Down-sampling from hierarchically structured corpus data

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Abstract. Resource constraints often require researchers to restrict their attention to a subset of the tokens returned by a corpus query. This paper sketches a methodology for down-sampling and offers a survey of current practices. The most prevalent approach, drawing a random sample from the list of corpus hits, has been shown to be inefficient if tokens are clustered by text file. We extend the evaluation of down-sampling designs to settings where tokens are also clustered by lexical item. Our case study, which deals with the replacement of third-person present-tense verb inflection *-(e)th* by *-(e)s* in Early Modern English, focuses on five predictors: time, gender, genre, frequency, and phonological context. Assuming we are able to analyze only 2,000 (out of 12,244) tokens, we compare two strategies for selecting a sub-sample of this size: simple down-sampling, where each hit has the same probability of being selected; and structured down-sampling, where this probability is inversely proportional to the author- and verb-specific token count. We form 500 sub-samples using each scheme and compare estimates based on mixed-effects logistic regression to a reference model fit to the full set of cases. We observe that structured down-sampling outperforms simple down-sampling on several evaluation criteria.

1. Introduction

As corpora grow in size, it is becoming increasingly common for the data returned by a corpus query to be too vast for certain types of linguistic analysis. Down-sampling may then be used to reduce the scale of effort by selecting from the full set of data a subset of elements for detailed study. The goal is (or should be) to construct this sub-sample in a way that maximizes its information content with regard to the objectives of the study. The down-sampling plan is therefore closely intertwined with the research questions asked. While down-sampling is commonplace in corpus-based work, the methodological state of research is weak. The default approach, which is implemented in corpus software, is to draw a random sample from the tokens returned by a query. It has been shown in previous work, however, that there are situations where this strategy may not be efficient or desirable (Smith and Waters 2019; Sönning & Krug 2022). Instead, down-sampling can rely on supplementary information in the data to sample (or select) elements in a systematic way and thereby optimize the linguistic information in the sub-sample.

The present paper pursues two goals. The first is to work toward a systematic account of down-sampling methods. We outline elementary components of down-sampling schemes, largely relying on concepts and terminology borrowed from sampling theory. This overview takes into account a recurrent feature of corpus data: the hierarchical organization of data points into clusters, which are most typically formed by the text files constituting the corpus. This data layout calls for distinct selection strategies, which have no direct analogue in sampling theory. We also report the results of a survey that maps down-sampling practices in current research and shows to what extent different methods are used in the research literature. This allows us to identify and draw attention to relatively underused techniques.

The second aim is to extend the evaluation of down-sampling designs to data settings where word tokens are doubly clustered, namely by text and item, and where the analysis centers on cluster-level predictors, i.e. variables measured at the level of the text or the item. We use, as a case study, the replacement of third-person verb inflection *-(e)th* by *-(e)s* in Early Modern English, where occurrences are grouped by author and verb. Our attention is restricted to five predictor variables, which are either measured at the level of the verb (FREQUENCY, PHONOLOGICAL CONTEXT) or the author/text (GENDER, YEAR, GENRE). Using an analysis of the full set of 12,244 tokens as a benchmark, we can quantify the loss of information entailed by a reduction of the data to a subset of only 2,000 tokens. Two down-sampling designs are compared: simple down-sampling, where we pick at random from the list of tokens; and structured down-sampling, which aims to balance the distribution of clustering variables (i.e. author and verb) in the sub-sample (Sönning and Krug 2022).

The remainder of this article is structured as follows. Section 2 provides an outline and survey of down-sampling methods in corpus-based research. Our case study is introduced in Section 3, followed in Section 4 by a description of our evaluation procedure. Section 5 presents the results and Section 6 closes with a summary and outlook.

2. Down-sampling in corpus-based work

This section sets the scene by providing a broad overview of down-sampling strategies in corpus research. Since the term down-sampling has come to be used for two distinct data reduction techniques, Section 2.1 clarifies the focus of the present study. Section 2.2 then gives a systematic overview of the building blocks of down-sampling designs and introduces relevant terminology. This is followed by a survey of down-sampling practices in current corpus-based work (Section 2.3) and a review of relevant methodological studies (Section 2.4).

2.1. Two types of down-sampling

We must distinguish between two very different types of down-sampling. The first deals with lists of occurrences extracted from a corpus and is used in studies that start out with a corpus query and a body of hits (often in the form of concordance lines). If the structure of interest is prevalent and/or the source corpus large, the researcher may (be forced to) reduce the number of data points studied. In particular, this will be necessary if the research task involves considerable manual work (e.g. disambiguation and annotation). In this form of down-sampling, the selection of elements usually proceeds (to some extent) at random, i.e. it involves a chance component. Simple techniques are implemented in corpus software, which allows users to extract from a list of hits a random sample.

A very different type of "down-sampling" is concerned with the selection of texts for close reading. Here, the objective is to pick from a corpus those texts that are likely to be most informative for a thorough qualitative analysis. This method, which Gabrielatos et al. (2012) refer to as "targeted down-sampling", uses surface-level features (such as the occurrence rate of certain forms) to detect relevant documents for critical discourse analysis (see also Baker et al. 2008: 285). A procedure much in the same spirit is discussed in Anthony & Baker (2015), where prototypical exemplars, i.e. texts that are most representative of their corpus of origin, are selected based on keyword profiles.

In the present paper, we will be concerned with the first type, i.e. where the number of hits returned by a corpus query is too large for detailed study. We now take a closer look at the elementary components of this form of down-sampling.

2.2. Down-sampling designs: Design features and terminology

This section gives a systematic account of down-sampling strategies, using terminology that is largely borrowed from sampling theory (see, e.g. Lohr 2022). The first distinction we will make is that between a *down-sampling design* and a *design feature*. Design features refer to specific procedures that are used to select elements from a list of corpus hits. As we will see shortly, these can be grouped into three classes. Each class offers different options, and by combining these we obtain a down-sampling design, i.e. a concrete plan (or scheme) that is then implemented to extract from a list of tokens a subset of elements. Three classes of design features are listed in Table 1, which serves as an advance organizer. We will now deal with them in turn.

Table 1. Classes of down-sampling techniques

Design feature	Data requirements
Unit of selection	
Sampling of tokens (individual corpus hits)	None
Sampling of clustering units (texts, items)	Hierarchical structure
Use of supplementary information	
Simple: No use of supplementary variables	None
Stratified: Use of predictor or adjustment variable(s)	Predictors readily obtainable
Structured: Use of clustering variables (texts, items)	Hierarchical structure
Outcome-based down-sampling	
Outcome-blind sampling	None
Case-control down-sampling	Outcome readily obtainable

The first dimension looks at the targets of down-sampling, i.e. which kinds of units are picked. The most straightforward unit is the word *token* (or corpus hit) returned by a query. In much corpus-based work, there are also higher-level units that may be the object of down-sampling: the text files constituting the corpus. These are the original sampling units (in corpus design; see Evert 2006) and they usually represent the language use of a speaker or author. We will use *texts* as a generic label for such higher-level units. Depending on the linguistic phenomenon studied, another type of higher-level unit may often be identified: Tokens can sometimes also be grouped along a language-internal dimension, usually according to word form or lexeme. This is the case for syntactic alternations, for instance (e.g. competing dative/genitive/comparative forms), where variable slots may host different lexical fillers. Borrowing from the domain of psycholinguistics (e.g. Baayen et al. 2008), we will use *item* as a generic label for linguistic units of this kind. In order for more abstract groupings to be the target of down-sampling (e.g. lemmas or lexemes), they must be annotated in the corpus.

The second class of techniques concerns the use of supplementary information to coordinate the selection of elements. We will refer to variables that are used to construct a down-sampling plan as *supplementary variables*. In order to be applicable, these variables must be readily available to the analyst (e.g. in the form of metadata, annotation, or surface-level features). We will refer to the most basic approach, where no additional information is built into the design, as *simple* down-sampling (a term adopted from sampling theory; see, e.g. Lohr 2022: 32; Sönning & Krug 2022: 143). Two alternative strategies, *stratified* and *structured* down-sampling, make use of different types of information in the data.

Structured down-sampling takes advantage of clustering (or structural) variables, which arise from corpus design and the linguistic phenomenon of interest. They are tied to the data layout and describe how tokens can be organized (or grouped) according to higher-level units such as texts and/or items. While these grouping variables are usually not central to the goals of a study, they are an inherent feature of the data and have implications for their analysis (see Johnson 2014; Winter & Grice 2021). Structured down-sampling may then be effective if the number of tokens varies across units. For instance, we may wish to down-scale the representation of texts that contribute a disproportionate number of tokens to our data. The same applies to token counts across items, which are (predictably) skewed in natural language use. Simple down-sampling would prioritize high-frequency forms, to the detriment of rare items, which may not find their way into the sub-sample. Structured down-sampling counteracts these imbalances by enforcing a (probabilistic) limit on the number of tokens that are sampled from each unit (e.g. text or item). The aim is to preserve underrepresented units and spread information more evenly. Sönning and Krug (2022) showed that this yields more precise estimates for cluster-level predictors (e.g. speaker or text attributes).

Stratified down-sampling (cf. Lohr 2022: 79) also relies on supplementary information to form subgroups of the data. In contrast to structural variables, however, stratification variables assume a (more) central role in the study, either in the form of predictors or adjustment ("control") variables. They may represent (cross-classifications of) discrete categories such as genres or speaker groups. If strata derive from predictor variables, comparisons among them are a central aim of the study. It may also be the case, however, that strata are formed to obtain some kind of adjustment or balance. For instance, we may wish to treat speech and writing equal-handedly and therefore extract (approximately) the same amount of information from each (sub)corpus. In general, stratified down-sampling aims to balance information across categories or subgroups of interest. Not only is this desirable if these are assumed to be equally important, but it also increases the precision of statistical comparisons among them (see, e.g. Cox & Donnelly 2011: 33). In order for stratified down-sampling to be feasible, however, supplementary variables must be readily available from corpus metadata.

The final component of down-sampling designs includes the option of using the outcome variable to guide the selection of observations. In epidemiology, this sampling technique is used in so-called retrospective or case-control studies (e.g. Rothman et al. 2008). In corpus research, this opportunity arises if the manifestation of the outcome variable can be readily obtained from the output of the query. *Case-control down-sampling* is particularly effective if one of the outcome levels (e.g. a variant in a syntactic alternation) is rare, since few instances of it would be captured by a random sample. The usual strategy is then to select the same number of tokens of each variant, which means that such designs cannot yield estimates of the relative frequency of variants. The strategy is useful, however, for detecting and quantifying associations between predictor(s) and outcome.[1]

We can now describe down-sampling designs by referring to the combinatorial possibilities listed in Table 1. The default implementation in corpus software, for instance, is "simple, outcome-blind down-sampling of tokens". When describing designs, it may be preferable, in general, to omit the attribute "outcome-blind" and instead require the label "case-control" to be specified if this option is implemented.

Some (outcome-blind) designs are illustrated in Figure 1, where a total of 32 tokens are distributed across 9 texts; texts, in turn, are grouped by genre (the predictor variable). Note how simple down-sampling can target tokens or texts, and how stratified down-sampling uses the predictor variable to balance tokens or texts across genres. Finally, structured down-sampling offers breadth by restricting the number of tokens sampled from each text. Elaborations of these simple designs are of course possible. For instance, stratified down-sampling of texts may be followed by structured down-sampling, and the selection of tokens can be directed by case-control strategies. A further complication arises when there are multiple structural variables (i.e. texts and items), which is the setting dealt with in the present study.

[1] However, this requires the use of appropriate measures of association (i.e. odds ratios) and analysis strategies (i.e. logistic regression) (see Agresti 2013: 46-47, 168-169).

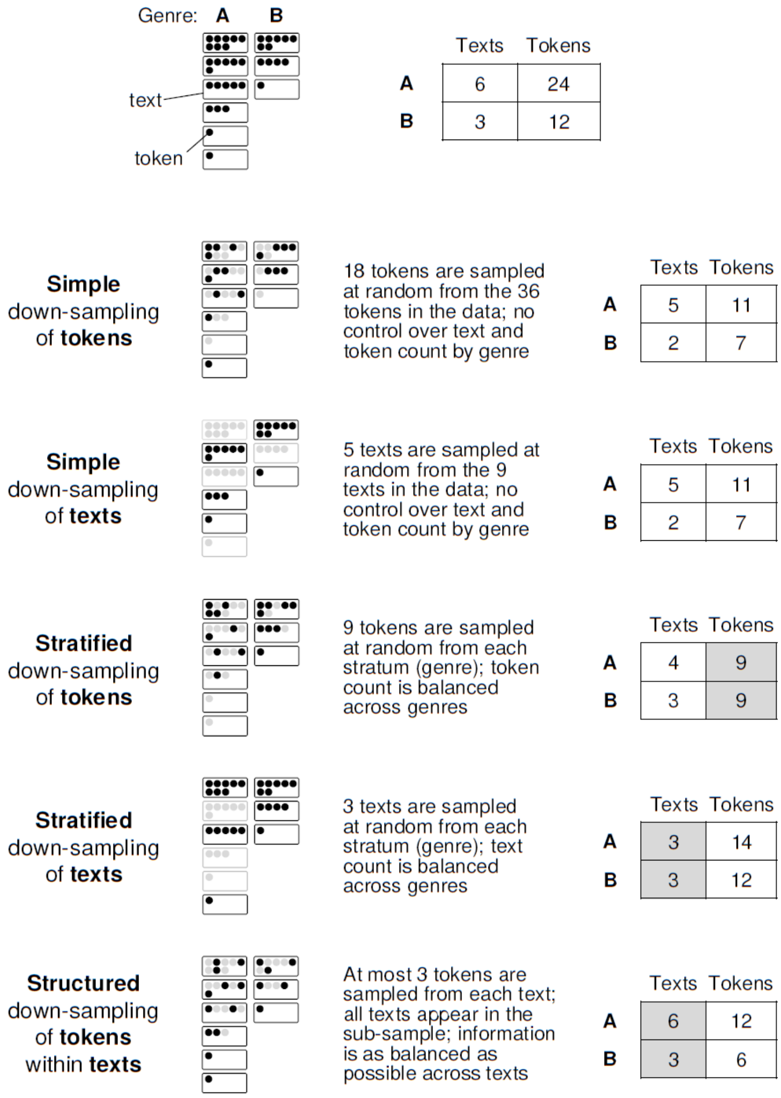

Figure 1. Illustration of some simple (outcome-blind) down-sampling designs.

2.3. A survey of down-sampling designs used in corpus-based work

To obtain an overview of down-sampling practices in recent corpus-based research, we conducted a survey of 582 articles published between 2012 and 2022 in four corpus linguistic journals (see Web appendix 1 for details: https://osf.io/d9xk3). To detect studies that use down-sampling, we searched articles for a number of expressions that we would expect to find in the methods section of relevant papers; the search terms are listed in Web appendix 1. This query returned 241 documents. In order for a study to be included into our survey, it had to meet a number of requirements. First, the sampling procedure had to be directed at observations from an existing corpus (rather than used as a method of corpus compilation). Further, the resulting subset must form the basis of a *linguistic* analysis (rather than serving methodological checks, e.g. reliability assessments). Finally, we excluded studies where it was the methodology that required an adjustment of text lengths (e.g. for the computation of frequency distribution parameters). Apart from this, we also set aside the methodological study by Smith & Waters (2019), to which we will turn shortly. This left us with 61 studies, which we annotated for the following variables:

- *Data structure*: Irrespective of how the data are analyzed, are the corpus hits grouped by text (e.g. text file, speaker, conversation) and/or item (e.g. lemma)?
- *Unit of selection*: Is down-sampling applied to tokens and/or higher-level units (e.g. texts, items)?
- *Stratified down-sampling*: Does down-sampling rely on supplementary variables to balance information?
- *Structured down-sampling*: Does the selection procedure effect some form of balance across clustering units, i.e. texts and/or items?
- *Case-control design*: Is the selection of tokens informed by the outcome variable?

Let us first consider data structure. In 53 studies (87%), tokens were clustered, either by text (n = 39; 64%) or by text and item (n = 14; 23%). The remaining studies (n = 8; 13%) did not rely on an initial corpus query but instead undertook more holistic text-level analyses (e.g. a move analysis or the coding of situational features). In these 8 studies, down-sampling involved the selection of texts from a corpus. In hierarchical data layouts, on the other hand, there are different levels at which elements can be selected. For studies where tokens are clustered only by text (n = 39), the vast majority of down-sampling schemes (n = 34) operated at the level of the tokens. In only 5 cases was sampling directed at texts, and no study implemented structured down-sampling. For studies with data points structured by both text and item (n = 14), just over half (n = 8) employed a form of structured down-sampling of tokens within items.[2] In four of these, the items themselves were purposefully selected beforehand (based on frequency).

As for stratified down-sampling, we identified 45 studies where predictor variables could have been employed to achieve a balanced selection of cases; in 33 of these (73%), stratification was implemented.[3] Finally, there were 12 articles in our survey where the outcome variable allowed for a case-control design, and in half of these studies this form of outcome-based sampling was used. Overall, we may summarize the results of our survey as follows:

- Studies using down-sampling often deal with hierarchically structured data
- Higher-level units only occasionally inform down-sampling designs
- Structured down-sampling of tokens within texts appears to be rare
- Stratified down-sampling is a commonly used technique
- Case-control designs are also fairly prevalent

Our survey has shown that corpus linguists make use of a variety of techniques when down-sampling corpus data. The methodological literature, however, appears to be lagging behind. To our knowledge, only two studies have so far dealt with the question of how to go about selecting elements (drawn) from a larger corpus. Their findings are summarized in the next section.

2.4. Previous methodological work

Smith and Waters (2019) compared two strategies for selecting, from a pool of 108 speakers, a subset of 60 individuals (for consistency, we will refer to these as texts). The 108 texts (i.e. speakers) were distributed unevenly across a number of sociolinguistic categories that were central in the illustrative analyses (age, gender, occupation, education). The study was therefore concerned with down-sampling at the level of texts (rather than tokens). Two designs were compared: (i) simple down-sampling of texts, which perpetuates the imbalance among sociolinguistic categories; and (ii) stratified down-sampling of texts, which balances the representation of these dimensions. Accordingly, two selections of 60 texts were made and then compared with regard to the frequency of several features (POS-tags, *ly*-adverbs and verb tenses). The authors observed that results and

[2] These designs operated at the level of items (rather than texts), and in each case these items were selected before running a corpus search.
[3] In 14 cases, this amounted to down-sampling from different corpora, a situation that invites stratification.

distributional patterns varied with the down-sampling design, and thereby demonstrated that stratification on text-level variables (here: speaker characteristics) may be desirable if these are of central interest in the investigation.

Sönning & Krug (2022) also turned to a sociolinguistic setting to compare down-sampling designs, using data from the demographically sampled spoken part of BNC1994. Their case study was concerned with the positional distribution of *actually* (peripheral vs. medial position in the clause) by age group and gender (i.e. speaker-level predictors). The corpus query returned 2,688 tokens, which were manually annotated for position. Envisaging a setting that permitted an analysis of only 1,000 tokens, the authors compared three down-sampling designs in terms of statistical precision (i.e. confidence interval width): (i) simple down-sampling of tokens; (ii) stratified down-sampling of tokens; and (iii) structured down-sampling of tokens within texts. To quantify the statistical precision yielded by the three schemes, results were averaged over 1,000 sub-samples each. Structured down-sampling yielded the best balance of inferential information across conditions (i.e. cross-classifications of age group and gender) and the smallest loss in precision relative to an exhaustive analysis of all 2,688 tokens. The authors also issued recommendations for down-sample size planning, noting that – in the kind of analysis setting they dealt with (which focuses on speaker-level predictors only) – it is inefficient to sample more than 5 to 10 tokens per text.

The present study builds on Sönning and Krug (2022) and evaluates the performance of different down-sampling designs on a slightly more complex data layout, where corpus hits are grouped by text and item and the predictors of main concern are text- or item-level features. Next, we present the case study on which our evaluation is based.

3. Case study and corpus data

This section takes a closer look at our illustrative data, which are drawn from Jenset and McGillivray (2017). We start by summarizing previous work on the linguistic structure of interest and identify the predictor variables that will take center stage in our evaluation study (Section 3.1). Section 3.2 then describes the preparation of the data for analysis and Section 3.3 summarizes their key structural features.

3.1. Third-person verb inflection in Early Modern English

During Early Modern English, third-person verb inflection involved a replacement of *-(e)th* by *-(e)s*. This change over time did not unfold uniformly, but is instead patterned with respect to a number of variables (cf. Kytö 1993; Nevalainen & Raumolin-Brunberg 2003; Gries & Hilpert 2010). In the present study, we will restrict our attention to five predictors, the first one being time (i.e. YEAR). A further explanatory variable is GENRE, since the progressive variant *-(e)s* emerged earlier in less formal contexts. The variable GENDER has also been observed to play a role: Female speakers appear to be earlier adopters of the incoming new form, a recurrent pattern in variationist research. The remaining predictor variables are attributes of the verb as such. First, the PHONOLOGICAL CONTEXT seems to be a conditioning variable, with novel *-(e)s* attaching less readily to verbal stems ending in a sibilant, most likely for reasons of identity avoidance. Finally, the factor FREQUENCY is considered, the expectation being that conservative behavior, i.e. prolonged resistance to change, is exhibited by inflected forms that are used at a high rate.

3.2. Data preparation

The data provided by Jenset and McGillivray (2017) are drawn from the PPCEME corpus (Kroch et al. 2010) and cover the period from 1500 to 1700. In total, 13,757 third-person singular tokens were annotated by these authors for a range of variables. We now describe in brief how we prepared these data for the purposes of our study and refer the interested reader to the commented R scripts in the online supplementary materials (https://osf.io/eygw9). We started by removing cases with missing information on AUTHOR (coded as "n/a" in the original data; n = 1,240 or 9%) and/or VERB (coded as "NA"; n = 181 or 0.3%). The coding of PHONOLOGICAL CONTEXT (stem-final sound) was revised and completed, relying on the Irvine Phonotactic Online Dictionary (Vaden et al. 2009). The variable was then dichotomized into sibilant vs. other sounds. Likewise, the variable GENRE was converted into two broad classes: relatively formal ones (bible, sermon, philosophy, law, trial, biography, science, education, history, handbook) and relatively informal ones (letter, diary, travelogue, drama, fiction). The predictors YEAR and FREQUENCY entered the analysis as continuous variables, but were re-scaled: Year was centered at zero (1600) and ranged from −1 (1500) to +1 (1700). Frequency was log-transformed and then rescaled to likewise extend from −1 (1 occurrence in the data) to roughly +1 (just under 3,000 tokens). We further made two minor modifications to GENRE and YEAR, to enforce a clean relationship between these features and the variable AUTHOR. As a result of these alterations, each author contributes data to only one genre and only one point in time.[4] This left us with 12,244 tokens for analysis. Table 2 provides an overview of the distribution and coding of the variables in our data.

3.3. Data structure

There are two structural variables, since the 12,224 data points are grouped by AUTHOR (n = 150) and VERB (n = 1,009). The token distribution across authors is shown in Figure 2a, where each dot represents an individual. We see a skewed profile: While most authors contribute 50 or fewer observations to our data, the tallies extend up to 500 for a handful of writers. The uneven distribution of token counts is even more dramatic when organizing cases by verb lemma. Though visually similar to panel (a), note that Figure 2b shows log-scaled token counts on the x-axis. Most lemmas occur only once (42%) or twice (17%), but the counts range up to 2,362 (for *have*). The top five lemmas are flagged in the graph (see also Table 2).

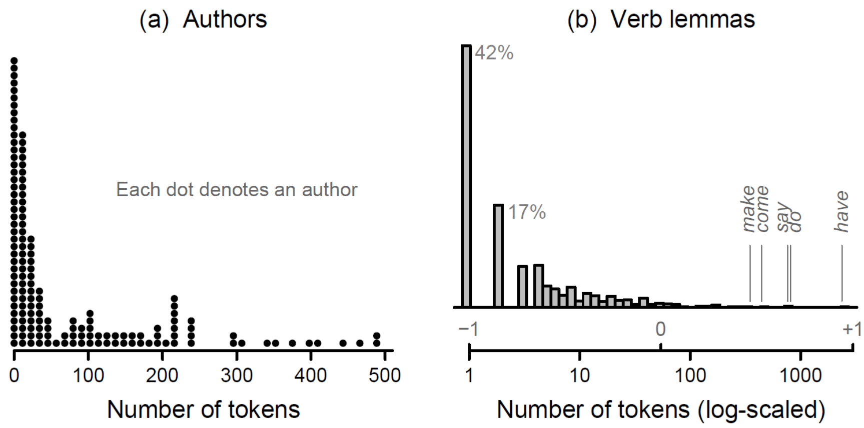

Figure 2. Distribution of token counts across the (a) 150 authors and (b) 1,009 verb lemmas.

[4] There was one author in the data who contributed data points to different genres (for this individual, tokens for the genre with the overall greater share of data were discarded), and there were 8 individuals who contributed texts with different years of publication, spanning a maximum of 16 years (for each author, all year values were replaced with the average year of publication of the data points for this individual). The purpose of these minor modifications is to streamline the data by requiring genre and year to be fully between-author variables (rather than partially within-author) in all down-sampled subsets of the data.

As each verb could (in principle) be uttered by every author, our structural variables are crossed (cf. Singer 1991: 57–58). Since not all combinations occur in our data, however, they are said to be partially crossed. As a result, we can cross-tabulate token counts by AUTHOR and VERB and then arrange these in a two-way table. The resulting distribution is visualized in Figure 3, which shows all authors but only the 150 most frequent verb lemmas. The size of the dots is proportional to the number of tokens for a specific verb-author combination. The largest point, which is sitting in the top left corner, denotes 150 *have*-tokens contributed by William Tyndale. The blank areas in the graph reflect combinations that – although possible – do not occur in our data. Finally, the spikes at the top and left margin show the overall (or marginal) token counts by author and verb, respectively: Note how the most frequent verb *have* (n = 2,362 tokens) clearly sticks out.

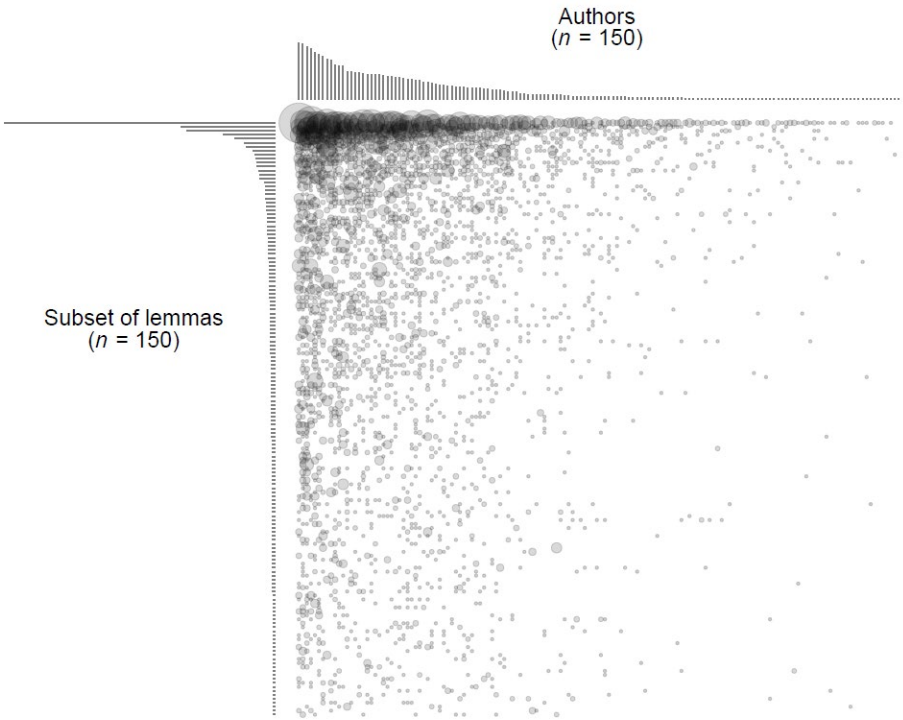

Figure 3. Distribution of token counts cross-tabulated by authors and the 150 most frequent verb lemmas.

Table 2 lists the variables used the present study, which are divided into four groups, starting with the outcome variable and the two structural variables discussed above. Predictor variables are arranged into author-level and verb-level features. Informally, a variable is considered (say) a verb-level predictor if it is an attribute of the verb and therefore measured at the level of this unit. This applies to FREQUENCY and PHONOLOGICAL CONTEXT. For the grouping variable AUTHOR, the same link holds with GENDER, which is an attribute of the individual. To understand why YEAR and GENRE are also author-level predictors, we need to consider what is referred to as a nesting relationship between variables (cf. Singer 1991: 58–61). Thus, AUTHOR is nested within GENDER, since, in the data at hand, each author only belongs to one gender group. Put differently, the variable GENDER does not vary within AUTHOR: Once we know the author, the variable GENDER is fixed. In our data, the same relationship holds between AUTHOR and YEAR, and AUTHOR and GENRE: Each author contributes data from only one year, and in only one genre.

Table 2. Descriptive statistics for the variables in the data set

Variable	Type and distribution	Coding
Outcome variable		
FORM	Binary *-(e)s*: 4,668 tokens (38%) *-(e)th*: 7,669 tokens (62%)	1 if *-(e)s,* 0 if *-(e)th*
Structural variables		
AUTHOR	Nominal 150 authors; quartiles for token counts: 5, 21 (= median), 121; *n* = 5 with > 400 tokens	Name; represented by random intercepts
VERB	Nominal 1,009 verb lemmas	Verb lemma; represented by random intercepts
Author-level predictors		
GENDER	Binary female: 34 authors (23%), 1,134 tokens (9%) male: 116 authors (77%), 11,203 tokens (91%)	Centered: +1 if female −1 if male;
YEAR	Continuous 1500–1550: 41 authors (27%), 2,633 tokens (21%) 1551–1600: 29 authors (19%), 3,352 tokens (27%) 1601–1650: 37 authors (25%), 2,792 tokens (23%) 1651–1707: 44 authors (29%), 3,560 tokens (29%)	Centered: 1500 = −1; 1600 = 0; 1700 = +1
GENRE	Binary formal: 41 authors (27%), 7,723 tokens (63%) informal: 110 authors (73%), 4,614 tokens (37%)	Centered: +1 if formal; −1 if informal
Verb-level predictors		
PHONOLOGICAL CONTEXT	Binary sibilant: 152 verbs (15%), 742 tokens (6%) other: 857 verbs (85%), 11,595 tokens (94%)	Centered: +1 if sibilant, −1 if other
FREQUENCY	Continuous quartiles for token counts: 1, 2 (= median), 5 15 verbs with > 100 tokens; *have* (2,362 tokens); *do* (810); *say* (763); *come* (443); *make* (348)	Rescaled to (log(tokens) – 4)/4; 1 token: −1, 10: −0.42, 100: +0.15, 1,000: +0.73

4. Method

Let us now turn to our evaluation study, which is documented in the OSF project associated with this article (https://osf.io/7ernz/). Section 4.1 describes how the down-sampling designs were implemented. Section 4.2 then presents the results of our reference model, i.e. an analysis of the complete data set. In Section 4.3, we outline how we quantified the performance of down-sampling schemes.

4.1. Implementation of down-sampling designs

Our evaluation study compares two designs: (i) simple down-sampling of tokens and (ii) structured down-sampling of tokens within author-verb combinations. Design (i) gives each of the 12,244 tokens the same probability of being selected. This yields a miniature version of the data, which preserves distributional patterns in the original list of hits. This means that authors who contribute a disproportionately large share of tokens will also be overrepresented in a sub-sample. The same is true for verbs: High-frequency lemmas will dominate our selection of cases. Structured down-sampling, on the other hand, aims to spread information more evenly across authors and verbs. The selection procedure assigns a handicap to high-frequency items and to authors with an excessive number of tokens. Low-frequency verbs and underrepresented authors, on the other hand, will be privileged in the selection process.

This regulation of the sampling process is achieved by manipulating inclusion probabilities. The basic procedure is to make the probability for a token inversely proportional to both the author-specific and verb-specific token count. The approach is illustrated in miniature in Figure 4, where we are dealing with five verbs and five authors. Panel (a) shows a hypothetical cross-table. There are 100 tokens in total, and these are spread unevenly across verbs and across authors. The table is flanked by the marginal counts for verbs (ranging from 5 to 60) and authors (ranging from 10 to 30) and the corresponding marginal proportions. To make selection probabilities inversely proportional to these marginal shares, we take their inverse, i.e. divide 1 by these proportions (e.g. *have*: 1/.60; *strive*: 1/.05) and then rescale the resulting set of scores to sum to 1. This produces the marginal inclusion probabilities shown in panel b (printed in boldface). The inclusion probabilities for verb-author combinations are then obtained through multiplication of these marginal probabilities. This allows us to assign a selection probability to each of the 100 tokens in the data. While down-sampling still involves a chance component, the selection of tokens is guided probabilistically. The online supplementary materials include a tutorial that explains how to construct (and implement) inclusion probabilities in R (https://osf.io/hvq3e).

(a) Marginal proportions

	Author A	B	C	D	E		
have	15	14	12	10	9	60	**.60**
say	7	6	4	3	0	20	**.20**
bring	4	3	2	1	0	10	**.10**
run	3	1	1	0	0	5	**.05**
strive	1	1	1	1	1	5	**.05**
	30	25	20	15	10		
	.30	**.25**	**.20**	**.15**	**.10**		

(b) Inclusion probabilities

	Author A	B	C	D	E	
have	.003	.004	.005	.007	.010	**.03**
say	.010	.012	.015	.020	.030	**.09**
bring	.020	.024	.030	.041	.061	**.18**
run	.041	.049	.061	.081	.122	**.35**
strive	.041	.049	.061	.081	.122	**.35**
	.11	**.14**	**.17**	**.23**	**.34**	

Figure 4. Illustration of the derivation of inclusion probabilities for structured down-sampling from partially crossed structural variables.

To appreciate the balance generated by these inclusion probabilities, let us consider Table 3, which draws upon the data of our case study and lists average features of 500 sub-samples produced by each scheme. These are shown alongside the corresponding quantities based on the full set of 12,244 tokens. Structured down-sampling tends to retain nearly all authors (97% vs. 81% for simple down-sampling) and nearly all verbs (95% vs. 41%). We also note that in simple down-sampling, the two most frequent verbs (*have* and *do*) show (almost) the same share of tokens as in the full data set. Structured down-sampling, on the other hand, de-emphasizes these high-frequency forms considerably.

Table 3. Average features of data subsets produced by the two designs

		Average over 500 sub-samples	
Feature	Full data set	Simple	Structured
Number of speakers	150	122 (81%)	146 (97%)
Number of verbs	1,009	415 (41%)	954 (95%)
Share of *have*-tokens	19.3%	19.1%	0.6%
Share of *do*-tokens	6.6%	6.6%	0.3%

4.2. The reference model

To determine the statistical information carried by the original data, we fit a mixed-effects binary logistic regression model to the full set of tokens.[5] This reference model is constructed from the variables listed in Table 2 and includes random intercepts for VERB and AUTHOR. Table 4 shows that it summarizes the data using three types of coefficients:

- The *intercept* denotes the log odds of *-(e)s* for a context in which all predictor variables are held at zero, averaging over authors and verbs on the model scale. The exact nature of this condition can be reconstructed from the coding information provided in Table 2.
- The *slopes* are usually the coefficients of primary interest, since they capture the association between predictor(s) and outcome. They express the difference in log odds between contexts that are 1 unit apart on the predictor scale. Reference to Table 2 reveals, for each variable, the amount signaled by this difference. In our coding of YEAR, for instance, it corresponds to a 100-year step. To understand the sign of coefficients for binary predictors, we must know the directionality of their scaling. To aid interpretation, the level with the higher coded value is cited in the table. Each slope is accompanied by a standard error, which expresses the statistical uncertainty surrounding the estimated difference, conditional on the data and the model used. Multiplying these by ±2 yields approximate 95% confidence intervals.
- The *random intercept standard deviations* provide a summary of the residual variation among verbs and among authors on the log odds scale. They express the amount of between-author and between-verb variability that is not captured by the predictors in our model.

We note, in passing, that the slope coefficients are in line with the expectations formulated in Section 3.1: The share of *-(e)s* increases over time and is greater among female speakers. Formal genres, high-frequency forms and verbal stems ending in a sibilant, on the other hand, tend to show prolonged retention of *-(e)th*.

The coefficients and standard errors, which are reported in Table 4, will serve as a point of reference for our evaluation study; we will refer to them as *benchmarks*. They represent the statistical information that we would obtain from the data if we had the resources for an exhaustive analysis. Our evaluation study looks at how close a subset of 2,000 tokens (about 16% of the data points) can get us to this state of information.

Table 4. Estimates and standard errors for the reference model[a]

Coefficient	Estimate	Standard error
Intercept[b]	−1.60	0.55
Slopes		
YEAR	7.76	0.69
GENDER = Female	0.89	0.48
GENRE = Formal	−1.83	0.43
FREQUENCY	−0.61	0.24
PHONOLOGICAL CONTEXT = Sibilant	−1.28	0.14
Random intercept SD		
VERB (n = 1,009)	1.28	
AUTHOR (n = 150)	3.99	

Note. [a] Model specification: `s ~ year + female + formal + log_freq + sibilant + (1|lemma) + (1|author)`
[b] To understand the condition referenced by the intercept, please refer to Table 2 for the coding/scaling of predictor variables.

[5] The R script for this analysis is available at https://osf.io/8rk42.

4.3. Evaluation of down-sampling designs

Since our down-sampling designs involve random draws at the token level, they can produce different subsets of observations. We therefore generate 500 sub-samples using each scheme, in order to be able to measure (and for some purposes average out) down-sampling variability (cf. Sönning and Krug 2022: 151). Each sub-sample then undergoes the same regression analysis (cf. Table 4) and coefficients and their standard errors are recorded. For each quantity (and design), we end up with a distribution of 500 values.[6] A commented R script documenting these steps can be found in the OSF project (https://osf.io/8rk42).

To assess the performance of down-sampling designs, we compare their regression output to the benchmark values using four criteria. Note that we draw these comparisons for each coefficient individually. The first feature we focus on is the amount of *bias* induced by a scheme, i.e. whether and to what extent its coefficient estimates are systematically off the mark. This is illustrated in Figure 5 (using hypothetical data), where the vertical line locates the benchmark and the histogram shows the distribution of the 500 estimates. To assess bias, we start by calculating the average value over the 500 sub-samples. We refer to this as the *expectation* (marked by a dot in Figure 5): It is the estimate we are most likely to obtain when opting for a design. This expectation can deviate from the benchmark, and the amount of deviation reflects the amount of systematic error induced by the design. In Figure 5, the distance between dot and vertical line reflects the amount (and direction) of bias. We will express this divergence in two ways: While *raw bias* reflects the difference between expectation and benchmark on the log odds scale, *percent bias* expresses this deviation as a proportion of the benchmark (absolute deviation divided by absolute size of benchmark). In Figure 5, bottom left panel, for instance, the benchmark is +2 and the expectation +1. The raw bias is therefore −1 and the percent bias is 50%.

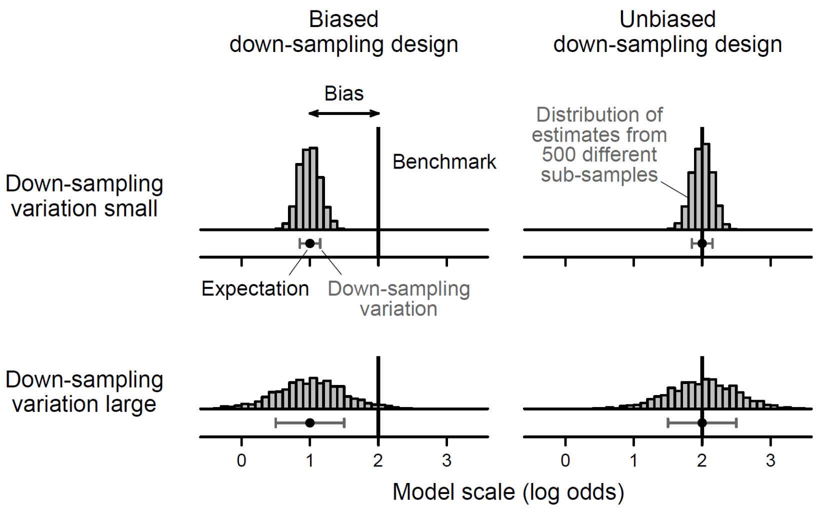

Figure 5. Illustration of two evaluation criteria: Bias and down-sampling variation.

The second property we will measure is the variability of the 500 estimates produced by a scheme. In Figure 5, this information can be gleaned from the "flatness" of the histograms. We refer to this quantity as *down-sampling variation*, and will express it using the standard deviation[7] of coefficient

[6] We excluded results from sub-samples where the regression model did not converge, which happened infrequently and for both designs. Thus, we actually generated more than 500 sub-samples using each scheme and then randomly picked 500 sets of results from those models that produced no warning message.

[7] More specifically, we use the R function `mad()` to obtain a robust estimate of the standard deviation (see, e.g. Gelman et al. 2021: 73).

estimates. Large down-sampling variation is undesirable, since it means that the chance component of the design produces sub-samples that tend to yield highly variable estimates for the coefficient in question.

Our third criterion considers how far a single study is likely to deviate from the benchmark value. To this end, we calculate, for each of the 500 estimates, the absolute deviation from the benchmark, and then take the average over these 500 values. We will refer to this quantity, which takes into account not only bias but also down-sampling variation (i.e. "variance"), as *absolute error*, the average absolute deviation from the benchmark.

Finally, we will consider precision (i.e. the amount of inferential information offered by each design), which is reflected in the standard errors of coefficients, with those from the reference model representing the information limit. For each coefficient, we express the precision offered by a design by averaging over the 500 standard errors. To assess the *loss in precision* caused by a reduction of the data (i.e. an analysis of only 2,000 instead of 12,244 tokens), we compare the average standard errors in the down-sampling designs with the benchmark analogues, and express this comparison as a ratio. A ratio of 1.20, for instance, would indicate that the margin of error grows by 20%.

5. Results

We come now to the results of our evaluation study.[8] Figure 6 shows the distribution of quantities for the two down-sampling designs using histograms. Grey fill color denotes structured down-sampling, and the results from the simple scheme are drawn using black profiles. Benchmark values are shown with thick vertical lines. The panels are arranged in accordance with Table 4, and therefore grouped into intercept (top), slopes (middle block), and random intercept standard deviations (bottom row). For the intercept and the slopes, panels come in pairs: The left column shows the coefficient estimates, the right column their standard error.

Let us consider what kind of information we are looking for in Figure 6. For the intercept and slope estimates, our gaze first rests on the benchmark, i.e. the black vertical line. We will then locate the two distributions relative to this target, and examine which design yields better estimates, i.e. whether the grey pile or the black contour is within closer reach. We then eyeball the expectation for each design, i.e. the center of gravity of each histogram. Its distance from the benchmark reflects the amount of bias afflicting down-sampled estimates. A further feature of interest is the spread of the piles, which indicates how stable estimates are across sub-samples.

For the standard error of the intercept and the slopes, we proceed similarly. The benchmark should be sitting at the left end of the scale, since it is a logical necessity that 12,244 tokens contain more inferential information than any selection of 2,000 data points can. For each pile we can then roughly pin down the expectation, i.e. the average standard error produced by the design. Its distance from the benchmark reflects the loss in inferential information. We will now discuss the general patterns that emerge from Figure 5.

Scanning the distributions for intercept and slope estimates, we note that structured down-sampling produces estimates that are more closely aligned with the benchmark values. This design is therefore generally less vulnerable to bias. The only exception is the predictor GENRE, for which this scheme yields slightly inferior results. Structured down-sampling also produces smaller down-sampling variation, which is at least in part due to the fact the inclusion probabilities lead to greater overlap among sub-samples. For the standard errors of intercept and slopes, we observe that structured down-sampling consistently produces more precise estimates and therefore yields a smaller loss in inferential information relative to the exhaustive analysis. Curiously, it is capable of

[8] The R script reproducing the figures and data summaries reported in this section can be found in the OSF project (https://osf.io/j9gq2).

producing standard errors that undercut benchmark values (i.e. for the intercept and the slope of GENDER and GENRE), which is somewhat counterintuitive.[9] Finally, for the random intercept standard deviations we obtain mixed results. Neither design performs well with the structural variable VERB, and the residual variability among authors is more accurately gauged by simple down-sampling.

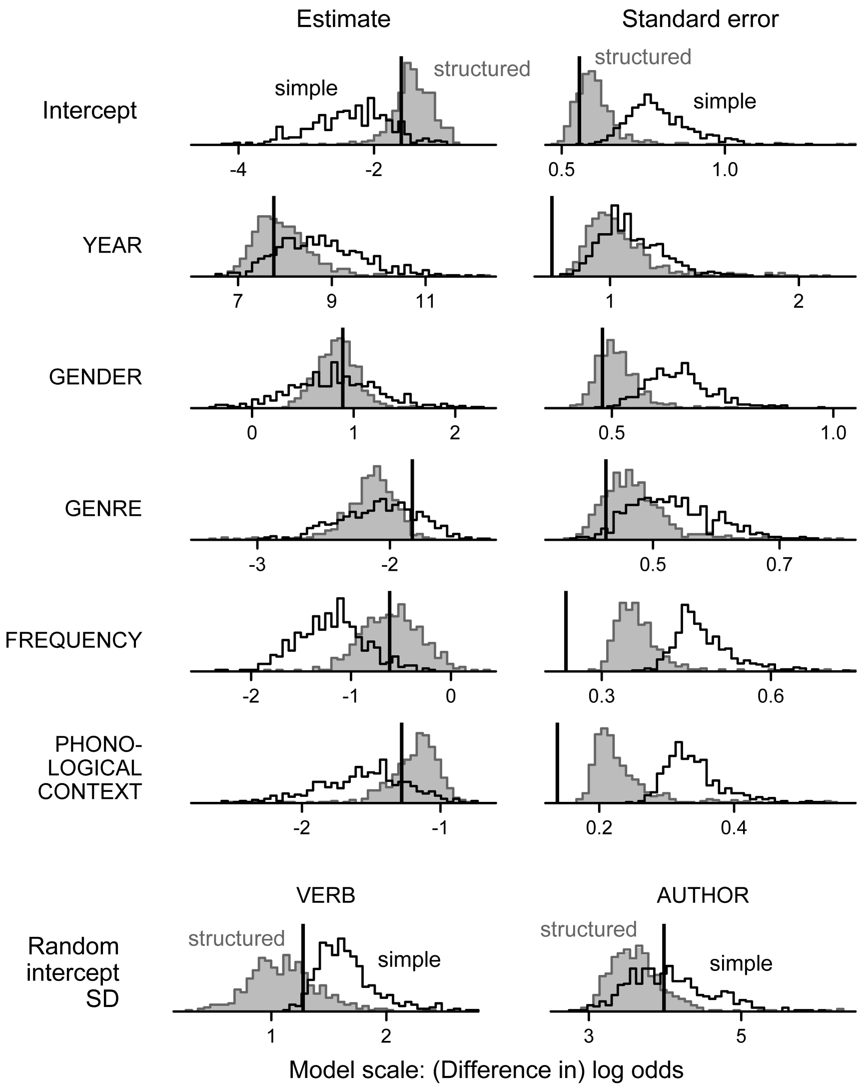

Figure 6. Results of our evaluation study.

Table 5 provides numerical summaries of these results. The left-most set of columns reports the coefficient estimates and standard errors. The benchmark values from the reference model ("Ref.") are repeated here for convenience (cf. Table 4), and the values for simple ("Sim.") and structured ("Str.") down-sampling are medians over the 500 sub-samples. The remaining columns of the table

[9] This can be explained as follows: The standard error of a cluster-level predictor depends on the random intercept variance of the clustering variable. This is because this variance measures the residual variability among units (e.g. authors or verbs), which serves as a yardstick against which the variation "explained" by the predictor is compared. As Figure 6 shows, structured down-sampling yields biased estimates of the random intercept variance for AUTHOR (which is here expressed as a standard deviation): It is underestimated, which explains why the standard errors attaching to the author-level predictors GENDER and GENRE may undercut benchmark values. Across the 500 sub-samples/models in our study, the correlation between these standard errors and the random-intercept variance for AUTHOR is +.96 for GENDER and +.97 for GENRE.

summarize and compare the performance of the two designs with regard to our four criteria (see Section 4.3). Grey highlighting indicates that simple down-sampling showed better performance. For each criterion (and coefficient), the column labeled "Ratio" offers a direct comparison of the performance of the two designs. The slope of YEAR, for instance, is off by +0.96 after simple down-sampling, but only by +0.12 after structured down-sampling. The raw bias induced by structured down-sampling therefore amounts to only 0.12 (or 12%) of the raw bias resulting from simple down-sampling. In general, ratios below 1 indicate better performance of structured down-sampling. Looking over these ratios in Table 5, we note that structured down-sampling in many cases shows an appreciable performance advantage.

Figure 7 offers a condensed summary of our evaluation criteria, focusing on the quantities of primary linguistic interest. We note that structured down-sampling shows better performance: It guards more effectively against bias and yields estimates that are, overall, less variable and on average closer to the target. It also reduces the loss in statistical precision relative to the benchmark standard errors.

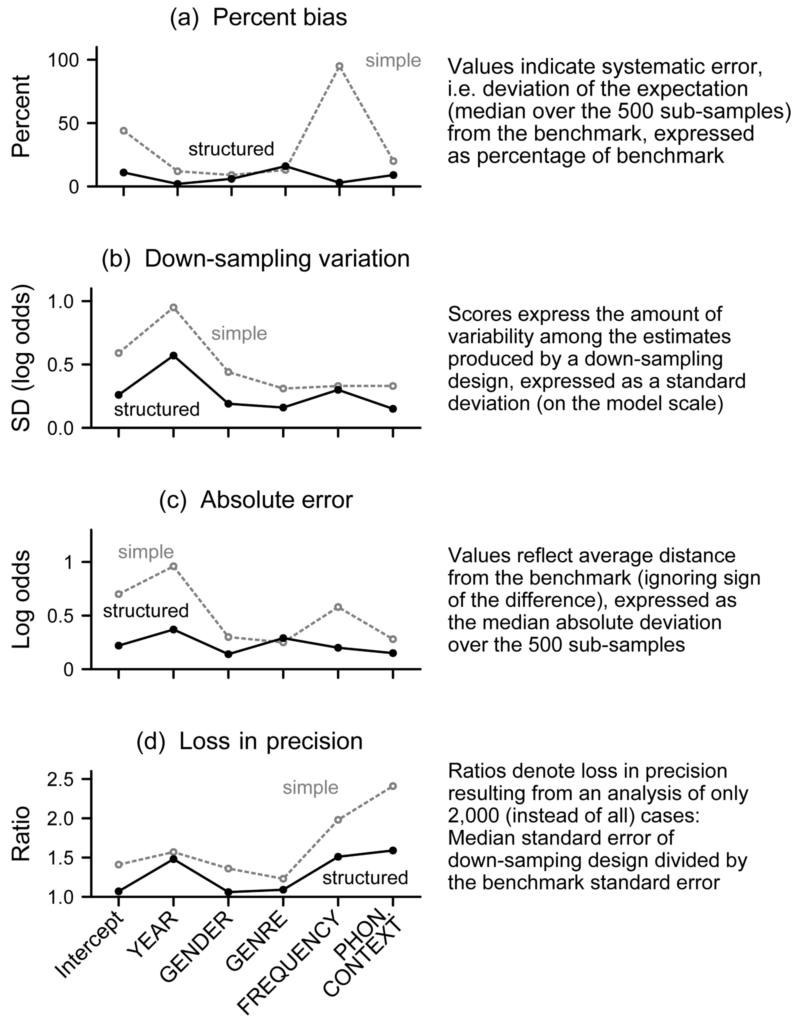

Figure 7. Results of our evaluation study.

Table 5. Results from the evaluation study: Reference model (Ref.), Simple down-sampling (Sim.), and Structured down-sampling (Str.). Grey highlighting denotes cases where simple down-sampling showed better performance

	Estimate[b] (Standard error)			Evaluation criteria[a]											
				Raw bias (Percent bias)			Down-sampling variation			Absolute error			Loss in precision		
Coefficient	Ref.	Sim.	Str.	Sim.	Str.	Ratio[c]	Sim.	Str.	Ratio	Sim.	Str.	Ratio	Sim.	Str.	Ratio
Intercept	−1.60 (0.55)	−2.30 (0.78)	−1.43 (0.59)	−0.70 (44%)	+0.17 (12%)	**0.24**	0.59	0.26	**0.45**	0.70	0.22	**0.32**	1.41	1.07	**0.76**
Slopes															
Year	7.76 (0.69)	8.72 (1.09)	7.88 (1.02)	+0.96 (12%)	+0.12 (2%)	**0.12**	0.95	0.57	**0.60**	0.96	0.37	**0.38**	1.57	1.48	**0.94**
Gender	0.89 (0.48)	0.81 (0.65)	0.84 (0.51)	−0.08 (9%)	−0.04 (6%)	**0.62**	0.44	0.19	**0.44**	0.30	0.14	**0.45**	1.36	1.06	**0.78**
Genre	−1.83 (0.43)	−2.06 (0.52)	−2.12 (0.47)	−0.23 (13%)	−0.29 (16%)	**1.26**	0.31	0.16	**0.52**	0.25	0.29	**1.18**	1.23	1.09	**0.89**
Frequency	−0.61 (0.24)	−1.20 (0.47)	−0.60 (0.36)	−0.58 (95%)	−0.02 (3%)	**0.03**	0.33	0.30	**0.93**	0.58	0.20	**0.35**	1.98	1.51	**0.76**
Phonological context	−1.28 (0.14)	−1.54 (0.33)	−1.16 (0.22)	−0.26 (20%)	+0.12 (9%)	**0.46**	0.33	0.15	**0.45**	0.28	0.15	**0.55**	2.41	1.59	**0.66**
Random intercept SD															
Verb	1.28	1.62	1.10	+0.34 (27%)	−0.18 (14%)	**0.52**	0.22	0.28	**1.27**	0.34	0.26	**0.77**			
Author	3.99	4.00	3.60	+0.02 (1%)	−0.39 (10%)	**23.64**	0.53	0.32	**0.60**	0.36	0.42	**1.18**			

Notes.
[a] Grey highlighting denotes contexts where simple down-sampling showed better performance
[b] For the down-sampling designs, the values reported here are medians over the 500 sub-samples.
[c] The columns headed "Ratio" (entries in bold print) directly compare the performance of the two design with regard to a specific criterion, by dividing the score for structured down-sampling by the score for simple down-sampling.

6. Summary and outlook

The present paper started out with two aims: (i) to work toward a methodology of down-sampling in corpus-based work and (ii) to extend previous research on the comparative evaluation of down-sampling designs. To gain an overview, we deconstructed down-sampling methods into their elementary components and organized these into three classes of techniques. Since a concrete down-sampling plan is built from these components, the proposed terminological arrangement may serve as a preliminary aid for the coordination of methodological research and the transparent documentation of procedures in corpus-linguistic work. The outline we provide builds on concepts from sampling theory and is grounded in current practice, as documented by our survey of down-sampling in corpus research. This survey showed that hierarchical data structures are often encountered in down-sampling work. Nevertheless, clustering variables rarely inform the construction of down-sampling plans: Texts are infrequently considered as a unit of selection, and structured down-sampling is rarely applied. This appears unfortunate in light of our findings, which can be summarized quite succinctly: If the corpus hits are structured hierarchically by text and item, and if the predictors of interest are cluster-level variables, structured down-sampling outperforms simple down-sampling on a number of criteria. The results of our evaluation study, which are consistent with those reported in Sönning and Krug (2022), therefore point to situations in corpus-based research where it may be possible to construct more efficient designs.

The current study has refined the methodological approach of Sönning and Krug (2022) by focusing on multiple evaluation criteria. That earlier paper was concerned with a single performance indicator: the loss in inferential precision induced by a design. Though undoubtedly an important criterion, it has become clear that bias is also a significant feature to look at. Thus, we have observed that down-sampling designs may produce systematic deviations from benchmark values, a feature that is likely to be of major concern to the practicing (corpus) linguist. We also monitored what we referred to as down-sampling variation, to assess the range of chance perturbations generated by a design. Finally, our measure of absolute error combined two aspects, systematic error and down-sampling variation, to express by how much a single study is likely to miss the benchmark. This extended set of criteria appears worthy of consideration in future evaluations of down-sampling designs.

As for the computational implementation of down-sampling schemes, we have introduced the notion of inclusion probabilities and demonstrated how they may serve as a probabilistic handle on the selection process. Accompanied by an online tutorial (https://osf.io/hvq3e), Section 4.1 described how to construct them based on observed data distributions (the marginal proportions in Figure 4) and illustrated their effect on the make-up of sub-samples. A key advantage of this approach is its flexibility. For instance, if the analyst wishes to preserve the natural (i.e. skewed) token counts across items, but considers the imbalance across texts (i.e. speakers or writers) a nuisance, sampling probabilities can be constructed based on a single set of marginal proportions. It is also possible to incorporate additional variables into the scheme. For instance, inclusion probabilities can be easily adjusted to (also) effect balance on stratification (or adjustment) variables, which suggests that they may be of broader utility for the execution of down-sampling plans.

Nevertheless, down-sampling clearly remains an underdeveloped branch of corpus-linguistic methodology. Individual studies such as the current one are necessarily limited to a certain analysis task and a specific data set(ting). Thus, while the hierarchical data layout we have dealt with is often encountered in down-sampling work, the nature of the predictor variables focused here is rather restricted: Like Sönning and Krug (2022), we only considered features that are measured at the level of texts or items. This means that we have disregarded predictors that are observed at the token level and can therefore vary both within texts and within items. An example in the context of our case study would be the speech sound following the inflected verb. In connected speech, the neighboring segment may induce right-to-left coarticulation patterns such as the anticipation of place features. Since this variable is a property of the immediate phonetic context, it can (and will) vary across tokens from the same text and/or verb. Apart from this, it should be kept in mind that a generalization of the findings reported here requires, at absolute minimum, support from further case studies targeting other outcome variables and distributional milieus.

As a result, much work remains to be done. We would therefore like to conclude this paper by pointing to two relatively open areas for methodological research. The first one, which has already been touched upon, concerns the treatment of token-level predictors, i.e. variables that are measured at the level of the individual corpus hits. Since it is quite typical for the coding of such variables to require manual inspection of the context of occurrence, we may need to distinguish, broadly, between two situations: whether the feature is available as a supplementary variable or not. If information on the token-level predictor cannot be built into the design, the only point that appears to be worthy of consideration concerns down-sample size planning. Thus, it would seem that the advice given by Sönning and Krug (2022), to select at most 5 to 10 tokens per text (or, more generally, per clustering unit), requires modification. Concrete recommendations, which remain to be developed in future research, will presumably have to be sensitive to the (expected) distribution of the token-level predictor in the data.

If the token-level attribute is readily obtainable from the context or corpus annotation, it may be incorporated into the design as a stratification variable. The most basic way of balancing the sub-sample with regard to a token-level feature would be to restrict attention to its marginal (i.e. overall) distribution. In hierarchical data settings, more effective stratification schemes can be drafted, however. Here, much can be learned from statistical principles for the design of experiments. Thus, precision may be improved by prioritizing balance within texts and/or within items. This means that we would try to select, say, from a specific text the same number of instances for each subgroup formed by the token-level variable. This form of local control – referred to as *blocking* in experimental design – allows us to measure the association between predictor and outcome within units, i.e. under relatively homogenous circumstances (see, e.g. Cox & Donnelly 2011: 40). It should be noted, however, that this stratification scheme complicates the planning and conduct of down-sampling operations – its implementation cannot (exclusively) rely on inclusion probabilities, since within-unit balance on token-level features will require purpose-built selection procedures. Further, within-cluster balance on token-level attributes may be undesirable if the envisaged analysis also includes cluster-level predictors.

Another technique that calls for deeper engagement is case-control down-sampling. Recall that, out of the 12 studies in our survey where this strategy was practicable, half (i.e. 6) opted for this design feature. The fact that the technique has its place in current practice calls for a development of methodological expertise in this form of outcome-based down-sampling. Here, we can learn from disciplines that routinely work with retrospective or case-control designs. Nevertheless, certain recurrent features of corpus data may eventually bring forth a distinct case-control down-sampling methodology. A case in point is the adaptation of selection strategies to hierarchical data layouts. There may be settings, for instance, where gains in efficiency are possible using structured case-control down-sampling, where balance on the outcome variable is primarily enforced within clustering units.

Apart from these directions for further inquiry, an aspect that is (eventually) worthy of attention is down-sample size planning. While it is relatively straightforward to offer advice for simple settings (e.g. Sönning and Krug 2022), corpus data analysts would profit from general heuristics that provide guidance for the construction of more elaborate designs. However, a focused engagement with this issue arguably requires consensus on a common core of techniques and designs, which may then be evaluated from the viewpoint of down-sample size planning.

While we have considerable work to do, there has never been a better time for down-sampling research. The open science movement has generated an increasing number of published data sets, which offer a wide variety of testing grounds for the development and evaluation of down-sampling designs. We do hope to have succeeded in conveying the relevance and appeal of this relatively uncharted territory of corpus-linguistic methodology.

Acknowledgements. We would like to thank Julia Schlüter for valuable comments on an earlier version of this paper, as well as Gard Jenset and Barbara McGillivray for making the data we used for our case study available along with their 2017 monograph.

References

Agresti, Alan. 2013. *Categorical data analysis*. Hoboken, NJ: Wiley.

Anthony, Lawrence & Paul Baker. 2015. ProtAnt: A tool for analysing the prototypicality ot texts. *International Journal of Corpus Linguistics* 20(3). 273-292.

Baayen, R. Harald, Douglas J. Davidson & Douglas M. Bates. 2008. Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language* 59(4). 390–412.

Baker, Paul, Costas Gabrielatos, Majid KhosraviNik, Michał Krzyzanowski, Tony McEnery & Ruth Wodak. 2008. A useful methodological synergy? Combining critical discourse analysis and corpus linguistics to examine discourses of refugees and asylum seekers in the UK press. *Discourse & Society* 19(3). 273-305.

Cox, David R. & Christl A. Donnelly. 2011. *Principles of applied statistics*. Cambridge: Cambridge University Press.

Crowdy, Steve. 1995. The BNC Spoken Corpus. In Geoffrey Leech, Greg Myers and Jenny Thomas, (eds.), *Spoken English on computer: Transcription, mark-up and annotation*, 224–234. Harlow: Longman.

Evert, Stefan. 2006. How random is a corpus? The library metaphor. *Zeitschrift für Anglistik und Amerikanistik* 54(2). 177–190. doi:10.1515/zaa-2006-0208

Gabrielatos, Costas, Tony McEnery, Peter J. Diggle & Paul Baker. 2012. The peaks and troughs of corpus-based contextual analysis. *International Journal of Corpus Linguistics* 17(2). 151-175.

Gelman, Andrew, Jennifer Hill & Aki Vehtari. 2021. *Regression and other stories*. Cambridge: Cambridge University Press.

Gries, Stefan Th. & Martin Hilpert. 2010. Modeling diachronic change in the third person singular: A multifactorial, verb- and author-specific exploratory approach. *English Language and Linguistics* 14(3), 293–320.

Jenset, Gard B. & Barbara McGillivray. 2017. *Quantitative historical linguistics: A corpus framework*. Oxford: Oxford University Press.

Johnson, Daniel E. 2014. Progress in regression: Why natural language data calls for mixed-effects models. Unpublished manuscript. www.danielezrajohnson.com/johnson_2014b.pdf.

Kroch, Anthony, Beatrice Santorini & Ariel Diertani. 2010. *Penn Parsed Corpus of Modern British English*. http://www.ling.upenn.edu/hist-corpora/PPCMBE-RELEASE-1/index.html

Kytö, Merja. 1993. Third-person singular verb inflection in early British and American English. *Language Variation and Change* 5(2), 113–39.

Love, Robbie, Claire Dembry, Andrew Hardie, Vaclav Brezina and Tony McEnery. 2017. The Spoken BNC2014: Designing and building a spoken corpus of everyday conversations. *International Journal of Corpus Linguistics* 22(3). 319–344.

Lohr, Sharon L. 2022. *Sampling: Design and analysis*. Boca Raton, FL: CRC Press.

Nevalainen, Terttu & Helena Raumolin-Brunberg. 2003. *Historical sociolinguistics: Language change in Tudor and Stuart England*. London: Pearson Education.

Rothman, Kenneth J. Sander Greenland & Timothy L. Lash. 2008. Case control studies. In Kenneth J. Rothman, Sander Greenland & Timothy L. Lash (eds.), *Modern epidemiology*, 111-127. Philadelphia: Wolters Kluwer.

Singer, Judith D. 1991. Types of factors and their structural layouts. In David C. Hoaglin, Frederick Mosteller & John W. Tukey (eds.), *Fundamentals of exploratory analysis of variance*, 50-71. New York: Wiley.

Smith, Nicholas & Cathleen Waters. 2019. Variation and change in a specialized register: A comparison of random and sociolinguistic sampling outcomes in Desert Island Discs. *International Journal of Corpus Linguistics* 24(2). 169-201.

Sönning, Lukas & Manfred Krug. 2022. Comparing study designs and down-sampling strategies in corpus analysis: The importance of speaker metadata in the BNCs of 1994 and 2014. In Ole Schützler & Julia Schlüter (eds.), *Data and methods in corpus linguistics: Comparative approaches*. Cambridge: Cambridge University Press, 127–160.

Vaden, Kenneth I., Harry R. Halpin & Gregory S. Hickok. 2009. Irvine Phonotactic Online Dictionary, Version 2.0. [Data file]. Available from http://www.iphod.com.

Winter, Bodo & Martine Grice. 2021. Independence and generalizability in linguistics. *Linguistics* 59(5). 1251–1277.