Applied Statistical Programming - Spring 2022

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Problem Set 3

Due Wednesday, March 16, 10:00 AM (Before Class)

Instructions

- 1. The following questions should each be answered within an Rmarkdown file. Be sure to provide many comments in your code blocks to facilitate grading. Undocumented code will not be graded.
- 2. Work on git. Continue to work in the repository you forked from https://github.com/johnsontr/AppliedStatisticalProgramming2022 and add your code for Problem Set 4. Commit and push frequently. Use meaningful commit messages because these will affect your grade.
- 3. You may work in teams, but each student should develop their own Rmarkdown file. To be clear, there should be no copy and paste. Each keystroke in the assignment should be your own.
- 4. For students new to programming, this may take a while. Get started.

tidyverse

Your task in this problem set is to combine two datasets in order to observe how many endorsements each candidate received using only dplyr functions. Use the same Presidential primary polls that were used for the in class worksheets on February 28 and March 2.

```
# Change eval=FALSE in the code block. Install packages as appropriate.
#install.packages("fivethirtyeight")
library(fivethirtyeight)
library(tidyverse)
# URL to the data that you've used.
url <- 'https://jmontgomery.github.io/PDS/Datasets/president_primary_polls_feb2020.csv'
polls <- read_csv(url)
Endorsements <- endorsements_2020 # from the fiverthirtyeight package</pre>
```

First, create two new objects polls and Endorsements. Then complete the following.

- Change the Endorsements variable name endorsee to candidate_name.
- Change the Endorsements dataframe into a tibble object.

```
# Check whether Endorsements is already tibble - this should already be the case is_tibble(Endorsements)
```

```
## [1] TRUE
```

```
# Rename endorsee variable
Endorsements <- Endorsements %>%
  rename(candidate_name = endorsee)
```

• Filter the poll variable to only include the following 6 candidates: Amy Klobuchar, Bernard Sanders, Elizabeth Warren, Joseph R. Biden Jr., Michael Bloomberg, Pete Buttigieg and subset the dataset to the following five variables: candidate_name, sample_size, start_date, party, pct

"Elizabeth Warren", "Joseph R. Biden Jr.",

filter(candidate_name %in% c("Amy Klobuchar", "Bernard Sanders",

```
"Michael Bloomberg", "Pete Buttigieg")) %>%
  select(candidate name, sample size, start date, party, pct)
# Check that it worked
unique(polls$candidate_name)
## [1] "Bernard Sanders"
                                                     "Joseph R. Biden Jr."
                              "Pete Buttigieg"
## [4] "Amy Klobuchar"
                              "Elizabeth Warren"
                                                     "Michael Bloomberg"
  • Compare the candidate names in the two datasets and find instances where the a candidates name is
    spelled differently i.e. Bernard vs. Bernie. Using only dplyr functions, make these the same across
    datasets.
unique(polls$candidate_name)
## [1] "Bernard Sanders"
                              "Pete Buttigieg"
                                                     "Joseph R. Biden Jr."
## [4] "Amy Klobuchar"
                              "Elizabeth Warren"
                                                     "Michael Bloomberg"
unique(Endorsements$candidate_name)
                              "Joe Biden"
                                                    "Julian Castro"
    [1] "John Delaney"
   [4] "Kamala Harris"
                              "Bernie Sanders"
                                                    "Cory Booker"
  [7] "Amy Klobuchar"
                              "Elizabeth Warren"
                                                    "Jav Inslee"
                              "Beto O'Rourke"
## [10] "John Hickenlooper"
                                                    "Kirsten Gillibrand"
## [13] "Pete Buttigieg"
                              "Eric Swalwell"
                                                    "Steve Bullock"
## [16] NA
Endorsements <- Endorsements %>%
  mutate(candidate_name = case_when(
    grepl("biden", candidate_name, ignore.case = TRUE) ~ "Joseph R. Biden Jr.",
    grepl("sanders", candidate_name, ignore.case = TRUE) ~ "Bernard Sanders",
    TRUE ~ candidate_name
  ))
unique(Endorsements$candidate name)
  [1] "John Delaney"
                               "Joseph R. Biden Jr." "Julian Castro"
    [4] "Kamala Harris"
                               "Bernard Sanders"
                                                       "Cory Booker"
  [7] "Amy Klobuchar"
                               "Elizabeth Warren"
                                                       "Jay Inslee"
## [10] "John Hickenlooper"
                               "Beto O'Rourke"
                                                      "Kirsten Gillibrand"
## [13] "Pete Buttigieg"
                               "Eric Swalwell"
                                                      "Steve Bullock"
## [16] NA
  • Now combine the two datasets by candidate name using dplyr (there will only be five candidates after
```

[1] 6

joining).

length(unique(polls\$candidate_name))

polls <- polls %>%

length(unique(Endorsements\$candidate_name)) ## [1] 16 polls <- polls %>% inner_join(Endorsements, by="candidate_name") length(unique(polls\$candidate_name))

[1] 5

• Create a variable which indicates the number of endorsements for each of the five candidates using dplyr.

```
# Create standalone dataset with counts
candidate_endorsements <- Endorsements %>%
   count(candidate_name) %>%
   rename(n_endorsements = n) %>%
   semi_join(polls, by="candidate_name")

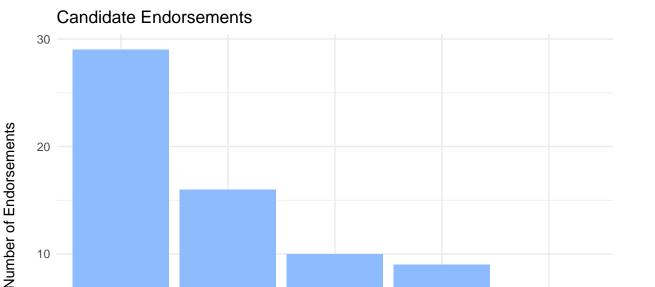
# Add counts to the merged dataset
polls <- polls %>%
   left_join(candidate_endorsements, by="candidate_name")
```

- Plot the number of endorsement each of the 5 candidates have using ggplot(). Save your plot as an object p.
- Rerun the previous line as follows: p + theme_dark(). Notice how you can still customize your plot without rerunning the plot with new options.
- Now, using the knowledge from the last step change the label of the X and Y axes to be more informative, add a title. Save the plot in your forked repository.

```
p <- ggplot(candidate_endorsements, aes(x=reorder(candidate_name, -n_endorsements), y=n_endorsements))+
    geom_col(fill="#8ebbfd")

# Didn't like the way this looked, used minimal theme instead
# p + theme_dark()

p +
    labs(x="\nCandidate", y="Number of Endorsements\n", title="Candidate Endorsements") +
    theme_minimal()</pre>
```



Candidate

Elizabeth Warren

Pete Buttigieg

Amy Klobuchar

ggsave("CandidateEndorsements.pdf", width = 7, height = 3)

Joseph R. Biden Jr. Bernard Sanders

Text-as-Data with tidyverse

0

For this question you will be analyzing Tweets from President Trump for various characteristics. Load in the following packages and data:

```
# Change eval=FALSE in the code block. Install packages as appropriate.
library(tidyverse)
#install.packages('tm')
library(tm)
#install.packages('lubridate')
library(lubridate)
#install.packages('wordcloud')
library(wordcloud)
trump_tweets_url <- 'https://politicaldatascience.com/PDS/Datasets/trump_tweets.csv'
tweets <- read_csv(trump_tweets_url)</pre>
```

• First separate the created_at variable into two new variables where the date and the time are in separate columns. After you do that, then report the range of dates that is in this dataset.

```
tweets <- tweets %>%
  separate(created_at, c("created_date", "created_time"), sep=" ") %>%
  mutate(created_date = as.Date(created_date, format="%m/%d/%Y"))

tweets %>%
  summarise(min=min(created_date), max=max(created_date))
```

```
## # A tibble: 1 x 2
## min max
## <date> <date>
## 1 2014-01-01 2020-02-14
```

• Using dplyr subset the data to only include original tweets (remove retweents) and show the text of the President's top 5 most popular and most retweeted tweets. (Hint: The match function can help you find the index once you identify the largest values.)

```
tweets <- tweets %>%
  filter(!is_retweet)

top_fav <- tweets %>%
  slice_max(favorite_count, n=5) %>%
  select(favorite_count)

top_rt <- tweets %>%
  slice_max(retweet_count, n=5) %>%
  select(retweet_count)

ten_tweets <- tweets %>%
  filter(retweet_count %in% top_rt$retweet_count | favorite_count %in% top_fav$favorite_count) %>%
  select(text)
```

- Create a *corpus* of the tweet content and put this into the object Corpus using the tm (text mining) package. (Hint: Do the assigned readings.)
- Remove extraneous whitespace, remove numbers and punctuation, convert everything to lower case and remove 'stop words' that have little substantive meaning (the, a, it).

```
# vignette("tm")
# This string wasn't getting caught by tm functions; fix in original dataset first
tweets$text = gsub("&amp", "", tweets$text)
# A bunch of attempts to get rid of URLs in tweets which end up with the highest tf.idf scores in the D
# Attempts unsuccessful so far
\# tweets\$text = gsub(regex("(https?(:\\/\))?[^\\s]+)."), "", tweets\$text)
 \# \ tweets\$text = gsub(regex("(http:\\/\\/www\\./https:\\/\\/\/www\\./https:\\/\\/)?[a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+([a-z0-9]+
# tweets %>%
              filter(grepl(regex("(http:\\/\\/www\\./https:\\/\\/)?[a-z0-9]+([\\-\www\\./https:\\/\\/)?[a-z0-9]+([\\-\www\\./https:\\/\\/)?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/\\/]?[a-z0-9]+([\\-\www\\./https:\\/]]
              mutate(new\_text = gsub(regex("(http:\\/\\/www\\./https:\\/\\//www\\./https:\\/\\/)?[a-z0]
              select(text, new_text)
#
# tweets %>%
              filter(grepl(regex("((www\\.)?(https?)(:\\/\)/)?[^\\s]+)."), text)) %>%
              mutate(new\_text = gsub(regex("((www\\.)?(https?)(:\\/\)/)?[^\\s]+)."), "", text)) %>%
#
              select(text, new_text)
#
```

```
# regex("((www\\.)?(https?)(:\\/\\/)?[^\\s]+).")

trump_tweets <- VCorpus(VectorSource(tweets$text))
inspect(trump_tweets[[1]])

## <<PlainTextDocument>>
## Metadata: 7
## Content: chars: 268
##

## I'm seeing Governor Cuomo today at The White House. He must understand that National Security far ex

trump_tweets <- trump_tweets %>%
    tm_map(content_transformer(tolower)) %>%
    tm_map(stripWhitespace) %>%
    tm_map(removeWords, stopwords("english")) %>%
    tm_map(removePunctuation) %>%
    tm_map(removePunctuation) %>%
    tm_map(removeNumbers)
```

• Now create a wordcloud to visualize the top 50 words the President uses in his tweets. Use only words that occur at least three times. Display the plot with words in random order and use 50 random colors. Save the plot into your forked repository.

Warning in wordcloud(trump_tweets, min.freq = 3, max.words = 50, random.order =
TRUE, : realdonaldtrump could not be fit on page. It will not be plotted.

much make hillarygoing can • today wantbig good years **Newdonald** fake 'one_{back} obama many news time runlike border now vote thanks america

- Create a document term matrix called DTM that includes the argument control = list(weighting = weightTfIdf)
- Finally, report the 50 words with the highest tf.idf scores using a lower frequency bound of .8.

```
DTM <- DocumentTermMatrix(trump_tweets, control = list(weighting = weightTfIdf, global=c(0.8,Inf)))
## Warning in weighting(x): empty document(s): 480 482 1824 8946 12142
inspect(removeSparseTerms(DTM, 0.98))
## <<DocumentTermMatrix (documents: 30199, terms: 59)>>
## Non-/sparse entries: 74209/1707532
## Sparsity
                     : 96%
## Maximal term length: 15
## Weighting
                     : term frequency - inverse document frequency (normalized) (tf-idf)
## Sample
##
          Terms
## Docs
            america donald
                               great just people president realdonaldtrump thank
     11327 0.000000
                         0 0.0000000
                                        0
                                               0
                                                         0
                                                                  0.000000
     13071 1.105439
                         0 0.6812955
                                               0
                                                         0
                                                                  0.000000
                                                                                0
##
                                        0
                       0 0.9083940
##
     146
           1.473919
                                        0
                                               0
                                                         0
                                                                  0.0000000
                                                                                0
##
     19657 0.000000
                         0 0.0000000
                                        0
                                               0
                                                         0
                                                                  0.0000000
                                                                                0
##
     20106 0.000000
                       0 0.0000000
                                        0
                                               0
                                                         0
                                                                  0.5535537
                                                                                0
     21008 0.000000
                       0 0.0000000
                                               0
                                                         0
##
                                        0
                                                                  0.3690358
                                                                                0
##
     2798 1.473919
                       0 0.9083940
                                        0
                                               0
                                                         0
                                                                 0.0000000
                                                                                0
                                               0
                                                         0
##
     3142 1.473919
                         0 0.9083940
                                        0
                                                                 0.0000000
                                                                                0
##
     3855 1.473919
                         0 0.9083940
                                               0
                                                         0
                                                                  0.0000000
                                                                                0
                                        0
##
     6952 0.000000
                         0.0000000
                                        0
                                               0
                                                         0
                                                                  0.0000000
                                                                                0
##
         Terms
## Docs
           trump will
##
     11327
               0
                    Ω
##
     13071
               0
                    0
                    0
##
     146
               Ω
##
                    0
     19657
##
     20106
               0
                    0
##
     21008
               0
                    0
                    0
##
     2798
               0
##
     3142
               0
                    0
##
     3855
               0
                    0
     6952
                    0
term_mat <- as.matrix(removeSparseTerms(DTM, 0.999))</pre>
nrow(term_mat)
## [1] 30199
ncol(term mat)
## [1] 1758
trump_tweets_tfidf <- as.tibble(term_mat) %>%
  summarise(across(everything(), max)) %>%
  pivot_longer(everything()) %>%
  rename(term=name, tf_idf=value) %>%
  filter(tf_idf > 0.8) %>%
  arrange(desc(tf_idf))
## Warning: 'as.tibble()' was deprecated in tibble 2.0.0.
## Please use 'as_tibble()' instead.
## The signature and semantics have changed, see '?as_tibble'.
```

```
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was generated.
trump_tweets_tfidf[1:50,]
```

```
## # A tibble: 50 x 2
     term
                    tf_idf
##
##
     <chr>
                     <dbl>
## 1 boring
                      8.88
## 2 whistleblower
                      8.63
## 3 name
                      7.78
## 4 celebapprentice
                      7.61
## 5 seanhannity
                      7.20
## 6 enjoy
                      6.64
## 7 usa
                      6.43
## 8 foxandfriends
                      5.93
## 9 cute
                      4.88
                      4.86
## 10 july
## # ... with 40 more rows
```