Nike x Colin Kaepernick

Class Project: MSBA 324
Web & Social Network Analytics
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Brand: Nike
Sentiment Analysis (with R Statistical)
+ Web & Social Media Strategy to
Handle Colin Kaepernick Controversy.

Date: 3/29/2024

1.1. Overview

1.2. Key Points from the research

1.3. Inputs that helped build an understanding

Introduction

The apparel market represents not just commerce but a cultural phenomenon. However, navigating its complexities requires more than just new products, innovative design, or celebrity endorsement – it demands an understanding of consumer preference, market trends, brand salience, and the ever-evolving economic landscape.

In this project, we delve deep into the conversations spurred during the Colin Kaepernick partnership and run an opinion scan, and with data-driven methodologies, we aim to decipher the pulse of consumer sentiment surrounding the brand. By unraveling the interplay between brand perception, artistic resonance, and market demand, we seek to uncover the narratives woven within and identify strategies to navigate the challenges and harness the opportunities presented by this partnership.

Nike, Inc.

Nike is the largest athletic footwear and apparel brand in the world. Key categories include basketball, running, and football (soccer). Footwear generates about two thirds of its sales. Its brands include Nike, Jordan, and Converse (casual footwear). Nike sells products worldwide through company-owned stores, franchised stores, and third-party retailers. The product sales correlate with various market and strategic indices, which will be explored further to understand their impact on revenue growth.

Situation

Nike Inc.'s collaboration with Colin Kaepernick for its "Just Do It" 30th anniversary sparked significant debate, underscored by the slogan "Believe in something, even if it means sacrificing everything." Kaepernick's protest against police brutality through not standing for the national anthem has made him a contentious figure, leading to a broad scale of public reactions, including remarks from President Donald Trump. This campaign has thrust Nike into the spotlight, impacting its brand perception, customer loyalty, and market position.

This project seeks to navigate the complex public sentiment surrounding Nike's decision by analyzing 5,000 tweets with the hashtag #JustDoIt from September 7, 2018. The aim is to dissect the public's perception, focusing on different U.S. states' emotions to guide Nike in strategizing effectively in response to the diverse opinions.

Problem Statement

Here lies the problem, and this is seemingly far rooted in the social media/web approach.
'Has Nike risked their partnership game that in turn could impact sales?'.

This project aims to refine and elevate Nike's digital and social media outreach by conducting a thorough sentiment analysis on both owned and third-party platforms. By delving into a broad array of insights, the objective is to pinpoint and address the root causes of consumer apprehensions, enabling informed, data-backed strategic decisions. A special focus will be placed on isolating and understanding the predominant negative sentiments and dialogues that could be influencing public perception. Through this meticulous examination, the intent is to craft targeted marketing campaigns. These campaigns will aim to diminish divisive opinions and enhance overall sentiment towards the brand, ultimately fostering a more positive and unified view of Nike in the digital realm. This enhanced approach not only aims to mitigate negative feedback but also seeks to leverage constructive criticism, turning challenges into opportunities for brand growth and stronger customer relationships.

Dependent Variable: Sentiment serves as a reflection of market trends, customer preferences, and future demand, all of which profoundly influence sales and market/stock performance. Here we look at what engagement stands to offer with respect to sentiment around the brand as the likely business outcome. Drawing parallel to Kanye West x Adidas partnership with Yeezys. The breakup with Kanye West has been tough for Adidas. The company saw its first annual loss in over three decades in 2023. The brand has hit a rough patch following the subsequent halt of its lucrative Yeezy sneaker line back in October 2022.

The results indicate that Nike share price were influenced right after the partnership. What is to be noticed is that the search trend for Nike and Kaepernick soared during the period.

Numerical Threshold: By analyzing sentiment across owned and earned channels. Find the insights that can be addressed, help identify customer pain points and make data-driven decision. The most frequent conversations making up for negative sentiment and discussions are analyzed to help create a targeted campaign so as to reduce division, and thus improve brand sentiment. Tackling the sentiment to improve the sales by 2x.

Sentiment analysis on Twitter with objective mapping

The sentiment analysis focused on extracting insights from Tweets regarding brand perception, and overall opinion.

Model Selection: Sentiment analysis is a multifaceted task that involves interpreting the emotional tone underlying textual data. To conduct sentiment analysis, the Syuzhet and NRC libraries in R were utilized.

These libraries are chosen for their diverse approaches to sentiment analysis, their capacity to capture nuanced emotions, and their ability to complement one another when used together. By leveraging their collective insights, the aim is to conduct a comprehensive sentiment analysis that is robust to the intricacies of natural language.

Reasons for selection:

- Syuzhet: This library excels in identifying emotional arcs within narrative texts, making it ideal for analyzing data with storytelling elements, such as customer reviews and social media posts. Its method, rooted in literary theory, offers a unique perspective on sentiment analysis.
- NRC Word-Emotion Association Lexicon: Unlike traditional sentiment analysis, NRC categorizes words into various emotions and sentiments, offering a more nuanced understanding of text. This depth allows us to capture complex emotional responses, including trust, fear, and surprise, enriching our analysis.

Success Factor: The success variable could be increasing engagement that in turn leads up to people sharing more positive sentiments and the same relies on insights derived from the sentiment analysis with which we find what are the areas that needs to improve and be addressed.

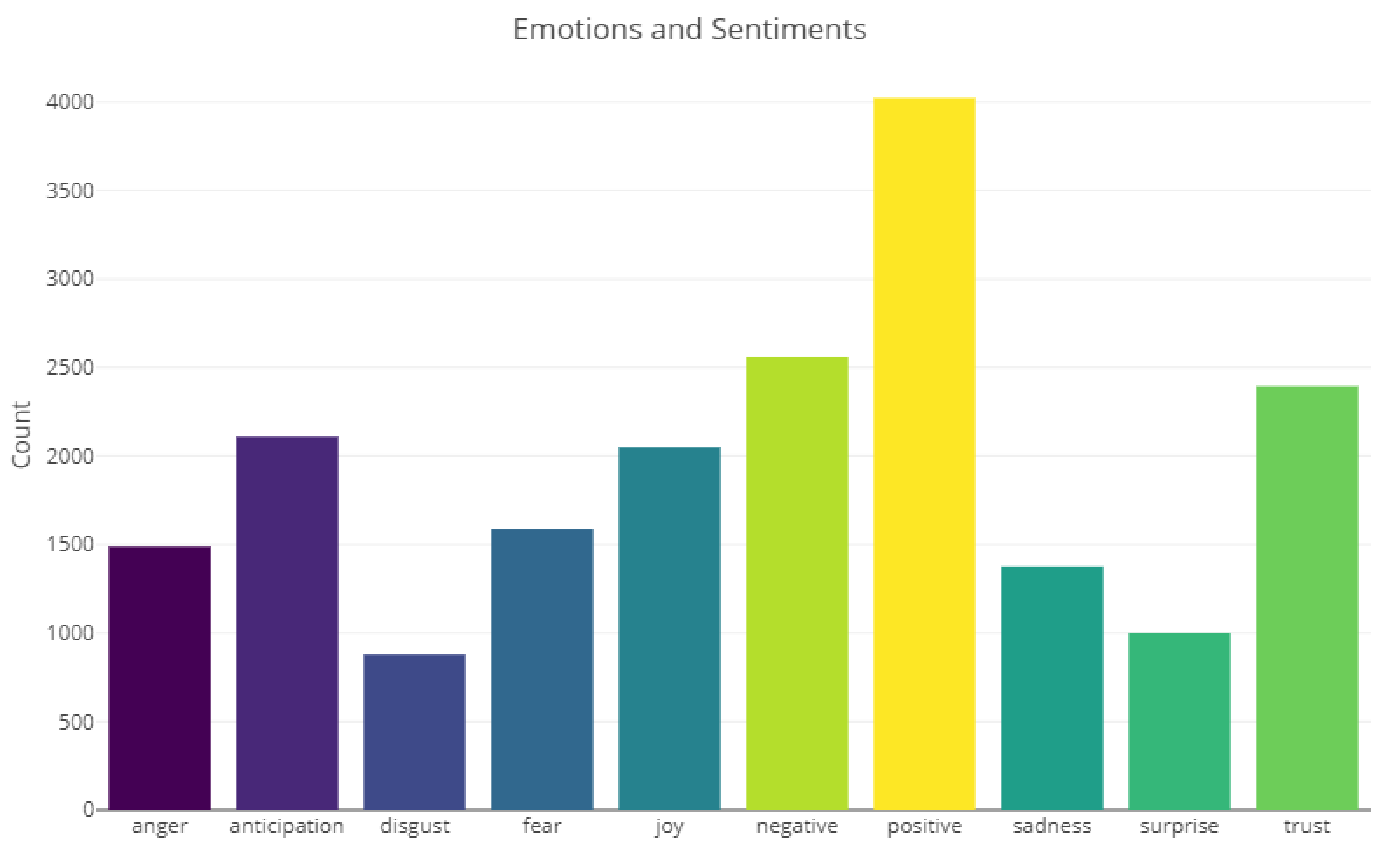
Since the R notebook for this has over 40 code chunks, only adding the graphical representations of the insights derived from running the code work.

Result interpretation

```{r}
# Emotions and Sentiments visualization
nrc_sentiment <- get_nrc_sentiment(All_Selected_Tweets$tweet_full_text)
sentisum <- colSums(nrc_sentiment)
interactive_bar <- plot_ly(x = names(sentisum), y = sentisum, type = 'bar',
                           marker = list(color = viridis::viridis(length(names(sentisum)), option = "D"))) %>%
  layout(title = 'Emotions and Sentiments', xaxis = list(title = ''), yaxis = list(title = 'Count'))
```
```{r}
# Display the plot
interactive_bar
```

The NRC library was employed to analyze Tweets, providing a multi-dimensional understanding of emotional responses within the dataset. Each observation represents a text segment, and emotion scores are assigned based on the presence of specific emotional words. Since the Tweets are limited by Character, it is essential to understand the emotions spectrum.

Visualization:



Analysis of the sentiment revealed predominantly positive sentiments, with indications of trust, joy, and surprise among the conversations. This suggests a favorable reception around brand and trend, indicating positive feedback on the product, partnership, and the brand’s stance (referenced conversation snippets provided below).

However, there is a growing anticipation and a sense of fear as evidenced in the data, potentially indicating dissatisfaction and negative sentiment with the backlash. Analysis was conducted to explore the comments contributing to these emotions.

Let’s look at the tweets that are indicative of anger, disgust, anticipation, trust, fear, and sadness. These are the mix of top conversations based on their Syuzhet scores.
Code chunk – 70-76 brings out the top 10 negative tweets basis the respective scores.

```
```{r}
# Displaying the tweets with the minimum Syuzhet score and limiting to 10 tweets
tweets_with_min_syuzhet <- All_Selected_Tweets$tweet_full_text[minScore][1:10]
# To print the tweets
print(tweets_with_min_syuzhet)
```
```

```
[1] "justdoit nike took a knee for kaepernick outrage ensues were you surprised "

[2] "realdonaldtrump they are thinking about the greatness in every single one something that you are incapable of comprehending too bad justdoit "

[3] "istandwithice icegov justdoit bringiton maga americafirst illegalaliens are criminals buildthatwallnow buildthewall secureourborders borderpatrol waityourturn vote red kag "

[4] "calling a dream crazy its not an insult its a compliment justdoit"

[5] "believe in something even if it means sacrificing every motherfucker in the jungle nike justdoit predator "

[6] "wtf people like gillum and other socialistsdems are why we cannot progress due to digging 150 yrs in the past to paint everyone racists and use black people from physical slavery to mental slavery thedemocrats never change and justdoit "

[7] "bet these are causing havoc for all those in the boycottnike side of thingsthe flag on nikes justdoit kaepernick "

[8] "sometimes you gotta knock a bitch out□ justdoit nik"

[9] "bigbrothergod1 don43pmdon amen colin didnt sacrifice anything he had a contract and turned down two offers he didnt sacrifice rather than justdoit he just quit and hes still a millionaire and a pouty whiny leftist"

[10] "weve seen the outrage on social media on nikes move to use colin kaepernick as a spokesperson for justdoit according to retail experts at brp despite the backlash its a calculated risk but the ad will only do good things more here nike "
```

Let’s look at the positive comments to get a sense of what good people are saying.
Code chunk – 95-100 brings out the top 10 positive tweets basis the respective scores.

```{r}
# Displaying the tweets with the maximum Syuzhet score and limiting to 10 tweets
tweets_with_max_syuzhet <- All_Selected_Tweets$tweet_full_text[maxScore][1:10]
# To print the tweets
print(tweets_with_max_syuzhet)
```

[1] "realdonaldtrump its clear why you kim respect each other so muchdonaldlovesdictators takeaknee colinkaepernick nike justdoit fightfascism "

[2] "im sure imchelseagreen will have her spot in a wwe ring soon after listening to eandcpodcastofawesomeness im even more inspired by her will to justdoit this woman is amazing 👏💪💪💪💪🖤🖤🖤🖤🖤🖤day1 fan riding with imchelseagreen all the wai"

[3] "september 19th interest free newmusic fridaymotivation justdoit album westcoast nyc vancouver "

[4] "omg woo me i just loved being wooed me fridayfeeling bigfacts justdoit uapb21 retweeet share listenbetter quote puregoals teamfollowback waitonit uapb21 naturalwoman afro "

[5] "botblocking is therapeutic justdoit "

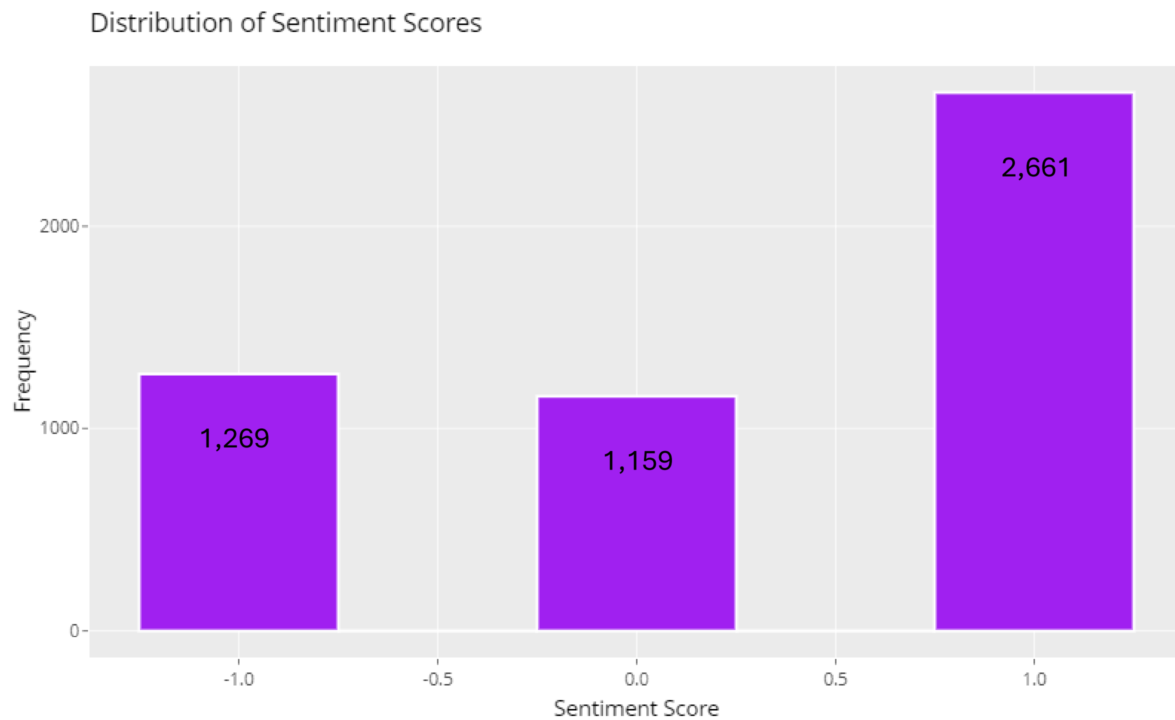
[6] "clear cut winner with the justdoit memes therock 😂 "

[7] "open mic □ performed real recognize real last night and had a good time doing it ybm justdoit dowhatmakesyouhappy ybm "

[8] "dont just buy shoes buy stock thelifeeengineer investlikealady livelikeaboss justdoit yesterday i purchased nike stock for all my children my nephew teach them ownership "

[9] "justdoit nikes stance on social justice by thereclaimed "

[10] "alternet why focus on wackiness trump is a threat to the constitution let comedians like kathygriffin make fun of him all other reporting should be on how do we get him out of office□🌴 🌴justdoit impeachtrump 25amendmentnow"



We now funnel these tweets to corresponding scores that are normalized to better understand the volume. This helps us to assess the immediate stance at glance for the brand. This method employs combining and normalizing the Syuzhet score.

This method helps uncover prevalent themes in consumer discussions, providing a nuanced understanding of what consumers care most about, whether it be product quality, sizing, price, or availability.

What do these scores indicate? The score of 1.0 signifies the total count of positive tweets which stands at 2,661 and the score of 0.0 are neutral tweet counts that makes up 1,159 and the -1.0 is the final count of negative tweets which is at 1,269.

Do note that given the sentiment analysis library and tools have varying degree of sensitivities and biases, calibrating the sentiments based on a manually annotated categories gives more accuracy and context.

Insights

Fetching the top 5 States with highest average sentiment.

As evidenced by the context of the below code, we see that there's more concerns around product availability and shipment issues, product sizing followed by last but not least being authenticity.

 # Top 5 states with the highest average sentiment

user_location_us <chr>	average_sentiment <dbl>
Montana	2.9750000
North Dakota	2.3250000
Wyoming	1.2500000
Delaware	0.9269231
Missouri	0.8440000

5 rows

 # The total sales count of the same 5 States

State <chr>	TotalSalesCount <int>
Delaware	123000
Missouri	96846
Montana	157124
North Dakota	77361
Wyoming	185783

5 rows

 # Bottom 5 states with the lowest average sentiment

user_location_us <chr>	average_sentiment <dbl>
Oklahoma	-0.6888889
West Virginia	-0.4000000
Alaska	-0.3500000
Nebraska	-0.2111111
Mississippi	-0.1875000

5 rows

 # The total sales count of the same 5 States

State <chr>	TotalSalesCount <int>
Alaska	69652
Mississippi	155927
Nebraska	59301
Oklahoma	106219
West Virginia	106906

5 rows

Code chunk – 178-196 brings out the top 5 States with highest and lowest average sentiment scores.
Code chunk – 204-216 brings out the total sales of the above top highest and lowest average sentiment rated States.

````
```{r}
# Calculate average sentiment for each state
state_sentiment <- All_Cleaned_Tweets %>%
  group_by(user_location_us) %>%
  summarise(average_sentiment = mean(Sentiment, na.rm = TRUE)) %>%
# Arrange data in descending order of average_sentiment
  arrange(desc(average_sentiment))
```
```{r}
# Top 5 states with the highest average sentiment
top_5_states <- state_sentiment %>%
  slice_max(order_by = average_sentiment, n = 5)
print(top_5_states, "Top 5 States by Average Sentiment")

# Bottom 5 states with the lowest average sentiment
bottom_5_states <- state_sentiment %>%
  slice_min(order_by = average_sentiment, n = 5)
print(bottom_5_states, "Bottom 5 States by Average Sentiment")
```
````

The above juxtaposition of sentiment analysis outcome and the sales count for the respective States provides a much-needed clarity on the correlation between the dependent variable being engagement (sentiment arc) and the outcome variable that is total sales. What sentiment stands to offer as an engagement and its effects on the brand and its performance as the likely business outcome.

We now will look at how the brand and partnership relationship is perceived with Colin Kaepernick.

Fetching the top 5 States with highest count of Positive and Negative tweets to understand with what context of engagement are being shared.

Code chunk – 247-272 brings out the top 5 States with highest positive and negative tweets.

```
# For Positive Tweets
top_5_positive_states <- positive_tweets %>%
  group_by(user_location_us) %>%
  summarise(PositiveTweetCount = n()) %>%
  arrange(desc(PositiveTweetCount)) %>%
  slice_head(n = 5)

# For Negative Tweets
top_5_negative_states <- negative_tweets %>%
  group_by(user_location_us) %>%
  summarise(NegativeTweetCount = n()) %>%
  arrange(desc(NegativeTweetCount)) %>%
  slice_head(n = 5)
```

 # Top 5 States with the highest positive tweets

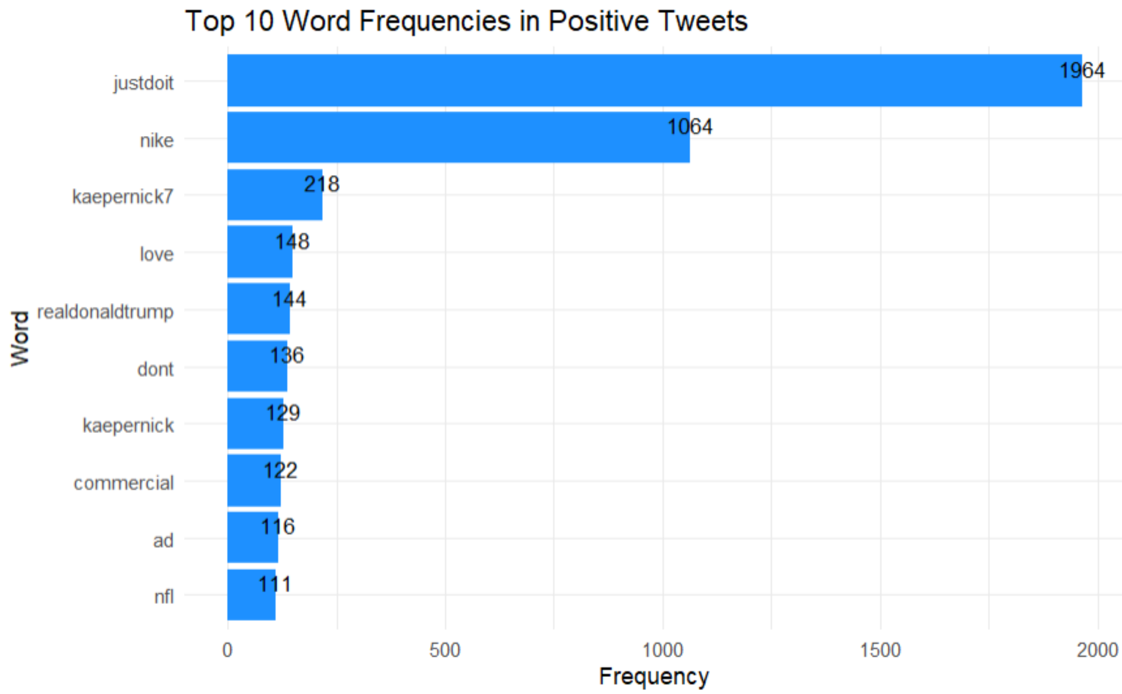
user_location_us <chr>	PositiveTweetCount <int>
Not Defined	1467
California	185
New York	103
Texas	99
Florida	90

 # Top 5 States with the highest positive tweets

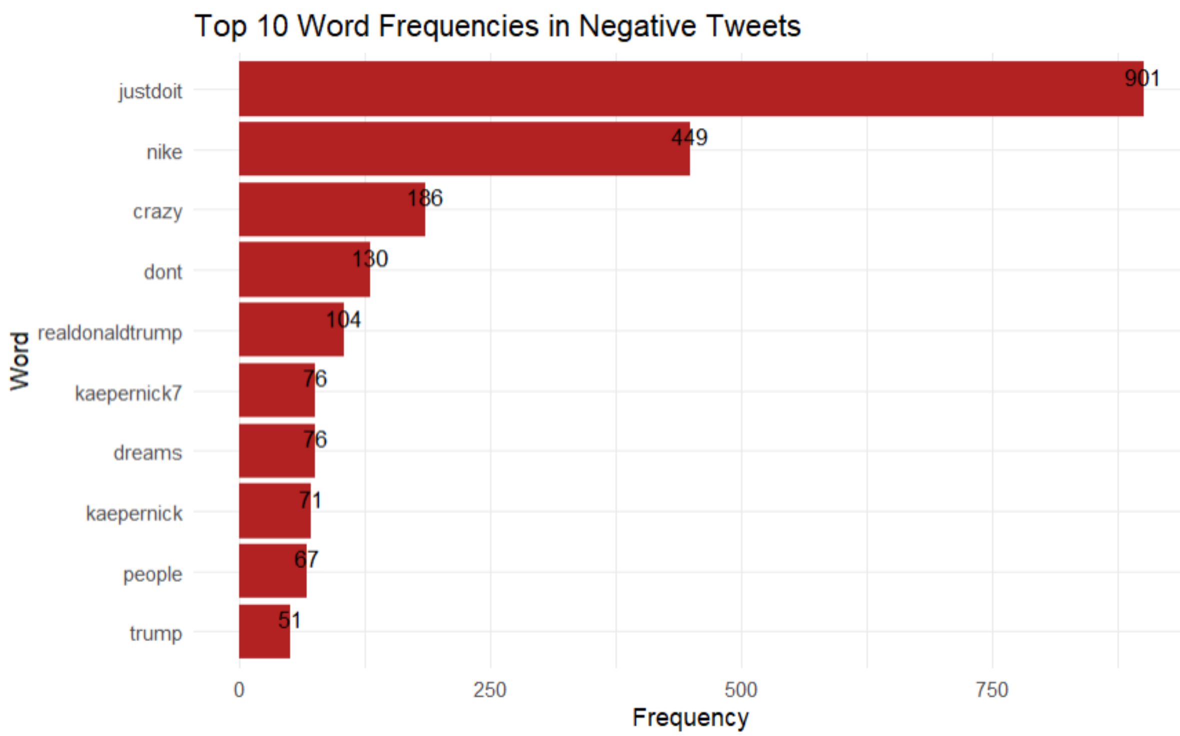
user_location_us <chr>	NegativeTweetCount <int>
Not Defined	730
Texas	51
California	50
New York	43
Florida	32

The chart below shows the keywords count, the frequently mentioned words from positive sentiment tweets and the frequently mentioned negative sentiment tweets. It also shows the emotional tendency of these words.

Visualization:



What can be derived from this is that the sentiment is overall skewed positively towards Nike's brand image and its association with Colin Kaepernick, words like love, commercial, ad, NFL have been used frequently showing that the partnership was well received and left a profound influence and impact.



What can be derived here is that the association stirred up some negative feelings. Words like crazy, dreams, crazy (which is a reference to the video campaign) followed by realdonaldtrump and trump had conversations in numbers since the then President tweeted about the incident that drew attention and intensified the breadth of polarity and also criticized the advert.

```{r}
library(ggplot2)

# Plot for positive word frequencies
ggplot(top_positive_word_freq, aes(x = reorder(word, n), y = n)) +
  geom_col(fill = "dodgerblue") +
  geom_text(aes(label = n), position = position_dodge(width = 0.9), vjust = -0.25, size = 3.5) +
  coord_flip() +
  labs(title = "Top 10 Word Frequencies in Positive Tweets",
       x = "Word",
       y = "Frequency") +
  theme_minimal()

# Plot for negative word frequencies
ggplot(top_negative_word_freq, aes(x = reorder(word, n), y = n)) +
  geom_col(fill = "firebrick") +
  geom_text(aes(label = n), position = position_dodge(width = 0.9), vjust = -0.25, size = 3.5) +
  coord_flip() +
  labs(title = "Top 10 Word Frequencies in Negative Tweets",
       x = "Word",
       y = "Frequency") +
  theme_minimal()
```

Situation Comparison

Nike’s involvement with Colin Kaepernick and the social media reactions can be paralleled with Pepsi's controversial "Live For Now" campaign in April 2017. Much like Nike's campaign, Pepsi’s initiative sought to tap into contemporary social movements, but it too faced a divided public reaction.

Pepsi’s Campaign: Pepsi’s "Live For Now" advertisement featured Kendall Jenner as she joined a protest and handed a Pepsi can to a police officer, seemingly resolving the conflict. The campaign intended to project a global message of unity, peace, and understanding. However, the execution was met with widespread criticism. Critics argued that the ad trivialized the seriousness of social justice protests and movements, reducing significant societal conflicts to problems that could be solved with a soft drink. This backlash was swift and severe, with many taking to social media to express their disapproval.

Similar to Nike’s situation, Pepsi's campaign became a hot topic of conversation across various platforms. However, while Nike's campaign with Kaepernick garnered both support and criticism, with a notable amount of positive sentiment in numerous states as seen from our analysis, Pepsi's attempt at addressing social issues without a clear stance resulted predominantly in negative sentiment. This adverse reaction was not only quick but also impactful, leading Pepsi to pull the ad and issue a public apology, acknowledging that they missed the mark in trying to convey their message.

Both campaigns underscore the risks and rewards associated with brands taking stands on social issues. Nike's campaign, despite its polarizing nature, ultimately reinforced the brand's identity and commitment to social causes, resonating positively with a significant segment of its target audience.

Conclusion

This project with its the in-depth analysis of 5,000 tweets using the Syuzhet package in R has provided us with a comprehensive understanding of public sentiment and highlights the dynamics of brand engagement with social and political issues and how it can significantly impact market performance for the brand. It underscores the essential need for authenticity, respect, and a deep understanding of the issues being addressed, lessons that are invaluable for any brand considering taking a stand on societal matters.

Recommendations

Nike should address public concerns by implementing strategic web and social media initiatives as part of the overall campaign. The web network and partnerships are a tool, a tool to engage users, establish rapport, and keep fans involved and informed.

Nike should cultivate bolder partnerships with entertainers in each State, engage with existing music artists from the roster, sport influencers, golfers, and collaborators who serve as brand ambassadors to amplify brand ethos, the social stance, and credibility with #DreamCrazy. These initiatives will help boost engagement for the brand and be the talking point for the public.

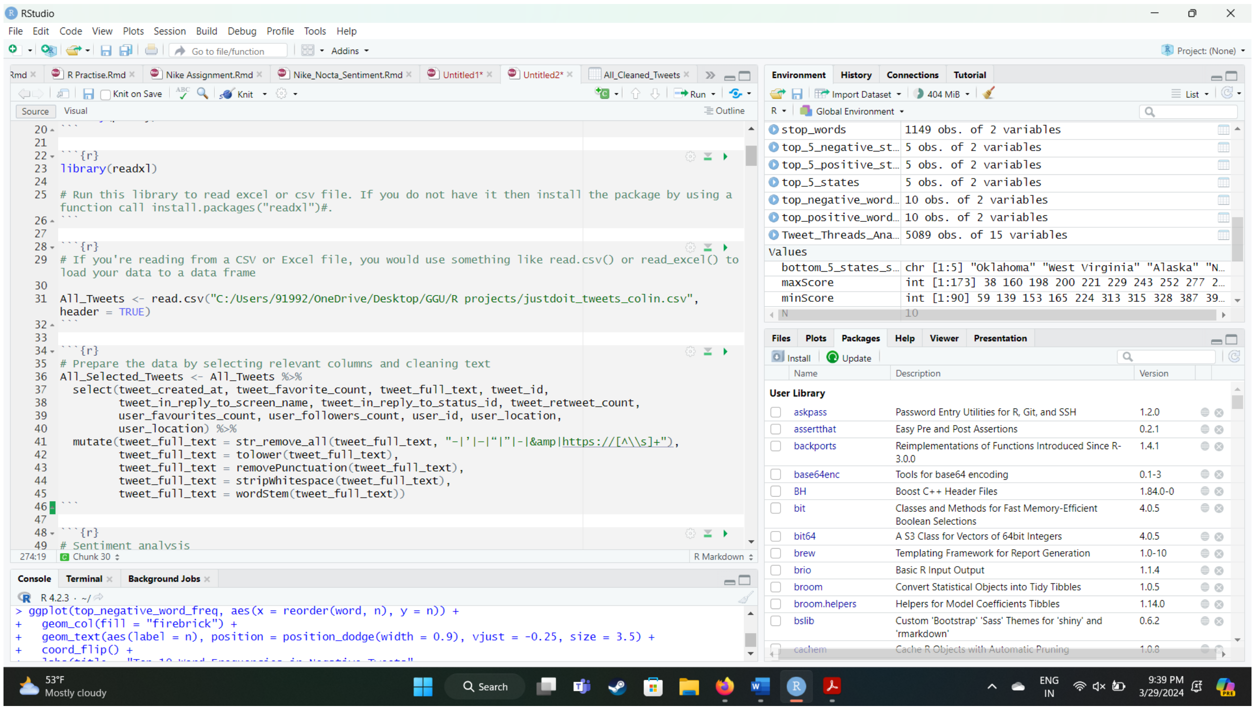
Education and Awareness: Address public concerns surrounding authenticity by launching a video series that spins off from the campaign commercial extending the narrative of “Believe in something.”. This content can educate the audience on the prevalent societal injustice that exists in the system, providing valuable information and awareness. This can become a precursor for a movement that can raise donations and fundings for the people who invariably are affected by racial injustice.

Collaborative Marketing: Implement an affiliate commissions model with luxury and sports channels such as GQ, Complex, Sports Illustrated. Do raffles to provide concert passes, tickets for games and engaging events with sports partners and entertainers. Collaborating with these platforms can expand brand visibility and reach a wider audience, driving engagement and sales.

These efforts would definitely help the brand attain 2x on their Share of Voice (SOV) which can drive the market performance for the brand. Evidently, from the analysis, it is seen that the ad campaign worked and that people loved the commercial as well since there was much positive buzz around it, the cheer for the player and the sport as well. The campaign was deemed a success, and the company’s stocks rose by 5% in the weeks following the advert’s release.

Solution process

Step 1: 5000 Tweets bank was the source to fetch followers feedback and conversations around the brand.



Codebase for the same has been shared along.

The raw data had several fields and columns that needed to be cleaned, normalized, and standardized for further analysis.

tweet_c	tweet_ic	tweet_ir	tweet_ir	tweet_r	user_fa	user_fol	user_id	user_loc	user_ve	tweet_fu	tweet_fa	user_loc	Sentime
Fri Sep 07	10381008579323944		NA	0	307	57983	3.19E+09	California,	FALSE	Done is be	0	California	2.35
Fri Sep 07	10381008308079042		NA	0	1178	13241	18387174	Miami, Flo	FALSE	Shout out	0	Florida	2.35
Fri Sep 07	10381007931472486		NA	0	11864	11377	32645612	Indianapol	TRUE	There are	0	Indiana	2.25
Fri Sep 07	10381007672849694		NA	0	487	218	1.76E+08	Tennessee	FALSE	#kapernicl	0	New Jersey	0
Fri Sep 07	10381007453447536		NA	0	32971	13731	22306628	Gamblevill	FALSE	One Hand,	0	Not Define	0.25
Fri Sep 07	10381007	realDonalc	10380181	0	9622	64	15566700	Austin, TX	FALSE	@realDona	0	Texas	0.8
Fri Sep 07	10381006813981777		NA	0	16358	11555	1.74E+08	World-Wid	FALSE	Why won't	0	Not Define	0.65
Fri Sep 07	10381006	Nike	NA	0	921	88	74385628	Newark, D	FALSE	@Nike goo	0	Delaware	2
Fri Sep 07	10381006205809336		NA	0	14866	393	21149200		FALSE	GREAT way	0	Not Define	1.85
Fri Sep 07	10381005428185333		NA	0	15	7	10322430	Federal Ca	FALSE	Lead,Trad	0	Not Define	1.75
Fri Sep 07	10381005015214161		NA	0	4192	493	2.87E+08	Chelsea Al	FALSE	My favorite	0	Alabama	0.8
Fri Sep 07	10381004973607157		NA	0	767	3298	5.39E+08	Nashville,	FALSE	Colin	0	Tennessee	0.05
Fri Sep 07	10381004	CSPension	10373849	0	736	329	3.06E+08	Abuja, Nige	FALSE	@CSPensi	0	Not Define	0.1
Fri Sep 07	10381004	realDonalc	10380181	0	2303	80	2.44E+09		FALSE	@realDona	0	Not Define	0
Fri Sep 07	10381004	RepAdamS	10378579	0	4120	192	42350706		FALSE	@RepAdar	0	Not Define	0.8

Step 2: On further cleaning up the .csv, kept only the relevant columns that would be necessary to run the code and do the text mining and sentiment analysis.

Ran two sentiment analysis models to find insights. The Syuzhet performed the best in terms of accuracy. However, there were still a few misinterpretations. By normalizing and combining the scores from these diverse libraries, I am looking to leverage the strengths of multiple sentiment analysis approaches, which can enhance the robustness and reliability of the analysis. Each library may capture certain linguistic nuances that others miss, so using a combination can offer a more comprehensive view of sentiment in your dataset.

Step 3: Utilized graphical representations to showcase the results with NRC emotions.

Step 4: Then the next stage involved reviewing and adjusting subset of data manually to ensure that the States are well defined to align with our course of analysis.

Step 5: Graphical representation of the sentiment score after normalizing the Syuzhet scores to understand the volume of positive, negative, and neutral tweets.

Step 6: Then the next stage involved reviewing and adjusting subset of data manually to ensure that the States.

Step 7: Further consolidated the frequency of words for the States with highest volume of tweets.

Step 8: Graphical representation of the comments in proportion to the frequency of words to understand the sentiment.

References:

1. Nike - 10-K Report 2023
2. Jack Baer (2018, September 13). Nike stock closes at all-time high in aftermath of Colin Kaepernick ad campaign. Yahoo Sports. https://sports.yahoo.com/nike-stock-closes-time-high-aftermath-colin-kaepernick-ad-campaign-225007582.html
3. Marek Polanský & Lucas Sylvester-Hvid. A Comparative Study Concerning Twitter's Influence on Company Stock Market Performance. May 2022. DOI:10.13140/RG.2.2.13006.95048
4. Jeff Beer (2020, September 5). One Year Later What Did We Learn From Nikes Blockbuster Colin Kaepernick Ad? Fast Company. https://www.fastcompany.com/90399316/one-year-later-what-did-we-learn-from-nikes-blockbuster-colin-kaepernick-ad
5. Betsy Reed (2019, September 16). Nike's 'Dream Crazy' advert starring Colin Kaepernick wins Emmy. The Guardian. https://www.theguardian.com/sport/2019/sep/16/nikes-dream-crazy-advert-starring-colin-kaepernick-wins-emmy
6. Datasets: Kaggle
7. Tool: RStudio