

# goldprice-prediction

September 1, 2024

```
[1]: import warnings
import itertools
import numpy as np
import matplotlib.pyplot as plt
warnings.filterwarnings("ignore")
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6
import pandas as pd

import statsmodels.api as sm
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.ar_model import AR
from statsmodels.tsa.arima_model import ARMA, ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX

from math import sqrt

import matplotlib
matplotlib.rcParams['axes.labelsize'] = 14
matplotlib.rcParams['xtick.labelsize'] = 12
matplotlib.rcParams['ytick.labelsize'] = 12
matplotlib.rcParams['text.color'] = 'k'
import seaborn as sns

from random import random

from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_absolute_error, mean_squared_log_error

[2]: goldprice = pd.read_csv("/content/drive/MyDrive/GoldPrice.csv")
```

```
[3]: headers = ['Date', 'Price', 'Open', 'High', 'Low', 'Chg%']
      parse_dates = ['Date']
```

```
[4]: goldprice
```

```
[4]:
```

	Date	Price	Open	High	Low	Chg%
0	Sep 11, 2020	1957.35	1952.55	1963.3	1944.35	-0.0035
1	Sep 10, 2020	1964.30	1955.30	1975.2	1948.60	0.0048
2	Sep 09, 2020	1954.90	1939.40	1959.7	1926.30	0.0060
3	Sep 08, 2020	1943.20	1938.00	1948.3	1911.70	0.0031
4	Sep 07, 2020	1937.10	1940.70	1947.4	1930.45	-0.0018
...	...	...	...	...	...	...
2526	Jan 07, 2011	1368.50	1372.70	1377.2	1355.50	-0.0021
2527	Jan 06, 2011	1371.40	1374.80	1376.5	1368.90	-0.0015
2528	Jan 05, 2011	1373.40	1383.40	1384.0	1364.20	-0.0037
2529	Jan 04, 2011	1378.50	1409.60	1410.9	1375.80	-0.0310
2530	Jan 03, 2011	1422.60	1415.60	1423.9	1413.70	0.0011

[2531 rows x 6 columns]

```
[5]: goldprice.dtypes
```

```
[5]: Date      object
      Price    float64
      Open     float64
      High     float64
      Low      float64
      Chg%     float64
      dtype: object
```

```
[6]: print ("Gold commodity has {} observations & {} features".format(*goldprice.
      ↪shape))
```

Gold commodity has 2531 observations & 6 features

```
[7]: def change_into_datetime(col):
      goldprice[col] = pd.to_datetime(goldprice[col])
```

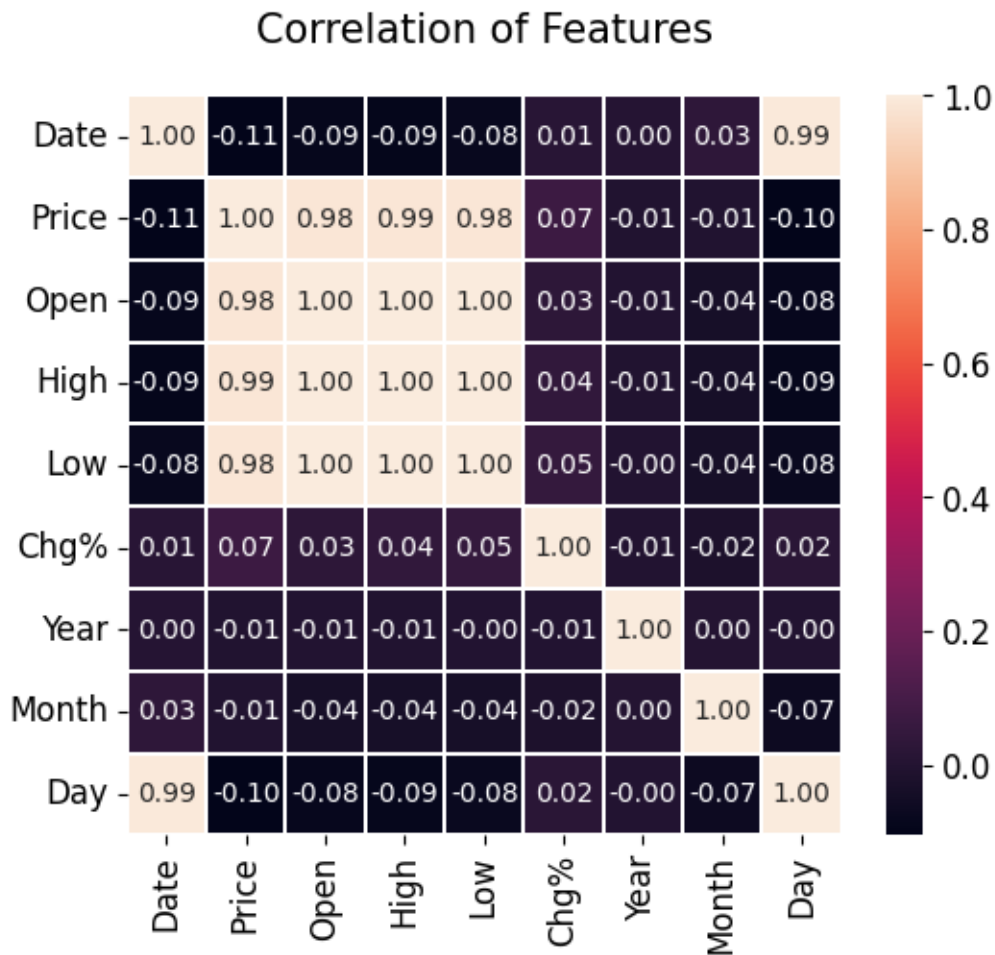
```
[8]: for i in ['Date']:
      change_into_datetime(i)
```

```
[9]: goldprice['Year'] = goldprice['Date'].dt.day
      goldprice['Month'] = goldprice['Date'].dt.month
      goldprice['Day'] = goldprice['Date'].dt.year
```

Visualization

```
[10]: corr = goldprice.corr()
plt.figure(figsize = (6,5))
sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values,
            annot=True,fmt='.2f',linewidths=0.30)
plt.title('Correlation of Features', y = 1.05, size=15)
```

```
[10]: Text(0.5, 1.05, 'Correlation of Features')
```



```
[11]: df = pd.DataFrame(goldprice, columns = ['Date', 'Price'])
df.head()
```

```
[11]:
```

	Date	Price
0	2020-09-11	1957.35
1	2020-09-10	1964.30
2	2020-09-09	1954.90

```
3 2020-09-08 1943.20
4 2020-09-07 1937.10
```

```
[12]: from IPython.display import display
display(df[:10].T)
```

	0	1	2 \
Date	2020-09-11 00:00:00	2020-09-10 00:00:00	2020-09-09 00:00:00
Price	1957.35	1964.3	1954.9

	3	4	5 \
Date	2020-09-08 00:00:00	2020-09-07 00:00:00	2020-09-06 00:00:00
Price	1943.2	1937.1	1940.65

	6	7	8 \
Date	2020-09-04 00:00:00	2020-09-03 00:00:00	2020-09-02 00:00:00
Price	1934.3	1937.8	1944.7

	9
Date	2020-09-01 00:00:00
Price	1978.9

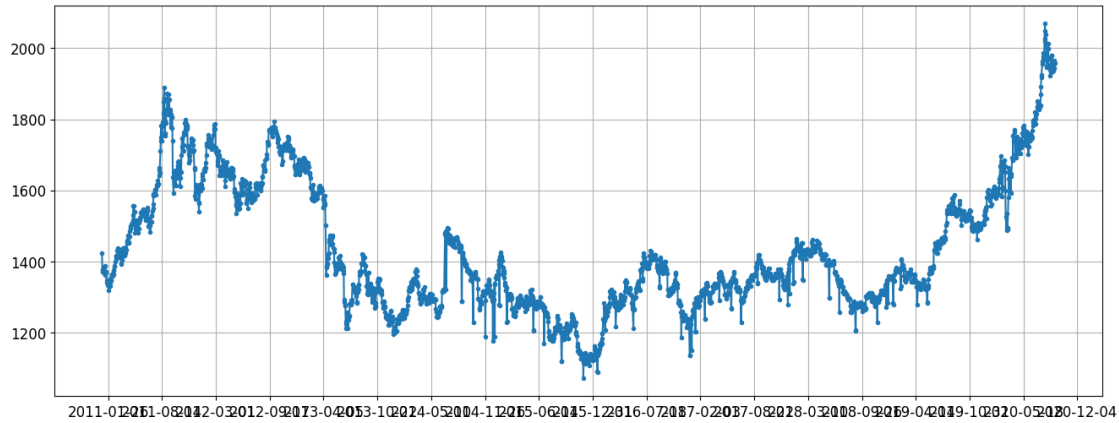
```
[13]: y = df.set_index('Date')
```

```
[14]: y.index
```

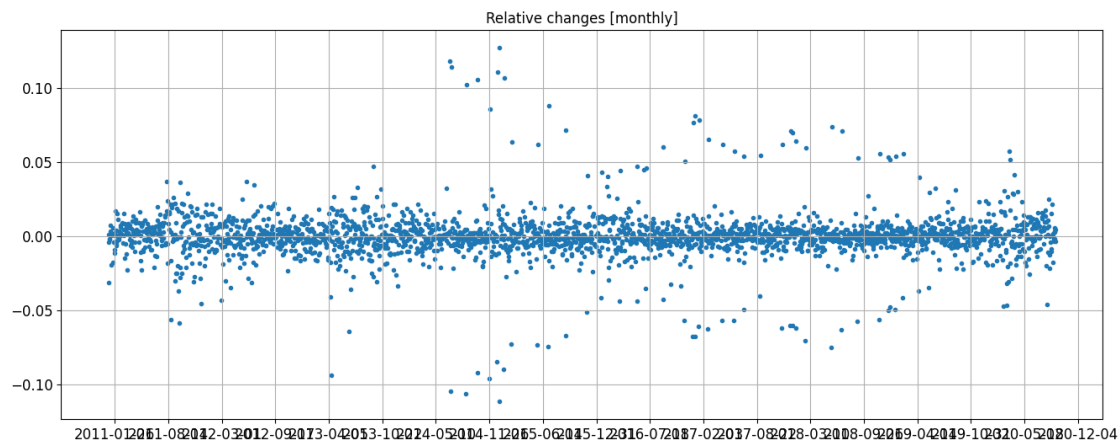
```
[14]: DatetimeIndex(['2020-09-11', '2020-09-10', '2020-09-09', '2020-09-08',
                    '2020-09-07', '2020-09-06', '2020-09-04', '2020-09-03',
                    '2020-09-02', '2020-09-01',
                    ...,
                    '2011-01-14', '2011-01-13', '2011-01-12', '2011-01-11',
                    '2011-01-10', '2011-01-07', '2011-01-06', '2011-01-05',
                    '2011-01-04', '2011-01-03'],
                    dtype='datetime64[ns]', name='Date', length=2531, freq=None)
```

Exploratory Data Analysis Explore price development

```
[15]: fig, ax = plt.subplots(figsize=(16,6))
ax.plot(df.Date, df.Price, marker='.')
ax.xaxis.set_major_locator(plt.MaxNLocator(20)) # reduce number of x-labels
plt.grid()
plt.show()
```

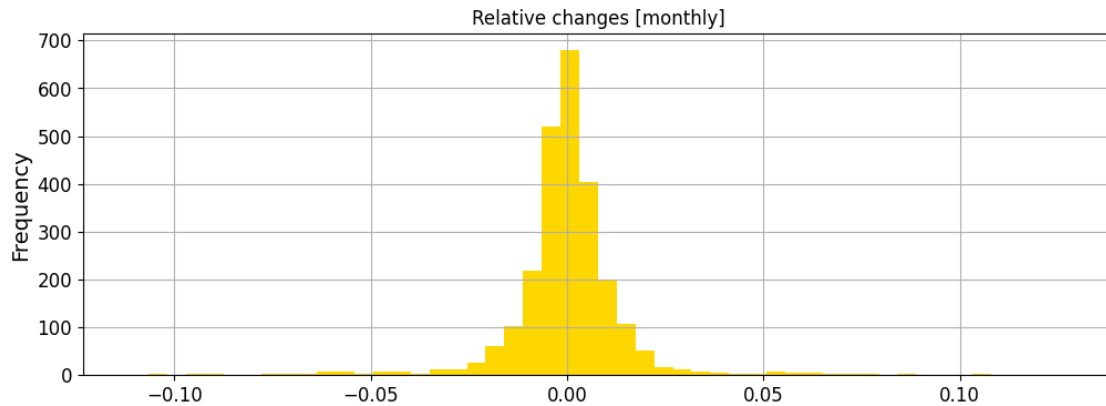


```
[16]: fig, ax = plt.subplots(figsize=(16,6))
ax.scatter(df['Date'], goldprice['Chg%'], marker='.')
ax.xaxis.set_major_locator(plt.MaxNLocator(20)) # reduce number of x-labels
plt.title('Relative changes [monthly]')
plt.grid()
plt.show()
```



Relative changes distribution

```
[17]: plt.figure(figsize=(12,4))
goldprice['Chg%'].plot(kind='hist', bins=50, color='gold')
plt.title('Relative changes [monthly]')
plt.grid()
plt.show()
```



```
[18]: y.isnull().sum()
```

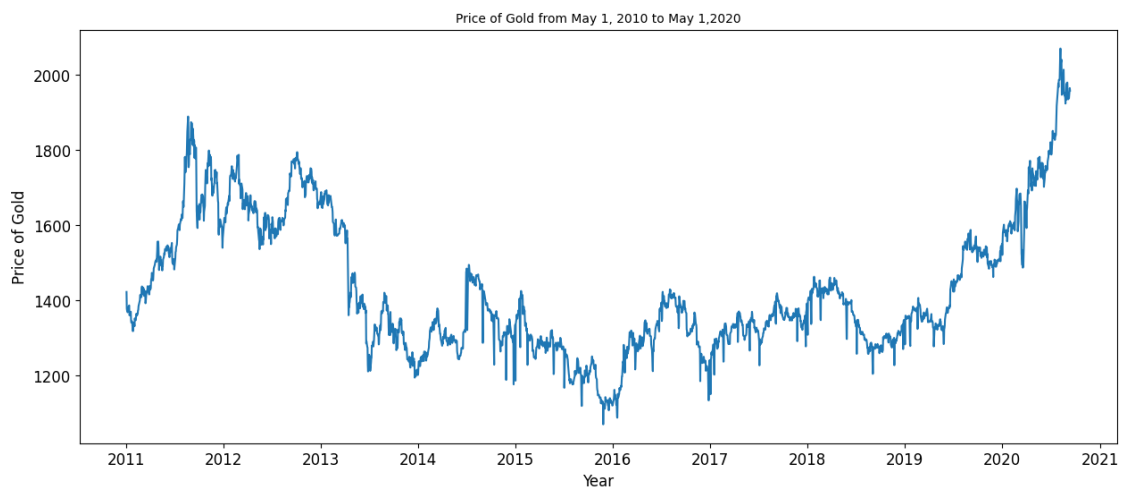
```
[18]: Price      0
      dtype: int64
```

```
[19]: stationary_check_gold = df.set_index(['Date'])

      stationary_check_gold_price = stationary_check_gold['Price']
```

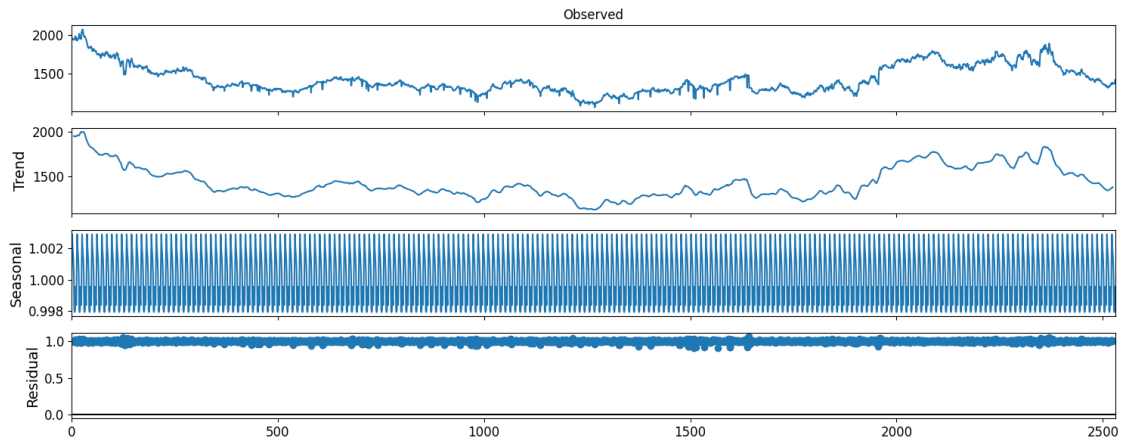
Non-Stationary time series of Gold

```
[20]: plt.plot(stationary_check_gold_price)
      plt.ylabel('Price of Gold', fontsize=12)
      plt.xlabel('Year', fontsize=12)
      plt.title('Price of Gold from May 1, 2010 to May 1,2020', fontsize=10)
      plt.show()
```



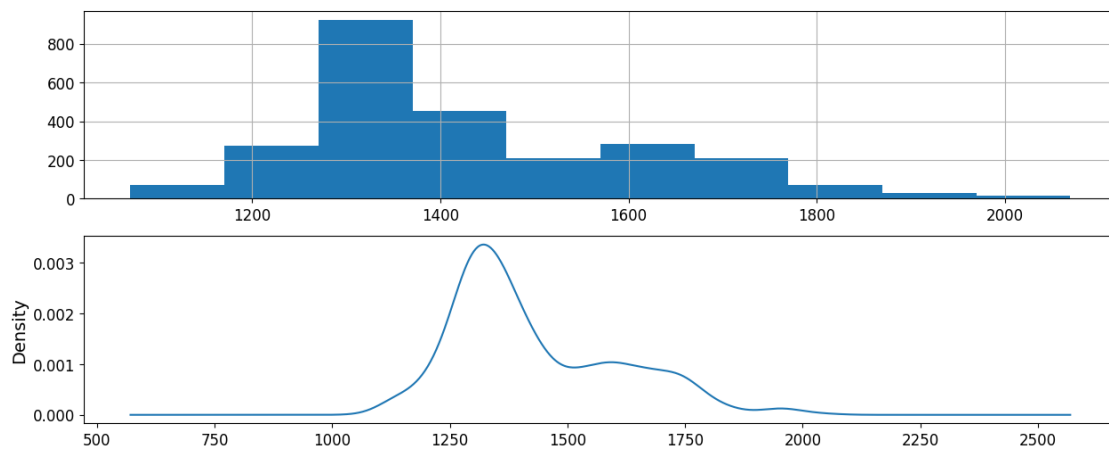
```
[25]: import statsmodels.api as sm

# multiplicative
res = sm.tsa.seasonal_decompose(stationary_check_gold_price.values, period=12,
    model="multiplicative")
fig = res.plot()
```



Box and Whisker Plots:

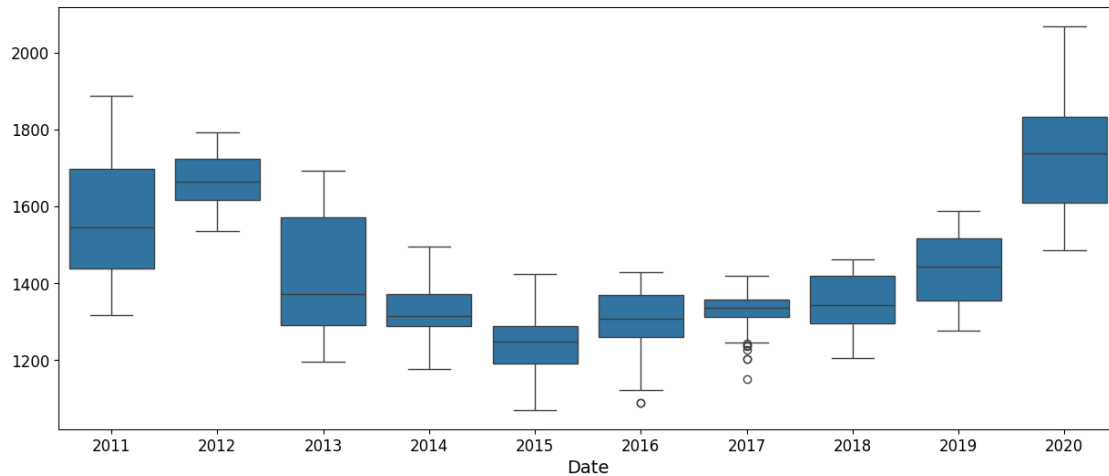
```
[26]: from pandas import Series
from matplotlib import pyplot
pyplot.figure(1)
pyplot.subplot(211)
stationary_check_gold_price.hist()
pyplot.subplot(212)
stationary_check_gold_price.plot(kind='kde')
pyplot.show()
```



```
[28]: import seaborn as sns
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(15, 6))
sns.boxplot(x=stationary_check_gold_price.index.year,
            y=stationary_check_gold_price.values, ax=ax)
```

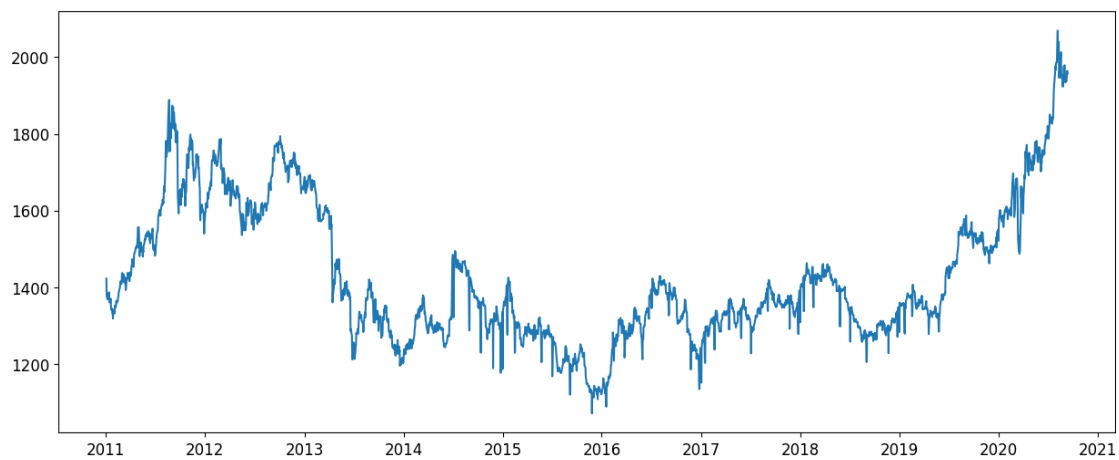
[28]: <Axes: xlabel='Date'>



Plotting the Stationarity

```
[29]: plt.plot(stationary_check_gold_price)
```

[29]: [<matplotlib.lines.Line2D at 0x7d41d9ce2c80>]

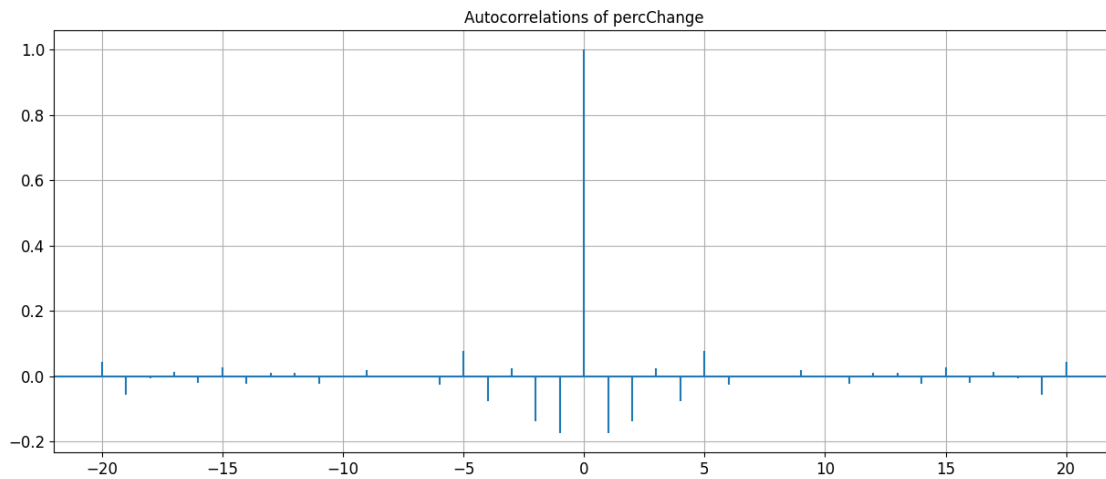




Analysing the Stationarity using Autocorrelation and Partial Autocorrelation functions

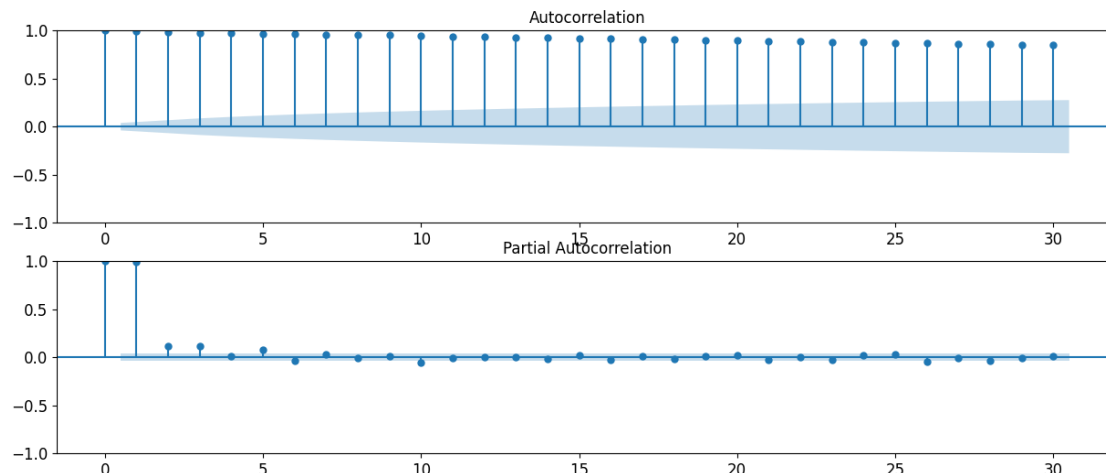
Autocorrelations

```
[30]: plt.acorr(goldprice['Chg%'], maxlags=20)
plt.title('Autocorrelations of percChange')
plt.grid()
plt.show()
```



```
[31]: from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

pyplot.figure()
pyplot.subplot(211)
plot_acf(stationary_check_gold_price, ax=pyplot.gca(), lags = 30)
pyplot.subplot(212)
plot_pacf(stationary_check_gold_price, ax=pyplot.gca(), lags = 30)
pyplot.show()
```



### Plotting Rolling Statistics

```
[32]: from statsmodels.tsa.stattools import adfuller
def test_stationarity(timeseries):

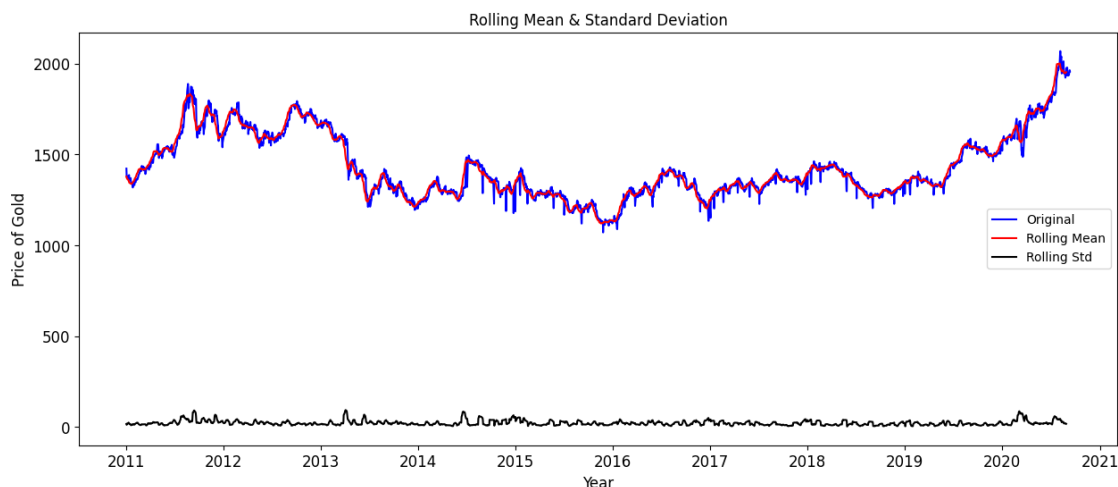
    #Determining rolling statistics
    #rolmean = pd.rolling_mean(timeseries, window=12)
    rolmean = timeseries.rolling(12).mean()
    rolstd = timeseries.rolling(12).std()

    #rolstd = pd.rolling_std(timeseries, window=12)

    #Plot rolling statistics:
    orig = plt.plot(timeseries, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.ylabel('Price of Gold', fontsize=12)
    plt.xlabel('Year', fontsize=12)
    plt.show(block=False)

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

```
test_stationarity(stationary_check_gold_price)
```



Results of Dickey-Fuller Test:

Test Statistic	-3.030208
p-value	0.032168
#Lags Used	6.000000
Number of Observations Used	2524.000000
Critical Value (1%)	-3.432943
Critical Value (5%)	-2.862686
Critical Value (10%)	-2.567380
dtype:	float64

Perfroming Augmented Dickey-Fuller Test

```
[33]: from statsmodels.tsa.stattools import adfuller
print ('Results of Dickey-Fuller Test:')
dfctest = adfuller(stationary_check_gold_price, autolag='AIC')
dfcoutput = pd.Series(dfctest[0:4], index=['Test Statistic','p-value','#Lags_
Used','Number of Observations Used'])
for key,value in dfctest[4].items():
    dfcoutput['Critical Value (%s)'%key] = value
print (dfcoutput)
```

Results of Dickey-Fuller Test:

Test Statistic	-3.030208
p-value	0.032168
#Lags Used	6.000000
Number of Observations Used	2524.000000
Critical Value (1%)	-3.432943
Critical Value (5%)	-2.862686
Critical Value (10%)	-2.567380

dtype: float64

```
[34]: def test_stationarity(timeseries):

    #Determining rolling statistics
    rolmean = timeseries.rolling(12).mean()
    rolstd = timeseries.rolling(12).std()

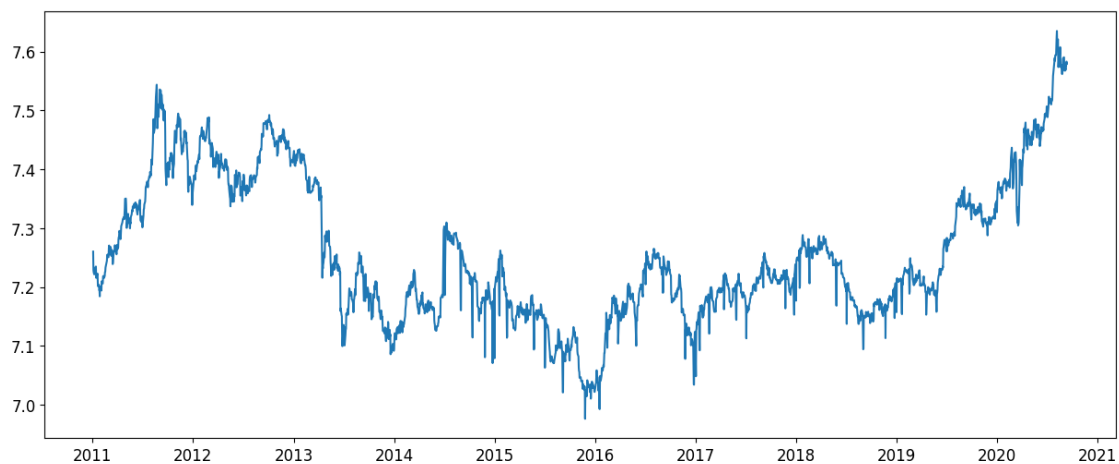
    #Plot rolling statistics:
    orig = plt.plot(timeseries, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

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

Making Time Series Stationary using Log Scale Transformation

```
[35]: ts_log = np.log(stationary_check_gold_price)
plt.plot(ts_log)
```

```
[35]: [ <matplotlib.lines.Line2D at 0x7d41d9add3f0>]
```



Using multiple techniques to remove Trend - Smoothing

Moving Average

```
[36]: moving_avg = ts_log.rolling(window=12,center=False).mean() # taking average of LAST 2 years (36-12) values
plt.figure(figsize=(9,7))
plt.plot(ts_log)
plt.plot(moving_avg, color='red')
plt.show()
```



```
[37]: ts_log_moving_avg_diff = ts_log - moving_avg
ts_log_moving_avg_diff.head(12)
```

```
[37]: Date
2020-09-11      NaN
2020-09-10      NaN
2020-09-09      NaN
2020-09-08      NaN
2020-09-07      NaN
2020-09-06      NaN
```

```

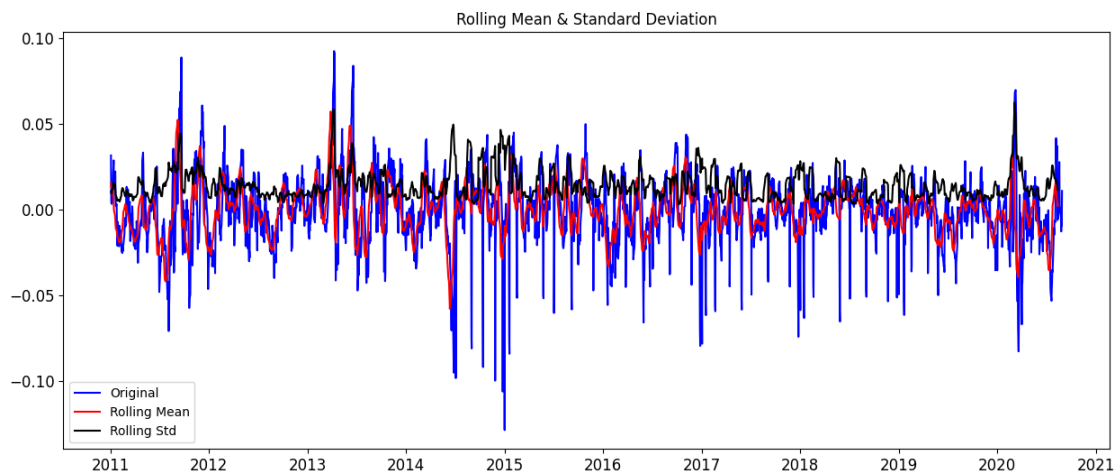
2020-09-04      NaN
2020-09-03      NaN
2020-09-02      NaN
2020-09-01      NaN
2020-08-31      NaN
2020-08-28    0.010728
Name: Price, dtype: float64

```

```

[38]: ts_log_moving_avg_diff.dropna(inplace=True)
      test_stationarity(ts_log_moving_avg_diff)

```



Results of Dickey-Fuller Test:

```

Test Statistic      -1.194664e+01
p-value              4.414553e-22
#Lags Used           1.100000e+01
Number of Observations Used  2.508000e+03
Critical Value (1%)    -3.432960e+00
Critical Value (5%)    -2.862693e+00
Critical Value (10%)   -2.567384e+00
dtype: float64

```

Splitting the data

```

[39]: X = goldprice.drop(['Date', 'Price'], axis=1)
      X

```

```

[39]:
   Open  High  Low  Chg%  Year  Month  Day
0  1952.55  1963.3  1944.35 -0.0035   11     9  2020
1  1955.30  1975.2  1948.60  0.0048   10     9  2020
2  1939.40  1959.7  1926.30  0.0060    9     9  2020
3  1938.00  1948.3  1911.70  0.0031    8     9  2020

```

4	1940.70	1947.4	1930.45	-0.0018	7	9	2020
...	...	...	...	...	...	...	...
2526	1372.70	1377.2	1355.50	-0.0021	7	1	2011
2527	1374.80	1376.5	1368.90	-0.0015	6	1	2011
2528	1383.40	1384.0	1364.20	-0.0037	5	1	2011
2529	1409.60	1410.9	1375.80	-0.0310	4	1	2011
2530	1415.60	1423.9	1413.70	0.0011	3	1	2011

[2531 rows x 7 columns]

```
[40]: X.shape
```

```
[40]: (2531, 7)
```

```
[41]: y = goldprice['Price']
y
```

```
[41]: 0      1957.35
      1      1964.30
      2      1954.90
      3      1943.20
      4      1937.10
      ...
      2526     1368.50
      2527     1371.40
      2528     1373.40
      2529     1378.50
      2530     1422.60
      Name: Price, Length: 2531, dtype: float64
```

```
[42]: y.shape
```

```
[42]: (2531,)
```

```
[43]: from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
      ↪random_state=2)
```

Using Random Forest Regressor

```
[44]: from sklearn.ensemble import RandomForestRegressor
      from sklearn import metrics
```

```
[45]: def predict(algorithm):
      model = algorithm.fit(X_train,y_train)
      print('Training Score: {}'.format(model.score(X_train,y_train)))
```

```

preds = model.predict(X_test)
print('Predictions are: {}'.format(preds))
print('\n')

r2_score = metrics.r2_score(y_test,preds)
print('r2_score is:{}'.format(r2_score))

print('MAE:',metrics.mean_absolute_error(y_test,preds))
print('MSE:',metrics.mean_squared_error(y_test,preds))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,preds)))
sns.distplot(y_test-preds,color='green')

```

```
[46]: from sklearn.ensemble import RandomForestRegressor
```

```
predict(RandomForestRegressor())
```

Training Score: 0.9995326156264086

Predictions are: [1280.284 1373.936 1346.3088 1717.1 1333.9285 1290.06  
1143.17

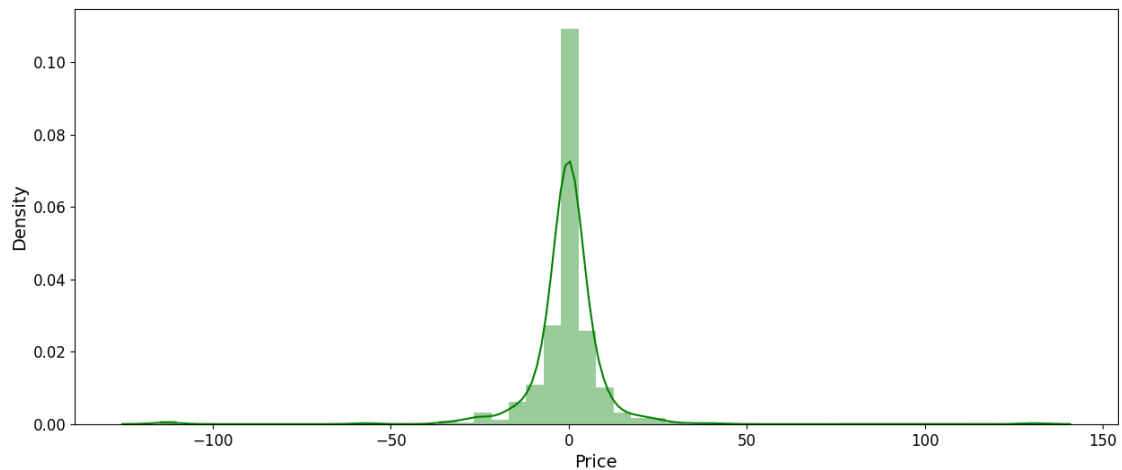
1345.377	1265.7441	1304.66	1713.792	1344.5534	1360.933	1282.2395
1571.057	1313.761	1332.64	1405.826	1524.6125	1335.533	1755.356
1337.6092	1416.282	1265.653	1328.467	1539.271	1748.603	1202.341
1593.175	1960.119	1360.125	1335.685	1678.566	1398.87	1322.862
1361.148	1586.6135	1394.888	1650.088	1368.564	1195.2665	1362.657
1427.808	1243.055	1312.154	1284.9925	1627.75	1367.933	1444.424
1335.351	1279.1755	1595.448	1355.406	1543.276	1445.99	1304.636
1272.199	1535.572	1265.2307	1520.025	1372.826	1755.281	1754.488
1583.347	1347.636	1640.882	1247.071	1676.051	1551.4415	1496.874
1629.197	1454.383	1580.9505	1678.369	1568.7385	1560.9535	1231.627
1233.0525	1323.9325	1257.384	1358.045	1493.05	1350.447	1340.049
1568.87	1596.266	1296.37	1446.255	1601.803	1573.794	1279.106
1322.667	1411.915	1433.752	1609.277	1535.5935	1788.911	1342.066
1280.928	1272.535	1788.894	1252.0235	1416.303	1198.4405	1367.042
1287.844	1453.178	1496.375	1574.127	1414.075	1732.88	1429.726
1388.8145	1939.9085	1676.575	1649.188	1306.045	1291.163	1762.267
1427.701	1327.04	1403.615	1404.66	1424.048	1177.566	1240.883
1218.034	1525.802	1413.176	1619.124	1553.8695	1404.57	1143.189
1433.976	1518.7705	1216.396	1311.642	1215.813	1373.649	1400.146
1292.576	1328.996	1369.152	1214.763	1939.7095	1610.31	1342.01
1331.091	1742.428	1574.766	1317.85	1949.232	1739.853	1403.768
1268.359	1236.638	1237.926	1409.819	1302.555	1300.666	1298.193
1275.7	1424.89	1203.0595	1355.355	1287.6157	1740.	1368.851
1264.0625	1284.9605	1301.397	1350.403	1428.395	1450.913	1729.255
1141.49	1358.912	1610.87	1615.234	1574.395	1537.0635	1330.052
1544.921	1503.674	1768.011	1239.482	1298.69	1602.084	1184.1695
1238.318	1415.758	1737.4045	1367.201	1123.302	1274.473	1495.1585
1367.199	1440.605	1325.55	1725.986	1282.6355	1282.6885	1368.193



1339.5052	1419.001	1350.185	1150.9085	1662.059	1347.073	1321.826
1418.196	1335.428	1297.544	1282.0895	1240.549	1774.699	1645.294
1574.9245	1271.6479	1748.626	1385.377	1334.204	1299.69	1407.538
1272.23	1591.833	1317.625	1613.852	1543.2455	1248.943	1657.308
1280.894	1344.697	1360.569	1435.415	1343.1062	1589.079	1375.015
1503.312	1698.624	1274.847	1659.156	1718.695	1467.636	1313.416
1239.516	1134.082	1662.477	1293.686	1839.177	1512.1775	1350.0715
1286.484	1299.321	1270.2062	1489.611	1283.1885	1759.891	1430.149
1418.83	1286.7127	1570.464	1773.178	1291.8086	1280.677	1697.425
1345.842	1753.009	1274.534	1276.766	1373.281	1311.873	1391.867
1304.167	1324.705	1205.0805	1645.087	1772.837	1587.929	1414.664
1228.0215	1434.986	1436.285	1553.641	1341.4	1787.464	1397.335
1744.654	1668.396	1520.765	1765.879	1229.636	1396.591	1319.801
1424.923	1335.923	1450.48	1338.542	1352.7698	1639.904	1335.383
1412.53	1342.9614	1272.023	1812.103	1392.2735	1253.633	1387.261
1887.0695	1205.182	1297.367	1665.399	1186.951	1324.705	1327.3945
1506.48	1666.703	1359.257	1502.39	1207.059	1760.337	1230.338
1237.975	1274.508	1298.797	1429.659	1252.33	1460.306	1284.9941
1343.08	1515.962	1318.547	1331.87	1848.261	1669.387	1324.395
1141.434	1381.712	1303.761	1300.923	1756.757	1618.135	1275.082
1598.949	1314.045	1615.067	1272.839	1322.478	1374.277	1647.97
1580.604	1318.431	1298.801	1848.6	1275.237	1604.483	1587.434
1249.184	1383.004	1325.213	1284.6795	1544.0855	1528.17	1499.176
1277.228	1371.278	1463.493	1278.792	1521.479	1505.7215	1580.3235
1227.2035	1365.565	1716.457	1239.129	1453.881	1297.685	1525.288
1417.523	1280.8465	1559.998	1342.1474	1213.264	1297.121	1355.454
1378.231	1559.4215	1306.721	1120.411	1388.618	1334.164	1386.327
1556.4525	1340.3798	1218.16	1578.8855	1587.168	1713.379	1293.8672
1380.904	1740.501	1535.849	1306.731	1560.998	1282.239	1322.827
1269.831	1378.18	1120.689	1342.7122	1396.835	1352.36	1619.37
1402.718	1369.075	1640.97	1348.1452	1375.191	1329.921	1425.451
1310.316	1317.034	1276.74	1497.257	1378.872	1447.622	1320.997
1450.714	1291.6698	1137.2355	1544.703	1828.537	1243.111	1702.196
1373.111	1288.4	1283.939	1288.241	1662.262	1434.051	1220.948
1705.5985	1452.199	1677.187	1628.536	1288.9545	1288.1835	1269.4212
1393.568	1864.5115	1225.286	1292.3362	1655.297	1329.163	1369.861
1644.714	1787.389	1350.921	1499.595	1308.871	1615.984	1304.205
1399.386	1670.848	1345.495	1335.02	1374.207	1360.832	1332.922
1286.5175	1289.9915	1357.008	1637.414	1599.287	1371.674	1415.156
1150.6645	1612.746	1313.577	1948.552	1306.125	1205.7555	1334.283
1826.144	1575.948	1342.817	1241.407	1271.877	1656.205	1669.139
1743.004	1743.756	1275.721	1290.9642	1310.141	1338.487	1251.379
1255.367	1727.294	1644.599	1140.818	1893.63	1182.7365	1809.622
1247.115	1574.4365	1134.0475]				

r2\_score is:0.9953972206753653  
MAE: 5.248176923076879

MSE: 146.969150953944  
RMSE: 12.123083393012852



Using Linear Regression

```
[47]: from sklearn.linear_model import LinearRegression  
  
predict(LinearRegression())
```

Training Score: 0.9720489762983339

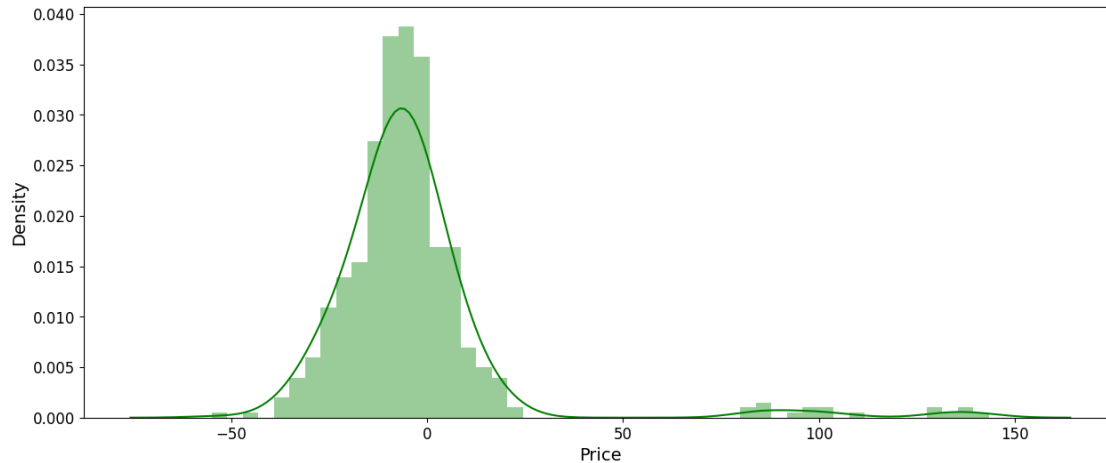
Predictions are: [1287.46509401 1381.1335197 1349.02699003 1708.15351128  
1337.6139623

1305.2974777	1176.84026124	1348.79406241	1274.67616002	1316.54671617
1722.3847627	1348.61530229	1370.70980134	1292.16250098	1569.34503439
1316.63295296	1335.3827299	1411.79896563	1527.80814535	1330.94094103
1739.072931	1341.43834851	1422.95738006	1270.20100171	1332.58185012
1548.35263609	1740.92377919	1218.09105188	1585.98911985	1952.22431769
1376.77944912	1345.10439649	1675.54758129	1278.10874728	1324.17910345
1363.29713204	1602.85035255	1396.97035239	1646.77730068	1375.16890577
1217.21910521	1392.55717245	1419.43210369	1265.89287443	1335.27249572
1288.03513898	1624.16678634	1369.81739241	1439.40405146	1337.01326427
1301.14760161	1597.38675689	1369.60254536	1544.02617924	1442.70147853
1309.45200532	1285.29685425	1540.80458533	1272.27537545	1541.33150534
1390.21604477	1749.5876601	1750.43403024	1610.78462962	1356.7009396
1658.18878433	1275.83479596	1669.92450397	1552.3960604	1502.95088031
1643.56574967	1457.81301702	1638.51558368	1673.63299606	1596.05803604
1563.74676947	1250.81659824	1263.19587148	1329.23955484	1277.97650253
1372.27202603	1503.39506273	1370.37387817	1261.63943477	1570.6992924
1608.98195708	1305.92412612	1445.60970697	1610.27059107	1571.66893787
1299.99729359	1327.84813092	1416.42169924	1444.7878836	1603.58268885
1534.65638009	1784.98938864	1266.02103589	1303.99663792	1285.33871336
1771.02421301	1277.44944975	1411.32748108	1217.36068073	1372.76800692

1298.52122991	1466.10247135	1503.91938831	1572.92900696	1412.83043475
1717.13018676	1436.22308454	1392.42030751	1910.45795641	1667.99553265
1644.70818267	1325.56365099	1294.62688288	1798.61507758	1419.90561608
1330.4122285	1406.27765129	1412.69240658	1418.8386838	1185.92900095
1266.1319676	1238.64226753	1529.20813842	1426.26816898	1620.88051596
1564.82578627	1400.1504797	1151.22123977	1446.05441156	1520.09768467
1232.11536487	1313.04908963	1241.38370612	1368.40385173	1408.17590513
1305.02092131	1337.61557807	1399.1602053	1234.06918365	1919.58256233
1618.39695183	1371.150752	1348.09955995	1739.54556113	1578.09020659
1321.96399992	1902.5397502	1730.6735642	1405.33436631	1272.8031996
1255.22415557	1258.2988033	1435.26168561	1224.69885287	1306.02084713
1301.76956418	1288.08728321	1432.98382815	1225.75970423	1355.49371261
1299.99761354	1730.15668795	1385.13874988	1282.92232737	1288.00050536
1318.64949269	1354.02320052	1423.48083159	1443.77622476	1743.24119545
1169.58331966	1372.42493958	1606.6949781	1616.18682199	1576.20106239
1550.39194028	1331.57234704	1551.16752295	1512.15753042	1767.68046735
1246.79928778	1295.58655892	1610.58892367	1200.75401012	1243.92641782
1412.31754624	1722.14086748	1406.91747098	1150.29637757	1281.60404293
1502.95846462	1374.42061468	1340.89091495	1328.26921456	1712.94464069
1293.35177788	1288.28766376	1407.93956664	1347.38267034	1295.54380588
1362.55148605	1163.14046017	1648.02161139	1359.51446545	1337.73441208
1416.60705489	1336.49624764	1310.51587107	1295.13203388	1261.68885031
1776.06444172	1638.42288073	1577.5275269	1278.72180676	1748.33330085
1392.0855222	1347.46875012	1306.57554187	1414.85853338	1278.03099581
1587.84246566	1336.99818957	1607.09873251	1559.49103418	1257.35869761
1647.23920508	1286.4973157	1366.8412935	1380.22684303	1431.91687984
1344.03580551	1589.15392876	1376.13502306	1515.48256805	1694.72458875
1297.55353969	1674.66256768	1706.62361585	1480.72650344	1331.43243241
1261.45972798	1161.61732396	1653.16269498	1310.33293738	1837.55834058
1518.18506851	1346.43911745	1293.96756556	1304.51815939	1281.91127042
1498.17681156	1290.54882577	1747.17771768	1308.56353	1433.67049426
1296.47693219	1571.78705856	1759.25277065	1293.44093606	1293.80906491
1700.60535502	1338.23396596	1747.59269154	1180.80263609	1293.4703229
1384.25500994	1326.65624637	1391.90538072	1311.89298289	1331.7967046
1224.56783748	1638.54087226	1762.05449326	1588.22862191	1418.87644313
1219.7537954	1434.08197186	1311.31251696	1555.14701907	1351.22312822
1792.63891426	1396.90499385	1731.91075696	1669.16238171	1521.80460372
1747.81929452	1245.73165685	1412.19588531	1325.39415497	1444.1193391
1339.87901284	1452.0936591	1237.22400613	1369.03539933	1656.52377725
1336.71244762	1405.07986171	1347.11415907	1286.25301305	1801.27338188
1405.68089557	1258.27400235	1403.67650738	1886.44428583	1227.64427079
1301.30119941	1666.43399234	1207.87316287	1336.1632604	1327.7261199
1508.33184814	1663.31075583	1359.77666185	1509.40532905	1225.05243547
1759.34405061	1251.7018554	1264.80417585	1280.44203047	1306.79671414
1434.79472061	1277.16870065	1466.97916163	1293.2176261	1329.78815323
1522.97033251	1340.92176317	1333.34373612	1886.43035693	1685.77567351
1330.52426664	1151.69413445	1392.08609275	1306.30724228	1310.55310213
1748.16272232	1619.55147659	1279.78658199	1583.04805687	1315.90298104

1611.47715431	1282.20121863	1326.027709	1376.13725232	1635.48104763
1564.08337818	1322.16315056	1308.36191485	1867.61493979	1285.60181573
1611.85099697	1590.48008598	1257.72636953	1385.5362506	1331.33479306
1291.24648573	1553.58364206	1534.14165858	1503.30410009	1290.9376268
1364.34145479	1481.59313125	1291.87260287	1526.80528381	1508.1439951
1585.37583444	1249.60421736	1380.34799167	1717.69247739	1264.20513121
1465.0053516	1301.55437387	1534.15753871	1419.91119195	1293.23935245
1562.89837332	1347.91887967	1236.30566905	1307.80687514	1366.37144897
1373.35347981	1559.76419466	1322.08858101	1149.12124386	1385.79120035
1338.3483722	1415.51643184	1549.1126367	1339.52254178	1237.82629479
1582.70932325	1587.56890394	1721.77613724	1295.68586409	1391.23509481
1742.75099888	1547.71943139	1221.29760294	1559.23390123	1290.61121356
1337.24700852	1291.70309131	1390.59090909	1148.40531016	1341.90161322
1398.09675603	1250.13837012	1641.17115666	1411.48789847	1376.337603
1634.72249517	1355.35548185	1240.03367054	1346.24233453	1429.46493872
1315.31704059	1326.3678542	1293.51848511	1502.48901322	1270.53595566
1439.541187	1329.33016728	1451.30348623	1299.14637529	1147.37393937
1550.2365856	1828.12042608	1257.92270216	1705.20488163	1384.99181691
1295.52079387	1309.00943025	1296.58316289	1663.27783898	1436.39306119
1247.80337747	1699.57524041	1452.26479374	1659.39387386	1639.98693335
1211.72142142	1222.31827563	1283.25880484	1391.37038232	1861.46671587
1231.37033378	1281.66721862	1648.28742997	1341.857217	1373.20000956
1656.86175795	1788.96473117	1352.18643318	1511.93415134	1311.3715105
1622.27331969	1320.12105943	1406.24762127	1661.26503945	1354.38988202
1342.47237883	1235.00051984	1376.91170224	1336.80326171	1288.81145917
1288.16843949	1254.96659406	1631.23167783	1591.98902816	1377.89058335
1418.87734273	1163.94413931	1620.01209502	1346.61998646	1907.80191687
1313.02927282	1222.96472577	1339.51746202	1821.08033387	1601.24734156
1327.7588794	1270.96702179	1283.41498134	1653.11619369	1687.52754669
1734.20885604	1780.59111262	1301.74684083	1296.6961092	1316.15165576
1337.90929207	1287.0321436	1274.11160609	1728.87876084	1651.72926529
1172.50716891	1894.26565442	1201.4708563	1830.93197818	1256.45089723
1589.08210733	1163.08763982]			

r2\_score is:0.981472312450999  
 MAE: 14.06129297282004  
 MSE: 591.5987528758549  
 RMSE: 24.322803145933957



Using KNNs

```
[48]: from sklearn.neighbors import KNeighborsRegressor

predict(KNeighborsRegressor())
```

Training Score: 0.9837444890953134

Predictions are: [1279.48 1374.9 1404.26 1724.9 1328.86 1323.04 1168.06  
1345.26 1265.88  
1305.78 1714.38 1342.8 1361.6 1282.3 1570.3 1313.98 1333.76 1409.06  
1525.58 1391.14 1746.76 1335.34 1418.38 1263.28 1328.9 1535.54 1756.98  
1246.56 1592.02 1968. 1356.22 1330.64 1684.4 1319.74 1322.74 1362.52  
1587.44 1394.04 1650.4 1370.28 1221.7 1368.46 1424.7 1243.72 1346.72  
1287.26 1628.64 1367.04 1441.18 1334.74 1277.46 1600.12 1355.3 1540.3  
1445.76 1303.64 1272.5 1536.56 1265.18 1528.82 1372.6 1753.12 1757.42  
1595.9 1347.3 1630.96 1249.8 1670.56 1552.92 1494.9 1613.12 1454.44  
1590.62 1674.54 1566.66 1561. 1255.75 1259.1 1320.39 1255.08 1358.76  
1490.02 1347.24 1296. 1563.72 1591.84 1326.8 1443.58 1599.68 1575.54  
1330.8 1325.96 1413.24 1431.56 1607.38 1537.47 1788.48 1291.58 1308.74  
1272.38 1779.96 1252.67 1417.5 1222.62 1366.28 1289.78 1459.58 1495.3  
1576.26 1413.76 1736.14 1428.78 1387.48 1946.28 1678.92 1651.72 1305.  
1291.72 1770.02 1424.58 1322.96 1403.56 1405.02 1424.04 1174.26 1240.82  
1249.16 1522.2 1411.96 1619.36 1547.02 1403.22 1140.88 1430.52 1522.78  
1262.85 1306.44 1252. 1372.74 1399.62 1295.12 1322.76 1368.24 1266.46  
1942.17 1610.24 1338.34 1467.56 1739.94 1582.3 1346.12 1934.32 1737.96  
1406.66 1270.68 1238.98 1277.21 1408.68 1300.46 1300.26 1297.88 1276.04  
1421.36 1202.6 1355.32 1318.09 1736.18 1366.46 1256. 1285.58 1304.88  
1350.14 1430.7 1450.88 1727.04 1165.54 1360.6 1615.96 1614.04 1570.28  
1534.24 1329.78 1542.76 1510.74 1770.24 1241.78 1293.94 1606.98 1206.28  
1268.58 1416.62 1739.2 1374.44 1126.14 1273.32 1503.74 1365.86 1437.44  
1341.36 1724.6 1281.72 1281.34 1374.06 1338.8 1307.94 1350.02 1152.68  
1663.46 1346.62 1320.68 1419. 1334.14 1329.74 1281.94 1266.98 1773.6

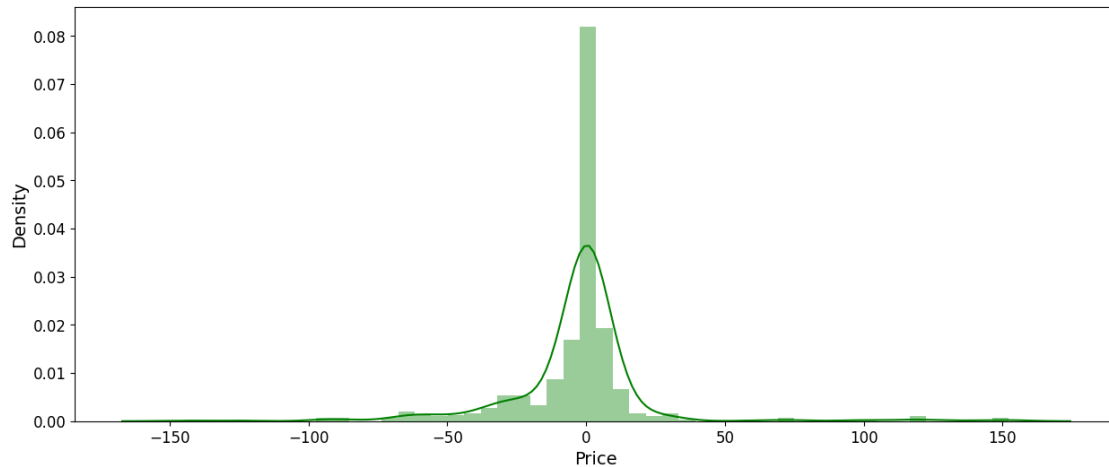
1640.86	1577.04	1329.06	1757.42	1385.52	1393.7	1298.82	1409.9	1271.9
1593.66	1349.68	1612.58	1542.42	1248.36	1659.3	1279.98	1322.92	1357.28
1436.08	1343.18	1579.84	1375.3	1501.62	1697.72	1276.1	1662.38	1725.56
1469.28	1307.4	1324.8	1133.96	1659.02	1324.44	1838.04	1533.62	1359.24
1287.55	1292.34	1271.6	1491.32	1285.84	1755.66	1330.04	1423.86	1317.01
1570.5	1776.06	1288.48	1348.3	1700.5	1378.78	1753.02	1257.66	1276.26
1372.1	1311.5	1391.74	1367.44	1321.95	1206.46	1651.5	1770.98	1591.48
1414.54	1264.12	1436.08	1351.4	1551.22	1342.58	1785.12	1395.06	1748.08
1665.44	1522.04	1766.48	1342.44	1393.64	1318.4	1422.3	1335.36	1450.6
1297.84	1341.04	1639.02	1333.38	1411.54	1342.06	1278.8	1792.6	1389.27
1246.34	1383.24	1860.2	1206.54	1321.28	1665.5	1187.9	1334.92	1327.7
1511.14	1670.26	1357.16	1503.96	1206.54	1759.18	1277.9	1291.1	1275.3
1299.96	1433.28	1248.52	1461.7	1313.93	1337.82	1517.04	1345.44	1330.82
1850.42	1663.16	1321.09	1138.6	1382.32	1303.04	1301.22	1750.7	1615.66
1271.98	1598.78	1314.44	1612.72	1268.5	1371.04	1381.42	1650.42	1580.18
1318.86	1298.9	1850.	1272.7	1606.08	1581.42	1248.36	1381.64	1321.34
1284.81	1542.94	1526.02	1499.26	1278.4	1371.78	1465.64	1279.16	1521.9
1502.76	1578.3	1252.98	1366.02	1719.84	1259.9	1458.84	1295.56	1521.02
1421.76	1282.1	1565.28	1342.8	1212.34	1296.54	1354.36	1378.74	1561.2
1307.76	1121.34	1379.86	1332.68	1417.36	1550.46	1336.92	1312.16	1578.18
1582.6	1710.98	1293.56	1380.2	1744.72	1535.96	1288.5	1565.28	1281.62
1323.86	1322.96	1378.84	1122.12	1344.48	1394.88	1277.9	1626.54	1393.64
1366.84	1635.88	1342.28	1247.56	1327.6	1423.	1311.64	1313.86	1276.88
1497.88	1251.05	1448.42	1320.28	1450.6	1292.72	1136.86	1541.06	1827.72
1277.68	1700.36	1376.56	1288.18	1286.68	1288.18	1662.86	1433.28	1277.83
1712.74	1451.48	1681.38	1624.32	1186.37	1284.52	1304.5	1391.66	1876.36
1285.36	1290.88	1655.46	1328.92	1372.24	1651.82	1792.96	1350.72	1504.58
1399.84	1613.74	1305.32	1398.66	1676.7	1345.46	1335.48	1277.94	1361.96
1333.42	1286.86	1310.96	1252.98	1639.72	1602.94	1375.06	1415.24	1150.14
1609.12	1337.36	1946.28	1304.22	1207.09	1323.96	1831.26	1582.14	1350.16
1286.6	1271.28	1651.78	1662.32	1751.32	1780.66	1275.	1292.24	1310.5
1334.9	1254.44	1258.08	1726.8	1647.26	1137.88	1880.22	1206.28	1812.28
1246.3	1575.68	1132.24]						

r2\_score is:0.9790869008282281

MAE: 12.115404339250498

MSE: 667.7661934911242

RMSE: 25.84117244807449



Using Decision Tree

```
[49]: from sklearn.tree import DecisionTreeRegressor

predict(DecisionTreeRegressor())
```

Training Score: 1.0

Predictions are: [1280.2 1374.5 1340.2 1714.1 1328.2 1293.8 1141.3 1345.6  
1265.8

1303.5	1708.8	1343.5	1363.8	1282.	1563.1	1313.7	1336.8	1408.
1523.	1332.	1755.2	1336.2	1419.	1267.6	1328.5	1535.1	1750.4
1203.5	1592.4	1946.5	1348.3	1328.2	1684.1	1439.	1322.5	1364.
1564.5	1394.8	1652.2	1368.	1195.2	1373.6	1433.1	1242.4	1312.4
1285.5	1625.7	1366.8	1434.1	1335.8	1276.4	1599.	1359.8	1545.4
1447.8	1297.6	1272.4	1537.2	1264.4	1515.	1371.2	1762.	1768.6
1592.5	1346.3	1638.9	1250.6	1683.3	1551.8	1499.1	1641.9	1456.
1524.9	1683.3	1581.4	1561.9	1225.3	1221.7	1325.9	1257.3	1358.1
1491.	1359.8	1366.6	1563.1	1586.2	1297.6	1446.3	1615.2	1562.9
1268.	1324.2	1410.7	1429.4	1587.	1539.6	1794.1	1358.5	1280.1
1271.7	1787.	1262.4	1416.2	1197.7	1368.	1287.6	1452.3	1493.2
1574.8	1414.2	1730.6	1428.1	1385.5	1934.3	1671.4	1659.1	1306.4
1291.9	1740.	1433.1	1323.1	1404.1	1406.	1424.	1178.7	1240.3
1218.4	1532.4	1415.7	1619.7	1556.	1401.8	1145.4	1429.7	1517.3
1214.1	1308.8	1198.	1373.2	1398.6	1294.6	1323.6	1373.6	1205.1
1937.8	1609.6	1342.5	1317.9	1753.6	1564.5	1319.	1952.5	1744.7
1404.1	1267.6	1234.5	1235.7	1415.7	1314.7	1300.6	1298.9	1275.7
1432.7	1202.3	1356.2	1286.5	1739.	1368.5	1262.4	1285.5	1297.6
1350.	1428.	1434.8	1731.2	1141.3	1356.6	1614.8	1615.2	1580.3
1541.7	1329.9	1544.1	1509.7	1772.7	1239.	1295.8	1603.7	1183.4
1240.3	1416.	1735.2	1386.8	1123.9	1275.9	1496.3	1373.6	1467.3
1306.9	1725.9	1282.6	1281.	1373.4	1341.4	1440.6	1350.1	1151.9

1663.7	1347.	1321.8	1418.	1336.2	1295.8	1282.05	1240.3	1790.9
1650.3	1576.9	1267.2	1755.2	1385.5	1319.7	1299.8	1408.	1272.1
1594.2	1314.5	1614.7	1542.1	1249.	1654.9	1280.9	1340.7	1373.6
1436.2	1343.5	1587.05	1379.4	1500.1	1692.8	1273.4	1650.8	1723.5
1465.5	1312.3	1241.7	1134.	1661.5	1296.6	1833.5	1574.5	1315.7
1285.	1294.9	1268.7	1491.	1283.	1768.6	1449.	1428.1	1286.5
1571.2	1762.1	1289.2	1280.6	1694.4	1314.6	1756.8	1281.3	1273.7
1372.3	1307.4	1391.3	1303.5	1325.9	1205.1	1646.7	1787.	1594.2
1414.	1231.7	1435.9	1472.	1543.3	1341.4	1790.3	1396.7	1742.7
1677.3	1523.2	1773.4	1235.7	1392.6	1323.1	1416.	1337.4	1450.6
1333.5	1337.7	1640.8	1335.8	1410.7	1341.2	1270.8	1816.1	1395.7
1263.6	1392.8	1892.6	1205.1	1287.3	1664.	1185.8	1324.8	1327.6
1501.	1664.	1357.4	1501.1	1207.9	1763.7	1228.2	1237.8	1274.7
1298.8	1427.9	1260.4	1449.	1283.3	1310.6	1514.4	1324.8	1331.6
1856.4	1669.6	1324.2	1141.3	1381.4	1302.8	1300.8	1768.4	1618.4
1274.7	1599.6	1314.1	1624.	1268.	1308.3	1375.9	1648.7	1587.
1314.6	1299.4	1856.4	1290.1	1604.	1589.1	1249.	1384.	1322.7
1294.4	1545.	1528.1	1504.8	1276.8	1369.8	1450.6	1278.8	1515.3
1508.8	1587.5	1231.7	1365.6	1720.9	1231.2	1454.9	1296.	1523.8
1428.1	1280.9	1575.4	1341.6	1213.8	1296.7	1357.3	1378.6	1556.7
1306.7	1120.6	1384.4	1333.7	1364.9	1543.3	1329.8	1218.8	1576.
1590.6	1714.3	1293.4	1372.9	1742.7	1541.7	1314.4	1556.7	1282.05
1323.1	1290.1	1378.7	1121.	1343.5	1395.95	1352.6	1625.7	1411.7
1373.4	1659.1	1343.4	1387.8	1328.5	1424.	1301.4	1317.1	1276.4
1493.4	1423.2	1434.8	1321.3	1450.6	1291.9	1137.1	1546.1	1826.
1242.2	1702.6	1366.6	1288.2	1283.8	1288.2	1657.9	1438.3	1205.4
1704.4	1448.8	1709.9	1639.9	1292.9	1291.	1267.2	1391.3	1848.9
1214.1	1292.7	1654.8	1327.7	1373.7	1639.9	1776.4	1359.6	1494.
1306.1	1617.9	1304.2	1399.2	1670.4	1345.6	1335.1	1376.4	1360.4
1336.8	1285.8	1279.05	1358.8	1642.3	1604.6	1370.2	1416.	1151.9
1612.9	1324.8	1952.5	1306.4	1204.4	1315.7	1823.5	1590.1	1324.7
1236.1	1272.1	1659.1	1669.6	1740.2	1739.2	1273.4	1291.9	1308.8
1333.1	1262.4	1255.1	1734.	1642.1	1141.3	1869.6	1183.4	1798.5
1247.1	1562.9	1134.	]					

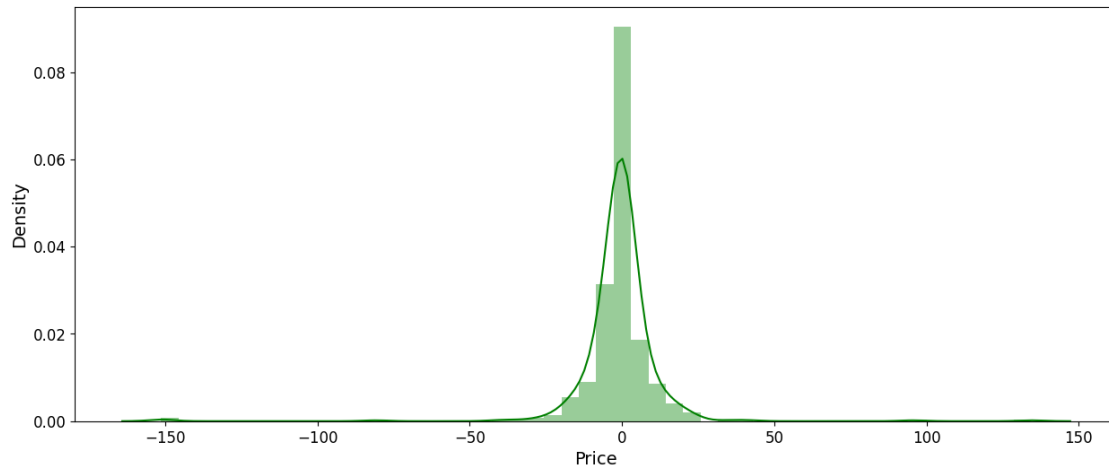
r2\_score is:0.9931313724172174

MAE: 6.038165680473366

MSE: 219.3188708086784

RMSE: 14.809418314325463





Using XGBoost

```
[51]: from xgboost import XGBRegressor

predict(XGBRegressor())
```

Training Score: 0.9999229443115288

Predictions are: [1278.1401 1371.271 1355.9695 1723.461 1334.4335 1297.1885  
1143.4845

1345.4817 1261.3967 1301.5546 1712.7925 1346.2677 1361.0388 1280.0442  
1570.3239 1307.7097 1330.5502 1405.5698 1528.4703 1334.4691 1751.9741  
1339.1648 1416.658 1269.2885 1328.5906 1542.5172 1746.5859 1201.6  
1589.8477 1968.6177 1368.1272 1332.0349 1681.0333 1411.5604 1321.3562  
1368.2838 1587.745 1392.7683 1653.4155 1365.9961 1190.6746 1366.0255  
1425.8407 1248.3562 1309.78 1283.9656 1634.9989 1366.5922 1443.5984  
1332.3934 1309.3379 1592.4606 1358.125 1543.663 1444.7942 1301.2952  
1272.8468 1533.4299 1265.3164 1530.9901 1368.8342 1759.8955 1754.0508  
1556.21 1344.388 1647.2428 1247.8563 1674.9934 1552.3225 1503.549  
1619.5886 1457.717 1614.9015 1673.7311 1571.3754 1561.7765 1238.839  
1240.098 1323.3727 1261.1567 1357.4338 1501.3079 1351.5875 1360.682  
1565.3318 1599.4858 1296.2756 1444.8475 1604.5632 1580.2817 1298.9015  
1335.5979 1414.1458 1437.333 1595.7356 1532.4955 1787.0574 1361.242  
1253.5277 1262.0485 1787.2238 1234.8044 1415.709 1202.5835 1361.9067  
1287.6216 1462.7489 1496.2802 1575.358 1413.6388 1725.308 1430.6484  
1384.8676 1940.5999 1668.3163 1648.9375 1304.911 1284.184 1773.7411  
1426.2117 1333.1687 1403.8514 1402.8187 1422.5507 1168.6296 1239.81  
1214.3531 1526.9353 1412.6139 1612.4258 1554.7963 1406.0164 1139.9231  
1438.9379 1515.0935 1205.7859 1307.9661 1218.8116 1374.0381 1400.606  
1301.995 1335.3917 1371.3673 1211.531 1934.105 1612.1024 1353.5139  
1330.0481 1748.1047 1575.8652 1317.6875 1872.7856 1737.0591 1403.7838  
1273.0391 1234.7642 1240.0137 1414.432 1300.219 1297.8947 1299.8444

1278.68	1426.6141	1208.2771	1356.5972	1283.8226	1739.9668	1364.4336
1242.8846	1283.6166	1304.3206	1352.0343	1429.5084	1450.4612	1730.4215
1139.5007	1370.532	1611.441	1614.9751	1572.8901	1539.9576	1326.8142
1542.6788	1504.8601	1764.9355	1245.9175	1293.2754	1607.317	1183.8771
1246.0428	1416.9904	1738.8918	1390.2001	1122.9612	1274.1154	1494.618
1365.8163	1458.0974	1321.9692	1720.5029	1281.0718	1283.1833	1385.4495
1342.2816	1405.2263	1349.0986	1154.5426	1661.524	1346.1055	1317.141
1415.5275	1336.6482	1292.6216	1281.9204	1245.883	1775.68	1645.6095
1573.7771	1267.9812	1744.5032	1383.0267	1330.4617	1297.8392	1408.6117
1270.3572	1592.0887	1317.3297	1609.0696	1543.3334	1247.458	1654.3256
1283.0173	1318.4066	1357.1974	1433.836	1343.501	1592.4296	1372.963
1501.176	1702.2039	1278.3516	1663.5883	1721.4946	1465.6284	1311.8967
1242.5391	1135.5974	1662.448	1311.4135	1846.7109	1513.1067	1320.5234
1283.8212	1297.8049	1272.0736	1488.8386	1285.9332	1768.5712	1438.0448
1425.0048	1287.2444	1572.3243	1776.2441	1251.2731	1276.9556	1698.985
1325.8254	1748.8888	1269.4489	1271.9973	1372.6641	1311.3741	1392.1544
1302.9042	1320.5657	1207.6532	1639.0042	1772.4243	1579.0714	1415.5527
1209.155	1435.0444	1467.249	1554.1332	1339.2148	1795.1394	1397.1542
1747.916	1669.2935	1517.7278	1760.9276	1227.056	1393.5388	1317.3552
1426.8419	1334.7557	1452.0264	1332.1422	1344.8751	1647.8969	1328.2809
1413.23	1341.2748	1273.141	1824.6028	1394.3624	1242.9128	1382.8298
1873.4943	1204.1012	1293.1136	1666.6737	1183.718	1323.9946	1326.8599
1515.3857	1662.9457	1364.6366	1501.3649	1207.0576	1759.8098	1231.2573
1234.8068	1275.5709	1299.433	1431.3004	1257.6656	1467.031	1287.0248
1310.6682	1517.8877	1316.6273	1331.2999	1860.5161	1669.3477	1332.1057
1138.7745	1380.8285	1303.7114	1298.4424	1751.7356	1615.1791	1276.3864
1596.1725	1313.7517	1612.1031	1269.102	1314.9797	1377.4923	1643.8844
1579.2393	1319.8379	1293.5724	1860.1747	1274.3198	1608.4713	1587.1663
1244.879	1378.7319	1320.2559	1281.9232	1543.0208	1525.9465	1500.1459
1279.07	1372.5803	1466.9852	1276.0702	1515.3767	1506.4999	1577.6522
1224.3018	1363.6818	1713.1558	1242.7108	1458.133	1293.2662	1526.407
1420.9037	1277.5219	1559.8522	1345.1552	1212.3429	1302.998	1356.5808
1374.2977	1558.4381	1307.9718	1115.7528	1392.3804	1331.8647	1379.9117
1553.872	1336.014	1217.5753	1583.6182	1583.1661	1713.5565	1288.2429
1381.2958	1740.9135	1536.98	1306.6041	1562.9935	1285.7896	1316.4216
1263.8276	1378.0854	1123.1833	1342.8508	1395.6616	1356.9032	1618.904
1398.7333	1365.0759	1642.5986	1323.7134	1369.7854	1331.4812	1423.9309
1308.6188	1325.2765	1277.1478	1496.7229	1379.2478	1438.8896	1319.3661
1451.4161	1287.5803	1135.426	1543.6741	1842.3591	1240.8102	1699.3098
1372.7012	1284.4009	1285.1558	1274.2968	1665.6487	1434.2847	1208.611
1690.3779	1450.391	1679.8824	1632.9539	1302.7577	1294.6521	1271.7325
1394.2062	1841.2067	1212.8605	1290.1649	1655.6014	1328.808	1369.7107
1649.6575	1785.3904	1350.008	1504.1289	1306.9027	1618.1052	1301.9467
1400.7657	1671.5106	1346.824	1334.9899	1371.2576	1364.4167	1326.105
1282.6528	1284.2422	1360.5416	1635.4604	1594.3336	1373.4031	1414.8662
1149.1198	1612.3893	1316.2723	1856.4001	1306.308	1209.5226	1317.1808
1838.4152	1573.8733	1316.6603	1244.446	1277.0359	1658.0624	1673.3661
1742.9031	1751.9768	1277.1068	1289.5853	1312.2646	1331.2972	1253.6708

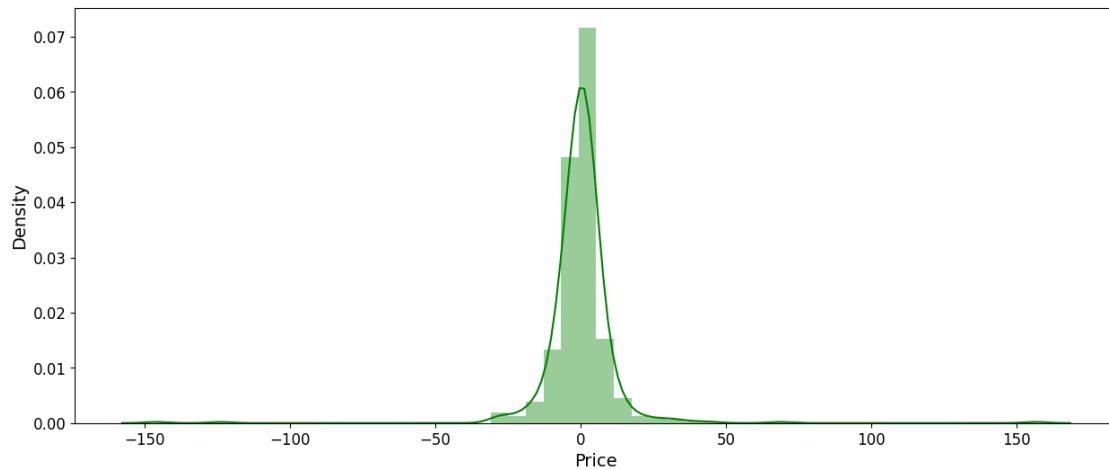
```
1258.6484 1724.9952 1641.7196 1133.873 1836.3104 1182.3663 1812.1621
1243.878 1592.7012 1136.4862]
```

r2\_score is:0.9940499332197056

MAE: 5.967990948979906

MSE: 189.98874400491664

RMSE: 13.783640448187722



Building the ARIMA model

```
[53]: import statsmodels.api as sm
from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt
from pandas import DataFrame

# fit model
model = ARIMA(stationary_check_gold_price, order=(5, 1, 0))
model_fit = model.fit()

# print model summary
print(model_fit.summary())

# plot residual errors
residuals = DataFrame(model_fit.resid)
residuals.plot(title="Residuals")
plt.show()

residuals.plot(kind='kde', title="Density of Residuals")
plt.show()
```

```
print(residuals.describe())
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
```

#### SARIMAX Results

```
=====
Dep. Variable:          Price    No. Observations:          2531
Model:                ARIMA(5, 1, 0)    Log Likelihood          -11341.408
Date:                 Sun, 01 Sep 2024    AIC                    22694.815
Time:                 07:09:32    BIC                    22729.831
Sample:                0    HQIC                    22707.520
                        - 2531
```

```
Covariance Type:          opg
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
ar.L1         -0.1807        0.010     -17.657      0.000      -0.201      -0.161
ar.L2         -0.1713        0.012     -13.747      0.000      -0.196      -0.147
ar.L3         -0.0402        0.022      -1.789      0.074      -0.084       0.004
ar.L4         -0.0975        0.018      -5.410      0.000      -0.133      -0.062
ar.L5          0.0290        0.016       1.764      0.078      -0.003       0.061
sigma2        459.1043        5.684      80.771      0.000      447.964      470.245
=====
```

```
===
```

```
Ljung-Box (L1) (Q):          0.00    Jarque-Bera (JB):
```

```

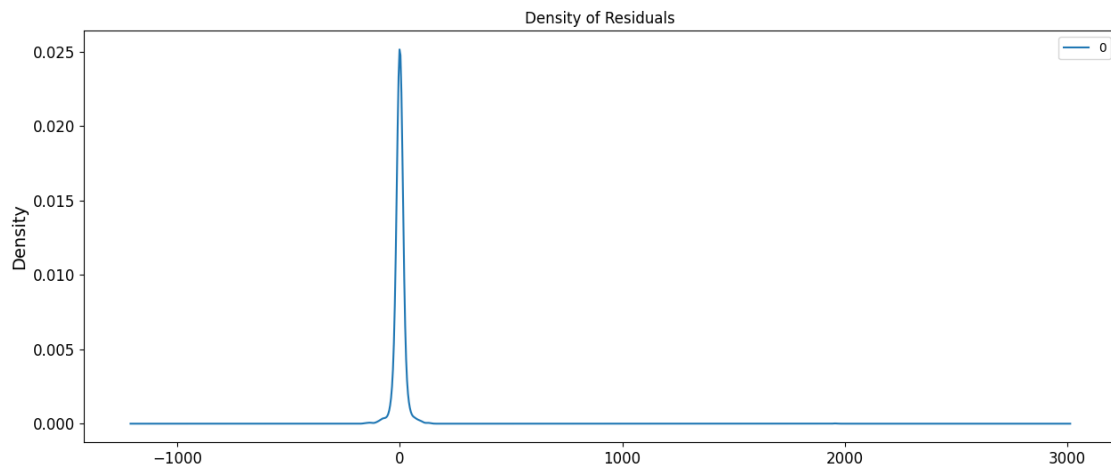
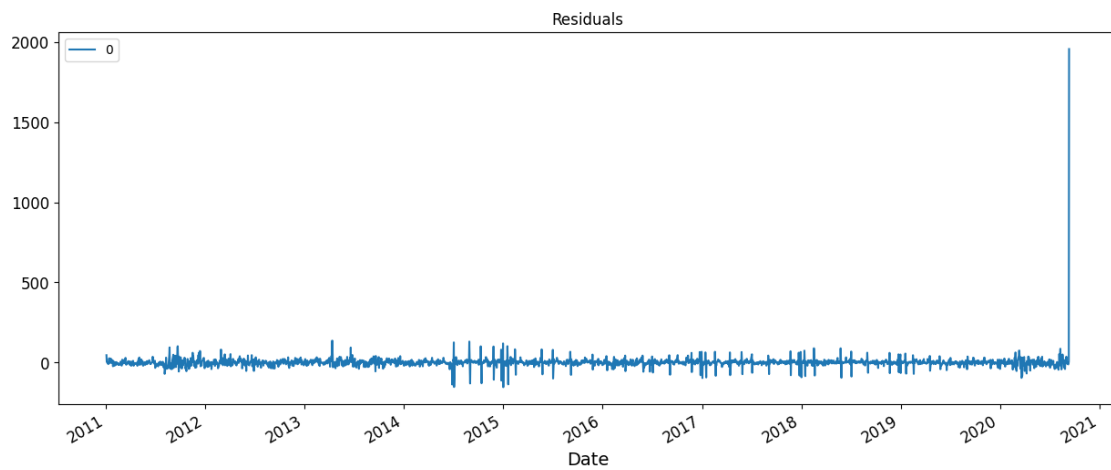
11703.18
Prob(Q):                                0.97   Prob(JB):
0.00
Heteroskedasticity (H):                 0.96   Skew:
-0.38
Prob(H) (two-sided):                   0.53   Kurtosis:
13.51
=====
===

```

```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).

```



0

```

count    2531.000000
mean      0.455939
std       44.412299
min      -154.536356
25%      -8.246394
50%      -0.037432
75%       7.817965
max      1957.350000

```

```
[54]: stationary_check_gold_price.values
```

```
[54]: array([1957.35, 1964.3 , 1954.9 , ..., 1373.4 , 1378.5 , 1422.6 ])
```

```

[57]: from sklearn.metrics import mean_squared_error
      from statsmodels.tsa.arima.model import ARIMA
      import matplotlib.pyplot as plt

      X = stationary_check_gold_price.values
      size = int(len(X) * 0.7)
      train, test = X[0:size], X[size:len(X)]
      history = [x for x in train]
      predictions = list()

      for t in range(len(test)):
          model = ARIMA(history, order=(5, 1, 0))
          model_fit = model.fit()
          output = model_fit.forecast()
          y_pred = output[0]
          predictions.append(y_pred)
          obs = test[t]
          history.append(obs)
          print('predicted=%f, expected=%f' % (y_pred, obs))

      error = mean_squared_error(test, predictions)
      print('Test MSE: %.3f' % error)

      # plot the forecast
      plt.plot(test)
      plt.plot(predictions, color='red')
      plt.show()

```

```

predicted=1212.490496, expected=1201.900000
predicted=1208.876591, expected=1203.100000
predicted=1207.223054, expected=1216.100000
predicted=1215.352889, expected=1214.100000
predicted=1211.395029, expected=1205.100000
predicted=1206.496677, expected=1198.400000
predicted=1200.701240, expected=1205.100000

```

predicted=1206.384925, expected=1195.000000  
predicted=1197.636004, expected=1236.100000  
predicted=1228.556401, expected=1231.200000  
predicted=1221.990986, expected=1245.500000  
predicted=1241.119519, expected=1235.700000  
predicted=1229.127670, expected=1226.000000  
predicted=1230.999538, expected=1258.500000  
predicted=1251.559874, expected=1262.400000  
predicted=1255.801621, expected=1235.300000  
predicted=1239.465422, expected=1230.300000  
predicted=1233.284087, expected=1233.200000  
predicted=1236.111901, expected=1248.200000  
predicted=1248.001865, expected=1221.700000  
predicted=1224.512974, expected=1222.300000  
predicted=1226.976684, expected=1250.600000  
predicted=1243.646926, expected=1243.800000  
predicted=1242.298600, expected=1237.800000  
predicted=1237.989712, expected=1241.400000  
predicted=1238.697681, expected=1241.100000  
predicted=1242.248677, expected=1244.000000  
predicted=1243.741719, expected=1243.500000  
predicted=1242.317584, expected=1257.900000  
predicted=1254.285040, expected=1273.400000  
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predicted=1679.962683, expected=1685.500000  
predicted=1681.210781, expected=1662.300000  
predicted=1664.467010, expected=1642.300000  
predicted=1648.442349, expected=1650.000000  
predicted=1654.513901, expected=1646.700000  
predicted=1649.614634, expected=1666.900000  
predicted=1664.380154, expected=1655.500000  
predicted=1652.515853, expected=1659.100000  
predicted=1660.111628, expected=1642.500000  
predicted=1643.598802, expected=1693.700000  
predicted=1687.719741, expected=1699.200000  
predicted=1687.729959, expected=1710.900000  
predicted=1706.255304, expected=1698.100000  
predicted=1691.889760, expected=1683.300000  
predicted=1689.305004, expected=1671.400000  
predicted=1676.569356, expected=1703.000000  
predicted=1701.291051, expected=1708.800000  
predicted=1703.099697, expected=1721.100000  
predicted=1716.307581, expected=1709.900000  
predicted=1705.522762, expected=1787.000000  
predicted=1772.155733, expected=1773.600000  
predicted=1760.306356, expected=1775.100000  
predicted=1774.532825, expected=1784.900000  
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predicted=1728.843708, expected=1715.900000  
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predicted=1727.138127, expected=1746.400000  
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predicted=1723.291861, expected=1737.900000  
predicted=1739.879998, expected=1756.800000



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predicted=1747.601023, expected=1737.800000  
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predicted=1728.469135, expected=1699.800000  
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predicted=1677.134071, expected=1678.000000  
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predicted=1668.742659, expected=1654.100000  
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predicted=1600.923616, expected=1611.900000  
predicted=1607.124256, expected=1615.600000  
predicted=1613.769932, expected=1594.400000  
predicted=1597.813194, expected=1595.600000  
predicted=1599.133147, expected=1574.600000  
predicted=1579.661473, expected=1584.300000  
predicted=1588.737180, expected=1659.900000  
predicted=1642.506721, expected=1664.200000  
predicted=1650.063877, expected=1712.800000  
predicted=1696.027865, expected=1709.800000  
predicted=1692.742569, expected=1740.900000  
predicted=1734.284634, expected=1727.900000  
predicted=1719.788984, expected=1730.700000  
predicted=1732.688332, expected=1747.000000  
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predicted=1736.763335, expected=1745.500000  
predicted=1744.084709, expected=1713.400000  
predicted=1717.083515, expected=1710.800000  
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predicted=1691.481224, expected=1695.700000  
predicted=1702.194563, expected=1702.200000

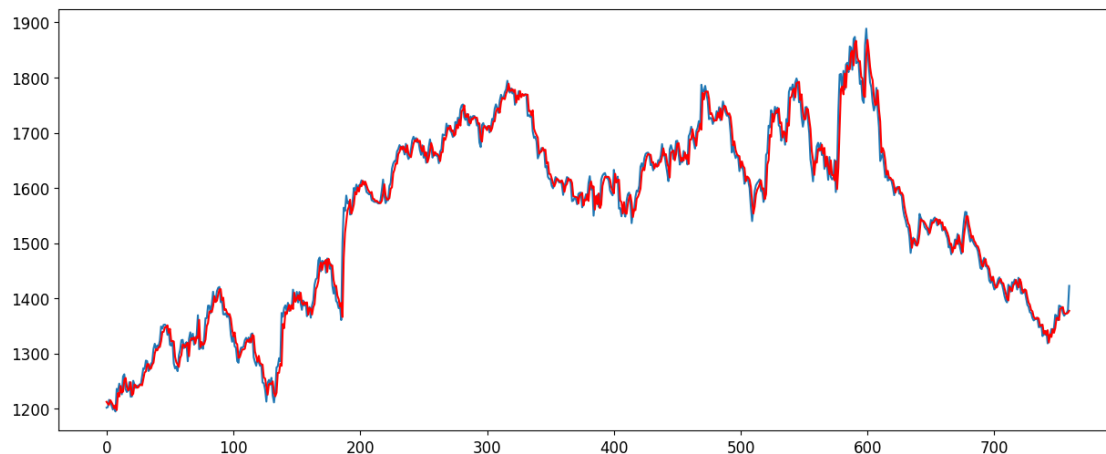
predicted=1699.575849, expected=1678.300000  
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predicted=1712.894539, expected=1773.800000  
predicted=1763.787447, expected=1781.700000  
predicted=1764.620101, expected=1777.800000  
predicted=1776.296188, expected=1787.500000  
predicted=1780.030222, expected=1758.900000  
predicted=1764.049430, expected=1790.900000  
predicted=1789.763592, expected=1798.400000  
predicted=1791.220753, expected=1790.300000  
predicted=1792.269784, expected=1755.300000  
predicted=1759.373815, expected=1764.200000  
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predicted=1737.288072, expected=1711.000000  
predicted=1724.142679, expected=1724.200000  
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predicted=1724.482278, expected=1699.600000  
predicted=1706.885763, expected=1651.500000  
predicted=1667.442024, expected=1635.100000  
predicted=1650.949074, expected=1611.900000  
predicted=1623.570137, expected=1646.000000  
predicted=1648.510716, expected=1651.700000  
predicted=1645.823232, expected=1675.500000  
predicted=1669.886127, expected=1681.800000  
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predicted=1668.216063, expected=1681.300000  
predicted=1678.423393, expected=1659.700000  
predicted=1662.282911, expected=1669.600000  
predicted=1672.503535, expected=1634.500000  
predicted=1639.043442, expected=1651.900000  
predicted=1656.851647, expected=1640.300000  
predicted=1639.710821, expected=1614.700000  
predicted=1625.057450, expected=1656.000000  
predicted=1649.953291, expected=1620.400000  
predicted=1623.294200, expected=1615.500000  
predicted=1623.195866, expected=1616.300000  
predicted=1613.680874, expected=1650.600000  
predicted=1648.640433, expected=1592.500000  
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predicted=1636.557389, expected=1739.200000  
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predicted=1769.583282, expected=1812.100000  
predicted=1807.109296, expected=1778.500000

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predicted=1801.011204, expected=1794.100000  
predicted=1798.297201, expected=1759.800000  
predicted=1767.370769, expected=1754.100000  
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predicted=1838.638194, expected=1888.700000  
predicted=1868.200369, expected=1848.900000  
predicted=1846.257153, expected=1818.900000  
predicted=1819.584004, expected=1791.200000  
predicted=1803.331417, expected=1782.400000  
predicted=1795.456196, expected=1755.500000  
predicted=1765.654286, expected=1740.200000  
predicted=1750.405226, expected=1748.800000  
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predicted=1776.869567, expected=1740.000000  
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predicted=1649.778150, expected=1619.000000  
predicted=1624.237949, expected=1628.300000  
predicted=1631.000083, expected=1613.400000  
predicted=1617.883344, expected=1615.000000  
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predicted=1615.075911, expected=1612.000000  
predicted=1614.264570, expected=1601.300000  
predicted=1603.451227, expected=1586.800000  
predicted=1591.455767, expected=1596.700000  
predicted=1598.354736, expected=1600.900000  
predicted=1599.937064, expected=1602.100000  
predicted=1601.863045, expected=1589.800000  
predicted=1590.299693, expected=1589.000000  
predicted=1591.117953, expected=1585.200000  
predicted=1586.572947, expected=1561.900000  
predicted=1568.199856, expected=1548.800000  
predicted=1555.197131, expected=1541.200000

predicted=1546.231455, expected=1530.200000  
predicted=1536.311996, expected=1528.700000  
predicted=1531.830894, expected=1512.300000  
predicted=1516.413466, expected=1482.300000  
predicted=1491.596510, expected=1502.300000  
predicted=1504.305891, expected=1509.900000  
predicted=1507.812133, expected=1499.700000  
predicted=1501.910510, expected=1496.000000  
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predicted=1500.579148, expected=1520.100000  
predicted=1517.075784, expected=1552.900000  
predicted=1543.320634, expected=1546.000000  
predicted=1540.210447, expected=1541.500000  
predicted=1540.403254, expected=1538.600000  
predicted=1537.569473, expected=1529.300000  
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predicted=1528.252029, expected=1523.800000  
predicted=1525.303502, expected=1515.000000  
predicted=1517.909395, expected=1528.600000  
predicted=1527.785750, expected=1542.100000  
predicted=1537.678165, expected=1538.100000  
predicted=1536.747165, expected=1543.300000  
predicted=1540.884721, expected=1546.500000  
predicted=1544.246569, expected=1541.700000  
predicted=1542.613058, expected=1532.000000  
predicted=1533.855313, expected=1542.400000  
predicted=1542.209089, expected=1535.900000  
predicted=1536.249957, expected=1536.300000  
predicted=1537.747667, expected=1522.800000  
predicted=1524.165073, expected=1526.600000  
predicted=1529.180491, expected=1523.200000  
predicted=1523.482868, expected=1515.300000  
predicted=1518.529680, expected=1508.800000  
predicted=1510.729318, expected=1492.200000  
predicted=1497.145382, expected=1495.600000  
predicted=1498.792810, expected=1479.800000  
predicted=1483.180726, expected=1490.400000  
predicted=1492.484809, expected=1493.400000  
predicted=1490.818826, expected=1506.600000  
predicted=1504.876625, expected=1501.100000  
predicted=1498.192786, expected=1516.600000  
predicted=1514.184732, expected=1502.900000  
predicted=1501.759883, expected=1491.200000  
predicted=1496.018714, expected=1480.900000  
predicted=1483.694715, expected=1514.900000  
predicted=1512.697094, expected=1540.100000  
predicted=1530.754057, expected=1556.700000  
predicted=1548.569930, expected=1556.000000

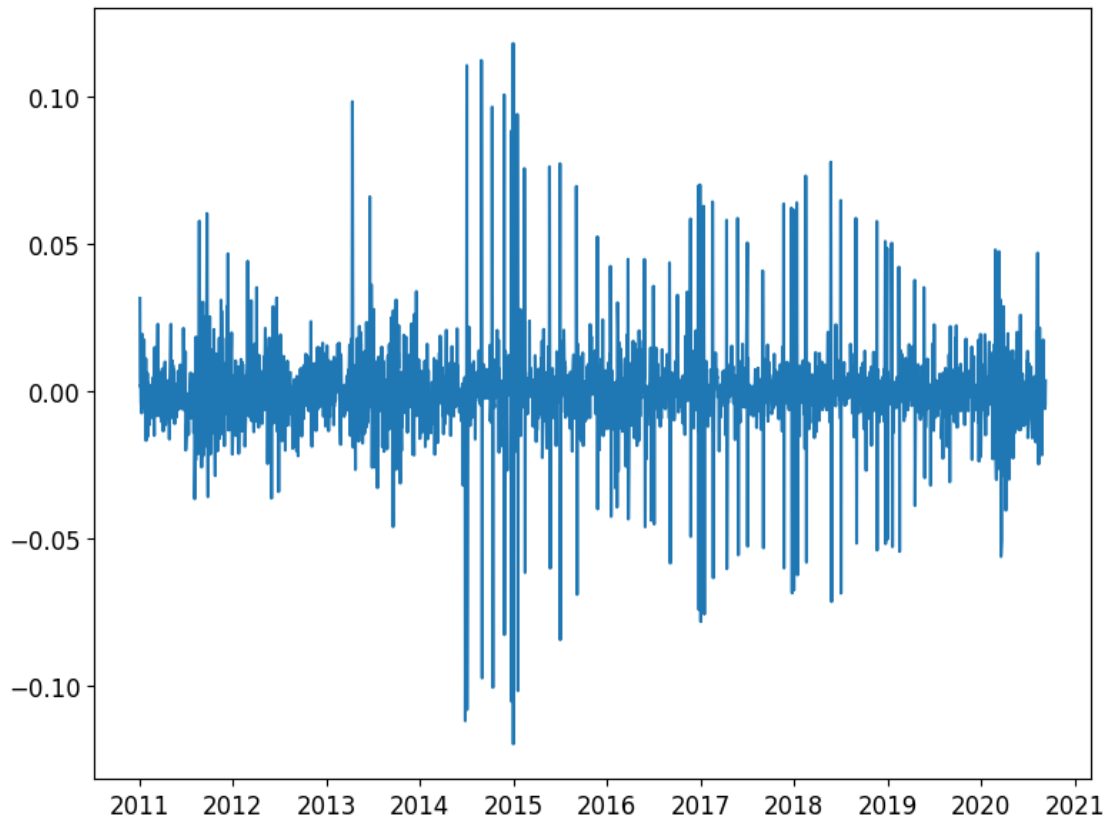
predicted=1548.575319, expected=1530.800000  
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predicted=1513.035382, expected=1503.200000  
predicted=1504.492176, expected=1498.300000  
predicted=1500.852418, expected=1494.500000  
predicted=1495.318161, expected=1492.300000  
predicted=1494.256359, expected=1485.300000  
predicted=1487.446386, expected=1471.700000  
predicted=1475.709378, expected=1454.900000  
predicted=1460.691577, expected=1452.900000  
predicted=1457.344881, expected=1467.400000  
predicted=1466.960180, expected=1473.400000  
predicted=1471.179676, expected=1458.500000  
predicted=1459.283130, expected=1457.700000  
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predicted=1438.454892, expected=1428.100000  
predicted=1432.112881, expected=1438.900000  
predicted=1439.025001, expected=1423.800000  
predicted=1426.624792, expected=1416.000000  
predicted=1419.411300, expected=1419.800000  
predicted=1419.891358, expected=1426.100000  
predicted=1426.426176, expected=1434.800000  
predicted=1432.322010, expected=1437.900000  
predicted=1434.982893, expected=1427.500000  
predicted=1427.975881, expected=1426.200000  
predicted=1427.415305, expected=1415.900000  
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predicted=1409.098061, expected=1396.000000  
predicted=1399.750076, expected=1392.600000  
predicted=1396.059832, expected=1424.600000  
predicted=1420.614734, expected=1421.500000  
predicted=1417.155974, expected=1412.200000  
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predicted=1424.659973, expected=1426.900000  
predicted=1425.987504, expected=1434.100000  
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predicted=1429.523938, expected=1409.300000  
predicted=1414.469789, expected=1408.700000  
predicted=1410.311580, expected=1415.300000  
predicted=1416.341125, expected=1413.400000  
predicted=1414.563896, expected=1400.500000  
predicted=1402.335451, expected=1388.200000

predicted=1392.058490, expected=1384.700000  
predicted=1388.360962, expected=1374.700000  
predicted=1378.829203, expected=1373.600000  
predicted=1376.500096, expected=1364.600000  
predicted=1366.804674, expected=1359.900000  
predicted=1363.221830, expected=1361.900000  
predicted=1362.525710, expected=1364.800000  
predicted=1364.976147, expected=1363.400000  
predicted=1363.271276, expected=1347.600000  
predicted=1350.240099, expected=1348.300000  
predicted=1350.721495, expected=1352.300000  
predicted=1352.320470, expected=1331.500000  
predicted=1336.049400, expected=1339.600000  
predicted=1341.019023, expected=1333.800000  
predicted=1333.919454, expected=1340.700000  
predicted=1342.285518, expected=1318.400000  
predicted=1320.074525, expected=1333.000000  
predicted=1334.709853, expected=1332.300000  
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predicted=1344.196118, expected=1341.000000  
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predicted=1382.582767, expected=1384.000000  
predicted=1384.140142, expected=1373.700000  
predicted=1373.102313, expected=1368.500000  
predicted=1372.169763, expected=1371.400000  
predicted=1372.310958, expected=1373.400000  
predicted=1373.702226, expected=1378.500000  
predicted=1377.321698, expected=1422.600000  
Test MSE: 417.137



Using this ARIMA model on differenced outputs

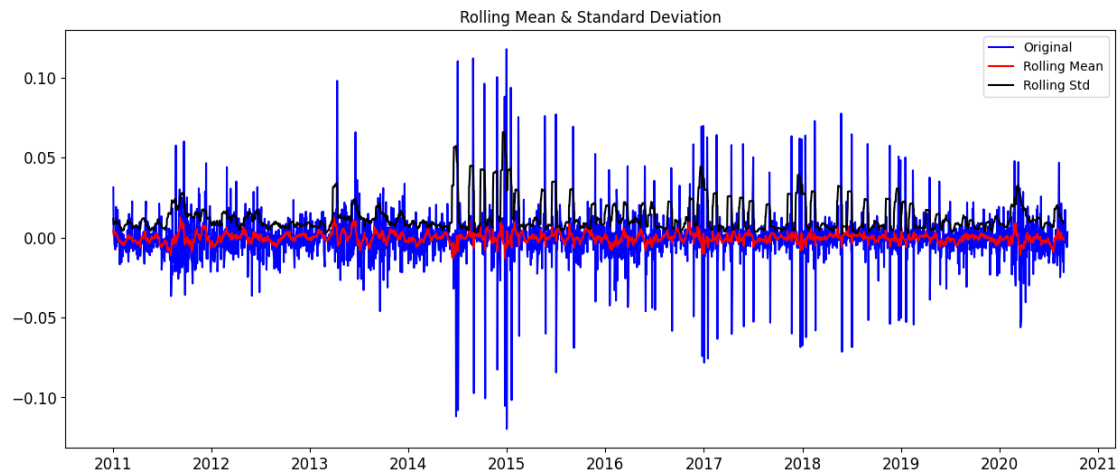
```
[58]: ts_log_diff = ts_log - ts_log.shift()
plt.figure(figsize=(9,7))
plt.plot(ts_log_diff)
plt.show()
```



```
[59]: ts_log_diff.head()
```

```
[59]: Date
2020-09-11      NaN
2020-09-10    0.003544
2020-09-09   -0.004797
2020-09-08   -0.006003
2020-09-07   -0.003144
Name: Price, dtype: float64
```

```
[60]: ts_log_diff.dropna(inplace=True)
test_stationarity(ts_log_diff)
```



Results of Dickey-Fuller Test:

Test Statistic	-24.003958
p-value	0.000000
#Lags Used	5.000000
Number of Observations Used	2524.000000
Critical Value (1%)	-3.432943
Critical Value (5%)	-2.862686
Critical Value (10%)	-2.567380
dtype:	float64

```
[61]: ts_log_diff.head()
```

```
[61]: Date
2020-09-10    0.003544
2020-09-09   -0.004797
2020-09-08   -0.006003
2020-09-07   -0.003144
2020-09-06    0.001831
Name: Price, dtype: float64
```

```
[62]: from statsmodels.tsa.stattools import acf, pacf

lag_acf = acf(ts_log_diff, nlags=20)
lag_pacf = pacf(ts_log_diff, nlags=20, method='ols')
```

```
[63]: plt.figure(figsize=(20,10))

#Plot ACF:
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
```

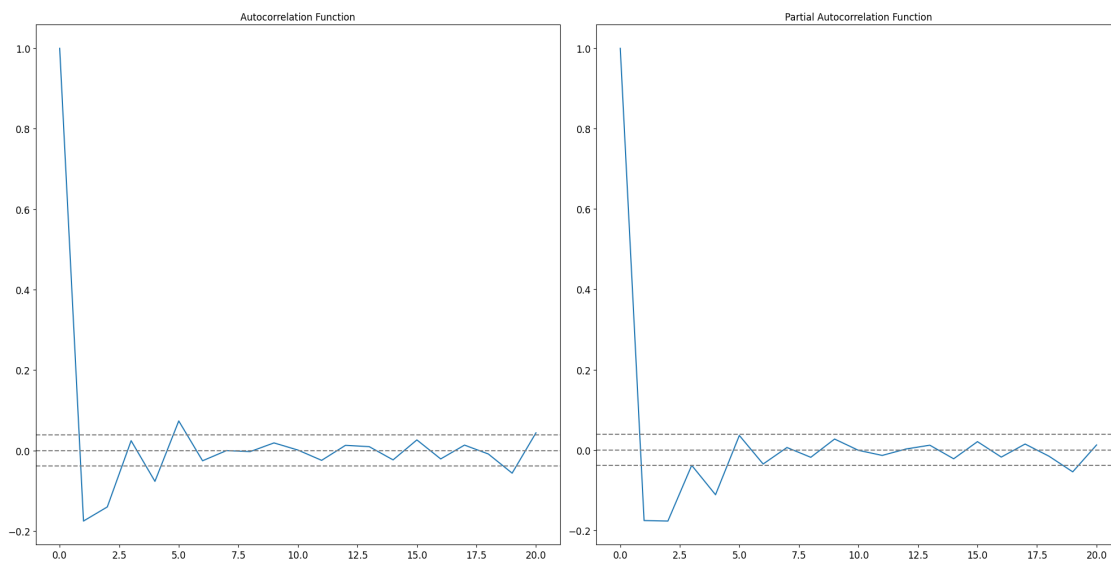


```

plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Function')

#Plot PACF:
plt.subplot(122)
plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
plt.title('Partial Autocorrelation Function')
plt.tight_layout()
plt.show()

```



```

[65]: from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt

# AR model
model = ARIMA(ts_log, order=(1, 1, 0))
results_AR = model.fit()

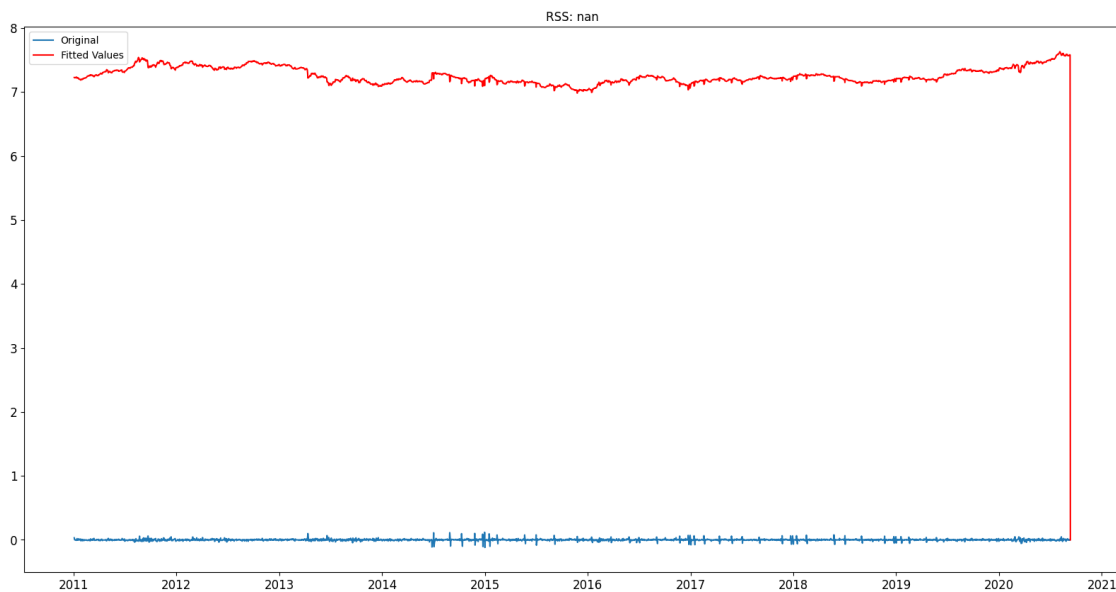
# Plotting the results
plt.figure(figsize=(20, 10))
plt.plot(ts_log_diff, label='Original')
plt.plot(results_AR.fittedvalues, color='red', label='Fitted Values')
plt.title('RSS: %.4f' % sum((results_AR.fittedvalues - ts_log_diff) ** 2))
plt.legend()
plt.show()

```

```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)

```



```

[67]: from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt

```

```

# MA model
model = ARIMA(ts_log, order=(0, 1, 1))
results_MA = model.fit()

# Plotting the results
plt.figure(figsize=(20, 10))
plt.plot(ts_log_diff, label='Original')
plt.plot(results_MA.fittedvalues, color='red', label='Fitted Values')
plt.title('RSS: %.4f' % sum((results_MA.fittedvalues - ts_log_diff) ** 2))
plt.legend()
plt.show()

```

```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.

```

```

    self._init_dates(dates, freq)

```

```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.

```

```

    self._init_dates(dates, freq)

```

```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.

```

```

    self._init_dates(dates, freq)

```

```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.

```

```

    self._init_dates(dates, freq)

```

```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.

```

```

    self._init_dates(dates, freq)

```

```

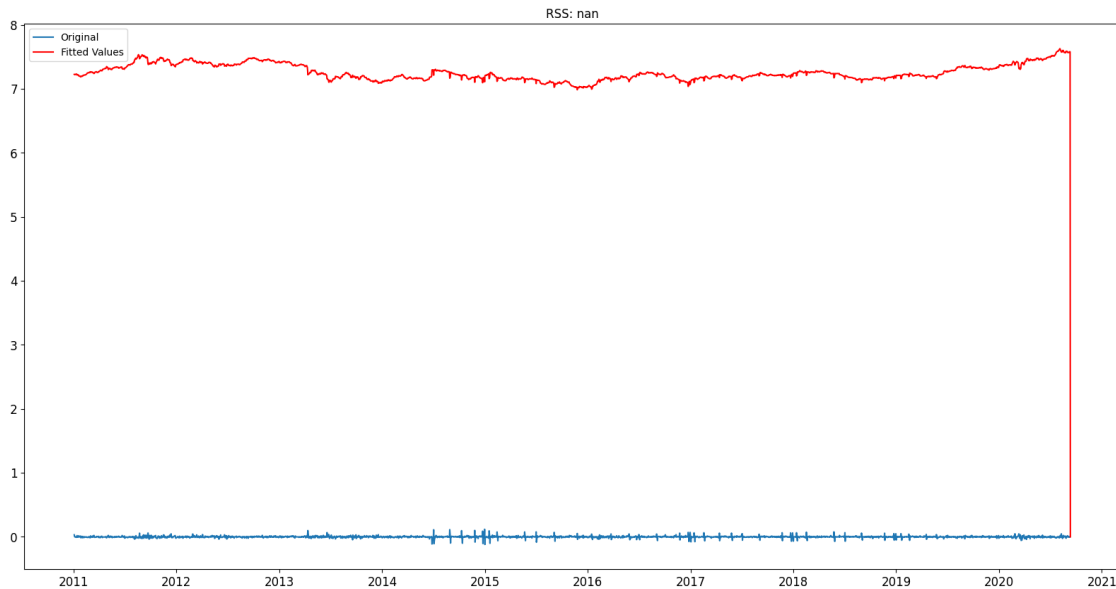
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.

```

```

    self._init_dates(dates, freq)

```



```
[76]: from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt

# Combined ARIMA model
model = ARIMA(ts_log, order=(1, 1, 1))
results_ARIMA = model.fit()

# Plotting the results
plt.figure(figsize=(20, 10))
plt.plot(ts_log_diff, label='Original')
plt.plot(results_ARIMA.fittedvalues, color='red', label='Fitted Values')
plt.title('RSS: %.4f' % sum((results_ARIMA.fittedvalues - ts_log_diff) ** 2))
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it is not monotonic and so
will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
```

ValueWarning: A date index has been provided, but it is not monotonic and so will be ignored when e.g. forecasting.

```
self._init_dates(dates, freq)
```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa\_model.py:473:

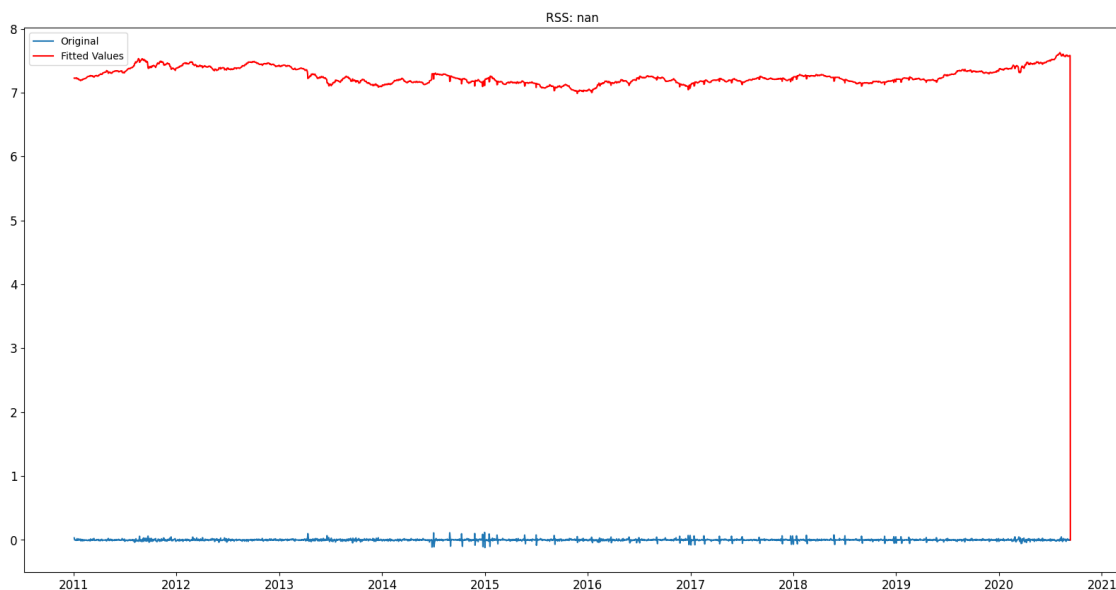
ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.

```
self._init_dates(dates, freq)
```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa\_model.py:473:

ValueWarning: A date index has been provided, but it is not monotonic and so will be ignored when e.g. forecasting.

```
self._init_dates(dates, freq)
```



```
[77]: predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues, copy=True)
print (predictions_ARIMA_diff.head())
```

Date

2020-09-11 0.000000

2020-09-10 7.579347

2020-09-09 7.582180

2020-09-08 7.578740

2020-09-07 7.573900

dtype: float64

```
[78]: predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
print (predictions_ARIMA_diff_cumsum.head())
```

Date

2020-09-11 0.000000

```

2020-09-10      7.579347
2020-09-09     15.161527
2020-09-08     22.740267
2020-09-07     30.314166
dtype: float64

```

```

[79]: predictions_ARIMA_log = pd.Series(ts_log.iloc[0], index=ts_log.index)
      predictions_ARIMA_log = predictions_ARIMA_log.
      ↪add(predictions_ARIMA_diff_cumsum,fill_value=0)
      predictions_ARIMA_log.head()

```

```

[79]: Date
2020-09-11      7.579347
2020-09-10     15.158694
2020-09-09     22.740874
2020-09-08     30.319614
2020-09-07     37.893513
dtype: float64

```

```

[80]: predictions_ARIMA = np.exp(predictions_ARIMA_log)
      predictions_ARIMA

```

```

[80]: Date
2020-09-11     1.957350e+03
2020-09-10     3.831219e+06
2020-09-09     7.520316e+09
2020-09-08     1.471096e+13
2020-09-07     2.863806e+16
...
2011-01-07              inf
2011-01-06              inf
2011-01-05              inf
2011-01-04              inf
2011-01-03              inf
Length: 2531, dtype: float64

```

```

[83]: import numpy as np
      from sklearn.metrics import mean_absolute_error

      # Ensure that predictions_ARIMA and the actual values have the same length
      # Assuming predictions_ARIMA is for the test set, extract the corresponding
      ↪test set from goldprice['Price']
      test_size = len(predictions_ARIMA)
      actual_test_values = goldprice['Price'][-test_size:]

      # Now calculate the MAE
      error = mean_absolute_error(actual_test_values, predictions_ARIMA)

```

```

print("MAE: %.3f" % error)

# Calculate RMSE
rmse = np.sqrt(np.mean((predictions_ARIMA - actual_test_values) ** 2))
print('RMSE: %.4f' % rmse)

```

MAE: 187318155507306782051480191768507153685797169349699122873278839050517062300  
42830550200811847059949983644618097142928800956996576163354225847120674965261846  
96711620863679131287296148963747060060835963376191285251254349922888743235955631  
55506589158045996999135388649185681732255179979020629161765432008376320.000  
RMSE: inf

Saving the predictions

```

[85]: from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor().fit(X_train,y_train)
preds1 = rf_model.predict(X_test)
preds1

```

```

[85]: array([1280.193 , 1374.073 , 1344.464 , 1719.095 , 1330.2575, 1290.322 ,
1142.758 , 1345.439 , 1265.819 , 1304.758 , 1713.282 , 1343.314 ,
1361.444 , 1283.829 , 1571.714 , 1313.723 , 1334.002 , 1405.699 ,
1524.442 , 1330.066 , 1754.894 , 1340.84 , 1415.928 , 1264.723 ,
1328.3265, 1538.194 , 1750.115 , 1201.84 , 1593.015 , 1965.949 ,
1355.739 , 1341.6765, 1679.31 , 1401.018 , 1321.546 , 1361.133 ,
1588.2785, 1394.9385, 1649.926 , 1368.629 , 1194.987 , 1361.547 ,
1427.017 , 1243.056 , 1312.657 , 1285.157 , 1627.973 , 1367.308 ,
1443.882 , 1335.14 , 1282.66 , 1594.6665, 1354.989 , 1542.866 ,
1444.81 , 1303.465 , 1272.255 , 1535.8885, 1265.5186, 1522.232 ,
1373.475 , 1754.11 , 1753.118 , 1585.909 , 1346.269 , 1638.211 ,
1247.906 , 1677.108 , 1551.7885, 1497.235 , 1627.759 , 1454.716 ,
1589.018 , 1678.562 , 1570.1 , 1561.8025, 1232.288 , 1233.003 ,
1324.6225, 1256.995 , 1358.082 , 1492.866 , 1350.229 , 1335.002 ,
1569.7555, 1596.955 , 1295.896 , 1444.964 , 1600.72 , 1574.5135,
1283.086 , 1323.3215, 1411.972 , 1432.978 , 1605.7115, 1537.412 ,
1788.608 , 1340.072 , 1284.518 , 1273.149 , 1789.13 , 1252.229 ,
1416.335 , 1198.326 , 1366.33 , 1287.827 , 1453.24 , 1495.668 ,
1574.493 , 1413.966 , 1734.222 , 1430.699 , 1386.362 , 1940.5485,
1677.73 , 1648.232 , 1306.084 , 1291.8442, 1762.954 , 1426.777 ,
1325.58 , 1403.498 , 1405.099 , 1423.897 , 1175.544 , 1240.845 ,
1219.825 , 1525.5235, 1413.583 , 1618.054 , 1554.0655, 1403.933 ,
1143.7435, 1433.782 , 1518.8375, 1215.046 , 1310.551 , 1215.703 ,
1373.728 , 1400.205 , 1293.093 , 1326.912 , 1369.55 , 1208.873 ,
1940.8325, 1611.086 , 1344.3156, 1330.11 , 1744.752 , 1580.455 ,
1317.522 , 1950.732 , 1740.198 , 1404.459 , 1268.263 , 1236.861 ,
1231.6825, 1412.599 , 1314.363 , 1300.549 , 1297.903 , 1275.654 ,
1425.022 , 1203.3025, 1355.217 , 1289.0686, 1740.277 , 1367.66 ,

```

1259.0285, 1285. , 1301.896 , 1350.306 , 1428.713 , 1451.175 ,  
 1729.39 , 1141.464 , 1358.247 , 1611.016 , 1616.03 , 1572.0145,  
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 1295.592 , 1601.568 , 1182.847 , 1238.092 , 1415.444 , 1737.2295,  
 1366.602 , 1123.431 , 1274.501 , 1495.1435, 1367.008 , 1453.759 ,  
 1322.108 , 1725.975 , 1282.592 , 1281.165 , 1367.0295, 1340.3758,  
 1410.803 , 1350.104 , 1150.613 , 1662.7 , 1347.011 , 1323.319 ,  
 1418.025 , 1335.23 , 1295.984 , 1283.687 , 1240.642 , 1775.206 ,  
 1643.999 , 1575.9695, 1268.2335, 1748.232 , 1385.317 , 1336.73 ,  
 1299.68 , 1407.658 , 1272.226 , 1591.701 , 1317.84 , 1613.573 ,  
 1544.263 , 1248.994 , 1657.205 , 1281.058 , 1332.588 , 1357.547 ,  
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 1278.229 , 1663.05 , 1722.064 , 1467.11 , 1311.209 , 1238.9 ,  
 1134.0965, 1662.76 , 1295.0545, 1839.83 , 1517.31 , 1333.935 ,  
 1286.7956, 1295.289 , 1270.263 , 1490.529 , 1283.1175, 1756.906 ,  
 1426.401 , 1418.752 , 1286.9336, 1570.411 , 1773.814 , 1295.5126,  
 1284.239 , 1699.675 , 1328.461 , 1753.035 , 1279.2965, 1276.344 ,  
 1372.914 , 1311.609 , 1392.748 , 1303.756 , 1324.714 , 1205.274 ,  
 1644.999 , 1774.59 , 1588.3095, 1414.584 , 1229.06 , 1434.567 ,  
 1454.799 , 1554.669 , 1341.404 , 1787.442 , 1397.2515, 1744.856 ,  
 1668.783 , 1520.056 , 1764.893 , 1225.895 , 1395.317 , 1324.245 ,  
 1423.474 , 1335.9398, 1450.142 , 1343.584 , 1344.8506, 1638.301 ,  
 1336.593 , 1412.505 , 1341.5266, 1270.657 , 1812.206 , 1391.424 ,  
 1251.719 , 1385.37 , 1887.9475, 1205.279 , 1299.691 , 1665.283 ,  
 1186.423 , 1316.948 , 1327.514 , 1508.075 , 1666.104 , 1359.594 ,  
 1503.334 , 1207.5695, 1760.525 , 1230.782 , 1237.9805, 1274.462 ,  
 1298.755 , 1430.625 , 1256.271 , 1459.595 , 1283.6455, 1329.111 ,  
 1516.495 , 1319.117 , 1333.16 , 1848.857 , 1670.673 , 1324.5275,  
 1141.143 , 1381.968 , 1303.652 , 1300.786 , 1757.075 , 1617.309 ,  
 1274.238 , 1599.025 , 1313.971 , 1614.691 , 1269.371 , 1318.859 ,  
 1373.839 , 1645.926 , 1580.9085, 1318.556 , 1298.765 , 1849.274 ,  
 1274.298 , 1604.362 , 1588.364 , 1249.384 , 1382.321 , 1323.98 ,  
 1286.538 , 1544.768 , 1528.926 , 1497.955 , 1277.283 , 1371.411 ,  
 1461.112 , 1278.724 , 1520.7655, 1505.582 , 1582.5055, 1227.389 ,  
 1365.703 , 1717.081 , 1238.154 , 1454.4545, 1296.204 , 1525.002 ,  
 1418.503 , 1280.988 , 1561.707 , 1342.1806, 1214.031 , 1297.18 ,  
 1356.085 , 1378.055 , 1560.593 , 1306.781 , 1120.463 , 1388.252 ,  
 1333.924 , 1387.196 , 1557.3445, 1337.2258, 1218.159 , 1577.197 ,  
 1587.29 , 1711.773 , 1293.4786, 1382.008 , 1740.114 , 1535.688 ,  
 1308.226 , 1561.0435, 1283.828 , 1322.918 , 1266.66 , 1378.288 ,  
 1120.864 , 1343.006 , 1396.524 , 1351.643 , 1618.464 , 1402.206 ,  
 1369.162 , 1639.94 , 1349.834 , 1375.501 , 1328.459 , 1425.089 ,  
 1309.695 , 1317.213 , 1276.851 , 1497.777 , 1377.3895, 1447.186 ,  
 1320.562 , 1450.309 , 1291.6412, 1137.3235, 1544.634 , 1829.263 ,  
 1243.323 , 1701.817 , 1373.348 , 1288.35 , 1284.165 , 1288.192 ,  
 1662.43 , 1434.162 , 1217.889 , 1706.765 , 1452.357 , 1677.001 ,  
 1628.794 , 1291.999 , 1287.1515, 1268.3324, 1394.051 , 1857.558 ,



```

1222.94 , 1298.836 , 1654.83 , 1327.794 , 1369.482 , 1642.453 ,
1787.931 , 1350.464 , 1499.428 , 1305.881 , 1616.367 , 1305.795 ,
1399.913 , 1672.065 , 1345.521 , 1335.229 , 1374.012 , 1361.275 ,
1333.246 , 1286.549 , 1292.0616, 1357.382 , 1637.414 , 1599.718 ,
1370.807 , 1415.023 , 1150.469 , 1612.642 , 1312.331 , 1949.6715,
1306.081 , 1205.534 , 1329.597 , 1827.18 , 1577.48 , 1331.735 ,
1241.4065, 1271.929 , 1657.559 , 1671.72 , 1744.865 , 1743.247 ,
1277.359 , 1292.7122, 1310.762 , 1334.905 , 1251.8475, 1255.356 ,
1727.7185, 1643.258 , 1140.88 , 1900.1565, 1182.8255, 1812.567 ,
1247.133 , 1574.341 , 1134.0895])

```

```

[86]: from xgboost import XGBRegressor

xgb_model = XGBRegressor().fit(X_train,y_train)
preds2 = xgb_model.predict(X_test)
preds2

```

```

[86]: array([1278.1401, 1371.271 , 1355.9695, 1723.461 , 1334.4335, 1297.1885,
1143.4845, 1345.4817, 1261.3967, 1301.5546, 1712.7925, 1346.2677,
1361.0388, 1280.0442, 1570.3239, 1307.7097, 1330.5502, 1405.5698,
1528.4703, 1334.4691, 1751.9741, 1339.1648, 1416.658 , 1269.2885,
1328.5906, 1542.5172, 1746.5859, 1201.6 , 1589.8477, 1968.6177,
1368.1272, 1332.0349, 1681.0333, 1411.5604, 1321.3562, 1368.2838,
1587.745 , 1392.7683, 1653.4155, 1365.9961, 1190.6746, 1366.0255,
1425.8407, 1248.3562, 1309.78 , 1283.9656, 1634.9989, 1366.5922,
1443.5984, 1332.3934, 1309.3379, 1592.4606, 1358.125 , 1543.663 ,
1444.7942, 1301.2952, 1272.8468, 1533.4299, 1265.3164, 1530.9901,
1368.8342, 1759.8955, 1754.0508, 1556.21 , 1344.388 , 1647.2428,
1247.8563, 1674.9934, 1552.3225, 1503.549 , 1619.5886, 1457.717 ,
1614.9015, 1673.7311, 1571.3754, 1561.7765, 1238.839 , 1240.098 ,
1323.3727, 1261.1567, 1357.4338, 1501.3079, 1351.5875, 1360.682 ,
1565.3318, 1599.4858, 1296.2756, 1444.8475, 1604.5632, 1580.2817,
1298.9015, 1335.5979, 1414.1458, 1437.333 , 1595.7356, 1532.4955,
1787.0574, 1361.242 , 1253.5277, 1262.0485, 1787.2238, 1234.8044,
1415.709 , 1202.5835, 1361.9067, 1287.6216, 1462.7489, 1496.2802,
1575.358 , 1413.6388, 1725.308 , 1430.6484, 1384.8676, 1940.5999,
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1139.9231, 1438.9379, 1515.0935, 1205.7859, 1307.9661, 1218.8116,
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1934.105 , 1612.1024, 1353.5139, 1330.0481, 1748.1047, 1575.8652,
1317.6875, 1872.7856, 1737.0591, 1403.7838, 1273.0391, 1234.7642,
1240.0137, 1414.432 , 1300.219 , 1297.8947, 1299.8444, 1278.68 ,
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1730.4215, 1139.5007, 1370.532 , 1611.441 , 1614.9751, 1572.8901,

```

1539.9576, 1326.8142, 1542.6788, 1504.8601, 1764.9355, 1245.9175,  
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1415.5275, 1336.6482, 1292.6216, 1281.9204, 1245.883 , 1775.68 ,  
1645.6095, 1573.7771, 1267.9812, 1744.5032, 1383.0267, 1330.4617,  
1297.8392, 1408.6117, 1270.3572, 1592.0887, 1317.3297, 1609.0696,  
1543.3334, 1247.458 , 1654.3256, 1283.0173, 1318.4066, 1357.1974,  
1433.836 , 1343.501 , 1592.4296, 1372.963 , 1501.176 , 1702.2039,  
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1438.0448, 1425.0048, 1287.2444, 1572.3243, 1776.2441, 1251.2731,  
1276.9556, 1698.985 , 1325.8254, 1748.8888, 1269.4489, 1271.9973,  
1372.6641, 1311.3741, 1392.1544, 1302.9042, 1320.5657, 1207.6532,  
1639.0042, 1772.4243, 1579.0714, 1415.5527, 1209.155 , 1435.0444,  
1467.249 , 1554.1332, 1339.2148, 1795.1394, 1397.1542, 1747.916 ,  
1669.2935, 1517.7278, 1760.9276, 1227.056 , 1393.5388, 1317.3552,  
1426.8419, 1334.7557, 1452.0264, 1332.1422, 1344.8751, 1647.8969,  
1328.2809, 1413.23 , 1341.2748, 1273.141 , 1824.6028, 1394.3624,  
1242.9128, 1382.8298, 1873.4943, 1204.1012, 1293.1136, 1666.6737,  
1183.718 , 1323.9946, 1326.8599, 1515.3857, 1662.9457, 1364.6366,  
1501.3649, 1207.0576, 1759.8098, 1231.2573, 1234.8068, 1275.5709,  
1299.433 , 1431.3004, 1257.6656, 1467.031 , 1287.0248, 1310.6682,  
1517.8877, 1316.6273, 1331.2999, 1860.5161, 1669.3477, 1332.1057,  
1138.7745, 1380.8285, 1303.7114, 1298.4424, 1751.7356, 1615.1791,  
1276.3864, 1596.1725, 1313.7517, 1612.1031, 1269.102 , 1314.9797,  
1377.4923, 1643.8844, 1579.2393, 1319.8379, 1293.5724, 1860.1747,  
1274.3198, 1608.4713, 1587.1663, 1244.879 , 1378.7319, 1320.2559,  
1281.9232, 1543.0208, 1525.9465, 1500.1459, 1279.07 , 1372.5803,  
1466.9852, 1276.0702, 1515.3767, 1506.4999, 1577.6522, 1224.3018,  
1363.6818, 1713.1558, 1242.7108, 1458.133 , 1293.2662, 1526.407 ,  
1420.9037, 1277.5219, 1559.8522, 1345.1552, 1212.3429, 1302.998 ,  
1356.5808, 1374.2977, 1558.4381, 1307.9718, 1115.7528, 1392.3804,  
1331.8647, 1379.9117, 1553.872 , 1336.014 , 1217.5753, 1583.6182,  
1583.1661, 1713.5565, 1288.2429, 1381.2958, 1740.9135, 1536.98 ,  
1306.6041, 1562.9935, 1285.7896, 1316.4216, 1263.8276, 1378.0854,  
1123.1833, 1342.8508, 1395.6616, 1356.9032, 1618.904 , 1398.7333,  
1365.0759, 1642.5986, 1323.7134, 1369.7854, 1331.4812, 1423.9309,  
1308.6188, 1325.2765, 1277.1478, 1496.7229, 1379.2478, 1438.8896,  
1319.3661, 1451.4161, 1287.5803, 1135.426 , 1543.6741, 1842.3591,  
1240.8102, 1699.3098, 1372.7012, 1284.4009, 1285.1558, 1274.2968,  
1665.6487, 1434.2847, 1208.611 , 1690.3779, 1450.391 , 1679.8824,  
1632.9539, 1302.7577, 1294.6521, 1271.7325, 1394.2062, 1841.2067,  
1212.8605, 1290.1649, 1655.6014, 1328.808 , 1369.7107, 1649.6575,  
1785.3904, 1350.008 , 1504.1289, 1306.9027, 1618.1052, 1301.9467,

```
1400.7657, 1671.5106, 1346.824 , 1334.9899, 1371.2576, 1364.4167,
1326.105 , 1282.6528, 1284.2422, 1360.5416, 1635.4604, 1594.3336,
1373.4031, 1414.8662, 1149.1198, 1612.3893, 1316.2723, 1856.4001,
1306.308 , 1209.5226, 1317.1808, 1838.4152, 1573.8733, 1316.6603,
1244.446 , 1277.0359, 1658.0624, 1673.3661, 1742.9031, 1751.9768,
1277.1068, 1289.5853, 1312.2646, 1331.2972, 1253.6708, 1258.6484,
1724.9952, 1641.7196, 1133.873 , 1836.3104, 1182.3663, 1812.1621,
1243.878 , 1592.7012, 1136.4862], dtype=float32)
```

```
[87]: gold_price = pd.read_csv("/content/drive/MyDrive/GoldPrice.csv")
```

```
[88]: rf_predictions = pd.DataFrame()
rf_predictions['Predicted Price'] = preds1
rf_predictions
```

```
[88]:      Predicted Price
0          1280.1930
1          1374.0730
2          1344.4640
3          1719.0950
4          1330.2575
..          ...
502         1182.8255
503         1812.5670
504         1247.1330
505         1574.3410
506         1134.0895
```

```
[507 rows x 1 columns]
```

```
[89]: xgb_predictions = pd.DataFrame()
xgb_predictions['Predicted Price'] = preds2
xgb_predictions
```

```
[89]:      Predicted Price
0          1278.140137
1          1371.270996
2          1355.969482
3          1723.461060
4          1334.433472
..          ...
502         1182.366333
503         1812.162109
504         1243.878052
505         1592.701172
506         1136.486206
```

[507 rows x 1 columns]

```
[93]: rf_predictions.to_csv(r'/content/drive/MyDrive/RandomForest.  
    ↳ csv',header=True,index=False)
```

```
[94]: xgb_predictions.to_csv(r'/content/drive/MyDrive/XGBoost predictions.  
    ↳ csv',header=True,index=False)
```