Nike's innovative business strategy has generated an impressive $163.5 million worth of media buzz without incurring any costs.

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Class name: MSBA324 Web and social analytics

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Contents

Situation

Back in 2018, Nike launched a campaign that was a part of Nike's 30th–anniversary celebration of the "#justdoit" slogan. During this campaign, Nike faced a lot of ignited controversy in the public and ex-president Donald Trump himself tweeted about this not once but twice, causing public burning, and calls for a boycott, which was extensively covered by the media, seemingly casting a shadow over Nike's brand image and customer loyalty.

Understanding and locating the diverse and region-specific public sentiment towards the brands is a key challenge. so I will be using the social media response from Twitter this dataset contains 5000 tweets from September 7, 2018. And I have also Did web scrapping of Twitter from the year 2020 to 2021 using APIFY software.

The analysis is done of Twitter text and identifies all 3 sentiments from positive, negative, and neutral and also looked at top used words and tried correlating it with sales of Nike

Problem Statement

Nike's 2018 campaign, put Colin at the center stage. This campaign sparked injustices and led to a polarization of public sentiment. This caused leading protests, shoe burnings, and boycotts of the Nike brand. Despite this, Nike experienced a notable surge in sales and stock value, suggesting a multifaceted consumer reaction. Understanding the factors behind both negative backlash and positive sales outcomes requires a thorough analysis of the campaign's impact on various demographics and regions. Our objective is to thoroughly examine social media sentiment and consumer behavior to create sophisticated marketing strategies that can effectively navigate and capitalize on these divergent responses. To help Nike strike a balance between social advocacy and maintaining broad consumer appeal, this analysis will guide how future campaigns can enhance the brand's image and market position while avoiding counterproductive controversy.

Dependent variable:

The primary dependent variable in this context is the "brand sentiment score," which quantifies public perception of Nike following the Kaepernick campaign. This score will be derived from sentiment analysis of social media data, particularly tweets, categorized by geographic and demographic factors. It reflects the aggregate public sentiment towards Nike, encompassing both positive and negative reactions. The sentiment score will be a critical measure of the campaign's impact on Nike's brand image, influencing subsequent marketing strategies and business decisions to enhance or rectify the company's standing in various consumer segments.

Numerical Threshold:

The numerical threshold for success in this analysis could be defined as achieving at least a 10% improvement in the brand sentiment score across targeted states or demographics following the implementation of tailored marketing campaigns. This improvement should be reflected in increased positive sentiment and reduced negative sentiment on social media platforms. For Nike, reaching or surpassing this threshold would indicate effective mitigation of the negative impacts of the controversy and a strengthened brand image, demonstrating successful navigation of the complex market dynamics and consumer perceptions following the Kaepernick campaign.

Model Selection

Model Selection: For the analysis, the Syuzhet sentiment analysis package and also tm package to create corpus, clean, and preprocessing text in R have been chosen.

Reason for Model Selection: Syuzhet is selected because it is adept at handling the complexity and nuances of language used on social media platforms. This package provides a more refined approach to sentiment analysis by taking into account the contextual use of words, which enhances the accuracy of sentiment classification. Its ability to dissect and interpret the emotional undertones of textual data makes it particularly suitable for analyzing diverse and often ambiguous public opinions on platforms like Twitter, where the sentiment can significantly sway brand perception. This makes Syuzhet an ideal tool for gauging public sentiment towards Nike's campaign and informing the brand's strategic response.

Tm package is used to remove any special character and conduct topic modeling it will also provide text transformation, including stemming, stop word removal, and n-gram creation.

Solution Process

I have 3 different analyses and validated the result according to the analysis in these 3 I have 2 sentimental analyses and one analysis is on sales data using the visualization tool Tableau.

Step 1: Import the required CSV files into r consoles.

Step 2: simply the problems by removing irrelevant columns from the dataset.

Step 3: Remove all special characters, and https in the tweeter text.

Step 4: processing sentiment score analysis.

Step 5: plotting a graph for emotions like sadness, surprise, trust, etc.

Step 5: Check for the most positive, most negative, and neutral tweets categorize them in several counts, and plot the graph.

Step 6: Check for most words used in the tweets and find out a few top-selling products by that.

Step 7: visualization of total sales in-store or wholesales

Step 8: Checking the sales by region by bar plot.

Step 9: recognize the top 15 selling products in the year 2020-2021.

Step 10: checking revenue growth from 2020 to 2031.

Research

Secondary research: this case study includes several relevant articles available on the internet to provide additional information and insight into my case study.

Primary research: the dataset was taken from "Kaggle.com" which is "JustDoIt_5000.csv" and I also Scraped if dataset from twitter.com by using the software called "Apify.com", it's a free platform. From scrapping data up to 1000 tweets. When it comes to sales data, I have browsed through "Statista.com".

Software

Since the program contains 100 lines of code, so I added here only the most significant screen shoot of code with their explanation.

Dataset from Kaggle.com

#Checking the Directory and setting it proper folder

```
> getwd()
[1] "C:/Users/nishc/Desktop/web social media nike case study/finally csv dataset"
> setwd("C:/Users/nishc/Desktop/web social media nike case study/finally csv dataset")
```

#importing required library for this analysis

```
> library(tidyverse)
> library(syuzhet)
> library(ggplot2)
> library(tm)
> library(stringi)
> library(tidytext)
```

reading JustDoIt_5000.csv

```
> df <- read_csv("justdoit_tweets_5000.csv")
Rows: 5089 Columns: 73
— Column specification ——————————————————————————————————————————————————————————————————————
Delimiter: ","
chr (34): tweet_coordinates, tweet_created_at, tweet_display_text_range, tweet_entities, tweet_extended_entities, tweet_full_text, tweet_geo, tweet_in_reply_to_sc...
dbl (17): tweet_favorite_count, tweet_id, tweet_id_str, tweet_in_reply_to_status_id, tweet_in_reply_to_status_id_str, tweet_in_reply_to_user_id, tweet_in_reply_to...
lgl (22): tweet_contributors, tweet_favorited, tweet_is_quote_status, tweet_possibly_sensitive, tweet_retweeted, tweet_truncated, user_contributors_enabled, user_...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
> head(df$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 #post
oftheday #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 #4YourMemeCol
lection \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 Griffin Story  https://t.co/OEbEmWULLF   #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"
> 
```

#Cleaning all special characters in this Twitter text

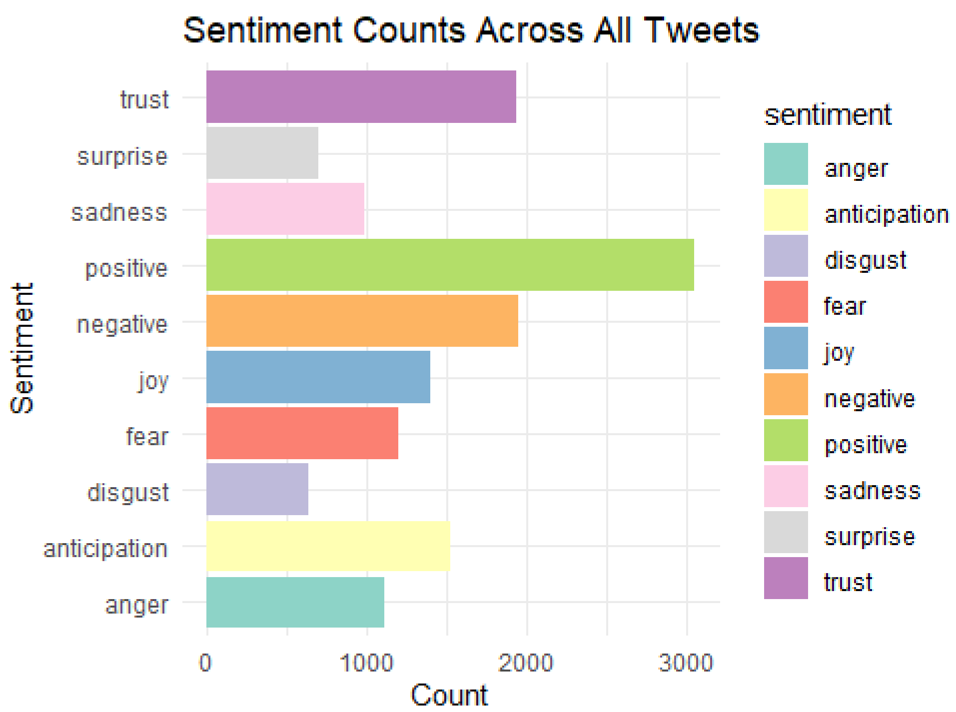
```
> tweets.df2 <- gsub("http.*","",df$tweet_full_text)
> tweets.df2 <- gsub("https.*","",tweets.df2)
> tweets.df2 <- stri_replace_all_regex(tweets.df2, "@\\w+", "")
> tweets.df2 <- stri_replace_all_regex(tweets.df2, "#\\w+", "")
> tweets.df2 <-str_remove_all(tweets.df2,"&amp")
> tweets.df2 <- gsub("!.*","",tweets.df2)
> tweets.df2 <- gsub("\n.*","",tweets.df2)
> 
```

Sentiment Score analysis

```
> word.df <- as.vector(tweets.df2)
> emotion.df <- get_nrc_sentiment(word.df)
> emotion.df2 <- cbind(tweets.df2,emotion.df)
> head(emotion.df2)
                                                                                    tweets.df2 anger anticipation disgust fear joy
1                                                  Done is better than perfect. - Sheryl Sandberg     0            1       0    0   1
2                                                Shout out to the Great Fire Department and the tour     1            0       0    1   0
3 There are some AMAZINGLY hilarious Nike Ad memes happening on my newsfeed.  Soooo, I decided to get a little creative too...     0            0       0    0   2
4                                                                 @ Lucas Bishop's Cigar Lounge     0            0       0    0   0
5                                                      One Hand, One Dream: The Shaquem Griffin Story     0            0       0    0   0
6                               It's time for me to stock up on some new running apparel. Nike it is     0            1       0    0   0
  sadness surprise trust negative positive
1       0        0     1        0        1
2       0        1     0        0        0
3       0        2     0        0        3
4       0        0     0        1        0
5       0        0     0        0        0
6       0        0     0        0        0
>
```

```
> sentiment_totals <- colSums(emotion.df2[, c("sadness", "surprise", "trust", "negative", "positive",
+                                              "anger", "anticipation", "disgust", "fear", "joy")])
> sentiment_df <- data.frame(sentiment = names(sentiment_totals), count = sentiment_totals)
>
> ggplot(sentiment_df, aes(x = sentiment, y = count, fill = sentiment)) +
+   geom_bar(stat = "identity") +
+   theme_minimal() +
+   labs(x = "Sentiment", y = "Count", title = "Sentiment Counts Across All Tweets") +
+   scale_fill_brewer(palette = "Set3") +
+   coord_flip()
>
```

#Now let's plot the graph.



The bar graph provides a sentiment analysis of tweets, with "trust" being the most frequent, indicating a strong confidence in the subject, possibly a brand or campaign. The significant "positive" sentiment shows general approval, which is beneficial for the business image. However, "negative" sentiment has a sizable presence, highlighting areas that may require attention and improvement. Emotions like "joy" and "anticipation" suggest optimistic engagement, while "anger" and "disgust" are less frequent but could point to specific issues needing to be addressed to maintain a positive brand reputation.

#Let's check positive tweets, negative tweets, neutral tweets.

```
> positive.tweets <- word.df[sentiment.value > 0]
> head(positive.tweets)
[1] "Done is better than perfect. - Sheryl Sandberg    "
[2] "Shout out to the Great Fire Department and the tour"
[3] "There are some AMAZINGLY hilarious Nike Ad memes happening on my newsfeed.  Soooo, I decided to get a little creative too... "
[4] "One Hand, One Dream: The Shaquem Griffin Story  "
[5] " It's time for me to stock up on some new running apparel. Nike it is"
[6] "Why won't Trump protect our elections?  Think it over.   Vote -   "
```

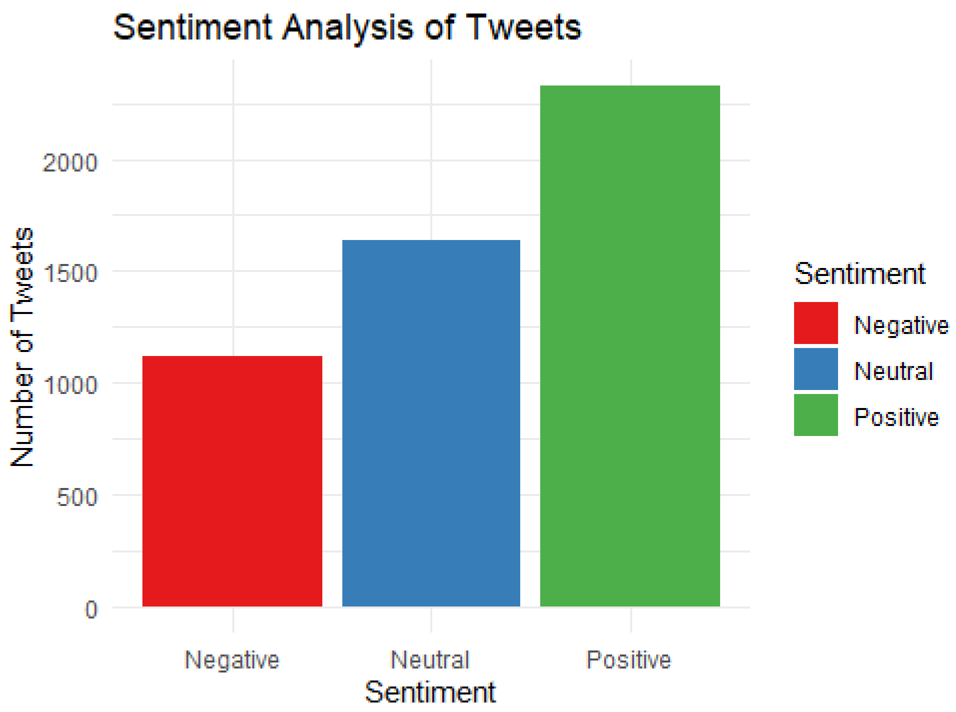
```
> negative.tweets <- word.df[sentiment.value < 0 ]
> head(negative.tweets)
[1] "I've seen a lot of memes re  but this particular one struck me.......haunting. "
[2] "Abortion stops a beating heart. Just imagine all the lives we can save if we get  on the court. Democrats should be eager to confirm him
n. "
[3] "You are never too broke to shop your favourite fashion brands when they are at   "
[4] "YOU STOLE MY GODDAMN HOUSE     "
[5] " is the only shoe I'll train in. I'm wearing the Nike Bruins from Back to the Future for my wedding. Hell yeah Nike. "
[6] "Mr  alone with    meeting to see how they can destroy   "
```

```
> neutral.tweets <-word.df[sentiment.value == 0]
> head(neutral.tweets)
[1] "   @ Lucas Bishop's Cigar Lounge "
[2] " They were thinking history will judge the treatment of  and will come out on his side, they decided to lead"
[3] "My kinda Lady ...   "
[4] "Hey"
[5] "Don't skip leg day y'all     "
[6] "\"Believe in something. Even if it means sacrificing everything.\""
```

#Let's check the total count of positive, negative, and neutral and plot them in a graph.

```
> category_sentiment <- ifelse(sentiment.value < 0, "Negative",
+                              ifelse(sentiment.value > 0,"Positive","Neutral"))
> table(category_sentiment)
category_sentiment
Negative  Neutral Positive
    1123     1640     2326
```

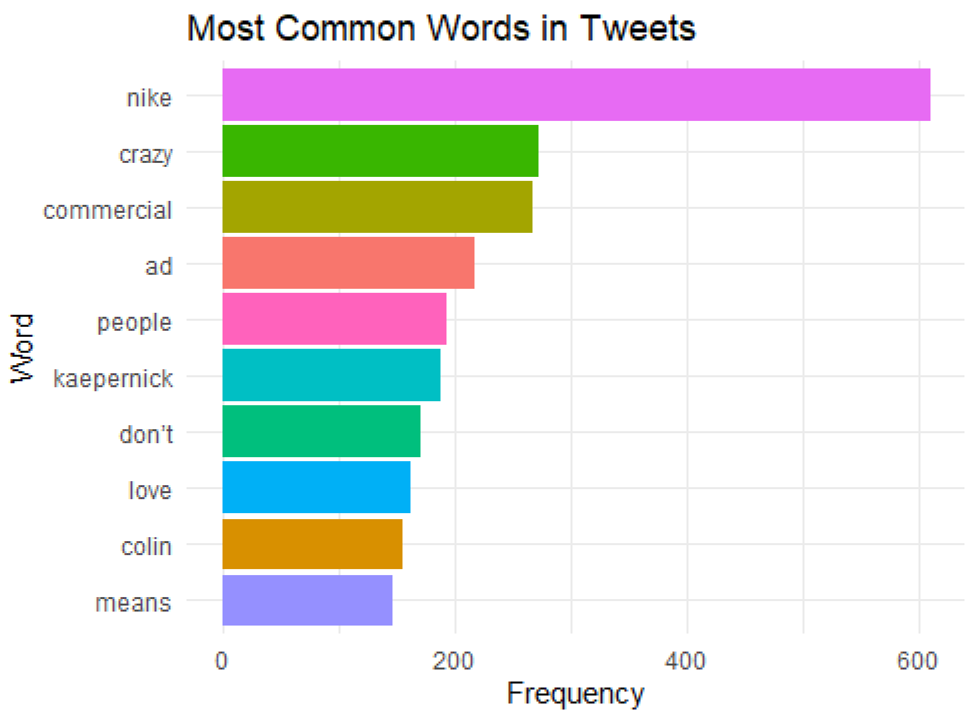
```
> visual_df <- data.frame(
+   Sentiment = c("Negative", "Neutral", "Positive"),
+   Number_of_Tweets = c(1123, 1640, 2326)
+ )
>
>
>
> ggplot(visual_df, aes(x = Sentiment, y = Number_of_Tweets, fill = Sentiment)) +
+   geom_bar(stat = "identity") +
+   labs(x = "Sentiment", y = "Number of Tweets", fill = "Sentiment") +
+   theme_minimal() +
+   scale_fill_brewer(palette = "Set1") +
+   ggtitle("Sentiment Analysis of Tweets")
```



The graph shows a higher number of positive tweets compared to negative ones, indicating a favorable overall sentiment. To convert negative tweets to positive, focus on the concerns behind negative sentiments and address them directly through customer service outreach. Engage with neutral tweeters to sway them positively by highlighting brand values, improvements, and positive stories. Implement feedback from negative tweets into tangible changes and communicate these effectively, turning critics into advocates. Leveraging positive customer testimonials and engaging influencers to share constructive narratives can also shift the sentiment balance further towards the positive.

#Now let's take a look at the most common words used in tweets and trun them into graph representation.

```
>
> tweets_words <- tweets %>%
+   unnest_tokens(word, text)
>
> data(stop_words)
> tweets_words <- tweets_words %>%
+   anti_join(stop_words)
Joining with `by = join_by(word)`
>
> word_counts <- tweets_words %>%
+   count(word, sort = TRUE)
>
> top_n <- 10
> word_counts_top_n <- head(word_counts, top_n)
>
> ggplot(word_counts_top_n, aes(x = reorder(word, n), y = n, fill = word)) +
+   geom_col(show.legend = FALSE) +
+   labs(x = "Word", y = "Frequency") +
+   coord_flip() +
+   theme_minimal() +
+   ggtitle("Most Common Words in Tweets")
> |
```



The graph highlights "Nike" as the most frequently mentioned word in tweets, indicating strong brand visibility. The presence of words like "crazy," "commercial," "ad," and "Kaepernick" suggests discussions are centered around a specific advertising campaign, likely polarizing given the context of "love" and "don't" in the mix. For business strategy, the insights could direct Nike to capitalize on this high engagement, possibly using "crazy" in a positive narrative spin. Emphasizing "love" and clarifying "means" may mitigate negative connotations. Engaging directly with the community on these key terms could further refine brand messaging and customer perception.

**Note: I have included my own case study on Nike's haste, in which I identified the most significant terms in tweets that are indirectly related to sales.

Dataset 2

Now let's look at the second Twitter dataset which we extracted from Apify.com and check sentimental analysis.

In this, the code is the same, but I will explain it accordingly to the analysis.

#Reading csv file to R.

```
> df <- read_csv("nike_tweet_scrapping_data_2020-2021.csv")
Rows: 219 Columns: 26
— Column specification ————————————————————————————————————————————————————————————
Delimiter: ","
chr (10): author/description, author/entities/url/urls/0/display_url, author/location, author/name, author/type, author/url, author/userName, entities/user_menti...
dbl  (7): author/favouritesCount, author/following, author/id, author/mediaCount, author/statusesCount, likeCount, replyCount
lgl  (9): author/canDm, author/canMediaTag, author/hasCustomTimelines, author/isTranslator, author/isVerified, isConversationControlled, isQuote, isReply, isRetweet

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
> head(df)
# A tibble: 6 x 26
  `author/canDm` `author/canMediaTag` `author/description`       author/entities/url/…¹ author/favouritesCou…² `author/following` author/hasCustomTime…³ `author/id`
  <lgl>          <lgl>                <chr>                      <chr>                                   <dbl>              <dbl> <lgl>                        <dbl>
1 FALSE          TRUE                 Spotlighting athlete* and … nike.com                                 7060                120 TRUE                     415859364
2 FALSE          TRUE                 Spotlighting athlete* and … nike.com                                 7060                120 TRUE                     415859364
3 FALSE          TRUE                 Spotlighting athlete* and … nike.com                                 7060                120 TRUE                     415859364
4 FALSE          TRUE                 Spotlighting athlete* and … nike.com                                 7060                120 TRUE                     415859364
5 FALSE          TRUE                 Spotlighting athlete* and … nike.com                                 7060                120 TRUE                     415859364
6 FALSE          TRUE                 Spotlighting athlete* and … nike.com                                 7060                120 TRUE                     415859364
# i abbreviated names: ¹`author/entities/url/urls/0/display_url`, ²`author/favouritesCount`, ³`author/hasCustomTimelines`
# i 18 more variables: `author/isTranslator` <lgl>, `author/isVerified` <lgl>, `author/location` <chr>, `author/mediaCount` <dbl>, `author/name` <chr>,
#   `author/statusesCount` <dbl>, `author/type` <chr>, `author/url` <chr>, `author/userName` <chr>, `entities/user_mentions/0/name` <chr>,
#   `entities/user_mentions/0/screen_name` <chr>, isConversationControlled <lgl>, isQuote <lgl>, isReply <lgl>, isRetweet <lgl>, likeCount <dbl>, replyCount <dbl>,
#   text <chr>
```

```
> colnames(df)
 [1] "author/canDm"                          "author/canMediaTag"                   "author/description"
 [4] "author/entities/url/urls/0/display_url" "author/favouritesCount"               "author/following"
 [7] "author/hasCustomTimelines"             "author/id"                            "author/isTranslator"
[10] "author/isVerified"                     "author/location"                      "author/mediaCount"
[13] "author/name"                           "author/statusesCount"                 "author/type"
[16] "author/url"                            "author/userName"                      "entities/user_mentions/0/name"
[19] "entities/user_mentions/0/screen_name"  "isConversationControlled"             "isQuote"
[22] "isReply"                               "isRetweet"                            "likeCount"
[25] "replyCount"                            "text"
>
> head(df$text)
[1] "Airphoria is back with a new experience in @fortnitegame. Enter the Dn Dimension on March 26   https://t.co/BwSVYjaegX"
[2] "RT @nikebasketball: It takes a once-in-a-generation player to break a record that's stood for generations.\n\nCongratulations to @caitlinclar…"
[3] "RT @nikebasketball: Numbers don't lie. \n\nYet again, @kingjames has rewritten the equation for greatness: 40k points, 10k assists, 10k rebou…"
[4] "RT @nikebasketball: Breaking records, breaking new ground. \n\n@CaitlinClark22 shatters the All-Time Women's NCAA Scoring Record and makes it…"
[5] "Champions always find a way.\n#justdoit https://t.co/qjKVxIg5Je"
[6] "RT @nikebasketball: Welcome to the World of Book \n\nAvailable on SNKRS and at select retailers February 17. https://t.co/PBalp0GAJI"
>
```

Cleaning the data

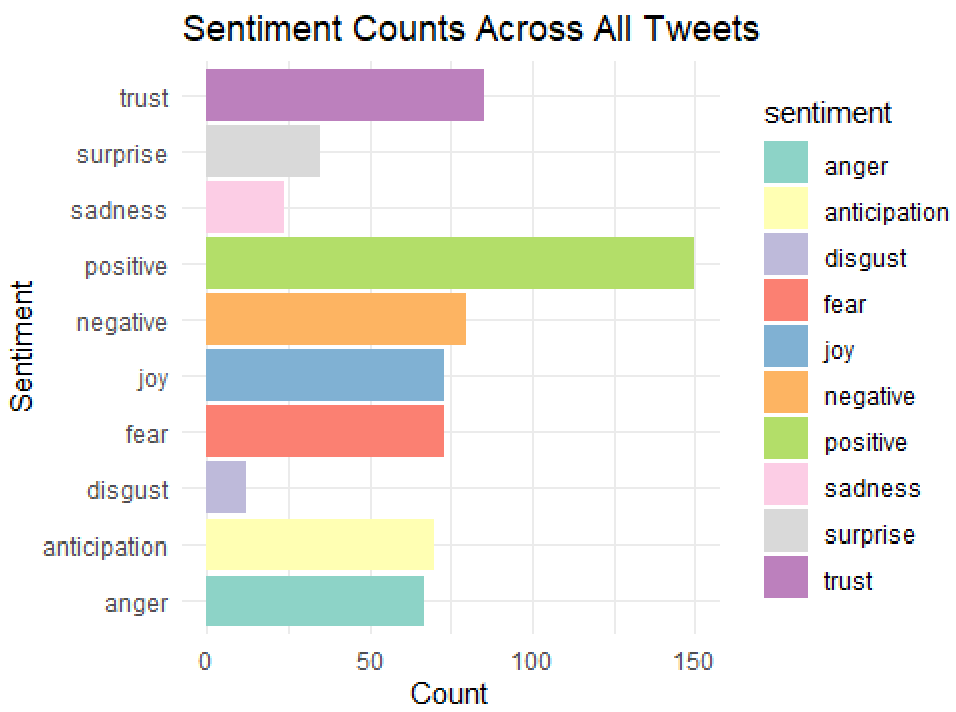
```
>
> tweets.df2 <- gsub("http.*","",df$text)
> tweets.df2 <- gsub("https.*","",tweets.df2)
> tweets.df2 <- stri_replace_all_regex(tweets.df2, "@\\w+", "")
> tweets.df2 <- stri_replace_all_regex(tweets.df2, "#\\w+", "")
> tweets.df2 <-str_remove_all(tweets.df2,"&amp")
> tweets.df2 <- gsub("!.*","",tweets.df2)
> tweets.df2 <- gsub("\n.*","",tweets.df2)
>
> print(head(tweets.df2))
[1] "Airphoria is back with a new experience in . Enter the Dn Dimension on March 26    "
[2] "RT : It takes a once-in-a-generation player to break a record that's stood for generations."
[3] "RT : Numbers don't lie.  "
[4] "RT : Breaking records, breaking new ground.  "
[5] "Champions always find a way."
[6] "RT : Welcome to the World of Book "
>
>
```

Sentiment Score analysis

```
> word.df <- as.vector(tweets.df2)
> emotion.df <- get_nrc_sentiment(word.df)
> emotion.df2 <- cbind(tweets.df2,emotion.df)
> head(emotion.df2)
                                                                          tweets.df2 anger anticipation disgust fear joy sadness surprise trust negative
1        Airphoria is back with a new experience in . Enter the Dn Dimension on March 26     0            0       0    0   0       0        0     0        0
2 RT : It takes a once-in-a-generation player to break a record that's stood for generations.     0            0       0    0   0       0        1     0        1
3                                                            RT : Numbers don't lie.     1            0       1    0   0       1        0     1        1
4                                            RT : Breaking records, breaking new ground.     0            0       0    0   0       0        0     1        0
5                                                       Champions always find a way.     0            0       0    0   0       0        0     0        0
6                                                         RT : Welcome to the World of Book     0            0       0    0   0       0        0     0        0
  positive
1        1
2        0
3        2
4        0
5        0
6        0
>
```

#Plotting the graph

```
> sentiment_totals <- colSums(emotion.df2[, c("sadness", "surprise", "trust", "negative", "positive",
+                                            "anger", "anticipation", "disgust", "fear", "joy")])
>
> sentiment_df <- data.frame(sentiment = names(sentiment_totals), count = sentiment_totals)
>
> ggplot(sentiment_df, aes(x = sentiment, y = count, fill = sentiment)) +
+   geom_bar(stat = "identity") +
+   theme_minimal() +
+   labs(x = "Sentiment", y = "Count", title = "Sentiment Counts Across All Tweets") +
+   scale_fill_brewer(palette = "Set3") +
+   coord_flip()
~
```



The graph shows sentiment distribution from tweets with "trust" as the most frequently occurring sentiment, a positive indicator of brand reliability and customer loyalty. "Positive" sentiment is also strong, suggesting good public reception. However, "negative" sentiment, while less frequent, still represents a significant portion that requires attention to maintain brand integrity. Other emotions like "joy" and "anticipation" are present but to a lesser extent. For a business, these insights suggest the need to reinforce trust-building measures, capitalize on positive perceptions, and address the underlying causes of negative sentiments to improve overall brand sentiment and customer engagement.

#Let's check positive tweets, negative tweets, neutral tweets.

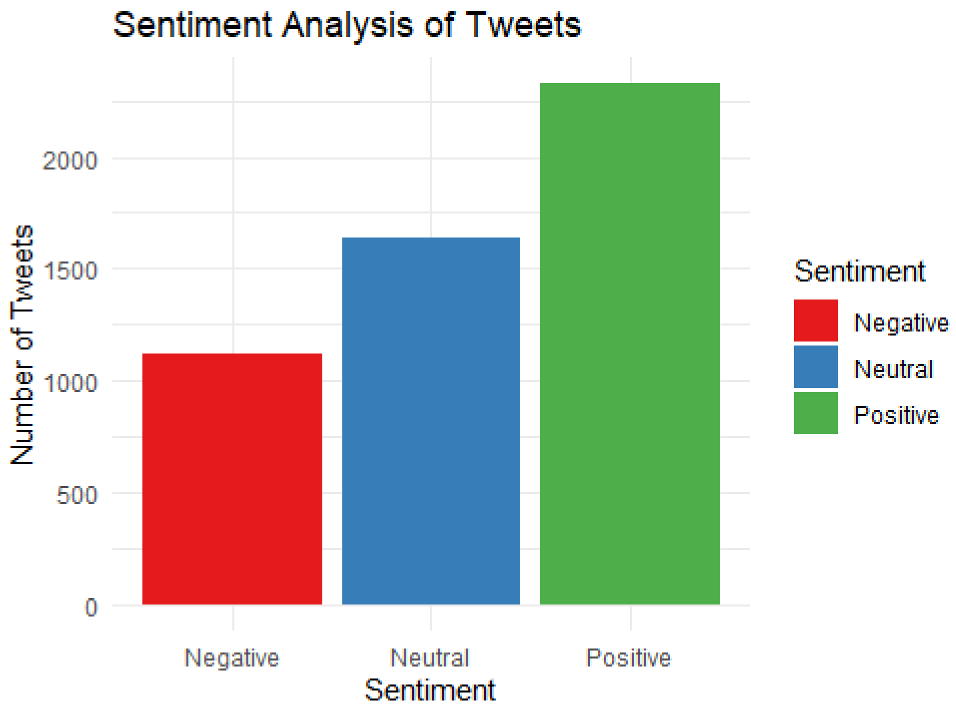
```
>
> positive.tweets <- word.df[sentiment.value > 0]
> head(positive.tweets)
[1] "Airphoria is back with a new experience in . Enter the Dn Dimension on March 26   "
[2] "RT : It takes a once-in-a-generation player to break a record that's stood for generations."
[3] "RT : Breaking records, breaking new ground.  "
[4] "RT : Welcome to the World of Book "
[5] "Victory belongs to the most persevering "
[6] "Grand Slam secured  "
```

```
> negative.tweets <- word.df[sentiment.value < 0 ]
> neutral.tweets <-word.df[sentiment.value == 0]
> head(neutral.tweets)
[1] "Champions always find a way."                                  "Keep on creating history "
[3] "RT : Count it. That's 1,203 victories for Stanford Coach Tara VanDerveer. " "Check it out here: "
[5] "First run in the Nike Air Zoom Pegasus 36 (Clemson Edition) "              "   Nike Men's Air Zoom Pegasus 36 Running Shoes "
>
```

#Let's check the total count of positive, negative, and neutral and plot them in a graph.

```
> category_Sentiment <- ifelse(sentiment.value < 0, "Negative",
+                              ifelse(sentiment.value > 0,"Positive","Neutral"))
> table(category_Sentiment)
category_Sentiment
Negative  Neutral Positive 
      43       76      100 
> 
```

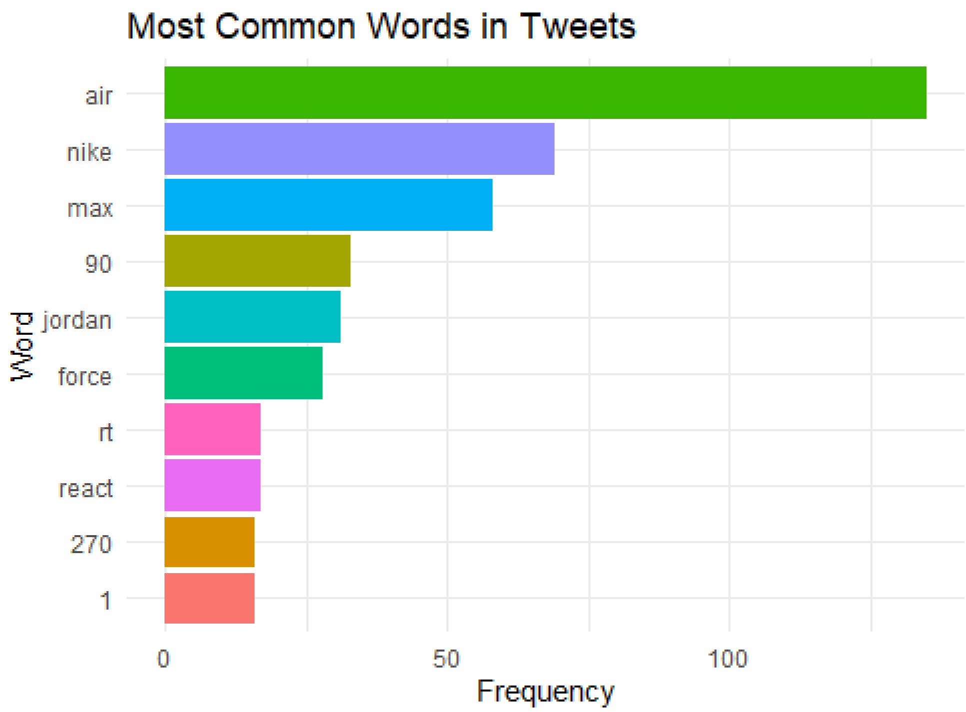
```
> 
> visual_df <- data.frame(
+   Sentiment = c("Negative", "Neutral", "Positive"),
+   Number_of_Tweets = c(1123, 1640, 2326)
+ )
> 
> 
> 
> ggplot(visual_df, aes(x = Sentiment, y = Number_of_Tweets, fill = Sentiment)) +
+   geom_bar(stat = "identity") +
+   labs(x = "Sentiment", y = "Number of Tweets", fill = "Sentiment") +
+   theme_minimal() +
+   scale_fill_brewer(palette = "Set1") +
+   ggtitle("Sentiment Analysis of Tweets")
```



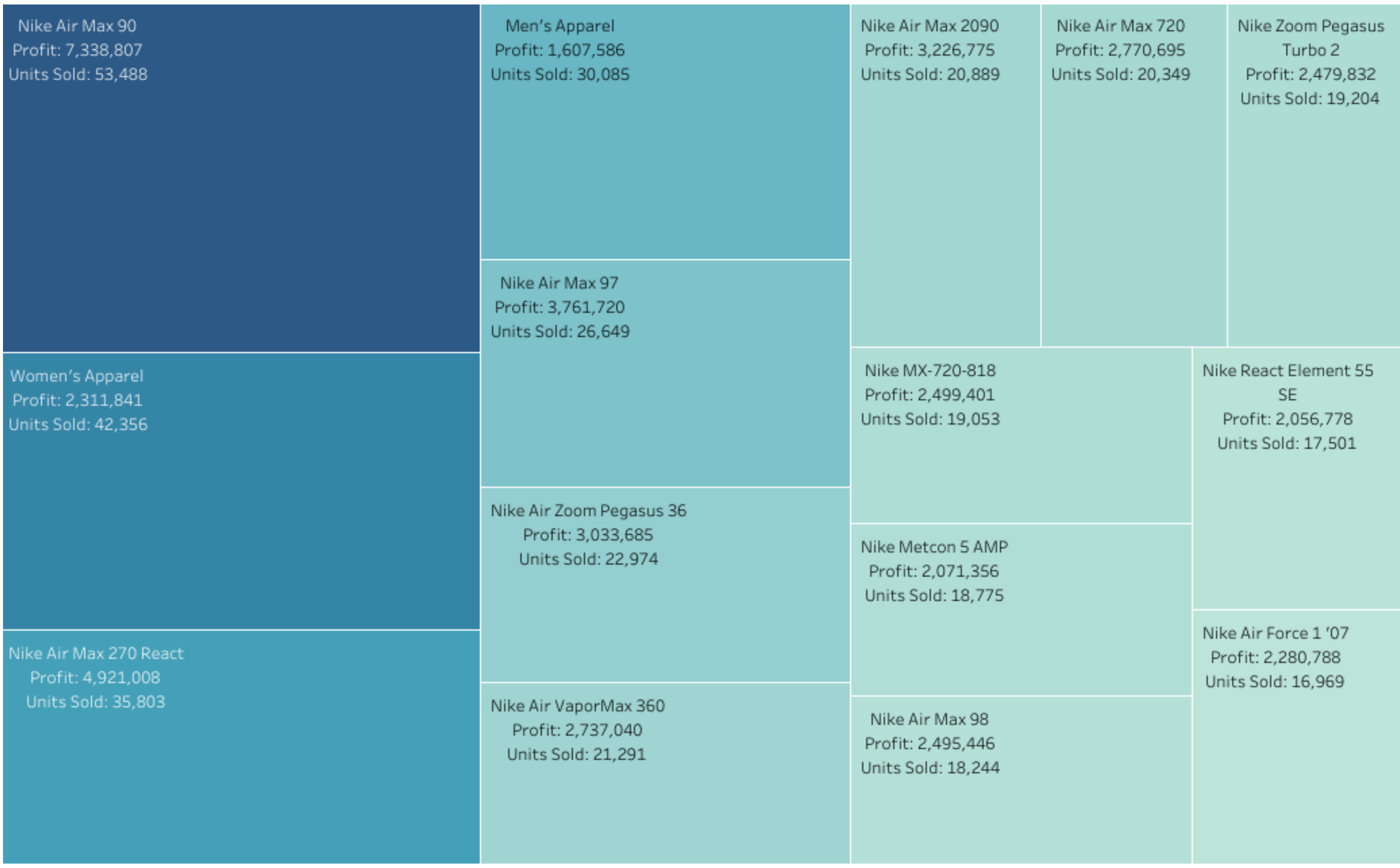
The graph shows more positive tweets than negative ones. Engage with unhappy customers to hear their complaints, provide solutions, and share changes or improvements to turn negative tweets positive. Enhancing consumer experience and displaying good brand stories may turn neutral emotion holders positive. Encourage pleased consumers to share their experiences to boost positivity. Transparency and aggressive customer service are important to turning negative attitudes positive.

#Now let's take a look at the most common words used in tweets and turn them into graph representation.

```
>
> tweets <- data.frame(text = tweets.df2)
>
> tweets_words <- tweets %>%
+   unnest_tokens(word, text)
>
> data(stop_words)
> tweets_words <- tweets_words %>%
+   anti_join(stop_words)
Joining with `by = join_by(word)`
>
> word_counts <- tweets_words %>%
+   count(word, sort = TRUE)
>
> top_n <- 10
> word_counts_top_n <- head(word_counts, top_n)
>
> ggplot(word_counts_top_n, aes(x = reorder(word, n), y = n, fill = word)) +
+   geom_col(show.legend = FALSE) +
+   labs(x = "Word", y = "Frequency") +
+   coord_flip() +
+   theme_minimal() +
+   ggtitle("Most Common Words in Tweets")
> |
```



This treemap depicts the show with the most sales during the years 2020-2021.



The first graph depicts the most common words in tweets, with "air" and "Nike" being highly frequent, indicating discussions likely revolve around Nike Air footwear. When correlated with the second image displaying sales data, we can infer that models like "Air Max 90" and "Air Max 270 React" are generating substantial conversation and sales. This suggests that these models are currently popular and resonate with the market. Business strategy should capitalize on this trend, focusing marketing efforts on these lines, and possibly exploring cross-promotional opportunities or limited-edition releases to further drive sales. Furthermore, incorporating these popular terms into digital marketing campaigns can amplify reach and engagement, as they reflect existing consumer interest and discussions.

As we examine the relationship between tweets and sales, let's also examine the sales mode.

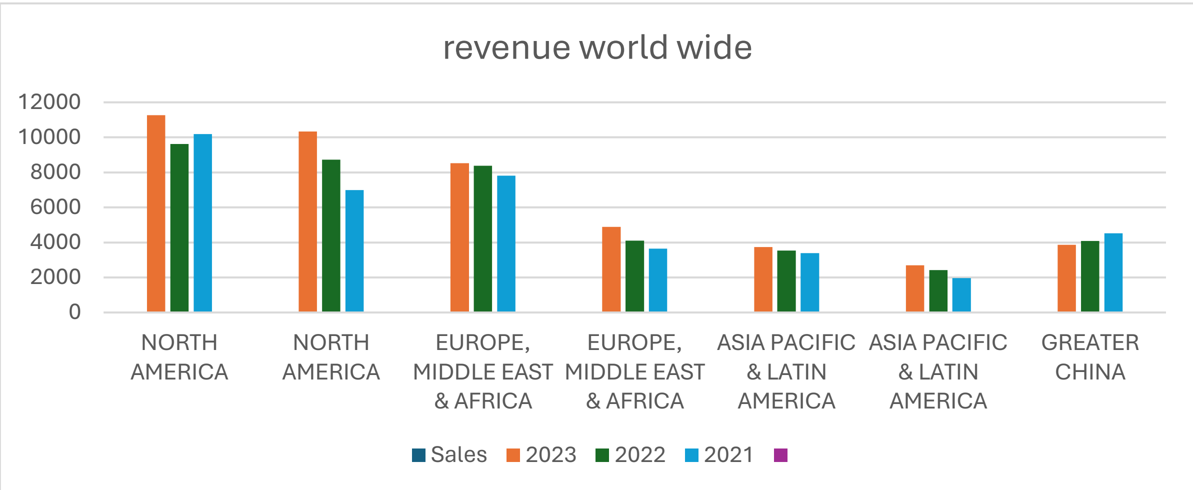
ASIA PACIFIC & LATIN AMERICA	NIKE Direct	2,695	2,426	1,956
	Wholesale	3,736	3,529	3,387
EUROPE, MIDDLE EAST & AFRICA	NIKE Direct	4,896	4,102	3,644
	Wholesale	8,522	8,377	7,812
GREATER CHINA	NIKE Direct	3,382	3,466	3,777
	Wholesale	3,866	4,081	4,513
NORTH AMERICA	NIKE Direct	10,335	8,732	6,993
	Wholesale	11,273	9,621	10,186

NIKE Direct
NIKE Direct
Wholesale
Wholesale

To shift from wholesale to Nike Direct in regions like Latin America, Nike could intensify its direct-to-consumer engagement through localized digital marketing and e-commerce optimization. Strengthening the online retail infrastructure, offering market-specific promotions, and enhancing Nike's mobile shopping experience could attract consumers to Nike Direct. Additionally, exclusive online product releases and personalized customer service could incentivize a direct purchasing preference over wholesale channels.

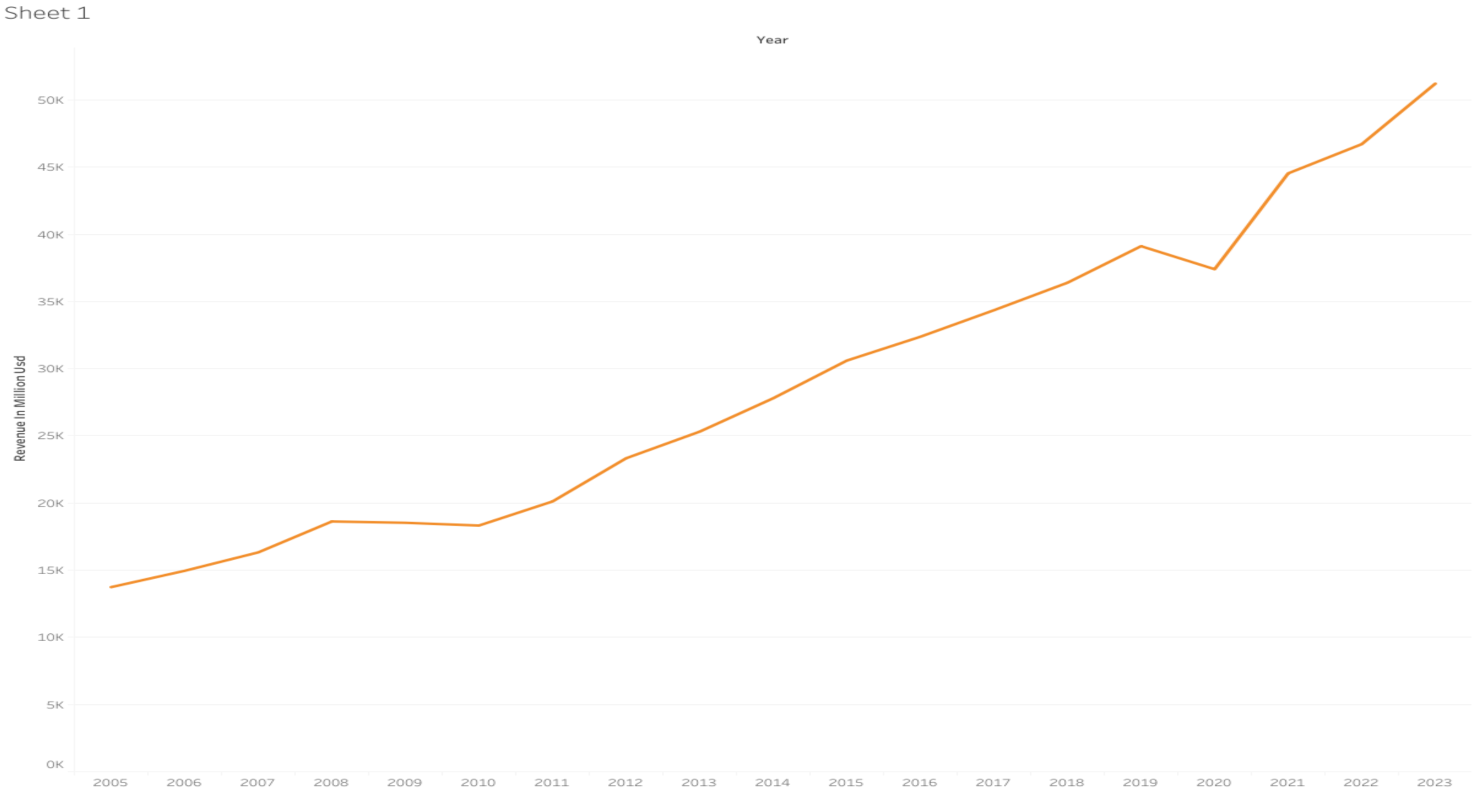
Note: (I was only able to find this data through Statista for this year so I included it has well.)

Now let's check sales revenue from worldwide from 2021-2023.



The bar graph indicates that North America is a strong revenue driver for Nike, maintaining solid sales performance over three years. While sales in Europe, the Middle East, and Africa show a slight decline, the Asia Pacific & Latin America region presents a growth opportunity as indicated by the upward trend. Greater China's market shows resilience with a recovery in the latest year. Strategic focus should continue in North America while exploring growth drivers in Asia Pacific & Latin America, and addressing the causes of decline in Europe, the Middle East & Africa to bolster overall global revenue.

Nike revenue overall from 2005-2023



Conclusion

The study reveals that despite initial challenges, possibly due to global economic disruptions like the COVID-19 pandemic, the business has shown resilience and an upward trajectory in sales. The positive response post-2021 suggests successful strategic adjustments and recovery in consumer spending.

To further improve sales, the business should:

1. Amplify marketing and sales initiatives in North America, the strongest region in terms of sales, to maximize revenue from this already strong base.
2. There's an evident trend towards successful direct sales channels. Enhancing digital platforms, offering personalized shopping experiences, and exclusive online products could convert more wholesale buyers to direct purchasers.
3. The sales fluctuations across different regions indicate the need for region-specific strategies. For example, addressing the dip in Latin America with targeted promotions or by resolving any distribution issues.
4. Analyzing social media sentiment and word frequency indicates particular product lines resonate with the audience. Prioritize these in advertising and stock to capitalize on current trends.
5. To foster brand loyalty and promote word-of-mouth recommendations, interact with customers on social media by responding to criticism and reiterating favorable opinions.
6. The favorable attitude toward innovation in social media conversations may suggest that you should innovate by introducing new items and technology that cater to changing customer requirements.

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Github Link: https://github.com/nishchal69