Text analysis

You can download this .qmd file from here. Just hit the Download Raw File button.

We will build on techniques you learned in SDS 164 using parts of Text Mining with R by Silge and Robinson.

Text analysis of books from Project Gutenberg

We will use the `gutenbergr` package to obtain several works from Project Gutenberg to examine using text analysis tools.

```
# How I obtained the three works from Project Gutenberg

# Notes:
# - might have to find mirror at https://www.gutenberg.org/MIRRORS.ALL
# - 84 = Frankenstein; 345 = Dracula; 43 = Jekyll and Hyde

# three_works <- gutenberg_download(
#  c(84, 345, 43),
#  meta_fields = "title",
#  mirror = "http://mirror.csclub.uwaterloo.ca/gutenberg/")

# write_csv(three_works, "~/264_fall_2024/Data/three_works.csv")
```

```
# three_works <- read_csv("https://proback.github.io/264_fall_2024/Data/three_works.csv")
# three_works2 <- read_csv("Data/three_works.csv")

library(RCurl)
```

```
Attaching package: 'RCurl'
```

```
The following object is masked from 'package:tidyr':

    complete
```

```r
three_works <- read_csv(
  file = getURL("https://raw.githubusercontent.com/proback/264_fall_2024/refs/heads/main/D
```

```
Rows: 25399 Columns: 3

-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): text, title
dbl (1): gutenberg_id

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
three_works |> count(title)
```

```
# A tibble: 3 x 2
  title                                           n
  <chr>                                       <int>
1 Dracula                                     15491
2 Frankenstein; Or, The Modern Prometheus      7357
3 The Strange Case of Dr. Jekyll and Mr. Hyde  2551
```

```r
three_works
```

```
# A tibble: 25,399 x 3
   gutenberg_id text                                        title
          <dbl> <chr>                                       <chr>
 1           43 The Strange Case Of Dr. Jekyll And Mr. Hyde The Strange Case of~
 2           43 <NA>                                        The Strange Case of~
 3           43 by Robert Louis Stevenson                   The Strange Case of~
 4           43 <NA>                                        The Strange Case of~
 5           43 <NA>                                        The Strange Case of~
 6           43 Contents                                    The Strange Case of~
 7           43 <NA>                                        The Strange Case of~
```

```
 8           43 <NA>                                          The Strange Case of~
 9           43 STORY OF THE DOOR                             The Strange Case of~
10           43 <NA>                                          The Strange Case of~
# i 25,389 more rows
```

```
frankenstein <- three_works |>
  filter(str_detect(title, "Frankenstein"))
```

We will begin by looking at a single book (Frankenstein) and then we'll compare and contrast 3 books (Frankenstein, Dracula, and Jekyll and Hyde).

1. Tidy Text Mining!

Now it's time to tokenize and tidy this text data.

```
tidy_book <- frankenstein |>
  mutate(line = row_number()) |>
  unnest_tokens(word, text, token = "words")   # (new name, input)
# default for unnest_tokens is token = "words", but can also use
#   "characters", "ngrams" with say n=2, "sentences", "regex" with
#   pattern, "tweets" with strip_url, etc.

tidy_book   # one row per word, instead of one per line
```

```
# A tibble: 76,204 x 4
   gutenberg_id title                                    line word
          <dbl> <chr>                                   <int> <chr>
 1           84 Frankenstein; Or, The Modern Prometheus     1 frankenstein
 2           84 Frankenstein; Or, The Modern Prometheus     2 <NA>
 3           84 Frankenstein; Or, The Modern Prometheus     3 or
 4           84 Frankenstein; Or, The Modern Prometheus     3 the
 5           84 Frankenstein; Or, The Modern Prometheus     3 modern
 6           84 Frankenstein; Or, The Modern Prometheus     3 prometheus
 7           84 Frankenstein; Or, The Modern Prometheus     4 <NA>
 8           84 Frankenstein; Or, The Modern Prometheus     5 by
 9           84 Frankenstein; Or, The Modern Prometheus     5 mary
10           84 Frankenstein; Or, The Modern Prometheus     5 wollstonecraft
# i 76,194 more rows
```

```r
frankenstein |> slice_tail(n = 10)
```

```
# A tibble: 10 x 3
   gutenberg_id text                                                          title
          <dbl> <chr>                                                         <chr>
 1           84 shall die, and what I now feel be no longer felt. Soon th~ Fran~
 2           84 miseries will be extinct. I shall ascend my funeral pile ~ Fran~
 3           84 exult in the agony of the torturing flames. The light of ~ Fran~
 4           84 will fade away; my ashes will be swept into the sea by th~ Fran~
 5           84 will sleep in peace, or if it thinks, it will not surely ~ Fran~
 6           84 Farewell."                                                   Fran~
 7           84 <NA>                                                         Fran~
 8           84 He sprang from the cabin-window as he said this, upon the~ Fran~
 9           84 which lay close to the vessel. He was soon borne away by ~ Fran~
10           84 lost in darkness and distance.                               Fran~
```

```r
tidy_book |> slice_tail(n = 20)
```

```
# A tibble: 20 x 4
   gutenberg_id title                                   line word
          <dbl> <chr>                                  <int> <chr>
 1           84 Frankenstein; Or, The Modern Prometheus  7356 which
 2           84 Frankenstein; Or, The Modern Prometheus  7356 lay
 3           84 Frankenstein; Or, The Modern Prometheus  7356 close
 4           84 Frankenstein; Or, The Modern Prometheus  7356 to
 5           84 Frankenstein; Or, The Modern Prometheus  7356 the
 6           84 Frankenstein; Or, The Modern Prometheus  7356 vessel
 7           84 Frankenstein; Or, The Modern Prometheus  7356 he
 8           84 Frankenstein; Or, The Modern Prometheus  7356 was
 9           84 Frankenstein; Or, The Modern Prometheus  7356 soon
10           84 Frankenstein; Or, The Modern Prometheus  7356 borne
11           84 Frankenstein; Or, The Modern Prometheus  7356 away
12           84 Frankenstein; Or, The Modern Prometheus  7356 by
13           84 Frankenstein; Or, The Modern Prometheus  7356 the
14           84 Frankenstein; Or, The Modern Prometheus  7356 waves
15           84 Frankenstein; Or, The Modern Prometheus  7356 and
16           84 Frankenstein; Or, The Modern Prometheus  7357 lost
17           84 Frankenstein; Or, The Modern Prometheus  7357 in
18           84 Frankenstein; Or, The Modern Prometheus  7357 darkness
19           84 Frankenstein; Or, The Modern Prometheus  7357 and
20           84 Frankenstein; Or, The Modern Prometheus  7357 distance
```

What are the most common words?

```r
tidy_book |>
  count(word, sort = TRUE)
```

```
# A tibble: 7,077 x 2
   word      n
   <chr> <int>
 1 the    4195
 2 and    2976
 3 i      2846
 4 of     2642
 5 to     2089
 6 my     1776
 7 a      1391
 8 in     1128
 9 was    1021
10 that   1017
# i 7,067 more rows
```

Stop words (get rid of common but not useful words)

Note: If you get "Error in loadNamespace(name) : there is no package called 'stopwords' ", first install package `stopwords`.

```r
get_stopwords() |> print(n = 50)   # snowball is default - somewhat smaller
```

```
# A tibble: 175 x 2
   word       lexicon
   <chr>      <chr>
 1 i          snowball
 2 me         snowball
 3 my         snowball
 4 myself     snowball
 5 we         snowball
 6 our        snowball
 7 ours       snowball
 8 ourselves  snowball
 9 you        snowball
10 your       snowball
```

```
11 yours      snowball
12 yourself   snowball
13 yourselves snowball
14 he         snowball
15 him        snowball
16 his        snowball
17 himself    snowball
18 she        snowball
19 her        snowball
20 hers       snowball
21 herself    snowball
22 it         snowball
23 its        snowball
24 itself     snowball
25 they       snowball
26 them       snowball
27 their      snowball
28 theirs     snowball
29 themselves snowball
30 what       snowball
31 which      snowball
32 who        snowball
33 whom       snowball
34 this       snowball
35 that       snowball
36 these      snowball
37 those      snowball
38 am         snowball
39 is         snowball
40 are        snowball
41 was        snowball
42 were       snowball
43 be         snowball
44 been       snowball
45 being      snowball
46 have       snowball
47 has        snowball
48 had        snowball
49 having     snowball
50 do         snowball
# i 125 more rows
```

```r
get_stopwords(source = "smart") |> print(n = 50)
```

```
# A tibble: 571 x 2
   word        lexicon
   <chr>       <chr>
 1 a           smart
 2 a's         smart
 3 able        smart
 4 about       smart
 5 above       smart
 6 according   smart
 7 accordingly smart
 8 across      smart
 9 actually    smart
10 after       smart
11 afterwards  smart
12 again       smart
13 against     smart
14 ain't       smart
15 all         smart
16 allow       smart
17 allows      smart
18 almost      smart
19 alone       smart
20 along       smart
21 already     smart
22 also        smart
23 although    smart
24 always      smart
25 am          smart
26 among       smart
27 amongst     smart
28 an          smart
29 and         smart
30 another     smart
31 any         smart
32 anybody     smart
33 anyhow      smart
34 anyone      smart
35 anything    smart
36 anyway      smart
37 anyways     smart
```

```
38 anywhere    smart
39 apart       smart
40 appear      smart
41 appreciate  smart
42 appropriate smart
43 are         smart
44 aren't      smart
45 around      smart
46 as          smart
47 aside       smart
48 ask         smart
49 asking      smart
50 associated  smart
# i 521 more rows
```

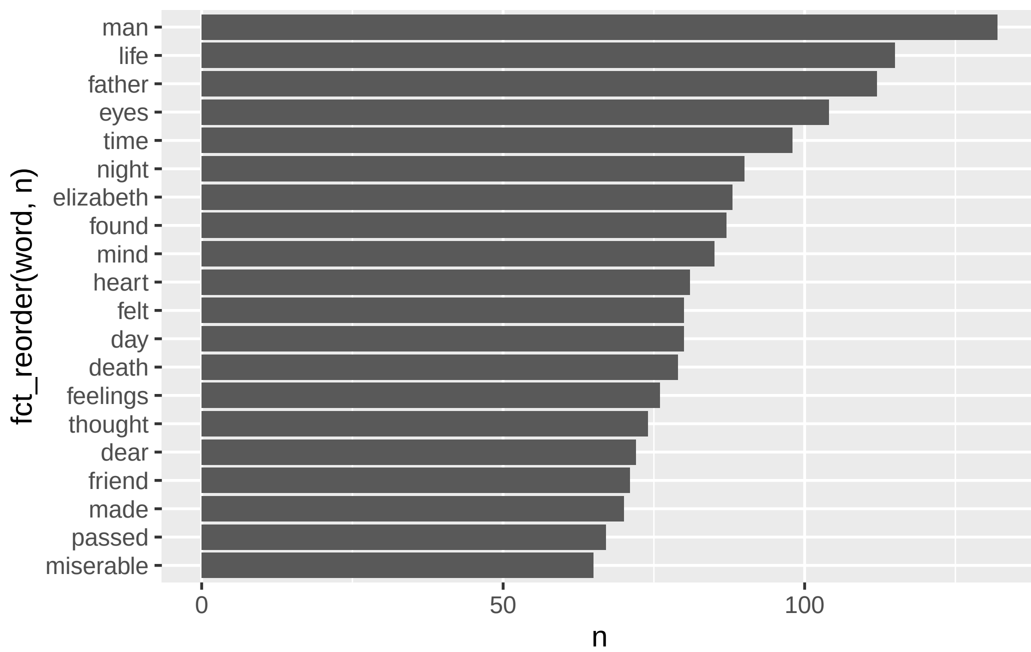
```
# will sometimes want to store if using over and over
#   - later with shiny apps will have to store and write as data file
smart_stopwords <- get_stopwords(source = "smart")
```

Try out using different languages (`language`) and different lexicons (`source`).

Another try at most common words

```
tidy_book |>
  anti_join(smart_stopwords) |>
  count(word, sort = TRUE) |>
  filter(word != "NA") |>
  slice_max(n, n = 20) |>
  ggplot(aes(fct_reorder(word, n), n)) +
  geom_col() +
  coord_flip()
```

```
Joining with `by = join_by(word)`
```



Sentiment analysis

Explore some sentiment lexicons. You'll want to match your choice of sentiment lexicon to your purpose:

- afinn: scored from -5 (very negative) to +5 (very positive)
- nrc: words are labeled with emotions like anger, fear, sadness, etc. There can be more than one row per word.
- bing: binary - listed words are either negative or positive

```
get_sentiments(lexicon = "afinn")
```

```
# A tibble: 2,477 x 2
   word       value
   <chr>      <dbl>
 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
# i 2,467 more rows
```

```r
get_sentiments(lexicon = "nrc")
```

```
# A tibble: 13,872 x 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
# i 13,862 more rows
```

```r
get_sentiments(lexicon = "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
# i 6,776 more rows
```

```r
afinn_sentiments <- get_sentiments(lexicon = "afinn")
nrc_sentiments <- get_sentiments(lexicon = "nrc")
bing_sentiments <- get_sentiments(lexicon = "bing")
```

Implement sentiment analysis using an `inner_join()`, so you only consider words both in your text and in the lexicon.

```r
tidy_book |>
  inner_join(bing_sentiments) |>
  count(sentiment)
```

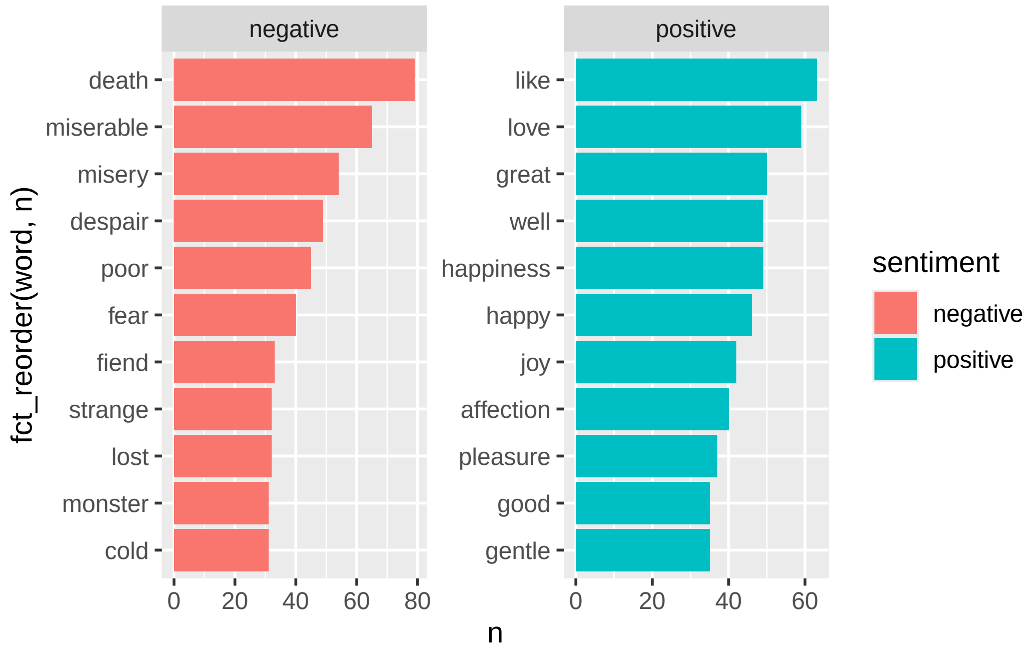
```
Joining with `by = join_by(word)`
```

```
# A tibble: 2 x 2
  sentiment     n
  <chr>     <int>
1 negative   3742
2 positive   2983
```

What words contribute the most to sentiment scores for Frankenstein? Let's walk through this pipe step-by-step.

```r
tidy_book |>
  inner_join(bing_sentiments) |>
  count(sentiment, word, sort = TRUE) |>
  group_by(sentiment) |>
  slice_max(n, n = 10) |>
  ungroup() |>
  ggplot(aes(x = fct_reorder(word, n), y = n, fill = sentiment)) +
    geom_col() +
    coord_flip() +
    facet_wrap(~ sentiment, scales = "free")
```

```
Joining with `by = join_by(word)`
```




```r
# Check out which words are associated with specific nrc emotions
get_sentiments("nrc") |>
  count(sentiment)
```

```
# A tibble: 10 x 2
   sentiment        n
   <chr>        <int>
 1 anger         1245
 2 anticipation   837
 3 disgust       1056
 4 fear          1474
 5 joy            687
 6 negative      3316
 7 positive      2308
 8 sadness       1187
 9 surprise       532
10 trust         1230
```

```r
get_sentiments("nrc") |>
  filter(sentiment == "joy") |>
  inner_join(tidy_book) |>
```

```
  count(word, sort = TRUE)
```

```
Joining with `by = join_by(word)`
```

```
# A tibble: 308 x 2
   word          n
   <chr>     <int>
 1 found        87
 2 friend       71
 3 love         59
 4 hope         50
 5 happiness    49
 6 happy        46
 7 sun          45
 8 joy          42
 9 affection    40
10 journey      36
# i 298 more rows
```

```
get_sentiments("nrc") |>
  filter(sentiment == "anger") |>
  inner_join(tidy_book) |>
  count(word, sort = TRUE)
```

```
Joining with `by = join_by(word)`
```

```
# A tibble: 370 x 2
   word          n
   <chr>     <int>
 1 death        79
 2 miserable    65
 3 misery       54
 4 words        54
 5 despair      49
 6 horror       45
 7 fear         40
 8 possessed    36
 9 fiend        33
10 feeling      27
# i 360 more rows
```

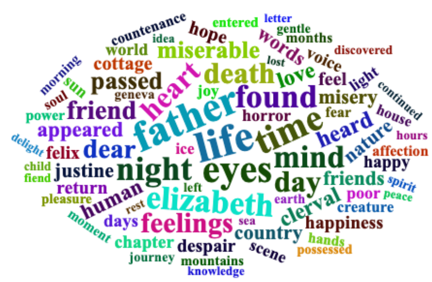
Make a wordcloud for Frankenstein.

```
# wordcloud wants a column with words and another column with counts
words <- tidy_book |>
  anti_join(stop_words) |>
  count(word) |>
  filter(word != "NA") |>
  arrange(desc(n))

# Note: this will look better in html than in the Plots window in RStudio
wordcloud(
  words = words$word,
  freq = words$n,
  max.words = 100,
  random.order = FALSE
)
```


```
# See Z's R Tip of the Day for suggestions on options
wordcloud(
  words = words$word,
  freq = words$n,
```

```
  max.words = 200,
  random.order = FALSE,
  rot.per = 0.35,
  scale = c(3.5, 0.25),
  colors = brewer.pal(6, "Dark2"))
```


```
# Or for even cooler looks, use wordcloud2 (for html documents)
words_df <- words |>
  slice_head(n = 80) |>
  data.frame()

wordcloud2(
  words_df,
  size = .25,
  shape = 'circle',
  minSize = 10
)
```



countenance
idea
entered
letter
gentle
months
hope
words
discovered
world
miserable
voice
lost
morning
cottage
death
love
feel
light
continued
sun
passed
heart
found
soul
geneva
joy
misery
power
friend
father
horror
fear
house
appeared
time
heard
life
nature
hours
delight
dear
mind
affection
felix
ice
happy
child
justine
night
eyes
day
friends
spirit
fiend
return
left
human
poor
peace
pleasure
elizabeth
clerval
earth
creature
rest
moment
days
feelings
sea
happiness
country
chapter
despair
hands
scene
possessed
journey
mountains
knowledge

```
# A couple of helpful links for customizing wordclouds:
#   https://www.youtube.com/watch?v=0cToDzeDLRI
#   https://towardsdatascience.com/create-a-word-cloud-with-r-bde3e7422e8a
```

You could do cool stuff here, like color the words by sentiment!

2. What is a document about?

Above, we read in a corpus called `three_works`. We'll use that here!

Count the word frequencies by title in this collection.

```
book_words <- three_works |>
  group_by(title) |>
  mutate(linenumber = row_number()) |>
  ungroup() |>
  unnest_tokens(word, text)

book_word_count <- book_words |>
  count(word, title, sort = TRUE)

book_word_count
```

```
# A tibble: 20,714 x 3
   word  title                                    n
   <chr> <chr>                                <int>
 1 the   Dracula                               7915
 2 and   Dracula                               5907
 3 i     Dracula                               4801
 4 to    Dracula                               4666
 5 the   Frankenstein; Or, The Modern Prometheus  4195
 6 of    Dracula                               3634
 7 and   Frankenstein; Or, The Modern Prometheus  2976
 8 a     Dracula                               2954
 9 i     Frankenstein; Or, The Modern Prometheus  2846
10 of    Frankenstein; Or, The Modern Prometheus  2642
# i 20,704 more rows
```

Look at positive/negative sentiment trajectory over the novels

```
book_words |>
  inner_join(bing_sentiments) |>
  count(title, index = linenumber %/% 80, sentiment) |>
# index approximates a chapter (every 80 lines)
  pivot_wider(names_from = sentiment, values_from = n, values_fill = 0) |>
  mutate(sentiment = positive - negative) |>
  ggplot(aes(x = index, y = sentiment, fill = title)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~title, ncol = 2, scales = "free_x")
```

```
Joining with `by = join_by(word)`
```

Calculate tf-idf.

The tf-idf statistic is term frequency times inverse document frequency, a quantity used for identifying terms that are especially important to a particular document. 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. We want to find words that define one document as opposed to others.

- tf = term frequency = proportion of times a term appears in a document.
- idf = inverse document frequency = log(number of documents / number of documents with the term), so that terms that appear in fewer documents are weighted higher, since those rarer words provide more information.

There's really no theory behind multiplying the two together - it just tends to work in practice. See this wikipedia entry for more details. (See also this site for a nice description of weaknesses of tf-idf.)

```r
book_tfidf <- book_word_count |>
  bind_tf_idf(word, title, n)

book_tfidf   # note idf = 0 when it appears in every document
```

```
# A tibble: 20,714 x 6
   word  title                                      n     tf   idf tf_idf
   <chr> <chr>                                  <int>  <dbl> <dbl>  <dbl>
 1 the   Dracula                                 7915 0.0480     0      0
 2 and   Dracula                                 5907 0.0358     0      0
 3 i     Dracula                                 4801 0.0291     0      0
 4 to    Dracula                                 4666 0.0283     0      0
 5 the   Frankenstein; Or, The Modern Prometheus 4195 0.0550     0      0
 6 of    Dracula                                 3634 0.0220     0      0
 7 and   Frankenstein; Or, The Modern Prometheus 2976 0.0391     0      0
 8 a     Dracula                                 2954 0.0179     0      0
 9 i     Frankenstein; Or, The Modern Prometheus 2846 0.0373     0      0
10 of    Frankenstein; Or, The Modern Prometheus 2642 0.0347     0      0
# i 20,704 more rows
```

Find *high* tf-idf words. The highest words will appear relatively often in one document, but not at all in others.

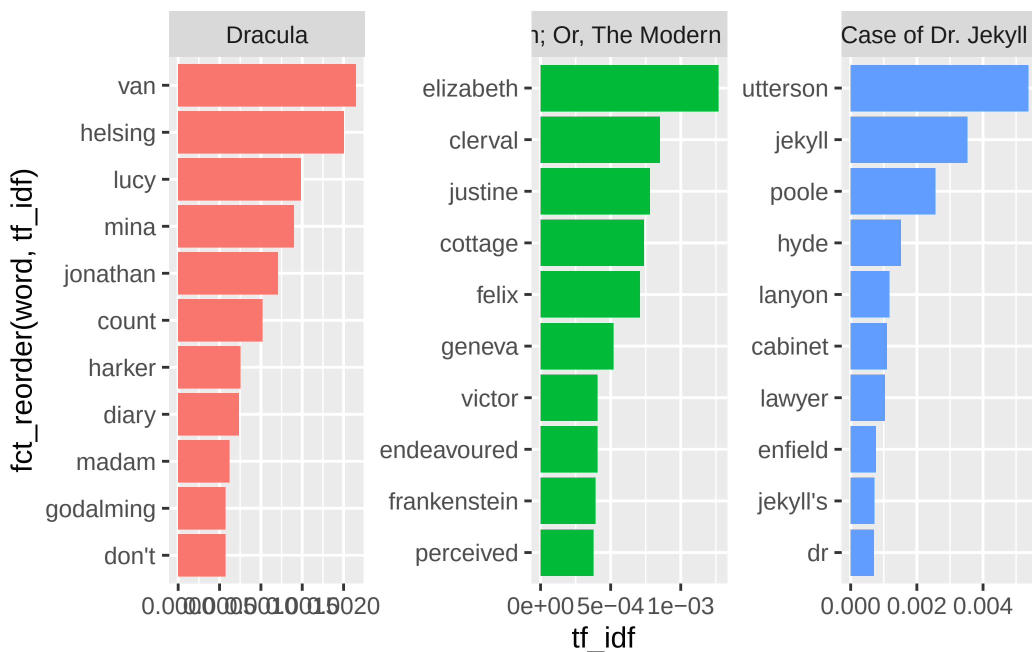
```r
book_tfidf |>
  arrange(-tf_idf)
```

```
# A tibble: 20,714 x 6
   word      title                                   n      tf   idf  tf_idf
   <chr>     <chr>                               <int>   <dbl> <dbl>   <dbl>
 1 utterson  The Strange Case of Dr. Jekyll and Mr.~   128 0.00489 1.10  0.00537
 2 jekyll    The Strange Case of Dr. Jekyll and Mr.~    84 0.00321 1.10  0.00353
```

```
 3 poole     The Strange Case of Dr. Jekyll and Mr.~    61 0.00233 1.10  0.00256
 4 van       Dracula                                   323 0.00196 1.10  0.00215
 5 helsing   Dracula                                   301 0.00182 1.10  0.00200
 6 hyde      The Strange Case of Dr. Jekyll and Mr.~    98 0.00375 0.405 0.00152
 7 lucy      Dracula                                   223 0.00135 1.10  0.00148
 8 mina      Dracula                                   210 0.00127 1.10  0.00140
 9 elizabeth Frankenstein; Or, The Modern Prometheus    88 0.00115 1.10  0.00127
10 jonathan  Dracula                                   181 0.00110 1.10  0.00120
# i 20,704 more rows
```

How can we visualize this? Let's go step-by-step.

```r
book_tfidf |>
  group_by(title) |>
  arrange(desc(tf_idf)) |>
  slice_max(tf_idf, n = 10) |>
  ungroup() |>
  ggplot(aes(x = fct_reorder(word, tf_idf), y = tf_idf, fill = title)) +
    geom_col(show.legend = FALSE) +
    coord_flip() +
    facet_wrap(~title, scales = "free")
```



```
# kind of boring - mostly proper nouns
```

N-grams… and beyond!

Let’s return to Frankenstein and look at 2-word combinations:

```
tidy_ngram <- frankenstein |>
  unnest_tokens(bigram, text, token = "ngrams", n = 2) |>
  filter(bigram != "NA")

tidy_ngram
```

```
# A tibble: 68,847 x 3
   gutenberg_id title                                  bigram
          <dbl> <chr>                                  <chr>
 1           84 Frankenstein; Or, The Modern Prometheus or the
 2           84 Frankenstein; Or, The Modern Prometheus the modern
 3           84 Frankenstein; Or, The Modern Prometheus modern prometheus
 4           84 Frankenstein; Or, The Modern Prometheus by mary
 5           84 Frankenstein; Or, The Modern Prometheus mary wollstonecraft
 6           84 Frankenstein; Or, The Modern Prometheus wollstonecraft godwin
 7           84 Frankenstein; Or, The Modern Prometheus godwin shelley
 8           84 Frankenstein; Or, The Modern Prometheus letter 1
 9           84 Frankenstein; Or, The Modern Prometheus letter 2
10           84 Frankenstein; Or, The Modern Prometheus letter 3
# i 68,837 more rows
```

What are the most common bigrams?

```
tidy_ngram |>
  count(bigram, sort = TRUE)
```

```
# A tibble: 38,574 x 2
   bigram      n
   <chr>   <int>
 1 of the    501
 2 of my     264
 3 in the    246
 4 i was     213
```

```
 5 i had     207
 6 that i    198
 7 and i     192
 8 and the   182
 9 to the    181
10 which i   145
# i 38,564 more rows
```

Let's use `separate()` from tidyr to remove stop words.

```r
# stop_words contains 1149 words from 3 lexicons
bigrams_filtered <- tidy_ngram |>
  separate(bigram, c("word1", "word2"), sep = " ") |>
  filter(!word1 %in% stop_words$word,
         !word2 %in% stop_words$word) |>
  count(word1, word2, sort = TRUE)
bigrams_filtered
```

```
# A tibble: 4,677 x 3
   word1       word2          n
   <chr>       <chr>      <int>
 1 natural     philosophy    11
 2 dear        victor        10
 3 native      country       10
 4 de          lacey          9
 5 fellow      creatures      8
 6 poor        girl           8
 7 mont        blanc          7
 8 native      town           6
 9 cornelius   agrippa        5
10 countenance expressed      5
# i 4,667 more rows
```

Now extend from a single document to our collection of documents. See which two-word combinations best identify books in the collection.

```r
book_twowords <- three_works |>
  group_by(title) |>
  mutate(linenumber = row_number()) |>
  ungroup() |>
  unnest_tokens(bigram, text, token = "ngrams", n = 2) |>
```

```r
  filter(bigram != "NA")

book_twowords |>
  count(bigram, sort = TRUE)
```

```
# A tibble: 102,837 x 2
   bigram       n
   <chr>    <int>
 1 of the    1494
 2 in the     952
 3 to the     596
 4 and the    579
 5 and i      554
 6 it was     526
 7 that i     526
 8 on the     507
 9 i was      484
10 i had      461
# i 102,827 more rows
```

```r
bigrams_filtered <- book_twowords |>
  separate(bigram, c("word1", "word2"), sep = " ") |>
  filter(!word1 %in% stop_words$word,
         !word2 %in% stop_words$word) |>
  count(word1, word2, sort = TRUE) |>
  filter(!is.na(word1) & !is.na(word2))

bigrams_filtered
```

```
# A tibble: 13,951 x 3
   word1    word2         n
   <chr>    <chr>     <int>
 1 van      helsing     282
 2 madam    mina         82
 3 lord     godalming    63
 4 dr       van          60
 5 dr       seward       55
 6 friend   john         54
 7 seward's diary        39
 8 poor     dear         34
```

```
 9 harker's journal      31
10 _dr      seward's     26
# i 13,941 more rows
```

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

bigrams_united
```

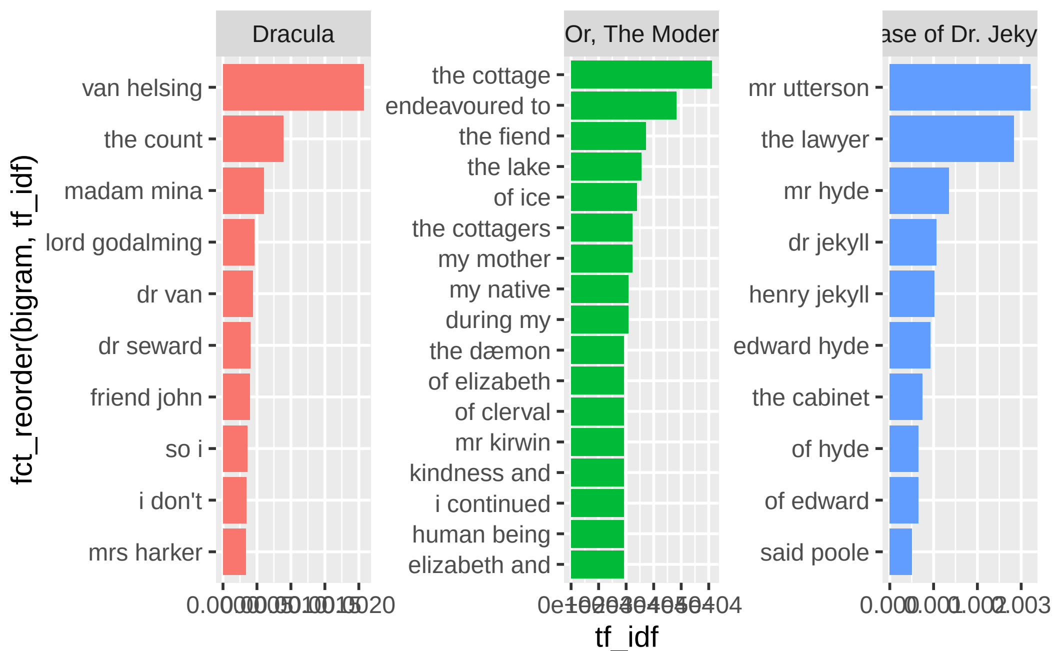
```
# A tibble: 13,951 x 2
   bigram              n
   <chr>           <int>
 1 van helsing       282
 2 madam mina         82
 3 lord godalming     63
 4 dr van             60
 5 dr seward          55
 6 friend john        54
 7 seward's diary     39
 8 poor dear          34
 9 harker's journal   31
10 _dr seward's       26
# i 13,941 more rows
```

```
bigram_tf_idf <- book_twowords |>
  count(title, bigram) |>
  bind_tf_idf(bigram, title, n) |>
  arrange(desc(tf_idf))

bigram_tf_idf |> arrange(desc(tf_idf))
```

```
# A tibble: 119,039 x 6
   title                                      bigram     n       tf   idf  tf_idf
   <chr>                                      <chr>  <int>    <dbl> <dbl>   <dbl>
 1 The Strange Case of Dr. Jekyll and Mr. Hy~ mr ut~    69 2.92e-3  1.10 3.21e-3
 2 The Strange Case of Dr. Jekyll and Mr. Hy~ the l~    61 2.58e-3  1.10 2.84e-3
 3 Dracula                                    van h~   282 1.88e-3  1.10 2.07e-3
 4 The Strange Case of Dr. Jekyll and Mr. Hy~ mr hy~    29 1.23e-3  1.10 1.35e-3
 5 The Strange Case of Dr. Jekyll and Mr. Hy~ dr je~    23 9.74e-4  1.10 1.07e-3
 6 The Strange Case of Dr. Jekyll and Mr. Hy~ henry~    22 9.32e-4  1.10 1.02e-3
```

```
 7 The Strange Case of Dr. Jekyll and Mr. Hy~ edwar~    20 8.47e-4  1.10 9.30e-4
 8 Dracula                                   the c~   121 8.08e-4  1.10 8.88e-4
 9 The Strange Case of Dr. Jekyll and Mr. Hy~ the c~    16 6.78e-4  1.10 7.44e-4
10 The Strange Case of Dr. Jekyll and Mr. Hy~ of ed~    14 5.93e-4  1.10 6.51e-4
# i 119,029 more rows
```

```
bigram_tf_idf |>
  group_by(title) |>
  arrange(desc(tf_idf)) |>
  slice_max(tf_idf, n = 10) |>
  ungroup() |>
  ggplot(aes(x = fct_reorder(bigram, tf_idf), y = tf_idf, fill = title)) +
    geom_col(show.legend = FALSE) +
    coord_flip() +
    facet_wrap(~title, scales = "free")
```



Sentence context using bigrams

Bigrams can also help us dive deeper into sentiment analysis. For example, even though "happy" carries positive sentiment, but when preceded by "not" as in this sentence: "I am not happy with you!" it conveys negative sentiment. Context can matter as much as mere presence!

Let's see which words associated with an afinn sentiment are most frequently preceded by "not":

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

bigrams_separated <- book_twowords |>
  separate(bigram, c("word1", "word2"), sep = " ") |>
  count(word1, word2, sort = TRUE) |>
  filter(!is.na(word1) & !is.na(word2))

bigrams_separated |> filter(word1 == "not")
```

```
# A tibble: 582 x 3
   word1 word2     n
   <chr> <chr> <int>
 1 not   be       77
 2 not   to       74
 3 not   know     62
 4 not   so       38
 5 not   have     36
 6 not   a        35
 7 not   yet      34
 8 not   the      31
 9 not   for      29
10 not   been     26
# i 572 more rows
```

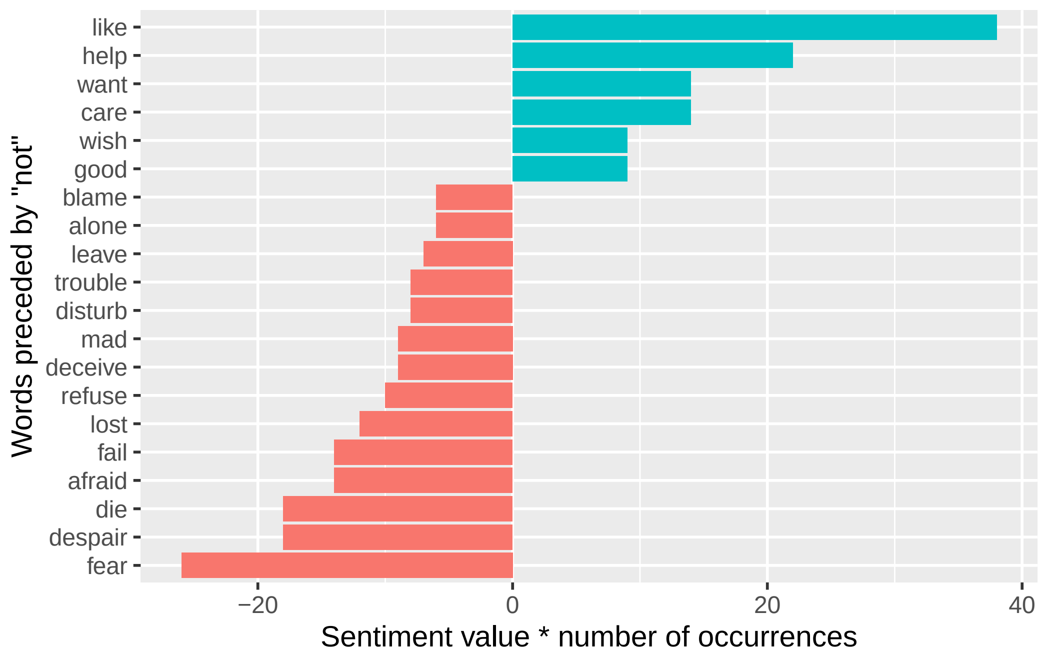
```
not_words <- bigrams_separated |>
  filter(word1 == "not") |>
  inner_join(afinn, by = c(word2 = "word")) |>
  arrange(desc(n))

not_words
```

```
# A tibble: 123 x 4
   word1 word2       n value
   <chr> <chr>   <int> <dbl>
 1 not   like       19     2
```

```
 2 not   want        14     1
 3 not   fear        13    -2
 4 not   help        11     2
 5 not   wish         9     1
 6 not   afraid       7    -2
 7 not   care         7     2
 8 not   fail         7    -2
 9 not   leave        7    -1
10 not   despair      6    -3
# i 113 more rows
```

We could then ask which words contributed the most in the "wrong" direction. One approach is to multiply their value by the number of times they appear (so that a word with a value of +3 occurring 10 times has as much impact as a word with a sentiment value of +1 occurring 30 times).

```
not_words |>
  mutate(contribution = n * value) |>
  arrange(desc(abs(contribution))) |>
  head(20) |>
  mutate(word2 = reorder(word2, contribution)) |>
  ggplot(aes(n * value, word2, fill = n * value > 0)) +
  geom_col(show.legend = FALSE) +
  labs(x = "Sentiment value * number of occurrences",
       y = "Words preceded by \"not\"")
```



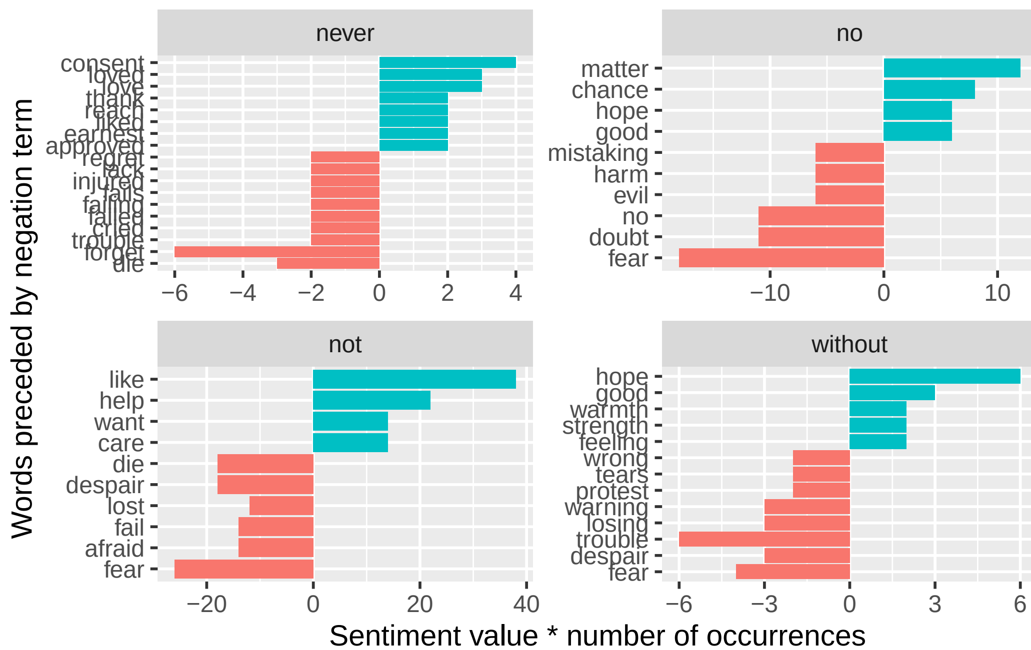
With this approach, we could expand our list of negation words, and then possibly even adjust afinn totals to reflect context!

```
# An example of expanding the list of negation words
negation_words <- c("not", "no", "never", "without")

negated_words <- bigrams_separated |>
  filter(word1 %in% negation_words) |>
  inner_join(afinn, by = c(word2 = "word")) |>
  arrange(desc(n))

negated_words
```

```
# A tibble: 232 x 4
   word1 word2      n value
   <chr> <chr>  <int> <dbl>
 1 not   like      19     2
 2 not   want      14     1
 3 not   fear      13    -2
 4 no    matter    12     1
 5 no    doubt     11    -1
 6 no    no        11    -1
```

```
 7 not    help       11      2
 8 no     fear        9     -2
 9 not    wish        9      1
10 not    afraid      7     -2
# i 222 more rows
```

```r
negated_words |>
  mutate(contribution = n * value) |>
  arrange(desc(abs(contribution))) |>
  group_by(word1) |>
  slice_max(abs(contribution), n = 10) |>
  ungroup() |>
  mutate(word2 = reorder(word2, contribution)) |>
  ggplot(aes(n * value, word2, fill = n * value > 0)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~ word1, scales = "free") +
    labs(x = "Sentiment value * number of occurrences",
         y = "Words preceded by negation term")
```



Creating a network graph

If we are interested in visualizing all relationships among words or bigrams, we can arrange the words into a network, which is a combination of connected nodes. A network graph has three elements:

- from: the node an edge is coming from
- to: the node an edge is going towards
- weight: A numeric value associated with each edge

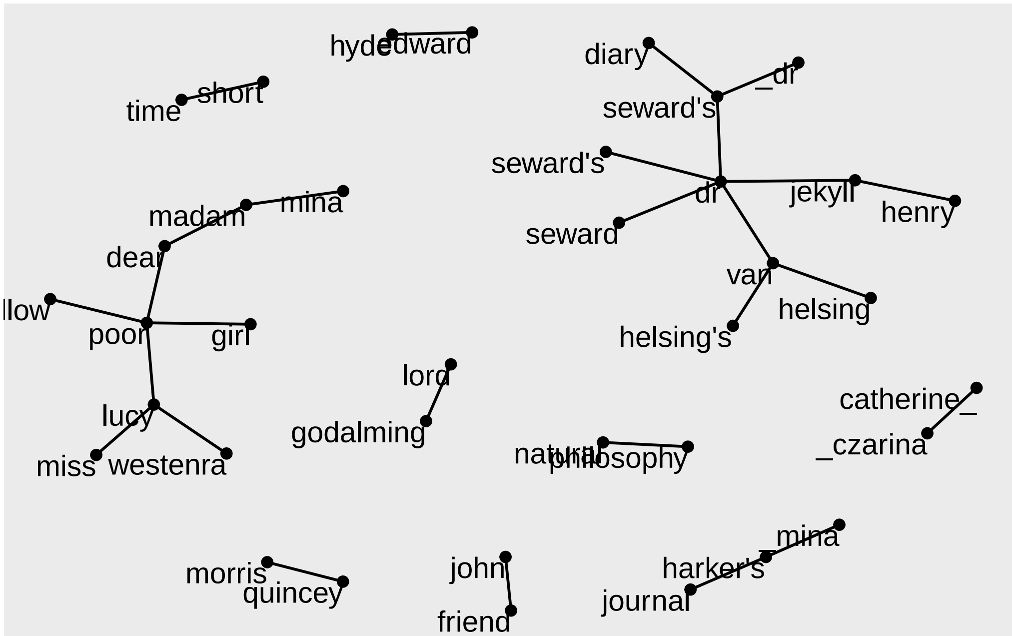
The `igraph` package has many powerful functions for manipulating and analyzing networks. One way to create an igraph object from tidy data is the `graph_from_data_frame()` function. Let's see how it works using Frankenstein:

```r
library(igraph)

# filter for only relatively common combinations
bigram_graph <- bigrams_filtered |>
  filter(n > 10) |>
  graph_from_data_frame()

bigram_graph
```

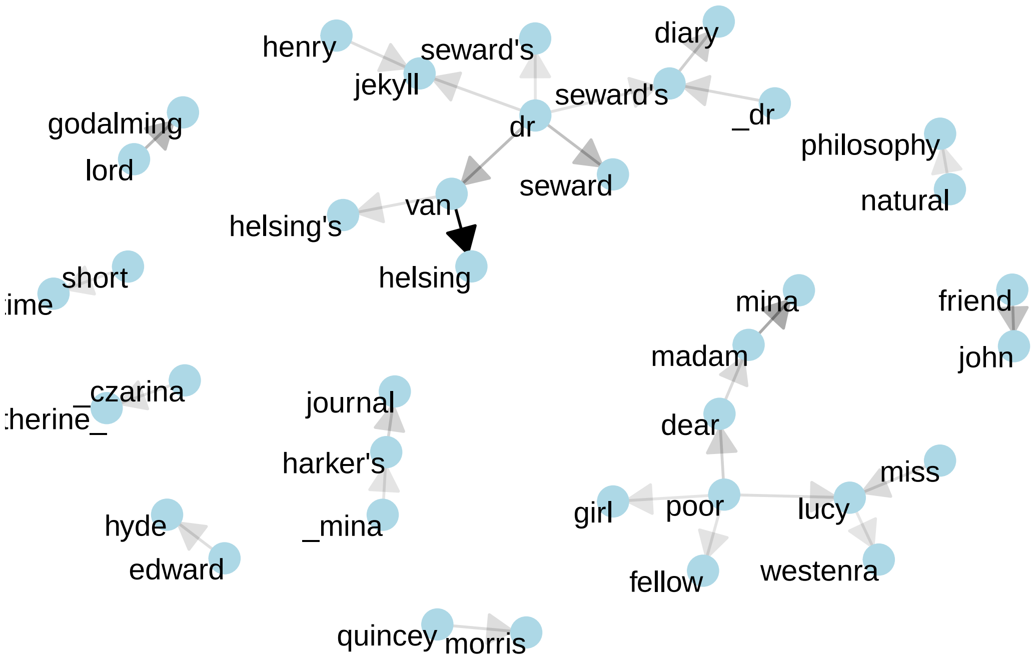
```
IGRAPH 6177fe9 DN-- 37 27 --
+ attr: name (v/c), n (e/n)
+ edges from 6177fe9 (vertex names):
 [1] van     ->helsing    madam   ->mina       lord    ->godalming
 [4] dr      ->van        dr      ->seward     friend  ->john
 [7] seward's->diary      poor    ->dear       harker's->journal
[10] _dr     ->seward's   dear    ->madam      miss    ->lucy
[13] dr      ->jekyll     henry   ->jekyll     poor    ->lucy
[16] quincey ->morris     edward  ->hyde       dr      ->seward's
[19] van     ->helsing's  _czarina->catherine_ poor    ->fellow
[22] _mina   ->harker's   poor    ->girl       dr      ->seward’s
+ ... omitted several edges
```

```r
# Use ggraph to convert into a network plot
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)
```




```
# polish the graph
set.seed(2020)
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()
```



Correlating pairs of words

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. Following Section 4.2 of Text Mining with R, we will use the `widyr` package.

Consider the book "Frankenstein" divided into 10-line sections. We may be interested in what words tend to appear within the same section.

```
frankenstein_section_words <- frankenstein |>
  select(-gutenberg_id) |>
  mutate(section = row_number() %/% 10) |>
  filter(section > 0) |>
  unnest_tokens(word, text) |>
  filter(!word %in% stop_words$word,
         !is.na(word))

frankenstein_section_words
```

```
# A tibble: 27,313 x 3
   title                                        section word
```

```
   <chr>                                       <dbl> <chr>
 1 Frankenstein; Or, The Modern Prometheus         1 letter
 2 Frankenstein; Or, The Modern Prometheus         1 1
 3 Frankenstein; Or, The Modern Prometheus         1 letter
 4 Frankenstein; Or, The Modern Prometheus         1 2
 5 Frankenstein; Or, The Modern Prometheus         1 letter
 6 Frankenstein; Or, The Modern Prometheus         1 3
 7 Frankenstein; Or, The Modern Prometheus         1 letter
 8 Frankenstein; Or, The Modern Prometheus         1 4
 9 Frankenstein; Or, The Modern Prometheus         1 chapter
10 Frankenstein; Or, The Modern Prometheus         1 1
# i 27,303 more rows
```

```
# count words co-occuring within sections
library(widyr)
word_pairs <- frankenstein_section_words |>
  pairwise_count(word, section, sort = TRUE)

word_pairs
```

```
# A tibble: 856,676 x 3
   item1     item2         n
   <chr>     <chr>     <dbl>
 1 elizabeth father       20
 2 father    elizabeth    20
 3 life      death        19
 4 death     life         19
 5 eyes      life         18
 6 justine   poor         18
 7 life      eyes         18
 8 poor      justine      18
 9 elizabeth dear         17
10 native    country      17
# i 856,666 more rows
```

```
# What words occur most often with "life"?
word_pairs |>
  filter(item1 == "life")
```

```
# A tibble: 2,330 x 3
```

```
   item1 item2        n
   <chr> <chr>    <dbl>
 1 life  death       19
 2 life  eyes        18
 3 life  friend      16
 4 life  father      16
 5 life  mind        14
 6 life  day         13
 7 life  feelings    13
 8 life  found       13
 9 life  time        12
10 life  passed      12
# i 2,320 more rows
```

We can quantify pairwise correlation using the Phi coefficient (which simplifies to the Pearson correlation coefficient with numeric data). The Phi coefficient measures how often two words appear together relative to how often they appear separately (so we don't just pick up the most common words).

```r
# we need to filter for at least relatively common words first
word_cors <- frankenstein_section_words |>
  group_by(word) |>
  filter(n() >= 10) |>
  pairwise_cor(word, section, sort = TRUE)

word_cors
```

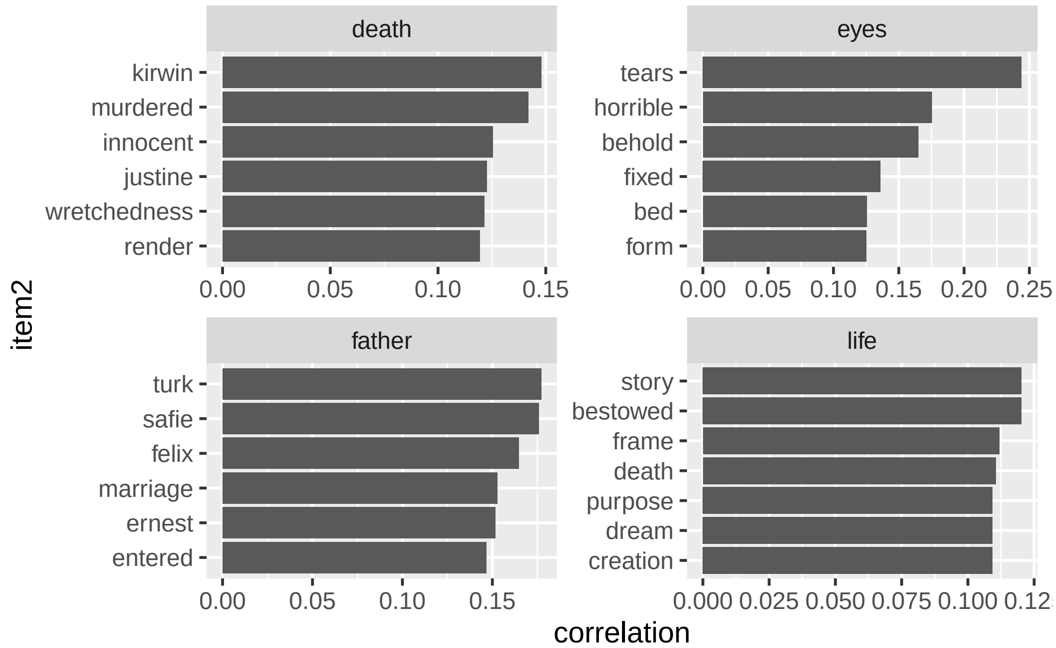
```
# A tibble: 406,406 x 3
   item1      item2      correlation
   <chr>      <chr>            <dbl>
 1 philosophy natural          0.703
 2 natural    philosophy       0.703
 3 thou       thy              0.550
 4 thy        thou             0.550
 5 understood language         0.499
 6 language   understood       0.499
 7 felix      agatha           0.470
 8 agatha     felix            0.470
 9 creatures  fellow           0.465
10 fellow     creatures        0.465
# i 406,396 more rows
```

```r
# What words are most correlated with "life"?
word_cors |>
  filter(item1 == "life")
```

```
# A tibble: 637 x 3
   item1 item2    correlation
   <chr> <chr>          <dbl>
 1 life  story          0.120
 2 life  bestowed       0.120
 3 life  frame          0.112
 4 life  death          0.111
 5 life  purpose        0.109
 6 life  dream          0.109
 7 life  creation       0.109
 8 life  deprived       0.108
 9 life  hideous        0.108
10 life  money          0.105
# i 627 more rows
```

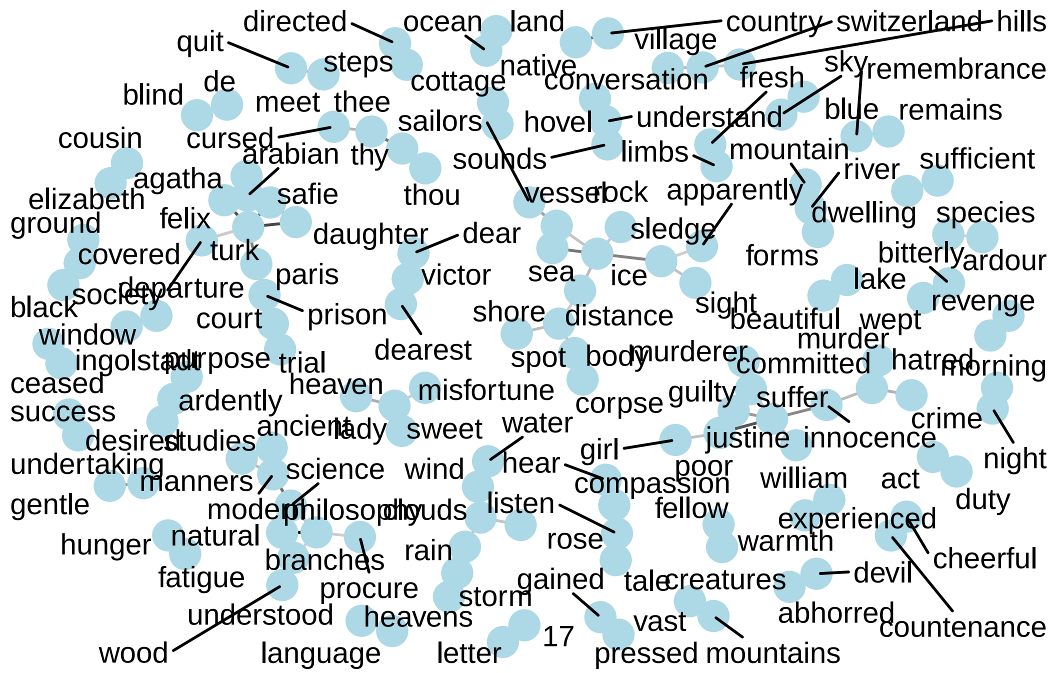
Plot words most associated with a set of interesting words:

```r
word_cors |>
  filter(item1 %in% c("life", "death", "father", "eyes")) |>
  group_by(item1) |>
  slice_max(correlation, n = 6) |>
  ungroup() |>
  mutate(item2 = reorder(item2, correlation)) |>
  ggplot(aes(item2, correlation)) +
    geom_bar(stat = "identity") +
    facet_wrap(~ item1, scales = "free") +
    coord_flip()
```



Finally, create a network graph to visualize the correlations and clusters of words that were found by the widyr package

```
set.seed(2016)

word_cors |>
  filter(correlation > .25) |>
  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()
```



Topic Modeling

As described in Ch 6 of Text Mining with R:

> In text mining, we often have collections of documents, such as blog posts or news articles, that we'd like to divide into natural groups so that we can understand them separately. Topic modeling is a method for unsupervised classification of such documents, similar to clustering on numeric data, which finds natural groups of items even when we're not sure what we're looking for.
>
> Latent Dirichlet allocation (LDA) is a particularly popular method for fitting a topic model. It treats each document as a mixture of topics, and each topic as a mixture of words. This allows documents to "overlap" each other in terms of content, rather than being separated into discrete groups, in a way that mirrors typical use of natural language.

We will attempt to apply LDA to our collection of three works. While not a typical application of topic modeling, it'll be interesting to see if any common themes or groupings emerge.

Again, from Ch 6:

> Latent Dirichlet allocation is one of the most common algorithms for topic modeling. Without diving into the math behind the model, we can understand it as being guided by two principles.

> > Every document is a mixture of topics. We imagine that each document may contain words from several topics in particular proportions. For example, in a two-topic model we could say "Document 1 is 90% topic A and 10% topic B, while Document 2 is 30% topic A and 70% topic B."
> >
> > Every topic is a mixture of words. For example, we could imagine a two-topic model of American news, with one topic for "politics" and one for "entertainment." The most common words in the politics topic might be "President", "Congress", and "government", while the entertainment topic may be made up of words such as "movies", "television", and "actor". Importantly, words can be shared between topics; a word like "budget" might appear in both equally.
>
> LDA is a mathematical method for estimating both of these at the same time: finding the mixture of words that is associated with each topic, while also determining the mixture of topics that describes each document.

In order to implement LDA on our three books, we need to first "cast" our tidy data as a document-term matrix (DTM) where:

- each row represents one document (such as a book or article),
- each column represents one term, and
- each value (typically) contains the number of appearances of that term in that document.

From Section 5.2 of Text Mining with R:

> Since most pairings of document and term do not occur (they have the value zero), DTMs are usually implemented as sparse matrices. These objects can be treated as though they were matrices (for example, accessing particular rows and columns), but are stored in a more efficient format.
>
> DTM objects cannot be used directly with tidy tools, just as tidy data frames cannot be used as input for most text mining packages. Thus, the tidytext package provides two verbs (`tidy` and `cast`) that convert between the two formats.
>
> A DTM is typically comparable to a tidy data frame after a count or a group_by/summarize that contains counts or another statistic for each combination of a term and document.

```r
# cast the collection of 3 works as a document-term matrix
library(tm)
```

```
Loading required package: NLP
```

```
Attaching package: 'NLP'

The following object is masked from 'package:ggplot2':

    annotate
```

```r
three_books_dtm <- book_word_count |>
  filter(!word %in% stop_words$word,
         !is.na(word)) |>
  cast_dtm(title, word, n)

# set a seed so that the output of the model is predictable
library(topicmodels)
three_books_lda <- LDA(three_books_dtm, k = 2, control = list(seed = 1234))
three_books_lda
```

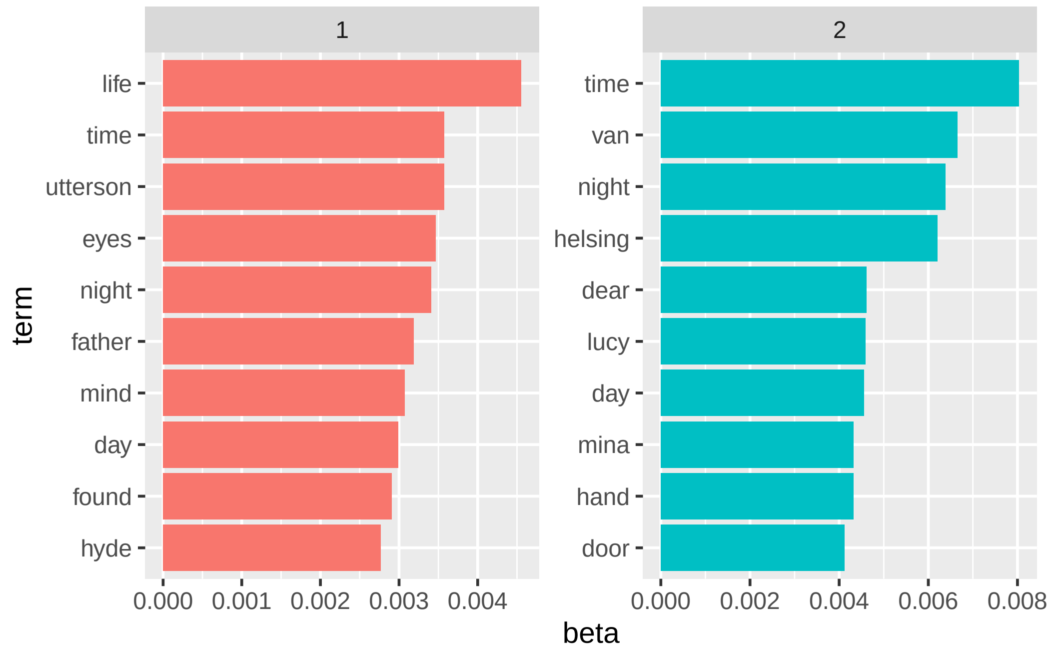
```
A LDA_VEM topic model with 2 topics.
```

After fitting our LDA model, we will first focus on the beta variable, which is the probability of a word being generated by a specific topic. Then we'll turn to the gamma variable, which are the per-document per-topic probabilities, or the proportion of words from a document generated by a specific topic.

```r
three_books_topics <- tidy(three_books_lda, matrix = "beta")
three_books_topics
```

```
# A tibble: 25,968 x 3
   topic term        beta
   <int> <chr>      <dbl>
 1     1 time    3.58e- 3
 2     2 time    8.03e- 3
 3     1 van     1.26e-14
 4     2 van     6.65e- 3
 5     1 night   3.41e- 3
 6     2 night   6.39e- 3
 7     1 helsing 1.91e-14
 8     2 helsing 6.20e- 3
 9     1 dear    2.18e- 3
10     2 dear    4.61e- 3
# i 25,958 more rows
```

```r
# Find the most common words within each topic
three_books_top_terms <- three_books_topics |>
  group_by(topic) |>
  slice_max(beta, n = 10) |>
  ungroup() |>
  arrange(topic, -beta)

three_books_top_terms |>
  mutate(term = reorder_within(term, beta, topic)) |>
  ggplot(aes(beta, term, fill = factor(topic))) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~ topic, scales = "free") +
    scale_y_reordered()
```




```r
# This would be much cooler with more documents and if we were able
#   to anti_join to remove proper nouns

# Find words with greatest difference between two topics, using log ratio
beta_wide <- three_books_topics |>
  mutate(topic = paste0("topic", topic)) |>
  pivot_wider(names_from = topic, values_from = beta) |>
```

```r
  filter(topic1 > .001 | topic2 > .001) |>
  mutate(log_ratio = log2(topic2 / topic1))

beta_wide
```

```
# A tibble: 196 x 4
   term      topic1  topic2 log_ratio
   <chr>      <dbl>   <dbl>     <dbl>
 1 time    3.58e- 3 0.00803     1.17 
 2 van     1.26e-14 0.00665    38.9  
 3 night   3.41e- 3 0.00639     0.906
 4 helsing 1.91e-14 0.00620    38.2  
 5 dear    2.18e- 3 0.00461     1.08 
 6 lucy    5.62e-14 0.00459    36.3  
 7 day     2.99e- 3 0.00455     0.607
 8 hand    1.98e- 3 0.00433     1.12 
 9 mina    2.40e-14 0.00433    37.4  
10 door    2.12e- 3 0.00412     0.956
# i 186 more rows
```

```r
beta_wide |>
  arrange(desc(abs(log_ratio))) |>
  slice_max(abs(log_ratio), n = 20) |>
  mutate(term = reorder(term, log_ratio)) |>
  ggplot(aes(log_ratio, term, fill = log_ratio > 0)) +
    geom_col(show.legend = FALSE) +
    labs(x = "Log ratio of Beta values",
         y = "Words in three works")
```


```
# find the gamma variable for each document and topic
three_books_documents <- tidy(three_books_lda, matrix = "gamma")
three_books_documents
```

```
# A tibble: 6 x 3
  document                                    topic      gamma
  <chr>                                       <int>      <dbl>
1 Dracula                                         1 0.000158
2 The Strange Case of Dr. Jekyll and Mr. Hyde     1 1.00
3 Frankenstein; Or, The Modern Prometheus         1 1.00
4 Dracula                                         2 1.00
5 The Strange Case of Dr. Jekyll and Mr. Hyde     2 0.00000613
6 Frankenstein; Or, The Modern Prometheus         2 0.00000190
```

```
# Dracula = Topic 2; other two books = Topic 1!
```

On Your Own: Harry Potter

The `potter_untidy` dataset includes the text of 7 books of the Harry Potter series by J.K. Rowling. For a brief overview of the books (or movies), see this quote from Wikipedia:

Harry Potter is a series of seven fantasy novels written by British author J. K. Rowling. The novels chronicle the lives of a young wizard, Harry Potter, and his friends Hermione Granger and Ron Weasley, all of whom are students at Hogwarts School of Witchcraft and Wizardry. The main story arc concerns Harry's conflict with Lord Voldemort, a dark wizard who intends to become immortal, overthrow the wizard governing body known as the Ministry of Magic, and subjugate all wizards and Muggles (non-magical people).

A few analyses from SDS 164:

```r
# 10 most common words in each book, excluding stop words
potter_tidy |>
  count(title, word) |>
  anti_join(stop_words) |>
  group_by(title) |>
  slice_max(n, n = 10) |>
  mutate(rank = 1:10) |>
   select(-n) |>
  pivot_wider (names_from = title, values_from = word) |>
  print(width = Inf)
```

```
Joining with `by = join_by(word)`
```

```
# A tibble: 10 x 8
    rank `Sorcerer's Stone` `Chamber of Secrets` `Prisoner of Azkaban`
   <int> <chr>              <chr>                <chr>
 1     1 harry              harry                harry
 2     2 ron                ron                  ron
 3     3 hagrid             hermione             hermione
 4     4 hermione           malfoy               professor
 5     5 professor          lockhart             lupin
 6     6 looked             professor            black
 7     7 snape              weasley              looked
 8     8 dumbledore         looked               hagrid
 9     9 uncle              time                 snape
10    10 time               eyes                 harry's
   `Goblet of Fire` `Order of the Phoenix` `Half-Blood Prince` `Deathly Hallows`
   <chr>            <chr>                  <chr>               <chr>
 1 harry            harry                  harry               harry
 2 ron              hermione               dumbledore          hermione
```

```
3 hermione         ron                    ron                  ron
4 dumbledore       sirius                 hermione             wand
5 looked           professor              looked               dumbledore
6 weasley          dumbledore             slughorn             looked
7 hagrid           looked                 snape                voldemort
8 eyes             umbridge               malfoy               eyes
9 moody            weasley                time                 death
10 professor       voice                  professor            time
```

```
# Repeat above after removing character first and last names
potter_tidy |>
  count(title, word) |>
  anti_join(stop_words) |>
  anti_join(potter_names, join_by(word == firstname)) |>
  anti_join(potter_names, join_by(word == lastname)) |>
  group_by(title) |>
  slice_max(n, n = 10, with_ties = FALSE) |>
  mutate(rank = 1:10) |>
   select(-n) |>
  pivot_wider (names_from = title, values_from = word) |>
  print(width = Inf)
```

```
Joining with `by = join_by(word)`
```

```
# A tibble: 10 x 8
    rank `Sorcerer's Stone` `Chamber of Secrets` `Prisoner of Azkaban`
   <int> <chr>              <chr>                <chr>
 1     1 professor          professor            professor
 2     2 looked             looked               looked
 3     3 uncle              time                 harry's
 4     4 time               eyes                 eyes
 5     5 harry's            harry's              time
 6     6 door               dobby                door
 7     7 eyes               door                 head
 8     8 yeh                head                 voice
 9     9 head               voice                heard
10    10 told               school               hand
   `Goblet of Fire` `Order of the Phoenix` `Half-Blood Prince` `Deathly Hallows`
   <chr>            <chr>                  <chr>               <chr>
 1 looked           professor              looked              wand
 2 eyes             looked                 time                looked
```

```
 3 professor        voice                professor          eyes
 4 crouch           time                 hand               death
 5 time             door                 eyes               time
 6 wand             head                 voice              voice
 7 voice            harry's              dark               harry's
 8 head             eyes                 wand               door
 9 told             wand                 door               hand
10 harry's          hand                 head               head
```

```
# still get "harry's" and "professor" but otherwise looks good

# top 10 names in each book (after excluding "the")
potter_tidy |>
  count(title, word) |>
  semi_join(potter_names, join_by(word == firstname)) |>
  filter(word != "the") |> # ADD for #6
  group_by(title) |>
  slice_max(n, n = 10, with_ties = FALSE) |>
  mutate(rank = 1:10) |>
   select(-n) |>
  pivot_wider (names_from = title, values_from = word) |>
  print(width = Inf)
```

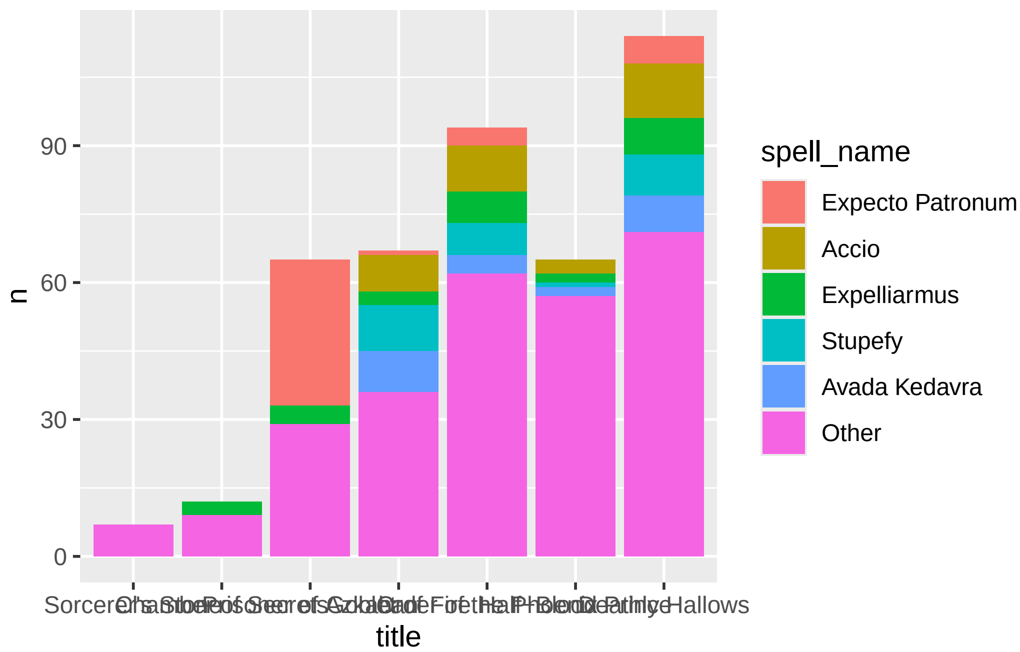
```
# A tibble: 10 x 8
    rank `Sorcerer's Stone` `Chamber of Secrets` `Prisoner of Azkaban`
   <int> <chr>              <chr>                <chr>
 1     1 harry              harry                harry
 2     2 ron                ron                  ron
 3     3 hermione           hermione             hermione
 4     4 dudley             fred                 sirius
 5     5 vernon             ginny                neville
 6     6 neville            sir                  madam
 7     7 great              george               great
 8     8 petunia            great                fred
 9     9 nearly             percy                vernon
10    10 madam              nearly               percy
   `Goblet of Fire` `Order of the Phoenix` `Half-Blood Prince` `Deathly Hallows`
   <chr>            <chr>                  <chr>               <chr>
 1 harry            harry                  harry               harry
 2 ron              hermione               ron                 hermione
 3 hermione         ron                    hermione            ron
```

```
 4 cedric          sirius             ginny          great
 5 sirius          fred               great          lord
 6 fred            george             sir            luna
 7 great           neville            lord           bill
 8 george          ginny              fred           ginny
 9 percy           great              tom            albus
10 rita            luna               draco          fred
```

```
# spell statistics by book
potter_tidy |>
  left_join(potter_spells, join_by(word == first_word)) |>
  group_by(title) |>
  summarize(num_spells_cast = sum(!is.na(spell_name)),
            spells_per_10kwords = mean(!is.na(spell_name)) * 10000,
            num_unique_spells = n_distinct(spell_name) - 1)  # Why -1??
```

```
# A tibble: 7 x 4
  title                 num_spells_cast spells_per_10kwords num_unique_spells
  <fct>                           <int>               <dbl>             <dbl>
1 Sorcerer's Stone                    7               0.899                 4
2 Chamber of Secrets                 12               1.41                  9
3 Prisoner of Azkaban                65               6.17                 14
4 Goblet of Fire                     67               3.49                 27
5 Order of the Phoenix                94               3.63                 28
6 Half-Blood Prince                  65               3.79                 24
7 Deathly Hallows                   114               5.77                 34
```

```
# plot of top spells by book
potter_tidy |>
  left_join(potter_spells, join_by(word == first_word)) |>
  drop_na(spell_name) |>
  mutate(spell_name = fct_infreq(spell_name),
         spell_name = fct_lump_n(spell_name, n = 5)) |>
    count(title, spell_name) |>
  ggplot() +
  geom_col(aes(x = title, y = n, fill = spell_name), position = "stack")
```



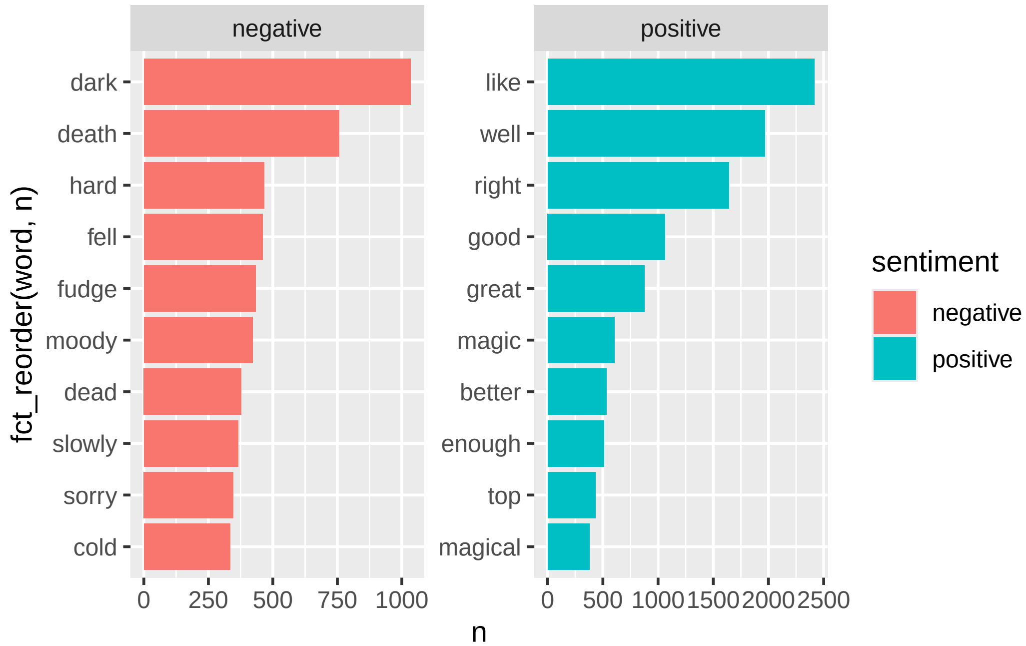
New stuff!

1. What words contribute the most to negative and positive sentiment scores? Show a faceted bar plot of the top 10 negative and the top 10 positive words (according to the "bing" lexicon) across the entire series.

```
bing_sentiments <- get_sentiments(lexicon = "bing")

potter_tidy |>
  inner_join(bing_sentiments) |>
  count(sentiment, word, sort = TRUE) |>
  group_by(sentiment) |>
  slice_max(n, n = 10) |>
  ungroup() |>
  ggplot(aes(x = fct_reorder(word, n), y = n, fill = sentiment)) +
    geom_col() +
    coord_flip() +
    facet_wrap(~ sentiment, scales = "free")
```

```
Joining with `by = join_by(word)`
```

```
Warning in inner_join(potter_tidy, bing_sentiments): Detected an unexpected many-to-many rela
i Row 41432 of `x` matches multiple rows in `y`.
i Row 2698 of `y` matches multiple rows in `x`.
i If a many-to-many relationship is expected, set `relationship =
  "many-to-many"` to silence this warning.
```



2. Find a list of the top 10 words associated with "fear" and with "trust" (according to the "nrc" lexicon) across the entire series.

```
potter_tidy |>
  inner_join(nrc_sentiments) |>
  filter(sentiment == c("fear", "trust")) |>
  count(sentiment, word, sort = TRUE) |>
  group_by(sentiment) |> #I'm not sure if you mean the 10 ten words associated with fear a
  slice_max(n, n = 10, with_ties = FALSE) |>
  print(n = Inf)
```

```
Joining with `by = join_by(word)`
```

```
Warning in inner_join(potter_tidy, nrc_sentiments): Detected an unexpected many-to-many rela
i Row 15 of `x` matches multiple rows in `y`.
```

```
i Row 11469 of `y` matches multiple rows in `x`.
i If a many-to-many relationship is expected, set `relationship =
  "many-to-many"` to silence this warning.
```

```
Warning: There was 1 warning in `filter()`.
i In argument: `sentiment == c("fear", "trust")`.
Caused by warning in `sentiment == c("fear", "trust")`:
! longer object length is not a multiple of shorter object length
```

```
# A tibble: 20 x 3
# Groups:   sentiment [2]
   sentiment word          n
   <chr>     <chr>     <int>
 1 fear      death       377
 2 fear      feeling     198
 3 fear      fire        185
 4 fear      crouch      152
 5 fear      mad         152
 6 fear      kill        143
 7 fear      scar        142
 8 fear      shaking     135
 9 fear      darkness    131
10 fear      bad         126
11 trust     professor   968
12 trust     good        544
13 trust     found       304
14 trust     ministry    299
15 trust     school      290
16 trust     sir         208
17 trust     top         204
18 trust     lord        196
19 trust     ground      194
20 trust     feeling     193
```

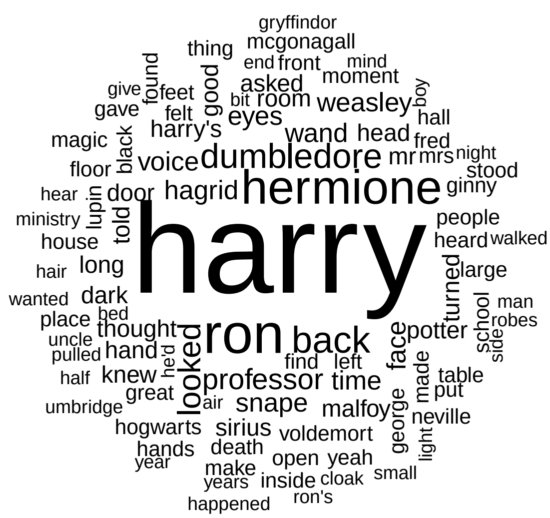
3. Make a wordcloud for the entire series after removing stop words using the “smart” source.

```
smart_stopwords <- get_stopwords(source = "smart")

hp_words <- potter_tidy |>
  anti_join(smart_stopwords) |>
  count(word) |>
```

```
  filter(word != "NA") |>
  arrange(desc(n))
```

```
Joining with `by = join_by(word)`
```

```
wordcloud(
  words = hp_words$word,
  freq = hp_words$n,
  max.words = 100,
  random.order = FALSE
)
```



4. Create a wordcloud with the top 20 negative words and the top 20 positive words in the Harry Potter series according to the bing lexicon. The words should be sized by their respective counts and colored based on whether their sentiment is positive or negative. (Feel free to be resourceful and creative to color words by a third variable!)

```
pos_neg <- potter_tidy |>
  inner_join(get_sentiments("bing")) |>
  count(sentiment, word, sort = TRUE) |>
```

```
  group_by(sentiment) |>
  top_n(20) |>
  ungroup()
```

```
Joining with `by = join_by(word)`
```

```
Warning in inner_join(potter_tidy, get_sentiments("bing")): Detected an unexpected many-to-ma
i Row 41432 of `x` matches multiple rows in `y`.
i Row 2698 of `y` matches multiple rows in `x`.
i If a many-to-many relationship is expected, set `relationship =
  "many-to-many"` to silence this warning.
```

```
Selecting by n
```

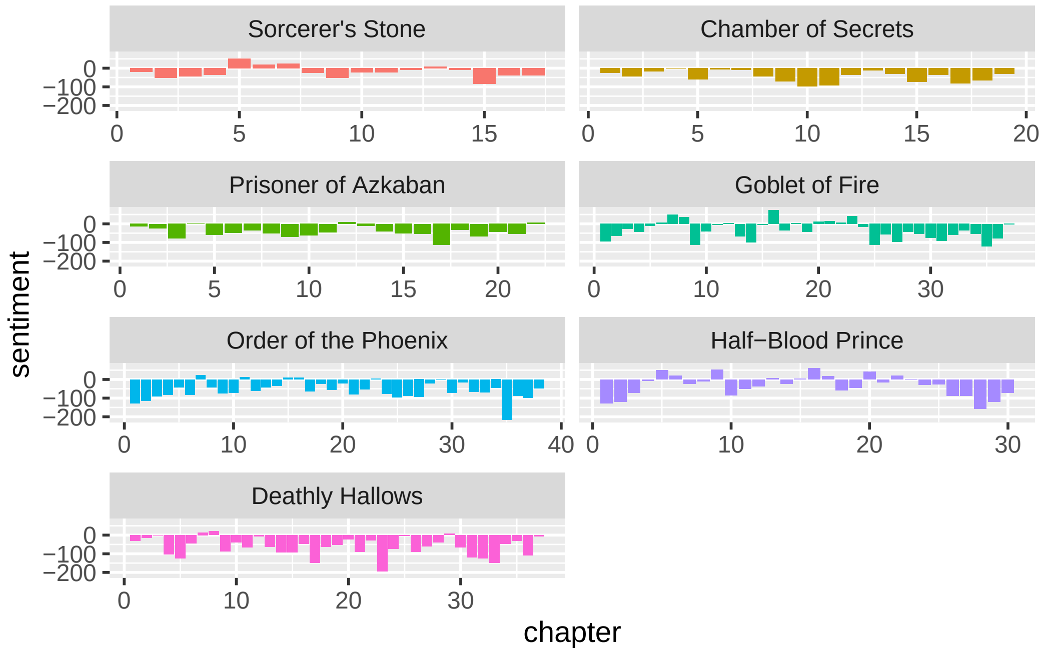
```
wordcloud(
  word = pos_neg$word,
  freq = pos_neg$n,
  random.order = FALSE,
  rot.per = 0,
  ordered.colors = TRUE,
  colors = brewer.pal(6, "Dark2")[factor(pos_neg$sentiment)]
)
```

5. Make a faceted bar chart to compare the positive/negative sentiment trajectory over the 7 Harry Potter books. You should have one bar per chapter (thus chapter becomes the index), and the bar should extend up from 0 if there are more positive than negative words in a chapter (according to the "bing" lexicon), and it will extend down from 0 if there are more negative than positive words.

```
potter_tidy |>
  inner_join(get_sentiments("bing")) |>
  count(title, chapter, sentiment) |>
  pivot_wider(names_from = sentiment, values_from = n, values_fill = 0) |>
  mutate(sentiment = positive - negative) |>
  ggplot(aes(x = chapter, y = sentiment, fill = title)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~title, ncol = 2, scales = "free_x")
```

```
Joining with `by = join_by(word)`
```

```
Warning in inner_join(potter_tidy, get_sentiments("bing")): Detected an unexpected many-to-ma
i Row 41432 of `x` matches multiple rows in `y`.
i Row 2698 of `y` matches multiple rows in `x`.
i If a many-to-many relationship is expected, set `relationship =
  "many-to-many"` to silence this warning.
```



6. Repeat (5) using a faceted scatterplot to show the average sentiment score according to the "afinn" lexicon for each chapter. (Hint: use `mutate(chapter_factor = factor(chapter))` to treat chapter as a factor variable.)

```
potter_tidy |>
  inner_join(get_sentiments("afinn")) |>
  mutate(chapter_factor = factor(chapter)) |>
  group_by(title, chapter) |>
    mutate(sentiment = mean(value)) |>
  ggplot(aes(x = chapter, y = sentiment, fill = title, color = title)) +
    geom_point(show.legend = FALSE) +
    facet_wrap(~title, ncol = 2, scales = "free_x")
```

```
Joining with `by = join_by(word)`
```

7. Make a faceted bar plot showing the top 10 words that distinguish each book according to the tf-idf statistic.

```
potter_tidy |>
  count(word, title, sort = TRUE) |>
  bind_tf_idf(word, title, n) |>
  group_by(title) |>
  arrange(desc(tf_idf)) |>
  slice_max(tf_idf, n = 10) |>
  ungroup() |>
  ggplot(aes(x = fct_reorder(word, tf_idf), y = tf_idf, fill = title)) +
    geom_col(show.legend = FALSE) +
    coord_flip() +
    facet_wrap(~title, scales = "free")
```

8. Repeat (7) to show the top 10 2-word combinations that distinguish each book.

```
hp_twowords <- potter_untidy |>
  unnest_tokens(bigram, text, token = "ngrams", n = 2) |>
  filter(bigram != "NA") |>
  separate(bigram, c("word1", "word2"), sep = " ") |>
  filter(!word1 %in% stop_words$word,
         !word2 %in% stop_words$word) |>
  filter(!is.na(word1) & !is.na(word2))

hp_twowords
```

```
# A tibble: 137,802 x 5
   title            chapter book_num word1     word2
   <fct>              <dbl>    <dbl> <chr>     <chr>
 1 Sorcerer's Stone       1        1 privet    drive
 2 Sorcerer's Stone       1        1 perfectly normal
 3 Sorcerer's Stone       1        1 firm      called
 4 Sorcerer's Stone       1        1 called    grunnings
 5 Sorcerer's Stone       1        1 usual     amount
 6 Sorcerer's Stone       1        1 time      craning
 7 Sorcerer's Stone       1        1 garden    fences
```

```
 8 Sorcerer's Stone       1        1 fences    spying
 9 Sorcerer's Stone       1        1 son       called
10 Sorcerer's Stone       1        1 called    dudley
# i 137,792 more rows
```

```
hp_bigrams_united <- hp_twowords |>
  unite(bigram, word1, word2, sep = " ")

hp_bigrams_united
```

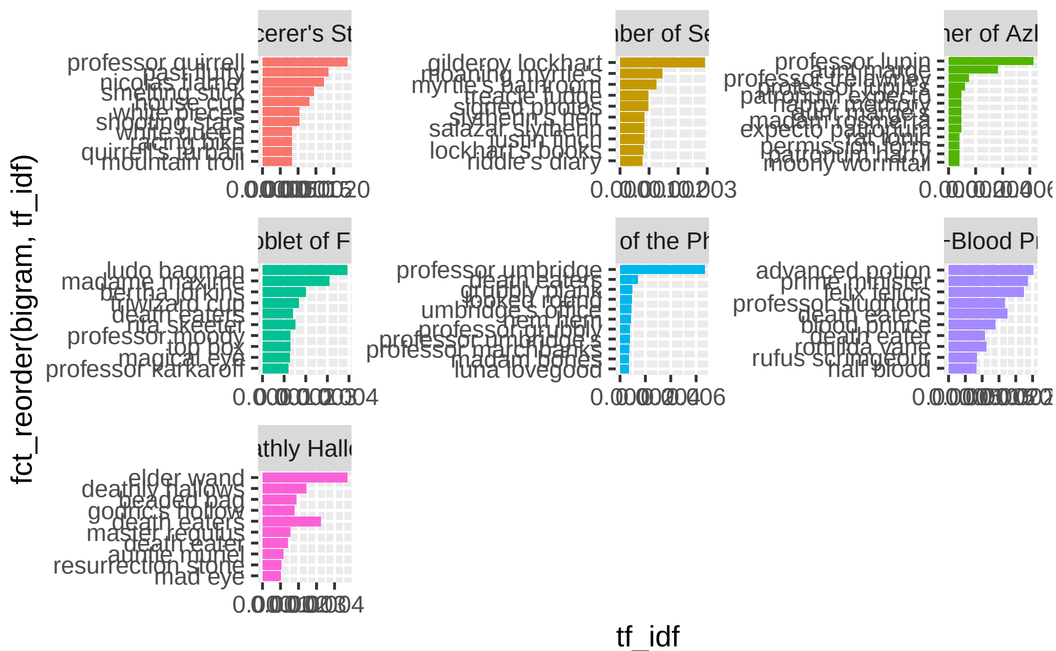
```
# A tibble: 137,802 x 4
   title            chapter book_num bigram
   <fct>              <dbl>    <dbl> <chr>
 1 Sorcerer's Stone       1        1 privet drive
 2 Sorcerer's Stone       1        1 perfectly normal
 3 Sorcerer's Stone       1        1 firm called
 4 Sorcerer's Stone       1        1 called grunnings
 5 Sorcerer's Stone       1        1 usual amount
 6 Sorcerer's Stone       1        1 time craning
 7 Sorcerer's Stone       1        1 garden fences
 8 Sorcerer's Stone       1        1 fences spying
 9 Sorcerer's Stone       1        1 son called
10 Sorcerer's Stone       1        1 called dudley
# i 137,792 more rows
```

```
hp_bigram_tf_idf <- hp_bigrams_united |>
  count(title, bigram) |>
  bind_tf_idf(bigram, title, n) |>
  arrange(desc(tf_idf))

hp_bigram_tf_idf |> arrange(desc(tf_idf))
```

```
# A tibble: 107,166 x 6
   title                bigram                  n      tf   idf  tf_idf
   <fct>                <chr>               <int>   <dbl> <dbl>   <dbl>
 1 Order of the Phoenix professor umbridge    173 0.00533 1.25  0.00667
 2 Prisoner of Azkaban  professor lupin       107 0.00738 0.847 0.00625
 3 Deathly Hallows      elder wand             58 0.00241 1.95  0.00470
 4 Goblet of Fire       ludo bagman            49 0.00201 1.95  0.00391
 5 Prisoner of Azkaban  aunt marge             42 0.00290 1.25  0.00363
```

```
 6 Deathly Hallows      death eaters           139 0.00578 0.560 0.00324
 7 Goblet of Fire       madame maxime           89 0.00365 0.847 0.00309
 8 Chamber of Secrets   gilderoy lockhart       28 0.00232 1.25  0.00291
 9 Half-Blood Prince    advanced potion         27 0.00129 1.95  0.00252
10 Deathly Hallows      deathly hallows         30 0.00125 1.95  0.00243
# i 107,156 more rows
```

```r
hp_bigram_tf_idf |>
  group_by(title) |>
  arrange(desc(tf_idf)) |>
  slice_max(tf_idf, n = 10) |>
  ungroup() |>
  ggplot(aes(x = fct_reorder(bigram, tf_idf), y = tf_idf, fill = title)) +
    geom_col(show.legend = FALSE) +
    coord_flip() +
    facet_wrap(~title, scales = "free")
```



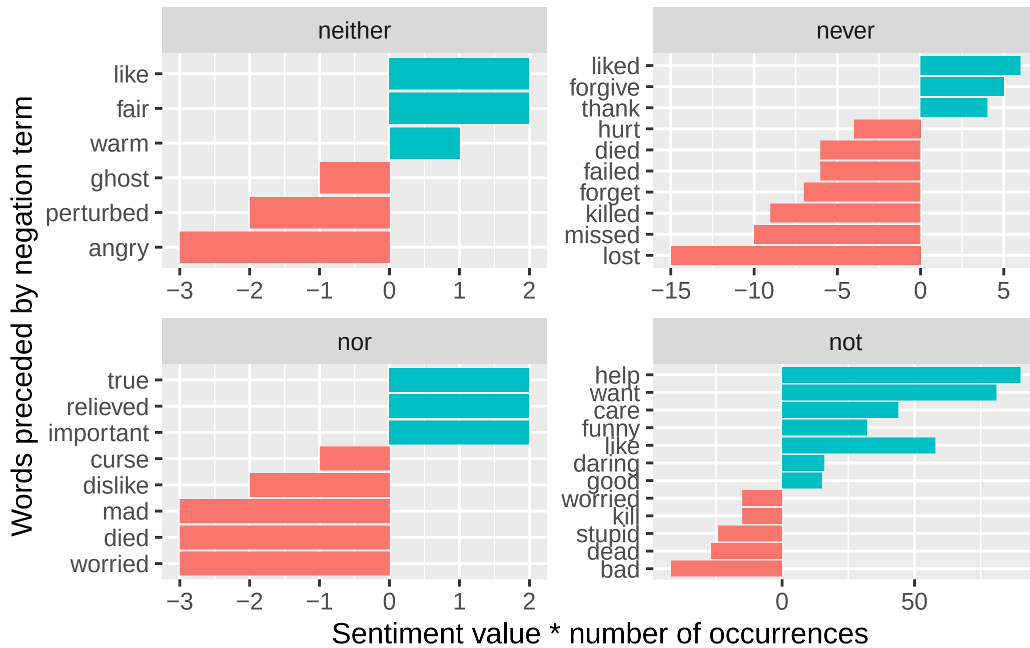
9. Find which words contributed most in the "wrong" direction using the afinn sentiment combined with how often a word appears among all 7 books. Come up with a list of 4 negation words, and for each negation word, illustrate the words associated with the largest "wrong" contributions in a faceted bar plot.

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

hp_twowords2 <- potter_untidy |>
  unnest_tokens(bigram, text, token = "ngrams", n = 2) |>
  filter(bigram != "NA")

hp_bigrams_separated <- hp_twowords2 |>
  separate(bigram, c("word1", "word2"), sep = " ") |>
  count(word1, word2, sort = TRUE) |>
  filter(!is.na(word1) & !is.na(word2))

hp_negation_words <- c("neither", "nor", "not", "never")

hp_negated_words <- hp_bigrams_separated |>
  filter(word1 %in% hp_negation_words) |>
  inner_join(afinn, by = c(word2 = "word")) |>
  arrange(desc(n))

hp_negated_words
```

```
# A tibble: 273 x 4
   word1 word2      n value
   <chr> <chr>  <int> <dbl>
 1 not   want      81     1
 2 not   help      45     2
 3 not   like      29     2
 4 not   care      22     2
 5 not   bad       14    -3
 6 not   wish      14     1
 7 not   stupid    12    -2
 8 not   stop      11    -1
 9 not   matter    10     1
10 not   dead       9    -3
# i 263 more rows
```

```r
hp_negated_words |>
  mutate(contribution = n * value) |>
  arrange(desc(abs(contribution))) |>
  group_by(word1) |>
  slice_max(abs(contribution), n = 10) |>
  ungroup() |>
```

```
  mutate(word2 = reorder(word2, contribution)) |>
  ggplot(aes(n * value, word2, fill = n * value > 0)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~ word1, scales = "free") +
    labs(x = "Sentiment value * number of occurrences",
         y = "Words preceded by negation term")
```



10. Select a set of 4 "interesting" terms and then use the Phi coefficient to find and plot the 6 words most correlated with each of your "interesting" words. Start by dividing `potter_tidy` into 80-word sections and then remove names and spells and stop words.

```
library(widyr)

potter_section_words <- potter_tidy |>
  mutate(section = 1 + row_number() %/% 80) |>
  filter(!word %in% stop_words$word,
         !is.na(word),
         !word %in% potter_names$firstname,
         !word %in% potter_names$lastname,
         !word %in% potter_spells$spell_name,
         !word %in% potter_spells$spell,
```

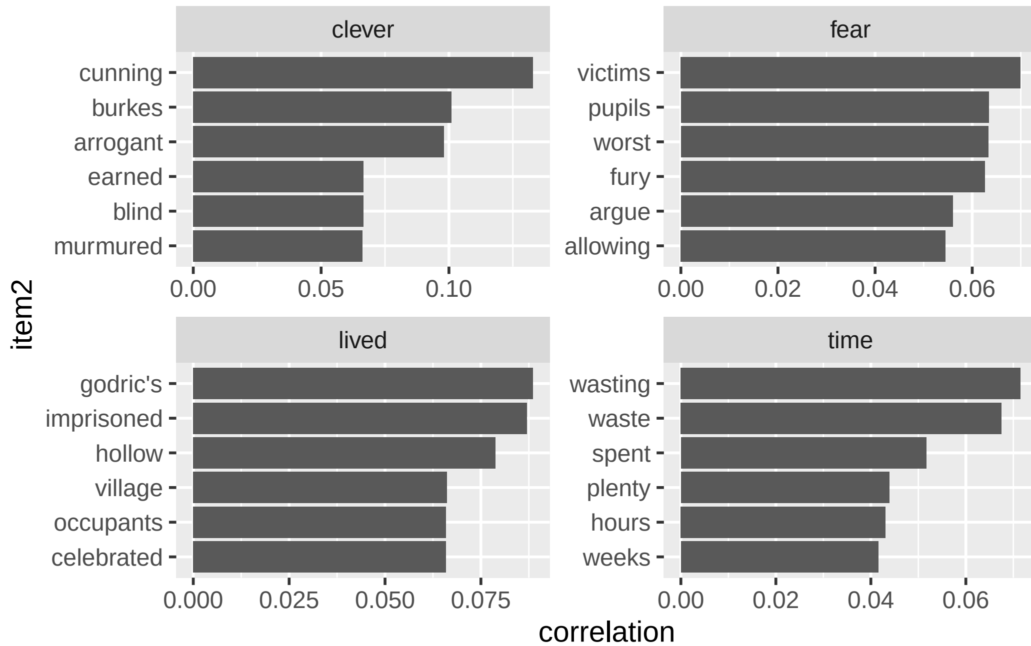
```r
         !word %in% potter_spells$first_word,
         !word %in% potter_spells$second_word)

potter_section_words
```

```
# A tibble: 346,372 x 5
   title            chapter book_num word      section
   <fct>              <dbl>    <dbl> <chr>       <dbl>
 1 Sorcerer's Stone       1        1 boy             1
 2 Sorcerer's Stone       1        1 lived           1
 3 Sorcerer's Stone       1        1 privet          1
 4 Sorcerer's Stone       1        1 drive           1
 5 Sorcerer's Stone       1        1 proud           1
 6 Sorcerer's Stone       1        1 perfectly       1
 7 Sorcerer's Stone       1        1 normal          1
 8 Sorcerer's Stone       1        1 people          1
 9 Sorcerer's Stone       1        1 expect          1
10 Sorcerer's Stone       1        1 involved        1
# i 346,362 more rows
```

```r
potter_word_cors <- potter_section_words |>
  group_by(word) |>
  filter(n() >= 10) |>
  pairwise_cor(word, section, sort = TRUE)

potter_word_cors
```

```
# A tibble: 28,222,656 x 3
   item1     item2     correlation
   <chr>     <chr>           <dbl>
 1 snare     devil's         1
 2 devil's   snare           1
 3 grubbly   plank           0.925
 4 plank     grubbly         0.925
 5 crescent  magnolia        0.904
 6 magnolia  crescent        0.904
 7 fletchley finch           0.897
 8 finch     fletchley       0.897
 9 prophet   daily           0.852
10 daily     prophet         0.852
# i 28,222,646 more rows
```

```
potter_word_cors |>
  filter(item1 %in% c("clever", "lived", "time", "fear")) |>
  group_by(item1) |>
  slice_max(correlation, n = 6) |>
  ungroup() |>
  mutate(item2 = reorder(item2, correlation)) |>
  ggplot(aes(item2, correlation)) +
    geom_bar(stat = "identity") +
    facet_wrap(~ item1, scales = "free") +
    coord_flip()
```



11. Create a network graph to visualize the correlations and clusters of words that were found by the `widyr` package in (10).

```
library(igraph)
set.seed(7777)

potter_word_cors |>
filter(correlation > .5) |>
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()
```

12. Use LDA to fit a 2-topic model to all 7 Harry Potter books. Be sure to remove names, spells, and stop words before running your topic models. (a) Make a plot to illustrate words with greatest difference between two topics, using log ratio. (b) Print a table with the gamma variable for each document and topic. Based on (a) and (b), can you interpret what the two topics represent?

```
library(tm)

potter_book_count <- potter_tidy |>
  count(word, title, sort = TRUE)

potter_tidy_dtm <- potter_book_count |>
  filter(!word %in% stop_words$word,
         !is.na(word),
         !word %in% potter_names$firstname,
         !word %in% potter_names$lastname,
```

```
          !word %in% potter_spells$spell_name,
          !word %in% potter_spells$spell,
          !word %in% potter_spells$first_word,
          !word %in% potter_spells$second_word) |>
  cast_dtm(title, word, n)

library(topicmodels)
potter_tidy_lda <- LDA(potter_tidy_dtm, k = 2, control = list(seed = 2003))
potter_tidy_lda
```

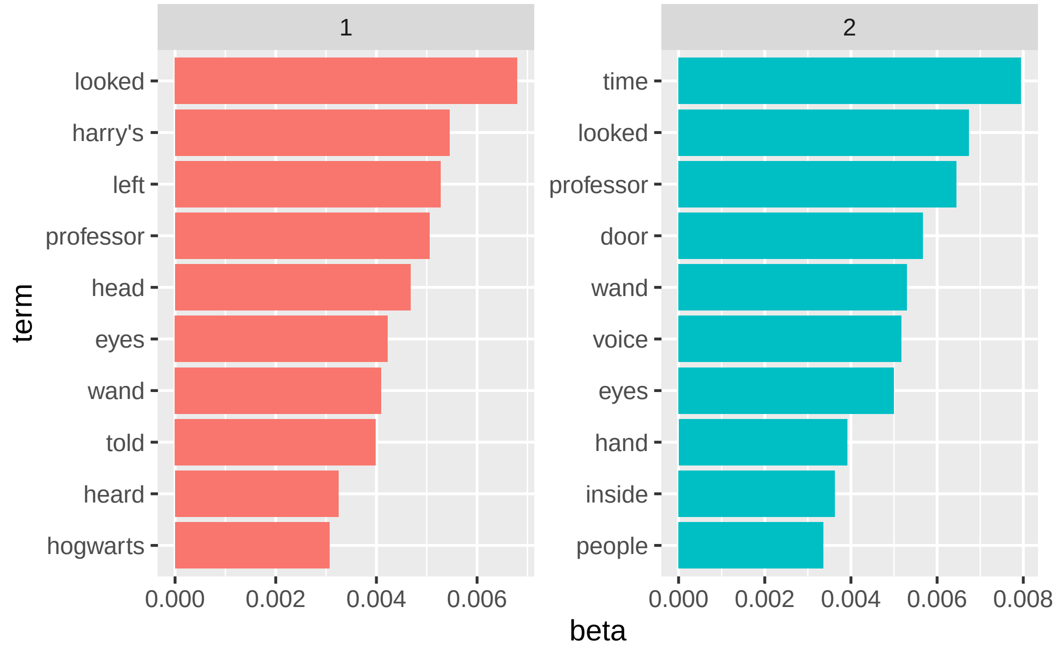
```
A LDA_VEM topic model with 2 topics.
```

```
potter_books_topics <- tidy(potter_tidy_lda, matrix = "beta")
three_books_topics
```

```
# A tibble: 25,968 x 3
   topic term        beta
   <int> <chr>      <dbl>
 1     1 time    3.58e- 3
 2     2 time    8.03e- 3
 3     1 van     1.26e-14
 4     2 van     6.65e- 3
 5     1 night   3.41e- 3
 6     2 night   6.39e- 3
 7     1 helsing 1.91e-14
 8     2 helsing 6.20e- 3
 9     1 dear    2.18e- 3
10     2 dear    4.61e- 3
# i 25,958 more rows
```

```
potter_books_top_terms <- potter_books_topics |>
  group_by(topic) |>
  slice_max(beta, n = 10) |>
  ungroup() |>
  arrange(topic, -beta)

potter_books_top_terms |>
  mutate(term = reorder_within(term, beta, topic)) |>
  ggplot(aes(beta, term, fill = factor(topic))) +
```

```r
    geom_col(show.legend = FALSE) +
    facet_wrap(~ topic, scales = "free") +
    scale_y_reordered()
```



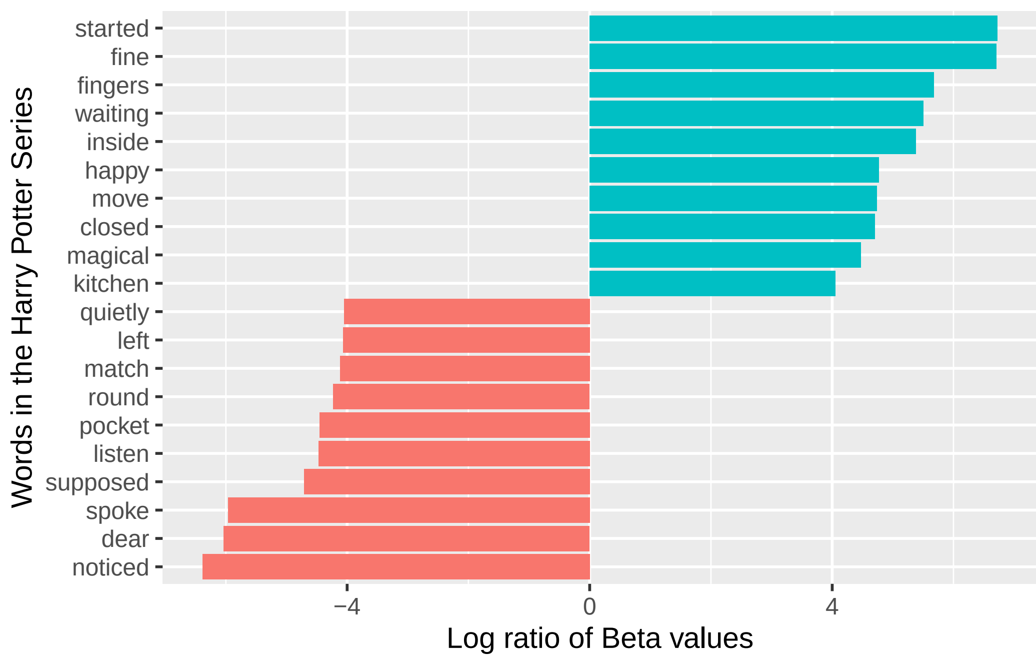
A.) A plot to illustrate words with greatest difference between two topics, using log ratio.

```r
potter_beta <- potter_books_topics |>
  mutate(topic = paste0("topic", topic)) |>
  pivot_wider(names_from = topic, values_from = beta) |>
  filter(topic1 > .001 | topic2 > .001) |>
  mutate(log_ratio = log2(topic2 / topic1))

potter_beta
```

```
# A tibble: 191 x 4
   term       topic1  topic2 log_ratio
   <chr>       <dbl>   <dbl>     <dbl>
 1 professor 0.00506 0.00645    0.351
 2 wand      0.00410 0.00530    0.373
 3 looked    0.00680 0.00674   -0.0124
 4 voice     0.00305 0.00517    0.763
```

```
 5 time       0.00160 0.00794    2.31
 6 door       0.00163 0.00567    1.80
 7 head       0.00468 0.00307   -0.609
 8 harry's    0.00545 0.00266   -1.04
 9 eyes       0.00422 0.00500    0.242
10 death      0.00249 0.00191   -0.385
# i 181 more rows
```

```
potter_beta |>
  arrange(desc(abs(log_ratio))) |>
  slice_max(abs(log_ratio), n = 20) |>
  mutate(term = reorder(term, log_ratio)) |>
  ggplot(aes(log_ratio, term, fill = log_ratio > 0)) +
    geom_col(show.legend = FALSE) +
    labs(x = "Log ratio of Beta values",
         y = "Words in the Harry Potter Series")
```



B.) A table with the gamma variable for each document and topic.

```
potter_documents <- tidy(potter_tidy_lda, matrix = "gamma")
potter_documents
```

```
# A tibble: 14 x 3
   document              topic gamma
   <chr>                 <int> <dbl>
 1 Sorcerer's Stone          1 0.506
 2 Chamber of Secrets        1 0.477
 3 Prisoner of Azkaban       1 0.524
 4 Goblet of Fire            1 0.464
 5 Order of the Phoenix      1 0.483
 6 Half-Blood Prince         1 0.484
 7 Deathly Hallows           1 0.427
 8 Sorcerer's Stone          2 0.494
 9 Chamber of Secrets        2 0.523
10 Prisoner of Azkaban       2 0.476
11 Goblet of Fire            2 0.536
12 Order of the Phoenix      2 0.517
13 Half-Blood Prince         2 0.516
14 Deathly Hallows           2 0.573
```

- Looking at the gamma variables, all of the books are pretty evenly split between topic 1 and topic 2, which isn't too surprising given that the books seem pretty similar content-wise. Looking at the words with the greatest different between the two topics a possibility for what the two topics represent is that one topic represents anticipation and success and the other represents challenges.