

Elon Musk's Tweets vs Bitcoin Price

Introduction

The cryptocurrency market is known for its extreme volatility, with prices frequently fluctuating due to various factors, including technological developments, regulatory news, and social media influence. Among these factors, social media platforms, particularly Twitter, play a crucial role in shaping investor sentiments and market dynamics. Elon Musk, CEO of companies such as Tesla and SpaceX, has emerged as one of the most influential figures in the cryptocurrency landscape. His tweets often impact the price of Bitcoin, causing substantial price movements in response to his statements. This project aims to explore the relationship between Elon Musk's tweets and Bitcoin price fluctuations. The hypothesis is that Elon Musk's tweets significantly influence Bitcoin prices, with changes in market prices closely correlated to the sentiment expressed in his tweets. By analyzing tweets and Bitcoin price data from 2022, this study seeks to test the hypothesis by examining the sentiment of each tweet and measuring the corresponding percentage change in Bitcoin prices. The study aims to provide insights into how influential figures on social media can impact the financial markets and guide investors in understanding market trends.

Importance of the Study

This study is important because it delves into the controversial and significant impact that influential individuals can have on financial markets through social media. In recent years, the power of social media has grown exponentially, allowing individuals with large followings to sway public opinion and market dynamics. Elon Musk, as one of the most prominent figures in the tech industry, exemplifies this phenomenon. His tweets have been known to cause immediate and drastic changes in the stock and cryptocurrency markets. Understanding the extent of this influence is crucial for investors, policymakers, and the general public. The ability of a single individual to manipulate market trends raises questions about market stability, investor protection, and the ethical implications of such power. As someone interested in the intersection of social media and financial markets, I am fascinated by how Musk's tweets serve as a case study for the broader implications of social media influence, potentially shaping future regulatory frameworks and investment strategies. This research aims to provide insights into the power dynamics at play and to inform discussions about the role of social media in modern financial markets.

Hypothesis

Elon Musk's tweets about Bitcoin significantly influence its market price, with positive sentiment tweets leading to a price increase and negative sentiment tweets causing a

price decrease within a 24-hour window of the tweet's posting.

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```
In [3]: %pip install -U textblob
```

```
Requirement already satisfied: textblob in /srv/conda/lib/python3.11/site-packages (0.18.0.post0)
Requirement already satisfied: nltk>=3.8 in /srv/conda/lib/python3.11/site-packages (from textblob) (3.8.1)
Requirement already satisfied: click in /srv/conda/lib/python3.11/site-packages (from nltk>=3.8->textblob) (8.1.7)
Requirement already satisfied: joblib in /srv/conda/lib/python3.11/site-packages (from nltk>=3.8->textblob) (1.4.2)
Requirement already satisfied: regex>=2021.8.3 in /srv/conda/lib/python3.11/site-packages (from nltk>=3.8->textblob) (2024.7.24)
Requirement already satisfied: tqdm in /srv/conda/lib/python3.11/site-packages (from nltk>=3.8->textblob) (4.66.2)
Note: you may need to restart the kernel to use updated packages.
```

```
In [5]: import requests
import json
import pandas as pd
from datetime import datetime, timedelta
import os
import json
import csv
import matplotlib.pyplot as plt
from textblob import TextBlob
import matplotlib.dates as mdates
import re
```

Accessing Bitcoin API

```
In [6]: # gettin the URL from a free open API
url= 'https://api.coincap.io/v2/assets'
```

```
In [7]: # using requests to get the url
response = requests.get(url)
```

```
In [8]: #testing the request command to see if i have access to the document, i shou
response.status_code
```

```
Out[8]: 200
```

```
In [9]: response.content
```

```

Out[9]: b'{"data":[{"id":"bitcoin","rank":"1","symbol":"BTC","name":"Bitcoin","supply":
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Accessing the data of API

I need to get bitcoin prices from the dates that will match with my twitter dataset that has only data from Jan 2022-October 2022 i need to input parameters and format the dates in milliseconds as required by API

the document has records of many cryptocurrencies, but i just want to retrieve bitcoin

i will name bitcoin as my asset_id to retrieve it from the url link

```
asset_id = 'bitcoin'
```

Define the new url link to retrieve bitcoin prices historically within its date parameters

```
url = f'https://api.coincap.io/v2/assets/{asset_id}/history'
```

```
In [10]: # Ill Define the start and end dates for historical data, i chose this because
# I had to match it with my twitter time frame
start_date = datetime(2022, 1, 27)
end_date = datetime(2022, 10, 27)
# I looked up for how to use the API
# I will now format the dates as required by the API (in milliseconds)
start_timestamp = int(start_date.timestamp() * 1000)
end_timestamp = int(end_date.timestamp() * 1000)
```

```
#the document has records of many cryptocurrencies, but i just want to retrieve  
#i will name bitcoin as my asset_id to retrieve it from the url link  
asset_id = 'bitcoin'  
# Define the new url link to retrieve bitcoin prices historically within its  
url = f'https://api.coincap.io/v2/assets/{asset_id}/history'  
  
# Define the parameters  
params = {  
    'interval': 'd1', # Daily data  
    'start': start_timestamp,  
    'end': end_timestamp  
}  
  
# Fetch the historical data  
response = requests.get(url, params=params)  
  
# Debug: Check the response status code and content  
print("Status Code:", response.status_code)  
print("Response Content:", response.text)
```

Status Code: 200

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3545579156890","time":1658966400000,"date":"2022-07-28T00:00:00.000Z"},{"priceUsd":"23877.1584364707963343","time":1659052800000,"date":"2022-07-29T00:00:00.000Z"},{"priceUsd":"24020.9524759555969075","time":1659139200000,"date":"2022-07-30T00:00:00.000Z"},{"priceUsd":"23716.7899427329563381","time":1659225600000,"date":"2022-07-31T00:00:00.000Z"},{"priceUsd":"23225.2188999642011118","time":1659312000000,"date":"2022-08-01T00:00:00.000Z"},{"priceUsd":"22982.8567173022410711","time":1659398400000,"date":"2022-08-02T00:00:00.000Z"},{"priceUsd":"23179.5672095090450380","time":1659484800000,"date":"2022-08-03T00:00:00.000Z"},{"priceUsd":"22858.4117117615296512","time":1659571200000,"date":"2022-08-04T00:00:00.000Z"},{"priceUsd":"23070.4866937298458687","time":1659657600000,"date":"2022-08-05T00:00:00.000Z"},{"priceUsd":"23186.3250686722211144","time":1659744000000,"date":"2022-08-06T00:00:00.000Z"},{"priceUsd":"23078.0320710185611256","time":1659830400000,"date":"2022-08-07T00:00:00.000Z"},{"priceUsd":"23783.2392939552061111","time":1659916800000,"date":"2022-08-08T00:00:00.000Z"},{"priceUsd":"23449.3837797126486714","time":1660003200000,"date":"2022-08-09T00:00:00.000Z"},{"priceUsd":"23408.4107145458129117","time":1660089600000,"date":"2022-08-10T00:00:00.000Z"},{"priceUsd":"24344.0852320755759706","time":1660176000000,"date":"2022-08-11T00:00:00.000Z"},{"priceUsd":"23977.4576016006532502","time":1660262400000,"date":"2022-08-12T00:00:00.000Z"},{"priceUsd":"24508.5536426190732008","time":1660348800000,"date":"2022-08-13T00:00:00.000Z"},{"priceUsd":"24488.0859465422984653","time":1660435200000,"date":"2022-08-14T00:00:00.000Z"},{"priceUsd":"24255.8871428333052239","time":1660521600000,"date":"2022-08-15T00:00:00.000Z"},{"priceUsd":"23972.0024577743949091","time":1660608000000,"date":"2022-08-16T00:00:00.000Z"},{"priceUsd":"23712.9558535298046064","time":1660694400000,"date":"2022-08-17T00:00:00.000Z"},{"priceUsd":"23431.1015411500218322","time":1660780800000,"date":"2022-08-18T00:00:00.000Z"},{"priceUsd":"21878.2962653204974895","time":1660867200000,"date":"2022-08-19T00:00:00.000Z"},{"priceUsd":"21229.0591957587435233","time":1660953600000,"date":"2022-08-20T00:00:00.000Z"},{"priceUsd":"21402.8485010277198121","time":1661040000000,"date":"2022-08-21T00:00:00.000Z"},{"priceUsd":"21294.4996759762938490","time":1661126400000,"date":"2022-08-22T00:00:00.000Z"},{"priceUsd":"21403.0242297512210827","time":1661212800000,"date":"2022-08-23T00:00:00.000Z"},{"priceUsd":"21481.3440044216305020","time":1661299200000,"date":"2022-08-24T00:00:00.000Z"},{"priceUsd":"21609.4253915315103795","time":1661385600000,"date":"2022-08-25T00:00:00.000Z"},{"priceUsd":"21183.5735756063046001","time":1661472000000,"date":"2022-08-26T00:00:00.000Z"},{"priceUsd":"20154.5957309998743038","time":1661558400000,"date":"2022-08-27T00:00:00.000Z"},{"priceUsd":"20029.6248747342820679","time":1661644800000,"date":"2022-08-28T00:00:00.000Z"},{"priceUsd":"19998.1665288612916130","time":1661731200000,"date":"2022-08-29T00:00:00.000Z"},{"priceUsd":"20154.9519653359199881","time":1661817600000,"date":"2022-08-30T00:00:00.000Z"},{"priceUsd":"20213.2109232438320960","time":1661904000000,"date":"2022-08-31T00:00:00.000Z"},{"priceUsd":"19983.7990937867826843","time":1661990400000,"date":"2022-09-01T00:00:00.000Z"},{"priceUsd":"20097.3870448434362048","time":1662076800000,"date":"2022-09-02T00:00:00.000Z"},{"priceUsd":"19854.8147320978405383","time":1662163200000,"date":"2022-09-03T00:00:00.000Z"},{"priceUsd":"19812.5100475392891408","time":1662249600000,"date":"2022-09-04T00:00:00.000Z"},{"priceUsd":"19796.8944810940855867","time":1662336000000,"date":"2022-09-05T00:00:00.000Z"},{"priceUsd":"19611.4637935699748953","time":1662422400000,"date":"2022-09-06T00:00:00.000Z"},{"priceUsd":"18913.4396739802198835","time":1662508800000,"date":"2022-09-07T00:00:00.000Z"},{"priceUsd":"19266.0458479421839061","time":1662595200000,"date":"2022-09-08T00:00:00.000Z"},{"priceUsd":"20741.4859866784575116","time":1662681600000,"date":"2022-09-09T00:00:00.000Z"},{"priceUsd":"21447.6165593487974651","time":1662768000000,"date":"2022-09-10T00:00:00.000Z"},{"priceUsd":"21670.0629506041114859","time":1662854400000,"date":"2022-09-11T00:00:00.000Z"}
```

```
00,"date":"2022-09-11T00:00:00.000Z"},{"priceUsd":"22140.164147683780785
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4.8801000666828668","time":1663027200000,"date":"2022-09-13T00:00:00.000Z"},
{"priceUsd":"20238.7856873031113938","time":1663113600000,"date":"2022-09-14
T00:00:00.000Z"},{"priceUsd":"20008.2773012904009055","time":1663200000000
0,"date":"2022-09-15T00:00:00.000Z"},{"priceUsd":"19720.5705226823934893","t
ime":1663286400000,"date":"2022-09-16T00:00:00.000Z"},{"priceUsd":"19957.332
5120549506732","time":1663372800000,"date":"2022-09-17T00:00:00.000Z"},{"pri
ceUsd":"19888.1371171612926995","time":1663459200000,"date":"2022-09-18T00:0
0:00.000Z"},{"priceUsd":"19026.3833494791095574","time":1663545600000,"dat
e":"2022-09-19T00:00:00.000Z"},{"priceUsd":"19195.9916600450500350","time":1
663632000000,"date":"2022-09-20T00:00:00.000Z"},{"priceUsd":"19020.606950308
3210076","time":1663718400000,"date":"2022-09-21T00:00:00.000Z"},{"priceUs
d":"18986.7018653814808726","time":1663804800000,"date":"2022-09-22T00:00:0
0.000Z"},{"priceUsd":"19064.1533363209492234","time":1663891200000,"date":"2
022-09-23T00:00:00.000Z"},{"priceUsd":"19078.0794554055902371","time":166397
7600000,"date":"2022-09-24T00:00:00.000Z"},{"priceUsd":"18992.03968754898013
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16.7516009444234207","time":1664150400000,"date":"2022-09-26T00:00:00.000
Z"},{"priceUsd":"19736.9532421797387537","time":1664236800000,"date":"2022-0
9-27T00:00:00.000Z"},{"priceUsd":"19125.8870731421173706","time":16643232000
00,"date":"2022-09-28T00:00:00.000Z"},{"priceUsd":"19397.581923975446435
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0.3777649587614644","time":1664496000000,"date":"2022-09-30T00:00:00.000Z"},
{"priceUsd":"19334.8725635547788566","time":1664582400000,"date":"2022-10-01
T00:00:00.000Z"},{"priceUsd":"19241.9778915758551072","time":1664668800000
0,"date":"2022-10-02T00:00:00.000Z"},{"priceUsd":"19324.0782159715121715","t
ime":1664755200000,"date":"2022-10-03T00:00:00.000Z"},{"priceUsd":"19945.944
8979267178359","time":1664841600000,"date":"2022-10-04T00:00:00.000Z"},{"pri
ceUsd":"20131.2846550523810728","time":1664928000000,"date":"2022-10-05T00:0
0:00.000Z"},{"priceUsd":"20155.9610630358586302","time":1665014400000,"dat
e":"2022-10-06T00:00:00.000Z"},{"priceUsd":"19774.7313006156171094","time":1
665100800000,"date":"2022-10-07T00:00:00.000Z"},{"priceUsd":"19498.404169313
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d":"19453.8379179464143741","time":1665273600000,"date":"2022-10-09T00:00:0
0.000Z"},{"priceUsd":"19333.8980915412074451","time":1665360000000,"date":"2
022-10-10T00:00:00.000Z"},{"priceUsd":"19077.3916663255568526","time":166544
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Z"},{"priceUsd":"19522.1250019535211336","time":1665705600000,"date":"2022-1
0-14T00:00:00.000Z"},{"priceUsd":"19148.9780133345209363","time":16657920000
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8","time":1665878400000,"date":"2022-10-16T00:00:00.000Z"},{"priceUsd":"1940
2.7803495392384055","time":1665964800000,"date":"2022-10-17T00:00:00.000Z"},
{"priceUsd":"19480.9355675661438511","time":1666051200000,"date":"2022-10-18
T00:00:00.000Z"},{"priceUsd":"19224.3127923764012537","time":1666137600000
0,"date":"2022-10-19T00:00:00.000Z"},{"priceUsd":"19131.3987163543915992","t
ime":1666224000000,"date":"2022-10-20T00:00:00.000Z"},{"priceUsd":"19074.177
4229364805013","time":1666310400000,"date":"2022-10-21T00:00:00.000Z"},{"pri
ceUsd":"19185.0092264516167929","time":1666396800000,"date":"2022-10-22T00:0
0:00.000Z"},{"priceUsd":"19273.6624737742414778","time":1666483200000,"dat
e":"2022-10-23T00:00:00.000Z"},{"priceUsd":"19360.5842930465872547","time":1
666569600000,"date":"2022-10-24T00:00:00.000Z"},{"priceUsd":"19598.030929591
1540323","time":1666656000000,"date":"2022-10-25T00:00:00.000Z"},{"priceUs
d":"20531.3679926951811212","time":1666742400000,"date":"2022-10-26T00:00:0
```

```
0.000Z"}],{"priceUsd":"20601.6409759486035653","time":1666828800000,"date":"2022-10-27T00:00:00.000Z"}],{"timestamp":1723071161582}
```

```
In [11]: # Fetch the historical data
response = requests.get(url, params=params)
response
# Check the response status
#converting the content to json format
historical_data = response.json()['data']
```

```
In [12]: # Convert to DataFrame
bitcoin = pd.DataFrame(historical_data)
bitcoin
```

```
Out[12]:
```

	priceUsd	time	date
0	37195.3337856870182247	1643328000000	2022-01-28T00:00:00.000Z
1	37936.3896273022133066	1643414400000	2022-01-29T00:00:00.000Z
2	38033.0044447868584383	1643500800000	2022-01-30T00:00:00.000Z
3	37639.1434117793428756	1643587200000	2022-01-31T00:00:00.000Z
4	38618.6985127117544049	1643673600000	2022-02-01T00:00:00.000Z
...
267	19273.6624737742414778	1666483200000	2022-10-23T00:00:00.000Z
268	19360.5842930465872547	1666569600000	2022-10-24T00:00:00.000Z
269	19598.0309295911540323	1666656000000	2022-10-25T00:00:00.000Z
270	20531.3679926951811212	1666742400000	2022-10-26T00:00:00.000Z
271	20601.6409759486035653	1666828800000	2022-10-27T00:00:00.000Z

272 rows x 3 columns

```
In [13]: # Noi i need to convert the date to a readable format
bitcoin['date'] = pd.to_datetime(bitcoin['date'])

# Extract only the date part
bitcoin['date'] = bitcoin['date'].dt.date

#rename columns
bitcoin= bitcoin.rename(columns = {'priceUsd':'Bitcoin_Price_USD'})
bitcoin= bitcoin.rename(columns = {'date':'Date'})

# Remove missing values in table
bitcoin= bitcoin[~bitcoin.isna().any(axis=1)]

# Convert 'time' to datetime and extract the time
bitcoin['time'] = pd.to_datetime(bitcoin['time'], unit='ms').dt.time
bitcoin.head(10)
```

Out [13]:

	Bitcoin_Price_USD	time	Date
0	37195.3337856870182247	00:00:00	2022-01-28
1	37936.3896273022133066	00:00:00	2022-01-29
2	38033.0044447868584383	00:00:00	2022-01-30
3	37639.1434117793428756	00:00:00	2022-01-31
4	38618.6985127117544049	00:00:00	2022-02-01
5	38110.0603107465800888	00:00:00	2022-02-02
6	36870.7517903112674538	00:00:00	2022-02-03
7	38707.1037056035187783	00:00:00	2022-02-04
8	41542.7084101260020495	00:00:00	2022-02-05
9	41641.7760563115049624	00:00:00	2022-02-06

In [14]:

```
# I see that most of the time is at 00:00:00

# checking if all the times where at 00:00, and if so, remove
bitcoin["time"].value_counts()
```

Out[14]:

```
time
00:00:00    272
Name: count, dtype: int64
```

In [15]:

```
#removing time column, since the dataset just gives me bitcoin prices by day
bitcoin= bitcoin.drop(columns=['time'])
bitcoin
```

Out [15]:

	Bitcoin_Price_USD	Date
0	37195.3337856870182247	2022-01-28
1	37936.3896273022133066	2022-01-29
2	38033.0044447868584383	2022-01-30
3	37639.1434117793428756	2022-01-31
4	38618.6985127117544049	2022-02-01
...
267	19273.6624737742414778	2022-10-23
268	19360.5842930465872547	2022-10-24
269	19598.0309295911540323	2022-10-25
270	20531.3679926951811212	2022-10-26
271	20601.6409759486035653	2022-10-27

272 rows × 2 columns

Getting Elon Musk's Tweeter (X) Data

I wanted to extract the data from an API but i had to pay for them so i gathered my data from kaggle i am using scv to extract the data

```
In [16]: # extracting data from tweeter csv
tweeter= pd.read_csv('cleandata.csv')
tweeter
```

Out [16]:

	Tweets	Retweets	Likes	Date	Cleaned_Tweets
0	@PeterSchiff 🙏 thanks	209	7021	2022-10-27 16:17:39	thanks
1	@ZubyMusic Absolutely	755	26737	2022-10-27 13:19:25	Absolutely
2	Dear Twitter Advertisers https://t.co/GMwHmlnPAS	55927	356623	2022-10-27 13:08:00	Dear Twitter Advertisers
3	Meeting a lot of cool people at Twitter today!	9366	195546	2022-10-26 21:39:32	Meeting a lot of cool people at Twitter today!
4	Entering Twitter HQ – let that sink in! https:...	145520	1043592	2022-10-26 18:45:58	Entering Twitter HQ – let that sink in!
...
2663	@LimitingThe @baglino Just that manganese is a...	171	3173	2022-01-27 22:01:06	Just that manganese is an alternative to iron ...
2664	@incentives101 @ICRicardoLara Exactly	145	4234	2022-01-27 21:23:20	Exactly
2665	@ICRicardoLara Your policies are directly resp...	421	6144	2022-01-27 21:13:57	Your policies are directly responsible for the...
2666	@ICRicardoLara You should be voted out of office	484	7029	2022-01-27 21:12:27	You should be voted out of office
2667	CB radios are free from govt/media control	11302	113429	2022-01-27 21:00:09	CB radios are free from govt/media control

2668 rows x 5 columns

```

In [17]: # in order to merge both tables i need to match the time column to same type
# Convert 'Date' from object to datetime64[ns] to match the bitcoin table
tweeter['Date'] = pd.to_datetime(tweeter['Date'])

# Add a new column with only the date (year, month, day)
tweeter['Date_Only'] = tweeter['Date'].dt.date

tweeter

```


Out [17]:

		Tweets	Retweets	Likes	Date	Cleaned_Tweets	Date_O
0	@PeterSchiff 🙏 thanks		209	7021	2022-10-27 16:17:39	thanks	2022-
1	@ZubyMusic Absolutely		755	26737	2022-10-27 13:19:25	Absolutely	2022-
2	Dear Twitter Advertisers https://t.co/GMwHmInPAS		55927	356623	2022-10-27 13:08:00	Dear Twitter Advertisers	2022-
3	Meeting a lot of cool people at Twitter today!		9366	195546	2022-10-26 21:39:32	Meeting a lot of cool people at Twitter today!	2022-
4	Entering Twitter HQ – let that sink in! https:...		145520	1043592	2022-10-26 18:45:58	Entering Twitter HQ – let that sink in!	2022-
...
2663	@LimitingThe @baglino Just that manganese is a...		171	3173	2022-01-27 22:01:06	Just that manganese is an alternative to iron ...	2022-
2664	@incentives101 @ICRicardoLara Exactly		145	4234	2022-01-27 21:23:20	Exactly	2022-
2665	@ICRicardoLara Your policies are directly resp...		421	6144	2022-01-27 21:13:57	Your policies are directly responsible for the...	2022-
2666	@ICRicardoLara You should be voted out of office		484	7029	2022-01-27 21:12:27	You should be voted out of office	2022-
2667	CB radios are free from govt/media control		11302	113429	2022-01-27 21:00:09	CB radios are free from govt/media control	2022-

2668 rows x 6 columns

Merging Datasets

now i will join tables and filter the twitter table so that i can gather the tweets from elon msuk related to cryptocurrency so that i can start analyzing the data.

```
In [18]: # Merge the DataFrames on the date column
btc_tweet = pd.merge(tweeter, bitcoin, left_on='Date_Only', right_on='Date',
```

```
# Select the desired columns
btc_tweet = btc_tweet[['Cleaned_Tweets', 'Date_tweet', 'Date_Only', 'Bitcoin_Price_USD']]

# Rename columns for clarity
btc_tweet = btc_tweet.rename(columns={'Date_tweet': 'Date'})

#removing the Date column
btc_tweet = btc_tweet.drop(columns=['Date'])
# Display the resulting DataFrame
btc_tweet
```

Out[18]:

	Cleaned_Tweets	Date_Only	Bitcoin_Price_USD
0	thanks	2022-10-27	20601.6409759486035653
1	Absolutely	2022-10-27	20601.6409759486035653
2	Dear Twitter Advertisers	2022-10-27	20601.6409759486035653
3	Meeting a lot of cool people at Twitter today!	2022-10-26	20531.3679926951811212
4	Entering Twitter HQ – let that sink in!	2022-10-26	20531.3679926951811212
...
2635	Tesla will support FSD licensing by other manu...	2022-01-28	37195.3337856870182247
2636	Disney in the streets,Euphoria in the sheets	2022-01-28	37195.3337856870182247
2637	I have one	2022-01-28	37195.3337856870182247
2638	Given how hard insanely FSD is, I think it may...	2022-01-28	37195.3337856870182247
2639	I have a feeling that the gerrymandering will ...	2022-01-28	37195.3337856870182247

2640 rows × 3 columns

```
In [19]: # i now need to filter the cleaned tweets
# choosing certain keywords will help me search for elon musk tweets related
keywords = ['bitcoin', 'btc', 'crypto', 'decentralization', 'mining']

# Convert keywords to lowercase for consistent matching
keywords = [keyword.lower() for keyword in keywords]

# Filter DataFrame based on the presence of keywords in Cleaned_tweets
filtered_btc_tweet = btc_tweet[btc_tweet['Cleaned_Tweets'].str.lower().str.contains(''.join(keywords))]
```

```
# Display the filtered DataFrame
filtered_btc_tweet
```

Out [19]:

	Cleaned_Tweets	Date_Only	Bitcoin_Price_USD
1179	Cryptonight	2022-06-15	21357.0473924801731143
1420	I swear my responsibility to the highest good ...	2022-05-29	29141.4135780451638386
1886	Haha he says "Bitcoin" so many times	2022-05-01	38177.8495368632446978
1992	So many "verified" scam crypto bots!	2022-04-23	39760.1750514015030788
2103	Now subtract crypto scam accounts that twitter...	2022-04-09	42545.5567667791201486
2112	Price of lithium has gone to insane levels! Te...	2022-04-08	43361.1193641799483156
2220	especially crypto spam!!	2022-03-25	44325.7281396889698303
2286	As a general principle, for those looking for ...	2022-03-14	38762.5729164011522312

First Visualization

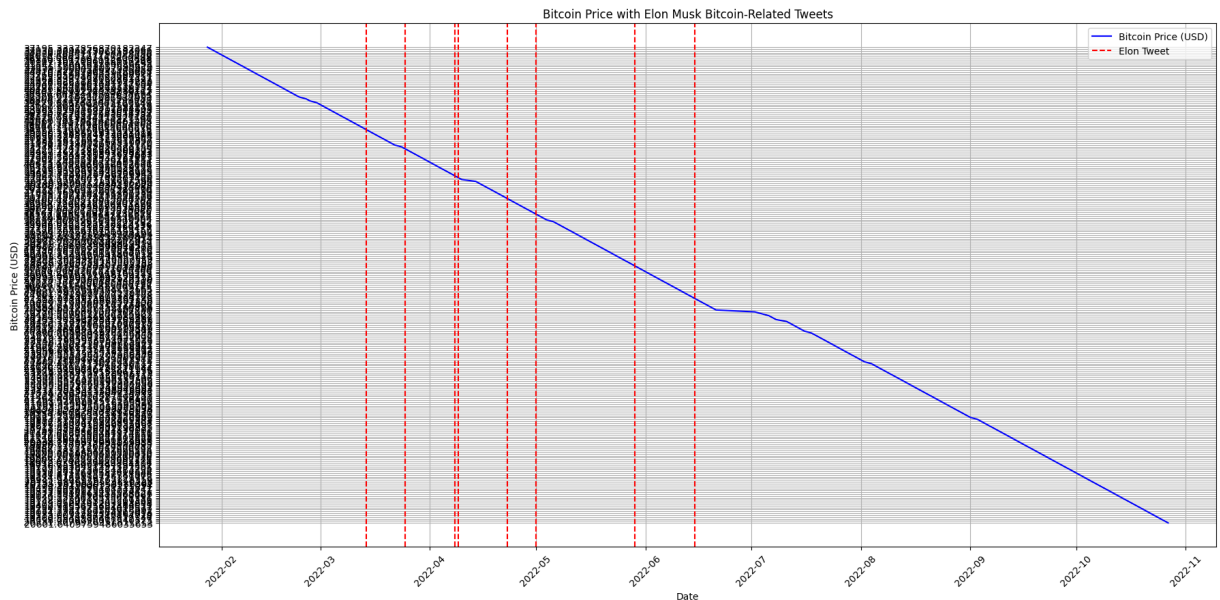
I want to show the price of bitcoin in a line graph during my data time frame, and for each bitcoin related tweet of elon musk i want to mark lines to see if the tweet affected the price of bitcoin.

```
In [20]: # Plot Bitcoin Prices
plt.figure(figsize=(18, 9))
plt.plot(btc_tweet['Date_Only'], btc_tweet['Bitcoin_Price_USD'], label='Bitcoin Price')

# Add vertical lines for Bitcoin-related tweets
for date in filtered_btc_tweet['Date_Only']:
    plt.axvline(x=date, color='red', linestyle='--', label='Elon Tweet' if c

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Bitcoin Price (USD)')
plt.title('Bitcoin Price with Elon Musk Bitcoin-Related Tweets')
plt.legend()
plt.grid(True)
plt.xticks(rotation=45)

# Show the plot
plt.tight_layout()
plt.show()
```



Second Visualization

It is hard to see in this graph so i will have to zoom in

```
In [21]: # Convert 'Bitcoin_Price_USD' to float to be able to perform arithmetic oper
btc_tweet['Bitcoin_Price_USD'] = btc_tweet['Bitcoin_Price_USD'].astype(float)

# Plot Bitcoin Prices
plt.figure(figsize=(12, 6))
plt.plot(btc_tweet['Date_Only'], btc_tweet['Bitcoin_Price_USD'], label='Bitcoin Price (USD)')

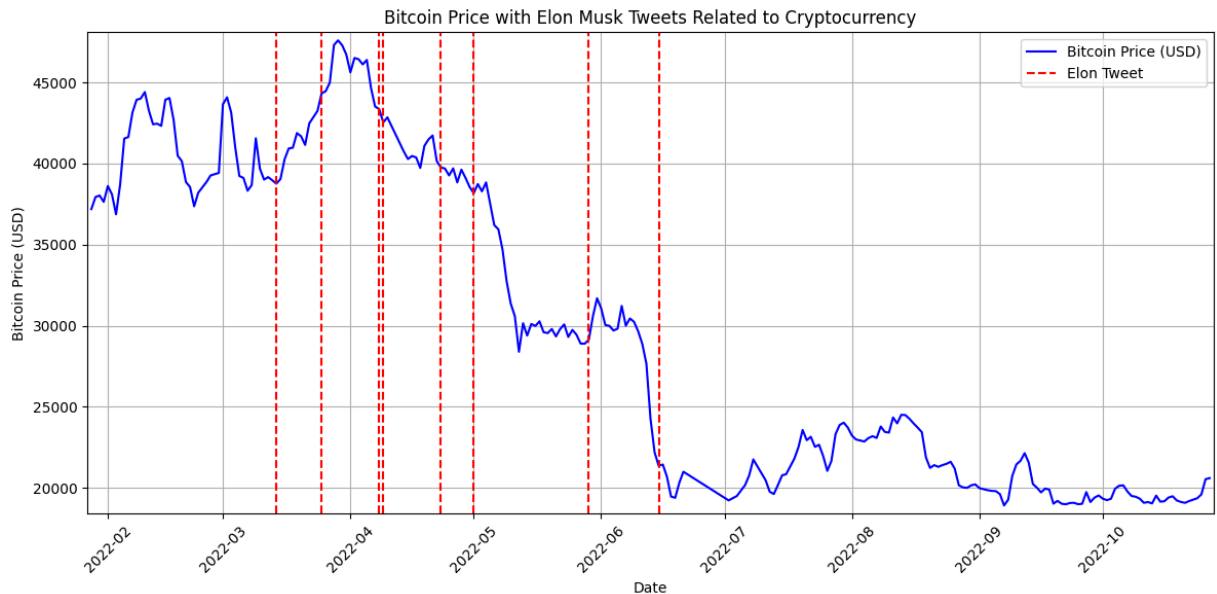
# Add vertical lines for tweets containing the keywords
for date in filtered_btc_tweet['Date_Only']:
    plt.axvline(x=date, color='red', linestyle='--', label='Elon Tweet' if c

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Bitcoin Price (USD)')
plt.title('Bitcoin Price with Elon Musk Tweets Related to Cryptocurrency')

# Set x and y limits based on data range
plt.xlim(btc_tweet['Date_Only'].min() - pd.Timedelta(days=1), btc_tweet['Date_Only'].max() + pd.Timedelta(days=1))
plt.ylim(btc_tweet['Bitcoin_Price_USD'].min() - 500, btc_tweet['Bitcoin_Price_USD'].max() + 500)

plt.legend()
plt.grid(True)
plt.xticks(rotation=45)

# Show the plot
plt.tight_layout()
plt.show()
```



Third Visualization

I decided i want to create a visualization that shows how Bitcoin prices shifted around each of Elon Musk's tweets, i'll follow these steps:

Extract the relevant tweets that contain specific keywords. For each tweet, create a window of three days: one day before, the day of the tweet, and one day after. Plot the Bitcoin price for each window, highlighting the tweet day.

```
In [22]: # Ensure that there are no missing or incorrect data types
print(btc_tweet.dtypes)
```

```
Cleaned_Tweets      object
Date_Only            object
Bitcoin_Price_USD    float64
dtype: object
```

```
In [23]: # Create a plot for each tweet by using a for loop
for i, row in filtered_btc_tweet.iterrows():
    tweet_date = row['Date_Only']

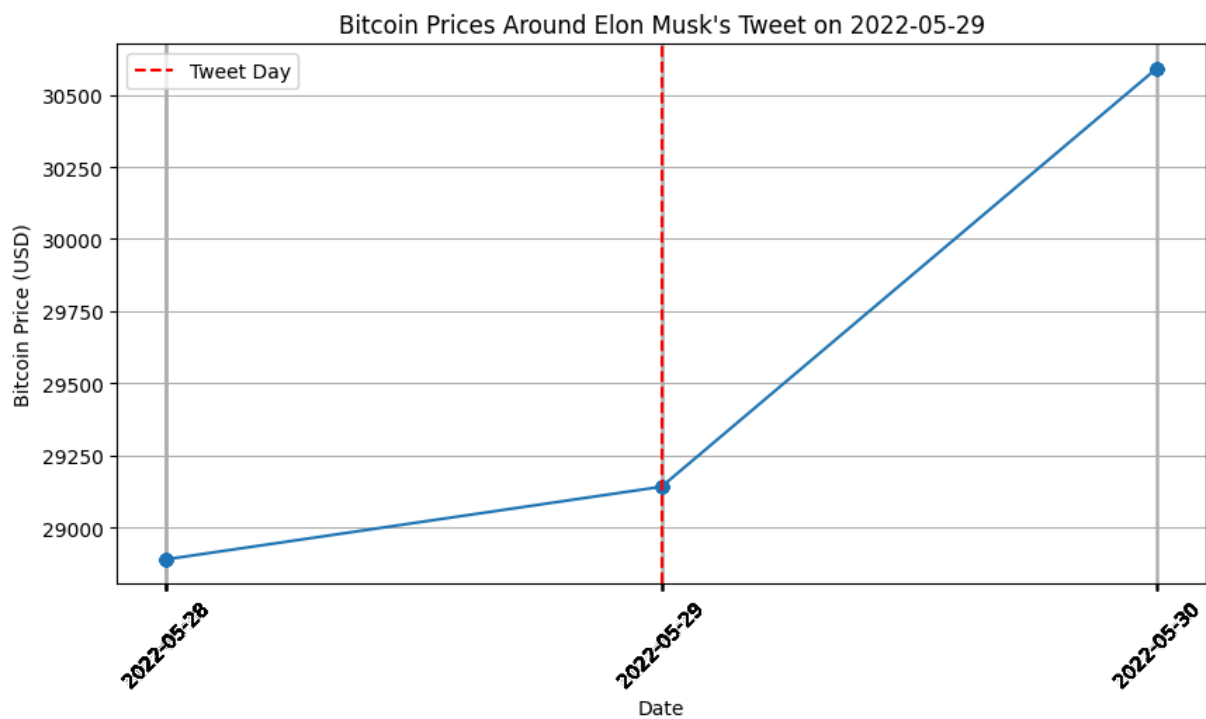
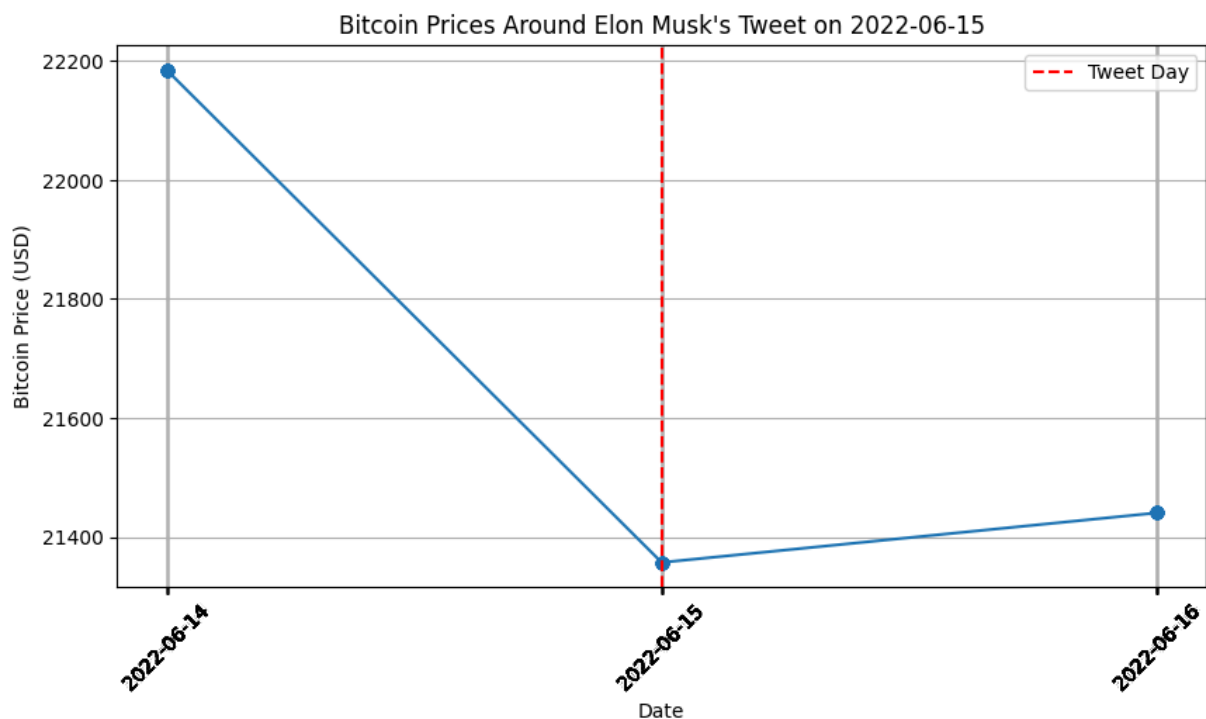
    # Create a window of one day before and one day after the tweet
    window_start = tweet_date - timedelta(days=1)
    window_end = tweet_date + timedelta(days=1)

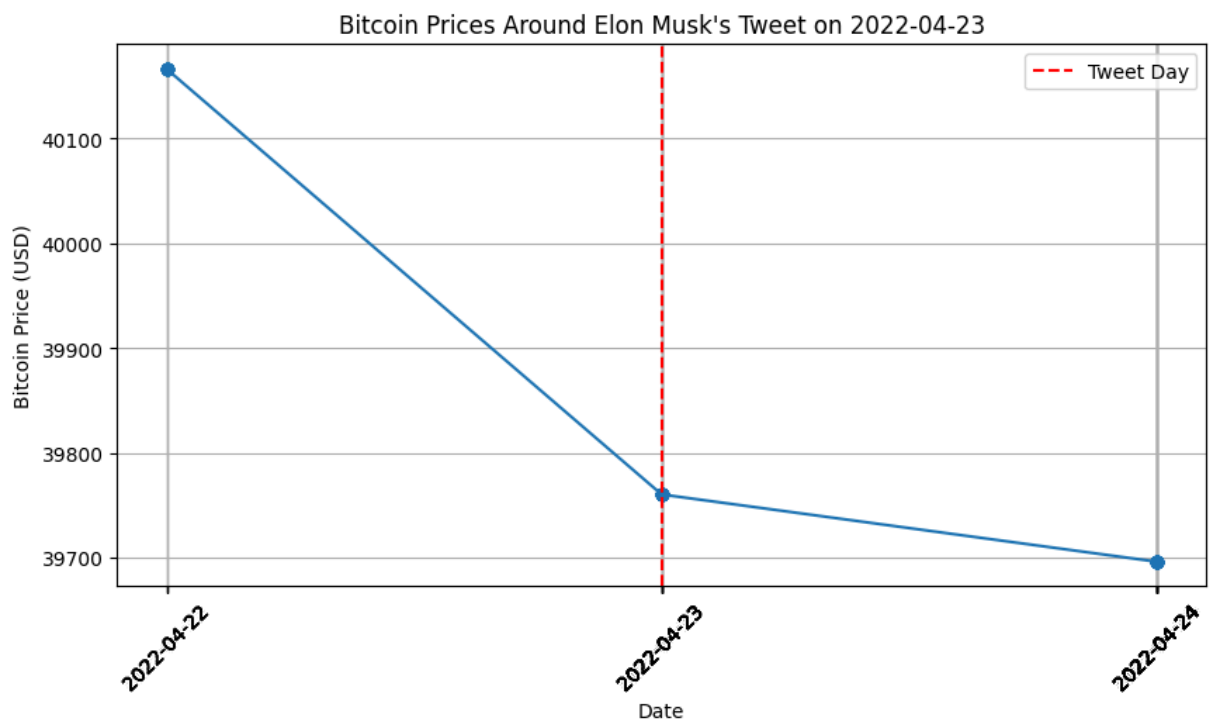
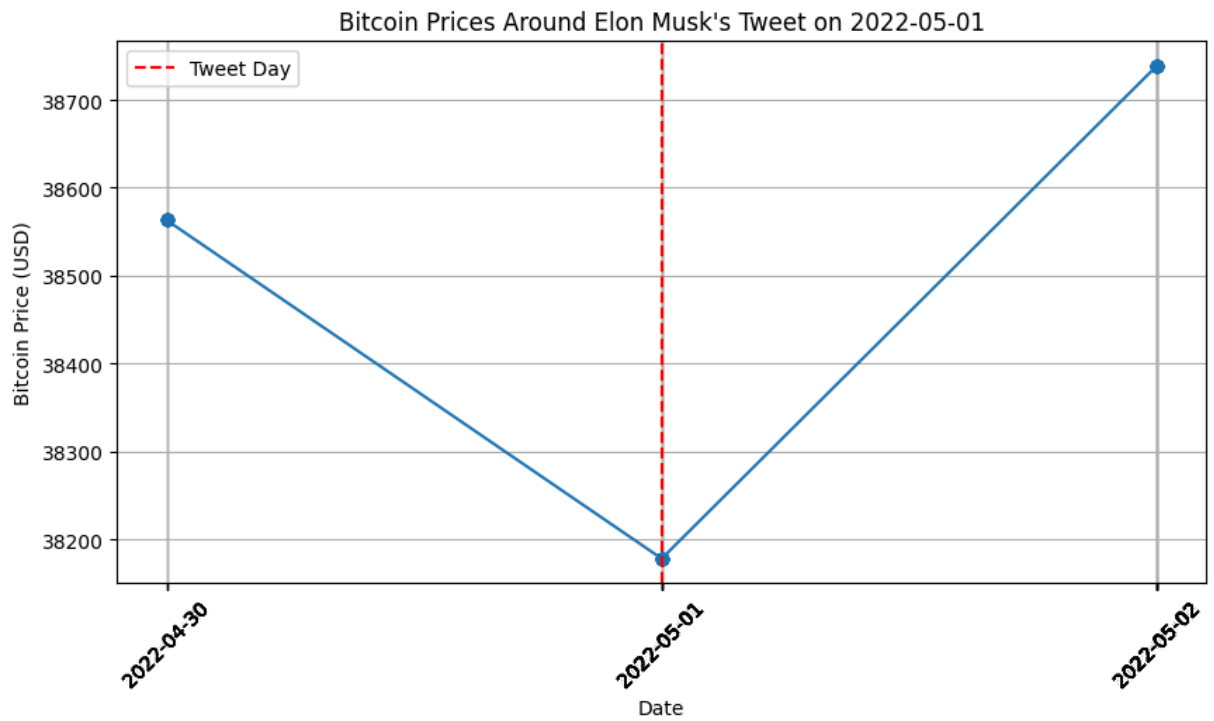
    # Filter the btc_tweet data for the window
    window_data = btc_tweet[(btc_tweet['Date_Only'] >= window_start) & (btc_

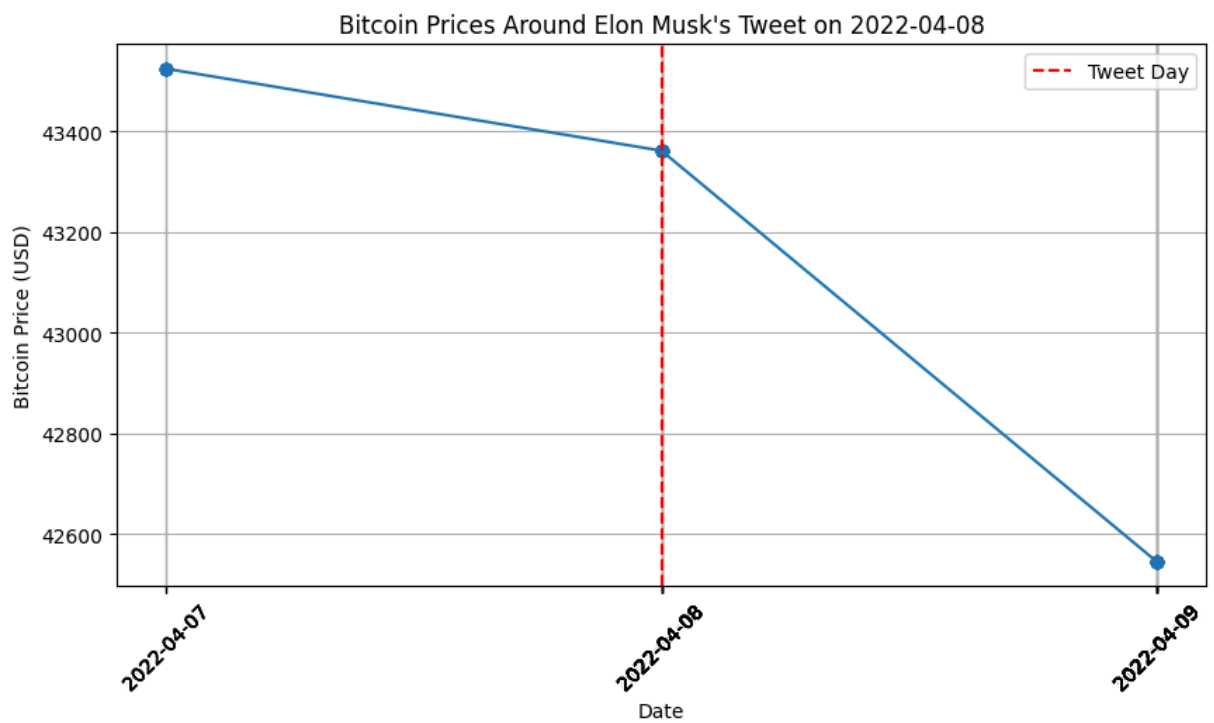
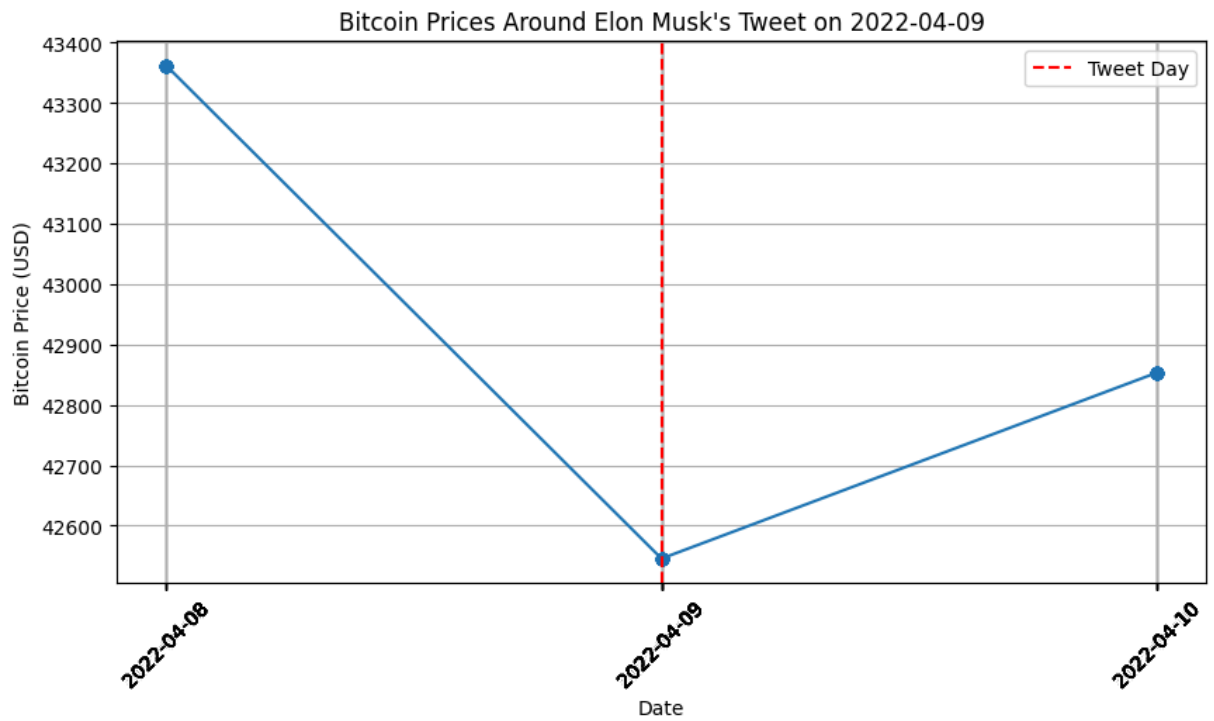
    # Plot
    plt.figure(figsize=(10, 5))
    plt.plot(window_data['Date_Only'], window_data['Bitcoin_Price_USD'], mar

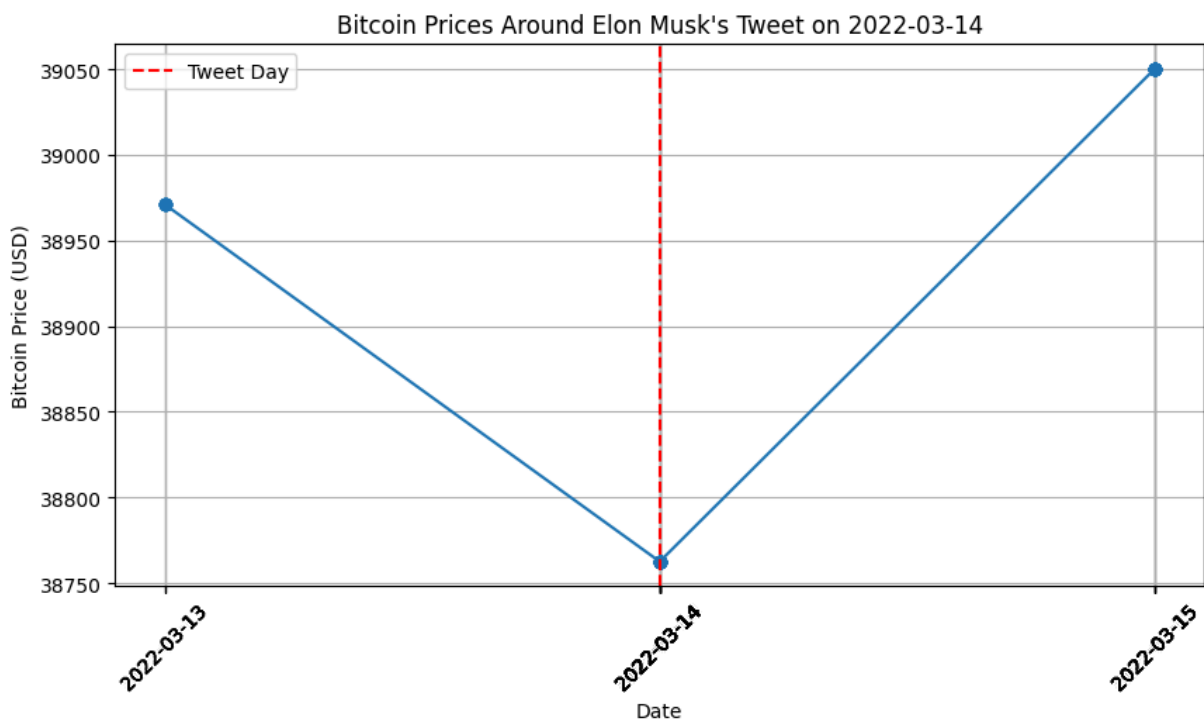
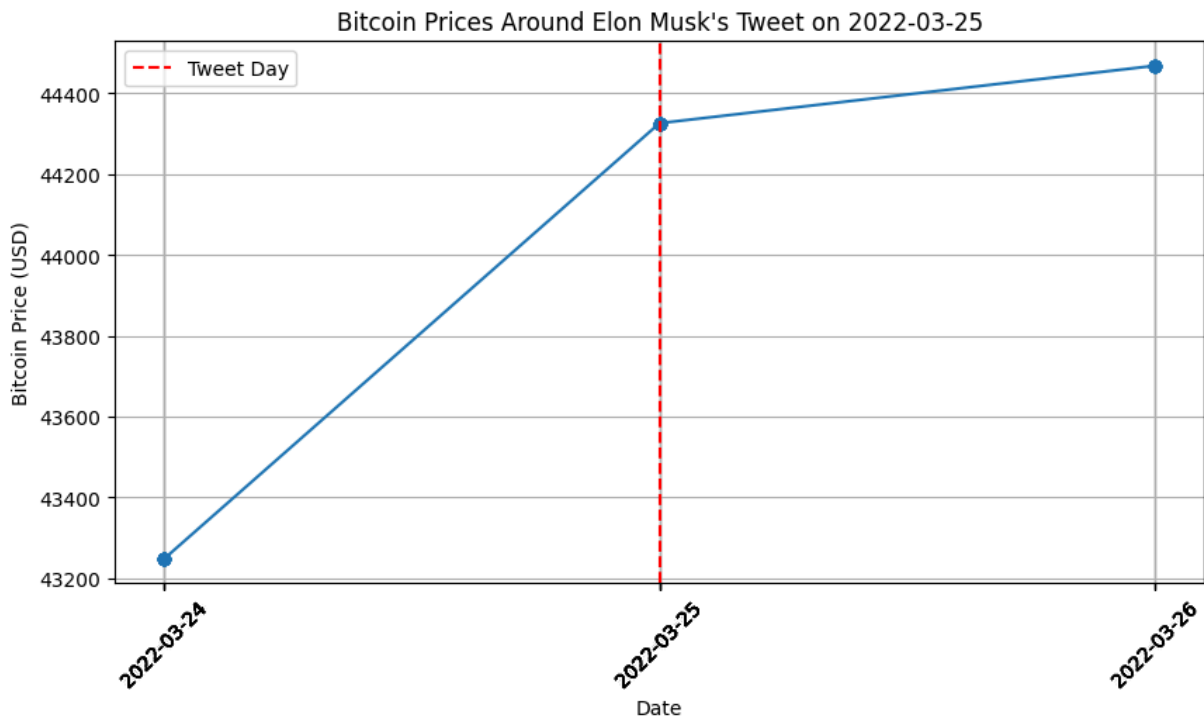
    # Highlight the tweet day
    plt.axvline(tweet_date, color='r', linestyle='--', label='Tweet Day')
    plt.title(f"Bitcoin Prices Around Elon Musk's Tweet on {tweet_date.strftime('%Y-%m-%d')})")
```

```
plt.xlabel('Date')
plt.ylabel('Bitcoin Price (USD)')
plt.xticks(window_data['Date_Only'], rotation=45)
plt.legend()
plt.grid(True)
plt.show()
```









Percentage Change in price for Every Elon Musk Tweet

I created a three-day window around each tweet: one day before, the day of the tweet, and one day after. just like in the plots above. This approach allows me to quantify the immediate influence of each tweet on bitcoins price, highlighting how Musk's public statements might affect cryptocurrency prices. By focusing on this specific timeframe, I aim to show the percentage change of Bitcoin prices are to Elon Musk tweets.

```

In [24]: # here im using the same for loop i used above
# Create a plot for each tweet
for i, row in filtered_btc_tweet.iterrows():
    tweet_date = row['Date_Only']

    # Create a window of one day before and one day after the tweet
    window_start = tweet_date - timedelta(days=1)
    window_end = tweet_date + timedelta(days=1)

    # Filter the btc_tweet data for the window
    window_data = btc_tweet[(btc_tweet['Date_Only'] >= window_start) & (btc_

    # Extract prices for the three days
    day_before_price = window_data.loc[window_data['Date_Only'] == window_st
    tweet_day_price = window_data.loc[window_data['Date_Only'] == tweet_date
    day_after_price = window_data.loc[window_data['Date_Only'] == window_end

    # Calculate percentage change
    percentage_change_before = ((tweet_day_price - day_before_price) / day_b
    percentage_change_after = ((day_after_price - tweet_day_price) / tweet_c

    # Output results
    print(f"Tweet on {tweet_date.strftime('%Y-%m-%d')}:")
    print(f"  Price change from day before: {percentage_change_before:.2f}%"
    print(f"  Price change to day after: {percentage_change_after:.2f}%\n")

```

Tweet on 2022-06-15:
 Price change from day before: -3.73%
 Price change to day after: 0.39%

Tweet on 2022-05-29:
 Price change from day before: 0.87%
 Price change to day after: 4.98%

Tweet on 2022-05-01:
 Price change from day before: -1.00%
 Price change to day after: 1.47%

Tweet on 2022-04-23:
 Price change from day before: -1.01%
 Price change to day after: -0.16%

Tweet on 2022-04-09:
 Price change from day before: -1.88%
 Price change to day after: 0.72%

Tweet on 2022-04-08:
 Price change from day before: -0.37%
 Price change to day after: -1.88%

Tweet on 2022-03-25:
 Price change from day before: 2.49%
 Price change to day after: 0.32%

Tweet on 2022-03-14:
 Price change from day before: -0.54%
 Price change to day after: 0.74%

Sentiment Analysis

In this part, I explore the relationship between the sentiment of Elon Musk's tweets and the changes in Bitcoin prices. By using the TextBlob library to calculate the sentiment polarity of each tweet, I can quantify the positivity or negativity of Musk's language. This sentiment score is then paired with the percentage change in Bitcoin prices before and after each tweet within a defined three-day window. This method allows me to see whether the tone of Musk's tweets correlates with significant market movements. By visualizing and analyzing this data, I can uncover patterns that may suggest the extent to which Musk's sentiment impacts the Bitcoin market.

```
In [25]: # Apply sentiment polarity to the filtered Bitcoin tweets
filtered_btc_tweet['sentiment_polarity'] = filtered_btc_tweet['Cleaned_Tweet

# Initialize a list to collect changes data
changes_data = []

# Create a plot for each tweet
for i, row in filtered_btc_tweet.iterrows():
```

```

tweet_date = row['Date_Only']

# Create a window of one day before and one day after the tweet
window_start = tweet_date - timedelta(days=1)
window_end = tweet_date + timedelta(days=1)

# Filter the btc_tweet data for the window
window_data = btc_tweet[(btc_tweet['Date_Only'] >= window_start) & (btc_

# Ensure there are prices for the three days
if len(window_data) < 3:
    continue

# Extract prices for the three days
try:
    day_before_price = window_data.loc[window_data['Date_Only'] == window_start, 'price']
    tweet_day_price = window_data.loc[window_data['Date_Only'] == tweet_date, 'price']
    day_after_price = window_data.loc[window_data['Date_Only'] == window_end, 'price']
except IndexError:
    continue

percentage_change_before = ((tweet_day_price - day_before_price) / day_before_price) * 100
percentage_change_after = ((day_after_price - tweet_day_price) / tweet_day_price) * 100

# Append to data list
changes_data.append({
    'Date': tweet_date,
    'Cleaned_Tweets': row['Cleaned_Tweets'],
    'Sentiment_Polarity': row['sentiment_polarity'],
    'Price_Change_Before': percentage_change_before,
    'Price_Change_After': percentage_change_after
})

# Create DataFrame from changes data
filtered_btc_tweet_polarity = pd.DataFrame(changes_data)
pd.set_option('display.max_colwidth', None)

# Display the changes_df
filtered_btc_tweet_polarity

```

/tmp/ipykernel_115/3561373451.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
filtered_btc_tweet['sentiment_polarity'] = filtered_btc_tweet['Cleaned_Tweets'].apply(lambda x: TextBlob(x).sentiment.polarity)

Out [25] :

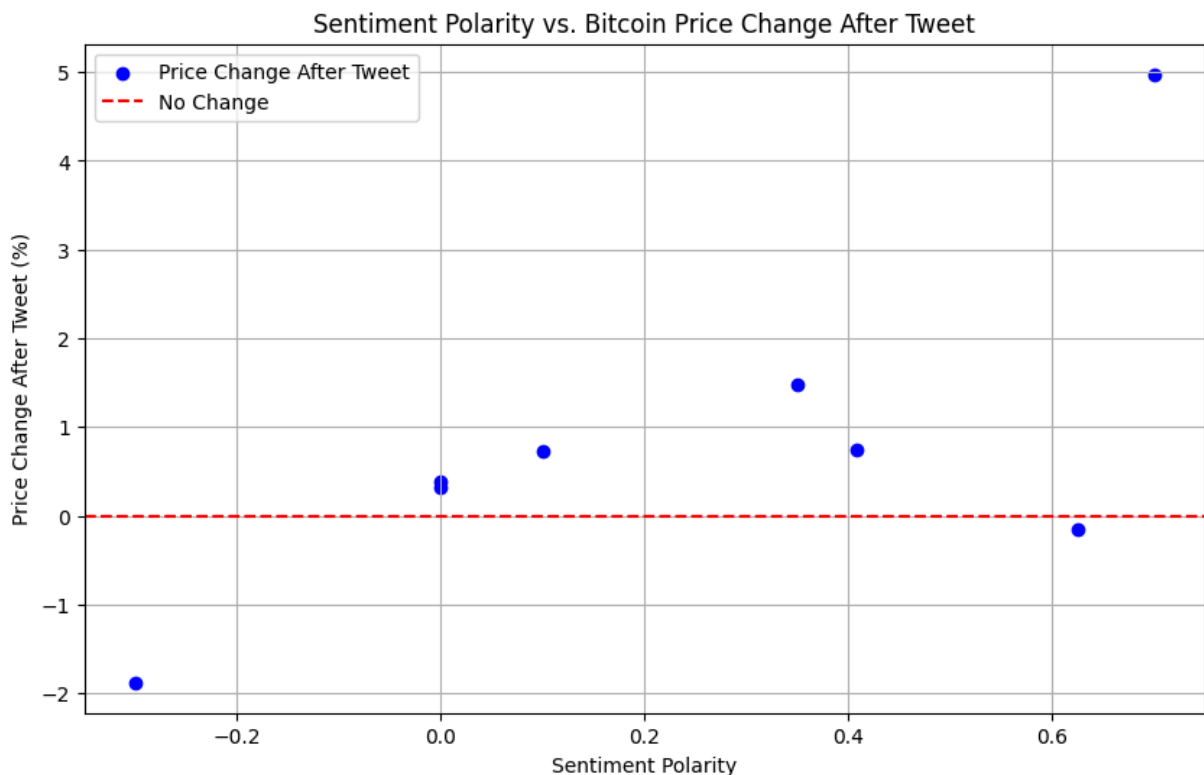
	Date	Cleaned_Tweets	Sentiment_Polarity	Price_Change_Before	Price_Change
0	2022-06-15	Cryptonight	0.000000	-3.732812	0.
1	2022-05-29	I swear my responsibility to the highest good for consciousness, while always re-examining what the highest good is	0.700000	0.870823	4.
2	2022-05-01	Haha he says "Bitcoin" so many times	0.350000	-0.999177	1.
3	2022-04-23	So many "verified" scam crypto bots!	0.625000	-1.011420	-0.
4	2022-04-09	Now subtract crypto scam accounts that twitter constantly shows as "real" people in everyone's feed	0.100000	-1.880861	0.
5	2022-04-08	Price of lithium has gone to insane levels! Tesla might actually have to get into the mining & refining directly at scale, unless costs improve. There is no shortage of the element itself, as lithium is almost everywhere on Earth, but pace of extraction/refinement is slow.	-0.300000	-0.373647	-1.
6	2022-03-25	especially crypto spam!!	0.000000	2.490848	0.
7	2022-03-14	As a general principle, for those looking for advice from this thread, it is generally better to own physical things like a home or stock in companies you think make good products, than dollars when inflation is high. I still own	0.408333	-0.535123	0.

Date	Cleaned_Tweets	Sentiment_Polarity	Price_Change_Before	Price_Change
	& won't sell my Bitcoin, Ethereum or Doge fwiw.			

Sentiment Polarity Visualization

In this visualization, I am plotting the sentiment polarity of Elon Musk's tweets against the percentage change in Bitcoin prices following each tweet. The scatter plot highlights how the positivity or negativity of the tweets correlates with subsequent price movements, with a horizontal line indicating no price change for reference. This helps to visually assess any patterns or trends between tweet sentiment and Bitcoin price fluctuations.

```
In [26]: plt.figure(figsize=(10, 6))
plt.scatter(filtered_btc_tweet_polarity['Sentiment_Polarity'], filtered_btc_
plt.axhline(y=0, color='red', linestyle='--', label='No Change')
plt.title('Sentiment Polarity vs. Bitcoin Price Change After Tweet')
plt.xlabel('Sentiment Polarity')
plt.ylabel('Price Change After Tweet (%)')
plt.grid(True)
plt.legend()
plt.show()
```



Conclusion

Based on the analysis of the sentiment polarity of tweets and their impact on Bitcoin price changes, we can draw some insightful conclusions. The scatter plot reveals a varying relationship between the sentiment of the tweets and the subsequent change in Bitcoin prices. Tweets with higher positive sentiment generally tend to be associated with positive price changes, as indicated by data points above the red dashed line representing no change. For example, a tweet with a sentiment polarity of 0.70 showed a significant positive price change of approximately 4.98% afterward. However, this trend is not consistent across all data points, as some tweets with positive sentiment also coincide with negative price changes. Additionally, tweets with neutral or slightly negative sentiment occasionally result in positive price changes, suggesting that other market factors might also play a role in influencing Bitcoin prices. Overall, while positive sentiment often correlates with an increase in Bitcoin price, it is clear that sentiment alone does not fully dictate market behavior, highlighting the complexity of Bitcoin price . It's important to note that the data set used for this analysis was relatively small. Having access to a larger set of Elon Musk's tweets related to Bitcoin would have allowed for a more comprehensive analysis and potentially more robust conclusions about the relationship between tweet sentiment and market movements.

Additionally, I wanted to gather real-time data on Bitcoin prices but faced constraints due to the cost of accessing APIs that provide minute-by-minute data. If I had been able to gather Bitcoin prices by the minute and analyze the influence of tweets on price changes within the hour, the results could have been more accurate and insightful. However, these constraints limited the scope of the data gathered.

Overall, this study highlights the critical role that influential figures like Elon Musk play in shaping market sentiment and emphasizes the need for investors to consider social media as a factor in their investment strategies.

```
In [27]: em_tweets= pd.read_csv('elon_musk_tweets.csv')
em_tweets
```

Out [27]:

id

user_name

user_location

user_description

user_created

0	1544379368478212100	Elon Musk	NaN	Mars & Cars, Chips & Dips	2009-06-20T12:29:00
1	1544377493263720450	Elon Musk	NaN	Mars & Cars, Chips & Dips	2009-06-20T12:29:00
2	1544377130590552064	Elon Musk	NaN	Mars & Cars, Chips & Dips	2009-06-20T12:29:00
3	1544375575724400645	Elon Musk	NaN	Mars & Cars, Chips & Dips	2009-06-20T12:29:00
4	1544375148605853699	Elon Musk	NaN	Mars & Cars, Chips & Dips	2009-06-20T12:29:00
...
5899	1665143503108677634	Elon Musk	NaN	NaN	2009-06-20T12:29:00
5900	1665139144425631747	Elon Musk	NaN	NaN	2009-06-20T12:29:00
5901	1665137204782419968	Elon Musk	NaN	NaN	2009-06-20T12:29:00
5902	1665131126900285445	Elon Musk	NaN	NaN	2009-06-20T12:29:00
5903	1665121551652474880	Elon Musk	NaN	NaN	2009-06-20T12:29:00

5904 rows × 6 columns

In []: