In [1]:
```
### Daily Gold Price (2015-2021) Time Series
```

Content

Daily gold prices (2014-01-01 to 2021-12-29)

Acknowledgements

Raw Data Source: https://in.investing.com/commodities/gold-mini This data frame is preprocessed to time series analysis and forecasting

Inspiration

Forecast, Predict Prices, Time Series Forecasting

Note

Gold Prices in this dataset makes no guarantee or warranty on the accuracy or completeness of the data provided.

In [2]:
```
##!mkdir ~/.kaggle
```

In [3]:
```
##!cp ./kaggle.json ~/.kaggle/
```

In [4]:
```
##!chmod 600 ~/.kaggle/kaggle.json
```

In [5]:
```
##! pip install kaggle
```

In [6]:
```
##!pip install keras-tuner
```

In [7]:
```
##! kaggle datasets download -d nisargchodavadiya/daily-gold-price-20152021-time-series
```

In [8]:
```
#! unzip ./daily-gold-price-20152021-time-series.zip
```

In [9]:
```
#! pip install tensorflow
```

In [10]:
```
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn import preprocessing
import matplotlib.pyplot as plt
tf.random.set_seed(123)
np.random.seed(123)
```

In [11]:
```
import pandas as pd
#import fbprophet
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

In [12]:
```
df=pd.read_csv('./Gold Price.csv')
df.head(3)
```

Out[12]:

	Date	Price	Open	High	Low	Volume	Chg%
0	2014-01-01	29542	29435	29598	29340	2930	0.25
1	2014-01-02	29975	29678	30050	29678	3140	1.47
2	2014-01-03	29727	30031	30125	29539	3050	-0.83

In [13]:
```
df.columns
```
Out[13]:
```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')
```
In [14]:
```
df.describe()
```
Out[14]:

	Price	Open	High	Low	Volume	Chg%
count	2072.000000	2072.000000	2072.000000	2072.000000	2072.000000	2072.000000
mean	34072.025579	34074.013514	34262.575772	33878.503378	13741.028475	0.026810
std	8205.749351	8209.173030	8267.486025	8133.066425	11487.027573	0.859132
min	24545.000000	24583.000000	24635.000000	24470.000000	0.000000	-5.980000
25%	28427.500000	28412.500000	28530.000000	28263.750000	6677.500000	-0.410000
50%	30423.000000	30399.000000	30547.500000	30267.000000	11595.000000	0.020000
75%	38948.000000	38983.250000	39385.250000	38655.000000	18360.000000	0.460000
max	56117.000000	56351.000000	56499.000000	55400.000000	106920.000000	5.300000

In [15]:
```
### Check if there is any null values
```
In [16]:
```
df.isnull().sum()
```
Out[16]:
```
Date      0
Price     0
Open      0
High      0
Low       0
Volume    0
Chg%      0
dtype: int64
```
In [17]:
```
le = preprocessing.LabelEncoder()
```
In [18]:
```
df['Date'] = le.fit_transform(df['Date'])
```
In [19]:
```
df.describe()
```
Out[19]:

	Date	Price	Open	High	Low	Volume	Chg%
count	2072.000000	2072.000000	2072.000000	2072.000000	2072.000000	2072.000000	2072.000000
mean	1035.500000	34072.025579	34074.013514	34262.575772	33878.503378	13741.028475	0.026810
std	598.279199	8205.749351	8209.173030	8267.486025	8133.066425	11487.027573	0.859132
min	0.000000	24545.000000	24583.000000	24635.000000	24470.000000	0.000000	-5.980000
25%	517.750000	28427.500000	28412.500000	28530.000000	28263.750000	6677.500000	-0.410000
50%	1035.500000	30423.000000	30399.000000	30547.500000	30267.000000	11595.000000	0.020000
75%	1553.250000	38948.000000	38983.250000	39385.250000	38655.000000	18360.000000	0.460000
max	2071.000000	56117.000000	56351.000000	56499.000000	55400.000000	106920.000000	5.300000

In [20]:
```
df.columns
```
Out[20]:
```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')
```

In [21]:

```
def custom_ts_multi_data_prep(dataset, target, start, end, window, horizon):
    X = []
    y = []
    start = start + window
    if end is None:
        end = len(dataset) - horizon

    for i in range(start, end):
        indices = range(i-window, i)
        X.append(dataset[indices])

        indicey = range(i+1, i+1+horizon)
        y.append(target[indicey])
    return np.array(X), np.array(y)
```

In [22]:

```
validate = df[['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%']].tail(10)
```

In [23]:

```
x_scaler = preprocessing.MinMaxScaler()
y_scaler = preprocessing.MinMaxScaler()
dataX = x_scaler.fit_transform(df[['Date', 'Open', 'High', 'Low', 'Volume', 'Chg%']])
dataY = y_scaler.fit_transform(df[['Price']])
```

In [24]:

```
hist_window = 48
horizon = 10
TRAIN_SPLIT = 1800
x_train_multi, y_train_multi = custom_ts_multi_data_prep(
    dataX, dataY, 0, TRAIN_SPLIT, hist_window, horizon)
x_val_multi, y_val_multi = custom_ts_multi_data_prep(
    dataX, dataY, TRAIN_SPLIT, None, hist_window, horizon)
```

In [25]:

```
print ('Single window of past history')
print(x_train_multi[0])
print ('\n Target horizon')
print (y_train_multi[0])
```

```
Single window of past history
[[0.00000000e+00 1.52732309e-01 1.55755712e-01 1.57452312e-01
  2.74036663e-02 5.52304965e-01]
 [4.82858522e-04 1.60381516e-01 1.69940999e-01 1.68380213e-01
  2.93677516e-02 6.60460993e-01]
 [9.65717045e-04 1.71493327e-01 1.72294753e-01 1.63886195e-01
  2.85260007e-02 4.56560284e-01]
 [1.44857557e-03 1.47821707e-01 1.45744414e-01 1.55480116e-01
  0.00000000e+00 3.96276596e-01]
 [1.93143409e-03 1.48482750e-01 1.49384886e-01 1.48108632e-01
  2.28020950e-01 4.81382979e-01]
 [2.41429261e-03 1.43131453e-01 1.43108210e-01 1.43614614e-01
  1.74990647e-01 4.81382979e-01]
 [2.89715113e-03 1.36395115e-01 1.37898569e-01 1.40640155e-01
  1.69659559e-01 5.22163121e-01]
 [3.38000966e-03 1.38724503e-01 1.38651770e-01 1.42095053e-01
  1.41507669e-01 5.49645390e-01]
 [3.86286818e-03 1.39983631e-01 1.43202360e-01 1.45166505e-01
  1.47867565e-01 5.82446809e-01]
 [4.34572670e-03 1.44390582e-01 1.47344966e-01 1.50759780e-01
  1.28881407e-01 5.73581560e-01]
 [4.82858522e-03 1.48136490e-01 1.49227969e-01 1.51471064e-01
  9.91395436e-02 4.95567376e-01]
 [5.31144375e-03 1.44107278e-01 1.42637459e-01 1.46524410e-01
  1.30751964e-01 5.15957447e-01]
 [5.79430227e-03 1.44233191e-01 1.44834296e-01 1.49369544e-01
  1.17658062e-01 5.35460993e-01]
 [6.27716079e-03 1.43194409e-01 1.50012553e-01 1.48205626e-01
  1.64983165e-01 5.95744681e-01]
 [6.76001931e-03 1.51945354e-01 1.52648757e-01 1.59133527e-01
  8.82903105e-02 5.39007092e-01]
 [7.24287784e-03 1.51378746e-01 1.49887020e-01 1.54736502e-01
  1.70314254e-01 5.14184397e-01]
 [7.72573636e-03 1.50182574e-01 1.50357771e-01 1.54025218e-01
  1.39356528e-01 5.01773050e-01]
```

```
 [8.20859488e-03 1.46279275e-01 1.51675872e-01 1.50210152e-01
  2.88439955e-01 5.68262411e-01]
 [8.69145340e-03 1.51599093e-01 1.58831283e-01 1.57613967e-01
  1.90703330e-01 5.84219858e-01]
 [9.17431193e-03 1.60507429e-01 1.66143610e-01 1.68509538e-01
  2.06883651e-01 6.29432624e-01]
 [9.65717045e-03 1.66456812e-01 1.64323374e-01 1.65405755e-01
  1.69566031e-01 4.47695035e-01]
 [1.01400290e-02 1.56981869e-01 1.64919659e-01 1.61946330e-01
  1.69659559e-01 5.92198582e-01]
 [1.06228875e-02 1.65764291e-01 1.65641476e-01 1.61655351e-01
  1.48802843e-01 4.29964539e-01]
 [1.11057460e-02 1.54180307e-01 1.58297766e-01 1.57937278e-01
  1.42162364e-01 5.24822695e-01]
 [1.15886045e-02 1.54841350e-01 1.63664323e-01 1.59456838e-01
  1.09988777e-01 6.22340426e-01]
 [1.20714631e-02 1.61766558e-01 1.62754205e-01 1.63271904e-01
  2.95548073e-02 4.53900709e-01]
 [1.25543216e-02 1.55250567e-01 1.71510168e-01 1.63110249e-01
  4.19940142e-02 5.85992908e-01]
 [1.30371801e-02 1.47632838e-01 1.51048205e-01 1.53281604e-01
  1.73587729e-01 3.84751773e-01]
 [1.35200386e-02 1.47192143e-01 1.50797138e-01 1.54833495e-01
  1.36737748e-01 5.54078014e-01]
 [1.40028972e-02 1.50025183e-01 1.54217926e-01 1.57743291e-01
  1.11391695e-01 5.78900709e-01]
 [1.44857557e-02 1.54778393e-01 1.58956816e-01 1.62625283e-01
  1.37860082e-01 5.90425532e-01]
 [1.49686142e-02 1.59500126e-01 1.59710018e-01 1.65211769e-01
  1.00729517e-01 5.38120567e-01]
 [1.54514727e-02 1.59814908e-01 1.60463219e-01 1.66020045e-01
  1.16629256e-01 5.38120567e-01]
 [1.59343312e-02 1.62647948e-01 1.66771278e-01 1.70708050e-01
  1.10830527e-01 5.91312057e-01]
 [1.64171898e-02 1.69824981e-01 1.91313081e-01 1.77820886e-01
  2.60007482e-01 7.47340426e-01]
 [1.69000483e-02 1.89404432e-01 1.93164700e-01 1.95311995e-01
  1.70033670e-01 5.59397163e-01]
 [1.73829068e-02 1.92111559e-01 1.95518453e-01 1.91884901e-01
  1.93789749e-01 5.14184397e-01]
 [1.78657653e-02 1.91922689e-01 1.89712528e-01 1.95182671e-01
  1.16535728e-01 5.00000000e-01]
 [1.83486239e-02 1.89089650e-01 1.91877981e-01 1.95667637e-01
  1.15319865e-01 5.50531915e-01]
 [1.88314824e-02 1.90443213e-01 1.98970625e-01 1.99256385e-01
  1.20650954e-01 6.01950355e-01]
 [1.93143409e-02 1.99760766e-01 1.99723826e-01 2.05205302e-01
  1.19341564e-01 5.43439716e-01]
 [1.97971994e-02 2.00453286e-01 1.98782325e-01 2.00678952e-01
  1.37860082e-01 4.84042553e-01]
 [2.02800579e-02 1.98344246e-01 1.97150389e-01 2.04267701e-01
  4.12457912e-02 5.38120567e-01]
 [2.07629165e-02 1.96329640e-01 1.96459955e-01 1.97122535e-01
  1.51515152e-01 4.71631206e-01]
 [2.12457750e-02 1.92552254e-01 2.39894552e-01 2.01422567e-01
  5.30303030e-02 9.40602837e-01]
 [2.17286335e-02 2.17734827e-01 2.43032890e-01 2.14031684e-01
  1.22521511e-02 2.73936170e-01]
 [2.22114920e-02 2.08291362e-01 2.46830279e-01 2.03685742e-01
  1.39356528e-02 8.79432624e-01]
 [2.26943506e-02 1.81534878e-01 1.82368817e-01 1.82185580e-01
  2.01084923e-01 0.00000000e+00]]

 Target horizon
[[0.18313696]
 [0.18611428]
 [0.19263905]
 [0.1948562 ]
 [0.19555302]
 [0.19042189]
 [0.18510072]
 [0.17813252]
 [0.17037248]
```

In [26]:

```
BATCH_SIZE = 256
BUFFER_SIZE = 150

train_data_multi = tf.data.Dataset.from_tensor_slices((x_train_multi, y_train_multi))
train_data_multi = train_data_multi.cache().shuffle(BUFFER_SIZE).batch(BATCH_SIZE).repeat()

val_data_multi = tf.data.Dataset.from_tensor_slices((x_val_multi, y_val_multi))
val_data_multi = val_data_multi.batch(BATCH_SIZE).repeat()
```

```
2022-04-13 13:58:53.351388: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load d
ynamic library 'libcuda.so.1'; dlerror: libcuda.so.1: cannot open shared object file: No such file or direct
ory; LD_LIBRARY_PATH: /usr/local/nvidia/lib:/usr/local/nvidia/lib64
```

In [27]:

```
Bi_lstm_model = tf.keras.models.Sequential([
  tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(300, return_sequences=True),
                              input_shape=x_train_multi.shape[-2:]),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(300)),
    tf.keras.layers.Dense(20, activation='tanh'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(units=horizon),
])
Bi_lstm_model.compile(optimizer='adam', loss='mse')
```

```
2022-04-13 13:58:53.351436: W tensorflow/stream_executor/cuda/cuda_driver.cc:269] failed call to cuInit: UNK
NOWN ERROR (303)
2022-04-13 13:58:53.351471: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:156] kernel driver does no
t appear to be running on this host (n8n29btfmg): /proc/driver/nvidia/version does not exist
2022-04-13 13:58:53.362023: I tensorflow/core/platform/cpu_feature_guard.cc:151] This TensorFlow binary is o
ptimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performan
ce-critical operations:  AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

In [28]:

```
EVALUATION_INTERVAL = 110
EPOCHS = 3
history = Bi_lstm_model.fit(train_data_multi, epochs=EPOCHS, steps_per_epoch=EVALUATION_INTERVAL, validatio
```

```
Epoch 1/3
110/110 [==============================] - 1092s 10s/step - loss: 0.0276 - val_loss: 0.0058
Epoch 2/3
110/110 [==============================] - 1078s 10s/step - loss: 0.0096 - val_loss: 0.0082
Epoch 3/3
110/110 [==============================] - 1087s 10s/step - loss: 0.0080 - val_loss: 0.0027
```

In [29]:

```
model_path = r'./time_series.h5'
```

In [30]:

```
tf.keras.models.save_model(
    Bi_lstm_model,
    model_path,
    overwrite=True,
    include_optimizer=True,
    save_format=None,
    signatures=None,
    options=None
)
```

In [31]:

```
Trained_model = tf.keras.models.load_model(model_path)
```

In [32]:

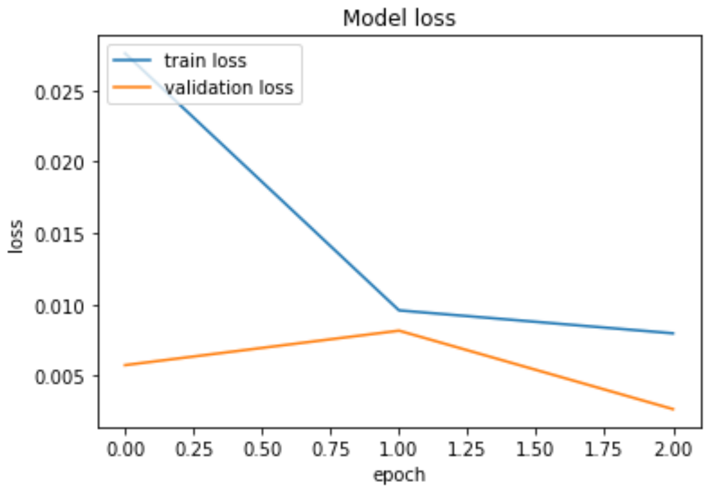
```
# Show the model architecture
Trained_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional (Bidirectiona  (None, 48, 600)          736800
 l)
```

```
 bidirectional_1 (Bidirectio  (None, 600)              2162400
 nal)

 dense (Dense)               (None, 20)                12020

 dropout (Dropout)           (None, 20)                0

 dense_1 (Dense)             (None, 10)                210

=================================================================
Total params: 2,911,430
Trainable params: 2,911,430
Non-trainable params: 0
```

In [33]:

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'validation loss'], loc='upper left')
plt.rcParams["figure.figsize"] = [16,9]
plt.show()
```



In [35]:

```
df.columns
```

Out[35]:

```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')
```

In [36]:

```
data_val = x_scaler.fit_transform(df[['Date', 'Open', 'High', 'Low', 'Volume', 'Chg%']].tail(48))
```

In [37]:

```
val_rescaled = data_val.reshape(1, data_val.shape[0], data_val.shape[1])
```

In [38]:

```
from sklearn import metrics
def timeseries_evaluation_metrics_func(y_true, y_pred):

    def mean_absolute_percentage_error(y_true, y_pred):
        y_true, y_pred = np.array(y_true), np.array(y_pred)
        return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
    print('Evaluation metric results:-')
    print(f'MSE is : {metrics.mean_squared_error(y_true, y_pred)}')
    print(f'MAE is : {metrics.mean_absolute_error(y_true, y_pred)}')
    print(f'RMSE is : {np.sqrt(metrics.mean_squared_error(y_true, y_pred))}')
    print(f'MAPE is : {mean_absolute_percentage_error(y_true, y_pred)}')
    print(f'R2 is : {metrics.r2_score(y_true, y_pred)}',end='\n\n')
```

Time Series ForeCasting

In [39]:

```
df2 = pd.read_csv('./Gold Price.csv')
```

In [40]:

```
df2.columns
```

Out[40]: Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')

In [44]:
```
df2.Date.head(2)
```

Out[44]:
```
0    2014-01-01
1    2014-01-02
Name: Date, dtype: object
```

In [45]:
```
df2['Date'] = pd.to_datetime(df2['Date'].astype(str), format='%Y-%m-%d')
```

In [46]:
```
df2 = df2[['Date', 'Price']]
```

In [47]:
```
# grouping sales according to Order Date
df2.groupby('Date')['Price'].sum().reset_index()
```

Out[47]:

	Date	Price
0	2014-01-01	29542
1	2014-01-02	29975
2	2014-01-03	29727
3	2014-01-04	29279
4	2014-01-06	29119
...	...	...
2067	2021-12-23	48012
2068	2021-12-24	47982
2069	2021-12-27	47933
2070	2021-12-28	47888
2071	2021-12-29	47515

2072 rows × 2 columns

In [48]:
```
# min and max values of Order Date
print(df2['Date'].min())
print(df2['Date'].max())
```

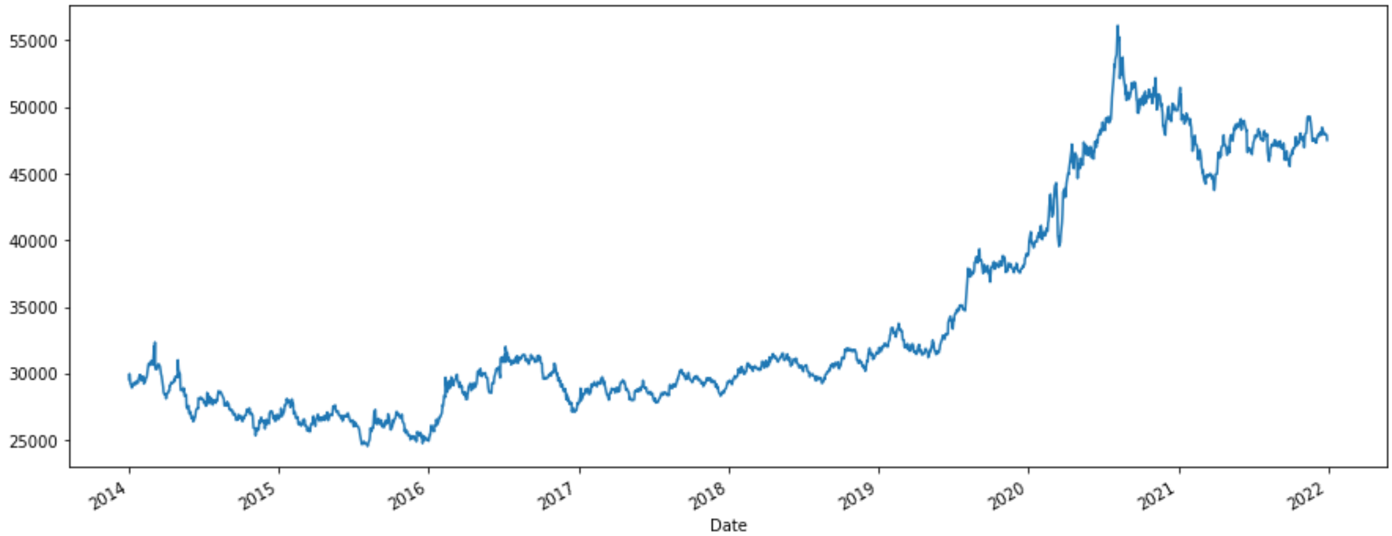
```
2014-01-01 00:00:00
2021-12-29 00:00:00
```

In [49]:
```
#set 'Date' as index
df2 = df2.set_index('Date')
df2.index
```

Out[49]:
```
DatetimeIndex(['2014-01-01', '2014-01-02', '2014-01-03', '2014-01-04',
               '2014-01-06', '2014-01-07', '2014-01-08', '2014-01-09',
               '2014-01-10', '2014-01-13',
               ...
               '2021-12-16', '2021-12-17', '2021-12-20', '2021-12-21',
               '2021-12-22', '2021-12-23', '2021-12-24', '2021-12-27',
               '2021-12-28', '2021-12-29'],
              dtype='datetime64[ns]', name='Date', length=2072, freq=None)
```

In [50]:
```
df2.sort_index(inplace=True)
y = df2['Price']
```

In [51]:
```
y.plot(figsize = (15, 6))
plt.show()
```

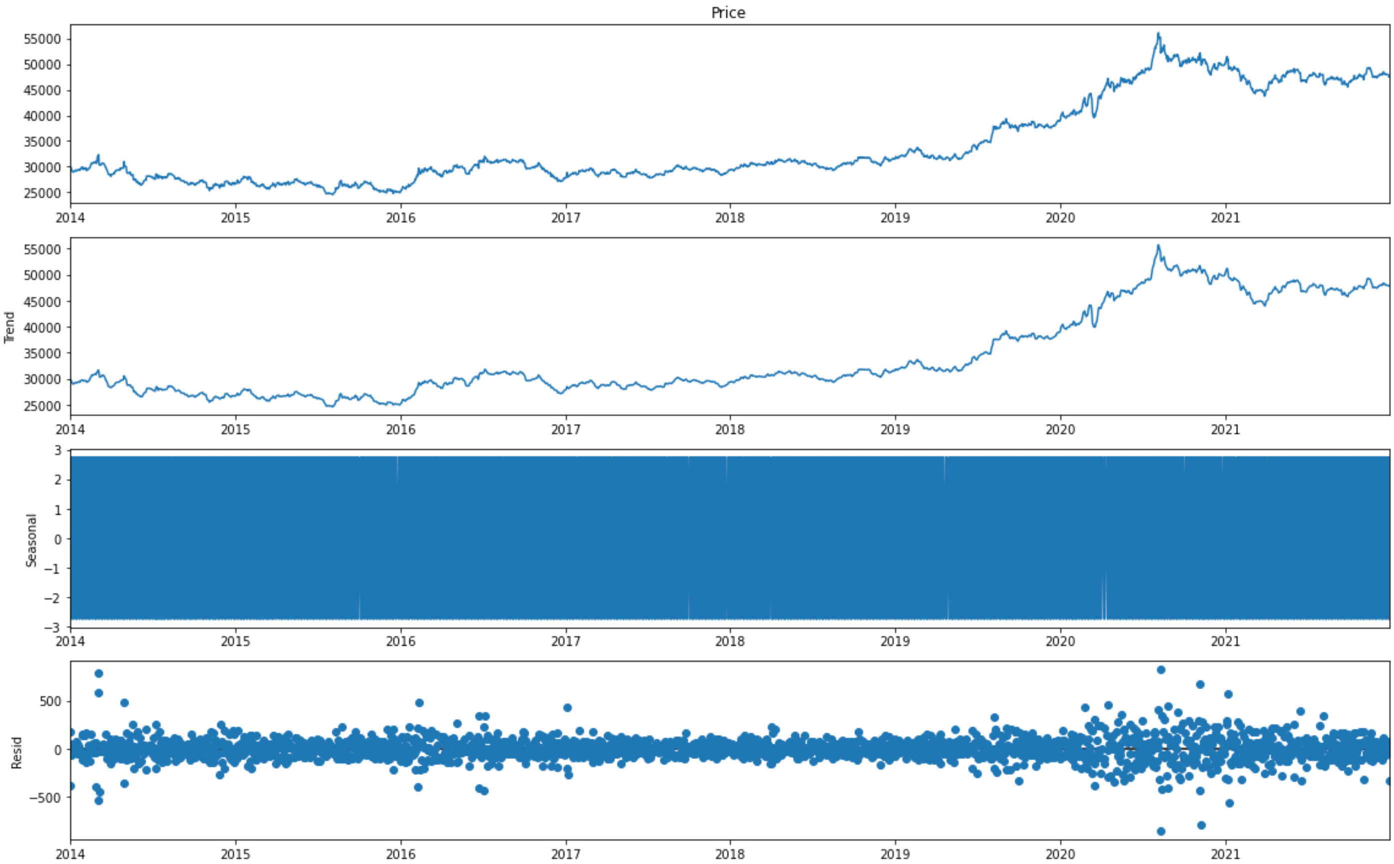


In [52]:

```
from pylab import rcParams
import statsmodels.api as sm
```

In [53]:

```
from pylab import rcParams
import statsmodels.api as sm
rcParams['figure.figsize'] = 16, 10
decomposition = sm.tsa.seasonal_decompose(y, model='additive', extrapolate_trend='freq', period=2)
fig = decomposition.plot()
plt.show()
```



In [54]:

```
df2.columns
```

Out[54]:

```
Index(['Price'], dtype='object')
```

Splitting the data into training and validation part

In [55]:

```
df3 = pd.read_csv('./Gold Price.csv')
```

In [56]:
```
df3.columns
```

Out[56]: Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')

In [58]:
```
df3['Date'] = pd.to_datetime(df3['Date'].astype(str), format='%Y-%m-%d')
```

In [59]:
```
#divide data into train and test
train_ind = int(len(df3)*0.8)
train = df[:train_ind]
valid = df[train_ind:]
```

In [60]:
```
train.head(2)
```

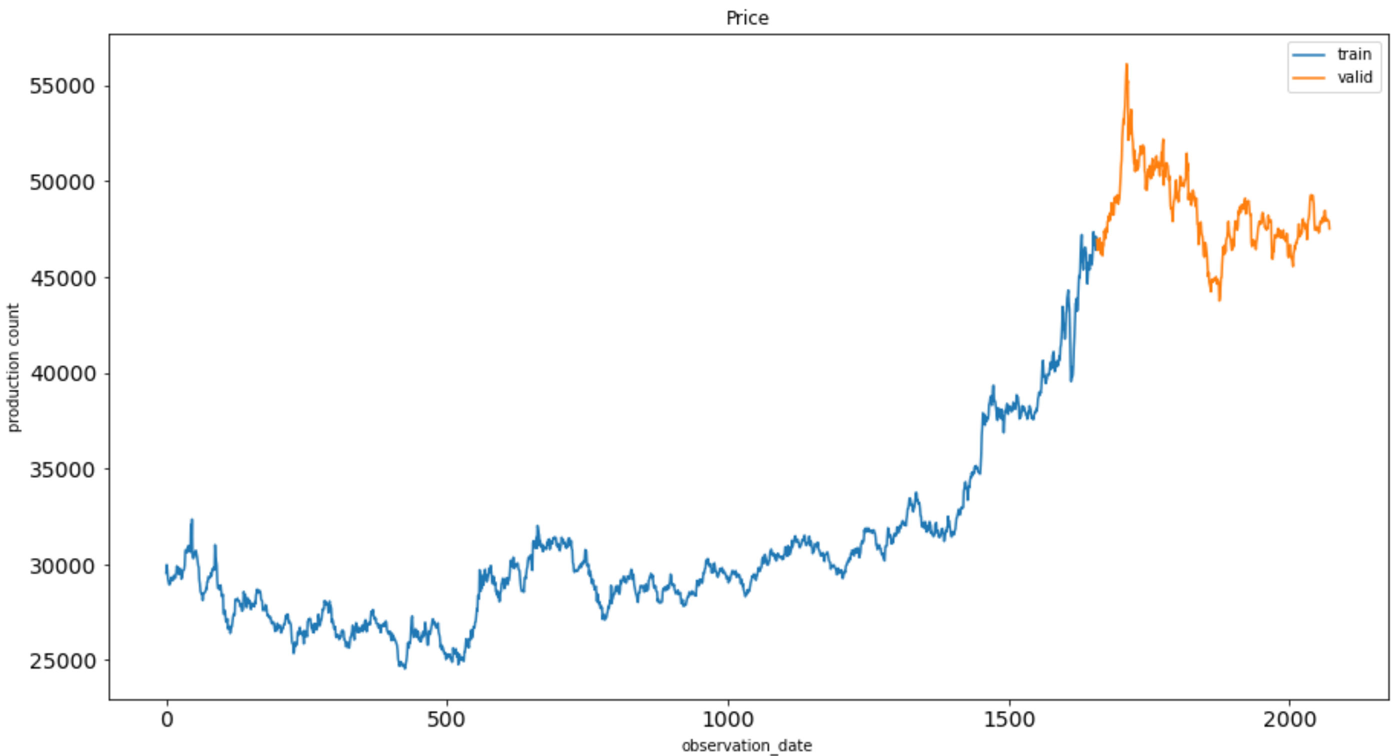
Out[60]:

	Date	Price	Open	High	Low	Volume	Chg%
0	0	29542	29435	29598	29340	2930	0.25
1	1	29975	29678	30050	29678	3140	1.47

In [61]:
```
print(train.shape, valid.shape)
```

(1657, 7) (415, 7)

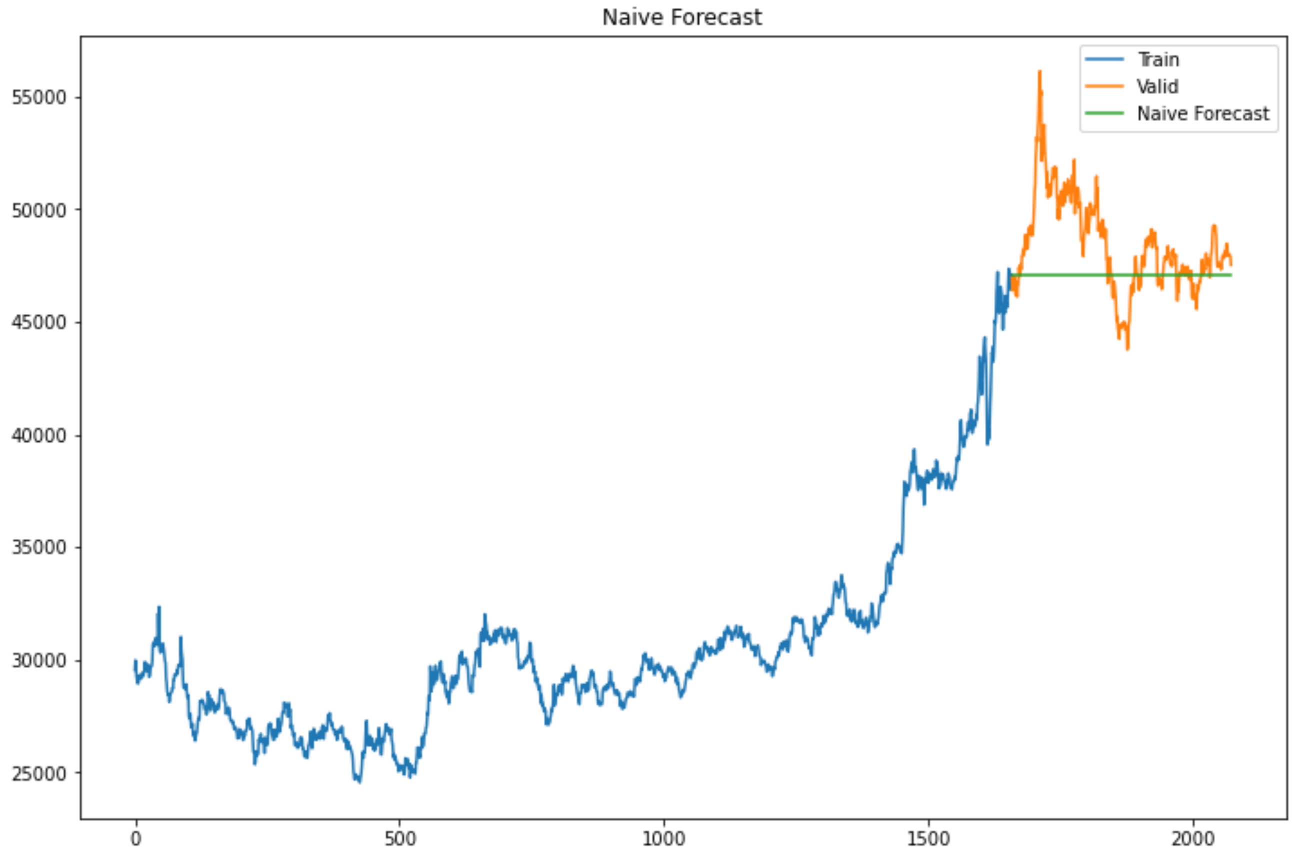
In [62]:
```
train.Price.plot(figsize=(15,8), title= 'Price', fontsize=14, label='train')
valid.Price.plot(figsize=(15,8), title= 'Price', fontsize=14, label='valid')
plt.xlabel("observation_date")
plt.ylabel("production count")
plt.legend(loc='best')
plt.show()
```



Simple models: Naive,Moving Average

In [63]:

```
# predictions using naive approach for the validation set.
dd= np.asarray(train['Price'])
y_hat = valid.copy()
y_hat['naive'] = dd[len(dd)-1]
plt.figure(figsize=(12,8))
plt.plot(train.index, train['Price'], label='Train')
plt.plot(valid.index,valid['Price'], label='Valid')
plt.plot(y_hat.index,y_hat['naive'], label='Naive Forecast')
plt.legend(loc='best')
plt.title("Naive Forecast")
plt.show()
```



In [65]:

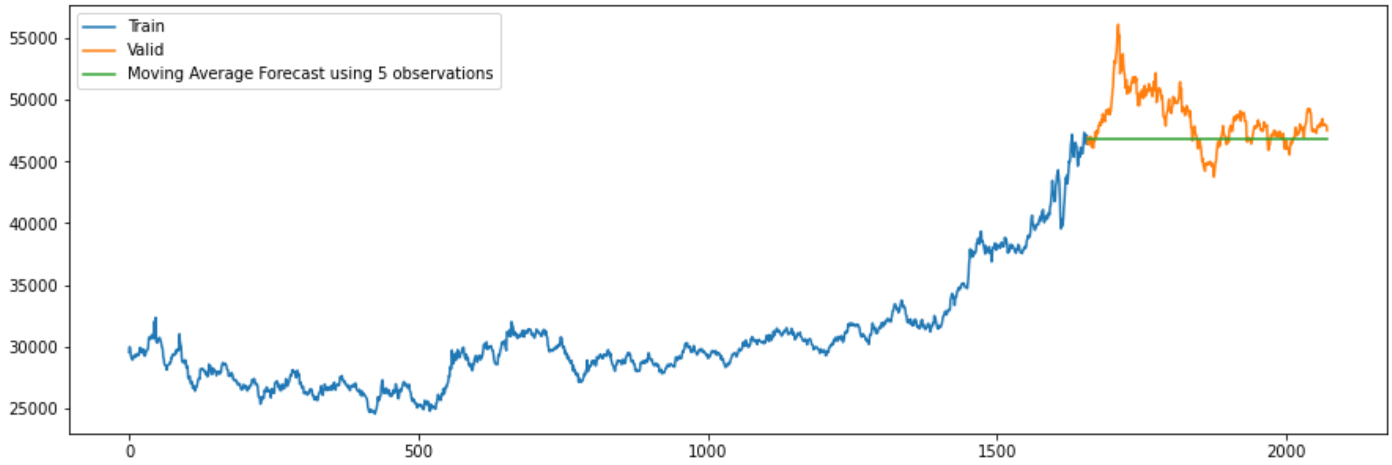
```
# RMSE(Root Mean Square Error) to check the accuracy of our model on validation data set.
from sklearn.metrics import mean_squared_error
from math import sqrt
rms = sqrt(mean_squared_error(valid['Price'], y_hat.naive))
print(rms)
```

```
2466.8205457266804
```

Moving Average

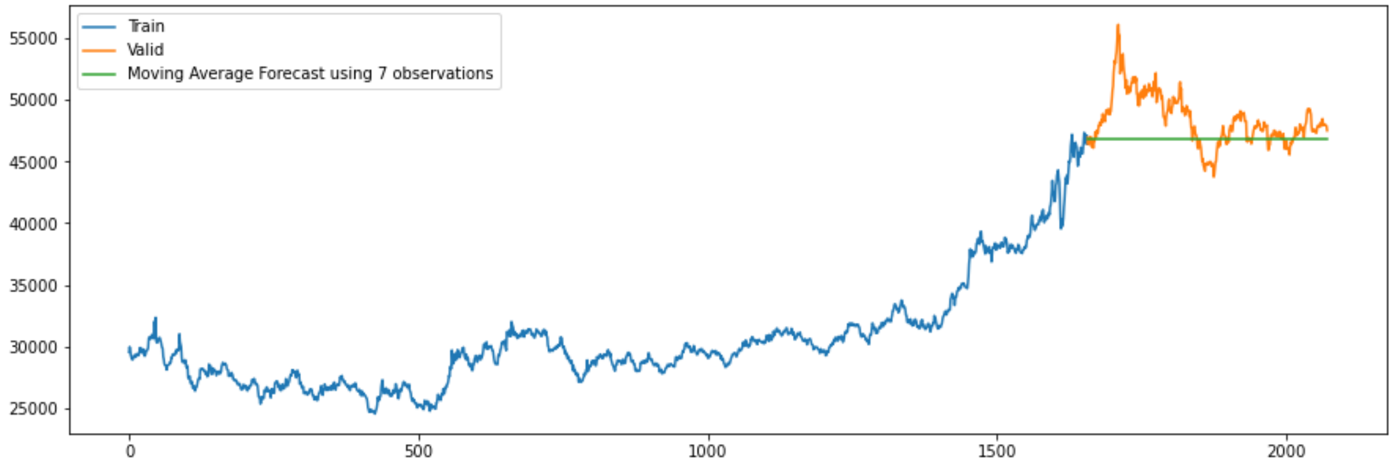
In [66]:

```
# last 5 observations.
y_hat_avg = valid.copy()
y_hat_avg['moving_avg_forecast'] = train['Price'].rolling(5).mean().iloc[-1] # average of last 5 observatio
plt.figure(figsize=(15,5))
plt.plot(train['Price'], label='Train')
plt.plot(valid['Price'], label='Valid')
plt.plot(y_hat_avg['moving_avg_forecast'], label='Moving Average Forecast using 5 observations')
plt.legend(loc='best')
plt.show()
```



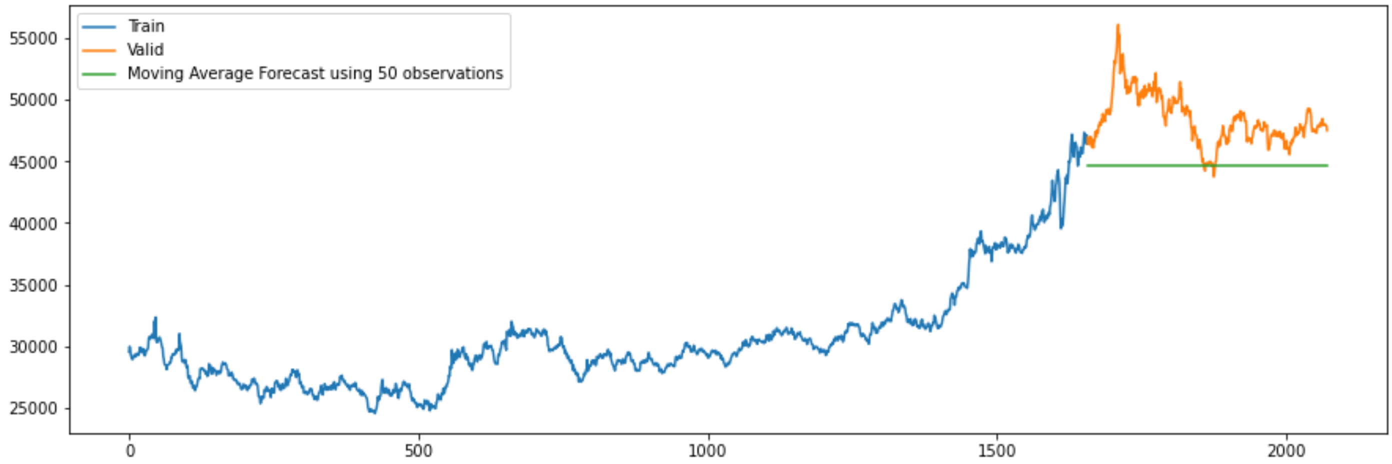
In [67]:

```
# last 7 observations.
y_hat_avg = valid.copy()
y_hat_avg['moving_avg_forecast'] = train['Price'].rolling(7).mean().iloc[-1] # average of last 7 observatio
plt.figure(figsize=(15,5))
plt.plot(train['Price'], label='Train')
plt.plot(valid['Price'], label='Valid')
plt.plot(y_hat_avg['moving_avg_forecast'], label='Moving Average Forecast using 7 observations')
plt.legend(loc='best')
plt.show()
```



In [68]:

```
# last 50 observations.
y_hat_avg = valid.copy()
y_hat_avg['moving_avg_forecast'] = train['Price'].rolling(50).mean().iloc[-1] # average of last 50 observat
plt.figure(figsize=(15,5))
plt.plot(train['Price'], label='Train')
plt.plot(valid['Price'], label='Valid')
plt.plot(y_hat_avg['moving_avg_forecast'], label='Moving Average Forecast using 50 observations')
plt.legend(loc='best')
plt.show()
```



In [70]:

```
rms = sqrt(mean_squared_error(valid['Price'], y_hat_avg.moving_avg_forecast))
print(rms)
```

```
4297.332149514746
```

Considering validate set, the Moving Average method showed better performance at some important metrics like RMSE and MAPE

Exponential models: Ses, Holt, Holt Winters

What is holt winter's method

Real-world data like that of demand data in any industry generally has a lot of seasonality and trends. When forecasting demands in such cases requires models which will account for the trend and seasonality in the data as the decision made by the business is going to be based on the result of this model. For such cases, Holt winter's method is one of the many time series prediction methods which can be used for forecasting.

Holt-Winter's Exponential Smoothing as named after its two contributors: Charles Holt and Peter Winter's is one of the oldest time series analysis techniques which takes into account the trend and seasonality while doing the forecasting. This method has 3 major aspects for performing the predictions. It has an average value with the trend and seasonality. The three aspects are 3 types of exponential smoothing and hence the hold winter's method is also known as triple exponential smoothing.

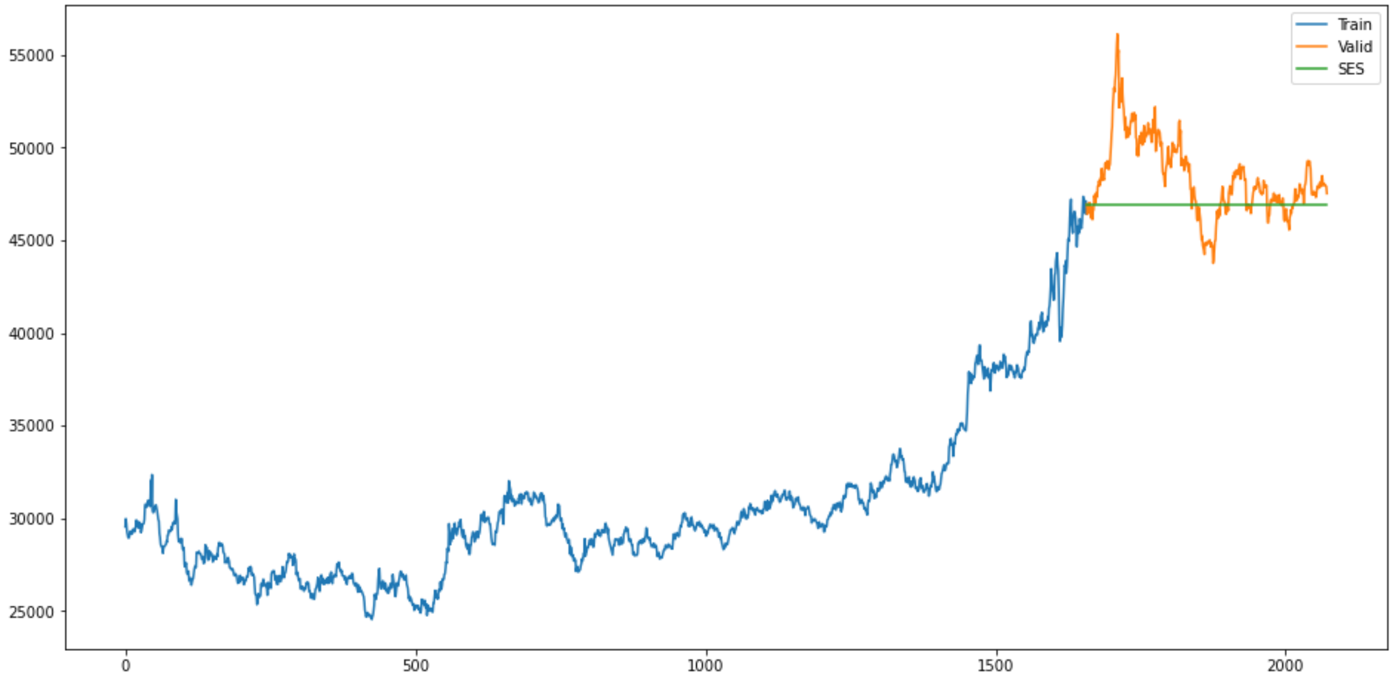
Exponential Smoothing: Simple exponential smoothing as the name suggest is used for forecasting when the data set has no trends or seasonality.

Holt's Smoothing method: Holt's smoothing technique, also known as linear exponential smoothing, is a widely known smoothing model for forecasting data that has a trend.

Winter's Smoothing method: Winter's smoothing technique allows us to include seasonality while making the prediction along with the trend.

In [71]:

```
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoothing, Holt
y_hat_ex = valid.copy()
fit2 = SimpleExpSmoothing(np.asarray(train['Price'])).fit(smoothing_level=0.6,optimized=False)
y_hat_ex['SES'] = fit2.forecast(len(valid))
plt.figure(figsize=(16,8))
plt.plot(train['Price'], label='Train')
plt.plot(valid['Price'], label='Valid')
plt.plot(y_hat_ex['SES'], label='SES')
plt.legend(loc='best')
plt.show()
```

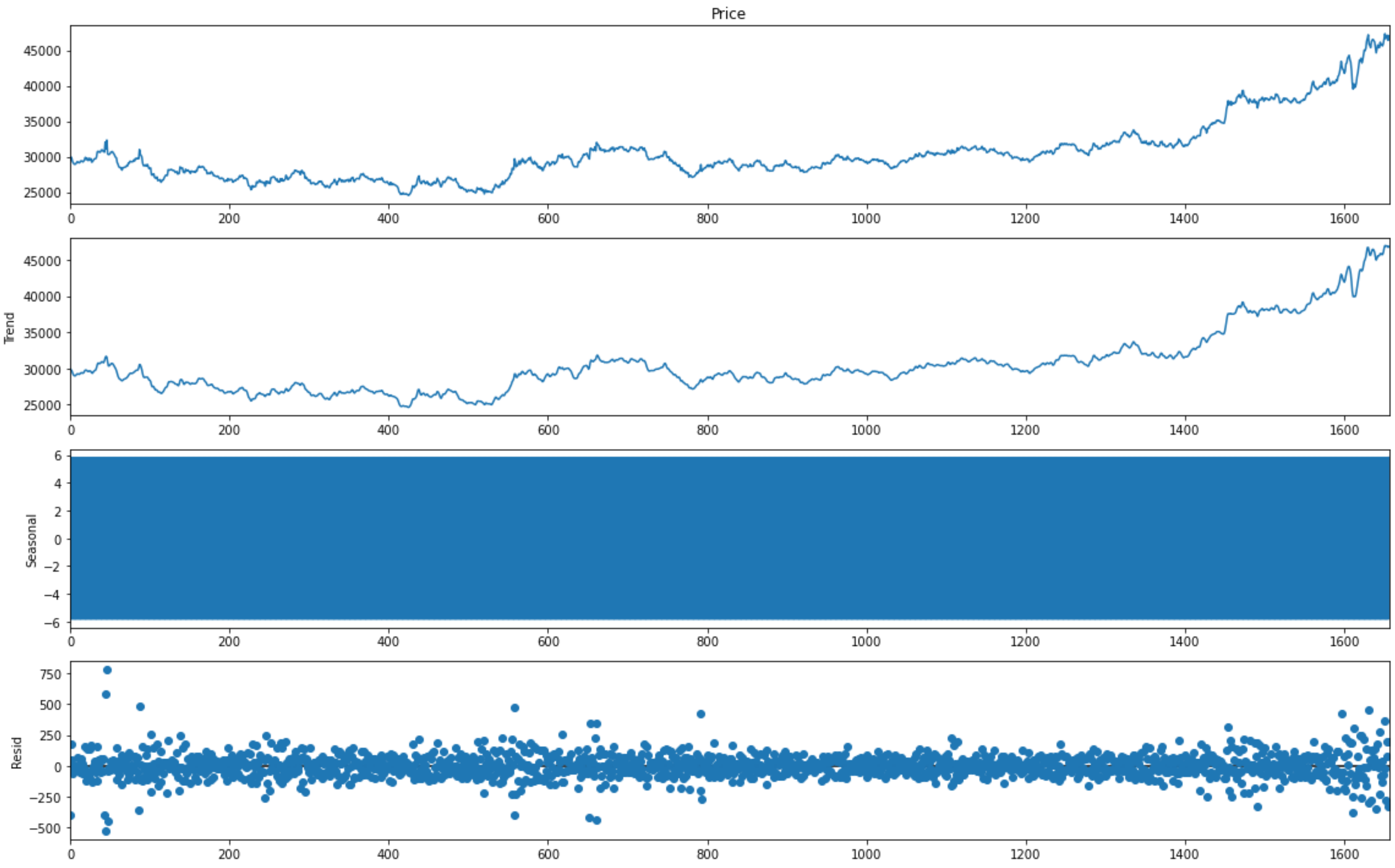


In [72]:
```
rms = sqrt(mean_squared_error(valid['Price'], y_hat_ex['SES']))
print(rms)
```

2554.0273732760647

Holt’s Linear Trend Model

In [73]:
```
import statsmodels.api as sm
decomposition = sm.tsa.seasonal_decompose(train['Price'], model='additive', extrapolate_trend='freq', perio
result = sm.tsa.stattools.adfuller(train['Price'])
plt.show()
```



In [74]:
```
y_hat_ex = valid.copy()

fit1 = Holt(np.asarray(train['Price'])).fit(smoothing_level = 0.3,smoothing_slope = 0.1)
y_hat_ex['Holt_linear'] = fit1.forecast(len(valid))

plt.figure(figsize=(16,8))
plt.plot(train['Price'], label='Train')
plt.plot(valid['Price'], label='Valid')
plt.plot(y_hat_ex['Holt_linear'], label='Holt_linear')
plt.legend(loc='best')
plt.show()
```

```
/tmp/ipykernel_262/593229442.py:3: FutureWarning: the 'smoothing_slope'' keyword is deprecated, use 'smoothi
ng_trend' instead
  fit1 = Holt(np.asarray(train['Price'])).fit(smoothing_level = 0.3,smoothing_slope = 0.1)
```

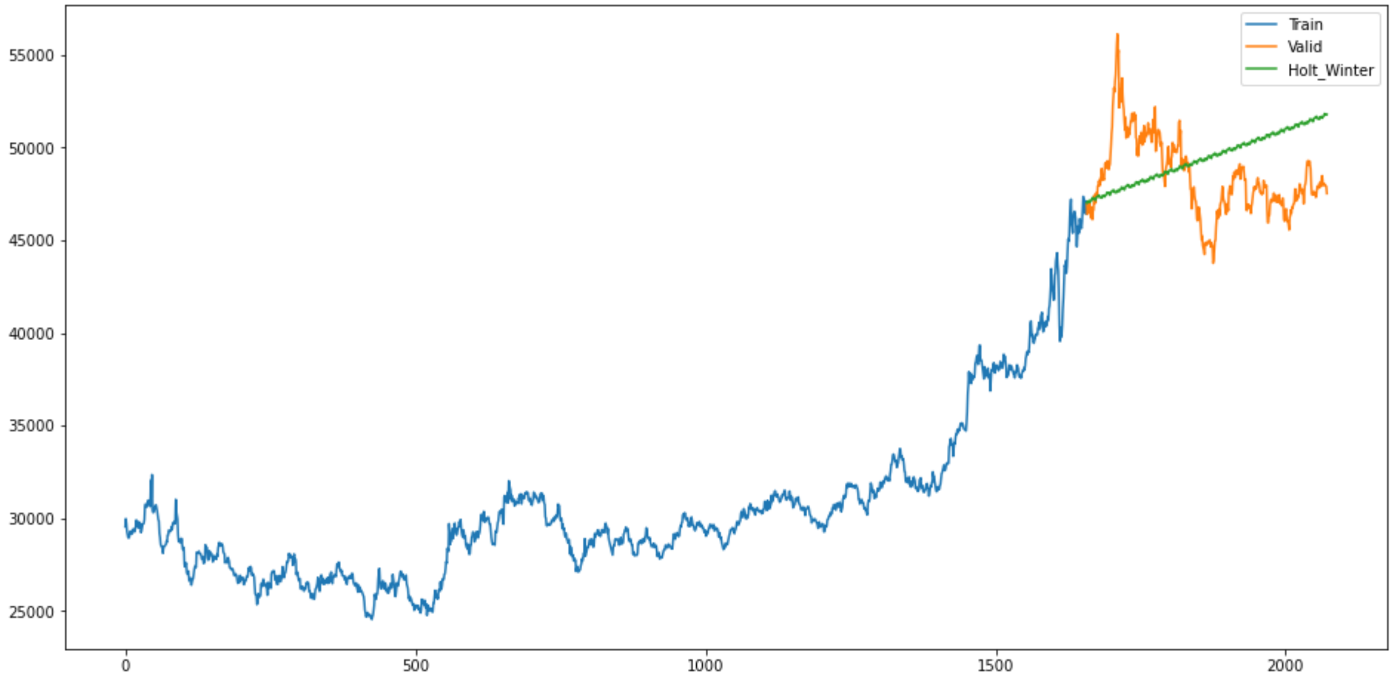
In [75]:
```
rms = sqrt(mean_squared_error(valid['Price'], y_hat_ex.Holt_linear))
print(rms)
```

```
19188.739136171516
```

Holt's Winter method

In [76]:
```
y_hat_win = valid.copy()
fit1 = ExponentialSmoothing(np.asarray(train['Price']) ,seasonal_periods=25 ,trend='add', seasonal='add',).
y_hat_win['Holt_Winter'] = fit1.forecast(len(valid))
plt.figure(figsize=(16,8))
plt.plot( train['Price'], label='Train')
plt.plot(valid['Price'], label='Valid')
plt.plot(y_hat_win['Holt_Winter'], label='Holt_Winter')
plt.legend(loc='best')
plt.show()
```

```
/opt/conda/envs/rapids/lib/python3.9/site-packages/statsmodels/tsa/holtwinters/model.py:915: ConvergenceWarn
ing: Optimization failed to converge. Check mle_retvals.
  warnings.warn(
```



In [77]:
```
valid['Price']
```

Out[77]:
```
1657    46953
1658    46393
1659    46647
1660    46474
1661    46858
        ...
2067    48012
2068    47982
2069    47933
2070    47888
2071    47515
Name: Price, Length: 415, dtype: int64
```

In [78]:
```
rms = sqrt(mean_squared_error(valid['Price'], y_hat_win.Holt_Winter))
print(rms)
```

```
3151.5959635192194
```

Dickey-Fuller TEST

ADF (Augmented Dickey-Fuller) test is a statistical significance test which means the test will give results in hypothesis tests with null and alternative hypotheses. As a result, we will have a p-value from which we will need to make inferences about the time series, whether it is stationary or not.

In [79]:

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

    #Determing rolling statistics
    rolmean = timeseries.rolling(24).mean()
    rolstd = timeseries.rolling(24).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:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observation
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
```

In [80]:

```
df4=pd.read_csv('./Gold Price.csv')
df4.head(3)
```

Out[80]:

	Date	Price	Open	High	Low	Volume	Chg%
0	2014-01-01	29542	29435	29598	29340	2930	0.25
1	2014-01-02	29975	29678	30050	29678	3140	1.47
2	2014-01-03	29727	30031	30125	29539	3050	-0.83

In [82]:

```
df4['Date'] = pd.to_datetime(df4['Date'].astype(str), format='%Y-%m-%d')
```

In [83]:

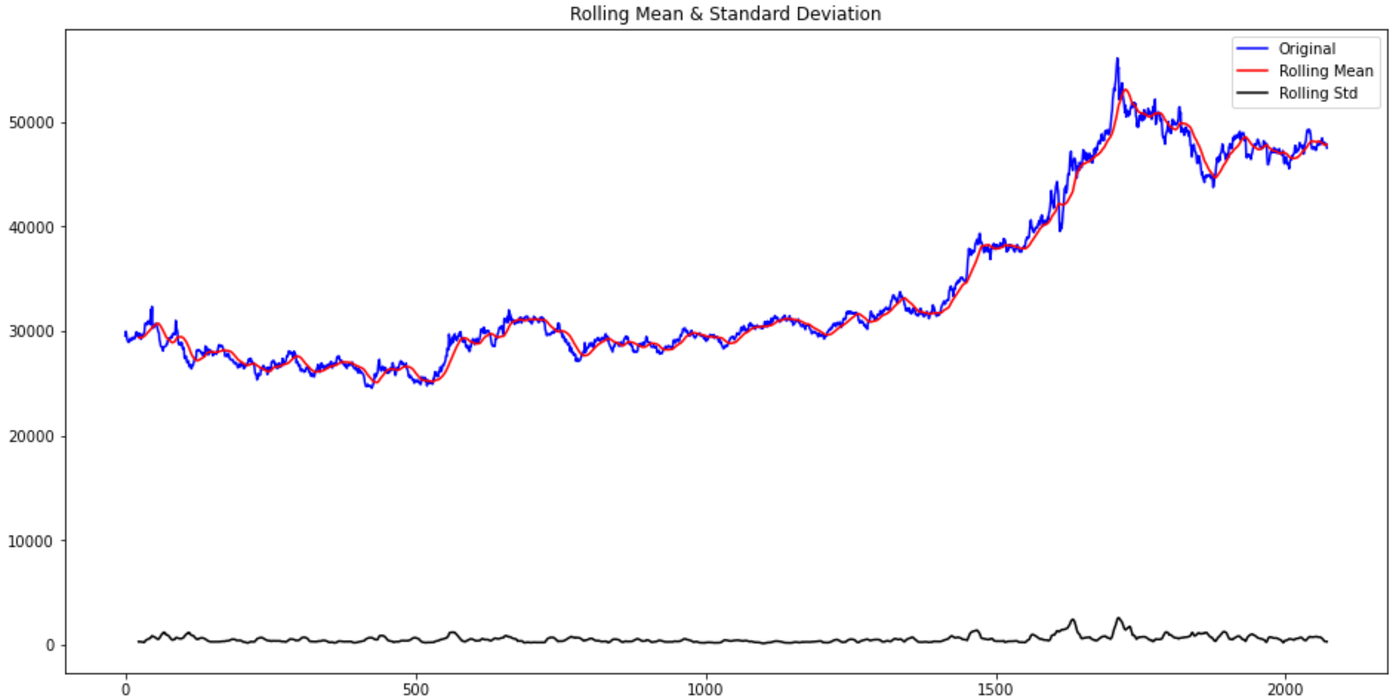
```
df4.columns
```

Out[83]:

```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')
```

In [84]:

```
plt.figure(figsize=(16,8))
test_stationarity(df4['Price'])
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -0.052063
p-value                          0.954009
#Lags Used                      14.000000
Number of Observations Used   2057.000000
Critical Value (1%)             -3.433533
Critical Value (5%)             -2.862946
Critical Value (10%)            -2.567519
dtype: float64
```

In [85]:

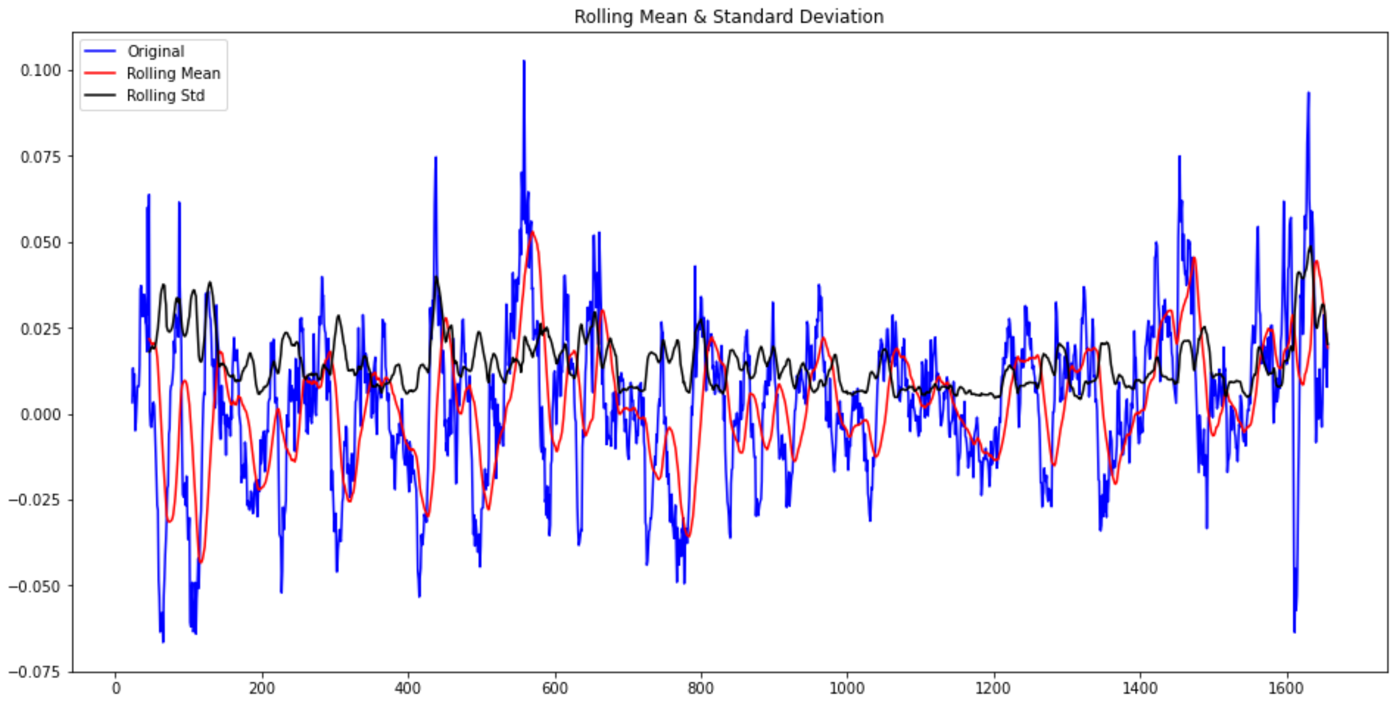
```
train_log = np.log(train['Price'])
valid_log = np.log(valid['Price'])

moving_avg = train_log.rolling(24).mean()
plt.figure(figsize=(16,8))
plt.plot(train_log)
plt.plot(moving_avg, color = 'red')
plt.show()
```

In [86]:

```
train_log_moving_avg_diff = train_log - moving_avg
```

In [87]:

```
train_log_moving_avg_diff.dropna(inplace = True)
plt.figure(figsize=(16,8))
test_stationarity(train_log_moving_avg_diff)
```




```
Results of Dickey-Fuller Test:
Test Statistic                 -9.163679e+00
p-value                         2.493655e-15
#Lags Used                      1.200000e+01
Number of Observations Used     1.621000e+03
Critical Value (1%)            -3.434391e+00
Critical Value (5%)            -2.863325e+00
Critical Value (10%)           -2.567720e+00
dtype: float64
```

In [88]:

```
from statsmodels.tsa.stattools import adfuller
```

In [89]:

```
test_result=adfuller(df4['Price'])
```

Stationay And Non-Stationary Time Series Data

A stationary time series has statistical properties or moments (e.g., mean and variance) that do not vary in time. Stationarity, then, is the status of a stationary time series. Conversely, nonstationarity is the status of a time series whose statistical properties are changing through time.

Dickey-Fuller Test To check If the Time Series Data Is Stationary Or Non- Stationary

In [90]:

```
#HYPOTHESIS TEST:
#Ho: It is non stationary
#H1: It is stationary

def adfuller_test(Price):

    result=adfuller(Price)

    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']

    for value,label in zip(result,labels):
        print(label+' : '+str(value) )

    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data has no uni
    else:
        print("weak evidence against null hypothesis, time series has a unit root, indicating it is non-sta
```

In [91]:
```
adfuller_test(df4['Price'])
```

```
ADF Test Statistic : -0.052063206205523994
p-value : 0.954008806001703
#Lags Used : 14
Number of Observations Used : 2057
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

AUTO-CORRELATION | PARTIAL AUTO-CORRELATION:

Just as correlation measures the extent of a linear relationship between two variables, autocorrelation measures the linear relationship between lagged values of a time series.

There are several autocorrelation coefficients, corresponding to each panel in the lag plot. <br?

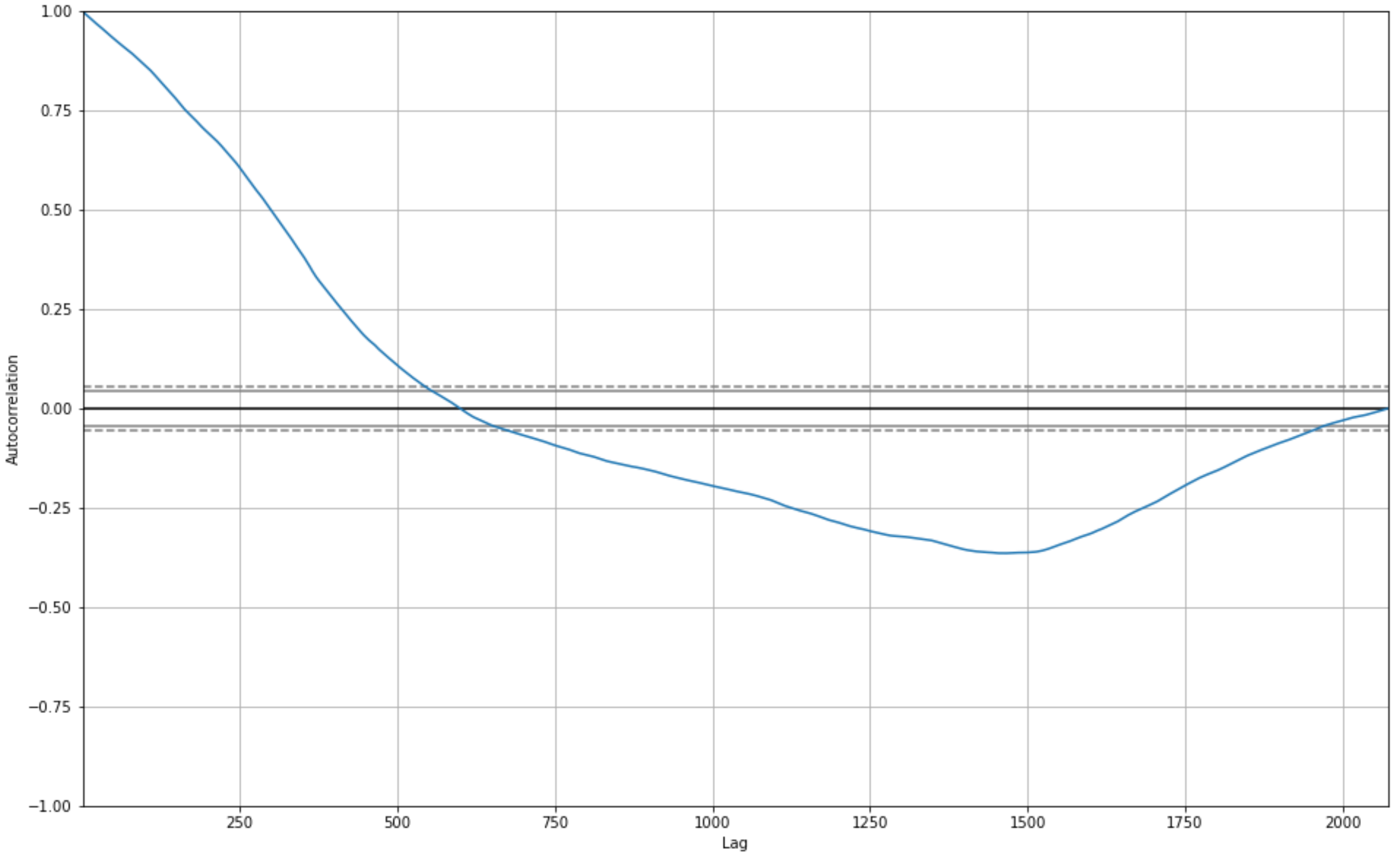
In [92]:
```
pd.DataFrame(train_log).isnull().sum()
```

Out[92]:
```
Price    0
dtype: int64
```

In [93]:
```
pd.DataFrame(train_log).Price.values
```

Out[93]:
```
array([10.29356826, 10.30811898, 10.299811  , ..., 10.7606438 ,
       10.74542105, 10.75911491])
```

In [94]:
```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df4['Price'])
plt.show()
```



Here these two graphs will help you to find the p and q values. Partial AutoCorrelation Graph is for the **p-value**. AutoCorrelation Graph for the q-value.

ARIMA MODEL

Let's Break it Down:-

AR: Autoregression. A model that uses the dependent relationship between an observation and some number of lagged observations.

I: Integrated. The use of differencing of raw observations in order to make the time series stationary. MA: Moving Average.

A model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

The parameters of the ARIMA model are defined as follows:

p: The number of lag observations included in the model, also called the lag order.

d: The number of times that the raw observations are differenced, also called the degree of differencing.

q: The size of the moving average window, also called the order of moving average.

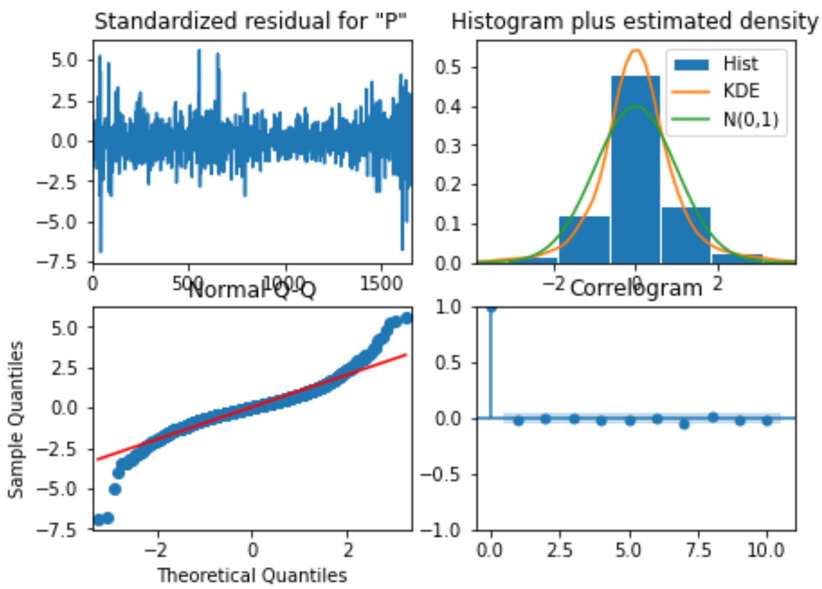
In [95]:
```
# For non-seasonal data
#p=1, d=1, q=0 or 1
import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARIMA
```

In [96]:
```
train.columns
```

Out[96]:
```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%'], dtype='object')
```

In [97]:
```
model=sm.tsa.arima.ARIMA(train['Price'],order=(1,1,2))
model_fit=model.fit()
```

In [98]:
```
model_fit.plot_diagnostics(figsize=(7,5))
plt.show()
```



In [99]:
```
model_fit.summary()
```

Out[99]:

SARIMAX Results

Dep. Variable:	Price	**No. Observations:**	1657
Model:	ARIMA(1, 1, 2)	**Log Likelihood**	-11614.737
Date:	Wed, 13 Apr 2022	**AIC**	23237.475
Time:	15:01:53	**BIC**	23259.124
Sample:	0	**HQIC**	23245.500
	- 1657		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.3379	0.269	-1.258	0.208	-0.864	0.189
ma.L1	0.3402	0.273	1.247	0.212	-0.194	0.875
ma.L2	0.0529	0.017	3.118	0.002	0.020	0.086
sigma2	7.238e+04	1302.966	55.547	0.000	6.98e+04	7.49e+04

Ljung-Box (L1) (Q):	0.13	**Jarque-Bera (JB):**	2544.43
Prob(Q):	0.72	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.32	**Skew:**	0.05
Prob(H) (two-sided):	0.00	**Kurtosis:**	9.07

Warnings:

In [100…

```
n_periods = 24
df4['forecast']=model_fit.predict(n_periods=n_periods, return_conf_int=True)
df4[['Price','forecast']].plot(figsize=(12,8))
```

Out[100…

<AxesSubplot:>

In [101…

```
df4[['Price','forecast']].head(4)
```

Out[101…

	Price	forecast
0	29542	0.000000
1	29975	29544.757643
2	29727	30080.090126
3	29279	29713.691741

The difference between **ARIMA** and **SARIMA (SARIMAX)** is about the seasonality of the dataset. if your data is seasonal, like it happen after a certain period of time. then we will use SARIMA.

SARIMAX MODEL

SARIMAX(Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors) is an updated version of the ARIMA model. we can say SARIMAX is a seasonal equivalent model like **SARIMA** and **Auto ARIMA**. it can also deal with external effects. This feature of the model differs from other models.

Please Note : Sarimax Consumes Large Memory to Execute. Here, Few parameters can be optimized and tried to make it working.

For Example Use, model.fit(low_memory=True)

In [102…
```
import statsmodels.api as sm
```

In [103…
```
model=sm.tsa.statespace.SARIMAX(train['Price'],order=(1, 1, 1),seasonal_order=(1,1,1,12),enforce_invertibil
```

In [104…
```
results=model.fit(low_memory=True)
```

```
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  7.08667D+00    |proj g|=  1.20511D-01
 This problem is unconstrained.
At iterate    5    f=  7.07064D+00    |proj g|=  1.75175D-02

At iterate   10    f=  7.07047D+00    |proj g|=  4.00640D-03

At iterate   15    f=  7.06233D+00    |proj g|=  1.12056D-01

At iterate   20    f=  7.05016D+00    |proj g|=  5.55649D-02

At iterate   25    f=  7.00267D+00    |proj g|=  2.82873D-01

At iterate   30    f=  6.98596D+00    |proj g|=  1.44263D-02

At iterate   35    f=  6.98593D+00    |proj g|=  1.69201D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     37     54      1     0     0   6.122D-05   6.986D+00
  F =   6.9859333349764139

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
```

In [105…
```
results.summary()
```

Out[105…

SARIMAX Results

Dep. Variable:	Price	**No. Observations:**	1657
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 12)	**Log Likelihood**	-11575.692
Date:	Wed, 13 Apr 2022	**AIC**	23161.383
Time:	15:02:43	**BIC**	23188.408
Sample:	0	**HQIC**	23171.404
	- 1657		
Covariance Type:	approx		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.9901	0.018	-54.372	0.000	-1.026	-0.954
ma.L1	0.9929	0.017	57.790	0.000	0.959	1.027
ar.S.L12	0.0783	0.025	3.101	0.002	0.029	0.128

ma.S.L12	-0.9935	0.017	-58.107	0.000	-1.027	-0.960
sigma2	7.124e+04	2598.639	27.413	0.000	6.61e+04	7.63e+04

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	1692.19
Prob(Q):	1.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.15	**Skew:**	-0.05
Prob(H) (two-sided):	0.10	**Kurtosis:**	7.97

Warnings:

In [106…

```
df4['forecast']=model_fit.predict(n_periods=n_periods, return_conf_int=True)
df4[['Price','forecast']].plot(figsize=(12,8))
```

Out[106…

```
<AxesSubplot:>
```

PREDICT FOR FUTURE DATASET:

In [107…

```
df4.columns
```

Out[107…

```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Volume', 'Chg%', 'forecast'], dtype='object')
```

In [108…

```
from pandas.tseries.offsets import DateOffset

#Here USING FOR LOOP we are adding some additional data for prediction purpose:

future_dates=[df4.iloc[-1]["Date"] + DateOffset(months=x)for x in range(0,24)]
```

In [109…

```
#Convert that list into DATAFRAME:

future_datest_df=pd.DataFrame(index=future_dates[1:],columns=df4.columns)
```

In [110…

```
#CONCATE THE ORIGINAL AND THE NEWLY CREATED DATASET FOR VISUALIZATION PURPOSE:
future_df=pd.concat([df4,future_datest_df])
```

In [111…

```
#PREDICT
future_df['forecast'] = model_fit.predict(n_periods=n_periods, return_conf_int=True)
future_df[['Price', 'forecast']].plot(figsize=(12, 8))
#model_fit.predict(start=100000,end=201008,dynamic=True)
```

Out[111…

<AxesSubplot:>

In [112…

```
future_df.head(9)
```

Out[112…

	Date	Price	Open	High	Low	Volume	Chg%	forecast
0	2014-01-01	29542	29435	29598	29340	2930	0.25	0.000000
1	2014-01-02	29975	29678	30050	29678	3140	1.47	29544.757643
2	2014-01-03	29727	30031	30125	29539	3050	-0.83	30080.090126
3	2014-01-04	29279	29279	29279	29279	0	-1.51	29713.691741
4	2014-01-06	29119	29300	29395	29051	24380	-0.55	29263.900382
5	2014-01-07	28959	29130	29195	28912	18710	-0.55	29100.785438
6	2014-01-08	28934	28916	29029	28820	18140	-0.09	28957.165052
7	2014-01-09	28997	28990	29053	28865	15130	0.22	28927.067773
8	2014-01-10	29169	29030	29198	28960	15810	0.59	28998.278034

In [ ]: