SOCIAL MEDIA STRATEGY FOR NIKE TO HANDLE KAEPERNICK CONTROVERSY

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INTRODUCTION

In an outburst of fury over Nike Inc.'s move to work with Colin Kaepernick in commemoration of the 30th anniversary of their well-known "Just Do It" campaign, social media users have taken to Twitter. With his contentious choice to protest police brutality by kneeling during the playing of the national anthem, Kaepernick has sparked controversy. The advertisement, with its theme "Believe in something, even if it means sacrificing everything," has exacerbated this issue.

Several social groups have taken notice of this collaboration and the campaign that followed, including President Donald Trump, who made a direct comment. This has generated a contentious national conversation. Nike is in a precarious scenario that could have an impact on the company's reputation, consumer loyalty, and market positioning due to the volume and scope of the public conversation.

The challenge is navigating public attitude towards the brand, which is influenced by the collaboration across different regions. Social media responses, particularly on Twitter, have become a reflection of popular sentiment. The study of 5,000 twitter posts from September 7, 2018, with the hashtag #JustDoIt provides insight into the general public's opinion. This project uses Twitter data to analyze public feelings and determine significant factors in the argument. The objective is to analyze reactions to Nike's campaign in various states across the US and determine general mood. Nike can use this data to strategize its next actions, including damage control, market reinforcement, and capitalizing on fresh support, based on the public reaction in different regions.

Considering the significant risks, this analysis is more than just a standard investigation of brand perception; rather, it is a vital assignment in guiding Nike through a difficult and maybe revolutionary time. Developing a successful response strategy requires an understanding of the intricacies of public opinion and the influence of prominent speakers.

PROBLEM STATEMENT

The project's goal is to improve Nike's marketing approach by examining social media reaction around their collaboration with Colin Kaepernick. To assist Nike in developing a focused social media strategy for each state that will lessen polarization and enhance brand sentiment, the most common terms in tweets expressing both positive and negative emotion are examined.

Dependent Variable: "Brand sentiment score", which will be measured by examining the sentiment of tweets for each state, will be the main dependent variable with a business focus. The sentiment analysis algorithm that will be used to determine this score will classify each tweet into negative, neutral, and positive categories, denoted by a negative, zero, or positive integer.
In order to grasp the range of public emotion, the main goal is to identify the terms that appear most frequently in tweets expressing both positive and negative attitude.

Numerical Threshold: Finding a group of terms that significantly correspond with positive sentiment in tweets about Nike, arranged by state, will be the measure of success. If these keywords are used in focused marketing efforts and each state's brand sentiment scores increase by at least 10%, the project will be deemed successful. It is anticipated that this enhancement will be indicative of a more positive social media presence, which is critical to strengthening Nike's consumer connections and online reputation.

MODEL SELECTION

Model selection: In this instance, I analyzed the sentiment of every tweet containing the Nike and JustDoIt slogan using R's Syuzhet Sentiment analysis package. This allowed me to provide a numerical sentiment score for each tweet, which could then be combined along state lines to create customized marketing campaigns for Nike.
Why the model was chosen: Because of its capacity to manage the intricacy and diversity of language seen in social media, the Syuzhet model was selected. By taking word context into account, it offers a more nuanced approach to sentiment analysis and improves sentiment classification accuracy.

SOLUTION PROCESS

Step1: Import ***tweets_justdoit_5000.csv***

Step 2: Make simpler the issue by eliminating irrelevant columns from the dataset and using only the columns that are relevant to our solution.

Step 3: For every tweet, calculate the sentiment with this Syuzhet program in R, then add a new column named Sentiment to the dataframe and save it to a new CSV file for the futher analysis.

Step 4: Reload this new CSV file using Sentiment, and then do data preprocessing processes such as deleting unnecessary stop words (most commonly utilized stop words and a few custom stop words were specified in a separate.csv file named stopwords.csv).

Step 5: Divided each tweet into both positive and negative categories, them identify the most often recurring word in these two categories of tweets and aggregate them by state.

Step 6: Identify the states with the greatest number of positive and negative attiudes about Nike and its #justdoit campaign during this time of controversy.

Step 7: I have opted for the first and last 5 states to analyze the terms Nike can utilize in their state-specific Social Media approach.

RESEARCH

The dataset was obtained from Kaggle.com. The dataset's author uses the Twitter API to source Twitter information. The usage of the Syuzhet package, which is well-known in the field of analysis of texts for its sentiment categorization abilities lends legitimacy to our sentiment analysis method. This case study includes various relevant articles from the Internet that provide extra data and insight into the case study. The sources are shown in the appropriate sections.

SOFTWARE

The software I have used here for this analysis is R console.

For detailed program structure, refer full codebase on https://github.com/pkg0726/Nike_MSBA324

#Setting directory

```
> setwd("/Users/aapg/Documents/Nike_MSBA324")
> getwd()
[1] "/Users/aapg/Documents/Nike_MSBA324"
```

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

```
>
>
> # Read the CSV file containing tweets data
> tweets <- read.csv("tweets_justdoit_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)

```
R 4.3.2 · ~/Documents/Nike_MSBA324/
>
>
> 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

tweet_full_text
1
Done is better than perfect. – Sheryl Sandberg #quote #motivation #justdoit https://t.co/J9lLdszdW6
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 #bestoftheday #justdoit #nike #picoftheday... https://t.co/sFobQ2ukpo
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 #4YourMorning #4YourMemeCollection \n\n🍪😂 https://t.co/6ok9qR6k6M
4
#kapernickeffect #swoosh #justdoit @ Lucas Bishop's Cigar Lounge https://t.co/BhPBnjOkuU
5                                                                                  One Hand, One Dream: The Shaquem Gr
iffin Story  https://t.co/0EbEmwULLF   #shaquem  #NFL #Seattle #Seahawks #griffin #JustDoIt #Nike https://t.co/pr8eosDZS7
6
@realDonaldTrump It's time for me to stock up on some new running apparel. Nike it is! #JUSTDOIT
     tweet_id tweet_in_reply_to_screen_name tweet_in_reply_to_status_id tweet_retweet_count user_favourites_count
1 1.038101e+18                                                       NA                   0                   307
2 1.038101e+18                                                       NA                   0                  1178
3 1.038101e+18                                                       NA                   0                 11864
4 1.038101e+18                                                       NA                   0                   487
5 1.038101e+18                                                       NA                   0                 32971
6 1.038101e+18               realDonaldTrump                 1.038018e+18                   0                  9622
  user_followers_count    user_id               user_location      user_location_us user_verified
1                57983 3188618684             California, USA            California         False
2                13241   18387174              Miami, Florida               Florida         False
3                11377   32645612             Indianapolis, IN               Indiana          True
4                  218  175932740 Tennessee by way of New Jersey          New Jersey         False
5                13731   22306628                 Gambleville Likely not a US state         False
6                   64   15566700                  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))

```
>
> 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 httpstcosfobqukpo"
[3] " amazingly hilarious nike ad memes happening newsfeed soooo decided little creative yourmorning yourmemecollect
ion 🍪😂 httpstcookqrkm"
[4] "kapernickeffect swoosh lucas cigar lounge httpstcobhpbnjokuu"
[5] "one hand one dream shaquem griffin story httpstcoebemwullf shaquem nfl seattle seahawks griffin nike httpstcopr
eosdzs"
[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)

```
1, 1
6
3, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                                                  top_words_with_freq
1              something(2), will(2), “(1), ”(1), “brodoyoumarvel(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(104), 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), 🤨(1), absolutely(1)
>
```

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

```
4, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
                                                 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), 🤦(1), gone(1), impeach(1), long(1)
5                nike(44), kaepernick(13), crazy(7), ad(6), shoes(6)
6                    nike(4), drive(2), kaepernick(2), saw(2), time(2)
>
```

```
>
> 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

```
> # Target states to analyze for Nike's targeted Social Media campaign
> states1 <- c("Michigan","Texas")
> states2 <- c("Illinois","California")
> states3 <- c("Florida","New York")
> # Loop through each state in the vector and create charts
> for(state in states1) {
+   # 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" = "green", "Negative" = "red")) +
+     theme_minimal()
+   # Save the chart as an image file
+   ggsave(paste0("tornado_chart_", state, ".jpeg"))
+ }
```

<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)

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

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)

<u>*TORNADO CHART OUTPUT FOR ABOVE CODE SNIPPET IS IN THE SECTION CALLED VISUALIZATION*</u>

MODEL RESULTS

Sentiment analysis using the Syuzhet package in R generated a sentiment score for each tweet, which was then classified as positive, neutral, or negative. These results were combined to calculate 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))

```
>
> print(head(positive_words_by_state))
  user_location_us
1          Alabama
2          Arizona
3         Arkansas
4       California
5         Colorado
6      Connecticut

tweet_full_text
1
2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
2
14, 7, 4, 3, 3, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
3
3, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
4 104, 47, 19, 19, 18, 17, 14, 14, 14, 13, 12, 12, 11, 11, 11, 11, 11, 10, 9, 9, 9, 8, 8, 8, 8, 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, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 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, 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,
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1               something(2), will(2), “(1), ”(1), “brodoyoumarvel(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(104), 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), 😮(1), absolutely(1)
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> print(head(negative_words_by_state))

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> print(head(negative_words_by_state))
  user_location_us
1          Alabama
2           Alaska
3          Arizona
4         Arkansas
5       California
6         Colorado

tweet_full_text
1
2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
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                                              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), 🌺(1), gone(1), impeach(1), long(1)
5                 nike(44), kaepernick(13), crazy(7), ad(6), shoes(6)
6                  nike(4), drive(2), kaepernick(2), saw(2), time(2)
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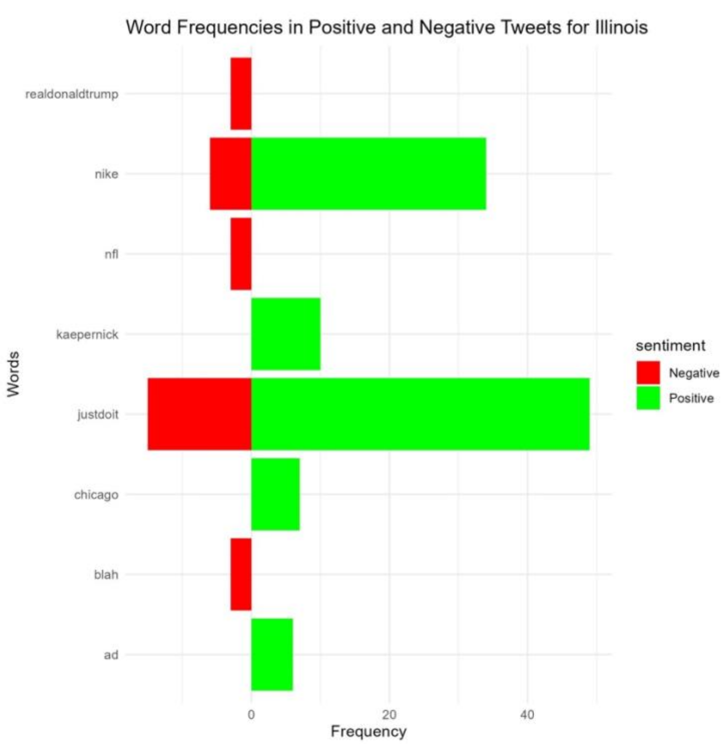
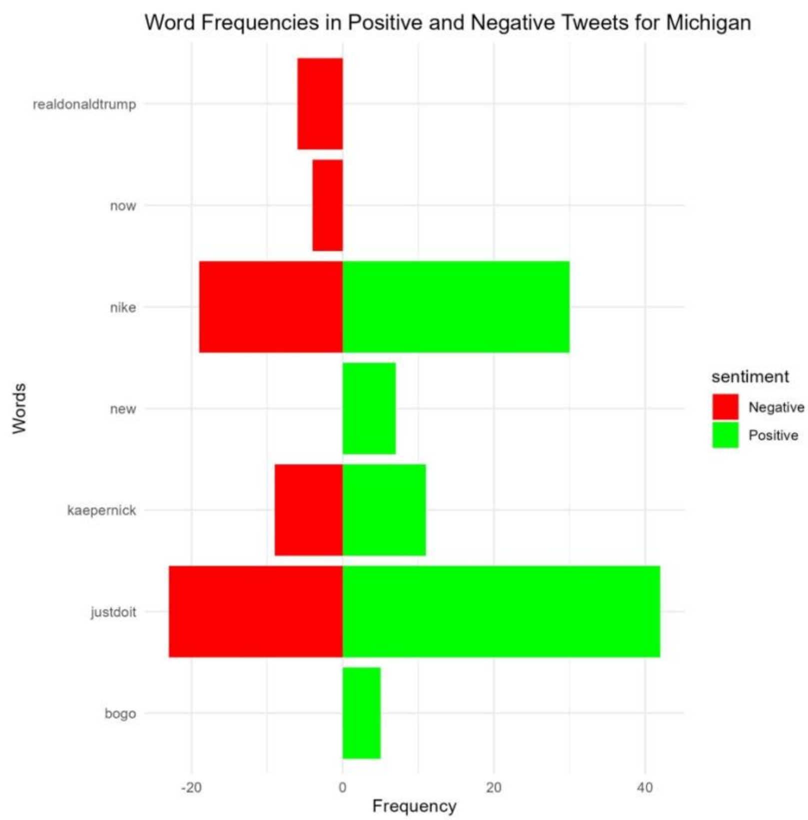
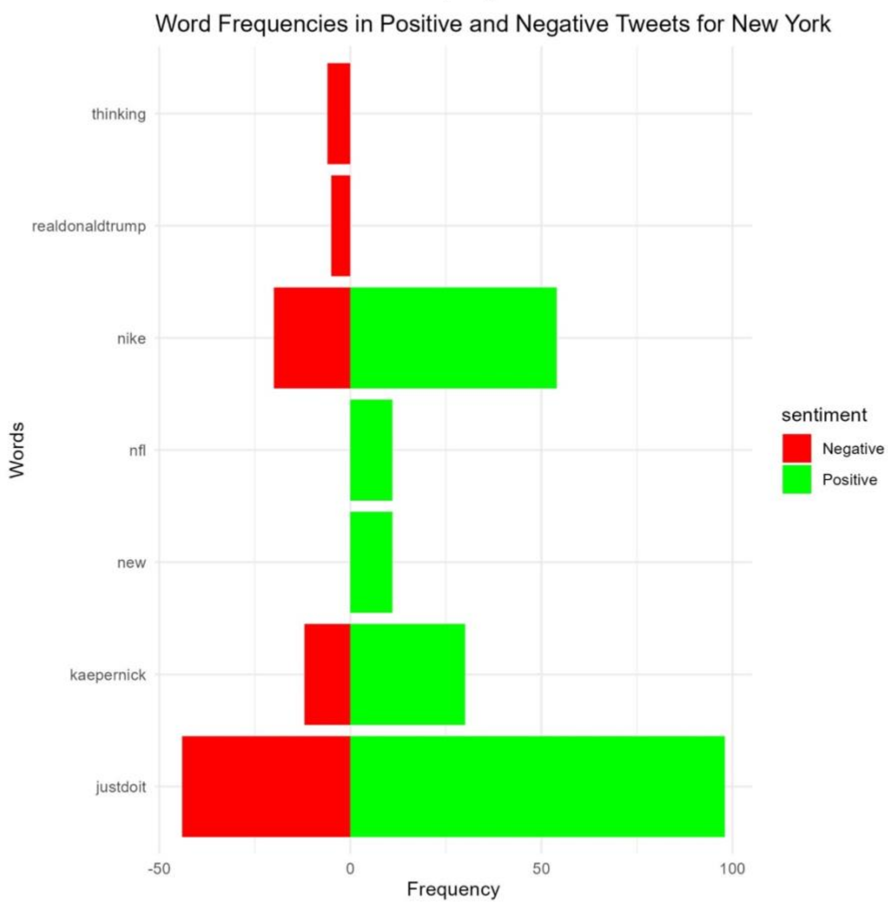
VISUALIZATION




Word Frequencies in Positive and Negative Tweets for Michigan
realdonaldtrump
now
nike
new
kaepernick
justdoit
bogo
Words
-20
0
20
40
Frequency
sentiment
Negative
Positive


Word Frequencies in Positive and Negative Tweets for New York
thinking
realdonaldtrump
nike
nfl
new
kaepernick
justdoit
Words
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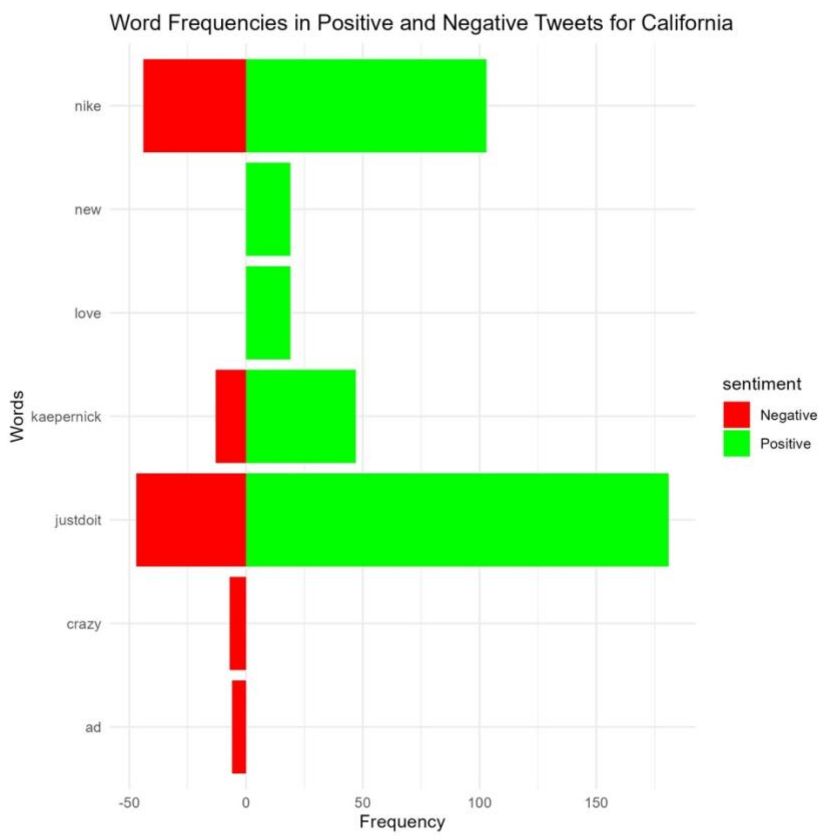
0
50
100
Frequency
sentiment
Negative
Positive


Word Frequencies in Positive and Negative Tweets for California
nike
new
love
kaepernick
justdoit
crazy
ad
Words
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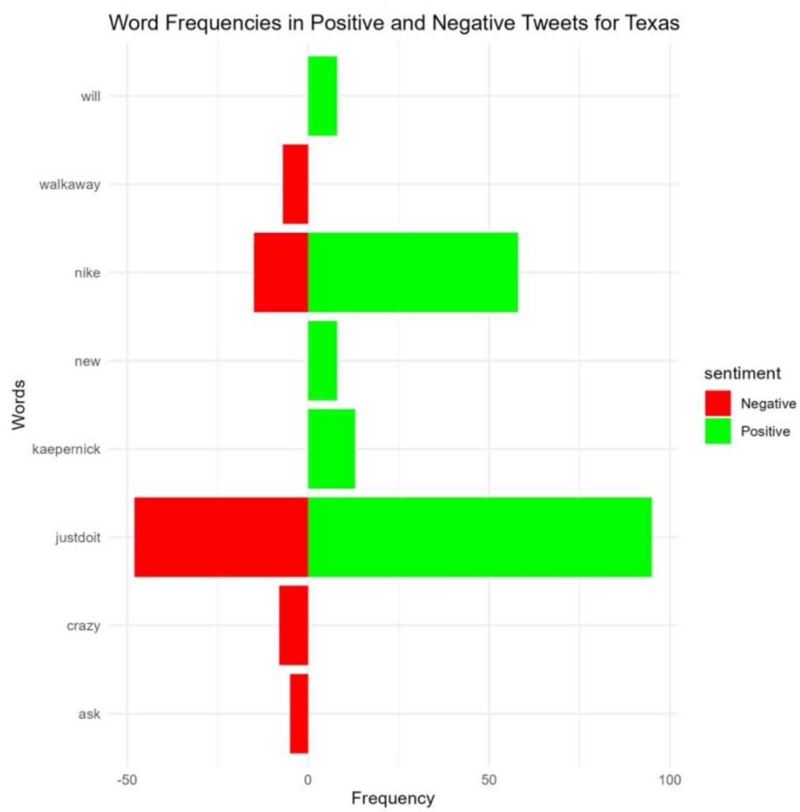
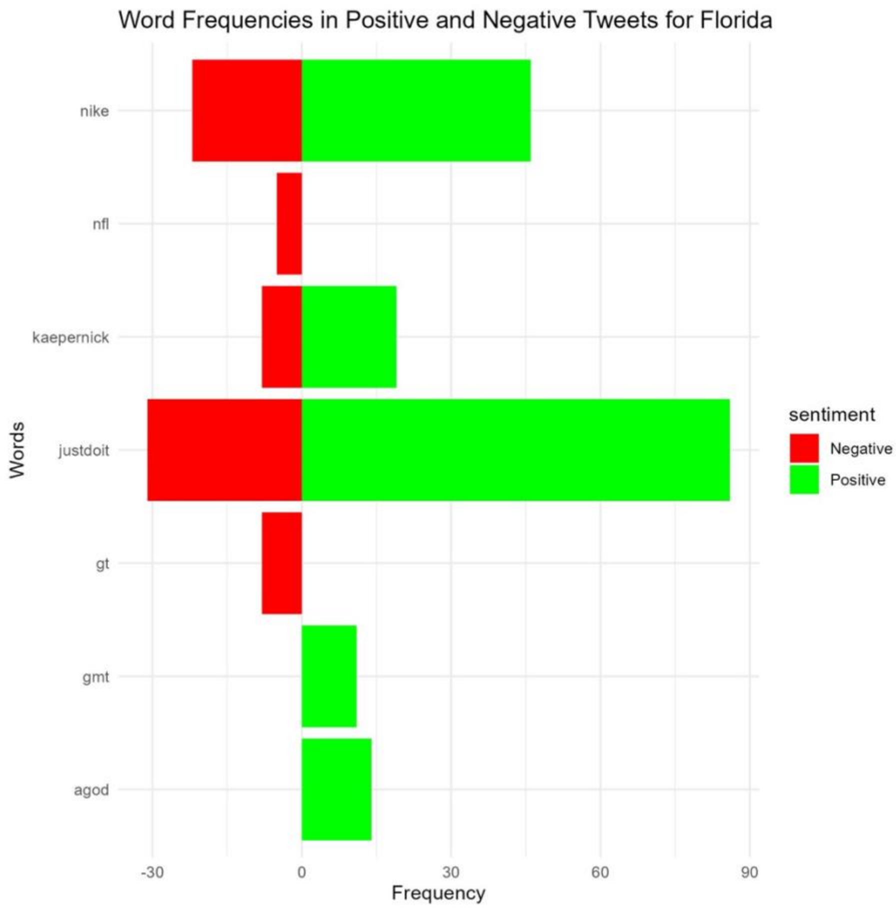
0
50
100
150
Frequency
sentiment
Negative
Positive


Word Frequencies in Positive and Negative Tweets for Texas
will
walkaway
nike
new
kaepernick
justdoit
crazy
ask
Words
-50
0
50
100
Frequency
sentiment
Negative
Positive



RESULTS

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 included 5 times positively, referring to Nike's Buy One, Get One offer for shoe sales at the time, demonstrating that Michiganders were receptive to this BOGO offer, so Nike should target Michiganders with this offer once more to improve brand sentiment.

Similarly, the social media hashtag campaign #justdidit and the word "new" imply 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) in response to this new campaign with Colin Kaepernick.

The favorable sentiments for "Nike" and "Kaepernick" substantially outnumber the negative sentiments in this state, so Nike was correct to double down on this marketing effort using Colin Kaepernick.

The negatives:

Likewise, in Georgia, as well as while Nike received normally favorable comments, Colin Kaepernick received massively negative feedback.

This was demonstrated by Nike's 45 favorable mentions and 16 negative mentions.
Similarly, Colin Kaepernick was never discussed positively and was only mentioned negatively five times.

Similarly, the word "flag" was used negatively three times in reference to Colin Kaepernick kneeling during the national anthem instead of standing and facing the flag, which enraged Georgia locals. This resulted in widespread negative attitude, as demonstrated by this news story. (CBS News, 2018).

Instead of doubling down on Colin Kaepernick, Georgia should have partnered with a singer who exhibits patriotism towards their country. Similarly, terms, sentiment, and frequency must be researched in other states in order for Nike to build a focused campaign to boost brand sentiment in each of these states.

CONCLUSION

After completing this project, the in-depth analysis of 5,000 tweets using the Syuzhet package in R gave us with a full insight of public attitude about Nike's choice to collaborate with Colin Kaepernick for their #JustDoIt campaign. The sentiment analysis sought to identify the most favorable and negative feelings expressed in tweets, as well as the terms most linked with these sentiments for each state.

PROBLEM RESOLUTION

The project's goal was to address the polarization of opinion produced by the Kaepernick endorsement and provide Nike with actionable insights for state-specific marketing initiatives to enhance social media sentiments. By quantifying attitudes and identifying important phrases, we have laid the groundwork for Nike's customized marketing strategy.

References

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6. For detailed program structure, refer full codebase on https://github.com/pkg0726/Nike_MSBA324