EDS 231 Topic 2: Text Data in R Assignment

Mia Forsline

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Set up: Load necessary packages

2. Connect to the New York Times API and send a query

- Query phrase: "bark beetle"

```
#create an object called x with the results of our query ("bark beetle")
# the from JSON flatten the JSON object, then convert to a data frame

key = "zwtPmtpUJiMGPfGjXz8maQyr3cx6YFdS"

x <- fromJSON("http://api.nytimes.com/svc/search/v2/articlesearch.json?q=bark+beetle&api-key=zwtPmtpUJi
              flatten = TRUE) #the string following "key=" is your API key

#convert x to a dataframe
x <- x %>%
  data.frame()
```

Examine a piece of text

- the data object has a variable called "response.docs.snippet" that contains a short excerpt, or "snippet" from the article.
- check the snippet to ensure that the query picked out articles containing the correct query word ("bark beetle")

```
x$response.docs.snippet[9]
```

Set some parameters for a bigger query

- searching for articles from 1990 - 2022

```
term <- "bark+beetle" # Need to use + to string together separate words
begin_date <- "19900101" #start date: Jan 1, 1990
end_date <- "20220101" #end date: Jan 1, 2022
key = "zwtPmtpUJiMGPfGjXz8maQyr3cx6YFdS"

#construct the query url using API operators
```

```
baseurl <- paste0("http://api.nytimes.com/svc/search/v2/articlesearch.json?q=",term,
                  "&begin_date=",begin_date,
                  "&end_date=",end_date,
                  "&facet_filter=true&api-key=",key, sep="")

#examine our query url
baseurl
```

```
## [1] "http://api.nytimes.com/svc/search/v2/articlesearch.json?q=bark+beetle&begin_date=19900101&end_da
```

Obtain multiple pages of query results

- retrieved 35 pages of results
- retrieved 358 articles

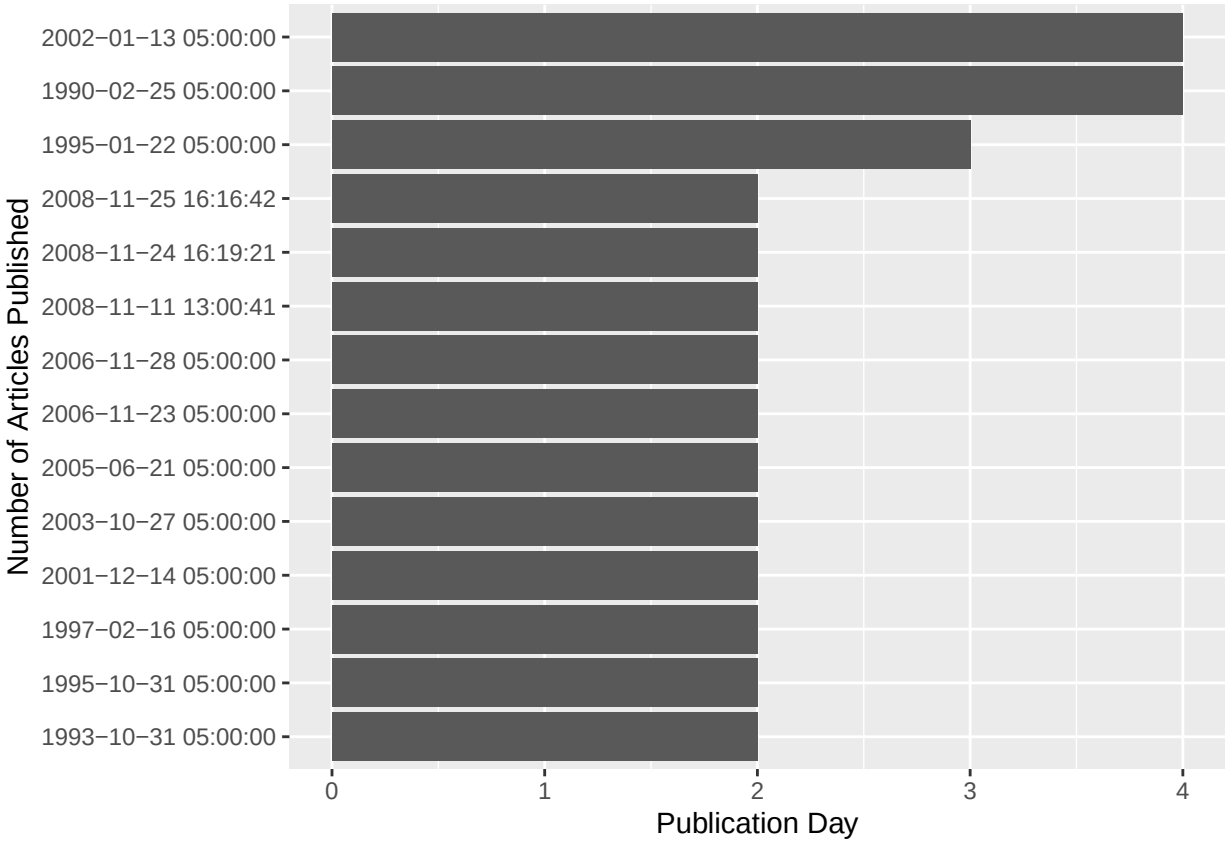
```
initialQuery <- fromJSON(baseurl)

maxPages <- round((initialQuery$response$meta$hits[1] / 10)-1)

pages <- list()

for(i in 0:maxPages){
  nytSearch <- fromJSON(paste0(baseurl, "&page=", i), flatten = TRUE) %>% data.frame()
  message("Retrieving page ", i)
  pages[[i+1]] <- nytSearch
  Sys.sleep(6)
}

#need to bind the pages and create a tibble from nytDat
nytDat <- rbind_pages(pages)

#save as bark beetle results as a CSV
write_csv(x = nytDat, path = here::here("data", "nytDat.csv"))
```

3. Visuzalize publications per day

```
nytDat <- read_csv(here::here("data", "nytDat.csv"))
```

```
## Rows: 358 Columns: 33

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (20): status, copyright, response.docs.abstract, response.docs.web_url,...
## dbl   (5): response.docs.print_page, response.docs.word_count, response.meta...
## lgl   (7): response.docs.multimedia, response.docs.keywords, response.docs.h...
## dttm  (1): response.docs.pub_date

##
## 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.
```

```
nytDat %>%
  mutate(pubDay=gsub("T.*","",response.docs.pub_date)) %>%
  group_by(pubDay) %>%
  summarise(count=n()) %>%
  filter(count >= 2) %>%
  ggplot() +
  geom_bar(aes(x=reorder(pubDay, count), y=count), stat="identity") + coord_flip() +
  labs(y = "Publication Day",
       x = "Number of Articles Published")
```



The New York Times doesn't make full text of the articles available through the API. But we can use the first paragraph of each article.

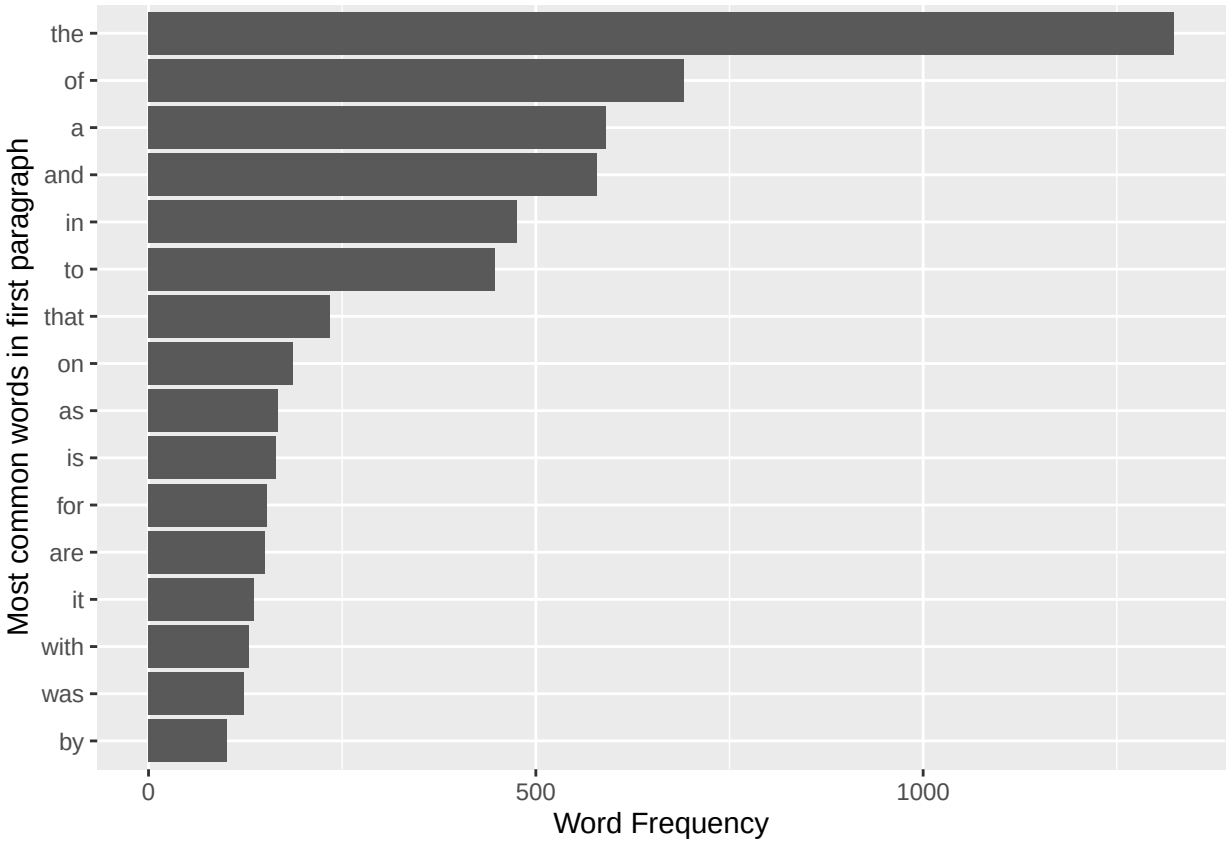
- unnest the words from the first paragraph of each article

```
#names(nytDat)

paragraph <- names(nytDat)[6] #The 6th column, "response.doc.lead_paragraph", is the one we want here.

tokenized <- nytDat %>%
  unnest_tokens(word, paragraph)

#tokenized[,34]
```

3. Visualize word frequency plotsusing the first paragraph of each article

- note that the most common words (occurring more than 100 times) are not at all meaningful

```
tokenized %>%
  count(word, sort = TRUE) %>%
  filter(n > 100) %>% #illegible with all the words displayed
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(n, word)) +
  geom_col() +
  labs(y = "Most common words in first paragraph",
       x = "Word Frequency")
```



Since this visual is not very helpful, we transform the corpus in various ways to help filter out less meaningful words from our visual

1. incorporate stop words
2. stem tribe words
3. remove numbers
4. remove possessive words

```r
#call common stop words from a lexicon
data(stop_words)
stop_words
```

```
## # A tibble: 1,149 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
## # ... with 1,139 more rows
```

```r
#use an anti-join to remove the stop words from our tokenized object
tokenized <- tokenized %>%
  anti_join(stop_words)
```

```
## Joining, by = "word"
```

```r
#inspect the list of tokens (words)
#tokenized$word

clean_tokens <- str_replace_all(tokenized$word,"fringe[a-z,A-Z]*","fringe")

#check to see if the transformation worked
# %>%
#   as.data.frame()
# clean_tokens$.

clean_tokens <- str_remove_all(clean_tokens, "[:digit:]")

#check to see if the transformation worked
# %>%
#   as.data.frame()
# clean_tokens$.

#clean_tokens <- gsub("'s", '', clean_tokens)

clean_tokens <- gsub("[^A-z]s", "", clean_tokens)

# %>%
#   as.data.frame()
# clean_tokens$.

#Put clean tokens into the `tokenized` dataframe

tokenized$clean <- clean_tokens
```

Visualize word frequency after transforming/cleaning

- remove the empty strings
- limit the graph to only include words that occur over 20 times

```
#remove the empty strings
tib <-subset(tokenized, clean!="")
tib <- subset(tib, clean!=",")

#reassign
tokenized <- tib

#visualize again
tokenized %>%
  count(clean, sort = TRUE) %>%
  filter(n > 20) %>%
  mutate(clean = reorder(clean, n)) %>%
  ggplot(aes(n, clean)) +
  geom_col() +
  labs(y = "Most common words in first paragraphs",
       x = "Word Occurrence Frequency") +
  theme_classic()

# ggsave(filename = "words_par.jpg",
#        width = 4,
#        height = 3,
#        units = c("in"),
#        dpi = 300)
```

4. Visualize publications per day

4. Visualize word frequency using headlines

```
headline <- names(nytDat)[21] #The 6th column, "response.doc.lead_paragraph", is the one we want here.

tokenized_h <- nytDat %>%
  unnest_tokens(word, headline)

#tokenized_h[,34]
```

Transform headline words

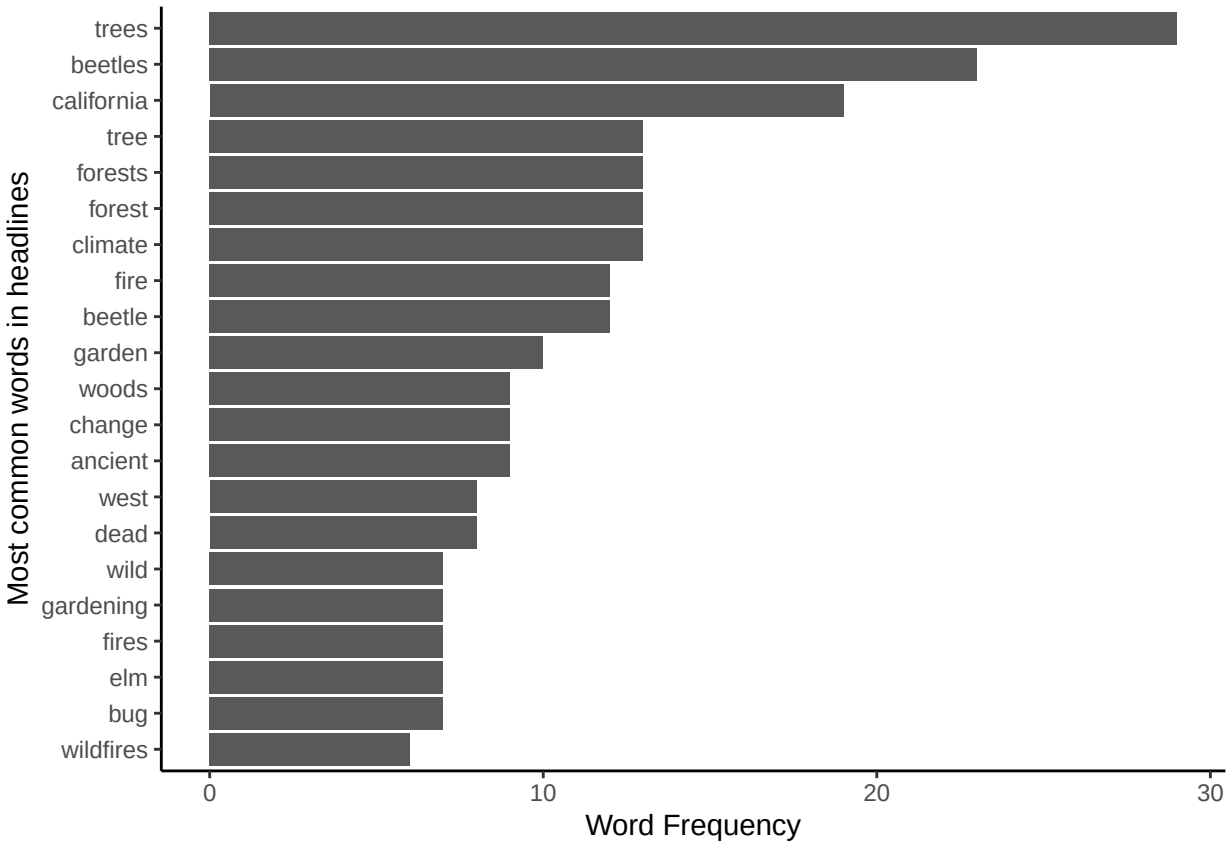
```
#remove stop words
tokenized_h <- tokenized_h %>%
  anti_join(stop_words)
```

```
## Joining, by = "word"
```

```
#stem tribe words
clean_tokens <- str_replace_all(tokenized_h$word,"land[a-z,A-Z]*","land")

#remove numbers
clean_tokens <- str_remove_all(clean_tokens, "[:digit:]")

clean_tokens <- gsub("'s", '', clean_tokens)

tokenized_h$clean <- clean_tokens

#remove the empty strings
tib <-subset(tokenized_h, clean!="")

#reassign
tokenized_h <- tib
```

4. Visualize common words based on headlines

```
tokenized_h %>%
  count(clean, sort = TRUE) %>%
  filter(n > 5) %>%
  mutate(clean = reorder(clean, n)) %>%
  ggplot(aes(n, clean)) +
  geom_col() +
  labs(y = NULL) +
  theme_classic() +
  labs(y = "Most common words in headlines",
       x = "Word Frequency")
```




```
# ggsave(filename = "words_headlines.jpg",
#        width = 4,
#        height = 3,
#        units = c("in"),
#        dpi = 300)
```

4. Comparing word frequencies of NY Times articles' first paragraphs and headlines

The most immediate difference between the word frequency plots using either NY Times articles' first paragraphs or headlines is that the plot visualizing word frequency of first paragraphs has much larger word frequencies. For example, the most common word "trees" is used approximately 75 times in first paragraphs while the other plot shows the word "trees" was found in headlines only approximately 30 times. This makes sense given that paragraphs are much longer than headlines, so it's just more likely for a common word like "trees" to be used.

Both plots shared exact words such as "trees," "beetle(s)", and "climate." However, there were some unique top words. For instance, headlines reported "elm" and "ancient" while first paragraphs reported "york" and "pine."

The overall data distribution shapes looked very similar with one or two extremely common words and a gentle slope downward towards less frequent words.