Quantitative text analysis: Supervised Scaling Methods

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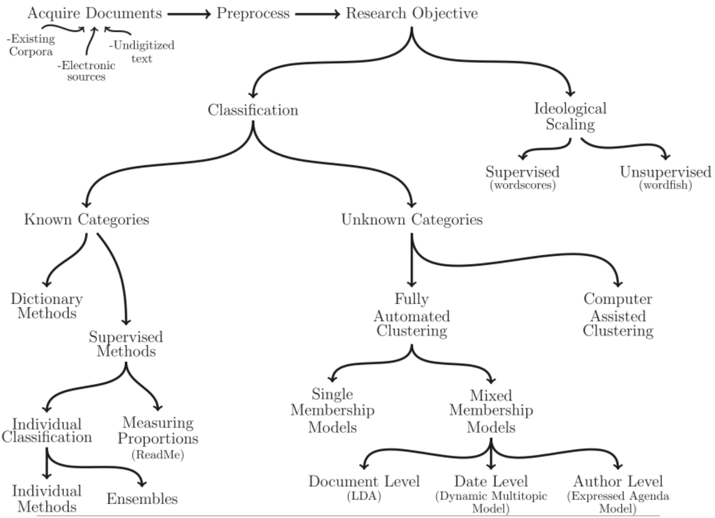
MY 459: Quantitative Text Analysis

February 15, 2021

Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

Overview of text as data methods



Outline

- From classification to scaling
  - Basics of supervised scaling methods
  - Wordscores
  - Practical aspects
  - Examples

From Classification to Scaling

- Machine learning focuses on identifying classes (classification), while social science is typically interested in locating things on latent traits (scaling), e.g.:
  - Policy positions on economic vs social dimension
  - Inter- and intra-party differences
  - Soft news vs hard news
  - Petitioner vs respondent in legal briefs
  - ...and any other continuous scale
- But the two methods overlap and can be adapted – will demonstrate later using the Naive Bayes classifier
- In fact, the class predictions for a collection of words from NB can be adapted to scaling

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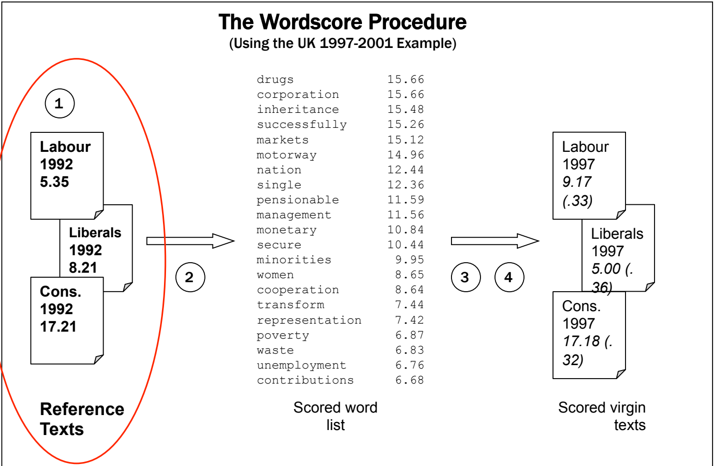
Supervised scaling methods

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

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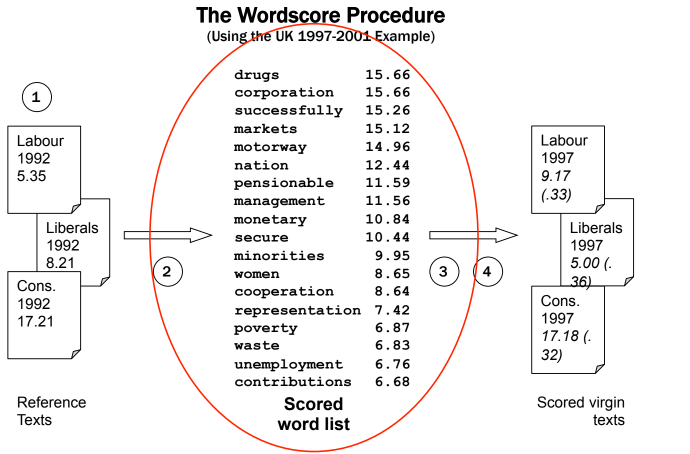

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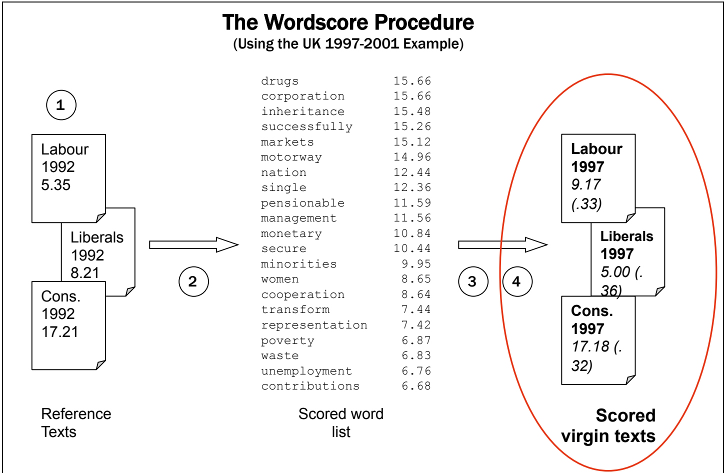

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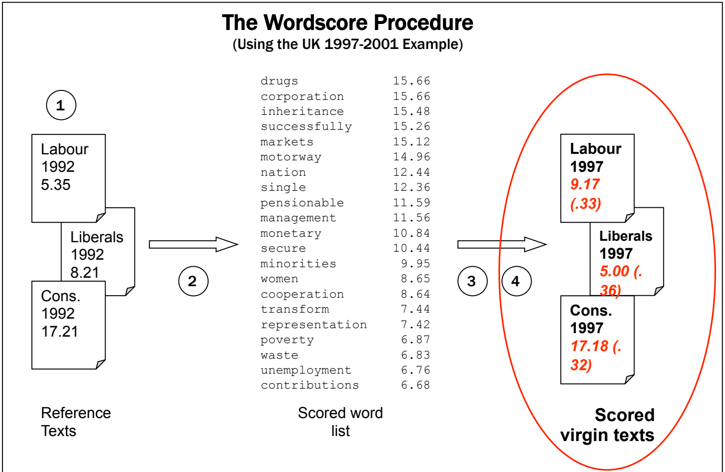

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- Start with a set of I *reference* texts, represented by an $I \times J$ document-feature matrix C_{ij}, where i indexes the document and j indexes the J total word types

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- 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:

$$F_{ij} = \frac{C_{ij}}{C_{i\cdot}} \tag{1}$$

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

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- 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

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- 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

$$P_{A\text{ ''choice''}} = \frac{.010}{(.010 + .030)} = 0.25 \tag{3}$$

$$P_{B\text{ ''choice''}} = \frac{.030}{(.010 + .030)} = 0.75 \tag{4}$$

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}:

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- 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

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- 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 $0.25(-1.0) + 0.75(1.0) = -0.25 + 0.75 = +0.50$

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- Note also that nothing prohibits reference documents from also being scored as virgin documents

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- Martin and Vanberg (2008) have proposed alternatives to the LBG (2003) rescaling

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- An alternative would be to bootstrap the textual data prior to constructing C_{ij} and C_{kj} — see Lowe and Benoit (2012)

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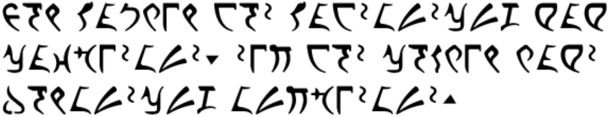
- Could potentially work on texts like this:



(See `http://www.kli.org`)

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- 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 $P(c_{\neg k}|w_j)$

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- 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:

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

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- 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:

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

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- 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

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- This is exactly the solution proposed by LBG (2003)

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- 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...

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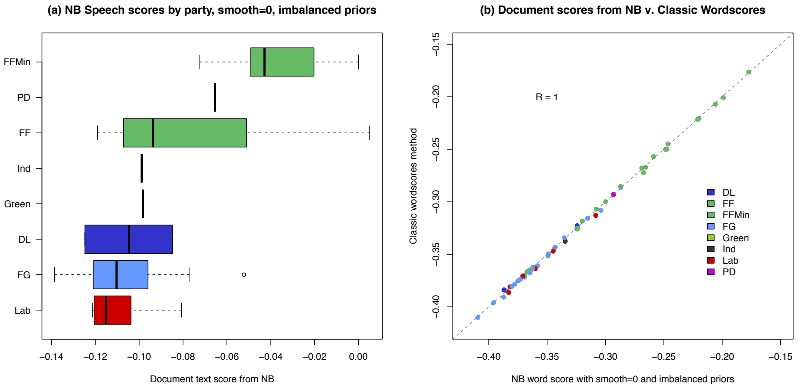
Application 1: Dail speeches from LBG (2003)



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

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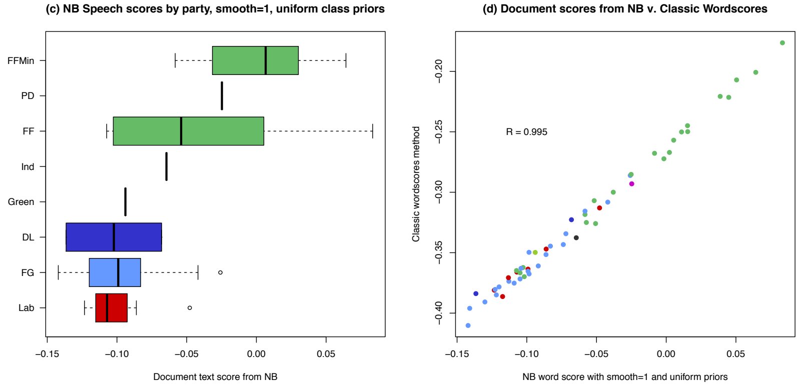
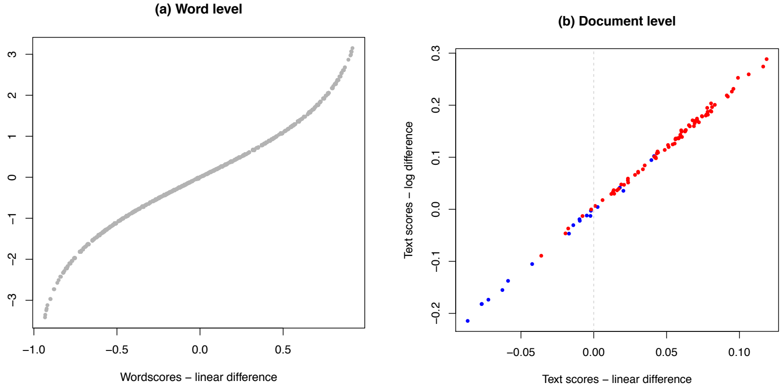


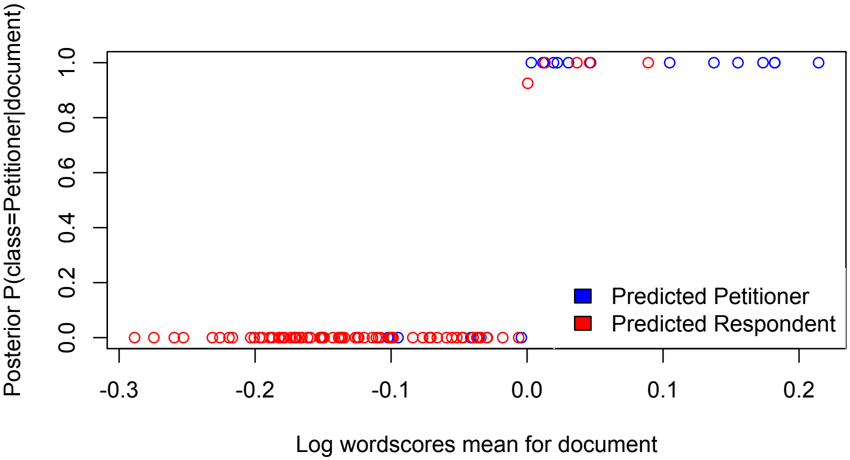
- two reference classes (Opposition+Opposition, Government) at {-1, 1}
- Laplace smoothing

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

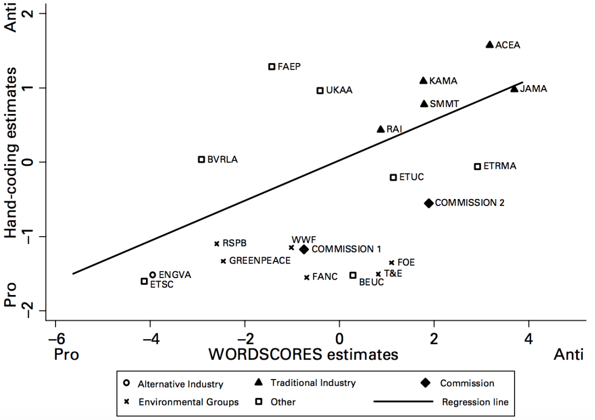


- Training set: Petitioner and Respondent litigant briefs from *Grutter/Gratz v. Bollinger* (a U.S. Supreme Court case)
- Test set: 98 amicus curiae briefs (whose P or R class is known)

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

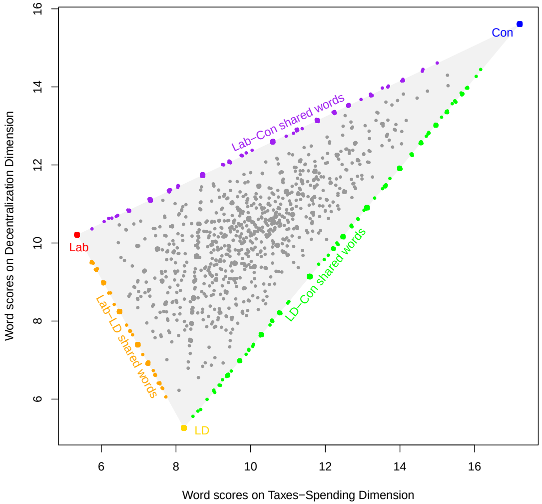


Application 3: Scaling environmental interest groups (Klüver 2009)



- 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 $\{10.21, 5.26, 15.61\}$