Final Project Draft - STA 199

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Abstract

NEED TO ADD

Introduction and Data

Background and Motivation

Relative to other forms of media, social media plays a much greater role in how people consume news in today's technology-driven society. A study conducted in 2016 by Pew Research points out how 62% of people get news on social media (Gottfried & Shearer, 2016). As a result, social media plays an integral role in politics, as the presence of a specific subset of information on a user's feed can influence the way they categorize and see the world around them. With more and more individuals on social media such as Twitter, the role that this platform can play is significantly greater than before.

Social media, and Twitter in particular, have become an increasingly large part of the political landscape in the wake of Donald Trump's 2016 election. Trump has been active on Twitter prior to and during his presidency and uses the platform as a tool to communicate with his constituency in real time, posting updates about policy, campaigning, and his feelings on everything from members of Congress to celebrities. He is one of the first politicians to use social media this frequently and has personally referred to his use of Twitter as "modern day presidential" (Trump, 2017).

Donald Trump's Twitter also has "unpresidented" reach among the American public, boasting a follower base of over 87 million. This makes him the second most-followed political personality and sixth most-followed overall account on Twitter (Wikipedia, 2020). On top of this, Trump's Twitter also receives significant attention in the media. Over 850,000 news articles have referenced his Twitter use since 2016 and 31% of his Tweets since then have received individual media coverage (Real Clear Politics, 2019).

Research Questions

Because Trump uses Twitter to convey his political agendas in short blurbs, analyzing his Tweets can give a unique insight into the way that he thinks. Of principal interest was the following research question: How does Donald Trump's sentiment in his Tweets vary across his "in-groups" and "out-groups?" We will define "in-groups" and "out-groups" in different ways, such as political party, gender, and topics that align with his beliefs vs. topics that don't align with his beliefs.

To answer this question, our team obtained a dataset of Donald Trump's Tweets (n = 53,697). In order to assess how his sentiment varies across people and various hot topics, we created indicator variables for different people and topics to indicate that a Tweet referenced a specific person/topic. We then used the sentimentr package to calculate the overall sentiment of each Tweet using the sentiment_by() function. Using the indicator variables, we were then able to distinguish the Tweets into discernable categories, allowing us to conduct hypothesis tests and create interesting visualizations.

Our hypothesis regarding our research questions is that Trump's Tweets about individuals in his "out-group" have a greater proportion of Tweets with a negative sentiment. Similarly, we hypothesize that his Tweets

about individuals in his "in-group" will have a greater proportion of Tweets with a positive sentiment. We will define in-group and out-group in different ways, and evaluate it from different perspectives as well.

Our Data

The data set was extracted from a website-TrumpTwitterArchive.com. The original curator of the data created their own Twitter scraper in order to obtain the data. They utilized Python, Selenium (which is a software suite that allows the automation of tests utilizing web browsers), and Tweepy (a Python library for accessing the Twitter API). Since Twitter makes it challenging to scrape all of a user's Tweets in one go, the way to get around this is to individually search for a specific day and extract all the Tweets from that user on that specific day. To do this manually would take ages, but the scraper that the curator built allows for automated accessing for any desired day and also a range of days. The scraper then obtains the Tweet ID, which contains all of the metadata of the Tweet, and then uses the metadata to obtain all the other information about the Tweet (such as the text, timestamp, number of favorites, etc.). This other information is then compiled into a data set, which is made available to the public. This data set is updated every minute, which also means that deleted Tweets would most likely also appear in this data set. However, as noted on the website, many of the Tweets are missing, either due to them being deleted before the data set was updated, or other reasons.

This data set includes 53,697 observations. Each individual observation is one of President Donald Trump's Tweets. The original data set contains 7 variables: source, text, created_at, reTweet_count, favorite_count, is_reTweeted, id_str. The descriptions of each of the original variables is given below.

- source: Original source where Tweet was posted

- text: text of the Tweet

- created_at: Date and time the Tweet was posted/created, provides context

- reTweet_count: number of reTweets

- favorite_count: number of favorites

- is_reTweeted: whether or not the Tweet was originally posted on a different account and Trump reTweeted

- id_str: The scrape.py script collects Tweet ids. If you know a Tweet's ID number, you can get all the information available about that Tweet using Tweepy

Setting Up Our Data   Our first step in analyzing the relationships between subject and sentiment of President Donald Trump's Tweets was to manipulate the data set, creating some new variables that we could use for analysis. We started by creating a set of identifier variables for different people that his Tweets might be about. These variables were created using multiple mutate commands to set them as either 1 or 0, 1 if the person or topic was mentioned in a Tweet, and 0 if they weren't.

We created these variables for a total of 11 relevant political figures: Barack Obama, Joe Biden, Hillary Clinton, Alexandria Ocasio-Cortez, Nancy Pelosi, Kamala Harris, Mike Pence, Mitch McConnell, Amy Coney Barrett, and Nikki Haley. For each of the person identifier variables, we searched for people's full names, their Twitter handles, and commonly-used nicknames to determine whether or not a particular Tweet was about them.

We also repeated the same process to create topical identifier variables for a range of subjects that are prevalent in the nation's political discourse. The topics were as follows: COVID-19, climate change, abortion, the Black Lives Matter movement, guns, news, immigration, Russia, and the United States. For each topic we searched for the name of the thing outright (such as "BLM" or "climate change"), as well as words and phrases that are commonly used in conjunction with these topics. For example, Tweets that mentioned ICE or the term "border wall" were categorized under immigration, and Tweets about CNN, FOX News and "media" all went under the "news" topic.

Next, using the pivot command in R, we were able to create a variable called "person," and manipulate our original data set into a data set that allowed us to count Tweets that had multiple people mentioned as an observation that counted towards both/all of the mentioned people, as it was a categorical variable that told us which of the identifier variables for people were equal to "1" for each Tweet. As a result, some of the Tweets were the same in this new pivoted data set, but it allowed us to do our analysis in a much more effective and representative manner.

From the new "person" variable, we created two new variables called party and gender. The party variable separated the 11 people we were looking at into either Democrats or Republicans and assigned Tweets about them to the appropriate party category. We did the same for the gender of each of these 11 people, and added another "gender" variable categorizing the Tweet as either about a "male" or "female."

We did a similar pivoting process for the topic variables as well.

Next, we used the package sentimentr to identify the sentiment of each of Trump's Tweets. For each Tweet, we created a new variable called ave_sentiment that contained the raw, numeric sentiment score of the text. This sentiment score was calculated using the sentiment_by() function. The function finds the mean sentiment score of the entire Tweet by averaging the individual sentiment scores of the words in the Tweet. We then used the mutate command to create a new variable called posNeg that grouped sentiment scores into three categories: positive, neutral, or negative. Finally, we used the separate command in r to break up the variable "created_at" into two separate variables for date and time. After this, each observation had a date variable in the mm/dd/yy format and a time variable in the 24-hour time format. After these manipulations, the data set contained the following variables:

- source: the version of Twitter used to share the Tweet. For example "Twitter for iPhone."

- text: the full text of the Tweet.

- created_at: gives the date (in mm/dd/yy format) and time (in 24-hour format) at which the Tweet was published.

- reTweet_count: number of reTweets that the Tweet received.

- favorite_count: number of favorites that the Tweet received.

- is_reTweet: assigns a value of either true or false for whether the Tweet is originally written by Trump or is a reTweet of someone else.

- id_str: The scrape.py script collects Tweet ids. If you know a Tweet's id you can get all the information available about that Tweet using Tweepy - text, timestamp, number of reTweets / replies / favorites, geolocation, etc.

- obama: 1 or 0 for whether the Tweet talks about Barack Obama.

- biden: 1 or 0 for whether the Tweet talks about Joe Biden.

- pelosi: 1 or 0 for whether the Tweet talks about Nancy Pelosi.

- kamala: 1 or 0 for whether the Tweet talks about Kamala Harris.

- hillary: 1 or 0 for whether the Tweet talks about Hillary Clinton.

- aoc: 1 or 0 for whether the Tweet talks about Alexandria Ocasio-Cortez.

- pence: 1 or 0 for whether the Tweet talks about Mike Pence.

- mcconnell: 1 or 0 for whether the Tweet talks about Mitch McConnell.

- fauci: 1 or 0 for whether the Tweet talks about Dr. Anthony Fauci.

- amy: 1 or 0 for whether the Tweet talks about Amy Coney Barrett.

- nikki: 1 or 0 for whether the Tweet talks about Nikki Haley.

- covid: 1 or 0 for whether the Tweet talks about COVID-19.

- climateChange: 1 or 0 for whether the Tweet talks about climate change.
- abortion: 1 or 0 for whether the Tweet talks about abortion.
- blm: 1 or 0 for whether the Tweet talks about the Black Lives Matter movement.
- guns: 1 or 0 for whether the Tweet talks about guns.
- news: 1 or 0 for whether the Tweet talks about news media.
- usa: 1 or 0 for whether the Tweet talks about the United States.
- russia: 1 or 0 for whether the Tweet talks about Russia.
- immigration: 1 or 0 for whether the Tweet talks about immigration.
- person: categorical variable for the name of the person that the Tweet is about (from among the 11 looked at in this analysis).
- party: political party of the person who is talked about in the Tweet (either democrat or republican).
- gender: gender of the person who is talked about in the Tweet (either male or female).
- ave_sentiment: numeric sentiment score of the Tweet.
- posNeg: categorical sentiment of the Tweet (either positive, neutral or negative).
- date: date that the Tweet was posted (mm/dd/yy).
- time: time that the Tweet was posted (24-hour format).

Methodology

The main variables in the data set that we used to address our research questions were the following:

- text: the full text of the Tweet.
- obama: 1 or 0 for whether the Tweet talks about Barack Obama.
- biden: 1 or 0 for whether the Tweet talks about Joe Biden.
- pelosi: 1 or 0 for whether the Tweet talks about Nancy Pelosi.
- kamala: 1 or 0 for whether the Tweet talks about Kamala Harris.
- hillary: 1 or 0 for whether the Tweet talks about Hillary Clinton.
- aoc: 1 or 0 for whether the Tweet talks about Alexandria Ocasio-Cortez.
- pence: 1 or 0 for whether the Tweet talks about Mike Pence.
- mcconnell: 1 or 0 for whether the Tweet talks about Mitch McConnell.
- fauci: 1 or 0 for whether the Tweet talks about Dr. Anthony Fauci.
- amy: 1 or 0 for whether the Tweet talks about Amy Coney Barrett.
- nikki: 1 or 0 for whether the Tweet talks about Nikki Haley.
- covid: 1 or 0 for whether the Tweet talks about COVID-19.
- climateChange: 1 or 0 for whether the Tweet talks about climate change.
- abortion: 1 or 0 for whether the Tweet talks about abortion.
- blm: 1 or 0 for whether the Tweet talks about the Black Lives Matter movement.
- guns: 1 or 0 for whether the Tweet talks about guns.
- news: 1 or 0 for whether the Tweet talks about news media.

- usa: 1 or 0 for whether the Tweet talks about the United States.

- russia: 1 or 0 for whether the Tweet talks about Russia.

- immigration: 1 or 0 for whether the Tweet talks about immigration.

- person: categorical variable for the name of the person that the Tweet is about (from among the 11 looked at in this analysis).

- party: political party of the person who is talked about in the Tweet (either democrat or republican).

- gender: gender of the person who is talked about in the Tweet (either male or female).

- ave_sentiment: numeric sentiment score of the Tweet.

- posNeg: categorical sentiment of the Tweet (either positive, neutral or negative).

- date: date that the Tweet was posted (mm/dd/yy).

- time: time that the Tweet was posted (24-hour format).

We created multiple visualizaitons to help us explore our data. In Figure 1, we created a word cloud of the most common words found in his Tweets. The most common words are displayed with the most frequent words being displayed larger. Given the results, we can see that some of the words he most commonly uses are "great", "Trump", "president", "people", "country", "America", and "time." While these words don't necessarily indicate the full scope of what he discusses on his Twitter account, we notice that most of his Tweets are in regard to his role as the President of the United States. In addition, his most commonly used words are quite polarizing in that he uses many positive words such as "great", "good", "strong", and "nice" while also using many negative words such as "fake", "false", "bad", and "crime". Given the polarity of his Tweets, we believed it would be interesting to see if a common theme would develop among his most common words, which is partially indicated in our results.

Similarly, Figure 2 is a frequency chart of his top 20 most used words in his Tweets. It is interesting to see how much more the word "great" is used in comparison to the other words displayed on the chart.
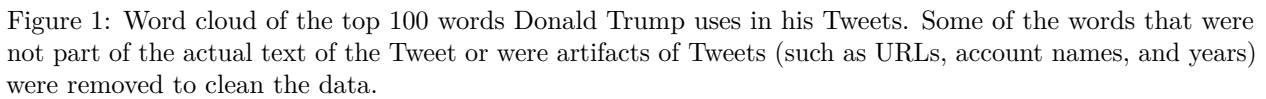
Figure 3 shows the relative proportions of Tweets with positive, neutral and negative overall sentiment that Donald Trump has shared about each of the people covered in our data set. By creating a percent stacked bar plot, we were able to actively compare the sentiments Trump tends to have towards specific people, making it easier to visualize the results. Overall, it appears that Alexadria Ocasio-Cortez, Hillary Clinton, and Nancy Pelosi recieved the highest proportion of Tweets with negative sentiment. Amy Coney Barrett had the lowest proportion of negative Tweets, followed by Vice President Mike Pence. Looking at positive Tweet proportions, Senate Majority Leader Mitch McConnell had the highest proportion of positive Tweets while Amy Coney Barrett, Mike Pence, and Nikki Haley also received a significant majority of Tweets with a positive sentiment. These results were particularly interesting because it shows that Trump tends to Tweet about people of the same party with positive sentiment at a greater proportion compared to the people of the Democratic party. We will explore this further with a Chi-squared test to see if people mentioned in his Tweet and sentiment are independent.

The purpose of Figure 4 is to explore the different sentiment Trump displays towards male versus female politicians. We decided to look at this based on party affiliation, because we believed that the results could be different depending if we were considering a Republican female politician versus a Democrat female politician (we just wanted to learn if he had a different sentiment towards strictly males or females, or whether it had to also do with politican affiliation). This visualization shows that when Donald Trump discusses Democratic politicians, he has a similar median sentiment towards male and female, which is fairly close to "neutral". We also noticed that for this visualization, the male Democrats had a larger range of sentiments than the female Democrats, but the lowest score was given to a female Democratic politician. In the visualization of male and female Republicans, the females had a slightly higher average sentiment compared to their male counterparts. This could indicate that he talks about males in his party in a less positive manner as compared to the females. We also recognized that, again, the male Republicans had a larger range of sentiments than the female Republicans, showing that his sentiments cover a larger range of positive and negative sentiments

when talking about Republican males. We will explore this further with a Chi-squared test to see if party of the politician mentioned in his Tweet and sentiment are independent, and if we have enough evidence to suggest that they are dependent, then we will use a t-test to see if there is enough evidence to suggest that he talks, on average, more negatively about Democrats than Republicans. Similarly, we will also do another Chi-squared test to investigate if gender of the politician mentioned in his Tweet and sentiment of the Tweet are independent, and if we have enough evidence to suggest that they are dependent, then we will use a t-test to see if there is enough evidence to suggest that he talks, on average, more positively about males than females.

Figure 5 shows the relative proportions of Tweets with positive, neutral and negative overall sentiment that Donald Trump has shared about each of the topics we covered in our data set. By using a percent stacked bar plot, we could see the percentages side-by-side. It seems that USA had the highest proportion of positive Tweets, whereas Russia had the lowest proportion of positive Tweets, however, we noticed that the other percentages did not appear to be drastically different. Upon seeing this, it prompted us to explore how his sentiment may have changed over time.

Figure 6 allows us to see the change in Donald Trump's sentiments towards specific "hot button topics" over time. We compiled all the Tweets into a line plot with time as the x-axis and average sentiment as the y-axis. By taking the average sentiment of each topic by year, we were able to create this visualization and see how his sentiments in his Tweets changed when discussing some specific topics. Sentiment scores for Tweets about each of the four topics covered (immigration, guns, climate change and news) were averaged by year and plotted on a line graph. This allows us to see how his sentiment towards each of these subjects on Twitter has evolved over time. These four topics were chosen because they have been prevalent for a long time in the political discourse of the United States as opposed to something like COVID-19 or the Black Lives Matter movement. This meant that we could more fully track the change in his sentiment towards them over the time period of our data set. We also added a horizontal red line denoting a 0 sentiment score to make it more clear where his sentiments were positive and where they were negative, as well as a vertical blue dashed line at the year 2016 to show how sentiments changed after his election to the office of US President. To investigate this further, we will do a CLT-based t-test to see if there is enough evidence to sugest that the mean sentiment score for Tweets on a specific topic before Trump was elected (before 2016) is not equal to the mean sentiment score for Tweets after he was elected. We will do this for the different topics shown on the visualization.

Figure 1: Word cloud of the top 100 words Donald Trump uses in his Tweets. Some of the words that were not part of the actual text of the Tweet or were artifacts of Tweets (such as URLs, account names, and years) were removed to clean the data.
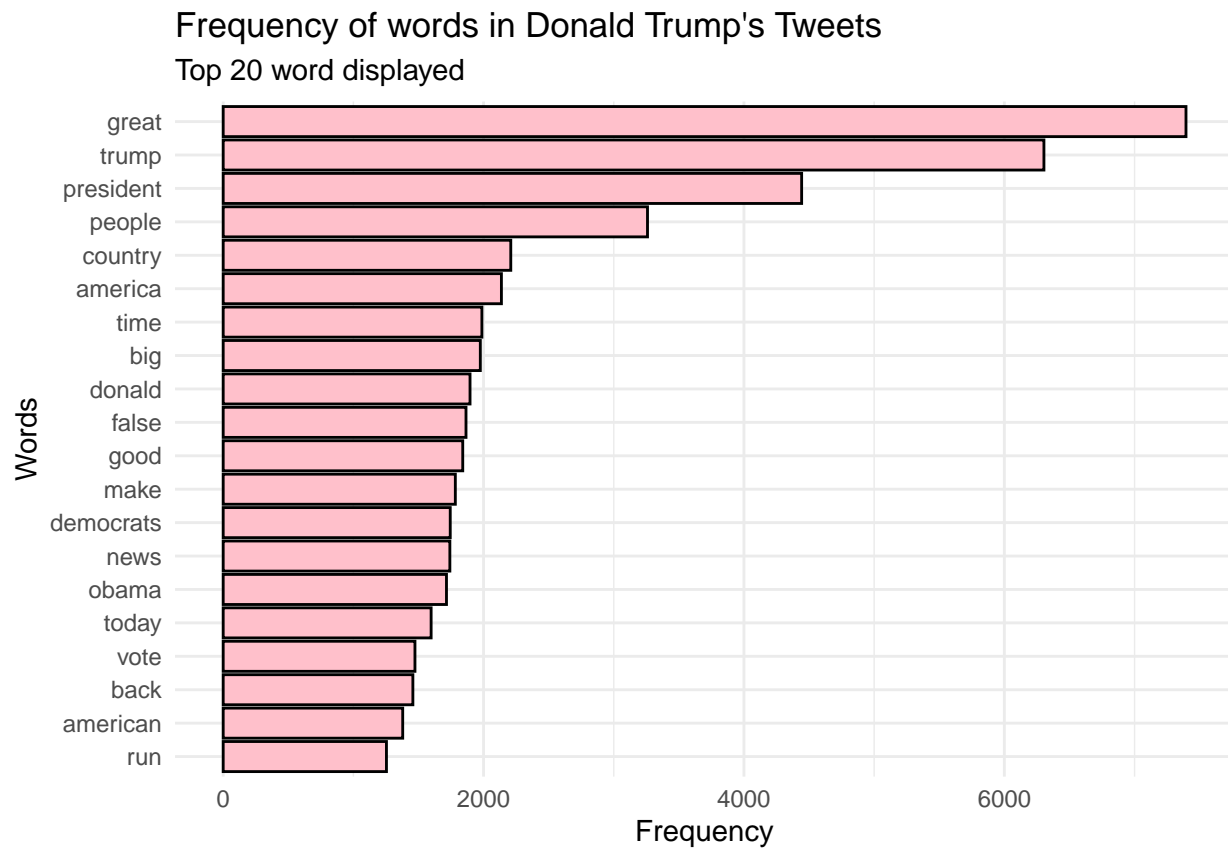
Figure 2: Frequency of Donald Trump's top 20 words that are used in his Tweets. Just like in Figure 1, some of the words that were not part of the actual text of the Tweet or were artifacts of Tweets (such as URLs, account names, and years) were removed to clean the data.
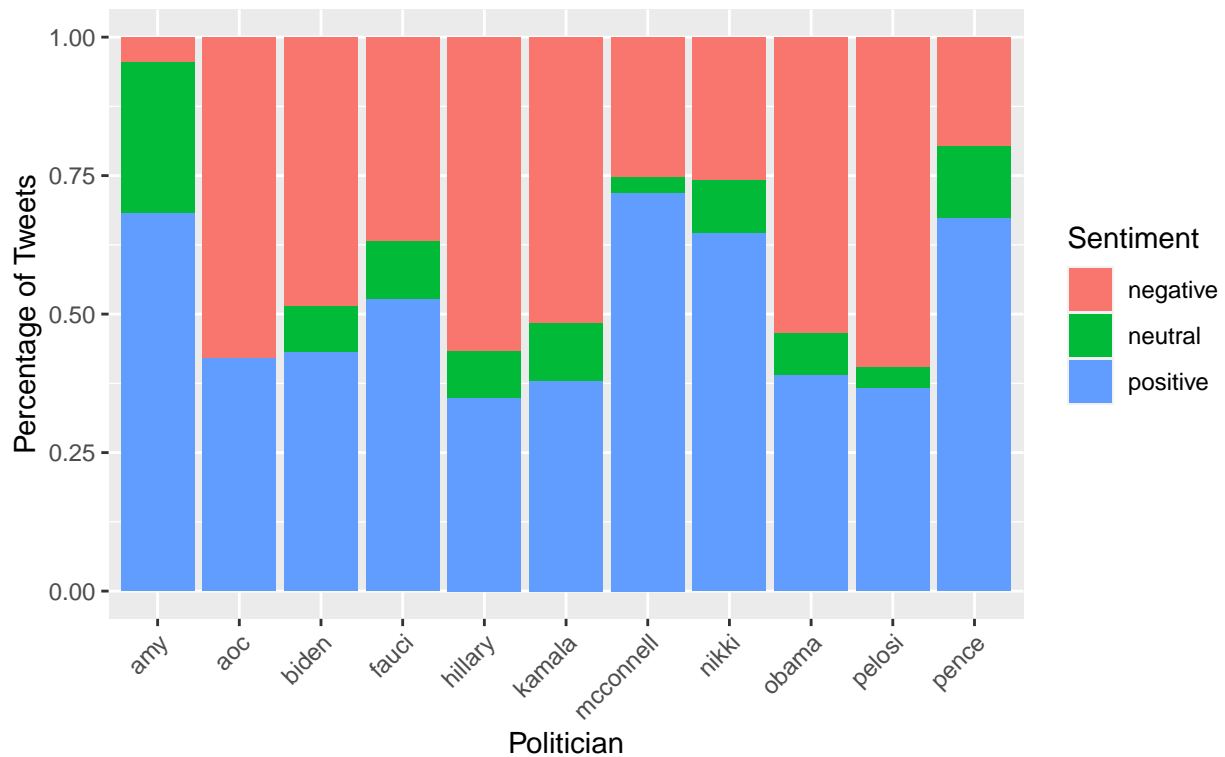
Figure 3: Illustrates the proportion of Tweets with average negative (<0), neutral ($=0$), and positive (>0) sentiment that mention a specific politician.

```
chisq.test(table(peopleData$person,
                 peopleData$posNeg))
```

```
## Warning in chisq.test(table(peopleData$person, peopleData$posNeg)): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(peopleData$person, peopleData$posNeg)
## X-squared = 240.26, df = 20, p-value < 2.2e-16
```
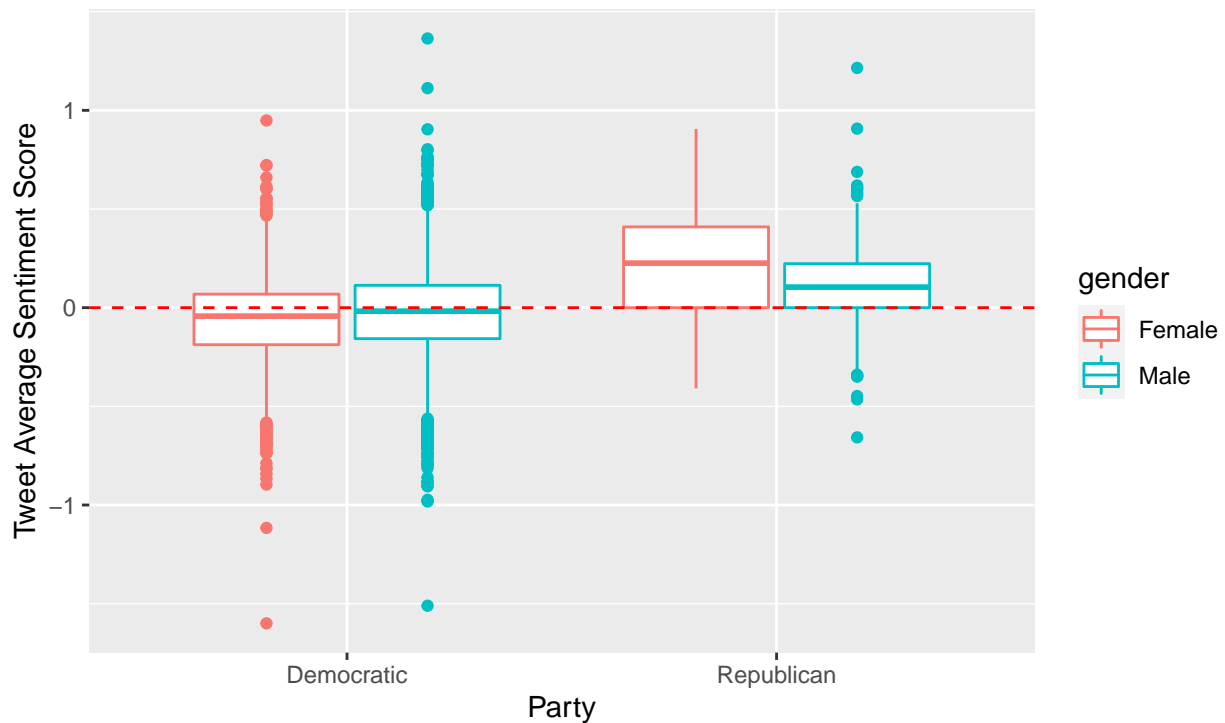
Figure 4: Boxplot showing the average sentiment scores for Tweets, divided by political party of the person mentioned in the Tweet, and split within party to show any differences in how he talks about politicians of different genders within either the Democratic or Republican party.

```
dems <- peopleData %>%
  filter(party=="Democratic")

repubs <- peopleData %>%
  filter(party=="Republican")

chisq.test(table(peopleData$party,
                 peopleData$posNeg))
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(peopleData$party, peopleData$posNeg)
## X-squared = 173.34, df = 2, p-value < 2.2e-16
```

```
t.test(dems$ave_sentiment,
       repubs$ave_sentiment,
       mu = 0,
       var.equal = FALSE,
       alternative = "less",
       conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  dems$ave_sentiment and repubs$ave_sentiment
## t = -14.678, df = 469.92, p-value < 2.2e-16
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##        -Inf -0.1414063
## sample estimates:
##   mean of x    mean of y
## -0.03922378   0.12006845
```

```
male <- peopleData %>%
  filter(gender=="Male")

female <- peopleData %>%
  filter(gender=="Female")

chisq.test(table(peopleData$gender,
                 peopleData$posNeg))
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(peopleData$gender, peopleData$posNeg)
## X-squared = 27.151, df = 2, p-value = 1.271e-06
```

```
t.test(male$ave_sentiment,
       female$ave_sentiment,
       mu = 0,
       var.equal = FALSE,
       alternative = "greater",
       conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  male$ave_sentiment and female$ave_sentiment
## t = 6.6948, df = 3900.6, p-value = 1.234e-11
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.03061738        Inf
## sample estimates:
##   mean of x   mean of y
## -0.01642442 -0.05701745
```

```r
topicData <- TweetsWithSentimentWithoutLink %>%
 pivot_longer(covid:immigration, names_to = "topic", values_to = "existenceOfTopic")

topicData <- topicData %>% filter(existenceOfTopic==1)
   ggplot(data=topicData, aes(x=topic, fill = factor(posNeg))) +
    geom_bar(position = "fill") +
   labs(title="Highest proportion of positive Tweets is about USA, lowest
        is about Russia",
   x="Topic",y ="Percentage of Tweets", fill="Sentiment") +
   theme(axis.text.x = element_text(angle = 45, hjust = 1))
```
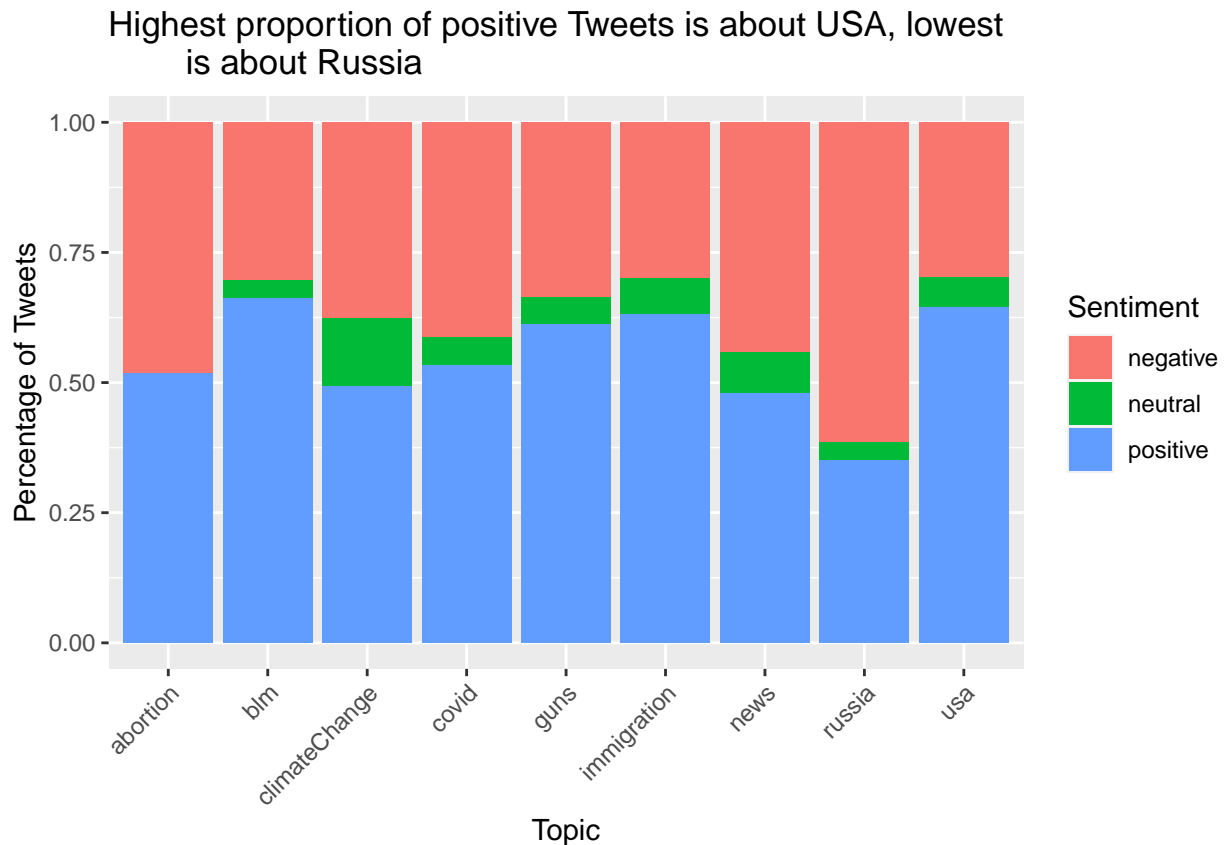

Figure 5: Illustrates the proportion of Tweets with average negative (<0), neutral ($=0$), and positive (>0) sentiment that mention a specific topic.
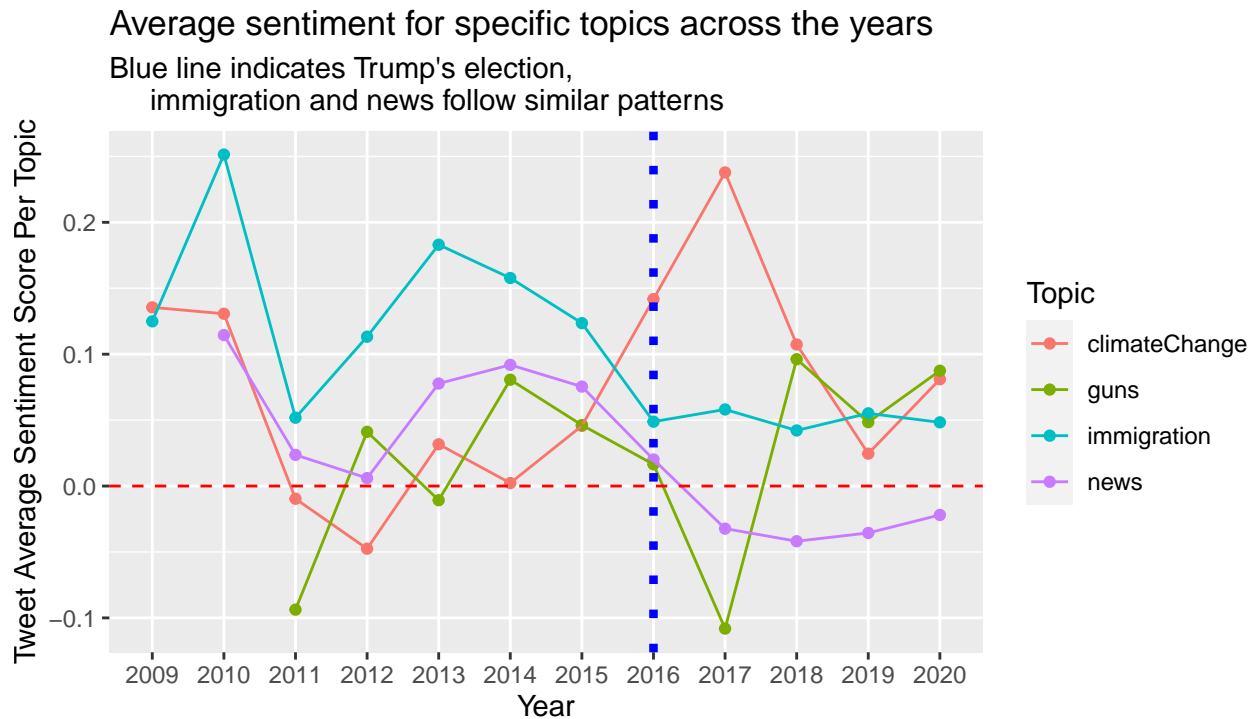
Figure 6: Shows change of average sentiment of Tweets referring to a specific topic across the years. Only showing a few topics, we selected the ones that have been Tweeted about for a long time. The vertical blue line indicates when Trump first became elected.

```r
yearVar <- TweetsWithSentimentDateTimeFormat %>%
  mutate(year = year(date))

#CLIMATE CHANGE
pre2016CC <- yearVar %>%
  filter(year<2016 & topic=="climateChange")

post2016CC <- yearVar %>%
  filter(year>=2016 & topic=="climateChange")

t.test(pre2016CC$ave_sentiment,
       post2016CC$ave_sentiment,
       mu = 0,
       var.equal = FALSE,
       alternative = "two.sided",
       conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  pre2016CC$ave_sentiment and post2016CC$ave_sentiment
## t = -3.5886, df = 107.75, p-value = 0.0005017
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.1449929 -0.0418101
## sample estimates:
##  mean of x  mean of y
## 0.01141679 0.10481831
```

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```
#GUNS
pre2016guns <- yearVar %>%
  filter(year<2016 & topic=="guns")

post2016guns <- yearVar %>%
  filter(year>=2016 & topic=="guns")

t.test(pre2016guns$ave_sentiment,
       post2016guns$ave_sentiment,
       mu = 0,
       var.equal = FALSE,
       alternative = "two.sided",
       conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  pre2016guns$ave_sentiment and post2016guns$ave_sentiment
## t = -1.4058, df = 191.94, p-value = 0.1614
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.09068635  0.01521016
## sample estimates:
##  mean of x  mean of y
## 0.03009099 0.06782909
```

```
#IMMIGRATION
pre2016imm <- yearVar %>%
  filter(year<2016 & topic=="immigration")

post2016imm <- yearVar %>%
  filter(year>=2016 & topic=="immigration")

t.test(pre2016imm$ave_sentiment,
       post2016imm$ave_sentiment,
       mu = 0,
       var.equal = FALSE,
       alternative = "two.sided",
       conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  pre2016imm$ave_sentiment and post2016imm$ave_sentiment
## t = 14.158, df = 5227.9, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.08499729 0.11231973
## sample estimates:
##  mean of x  mean of y
## 0.14845124 0.04979272
```

```
#NEWS
pre2016News <- yearVar %>%
  filter(year<2016 & topic=="news")
```

```
post2016News <- yearVar %>%
  filter(year>=2016 & topic=="news")

t.test(pre2016News$ave_sentiment,
       post2016News$ave_sentiment,
       mu = 0,
       var.equal = FALSE,
       alternative = "two.sided",
       conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  pre2016News$ave_sentiment and post2016News$ave_sentiment
## t = 14.018, df = 3938, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.08003049 0.10605732
## sample estimates:
##   mean of x   mean of y
##  0.06856458 -0.02447932
```

Results

ADD CHI SQUARE PEOPLE VS. SENTIMENT

ADD CHI SQUARE POLITICAL PARTY VS SENTIMENT, THEN SAY SINCE THEY WERE DEPENDENT, WE DECIDED TO DO T TEST (WHICH IS ALREADY WRITTEN BELOW)

Sentiment across political party: In order to determine if the true mean sentiment score of Donald Trump's Tweets about Democratic politicians is less than the mean sentiment score of Donald Trump's Tweets about Republican politicians, a CLT-based t-test was used. The null hypothesis, H_0, is that the true mean sentiment score of Donald Trump's Tweets about Democratic politicians is equal to the true mean sentiment score of Donald Trump's Tweets about Republican politicians. This is being tested against the alternative hypothesis, H_1, which is that the true mean sentiment score of Donald Trump's Tweets about Democratic politicians is less than the true mean sentiment score of Donald Trump's Tweets about Republican politicians. We used the Central Limit Theorem to conduct this hypothesis test at the $\alpha = 0.05$ significance level. We know that we can use the CLT because our observations are independently selected and our sample size is greater than 30 which means we can expect the CLT to apply. The CLT tells us that we will have a t distribution with 469.92 degrees of freedom since we do not have the population standard deviation (σ) of sentiment scores. Under the null hypothesis, we also know that the distribution of the test statistic can be approximated by a normal distribution which means that it is unimodal, symmetric, and centered at zero. The value of out test statistic, t, is -14.678. Our p-value is less than $2.2 * 10^{-16}$, which is very close to zero and less than our α of 0.05. This means that we reject the null hypothesis. In the context of our data, this tells us that there is sufficient evidence to suggest that the true mean sentiment score of Donald Trump's Tweets about Democratic politicians is less than the true mean sentiment score of Donald Trump's Tweets about Republican politicians.

ADD CHI SQUARE GENDER VS SENTIMENT, THEN SAY SINCE THEY WERE DEPENDENT, WE DECIDED TO DO T TEST (WHICH IS ALREADY WRITTEN BELOW)

Sentiment across gender: In order to determine if the true mean sentiment score of Donald Trump's Tweets about male politicians is greater than the mean sentiment score of Donald Trump's Tweets about female politicians, a CLT-based t-test was used. The null hypothesis, H_0, is that the true mean sentiment score of Donald Trump's Tweets about male politicians is equal to the true mean sentiment score of Donald Trump's Tweets about female politicians. This is being tested against the alternative hypothesis, H_1, which is that the true mean sentiment score of Donald Trump's Tweets about male politicians is greater than the true mean sentiment score of Donald Trump's Tweets about female politicians. We used the Central Limit Theorem to conduct this hypothesis test at the $\alpha = 0.05$ significance level. We know that we can use the CLT because our observations are independently selected and our sample size is greater than 30 which means we can expect the CLT to apply. The CLT tells us that we will have a t distribution with 3900.6 degrees of freedom since we do not have the population standard deviation (σ) of sentiment scores. Under the null hypothesis, we also know that the distribution of the test statistic can be approximated by a normal distribution which means that it is unimodal, symmetric, and centered at zero. The value of out test statistic, t, is 6.6948. Our p-value is $1.234*10^{-11}$, which is very close to zero and less than our α of 0.05. This means that we reject the null hypothesis. In the context of our data, this tells us that there is sufficient evidence to suggest that the true mean sentiment score of Donald Trump's Tweets about male politicians is greater than the true mean sentiment score of Donald Trump's Tweets about female politicians.

ADD T TESTS FOR THE FOUR TOPICS THAT WE HAVE ON THE GRAPH

Discussion

NEED TO ADD

Sources

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