

IDENTIFYING THE BEST TRADING STRATEGY BASED ON SENTIMENT ANALYSIS FOR TATAMOTORS

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1. Objective

To identify the best investment strategy by performing sentiment analysis on the outlook of “Tatamotors Stock” for the following periods:

- Pre- Covid (Q3 2019 Results) – Tatamotors Q3 2019 result date is “30/01/2020”
- Post-Covid (Q1 2020 Results) - Tatamotors Q1 2020 result date is “31/07/2020”

The focus of this project is to identify the efficient algorithm to predict the employees’ intention to exit from an organisation which may be further utilised to create an easy to understand & easy to use “UI (User Interface)” that can populate important KPIs (Key Performance Indicators) with just click of a button.

2. Methodology

The study is divided into two categories of – “Pre Covid Period” & “Post Covid Period”.

Same methodology (explained in following sections) is followed for both the categories.

Methodology Architecture

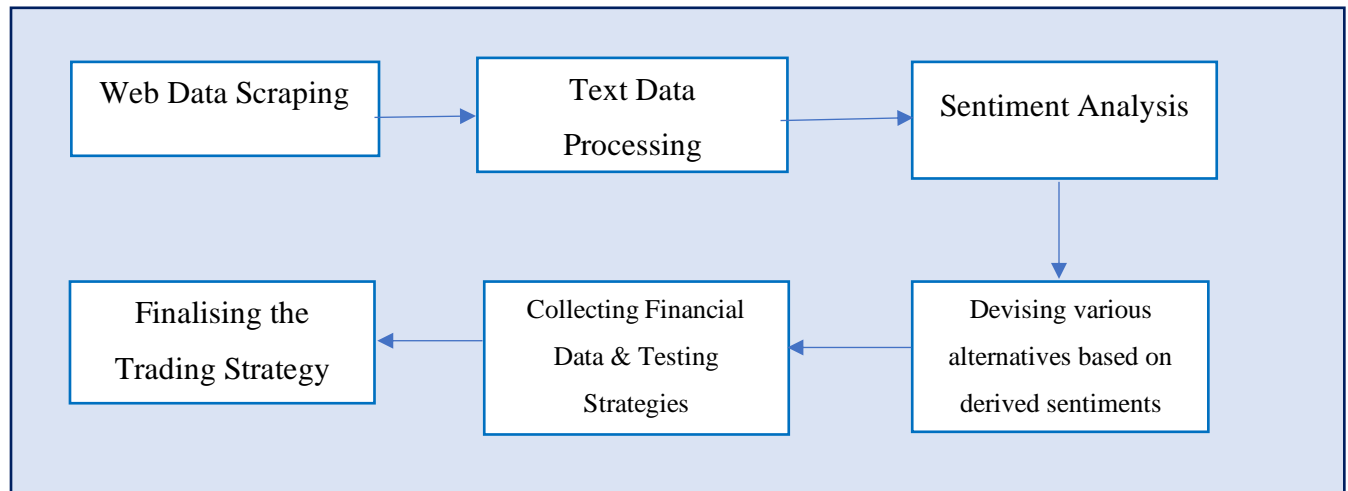


Figure 1 - Project Methodology Architecture

2.1 Web Data Scraping-

To identify the general market sentiments, I have scraped the twitter textual data related to “Tata Motors” for the following period:

Category	Quarter Results	Results Announcement Date	Twitter Data Date Range	Days (in number)
Pre Covid	Q3 for FY 2019	30/01/2020	20/01/2020 to 29/01/2020	10
Post Covid	Q1 for FY 2020	31/07/2020	21/07/2020 to 30/07/2020	10

The news archive data was not available through the open source methods. Hence, I have used twitter data which was scraped by using Python’s “snsrape library”.

2.2 Text Data Preprocessing

1. Collected data was loaded in the pandas data frame
2. Converted the content in lower case
3. Removed URLs from the text
4. Removed special characters like “@,#,\$,etc.” from the text
5. Tokenized (splitting into individual words) the text data

- ```
Defining my NLTK stop words and my user-defined stop words
stop_words = list(stopwords.words('english'))
user_stop_words = ['2020', 'year', 'many', 'much', 'electric', 'next', 'motor', 'tate', 'hadnt',
 'havent', 'hasnt', 'isnt', 'shouldnt', 'couldnt', 'wasnt', 'werent', 'new',
 'mustnt', 'i', '...', '...', '...', '...', '...', '...', '...', '...', '...', '...',
 'three', 'four', 'five', 'six', 'seven', 'eight', 'nine', 'ten', 'aht', 'car',
 've', 'next', 'variant', 'automatic', 'last', 'affordable', 'full']

alphabets = list(string.ascii_lowercase)
stop_words = stop_words + user_stop_words + alphabets
word_list = words.words() # all words in English language

tweets_df['Processed_Tweets'] = tweets_df['Text'].apply(preprocessTweets)

Apply getAdjectives function to the new 'Processed Tweets' column to generate a new column called 'Tweets_Adjectives'
tweets_df['Tweets_Adjectives'] = tweets_df['Processed_Tweets'].apply(getAdjectives)

unpunctuated_words = [char for char in filtered_words if char not in string.punctuation]
unpunctuated_words = ' '.join(unpunctuated_words)

function to return words to their base form using Lemmatizer
def preprocessTweetsSentiments(tweet):
 tweet_tokens = word_tokenize(tweet)
 lemmatizer = WordNetLemmatizer() # initiate an object WordNetLemmatizer Class
 lemma_words = [lemmatizer.lemmatize(w) for w in tweet_tokens]
 return " ".join(lemma_words)

 if tag == "JJ" # pos_tag module in NLTK library
 return " ".join(tweet) # join words with a space in between them
```

- ✓ Pre-covid Period

|   | Text                                     | Processed_Tweets                        | Tweets_Adjectives | Tweets_Sentiments                       |
|---|------------------------------------------|-----------------------------------------|-------------------|-----------------------------------------|
| 0 | @BosePratap @TataMotors_Gars Congrat...  | congratuation                           |                   | congratuation                           |
| 1 | \$TSLA market cap increase in after h... | market cap increase trading total ma... | total             | market cap increase trading total ma... |
| 2 | in "Electric vehicle race picks up in... | vehicle race momentum                   |                   | vehicle race momentum                   |
| 3 | @TataMotors I've want to repair of T...  | want repair safari strome guinea pro... | want strome       | want repair safari strome guinea pro... |
| 4 | Tata Nexon Electric launched at ₹14...   | follow                                  |                   | follow                                  |

- |   | Text                                     | Processed_Tweets                        | Tweets_Adjectives | Tweets_Sentiments                       |
|---|------------------------------------------|-----------------------------------------|-------------------|-----------------------------------------|
| 0 | 1000 Driven Tata Altroz XZ(P) faces ...  | driven oil pump issue service center... |                   | driven oil pump issue service center... |
| 1 | @RNTata2000 hi sal, one question and...  | hi sal question may idea make low co... | sal low           | hi sal question may idea make low co... |
| 2 | @AmargreeshKale @TataCompanies @TataS... | great visionary iron man                | great visionary   | great visionary iron man                |
| 3 | @NtokozoKhamoo @TataMotors Mara ai...    | ka di                                   |                   | ka di                                   |
| 4 | @IND_Moche @TataMotors 🇳🇪                |                                         |                   |                                         |

- ### 13. Created function to generate the blue colour for the Word Cloud

14. Initiated the Twitter word cloud object

```
Extract all tweets into one long string with each word separate with a "space"
tweets_long_string = tweets_df['Tweets_Adjectives'].tolist()
tweets_long_string = " ".join(tweets_long_string)

Create function to generate the blue colour for the Word Cloud

def blue_color_func(word, font_size, position, orientation, random_state=None,**kwargs):
 return "hsl(210, 100%, %d%%)" % random.randint(50, 70)

Instantiate the Twitter word cloud object
twitter_wc = WordCloud(background_color='white', max_words=1500)

generate the word cloud
twitter_wc.generate(tweets_long_string)

display the word cloud
fig = plt.figure()
fig.set_figwidth(14) # set width
fig.set_figheight(18) # set height

plt.imshow(twitter_wc.recolor(color_func=blue_color_func, random_state=3),
 interpolation="bilinear")
plt.axis('off')
plt.show()
```

### 15. Generated & Display the word cloud

✓ Pre Covid



✓ Post Covid



16. Displaying top words from the word cloud

```
Combine all words into a list
tweets_long_string = tweets_df['Tweets_Adjectives'].tolist()
tweets_list=[]
for item in tweets_long_string:
 item = item.split()
 for i in item:
 tweets_list.append(i)
```

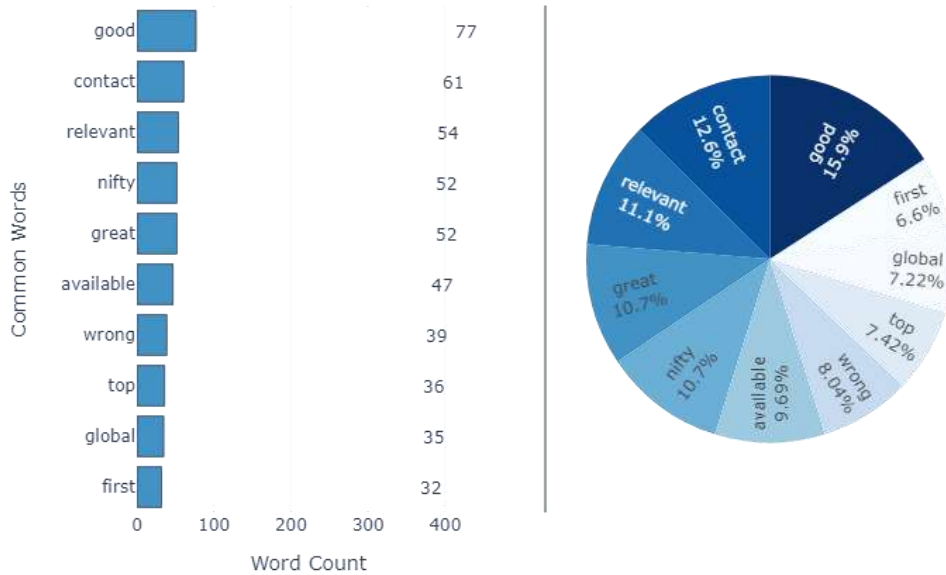
```
Use the Built-in Python Collections module to determine Word frequency
from collections import Counter
counts = Counter(tweets_list)
df = pd.DataFrame.from_dict(counts, orient='index').reset_index()
df.columns = ['Words', 'Count']
df.sort_values(by='Count', ascending=False, inplace=True)
```

|     | Words     | Count |
|-----|-----------|-------|
| 8   | good      | 77    |
| 17  | contact   | 61    |
| 19  | relevant  | 54    |
| 81  | great     | 52    |
| 24  | nifty     | 52    |
| 60  | available | 47    |
| 130 | wrong     | 39    |
| 51  | top       | 36    |
| 22  | global    | 35    |
| 20  | first     | 32    |



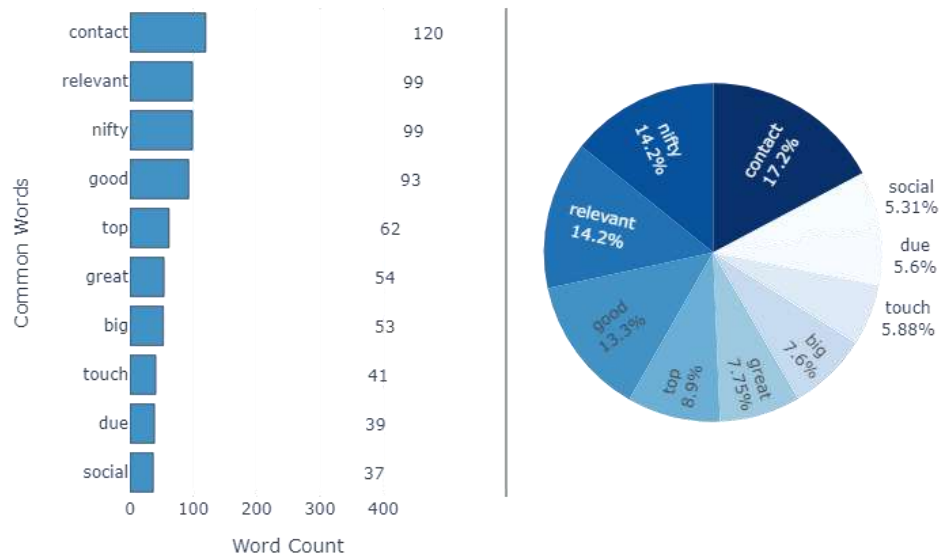
✓ Pre Covid

Twitter Users' 2020 Refections (10 Most Common Words)



✓ Post Covid

Twitter Users' 2020 Refections (10 Most Common Words)





## 2.3 Sentiment Analysis

### 1. Using “TextBlob” module to identify sentiment polarity score

```
Create function to obtain Subjectivity Score
def getSubjectivity(tweet):
 return TextBlob(tweet).sentiment.subjectivity

Create function to obtain Polarity Score
def getPolarity(tweet):
 return TextBlob(tweet).sentiment.polarity

Create function to obtain Sentiment category
def getSentimentTextBlob(polarity):
 if polarity < 0:
 return "Negative"
 elif polarity == 0:
 return "Neutral"
 else:
 return "Positive"
```

### 2. Summarising the sentiments

```
Apply all functions above to respective columns
tweets_df['Subjectivity']=tweets_df['Tweets_Sentiments'].apply(getSubjectivity)
tweets_df['Polarity']=tweets_df['Tweets_Sentiments'].apply(getPolarity)
tweets_df['Sentiment']=tweets_df['Polarity'].apply(getSentimentTextBlob)

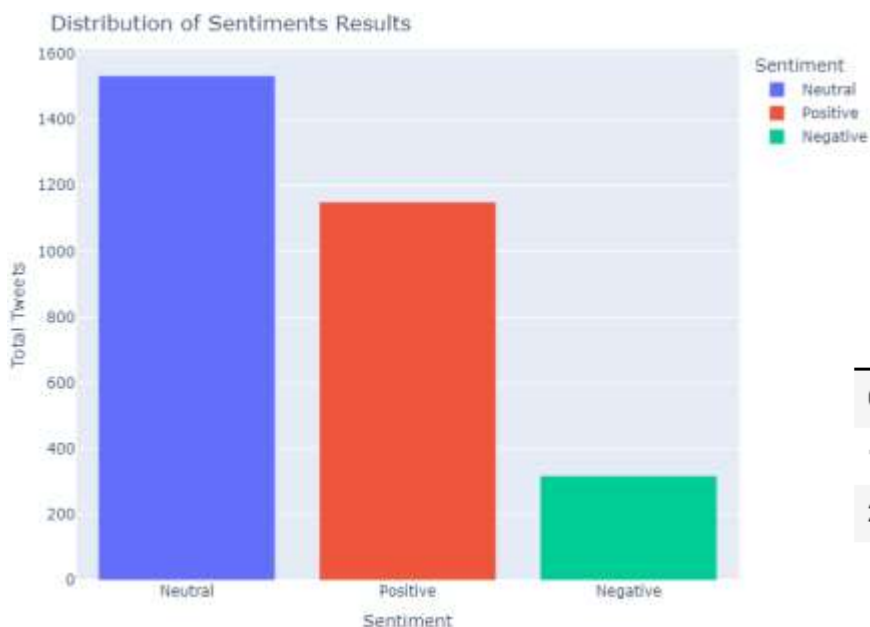
See quick results of the Sentiment Analysis
tweets_df['Sentiment'].value_counts()

Neutral 1534
Positive 1150
Negative 317
Name: Sentiment, dtype: int64

Create dataframe for Count of Sentiment Categories
bar_chart = tweets_df['Sentiment'].value_counts().rename_axis('Sentiment').to_frame('Total Tweets').reset_index()
```

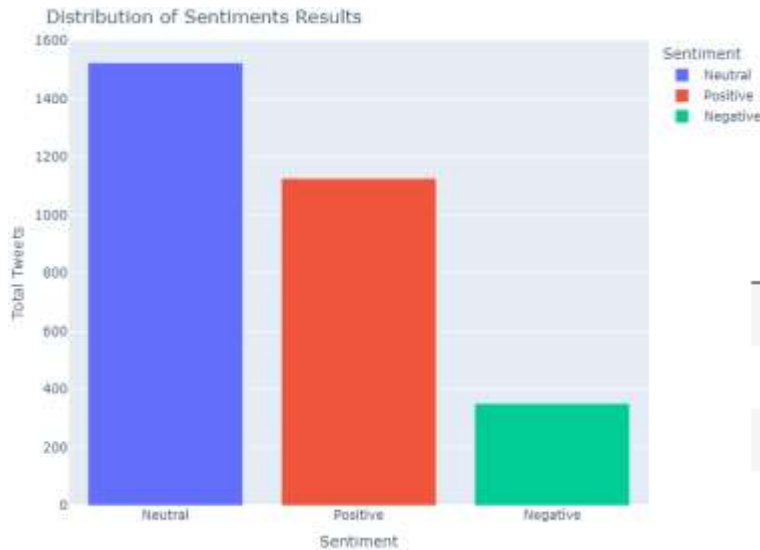
### 3. Identifying the sentiments:

✓ **Pre Covid Period:**



|   | Sentiment | Total Tweets |
|---|-----------|--------------|
| 0 | Neutral   | 1534         |
| 1 | Positive  | 1150         |
| 2 | Negative  | 317          |

✓ **Post-Covid Period:**



|   | Sentiment | Total Tweets |
|---|-----------|--------------|
| 0 | Neutral   | 1524         |
| 1 | Positive  | 1126         |
| 2 | Negative  | 351          |

## 2.4 Devising Possible Strategies -

### 1. Pre Covid Period

#### ## [Case - I]:

- \* Purchase stock on Q3 2019 Result announcement day
- \* Hold it for next 10 days then sell it
- \* compare the 10 days tata return with 10 days market return & 10 years average return
- \* Also compare the outcome with the historical return

#### ## [Case - II]:

- \* Sell the stock on Q3 2019 Result announcement day
- \* wait for next 10 days then buy back
- \* calculate return
- \* Also compare the outcome with the historical return

### 2. Post Covid Period

#### ## [Case - I]:

- \* Purchase stock on Q1 2020 Result announcement day
- \* Hold it for next 10 days then sell it
- \* compare the 10 days tata return with 10 days market return & 10 years average return

\* Also compare the outcome with the historical return

## ## [Case - II]:

\* Sell the stock on Q1 2020 Result announcement day

\* wait for next 10 days then buy back

\* calculate return

\* Also compare the outcome with the historical return

## 2.5 Testing Possible Strategies (Assumption: for all types of return calculations, I have used Adjusted Closing Price) -

### 2.5.1. Pre Covid Period

#### 3. Validating sentiments from financial data during that period

1. Collected "Tatamotors Stock Price" data for 10 days (excluding weekends) before the Q3(2019) announcement

```
#fetching Data
```

```
stock = 'TATAMOTORS.NS'
start = '2020-01-16'
end = '2020-01-30'
df = pdr.get_data_yahoo(stock, start, end)
```

```
[*****100%*****] 1 of 1 completed
```

```
df
```

|            | Open       | High       | Low        | Close      | Adj Close  | Volume   |
|------------|------------|------------|------------|------------|------------|----------|
| Date       |            |            |            |            |            |          |
| 2020-01-16 | 199.500000 | 200.600006 | 196.899994 | 197.550003 | 197.550003 | 28118140 |
| 2020-01-17 | 197.250000 | 199.449997 | 195.699997 | 197.300003 | 197.300003 | 18204088 |
| 2020-01-20 | 198.000000 | 201.449997 | 194.300003 | 195.000000 | 195.000000 | 28976013 |

2. Checked the price movement



3. 10 Days prices were reflecting growing sentiment in favour for tatamotors

#### 4. Calculating 10 Year Period Return prior to sentiments

1. Data fetching

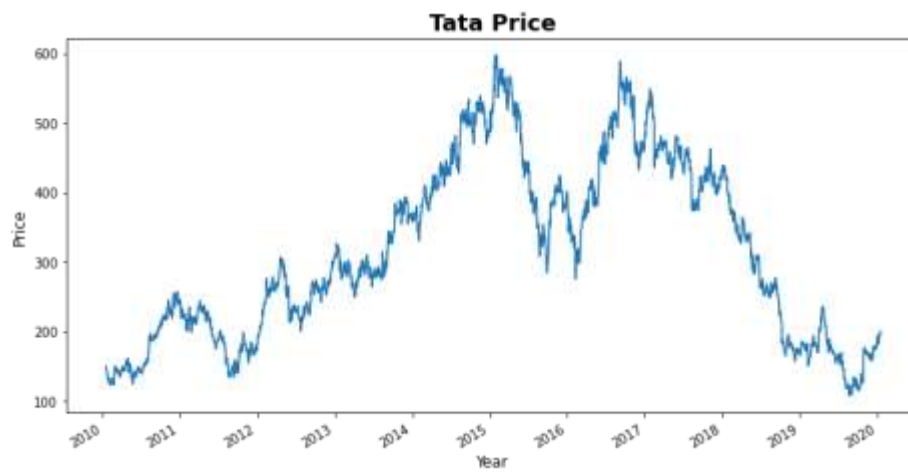
```
stock = 'TATAMOTORS.NS'
start = '2010-01-16'
end = '2020-01-16'
df_10 = pdr.get_data_yahoo(stock, start, end)

[*****100%*****] 1 of 1 completed

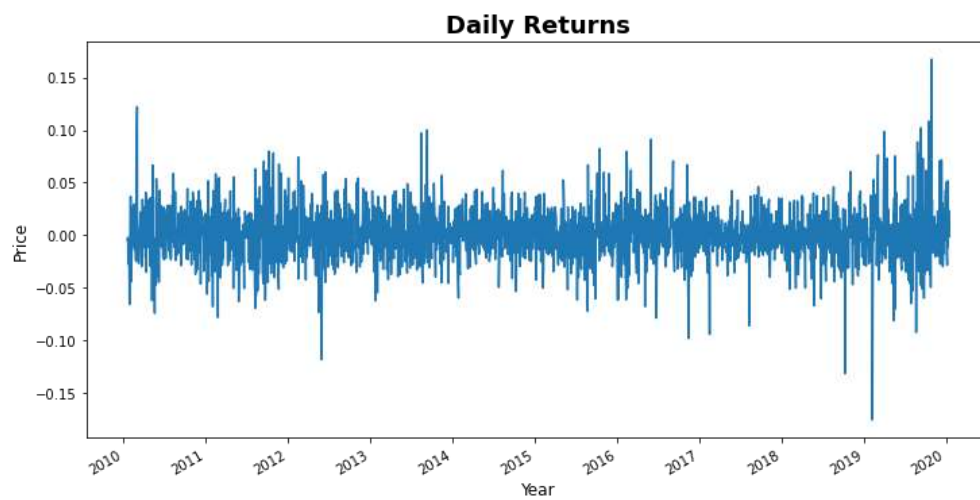
df_10.head()
```

|            | Open       | High       | Low        | Close      | Adj Close  | Volume   |
|------------|------------|------------|------------|------------|------------|----------|
| Date       |            |            |            |            |            |          |
| 2010-01-18 | 157.045532 | 161.012970 | 155.383362 | 160.449020 | 150.250122 | 18756613 |
| 2010-01-19 | 160.874466 | 162.022156 | 158.707703 | 159.627838 | 149.481110 | 11559642 |
| 2010-01-20 | 160.280823 | 160.755737 | 158.114075 | 159.281540 | 149.156846 | 10185363 |
| 2010-01-21 | 158.242691 | 159.024307 | 154.403870 | 154.888657 | 145.043182 | 9291983  |
| 2010-01-22 | 150.861862 | 155.828583 | 149.199677 | 153.958633 | 144.172272 | 12698513 |

## 2. Plotting Prices



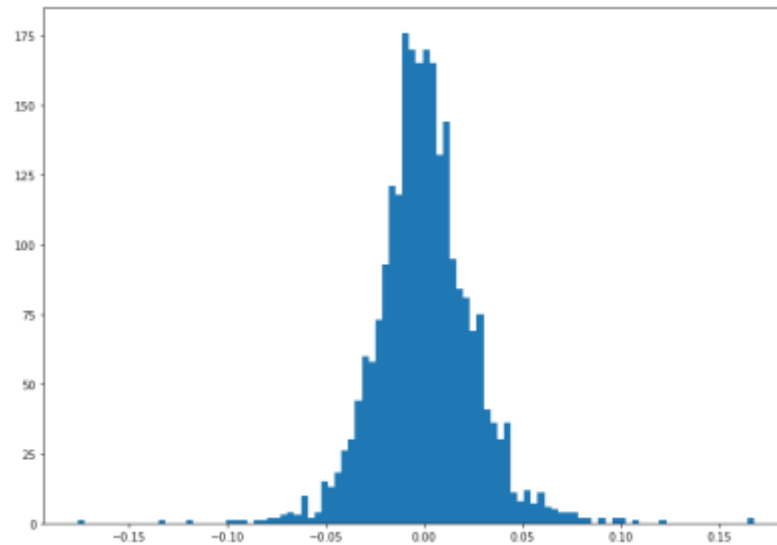
## 3. Daily Returns plot (highly volatile & mean reversing pattern is observed)



4. Daily Return Histogram
5. Important Statistics

|       | Open        | High        | Low         | Close       | Adj Close   | Volume       | Log_Returns | Daily_Returns | cumulative_return |
|-------|-------------|-------------|-------------|-------------|-------------|--------------|-------------|---------------|-------------------|
| count | 2463.000000 | 2463.000000 | 2463.000000 | 2463.000000 | 2463.000000 | 2.463000e+03 | 2462.000000 | 2462.000000   | 2462.000000       |
| mean  | 319.118188  | 323.643771  | 314.051573  | 318.664292  | 315.909616  | 1.285835e+07 | 0.000117    | 0.000425      | 2.103006          |
| std   | 124.334269  | 125.372289  | 122.973737  | 124.077697  | 126.045454  | 1.243713e+07 | 0.024836    | 0.024869      | 0.838780          |
| min   | 108.900002  | 111.599998  | 106.000000  | 107.699997  | 107.699997  | 0.000000e+00 | -0.193375   | -0.175827     | 0.716805          |
| 25%   | 208.133072  | 212.025810  | 204.640030  | 208.602531  | 201.364890  | 6.146748e+06 | -0.013703   | -0.013610     | 1.340876          |
| 50%   | 298.349884  | 304.681976  | 292.759857  | 298.152008  | 295.440979  | 9.181680e+06 | -0.000508   | -0.000508     | 1.967023          |
| 75%   | 423.750000  | 428.849991  | 418.300003  | 423.149994  | 422.699997  | 1.475572e+07 | 0.013513    | 0.013604      | 2.813476          |
| max   | 600.212097  | 605.901123  | 589.873047  | 598.134399  | 597.892273  | 1.844356e+08 | 0.154924    | 0.167569      | 3.979313          |

10 years return are 0.4%



- **Purchased stock on quarter results announcement day & Analysed for 10 Days**
  1. Return analysed for 10 days period (excluding weekends) - from '30/01/2020' to '12/02/2020'

## 2. Data Fetching, calculating Daily Return & Cumulative Return

|            | Open       | High       | Low        | Close      | Adj Close  | Volume   | Daily_Returns | cumulative_return |
|------------|------------|------------|------------|------------|------------|----------|---------------|-------------------|
| Date       |            |            |            |            |            |          |               |                   |
| 2020-01-30 | 190.949997 | 192.550003 | 184.250000 | 186.199997 | 186.199997 | 70900581 | NaN           | NaN               |
| 2020-01-31 | 186.300003 | 188.350006 | 175.949997 | 176.600006 | 176.600006 | 75621897 | -0.051557     | 0.948443          |
| 2020-02-03 | 163.500000 | 168.300003 | 159.550003 | 163.850006 | 163.850006 | 66616190 | -0.072197     | 0.879968          |
| 2020-02-04 | 166.550003 | 168.600008 | 161.199997 | 165.699997 | 165.699997 | 49034642 | 0.011291      | 0.889903          |
| 2020-02-05 | 167.399994 | 184.949997 | 166.600006 | 183.750000 | 183.750000 | 92982265 | 0.108932      | 0.986842          |
| 2020-02-06 | 182.000000 | 183.399994 | 175.750000 | 178.850006 | 178.850006 | 61821140 | -0.026667     | 0.960526          |
| 2020-02-07 | 177.399994 | 178.149994 | 173.000000 | 173.600006 | 173.600006 | 45195760 | -0.029354     | 0.932331          |
| 2020-02-10 | 173.199997 | 173.199997 | 168.000000 | 168.899994 | 168.899994 | 33279372 | -0.027074     | 0.907089          |
| 2020-02-11 | 171.850006 | 175.149994 | 168.399994 | 169.750000 | 169.750000 | 42868276 | 0.005033      | 0.911654          |
| 2020-02-12 | 173.000000 | 173.300003 | 169.000000 | 170.949997 | 170.949997 | 34621395 | 0.007069      | 0.918099          |

- INR 1 invested on 30\_jan\_2020 fallen to INR 0.92

## 3. Two Strategy Returns

### ✓ Strategy 1

```
Return on holding the stock
Purchased at 186 on 30_Jan_2020 & sold at INR 170.94 on 13_Feb_2020
holding_return = (170.949997-186.199997)/186.199997*100
print(holding_return)
```

-8.19011828448096

- we're making loss of 8.2%

### ✓ Strategy 2

```
#Short Selling Return (assuming '0' transaction cost)
#Sold at INR 186.199 on 30_Jan_2020 & Re-Purchased at at INR 170.94 on 13_Feb_2020

buy_back_return = (186.199-170.94)/170.94*100
print(buy_back_return)
```

8.926523926523936

- We are making 8.92% of profit



- **Purchased Nifty 50 on quarter results announcement day & Analysed for 10 Days**

| Date       |              |              |              |              |              |        |           |
|------------|--------------|--------------|--------------|--------------|--------------|--------|-----------|
| 2020-01-30 | 12147.750000 | 12150.299805 | 12010.599609 | 12035.799805 | 12035.799805 | 538100 | NaN       |
| 2020-01-31 | 12100.400391 | 12103.549805 | 11945.849609 | 11962.099609 | 11962.099609 | 771300 | -0.006123 |
| 2020-02-03 | 11627.450195 | 11749.849609 | 11614.500000 | 11707.900391 | 11707.900391 | 669800 | -0.021250 |
| 2020-02-04 | 11786.250000 | 11986.150391 | 11783.400391 | 11979.650391 | 11979.650391 | 560400 | 0.023211  |
| 2020-02-05 | 12005.849609 | 12098.150391 | 11953.349609 | 12089.150391 | 12089.150391 | 758000 | 0.009141  |
| 2020-02-06 | 12120.000000 | 12160.599609 | 12084.650391 | 12137.950195 | 12137.950195 | 565100 | 0.004037  |
| 2020-02-07 | 12151.150391 | 12154.700195 | 12073.950195 | 12098.349609 | 12098.349609 | 473500 | -0.003263 |
| 2020-02-10 | 12102.349609 | 12103.549805 | 11990.750000 | 12031.500000 | 12031.500000 | 524700 | -0.005526 |
| 2020-02-11 | 12108.400391 | 12172.299805 | 12099.000000 | 12107.900391 | 12107.900391 | 480000 | 0.006350  |
| 2020-02-12 | 12151.000000 | 12231.750000 | 12144.299805 | 12201.200195 | 12201.200195 | 411700 | 0.007706  |

```
holding_return_mkt = (12201.200195-12035.799805)/12035.799805*100
print(holding_return_mkt)
```

1.3742367992136846

- market gave 1.4% return

## ▪ Pre-Covid Strategy Evaluation

### Pre-Covid Strategy Summary:

10 Year Return = 0.04% ; 10 Days Tata Return = -8.2% ; 10 Days Nifty 50 Return = 1.4%

Case - I: Abnormal Profit/Loss on holding 'TATAMOTORS' = -8.2%-1.4% = -9.6%. 10 Years returns yielded better result that using 'sentiment driven holding strategy'

Case - II: Abnormal Profit/Loss on short selling 'TATAMOTORS' = 8.9%-1.4% = 7.5%

**Best Pre-covid Strategy : Short when market sentiment is bullish and purchase it after holding for a shorter duration.**

**Best strategy abnormal return on Tatamotors = 7.5%**

## 2.5.2. Post Covid Period

### 1. Validating sentiments from financial data during that period

1. Collected “Tatamotors Stock Price” data for 10 days (excluding weekends) before the Q31(2020) announcement

```
#fetching Data

stock = 'TATAMOTORS.NS'
start = '2020-07-18'
end = '2020-07-31'
df_post = pdr.get_data_yahoo(stock, start, end)

[*****100%*****] 1 of 1 completed

df_post
```

|            | Open       | High       | Low        | Close      | Adj Close  | Volume   |
|------------|------------|------------|------------|------------|------------|----------|
| Date       |            |            |            |            |            |          |
| 2020-07-20 | 106.349998 | 106.349998 | 103.849998 | 105.050003 | 105.050003 | 39786731 |
| 2020-07-21 | 106.000000 | 109.699997 | 105.500000 | 108.449997 | 108.449997 | 66008143 |

2. Chchecked the price movement



3. 10 Days prices were not reflecting growing sentiment correctly for tatamotors for Q1 2020

## 2. Calculating 10 Year Period Return prior to sentiments

### 1. Data fetching

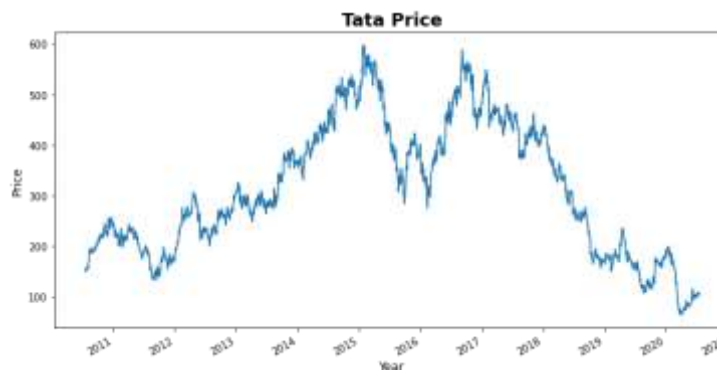
```
stock = 'TATAMOTORS.NS'
start = '2010-07-18'
end = '2020-07-18'
df_10_post = pdr.get_data_yahoo(stock, start, end)

[*****100%*****] 1 of 1 completed
```

```
df_10_post.head()
```

|            | Open       | High       | Low        | Close      | Adj Close  | Volume   |
|------------|------------|------------|------------|------------|------------|----------|
| Date       |            |            |            |            |            |          |
| 2010-07-19 | 163.644745 | 165.010101 | 162.487167 | 163.308350 | 152.927689 | 9332836  |
| 2010-07-20 | 164.040497 | 164.832016 | 160.082947 | 160.884354 | 150.657761 | 8860549  |
| 2010-07-21 | 161.863846 | 163.427078 | 161.547241 | 162.328857 | 152.010452 | 9242644  |
| 2010-07-22 | 162.061722 | 166.217148 | 161.270218 | 165.623520 | 155.095688 | 13248283 |
| 2010-07-23 | 165.820800 | 167.500107 | 164.515111 | 165.000513 | 155.355103 | 12104008 |

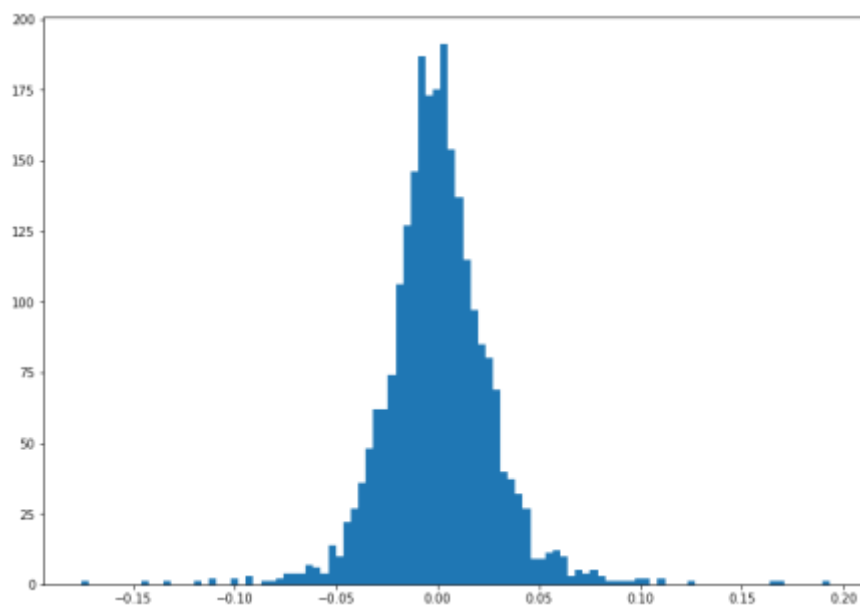
### 2. Plotting Prices



### 3. Daily Returns plot (highly volatile & mean reversing pattern is observed)



#### 4. Daily Return Histogram



#### 5. Important Statistics

|       | Open        | High        | Low         | Close       | Adj Close   | Volume       | Daily_Returns | cumulative_return |
|-------|-------------|-------------|-------------|-------------|-------------|--------------|---------------|-------------------|
| count | 2463.000000 | 2463.000000 | 2463.000000 | 2463.000000 | 2463.000000 | 2.463000e+03 | 2462.000000   | 2462.000000       |
| mean  | 317.113977  | 321.640536  | 312.029806  | 316.626515  | 314.356613  | 1.511727e+07 | 0.000195      | 2.056019          |
| std   | 127.598548  | 128.637718  | 126.247767  | 127.382675  | 126.628916  | 1.858864e+07 | 0.026198      | 0.841011          |
| min   | 66.500000   | 66.900002   | 63.500000   | 65.300003   | 65.300003   | 0.000000e+00 | -0.175827     | 0.426999          |
| 25%   | 208.133072  | 212.025810  | 204.640030  | 208.602531  | 201.364963  | 6.146748e+06 | -0.013935     | 1.317401          |
| 50%   | 296.349884  | 304.661976  | 292.759857  | 296.152006  | 295.440948  | 9.207354e+06 | -0.000508     | 1.932583          |
| 75%   | 423.750000  | 428.849991  | 418.300003  | 423.149984  | 422.699997  | 1.525352e+07 | 0.013770      | 2.764215          |
| max   | 600.212097  | 605.901123  | 589.673047  | 588.134399  | 597.892273  | 2.154767e+08 | 0.193218      | 3.906640          |

• 0% is the 10 year average return

10 years return are 0%

- **Purchased stock on quarter results announcement day & Analysed for 10 Days**
  1. Return analysed for 10 days period (excluding weekends) - from '31/07/2020' to '14/08/2020'

## 2. Data Fetching, calculating Daily Return & Cumulative Return

df\_strategy\_post

|            | Open       | High       | Low        | Close      | Adj Close  | Volume    | Daily_Returns | cumulative_return |
|------------|------------|------------|------------|------------|------------|-----------|---------------|-------------------|
| Date       |            |            |            |            |            |           |               |                   |
| 2020-07-31 | 104.000000 | 105.400002 | 102.300003 | 104.650002 | 104.650002 | 33808018  | NaN           | NaN               |
| 2020-08-03 | 103.000000 | 114.400002 | 102.900002 | 113.050003 | 113.050003 | 194765344 | 0.080268      | 1.080268          |
| 2020-08-04 | 112.949997 | 115.099998 | 110.800003 | 111.449997 | 111.449997 | 95906477  | -0.014153     | 1.064978          |
| 2020-08-05 | 112.400002 | 117.650002 | 112.000000 | 115.400002 | 115.400002 | 99371050  | 0.035442      | 1.102723          |
| 2020-08-06 | 116.199997 | 117.699997 | 115.500000 | 116.800003 | 116.800003 | 60082530  | 0.012132      | 1.116101          |
| 2020-08-07 | 117.000000 | 119.699997 | 116.000000 | 119.099998 | 119.099998 | 56489390  | 0.019692      | 1.138079          |
| 2020-08-10 | 119.949997 | 124.699997 | 119.899997 | 123.849998 | 123.849998 | 71093810  | 0.039882      | 1.183469          |
| 2020-08-11 | 125.000000 | 125.800003 | 121.400002 | 122.300003 | 122.300003 | 50224685  | -0.012515     | 1.168657          |
| 2020-08-12 | 121.000000 | 126.400002 | 120.599998 | 125.349998 | 125.349998 | 50713617  | 0.024939      | 1.197802          |
| 2020-08-13 | 126.099998 | 131.899994 | 124.400002 | 131.149994 | 131.149994 | 95489249  | 0.048270      | 1.253225          |

- INR 1 invested on 31\_jan\_2021 grew to INR 1.25

### Two Strategy Returns

#### ✓ Strategy 1

```
Return on holding the stock
Purchased at 104.65 on 31_Jul_2020 & sold at INR 131.14 on 13_Aug_2020
holding_return_post = (131.14-104.65)/104.65*100
print(holding_return_post)
```

25.312947921643552

- we're making profit of 25%

#### ✓ Strategy 2

```
#Short Selling Return (assuming '0' transaction cost)
#Sold at INR 104.65 on 31_Jul_2020 & Re-Purchased at at INR 131.14 on 13_Aug_2020

buy_back_return_post = (104.65-131.14)/131.14*100
print(buy_back_return_post)
```

-20.19978648772303

- We are making loss of 20%

- **Purchased Nifty 50 on quarter results announcement day & Analysed for 10 Days**

| Date       | Open         | High         | Low          | Close        | Adj Close    | Volume | Daily_Returns |
|------------|--------------|--------------|--------------|--------------|--------------|--------|---------------|
| 2020-07-31 | 11139.500000 | 11150.400391 | 11026.650391 | 11073.450195 | 11073.450195 | 642600 | NaN           |
| 2020-08-03 | 11057.549805 | 11058.049805 | 10882.250000 | 10891.599609 | 10891.599609 | 680900 | -0.016422     |
| 2020-08-04 | 10946.650391 | 11112.250000 | 10908.099609 | 11095.250000 | 11095.250000 | 625700 | 0.018698      |
| 2020-08-05 | 11155.750000 | 11225.650391 | 11064.049805 | 11101.650391 | 11101.650391 | 667600 | 0.000577      |
| 2020-08-06 | 11185.700195 | 11256.799805 | 11127.299805 | 11200.150391 | 11200.150391 | 600400 | 0.008873      |
| 2020-08-07 | 11186.650391 | 11231.900391 | 11142.049805 | 11214.049805 | 11214.049805 | 452600 | 0.001241      |
| 2020-08-10 | 11270.250000 | 11337.299805 | 11238.000000 | 11270.150391 | 11270.150391 | 492000 | 0.005003      |
| 2020-08-11 | 11322.250000 | 11373.599609 | 11299.150391 | 11322.500000 | 11322.500000 | 586100 | 0.004645      |
| 2020-08-12 | 11289.000000 | 11322.000000 | 11242.650391 | 11308.400391 | 11308.400391 | 609900 | -0.001245     |
| 2020-08-13 | 11334.849609 | 11359.299805 | 11269.950195 | 11300.450195 | 11300.450195 | 562400 | -0.000703     |

```
holding_return_mkt_post = (11300-11073)/11073*100
print(holding_return_mkt_post)
```

2.05003160841687

- market gave 2% return

## ▪ **Post-Covid Strategy Evaluation**

### **Pre-Covid Strategy Summary:**

**10 Year Return = 0% ; 10 Days Tata Return = 25% ; 10 Days Return on short selling = -20%; 10 Days Nifty 50 Return = 2%**

**Case - I: Abnormal Profit/Loss on holding 'TATAMOTORS' = 25%-2% = 23%.**

**Case - II: Abnormal Profit/Loss on short selling 'TATAMOTORS' = -20%-2% = -22%**

**Best Post-covid Strategy : Buy when market sentiment is bullish and later sell it after holding for a shorter duration.**

**Best strategy abnormal return on Tatamotors = 23%**

### 3. Finalising the trading strategy & conclusion

As an investor, we should reap the benefit of “Busllish” sentiment to get the maximum abnormal return. However, the findings were different for the pre & post covid period. This strategy is not showing any return in pre covid bcause the general market sentiments (**market risk**) were bearish about most of the stocks bcause of the economic slowdown since covid spread.

| Period     | Chosen Strategy                                  | Abnormal Profit | Remark                                                                     |
|------------|--------------------------------------------------|-----------------|----------------------------------------------------------------------------|
| Pre Covid  | Buy on result day & sell on 10 <sup>th</sup> day | -9.6%           | Strategy failed due to increased market risk because of covid led slowdown |
| Post Covid | Buy on result day & sell on 10 <sup>th</sup> day | 23%             | Normal Economic Condition                                                  |