Topic: Social Media Strategy for Nike to handle the Kaepernick controversy

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Brand of company: Nike

Agenda

Situation

The decision by Nike Inc. to partner with Colin Kaepernick for the 30th anniversary of its iconic "Just Do It" campaign has ignited a firestorm of public reaction on social media. Kaepernick, known for his controversial stance of not standing during the national anthem as a protest against police brutality, has been a polarizing figure. The campaign, featuring the slogan "Believe in something, even if it means sacrificing everything," has further intensified this polarization.

This partnership and the ensuing campaign have sparked a heated national debate, drawing attention from various societal segments, including a direct comment from President Donald Trump. The intensity and breadth of the public discourse have created a critical situation for Nike, with potential implications for the brand's image, customer loyalty, and market positioning.

The core of the problem lies in understanding and navigating the diverse and region-specific public sentiment towards the brand, influenced by this partnership. The social media response, especially on platforms like Twitter, has become a barometer of public opinion. The analysis of 5,000 tweets from September 7, 2018 – days after Nike's announcement – containing the hashtag #JustDoIt offers a valuable window into the public's perception.

This project aims to dissect public sentiment and identify key influencers in this debate by analyzing Twitter data. The goal is to understand the varying reactions across different states in the U.S. and gauge the overall sentiment towards Nike's campaign. This insight is crucial for Nike to strategize its next steps, whether in damage control, market reinforcement, or capitalizing on newfound support, depending on the nature and tone of the public reaction in different regions.

As evidenced by these 2 research papers (Samuel B, 2022) and (Mendoza U, 2022), we see that Positive Social Media sentiment and Negative Social Media sentiment for a company lead to good and poor business outcomes such as Firm value and Stock price respectively.

Given the high stakes involved, this analysis is not just a routine examination of brand perception but a crucial exercise in navigating a challenging and potentially transformative period for Nike. Understanding the nuances of public sentiment and the role of influential voices in shaping these opinions is essential for formulating an effective response strategy.

Problem Statement

<u>Objective of Project</u>: To enhance Nike's marketing strategy by analyzing social media sentiment related to their partnership with Colin Kaepernick. The most frequent words in positive and negative sentiment tweets are analyzed for each state, to help Nike create a targeted Social Media campaign for each state so as to reduce Polarization, and thus improve Brand Sentiment.

<u>Dependent Variable</u>: The primary business-oriented dependent variable will be 'brand sentiment score', which will be quantified by analyzing the sentiment of tweets for each state. This score

will be derived from a sentiment analysis algorithm that categorizes each tweet with a negative integer or zero or positive integer representing negative, neutral, and positive sentiments. The focus is to find the most frequently occurring words in positive and negative sentiment tweets to understand the spectrum of public sentiment.

Numerical Threshold: Success will be defined as identifying a set of keywords that correlate strongly with positive sentiment in tweets about Nike, categorized by state. The project will be considered successful if these keywords can be integrated into targeted marketing campaigns, resulting in at least a 10% improvement in brand sentiment scores within each state. This improvement is expected to be reflective of a more positive social media engagement, which is instrumental in bolstering Nike's online reputation and customer relations.

Model Selection

<u>Model selection</u>: In this case, I have used R's Syuzhet Sentiment analysis package to analyze the Sentiment of each tweet associated with the Nike and JustDoIt slogan, thus providing a numeric Sentiment score for each tweet, which can be then aggregated along States to craft targeted marketing campaigns for Nike.

<u>Reason for selecting the model:</u> The Syuzhet model was chosen due to its ability to handle the complexity and variability of language in social media. It provides a nuanced approach to sentiment analysis by considering the context in which words are used, thereby enhancing the accuracy of sentiment classification.

Solution Process

Step 1: Import the CSV file ***justdoit_tweets_5000.csv*** containing the 5000 tweets.

Step 2: Simplify the problem by removing irrelevant columns from the dataset and using only the columns that are relevant to our solution, such as *tweet_created_at, tweet_favorite_count, tweet_full_text, tweet_id, tweet_in_reply_to_screen_name, tweet_in_reply_to_status_id, tweet_retweet_count, user_favourites_count, user_followers_count, user_id, user_location, user_location_us, user_verified.*

Step 3: Calculate the Sentiment using the Syuzhet package in R for every tweet, and then create a new column called Sentiment in the dataframe and save it to a new CSV file for reference.

Step 4: Reload this new CSV file with Sentiment, and then perform data preprocessing steps such as removing irrelevant stopwords (most commonly used stopwords and some custom stopwords have been defined in a separate .csv file called stopwords.csv)

Step 5: Segment the tweets into positive and negative tweets, then find the most frequently occurring words in these 2 categories of tweets, then aggregate them for each state.

Step 6: Find the states with the most positive and negative sentiments associated with Nike and its #justdoit campaign at this time of controversy.

Step 7: Here, for brevity, I have picked 2 states in particular to analyze which words (and their frequency of occurrence) Nike can use in their tailor-made Social Media strategy for each state. Line 136 in the code can be easily changed to accommodate all 50 states for the campaign.

Step 8: Tornado charts have been used to represent the most frequently occurring words in a very positive and negative sentiment context.

Research

Secondary Research: This case study includes several relevant articles available on the Internet to provide additional data and insight for the case study. The sources are shown in their relevant sections.
Primary Research: The dataset was sourced from Kaggle.com, https://www.kaggle.com/datasets/eliasdabbas/5000-justdoit-tweets-dataset. The author of the dataset themself has used the Twitter API to source Twitter information. The data's validity is reinforced by the authentication standards imposed by the Twitter API, which ensures that the tweets collected are genuine and the metadata accurate. The use of the Syuzhet package, which is widely recognized in the field of text analysis for its sentiment classification capabilities, adds an additional layer of credibility to our sentiment analysis process.

Software
Since the program contains 172 lines of code, I have added here only the most significant snippets of code with their explanation.

Full codebase on https://github.com/axaysd/Nike_SentimentAnalysis

```
# Read the CSV file containing tweets data
tweets <- read.csv("justdoit_tweets_5000.csv", fileEncoding = "UTF-8")

# Selecting the necessary columns for processing
tweets_selected <- tweets %>%
# Select specific columns for analysis
  select(tweet_created_at, tweet_favorite_count, tweet_full_text, tweet_id,
         tweet_in_reply_to_screen_name, tweet_in_reply_to_status_id, tweet_retweet_count,
         user_favourites_count, user_followers_count, user_id, user_location,
         user_location_us, user_verified)
```

```
> print(head(tweets_selected))
              tweet_created_at tweet_favorite_count
1 Fri Sep 07 16:25:06 +0000 2018                    0
2 Fri Sep 07 16:24:59 +0000 2018                    0
3 Fri Sep 07 16:24:50 +0000 2018                    0
4 Fri Sep 07 16:24:44 +0000 2018                    0
5 Fri Sep 07 16:24:39 +0000 2018                    0
6 Fri Sep 07 16:24:35 +0000 2018                    0
                                                                                                                                                                  $
1                                                                                                                            Done is better than perfect. — Sheryl Sandbe$
2 Shout out to the Great Fire Department and the tour! Much love to NYC! \n•\n•\n•\n#hero #fdny #likesforlikes #promo #music #instagood #instadaily #postoftheday #besto$
3                                 There are some AMAZINGLY hilarious Nike Ad memes happening on my newsfeed.  Soooo, I decided to get a little creative too... \n\n#JustDoIt #4YourMorn$
4                                                                                                                                    #kapernickeffect #swoosh #justdoi$
5                                                                                     One Hand, One Dream: The Shaquem Griffin Story  https://t.co/0EbEmwULLF   #shaquem  #NFL #Seattle #Se$
6                                                                                                                             @realDonaldTrump It's time for me to stoc$
      tweet_id tweet_in_reply_to_screen_name tweet_in_reply_to_status_id
1 1.038101e+18                                                        NA
2 1.038101e+18                                                        NA
3 1.038101e+18                                                        NA
4 1.038101e+18                                                        NA
5 1.038101e+18                                                        NA
6 1.038101e+18               realDonaldTrump                1.038018e+18
  tweet_retweet_count user_favourites_count user_followers_count    user_id
1                   0                   307                57983 3188618684
2                   0                  1178                13241   18387174
3                   0                 11864                11377   32645612
4                   0                   487                  218  175932740
5                   0                 32971                13731   22306628
6                   0                  9622                   64   15566700
                user_location      user_location_us user_verified
1             California, USA            California         False
2              Miami, Florida               Florida         False
3            Indianapolis, IN               Indiana          True
4 Tennessee by way of New Jersey          New Jersey         False
5                 Gambleville Likely not a US state         False
6                 Austin, TX                  Texas         False
```

Adding a Sentiment column to dataset by calculating the Sentiment score using Syuzhet
tweets_selected$Sentiment <- get_sentiment(tweets_selected$tweet_full_text, method="syuzhet")

```
> print(head(tweets_selected$Sentiment))
[1] 2.35 2.35 2.25 0.00 0.25 0.80
```

# Define cleaning function to handle for irrelevant content
clean_text <- function(text) {

    text <- tolower(text) # Convert to lower case
    text <- removePunctuation(text) # Remove punctuation
    text <- removeNumbers(text) # Remove numbers

    # Combining default English stopwords with my custom stopwords
    all_stopwords <- c(stopwords("en"), stopwords_custom)
    text <- removeWords(text, all_stopwords) # Remove common and custom stopwords
    text <- stripWhitespace(text) # Remove extra white spaces
    return(text)
}

Apply the cleaning function to the tweets
tweets$tweet_full_text <- sapply(tweets$tweet_full_text, clean_text)

```
> print(head(tweets$tweet_full_text))
[1] "done better perfect – sheryl sandberg quote motivation httpstcojlldszdw"
[2] "shout great fire department tour □□□□ much love nyc □ □ • • • hero fdny likesforlikes promo music instagood instadaily postoftheday bestoftheday nike picoftheday httpstcosf
[3] " amazingly hilarious nike ad memes happening newsfeed soooo decided little creative yourmorning yourmemecollection httpstcookqrkm"
[4] "kapernickeffect swoosh lucas cigar lounge httpstcobhpbnjokuu"
[5] "one hand one dream shaquem griffin story httpstcoebemwullf shaquem nfl seattle seahawks griffin nike httpstcopreosdzs"
[6] "realdonaldtrump time stock new running apparel nike "
```

```
# Apply the function to positive and negative tweets
positive_tweets <- tweets[tweets$Sentiment > 0, ]
negative_tweets <- tweets[tweets$Sentiment < 0, ]

# Get most frequent words for each state for positive and negative tweets
positive_words_by_state <- aggregate(tweet_full_text ~ user_location_us, data =
positive_tweets, FUN = function(x) get_most_frequent_words(paste(x, collapse = " ")))

negative_words_by_state <- aggregate(tweet_full_text ~ user_location_us, data =
negative_tweets, FUN = function(x) get_most_frequent_words(paste(x, collapse = " ")))

# Function to extract top frequently occuring 5 words with their frequency
extract_top_words_with_freq <- function(freq_table, top_n = 5) {
  top_words <- head(sort(freq_table, decreasing = TRUE), top_n)
  words_with_freq <- paste(names(top_words), "(", top_words, ")", sep = "")
  return(words_with_freq)
}

# Apply the function to positive and negative tweets for each state
positive_words_by_state$top_words_with_freq <-
lapply(positive_words_by_state$tweet_full_text, extract_top_words_with_freq)
```

```
> print(head(positive_words_by_state))
  user_location_us
1          Alabama
2          Arizona
3         Arkansas
4       California
5         Colorado
6      Connecticut
                                                                                                                                                                  $
1                                                                                                                                                                 $
2                                                                                                                                                                 $
3                                                                                                                                                                 $
4 103, 47, 19, 19, 18, 17, 14, 14, 14, 13, 12, 12, 11, 11, 11, 11, 11, 9, 9, 9, 8, 8, 8, 8, 7, 7, 7, 7, 7, 7, 7, 7, 6, 6, 6, 6, 6, 6, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 4, 4,$
5                                                                                                                                                                 $
6                                                                                                                                                                 $
                                                     top_words_with_freq
1              something(2), will(2), "(1), "brodoyoumarvel(1), "(1)
2          nike(14), kaepernick(7), commercial(4), best(3), someone(3)
3                         nike(3), care(2), dream(2), girls(2), new(2)
4               nike(103), kaepernick(47), love(19), new(19), believe(18)
5   nike(11), kaepernick(4), inspired(3), realdonaldtrump(3), shoes(3)
6 realdonaldtrump(3), nike(2), thinking(2), absolutely(1), achieveit(1)
```

```
negative_words_by_state$top_words_with_freq <-
lapply(negative_words_by_state$tweet_full_text, extract_top_words_with_freq)
```

```
> print(head(negative_words_by_state))
  user_location_us
1          Alabama
2           Alaska
3          Arizona
4         Arkansas
5       California
6         Colorado
                                                                                                                                                                  $
1                                                                                                                                                                 $
2                                                                                                                                                                 $
3                                                                                                                                                                 $
4                                                                                                                                                                 $
5 44, 13, 7, 6, 6, 4, 4, 4, 4, 4, 4, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, $
6                                                                                                                                                                 $
                                                  top_words_with_freq
1        nike(2), album…(1), btsworldtour(1), cancer(1), childhood(1)
2 americans(1), beheretomorrow(1), corybooker(1), crazy(1), dreams(1)
3                 nike(11), burning(5), crazy(5), dreams(4), ask(2)
4                    will(2), gone(1), impeach(1), long(1), pay(1)
5                nike(44), kaepernick(13), crazy(7), ad(6), shoes(6)
6                 nike(4), drive(2), kaepernick(2), saw(2), time(2)
```

```
> # Get the top 5 and bottom 5 states by average sentiment
> top_5_states <- head(average_sentiment_by_state, 5)
> bottom_5_states <- tail(average_sentiment_by_state, 5)
>
> # Print the results
> print("Top 5 States by Average Brand Sentiment")
[1] "Top 5 States by Average Brand Sentiment"
> print(top_5_states)
# A tibble: 5 × 2
  user_location_us average_sentiment
  <chr>                        <dbl>
1 Illinois                     0.622
2 California                   0.573
3 Georgia                      0.493
4 Florida                      0.446
5 New York                     0.370
> print("Bottom 5 States by Average Brand Sentiment")
[1] "Bottom 5 States by Average Brand Sentiment"
> print(bottom_5_states)
# A tibble: 5 × 2
  user_location_us      average_sentiment
  <chr>                             <dbl>
1 New York                          0.370
2 Indiana                           0.333
3 Likely not a US state             0.312
4 Texas                             0.230
5 Michigan                          0.221
>
```

```
# Target states to analyze for Nike's targeted Social Media campaign
states <- c("Michigan", "Georgia")

# Loop through each state in the vector and create charts
for(state in states) {

  # Filter data for the current state
  positive_state <- subset(positive_words_by_state, user_location_us == state)
  negative_state <- subset(negative_words_by_state, user_location_us == state)

  # Prepare data for the chart
  prepare_chart_data <- function(data, sentiment) {
     words_with_freq <- unlist(strsplit(data$top_words_with_freq, ", "))
     words <- gsub("\\s*\\(.*\\)$", "", words_with_freq)
     freq <- as.numeric(gsub(".*\\((.*)\\)", "\\1", words_with_freq))
     return(data.frame(word = words, freq = freq, sentiment = sentiment))
}

  positive_chart_data <- prepare_chart_data(positive_state, "Positive")

  negative_chart_data <- prepare_chart_data(negative_state, "Negative")
```

```
  # Combine positive and negative data
  combined_chart_data <- rbind(positive_chart_data, transform(negative_chart_data, freq = -
freq))

  # Create the tornado chart
  ggplot(combined_chart_data, aes(x = word, y = freq, fill = sentiment)) +
    geom_bar(stat = "identity", position = "identity") +
    coord_flip() +
    labs(title = paste("Word Frequencies in Positive and Negative Tweets for", state),
         x = "Words",
         y = "Frequency") +
    scale_fill_manual(values = c("Positive" = "blue", "Negative" = "red")) +
    theme_minimal()

# Save the chart as an image file
  ggsave(paste0("tornado_chart_", state, ".png"))
}
```

<u>CSV output: Most frequently occurring words in positive sentiment tweets, with their frequency, for first 27 states</u>:

user_location_us	top_words_with_freq
Alabama	something(2), will(2), â€œ(1), â€œbrodoyoumarvel(1), â€(1)
Arizona	nike(14), kaepernick(7), commercial(4), best(3), someone(3)
Arkansas	nike(3), care(2), dream(2), girls(2), new(2)
California	nike(103), kaepernick(47), love(19), new(19), believe(18)
Colorado	nike(11), kaepernick(4), inspired(3), realdonaldtrump(3), shoes(3)
Connecticut	realdonaldtrump(3), nike(2), thinking(2), absolutely(1), achieveit(1)
Delaware	nike(4), kaepernick(3), campaign(2), commercial(2), compassion(2)
Florida	nike(46), kaepernick(19), agod(14), gmt(11), message(9)
Georgia	nike(45), nfl(28), music(26), â-ï¸stream(25), adidasfootball(25)
Hawaii	nike(6), kaepernick(2), allegiance(1), alot(1), change(1)
Idaho	kaepernick(2), alive(1), atlantafalcons(1), back(1), cure(1)
Illinois	nike(34), kaepernick(10), chicago(7), ad(6), brand(5)
Indiana	nike(31), kaepernick(10), new(7), commercial(6), ad(5)
Iowa	verydice(2), want(2), blackout(1), blackpink(1), blogging(1)
Kansas	nike(6), size(5), shoe(4), kid(2), old(2)
Kentucky	imwithkap(3), one(3), beats(2), make(2), nessnitty(2)
Likely not a US state	nike(819), kaepernick(235), new(126), realdonaldtrump(115), love(114)
Louisiana	nike(19), kaepernick(5), will(4), commercial(3), good(3)
Maine	america(1), american(1), anything(1), coherent(1), commercial(1)
Maryland	nike(11), kaepernick(3), will(3), black(2), commercial(2)
Massachusetts	nike(13), believe(4), best(4), great(4), serenawilliams(4)
Michigan	nike(30), kaepernick(11), new(7), bogo(5), justdidit(5)
Minnesota	nike(11), kaepernick(5), done(3), ad(2), colin(2)
Mississippi	â€œscholarshipsâ€(1), alabama(1), athletes(1), begreatallthetime(1), endorsement(1)
Missouri	nike(8), will(3), colin(2), golf(2), got(2)
Montana	standing(5), american(3), right(3), believeinsomething(2), blockbrett(1)

CSV output: Most frequently occurring words in negative sentiment tweets, with their frequency, for first 27 states:

user_location_us	top_words_with_freq
Alabama	nike(2), albumâ€¦(1), btsworldtour(1), cancer(1), childhood(1)
Alaska	americans(1), beheretomorrow(1), corybooker(1), crazy(1), dreams(1)
Arizona	nike(11), burning(5), crazy(5), dreams(4), ask(2)
Arkansas	will(2), gone(1), impeach(1), long(1), pay(1)
California	nike(44), kaepernick(13), crazy(7), ad(6), shoes(6)
Colorado	nike(4), drive(2), kaepernick(2), saw(2), time(2)
Connecticut	patriots(2), feeling(1), football(1), fouls(1), goo(1)
Delaware	ask(4), crazy(4), boxe(2), dreams(2), enough(2)
Florida	nike(22), gt(8), kaepernick(8), nfl(5), maga(4)
Georgia	nike(16), kaepernick(5), flag(3), burn(2), cathyareu(2)
Hawaii	nike(6), dare(3), crazy(2), people(2), still(2)
Idaho	work(2), asses(1), boots(1), go(1), grab(1)
Illinois	nike(6), blah(3), nfl(3), realdonaldtrump(3), boycott(2)
Indiana	man(5), nike(5), realdonaldtrump(5), kaepernick(3), butt(2)
Iowa	control(1), dying(1), httpstcoqyrvzejus(1), looking(1), memes(1)
Kansas	nike(7), crazy(3), realdonaldtrump(3), ask(2), make(2)
Kentucky	nike(5), believe(3), go(3), believeinsomething(2), knee(2)
Likely not a US state	nike(361), crazy(167), ask(115), kaepernick(109), realdonaldtrump(90)
Louisiana	nike(10), kaepernick(3), destroy(2), face(2), fatigue(2)
Maine	nike(3), athlete(2), one(2), will(2), accident(1)
Maryland	nike(11), crazy(3), boycotting(2), business(2), colinkaepernick(2)
Massachusetts	nike(4), kaepernick(3), c(2), feed(2), learned(2)
Michigan	nike(19), kaepernick(9), realdonaldtrump(6), now(4), state(4)
Minnesota	maybe(3), nike(3), items(2), think(2), âœ”ï¸ðŸ–µâœŠðŸ†µ(1)
Mississippi	nike(2), bigotry(1), cofohardworku(1), colinkaepernick(1), continue(1)
Missouri	nike(3), work(2), ðŸ•©ðŸ•©ðŸ•©(2), Â°(1), asses(1)

TORNADO CHART OUTPUT FOR ABOVE CODE SNIPPET IS IN THE SECTION CALLED VISUALIZATION

Model Results

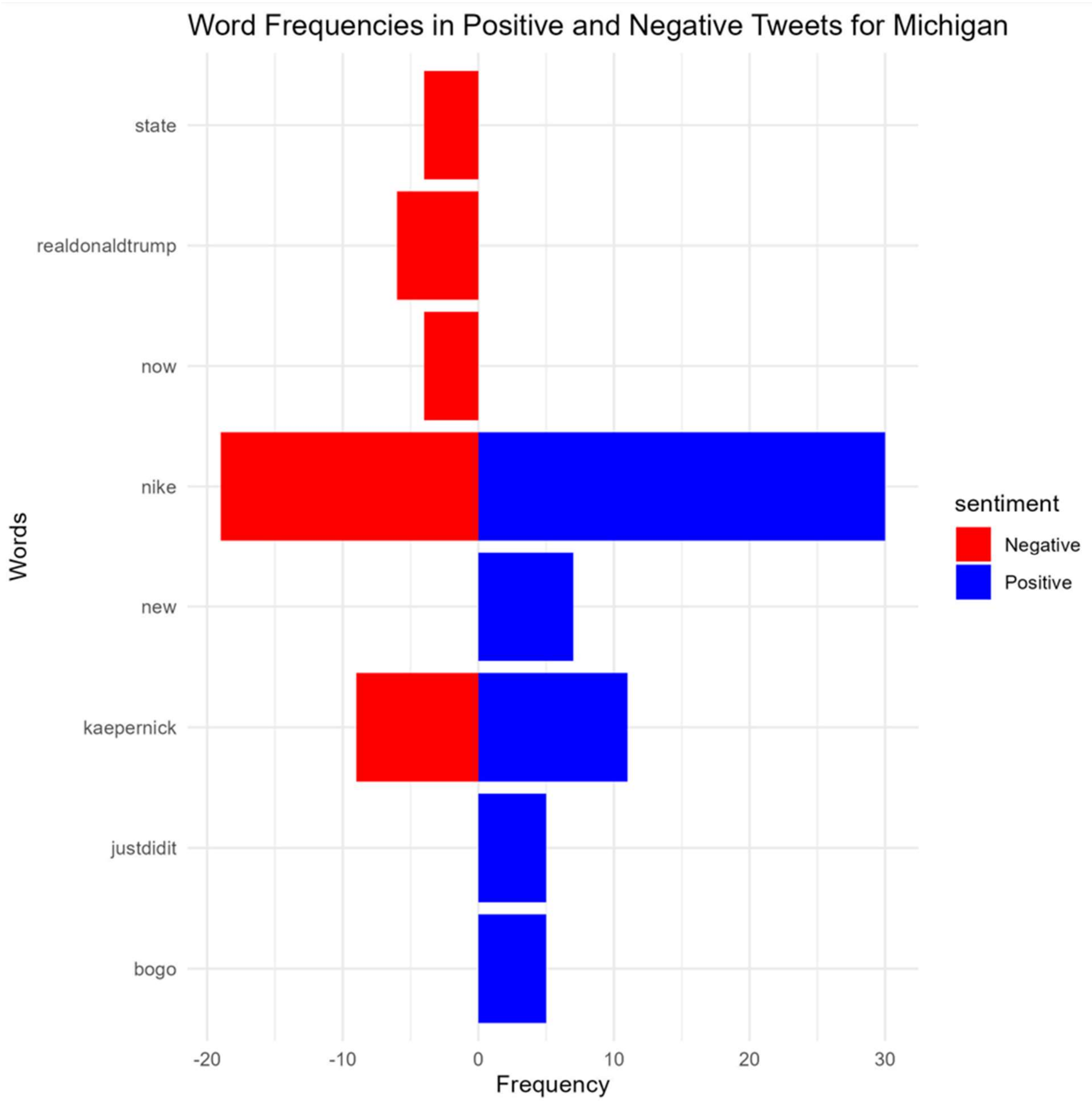
The sentiment analysis conducted via the Syuzhet package in R provided a sentiment score for each tweet, which was then categorized as positive, neutral, or negative. These scores were aggregated to derive the average sentiment score for each state.

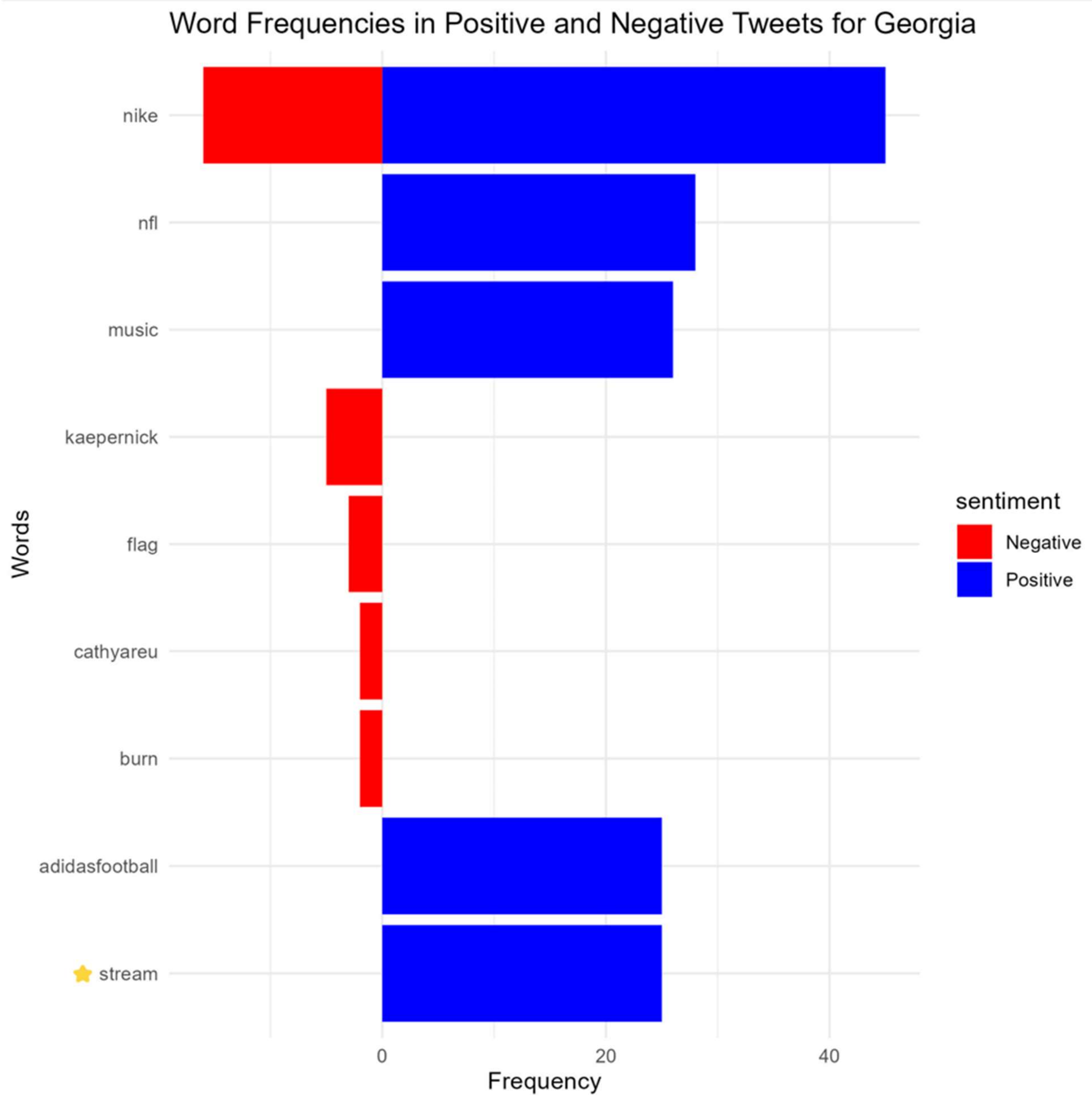
```
> print(head(tweets_selected$Sentiment))
[1] 2.35 2.35 2.25 0.00 0.25 0.80
```

```
> print(head(positive_words_by_state))
  user_location_us
1          Alabama
2          Arizona
3         Arkansas
4       California
5         Colorado
6      Connecticut
                                                                                                                                                                            $
1                                                                                                                                                                           $
2                                                                                                                                                                           $
3                                                                                                                                                                           $
4 103, 47, 19, 19, 18, 17, 14, 14, 14, 13, 12, 12, 11, 11, 11, 11, 11, 9, 9, 9, 8, 8, 8, 8, 7, 7, 7, 7, 7, 7, 7, 7, 6, 6, 6, 6, 6, 6, 6, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 4, 4,$
5                                                                                                                                                                           $
6                                                                                                                                                                           $
                                                    top_words_with_freq
1                 something(2), will(2), "(1), "brodoyoumarvel(1), "(1)
2          nike(14), kaepernick(7), commercial(4), best(3), someone(3)
3                        nike(3), care(2), dream(2), girls(2), new(2)
4            nike(103), kaepernick(47), love(19), new(19), believe(18)
5   nike(11), kaepernick(4), inspired(3), realdonaldtrump(3), shoes(3)
6 realdonaldtrump(3), nike(2), thinking(2), absolutely(1), achieveit(1)
```

```
> print(head(negative_words_by_state))
  user_location_us
1          Alabama
2           Alaska
3          Arizona
4         Arkansas
5       California
6         Colorado
                                                                                                                                                                            $
1                                                                                                                                                                           $
2                                                                                                                                                                           $
3                                                                                                                                                                           $
4                                                                                                                                                                           $
5 44, 13, 7, 6, 6, 4, 4, 4, 4, 4, 4, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, $
6                                                                                                                                                                           $
                                                  top_words_with_freq
1        nike(2), album…(1), btsworldtour(1), cancer(1), childhood(1)
2 americans(1), beheretomorrow(1), corybooker(1), crazy(1), dreams(1)
3                  nike(11), burning(5), crazy(5), dreams(4), ask(2)
4                      will(2), gone(1), impeach(1), long(1), pay(1)
5                nike(44), kaepernick(13), crazy(7), ad(6), shoes(6)
6                  nike(4), drive(2), kaepernick(2), saw(2), time(2)
```

Visualization





Results Interpretation

The Tornado chart above shows for each state, the frequently mentioned words from positive sentiment tweets and the frequently mentioned negative sentiment tweets. It also shows the emotional frequency of these words.

For example, in the state of **Michigan**, the brand sentiment of Nike itself was found to be both positive and negative among different sections of people due to this controversy, as evidenced by the frequency of being mentioned 30 times positively and 19 times negatively.

Similarly, Kaepernick had a polarizing effect too as evidenced by the frequency of being mentioned 11 times positively and 9 times negatively.

The positives:

But more importantly, the word "**bogo**" was mentioned 5 times positively, referring to the **B**uy **O**ne, **G**et **O**ne offer that Nike was running then for its sale of shoes, which implies that Michiganders were preceptive to this BOGO offer and hence Nike should further target Michiganders with this offer to improve Brand sentiment.

Similarly, the social media hashtag campaign **#justdidit** and the word "**new**" implying that people liked the new campaign with Colin Kaepernick, and that they were buying new shoes (when the word was seen in context with the respective tweets) as a response to this new campaign with Colin Kaepernick respectively.

The positive sentiments for "**Nike**" and "**Kaepernick**" far outweigh the negative sentiments in this state, and hence Nike was right to have doubled down on this marketing campaign with Colin Kaepernick.

The negatives:

Similarly, in the state of Georgia, while there was mostly positive sentiment towards Nike, there was clear negative sentiment observed towards Colin Kaepernick.

This was evidenced by the frequency of Nike being positively mentioned 45 times, and the frequency of Nike being negatively mentioned 16 times.
Similarly, Colin Kaepernick was never positively mentioned even once and had a frequency of being negatively mentioned 5 times.

Similarly, the word "**flag**" was mentioned negatively 3 times in the context of Colin Kaepernick kneeling when the national anthem was being played, instead of standing and facing the flag which individuals are expected to do, which angered the residents of Georgia. This led to huge negative sentiment as evidenced by this news item. (CBS News, 2018)

The word "**burn**" was also mentioned twice, where angry netizens burned Nike shoes they owned to protest Nike, as a response to Nike doubling down on this controversy. This is also evidenced by this news item. (Bostock, 2018)

The words **adidasfootball** (25x mentioned) and **music** (26x mentioned) were also positively mentioned. While adidasfootball trending positively in Georgia is bad for Nike's social media presence, Nike could have roped in a famous musician to represent them which would have boosted the positive sentiment for Nike.

Thus, in the state of Georgia, they should not have doubled down on their Colin Kaepernick campaign and should have instead roped in a musician that expresses patriotism for their country. Similarly, the words, their sentiment and their frequency must be studied in other states to create a targeted campaign for Nike to improve brand sentiment in each of these states.

Situation Comparison

Nike’s situation involving the endorsement of Colin Kaepernick and the resultant social media sentiment can be compared to a similarly polarizing situation faced by Gillette. In January 2019, Gillette released an advertisement that took a stance on toxic masculinity, which, much like Nike’s campaign, received a mix of praise and backlash on social media. (Georgiev, 2020)

Gillette's Campaign: Gillette’s advertisement, as part of their "The Best Men Can Be" campaign, aimed to promote positive male behavior and support the #MeToo movement. The ad urged men to hold each other accountable for actions of bullying and harassment. The campaign quickly became a subject of intense debate, with some praising the brand for addressing social issues, while others criticized it for what they perceived as an attack on traditional masculinity.

However, as referenced by this article, unlike Nike which had a polarizing sentiment with mostly positive sentiment in many states and negative sentiment in some states, Gillette had mostly negative sentiment which led to business loss.

Conclusion

Upon the completion of this project, the in-depth analysis of 5,000 tweets using the Syuzhet package in R has provided us with a comprehensive understanding of public sentiment towards Nike's decision to partner with Colin Kaepernick for their #JustDoIt campaign. The sentiment analysis aimed to parse out the most positive and negative sentiments expressed in the tweets and to identify the most frequently mentioned words associated with these sentiments for each state.

Problem Resolution: The project's objective was to address the polarization in sentiment caused by the Kaepernick endorsement and to equip Nike with actionable insights for state-specific marketing campaigns to improve social media sentiments. By quantifying the sentiments and extracting key phrases, we have created a foundation upon which Nike can build targeted marketing strategies.

Recommendations

Tailored Marketing Campaigns: Develop state-specific campaigns that align with the positive sentiments uncovered in the sentiment analysis. Focus on the words and themes that resonated positively within each state, using them to create localized advertisements and social media content that could foster a more positive brand image for Nike.

Community Engagement: In states where negative sentiment was predominant, Nike should consider community engagement initiatives that address the concerns and values expressed. This could involve sponsoring local sports events, community discussions, or educational programs that align with Nike's brand values and Kaepernick’s activism.

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