CRUDE OIL PRICE PREDICTION

PNT2022TMID26965

Importing libraries

```
import numpy as np
import pandas as pd
import datetime
from pylab import rcParams
import matplotlib.pyplot as plt
import warnings
import itertools
import statsmodels.api as sm
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
from sklearn.metrics import mean_squared_error
from keras.callbacks import ReduceLROnPlateau, EarlyStopping,
ModelCheckpoint
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
import seaborn as sns
sns.set_context("paper", font_scale=1.3)
sns.set_style('white')
import math
from sklearn.preprocessing import MinMaxScaler
warnings.filterwarnings("ignore")
plt.style.use('fivethirtyeight')
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

Importing data

```
dateparse = lambda x: pd.datetime.strptime(x, '%b %d, %Y')
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving Crude Oil Prices Daily.xlsx to Crude Oil Prices Daily.xlsx
```

```
import io
df = pd.read_excel(io.BytesIO(uploaded['Crude Oil Prices
Daily.xlsx']))
```

```
df.head()
df[:10]
```

```
        Date  Closing Value
0 1986-01-02          25.56
1 1986-01-03          26.00
2 1986-01-06          26.53
3 1986-01-07          25.85
4 1986-01-08          25.87
5 1986-01-09          26.03
6 1986-01-10          25.65
7 1986-01-13          25.08
8 1986-01-14          24.97
9 1986-01-15          25.18
```

```
#Sort dataset by column Date
df = df.sort_values('Date')
df = df.groupby('Date')['Closing Value'].sum().reset_index()
df.set_index('Date', inplace=True)
df=df.loc[datetime.date(year=2000,month=1,day=1):]

df.head()
```

```
            Closing Value
Date
2000-01-04          25.56
2000-01-05          24.65
2000-01-06          24.79
2000-01-07          24.79
2000-01-10          24.71
```

Data preprocessing

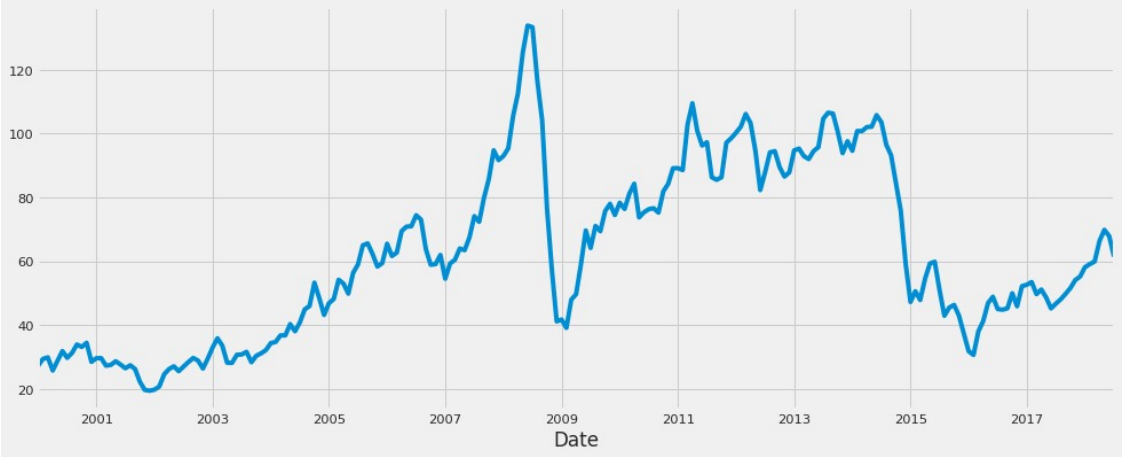
```
def DfInfo(df_initial):
    tab_info = pd.DataFrame(df_initial.dtypes).T.rename(index={0:
'column type'})
    tab_info =
tab_info.append(pd.DataFrame(df_initial.isnull().sum()).T.rename(index
={0: 'null values (nb)'}))
    tab_info = tab_info.append(pd.DataFrame(df_initial.isnull().sum()
/ df_initial.shape[0] * 100).T.rename(index={0: 'null values (%)'}))
    return tab_info

DfInfo(df)
```

```
                 Closing Value
column type            float64
null values (nb)             0
null values (%)            0.0
```

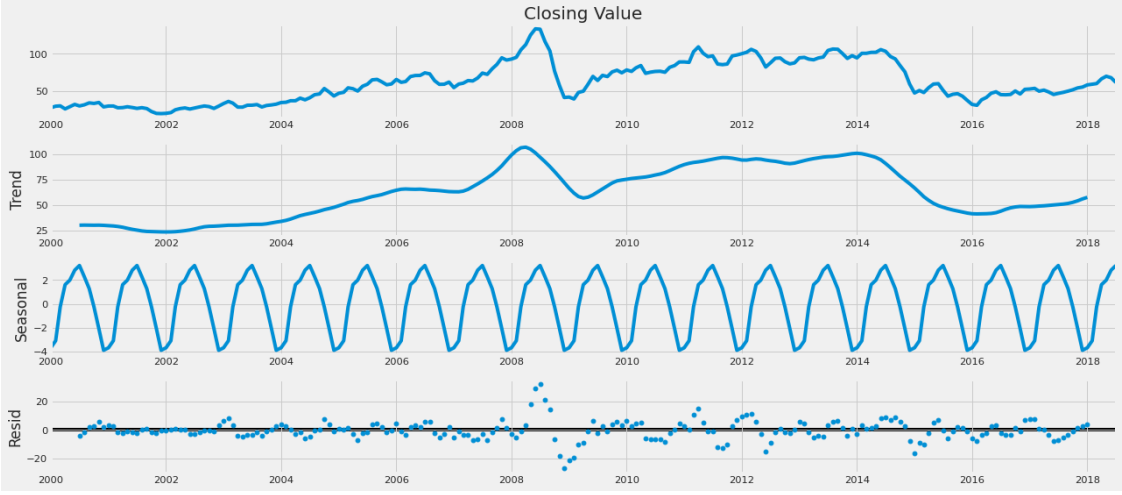
```
df.index
```

```
DatetimeIndex(['2000-01-04', '2000-01-05', '2000-01-06', '2000-01-07',
               '2000-01-10', '2000-01-11', '2000-01-12', '2000-01-13',
               '2000-01-14', '2000-01-18',
               ...
               '2018-06-26', '2018-06-27', '2018-06-28', '2018-06-29',
               '2018-07-02', '2018-07-03', '2018-07-04', '2018-07-05',
               '2018-07-06', '2018-07-09'],
              dtype='datetime64[ns]', name='Date', length=4673,
freq=None)
```

```
y = df['Closing Value'].resample('MS').mean()
y.plot(figsize=(15, 6))
plt.show()
```




```
rcParams['figure.figsize'] = 18, 8
decomposition = sm.tsa.seasonal_decompose(y, model='additive')
fig = decomposition.plot()
plt.show()
```




```
sc = MinMaxScaler(feature_range = (0, 1))
df = sc.fit_transform(df)
```

Training and testing

```
train_size = int(len(df) * 0.70)
test_size = len(df) - train_size
train, test = df[0:train_size, :], df[train_size:len(df), :]

def create_data_set(_data_set, _look_back=1):
    data_x, data_y = [], []
    for i in range(len(_data_set) - _look_back - 1):
        a = _data_set[i:(i + _look_back), 0]
        data_x.append(a)
        data_y.append(_data_set[i + _look_back, 0])
    return np.array(data_x), np.array(data_y)

look_back =90
X_train,Y_train,X_test,Ytest = [],[],[],[]
X_train,Y_train=create_data_set(train,look_back)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test,Y_test=create_data_set(test,look_back)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

LSTM layer

```
regressor = Sequential()
regressor.add(LSTM(units = 60, return_sequences = True, input_shape =
(X_train.shape[1], 1)))
regressor.add(Dropout(0.1))
regressor.add(LSTM(units = 60, return_sequences = True))
regressor.add(Dropout(0.1))
regressor.add(LSTM(units = 60))
regressor.add(Dropout(0.1))
regressor.add(Dense(units = 1))

regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
reduce_lr = ReduceLROnPlateau(monitor='val_loss',patience=5)
history =regressor.fit(X_train, Y_train, epochs = 20, batch_size =
15,validation_data=(X_test, Y_test),
callbacks=[reduce_lr],shuffle=False)

Epoch 1/20
212/212 [==============================] - 29s 112ms/step - loss:
0.0055 - val_loss: 0.0202 - lr: 0.0010
Epoch 2/20
212/212 [==============================] - 24s 113ms/step - loss:
0.0096 - val_loss: 0.0478 - lr: 0.0010
Epoch 3/20
212/212 [==============================] - 23s 108ms/step - loss:
0.0105 - val_loss: 0.0523 - lr: 0.0010
Epoch 4/20
212/212 [==============================] - 23s 107ms/step - loss:
0.0180 - val_loss: 0.0458 - lr: 0.0010
```

```
Epoch 5/20
212/212 [==============================] - 23s 106ms/step - loss:
0.0161 - val_loss: 0.0451 - lr: 0.0010
Epoch 6/20
212/212 [==============================] - 22s 104ms/step - loss:
0.0172 - val_loss: 0.0355 - lr: 0.0010
Epoch 7/20
212/212 [==============================] - 22s 104ms/step - loss:
0.0168 - val_loss: 0.0034 - lr: 1.0000e-04
Epoch 8/20
212/212 [==============================] - 22s 104ms/step - loss:
0.0034 - val_loss: 0.0022 - lr: 1.0000e-04
Epoch 9/20
212/212 [==============================] - 23s 107ms/step - loss:
0.0025 - val_loss: 0.0019 - lr: 1.0000e-04
Epoch 10/20
212/212 [==============================] - 22s 104ms/step - loss:
0.0019 - val_loss: 0.0017 - lr: 1.0000e-04
Epoch 11/20
212/212 [==============================] - 22s 104ms/step - loss:
0.0016 - val_loss: 0.0016 - lr: 1.0000e-04
Epoch 12/20
212/212 [==============================] - 23s 107ms/step - loss:
0.0014 - val_loss: 0.0015 - lr: 1.0000e-04
Epoch 13/20
212/212 [==============================] - 23s 106ms/step - loss:
0.0012 - val_loss: 0.0014 - lr: 1.0000e-04
Epoch 14/20
212/212 [==============================] - 23s 108ms/step - loss:
0.0011 - val_loss: 0.0013 - lr: 1.0000e-04
Epoch 15/20
212/212 [==============================] - 23s 109ms/step - loss:
0.0010 - val_loss: 0.0013 - lr: 1.0000e-04
Epoch 16/20
212/212 [==============================] - 24s 111ms/step - loss:
0.0010 - val_loss: 0.0013 - lr: 1.0000e-04
Epoch 17/20
212/212 [==============================] - 23s 110ms/step - loss:
0.0010 - val_loss: 0.0014 - lr: 1.0000e-04
Epoch 18/20
212/212 [==============================] - 22s 105ms/step - loss:
0.0010 - val_loss: 0.0014 - lr: 1.0000e-04
Epoch 19/20
212/212 [==============================] - 23s 107ms/step - loss:
9.6607e-04 - val_loss: 0.0014 - lr: 1.0000e-04
Epoch 20/20
212/212 [==============================] - 23s 106ms/step - loss:
9.8763e-04 - val_loss: 0.0013 - lr: 1.0000e-05
```

Model training

```
train_predict = regressor.predict(X_train)
test_predict = regressor.predict(X_test)
```

```
100/100 [==============================] - 5s 36ms/step
41/41 [==============================] - 1s 36ms/step
```

```
train_predict = sc.inverse_transform(train_predict)
Y_train = sc.inverse_transform([Y_train])
test_predict = sc.inverse_transform(test_predict)
Y_test = sc.inverse_transform([Y_test])
```

Prediction

```
print('Train Mean Absolute Error:', mean_absolute_error(Y_train[0],
train_predict[:,0]))
print('Train Root Mean Squared
Error:',np.sqrt(mean_squared_error(Y_train[0], train_predict[:,0])))
print('Test Mean Absolute Error:', mean_absolute_error(Y_test[0],
test_predict[:,0]))
print('Test Root Mean Squared
Error:',np.sqrt(mean_squared_error(Y_test[0], test_predict[:,0])))
plt.figure(figsize=(8,4))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epochs')
plt.legend(loc='upper right')
plt.show();
```

```
Train Mean Absolute Error: 2.469099854355338
Train Root Mean Squared Error: 3.325991860387499
Test Mean Absolute Error: 2.4272213645021394
Test Root Mean Squared Error: 5.283315170027136
```


```
aa=[x for x in range(180)]
plt.figure(figsize=(8,4))
plt.plot(aa, Y_test[0][:180], marker='.', label="actual")
plt.plot(aa, test_predict[:,0][:180], 'r', label="prediction")
plt.tight_layout()
sns.despine(top=True)
plt.subplots_adjust(left=0.07)
plt.ylabel('Price', size=15)
plt.xlabel('Time step', size=15)
plt.legend(fontsize=15)
plt.show();
```