

# ELON TWEET ANALYSIS



Elon Musk, the richest man on Earth with over 107M followers on twitter, uses the platform to share his opinions, often controversial.

But does he wield pricing power?

VS



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# QUESTIONS WE HOPE TO ANSWER:

- Does a correlation exist between Elons tweets and stock market reactions ?
- Is it possible to predict whether or not a stock will rise/fall/remain with the sentiment of his tweets?
- Can we design a stock purchase method based on Elons tweets?



VS

A purple diagonal banner with the letters "VS" in white, suggesting a comparison or competition.

# QUESTIONS WE HOPE TO ANSWER:



- Do Elons tweets affect companies other than TSLA? (TEST: 'DOGE' + 'TWTR')
- Should we consider Elons tweet history on a certain company before investing?



VS

A purple diagonal banner with the letters "VS" in white, stylized to look like a lightning bolt or a checkmark.

TWEET DATA  
pulled from



\*Timeframe:  
December 1 2011 - April 13, 2021

# STOCKS ANALYZED

Tesla (TSLA)

\*Timeframe:  
June 29 2010 - April 13, 2021

Dogecoin (DOGE)

\*Timeframe:  
November 9 2017 - April 13, 2021

SP500 (SPY)

\*Timeframe:  
June 29 2010 - April 13, 2021

## STOCK DATA

pulled from

**yahoo!**  
**finance**

# TWEETS IMPORTED

## Elon\_Tweet\_Sentiment\_Analysis

```
[214...  
import pandas as pd  
from pathlib import Path  
import warnings  
warnings.filterwarnings("ignore")  
import yfinance as yf
```

```
[215...  
elon_tweets_reply = pd.read_csv(Path("../Resources/tweets_and_replies.csv"))  
display(elon_tweets_reply.head())  
display(elon_tweets_reply.tail())
```

	<b>Id</b>	<b>Date</b>	<b>Text</b>	<b>ConversationId</b>
0	1575021541103874048	2022-09-28 07:16:12+00:00	<a href="https://t.co/mEBAgBCCkj">https://t.co/mEBAgBCCkj</a>	1575021541103874048
1	1574958348163612672	2022-09-28 03:05:06+00:00	I guess this joke is a slow burn ... 🤪	1574895951973449729
2	1574957722415398912	2022-09-28 03:02:36+00:00	@WholeMarsBlog Big improvement in high speed c...	1574940528520536064
3	1574956999938256896	2022-09-28 02:59:44+00:00	@chrispavlovski @dbongino @rustyrockets Maybe ...	1574861160502927385
4	1574901832622612480	2022-09-27 23:20:31+00:00	Make "hair on fire" not just a metaphor	1574901832622612480

	<b>Id</b>	<b>Date</b>	<b>Text</b>	<b>ConversationId</b>
7248	1433137351203561474	2021-09-01 18:39:05+00:00	@Kristennetten @StianWalgermo @Tesla @ARKInves...	1433080556376530952
7249	1433123220643717120	2021-09-01 17:42:56+00:00	@thesheetztweetz They can shake their fist at ...	1433081862918975496
7250	1433122554156257280	2021-09-01 17:40:17+00:00	@StianWalgermo @Tesla @ARKInvest @WholeMarsBlo...	1433080556376530952
7251	1433121450446127106	2021-09-01 17:35:54+00:00	@Max9907826460 @TeslaratiTeam Our new crane!	1433001281753337856
7252	1433115031940440065	2021-09-01 17:10:24+00:00	@AaronS5_ @ashleevance 2021 has been the year ...	1433110569100333061

```
[216...  
elon_tweets_reply.info()
```

# TWEETS 'CLEANED'

```
[219...  
def preprocess_tweet(sen):  
    '''Cleans text data up, leaving only 2 or more char long non-stopwords composed of A-Z & a-z only  
    in lowercase'''  
  
    sentence = sen.lower()  
  
    # Remove RT  
    sentence = re.sub('RT @\w+:', ' ', sentence)  
  
    # Remove special characters  
    sentence = re.sub("@[A-Za-z0-9]+|([^\w+\.\/\.\$+])|(\w+\.\.\.\w+)", " ", sentence)  
  
    # Single character removal  
    sentence = re.sub(r"\s+[a-zA-Z]\s+", ' ', sentence) # When we remove apostrophe from the word "Mark's", the apostrophe is replaced by an empty  
    # Remove multiple spaces  
    sentence = re.sub(r'\s+', ' ', sentence) # Next, we remove all the single characters and replace it by a space which creates multiple spaces in  
  
    return sentence  
  
[220...  
cleaned_tweets = []  
  
for tweet in elon_tweets_reply['Text']:  
    cleaned_tweet = preprocess_tweet(tweet)  
    cleaned_tweets.append(cleaned_tweet)  
  
[221...  
elon_tweets_reply['cleaned'] = pd.DataFrame(cleaned_tweets)  
elon_tweets_reply.head(5)  
  
[221...  


|   | Id                  | Date                      | Text                                              | ConversationId      | cleaned                                          |
|---|---------------------|---------------------------|---------------------------------------------------|---------------------|--------------------------------------------------|
| 0 | 1575021541103874048 | 2022-09-28 07:16:12+00:00 | https://t.co/mEBAgBCCkj                           | 1575021541103874048 |                                                  |
| 1 | 1574958348163612672 | 2022-09-28 03:05:06+00:00 | I guess this joke is a slow burn ... 🤪            | 1574895951973449729 | i guess this joke is slow burn                   |
| 2 | 1574957722415398912 | 2022-09-28 03:02:36+00:00 | @WholeMarsBlog Big improvement in high speed c... | 1574940528520536064 | big improvement in high speed cross traffic v... |
| 3 | 1574956999938256896 | 2022-09-28 02:59:44+00:00 | @chrispavlovski @dbongino @rustyrockets Maybe ... | 1574861160502927385 | maybe worth talking at some point                |
| 4 | 1574901832622612480 | 2022-09-27 23:20:31+00:00 | Make "hair on fire" not just a metaphor           | 1574901832622612480 | make hair on fire not just metaphor              |


```

# CALCULATING NEGATIVE, POSITIVE, NEUTRAL AND COMPOUND VALUES

```
#Calculating Negative, Positive, Neutral and Compound values
```

```
elon_tweets_reply[['polarity', 'subjectivity']] = elon_tweets_reply['cleaned'].apply(lambda Text: pd.Series(TextBlob(Text).sentiment))
for index, row in elon_tweets_reply['cleaned'].iteritems():
    score = SentimentIntensityAnalyzer().polarity_scores(row)
    neg = score['neg']
    neu = score['neu']
    pos = score['pos']
    comp = score['compound']
    if comp <= -0.05:
        elon_tweets_reply.loc[index, 'sentiment'] = "negative"
    elif comp >= 0.05:
        elon_tweets_reply.loc[index, 'sentiment'] = "positive"
    else:
        elon_tweets_reply.loc[index, 'sentiment'] = "neutral"
    elon_tweets_reply.loc[index, 'neg'] = neg
    elon_tweets_reply.loc[index, 'neu'] = neu
    elon_tweets_reply.loc[index, 'pos'] = pos
    elon_tweets_reply.loc[index, 'compound'] = comp

elon_tweets_reply.head(5)[['polarity', 'subjectivity']] = elon_tweets_reply['cleaned'].apply(lambda Text: pd.Series(TextBlob(Text).sentiment))
for index, row in elon_tweets_reply['cleaned'].iteritems():
    score = SentimentIntensityAnalyzer().polarity_scores(row)
    neg = score['neg']
    neu = score['neu']
    pos = score['pos']
    comp = score['compound']
    if comp <= -0.05:
        elon_tweets_reply.loc[index, 'sentiment'] = "negative"
    elif comp >= 0.05:
        elon_tweets_reply.loc[index, 'sentiment'] = "positive"
    else:
        elon_tweets_reply.loc[index, 'sentiment'] = "neutral"
    elon_tweets_reply.loc[index, 'neg'] = neg
    elon_tweets_reply.loc[index, 'neu'] = neu
    elon_tweets_reply.loc[index, 'pos'] = pos
    elon_tweets_reply.loc[index, 'compound'] = comp

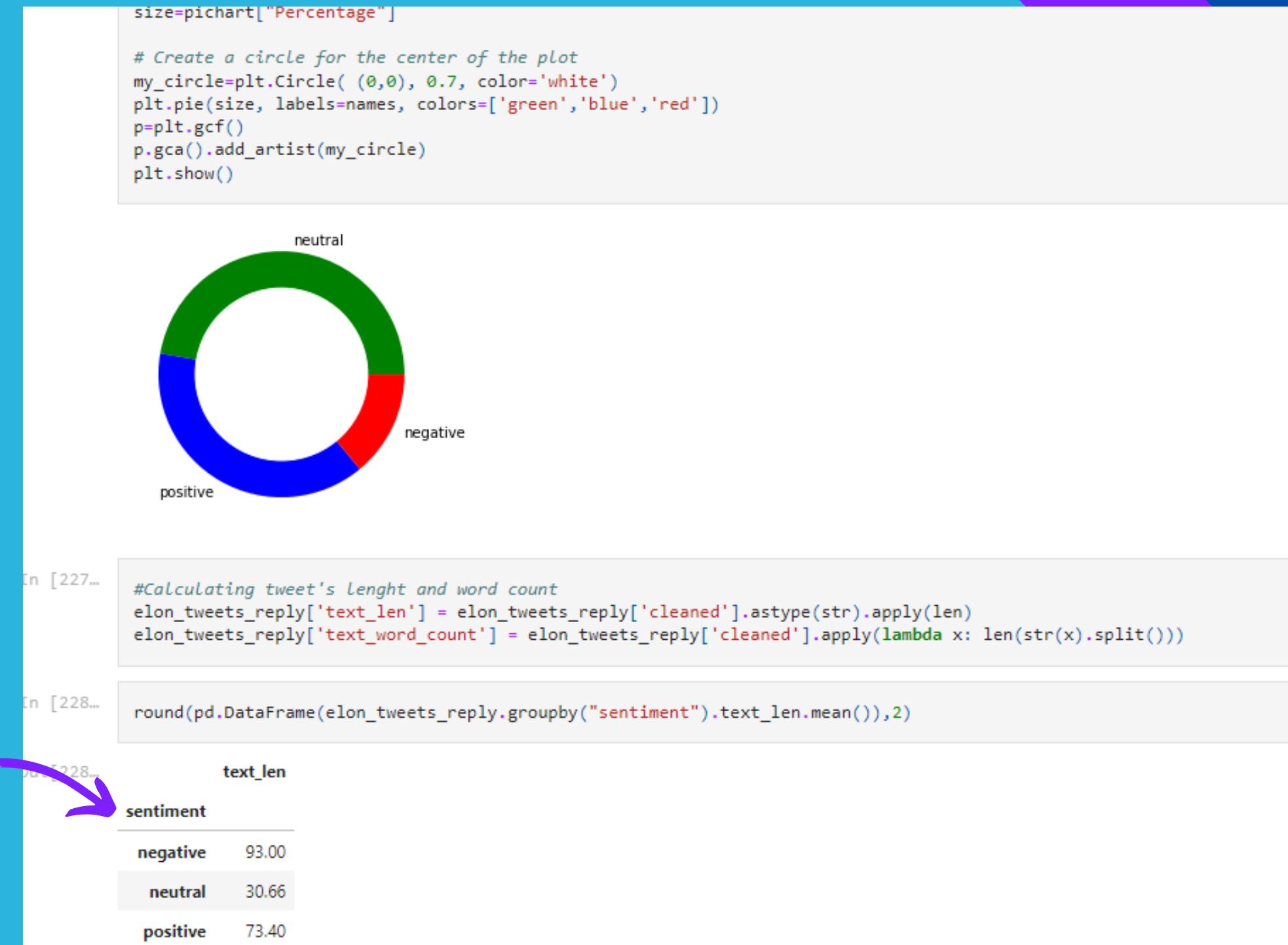
elon_tweets_reply.head(5)
```

	Total	Percentage
neutral	3430	47.29
positive	2807	38.70
negative	1016	14.01

	Date	Text	ConversationId	cleaned	polarity	subjectivity	sentiment	neg	neu	pos	compound
0	2022-09-28 07:16:12+00:00	https://t.co/mEBAgBCCkj	1575021541103874048		0.00	0.00	neutral	0.000	0.000	0.000	0.0000
1	2022-09-28 03:05:06+00:00	I guess this joke is a slow burn ... 🤪	1574895951973449729	i guess this joke is slow burn	-0.30	0.40	positive	0.000	0.694	0.306	0.2960
2	2022-09-28 03:02:36+00:00	@WholeMarsBlog Big improvement in high speed c...	1574940528520536064	big improvement in high speed cross traffic v...	0.04	0.16	positive	0.000	0.786	0.214	0.4588
3	2022-09-28 02:59:44+00:00	@chrisspavlovski @dbongino @rustyrockets Maybe ...	1574861160502927385	maybe worth talking at some point	0.30	0.10	positive	0.000	0.725	0.275	0.2263
4	2022-09-27 23:20:31+00:00	Make "hair on fire" not just a metaphor	1574901832622612480	make hair on fire not just metaphor	0.00	0.00	negative	0.286	0.714	0.000	-0.3400

# ELON HAS MORE TO SAY WHEN THINGS AREN'T GOING HIS WAY....

Tweets are longer when the sentiment has feeling...especially negative



# VERIFYING TWEET SENTIMENT TO MARKET HAPPENINGS

```
import time

# Load env variables in from .env
load_dotenv()

# Set base URL for meaningcloud API
url = "https://api.meaningcloud.com/sentiment-2.1"

# Create payload to send to meaningcloud API
payload={
    'key': os.getenv("MEANINGCLOUD_API_KEY"),
    'txt': '',
    'lang': 'en'
}

# Read the CSV of yesterday's tweets and gather the sentiments from meaningcloud
yesterdays_elon_tweets_df = pd.read_csv('yesterday.csv')

# Iterate through yesterdays_tweets dataframe and get sentiment from meaningcloud API
for index, row in yesterdays_elon_tweets_df.iterrows():
    time.sleep(1)
    # Set the payload text to the raw tweet text
    payload['txt'] = row['Tweet']

    # Call meaningcloud API and store response as JSON
    response = requests.post(url, data=payload).json()

    # Update the dataframe with the new columns for score_tag and confidence
    yesterdays_elon_tweets_df.at[index, 'score_tag'] = response['score_tag']
    yesterdays_elon_tweets_df.at[index, 'confidence'] = response['confidence']

# Create a column 'datetime' by concatenating the 'date' and 'time' columns
yesterdays_elon_tweets_df['datetime'] = pd.to_datetime(yesterdays_elon_tweets_df['date'] + ' ' + yesterdays_elon_tweets_df['time'])

# Set the 'datetime' column as the index
yesterdays_elon_tweets_df = yesterdays_elon_tweets_df.set_index('datetime')

# Localize the times to UTC
yesterdays_elon_tweets_df = yesterdays_elon_tweets_df.tz_localize('utc')

# Output the resulting dataframe to CSV
yesterdays_elon_tweets_df.to_csv('yesterdays_elon_tweets_df.csv')
```

Tweet sentiment is determined

Dataframe now includes tweet and sentiment

df to csv...

# DATASET NOW INCLUDES SENTIMENT

	datetime	id	conversation_id	created_at	date	time	timezone	user_id	username
9	2021-04-11 01:09:02+...	1381006333864861696	1381006333864861696	2021-04-11 01:09:02 ...	2021-04-11	01:09:02	300	44196397	elonmusk
10	2021-04-10 23:22:20...	1380979481309945856	1380949316215451649	2021-04-10 23:22:20 ...	2021-04-10	23:22:20	300	44196397	elonmusk
11	2021-04-10 22:49:26...	1380971204299747328	1380873129535418369	2021-04-10 22:49:26 ...	2021-04-10	22:49:26	300	44196397	elonmusk
12	2021-04-10 22:46:36...	1380970491356225536	1380860614990499840	2021-04-10 22:46:36 ...	2021-04-10	22:46:36	300	44196397	elonmusk
13	2021-04-10 11:32:35+...	1380800869382320134	1379310700011479043	2021-04-10 11:32:35 ...	2021-04-10	11:32:35	300	44196397	elonmusk
14	2021-04-10 11:23:03+...	1380798469862957057	1379310700011479043	2021-04-10 11:23:03 ...	2021-04-10	11:23:03	300	44196397	elonmusk
15	2021-04-10 11:16:58+...	1380796939151704071	1379310700011479043	2021-04-10 11:16:58 ...	2021-04-10	11:16:58	300	44196397	elonmusk
16	2021-04-10 10:46:16...	1380789209582034944	1379310700011479043	2021-04-10 10:46:16 ...	2021-04-10	10:46:16	300	44196397	elonmusk
17	2021-04-10 10:45:17...	1380788962558496768	1380788934905503744	2021-04-10 10:45:17 ...	2021-04-10	10:45:17	300	44196397	elonmusk
18	2021-04-10 10:45:10...	1380788934905503744	1380788934905503744	2021-04-10 10:45:10 ...	2021-04-10	10:45:10	300	44196397	elonmusk
19	2021-04-10 10:29:45...	1380785053542666242	1380784868729122818	2021-04-10 10:29:45 ...	2021-04-10	10:29:45	300	44196397	elonmusk
20	2021-04-10 10:29:01...	1380784868729122818	1380784868729122818	2021-04-10 10:29:01 ...	2021-04-10	10:29:01	300	44196397	elonmusk
21	2021-04-10 10:25:11+...	1380783907096850433	1380419366169153537	2021-04-10 10:25:11 ...	2021-04-10	10:25:11	300	44196397	elonmusk
22	2021-04-10 10:15:47...	1380781539647053826	1380781539647053826	2021-04-10 10:15:47 ...	2021-04-10	10:15:47	300	44196397	elonmusk
23	2021-04-10 10:12:20...	1380780669895208961	1380777569964883969	2021-04-10 10:12:20 ...	2021-04-10	10:12:20	300	44196397	elonmusk
24	2021-04-10 09:51:12...	1380775355502317568	1380138845145038858	2021-04-10 09:51:12 ...	2021-04-10	09:51:12	300	44196397	elonmusk
25	2021-04-10 09:44:23...	1380773639038111751	1380772975733923841	2021-04-10 09:44:23 ...	2021-04-10	09:44:23	300	44196397	elonmusk
26	2021-04-10 09:41:45...	1380772975733923841	1380772975733923841	2021-04-10 09:41:45 ...	2021-04-10	09:41:45	300	44196397	elonmusk
27	2021-04-10 04:07:04...	1380688750179586049	1380388899193712642	2021-04-10 04:07:04 ...	2021-04-10	04:07:04	300	44196397	elonmusk
28	2021-04-10 04:04:26...	1380688087697612802	1380388899193712642	2021-04-10 04:04:26 ...	2021-04-10	04:04:26	300	44196397	elonmusk
29	2021-04-10 03:33:12...	1380680228230426625	1380332424467341315	2021-04-10 03:33:12 ...	2021-04-10	03:33:12	300	44196397	elonmusk
30	2021-04-10 01:24:01...	1380647716959645700	1380647716959645700	2021-04-10 01:24:01 ...	2021-04-10	01:24:01	300	44196397	elonmusk
31	2021-04-10 01:21:50...	1380647165597339650	1380313600187719682	2021-04-10 01:21:50 ...	2021-04-10	01:21:50	300	44196397	elonmusk
32	2021-04-09 22:41:08...	1380606725380706304	1380388899193712642	2021-04-09 22:41:08 ...	2021-04-09	22:41:08	300	44196397	elonmusk
33	2021-04-09 22:41:01...	1380606694816800768	1380388899193712642	2021-04-09 22:41:01 ...	2021-04-09	22:41:01	300	44196397	elonmusk
34	2021-04-09 22:39:26...	1380606296945135617	1380575287516176384	2021-04-09 22:39:26 ...	2021-04-09	22:39:26	300	44196397	elonmusk
35	2021-04-09 22:14:21...	1380599983481577472	1380599009874743298	2021-04-09 22:14:21 ...	2021-04-09	22:14:21	300	44196397	elonmusk
36	2021-04-09 22:13:12...	1380599694154362882	1380388899193712642	2021-04-09 22:13:12 ...	2021-04-09	22:13:12	300	44196397	elonmusk

# BUILDING THE TWEET SENTIMENT LAB...

All data is loaded

```
# elon_tweets = Path("./TweetsElonMusk.csv")
doge = Path("./doge.csv")
sp500 = Path("./sp500.csv")
tsla = Path("./tsla.csv")
sentiment = Path("./sentiment_df.csv")
```

Calculating (+) or (-) returns

```
pct_chgs = doge_df["Close"].pct_change()
neg = 0
pos = 0
for i in pct_chgs:
    if i < 0:
        neg += 1
    else:
        pos += 1
display(neg)
display(pos)
```

906

877

```
# Shift the percent change outcome up one day because we are trying to predict the price change for the next day
merged_df["pct_chg"] = merged_df["pct_chg"].shift(-1)
merged_df.dropna(inplace=True)
```

```
X = merged_df.iloc[:, :-1]
y = merged_df.iloc[:, -1]
```

```
X = X.drop("Date", axis=1)
```

```
# change to -1 for negative and 1 for positive
for i, v in y.items():
    if v > 0:
        y[i] = 1
    elif v < 0:
        y[i] = -1
    else:
        y[i] = -1
```

merged\_df includes tsla data and sentiment data



# DIFFERENT MACHINE LEARNING MODELS

## Logistic Regression

lr Classification Report for Tesla

	precision	recall	f1-score	support
0.0	0.57	0.89	0.70	198
1.0	0.54	0.16	0.25	158
accuracy			0.57	356
macro avg	0.56	0.53	0.47	356
weighted avg	0.56	0.57	0.50	356

## SVC

SVC Classification Report for Tesla

	precision	recall	f1-score	support
0.0	0.0	0.70	0.80	0.75
1.0	1.0	0.70	0.57	0.63
accuracy			0.70	356
macro avg	0.70	0.69	0.69	356
weighted avg	0.70	0.70	0.69	356

## Decision Tree Classifier

DTC Classification Report for Tesla

	precision	recall	f1-score	support
0.0	0.64	0.69	0.66	198
1.0	0.57	0.52	0.54	158
accuracy			0.61	356
macro avg	0.61	0.60	0.60	356
weighted avg	0.61	0.61	0.61	356

## Random Forest Classifier

rf Classification Report for Tesla

	precision	recall	f1-score	support
0.0	0.0	0.69	0.75	0.72
1.0	1.0	0.65	0.58	0.61
accuracy			0.67	356
macro avg	0.67	0.66	0.67	356
weighted avg	0.67	0.67	0.67	356



# ATTEMPT TO FINE TUNE:

Randomized Search

	{'kernel': 'rbf', 'gamma': 0.1, 'degree': 1, 'C': 10}			
	precision	recall	f1-score	support
-1.0	0.66	0.72	0.69	199
1.0	0.60	0.54	0.57	158
accuracy			0.64	357
macro avg	0.63	0.63	0.63	357
weighted avg	0.64	0.64	0.64	357

```
param_grid = {'C': [0.1, 1, 10, 100, 1000],  
             'gamma': [1, 0.1, 0.01, 0.001, 0.0001],  
             'kernel': ['sigmoid', 'rbf'],  
             'degree': [1, 2, 3, 4]}  
}
```

Halving Grid Search:

	{'C': 1, 'degree': 3, 'gamma': 0.1, 'kernel': 'rbf'}			
	precision	recall	f1-score	support
-1.0	0.65	0.72	0.69	199
1.0	0.60	0.52	0.56	158
accuracy			0.63	357
macro avg	0.63	0.62	0.62	357
weighted avg	0.63	0.63	0.63	357

# ATTEMPT TO FINE TUNE CONT. :

Grid Search

	precision	recall	f1-score	support
-1.0	0.66	0.72	0.69	199
1.0	0.60	0.54	0.57	158
accuracy			0.64	357
macro avg	0.63	0.63	0.63	357
weighted avg	0.64	0.64	0.64	357

```
param_grid = {'C': [0.1, 1, 10, 100, 1000],  
             'gamma': [1, 0.1, 0.01, 0.001, 0.0001],  
             'kernel': ['sigmoid', 'rbf'],  
             'degree': [1, 2, 3, 4]}  
}
```

Halving Random Search:

	precision	recall	f1-score	support
-1.0	0.65	0.72	0.69	199
1.0	0.60	0.52	0.56	158
accuracy			0.63	357
macro avg	0.63	0.62	0.62	357
weighted avg	0.63	0.63	0.63	357

# BUT DOES HE AFFECT MORE THAN TESLA?

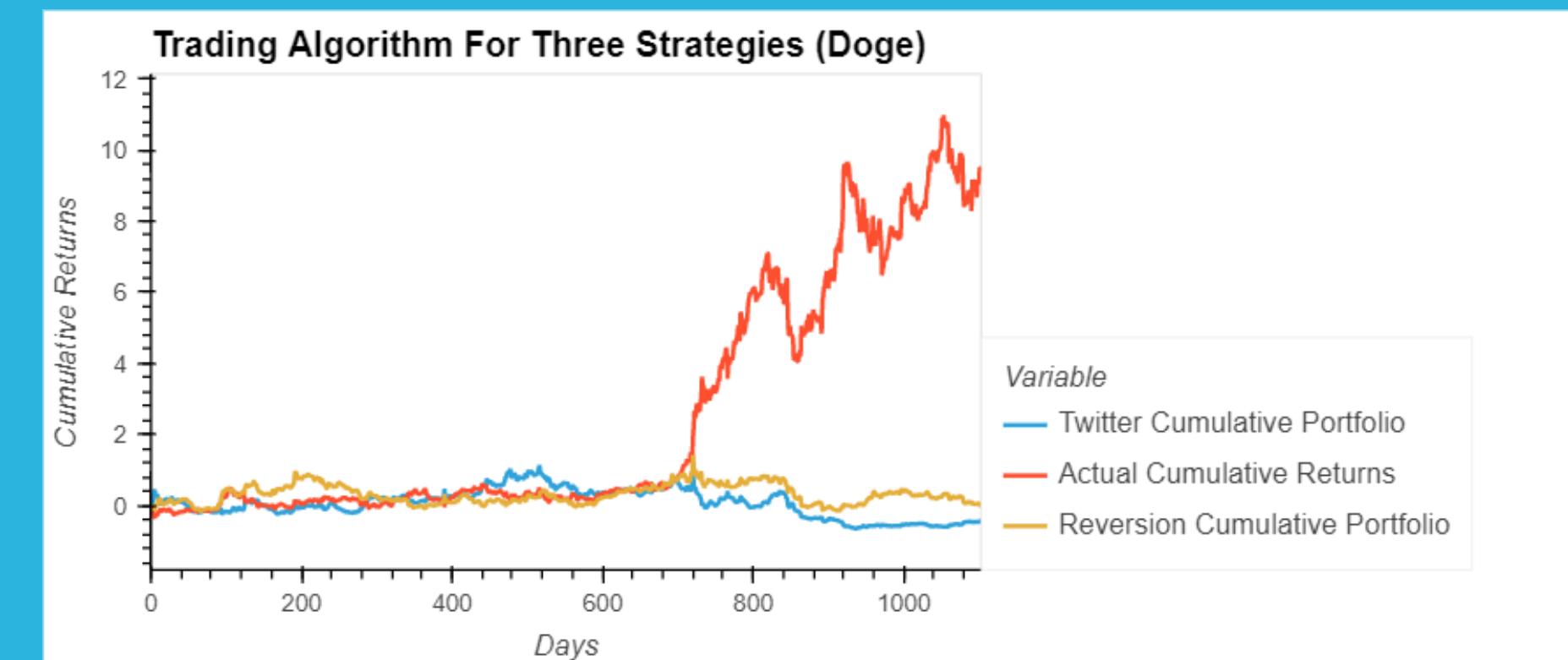
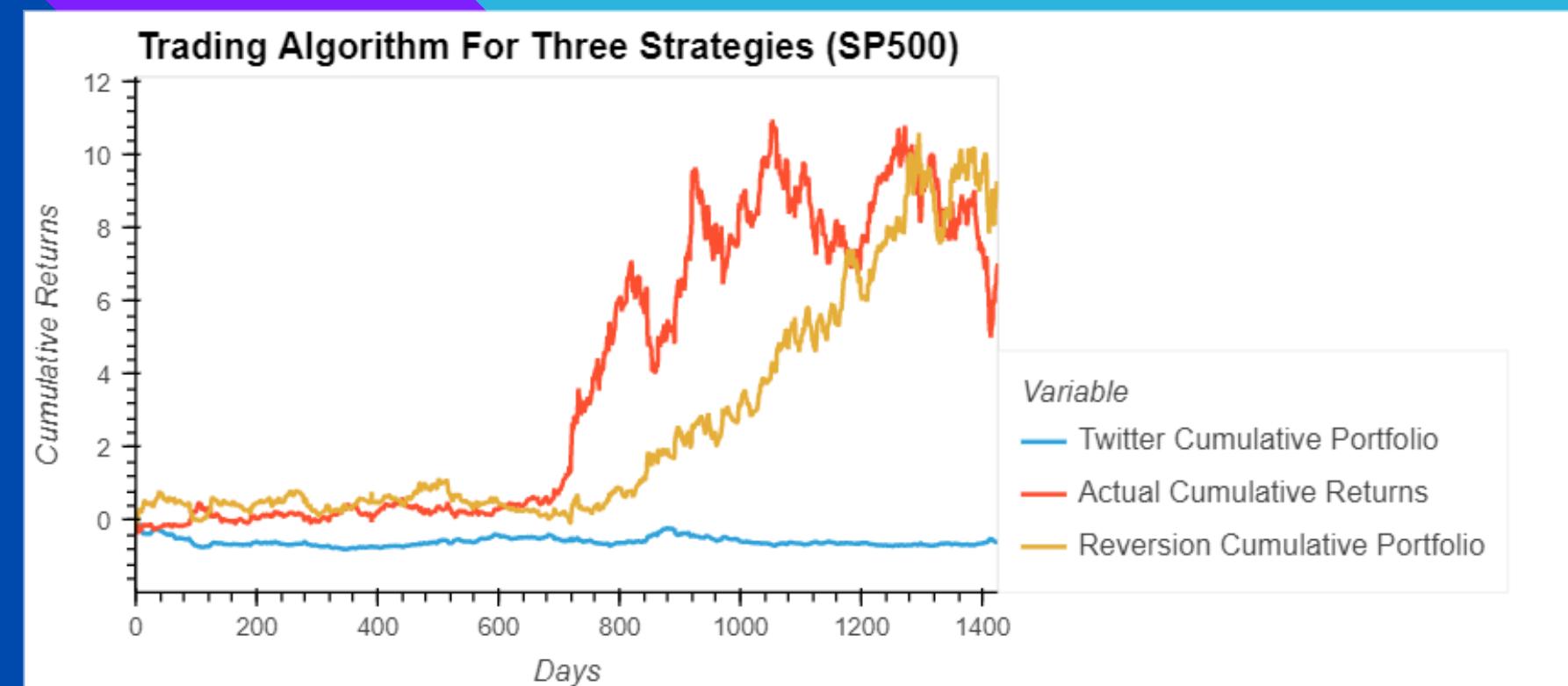
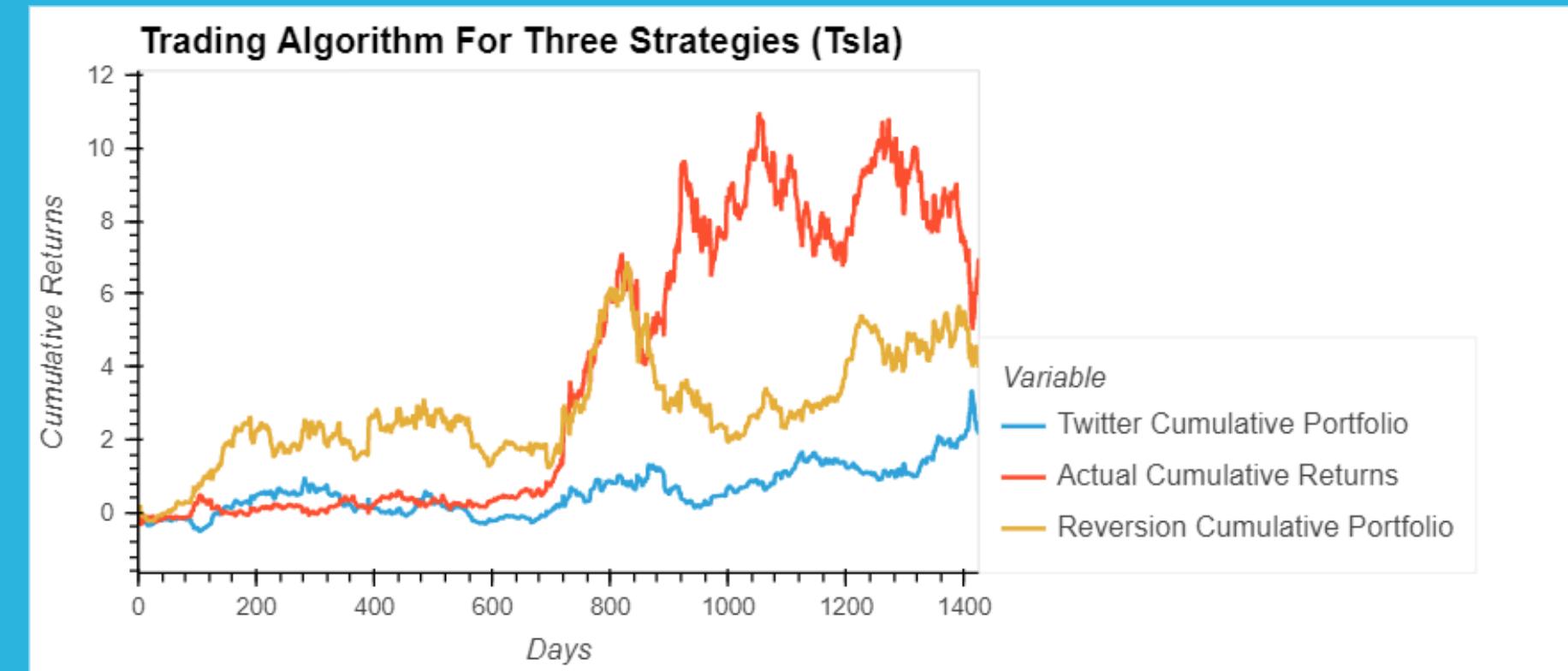
SVC Model on 'DOGE'

	precision	recall	f1-score	support
-1.0	0.66	0.73	0.69	163
1.0	0.54	0.46	0.50	113
accuracy			0.62	
macro avg	0.60	0.60	0.60	276
weighted avg	0.61	0.62	0.61	276

SVC Model on 'SPY'

	precision	recall	f1-score	support
-1.0	0.69	0.83	0.75	224
1.0	0.57	0.38	0.46	133
accuracy			0.66	
macro avg	0.63	0.60	0.61	357
weighted avg	0.65	0.66	0.64	357

# ALGORITHMIC TRADING:



# RESULTS:

Does a correlation exist between Elon's tweets and stock market reactions ?

- YES Elon's tweets have a greater correlation to stock prices than what a simple binary example would infer

Is it possible to predict whether or not a stock will rise/fall/remain with the sentiment of his tweets?

- YES Using our SVC machine learning model we have 70+% accuracy rate of correctly predicting the market reaction

Can we design a stock purchase method based on Elon's tweets?

- YES Using our SVC machine learning model we have 70+% accuracy rate of correctly predicting the market reaction

# TESTING AGAINST YESTERDAY'S TWEETS...

\*Timeframe:  
October 2, 2022

Search this file...							Retweets	Quote Tweets	Likes	score_tag	confidence
1	datetime	date	time	Tweet							
2	2022-10-02 11:49:00+00:00	2022-10-02	11:49:00	Do not let ancient grudge break to new mutiny			7619	623	93000	P	92
3	2022-10-02 16:03:00+00:00	2022-10-02	16:03:00	Pruferock II emerging from the ground			3584	349	59300	NONE	100
4	2022-10-02 16:47:00+00:00	2022-10-02	16:47:00	The embarrassing hose down photos were highly motivating tbh			178	58	5817	P	100
5	2022-10-02 16:27:00+00:00	2022-10-02	16:27:00	Tunneled under the road from one property to another. This is to test the new machine			223	27	5458	NONE	100
6	2022-10-02 16:26:00+00:00	2022-10-02	16:26:00	Unfortunately, snail is still faster, but TBC might beat snail by end of 2024			179	28	4390	N	100
7	2022-10-02 15:08:00+00:00	2022-10-02	15:08:00	But between now and then, we do actually need to work hard			229	43	3985	NONE	100
8	2022-10-02 15:07:00+00:00	2022-10-02	15:07:00	I don't care about boosting the stock, but the economic implications are obvious			842	162	15500	N	92
9	2022-10-02 11:32:00+00:00	2022-10-02	11:32:00	So many talented Russians in America			139	25	3354	P+	100
10	2022-10-02 11:22:00+00:00	2022-10-02	11:22:00	Customer experience suffers when there is an end of quarter rush. Steady as she goes is the right move.			328	51	4833	NEU	94
11	2022-10-02 09:46:00+00:00	2022-10-02	9:46:00	Master Plan (ménage à Trois) is all about tonnage			357	43	6073	NONE	100
12	2022-10-02 08:04:00+00:00	2022-10-02	8:04:00	Thanks, we have a great team			264	22	6808	P+	100
13	2022-10-02 08:03:00+00:00	2022-10-02	8:03:00	Beautiful			494	47	15200	P	100
14	2022-10-02 04:41:00+00:00	2022-10-02	4:41:00	Exactly			250	35	7413	NONE	100

# HOW WAS THE MODEL FOR OCT 2?

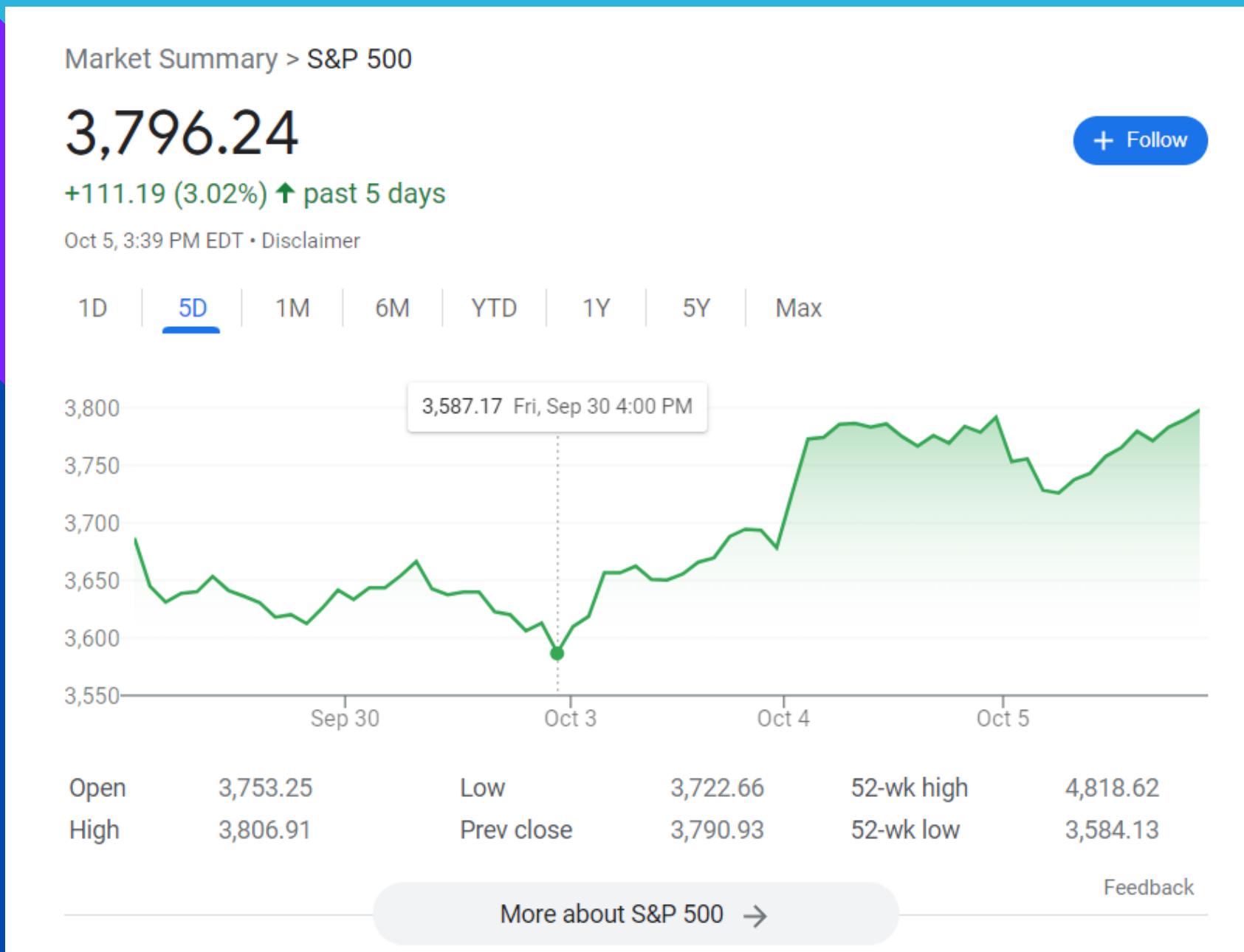
## TESLA:



Prediction for October  
2nd, 2022: Sell

(Good prediction)

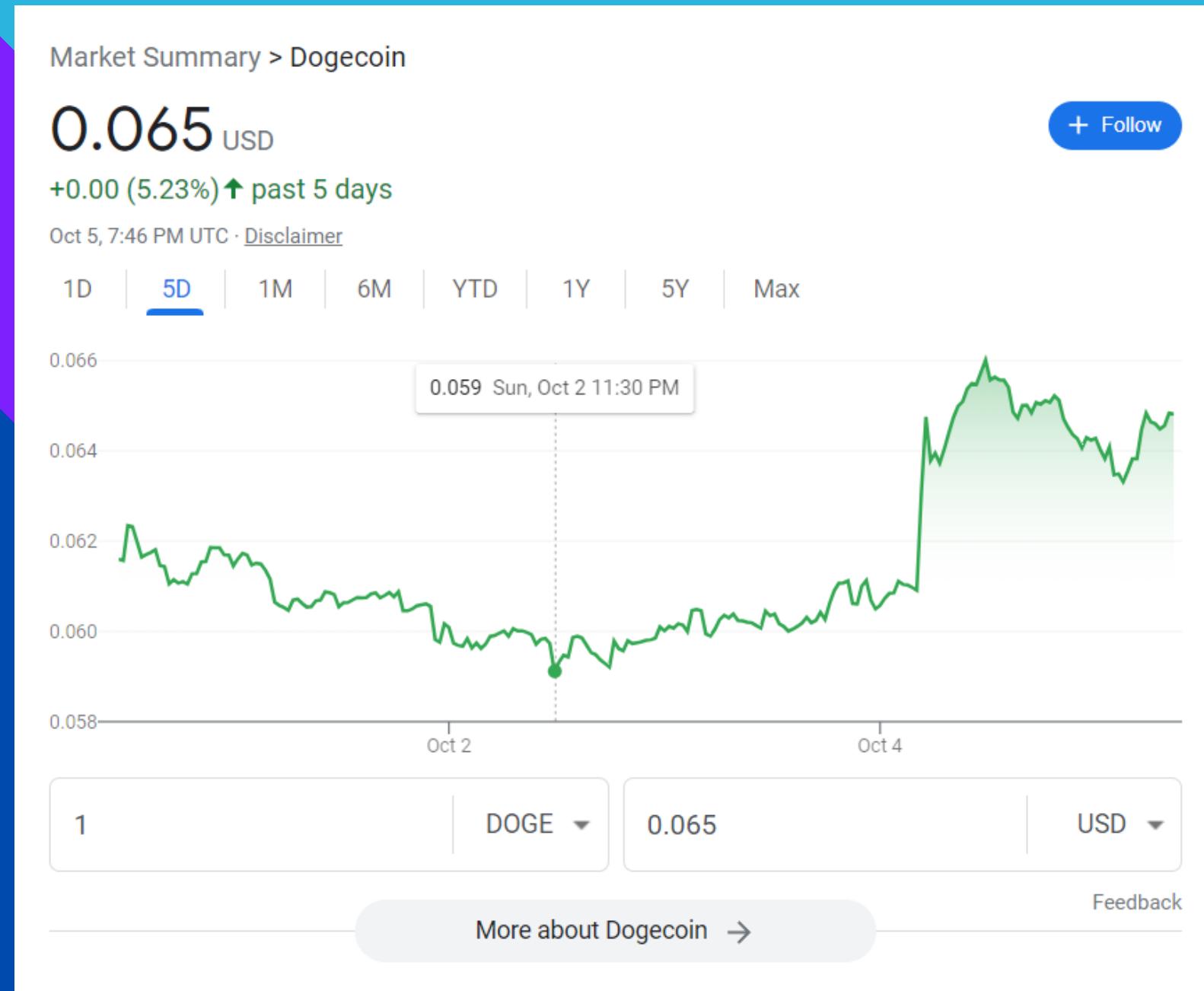
# HOW WAS THE MODEL FOR OCT 2? S&P 500:



Prediction for October 2nd, 2022: Sell

(Bad prediction)

# HOW WAS THE MODEL FOR OCT 2? DOGE<sup>COIN</sup>:



Prediction for October  
2nd, 2022: Sell

(Bad prediction)

# RESULTS:

Do Elons tweets affect companies other than TSLA?  
(TEST: 'DOGE' + 'TWTR')

- YES Elon's tweets have a greater correlation to stock prices than what a simple binary example would infer -EVEN for stocks outside of TSLA

Is it possible to predict whether or not a stock will rise/fall/remain with the sentiment of his tweets?

- YES Using our SVC machine learning model we have 60+% accuracy rate of correctly predicting the market reaction

*However - this model is consistently less profitable than just maintaining a long position in the market*

# FIND MORE ON GITHUB

[https://github.com/  
smruthid/ElonTweetAnalysis](https://github.com/smruthid/ElonTweetAnalysis)

The screenshot shows the GitHub repository page for smruthid/ElonTweetAnalysis. The repository is public and contains 5 branches and 0 tags. The main branch has 18 commits. The commit history includes various files like KaggleData, images, .gitignore, LICENSE, README.md, TweetsElonMusk.csv, acetone\_font.otf, doge.csv, doge.ipynb, doge\_hourly.csv, lab.ipynb, requirements.txt, sentiment\_analyzer.ipynb, sentiment\_df.csv, sp500.csv, sp500.ipynb, sp500\_hourly.csv, and sp500\_model\_training.ipynb. The commits range from 2 hours ago to 6 days ago.

The screenshot shows the README.md file for the project. It features a header image with the Twitter logo and a portrait of Elon Musk, with the text "ELON TWEET ANALYSIS". The text describes the project as comparing the sentiments of Elon Musk's tweets against stock market reactions. It also mentions that Elon Musk, the richest man on Earth with over 107M followers on Twitter, uses the platform to share his opinions, often controversial. A tweet from Elon Musk (@elonmusk) is displayed, stating "Tesla stock price is too high imo". A callout bubble provides context about the SEC's review of the tweet. The "BACKGROUND" section explains the purpose of the project, and the "PROJECT OVERVIEW" section lists the goals.

Elon Musk, the richest man on Earth with over 107M followers on Twitter, uses the platform to share his opinions, often controversial. In addition, Elon was charged with securities fraud by the SEC because of misleading tweets causing price fluctuations.

**BACKGROUND**

This is a multi-function jupyter lab notebook (stored as `sentiment_analyzer.ipynb`) that compares the sentiments of Elon Musk tweets versus stock market reactions from the individual stocks referenced in his tweets. Elon Musk, the richest man on Earth with over 107M followers on Twitter, uses the platform to share his opinions, often controversial. In addition, Elon was charged with securities fraud by the SEC because of misleading tweets causing price fluctuations.

**PROJECT OVERVIEW**

In this notebook we hope to answer the following questions:

- Does a correlation exist between Elons tweets and stock market reactions ?