# CHAPTER 1
# The Tidy Text Format

Using tidy data principles is a powerful way to make handling data easier and more effective, and this is no less true when it comes to dealing with text. As described by Hadley Wickham (Wickham 2014), tidy data has a specific structure:

- Each variable is a column.
- Each observation is a row.
- Each type of observational unit is a table.

We thus define the tidy text format as being *a table with one token per row*. A token is a meaningful unit of text, such as a word, that we are interested in using for analysis, and tokenization is the process of splitting text into tokens. This one-token-per-row structure is in contrast to the ways text is often stored in current analyses, perhaps as strings or in a document-term matrix. For tidy text mining, the *token* that is stored in each row is most often a single word, but can also be an n-gram, sentence, or paragraph. In the tidytext package, we provide functionality to tokenize by commonly used units of text like these and convert to a one-term-per-row format.

Tidy data sets allow manipulation with a standard set of "tidy" tools, including popular packages such as dplyr (Wickham and Francois 2016), tidyr (Wickham 2016), ggplot2 (Wickham 2009), and broom (Robinson 2017). By keeping the input and output in tidy tables, users can transition fluidly between these packages. We've found these tidy tools extend naturally to many text analyses and explorations.

At the same time, the tidytext package doesn't expect a user to keep text data in a tidy form at all times during an analysis. The package includes functions to `tidy()` objects (see the broom package [Robinson, cited above]) from popular text mining R packages such as tm (Feinerer et al. 2008) and quanteda (Benoit and Nulty 2016). This allows, for example, a workflow where importing, filtering, and processing is done

using dplyr and other tidy tools, after which the data is converted into a document-term matrix for machine learning applications. The models can then be reconverted into a tidy form for interpretation and visualization with ggplot2.

## Contrasting Tidy Text with Other Data Structures

As we stated above, we define the tidy text format as being a table with *one token per row*. Structuring text data in this way means that it conforms to tidy data principles and can be manipulated with a set of consistent tools. This is worth contrasting with the ways text is often stored in text mining approaches:

*String*
: Text can, of course, be stored as strings (i.e., character vectors) within R, and often text data is first read into memory in this form.

*Corpus*
: These types of objects typically contain raw strings annotated with additional metadata and details.

*Document-term matrix*
: This is a sparse matrix describing a collection (i.e., a corpus) of documents with one row for each document and one column for each term. The value in the matrix is typically word count or tf-idf (see Chapter 3).

Let's hold off on exploring corpus and document-term matrix objects until Chapter 5, and get down to the basics of converting text to a tidy format.

## The unnest_tokens Function

Emily Dickinson wrote some lovely text in her time.

```
text <- c("Because I could not stop for Death -",
          "He kindly stopped for me -",
          "The Carriage held but just Ourselves -",
          "and Immortality")

text
```

```
## [1] "Because I could not stop for Death -"   "He kindly stopped for me -"
## [3] "The Carriage held but just Ourselves -" "and Immortality"
```

This is a typical character vector that we might want to analyze. In order to turn it into a tidy text dataset, we first need to put it into a data frame.

```
library(dplyr)
text_df <- data_frame(line = 1:4, text = text)

text_df
```

```
## # A tibble: 4 × 2
##    line                                    text
##   <int>                                   <chr>
## 1     1  Because I could not stop for Death -
## 2     2             He kindly stopped for me -
## 3     3 The Carriage held but just Ourselves -
## 4     4                          and Immortality
```

What does it mean that this data frame has printed out as a "tibble"? A *tibble* is a modern class of data frame within R, available in the dplyr and tibble packages, that has a convenient print method, will not convert strings to factors, and does not use row names. Tibbles are great for use with tidy tools.

Notice that this data frame containing text isn't yet compatible with tidy text analysis. We can't filter out words or count which occur most frequently, since each row is made up of multiple combined words. We need to convert this so that it has *one token per document per row.* → ie "tokenize it".

A token is a meaningful unit of text, most often a word, that we are interested in using for further analysis, and tokenization is the process of splitting text into tokens.

In this first example, we only have one document (the poem), but we will explore examples with multiple documents soon. → "corpus"

Within our tidy text framework, we need to both break the text into individual tokens (a process called *tokenization*) *and* transform it to a tidy data structure. To do this, we use the tidytext `unnest_tokens()` function.

untidy text → tokenize
& tidy → data analysis

```
library(tidytext)

text_df %>%
  unnest_tokens(word, text)
```

```
## # A tibble: 20 × 2
##     line    word
##    <int>   <chr>
## 1      1 because
## 2      1       i
## 3      1   could
## 4      1     not
## 5      1    stop
## 6      1     for
## 7      1   death
## 8      2      he
## 9      2  kindly
## 10     2 stopped
## # ... with 10 more rows
```

The two basic arguments to `unnest_tokens` used here are column names. First we have the output column name that will be created as the text is unnested into it (`word`, in this case), and then the input column that the text comes from (`text`, in this case). Remember that `text_df` above has a column called `text` that contains the data of interest.

After using `unnest_tokens`, we've split each row so that there is one token (word) in each row of the new data frame; the default tokenization in `unnest_tokens()` is for single words, as shown here. Also notice:

- Other columns, such as the line number each word came from, are retained.
- Punctuation has been stripped.
- By default, `unnest_tokens()` converts the tokens to lowercase, which makes them easier to compare or combine with other datasets. (Use the `to_lower = FALSE` argument to turn off this behavior).

Having the text data in this format lets us manipulate, process, and visualize the text using the standard set of tidy tools, namely dplyr, tidyr, and ggplot2, as shown in Figure 1-1.

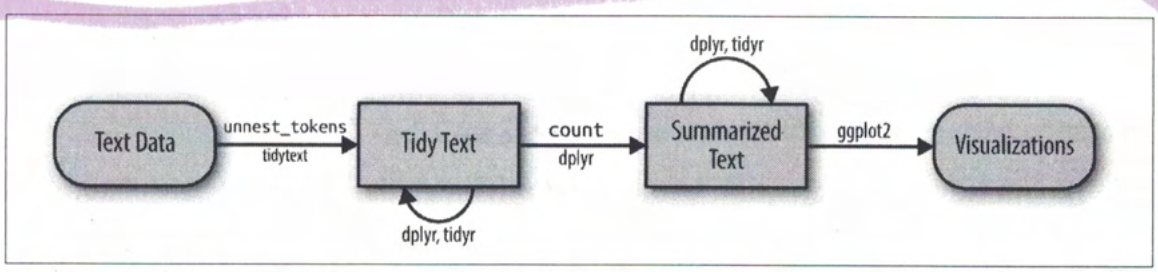



*Figure 1-1. A flowchart of a typical text analysis using tidy data principles. This chapter shows how to summarize and visualize text using these tools.*

## Tidying the Works of Jane Austen

Let's use the text of Jane Austen's six completed, published novels from the janeaustenr package (Silge 2016), and transform them into a tidy format. The janeaustenr package provides these texts in a one-row-per-line format, where a line in this context is analogous to a literal printed line in a physical book. Let's start with that, and also use `mutate()` to annotate a `linenumber` quantity to keep track of lines in the original format, and a `chapter` (using a regex) to find where all the chapters are.

```
library(janeaustenr)
library(dplyr)
library(stringr)

original_books <- austen_books() %>%
  group_by(book) %>%
```

```
  mutate(linenumber = row_number(),
         chapter = cumsum(str_detect(text, regex("^chapter [\\divxlc]",
                                                 ignore_case = TRUE)))) %>%
  ungroup()

original_books
```

```
## # A tibble: 73,422 × 4
##                     text                book linenumber chapter
##                    <chr>              <fctr>      <int>   <int>
## 1  SENSE AND SENSIBILITY Sense & Sensibility          1       0
## 2                        Sense & Sensibility          2       0
## 3         by Jane Austen Sense & Sensibility          3       0
## 4                        Sense & Sensibility          4       0
## 5                (1811) Sense & Sensibility          5       0
## 6                       Sense & Sensibility          6       0
## 7                       Sense & Sensibility          7       0
## 8                       Sense & Sensibility          8       0
## 9                       Sense & Sensibility          9       0
## 10            CHAPTER 1 Sense & Sensibility         10       1
## # ... with 73,412 more rows
```

To work with this as a tidy dataset, we need to restructure it in the *one-token-per-row* format, which as we saw earlier is done with the `unnest_tokens()` function.

```
library(tidytext)
tidy_books <- original_books %>%
  unnest_tokens(word, text)

tidy_books
```

```
## # A tibble: 725,054 × 4
##                   book linenumber chapter        word
##                 <fctr>      <int>   <int>       <chr>
## 1  Sense & Sensibility          1       0       sense
## 2  Sense & Sensibility          1       0         and
## 3  Sense & Sensibility          1       0 sensibility
## 4  Sense & Sensibility          3       0          by
## 5  Sense & Sensibility          3       0        jane
## 6  Sense & Sensibility          3       0      austen
## 7  Sense & Sensibility          5       0        1811
## 8  Sense & Sensibility         10       1     chapter
## 9  Sense & Sensibility         10       1           1
## 10 Sense & Sensibility         13       1         the
## # ... with 725,044 more rows
```

This function uses the tokenizers package to separate each line of text in the original data frame into tokens. The default tokenizing is for words, but other options include characters, n-grams, sentences, lines, paragraphs, or separation around a regex pattern.

Now that the data is in one-word-per-row format, we can manipulate it with tidy tools like dplyr. Often in text analysis, we will want to remove *stop words*, which are

words that are not useful for an analysis, typically extremely common words such as "the," "of," "to," and so forth in English. We can remove stop words (kept in the tidytext dataset `stop_words`) with an `anti_join()`.

```
data(stop_words)

tidy_books <- tidy_books %>%
  anti_join(stop_words)
```

The `stop_words` dataset in the tidytext package contains stop words from three lexicons. We can use them all together, as we have here, or `filter()` to only use one set of stop words if that is more appropriate for a certain analysis.

We can also use dplyr's `count()` to find the most common words in all the books as a whole.

```
tidy_books %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 13,914 × 2
##      word     n
##     <chr> <int>
## 1    miss  1855
## 2    time  1337
## 3   fanny   862
## 4    dear   822
## 5    lady   817
## 6     sir   806
## 7     day   797
## 8    emma   787
## 9  sister   727
## 10  house   699
## # ... with 13,904 more rows
```

Because we've been using tidy tools, our word counts are stored in a tidy data frame. This allows us to pipe directly to the ggplot2 package, for example to create a visualization of the most common words (Figure 1-2).

```
library(ggplot2)

tidy_books %>%
  count(word, sort = TRUE) %>%
  filter(n > 600) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n)) +
  geom_col() +
  xlab(NULL) +
  coord_flip()
```

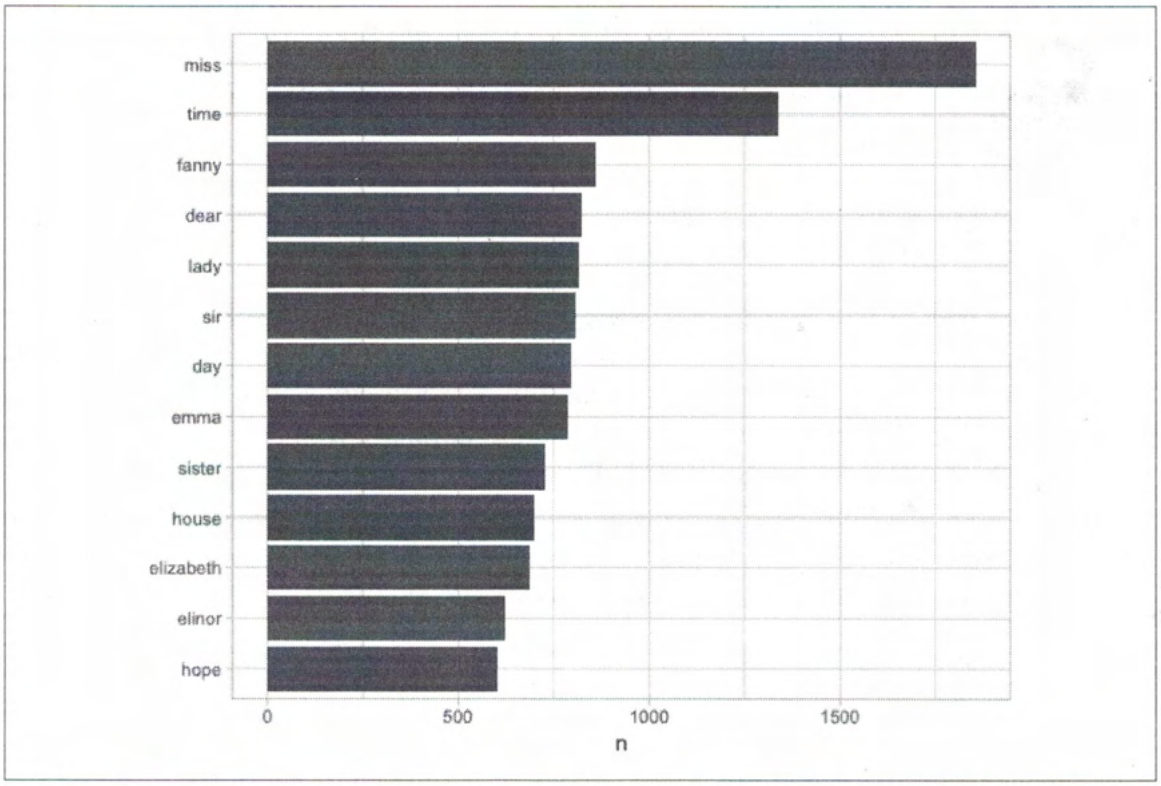



*Figure 1-2. The most common words in Jane Austen's novels*

Note that the `austen_books()` function started us with exactly the text we wanted to analyze, but in other cases we may need to perform cleaning of text data, such as removing copyright headers or formatting. You'll see examples of this kind of preprocessing in the case study chapters, particularly "Preprocessing" on page 153.

## The gutenbergr Package

Now that we've used the janeaustenr package to explore tidying text, let's introduce the gutenbergr package (Robinson 2016). The gutenbergr package provides access to the public domain works from the Project Gutenberg collection. The package includes tools both for downloading books (stripping out the unhelpful header/footer information), and a complete dataset of Project Gutenberg metadata that can be used to find works of interest. In this book, we will mostly use the `gutenberg_download()` function that downloads one or more works from Project Gutenberg by ID, but you can also use other functions to explore metadata, pair Gutenberg ID with title, author, language, and so on, or gather information about authors.

To learn more about gutenbergr, check out the package's tutorial at rOpenSci, where it is one of rOpenSci's packages for data access.

## Word Frequencies

A common task in text mining is to look at word frequencies, just like we have done above for Jane Austen's novels, and to compare frequencies across different texts. We can do this intuitively and smoothly using tidy data principles. We already have Jane Austen's works; let's get two more sets of texts to compare to. First, let's look at some science fiction and fantasy novels by H.G. Wells, who lived in the late 19th and early 20th centuries. Let's get *The Time Machine*, *The War of the Worlds*, *The Invisible Man*, and *The Island of Doctor Moreau*. We can access these works using `gutenberg_download()` and the Project Gutenberg ID numbers for each novel.

? How do we find the Project Gutenberg ID numbers for each novel?

```
library(gutenbergr)

hgwells <- gutenberg_download(c(35, 36, 5230, 159))

tidy_hgwells <- hgwells %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words)
```

? What does the "%>%" actually do?

Just for kicks, what are the most common words in these novels of H.G. Wells?

```
tidy_hgwells %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 11,769 × 2
##      word     n
##     <chr> <int>
## 1    time   454
## 2  people   302
## 3    door   260
## 4   heard   249
## 5   black   232
## 6   stood   229
## 7   white   222
## 8    hand   218
## 9    kemp   213
## 10   eyes   210
## # ... with 11,759 more rows
```

Now let's get some well-known works of the Brontë sisters, whose lives overlapped with Jane Austen's somewhat, but who wrote in a rather different style. Let's get *Jane Eyre*, *Wuthering Heights*, *The Tenant of Wildfell Hall*, *Villette*, and *Agnes Grey*. We will again use the Project Gutenberg ID numbers for each novel and access the texts using `gutenberg_download()`.

```
bronte <- gutenberg_download(c(1260, 768, 969, 9182, 767))

tidy_bronte <- bronte %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words)
```

What are the most common words in these novels of the Brontë sisters?

```
tidy_bronte %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 23,051 × 2
##      word     n
##     <chr> <int>
## 1    time  1065
## 2    miss   855
## 3     day   827
## 4    hand   768
## 5    eyes   713
## 6   night   647
## 7   heart   638
## 8  looked   602
## 9    door   592
## 10   half   586
## # ... with 23,041 more rows
```

Interesting that "time," "eyes," and "hand" are in the top 10 for both H.G. Wells and the Brontë sisters. → well don't stop there! CLA is literary analysis too; what does it MEAN?

Now, let's calculate the frequency for each word in the works of Jane Austen, the Brontë sisters, and H.G. Wells by binding the data frames together. We can use spread and gather from tidyr to reshape our data frame so that it is just what we need for plotting and comparing the three sets of novels.

```
library(tidyr)

frequency <- bind_rows(mutate(tidy_bronte, author = "Brontë Sisters"),
                       mutate(tidy_hgwells, author = "H.G. Wells"),
                       mutate(tidy_books, author = "Jane Austen")) %>%
  mutate(word = str_extract(word, "[a-z']+")) %>%
  count(author, word) %>%
  group_by(author) %>%
  mutate(proportion = n / sum(n)) %>%
  select(-n) %>%
  spread(author, proportion) %>%
  gather(author, proportion, `Brontë Sisters`:`H.G. Wells`)
```

→ this is on top left of your keyboard

We use str_extract() here because the UTF-8 encoded texts from Project Gutenberg have some examples of words with underscores around them to indicate emphasis (like italics). The tokenizer treated these as words, but we don't want to count "*any*" separately from "any" as we saw in our initial data exploration before choosing to use str_extract().

Now let's plot (Figure 1-3).

```
library(scales)

# expect a warning about rows with missing values being removed
ggplot(frequency, aes(x = proportion, y = `Jane Austen`,
                      color = abs(`Jane Austen` - proportion))) +
  geom_abline(color = "gray40", lty = 2) +
  geom_jitter(alpha = 0.1, size = 2.5, width = 0.3, height = 0.3) +
  geom_text(aes(label = word), check_overlap = TRUE, vjust = 1.5) +
  scale_x_log10(labels = percent_format()) +
  scale_y_log10(labels = percent_format()) +
  scale_color_gradient(limits = c(0, 0.001),
                       low = "darkslategray4", high = "gray75") +
  facet_wrap(~author, ncol = 2) +
  theme(legend.position="none") +
  labs(y = "Jane Austen", x = NULL)
```


*Figure 1-3. Comparing the word frequencies of Jane Austen, the Brontë sisters, and H.G. Wells*

Words that are close to the line in these plots have similar frequencies in both sets of texts, for example, in both Austen and Brontë texts ("miss," "time," and "day" at the high frequency end) or in both Austen and Wells texts ("time," "day," and "brother" at the high frequency end). Words that are far from the line are words that are found more in one set of texts than another. For example, in the Austen-Brontë panel, words like "elizabeth," "emma," and "fanny" (all proper nouns) are found in Austen's texts but not much in the Brontë texts, while words like "arthur" and "dog" are found in the Brontë texts but not the Austen texts. In comparing H.G. Wells with Jane Aus-

ten, Wells uses words like "beast," "guns," "feet," and "black" that Austen does not, while Austen uses words like "family", "friend," "letter," and "dear" that Wells does not.

Overall, notice in Figure 1-3 that the words in the Austen-Brontë panel are closer to the zero-slope line than in the Austen-Wells panel. Also notice that the words extend to lower frequencies in the Austen-Brontë panel; there is empty space in the Austen-Wells panel at low frequency. These characteristics indicate that Austen and the Brontë sisters use more similar words than Austen and H.G. Wells. Also, we see that not all the words are found in all three sets of texts, and there are fewer data points in the panel for Austen and H.G. Wells.

Let's quantify how similar and different these sets of word frequencies are using a correlation test. How correlated are the word frequencies between Austen and the Brontë sisters, and between Austen and Wells?

```
cor.test(data = frequency[frequency$author == "Brontë Sisters",],
         ~ proportion + `Jane Austen`)

##
##  Pearson's product-moment correlation
##
## data:  proportion and Jane Austen
## t = 119.64, df = 10404, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.7527837 0.7689611
## sample estimates:
##       cor
## 0.7609907

cor.test(data = frequency[frequency$author == "H.G. Wells",],
         ~ proportion + `Jane Austen`)

##
##  Pearson's product-moment correlation
##
## data:  proportion and Jane Austen
## t = 36.441, df = 6053, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.4032820 0.4446006
## sample estimates:
##       cor
## 0.424162
```

Just as we saw in the plots, the word frequencies are more correlated between the Austen and Brontë novels than between Austen and H.G. Wells.

I got a cor.value of=0.7376. Why is it not the same? Did something in the corpus change since the writing of this book?

I got a cor.value of=0.41377. Why ...?

# CHAPTER 2

# Sentiment Analysis with Tidy Data

In the previous chapter, we explored in depth what we mean by the tidy text format and showed how this format can be used to approach questions about word frequency. This allowed us to analyze which words are used most frequently in documents and to compare documents, but now let's investigate a different topic. Let's address the topic of opinion mining or sentiment analysis. When human readers approach a text, we use our understanding of the emotional intent of words to infer whether a section of text is positive or negative, or perhaps characterized by some other more nuanced emotion like surprise or disgust. We can use the tools of text mining to approach the emotional content of text programmatically, as shown in Figure 2-1.

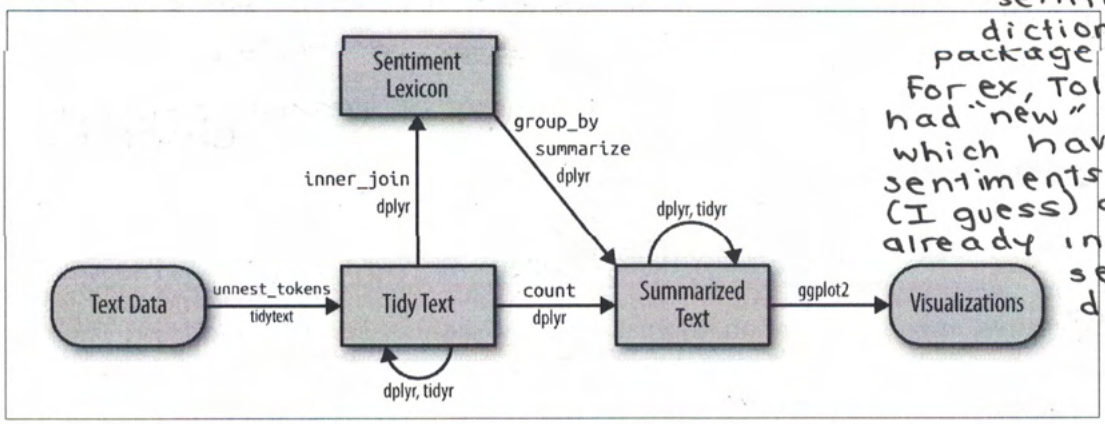



*Figure 2-1. A flowchart of a typical text analysis that uses tidytext for sentiment analysis. This chapter shows how to implement sentiment analysis using tidy data principles.*

One way to analyze the sentiment of a text is to consider the text as a combination of its individual words, and the sentiment content of the whole text as the sum of the sentiment content of the individual words. This isn't the only way to approach senti-

ment analysis, but it is an often-used approach, *and* an approach that naturally takes advantage of the tidy tool ecosystem.

## The sentiments Dataset

As discussed above, there are a variety of methods and dictionaries that exist for evaluating opinion or emotion in text. The tidytext package contains several sentiment lexicons in the sentiments dataset.

"lexicon" is the vocabulary of a specific branch of knowledge

```
library(tidytext)

sentiments
```

```
## # A tibble: 27,314 × 4
##           word sentiment lexicon score
##          <chr>     <chr>   <chr> <int>
## 1       abacus     trust     nrc    NA
## 2      abandon      fear     nrc    NA
## 3      abandon  negative     nrc    NA
## 4      abandon   sadness     nrc    NA
## 5    abandoned     anger     nrc    NA
## 6    abandoned      fear     nrc    NA
## 7    abandoned  negative     nrc    NA
## 8    abandoned   sadness     nrc    NA
## 9  abandonment     anger     nrc    NA
## 10 abandonment      fear     nrc    NA
## # ... with 27,304 more rows
```

2.

when I run the "sentiments" command, I get a different set of words, is this bc the dataset has been updated?

The three general-purpose lexicons are:

- AFINN from Finn Årup Nielsen → −5 TO +5 SCORE
- Bing from Bing Liu and collaborators → POSITIVE/NEGATIVE
- NRC from Saif Mohammad and Peter Turney → YES/NO FOR ALL EMOTIONS

All three lexicons are based on unigrams, i.e., single words. These lexicons contain many English words and the words are assigned scores for positive/negative sentiment, and also possibly emotions like joy, anger, sadness, and so forth. The NRC lexicon categorizes words in a binary fashion ("yes"/"no") into categories of positive, negative, anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. The Bing lexicon categorizes words in a binary fashion into positive and negative categories. The AFINN lexicon assigns words with a score that runs between -5 and 5, with negative scores indicating negative sentiment and positive scores indicating positive sentiment. All of this information is tabulated in the sentiments dataset, and tidytext provides the function get_sentiments() to get specific sentiment lexicons without the columns that are not used in that lexicon.

so does "unigrams" include hyphenated words? we know Tolkien loved using hyphenated words, so having these three general-purpose lexicons might NOT work on Tolkien CLA.

```
get_sentiments("afinn")
```

```
## # A tibble: 2,476 × 2
##          word score
##         <chr> <int>
## 1     abandon    -2
## 2   abandoned    -2
## 3    abandons    -2
## 4    abducted    -2
## 5   abduction    -2
## 6  abductions    -2
## 7       abhor    -3
## 8    abhorred    -3
## 9   abhorrent    -3
## 10     abhors    -3
## # ... with 2,466 more rows
```

```
get_sentiments("bing")
```

```
## # A tibble: 6,788 × 2
##           word sentiment
##          <chr>     <chr>
## 1      2-faced  negative
## 2      2-faces  negative
## 3           a+  positive
## 4     abnormal  negative
## 5      abolish  negative
## 6   abominable  negative
## 7   abominably  negative
## 8    abominate  negative
## 9  abomination  negative
## 10       abort  negative
## # ... with 6,778 more rows
```

```
get_sentiments("nrc")
```

```
## # A tibble: 13,901 × 2
##           word sentiment
##          <chr>     <chr>
## 1       abacus     trust
## 2      abandon      fear
## 3      abandon  negative
## 4      abandon   sadness
## 5    abandoned     anger
## 6    abandoned      fear
## 7    abandoned  negative
## 8    abandoned   sadness
## 9  abandonment     anger
## 10 abandonment      fear
## # ... with 13,891 more rows
```

How were these sentiment lexicons put together and validated? They were constructed via either crowdsourcing (using, for example, Amazon Mechanical Turk) or by the labor of one of the authors, and were validated using some combination of

crowdsourcing again, restaurant or movie reviews, or Twitter data. Given this information, we may hesitate to apply these sentiment lexicons to styles of text dramatically different from what they were validated on, such as narrative fiction from 200 years ago. While it is true that using these sentiment lexicons with, for example, Jane Austen's novels may give us less accurate results than with tweets sent by a contemporary writer, we still can measure the sentiment content for words that are shared across the lexicon and the text.

There are also some domain-specific sentiment lexicons available, constructed to be used with text from a specific content area. "Example: Mining Financial Articles" on page 81 explores an analysis using a sentiment lexicon specifically for finance.

Dictionary-based methods like the ones we are discussing find the total sentiment of a piece of text by adding up the individual sentiment scores for each word in the text.

Not every English word is in the lexicons because many English words are pretty neutral. It is important to keep in mind that these methods do not take into account qualifiers before a word, such as in "no good" or "not true"; a lexicon-based method like this is based on unigrams only. For many kinds of text (like the narrative examples below), there are no sustained sections of sarcasm or negated text, so this is not an important effect. Also, we can use a tidy text approach to begin to understand what kinds of negation words are important in a given text; see Chapter 9 for an extended example of such an analysis.

One last caveat is that the size of the chunk of text that we use to add up unigram sentiment scores can have an effect on an analysis. A text the size of many paragraphs can often have positive and negative sentiment averaging out to about zero, while sentence-sized or paragraph-sized text often works better.

## Sentiment Analysis with Inner Join

With data in a tidy format, sentiment analysis can be done as an inner join. This is another of the great successes of viewing text mining as a tidy data analysis task—much as removing stop words is an anti-join operation, performing sentiment analysis is an inner join operation.

Let's look at the words with a "joy" score from the NRC lexicon. What are the most common joy words in *Emma*? First, we need to take the text of the novel and convert the text to the tidy format using `unnest_tokens()`, just as we did in "Tidying the Works of Jane Austen" on page 4. Let's also set up some other columns to keep track

of which line and chapter of the book each word comes from; we use `group_by` and `mutate` to construct those columns.

```
library(janeaustenr)
library(dplyr)
library(stringr)

tidy_books <- austen_books() %>%
  group_by(book) %>%
  mutate(linenumber = row_number(),
         chapter = cumsum(str_detect(text, regex("^chapter [\\divxlc]",
                                                 ignore_case = TRUE)))) %>%
  ungroup() %>%
  unnest_tokens(word, text)
```

Notice that we chose the name `word` for the output column from `unnest_tokens()`. This is a convenient choice because the sentiment lexicons and stop-word datasets have columns named `word`; performing inner joins and anti-joins is thus easier.

Now that the text is in a tidy format with one word per row, we are ready to do the sentiment analysis. First, let's use the NRC lexicon and `filter()` for the joy words. Next, let's `filter()` the data frame with the text from the book for the words from *Emma* and then use `inner_join()` to perform the sentiment analysis. What are the most common joy words in *Emma*? Let's use `count()` from dplyr.

```
nrcjoy <- get_sentiments("nrc") %>%
  filter(sentiment == "joy")

tidy_books %>%
  filter(book == "Emma") %>%
  inner_join(nrcjoy) %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 303 × 2
##       word     n
##      <chr> <int>
## 1     good   359
## 2    young   192
## 3   friend   166
## 4     hope   143
## 5    happy   125
## 6     love   117
## 7     deal    92
## 8    found    92
## 9  present    89
## 10    kind    82
## # ... with 293 more rows
```

Again, I'm getting similar but not same results.

good, friend, hope, happy, love ...

why?

We see many positive, happy words about hope, friendship, and love here.

Or instead we could examine how sentiment changes throughout each novel. We can do this with just a handful of lines that are mostly dplyr functions. First, we find a sentiment score for each word using the Bing lexicon and `inner_join()`.

Next, we count up how many positive and negative words there are in defined sections of each book. We define an `index` here to keep track of where we are in the narrative; this index (using integer division) counts up sections of 80 lines of text.

The `%/%` operator does integer division (`x %/% y` is equivalent to `floor(x/y)`) so the index keeps track of which 80-line section of text we are counting up negative and positive sentiment in.

Small sections of text may not have enough words in them to get a good estimate of sentiment, while really large sections can wash out narrative structure. For these books, using 80 lines works well, but this can vary depending on individual texts, how long the lines were to start with, etc. We then use `spread()` so that we have negative and positive sentiment in separate columns, and lastly calculate a net sentiment (`positive - negative`).

```
library(tidyr)

janeaustensentiment <- tidy_books %>%
  inner_join(get_sentiments("bing")) %>%
  count(book, index = linenumber %/% 80, sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
```

Now we can plot these sentiment scores across the plot trajectory of each novel. Notice that we are plotting against the `index` on the x-axis that keeps track of narrative time in sections of text (Figure 2-2).

```
library(ggplot2)

ggplot(janeaustensentiment, aes(index, sentiment, fill = book)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~book, ncol = 2, scales = "free_x")
```

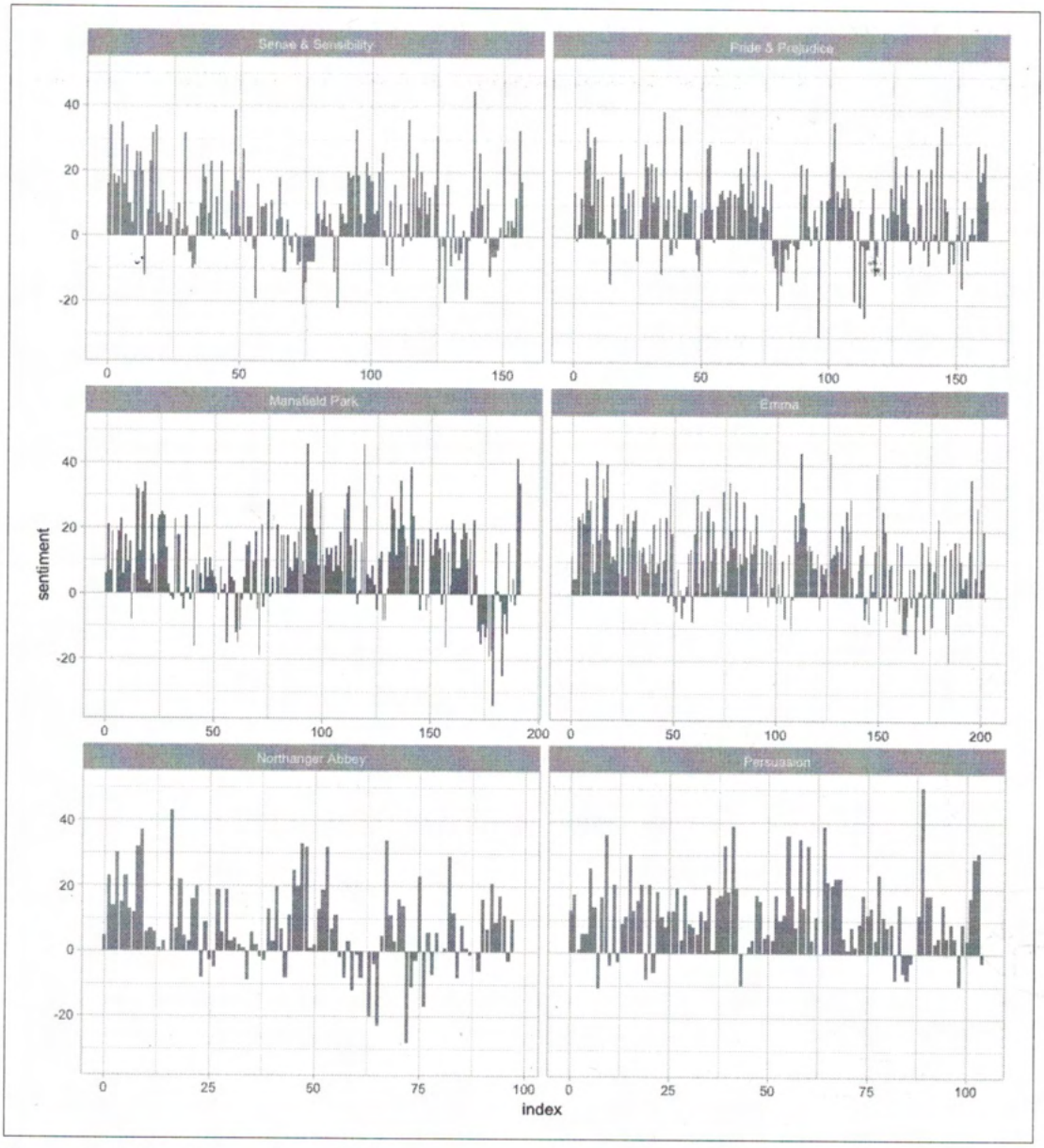



*Figure 2-2. Sentiment through the narratives of Jane Austen's novels*

We can see in Figure 2-2 how the plot of each novel changes toward more positive or negative sentiment over the trajectory of the story.

## Comparing the Three Sentiment Dictionaries

With several options for sentiment lexicons, you might want some more information on which one is appropriate for your purposes. Let's use all three sentiment lexicons and examine how the sentiment changes across the narrative arc of *Pride and Preju-*

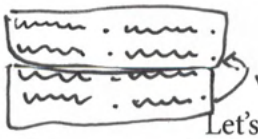
*dice*. First, let's use `filter()` to choose only the words from the one novel we are interested in.

```
pride_prejudice <- tidy_books %>%
  filter(book == "Pride & Prejudice")

pride_prejudice
```

```
## # A tibble: 122,204 × 4
##                book linenumber chapter      word
##              <fctr>      <int>   <int>     <chr>
## 1  Pride & Prejudice          1       0     pride
## 2  Pride & Prejudice          1       0       and
## 3  Pride & Prejudice          1       0 prejudice
## 4  Pride & Prejudice          3       0        by
## 5  Pride & Prejudice          3       0      jane
## 6  Pride & Prejudice          3       0    austen
## 7  Pride & Prejudice          7       1   chapter
## 8  Pride & Prejudice          7       1         1
## 9  Pride & Prejudice         10       1        it
## 10 Pride & Prejudice         10       1        is
## # ... with 122,194 more rows
```

Now, we can use `inner_join()` to calculate the sentiment in different ways.

Remember from above that the AFINN lexicon measures sentiment with a numeric score between -5 and 5, while the other two lexicons categorize words in a binary fashion, either positive or negative. To find a sentiment score in chunks of text throughout the novel, we will need to use a different pattern for the AFINN lexicon than for the other two.



vs.

Let's again use integer division (`%/%`) to define larger sections of text that span multiple lines, and we can use the same pattern with `count()`, `spread()`, and `mutate()` to find the net sentiment in each of these sections of text.

```
afinn <- pride_prejudice %>%
  inner_join(get_sentiments("afinn")) %>%
  group_by(index = linenumber %/% 80) %>%
  summarise(sentiment = sum(score)) %>%
  mutate(method = "AFINN")

bing_and_nrc <- bind_rows(
  pride_prejudice %>%
    inner_join(get_sentiments("bing")) %>%
    mutate(method = "Bing et al."),
  pride_prejudice %>%
    inner_join(get_sentiments("nrc") %>%
                 filter(sentiment %in% c("positive",
                                         "negative"))) %>%
    mutate(method = "NRC")) %>%
```

```
    count(method, index = linenumber %/% 80, sentiment) %>%
    spread(sentiment, n, fill = 0) %>%
    mutate(sentiment = positive - negative)
```

We now have an estimate of the net sentiment (`positive - negative`) in each chunk of the novel text for each sentiment lexicon. Let's bind them together and visualize them in Figure 2-3.

```
bind_rows(afinn,
          bing_and_nrc) %>%
  ggplot(aes(index, sentiment, fill = method)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~method, ncol = 1, scales = "free_y")
```

of course here I could not graph this since I did not have "afinn" from previous error.

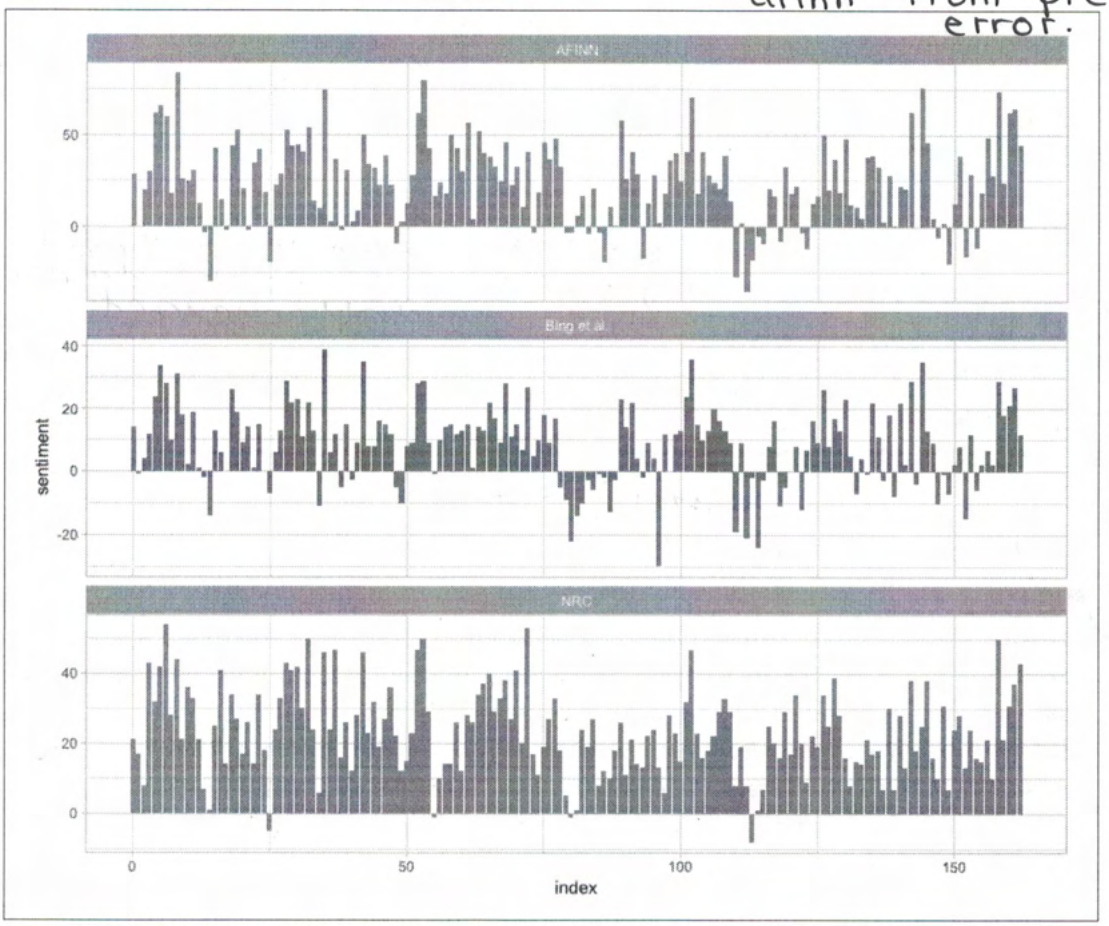



*Figure 2-3. Comparing three sentiment lexicons using Pride and Prejudice*

The three different lexicons for calculating sentiment give results that are different in an absolute sense but have similar relative trajectories through the novel. We see similar dips and peaks in sentiment at about the same places in the novel, but the absolute values are significantly different. The AFINN lexicon gives the largest absolute values, with high positive values. The lexicon from Bing et al. has lower absolute val-

ues and seems to label larger blocks of contiguous positive or negative text. The NRC results are shifted higher relative to the other two, labeling the text more positively, but detects similar relative changes in the text. We find similar differences between the methods when looking at other novels; the NRC sentiment is high, the AFINN sentiment has more variance, and the Bing et al. sentiment appears to find longer stretches of similar text, but all three agree roughly on the overall trends in the sentiment through a narrative arc.

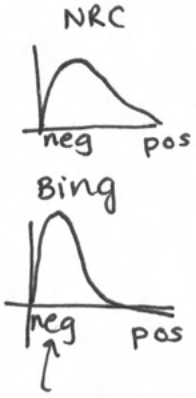
Why is, for example, the result for the NRC lexicon biased so high in sentiment compared to the Bing et al. result? Let's look briefly at how many positive and negative words are in these lexicons.

```
get_sentiments("nrc") %>%
     filter(sentiment %in% c("positive",
                             "negative")) %>%
  count(sentiment)
```

```
## # A tibble: 2 × 2
##   sentiment     n
##       <chr> <int>
## 1  negative  3324
## 2  positive  2312
```

```
get_sentiments("bing") %>%
  count(sentiment)
```

```
## # A tibble: 2 × 2
##   sentiment     n
##       <chr> <int>
## 1  negative  4782
## 2  positive  2006
```




Both lexicons have more negative than positive words, but the ratio of negative to positive words is higher in the Bing lexicon than the NRC lexicon. This will contribute to the effect we see in the plot above, as will any systematic difference in word matches, for example, if the negative words in the NRC lexicon do not match very well with the words that Jane Austen uses. Whatever the source of these differences, we see similar relative trajectories across the narrative arc, with similar changes in slope, but marked differences in absolute sentiment from lexicon to lexicon. This is important context to keep in mind when choosing a sentiment lexicon for analysis.

## Most Common Positive and Negative Words

One advantage of having the data frame with both `sentiment` and `word` is that we can analyze word counts that contribute to each sentiment. By implementing `count()` here with arguments of both `word` and `sentiment`, we find out how much each word contributed to each sentiment.

```
bing_word_counts <- tidy_books %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()

bing_word_counts
```

```
## # A tibble: 2,585 × 3
##         word sentiment     n
##        <chr>     <chr> <int>
## 1       miss  negative  1855
## 2       well  positive  1523
## 3       good  positive  1380
## 4      great  positive   981
## 5       like  positive   725
## 6     better  positive   639
## 7     enough  positive   613
## 8      happy  positive   534
## 9       love  positive   495
## 10 pleasure  positive   462
## # ... with 2,575 more rows
```

This can be shown visually, and we can pipe straight into ggplot2, if we like, because of the way we are consistently using tools built for handling tidy data frames (Figure 2-4).

```
bing_word_counts %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n, fill = sentiment)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment",
       x = NULL) +
  coord_flip()
```

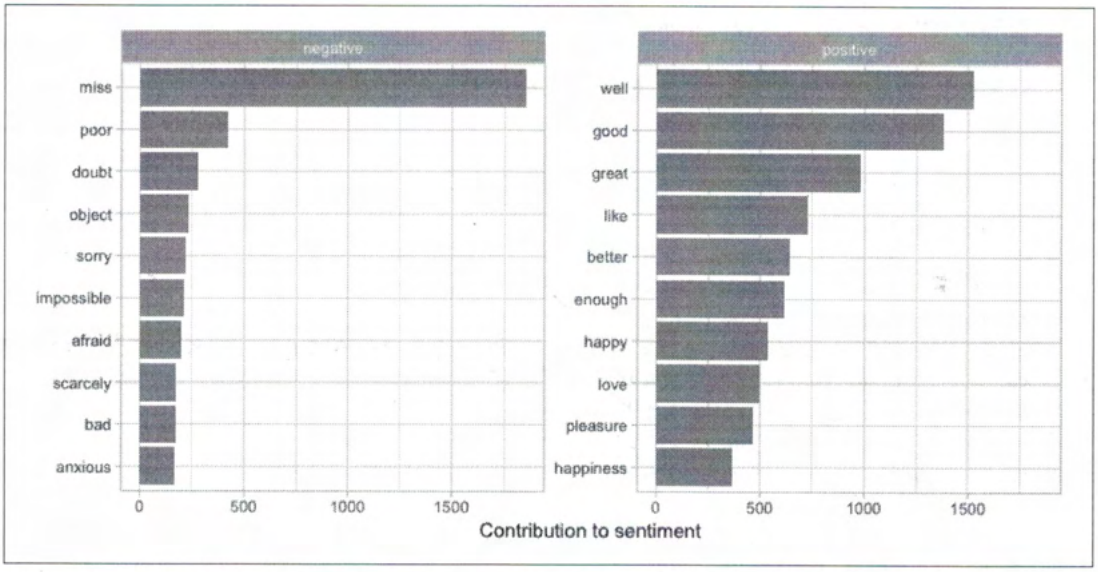



*Figure 2-4. Words that contribute to positive and negative sentiment in Jane Austen's novels*

Figure 2-4 lets us spot an anomaly in the sentiment analysis; the word "miss" is coded as negative but it is used as a title for young, unmarried women in Jane Austen's works. If it were appropriate for our purposes, we could easily add "miss" to a custom stop-words list using `bind_rows()`. We could implement that with a strategy such as this:

```
custom_stop_words <- bind_rows(data_frame(word = c("miss"),
                                          lexicon = c("custom")),
                               stop_words)

custom_stop_words
```

```
## # A tibble: 1,150 × 2
##           word lexicon
##          <chr>   <chr>
## 1         miss  custom
## 2            a   SMART
## 3          a's   SMART
## 4         able   SMART
## 5        about   SMART
## 6        above   SMART
## 7    according   SMART
## 8  accordingly   SMART
## 9       across   SMART
## 10    actually   SMART
## # ... with 1,140 more rows
```

good, so these are a list of all of the stopwords used /removed from our text when we use the command "anti_join"

## Wordclouds

We've seen that this tidy text mining approach works well with ggplot2, but having our data in a tidy format is useful for other plots as well.

For example, consider the wordcloud package, which uses base R graphics. Let's look at the most common words in Jane Austen's works as a whole again, but this time as a wordcloud in Figure 2-5.

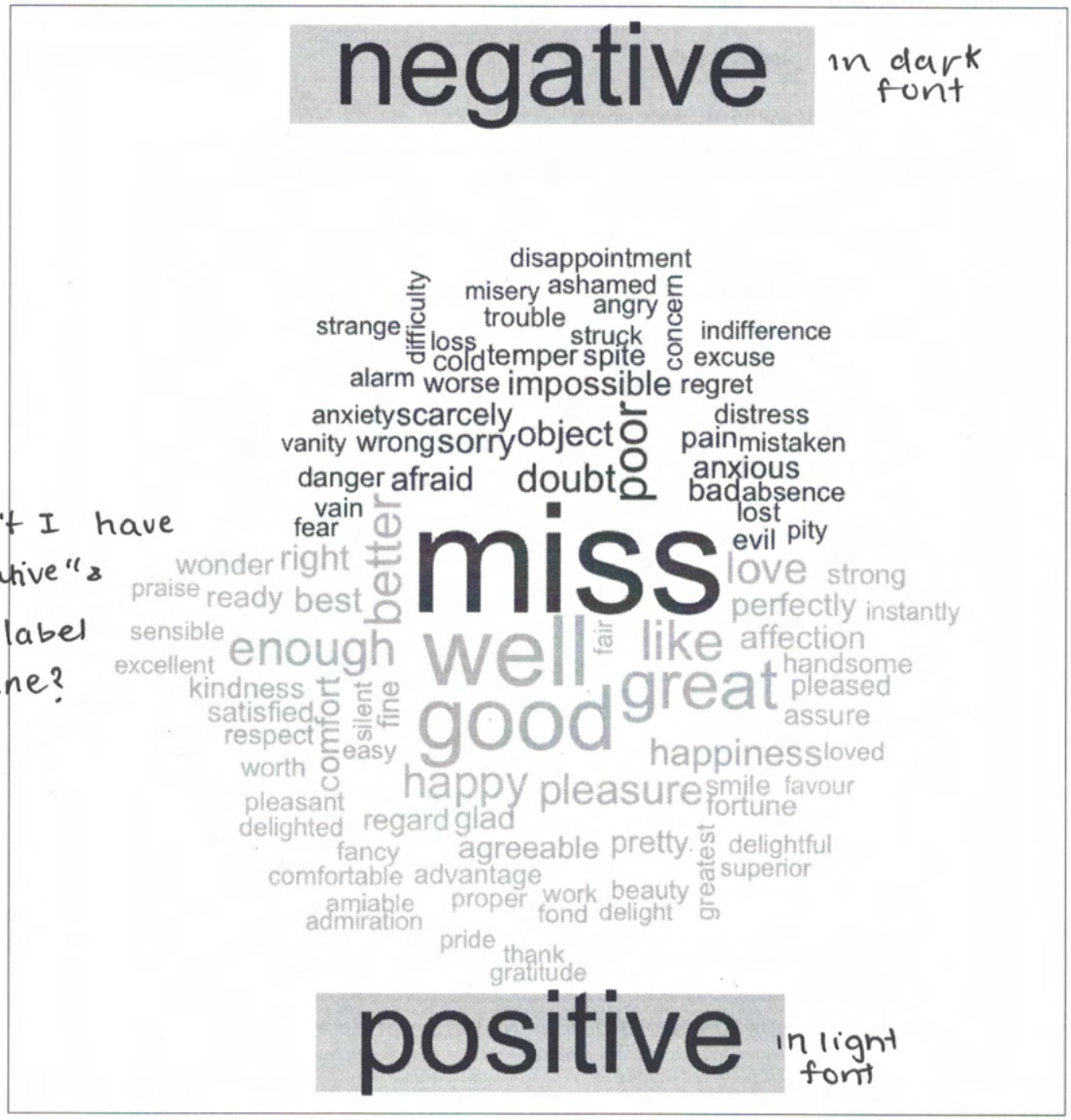
```
library(wordcloud)

tidy_books %>%
  anti_join(stop_words) %>%
  count(word) %>%
  with(wordcloud(word, n, max.words = 100))
```


*Figure 2-5. The most common words in Jane Austen's novels*

In other functions, such as `comparison.cloud()`, you may need to turn the data frame into a matrix with reshape2's `acast()`. Let's do the sentiment analysis to tag positive and negative words using an inner join, then find the most common positive and negative words. Until the step where we need to send the data to `compari`

son.cloud(), this can all be done with joins, piping, and dplyr because our data is in tidy format (Figure 2-6).

```
library(reshape2)

tidy_books %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  acast(word ~ sentiment, value.var = "n", fill = 0) %>%
  comparison.cloud(colors = c("gray20", "gray80"),
                   max.words = 100)
```




Why don't I have the "negative"s "positive" label on mine?

*Figure 2-6. Most common positive and negative words in Jane Austen's novels*

The size of a word's text in Figure 2-6 is in proportion to its frequency within its sentiment. We can use this visualization to see the most important positive and negative words, but the sizes of the words are not comparable across sentiments.

## Looking at Units Beyond Just Words

Lots of useful work can be done by tokenizing at the word level, but sometimes it is useful or necessary to look at different units of text. For example, some sentiment analysis algorithms look beyond only unigrams (i.e., single words) to try to understand the sentiment of a sentence as a whole. These algorithms try to understand that "I am not having a good day" is a sad sentence, not a happy one, because of negation. R packages including coreNLP (Arnold and Tilton 2016), cleanNLP (Arnold 2016), and sentimentr (Rinker 2017) are examples of such sentiment analysis algorithms. For these, we may want to tokenize text into sentences, and it makes sense to use a new name for the output column in such a case.

```
PandP_sentences <- data_frame(text = prideprejudice) %>%
  unnest_tokens(sentence, text, token = "sentences")
```

Let's look at just one.

```
PandP_sentences$sentence[2]
```

```
## [1] "however little known the feelings or views of such a man may be on his
first entering a neighbourhood, this truth is so well fixed in the minds of
the surrounding families, that he is considered the rightful property of some
one or other of their daughters."
```

The sentence tokenizing does seem to have a bit of trouble with UTF-8 encoded text, especially with sections of dialogue; it does much better with punctuation in ASCII. One possibility, if this is important, is to try using `iconv()` with something like `iconv(text, to = 'latin1')` in a mutate statement before unnesting.

Another option in `unnest_tokens()` is to split into tokens using a regex pattern. We could use this, for example, to split the text of Jane Austen's novels into a data frame by chapter.

```
austen_chapters <- austen_books() %>%
  group_by(book) %>%
  unnest_tokens(chapter, text, token = "regex",
                pattern = "Chapter|CHAPTER [\\dIVXLC]") %>%
  ungroup()

austen_chapters %>%
  group_by(book) %>%
  summarise(chapters = n())
```

```
## # A tibble: 6 × 2
##                 book chapters
##               <fctr>    <int>
```

```
## 1 Sense & Sensibility        51
## 2   Pride & Prejudice        62
## 3      Mansfield Park        49
## 4                Emma        56
## 5    Northanger Abbey        32
## 6           Persuasion        25
```

We have recovered the correct number of chapters in each novel (plus an "extra" row for each novel title). In the `austen_chapters` data frame, each row corresponds to one chapter.

Near the beginning of this chapter, we used a similar regex to find where all the chapters were in Austen's novels for a tidy data frame organized by one word per row. We can use tidy text analysis to ask questions such as what are the most negative chapters in each of Jane Austen's novels? First, let's get the list of negative words from the Bing lexicon. Second, let's make a data frame of how many words are in each chapter so we can normalize for chapter length. Then, let's find the number of negative words in each chapter and divide by the total words in each chapter. For each book, which chapter has the highest proportion of negative words?

```
bingnegative <- get_sentiments("bing") %>%
  filter(sentiment == "negative")

wordcounts <- tidy_books %>%
  group_by(book, chapter) %>%
  summarize(words = n())

tidy_books %>%
  semi_join(bingnegative) %>%
  group_by(book, chapter) %>%
  summarize(negativewords = n()) %>%
  left_join(wordcounts, by = c("book", "chapter")) %>%
  mutate(ratio = negativewords/words) %>%
  filter(chapter != 0) %>%
  top_n(1) %>%
  ungroup()
```

```
## # A tibble: 6 × 5
##                 book chapter negativewords words      ratio
##               <fctr>   <int>         <int> <int>      <dbl>
## 1 Sense & Sensibility      43           161  3405 0.04728341
## 2   Pride & Prejudice      34           111  2104 0.05275665
## 3      Mansfield Park      46           173  3685 0.04694708
## 4                Emma      15           151  3340 0.04520958
## 5    Northanger Abbey      21           149  2982 0.04996647
## 6           Persuasion       4            62  1807 0.03431101
```

These are the chapters with the most sad words in each book, normalized for number of words in the chapter. What is happening in these chapters? In Chapter 43 of *Sense and Sensibility*, Marianne is seriously ill, near death; and in Chapter 34 of *Pride and Prejudice*, Mr. Darcy proposes for the first time (so badly!). Chapter 46 of *Mansfield*

*Park* is almost the end, when everyone learns of Henry's scandalous adultery; Chapter 15 of *Emma* is when horrifying Mr. Elton proposes; and in Chapter 21 of *Northanger Abbey*, Catherine is deep in her Gothic faux fantasy of murder. Chapter 4 of *Persuasion* is when the reader gets the full flashback of Anne refusing Captain Wentworth, how sad she was, and what a terrible mistake she realized it to be.

## Summary

Sentiment analysis provides a way to understand the attitudes and opinions expressed in texts. In this chapter, we explored how to approach sentiment analysis using tidy data principles; when text data is in a tidy data structure, sentiment analysis can be implemented as an inner join. We can use sentiment analysis to understand how a narrative arc changes throughout its course or what words with emotional and opinion content are important for a particular text. We will continue to develop our toolbox for applying sentiment analysis to different kinds of text in our case studies later in this book.

CHAPTER 3

# Analyzing Word and Document Frequency: tf-idf

A central question in text mining and natural language processing is how to quantify "what a document is about." Can we do this by looking at the words that make up the document? One measure of how important a word may be is its *term frequency* (tf), how frequently a word occurs in a document, as we examined in Chapter 1. There are words in a document, however, that occur many times but may not be important; in English, these are probably words like "the," "is," "of," and so forth. We might take the approach of adding words like these to a list of stop words and removing them before analysis, but it is possible that some of these words might be more important in some documents than others. A list of stop words is not a very sophisticated approach to adjusting term frequency for commonly used words.

Another approach is to look at a term's *inverse document frequency* (idf), which decreases the weight for commonly used words and increases the weight for words that are not used very much in a collection of documents. This can be combined with term frequency to calculate a term's *tf-idf* (the two quantities multiplied together), the frequency of a term adjusted for how rarely it is used.

The statistic tf-idf is intended to measure how important a word is to a document in a collection (or corpus) of documents, for example, to one novel in a collection of novels or to one website in a collection of websites.

The statistic tf-idf is a rule of thumb or heuristic quantity; while it has proved useful in text mining, search engines, etc., its theoretical foundations are considered less than firm by information theory experts. The inverse document frequency for any given term is defined as:

$$idf(\text{term}) = \ln\left(\frac{n_{\text{documents}}}{n_{\text{documents containing term}}}\right)$$

We can use tidy data principles, as described in Chapter 1, to approach tf-idf analysis and use consistent, effective tools to quantify how important various terms are in a document that is part of a collection.

## Term Frequency in Jane Austen's Novels

Let's start by looking at the published novels of Jane Austen and first examine term frequency, then tf-idf. We can start just by using dplyr verbs such as `group_by()` and `join()`. What are the most commonly used words in Jane Austen's novels? (Let's also calculate the total words in each novel here, for later use.)

```
library(dplyr)
library(janeaustenr)
library(tidytext)

book_words <- austen_books() %>%
  unnest_tokens(word, text) %>%
  count(book, word, sort = TRUE) %>%
  ungroup()

total_words <- book_words %>%
  group_by(book) %>%
  summarize(total = sum(n))

book_words <- left_join(book_words, total_words)

book_words
```

```
## # A tibble: 40,379 × 4
##                book  word     n  total
##              <fctr> <chr> <int>  <int>
## 1  Mansfield Park   the  6206 160460
## 2  Mansfield Park    to  5475 160460
## 3  Mansfield Park   and  5438 160460
## 4               Emma    to  5239 160996
## 5               Emma   the  5201 160996
## 6               Emma   and  4896 160996
## 7  Mansfield Park    of  4778 160460
## 8  Pride & Prejudice   the  4331 122204
## 9               Emma    of  4291 160996
## 10 Pride & Prejudice    to  4162 122204
## # ... with 40,369 more rows
```

There is one row in this `book_words` data frame for each word-book combination; `n` is the number of times that word is used in that book, and `total` is the total number of words in that book. The usual suspects are here with the highest `n`, "the," "and," "to,"

and so forth. In Figure 3-1, let's look at the distribution of `n/total` for each novel: the number of times a word appears in a novel divided by the total number of terms (words) in that novel. This is exactly what term frequency is.

```
library(ggplot2)

ggplot(book_words, aes(n/total, fill = book)) +
  geom_histogram(show.legend = FALSE) +
  xlim(NA, 0.0009) +
  facet_wrap(~book, ncol = 2, scales = "free_y")
```

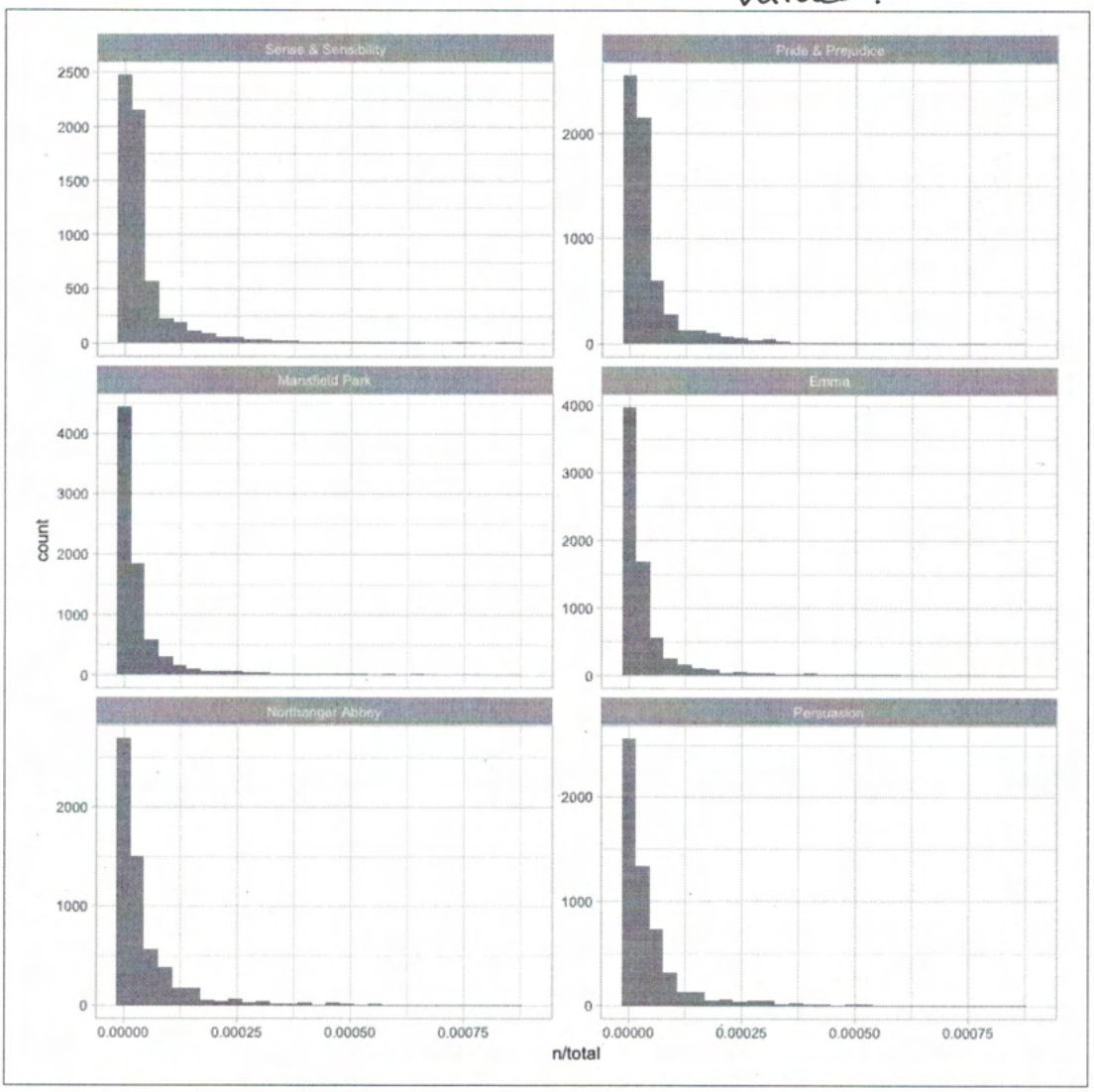



*Figure 3-1. Term frequency distribution in Jane Austen's novels*

There are very long tails to the right for these novels (those extremely common words!) that we have not shown in these plots. These plots exhibit similar distribu-

tions for all the novels, with many words that occur rarely and fewer words that occur frequently.

## Zipf's Law

Distributions like those shown in Figure 3-1 are typical in language. In fact, those types of long-tailed distributions are so common in any given corpus of natural language (like a book, or a lot of text from a website, or spoken words) that the relationship between the frequency that a word is used and its rank has been the subject of study. A classic version of this relationship is called Zipf's law, after George Zipf, a 20th-century American linguist.

Zipf's law states that the frequency that a word appears is inversely proportional to its rank.

Since we have the data frame we used to plot term frequency, we can examine Zipf's law for Jane Austen's novels with just a few lines of dplyr functions.

```
freq_by_rank <- book_words %>%
  group_by(book) %>%
  mutate(rank = row_number(),
         `term frequency` = n/total)

freq_by_rank
```

```
## Source: local data frame [40,379 x 6]
## Groups: book [6]
##
##                 book  word     n  total  rank `term frequency`
##               <fctr> <chr> <int>  <int> <int>            <dbl>
## 1     Mansfield Park   the  6206 160460     1       0.03867631
## 2     Mansfield Park    to  5475 160460     2       0.03412065
## 3     Mansfield Park   and  5438 160460     3       0.03389007
## 4               Emma    to  5239 160996     1       0.03254118
## 5               Emma   the  5201 160996     2       0.03230515
## 6               Emma   and  4896 160996     3       0.03041069
## 7     Mansfield Park    of  4778 160460     4       0.02977689
## 8  Pride & Prejudice   the  4331 122204     1       0.03544074
## 9               Emma    of  4291 160996     4       0.02665284
## 10 Pride & Prejudice    to  4162 122204     2       0.03405780
## # ... with 40,369 more rows
```

The `rank` column here tells us the rank of each word within the frequency table; the table was already ordered by `n`, so we could use `row_number()` to find the rank. Then, we can calculate the term frequency in the same way we did before. Zipf's law is often visualized by plotting rank on the x-axis and term frequency on the y-axis, on loga-

rithmic scales. Plotting this way, an inversely proportional relationship will have a constant, negative slope (Figure 3-2).

```
freq_by_rank %>%
  ggplot(aes(rank, `term frequency`, color = book)) +
  geom_line(size = 1.1, alpha = 0.8, show.legend = FALSE) +
  scale_x_log10() +
  scale_y_log10()
```

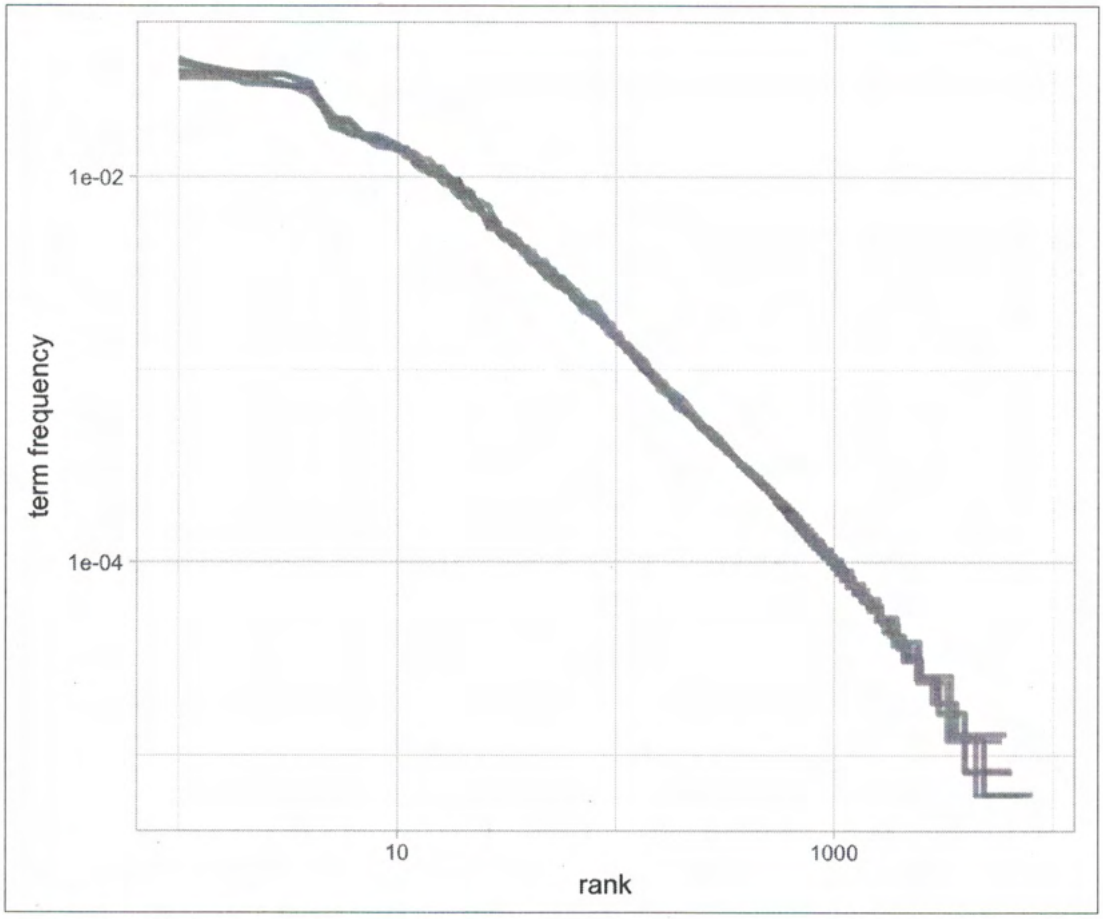



*Figure 3-2. Zipf's law for Jane Austen's novels*

Notice that Figure 3-2 is in log-log coordinates. We see that all six of Jane Austen's novels are similar to each other, and that the relationship between rank and frequency does have negative slope. It is not quite constant, though; perhaps we could view this as a broken power law with, say, three sections. Let's see what the exponent of the power law is for the middle section of the rank range.

```
rank_subset <- freq_by_rank %>%
  filter(rank < 500,
         rank > 10)

lm(log10(`term frequency`) ~ log10(rank), data = rank_subset)
```

gives coefficients ⇒ intercept = −0.6
log10(rank) = −1.1125

```
##
## Call:
## lm(formula = log10(`term frequency`) ~ log10(rank), data = rank_subset)
##
## Coefficients:
## (Intercept)  log10(rank)
##     -0.6225      -1.1125
```

Classic versions of Zipf's law have frequency $\propto \frac{1}{\text{rank}}$ and we have in fact gotten a slope close to –1 here. Let's plot this fitted power law with the data in Figure 3-3 to see how it looks.

```
freq_by_rank %>%
  ggplot(aes(rank, `term frequency`, color = book)) +
  geom_abline(intercept = -0.62, slope = -1.1, color = "gray50", linetype = 2) +
  geom_line(size = 1.1, alpha = 0.8, show.legend = FALSE) +
  scale_x_log10() +
  scale_y_log10()
```

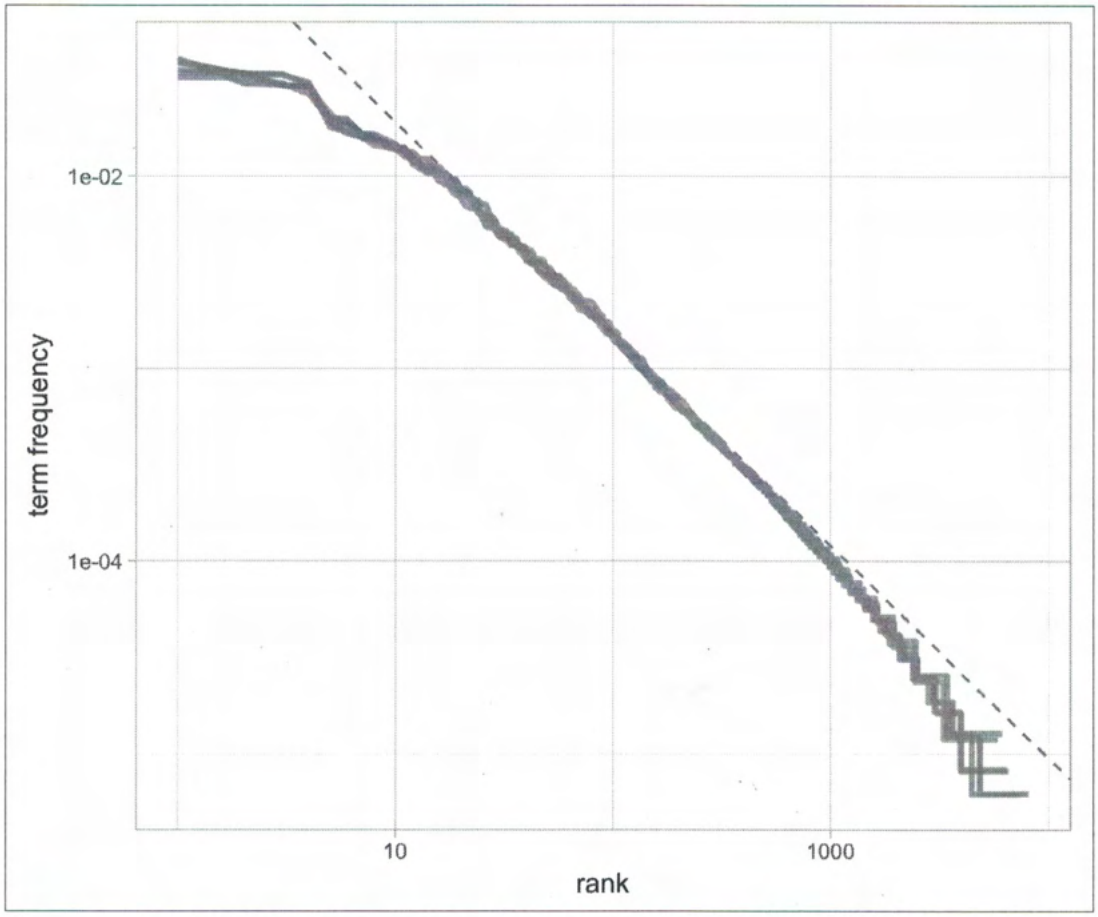



*Figure 3-3. Fitting an exponent for Zipf's law with Jane Austen's novels*

We have found a result close to the classic version of Zipf's law for the corpus of Jane Austen's novels. The deviations we see here at high rank are not uncommon for many kinds of language; a corpus of language often contains fewer rare words than predicted by a single power law. The deviations at low rank are more unusual. Jane Austen uses a lower percentage of the most common words than many collections of language. This kind of analysis could be extended to compare authors, or to compare any other collections of text; it can be implemented simply using tidy data principles.

## The bind_tf_idf Function

The idea of tf-idf is to find the important words for the content of each document by decreasing the weight for commonly used words and increasing the weight for words that are not used very much in a collection or corpus of documents, in this case, the group of Jane Austen's novels as a whole. Calculating tf-idf attempts to find the words that are important (i.e., common) in a text, but not *too* common. Let's do that now.

The `bind_tf_idf` function in the tidytext package takes a tidy text dataset as input with one row per token (term), per document. One column (`word` here) contains the terms/tokens, one column contains the documents (`book` in this case), and the last necessary column contains the counts, or how many times each document contains each term (`n` in this example). We calculated a `total` for each book for our explorations in previous sections, but it is not necessary for the `bind_tf_idf` function; the table only needs to contain all the words in each document.

```
book_words <- book_words %>%
  bind_tf_idf(word, book, n)
book_words
```

```
## # A tibble: 40,379 × 7
##                 book  word     n  total         tf   idf tf_idf
##               <fctr> <chr> <int>  <int>      <dbl> <dbl>  <dbl>
## 1     Mansfield Park   the  6206 160460 0.03867631     0      0
## 2     Mansfield Park    to  5475 160460 0.03412065     0      0
## 3     Mansfield Park   and  5438 160460 0.03389007     0      0
## 4               Emma    to  5239 160996 0.03254118     0      0
## 5               Emma   the  5201 160996 0.03230515     0      0
## 6               Emma   and  4896 160996 0.03041069     0      0
## 7     Mansfield Park    of  4778 160460 0.02977689     0      0
## 8  Pride & Prejudice   the  4331 122204 0.03544074     0      0
## 9               Emma    of  4291 160996 0.02665284     0      0
## 10 Pride & Prejudice    to  4162 122204 0.03405780     0      0
## # ... with 40,369 more rows
```

Notice that idf and thus tf-idf are zero for these extremely common words. These are all words that appear in all six of Jane Austen's novels, so the idf term (which will then be the natural log of 1) is zero. The inverse document frequency (and thus tf-idf) is very low (near zero) for words that occur in many of the documents in a collection;

this is how this approach decreases the weight for common words. The inverse document frequency will be a higher number for words that occur in fewer of the documents in the collection.

Let's look at terms with high tf-idf in Jane Austen's works.

```
book_words %>%
  select(-total) %>%
  arrange(desc(tf_idf))
```

```
## # A tibble: 40,379 × 6
##                   book      word     n          tf      idf      tf_idf
##                 <fctr>     <chr> <int>       <dbl>    <dbl>       <dbl>
## 1  Sense & Sensibility    elinor   623 0.005193528 1.791759 0.009305552
## 2  Sense & Sensibility  marianne   492 0.004101470 1.791759 0.007348847
## 3       Mansfield Park  crawford   493 0.003072417 1.791759 0.005505032
## 4    Pride & Prejudice     darcy   373 0.003052273 1.791759 0.005468939
## 5            Persuasion    elliot   254 0.003036207 1.791759 0.005440153
## 6                  Emma      emma   786 0.004882109 1.098612 0.005363545
## 7     Northanger Abbey    tilney   196 0.002519928 1.791759 0.004515105
## 8                  Emma    weston   389 0.002416209 1.791759 0.004329266
## 9    Pride & Prejudice    bennet   294 0.002405813 1.791759 0.004310639
## 10           Persuasion wentworth   191 0.002283132 1.791759 0.004090824
## # ... with 40,369 more rows
```

so many names means...

Here we see all proper nouns, names that are in fact important in these novels. None of them occur in all of the novels, and they are important, characteristic words for each text within the corpus of Jane Austen's novels.

Some of the values for idf are the same for different terms because there are six documents in this corpus and we are seeing the numerical value for ln(6/1), ln(6/2), etc.

Let's look at a visualization for these high tf-idf words in Figure 3-4.

```
book_words %>%
  arrange(desc(tf_idf)) %>%
  mutate(word = factor(word, levels = rev(unique(word)))) %>%
  group_by(book) %>%
  top_n(15) %>%
  ungroup %>%
  ggplot(aes(word, tf_idf, fill = book)) +
  geom_col(show.legend = FALSE) +
  labs(x = NULL, y = "tf-idf") +
  facet_wrap(~book, ncol = 2, scales = "free") +
  coord_flip()
```

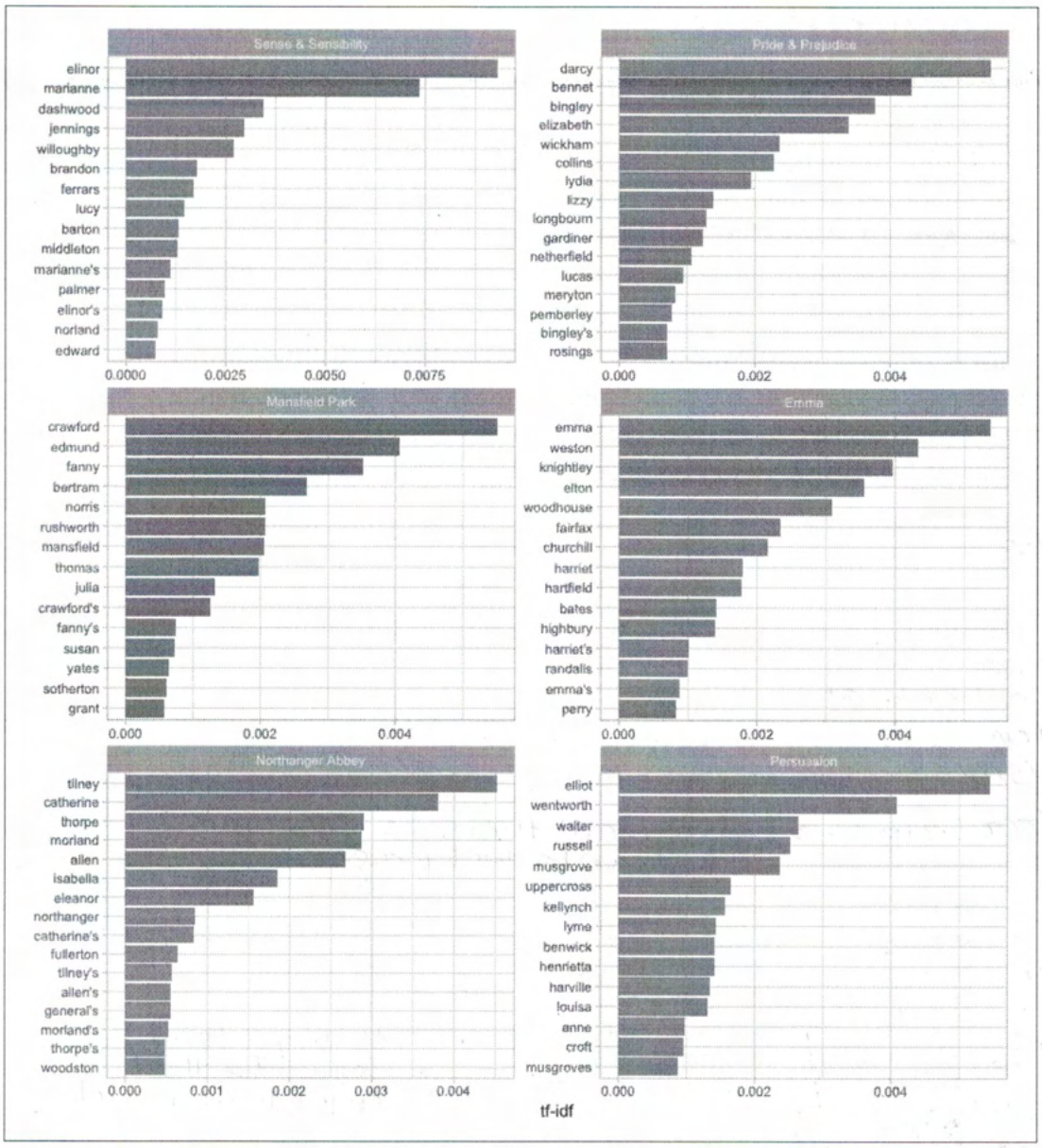



*Figure 3-4. Highest tf-idf words in each of Jane Austen's novels*

Still all proper nouns in Figure 3-4! These words are, as measured by tf-idf, the most important to each novel and most readers would likely agree. What measuring tf-idf has done here is show us that Jane Austen used similar language across her six novels, and what distinguishes one novel from the rest within the collection of her works are the proper nouns, the names of people and places. This is the point of tf-idf; it identifies words that are important to one document within a collection of documents.

use this technique on Lúthien stories!

## A Corpus of Physics Texts

Let's work with another corpus of documents to see what terms are important in a different set of works. In fact, let's leave the world of fiction and narrative entirely. Let's download some classic physics texts from Project Gutenberg and see what terms are important in these works, as measured by tf-idf. Let's download *Discourse on Floating Bodies* by Galileo Galilei, *Treatise on Light* by Christiaan Huygens, *Experiments with Alternate Currents of High Potential and High Frequency* by Nikola Tesla, and *Relativity: The Special and General Theory* by Albert Einstein.

This is a pretty diverse bunch. They may all be physics classics, but they were written across a 300-year time span, and some of them were first written in other languages and then translated to English. Perfectly homogeneous these are not, but that doesn't stop this from being an interesting exercise!

Error downloading 5001 (Einstein): "Could not download a book at aleph.gutenberg.org/5/1/0/5001/5001.zip" → I also went there & there was a blank webpage?

```
library(gutenbergr)
physics <- gutenberg_download(c(37729, 14725, 13476, 5001),
                              meta_fields = "author")
```

Now that we have the texts, let's use `unnest_tokens()` and `count()` to find out how many times each word is used in each text.

```
physics_words <- physics %>%
  unnest_tokens(word, text) %>%
  count(author, word, sort = TRUE) %>%
  ungroup()

physics_words
```

```
## # A tibble: 12,592 × 3
##                 author  word     n
##                  <chr> <chr> <int>
## 1     Galilei, Galileo   the  3760
## 2        Tesla, Nikola   the  3604
## 3  Huygens, Christiaan   the  3553
## 4     Einstein, Albert   the  2994
## 5     Galilei, Galileo    of  2049
## 6     Einstein, Albert    of  2030
## 7        Tesla, Nikola    of  1737
## 8  Huygens, Christiaan    of  1708
## 9  Huygens, Christiaan    to  1207
## 10       Tesla, Nikola     a  1176
## # ... with 12,582 more rows
```

✓ Oh boy, lots of stopwords that don't tell us much.

Yeah, we need a tf-idf or some other meaningful value

Here we see just the raw counts; we need to remember that these documents are all different lengths. Let's go ahead and calculate tf-idf, then visualize the high tf-idf words in Figure 3-5.

```
plot_physics <- physics_words %>%
  bind_tf_idf(word, author, n) %>%
  arrange(desc(tf_idf)) %>%
```

✓

```
  mutate(word = factor(word, levels = rev(unique(word)))) %>%
  mutate(author = factor(author, levels = c("Galilei, Galileo",
                                            "Huygens, Christiaan",
                                            "Tesla, Nikola",
                                            "Einstein, Albert")))

plot_physics %>%
  group_by(author) %>%
  top_n(15, tf_idf) %>%
  ungroup() %>%
  mutate(word = reorder(word, tf_idf)) %>%
  ggplot(aes(word, tf_idf, fill = author)) +
  geom_col(show.legend = FALSE) +
  labs(x = NULL, y = "tf-idf") +
  facet_wrap(~author, ncol = 2, scales = "free") +
  coord_flip()
```

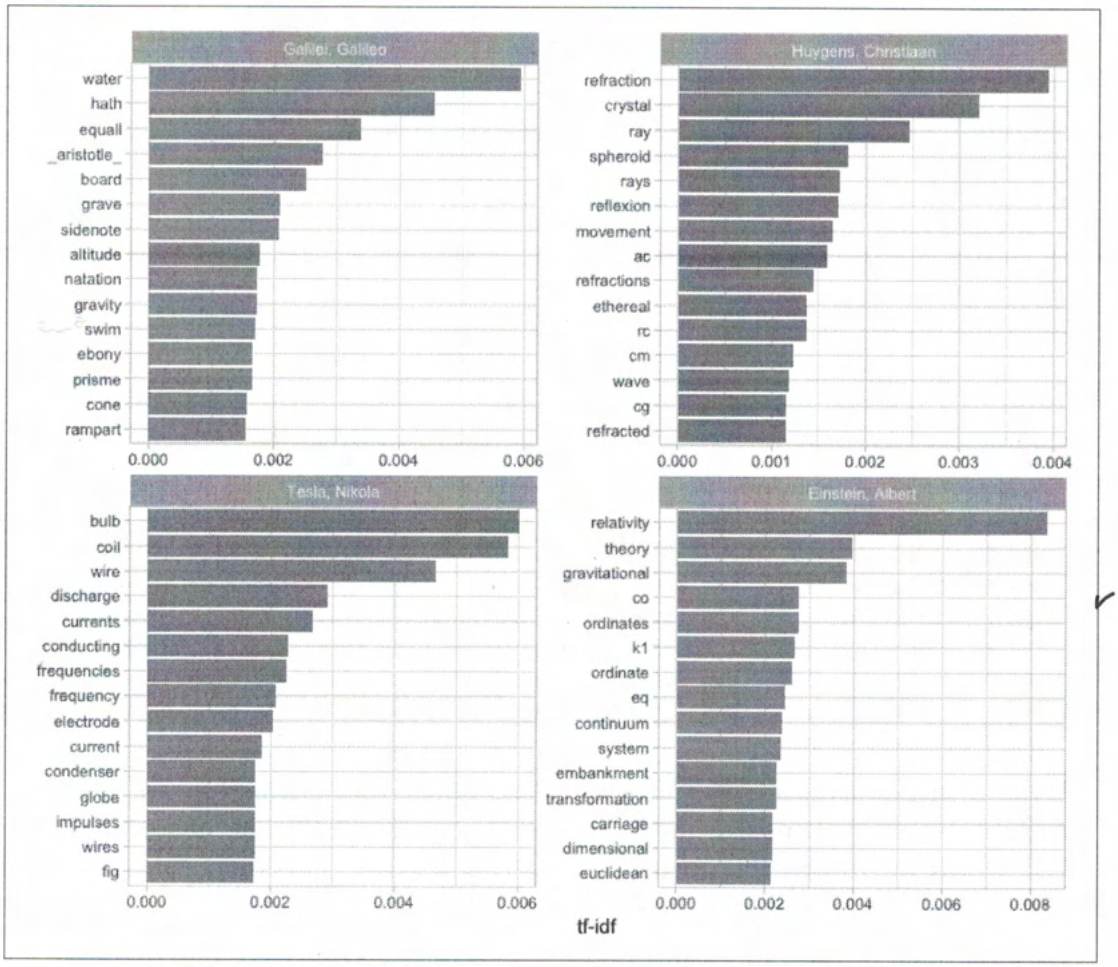



*Figure 3-5. Highest tf-idf words in each physics text*

Very interesting indeed. One thing we see here is "eq" in the Einstein text?!

```
library(stringr)

physics %>%
  filter(str_detect(text, "eq\\.")) %>%
  select(text)
```

```
## # A tibble: 55 × 1
##                                                                    text
##                                                                   <chr>
## 1                                                  eq. 1: file eq01.gif
## 2                                                  eq. 2: file eq02.gif
## 3                                                  eq. 3: file eq03.gif
## 4                                                  eq. 4: file eq04.gif
## 5                                               eq. 05a: file eq05a.gif
## 6                                               eq. 05b: file eq05b.gif
## 7                        the distance between the points being eq. 06 .
## 8  direction of its length with a velocity v is eq. 06 of a metre.
## 9                                velocity v=c we should have eq. 06a ,
## 10                 the rod as judged from K1 would have been eq. 06 ;
## # ... with 45 more rows
```

Some cleaning up of the text may be in order. "K1" is the name of a coordinate system for Einstein:

```
physics %>%
  filter(str_detect(text, "K1")) %>%
  select(text)
```

```
## # A tibble: 59 × 1
##                                                                                text
##                                                                               <chr>
## 1           to a second co-ordinate system K1 provided that the latter is
## 2          condition of uniform motion of translation. Relative to K1 the
## 3     tenet thus: If, relative to K, K1 is a uniformly moving co-ordinate
## 4   with respect to K1 according to exactly the same general laws as with
## 5  does not hold, then the Galileian co-ordinate systems K, K1, K2, etc.,
## 6   Relative to K1, the same event would be fixed in respect of space and
## 7   to K1, when the magnitudes x, y, z, t, of the same event with respect
## 8    of light (and of course for every ray) with respect to K and K1. For
## 9  reference-body K and for the reference-body K1. A light-signal is sent
## 10  immediately follows. If referred to the system K1, the propagation of
## # ... with 49 more rows
```

Maybe it makes sense to keep this one. Also notice that in this line we have "co-ordinate," which explains why there are separate "co" and "ordinate" items in the high tf-idf words for the Einstein text; the `unnest_tokens()` function separates around punctuation. Notice that the tf-idf scores for "co" and "ordinate" are close to the same!

"AB," "RC," and so forth are names of rays, circles, angles, and so on for Huygens:

```
physics %>%
  filter(str_detect(text, "AK")) %>%
  select(text)
```

```
## # A tibble: 34 × 1
##                                                                    text
##                                                                   <chr>
## 1   Now let us assume that the ray has come from A to C along AK, KC; the
## 2    be equal to the time along KMN. But the time along AK is longer than
## 3  that along AL: hence the time along AKN is longer than that along ABC.
## 4     And KC being longer than KN, the time along AKC will exceed, by as
## 5     line which is comprised between the perpendiculars AK, BL. Then it
## 6  ordinary refraction. Now it appears that AK and BL dip down toward the
## 7  side where the air is less easy to penetrate: for AK being longer than
## 8    than do AK, BL. And this suffices to show that the ray will continue
## 9     surface AB at the points AK_k_B. Then instead of the hemispherical
## 10 along AL, LB, and along AK, KB, are always represented by the line AH,
## # ... with 24 more rows
```

Let's remove some of these less meaningful words to make a better, more meaningful plot. Notice that we make a custom list of stop words and use `anti_join()` to remove them; this is a flexible approach that can be used in many situations. We will need to go back a few steps since we are removing words from the tidy data frame (Figure 3-6).

```
mystopwords <- data_frame(word = c("eq", "co", "rc", "ac", "ak", "bn",
                                   "fig", "file", "cg", "cb", "cm"))
physics_words <- anti_join(physics_words, mystopwords, by = "word")
plot_physics <- physics_words %>%
  bind_tf_idf(word, author, n) %>%
  arrange(desc(tf_idf)) %>%
  mutate(word = factor(word, levels = rev(unique(word)))) %>%
  group_by(author) %>%
  top_n(15, tf_idf) %>%
  ungroup %>%
  mutate(author = factor(author, levels = c("Galilei, Galileo",
                                            "Huygens, Christiaan",
                                            "Tesla, Nikola",
                                            "Einstein, Albert")))

ggplot(plot_physics, aes(word, tf_idf, fill = author)) +
  geom_col(show.legend = FALSE) +
  labs(x = NULL, y = "tf-idf") +
  facet_wrap(~author, ncol = 2, scales = "free") +
  coord_flip()
```

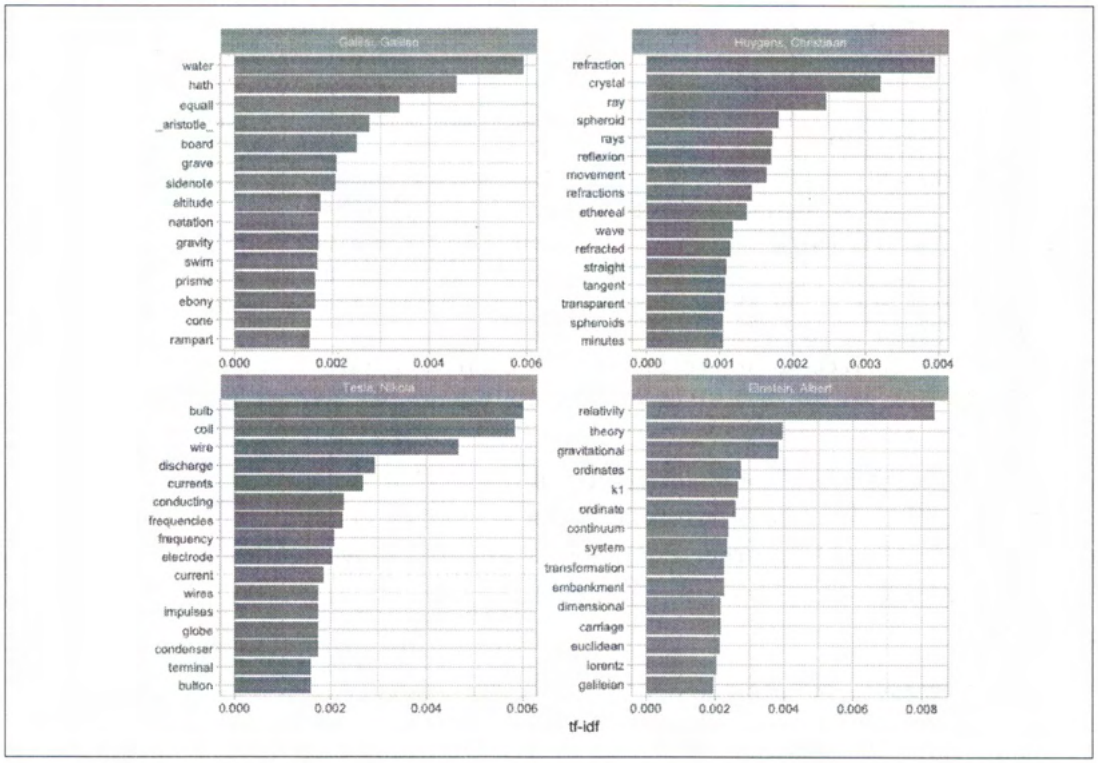



*Figure 3-6. Highest tf-idf words in classic physics texts*

One thing we can conclude from Figure 3-6 is that we don't hear enough about ramparts or things being ethereal in physics today.

# Summary

Using term frequency and inverse document frequency allows us to find words that are characteristic for one document within a collection of documents, whether that document is a novel or physics text or webpage. Exploring term frequency on its own can give us insight into how language is used in a collection of natural language, and dplyr verbs like `count()` and `rank()` give us tools to reason about term frequency. The tidytext package uses an implementation of tf-idf consistent with tidy data principles that enables us to see how different words are important in documents within a collection or corpus of documents.

CHAPTER 4

# Relationships Between Words: N-grams and Correlations

So far we've considered words as individual units, and considered their relationships to sentiments or to documents. However, many interesting text analyses are based on the relationships between words, whether examining which words tend to follow others immediately, or words that tend to co-occur within the same documents.

In this chapter, we'll explore some of the methods tidytext offers for calculating and visualizing relationships between words in your text dataset. This includes the `token = "ngrams"` argument, which tokenizes by pairs of adjacent words rather than by individual ones. We'll also introduce two new packages: ggraph, by Thomas Pedersen, which extends ggplot2 to construct network plots, and widyr, which calculates pairwise correlations and distances within a tidy data frame. Together these expand our toolbox for exploring text within the tidy data framework.

## Tokenizing by N-gram

We've been using the `unnest_tokens` function to tokenize by word, or sometimes by sentence, which is useful for the kinds of sentiment and frequency analyses we've been doing so far. But we can also use the function to tokenize into consecutive sequences of words, called *n-grams*. By seeing how often word X is followed by word Y, we can then build a model of the relationships between them.

We do this by adding the `token = "ngrams"` option to `unnest_tokens()`, and setting `n` to the number of words we wish to capture in each n-gram. When we set `n` to 2, we are examining pairs of two consecutive words, often called "bigrams":

```
library(dplyr)
library(tidytext)
```

```
library(janeaustenr)

austen_bigrams <- austen_books() %>%
  unnest_tokens(bigram, text, token = "ngrams", n = 2)

austen_bigrams
```

```
## # A tibble: 725,048 × 2
##                   book          bigram
##                 <fctr>           <chr>
## 1  Sense & Sensibility       sense and
## 2  Sense & Sensibility and sensibility
## 3  Sense & Sensibility  sensibility by
## 4  Sense & Sensibility         by jane
## 5  Sense & Sensibility     jane austen
## 6  Sense & Sensibility     austen 1811
## 7  Sense & Sensibility    1811 chapter
## 8  Sense & Sensibility       chapter 1
## 9  Sense & Sensibility           1 the
## 10 Sense & Sensibility      the family
## # ... with 725,038 more rows
```

This data structure is still a variation of the tidy text format. It is structured as one token per row (with extra metadata, such as book, still preserved), but each token now represents a bigram.

Notice that these bigrams overlap: "sense and" is one token, while "and sensibility" is another.

## Counting and Filtering N-grams

Our usual tidy tools apply equally well to n-gram analysis. We can examine the most common bigrams using dplyr's `count()`:

```
austen_bigrams %>%
  count(bigram, sort = TRUE)
```

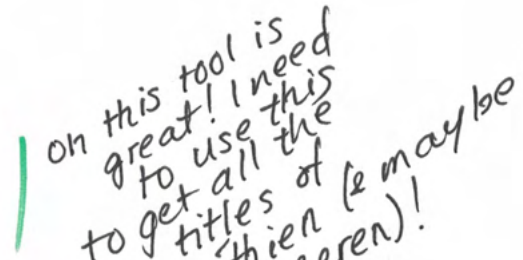
```
## # A tibble: 211,237 × 2
##      bigram     n
##       <chr> <int>
## 1    of the  3017
## 2     to be  2787
## 3    in the  2368
## 4    it was  1781
## 5      i am  1545
## 6   she had  1472
## 7    of her  1445
## 8    to the  1387
## 9   she was  1377
```

```
## 10 had been  1299
## # ... with 211,227 more rows
```

As one might expect, a lot of the most common bigrams are pairs of common (uninteresting) words, such as "of the" and "to be," what we call "stop words" (see Chapter 1). This is a useful time to use tidyr's `separate()`, which splits a column into multiple columns based on a delimiter. This lets us separate it into two columns, "word1" and "word2," at which point we can remove cases where either is a stop word.

```
library(tidyr)

bigrams_separated <- austen_bigrams %>%
  separate(bigram, c("word1", "word2"), sep = " ")

bigrams_filtered <- bigrams_separated %>%
  filter(!word1 %in% stop_words$word) %>%
  filter(!word2 %in% stop_words$word)

# new bigram counts:
bigram_counts <- bigrams_filtered %>%
  count(word1, word2, sort = TRUE)

bigram_counts
```

```
## Source: local data frame [33,421 x 3]
## Groups: word1 [6,711]
##
##      word1     word2     n
##      <chr>     <chr> <int>
## 1      sir    thomas   287
## 2     miss  crawford   215
## 3  captain wentworth   170
## 4     miss woodhouse   162
## 5    frank churchill   132
## 6     lady   russell   118
## 7     lady   bertram   114
## 8      sir    walter   113
## 9     miss   fairfax   109
## 10 colonel   brandon   108
## # ... with 33,411 more rows
```




We can see that names (whether first and last or with a salutation) are the most common pairs in Jane Austen books.

In other analyses, we may want to work with the recombined words. tidyr's `unite()` function is the inverse of `separate()`, and lets us recombine the columns into one. Thus, "`separate/filter/count/unite`" let us find the most common bigrams not containing stop words.

```
bigrams_united <- bigrams_filtered %>%
  unite(bigram, word1, word2, sep = " ")
```

```
bigrams_united
```

```
## # A tibble: 44,784 × 2
##                   book                 bigram
## *                <fctr>                  <chr>
## 1  Sense & Sensibility              jane austen
## 2  Sense & Sensibility              austen 1811
## 3  Sense & Sensibility             1811 chapter
## 4  Sense & Sensibility                chapter 1
## 5  Sense & Sensibility             norland park
## 6  Sense & Sensibility surrounding acquaintance
## 7  Sense & Sensibility               late owner
## 8  Sense & Sensibility             advanced age
## 9  Sense & Sensibility       constant companion
## 10 Sense & Sensibility             happened ten
## # ... with 44,774 more rows
```

In other analyses you may be interested in the most common trigrams, which are consecutive sequences of three words. We can find this by setting `n = 3`.

```
austen_books() %>%
  unnest_tokens(trigram, text, token = "ngrams", n = 3) %>%
  separate(trigram, c("word1", "word2", "word3"), sep = " ") %>%
  filter(!word1 %in% stop_words$word,
         !word2 %in% stop_words$word,
         !word3 %in% stop_words$word) %>%
  count(word1, word2, word3, sort = TRUE)
```

```
## Source: local data frame [8,757 x 4]
## Groups: word1, word2 [7,462]
##
##        word1     word2     word3     n
##        <chr>     <chr>     <chr> <int>
## 1       dear      miss woodhouse    23
## 2       miss        de    bourgh    18
## 3       lady catherine        de    14
## 4  catherine        de    bourgh    13
## 5       poor      miss    taylor    11
## 6        sir    walter    elliot    11
## 7        ten  thousand    pounds    11
## 8       dear       sir    thomas    10
## 9     twenty  thousand    pounds     8
## 10   replied      miss  crawford     7
## # ... with 8,747 more rows
```

## Analyzing Bigrams

This one-bigram-per-row format is helpful for exploratory analyses of the text. As a simple example, we might be interested in the most common "streets" mentioned in each book.

```
bigrams_filtered %>%
  filter(word2 == "street") %>%
  count(book, word1, sort = TRUE)
```

```
## Source: local data frame [34 x 3]
## Groups: book [6]
##
##                   book       word1     n
##                 <fctr>       <chr> <int>
## 1  Sense & Sensibility    berkeley    16
## 2  Sense & Sensibility      harley    16
## 3     Northanger Abbey    pulteney    14
## 4     Northanger Abbey      milsom    11
## 5       Mansfield Park     wimpole    10
## 6    Pride & Prejudice gracechurch     9
## 7  Sense & Sensibility     conduit     6
## 8  Sense & Sensibility        bond     5
## 9            Persuasion      milsom     5
## 10           Persuasion      rivers     4
## # ... with 24 more rows
```

A bigram can also be treated as a term in a document in the same way that we treated individual words. For example, we can look at the tf-idf (Chapter 3) of bigrams across Austen novels. These tf-idf values can be visualized within each book, just as we did for words (Figure 4-1).

```
bigram_tf_idf <- bigrams_united %>%
  count(book, bigram) %>%
  bind_tf_idf(bigram, book, n) %>%
  arrange(desc(tf_idf))

bigram_tf_idf
```

```
## Source: local data frame [36,217 x 6]
## Groups: book [6]
##
##                   book            bigram     n         tf      idf     tf_idf
##                 <fctr>             <chr> <int>      <dbl>    <dbl>      <dbl>
## 1            Persuasion captain wentworth   170 0.02985599 1.791759 0.05349475
## 2        Mansfield Park        sir thomas   287 0.02873160 1.791759 0.05148012
## 3        Mansfield Park     miss crawford   215 0.02152368 1.791759 0.03856525
## 4            Persuasion      lady russell   118 0.02072357 1.791759 0.03713165
## 5            Persuasion        sir walter   113 0.01984545 1.791759 0.03555828
## 6                  Emma    miss woodhouse   162 0.01700966 1.791759 0.03047722
## 7     Northanger Abbey       miss tilney    82 0.01594400 1.791759 0.02856782
## 8  Sense & Sensibility   colonel brandon   108 0.01502086 1.791759 0.02691377
## 9                  Emma   frank churchill   132 0.01385972 1.791759 0.02483329
## 10   Pride & Prejudice    lady catherine   100 0.01380453 1.791759 0.02473439
## # ... with 36,207 more rows
```

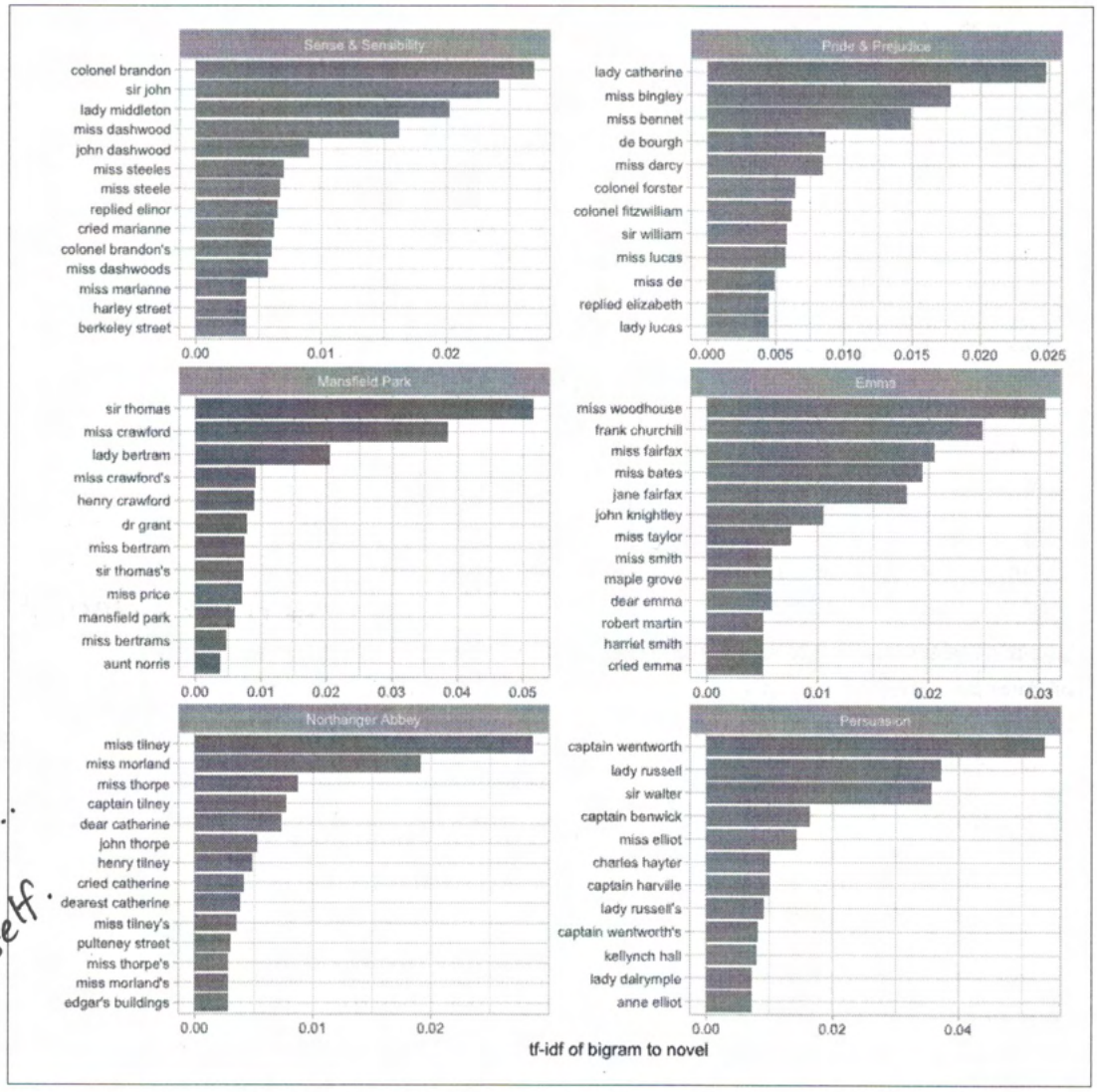



*Figure 4-1. The 12 bigrams with the highest tf-idf from each Jane Austen novel*

Much as we discovered in Chapter 3, the units that distinguish each Austen book are almost exclusively names. We also notice some pairings of a common verb and a name, such as "replied elizabeth" in *Pride and Prejudice*, or "cried emma" in *Emma*.

There are advantages and disadvantages to examining the tf-idf of bigrams rather than individual words. Pairs of consecutive words might capture structure that isn't present when one is just counting single words, and may provide context that makes tokens more understandable (for example, "pulteney street," in *Northanger Abbey*, is more informative than "pulteney"). However, the per-bigram counts are also *sparser*: a typical two-word pair is rarer than either of its component words. Thus, bigrams can be especially useful when you have a very large text dataset.

## Using Bigrams to Provide Context in Sentiment Analysis

Our sentiment analysis approch in Chapter 2 simply counted the appearance of positive or negative words, according to a reference lexicon. One of the problems with this approach is that a word's context can matter nearly as much as its presence. For example, the words "happy" and "like" will be counted as positive, even in a sentence like "I'm not **happy** and I don't **like** it!"

Now that we have the data organized into bigrams, it's easy to tell how often words are preceded by a word like "not."

```
bigrams_separated %>%
  filter(word1 == "not") %>%
  count(word1, word2, sort = TRUE)
```

```
## Source: local data frame [1,246 x 3]
## Groups: word1 [1]
##
##    word1 word2     n
##    <chr> <chr> <int>
## 1    not    be   610
## 2    not    to   355
## 3    not  have   327
## 4    not  know   252
## 5    not     a   189
## 6    not think   176
## 7    not  been   160
## 8    not   the   147
## 9    not    at   129
## 10   not    in   118
## # ... with 1,236 more rows
```

By performing sentiment analysis on the bigram data, we can examine how often sentiment-associated words are preceded by "not" or other negating words. We could use this to ignore or even reverse their contribution to the sentiment score.

Let's use the AFINN lexicon for sentiment analysis, which you may recall gives a numeric sentiment score for each word, with positive or negative numbers indicating the direction of the sentiment.

```
AFINN <- get_sentiments("afinn")

AFINN
```

```
## # A tibble: 2,476 × 2
##          word score
##         <chr> <int>
## 1     abandon    -2
## 2   abandoned    -2
## 3    abandons    -2
## 4    abducted    -2
## 5   abduction    -2
```

```
## 6  abductions    -2
## 7       abhor    -3
## 8    abhorred    -3
## 9   abhorrent    -3
## 10     abhors    -3
## # ... with 2,466 more rows
```

We can then examine the most frequent words that were preceded by "not" and were associated with a sentiment.

```
not_words <- bigrams_separated %>%
  filter(word1 == "not") %>%
  inner_join(AFINN, by = c(word2 = "word")) %>%
  count(word2, score, sort = TRUE) %>%
  ungroup()

not_words
```

```
## # A tibble: 245 × 3
##      word2 score     n
##      <chr> <int> <int>
## 1     like     2    99
## 2     help     2    82
## 3     want     1    45
## 4     wish     1    39
## 5    allow     1    36
## 6     care     2    23
## 7    sorry    -1    21
## 8    leave    -1    18
## 9  pretend    -1    18
## 10   worth     2    17
## # ... with 235 more rows
```

For example, the most common sentiment-associated word to follow "not" was "like," which would normally have a (positive) score of 2.

It's worth asking which words contributed the most in the "wrong" direction. To compute that, we can multiply their score by the number of times they appear (so that a word with a score of +3 occurring 10 times has as much impact as a word with a sentiment score of +1 occurring 30 times). We visualize the result with a bar plot (Figure 4-2).

```
not_words %>%
  mutate(contribution = n * score) %>%
  arrange(desc(abs(contribution))) %>%
  head(20) %>%
  mutate(word2 = reorder(word2, contribution)) %>%
  ggplot(aes(word2, n * score, fill = n * score > 0)) +
  geom_col(show.legend = FALSE) +
  xlab("Words preceded by \"not\"") +
  ylab("Sentiment score * number of occurrences") +
  coord_flip()
```

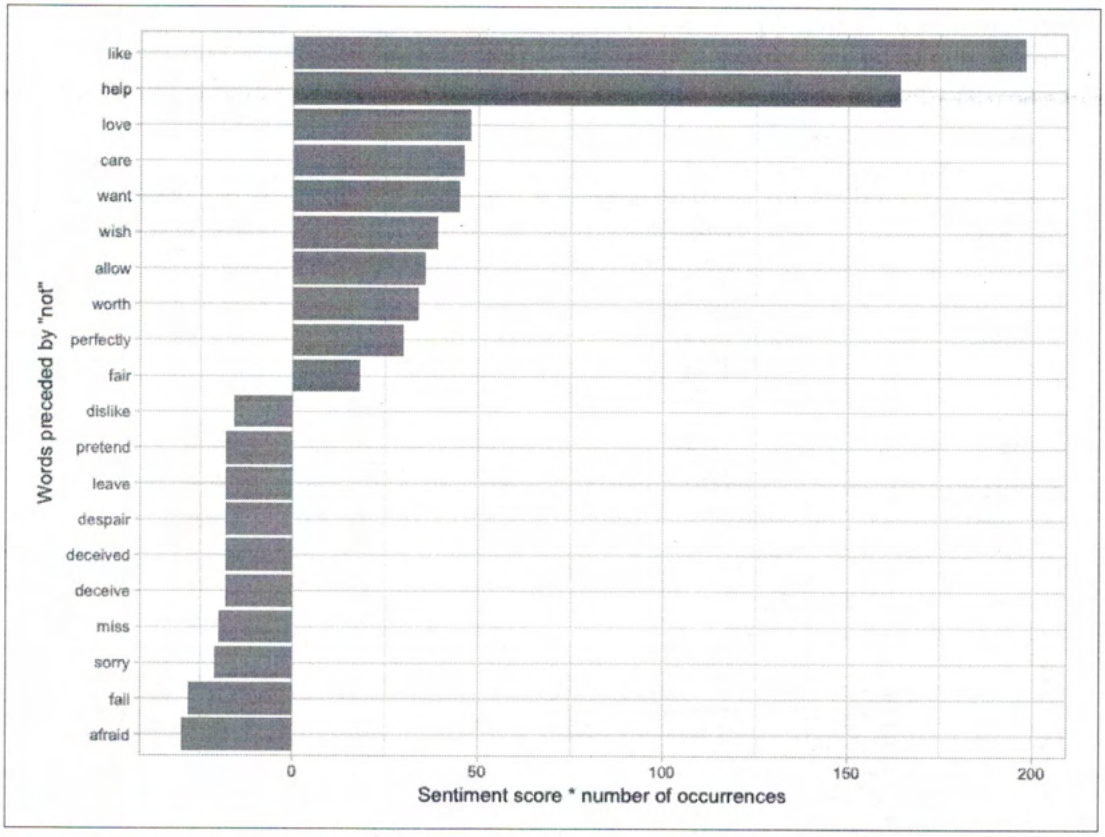



*Figure 4-2. The 20 words followed by "not" that had the greatest contribution to sentiment scores, in either a positive or negative direction*

The bigrams "not like" and "not help" were overwhelmingly the largest causes of misidentification, making the text seem much more positive than it is. But we can see that phrases like "not afraid" and "not fail" sometimes suggest text is more negative than it is.

"Not" isn't the only term that provides some context for the following word. We could pick four common words (or more) that negate the subsequent term, and use the same joining and counting approach to examine all of them at once.

```
negation_words <- c("not", "no", "never", "without")

negated_words <- bigrams_separated %>%
  filter(word1 %in% negation_words) %>%
  inner_join(AFINN, by = c(word2 = "word")) %>%
  count(word1, word2, score, sort = TRUE) %>%
  ungroup()
```

We could then visualize what the most common words to follow each particular negation are (Figure 4-3). While "not like" and "not help" are still the two most common examples, we can also see pairings such as "no great" and "never loved." We could

combine this with the approaches in Chapter 2 to reverse the AFINN scores of each word that follows a negation. These are just a few examples of how finding consecutive words can give context to text mining methods.

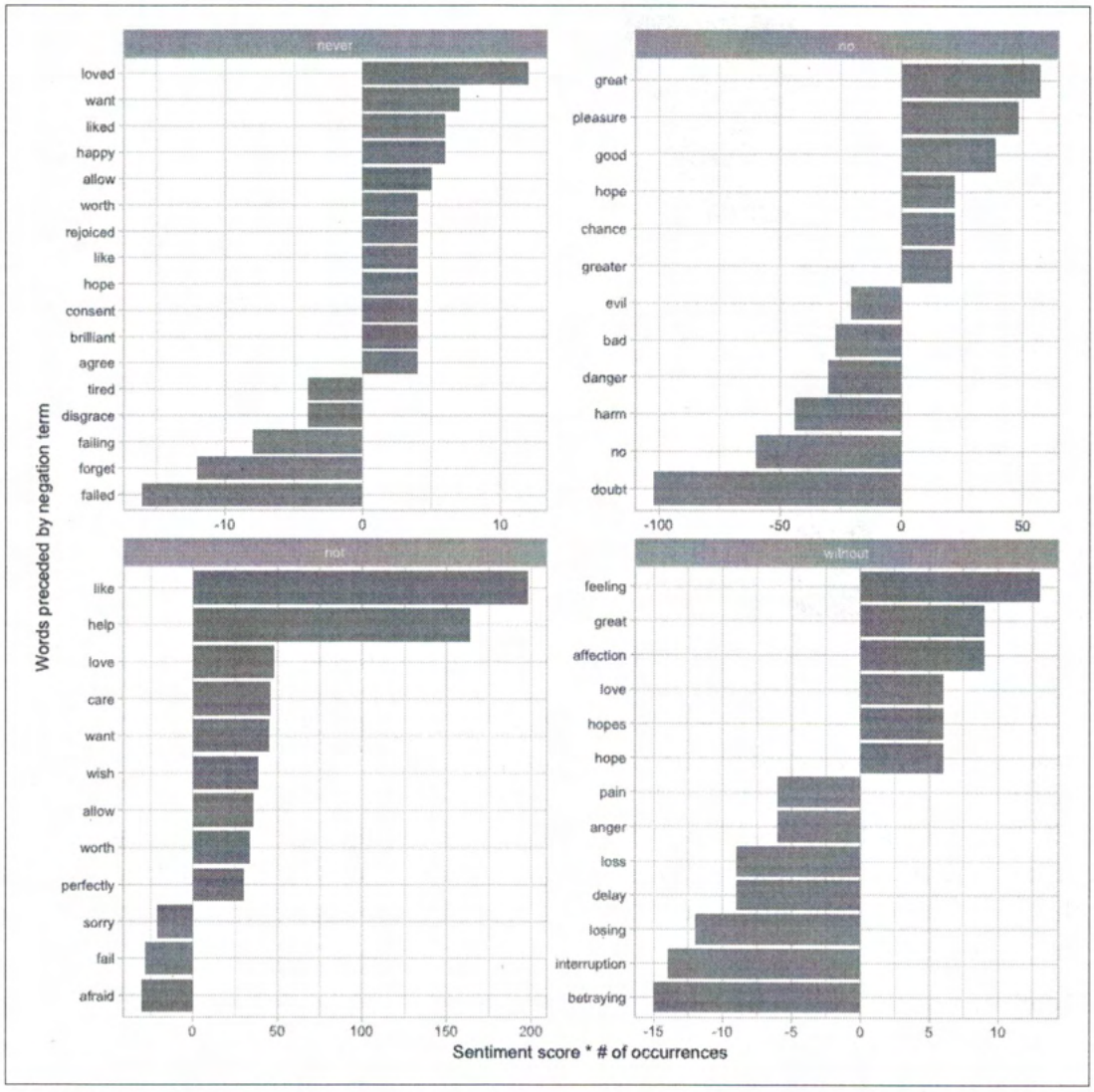


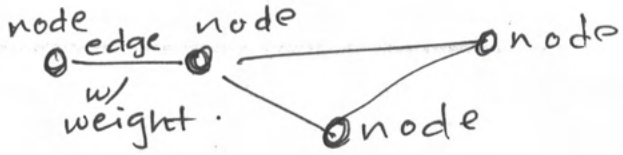

*Figure 4-3. The most common positive or negative words to follow negations such as "never," "no," "not," and "without"*

## Visualizing a Network of Bigrams with ggraph

We may be interested in visualizing all of the relationships among words simultaneously, rather than just the top few at a time. As one common visualization, we can arrange the words into a network, or "graph." Here we'll be referring to a graph not in the sense of a visualization, but as a combination of connected nodes. A graph can be constructed from a tidy object since it has three variables:

*from*
: The node an edge is coming from

*to*
: The node an edge is going toward




*weight*
: A numeric value associated with each edge

The igraph package has many powerful functions for manipulating and analyzing networks. One way to create an igraph object from tidy data is the `graph_from_data_frame()` function, which takes a data frame of edges with columns for "from," "to," and edge attributes (in this case `n`):

```
library(igraph)

# original counts
bigram_counts
```

```
## Source: local data frame [33,421 x 3]
## Groups: word1 [6,711]
##
##      word1     word2     n
##      <chr>     <chr> <int>
## 1      sir    thomas   287
## 2     miss  crawford   215
## 3  captain wentworth   170
## 4     miss woodhouse   162
## 5    frank churchill   132
## 6     lady   russell   118
## 7     lady   bertram   114
## 8      sir    walter   113
## 9     miss   fairfax   109
## 10 colonel   brandon   108
## # ... with 33,411 more rows
```

```
# filter for only relatively common combinations
bigram_graph <- bigram_counts %>%
  filter(n > 20) %>%
  graph_from_data_frame()

bigram_graph
```

```
## IGRAPH DN-- 91 77 --
## + attr: name (v/c), n (e/n)
## + edges (vertex names):
##  [1] sir     ->thomas     miss    ->crawford   captain ->wentworth
##  [4] miss    ->woodhouse  frank   ->churchill  lady    ->russell
##  [7] lady    ->bertram    sir     ->walter     miss    ->fairfax
## [10] colonel ->brandon    miss    ->bates      lady    ->catherine
## [13] sir     ->john       jane    ->fairfax    miss    ->tilney
## [16] lady    ->middleton  miss    ->bingley    thousand->pounds
## [19] miss    ->dashwood   miss    ->bennet     john    ->knightley
```

```
## [22] miss    ->morland    captain ->benwick    dear    ->mis
## + ... omitted several edges
```

igraph has plotting functions built in, but they're not what the package is designed to do, so many other packages have developed visualization methods for graph objects. We recommend the ggraph package (Pedersen 2017), because it implements these visualizations in terms of the grammar of graphics, which we are already familiar with from ggplot2.

We can convert an igraph object into a ggraph with the `ggraph` function, after which we add layers to it, much like layers are added in ggplot2. For example, for a basic graph we need to add three layers: nodes, edges, and text (Figure 4-4).

```
library(ggraph)
set.seed(2017)

ggraph(bigram_graph, layout = "fr") +
  geom_edge_link() +
  geom_node_point() +
  geom_node_text(aes(label = name), vjust = 1, hjust = 1)
```

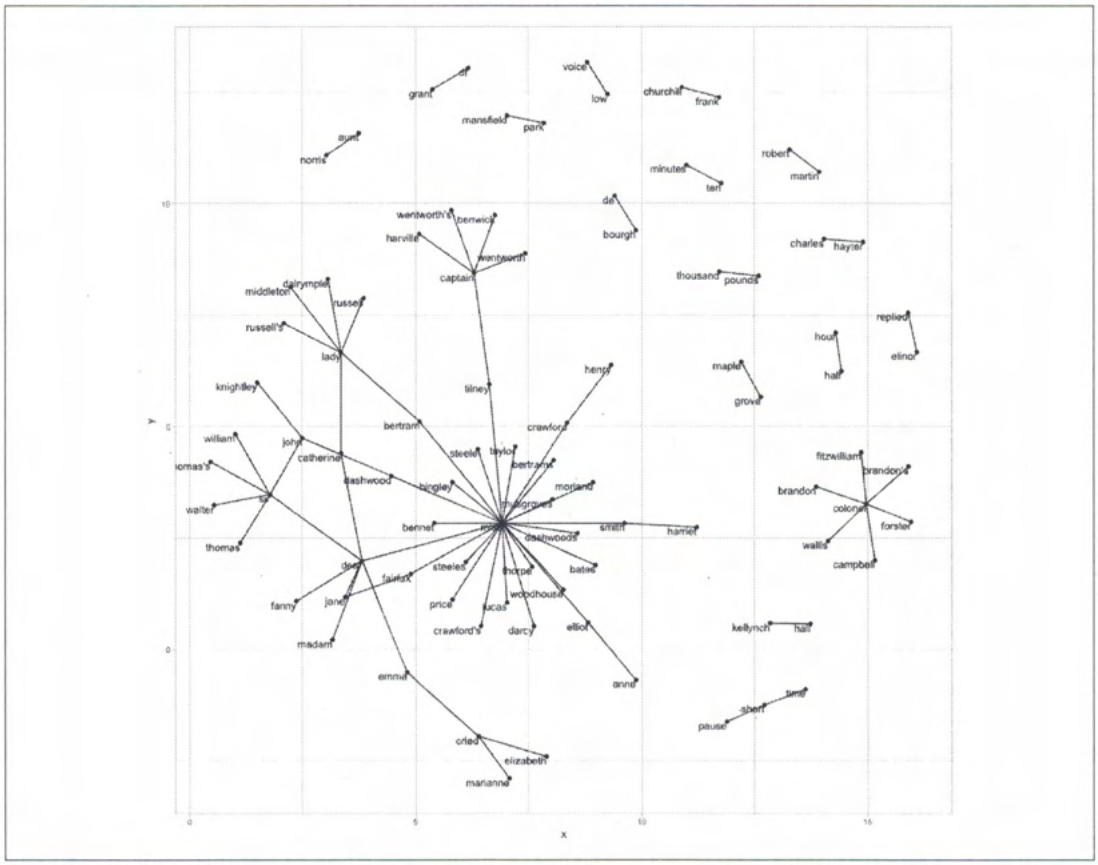



*Figure 4-4. Common bigrams in Pride and Prejudice, showing those that occurred more than 20 times and where neither word was a stop word*

In Figure 4-4, we can visualize some details of the text structure. For example, we see that salutations such as "miss," "lady," "sir," and "colonel" form common centers of nodes, which are often followed by names. We also see pairs or triplets along the outside that form common short phrases ("half hour," "thousand pounds," or "short time/pause").

We conclude with a few polishing operations to make a better-looking graph (Figure 4-5):

- We add the `edge_alpha` aesthetic to the link layer to make links transparent based on how common or rare the bigram is.
- We add directionality with an arrow, constructed using `grid::arrow()`, including an `end_cap` option that tells the arrow to end before touching the node.
- We tinker with the options to the node layer to make the nodes more attractive.
- We add a theme that's useful for plotting networks, `theme_void()`.

```
set.seed(2016)

a <- grid::arrow(type = "closed", length = unit(.15, "inches"))

ggraph(bigram_graph, layout = "fr") +
  geom_edge_link(aes(edge_alpha = n), show.legend = FALSE,
                 arrow = a, end_cap = circle(.07, 'inches')) +
  geom_node_point(color = "lightblue", size = 5) +
  geom_node_text(aes(label = name), vjust = 1, hjust = 1) +
  theme_void()
```

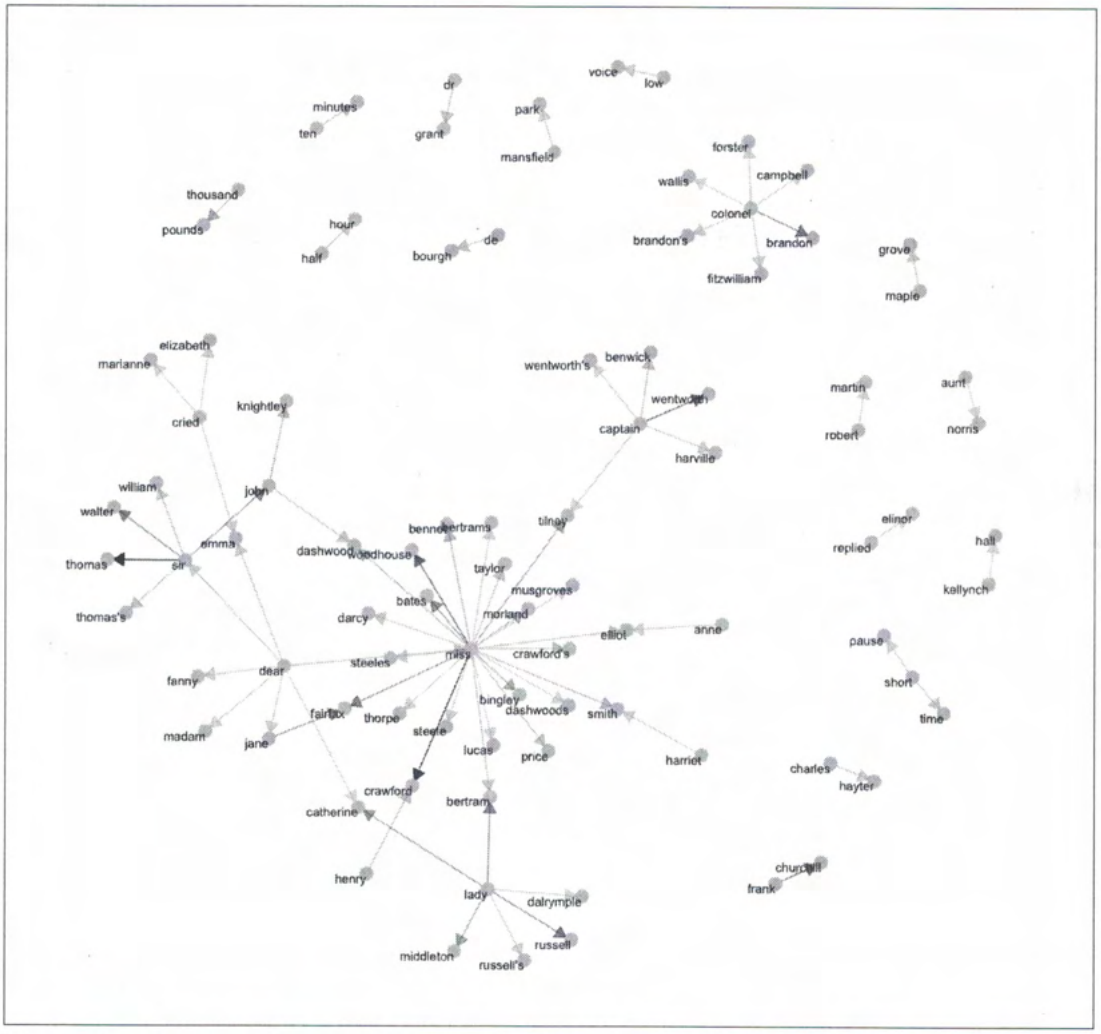



*Figure 4-5. Common bigrams in Pride and Prejudice, with some polishing*

It may take a some experimentation with ggraph to get your networks into a presentable format like this, but the network structure is a useful and flexible way to visualize relational tidy data.

Note that this is a visualization of a *Markov chain*, a common model in text processing. In a Markov chain, each choice of word depends only on the previous word. In this case, a random generator following this model might spit out "dear," then "sir," then "william/walter/thomas/thomas's" by following each word to the most common words that follow it. To make the visualization interpretable, we chose to show only the most common word-to-word connections, but one could imagine an enormous graph representing all connections that occur in the text.

## Visualizing Bigrams in Other Texts

We went to a good amount of work in cleaning and visualizing bigrams on a text dataset, so let's collect it into a function so that we can easily perform it on other text datasets.

To make it easy to use the functions `count_bigrams()` and `visualize_bigrams()` yourself, we've also reloaded the packages necessary for them.

```
library(dplyr)
library(tidyr)
library(tidytext)
library(ggplot2)
library(igraph)
library(ggraph)

count_bigrams <- function(dataset) {
  dataset %>%
    unnest_tokens(bigram, text, token = "ngrams", n = 2) %>%
    separate(bigram, c("word1", "word2"), sep = " ") %>%
    filter(!word1 %in% stop_words$word,
           !word2 %in% stop_words$word) %>%
    count(word1, word2, sort = TRUE)
}

visualize_bigrams <- function(bigrams) {
  set.seed(2016)
  a <- grid::arrow(type = "closed", length = unit(.15, "inches"))

  bigrams %>%
    graph_from_data_frame() %>%
    ggraph(layout = "fr") +
    geom_edge_link(aes(edge_alpha = n), show.legend = FALSE, arrow = a) +
    geom_node_point(color = "lightblue", size = 5) +
    geom_node_text(aes(label = name), vjust = 1, hjust = 1) +
    theme_void()
}
```

At this point, we could visualize bigrams in other works, such as the King James Bible (Figure 4-6):

```
# the King James version is book 10 on Project Gutenberg:
library(gutenbergr)
kjv <- gutenberg_download(10)

library(stringr)

kjv_bigrams <- kjv %>%
```

```
  count_bigrams()

# filter out rare combinations, as well as digits
kjv_bigrams %>%
  filter(n > 40,
         !str_detect(word1, "\\d"),
         !str_detect(word2, "\\d")) %>%
  visualize_bigrams()
```

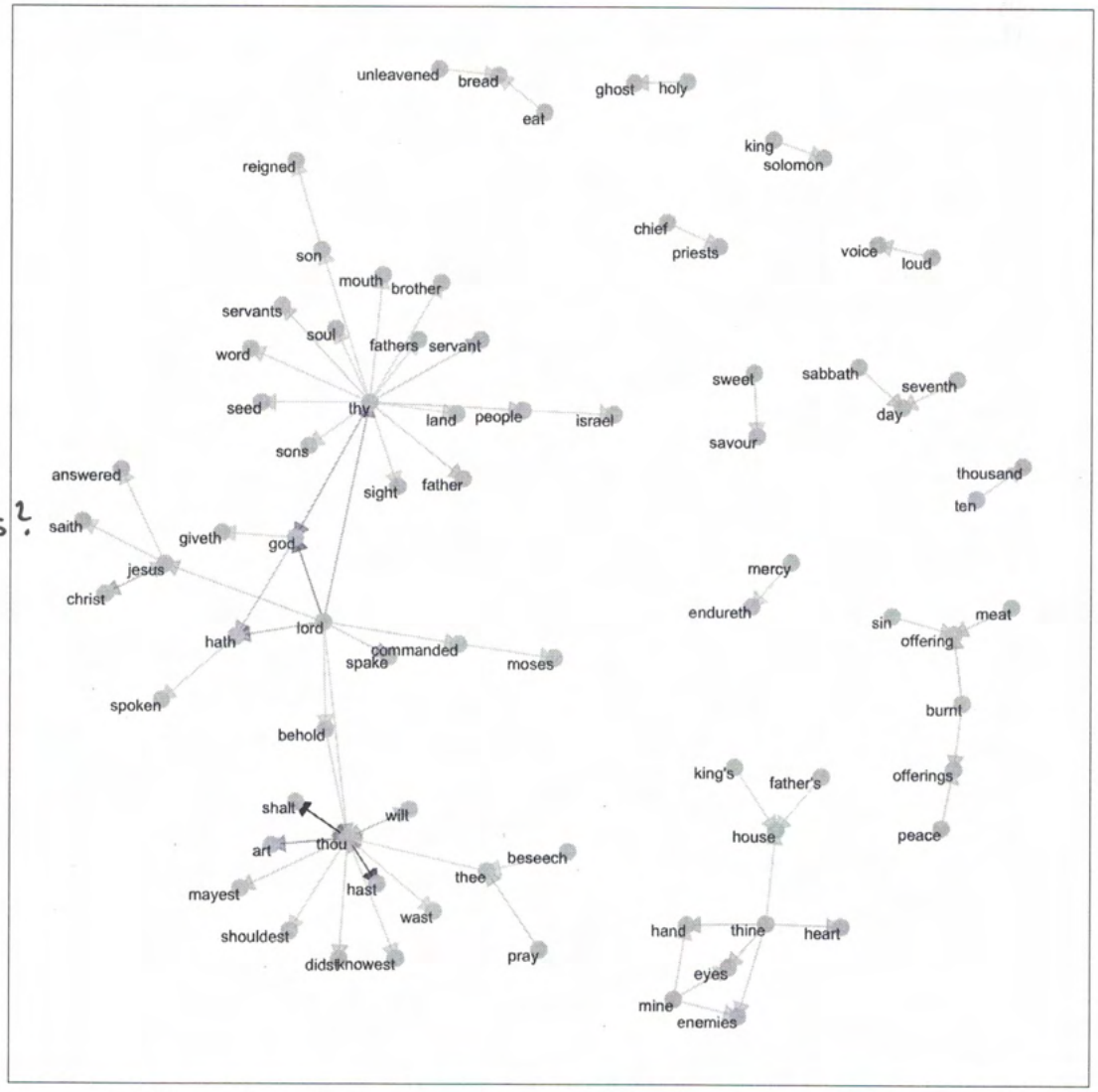



*Figure 4-6. Directed graph of common bigrams in the King James Bible, showing those that occurred more than 40 times*

Figure 4-6 thus lays out a common "blueprint" of language within the Bible, particularly focused around "thy" and "thou" (which could probably be considered stop words!). You can use the gutenbergr package and the `count_bigrams/visual`

ize_bigrams functions to visualize bigrams in other classic books you're interested in.

## Counting and Correlating Pairs of Words with the widyr Package

Tokenizing by n-gram is a useful way to explore pairs of adjacent words. However, we may also be interested in words that tend to co-occur within particular documents or particular chapters, even if they don't occur next to each other.

Tidy data is a useful structure for comparing between variables or grouping by rows, but it can be challenging to compare between rows: for example, to count the number of times that two words appear within the same document, or to see how correlated they are. Most operations for finding pairwise counts or correlations need to turn the data into a wide matrix first.

We'll examine some of the ways tidy text can be turned into a wide matrix in Chapter 5, but in this case it isn't necessary. The widyr package makes operations such as computing counts and correlations easy by simplifying the pattern of "widen data, perform an operation, then re-tidy data" (Figure 4-7). We'll focus on a set of functions that make pairwise comparisons between groups of observations (for example, between documents, or sections of text).

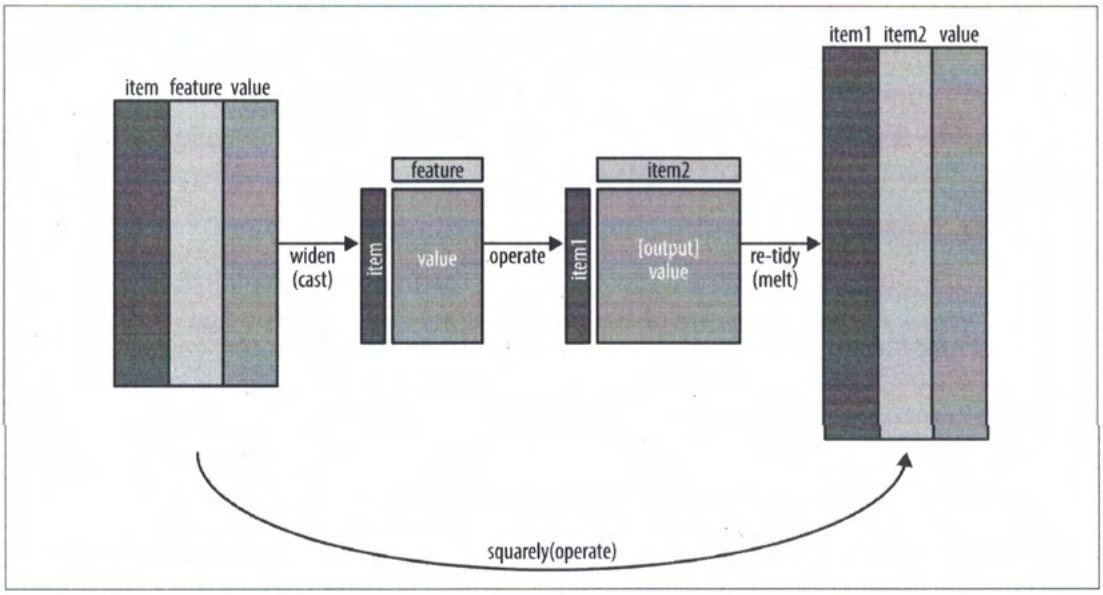



*Figure 4-7. The philosophy behind the widyr package, which can perform operations such as counting and correlating on pairs of values in a tidy dataset. The widyr package first "casts" a tidy dataset into a wide matrix, performs an operation such as a correlation on it, then re-tidies the result.*

## Counting and Correlating Among Sections

Consider the book *Pride and Prejudice* divided into 10-line sections, as we did (with larger sections) for sentiment analysis in Chapter 2. We may be interested in what words tend to appear within the same section.

```
austen_section_words <- austen_books() %>%
  filter(book == "Pride & Prejudice") %>%
  mutate(section = row_number() %/% 10) %>%
  filter(section > 0) %>%
  unnest_tokens(word, text) %>%
  filter(!word %in% stop_words$word)

austen_section_words
```

```
## # A tibble: 37,240 × 3
##                book section         word
##              <fctr>   <dbl>        <chr>
## 1  Pride & Prejudice       1        truth
## 2  Pride & Prejudice       1  universally
## 3  Pride & Prejudice       1 acknowledged
## 4  Pride & Prejudice       1       single
## 5  Pride & Prejudice       1   possession
## 6  Pride & Prejudice       1      fortune
## 7  Pride & Prejudice       1         wife
## 8  Pride & Prejudice       1     feelings
## 9  Pride & Prejudice       1        views
## 10 Pride & Prejudice       1     entering
## # ... with 37,230 more rows
```

One useful function from widyr is the `pairwise_count()` function. The prefix `pairwise_` means it will result in one row for each pair of words in the `word` variable. This lets us count common pairs of words co-appearing within the same section.

```
library(widyr)

# count words co-occuring within sections
word_pairs <- austen_section_words %>%
  pairwise_count(word, section, sort = TRUE)

word_pairs
```

```
## # A tibble: 796,008 × 3
##        item1     item2     n
##        <chr>     <chr> <dbl>
## 1      darcy elizabeth   144
## 2  elizabeth     darcy   144
## 3       miss elizabeth   110
## 4  elizabeth      miss   110
## 5  elizabeth      jane   106
## 6       jane elizabeth   106
## 7       miss     darcy    92
## 8      darcy      miss    92
```

```
## 9  elizabeth   bingley    91
## 10   bingley elizabeth    91
## # ... with 795,998 more rows
```

Notice that while the input had one row for each pair of a document (a 10-line section) and a word, the output has one row for each pair of words. This is also a tidy format, but of a very different structure that we can use to answer new questions.

For example, we can see that the most common pair of words in a section is "Elizabeth" and "Darcy" (the two main characters). We can easily find the words that most often occur with Darcy.

```
word_pairs %>%
  filter(item1 == "darcy")
```

```
## # A tibble: 2,930 × 3
##    item1     item2     n
##    <chr>     <chr> <dbl>
## 1  darcy elizabeth   144
## 2  darcy      miss    92
## 3  darcy   bingley    86
## 4  darcy      jane    46
## 5  darcy    bennet    45
## 6  darcy    sister    45
## 7  darcy      time    41
## 8  darcy      lady    38
## 9  darcy    friend    37
## 10 darcy   wickham    37
## # ... with 2,920 more rows
```

"Darcy" tends to be paired with "Elizabeth", "miss"...

## Examining Pairwise Correlation

Pairs like "Elizabeth" and "Darcy" are the most common co-occurring words, but that's not particularly meaningful since *they're also the most common individual words.* We may instead want to examine *correlation* among words, which indicates how often they appear together relative to how often they appear separately. → create coefficien

In particular, here we'll focus on the phi coefficient, a common measure for binary correlation. The phi coefficient focuses on how much more likely it is that either *both* word X and Y appear, or *neither* do, than that one appears without the other.

is a correlation measu of strength of association between a continuous-level variable & a binary variable.

Consider Table 4-1.

*Table 4-1. Values used to calculate the phi coefficient*

| | Has word Y | No word Y | Total |
|---|---|---|---|
| Has word X | $n_{11}$ | $n_{10}$ | $n_{1.}$ |
| No word X | $n_{01}$ | $n_{00}$ | $n_{0.}$ |
| Total | $n_{.1}$ | $n_{.0}$ | $n$ |

For example, $n_{11}$ represents the number of documents where both word X and word Y appear, $n_{00}$ the number where neither appears, and $n_{10}$ and $n_{01}$ the cases where one appears without the other. In terms of this table, the phi coefficient is:

$$\phi = \frac{n_{11}n_{00} - n_{10}n_{01}}{\sqrt{n_{1\cdot}n_{0\cdot}n_{\cdot 0}n_{\cdot 1}}}$$

The phi coefficient is equivalent to the Pearson correlation, which you may have heard of elsewhere, when it is applied to binary data.

The `pairwise_cor()` function in widyr lets us find the phi coefficient between words based on how often they appear in the same section. Its syntax is similar to `pairwise_count()`.

```
# we need to filter for at least relatively common words first
word_cors <- austen_section_words %>%
  group_by(word) %>%
  filter(n() >= 20) %>%
  pairwise_cor(word, section, sort = TRUE)

word_cors
```

```
## # A tibble: 154,842 × 3
##        item1     item2 correlation
##        <chr>     <chr>       <dbl>
## 1     bourgh        de   0.9508501
## 2         de    bourgh   0.9508501
## 3     pounds  thousand   0.7005808
## 4   thousand    pounds   0.7005808
## 5    william       sir   0.6644719
## 6        sir   william   0.6644719
## 7  catherine      lady   0.6633048
## 8       lady catherine   0.6633048
## 9    forster   colonel   0.6220950
## 10   colonel   forster   0.6220950
## # ... with 154,832 more rows
```

This output format is helpful for exploration. For example, we could find the words most correlated with a word like "pounds" using a `filter` operation.

```
word_cors %>%
  filter(item1 == "pounds")
```

```
## # A tibble: 393 × 3
##     item1     item2 correlation
##     <chr>     <chr>       <dbl>
## 1  pounds  thousand  0.70058081
```

```
## 2  pounds       ten  0.23057580
## 3  pounds   fortune  0.16386264
## 4  pounds   settled  0.14946049
## 5  pounds wickham's  0.14152401
## 6  pounds  children  0.12900011
## 7  pounds  mother's  0.11905928
## 8  pounds  believed  0.09321518
## 9  pounds    estate  0.08896876
## 10 pounds     ready  0.08597038
## # ... with 383 more rows
```

This lets us pick particular interesting words and find the other words most associated with them (Figure 4-8).

```
word_cors %>%
  filter(item1 %in% c("elizabeth", "pounds", "married", "pride")) %>%
  group_by(item1) %>%
  top_n(6) %>%
  ungroup() %>%
  mutate(item2 = reorder(item2, correlation)) %>%
  ggplot(aes(item2, correlation)) +
  geom_bar(stat = "identity") +
  facet_wrap(~ item1, scales = "free") +
  coord_flip()
```

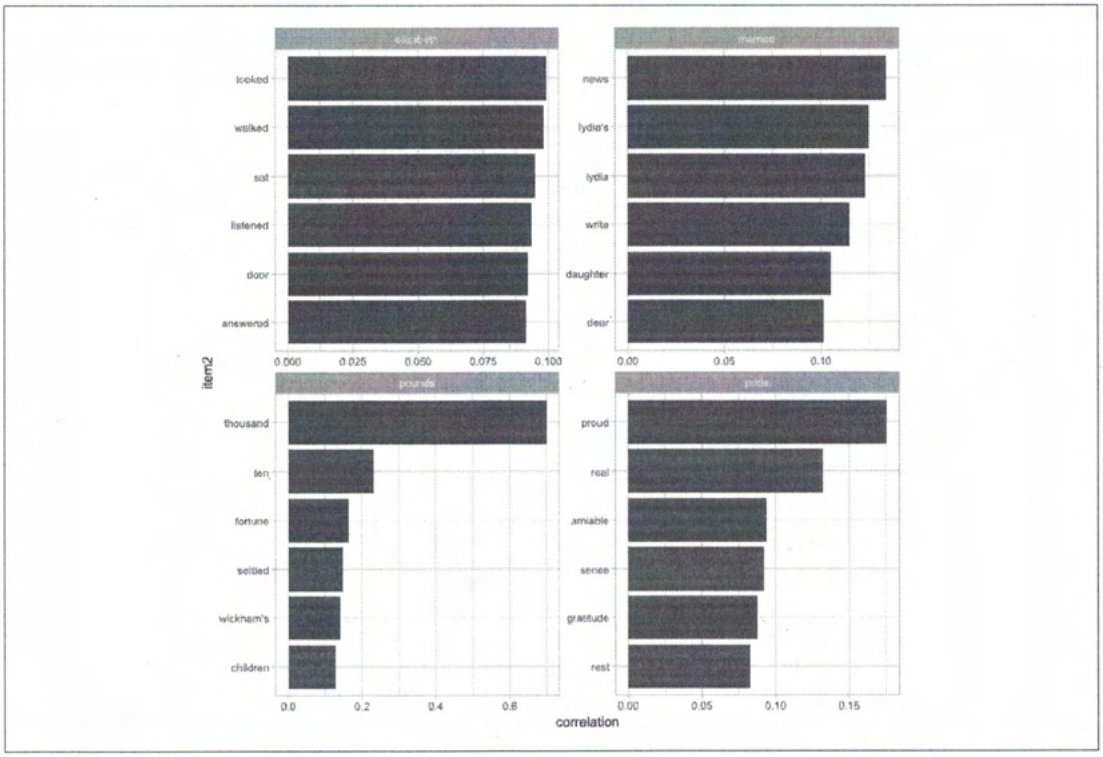



*Figure 4-8. Words from Pride and Prejudice that were most correlated with "elizabeth," "pounds," "married," and "pride"*

Just as we used ggraph to visualize bigrams, we can use it to visualize the correlations and clusters of words that were found by the widyr package (Figure 4-9).

I wonder? how we know which seed to pick

```
set.seed(2016)

word_cors %>%
  filter(correlation > .15) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = correlation), show.legend = FALSE) +
  geom_node_point(color = "lightblue", size = 5) +
  geom_node_text(aes(label = name), repel = TRUE) +
  theme_void()
```

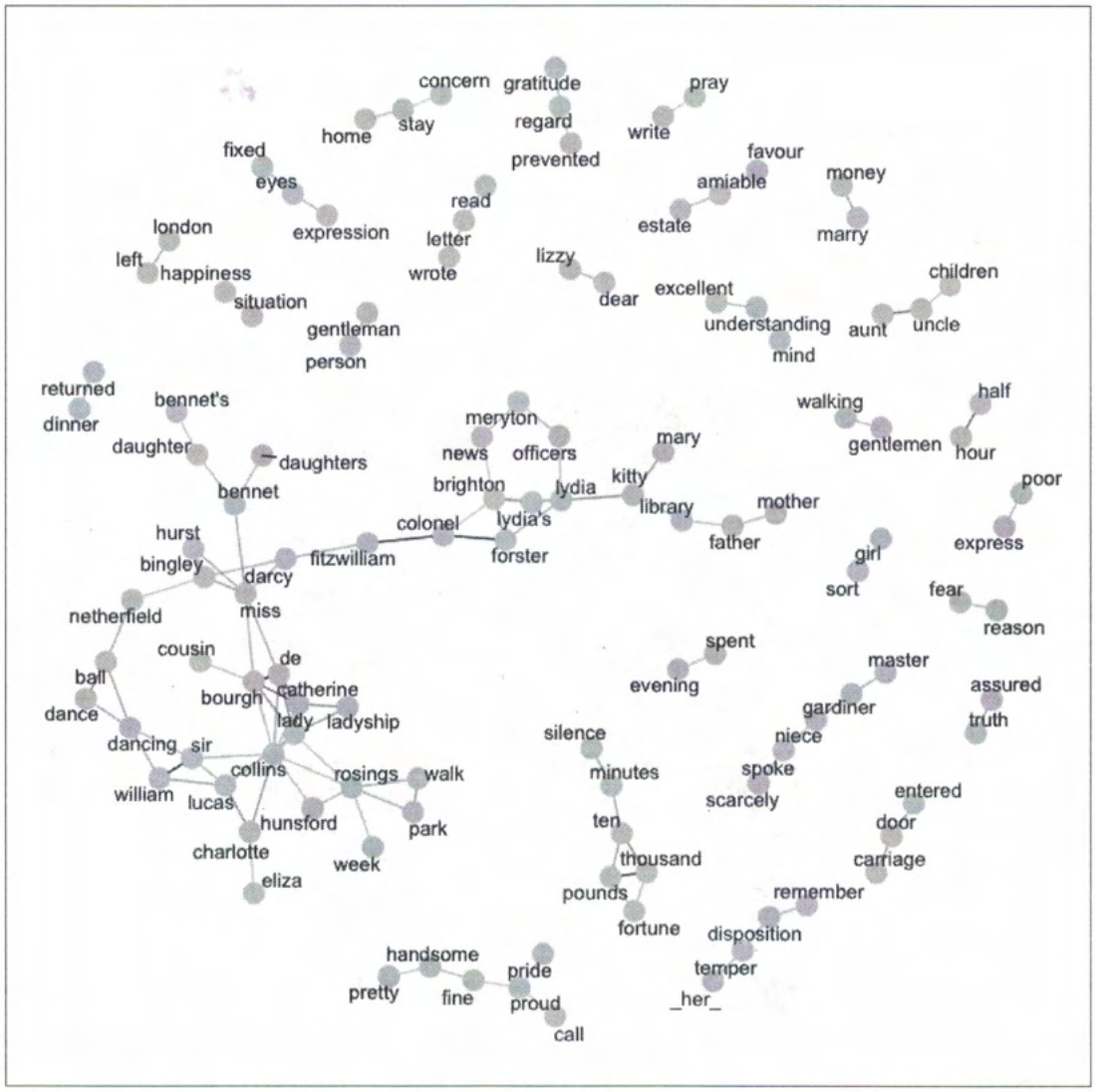



*Figure 4-9. Pairs of words in Pride and Prejudice that show at least a 0.15 correlation of appearing within the same 10-line section*

Note that unlike the bigram analysis, the relationships here are symmetrical, rather than directional (there are no arrows). We can also see that while pairings of names and titles that dominated bigram pairings are common, such as "colonel/fitzwilliam," we can also see pairings of words that appear close to each other, such as "walk" and "park," or "dance" and "ball."

## Summary

This chapter showed how the tidy text approach is useful not only for analyzing individual words, but also for exploring the relationships and connections between words. Such relationships can involve n-grams, which enable us to see what words tend to appear after others, or co-occurences and correlations, for words that appear in proximity to each other. This chapter also demonstrated the ggraph package for visualizing both of these types of relationships as networks. These network visualizations are a flexible tool for exploring relationships, and will play an important role in the case studies in later chapters.