

Creating dataset with sliding windows & Model building

PNT2022TMID26965

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
ds=pd.read_csv(r"/content/Crude-Oil-Prices-Daily.csv",parse_dates
=["Date"], index_col ="Date")
ds.head()
ds[:10]
```

	Closing Value
Date	
1986-01-02	25.56
1986-01-03	26.00
1986-01-06	26.53
1986-01-07	25.85
1986-01-08	25.87
1986-01-09	26.03
1986-01-10	25.65
1986-01-13	25.08
1986-01-14	24.97
1986-01-15	25.18

```
ds.isnull().sum()
```

```
Closing Value    7
dtype: int64
```

```
ds.dropna(axis=0,inplace=True)
ds.isnull().sum()
```

```
Closing Value    0
dtype: int64
```

```
data=ds.reset_index()['Closing Value']
data
```

0	25.56
1	26.00
2	26.53
3	25.85
4	25.87
	...
8211	73.89
8212	74.19
8213	73.05
8214	73.78

```

8215    73.93
Name: Closing Value, Length: 8216, dtype: float64

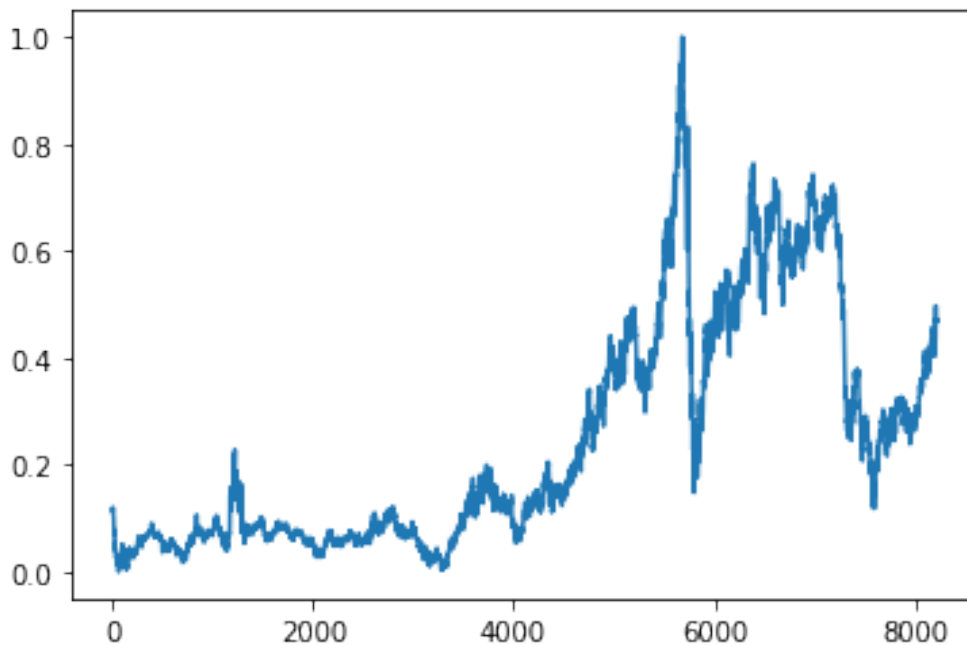
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
data=scaler.fit_transform(np.array(data).reshape(-1,1))
data

array([[0.11335703],
       [0.11661484],
       [0.12053902],
       ...,
       [0.46497853],
       [0.47038353],
       [0.47149415]])

plt.plot(data)

[<matplotlib.lines.Line2D at 0x7f334e6d1150>]

```



```

training_size=int(len(data)*0.65)
test_size=len(data)-training_size
train_data,test_data=data[0:training_size:],data[training_size:len(da
ta),:]
training_size,test_size

(5340, 2876)

train_data.shape

(5340, 1)

```

```

def create_dataset(dataset,time_step=1):
    dataX,dataY=[],[]
    for i in range(len(dataset)-time_step-1):
        a=dataset[i:(i+time_step),0]
        dataX.append(a)
        dataY.append(dataset[i+time_step,0])
    return np.array(dataX),np.array(dataY)

time_step=10
x_train,y_train=create_dataset(train_data,time_step)
x_test,y_test=create_dataset(test_data,time_step)
print(x_train.shape)
print(y_train.shape)

(5329, 10)
(5329,)

print(x_test.shape)
print(y_test.shape)

(2865, 10)
(2865,)

x_train
array([[0.11335703, 0.11661484, 0.12053902, ..., 0.10980305, 0.1089886
,
        0.11054346],
       [0.11661484, 0.12053902, 0.11550422, ..., 0.1089886 ,
0.11054346,
        0.10165852],
       [0.12053902, 0.11550422, 0.1156523 , ..., 0.11054346,
0.10165852,
        0.09906708],
       ...,
       [0.36731823, 0.35176958, 0.36080261, ..., 0.36391234,
0.37042796,
        0.37042796],
       [0.35176958, 0.36080261, 0.35354657, ..., 0.37042796,
0.37042796,
        0.37879461],
       [0.36080261, 0.35354657, 0.35295424, ..., 0.37042796,
0.37879461,
        0.37916482]])

x_test
array([[0.38005331, 0.36872501, 0.37324152, ..., 0.3537687 ,
0.35465719,
        0.3499926 ],
       [0.36872501, 0.37324152, 0.38205242, ..., 0.35465719, 0.3499926
,

```

```

        0.3465867 ],
        [0.37324152, 0.38205242, 0.38042352, ..., 0.3499926 , 0.3465867
,
        0.34355101],
        ...,
        [0.40604176, 0.41218718, 0.41041019, ..., 0.46794017,
0.47297497,
        0.47119799],
        [0.41218718, 0.41041019, 0.43513994, ..., 0.47297497,
0.47119799,
        0.47341922],
        [0.41041019, 0.43513994, 0.4417296 , ..., 0.47119799,
0.47341922,
        0.46497853]])

```

```

x_train1=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)
x_train1

```

```

array([[ [0.11335703],
        [0.11661484],
        [0.12053902],
        ...,
        [0.10980305],
        [0.1089886 ],
        [0.11054346]],

       [ [0.11661484],
        [0.12053902],
        [0.11550422],
        ...,
        [0.1089886 ],
        [0.11054346],
        [0.10165852]],

       [ [0.12053902],
        [0.11550422],
        [0.1156523 ],
        ...,
        [0.11054346],
        [0.10165852],
        [0.09906708]],

       ...,

       [ [0.36731823],
        [0.35176958],
        [0.36080261],
        ...,
        [0.36391234],

```

```

[0.37042796],
[0.37042796]],

[[0.35176958],
[0.36080261],
[0.35354657],
...,
[0.37042796],
[0.37042796],
[0.37879461]],

[[0.36080261],
[0.35354657],
[0.35295424],
...,
[0.37042796],
[0.37879461],
[0.37916482]]])

```

Model building

Importing model building libraries

```

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM

```

Initializing the model

```
model=Sequential()
```

Adding LSTM and output layers

```

model.add(LSTM(50, return_sequences=True, input_shape=(10, 1)))
model.add(LSTM(50, return_sequences=True))
model.add(LSTM(50))

```

```
model.add(Dense(1))
```

```
model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
=====		
lstm (LSTM)	(None, 10, 50)	10400
lstm_1 (LSTM)	(None, 10, 50)	20200
lstm_2 (LSTM)	(None, 50)	20200
dense (Dense)	(None, 1)	51

```
=====
Total params: 50,851
Trainable params: 50,851
Non-trainable params: 0
=====
```

Configuring the learning process

```
model.compile(loss='mean_squared_error',optimizer='adam')
```

Model training

```
model.fit(x_train,y_train,validation_data=(x_test,y_test),epochs=3,batch_size=64,verbose=1)
```

```
Epoch 1/3
84/84 [=====] - 10s 48ms/step - loss: 0.0021
- val_loss: 0.0011
Epoch 2/3
84/84 [=====] - 3s 30ms/step - loss: 1.3056e-04
- val_loss: 7.6737e-04
Epoch 3/3
84/84 [=====] - 2s 29ms/step - loss: 1.2407e-04
- val_loss: 7.6907e-04
```

```
<keras.callbacks.History at 0x7f32f48cef10>
```

Evaluation

```
train_predict=scaler.inverse_transform(train_data)
test_predict=scaler.inverse_transform(test_data)
```

```
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(train_data,train_predict))

29.347830443269938
```

Model saving

```
from tensorflow.keras.models import load_model

model.save("crude_oil.hs")
```

```
WARNING:absl:Found untraced functions such as lstm_cell_layer_call_fn,
lstm_cell_layer_call_and_return_conditional_losses,
lstm_cell_1_layer_call_fn,
lstm_cell_1_layer_call_and_return_conditional_losses,
lstm_cell_2_layer_call_fn while saving (showing 5 of 6). These
functions will not be directly callable after loading.
```

Model testing

```
look_back=10
trainpredictPlot = np.empty_like(data)
```

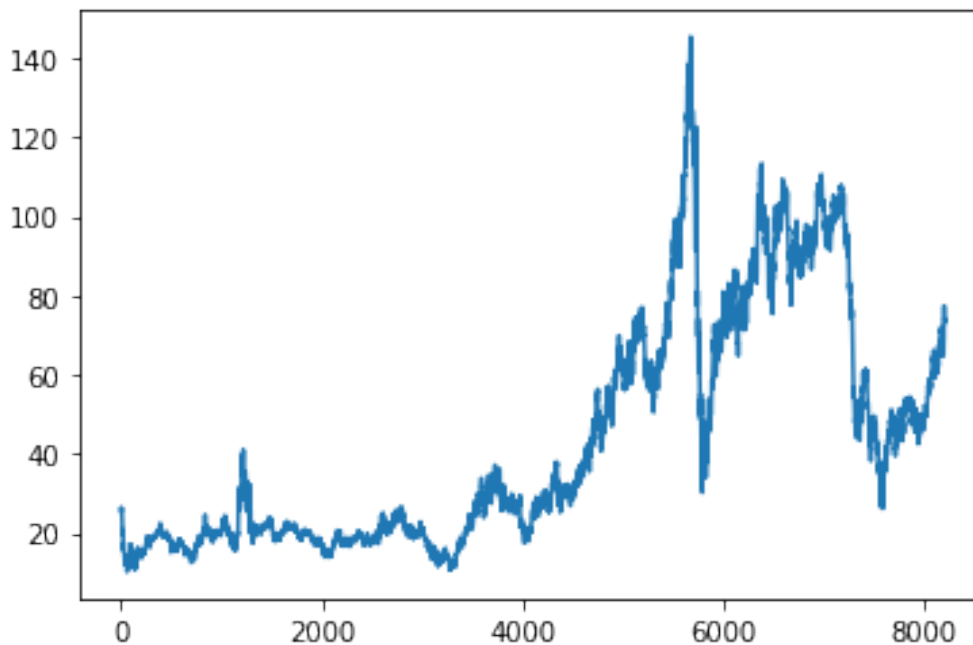
```

trainpredictPlot[:, :]= np.nan
trainpredictPlot[look_back:len(train_predict)+look_back, :] =
train_predict

testPredictplot = np.empty_like(data)
testPredictplot[:, : ] = np.nan
testPredictplot[look_back:len(test_predict)+look_back, :] =
test_predict

plt.plot(scaler.inverse_transform(data))
plt.show()

```



```

len(test_data)

2876

x_input=test_data[2866:].reshape(1, -1)
x_input.shape

(1, 10)

temp_input=list(x_input)
temp_input=temp_input[0].tolist()
temp_input

[0.44172960165852215,
 0.48111950244335855,
 0.49726047682511476,
 0.4679401747371539,
 0.4729749740855915,
 0.47119798608026064,
 0.47341922108692425,

```

```
0.4649785280616022,  
0.4703835332444839,  
0.47149415074781587]
```

```
lst_output=[]  
n_steps=10  
i=0  
while(i<10):  
    if(len(temp_input)>10):  
        x_input=np.array(temp_input[1:])  
        print("{} day input {}".format(i,x_input))  
        x_input=x_input.reshape(1,-1)  
        x_input = x_input.reshape((1, n_steps, 1))  
        yhat = model.predict(x_input, verbose=0)  
        print("{} day output {}".format(i,yhat))  
        temp_input.extend(yhat[0].tolist())  
        temp_input=temp_input[1:]  
        lst_output.extend(yhat.tolist())  
        i=i+1  
    else:  
        x_input = x_input.reshape((1, n_steps, 1))  
        yhat = model.predict(x_input, verbose=0)  
        print(yhat[0])  
        temp_input.extend(yhat[0].tolist())  
        print(len(temp_input))  
        lst_output.extend(yhat.tolist())  
        i=i+1
```

```
[0.4779267]
```

```
11
```

```
1 day input [0.4811195  0.49726048 0.46794017 0.47297497 0.47119799  
0.47341922  
0.46497853 0.47038353 0.47149415 0.4779267 ]  
1 day output [[0.48198324]]  
2 day input [0.49726048 0.46794017 0.47297497 0.47119799 0.47341922  
0.46497853  
0.47038353 0.47149415 0.4779267  0.48198324]  
2 day output [[0.48077223]]  
3 day input [0.46794017 0.47297497 0.47119799 0.47341922 0.46497853  
0.47038353  
0.47149415 0.4779267  0.48198324 0.48077223]  
3 day output [[0.4776754]]  
4 day input [0.47297497 0.47119799 0.47341922 0.46497853 0.47038353  
0.47149415  
0.4779267  0.48198324 0.48077223 0.47767541]  
4 day output [[0.47881684]]  
5 day input [0.47119799 0.47341922 0.46497853 0.47038353 0.47149415  
0.4779267  
0.48198324 0.48077223 0.47767541 0.47881684]  
5 day output [[0.4794408]]  
6 day input [0.47341922 0.46497853 0.47038353 0.47149415 0.4779267
```



```

0.48198324
0.48077223 0.47767541 0.47881684 0.47944081]
6 day output [[0.4804469]]
7 day input [0.46497853 0.47038353 0.47149415 0.4779267 0.48198324
0.48077223
0.47767541 0.47881684 0.47944081 0.4804469 ]
7 day output [[0.48127162]]
8 day input [0.47038353 0.47149415 0.4779267 0.48198324 0.48077223
0.47767541
0.47881684 0.47944081 0.4804469 0.48127162]
8 day output [[0.48332173]]
9 day input [0.47149415 0.4779267 0.48198324 0.48077223 0.47767541
0.47881684
0.47944081 0.4804469 0.48127162 0.48332173]
9 day output [[0.4847059]]

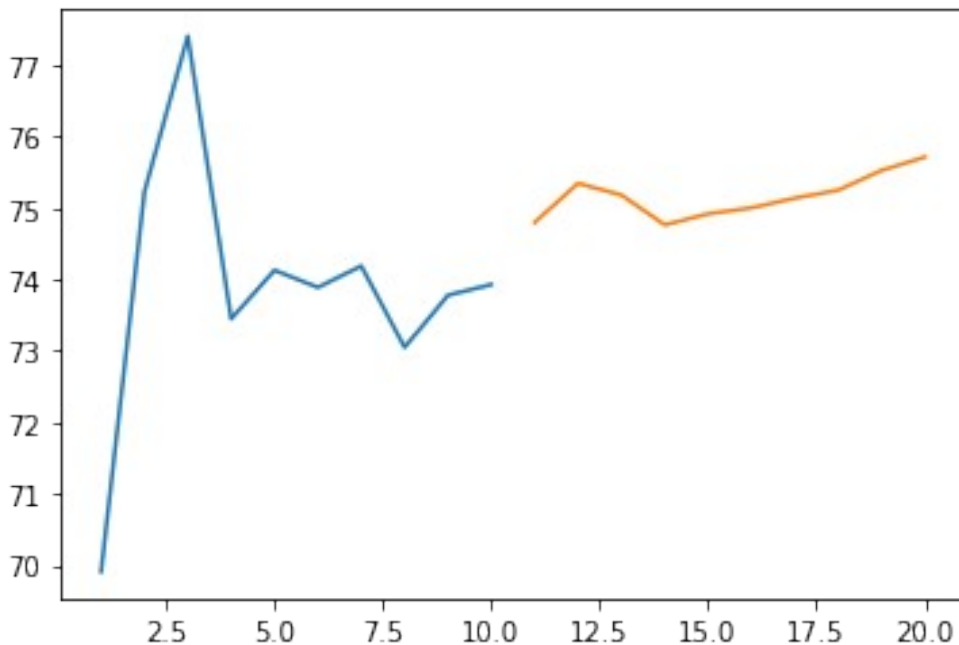
```

```

day_new=np.arange(1,11)
day_pred=np.arange(11,21)
len(data)
plt.plot(day_new, scaler.inverse_transform(data[8206:]))
plt.plot(day_pred, scaler.inverse_transform(lst_output))

[<matplotlib.lines.Line2D at 0x7f32ebb04950>]

```

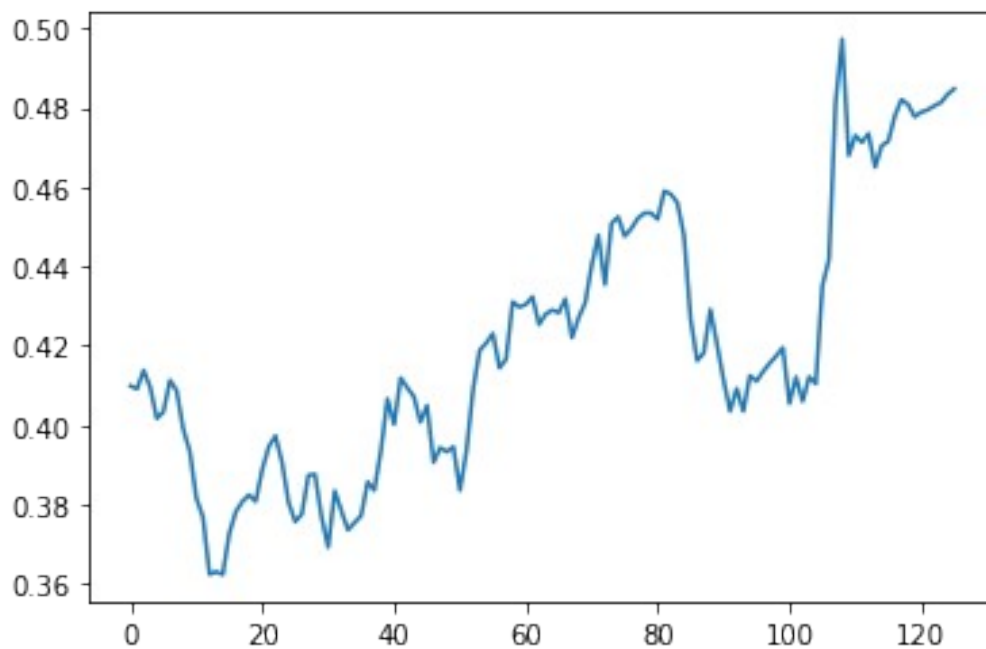


```

df3=data.tolist()
df3.extend(lst_output)
plt.plot(df3[8100:])

[<matplotlib.lines.Line2D at 0x7f32efc1dad0>]

```



```
df3=scaler.inverse_transform(df3).tolist()  
plt.plot(scaler.inverse_transform(data))
```

[<matplotlib.lines.Line2D at 0x7f32f00b5890>]

