Textbook English: A Multi-Dimensional Approach

Online Supplements

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About

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 Together with dull gap-fill exercises and photos of out-of-date technology, for many adults, the very mention of the word textbook evokes vivid memories of such artificially sounding, contrived and sometimes even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

Another important insight from the methodological part of the literature review (see Section 3.1 in book publication) is that, to the author's best knowledge, no Textbook English study published so far has included (as an appendix or supplementary materials) the data and code necessary to reproduce or replicate the published results. As a result, it is very difficult to evaluate the reliability or robustness of the results reported (see also Le Foll 2024).

Though the terms are sometimes used interchangeably and different (at times incompatible) definitions abound, in computational sciences, 'reproducibility' usually refers to the ability to obtain the same results as an original study using the researchers' data and code, whilst 'replicability' refers to obtaining compatible results with the same method but different data (Association for Computing Machinery 2020; see also Berez-Kroeker et al. 2018).

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 to be able to successfully replicate the full procedures. This step can enable others to conduct detailed reviews of our methodologies and conceptual replications of our results on different data.

Aside from data protection and copyright regulations, there are, of course, many reasons why researchers may be reluctant to share their data and code (Berez-Kroeker et al. 2018; McManus 2021). It is not within the scope of this monograph to discuss these; however, it is clear 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 myself, who have had no formal training in data management or programming and have 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 all the raw data and code necessary to reproduce the results reported in the present monograph following the FAIR principles (i.e., ensuring that research data are Findable, Accessible, Interoperable and Reusable, see Wilkinson et al. 2016). For copyright reasons, the corpora themselves and

annotated corpus data in the form of concordance lines cannot be made available. However, the outcome of both manual and automatic annotation processes is published in tabular formats in the Online Appendix. These tables allow for the reproduction of all the analyses reported on in the following chapters using the reproducible data analysis scripts also published in the Online Supplements and in the associated Open Science Framework (OSF) repository.

In all chapters of this monograph, full transparency is strived for by reporting on how each sample size was determined and on which grounds 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). Most of the data processing and analysis scripts therefore consist of R markdown documents. These were 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. These scripts also feature 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 additional software or open-source code from other researchers were used, links to these are also provided in the Online Supplements (in addition to the corresponding references in the bibliography).

Appendix A: Literature review

This is a tabular overview of the Textbook English studies that I examined as part of my literature review. It presents the results of a 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 that are either not applicable to this particular study or for which no information could be found. Intended as a dynamic resource, this interactive, searchable, and filterable table currently lists over 80 studies on the language content of English L2 textbooks, thereby demonstrating the breadth of Textbook English studies published as of early 2022.

Appendix B: Corpus data

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.

Reference corpora

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

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.

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.

Appendix D: 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).

Packages required

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

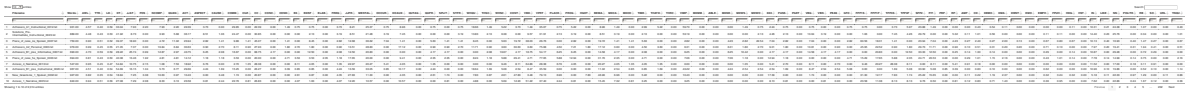
```
#renv::restore() # Restore the project's dependencies from the lockfile to
 ↪  ensure that same package versions are used as in the original study

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
```

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 2021a).

```
# 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(2: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

Textbook Name	# of texts
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)
```

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"))
```

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"))
```

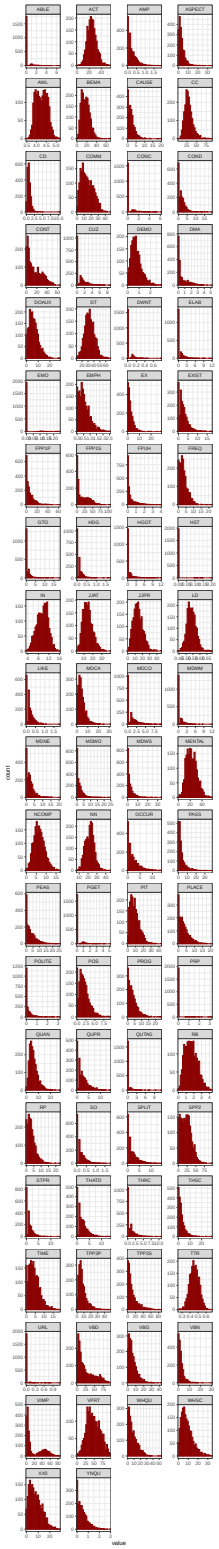
Register	# texts
Conversation	593
Fiction	285
Informative	364
Instructional	647
Personal	88

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
CD
COMM
CONC
COND
CONT
CUZ
DEMO
DWA
DOMJX
DT
DWNT
ELAB
EMO
EMPH
EX
EXIST
FPPSP
FPPSS
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
PSP
QUAN
QUPR
QUTAG
RB
RP
SO
SPLIT
SPP2
STPR
THATD
THRC
THSC
TIME
TPPSP
TPP2S
TTR
URL
VBD
VBG
VBN
VIMP
VPRT
WHQU
WHSC
XXC
YNQU
count
value

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

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 2021b).

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
```

```
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

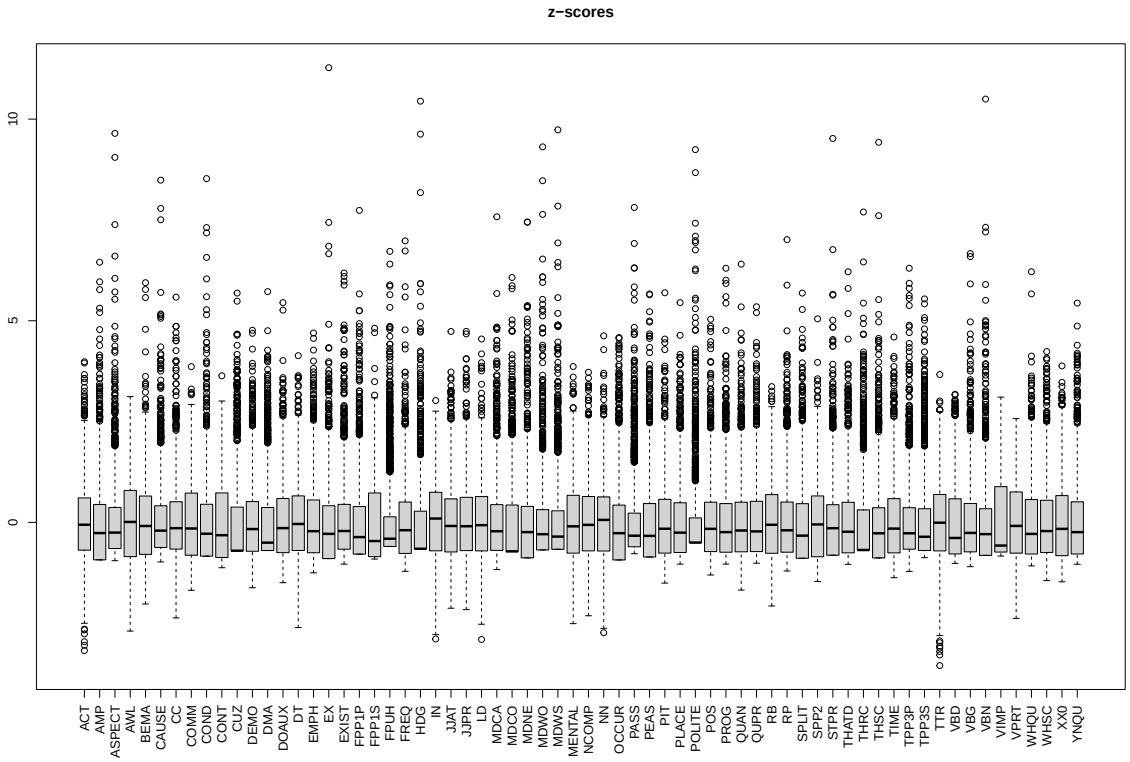
```
# Drop variables with low document frequency
TxBcounts <- select(TxBcounts, -one_of(zero_features2$rowname))
#ncol(TxBcounts)-8 # Number of linguistic features remaining

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

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

Identifying potential 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
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
```

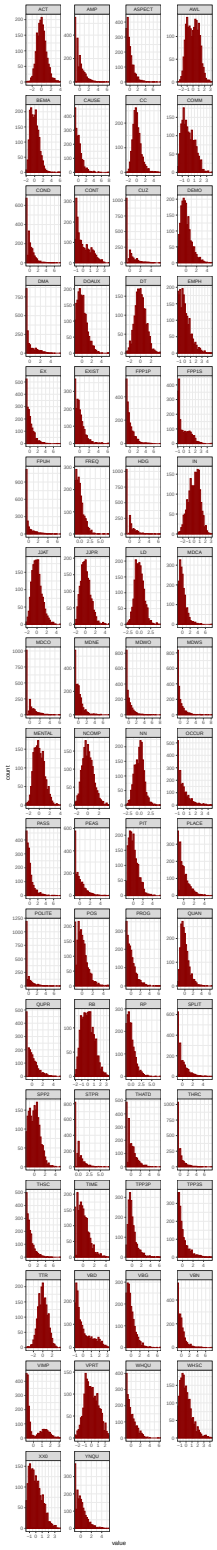
```
                                          Filename
1                            POC_4e_Spoken_0007.txt
2              Solutions_Elementary_Personal_0001.txt
3                        NGL_5_Instructional_0018.txt
4                            Access_1_Spoken_0011.txt
5                               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
INF
JJPR
LD
MDCA
MDCO
MDNE
MDNO
MDWS
MENTAL
NCOMP
NN
OCCUR
PASS
PEAS
PIT
PLACE
POLITE
POS
PROG
QUAN
QUPR
RB
RP
SPLIT
SPTV
STPR
THATD
THEC
THSC
TIME
TPFSP
TPP2S
TTR
VBD
VBG
VBN
VMP
VPIT
WHQU
WHSC
XX0
YNQU
count
value

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

Signed log transformation

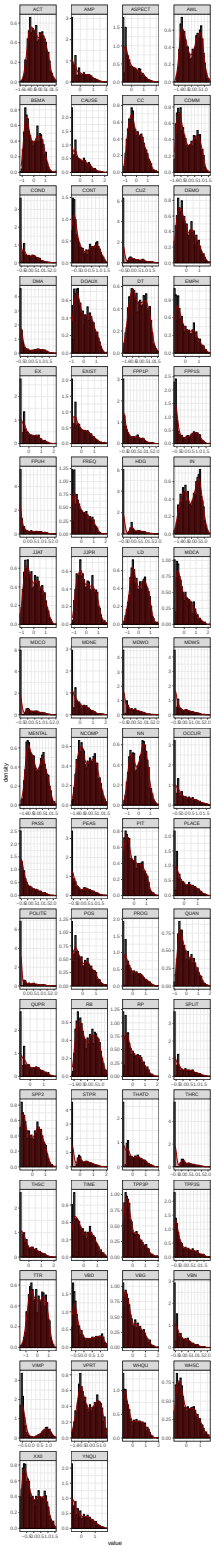
A signed logarithmic transformation was applied to (further) deskew the feature distributions (Diwersy, Evert, and Neumann 2014; Neumann and Evert 2021).

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
FPUM
FREQ
HDG
IN
JJAT
JJPR
LID
MODA
MOCO
MONE
MONO
MOWS
NEATAL
NCOMP
NU
OCCUR
PAGS
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

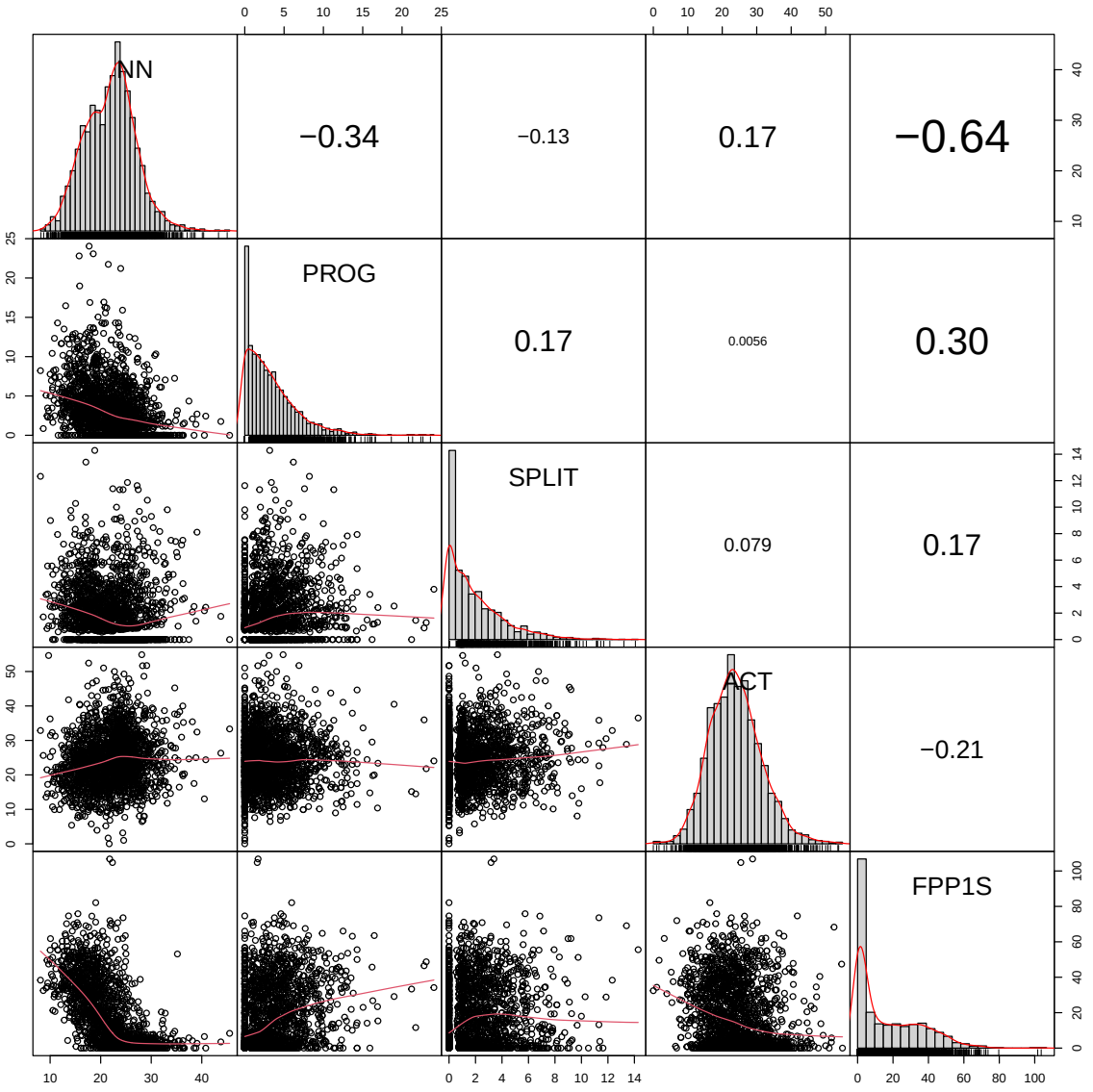
```
#ggsave(here("plots", "DensityPlotsAllVariablesSignedLog-TEC-only.svg"),
 ↪  width = 15, height = 49)
```

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)
```

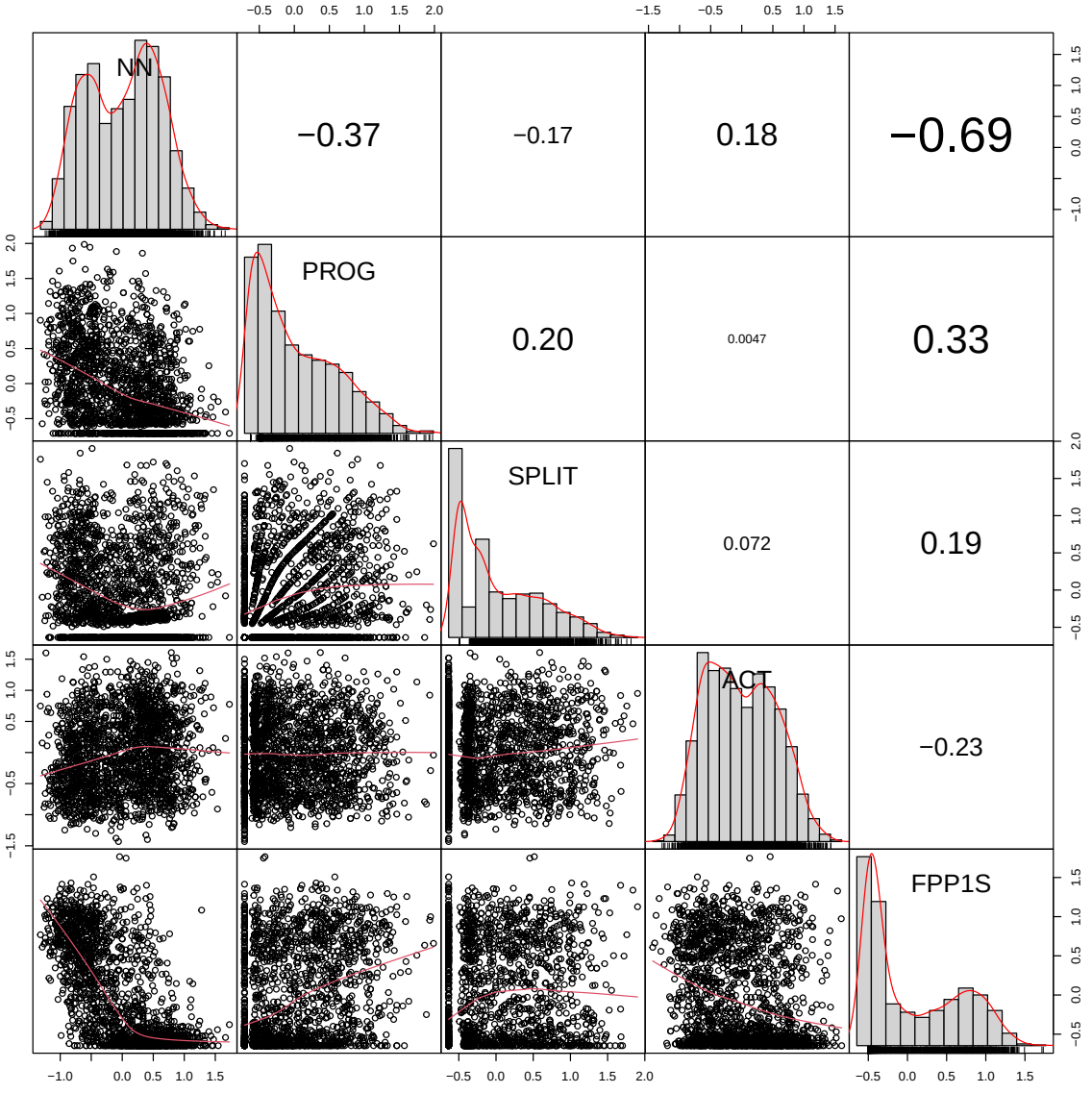



```
#dev.off()
```

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)
```

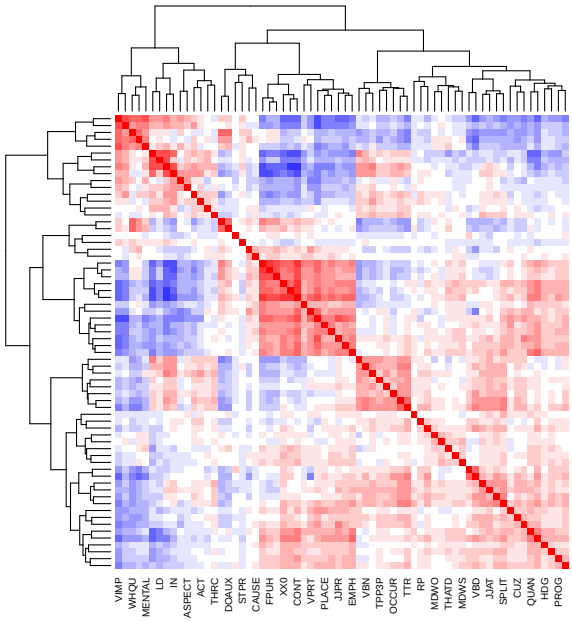



```
#dev.off()
```

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

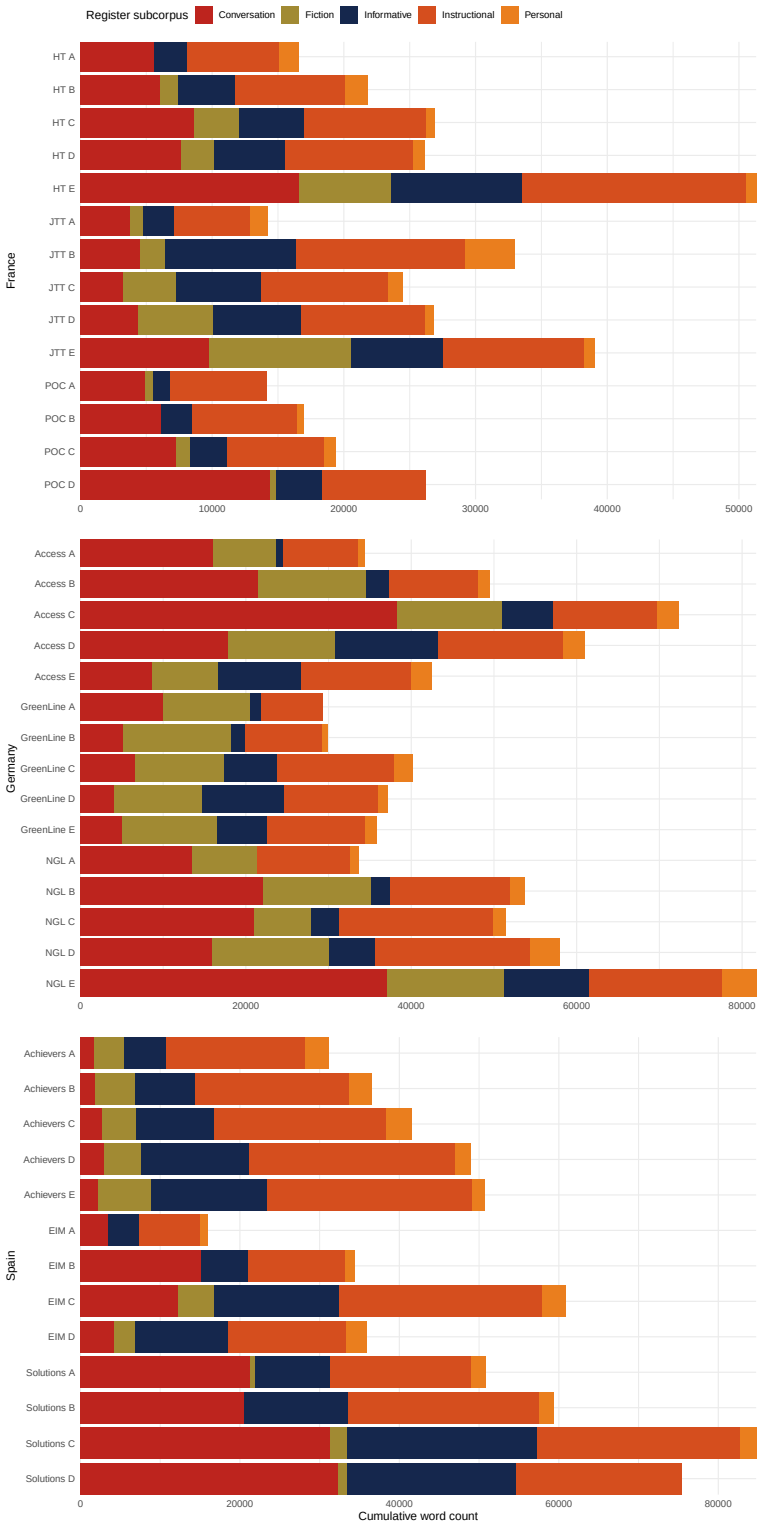
```
#dev.off()

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

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")
```

```
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")

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

Appendix E: 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.

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
```

Preparing the data for PCA

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.

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
```

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:

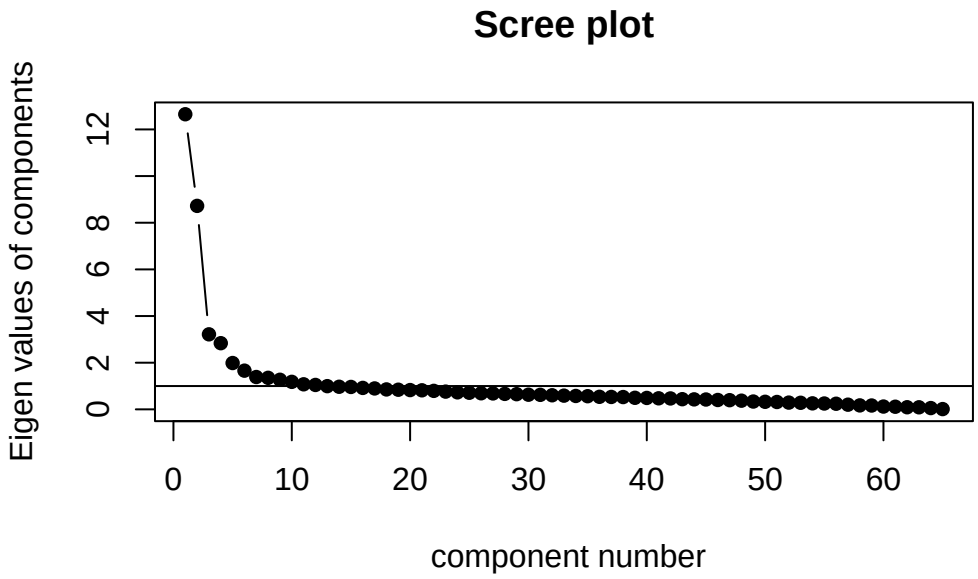
```
kmo2$MSAi[order(kmo2$MSAi)] |>  round(2)
```

```
  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
```

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
```

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.

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))
```

Principal Component Analysis (PCA)

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"))
```

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).
```

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, n.d.) 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).
```

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
```

Plotting PCA results

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")
```

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.

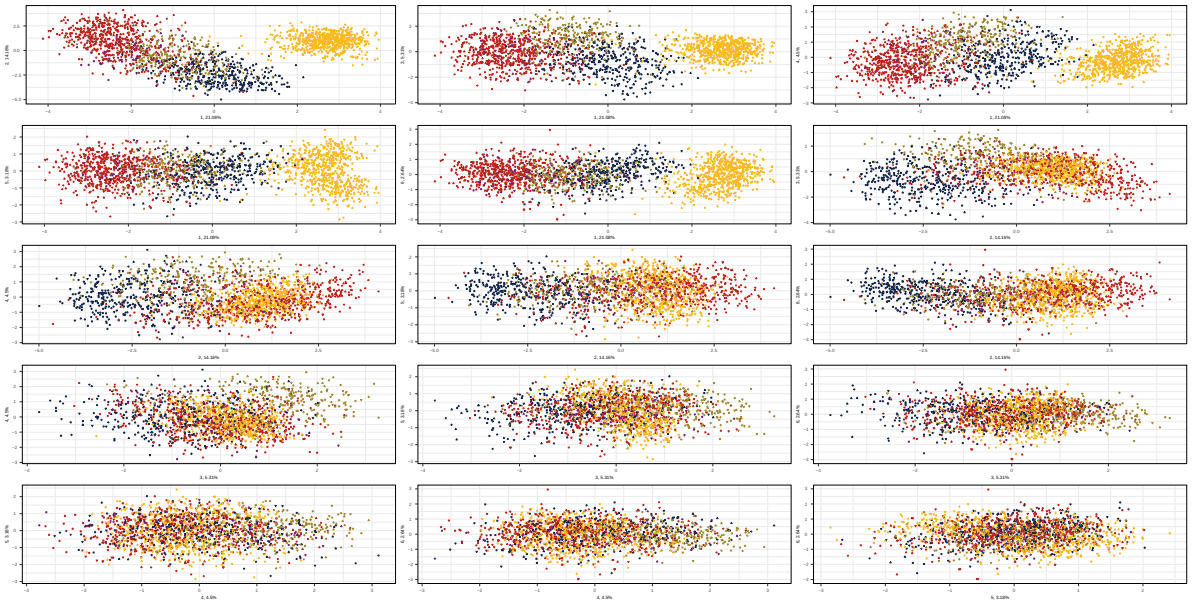
Data wrangling for PCAtools

```
#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)
```

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")
```

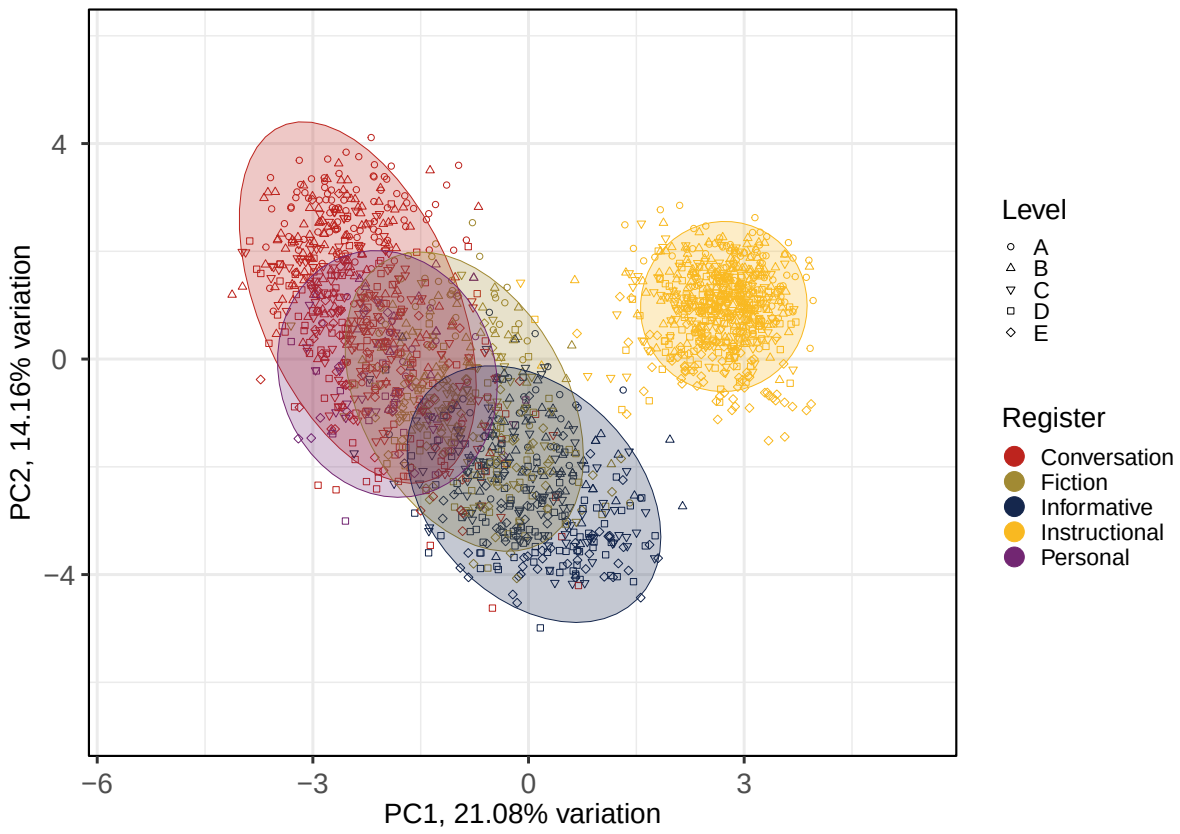


Bi-plots

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"))
```



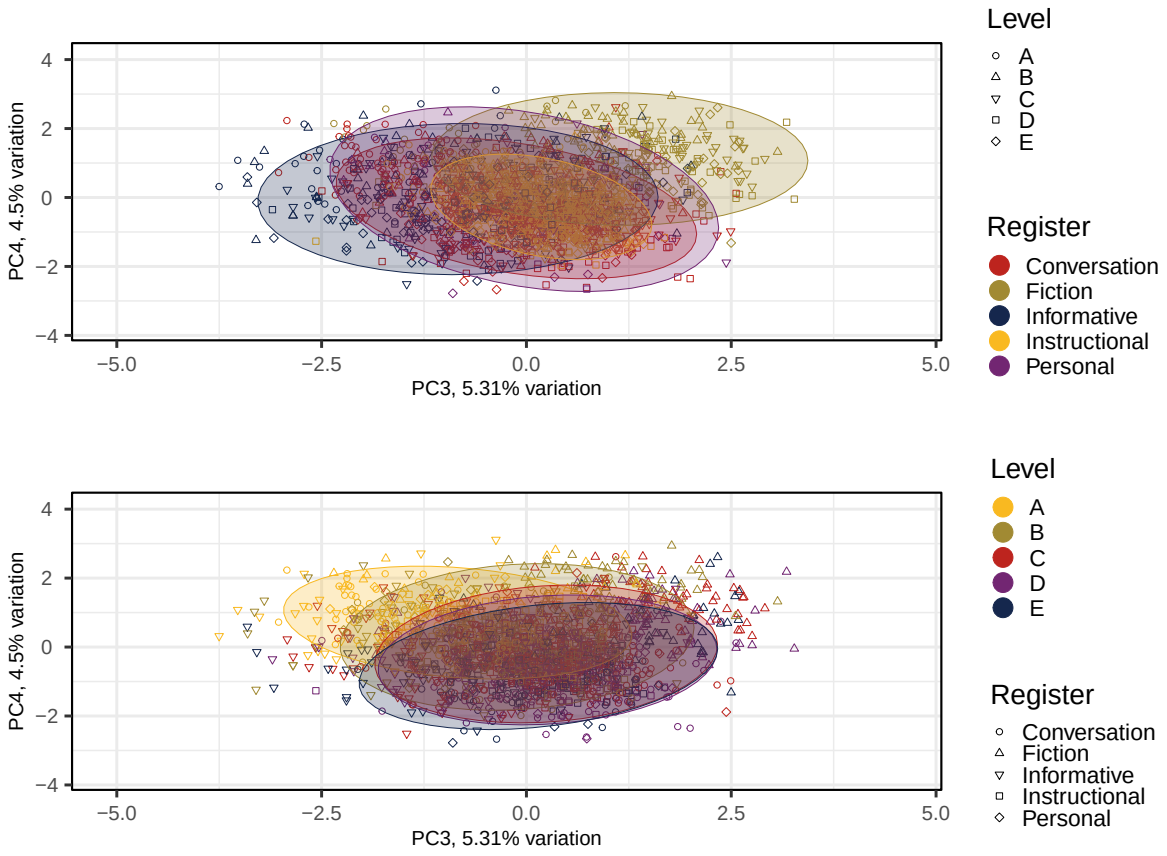

```
#dev.off()
#ggsave(here("plots", "PCA_TxB_BiplotPC1_PC2.svg"), width = 12, height = 10)

# 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.

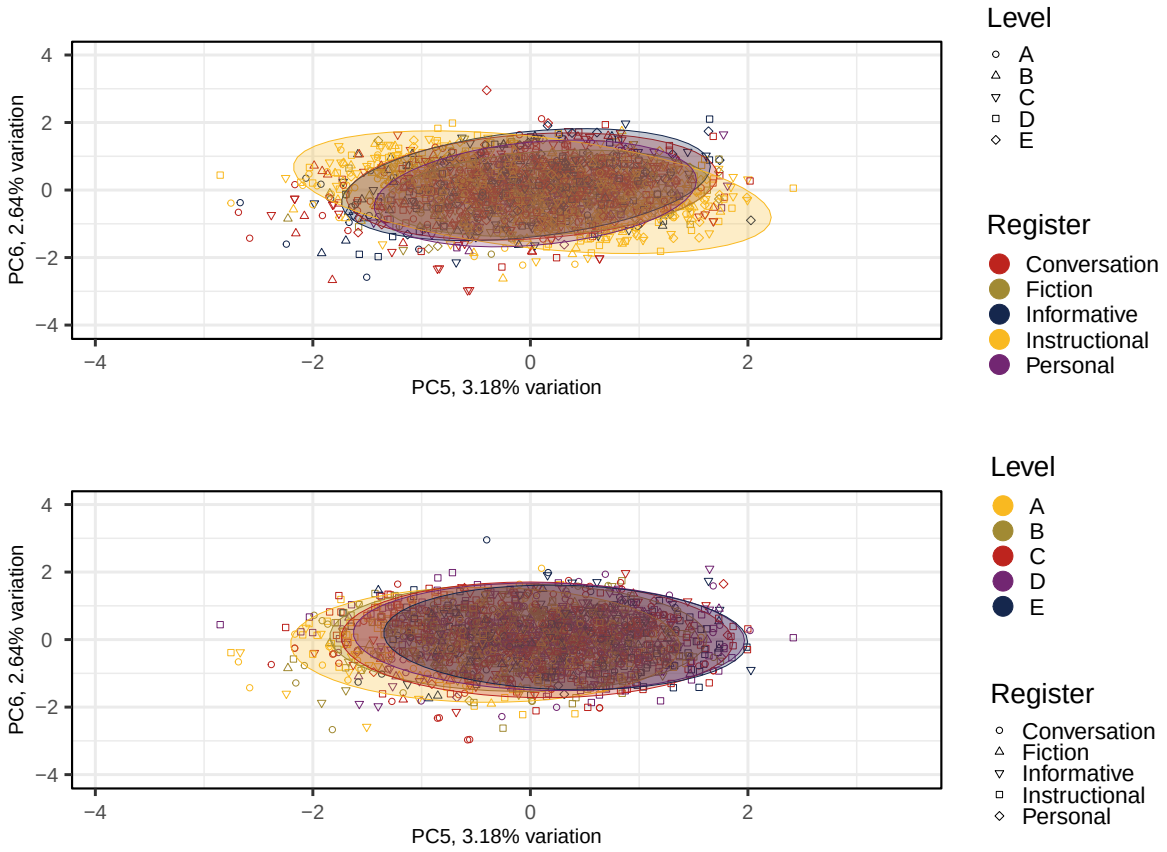
```
# Inverted keys for the biplots with ellipses for Level rather than Register
colkeyLevels = c(A="#F9B921", B="#A18A33", C="#BD241E", D="#722672",
 ↪  E="#15274D")
shapekeyLevels = c(Conversation=1, Fiction=2, Informative=6, Instructional=0,
 ↪  Personal=5)

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)
```

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
```

```r
# 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

	PC1	PC2	PC3	PC4
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
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

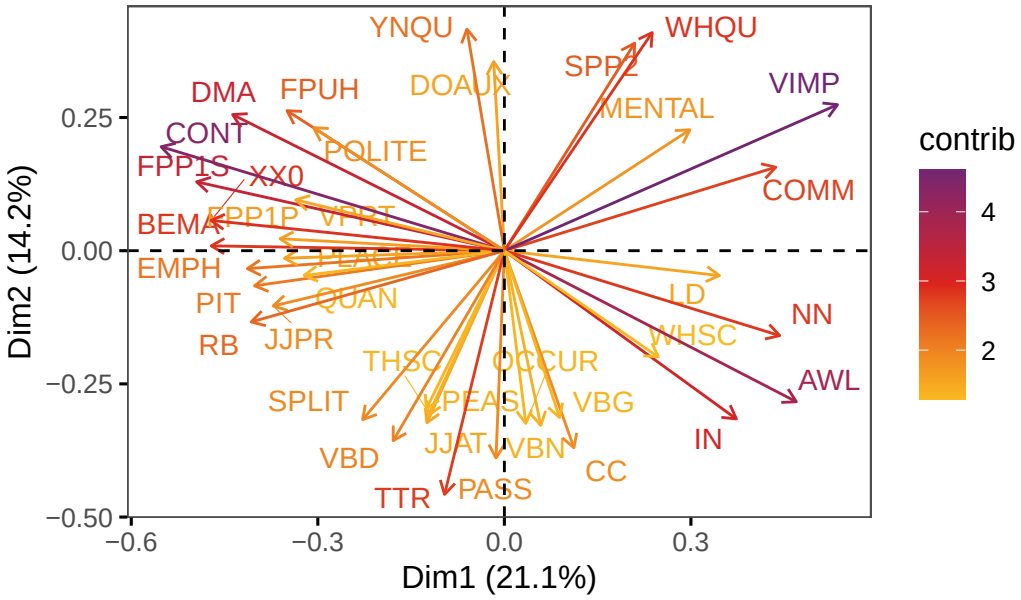
We can go back to the normalised frequencies of the individual features to compare them across different registers and levels, e.g.:

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

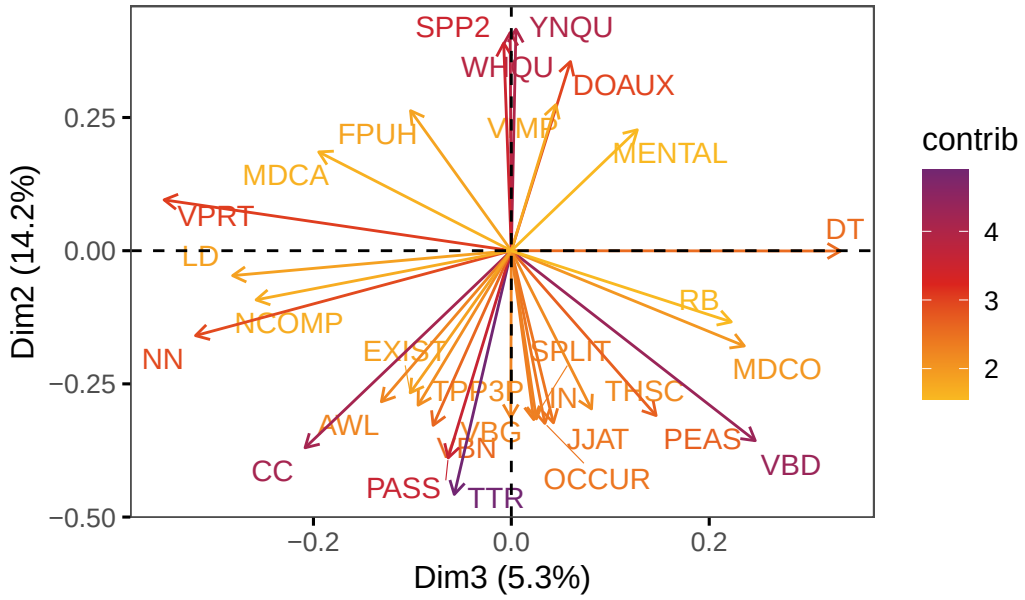
Register	Level	median(NCOMP)	MAD(NCOMP)
Conversation	A	5.69	2.79
Conversation	B	5.48	2.66
Conversation	C	5.32	2.58
Conversation	D	6.18	2.91
Conversation	E	6.21	2.62
Fiction	A	4.14	2.34
Fiction	B	3.96	2.17
Fiction	C	4.05	1.86
Fiction	D	5.05	2.34
Fiction	E	5.05	2.16
Informative	A	8.07	2.48
Informative	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.

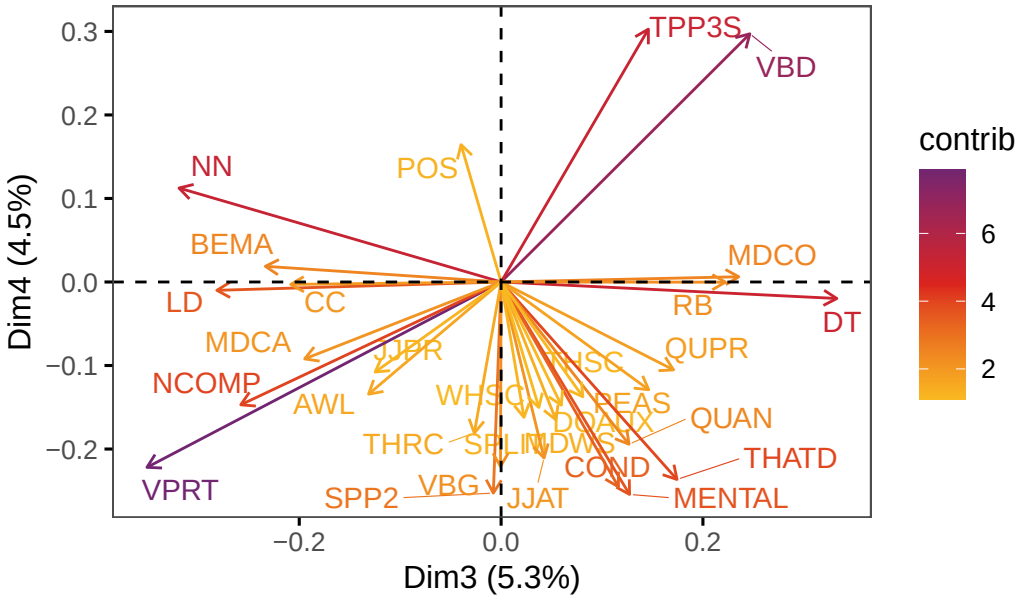
```
factoextra::fviz_pca_var(pca,
             axes = c(1,2),
             select.var = list(cos2 = 0.1),
             col.var = "contrib", # Colour by contributions to the PC
             gradient.cols = c("#F9B921", "#DB241E", "#722672"),
             title = "",
             repel = TRUE, # Try to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

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

```
# res.ind |>
#   select(Register, Level, PC2) |>
#   group_by(Register, Level) |>
#   summarise_if(is.numeric, c(Median = median, MAD = mad))|>
#   mutate(across(where(is.numeric), round, 2)) |>
#   as.data.frame()
```

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 for 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

Computing mixed-effects models of the dimension scores

Dimension 1: 'Overt instructions and explanations'

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

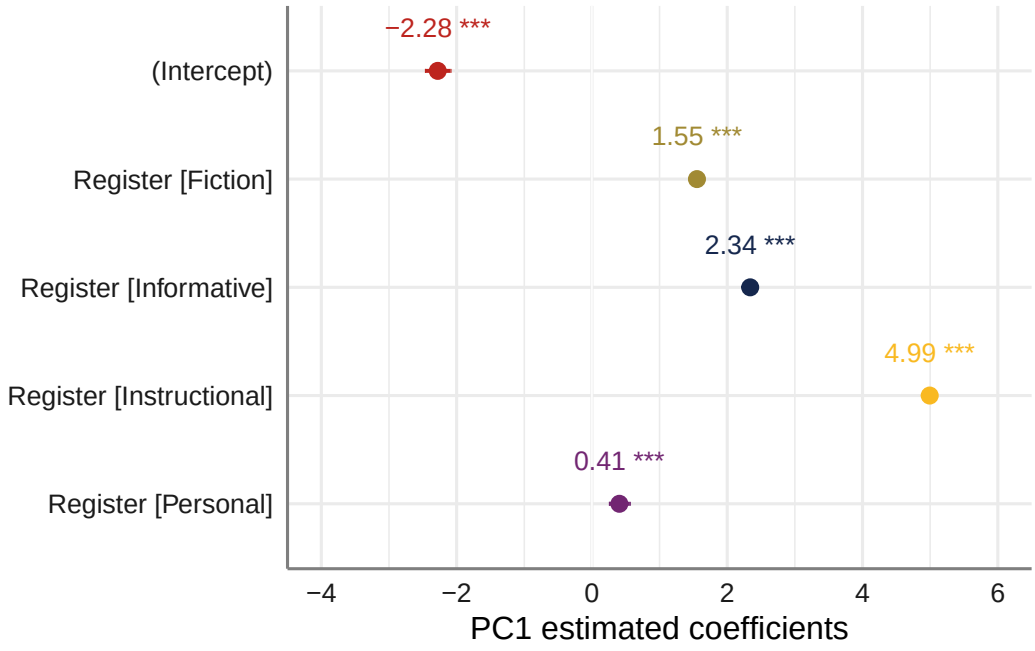
```
# Models with Textbook series as random intercepts
md1 <- lmer(PC1 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md1Register <- lmer(PC1 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md1Level <- lmer(PC1 ~ Level + (1|Series), data = res.ind, REML = FALSE)

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
```

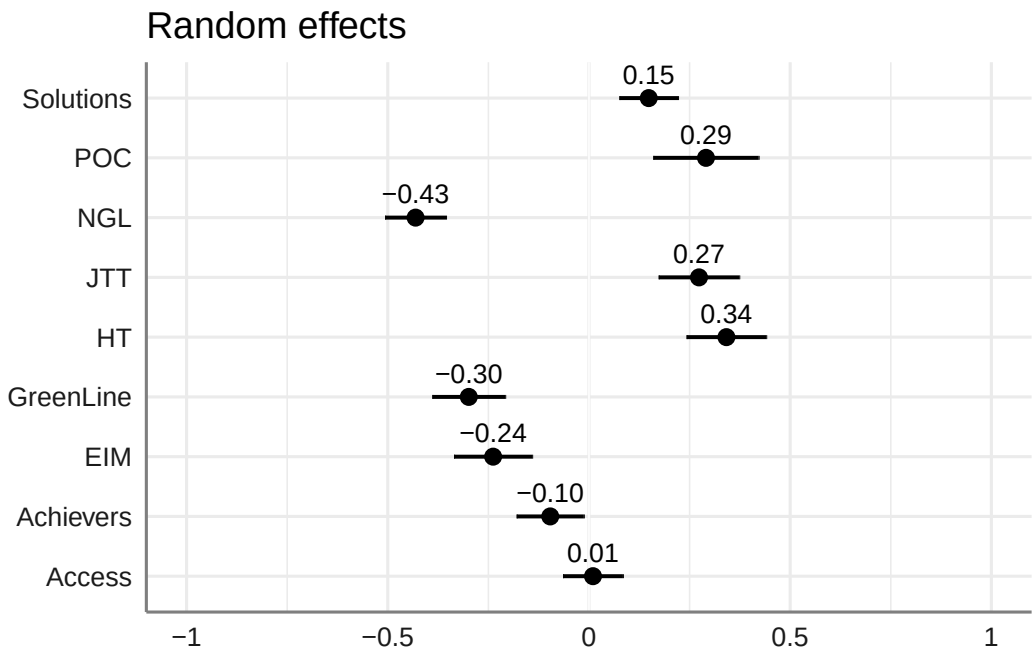
```
#write_last_clip()
confint(comparisons)
```

```
 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)
```

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)
```

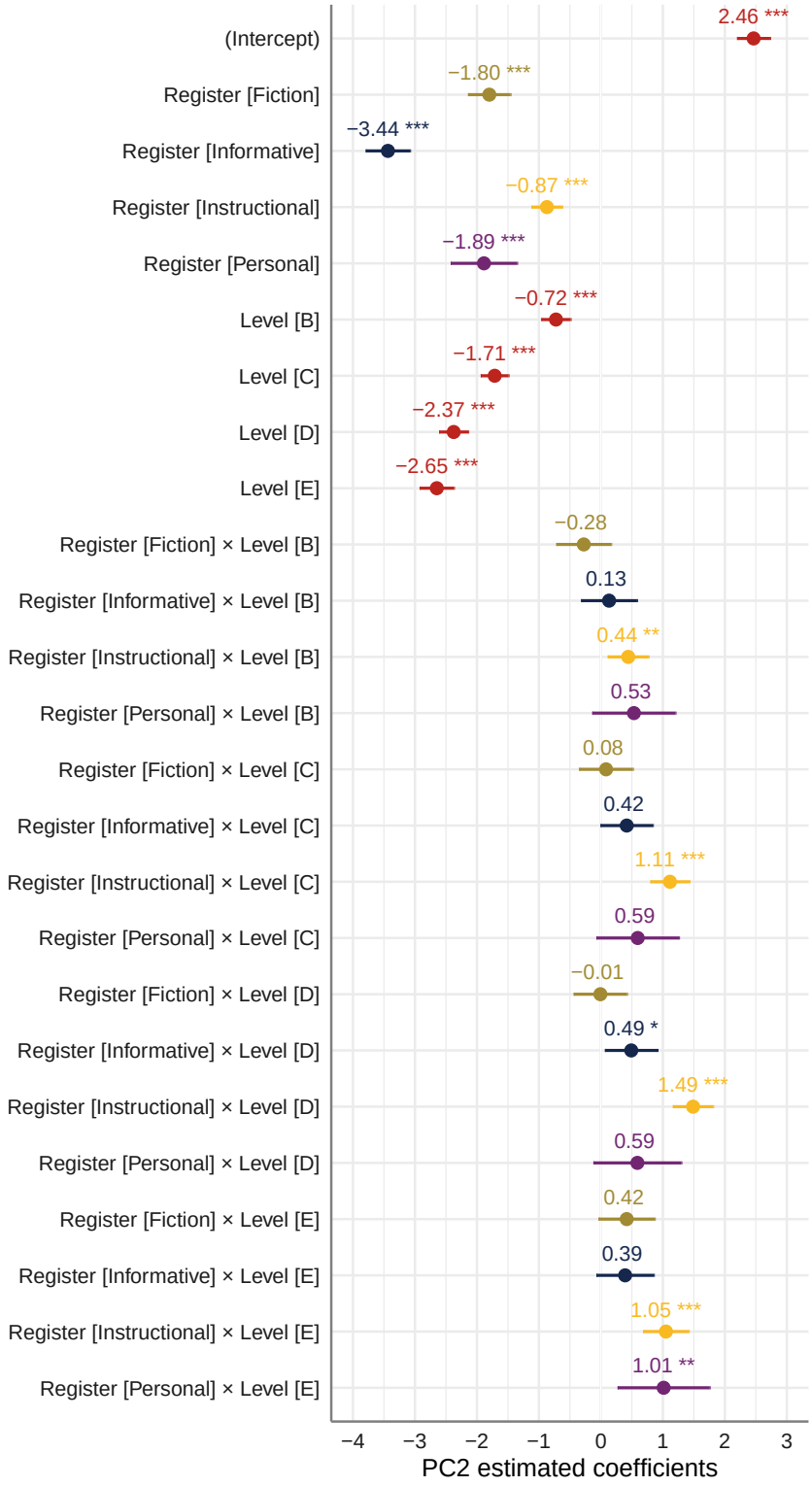
```
Data: res.ind
Models:
md2Register: PC2 ~ Register + (1 | Series)
md2Level: PC2 ~ Level + (1 | Series)
md2: PC2 ~ Register * Level + (1 | Series)
            npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
md2Register    7 6155.2 6194.3 -3070.6   6141.2
md2Level       7 7290.1 7329.2 -3638.1   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:

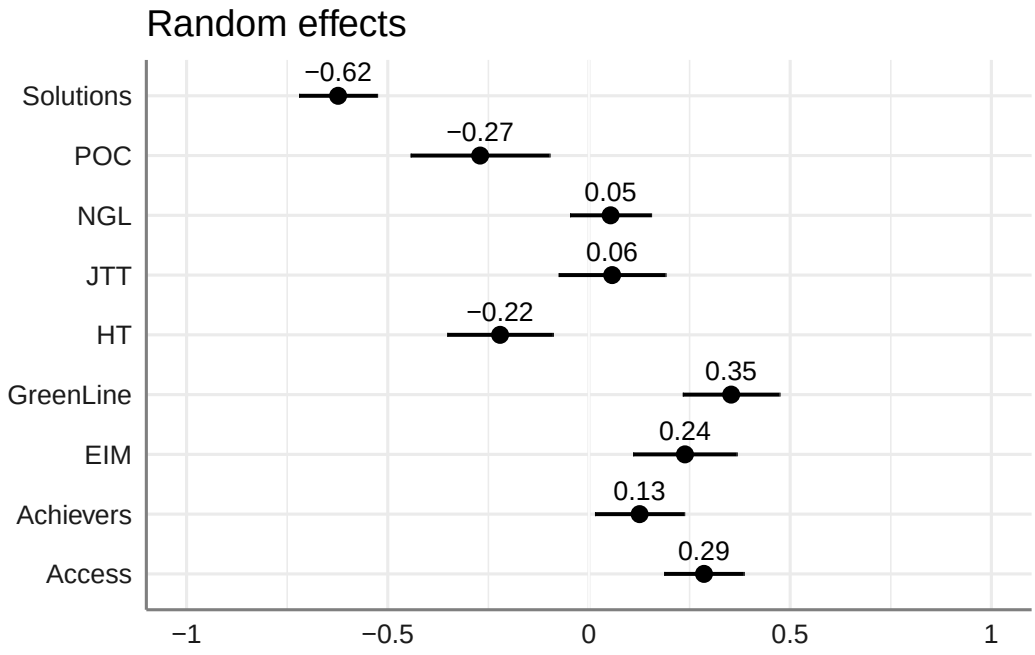
```
plot_model(md2,
           type = "est",
           show.intercept = TRUE,
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           colors = palette[c(1:3,8,7)],
           group.terms = c(1:5,1,1,1,1,2:5,2:5,2:5,2:5),
           title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

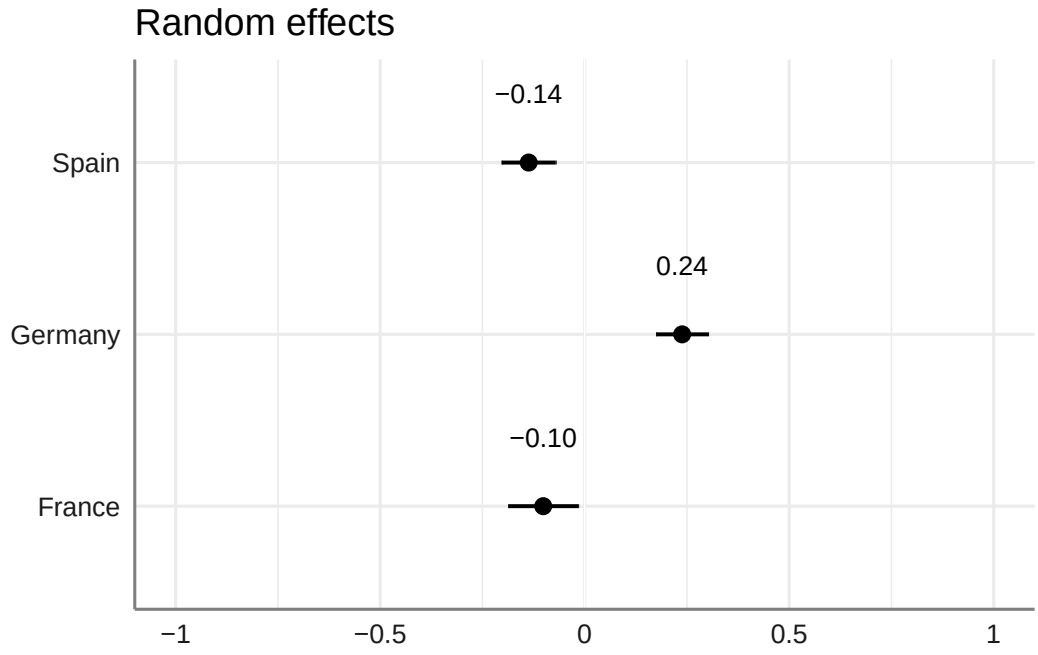
Estimated coefficients of random effects on Dim2 scores:

```
## 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
```

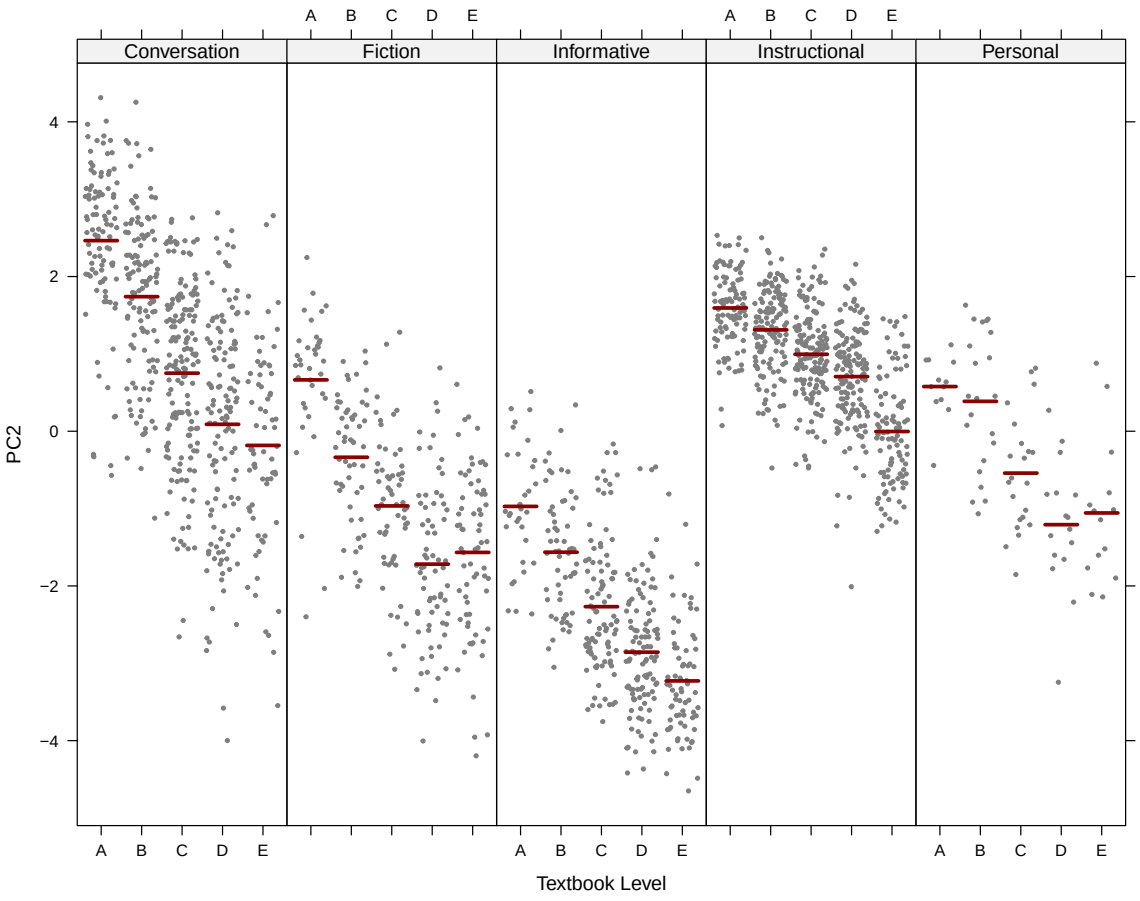
```
md2country <- lmer(PC2 ~ Register*Level + (1|Country), data = res.ind, REML =
 ↪  FALSE)

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()
```



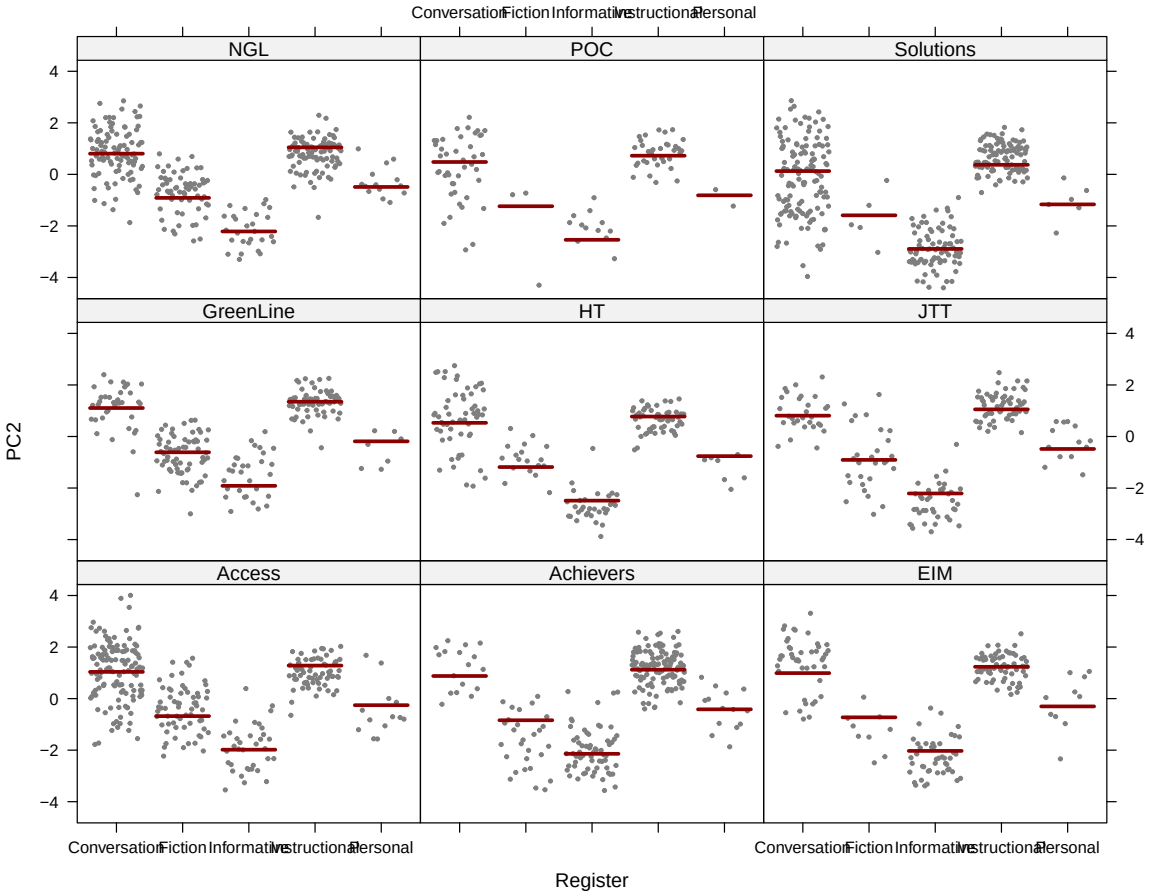

```
#ggsave(here("plots", "TxB_PCA2_lmer_randomeffects_country.svg"), height = 3,
 ↪  width = 8)
```

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

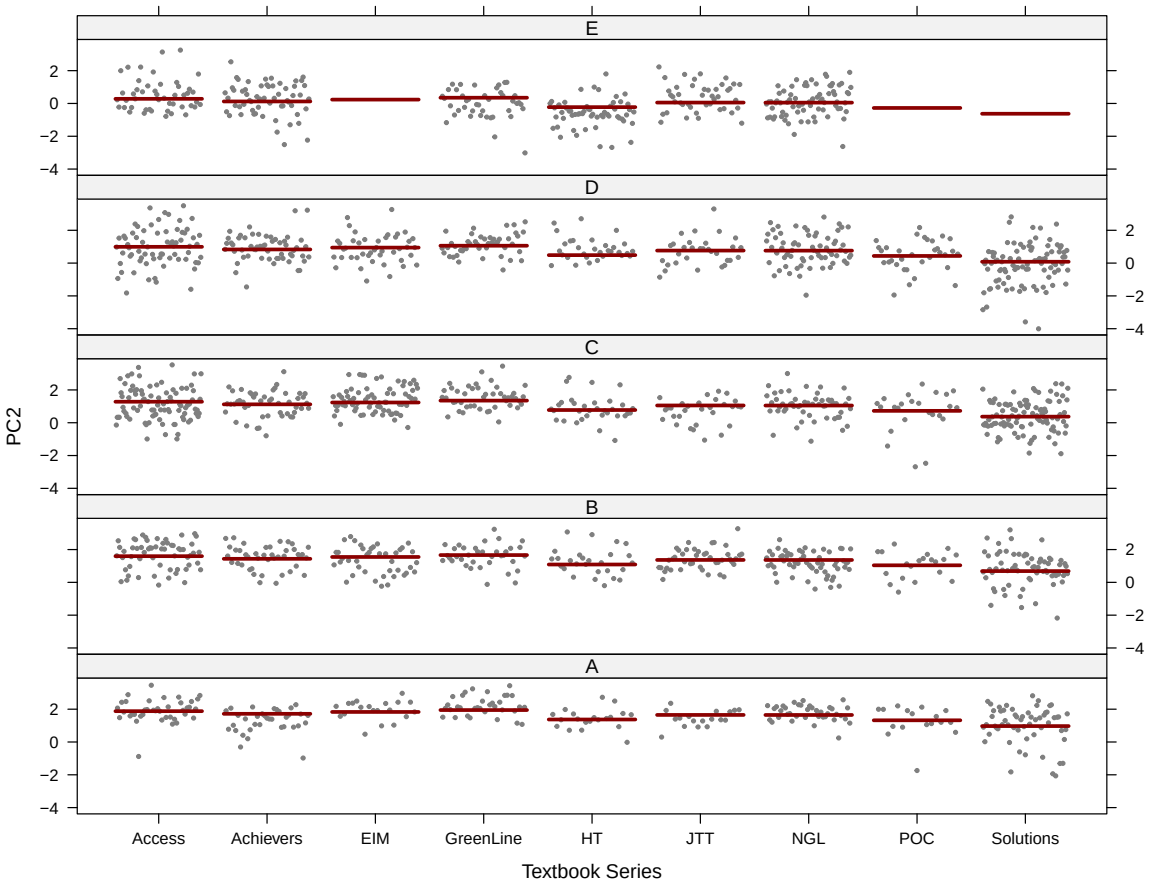
```
# svg(here("plots", "TxB_predicted_PC2_scores_interactions.svg"), height = 5,
 ↪  width = 8)
visreg(md2, xvar = "Level", by="Register", type = "conditional",
       line=list(col="darkred"),
       xlab = "Textbook Level", ylab = "PC2"
       #,gg = TRUE
       ,layout=c(5,1)
)
```



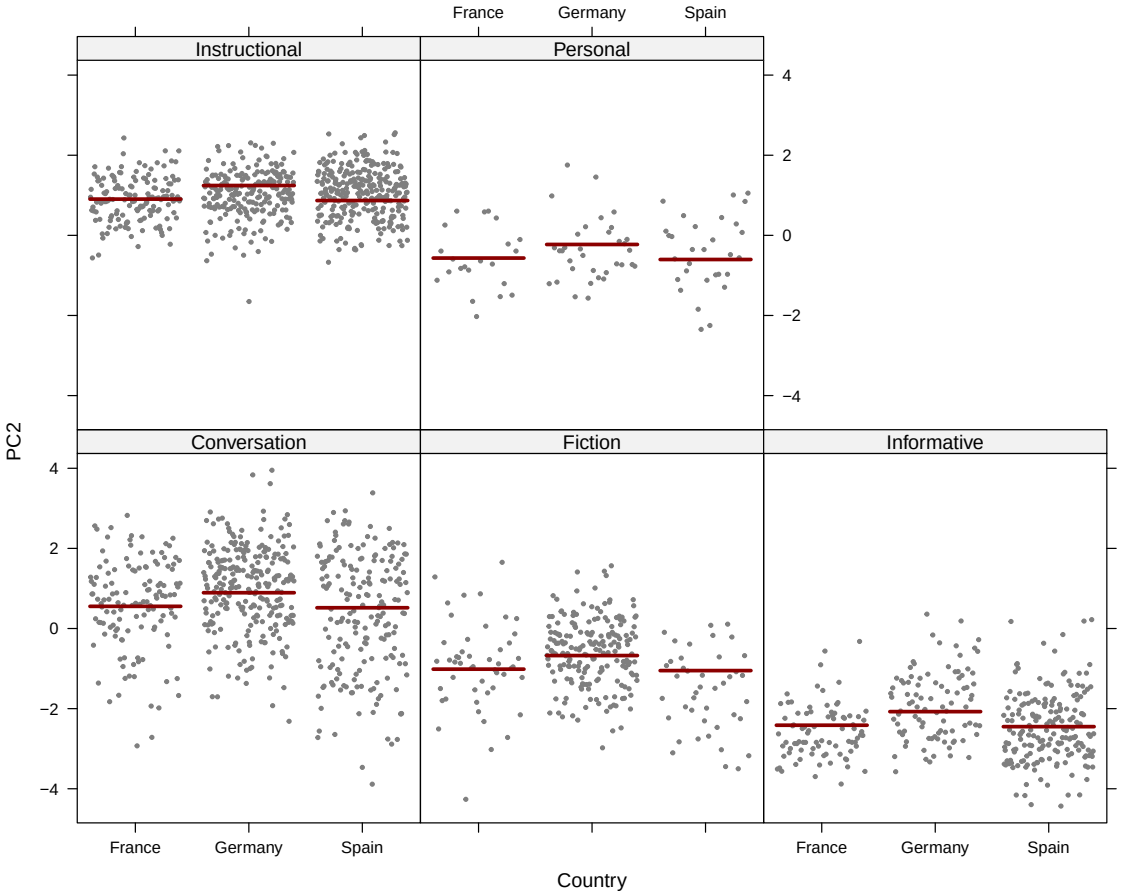

```
# dev.off()

# 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()
```

Dimension 3: 'Narrative vs. factual discourse'

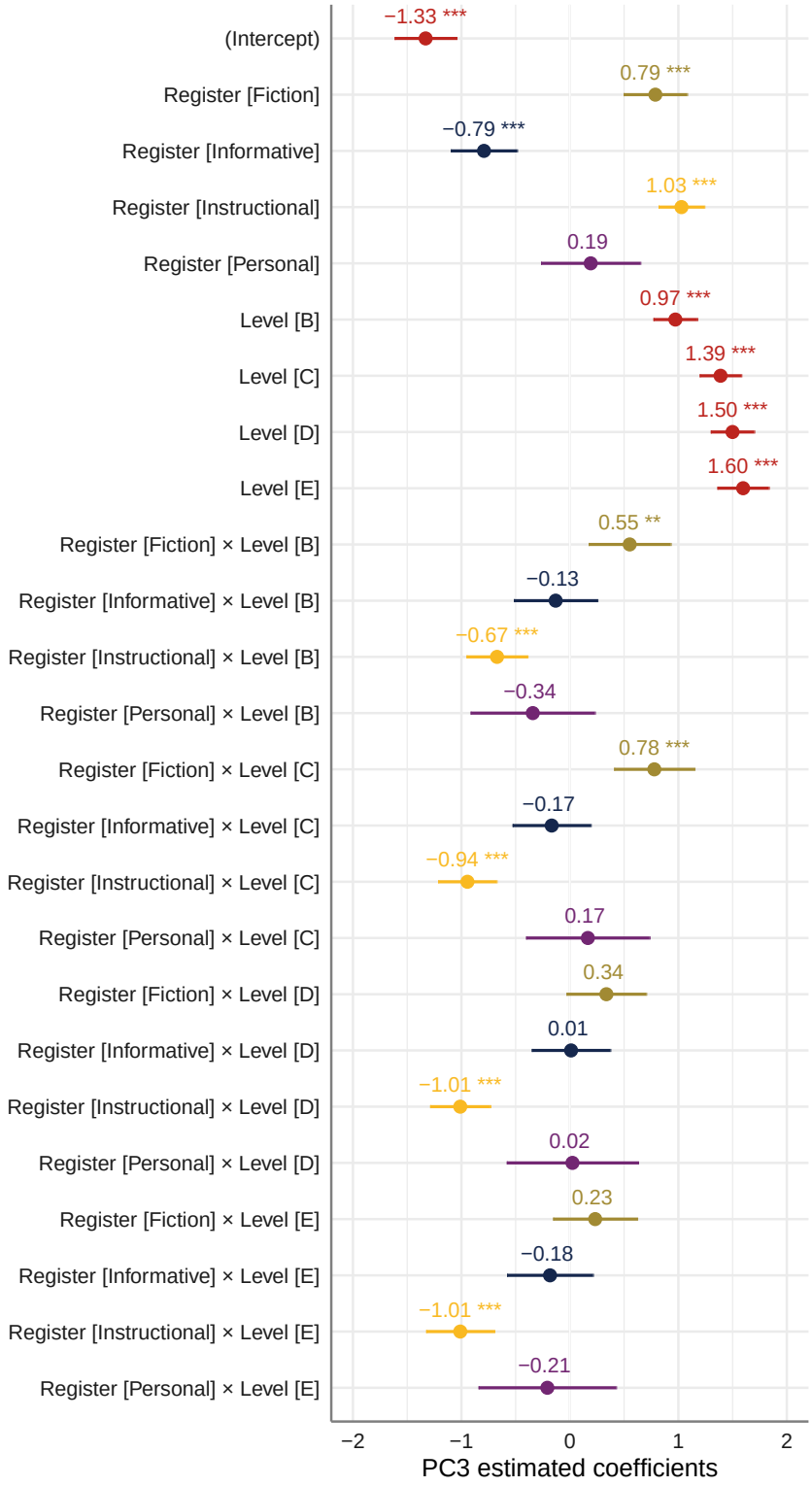
```
md3 <- lmer(PC3 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md3Register <- lmer(PC3 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md3Level <- lmer(PC3 ~ Level + (1|Series), data = res.ind, REML = FALSE)

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
```

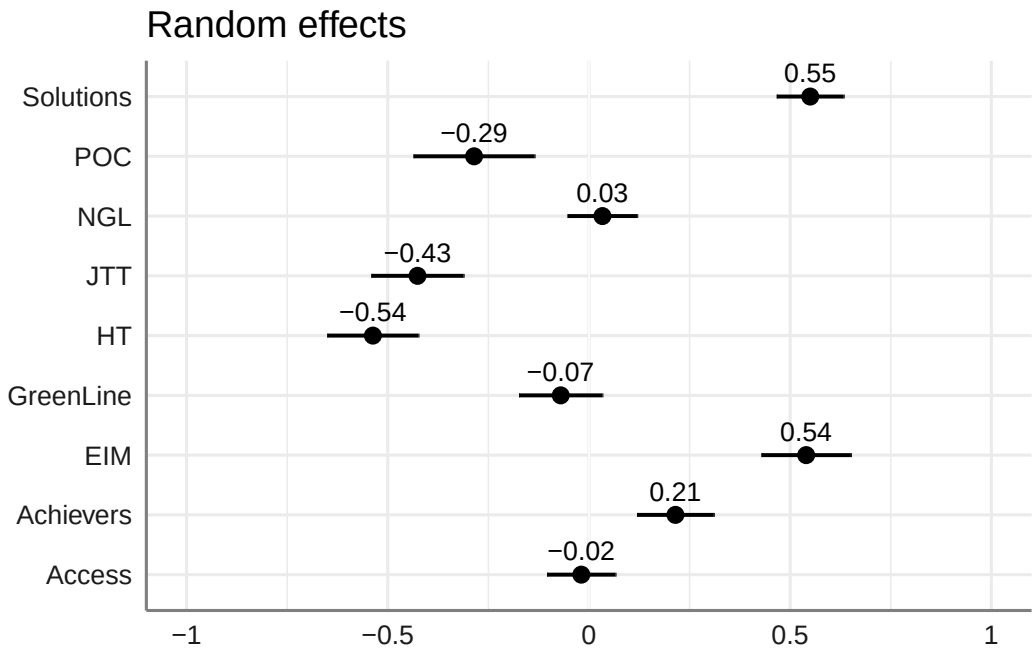
```
tab_model(md3) # Marginal R2 = 0.436
```

```
# 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()
```


(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]
−1.33 ***
0.79 ***
−0.79 ***
1.03 ***
0.19
0.97 ***
1.39 ***
1.50 ***
1.60 ***
0.55 **
−0.13
−0.67 ***
−0.34
0.78 ***
−0.17
−0.94 ***
0.17
0.34
0.01
−1.01 ***
0.02
0.23
−0.18
−1.01 ***
−0.21
−2
−1
0
1
2
PC3 estimated coefficients

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

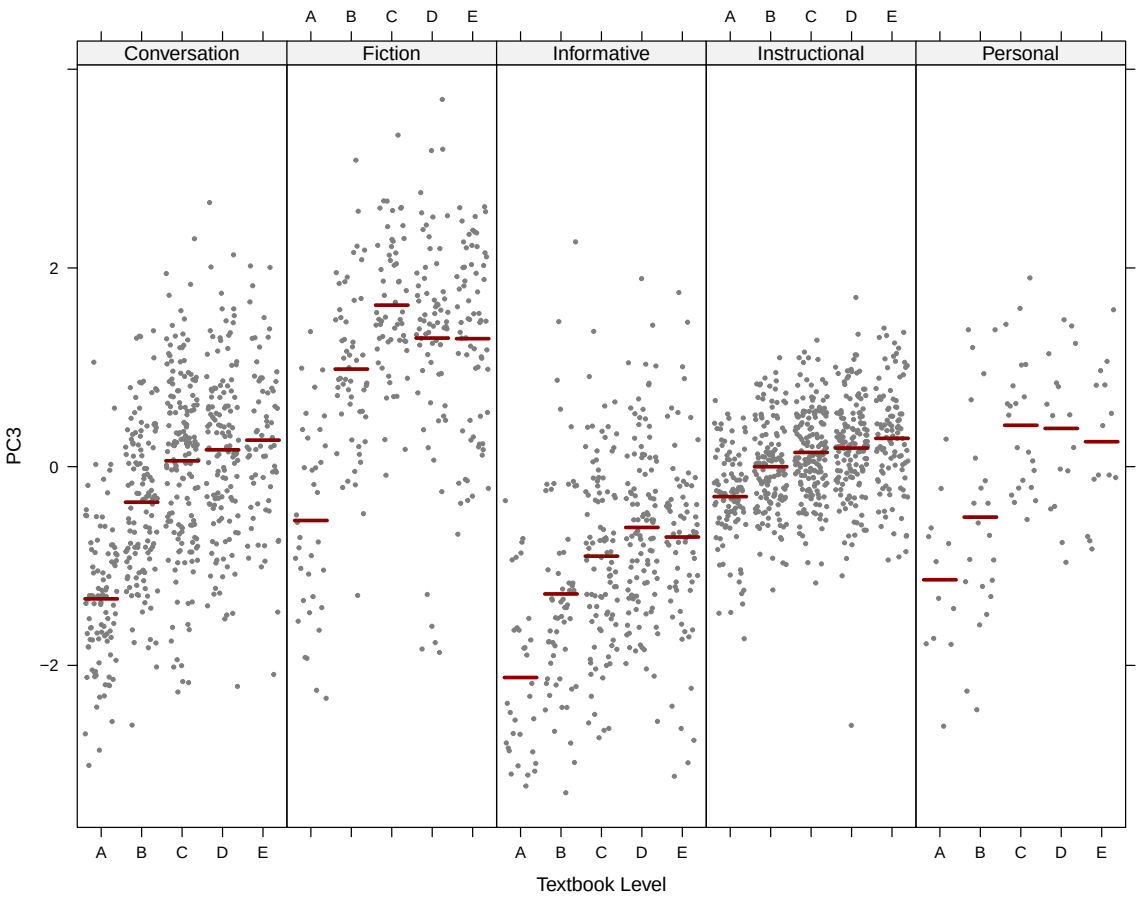
```
# Plot of random effects:
plot_model(md3,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           color = "bw",
           wrap.labels = 40,
           axis.title = "PC3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



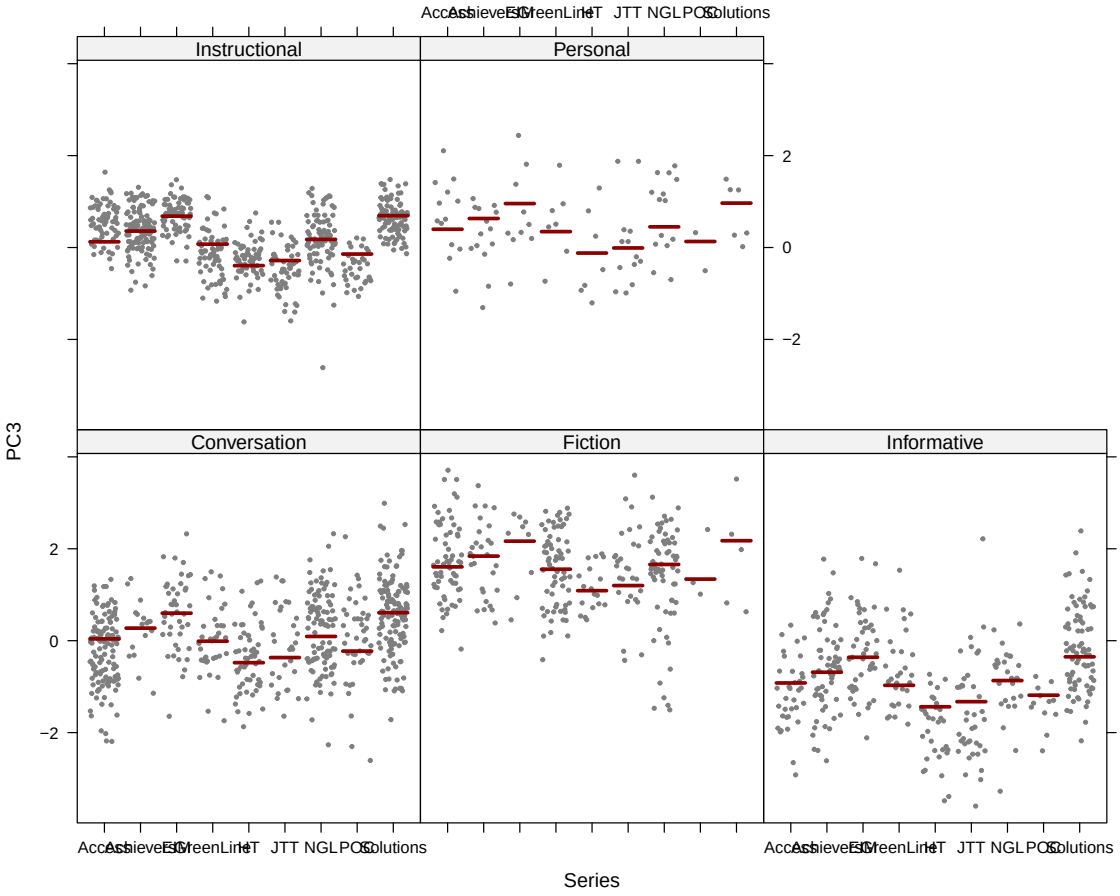

```
#ggsave(here("plots", "TxB_PCA3_lmer_randomeffects.svg"), height = 3, width =
 ↪  8)
```

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

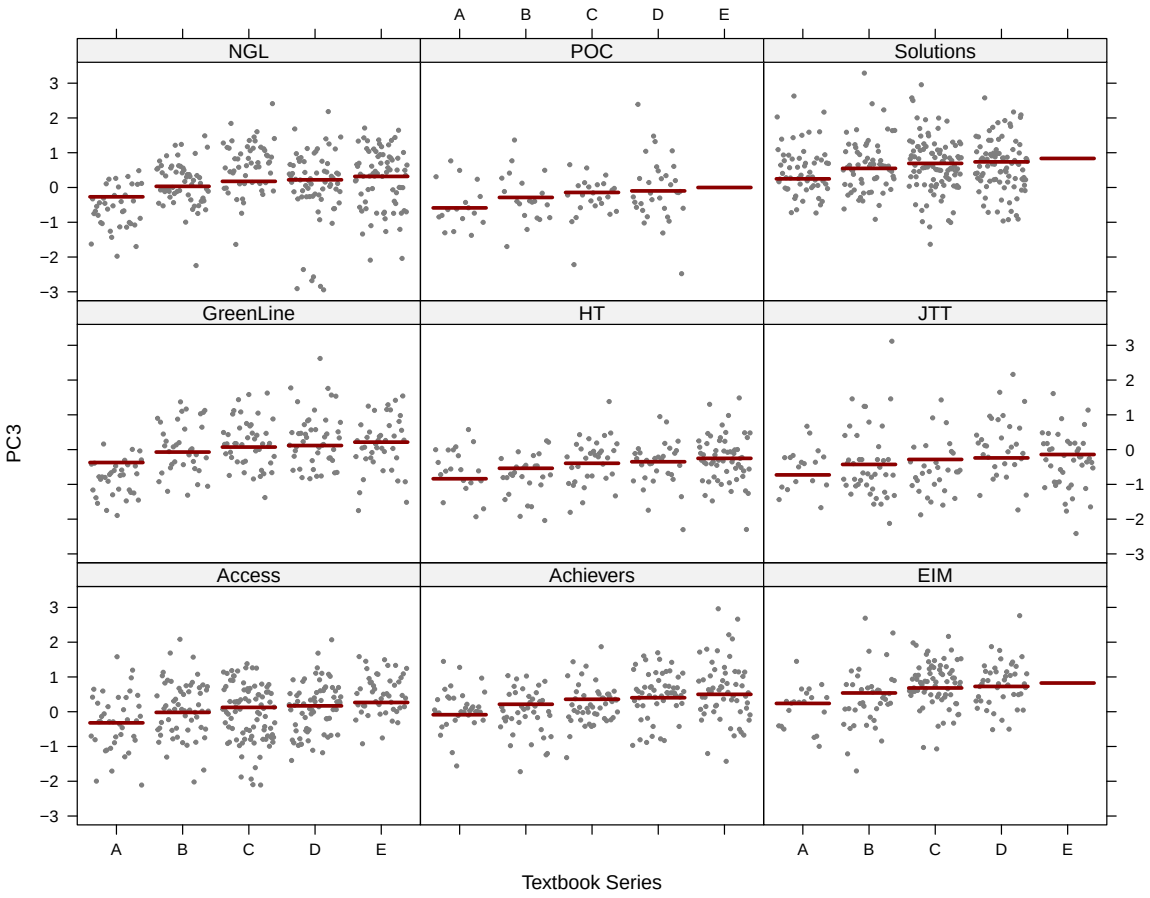
```
        line=list(col="darkred"),
        xlab = "Textbook Level", ylab = "PC3"
        #,gg = TRUE
        ,layout=c(5,1)
)
```




```
# 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")
```



Dimension 4: 'Informational compression vs. elaboration'

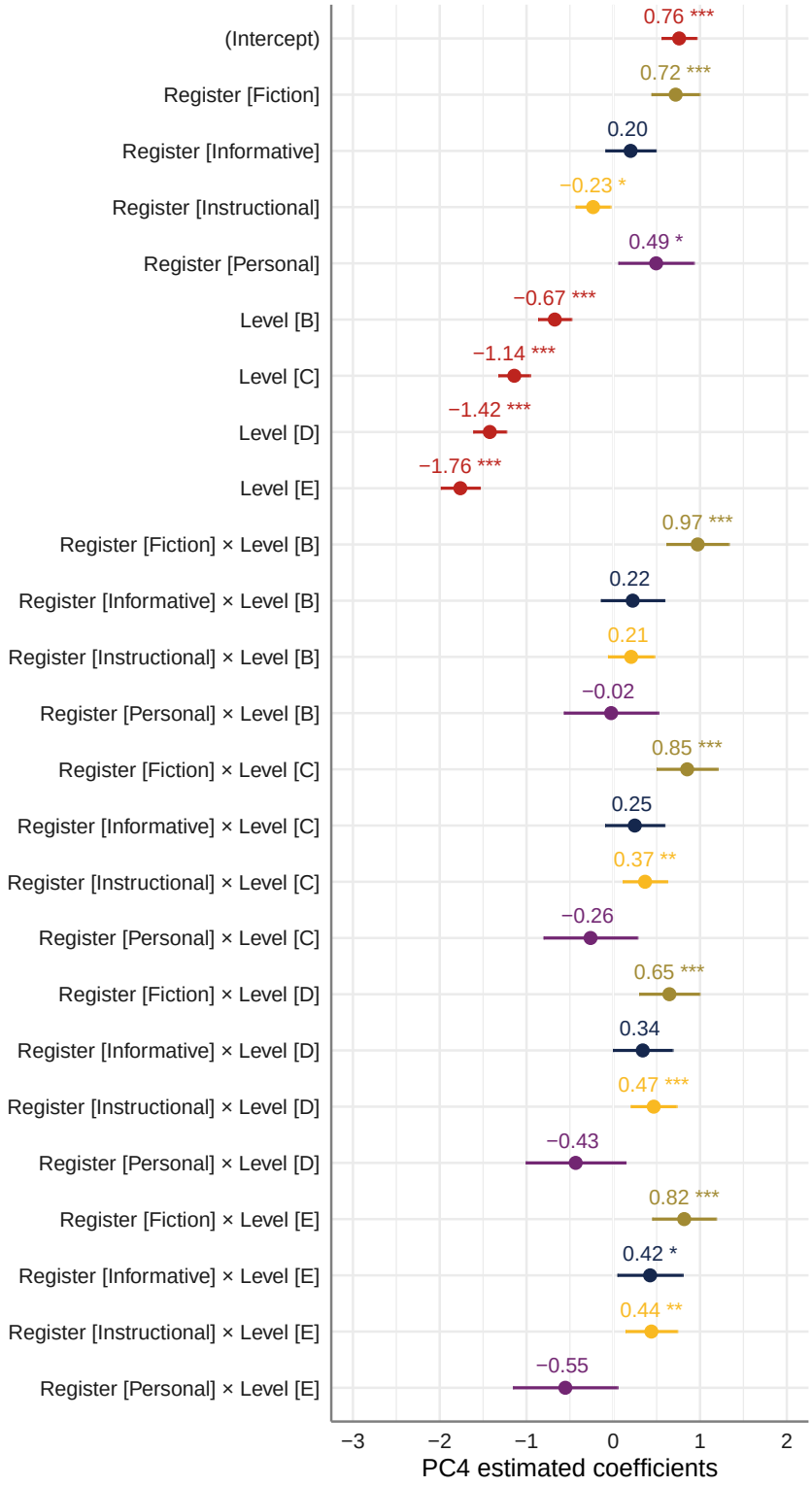
```
md4 <- lmer(PC4 ~ Register*Level + (1|Series), data = res.ind, REML = FALSE)
md4Register <- lmer(PC4 ~ Register + (1|Series), data = res.ind, REML =
 ↪  FALSE)
md4Level <- lmer(PC4 ~ Level + (1|Series), data = res.ind, REML = FALSE)

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
```

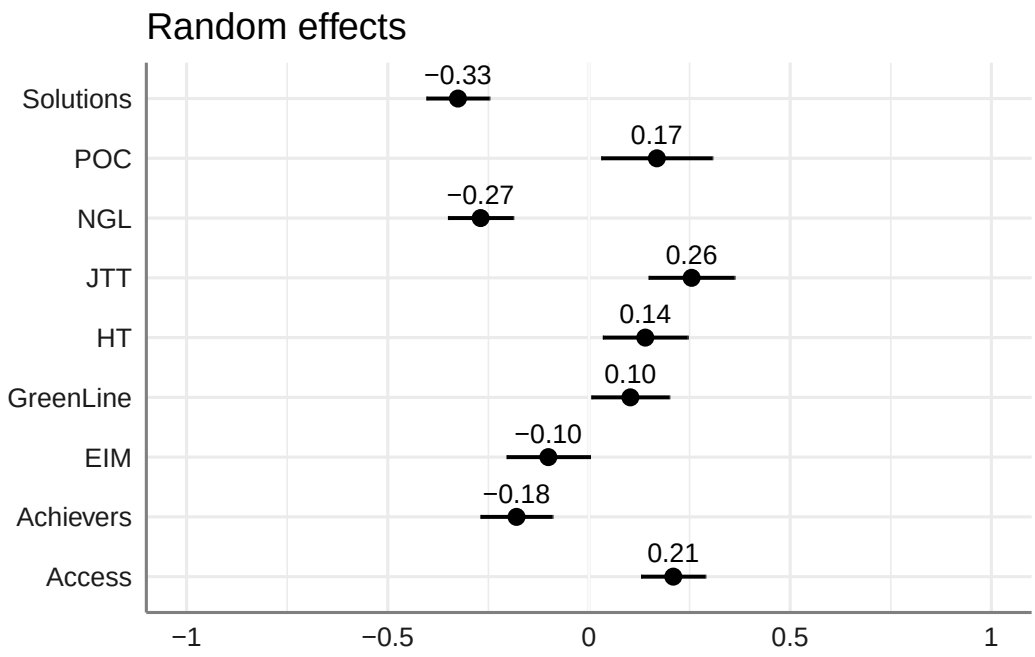
```
tab_model(md4) # Marginal R2 = 0.426
```

```
# 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)
```

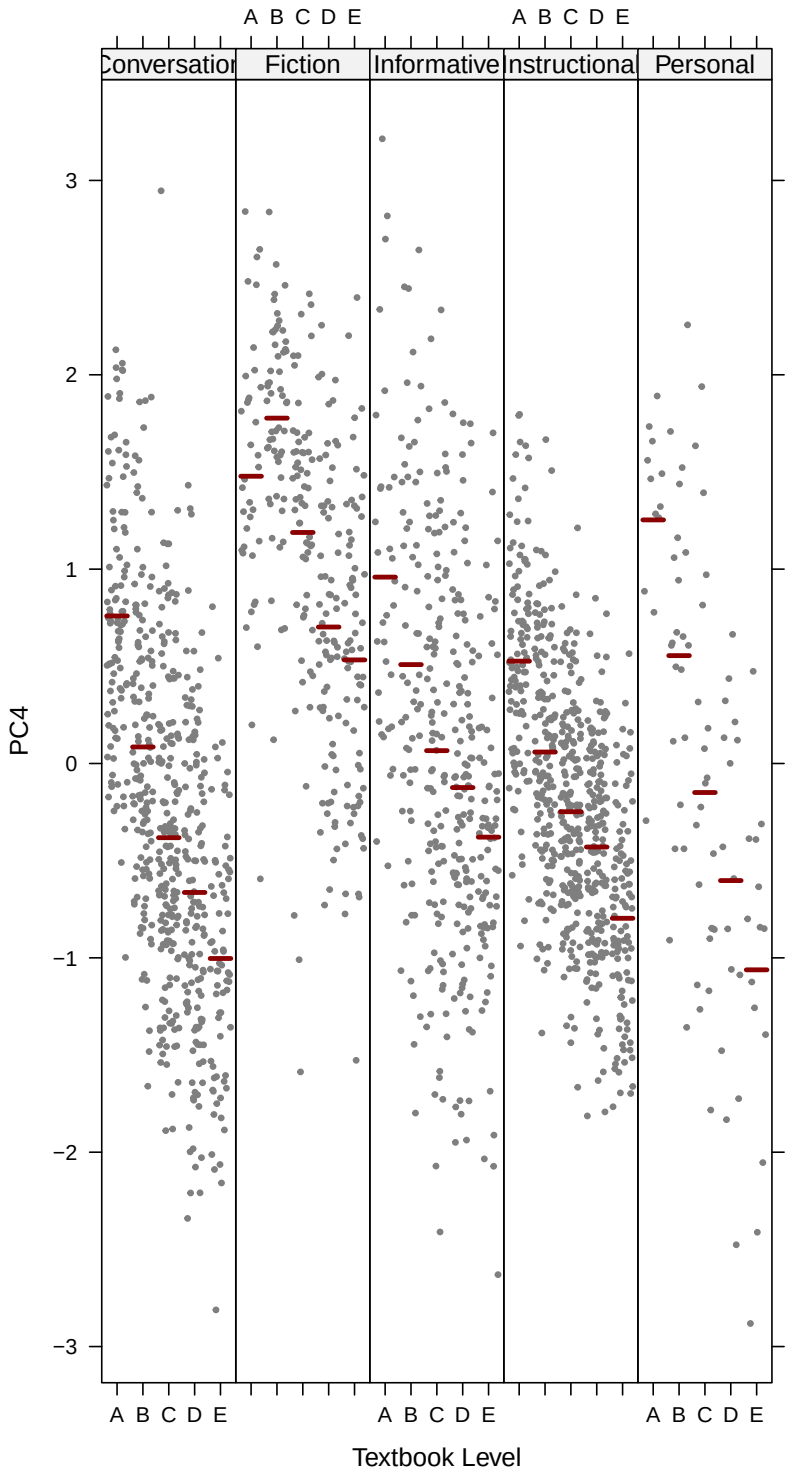
```
# Plot of random effects:
plot_model(md4,
           type = "re", # Option to visualise random effects
           show.values=TRUE,
           show.p=TRUE,
           value.offset = .4,
           value.size = 3.5,
           color = "bw",
           wrap.labels = 40,
           axis.title = "PC4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

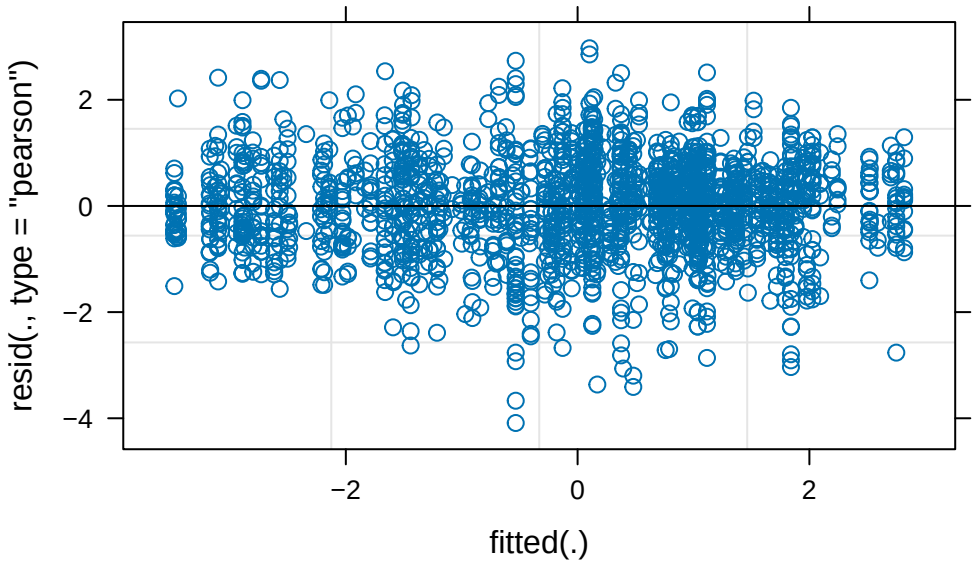

A B C D E
A B C D E
Conversation
Fiction
Informative
Instructiona
Personal
3
2
1
0
−1
−2
−3
PC4
A B C D E
A B C D E
A B C D E
Textbook Level

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

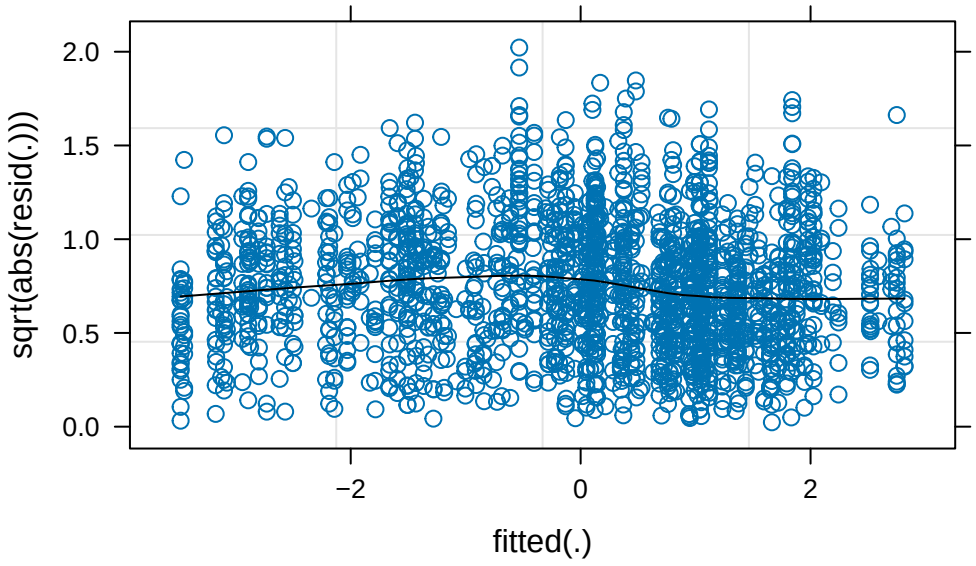
Testing model assumptions

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.

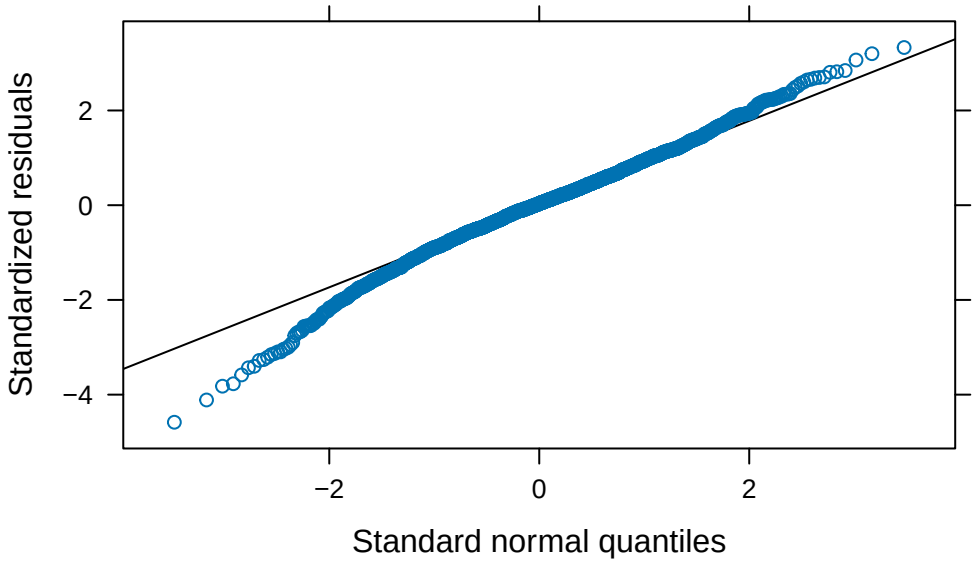
```
model2test <- md2

# 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)
```



Appendix F: 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).

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(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

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

```
# Colours used in Register Studies paper and included in Open Access plots
 ↪  published on Zenodo:
#colours <- suf_palette(name = "london", n = 6, type = "continuous") # Very
 ↪  nice, similar to OrRd palette
#scales::show_col(colours)
#colours <- colours[6:1]

# Colour scheme used in PhD thesis:
colours = c("#F9B921", "#A18A33",  "#722672", "#BD241E", "#15274D",
 ↪  "#D54E1E")
# scales::show_col(colours)
```

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 2021a).

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).

```
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"
```

Youth Fiction corpus

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).

```
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"
```

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.

Merging TEC and reference corpora data

```
[1] "Conversation"   "Fiction"        "Info Teens"     "Informative"
[5] "Spoken BNC2014" "Youth Fiction"
```

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-life English.

```
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 = ","))
```

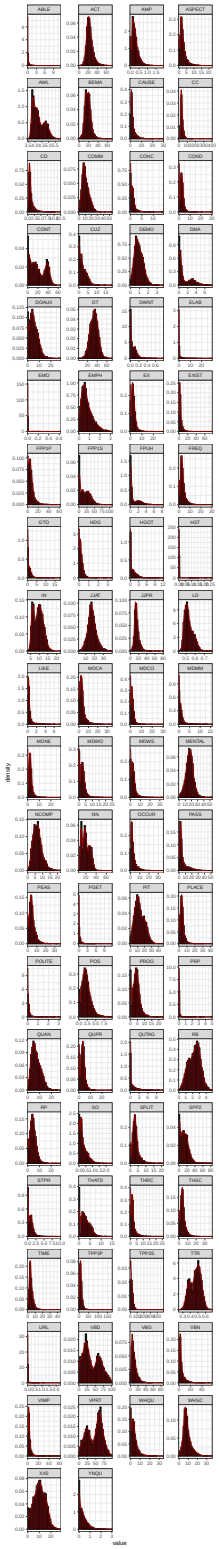
Register	totaltexts	totalwords	mean	sd	TTRmean
Conversation	1,844	13,804,196	7,486	8,690	0.40
Fiction	1,476	7,321,747	4,960	2,022	0.49
Informative	1,775	1,436,732	809	188	0.51

Data preparation for PCA

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.

```r
#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
THNC
THSC
TIME
TPP3P
TPP3S
TTR
URL
VBD
VBG
VBN
VIMP
VPRT
WHQU
WHSC
XXC
TNOU
density
value

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

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 2021b).

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.

Identifying potential 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, Series, Register, Level, Words)
```

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

```
# These are potential outlier texts :
outliers
```

	Filer
1	POC_4e_Spoken_0007
2	Solutions_Elementary_ELF_Spoken_0013
3	EIM_Starter_Informative_0004
4	GreenLine_1_Spoken_0003
5	Access_1_Spoken_0011
6	Achievers_B1_Informative_0003
7	EIM_Starter_Spoken_0002
8	GreenLine_1_Spoken_0008
9	JTT_3_Informative_0003
10	GreenLine_1_Spoken_0010
11	EIM_1_Spoken_0012
12	NGL_1_Spoken_0013
13	NGL_3_Spoken_0018
14	Solutions_Intermediate_Spoken_0029
15	NGL_1_Spoken_0012
16	GreenLine_1_Spoken_0006
17	GreenLine_2_Spoken_0004
18	Access_2_Spoken_0023
19	HT_4_Informative_0006
20	Solutions_Intermediate_Informative_0017
21	EIM_1_Spoken_0013
22	Solutions_Elementary_ELF_Spoken_0021
23	Solutions_Intermediate_Plus_Spoken_0022
24	Access_2_Spoken_0028
25	NGL_1_Spoken_0005
26	Solutions_Elementary_ELF_Spoken_0016
27	Solutions_Pre-Intermediate_ELF_Spoken_0007
28	Solutions_Intermediate_Informative_0013

GreenLine_2_Spoken_0003
HT_4_Spoken_0010
Solutions_Elementary_Informative_0003
Access_2_Informative_0001
Solutions_Elementary_Informative_0010
GreenLine_1_Informative_0001
Access_2_Spoken_0002
Solutions_Intermediate_Spoken_0019
Access_3_Informative_0003
Access_1_Spoken_0019
Access_2_Spoken_0013
Solutions_Intermediate_Plus_Informative_0014
Revision_World_GCSE_10525362_literary-terms
Revision_World_GCSE_10528697_p6-physics-radioactive-materials
Science_Tech_Kinds_NZ_10382383_math
Science_for_students_10064820_scientists-say-metabolism
Science_Tech_Kinds_NZ_10382388_recycling
History_Kids_BBC_10404337_go_furthers
Science_Tech_Kinds_NZ_10382391_sports
Teen_Kids_News_10402607_so-you-want-to-be-an-archivist
Science_Tech_Kinds_NZ_10382234_biology
Science_Tech_Kinds_NZ_10382372_astronomy
Dogo_News_file10060404_banana-plant-extract-may-be-the-key-to-slower-melting-ice-cream
Science_Tech_Kinds_NZ_10382667_countries
Quatr_us_file10390777_quick-summary-geological-erashtm
Science_Tech_Kinds_NZ_10382873_physics
Science_Tech_Kinds_NZ_10382382_light
Factmonster_10053687_august-13
Revision_World_GCSE_10526703_limited-companies
Revision_World_GCSE_10529637_transition-metals
Quatr_us_10390856_early-african-historyhtm
History_Kids_BBC_10401873_ff6_sicilylandingss
Quatr_us_10394250_harappan
Ducksters_10398301_iraqphp
History_Kids_BBC_10403171_death_sakkara_gallery_04s
Revision_World_GCSE_10528246_agricultural-change
Revision_World_GCSE_10528086_uk-government-judiciary
Revision_World_GCSE_10529794_definitions
Encyclopedia_Kinds_au_10085347_Nobel_Prize_in_Chemistry
Science_for_students_10064875_questions-big-melt-earths-ice-sheets-are-under-attack
Teen_Kids_News_10403301_golden-globe-winners-2019-the-complete-list
Science_Tech_Kinds_NZ_10382201_projects
Revision_World_GCSE_10529753_probability

72 Encyclopedia_Kinds_au_10085531_Complex_analysis
73 History_Kids_BBC_10401890_ff7_ddays
74 History_Kids_BBC_10403434s
75 History_Kids_BBC_10401872_ff6_italys
76 Science_Tech_Kinds_NZ_10382371_amazing
77 Quatr_us_10391129_athabascan
78 Encyclopedia_Kinds_au_10085355_20th_century
79 Dogo_News_10060755_luxury-space-hotel-promises-guests-a-truly-out-of-this-world-vacation
80 Revision_World_GCSE_10528072_nationalism-practice
81 Quatr_us_10390861_quatr-us-privacy-policyhtm
82 History_Kids_BBC_10401909_ff7_bulges
83 History_kids_10381259_timeline-of-mesopotamia
84 Revision_World_GCSE_10528123_gender-written-textual-analysis-framework
85 Science_Tech_Kinds_NZ_10386406_floods
86 Revision_World_GCSE_10529693_advantages
87 Science_Tech_Kinds_NZ_10382378_geography
88 Science_Tech_Kinds_NZ_10382374_earth
89 Science_for_students_10066286_watering-plants-wastewater-can-spread-germs
90 Science_Tech_Kinds_NZ_10382393_water
91 World_Dteen_10406069_website_policies
92 Science_Tech_Kinds_NZ_10382384_metals
93 Dogo_News_10062028_puppy-bowl-14-promises-viewers-a-paw-some-time-on-super-bowl-sunday
94 History_Kids_BBC_10404730_go_furthers
95 Science_Tech_Kinds_NZ_10382385_nature
96 Science_for_students_10065015_scientists-say-dna-sequencing
97 Quatr_us_file10390817_conifers-pine-trees-gymnospermshtm
98 TweenTribute_10051509_it-true-elephants-cant-jump
99 Revision_World_GCSE_10528494_application-software
100 Revision_World_GCSE_10529581_different-types-questions-examinations
101 Dogo_News_10061669_the-chinese-city-of-chengdu-may-soon-be-home-to-multiple-moons
102 Ducksters_10398306_geography_of_ancient_chinaphp
103 Science_for_students_10065144_scientists-say-multiverse
104 Science_Tech_Kinds_NZ_10382211_images
105 Factmonster_10053754_may-18
106 World_Dteen_10406047_AboutWORLDteen
107 Ducksters_10398078_first_new_dealphp
108 Revision_World_GCSE_10526926_economies-scale
109 Factmonster_10053201_september-03
110 Science_Tech_Kinds_NZ_10387183_calciumcarbonates
111 Science_Tech_Kinds_NZ_10382380_health
112 Revision_World_GCSE_10529587_sources-finance
113 Quatr_us_10393444_fishing
114 Ducksters_10398315_glossary_and_termsphp

	Corpus	Series	Register	Level	Words
1	Textbook.English	POC	Conversation	C	750
2	Textbook.English	Solutions	Conversation	A	931
3	Textbook.English	EIM	Informative	A	534
4	Textbook.English	GreenLine	Conversation	A	970
5	Textbook.English	Access	Conversation	A	784
6	Textbook.English	Achievers	Informative	C	926
7	Textbook.English	EIM	Conversation	A	824
8	Textbook.English	GreenLine	Conversation	A	876
9	Textbook.English	JTT	Informative	D	699
10	Textbook.English	GreenLine	Conversation	A	701
11	Textbook.English	EIM	Conversation	B	640
12	Textbook.English	NGL	Conversation	A	940
13	Textbook.English	NGL	Conversation	C	751
14	Textbook.English	Solutions	Conversation	C	672
15	Textbook.English	NGL	Conversation	A	910
16	Textbook.English	GreenLine	Conversation	A	622
17	Textbook.English	GreenLine	Conversation	B	1102
18	Textbook.English	Access	Conversation	B	875
19	Textbook.English	HT	Informative	C	513
20	Textbook.English	Solutions	Informative	C	816
21	Textbook.English	EIM	Conversation	B	967
22	Textbook.English	Solutions	Conversation	A	846
23	Textbook.English	Solutions	Conversation	D	596
24	Textbook.English	Access	Conversation	B	813
25	Textbook.English	NGL	Conversation	A	1020
26	Textbook.English	Solutions	Conversation	A	871
27	Textbook.English	Solutions	Conversation	B	630
28	Textbook.English	Solutions	Informative	C	770
29	Textbook.English	GreenLine	Conversation	B	850
30	Textbook.English	HT	Conversation	C	727
31	Textbook.English	Solutions	Informative	A	1051
32	Textbook.English	Access	Informative	B	655
33	Textbook.English	Solutions	Informative	A	708
34	Textbook.English	GreenLine	Informative	A	731
35	Textbook.English	Access	Conversation	B	572
36	Textbook.English	Solutions	Conversation	C	1024
37	Textbook.English	Access	Informative	C	1000
38	Textbook.English	Access	Conversation	A	701
39	Textbook.English	Access	Conversation	B	981
40	Textbook.English	Solutions	Informative	D	537
41	Informative.Teens	Info Teens	Informative	Ref.	790

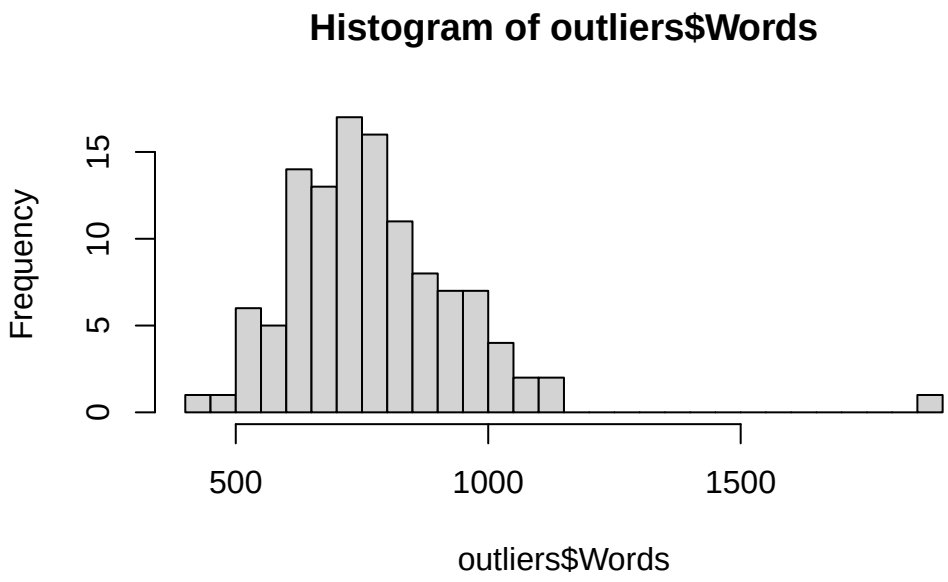
```
42  Informative.Teens     Info Teens  Informative  Ref.  1015
43  Informative.Teens     Info Teens  Informative  Ref.   522
44  Informative.Teens     Info Teens  Informative  Ref.   895
45  Informative.Teens     Info Teens  Informative  Ref.   666
46  Informative.Teens     Info Teens  Informative  Ref.   620
47  Informative.Teens     Info Teens  Informative  Ref.   657
48  Informative.Teens     Info Teens  Informative  Ref.   763
49  Informative.Teens     Info Teens  Informative  Ref.   843
50  Informative.Teens     Info Teens  Informative  Ref.   900
51  Informative.Teens     Info Teens  Informative  Ref.   611
52  Informative.Teens     Info Teens  Informative  Ref.   717
53  Informative.Teens     Info Teens  Informative  Ref.   643
54  Informative.Teens     Info Teens  Informative  Ref.   722
55  Informative.Teens     Info Teens  Informative  Ref.   639
56  Informative.Teens     Info Teens  Informative  Ref.   523
57  Informative.Teens     Info Teens  Informative  Ref.   714
58  Informative.Teens     Info Teens  Informative  Ref.   787
59  Informative.Teens     Info Teens  Informative  Ref.  1136
60  Informative.Teens     Info Teens  Informative  Ref.   813
61  Informative.Teens     Info Teens  Informative  Ref.   651
62  Informative.Teens     Info Teens  Informative  Ref.   657
63  Informative.Teens     Info Teens  Informative  Ref.   844
64  Informative.Teens     Info Teens  Informative  Ref.   789
65  Informative.Teens     Info Teens  Informative  Ref.  1019
66  Informative.Teens     Info Teens  Informative  Ref.   904
67  Informative.Teens     Info Teens  Informative  Ref.   598
68  Informative.Teens     Info Teens  Informative  Ref.   685
69  Informative.Teens     Info Teens  Informative  Ref.   800
70  Informative.Teens     Info Teens  Informative  Ref.   947
71  Informative.Teens     Info Teens  Informative  Ref.   816
72  Informative.Teens     Info Teens  Informative  Ref.   735
73  Informative.Teens     Info Teens  Informative  Ref.   759
74  Informative.Teens     Info Teens  Informative  Ref.   732
75  Informative.Teens     Info Teens  Informative  Ref.   786
76  Informative.Teens     Info Teens  Informative  Ref.   629
77  Informative.Teens     Info Teens  Informative  Ref.   637
78  Informative.Teens     Info Teens  Informative  Ref.   864
79  Informative.Teens     Info Teens  Informative  Ref.   722
80  Informative.Teens     Info Teens  Informative  Ref.   776
81  Informative.Teens     Info Teens  Informative  Ref.   960
82  Informative.Teens     Info Teens  Informative  Ref.   732
83  Informative.Teens     Info Teens  Informative  Ref.   768
84  Informative.Teens     Info Teens  Informative  Ref.   905
```

```
85  Informative.Teens     Info Teens  Informative  Ref.   580
86  Informative.Teens     Info Teens  Informative  Ref.   782
87  Informative.Teens     Info Teens  Informative  Ref.   761
88  Informative.Teens     Info Teens  Informative  Ref.   726
89  Informative.Teens     Info Teens  Informative  Ref.   836
90  Informative.Teens     Info Teens  Informative  Ref.   856
91  Informative.Teens     Info Teens  Informative  Ref.   995
92  Informative.Teens     Info Teens  Informative  Ref.   669
93  Informative.Teens     Info Teens  Informative  Ref.   581
94  Informative.Teens     Info Teens  Informative  Ref.   611
95  Informative.Teens     Info Teens  Informative  Ref.   722
96  Informative.Teens     Info Teens  Informative  Ref.   953
97  Informative.Teens     Info Teens  Informative  Ref.   533
98  Informative.Teens     Info Teens  Informative  Ref.   790
99  Informative.Teens     Info Teens  Informative  Ref.   855
100 Informative.Teens     Info Teens  Informative  Ref.   742
101 Informative.Teens     Info Teens  Informative  Ref.   614
102 Informative.Teens     Info Teens  Informative  Ref.   638
103 Informative.Teens     Info Teens  Informative  Ref.   712
104 Informative.Teens     Info Teens  Informative  Ref.   793
105 Informative.Teens     Info Teens  Informative  Ref.   497
106 Informative.Teens     Info Teens  Informative  Ref.  1053
107 Informative.Teens     Info Teens  Informative  Ref.   649
108 Informative.Teens     Info Teens  Informative  Ref.   621
109 Informative.Teens     Info Teens  Informative  Ref.   445
110 Informative.Teens     Info Teens  Informative  Ref.   804
111 Informative.Teens     Info Teens  Informative  Ref.   694
112 Informative.Teens     Info Teens  Informative  Ref.   665
113 Informative.Teens     Info Teens  Informative  Ref.   656
114 Informative.Teens     Info Teens  Informative  Ref.   684
115    Spoken.BNC2014 Spoken BNC2014 Conversation  Ref.  1869
```

```r
# Checking that outlier texts are not particularly long or short texts
summary(outliers$Words)
```

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

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




```
# Distribution of outlier texts across the four corpora
summary(outliers$Corpus)
```

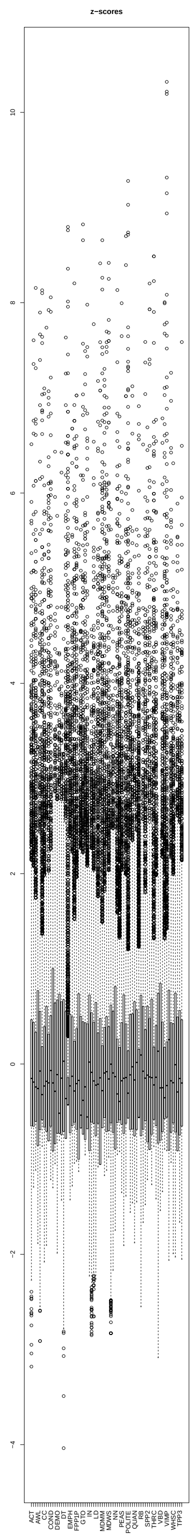
```
 Textbook.English Informative.Teens     Spoken.BNC2014      Youth.Fiction
               40                74                  1                  0
```

```
# 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-life' 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
```


z−scores
10
8
6
4
2
0
−2
−4
ACT
AWL
CC
COND
DEMO
DT
EMPH
FPP1P
GTO
IN
LD
MDMM
MDWS
NN
PEAS
POLITE
QUAN
RB
SPP2
THRC
VBD
VIMP
WHSC
TPP3

Signed log transformation

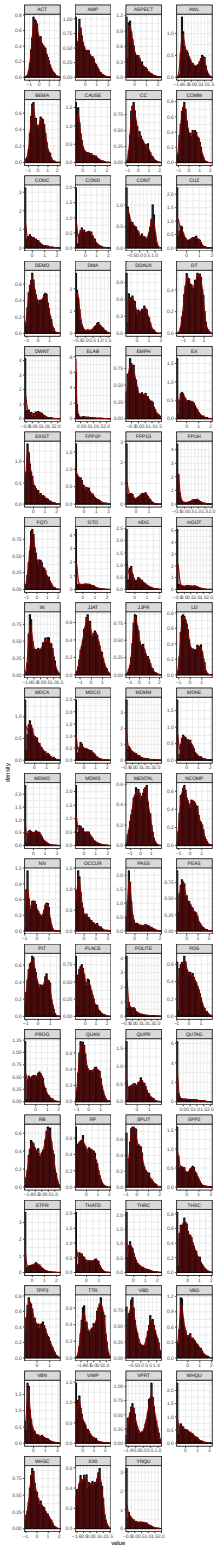
A signed logarithmic transformation was applied to (further) deskew the feature distributions (Diwersy, Evert, and Neumann 2014; Neumann and Evert 2021).

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)}

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

#saveRDS(zlogcounts, here("data", "processed", "zlogcounts_3Reg.rds")) # Last
 ↪  saved 16 March 2024
```

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
OPPOP
FPP1S
FPUH
FQTI
GTO
HGG
HGOT
IN
LIMT
LINN
LO
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
XXX
YNQU
density
value

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

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:

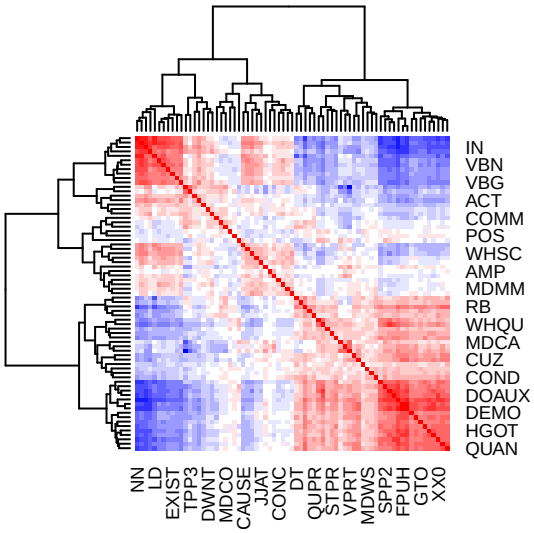
```
Textbook Conversation      Textbook Fiction       Info Teens Ref.
                  565                   285                 1337
 Textbook Informative   Spoken BNC2014 Ref.    Youth Fiction Ref.
                  352                  1250                 1191
```

Testing factorability of data

Visualisation of feature correlations

```
# 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()
```

Checking the factorability of data

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 highly correlated:

```
cor(data$VPRT, data$VBD)
```

```
[1] -0.9731048
```

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

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

MSA

```
kmo <- KMO(data[,9:ncol(data)])
```

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

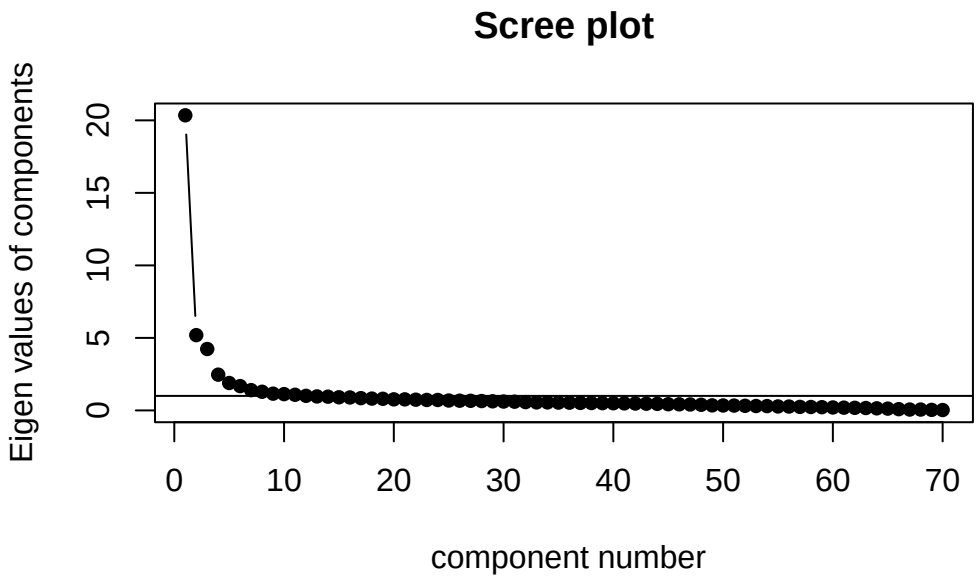
```
kmo$MSAi[order(kmo$MSAi)] |>  round(2)
```

```
   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 larger category earlier on).

Scree plot

```
# 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) # 6 components were
 ↪  originally retained on the basis of this screeplot (on the advice of an
 ↪  anonymous peer reviewer, only four were later retained).
```




```
# dev.off()

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

Communalities

If features with final communalities of < 0.2 are removed, we would remove TIME. 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.

3 Summary

In summary, this book has no content whatsoever.

References

Association for Computing Machinery, (ACM). 2020. "Artifact Review and Badging Version 1.1." https://www.acm.org/publications/policies/artifact-review-and-badging-current.

Berez-Kroeker, Andrea L., Lauren Gawne, Susan Smythe Kung, Barbara F. Kelly, Tyler Heston, Gary Holton, Peter Pulsifer, et al. 2018. "Reproducible Research in Linguistics: A Position Statement on Data Citation and Attribution in Our Field." *Linguistics* 56 (1): 1–18. https://doi.org/10.1515/ling-2017-0032.

Diwersy, Sascha, Stephanie Evert, and Stella Neumann. 2014. "A Weakly Supervised Multivariate Approach to the Study of Language Variation." In, edited by Benedikt Szmrecsanyi and Bernhard Wälchli, 174–204. Berlin: De Gruyter.

Le Foll, Elen. 2021a. *Introducing the Multi-Feature Tagger of English (MFTE)*. Osnabrück University. https://github.com/elenlefoll/MultiFeatureTaggerEnglish.

———. 2021b. *Introducing the Multi-Feature Tagger of English (MFTE)*. Osnabrück University. https://github.com/elenlefoll/MultiFeatureTaggerEnglish.

———. 2024. "Why We Need Open Science and Open Education to Bridge the Corpus Research–practice Gap." In, edited by Peter Crosthwaite, 142–56. London: Routledge.

———. n.d. "*Schulenglisch*: A Multi-Dimensional Model of the Variety of English Taught in German Secondary Schools." *AAA: Arbeiten Aus Anglistik Und Amerikanistik* 49.

Love, Robbie, Vaclav Brezina, Tony McEnery, Abi Hawtin, Andrew Hardie, and Claire Dembry. 2019. "Functional Variation in the Spoken BNC2014 and the Potential for Register Analysis." *Register Studies* 1 (2): 296–317. https://doi.org/10.1075/rs.18013.lov.

Love, Robbie, Claire Dembry, Andrew Hardie, Vaclav Brezina, and Tony McEnery. 2017. "The Spoken BNC2014." *International Journal of Corpus Linguistics* 22 (3): 319–44. https://doi.org/https://doi.org/10.1075/ijcl.22.3.02lov.

McManus, Kevin. 2021. "Are Replication Studies Infrequent Because of Negative Attitudes? Insights from a Survey of Attitudes and Practices in Second Language Research." *Studies in Second Language Acquisition*, December, 1–14. https://doi.org/10.1017/S0272263121000838.

Neumann, Stella, and Stephanie Evert. 2021. "A Register Variation Perspective on Varieties of English." In, edited by Elena Seoane and Douglas Biber, 144178. Studies in Corpus Linguistics 103. Amsterdam: Benjamins.

R Core Team. 2022. "R: A Language and Environment for Statistical Computing." Vienna, Austria. https://www.R-project.org/.

Wilkinson, Mark D., Michel Dumontier, IJsbrand Jan Aalbersberg, Gabrielle Appleton, Myles Axton, Arie Baak, Niklas Blomberg, et al. 2016. "The FAIR Guiding Principles for

Scientific Data Management and Stewardship." *Scientific Data* 3 (1): 160018. https://doi.org/10.1038/sdata.2016.18.