Twitter Sentiment vs Bitcoin Price

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Bitcoin

It is a descentralized digital currency without a bank and can be sent from user to user(peer to peer) without intermediares.

Twitter

Social networking servisse on which users post and interact with messages known as "tweets"

Sentiment analysis

Use the natural language processing to mine and identify the sentiment polarity and subjectivity in sentences.

What is a subjective sentence?

A subjective statement relies on assumptions, beliefs, opinions and influenced by emotions and personal feelings.

What is a objective or neutral sentence?

A objective or neutral sentences relies on facts where the information is provable measurable and observable.

Problem:

Analyze the sentiment extrated from tweets and check if there is any correlation with the Bitcoin price change.

Strategy used:

For our problem we going to use two classifiers.

The first one is going to determine if the sentence is subjective or not.

Then if the sentence it's subjective we are going to use the polarity classificator to find out if the sentence is positive or negative.

Method Step by Step:

1) Tweet Scraping

Tweets were collected with the tool twitterscrapter that contains the words "BTC" or "Bitcoin".

Number tweets: 40000 tweets

Date Range: 2017-11-5 to 2018-02-28.

2) Pre Processing

For each dataset and tweet it was necessary to clean the text and convert into vectors.

Clean text includes:

- Convert text to lowercase
- Remove numbers
- Remove punctuation
- Remove urls
- Remove hashtags
- Remove twitter usernames
- Remove Stop Words(the", "a", "on", "is", "all")
- Use Steeming Is a process of reducing words to their root form
 - Use Lemmazation- Uses lexical knowledge bases to get the correct base forms of words.

Text into vector :

After we clean our sentences we are going to use the bag of words concept which creates a dicionary for every existent words in our datasets. One word will correspond a position in the dicionary list which will contain the number of times the corresponding word has occured in the document.

3) Training and Test

For both classifiers it was used Naive Bayes

Subjectivity Classifier:

Datasets:

- quote.tok.gt9.5000 contains the subjective sentences.
- plot.tok.gt9.5000 contains the non subjective sentences(objective sentences)

Train and test performance:

Accuracy Train NB: 0.9119474733262986 Accuracy Test NB: 0.7805907172995781

Polarity Classifier:

Datasets:

- rt-polarity.pos contains the positive sentences
- rt-polarity.neg contains the negative sentences

• Train and test performance:

Accuracy Train NB: 0.95575 Accuracy Test NB: 0.914

4) Classify Tweets

Some tweet classifications:

>	likes	text	dates	classification
	0 0		2017- 11-09	Positive
	1 1		2017- 11-09	Neutral
	2 0		2017- 11-09	Positive
	3 0		2017- 11-09	Positive
	4 1		2017- 11-09	Positive
	5 0		2017- 11-09	Neutral
	6 1		2017- 11-09	Negative
	7 2		2017- 11-09	Positive
	8 1		2017- 11-09	Neutral
	9 1		2017- 11-09	Negative
	10 0		2017- 11-09	Neutral

5) Calculations

For each day it was calculated the % of positive and negative tweets with at least 10 likes. The neutral tweets were ignored.

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6) Bitcoin historical data

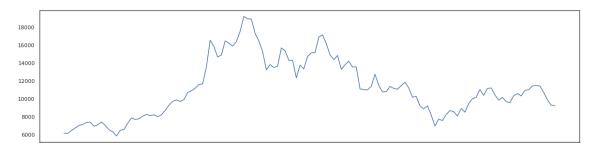
- It was used the cryptocompare api to get the following historical data:
 - Bitcoin closing prices
 - Trading volume
 - Timestamp

The % positive and negative tweets were added to the dataset:

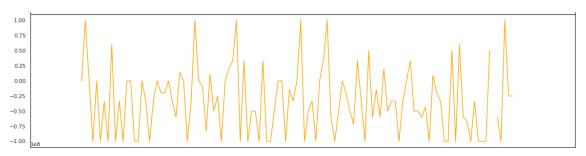
	close	volumeto	timestamp	positive	negative	samples
0	6155.00	3.317674e+07	2017-10-29	NaN	NaN	0
1	6125.00	1.754572e+07	2017-10-30	NaN	NaN	0
2	6450.02	2.411846e+07	2017-10-31	NaN	NaN	0
3	6739.79	3.082127e+07	2017-11-01	NaN	NaN	0
4	7025.00	7.440179e+07	2017-11-02	NaN	NaN	0
5	7124.36	4.260343e+07	2017-11-03	NaN	NaN	0
6	7366.00	3.676271e+07	2017-11-04	NaN	NaN	0
7	7379.17	3.223164e+07	2017-11-05	0.000000	0.000000	0
8	6929.97	4.709258e+07	2017-11-06	1.000000	0.000000	1
9	7084.87	2.911407e+07	2017-11-07	0.000000	0.000000	0
10	7410.00	6.844777e+07	2017-11-08	0.000000	1.000000	1
11	7020.00	4.456109e+07	2017-11-09	0.000000	0.000000	0
12	6543.20	9.082739e+07	2017-11-10	0.000000	1.000000	1
13	6300.00	8.234972e+07	2017-11-11	0.333333	0.666667	6
14	5835.00	1.700409e+08	2017-11-12	0.000000	1.000000	3
15	6475.78	1.136491e+08	2017-11-13	0.800000	0.200000	5
16	6554.92	4.431548e+07	2017-11-14	0.000000	1.000000	2
17	7275.12	6.712821e+07	2017-11-15	0.333333	0.666667	3
18	7858.00	8.362667e+07	2017-11-16	0.000000	1.000000	3
19	7687.51	6.982431e+07	2017-11-17	0.000000	0.000000	0
20	7770.00	4.481716e+07	2017-11-18	0.000000	0.000000	0

7) Plot the results from dataset

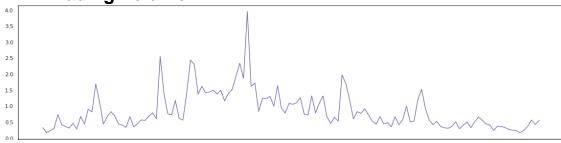
• Bitcoin Close Prices:



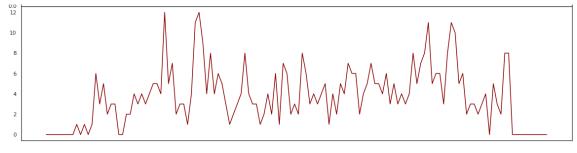
% Positive and Negative tweets



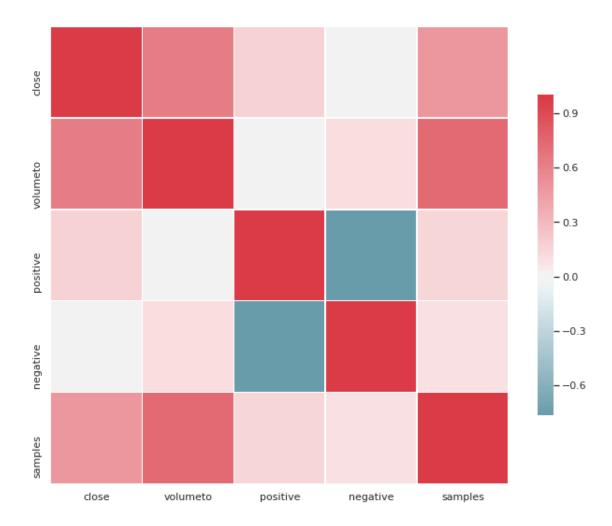
Trading Volume



• Number of tweets >=10 likes



8) Plot Heatmap and check for coorelation between features



We can see some correlation between the price, trading volume, and the number of tweets.

References:

Motivation to do it:

https://hackernoon.com/twitter-scraping-text-mining-and-sentiment-analysis-using-python-b95e792a4d64

Theory:

http://www.cs.cornell.edu/home/llee/papers/cutsent.pdf

Pre Processing:

https://medium.com/@datamonsters/text-preprocessing-in-pythonsteps-tools-and-examples-bf025f872908

https://www.freecodecamp.org/news/an-introduction-to-bag-of-words-and-how-to-code-it-in-python-for-nlp-282e87a9da04/

Datasets used:

https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

Code Inspiration:

http://blog.chapagain.com.np/python-nltk-twitter-sentiment-analysis-natural-language-processing-nlp/

https://www.kaggle.com/paul92s/bitcoin-lstm-model-with-tweet-volume-and-sentiment

API for historical data:

https://min-api.cryptocompare.com/