MScFE_Capstone_Workbook_M4

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1 Market Timing Strategies using Kalman Filter

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2 Introduction

In this section, I will explore the implementation of a Kalman filter in Python using the library Pykalman to forecast stock prices. The 2 stocks we are targeting are Ethereum and Bitcoin. As discussed in the literature review, research shows that Kalman filters have better outcomes for time series forecasting and can be used with various pricing algorithms, such as Heston, Bates, etc.

[ ]:
```
# installation of libraries

!pip install pykalman
!pip install plotly
!pip install statsmodels
```

```
Requirement already satisfied: pykalman in /usr/local/lib/python3.10/dist-
packages (0.9.7)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from pykalman) (1.26.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from pykalman) (1.13.1)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages
(5.24.1)
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from plotly) (9.0.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from plotly) (24.1)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-
packages (0.14.3)
Requirement already satisfied: numpy<3,>=1.22.3 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (1.26.4)
Requirement already satisfied: scipy!=1.9.2,>=1.8 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (1.13.1)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (2.1.4)
```

```
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels) (0.5.6)
Requirement already satisfied: packaging>=21.3 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (24.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas!=2.1.0,>=1.4->statsmodels) (2024.2)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas!=2.1.0,>=1.4->statsmodels) (2024.1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels) (1.16.0)
```

[ ]:
```
# importing of libraries

import pandas as pd
import yfinance as yf
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import statsmodels.api as sm
```

3 Exploratory Data Analysis

[ ]:
```
# crypto currencies of interest - Bitcoin and Ethereum

stock_list = ['BTC-USD', 'ETH-USD']
```

[ ]:
```
# extracting the stock price for the last 2 years
data = yf.download(stock_list, start='2022-09-01', end='2024-09-01')
data.head()
```

```
 [                        0%                        ]
[*********************100%***********************]  2 of 2 completed
```

[ ]:
```
Price                         Adj Close                        Close  \
Ticker                          BTC-USD      ETH-USD         BTC-USD
Date
2022-09-01 00:00:00+00:00  20127.140625  1586.176758  20127.140625
2022-09-02 00:00:00+00:00  19969.771484  1577.220459  19969.771484
2022-09-03 00:00:00+00:00  19832.087891  1556.872681  19832.087891
2022-09-04 00:00:00+00:00  19986.712891  1577.641602  19986.712891
2022-09-05 00:00:00+00:00  19812.371094  1617.183228  19812.371094

Price                                              High              \
Ticker                         ETH-USD          BTC-USD       ETH-USD
```

```
Date
2022-09-01 00:00:00+00:00  1586.176758  20198.390625  1593.082764
2022-09-02 00:00:00+00:00  1577.220459  20401.568359  1643.183228
2022-09-03 00:00:00+00:00  1556.872681  20037.009766  1579.454346
2022-09-04 00:00:00+00:00  1577.641602  19999.689453  1578.009277
2022-09-05 00:00:00+00:00  1617.183228  20031.160156  1621.661377

Price                               Low                      Open  \
Ticker                          BTC-USD      ETH-USD      BTC-USD
Date
2022-09-01 00:00:00+00:00  19653.968750  1520.188354  20050.498047
2022-09-02 00:00:00+00:00  19814.765625  1551.877930  20126.072266
2022-09-03 00:00:00+00:00  19698.355469  1541.672119  19969.718750
2022-09-04 00:00:00+00:00  19636.816406  1543.698853  19832.470703
2022-09-05 00:00:00+00:00  19673.046875  1559.781860  19988.789062

Price                                     Volume
Ticker                         ETH-USD       BTC-USD      ETH-USD
Date
2022-09-01 00:00:00+00:00  1553.756348  30182031010  16434276817
2022-09-02 00:00:00+00:00  1586.017944  29123998928  17708478709
2022-09-03 00:00:00+00:00  1577.213745  23613051457   9516825994
2022-09-04 00:00:00+00:00  1556.895874  25245861652   8884144998
2022-09-05 00:00:00+00:00  1577.884033  28813460025  13060541168
```

[ ]:
```
data.describe()
```

[ ]:
```
Price      Adj Close                   Close                      High  \
Ticker       BTC-USD      ETH-USD       BTC-USD      ETH-USD       BTC-USD
count     731.000000   731.000000    731.000000   731.000000    731.000000
mean    37547.665388  2155.140591  37547.665388  2155.140591  38191.235700
std     17690.953806   760.453241  17690.953806   760.453241  18088.636362
min     15787.284180  1100.169800  15787.284180  1100.169800  16253.047852
25%     23685.160156  1621.294556  23685.160156  1621.294556  24135.458008
50%     29415.964844  1866.564209  29415.964844  1866.564209  29871.546875
75%     56348.345703  2639.745850  56348.345703  2639.745850  57929.109375
max     73083.500000  4066.445068  73083.500000  4066.445068  73750.070312

Price                            Low                      Open               \
Ticker      ETH-USD       BTC-USD      ETH-USD       BTC-USD      ETH-USD
count    731.000000    731.000000   731.000000    731.000000   731.000000
mean    2198.338434  36811.021476  2107.786271  37493.767616  2153.848979
std      780.759468  17228.145539   736.299033  17684.457403   760.660702
min     1136.442627  15599.046875  1081.138184  15782.300781  1100.107178
25%     1645.000488  23262.488281  1581.191528  23634.151367  1618.469055
50%     1888.193726  29114.021484  1845.849243  29408.048828  1866.094238
75%     2708.436523  54402.609375  2583.886230  55945.103516  2639.495850
```

```
max     4092.284180  71334.093750  3936.627197  73079.375000  4066.690430

Price          Volume
Ticker        BTC-USD       ETH-USD
count   7.310000e+02  7.310000e+02
mean    2.493208e+10  1.110867e+10
std     1.410378e+10  6.914517e+09
min     5.331173e+09  2.081626e+09
25%     1.469595e+10  6.297964e+09
50%     2.160965e+10  9.407051e+09
75%     3.143342e+10  1.412190e+10
max     1.189925e+11  6.766813e+10
```

The data shows that open, close, High,low are correlated, we can check this in our plot

[ ]:
```
data.corr().style.background_gradient(cmap='coolwarm')
```

[ ]:
```
<pandas.io.formats.style.Styler at 0x7f8df3ad25f0>
```

[ ]:
```
data.isnull().any()
```

[ ]:
```
Price      Ticker
Adj Close  BTC-USD    False
           ETH-USD    False
Close      BTC-USD    False
           ETH-USD    False
High       BTC-USD    False
           ETH-USD    False
Low        BTC-USD    False
           ETH-USD    False
Open       BTC-USD    False
           ETH-USD    False
Volume     BTC-USD    False
           ETH-USD    False
dtype: bool
```

The dataset do not contain any null values

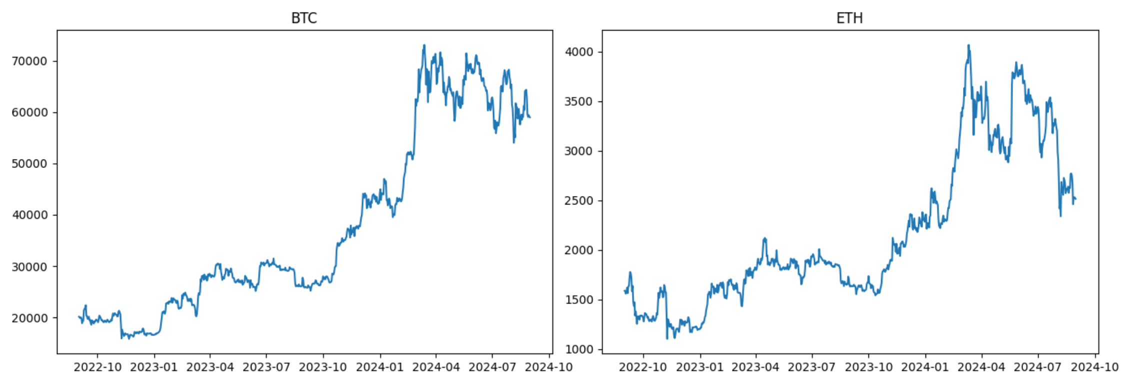
[ ]:
```
closing_data = data['Adj Close']['BTC-USD']
closing_data.head()
```

[ ]:
```
Date
2022-09-01 00:00:00+00:00    20127.140625
2022-09-02 00:00:00+00:00    19969.771484
2022-09-03 00:00:00+00:00    19832.087891
2022-09-04 00:00:00+00:00    19986.712891
2022-09-05 00:00:00+00:00    19812.371094
Name: BTC-USD, dtype: float64
```

```
[ ]: closing_data = data['Adj Close']['ETH-USD']
     closing_data.head()
```

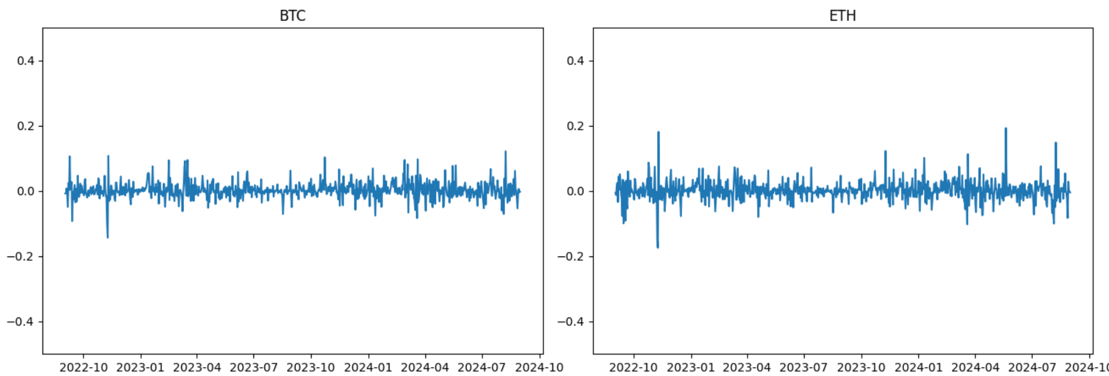
```
[ ]: Date
     2022-09-01 00:00:00+00:00    1586.176758
     2022-09-02 00:00:00+00:00    1577.220459
     2022-09-03 00:00:00+00:00    1556.872681
     2022-09-04 00:00:00+00:00    1577.641602
     2022-09-05 00:00:00+00:00    1617.183228
     Name: ETH-USD, dtype: float64
```

```
[ ]: fig, axs =plt.subplots(1,2,figsize=(16, 5),gridspec_kw ={'hspace': 0.2,␣
      ↪'wspace': 0.1})
     axs[0].plot(data['Adj Close']['BTC-USD'])
     axs[0].set_title('BTC')
     axs[1].plot(data['Adj Close']['ETH-USD'])
     axs[1].set_title('ETH')
     plt.show()
```




```
[ ]: fig, axs = plt.subplots(1,2,figsize=(16,5),gridspec_kw ={'hspace': 0.2,␣
      ↪'wspace': 0.1})
     btc = data['Adj Close']['BTC-USD'].pct_change().dropna(axis=0)
     axs[0].plot(btc)
     axs[0].set_title('BTC')
     axs[0].set_ylim([-0.5,0.5])

     eth = data['Adj Close']['ETH-USD'].pct_change().dropna(axis=0)
     axs[1].plot(eth)
     axs[1].set_title('ETH')
     axs[1].set_ylim([-0.5,0.5])
```

```
[ ]: (-0.5, 0.5)
```



OHLC plots - Price movements A candle stick plot helps us understand the spread between the prices of the crypto currency from the opening and closing price and identity the periods where they were coninuously on the rise.

[ ]:
```
fig = go.Figure(data=[go.Candlestick(x=data.index,
                open=data['Open']['BTC-USD'], high=data['High']['BTC-USD'],
                low=data['Low']['BTC-USD'], close=data['Close']['BTC-USD'])
                     ])
fig.update_layout(xaxis_rangeslider_visible=True)
fig.show()
```

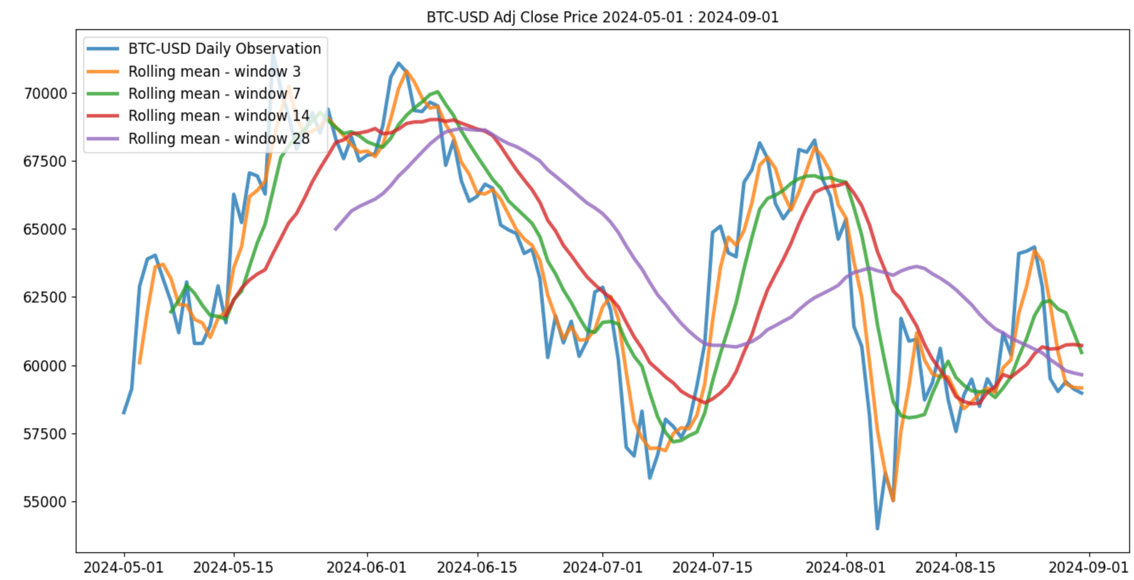
[ ]:
```
fig = go.Figure(data=[go.Candlestick(x=data.index,
                open=data['Open']['ETH-USD'], high=data['High']['ETH-USD'],
                low=data['Low']['ETH-USD'], close=data['Close']['ETH-USD'])
                     ])
fig.update_layout(xaxis_rangeslider_visible=True)
fig.show()
```

Understanding the Price shocks

We can see how the rolling mean for various intervals looks like for our crypto data, we find that with increasing window size our data gets smoother and allows us to see the trend over which can be used for generating feature engineering. The shorter the window closer it is to the actual stock price and considers the price shocks.

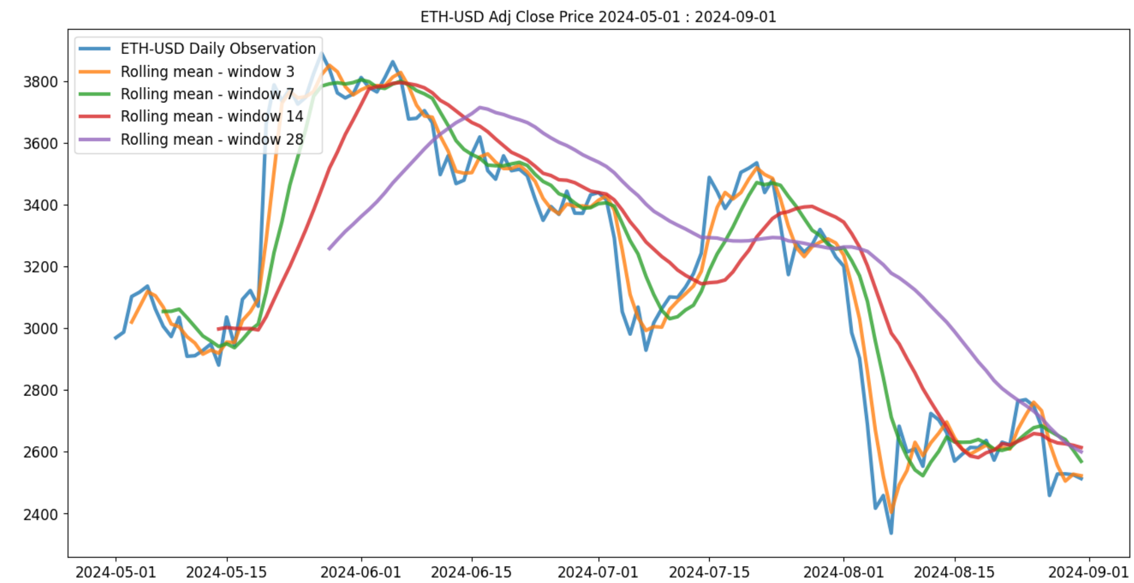
[ ]:
```
btc_closing_data = data['Adj Close']['BTC-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = btc_closing_data.rolling(window=3).mean()
rolling_7d = btc_closing_data.rolling(window=7).mean()
rolling_14d = btc_closing_data.rolling(window=14).mean()
rolling_28d = btc_closing_data.rolling(window=28).mean()


plt.figure(figsize=(16, 8))
plt.plot(btc_closing_data.index, btc_closing_data, lw=3, alpha=0.8,␣
 ↪label='BTC-USD Daily Observation')
```

```
plt.plot(btc_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 3')
plt.plot(btc_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 7')
plt.plot(btc_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 14')
plt.plot(btc_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 28')

plt.title('BTC-USD Adj Close Price 2024-05-01 : 2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



[ ]:
```
eth_closing_data = data['Adj Close']['ETH-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = eth_closing_data.rolling(window=3).mean()
rolling_7d = eth_closing_data.rolling(window=7).mean()
rolling_14d = eth_closing_data.rolling(window=14).mean()
rolling_28d = eth_closing_data.rolling(window=28).mean()


plt.figure(figsize=(16, 8))
plt.plot(eth_closing_data.index, eth_closing_data, lw=3, alpha=0.8,␣
    ↪label='ETH-USD Daily Observation')
plt.plot(eth_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 3')
```

```
plt.plot(eth_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 7')
plt.plot(eth_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 14')
plt.plot(eth_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 28')

plt.title('ETH-USD Adj Close Price 2024-05-01 : 2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



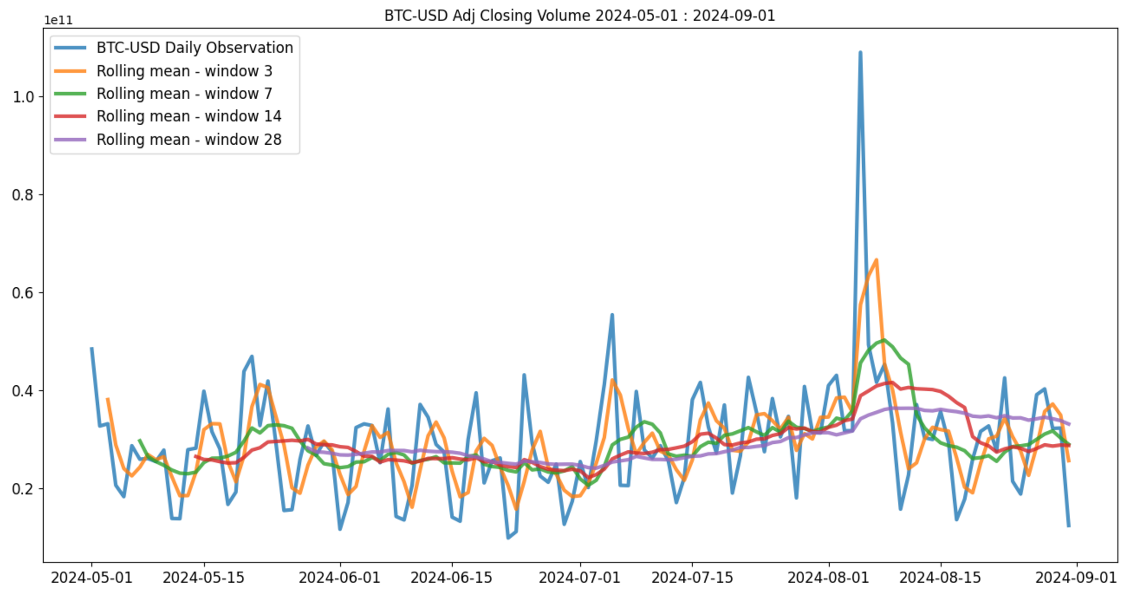
Ethereum rolling means are lot steeper than BTC, in the further sections we will do the causality tests to see autocorrelation.

Understanding the Volume Shocks

Positive volume shocks can be leveraged to improve returns and it is signifcant for volume based trading in crypto. Trading strategists can buy stocks on a positive volume jump and sell stocks on volume downsides to make profit over a period of time. A shock is defined as the increase or decrease in the volume comapred to the 12-month average. Compared to the rolling mean for 28 days, daily volume shows significant upward spikes compared to downfalls.

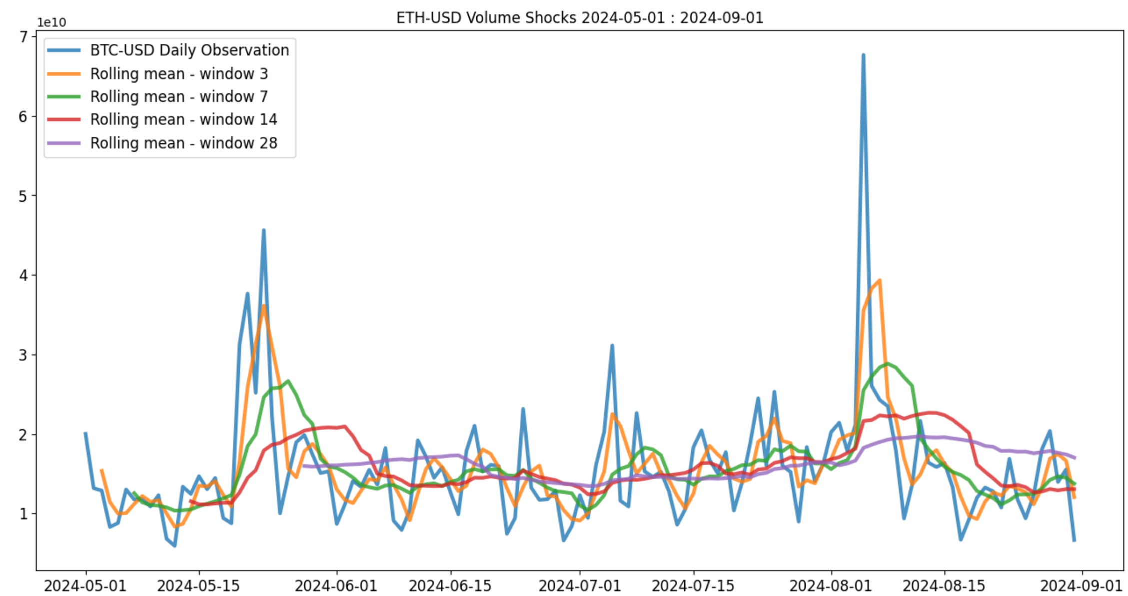
[ ]:
```
btc_closing_data = data['Volume']['BTC-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = btc_closing_data.rolling(window=3).mean()
rolling_7d = btc_closing_data.rolling(window=7).mean()
rolling_14d = btc_closing_data.rolling(window=14).mean()
rolling_28d = btc_closing_data.rolling(window=28).mean()
```

```
plt.figure(figsize=(16, 8))
plt.plot(btc_closing_data.index, btc_closing_data, lw=3, alpha=0.8,␣
 ↪label='BTC-USD Daily Observation')
plt.plot(btc_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 3')
plt.plot(btc_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 7')
plt.plot(btc_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 14')
plt.plot(btc_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 28')

plt.title('BTC-USD Adj Closing Volume 2024-05-01 : 2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



[ ]:
```
btc_closing_data = data['Volume']['ETH-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = btc_closing_data.rolling(window=3).mean()
rolling_7d = btc_closing_data.rolling(window=7).mean()
rolling_14d = btc_closing_data.rolling(window=14).mean()
rolling_28d = btc_closing_data.rolling(window=28).mean()


plt.figure(figsize=(16, 8))
```

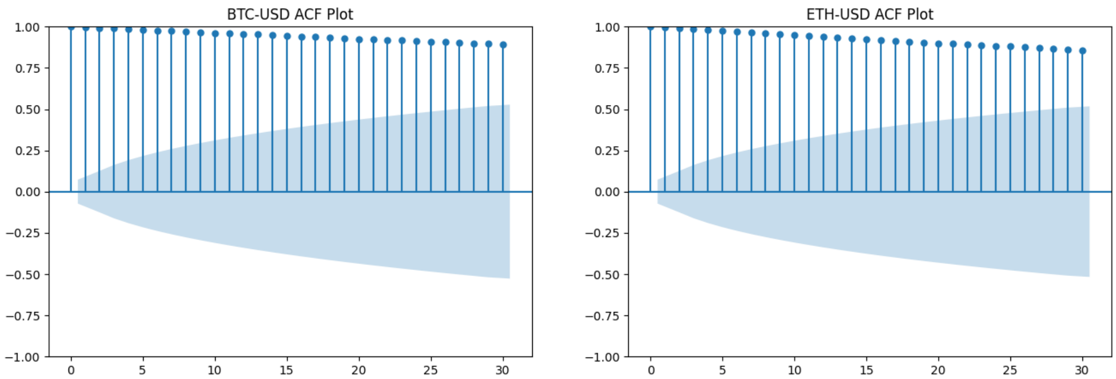
```
plt.plot(btc_closing_data.index, btc_closing_data, lw=3, alpha=0.8,␣
 ↪label='BTC-USD Daily Observation')
plt.plot(btc_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 3')
plt.plot(btc_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 7')
plt.plot(btc_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 14')
plt.plot(btc_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 28')

plt.title('ETH-USD Volume Shocks 2024-05-01 : 2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



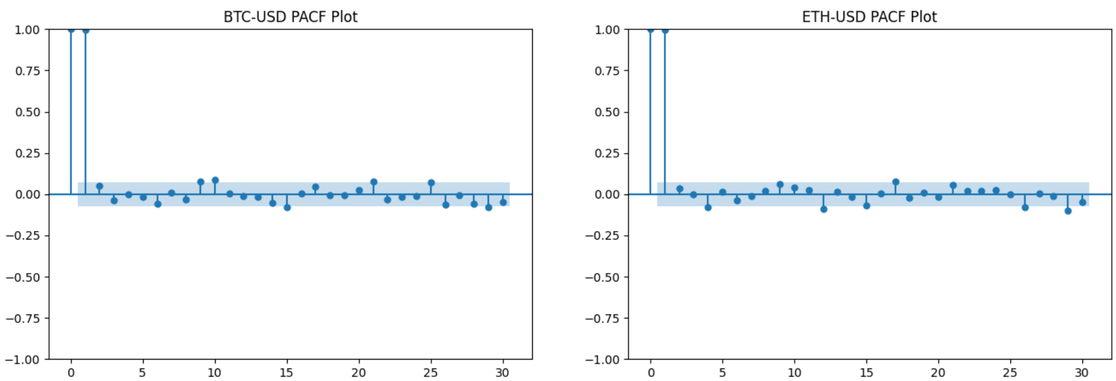
Check for Autocorrelation and Partial autocorrelation

[ ]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 5))

btc_data = data['Adj Close']['BTC-USD']
sm.graphics.tsa.plot_acf(btc_data.values.squeeze(), lags=30, ax=ax1,␣
 ↪title="BTC-USD ACF Plot")

eth_data = data['Adj Close']['ETH-USD']
sm.graphics.tsa.plot_acf(eth_data.values.squeeze(), lags=30, ax=ax2,␣
 ↪title="ETH-USD ACF Plot")
```

```
plt.show()
```




```
[ ]: fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 5))

btc_data = data['Adj Close']['BTC-USD']
sm.graphics.tsa.plot_pacf(btc_data.values.squeeze(), lags=30, ax=ax1,␣
 ↪title="BTC-USD PACF Plot")

eth_data = data['Adj Close']['ETH-USD']
sm.graphics.tsa.plot_pacf(eth_data.values.squeeze(), lags=30, ax=ax2,␣
 ↪title="ETH-USD PACF Plot")
plt.show()
```



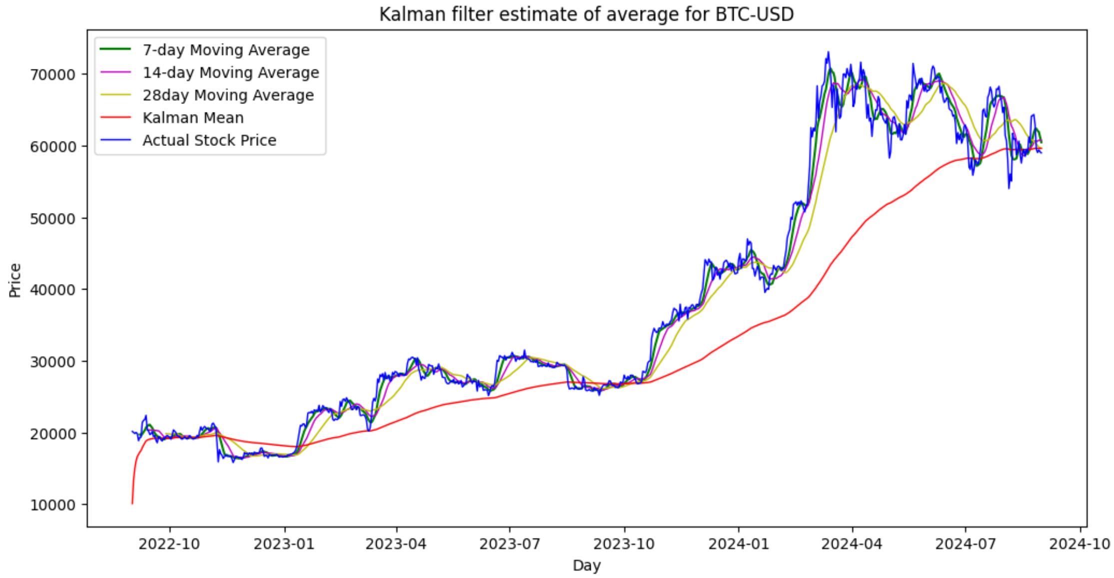
The plot shows significant autocorrelation, the previous value of the currenty determines days closing price. From the PACF plot it is clear that price of certain period of time is correlated than others, say for example price on day 4, 9, 12, 15 etc.

4 Exploring Kalman Filter

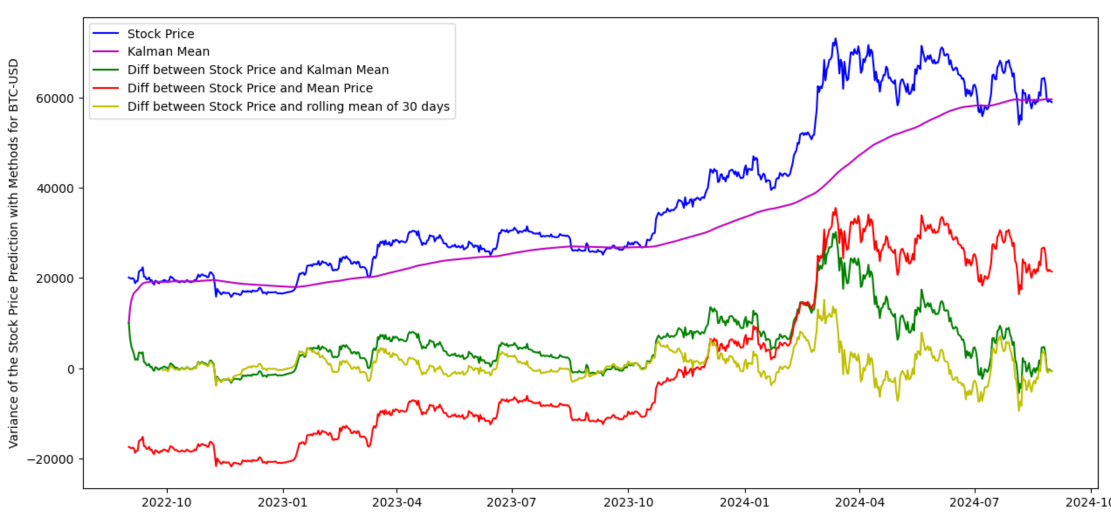
Getting started with Kalman Filters for the data, we will be using the algorithms implementation in pykalman. Let us do the Kalman smoothing and filtering methods to remove the trend here. Stock price by nature is very noisy and with an underlying trend. The identification of this trend can be useful in many ways and can also be used as a feature for stock price forecasting using ARIMA, Linear Regression or any other methods.

[ ]:
```
# initializing kalman filters

from pykalman import KalmanFilter
import numpy as np


kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.0001)
```

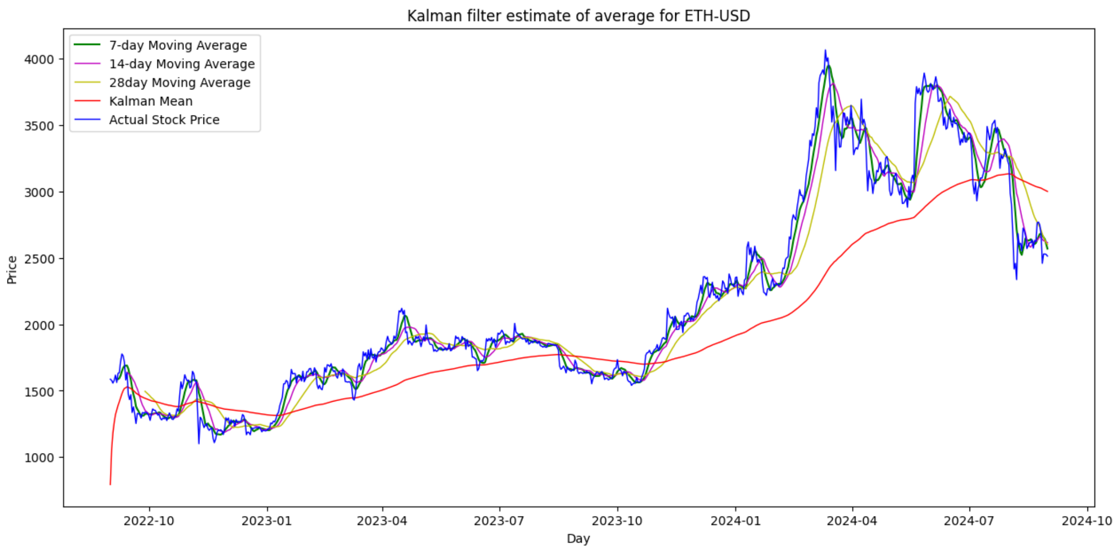
[ ]:
```
# using Kalman Filters for BTC-USD

stock_price = data['Adj Close']['BTC-USD']
mean, cov = kalmanFilter.filter(stock_price)
kalman_mean = pd.Series(mean.flatten(), index=stock_price.index)



rolling_3d = stock_price.rolling(window=3).mean()
rolling_7d = stock_price.rolling(window=7).mean()
rolling_14d = stock_price.rolling(window=14).mean()
rolling_28d = stock_price.rolling(window=28).mean()

plt.figure(figsize=(12,6))
plt.plot(rolling_7d,'-g',lw=1.5)
plt.plot(rolling_14d, 'm', lw=1)
plt.plot(rolling_28d, 'y', lw=1)
plt.plot(kalman_mean, 'r', lw=1)
plt.plot(stock_price, 'b', lw=1)
plt.title('Kalman filter estimate of average for BTC-USD')
plt.legend(['7-day Moving Average', '14-day Moving Average', '28day Moving␣
↪Average', 'Kalman Mean', 'Actual Stock Price'])
plt.xlabel('Day')
plt.ylabel('Price');
```



[ ]:
```
plt.figure(figsize=(15,7))
plt.plot(stock_price ,'b',lw=1.5)
plt.plot(kalman_mean ,'m',lw=1.5)
plt.plot(stock_price - kalman_mean,'-g',lw=1.5)
plt.plot(stock_price - stock_price.mean() ,'r',lw=1.5)
plt.plot(stock_price - rolling_28d ,'y',lw=1.5)
plt.legend(['Stock Price', 'Kalman Mean', 'Diff between Stock Price and Kalman␣
↪Mean', 'Diff between Stock Price and Mean Price',  'Diff between Stock Price␣
↪and rolling mean of 30 days'])
plt.xlabel('Day')
plt.ylabel('Variance of the Stock Price Prediction with Methods for BTC-USD');
```

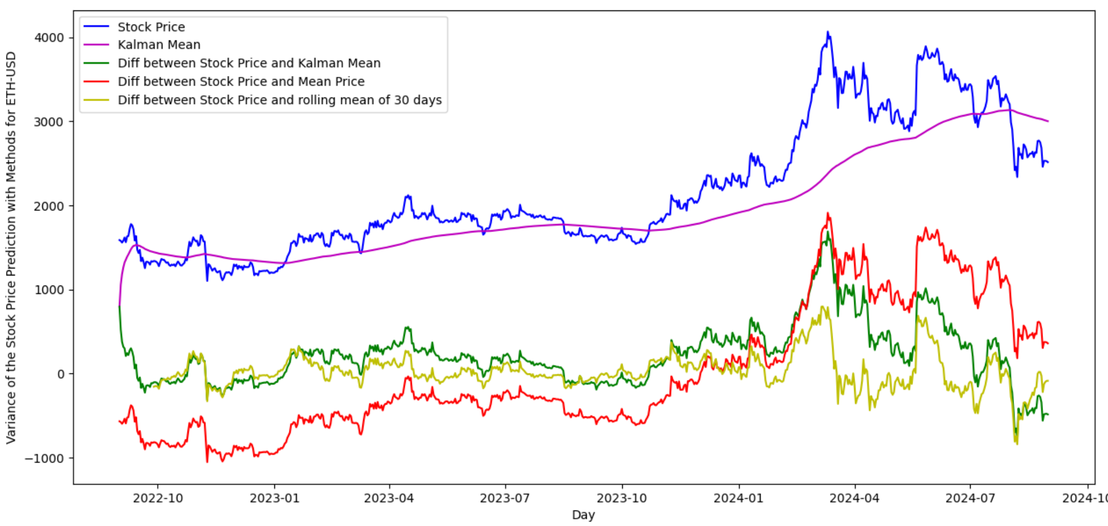


[ ]:
```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.0001)

stock_price = data['Adj Close']['ETH-USD']
mean, cov = kalmanFilter.filter(stock_price)
kalman_mean = pd.Series(mean.flatten(), index=stock_price.index)



rolling_3d = stock_price.rolling(window=3).mean()
rolling_7d = stock_price.rolling(window=7).mean()
rolling_14d = stock_price.rolling(window=14).mean()
rolling_28d = stock_price.rolling(window=28).mean()

plt.figure(figsize=(15,7))
plt.plot(rolling_7d,'-g',lw=1.5)
plt.plot(rolling_14d, 'm', lw=1)
plt.plot(rolling_28d, 'y', lw=1)
plt.plot(kalman_mean, 'r', lw=1)
plt.plot(stock_price, 'b', lw=1)
plt.title('Kalman filter estimate of average for ETH-USD')
plt.legend(['7-day Moving Average', '14-day Moving Average', '28day Moving␣
 ↪Average', 'Kalman Mean', 'Actual Stock Price'])
plt.xlabel('Day')
plt.ylabel('Price');
```



From the kalman Filter for Bitcoin it can be seen that it produces much more smooth signal than others and is more generalised than the rolling window prediction. Kalman fiklter helps in separating the noise from the signals and can be used for prediction

[ ]:
```
plt.figure(figsize=(15,7))
plt.plot(stock_price ,'b',lw=1.5)
plt.plot(kalman_mean ,'m',lw=1.5)
plt.plot(stock_price - kalman_mean,'-g',lw=1.5)
plt.plot(stock_price - stock_price.mean() ,'r',lw=1.5)
plt.plot(stock_price - rolling_28d ,'y',lw=1.5)
plt.legend(['Stock Price', 'Kalman Mean', 'Diff between Stock Price and Kalman␣
↪Mean', 'Diff between Stock Price and Mean Price',  'Diff between Stock Price␣
↪and rolling mean of 30 days'])
plt.xlabel('Day')
plt.ylabel('Variance of the Stock Price Prediction with Methods for ETH-USD');
```



Kalman Filters gives a time-evolving mean and shows fluctuations with time than the and difference stays closer to 0 compared to the other steps such as rolling mean and static mean. Such updated mean for each time point could help us manage aggressive trading strategies.

In the below section we will using Kalman Filter update method to do stock price forecasts for each day using the previous data as the prior and will keep on update the price on based on the daily available actual price like a dynamic system.

[ ]:
```
kalmanFilter = KalmanFilter(transition_matrices = [1],
                 observation_matrices = [1],
                 initial_state_mean = 0,
                 initial_state_covariance = 1,
```

```
                observation_covariance=1,
                transition_covariance=.0001)

mean, cov = kalmanFilter.em(stock_price[:-10], n_iter=10).smooth(stock_price[:
 ↪-10])

next_means = []
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(10):
  next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov,␣
 ↪stock_price[-(10 - i * 1)])
  next_means.append(next_mean[0])
  next_covs.append(next_cov[0])
```

```
<ipython-input-86-f8125cd5b091>:15: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```

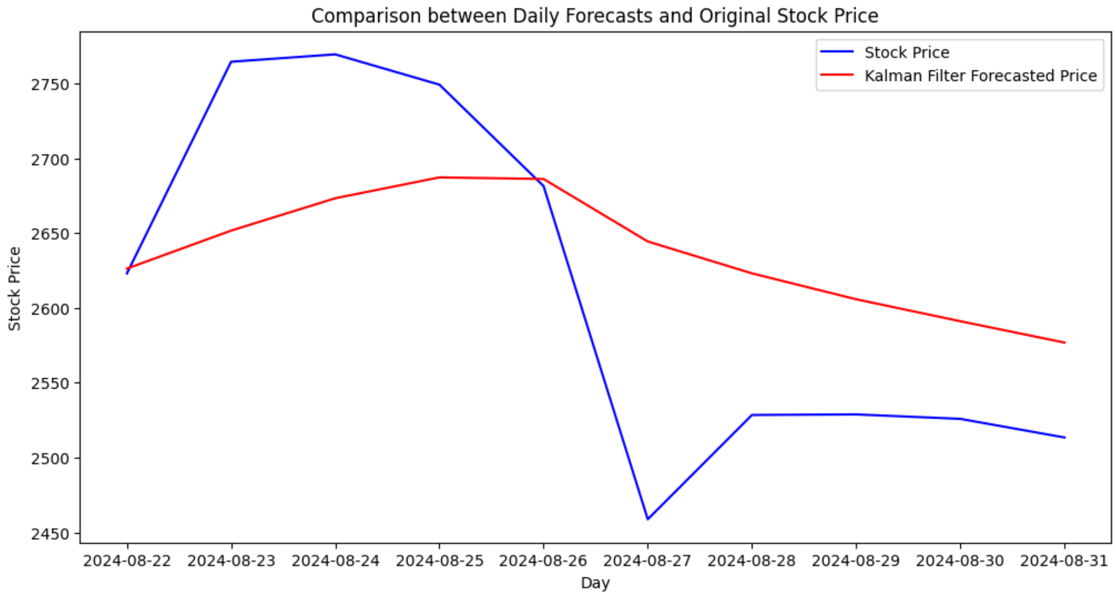
[ ]:
```
next_means # forecasted means
```

[ ]:
```
[2626.221519553881,
 2651.605650741153,
 2673.235844934905,
 2687.17835683635,
 2686.106289901089,
 2644.3496187437095,
 2623.0591466956967,
 2605.747788144818,
 2591.0699890569754,
 2576.8053086951118]
```

[ ]:
```
# replacing the forecasted price for the last 10 days
forecasted_price = pd.DataFrame(data=np.concatenate([stock_price[:-10].values,␣
 ↪next_means]),
                  index=stock_price.index)
```

[ ]:
```
plt.figure(figsize=(12,6))
plt.plot(stock_price[len(stock_price)-10:] ,'b',lw=1.5)
plt.plot(forecasted_price[len(stock_price)-10:] ,'r',lw=1.5)
plt.legend(['Stock Price', 'Kalman Filter Forecasted Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
```

```
plt.title('Comparison between Daily Forecasts and Original Stock Price');
```



[ ]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

_y_stock = stock_price[len(stock_price)-10:]
kalman_forecast_y = forecasted_price[len(stock_price)-10:]
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.3388933894370876
Mean absolute percentage error 0.029552888758174134
Root Mean Square Error RMSE 91.36044420630614
Mean absolute error 76.48915660913735
```

5 Using Traditional ML for Prediction

In this section we will explore how traditional methods work for stock price prediction. We will be using multivariable regression technique to predict closing price of the stock for the next day. The feature engineering for this model will include column values high, low, open, close, volume to determine the Adjusted close price for the next day.

```
[ ]: data.head()
```

```
[ ]: Price                       Adj Close                    Close  \
     Ticker                        BTC-USD      ETH-USD      BTC-USD
     Date
     2022-09-01 00:00:00+00:00  20127.140625  1586.176758  20127.140625
     2022-09-02 00:00:00+00:00  19969.771484  1577.220459  19969.771484
     2022-09-03 00:00:00+00:00  19832.087891  1556.872681  19832.087891
     2022-09-04 00:00:00+00:00  19986.712891  1577.641602  19986.712891
     2022-09-05 00:00:00+00:00  19812.371094  1617.183228  19812.371094

     Price                                           High                \
     Ticker                        ETH-USD      BTC-USD      ETH-USD
     Date
     2022-09-01 00:00:00+00:00  1586.176758  20198.390625  1593.082764
     2022-09-02 00:00:00+00:00  1577.220459  20401.568359  1643.183228
     2022-09-03 00:00:00+00:00  1556.872681  20037.009766  1579.454346
     2022-09-04 00:00:00+00:00  1577.641602  19999.689453  1578.009277
     2022-09-05 00:00:00+00:00  1617.183228  20031.160156  1621.661377

     Price                             Low                     Open  \
     Ticker                        BTC-USD      ETH-USD      BTC-USD
     Date
     2022-09-01 00:00:00+00:00  19653.968750  1520.188354  20050.498047
     2022-09-02 00:00:00+00:00  19814.765625  1551.877930  20126.072266
     2022-09-03 00:00:00+00:00  19698.355469  1541.672119  19969.718750
     2022-09-04 00:00:00+00:00  19636.816406  1543.698853  19832.470703
     2022-09-05 00:00:00+00:00  19673.046875  1559.781860  19988.789062

     Price                                          Volume
     Ticker                        ETH-USD      BTC-USD      ETH-USD
     Date
     2022-09-01 00:00:00+00:00  1553.756348  30182031010  16434276817
     2022-09-02 00:00:00+00:00  1586.017944  29123998928  17708478709
     2022-09-03 00:00:00+00:00  1577.213745  23613051457   9516825994
     2022-09-04 00:00:00+00:00  1556.895874  25245861652   8884144998
     2022-09-05 00:00:00+00:00  1577.884033  28813460025  13060541168
```

```
[ ]: btc_data = {'Open': data['Open']['BTC-USD'],
                 'Close': data['Close']['BTC-USD'],
                 'High': data['High']['BTC-USD'],
                 'Low': data['Low']['BTC-USD'],
                 'Volume': data['Low']['BTC-USD'],
                 'Adj Close': data['Adj Close']['BTC-USD']
                 }

     eth_data = {'Open': data['Open']['ETH-USD'],
```

```
            'Close': data['Close']['ETH-USD'],
            'High': data['High']['ETH-USD'],
            'Low': data['Low']['ETH-USD'],
            'Volume': data['Low']['ETH-USD'],
            'Adj Close': data['Adj Close']['ETH-USD']
            }

btc_df = pd.DataFrame(btc_data, columns = ['Open', 'Close', 'High', 'Low',␣
 ↪'Volume', 'Adj Close'])
eth_df = pd.DataFrame(eth_data, columns = ['Open', 'Close', 'High', 'Low',␣
 ↪'Volume', 'Adj Close'])
```

[ ]:
```
eth_df.head()
```

[ ]:
```
                                  Open        Close         High          Low  \
Date
2022-09-01 00:00:00+00:00  1553.756348  1586.176758  1593.082764  1520.188354
2022-09-02 00:00:00+00:00  1586.017944  1577.220459  1643.183228  1551.877930
2022-09-03 00:00:00+00:00  1577.213745  1556.872681  1579.454346  1541.672119
2022-09-04 00:00:00+00:00  1556.895874  1577.641602  1578.009277  1543.698853
2022-09-05 00:00:00+00:00  1577.884033  1617.183228  1621.661377  1559.781860

                                Volume    Adj Close
Date
2022-09-01 00:00:00+00:00  1520.188354  1586.176758
2022-09-02 00:00:00+00:00  1551.877930  1577.220459
2022-09-03 00:00:00+00:00  1541.672119  1556.872681
2022-09-04 00:00:00+00:00  1543.698853  1577.641602
2022-09-05 00:00:00+00:00  1559.781860  1617.183228
```

[ ]:
```
eth_df['Target'] = eth_df['Adj Close'].shift(-1)
eth_df.dropna(inplace=True)
eth_df.head()
```

[ ]:
```
                                  Open        Close         High          Low  \
Date
2022-09-01 00:00:00+00:00  1553.756348  1586.176758  1593.082764  1520.188354
2022-09-02 00:00:00+00:00  1586.017944  1577.220459  1643.183228  1551.877930
2022-09-03 00:00:00+00:00  1577.213745  1556.872681  1579.454346  1541.672119
2022-09-04 00:00:00+00:00  1556.895874  1577.641602  1578.009277  1543.698853
2022-09-05 00:00:00+00:00  1577.884033  1617.183228  1621.661377  1559.781860

                                Volume    Adj Close       Target
Date
2022-09-01 00:00:00+00:00  1520.188354  1586.176758  1577.220459
2022-09-02 00:00:00+00:00  1551.877930  1577.220459  1556.872681
2022-09-03 00:00:00+00:00  1541.672119  1556.872681  1577.641602
```

```
2022-09-04 00:00:00+00:00  1543.698853  1577.641602  1617.183228
2022-09-05 00:00:00+00:00  1559.781860  1617.183228  1561.748535
```

[ ]:
```
eth_df.tail()
```

[ ]:
```
                                  Open        Close         High          Low  \
Date
2024-08-26 00:00:00+00:00  2749.247559  2681.340576  2763.004150  2668.886719
2024-08-27 00:00:00+00:00  2681.622803  2458.726562  2700.152832  2401.175049
2024-08-28 00:00:00+00:00  2458.904785  2528.415527  2553.820068  2422.293701
2024-08-29 00:00:00+00:00  2528.362305  2528.792725  2595.977051  2507.502441
2024-08-30 00:00:00+00:00  2528.732178  2525.822021  2539.915283  2432.834473

                                Volume    Adj Close       Target
Date
2024-08-26 00:00:00+00:00  2668.886719  2681.340576  2458.726562
2024-08-27 00:00:00+00:00  2401.175049  2458.726562  2528.415527
2024-08-28 00:00:00+00:00  2422.293701  2528.415527  2528.792725
2024-08-29 00:00:00+00:00  2507.502441  2528.792725  2525.822021
2024-08-30 00:00:00+00:00  2432.834473  2525.822021  2513.393799
```

We can define as the forecast set for the last 10 data points to compare with our Kalman Forecast.

[ ]:
```
forecast_set = eth_df[-10:] # validation set
training_set = eth_df[:-10]
```

[ ]:
```
forecast_set
```

[ ]:
```
                                  Open        Close         High          Low  \
Date
2024-08-21 00:00:00+00:00  2573.108887  2631.395508  2662.953369  2538.657715
2024-08-22 00:00:00+00:00  2630.864258  2622.951416  2644.823730  2587.110596
2024-08-23 00:00:00+00:00  2622.916016  2764.447021  2799.329834  2622.581055
2024-08-24 00:00:00+00:00  2765.481445  2769.389648  2820.020508  2737.776611
2024-08-25 00:00:00+00:00  2769.098145  2749.157715  2793.012939  2736.088867
2024-08-26 00:00:00+00:00  2749.247559  2681.340576  2763.004150  2668.886719
2024-08-27 00:00:00+00:00  2681.622803  2458.726562  2700.152832  2401.175049
2024-08-28 00:00:00+00:00  2458.904785  2528.415527  2553.820068  2422.293701
2024-08-29 00:00:00+00:00  2528.362305  2528.792725  2595.977051  2507.502441
2024-08-30 00:00:00+00:00  2528.732178  2525.822021  2539.915283  2432.834473

                                Volume    Adj Close       Target
Date
2024-08-21 00:00:00+00:00  2538.657715  2631.395508  2622.951416
2024-08-22 00:00:00+00:00  2587.110596  2622.951416  2764.447021
2024-08-23 00:00:00+00:00  2622.581055  2764.447021  2769.389648
2024-08-24 00:00:00+00:00  2737.776611  2769.389648  2749.157715
2024-08-25 00:00:00+00:00  2736.088867  2749.157715  2681.340576
```

```
2024-08-26 00:00:00+00:00  2668.886719  2681.340576  2458.726562
2024-08-27 00:00:00+00:00  2401.175049  2458.726562  2528.415527
2024-08-28 00:00:00+00:00  2422.293701  2528.415527  2528.792725
2024-08-29 00:00:00+00:00  2507.502441  2528.792725  2525.822021
2024-08-30 00:00:00+00:00  2432.834473  2525.822021  2513.393799
```

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

X = training_set.drop('Target', axis=1)
y = training_set['Target']

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,␣
↪random_state=42, shuffle=False)


lr = LinearRegression(n_jobs=-1)
lr.fit(X_train, y_train)

score = lr.score(X_test, y_test)
print('The linear regression confidence is {}'.format(score))
```

```
The linear regression confidence is 0.9031333486963974
```

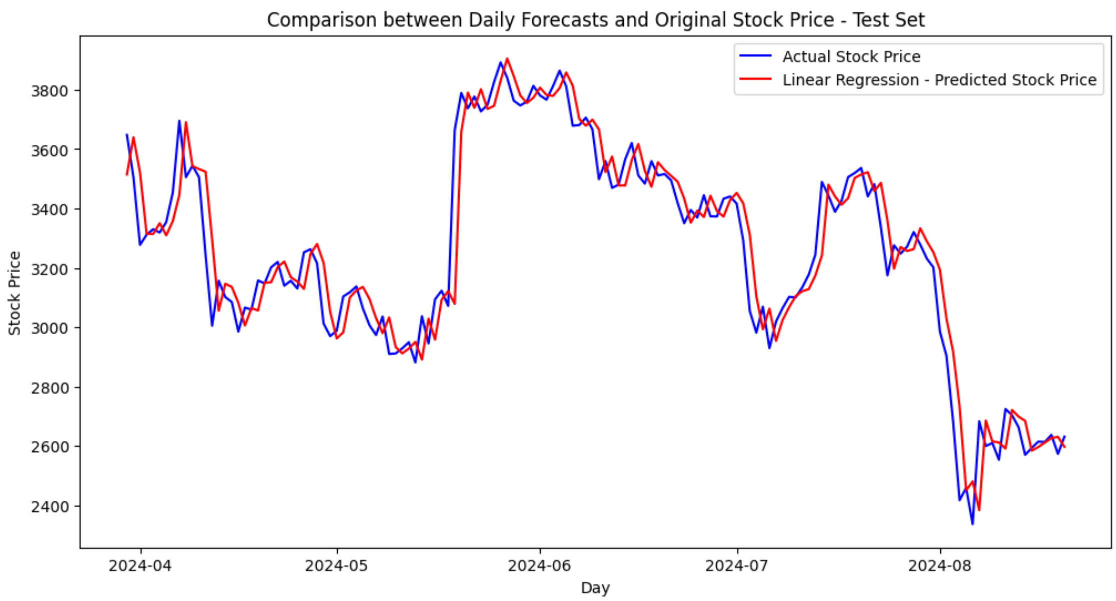
[ ]:
```
prediction = lr.predict(X_test)

from sklearn.metrics import r2_score , mean_absolute_percentage_error
print("R square {}".format(r2_score(y_test, prediction)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(y_test, prediction)))
```

```
R square 0.9031333486963974
Mean absolute percentage error 0.024258713366402 52
```

[ ]:
```
y_test[:10]
```

[ ]:
```
Date
2024-03-30 00:00:00+00:00    3647.856445
2024-03-31 00:00:00+00:00    3505.030029
2024-04-01 00:00:00+00:00    3277.234619
2024-04-02 00:00:00+00:00    3311.441895
2024-04-03 00:00:00+00:00    3330.040527
2024-04-04 00:00:00+00:00    3318.885254
2024-04-05 00:00:00+00:00    3354.183838
2024-04-06 00:00:00+00:00    3453.494629
2024-04-07 00:00:00+00:00    3695.292725
2024-04-08 00:00:00+00:00    3505.163330
Name: Target, dtype: float64
```

[ ]:
```
plt.figure(figsize=(12,6))
plt.plot(y_test ,'b',lw=1.5)
plt.plot(pd.DataFrame(data=prediction, index=y_test.index) ,'r',lw=1.5)
plt.legend(['Actual Stock Price', 'Linear Regression - Predicted Stock Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price - Test␣
↪Set');
```



[ ]:
```
# We will not forecast for the next days based on this model
forecast_X = forecast_set.drop('Target', axis=1)
forecast_y = forecast_set['Target']
forecast_pred = lr.predict(forecast_X)
forecast_pred
```

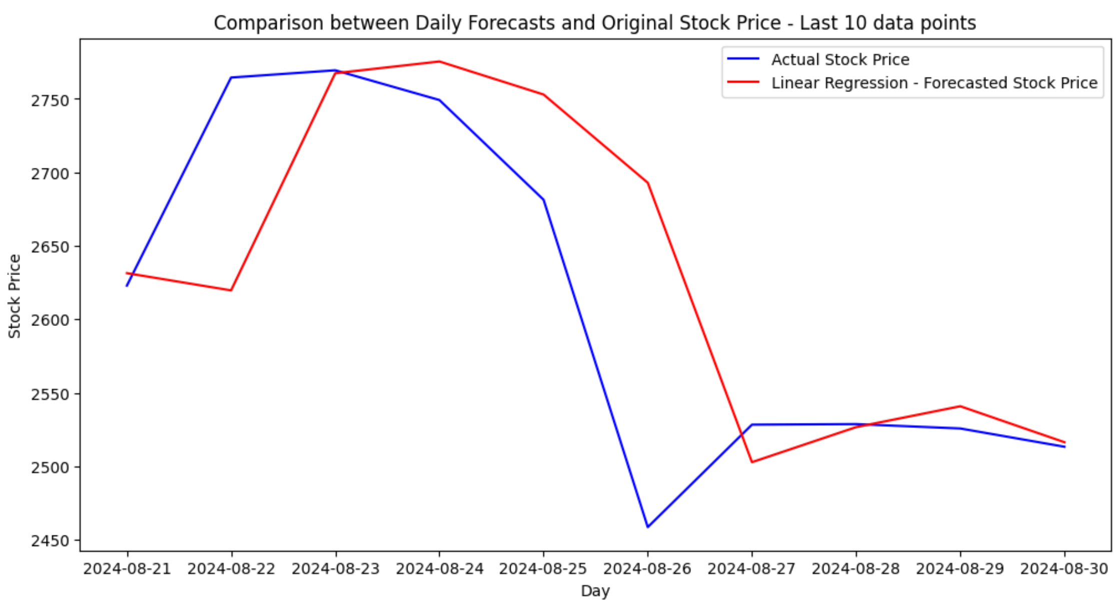
[ ]:
```
array([2631.44411925, 2619.72329109, 2767.39937414, 2775.39052501,
       2752.90979733, 2692.90546881, 2502.90825781, 2526.75050839,
       2540.95400849, 2516.47833623])
```

[ ]:
```
forecast_y
```

[ ]:
```
Date
2024-08-21 00:00:00+00:00    2622.951416
2024-08-22 00:00:00+00:00    2764.447021
2024-08-23 00:00:00+00:00    2769.389648
2024-08-24 00:00:00+00:00    2749.157715
2024-08-25 00:00:00+00:00    2681.340576
```

```
2024-08-26 00:00:00+00:00    2458.726562
2024-08-27 00:00:00+00:00    2528.415527
2024-08-28 00:00:00+00:00    2528.792725
2024-08-29 00:00:00+00:00    2525.822021
2024-08-30 00:00:00+00:00    2513.393799
Name: Target, dtype: float64
```

[ ]:
```
plt.figure(figsize=(12,6))
plt.plot(forecast_y ,'b',lw=1.5)
plt.plot(pd.DataFrame(data=forecast_pred, index=forecast_y.index) ,'r',lw=1.5)
plt.legend(['Actual Stock Price', 'Linear Regression - Forecasted Stock Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price - Last␣
↪10 data points');
```



Metrics from LR for the stock price

[ ]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

print("R square {}".format(r2_score(forecast_y, forecast_pred)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(forecast_y, forecast_pred)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(forecast_y, forecast_pred))))
```

```
print("Mean absolute error {}".format(mean_absolute_error(forecast_y,␣
↪forecast_pred)))
```

```
R square 0.3460448940489449
Mean absolute percentage error 0.02058999673559557
Root Mean Square Error RMSE 90.8649558927459
Mean absolute error 53.295365570960215
```

Metrics from the Kalman Filter forecast

```
[ ]: _y_stock = stock_price[len(stock_price)-10:]
kalman_forecast_y = forecasted_price[len(stock_price)-10:]
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.3388933894370876
Mean absolute percentage error 0.029552888758174134
Root Mean Square Error RMSE 91.36044420630614
Mean absolute error 76.48915660913735
```