In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose
import torch
import torch.nn as nn
import torch.optim as optim
import torch.utils.data as data
```

In [5]:

```
# Reading the datset
df=pd.read_csv('gold_monthly_csv.csv',index_col='Date',parse_dates=True)
df.head()
```

Out[5]:

	Price
Date	
1950-01-01	34.73
1950-02-01	34.73
1950-03-01	34.73
1950-04-01	34.73
1950-05-01	34.73

In [8]:

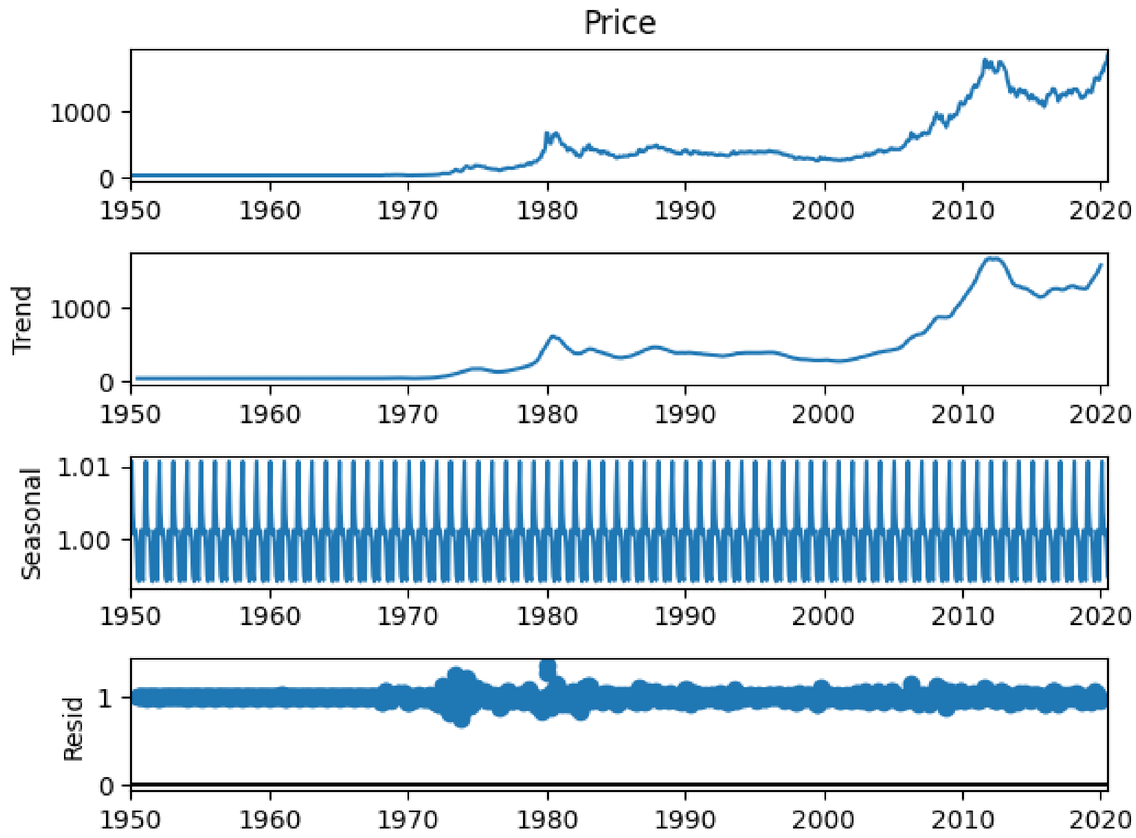
```
df.plot()
```

Out[8]:

```
<Axes: xlabel='Date'>
```

In [7]:

```
## Decomposition of time series
result=seasonal_decompose(df['Price'],model='multiplicative')
result.plot()
plt.tight_layout()
```



In [9]:

```
import statsmodels.api as sm
```

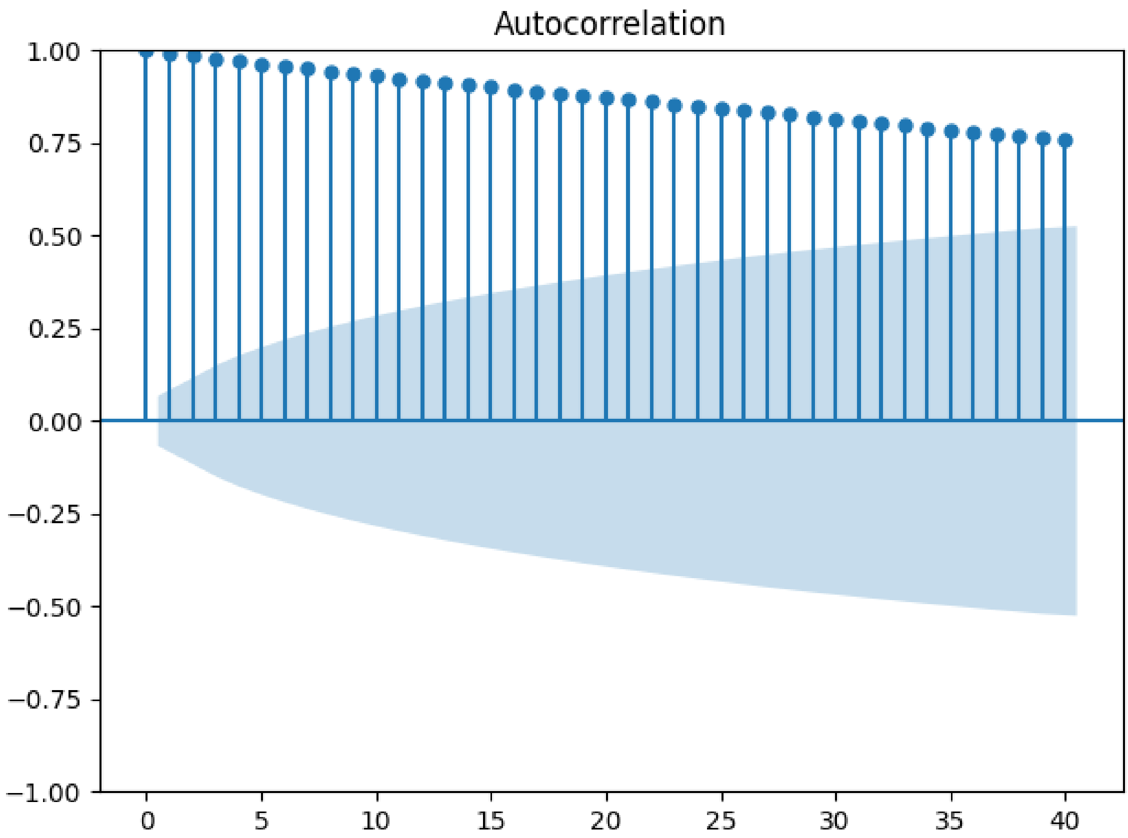
Analyzing acf & pacf when series is not stationary

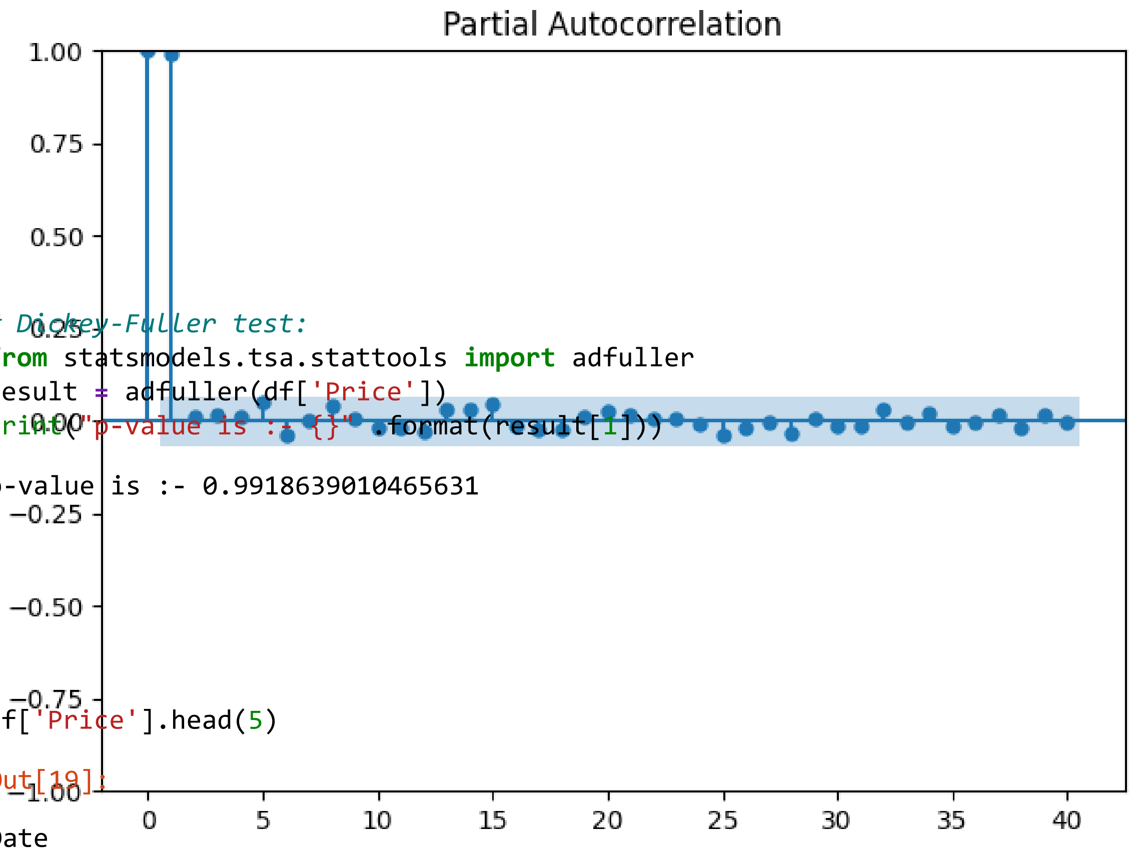
In [11]:

```
sm.graphics.tsa.plot_acf(df['Price'], lags=40)
plt.tight_layout()

sm.graphics.tsa.plot_pacf(df['Price'], lags=40)
plt.tight_layout()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py:3
48: FutureWarning: The default method 'yw' can produce PACF values outside
of the [-1,1] interval. After 0.13, the default will change tounadjusted Y
ule-Walker ('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```






```python
# Dickey-Fuller test:
from statsmodels.tsa.stattools import adfuller
result = adfuller(df['Price'])
print("p-value is :- {}".format(result[1]))
```

```
p-value is :- 0.9918639010465631
```

```python
df['Price'].head(5)
```

Out[19]:

```
Date
1950-01-01    34.73
1950-02-01    34.73
1950-03-01    34.73
1950-04-01    34.73
1950-05-01    34.73
Name: Price, dtype: float64
```

In [20]:

```python
df['Price']-df['Price'].shift(1)
```

Out[20]:

```
Date
1950-01-01        NaN
1950-02-01      0.000
1950-03-01      0.000
1950-04-01      0.000
1950-05-01      0.000
                ...  
2020-03-01     -5.054
2020-04-01     86.266
2020-05-01     35.667
2020-06-01     18.335
2020-07-01    106.775
Name: Price, Length: 847, dtype: float64
```

Checking stationaity again after differencing

In [31]:

```
from statsmodels.tsa.stattools import adfuller
n=1
result = adfuller(df['Price'].diff(periods=n)[n:])
print("p-value is :- {}" .format(result[1]))
```

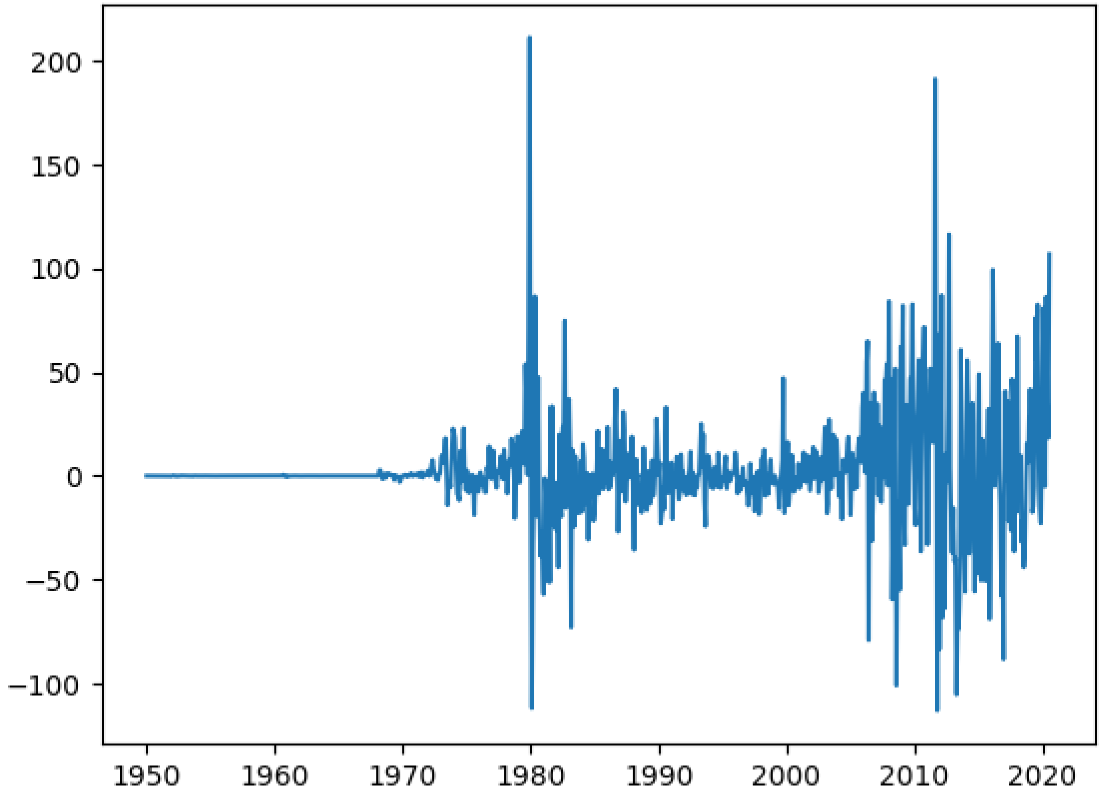
```
p-value is :- 5.33328251334224e-08
```

In [32]:

```
plt.plot(df['Price']-df['Price'].shift(1)[1:])
```

Out[32]:

```
[<matplotlib.lines.Line2D at 0x7f24a5fed1b0>]
```



In [33]:

```
n=1
data_1=df['Price'].diff(periods=n)[n:]
```

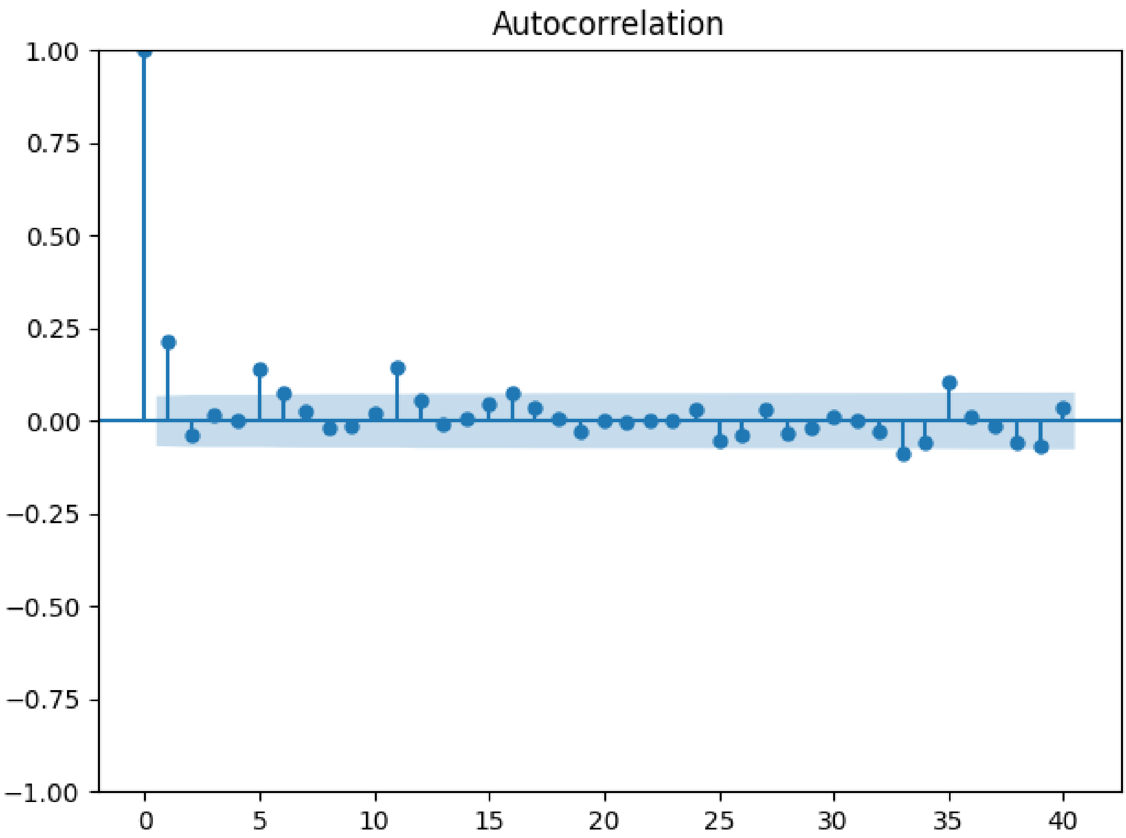
Deciding order of p& q after making series stationary and analyzing the acf & pacf

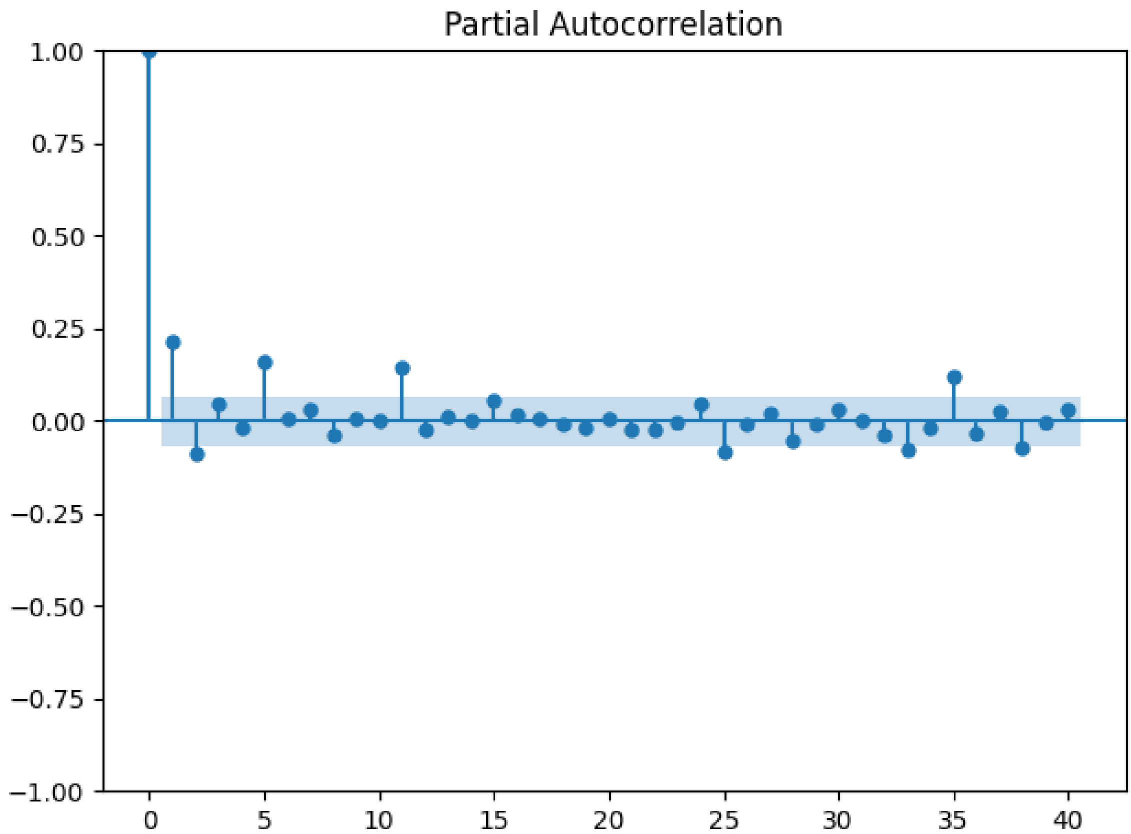
In [34]:

```
sm.graphics.tsa.plot_acf(data_1, lags=40)
plt.tight_layout()

sm.graphics.tsa.plot_pacf(data_1, lags=40)
plt.tight_layout()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py:3
48: FutureWarning: The default method 'yw' can produce PACF values outside
of the [-1,1] interval. After 0.13, the default will change tounadjusted Y
ule-Walker ('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```





Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40

In [37]:

```
from statsmodels.tsa.arima.model import ARIMA
model=ARIMA(df['Price'],order=(4,1,3))
results=model.fit()
print(results.summary())
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:
471: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:
471: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:
471: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  self._init_dates(dates, freq)
```

```
                               SARIMAX Results
==============================================================================
====
Dep. Variable:                  Price   No. Observations:
847
Model:                 ARIMA(4, 1, 3)   Log Likelihood               -388
2.453
Date:                Fri, 28 Apr 2023   AIC                           778
0.907
Time:                        09:09:04   BIC                           781
8.831
Sample:                    01-01-1950   HQIC                          779
5.437
                         - 07-01-2020
Covariance Type:                  opg
==============================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
```

Automatic Arima (Model by self decides the parameters)

```
------------------------------------------------------------------------------
----
ar.L1          0.3820      0.048      8.026      0.000       0.289
0.475
ar.L2         -0.2428      0.058     -4.163      0.000      -0.357      -
0.128
ar.L3         -0.7196      0.051    -14.119      0.000      -0.819      -
0.620
ar.L4          0.1398      0.024      5.817      0.000       0.093
0.187
ma.L1         -0.1174      0.040     -2.908      0.004      -0.197      -
0.038
ma.L2          0.0721      0.044      1.640      0.101      -0.014
0.158
ma.L3          0.8414      0.035     24.095      0.000       0.773
0.910
sigma2       564.7272     11.171     50.555      0.000     542.833      58
6.621
==============================================================================
=========
Ljung-Box (L1) (Q):                   0.16   Jarque-Bera (JB):
5845.45
Prob(Q):                              0.69   Prob(JB):
0.00
Heteroskedasticity (H):             528.31   Skew:
1.02
Prob(H) (two-sided):                  0.00   Kurtosis:
15.71
==============================================================================
=========

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

```
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:604: Con
vergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

In [38]:

```
!pip install pmdarima
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) ht
tps://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pk
g.dev/colab-wheels/public/simple/)
Collecting pmdarima
  Downloading pmdarima-2.0.3-cp310-cp310-manylinux_2_17_x86_64.manylinux20
14_x86_64.manylinux_2_28_x86_64.whl (1.8 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.8/1.8 MB 21.6 MB/s eta 0:0
0:00
Requirement already satisfied: statsmodels>=0.13.2 in /usr/local/lib/pytho
n3.10/dist-packages (from pmdarima) (0.13.5)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.10/d
ist-packages (from pmdarima) (1.5.3)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in /usr/lo
cal/lib/python3.10/dist-packages (from pmdarima) (0.29.34)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-p
ackages (from pmdarima) (1.26.15)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/d
ist-packages (from pmdarima) (1.10.1)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/l
ib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python
3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/d
ist-packages (from pmdarima) (1.2.0)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/
dist-packages (from pmdarima) (1.22.4)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/d
ist-packages (from pandas>=0.19->pmdarima) (2022.7.1)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/py
thon3.10/dist-packages (from pandas>=0.19->pmdarima) (2.8.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/pyth
on3.10/dist-packages (from scikit-learn>=0.22->pmdarima) (3.1.0)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.1
0/dist-packages (from statsmodels>=0.13.2->pmdarima) (23.1)
Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.10/d
ist-packages (from statsmodels>=0.13.2->pmdarima) (0.5.3)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packa
ges (from patsy>=0.5.2->statsmodels>=0.13.2->pmdarima) (1.16.0)
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.3
```

In [39]:

```python
from pmdarima.arima import auto_arima
# Find the optimal parameters
model = auto_arima(df['Price'],suppress_warnings=True)
print(model.summary())
```

```
                               SARIMAX Results
==========================================================================
====
Dep. Variable:                      y   No. Observations:
847
Model:               SARIMAX(1, 2, 2)   Log Likelihood               -388
9.393
Date:                Fri, 28 Apr 2023   AIC                           778
6.785
Time:                        09:10:00   BIC                           780
5.743
Sample:                    01-01-1950   HQIC                          779
4.049
                         - 07-01-2020
Covariance Type:                  opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ar.L1         -0.6018      0.041    -14.786      0.000      -0.682      -
0.522
ma.L1         -0.1598      0.031     -5.173      0.000      -0.220      -
0.099
ma.L2         -0.7731      0.028    -27.501      0.000      -0.828      -
0.718
sigma2       581.0090     10.903     53.287      0.000     559.639      60
2.379
==========================================================================
=========
Ljung-Box (L1) (Q):                   0.57   Jarque-Bera (JB):
5297.12
Prob(Q):                              0.45   Prob(JB):
0.00
Heteroskedasticity (H):             445.42   Skew:
0.49
Prob(H) (two-sided):                  0.00   Kurtosis:
15.23
==========================================================================
=========

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

Concept of Moving Averages

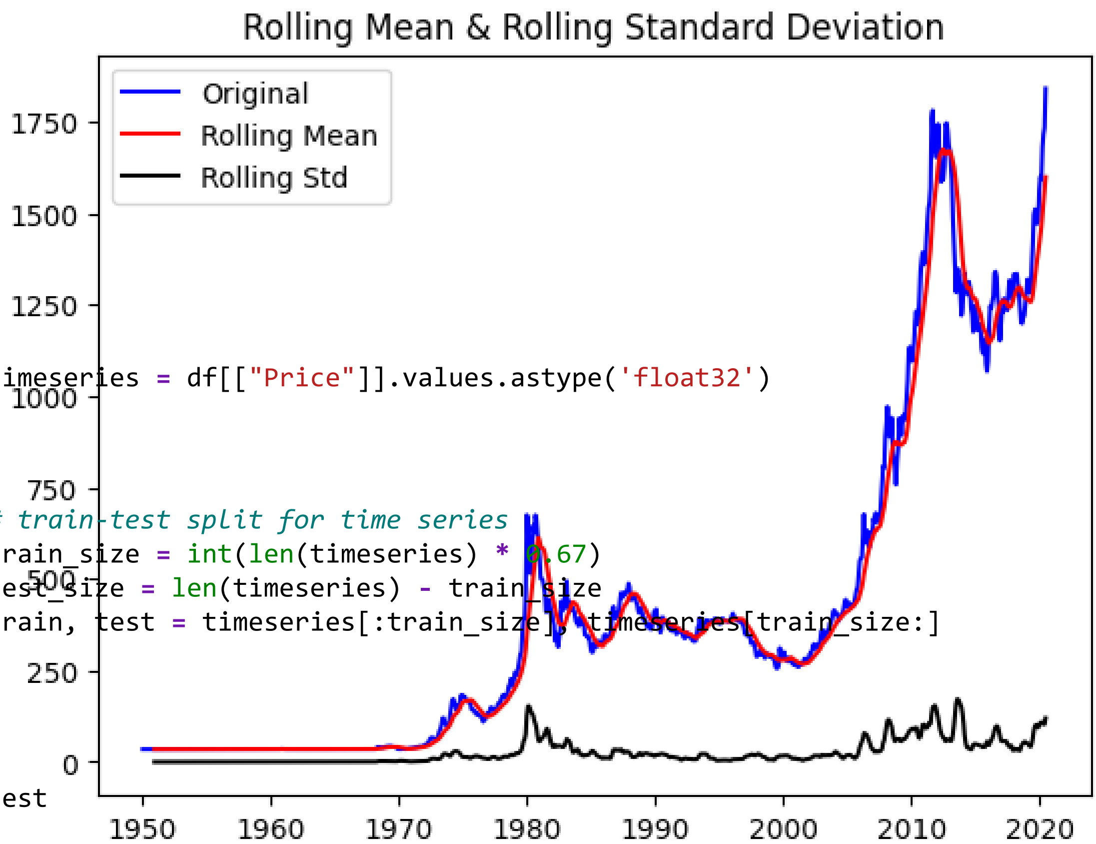
In [40]:

```python
#Determing rolling statistics
rolmean = df.rolling(window = 12).mean()
rolstd = df.rolling(window = 12).std()
print(rolmean,rolstd)
#plot rolling statistics
orig=plt.plot(df, 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 & Rolling Standard Deviation')
plt.show()
```

```
                  Price
Date
1950-01-01          NaN
1950-02-01          NaN
1950-03-01          NaN
1950-04-01          NaN
1950-05-01          NaN
...                 ...
2020-03-01  1462.550667
2020-04-01  1495.249000
2020-05-01  1531.352083
2020-06-01  1562.647417
2020-07-01  1598.163750

[847 rows x 1 columns]                   Price
Date
1950-01-01         NaN
1950-02-01         NaN
1950-03-01         NaN
1950-04-01         NaN
1950-05-01         NaN
...                ...
2020-03-01  107.225773
2020-04-01  108.856818
2020-05-01  103.583451
2020-06-01  103.339347
2020-07-01  119.768823

[847 rows x 1 columns]
```




```
timeseries = df[["Price"]].values.astype('float32')
```

```
# train-test split for time series
train_size = int(len(timeseries) * 0.67)
test_size = len(timeseries) - train_size
train, test = timeseries[:train_size], timeseries[train_size:]
```

```
test
```

Out[43]:

```
array([[ 344.707],
       [ 344.1  ],
       [ 340.805],
       [ 323.78 ],
       [ 323.998],
       [ 322.616],
       [ 324.863],
       [ 306.345],
       [ 288.776],
       [ 289.264],
       [ 297.743],
       [ 295.87 ],
       [ 308.558],
       [ 298.971],
       [ 292.223],
       [ 292.874],
       [ 284.228],
       [ 288.661],
```

In [45]:

```
def create_dataset(dataset, lookback):
    """Transform a time series into a prediction dataset

    Args:
        dataset: A numpy array of time series, first dimension is the time steps
        lookback: Size of window for prediction
    """
    X, y = [], []
    for i in range(len(dataset)-lookback):
        feature = dataset[i:i+lookback]
        target = dataset[i+1:i+lookback+1]
        X.append(feature)
        print(X)
        y.append(target)
        print(y)
    return torch.tensor(X), torch.tensor(y)

lookback = 4
X_train, y_train = create_dataset(train, lookback=lookback)
X_test, y_test = create_dataset(test, lookback=lookback)
```

```
Streaming output truncated to the last 5000 lines.
       [34.49],
       [34.49],
       [34.68]], dtype=float32), array([[34.49],
       [34.49],
       [34.68],
       [34.82]], dtype=float32), array([[34.49],
       [34.68],
       [34.82],
       [34.73]], dtype=float32), array([[34.68],
       [34.82],
       [34.73],
       [34.53]], dtype=float32), array([[34.82],
       [34.73],
       [34.53],
       [34.57]], dtype=float32), array([[34.73],
       [34.53],
       [34.57],
       [34.58]], dtype=float32), array([[34.53],
```

In [46]:

```
X_train
```

Out[46]:

```
tensor([[[ 34.7300],
         [ 34.7300],
         [ 34.7300],
         [ 34.7300]],

        [[ 34.7300],
         [ 34.7300],
         [ 34.7300],
         [ 34.7300]],

        [[ 34.7300],
         [ 34.7300],
         [ 34.7300],
         [ 34.7300]],

        ...,

        [[383.2900],
         [380.9090],
         [377.8690],
         [369.3380]],

        [[380.9090],
         [377.8690],
         [369.3380],
         [355.0250]],

        [[377.8690],
         [369.3380],
         [355.0250],
         [346.4000]]])
```

In [50]:

```
class gold(nn.Module):
    def __init__(self):
        super().__init__()
        self.lstm = nn.LSTM(input_size=1, hidden_size=50, num_layers=1, batch_first=True)
        self.linear = nn.Linear(50, 1)
    def forward(self, x):
        x, _ = self.lstm(x)
        x = self.linear(x)
        return x

model = gold()
optimizer = optim.Adam(model.parameters())
loss_fn = nn.MSELoss()
loader = data.DataLoader(data.TensorDataset(X_train, y_train), shuffle=True, batch_size=8
```

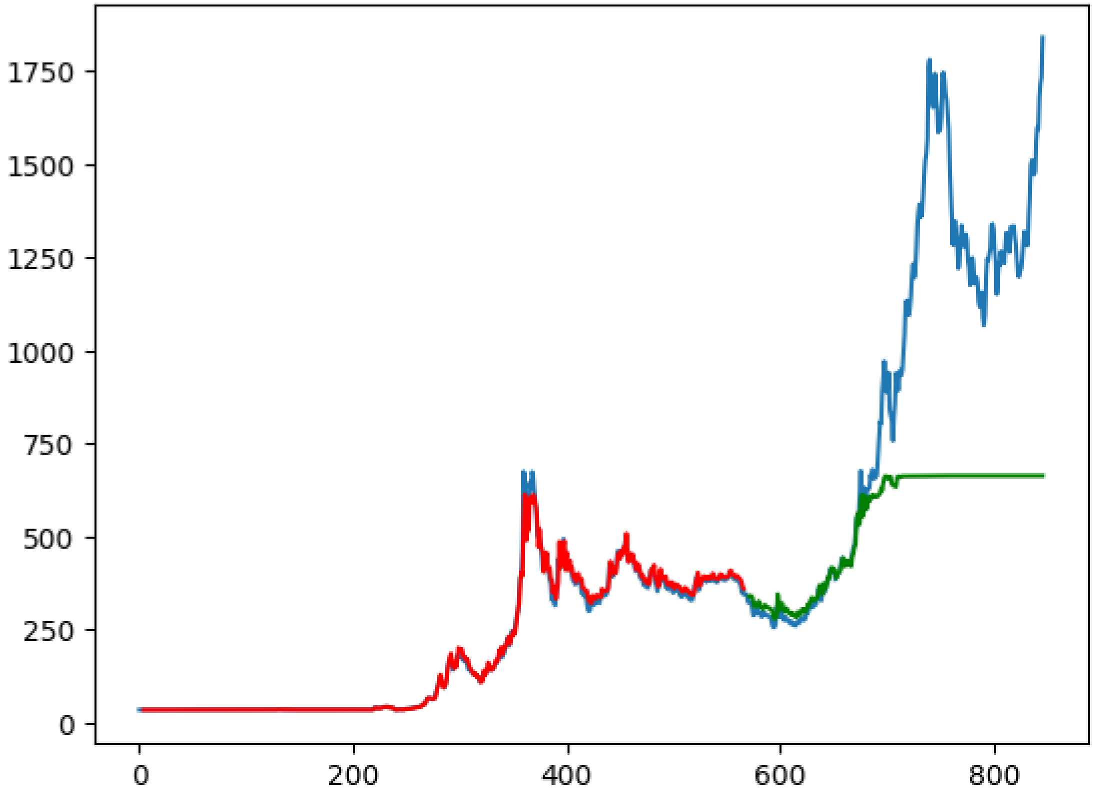
In [51]:

```
n_epochs = 2000
for epoch in range(n_epochs):
    model.train()
    for X_batch, y_batch in loader:
        y_pred = model(X_batch)
        loss = loss_fn(y_pred, y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
    # Validation
    if epoch % 100 != 0:
        continue
    model.eval()
    with torch.no_grad():
        y_pred = model(X_train)
        train_rmse = np.sqrt(loss_fn(y_pred, y_train))
        y_pred = model(X_test)
        test_rmse = np.sqrt(loss_fn(y_pred, y_test))
    print("Epoch %d: train RMSE %.4f, test RMSE %.4f" % (epoch, train_rmse, test_rmse))
```

```
Epoch 0: train RMSE 254.0666, test RMSE 1003.0829
Epoch 100: train RMSE 88.3600, test RMSE 776.8701
Epoch 200: train RMSE 31.4078, test RMSE 646.7322
Epoch 300: train RMSE 23.1997, test RMSE 587.2918
Epoch 400: train RMSE 18.8090, test RMSE 560.5261
Epoch 500: train RMSE 16.2786, test RMSE 533.0656
Epoch 600: train RMSE 16.9624, test RMSE 541.2823
Epoch 700: train RMSE 18.2819, test RMSE 549.5848
Epoch 800: train RMSE 18.4295, test RMSE 532.7458
Epoch 900: train RMSE 15.2706, test RMSE 511.0143
Epoch 1000: train RMSE 15.9632, test RMSE 511.8165
Epoch 1100: train RMSE 14.7618, test RMSE 494.6883
Epoch 1200: train RMSE 15.5362, test RMSE 483.8882
Epoch 1300: train RMSE 15.8004, test RMSE 487.6682
Epoch 1400: train RMSE 14.5671, test RMSE 484.6274
Epoch 1500: train RMSE 15.0636, test RMSE 485.3816
Epoch 1600: train RMSE 15.7495, test RMSE 493.0474
Epoch 1700: train RMSE 17.5488, test RMSE 479.3979
Epoch 1800: train RMSE 15.1222, test RMSE 496.6671
Epoch 1900: train RMSE 17.3245, test RMSE 534.6686
```

In [53]:

```
with torch.no_grad():
    # shift train predictions for plotting
    train_plot = np.ones_like(timeseries) * np.nan
    y_pred = model(X_train)
    y_pred = y_pred[:, -1, :]
    train_plot [lookback:train_size] = model(X_train)[:, -1, :]
    # shift test predictions for plotting
    test_plot = np.ones_like(timeseries) * np.nan
    test_plot[train_size+lookback:len(timeseries)] = model(X_test)[:, -1, :]
# plot
plt.plot(timeseries)
plt.plot(train_plot, c='r')
plt.plot(test_plot, c='g')
plt.show()
```



In [ ]: