In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [2]:

```
df = pd.read_csv("gold_price_data.csv")
# LET IMPORT OUR DATA DOE GOLD PREDICTION.
```

In [3]:

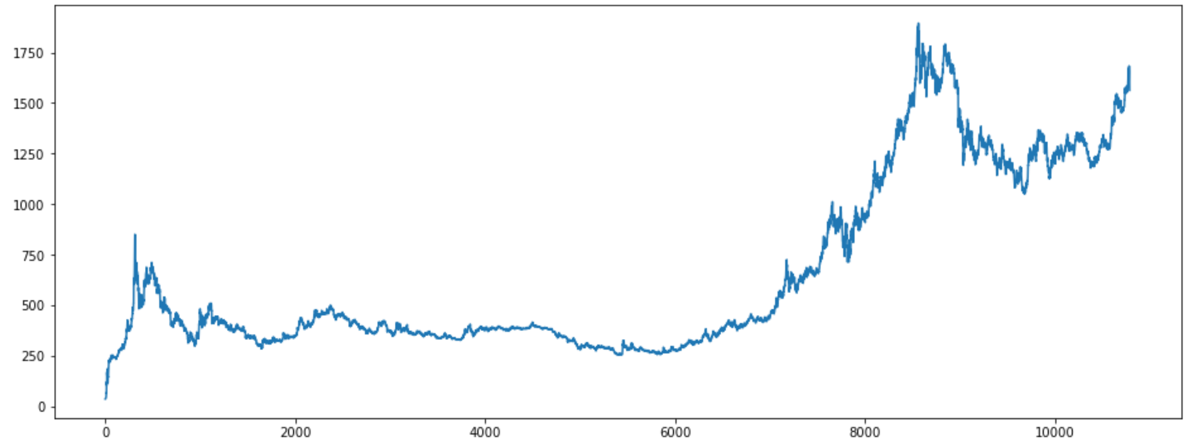
```
df.head()
```

Out[3]:

	Date	Value
0	1970-01-01	35.2
1	1970-04-01	35.1
2	1970-07-01	35.4
3	1970-10-01	36.2
4	1971-01-01	37.4

In [4]:

```
plt.figure(figsize=(16,6))
plt.plot(df["Value"])
plt.show()
```

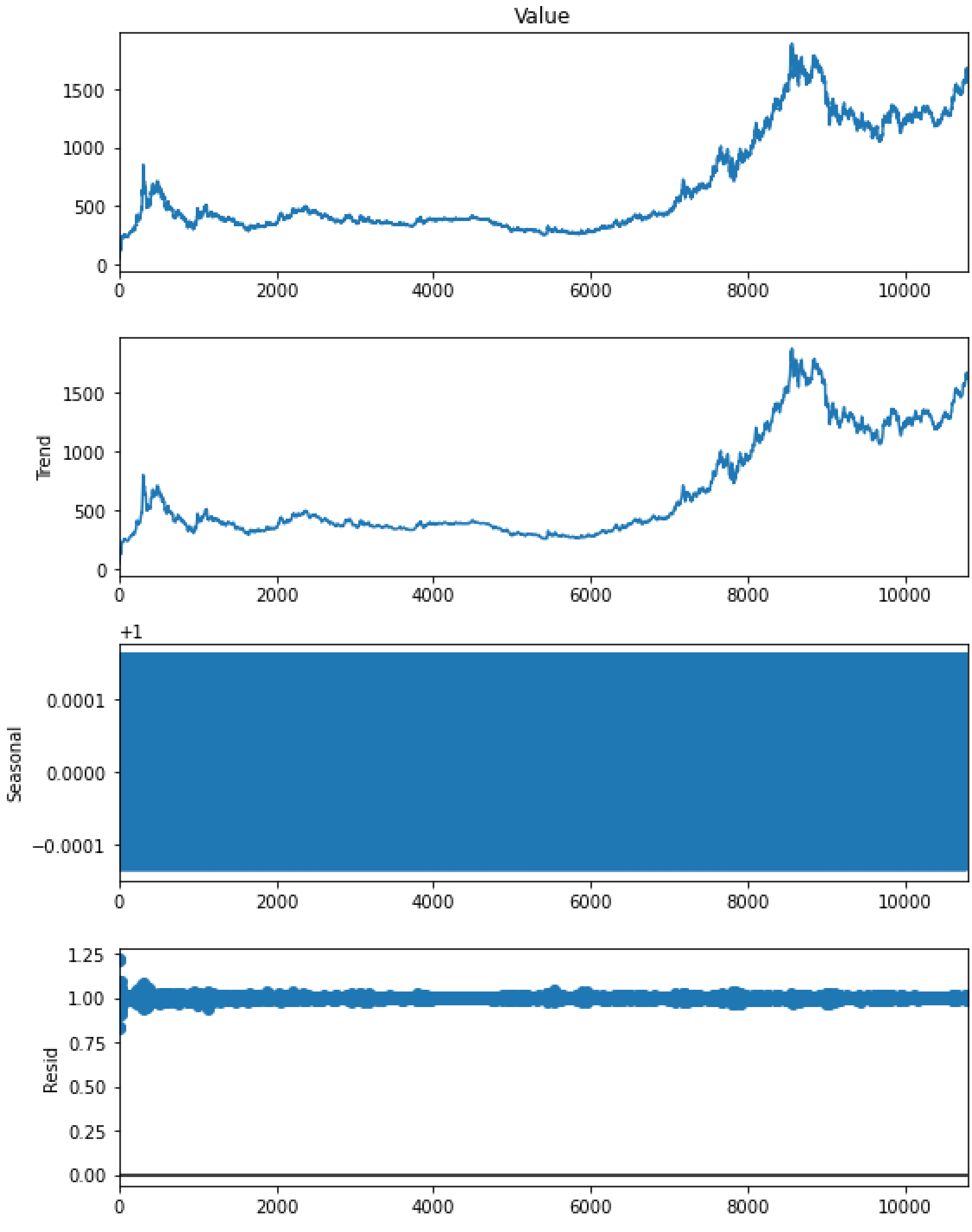


In [5]:

```
result = seasonal_decompose(x=df["Value"], model ="multiplicative", period=4)
```

In [6]:

```
plt.rcParams.update({'figure.figsize': (8,10)})
result.plot()
plt.show()
```



There is Trend and Possible Sesonality

In [7]:

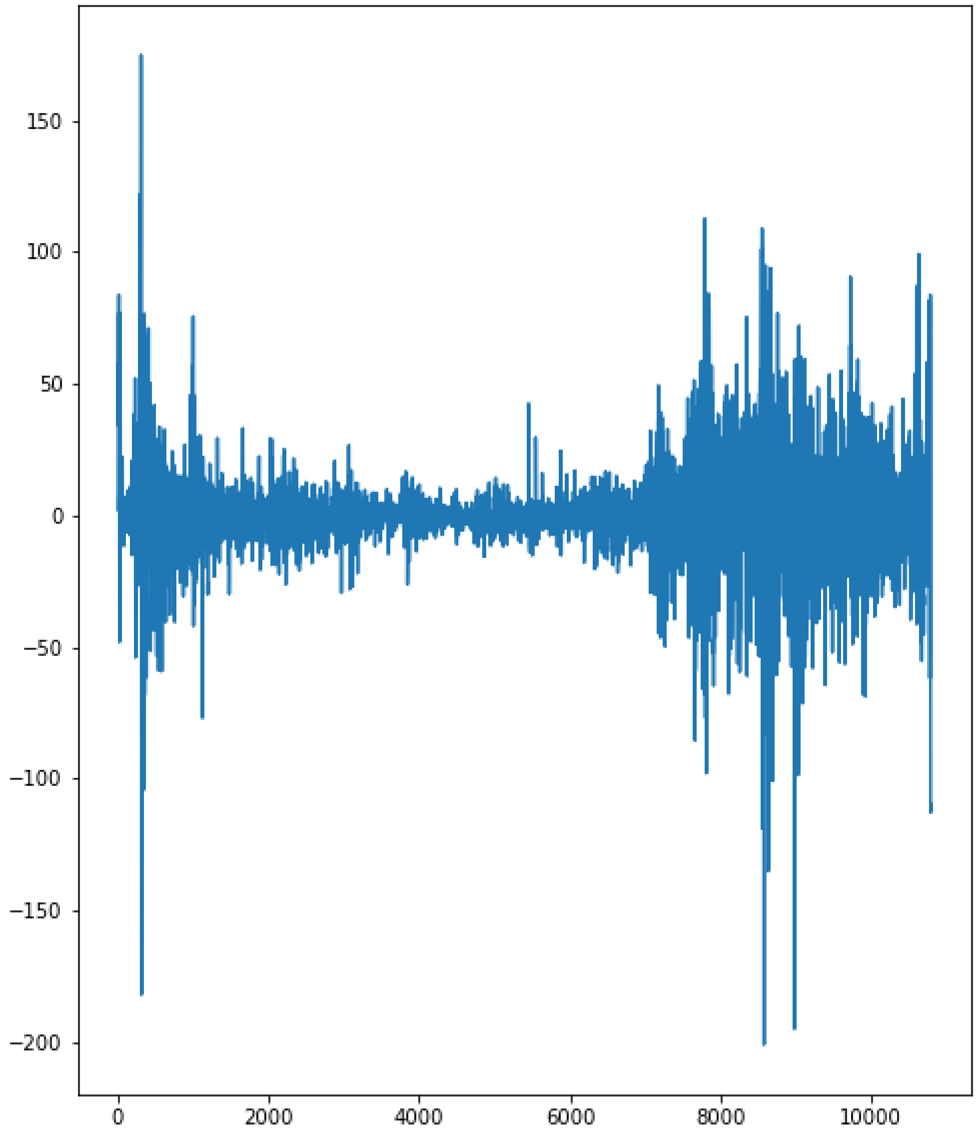
```
difference = df["Value"] - df["Value"].shift(4)
```

In [8]:

```
plt.plot(difference.dropna())
```

Out[8]:

```
[<matplotlib.lines.Line2D at 0x297fee7c190>]
```



In [10]:

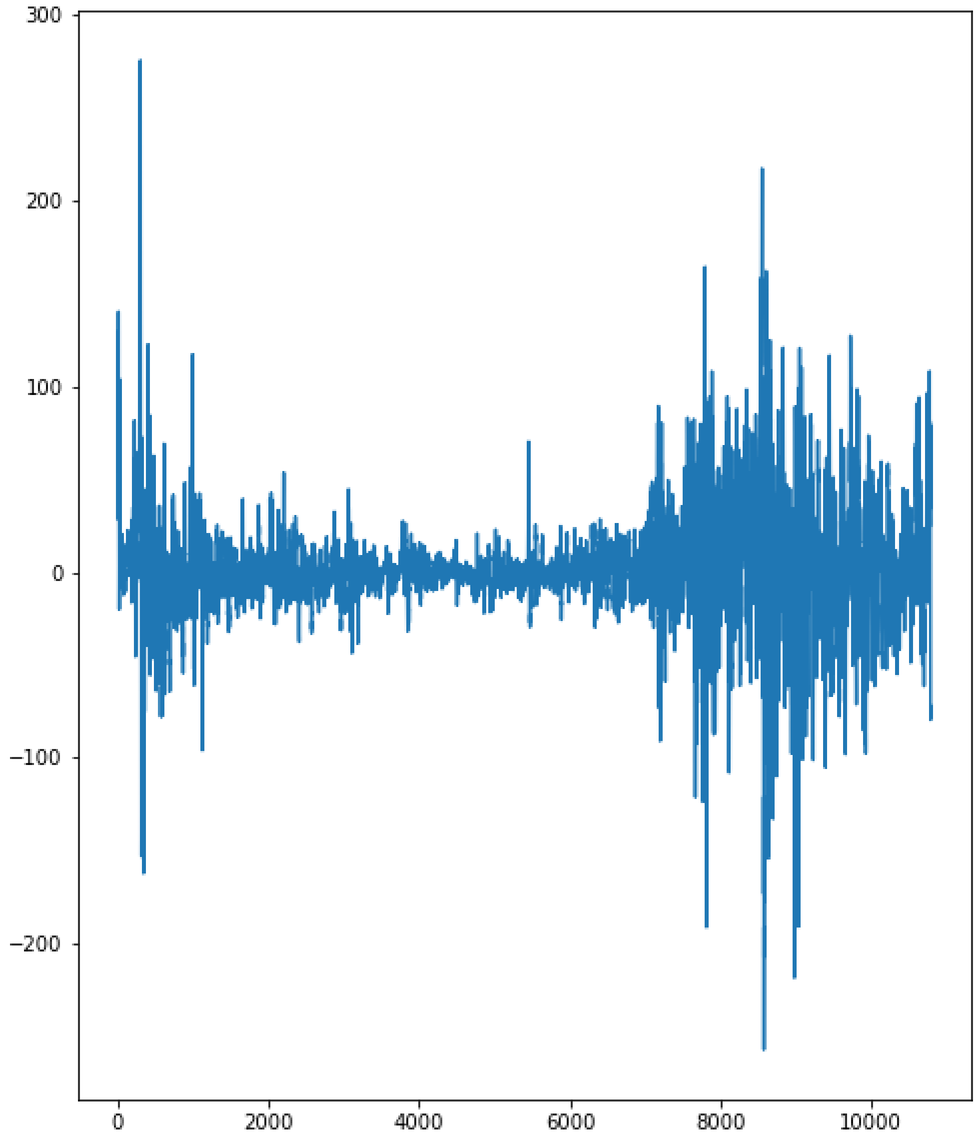
```
seasonal_difference = df["Value"] - df["Value"].shift(12)
```

In [11]:

```
plt.plot(seasonal_difference.dropna())
```

Out[11]:

```
[<matplotlib.lines.Line2D at 0x297914b1490>]
```



In [12]:

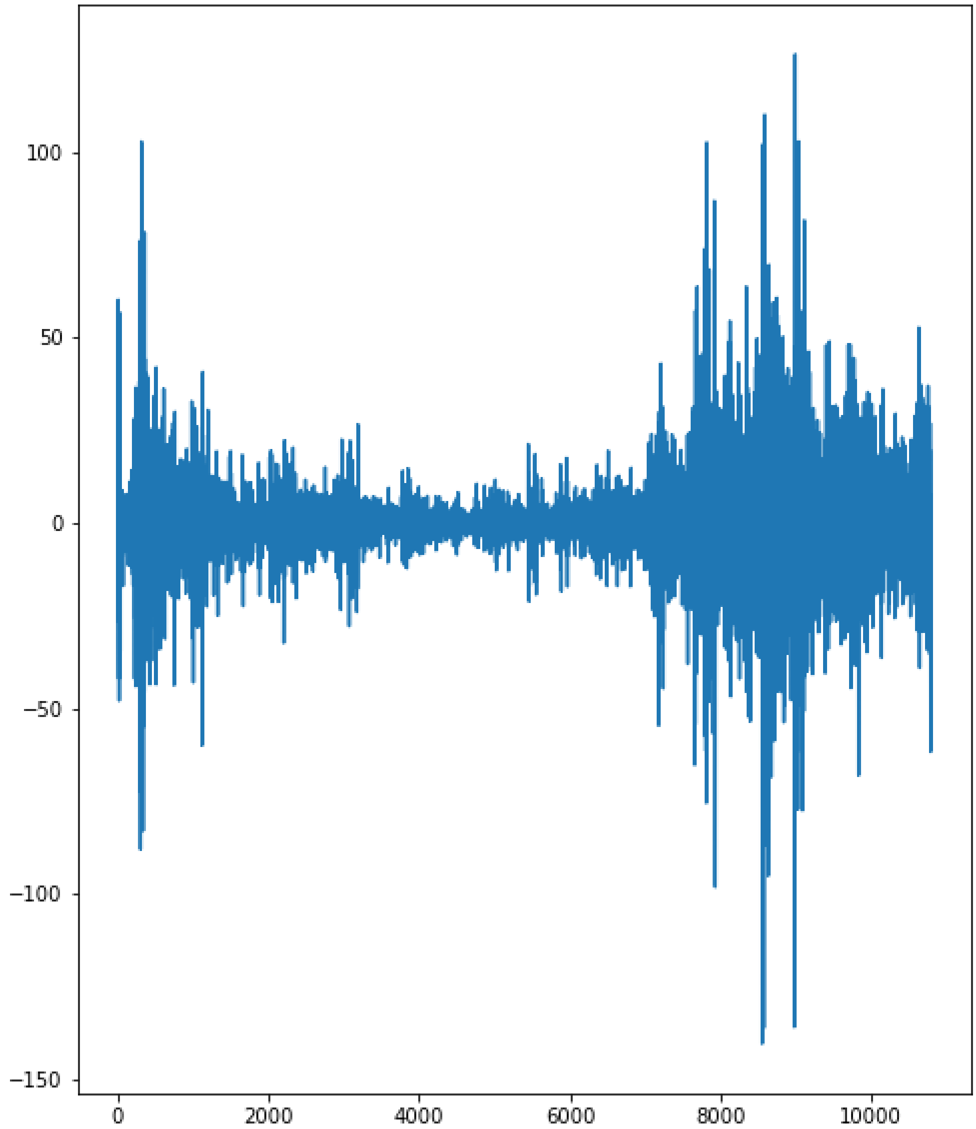
```
double_difference = seasonal_difference - seasonal_difference.shift(1)
```

In [13]:

```
plt.plot(double_difference.dropna())
```

Out[13]:

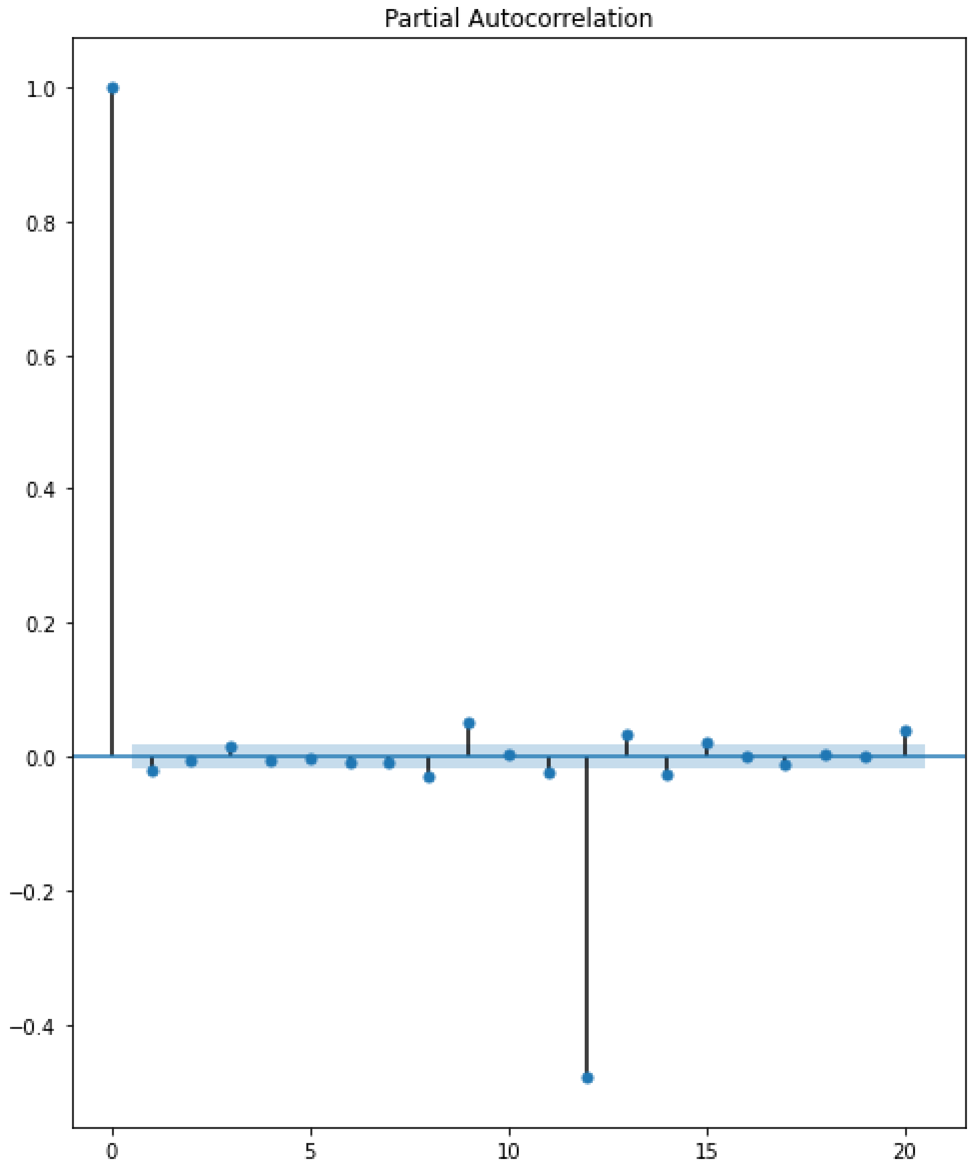
```
[<matplotlib.lines.Line2D at 0x297914ffaf0>]
```



We have done second order difference hence d = 2

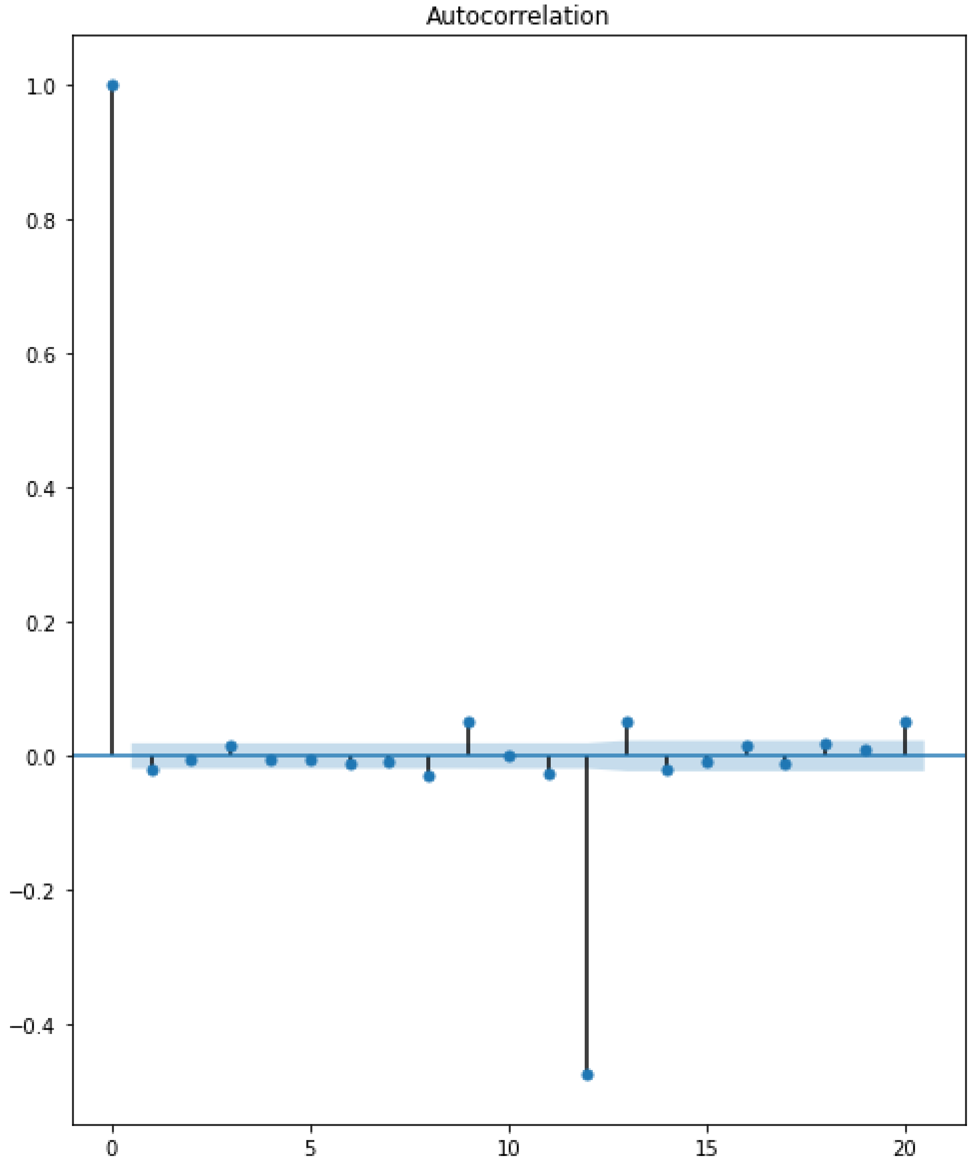
In [14]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_pacf(double_difference.dropna(), lags=20)
plt.show()
```



In [15]:

```
plot_acf(double_difference.dropna(), lags=20)
plt.show()
```




```
Value of p = 1, d = 2, q = 1
```

In [19]:

```
df["Value"].shape
```

Out[19]:

```
(10787,)
```

Now lets move to use ARIMA model.

ARIMA is an acronym for “autoregressive integrated moving average.” It's a model used in statistics and econometrics to measure events that happen over a period of time. The model is used to understand past data or predict future data in a series.

In [20]:

```
from statsmodels.tsa.arima_model import ARIMA
```

In [44]:

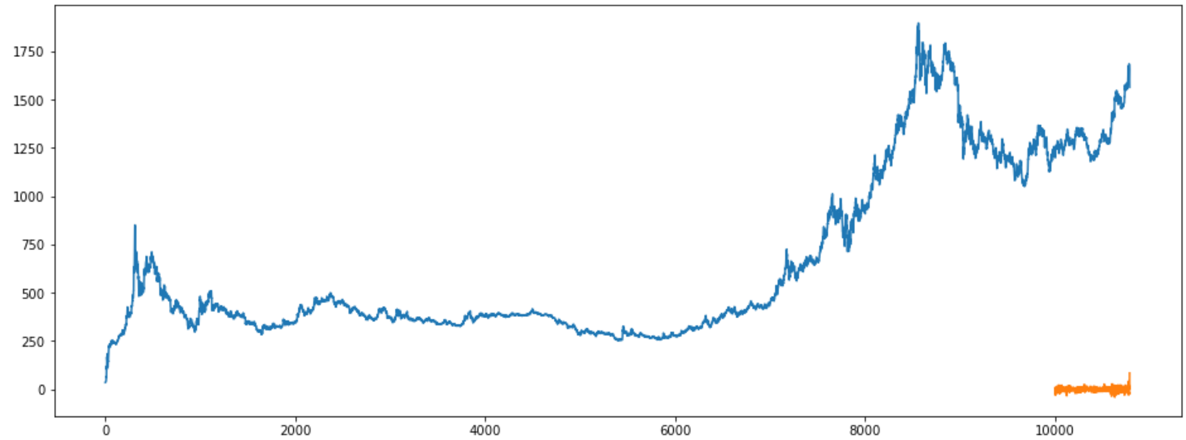
```
model=ARIMA(df["Value"],order=(1,2,1))
model=model.fit()
```

In [46]:

```
df["forecast"] = model.predict(start=10000, end=11000)
```

In [49]:

```
plt.figure(figsize=(16,6))
plt.plot(df[["Value","forecast"]])
plt.show()
```



The prediction is not what we expect, this might be because of residuals or trend or sesonality. Lets try SARIMAX

We are using SARIMAX since there is sesonality present there.

In [52]:

```
import statsmodels.api as sm
import warnings
warnings.filterwarnings("ignore")
```

In [53]:

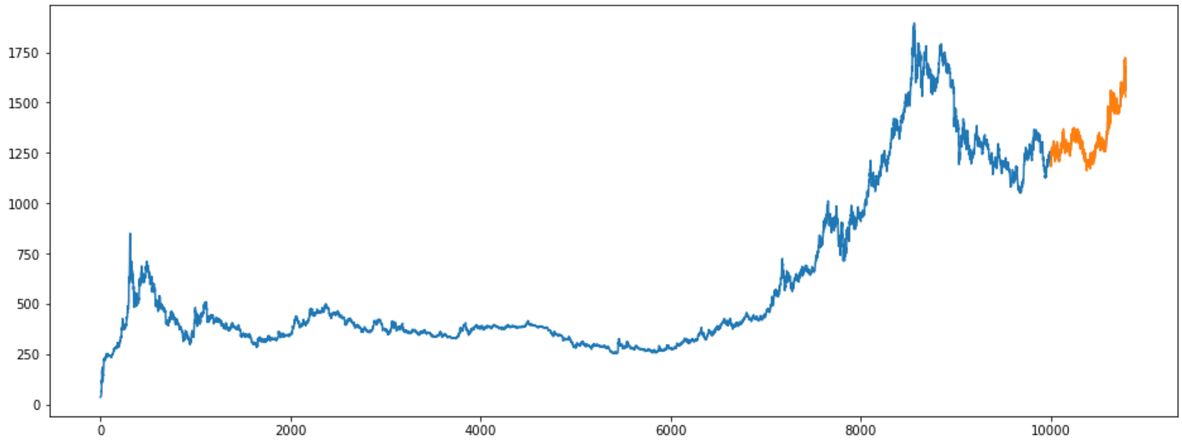
```
model = sm.tsa.statespace.SARIMAX(df['Value'],order=(1, 2, 1),seasonal_order=(1,2,1,4), tre
model = model.fit()
```

In [54]:

```
df['forecast2']=model.predict(start=10000,end=11000)
```

In [56]:

```
plt.figure(figsize=(16,6))
plt.plot(df[["Value","forecast2"]])
plt.show()
```



Lets MOve to using Simple ANN

In [22]:

```
df = pd.read_csv("gold_price_data.csv")
df.head()
```

Out[22]:

	Date	Value
0	1970-01-01	35.2
1	1970-04-01	35.1
2	1970-07-01	35.4
3	1970-10-01	36.2
4	1971-01-01	37.4

In [23]:

```
df.shape
```

Out[23]:

```
(10787, 2)
```

In [24]:

```
train =df["Value"][:7550]
test = df["Value"][7550:]
```

In [25]:

```
train.shape
```

Out[25]:

```
(7550,)
```

In [26]:

```
test.shape
```

Out[26]:

```
(3237,)
```

In [27]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,SimpleRNN, LSTM

from sklearn.preprocessing import MinMaxScaler

from sklearn.metrics import mean_squared_error

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

In [28]:

```

scaler = MinMaxScaler()
train_scaled = scaler.fit_transform(np.array(train).reshape(-1,1))
test_scaled = scaler.transform(np.array(test).reshape(-1,1))
```

In [29]:

```
#Array values converted to matrix data set
def create_dataset(dataset, time_step=1):
    X, y = [], []
    for i in range(len(dataset)-time_step-1):
        sample = dataset[i:(i+time_step), 0]
        X.append(sample)
        y.append(dataset[i + time_step, 0])
    return np.array(X), np.array(y)
```

Converting the data in order to make it feasible for Neural Network

In [30]:

```
time_step = 50
X_train, y_train = create_dataset(train_scaled, time_step)
X_test, y_test = create_dataset(test_scaled, time_step)
```

In [31]:

```
# reshape into (samples, time steps, features)
X_train = X_train.reshape(X_train.shape[0],X_train.shape[1] , 1)
X_test  = X_test.reshape(X_test.shape[0],X_test.shape[1] , 1)
```

In [32]:

```
model = Sequential()
model.add(SimpleRNN(32, return_sequences=True, input_shape=(time_step,1)))
model.add(SimpleRNN(32))
model.add(Dense(1))
model.compile(loss='mean_squared_error',optimizer='adam')
```

In [33]:

```
model.fit(X_train,y_train, epochs=20, batch_size=32)
```

```
Epoch 1/20
235/235 [==============================] - 5s 14ms/step - loss: 0.0066
Epoch 2/20
235/235 [==============================] - 3s 13ms/step - loss: 1.3104e-04
Epoch 3/20
235/235 [==============================] - 3s 14ms/step - loss: 1.0290e-04
Epoch 4/20
235/235 [==============================] - 3s 14ms/step - loss: 8.8516e-05
Epoch 5/20
235/235 [==============================] - 3s 14ms/step - loss: 1.2146e-04
Epoch 6/20
235/235 [==============================] - 3s 14ms/step - loss: 1.5285e-04
Epoch 7/20
235/235 [==============================] - 3s 14ms/step - loss: 1.9823e-04
Epoch 8/20
235/235 [==============================] - 3s 14ms/step - loss: 8.8392e-05
Epoch 9/20
235/235 [==============================] - 3s 14ms/step - loss: 8.5812e-05
Epoch 10/20
235/235 [==============================] - 3s 14ms/step - loss: 9.6429e-05
Epoch 11/20
235/235 [==============================] - 3s 14ms/step - loss: 1.1541e-04
Epoch 12/20
235/235 [==============================] - 3s 14ms/step - loss: 1.1538e-04
Epoch 13/20
235/235 [==============================] - 3s 14ms/step - loss: 9.7159e-05
Epoch 14/20
235/235 [==============================] - 3s 14ms/step - loss: 9.6886e-05
Epoch 15/20
235/235 [==============================] - 3s 14ms/step - loss: 9.3108e-05
Epoch 16/20
235/235 [==============================] - 3s 14ms/step - loss: 8.1992e-05:
Epoch 17/20
235/235 [==============================] - 3s 14ms/step - loss: 8.8487e-05
Epoch 18/20
235/235 [==============================] - 3s 14ms/step - loss: 9.6077e-05
Epoch 19/20
235/235 [==============================] - 3s 14ms/step - loss: 1.0486e-04
Epoch 20/20
235/235 [==============================] - 3s 14ms/step - loss: 6.8417e-05
```

Out[33]:

```
<tensorflow.python.keras.callbacks.History at 0x2979f9afa60>
```

In [34]:

```
y_pred = model.predict(X_test)
mean_squared_error(y_test,y_pred)
```

Out[34]:

```
0.0722704488194497
```

In [35]:

```
plt.figure(figsize=(16,6))
plt.plot(scaler.inverse_transform(np.array(y_test).reshape(-1,1)))
plt.plot(scaler.inverse_transform(y_pred))
plt.show()
```

Now we use LSTM Model to predict.

The LSTM model is a type of RNN model that will learn a function that maps a sequence of past observations as input to an further outputs.

In [36]:

```
model = Sequential()
model.add(LSTM(32, return_sequences=True, input_shape=(time_step,1)))
model.add(LSTM(32, return_sequences=True))
model.add(LSTM(32))
model.add(Dense(1))
model.compile(loss='mean_squared_error',optimizer='adam')
```

In [37]:

```
model.fit(X_train,y_train, epochs=50, batch_size=32)
```

```
Epoch 1/50
235/235 [==============================] - 16s 45ms/step - loss: 0.0202 1s -
loss: 0.0 - ETA: 0s - l
Epoch 2/50
235/235 [==============================] - 10s 41ms/step - loss: 4.2216e-04
Epoch 3/50
235/235 [==============================] - 10s 41ms/step - loss: 4.3771e-04
Epoch 4/50
235/235 [==============================] - 10s 41ms/step - loss: 3.2887e-04
Epoch 5/50
235/235 [==============================] - 9s 40ms/step - loss: 3.0652e-04
Epoch 6/50
235/235 [==============================] - 9s 40ms/step - loss: 2.5349e-04
Epoch 7/50
235/235 [==============================] - 10s 41ms/step - loss: 2.2828e-04
Epoch 8/50
235/235 [==============================] - 9s 40ms/step - loss: 2.5157e-04
Epoch 9/50
235/235 [==============================] - 9s 40ms/step - loss: 1.7881e-04
Epoch 10/50
235/235 [==============================] - 9s 40ms/step - loss: 1.7458e-04
Epoch 11/50
235/235 [==============================] - 9s 40ms/step - loss: 2.1181e-04
Epoch 12/50
235/235 [==============================] - 10s 41ms/step - loss: 1.7323e-04
0s - loss
Epoch 13/50
235/235 [==============================] - 9s 40ms/step - loss: 1.2793e-04
Epoch 14/50
235/235 [==============================] - 10s 42ms/step - loss: 1.1975e-04
Epoch 15/50
235/235 [==============================] - 10s 42ms/step - loss: 9.6940e-05
Epoch 16/50
235/235 [==============================] - 10s 42ms/step - loss: 1.0118e-04
Epoch 17/50
235/235 [==============================] - 10s 41ms/step - loss: 9.3721e-05
Epoch 18/50
235/235 [==============================] - 10s 44ms/step - loss: 8.2913e-05
0s - loss: 8.277
Epoch 19/50
235/235 [==============================] - 10s 44ms/step - loss: 9.2974e-05
Epoch 20/50
235/235 [==============================] - 10s 43ms/step - loss: 8.0123e-05
Epoch 21/50
235/235 [==============================] - 10s 42ms/step - loss: 8.4754e-05
Epoch 22/50
235/235 [==============================] - 10s 43ms/step - loss: 8.3024e-05
Epoch 23/50
235/235 [==============================] - 10s 43ms/step - loss: 5.9719e-05
Epoch 24/50
235/235 [==============================] - 10s 44ms/step - loss: 6.9351e-05
Epoch 25/50
235/235 [==============================] - 10s 44ms/step - loss: 7.5569e-05
Epoch 26/50
235/235 [==============================] - 10s 43ms/step - loss: 7.9095e-05
Epoch 27/50
235/235 [==============================] - 10s 44ms/step - loss: 7.6704e-05
```

```
Epoch 28/50
235/235 [==============================] - 10s 43ms/step - loss: 7.9571e-05
Epoch 29/50
235/235 [==============================] - 10s 44ms/step - loss: 7.3318e-05
Epoch 30/50
235/235 [==============================] - 10s 44ms/step - loss: 7.3396e-05
Epoch 31/50
235/235 [==============================] - 10s 43ms/step - loss: 6.9684e-05
Epoch 32/50
235/235 [==============================] - 10s 43ms/step - loss: 7.4595e-05
Epoch 33/50
235/235 [==============================] - 10s 41ms/step - loss: 8.3897e-05
Epoch 34/50
235/235 [==============================] - 9s 40ms/step - loss: 6.9925e-05
Epoch 35/50
235/235 [==============================] - 9s 40ms/step - loss: 6.3249e-05
Epoch 36/50
235/235 [==============================] - 9s 40ms/step - loss: 6.2737e-05
Epoch 37/50
235/235 [==============================] - 9s 40ms/step - loss: 6.3945e-05
Epoch 38/50
235/235 [==============================] - 10s 41ms/step - loss: 6.6638e-05
Epoch 39/50
235/235 [==============================] - 10s 42ms/step - loss: 6.6165e-05
Epoch 40/50
235/235 [==============================] - 12s 52ms/step - loss: 8.1006e-05
Epoch 41/50
235/235 [==============================] - 12s 50ms/step - loss: 6.9596e-05
Epoch 42/50
235/235 [==============================] - 12s 51ms/step - loss: 6.7506e-05
Epoch 43/50
235/235 [==============================] - 12s 51ms/step - loss: 6.9058e-05
Epoch 44/50
235/235 [==============================] - 12s 51ms/step - loss: 5.7760e-05
Epoch 45/50
235/235 [==============================] - 12s 51ms/step - loss: 6.5304e-05
Epoch 46/50
235/235 [==============================] - 12s 50ms/step - loss: 6.7570e-05
Epoch 47/50
235/235 [==============================] - 12s 51ms/step - loss: 6.7598e-05
Epoch 48/50
235/235 [==============================] - 12s 51ms/step - loss: 6.6122e-05
Epoch 49/50
235/235 [==============================] - 12s 51ms/step - loss: 6.5834e-05
Epoch 50/50
235/235 [==============================] - 12s 51ms/step - loss: 5.8896e-05
```

Out[37]:

```
<tensorflow.python.keras.callbacks.History at 0x297a42213d0>
```

In [38]:

```
y_pred = model.predict(X_test)
mean_squared_error(y_test,y_pred)
```

Out[38]:

```
0.05043307465437072
```

In [39]:

```
plt.figure(figsize=(16,6))
plt.plot(scaler.inverse_transform(np.array(y_test).reshape(-1,1)))
plt.plot(scaler.inverse_transform(y_pred))
plt.show()
```

In [40]:

```
days = 50
last_input = X_test[-1]
last_output = y_pred[-1]
y_forecast = []

for i in range(1,days+1):
    last_input = np.append(last_input[1:], last_output)
    last_output = model.predict(last_input.reshape(1,50,1))
    y_forecast.append(last_output[0][0])
```

In [41]:

```
all_predictions = np.append(y_pred,y_forecast)
```

In [42]:

```
plt.figure(figsize=(16,6))
plt.plot(scaler.inverse_transform(np.array(y_test).reshape(-1,1)))
plt.plot(scaler.inverse_transform(all_predictions.reshape(-1,1)))
plt.show()
```

The prediction obtained here is dropping off this shows the initial data as a whole needs some proper preproccessing, also it might still have sesonality and trend at a local scale since the data is very vast.

In [ ]: