Can we determine the Doge-coin Price Direction from Twitter Influencers

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Agenda

Motivation

- There has been huge spike in the Dogecoin price YTD during the week of Apr 25 and subsequently, the prices plummeted in the week of May 9. We understand why this happened?

- In the past, opinions and sentiment towards cryptocurrencies have been mined using Twitter.

- Our study primarily focuses on studying whether there is a relation between the Crypto-tastemaker Elon Musk's tweets and the DogeCoin price.

Related Work

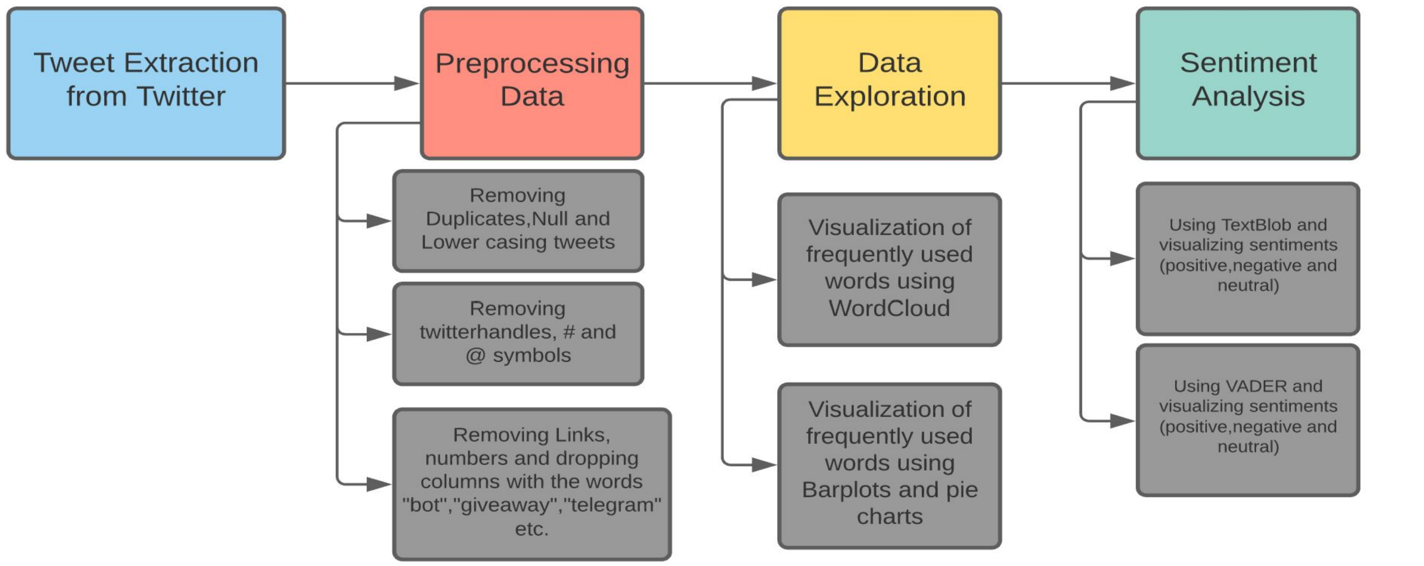
1. Lastly , according to a poll conducted by Gartner, the majority of consumers use social media to influence their buying decisions.
2. Others, including O’Connor found that sentiment expressed in the tweet mirrored public opinion on a variety of topics in a national poll [15].
3. The tweets have been excluded from non-alphanumeric symbols (using ”” and ”@” as examples of symbols removed). Posts that were later deemed irrelevant or too influential were removed from the analysis. The author then uses the Valence Perception Dictionary and the Emotional Regulatory Authority (VADER) to analyze the emotion of each tweet and categorize it as negative, neutral, or positive. The final analysis retained only tweets that could be considered positive or negative [21].We used a similar study inspired from her work.

Terminology

- Event 1- 28th April to 8th May 2021
- Event 2- 8th May to 17th May 2021

For the purpose of this study.

Methodology



Data Collection and Processing

Data Collection

- Tweets were fetched using Tweepy API Researcher account.

Segregating the data based on Events

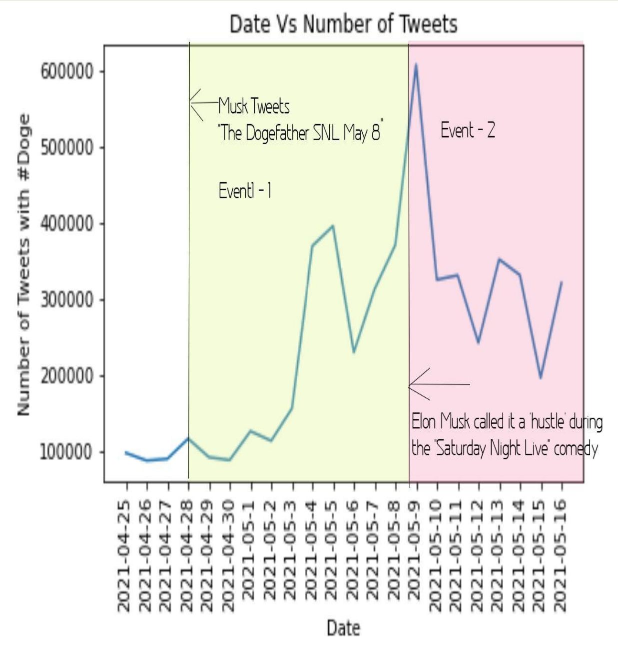
- Event 1- Tweets extracted from 28th April to 8th May 2021
- Event 2- Tweets extracted from 8th May to 17th May 2021

Keyword Search

- We used Keywords and Hashtags like “Doge-coin” , “Elon Musk's”, “Crypto” to extract relevant tweets.
- We used text pre-processing techniques to clean the data for interpretation.
- We fetched 115,837 tweets for Event-1 and 255,000 for Event-2

We can similar highs and lows in the Chart plotted below between No of tweets Tweeted , Price Trends and Google Search Trends

Tweet Volumes



DogeCoin Price Chart

Source:coin base

Google Trends Chart

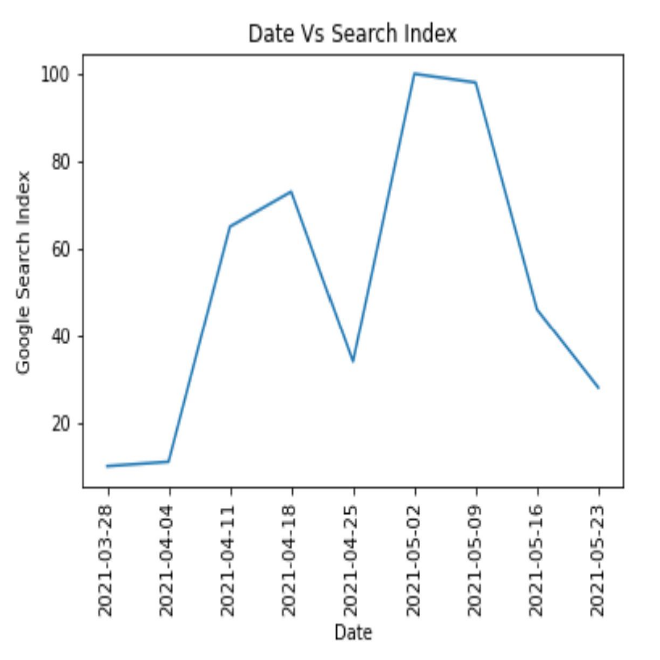


Figure 2: Plots of Tweet Volume , Actual Price Chart and Google Trends

Event 1: Top Keywords

Event 2: Top Keywords

From the wordcloud of event 1 we see that ”Buy” and ”Moon” are the most frequent words.
From the wordcloud of event 2 we see that ”Sell ”,”One” and ”drop” are the most frequent words

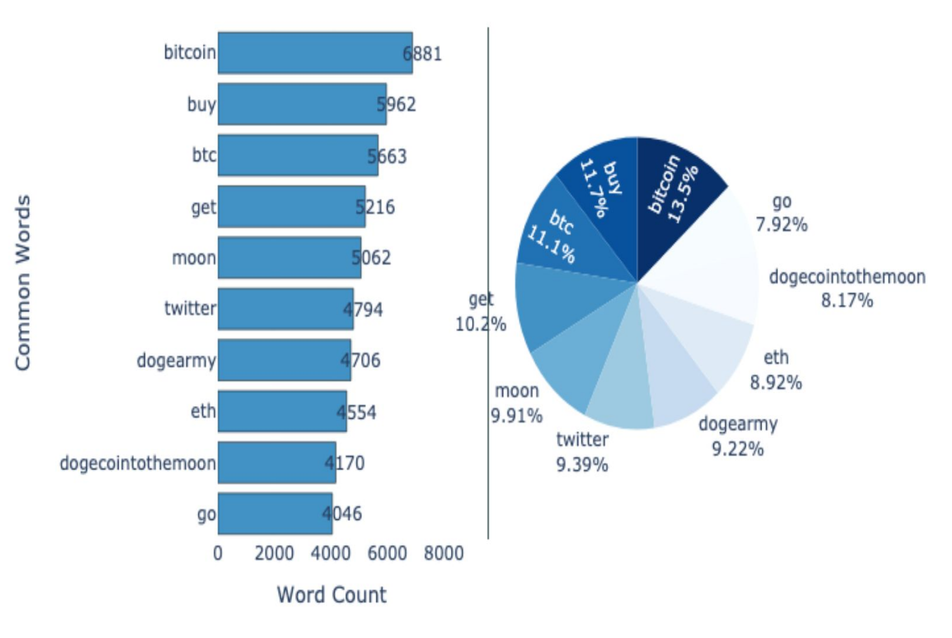
Sample Elon Musk's Tweets

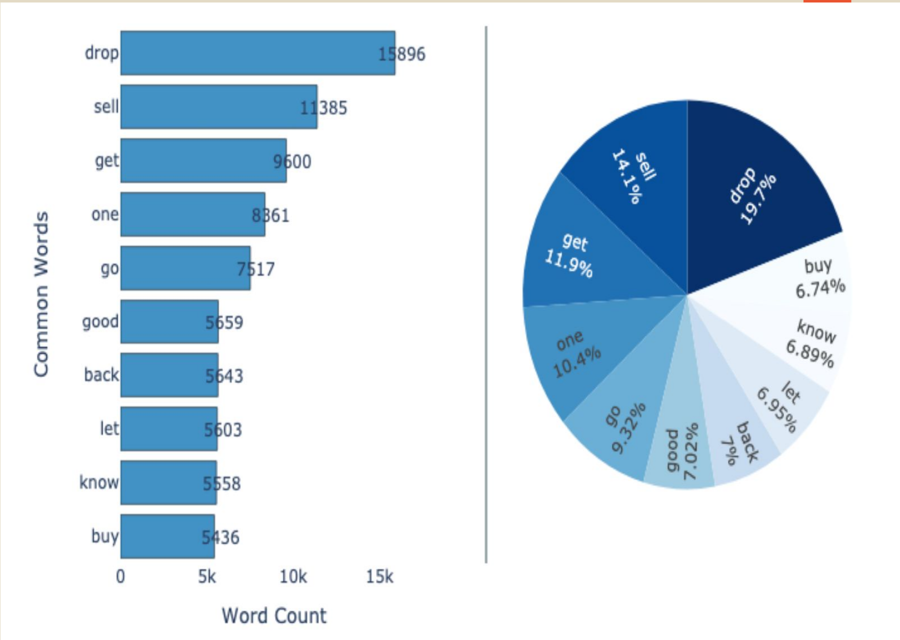
The words moon and dogefather appear in most frequent words used in event 1, indicating Elon Musk's influence

Top 10 Words in both Event 1 &2

Event 1 – Bitcoin/Btc ,Buy,Get

Event 2– Drop ,Sell,Get



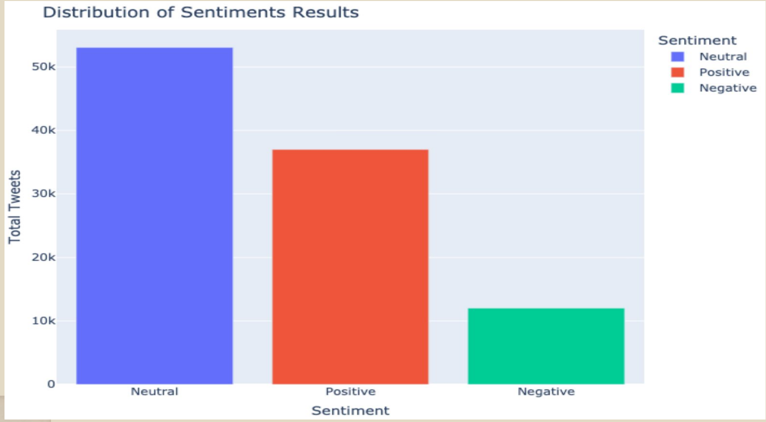


Topics of tweets from Event1 (left) and Event2 (right)

Sentiment Analysis (TextBlob)

- After classifying and pre-processing the data we used texblob and obtained the following results.
- We interpreted that Overall positive buying sentiment remained in both events , but both positive negative negative sentiments increased in the case of Event 2

Event 1



Event 2

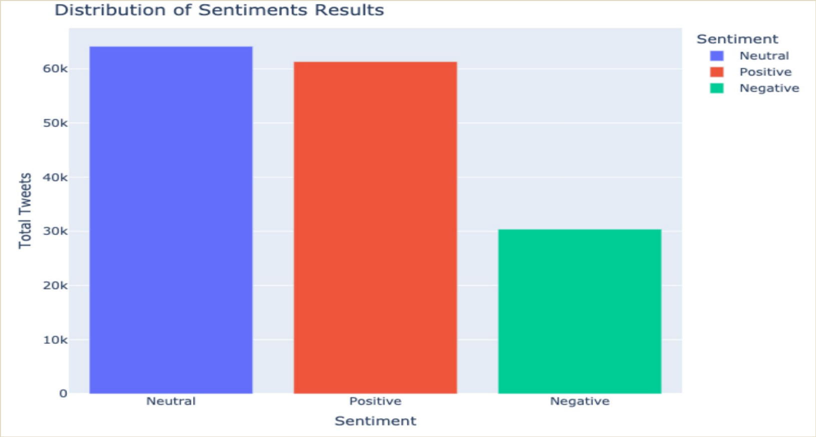
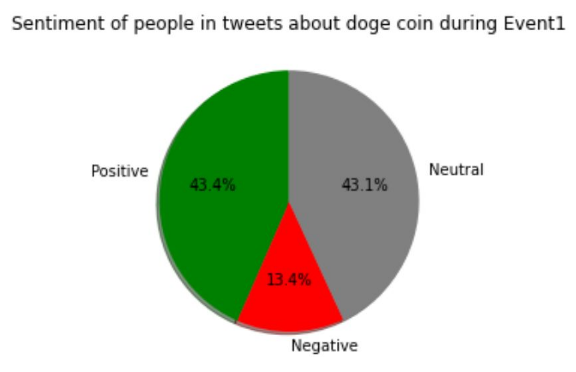


Figure 4: Distribution of sentiments in Event 1 and Event 2

Sentiment Analysis (Vader)

- **Upon using Vader Sentiment analyzer We interpreted that Overall positive buying sentiment remained in both events , but negative sentiment scores increased in the case of Event 2.**

Event 1



Event 2

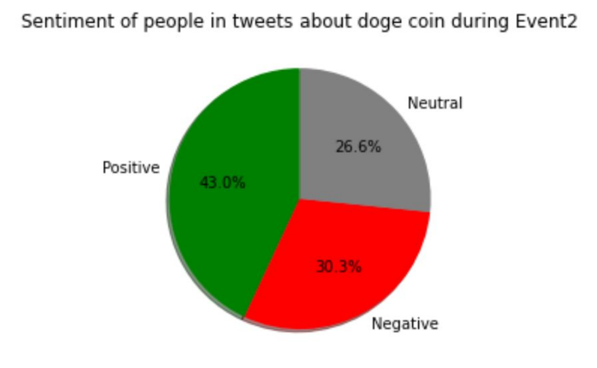


Figure 4: Distribution of sentiments in Event 1 and Event 2

Conclusion

In this experiment, We found that it is not possible to show the relationship between the price movements and twitter sentiments floating over the crypto-tastemakers like Elon Musk.

We were able to process enough tweets and pass it to textblob and VADER to understand the public's sentiment in two events. We observed that the overall sentiment remained majorly positive, even though the prices plunged after event 2.

Future work

1. There are many areas of improvement to our study , by improving the quality of the input data , by increasing the number of sources where such content is gathered.
2. Other areas of work can be done by using more specialized models like LSTM’s and T-MLP’s , which can inherit the ”moods” of the market and adapt according to it

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