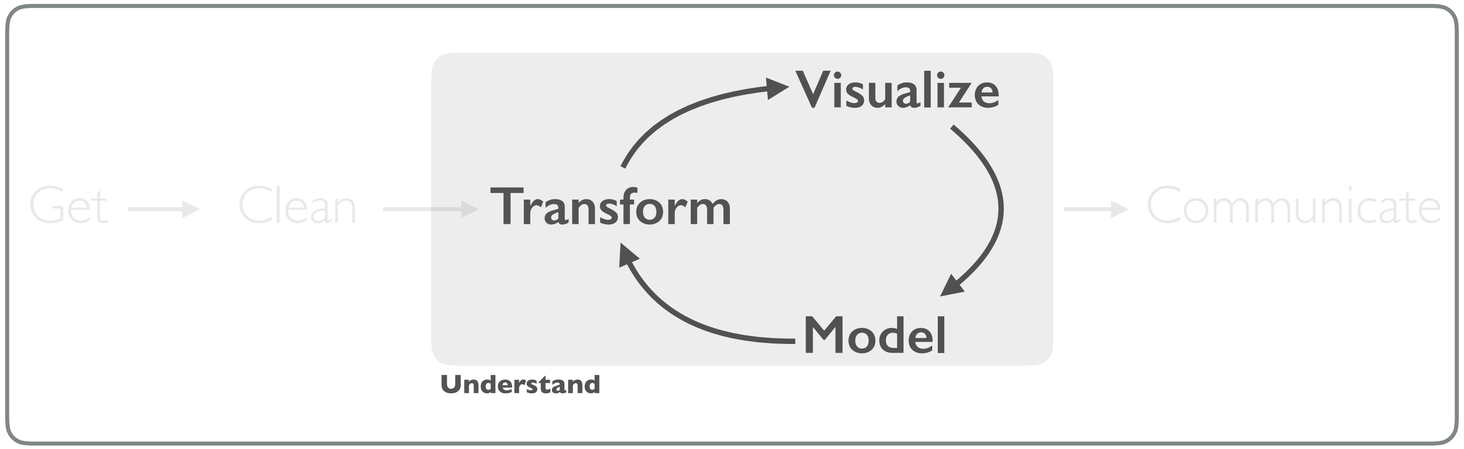
SENTIMENT ANALYSIS



†A modified version of Hadley Wickham's analytic process

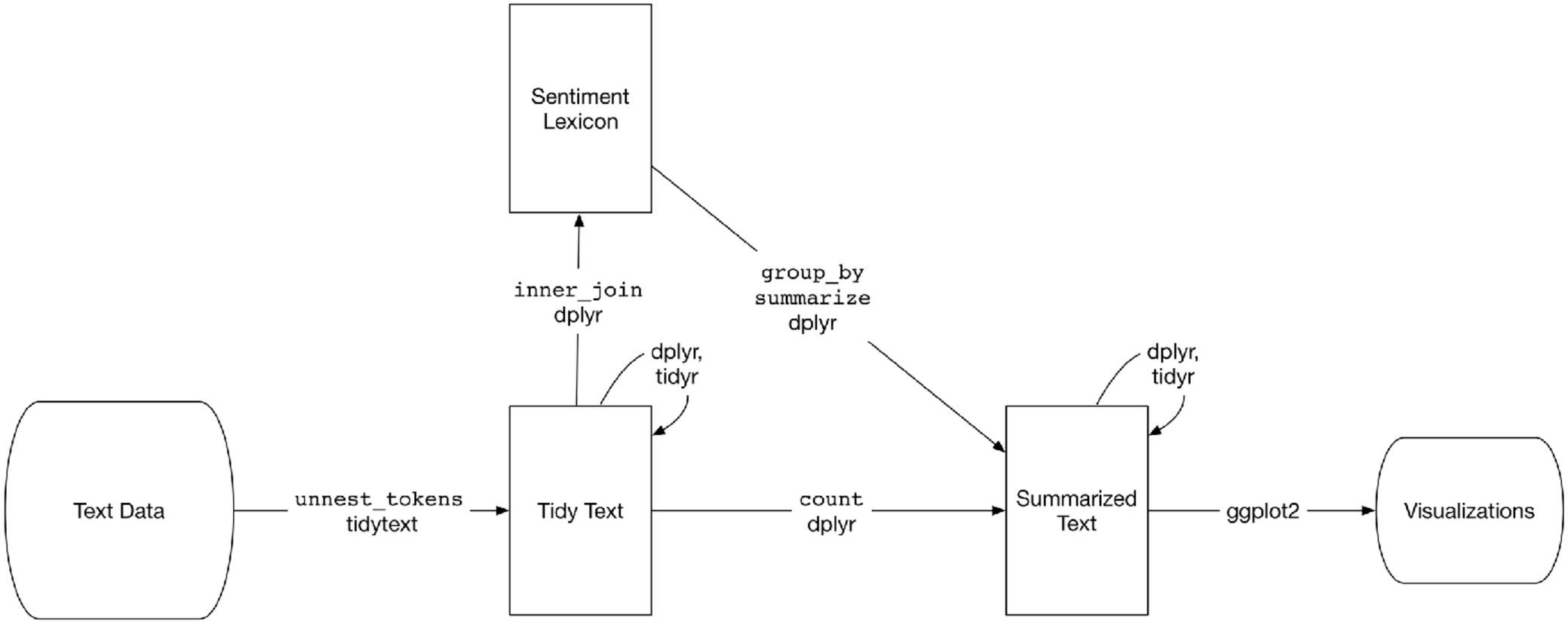
"When human readers approach a text, we use our understanding of the emotional intent of words to infer whether a section of text is positive or negative, or perhaps characterized by some other more nuanced emotion like surprise or disgust."

– Julia Silge and David Robinson

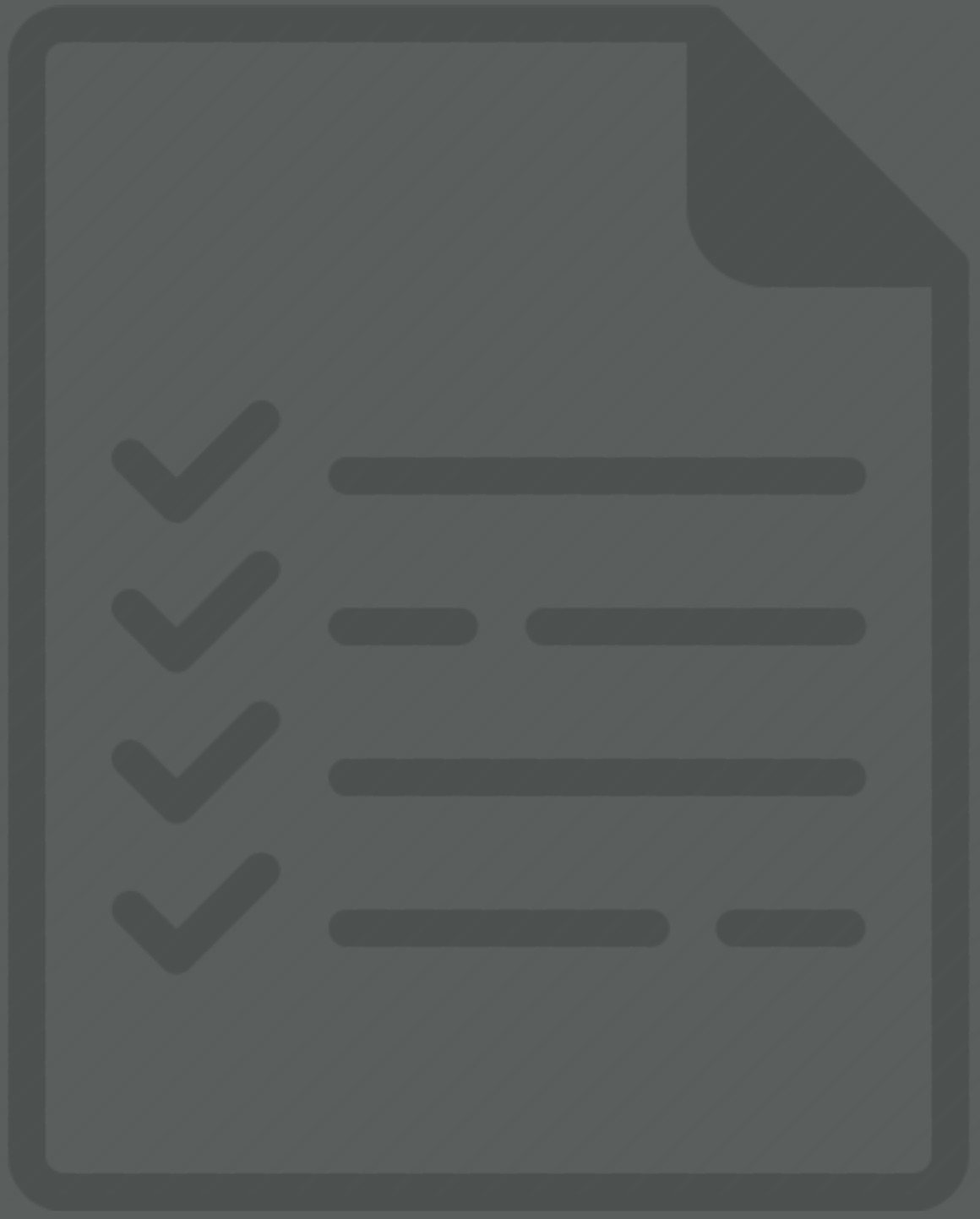
SENTIMENT

- I love this class!
- I hate this teacher, he stinks!
- I feel tired this morning.
- This view is amazing.
- I am not looking forward to the concert.
- There is a book on the desk

SENTIMENT ANALYSIS



PREREQUISITES



PACKAGE PREREQUISITE

```
library(tidyverse)
library(tidytext)
library(sentimentr)
library(magrittr)
library(harrypotter)
```

SENTIMENT LEXICONS

The good, bad, and the ugly

SENTIMENT LEXICONS

```
sentiments
# A tibble: 23,165 x 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 23,155 more rows
```

- **AFINN** from Finn Årup Nielsen
- **bing** from Bing Liu and collaborators
- **nrc** from Saif Mohammad and Peter Turney
- to see the individual lexicons try
  - `get_sentiments("afinn")`
  - `get_sentiments("bing")`
  - `get_sentiments("nrc")`

SENTIMENT LEXICONS

These lexicons represent different ways to score some contextual words

```
get_sentiments("afinn") %>%
  count(score)
# A tibble: 11 x 2
   score     n
   <int> <int>
 1    -5    16
 2    -4    43
 3    -3   264
 4    -2   965
 5    -1   309
 6     0     1
 7     1   208
 8     2   448
 9     3   172
10     4    45
11     5     5
```

```
get_sentiments("bing") %>%
  count(sentiment)
# A tibble: 2 x 2
  sentiment     n
      <chr> <int>
1  negative  4782
2  positive  2006
```

```
get_sentiments("nrc") %>%
  count(sentiment)
# A tibble: 10 x 2
       sentiment     n
           <chr> <int>
 1         anger  1247
 2 anticipation   839
 3       disgust  1058
 4          fear  1476
 5           joy   689
 6      negative  3324
 7      positive  2312
 8       sadness  1191
 9      surprise   534
10         trust  1231
```

BASIC SENTIMENT ANALYSIS

Finding the good, bad, and the ugly

BASIC SENTIMENT

```
ps_df <- tibble(
  chapter = seq_along(philosophers_stone),
  text    = philosophers_stone
) %>%
  unnest_tokens(word, text)

ps_df
# A tibble: 77,875 x 2
   chapter word
     <int> <chr>
 1       1 the
 2       1 boy
 3       1 who
 4       1 lived
 5       1 mr
 6       1 and
 7       1 mrs
 8       1 dursley
```

- First, let's tidy our text

BASIC SENTIMENT

```
ps_df %>%
  inner_join(get_sentiments("bing")) %>%
  count(sentiment, sort = TRUE)
# A tibble: 2 x 2
  sentiment     n
  <chr>     <int>
1 negative   2335
2 positive   1986
```

- First, let's tidy our text
- We can get the overall positive vs. negative sentiment with the Bing lexicon.

But what about the most common types of emotions in the text?

BASIC SENTIMENT

```
ps_df %>%
  inner_join(get_sentiments("nrc"))
# A tibble: 18,054 x 3
   chapter word   sentiment
     <int> <chr>  <chr>
 1       1 boy    disgust
 2       1 boy    negative
 3       1 proud  anticipation
 4       1 proud  joy
 5       1 proud  positive
 6       1 proud  trust
 7       1 expect anticipation
 8       1 expect positive
 9       1 expect surprise
10       1 expect trust
# ... with 18,044 more rows
```

- First, let's tidy our text
- We can get the overall positive vs. negative sentiment with the Bing lexicon.
- We can use the NRC lexicon
- Notice how "boy" ,"proud", "expect" have more than one feeling.

BASIC SENTIMENT

```
ps_df %>%
  inner_join(get_sentiments("nrc")) %>%
  count(sentiment, sort = TRUE)
   chapter word   sentiment
     <int> <chr>  <chr>
 # A tibble: 10 x 2
   sentiment        n
   <chr>        <int>
 1 negative      3678
 2 positive      2608
 3 sadness       2371
 4 anger         2239
 5 trust         1623
 6 anticipation  1439
 7 fear          1323
 8 joy           1034
 9 surprise       873
10 disgust        866
```

- First, let's tidy our text
- We can get the overall positive vs. negative sentiment with the Bing lexicon.
- We can use the NRC lexicon
- Notice how "boy" ,"proud", "expect" have more than one feeling.

YOUR TURN!

Using the AFINN lexicon, can you rank-order the chapters in Philosopher's Stone by sentiment score?

SOLUTION

```
ps_df %>%
  inner_join(get_sentiments("afinn")) %>%
  group_by(chapter) %>%
  summarise(score = sum(score)) %>%
  arrange(desc(score))
# A tibble: 17 x 2
   chapter score
     <int> <int>
 1       5   109
 2       7   103
 3       6    79
 4       1    74
 5      12    61
 6      10    37
 7       8    24
 8      13    14
 9      16     6
```

GRANULARITY

What if we want a finer level of sentiment understanding

FINER GRANULARITY

```
ps_df %>%
  mutate(
    word_count = 1:n(),
    page = word_count %/% 275 + 1
    )
 # A tibble: 77,875 x 4
   chapter word    word_count  page
     <int> <chr>        <int> <dbl>
 1       1 the              1  1.00
 2       1 boy              2  1.00
 3       1 who              3  1.00
 4       1 lived            4  1.00
 5       1 mr               5  1.00
 6       1 and              6  1.00
 7       1 mrs              7  1.00
 8       1 dursley          8  1.00
 9       1 of               9  1.00
10       1 number          10  1.00
```

- We can break up our book by apprx page (250-300 words per page)

FINER GRANULARITY

```
ps_df %>%
  mutate(
    word_count = 1:n(),
    page = word_count %/% 275 + 1
    ) %>%
  inner_join(get_sentiments("bing")) %>%
  count(page, sentiment)
 # A tibble: 567 x 3
    page sentiment     n
   <dbl> <chr>     <int>
 1  1.00 negative      4
 2  1.00 positive      9
 3  2.00 negative     10
 4  2.00 positive      4
 5  3.00 negative      9
 6  3.00 positive      1
 7  4.00 negative      8
 8  4.00 positive      7
```

- We can break up our book by apprx page (250-300 words per page)
- We can then get positive vs negative sentiment by page

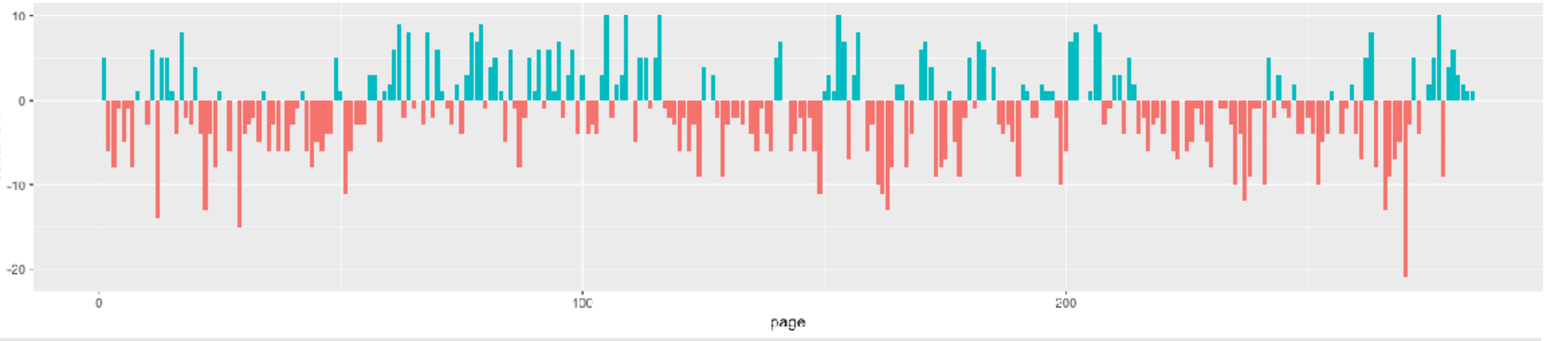
FINER GRANULARITY

```
ps_df %>%
  mutate(
    word_count = 1:n(),
    page = word_count %/% 275 + 1
    ) %>%
  inner_join(get_sentiments("bing")) %>%
  count(page, sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
# A tibble: 284 x 4
    page negative positive sentiment
   <dbl>    <dbl>    <dbl>     <dbl>
 1  1.00     4.00     9.00      5.00
 2  2.00    10.0      4.00     -6.00
 3  3.00     9.00     1.00     -8.00
 4  4.00     8.00     7.00     -1.00
 5  5.00    13.0      8.00     -5.00
 6  6.00     6.00     5.00     -1.00
```

- We can break up our book by apprx page (250-300 words per page)
- We can then get positive vs negative sentiment by page
- Then spread our data and compute the net sentiment

FINER GRANULARITY

```
ps_df %>%
  mutate(
    word_count = 1:n(),
    page = word_count %/% 275 + 1
    ) %>%
  inner_join(get_sentiments("bing")) %>%
  count(page, sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative) %>%
  ggplot(aes(page, sentiment, fill = sentiment > 0)) +
  geom_col(show.legend = FALSE)
```



- We can break up our book by apprx page (250-300 words per page)
- We can then get positive vs negative sentiment by page
- Then spread our data and compute the net sentiment
- And plot the results

YOUR TURN!

Compare the Bing and AFINN sentiment for deathly_hallows. Do they differ?

SOLUTION

Step 1: Tidy

```
dh_df <- tibble(
  chapter = seq_along(deathly_hallows),
  text    = deathly_hallows
) %>%
  unnest_tokens(word, text) %>%
  mutate(
    word_count = 1:n(),
    page = word_count %/% 275 + 1
  )

dh_df
# A tibble: 198,906 x 4
   chapter word     word_count  page
     <int> <chr>         <int> <dbl>
 1       1 the               1  1.00
 2       1 two               2  1.00
 3       1 men               3  1.00
 4       1 appeared          4  1.00
```

Step 2: Bing Sentiment

```
dh_bing <- dh_df %>%
  inner_join(get_sentiments("bing")) %>%
  count(page, sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(
    sentiment = positive - negative,
    lexicon = "Bing"
    ) %>%
  select(page, sentiment, lexicon)

dh_bing
# A tibble: 724 x 3
    page sentiment lexicon
   <dbl>     <dbl> <chr>
 1  1.00      2.00 Bing
 2  2.00     -3.00 Bing
 3  3.00      2.00 Bing
 4  4.00      1.00 Bing
```

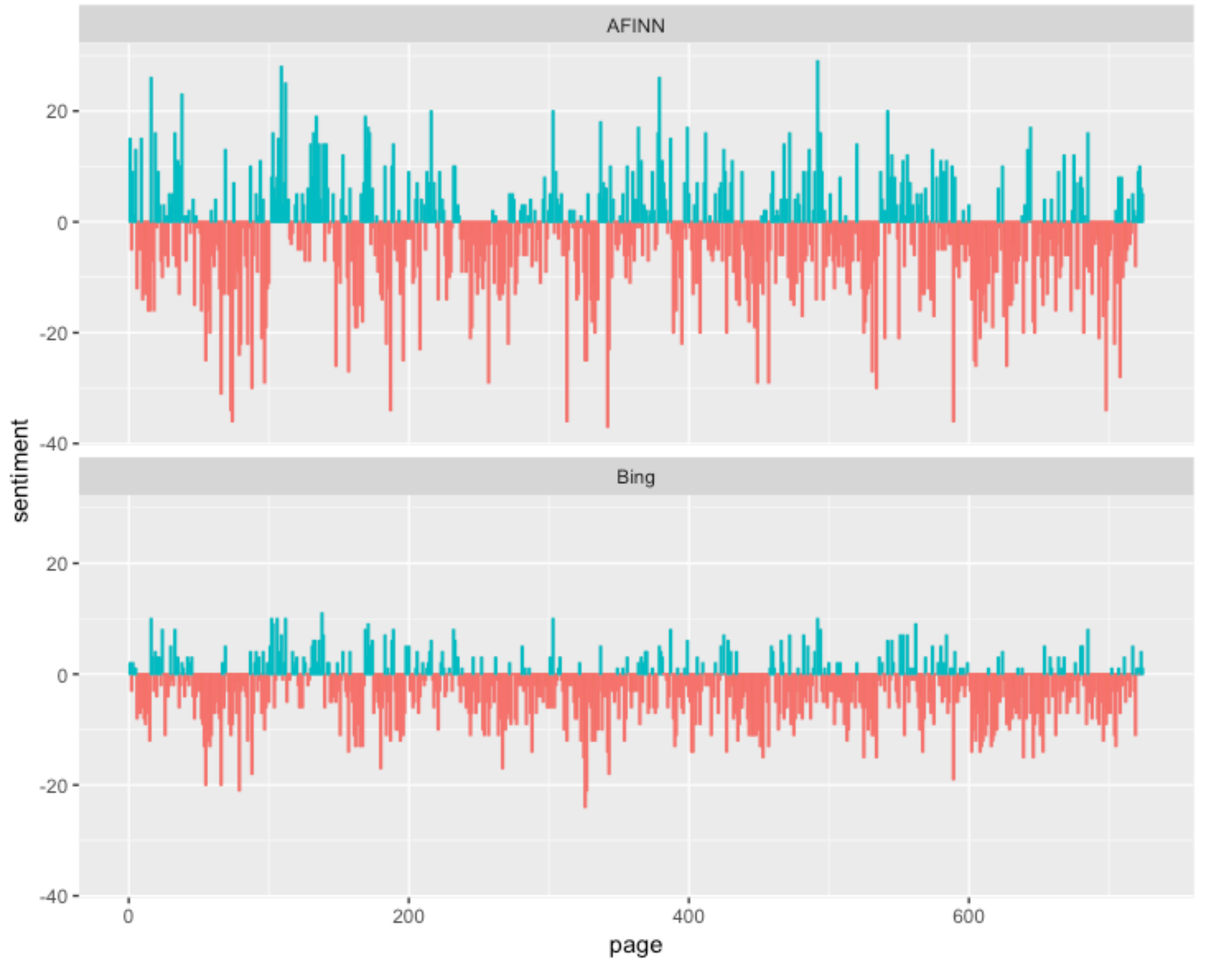
Step 3: AFINN sentiment

```
dh_afinn <- dh_df %>%
  inner_join(get_sentiments("afinn")) %>%
  group_by(page) %>%
  summarise(sentiment = sum(score)) %>%
  mutate(lexicon = "AFINN")

dh_afinn
# A tibble: 724 x 3
    page sentiment lexicon
   <dbl>     <int> <chr>
 1  1.00        15 AFINN
 2  2.00       - 5 AFINN
 3  3.00         9 AFINN
 4  4.00         1 AFINN
```

SOLUTION

Step 4: Visually compare

```
rbind(dh_bing, dh_afinn) %>%
  ggplot(aes(page, sentiment, color = sentiment > 0)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ lexicon, ncol = 1)
```



INFLUENCERS

What is driving sentiment?

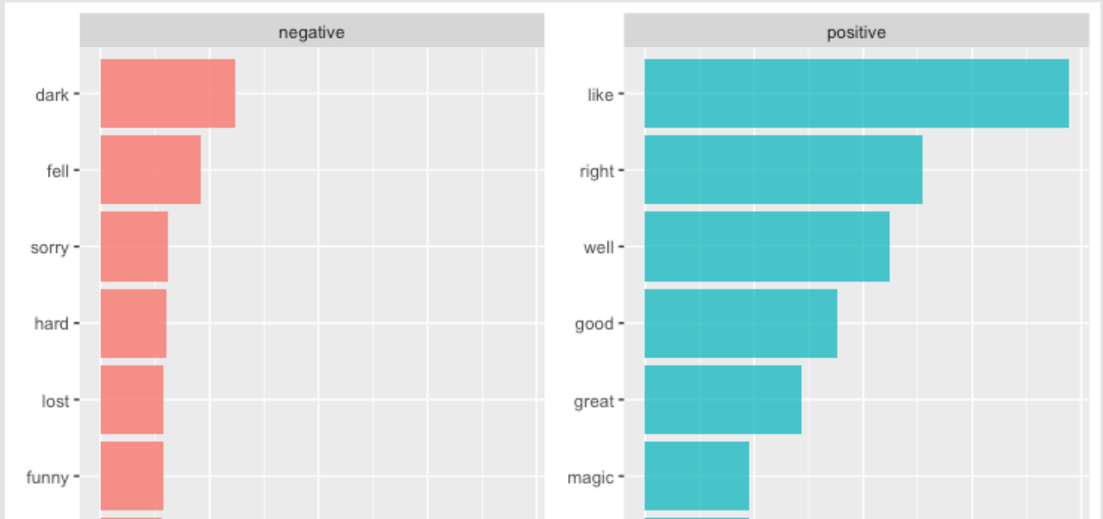
DRIVERS OF SENTIMENT

```
ps_df %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE)

# A tibble: 925 x 3
   word   sentiment     n
   <chr>  <chr>     <int>
 1 like   positive    194
 2 right  positive    127
 3 well   positive    112
 4 good   positive     88
 5 great  positive     72
 6 dark   negative     62
 7 enough positive     48
 8 magic  positive     48
 9 fell   negative     46
10 better positive     41
# ... with 915 more rows
```

- To understand what words are driving sentiment we simply count by word and sentiment

DRIVERS OF SENTIMENT

```
ps_df %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```



- To understand what words are driving sentiment we simply count by word and sentiment
- And then plot the top 10 influential words

RISK OF NEGATION

Getting better context

SENTIMENT

- I haven't been sad in a long time.
- I am extremely happy today.
- It's a good day.
- But suddenly I'm only a little bit happy.
- Then I'm not happy at all.
- In fact, I am now the least happy person on the planet.
- There is no happiness left in me.
- Wait, it's returned!
- I don't feel so bad after all!

OPTION 1: ASSESS AT THE UNIT LEVEL

```
ps_lines <- tibble(
  chapter = seq_along(philosophers_stone),
  text    = philosophers_stone
) %>%
  unnest_tokens(sentence_text, text, token = "sentences") %>%
  mutate(sentence = 1:n()) %>%
  unnest_tokens(word, sentence_text)

ps_lines %>%
  inner_join(get_sentiments("afinn")) %>%
  group_by(sentence) %>%
  summarize(score = sum(score, na.rm = TRUE))

# A tibble: 2,655 x 2
   sentence score
      <int> <int>
 1        2     7
 2        3    -3
 3        6     1
 4        8     2
```

- We can unnest at the sentence level
- Then we can get the overall sentiment score for that sentence.
- However, this still treats each sentence as a bag of words rather than trying to understand the context.

OPTION 2: ASSESS POLARITY AT THE SENTENCE LEVEL

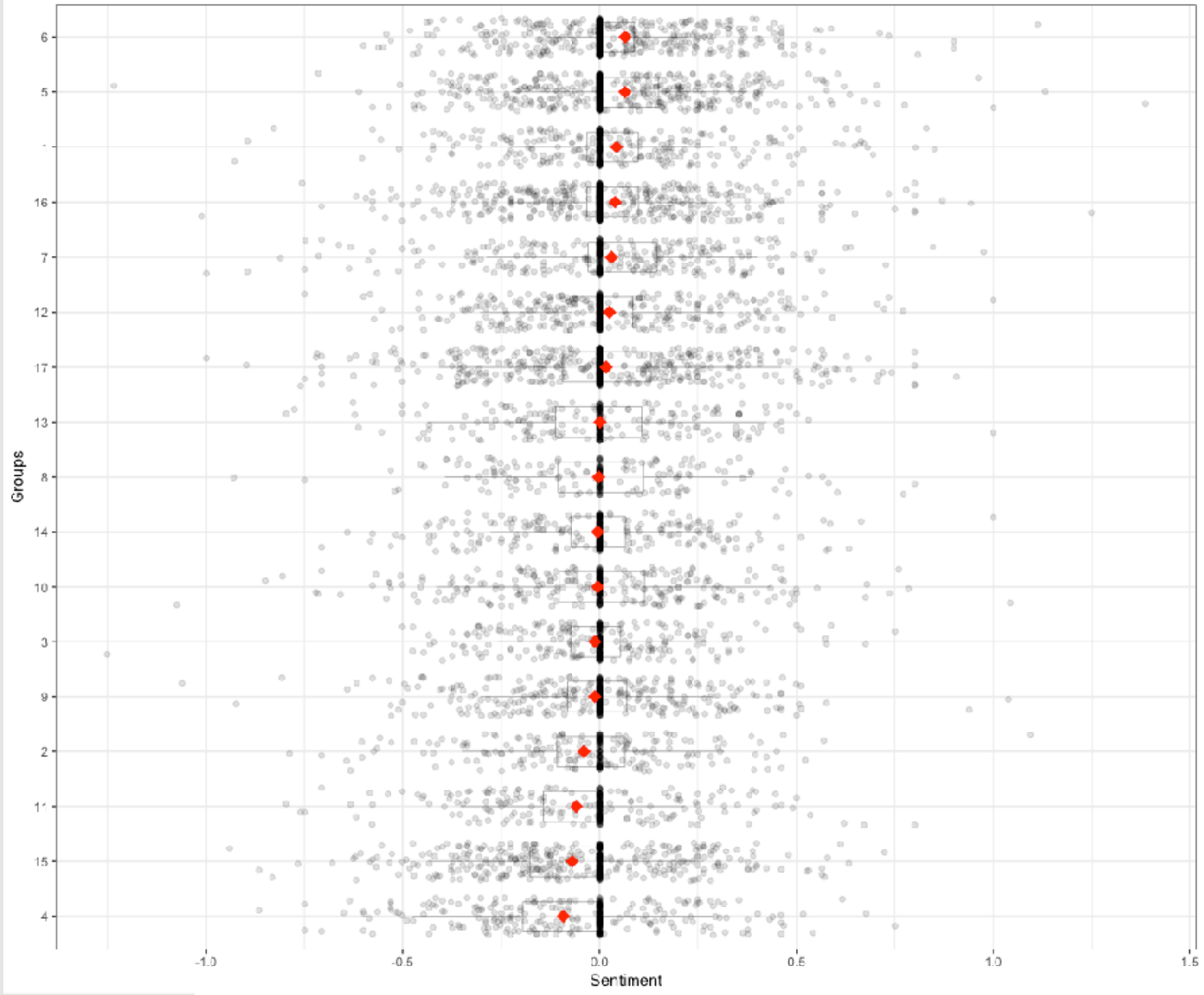
```
ch_sentiment <- tibble(
  chapter = seq_along(philosophers_stone),
  text    = philosophers_stone
) %$%
  sentiment_by(
    get_sentences(text),
    list(chapter)
  )

ch_sentiment
    chapter word_count        sd ave_sentiment
 1:       1       4622 0.2377134   0.042569167
 2:       2       3456 0.2292486  -0.039026682
 3:       3       3853 0.1980889  -0.011839610
 4:       4       3700 0.2420885  -0.092671054
```

- **`sentmentr`** package provides a method for incorporating weighting for valence shifters (negation and amplifiers/ deamplifiers)
- **`get_sentence`** splits text up by sentence
- **`sentiment_by`** will assess net sentiment at the sentence level grouped at a certain level (chapters in this example)

OPTION 2: ASSESS POLARITY AT THE SENTENCE LEVEL

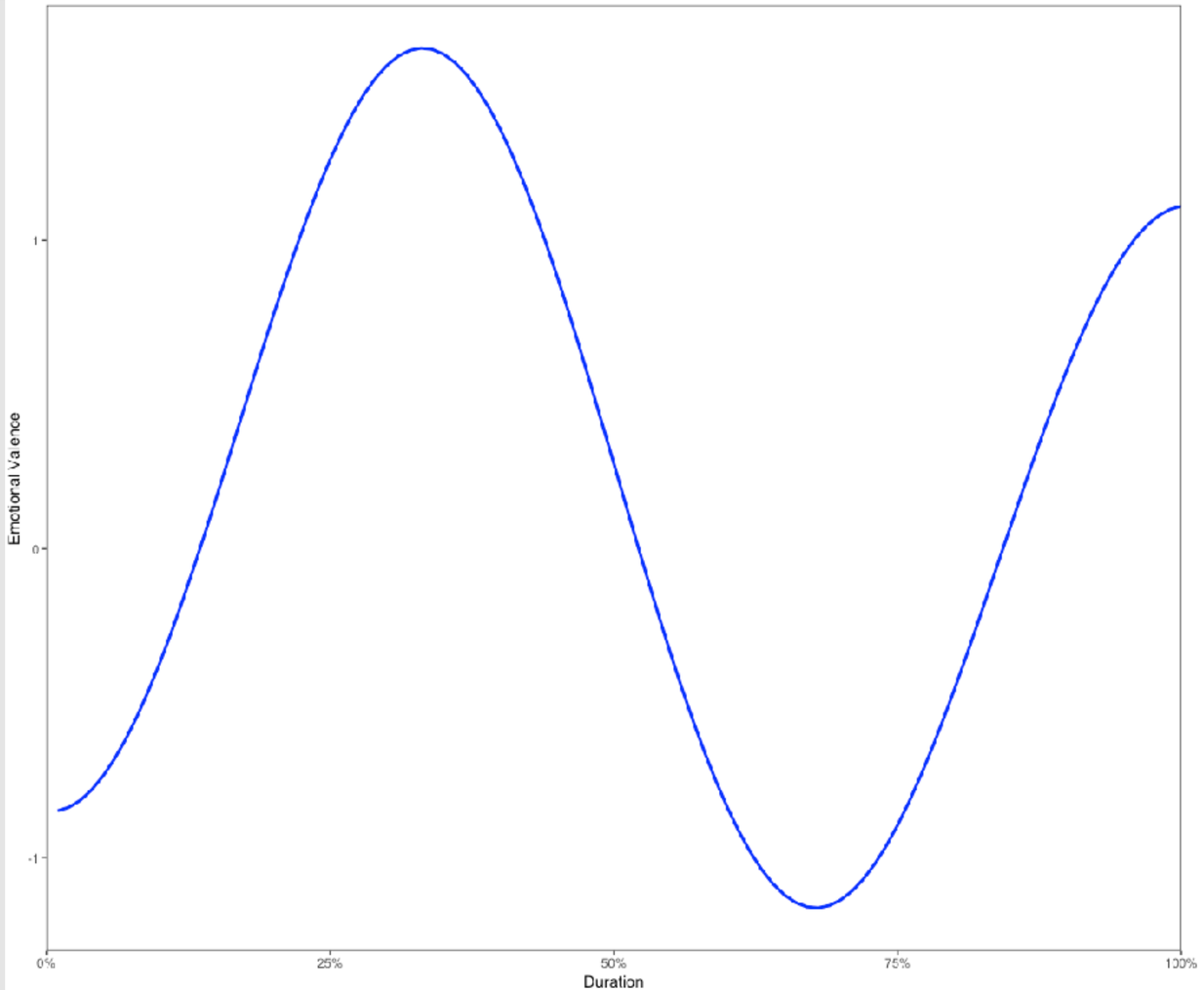
```
plot(ch_sentiment)
```

Chapters in rank order based on average sentiment



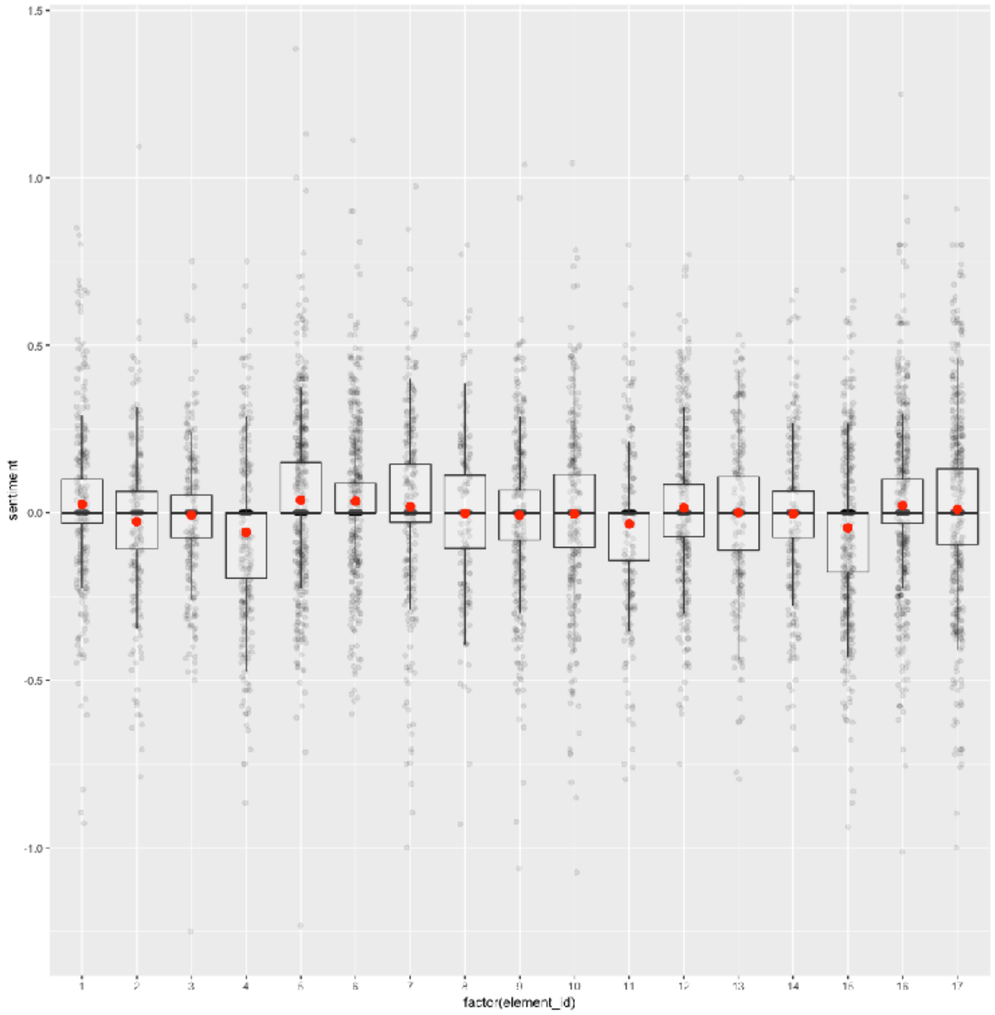
OPTION 2: ASSESS POLARITY AT THE SENTENCE LEVEL

```
plot(ch_sentiment)
plot(uncombine(ch_sentiment))
```



OPTION 2: ASSESS POLARITY AT THE SENTENCE LEVEL

```
plot(ch_sentiment)
plot(uncombine(ch_sentiment))
ch_sentiment %>%
  uncombine() %>%
  ggplot(aes(factor(element_id), sentiment)) +
  geom_jitter(alpha = .1, width = .1, height = 0) +
  geom_boxplot(outlier.shape = NA, alpha = .25) +
  stat_summary(fun.y = "mean", geom = "point", size = 3,
color = “red")
```



YOUR TURN!

1. *Rank order the three review files provided in your .R script by overall positive vs. negative sentiment.*

2. *Identify the top 5 emotions in each file.*

3. *Within each file can you identify the most negative review?*

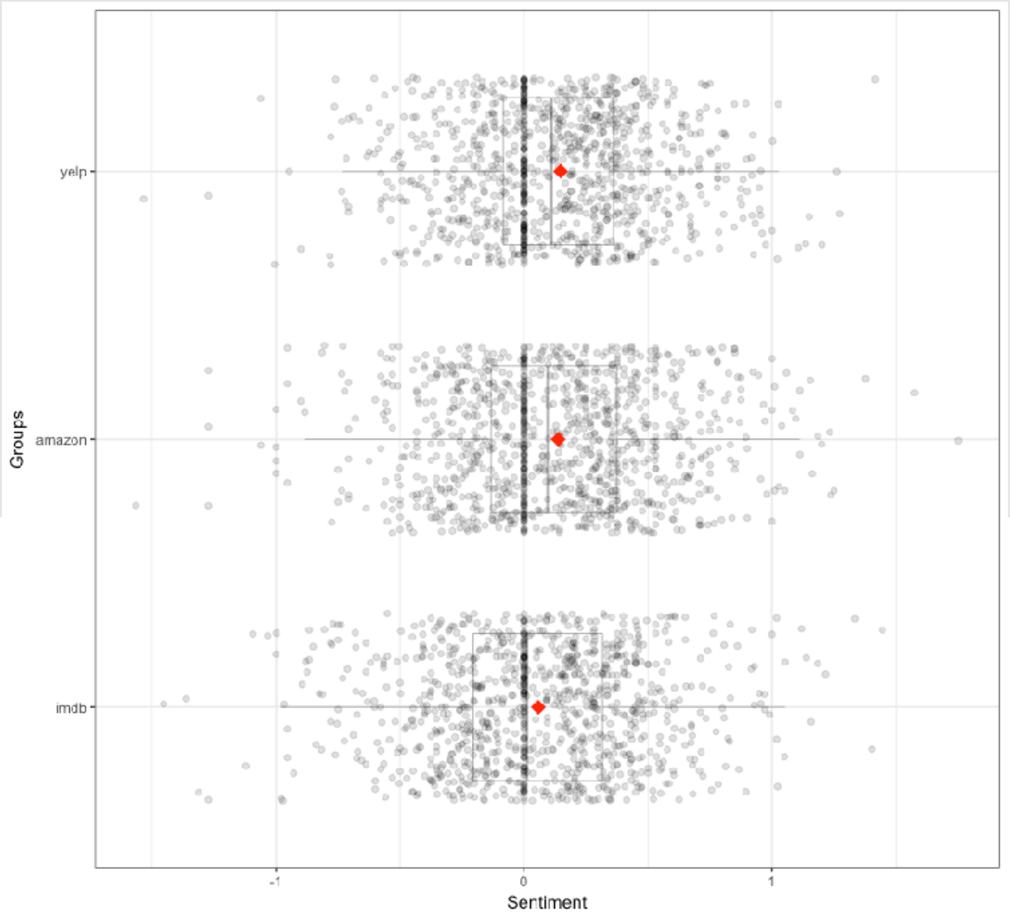
4. *Within each file can you identify the most positive review?*

SOLUTION

```
# Review files
amazon <- mutate(kotzias_reviews_amazon_cells, file = "amazon")
imdb   <- mutate(kotzias_reviews_imdb, file = "imdb")
yelp   <- mutate(kotzias_reviews_yelp, file = "yelp")

all_3 <- amazon %>%
  rbind(imdb) %>%
  rbind(yelp) %>%
  as_tibble()
```

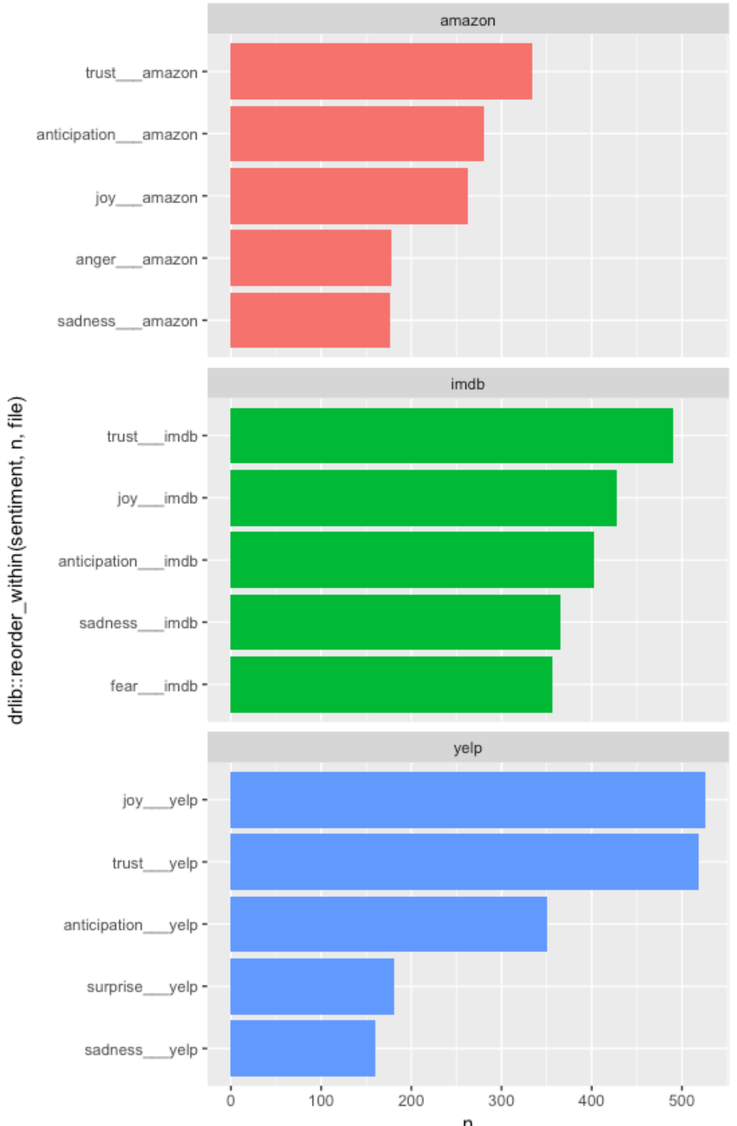
SOLUTION

```
# 1. Rank order the three review files by overall positive vs. negative sentiment.
all_3 %$%
  sentiment_by(
    get_sentences(text),
    list(file)
  ) %>%
  plot()
```



SOLUTION

```
# 2. Identify the top 5 emotions in each file.
all_3 %>%
  select(file, text) %>%
  unnest_tokens(word, text) %>%
  inner_join(get_sentiments("nrc")) %>%
  count(file, sentiment) %>%
  filter(!sentiment %in% c("positive", "negative")) %>%
  group_by(file) %>%
  top_n(5) %>%
  ggplot(aes(drlib::reorder_within(sentiment, n, file), n, fill = file)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ file, ncol = 1, scales = "free_y") +
  coord_flip()
```



SOLUTION

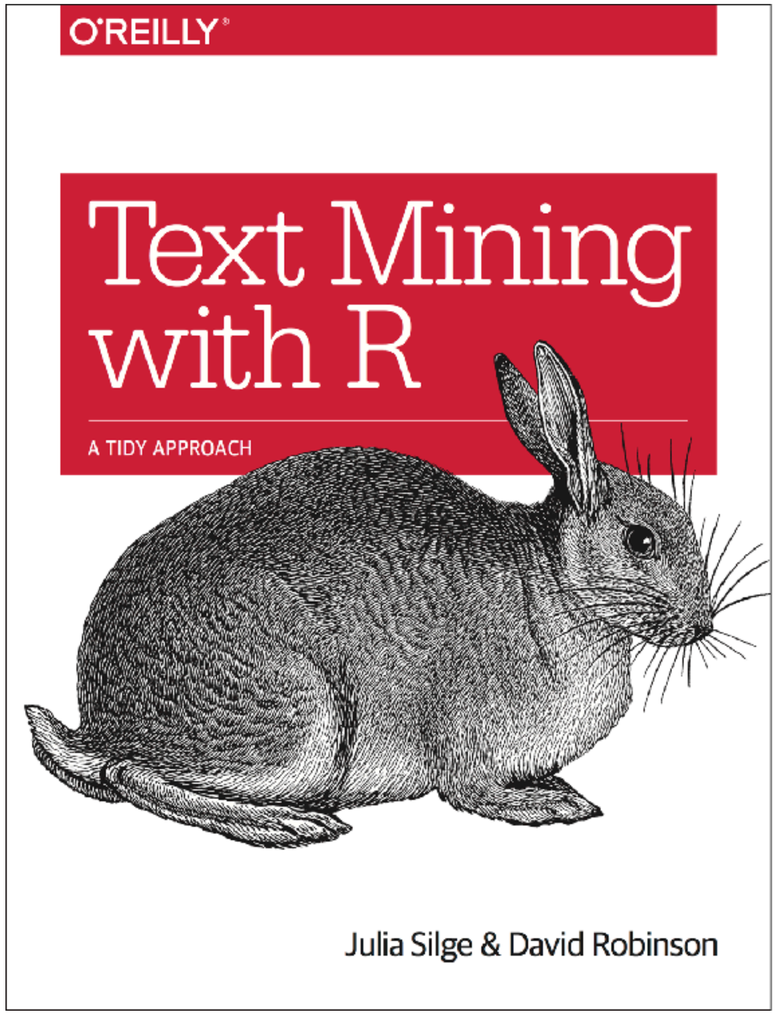
```
# 3. Within each file can you identify the most negative review?
net_sentiment <- all_3 %$%
  sentiment_by(
    get_sentences(text),
    list(file)
  ) %>%
  uncombine()

net_sentiment %>%
  group_by(file) %>%
  filter(sentiment == min(sentiment))
# A tibble: 3 x 5
# Groups:   file [3]
  file   element_id sentence_id word_count sentiment
  <chr>       <int>       <int>      <int>     <dbl>
1 amazon        822           1         18     -1.57
2 imdb         1771           1         37     -1.45
3 yelp         3109           1         14     -1.53

all_3 %>%
  filter(row_number() %in% c(822, 1771, 3109))
# A tibble: 3 x 3
  sentiment text                                                                                                  file
      <dbl> <chr>                                                                                                 <chr>
1     -1.00 I really wanted the Plantronics 510 to be the right one, but it has too many issues for me.            amaz…
2      1.00 It felt like a very gripping, intelligent stage play (but without the overly theatrical feeling one actually gets from watching pe… imdb
3     -1.00 She was quite disappointed although some blame needs to be placed at her door.                         yelp
```

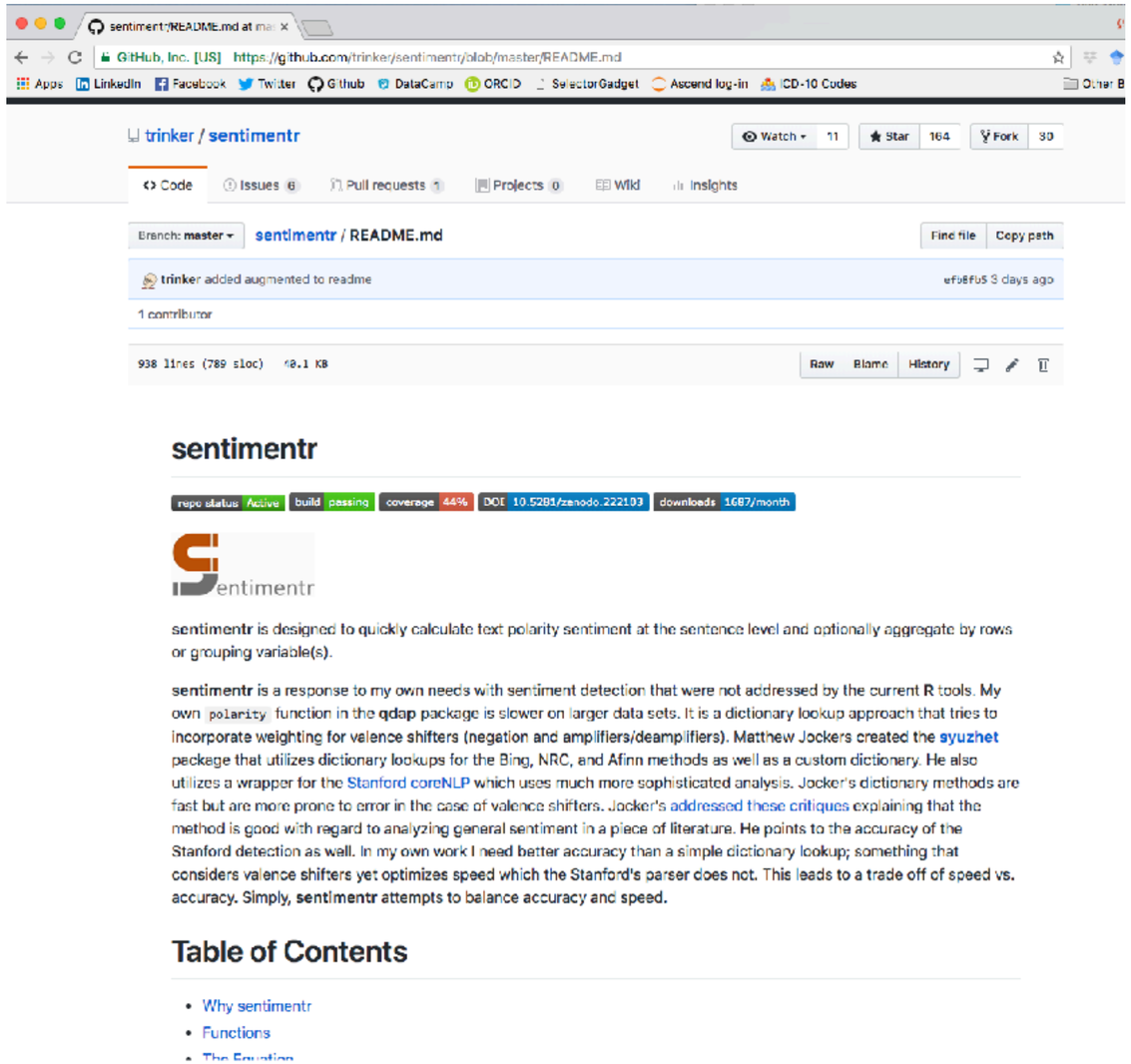
SOLUTION

```
# 4. Within each file can you identify the most positive review?
net_sentiment %>%
  group_by(file) %>%
  filter(sentiment == max(sentiment))
# A tibble: 3 x 5
# Groups:   file [3]
  file   element_id sentence_id word_count sentiment
  <chr>       <int>       <int>      <int>     <dbl>
1 amazon        583           1          9      1.75
2 imdb         1687           1         28      1.45
3 yelp         2594           1          9      1.42

all_3 %>%
  filter(row_number() %in% c(583, 1687, 2594))
# A tibble: 3 x 3
  sentiment text                                                                                                  file
      <dbl> <chr>                                                                                                 <chr>
1      1.00 I love the camera, it's really pretty good quality.                                                    amaz…
2      1.00 Being a 90's child, I truly enjoyed this show and I can proudly say that I enjoyed it big time and even more than the classical WB… imdb
3      1.00 The inside is really quite nice and very clean.                                                        yelp
```


SO LITTLE TIME!

LEARN MORE


O'REILLY
Text Mining with R
A TIDY APPROACH
Julia Silge & David Robinson


sentimentr/README.md at ma
GitHub, Inc. [US] https://github.com/trinker/sentimentr/blob/master/README.md
Apps LinkedIn Facebook Twitter Github DataCamp ORCID SelectorGadget Ascend log-in ICD-10 Codes
trinker / sentimentr
Watch 11 Star 164 Fork 30
Code Issues 6 Pull requests 1 Projects 0 Wiki Insights
Branch: master sentimentr / README.md Find file Copy path
trinker added augmented to readme ef08f05 3 days ago
1 contributor
938 lines (789 sloc) 48.1 KB Raw Blame History
sentimentr
repo status Active build passing coverage 44% DOI 10.5281/zenodo.222103 downloads 1687/month
sentimentr is designed to quickly calculate text polarity sentiment at the sentence level and optionally aggregate by rows or grouping variable(s).
sentimentr is a response to my own needs with sentiment detection that were not addressed by the current R tools. My own polarity function in the qdap package is slower on larger data sets. It is a dictionary lookup approach that tries to incorporate weighting for valence shifters (negation and amplifiers/deamplifiers). Matthew Jockers created the syuzhet package that utilizes dictionary lookups for the Bing, NRC, and Afinn methods as well as a custom dictionary. He also utilizes a wrapper for the Stanford coreNLP which uses much more sophisticated analysis. Jocker's dictionary methods are fast but are more prone to error in the case of valence shifters. Jocker's addressed these critiques explaining that the method is good with regard to analyzing general sentiment in a piece of literature. He points to the accuracy of the Stanford detection as well. In my own work I need better accuracy than a simple dictionary lookup; something that considers valence shifters yet optimizes speed which the Stanford's parser does not. This leads to a trade off of speed vs. accuracy. Simply, sentimentr attempts to balance accuracy and speed.
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WHAT TO REMEMBER

FUNCTIONS TO REMEMBER

Operator/Function	Description
`tidytext::sentiments`	Data frame containing common sentiment words established by the lexicons Bing, NRC, and AFINN
`tidytext::get_sentiments`	Get word list and sentiment for a specific lexicon
`sentimentr::get_sentences`	Break an observation up into discrete sentences
`sentimentr::sentiment_by`	Compute sentiment (along with capturing context via valence shifters) at a specified aggregated level (i.e. chapter, document).
`sentimentr::uncombine`	Disaggregate sentiment to the observation level.