In [1]:

```
%matplotlib inline
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')

import matplotlib.dates as mdates
from mpl_finance import candlestick_ohlc #!!! pip install mplfinance, pip install --upgrade
```

```
C:\anaconda3\lib\site-packages\mpl_finance.py:16: DeprecationWarning:

  =================================================================

   WARNING: `mpl_finance` is deprecated:

    Please use `mplfinance` instead (no hyphen, no underscore).

    To install: `pip install --upgrade mplfinance`

   For more information, see: https://pypi.org/project/mplfinance/ (https://
pypi.org/project/mplfinance/)

  =================================================================

  __warnings.warn('\n\n  ===================================================
==============='+
```

Tweets And Bitcoin Price

Research how the tweets with "btc" or "bitcoin" is corelated with Bitcoin price / 2018

Abstract

By using twitter activities can help to predict movement of bitcoin price. Activity is measured by the numbers of creating tweets and replies which they receive. It can be seen that when the activity increases it leads to the end of a trend, a reversal of a trend, or the beginning of a new trend. All of this allows for the realization of a fundamental indicator in real-time, which should help active traders to properly assess the action and make better decisions.

Introduction

Why Tweets?

Twitter is the most used social network for sharing and communicating about bitcoin news, rumors, ideas and prices. There is a term Crypto Twitter on the Internet. Because there is the first place where someone shares news and all kinds of information about cryptocurrencies.

Why we try to find corelation betwin tweets and bitcoin prices

There are many technical indicators in the world of finance. Many traders try to guess the price movement through them, but in most cases, this is not enough. 50% success is neutrality, that is you neither guess nor do not guess it. 70%+ guessing can be considered a winning strategy. All these technical indicators are based solely on the price and its movement. In analyzing the tweets, we begin to analyze the fundamental aspect by turning it into numbers and begin to measure it.

Why we choise 2018

2018 is characterized by a strong positive attitude of many market participants in anticipation of continued price growth, just after the All Time High (ATH) of $ 20,000 for a bitcoin in December 2017. And the price throughout the 2018 year was in a downtrend or bearish trend.
The data sets used are quite large and therefore we will consider analyzing at this stage only for 2018. As one quite interesting year with its contradictions, expectation vs reality.

What we expected?

- In one case, we can find that certain activity in tweets leads to a change in price.
- In the opposite case, we can find that the activity in the tweeter is a consequence of a change in price and this in no way gives us a preliminary sign that there will be movement.
- Or somewhere in the middle. 50%/50%, which does not bring additional benefit to our assumptions.

Load big data

We use two data sets, one for the price of bitcoin and other for the tweets on Twitter containing "btc" or "bitcoin".

!!! Important, first you have to download the data sets in the same folder. The Notebook can work with booth combination of date sets. Big is 4GB+, Small(2018) is ~400MB.

Big Data Sets

- https://www.kaggle.com/mczielinski/bitcoin-historical-data (https://www.kaggle.com/mczielinski/bitcoin-historical-data) (bitstampUSD_1-min_data_2012-01-01_to_2020-04-22.csv)
- https://www.kaggle.com/alaix14/bitcoin-tweets-20160101-to-20190329 (https://www.kaggle.com/alaix14/bitcoin-tweets-20160101-to-20190329) (tweets.csv) Scrapped from twitters from 2016-01-01 to 2019-03-29, Collecting Tweets containing Bitcoin or BTC

2018 Data Sets

- www.kaggle.com/dataset/c7e296ccd23d8f0ddcf62482685a626993baac892491ecb9336875f6165f5595 (http://www.kaggle.com/dataset/c7e296ccd23d8f0ddcf62482685a626993baac892491ecb9336875f6165f559
Private, only link share

In [3]:

```
prices_btc = pd.read_csv("bitstampUSD_1-min_data_2012-01-01_to_2020-04-22.csv", low_memory
#https://www.kaggle.com/mczielinski/bitcoin-historical-data
prices_btc
```

Out[3]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	W
0	1325317920	4.39	4.39	4.39	4.39	0.455581	2.000000	
1	1325317980	NaN	NaN	NaN	NaN	NaN	NaN	
2	1325318040	NaN	NaN	NaN	NaN	NaN	NaN	
3	1325318100	NaN	NaN	NaN	NaN	NaN	NaN	
4	1325318160	NaN	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	
4363452	1587513360	6847.97	6856.35	6847.97	6856.35	0.125174	858.128697	
4363453	1587513420	6850.23	6856.13	6850.23	6850.89	1.224777	8396.781459	
4363454	1587513480	6846.50	6857.45	6846.02	6857.45	7.089168	48533.089069	
4363455	1587513540	6854.18	6854.98	6854.18	6854.98	0.012231	83.831604	
4363456	1587513600	6850.60	6850.60	6850.60	6850.60	0.014436	98.896906	

4363457 rows × 8 columns

In [4]:

```
tweets_btc_small_part = pd.read_csv("tweets.csv", low_memory = False, nrows=50000, delimite
#https://www.kaggle.com/alaix14/bitcoin-tweets-20160101-to-20190329
tweets_btc_small_part
```

0	[illegible]	[illegible]	[illegible]	NaN	11:49:14+00	0	0	0	
1	1132977073402736640	bitcointe	Bitcointe	NaN	2019-05-27 11:49:18+00	0	0	0	
2	1132977023893139456	3eyedbran	Bran - 3 Eyed Raven	NaN	2019-05-27 11:49:06+00	0	2	1	And
3	1132977089089556481	DetroitCrypto	J. Scardina	NaN	2019-05-27 11:49:22+00	0	0	0	Cu
4	1132977092340191232	mmursaleen72	Muhammad Mursaleen	NaN	2019-05-27 11:49:23+00	0	0	0	B
...	...	...	...	...	...	...	...	...	

Save 2018 Data

We filter data sets only for the 2018 year. The code which saving the files is commented. Now we have these files.

In [5]:

```
prices_btc
prices_btc["Timestamp"] = pd.to_datetime(prices_btc["Timestamp"], unit="s")
price_btc_2018 = prices_btc[(prices_btc["Timestamp"] >= "2018-01-01 00:00:00") & (prices_bt
#price_btc_2018.dtypes #checking for missing values
#price_btc_2018.to_csv('price_btc_2018.csv', index = False, header=True) # SAVE DATA 2018
price_btc_2018
```

Out[5]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)
3150976	2018-01-01 00:00:00	13880.00	13906.37	13841.00	13841.01	4.967997	69030.718890
3150977	2018-01-01 00:01:00	13841.01	13890.43	13841.01	13890.43	1.665850	23064.082359
3150978	2018-01-01 00:02:00	13846.64	13890.35	13846.64	13847.51	0.269346	3739.690844
3150979	2018-01-01 00:03:00	13847.51	13874.92	13823.19	13823.19	1.155274	15986.279494
3150980	2018-01-01 00:04:00	13823.19	13826.75	13803.20	13803.20	0.646691	8930.465767
...	...	...	...	...	...	...	...
3676571	2018-12-31 23:55:00	3688.28	3688.85	3685.00	3688.85	7.665703	28263.698185
3676572	2018-12-31 23:56:00	3687.87	3689.65	3686.92	3686.92	7.610240	28063.290959
3676573	2018-12-31 23:57:00	3688.83	3689.26	3688.83	3689.26	0.560833	2068.943311
3676574	2018-12-31 23:58:00	3689.26	3691.35	3689.26	3691.35	0.560000	2066.110758
3676575	2018-12-31 23:59:00	3689.26	3693.30	3689.26	3693.30	9.838855	36311.346546

525600 rows × 8 columns

In [6]:

```
# Need more time to process!!!
tweets_2018 = pd.DataFrame()
for chunk in pd.read_csv("tweets.csv", "r", chunksize = 100000, delimiter=";", lineterminat
    chunk["timestamp"] = pd.to_datetime(chunk["timestamp"])
    tweets_2018 = pd.concat([tweets_2018, chunk[(chunk["timestamp"] >= "2018-01-01 00:00:00
```

In [7]:

```
tweets_2018 = tweets_2018.sort_values(by="timestamp")
#tweets_2018.dtypes#checking for missing values
#tweets_2018.to_csv('tweets_2018.csv', index = False, header=True) # SAVE DATA 2018
tweets_2018
```

2835821	9.476335e+17	FluPhotos	FluPhotos	/FluPhotos/status/947633484482400256	2018-01- 00:00:03+00:
2374144	9.476335e+17	BitcoinCash_ES	BitcoinCash_es	/BitcoinCash_ES/status/947633482716590080	2018-01- 00:00:03+00:
...	...	...	...	...	
2739953	1.079901e+18	analyst5_bot	analyst5	/analyst5_bot/status/1079901346114035712	2018-12- 23:45:19+00:
7242516	1.079888e+18	CRESIOcoin	CRESIO Multi-Exchange	NaN	2018-12- 23:52:24+00:
2739952	1.079904e+18	tr_ticker	Tr Ticker Bot	/tr_ticker/status/1079903912138891269	2018-12- 23:55:30+00:
2739950	1.079904e+18	xtradebot	ProjectX - XtradeBOT	/xtradebot/status/1079904379275223040	2018-12- 23:57:22+00:
2739949	1.079905e+18	cointrend_jp	COINTREND	/cointrend_jp/status/1079904546636193793	2018-12- 23:58:02+00:

Load 2018 data

In [8]:

```
price_btc_2018 = pd.read_csv("price_btc_2018.csv", low_memory = False)
```

In [9]:

```
price_btc_2018_jan = price_btc_2018[(price_btc_2018["Timestamp"] >= "2018-01-01 00:00:00")
price_btc_2018_jan["Timestamp"] = pd.to_datetime(price_btc_2018_jan["Timestamp"])
price_btc_2018_jan.dtypes # check the Timestamp column
```

Out[9]:

```
Timestamp            datetime64[ns]
Open                        float64
High                        float64
Low                         float64
Close                       float64
Volume_(BTC)                float64
Volume_(Currency)           float64
Weighted_Price              float64
dtype: object
```

In [10]:

```
tweets_btc_2018 = pd.read_csv("tweets_2018.csv", low_memory = False)
```

In [11]:

```
tweets_btc_2018_jan = tweets_btc_2018[(tweets_btc_2018["timestamp"] >= "2018-01-01 00:00:00
tweets_btc_2018_jan["timestamp"] = pd.to_datetime(tweets_btc_2018_jan["timestamp"])
tweets_btc_2018_jan["timestamp"] = tweets_btc_2018_jan["timestamp"].dt.tz_localize(None)
tweets_btc_2018_jan.dtypes # check the timestamp column
```

Out[11]:

```
id                   float64
user                  object
fullname              object
url                   object
timestamp    datetime64[ns]
replies                int64
likes                  int64
retweets               int64
text\r                object
dtype: object
```

Replies vs Likes vs Retweets

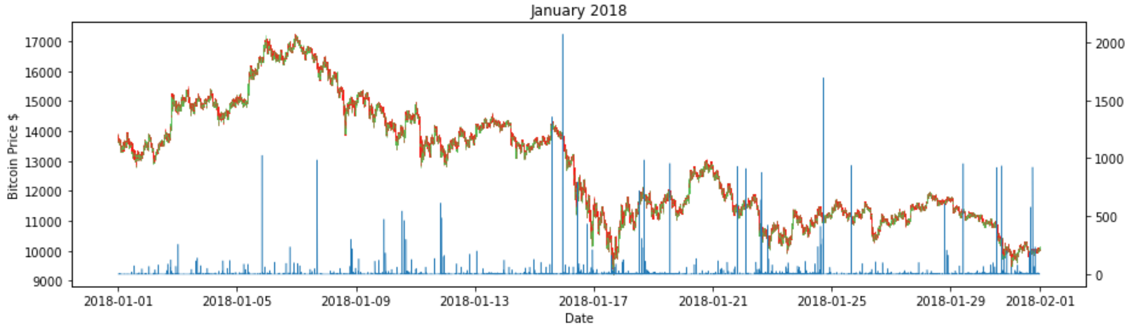
We combine the three parameters on the price charts to see which of them would be suitable as an indicator. We notice that the Replies parameter shows the best correlates with the price. In reality, liking and retweeting of tweets requires the least energy and maybe is "actionless talk" and commenting on tweets is real action and effort and correlates best of the three with future price movements.

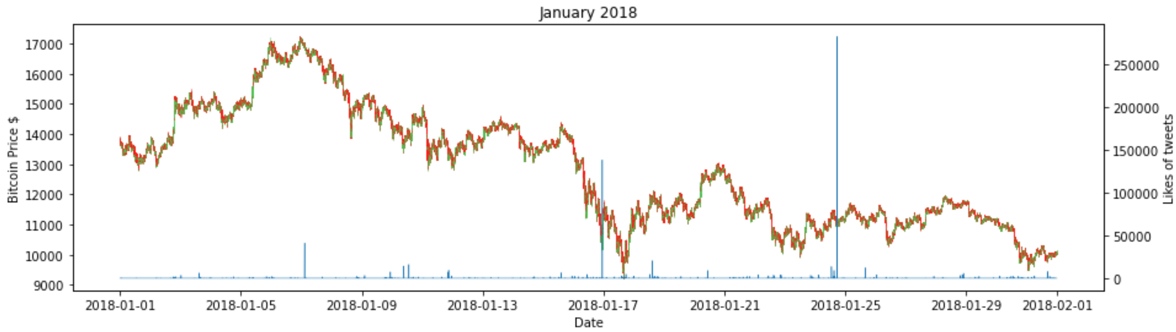
The disadvantage, in this case, is that the comments in the data set which we have them ready and in a real situation they appear within a few hours after the publication of the tweet, which creates a lag in the idea of our indicator, which can be ignored in some cases but not in all. Additional analysis is needed to take into account the speed of creates of comments and at what point they reach 80-90% of all comments. The first view in tweeter shows that the period is some hours.

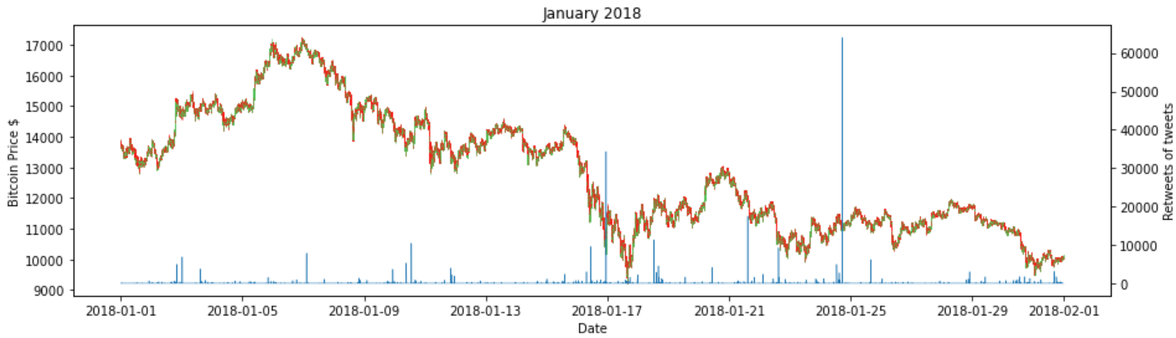
Another characteristic feature is that data frames have a timestamp with accuracy a second. This allows you to have two or more tweets in one second and then on the chart we will see them as a single tweet, which is ok for the indicator.

In [12]:

```
# Need more time to process!!!
from_date = "2018-01-01 00:00:00"
to_date = "2018-01-31 23:59:59"
month = "January "

price_btc_2018_month = price_btc_2018[(price_btc_2018["Timestamp"] >= from_date) & (price_b
price_btc_2018_month["Timestamp"] = pd.to_datetime(price_btc_2018_month["Timestamp"])
df_price = price_btc_2018_month[["Timestamp", "Open", "High", "Low", "Close"]]
df_price["Timestamp"] = df_price["Timestamp"].apply(mdates.date2num)

tweets_btc_2018_month = tweets_btc_2018[(tweets_btc_2018["timestamp"] >= from_date) & (twee
tweets_btc_2018_month["timestamp"] = pd.to_datetime(tweets_btc_2018_month["timestamp"])
tweets_btc_2018_month["timestamp"] = tweets_btc_2018_month["timestamp"].dt.tz_localize(None
df_tweets = tweets_btc_2018_month

fig = plt.figure(figsize=(15,4))
f1 = fig.add_subplot()
candlestick_ohlc(f1, df_price.values, width=.01, colorup="#53c156", colordown="#ff1717")
f1.xaxis_date()
f1.set_ylabel("Bitcoin Price $")
f1.set_xlabel("Date")

f2 = f1.twinx()
f2.plot(df_tweets.timestamp, df_tweets.replies, linewidth=.5)
f2.set_ylabel("Replies of tweets")

plt.title(month + "2018")
plt.show()

fig = plt.figure(figsize=(15,4))
f1 = fig.add_subplot()
candlestick_ohlc(f1, df_price.values, width=.01, colorup="#53c156", colordown="#ff1717")
f1.xaxis_date()
f1.set_ylabel("Bitcoin Price $")
f1.set_xlabel("Date")

f3 = f1.twinx()
f3.plot(df_tweets.timestamp, df_tweets.likes, linewidth=.5)
f3.set_ylabel("Likes of tweets")

plt.title(month + "2018")
plt.show()

fig = plt.figure(figsize=(15,4))
f1 = fig.add_subplot()
candlestick_ohlc(f1, df_price.values, width=.01, colorup="#53c156", colordown="#ff1717")
f1.xaxis_date()
f1.set_ylabel("Bitcoin Price $")
f1.set_xlabel("Date")

f4 = f1.twinx()
f4.plot(df_tweets.timestamp, df_tweets.retweets, linewidth=.5)
f4.set_ylabel("Retweets of tweets")

plt.title(month + "2018")
plt.show()
```







Reused code

Create a function that we can reuse for our charts by month

Volume Of Tweets

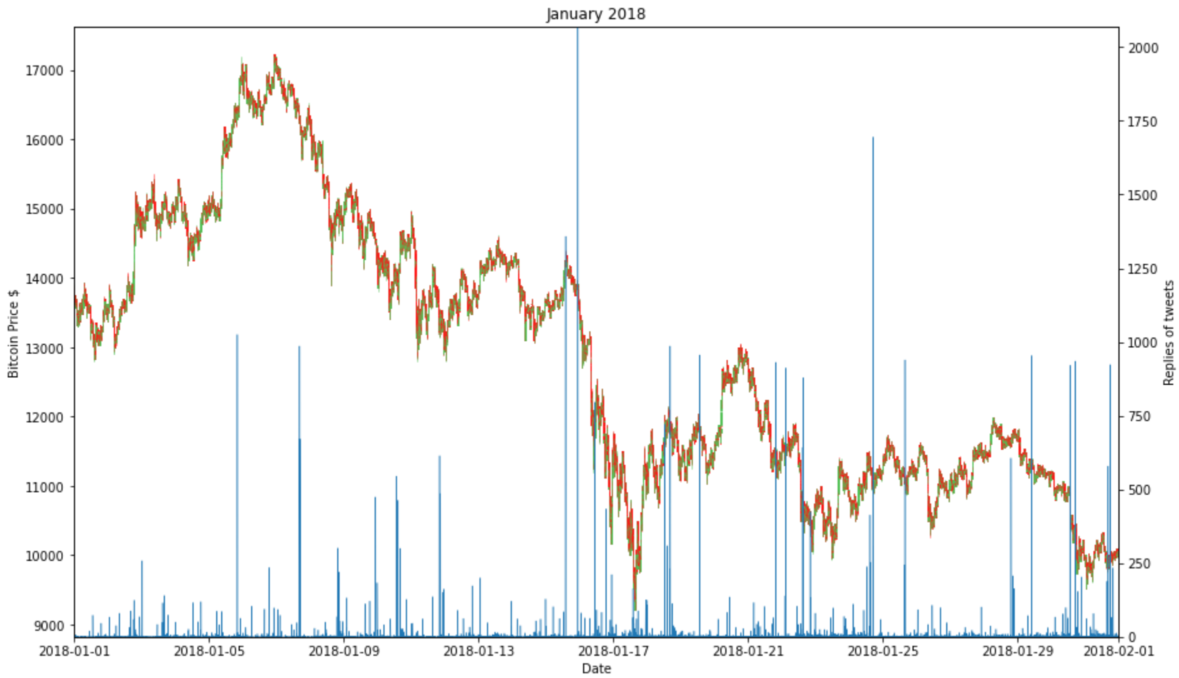
We add the total number of tweets per day, which also shows the current interest and the trend by days/weeks/months.

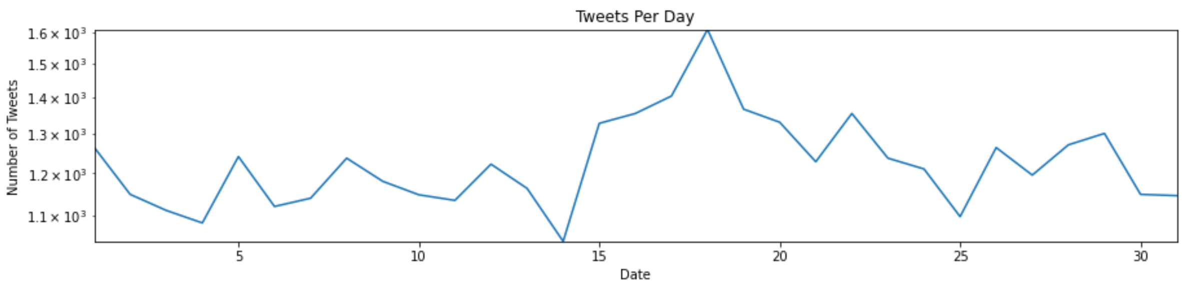
In [13]:

```
# Need more time to process!!!
def chart_by_period(from_date = "2018-01-01 00:00:00", to_date = "2018-01-31 23:59:59", mon

    price_btc_2018_month = price_btc_2018[(price_btc_2018["Timestamp"] >= from_date) & (pri
    price_btc_2018_month["Timestamp"] = pd.to_datetime(price_btc_2018_month["Timestamp"])
    df_price = price_btc_2018_month[["Timestamp", "Open", "High", "Low", "Close"]]
    df_price["Timestamp"] = df_price["Timestamp"].apply(mdates.date2num)

    tweets_btc_2018_month = tweets_btc_2018[(tweets_btc_2018["timestamp"] >= from_date) & (
    tweets_btc_2018_month["timestamp"] = pd.to_datetime(tweets_btc_2018_month["timestamp"])
    tweets_btc_2018_month["timestamp"] = tweets_btc_2018_month["timestamp"].dt.tz_localize(
    df_tweets = tweets_btc_2018_month

    fig = plt.figure(figsize=(15, 9))
    f1 = fig.add_subplot()
    candlestick_ohlc(f1, df_price.values, width=.01, colorup="#53c156", colordown="#ff1717"
    f1.xaxis_date()
    #f1.xaxis.set_major_formatter(mdates.DateFormatter('%d')) # %H:%M:%S -%y-%m
    f1.set_ylabel("Bitcoin Price $")
    f1.set_xlabel("Date")

    f2 = f1.twinx()
    f2.plot(df_tweets.timestamp, df_tweets.replies, linewidth=.5)
    f2.set_ylabel("Replies of tweets")

    # f3 = fig.add_subplot()
    # f3.plot(df_tweets.groupby(df_tweets["timestamp"].dt.day).count())

    plt.title(month + "2018")
    #plt.xticks(rotation=45)
    plt.margins(0)
    plt.show()

    fig2 = plt.figure(figsize=(15,3))
    f = fig2.add_subplot()
    f.plot(df_tweets["timestamp"].groupby(df_tweets["timestamp"].dt.day).count())
    plt.title("Tweets Per Day")
    f.set_ylabel("Number of Tweets")
    f.set_yscale('log')
    #f.xaxis_date()
    #plt.xlim((1))
    plt.margins(0)
    f.set_xlabel("Date")
    plt.show()
```

In [14]:

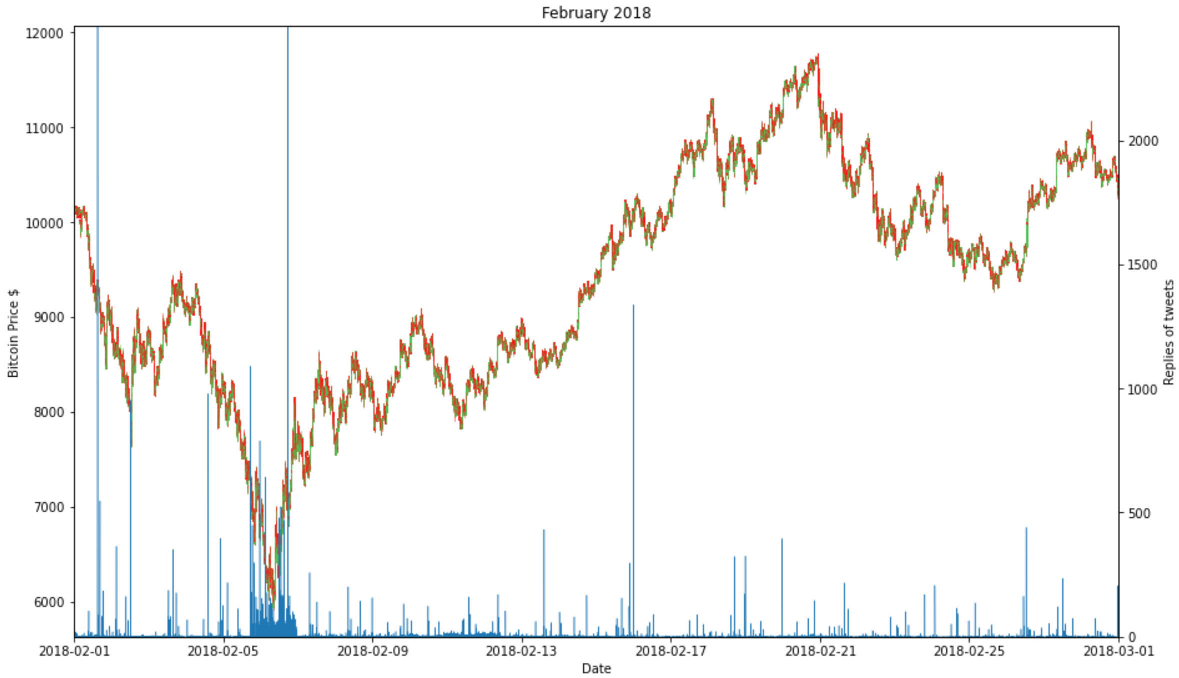
```
# Need more time to process!!!
chart_by_period("2018-01-01 00:00:00", "2018-01-31 23:59:59", "January ")
```

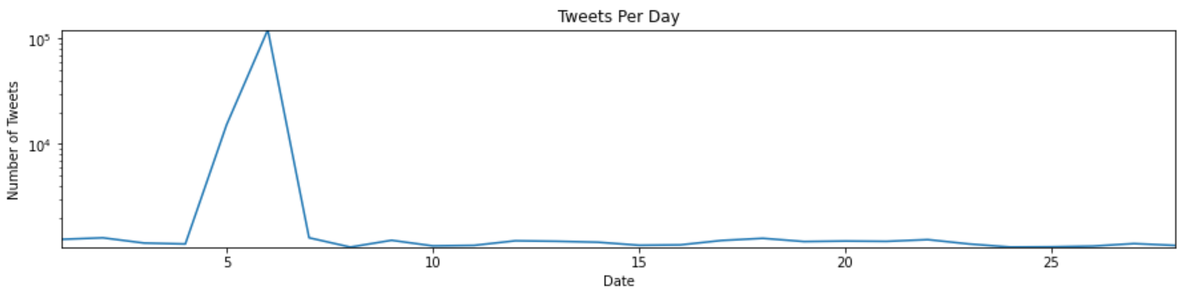




In [15]:

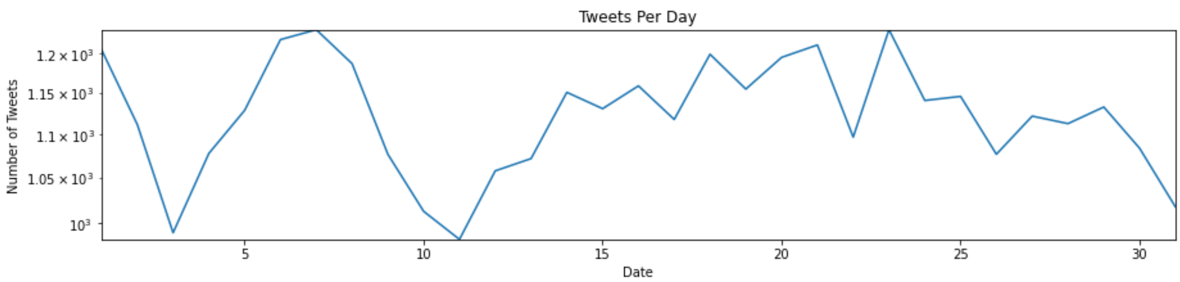
```
chart_by_period("2018-02-01 00:00:00", "2018-02-28 23:59:59", "February ")
```





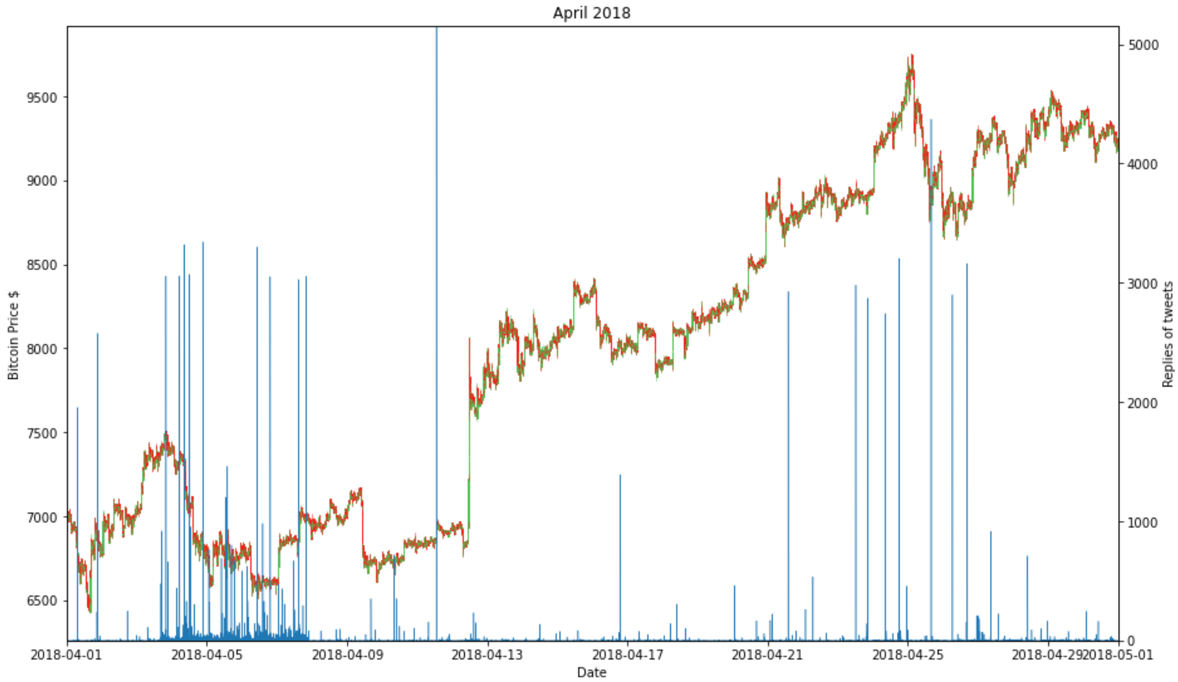
In [16]:

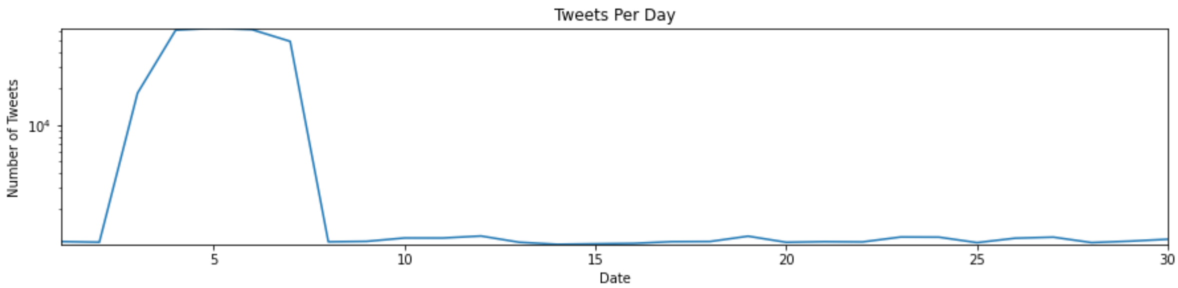
```
chart_by_period("2018-03-01 00:00:00", "2018-03-31 23:59:59", "Mart ")
```



In [17]:

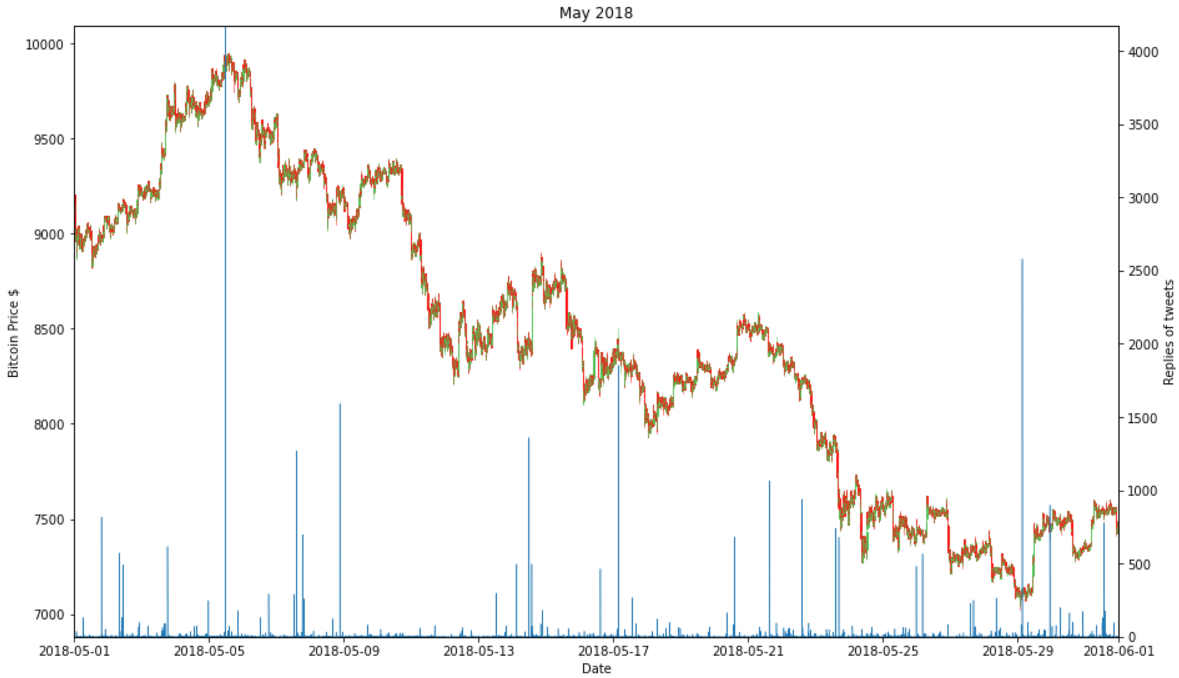
```
chart_by_period("2018-04-01 00:00:00", "2018-04-30 23:59:59", "April ")
```

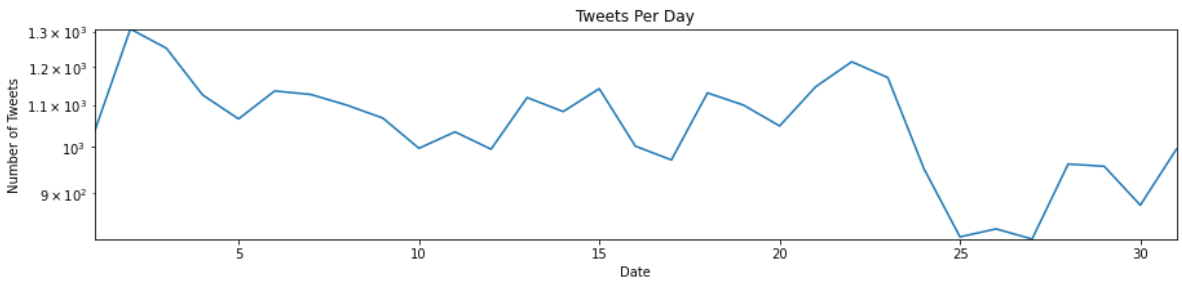




In [18]:

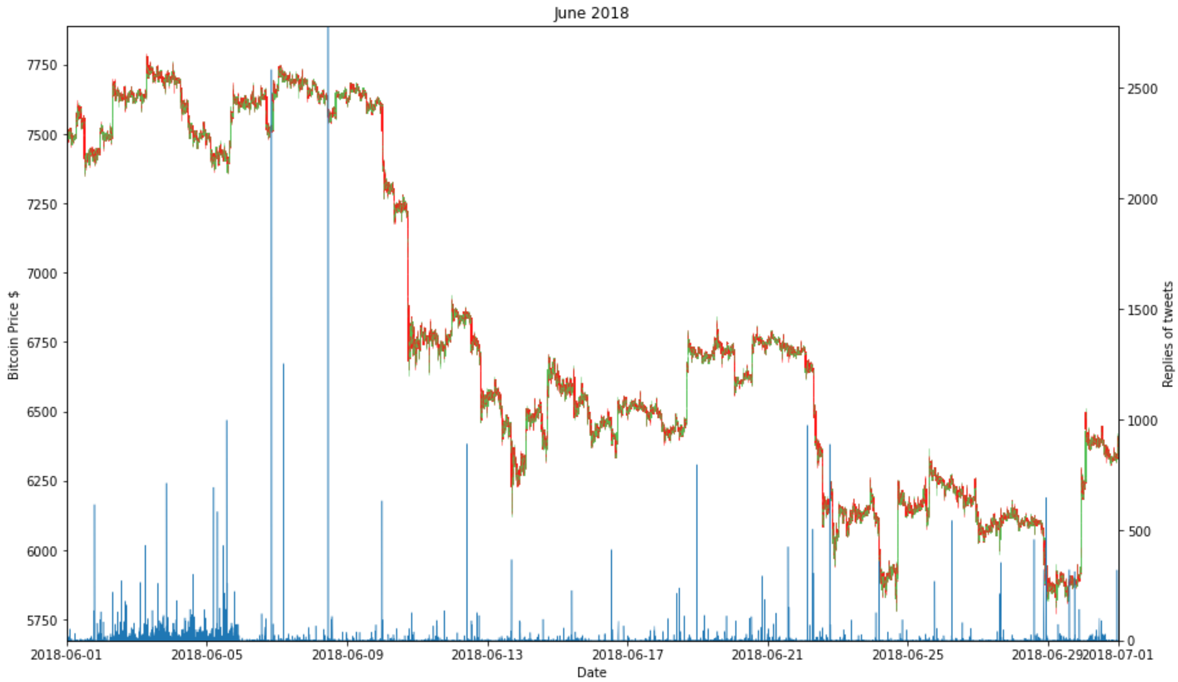
```
chart_by_period("2018-05-01 00:00:00", "2018-05-31 23:59:59", "May ")
```

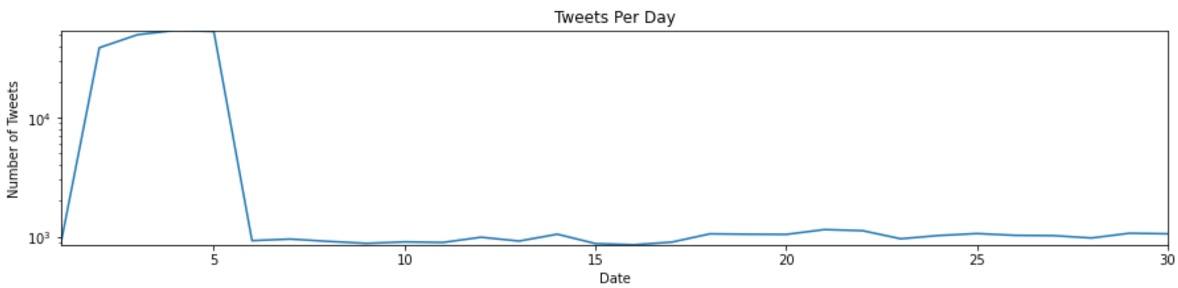




In [19]:

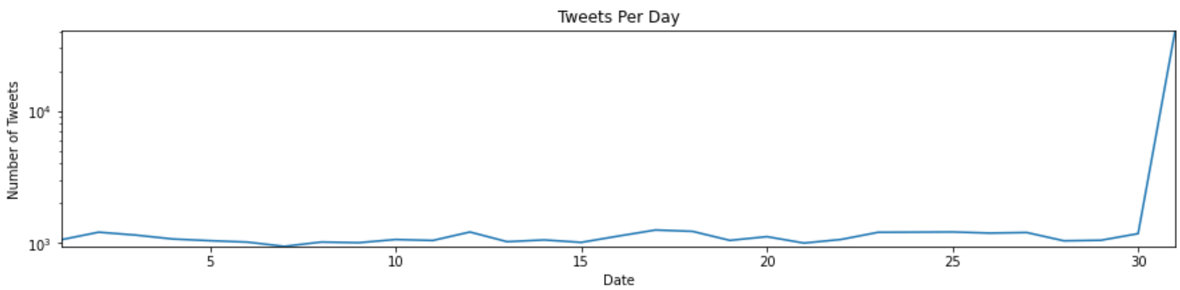
```
chart_by_period("2018-06-01 00:00:00", "2018-06-30 23:59:59", "June ")
```





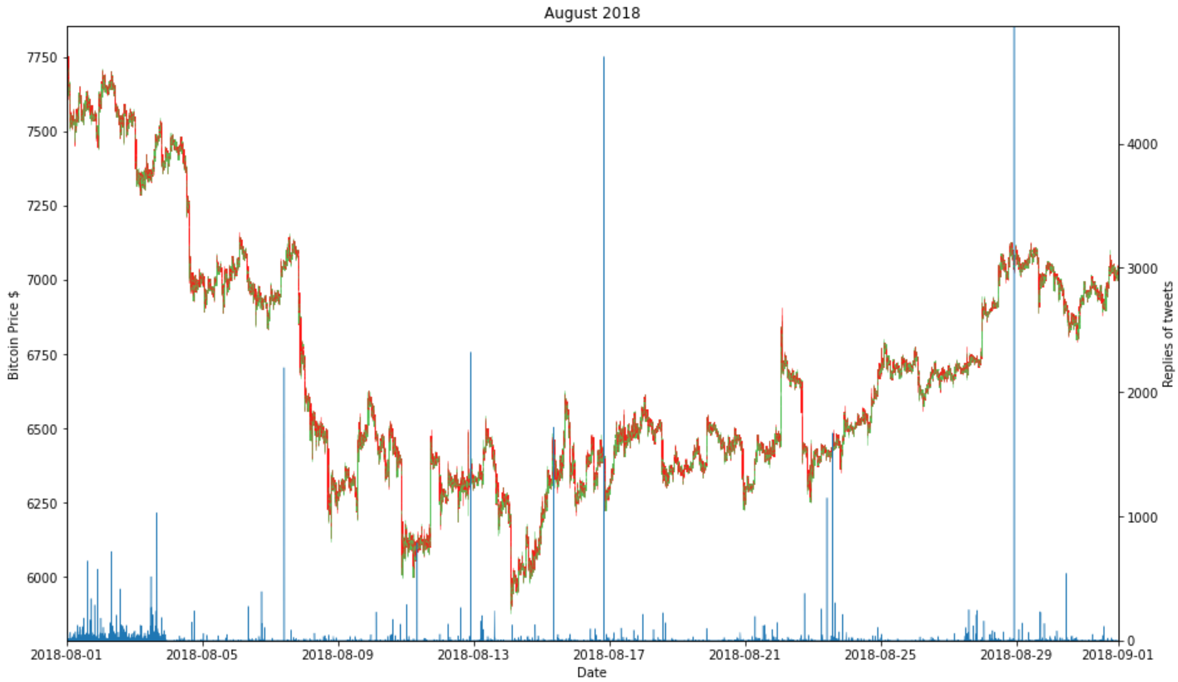
In [20]:

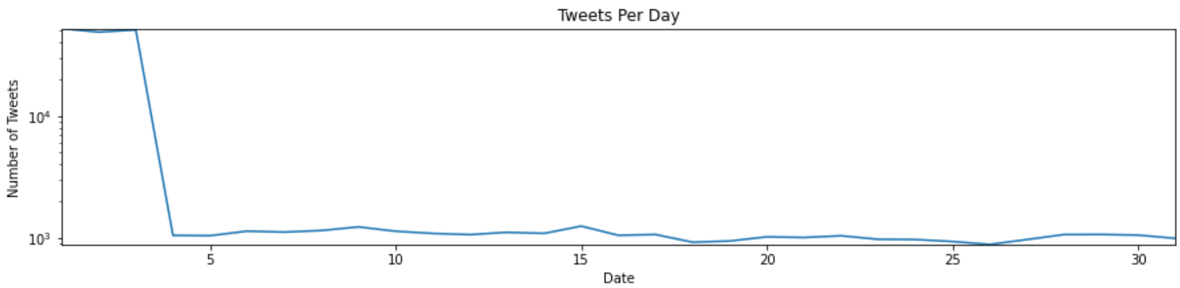
```
chart_by_period("2018-07-01 00:00:00", "2018-07-31 23:59:59", "July ")
```



In [21]:

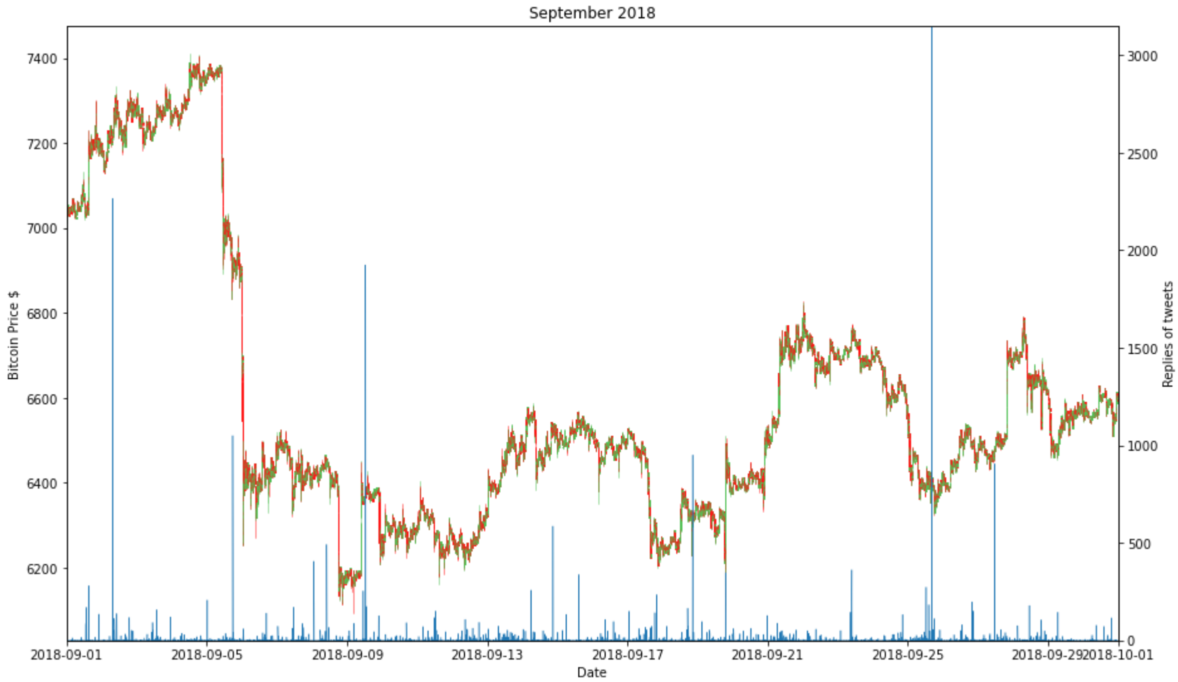
```
chart_by_period("2018-08-01 00:00:00", "2018-08-31 23:59:59", "August ")
```

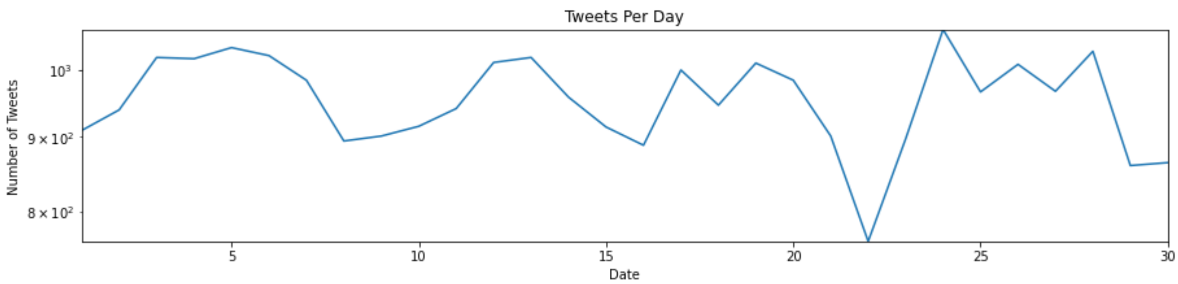




In [22]:

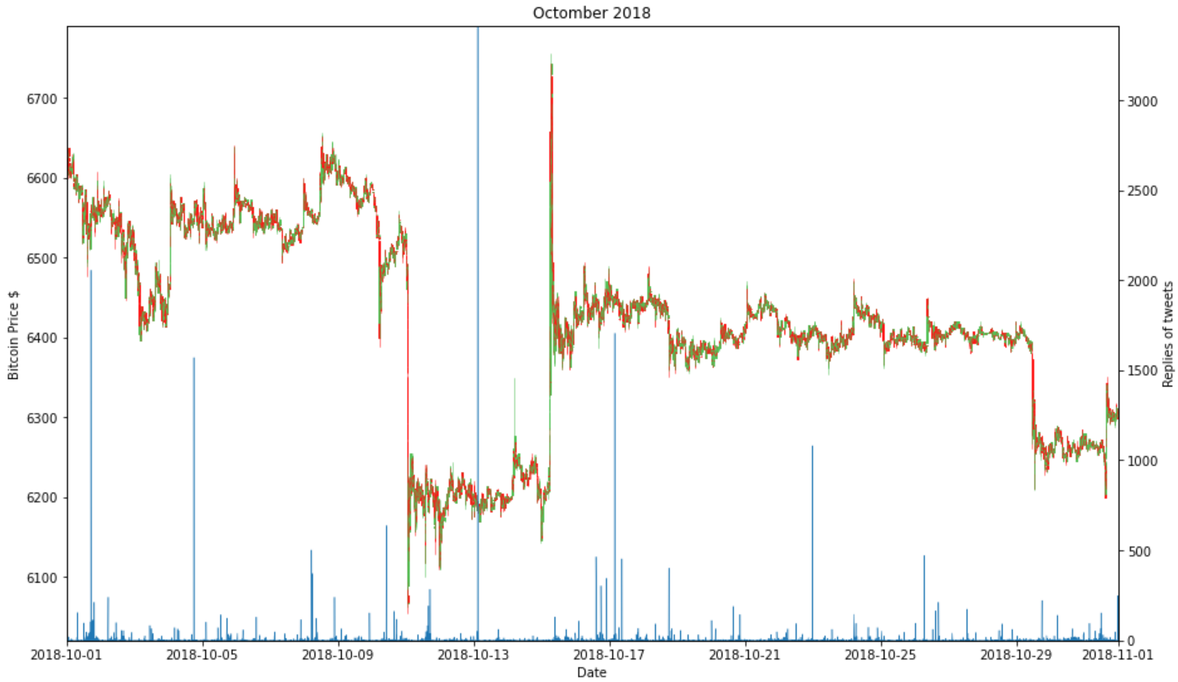
```
chart_by_period("2018-09-01 00:00:00", "2018-09-30 23:59:59", "September ")
```

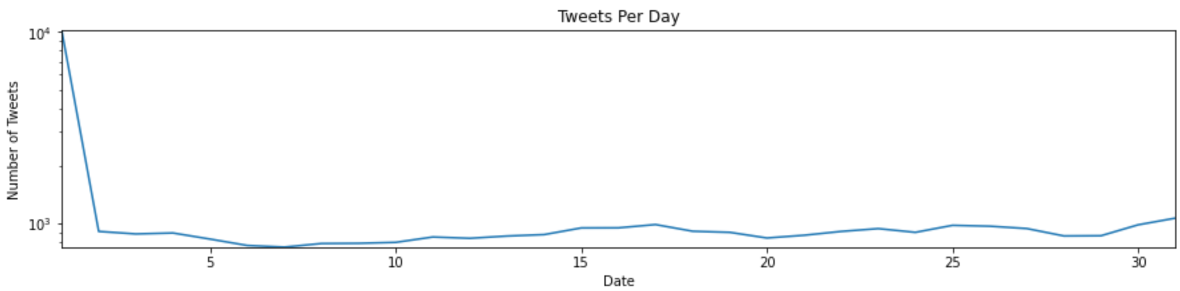




In [23]:

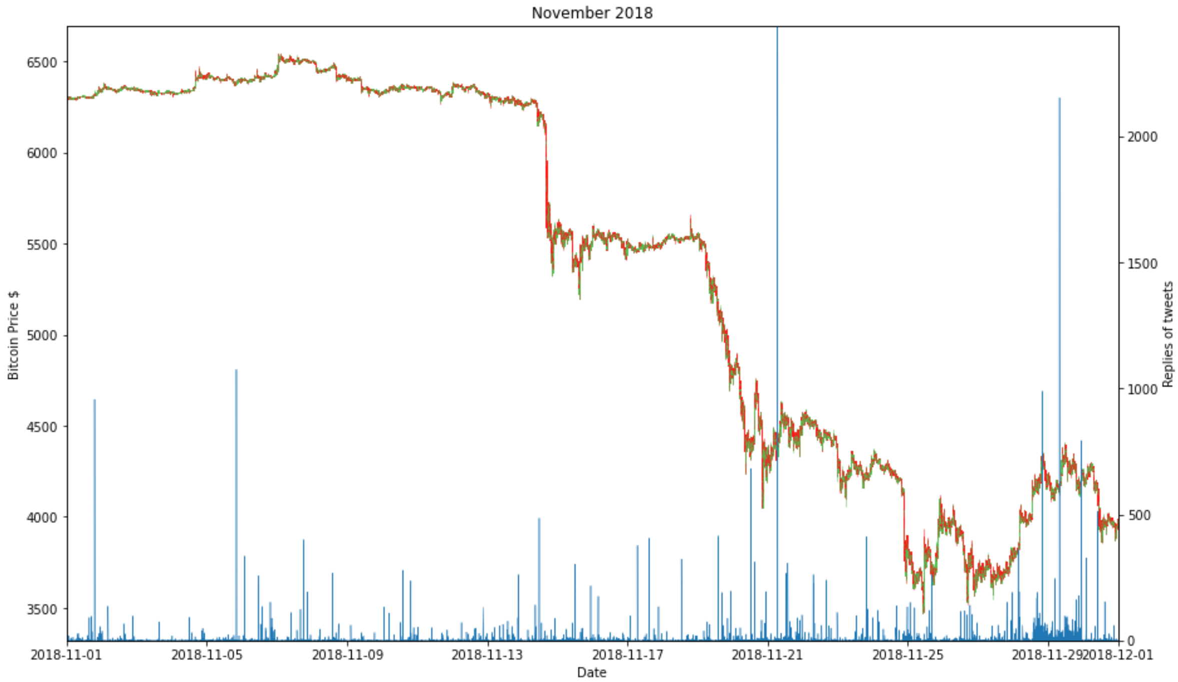
```
chart_by_period("2018-10-01 00:00:00", "2018-10-31 23:59:59", "Octomber ")
```

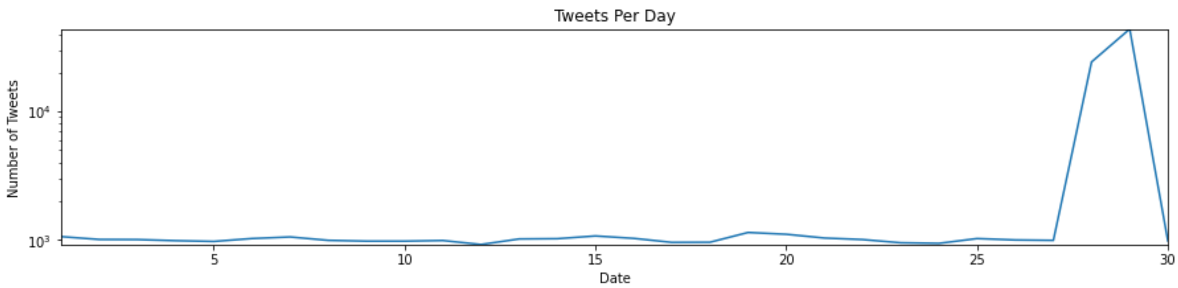




In [24]:

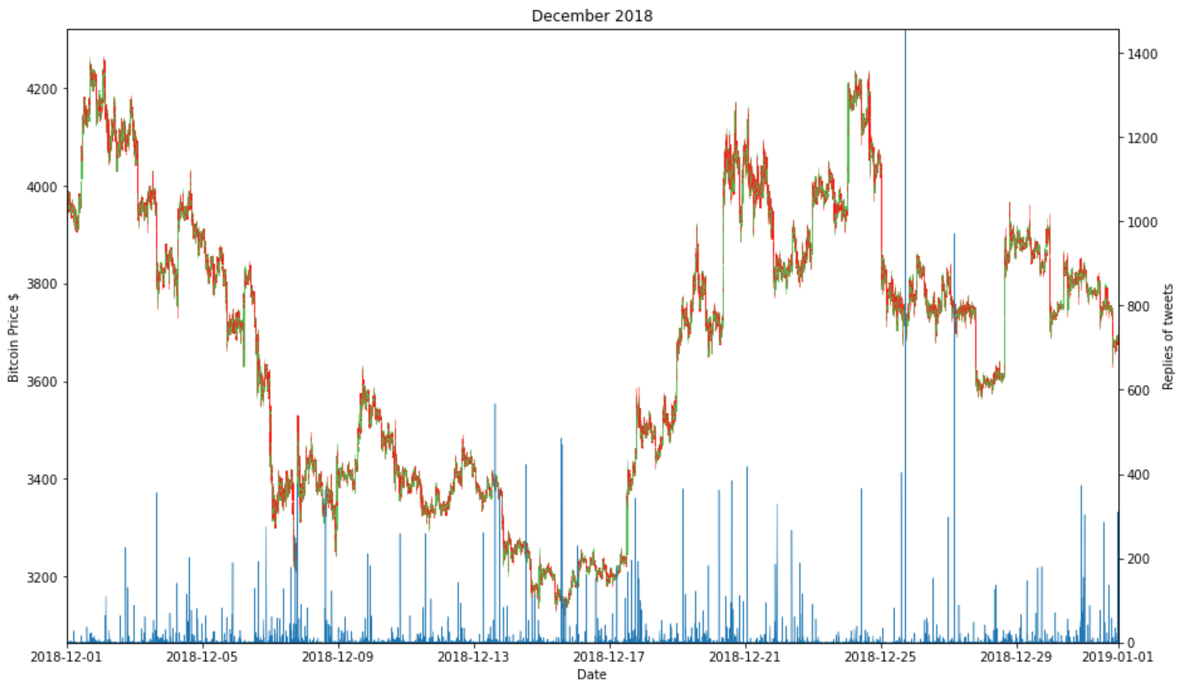
```
chart_by_period("2018-11-01 00:00:00", "2018-11-30 23:59:59", "November ")
```

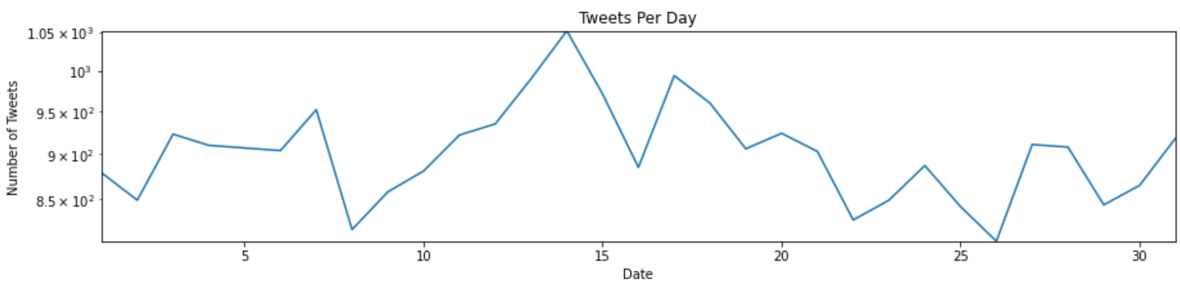




In [25]:

```
chart_by_period("2018-12-01 00:00:00", "2018-12-31 23:59:59", "December ")
```





Conclusion

You can see how the activity of the tweets shows an upcoming movement, different from the previous one. Sometimes the movement starts immediately, sometimes after an interval of time. Overall, it shows good potential, as long as it is calculated correctly in a specific situation. For active traders following the fundamental news and analysis and other technical indicators, it would be a good helper.

References

Big Data Sets

- https://www.kaggle.com/mczielinski/bitcoin-historical-data (https://www.kaggle.com/mczielinski/bitcoin-historical-data)
- https://www.kaggle.com/alaix14/bitcoin-tweets-20160101-to-20190329 (https://www.kaggle.com/alaix14/bitcoin-tweets-20160101-to-20190329)

2018 Data Sets

- www.kaggle.com/dataset/c7e296ccd23d8f0ddcf62482685a626993baac892491ecb9336875f6165f5595 (http://www.kaggle.com/dataset/c7e296ccd23d8f0ddcf62482685a626993baac892491ecb9336875f6165f559
  Private, only link share

Other

- https://bitinfocharts.com/comparison/tweets-btc.html (https://bitinfocharts.com/comparison/tweets-btc.html)