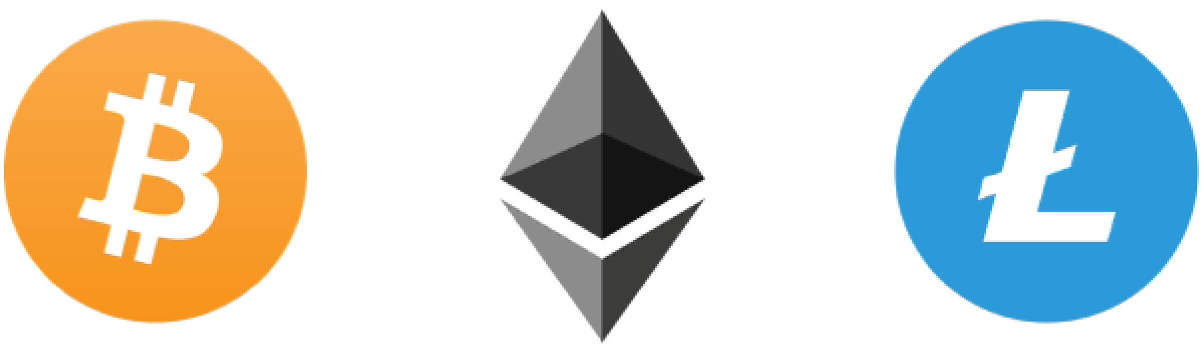
Cryptocurrency Analysis with Python — Buy and Hold

Roman Orac Aug 31, 2019 · 6 min read ★



Bitcoin, Ethereum, and Litecoin

In this part, I am going to analyze which coin (**Bitcoin**, **Ethereum** or **Litecoin**) was the most profitable in the last two months using buy and hold strategy. We'll go through the analysis of these 3 cryptocurrencies and try to give an objective answer.

In case you've missed my other articles about this topic:

Stock Market Analysis in Python

A curated list of articles I've written about Stock Market and

Here are few links that might interest you:

```
- Complete your Python analyses 10x faster with Mito [Product]

- Free skill tests for Data Scientists & ML Engineers [Test]

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Would you like to read more such articles? If so, you can support me by clicking on any links above. Some of them are affiliate links, but you don't need to buy anything.

Disclaimer

I am not a trader and this blog post is not financial advice. This is purely introductory knowledge. The conclusion here can be misleading as we analyze the period with immense growth.

Requirements

- seaborn: statistical data visualization

For other requirements, see my previous blog post in this series.

Getting the data

To get the latest data, go to the previous blog post, where I described how to download it using Cryptocompare API. You can also use the data I work within this example.

First, let's download hourly data for BTC, ETH, and LTC from Coinbase exchange. This time we work with an hourly time interval as it has higher granularity. Cryptocompare API limits response to 2000 samples, which is 2.7 months of data for each coin.

```
import pandas as pd

def get_filename(from_symbol, to_symbol, exchange,
datetime_interval, download_date):
    return '%s_%s_%s_%s_%s.csv' % (from_symbol, to_symbol, exchange,
datetime_interval, download_date)
```

```
    df.datetime = pd.to_datetime(df.datetime) # change to datetime
    df = df.set_index('datetime')
    df = df.sort_index() # sort by datetime
    print(df.shape)
    return df
```

Load the data

```
df_btc = read_dataset(get_filename('BTC', 'USD', 'Coinbase', 'hour',
'2017-12-24'))
df_eth = read_dataset(get_filename('ETH', 'USD', 'Coinbase', 'hour',
'2017-12-24'))
df_ltc = read_dataset(get_filename('LTC', 'USD', 'Coinbase', 'hour',
'2017-12-24'))

df_btc.head()
```

	low	high	open	close	volumefrom	volumeto
datetime						
2017-10-02 08:00:00	4435.00	4448.98	4435.01	4448.85	85.51	379813.67
2017-10-02 09:00:00	4448.84	4470.00	4448.85	4464.49	165.17	736269.53
2017-10-02 10:00:00	4450.27	4469.00	4464.49	4461.63	194.95	870013.62
2017-10-02 11:00:00	4399.00	4461.63	4461.63	4399.51	326.71	1445572.02
2017-10-02 12:00:00	4378.22	4417.91	4399.51	4383.00	549.29	2412712.73

Few entries in the dataset.

Extract closing prices

We are going to analyze closing prices, which are prices at which the hourly period closed. We merge BTC, ETH and LTC closing prices to a Dataframe to make analysis easier.

```
df = pd.DataFrame({'BTC': df_btc.close,
                   'ETH': df_eth.close,
                   'LTC': df_ltc.close})

df.head()
```

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	BTC	ETH	LTC
datetime			
2017-10-02 08:00:00	4448.85	301.37	54.72
2017-10-02 09:00:00	4464.49	301.84	54.79
2017-10-02 10:00:00	4461.63	301.95	54.63
2017-10-02 11:00:00	4399.51	300.02	54.01
2017-10-02 12:00:00	4383.00	297.51	53.71

Analysis

Basic statistics

In 2.7 months, all three cryptocurrencies fluctuated a lot as you can observe in the table below.

For each coin, we count the number of events and calculate mean, standard deviation, minimum, quartiles, and maximum closing price.

Observations

- The difference between the highest and the lowest BTC price was more than $15000 in 2.7 months.
- The LTC surged from $48.61 to $378.66 at a certain point, which is an increase of 678.98%.

```
df.describe()
```

	BTC	ETH	LTC
count	2001.000000	2001.000000	2001.000000
mean	9060.256122	407.263793	106.790100
std	4404.269591	149.480416	89.142241
min	4150.020000	277.810000	48.610000
25%	5751.020000	301.510000	55.580000

max	19847.110000	858.900000	378.660000

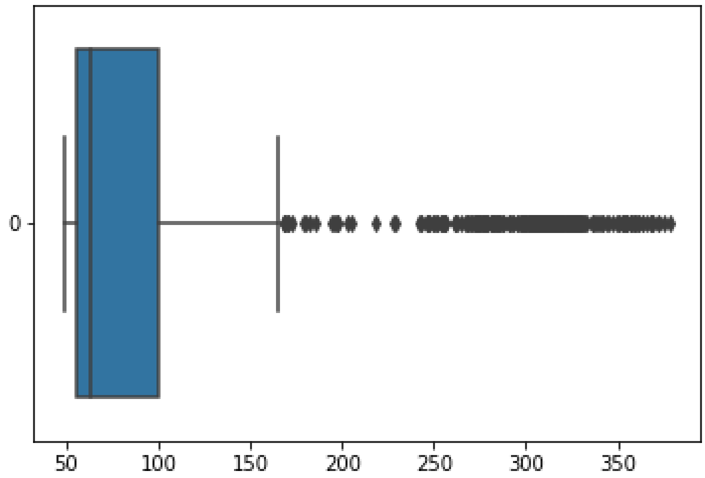
Let's dive deeper into LTC

We visualize the data in the table above with a box plot. A box plot shows the quartiles of the dataset with points that are determined to be outliers using a method of the inter-quartile range (IQR). In other words, the IQR is the first quartile (25%) subtracted from the third quartile (75%).

On the box plot below, we see that LTC closing hourly price was most of the time between $50 and $100 in the last 2.7 months. All values over $150 are outliers (using IQR). Note that outliers are specific to this data sample.

```
import seaborn as sns

ax = sns.boxplot(data=df['LTC'], orient="h")
```



LTC Boxplot with closing hourly prices

Histogram of LTC closing price

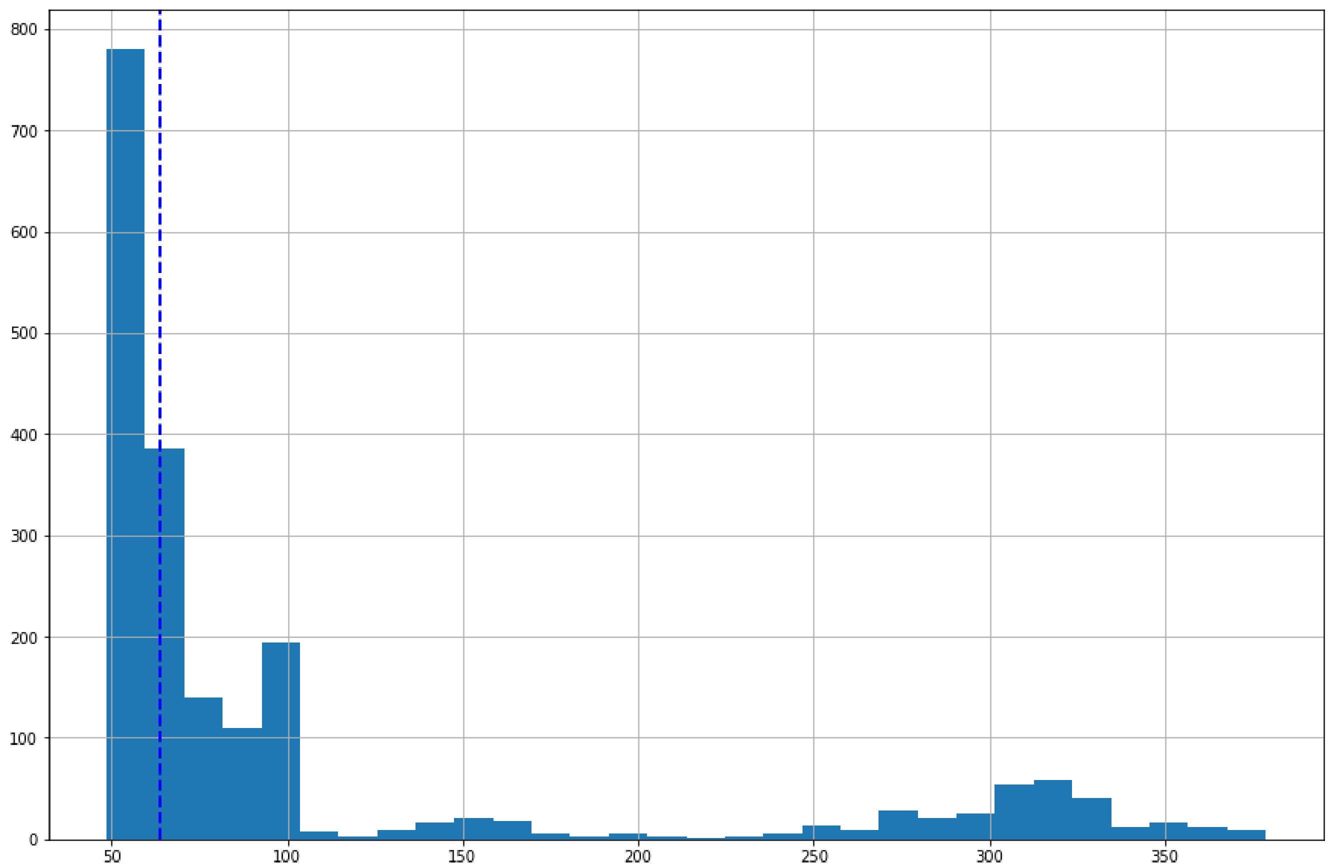
Let's estimate the frequency distribution of LTC closing prices. The histogram shows the number of hours LTC had a certain value.

Observations

- LTC closing price was not over $100 for many hours.

- blue dashed line (median) shows that half of the time closing prices were under $63.50.

```
df['LTC'].hist(bins=30, figsize=(15,10)).axvline(df['LTC'].median(),
color='b', linestyle='dashed', linewidth=2)
```



Histogram for LTC with the median

Visualize absolute closing prices

The chart below shows the absolute closing prices. It is not of much use as BTC closing prices are much higher than prices of ETH and LTC.

```
df.plot(grid=True, figsize=(15, 10))
```

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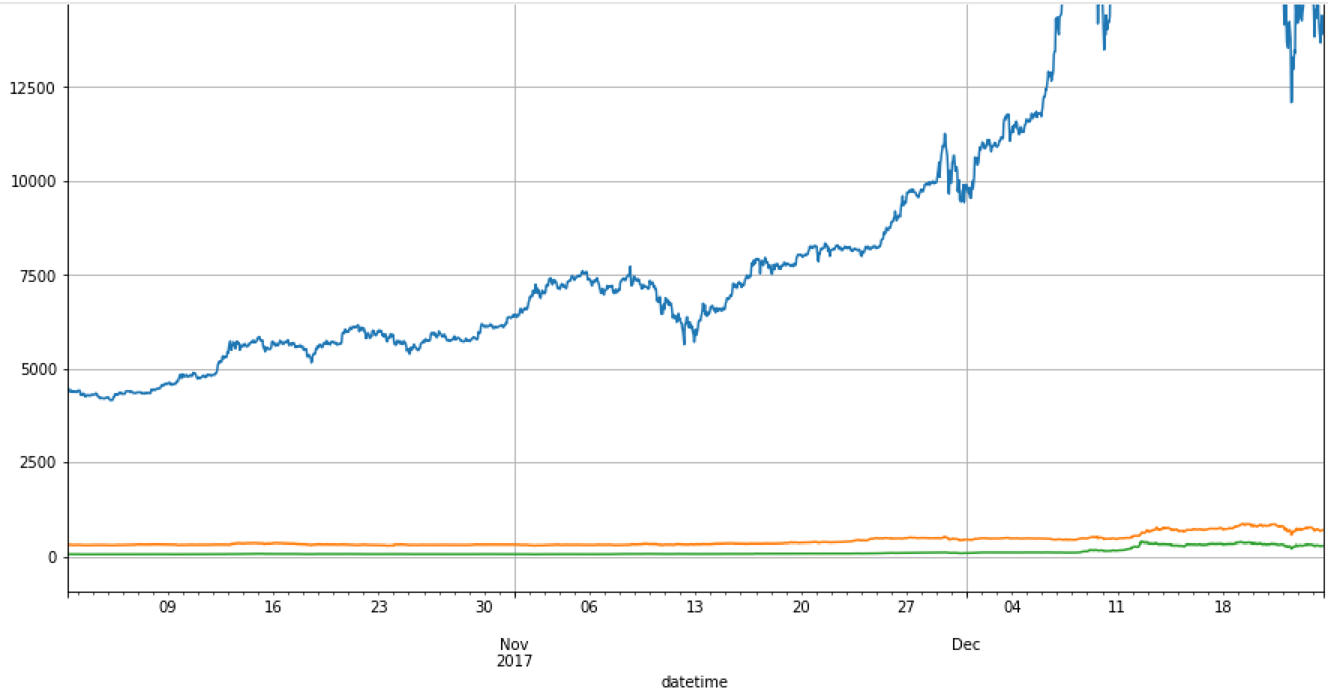


Absolute closing price changes of BTC, ETH and LTC

Visualize relative changes in closing prices

We are interested in a relative change of the price rather than in absolute price, so we use three different y-axis scales.

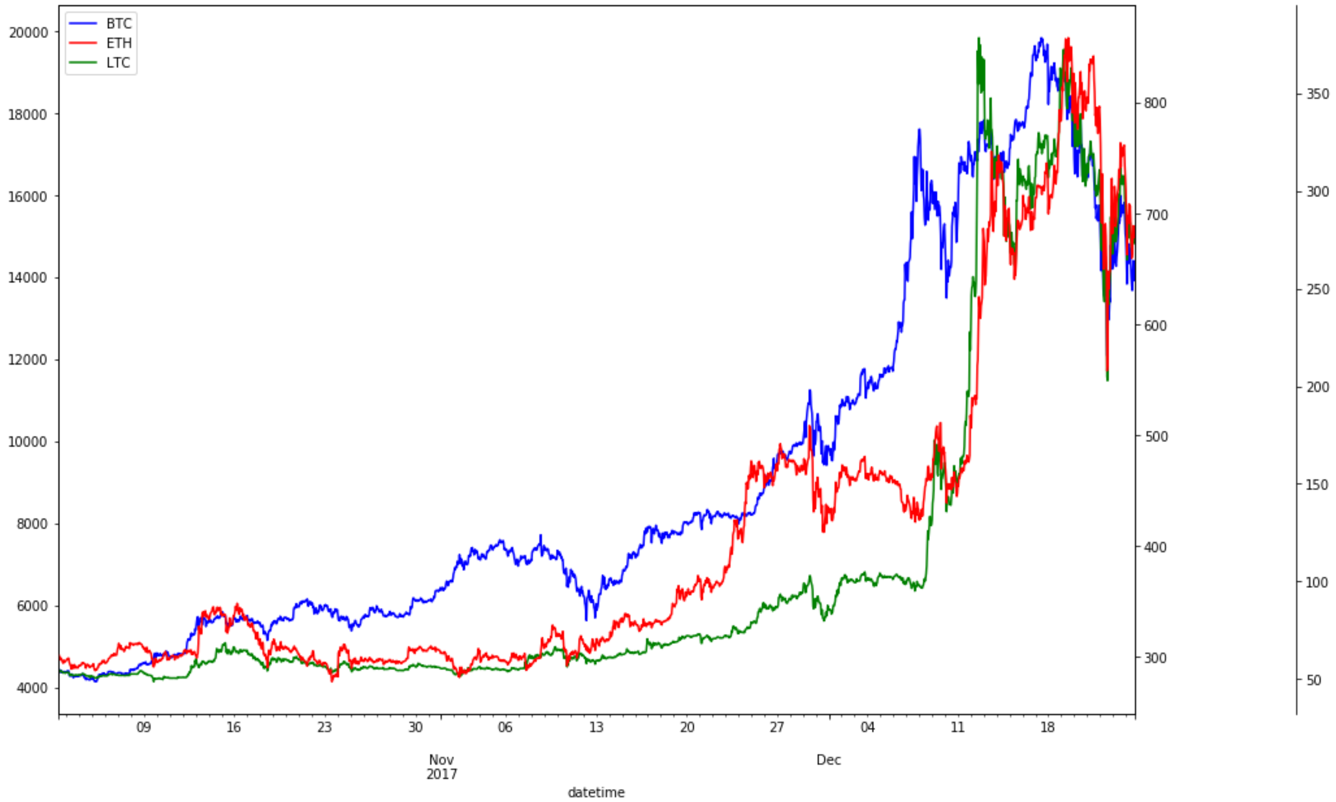
We see that closing prices move in tandem. When one coin closing price increases so do the other.

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

fig, ax1 = plt.subplots(figsize=(20, 10))
ax2 = ax1.twinx()
rspine = ax2.spines['right']
rspine.set_position(('axes', 1.15))
ax2.set_frame_on(True)
ax2.patch.set_visible(False)
fig.subplots_adjust(right=0.7)

df['BTC'].plot(ax=ax1, style='b-')
df['ETH'].plot(ax=ax1, style='r-', secondary_y=True)
df['LTC'].plot(ax=ax2, style='g-')

# legend
ax2.legend([ax1.get_lines()[0],
            ax1.right_ax.get_lines()[0],
```



Relative closing price changes of BTC, ETH and LTC

Measure the correlation of closing prices

We calculate the Pearson correlation between the closing prices of BTC, ETH, and LTC. Pearson correlation is a measure of the linear correlation between two variables X and Y. It has a value between +1 and −1, where 1 is the total positive linear correlation, 0 is no linear correlation, and −1 is the total negative linear correlation. The correlation matrix is symmetric so we only show the lower half.

Sifr Data daily updates Pearson correlations for many cryptocurrencies.

Observations

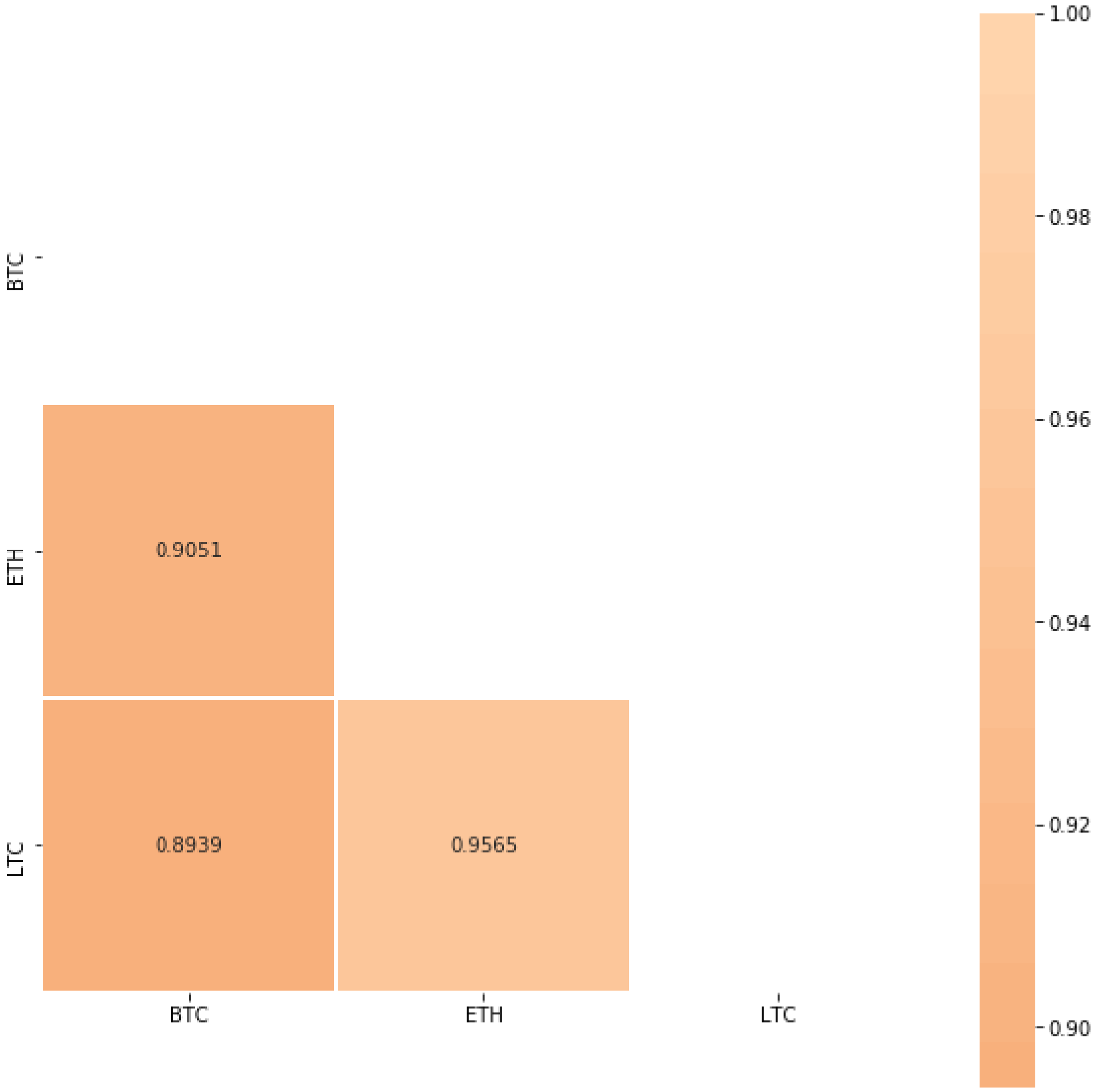
- Closing prices aren't normalized, see Log Returns, where we normalize closing prices before calculating correlation,
- BTC, ETH and LTC were highly correlated in the past 2 months. This means, when BTC closing price increased, ETH and LTC followed.
- ETH and LTC were even more correlated with 0.9565 Pearson correlation coefficient.

```
# Compute the correlation matrix
corr = df.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(10, 10))

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, annot=True, fmt = '.4f', mask=mask, center=0,
square=True, linewidths=.5)
```



Pearson Correlation for BTC, ETH and LTC

Buy and hold strategy

Let's analyze returns using the Buy and hold strategy for the past 2.7 months. We calculate the return percentage, where *t* represents a certain period and *price0* is the initial closing price:

$$return_{t,0} = \frac{price_t}{price_0}$$

```
df_return = df.apply(lambda x: x / x[0])
df_return.head()
```

	BTC	ETH	LTC
datetime			
2017-10-02 08:00:00	1.000000	1.000000	1.000000
2017-10-02 09:00:00	1.003516	1.001560	1.001279
2017-10-02 10:00:00	1.002873	1.001925	0.998355
2017-10-02 11:00:00	0.988909	0.995520	0.987025
2017-10-02 12:00:00	0.985198	0.987192	0.981542

Visualize returns

We show that LTC was the most profitable for the period between October 2, 2017 and December 24, 2017.

```
df_return.plot(grid=True, figsize=(15, 10)).axhline(y = 1, color =
"black", lw = 2)
```

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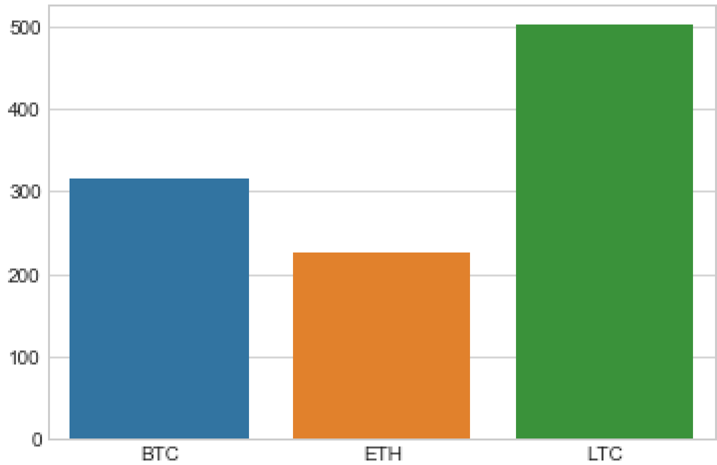
The factor of returns for BTC, ETH and LTC in 2.7 months

Conclusion

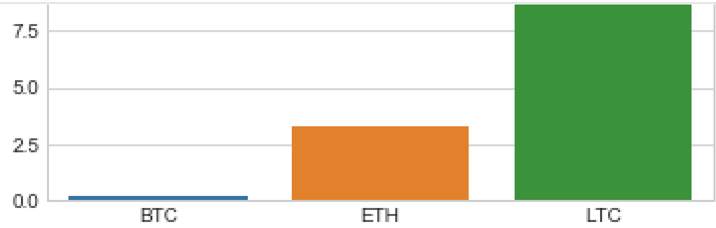
The cryptocurrencies we analyzed fluctuated a lot but all gained in a given 2.7 months period.

What about the percentage increase?



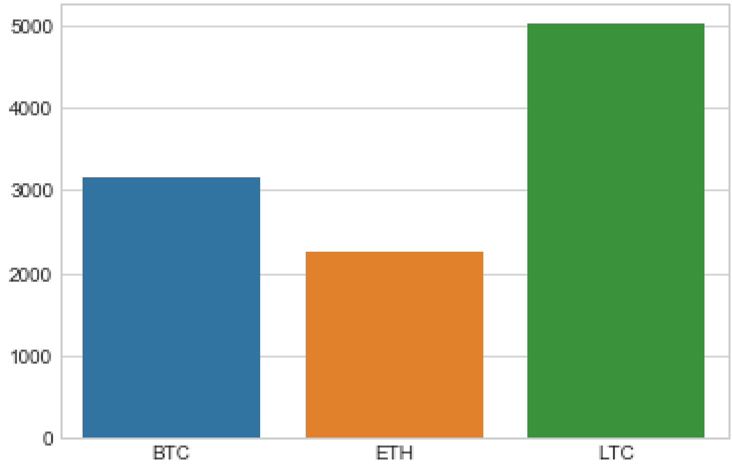
The percentage increase for BTC, ETH and LTC in 2.7 months

How many coins could we buy for $1000?



The number of coins we could buy with $1000 a while ago

How much money would we make?



The amount of money we would make if we invested $1000 a while ago

Before you go

To run this code download the Jupyter notebook.

Follow me on Twitter, where I regularly tweet about Data Science and Machine Learning.

Photo by Courtney Hedger on Unsplash

Data Science Cryptocurrency Programming