

In [1]:

```
import requests
import json
import pandas as pd
import numpy as np
import datetime as dt
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
from math import sqrt
from datetime import datetime
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.ar_model import AutoReg
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings("ignore")
```

In [2]:

```
frequency = input("Please enter the frequency (1m/5m/30m/.../1h/6h/1d/ : ")

def get_bars(symbol, interval=frequency):
    root_url = 'https://api.binance.com/api/v1/klines'
    url = root_url + '?symbol=' + symbol + '&interval=' + interval
    data = json.loads(requests.get(url).text)
    df = pd.DataFrame(data)
    df.columns = ['open_time',
                  'o', 'h', 'l', 'c', 'v',
                  'close_time', 'qav', 'num_trades',
                  'taker_base_vol', 'taker_quote_vol', 'ignore']
    df.index = [dt.datetime.fromtimestamp(x / 1000.0) for x in df.close_time]
    return df

btcusdt = get_bars('BTCUSDT')
ethusdt = get_bars('ETHUSDT')
bnbusdt = get_bars('BNBUSDT')
adausdt = get_bars('ADAUSDT')
solusdt = get_bars('SOLUSDT')
```

Please enter the frequency (1m/5m/30m/.../1h/6h/1d/ : 1d

In [3]:

```
d_1=[]
for date in btcusdt.index:
    d=datetime.date(date)
    d_1.append(d)
d_2=[]
for date in ethusdt.index:
    d=datetime.date(date)
    d_2.append(d)
d_3=[]
for date in bnbusdt.index:
    d=datetime.date(date)
    d_3.append(d)
d_4=[]
for date in adausdt.index:
    d=datetime.date(date)
    d_4.append(d)
d_5=[]
for date in solusdt.index:
    d=datetime.date(date)
    d_5.append(d)
```

In [4]:

```
bnbusdt["date"]=d_1
```

```
bnbusdt.set_index("date")
train_data_h_1 = bnbusdt["h"].iloc[:].astype("float32")
train_data_l_1= bnbusdt["l"].iloc[:].astype("float32")
```

In [5]:

```
ethusdt["date"]=d_2
ethusdt.set_index("date")
train_data_h_2 = ethusdt["h"].iloc[:].astype("float32")
train_data_l_2= ethusdt["l"].iloc[:].astype("float32")
```

In [6]:

```
solusdt["date"]=d_5
solusdt.set_index("date")
train_data_h_3 = solusdt["h"].iloc[:].astype("float32")
train_data_l_3= solusdt["l"].iloc[:].astype("float32")
```

In [7]:

```
btcusdt["date"]=d_3
btcusdt.set_index("date")
train_data_h_4 = btcusdt["h"].iloc[:].astype("float32")
train_data_l_4= btcusdt["l"].iloc[:].astype("float32")
```

In [8]:

```
adausdt["date"]=d_4
adausdt.set_index("date")
train_data_h_5=adausdt["h"].iloc[:].astype("float32")
train_data_l_5= adausdt["l"].iloc[:].astype("float32")
```

Probablity and Partical Correlation Plot

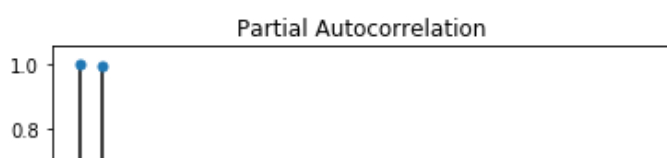
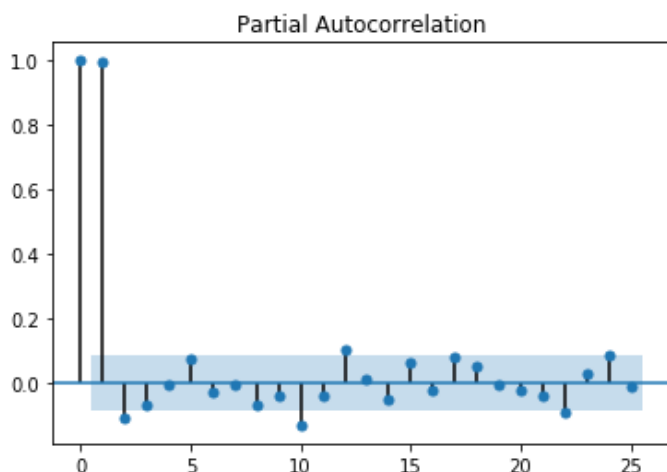
In [9]:

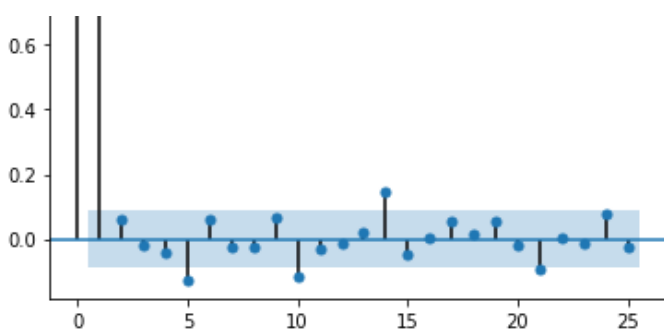
```
print("BNB")
df_stationarityTest_h = adfuller(bnbusdt["h"].astype("float32"), autolag='AIC')
df_stationarityTest_l= adfuller(bnbusdt["l"].astype("float32"), autolag='AIC')
print("P-value for high: ", df_stationarityTest_h[1])
print("P-value for low: ", df_stationarityTest_l[1])
pacf = plot_pacf(bnbusdt["h"], lags=25)
pacf = plot_pacf(bnbusdt["l"], lags=25)
```

BNB

P-value for high: 0.7226454368782608

P-value for low: 0.7766815885364831





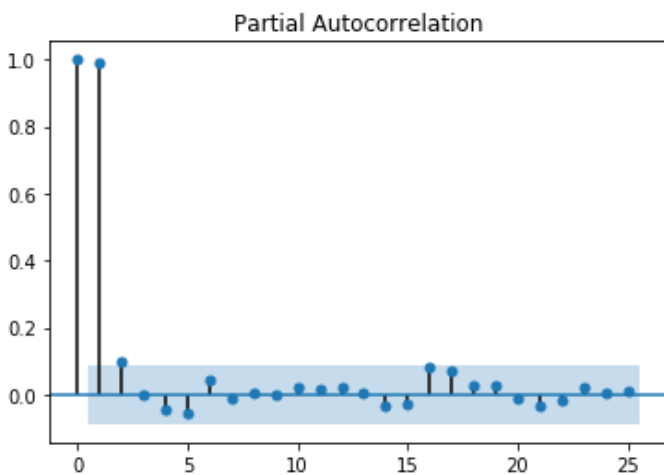
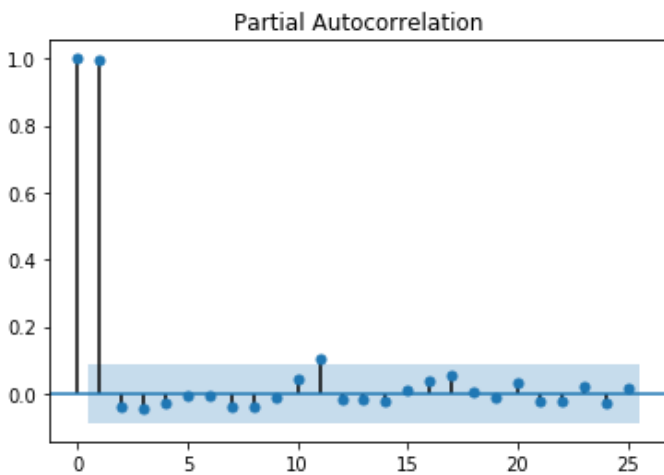
In [10]:

```
print("ETH")
df_stationarityTest_h = adfuller(ethusdt["h"].astype("float32"), autolag='AIC')
df_stationarityTest_l= adfuller(ethusdt["l"].astype("float32"), autolag='AIC')
print("P-value for high: ", df_stationarityTest_h[1])
print("P-value for low: ", df_stationarityTest_l[1])
pacf = plot_pacf(ethusdt["h"], lags=25)
pacf = plot_pacf(ethusdt["l"], lags=25)
```

ETH

P-value for high: 0.9453052840969027

P-value for low: 0.9449717503291432



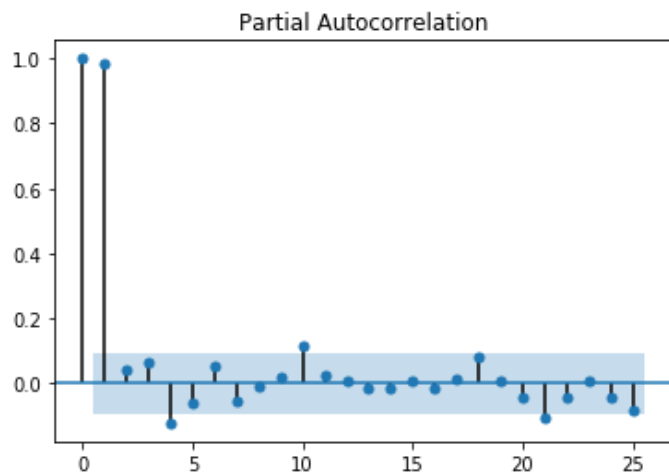
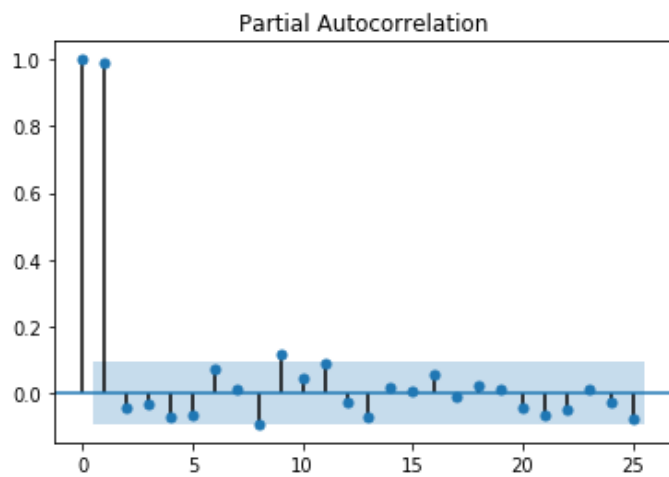
In [11]:

```
print("Sol")
df_stationarityTest_h = adfuller(solusdt["h"].astype("float32"), autolag='AIC')
df_stationarityTest_l= adfuller(solusdt["l"].astype("float32"), autolag='AIC')
print("P-value for high: ", df_stationarityTest_h[1])
print("P-value for low: ", df_stationarityTest_l[1])
pacf = plot_pacf(solusdt["h"], lags=25)
pacf = plot_pacf(solusdt["l"], lags=25)
```

Sol

P-value for high: 0.9962098177028296

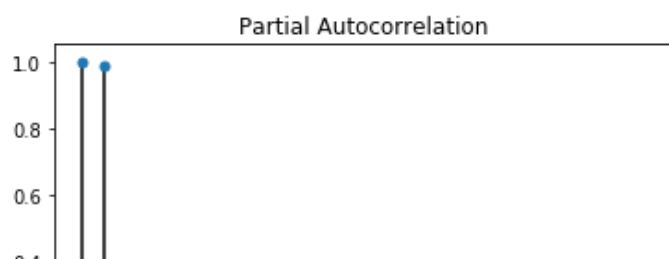
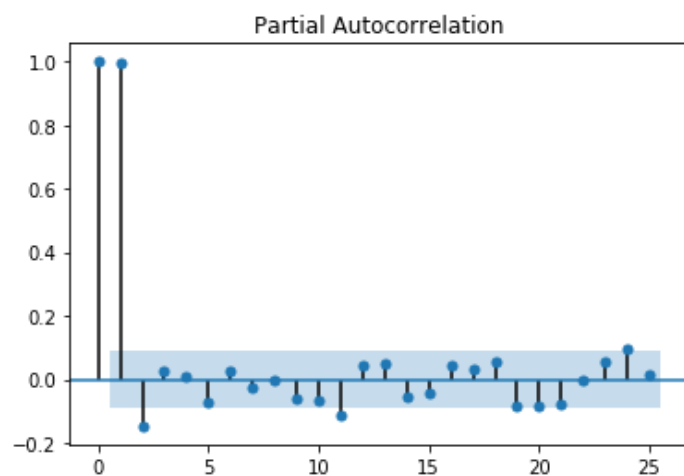
P-value for low: 0.998758297519044

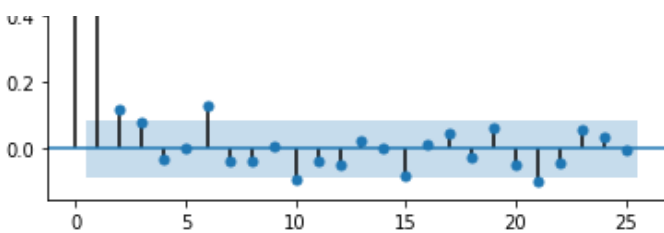


In [12]:

```
print("ADA")
df_stationarityTest_h = adfuller(adausdt["h"].astype("float32"), autolag='AIC')
df_stationarityTest_l = adfuller(adausdt["l"].astype("float32"), autolag='AIC')
print("P-value for high: ", df_stationarityTest_h[1])
print("P-value for low: ", df_stationarityTest_l[1])
pacf = plot_pacf(adausdt["h"], lags=25)
pacf = plot_pacf(adausdt["l"], lags=25)
```

ADA
P-value for high: 0.7162766203641826
P-value for low: 0.8810977481534017

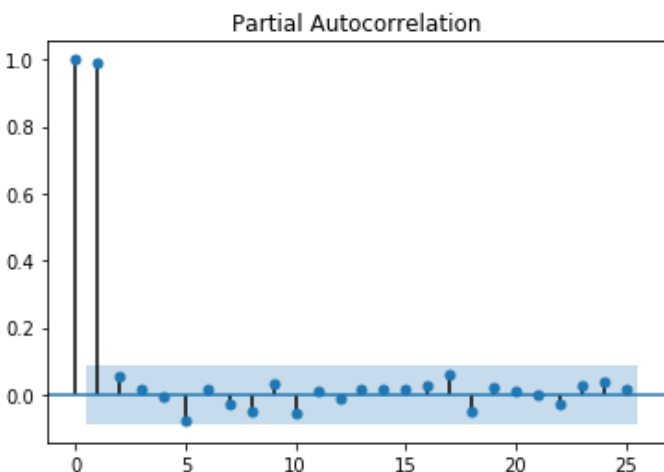
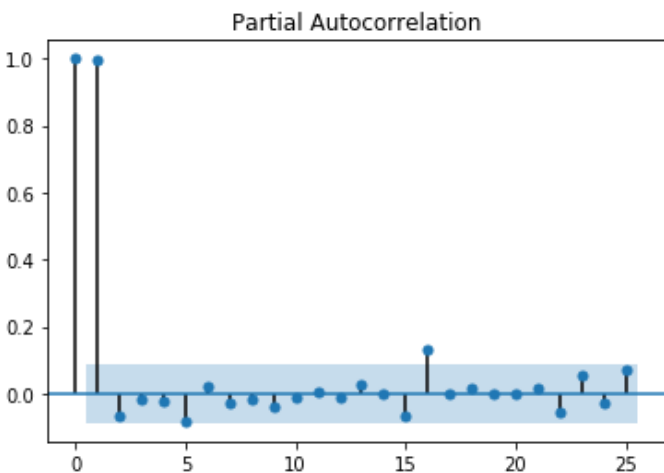




In [13]:

```
print("BTC")
df_stationarityTest_h = adfuller(btcusdt["h"].astype("float32"), autolag='AIC')
df_stationarityTest_l= adfuller(btcusdt["l"].astype("float32"), autolag='AIC')
print("P-value for high: ", df_stationarityTest_h[1])
print("P-value for low: ", df_stationarityTest_l[1])
pacf = plot_pacf(btcusdt["h"], lags=25)
pacf = plot_pacf(btcusdt["l"], lags=25)
```

BTC
P-value for high: 0.7878045401475804
P-value for low: 0.8122483296467151



AutoRegression and plot of High and Low Prices of Crypto

In [14]:

```
print("BNB")
ar_h_model = AutoReg(np.asarray(train_data_h_1), lags=8).fit()
ar_l_model = AutoReg(np.asarray(train_data_l_1), lags=8).fit()
print(ar_h_model.summary())
print(ar_l_model.summary())
plt.plot(train_data_h_1)
plt.plot(train_data_l_1)
```

BNB

AutoReg Model Results

=====

```

Dep. Variable:          y      No. Observations:          500
Model:                  AutoReg(8)      Log Likelihood      -2076.485
Method:                  Conditional MLE      S.D. of innovations      16.470
Date:                    Fri, 29 Oct 2021      AIC                  5.644
Time:                    17:44:24      BIC                  5.729
Sample:                  8      HQIC                  5.677
                        500

```

	coef	std err	z	P> z	[0.025	0.975]
intercept	1.5760	1.109	1.421	0.155	-0.598	3.750
y.L1	1.1331	0.045	25.157	0.000	1.045	1.221
y.L2	-0.0346	0.068	-0.508	0.611	-0.168	0.099
y.L3	-0.1026	0.068	-1.508	0.132	-0.236	0.031
y.L4	-0.1041	0.068	-1.532	0.126	-0.237	0.029
y.L5	0.1427	0.068	2.101	0.036	0.010	0.276
y.L6	-0.0418	0.068	-0.613	0.540	-0.175	0.092
y.L7	0.0513	0.068	0.754	0.451	-0.082	0.185
y.L8	-0.0476	0.045	-1.055	0.291	-0.136	0.041

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	1.0045	-0.0000j	1.0045	-0.0000
AR.2	1.5073	-0.0000j	1.5073	-0.0000
AR.3	0.9711	-1.0711j	1.4457	-0.1328
AR.4	0.9711	+1.0711j	1.4457	0.1328
AR.5	-1.2511	-0.7519j	1.4597	-0.4139
AR.6	-1.2511	+0.7519j	1.4597	0.4139
AR.7	-0.4369	-1.7097j	1.7646	-0.2898
AR.8	-0.4369	+1.7097j	1.7646	0.2898

AutoReg Model Results

```

Dep. Variable:          y      No. Observations:          500
Model:                  AutoReg(8)      Log Likelihood      -2128.536
Method:                  Conditional MLE      S.D. of innovations      18.308
Date:                    Fri, 29 Oct 2021      AIC                  5.855
Time:                    17:44:24      BIC                  5.941
Sample:                  8      HQIC                  5.889
                        500

```

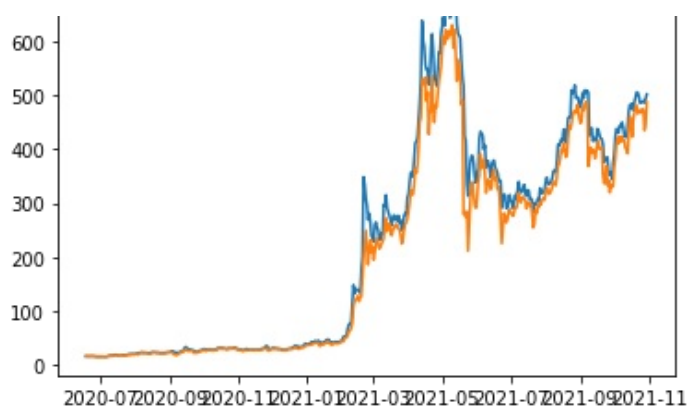
	coef	std err	z	P> z	[0.025	0.975]
intercept	1.7579	1.231	1.428	0.153	-0.655	4.171
y.L1	0.9999	0.045	22.090	0.000	0.911	1.089
y.L2	0.0290	0.064	0.454	0.650	-0.096	0.154
y.L3	-0.0546	0.064	-0.852	0.394	-0.180	0.071
y.L4	0.1676	0.063	2.645	0.008	0.043	0.292
y.L5	-0.2354	0.063	-3.715	0.000	-0.360	-0.111
y.L6	0.1112	0.064	1.733	0.083	-0.015	0.237
y.L7	0.0252	0.064	0.392	0.695	-0.101	0.151
y.L8	-0.0476	0.046	-1.046	0.296	-0.137	0.042

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-0.2826	-1.3377j	1.3672	-0.2831
AR.2	-0.2826	+1.3377j	1.3672	0.2831
AR.3	-1.4998	-0.0000j	1.4998	-0.5000
AR.4	-1.9574	-0.0000j	1.9574	-0.5000
AR.5	1.0426	-1.2314j	1.6135	-0.1382
AR.6	1.0426	+1.2314j	1.6135	0.1382
AR.7	1.0054	-0.0000j	1.0054	-0.0000
AR.8	1.4613	-0.0000j	1.4613	-0.0000

Out[14]:

[<matplotlib.lines.Line2D at 0x1b2c8e24c88>]



In [15]:

```
print("ETH")
ar_h_model = AutoReg(np.asarray(train_data_h_2), lags=8).fit()
ar_l_model = AutoReg(np.asarray(train_data_l_2), lags=8).fit()
print(ar_h_model.summary())
print(ar_l_model.summary())
plt.plot(train_data_h_2)
plt.plot(train_data_l_2)
```

ETH

AutoReg Model Results			
Dep. Variable:	y	No. Observations:	500
Model:	AutoReg(8)	Log Likelihood	-2900.828
Method:	Conditional MLE	S.D. of innovations	87.975
Date:	Fri, 29 Oct 2021	AIC	8.995
Time:	17:44:24	BIC	9.080
Sample:	8	HQIC	9.028
	500		

	coef	std err	z	P> z	[0.025	0.975]
intercept	8.4437	6.809	1.240	0.215	-4.903	21.790
y.L1	1.1330	0.045	25.137	0.000	1.045	1.221
y.L2	-0.0856	0.068	-1.255	0.209	-0.219	0.048
y.L3	-0.0185	0.068	-0.271	0.786	-0.152	0.115
y.L4	-0.0175	0.068	-0.256	0.798	-0.151	0.116
y.L5	-0.0048	0.068	-0.070	0.944	-0.139	0.129
y.L6	0.0636	0.068	0.931	0.352	-0.070	0.197
y.L7	-0.0133	0.068	-0.195	0.846	-0.147	0.120
y.L8	-0.0587	0.045	-1.297	0.194	-0.147	0.030

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	1.0027	-0.0000j	1.0027	-0.0000
AR.2	1.2705	-0.0000j	1.2705	-0.0000
AR.3	0.8366	-1.1276j	1.4041	-0.1484
AR.4	0.8366	+1.1276j	1.4041	0.1484
AR.5	-0.4790	-1.4313j	1.5093	-0.3014
AR.6	-0.4790	+1.4313j	1.5093	0.3014
AR.7	-1.6075	-0.6278j	1.7257	-0.4407
AR.8	-1.6075	+0.6278j	1.7257	0.4407

AutoReg Model Results			
Dep. Variable:	y	No. Observations:	500
Model:	AutoReg(8)	Log Likelihood	-3047.635
Method:	Conditional MLE	S.D. of innovations	118.563
Date:	Fri, 29 Oct 2021	AIC	9.592
Time:	17:44:24	BIC	9.677
Sample:	8	HQIC	9.625
	500		

	coef	std err	z	P> z	[0.025	0.975]
intercept	10.0718	9.168	1.099	0.272	-7.898	28.041

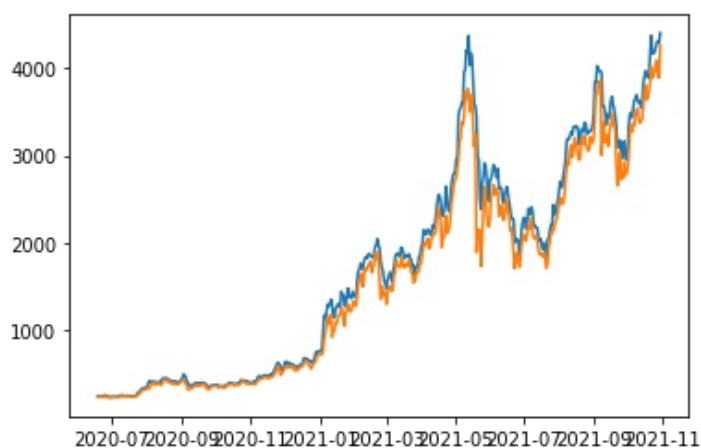
y.L1	0.9385	0.046	20.620	0.000	0.849	1.028
y.L2	0.0536	0.062	0.858	0.391	-0.069	0.176
y.L3	0.0062	0.062	0.099	0.921	-0.116	0.129
y.L4	0.0777	0.062	1.248	0.212	-0.044	0.200
y.L5	-0.1375	0.062	-2.208	0.027	-0.260	-0.015
y.L6	0.0886	0.063	1.416	0.157	-0.034	0.211
y.L7	-0.0353	0.063	-0.564	0.573	-0.158	0.087
y.L8	0.0071	0.046	0.156	0.876	-0.083	0.097

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-1.4053	-0.0000j	1.4053	-0.5000
AR.2	1.0010	-0.0000j	1.0010	-0.0000
AR.3	-0.5810	-1.5368j	1.6430	-0.3075
AR.4	-0.5810	+1.5368j	1.6430	0.3075
AR.5	0.9375	-2.3051j	2.4885	-0.1885
AR.6	0.9375	+2.3051j	2.4885	0.1885
AR.7	2.3173	-0.7619j	2.4393	-0.0506
AR.8	2.3173	+0.7619j	2.4393	0.0506

Out[15]:

[<matplotlib.lines.Line2D at 0x1b2c8bf4ac8>]



In [16]:

```
print("SOL")
ar_h_model = AutoReg(np.asarray(train_data_h_3), lags=8).fit()
ar_l_model = AutoReg(np.asarray(train_data_l_3), lags=8).fit()
print(ar_h_model.summary())
print(ar_l_model.summary())
plt.plot(train_data_h_3)
plt.plot(train_data_l_3)
```

SOL

AutoReg Model Results

Dep. Variable:	y	No. Observations:	445
Model:	AutoReg(8)	Log Likelihood	-1245.494
Method:	Conditional MLE	S.D. of innovations	4.184
Date:	Fri, 29 Oct 2021	AIC	2.908
Time:	17:44:24	BIC	3.001
Sample:	8	HQIC	2.945
	445		

	coef	std err	z	P> z	[0.025	0.975]
intercept	0.2214	0.248	0.892	0.372	-0.265	0.708
y.L1	1.2146	0.047	25.646	0.000	1.122	1.307
y.L2	-0.2463	0.074	-3.331	0.001	-0.391	-0.101
y.L3	0.0628	0.075	0.841	0.401	-0.084	0.209
y.L4	0.0703	0.075	0.942	0.346	-0.076	0.217
y.L5	-0.1307	0.076	-1.731	0.083	-0.279	0.017
y.L6	-0.0953	0.076	-1.250	0.211	-0.245	0.054
y.L7	0.2740	0.076	3.615	0.000	0.125	0.423


```
y.L8      -0.1469      0.049      -2.977      0.003      -0.244      -0.050
```

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-1.1579	-0.5783j	1.2943	-0.4263
AR.2	-1.1579	+0.5783j	1.2943	0.4263
AR.3	-0.1187	-1.2135j	1.2193	-0.2655
AR.4	-0.1187	+1.2135j	1.2193	0.2655
AR.5	1.0230	-0.9731j	1.4119	-0.1210
AR.6	1.0230	+0.9731j	1.4119	0.1210
AR.7	0.9965	-0.0000j	0.9965	-0.0000
AR.8	1.3757	-0.0000j	1.3757	-0.0000

AutoReg Model Results

```
Dep. Variable:      y      No. Observations:      445
Model:              AutoReg(8)      Log Likelihood      -1258.572
Method:              Conditional MLE      S.D. of innovations      4.311
Date:                Fri, 29 Oct 2021      AIC      2.968
Time:                17:44:24      BIC      3.061
Sample:              8      HQIC      3.005
                   445
```

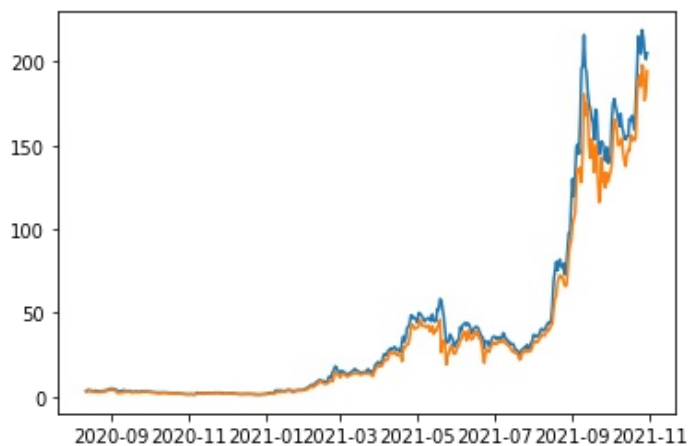
	coef	std err	z	P> z	[0.025	0.975]
intercept	0.1876	0.255	0.736	0.462	-0.312	0.687
y.L1	1.0563	0.048	22.081	0.000	0.963	1.150
y.L2	-0.2290	0.070	-3.290	0.001	-0.365	-0.093
y.L3	0.2145	0.071	3.019	0.003	0.075	0.354
y.L4	0.0559	0.072	0.779	0.436	-0.085	0.196
y.L5	-0.1748	0.072	-2.428	0.015	-0.316	-0.034
y.L6	0.1717	0.073	2.361	0.018	0.029	0.314
y.L7	-0.0223	0.073	-0.305	0.760	-0.165	0.121
y.L8	-0.0663	0.050	-1.315	0.189	-0.165	0.033

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	0.9935	-0.0000j	0.9935	-0.0000
AR.2	1.3877	-0.0000j	1.3877	-0.0000
AR.3	0.7996	-1.1610j	1.4097	-0.1540
AR.4	0.7996	+1.1610j	1.4097	0.1540
AR.5	-0.3252	-1.2264j	1.2688	-0.2913
AR.6	-0.3252	+1.2264j	1.2688	0.2913
AR.7	-1.8329	-0.2485j	1.8497	-0.4786
AR.8	-1.8329	+0.2485j	1.8497	0.4786

Out[16]:

[<matplotlib.lines.Line2D at 0x1b2c8d03c88>]



In [17]:

```
print("BTC")
```

```

ar_h_model = AutoReg(np.asarray(train_data_h_4), lags=8).fit()
ar_l_model = AutoReg(np.asarray(train_data_l_4), lags=8).fit()
print(ar_h_model.summary())
print(ar_l_model.summary())
plt.plot(train_data_h_4)
plt.plot(train_data_l_4)

```

```

BTC

AutoReg Model Results
=====
Dep. Variable:          y      No. Observations:          500
Model:                AutoReg(8)  Log Likelihood          -4231.608
Method:              Conditional MLE  S.D. of innovations      1315.394
Date:                Fri, 29 Oct 2021  AIC                      14.404
Time:                17:44:25      BIC                      14.490
Sample:              8            HQIC                      14.438
                        500

```

	coef	std err	z	P> z	[0.025	0.975]
intercept	184.2938	126.614	1.456	0.146	-63.866	432.453
y.L1	1.0837	0.045	24.053	0.000	0.995	1.172
y.L2	-0.0424	0.067	-0.637	0.524	-0.173	0.088
y.L3	-0.0849	0.067	-1.273	0.203	-0.216	0.046
y.L4	0.1642	0.067	2.462	0.014	0.033	0.295
y.L5	-0.0955	0.067	-1.429	0.153	-0.227	0.036
y.L6	-0.0188	0.067	-0.281	0.779	-0.150	0.113
y.L7	-0.0507	0.067	-0.757	0.449	-0.182	0.081
y.L8	0.0415	0.045	0.912	0.362	-0.048	0.131

Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	-1.4244	-0.0000j	1.4244	-0.5000		
AR.2	-1.0735	-1.3844j	1.7518	-0.3550		
AR.3	-1.0735	+1.3844j	1.7518	0.3550		
AR.4	0.3181	-1.3980j	1.4338	-0.2144		
AR.5	0.3181	+1.3980j	1.4338	0.2144		
AR.6	1.0037	-0.0000j	1.0037	-0.0000		
AR.7	1.5772	-0.4319j	1.6353	-0.0425		
AR.8	1.5772	+0.4319j	1.6353	0.0425		

```

AutoReg Model Results
=====
Dep. Variable:          y      No. Observations:          500
Model:                AutoReg(8)  Log Likelihood          -4335.393
Method:              Conditional MLE  S.D. of innovations      1624.306
Date:                Fri, 29 Oct 2021  AIC                      14.826
Time:                17:44:25      BIC                      14.912
Sample:              8            HQIC                      14.860
                        500

```

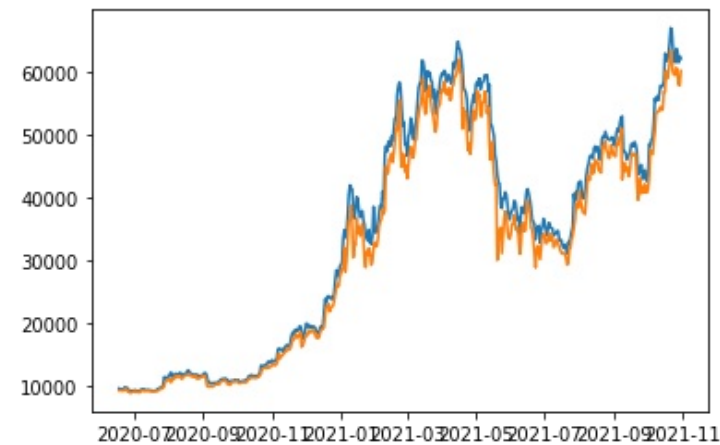
	coef	std err	z	P> z	[0.025	0.975]
intercept	225.8366	156.637	1.442	0.149	-81.167	532.840
y.L1	0.9540	0.045	21.163	0.000	0.866	1.042
y.L2	0.0038	0.062	0.060	0.952	-0.118	0.126
y.L3	-0.0062	0.062	-0.100	0.920	-0.128	0.116
y.L4	0.1400	0.062	2.252	0.024	0.018	0.262
y.L5	-0.1122	0.062	-1.805	0.071	-0.234	0.010
y.L6	0.0560	0.062	0.897	0.370	-0.066	0.178
y.L7	0.0207	0.062	0.331	0.740	-0.102	0.143
y.L8	-0.0599	0.045	-1.325	0.185	-0.149	0.029

Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	1.0043	-0.0000j	1.0043	-0.0000		
AR.2	1.4080	-0.0000j	1.4080	-0.0000		
AR.3	0.8287	-1.2386j	1.4903	-0.1562		
AR.4	0.8287	+1.2386j	1.4903	0.1562		
AR.5	-0.3141	-1.3949j	1.4299	-0.2853		

AR.6	-0.3141	+1.3949j	1.4299	0.2853
AR.7	-1.5480	-0.4509j	1.6123	-0.4549
AR.8	-1.5480	+0.4509j	1.6123	0.4549

Out[17]:

[<matplotlib.lines.Line2D at 0x1b2c8ff29c8>]



In [18]:

```
print("ADA")
ar_h_model = AutoReg(np.asarray(train_data_h_5), lags=8).fit()
ar_l_model = AutoReg(np.asarray(train_data_l_5), lags=8).fit()
print(ar_h_model.summary())
print(ar_l_model.summary())
plt.plot(train_data_h_5)
plt.plot(train_data_l_5)
```

ADA						
AutoReg Model Results						
=====						
Dep. Variable:	y	No. Observations:	500			
Model:	AutoReg(8)	Log Likelihood	655.676			
Method:	Conditional MLE	S.D. of innovations	0.064			
Date:	Fri, 29 Oct 2021	AIC	-5.463			
Time:	17:44:25	BIC	-5.377			
Sample:	8	HQIC	-5.429			
	500					
=====						
	coef	std err	z	P> z	[0.025	0.975]

intercept	0.0062	0.004	1.417	0.156	-0.002	0.015
y.L1	1.1845	0.045	26.277	0.000	1.096	1.273
y.L2	-0.2718	0.070	-3.888	0.000	-0.409	-0.135
y.L3	0.0430	0.071	0.607	0.544	-0.096	0.182
y.L4	0.1474	0.071	2.091	0.037	0.009	0.286
y.L5	-0.1646	0.071	-2.334	0.020	-0.303	-0.026
y.L6	0.0973	0.071	1.373	0.170	-0.042	0.236
y.L7	-0.0567	0.070	-0.810	0.418	-0.194	0.080
y.L8	0.0181	0.045	0.400	0.689	-0.071	0.107
Roots						
=====						
	Real	Imaginary	Modulus	Frequency		

AR.1	-1.4242	-0.0000j	1.4242	-0.5000		
AR.2	1.0031	-0.0000j	1.0031	-0.0000		
AR.3	-0.5952	-1.6635j	1.7667	-0.3047		
AR.4	-0.5952	+1.6635j	1.7667	0.3047		
AR.5	0.5011	-1.7052j	1.7773	-0.2045		
AR.6	0.5011	+1.7052j	1.7773	0.2045		
AR.7	1.8723	-0.6482j	1.9813	-0.0530		
AR.8	1.8723	+0.6482j	1.9813	0.0530		

AutoReg Model Results						
=====						
Dep. Variable:	y	No. Observations:	500			

```

Model:          AutoReg(8)      Log Likelihood      497.268
Method:         Conditional MLE  S.D. of innovations  0.088
Date:           Fri, 29 Oct 2021 AIC                    -4.819
Time:           17:44:25       BIC                    -4.733
Sample:         8              HQIC                     -4.785
                    500

```

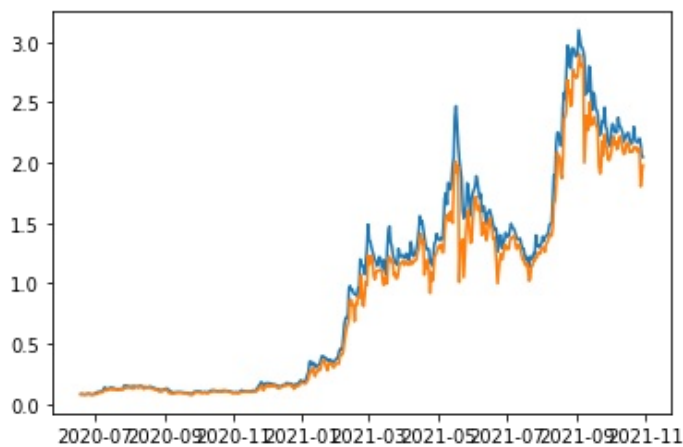
	coef	std err	z	P> z	[0.025	0.975]
intercept	0.0083	0.006	1.388	0.165	-0.003	0.020
y.L1	0.8616	0.045	19.115	0.000	0.773	0.950
y.L2	0.0588	0.060	0.988	0.323	-0.058	0.175
y.L3	0.0145	0.060	0.243	0.808	-0.102	0.131
y.L4	0.0205	0.060	0.344	0.731	-0.097	0.138
y.L5	-0.1163	0.060	-1.947	0.051	-0.233	0.001
y.L6	0.1828	0.060	3.047	0.002	0.065	0.300
y.L7	0.0089	0.060	0.147	0.883	-0.110	0.127
y.L8	-0.0339	0.046	-0.741	0.459	-0.124	0.056

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	1.0022	-0.0000j	1.0022	-0.0000
AR.2	0.9457	-1.0319j	1.3997	-0.1319
AR.3	0.9457	+1.0319j	1.3997	0.1319
AR.4	-0.4474	-1.2804j	1.3563	-0.3035
AR.5	-0.4474	+1.2804j	1.3563	0.3035
AR.6	2.2095	-0.0000j	2.2095	-0.0000
AR.7	-1.5287	-0.0000j	1.5287	-0.5000
AR.8	-2.4180	-0.0000j	2.4180	-0.5000

Out[18]:

[<matplotlib.lines.Line2D at 0x1b2c8ff26c8>]



Augmented Dickey-Fuller test

ADF Function

In [19]:

```

def adf_test(timeseries):
    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dfctest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dfctest[0:4], index=['Test Statistic', 'p-value', '#Lags Used', 'Number of Observations Used'])
    for key,value in dfctest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)

```

In [20]:

```
print("BNB")
print("-----")
adf_test(train_data_h_1)
adf_test(train_data_l_1)
```

BNB

Results of Dickey-Fuller Test:

Test Statistic	-1.080856
p-value	0.722645
#Lags Used	11.000000
Number of Observations Used	488.000000
Critical Value (1%)	-3.443821
Critical Value (5%)	-2.867481
Critical Value (10%)	-2.569934

dtype: float64

Results of Dickey-Fuller Test:

Test Statistic	-0.933672
p-value	0.776682
#Lags Used	13.000000
Number of Observations Used	486.000000
Critical Value (1%)	-3.443877
Critical Value (5%)	-2.867505
Critical Value (10%)	-2.569947

dtype: float64

In [21]:

```
print("ETH")
print("-----")
adf_test(train_data_h_2)
adf_test(train_data_l_2)
```

ETH

Results of Dickey-Fuller Test:

Test Statistic	-0.140004
p-value	0.945305
#Lags Used	10.000000
Number of Observations Used	489.000000
Critical Value (1%)	-3.443794
Critical Value (5%)	-2.867469
Critical Value (10%)	-2.569928

dtype: float64

Results of Dickey-Fuller Test:

Test Statistic	-0.143110
p-value	0.944972
#Lags Used	1.000000
Number of Observations Used	498.000000
Critical Value (1%)	-3.443549
Critical Value (5%)	-2.867361
Critical Value (10%)	-2.569870

dtype: float64

In [22]:

```
print("SOL")
print("-----")
adf_test(train_data_h_3)
adf_test(train_data_l_3)
```

SOL

Results of Dickey-Fuller Test:

Test Statistic	1.233571
p-value	0.996210
#Lags Used	18.000000
Number of Observations Used	426.000000
Critical Value (1%)	-3.445794
Critical Value (5%)	-2.868349
Critical Value (10%)	-2.570397

dtype: float64

```
Results of Dickey-Fuller Test:
Test Statistic          2.070911
p-value                 0.998758
#Lags Used              17.000000
Number of Observations Used 427.000000
Critical Value (1%)     -3.445758
Critical Value (5%)     -2.868333
Critical Value (10%)    -2.570388
dtype: float64
```

In [23]:

```
print("BTC")
print("-----")
adf_test(train_data_h_4)
adf_test(train_data_l_4)
```

BTC

```
-----
Results of Dickey-Fuller Test:
Test Statistic          -0.900510
p-value                 0.787805
#Lags Used              4.000000
Number of Observations Used 495.000000
Critical Value (1%)     -3.443630
Critical Value (5%)     -2.867397
Critical Value (10%)    -2.569889
dtype: float64
Results of Dickey-Fuller Test:
Test Statistic          -0.823080
p-value                 0.812248
#Lags Used              0.000000
Number of Observations Used 499.000000
Critical Value (1%)     -3.443523
Critical Value (5%)     -2.867350
Critical Value (10%)    -2.569864
dtype: float64
```

In [24]:

```
print("ADA")
print("-----")
adf_test(train_data_h_5)
adf_test(train_data_l_5)
```

ADA

```
-----
Results of Dickey-Fuller Test:
Test Statistic          -1.096975
p-value                 0.716277
#Lags Used              11.000000
Number of Observations Used 488.000000
Critical Value (1%)     -3.443821
Critical Value (5%)     -2.867481
Critical Value (10%)    -2.569934
dtype: float64
Results of Dickey-Fuller Test:
Test Statistic          -0.553732
p-value                 0.881098
#Lags Used              5.000000
Number of Observations Used 494.000000
Critical Value (1%)     -3.443657
Critical Value (5%)     -2.867408
Critical Value (10%)    -2.569896
dtype: float64
```

Arima Test Accuracy For each Crypto

In [25]:

```

print("BNB")
print("-----")
print("accruarcy of high")
history = [x for x in train_data_h_1.iloc[:-5]]
test_data=train_data_h_1.iloc[-5:]
predictions = list()
# walk-forward validation
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
print("accruarcy of low")
history = [x for x in train_data_l_1.iloc[:-5]]
test_data=train_data_l_1.iloc[-5:]
predictions = list()
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,3))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)

```

BNB

```

-----
accruarcy of high
predicted=486.630131, expected=488.600006
predicted=490.525355, expected=489.799988
predicted=491.963982, expected=486.399994
predicted=486.205518, expected=494.799988
predicted=496.200329, expected=502.000000
Test RMSE: 5.345
accruarcy of low
predicted=465.713966, expected=474.700012
predicted=482.372559, expected=473.500000
predicted=474.282588, expected=435.299988
predicted=427.501911, expected=446.399994
predicted=457.344015, expected=487.600006
Test RMSE: 24.297

```

In [26]:

```

print("ETH")
print("-----")
print("accruarcy of high")
history = [x for x in train_data_h_2.iloc[:-5]]
test_data=train_data_h_2.iloc[-5:]
predictions = list()
# walk-forward validation
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,3))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts

```

```

rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
print("accruarcy of low")
history = [x for x in train_data_l_2.iloc[:-5]]
test_data=train_data_l_2.iloc[-5:]
predictions = list()
for t in range(len(test_data)):
    model = ARIMA(history, order=(6,3,3))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)

```

ETH

```

-----
accruarcy of high
predicted=4188.054968, expected=4236.000000
predicted=4254.324398, expected=4297.000000
predicted=4308.563353, expected=4307.000000
predicted=4325.221677, expected=4295.000000
predicted=4301.054819, expected=4405.500000
Test RMSE: 56.470
accruarcy of low
predicted=3980.386098, expected=4067.709961
predicted=4055.050105, expected=4090.209961
predicted=4118.170062, expected=3909.000000
predicted=3938.344607, expected=3890.169922
predicted=3906.566067, expected=4265.970215
Test RMSE: 191.888

```

In [27]:

```

print("SOL")
print("-----")
print("accruarcy of high")
history = [x for x in train_data_h_3.iloc[:-5]]
test_data=train_data_h_3.iloc[-5:]
predictions = list()
# walk-forward validation
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
print("accruarcy of low")
history = [x for x in train_data_l_3.iloc[:-5]]
test_data=train_data_l_3.iloc[-5:]
predictions = list()
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))

```



```
print('Test RMSE: %.3f' % rmse)
```

SOL

```
-----
accruarcy of high
predicted=206.552501, expected=218.929993
predicted=224.627723, expected=214.199997
predicted=211.942439, expected=205.490005
predicted=205.845363, expected=201.380005
predicted=202.937105, expected=205.220001
Test RMSE: 8.108
accruarcy of low
predicted=187.077562, expected=198.000000
predicted=201.102069, expected=196.360001
predicted=195.603935, expected=176.940002
predicted=176.897629, expected=181.639999
predicted=187.582833, expected=194.449997
Test RMSE: 10.581
```

In [28]:

```
print("BTC")
print("-----")
print("accruarcy of high")
history = [x for x in train_data_h_4.iloc[:-5]]
test_data=train_data_h_4.iloc[-5:]
predictions = list()
# walk-forward validation
for t in range(len(test_data)):
    model = ARIMA(history, order=(10,4,2))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
print("accruarcy of low")
history = [x for x in train_data_l_4.iloc[:-5]]
test_data=train_data_l_4.iloc[-5:]
predictions = list()
for t in range(len(test_data)):
    model = ARIMA(history, order=(10,2,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
```

BTC

```
-----
accruarcy of high
predicted=62264.852360, expected=63710.628906
predicted=64056.499777, expected=63293.480469
predicted=62808.896413, expected=61496.000000
predicted=60995.054301, expected=62499.000000
predicted=63223.919174, expected=62100.000000
Test RMSE: 1258.667
accruarcy of low
predicted=59863.222759, expected=60650.000000
predicted=60654.372268, expected=59817.550781
predicted=59864.962552, expected=58000.000000
predicted=57802.670701, expected=57820.000000
predicted=58276.940585, expected=60174.808594
Test RMSE: 1296.116
```

In [29]:

```
print("ADA")
print("-----")
print("accruarcy of high")
history = [x for x in train_data_h_5.iloc[:-5]]
test_data=train_data_h_5.iloc[-5:]
predictions = list()
# walk-forward validation
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
print("accruarcy of low")
history = [x for x in train_data_l_5.iloc[:-5]]
test_data=train_data_l_5.iloc[-5:]
predictions = list()
for t in range(len(test_data)):
    model = ARIMA(history, order=(5,2,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test_data[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test_data, predictions))
print('Test RMSE: %.3f' % rmse)
```

ADA

```
-----
accruarcy of high
predicted=2.185643, expected=2.178000
predicted=2.171305, expected=2.202000
predicted=2.211027, expected=2.156000
predicted=2.150181, expected=2.058000
predicted=2.046819, expected=2.048000
Test RMSE: 0.050
accruarcy of low
predicted=2.102552, expected=2.114000
predicted=2.113767, expected=2.122000
predicted=2.128805, expected=1.804000
predicted=1.851007, expected=1.905000
predicted=1.926178, expected=1.979000
Test RMSE: 0.149
```

Future Prediction

In [30]:

```
print("BNB")
print("-----")
history = [x for x in train_data_h_1]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(5,2,1))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_h_1 = output
print("high_prediction")
```

```

print(yhat_h_1)
history = [x for x in train_data_l_1]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(5,2,3))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_l_1 = output
print("low_prediction")
print(yhat_l_1)

```

BNB

```

-----
high_prediction
[504.64507531 506.91190131 507.23477341 507.9097058 ]
low_prediction
[483.03673314 481.26367727 489.30128311 488.19469979]

```

In [31]:

```

print("ETH")
print("-----")
history = [x for x in train_data_h_2]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(10,4,2))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_h_2 = output
print("high_prediction")
print(yhat_h_2)
history = [x for x in train_data_l_2]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(6,3,3))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_l_2 = output
print("low_prediction")
print(yhat_l_2)

```

ETH

```

-----
high_prediction
[4474.47751522 4479.47104476 4552.17896845 4634.99167878]
low_prediction
[4308.69786043 4319.95765647 4406.08132972 4511.22440219]

```

In [32]:

```

print("SOL")
print("-----")
history = [x for x in train_data_h_3]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(5,2,1))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_h_3 = output
print("high_prediction")
print(yhat_h_3)
history = [x for x in train_data_l_3]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(5,2,1))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_l_3 = output
print("low_prediction")
print(yhat_l_3)

```

SOL

```
-----
high_prediction
[205.35517344 205.06722979 205.87561345 207.41084163]
low_prediction
[193.58617906 191.49579288 195.55852001 198.11147413]
```

In [33]:

```
print("BTC")
print("-----")
history = [x for x in train_data_h_4]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(10,4,2))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_h_4 = output
print("high_prediction")
print(yhat_h_4)
history = [x for x in train_data_l_4]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(10,2,1))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_l_4 = output
print("low_prediction")
print(yhat_l_4)
```

BTC

```
-----
high_prediction
[62644.61437552 62487.78609096 62032.32109951 61264.2525689 ]
low_prediction
[60369.9445797 60226.00075934 60258.81613409 60383.26840963]
```

In [34]:

```
print("ADA")
print("-----")
history = [x for x in train_data_h_5]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(5,2,1))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_h_5 = output
print("high_prediction")
print(yhat_h_5)
history = [x for x in train_data_l_5]
predictions = list()
# walk-forward validation
model = ARIMA(history, order=(5,2,1))
model_fit = model.fit()
output = model_fit.forecast(4)
yhat_l_5 = output
print("low_prediction")
print(yhat_l_5)
```

ADA

```
-----
high_prediction
[2.06149737 2.06649061 2.06244569 2.06830927]
low_prediction
[1.98297252 1.98833374 2.03487589 2.01398478]
```

In [35]:

```
option=int(input("What do you want to do 1.Buy Or 2.Sell :"))
if option==1:
    crypto=int(input("Which Crypto 1.BNB 2.BTC 3.ADA 4.SOL 5.ETH :"))
    if crypto==1:
```

```

        print("This is the lowest prize that you should buy your crypto at ",min(yhat_h_1
), "in the next 4 days")
    elif crypto==2:
        print("This is the lowest prize that you should buy your crypto at ",min(yhat_h_3
), "in the next 4 days")
    elif crypto==3:
        print("This is the lowest prize that you should buy your crypto at ",min(yhat_h_4
), "in the next 4 days")
    elif crypto==4:
        print("This is the lowest prize that you should buy your crypto at ",min(yhat_h_5
), "in the next 4 days")
    elif crypto==5:
        print("This is the lowest prize that you should buy your crypto at ",min(yhat_h_2
), "in the next 4 days")
else:
    crypto=int(input("Which Crypto 1.BNB 2.BTC 3.ADA 4.SOL 5.ETH :"))
    if crypto==1:
        print("This is the highest prize that you should sell your crypto at ",max(yhat_h
_1), "in the next 4 days")
    elif crypto==2:
        print("This is the highest prize that you should sell your crypto at ",max(yhat_h
_3), "in the next 4 days")
    elif crypto==3:
        print("This is the highest prize that you should sell your crypto at ",max(yhat_h
_4), "in the next 4 days")
    elif crypto==4:
        print("This is the highest prize that you should sell your crypto at ",max(yhat_h
_5), "in the next 4 days")
    elif crypto==5:
        print("This is the highest prize that you should sell your crypto at ",max(yhat_h
_2), "in the next 4 days")

```

What do you want to do 1.Buy Or 2.Sell :1

Which Crypto 1.BNB 2.BTC 3.ADA 4.SOL 5.ETH :1

This is the lowest prize that you should buy your crypto at 504.6450753095979 in the next 4 days