

Introduction to Text Mining

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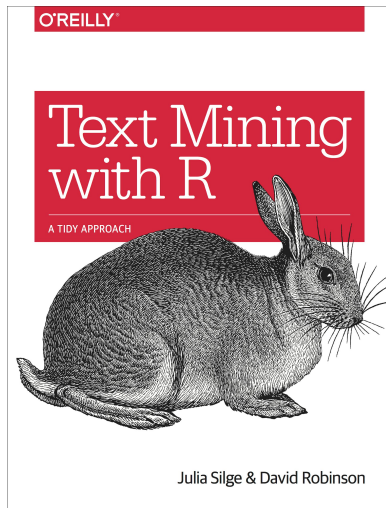
T: [@ajstewart_lang](https://twitter.com/ajstewart_lang)

G: [ajstewartlang](https://github.com/ajstewartlang)



Text Mining in R

In any set of texts (such as books, interview transcripts etc.) it's often useful to be able to quantify key aspects of the constituent parts (e.g., words, phrases). For example, some types of language may be more common in one interview transcript vs. another, and it can be useful to visualise the content of a particular text to compare it with others.



What we'll cover in this introduction...

Summarising text data.

Sentiment analysis.

Extracting frequency information (and demonstrating Zipf's law).

Characterising text that makes a unique contribution to a particular instance.

N-gram analysis.

The Packages We'll Be Using

We'll use the `{tidyverse}` as we'll need to do some data wrangling and visualisation. We'll also use `{tidytext}` for working with text in a tidy format, and `{gutenbergr}` which allows us to connect to [Project Gutenberg](#) in order to download public domain texts.

```
library(tidyverse)
library(tidytext)
library(gutenbergr)
```

We'll use the texts of some books by HG Wells in our examples...

We are going to download from Project Gutenberg the text of four books by HG Wells. We will combine these four books into a dataframe called `books`

```
titles <- c("The War of the Worlds",  
           "The Time Machine",  
           "Twenty Thousand Leagues under the Sea",  
           "The Invisible Man: A Grotesque Romance")
```

```
books <- gutenbergs_works(title %in% titles) %>%  
  gutenbergs_download(meta_fields = "title")
```

```
str(books)
tibble [27,540 × 3] (S3: tbl_df/tbl/data.frame)
 $ gutenber_id: int [1:27540] 35 35 35 35 35 35 35 35 35 35 ...
 $ text       : chr [1:27540] "The Time Machine" "" "An Invention" "" ...
 $ title      : chr [1:27540] "The Time Machine" "The Time Machine" "The Time Machine" "The Time
Machine" ...
```

```
head(books, n = 8)
# A tibble: 15 × 3
  gutenber_id text                title
  <int> <chr>                <chr>
1     35 "The Time Machine"    The Time Machine
2     35 ""                The Time Machine
3     35 "An Invention"     The Time Machine
4     35 ""                The Time Machine
5     35 "by H. G. Wells"  The Time Machine
6     35 ""                The Time Machine
7     35 ""                The Time Machine
8     35 "CONTENTS"      The Time Machine
```

```
books %>% distinct(title)
# A tibble: 4 × 1
  title
  <chr>
1 The Time Machine
2 The War of the Worlds
3 Twenty Thousand Leagues under the Sea
4 The Invisible Man: A Grotesque Romance
```

Examining rows 31:40 of the `text` column of our `books` tibble:

```
books$text[31:40]
```

```
[1] " I."
[2] " Introduction"
[3] ""
[4] ""
[5] "The Time Traveller (for so it will be convenient to speak of him) was"
[6] "expounding a recondite matter to us. His pale grey eyes shone and"
[7] "twinkled, and his usually pale face was flushed and animated. The fire"
[8] "burnt brightly, and the soft radiance of the incandescent lights in the"
[9] "lilies of silver caught the bubbles that flashed and passed in our"
[10] "glasses. Our chairs, being his patents, embraced and caressed us rather"
```

Currently the text is all in one column in our dataframe - we need to transform it into tidy format such that one word appears in each row. We do this by 'unnesting' the text column and removing 'stop words'. These are common words (e.g., function words like 'the' and 'of').

```
all_text <- books %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words)
```

```
all_text
```

```
# A tibble: 91,676 x 3
```

```
  gutenber
```

```
gutenberg_id title          word
```

```
<int> <chr>          <chr>
```

```
1      35 The Time Machine time
2      35 The Time Machine machine
3      35 The Time Machine invention
4      35 The Time Machine contents
5      35 The Time Machine introduction
6      35 The Time Machine ii
7      35 The Time Machine machine
8      35 The Time Machine iii
9      35 The Time Machine time
10     35 The Time Machine traveller
```

```
# ... with 91,666 more rows
```


Summary Data of “The Time Machine”

```
all_text %>%  
  filter(title == "The Time Machine") %>%  
  count(word, sort = TRUE) %>%  
  top_n(10)
```

Selecting by n

```
# A tibble: 10 x 2
```

	word	n
	<chr>	<int>
1	time	207
2	machine	88
3	white	61
4	traveller	57
5	hand	49
6	morlocks	48
7	people	46
8	weena	46
9	found	44
10	light	43

Summary Data of “The War of the Worlds”

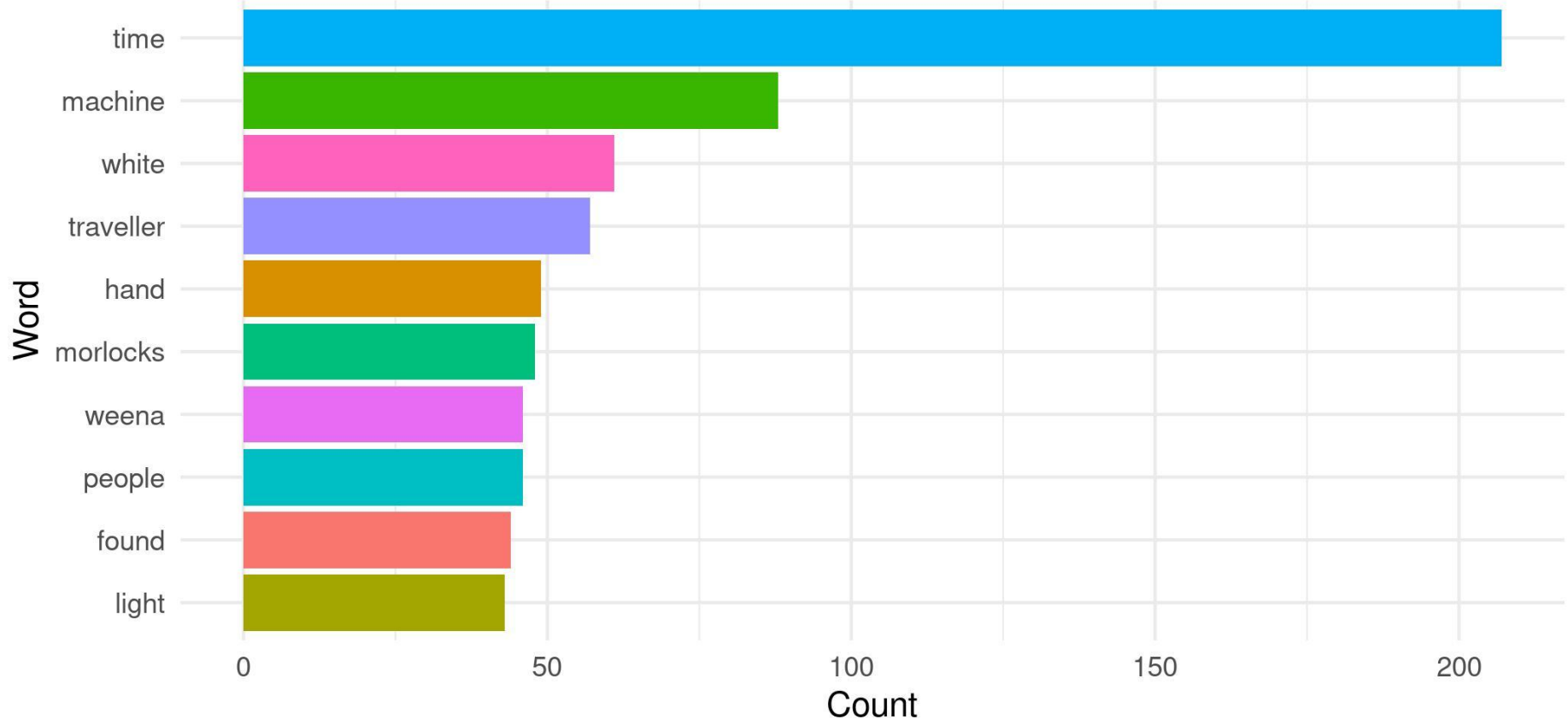
```
all_text %>%  
  filter(title == "The War of the Worlds") %>%  
  count(word, sort = TRUE) %>%  
  top_n(10)
```

Selecting by n

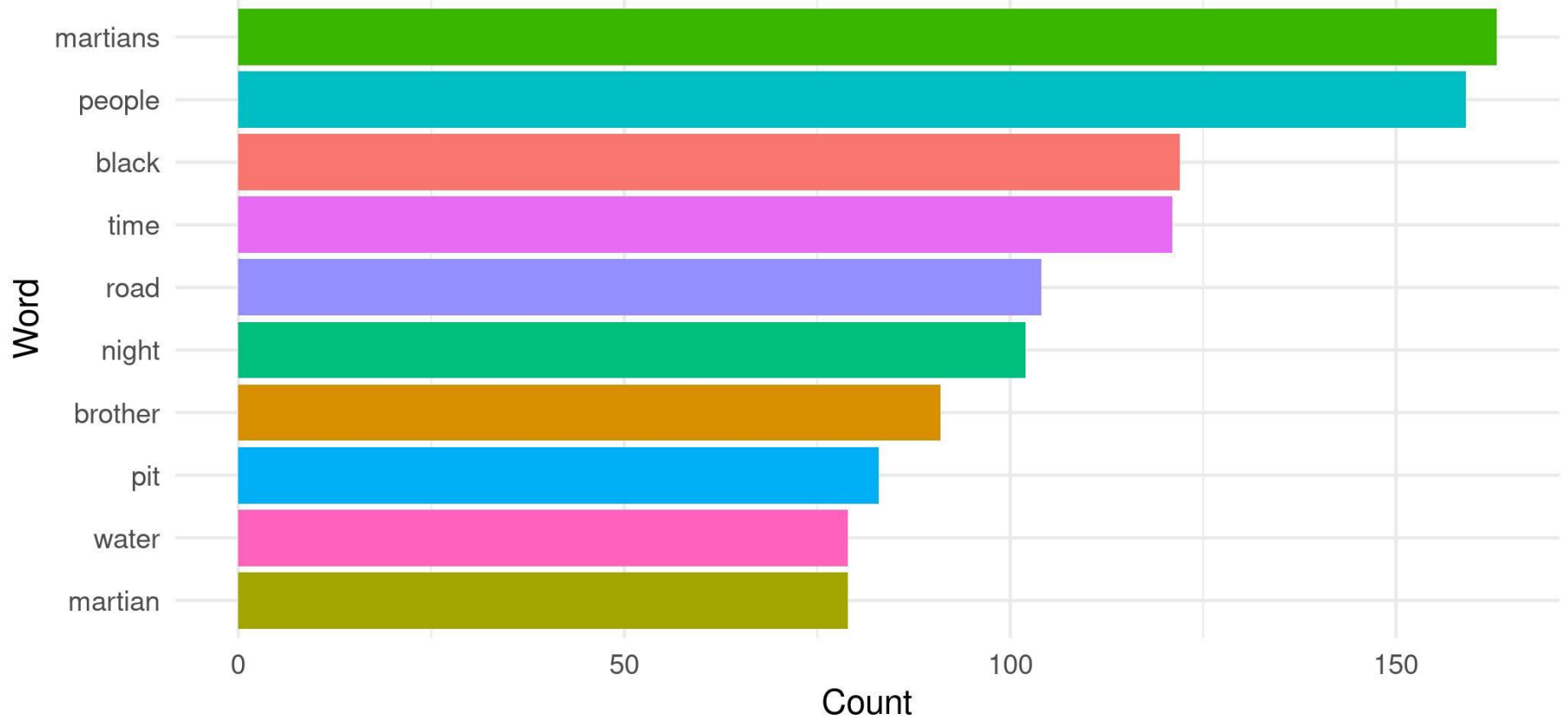
```
# A tibble: 10 x 2
```

	word	n
	<chr>	<int>
1	martians	163
2	people	159
3	black	122
4	time	121
5	road	104
6	night	102
7	brother	91
8	pit	83
9	martian	79
10	water	79

Top 10 most commonly occurring words in The Time Machine



Top 10 most commonly occurring words in The War of the Worlds



Sentiment Analysis

We can use one of the sentiment databases built-in to the tidytext package. The 'bing' database has sentiment ratings (positive vs. negative) for almost 7,000 words.

```
get_sentiments("bing")  
# A tibble: 6,786 x 2  
  word      sentiment  
  <chr>    <chr>  
1 2-faces    negative  
2 abnormal  negative  
3 abolish   negative  
4 abominable negative  
5 abominably negative  
6 abominate  negative  
7 abomination negative  
8 abort      negative  
9 aborted    negative  
10 aborts    negative  
# ... with 6,776 more rows
```

Sentiment Analysis

We can 'join' our `all_text` data to the sentiment dataset using the `inner_join()` function from `{dplyr}`

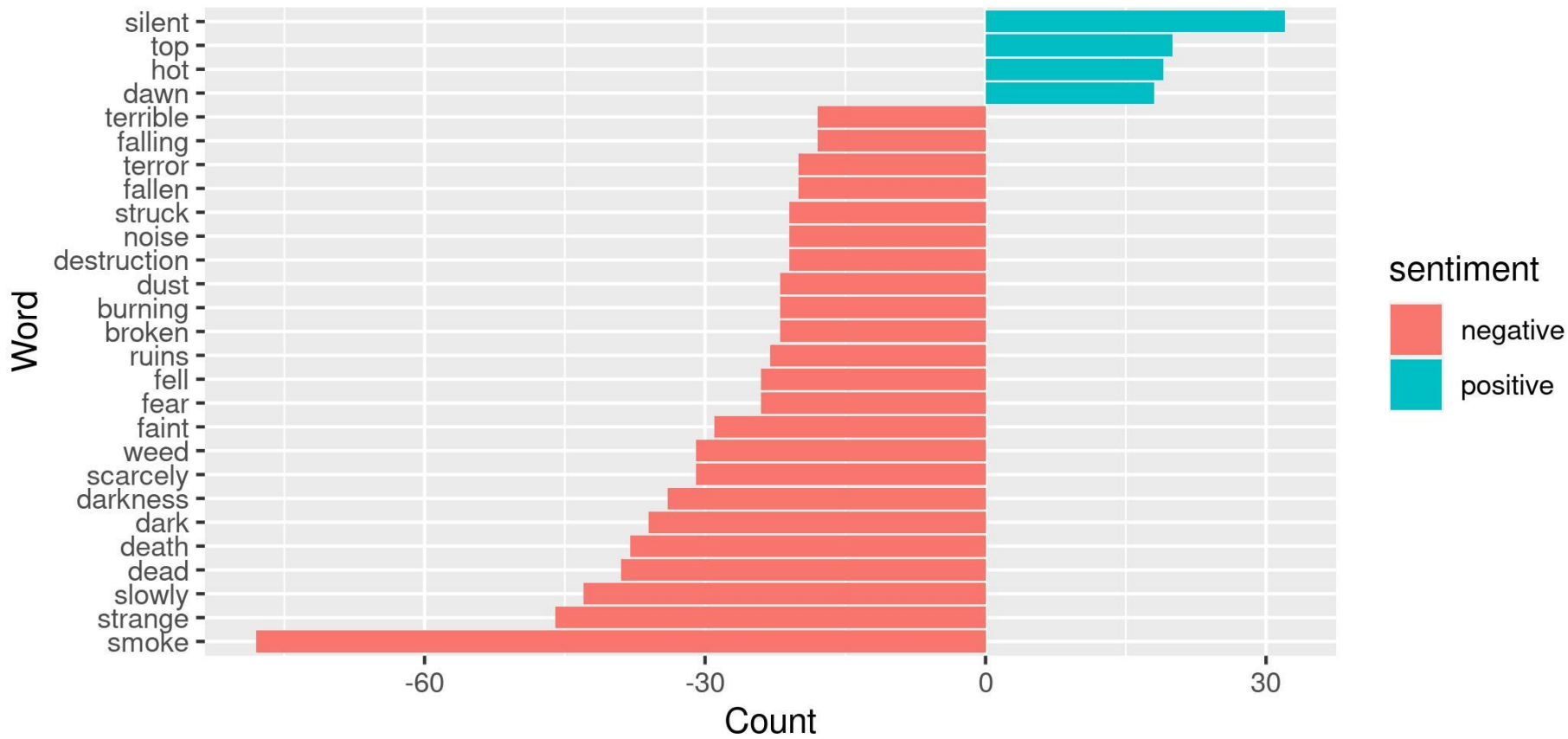
```
all_text_sentiments <- all_text %>%  
  inner_join(get_sentiments("bing"))
```

```
head(all_text_sentiments)
```

```
# A tibble: 6 x 4
```

	gutenberg_id	title	word	sentiment
	<int>	<chr>	<chr>	<chr>
1	35	The Time Machine	golden	positive
2	35	The Time Machine	shock	negative
3	35	The Time Machine	darkness	negative
4	35	The Time Machine	trap	negative
5	35	The Time Machine	convenient	positive
6	35	The Time Machine	pale	negative

Sentiment Analysis of Top 25 Words in The War of the Worlds



Examining the proportion of useage of each word in each book

```
book_words <- all_text %>%
  group_by(title) %>%
  count(title, word, sort = TRUE)

total_words <- book_words %>%
  group_by(title) %>%
  summarise(total = sum(n))

book_words <- left_join(book_words, total_words)

book_words %>%
  mutate(proportion = n/total) %>%
  group_by(title) %>%
  arrange(desc(title, proportion)) %>%
  top_n(3) %>%
  select(-n, -total)
```

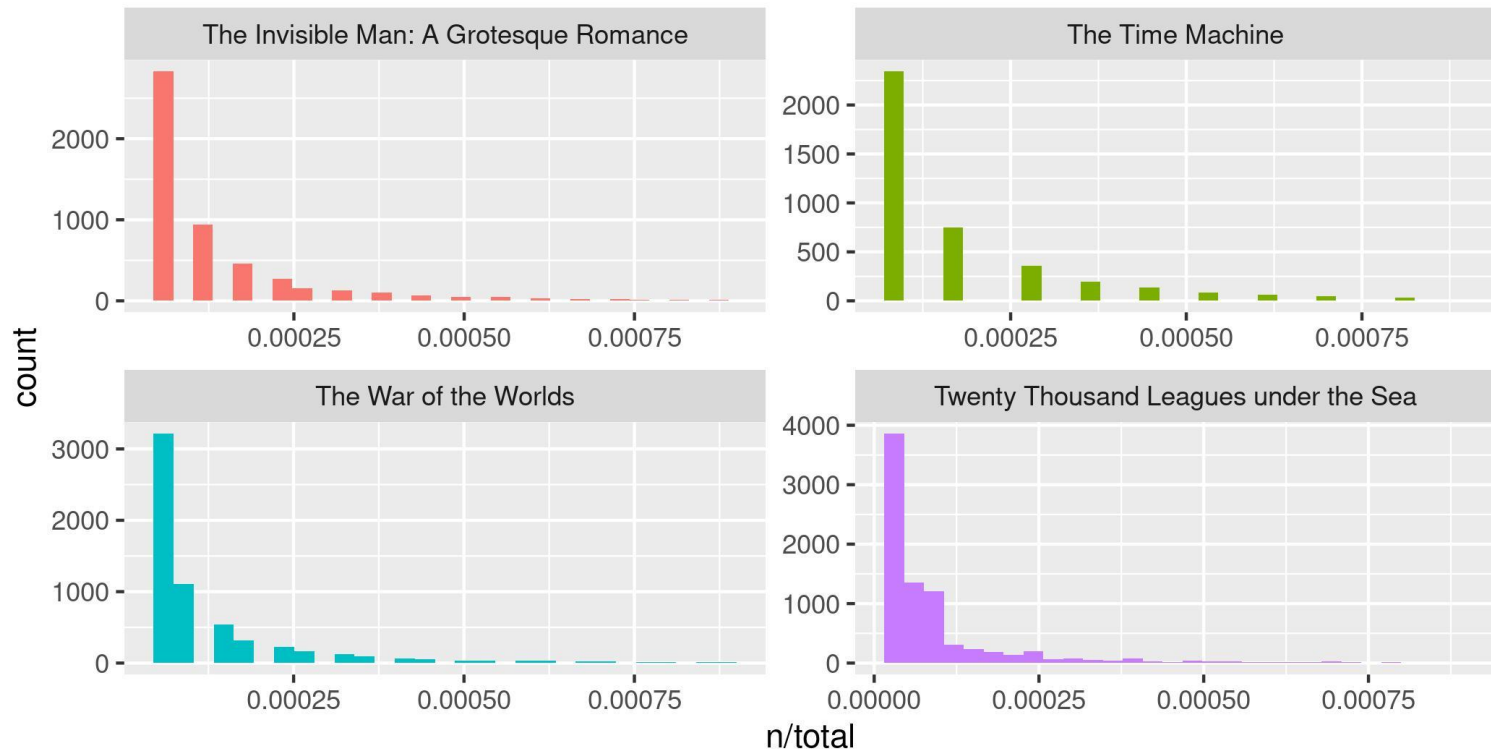

Selecting by proportion

A tibble: 12 x 3

Groups: title [4]

	title	word	proportion
	<chr>	<chr>	<dbl>
1	Twenty Thousand Leagues under the Sea	captain	0.0153
2	Twenty Thousand Leagues under the Sea	nautilus	0.0131
3	Twenty Thousand Leagues under the Sea	sea	0.00880
4	The War of the Worlds	martians	0.00722
5	The War of the Worlds	people	0.00704
6	The War of the Worlds	black	0.00540
7	The Time Machine	time	0.0184
8	The Time Machine	machine	0.00781
9	The Time Machine	white	0.00541
10	The Invisible Man: A Grotesque Romance	kemp	0.0117
11	The Invisible Man: A Grotesque Romance	invisible	0.00990
12	The Invisible Man: A Grotesque Romance	door	0.00930

Visualizing the data - Zipf's Law

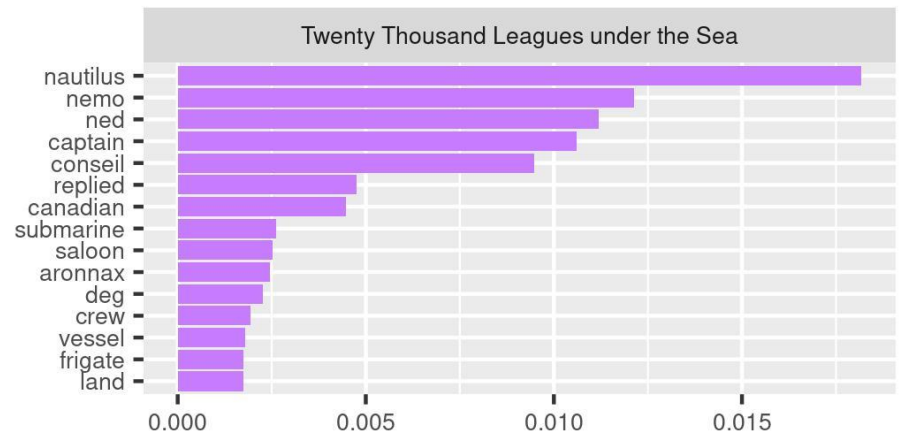
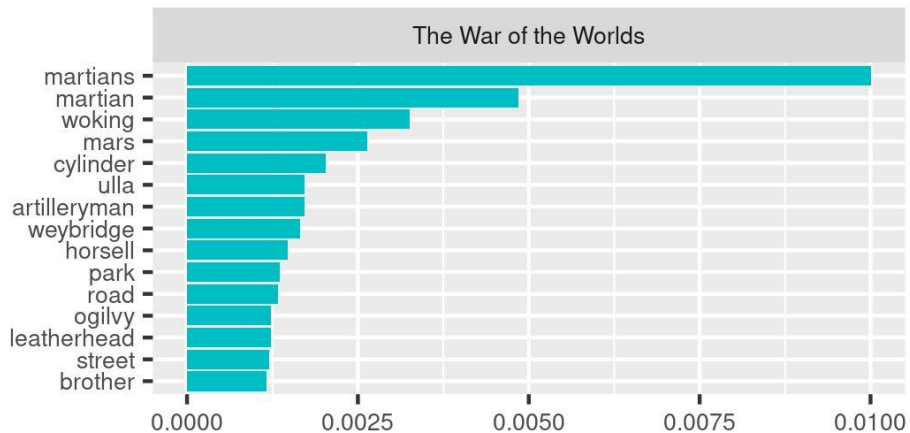
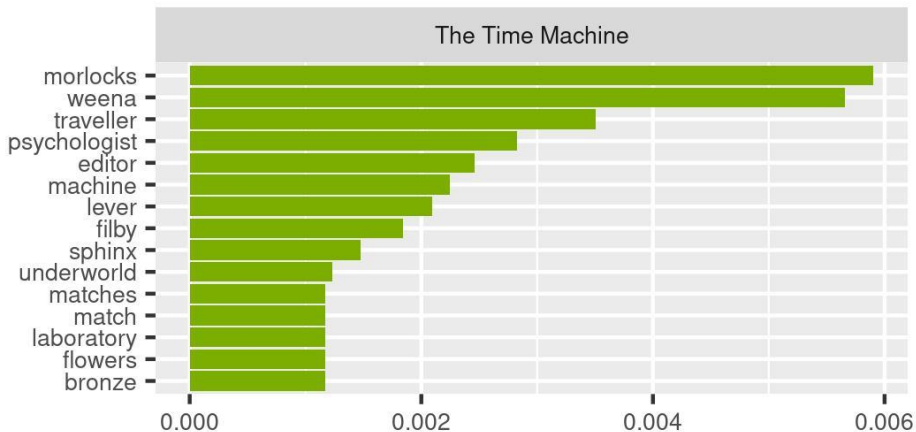
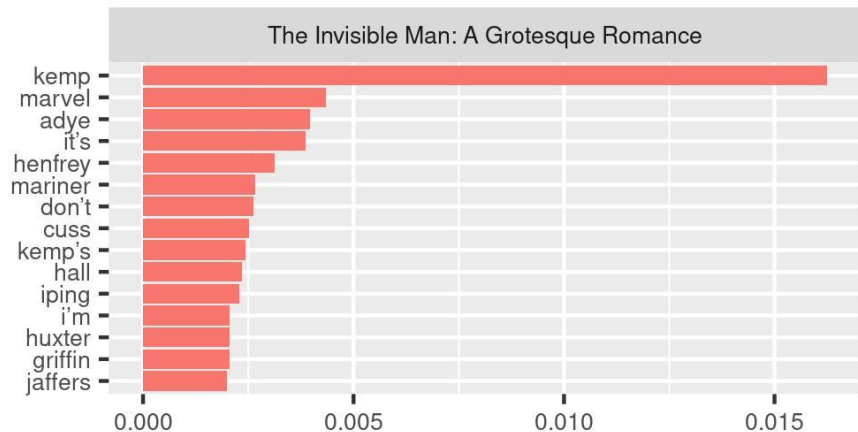


Which words are most important (and most unique) to each book?

The `bind_tf_idf()` function works out the important words for each book by adding a weighting to each word - decreasing the weight for commonly used words and increasing the weight for words not used much in the overall corpus. This is the term frequency-inverse document frequency measure used widely in text analysis.

This allows us to identify what words tend to be uniquely associated with each of the four books. This is known as the term frequency-inverse document frequency statistic.

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



Term Frequency-Inverse Document Frequency

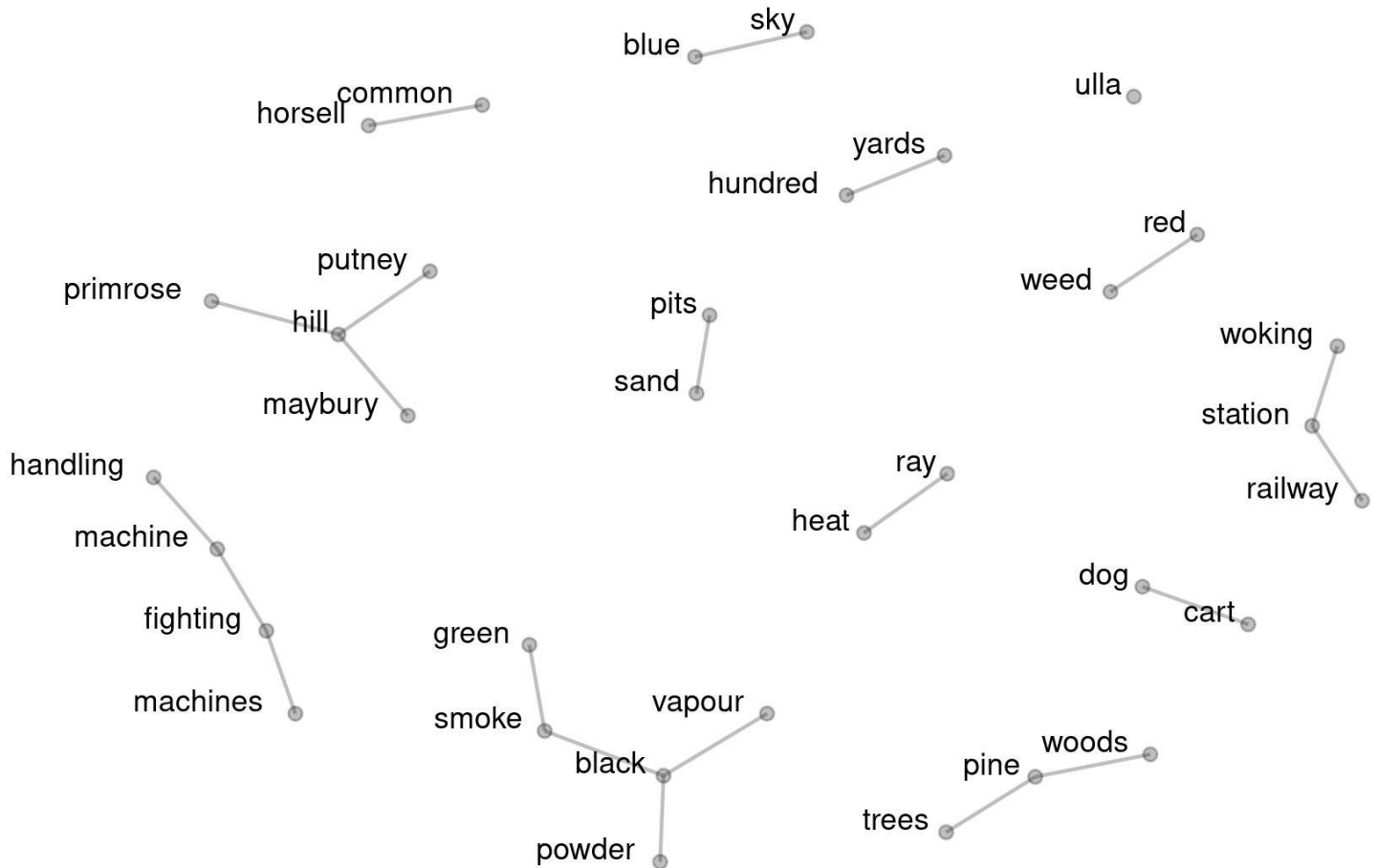
N-gram tokenizing

So far we've unnested such that each word is separate. But we can also unnest by n-grams to capture *sequences* of words. In this example, let's look at tokenizing by bigram.

```
wotw_bigrams <- books %>%  
  filter(title == "The War of the Worlds") %>%  
  unnest_tokens(bigram, text, token = "ngrams", n = 2) %>%  
  separate(col = bigram, into = c("word1", "word2", sep = " ")) %>%  
  filter(!word1 %in% stop_words$word) %>%  
  filter(!word2 %in% stop_words$word) %>%  
  count(word1, word2, sort = TRUE)
```

Plotting a network graph of bigrams

```
bigram_graph <- wotw_bigrams %>%  
  filter(n > 5) %>%  
  graph_from_data_frame()  
  
set.seed(1234)  
ggraph(bigram_graph, layout = "fr") +  
  geom_edge_link(alpha = .25) +  
  geom_node_point(alpha = .25) +  
  geom_node_text(aes(label = name), vjust = -.1, hjust = 1.25, size = 3) +  
  guides(size = FALSE) +  
  xlim(10, 22) +  
  theme_void()
```



Summary

With `{tidytext}` in R you can extract a lot of information about different texts - you might consider applying the approach to interview transcripts (for example) as a way of providing quantitative insights in addition to qualitative approaches.

You might even want to use the term frequency-inverse document frequency measure as a way of understanding what words or n-grams are associated with particular interviews (or sets of interviews) and not with others.