Estimating Uncertainty in Quantitative Text Analysis*

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Abstract

Several methods have now become popular in political science for scaling latent traits—usually left-right policy positions—from political texts. Following a great deal of development, application, and replication, we now have a fairly good understanding of the estimates produced by scaling models such as "Wordscores", "Wordfish", and other variants (i.e. Monroe and Maeda's two-dimensional estimates). Less well understood, however, are the appropriate methods for estimating uncertainty around these estimates, which are based on untested assumptions about the stochastic processes that generate text. In this paper we address this gap in our understanding on three fronts. First, we lay out the model assumptions of scaling models and how to generate uncertainty estimates that would be appropriate if all assumptions are correct. Second, we examine a set of real texts to see where and to what extent these assumptions fail. Finally, we introduce a sequence of bootstrap methods to deal with assumption failure and demonstrate their application using a series of simulated and real political texts.

Keywords: quantitative text analysis, bootstrapping, Poisson scaling model, wordfish, wordscores, correspondence analysis

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The quantitative analysis of text as data, especially when it involves scaling models to estimate latent traits, requires strong assumptions about the stochastic distribution for observed text frequencies conditional on some generating function. In political science, text scaling methods are typically used to estimate unobservable characteristics treated as latent traits—usually left-right policy positions—or latent classes—such as topics—from political texts. Following a great deal of development, application, and replication, we now have a fairly good understanding of the estimates produced by scaling models such as "Wordscores", "Wordfish", and other variants (i.e. Monroe and Maeda's two-dimensional estimates). Less well understood, however, are the appropriate methods for estimating uncertainty around these estimates, which are based on untested assumptions about the stochastic processes that generate text. In analyzing data using statistical models when strong parametric assumptions are doubtful, or cannot be easily derived, resampling methods such as bootstrapping are commonly used. In quantitative text analysis, however, despite precisely being unable to make strong parametric assumptions about the data-generating process, bootstrapping methods are almost never applied (Benoit, Laver and Mikhaylov (2009) is an exception, although here coded units of text rather than text was resampled.)

In this paper we explore bootstrap methods for estimating uncertainty from estimates based on parametric text scaling models, following a detailed discussion of the stochastic process generating observed text. We use both simulated and real political texts to demonstrate the textual bootstrap approach, including a simple i.i.d. bootstrap applied to words, a unit-level bootstrap applied to sentences, and a block bootstrap applied to fixed-length word sequences.

Our paper proceeds as follows. First, we review the conceptual foundations of the stochastic process leading to observed texts and what this means for the most commonly observed textual unit: the (relative) word frequency. Second, we explore parametric scaling models for estimating latent parameters generating observed word counts, and discuss several methods of generating uncertainty estimates in inference about these latent parameters, including the bootstrap solutions we provide here. We then apply the different methods to artificial and real-world texts, comparing the bootstrap estimates of uncertainty to parametric and semi-parametric methods of accounting for uncertainty. Our paper concludes with some recommendations for employing non-parametric bootstrap methods in quantitative text analysis.

1 Scaling as Measurement: The conceptual foundations of θ to data

Political scientists have analysed linguistic data at many levels, from the topic of a complete text (e.g. Hopkins and King, 2010; Hilliard, Purpura and Wilkerson, 2006) to the balance of topics within a text (Quinn et al., 2010; Blei, Ng and Jordan, 2003; Grimmer, 2010), to individually topic-coded sentences (Budge, Robertson and Hearl, 1987; Pennings and Keman, 2002), to counts of individual words (Monroe and Maeda, 2004; Laver, Benoit and Garry, 2003*a*; Slapin and Proksch, 2008). In all of these cases, the primary focus lies in inferring unobserved content, such as an an ideological position in scaling models or a topic in other methods. In what follows, we refer to this content generically as θ_i, and treat it as a latent, unobservable attribute of each political actor i. While all our arguments should apply equally to discrete content, the extensions to topic models we leave to further work.

We will also work with matrices of counts of words, rather than any large unit. This involves no loss of generality because methods to deal with word count data are applicable to counts of any other quantity. Indeed this is arguably the hardest unit to deal with since it is the closest to the linguistic variation that, while "signal" for linguists is "noise" relative to our interest in θ. We also do not distinguish between speeches and written materials. Although there are good linguistic reasons to expect linguistic structures to differ between these modes, e.g. type-token ratios are substantially larger in written language, there is no reason to think that political content is differently expressed, except where the institutional context motivates a different choice of θ. We also assume that θ is constant within whatever unit is chosen as the text[1].

For this paper then, our focus will be on models that are designed for extracting continuous unobserved positions from matrices representing the number of times each word in a vocabulary appears in each text in a corpus.

The general framework for thinking about inferring an unobserved θ from observational data is measurement theory and its realizations in the form of item response theory (IRT) models. In the following we trace the application of this style of modeling from its original applications scaling student ability from tests, scaling ideological position from voting records, to scaling policy position from word counts. This exposition clarifies the similarities and differences between the methods and focuses attention on model assumptions and which might be problematic.

IRT models were designed for, and are most often applied in formal educational testing contexts. In this setting, students are presented a set of questions in an asocial setting where the only aim is generate as many correct answers as possible. The IRT model approach assumes that (1) questions are not chosen by the student; (2) social and strategic context is minimal or absent; and (3) that the main determinant of each answer is student ability, an underlying trait that cannot be directly observed. Instead, this underlying ability trait θ must be estimated using observations on item response modeled as Bernoulli random with the dichotomous outcome of a correct answer (1) or a false answer (0). The observed data is then an $N \times V$ matrix Y where $Y_{ij} = 1$ when the i-th of N student answers the j-th of V questions correctly. This model generalizes readily to other contexts, and in political science has received the widest application to the scaling of roll call votes (Jackman, 2001; Clinton, Jackman and Rivers, 2004), where Y represent Yeas or Nays and θ represents an ideological position instead of an ability parameter.

Together the assumptions justify the idea that answers are conditionally independent given ability

$$P(\{Y_1 \ldots Y_V\} \mid \theta_i) = \prod_{j=1}^{V} P(Y_j \mid \theta_i). \tag{1}$$

[1] See Lo and Proksch (this panel) for ways to relax this assumption

This is combined with a logistic model of the relationship between answers and ability

$$\log \frac{\pi_{ij}}{1-\pi_{ij}} = \psi_j + \theta_i \beta_j \tag{2}$$

where π_{ij} is the parameter of a Bernoulli variable. In this model, β_j reflects the sensitivity of the question the students ability and ψ_j is an offset representing the baseline difficulty of the question.[2] Inference about θ is performed by estimating the model parameters and using a factor scoring procedure to back out θ and a measure of uncertainty for each individual via regression, factor, or maximum *a posteriori* techniques.

The general IRT-type scaling model generalizes easily to word counts, where θ_i represents an underlying ideological position found in text i, and Y_{ij} is the number of times the j-th word occurs in the i-th text (Monroe and Maeda, 2004; Slapin and Proksch, 2008). Word counts are still considered to be conditionally independent given θ, but different models make different distributional assumptions. In Laver et al.'s Wordscores model (Laver, Benoit and Garry, 2003*a*) and in correspondence analysis (Benzécri, 1992; Greenacre, 2007), this means that words have a position themselves and occur most often as the words' positions moves closer to θ. In Slapin and Proksch's Poisson scaling model ("wordfish"), model word rates have an log-linear relationship to θ. In this model

$$\log \lambda_{ij} = \psi_j^* + \theta_i \beta_j^* + \alpha_i \tag{3}$$

where λ is the mean parameter of a Poisson distribution representing the rate of generating word type j in the i-th text[3]. The parameter β_j^* represents the sensitivity of the word rate to θ_i, and ψ_j^* reflects the baseline frequency of the word when expressing ideologically centre positions. The parameter α_i is a fixed effect for each text. The remainder of our discussion of parametric scaling approaches for text focuses on this model.

[2] This is not the standard parameterization in IRT texts, but is equivalent and designed to make comparisons with text scaling models more obvious.

[3] Monroe and Maeda add a grand mean which simply rescales the model parameters.

2 Two Key Assumptions of Text Scaling Models

The Poisson text-scaling model (Eq. 3) rests on two principal statistical assumptions common to all parametric IRT-type scaling models: the conditional independence assumption in Eq. 1, and the distributional assumption in Eq. 2. Here, as in all subsequent models, failures in the model assumptions lead to over-certain inferences, even in the absence of systematic bias.

2.1 Assumption: Observed text units are conditionally independent

The assumption that observed text units are conditionally independent means that conditional on the model being correct, words are generated independently from one another, without regard to structure, sequence, or the occurrence of other words. When this assumption is unmet, then the information from one observed word (or question or vote or other IRT-scaled outcome) provides *less information* about θ than the model assumes, which translates into over-certainty about $\hat{\theta}_i$ and inappropriately small standard errors.

In educational testing applications, the conditional independence and distributional assumptions can be quite plausible, and easily fixed if violated. For example, if conditional independence *is* violated by a block of questions all relating to a particular stimulus, then changes to the distributional assumption in Eq. 2 can solve the problem (see e.g. Samejima, 1969, or methods for "testlets").

The conditional independence and distributional assumptions have seemed more doubtful, however, in the context of vote scaling. Deal making between legislators acts to couple voting outcomes even conditional on policy position. It is also well-established that roll-call votes do not reflect in any sense a random assignment of issues, since they could useful depend on strategies to exploit expectations about the distribution, or particular values of θ_i in the chamber (Carrubba, Gabel and Hug, 2008; Hoyland, 2010). In addition, roll-call voting is subject to party discipline, meaning that political factors external to the model (threat of punishment or even expulsion by party leaders) affect the link between ideological position θ_i and observed votes Y_{ij}. Finally, the outcome in voting applications is not truly dichotomous: voting outcomes are in fact yea, nay, or abstention, where the latter is typically treated as a value that is missing at random. If this is acceptable then this implies that the total number of votes a legislator casts is uninformative about their policy position. This seems unlikely in legislative contexts where we would expect careful choice of abstentions to be a useful strategy[4]. We return to this particular assumption when turning to scaling models for text, where it seems more reasonable.

Text models bring still more problems. Words will typically *not* be conditionally independent given θ. To begin, word order matters in natural language, and words simply do not occur without respect to the occurrence of other words. For example, the observance of the word word "conditional" in this section of the paper, for instance, greatly increases the probability of observing the word "independence".

In defense of the conditional independence assumption, Laver, Benoit and Garry (2003) point out that some single words do have strongly direction associations — the word *tax* and its variants, for instance, is used almost exclusively by more right-leaning parties (who prefer to cut taxes). However, this fails to distinguish all sorts of politically interesting differences among taxes however such as "income taxes", "taxes on banks", "carbon taxes", "inheritance taxes", and "capital gains taxes". A similar argument can be made for another right-leaning word 'free' which can nevertheless can, and is used for "free enterprise" and "GMO-free". From this perspective, it may seem remarkable that text scaling models based purely on the relative frequencies of atomic words—what linguists call the "bag of words" approach—work at all.[5]

There is also the fact that political texts in particular — but also texts generally — tend to be written in sections on similar topics. A text unit found in one section of a text is more likely to be from the same category as text units from the same section, as texts are grouped into sentences, and sentences are grouped into paragraphs, contained in sections. If θ represents topic then this is obviously not a problem but when this is not the case the third assumption – that θ is the main determinant of word rates will be

[4]In the extreme case legislators from one party abstain by leaving the state.

[5](Zhang, 2004) has offered some interesting arguments why tight collocations like the ones above need not compromise inferences about θ in models with strong conditional independence assumptions, although he admits they will still bias uncertainty estimates downwards.

compromised. This affects all attempts to generate country-comparable general left-right scores from manifestos. If the extracted θ is a weighted average of issue specific θs then the changes in the topic distribution will compromise inferences about general left-right positioning. Slapin and Proksch (2008) avoid this by manually isolating text on particular policy issues and scaling them separately.

2.2 Assumption: The stochastic process of text generation is correctly specified

Distributional assumptions also pose unique problems in text scaling models. If θ were genuinely the only cause of word rate variation, then we might expect Poisson structured count distributions. In natural language texts, however we do not expect conditional text frequencies to fit the Poisson model well. In particular, we expect three varieties of problem to occur: overdispersion, underdispersion, and zero inflation.

Overdispersion occurs when $\text{Var}(Y_{ij}) > \lambda_{ij}$ and may have many causes, some of which are substantively interesting for political scientists and some not. Of interest is within text variation in θ, particularly when it is caused by genuine intra-party policy disagreement. From a statistical perspective any source of within-text variation in θ will generate over-dispersion.

Word counts can also be under-dispersed across documents. Underdispersion occurs when $\text{Var}(Y_{ij}) < \lambda_{ij}$. For example, in English each sentence contains on average about one instance of the word "the". This regularity is very strong: In the Irish budget debate speeches we examine in more depth later, the rate per 100 words of the word "the" is 7.28 with variance 0.75, about 10 times smaller than even a Poisson model with no covariates would predict. Regrettably this phenomena is strongest for function words that have almost no role in expressing ideological positions, and are in any case never a large proportion of any vocabulary list, despite generating very high counts. Hence we cannot reasonably expect the underestimation of θ uncertainty they could bring to offset their over dispersed colleagues.

A pure form of zero-inflation problem appears when a word has *no* chance of occurring in some documents, e.g. the term “European Union” prior to the 1980s for instance (when the EU was still called the European Economic Community) or in the party manifestos if Australia where EU policy was never a feature of the political discourse. Within a single context, furthermore, there may be single-issue parties tending to use particular words, word which are strongly associated with their ideological positions, but which other parties may avoid using altogether. The result for estimation is that some words, even within a context where they do occur in the corpus, may be completely absent from particular texts at a rate quite different from that predicted for texts that do not avoid using them.

It is important to note, when applying such terms as “under-” and “over-dispersion” and “zero inflation”, that these are descriptive terms that can only roughly reflect the root causes of non-Poisson variance structure. As an extreme example, it has long been known that the Negative Binomial distribution can be motivated as an over-dispersed alternative for the Poisson in cases where there is real dependency between nearby Y – called ‘true contagion’ in the biostatistics literature, when there is no true contagion but there is variation in the value of θ within units that follows a Gamma distribution, and when there is ‘apparent contagion’ due to serial correlation in values of θ (see Cameron and Trivedi, 1998, p.106 for a review).

In text scaling applications we can immediately identify ‘true contagion’ as what computational linguists call “burstiness”. First described by Church and Gale (1995), *burstiness* refers to the fact that once a word has occurred, it is significantly more likely to re-occur — implying that variation in word counts is much less informative about θ than the Poisson model assumes. Indeed, burstiness has prompted some authors give up on using word *counts* altogether in favor of recording presence of absence of word (Wilbur and Kim, 2009, e.g.). This approach loses information (though perhaps not very much) and leads fairly directly back to Eq. 2. Burstiness also shows up in the form of excess zeros relative to the Poisson assumption.

To conclude, the problems with conditional independence point to a fundamental observation about applying measurement models to the text scaling task: We have very little idea what the functional form of the relationship between Y and θ is.[6] Even less, perhaps, than for voting in legislatures. The best we can do is identify the model assumptions that fail, and find ways to correct them. We turn now to this task.

3 Accounting for Uncertainty in Text Scaling

The starting point for all our subsequent suggestions about uncertainty accounting in text scaling models is the standard errors that would be appropriate if all model assumption held. Slapin and Proksch (2008) do not offer standard errors for their model, suggesting parametric bootstrapping instead. This makes the model considerably more time consuming to fit while, as we shall see later, still depending fundamentally on the correctness of the model assumptions. In this section we digress slightly to show how to get standard errors for the Wordfish model easily.

As a model fitted by by (penalized) maximum likelihood it is natural to want to compute and invert the information matrix for all fitted parameters. However, with a reasonable number of documents the word parameters β^* and ψ^* are quite accurately estimated so we may fix these at their ML estimates and consider the profile likelihood of θ. However there is still the question of α. A direct IRT approach would not require an offset like α, so what is it for?

If the length of a text N_i is not informative about θ then we can condition on it. If moreover the elements in the word count vector representing text i are Poisson distributed, as they are in Wordfish by assumption, then the distribution of counts given N_i is multinomial.

A product multinomial formulation does offer a reasonable substantive story about text generation: many legislative speeches are time limited by various institutional mechanisms which are reasonably modeled by constraints on N_i and these institutional constraints independent of the position being expressed within their bounds.[7] From an IRT perspective it might seem more natural to model the text generating process from the start as

[6] If we did have a plausible generative model of generating text from policy positions, then we would in fact have solved most of the problems of linguistics and a large portion of artificial intelligence.

[7] Note that this is is true at the constitutional level but not in the case where parties themselves determine who gets to speak.

multinomial, but this will necessarily correlate (negatively) counts of different words and complicate the estimation.

In fact α is part of the multinomial-Poisson (MP) transformation, first formulated in a general fashion by Baker (1994) that connects Poisson and multinomial regression models. According to the MP each multinomial regression model has an equivalent log linear formulation with an extra set of parameters, here called α, corresponding to each case that mimic explicit conditioning on N_i. It is well known that the multinomial likelihood is separable into a part modeling the N_i and a part modeling the conditional distribution of words (Agresti, 2002). The MP transformation simply puts parameters on both parts. The equivalent log-linear style model is then much easier to fit than the original multinomial because each set of word parameters can then be fitted in separate Poisson regression-structured maximizations.

The general maximization strategy of alternating Poisson regressions (with offsets) is noted in Monroe and Maeda (2004) and taken for an Expectation Maximisation algorithm in Slapin and Proksch (2008)[8]. What these authors do not explore is the equivalent multinomial choice model that is implicitly also being fitted this way. What is this model? If the multinomial logistic regression of word counts given document positions uses the count of word 1 as a reference category then the original scaling formulation and the MP-transformed multinomial parameter sets are related as

$$\psi_j = \psi_j^* - \psi_1^*$$
$$\beta_j = \beta_j^* - \beta_1^*$$

in a multinomial model with log-linear contrast as in Eq. 2. Because only word count contrasts are being computed in the multinomial logistic formulation the α parameters (and any grand mean parameters) will cancel out.

There are three advantages to thinking about scaling models this way: First the MP transformation clarifies what α is – a free parameter designed to substitute for explicit

[8]It cannot be an EM algorithm because there is no random variable whose expectation could be taken. The model contains only fixed effects.

conditioning on N_i and speed up fitting. Substantively speaking, the *real* model is a multinomial choice model and the Poisson formulation is simply a means to this end.

Second, since we know that α parameters are designed to capture the marginal totals N_i it is straightforward to derive their (profile) maximum likelihood values in closed form. Capturing these totals requires that

$$\sum_{j=1}^{V} \exp(\psi_j^* + \beta_j^* \theta_i + \alpha_i) \;=\; N_i$$

For fixed values of all other parameters therefore

$$\hat{\alpha}_i \;=\; -\log \sum_{j=1}^{V} \exp(\psi_j^* + \beta_j^* \theta_i) + \log N_i$$

will exactly fulfill the constraint. The first term on the right hand side ensures the elements sum to 1 and the second inflates the total up to N_i. For identification in the main maximisation (since everything on the right hand side is unobserved) α_1 can be set to 0.

Aside from speeding the model fitting procedure the the MP transform has a third advantage: easy asymptotic standard errors. Palmgren (1981) proved that the Fisher information for both sides of the MP transformation is the same. We therefore switch to the multinomial formulation so as not to have to deal with α nuisance parameters and compute the information there. Taking the word parameters as known, and noting that the problem can be solved for each text separately, we then compute the square root of one over the negative second derivative of the data Likelihood with respect to θ to get a measure of estimation uncertainty[9]. Standard errors derived this way tend, empirically, to be very slightly larger than the standard errors provided by a parametric bootstrap according to the procedure recommended by Slapin and Proksch, but effectively instantaneous to compute. If accounting for word parameter uncertainty is of interest, a CLARIFY procedure can be used where word parameters are sampled from the Normal approximations to their sampling distributions and the θ point and uncertainty estimates are averaged across draws.

[9]These are implemented by finite differencing in the R package Austin

4 Relaxing Model Assumptions Using the Bootstrap

Now that standard errors that assume the correctness of the model assumptions are in hand, we can investigate ways to address departures from these assumptions and compare the results. There are, as always, two directions to take when relaxing model assumptions. We can find a way to represent departures within the model itself, effectively making a more complex model, or we can find a way to make fewer assumptions in the model and attempt to deal with divergences within the estimation method. Bayesian approaches such as that taken by Monroe and Maeda are an example of the former, more detailed modeling approach. For this paper we pursue some examples of the latter approach based around the bootstrap (Efron and Tibshirani, 1994; Davison and Hinkley, 1997).

Simple bootstrapping involves resampling cases or residuals with replacement from the original data, refitting the model on each resampled data set and summarizing the quantity of interest. Here the quantity of interest is θ and the cases are texts. Bootstrapping works in general because the empirical distribution function computed from a single sample is informative about the population distribution function from which we imagine that sample was drawn.

When the population distribution function is known or can be assumed, and when it is a familiar algebraic form, then we can account for uncertainty using analytic methods. In these cases bootstrapping is mostly unnecessary, except as a check on the assumptions, or in some cases as a way to adjust asymptotic uncertainty estimates to deal with small numbers of cases.

In simple models, cases are assumed to be independent so resampling cases gives a good view of the distribution function. When cases are not independent, we need find a suitable i.i.d. quantity to resample. A simple example is a linear regression model. The dependent variable is only independent conditional on some covariates, so it is only the residuals that are identically and independently distributed. Consequently we resample them instead. The minimal requirement then is to resample on quantities whose functional dependencies have been effectively removed. Bootstrap methods are typically more accurate if pivotal or asymptotically pivotal quantities are used and there is a considerable literature discussing variations on these themes (see Davison and Hinkley, 1997, for a review). Here we eschew this level of sophistication, focusing attention instead on correctly identifying the (re)sampling unit.

In the following we will assume that the mean word rate λ is correctly modeled as log-linear function of θ and some word parameters. However, we will not, except in the section on parametric bootstrapping, assume that the conditional variance is correctly specified. The sections below deal with the concerns about dispersion and auto-correlation discussed above.

4.1 Parametric Bootstrap Standard Errors

To estimate uncertainty about θ in the Poisson scaling model, Slapin and Proksch (2008) suggest a parametric bootstrap. This variety of bootstrap does not resample the texts directly (or even residuals) but rather draws samples from the fitted model and uses the count matrix thus derived as resampled data to refit the model. In each refitting the θ estimates are saved. The final point estimate and uncertainty is constructed from the set of refitted values, for example using the mean as the point estimate and the standard deviation as a standard error. Alternatively, percentiles can be computed to provide confidence intervals that do not assume normality.

Whatever the precise method, these samples clearly reflect *all* the model's assumptions. In particular, they will by construction be equidispersed, non-autocorrelated and reflect the relevant conditional independence assumptions. Parametric bootstrapping should therefore recover the asymptotic standard errors for θ whose computation was discussed — something clearly shown below in Figure 1. Thus, while very easy to implement, a parametric bootstrap approach is no use for relaxing model assumptions to better reflect what we think is going on with real political text.

4.2 Non-parametric Bootstrap Standard Errors

A tempting step away from the parametric bootstrap is to make less restrictive assumptions about the distribution from which counts are drawn. The weakest such assumption is that each text is a multinomial with probabilities given by its normalized word counts. Bootstrapping this way, however, may remove too much information, leading to overly wide confidence intervals for θ.

If we had constructed and sampled from the multinomial formulation of the wordfish model we would have returned to the parametric bootstrap approach. Here we resample from the raw data but without allowing any relationship to θ to be part of the sampling procedure. Worse, while removing the dependency on θ we have enforced the dispersion to structure to reflect the Poisson assumptions that we doubted above. Word-level bootstrapping, in other words, loosens the distributional assumptions that are untested in real text, but does nothing directly against violations of conditional independence. A superior procedure would be a non-parametric bootstrapping approach that did both: a block bootstrap method.

4.3 Block Bootstrap Standard Errors

To motivate block bootstrapping, our preferred option, we start by noting that text is fundamentally multivariate time series count data with multiple unknown dependencies even after we have conditioned on θ. Using the bootstrap for any kind of time series data is not common outside econometrics and the the theory is still begin developed – Lahiri (2010) seems to be the first book-length review.

Existing bootstrap approaches to time series take one of two directions. In the first, a parametric time series model is estimated and its residuals are resampled as in the non-time series context (see Davison and Hinkley, 1997, ch. 8 for a discussion). A variant of this approach that would seem better suited to textual data is based on estimating and then making use of the Markov transition matrix of the series (Horowitz, 2003). Here the state space of the chain is the V-length indicator matrix indicating which word is spoken or written and the transition matrix is the conditional probability of any other word in the vocabulary. In the Markov chain framework temporal dependencies are reflected by the number of transitions necessary to return the conditional probabilities to their marginal values and this information can be used during bootstrapping. Unfortunately, estimating such a transition matrix is computationally prohibitive, and only addresses temporal dependency issues and not the full range of concerns discussed above.

In the second bootstrap approach to times series data, the cases are resampled directly but in a way that encapsulates their temporal dependency structure. This leads to the block bootstrap methods. In block bootstrap, consecutive blocks of observations of length K are resampled from the original time series, either in fixed blocks (Carlstein, 1986) or overlapping blocks (Künsch, 1989). These methods assume that the time series is stationary, which is reasonable for our applications since we are thinking of texts as being segments of discourse about θ which can be generated at arbitrary length given time or institutional constraints. Politis and Romano (1994) suggest K be drawn from a geometric distribution for the resulting bootstrap samples to maintain stationarity. However, reviewing the choices among block bootstrapping procedures

Lahiri (1999) shows that K is effectively a smoothing parameter that can will, depending on its value, increase the bias or variance components of an estimator's mean square error. Specifically, as K increases bias decreases and variance increases. However, for fixed block length the asymptotic bias of fixed blocks or overlapping blocks estimators is the same but the variance is asymptotically higher for fixed blocks, and substantially higher for randomized K. Although we typically will not know K this is nevertheless a reason to choose overlapping blocks of fixed size.

In theory there is, for any block bootstrap approach and data set, an optimal K that fully encapsulates the temporal dependencies, although all values do better than non-resampling estimation methods that do not model the relevant dependencies. In practice we find that results are very similar within a wide range of K values. This is important because we have very little idea what dependencies we are up against in text and would find it hard to justify particular values of K on substantive grounds.

Practically speaking, we block bootstrap a document containing N words by first sampling $\lceil N/K \rceil$ starting points from the document's word offsets with replacement, extracting K consecutive words from each start point, and constructing a bootstrap document by pasting the sequences together to match the length of the original text. The (relatively rare) sequences that run over past the end of the document are wrapped to the beginning, a choice that appears not to make any difference to our results.

For comparison, we implement a sentence-level bootstrap that resamples only sentences. We choose sentences because they are a natural unit of linguistic dependency that is also easily identified in most most languages. Clearly this is equivalent to allowing K to vary (although sentence lengths are more log-normal than Gamma in our samples) but we hope that they capture better the linguistic dependencies.

5 Uncertainty Estimation Using Simulated Texts

One of the chief problems involved in estimating latent traits from text scaling models concerns the basic fact that we have no benchmark of "truth" with which to compare estimated parameters, coupled with the fact that these parameters — and their standard errors — are heavily model-dependent. In an attempt to get around this problem, in this section we generate some artificial texts and attempt to recover the parameter values using different methods for estimating uncertainty.

5.1 Simulated texts that conform to the Poisson model

Our first set of tests applied the Poisson scaling model to data generated from this model, to attempt to recover the θ_i parameters. We simulated a set of textual frequencies that conformed to the Poisson scaling model for with 10 documents, using a 100-word vocabulary, and document lengths of (approximately) 1000 words. We then estimated the θ_i latent positions and estimated the uncertainty of these positions using three methods: analytically computed standard errors, the parametric bootstrapped standard errors used by Slapin and Proksch (2008), and a simple (i.i.d.) non-parametric bootstrap from resampling the word frequencies of the texts themselves.

*** FIGURE 1 ABOUT HERE ***

The results from the Poisson-conformant data can be seen in Figure 2. The top panel compares the analytically computed standard errors for $\hat{\theta}_i$ (in black) to the standard errors from the parametric bootstrap (in blue). The brown dots indicate the true θ_i from which the data were generated. As can be easily seen from a comparison of the intervals, there is virtually no difference between the two methods of computing uncertainty — except that the analytical method is vastly more efficient computationally.

The bottom panel of Figure 1 shows the results from the non-parametric bootstrap, using word-level resampling with 100 replicates. The results are also virtually identical to those from the analytical and parametric bootstrapping procedures, in terms of both the point estimates and the width of the intervals. The conclusion is clear: when the distributional and conditional independence assumptions of the estimation model are fully met, then all three methods of estimating uncertainty — analytical errors, parametric bootstrapping, and non-parametric bootstrapping — yield identical intervals and accurate point estimates.

5.2 Simulated texts with non-Poisson noise

That the estimated parameters from the Poisson model fit the Poisson-generated text so well is not surprising, since the word frequencies behave perfectly according to the model assumptions. In practice, however, for the many reasons we have outlined above, it is very unlikely that natural language text will fit such model assumptions. Instead, observed word frequencies will have additional noise that cannot be described by the Poisson distribution's characterization of word rate variance being equal to its conditional mean. A closely related distribution is the negative binomial distribution, which adds an additional variance parameter δ_j to allow count data to be over- or under-dispersed. To simulate this effect, we generated artificial data from this distribution, using the parameterization from Venables and Ripley (2002, 206) wherein $\text{Var}(Y_{ij}) = \lambda_{ij} + \frac{\lambda_{ij}^2}{\delta_j}$, with δ_j measuring overdispersion.[10]

*** FIGURE 2 ABOUT HERE ***

The results can be seen in Figure 2. Clearly, when the model assumptions no longer

[10]This is what Cameron and Trivedi (2005, 670) parameterize as α where $\alpha = 1/\delta$. We use δ instead of θ since the latter is already used for a different parameter in the Poisson text scaling model!

fit because of added noise, no method accurately recovers θ_i, although the non-parametric bootstrapping standard errors are significantly larger, especially for the severely overdispersed case. The poorer fit of the Poisson scaling model causes the non-parametric bootstrapped standard errors to be larger, although in 4 of the 10 cases (in the severely overdispersed case) the intervals still do not contain the true θ_i values — although this compares to none of the analytically computed standard errors. In the mildly overdispersed case, only three of the bootstrapped confidence intervals contained the true θ_i, compared with zero for the analytical method. The non-parametric bootstrap is superior to more model-dependent parametric methods, but still unsatisfactory when the model assumptions are badly violated.

6 Non-parametric bootstrap applied to real texts

Just how badly the assumptions of the Poisson scaling model are violated in natural language texts is unknown. As a first means of assessing this problem, we fit the model to two sets of political texts that have been analyzed in previous work, comparing the $\hat{\theta}_i$ and the $\hat{se}\hat{\theta}_i$ from the analytical model to different types of non-parametric block bootstrapping.

6.1 Irish Budget Debate of 2009

The first example comes from a set of legislative speeches for and against the Irish budget of 2009, made in December 2009 in the Irish *Daíl*, the lower house of the Irish parliament. Before 2010 at least, this budget was widely acknowledged to be the harshest budget in Irish history. Consisting of 14 speeches by party leaders, the speeches urged either adoption of the harsh fiscal measures or rejection of the budget and the government behind it. On the government side, speeches by the *Taoiseach* Brian Cowan of the governing Fianna Fáil party, and Finance Minister Brian Lenihan of the same party, represented the most pro-budget positions. Three speeches from Green party ministers (Gormley, Cuffe, and Ryan) provided support for the budget but somewhat more reluctantly, as many in the party regretted the austerity measures but the party leadership was bound to support the budget by the terms of the coalition agreement. On the opposition side, the leaders of the Fine Gael and Labour parties shows the greatest opposition to the budget. In all, the budget debates provide a good example of text expressing positions that plausibly reflects a single dimension of relative preference for fiscal austerity versus social protection, and also directly relates to the approval or rejection of specific legislation.

*** FIGURE 3 ABOUT HERE ***

Figure 3 provides estimates of the positions of each speaker, using the analytical standard errors and point estimates (in black), which in our tests (not shown) were also identical to the parametric bootstrapped error estimates. Our focus here is on comparing the non-parametric bootstrap to these analytic estimates. The three panels show the word-, sentence-, and random block-level bootstrap methods.

One result immediately apparent is the robustness of the three approaches in terms of the relative placement of the speakers, although this is to be expected given that each resampled is estimated using this model. Another noticeable result is that the error estimates from non-parametric bootstrapping are far wider than those from the analytic errors: up to 6 times wider in some cases. From a substantive standpoint, the edges of the intervals (for the word-level bootstrap especially) almost perfectly divide the government coalition parties (Fianna Fáil and the Greens) from the opposition parties. From these results, given these short speeches, the non-parametric model suggests a division at 0 of opposition and government positions, but far less ability to distinguish additional differences within each side from sampling error. The width of the non-parametric intervals in all three applications suggests that the more model-dependent analytical (and parametric bootstrapped results, which are identical) are far too small, suggesting far more certainty even in these relatively short texts than is warranted.

The widest intervals are produced by the sentence-level bootstrap, produced here by resampling texts sentence-by-sentence, before converting these into word frequency matrices. The zero-position line still divides government and opposition in the debate, but Eamon Ryan (then Minister for Communications, Energy and Natural Resources) produced a speech that might have been net opposed to the budget.[11] The same result occurs for the two Sinn Féin deputies, who were not only strongly opposed to the government but also to the solutions debated overall by the mainstream parties (including Fine Gael and Labour in mainstream opposition). From the non-parametric bootstrap results, the Sinn Féin positions have the widest uncertainty and stray into the pro-budget positions, a result that seems to indicate ambiguity with respect to the main government-opposition divide. (It also suggests a second possible dimension to the budget debate not captured here in the one-dimensional scaling result.)

In our implementation of the 50-word and 20-word length block bootstrap (the latter, while not shown, produced results indistinguishable from those in Figure 3), there were few noticeable differences between the word-level and random-block bootstrap methods, probably because the random starting points and overlapping blocks produced results not too different from simple word-level resamples, although producing slightly wider uncertainty estimates. The real difference was seen in the sentence-level bootstrap results, which produced much wider intervals in most cases than the other methods. Linguistically, there are strong reasons to prefer the sentence-level bootstrap over the other methods, because word dependencies tend to occur mainly at the sentence-level, and because sentences provide a naturally occurring (variable) block within which alternative texts could be reconstructed with the greatest theoretical justification. While we intend to investigate this more thoroughly, we recommend sentence-level resampling as the best method for non-parametric block bootstrapping of natural language texts.

6.2 Economic sections of German party manifestos

For the second example of real texts, we replicated Slapin and Proksch (2008)'s analysis of economic positions using the economic segments from 25 German party manifestos. These results are shown in Figure 4.

[11] In his speech, Ryan urged protection from many of the austerity measures, although he did not specify how this would take place: "One of the egalitarian questions raised in this budget was whether to cut services. That was a prospect to which I say no. It is better for us to manage our affairs here, taking some of the hard decisions on pay and social welfare to protect the services that are integral to an equal society. . . I am not sure that the IMF would make a similar call."

*** FIGURE 4 ABOUT HERE ***

As a matter of fact, the results shown in Figure 4 are not exactly what we wished to show — what we aimed to produce were results similar to those in Figure 3. However we have been having difficult reproducing even the basic "Wordfish" estimates when working from word frequency matrices that we created from the original texts,[12] rather than the already-compiled word frequency matrices supplied with Slapin and Proksch (2008).

What the existing Figure 4 does show is further confirmation — as with our simulated texts — that the analytical method of computing standard errors is identical to those from the parametric bootstrap, even for natural language texts (and in this case, in German). The bottom panel also shows that the non-parametric word-level bootstrap (for which we did not require the original texts) produces wider uncertainty estimates than the parametric methods. In both cases, similar to the Irish budget debate results, we see a clean division between opposition and government parties, which during the period examined tended to consist of the CDU/CSU-FDP pair alternating with the SPD-Green alliance.

7 Extension to non-parametric scaling models

The maximum-likelihood solution to the Poisson scaling model (equation 3) can be very computationally demanding to estimate, a demand that is compounded when bootstrapping (parametrically or not) standard errors from the model. A very general alternative exists in the form of a non-parametric technique known as *correspondence analysis*, first introduced by Benzécri (1973), and described in detail by Greenacre (2007). Correspondence analysis is a descriptive method for analyzing contingency tables that is equivalent to principal components analysis but for categorical data. Because its computation is based on singular value decomposition rather than any iterative or numerical procedures, it can be applied very efficiently to even very large word frequency matrices to score documents on one or more latent dimensions.[13]

[12] We thank Oli Proksch for sending us these texts.

[13] Our results here score document positions in one dimension, although several popular software packages, such as Alceste, provide two-dimensional representations by default.

As a method of estimating uncertainty, we use the i.i.d. word-level non-parametric bootstrap. While bootstrapping methods are considered problematic for data-reduction techniques driven by singular value decomposition (see Milan and Whittaker, 1995), the application of bootstrapping to correspondence analysis has been demonstrated by Greenacre (2007), who suggests "peeling" the outer 5% of the convex hull of replicates, a procedure that removes the most influential points to produce an approximate 95% confidence interval.[14] Our procedure estimates 100 replicates of the document scores (approximating $\hat{\theta}_i$) and plots the 95% empirical confidence intervals along with point estimates from the mean of the replicates.

*** FIGURE 5 ABOUT HERE ***

In Figure 5, we apply word-bootstrapped one-dimensional correspondence analysis to the same set of simulated texts used in Figure 1. The results look almost indistinguishable from the much more time-consuming parametric model estimates. The Poisson-generated results are almost perfectly recovered, with intervals extremely similar to the analytically computed intervals from the parametric model. The mild overdispersion intervals contain the true values in 3 of 10 cases, compared to 6 of 10 for the severely overdispersed case (slightly better, even, than the word-bootstrapped parametric scaling approach). Not only did the correspondence analysis estimates perform as well or better than the Poisson scaling model, but also took a fraction of the time to estimate and to bootstrap — a matter of seconds rather than hours.

*** FIGURE 6 ABOUT HERE ***

In figure 6, we have applied one-dimensional correspondence analysis to scale the document positions from the Irish and German political text examples. The dividing line of zero still demarcates government and opposition in both debates, with only minor differ-

[14]Another key problem with bootstrapping different data (re)samples with correspondence analysis concerns rotation and inversion, although problems with rotation are mitigated in our estimates by using a one-dimensional approach. We eliminate the problem of inversion by anchoring all scaled estimates to an orientation determined in advance by specifying the ordering a pair of texts whose relative positions are "known" to be different.

ences that are almost always explained by the confidence intervals. The intervals are much wider for the German economic manifestos, whose parametrically computed confidence intervals suggest an extremely low amount of uncertainty compared to the bootstrapped CA estimates.

While here we do not take the non-parametric bootstrapping of non-parametric scaling further, we have demonstrated how the very general technique of text-level, non-parametric bootstrapping can be used with almost any text-based scaling model, including models that have no parametric models for error computation, such as correspondence analysis. This includes the Laver, Benoit and Garry (2003*b*) method of "wordscores", as Lowe (2008) showed that this method is directly related to one-dimensional correspondence analysis. While we have applied only word-level bootstrapping here, there is no reason why correspondence analysis could not also be used with the sentence-level bootstrap. And because it involves no iterative, numerical estimation, correspondence analysis produces extremely fast results, even when repeating the estimation on hundreds or even thousands of bootstrapped resamples.

8 Recommendations

Our investigation of uncertainty in text scaling models suggests the following conclusions. First, all scaling results are heavily dependent on the data-generation process and on the assumption of conditional independence, even non-parametric scaling methods. When irregular data generation is introduced in artificial texts by increasing the variance relative to the expected word rate, point estimates from every procedure are badly affected. We cannot offer a solution for this problem here, but wish to underscore the importance of scaling models whose assumptions reflect the data-generating process as accurately as possible. This includes both correctly accounting for the inter-dependencies and serial processes generating text units, as well as correctly modeling the stochastic processes that generates observed text units even when conditional independence can be assumed.

Next, all of our results from non-parametric bootstrapping methods of estimating uncertainty in textual positions suggest that standard errors from analytical and parametric bootstrap procedures are far too small, grossly underestimating the uncertainty present in underlying positions estimated from text scaling. In some applications, parametric estimates were smaller by a factor of five or six. Substantively, the overly small parametric-based intervals suggest very different interpretations of textual similarities and differences on the dimensions of underlying traits (such as left-right or pro- versus anti-budget).

Finally, while a firmer recommendation will require more investigation, we tentatively embrace the sentence-level bootstrap as the most realistic and linguistically justified method for estimating uncertainty in text scaling applications. The sentence the naturally occurring variable-length block that is most likely to contain the word-level interdependencies that violate model assumptions regarding conditional independence. The non-parametric bootstrap is most likely to reflect this uncertainty by recreating the sampling distribution from observed texts, in the absence of clear, tenable assumptions about the stochastic processes generating natural language texts — assumptions that simply do not hold in the manner stipulated by the simple Poisson scaling model.

Our study points to two promising areas for additional work. First, we suggest broadening the tests on block-level bootstrapping, especially sentences, in the face of specific problems such as serial correlation, word clustering ("burstiness"), and zero-inflation that could be created in simulated data. We are currently working on simulation methods as well as diagnostic tests to create, diagnose, and attempt to solve problems of this sort.

Our results also suggest that promising results may be achieved by metric scaling models such as correspondence analysis that do not require a generative, parametric model of the word-generation process. Our demonstration of non-parametric bootstrapping to one-dimensional correspondence analysis suggests that it offers a cheap, robust, and valid alternative to much more computationally intensive scaling methods, warranting more detailed research and development.

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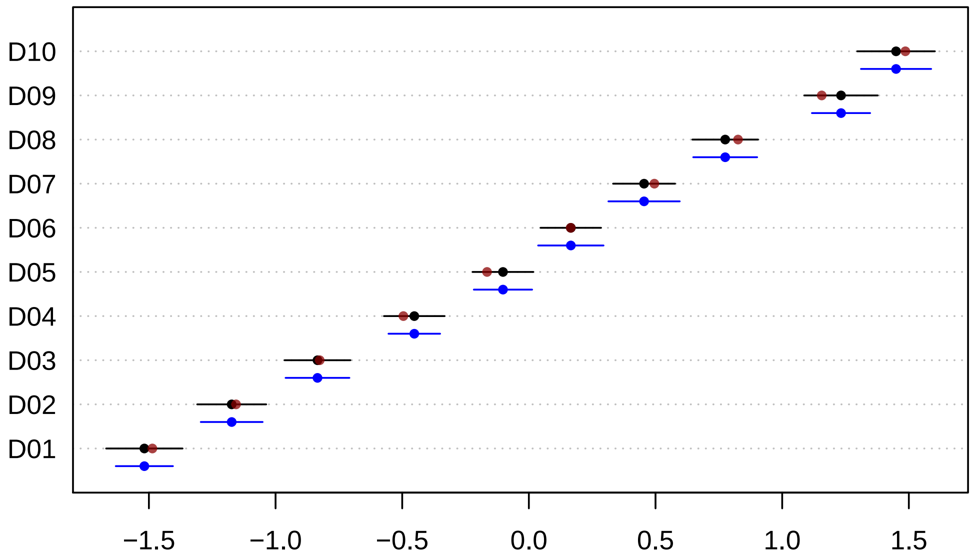
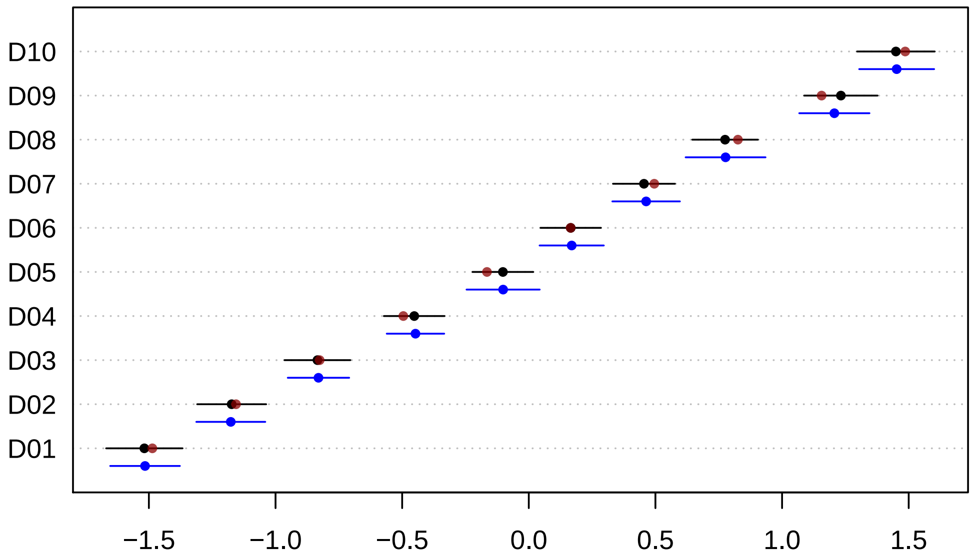
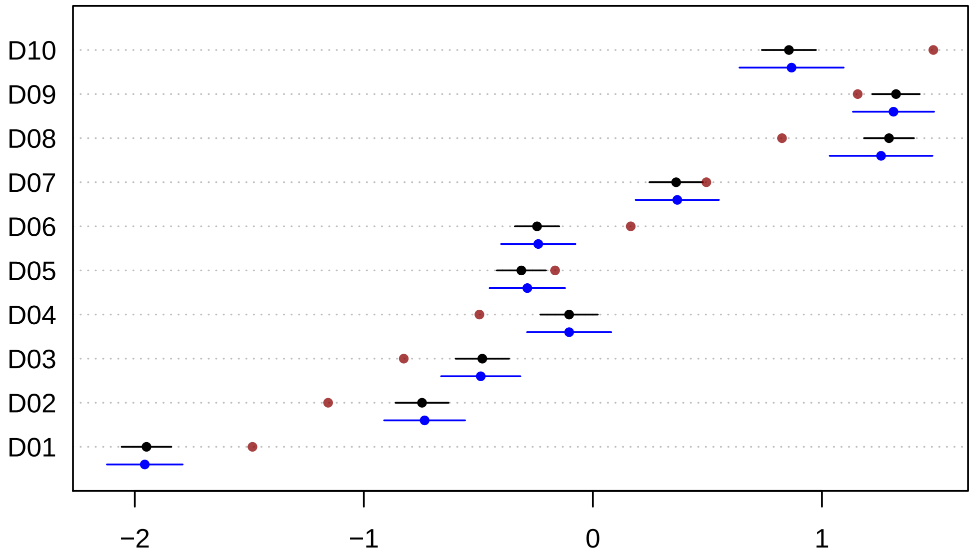


(a) Parametric bootstrap in blue

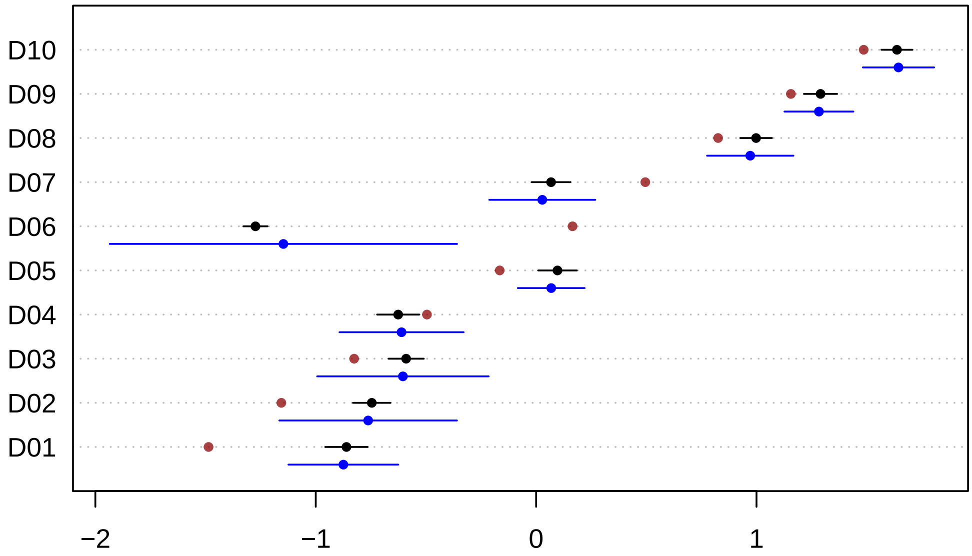


(b) Non−parametric (iid) bootstrap in blue

Figure 1: *Point estimates of θ_i and 95% confidence intervals in Poisson-simulated texts.* Brown dots represent the true θ_i from which the texts were generated; black lines are from analytical point estimates and standard errors; blue points and lines are non-parametric bootstrapped point estimates and confidence intervals. Texts were generated according to the Poisson generative model, with 10 documents, a 100-word vocabulary, and document lengths of (approximately) 1000 words.



(a) Mild overdispersion model, 1/δ=0.8



(b) Severe overdispersion model, 1/δ=2.0

Figure 2: *Point estimates of θ_i and 95% confidence intervals in non-Poisson simulated texts.* Brown dots represent the true θ_i from which the texts were generated; black lines are from analytical point estimates and standard errors; blue points and lines are non-parametric bootstrapped point estimates and confidence intervals. Texts were generated according to a negative binomial distributions, conditional on the Poisson scaling model, with 10 documents, a 100-word vocabulary, and document lengths of (approximately) 1000 words. The two negative binomial distributions were simulated with $\delta_j = 0.5$ and $\delta_j = 1.25 \forall j$.

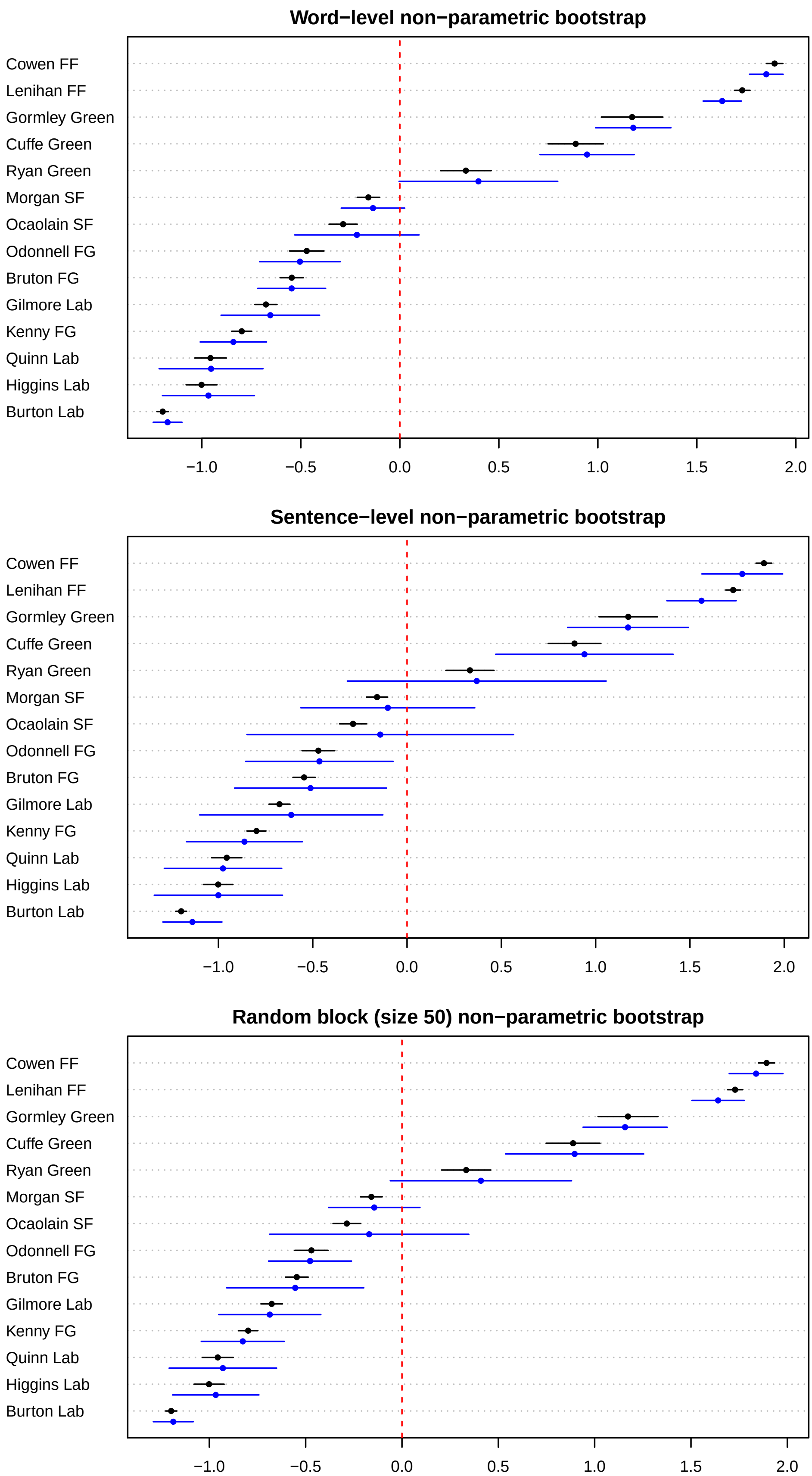


Figure 3: *Estimates of θ_i and 95% confidence intervals from the 2009 Irish Budget Debates using Block Bootstrapping.* Black points and lines are analytical SEs; blue point estimates and 95% CIs correspond to the labelled method.

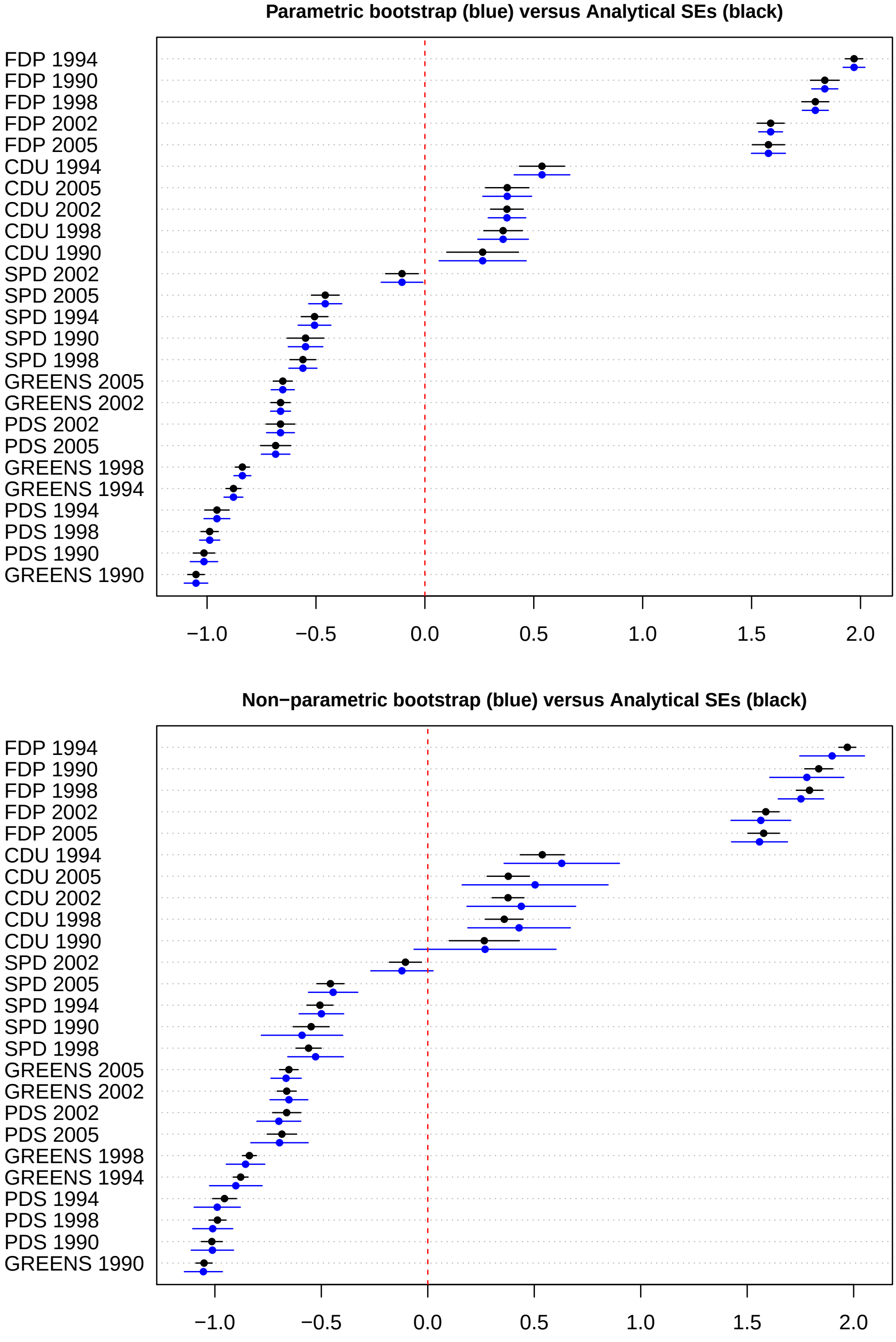


Figure 4: *Point estimates of θ_i and 95% confidence intervals from German (economic) manifestos.* Black points and lines are analytical SEs; blue point estimates and 95% CIs correspond to the labelled method.

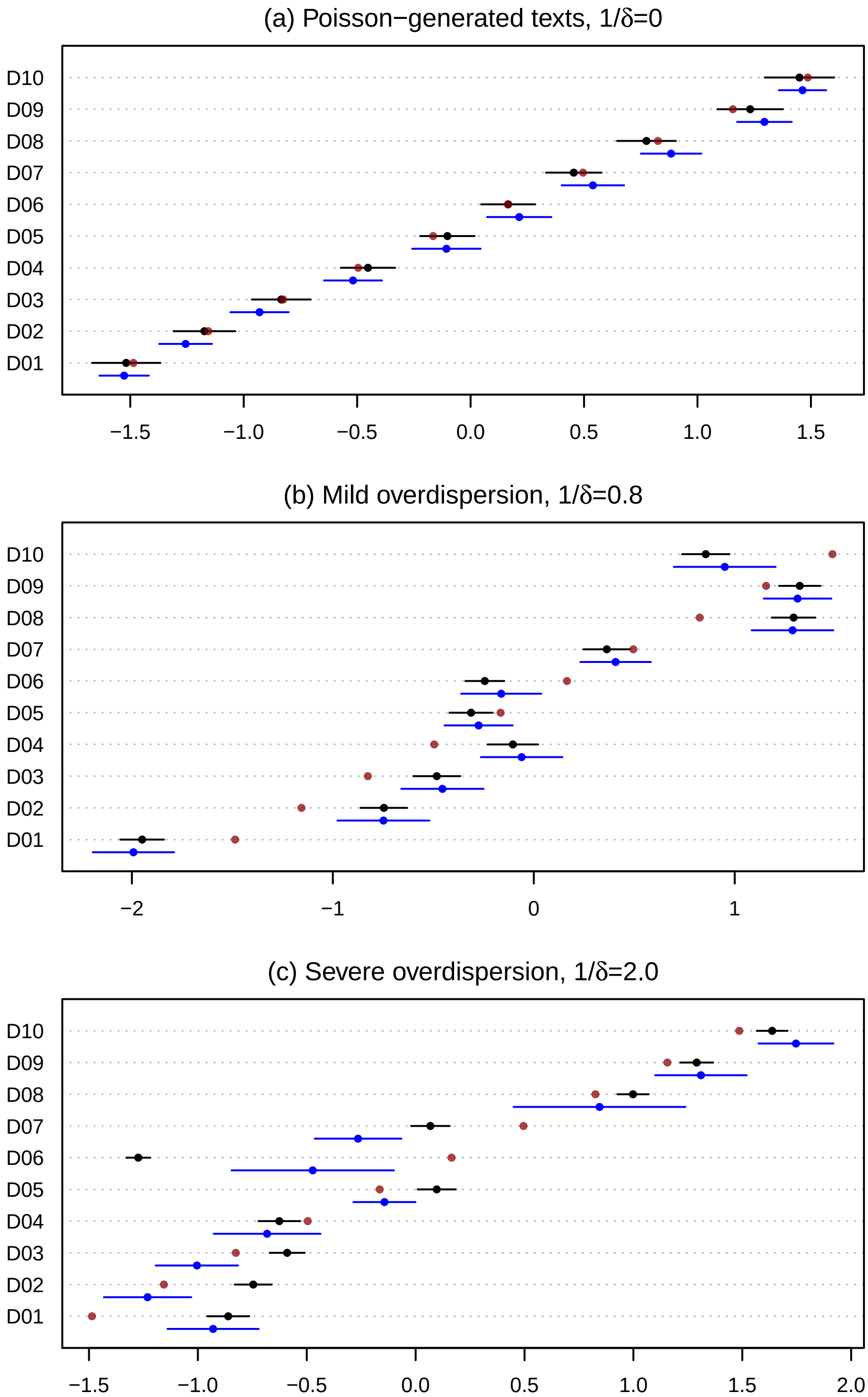


Figure 5: *Correspondence Analysis point estimates of θ_i using simulated texts, with 95% confidence intervals from non-parametric bootstrapping.* Black points and lines are Poisson-scaled estimates and analytical SEs; blue are CA estimates and non-parametric word-level bootstrapped 95% CIs.

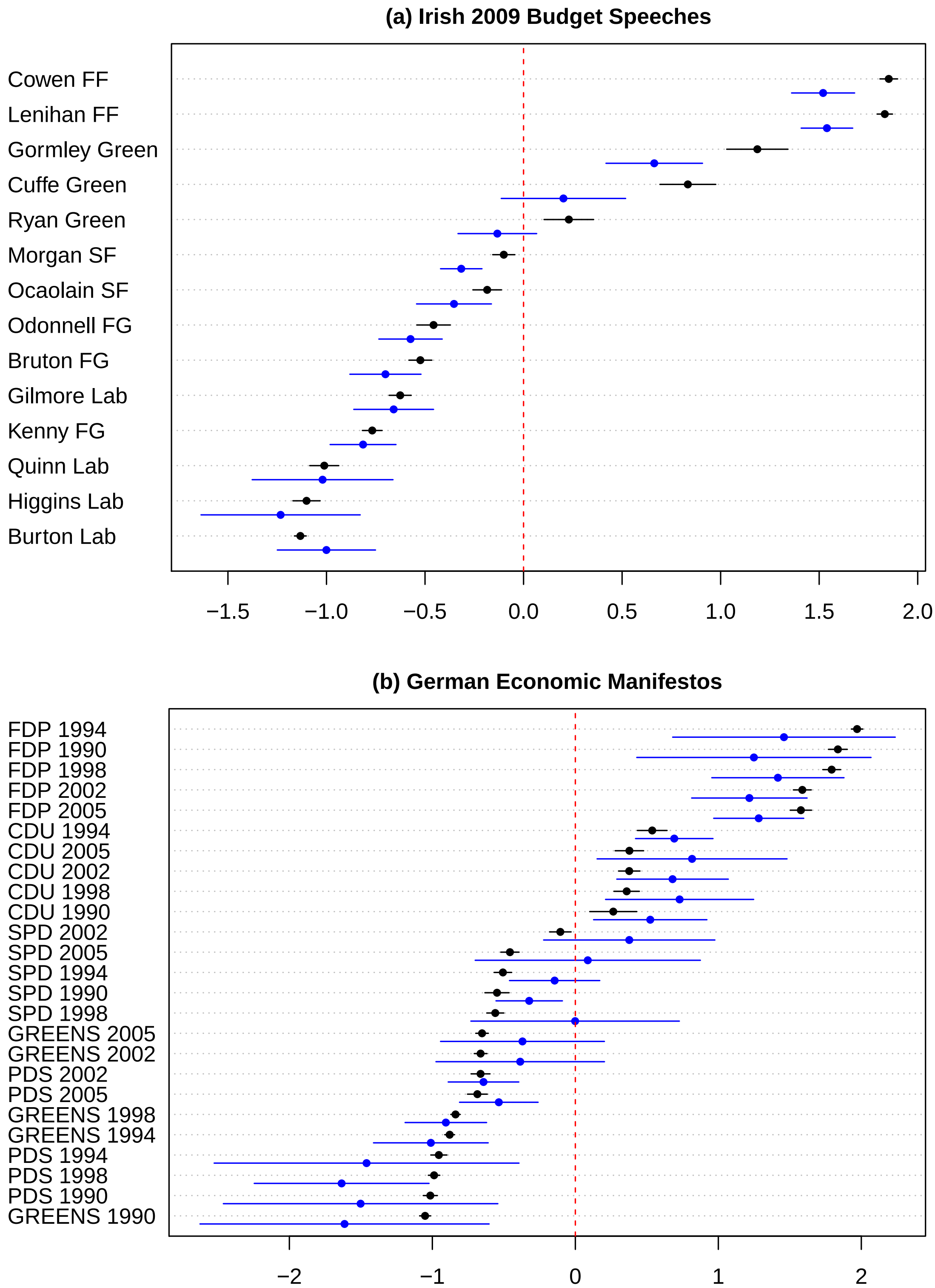


Figure 6: *Correspondence Analysis point estimates of θ_i using real texts, with 95% confidence intervals from non-parametric bootstrapping.* Black points and lines are Poisson-scaled estimates and analytical SEs; blue are CA estimates and non-parametric word-level bootstrapped 95% CIs.