Sentiment Analysis of Twitter Data for predicting Stock Price

Introduction: This rpoject involves evaluation TESLA's social media data and uses sentiment classification to estimate its future stock trend. We employed sentiment analysis and machine learning principles to estimate the impact of "public sentiment" on "market fluctuations."

Import Required Python Packages

In [53]:
```
import pandas as pd
import numpy as np
import requests
from flask import Response
import re

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier

from matplotlib import rcParams
rcParams['figure.figsize'] = 12, 6
import matplotlib.pyplot as plt
plt.style.use('ggplot')


from sklearn.metrics import *
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
from Scweet.scweet import scrape
from Scweet.user import get_user_information, get_users_following, get_users_followers
```

In [3]:
```
import flair
sentiment_model = flair.models.TextClassifier.load('en-sentiment')
```
```
2021-11-10 02:41:34,974 loading file C:\Users\fahad\.flair\models\sentiment-en-mix-distillbert_4.pt
```

Scweet Python Scraper

In [4]:
```
# Python API allows to scrape only 7 days of data in free tier, So we managed to use Scweet tweets scraper t
#that can scrape the data between two given dates
#data = scrape(words=['tesla'], since="2020-10-31", until="2021-10-31",interval=1,
 #    headless=True, display_type="Top")
```

In [5]:
```
# data saved to csv file after scraping
#data.to_csv('scraped_data.csv', index = False)
```

In [7]:
```
data = pd.read_csv('scraped_data.csv')
data.head()
```

Out[7]:

	UserScreenName	UserName	Timestamp	Text	Embedded_text	Emojis	Comments	Likes	Retwe
0	East Bay Tesla Club | Fremont |	@TeslaOwnersEBay	2020-10-31T23:10:55.000Z	East Bay Tesla Club | Fremont |\n@TeslaOwnersE...	Happy Halloween all you \n@Tesla\n Freaks!\n...	🎃 😺	5	40	
1	Kim Paquette	@kimpaquette	2020-10-31T21:02:45.000Z	Kim Paquette\n@kimpaquette\n·\n1 Nov 2020	Guess what I am for Halloween! #FSDBeta #Tes...	🥽 🎃 😺 😨	150	46	
2	Dogs of Tesla	@dogsoftesla	2020-10-31T21:58:30.000Z	Dogs of Tesla\n@dogsoftesla\n·\n1 Nov 2020	F R A N K I E \n\nHappy Halloween! \n\n#Tesla...	✨ 🖤 🖤 ✨ 🎃	10	21	
3	Luke	@tweetoflbc	2020-10-31T22:54:04.000Z	Luke\n@tweetoflbc\n·\n1 Nov 2020	Major vibes anyone know whose this is? #tesla...	🔥	2	4	
4	Randy 'DUO' Mongenel	@RandyMongenel	2020-10-31T20:22:41.000Z	Randy 'DUO' Mongenel\n@RandyMongenel\n·\n1 Nov...	One of the more interesting decals I've seen o...	NaN	2	NaN	

Select only the Date and Text of speech from scraped data

In [8]:
```
import datetime
data['date'] = pd.to_datetime(data['Timestamp']).dt.date
df = data[['date', 'Embedded_text']]
df.head(20)
```

Out[8]:

	date	Embedded_text
0	2020-10-31	Happy Halloween all you \n@Tesla\n Freaks!\n...
1	2020-10-31	Guess what I am for Halloween! #FSDBeta #Tes...
2	2020-10-31	F R A N K I E \n\nHappy Halloween! \n\n#Tesla...
3	2020-10-31	Major vibes anyone know whose this is? #tesla...
4	2020-10-31	One of the more interesting decals I've seen o...
5	2020-10-31	Just realized that even with the dozen or so F...
6	2020-10-31	How did you get a hold of that Chester? Thank ...
7	2020-10-31	Our #sociallydistanced #trickortreat solution....
8	2020-10-31	zombie apocalypse happen i'm stealing a tesla\...
9	2020-10-31	Demand problem Natick Massachusetts . You know...
10	2020-10-31	What kind of science do you think is the futur...
11	2020-10-31	Hiring Bo Pelini to run an SEC defense in 2020...
12	2020-10-31	"I do not think you can name many great invent...
13	2020-10-31	Patiently waiting for our new and final \n@Tes...
14	2020-10-31	The all-new, fully electric #Polestar2 is the ...
15	2020-10-31	What is it that \n@Tesla\n @bp_plc\n @HSBC\n @...
16	2020-10-31	My kid just pointed out to me that when the \n...
17	2020-10-31	Can't wait for \n@Tesla\n #FSDbeta to be rolle...
18	2020-10-31	Replying to \n@TeslaOwnersEBay\n @Tesla\n and...
19	2020-10-31	Replying to \n@dogsoftesla\n, \n@elonmusk\n an...

Combine the tweets for each date in same rows.

In [9]:
```
df['Embedded_text'] = df.groupby('date')[['Embedded_text']].transform(lambda x : ' '.join(x))
df = df.drop_duplicates().reset_index().drop('index', axis = 1)
df.head()
```

Out[9]:

	date	Embedded_text
0	2020-10-31	Happy Halloween all you \n@Tesla\n Freaks!\n...
1	2020-11-01	Is this the first Tesla in the country?\n118\n...
2	2020-11-02	Tesla Model Y is here! And quality is pretty d...
3	2020-11-03	I like that the Tesla maps now identify inters...
4	2020-11-04	Hey Tesla take me to Kinoo\n\nAutopilot :\n3\n...

Sentiment Analysis

- Flair
- Analyzing Tesla Tweets

In [10]:
```
# function to clean tweet text by removing links, special characters using simple regex statements
def clean_tweet(tweet):
    """ Utility . """
    return ' '.join(re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z \t])|(\w+://\S+)", " ", tweet).split())
```

Note: We'll be using the flair library's pre-trained sentiment analysis model. This model divides the text into character-level tokens and makes predictions using the DistilBERT model. Working at the character level (rather than the word level) has the advantage of allowing the network to attribute a feeling to words it has never encountered before.

In [11]:
```
probs = []
sentiments = []

for tweet in df['Embedded_text'].to_list():
    # make prediction
    tweet = clean_tweet(tweet)
    sentence = flair.data.Sentence(tweet)
    sentiment_model.predict(sentence)
    #extract sentiment prediction
    probs.append(sentence.labels[0].score)  # numerical score 0-1
    sentiments.append(sentence.labels[0].value)  # 'POSITIVE' or 'NEGATIVE'

# add probability and sentiment predictions to tweets dataframe
df['probability'] = probs
df['sentiment'] = sentiments
```

In [12]:
```
tweet_prob = df[['date', 'probability', 'sentiment']]
tweet_prob['date'] = pd.to_datetime(tweet_prob['date']) # convert string date object to datetime object
```

Use Textblob to calculate polarity parameter from the tweet text

In [13]:
```
from textblob import TextBlob
from nltk.sentiment.vader import SentimentIntensityAnalyzer

polarity = 0
tweet_polarity = []

 #print(tweet.text)
for tweet in df['Embedded_text'].to_list():
    analysis = TextBlob(tweet)
    score = SentimentIntensityAnalyzer().polarity_scores(tweet)
    polarity = analysis.sentiment.polarity
    tweet_polarity.append(polarity)
```

In [14]:
```
tweet_prob['tweet_polarity'] =  tweet_polarity
```

Inference: We can observe from the above results flair model has created the positive and negative sentiments for compiled tweets of each day of last one year.

In [16]:
```
# The yahoo finance API is not working fine to scrape the data, so we direclty
# downloaded one year of data from https://finance.yahoo.com/quote/TSLA/

tesla = pd.read_csv('tsla.csv')
tesla['Date'] = pd.to_datetime(tesla['Date']) # convert string date object to datetime object
tesla
```

Out[16]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2020-02-11	394.000000	406.980011	392.299988	400.510010	400.510010	29021100
1	2020-03-11	409.730011	427.769989	406.690002	423.899994	423.899994	34351700
2	2020-04-11	430.619995	435.399994	417.100006	420.980011	420.980011	32143100
3	2020-05-11	428.299988	440.000000	424.000000	438.089996	438.089996	28414500
4	2020-06-11	436.100006	436.570007	424.279999	429.950012	429.950012	21706000
...	...	...	...	...	...	...	...
246	2021-10-25	950.530029	1045.020020	944.200012	1024.859985	1024.859985	62852100
247	2021-10-26	1024.689941	1094.939941	1001.440002	1018.429993	1018.429993	62415000
248	2021-10-27	1039.660034	1070.880005	1030.780029	1037.859985	1037.859985	38526500
249	2021-10-28	1068.310059	1081.000000	1054.199951	1077.040039	1077.040039	27213200
250	2021-10-29	1081.859985	1115.209961	1073.209961	1114.000000	1114.000000	29918400

251 rows × 7 columns

In [17]:
```
df_merged = pd.merge(left=tweet_prob, right=tesla, left_on='date', right_on='Date')
df_merged
```

Out[17]:

	date	probability	sentiment	tweet_polarity	Date	Open	High	Low	Close	Adj Close	Volume
0	2020-11-11	0.821078	POSITIVE	0.150447	2020-11-11	416.450012	418.700012	410.579987	417.130005	417.130005	17357700
1	2020-11-12	0.942596	NEGATIVE	0.217726	2020-11-12	615.010010	624.000000	596.799988	609.989990	609.989990	46475000
2	2020-11-13	0.999725	NEGATIVE	0.092293	2020-11-13	410.850006	412.529999	401.660004	408.500000	408.500000	19771100
3	2020-11-16	0.998980	POSITIVE	0.200596	2020-11-16	408.929993	412.450012	404.089996	408.089996	408.089996	26838600
4	2020-11-17	0.998251	POSITIVE	0.192465	2020-11-17	460.170013	462.000000	433.010010	441.609985	441.609985	61188300
...	...	...	...	...	...	...	...	...	...	...	...
211	2021-10-25	0.998716	POSITIVE	0.190844	2021-10-25	950.530029	1045.020020	944.200012	1024.859985	1024.859985	62852100
212	2021-10-26	0.999432	NEGATIVE	0.124890	2021-10-26	1024.689941	1094.939941	1001.440002	1018.429993	1018.429993	62415000
213	2021-10-27	0.999017	NEGATIVE	0.085150	2021-10-27	1039.660034	1070.880005	1030.780029	1037.859985	1037.859985	38526500
214	2021-10-28	0.534431	POSITIVE	0.192312	2021-10-28	1068.310059	1081.000000	1054.199951	1077.040039	1077.040039	27213200
215	2021-10-29	0.885372	POSITIVE	0.241323	2021-10-29	1081.859985	1115.209961	1073.209961	1114.000000	1114.000000	29918400

216 rows × 11 columns

In [18]:
```
#Stock Trend is calculated by taking the difference between today's price and the previous day's
#price and converting it to a '0' for a decline and a '1' for an increase in stock price.
df_merged['Price Diff'] = df_merged['Adj Close'].diff()
df_merged.dropna(inplace = True)
df_merged['Trend'] = np.where(df_merged['Price Diff'] > 0 , 1, 0)

df_merged.head()
```

Out[18]:

	date	probability	sentiment	tweet_polarity	Date	Open	High	Low	Close	Adj Close	Volume	Price Diff
1	2020-11-12	0.942596	NEGATIVE	0.217726	2020-11-12	615.010010	624.000000	596.799988	609.989990	609.989990	46475000	192.859985
2	2020-11-13	0.999725	NEGATIVE	0.092293	2020-11-13	410.850006	412.529999	401.660004	408.500000	408.500000	19771100	-201.489990
3	2020-11-16	0.998980	POSITIVE	0.200596	2020-11-16	408.929993	412.450012	404.089996	408.089996	408.089996	26838600	-0.410004
4	2020-11-17	0.998251	POSITIVE	0.192465	2020-11-17	460.170013	462.000000	433.010010	441.609985	441.609985	61188300	33.519989
5	2020-11-18	0.997662	NEGATIVE	0.201802	2020-11-18	448.350006	496.000000	443.500000	486.640015	486.640015	78044000	45.030030

Create seperate binary variables for Sentiment features

In [19]:
```
# encode each categorical variable in the loop
df_e = pd.get_dummies(df_merged['sentiment'], prefix = 'sentiment', drop_first = False)

    # combine the insurance dataset with the encoded categorical variable
df_merged = pd.concat([df_merged, df_e], axis = 1)

    # drop the original non-encoded categorical variable from the dataset
del df_merged['sentiment']
df_merged = df_merged.set_index('date')
```

In [20]:
```
df_merged.head()
```

Out[20]:

	probability	tweet_polarity	Date	Open	High	Low	Close	Adj Close	Volume	Price Diff	Trend	sentime
date												
2020-11-12	0.942596	0.217726	2020-11-12	615.010010	624.000000	596.799988	609.989990	609.989990	46475000	192.859985	1	
2020-11-13	0.999725	0.092293	2020-11-13	410.850006	412.529999	401.660004	408.500000	408.500000	19771100	-201.489990	0	
2020-11-16	0.998980	0.200596	2020-11-16	408.929993	412.450012	404.089996	408.089996	408.089996	26838600	-0.410004	0	
2020-11-17	0.998251	0.192465	2020-11-17	460.170013	462.000000	433.010010	441.609985	441.609985	61188300	33.519989	1	
2020-11-18	0.997662	0.201802	2020-11-18	448.350006	496.000000	443.500000	486.640015	486.640015	78044000	45.030030	1	

Predicting TESLA Stock TREND with Random Forest Classifier Model

In [21]:
```
# Select independent and dependent variales
X = df_merged[['Adj Close', 'Volume', 'tweet_polarity', 'sentiment_NEGATIVE', 'sentiment_POSITIVE']]
y = df_merged['Trend']
```

In [22]:
```
## Scale the X data onto same scale
from sklearn import preprocessing

X = preprocessing.StandardScaler().fit(X).transform(X.astype(float))
X[:5]
```

Out[22]:
```
array([[-0.87246471,  0.85090562,  0.97004924,  0.61498384, -0.61498384],
       [-2.7494569 , -0.54696907, -1.67908558,  0.61498384, -0.61498384],
       [-2.75327632, -0.17700516,  0.60826108, -1.62605898,  1.62605898],
       [-2.44101883,  1.62110585,  0.43653402, -1.62605898,  1.62605898],
       [-2.02153886,  2.50345474,  0.63374177,  0.61498384, -0.61498384]])
```

Split the data into Train and Test sets

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.25, random_state = 40)
```

Create a Random Forest Classifier Model

In [24]:
```
# Create RFClassifier model
rf_model = RandomForestClassifier(n_estimators=500, random_state=78)

# Fit the model
rf_model = rf_model.fit(X_train, y_train)
```

In [25]:
```
# Make predictions
predictions = rf_model.predict(X_test)
pd.DataFrame({"Prediction": predictions, "Actual": y_test}).head(20)

# Generate accuracy score for predictions using y_test
acc_score = accuracy_score(y_test, predictions)
print(f"Accuracy Score : {acc_score}")
```
```
Accuracy Score : 0.5185185185185185
```

In [26]:
```
cm = confusion_matrix(y_test, predictions)
cm_df = pd.DataFrame(
    cm, index=["Actual 0", "Actual 1"],
    columns=["Predicted 0", "Predicted 1"]
)
display(cm_df)
```

	Predicted 0	Predicted 1
Actual 0	8	21
Actual 1	5	20

In [27]:
```
# Generating classification report
print("Classification Report")
print(classification_report(y_test, predictions))
```
```
Classification Report
              precision    recall  f1-score   support

           0       0.62      0.28      0.38        29
           1       0.49      0.80      0.61        25

    accuracy                           0.52        54
   macro avg       0.55      0.54      0.49        54
weighted avg       0.56      0.52      0.49        54
```

Create a Gradient Booster Model

In [28]:
```
# Choosing learning rate

model = GradientBoostingClassifier(n_estimators=20,
                                   learning_rate=0.05,
                                   max_features=2,
                                   max_depth=3,
                                   random_state=0)
model.fit(X_train,y_train)
GB_pred = model.predict(X_test)


# Scoring the model
print("Accuracy score (training): {0:.3f}".format(
        model.score(
            X_train,
            y_train)))
print("Accuracy score (validation): {0:.3f}".format(
        model.score(
            X_test,
            y_test)))
print()
```
```
Accuracy score (training): 0.801
Accuracy score (validation): 0.426
```

Evaluation of a Model

Using sklearn to build the confusion matrix and generate the classification report, evaluating the model's findings.

In [29]:
```
cm = confusion_matrix(y_test, GB_pred)
cm_df = pd.DataFrame(
    cm, index=["Actual 0", "Actual 1"],
    columns=["Predicted 0", "Predicted 1"]
)
display(cm_df)
```

	Predicted 0	Predicted 1
Actual 0	1	28
Actual 1	3	22

In [30]:
```
# Generating classification report
print("Classification Report")
print(classification_report(y_test, GB_pred))
```
```
Classification Report
              precision    recall  f1-score   support

           0       0.25      0.03      0.06        29
           1       0.44      0.88      0.59        25

    accuracy                           0.43        54
   macro avg       0.34      0.46      0.32        54
weighted avg       0.34      0.43      0.30        54
```

Random Forest Regressor Model - TESLA Stock Price Prediction

In this approach the tweet polarity, price differeces the adjusted closing prices were used to predict the future movement in Apple stock price. The adjusted closing prices data was stuctured such that previous time steps were used as input variables and the next time step as the output variable.

Select required data for regression analysis variables

In [31]:
```
df2 = df_merged[['Adj Close','Price Diff', 'sentiment_POSITIVE', 'Volume', 'tweet_polarity']]
df2.head()
```

Out[31]:

	Adj Close	Price Diff	sentiment_POSITIVE	Volume	tweet_polarity
date					
2020-11-12	609.989990	192.859985	0	46475000	0.217726
2020-11-13	408.500000	-201.489990	0	19771100	0.092293
2020-11-16	408.089996	-0.410004	1	26838600	0.200596
2020-11-17	441.609985	33.519989	1	61188300	0.192465
2020-11-18	486.640015	45.030030	0	78044000	0.201802

In [32]:
```
# pct change based on Adj close value
df2["Pct_change"] = df2["Adj Close"].pct_change()
# Drop null values
df2.dropna(inplace = True)
df2.head()
```

Out[32]:

	Adj Close	Price Diff	sentiment_POSITIVE	Volume	tweet_polarity	Pct_change
date						
2020-11-13	408.500000	-201.489990	0	19771100	0.092293	-0.330317
2020-11-16	408.089996	-0.410004	1	26838600	0.200596	-0.001004
2020-11-17	441.609985	33.519989	1	61188300	0.192465	0.082139
2020-11-18	486.640015	45.030030	0	78044000	0.201802	0.101968
2020-11-19	499.269989	12.629974	0	62475300	0.163081	0.025953

Creating the features and target variables data

This function fragments the data with an Xt - window to forecast Xt - rolling window.

Two numpy arrays are returned by the function:

X: The input consists of vectors.

y: The vector to be targeted.

The following are the parameters for the function:

df: The time series data's original DataFrame.

window: The number of days in which past closing prices will be utilised to make the forecast.
feature col number: The column number in the original DataFrame that contains the features.
target col number: The target's column number in the original DataFrame.

In [33]:
```
# It slices the data up using a rolling window of Xt-n to forecast Xt.
# This function "rolling_window" accepts the column number for the features (X) and the target (y).
# It gives you a numpy array with X and y values.

def rolling_window(df, window, feature_col_number1, feature_col_number2, feature_col_number3, target_col_num
    # Create empty lists "X_close", "X_Price_Diff", "Tweet score polarity" and y
    X_close = []
    X_Price_Diff = []
    X_tweet_polarity = []
    y = []
    for i in range(len(df) - window):

        # Get close, Price_Diff, sentiment, and target in the loop
        close = df.iloc[i:(i + window), feature_col_number1]
        Price_Diff = df.iloc[i:(i + window), feature_col_number2]
        polarity = df.iloc[i:(i + window), feature_col_number3]
        target = df.iloc[(i + window), target_col_number]

        # Append values in the lists
        X_close.append(close)
        X_Price_Diff.append(Price_Diff)
        X_tweet_polarity.append(polarity)
        y.append(target)

    return np.hstack((X_close,X_Price_Diff,X_tweet_polarity)), np.array(y).reshape(-1, 1)
```

In [34]:
```
# Predict Closing Prices using a 3 day window of previous closing prices
window_size = 3

feature_col_number1 = 0
feature_col_number2 = 1
feature_col_number3 = 2
target_col_number = 0
X, y = rolling_window(df2, window_size, feature_col_number1, feature_col_number2, feature_col_number3, targe
```

In [35]:
```
## Preprocess the data to scale in same minimum and maximum
X = preprocessing.StandardScaler().fit(X).transform(X.astype(float))
```

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.25, random_state = 40)
```

In [37]:
```
from xgboost import XGBRegressor

# Create the XG Boost regressor instance
model = XGBRegressor(objective='reg:squarederror', n_estimators=1000)
```

In [38]:
```
# Fit the model
model.fit(X_train, y_train)
```

Out[38]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=1000, n_jobs=4, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

In [39]:
```
# Make some predictions
predicted = model.predict(X_test)
```

In [40]:
```
# Evaluating the model
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, predicted)))
print('R-squared :', r2_score(y_test, predicted))
```
```
Root Mean Squared Error: 55.72430181881234
R-squared : 0.3820163267067429
```

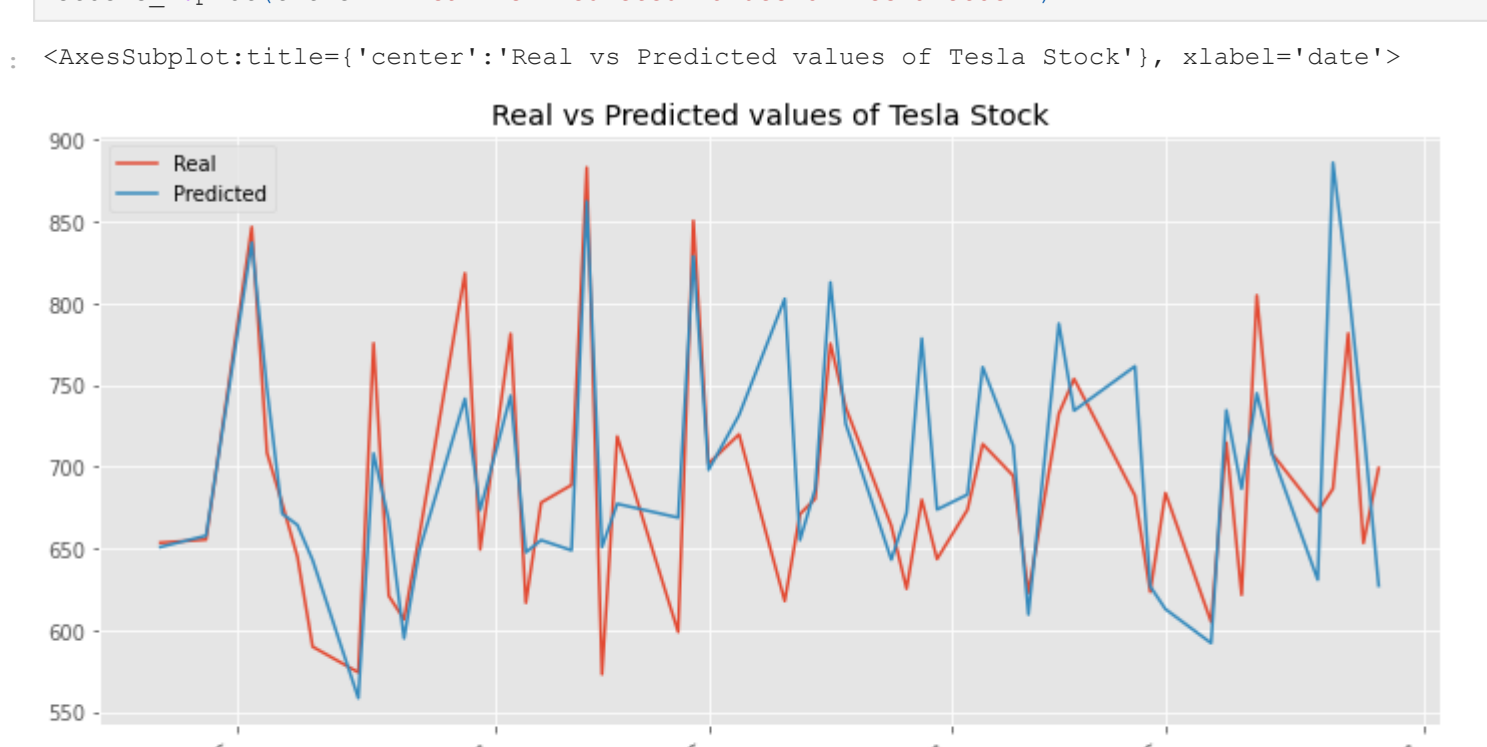
In [41]:
```
# Create a DataFrame of Real and Predicted values
stocks_1 = pd.DataFrame({"Real": y_test.ravel(), "Predicted": predicted},
                        index = df2.index[-len(y_test): ])
stocks_1.head()
```

Out[41]:

	Real	Predicted
date		
2021-08-10	653.380005	650.765625
2021-08-13	655.289978	657.669189
2021-08-16	846.640015	837.144958
2021-08-17	708.489990	747.709839
2021-08-18	677.349976	671.159851

In [54]:
```
# Plot the real vs predicted values as a line chart
import matplotlib.pyplot as plt
stocks_1.plot(title = "Real vs Predicted values of Tesla Stock")
```

Out[54]:
```
<AxesSubplot:title={'center':'Real vs Predicted values of Tesla Stock'}, xlabel='date'>
```



Random Forest Model

In [47]:
```
# Create the Random Forest regressor instance
rf_model = RandomForestRegressor(n_estimators=1000, max_depth=2, bootstrap=False, min_samples_leaf=1)
```

In [48]:
```
# Fit the model
rf_model.fit(X_train, y_train)
```

Out[48]:
```
RandomForestRegressor(bootstrap=False, max_depth=2, n_estimators=1000)
```

In [49]:
```
# Make some predictions
RF_pred = rf_model.predict(X_test)
```

Model EValuation:

- Using the X test and y test data, evaluate the model.
- Make predictions based on the X test data.
- Make a DataFrame with Real (y test) and Predicted (y test) values.
- Make a line graph of the real vs. expected values.

In [50]:
```
# Evaluating the model
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, predicted)))
print('R-squared :', r2_score(y_test, predicted))
```
```
Root Mean Squared Error: 55.72430181881234
R-squared : 0.3820163267067429
```

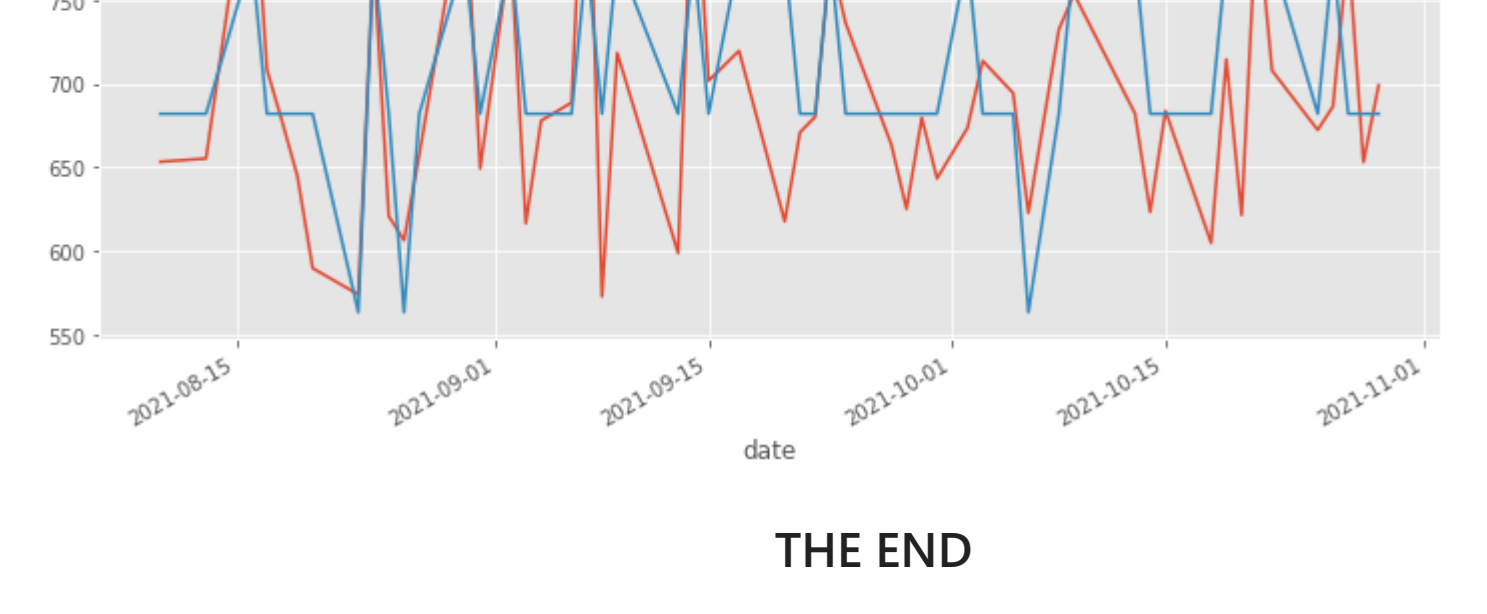
In [51]:
```
# Create a DataFrame of Real and Predicted values
stocks_2 = pd.DataFrame({"Real": y_test.ravel(), "Predicted": RF_pred},
                        index = df2.index[-len(y_test): ])
stocks_2.head()
```

Out[51]:

	Real	Predicted
date		
2021-08-10	653.380005	682.052715
2021-08-13	655.289978	682.052715
2021-08-16	846.640015	776.024811
2021-08-17	708.489990	682.052715
2021-08-18	677.349976	682.052715

In [55]:
```
# Plot the real vs predicted values as a line chart
stocks_2.plot(title = "Real vs Predicted values of TESLA")
```

Out[55]:
```
<AxesSubplot:title={'center':'Real vs Predicted values of TESLA'}, xlabel='date'>
```



THE END

In [ ]: