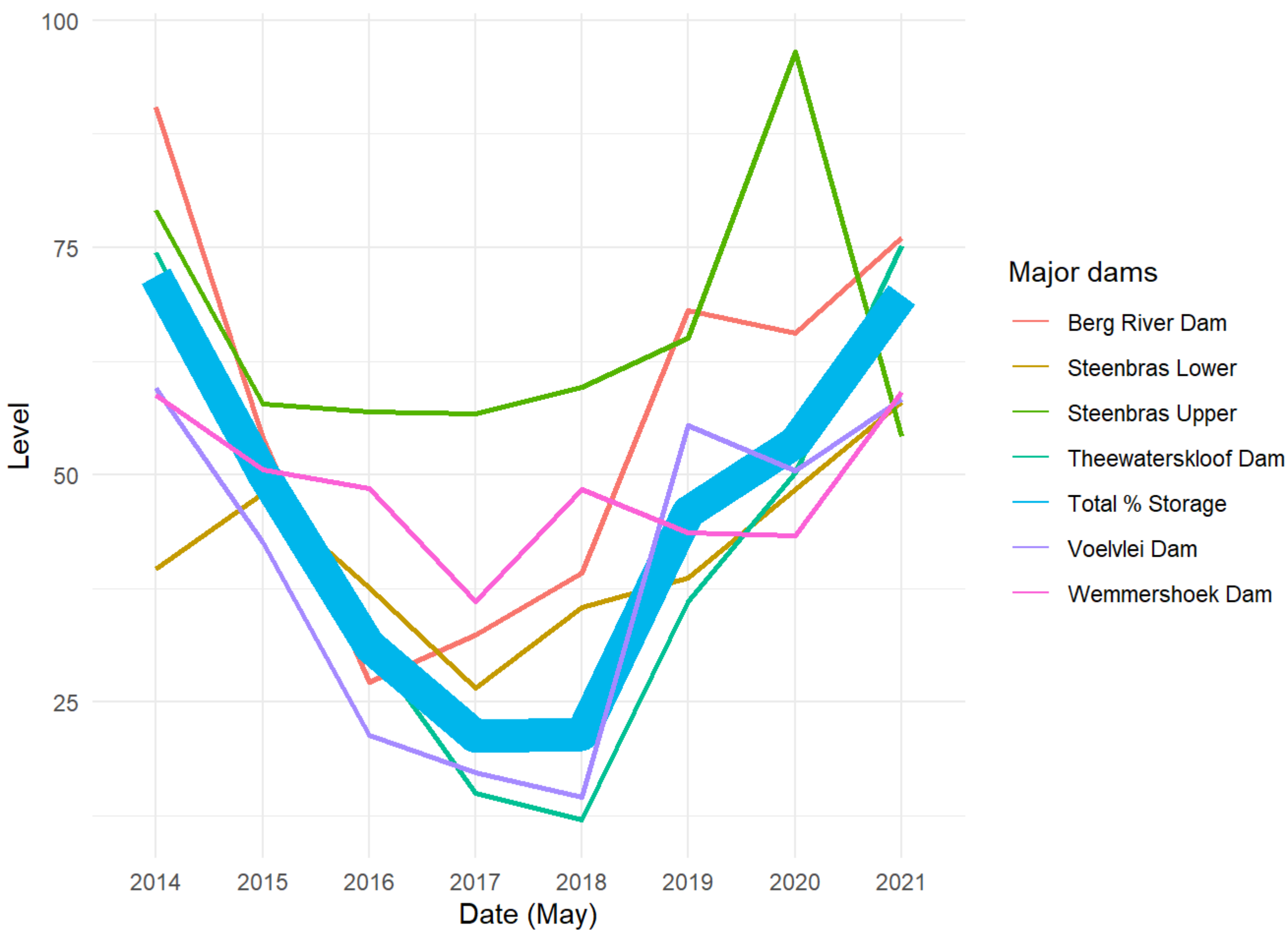
Chapter 4 Text Analysis Tools Part 2, Sentiment

In this section, we take our analysis of text data a bit further, looking into the *sentiment* of language.

4.1 Cape Town Water Crisis

Between 2015 and 2018, Cape Town experienced a severe water crisis that threatened its residents with the possibility of “Day Zero,” when city taps would be shut off.



The above data, from Wikipedia, show water levels at various dams around Cape Town, as well as for the city as a whole. We can see that in 2017 and 2018, water levels became extremely low, inducing a series of water regulations from the Cape Town government with the possibility of taps ultimately shutting off and residents having to collect water at public points.

The Cape Town Water Crisis is a useful case to look at as we think about our global climate crisis. In some ways, this event can be looked at as a microcosm of our climate challenges: volatility in weather patterns, which climate change contributes to, caused long droughts and unpredictable rainfall in the region surrounding Cape Town. The solution to the water crisis required dramatic changes in water consumption, and people were unable to make these changes in a way that responded quickly enough to the ongoing drought. Governments encouraged residents to consume less and began to ration water, but these policies came too late to have the needed impacts on the reservoirs, and were nearly not enough to prevent catastrophe.

What ultimately spared Cape Town was a combination of policies, communication, and rainfall. A city government report highlights the strategies that officials took, including “steep tariff increases,” in particular for the largest water consumers, and messaging across various types of media encouraging residents to limit their usage. These tactics had success: the average resident in March 2015 used 1,100 MegaLiters of water per day, compared to 500 in March 2018. The drought also ended in 2018 when Cape Town had near-average rainfall, restoring dam levels much closer to pre-crisis levels.

Other cities around the world will soon surely experience droughts and water crises of their own, and we cannot expect that these other places always have the luck of fortuitous rainfalls. Therefore, we can potentially learn a lot from how the Cape Town Water Crisis unfolded. We know roughly what happened in terms of water levels, consumption, and government messaging. But we know less about how people felt and reacted to these changes. In this chapter, we will investigate some different ways to analyze *sentiment* around climate change and the water crisis.

4.2 Using Reddit Data

In the Week 2 Problem Set, you learned a bit more about using APIs in R. Hopefully this was a good experience, and you are ready for more! Here, we’ll learn how to pull information from the social media site Reddit.

You are first going to want to install and library the `RedditextractoR` package.

```
library(RedditExtractoR)
```

We can now do things like pull all the subreddits about specific topics, like climate change:

```
# extract climate change subreddits
climate_subreddits <- find_subreddits("climate change")
```

Great! If we want to extract the comments in these subreddits, we first find the urls of the above pages, and then plug these into the `get_thread_content()` function. Let's see what we get in return. There are two ways to find the urls, either by searching the subreddits or the keywords themselves. With the former approach, you can only search one subreddit at a time. The latter generally returns more results, since it includes lots of different subreddits. However, getting the urls this way sometimes returns `NA`, so you may want to use the subreddit method. Both methods are shown below.

```
# get urls of the climate subreddit
climate_urls <- find_thread_urls(subreddit = "climate",
                                 period = "all")

# alternatively, we can find urls of all pages related to climate change
climate_urls <- find_thread_urls(keywords = "climate change")

# extract comments from these pages
climate_comments <- get_thread_content(climate_urls$url)

# take a look
climate_comments$threads

climate_comments$comments
```

```
## # A tibble: 242 × 15
##    url           author date       timestamp title text  subreddit score upvotes
##    <chr>         <chr>  <date>         <dbl> <chr> <chr> <chr>     <dbl>   <dbl>
##  1 https://www.… Kingk… 2023-06-07    1.69e9 "Ele… "I (… unpopula…   400     400
##  2 https://www.… Down-… 2023-06-20    1.69e9 "Thi…  <NA> Conserva…   395     395
##  3 https://www.… iamon… 2023-06-07    1.69e9 "I m… "Hey… dataanal…   391     391
##  4 https://www.… eric-… 2023-06-03    1.69e9 "It'…  <NA> alberta     388     388
##  5 https://www.… Relat… 2023-06-15    1.69e9 "The… "1. … unitedst…   386     386
##  6 https://www.… TheCo… 2023-06-16    1.69e9 "I H…  <NA> autismme…   385     385
##  7 https://www.… Velve… 2023-06-10    1.69e9 "Hel… "Hi … TwoBestF…   391     391
##  8 https://www.… Carel… 2023-06-24    1.69e9 "EU … "Con… neoliber…   387     387
##  9 https://www.… Alan_… 2023-06-19    1.69e9 "Onl…  <NA> newjersey   379     379
## 10 https://www.… Femal… 2023-06-21    1.69e9 "It\… "US … HVAC        379     379
## # ℹ 232 more rows
## # ℹ 6 more variables: downvotes <dbl>, up_ratio <dbl>,
## #   total_awards_received <dbl>, golds <dbl>, cross_posts <dbl>, comments <dbl>
```

```
## # A tibble: 34,361 × 10
##    url          author date       timestamp score upvotes downvotes golds comment
##    <chr>        <chr>  <date>         <dbl> <dbl>   <dbl>     <dbl> <dbl> <chr>
##  1 https://ww… AutoM… 2023-06-07    1.69e9     1       1         0     0 "Pleas…
##  2 https://ww… rogd1… 2023-06-08    1.69e9    18      18         0     0 "Cost …
##  3 https://ww… davek… 2023-06-08    1.69e9     6       6         0     0 "That …
##  4 https://ww… Gamem… 2023-06-08    1.69e9     4       4         0     0 "The r…
##  5 https://ww… soft_… 2023-06-08    1.69e9     0       0         0     0 "Home …
##  6 https://ww… b1ue_… 2023-06-08    1.69e9   130     130         0     0 "The p…
##  7 https://ww… Suita… 2023-06-08    1.69e9    41      41         0     0 "If yo…
##  8 https://ww… Abase… 2023-06-08    1.69e9    55      55         0     0 "If yo…
##  9 https://ww… BobDe… 2023-06-08    1.69e9    31      31         0     0 "But w…
## 10 https://ww… Turbo… 2023-06-08    1.69e9    10      10         0     0 "Yeah …
## # ℹ 34,351 more rows
## # ℹ 1 more variable: comment_id <chr>
```

Let's look at the comments first. We'll want to use the `unnest_tokens()` function to put the data in tidytext format. We can also remove the stop words.

```
library(dplyr)
library(tidytext)

tidy_comments <- climate_comments$comments %>%
   unnest_tokens(word, comment) %>%
  anti_join(stop_words)

# look at words and timestamps
tidy_comments %>%
  select(timestamp, word)
```

```
## # A tibble: 512,800 × 2
##     timestamp word
##         <dbl> <chr>
##  1 1686181081 remember
##  2 1686181081 subreddit
##  3 1686181081 unpopular
##  4 1686181081 opinion
##  5 1686181081 civil
##  6 1686181081 unpopular
##  7 1686181081 takes
##  8 1686181081 discussion
##  9 1686181081 uncivil
## 10 1686181081 tos
## # ℹ 512,790 more rows
```

Now that we have the data in `tidytext` format, we can start to look at the sentiments.

4.3 What is Sentiment Analysis?

Sentiment analysis is just what is sounds like - analyzing the emotions and feelings that language conveys. The `tidytext` package comes with three general-purpose sentiment lexicons. Let's explore these three a little bit. Note that before you can view these lexicons, you may need to install packages such as `textdata` and answer some prompts in R.

```
# look at afinn lexicon
get_sentiments("afinn")
```

```
## # A tibble: 2,477 × 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
```

```
# look at bing lexicon
get_sentiments("bing")
```

```
## # A tibble: 6,786 × 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
```

```
# look at nrc lexicon
get_sentiments("nrc")
```

```
## # A tibble: 13,872 × 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
```

Let’s take a look at what emotions from the NRC lexicon show up in our dataset of climate change comments.

```
# join nrc with tidy comments
tidy_comments %<>%
  inner_join(get_sentiments("nrc"))

# take a look
tidy_comments %>%
  select(word, sentiment)
```

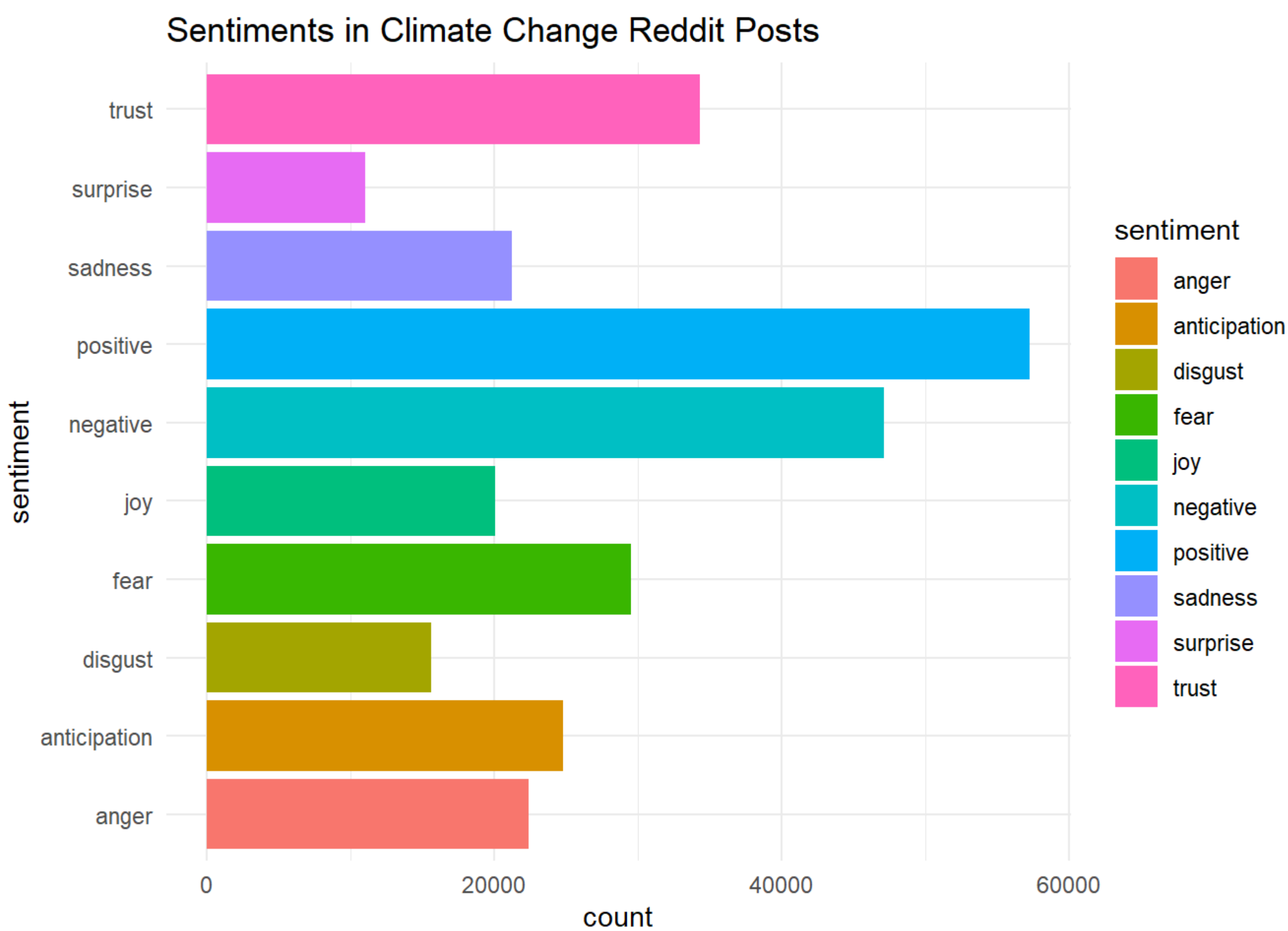
```
## # A tibble: 283,239 × 2
##    word       sentiment
##    <chr>      <chr>
##  1 unpopular  disgust
##  2 unpopular  negative
##  3 unpopular  sadness
##  4 civil      positive
##  5 unpopular  disgust
##  6 unpopular  negative
##  7 unpopular  sadness
##  8 discussion positive
##  9 subject    negative
## 10 ban        negative
## # ℹ 283,229 more rows
```

```
# in table form
table(tidy_comments$sentiment)
```

```
##
##        anger anticipation      disgust         fear          joy     negative
##        22362        24768        15598        29491        20057        47168
##     positive      sadness     surprise        trust
##        57283        21224        10982        34306
```

We can also look at the sentiments in the form of a graph.

```
library(ggplot2)
ggplot(tidy_comments, aes(y = sentiment))+
  geom_bar(aes(fill = sentiment))+
  theme_minimal()+
  labs(title = "Sentiments in Climate Change Reddit Posts")
```



Is this surprising at all? Perhaps, but it is a little difficult to know what to make of this analysis without a good comparison. We can first look at how sentiments in comment threads compare to the original posts.

To do so, we are going to first perform the same analysis on the threads dataset.

```
# now turn to threads
tidy_threads <- climate_comments$threads %>%
   unnest_tokens(word, text) %>%
  anti_join(stop_words)

# join nrc with tidy threads
tidy_threads %<>%
  inner_join(get_sentiments("nrc"))
```

Now we have a `tidy_comments` dataset and a `tidy_threads` dataset. But if we simply bind them together, will we know which observations came from which? We should first make sure we label each with the same variable. We'll call this `type` .

```
# add identifier for thread/comment
tidy_comments %<>%
  mutate(type = "comment")

tidy_threads %<>%
  mutate(type = "thread")
```

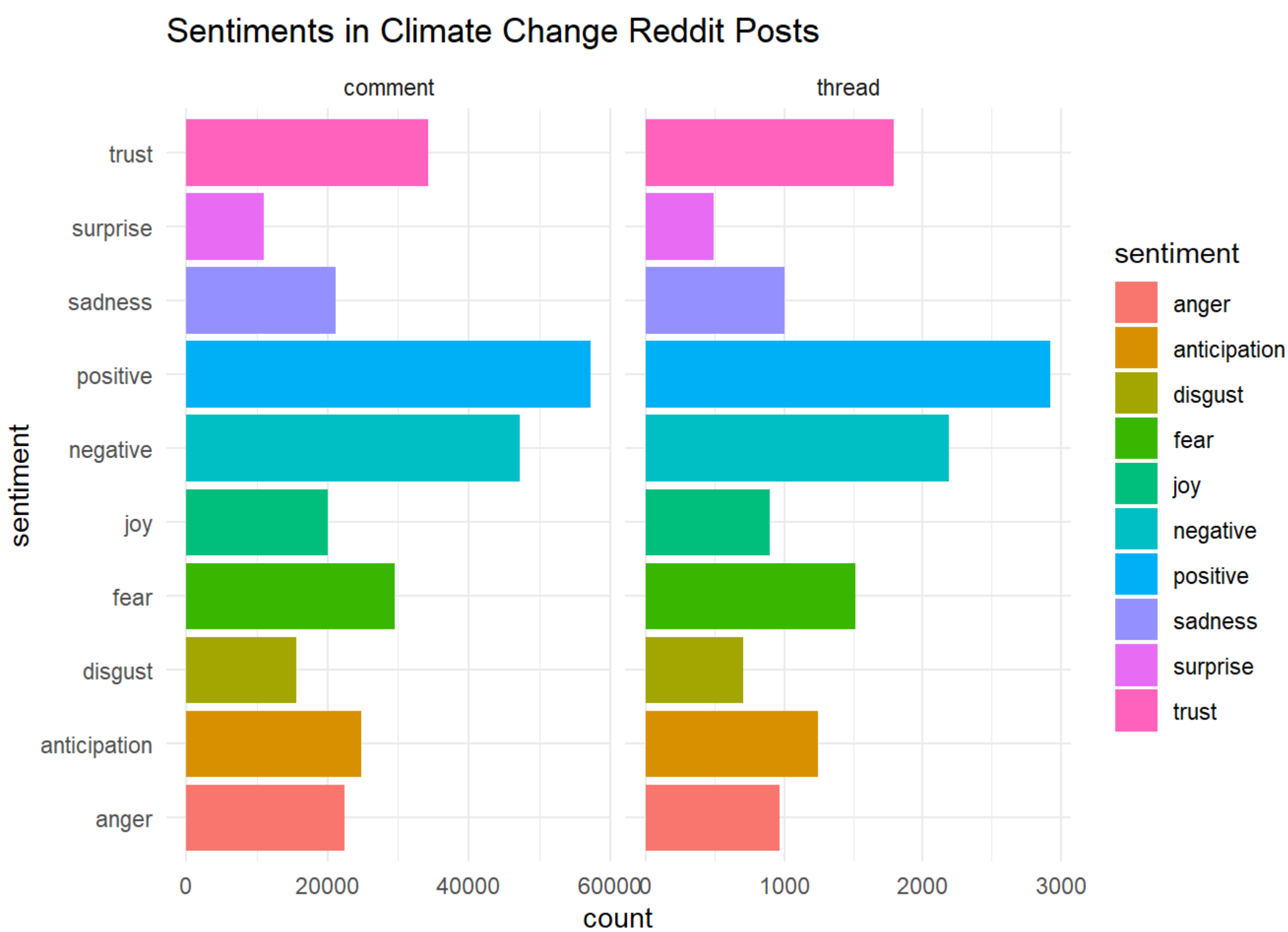
Lastly, we will bind the relevant variables from each dataset together using `bind_rows()` .

```
# bind threads and comments (want to select the same columns in each)
tidy_comments_threads <-
  bind_rows(select(tidy_comments, word, timestamp, score, sentiment, type),
            select(tidy_threads, word, timestamp, score, sentiment, type))
```

And now we can make a similar graph to the one before, but where we compare across comments and threads.

```
library(ggplot2)

ggplot(tidy_comments_threads, aes(y = sentiment))+
  geom_bar(aes(fill = sentiment))+
  theme_minimal()+
  labs(title = "Sentiments in Climate Change Reddit Posts")+
  facet_grid(cols = vars(type), scales = "free_x")
```



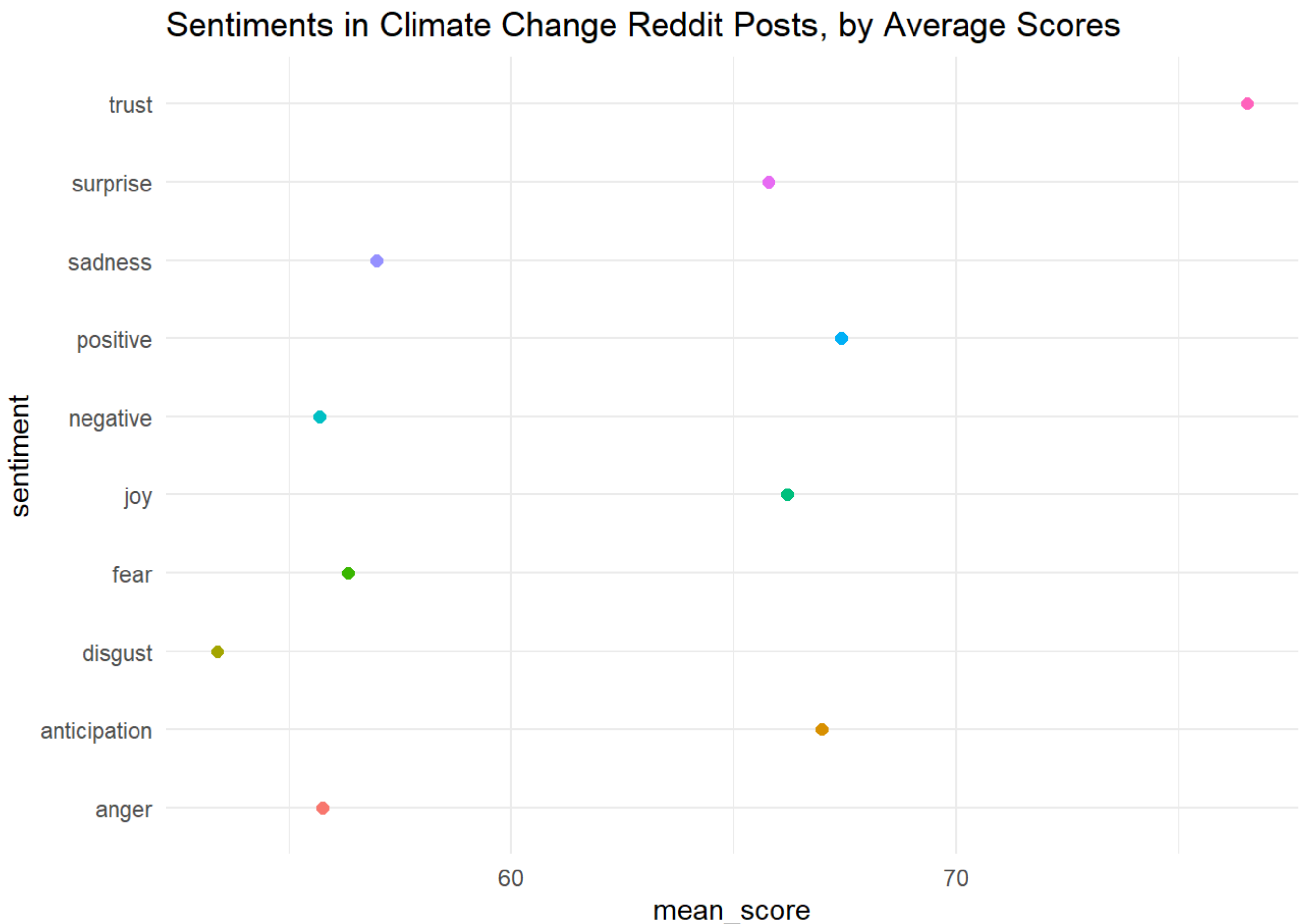
One feature of the Reddit data is that comments and posts have “scores” which denote their number of upvotes minus their number of downvotes. It could be that the sentiments of these climate change-related comments and posts are related to whether they receive upvotes or downvotes. Let’s do some investigating.

```
# create dataset with one row for each sentiment
sentiments_scores <- tidy_comments_threads %>%
  group_by(sentiment) %>%
  summarise(mean_score = mean(score, na.rm = T))
```

Let's pause for a moment. What did we just do? We used the `group_by()` to organize our dataset by the sentiment categories (running `group_by()` on its own doesn't change the structure of your data, but it will change how other operations affect your data). When we calculate the mean score, R does this for each group. That is, we know the average score of a joyful comment, for example. We specify `na.rm = T` so that the mean will just be calculated with non-missing entries. What if we had grouped by another variable instead, like type?

For now, we will stick with the `sentiments_scores` dataset we just created, and use this to produce another visualization.

```
# look at the scores of different sentiments
ggplot(sentiments_scores, aes(x = sentiment, y = mean_score))+
  coord_flip()+
  geom_point(aes(col = sentiment), size = 2)+
  theme_minimal()+
  theme(legend.position = "none")+
  labs(title = "Sentiments in Climate Change Reddit Posts, by Average Scores")
```

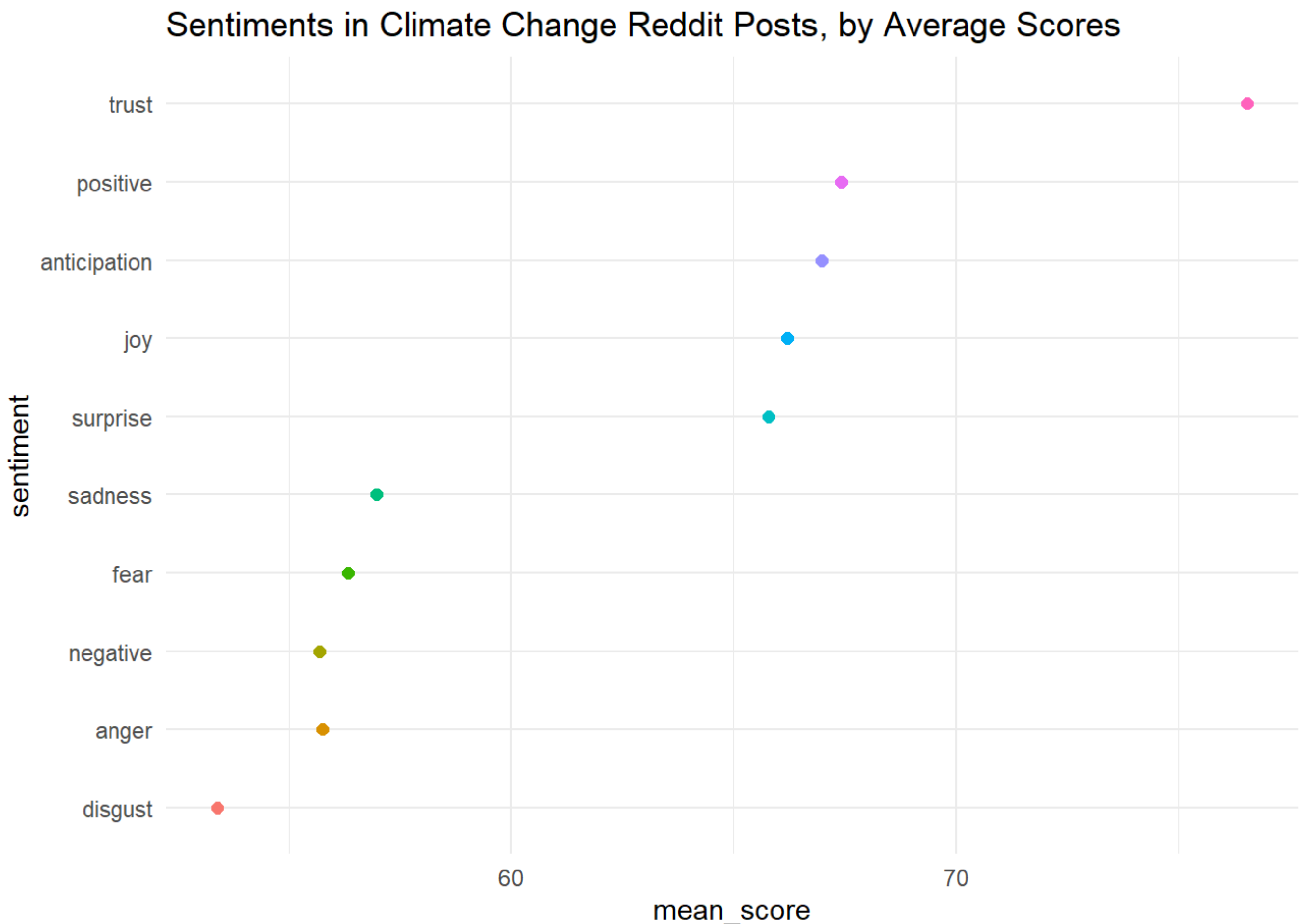


The graph is a little hard to read. Can we alter it so that the points are ranked by value, not alphabetically based on sentiment? We'll do this manually by changing the `levels` in the `factor()` command.

```
# manually change order
sentiments_scores %<>%
  mutate(sentiment = factor(sentiment,
                            levels = c("disgust",
                                       "anger",
                                       "negative",
                                       "fear",
                                       "sadness",
                                       "surprise",
                                       "joy",
                                       "anticipation",
                                       "positive",
                                       "trust")))
```

Great. Now let's look at the plot again.

```
# look at the scores of different sentiments
ggplot(sentiments_scores, aes(x = sentiment, y = mean_score))+
  coord_flip()+
  geom_point(aes(col = sentiment), size = 2)+
  theme_minimal()+
  theme(legend.position = "none")+
  labs(title = "Sentiments in Climate Change Reddit Posts, by Average Scores")
```



This is a bit easier to read! It looks like anger and disgust score the lowest, while trust, positive emotions, and anticipation score the highest. Are we surprised?

4.4 Examining Sentiment Over Time

Next, we might want to look at sentiment over time. Unfortunately, when we pull data from the Reddit API through `RedditextractoR`, we only receive data for the previous two weeks. This might be enough time to analyze a specific issue (for example, a wildfire or other event that just happened), but it is probably not enough time to analyze change in language around climate issues.

Lucky for us, someone has already aggregated all the Reddit comments and threads that mention “climate change” through September 2022. We can download that dataset on Kaggle, which is a great resource for open source data. We’ll start with the posts.

```
# read all time climate change posts
cc_alltime_reddit <- read_csv("Data/the-reddit-climate-change-dataset-posts.csv")
```

Once again, we will unnest the tokens (words) and remove stop words.

```
# tidytext format
tidy_cc <- cc_alltime_reddit %>%
   unnest_tokens(word, title)

# now remove stop words
tidy_cc %<>%
  anti_join(stop_words)
```

We can now look at sentiment over time. We'll start with the afinn dictionary, which ranges from -5 to 5. Our time indicator is the variable `created_utc`, which is measured in seconds since January 1 1970 (as a side note, you can use this website to convert unix timestamps to human dates and times). We probably want to measure time in a larger unit, like days or weeks. Let's see how many seconds are in a week.

```
60*60*24*7
```

```
## [1] 604800
```

Ok great, so there are 604800 seconds in a week. We use `%/%` to perform *integral division* on `created_utc`. That is, we want the result to be in integer form so that we can group the time periods by weeks.

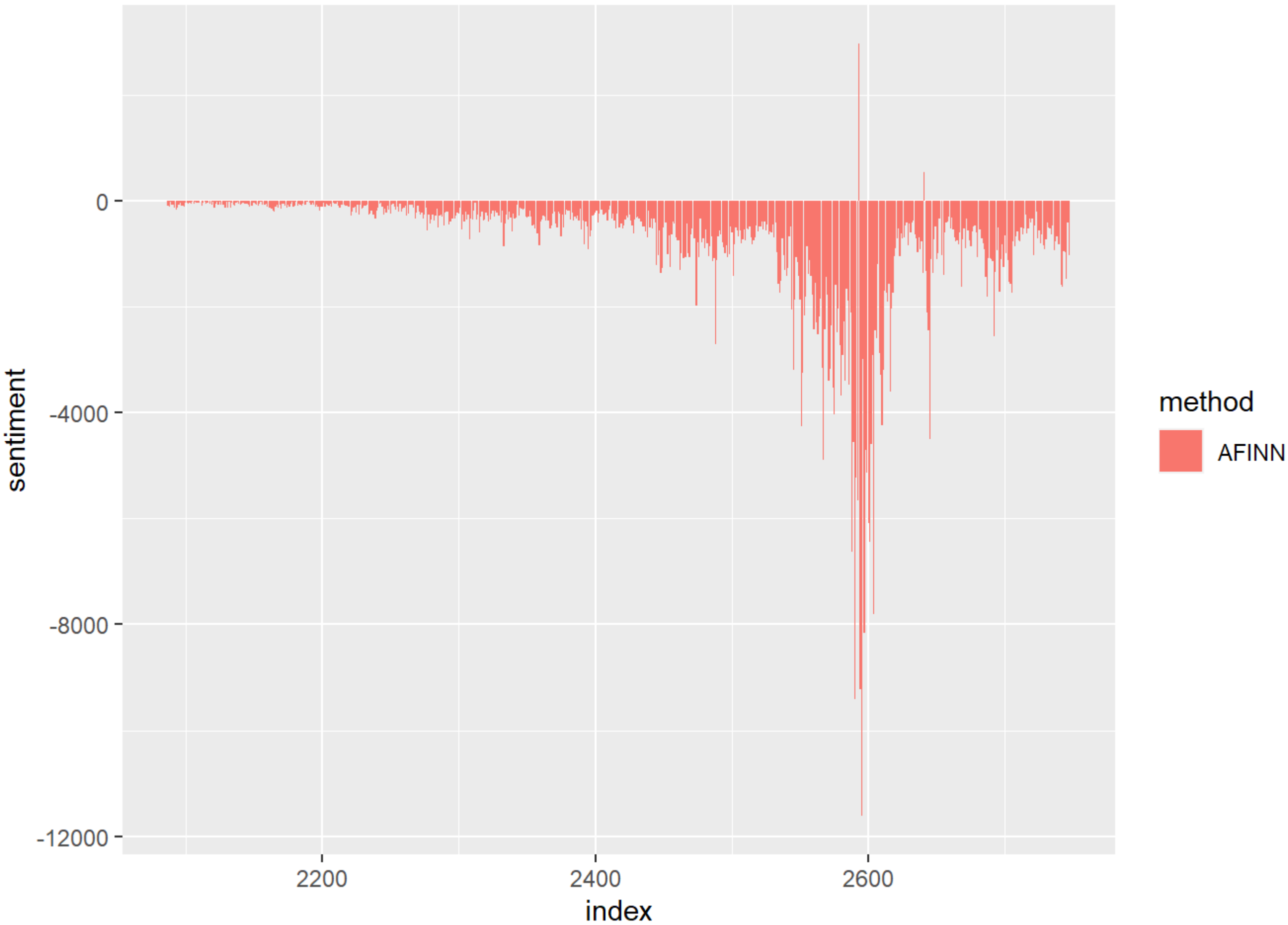
```
afinn <- tidy_cc %>%
  inner_join(get_sentiments("afinn")) %>%
  group_by(index = created_utc %/% 604800) %>%
  summarise(sentiment = sum(value)) %>%
  mutate(method = "AFINN")

afinn
```

```
## # A tibble: 661 × 3
##    index sentiment method
##    <dbl>     <dbl> <chr>
##  1  2087       -92 AFINN
##  2  2088      -115 AFINN
##  3  2089       -32 AFINN
##  4  2090       -87 AFINN
##  5  2091       -72 AFINN
##  6  2092      -143 AFINN
##  7  2093      -170 AFINN
##  8  2094      -130 AFINN
##  9  2095       -87 AFINN
## 10  2096       -45 AFINN
## # ℹ 651 more rows
```

Great! Now we can plot our result.

```
ggplot(afinn, aes(index, sentiment, fill = method)) +
  geom_col()
```



Interesting! Any guesses for why the sentiment became so negative around 2600? (This is October 2019).

We notice that the plot is mostly negative. This could be a function of the topic or the forum. But we might want to check that this is not due to the lexicon dictionary that we are using. So let's try with the "bing" and "nrc" dictionaries as well, and see if we get the same result.

```
library(tidyr)
# try with the bing dictionary
bing <- tidy_cc %>%
  inner_join(get_sentiments("bing")) %>%
  mutate(method = "Bing et al.") %>%
   count(method, index = created_utc %/% 604800, sentiment) %>%
   pivot_wider(names_from = sentiment,
              values_from = n,
              values_fill = 0) %>%
  mutate(sentiment = positive - negative)

bing
```

```
## # A tibble: 661 × 5
##    method      index negative positive sentiment
##    <chr>       <dbl>    <int>    <int>     <int>
##  1 Bing et al.  2087       83       19       -64
##  2 Bing et al.  2088      103       26       -77
##  3 Bing et al.  2089       55       38       -17
##  4 Bing et al.  2090       98       36       -62
##  5 Bing et al.  2091       84       38       -46
##  6 Bing et al.  2092      118       35       -83
##  7 Bing et al.  2093      134       71       -63
##  8 Bing et al.  2094       96       34       -62
##  9 Bing et al.  2095      104       35       -69
## 10 Bing et al.  2096       53       31       -22
## # ℹ 651 more rows
```

```
# try with the nrc dictionary
nrc <- tidy_cc %>%
  inner_join(get_sentiments("nrc") %>%
               # only get positive and negative sentiments
               filter(sentiment %in% c("positive", "negative"))) %>%
    mutate(method = "NRC") %>%
  count(method, index = created_utc %/% 604800, sentiment) %>%
   pivot_wider(names_from = sentiment,
              values_from = n,
              values_fill = 0) %>%
  mutate(sentiment = positive - negative)

nrc
```

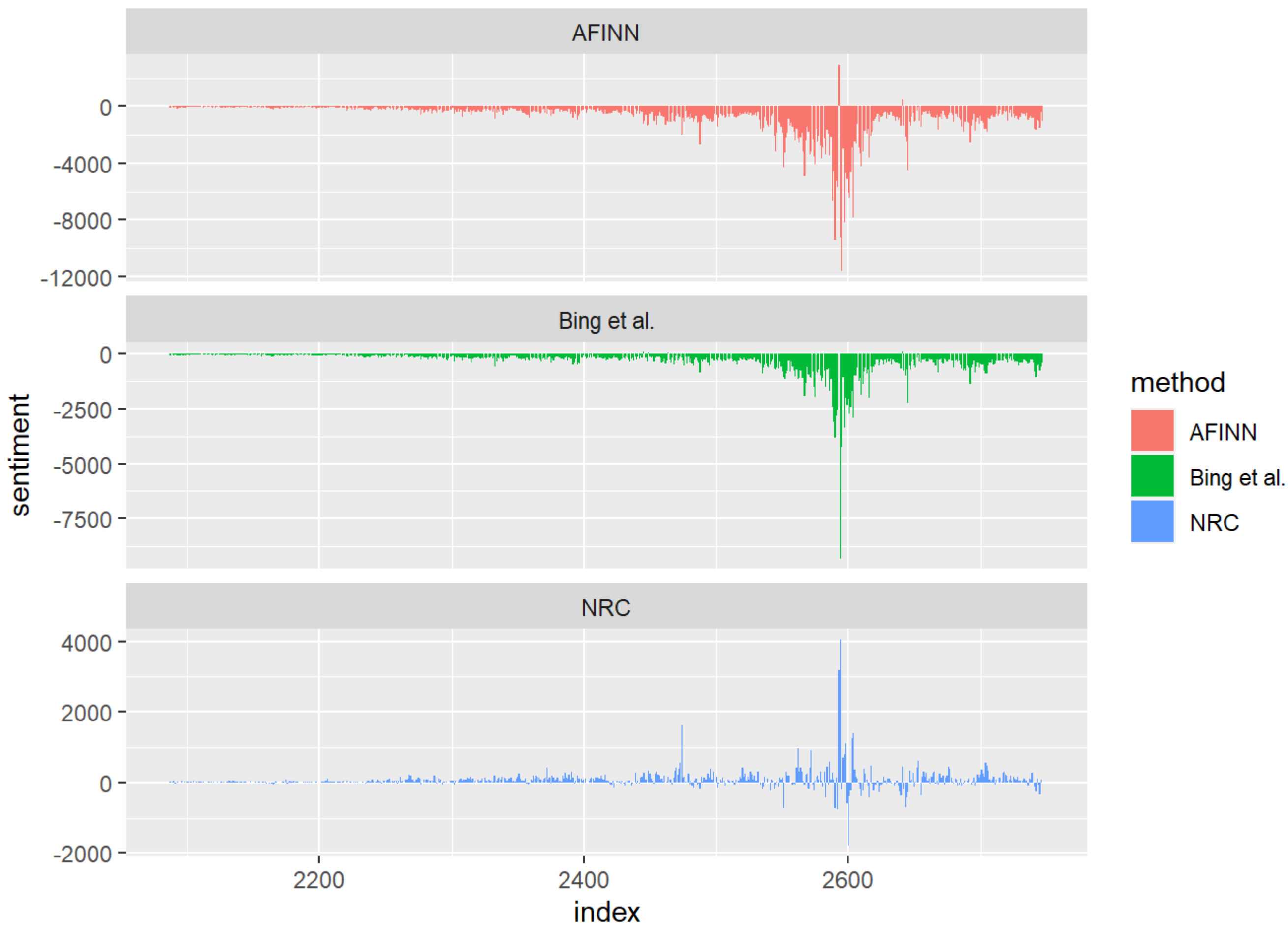
```
## # A tibble: 661 × 5
##    method index negative positive sentiment
##    <chr>  <dbl>    <int>    <int>     <int>
##  1 NRC     2087       71       82        11
##  2 NRC     2088       91      111        20
##  3 NRC     2089       58       83        25
##  4 NRC     2090       67      109        42
##  5 NRC     2091      116       92       -24
##  6 NRC     2092       95      102         7
##  7 NRC     2093      126      137        11
##  8 NRC     2094       88       76       -12
##  9 NRC     2095      121      109       -12
## 10 NRC     2096       68      108        40
## # ℹ 651 more rows
```

Now we can bind these together (using the `bind_rows()` function) and create a plot that summarizes all three.

```
all_three <- bind_rows(afinn,
                       bing,
                       nrc)
```

And now we can plot all three!

```
ggplot(all_three, aes(index, sentiment, fill = method)) +
  geom_col(aes(fill = method))+
  facet_wrap(~method, ncol = 1, scales = "free_y")
```



We notice some similarities between the first two dictionaries, but the third one is a bit different. Why might this be?

4.5 Sentiments and Language Around the Cape Town Water Crisis

Let’s now turn back to the Cape Town Water Crisis. We might wonder how discourse around this crisis evolved on social media sites such as Reddit. We can limit the Reddit posts on climate change to just those mentioning Cape Town with the following code:

```
# limit to data with mention of cape town water crisis
cape_town_words <- c("Cape Town", "water crisis", "Water Crisis",
                     "cape town")

# limit to posts that include any cape town or water crisis related words
cape_town_posts <- cc_alltime_reddit %>%
  filter(str_detect(title, paste(cape_town_words, collapse = "|")))

# make tidytext
tidy_cape_town <- cape_town_posts %>%
  unnest_tokens(word, title) %>%
  anti_join(stop_words)
```

We can also look at lists of the most common positive and negative words in the language used by Reddit posts on the Cape Town Water Crisis.

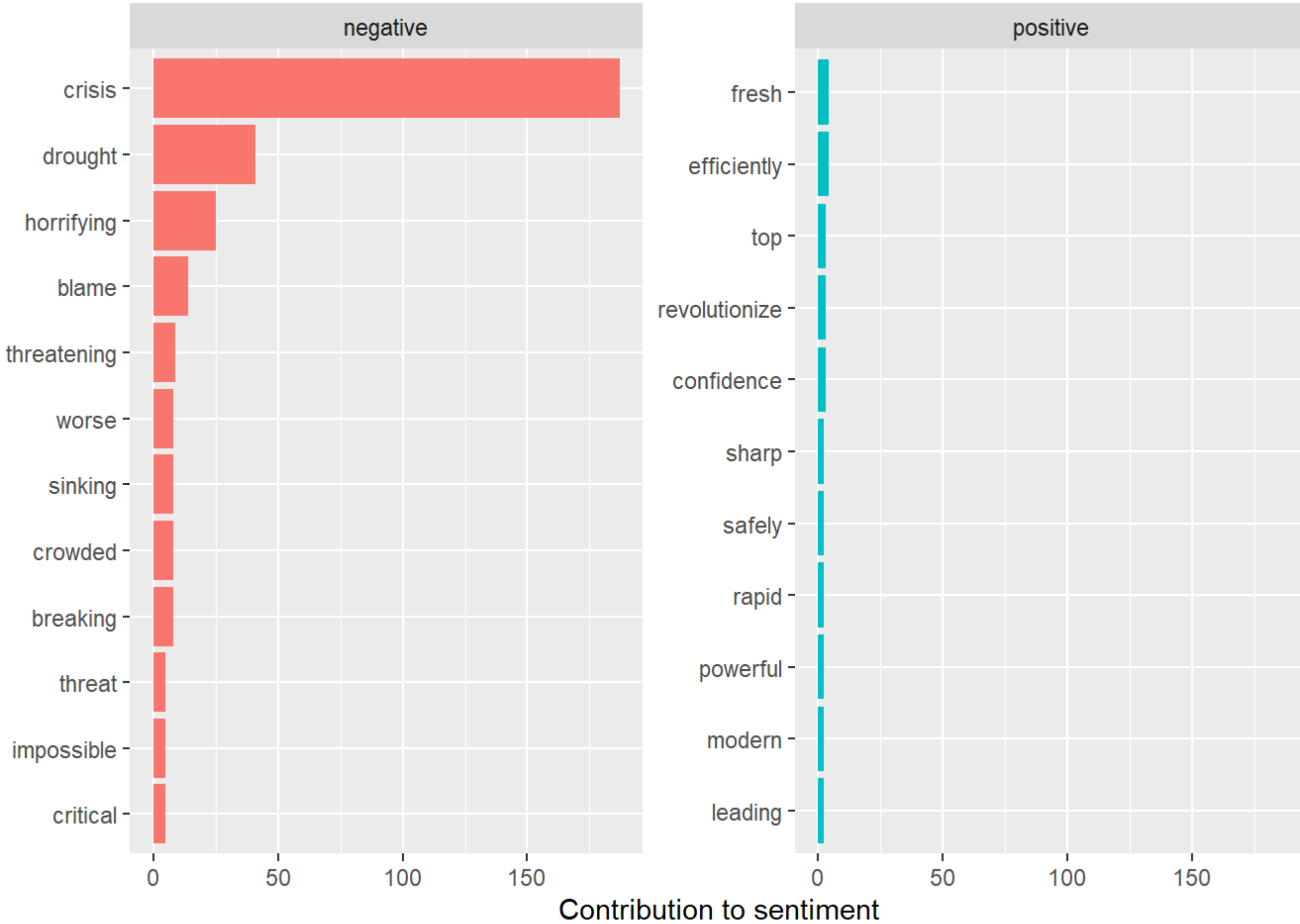
```
bing_word_counts <- tidy_cape_town %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


bing_word_counts
```

```
## # A tibble: 103 × 3
##    word        sentiment     n
##    <chr>       <chr>     <int>
##  1 crisis      negative    187
##  2 drought     negative     41
##  3 horrifying  negative     25
##  4 blame       negative     14
##  5 threatening negative      9
##  6 breaking    negative      8
##  7 crowded     negative      8
##  8 sinking     negative      8
##  9 worse       negative      8
## 10 critical    negative      5
## # ℹ 93 more rows
```

We can also plot the results.

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



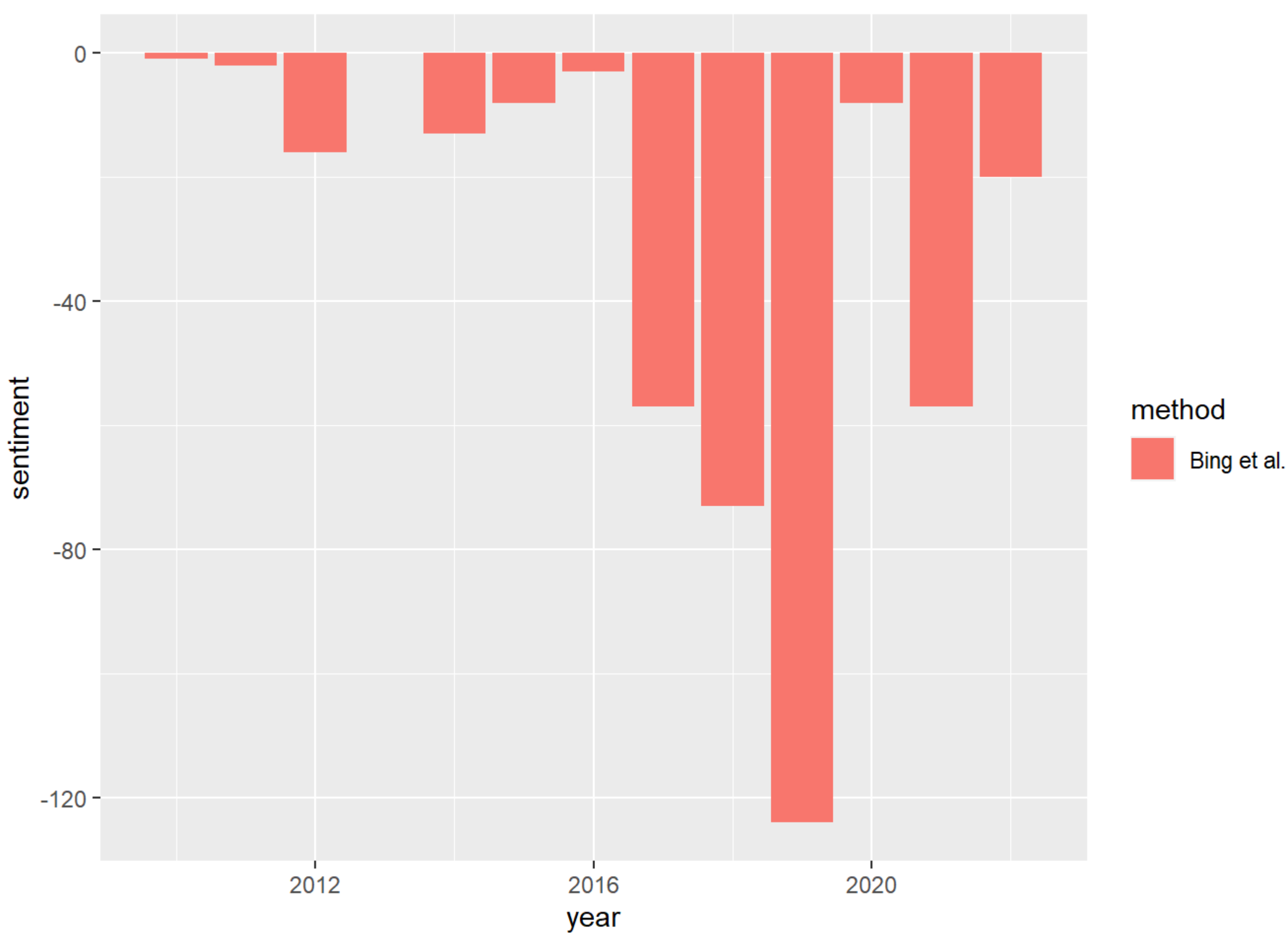
Perhaps unsurprisingly, the frequencies of negative words are much larger than those of positive words. The words “crisis” and “drought” contribute the most to negative sentiments. The next two words, however, are perhaps not so obvious: “horrifying” and “blame.” These give us a fuller picture of the sentiments that appeared, at least on the social media site Reddit, as people discussed this topic.

We can also look at sentiment over time. We’ll try using the Bing Lexicon, and aggregating the sentiment for periods of years (we note that each year has `31556926` seconds).

```
# create bing sentiment dataframe for cape town posts, each observation is a year
bing_ct <- tidy_cape_town %>%
  inner_join(get_sentiments("bing")) %>%
  mutate(method = "Bing et al.") %>%
   count(method, index = created_utc %/% 31556926, sentiment) %>%
   pivot_wider(names_from = sentiment,
               values_from = n,
               values_fill = 0) %>%
  mutate(sentiment = positive - negative,
         year = as.numeric(index + 1970))
```

Now we can plot the results for Cape Town.

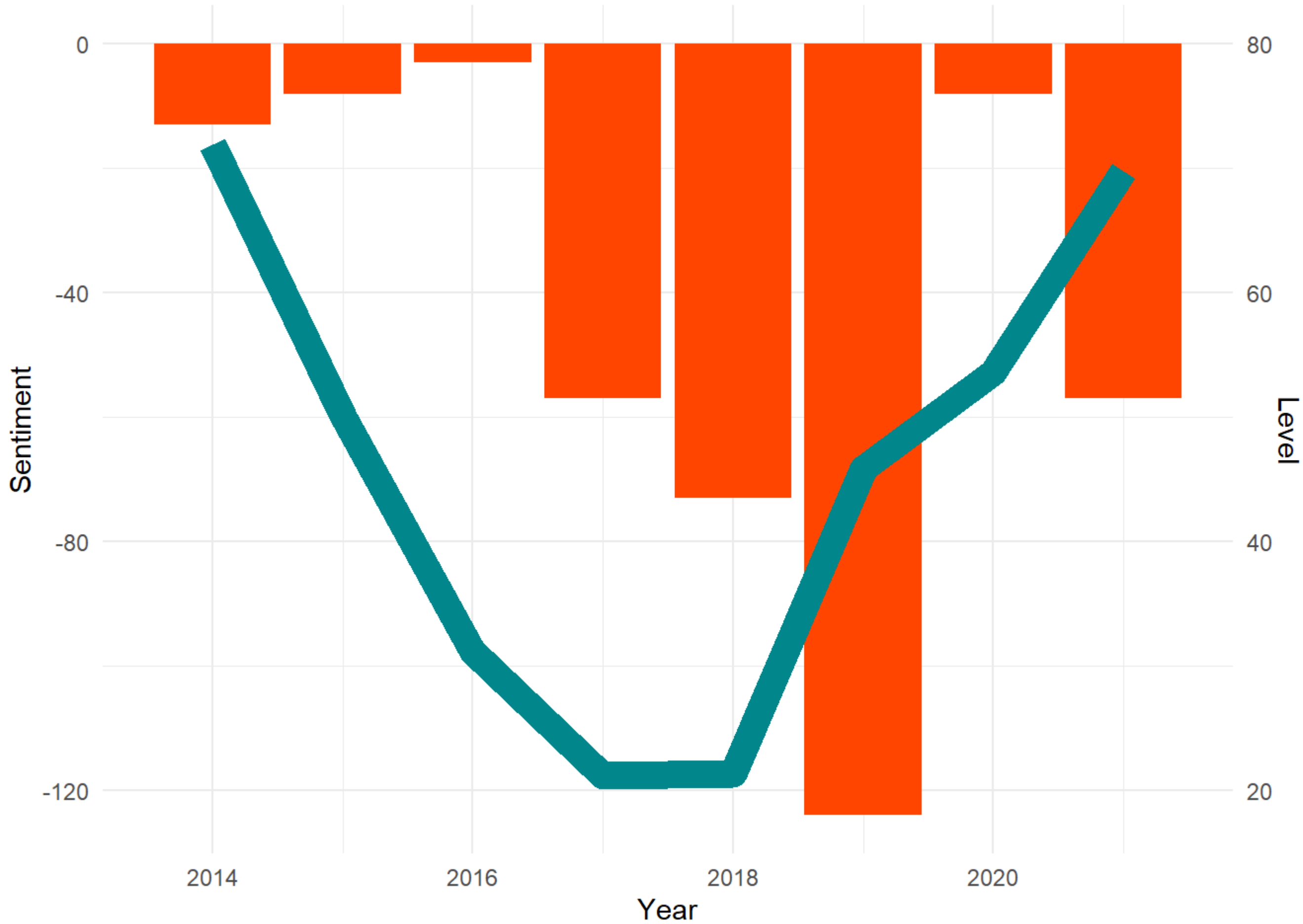
```
# plot sentiment over time for cape town posts
ggplot(bing_ct, aes(year, sentiment, fill = method)) +
  geom_col()
```



Does this chart remind us of anything? The trend in sentiment is lowest around 2017 and 2018, right when water levels were lowest and the crisis was at its most extreme. We might be interested in plotting *both* the water levels and the Reddit sentiments. We can do this in `ggplot2` ! But it will take a bit of work. If you're curious, this page has some useful information on how to set up a chart with two separate y-axes.

```
# create dataset for overlayed plot
combined_plot <- cape_town_table %>%
              mutate(year = as.numeric(as.character(Date))) %>%
              filter(total == 1.5 & !is.na(total)) %>%
                       left_join(bing_ct)

# plot both results
ggplot(combined_plot, aes(x = year, y = (Level-80)*2, group = `Major dams`))+
  geom_col(aes(year, sentiment), fill = "orangered")+
  geom_line(lwd = 5, col = "turquoise4")+
  scale_y_continuous(name = "Sentiment",
                     sec.axis = sec_axis(trans = ~./2+80,
                                         name = "Level"))+
  labs(x = "Year")+
  guides(lwd = FALSE)+
  theme_minimal()
```



4.6 Problem Set 4

Recommended Resources:

Extracting Reddit Data with R

Text Mining with R: A Tidy Approach

1. Choose a topic related to climate change. Use the `RedditextractoR` package to get the thread content of posts related to this topic. Put your data in `tidytext` format, and show the first 6 rows of the threads and comments, separately.
2. Using the NRC lexicon, create a chart of sentiment for your comments or threads, similar to the one in section 4.3. BONUS: try comparing the sentiment of your comments and threads!
3. Now, download the Reddit Climate Change dataset from Kaggle here. Read in the data and create the `tidy_cc` dataset that we created in section 4.4. Then, choose a lexicon (Bing, NRC, or AFINN), and graph the post sentiments according to their scores (similarly to what

we did in section 4.3). What do you find?

4. Limit the climate change Reddit posts in some way (for example, you can filter them to posts about Cape Town, or some other place or event, such as the IPCC, or Australian Wildfires). Choose a lexicon (Bing, NRC, or AFINN), and plot the sentiment over time. Can you explain the volatility? BONUS: Plot all three dictionaries. Do you find differences between them?

5. Considering disasters such as the Cape Town Water Crisis and Hurricane Katrina, reflect on the implications of people's sentiments for broader social behaviors. What can we learn by analyzing the sentiments of what people say? Describe another source of text data for which you would like to analyze sentiment related to a disaster, and explain why this would be interesting. Could governments or other organizations benefit from the analysis you describe?