

# Metal\_Options (1)

April 25, 2021

```
[1]: 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
```

```
[2]: # 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
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
import pandas.util.testing as tm
```

```
[71]: df = pd.read_csv("https://raw.githubusercontent.com/shauryashivam/
↳commodity-futures/main/Dataset/Gold5.csv?
↳token=AMF2Z3LBLLFT62EDL6NOAGDARINHK",header=0, index_col=0, parse_dates=True,
squeeze=True)
```

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

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

```
[5]:          Close
Date
```

```

2016-01-04    1075.099976
2016-01-05    1078.400024
2016-01-06    1091.900024
2016-01-07    1107.699951
2016-01-08    1097.800049

```

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

```

[6]:          Close
count    1246.000000
mean     1388.680578
std       217.880280
min       1073.900024
25%       1249.000000
50%       1299.400024
75%       1482.649963
max       2051.500000

```

## 1 Single Lag

```

[7]: 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	1075.099976
1	1075.099976	1078.400024
2	1078.400024	1091.900024
3	1091.900024	1107.699951
4	1107.699951	1097.800049

```

[8]: 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	1075.099976
1	NaN	NaN	1075.099976	1078.400024
2	NaN	1075.099976	1078.400024	1091.900024
3	1075.099976	1078.400024	1091.900024	1107.699951
4	1078.400024	1091.900024	1107.699951	1097.800049

```

[9]: 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	1075.099976
1	NaN	1078.400024
2	1076.750000	1091.900024
3	1085.150024	1107.699951
4	1099.799988	1097.800049

```

[10]: 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	1075.099976	1075.099976	1075.099976	1078.400024
1	1075.099976	1076.750000	1078.400024	1091.900024
2	1075.099976	1081.800008	1091.900024	1107.699951
3	1075.099976	1088.274994	1107.699951	1097.800049
4	1075.099976	1090.180005	1107.699951	1096.500000

```

[11]: 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))

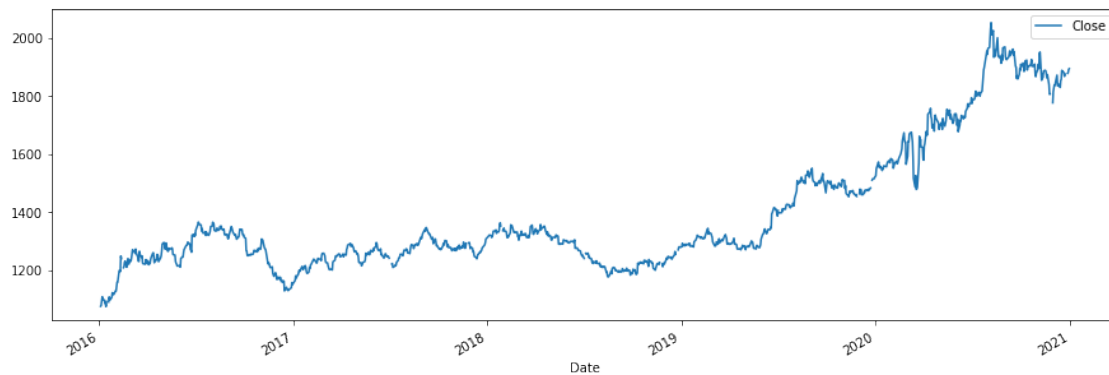
```

	month	day	Close
0	1	4	Date
	2016-01-04		1075.099976
	2016-01-05	1...	
1	1	5	Date
	2016-01-04		1075.099976
	2016-01-05	1...	
2	1	6	Date
	2016-01-04		1075.099976
	2016-01-05	1...	
3	1	7	Date
	2016-01-04		1075.099976
	2016-01-05	1...	
4	1	8	Date
	2016-01-04		1075.099976

2016-01-05 1...

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

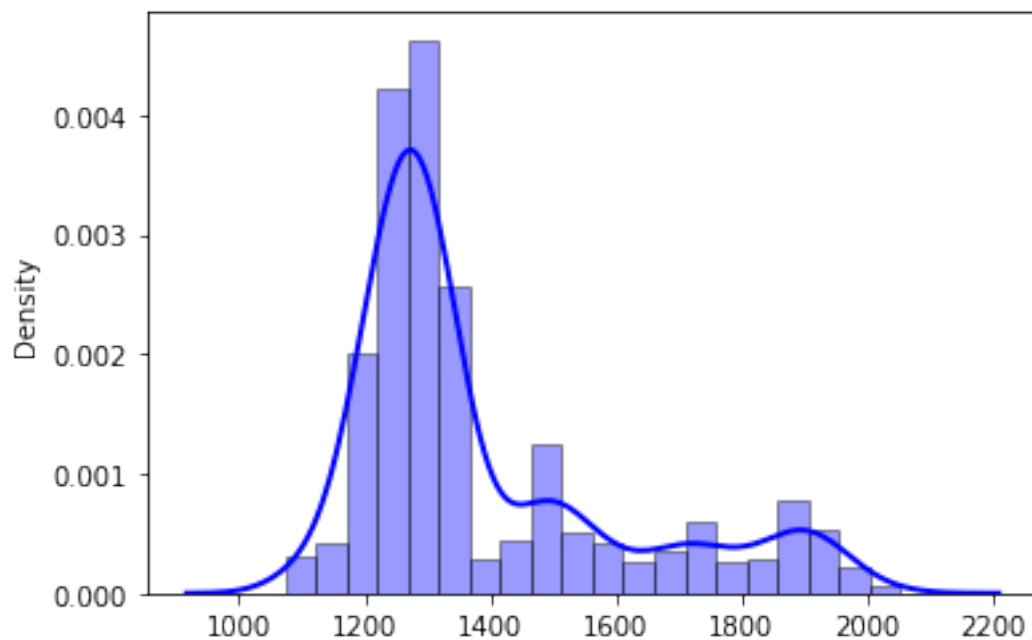
```
[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a85a08f50>
```



```
[13]: 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)
```

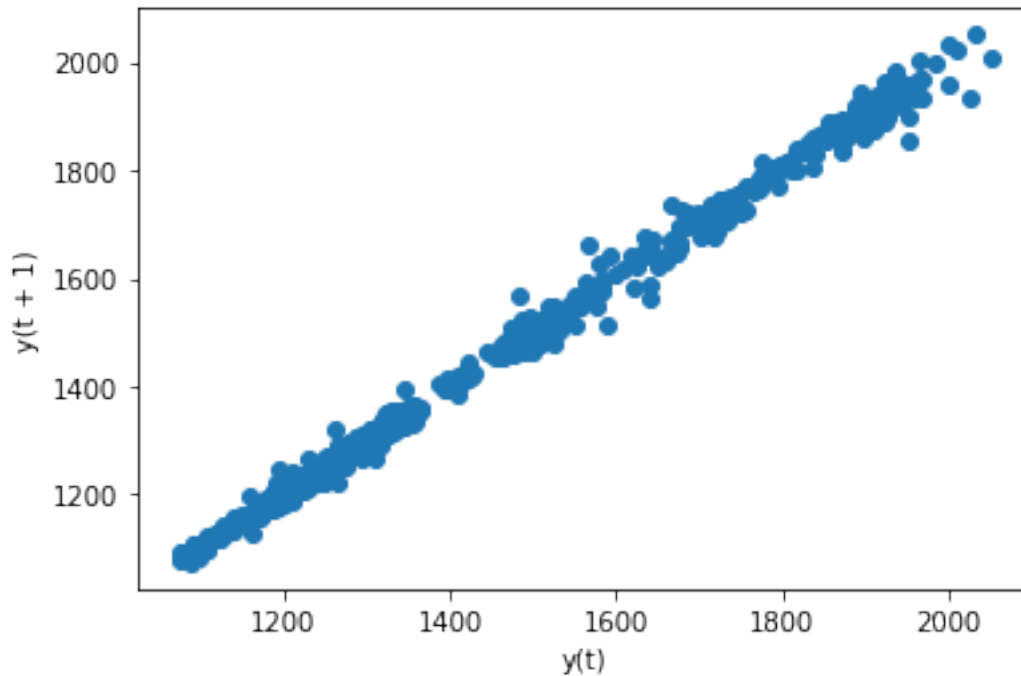
```
[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a84bdf590>
```



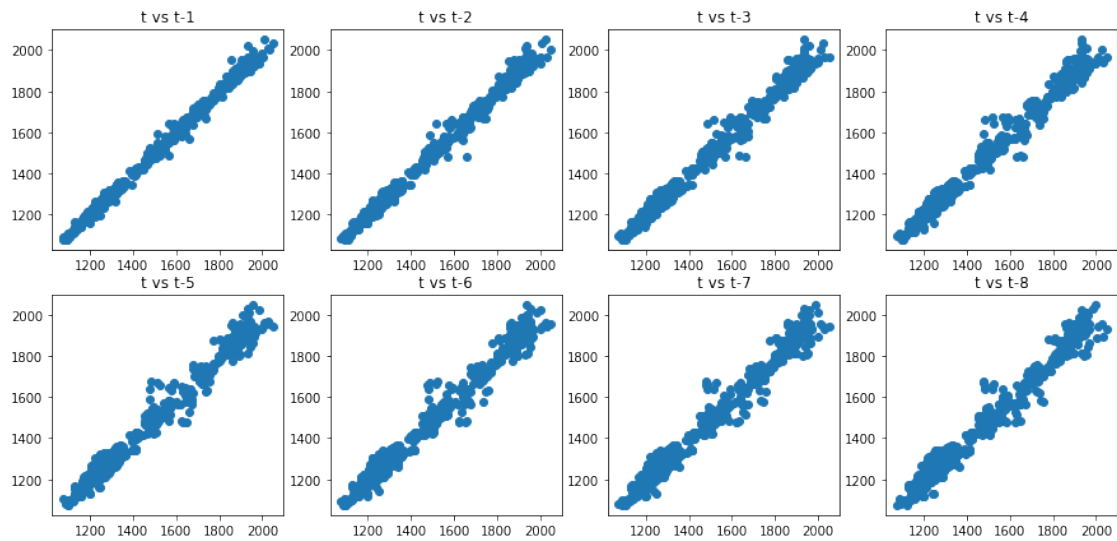
```
[14]: df.head(
)
```

```
[14]:          Close
Date
2016-01-04  1075.099976
2016-01-05  1078.400024
2016-01-06  1091.900024
2016-01-07  1107.699951
2016-01-08  1097.800049
```

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

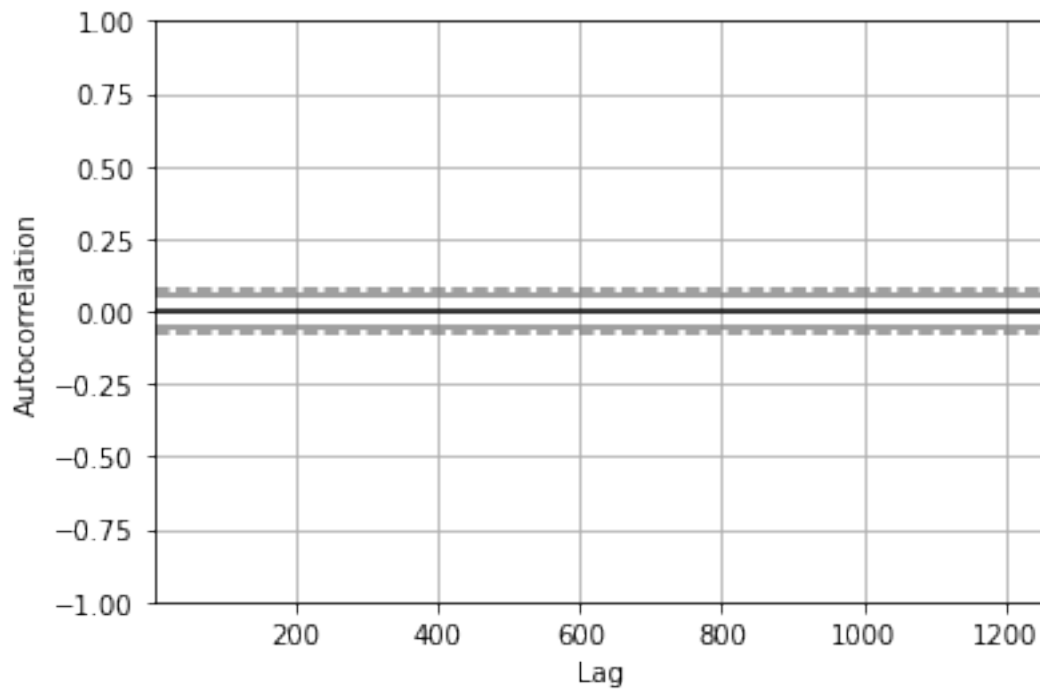


```
[17]: values = pd.DataFrame(df.values)
lags = 8
columns = [values]
for i in range(1,(lags + 1)):
    columns.append(values.shift(i))
dataframe = pd.concat(columns, axis=1)
columns = ['t']
for i in range(1,(lags + 1)):
    columns.append('t-' + str(i))
dataframe.columns = columns
pyplot.figure(1,figsize=(15,7))
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()
```



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

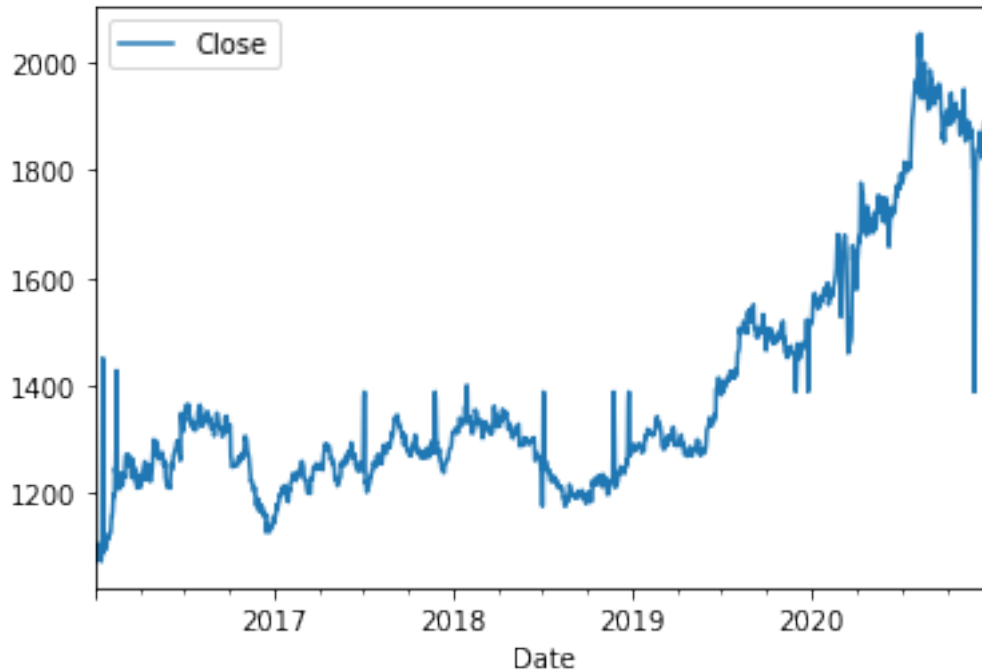
```
[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0a81a2b810>
```



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

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

[23]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f0a78f6e9d0>



```
[24]: pip install mxnet
```

Collecting mxnet

Downloading [https://files.pythonhosted.org/packages/30/07/66174e78c12a3048db9039aaa09553e35035ef3a008ba3e0ed8d2aa3c47b/mxnet-1.8.0.post0-py2.py3-none-manylinux2014\\_x86\\_64.whl](https://files.pythonhosted.org/packages/30/07/66174e78c12a3048db9039aaa09553e35035ef3a008ba3e0ed8d2aa3c47b/mxnet-1.8.0.post0-py2.py3-none-manylinux2014_x86_64.whl) (46.9MB)  
| 46.9MB 98kB/s

Collecting graphviz<0.9.0,>=0.8.1

Downloading <https://files.pythonhosted.org/packages/53/39/4ab213673844e0c004bed8a0781a0721a3f6bb23eb8854ee75c236428892/graphviz-0.8.4-py2.py3-none-any.whl>

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: 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: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests<3,>=2.20.0->mxnet) (2.10)



```
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)
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)
Installing collected packages: graphviz, mxnet
  Found existing installation: graphviz 0.10.1
  Uninstalling graphviz-0.10.1:
    Successfully uninstalled graphviz-0.10.1
Successfully installed graphviz-0.8.4 mxnet-1.8.0.post0
```

```
[25]: 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
```

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

```
[26]:
```

	Close
count	1259.000000
mean	1388.680578
std	216.751584
min	1073.900024
25%	1249.250000
50%	1301.500000
75%	1481.849976
max	2051.500000

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(
...     X, y, test_size=0.15, random_state=42)
```

```
[ ]: model = tf.keras.Sequential()

[ ]: model.add(tf.keras.layers.
    ↳Conv1D(kernel_size=64,filters=3*3, strides=1,activation="relu"))
model.add(tf.keras.layers.MaxPooling1D(pool_size=2))

[ ]: model.summary()
```

## 2 BUILDING MODEL

### 2.1 LSTM-GRU

```
[66]: 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

```
[31]: !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: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-
packages (from keras->keras-attention) (1.19.5)
Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.7/dist-
packages (from keras->keras-attention) (1.4.1)
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages
(from keras->keras-attention) (2.10.0)
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)
Collecting keras-self-attention
  Downloading https://files.pythonhosted.org/packages/c3/34/e21dc6adcdab2be03781
bde78c6c5d2b2136d35a1dd3e692d7e160ba062a/keras-self-attention-0.49.0.tar.gz
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages
(from keras-self-attention) (1.19.5)
Requirement already satisfied: Keras in /usr/local/lib/python3.7/dist-packages
(from keras-self-attention) (2.4.3)
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages
(from Keras->keras-self-attention) (2.10.0)
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: pyyaml in /usr/local/lib/python3.7/dist-packages
(from Keras->keras-self-attention) (3.13)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
(from h5py->Keras->keras-self-attention) (1.15.0)
Building wheels for collected packages: keras-self-attention
  Building wheel for keras-self-attention (setup.py) ... done
  Created wheel for keras-self-attention:
filename=keras_self_attention-0.49.0-cp37-none-any.whl size=19468
sha256=08334fe68e10170a4bbd13359e0d4d6d9b2a891df99e311412a43047eb7aff
  Stored in directory: /root/.cache/pip/wheels/6f/9d/c5/26693a5092d9313daee94db
04818fc0a2b7a48ea381989f34
Successfully built keras-self-attention
Installing collected packages: keras-self-attention
Successfully installed keras-self-attention-0.49.0

```

```

[67]: 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

```

```

[47]: 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)

```

```

[68]: 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	
2016-01-04	-1.447303e+00
2016-01-05	-1.432072e+00
2016-01-06	-1.369764e+00
2016-01-07	-1.296841e+00
2016-01-08	-1.342533e+00
	...
2020-12-24	-8.203802e-15
2020-12-28	2.254717e+00
2020-12-29	2.266256e+00
2020-12-30	2.318410e+00
2020-12-31	2.328102e+00

Name: Close, Length: 1259, dtype: float64  
Model: "sequential\_14"

Layer (type)	Output Shape	Param #
gru_1 (GRU)	(None, 7, 6)	162
Attention (SeqSelfAttention)	(None, None, 6)	449
conv1d_6 (Conv1D)	(None, None, 64)	832
max_pooling1d_5 (MaxPooling1	(None, None, 64)	0
dropout_4 (Dropout)	(None, None, 64)	0
activation_8 (Activation)	(None, None, 64)	0
dense_6 (Dense)	(None, None, 1)	65
activation_9 (Activation)	(None, None, 1)	0

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

```

None
Epoch 1/100
13/13 [=====] - 3s 8ms/step - loss: 0.5087
Epoch 2/100
13/13 [=====] - 0s 9ms/step - loss: 0.2243
Epoch 3/100
13/13 [=====] - 0s 8ms/step - loss: 0.0800
Epoch 4/100
13/13 [=====] - 0s 9ms/step - loss: 0.0439
Epoch 5/100
13/13 [=====] - 0s 8ms/step - loss: 0.0343
Epoch 6/100
13/13 [=====] - 0s 9ms/step - loss: 0.0306
Epoch 7/100
13/13 [=====] - 0s 9ms/step - loss: 0.0317
Epoch 8/100
13/13 [=====] - 0s 10ms/step - loss: 0.0299
Epoch 9/100
13/13 [=====] - 0s 9ms/step - loss: 0.0266
Epoch 10/100
13/13 [=====] - 0s 9ms/step - loss: 0.0237
Epoch 11/100
13/13 [=====] - 0s 9ms/step - loss: 0.0260

```

Epoch 12/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0235  
Epoch 13/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0232  
Epoch 14/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0227  
Epoch 15/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0229  
Epoch 16/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0233  
Epoch 17/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0213  
Epoch 18/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0227  
Epoch 19/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0223  
Epoch 20/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0210  
Epoch 21/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0196  
Epoch 22/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0222  
Epoch 23/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0201  
Epoch 24/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0214  
Epoch 25/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0189  
Epoch 26/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0218  
Epoch 27/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0183  
Epoch 28/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0176  
Epoch 29/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0183  
Epoch 30/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0182  
Epoch 31/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0187  
Epoch 32/100  
13/13 [=====] - 0s 11ms/step - loss: 0.0187  
Epoch 33/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0200  
Epoch 34/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0178  
Epoch 35/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0186



Epoch 36/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0170  
Epoch 37/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0175  
Epoch 38/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0181  
Epoch 39/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0165  
Epoch 40/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0173  
Epoch 41/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0176  
Epoch 42/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0168  
Epoch 43/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0157  
Epoch 44/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0165  
Epoch 45/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0166  
Epoch 46/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0152  
Epoch 47/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0152  
Epoch 48/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0152  
Epoch 49/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0145  
Epoch 50/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0136  
Epoch 51/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0156  
Epoch 52/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0141  
Epoch 53/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0153  
Epoch 54/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0146  
Epoch 55/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0160  
Epoch 56/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0144  
Epoch 57/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0134  
Epoch 58/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0143  
Epoch 59/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0145

Epoch 60/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0129  
Epoch 61/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0154  
Epoch 62/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0144  
Epoch 63/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0143  
Epoch 64/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0144  
Epoch 65/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0136  
Epoch 66/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0130  
Epoch 67/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0132  
Epoch 68/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0136  
Epoch 69/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0131  
Epoch 70/100  
13/13 [=====] - 0s 8ms/step - loss: 0.0131  
Epoch 71/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0131  
Epoch 72/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0136  
Epoch 73/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0125  
Epoch 74/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0131  
Epoch 75/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0126  
Epoch 76/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0132  
Epoch 77/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0134  
Epoch 78/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0122  
Epoch 79/100  
13/13 [=====] - 0s 10ms/step - loss: 0.0128  
Epoch 80/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0130  
Epoch 81/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0141  
Epoch 82/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0137  
Epoch 83/100  
13/13 [=====] - 0s 9ms/step - loss: 0.0136

```

Epoch 84/100
13/13 [=====] - 0s 8ms/step - loss: 0.0151
Epoch 85/100
13/13 [=====] - 0s 9ms/step - loss: 0.0135
Epoch 86/100
13/13 [=====] - 0s 9ms/step - loss: 0.0131
Epoch 87/100
13/13 [=====] - 0s 9ms/step - loss: 0.0127
Epoch 88/100
13/13 [=====] - 0s 9ms/step - loss: 0.0123
Epoch 89/100
13/13 [=====] - 0s 9ms/step - loss: 0.0136
Epoch 90/100
13/13 [=====] - 0s 9ms/step - loss: 0.0133
Epoch 91/100
13/13 [=====] - 0s 8ms/step - loss: 0.0128
Epoch 92/100
13/13 [=====] - 0s 9ms/step - loss: 0.0128
Epoch 93/100
13/13 [=====] - 0s 9ms/step - loss: 0.0133
Epoch 94/100
13/13 [=====] - 0s 9ms/step - loss: 0.0116
Epoch 95/100
13/13 [=====] - 0s 9ms/step - loss: 0.0122
Epoch 96/100
13/13 [=====] - 0s 9ms/step - loss: 0.0127
Epoch 97/100
13/13 [=====] - 0s 9ms/step - loss: 0.0125
Epoch 98/100
13/13 [=====] - 0s 10ms/step - loss: 0.0125
Epoch 99/100
13/13 [=====] - 0s 10ms/step - loss: 0.0128
Epoch 100/100
13/13 [=====] - 0s 9ms/step - loss: 0.0119

```

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 7.236283e-01

The RMAE is 7.819518e-01

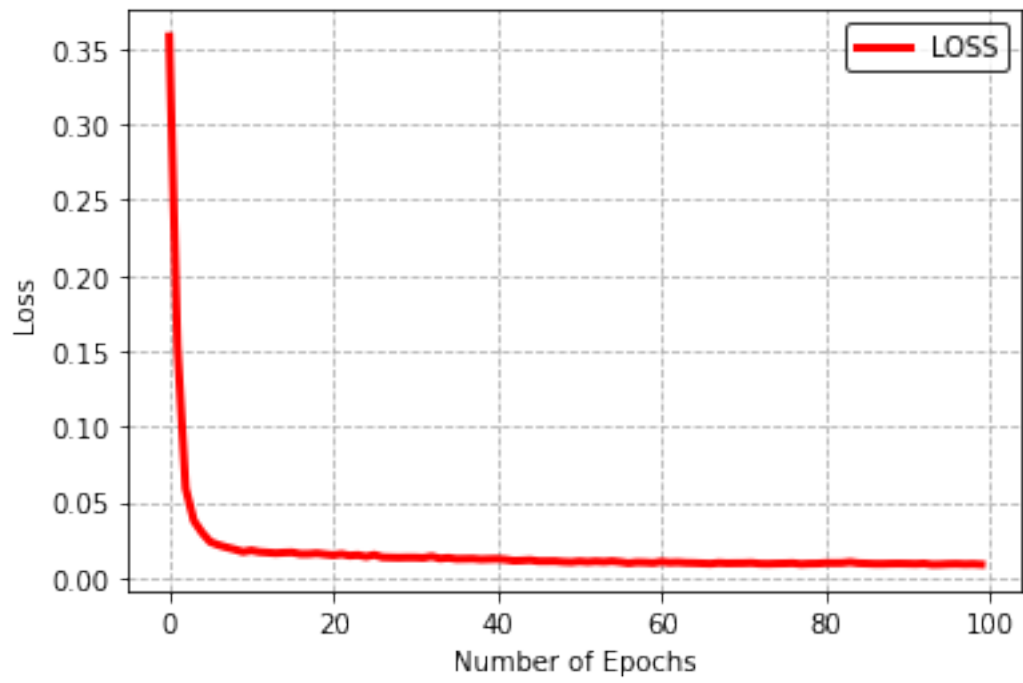
The MAPE is 1.353704e+14



```
[69]: # 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()
```

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.



[69] :