

Metal_Options (2)

April 25, 2021

```
[121]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from sklearn.model_selection import train_test_split
```

```
[122]: # Import required libraries
import pandas as pd
import numpy as np
from pandas.plotting import lag_plot
from pandas.plotting import autocorrelation_plot
from matplotlib import pyplot
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
import math as math
from scipy.stats import boxcox
from random import randrange
from random import seed
from random import random
from random import gauss
```

```
[123]: df = pd.read_csv("https://raw.githubusercontent.com/shauryashivam/
↳commodity-futures/main/Dataset/Gold10.csv?
↳token=AMF2Z3NMUTVJFFMLGV35QJLARWXAS",header=0, index_col=0, parse_dates=True,
squeeze=True)
```

```
[124]: df.drop(columns=['Open','High','Low','Adj Close','Volume'],axis=1,inplace=True)
```

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

```
[125]:
```

	Close
Date	
2011-01-03	1422.599976
2011-01-04	1378.500000
2011-01-05	1373.400024
2011-01-06	1371.400024
2011-01-07	1368.500000

```
[126]: df.describe()
```

```
[126]:
```

	Close
count	2494.000000
mean	1401.598516
std	216.463398
min	1050.800049
25%	1243.425018
50%	1317.400024
75%	1574.674957
max	2051.500000

1 Single Lag

```
[127]: var = pd.DataFrame(df.values)
dataframe = pd.concat([var.shift(1), var], axis=1)
dataframe.columns = ['t', 't+1']
print(dataframe.head(5))
```

	t	t+1
0	NaN	1422.599976
1	1422.599976	1378.500000
2	1378.500000	1373.400024
3	1373.400024	1371.400024
4	1371.400024	1368.500000

```
[128]: var = pd.DataFrame(df.values)
dataframe = pd.concat([var.shift(3), var.shift(2), var.shift(1), var], axis=1)
dataframe.columns = ['t-2', 't-1', 't', 't+1']
print(dataframe.head(5))
```

	t-2	t-1	t	t+1
0	NaN	NaN	NaN	1422.599976
1	NaN	NaN	1422.599976	1378.500000
2	NaN	1422.599976	1378.500000	1373.400024
3	1422.599976	1378.500000	1373.400024	1371.400024
4	1378.500000	1373.400024	1371.400024	1368.500000

```
[129]: var = pd.DataFrame(df.values)
shifted = var.shift(1)
window = shifted.rolling(window=2)
means = window.mean()
dataframe = pd.concat([means, var], axis=1)
dataframe.columns = ['mean(t-1,t)', 't+1']
print(dataframe.head(5))
```

	mean(t-1,t)	t+1
--	-------------	-----

```

0          NaN  1422.599976
1          NaN  1378.500000
2  1400.549988  1373.400024
3  1375.950012  1371.400024
4  1372.400024  1368.500000

```

```

[130]: var = pd.DataFrame(df.values)
window = var.expanding()
dataframe = pd.concat([window.min(), window.mean(), window.max(), var.
    ↪shift(-1)], axis=1)
dataframe.columns = ['min', 'mean', 'max', 't+1']
print(dataframe.head(5))

```

```

      min      mean      max      t+1
0  1422.599976  1422.599976  1422.599976  1378.500000
1  1378.500000  1400.549988  1422.599976  1373.400024
2  1373.400024  1391.500000  1422.599976  1371.400024
3  1371.400024  1386.475006  1422.599976  1368.500000
4  1368.500000  1382.880005  1422.599976  1373.699951

```

```

[131]: dataframe = pd.DataFrame()
dataframe['month'] = [df.index[i].month for i in range(len(df))]
dataframe['day'] = [df.index[i].day for i in range(len(df))]
dataframe['Close'] = [df['Close'] for i in range(len(df))]
print(dataframe.head(5))

```

```

      month  day      Close
0         1    3  Date
2011-01-03  1422.599976
2011-01-04    1...
1         1    4  Date
2011-01-03  1422.599976
2011-01-04    1...
2         1    5  Date
2011-01-03  1422.599976
2011-01-04    1...
3         1    6  Date
2011-01-03  1422.599976
2011-01-04    1...
4         1    7  Date
2011-01-03  1422.599976
2011-01-04    1...

```

```

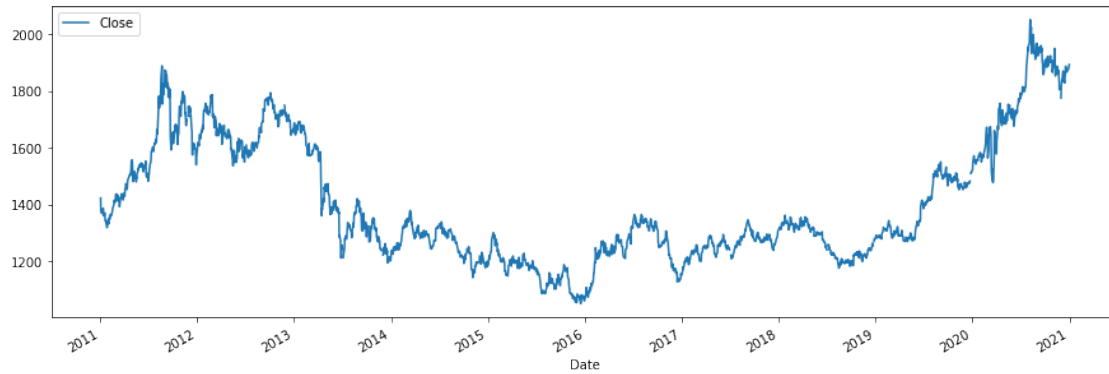
[132]: df.plot(figsize=(15,5))

```

```

[132]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a81d4c090>

```

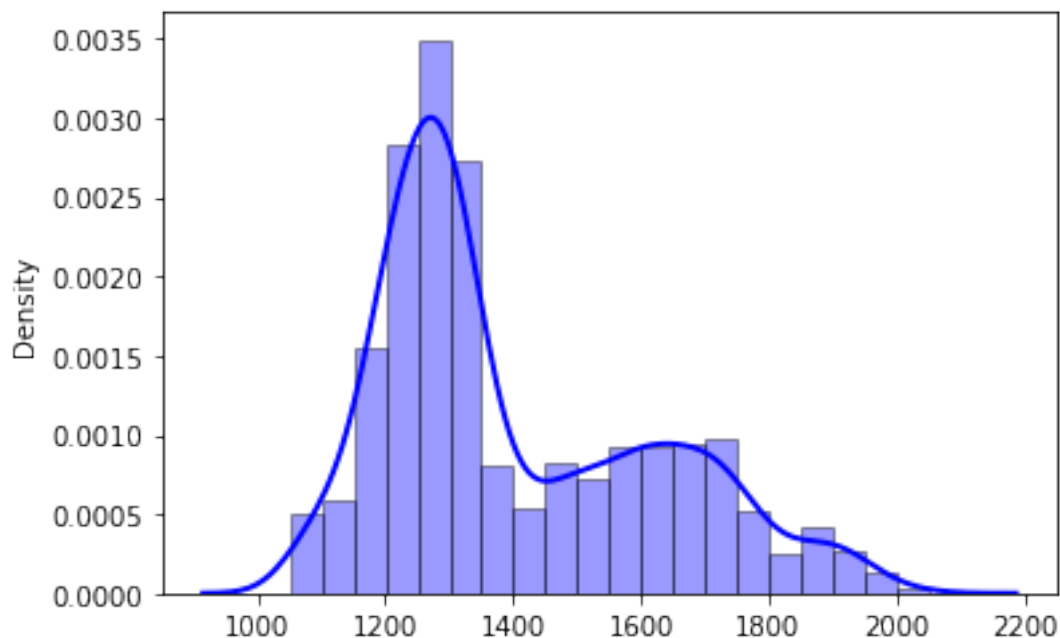


```
[133]: import seaborn as sns
sns.distplot(df, hist=True, kde=True,
             bins=20,
             color = 'blue',
             hist_kws={'edgecolor': 'black'},
             kde_kws={'linewidth': 2})
```

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

```
[133]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a81da9450>
```

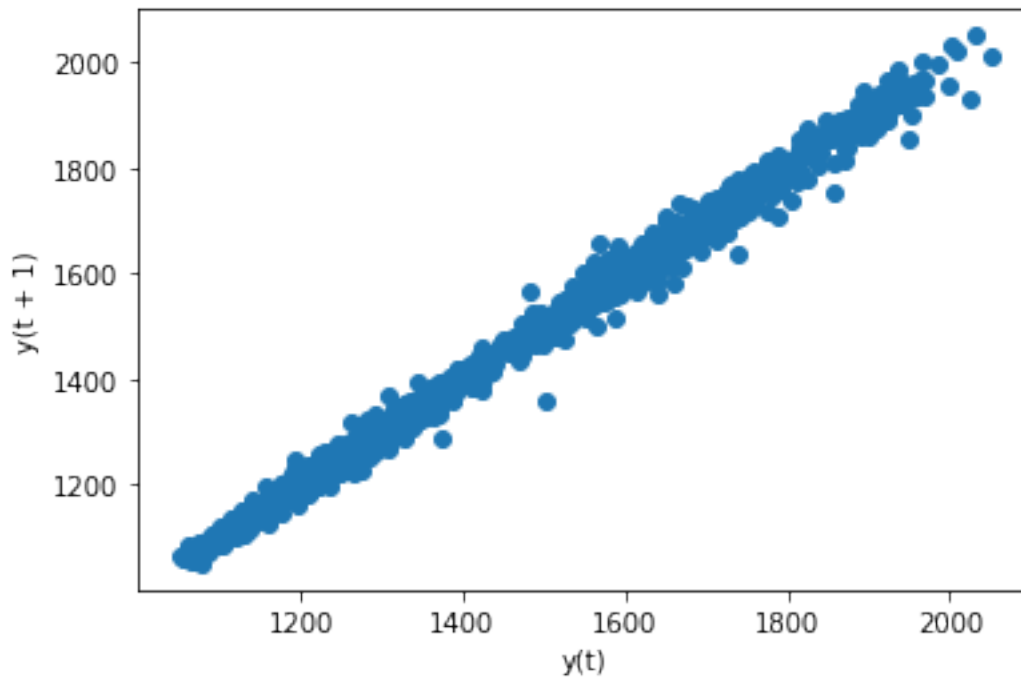


```
[134]: df.head(
)
```

```
[134]:
```

	Close
Date	
2011-01-03	1422.599976
2011-01-04	1378.500000
2011-01-05	1373.400024
2011-01-06	1371.400024
2011-01-07	1368.500000

```
[135]: lag_plot(df)
pyplot.show()
```

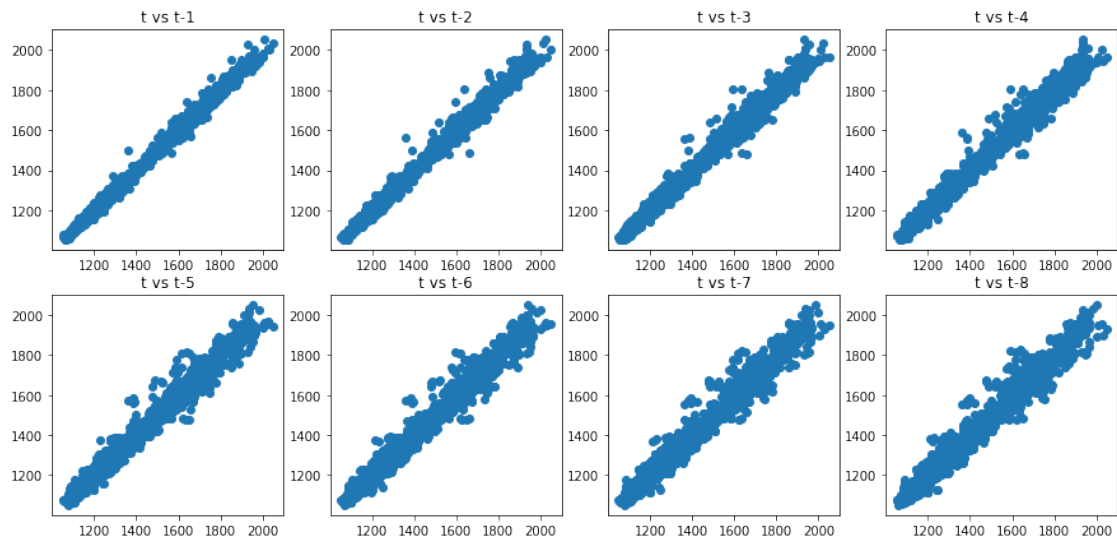


```
[136]: values = pd.DataFrame(df.values)
lags = 8
columns = [values]
for i in range(1,(lags + 1)):
    columns.append(values.shift(i))
dataframe = pd.concat(columns, axis=1)
columns = ['t']
for i in range(1,(lags + 1)):
```

```

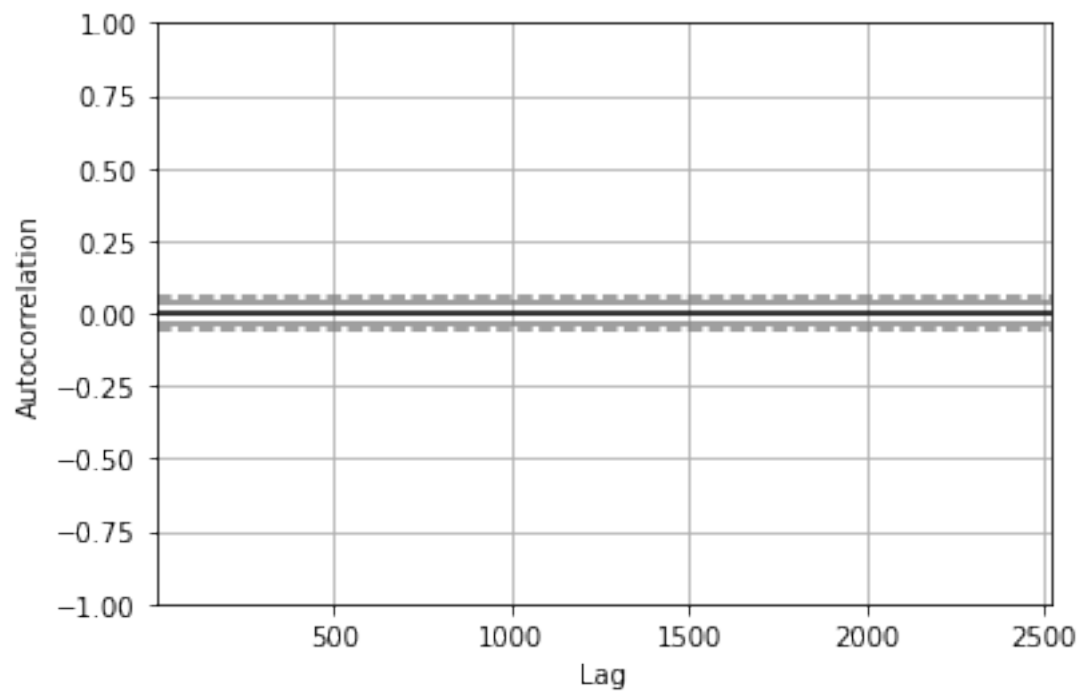
columns.append('t-' + str(i))
dataframe.columns = columns
pyplot.figure(1,figsize=(15,7))
for i in range(1,(lags + 1)):
    ax = pyplot.subplot(240 + i)
    ax.set_title('t vs t-' + str(i))
    pyplot.scatter(x=dataframe['t'].values, y=dataframe['t-'+str(i)].values)
pyplot.show()

```



```
[137]: autocorrelation_plot(df)
```

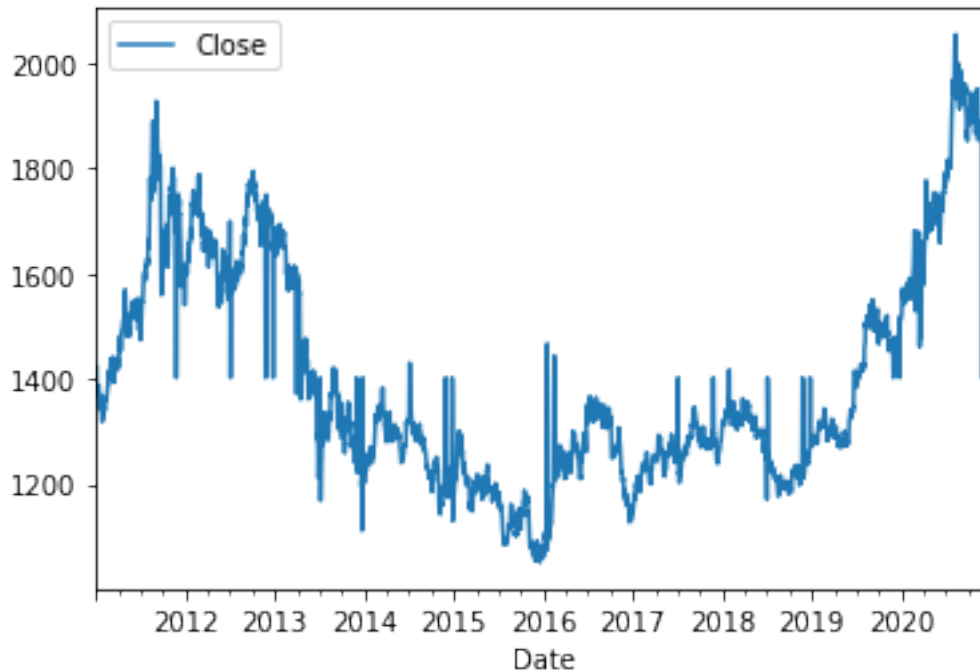
```
[137]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a81c682d0>
```



```
[138]: df=df.fillna(df.mean())
```

```
[139]: upsampled = df.resample('D').mean()  
interpolated = upsampled.interpolate(method='quadratic')  
interpolated.plot()
```

```
[139]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a4c005b90>
```



```
[140]: pip install mxnet
```

```
Requirement already satisfied: mxnet in /usr/local/lib/python3.7/dist-packages
(1.8.0.post0)
Requirement already satisfied: graphviz<0.9.0,>=0.8.1 in
/usr/local/lib/python3.7/dist-packages (from mxnet) (0.8.4)
Requirement already satisfied: requests<3,>=2.20.0 in
/usr/local/lib/python3.7/dist-packages (from mxnet) (2.23.0)
Requirement already satisfied: numpy<2.0.0,>1.16.0 in
/usr/local/lib/python3.7/dist-packages (from mxnet) (1.19.5)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from requests<3,>=2.20.0->mxnet) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.7/dist-packages (from requests<3,>=2.20.0->mxnet)
(1.24.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/dist-packages (from requests<3,>=2.20.0->mxnet)
(2020.12.5)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from requests<3,>=2.20.0->mxnet) (3.0.4)
```

```
[141]: import time
import numpy as np

from mxnet import nd, autograd, gluon
```



```

from mxnet.gluon import nn, rnn
import mxnet as mx
import datetime
import seaborn as sns

import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.decomposition import PCA

import math

from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler

import xgboost as xgb
from sklearn.metrics import accuracy_score

```

```
[142]: df.describe()
```

```

[142]:          Close
count  2518.000000
mean   1401.598516
std     215.428920
min     1050.800049
25%     1243.724976
50%     1318.900024
75%     1572.325012
max     2051.500000

```

2 BUILDING MODEL

2.1 LSTM-GRU

```

[143]: model = tf.keras.Sequential()
model.add(tf.keras.layers.GRU(5,activation = 'relu', input_shape=(1,1)))
model.add(Dense(100,activation='relu'))
model.add(Dense(1))
model.compile(loss='mse',optimizer='adam',metrics=['mae'])

```

2.2 LSTM CNN Attention

```

[144]: !pip install keras-attention
!pip install keras-self-attention

```

Requirement already satisfied: keras-attention in /usr/local/lib/python3.7/dist-packages (1.0.0)

Requirement already satisfied: keras in /usr/local/lib/python3.7/dist-packages (from keras-attention) (2.4.3)

Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from keras->keras-attention) (2.10.0)

Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.7/dist-packages (from keras->keras-attention) (1.4.1)

Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages (from keras->keras-attention) (1.19.5)

Requirement already satisfied: pyyaml in /usr/local/lib/python3.7/dist-packages (from keras->keras-attention) (3.13)

Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from h5py->keras->keras-attention) (1.15.0)

Requirement already satisfied: keras-self-attention in /usr/local/lib/python3.7/dist-packages (0.49.0)

Requirement already satisfied: Keras in /usr/local/lib/python3.7/dist-packages (from keras-self-attention) (2.4.3)

Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from keras-self-attention) (1.19.5)

Requirement already satisfied: pyyaml in /usr/local/lib/python3.7/dist-packages (from Keras->keras-self-attention) (3.13)

Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.7/dist-packages (from Keras->keras-self-attention) (1.4.1)

Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from Keras->keras-self-attention) (2.10.0)

Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from h5py->Keras->keras-self-attention) (1.15.0)

```
[145]: import os
import time
import warnings
import numpy as np
import pandas as pd
import operator
from functools import reduce
import h5py
from numpy import newaxis
from keras.layers.core import Dense, Activation, Dropout
from keras.layers import Convolution1D, MaxPooling1D, Flatten, Embedding, Bidirectional, GRU
from keras.layers import Conv1D, GlobalMaxPooling1D, merge
from keras.layers.recurrent import LSTM
from keras.models import Sequential
from keras_self_attention import SeqSelfAttention
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler, Normalizer
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
from math import sqrt
```

```
[146]: def create_dataset(dataset, look_back=1, columns = ['Close']):
        dataX, dataY = [], []
        for i in range(len(dataset.index)):
            if i < look_back:
                continue
            a = None
            for c in columns:
                b = dataset.loc[dataset.index[i-look_back:i], c].to_numpy()
                if a is None:
                    a = b
                else:
                    a = np.append(a,b)
            dataX.append(a)
            dataY.append(dataset.loc[dataset.index[i-look_back], columns].
→to_numpy())
        return np.array(dataX), np.array(dataY)
```

```
[147]: look_back = 7 # 10, 13
        sc = StandardScaler()
        df.loc[:, 'Close'] = sc.fit_transform(df.Close.values.reshape(-1,1)) # fit.
→transform()
        print(df.loc[:, 'Close'])

        # Create training data
        #train_df = df.loc[df.index < pd.to_datetime('2010-01-01')]
        train_df = df.loc[df.index < df.index[int(len(df.index)*0.8)]]
        train_x, train_y = create_dataset(train_df, look_back=look_back)

        # Construct the whole LSTM + CNN
        model = Sequential()
        # LSTM
        model.add(GRU(6,input_shape = (look_back, 1), input_dim=1 ,
→return_sequences=True))

        #model.add(LSTM(input_shape = (look_back,1), input_dim=1, output_dim=6,
→return_sequences=True))
        #model.add(Dense(1))
        #model.add(Activation('relu')) # ReLU :  $y = \max(0, x)$ 

        # Attention Mechanism
        model.add(SeqSelfAttention(attention_activation='sigmoid', name='Attention'))

        # CNN
        model.add(Convolution1D(input_shape = (look_back,1),
```

```

        filters=64,# 32,128
        kernel_size=2,
        activation='relu',
    ))
#model.add(MaxPooling1D(pool_length=2))

'''model.add(Convolution1D(input_shape = (look_back,1),
        nb_filter=64,
        filter_length=2,
        border_mode='valid',
        activation='relu',
        subsample_length=1))'''
model.add(MaxPooling1D(pool_size=(2)))

model.add(Dropout(0.25))

#model.add(Dense(250))
#model.add(Dropout(0.25,input_shape=(2,)))
model.add(Activation('relu')) # ReLU :  $y = \max(0, x)$ 
model.add(Dense(1))
model.add(Activation('linear')) # Linear :  $y = x$ 

# Print whole structure of the model
print(model.summary())

# training the train data with n epoch
model.compile(loss="mse", optimizer="adam") # adam, rmsprop
result = model.fit(np.atleast_3d(np.array(train_x)),
        np.atleast_3d(train_y),
        epochs=100,
        batch_size=80, verbose=1, shuffle=False)

with open('data_lstm_attention_cnn_palladium.txt','w') as f:
    f.write(str(result.history))

model.save('lstm_attention_cnn_palladium.h5')

# Make prediction and specify on the line chart
predictors = ['Close']
df['Pred'] = df.loc[df.index[0], 'Close']
for i in range(len(df.index)):
    if i < look_back:
        continue
    a = None
    for c in predictors:

```

```

        b = df.loc[df.index[i-look_back:i], c].to_numpy()
        if a is None:
            a = b
        else:
            a = np.append(a,b)
        a = a
    y = model.predict(a.reshape(1,look_back*len(predictors),1))
    df.loc[df.index[i], 'Pred']=y[0][0]

df.loc[:, 'Close'] = sc.inverse_transform(df.loc[:, 'Close'])
df.loc[:, 'Pred'] = sc.inverse_transform(df.loc[:, 'Pred'])

def mape(y_true, y_pred):
    n = len(y_true)
    mape = sum(np.abs((y_true - y_pred) / y_true)) / n * 100
    return mape

# present the line chart and some parameters like MSE, which reflects the
→accuracy of the model in sample or out sample

plt.grid(ls='--')
plt.plot(df.loc[df.index < df.index[int(len(df.index)*0.8)], 'Pred'], 'orange',
→label = 'Insample Prediction')
plt.plot(df.loc[df.index >= df.index[int(len(df.index)*0.8)], 'Pred'], 'g',
→label = 'Outsample Prediction')
plt.plot(df.Close, 'b', label = 'Price')
plt.xlabel('Date')
plt.ylabel('Closing Price')
#print('%e'%mean_squared_error(df.loc[df.index < pd.
→to_datetime('2010-01-01'),'Close'],df.loc[df.index < pd.
→to_datetime('2010-01-01'),'Pred']))
#print('%e'%mean_squared_error(df.loc[df.index >= pd.
→to_datetime('2010-01-01'),'Close'],df.loc[df.index >= pd.
→to_datetime('2010-01-01'),'Pred']))
print('The RMSE is ', '%e'%sqrt(mean_squared_error(df.loc[df.index >= df.
→index[int(len(df.index)*0.8)], 'Close'], df.loc[df.index >= df.
→index[int(len(df.index)*0.8)], 'Pred'])))
print('The RMAE is ', '%e'%sqrt(mean_absolute_error(df.loc[df.index >= df.
→index[int(len(df.index)*0.8)], 'Close'], df.loc[df.index >= df.
→index[int(len(df.index)*0.8)], 'Pred'])))
print('The MAPE is ', '%e'%mape(df.loc[df.index >= df.index[int(len(df.index)*0.
→8)], 'Close'], df.loc[df.index >= df.index[int(len(df.index)*0.8)], 'Pred'])))

plt.legend()
plt.savefig("lstm_attention_cnn_palladium.eps", format='eps', dpi=1000)

```

```
plt.show()
```

```
Date
2011-01-03    0.097506
2011-01-04   -0.107242
2011-01-05   -0.130921
2011-01-06   -0.140206
2011-01-07   -0.153671
...
2020-12-24    0.000000
2020-12-28    2.208134
2020-12-29    2.219741
2020-12-30    2.272205
2020-12-31    2.281955
Name: Close, Length: 2518, dtype: float64
Model: "sequential_17"
```

Layer (type)	Output Shape	Param #
gru_3 (GRU)	(None, 7, 6)	162
Attention (SeqSelfAttention)	(None, None, 6)	449
conv1d_8 (Conv1D)	(None, None, 64)	832
max_pooling1d_7 (MaxPooling1D)	(None, None, 64)	0
dropout_5 (Dropout)	(None, None, 64)	0
activation_10 (Activation)	(None, None, 64)	0
dense_9 (Dense)	(None, None, 1)	65
activation_11 (Activation)	(None, None, 1)	0

```
Total params: 1,508
Trainable params: 1,508
Non-trainable params: 0
```

```
None
Epoch 1/100
26/26 [=====] - 3s 8ms/step - loss: 0.8690
Epoch 2/100
26/26 [=====] - 0s 9ms/step - loss: 0.4860
Epoch 3/100
26/26 [=====] - 0s 8ms/step - loss: 0.2470
Epoch 4/100
```

26/26 [=====] - 0s 9ms/step - loss: 0.1049
 Epoch 5/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0598
 Epoch 6/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0538
 Epoch 7/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0549
 Epoch 8/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0537
 Epoch 9/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0537
 Epoch 10/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0502
 Epoch 11/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0502
 Epoch 12/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0498
 Epoch 13/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0488
 Epoch 14/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0503
 Epoch 15/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0484
 Epoch 16/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0470
 Epoch 17/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0446
 Epoch 18/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0429
 Epoch 19/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0421
 Epoch 20/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0409
 Epoch 21/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0414
 Epoch 22/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0408
 Epoch 23/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0398
 Epoch 24/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0411
 Epoch 25/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0380
 Epoch 26/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0405
 Epoch 27/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0393
 Epoch 28/100

26/26 [=====] - 0s 8ms/step - loss: 0.0412
Epoch 29/100
26/26 [=====] - 0s 9ms/step - loss: 0.0427
Epoch 30/100
26/26 [=====] - 0s 10ms/step - loss: 0.0455
Epoch 31/100
26/26 [=====] - 0s 8ms/step - loss: 0.0489
Epoch 32/100
26/26 [=====] - 0s 9ms/step - loss: 0.0518
Epoch 33/100
26/26 [=====] - 0s 9ms/step - loss: 0.0568
Epoch 34/100
26/26 [=====] - 0s 8ms/step - loss: 0.0552
Epoch 35/100
26/26 [=====] - 0s 8ms/step - loss: 0.0632
Epoch 36/100
26/26 [=====] - 0s 9ms/step - loss: 0.0548
Epoch 37/100
26/26 [=====] - 0s 9ms/step - loss: 0.0598
Epoch 38/100
26/26 [=====] - 0s 9ms/step - loss: 0.0497
Epoch 39/100
26/26 [=====] - 0s 9ms/step - loss: 0.0472
Epoch 40/100
26/26 [=====] - 0s 9ms/step - loss: 0.0429
Epoch 41/100
26/26 [=====] - 0s 9ms/step - loss: 0.0397
Epoch 42/100
26/26 [=====] - 0s 9ms/step - loss: 0.0393
Epoch 43/100
26/26 [=====] - 0s 9ms/step - loss: 0.0372
Epoch 44/100
26/26 [=====] - 0s 9ms/step - loss: 0.0362
Epoch 45/100
26/26 [=====] - 0s 9ms/step - loss: 0.0390
Epoch 46/100
26/26 [=====] - 0s 8ms/step - loss: 0.0389
Epoch 47/100
26/26 [=====] - 0s 9ms/step - loss: 0.0393
Epoch 48/100
26/26 [=====] - 0s 8ms/step - loss: 0.0385
Epoch 49/100
26/26 [=====] - 0s 9ms/step - loss: 0.0420
Epoch 50/100
26/26 [=====] - 0s 9ms/step - loss: 0.0425
Epoch 51/100
26/26 [=====] - 0s 9ms/step - loss: 0.0411
Epoch 52/100

26/26 [=====] - 0s 8ms/step - loss: 0.0395
 Epoch 53/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0417
 Epoch 54/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0386
 Epoch 55/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0420
 Epoch 56/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0440
 Epoch 57/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0483
 Epoch 58/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0478
 Epoch 59/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0531
 Epoch 60/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0474
 Epoch 61/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0512
 Epoch 62/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0464
 Epoch 63/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0492
 Epoch 64/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0422
 Epoch 65/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0427
 Epoch 66/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0415
 Epoch 67/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0422
 Epoch 68/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0401
 Epoch 69/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0407
 Epoch 70/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0379
 Epoch 71/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0396
 Epoch 72/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0397
 Epoch 73/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0420
 Epoch 74/100
 26/26 [=====] - 0s 8ms/step - loss: 0.0375
 Epoch 75/100
 26/26 [=====] - 0s 9ms/step - loss: 0.0373
 Epoch 76/100

26/26 [=====] - 0s 9ms/step - loss: 0.0363
Epoch 77/100
26/26 [=====] - 0s 10ms/step - loss: 0.0381
Epoch 78/100
26/26 [=====] - 0s 9ms/step - loss: 0.0388
Epoch 79/100
26/26 [=====] - 0s 9ms/step - loss: 0.0405
Epoch 80/100
26/26 [=====] - 0s 9ms/step - loss: 0.0392
Epoch 81/100
26/26 [=====] - 0s 9ms/step - loss: 0.0423
Epoch 82/100
26/26 [=====] - 0s 9ms/step - loss: 0.0414
Epoch 83/100
26/26 [=====] - 0s 9ms/step - loss: 0.0440
Epoch 84/100
26/26 [=====] - 0s 9ms/step - loss: 0.0416
Epoch 85/100
26/26 [=====] - 0s 9ms/step - loss: 0.0451
Epoch 86/100
26/26 [=====] - 0s 9ms/step - loss: 0.0419
Epoch 87/100
26/26 [=====] - 0s 9ms/step - loss: 0.0434
Epoch 88/100
26/26 [=====] - 0s 9ms/step - loss: 0.0395
Epoch 89/100
26/26 [=====] - 0s 9ms/step - loss: 0.0418
Epoch 90/100
26/26 [=====] - 0s 9ms/step - loss: 0.0398
Epoch 91/100
26/26 [=====] - 0s 9ms/step - loss: 0.0431
Epoch 92/100
26/26 [=====] - 0s 9ms/step - loss: 0.0386
Epoch 93/100
26/26 [=====] - 0s 9ms/step - loss: 0.0412
Epoch 94/100
26/26 [=====] - 0s 9ms/step - loss: 0.0387
Epoch 95/100
26/26 [=====] - 0s 8ms/step - loss: 0.0405
Epoch 96/100
26/26 [=====] - 0s 9ms/step - loss: 0.0383
Epoch 97/100
26/26 [=====] - 0s 10ms/step - loss: 0.0391
Epoch 98/100
26/26 [=====] - 0s 10ms/step - loss: 0.0399
Epoch 99/100
26/26 [=====] - 0s 10ms/step - loss: 0.0414
Epoch 100/100

26/26 [=====] - 0s 9ms/step - loss: 0.0397

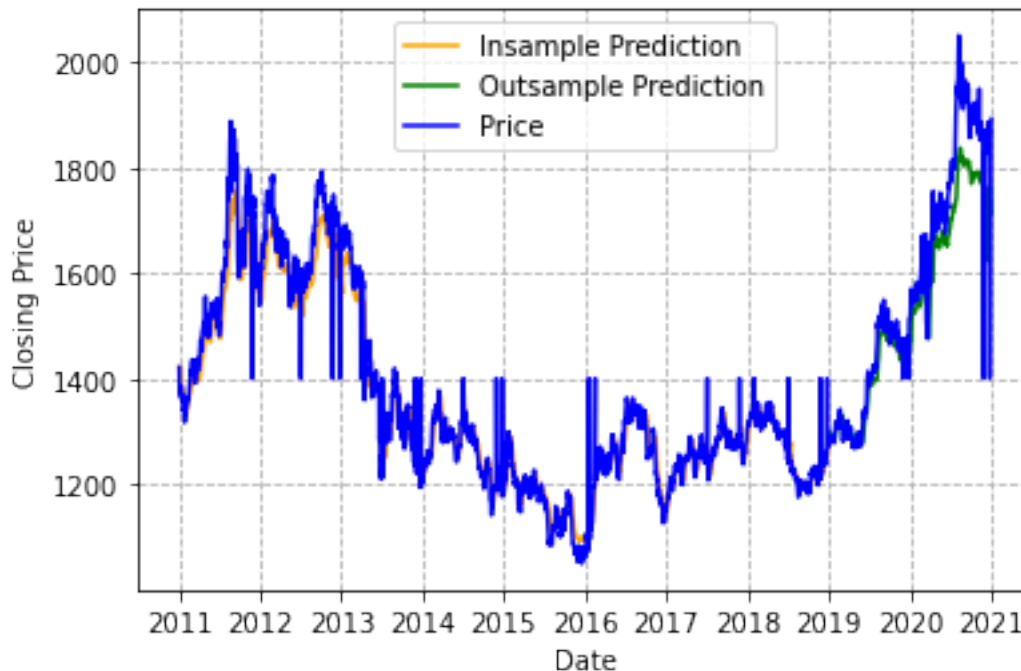
The PostScript backend does not support transparency; partially transparent artists will be rendered opaque.

The PostScript backend does not support transparency; partially transparent artists will be rendered opaque.

The RMSE is 7.786148e+01

The RMAE is 7.530844e+00

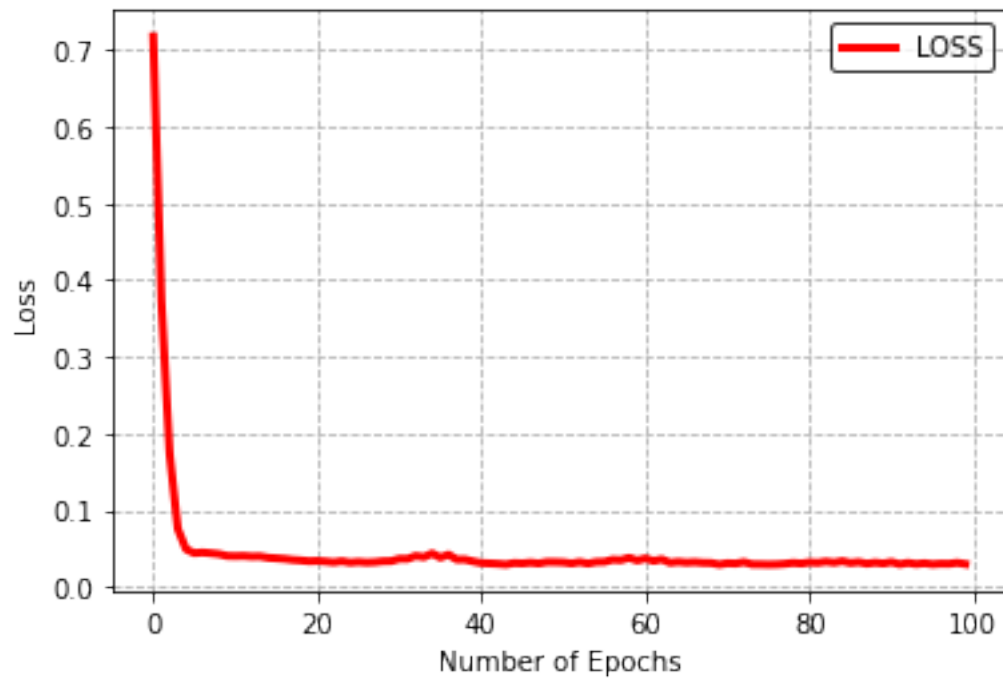
The MAPE is 3.299578e+00



```
[148]: # sketch loss
#plt.cla() # clear the axis
plt.grid(ls='--')
plt.plot(result.epoch,result.history['loss'],label='LOSS',c='r',lw=3)
#plt.scatter(result.epoch,result.history['loss'],s=15,c='r')
plt.xlabel('Number of Epochs')
plt.ylabel('Loss')
plt.legend(loc='upper right', frameon=True, edgecolor='black')
plt.savefig("LC_loss.eps", format='eps', dpi=1000)
plt.close(0)
```

The PostScript backend does not support transparency; partially transparent artists will be rendered opaque.

The PostScript backend does not support transparency; partially transparent artists will be rendered opaque.



[148]:

