Driving Tesla’s Website Traffic Visits from Twitter

MSBA-324

Web and Social Analytics

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Agenda

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- **Problem Statement** - All Members
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Situation

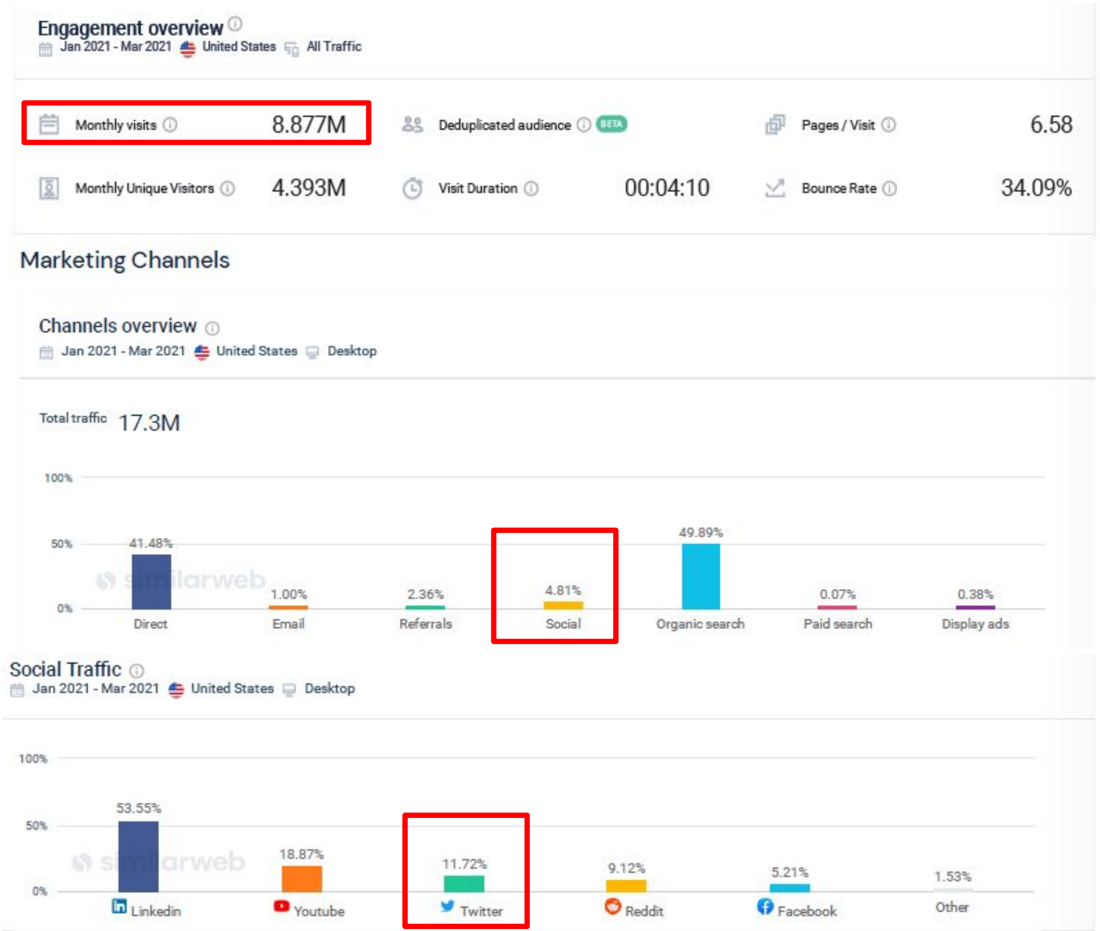
- Tesla sold 936K EV in 2021, #1 in world [5].
- Website sales are most effective Tesla selling strategy [3]
- Tesla is limited to online sales in most US states due to regulations on franchise dealerships [3]
- Global EV market expected to grow from $287B in 2021 to $1.3T in 2028 [4] .
- Analysts believe Tesla's EV market share could fall from 70% to 20% as new and legacy automakers EV production ramps up [4].
- Tesla must enact a long term strategy to withstand competition

Situation

Tesla.com averages **9M total visits** per month, with only **4.81%** via social media i.e. **432,000** monthly visitors via social media

Social media distribution, with only **11.72%** from Twitter i.e. **50,630** visitors via Twitter [1].

Tesla recently altered marketing strategy to close retail stores, increase online sales focus [2].



Problem Statement

- **Objective:** Grow traffic on Tesla.com, using Twitter social media page. We employ the data from Twitter to analyze how a tech giant, a global icon can influence the emotions of the millions connected, and in turn how these emotions play a role in the increase or decrease of daily website visitors. We will also examine impact of potential other explanatory variables driving traffic to Tesla.com from Twitter.
- **Metric to track objective:** The variable "Visitor", representing the factor which bring visitors to Tesla.com, will be used as the dependent variable.
- **Success criteria:** Project successful we can show how to increase "Visitors" from Twitter to Tesla.com by 10% or more, i.e. Increase from 50,630 to **55,693 monthly visitors or 1,856 average daily visitors** to tesla.com from Twitter.

Model Selection

- **Twitter Sentiment Model:** We will use sentiment analysis to extract tweets related to #tesla and analyse them to measure how positive or negative the tweets are by using “Average daily sentiment score”.
- **Reason for Selecting the Model:**
    - Sentiment Analysis model is the best possible model which helps in gauging the emotions and perspective of people towards a certain brand.
    - The “Average daily sentiment score” obtained from this analysis will be used to analyze if it has any impact on the daily website traffic.

Model Selection

- **Regression Model:** To test the relationship between “Average daily sentiment score” and other potential explanatory variables driving traffic to Tesla.com from Twitter. The explanatory variables will be perceived as statistically valid if they explain behavior at the 95% confidence level.
- **Reason for Selecting the Model:**
    - It will help us identify the most **strongly correlated potential variables** that will have influence over website visitors.
    - This will help concentrate our efforts on areas that will increase “Visitors” from twitter to Tesla.com.
    - Since, Tesla.com is the most relevant resource for sales and revenue for tesla, therefore it is important to focus on maximizing the daily visitors to tesla.com.
    - With social media playing an important role in influencing the consumer behaviour, it is important to use this platform to drive traffic to the website.

Solution Process

Steps 1: Perform Sentiment Analysis to extract “average daily sentiment score” regarding #Tesla.

Step 2: Extract Tesla’s average daily web traffic data from visitor detective.com and load into R.

Step 3: Conduct correlation and regression analysis between average daily web traffic and average daily sentiments. Calculate the p-value and check the confidence at 95% for all the variables. Interpret the model results.

Step 4: Compare Tesla situation

Step 5: Provide conclusion and recommendations for Tesla, based on the analysis

Research

- **Primary Research:** The "Average daily sentiment score" data was extracted using Sentiment analysis. Extracting direct audience tweets with #tesla from twitter.
- **Secondary Research:** The other variables data was extracted from the following sources:
  - **Visitor** – Visitor detective. Com, which is an advanced website traffic estimator that offers an accurate report about the number of visitors to a website.[11]
  - **Engagement** – socialtracker.io, which tracks the social media performance of various Brands. [10]
  - **Mentions –** strike.market.com [8]
  - **Retweets -** socialtracker.io [10]
  - **Followers -** socialtracker.io [10]

Software

Collect tweets for #tesla

```
> data <- search_tweets("#tesla", n=20000, include_rts = FALSE)
```

Clean tweets

```
> tweet.Data = data %>% select(screen_name, text, created_at)
> #removing elements
> tweet.Data$stripped_text1 <- gsub("http.*","",tweet.Data$text)
> tweet.Data$stripped_text1 <- gsub("https.*","",tweet.Data$stripped_text1)
> tweet.Data$stripped_text1 <- gsub("#.*","",tweet.Data$stripped_text1)
> tweet.Data$stripped_text1 <- gsub("@.*","",tweet.Data$stripped_text1)
>
> #convert to lowercase
> #remove punctuation, and id for each tweet
> tweet.Data_stem <- tweet.Data %>%
+   select(stripped_text1) %>%
+   unnest_tokens(word, stripped_text1)
> #remove blank cleaned tweets
>  tweet.DataClean = tweet.Data[!(is.na(tweet.Data$stripped_text1) | tweet.Data$stripped_text1==""),]
```

Software

Remove stop words from tweets

from CRAN: install.packages("stopwords")

```
> #remove stopwords words from words list
> cleaned_tweets.Data <- tweet.Data_stem %>%
+   anti_join(stop_words)
```

Get sentiment score for each tweet

```
> tweet.DataClean$sentiment = get_sentiment(tweet.DataClean$stripped_text1)
```

Calculate a daily average tweet sentiment

```
> #group by date and average daily sentiment
> tweet.Summary = aggregate(x = tweet.DataClean$sentiment,
+             by = list(tweet.DataClean$created_at),
+             FUN = mean)
```

Software

Manually adding daily website traffic, engagement, mentions, retweets, and followers to create a final data frame and loading into R.

Summary function is used to show the descriptive statistics of the data. It summarizes the results of various function like mean, median, min, and max.

```
> setwd("F:/DELLPC/Desktop/GGU WORK/MSBA 324/Final Project")
> tesla = read.csv("MSBA 324 - Final Project Data.csv", header=T)
> names(tesla)
[1] "Date"         "Sentiment"  "Engagement" "Mentions"   "retweets"
[6] "Followers"   "Visitors"
> summary(tesla)
     Date             Sentiment         Engagement         Mentions
 Length:14          Min.   :0.1775   Min.   :0.2000   Min.   : 2600
 Class :character   1st Qu.:0.2621   1st Qu.:0.2100   1st Qu.: 4595
 Mode  :character   Median :0.2942   Median :0.2150   Median : 5610
                    Mean   :0.2896   Mean   :0.2193   Mean   : 5893
                    3rd Qu.:0.3164   3rd Qu.:0.2300   3rd Qu.: 6478
                    Max.   :0.3932   Max.   :0.2400   Max.   :11350
    retweets        Followers          Visitors
 Min.   :2360   Min.   : 3998   Min.   :314197
 1st Qu.:2478   1st Qu.:10322   1st Qu.:328801
 Median :2920   Median :12013   Median :341102
 Mean   :2752   Mean   :13418   Mean   :344645
 3rd Qu.:2985   3rd Qu.:13789   3rd Qu.:362457
 Max.   :3030   Max.   :37087   Max.   :388489
```

Model Results

Correlation 1: Sentiment and visitors from the same day

```
> cor(corr_df)
          Sentiment  Visitors
Sentiment 1.0000000 0.0912898
Visitors  0.0912898 1.0000000
```

Correlation 2: Correlation for a day offset (Visitors from the previous days sentiment)

```
> cor(offset_corr_df)
          Sentiment  Visitors
Sentiment 1.0000000 0.3040731
Visitors  0.3040731 1.0000000
```

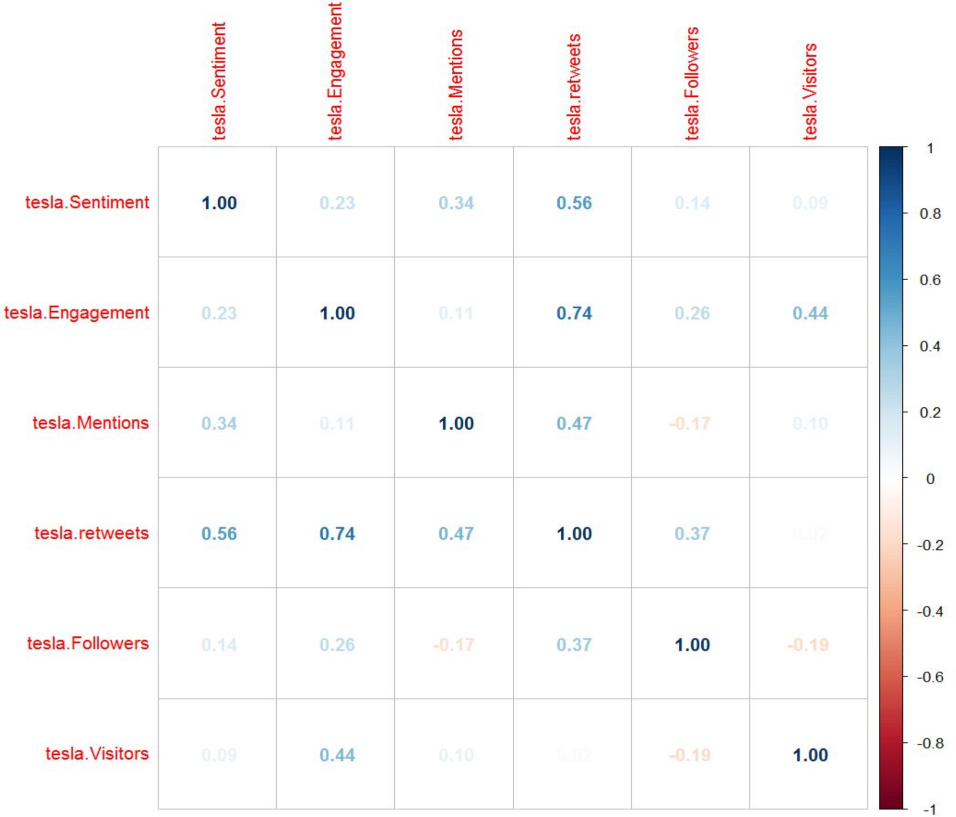
Model Results - cont.

Correlation 3:

Visitor ~ Sentiment + Engagement + retweet + Mention + Followers

The correlation chart shows the level of correlation between each variable. We can see the Engagement has a strong correlation with the visitors.

```
> data = cor(df)
> corrplot(data)
```



Model Results - cont.

Comparison between three Correlation Results

Comparing the values from the table, we found that “Visitors” has the highest correlation with the “Engagement” variable.

Correlation	Correlation coefficient
Sentiment and visitors from the same day	0.09
Correlation for a day offset (Visitors from the previous days sentiment)	0.30
Visitor ~ Sentiment + Engagement + retweet + Mention + Followers	0.44 (Engagement)

Model Results - cont.

Model 1: Visitor ~ Sentiment + Engagement + retweet + Mention + Followers

```
> model1 = lm(formula = df$tesla.Visitors ~  ., data = df)
> summary(model1)

Call:
lm(formula = df$tesla.Visitors ~ ., data = df)

Residuals:
   Min     1Q Median     3Q    Max 
-36033  -4930   1574   7221  17855 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)   
(Intercept)      1.557e+05  7.269e+04   2.141  0.06464 . 
tesla.Sentiment  2.041e+05  1.276e+05   1.600  0.14825   
tesla.Engagement 2.095e+06  5.633e+05   3.720  0.00587 **
tesla.Mentions   4.461e+00  2.687e+00   1.660  0.13543   
tesla.retweets  -1.296e+02  4.523e+01  -2.865  0.02098 * 
tesla.Followers  5.813e-02  7.971e-01   0.073  0.94365   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 17750 on 8 degrees of freedom
Multiple R-squared:  0.6531,	Adjusted R-squared:  0.4362 
F-statistic: 3.012 on 5 and 8 DF,  p-value: 0.08046
```

Highly Significant Variables

Model Results - cont.

Model 2: **Visitors ~ Sentiment (Previous Day Sentiment)**

```
> model2<-lm(Visitors~Sentiment)
> summary(model2)

Call:
lm(formula = Visitors ~ Sentiment)

Residuals:
   Min     1Q Median     3Q    Max 
-35886 -13990   1140  24686  33282 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   303437      40055   7.576 1.09e-05 ***
Sentiment     145362     137312   1.059    0.312    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 24380 on 11 degrees of freedom
Multiple R-squared:  0.09246,	Adjusted R-squared:  0.009957 
F-statistic: 1.121 on 1 and 11 DF,  p-value: 0.3125
```

Not Significant

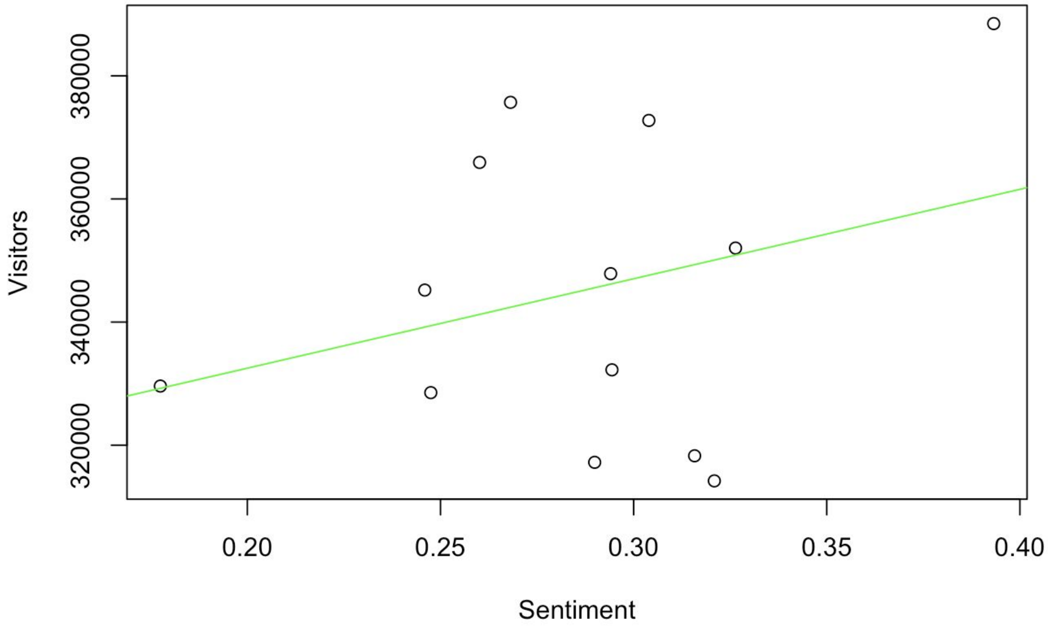
Can use the model to predict users from the previous days sentiment

```
> #predict visitors based on a sentiment value
> predict(model2,list(Sentiment=.3))
     1 
347046 
```

Model Results - cont.

Plot Visitors given Sentiment

```
> plot(Sentiment,Visitors)
> abline(lm(Visitors~Sentiment),col='green')
```



Model Results - cont.

Model 3: Visitor ~ Engagement + retweet (taking the variables with lowest p-values from Model 1)

```
> model3 = lm(formula = df$tesla.Visitors ~ df$tesla.Engagement + df$tesla.retweets, data = df)
> summary(model3)

Call:
lm(formula = df$tesla.Visitors ~ df$tesla.Engagement + df$tesla.retweets,
    data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-31229.7 -14482.4   -468.7  13069.3  30514.7

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          192342.8    78612.3   2.447   0.0324 *
df$tesla.Engagement 1446308.2   532771.9   2.715   0.0201 *
df$tesla.retweets       -59.9       30.8  -1.944   0.0779 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 19890 on 11 degrees of freedom
Multiple R-squared:  0.4015,    Adjusted R-squared:  0.2927
F-statistic:  3.69 on 2 and 11 DF,  p-value: 0.0594
```

Highly Significant Variables

Model Results - cont.

Comparison between three Regression Models Results

Comparing the values from the table, we found that the model with “**Engagement** ” and “**retweet**” has the lowest p-value (**0.05)** with the “Visitors” to Tesla.com.

Regression Models	p-value	R-squared Value
Visitor ~ Sentiment + Engagement + retweet + Mention + Followers	0.08	0.65
Visitors ~ Sentiment (Previous Day Sentiment)	0.31	0.092
Visitor ~ Engagement + retweet	0.05	0.40

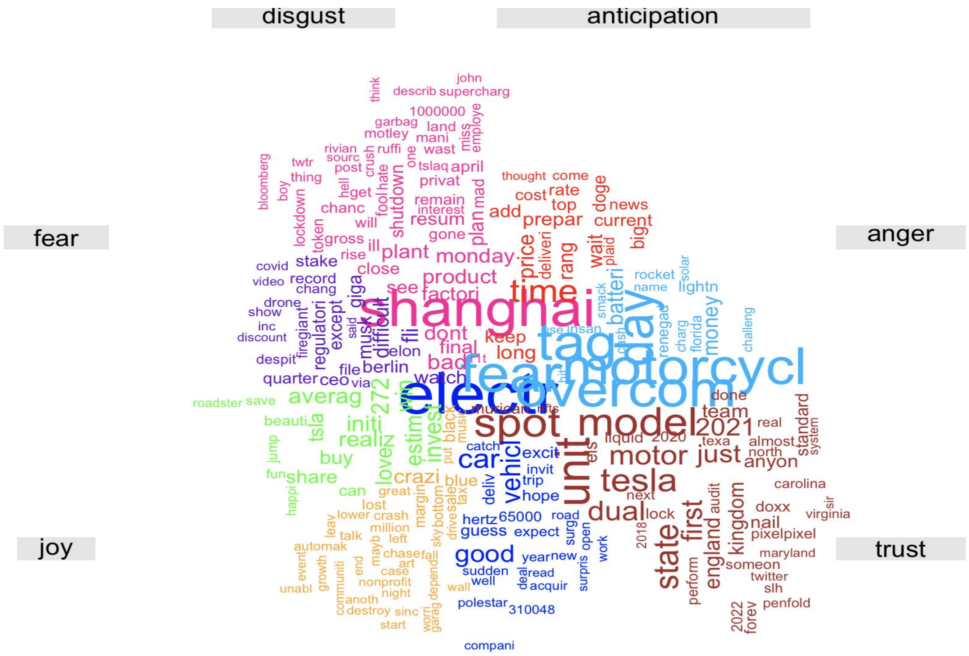
Visualization

Word Cloud Visualization

The word cloud is created to demonstrate the most frequently discussed words by customers related to #tesla on Twitter.

From this word cloud we see the most frequent words like **#Fear, #Overcom, #Motorcycl, #tag, #day, #electr**

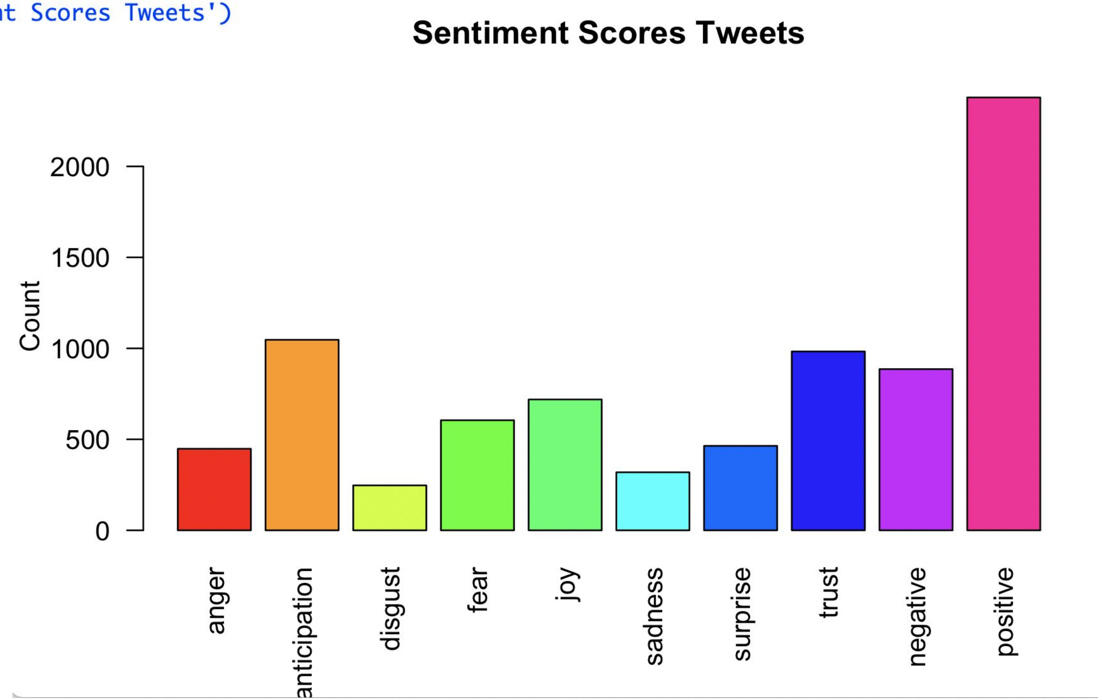
```
> # create document term matrixtdm = TermDocumentMatrix(corpus)
> # convert as matrix
> tdm = as.matrix(tdm)
> tdmnew <- tdm[nchar(rownames(tdm)) < 11,]
> # column name binding
> colnames(tdm) = c('anger', 'anticipation', 'disgust', 'fear', 'joy', 'sadness', 'surprise', 'trust')
> colnames(tdmnew) <- colnames(tdm)
> comparison.cloud(tdmnew, random.order=FALSE,
+                  colors = c("#00B2FF", "red", "#FF0099", "#6600CC", "green", "orange", "blue", "brown"),
+                  title.size=1, max.words=250, scale=c(2.5, 0.4),rot.per=0.4)
```



Visualization - cont.

Sentiment Scores Tweets

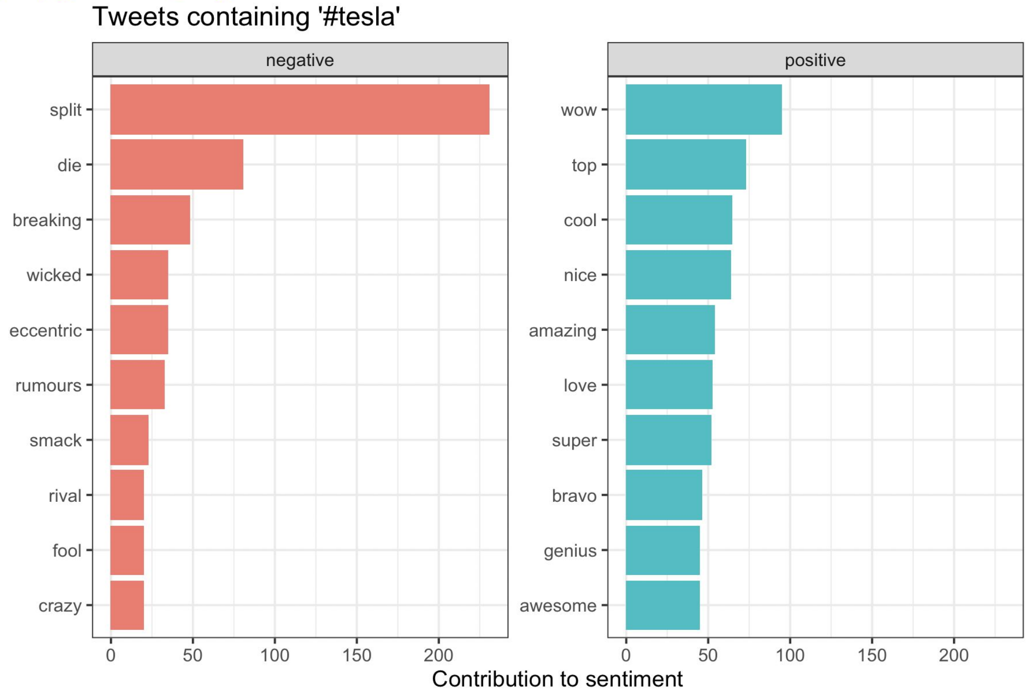
```
> barplot(colSums(s),
+         las = 2,
+         col = rainbow(10),
+         ylab = 'Count',
+         main = 'Sentiment Scores Tweets')
```



Visualization - cont.

Positive & Negative words contribution to sentiment analysis

```
> #positive and negative emotions.bing_data %>% group_by(sentiment) %>% top_n(10) %>% ungroup() %>%
>   mutate(word = reorder(word, n)) %>% ggplot(aes(word, n, fill = sentiment))+
+   geom_col(show.legend = FALSE) + facet_wrap(~sentiment, scales = "free_y") +
+   labs(title = "Tweets containing '#tesla'", y = "Contribution to sentiment",
+        x = NULL) + coord_flip() + theme_bw()
```



Results Interpretation

Sentiment Analysis:

The Tesla sentiment analysis revealed that 28% of Tweets captured in the study were negative in nature, while **72% were generally positive.**

Regression Analysis:

Conducted three correlation analysis of Tesla website's Visitors given Sentiment and other potential explanatory variables

> **Correlation 1:** Correlation between visitors and sentiment within the same day returned correlation coefficient of **0.091**
>
> **Correlation 2:** Correlation for a day offset returned correlation coefficient of **0.304**
>
> **Correlation 3:** Correlation with other explanatory variables like engagement returned correlation coefficient of **0.44.**

Results Interpretation cont.

- In our case, we identify the top 2 explanatory variables (Engagement and retweets), that helps drive "Visitor" from twitter to Tesla.com.

- At a 95% confidence level, our p value should be less than 5% in order to invalidate the null hypothesis.

- Examining the p-values from the Model Results section, we make the following interpretations from:

  Model 1: (Visitor ~ Sentiment + Engagement + retweet + Mention + Followers)

  - **re - tweets:** At a p value of 2%, we satisfy the 5% maximum limit. We can fairly confidently state that retweets is an important driver for Visitors to Tesla.com.

  - engagement: At a p value of 0.5%, we satisfy the 5% maximum limit. We can fairly confidently state that Engagement is an important driver for Visitors to Tesla.com.

Results Interpretation cont.

- We ran a regression analysis, including only the “Sentiment” variables over “Visitors” to Tesla.com.

  Model 2: (Visitor ~ Sentiment) - We can clearly state that sentiments do not impact the website visitors to tesla.com as the p-value is 31.25% which highly violates our 5% maximum limit.

- We will re-run our regression analysis, including only the variables that we determined was relevant, retweets and engagement.

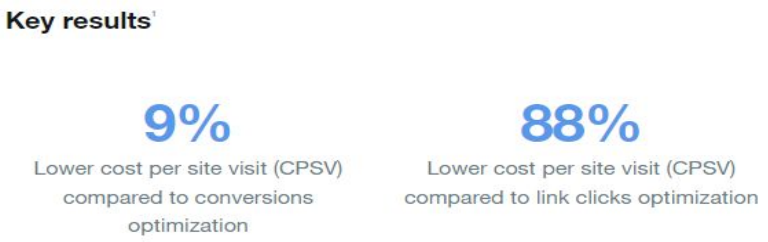
  Model 3: (Visitor ~ Engagement + retweet)

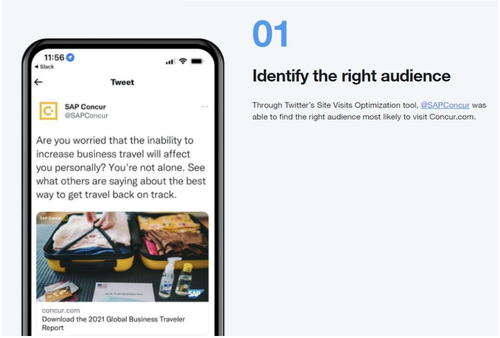
  - **re - tweets:** At a p value of 7%, it slightly violates our 5% maximum limit. That being said, the 7% value is much lower than all of the p values associated with the other variables not on this list.

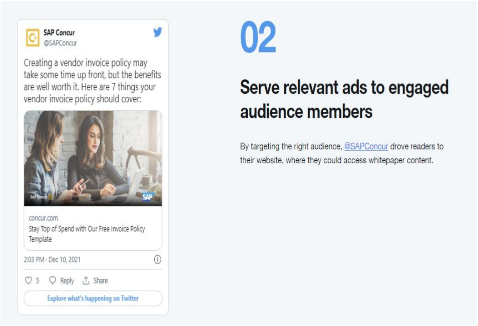
  - **engagement:** At a p value of 2%, we satisfy the 5% maximum limit. We can fairly confidently state that Engagement is an important driver for Visitors to Tesla.com.

Situation Comparison

- SAP Concur used Twitter to drive website traffic.
- Employed Twitter function Site Visits Optimization.
- Identified the target Audience.
- Used analytics to post relevant ads.
- Increased website asset engagement 11% vs conversion objective [7].

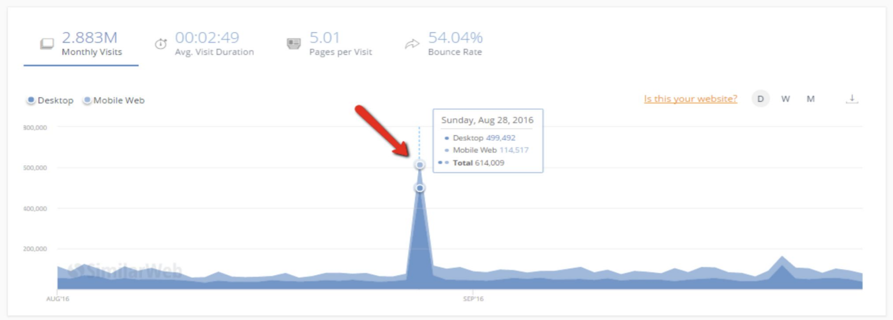




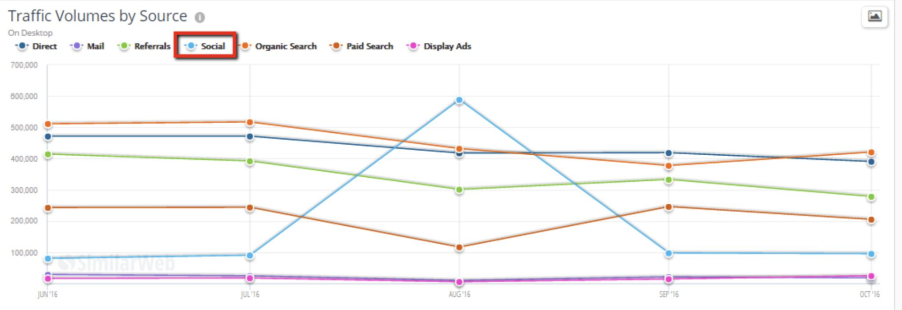


Situation Comparison Cont.

- Website Barneys.com receives 80K visits per day using Reddit Post.
- August 28, 2016 received 600K website visits.
- Traffic volume was traced to social media.
- Traffic volume traced to Reddit post.
- Displays effect of social on web traffic [6].



	Referring Pages 808	Traffic share		Change
1	reddit.com/r/AskReddit/comments/4zxirj/what_are_the_beats_hea... (1!	80.32%		-
2	facebook.com (8)	4.12%		-
3	youtube.com/watch (86)	2.01%		-
4	twitter.com	2.00%		-



Conclusion

- In conclusion, we solved the problem, we can increase the number of Visitors from Twitter to the Tesla.com website of 10% by increasing the engagement rate substantially, from 0.21 to 0.23. By increasing the engagement rate to 0.23 we can increase the number of monthly visitors from **50,630 to 55,693 monthly visitors or 1,856 average daily visitors** to Tesla.com via twitter
- Our findings appear to be consistent with two additional occurrences, one at the SAP Concur and the other at Barneys. The SAP Concur firm used twitter to drive website traffic and experienced a 11% increase in “engagement” to their corporate website. Similarly, the Barneys firm increased its traffic volume of “visits” from 80k to 160k customer visitors per day.

Recommendations

Tesla should examine methods to increase the engagement rate on its twitter page. Specifically, it could execute the following tactics to drive those variables:

- Twitter is made for conversation. Tesla's marketing team should start by asking followers interesting questions, **conduct polls** which will prompt users to respond. This will help drive engagement. For example would be: Cisco UK used Promoted Polls to drive engagement by 4.1% [9]
- **Hashtags** play a crucial part in expanding the reach of tweets. Tweets with 1 or 2 most popular hashtags will help Tesla **drive 2x engagement**
- Tesla should at least **tweet 15-20 times a day**, starting 2:00 am to 10:00 pm for **better engagement**.
- Based on our sentiment analysis many people associate the emotion fear with Tesla. The marketing team should **implement positive sentiment** by posting videos or pictures with their real customer feeling happy and safe while driving Tesla. **Posting Videos** and **pictures** will help drive engagement.
- **Including website link** to the post containing videos and pictures will help drive traffic to Tesla.com.

References

[1] *tesla.com Traffic Analytics & Market Share | Similarweb*. (n.d.). Similarweb. https://www.similarweb.com/website/tesla.com/#social-media

[2] Lambert, F. (2021, July 28). *Tesla (TSLA) launches major shift in retail strategy: cheaper locations, remote working, and more*. Electrek. https://electrek.co/2021/07/28/tesla-tsla-major-shift-retail-strategy-cheaper-locations-remote-working/

[3] *tsla-10k_20201231.htm*. (2021, February 8). Www.sec.gov. https://www.sec.gov/Archives/edgar/data/1318605/000156459021004599/tsla-10k_20201231.htm

[4] Reeth, M. (2020). *Tesla Competitors: 6 Rival Electric Vehicle Stocks*. US News & World Report; U.S. News & World Report. https://money.usnews.com/investing/stock-market-news/slideshows/upstart-tesla-competitors-to-watch

[5] *Tesla Q4 2021 Final EV Delivery Numbers And Outlook*. (n.d.). InsideEVs. https://insideevs.com/news/563407/tesla-2021q4-final-delivery-numbers/

[6] (2022, April 8). *How a Social Media Post Can Increase the Traffic & Sales to your Site*. similarweb. https://support.similarweb.com/hc/en-us/articles/360015026458-How-a-Social-Media-Post-Can-Increase-the-Traffic-Sales-to-your-Site

References

[7] *How the SAP Concur team helped drive efficient website traffic visits from Twitter*. (n.d.). Marketing.twitter.com. Retrieved April 8, 2022, from https://marketing.twitter.com/en/success-stories/how-sap-concur-drove-website-traffic-visits-from-twitter

[8] *Tesla, Inc. – TSLA social media sentiment*. Strike.Market. (n.d.). Retrieved April 8, 2022, from https://strike.market/stocks/TSLA/sentiment

[9] Twitter. (n.d.). *Cisco engages a wide business audience with a phased campaign on Twitter*. Twitter. Retrieved April 13, 2022, from https://marketing.twitter.com/en_gb/success-stories/cisco-engages-a-wide-business-audience-with-a-phased-campaign-on

[10] *Tesla, Inc. – Daily changes data*.SocialTracker. (n.d.). Retrieved April 8, 2022, from https://www.socialtracker.io/twitter/tesla/

[11] *Tesla, Inc. – Daily Website Traffic*.VisitorDetective. (n.d.). Retrieved April 8, 2022, from https://www.visitorsdetective.com/profile/tesla.com/en/