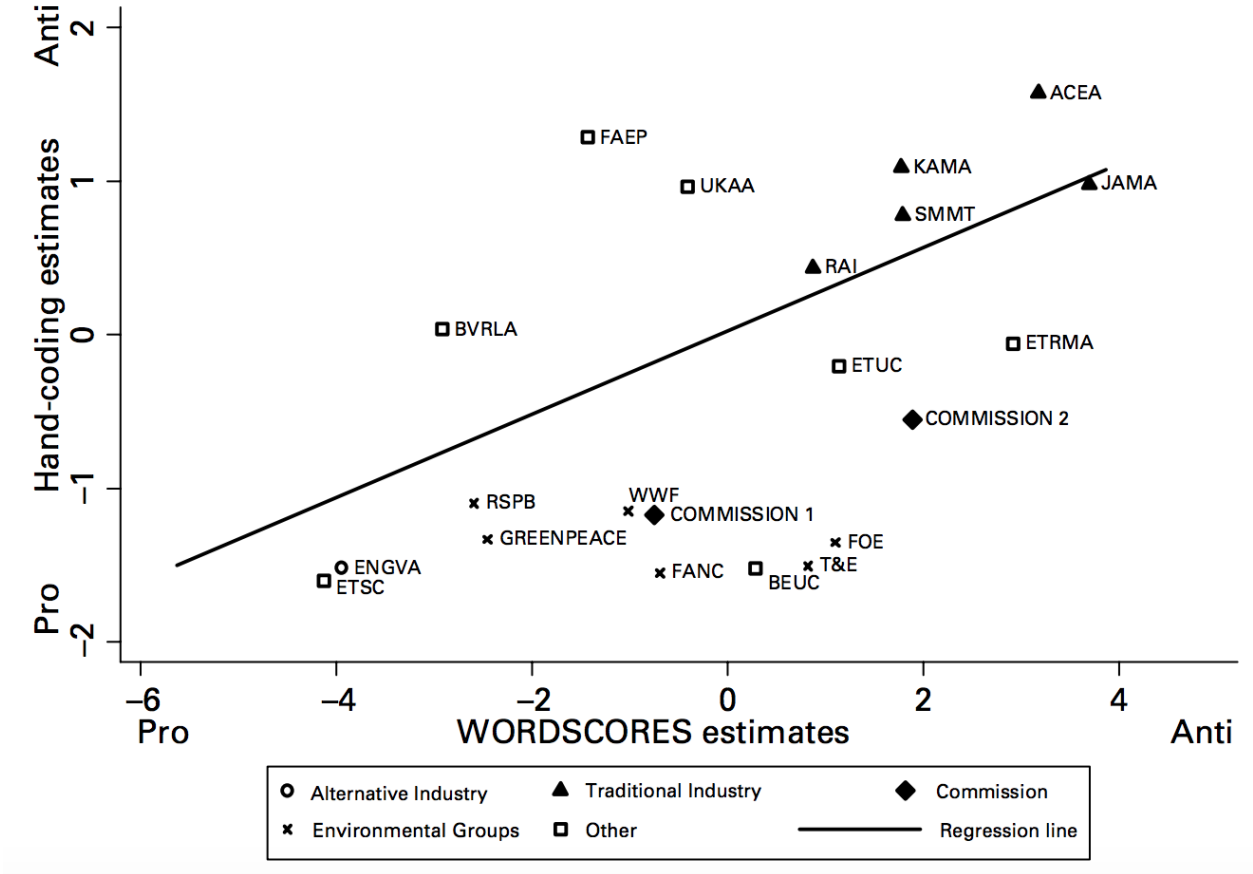


- Training set: Petitioner and Respondent litigant briefs from *Grutter/Gratz v. Bollinger* (a U.S. Supreme Court case)
- Test set: 98 amicus curiae briefs (whose P or R class is known)

Application 2: Classifying legal briefs (Evans et al 2007)
Posterior class prediction from NB versus log wordscores

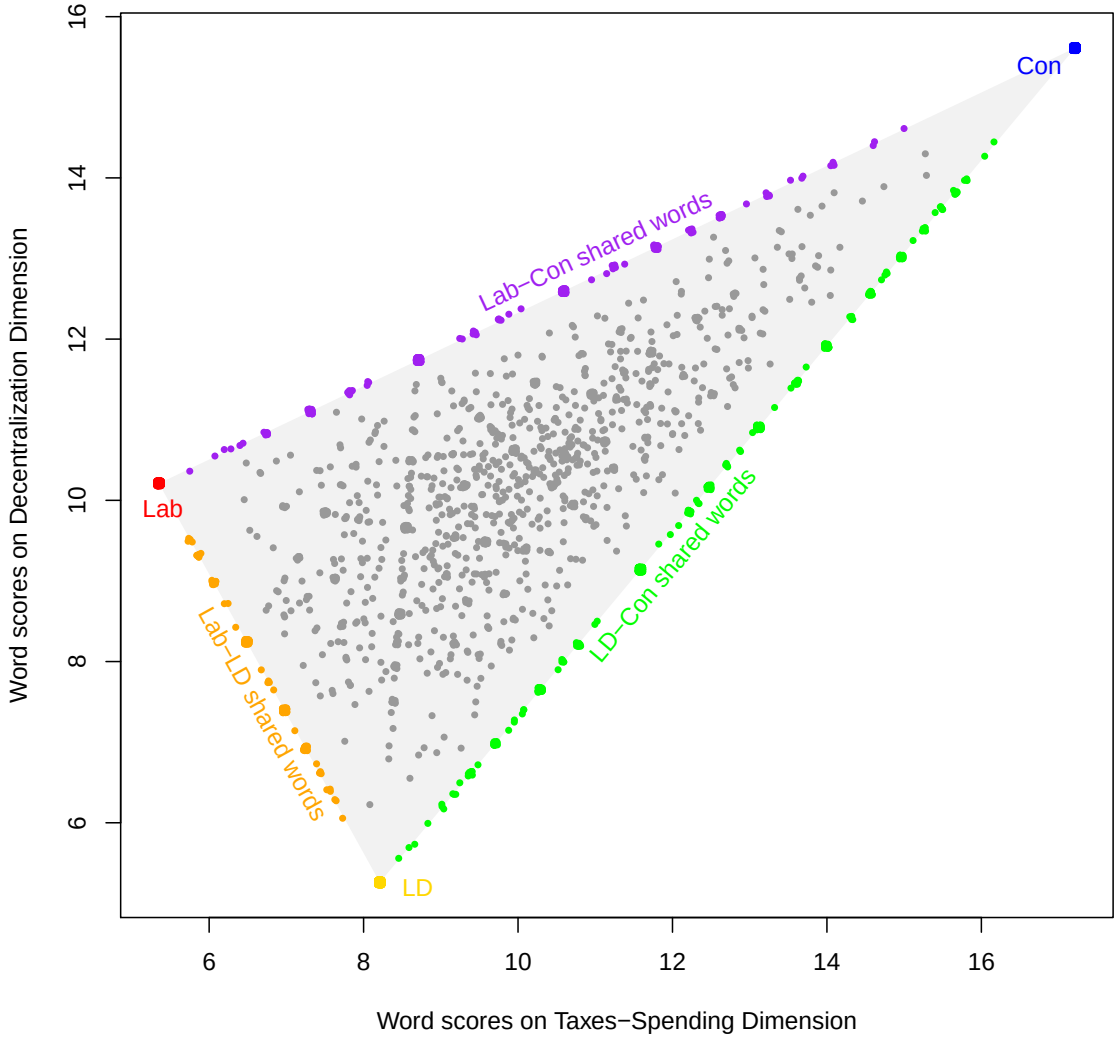


Application 3: Scaling environmental interest groups (Klüver 2009)



- Dataset: text of online consultation on EU environmental regulations
- Reference texts: most extreme pro- and anti-regulation groups

Application 4: LBG's British manifestos
More than two reference classes



- x-axis: Reference scores of $\{5.35, 8.21, 17.21\}$ for Lab, LD, Conservatives
- y-axis: Reference scores of $\{10.21, 5.26, 15.61\}$

Unsupervised methods scale distance

- Text gets converted into a quantitative matrix of features
  - words, typically
  - could be dictionary entries, or parts of speech
- Documents are scaled based on similarity or distance in feature use
- Fundamental problem: distance on which scale?
  - Ideally, something we care about, e.g. policy positions, ideology, preferences, sentiment
  - But often other dimensions (language, rhetoric style, authorship) are more predictive
- First dimension in unsupervised scaling will capture main source of variation, whatever that is
- Unlike supervised models, validation comes after estimating the model

Unsupervised scaling methods

Two main approaches

- Parametric methods model feature occurrence according to some stochastic distribution, typically in the form of a measurement model
  - for instance, model words as a multi-level Bernoulli distribution, or a Poisson distribution
  - word effects and "positional" effects are unobserved parameters to be estimated
  - e.g. Wordfish (Slapin and Proksch 2008) and Wordshoal (Lauderdale and Herzog 2016)

- Non-parametric methods typically based on the Singular Value Decomposition of a matrix
  - correspondence analysis
  - factor analysis
  - other (multi)dimensional scaling methods

more flexible as without a functional form

Wordfish (Slapin and Proksch 2008)

- Goal: unsupervised scaling of ideological positions
- The frequency with which politician i uses word k is drawn from a Poisson distribution:

$$w_{ik} \sim \text{Poisson}(\lambda_{ik})$$
$$\lambda_{ik} = exp(\alpha_i + \psi_k + \beta_k \times \theta_i)$$

- with latent parameters:

  α_i is "loquaciousness" of politician i
  ψ_k is frequency of word k
  β_k is discrimination parameter of word k
  θ_i is the politician's ideological position

, basically how much you can infer based on just this one word

- Key intuition: controlling for document length and word frequency, words with negative β_k will tend to be used more often by politicians with negative θ_i (and vice versa)

Wordfish (Slapin and Proksch 2008)

Why Poisson?

- Poisson-distributed variables are bounded between $(0, \infty)$ and take on only discrete values $0, 1, 2, \ldots, \infty$
- Exponential transformation: word counts are function of log document length and word frequency

$$
\begin{aligned}
w_{ik} &\sim \text{Poisson}(\lambda_{ik}) \\
\lambda_{ik} &= exp(\alpha_i + \psi_k + \beta_k \times \theta_i) \\
log(\lambda_{ik}) &= \alpha_i + \psi_k + \beta_k \times \theta_i
\end{aligned}
$$

How to estimate this model

Conditional maximum likelihood estimation:

- If we knew ψ and β (the word parameters) then we have a Poisson regression model
- If we knew α and θ (the party / politician / document parameters) then we have a Poisson regression model too!
- So we alternate them and hope to converge to reasonable estimates for both
- Implemented in the `quanteda` package as `textmodel_wordfish`

An alternative is MCMC with a Bayesian formulation or variational inference using an Expectation-Maximization algorithm (Imai et al 2016)

Conditional maximum likelihood for wordfish

Start by guessing the parameters (some guesses are better than others, e.g. SVD)

Algorithm:

1. Assume the current legislator parameters are correct and fit as a Poisson regression model
2. Assume the current word parameters are correct and fit as a Poisson regression model
3. Normalize θs to mean 0 and variance 1

Iterate until convergence (change in values is below a certain threshold)

Identification

The *scale* and *direction* of θ is undetermined — like most models with latent variables

To identify the model in Wordfish

- Fix one α to zero to specify the left-right direction (Wordfish option 1)
- Fix the $\hat{\theta}$s to mean 0 and variance 1 to specify the scale (Wordfish option 2)
- Fix two $\hat{\theta}$s to specify the direction and scale (Wordfish option 3 and Wordscores)

Note: Fixing two reference scores does not specify the policy domain, it just identifies the model

"Features" of the parametric scaling approach

- Standard (statistical) inference about parameters
- Uncertainty accounting for parameters
- Distributional assumptions are made explicit (as part of the data generating process motivating the choice of stochastic distribution)
  - *conditional independence*
  - *stochastic process* (e.g. $\mathrm{E}(Y_{ij}) = \mathrm{Var}(Y_{ij}) = \lambda_{ij}$)
- Permits hierarchical reparameterization (to add covariates)
- Generative model: given the estimated parameters, we could generate a document for any specified length

used in (the family of) generative models

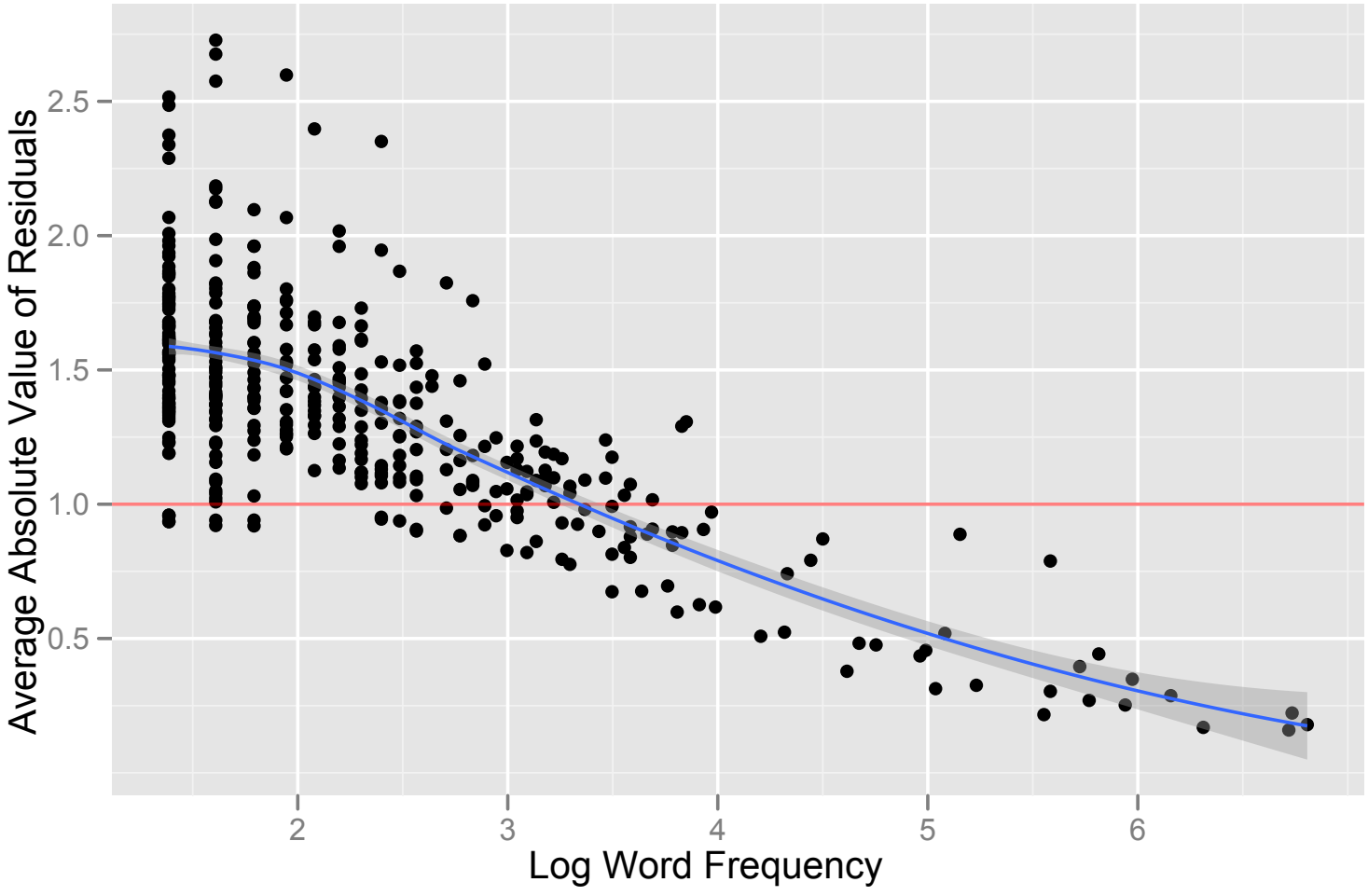
Some reasons why this model is wrong

- Violations of conditional independence:
  - Words occur in sequence (serial correlation)
  - Words occur in combinations (e.g. as collocations) "carbon tax" / "income tax" / "inheritance tax" / "capital gains tax" /"bank tax"
  - Legislative speech uses rhetoric that contains frequent synonyms and repetition for emphasis (e.g. "Yes we can!")
- Heteroskedastic errors (variance not constant and equal to mean):
  - overdispersion when "informative" words tend to cluster together
  - underdispersion could (possibly) occur when words of high frequency are uninformative and have relatively low between-text variation (once length is considered)

Overdispersion in German manifesto data

(data taken from Slapin and Proksch 2008)

OVERDIS



One solution to model overdispersion

Negative binomial model (Lo, Proksch, and Slapin 2014):

$$w_{ik} \sim \text{NB}\left(r, \frac{\lambda_{ik}}{\lambda_{ik} + r_i}\right)$$

$$\lambda_{ik} = exp(\alpha_i + \psi_k + \beta_k \times \theta_i)$$

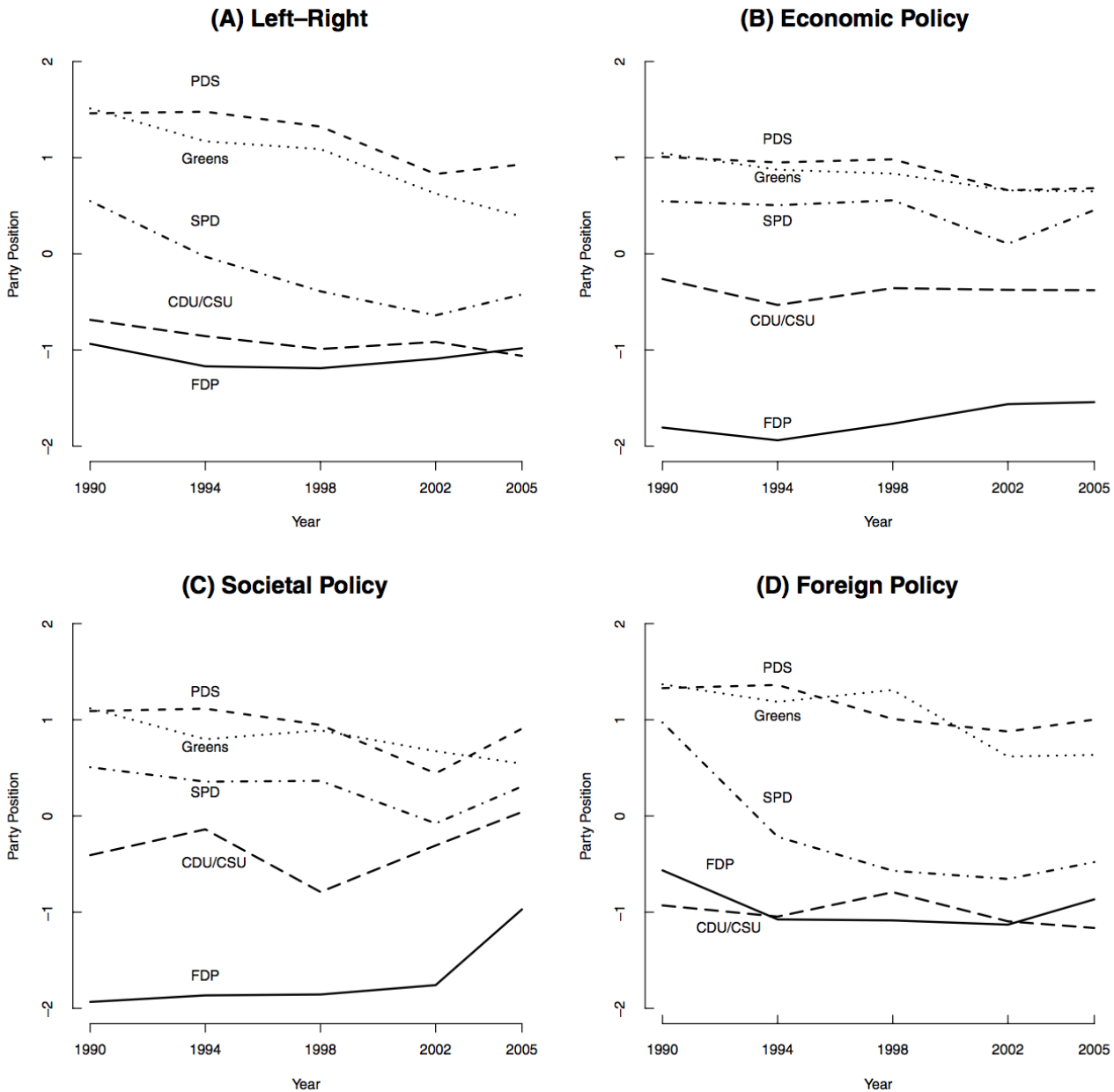
Negative Binomial is a statistical correction for heteroskedasticity problem. It has its drawbacks.

where r_i is a variance inflation parameter that varies across documents.

It can have a substantive interpretation (ideological ambiguity), e.g. when a party emphasizes an issue but fails to mention key words associated with it that a party with similar ideology mentions.

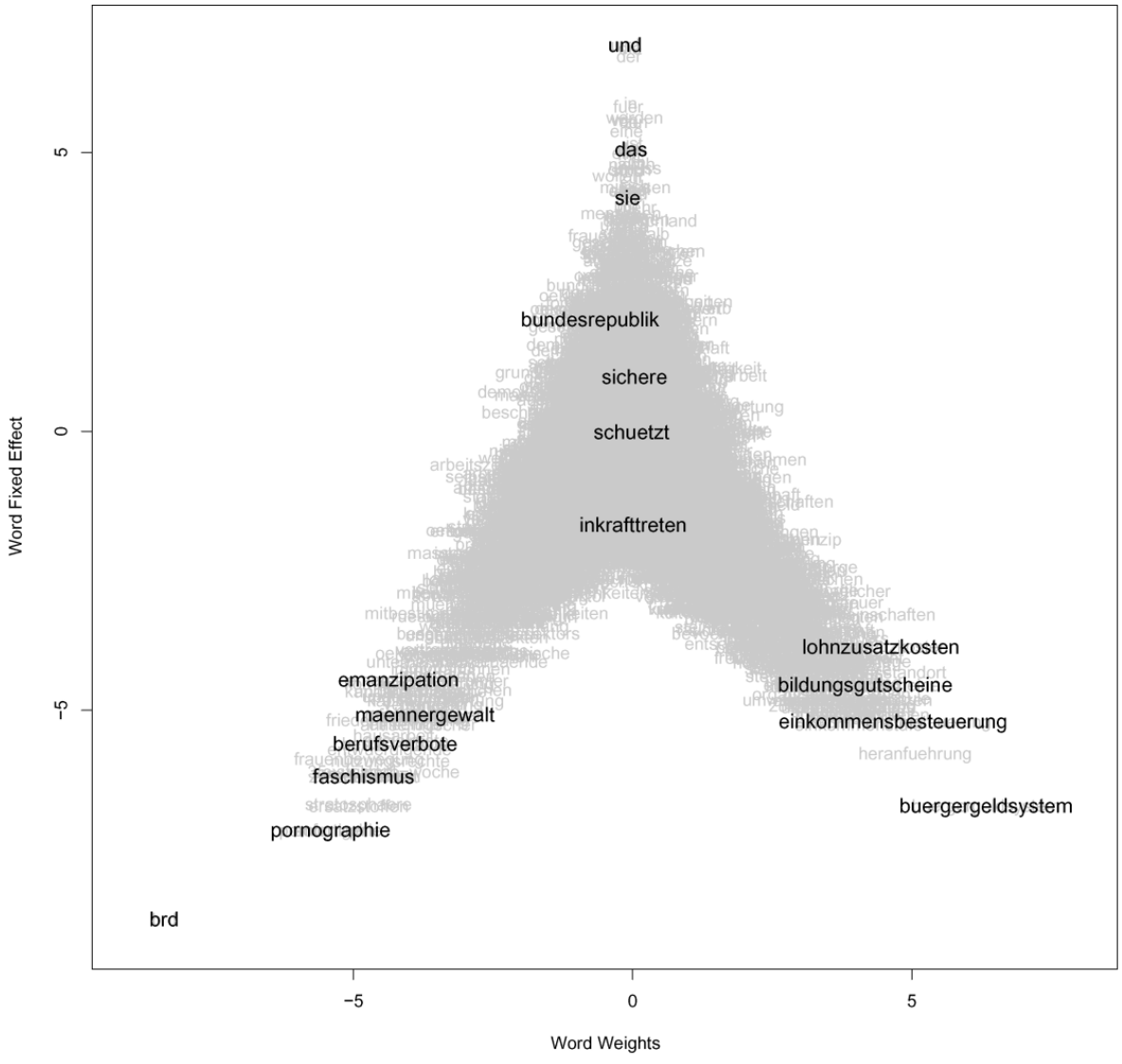
Example from Slapin and Proksch 2008

FIGURE 1 Estimated Party Positions in Germany, 1990–2005



Example from Slapin and Proksch 2008

FIGURE 2 **Word Weights vs. Word Fixed Effects. Left-Right Dimension, Germany 1990–2005 (Translations given in text)**



Example from Slapin and Proksch 2008

TABLE 1 Top 10 Words Placing Parties on the Left and Right

	Top 10 Words Placing Parties on the. . .	
Dimension	**Left**	**Right**
Left-Right	Federal Republic of Germany (BRD)	general welfare payments (Bürgergeldsystem)
	immediate (sofortiger)	introduction (Heranführung)
	pornography (Pornographie)	income taxation (Einkommensbesteuerung)
	sexuality (Sexualität)	non-wage labor costs (Lohnzusatzkosten)
	substitute materials (Ersatzstoffen)	business location (Wirtschaftsstandort)
	stratosphere (Stratosphäre)	university of applied sciences (Fachhochschule)
	women's movement (Frauenbewegung)	education vouchers (Bildungsgutscheine)
	fascism (Faschismus)	mobility (Beweglichkeit)
	Two thirds world (Zweidrittelwelt)	peace tasks (Friedensaufgaben)
	established (etablierten)	protection (Protektion)
Economic	Federal Republic of Germany (BRD)	to seek (anzustreben)
	democratization (Demokratisierung)	general welfare payments (Bürgergeldsystem)
	to prohibit (verbieten)	inventors (Erfinder)
	destruction (Zerstörung)	mobility (Beweglichkeit)
	mothers (Mütter)	location (Standorts)
	debasing (entwürdigende)	negotiated wages (Tarif-Löhne)
	weeks (Wochen)	child-raising allowance (Erziehungsgeld)
	quota (Quotierung)	utilization (Verwertung)
	unprotected (ungeschützter)	savings (Ersparnis)
	workers' participation (Mitbestimmungs-möglichkeiten)	reliable (verlässlich)

Example from Slapin and Proksch 2008

TABLE 2 Cross-Validation: Correlations between German Party Position Estimates

	Poisson Scaling Model			
	Left-Right	**Economic**	**Societal**	**Foreign**
Hand-coding manifestos				
CMP: Left-Right (n = 15, 1990–1998)	−0.82			
CMP: Markeco (n = 15, 1990–1998)		0.81		
CMP: Welfare (n = 15, 1990–1998)			0.58	
CMP: Intpeace (n = 15, 1990–1998)				0.81
Expert Survey				
Benoit/Laver 2006: Left-Right (n = 5, 2002)	−0.91			
Benoit/Laver 2006: Taxes-Spending (n = 5, 2002)		0.86		
Wordscores				
Laver et al. 2003: Economic (n = 10, 1990–1994)		0.93		
Laver et al. 2003: Social (n = 10, 1990–1994)			−0.47	
Proksch/Slapin 2006: Economic (n = 5, 2005)		0.98		
Proksch/Slapin 2006: Social (n = 5, 2005)			−0.47	

Wordshoal (Lauderdale and Herzog 2016)

aka "there's a temporal dimension in topicality"

Two key **limitations** of wordfish applied to legislative text:

- Word discrimination parameters assumed to be constant across debates (unrealistic, think e.g. "debt")
- May not capture left-right ideology but topic variation

Slapin and Proksch partially avoid these issues by scaling different types of debates separately.

But resulting estimates are confined to set of speakers who spoke on each topic.

Wordshoal solution: aggregate debate-specific ideal points into a reduced number of scales.

Wordshoal (Lauderdale and Herzog 2016)

- The frequency with which politician i uses word k in debate j is drawn from a Poisson distribution:

$$
\begin{aligned}
w_{ijk} &\sim \text{Poisson}(\lambda_{ijk}) \\
\lambda_{ijk} &= exp(\alpha_{ij} + \psi_{jk} + \beta_{jk} \times \theta_{ij}) \\
\theta_{ij} &\sim \mathcal{N}(\nu_j + \kappa_j \mu_i, \tau_i)
\end{aligned}
$$

- with latent parameters:

  α_{ij} is "loquaciousness" of politician i in debate j
  ψ_{jk} is frequency of word k in debate j
  β_{kj} is discrimination parameter of word k in debate j
  θ_{ij} is the politician's ideological position in debate j
  ν_j is baseline ideological position of debate j
  κ_j is correlation of debate j with common dimension
  μ_i is overall ideological position of politician i

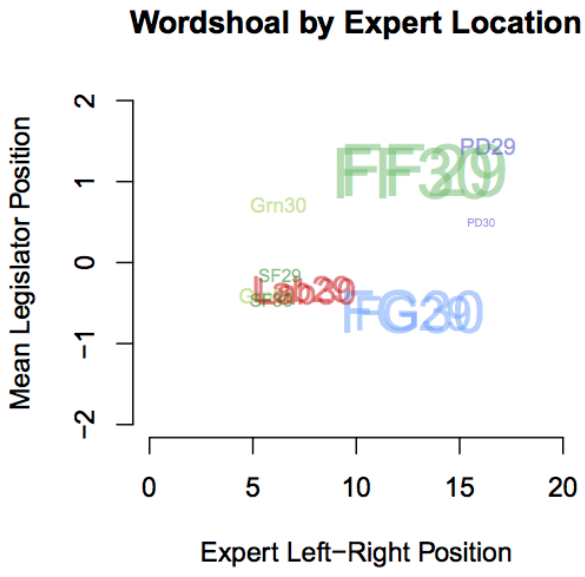
- Intuition: debate-specific estimates are aggregated into a single position using dimensionality reduction

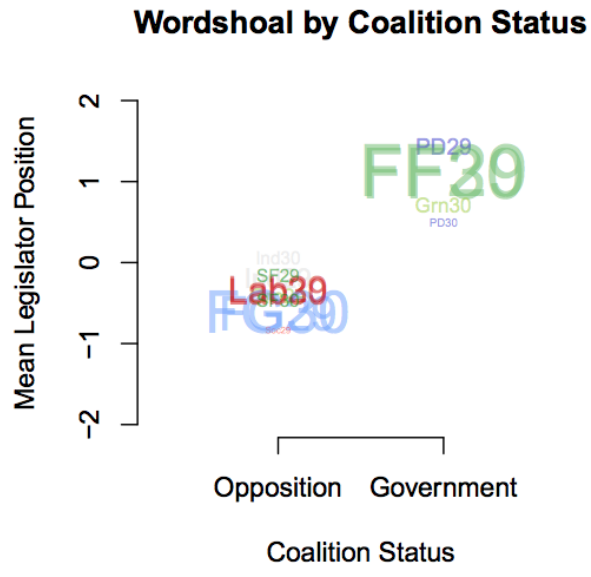
Wordshoal (Lauderdale and Herzog 2016)

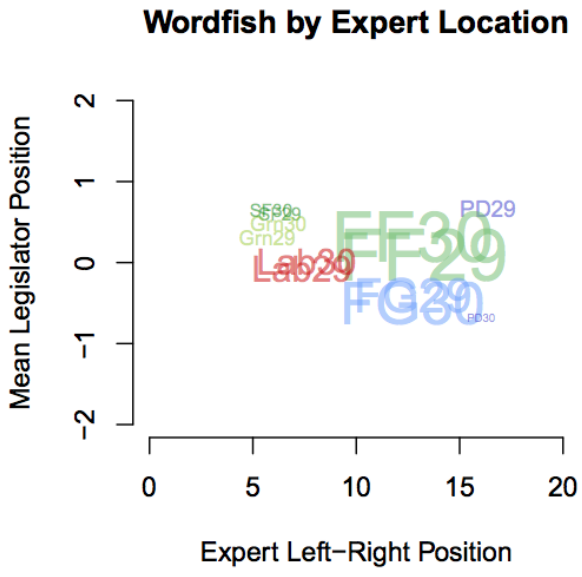
New quantities of interest to estimate:

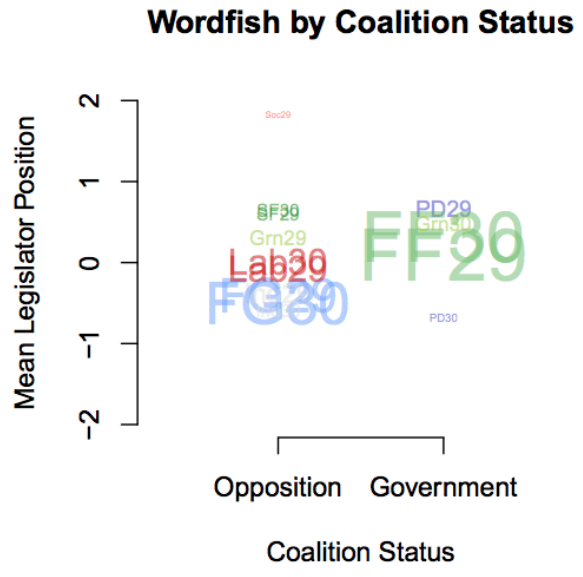
- Politicians' overall position vs debate-specific positions
- Strength of association between debate scales and general ideological scale
- Association of words with general scales, and stability of word discrimination parameters across debates

Example from Lauderdale and Herzog 2016

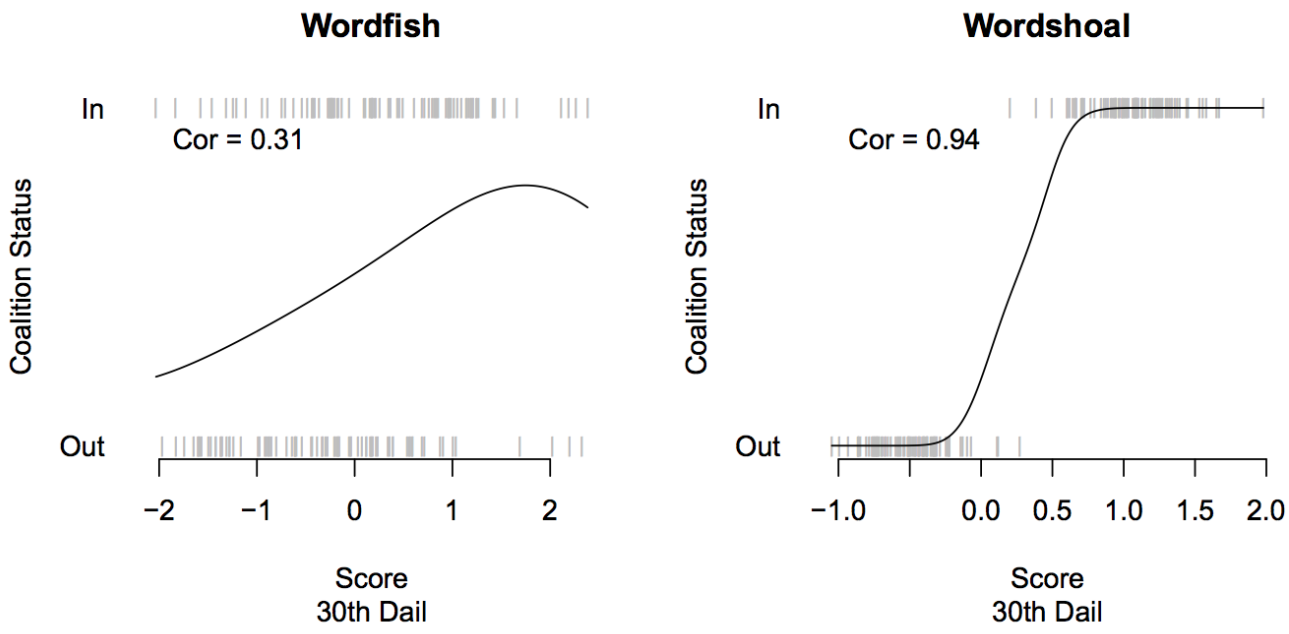


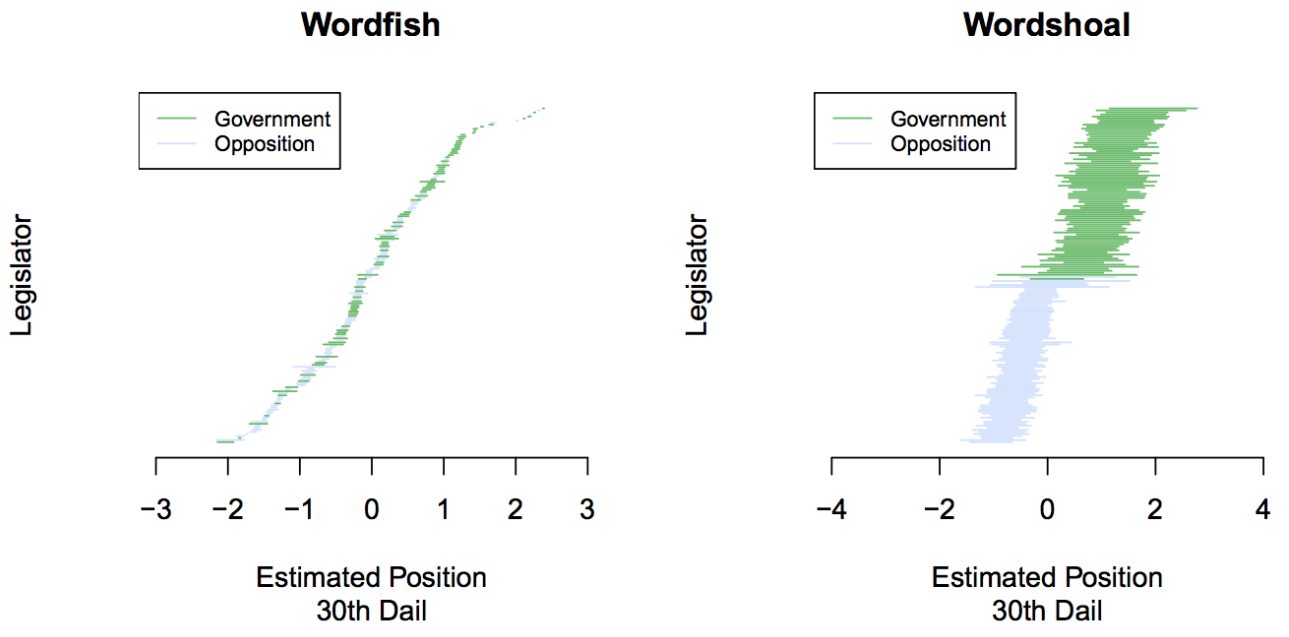




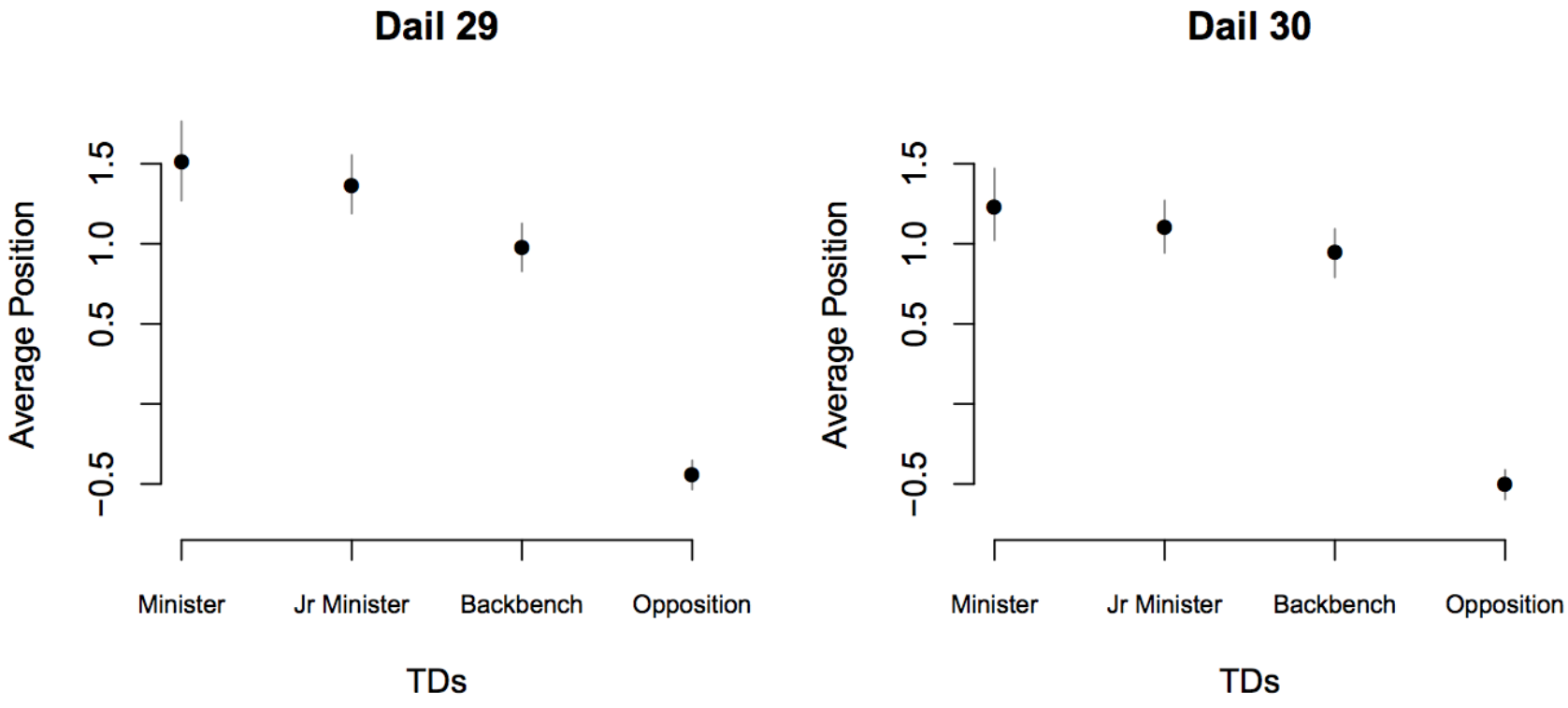


Example from Lauderdale and Herzog 2016





Example from Lauderdale and Herzog 2016

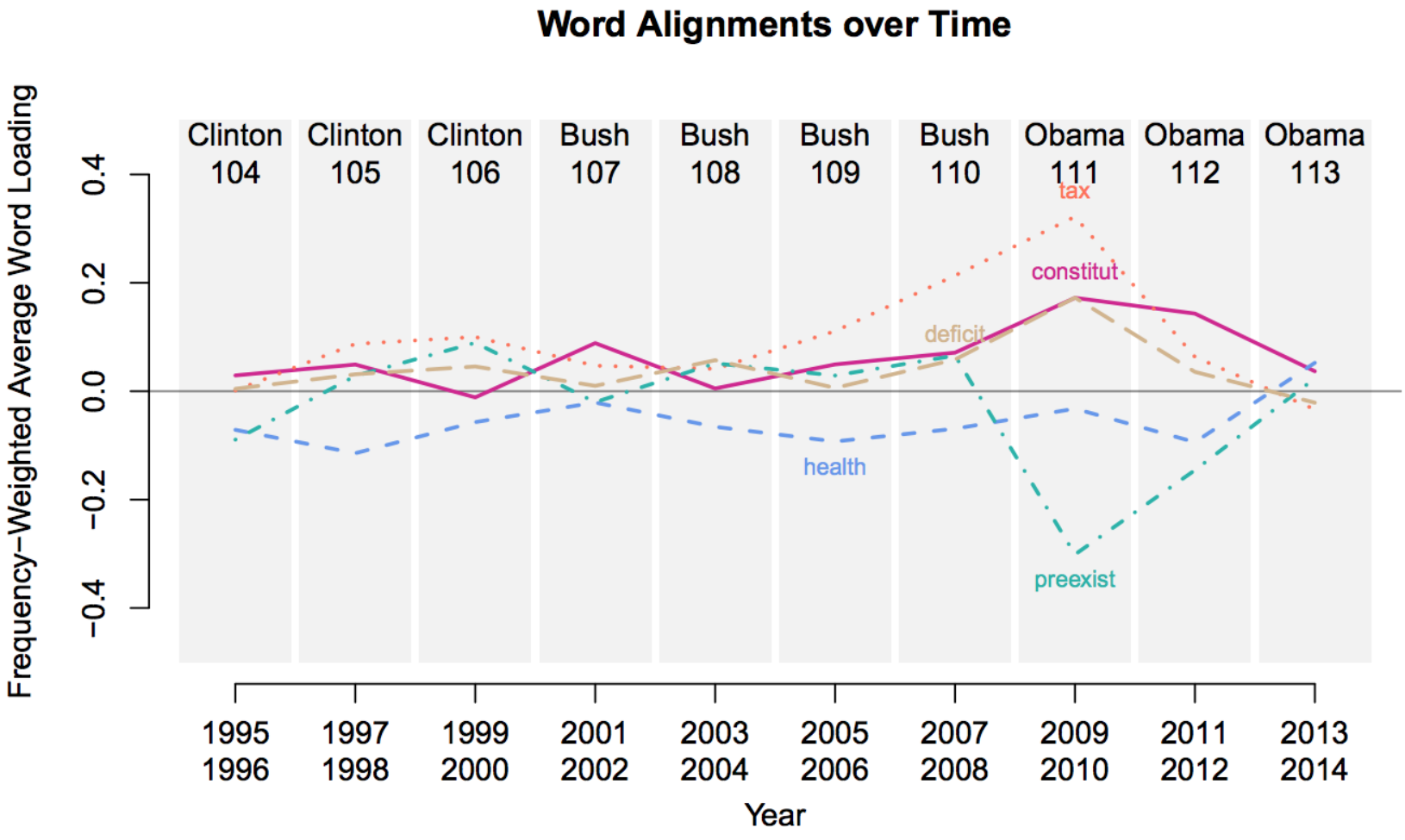


Example from Lauderdale and Herzog 2016

Table 2: The five debates with the highest and lowest loadings on the government versus opposition dimension, as measured by the absolute value of β_j ranging from 0 to 1.

High government-opposition polarization	Abs. β_j
Social Welfare and Pensions (No. 2) Bill 2009 (Second Stage)	0.942
Early Childhood Care and Education (Motion)	0.887
Private Members' Business – Vaccination Programme (Motion)	0.824
Capitation Grants (Motion)	0.819
Confidence in Government (Motion)	0.814
Low government-opposition polarization	
Cancer Services Reports (Motion)	0.003
Finance (No. 2) Bill 2007 (Committee and Remaining Stages)	0.002
Finance Bill 2011 (Report and Final Stages)	0.002
Private Members' Business – Mortgage Arrears (Motion)	0.002
Wildlife (Amendment) Bill 2010 (Committee and Remaining Stages)	0.001

Example from Lauderdale and Herzog 2016



Non-parametric methods

- Non-parametric methods are algorithmic, involving no "parameters" in the procedure that are estimated
- Hence there is no uncertainty accounting given distributional theory
- Advantage: don't have to make assumptions
- Disadvantages:
  - cannot leverage probability conclusions given distributional assumptions and statistical theory
  - results highly fit to the data
  - not really assumption-free, if we are honest

Correspondence Analysis

- CA is like factor analysis for categorical data
- Following normalization of the marginals, it uses Singular Value Decomposition to reduce the dimensionality of the document-feature matrix
- This allows projection of the positioning of the words as well as the texts into multi-dimensional space
- The number of dimensions – as in factor analysis – can be decided based on the eigenvalues from the SVD

Singular Value Decomposition

TODTODO

- A matrix $\underset{n \times k}{\mathbf{X}}$ can be represented in a dimensionality equal to its rank d as:

$$\underset{n \times k}{\mathbf{X}} = \underset{n \times d}{\mathbf{U}} \; \underset{d \times d}{\mathbf{\Sigma}} \; \underset{d \times k}{\mathbf{V}'} \tag{1}$$

- The **U**, **Σ**, and **V** matrixes "relocate" the elements of **X** onto new coordinate vectors in d-dimensional Euclidean space
- Row variables of **X** become points on the **U** column coordinates, and the column variables of **X** become points on the **V** column coordinates
- The coordinate vectors are perpendicular (*orthogonal*) to each other and are normalized to unit length

Correspondence analysis

1. Compute matrix of standardized residuals, $\mathbf{S}$:

$$\mathbf{S} = \mathbf{D}_r^{1/2}(\mathbf{P} - \mathbf{r}\mathbf{c}^T)\mathbf{D}_c^{1/2}$$

where $\mathbf{P} = \mathbf{Y} / \sum_{ij} y_{ij}$

$\mathbf{r}$, $\mathbf{c}$ are row/column masses: e.g. $r_i = \sum_j p_{ij}$

$\mathbf{D}_r = \mathrm{diag}(\mathbf{r})$, $\mathbf{D}_c = \mathrm{diag}(\mathbf{c})$

2. Calculate SVD of $\mathbf{S}$

3. Project rows and columns onto low-dimensional space:

$$\theta = \mathbf{D}_r^{1/2}\mathbf{U} \text{ for rows (documents)}$$

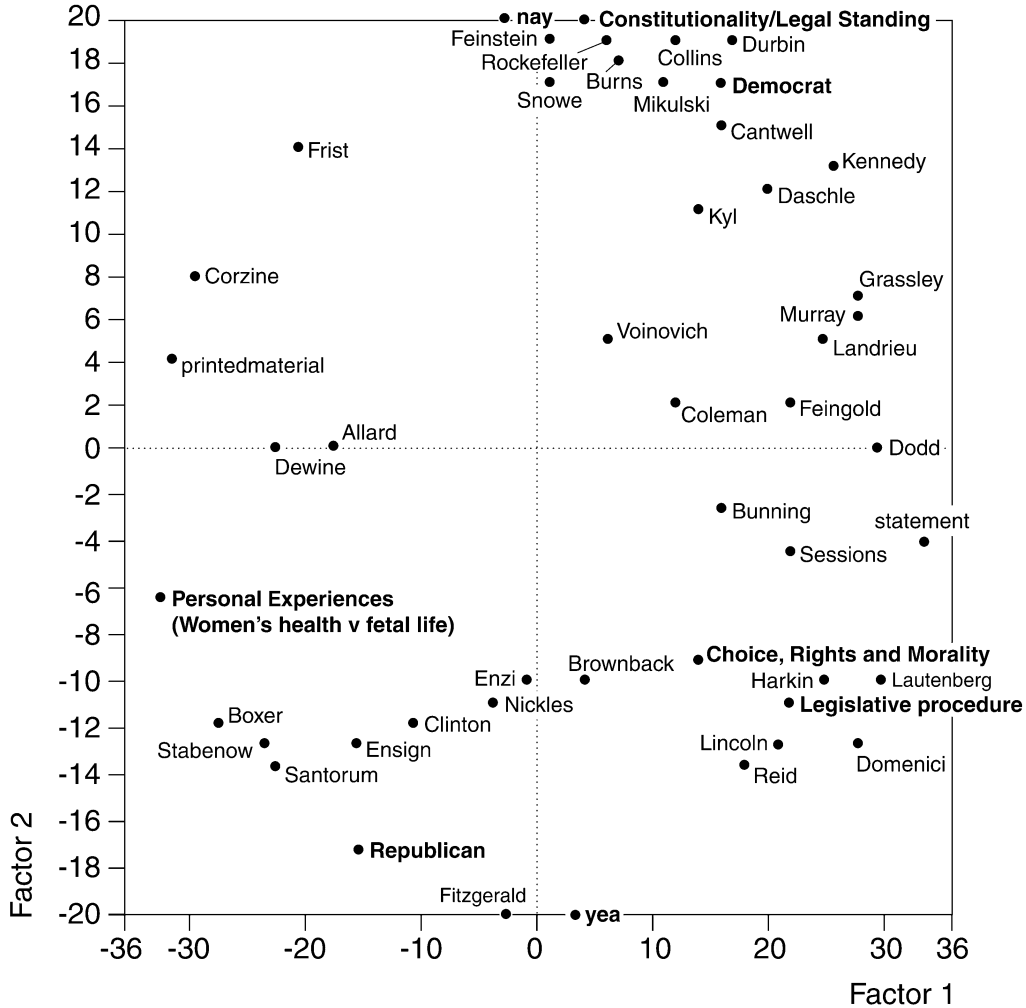
$$\phi = \mathbf{D}_c^{1/2}\mathbf{V} \text{ for columns (words)}$$

Mathematically close to log-linear poisson regression model

TH?

(Lowe, 2008)

Example: Schonhardt-Bailey (2008) - speakers



	Eigenvalue	% Association	% Cumulative
Factor 1	0.30	44.4	44.4
Factor 2	0.22	32.9	77.3

Fig. 3. Correspondence analysis of classes and tags from Senate debates on Partial-Birth Abortion Ban Act

Example: Schonhardt-Bailey (2008) - words