Textbook English: A Multi-Dimensional Approach

Online Supplements

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Table of contents

About **5**

1 Introduction **6**
1.1 Research objectives and methodological approach 6
1.2 Outline of the book 8

2 Open Science statement **9**

3 Synthesis **11**
3.1 Summary 11
3.2 Future directions 14

References **17**

Appendices **21**

A Literature Review Data **21**

B Corpus Data **23**
B.1 Textbook English Corpus (TEC) 23
B.2 Reference corpora 23
B.2.1 Spoken BNC2014 23
B.2.2 Informative Texts for Teens Corpus (Info Teens) 23
B.2.3 Youth Fiction corpus 24

C Linguistic Features **25**

D Evaluation of the Multi-Feature Tagger of English (MFTE) **27**
D.1 Packages required 27
D.2 Data import from evaluation files 28
D.3 Estimating MFTE accuracy for Textbook English 34
D.4 MFTE accuracy for reference corpora (or comparable corpora) 37
D.4.1 Conversation 37
D.4.2 Fiction 38
D.4.3 Informative 38

D.5 Estimating the overall MFTE accuracy for corpora used in the study 39
D.6 Exploring tagger errors 45

E Data Preparation for the Model of Intra-Textbook Variation 49
E.1 Packages required 49
E.2 Data import from MFTE output 49
E.2.1 Corpus size 53
E.3 Data preparation for PCA 53
E.3.1 Feature distributions 54
E.3.2 Feature removal 57
E.3.3 Identifying potential outlier texts 58
E.3.4 Signed log transformation 63
E.3.5 Feature correlations 69
E.4 Composition of TEC texts/files 71

F Data Analysis for the Model of Intra-Textbook Variation 76
F.1 Packages required 76
F.2 Preparing the data for PCA 77
F.2.1 TEC data import 77
F.3 Checking the factorability of data 77
F.3.1 Removal of feature with MSAs of < 0.5 78
F.3.2 Choosing the number of principal components to retain 78
F.3.3 Excluding features with low final communalites 79
F.4 Testing the effect of rotating the components 80
F.5 Principal Component Analysis (PCA) 81
F.5.1 Using the full dataset 81
F.5.2 Using random subsets of the data 82
F.5.3 Using specific subsets of the data 82
F.5.4 Performing the PCA 82
F.6 Plotting PCA results 83
F.6.1 3D plots 83
F.7 Two-dimensional plots (biplots) 84
F.7.1 Data wrangling for PCAtools 84
F.7.2 Pairs plot 85
F.7.3 Bi-plots 87
F.8 Feature contributions (loadings) on each component 92
F.9 Exploring the dimensions of the model 98
F.10 Computing mixed-effects models of the dimension scores 100
F.10.1 Dimension 1: 'Overt instructions and explanations' 100
F.10.2 Dimension 2: 'Involved vs. Informational Production' 104
F.10.3 Dimension 3: 'Narrative vs. factual discourse' 112
F.10.4 Dimension 4: 'Informational compression vs. elaboration' 118
F.10.5 Testing model assumptions 124

G Data Preparation for the Model of Textbook English vs. 'real-world' English 126
G.1 Packages required . . . 126
G.2 Data import from MFTE outputs . . . 127
G.2.1 Spoken BNC2014 . . . 127
G.2.2 Youth Fiction corpus . . . 127
G.2.3 Informative Texts for Teens (InfoTeens) corpus . . . 128
G.3 Merging TEC and reference corpora data . . . 129
G.3.1 Corpus size . . . 129
G.4 Data preparation for PCA . . . 130
G.4.1 Feature distributions . . . 130
G.4.2 Feature removal . . . 132
G.4.3 Identifying outlier texts . . . 133
G.4.4 Signed log transformation . . . 140
G.4.5 Merging of data for MDA . . . 143
G.5 Testing factorability of data . . . 143
G.5.1 Visualisation of feature correlations . . . 143
G.5.2 Collinearity . . . 144
G.5.3 MSA . . . 145
G.5.4 Scree plot . . . 145
G.5.5 Communalities . . . 146

H Data Analysis for the Model of Textbook English vs. 'real-world' English 148
H.1 Packages required . . . 148
H.2 Conducting the PCA . . . 149
H.3 Plotting PCA results . . . 150
H.3.1 3D plots . . . 150
H.4 Two-dimensional plots (biplots) . . . 151
H.4.1 Data wrangling for PCAtools . . . 151
H.4.2 Pairs plot . . . 151
H.4.3 Bi-plots . . . 154
H.5 Feature contributions (loadings) on each component . . . 158
H.6 Graphs of features of that contribute most to each component/dimension . . . 161
H.7 Exploring feature contributions in terms of normalised frequencies . . . 163
H.8 Exploring the dimensions of the model . . . 166
H.9 Raincloud plots visualising dimension scores . . . 169
H.10 Computing mixed-effects models of the dimension scores . . . 172
H.10.1 Data preparation . . . 172
H.10.2 Dimension 1: 'Spontaneous interactional vs. Edited informational' . . . 173
H.10.3 Dimension 2: 'Narrative vs. Non-narrative' . . . 176
H.10.4 Dimension 3: 'Pedagogically adapted vs. Natural' . . . 181
H.10.5 Dimension 4: 'Factual vs. Speculative' / 'Simple vs. complex verb forms'? 187
H.10.6 Testing model assumptions . . . 193

About

> **Warning**
>
> This Quarto book is **work in progress**. It will eventually contain the online supplements to:
>
> > Le Foll, Elen. to appear. *Textbook English: A Multi-Dimensional Approach* [Studies in Corpus Linguistics]. Amsterdam: John Benjamins.

The book is based on my PhD thesis, which is accessible in Open Access:

> Le Foll, Elen. 2022. *Textbook English: A Corpus-Based Analysis of the Language of EFL textbooks used in Secondary Schools in France, Germany and Spain.* Osnabrück, Germany: Osnabrück University. PhD thesis. https://doi.org/10.48693/278.

1 Introduction

Asked "Where is Brian?", French nationals of a certain generation will immediately reply: "Brian is in the kitchen". Those with a particularly good memory may follow up with: "Where is Jenny, the sister of Brian?" – and, to those in the know, the correct answer is: "Jenny is in the bathroom".[1] There is hardly any need for an in-depth linguistic analysis to conclude that this interaction is highly unlikely to have ever taken place in a real English-speaking family home. To most teachers and learners, it will be evident that it is the result of a none too inspired attempt to model WH-question forms in a textbook dialogue aimed at beginner learners of English as a Foreign Language (EFL). Together with dull gap-fill exercises and photos of out-of-date technology, for many adults, the very mention of the word textbook evokes vivid memories of such artificially sounding, contrived and sometimes even nonsensical dialogues.

This raises the question of the status and nature of textbook language as a specific 'variety' of language, which is at the heart of the present study. It focuses on contemporary EFL textbooks in use in European secondary schools. Situated at the interface between linguistics and foreign language teaching, this study examines the linguistic content of these textbooks and seeks empirical answers to the questions: What kind of English do school EFL textbooks portray? And how far removed is this variety of English from the kind of English that learners can be expected to encounter outside the EFL classroom?

1.1 Research objectives and methodological approach

The above questions are critical because, as many adults' lingering memories of school foreign language lessons testify (see also, e.g., Freudenstein 2002: 55), textbooks play an absolutely central role in classroom-based foreign language learning. In the following, we will see that the dominance of textbooks in EFL school contexts persists to this day. According to Thornbury (2012 in a response to Chong 2012: n.p.), they "(more often [than] not) instantiate the curriculum, provide the texts, and - to a large extent - guide the methodology". In lower secondary EFL instructional contexts, in particular, textbooks constitute a major vector of foreign language input. Yet, numerous studies have shown that "considerable mismatches

[1] Dialogue from *Speak English 6e série verte* (Benhamou & Dominique 1977: 167). It was made popular by stand-up comedian Gad Elmaleh. More information on the context of this textbook dialogue can be found here. An extract of the comedy sketch by Gad Elmaleh that popularised the dialogue can be viewed here with English subtitles: https://youtu.be/11jG7lkwDwU?t=50.

between naturally occurring English and the English that is put forward as a model in pedagogical descriptions" (Römer 2006: 125-26) exist. These mismatches have been observed and sometimes extensively described in textbooks' representations of numerous language features ranging from the use of individual words and phraseological patterns (e.g., Conrad 2004 on the preposition though; Gouverneur 2008 on the high-frequency verbs make and take), to tenses and aspects (e.g., Barbieri & Eckhardt 2007 on reported speech; Römer 2005 on the progressive). More rarely, textbook language studies have also ventured into the study of spoken grammar (e.g., Gilmore 2004) and pragmatics (e.g., Hyland 1994 on hedging in ESP/EAP textbooks).

However, as we will see in Chapter 2, previous EFL textbook studies have tended to focus on one or at most a handful of individual linguistic features. Taken together, they provide valuable insights into "the kind of synthetic English" (Römer 2004b: 185) that pupils are exposed to via their textbooks; yet, what is missing is a more comprehensive, broader understanding of what constitutes 'Textbook English' from a linguistic point of view. Although corpus-based[2] textbook analysis can be traced back to the pioneering work of Dieter Mindt in the 1980s, the language of secondary school EFL textbooks (as opposed to that of general adult EFL or English for Specific Purposes [ESP] coursebooks) remains an understudied area.

The present study therefore sets out to describe the linguistic content of secondary school EFL textbooks and to survey the similarities and most striking differences between 'Textbook English' and 'naturally occurring English' as used outside the EFL classroom, with respect to a wide range of lexico-grammatical features.

To this end, a corpus of nine series of secondary school EFL textbooks (43 textbook volumes) used at lower secondary level in France, Germany, and Spain was compiled (see 4.3.1). In addition, three reference corpora are used as baselines for comparisons between the language input EFL learners are confronted with via their school textbooks and the kind of naturally occurring English that they can be expected to encounter, engage with, and produce themselves on leaving school. Two of these have been built specifically for this project with the aim of representing comparable 'authentic' (for a discussion of this controversial term in ELT, see 2.2) and age-appropriate learner target language.

A bottom-up, corpus-based approach is adopted (e.g., Mindt 1992, 1995a; Biber & Quirk 2012; Biber & Gray 2015; Ronald Carter & McCarthy 2006a). A broad range of linguistic features are considered: ranging from tenses and aspects to negation and discourse markers. We will pay particular attention to the lexico-grammatical aspects of Textbook English that substantially diverge from the target learner language reference corpora and examine these with direct comparisons of textbook excerpts with comparable texts from the reference data.

[2]Here the adjectives 'corpus-based' and 'corpus-driven' are used synonymously (see, e.g., Meunier & Reppen 2015: 499 for further information as to how these terms are sometimes distinguished).

1.2 Outline of the book

The following chapter outlines the background to and motivation behind the present study. Chapter 3 then provides a literature review of state-of-the-art research on the language of school EFL textbooks. It is divided in two parts. Part 1 is a methodological review in which the various methods employed so far to analyse, describe, and evaluate Textbook English are explained and illustrated with selected studies. Part 2 summarises the results of existing studies on various aspects of Textbook English, including lexical, grammatical and pragmatic aspects. Based on the methodological limitations and the gaps identified in the existing literature, Chapter 4 elaborates the specific research questions addressed in the present study. These research questions informed the decision-making processes involved in the compilation of the Textbook English Corpus (TEC) and the selection/compilation of three reference corpora designed to represent learners' target language. These processes and their motivations are explained in the remaining sections of Chapter 4.

Chapter 5 describes the multivariable statistical methods applied to describe the linguistic nature of Textbook English on multiple dimensions of linguistic variation. It begins by explaining the well-established multi-feature/dimensional analysis (MDA) method pioneered by Biber (1988, 1995; see also Berber Sardinha & Veirano Pinto 2014, 2019), before outlining the reasoning for the modified MDA framework applied in the present study. Chapter 6 presents the results of an MDA model of Textbook English which highlights the sources of linguistic variation within EFL textbooks across several dimensions of intra-textbook linguistic variation. Chapter 7 presents the results of a second MDA model that shows how Textbook English is both, in some respects, similar to and, in others, different from the kind of English that EFL learners are likely to encounter outside the classroom.

Chapter 8 explains how the two models contribute to a new understanding of the linguistic characteristics of Textbook English. This, in turn, has implications for teachers, textbook authors, editors, publishers, and policy-makers. These implications are discussed in Chapter 9. It first considers the potential impact of the substantial gaps between Textbook English and the target reference corpora before making suggestions as to how teachers, textbook authors, and editors may want to improve or supplement unnatural-sounding pedagogical texts using corpora and corpus tools. Chapter 10 focuses on the study's methodological strengths and limitations. It explains how the modified MDA framework presented and applied in this study may be of interest to corpus linguists working on a broad range of research questions. Chapter 11 concludes with a synthesis of the most important take-aways from the study. It also points to promising future research avenues.

2 Open Science statement

Among the wealth of Textbook English publications summarised in Chapter 3 (see also Appendix A), very few have included the data and, where relevant, the code necessary to reproduce or replicate the findings that they report (thereby reflecting current sharing practices in linguistics more broadly, see Bochynska et al. 2023).[1]

Although the terms are sometimes used interchangeably (see Parsons et al. 2022 for a comprehensive glossary of Open Science terminology), 'reproducibility' is used here to refer to the ability to obtain the same results using the researchers' original data and code, whilst 'replicability'[2] entails repeating a study and obtaining compatible results with different data analysed with either the same or different methods (Berez-Kroeker et al. 2018: 4; Porte & McManus 2018: 6–7). Not only does not sharing data and materials mean that published results are not reproducible, hereby making it difficult to assess their reliability, it also makes it very difficult to attempt to replicate the results to gain insights into the extent to which they are generalisable, e.g., across a different set of EFL textbooks used in a different educational context (see also Le Foll 2022d; McManus).

A major barrier to the reproducibility of (corpus) linguistic research is that it is often not possible for copyright or, when participants are involved, data protection reasons to make linguistic data available to the wider public. However, both research practice and the impact of our research can already be greatly improved if we publish our code or, when using GUI software, methods sections detailed enough for an independent researcher to be able to perfectly repeat the full procedure. If this is done, it is possible to conduct detailed reviews of our methodologies and replicate the effects reported in published literature using different data.

Aside from data protection and copyright restrictions, there are, of course, many more reasons why researchers may be reluctant to share their data and code (see, e.g., Al-Hoorie & Marsden; Gomes et al. 2022). It is not within the scope of this monograph to discuss these; however, it is important to acknowledge that, in many ways, such transparency makes us vulnerable. At the end of the day: to err is human. Yet, the risks involved in committing to Open Science practices are particularly tangible for researchers working on individual projects, like me, who have had no formal training in project management, programming, or versioning, and have

[1] This is also true of my own earlier work on the language of EFL textbooks (Le Foll 2021a; 2022a; 2022b). More recent work conducted as part of this project , however, was published alongside with the data and code (Le Foll 2022c; 2023b; 2024).

[2] Confusingly, other terms are also frequently used to refer to the same or related concepts, e.g., *repeatability*, *robustness* and *generalisability* (see, e.g., Belz et al. 2021: 2–3; Parsons et al. 2022).

therefore had to learn "on the job". Nonetheless, I am convinced that the advantages outweigh the risks. Striving for transparency helps both the researchers themselves and others reviewing the work to spot and address problems. As a result, the research community can build on both the mishaps and successes of previous research, thus improving the efficiency of research processes and ultimately contributing to advancing scientific progress.

It is with this in mind that I have decided, whenever possible, to publish the data and code necessary to reproduce the results reported in the present monograph following the FAIR principles (i.e., ensuring that research materials are Findable, Accessible, Interoperable and Reusable, see Wilkinson et al. 2016). For copyright reasons, the corpora themselves cannot be made available. However, the full, unedited tabular outputs of the tool used for automatic corpus annotation (the MFTE Perl; see 5.3.2 and Appendix C) are published in the Online Supplements. Together with the commented data analysis scripts also published in the Online Supplements, as well as in the associated Open Science Framework (OSF) repository, these tables allow for the computational reproduction of all of the results and plots discussed in the following chapters.

In describing the study's methodology, maximum transparency is strived for by reporting on how each sample size was determined and on which grounds variables and data points were excluded, manipulated and/or transformed. Most of these operations were conducted in the open-source programming language and environment R (R Core Team 2022). The annotated data processing and analysis scripts have been rendered to HTML pages (viewable in the Online Supplements) thus allowing researchers to review the procedures followed without necessarily installing all the required packages and running the code themselves. Furthermore, these scripts include additional analyses, tables, and plots that were made as part of this study but which, for reasons of space, were not reported on in detail here. Whenever data, packages or other open-source scripts from other researchers were used, links to these are also provided in the Online Supplements (in addition to the corresponding references in the bibliography).

3 Synthesis

3.1 Summary

This study has provided a systematic, empirical account of the kind of English that secondary school EFL learners interact with via their textbooks as compared to the kind of English that they can be expected to encounter outside the EFL classroom. This new understanding of Textbook English is important because textbooks constitute one of the major, if not the most important, vector of English language input that EFL learners encounter in the first four to five years of their secondary education. Although it is popular knowledge that the language portrayed in EFL textbooks somehow "feels" different from how English is generally used outside the classroom, this study is the first to attempt to model the nature of these linguistic peculiarities across different registers and textbook proficiency levels by accounting for a broad range of linguistic features and their co-occurrences. Specifically, it set out to describe the language that secondary school pupils in France, Germany, and Spain are exposed to via their coursebooks and their accompanying audio and audio-visual materials.

To this end, the Textbook English Corpus (TEC) was compiled. It comprises nine series of secondary school EFL textbooks (42 textbook volumes) used at lower secondary level in France, Germany, and Spain and was manually annotated for register. Three reference corpora (Spoken BNC2014, Info Teens, and Youth Fiction) were used as baselines for comparisons between the language of the TEC and the kind of naturally occurring English that learners can be expected to encounter, engage with, and produce themselves outside the EFL classroom.

From the literature review (Chapter 3), we concluded that, to date, a multitude of studies have focused on the representations of individual linguistic features in EFL and ESL textbooks. Some of these studies were described as 'intra-textbook analyses' because they seek to explore and describe the language of textbooks without relying on any comparison benchmarks. By contrast, 'comparative textbook language analyses' draw on reference corpora or corpus-driven lists to infer what is special about the language of textbooks. In this second paradigm, we identified three recurrent issues. First, previous research has failed to consider interactions between the individual linguistic features examined. Thus, whilst some influential studies have helped us to understand how English learners can be misled by their textbooks into making unidiomatic use of specific lexico-grammatical features (e.g., Römer 2005 on the progressive aspect), we concluded that only a multivariable approach can paint the full picture as to how Textbook English – as a whole – differs from the English that language learners are likely to encounter outside the EFL classroom. Second, we saw that prior scholarship has

mostly ignored register differences between the various types of texts typically included in school foreign language textbooks. Given that school EFL textbooks frequently feature, for example, extracts from short stories, dialogues, instructions, and exercises on a single double page, we argued that a meaningful analysis of Textbook English requires a register-based approach. Third, previous quantitative corpus-based studies have usually been undertaken at the corpus level, e.g., comparing the occurrences of a linguistic feature across an entire textbook corpus with those from a reference corpus, and have therefore often failed to account for the effects of varying textbook proficiency levels or the potential idiosyncrasies of individual textbook authors, editors, or publishers. Thus, prior to the present study, much textbook language research had (often implicitly) assumed that Textbook English constitutes a homogenous variety of English with no (systematic) sources of internal variation.

This study set out to test this assumption and uncover the linguistic specificities of Textbook English. Specifically, it examined the extent to which the language of current EFL textbooks used in secondary schools in France, Germany, and Spain is representative of 'real-world' English as used by native/proficient English speakers in similar communicative situations. It asked whether some textbook registers are more faithfully represented than others and whether textbooks' portrayal of different registers becomes more natural-like as the textbooks' targeted proficiency level increases. Finally, the study also sought to identify the clusters of linguistic features that characterise Textbook English across different registers and learner proficiency levels.

To answer these research questions, Biber's (1988; 1995) multi-feature/multi-dimensional analysis (MDA) framework was chosen as a method capable of summarising the patterns of co-occurrences of many linguistic features across different groups of texts. In a preliminary study, the texts of the TEC were compared against the dimensions of Biber's (1988) seminal model of variation in general spoken and written registers of English (Le Foll 2021a; 2022c: chap. 6). On this basis, the present study identified a number of potential methodological issues linked to both the use of Biber's (1988) model as a baseline and the MDA framework as it is traditionally applied. Consequently, a modified MDA framework was developed and implemented for the present study. This modified framework relies on a stringent selection of linguistic features, the normalisation of feature counts to linguistically informed baselines, the application of a computationally stable dimension reduction method (Principal Component Analysis; PCA), the use of mixed-effects linear regression modelling to tease out the potential mediating effects of various variables, and the interpretation of the results using multi-dimensional graphs that expose, rather than obscure, the full breadth of linguistic variation.

In applying the modified MDA framework, the results of the study have convincingly debunked the long-held assumption that the language of school EFL textbooks can meaningfully be considered a homogenous variety of English. Mode and register emerge as significant drivers of intra-textbook linguistic variation, making it impossible to adequately describe Textbook English without considering situationally determined, functional variation. Despite few significant differences between the language of EFL textbooks used in France, Germany, and Spain or between the nine different textbook series of the TEC, this study did uncover noteworthy

interactions between the different text registers and target proficiency levels. The clusters responsible for these interactions underwent close examination. The study also explains and illustrates the key linguistic differences that distinguish stereotypically textbook-like texts from situationally similar 'real-world' texts.

Corroborating the findings of previous Textbook English studies, notably Mindt (1987; 1992; 1995) and Römer (2004; 2005), the present study identified a wide gap between conversational English as it is presented in contemporary secondary school EFL textbooks and 'real-world' conversation that learners can be expected to be involved in outside the EFL classroom. Whilst we are not claiming that all textbook dialogues should resemble the everyday, casual conversations of English L1 speakers (as represented, e.g., in the reference Spoken BNC2014 corpus), it is somewhat disconcerting that, across all nine textbook series of the TEC, textbooks' representations of conversational spoken English become less authentic as learners are expected to become more proficient in English.

By contrast, and more reassuringly, as the target proficiency levels of the textbooks increased, so did the observed similarities between the informative and fiction subcorpora of the TEC and their respective reference corpora. This latter trend likely points to well-intended pedagogical progressions aimed at scaffolding the development of learners' linguistic competences. Despite this general trend towards more authentic informative texts as the textbooks' target proficiency level increases, the results also highlighted potentially problematic textbook texts, even at the highest proficiency levels represented in the TEC (B2). We concluded that some informative texts featured in B2 textbooks were characterised by a lack of register coherence, e.g., pairing words and phrases typical of formal, written English with others more commonly found in informal, (pseudo-)spoken registers. Although this descriptive study makes no claim as to any potential causal links between Textbook English and EFL learners' production, we did note that a lack of register awareness is an issue that has also been observed in learner corpus research (e.g., Gilquin & Paquot 2008).

We acknowledged that not all textbook texts are designed to reflect naturally occurring English. However, when it is the aim, the results of the present study, along with the use of corpus tools, can be used to adapt or create textbook texts that better reflect the kind of English learners can expect to encounter outside the EFL classroom. The results of the present study support the adoption of a "register approach" to ELT, which entails exposing learners to lexico-grammatical patterns of use in the form of situationally contextualised, meaningful constructions and texts, as proposed by Rühlemann (2008). In terms of pedagogical implications, Section 9.4 spelt out the wide-reaching implications of such a register approach for teacher education and materials design.

Although it was originally conceived with the analysis of Textbook English in mind, it is hoped that many of the changes implemented in the modified MDA framework (see 5.3) will be of interest to corpus linguists working on a wide range of research questions and language varieties. Indeed, many of the issues raised in Chapter 5 are not by any means confined to the analysis of textbook language. For instance, the solutions proposed in 5.3.1 to overcome issues such as the comparison of texts of radically different lengths, the lack of punctuation in

transcriptions of spoken language (see 5.3.2), and the non-independence of texts/text samples from the same textbook series, web domain or novel (see 5.3.8) are relevant to many other research areas. These include the study of many e-language registers (e.g., social media posts, blogs, forums, product reviews) and texts produced by young L1 users and L2 learners of all ages and proficiency levels.

Whilst by no means claiming to be fail-safe, the publication of the full code and data used to perform the analyses presented in this study is intended to allow for the computational reproducibility of the results. Crucially, it also allows for additional, independent replications. The Online Supplements exemplify how quantitative (corpus)linguistic methods can, with relatively simple means, be made more transparent, robust, and replicable. Thus, it is hoped that this study may serve as a springboard for further methodological innovations in the multivariate analysis of linguistic data.

3.2 Future directions

The present study is descriptive and exploratory in nature. As such, it opens many avenues for future research. It has contributed some methodological innovations to the MDA framework that may be further explored and tested in future MDA studies on diverse language varieties and registers. Regarding the analysis of school EFL textbooks, it has shown how Textbook English can be examined across a broad range of linguistic features both as a variety of English in its own right, and in comparison to various target reference varieties. Future studies could apply the method to study the language of different EFL, ESL and ESP textbooks and other pedagogical materials (e.g., online e learning courses) used in different educational systems and/or at different proficiency levels.

Another avenue to be explored concerns the quality and quantity of the lexical input provided by EFL textbooks. For each textbook volume and series, the word and phraseme types can be extracted and their rates of repetition across each textbook volume and series can be calculated. The lexical input of the 42 textbook volumes and nine textbook series of the TEC could then be compared to examine the extent to which they share a common core EFL lexical syllabus. In addition, the textbooks' lexical range may be compared to corpus-based lists such as the new General Service List (Brezina & Gablasova 2015) and the PHRASE List (Martinez & Schmitt 2012). Given the TEC's register annotation, it would also be possible to compare the words and phrasemes of an individual textbook register, e.g., the Conversation subcorpus of the TEC with corpus-derived lists of the most frequent words and phrasemes in spoken English (e.g., Fankhauser).

The modified MDA framework could also be applied to analyses of secondary school textbooks of other languages. Indeed, it would be most interesting to compare the present multi-feature/multi-dimensional models of Textbook English with those of other "textbook

languages". Such comparisons may reveal that, cross-linguistically, some of the observed characteristics of Textbook English are in fact universal features of foreign language textbooks – representative of what we might then call: '(School) Textbook Language'.

It is important to stress that, on the basis of the present study, we can only speculate as to the impact of Textbook English in and outside the EFL classroom. As vividly put by Cook (Cook 2002: 268), [i]t may be better to teach people how to draw with idealised squares and triangles than with idiosyncratic human faces. Or it may not. The job of applied linguists is to present evidence to demonstrate the learning basis for their claims […]. Whilst a large body of evidence from usage-based linguistic studies and related disciplines has consistently highlighted the strong connection between input exposure and L2 learners' developmental patterns (e.g., Achard & Niemeier 2004; Pérez-Paredes, Mark & O'Keeffe 2020; Tyler 2012; Tyler & Ortega 2018), it still remains unclear the extent to which "bring[ing] textbooks for teaching English as a foreign language into closer correspondence with actual English" (Mindt 1996: 247) will facilitate or hamper learners' progress. Crucially, we must remember that, as insightful as these multi-dimensional descriptions of Textbook English have been, textbooks do not exist in a vacuum. Yet surprisingly few empirical studies have looked into how textbooks – i.e., not only their language, but also their structures, tasks, and activities – mediate classroom interactions and learning outcomes (Rösler & Schart 2016: 490). In addition, much research remains to be done on how teachers and students actually use textbooks in the classroom. Empirical data on the status quo in secondary EFL classrooms is urgently needed to a) understand the real impact of textbooks and b) develop research-informed recommendations for materials designers and new pre- and in-service teacher training courses that genuinely address current problems and meet teachers' and learners' needs.

In addition to classroom-based investigations into textbook use and learning outcome, the results of the present study and follow-up corpus-based textbook language studies may be triangulated with findings from learner corpora to gain new insights into L2 learning processes. Such research could test McEnery and Kifle's (1998) hypothesis that "[w]here textbooks are included in an exploration of L2 learning, they can explain differences between NS [native speaker] and NNS [non-native speaker] usage" (as cited in Tono 2004: 52). In such endeavours, robust models of textbook language are potentially very useful because few large-scale research projects will realistically be able to investigate both the language of the textbooks that learners use and the language production of these same learners (though see Möller 2020 for such a research design in the context of Content and Language Integrated Learning). The hope is that, if the models of Textbook English elaborated in the present study are shown to be generalisable to further EFL textbooks, they may be used as a means of better understanding certain usage patterns that are more frequent in the language of instructed EFL learners than in that of naturalistic ESL learners (for first attempts in this direction, see Winter & Le Foll 2022 on EFL learners' use of if-conditionals; and Le Foll 2023a on periphrastic causative constructions).

In sum, there is still much to be learnt from "pedagogically-driven corpus-based research" (Gabrielatos 2006: 1). In this study, we have even seen how MDA can be applied to describe the

language of textbooks on multiple dimensions of variation and to point to potential pedagogical issues. These corpus-based findings highlight the need for greater consideration of register in language teaching and learning. The findings were used to point to the benefits of using freely available corpora and tools to create more meaningful, content-rich learning contexts. In other words, this study has not only demonstrated how multivariable corpus-linguistic methods can be used to analyse Textbook English, but it has also outlined ways in which corpora and corpus tools can be used to boost the representativeness of 'real-world' language use in school EFL textbooks. As such, this pedagogically-driven corpus-based study can be said to have "corpused" full circle.

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A Literature Review Data

This table provides a tabular overview of the studies surveyed as part of this study's literature review on textbook research examining describing and/or evaluating the language of English textbooks designed for English L2 learners in various instructional settings.

It presents the results of this non-exhaustive survey of Textbook English studies published over the past four decades, summarising some of the key information on each study, including its main language focus, methodological approach, information on the textbooks investigated, and, if applicable, on any reference corpora used. Empty cells represent fields for which no information was published. The table is fully searchable and filterable. You can adjust the widths of the individual columns to best fit your screen size.

This list is intended to be a dynamic resource that will grow over time. If you would like to contribute any studies to the table, please either fork the corresponding CSV file in the repository or send me an e-mail with the corresponding details of the studies that you would like to add.

This page was last updated on 07 April 2024.

Search

Author	Year	Title	Focus	Nb.TxB	Settin	TxB.level	TxB.market	TxB.p	TxB.content	Method	Ref.corpus	Reference
Al Khateen & Almujaiwel	2018	Communicative Activities in Saudi EFL Textbooks: A Corpus-driven Analysis	speaking tasks	57	EFL	primary and secondary	local, Saudi Arabia	2016–2018		corpus-driven		Al Khateeb, Ahmad, & Almujaiwel, Sultan. 201 Communicative Activities in Saudi EFL Textbo Corpus-driven Analysis. Journal of Language Teaching and Research, 9(6), 1301. https://doi.org/10.17507/jltr.0906.20
Alejo González et al.	2010	Phrasal verbs in EFL course books	phrasal verbs	8	EFL	ESO3 and Bac1	local: Spain, secondary schools	2002–2008		page-by-page survey, comparison with BNC data	BNC1994	Alejo González, Rafael, Ana Piquer Píriz & Guadalupe Revériego Sierra. 2010. Phrasal ve EFL course books. In Sabine De Knop, Frank E Antoon De Rycker (eds.), Fostering Language Teaching Efficiency through Cognitive Linguisti (Applications of Cognitive Linguistics 17), 59–7 Berlin, New York: De Gruyter Mouton. https://doi.org/10.1515/9783110245837.59
Barbieri & Eckhardt	2007	Applying corpus-based findings to form-focused instruction: The case of reported speech	reported speech	7	ESL /EFL		international grammar textbooks	1989–2001		page-by-page survey of textbooks, corpus analysis of reference corpus	Conversation from the American Conversation component of the LSWE corpus and Service Encounters, Study Groups, and Office Hours from the TOEFL 2000 Spoken and Written Academic Language	Barbieri, Federica & Suzanne EB Eckhardt. 20 Applying Corpus-Based Findings to Form-Focu Instruction: The Case of Reported Speech. Lar Teaching Research 11(3). 319–346. http://dx.doi.org/10.1177/1362168807077563
Bardovi-Harlig et al.	1991	Developing pragmatic awareness: Closing the conversation	conversation closings	20	ESL	beginner-intermediate	international	"current"		page-by-page survey		Bardovi-Harling, Kathleen, Beverly A. S. Hartfo Rebecca Mahan-Taylor, Mary J. Morgan & Duc Reynolds. 1991. Developing pragmatic awaren closing the conversation. ELT Journal 45(1). 4- https://doi.org/10.1093/elt/45.1.4
Biber	2002	What does frequency have to do with grammar teaching?	noun premodifiers, present progressive vs. simple present	6	EFL/ ESL	intermediate-advanced	international grammar books	1986–2000		comparative corpus-driven	LGSWE (20 million words)	Biber, Douglas & Randi Reppen. 2002. What D Frequency Have to Do with Grammar Teaching Studies in Second Language Acquisition 24(02 208. https://doi.org/10.1017/S0272263102002
Biber	2006	University language: a corpus-based study of spoken and written registers	lexical bundles	at least 18	EAP /ESP	university	university textbooks, from a total of six broad disciplines		87 texts from the textbooks	MDA	TOEFL 2000 Spoken and Written Academic Language	Biber, Douglas. 2006. University language: a c based study of spoken and written registers (S in Corpus Linguistics v. 23). Amsterdam; Phila John Benjamins.
Biber et al.	2002	Speaking and Writing in the University: A Multidimensional Comparison	wide range of lexico-grammatical features	at least 18	EAP /ESP	university	university textbooks, from a total of six broad disciplines		87 texts from the textbooks	MDA	TOEFL 2000 Spoken and Written Academic Language	Biber, Douglas, Susan Conrad, Randi Reppen, Byrd & Marie Helt. 2002. Speaking and Writing University: A Multidimensional Comparison. TE Quarterly 36(1). 9. https://doi.org/10.2307/3586
Bouhlal Horst, & Martini	2018	Modality in ESL Textbooks: Insights from a Contrastive Corpus-Based Analysis.	central modals	9 (3 series)	ESL	intermediate	local: Québec, upper secondary school	2007–2009		comparative corpus-based	BNC1994 and COCA	Bouhlal, Fatma, Horst, Marlise, & Martini, Julia 2018. Modality in ESL Textbooks: Insights from Contrastive Corpus-Based Analysis. The Cana Modern Language Review, 74(2), 227–252. https://doi.org/10.3138/cmlr.3075
Boxer & Pickering	1995	Problems in the presentation of speech acts in ELT materials: the case of complaints	speech acts of complaints	7	EFL/ ESL	intermediate-advanced	international	1981–1991		page-by-page analysis		Boxer, Diana & Lucy Pickering. 1995. Problem Presentation of Speech Acts in ELT Materials: Case of Complaints. ELT Journal 49(1). 44–58 https://doi.org/10.1093/elt/49.1.44
Cane	1998	Teaching conversation skills more effectively	lexico-grammatical features of conversation		EFL		international	"recent"		page-by-page survey		Cane, Graeme. 1998. Teaching Conversation S More Effectively. The Korea TESOL Journal 51 31–37.

1–10 of 87 rows Show 10

Previous 1 2 3 4 5 ... 9 Next

The raw data can be downloaded as a comma-separated file from the project GitHub repository.

B Corpus Data

B.1 Textbook English Corpus (TEC)

A detailed tabular overview of the composition of the Textbook English Corpus (TEC) together with the full bibliographic metadata is available at doi.org/10.5281/zenodo.4922819.

Note that, for copyright reasons, the corpus itself cannot be published. If you are interested in using the corpus for non-commercial research purposes and/or in a potential research collaboration, please get in touch with me via e-mail.

B.2 Reference corpora

B.2.1 Spoken BNC2014

The original corpus files of the Spoken British National Corpus (BNC) 2014 (Love et al. 2017; Love et al. 2019) can be downloaded for free for research purposes from: http://corpora.lancs.ac.uk/bnc2014/signup.php. I used the untagged XML version.

The R script used to pre-process the untagged XML files into the format used in this study (the "John and Jill in Ivybridge" version with added full stops at speaker turns, as explained in Section 4.3.2.2 of the book) can be found here: https://github.com/elenlefoll/TextbookEnglish/blob/main/3_Data/BNCspoken_nomark-up_JackJill.R

B.2.2 Informative Texts for Teens Corpus (Info Teens)

For copyright reasons, the corpus itself cannot be made available. Details of its composition can be found in Section 4.3.2.5 of the book. If you are interested in using this corpus for non-commercial research purposes and/or in a potential research collaboration, please get in touch with me via e-mail.

B.2.3 Youth Fiction corpus

For copyright reasons, the corpus itself cannot be made available. The corresponding metadata can be found here: https://github.com/elenlefoll/TextbookEnglish/blob/main/3_Data/3_Youth_Fiction_Index.csv. If you are interested in using this corpus for non-commercial research purposes and/or in a potential research collaboration, please get in touch with me via e-mail.

C Linguistic Features

This table provides a tabular overview of the linguistic features tagged by the MFTE Perl at the time of the data analysis.

For more information on the development of the tagger, see Le Foll (2021b) and https://github.com/elenlefoll/MultiFeatureTaggerEnglish.

> Using the MFTE
>
> The Multi-Feature Tagger of English (MFTE) Perl is free to use and was released under an Open Source licence. If you are interested in using the MFTE for your own project, I recommend using the latest version of the MFTE Python, which is much easier to use, can tag many more features, and also underwent a thorough evaluation. Note also that all future developments of the MFTE will be made on the MFTE Python. To find out more, see Le Foll & Shakir (2023) and https://github.com/mshakirDr/MFTE.

The following features were originally considered in this study. This table is also available for download as a PDF at https://github.com/elenlefoll/MultiFeatureTaggerEnglish/blob/main/tables/ListFullMDAFeatures_3.1.pdf.

Table C.1

Category	Feature	Code	
General text properties	Total number of words	Words	*It's a shame that you'd h*
General text properties	Average word length	AWL	*It's a shame that you'd h*
General text properties	Lexical diversity	TTR	*It's a shame that you'd h*
General text properties	Lexical density	LDE	*It's a shame that you'd h*
General text properties	Finite verbs	--	*He discovered that the m*
Adjectives	Attributive adjectives	JJAT	*I've got a fantastic idea!*
Adjectives	Predicative adjectives	JJPR	*That's right. One of the*
Adverbials	Frequency references	FREQ	*We should always wear a*
Adverbials	Place references	PLACE	*It's not far to go. I'll get*
Adverbials	Time references	TIME	*It will soon be possible. N*
Adverbials	Other adverbs	RB	*Unfortunately that's the*
Determinatives	s-genitives	POS	*the world's two most popu*
Determinatives	Determiners	DT	*Is that a new top? The fi*
Determinatives	Quantifiers	QUAN	*Such a good time in like*
Determinatives	Numbers	CD	*That's her number one s*
Determinatives	Demonstratives	DEMO	*What are you doing this*
Discourse organisation	Elaborating conjunctions	ELAB	*Similarly, you may, for e*
Discourse organisation	Coordinating conjunctions	CC	*Instead of listening to us,*
Discourse organisation	Causal conjunctions	CUZ	*He was scared because of*
Discourse organisation	Concessive conjunctions	CONC	*Even though the antigens*
Discourse organisation	Conditional conjunctions	COND	*If I were you... Even if t*
Discourse organisation	Discourse/pragmatic markers	DMA	*Well no they didn't say a*
Discourse organisation	Filled pauses and interjections	FPUH	*Oh noooooo, Tiger's furio*
Discourse organisation	*Like*	LIKE	*Sounds like me. And just*
Discourse organisation	*So*	SO	*She had spent so many s*
Discourse organisation	Direct WH-questions	WHQU	*What's happening? Why*
Discourse organisation	Question tags	QUTAG	*Do they? Were you? It's*
Discourse organisation	Yes/no questions	YNQU	*Have you thought about g*
Discourse organisation	that relative clauses	THRC	*You must be very clever t*
Discourse organisation	*that subordinate clauses (other than relatives)*	THSC	*Did you know that the ca*
Discourse organisation	Subordinator that omission	THATD	*I mean [THATD] you'll*
Discourse organisation	WH subordinate clauses	WHSC	*I'm thinking of someone*
Lexis	Total nouns (including proper nouns)	NN	*a cut, my coat, the findin*
Lexis	Noun compounds	NCOMP	*Surely this stone must be*
Lexis	Emoji and emoticons	EMO	:-) :DD XD <3 :/
Lexis	Hashtags	HST	*#phdlife #Buy1Get1Free*
Lexis	URL and e-mail addresses	URL	*www.faz.net https://twitt*
Negation	Negation	XXO	*Why don't you believe me*
Prepositions	Prepositions	IN	*The Great Wall of China*
Pronouns	Reference to the speaker/writer	FPP1S	*I don't know. It isn't my*
Pronouns	Reference to the speaker/writer and other(s)	FPP1P	*We were told to deal with*
Pronouns	Reference to the addressee	SPP2	*If your model was good e*
Pronouns	it pronoun reference	PIT	*It fell and broke. I imple*
Pronouns	One as a personal pronoun	PRP	*One would hardly suppos*
Pronouns	Reference to one non-interactant	TPP3S	*He is beginning to form h*
Pronouns	Reference to more than one non-interactant	TPP3P	*The text allows readers t*
Pronouns	Quantifying pronouns	QUPR	*said Alice aloud, addressi*
Stance-taking devices	Politeness markers	POLITE	*Can you open the windo*
Stance-taking devices	Amplifiers	AMP	*I am very tired. They we*

D Evaluation of the Multi-Feature Tagger of English (MFTE)

For more information on the tagger itself, as well as the evaluation data and methods, see Le Foll (2021b) and https://github.com/elenlefoll/MultiFeatureTaggerEnglish.

> Using the MFTE
>
> The Multi-Feature Tagger of English (MFTE) Perl is free to use and was released under an Open Source licence. If you are interested in using the MFTE for your own project, I recommend using the latest version of the MFTE Python, which is much easier to use, can tag many more features, and also underwent a thorough evaluation. Note also that all future developments of the tool will be made on the MFTE Python. To find out more, see Le Foll & Shakir (2023) and https://github.com/mshakirDr/MFTE.

D.1 Packages required

The following packages must be installed and loaded to process the evaluation data.

```
#renv::restore() # Restore the project's dependencies from the lockfile to
 ↪  ensure that same package versions are used as in the original thesis.

library(caret) # For computing confusion matrices
library(harrypotter) # Only for colour scheme
library(here) # For path management
library(knitr) # Loaded to display the tables using the kable() function
library(paletteer) # For nice colours
library(readxl) # For the direct import of Excel files
library(tidyverse) # For everything else!
```

D.2 Data import from evaluation files

The data is imported directly from the Excel files in which the manual tag check and corrections was performed. A number of data wrangling steps need to be made for the data to be converted to a tidy format.

```
# Function to import and wrangle the evaluation data from the Excel files in
 ↪  which the manual evaluation was conducted
importEval3 <- function(file, fileID, register, corpus) {
  Tag1 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag1, Tag1Gold) |>
  rename(Tag = Tag1, TagGold = Tag1Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

  Tag2 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag2, Tag2Gold) |>
  rename(Tag = Tag2, TagGold = Tag2Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

Tag3 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag3, Tag3Gold) |>
  rename(Tag = Tag3, TagGold = Tag3Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

output <- rbind(Tag1, Tag2, Tag3) |>
  mutate(across(where(is.factor), str_remove_all, pattern = fixed(" "))) |> #
   ↪  Removes all white spaces which are found in the excel files
```

```
  filter(!is.na(Output)) |>
  mutate_if(is.character, as.factor)
}

# Second function to import and wrangle the evaluation data for Excel files
 ↪  with four tag columns as opposed to three
importEval4 <- function(file, fileID, register, corpus) {
  Tag1 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag1, Tag1Gold) |>
  rename(Tag = Tag1, TagGold = Tag1Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

  Tag2 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag2, Tag2Gold) |>
  rename(Tag = Tag2, TagGold = Tag2Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

Tag3 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag3, Tag3Gold) |>
  rename(Tag = Tag3, TagGold = Tag3Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

Tag4 <- file |>
  add_column(FileID = fileID, Register = register, Corpus = corpus) |>
  select(FileID, Corpus, Register, Output, Tokens, Tag4, Tag4Gold) |>
  rename(Tag = Tag4, TagGold = Tag4Gold, Token = Tokens) |>
  mutate(Evaluation = ifelse(is.na(TagGold), TRUE, FALSE)) |>
```

```
  mutate(TagGold = ifelse(is.na(TagGold), as.character(Tag),
   ↪  as.character(TagGold))) |>
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

output <- rbind(Tag1, Tag2, Tag3, Tag4) |>
  mutate(across(where(is.factor), str_remove_all, pattern = fixed(" "))) |> #
   ↪  Removes all white spaces which are found in the excel files
  filter(!is.na(Tag)) |>
  mutate_if(is.character, as.factor)

}

# Function to decide which of the two above functions should be used
importEval <- function(file, fileID, register, corpus) {
  if(sum(!is.na(file$Tag4)) > 0) {
    output = importEval4(file = file, fileID = fileID, register = register,
 ↪  corpus = corpus)
  }
  else{
    output = importEval3(file = file, fileID = fileID, register = register,
 ↪  corpus = corpus)
  }
}

Solutions_Intermediate_Spoken_0032 <- importEval(file =
 ↪  read_excel(here("data", "MFTE", "evaluation",
 ↪  "Solutions_Intermediate_Spoken_0032_Evaluation.xlsx")), fileID =
 ↪  "Solutions_Intermediate_Spoken_0032", register = "Conversation", corpus =
 ↪  "TEC-Sp")

HT_5_Poetry_0001 <- importEval(file = read_excel(here("data", "MFTE",
 ↪  "evaluation", "HT_5_Poetry_0001_Evaluation.xlsx")), fileID =
 ↪  "HT_5_Poetry_0001", register = "Poetry", corpus = "TEC-Fr")

Achievers_A1_Informative_0006 <- importEval(file = read_excel(here("data",
 ↪  "MFTE", "evaluation", "Achievers_A1_Informative_0006_Evaluation.xlsx")),
 ↪  fileID = "Achievers_A1_Informative_0006", register = "Informative",
 ↪  corpus = "TEC-Sp")

New_GreenLine_5_Personal_0003 <- importEval(file = read_excel(here("data",
 ↪  "MFTE", "evaluation", "New_GreenLine_5_Personal_0003_Evaluation.xlsx")),
 ↪  fileID = "New_GreenLine_5_Personal_0003", register = "Personal
 ↪  communication", corpus = "TEC-Ger")
```

```
Piece_of_cake_3e_Instructional_0006 <- importEval(file =
 ↪  read_excel(here("data", "MFTE", "evaluation",
 ↪  "Piece_of_cake_3e_Instructional_0006_Evaluation.xlsx")), fileID =
 ↪  "Piece_of_cake_3e_Instructional_0006", register = "Instructional", corpus
 ↪  = "TEC-Fr")

Access_4_Narrative_0006 <- importEval(file = read_excel(here("data", "MFTE",
 ↪  "evaluation", "Access_4_Narrative_0006_Evaluation.xlsx")), fileID =
 ↪  "Access_4_Narrative_0006", register = "Fiction", corpus = "TEC-Ger")

BNCBFict_b2 <- importEval(file = read_excel(here("data", "MFTE",
 ↪  "evaluation", "BNCBFict_b2.xlsx")), fileID = "BNCBFict_b2", register =
 ↪  "fiction", corpus = "BNC2014")

BNCBFict_m54 <- importEval(file = read_excel(here("data", "MFTE",
 ↪  "evaluation", "BNCBFict_m54.xlsx")), fileID = "BNCBFict_m54", register =
 ↪  "fiction", corpus = "BNC2014")

BNCBFict_e27 <- importEval(file = read_excel(here("data", "MFTE",
 ↪  "evaluation", "BNCBFict_e27.xlsx")), fileID = "BNCBFict_e27", register =
 ↪  "fiction", corpus = "BNC2014")

BNCBMass16 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBMass16.xlsx")), fileID = "BNCBMass16", register = "news", corpus =
 ↪  "BNC2014")

BNCBMass23 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBMass23.xlsx")), fileID = "BNCBMass23", register = "news", corpus =
 ↪  "BNC2014")

BNCBReg111 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBReg111.xlsx")), fileID = "BNCBReg111", register = "news", corpus =
 ↪  "BNC2014")

BNCBReg750 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBReg750.xlsx")), fileID = "BNCBReg750", register = "news", corpus =
 ↪  "BNC2014")

BNCBSer486 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBSer486.xlsx")), fileID = "BNCBSer486", register = "news", corpus =
 ↪  "BNC2014")
```

```
BNCBSer562 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBSer562.xlsx")), fileID = "BNCBSer562", register = "news", corpus =
 ↪  "BNC2014")

BNCBEB18 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBEB18.xlsx")), fileID = "BNCBEB18", register = "internet", corpus =
 ↪  "BNC2014")

BNCBEFor32 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "BNCBEFor32.xlsx")), fileID = "BNCBEFor32", register = "internet", corpus
 ↪  = "BNC2014")

S2DD <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "S2DD.xlsx")), fileID = "S2DD", register = "spoken", corpus = "BNC2014")

S3AV <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "S3AV.xlsx")), fileID = "S3AV", register = "spoken", corpus = "BNC2014")

SEL5 <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "SEL5.xlsx")), fileID = "SEL5", register = "spoken", corpus = "BNC2014")

SVLK <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "SVLK.xlsx")), fileID = "SVLK", register = "spoken", corpus = "BNC2014")

SZXQ <- importEval(file = read_excel(here("data", "MFTE", "evaluation",
 ↪  "SZXQ.xlsx")), fileID = "SZXQ", register = "spoken", corpus = "BNC2014")

TaggerEval <- rbind(Solutions_Intermediate_Spoken_0032, HT_5_Poetry_0001,
 ↪  Achievers_A1_Informative_0006, New_GreenLine_5_Personal_0003,
 ↪  Piece_of_cake_3e_Instructional_0006, Access_4_Narrative_0006, BNCBEB18,
 ↪  BNCBFict_b2, BNCBFict_m54, BNCBFict_e27, BNCBEFor32, BNCBMass16,
 ↪  BNCBMass23, BNCBReg111, BNCBReg750, BNCBSer486, BNCBSer562, S2DD, S3AV,
 ↪  SEL5, SVLK, SZXQ)
```

Some tags had to be merged to account for changes made to the MFTE between the evaluation and the tagging of the corpora included in the present study.

```
TaggerEval <- TaggerEval |>
  mutate(Tag = ifelse(Tag == "PHC", "CC", as.character(Tag))) |>
  mutate(TagGold = ifelse(TagGold == "PHC", "CC", as.character(TagGold))) |>
```

```
  mutate(Tag = ifelse(Tag == "QLIKE", "LIKE", as.character(Tag))) |>
  mutate(TagGold = ifelse(TagGold == "QLIKE", "LIKE", as.character(TagGold)))
   ↪  |>
  mutate(Tag = ifelse(Tag == "TO", "IN", as.character(Tag))) |>
  mutate(TagGold = ifelse(TagGold == "TO", "IN", as.character(TagGold))) |>
  mutate_if(is.character, as.factor) |>
  mutate(Evaluation = ifelse(as.character(Tag) == as.character(TagGold),
   ↪  TRUE, FALSE))

# head(TaggerEval) # Check sanity of data
# summary(TaggerEval) # Check sanity of data

# saveRDS(TaggerEval, here("data", "processed",
 ↪  "MFTE_Evaluation_Results.rds"))

# write.csv(TaggerEval, here("data", "processed",
 ↪  "MFTE_Evaluation_Results.csv"))
```

This table provides a summary of the complete evaluation dataset. It comprises 25,233 tags that were checked (and, if needs be, corrected) by at least one human annotator. This number includes tags for punctuation marks, which make up a considerable proportion of the tags.

```
          FileID          Corpus               Register        Output
 BNCBFict_b2 : 2621   TEC-Sp : 1042   fiction      :6500   ._.     : 1156
 BNCBFict_e27: 2104   TEC-Fr : 2058   news         :6312   the_DT :  820
 BNCBFict_m54: 1775   TEC-Ger: 1415   spoken       :6047   ,_,     :  720
 BNCBMass16  : 1619   BNC2014:20718   internet     :1859   a_DT    :  466
 SEL5        : 1463                   Instructional:1048   of_IN   :  328
 BNCBEFor32  : 1305                   Poetry       :1010   (Other):21742
 (Other)     :14346                   (Other)      :2457   NA's    :    1
     Token            Tag           TagGold      Evaluation
 .       : 1156   NN     : 4415   NN     : 4328   Mode :logical
 the     :  820   IN     : 2145   IN     : 2113   FALSE:832
 ,       :  720   DT     : 1454   DT     : 1457   TRUE :24401
 to      :  495   .      : 1367   .      : 1367
 's      :  493   VPRT   : 1044   VPRT   : 1054
 (Other):21547   VBD    :  899   VBD    :  895
 NA's    :    2   (Other):13909   (Other):14019
```

D.3 Estimating MFTE accuracy for Textbook English

In total, 4,515 tags from the TEC were manually checked. This chunk calculates the recall and precision rates of each feature, ignoring all punctuation and symbols.

```
data <- TaggerEval |>
  filter(Corpus %in% c("TEC-Fr", "TEC-Ger", "TEC-Sp")) |>
  filter(TagGold != "UNCLEAR") |>
  filter(Tag %in% c(str_extract(Tag, "[A-Z0-9]+"))) |> # Remove punctuation
   ↪  tags which are uninteresting here.
  filter(Tag != "SYM" & Tag != "``") |>
  droplevels() |>
  mutate(Tag = factor(Tag, levels = union(levels(Tag), levels(TagGold)))) |>
   ↪  # Ensure that the factor levels are the same for the next caret
   ↪  operation
  mutate(TagGold = factor(TagGold, levels = union(levels(Tag),
   ↪  levels(TagGold))))

# Spot gold tag corrections that are not actually errors (should return zero
 ↪  rows if all is well)
# data[data$Tag==data$TagGold & data$Evaluation == FALSE,] |> as.data.frame()
```

The breakdown of inaccurate vs. accurate tags in this TEC evaluation sample is:

```
   Mode   FALSE    TRUE
logical     114    3831
```

Note that the following accuracy metrics calculated using the `caret::confusionMatrix` are not very representative because they include tags, which were not entered in the study, e.g., LS and FW.

```
      Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
          0.97           0.97           0.97           0.98           0.20
AccuracyPValue  McnemarPValue
          0.00            NaN
```

Accuracy metrics per feature are more interesting and relevant.

	Precision	Recall	F1
Class: ABLE	1.00	1.00	1.00
Class: ACT	0.97	0.98	0.98
Class: AMP	1.00	1.00	1.00
Class: ASPECT	1.00	1.00	1.00
Class: BEMA	1.00	1.00	1.00
Class: CAUSE	1.00	1.00	1.00
Class: CC	1.00	0.99	1.00
Class: CD	0.95	0.95	0.95
Class: COMM	1.00	0.98	0.99
Class: COND	1.00	1.00	1.00
Class: CONT	1.00	1.00	1.00
Class: CUZ	1.00	1.00	1.00
Class: DEMO	0.97	0.97	0.97
Class: DMA	1.00	1.00	1.00
Class: DOAUX	0.86	1.00	0.92
Class: DT	1.00	1.00	1.00
Class: DWNT	0.67	1.00	0.80
Class: ELAB	1.00	1.00	1.00
Class: EMPH	0.83	1.00	0.91
Class: EX	1.00	1.00	1.00
Class: EXIST	1.00	1.00	1.00
Class: FPP1P	1.00	1.00	1.00
Class: FPP1S	1.00	1.00	1.00
Class: FPUH	1.00	1.00	1.00
Class: FREQ	1.00	1.00	1.00
Class: FW	0.10	1.00	0.18
Class: GTO	1.00	1.00	1.00
Class: HDG	1.00	1.00	1.00
Class: HGOT	1.00	1.00	1.00
Class: IN	1.00	1.00	1.00
Class: JJ	0.96	0.98	0.97
Class: JPRED	0.97	0.90	0.94
Class: LIKE	0.83	1.00	0.91
Class: MDCA	1.00	1.00	1.00
Class: MDCO	1.00	1.00	1.00
Class: MDMM	1.00	0.67	0.80
Class: MDNE	1.00	0.80	0.89
Class: MDWO	1.00	1.00	1.00
Class: MDWS	1.00	1.00	1.00
Class: MENTAL	0.99	0.99	0.99
Class: NCOMP	0.88	1.00	0.94

	Precision	Recall	F1
Class: NN	0.95	0.99	0.97
Class: NULL	1.00	0.08	0.14
Class: OCCUR	0.94	1.00	0.97
Class: PASS	0.89	0.89	0.89
Class: PEAS	1.00	0.87	0.93
Class: PGET	1.00	1.00	1.00
Class: PIT	1.00	1.00	1.00
Class: PLACE	1.00	0.83	0.91
Class: POLITE	1.00	1.00	1.00
Class: POS	1.00	1.00	1.00
Class: PROG	1.00	0.89	0.94
Class: QUAN	0.96	0.98	0.97
Class: QUPR	1.00	1.00	1.00
Class: RB	1.00	0.99	0.99
Class: RP	1.00	1.00	1.00
Class: SO	1.00	0.64	0.78
Class: SPLIT	1.00	1.00	1.00
Class: SPP2	1.00	1.00	1.00
Class: STPR	0.60	1.00	0.75
Class: THATD	0.86	1.00	0.92
Class: THRC	1.00	0.71	0.83
Class: THSC	0.69	1.00	0.82
Class: TIME	1.00	0.97	0.98
Class: TPP3P	1.00	1.00	1.00
Class: TPP3S	1.00	1.00	1.00
Class: VB	0.94	0.94	0.94
Class: VBD	0.97	0.99	0.98
Class: VBG	0.96	1.00	0.98
Class: VBN	0.85	0.92	0.88
Class: VIMP	0.99	0.88	0.93
Class: VPRT	0.98	0.98	0.98
Class: WHQU	0.97	1.00	0.98
Class: WHSC	1.00	0.97	0.99
Class: XX0	1.00	1.00	1.00
Class: YNQU	1.00	1.00	1.00
Class: OCR	NA	0.00	NA

D.4 MFTE accuracy for reference corpora (or comparable corpora)

D.4.1 Conversation

These are extracts from the Spoken BNC2014 (as entered in the study). The evaluation data for this sample excludes 7 tokens deemed *unclear* by at least one human annotator.

```
data <- TaggerEval |>
  filter(Register == "spoken") |>
  filter(TagGold != "UNCLEAR") |>
  filter(Tag %in% c(str_extract(Tag, "[A-Z0-9]+"))) |> # Remove all
   ↪ punctuation tags which are uninteresting here.
  droplevels() |>
  mutate(Tag = factor(Tag, levels = union(levels(Tag), levels(TagGold)))) |>
   ↪ # Ensure that the factor levels are the same for the next caret
   ↪ operation
  mutate(TagGold = factor(TagGold, levels = union(levels(Tag),
   ↪ levels(TagGold))))

# Spot gold tag corrections that are not actually errors (should return zero
 ↪ rows if all is well)
# data[data$Tag==data$TagGold & data$Evaluation == FALSE,] |> as.data.frame()
```

The breakdown of inaccurate vs. accurate tags in this evaluation sample is:

```
   Mode   FALSE    TRUE
logical     224    5388
```

Note that the following accuracy metrics calculated using the `caret::confusionMatrix` are not very representative because they include tags, which were not entered in the study, e.g., LS and FW.

```
      Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
          0.96           0.96           0.95           0.97           0.12
AccuracyPValue  McnemarPValue
          0.00            NaN
```

D.4.2 Fiction

The evaluation data for this sample excludes 0 tokens deemed *unclear* by at least one human annotator.

```
data <- TaggerEval |>
  filter(Register == "fiction") |>
  filter(TagGold != "UNCLEAR") |>
  filter(Tag %in% c(str_extract(Tag, "[A-ZÖ-9]+"))) |> # Remove all
   ↪ punctuation tags which are uninteresting here.
  filter(Tag != "SYM" & Tag != "``") |>
  droplevels() |>
  mutate(Tag = factor(Tag, levels = union(levels(Tag), levels(TagGold)))) |>
   ↪ # Ensure that the factor levels are the same for the next caret
   ↪ operation
  mutate(TagGold = factor(TagGold, levels = union(levels(Tag),
   ↪ levels(TagGold))))

# Spot gold tag corrections that are not actually errors (should return zero
 ↪ rows if all is well)
# data[data$Tag==data$TagGold & data$Evaluation == FALSE,] |> as.data.frame()
```

The breakdown of inaccurate vs. accurate tags in this evaluation sample is:

```
   Mode   FALSE    TRUE
logical     168    5346
```

Note that the following accuracy metrics calculated using the `caret::confusionMatrix` are not very representative because they include tags, which were not entered in the study, e.g., LS and FW.

```
      Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
          0.97           0.97           0.96           0.97           0.19
AccuracyPValue  McnemarPValue
          0.00            NaN
```

D.4.3 Informative

The evaluation data for this sample excludes 8 tokens deemed *unclear* by at least one human annotator.

```
data <- TaggerEval |>
  filter(Register == "news" | FileID %in% c("BNCBEFor32", "BNCBEBl8")) |>
  filter(TagGold != "UNCLEAR") |>
  filter(Tag %in% c(str_extract(Tag, "[A-Z0-9]+"))) |> # Remove all
   ↪  punctuation tags which are uninteresting here.
  filter(Tag != "SYM" & Tag != "``") |>
  droplevels() |>
  mutate(Tag = factor(Tag, levels = union(levels(Tag), levels(TagGold)))) |>
   ↪  # Ensure that the factor levels are the same for the next caret
   ↪  operation
  mutate(TagGold = factor(TagGold, levels = union(levels(Tag),
   ↪  levels(TagGold))))

# Spot gold tag corrections that are not actually errors (should return zero
 ↪  rows if all is well)
# data[data$Tag==data$TagGold & data$Evaluation == FALSE,] |> as.data.frame()
```

The breakdown of inaccurate vs. accurate tags in this evaluation sample is:

```
   Mode   FALSE    TRUE
logical     309    7113
```

Note that the following accuracy metrics calculated using the `caret::confusionMatrix` are not very representative because they include tags, which were not entered in the study, e.g., LS and FW.

```
      Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
          0.96           0.95           0.95           0.96           0.24
AccuracyPValue  McnemarPValue
          0.00            NaN
```

D.5 Estimating the overall MFTE accuracy for corpora used in the study

```
data <- TaggerEval |>
  filter(TagGold != "UNCLEAR") |>
  filter(Tag %in% c(str_extract(Tag, "[A-Z0-9]+"))) |> # Remove all
   ↪  punctuation tags which are uninteresting here.
```

```
  filter(Tag != "SYM" & Tag != "``") |>
  filter(TagGold != "SYM" & TagGold != "``") |>
  droplevels() |>
  mutate(Tag = factor(Tag, levels = union(levels(Tag), levels(TagGold)))) |>
   ↪  # Ensure that the factor levels are the same for the next caret
   ↪  operation
  mutate(TagGold = factor(TagGold, levels = union(levels(Tag),
   ↪  levels(TagGold))))

# Generate a better formatted results table for export: recall, precision and
 ↪  f1
confusion_matrix <- cm$table
total <- sum(confusion_matrix)
number_of_classes <- nrow(confusion_matrix)
correct <- diag(confusion_matrix)
# sum all columns
total_actual_class <- apply(confusion_matrix, 2, sum)
# sum all rows
total_pred_class <- apply(confusion_matrix, 1, sum)
# Precision = TP / all that were predicted as positive
precision <- correct / total_pred_class
# Recall = TP / all that were actually positive
recall <- correct / total_actual_class
# F1
f1 <- (2 * precision * recall) / (precision + recall)
# create data frame to output results
results <- data.frame(precision, recall, f1, total_actual_class)

results |>
  kable(digits = 2)
```

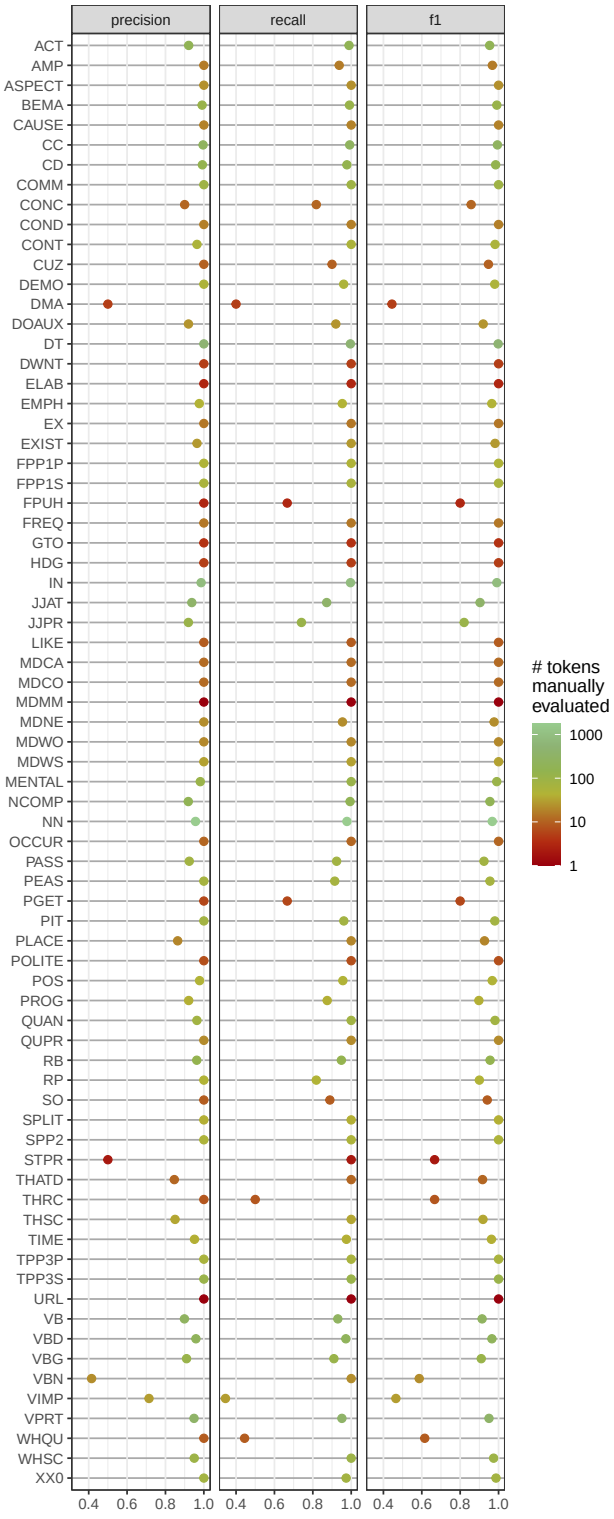
	precision	recall	f1	total_actual_class
ACT	0.92	0.99	0.95	177
AMP	1.00	0.94	0.97	16
ASPECT	1.00	1.00	1.00	23
BEMA	0.99	0.99	0.99	111
CAUSE	1.00	1.00	1.00	18
CC	1.00	0.99	0.99	254
CD	0.99	0.98	0.98	134
COMM	1.00	1.00	1.00	88
CONC	0.90	0.82	0.86	11

	precision	recall	f1	total_actual_class
COND	1.00	1.00	1.00	17
CONT	0.96	1.00	0.98	54
CUZ	1.00	0.90	0.95	10
DEMO	1.00	0.96	0.98	51
DMA	0.50	0.40	0.44	5
DOAUX	0.92	0.92	0.92	25
DT	1.00	1.00	1.00	490
DWNT	1.00	1.00	1.00	5
ELAB	1.00	1.00	1.00	3
EMPH	0.98	0.95	0.96	43
EX	1.00	1.00	1.00	15
EXIST	0.96	1.00	0.98	27
FPP1P	1.00	1.00	1.00	49
FPP1S	1.00	1.00	1.00	59
FPUH	1.00	0.67	0.80	3
FREQ	1.00	1.00	1.00	15
FW	0.29	0.40	0.33	5
GTO	1.00	1.00	1.00	4
HDG	1.00	1.00	1.00	5
IN	0.99	1.00	0.99	836
JJAT	0.94	0.87	0.90	360
JJPR	0.92	0.74	0.82	108
LIKE	1.00	1.00	1.00	9
MDCA	1.00	1.00	1.00	12
MDCO	1.00	1.00	1.00	12
MDMM	1.00	1.00	1.00	1
MDNE	1.00	0.95	0.98	22
MDWO	1.00	1.00	1.00	20
MDWS	1.00	1.00	1.00	31
MENTAL	0.98	1.00	0.99	106
NCOMP	0.92	0.99	0.96	171
NN	0.96	0.98	0.97	1805
OCCUR	1.00	1.00	1.00	11
PASS	0.92	0.92	0.92	79
PEAS	1.00	0.91	0.96	70
PGET	1.00	0.67	0.80	6
PIT	1.00	0.96	0.98	78
PLACE	0.86	1.00	0.93	19
POLITE	1.00	1.00	1.00	7
POS	0.98	0.96	0.97	46
PROG	0.92	0.88	0.90	40

	precision	recall	f1	total_actual_class
PRP	0.00	0.00	NaN	1
QUAN	0.96	1.00	0.98	80
QUPR	1.00	1.00	1.00	21
RB	0.96	0.95	0.96	137
RP	1.00	0.82	0.90	44
SO	1.00	0.89	0.94	9
SPLIT	1.00	1.00	1.00	40
SPP2	1.00	1.00	1.00	53
STPR	0.50	1.00	0.67	2
THATD	0.85	1.00	0.92	11
THRC	1.00	0.50	0.67	8
THSC	0.85	1.00	0.92	34
TIME	0.95	0.98	0.96	40
TPP3P	1.00	1.00	1.00	61
TPP3S	1.00	1.00	1.00	108
URL	1.00	1.00	1.00	1
USEDTO	0.00	NaN	NaN	0
VB	0.90	0.93	0.91	258
VBD	0.96	0.97	0.97	215
VBG	0.91	0.91	0.91	111
VBN	0.42	1.00	0.59	22
VIMP	0.71	0.34	0.47	29
VPRT	0.95	0.95	0.95	351
WHQU	1.00	0.44	0.62	9
WHSC	0.95	1.00	0.97	95
XX0	1.00	0.97	0.99	76
YNQU	0.00	NaN	NaN	0
“	NaN	0.00	NaN	1
NULL	NaN	0.00	NaN	38
SYM	NaN	0.00	NaN	1

```
resultslong <- results |>
  drop_na() %>%
  mutate(tag = row.names(.)) |>
  filter(tag != "NULL" & tag != "SYM" & tag != "OCR" & tag != "FW" & tag !=
   ↪  "USEDTO") |>
  rename(n = total_actual_class) |>
  pivot_longer(cols = c("precision", "recall", "f1"), names_to = "metric",
   ↪  values_to = "value") |>
  mutate(metric = factor(metric, levels = c("precision", "recall", "f1")))
```

```r
# summary(resultslong$n)

ggplot(resultslong, aes(y = reorder(tag, desc(tag)), x = value, group =
 ↪  metric, colour = n)) +
  geom_point(size = 2) +
  ylab("") +
  xlab("") +
  facet_wrap(~ metric) +
  scale_color_paletteer_c("harrypotter::harrypotter", trans = "log", breaks =
   ↪  c(1,10, 100, 1000), labels = c(1,10, 100, 1000), name = "# tokens
   ↪  \nmanually\nevaluated") +
  theme_bw() +
  theme(panel.grid.major.y = element_line(colour = "darkgrey")) +
  theme(legend.position = "right")
```


precision
recall
f1
ACT
AMP
ASPECT
BEMA
CAUSE
CC
CD
COMM
CONC
COND
CONT
CUZ
DEMO
DMA
DOAUX
DT
DWNT
ELAB
EMPH
EX
EXIST
FPP1P
FPP1S
FPUH
FREQ
GTO
HDG
IN
JJAT
JJPR
LIKE
MDCA
MDCO
MDMM
MDNE
MDWO
MDWS
MENTAL
NCOMP
NN
OCCUR
PASS
PEAS
PGET
PIT
PLACE
POLITE
POS
PROG
QUAN
QUPR
RB
RP
SO
SPLIT
SPP2
STPR
THATD
THRC
THSC
TIME
TPP3P
TPP3S
URL
VB
VBD
VBG
VBN
VIMP
VPRT
WHQU
WHSC
XX0
0.4
0.6
0.8
1.0
tokens manually evaluated
1000
100
10
1

```
#ggsave(here("plots", "TaggerAccuracyPlot.svg"), width = 7, height = 12)
```

D.6 Exploring tagger errors

To inspect regular/systematic tagger errors, we add an error tag with the incorrectly assigned tag and underscore and then the correct "gold" label.

```
errors <- TaggerEval |>
  filter(Evaluation=="FALSE") |>
  filter(TagGold != "UNCLEAR") |>
  mutate(Error = paste(Tag, TagGold, sep = " -> "))

FreqErrors <- errors |>
  #filter(Corpus %in% c("TEC-Fr", "TEC-Ger", "TEC-Sp")) |>
  count(Error) |>
  arrange(desc(n))

# Number of error types that only occur once
once <- FreqErrors |>
  filter(n == 1) |>
  nrow()
```

The total number of errors is 817. Of those, 94 occur just once. In total, there are 198 different types of errors. The most frequent 10 are:

```
FreqErrors |>
  filter(n > 10) |>
  kable(digits = 2)
```

Error	n
NCOMP -> NULL	37
NN -> JJAT	35
JJAT -> NN	27
NN -> VB	27
IN -> RP	25
NN -> VPRT	24
VB -> NN	22
THSC -> DEMO	19

Error	n
VB -> VIMP	19
NN -> OCR	16
VBN -> JJAT	16
ACT -> NULL	15
THATD -> NULL	15
CD -> NN	12
MENTAL -> NULL	12
NN -> VBG	11
NN -> VIMP	11
THSC -> THRC	11
VBG -> PROG	11
VBN -> JJPR	11

The code in the following chunk can be used to take a closer look at specific types of frequent errors.

```
errors |>
  filter(Error == "NN -> JJAT") |>
  select(-Output, -Corpus, -Tag, -TagGold) |>
  filter(grepl(x = Token, pattern = "[A-Z]+.")) |>
  kable(digits = 2)
```

FileID	Register	Token	Evaluation	Error
BNCBEFor32	internet	Intermediate	FALSE	NN -> JJAT
BNCBMass16	news	FINAL	FALSE	NN -> JJAT
BNCBMass16	news	Big	FALSE	NN -> JJAT
BNCBReg111	news	Scottish	FALSE	NN -> JJAT
BNCBReg111	news	Scottish	FALSE	NN -> JJAT
BNCBReg111	news	Mental	FALSE	NN -> JJAT
BNCBReg111	news	Scottish	FALSE	NN -> JJAT
BNCBReg111	news	Central	FALSE	NN -> JJAT
BNCBReg750	news	English	FALSE	NN -> JJAT
BNCBReg750	news	Natural	FALSE	NN -> JJAT
BNCBReg750	news	European	FALSE	NN -> JJAT
BNCBReg750	news	Christian	FALSE	NN -> JJAT
BNCBReg750	news	Social	FALSE	NN -> JJAT
BNCBReg750	news	Common	FALSE	NN -> JJAT
BNCBSer486	news	Northern	FALSE	NN -> JJAT

FileID	Register	Token	Evaluation	Error
BNCBSer486	news	Northern	FALSE	NN -> JJAT
BNCBSer486	news	Northern	FALSE	NN -> JJAT
BNCBSer562	news	United	FALSE	NN -> JJAT
BNCBSer562	news	White	FALSE	NN -> JJAT
BNCBSer562	news	Untold	FALSE	NN -> JJAT
BNCBSer562	news	New	FALSE	NN -> JJAT
SEL5	spoken	Black	FALSE	NN -> JJAT

```
errors |>
  filter(Error %in% c("NN -> VB", "VB -> NN", "NN -> VPRT", "VPRT -> NN")) |>
  count(Token) |>
  arrange(desc(n)) |>
  filter(n > 1) |>
  kable(digits = 2)
```

Token	n
mince	5
build	4
win	4
hunt	3
wags	3
throw	2
look	2
swamp	2
stop	2
defeats	2

```
errors |>
  filter(Error == "ACT -> NULL") |>
  count(Token) |>
  arrange(desc(n)) |>
  kable(digits = 2)
```

Token	n
win	3
throw	2

Token	n
lost	2
left	1
waiting	1
working	1
running	1
done	1
fixed	1
Play	1
reached	1

For more information on the MFTE evaluation, see (Le Foll 2021b) and https://github.com/elenlefoll/MultiFeatureTaggerEnglish.

E Data Preparation for the Model of Intra-Textbook Variation

This script documents the steps taken to pre-process the Textbook English Corpus (TEC) data that were entered in the multi-dimensional model of intra-textbook linguistic variation (Chapter 6).

E.1 Packages required

The following packages must be installed and loaded to process the data.

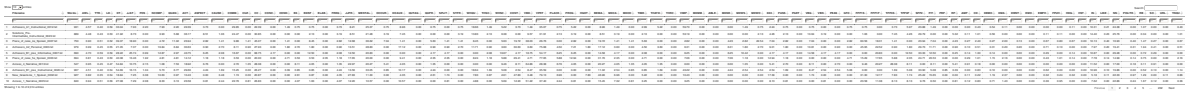
```
#renv::restore() # Restore the project's dependencies from the lockfile to
 ↪  ensure that same package versions are used as in the original study

library(caret) # For its confusion matrix function
library(DT) # To display interactive HTML tables
library(here) # For dynamic file paths
library(knitr) # Loaded to display the tables using the kable() function
library(patchwork) # Needed to put together Fig. 1
library(PerformanceAnalytics) # For the correlation plot
library(psych) # For various useful, stats function
library(tidyverse) # For data wrangling
```

E.2 Data import from MFTE output

The raw data used in this script is a tab-separated file that corresponds to the tabular output of mixed normalised frequencies as generated by the MFTE Perl v. 3.1 (Le Foll 2021b).

```
# Read in Textbook Corpus data
TxBcounts <- read.delim(here("data", "MFTE",
 ↪  "TxB900MDA_3.1_normed_complex_counts.tsv"), header = TRUE,
 ↪  stringsAsFactors = TRUE)
```

```
TxBcounts <- TxBcounts |>
  filter(Filename!=".DS_Store") |>
  droplevels()

#str(TxBcounts) # Check sanity of data
#nrow(TxBcounts) # Should be 2014 files

datatable(TxBcounts,
  filter = "top",
) |>
  formatRound(3:ncol(TxBcounts), digits=2)
```



Metadata was added on the basis of the filenames.

```
# Adding a textbook proficiency level
TxBLevels <- read.delim(here("data", "metadata",
 ↪  "TxB900MDA_ProficiencyLevels.csv"), sep = ",")
TxBcounts <- full_join(TxBcounts, TxBLevels, by = "Filename") |>
  mutate(Level = as.factor(Level)) |>
  mutate(Filename = as.factor(Filename))

# Check distribution and that there are no NAs
summary(TxBcounts$Level) |>
  kable(col.names = c("Textbook Level", "# of texts"))
```

Textbook Level	# of texts
A	292
B	407
C	506
D	478
E	331

```
# Check matching on random sample
# TxBcounts |>
#   select(Filename, Level) |>
#   sample_n(20)

# Adding a register variable from the file names
TxBcounts$Register <- as.factor(stringr::str_extract(TxBcounts$Filename,
 ↪  "Spoken|Narrative|Other|Personal|Informative|Instructional|Poetry")) #
 ↪  Add a variable for Textbook Register
summary(TxBcounts$Register) |>
  kable(col.names = c("Textbook Register", "# of texts"))
```

Textbook Register	# of texts
Informative	364
Instructional	647
Narrative	285
Personal	88
Poetry	37
Spoken	593

```
TxBcounts$Register <- car::recode(TxBcounts$Register, "'Narrative' =
 ↪  'Fiction'; 'Spoken' = 'Conversation'")
#colnames(TxBcounts) # Check all the variables make sense

# Adding a textbook series variable from the file names
TxBcounts$Filename <- stringr::str_replace(TxBcounts$Filename,
 ↪  "English_In_Mind|English_in_Mind", "EIM")
TxBcounts$Filename <- stringr::str_replace(TxBcounts$Filename,
 ↪  "New_GreenLine", "NGL") # Otherwise the regex for GreenLine will override
 ↪  New_GreenLine
TxBcounts$Filename <- stringr::str_replace(TxBcounts$Filename,
 ↪  "Piece_of_cake", "POC") # Shorten label for ease of plotting
TxBcounts$Series <- as.factor(stringr::str_extract(TxBcounts$Filename,
 ↪  "Access|Achievers|EIM|GreenLine|HT|NB|NM|POC|JTT|NGL|Solutions")) #
 ↪  Extract textbook series from (ammended) filenames
summary(TxBcounts$Series)  |>
  kable(col.names = c("Textbook Name", "# of texts"))
```

Textbook Name	# of texts
Access	315
Achievers	240
EIM	180
GreenLine	209
HT	115
JTT	129
NB	44
NGL	298
NM	59
POC	98
Solutions	327

```
# Including the French textbooks for the first year of Lycée to their
 ↪  corresponding publisher series from collège
TxBcounts$Series <-car::recode(TxBcounts$Series, "c('NB', 'JTT') = 'JTT';
 ↪  c('NM', 'HT') = 'HT'") # Recode final volumes of French series (see
 ↪  Section 4.3.1.1 on textbook selection for details)
summary(TxBcounts$Series) |>
  kable(col.names = c("Textbook Series", "# of texts"))
```

Textbook Series	# of texts
Access	315
Achievers	240
EIM	180
GreenLine	209
HT	174
JTT	173
NGL	298
POC	98
Solutions	327

```
# Adding a textbook country of use variable from the series variable
TxBcounts$Country <- TxBcounts$Series
TxBcounts$Country <- car::recode(TxBcounts$Series, "c('Access', 'GreenLine',
 ↪  'NGL') = 'Germany'; c('Achievers', 'EIM', 'Solutions') = 'Spain'; c('HT',
 ↪  'NB', 'NM', 'POC', 'JTT') = 'France'")
summary(TxBcounts$Country) |>
  kable(col.names = c("Country of Use", "# of texts"))
```

Country of Use	# of texts
France	445
Germany	822
Spain	747

```
# Re-order variables
#colnames(TxBcounts)
TxBcounts <- select(TxBcounts, order(names(TxBcounts))) %>%
  select(Filename, Country, Series, Level, Register, Words, everything())
#colnames(TxBcounts)
```

E.2.1 Corpus size

This table provides some summary statistics about the number of words included in the TEC texts originally tagged for this study.

```
TxBcounts  |>
  group_by(Register) |>
  summarise(totaltexts = n(), totalwords = sum(Words), mean =
   ↪  as.integer(mean(Words)), sd = as.integer(sd(Words)), TTRmean =
   ↪  mean(TTR)) |>
  kable(digits = 2, format.args = list(big.mark = ","))
```

Register	totaltexts	totalwords	mean	sd	TTRmean
Conversation	593	505,147	851	301	0.44
Fiction	285	241,512	847	208	0.47
Informative	364	304,695	837	177	0.51
Instructional	647	585,049	904	94	0.42
Personal	88	69,570	790	177	0.48
Poetry	37	26,445	714	192	0.44

```
#TxBcounts <- saveRDS(TxBcounts, here("data", "processed", "TxBcounts.rds"))
```

E.3 Data preparation for PCA

Poetry texts were removed for this analysis as there were too few compared to the other register categories.

```
summary(TxBcounts$Register) |>
  kable(col.names = c("Register", "# texts"))
```

Register	# texts
Conversation	593
Fiction	285
Informative	364
Instructional	647
Personal	88
Poetry	37

This led to the following distribution of texts across the five textbook English registers examined in the model of intra-textbook linguistic variation:

```
TxBcounts <- TxBcounts |>
  filter(Register!="Poetry") |>
  droplevels()

summary(TxBcounts$Register) |>
  kable(col.names = c("Register", "# texts"))
```

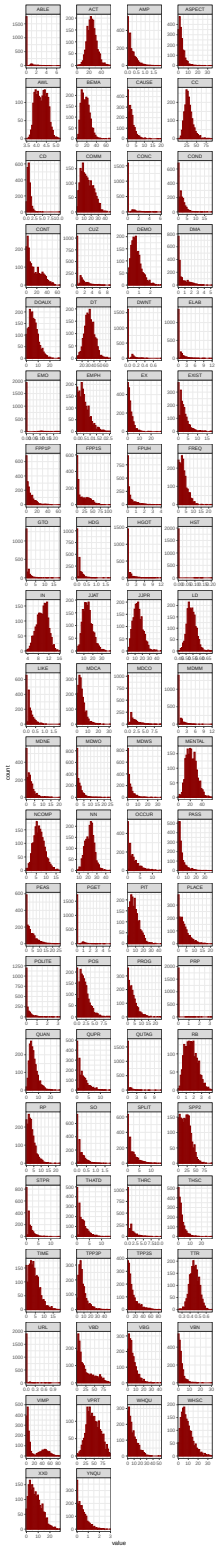
Register	# texts
Conversation	593
Fiction	285
Informative	364
Instructional	647
Personal	88

E.3.1 Feature distributions

The distributions of each linguistic features were examined by means of visualisation. As shown below, before transformation, many of the features displayed highly skewed distributions.

```
TxBcounts |>
  select(-Words) |>
  keep(is.numeric) |>
  tidyr::gather() |>  # This function from tidyr converts a selection of
 ↪  variables into two variables: a key and a value. The key contains the
 ↪  names of the original variable and the value the data. This means we can
 ↪  then use the facet_wrap function from ggplot2
```

```
ggplot(aes(value)) +
  theme_bw() +
  facet_wrap(~ key, scales = "free", ncol = 4) +
  scale_x_continuous(expand=c(0,0)) +
  geom_histogram(bins = 30, colour= "darkred", fill = "darkred", alpha =
   ↪  0.5)
```


ABLE
ACT
AMP
ASPECT
AWL
BEMA
CAUSE
CC
CE
COMM
CONC
COND
CONT
CUZ
DEMO
DWA
DOALK
DT
DWNT
ELAB
EMO
EMPH
EX
EXIST
FPPUP
FPPUS
FPUH
FREQ
GTO
HDO
HGOT
HST
IN
JJR
JJPR
LO
LIKE
MDCA
MDCO
MDMM
MDNE
MDWO
MDWS
MENTAL
NCOMP
NN
OCCUR
PASS
PEAS
PGET
PIT
PLACE
POLITE
POS
PROG
PRP
QUAN
QUPR
QUTAG
RB
RP
SO
SPLIT
SPP2
STPR
THATD
THEC
THSC
TIME
TPPJP
TPPJS
TTR
URL
VBD
VBG
VBN
VIMP
VPRT
WHQU
WHSC
XX0
YNQU
count
value

```
#ggsave(here("plots", "TEC-HistogramPlotsAllVariablesTEC-only.svg"), width =
 ↪  20, height = 45)
```

E.3.2 Feature removal

A number of features were removed from the dataset as they are not linguistically interpretable. In the case of the TEC, this included the variable CD because numbers spelt out as digits were removed from the textbooks before these were tagged with the MFTE. In addition, the variables LIKE and SO because these are "bin" features included in the output of the MFTE to ensure that the counts for these polysemous words do not inflate other categories due to mistags (Le Foll 2021c).

Whenever linguistically meaningful, very low-frequency features were merged. Finally, features absent from more than third of texts were also excluded. For the analysis intra-textbook register variation, the following linguistic features were excluded from the analysis due to low dispersion:

```
# Removal of meaningless features:
TxBcounts <- TxBcounts |>
  select(-c(CD, LIKE, SO))

# Function to compute percentage of texts with occurrences meeting a
 ↪  condition
compute_percentage <- function(data, condition, threshold) {
  numeric_data <- Filter(is.numeric, data)
  percentage <- round(colSums(condition[, sapply(numeric_data,
 ↪  is.numeric)])/nrow(data) * 100, 2)
  percentage <- as.data.frame(percentage)
  colnames(percentage) <- "Percentage"
  percentage <- percentage |>
    filter(!is.na(Percentage)) |>
    rownames_to_column() |>
    arrange(Percentage)
  if (!missing(threshold)) {
    percentage <- percentage |>
      filter(Percentage > threshold)
  }
  return(percentage)
}

# Calculate percentage of texts with 0 occurrences of each feature
```

```r
zero_features <- compute_percentage(TxBcounts, TxBcounts == 0, 66.6)
# zero_features |>
#   kable(col.names = c("Feature", "% texts with zero occurrences"))

# Combine low frequency features into meaningful groups whenever this makes
 ↪  linguistic sense
TxBcounts <- TxBcounts |>
  mutate(JJPR = ABLE + JJPR, ABLE = NULL) |>
  mutate(PASS = PGET + PASS, PGET = NULL)

# Re-calculate percentage of texts with 0 occurrences of each feature
zero_features2 <- compute_percentage(TxBcounts, TxBcounts == 0, 66.6)
zero_features2 |>
  kable(col.names = c("Feature", "% texts with zero occurrences"))
```

Feature	% texts with zero occurrences
GTO	67.07
ELAB	69.30
MDMM	70.81
HGOT	73.75
CONC	80.48
DWNT	81.44
QUTAG	85.99
URL	96.51
EMO	97.82
PRP	98.33
HST	99.44

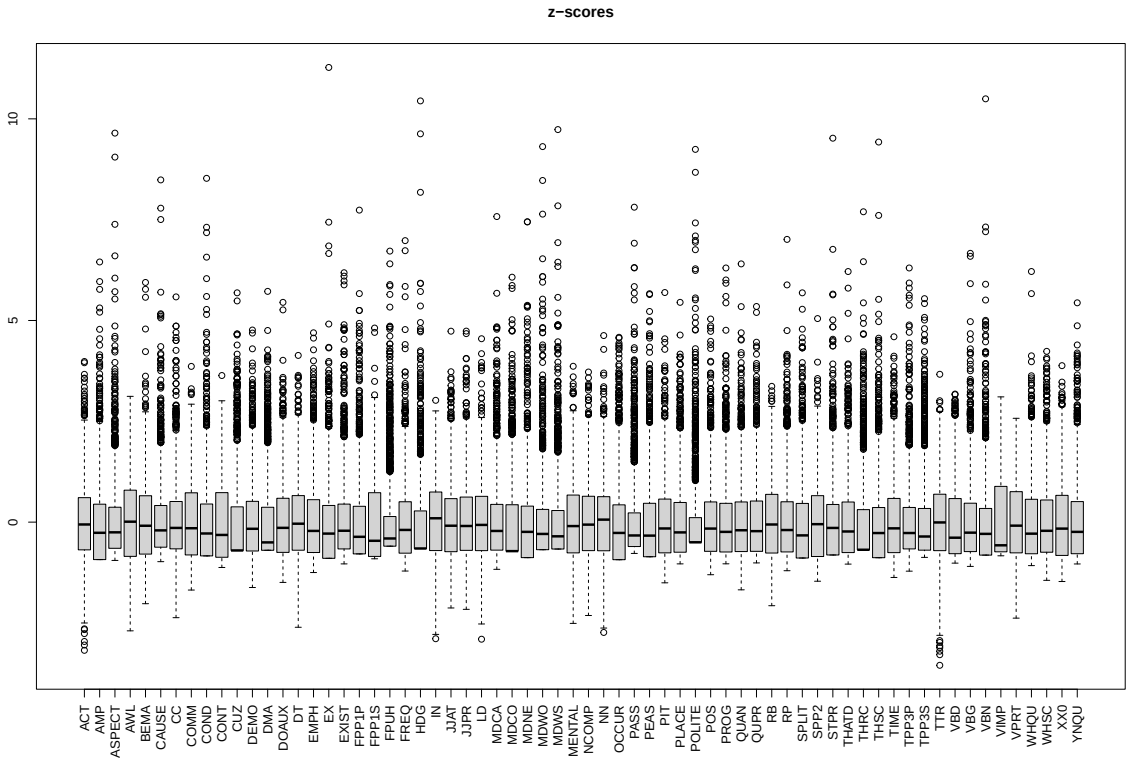
```r
# Drop variables with low document frequency
TxBcounts <- select(TxBcounts, -one_of(zero_features2$rowname))
#ncol(TxBcounts)-8 # Number of linguistic features remaining

# List of features
#colnames(TxBcounts)
```

These feature removal operations resulted in a feature set of 64 linguistic variables.

E.3.3 Identifying potential outlier texts

All normalised frequencies were normalised to identify any potential outlier texts.

```
TxBzcounts <- TxBcounts |>
  select(-Words) |>
  keep(is.numeric) |>
  scale()

boxplot(TxBzcounts, las = 3, main = "z-scores") # Slow to open!
```




```
# If necessary, remove any outliers at this stage.
TxBdata <- cbind(TxBcounts[,1:6], as.data.frame(TxBzcounts))

outliers <- TxBdata |>
  select(-c(Words, LD, TTR)) |>
  filter(if_any(where(is.numeric), ~ .x > 8)) |>
  select(Filename)
```

The following outlier texts were identified and excluded in subsequent analyses.

```
outliers
```

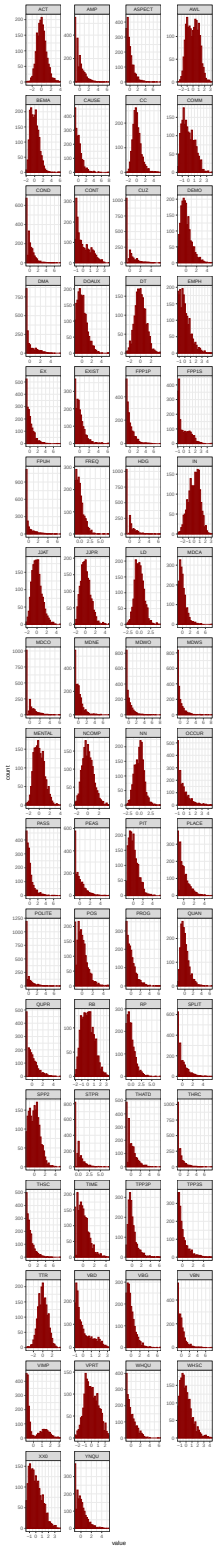
```
                                          Filename
1                            POC_4e_Spoken_0007.txt
2              Solutions_Elementary_Personal_0001.txt
3                        NGL_5_Instructional_0018.txt
4                            Access_1_Spoken_0011.txt
5                               EIM_1_Spoken_0012.txt
6                               NGL_4_Spoken_0011.txt
7       Solutions_Intermediate_Plus_Personal_0001.txt
8            Solutions_Elementary_ELF_Spoken_0021.txt
9                           NB_2_Informative_0009.txt
10        Solutions_Intermediate_Plus_Spoken_0022.txt
11      Solutions_Intermediate_Instructional_0025.txt
12 Solutions_Pre-Intermediate_Instructional_0024.txt
13                           POC_4e_Spoken_0010.txt
14             Solutions_Intermediate_Spoken_0019.txt
15                           Access_1_Spoken_0019.txt
16     Solutions_Pre-Intermediate_ELF_Spoken_0005.txt
```

```
TxBcounts <- TxBcounts |>
  filter(!Filename %in% outliers$Filename)

#saveRDS(TxBcounts, here("data", "processed", "TxBcounts3.rds")) # Last saved
 ↪  6 March 2024

TxBzcounts <- TxBcounts |>
  select(-Words) |>
  keep(is.numeric) |>
  scale()
```

This resulted in 1,961 TEC texts being included in the model of intra-textbook linguistic variation with the following standardised feature distributions.

```
TxBzcounts |>
  as.data.frame() |>
  gather() |>  # This function from tidyr converts a selection of variables
   ↪  into two variables: a key and a value. The key contains the names of
   ↪  the original variable and the value the data. This means we can then
   ↪  use the facet_wrap function from ggplot2
  ggplot(aes(value)) +
```

```
    theme_bw() +
    facet_wrap(~ key, scales = "free", ncol = 4) +
    scale_x_continuous(expand=c(0,0)) +
    geom_histogram(bins = 30, colour= "darkred", fill = "darkred", alpha =
     ↪  0.5)
```


ACT
AMP
ASPECT
AWL
BENIA
CAUSE
CC
COMM
COND
CONT
CUZ
DENO
DMA
DOAUX
DT
EMPH
EX
EXIST
FPFUP
FPFUS
FPUH
FREQ
HDG
IN
JAF
JJPR
LD
MDCA
MDCO
MDNE
MDNO
MDWS
MENTAL
NCOMP
NN
OCCUR
PASS
PEAS
PIT
PLACE
POLITE
POS
PROG
QUAN
QUPR
RB
RP
SPLIT
SPIV
STPR
THATD
THIC
THSC
TIME
TPFSP
TPP2S
TTR
VBD
VBG
VBN
VIMP
VPRT
WHQU
WHSC
XX0
YNQU
count
value

```
#ggsave(here("plots", "TEC-zscores-HistogramsAllVariablesTEC-only.svg"),
 ↪  width = 20, height = 45)
```

E.3.4 Signed log transformation

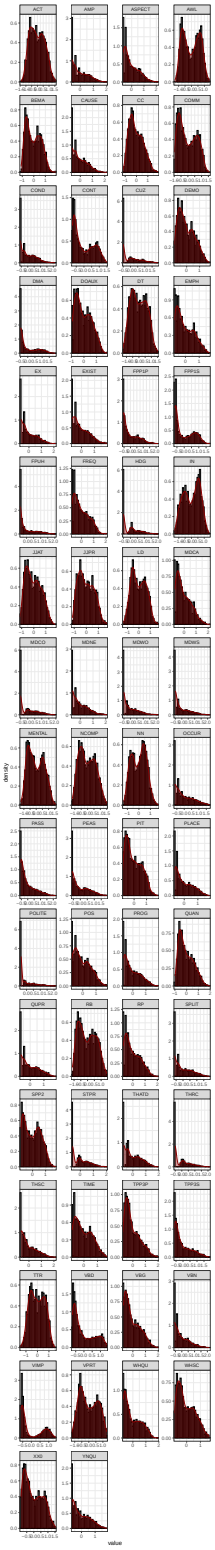
A signed logarithmic transformation was applied to (further) deskew the feature distributions (Diwersy, Evert & Neumann 2014; Neumann & Evert 2021).

The signed log transformation function was inspired by the SignedLog function proposed in https://cran.r-project.org/web/packages/DataVisualizations/DataVisualizations.pdf

```
# All features are signed log-transformed (note that this is also what
 ↪  Neumann & Evert 2021 propose)
signed.log <- function(x) {
  sign(x) * log(abs(x) + 1)
  }

TxBzlogcounts <- signed.log(TxBzcounts) # Standardise first, then signed log
 ↪  transform

#saveRDS(TxBzlogcounts, here("data", "processed", "TxBzlogcounts.rds")) #
 ↪  Last saved 6 March 2024
```

The new feature distributions are visualised below.

```
TxBzlogcounts |>
  as.data.frame() |>
  gather() |>  # This function from tidyr converts a selection of variables
   ↪  into two variables: a key and a value. The key contains the names of
   ↪  the original variable and the value the data. This means we can then
   ↪  use the facet_wrap function from ggplot2
  ggplot(aes(value, after_stat(density))) +
  theme_bw() +
  facet_wrap(~ key, scales = "free", ncol = 4) +
  scale_x_continuous(expand=c(0,0)) +
  scale_y_continuous(limits = c(0,NA)) +
  geom_histogram(bins = 30, colour= "black", fill = "grey") +
  geom_density(colour = "darkred", weight = 2, fill="darkred", alpha = .4)
```


ACT
AMP
ASPECT
AWL
BRAA
CAUSE
CC
COMM
COND
CONT
CUZ
DEMO
DMA
DOAUX
DT
EMPH
EX
EXIST
FPFSP
FPFSS
FPRJM
FREQ
HDG
IN
JJAT
JJPR
LID
MODA
MOCO
MONE
MONO
MOWS
NEATAL
NCOMP
NU
OCCUR
PASS
PEAS
PIT
PLACE
POLITE
POS
PROG
QUAN
QUPR
RB
RP
SPLIT
SPP2
STPR
THATD
THEC
THSC
TIME
TPFSP
TPFSS
TTR
VBD
VBG
VBN
VIMP
VINIT
WHQU
WHSC
XXD
YNQU
density
value

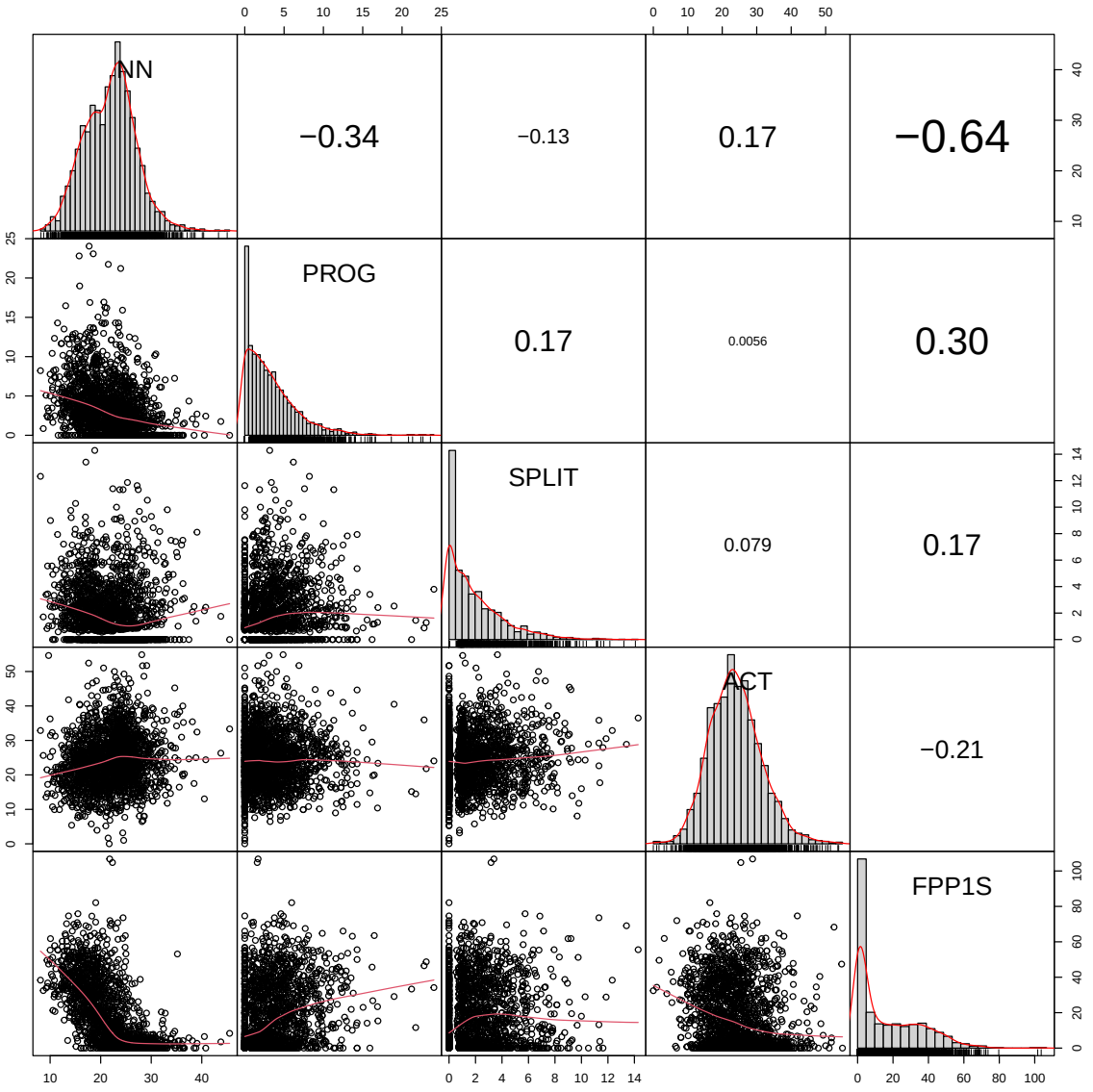
```
#ggsave(here("plots", "DensityPlotsAllVariablesSignedLog-TEC-only.svg"),
 ↪  width = 15, height = 49)
```

The following correlation plots serve to illustrate the effect of the variable transformations performed in the above chunks.

Example feature distributions before transformations:

```
# This is a slightly amended version of the
 ↪  PerformanceAnalytics::chart.Correlation() function. It simply removes the
 ↪  significance stars that are meaningless with this many data points (see
 ↪  commented out lines below)

chart.Correlation.nostars <- function (R, histogram = TRUE, method =
 ↪  c("pearson", "kendall", "spearman"), ...) {
  x = checkData(R, method = "matrix")
  if (missing(method))
    method = method[1]
  panel.cor <- function(x, y, digits = 2, prefix = "", use =
 ↪  "pairwise.complete.obs", method = "pearson", cex.cor, ...) {
    usr <- par("usr")
    on.exit(par(usr))
    par(usr = c(0, 1, 0, 1))
    r <- cor(x, y, use = use, method = method)
    txt <- format(c(r, 0.123456789), digits = digits)[1]
    txt <- paste(prefix, txt, sep = "")
    if (missing(cex.cor))
      cex <- 0.8/strwidth(txt)
    test <- cor.test(as.numeric(x), as.numeric(y), method = method)
    # Signif <- symnum(test$p.value, corr = FALSE, na = FALSE,
    #                  cutpoints = c(0, 0.001, 0.01, 0.05, 0.1, 1), symbols =
     ↪  c("***",
    #
     ↪  "**", "*", ".", " "))
    text(0.5, 0.5, txt, cex = cex * (abs(r) + 0.3)/1.3)
    # text(0.8, 0.8, Signif, cex = cex, col = 2)
  }
  f <- function(t) {
    dnorm(t, mean = mean(x), sd = sd.xts(x))
  }
  dotargs <- list(...)
  dotargs$method <- NULL
```

```
  rm(method)
  hist.panel = function(x, ... = NULL) {
    par(new = TRUE)
    hist(x, col = "light gray", probability = TRUE,
         axes = FALSE, main = "", breaks = "FD")
    lines(density(x, na.rm = TRUE), col = "red", lwd = 1)
    rug(x)
  }
  if (histogram)
    pairs(x, gap = 0, lower.panel = panel.smooth, upper.panel = panel.cor,
          diag.panel = hist.panel)
  else pairs(x, gap = 0, lower.panel = panel.smooth, upper.panel = panel.cor)
}

# Example plot without any variable transformation
example1 <- TxBcounts |>
  select(NN,PROG,SPLIT,ACT,FPP1S)

#png(here("plots", "CorrChart-TEC-examples-normedcounts.png"), width = 20,
 ↪  height = 20, units = "cm", res = 300)
chart.Correlation.nostars(example1, histogram=TRUE, pch=19)
```

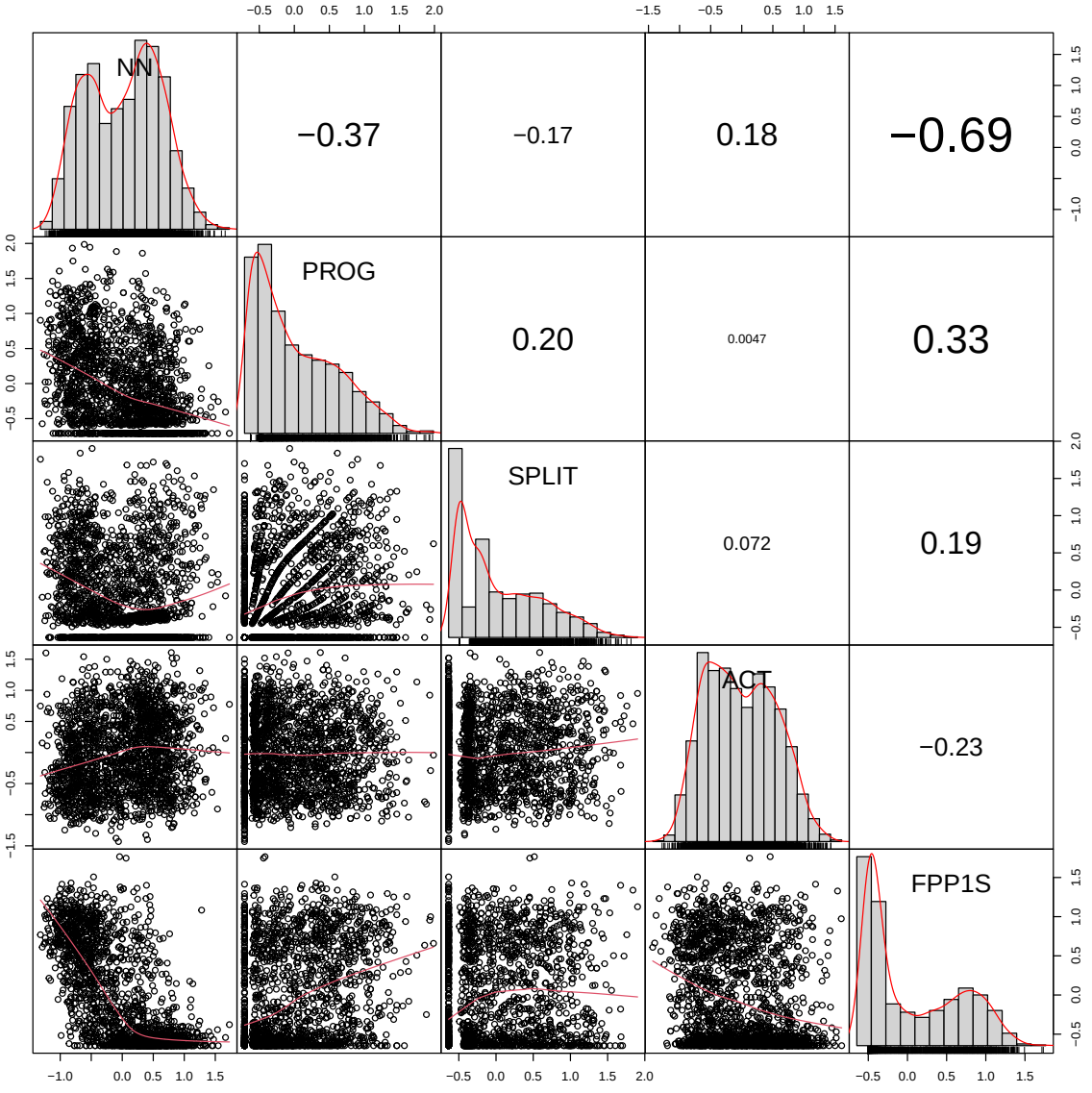



```
#dev.off()
```

Example feature distributions after transformations:

```
# Example plot with transformed variables
example2 <- TxBzlogcounts |>
  as.data.frame() |>
  select(NN,PROG,SPLIT,ACT,FPP1S)
```

```
#png(here("plots", "CorrChart-TEC-examples-zsignedlogcounts.png"), width =
 ↪  20, height = 20, units = "cm", res = 300)
chart.Correlation.nostars(example2, histogram=TRUE, pch=19)
```

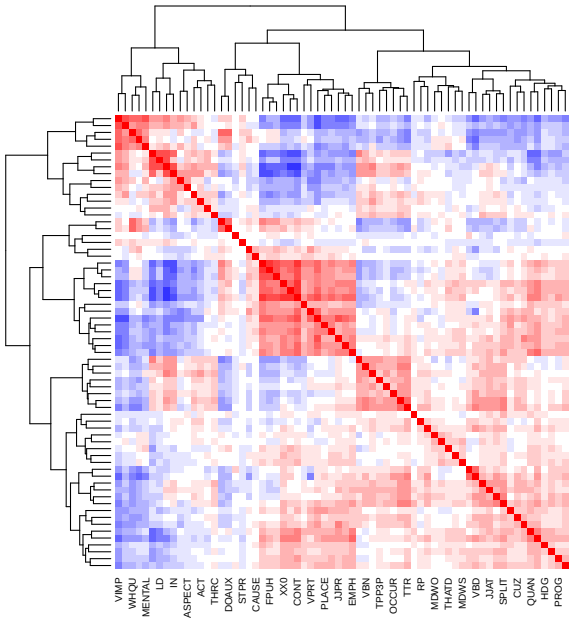



```
#dev.off()
```

E.3.5 Feature correlations

The correlations of the transformed feature frequencies can be visualised in the form of a heatmap. Negative correlations are rendered in blue, whereas positive ones are in red.

```
# Simple heatmap in base R (inspired by Stephanie Evert's SIGIL code)
cor.colours <- c(
  hsv(h=2/3, v=1, s=(10:1)/10), # blue = negative correlation
  rgb(1,1,1), # white = no correlation
  hsv(h=0, v=1, s=(1:10/10))) # red = positive correlation

#png(here("plots", "heatmapzlogcounts-TEC-only.png"), width = 30, height= 30,
 ↪  units = "cm", res = 300)
heatmap(cor(TxBzlogcounts),
        symm=TRUE,
        zlim=c(-1,1),
        col=cor.colours,
        margins=c(0,0))
```


VIMP
WHQU
MENTAL
LD
IN
ASPECT
ACT
THRC
DOAUX
STPR
CAUSE
PPUH
XX0
COMT
VPRT
PLACE
JJR
BMPH
VBN
TPP3P
OCCUR
TTR
RP
MDWO
THATD
MDWS
VBD
JJAT
SPLIT
CUZ
QUAN
HDG
PROG

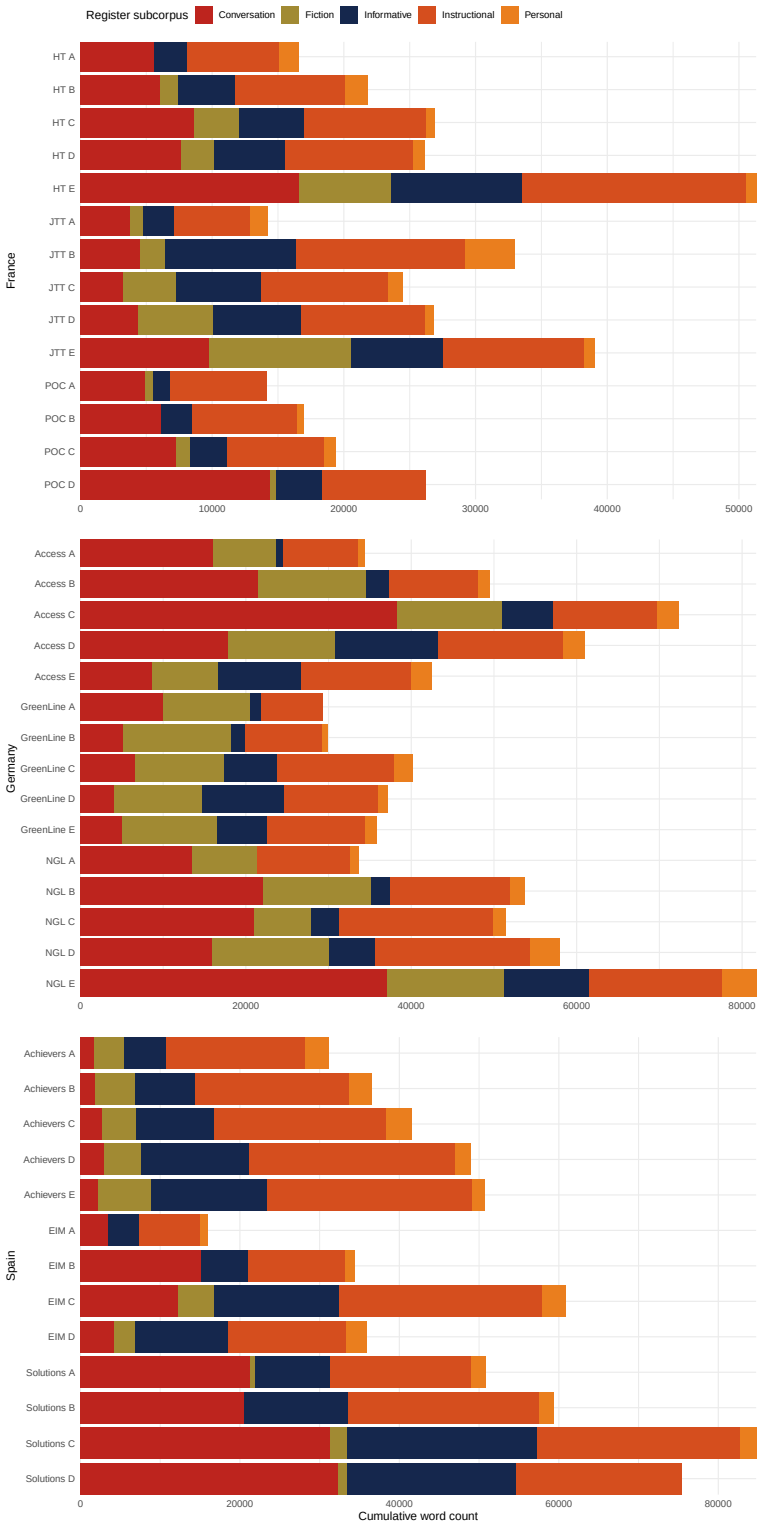
```
#dev.off()

# Calculate the sum of all the words in the tagged texts of the TEC
totalwords <- TxBcounts |>
  select(Words) |>
  sum() |>
  format(big.mark=",")
```

E.4 Composition of TEC texts/files

These figures and tables provide summary statistics on the texts/files of the TEC that were entered in the multi-dimensional model of intra-textbook linguistic variation. In total, the TEC texts entered amounted to 1,693,650 words.

```
metadata <- TxBcounts |>
  select(Filename, Country, Series, Level, Register, Words) |>
  mutate(Volume = paste(Series, Level)) |>
  mutate(Volume = fct_rev(Volume)) |>
  mutate(Volume = fct_reorder(Volume, as.numeric(Level))) |>
  group_by(Volume) |>
  mutate(wordcount = sum(Words)) |>
  ungroup() |>
  distinct(Volume, .keep_all = TRUE)

# Plot for book
metadata2 <- TxBcounts |>
  select(Country, Series, Level, Register, Words) |>
  mutate(Volume = paste(Series, Level)) |>
  mutate(Volume = fct_rev(Volume)) |>
  #mutate(Volume = fct_reorder(Volume, as.numeric(Level))) |>
  group_by(Volume, Register) |>
  mutate(wordcount = sum(Words)) |>
  ungroup() |>
  distinct(Volume, Register, .keep_all = TRUE)

# This is the palette created above on the basis of the suffrager pakcage
 ↪  (but without needed to install the package)
palette <- c("#BD241E", "#A18A33", "#15274D", "#D54E1E", "#EA7E1E",
 ↪  "#4C4C4C", "#722672", "#F9B921", "#267226")
```

```r
PlotSp <- metadata2 |>
  filter(Country=="Spain") |>
  #arrange(Volume) |>
  ggplot(aes(x = Volume, y = wordcount, fill = fct_rev(Register))) +
    geom_bar(stat = "identity", position = "stack") +
    coord_flip(expand = FALSE) + # Removes those annoying ticks before each
     ↪  bar label
    theme_minimal() + theme(legend.position = "none") +
    labs(x = "Spain", y = "Cumulative word count") +
    scale_fill_manual(values = palette[c(5,4,3,2,1)],
                      guide = guide_legend(reverse = TRUE))

PlotGer <- metadata2 |>
  filter(Country=="Germany") |>
  #arrange(Volume) |>
  ggplot(aes(x = Volume, y = wordcount, fill = fct_rev(Register))) +
    geom_bar(stat = "identity", position = "stack") +
    coord_flip(expand = FALSE) +
    labs(x = "Germany", y = "") +
    scale_fill_manual(values = palette[c(5,4,3,2,1)], guide =
     ↪  guide_legend(reverse = TRUE)) +
    theme_minimal() + theme(legend.position = "none")

PlotFr <- metadata2 |>
  filter(Country=="France") |>
  #arrange(Volume) |>
  ggplot(aes(x = Volume, y = wordcount, fill = fct_rev(Register))) +
    geom_bar(stat = "identity", position = "stack") +
    coord_flip(expand = FALSE) +
    labs(x = "France", y  = "", fill = "Register subcorpus") +
    scale_fill_manual(values = palette[c(5,4,3,2,1)], guide =
     ↪  guide_legend(reverse = TRUE, legend.hjust = 0)) +
    theme_minimal() + theme(legend.position = "top", legend.justification =
     ↪  "left")

library(patchwork)

PlotFr /
PlotGer /
PlotSp
```


Register subcorpus
Conversation
Fiction
Informative
Instructional
Personal
France
HT A
HT B
HT C
HT D
HT E
JTT A
JTT B
JTT C
JTT D
JTT E
POC A
POC B
POC C
POC D
0
10000
20000
30000
40000
50000
Germany
Access A
Access B
Access C
Access D
Access E
GreenLine A
GreenLine B
GreenLine C
GreenLine D
GreenLine E
NGL A
NGL B
NGL C
NGL D
NGL E
0
20000
40000
60000
80000
Spain
Achievers A
Achievers B
Achievers C
Achievers D
Achievers E
EIM A
EIM B
EIM C
EIM D
Solutions A
Solutions B
Solutions C
Solutions D
0
20000
40000
60000
80000
Cumulative word count

```
#ggsave(here("plots", "TEC-T_wordcounts_book.svg"), width = 8, height = 12)
```

The following table provides information about the proportion of instructional language featured in each textbook series.

```
metadataInstr <- TxBcounts |>
  select(Country, Series, Level, Register, Words) |>
  filter(Register=="Instructional") |>
  mutate(Volume = paste(Series, Register)) |>
  mutate(Volume = fct_rev(Volume)) |>
  mutate(Volume = fct_reorder(Volume, as.numeric(Level))) |>
  group_by(Volume, Register) |>
  mutate(InstrWordcount = sum(Words)) |>
  ungroup() |>
  distinct(Volume, .keep_all = TRUE) |>
  select(Series, InstrWordcount)

metaWordcount <- TxBcounts |>
  select(Country, Series, Level, Register, Words) |>
  group_by(Series) |>
  mutate(TECwordcount = sum(Words)) |>
  ungroup() |>
  distinct(Series, .keep_all = TRUE) |>
  select(Series, TECwordcount)

wordcount <- merge(metaWordcount, metadataInstr, by = "Series")

wordcount |>
  mutate(InstrucPercent = InstrWordcount/TECwordcount*100) |>
  arrange(InstrucPercent) |>
  mutate(InstrucPercent = round(InstrucPercent, 2)) |>
  kable(col.names = c("Textbook Series", "Total words", "Instructional
   ↪  words", "% of textbook content"),
        digits = 2,
        format.args = list(big.mark = ","))
```

Textbook Series	Total words	Instructional words	% of textbook content
Access	259,679	60,938	23.47
NGL	278,316	79,312	28.50
GreenLine	172,267	54,263	31.50

Textbook Series	Total words	Instructional words	% of textbook content
Solutions	270,278	87,829	32.50
JTT	137,557	48,375	35.17
HT	142,676	51,550	36.13
POC	76,714	30,548	39.82
EIM	147,185	59,928	40.72
Achievers	208,978	109,886	52.58

F Data Analysis for the Model of Intra-Textbook Variation

This script documents the analysis of the pre-processed data from the Textbook English Corpus (TEC) to arrive at the multi-dimensional model of intra-textbook linguistic variation (Chapter 6). It generates all of the statistics and plots included in the book, as well as many others that were used in the analysis, but not included in the book for reasons of space.

F.1 Packages required

The following packages must be installed and loaded to carry out the following analyses.

```
#renv::restore() # Restore the project's dependencies from the lockfile to
 ↪  ensure that same package versions are used as in the original study

library(caret) # For its confusion matrix function
library(cowplot)
library(DescTools) # For 95% CI
library(emmeans)
library(factoextra) # For circular graphs of variables
library(forcats) # For data manipulation
library(ggthemes) # For theme of factoextra plots
library(here) # For dynamic file paths
library(knitr) # Loaded to display the tables using the kable() function
library(lme4) # For linear regression modelling
library(patchwork) # To create figures with more than one plot
library(PCAtools) # For nice biplots of PCA results
library(psych) # For various useful stats function
library(sjPlot) # For model plots and tables
library(tidyverse) # For data wrangling
library(visreg) # For plots of interaction effects

# From https://github.com/RainCloudPlots/RainCloudPlots:
source(here("R_rainclouds.R")) # For geom_flat_violin rainplots
```

F.2 Preparing the data for PCA

F.2.1 TEC data import

```
TxBcounts <- readRDS(here("data", "processed", "TxBcounts3.rds"))
# colnames(TxBcounts)
# nrow(TxBcounts)

TxBzlogcounts <- readRDS(here("data", "processed", "TxBzlogcounts.rds"))
# nrow(TxBzlogcounts)
# colnames(TxBzlogcounts)

TxBdata <- cbind(TxBcounts[,1:6], as.data.frame(TxBzlogcounts))
# str(TxBdata)
```

First, the TEC data as processed in Appendix D is imported. It comprises 1,961 texts/files, each with logged standardised normalised frequencies for 66 linguistic features.

F.3 Checking the factorability of data

```
kmo <- KMO(TxBdata[,7:ncol(TxBdata)])
```

The overall MSA value of the dataset is 0.86. The features have the following individual MSA values (ordered from lowest to largest):

```
kmo$MSAi[order(kmo$MSAi)] |>  round(2)
```

```
  MDWO   MDWS   MDNE   MDCA    VBD   VPRT    POS    ACT   FREQ  TPP3S     LD
  0.34   0.46   0.52   0.53   0.59   0.60   0.64   0.65   0.65   0.66   0.68
 CAUSE   COND   MDCO   VIMP  NCOMP     DT  TPP3P   STPR     RP   SPP2 MENTAL
  0.69   0.75   0.77   0.78   0.79   0.80   0.80   0.81   0.81   0.83   0.84
 DOAUX   WHSC    VBG  EXIST  THATD   COMM  FPP1S     IN     NN   WHQU   JJAT
  0.84   0.85   0.86   0.86   0.86   0.87   0.87   0.88   0.88   0.89   0.89
  DEMO   THRC ASPECT     CC     EX  OCCUR   PEAS    TTR   YNQU    AWL   QUAN
  0.89   0.89   0.90   0.90   0.90   0.90   0.91   0.91   0.91   0.92   0.92
 FPP1P   PROG    XXO   CONT   TIME   BEMA  SPLIT   PASS   JJPR    AMP   QUPR
  0.92   0.92   0.92   0.92   0.93   0.93   0.93   0.94   0.94   0.95   0.95
```

```
  THSC     RB   FPUH    CUZ    VBN    PIT    DMA POLITE   EMPH    HDG  PLACE
  0.95   0.95   0.95   0.95   0.95   0.96   0.96   0.96   0.96   0.96   0.97
```

F.3.1 Removal of feature with MSAs of < 0.5

We first remove the first feature with an individual MSA < 0.5, then check the MSA values again and continue removing features one by one if necessary.

```
TxBdata <- TxBdata |>
  select(-c(MDWO))

kmo2 <- KMO(TxBdata[,7:ncol(TxBdata)])
```

The overall MSA value of the dataset is now 0.87. None of the remaining features have individual MSA values below 0.5:

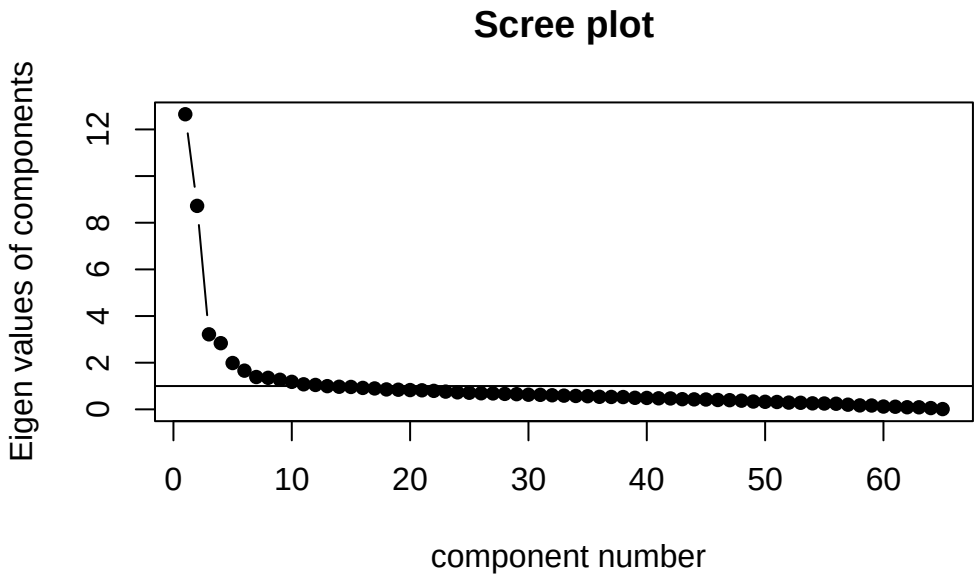
```
kmo2$MSAi[order(kmo2$MSAi)] |>  round(2)
```

```
  MDWS   MDNE   MDCA    VBD    POS   VPRT   FREQ    ACT  TPP3S     LD  CAUSE
  0.55   0.58   0.61   0.63   0.64   0.65   0.65   0.66   0.66   0.69   0.70
  MDCO   COND     DT  TPP3P   VIMP  NCOMP     RP   STPR   SPP2  DOAUX MENTAL
  0.77   0.80   0.80   0.80   0.81   0.81   0.81   0.82   0.83   0.84   0.85
   VBG   WHSC  EXIST  THATD  FPP1S   COMM     IN     NN   DEMO   WHQU   THRC
  0.85   0.85   0.86   0.87   0.87   0.87   0.88   0.89   0.89   0.89   0.89
  JJAT ASPECT   PEAS     EX  OCCUR     CC    TTR   YNQU    AWL   QUAN  FPP1P
  0.89   0.89   0.90   0.90   0.91   0.91   0.91   0.91   0.92   0.92   0.92
  TIME    XXO   CONT   PROG   BEMA  SPLIT   PASS   JJPR   THSC    AMP     RB
  0.92   0.92   0.93   0.93   0.93   0.93   0.94   0.94   0.95   0.95   0.95
  QUPR   FPUH    PIT    VBN    DMA    CUZ POLITE   EMPH    HDG  PLACE
  0.95   0.95   0.96   0.96   0.96   0.96   0.96   0.96   0.96   0.97
```

F.3.2 Choosing the number of principal components to retain

On the basis of this scree plot, six principal components were initially retained.

```
# Plot screen plot
#png(here("plots", "screeplot-TEC-only.png"), width = 20, height= 12, units =
 ↪  "cm", res = 300)
scree(TxBdata[,7:ncol(TxBdata)], factors = FALSE, pc = TRUE) # Retain six
 ↪  components
```




```
#dev.off()

# Perform PCA
pca1 <- psych::principal(TxBdata[,7:ncol(TxBdata)],
                         nfactors = 6,
                         rotate = "none")
#pca1$loadings
```

F.3.3 Excluding features with low final communalites

We first check whether some feature have extremely low communalities (see https://rdrr.io/cran/FactorAssumpti

STPR	MDNE	HDG	CAUSE	FREQ	THRC	POS	PROG	ACT	DEMO	MDWS
0.09	0.17	0.17	0.19	0.22	0.22	0.24	0.26	0.26	0.27	0.28
CUZ	COND	QUPR	EXIST	MDCO	NCOMP	OCCUR	TIME	ASPECT	TPP3P	AMP
0.28	0.28	0.29	0.29	0.31	0.31	0.32	0.32	0.33	0.33	0.34
RP	THATD	THSC	EX	FPP1P	PLACE	PIT	VBG	PEAS	MDCA	DOAUX
0.34	0.36	0.39	0.43	0.43	0.43	0.45	0.46	0.47	0.48	0.48
VBN	JJPR	JJAT	WHSC	SPLIT	EMPH	QUAN	MENTAL	TPP3S	PASS	YNQU
0.48	0.49	0.49	0.50	0.51	0.53	0.55	0.56	0.56	0.57	0.58
POLITE	RB	CC	XXO	DT	COMM	WHQU	TTR	FPP1S	IN	LD

```
 0.58   0.58   0.58   0.59   0.62   0.62   0.64   0.65   0.67   0.68   0.68
 FPUH   VPRT   SPP2   BEMA    DMA    VBD    AWL   CONT     NN   VIMP
 0.70   0.71   0.72   0.74   0.74   0.80   0.85   0.85   0.87   0.90
```

As we chose to exclude features with communalities of < 0.2, we remove STPR, HDG, MDNE and CAUSE from the dataset to be analysed.

```
TxBdataforPCA <- TxBdata |>
  select(-c(STPR, MDNE, HDG, CAUSE))
```

The overall MSA value of the dataset is now 0.88. None of the remaining features have individual MSA values below 0.5:

```
kmo3$MSAi[order(kmo3$MSAi)] |>round(2)
```

```
  MDWS   MDCA    POS   FREQ    VBD  TPP3S   VPRT    ACT     LD   COND     DT
  0.54   0.64   0.64   0.65   0.65   0.66   0.66   0.67   0.69   0.78   0.79
  MDCO  TPP3P     RP  NCOMP   VIMP   SPP2  DOAUX MENTAL   WHSC    VBG  THATD
  0.79   0.81   0.82   0.82   0.82   0.82   0.84   0.85   0.86   0.86   0.86
 EXIST  FPP1S   COMM     NN     IN   WHQU   DEMO ASPECT   JJAT   THRC     EX
  0.86   0.87   0.88   0.89   0.89   0.89   0.89   0.89   0.89   0.90   0.90
 OCCUR   PEAS     CC   YNQU   QUAN    AWL   TIME    XXO  FPP1P    TTR   CONT
  0.90   0.91   0.91   0.91   0.91   0.92   0.92   0.92   0.92   0.92   0.93
  PROG   BEMA  SPLIT   PASS   JJPR   THSC     RB   QUPR    AMP   FPUH    PIT
  0.93   0.93   0.93   0.94   0.94   0.95   0.95   0.95   0.95   0.95   0.95
   VBN    DMA POLITE    CUZ   EMPH  PLACE
  0.95   0.96   0.96   0.96   0.96   0.97
```

The final number of linguistic features entered in the intra-textbook model of linguistic variation is 61.

F.4 Testing the effect of rotating the components

This chunk was used when considering whether or not to rotate the components (see methods section). Ultimately, the components were not rotated.

```
# Comparing a rotated vs. a non-rotated solution

#TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds"))

# No rotation
pca2 <- psych::principal(TxBdata[,7:ncol(TxBdata)],
                         nfactors = 6,
                         rotate = "none")

pca2$loadings

biplot.psych(pca2,
             vars = TRUE,
             choose=c(1,2),
             )

# Promax rotation
pca2.rotated <- psych::principal(TxBdata[,7:ncol(TxBdata)],
                         nfactors = 6,
                         rotate = "promax")

# This summary shows the component correlations which is particularly
 ↪  interesting
pca2.rotated

pca2.rotated$loadings

biplot.psych(pca2.rotated, vars = TRUE, choose=c(1,2))
```

F.5 Principal Component Analysis (PCA)

F.5.1 Using the full dataset

Except outliers removed as part of the data preparation (see Appendix D).

```
# Perform PCA on full data
TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds"))
```

F.5.2 Using random subsets of the data

Alternatively, it is possible to conduct the PCA on random subsets of the data to test the stability of the solution. Re-running this line will generate a new subset of the TEC texts containing 2/3 of the texts randomly sampled.

```
TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds")) |>
  slice_sample(n = round(1961*0.6), replace = FALSE)

nrow(TxBdata)
TxBdata$Filename[1:10]
nrow(TxBdata) / (ncol(TxBdata)-6) # Check that there is enough data to
 ↪  conduct a PCA. This ratio should be at least 5 (see Friginal & Hardy
 ↪  2014: 303-304).
```

F.5.3 Using specific subsets of the data

The following chunk can be used to perform the PCA on a country subset of the data to test the stability of the solution. See (Le Foll) for a detailed analysis of the subcorpus of textbooks used in Germany.

```
TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds")) |>
  #filter(Country == "France")
  #filter(Country == "Germany")
  filter(Country == "Spain")

nrow(TxBdata)
TxBdata$Filename[1:10] # Check data
nrow(TxBdata) / (ncol(TxBdata)-6) # Check that there is enough data to
 ↪  conduct a PCA. This should be > 5 (see Friginal & Hardy 2014: 303-304).
```

F.5.4 Performing the PCA

We perform the PCA using the `prcomp` function and print a summary of the results.

```
pca <- prcomp(TxBdata[,7:ncol(TxBdata)], scale.=FALSE, rank. = 6) # All
 ↪  quantitative variables for all TxB files except outliers
register  <- factor(TxBdata[,"Register"]) # Register
level <- factor(TxBdata[,"Level"]) # Textbook proficiency level
```

```
# summary(register)
# summary(level)
summary(pca)
```

```
Importance of first k=6 (out of 61) components:
                          PC1    PC2     PC3     PC4     PC5     PC6
Standard deviation     2.1693 1.7776 1.08902 1.00207 0.84288 0.76792
Proportion of Variance 0.2108 0.1416 0.05313 0.04499 0.03183 0.02642
Cumulative Proportion  0.2108 0.3524 0.40553 0.45051 0.48234 0.50876
```

F.6 Plotting PCA results

F.6.1 3D plots

The following chunk can be used to create projections of TEC texts on three dimensions of the model. These plots cannot be rendered in two dimensions and are therefore not generated in the present document. For more information on the `pca3d` library, see: https://cran.r-project.org/web/packages/pca3d/vignettes/pca3d.pdf.

```
library(pca3d) # For 3-D plots

col <- palette[c(1:3,8,7)] # without poetry
names(col) <- c("Conversation", "Fiction", "Informative", "Instructional",
 ↪  "Personal")
scales::show_col(col) # Check colours

pca3d(pca,
      group = register,
      components = 1:3,
      #components = 4:6,
      show.ellipses=FALSE,
      ellipse.ci=0.75,
      show.plane=FALSE,
      col = col,
      shape = "sphere",
      radius = 1,
      legend = "right")

snapshotPCA3d(here("plots", "PCA_TxB_3Dsnapshot.png"))
```

```
names(col) <- c("C", "B", "E", "A", "D") # To colour the dots according to
 ↪  the profiency level of the textbooks
pca3d(pca,
      components = 4:6,
      group = level,
      show.ellipses=FALSE,
      ellipse.ci=0.75,
      show.plane=FALSE,
      col = col,
      shape = "sphere",
      radius = 0.8,
      legend = "right")
```

F.7 Two-dimensional plots (biplots)

These plots were generated using the `PCAtools` package, which requires the data to be formatted in a rather unconventional way so it needs to wrangled first.

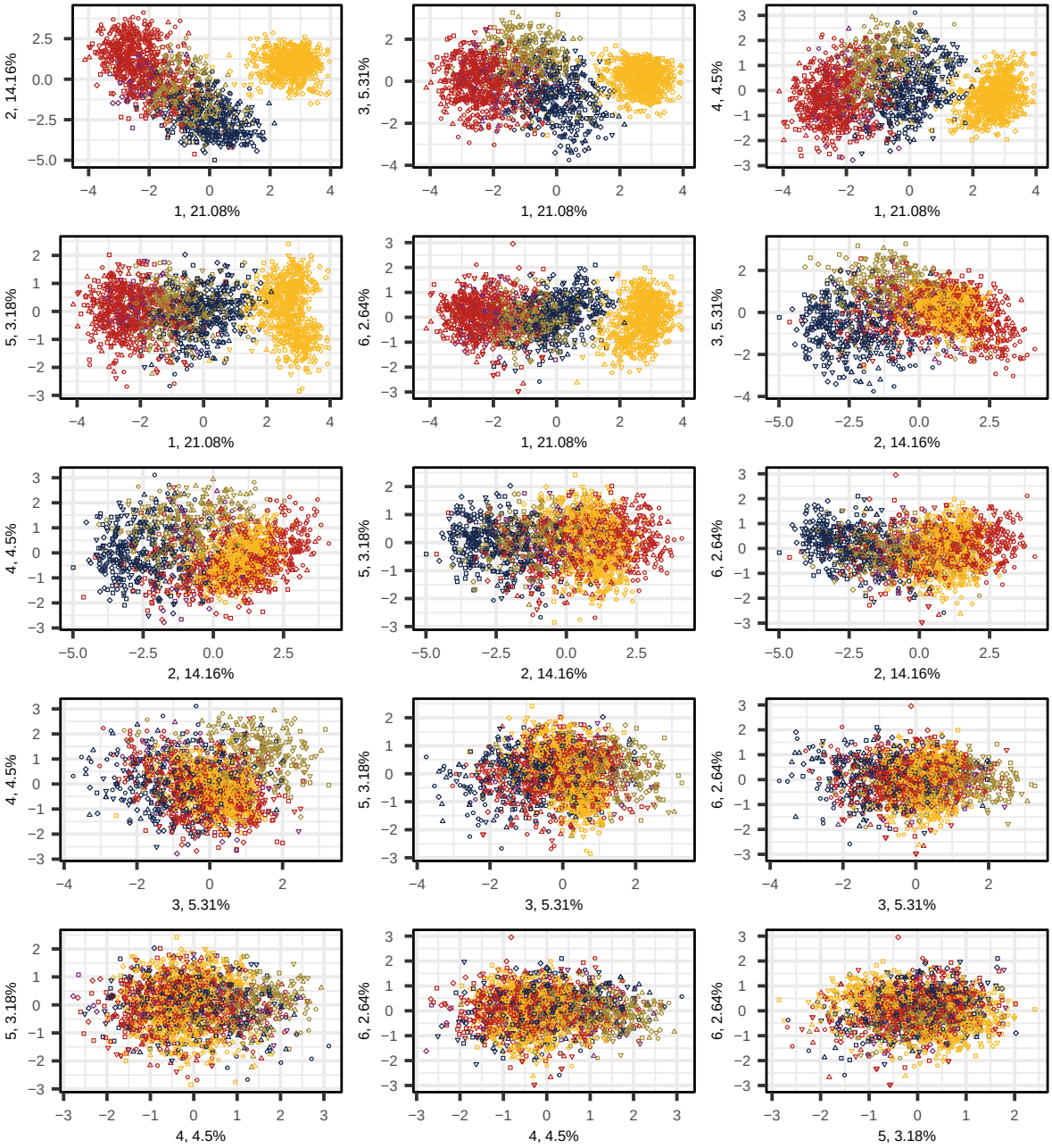
F.7.1 Data wrangling for PCAtools

```
#TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds"))

TxBdata2meta <- TxBdata[,1:6]
rownames(TxBdata2meta) <- TxBdata2meta$Filename
TxBdata2meta <- TxBdata2meta |> select(-Filename)
#head(TxBdata2meta)

TxBdata2 = TxBdata
rownames(TxBdata2) <- TxBdata2$Filename
TxBdata2num <- as.data.frame(base::t(TxBdata2[,7:ncol(TxBdata2)]))
#TxBdata2num[1:12,1:3] # Check sanity of data

p <- PCAtools::pca(TxBdata2num,
         metadata = TxBdata2meta,
         scale = FALSE)
```

F.7.2 Pairs plot

We first produce a scatterplot matrix of all the combinations of the first six dimensions of the model of intra-textbook variation. Note that the number before the comma on each axis label shows which principal component is plotted on that axis; this is followed by the percentage of the total variance explained by that particular component. The colours correspond to the text registers.

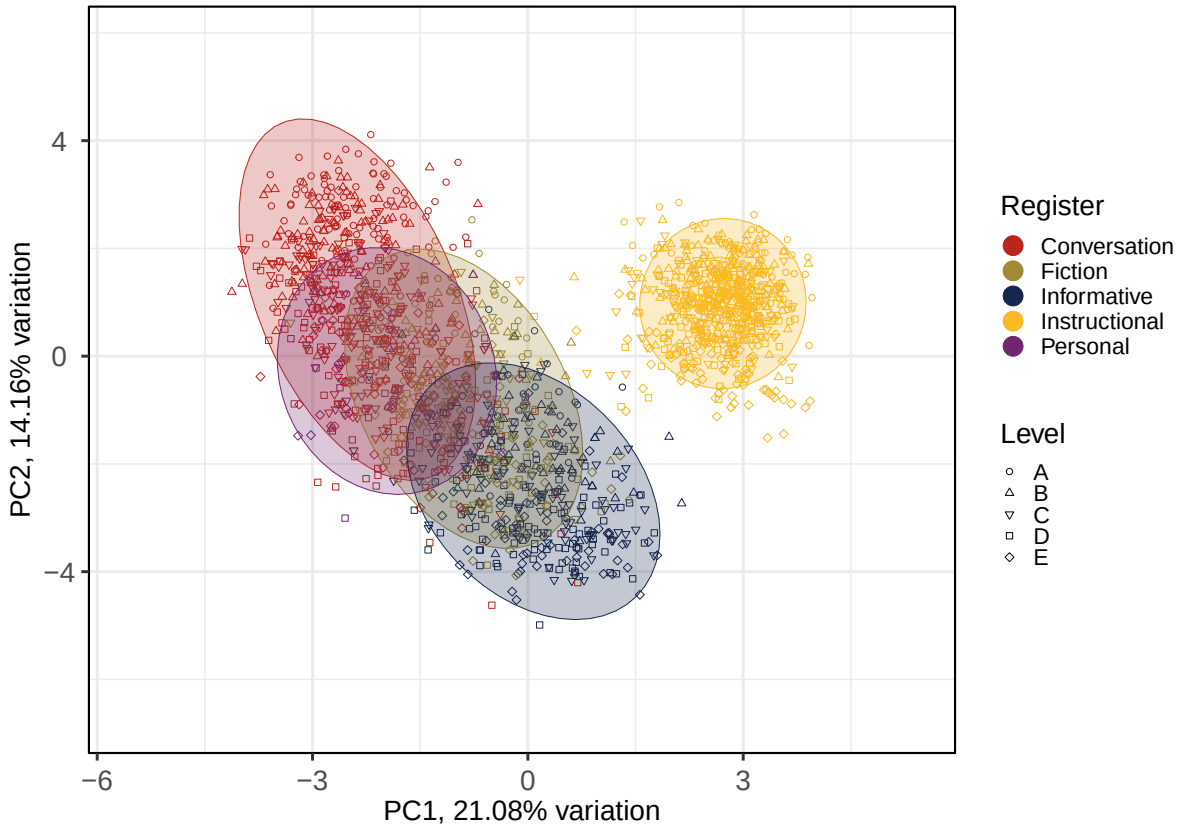
```
## Colour and shape scheme for all biplots
colkey = c(Conversation="#BD241E", Fiction="#A18A33", Informative="#15274D",
 ↪  Instructional="#F9B921", Personal="#722672")
shapekey = c(A=1, B=2, C=6, D=0, E=5)

## Very slow, open in zoomed out window!
# Add legend manually? Yes (take it from the biplot code below), sadly really
 ↪  the simplest solution, here. Or use Evert's mvar.pairs plot function
 ↪  (though that also requires manual axis annotation).

# png(here("plots", "PCA_TxB_pairsplot.png"), width = 12, height= 19, units =
 ↪  "cm", res = 300)
PCAtools::pairsplot(p,
                 triangle = FALSE,
                 components = 1:6,
                 ncol = 3,
                 nrow = 5,
                 pointSize = 0.8,
                 lab = NULL, # Otherwise will try to label each data point!
                 colby = "Register",
                 colkey = colkey,
                 shape = "Level",
                 shapekey = shapekey,
                 margingaps = unit(c(0.2, 0.2, 0.2, 0.2), "cm"),
                 legendPosition = "none")
```


2, 14.16%
1, 21.08%
3, 5.31%
1, 21.08%
4, 4.5%
1, 21.08%
5, 3.18%
1, 21.08%
6, 2.64%
1, 21.08%
3, 5.31%
2, 14.16%
4, 4.5%
2, 14.16%
5, 3.18%
2, 14.16%
6, 2.64%
2, 14.16%
4, 4.5%
3, 5.31%
5, 3.18%
3, 5.31%
6, 2.64%
3, 5.31%
5, 3.18%
4, 4.5%
6, 2.64%
4, 4.5%
6, 2.64%
5, 3.18%

F.7.3 Bi-plots

Then, biplots of the most important dimensions are generated to examine components more carefully.

```
colkey = c(Conversation="#BD241E", Fiction="#A18A33", Informative="#15274D",
 ↪  Instructional="#F9B921", Personal="#722672")
shapekey = c(A=1, B=2, C=6, D=0, E=5)

#png(here("plots", "PCA_TxB_Biplot_PC1_PC2.png"), width = 40, height= 25,
 ↪  units = "cm", res = 300)
PCAtools::biplot(p,
                 x = "PC1",
                 y = "PC2",
                 lab = NULL, # Otherwise will try to label each data point!
                 #xlim = c(min(p$rotated$PC1)-0.5, max(p$rotated$PC1)+0.5),
                 #ylim = c(min(p$rotated$PC2)-0.5, max(p$rotated$PC2)+0.5),
                 colby = "Register",
                 pointSize = 2,
                 colkey = colkey,
                 shape = "Level",
                 shapekey = shapekey,
                 showLoadings = FALSE,
                 ellipse = TRUE,
                 axisLabSize = 22,
                 legendPosition = 'right',
                 legendTitleSize = 22,
                 legendLabSize = 18,
                 legendIconSize = 7) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))
```




```
#dev.off()
#ggsave(here("plots", "PCA_TxB_BiplotPC1_PC2.svg"), width = 12, height = 10)
```

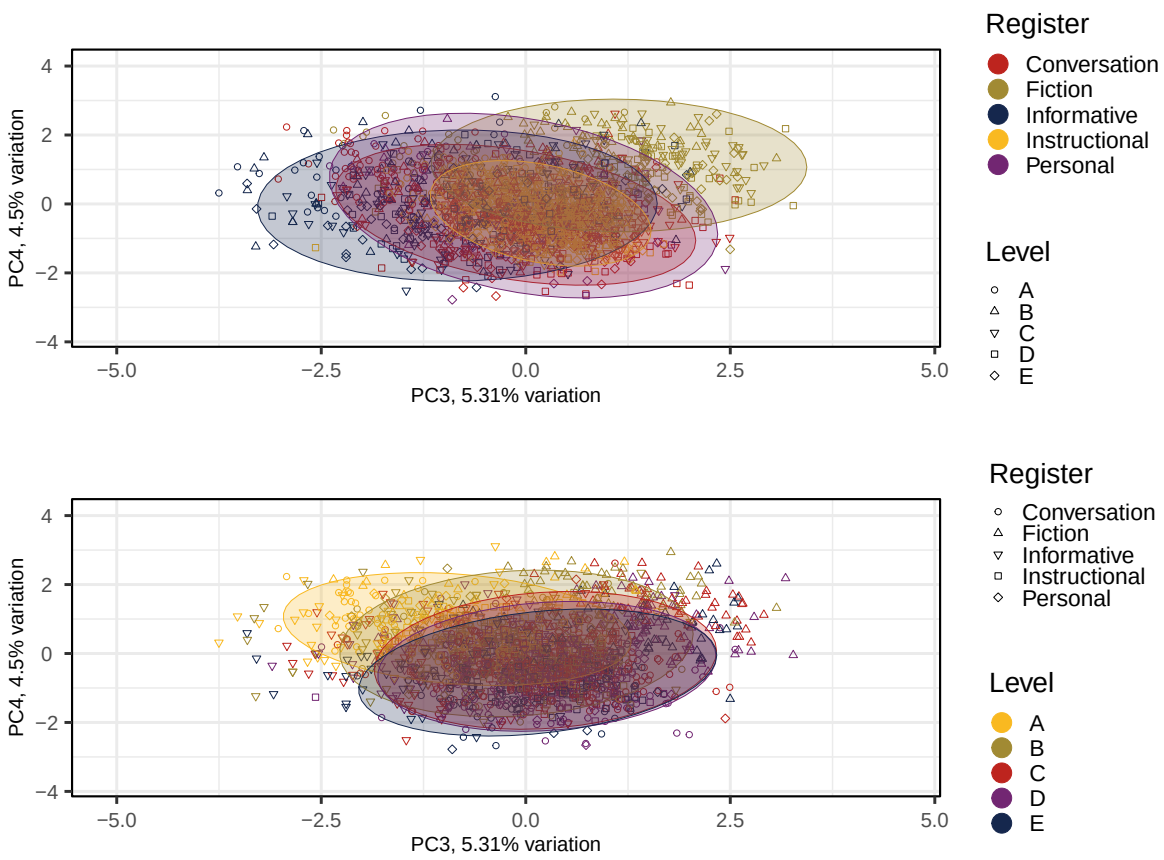
```
# Biplots to examine components more carefully
pRegisters <- PCAtools::biplot(p,
                x = "PC3",
                y = "PC4",
                lab = NULL, # Otherwise will try to label each data point!
                colby = "Register",
                pointSize = 2,
                colkey = colkey,
                shape = "Level",
                shapekey = shapekey,
                showLoadings = FALSE,
                ellipse = TRUE,
                legendPosition = 'right',
```

```
                  legendTitleSize = 22,
                  legendLabSize = 18,
                  legendIconSize = 7) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))

#ggsave(here("plots", "PCA_TxB_BiplotPC3_PC4.svg"), width = 12, height = 10)

# Biplots to examine components more carefully
pRegisters2 <- PCAtools::biplot(p,
                  x = "PC5",
                  y = "PC6",
                  lab = NULL, # Otherwise will try to label each data point!
                  colby = "Register",
                  pointSize = 2,
                  colkey = colkey,
                  shape = "Level",
                  shapekey = shapekey,
                  showLoadings = FALSE,
                  ellipse = TRUE,
                  legendPosition = 'right',
                  legendTitleSize = 22,
                  legendLabSize = 18,
                  legendIconSize = 7) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))

#ggsave(here("plots", "PCA_TxB_BiplotPC5_PC6.svg"), width = 12, height = 10)
```

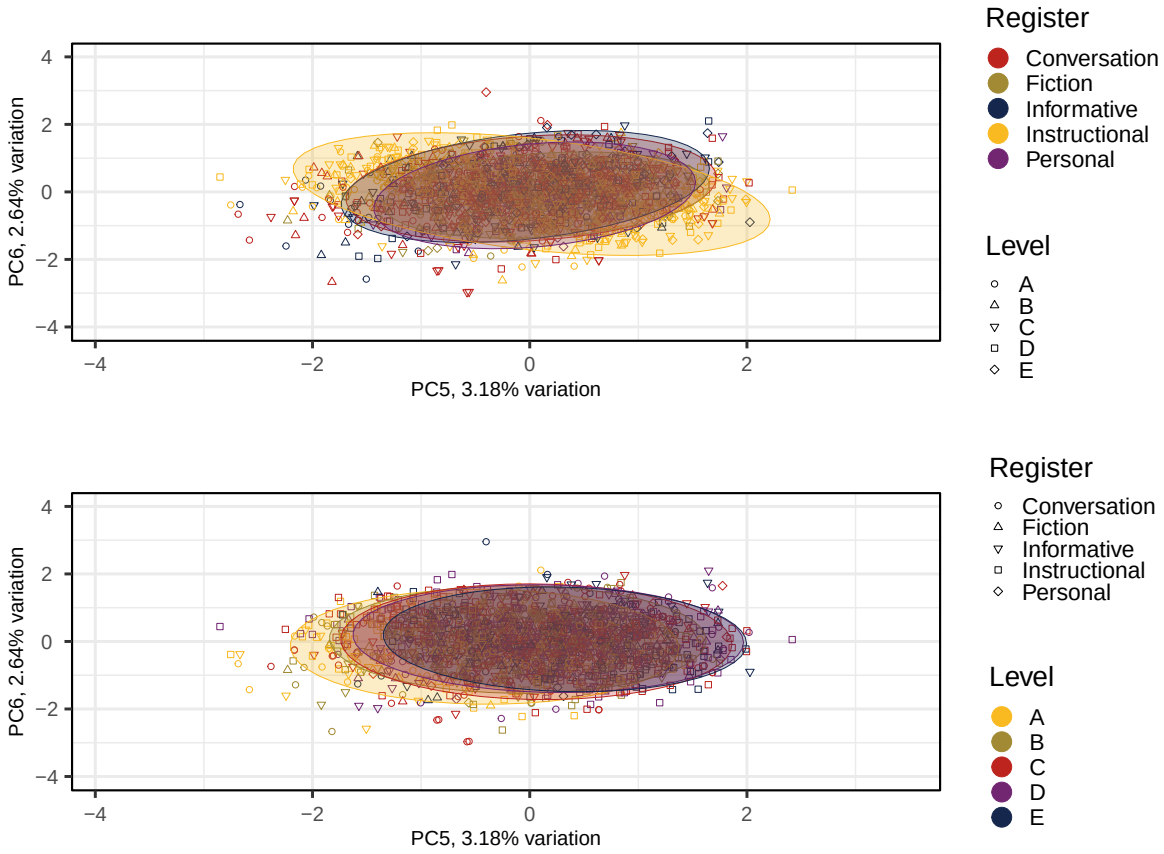
Changing the colour of the points and the ellipses to represent the texts' target proficiency levels instead of the register allows for a different interpretation of the model.

```
# Inverted keys for the biplots with ellipses for Level rather than Register
colkeyLevels = c(A="#F9B921", B="#A18A33", C="#BD241E", D="#722672",
 ↪  E="#15274D")
shapekeyLevels = c(Conversation=1, Fiction=2, Informative=6, Instructional=0,
 ↪  Personal=5)

pLevels <- PCAtools::biplot(p,
                  x = "PC3",
                  y = "PC4",
                  lab = NULL, # Otherwise will try to label each data point!
                  #xlim = c(min(p$rotated$PC1)-0.5, max(p$rotated$PC1)+0.5),
```

```
                #ylim = c(min(p$rotated$PC2)-0.5, max(p$rotated$PC2)+0.5),
                colby = "Level",
                pointSize = 2,
                colkey = colkeyLevels,
                shape = "Register",
                shapekey = shapekeyLevels,
                showLoadings = FALSE,
                ellipse = TRUE,
                legendPosition = 'right',
                legendTitleSize = 22,
                legendLabSize = 18,
                legendIconSize = 7) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))
#ggsave(here("plots", "PCA_TxB_BiplotPC3_PC4_Level.svg"), width = 12, height
 ↪  = 10)

pLevels2 <- PCAtools::biplot(p,
                x = "PC5",
                y = "PC6",
                lab = NULL, # Otherwise will try to label each data point!
                #xlim = c(min(p$rotated$PC1)-0.5, max(p$rotated$PC1)+0.5),
                #ylim = c(min(p$rotated$PC2)-0.5, max(p$rotated$PC2)+0.5),
                colby = "Level",
                pointSize = 2,
                colkey = colkeyLevels,
                shape = "Register",
                shapekey = shapekeyLevels,
                showLoadings = FALSE,
                ellipse = TRUE,
                legendPosition = 'right',
                legendTitleSize = 22,
                legendLabSize = 18,
                legendIconSize = 7) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))
#ggsave(here("plots", "PCA_TxB_BiplotPC5_PC6_Level.svg"), width = 12, height
 ↪  = 10)


# Display and save the two different representations of data points on PC2
 ↪  and PC3 using the {patchwork} package
pRegisters / pLevels
```




```
#ggsave(here("plots", "PCA_TxB_BiplotPC3_PC4_Register_vs_Level.svg"), width =
 ↪  14, height = 20)

# Display and save the two different representations of data points on PC5
 ↪  and PC6 using the {patchwork} package
pRegisters2 / pLevels2
```




```
#ggsave(here("plots", "PCA_TxB_BiplotPC5_PC6_Register_vs_Level.svg"), width =
 ↪  14, height = 20)
```

F.8 Feature contributions (loadings) on each component

```
#TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds"))

pca <- prcomp(TxBdata[,7:ncol(TxBdata)], scale.=FALSE) # All quantitative
 ↪  variables for all TEC files

# The rotated data that represents the observations / samples is stored in
 ↪  rotated, while the variable loadings are stored in loadings
loadings <- as.data.frame(pca$rotation[,1:4])
```

```
loadings |>
  round(2) |>
  kable()
```

	PC1	PC2	PC3	PC4
ACT	0.08	-0.11	0.04	-0.10
AMP	-0.12	-0.10	-0.11	0.01
ASPECT	0.10	-0.05	0.14	-0.01
AWL	0.22	-0.16	-0.12	-0.13
BEMA	-0.22	0.01	-0.21	0.02
CC	0.05	-0.21	-0.19	0.00
COMM	0.20	0.09	0.14	-0.04
COND	-0.01	-0.02	0.11	-0.24
CONT	-0.25	0.11	-0.03	-0.06
CUZ	-0.09	-0.13	-0.06	-0.02
DEMO	-0.12	0.08	0.03	-0.09
DMA	-0.20	0.14	-0.02	0.00
DOAUX	-0.01	0.20	0.05	-0.15
DT	0.12	0.00	0.31	-0.02
EMPH	-0.19	-0.02	0.06	-0.14
EX	-0.10	-0.05	-0.11	0.05
EXIST	-0.02	-0.15	-0.09	-0.09
FPP1P	-0.17	0.01	-0.07	0.00
FPP1S	-0.23	0.07	0.08	-0.01
FPUH	-0.16	0.15	-0.09	0.07
FREQ	-0.03	-0.05	0.01	-0.10
IN	0.17	-0.18	0.02	-0.08
JJAT	-0.06	-0.18	0.04	-0.21
JJPR	-0.17	-0.06	-0.11	-0.11
LD	0.16	-0.03	-0.26	-0.01
MDCA	-0.04	0.10	-0.18	-0.09
MDCO	-0.05	-0.10	0.22	0.01
MDWS	-0.07	-0.01	0.05	-0.16
MENTAL	0.14	0.13	0.12	-0.25
NCOMP	0.04	-0.05	-0.24	-0.15
NN	0.20	-0.09	-0.29	0.11
OCCUR	0.02	-0.18	0.03	0.02
PASS	-0.01	-0.22	-0.06	-0.05
PEAS	-0.06	-0.17	0.13	-0.13
PIT	-0.19	-0.04	-0.06	-0.06
PLACE	-0.16	-0.01	-0.07	0.09

	PC1	PC2	PC3	PC4
POLITE	-0.14	0.13	-0.07	0.02
POS	-0.01	0.03	-0.04	0.16
PROG	-0.11	-0.02	0.11	0.00
QUAN	-0.15	-0.03	0.12	-0.19
QUPR	-0.10	-0.05	0.16	-0.11
RB	-0.19	-0.08	0.20	0.00
RP	0.00	-0.09	0.14	0.02
SPLIT	-0.11	-0.18	0.02	-0.16
SPP2	0.10	0.22	-0.01	-0.25
THATD	-0.05	0.04	0.16	-0.24
THRC	0.02	-0.11	-0.02	-0.18
THSC	-0.06	-0.17	0.07	-0.14
TIME	-0.12	-0.08	-0.01	0.06
TPP3P	-0.01	-0.16	-0.09	-0.02
TPP3S	-0.06	-0.11	0.13	0.30
TTR	-0.04	-0.26	-0.05	-0.01
VBD	-0.08	-0.20	0.23	0.30
VBG	0.04	-0.18	0.00	-0.22
VBN	0.03	-0.18	-0.07	-0.04
VIMP	0.25	0.15	0.04	-0.08
VPRT	-0.15	0.05	-0.32	-0.22
WHQU	0.11	0.23	0.00	-0.09
WHSC	0.11	-0.11	0.03	-0.15
XX0	-0.22	0.03	0.06	-0.06
YNQU	-0.03	0.23	0.00	-0.08

We can go back to the normalised frequencies of the individual features to compare them across different registers and levels, e.g.:

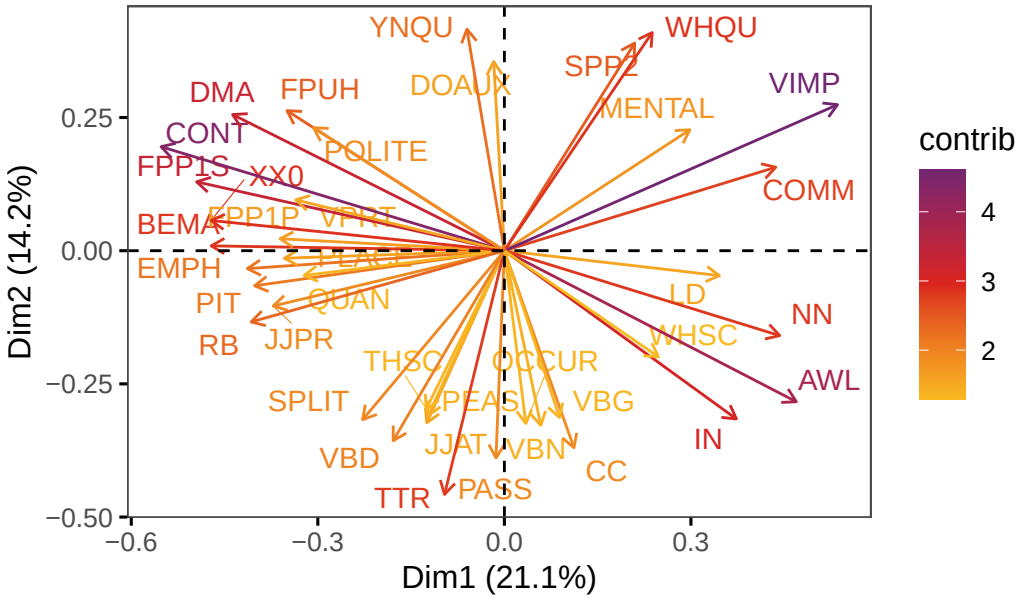
```
TxBcounts |>
  group_by(Register, Level) |>
  summarise(median(NCOMP), MAD(NCOMP)) |>
  select(1:4) |>
  kable(digits=2)
```

Register	Level	median(NCOMP)	MAD(NCOMP)
Conversation	A	5.69	2.79
Conversation	B	5.48	2.66

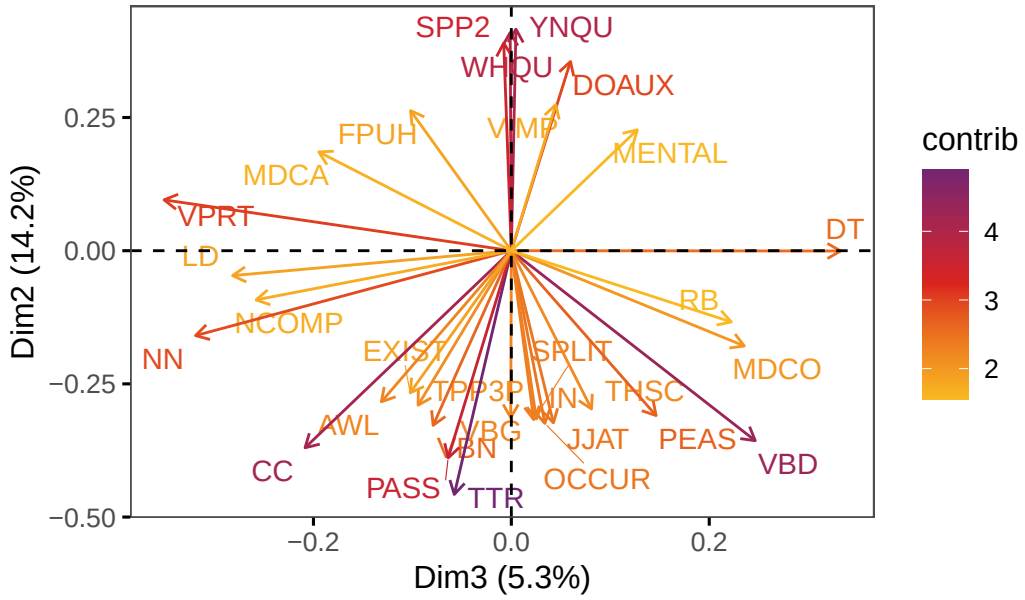
Register	Level	median(NCOMP)	MAD(NCOMP)
Conversation	C	5.32	2.58
Conversation	D	6.18	2.91
Conversation	E	6.21	2.62
Fiction	A	4.14	2.34
Fiction	B	3.96	2.17
Fiction	C	4.05	1.86
Fiction	D	5.05	2.34
Fiction	E	5.05	2.16
Informative	A	8.07	2.48
Informative	B	7.62	2.40
Informative	C	7.49	3.16
Informative	D	7.56	2.46
Informative	E	8.77	2.45
Instructional	A	6.84	2.54
Instructional	B	6.80	2.65
Instructional	C	6.14	2.35
Instructional	D	6.22	2.29
Instructional	E	6.75	2.69
Personal	A	6.72	1.42
Personal	B	4.92	2.33
Personal	C	5.75	1.45
Personal	D	6.46	3.19
Personal	E	8.22	3.09

Graphs of features display the features with the strongest contributions to any two dimensions of the model of intra-textbook variation. They are created using the `factoextra::fviz_pca_var` function.

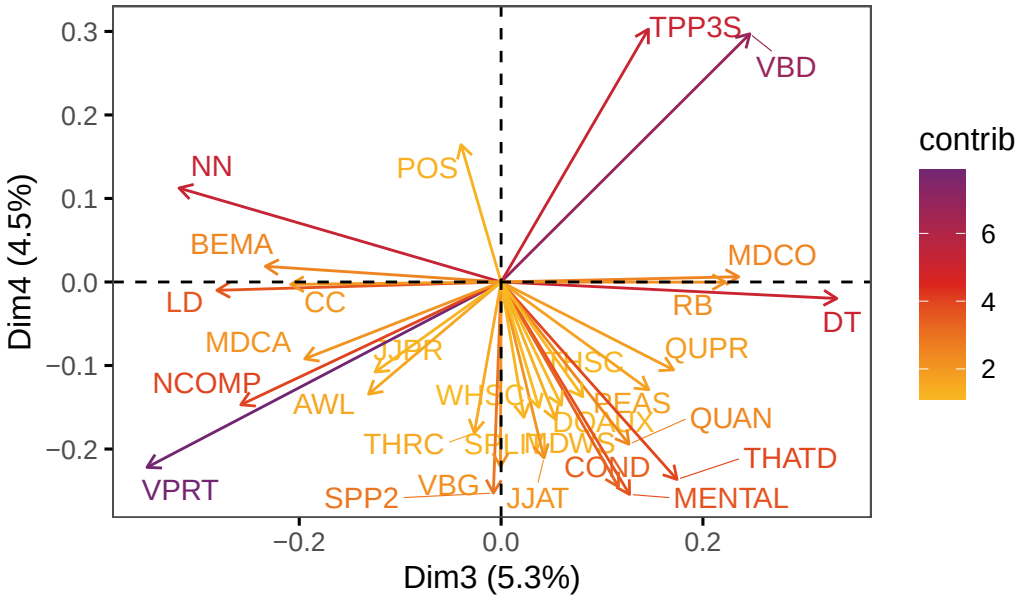
```
factoextra::fviz_pca_var(pca,
             axes = c(1,2),
             select.var = list(cos2 = 0.1),
             col.var = "contrib", # Colour by contributions to the PC
             gradient.cols = c("#F9B921", "#DB241E", "#722672"),
             title = "",
             repel = TRUE, # Try to avoid too much text overlapping
             ggtheme = ggthemes::theme_few())
```




```
#ggsave(here("plots", "fviz_pca_var_PC1_PC2.svg"), width = 11, height = 9)

factoextra::fviz_pca_var(pca,
             axes = c(3,2),
             select.var = list(contrib = 30),
             col.var = "contrib", # Colour by contributions to the PC
             gradient.cols = c("#F9B921", "#DB241E", "#722672"),
             title = "",
             repel = TRUE, # Try to avoid too much text overlapping
             ggtheme = ggthemes::theme_few())
```




```
#ggsave(here("plots", "fviz_pca_var_PC3_PC2.svg"), width = 9, height = 8)

factoextra::fviz_pca_var(pca,
             axes = c(3,4),
             select.var = list(contrib = 30),
             col.var = "contrib", # Colour by contributions to the PC
             gradient.cols = c("#F9B921", "#DB241E", "#722672"),
             title = "",
             repel = TRUE, # Try to avoid too much text overlapping
             ggtheme = ggthemes::theme_few())
```




```
#ggsave(here("plots", "fviz_pca_var_PC3_PC4.svg"), width = 9, height = 8)
```

F.9 Exploring the dimensions of the model

We begin with some descriptive statistics of the dimension scores.

```
#
 ↪  http://www.sthda.com/english/articles/31-principal-component-methods-in-r-practical-guide

#TxBdata <- readRDS(here("data", "processed", "TxBdataforPCA.rds"))

pca <- prcomp(TxBdata[,7:ncol(TxBdata)], scale.=FALSE) # All quantitative
 ↪  variables for all TxB files
register  <- factor(TxBdata[,"Register"]) # Register
level <- factor(TxBdata[,"Level"]) # Textbook proficiency level

# summary(register)
# summary(level)
# summary(pca)

## Access to the PCA results for individual PC
```

```
#pca$rotation[,1]

res.ind <- cbind(TxBdata[,1:5], as.data.frame(pca$x)[,1:6])

res.ind |>
  group_by(Register) |>
  summarise_if(is.numeric, mean) |>
  kable(digits = 2)
```

Register	PC1	PC2	PC3	PC4	PC5	PC6
Conversation	-2.29	0.93	-0.14	-0.27	-0.02	0.06
Fiction	-0.85	-0.81	1.02	1.09	0.11	-0.10
Informative	0.06	-2.45	-0.83	0.01	-0.08	0.12
Instructional	2.68	0.93	0.15	-0.24	0.01	-0.07
Personal	-1.92	-0.29	-0.05	-0.02	0.07	-0.09

```
res.ind |>
  group_by(Register, Level) |>
  summarise_if(is.numeric, mean) |>
  kable(digits = 2)
```

Register	Level	PC1	PC2	PC3	PC4	PC5	PC6
Conversation	A	-2.39	2.39	-1.23	0.71	-0.45	-0.01
Conversation	B	-2.54	1.72	-0.25	0.04	-0.14	0.13
Conversation	C	-2.25	0.70	0.18	-0.41	0.09	-0.02
Conversation	D	-2.10	-0.08	0.28	-0.73	0.17	0.09
Conversation	E	-2.13	-0.14	0.07	-0.98	0.16	0.17
Fiction	A	-0.95	0.85	-0.54	1.48	-0.31	-0.46
Fiction	B	-0.89	-0.14	0.95	1.78	-0.06	-0.03
Fiction	C	-0.98	-0.81	1.62	1.23	0.26	-0.16
Fiction	D	-0.71	-1.57	1.27	0.72	0.21	-0.01
Fiction	E	-0.80	-1.45	1.16	0.56	0.25	-0.01
Informative	A	-0.09	-1.11	-1.94	0.87	-0.88	-0.15
Informative	B	0.15	-1.67	-1.19	0.46	-0.38	0.13
Informative	C	-0.02	-2.37	-0.68	-0.03	-0.06	-0.01
Informative	D	0.06	-2.89	-0.45	-0.19	0.06	0.10
Informative	E	0.15	-3.13	-0.79	-0.38	0.30	0.43
Instructional	A	2.89	1.55	-0.20	0.46	-0.34	-0.24

Register	Level	PC1	PC2	PC3	PC4	PC5	PC6
Instructional	B	2.68	1.27	0.09	0.00	-0.12	-0.12
Instructional	C	2.59	0.99	0.28	-0.32	-0.07	0.01
Instructional	D	2.63	0.70	0.28	-0.49	0.12	0.07
Instructional	E	2.64	0.09	0.20	-0.80	0.49	-0.16
Personal	A	-1.84	0.53	-1.11	1.21	-0.31	0.12
Personal	B	-1.85	0.40	-0.58	0.59	0.21	-0.07
Personal	C	-2.05	-0.46	0.52	-0.17	0.06	-0.03
Personal	D	-1.89	-1.05	0.45	-0.63	0.39	-0.06
Personal	E	-1.96	-0.92	0.21	-1.10	-0.19	-0.45

The following chunk can be used to search for example texts that are located in specific areas of the biplots. For example, we can search for texts that have high scores on Dim3 and low ones on Dim2 to proceed with a qualitative comparison and analysis of these texts.

```
res.ind |>
  filter(PC3 > 2.5 & PC2 < -2) |>
  select(Filename, PC2, PC3) |>
  kable(digits = 2)
```

Filename	PC2	PC3
Achievers_B1_plus_Narrative_0005.txt	-3.88	2.60
Solutions_Intermediate_Plus_Spoken_0018.txt	-2.08	2.56
JTT_3_Narrative_0005.txt	-2.85	2.76
Achievers_B2_Narrative_00031.txt	-2.61	2.59
Access_4_Narrative_0006.txt	-2.19	3.18

F.10 Computing mixed-effects models of the dimension scores

F.10.1 Dimension 1: 'Overt instructions and explanations'

Having compared various models, the following model is chosen as the best-fitting one.

```
# Models with Textbook series as random intercepts
md1 <- lmer(PC1 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md1Register <- lmer(PC1 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md1Level <- lmer(PC1 ~ Level + (1|Series), data = res.ind, REML = FALSE)
```

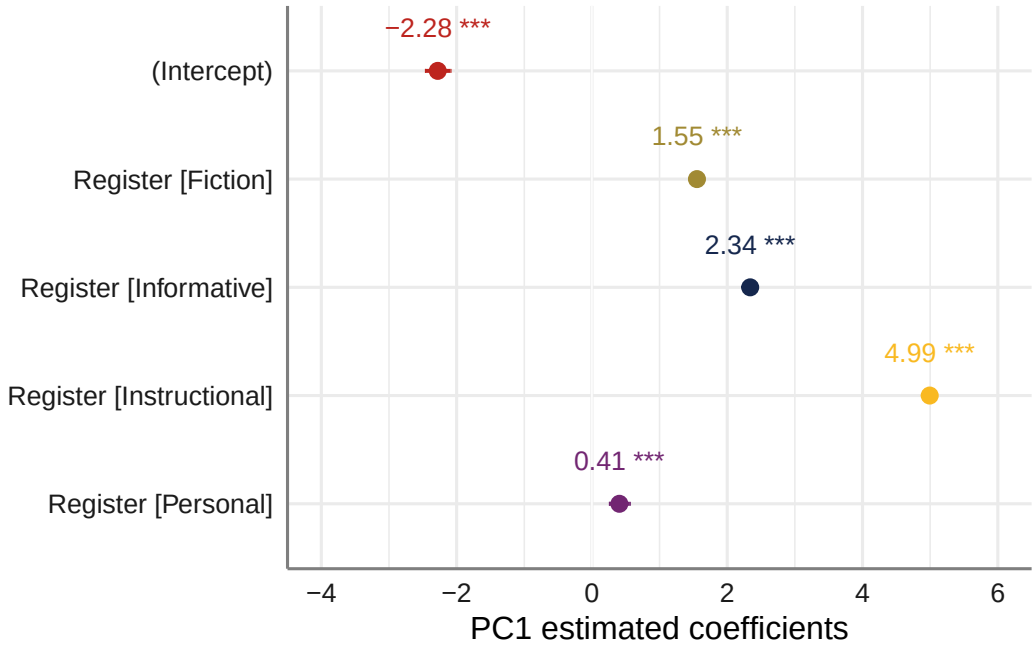
```
anova(md1, md1Register, md1Level)
```

```
Data: res.ind
Models:
md1Register: PC1 ~ Register + (1 | Series)
md1Level: PC1 ~ Level + (1 | Series)
md1: PC1 ~ Register * Level + (1 | Series)
            npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
md1Register    7 4080.4 4119.4 -2033.2   4066.4
md1Level       7 8533.0 8572.0 -4259.5   8519.0    0.0  0
md1           27 4068.3 4219.0 -2007.2   4014.3 4504.6 20  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tab_model(md1, wrap.labels = 300) # Marginal R2 = 0.890
```

Its estimated coefficients are visualised in the plot below.

```
# Plot of fixed effects:
plot_model(md1Register,
           type = "est",
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,8,7)],
           group.terms = c(1:5),
           title = "",
           wrap.labels = 40,
           axis.title = "PC1 estimated coefficients") +
  theme_sjplot2()
```




```
#ggsave(here("plots", "TxB_PCA1_lmer_fixedeffects_Register.svg"), height = 3,
 ↪  width = 8)
```

The `emmeans` and `pairs` functions are used to compare the estimated Dim1 scores for each register and to compare these to one another.

```
Register_results <- emmeans(md1Register, "Register")
summary(Register_results)
```

```
 Register       emmean    SE   df lower.CL upper.CL
 Conversation  -2.2793 0.102 11.6   -2.502   -2.056
 Fiction       -0.7267 0.106 13.9   -0.955   -0.498
 Informative    0.0603 0.104 12.7   -0.165    0.286
 Instructional  2.7141 0.101 11.3    2.492    2.937
 Personal      -1.8734 0.122 25.5   -2.125   -1.622

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95
```

```
comparisons <- pairs(Register_results, adjust = "tukey")
comparisons
```

```
 contrast                      estimate     SE   df  t.ratio p.value
 Conversation - Fiction          -1.553 0.0508 1963  -30.535  <.0001
 Conversation - Informative      -2.340 0.0465 1961  -50.341  <.0001
 Conversation - Instructional    -4.993 0.0399 1961 -125.141  <.0001
 Conversation - Personal         -0.406 0.0791 1958   -5.134  <.0001
 Fiction - Informative           -0.787 0.0557 1962  -14.135  <.0001
 Fiction - Instructional         -3.441 0.0497 1962  -69.168  <.0001
 Fiction - Personal               1.147 0.0840 1958   13.645  <.0001
 Informative - Instructional     -2.654 0.0447 1957  -59.399  <.0001
 Informative - Personal           1.934 0.0816 1957   23.692  <.0001
 Instructional - Personal         4.587 0.0780 1957   58.820  <.0001

Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 5 estimates
```

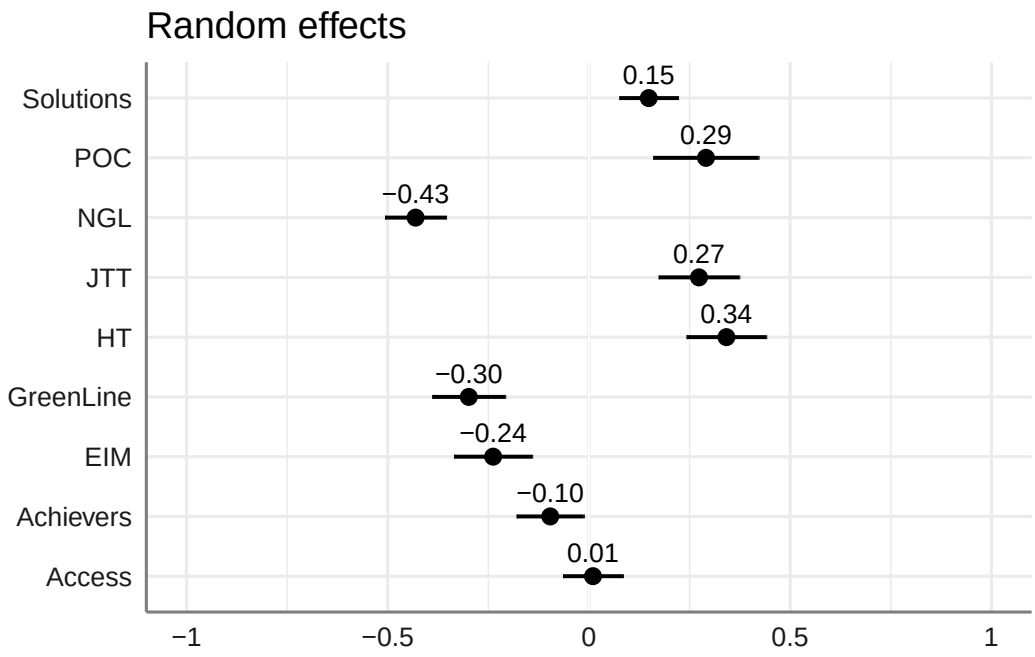
```
#write_last_clip()
confint(comparisons)
```

```
 contrast                      estimate     SE   df lower.CL upper.CL
 Conversation - Fiction          -1.553 0.0508 1963   -1.691   -1.414
 Conversation - Informative      -2.340 0.0465 1961   -2.466   -2.213
 Conversation - Instructional    -4.993 0.0399 1961   -5.102   -4.884
 Conversation - Personal         -0.406 0.0791 1958   -0.622   -0.190
 Fiction - Informative           -0.787 0.0557 1962   -0.939   -0.635
 Fiction - Instructional         -3.441 0.0497 1962   -3.577   -3.305
 Fiction - Personal               1.147 0.0840 1958    0.917    1.376
 Informative - Instructional     -2.654 0.0447 1957   -2.776   -2.532
 Informative - Personal           1.934 0.0816 1957    1.711    2.156
 Instructional - Personal         4.587 0.0780 1957    4.374    4.800

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95
Conf-level adjustment: tukey method for comparing a family of 5 estimates
```

```
#write_last_clip()
```

We can also visualise the estimated coefficients for the textbook series, which is modelled here as a random effect.

```
plot_model(md1,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = "bw",
           wrap.labels = 40,
           axis.title = "PC1 estimated coefficients") +
  theme_sjplot2()
```




```
#ggsave(here("plots", "TxB_PCA1_lmer_randomeffects.svg"), height = 3, width =
 ↪  8)
```

F.10.2 Dimension 2: 'Involved vs. Informational Production'

```
md2 <- lmer(PC2 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md2Register <- lmer(PC2 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md2Level <- lmer(PC2 ~ Level + (1|Series), data = res.ind, REML = FALSE)
anova(md2, md2Register, md2Level)
```

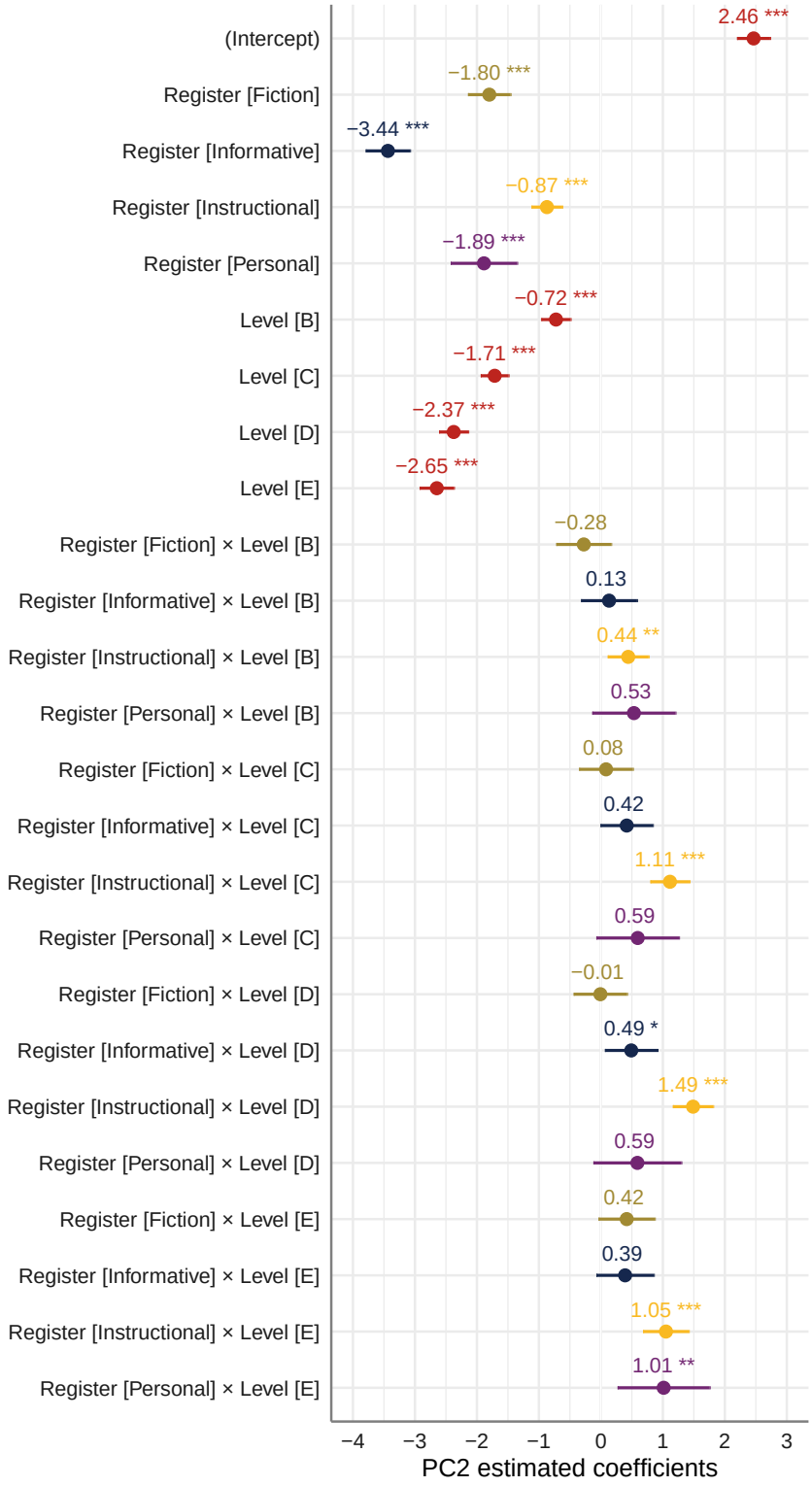
```
Data: res.ind
Models:
md2Register: PC2 ~ Register + (1 | Series)
md2Level: PC2 ~ Level + (1 | Series)
md2: PC2 ~ Register * Level + (1 | Series)
            npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
md2Register    7 6155.2 6194.3 -3070.6   6141.2
md2Level       7 7290.1 7329.2 -3638.1   7276.1    0.0  0
md2           27 5200.9 5351.6 -2573.4   5146.9 2129.2 20  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tab_model(md2) # Marginal R2 = 0.723
```

```
# tab_model(md2Register) # Marginal R2 = 0.558
# tab_model(md2Level) # Marginal R2 = 0.228
```

Estimated coefficients of fixed effects on Dim2 scores:

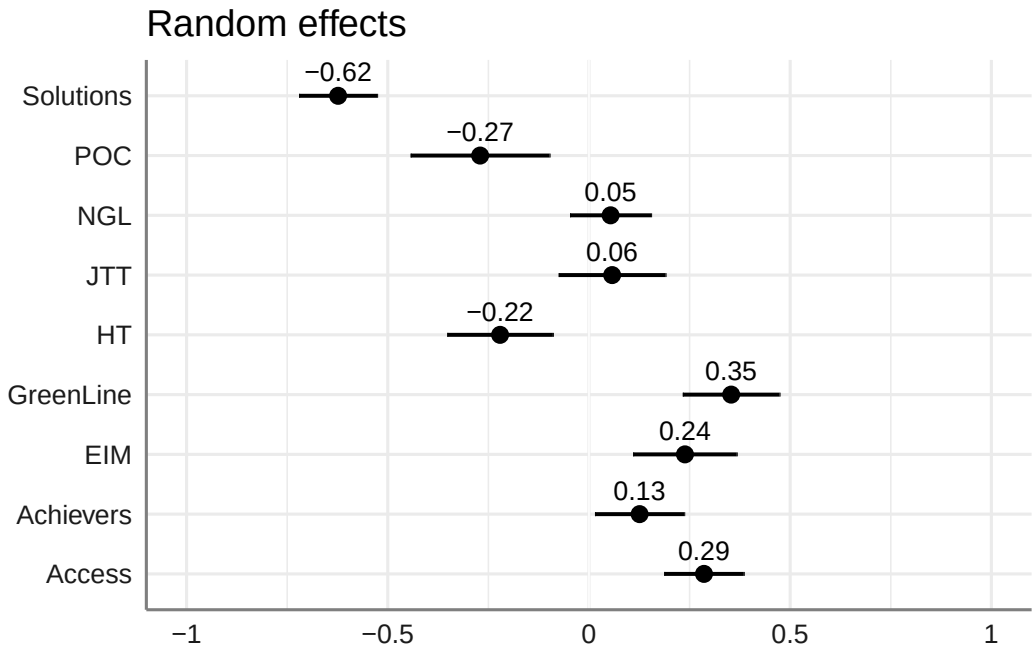
```
plot_model(md2,
           type = "est",
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,8,7)],
           group.terms = c(1:5,1,1,1,1,2:5,2:5,2:5,2:5),
           title = "",
           wrap.labels = 40,
           axis.title = "PC2 estimated coefficients") +
  theme_sjplot2()
```


(Intercept)
Register [Fiction]
Register [Informative]
Register [Instructional]
Register [Personal]
Level [B]
Level [C]
Level [D]
Level [E]
Register [Fiction] × Level [B]
Register [Informative] × Level [B]
Register [Instructional] × Level [B]
Register [Personal] × Level [B]
Register [Fiction] × Level [C]
Register [Informative] × Level [C]
Register [Instructional] × Level [C]
Register [Personal] × Level [C]
Register [Fiction] × Level [D]
Register [Informative] × Level [D]
Register [Instructional] × Level [D]
Register [Personal] × Level [D]
Register [Fiction] × Level [E]
Register [Informative] × Level [E]
Register [Instructional] × Level [E]
Register [Personal] × Level [E]
2.46 ***
−1.80 ***
−3.44 ***
−0.87 ***
−1.89 ***
−0.72 ***
−1.71 ***
−2.37 ***
−2.65 ***
−0.28
0.13
0.44 **
0.53
0.08
0.42
1.11 ***
0.59
−0.01
0.49 *
1.49 ***
0.59
0.42
0.39
1.05 ***
1.01 **
−4
−3
−2
−1
0
1
2
3
PC2 estimated coefficients

```
#ggsave(here("plots", "TxB_PCA2_lmer_fixedeffects.svg"), height = 8, width =
 ↪  8)
```

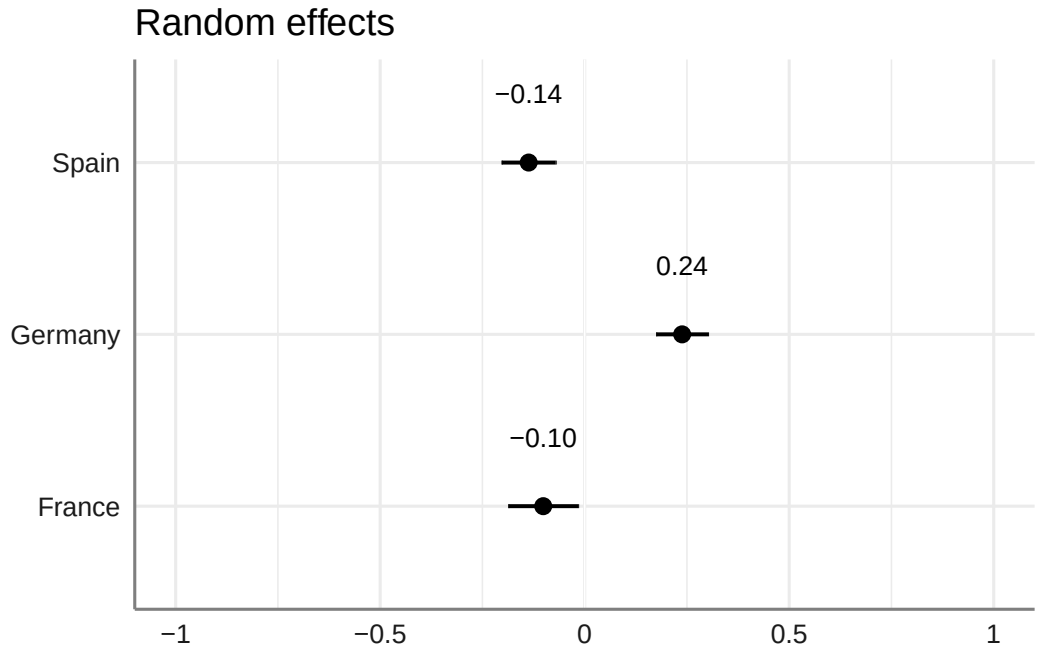
Estimated coefficients of random effects on Dim2 scores:

```
## Random intercepts
plot_model(md2,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = "bw",
           wrap.labels = 40,
           axis.title = "PC2 estimated coefficients") +
  theme_sjplot2()
```




```
#ggsave(here("plots", "TxB_PCA2_lmer_randomeffects.svg"), height = 3, width =
 ↪  8)

# Textbook Country as a random effect variable
```

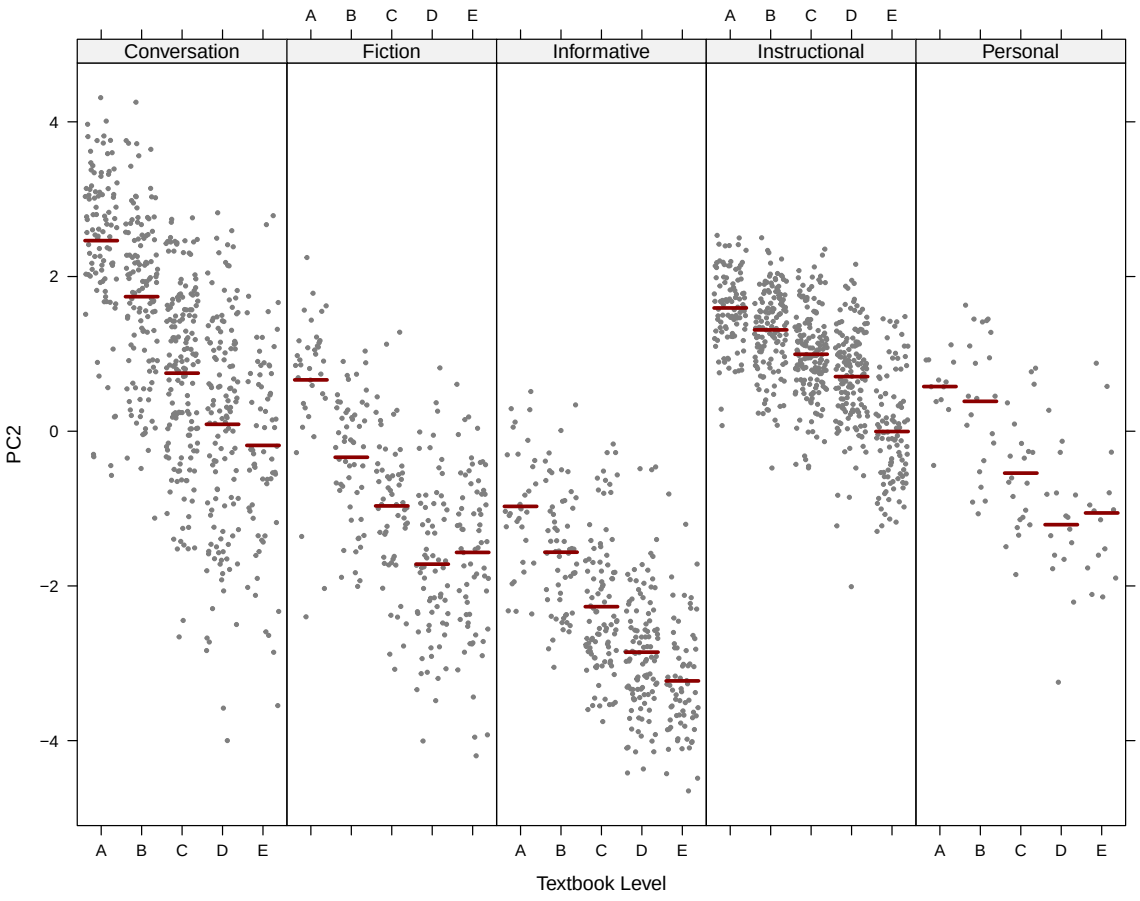
```
md2country <- lmer(PC2 ~ Register*Level + (1|Country), data = res.ind, REML =
 ↪  FALSE)

plot_model(md2country,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = "bw",
           wrap.labels = 40,
           axis.title = "PC2 estimated coefficients") +
  theme_sjplot2()
```



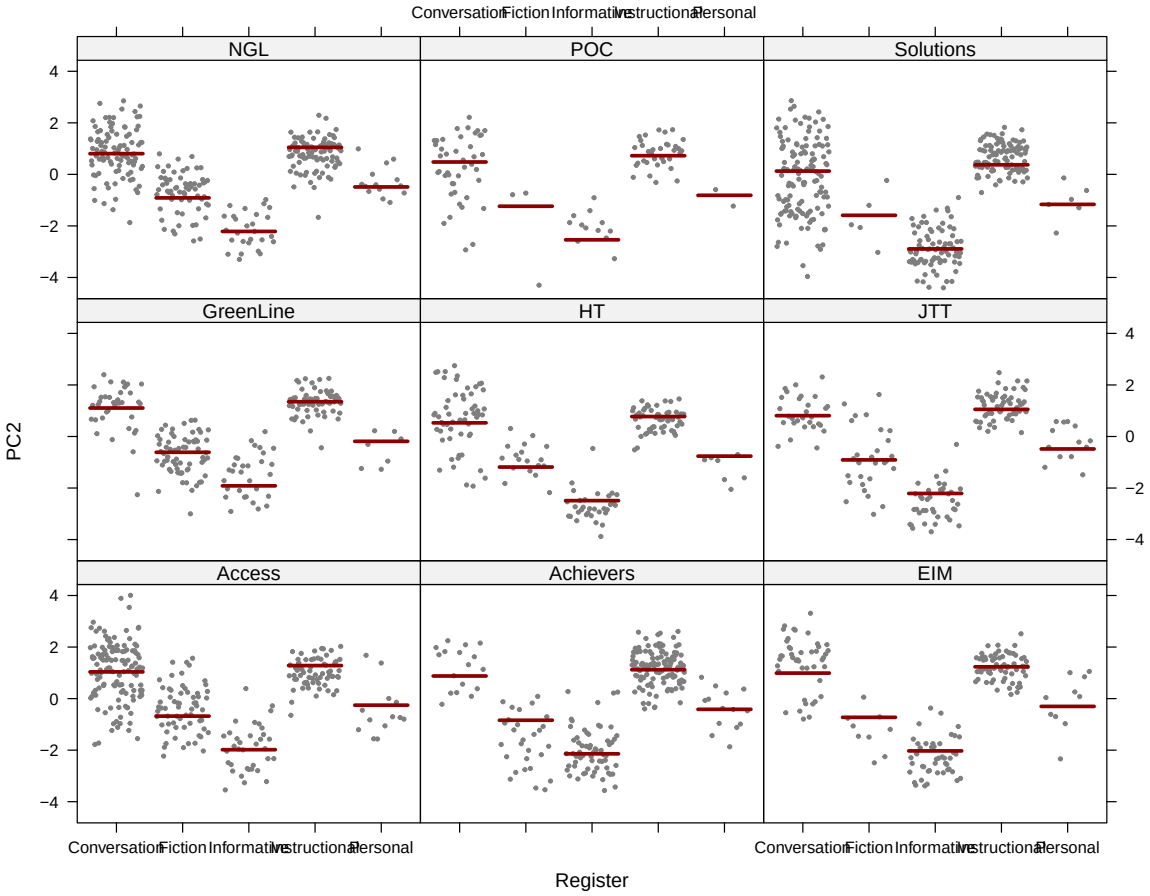

```
#ggsave(here("plots", "TxB_PCA2_lmer_randomeffects_country.svg"), height = 3,
 ↪  width = 8)
```

The `visreg` function is used to visualise the distributions of the modelled Dim2 scores:

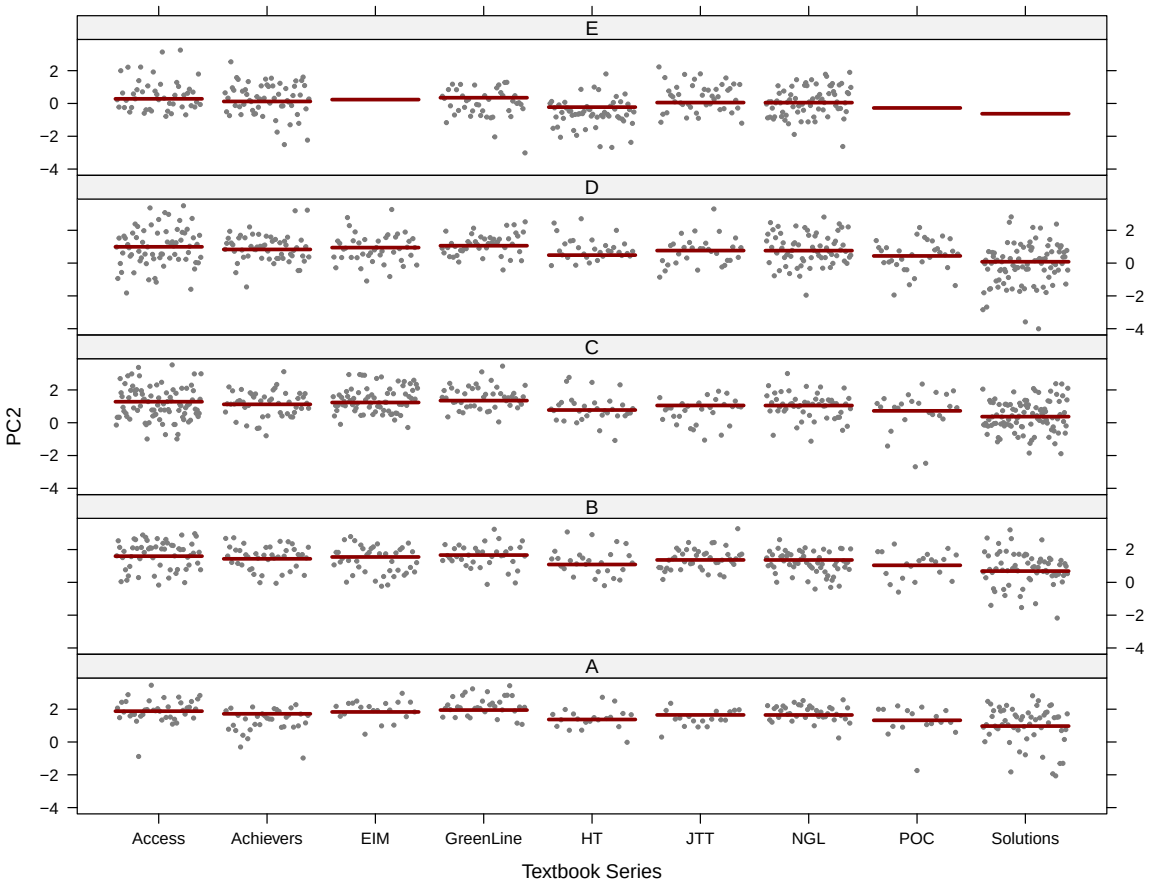
```
# svg(here("plots", "TxB_predicted_PC2_scores_interactions.svg"), height = 5,
 ↪  width = 8)
visreg(md2, xvar = "Level", by="Register", type = "conditional",
       line=list(col="darkred"),
       xlab = "Textbook Level", ylab = "PC2"
       #,gg = TRUE
       ,layout=c(5,1)
)
```



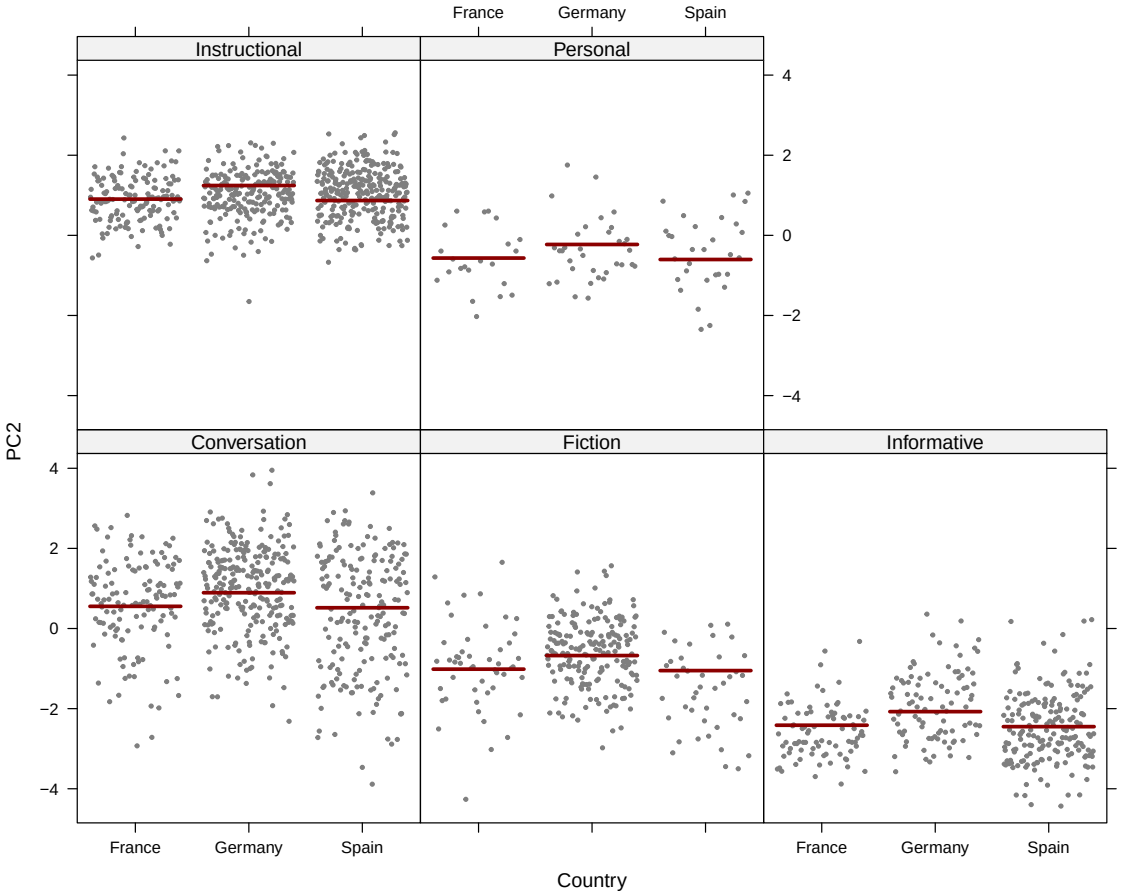

```
# dev.off()

# Textbook Series-Register interactions
visreg::visreg(md2, "Register", by="Series", re.form=~(1|Series),
               ylab="PC2", line=list(col="darkred"))
```




```
visreg(md2, xvar = "Series", by="Level", type = "conditional",
 ↪  re.form=~(1|Series),
       line=list(col="darkred"), xlab = "Textbook Series", ylab = "PC2",
       layout=c(1,5))
```




```
# Textbook Series-Register interactions
# svg(here("plots", "TxB_PCA2_lmer_randomeffects_country_register.svg"),
 ↪  height = 5, width = 8)
visreg::visreg(md2country, "Country", by="Register", re.form=~(1|Country),
               ylab="PC2", line=list(col="darkred"))
```




```
# dev.off()
```

F.10.3 Dimension 3: 'Narrative vs. factual discourse'

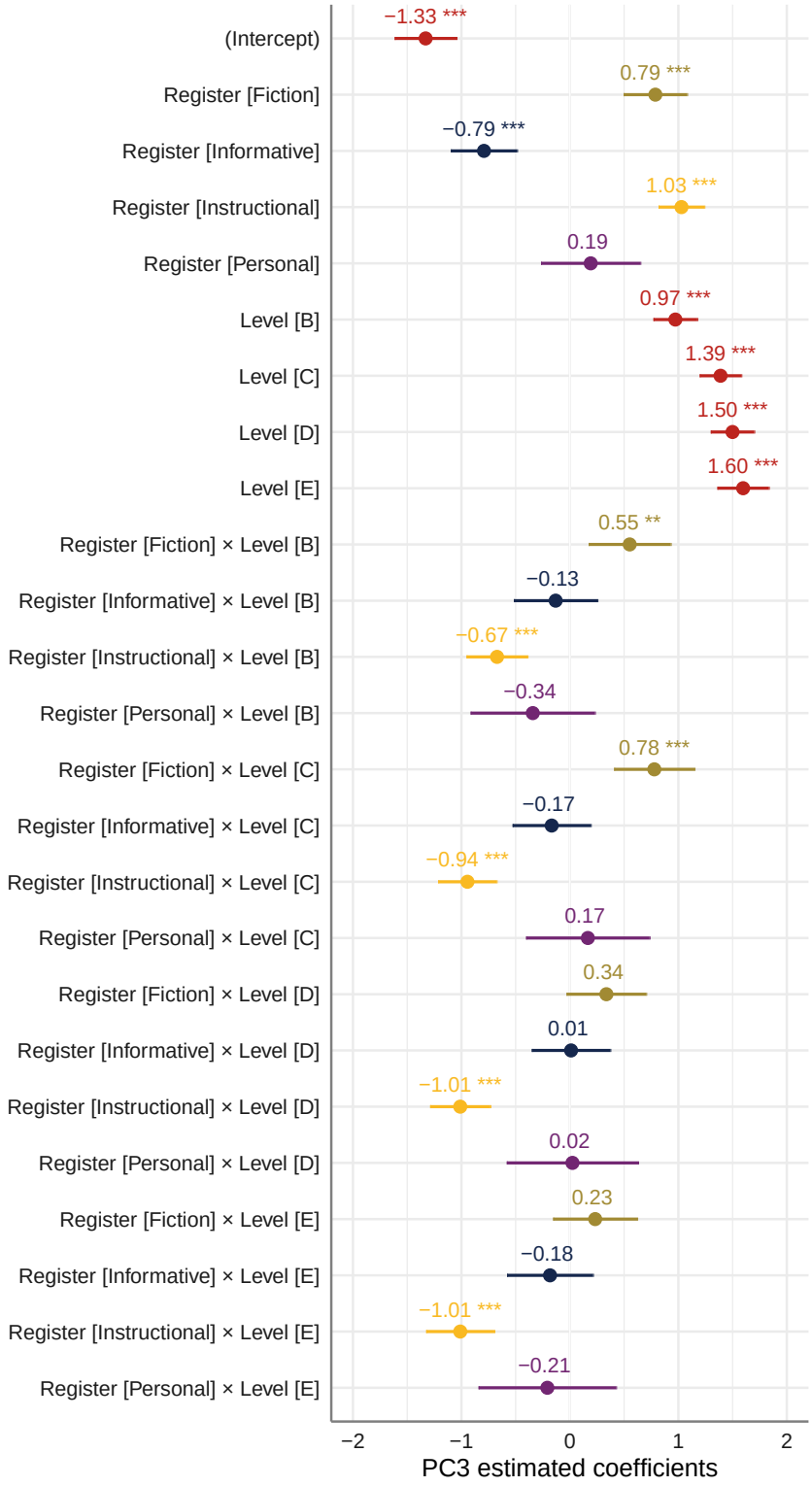
```
md3 <- lmer(PC3 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md3Register <- lmer(PC3 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md3Level <- lmer(PC3 ~ Level + (1|Series), data = res.ind, REML = FALSE)

anova(md3, md3Register, md3Level)
```

```
Data: res.ind
```

```
Models:
md3Register: PC3 ~ Register + (1 | Series)
md3Level: PC3 ~ Level + (1 | Series)
md3: PC3 ~ Register * Level + (1 | Series)
            npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
md3Register    7 5139.9 5179.0 -2563.0   5125.9
md3Level       7 5528.8 5567.9 -2757.4   5514.8   0.00  0
md3           27 4582.6 4733.3 -2264.3   4528.6 986.21 20  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

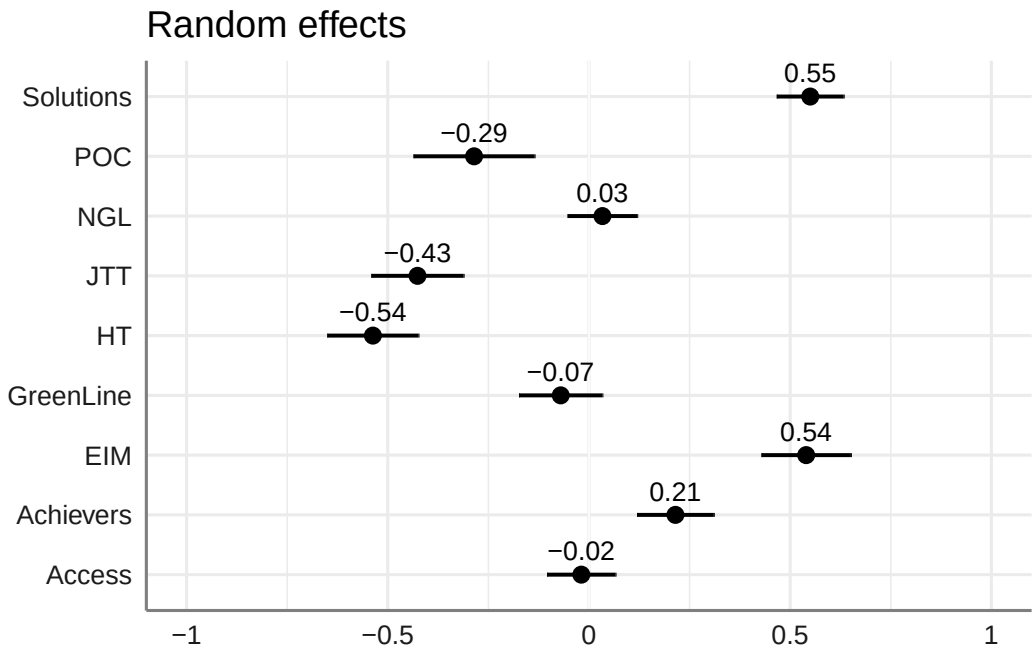
```
tab_model(md3) # Marginal R2 = 0.436
```

```
# tab_model(md3Register) # Marginal R2 = 0.272
# tab_model(md3Level) # Marginal R2 = 0.119

# Plot of fixed effects:
plot_model(md3,
           type = "est",
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,8,7)],
           group.terms = c(1:5,1,1,1,1,2:5,2:5,2:5,2:5),
           title = "",
           wrap.labels = 40,
           axis.title = "PC3 estimated coefficients") +
  theme_sjplot2()
```


−1.33 ***
(Intercept)
0.79 ***
Register [Fiction]
−0.79 ***
Register [Informative]
1.03 ***
Register [Instructional]
0.19
Register [Personal]
0.97 ***
Level [B]
1.39 ***
Level [C]
1.50 ***
Level [D]
1.60 ***
Level [E]
0.55 **
Register [Fiction] × Level [B]
−0.13
Register [Informative] × Level [B]
−0.67 ***
Register [Instructional] × Level [B]
−0.34
Register [Personal] × Level [B]
0.78 ***
Register [Fiction] × Level [C]
−0.17
Register [Informative] × Level [C]
−0.94 ***
Register [Instructional] × Level [C]
0.17
Register [Personal] × Level [C]
0.34
Register [Fiction] × Level [D]
0.01
Register [Informative] × Level [D]
−1.01 ***
Register [Instructional] × Level [D]
0.02
Register [Personal] × Level [D]
0.23
Register [Fiction] × Level [E]
−0.18
Register [Informative] × Level [E]
−1.01 ***
Register [Instructional] × Level [E]
−0.21
Register [Personal] × Level [E]
−2
−1
0
1
2
PC3 estimated coefficients

```
#ggsave(here("plots", "TxB_PCA3_lmer_fixedeffects.svg"), height = 8, width =
 ↪  8)
```

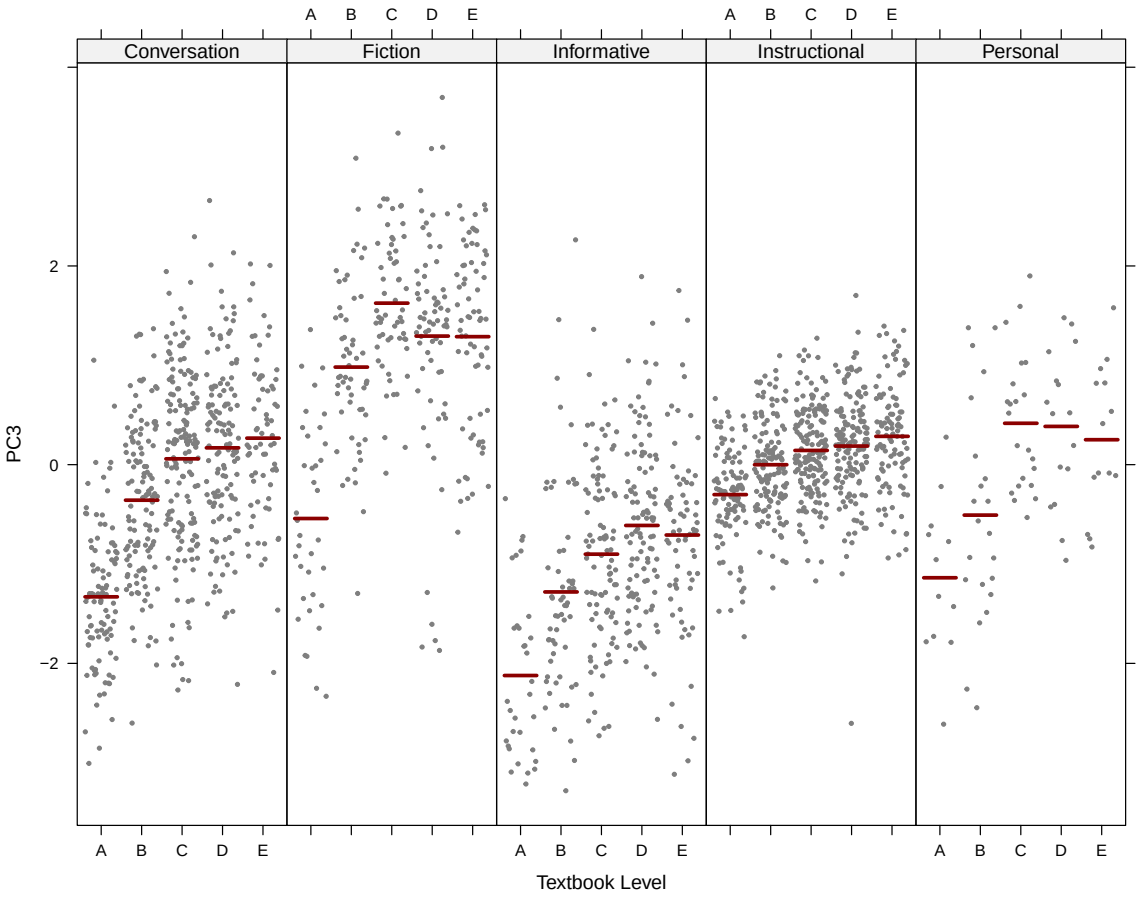
```
# Plot of random effects:
plot_model(md3,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           color = "bw",
           wrap.labels = 40,
           axis.title = "PC3 estimated coefficients") +
  theme_sjplot2()
```



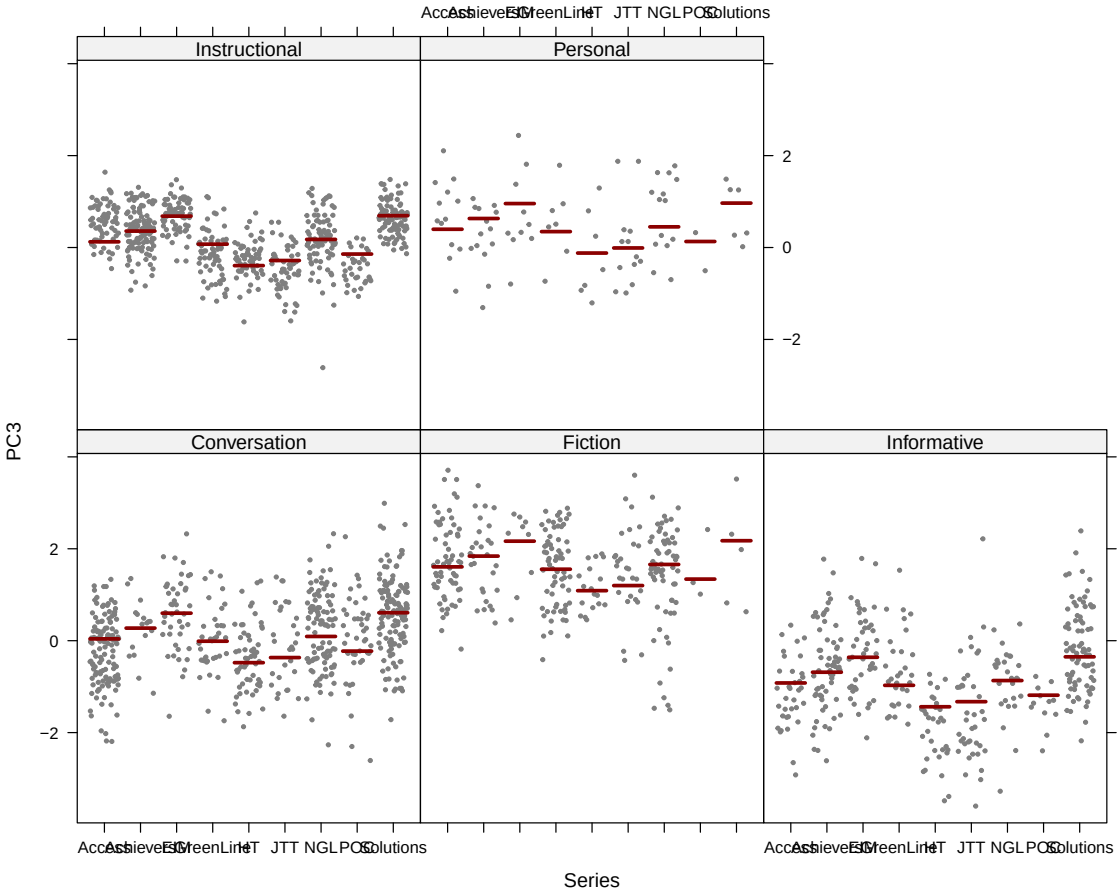

```
#ggsave(here("plots", "TxB_PCA3_lmer_randomeffects.svg"), height = 3, width =
 ↪  8)
```

```
# svg(here("plots", "TxB_predicted_PC3_scores_interactions.svg"), height = 5,
 ↪  width = 8)
visreg(md3, xvar = "Level", by="Register", type = "conditional",
```

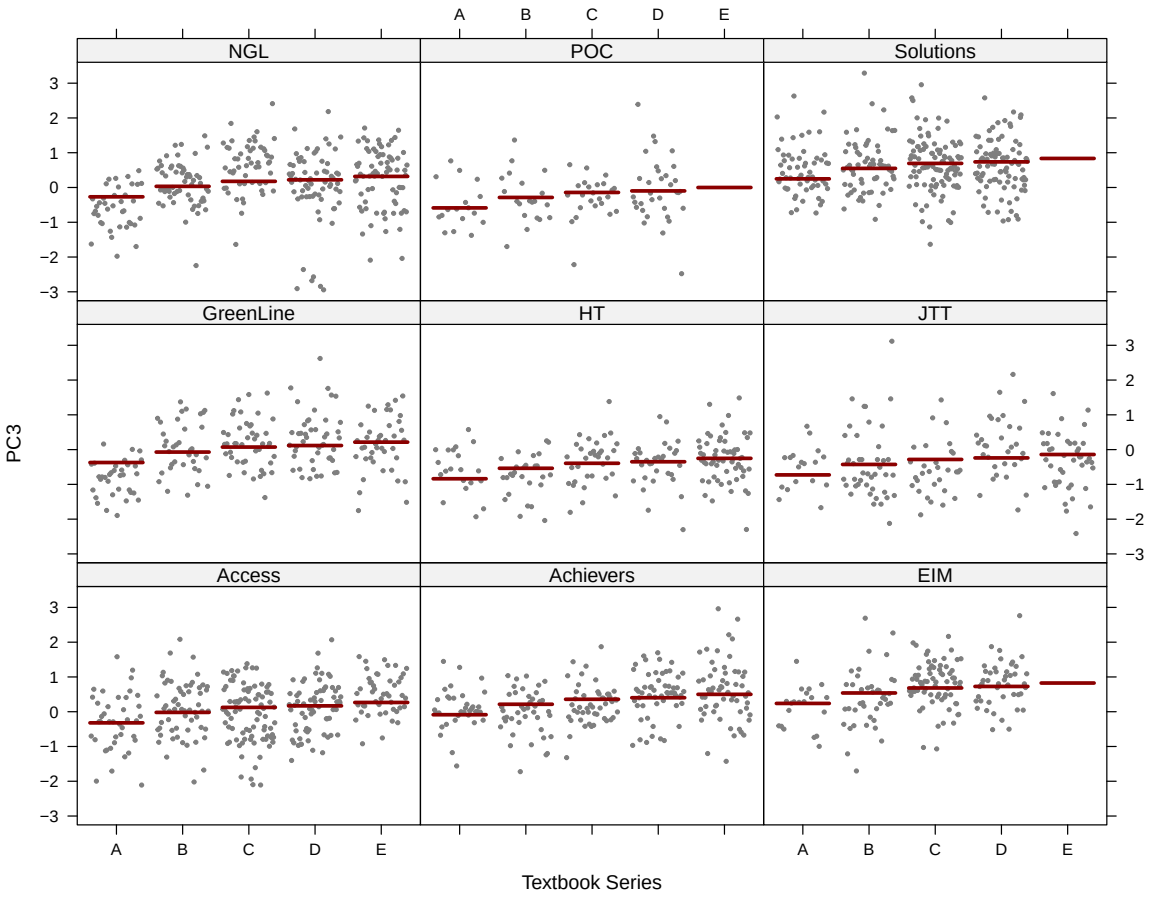
```
        line=list(col="darkred"),
        xlab = "Textbook Level", ylab = "PC3"
        #,gg = TRUE
        ,layout=c(5,1)
)
```




```
# dev.off()

# Textbook Series-Register interactions
visreg::visreg(md3, "Series", by="Register", re.form=~(1|Series),
               ylab="PC3", line=list(col="darkred"))
```




```
visreg(md3, xvar = "Level", by="Series", type = "conditional",
 ↪  re.form=~(1|Series),
      line=list(col="darkred"), xlab = "Textbook Series", ylab = "PC3")
```



F.10.4 Dimension 4: 'Informational compression vs. elaboration'

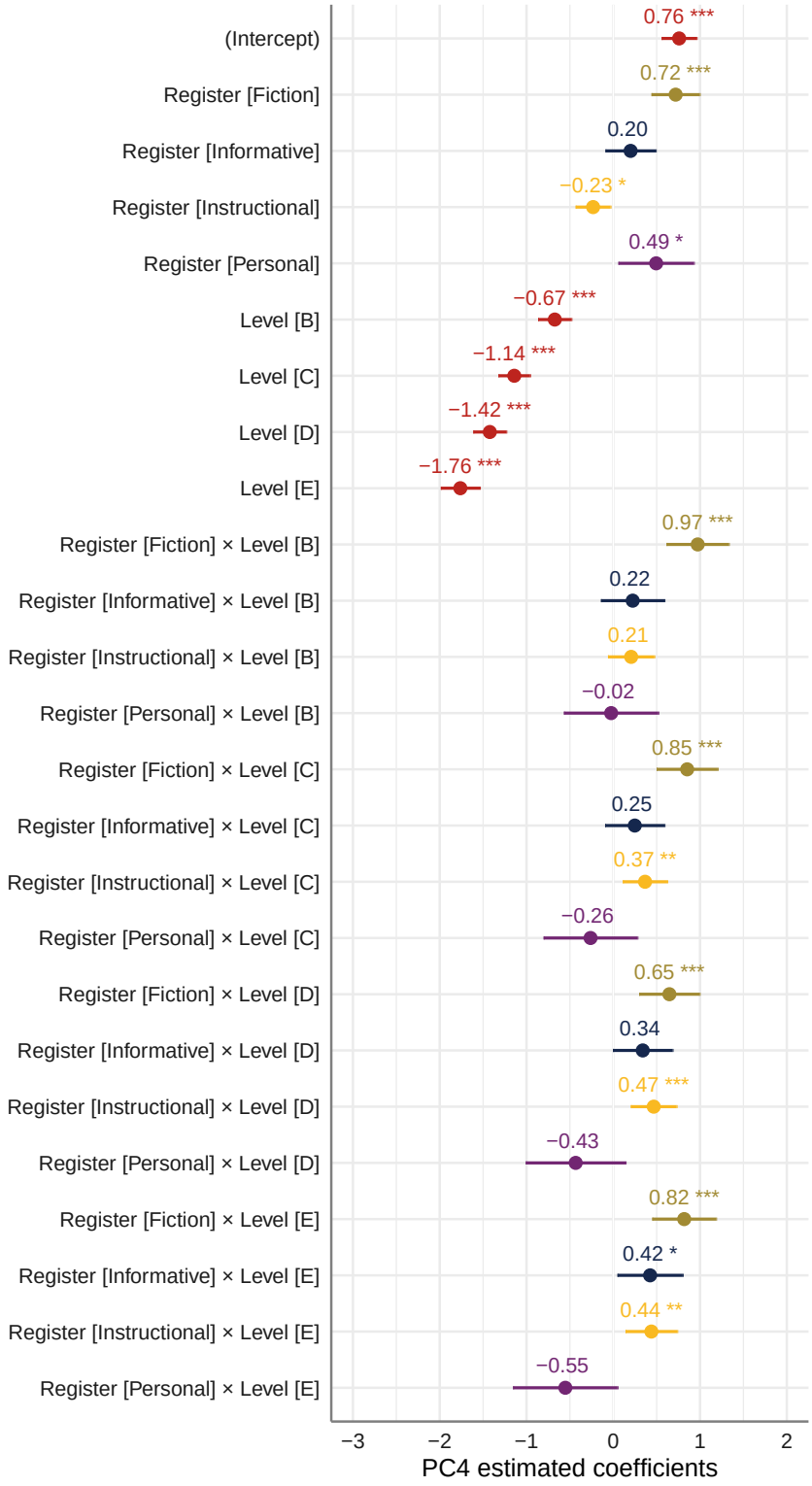
```
md4 <- lmer(PC4 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md4Register <- lmer(PC4 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md4Level <- lmer(PC4 ~ Level + (1|Series), data = res.ind, REML = FALSE)

anova(md4, md4Register, md4Level)
```

```
Data: res.ind
Models:
md4Register: PC4 ~ Register + (1 | Series)
md4Level: PC4 ~ Level + (1 | Series)
```

```
md4: PC4 ~ Register * Level + (1 | Series)
            npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
md4Register    7 5034.0 5073.0 -2510.0   5020.0
md4Level       7 5043.6 5082.7 -2514.8   5029.6   0.00  0
md4           27 4372.1 4522.8 -2159.1   4318.1 711.52 20  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

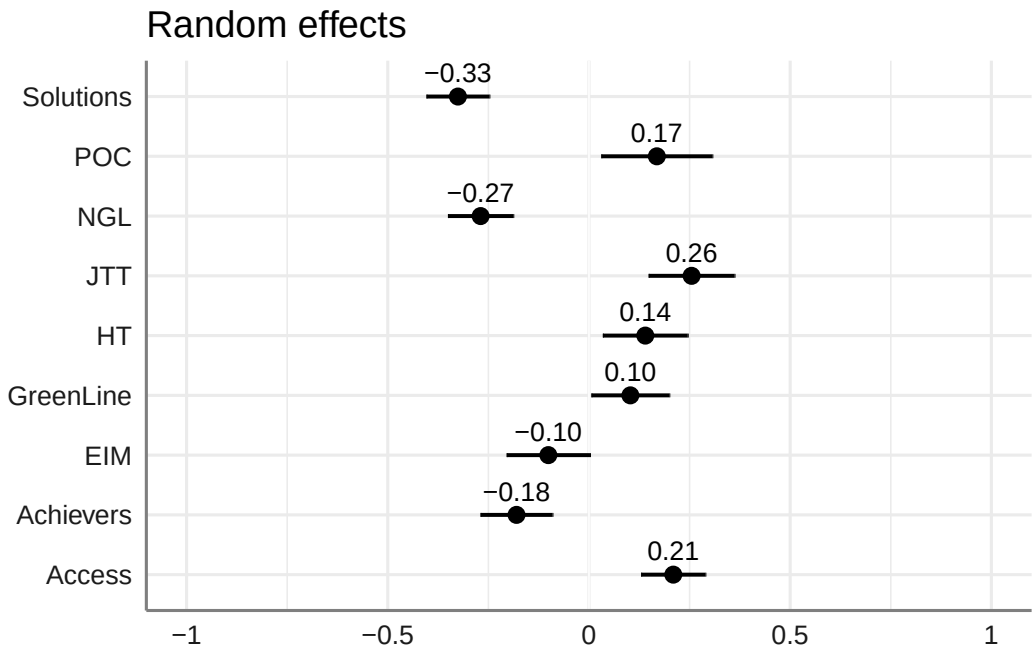
```
tab_model(md4) # Marginal R2 = 0.426
```

```
# tab_model(md4Register) # Marginal R2 = 0.203
# tab_model(md4Level) # Marginal R2 = 0.187

# Plot of fixed effects:
plot_model(md4,
           type = "est",
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,8,7)],
           group.terms = c(1:5,1,1,1,1,2:5,2:5,2:5,2:5),
           title = "",
           wrap.labels = 40,
           axis.title = "PC4 estimated coefficients") +
  theme_sjplot2()
```


(Intercept)
Register [Fiction]
Register [Informative]
Register [Instructional]
Register [Personal]
Level [B]
Level [C]
Level [D]
Level [E]
Register [Fiction] × Level [B]
Register [Informative] × Level [B]
Register [Instructional] × Level [B]
Register [Personal] × Level [B]
Register [Fiction] × Level [C]
Register [Informative] × Level [C]
Register [Instructional] × Level [C]
Register [Personal] × Level [C]
Register [Fiction] × Level [D]
Register [Informative] × Level [D]
Register [Instructional] × Level [D]
Register [Personal] × Level [D]
Register [Fiction] × Level [E]
Register [Informative] × Level [E]
Register [Instructional] × Level [E]
Register [Personal] × Level [E]
0.76 ***
0.72 ***
0.20
−0.23 *
0.49 *
−0.67 ***
−1.14 ***
−1.42 ***
−1.76 ***
0.97 ***
0.22
0.21
−0.02
0.85 ***
0.25
0.37 **
−0.26
0.65 ***
0.34
0.47 ***
−0.43
0.82 ***
0.42 *
0.44 **
−0.55
−3
−2
−1
0
1
2
PC4 estimated coefficients

```
#ggsave(here("plots", "TxB_PCA4_lmer_fixedeffects.svg"), height = 8, width =
 ↪  8)
```

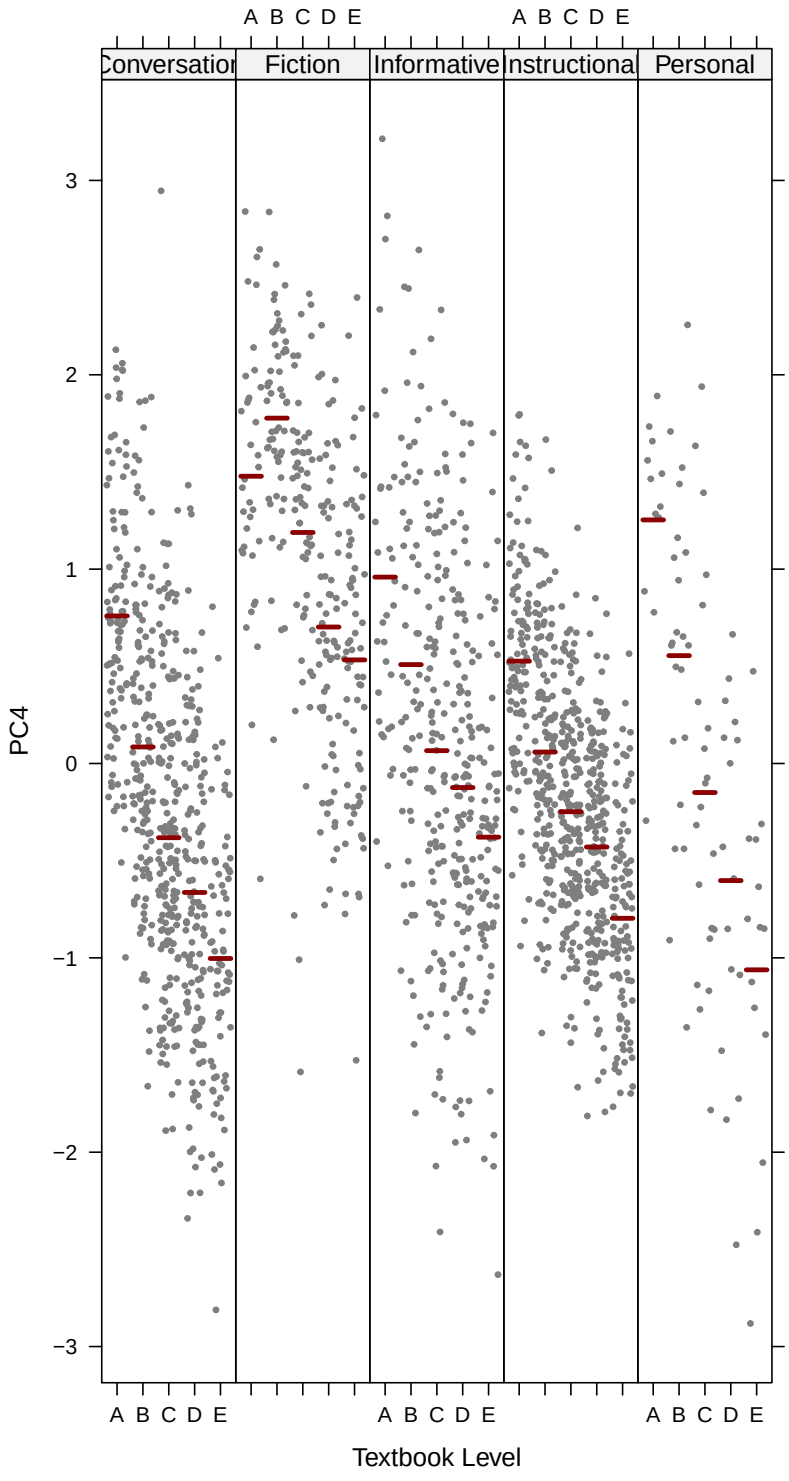
```
# Plot of random effects:
plot_model(md4,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           color = "bw",
           wrap.labels = 40,
           axis.title = "PC4 estimated coefficients") +
  theme_sjplot2()
```




```
#ggsave(here("plots", "TxB_PCA4_lmer_randomeffects.svg"), height = 3, width =
 ↪  8)
```

```
# svg(here("plots", "TxB_predicted_PC4_scores_interactions.svg"), height = 5,
 ↪  width = 8)
visreg(md4, xvar = "Level", by="Register", type = "conditional",
```

```
        line=list(col="darkred"),
        xlab = "Textbook Level", ylab = "PC4"
        #,gg = TRUE
        ,layout=c(5,1)
)
```

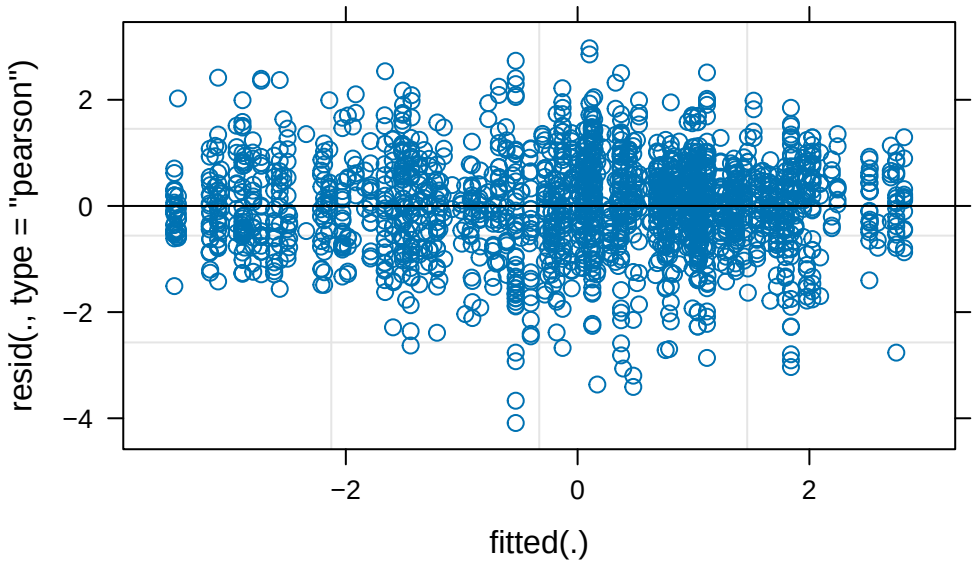

A B C D E
A B C D E
Conversation
Fiction
Informative
Instructiona
Personal
3
2
1
0
−1
−2
−3
PC4
A B C D E
A B C D E
A B C D E
Textbook Level

```
# dev.off()
```

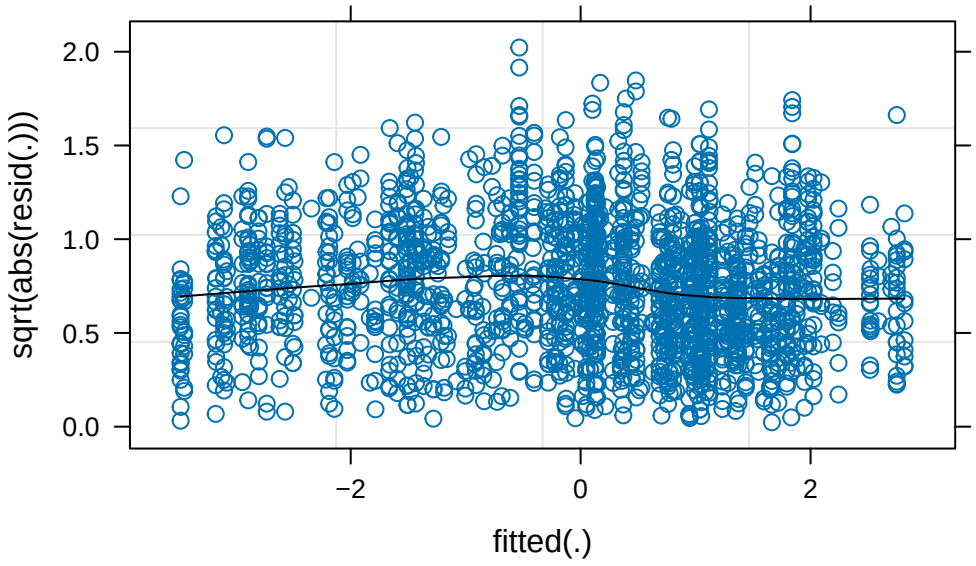
F.10.5 Testing model assumptions

This chunk can be used to check the assumptions of all of the models computed above. In the following example, we examine the final model selected to predict Dim2 scores.

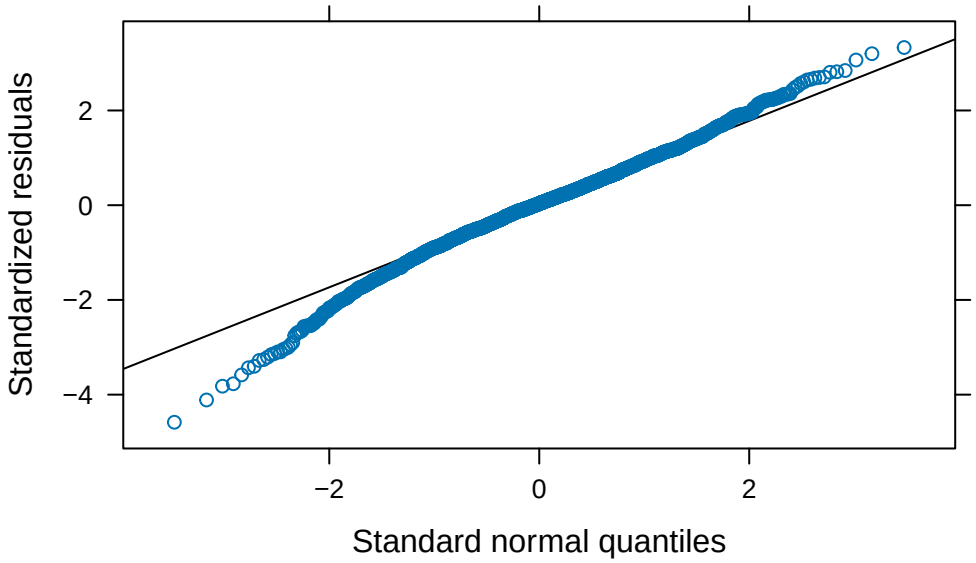
```
model2test <- md2

# check distribution of residuals
plot(model2test)
```




```
# scale-location plot
plot(model2test,
     sqrt(abs(resid(.)))~fitted(.),
     type=c("p","smooth"), col.line=1)
```




```
# Q-Q plot
lattice::qqmath(model2test)
```



G Data Preparation for the Model of Textbook English vs. 'real-world' English

This script documents the steps taken to pre-process the data extracted from the Textbook English Corpus (TEC) and the three reference corpora that were ultimately entered in the comparative multi-dimensional model of Textbook English as compared to English outside the EFL classroom (Chapter 7).

G.1 Packages required

The following packages must be installed and loaded to process the data.

```
#renv::restore() # Restore the project's dependencies from the lockfile to
 ↪  ensure that same package versions are used as in the original thesis.

library(broom.mixed) # For checking singularity issues
library(car) # For recoding data
library(corrplot) # For the feature correlation matrix
library(cowplot) # For nice plots
library(DT) # To display interactive HTML tables
library(emmeans) # Comparing group means of predicted values
library(GGally) # For ggpairs
library(gridExtra) # For making large faceted plots
library(here) # For ease of sharing
library(knitr) # Loaded to display the tables using the kable() function
library(lme4) # For mixed effects modelling
library(psych) # For various useful stats function, including KMO()
library(scales) # For working with colours
library(sjPlot) # For nice tabular display of regression models
library(tidyverse) # For data wrangling and plotting
library(visreg) # For nice visualisations of model results
select <- dplyr::select
filter <- dplyr::filter
```

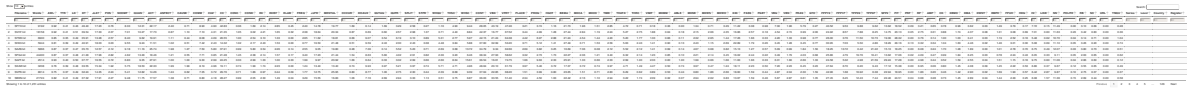
G.2 Data import from MFTE outputs

The raw data used in this script comes from the matrices of mixed normalised frequencies as output by the MFTE Perl v. 3.1 (Le Foll 2021b).

G.2.1 Spoken BNC2014

```
SpokenBNC2014 <- read.delim(here("data", "MFTE",
 ↪  "SpokenBNC2014_3.1_normed_complex_counts.tsv"), header = TRUE,
 ↪  stringsAsFactors = TRUE)

SpokenBNC2014$Series <- "Spoken BNC2014"
SpokenBNC2014$Level <- "Ref."
SpokenBNC2014$Country <- "Spoken BNC2014"
SpokenBNC2014$Register <- "Spoken BNC2014"
```

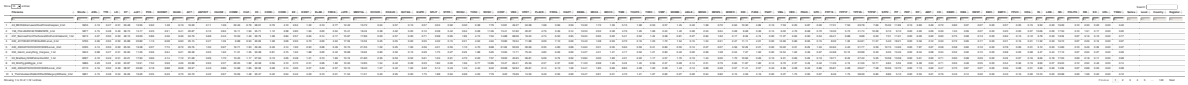
These normalised frequencies were computed on the basis of my own "John and Jill in Ivybridge" version of the Spoken BNC2014 with added full stops at speaker turns (see Appendix B for details). This corpus comprises of 1,251 texts, all of which were used in the following analyses.



G.2.2 Youth Fiction corpus

```
YouthFiction <- read.delim(here("data", "MFTE",
 ↪  "YF_sampled_500_3.1_normed_complex_counts.tsv"), header = TRUE,
 ↪  stringsAsFactors = TRUE)

YouthFiction$Series <- "Youth Fiction"
YouthFiction$Level <- "Ref."
YouthFiction$Country <- "Youth Fiction"
YouthFiction$Register <- "Youth Fiction"
```

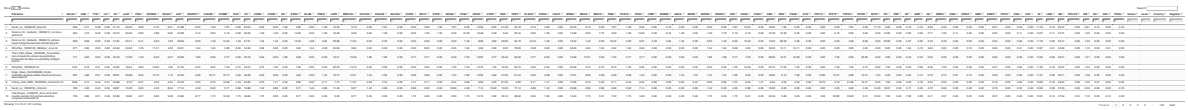
These normalised frequencies were computed on the basis of the random samples of approximately 5,000 words of the books of the Youth Fiction corpus (for details of the works included in this corpus, see Appendix B). The sampling procedure is described in Section 4.3.2.4 of the book. This dataset consists of 1,191 files.



G.2.3 Informative Texts for Teens (InfoTeens) corpus

```
InfoTeen <- read.delim(here("data", "MFTE",
 ↪  "InfoTeen_3.1_normed_complex_counts.tsv"), header = TRUE,
 ↪  stringsAsFactors = TRUE)

# Removes three outlier files which should not have been included in the
 ↪  corpus as they contain exam papers only
InfoTeen <- InfoTeen |>
  filter(Filename!=".DS_Store" &
   ↪  Filename!="Revision_World_GCSE_10529068_wjec-level-law-past-papers.txt"
   ↪  &
   ↪  Filename!="Revision_World_GCSE_10528474_wjec-level-history-past-papers.txt"
   ↪  &
   ↪  Filename!="Revision_World_GCSE_10528472_edexcel-level-history-past-papers.txt")

InfoTeen$Series <- "Info Teens"
InfoTeen$Level <- "Ref."
InfoTeen$Country <- "Info Teens"
InfoTeen$Register <- "Info Teens"
```

Details of the composition of the Info Teens corpus can be found in Section 4.3.2.5 of the book. The version used in the present study comprises 1,411 texts.



G.3 Merging TEC and reference corpora data

G.3.1 Corpus size

These tables provide some summary statistics about the texts/files whose normalised feature frequencies were entered in the model of Textbook English vs. real-world English described in Chapter 7.

```
summary(ncounts$Subcorpus) |>
  kable(col.names = c("(Sub)corpus", "# texts"),
        format.args = list(big.mark = ","))
```

(Sub)corpus	# texts
Textbook Conversation	593
Textbook Fiction	285
Info Teens Ref.	1,411
Textbook Informative	364
Spoken BNC2014 Ref.	1,251
Youth Fiction Ref.	1,191

```
ncounts  |>
  group_by(Register) |>
  summarise(totaltexts = n(),
            totalwords = sum(Words),
            mean = as.integer(mean(Words)),
            sd = as.integer(sd(Words)),
            TTRmean = mean(TTR)) |>
  kable(digits = 2,
        format.args = list(big.mark = ","),
        col.names = c("Register", "# texts/files", "# words", "mean # words
         ↪  per text", "SD", "mean TTR"))
```

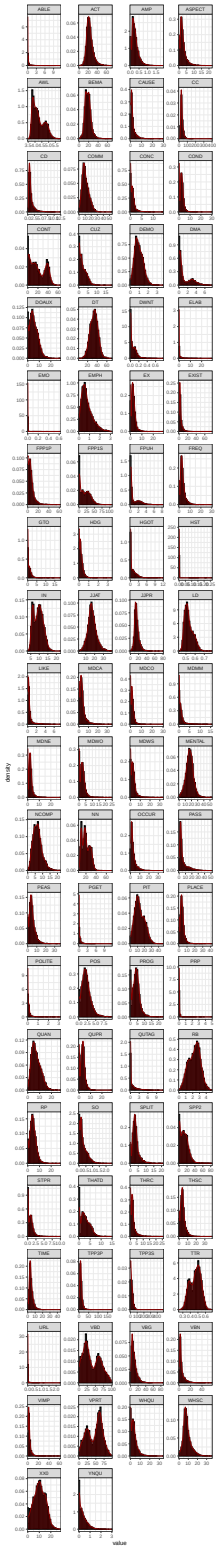
Register	# texts/files	# words	mean # words per text	SD	mean TTR
Conversation	1,844	13,804,196	7,486	8,690	0.40
Fiction	1,476	7,321,747	4,960	2,022	0.49
Informative	1,775	1,436,732	809	188	0.51

G.4 Data preparation for PCA

G.4.1 Feature distributions

The distributions of each linguistic features were examined by means of visualisation. As shown below, before transformation, many of the features displayed highly skewed distributions.

```
#ncounts <- readRDS(here("data", "processed", "counts3Reg.rds"))

ncounts |>
  select(-Words) |>
  keep(is.numeric) |>
  gather() |> # This function from tidyr converts a selection of variables
   ↪  into two variables: a key and a value. The key contains the names of
   ↪  the original variable and the value the data. This means we can then
   ↪  use the facet_wrap function from ggplot2
  ggplot(aes(value, after_stat(density))) +
    theme_bw() +
    facet_wrap(~ key, scales = "free", ncol = 4) +
    scale_x_continuous(expand=c(0,0)) +
    scale_y_continuous(limits = c(0,NA)) +
    geom_histogram(bins = 30, colour= "black", fill = "grey") +
    geom_density(colour = "darkred", weight = 2, fill="darkred", alpha = .4)
```


ABLE
ACT
AMP
ASPECT
AWL
BEMA
CAUSE
CC
CD
COMM
CONC
COND
CONT
CU2
DEMO
DMA
DOAUX
EF
EMINT
ELAB
EMO
EMPH
EX
EXIST
FPP1P
FPP1S
FPSH
FREQ
GTO
HDG
HGOT
HAT
IN
JJAT
JJPR
LD
LIKE
MOCA
MOCO
MOMM
MONE
MOMO
MOWS
MENTAL
NCOMP
NN
OCCUR
PASS
PEAS
PGET
PIT
PLACE
POLITE
POS
PROG
PRP
QUAN
QUPR
QUTAG
RB
RP
SO
SPLIT
SPPO
STPR
THATO
THEC
THSC
TIME
TPP3P
TPP3S
TTR
URL
VBD
VBG
VBN
VIMP
VPRT
WHQU
WHSC
XXE
TAQU
density
value

```
#ggsave(here("plots", "DensityPlotsAllVariables.svg"), width = 15, height =
 ↪  49)
```

G.4.2 Feature removal

A number of features were removed from the dataset as they are not linguistically interpretable. In the case of the TEC, this included the variable CD because numbers spelt out as digits were removed from the textbooks before these were tagged with the MFTE. In addition, the variables LIKE and SO because these are "bin" features included in the output of the MFTE to ensure that the counts for these polysemous words do not inflate other categories due to mistags (Le Foll 2021c).

Whenever linguistically meaningful, very low-frequency features, features with low MSA or communalities (see chunks below) were merged. Finally, features absent from more than third of texts were also excluded. For the comparative analysis of TEC and the reference corpora, the following linguistic features were excluded from the analysis due to low dispersion:

```
# Removal of meaningless feature: CD because numbers as digits were mostly
 ↪  removed from the textbooks, LIKE and SO because they are dustbin
 ↪  categories
ncounts <- ncounts |>
  select(-c(CD, LIKE, SO))

# Combine problematic features into meaningful groups whenever this makes
 ↪  linguistic sense
ncounts <- ncounts |>
  mutate(JJPR = JJPR + ABLE, ABLE = NULL) |>
  mutate(PASS = PGET + PASS, PGET = NULL) |>
  mutate(TPP3 = TPP3S + TPP3P, TPP3P = NULL, TPP3S = NULL) |> # Merged due to
   ↪  TTP3P having an individual MSA < 0.5
  mutate(FQTI = FREQ + TIME, FREQ = NULL, TIME = NULL) # Merged due to TIME
   ↪  communality < 0.2 (see below)

# Function to compute percentage of texts with occurrences meeting a
 ↪  condition
compute_percentage <- function(data, condition, threshold) {
  numeric_data <- Filter(is.numeric, data)
  percentage <- round(colSums(condition[, sapply(numeric_data,
 ↪  is.numeric)])/nrow(data) * 100, 2)
  percentage <- as.data.frame(percentage)
  colnames(percentage) <- "Percentage"
```

```
  percentage <- percentage |>
    filter(!is.na(Percentage)) |>
    rownames_to_column() |>
    arrange(Percentage)
  if (!missing(threshold)) {
    percentage <- percentage |>
      filter(Percentage > threshold)
  }
  return(percentage)
}

# Calculate percentage of texts with 0 occurrences of each feature
zero_features <- compute_percentage(ncounts, ncounts == 0, 66.6)
zero_features |>
  kable(col.names = c("Feature", "% texts with zero occurrences"))
```

Feature	% texts with zero occurrences
PRP	85.34
URL	93.03
EMO	98.98
HST	99.55

```
# Drop variables with low document frequency
ncounts2 <- select(ncounts, -one_of(zero_features$rowname))
```

These feature removal operations resulted in a feature set of 71 linguistic variables.

G.4.3 Identifying outlier texts

All normalised frequencies were normalised to identify any potential outlier texts.

```
# First scale the normalised counts (z-standardisation) to be able to compare
 ↪  the various features
zcounts <- ncounts2 |>
  select(-Words) |>
  keep(is.numeric) |>
  scale()
```

```
# If necessary, remove any outliers at this stage.
data <- cbind(ncounts2[,1:8], as.data.frame(zcounts))
outliers <- data |>
 filter(if_any(where(is.numeric) & !Words,  .fns = function(x){x > 8}))  |>
  select(Filename, Corpus, Register, Words)
```

The following outlier texts were identified according to the above conditions and excluded in subsequent analyses.

```
# These are potential outlier texts :
outliers |>
  kable(col.names = c("Filename", "Corpus", "Register", "# words"))
```

Filename	Corpus	Register	# words
POC_4e_Spoken_0007.txt	Textbook.English	Conversation	750
Solutions_Elementary_ELF_Spoken_0013.txt	Textbook.English	Conversation	931
EIM_Starter_Informative_0004.txt	Textbook.English	Informative	534
GreenLine_1_Spoken_0003.txt	Textbook.English	Conversation	970
Access_1_Spoken_0011.txt	Textbook.English	Conversation	784
Achievers_B1_Informative_0003.txt	Textbook.English	Informative	926
EIM_Starter_Spoken_0002.txt	Textbook.English	Conversation	824
GreenLine_1_Spoken_0008.txt	Textbook.English	Conversation	876
JTT_3_Informative_0003.txt	Textbook.English	Informative	699
GreenLine_1_Spoken_0010.txt	Textbook.English	Conversation	701
EIM_1_Spoken_0012.txt	Textbook.English	Conversation	640
NGL_1_Spoken_0013.txt	Textbook.English	Conversation	940
NGL_3_Spoken_0018.txt	Textbook.English	Conversation	751
Solutions_Intermediate_Spoken_0029.txt	Textbook.English	Conversation	672
NGL_1_Spoken_0012.txt	Textbook.English	Conversation	910
GreenLine_1_Spoken_0006.txt	Textbook.English	Conversation	622
GreenLine_2_Spoken_0004.txt	Textbook.English	Conversation	1102
Access_2_Spoken_0023.txt	Textbook.English	Conversation	875
HT_4_Informative_0006.txt	Textbook.English	Informative	513
Solutions_Intermediate_Informative_0017.txt	Textbook.English	Informative	816
EIM_1_Spoken_0013.txt	Textbook.English	Conversation	967
Solutions_Elementary_ELF_Spoken_0021.txt	Textbook.English	Conversation	846
Solutions_Intermediate_Plus_Spoken_0022.txt	Textbook.English	Conversation	596
Access_2_Spoken_0028.txt	Textbook.English	Conversation	813
NGL_1_Spoken_0005.txt	Textbook.English	Conversation	1020

Filename	Corpus	Register	# words
Solutions_Elementary_ELF_Spoken_0016.txt	Textbook.English	Conversation	871
Solutions_Pre-Intermediate_ELF_Spoken_0007.txt	Textbook.English	Conversation	630
Solutions_Intermediate_Informative_0013.txt	Textbook.English	Informative	770
GreenLine_2_Spoken_0003.txt	Textbook.English	Conversation	850
HT_4_Spoken_0010.txt	Textbook.English	Conversation	727
Solutions_Elementary_Informative_0003.txt	Textbook.English	Informative	1051
Access_2_Informative_0001.txt	Textbook.English	Informative	655
Solutions_Elementary_Informative_0010.txt	Textbook.English	Informative	708
GreenLine_1_Informative_0001.txt	Textbook.English	Informative	731
Access_2_Spoken_0002.txt	Textbook.English	Conversation	572
Solutions_Intermediate_Spoken_0019.txt	Textbook.English	Conversation	1024
Access_3_Informative_0003.txt	Textbook.English	Informative	1000
Access_1_Spoken_0019.txt	Textbook.English	Conversation	701
Access_2_Spoken_0013.txt	Textbook.English	Conversation	981
Solutions_Intermediate_Plus_Informative_0014.txt	Textbook.English	Informative	537
Revision_World_GCSE_10525362_literary-terms.txt	Informative.Teen	Informative	790
Revision_World_GCSE_10528697_p6-physics-radioactive-materials.txt	Informative.Teen	Informative	1015
Science_Tech_Kinds_NZ_10382383_math.txt	Informative.Teen	Informative	522
Science_for_students_10064820_scientists-say-metabolism.txt	Informative.Teen	Informative	895
Science_Tech_Kinds_NZ_10382388_recycling.txt	Informative.Teen	Informative	666
History_Kids_BBC_10404337_go_furthers.txt	Informative.Teen	Informative	620
Science_Tech_Kinds_NZ_10382391_sports.txt	Informative.Teen	Informative	657
Teen_Kids_News_10402607_so-you-want-to-be-an-archivist.txt	Informative.Teen	Informative	763
Science_Tech_Kinds_NZ_10382234_biology.txt	Informative.Teen	Informative	843
Science_Tech_Kinds_NZ_10382372_astronomy.txt	Informative.Teen	Informative	900
Dogo_News_file10060404_banana-plant-extract-may-be-the-key-to-slower-melting-ice-cream.txt	Informative.Teen	Informative	611
Science_Tech_Kinds_NZ_10382667_countries.txt	Informative.Teen	Informative	717
Quatr_us_file10390777_quick-summary-geological-erashtm.txt	Informative.Teen	Informative	643
Science_Tech_Kinds_NZ_10382873_physics.txt	Informative.Teen	Informative	722
Science_Tech_Kinds_NZ_10382382_light.txt	Informative.Teen	Informative	639
Factmonster_10053687_august-13.txt	Informative.Teen	Informative	523
Revision_World_GCSE_10526703_limited-companies.txt	Informative.Teen	Informative	714
Revision_World_GCSE_10529637_transition-metals.txt	Informative.Teen	Informative	787
Quatr_us_10390856_early-african-historyhtm.txt	Informative.Teen	Informative	1136
History_Kids_BBC_10401873_ff6_sicilylandingss.txt	Informative.Teen	Informative	813

Filename	Corpus	Register	# words
Quatr_us_10394250_harappan.txt	Informative.Teen	Informative	651
Ducksters_10398301_iraqphp.txt	Informative.Teen	Informative	657
History_Kids_BBC_10403171_death_sakkara_gallery_04s.txt	Informative.Teen	Informative	844
Revision_World_GCSE_10528246_agricultural-change.txt	Informative.Teen	Informative	789
Revision_World_GCSE_10528086_uk-government-judiciary.txt	Informative.Teen	Informative	1019
Revision_World_GCSE_10529794_definitions.txt	Informative.Teen	Informative	904
Encyclopedia_Kinds_au_10085347_Nobel_Prize_in_Chemistry.txt	Informative.Teen	Informative	598
Science_for_students_10064875_questions-big-melt-earths-ice-sheets-are-under-attack.txt	Informative.Teen	Informative	685
Teen_Kids_News_10403301_golden-globe-winners-2019-the-complete-list.txt	Informative.Teen	Informative	800
Science_Tech_Kinds_NZ_10382201_projects.txt	Informative.Teen	Informative	947
Revision_World_GCSE_10529753_probability.txt	Informative.Teen	Informative	816
Encyclopedia_Kinds_au_10085531_Complex_analysis.txt	Informative.Teen	Informative	735
History_Kids_BBC_10401890_ff7_ddays.txt	Informative.Teen	Informative	759
History_Kids_BBC_10403434s.txt	Informative.Teen	Informative	732
History_Kids_BBC_10401872_ff6_italys.txt	Informative.Teen	Informative	786
Science_Tech_Kinds_NZ_10382371_amazing.txt	Informative.Teen	Informative	629
Quatr_us_10391129_athabascan.txt	Informative.Teen	Informative	637
Encyclopedia_Kinds_au_10085355_20th_century.txt	Informative.Teen	Informative	864
Dogo_News_10060755_luxury-space-hotel-promises-guests-a-truly-out-of-this-world-vacation.txt	Informative.Teen	Informative	722
Revision_World_GCSE_10528072_nationalism-practice.txt	Informative.Teen	Informative	776
Quatr_us_10390861_quatr-us-privacy-policyhtm.txt	Informative.Teen	Informative	960
History_Kids_BBC_10401909_ff7_bulges.txt	Informative.Teen	Informative	732
History_kids_10381259_timeline-of-mesopotamia.txt	Informative.Teen	Informative	768
Revision_World_GCSE_10528123_gender-written-textual-analysis-framework.txt	Informative.Teen	Informative	905
Science_Tech_Kinds_NZ_10386406_floods.txt	Informative.Teen	Informative	580
Revision_World_GCSE_10529693_advantages.txt	Informative.Teen	Informative	782
Science_Tech_Kinds_NZ_10382378_geography.txt	Informative.Teen	Informative	761
Science_Tech_Kinds_NZ_10382374_earth.txt	Informative.Teen	Informative	726
Science_for_students_10066286_watering-plants-wastewater-can-spread-germs.txt	Informative.Teen	Informative	836
Science_Tech_Kinds_NZ_10382393_water.txt	Informative.Teen	Informative	856
World_Dteen_10406069_website_policies.txt	Informative.Teen	Informative	995
Science_Tech_Kinds_NZ_10382384_metals.txt	Informative.Teen	Informative	669

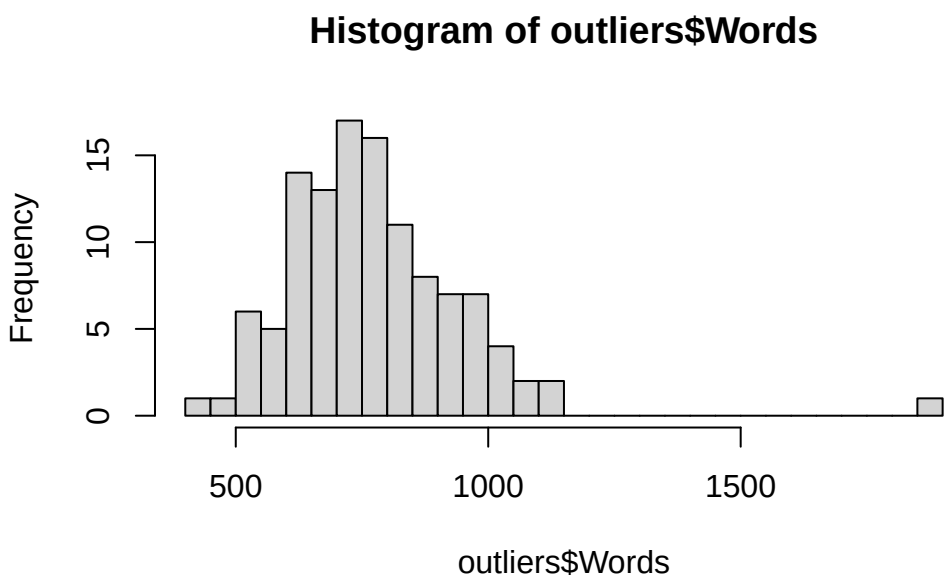
Filename	Corpus	Register	# words
Dogo_News_10062028_puppy-bowl-14-promises-viewers-a-paw-some-time-on-super-bowl-sunday.txt	Informative.Teens	Informative	581
History_Kids_BBC_10404730_go_furthers.txt	Informative.Teens	Informative	611
Science_Tech_Kinds_NZ_10382385_nature.txt	Informative.Teens	Informative	722
Science_for_students_10065015_scientists-say-dna-sequencing.txt	Informative.Teens	Informative	953
Quatr_us_file10390817_conifers-pine-trees-gymnospermshtm.txt	Informative.Teens	Informative	533
TweenTribute_10051509_it-true-elephants-cant-jump.txt	Informative.Teens	Informative	790
Revision_World_GCSE_10528494_application-software.txt	Informative.Teens	Informative	855
Revision_World_GCSE_10529581_different-types-questions-examinations.txt	Informative.Teens	Informative	742
Dogo_News_10061669_the-chinese-city-of-chengdu-may-soon-be-home-to-multiple-moons.txt	Informative.Teens	Informative	614
Ducksters_10398306_geography_of_ancient_chinaphp.txt	Informative.Teens	Informative	638
Science_for_students_10065144_scientists-say-multiverse.txt	Informative.Teens	Informative	712
Science_Tech_Kinds_NZ_10382211_images.txt	Informative.Teens	Informative	793
Factmonster_10053754_may-18.txt	Informative.Teens	Informative	497
World_Dteen_10406047_AboutWORLDteen.txt	Informative.Teens	Informative	1053
Ducksters_10398078_first_new_dealphp.txt	Informative.Teens	Informative	649
Revision_World_GCSE_10526926_economies-scale.txt	Informative.Teens	Informative	621
Factmonster_10053201_september-03.txt	Informative.Teens	Informative	445
Science_Tech_Kinds_NZ_10387183_calciumcarbonates.txt	Informative.Teens	Informative	804
Science_Tech_Kinds_NZ_10382380_health.txt	Informative.Teens	Informative	694
Revision_World_GCSE_10529587_sources-finance.txt	Informative.Teens	Informative	665
Quatr_us_10393444_fishing.txt	Informative.Teens	Informative	656
Ducksters_10398315_glossary_and_termsphp.txt	Informative.Teens	Informative	684
S5AA.txt	Spoken.BNC2014	Conversation	1869

We check that that outlier texts are not particularly long or short texts by looking at the distribution of text/file length of the outliers.

```
summary(outliers$Words)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  445.0   655.5   751.0   773.6   860.0  1869.0
```

```
hist(outliers$Words, breaks = 30)
```



We also check the distribution of outlier texts across the four corpora. The majority come from the Info Teens corpus, though quite a few are also from the TEC.

```
summary(outliers$Corpus) |>
  kable(col.names = c("(Sub)corpus", "# outlier texts"))
```

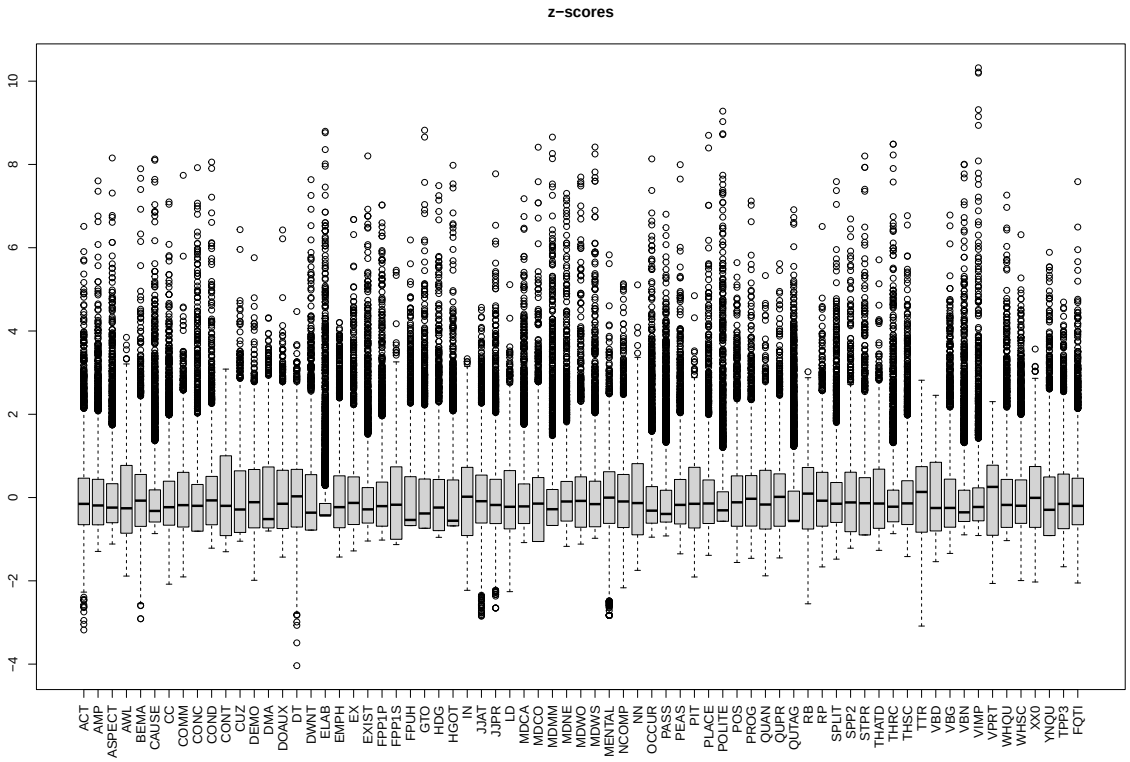
(Sub)corpus	# outlier texts
Textbook.English	40
Informative.Teens	74
Spoken.BNC2014	1
Youth.Fiction	0

```
# Report on the manual check of a sample of these outliers:

# Encyclopedia_Kinds_au_10085347_Nobel_Prize_in_Chemistry.txt is essentially
 ↪  a list of Nobel prize winners but with some additional information. In
 ↪  other words, not a bad representative of the type of texts of the Info
 ↪  Teen corpus.
# Solutions_Elementary_ELF_Spoken_0013 --> Has a lot of "going to"
 ↪  constructions because they are learnt in this chapter but is otherwise a
 ↪  well-formed text.
```

```
# Teen_Kids_News_10403972_a-brief-history-of-white-house-weddings --> No
 ↪  issues
# Teen_Kids_News_10403301_golden-globe-winners-2019-the-complete-list -->
 ↪  Similar to the Nobel prize laureates text.
# Revision_World_GCSE_10528123_gender-written-textual-analysis-framework -->
 ↪  Text includes bullet points tokenised as the letter "o" but otherwise a
 ↪  fairly typical informative text.

# Removing the outliers at the request of the reviewers (but comparisons of
 ↪  models including the outliers showed that the results are very similar):
ncounts3 <- ncounts2 |>
  filter(!Filename %in% outliers$Filename)

#saveRDS(ncounts3, here("data", "processed", "ncounts3_3Reg.rds")) # Last
 ↪  saved 6 March 2024
```

This resulted in 4,980 texts/files being included in the comparative model of Textbook English vs. 'real-world' English. These standardised feature frequencies were distributed as follows:

```
zcounts3 <- ncounts3 |>
  select(-Words) |>
  keep(is.numeric) |>
  scale()

boxplot(zcounts3, las = 3, main = "z-scores") # Slow
```



G.4.4 Signed log transformation

A signed logarithmic transformation was applied to (further) deskew the feature distributions (see Diwersy, Evert & Neumann 2014; Neumann & Evert 2021).

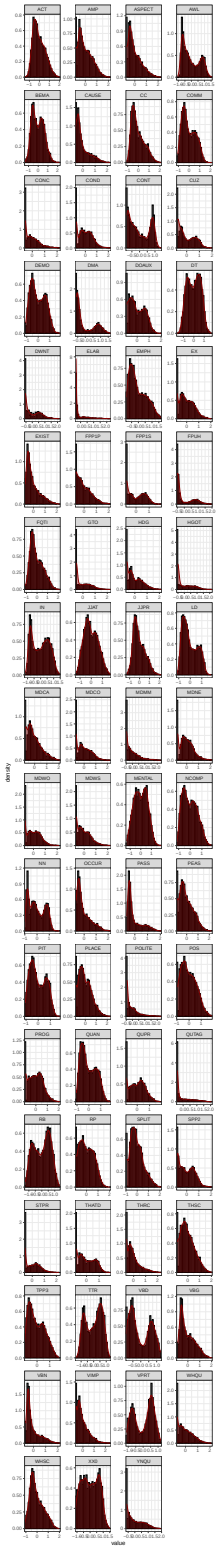
The signed log transformation function was inspired by the SignedLog function proposed in https://cran.r-project.org/web/packages/DataVisualizations/DataVisualizations.pdf.

```
signed.log <- function(x) {sign(x)*log(abs(x)+1)}

# Standardise first, then sign log transform
zlogcounts <- signed.log(zcounts3)
```

The new feature distributions are visualised below.

```
zlogcounts |>
  as.data.frame() |>
  gather() |> # This function from tidyr converts a selection of variables
   ↪  into two variables: a key and a value. The key contains the names of
   ↪  the original variable and the value the data. This means we can then
   ↪  use the facet_wrap function from ggplot2
```

```
ggplot(aes(value, after_stat(density))) +
theme_bw() +
facet_wrap(~ key, scales = "free", ncol = 4) +
scale_x_continuous(expand=c(0,0)) +
scale_y_continuous(limits = c(0,NA)) +
geom_histogram(bins = 30, colour= "black", fill = "grey") +
geom_density(colour = "darkred", weight = 2, fill="darkred", alpha = .4)
```


ACT
AMP
ASPECT
AWL
BEMA
CAUSE
CC
COMM
CONC
COND
CONT
CUZ
DEMO
DMA
DONUX
DT
DWNT
ELAB
EMPH
EX
EXIST
GRPSP
FFP1S
FPUH
FQTI
GTO
HGG
HGOT
IN
LIMT
LRPI
LD
MDCA
MDCO
MDMM
MDNE
MDWO
MDWS
MONTAL
NCOMP
NN
OCCUR
PASS
PEAS
PIT
PLACE
POLITE
POS
PROG
QUAN
QUPR
QUTAG
RB
RP
SPLIT
SPP2
STPR
THATD
THRC
THSC
TPP3
TTR
VBD
VBG
VBN
VMP
VPRT
WHQU
WHSC
XXS
YNQU
density
value

```
#ggsave(here("plots", "DensityPlotsAllVariablesSignedLog.svg"), width = 15,
 ↪  height = 49)
```

G.4.5 Merging of data for MDA

```
zlogcounts <- readRDS(here("data", "processed", "zlogcounts_3Reg.rds"))
#nrow(zlogcounts)
#colnames(zlogcounts)

ncounts3 <- readRDS(here("data", "processed", "ncounts3_3Reg.rds"))
#nrow(ncounts3)
#colnames(ncounts3)

data <- cbind(ncounts3[,1:8], as.data.frame(zlogcounts))
#saveRDS(data, here("data", "processed", "datazlogcounts_3Reg.rds")) # Last
 ↪  saved 16 March 2024
```

The final dataset comprises of 4,980 texts/files, divided as follows:

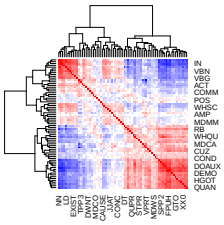
(Sub)corpus	# texts/files
Textbook Conversation	565
Textbook Fiction	285
Info Teens Ref.	1337
Textbook Informative	352
Spoken BNC2014 Ref.	1250
Youth Fiction Ref.	1191

G.5 Testing factorability of data

G.5.1 Visualisation of feature correlations

We begin by visualising the correlations of the transformed feature frequencies using the `heatmap` function of the `stats` library. Negative correlations are rendered in blue; positive ones are in red.

```
# Simple heatmap in base R (inspired by Stephanie Evert's SIGIL code)
cor.colours <- c(
  hsv(h=2/3, v=1, s=(10:1)/10), # blue = negative correlation
  rgb(1,1,1), # white = no correlation
  hsv(h=0, v=1, s=(1:10/10))) # red = positive correlation

#png(here("plots", "heatmapzlogcounts.png"), width = 30, height= 30, units =
 ↪  "cm", res = 300)
heatmap(cor(zlogcounts),
        symm=TRUE,
        zlim=c(-1,1),
        col=cor.colours,
        margins=c(7,7))
```




```
#dev.off()
```

G.5.2 Collinearity

As a result of the normalisation unit of finite verb phrases for verb-based features, the present tense (VPRT) and past tense (VBD) variables are correlated to a very high degree:

```
cor(data$VPRT, data$VBD) |> round(2)
```

```
[1] -0.97
```

We therefore remove the least marked of the pair of collinear variables: VPRT.

```
data <- data |>
  select(-c(VPRT))
```

G.5.3 MSA

```
kmo <- KMO(data[,9:ncol(data)]) # The first eight columns contain metadata.
```

The overall MSA value of the dataset is 0.95. The features have the following individual MSA values (ordered from lowest to largest):

```
kmo$MSAi[order(kmo$MSAi)] |>  round(2)
```

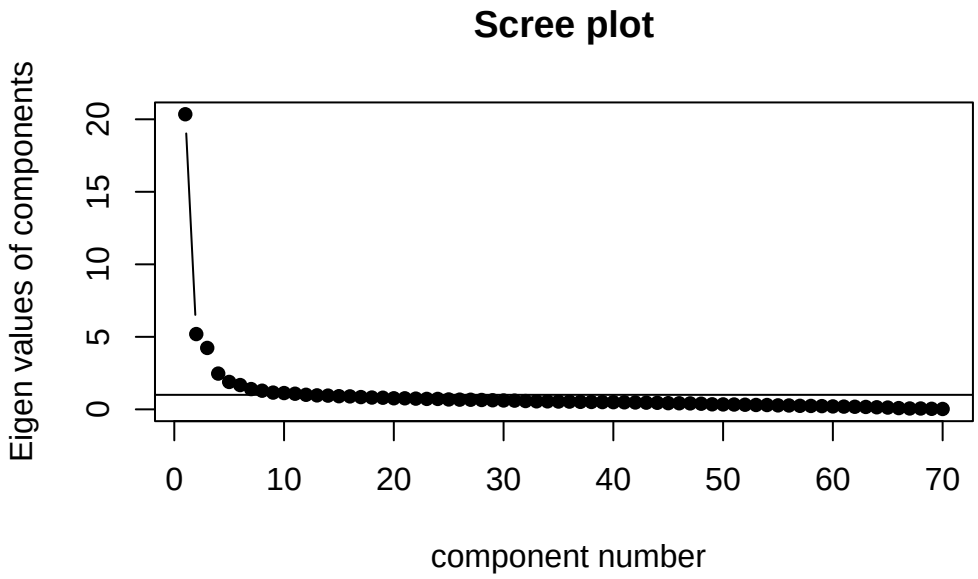
```
   AMP   COMM    POS   TPP3   JJPR  PLACE  SPLIT     DT   JJAT   VIMP   MDCO
  0.67   0.69   0.70   0.74   0.76   0.82   0.83   0.83   0.84   0.84   0.85
    RP     EX   THSC     LD  NCOMP   BEMA   MDWS   FQTI  FPP1P   MDCA    ACT
  0.85   0.85   0.86   0.87   0.88   0.88   0.89   0.89   0.89   0.89   0.89
MENTAL    VBD  FPP1S   MDMM   PEAS   CONC   MDWO   THRC     NN   COND   PROG
  0.91   0.91   0.91   0.91   0.91   0.93   0.93   0.94   0.94   0.95   0.95
    CC   SPP2     RB   DWNT   MDNE   WHSC   CONT   QUPR    XXO  CAUSE   WHQU
  0.95   0.95   0.95   0.95   0.95   0.96   0.96   0.96   0.96   0.96   0.96
   VBG    AWL POLITE   PASS    PIT  DOAUX   ELAB ASPECT    DMA   DEMO    HDG
  0.96   0.96   0.96   0.96   0.97   0.97   0.97   0.97   0.97   0.97   0.97
    IN   FPUH  OCCUR    CUZ   EMPH   YNQU   QUAN    TTR  QUTAG  THATD    VBN
  0.97   0.97   0.97   0.97   0.98   0.98   0.98   0.98   0.98   0.98   0.98
 EXIST   STPR    GTO   HGOT
  0.98   0.99   0.99   0.99
```

We aim to remove features with an individual MSA < 0.5. All features have individual MSAs of > 0.5 (but only because TPP3P was merged into a broader category in an earlier chunk).

G.5.4 Scree plot

Six components were originally retained on the basis of the following screeplot, though only the first four were found to be interpretable and were therefore included in the model.

```
# png(here("plots", "screeplot-TEC-Ref_3Reg.png"), width = 20, height= 12,
 ↪  units = "cm", res = 300)
scree(data[,9:ncol(data)], factors = FALSE, pc = TRUE) #
```




```
# dev.off()

# Perform PCA
pca1 <- psych::principal(data[9:ncol(data)],
                         nfactors = 6)
```

G.5.5 Communalities

If features with final communalities of < 0.2 are removed, TIME would have to be removed. TIME was therefore merged with FREQ in an earlier chunk so that now all features have final communalities of > 0.2 (note that this is a very generous threshold!).

```
pca1$communality |> sort() |> round(2)
```

```
  DWNT   STPR   CONC   FQTI    POS ASPECT   MDNE  FPP1P   PROG   MDCO   MDMM
  0.22   0.23   0.23   0.23   0.24   0.25   0.27   0.28   0.29   0.32   0.32
  MDWO  SPLIT   MDWS   PEAS   QUPR    AMP  PLACE    HDG   COMM  CAUSE     EX
  0.32   0.33   0.34   0.35   0.35   0.35   0.37   0.38   0.38   0.38   0.38
  THSC  OCCUR   WHSC   THRC   JJAT   COND MENTAL    ACT   VIMP   ELAB  EXIST
  0.40   0.40   0.42   0.43   0.44   0.44   0.45   0.45   0.46   0.46   0.46
  JJPR  NCOMP     RP    GTO   DEMO   MDCA POLITE    CUZ     CC   WHQU   TPP3
```

```
  0.46   0.48   0.49   0.50   0.50   0.52   0.52   0.53   0.57   0.58   0.58
   VBG  THATD    PIT   BEMA  FPP1S     DT   HGOT     RB    VBN  QUTAG   EMPH
  0.60   0.60   0.61   0.61   0.61   0.61   0.62   0.62   0.64   0.64   0.64
  PASS    XXO   QUAN   SPP2  DOAUX    TTR   YNQU    VBD     LD   FPUH     IN
  0.65   0.65   0.67   0.68   0.69   0.71   0.74   0.78   0.81   0.83   0.86
  CONT    DMA    AWL     NN
  0.89   0.89   0.91   0.93
```

```
#saveRDS(data, here("data", "processed", "dataforPCA.rds")) # Last saved on 6
 ↪  March 2024
```

The final dataset entered in the analysis described in Chapter 7 therefore comprises 4,980 texts/files, each with logged standardised normalised frequencies for 70 linguistic features.

H Data Analysis for the Model of Textbook English vs. 'real-world' English

This script documents the analysis of data from the TEC and reference corpus data (as pre-processed in Appendix F) to arrive at the multi-dimensional model of Textbook Englisch vs. 'real-world' English described in Chapter 7. It generates all of the statistics and plots included in the book, as well as many others that were used in the analysis, but were not included in the book for reasons of space.

H.1 Packages required

The following packages must be installed and loaded to process the data.

```
#renv::restore() # Restore the project's dependencies from the lockfile to
 ↪  ensure that same package versions are used as in the original thesis.

library(caret) # For its confusion matrix function
library(cowplot) # For its plot themes
library(DescTools) # For 95% CI
library(emmeans) # For the emmeans function
library(factoextra) # For circular graphs of variables
library(gtsummary) # For nice table of summary statistics (optional)
library(gridExtra) # For Fig. 35
library(here) # For dynamic file paths
library(ggthemes) # For theme of factoextra plots
library(knitr) # Loaded to display the tables using the kable() function
library(lme4) # For linear regression modelling
library(patchwork) # To create figures with more than one plot
#library(pca3d) # For 3-D plots (not rendered in exports)
library(PCAtools) # For nice biplots of PCA results
library(psych) # For various useful stats function
library(sjPlot) # For model plots and tables
library(tidyverse) # For data wrangling
library(visreg) # For plots of interaction effects
```

```
source(here("R_rainclouds.R")) # For geom_flat_violin rainplots
```

H.2 Conducting the PCA

We first import the full dataset (see Appendix F for data preparation steps).

The following chunks can be used to perform the MDA on various subsets of the data (see also Section 10.1.1 in the book).

i. Subset of the data that excludes the lower-level textbooks:

```
data <- readRDS(here("processed_data", "dataforPCA.rds")) |>
  filter(Level !="A" & Level != "B") |>
  droplevels()
summary(data$Level)
```

i. Subset of the data that includes only one `Country`‘ subcorpus of the TEC (note that a detailed analysis of the German subcorpus can be found in (Le Foll)):

```
data <- readRDS(here("processed_data", "dataforPCA.rds")) |>
  #filter(Country != "France" & Country != "Germany") |> # Spain only
  #filter(Country != "France" & Country != "Spain") |> # Germany only
  filter(Country != "Spain" & Country != "Germany") |> # France only
  droplevels()
summary(data$Country)
```

i. Random subsets of the data to test the stability of the model proposed in Chapter 7. Re-running this line will generate a new subset of 2/3 of the texts randomly sampled. `set.seed(13)` was used for the analyses reported on in Section 10.1.1.

```
set.seed(13)
data <- readRDS(here("processed_data", "dataforPCA.rds")) |>
  slice_sample(n = 4980*0.6, replace = FALSE)
nrow(data)
data$Filename[1:4]
#Using the set.seed(13), these should be:
#[1] HT_4_Spoken_0009.txt
#[2] Solutions_Intermediate_Plus_Spoken_0020.txt
#[3] 141_PRATCHETT1992DW13GODS_4.txt
#[4] Achievers_B2_Informative_0004.txt
```

H.3 Plotting PCA results

H.3.1 3D plots

The following chunk can be used to create projections of TEC texts on three dimensions of the model. These plots cannot be rendered in two dimensions and are therefore not generated in the present document. For more information on the `pca3d` library, see: https://cran.r-project.org/web/packages/pca3d/vignettes/pca3d.pdf.

```
# Data preparation for 3D plots
colnames(data) # Checking that the features start at the 9th column
pca <- prcomp(data[,9:ncol(data)], scale.=FALSE) # All quantitative variables
 ↪  that contribute to the model
register <- factor(data[,"Register"])
corpus <- factor(data[,"Corpus"])
subcorpus <- factor(data[,"Subcorpus"])

library(pca3d)

pca3d(pca, group = subcorpus,
       components = 1:3,
       components = 4:6,
       show.plane=FALSE,
       col = col6,
       shape = shapes6,
       radius = 0.7,
       legend = "right")

snapshotPCA3d(here("plots", "PCA_TxB_3Ref_3Dsnapshot.png"))

# Alternative visualisation, looking at all three Textbook English registers
 ↪  in one colour

pca3d(pca, group = corpus,
      show.plane=FALSE,
      components = 1:3,
      col = col4,
      shape = shapes4,
      radius = 0.7,
      legend = "right")
```

H.4 Two-dimensional plots (biplots)

These plots were generated using the `PCAtools` package, which requires the data to be formatted in a rather unconventional way so it needs to wrangled first.

H.4.1 Data wrangling for PCAtools

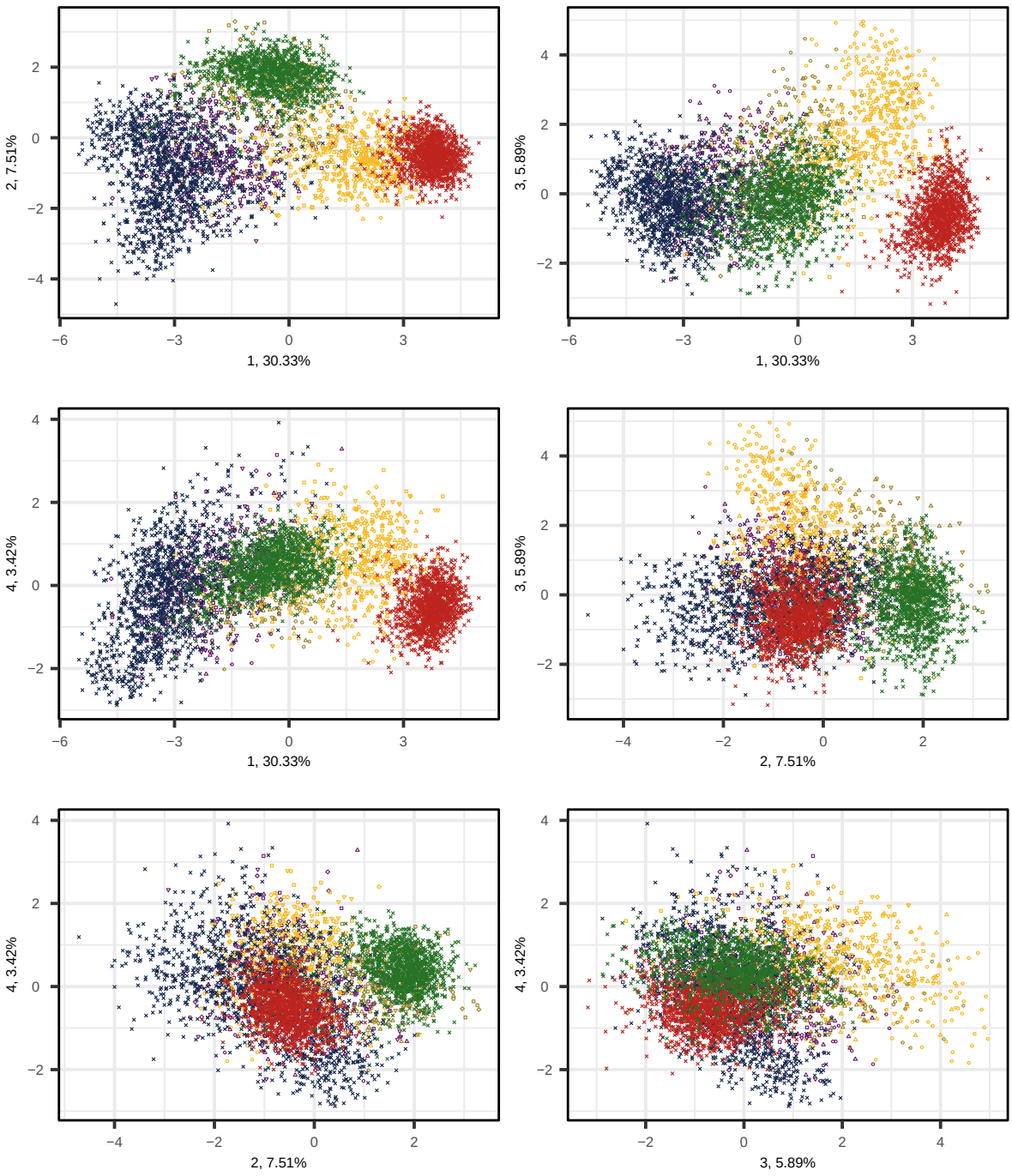
```
# Data wrangling
data2 <- data |>
  mutate(Source = recode_factor(Corpus, Textbook.English = "Textbook English
   ↪  (TEC)", Informative.Teens = "Reference corpora", Spoken.BNC2014 =
   ↪  "Reference corpora", Youth.Fiction = "Reference corpora")) |>
  mutate(Corpus = fct_relevel(Subcorpus, "Info Teens Ref.", after = 9)) |>
  relocate(Source, .after = "Corpus") |>
  droplevels()

# colnames(data2)
data2meta <- data2[,1:9]
rownames(data2meta) <- data2meta$Filename
data2meta <- data2meta |> select(-Filename)
# head(data2meta)
rownames(data2) <- data2$Filename
data2num <- as.data.frame(base::t(data2[,10:ncol(data2)]))
# data2num[1:5,1:5] # Check data frame format is correct by comparing to
 ↪  output of head(data2meta) above

p <- PCAtools::pca(data2num,
         metadata = data2meta,
         scale = FALSE)
```

The cumulative proportion of variance in the dataset explained the first four components explain 47.15%.

H.4.2 Pairs plot

This chunk produces a scatterplot matrix of combinations of the four dimensions of the model of Textbook English vs. 'real-world' English. Note that the number before the comma on each axis label shows which principal component is plotted on that axis; this is followed by the percentage of the total variance explained by that particular component. The colours correspond to the text registers.

```
# For five TEC registers
# colkey = c(`Spoken BNC2014 Ref.`="#BD241E", `Info Teens Ref.`="#15274D",
 ↪  `Youth Fiction Ref.`="#267226", `Textbook Fiction`="#A18A33", `Textbook
 ↪  Conversation`="#F9B921", `Textbook Informative` = "#722672", `Textbook
 ↪  Instructional` = "grey", `Textbook Personal` = "black")

# For three TEC registers
# summary(data2$Corpus)
colkey = c(`Spoken BNC2014 Ref.`="#BD241E", `Info Teens Ref.`="#15274D",
 ↪  `Youth Fiction Ref.`="#267226", `Textbook Fiction`="#A18A33", `Textbook
 ↪  Conversation`="#F9B921", `Textbook Informative` = "#722672")

#summary(data2$Source)
#shapekey = c(`Textbook English (TEC)`=6, `Reference corpora`=1)

# summary(data2$Level)
shapekey = c(A=1, B=2, C=6, D=0, E=5, `Ref.`=4)

## Warning: this can be very slow! Open in extra zoomed out window!

#png(here("plots", "PCA_3Ref_pairsplot.png"), width = 12, height= 19, units =
 ↪  "cm", res = 300)
PCAtools::pairsplot(p,
                triangle = FALSE,
                components = 1:4,
                ncol = 2,
                nrow = 3,
                pointSize = 0.6,
                shape = "Level",
                shapekey = shapekey,
                lab = NULL, # Otherwise will try to label each data point!
                colby = "Corpus",
                legendPosition = "none",
                margingaps = unit(c(0.2, 0.2, 0.8, 0.2), "cm"),
                colkey = colkey)
```

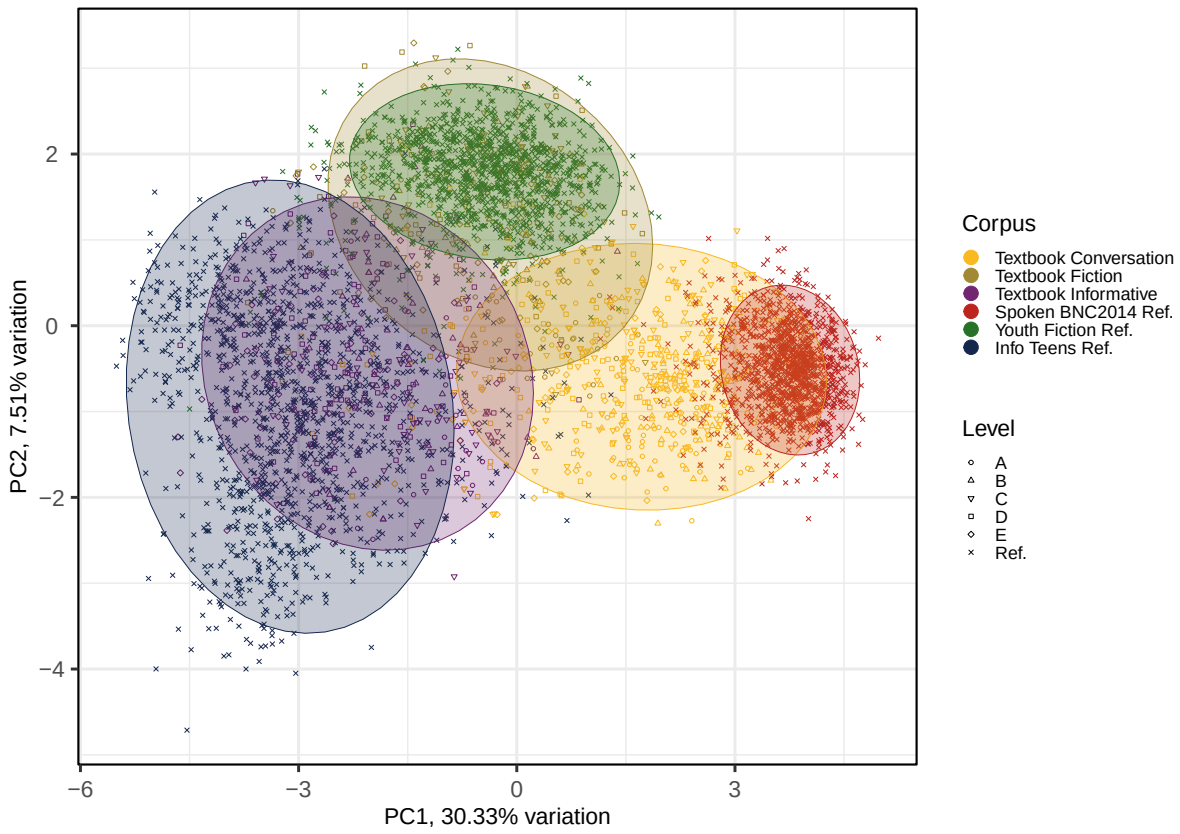

2, 7.51%
1, 30.33%
3, 5.89%
1, 30.33%
4, 3.42%
1, 30.33%
3, 5.89%
2, 7.51%
4, 3.42%
2, 7.51%
4, 3.42%
3, 5.89%

```
#dev.off()
#ggsave(here("plots", "PCA_TxB_pairsplot.svg"), width = 6, height = 10)
# Note that the legend has to be added manually (it was taken from the biplot
 ↪  code below).
```

H.4.3 Bi-plots

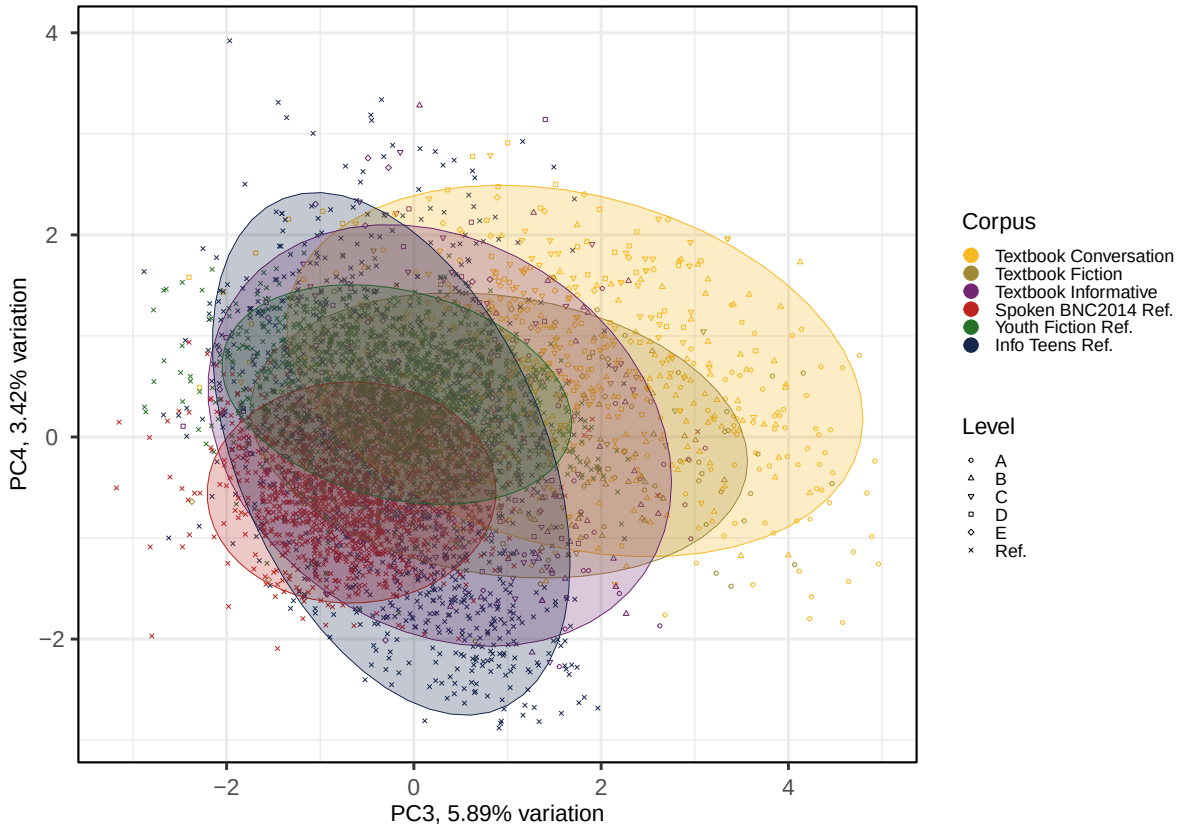
Biplots are used to more closely examine the position of texts on just two dimensions.

```
# These settings (with legendPosition = "top") were used to generate the
 ↪  legend for the scatterplot matrix above:
#png(here("plots", "PCA_3Ref_Biplot_PC1_PC2test.png"), width = 40, height=
 ↪  25, units = "cm", res = 300)

PCAtools::biplot(p,
                 x = "PC1",
                 y = "PC2",
                 lab = NULL, # Otherwise will try to label each data point!
                 colby = "Corpus",
                 pointSize = 1.3,
                 colkey = colkey,
                 shape = "Level",
                 shapekey = shapekey,
                 xlim = c(min(p$rotated[, "PC1"]), max(p$rotated[, "PC1"])),
                 ylim = c(min(p$rotated[, "PC2"]), max(p$rotated[, "PC2"])),
                 showLoadings = FALSE,
                 ellipse = TRUE,
                 axisLabSize = 18,
                 legendPosition = 'right',
                 legendTitleSize = 18,
                 legendLabSize = 14,
                 legendIconSize = 5) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))
```




```
#ggsave(here("plots", "PCA_Ref3TxB_BiplotPC1_PC2.svg"), width = 12, height =
 ↪  8)

# Biplots to examine components more carefully
PCAtools::biplot(p,
                 x = "PC3",
                 y = "PC4",
                 lab = NULL, # Otherwise will try to label each data point!
                 colby = "Corpus",
                 pointSize = 1.2,
                 colkey = colkey,
                 shape = "Level",
                 shapekey = shapekey,
                 xlim = c(min(p$rotated[, "PC3"]), max(p$rotated[, "PC3"])),
                 ylim = c(min(p$rotated[, "PC4"]), max(p$rotated[, "PC4"])),
                 showLoadings = FALSE,
```

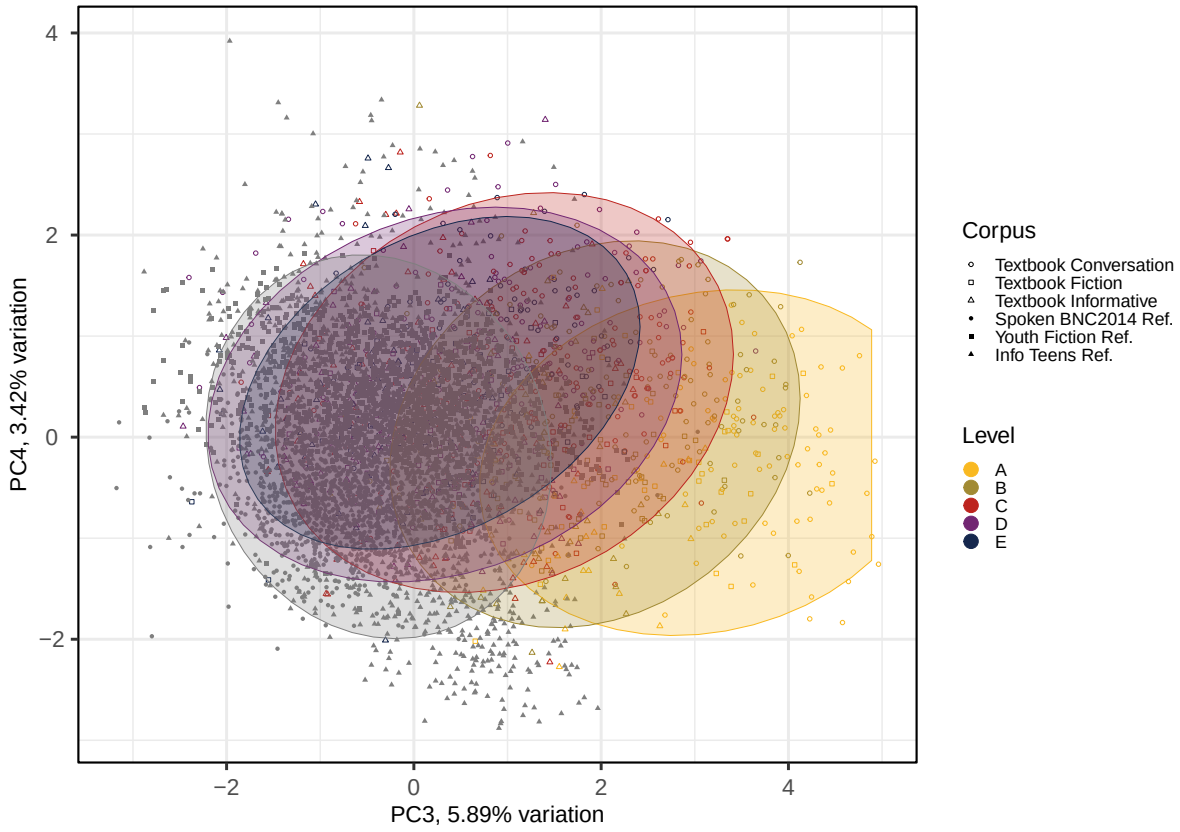
```
                ellipse = TRUE,
                axisLabSize = 18,
                legendPosition = 'right',
                legendTitleSize = 18,
                legendLabSize = 14,
                legendIconSize = 5) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))
```




```
#ggsave(here("plots", "PCA_Ref3TxB_BiplotPC3_PC4.svg"), width = 12, height =
 ↪  8)
```

The colours and corresponding ellipses can be used to visualise different clusters and patterns. In the following, we change the colour of the points and the ellipses to represent the texts' target proficiency levels instead of the register, allowing for a different interpretation of the model.

```r
# Biplot with ellipses for Level rather than Register
colkeyLevels = c(A="#F9B921", B="#A18A33", C="#BD241E", D="#722672",
 ↪  E="#15274D", `Ref. data`= "darkgrey")
shapekeyLevels = c(`Spoken BNC2014 Ref.`=16, `Info Teens Ref.`=17, `Youth
 ↪  Fiction Ref.`=15, `Textbook Fiction`=0, `Textbook Conversation`=1,
 ↪  `Textbook Informative`=2)

PCAtools::biplot(p,
                 x = "PC3",
                 y = "PC4",
                 lab = NULL, # Otherwise will try to label each data point!
                 colby = "Level",
                 pointSize = 1.3,
                 colkey = colkeyLevels,
                 shape = "Corpus",
                 shapekey = shapekeyLevels,
                 xlim = c(min(p$rotated[, "PC3"]), max(p$rotated[, "PC3"])),
                 ylim = c(min(p$rotated[, "PC4"]), max(p$rotated[, "PC4"])),
                 showLoadings = FALSE,
                 ellipse = TRUE,
                 axisLabSize = 18,
                 legendPosition = 'right',
                 legendTitleSize = 18,
                 legendLabSize = 14,
                 legendIconSize = 5) +
  theme(plot.margin = unit(c(0,0,0,0.2), "cm"))
```




```
#ggsave(here("plots", "PCA_Ref3TxB_BiplotPC3_PC4_levels.svg"), width = 12,
 ↪  height = 8)
```

H.5 Feature contributions (loadings) on each component

```
#data <- readRDS(here("processed_data", "dataforPCA.rds"))
pca <- prcomp(data[,9:ncol(data)], scale.=FALSE) # All quantitative variables
 ↪  to be included in the model

# The rotated data that represents the observations / samples is stored in
 ↪  rotated, while the variable loadings are stored in loadings
loadings <- as.data.frame(pca$rotation[,1:4])
```

```
# Table of loadings with no minimum threshold applied
loadings |>
  round(2) |>
  kable()
```

	PC1	PC2	PC3	PC4
ACT	-0.10	0.01	-0.01	0.12
AMP	0.00	-0.05	-0.05	0.09
ASPECT	-0.08	0.10	-0.01	0.00
AWL	-0.21	-0.13	-0.06	-0.01
BEMA	0.08	-0.24	0.06	-0.02
CAUSE	-0.08	-0.12	0.06	0.14
CC	-0.14	-0.13	-0.09	-0.09
COMM	-0.03	0.19	0.03	0.20
CONC	-0.03	-0.03	-0.18	-0.06
COND	0.08	-0.02	-0.17	0.23
CONT	0.22	-0.05	0.03	0.00
CUZ	0.10	-0.14	-0.20	-0.18
DEMO	0.15	-0.12	-0.08	-0.04
DMA	0.20	-0.09	-0.04	-0.16
DOAUX	0.18	-0.02	0.06	0.00
DT	0.08	0.16	-0.24	-0.03
DWNT	-0.04	0.10	-0.12	0.09
ELAB	-0.07	-0.17	-0.04	0.07
EMPH	0.17	-0.07	-0.09	-0.03
EX	0.06	-0.02	-0.04	0.00
EXIST	-0.13	-0.09	-0.05	0.00
FPP1P	0.08	-0.02	0.09	0.19
FPP1S	0.17	0.06	0.06	0.08
FPUH	0.18	-0.10	-0.05	-0.19
GTO	0.14	0.00	-0.04	0.00
HDG	0.10	-0.07	-0.14	-0.12
HGOT	0.16	-0.05	-0.01	-0.11
IN	-0.21	-0.01	-0.08	0.01
JJAT	-0.05	-0.13	-0.25	0.07
JJPR	-0.03	-0.17	-0.03	0.21
LD	-0.17	-0.16	0.13	-0.04
MDCA	0.05	-0.21	0.11	0.22
MDCO	0.00	0.19	-0.15	0.10
MDMM	-0.02	-0.10	-0.14	0.17
MDNE	0.06	-0.02	-0.06	0.22

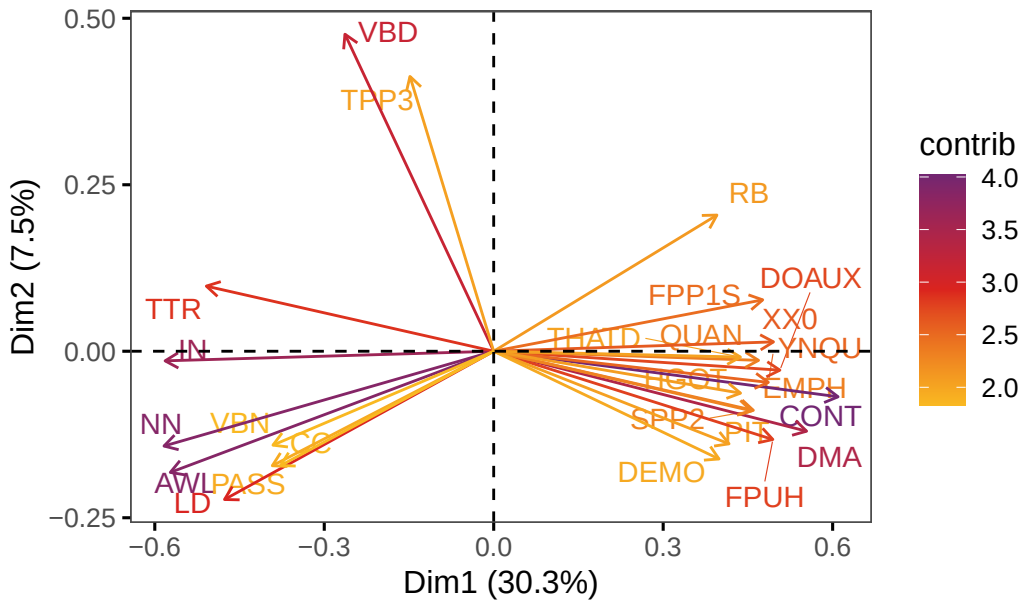
	PC1	PC2	PC3	PC4
MDWO	0.07	0.11	-0.18	0.04
MDWS	0.06	-0.02	-0.01	0.25
MENTAL	0.11	-0.02	-0.05	0.16
NCOMP	0.00	-0.27	-0.05	0.03
NN	-0.21	-0.10	0.10	-0.07
OCCUR	-0.13	-0.02	-0.05	-0.06
PASS	-0.14	-0.13	-0.09	-0.10
PEAS	-0.06	0.12	-0.19	0.12
PIT	0.15	-0.10	-0.15	-0.07
PLACE	0.02	0.09	0.09	0.07
POLITE	0.09	0.00	0.20	0.11
POS	0.02	0.09	0.04	-0.05
PROG	0.09	0.08	-0.04	0.15
QUAN	0.17	-0.01	-0.16	0.01
QUPR	0.08	0.11	-0.12	0.21
QUTAG	0.15	-0.04	-0.07	-0.15
RB	0.14	0.15	-0.18	0.07
RP	-0.01	0.22	-0.09	0.15
SPLIT	-0.03	-0.11	-0.21	0.08
SPP2	0.17	-0.07	0.10	0.16
STPR	0.10	0.01	0.01	-0.04
THATD	0.16	-0.01	-0.14	-0.02
THRC	-0.05	-0.17	-0.15	-0.02
THSC	-0.02	-0.08	-0.27	0.07
TTR	-0.19	0.07	-0.02	0.16
VBD	-0.10	0.35	-0.05	-0.20
VBG	-0.14	-0.02	-0.14	0.12
VBN	-0.14	-0.10	-0.08	-0.07
VIMP	0.01	-0.07	0.21	0.21
WHQU	0.13	-0.02	0.20	0.07
WHSC	-0.09	-0.10	-0.20	0.05
XX0	0.18	0.01	-0.06	0.06
YNQU	0.18	-0.03	0.14	-0.02
TPP3	-0.05	0.30	-0.04	-0.15
FQTI	-0.07	0.03	0.01	0.14

```
#clipr::write_last_clip()
```

H.6 Graphs of features of that contribute most to each component/dimension

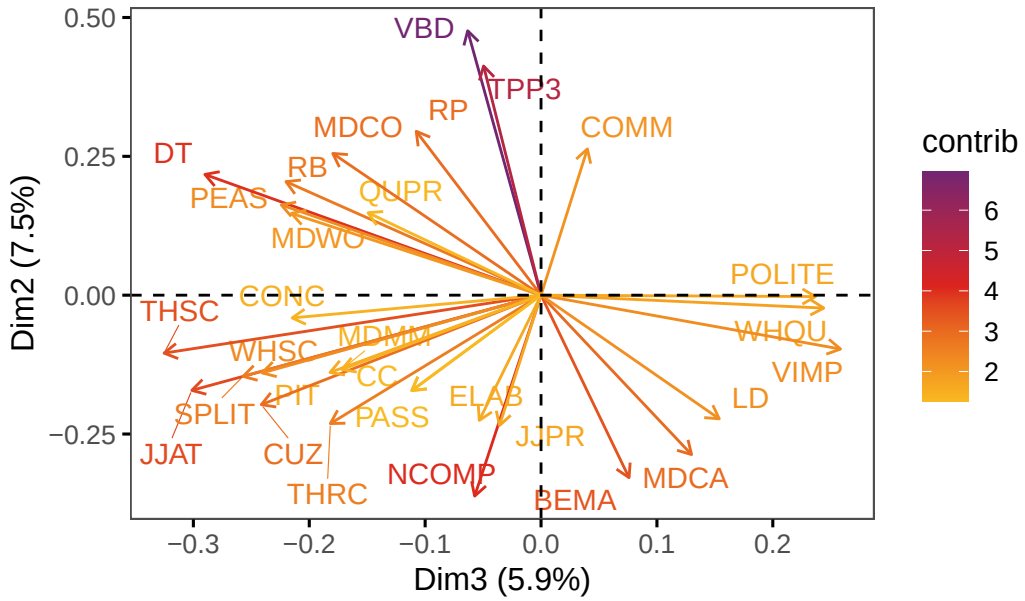
Graphs of features display the features with the strongest contributions to any two dimensions of the model of intra-textbook variation. They are created using the `factoextra::fviz_pca_var` function.

```
factoextra::fviz_pca_var(pca,
             axes = c(1,2),
             select.var = list(contrib = 25),
             col.var = "contrib", # Colour by contributions to the PC
             gradient.cols = c("#F9B921", "#DB241E", "#722672"),
             title = "",
             repel = TRUE, # Try to avoid too much text overlapping
             ggtheme = ggthemes::theme_few())
```

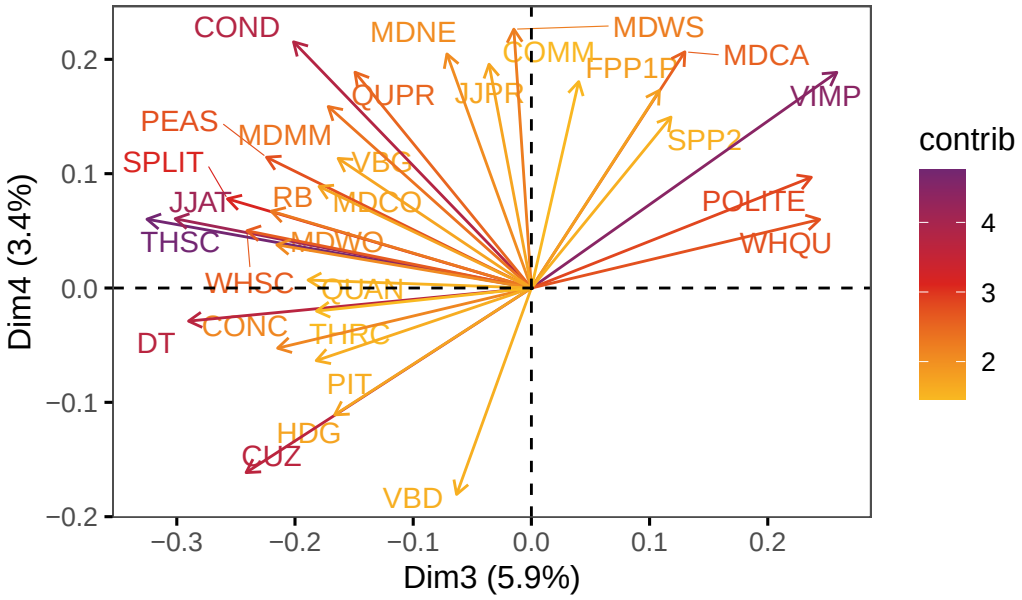



```
#ggsave(here("plots", "fviz_pca_var_PC1_PC2_Ref3Reg.svg"), width = 9, height
 ↪  = 7)

factoextra::fviz_pca_var(pca,
             axes = c(3,2),
```

```
              select.var = list(contrib = 30),
              col.var = "contrib", # Colour by contributions to the PC
              gradient.cols = c("#F9B921", "#DB241E", "#722672"),
              title = "",
              repel = TRUE, # Try to avoid too much text overlapping
              ggtheme = ggthemes::theme_few())
```




```
#ggsave(here("plots", "fviz_pca_var_PC3_PC2_Ref3Reg.svg"), width = 9, height
 ↪  = 8)

factoextra::fviz_pca_var(pca,
              axes = c(3,4),
              select.var = list(contrib = 30),
              col.var = "contrib", # Colour by contributions to the PC
              gradient.cols = c("#F9B921", "#DB241E", "#722672"),
              title = "",
              repel = TRUE, # Try to avoid too much text overlapping
              ggtheme = ggthemes::theme_few())
```




```
#ggsave(here("plots", "fviz_pca_var_PC3_PC4_Ref3Reg.svg"), width = 9, height
↪  = 8)
```

H.7 Exploring feature contributions in terms of normalised frequencies

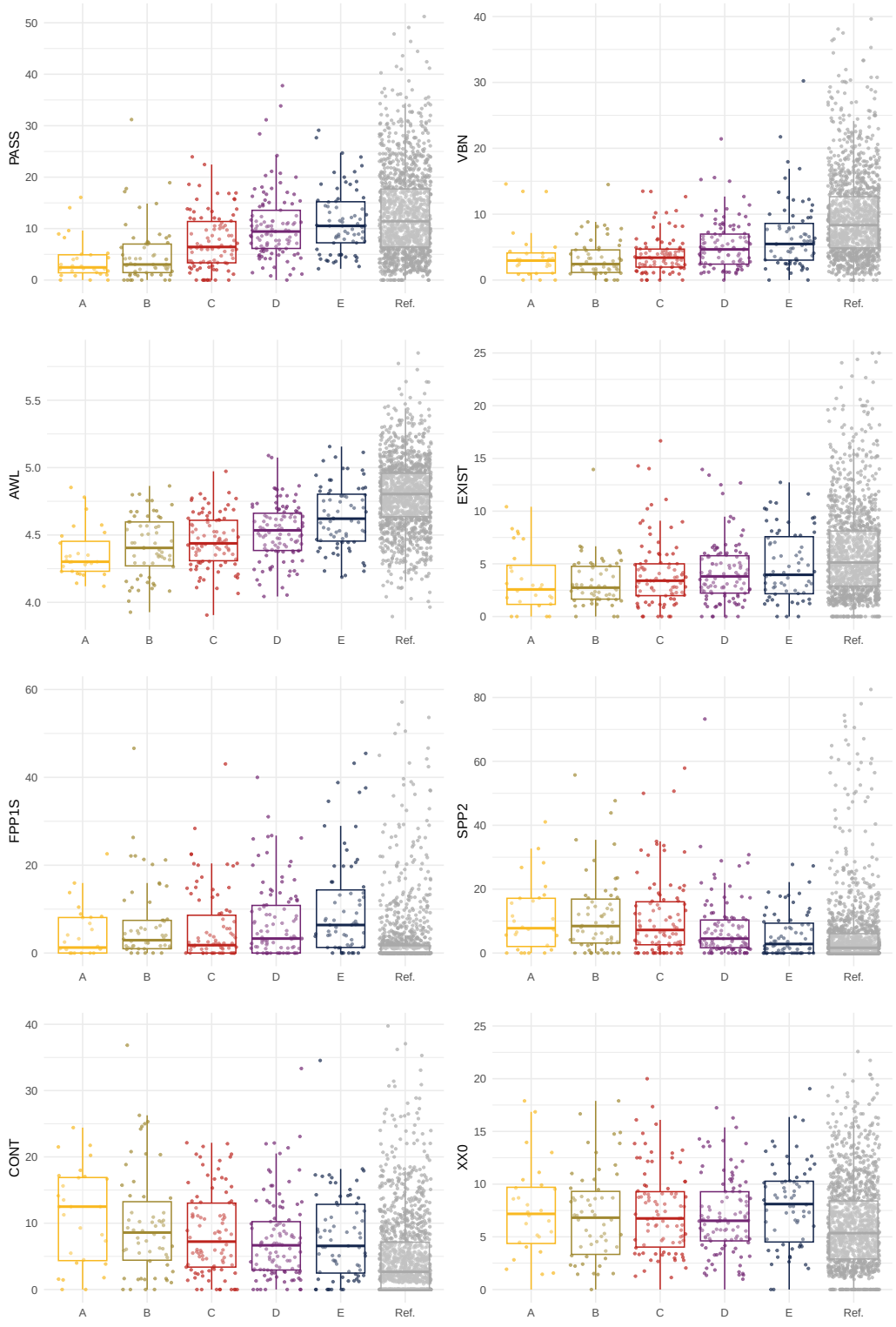
We can go back to the normalised frequencies of the individual features to compare them across different registers and levels, e.g.,:

```
ncounts <- readRDS(here("data", "processed", "ncounts3_3Reg.rds"))

ncounts |>
  filter(Register=="Informative") |>
  #filter(Level %in% c("C", "D", "E")) |>
  select(Level, VBD, PEAS) |>
  group_by(Level) |>
  summarise_if(is.numeric, mean) |>
  kable(digits=2)
```

Level	VBD	PEAS
A	28.11	0.21
B	34.11	2.49
C	35.21	5.36
D	39.83	7.63
E	35.17	6.91
Ref.	39.73	4.94

The following chunk produces Figure 35 which shows normalised counts of selected features with salient loadings on PC1 in the Textbook Informative subcorpus (Levels A to E) and the reference Info Teens corpus (Ref.). This plots visualises the observed normalised frequencies as they were extracted using the MFTE Perl (see Appendices C and F).

```
cols = c("#F9B921", "#A18A33", "#BD241E", "#722672", "#15274D", "darkgrey")

boxfeature <- ncounts |>
  filter(Register=="Informative") |>
  #filter(Level %in% c("C", "D", "E")) |>
  select(Level, FPP1S, SPP2, CONT, EXIST, AWL, XX0, PASS, VBN) |>
  ggplot(aes(x = Level, y = CONT, colour = Level, fill = Level)) +
  geom_jitter(size=0.7, alpha=.7) +
  geom_boxplot(outlier.shape = NA, fatten = 2, fill = "white", alpha = 0.3) +
  scale_colour_manual(values = cols) +
  theme_minimal() +
  theme(legend.position = "none") +
  xlab("")

CONT = boxfeature
SPP2 <- boxfeature + aes(y = SPP2)
EXIST <- boxfeature + aes(y = EXIST) + ylim(c(0,25)) # These y-axis limits
 ↪  remove individual outliers that overextend the scales and make the
 ↪  existing differences invisible to the naked eye. They can be removed to
 ↪  visualise all data points.
FFP1 <- boxfeature + aes(y = FPP1S) + ylim(c(0,60))
AWL <- boxfeature + aes(y = AWL)
XX0 <- boxfeature + aes(y = XX0) + ylim(c(0,25))
PASS <- boxfeature + aes(y = PASS)
VBN <- boxfeature + aes(y = VBN) + ylim(c(0,40))

boxplots <- gridExtra::grid.arrange(PASS, VBN, AWL, EXIST, FFP1, SPP2, CONT,
 ↪  XX0, ncol=2, nrow=4)
```


PASS
VBN
AWL
EXIST
FPP1S
SPP2
CONT
XX0
A
B
C
D
E
Ref.

```
#ggsave(here("plots", "BoxplotsInformativeFeatures.svg"), plot = boxplots,
 ↪  dpi = 300, width = 9, height = 11)
```

H.8 Exploring the dimensions of the model

We begin with some descriptive statistics of the dimension scores.

```
#data <- readRDS(here("data", "processed", "dataforPCA.rds"))
#colnames(data)
pca <- prcomp(data[,9:ncol(data)], scale.=FALSE) # All quantitative variables

## Access to the PCA results
#colnames(data)
res.ind <- cbind(data[,1:8], as.data.frame(pca$x)[,1:4])

## Summary statistics
res.ind |>
  group_by(Subcorpus, Level) |>
  summarise_if(is.numeric, c(mean = mean, sd = sd)) |>
  kable(digits = 2)
```

Subcorpus	Level	Words_mean	PC1_mean	PC2_mean	PC3_mean	PC4_mean	Words_sd	PC1_sd	PC2_sd	PC3_sd	PC4_sd
Textbook Conversation	A	813.02	1.91	-1.02	3.49	-0.17	154.57	0.89	0.60	1.03	0.73
Textbook Conversation	B	819.48	2.11	-0.64	2.33	0.39	218.88	0.91	0.69	1.04	0.79
Textbook Conversation	C	823.69	1.59	-0.38	1.39	0.75	279.14	1.20	0.73	1.04	0.79
Textbook Conversation	D	797.85	1.09	-0.43	0.79	0.91	187.98	1.45	0.72	1.26	0.79
Textbook Conversation	E	1132.79	1.03	-0.61	0.86	1.09	569.85	1.30	0.78	0.88	0.62
Textbook Fiction	A	886.00	0.13	0.22	2.74	-0.27	242.78	0.97	0.69	0.90	0.81

Subcorpus	Level	Words_mean	PC1_mean	PC2_mean	PC3_mean	PC4_mean	Words_sd	PC1_sd	PC2_sd	PC3_sd	PC4_sd
Textbook Fiction	B	864.16	-0.21	1.34	1.73	-0.29	222.44	0.79	0.62	0.73	0.53
Textbook Fiction	C	854.21	-0.27	1.63	0.76	0.12	198.21	0.89	0.78	0.96	0.63
Textbook Fiction	D	801.78	-0.84	1.38	0.26	0.15	196.33	1.15	0.79	0.83	0.59
Textbook Fiction	E	853.26	-0.65	1.27	0.26	0.20	195.97	1.10	0.75	0.92	0.57
Textbook Informative	A	851.71	-1.46	-0.96	1.86	-0.70	199.77	0.82	0.86	0.69	0.85
Textbook Informative	B	844.03	-1.63	-0.50	1.23	-0.27	182.83	0.92	1.03	0.80	1.08
Textbook Informative	C	838.90	-1.87	-0.54	0.25	0.14	160.21	1.09	0.98	0.93	1.06
Textbook Informative	D	847.65	-2.24	-0.32	-0.15	0.13	179.25	0.95	0.92	0.95	0.83
Textbook Informative	E	823.23	-2.57	-0.66	-0.28	0.37	180.39	0.99	0.90	0.79	0.82
Spoken BNC2014 Ref.	Ref.	10637.74	3.71	-0.52	-0.64	-0.53	8974.14	0.49	0.47	0.76	0.52
Youth Fiction Ref.	Ref.	5944.78	-0.49	1.75	-0.21	0.41	198.64	0.90	0.52	0.88	0.52
Info Teens Ref.	Ref.	805.41	-3.06	-0.96	-0.23	-0.15	193.31	1.09	1.19	0.88	1.19

```
res.ind <- res.ind |>
  mutate(Subsubcorpus = paste(Corpus, Register, sep = "_")) |>
  mutate(Subsubcorpus = as.factor(Subsubcorpus))

res.ind |>
  select(PC1, PC2, PC3, PC4, Subsubcorpus) |>
  tbl_summary(by = Subsubcorpus,
              digits = list(all_continuous() ~ c(2, 2)),
              statistic = all_continuous() ~  "{mean} ({sd})")
```

Characteristic	Informative_Written_BNC2014, N = 1,337	Spoken_BNC2014, N = 1,250	Academic_Prose, N = 565	Conversation, N = 285	Fiction, N = 352	Informative, N = 1,191
PC1	-3.06 (1.09)	3.71 (0.49)	1.56 (1.25)	-0.43 (1.05)	-2.05 (1.04)	-0.49 (0.90)
PC2	-0.96 (1.19)	-0.52 (0.47)	-0.57 (0.74)	1.25 (0.84)	-0.52 (0.96)	1.75 (0.52)
PC3	-0.23 (0.88)	-0.64 (0.76)	1.71 (1.43)	0.96 (1.22)	0.31 (1.10)	-0.21 (0.88)
PC4	-0.15 (1.19)	-0.53 (0.52)	0.61 (0.86)	0.02 (0.64)	0.05 (0.98)	0.41 (0.52)

```
res.ind |>
  select(Register, Level, PC4) |>
  group_by(Register, Level) |>
  summarise_if(is.numeric, c(Median = median, MAD = mad)) |>
  kable(digits = 2)
```

Register	Level	Median	MAD
Conversation	A	-0.07	0.68
Conversation	B	0.42	0.80
Conversation	C	0.73	0.80
Conversation	D	0.86	0.70
Conversation	E	1.09	0.61
Conversation	Ref.	-0.54	0.52
Fiction	A	-0.38	0.75
Fiction	B	-0.39	0.53
Fiction	C	0.13	0.67
Fiction	D	0.01	0.54
Fiction	E	0.12	0.67
Fiction	Ref.	0.40	0.50
Informative	A	-0.71	0.82
Informative	B	-0.37	1.10
Informative	C	0.07	1.09
Informative	D	0.04	0.79
Informative	E	0.37	0.57
Informative	Ref.	-0.08	1.21

The following chunk can be used to search for example texts that are located in specific areas of the biplots. For example, we can search for texts that have high scores on Dim3 and low ones on Dim2 to proceed with a qualitative comparison and analysis of these texts.

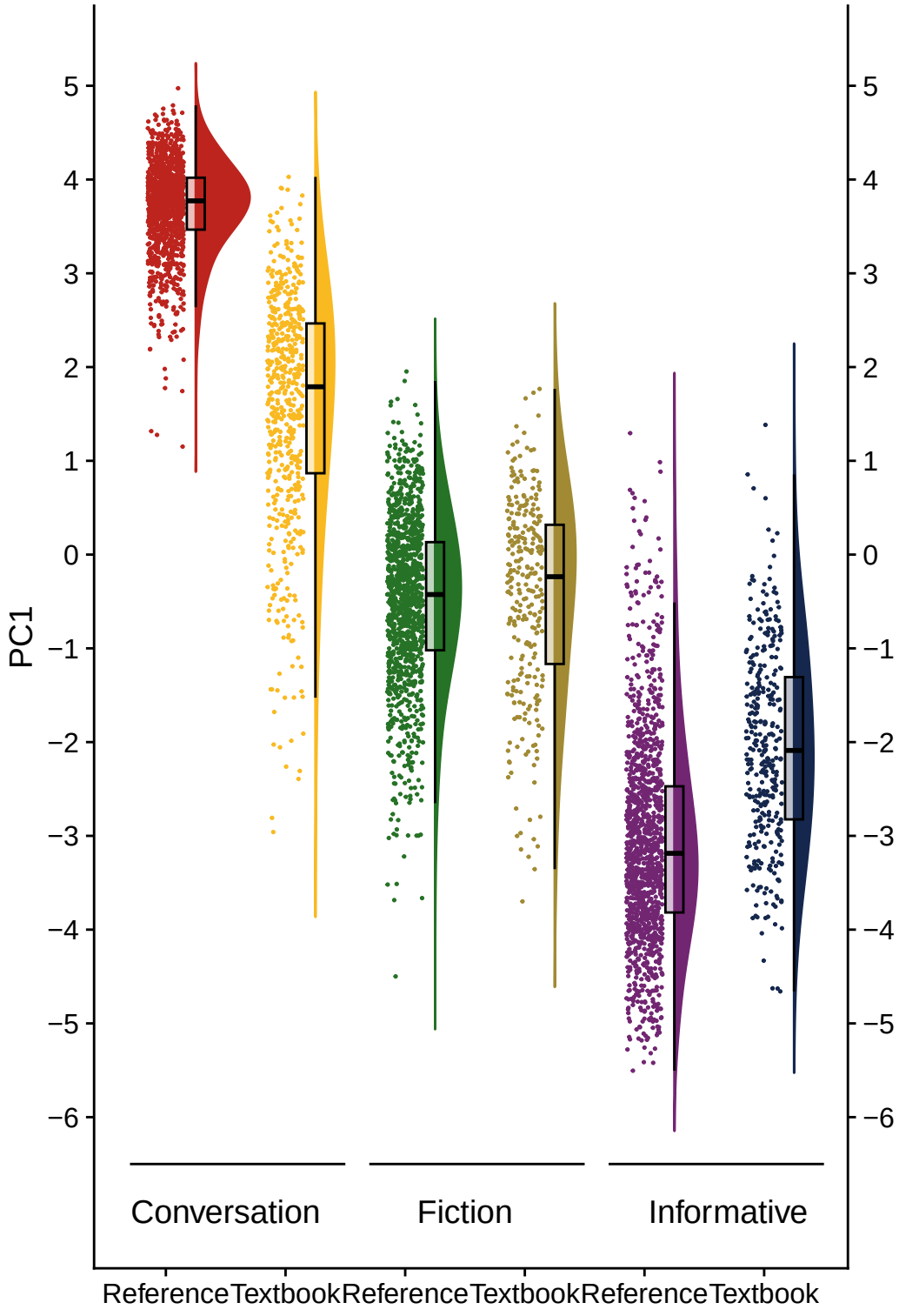
```
# Search for example texts to illustrate results
res.ind |>
  filter(PC3 > 2 & PC2 < -2) |>
  #filter(Register=="Conversation") |>
  #filter(Level == "B") |>
  #filter(PC1 > 4.7) |>
  select(Filename, PC1, PC2, PC3) |>
  kable(digits=2)
```

Filename	PC1	PC2	PC3
NGL_1_Spoken_0002.txt	2.41	-2.27	4.36
HT_5_ELF_Spoken_0003.txt	1.94	-2.30	3.49
HT_6_Informative_0001.txt	-2.19	-2.36	3.11
Science_Tech_Kinds_NZ_10383721_typesofrobots.txt	-3.09	-2.62	2.24
History_Kids_BBC_10402894_go_furthers.txt	-4.26	-2.07	2.08

H.9 Raincloud plots visualising dimension scores

```
res.ind$Subcorpus <- fct_relevel(res.ind$Subcorpus, "Spoken BNC2014 Ref.",
 ↪  "Textbook Conversation", "Youth Fiction Ref.", "Textbook Fiction", "Info
 ↪  Teens Ref.", "Textbook Informative")

# colours <- suf_palette(name = "london", n = 6, type = "continuous")
# colours2 <- suf_palette(name = "classic", n = 5, type = "continuous")
# colours <- c(colours, colours2[c(2:4)]) # Nine colours range
# palette <- colours[c(1,5,6,2,3,8,7,4,9)] # Good order for PCA
# colours <- palette[c(1,8,9,2,7,3)]

# This translates as:
palette <- c("#BD241E", "#A18A33", "#15274D", "#D54E1E", "#EA7E1E",
 ↪  "#4C4C4C", "#722672", "#F9B921", "#267226")
colours <- c("#BD241E", "#F9B921", "#267226", "#A18A33", "#722672","#15274D")

ggplot(res.ind, aes(x=Subcorpus,y=PC1, fill = Subcorpus, colour =
 ↪  Subcorpus))+ # Or leave out "colour = Register" to keep the dots in black
  geom_flat_violin(position = position_nudge(x = .25, y = 0),adjust = 2, trim
   ↪  = FALSE)+
  geom_point(position = position_jitter(width = .15), size = .25)+
```

```
# note that here we need to set the x-variable to a numeric variable and bump
 ↪  it to get the boxplots to line up with the rainclouds.
  geom_boxplot(aes(x = as.numeric(Subcorpus)+0.25, y = PC1), outlier.shape =
   ↪  NA, alpha = 0.3, width = .15, colour = "BLACK") +
  ylab('PC1')+
  theme_cowplot()+
  theme(axis.title.x=element_blank())+
  guides(fill = "none", colour = "none") +
  scale_colour_manual(values = colours)+
  scale_fill_manual(values = colours) +
  annotate(geom = "text", x = 1.5, y = -7, label = "Conversation", size = 5)
   ↪  +
  annotate(geom = "segment", x = 0.7, xend = 2.5, y = -6.5, yend = -6.5) +
  annotate(geom = "text", x = 3.5, y = -7, label = "Fiction", size = 5) +
  annotate(geom = "segment", x = 2.7, xend = 4.5, y = -6.5, yend = -6.5) +
  annotate(geom = "text", x = 5.7, y = -7, label = "Informative", size = 5) +
  annotate(geom = "segment", x = 4.7, xend = 6.5, y = -6.5, yend = -6.5) +
  scale_x_discrete(labels=rep(c("Reference", "Textbook"), 3))+
  scale_y_continuous(sec.axis = dup_axis(name=NULL), breaks = seq(from = -6,
   ↪  to = 5, by = 1))
```


PC1
5
4
3
2
1
0
−1
−2
−3
−4
−5
−6
Conversation
Fiction
Informative
Reference
Textbook
Reference
Textbook
Reference
Textbook

```
#ggsave(here("plots", "PC1_3RegComparison.svg"), width = 13, height = 8)
#ggsave(here("plots", "PC1_3RegComparison.png"), width = 20, height = 15,
 ↪  units = "cm", dpi = 300)
```

H.10 Computing mixed-effects models of the dimension scores

H.10.1 Data preparation

In this chunk, we add a `Source` variable to be used as a random effect variable in the following mixed-effects models (see 5.3.8 for details).

```
res.ind <- res.ind |>
  mutate(Source = case_when(
  Corpus=="Youth.Fiction" ~ paste("Book", str_extract(Filename,
 ↪  "[0-9]{1,3}"), sep = ""),
  Corpus=="Spoken.BNC2014" ~ "Spoken.BNC2014",
  Corpus=="Textbook.English" ~ as.character(Series),
  Corpus=="Informative.Teens" ~ str_extract(Filename, "BBC|Science_Tech"),
  TRUE ~ "NA")) |>
  mutate(Source = case_when(
  Corpus=="Informative.Teens" & is.na(Source) ~ str_remove(Filename, "_.*"),
  TRUE ~ as.character(Source))) |>
  mutate(Source = as.factor(Source)) |>
  mutate(Corpus = case_when(
    Corpus=="Textbook.English" ~ "Textbook",
    Corpus=="Informative.Teens" ~ "Reference",
    Corpus=="Spoken.BNC2014" ~ "Reference",
    Corpus=="Youth.Fiction" ~ "Reference"
  )) |>
  mutate(Corpus = as.factor(Corpus))

# Change the reference levels to theoretically more meaningful levels and one
 ↪  that is better populated (see, e.g.,
 ↪  https://stats.stackexchange.com/questions/430770/in-a-multilevel-linear-regression-how-d
# summary(res.ind$Corpus)
res.ind$Corpus <- relevel(res.ind$Corpus, "Reference")

# summary(res.ind$Subcorpus)
res.ind$Subcorpus <- factor(res.ind$Subcorpus, levels = c("Spoken BNC2014
 ↪  Ref.", "Textbook Conversation", "Youth Fiction Ref.", "Textbook Fiction",
 ↪  "Info Teens Ref.", "Textbook Informative"))
```

```
# summary(res.ind$Level)
res.ind$Level <- relevel(res.ind$Level, "Ref.")
```

H.10.2 Dimension 1: 'Spontaneous interactional vs. Edited informational'

We first compare various models and then present a tabular summary of the best-fitting one.

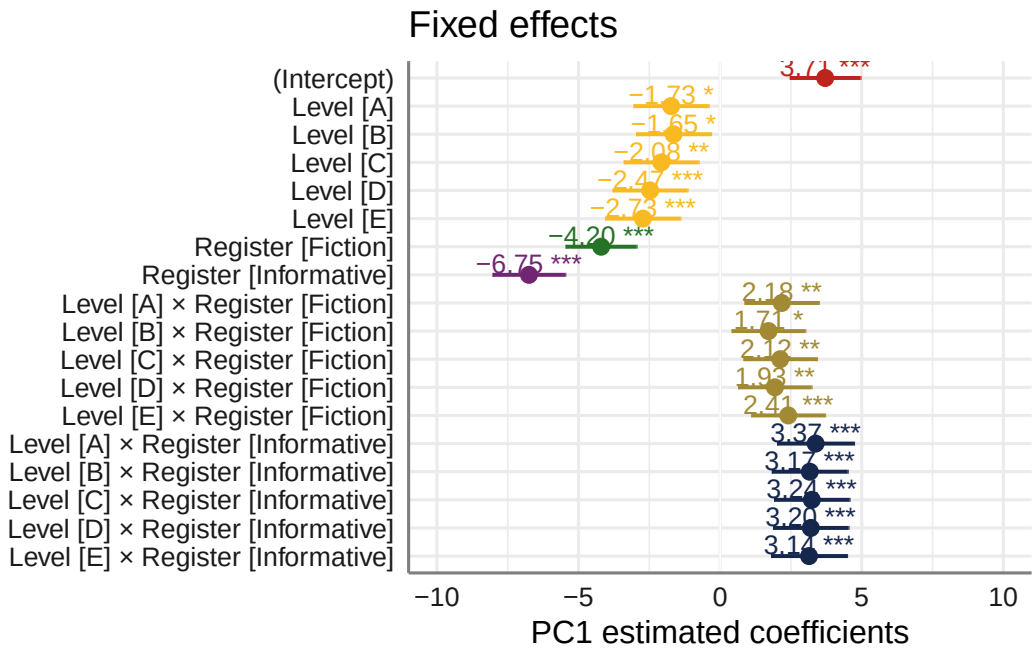
```
md_source <- lmer(PC1 ~ 1 + (Register|Source), res.ind, REML = FALSE)
md_corpus <- update(md_source, .~. + Level) # Failed to converge
md_register <- update(md_source, . ~ . + Register)
md_both <- update(md_corpus, .~. + Register)
md_interaction <- update(md_both, . ~ . + Level:Register)

anova(md_source, md_corpus, md_register, md_both, md_interaction)
```

```
Data: res.ind
Models:
md_source: PC1 ~ 1 + (Register | Source)
md_register: PC1 ~ (Register | Source) + Register
md_corpus: PC1 ~ (Register | Source) + Level
md_both: PC1 ~ (Register | Source) + Level + Register
md_interaction: PC1 ~ (Register | Source) + Level + Register + Level:Register
               npar   AIC   BIC  logLik deviance   Chisq Df Pr(>Chisq)
md_source         8 12421 12473 -6202.5    12405
md_register      10 12357 12422 -6168.4    12337  68.106  2  1.625e-15 ***
md_corpus        13 12181 12266 -6077.5    12155 181.996  3  < 2.2e-16 ***
md_both          15 12117 12215 -6043.5    12087  67.843  2  1.854e-15 ***
md_interaction   25 12098 12261 -6024.0    12048  39.104 10  2.435e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
md_interaction <- lmer(PC1 ~ Level + Register + Level*Register +
 ↪  (Register|Source), res.ind, REML = FALSE)

tab_model(md_interaction, wrap.labels = 200) # R2 = 0.870 / 0.923
```

Its estimated coefficients are visualised in the plot below.

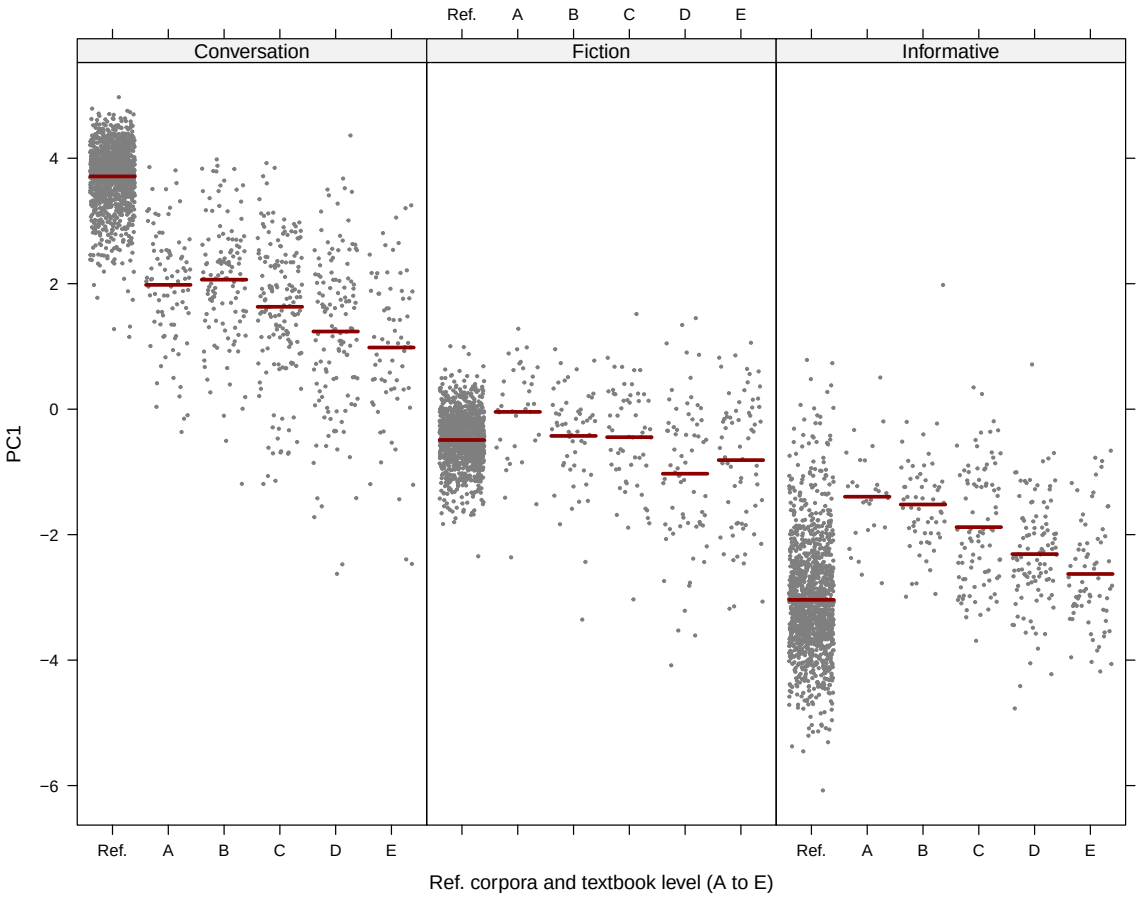
```
# Tweak plot aesthetics with:
 ↪  https://cran.r-project.org/web/packages/sjPlot/vignettes/custplot.html
# Colour customisation trick from:
 ↪  https://stackoverflow.com/questions/55598920/different-line-colors-in-forest-plot-output-

plot_model(md_interaction,
           #type = "re", # Option to visualise random effects
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,7:9)],
           group.terms = c(1,5,5,5,5,5,6,4,2,2,2,2,2,3,3,3,3,3),
           title="Fixed effects",
           wrap.labels = 40,
           axis.title = "PC1 estimated coefficients") +
  theme_sjplot2()
```




```
#ggsave(here("plots", "TxBRef3Reg_PC1_lmer_fixed.svg"), height = 6, width =
 ↪  9)
```

The `visreg` function is used to visualise the distributions of the modelled Dim1 scores:

```
# svg(here("plots", "TxBReg3Reg_predicted_PC1_scores_interactions.svg"),
 ↪  height = 8, width = 9)
visreg(md_interaction, xvar = "Level", by="Register",
       #type = "contrast",
       type = "conditional",
       line=list(col="darkred"),
       points=list(cex=0.3),
       xlab = "Ref. corpora and textbook level (A to E)", ylab = "PC1",
       layout=c(3,1)
)
```



```
# dev.off()
```

For PC2 to PC4, the models with random intercepts and slopes failed to converge, which is why only slopes are included in the following models.

```
# Function to avoid repeating model fitting and comparison process for each
 ↪  PC.
run_anova <- function(response_var, data) {
  # Fit the initial model
  md_source <- lmer(formula = paste(response_var, "~ 1 + (1|Source)"), data =
 ↪  data, REML = FALSE)

  # Update models
  md_corpus <- update(md_source, . ~ . + Level)
  md_register <- update(md_source, . ~ . + Register)
  md_both <- update(md_corpus, . ~ . + Register)
  md_interaction <- update(md_both, . ~ . + Level:Register)

  # Perform ANOVA
  anova_results <- anova(md_source, md_corpus, md_register, md_both,
 ↪  md_interaction)

  # Print ANOVA results
  print(anova_results)

  # Save model object with appropriate name
  pc_number <- gsub("PC", "", response_var)
  assign(paste("md_interaction_PC", pc_number, sep = ""), md_interaction,
   ↪  envir = .GlobalEnv)

  # Return tabulated model
  return(md_interaction)
}
```

H.10.3 Dimension 2: 'Narrative vs. Non-narrative'

We first compare various models and then present a tabular summary of the best-fitting one.

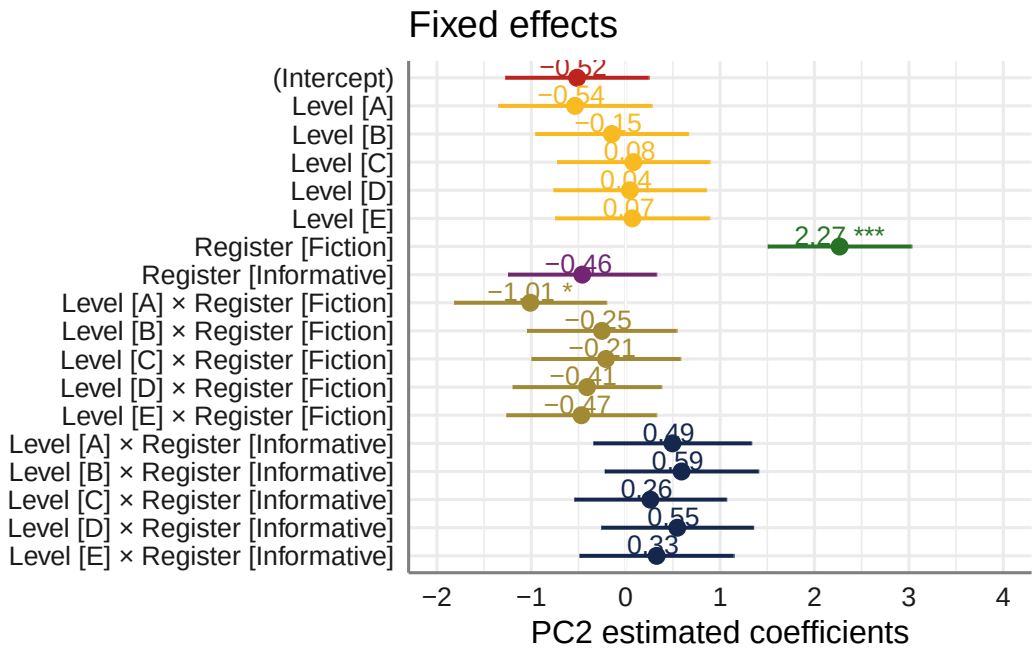
```
PC2_models <- run_anova("PC2", res.ind)
```

```
Data: data
Models:
md_source: PC2 ~ 1 + (1 | Source)
md_register: PC2 ~ (1 | Source) + Register
md_corpus: PC2 ~ (1 | Source) + Level
md_both: PC2 ~ (1 | Source) + Level + Register
md_interaction: PC2 ~ (1 | Source) + Level + Register + Level:Register
               npar   AIC   BIC  logLik deviance    Chisq Df Pr(>Chisq)
md_source         3 12281 12301 -6137.6    12275
md_register       5 10761 10794 -5375.7    10751 1523.882  2  < 2.2e-16 ***
md_corpus         8 12138 12190 -6061.1    12122    0.000  3          1
md_both          10 10616 10681 -5298.1    10596 1525.963  2  < 2.2e-16 ***
md_interaction   20 10550 10680 -5254.9    10510   86.436 10  2.718e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tab_model(md_interaction_PC2) # R2 = 0.671 / 0.753
```

Visualisation of the coefficient estimates of the fixed effects:

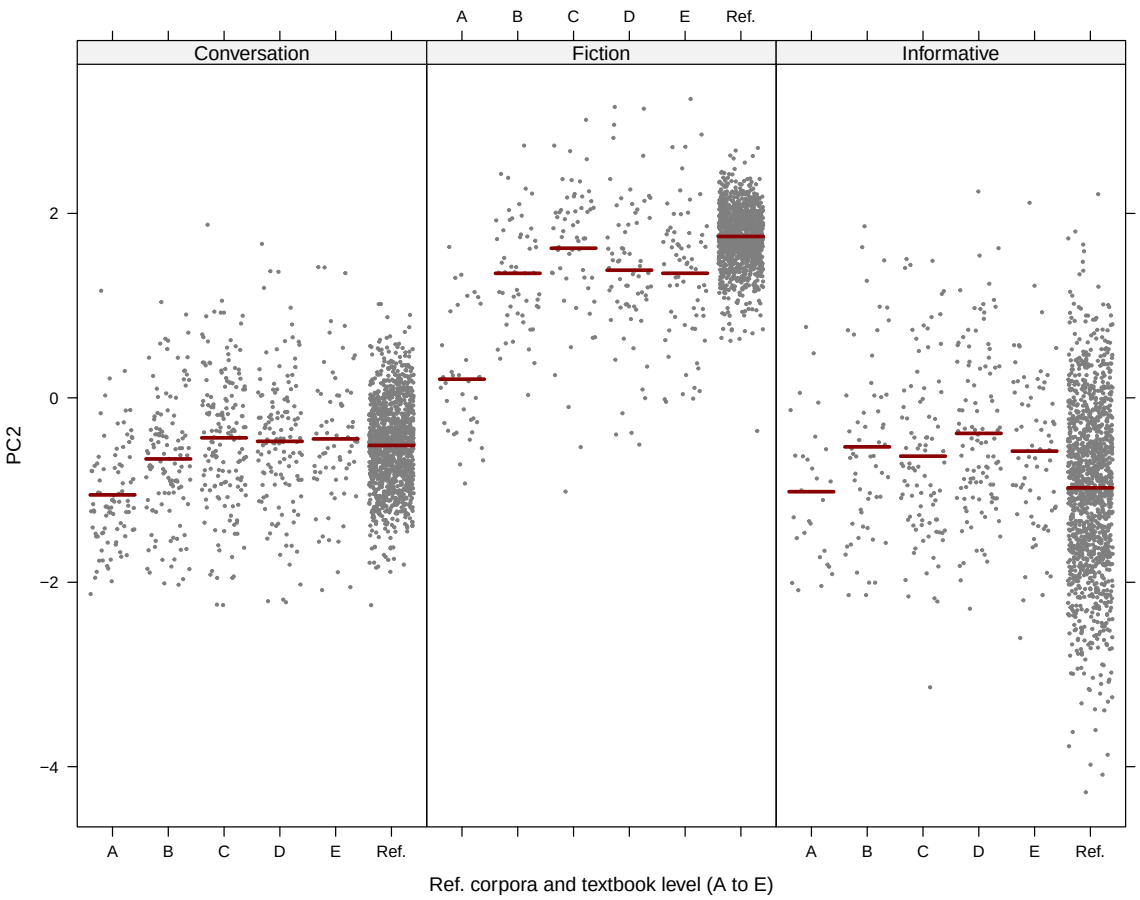
```
plot_model(md_interaction_PC2,
           #type = "re", # Option to visualise random effects
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,7:9)],
           group.terms = c(1,5,5,5,5,5,6,4,2,2,2,2,2,3,3,3,3,3),
           title="Fixed effects",
           wrap.labels = 40,
           axis.title = "PC2 estimated coefficients") +
  theme_sjplot2()
```




```
#ggsave(here("plots", "TxBRef3Reg_PC2_lmer_fixed.svg"), height = 6, width =
 ↪  9)
```

Visualisation of the predicted Dim2 scores:

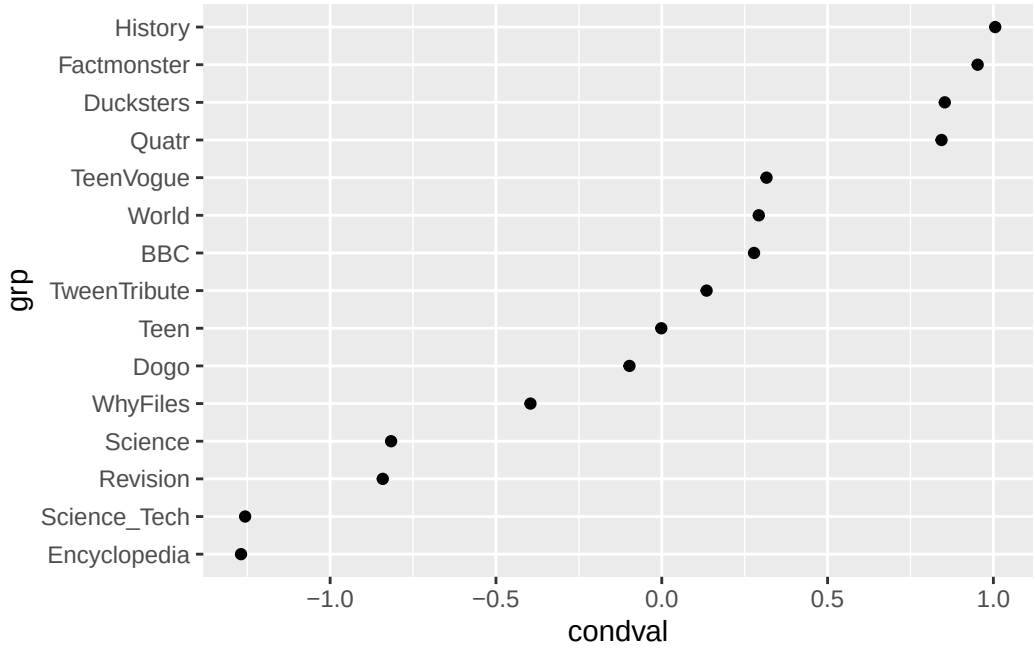
```
# svg(here("plots", "TxBReg3Reg_predicted_PC2_scores_interactions.svg"),
 ↪  height = 8, width = 9)
visreg(md_interaction_PC2, xvar = "Level", by="Register",
       #type = "contrast",
       type = "conditional",
       line=list(col="darkred"),
       points=list(cex=0.3),
       xlab = "Ref. corpora and textbook level (A to E)", ylab = "PC2",
       layout=c(3,1)
)
```



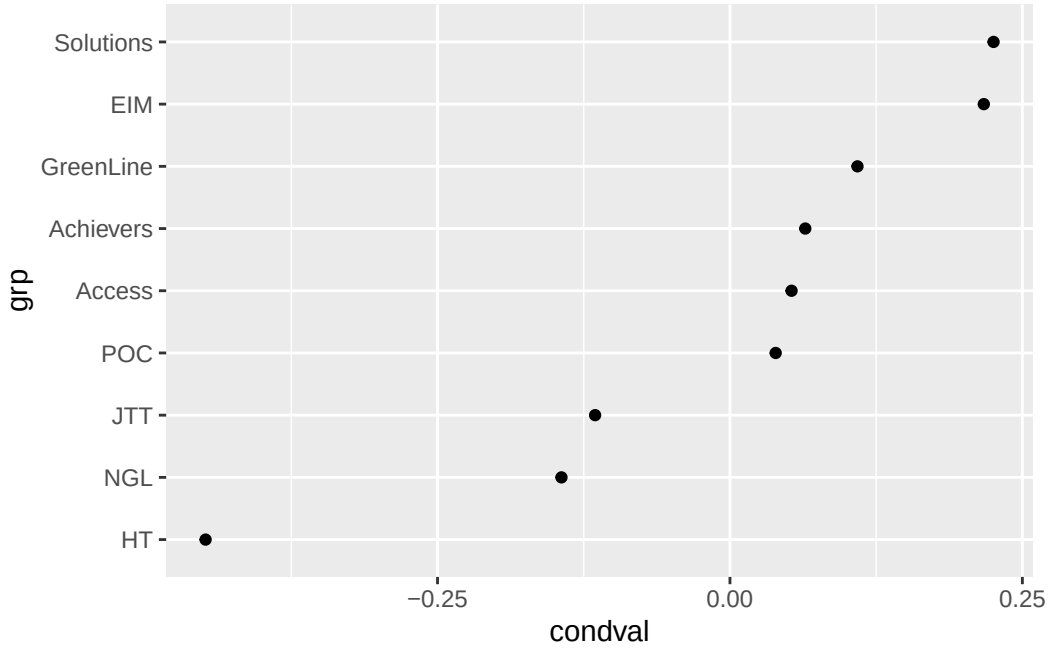

```
# dev.off()
```

We can also explore the random effect structure.

```
# Random effects
ranef <- as.data.frame(ranef(md_interaction_PC2))

# Exploring the random effects of the sources of the Info Teens corpus
ranef |>
  filter(grp %in% c("TeenVogue", "BBC", "Dogo", "Ducksters", "Encyclopedia",
   ↪  "Factmonster", "History", "Quatr", "Revision", "Science",
   ↪  "Science_Tech", "Teen", "TweenTribute", "WhyFiles", "World")) |>
  ggplot(aes(x = grp, y = condval)) +
  geom_point() +
  coord_flip()
```




```
# Exploring the random effects associated with textbook series
ranef |>
  filter(grp %in% levels(data$Series)) |>
  ggplot(aes(x = grp, y = condval)) +
  geom_point() +
  coord_flip()
```



H.10.4 Dimension 3: 'Pedagogically adapted vs. Natural'

We first compare various models and then present a tabular summary of the best-fitting one.

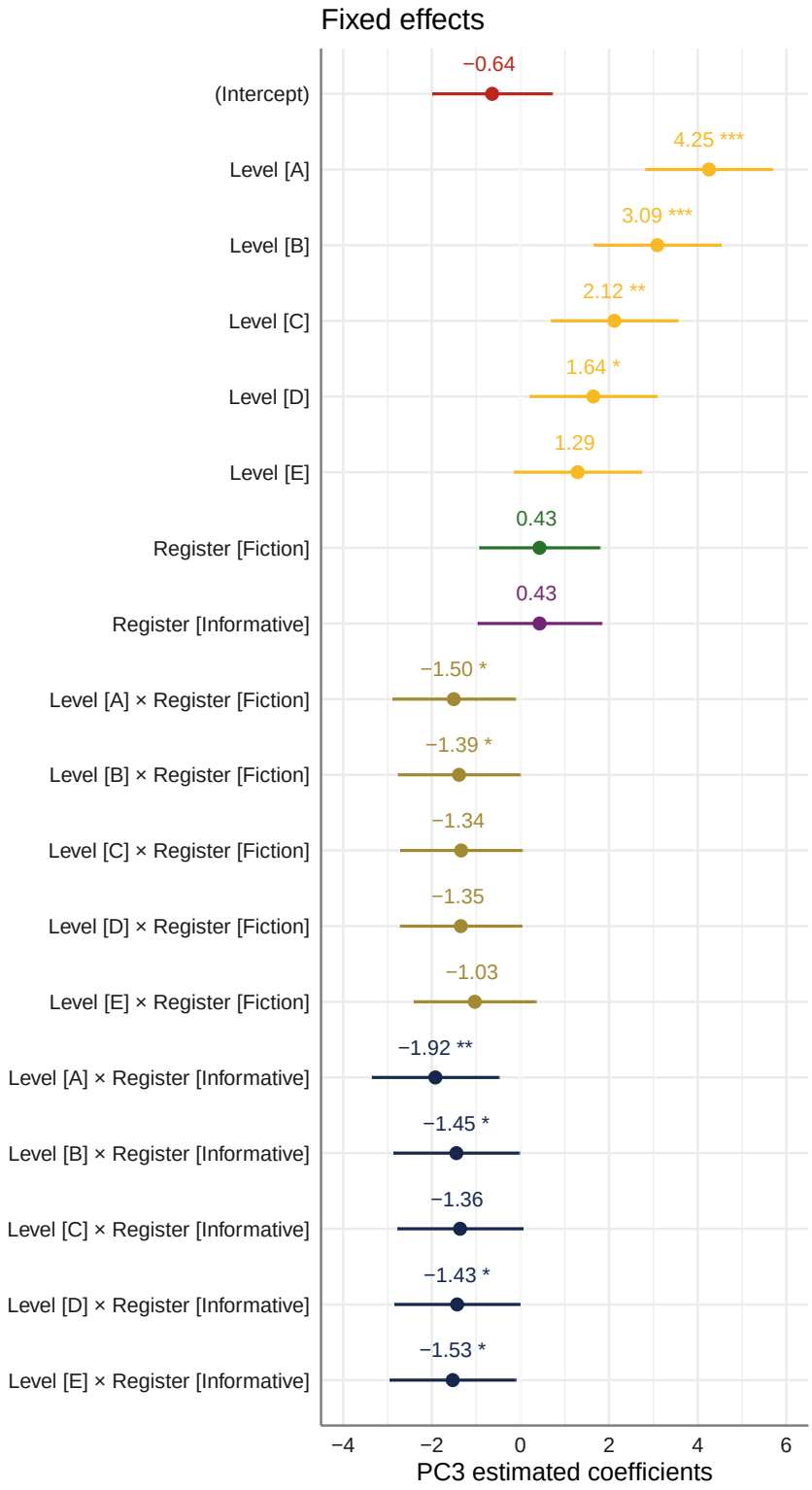
```
PC3_models <- run_anova("PC3", res.ind)
```

```
Data: data
Models:
md_source: PC3 ~ 1 + (1 | Source)
md_register: PC3 ~ (1 | Source) + Register
md_corpus: PC3 ~ (1 | Source) + Level
md_both: PC3 ~ (1 | Source) + Level + Register
md_interaction: PC3 ~ (1 | Source) + Level + Register + Level:Register
               npar   AIC   BIC  logLik deviance    Chisq Df Pr(>Chisq)
md_source         3 13523 13542 -6758.3    13517
md_register       5 12988 13020 -6489.0    12978  538.750  2  < 2.2e-16 ***
md_corpus         8 11928 11981 -5956.2    11912 1065.455  3  < 2.2e-16 ***
md_both          10 11466 11531 -5722.8    11446  466.870  2  < 2.2e-16 ***
md_interaction   20 11461 11592 -5710.7    11421   24.264 10   0.006929 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tab_model(md_interaction_PC3) # R2 = 0.425 / 0.700
```

Visualisation of the coefficient estimates of the fixed effects:

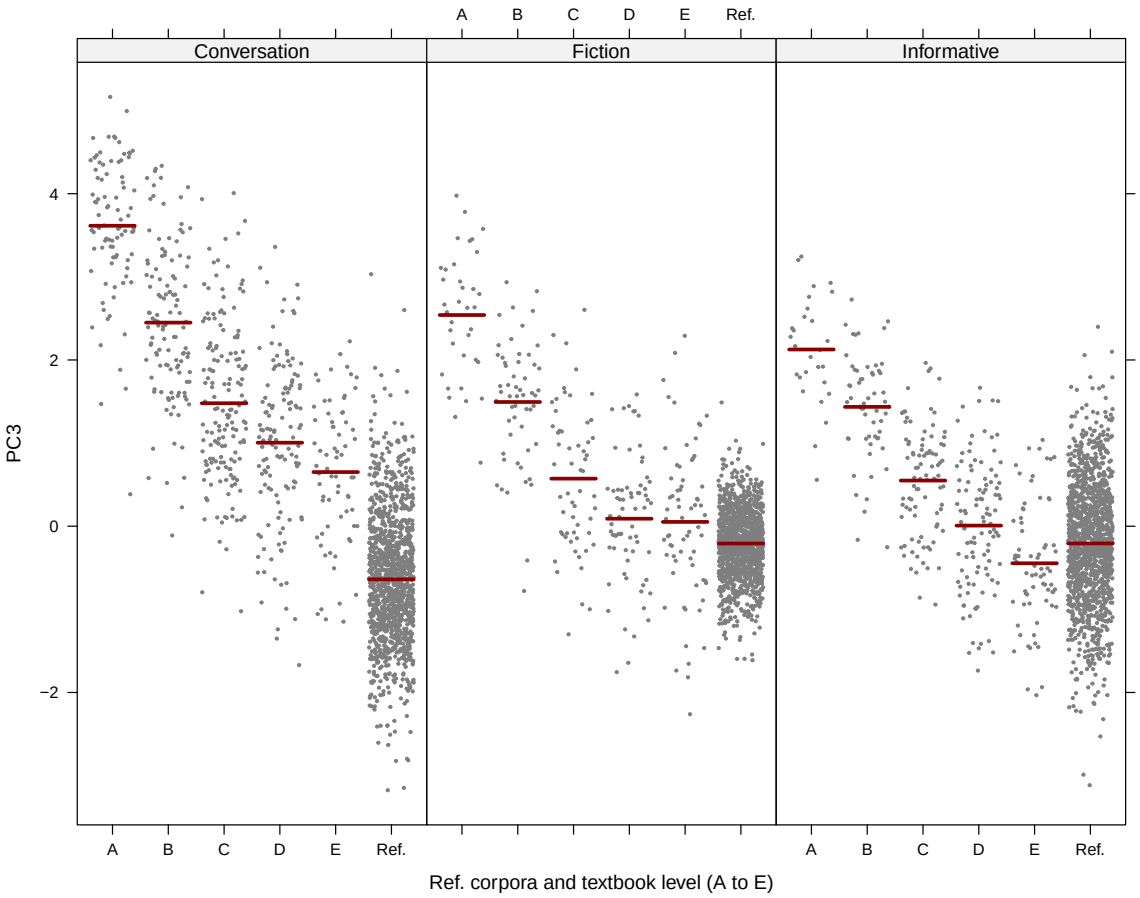
```
plot_model(md_interaction_PC3,
           #type = "re", # Option to visualise random effects
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,7:9)],
           group.terms = c(1,5,5,5,5,5,6,4,2,2,2,2,2,3,3,3,3,3),
           title="Fixed effects",
           wrap.labels = 40,
           axis.title = "PC3 estimated coefficients") +
  theme_sjplot2()
```


Fixed effects
−0.64
(Intercept)
4.25 ***
Level [A]
3.09 ***
Level [B]
2.12 **
Level [C]
1.64 *
Level [D]
1.29
Level [E]
0.43
Register [Fiction]
0.43
Register [Informative]
−1.50 *
Level [A] × Register [Fiction]
−1.39 *
Level [B] × Register [Fiction]
−1.34
Level [C] × Register [Fiction]
−1.35
Level [D] × Register [Fiction]
−1.03
Level [E] × Register [Fiction]
−1.92 **
Level [A] × Register [Informative]
−1.45 *
Level [B] × Register [Informative]
−1.36
Level [C] × Register [Informative]
−1.43 *
Level [D] × Register [Informative]
−1.53 *
Level [E] × Register [Informative]
−4
−2
0
2
4
6
PC3 estimated coefficients

```
#ggsave(here("plots", "TxBRef3Reg_PC3_lmer_fixed.svg"), height = 6, width =
 ↪  9)
```

Visualisation of the predicted Dim3 scores:

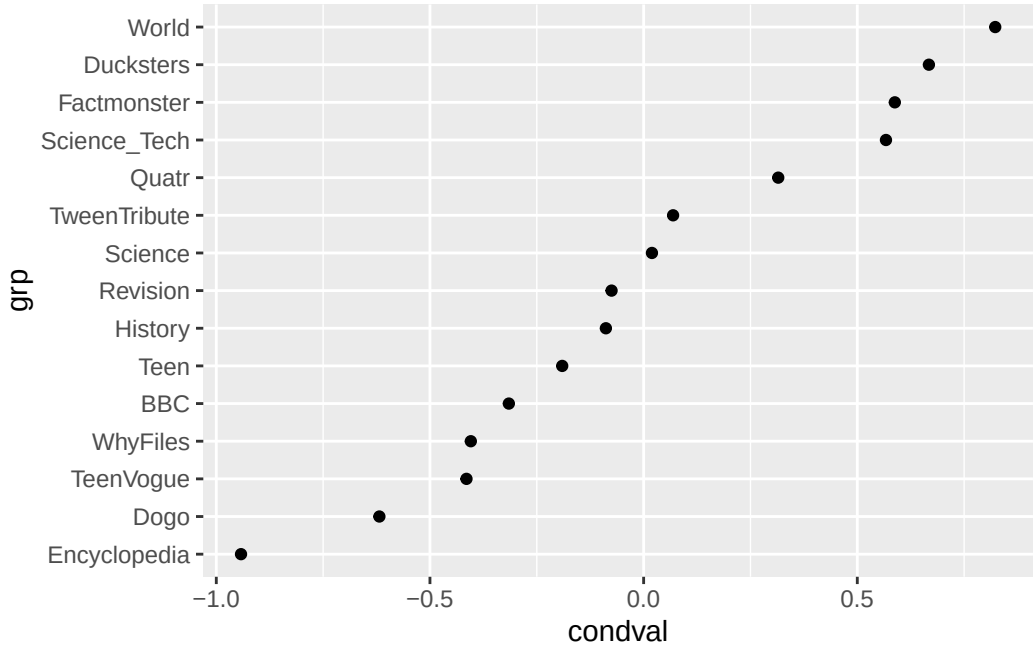
```
# svg(here("plots", "TxBReg3Reg_predicted_PC3_scores_interactions.svg"),
 ↪  height = 8, width = 9)
visreg(md_interaction_PC3, xvar = "Level", by="Register",
       #type = "contrast",
       type = "conditional",
       line=list(col="darkred"),
       points=list(cex=0.3),
       xlab = "Ref. corpora and textbook level (A to E)", ylab = "PC3",
       layout=c(3,1)
)
```



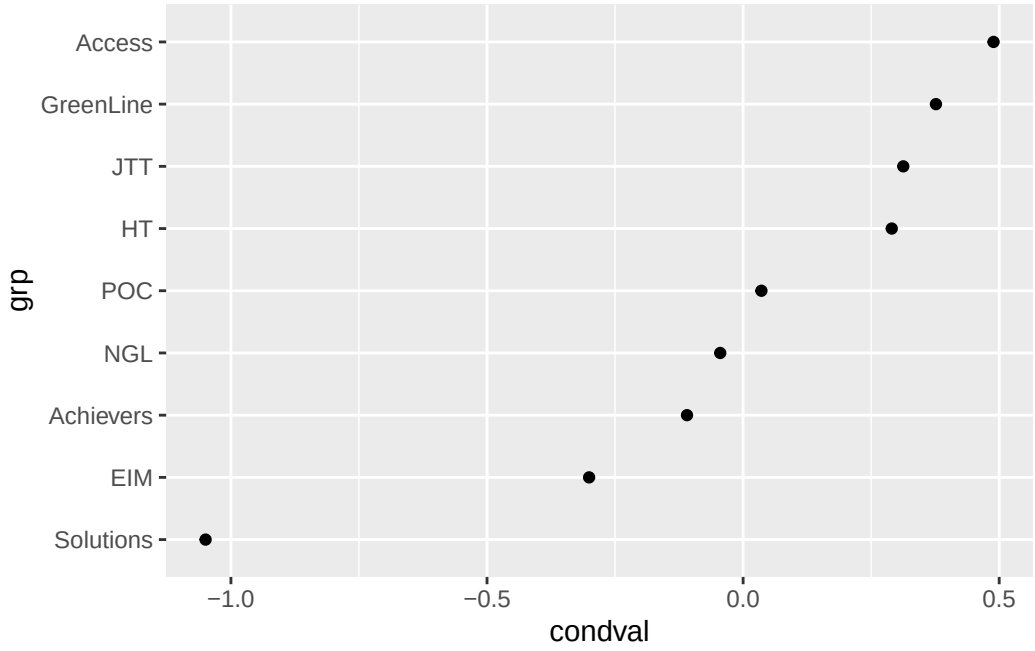

```
# dev.off()
```

We can also explore the random effect structure.

```
# Random effects
ranef <- as.data.frame(ranef(md_interaction_PC3))

# Exploring the random effects of the sources of the Info Teens corpus
ranef |>
  filter(grp %in% c("TeenVogue", "BBC", "Dogo", "Ducksters", "Encyclopedia",
   ↪  "Factmonster", "History", "Quatr", "Revision", "Science",
   ↪  "Science_Tech", "Teen", "TweenTribute", "WhyFiles", "World")) |>
  ggplot(aes(x = grp, y = condval)) +
  geom_point() +
  coord_flip()
```




```
# Exploring the random effects associated with textbook series
ranef |>
  filter(grp %in% levels(data$Series)) |>
  ggplot(aes(x = grp, y = condval)) +
  geom_point() +
  coord_flip()
```



H.10.5 Dimension 4: 'Factual vs. Speculative' / 'Simple vs. complex verb forms'?

We first compare various models and then present a tabular summary of the best-fitting one.

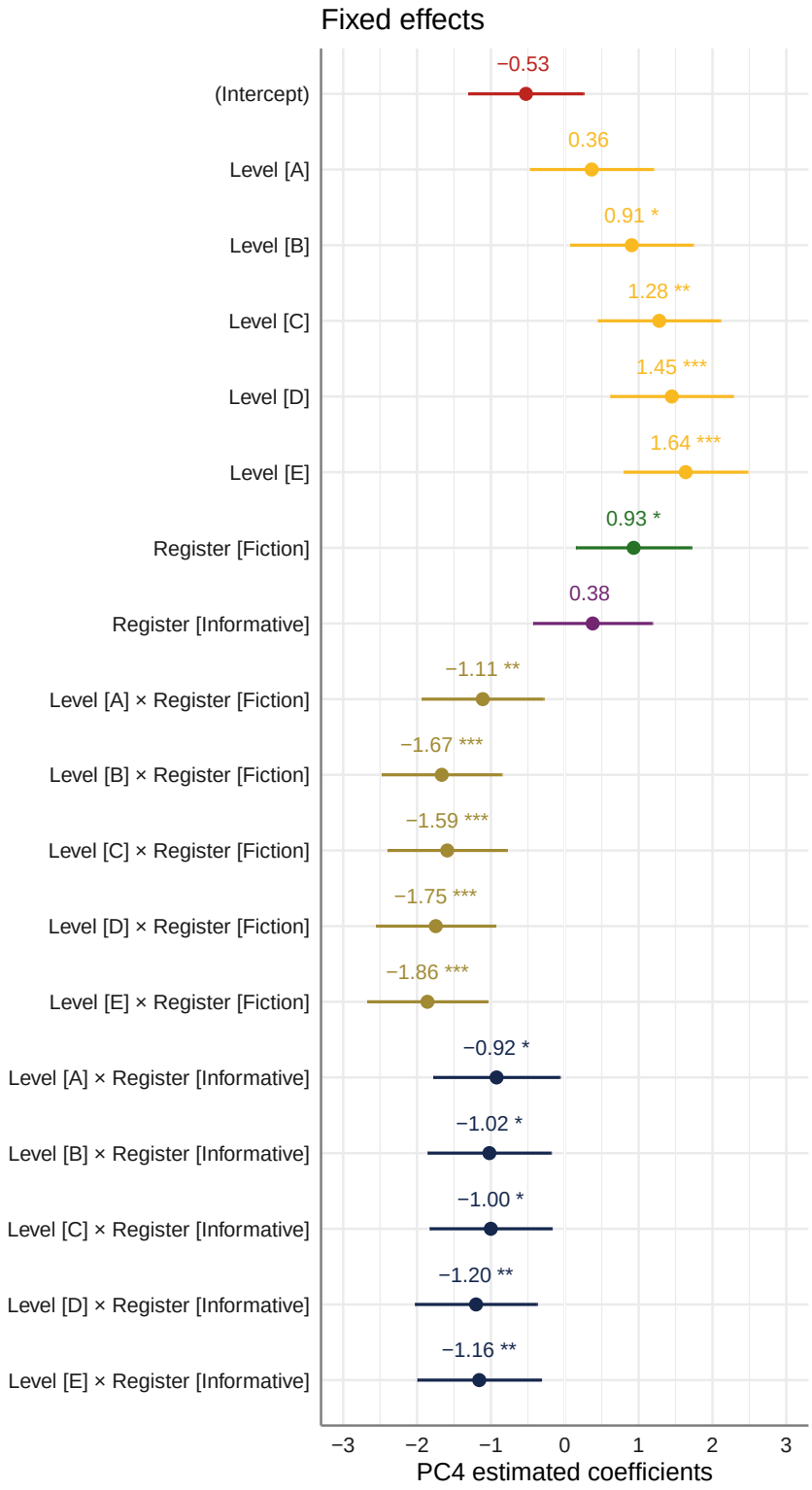
```
PC4_models <- run_anova("PC4", res.ind)
```

```
Data: data
Models:
md_source: PC4 ~ 1 + (1 | Source)
md_register: PC4 ~ (1 | Source) + Register
md_corpus: PC4 ~ (1 | Source) + Level
md_both: PC4 ~ (1 | Source) + Level + Register
md_interaction: PC4 ~ (1 | Source) + Level + Register + Level:Register
               npar   AIC   BIC  logLik deviance    Chisq Df Pr(>Chisq)
md_source         3 11019 11039 -5506.5    11013
md_register       5 10825 10857 -5407.4    10815 198.2593  2    < 2e-16 ***
md_corpus         8 10827 10879 -5405.3    10811   4.0956  3     0.2513
md_both          10 10563 10628 -5271.6    10543 267.5805  2    < 2e-16 ***
md_interaction   20 10527 10657 -5243.3    10487  56.4370 10    1.7e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tab_model(md_interaction_PC4) # R2 = 0.234 / 0.434
```

Visualisation of the coefficient estimates of the fixed effects:

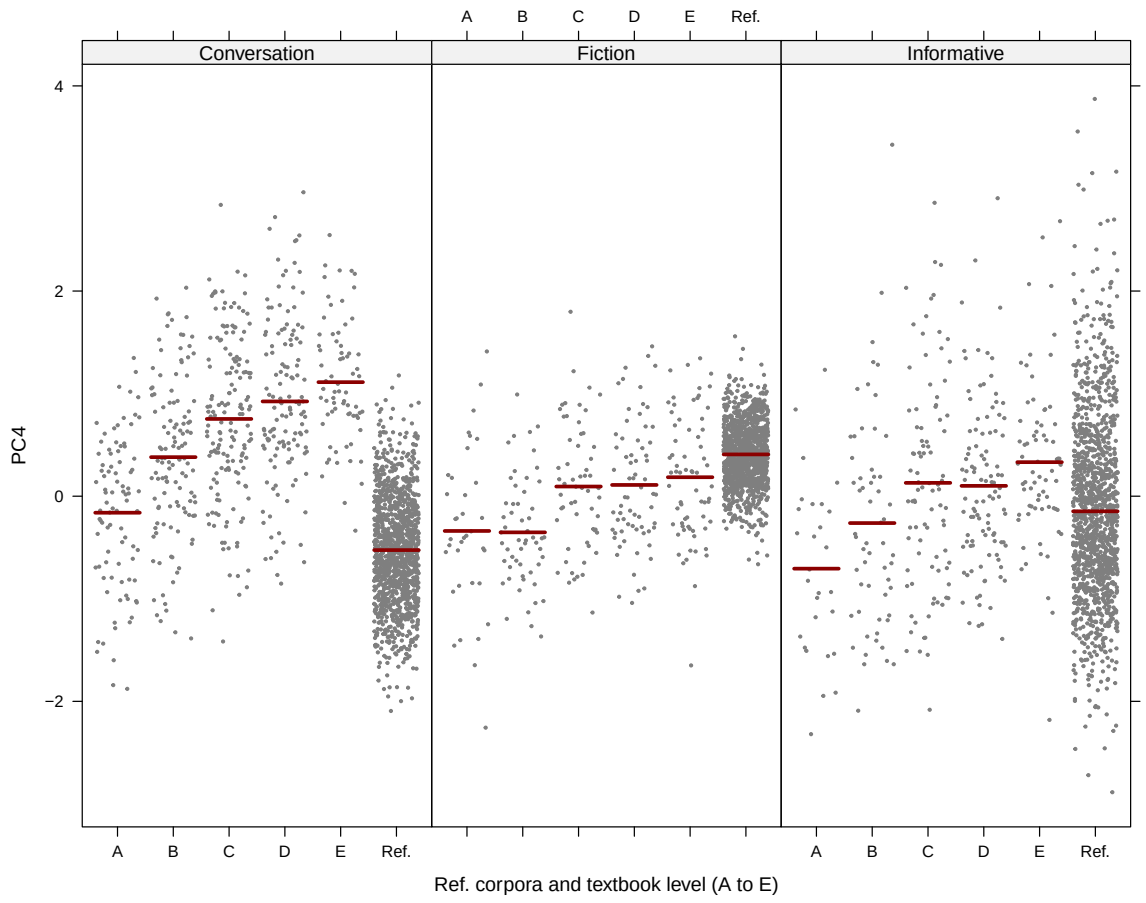
```
plot_model(md_interaction_PC4,
           #type = "re", # Option to visualise random effects
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,7:9)],
           group.terms = c(1,5,5,5,5,5,6,4,2,2,2,2,2,3,3,3,3,3),
           title="Fixed effects",
           wrap.labels = 40,
           axis.title = "PC4 estimated coefficients") +
  theme_sjplot2()
```


Fixed effects
(Intercept)
−0.53
Level [A]
0.36
Level [B]
0.91 *
Level [C]
1.28 **
Level [D]
1.45 ***
Level [E]
1.64 ***
Register [Fiction]
0.93 *
Register [Informative]
0.38
Level [A] × Register [Fiction]
−1.11 **
Level [B] × Register [Fiction]
−1.67 ***
Level [C] × Register [Fiction]
−1.59 ***
Level [D] × Register [Fiction]
−1.75 ***
Level [E] × Register [Fiction]
−1.86 ***
Level [A] × Register [Informative]
−0.92 *
Level [B] × Register [Informative]
−1.02 *
Level [C] × Register [Informative]
−1.00 *
Level [D] × Register [Informative]
−1.20 **
Level [E] × Register [Informative]
−1.16 **
−3
−2
−1
0
1
2
3
PC4 estimated coefficients

```
#ggsave(here("plots", "TxBRef3Reg_PC4_lmer_fixed.svg"), height = 6, width =
 ↪  9)
```

Visualisation of the predicted Dim4 scores:

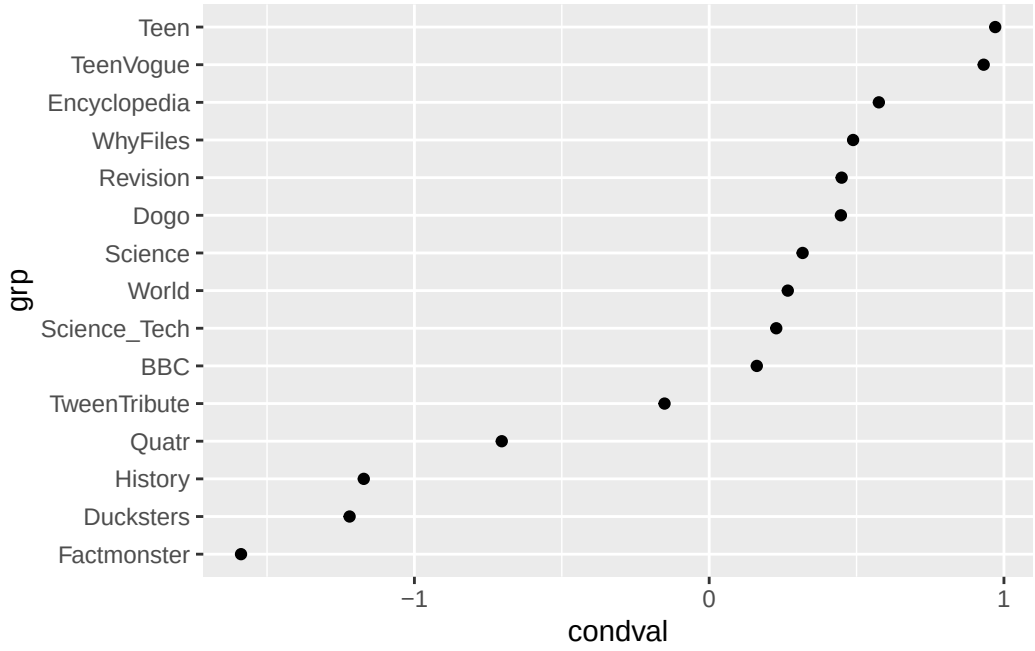
```
# svg(here("plots", "TxBReg3Reg_predicted_PC4_scores_interactions.svg"),
 ↪  height = 8, width = 9)
visreg(md_interaction_PC4, xvar = "Level", by="Register",
       #type = "contrast",
       type = "conditional",
       line=list(col="darkred"),
       points=list(cex=0.3),
       xlab = "Ref. corpora and textbook level (A to E)", ylab = "PC4",
       layout=c(3,1)
)
```



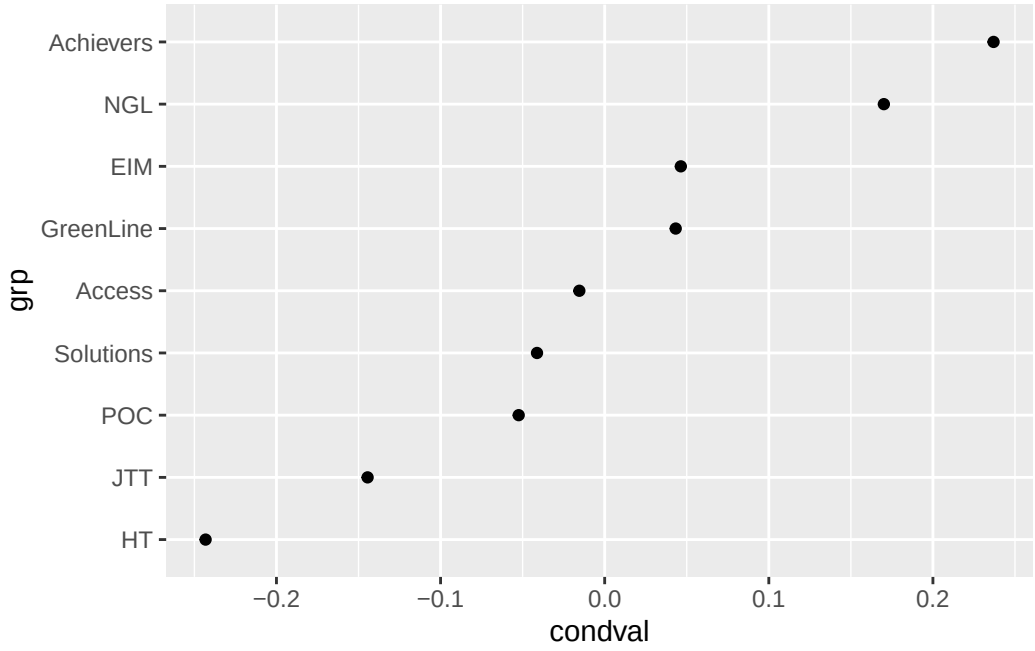

```
# dev.off()
```

We can also explore the random effect structure.

```
# Random effects
ranef <- as.data.frame(ranef(md_interaction_PC4))

# Exploring the random effects of the sources of the Info Teens corpus
ranef |>
  filter(grp %in% c("TeenVogue", "BBC", "Dogo", "Ducksters", "Encyclopedia",
   ↪  "Factmonster", "History", "Quatr", "Revision", "Science",
   ↪  "Science_Tech", "Teen", "TweenTribute", "WhyFiles", "World")) |>
  ggplot(aes(x = grp, y = condval)) +
  geom_point() +
  coord_flip()
```



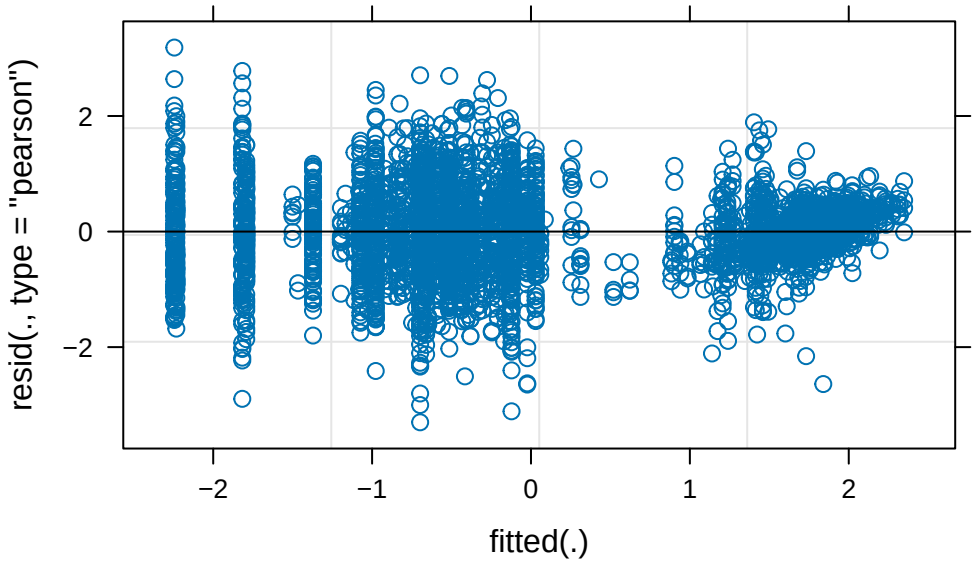

```
# Exploring the random effects associated with textbook series
ranef |>
  filter(grp %in% levels(data$Series)) |>
  ggplot(aes(x = grp, y = condval)) +
  geom_point() +
  coord_flip()
```



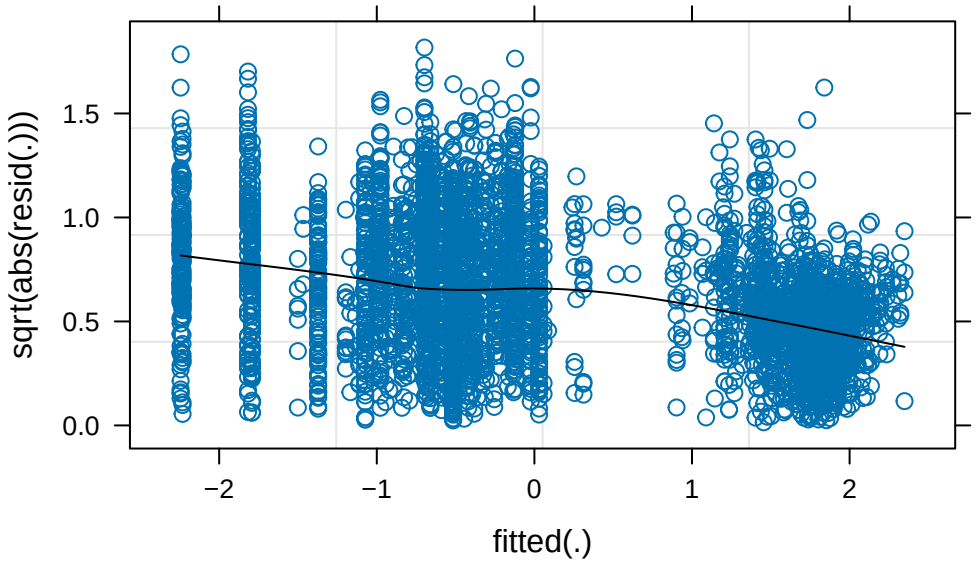
H.10.6 Testing model assumptions

This chunk can be used to check the assumptions of all of the models computed above. In the following example, we examine the final model selected to predict Dim2 scores.

```
model2test <- md_interaction_PC2

# check distribution of residuals
plot(model2test)
```




```
# scale-location plot
plot(model2test,
     sqrt(abs(resid(.)))~fitted(.),
     type=c("p","smooth"), col.line=1)
```




```
# Q-Q plot
lattice::qqmath(model2test)
```