Import Packages

```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns
from math import sqrt
from sklearn.model selection import train test split
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from keras.models import Sequential, load model
from keras.layers import Dense, LSTM, Dropout, BatchNormalization
from sklearn.metrics import mean squared error as mse
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.losses import MeanSquaredError
from tensorflow.keras.metrics import RootMeanSquaredError
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
/opt/conda/lib/python3.10/site-packages/scipy/ init .py:146:
UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this
version of SciPy (detected version 1.23.5
  warnings.warn(f"A NumPy version >={np minversion} and
<{np maxversion}"</pre>
```

Load Data

```
df_train = pd.read_csv('/kaggle/input/lstm-datasets-multivariate-
univariate/LSTM-Multivariate pollution.csv')
df train
                      date pollution dew temp
                                                  press wnd dir
wnd_spd \
       2010-01-02 00:00:00
                                129.0
                                      - 16
                                           -4.0 1020.0
                                                              SE
1.79
       2010-01-02 01:00:00
                                148.0
                                      -15 -4.0 1020.0
                                                              SE
2.68
       2010-01-02 02:00:00
                                159.0
                                      - 11
                                          -5.0 1021.0
                                                              SE
3.57
       2010-01-02 03:00:00
                                181.0
                                      -7 -5.0 1022.0
                                                              SE
5.36
       2010-01-02 04:00:00
                                                              SE
4
                                138.0
                                        -7 -5.0 1022.0
6.25
. . .
       2014-12-31 19:00:00
43795
                                  8.0
                                      -23 -2.0 1034.0
                                                              NW
231.97
                                 10.0
43796 2014-12-31 20:00:00
                                       -22 -3.0 1034.0
                                                              NW
```

```
237.78
43797
       2014-12-31 21:00:00
                                  10.0 -22 -3.0 1034.0
                                                                NW
242.70
43798 2014-12-31 22:00:00
                                   8.0
                                        -22
                                            -4.0
                                                   1034.0
                                                                NW
246.72
43799
       2014-12-31 23:00:00
                                  12.0 -21 -3.0 1034.0
                                                                NW
249.85
             rain
       snow
0
          0
                0
1
          0
                0
2
          0
                0
3
          1
                0
4
          2
                0
        . . .
43795
          0
                0
          0
                0
43796
43797
          0
                0
43798
          0
                0
43799
          0
                0
[43800 rows x 9 columns]
df train.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 43800 entries, 0 to 43799
Data columns (total 9 columns):
                Non-Null Count Dtype
     Column
     -----
 0
                43800 non-null
                                 object
     date
1
     pollution
                43800 non-null
                                float64
 2
                43800 non-null
     dew
                                 int64
 3
     temp
                43800 non-null float64
4
                43800 non-null
                                 float64
     press
 5
                43800 non-null
     wnd dir
                                 object
 6
     wnd_spd
                43800 non-null
                                float64
7
     snow
                43800 non-null
                                 int64
 8
     rain
                43800 non-null
                                 int64
dtypes: float64(4), int64(3), object(2)
memory usage: 3.0+ MB
df test = pd.read csv("/kaggle/input/lstm-datasets-multivariate-
univariate/pollution test data1.csv")
df_test
     dew
          temp
                press wnd dir
                               wnd spd
                                         snow
                                               rain
                                                     pollution
0
     - 16
             4
                 1027
                            SE
                                   3.58
                                            0
                                                  0
                                                            128
1
     - 17
             5
                 1027
                            SE
                                   7.60
                                            0
                                                  0
                                                             77
2
     - 16
             4
                 1027
                            SE
                                   9.39
                                            0
                                                  0
                                                             65
```

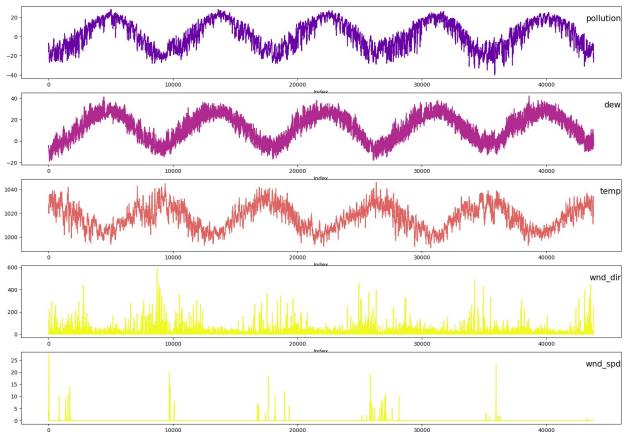
```
3
     - 16
                  1028
                             CV
                                     0.89
                                              0
                                                     0
                                                                79
              1
4
     - 14
                  1028
                                     1.79
                                                                93
              0
                             NE
                                              0
                                                     0
     . . .
                   . . .
                                      . . .
                                                               . . .
            . . .
                            . . .
                  1034
341
     -23
                                  231.97
                                              0
                                                     0
                                                                 8
             - 2
                             NW
342
     -22
             - 3
                  1034
                             NW
                                  237.78
                                              0
                                                     0
                                                                10
                  1034
                                  242.70
343
     -22
             -3
                             NW
                                              0
                                                     0
                                                                10
     -22
                                  246.72
                                                                8
344
             - 4
                  1034
                             NW
                                              0
                                                     0
345
     -21
             -3
                  1034
                             NW
                                  249.85
                                              0
                                                     0
                                                                12
[346 rows x 8 columns]
# Checking null values
print(df train.isnull().sum() , "\n----- \n" ,
df test.isnull().sum() )
date
pollution
              0
dew
              0
temp
              0
              0
press
              0
wnd dir
wnd_spd
              0
              0
snow
rain
              0
dtype: int64
dew
               0
temp
              0
              0
press
              0
wnd dir
wnd_spd
              0
              0
snow
              0
rain
              0
pollution
dtype: int64
df train.describe()
          pollution
                                dew
                                              temp
                                                            press
wnd_spd \
count 43800.000000
                      43800.000000
                                      43800.000000
                                                     43800.000000
43800.000000
          94.013516
                                         12.459041
                                                      1016.447306
mean
                           1.828516
23.894307
          92.252276
                          14.429326
                                         12.193384
                                                        10.271411
std
50.022729
min
           0.000000
                         -40.000000
                                        -19.000000
                                                       991.000000
0.450000
                         -10.000000
                                                      1008.000000
25%
          24.000000
                                          2.000000
1.790000
```

50%	68.000000	2.000000	14.000000	1016.000000			
5.370000							
75%	132.250000	15.000000	23.000000	1025.000000			
21.910000							
max	994.000000	28.000000	42.000000	1046.000000			
585.600000							
	snow	rain					
count	43800.000000	43800.000000					
mean	0.052763	0.195023					
std	0.760582	1.416247					
min	0.000000	0.000000					
25%	0.000000	0.000000					
50%	0.000000	0.00000					
75%	0.000000	0.00000					
max	27.000000	36.000000					

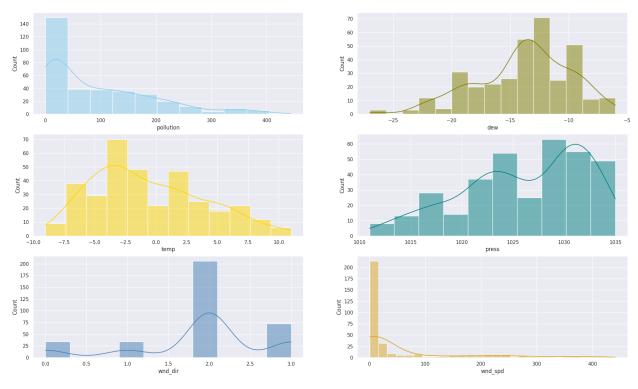
Data vislualization and Feature scaling

```
df train scaled = df train.copy()
df_test_scaled = df_test.copy()
# Define the mapping dictionary
mapping = {'NE': 0, 'SE': 1, 'NW': 2, 'cv': 3}
# Replace the string values with numerical values
df_train_scaled['wnd_dir'] = df_train_scaled['wnd_dir'].map(mapping)
df test scaled['wnd dir'] = df test scaled['wnd dir'].map(mapping)
df_train_scaled['date'] = pd.to_datetime(df_train_scaled['date'])
# Resetting the index
df train scaled.set index('date', inplace=True)
df train scaled.head()
                     pollution dew temp press wnd dir wnd spd
snow \
date
2010-01-02 00:00:00
                                                               1.79
                         129.0
                                -16 -4.0
                                           1020.0
2010-01-02 01:00:00
                         148.0
                                -15 -4.0
                                           1020.0
                                                         1
                                                               2.68
2010-01-02 02:00:00
                                -11 -5.0
                         159.0
                                           1021.0
                                                         1
                                                               3.57
2010-01-02 03:00:00
                                                               5.36
                         181.0
                                -7 -5.0
                                           1022.0
2010-01-02 04:00:00
                         138.0
                                 -7 -5.0 1022.0
                                                         1
                                                               6.25
                     rain
```

```
date
2010-01-02 00:00:00
                        0
2010-01-02 01:00:00
                        0
2010-01-02 02:00:00
                        0
2010-01-02 03:00:00
                        0
2010-01-02 04:00:00
                        0
values = df train scaled.values
# specify columns to plot
groups = [1, 2, 3, 5, 6]
i = 1
# plot each column
plt.figure(figsize=(20,14))
for group in groups:
    plt.subplot(len(groups), 1, i)
    plt.plot(values[:, group], color=cm.plasma(group/len(groups)))
    plt.xlabel('Index')
   plt.title(df_train.columns[group], y=0.75, loc='right', fontsize =
15)
    i += 1
plt.show()
```



```
sns.set(style="darkgrid")
fig, axs = plt.subplots(3,2, figsize=(24,14))
sns.histplot(data=df_test_scaled, x="pollution", kde=True,
color="skyblue", ax=axs[0, 0])
sns.histplot(data=df_test_scaled, x="dew", kde=True, color="olive",
ax=axs[0, 1])
sns.histplot(data=df_test_scaled, x="temp", kde=True, color="gold",
ax=axs[1, 0])
sns.histplot(data=df_test_scaled, x="press", kde=True, color="teal",
ax=axs[1, 1])
sns.histplot(data=df_test_scaled, x="wnd_dir", kde=True,
color="steelblue", ax=axs[2, 0])
sns.histplot(data=df_test_scaled, x="wnd_spd", kde=True,
color="goldenrod", ax=axs[2, 1])
plt.show()
```



```
# Scale the selected columns to the range 0-1
df train scaled[columns] =
scaler.fit_transform(df_train_scaled[columns])
df_test_scaled[columns] = scaler.transform(df_test_scaled[columns])
# Show the scaled data
df_train_scaled.head()
                                                               wnd dir
                     pollution
                                     dew
                                              temp
                                                       press
date
2010-01-02 00:00:00
                      0.129779 0.352941 0.245902 0.527273
                                                              0.333333
2010-01-02 01:00:00
                      0.148893
                                0.367647
                                          0.245902
                                                    0.527273
                                                              0.333333
2010-01-02 02:00:00
                      0.159960 0.426471
                                         0.229508
                                                    0.545455
                                                              0.333333
2010-01-02 03:00:00
                      0.182093 0.485294
                                         0.229508 0.563636
                                                              0.333333
2010-01-02 04:00:00
                      0.138833 0.485294
                                         0.229508 0.563636
                                                              0.333333
                      wnd spd
                                   snow
                                         rain
date
2010-01-02 00:00:00
                     0.002290
                               0.000000
                                          0.0
2010-01-02 01:00:00
                     0.003811
                               0.000000
                                          0.0
2010-01-02 02:00:00
                     0.005332
                               0.000000
                                          0.0
2010-01-02 03:00:00
                     0.008391
                               0.037037
                                          0.0
2010-01-02 04:00:00
                    0.009912
                               0.074074
                                          0.0
df test scaled.head()
   pollution
                   dew
                                     press
                                            wnd_dir
                                                       wnd_spd
                            temp
                                                                snow
rain
0
   0.128773 0.352941
                        0.377049
                                 0.654545
                                            0.333333
                                                      0.005349
                                                                 0.0
0.0
   0.077465 0.338235
                        0.393443
                                 0.654545 0.333333 0.012219
                                                                 0.0
1
0.0
2
   0.065392
             0.352941
                        0.377049 0.654545 0.333333
                                                      0.015278
                                                                 0.0
0.0
   0.079477
3
             0.352941
                                 0.672727
                        0.327869
                                            1.000000
                                                      0.000752
                                                                 0.0
0.0
4
   0.093561 0.382353
                        0.311475
                                 0.672727
                                            0.000000
                                                      0.002290
                                                                 0.0
0.0
```

Split the data into training and test sets

```
df_train_scaled = np.array(df_train_scaled)
df_test_scaled = np.array(df_test_scaled)
```

```
X = []
y = []
n future = 1
n past = 11
# Train Sets
for i in range(n past, len(df train scaled) - n future+1):
    X.append(df train scaled[i - n past:i,
1:df train scaled.shape[1]])
    y.append(df train scaled[i + n future - 1:i + n future, 0])
X train, y train = np.array(X), np.array(y)
# Test Sets
X = []
y = []
for i in range(n_past, len(df_test_scaled) - n_future+1):
    X.append(df test scaled[i - n past:i, 1:df test scaled.shape[1]])
    y.append(df test scaled[i + n future - 1:i + n future, 0])
X \text{ test}, y \text{ test} = np.array(X), np.array(y)
print('X_train shape : {}  y_train shape : {} \n'
      'X_test shape : {}
                             y_test shape : {}
'.format(X train.shape, y train.shape, X test.shape, y test.shape))
X train shape : (43789, 11, 7) y train shape : (43789, 1)
X test shape : (335, 11, 7) y test shape : (335, 1)
```

Create a LSTM model

```
# design network

model = Sequential()
model.add(LSTM(32, input_shape=(X_train.shape[1], X_train.shape[2]),
return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(16, return_sequences=False))
model.add(Dense(y_train.shape[1]))

# Compile the model
model.compile(loss='mse', optimizer=Adam(learning_rate=0.001),
metrics=[RootMeanSquaredError()])

# Define callbacks for avoiding overfitting
early_stopping = EarlyStopping(monitor='val_loss', patience=10,
restore_best_weights=True)
checkpoint = ModelCheckpoint('best_model.h5', monitor='val_loss',
save_best_only=True)
```

model.summary()		
Model: "sequential"		
Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 11, 32)	5120
dropout (Dropout)	(None, 11, 32)	0
lstm_1 (LSTM)	(None, 16)	3136
dense (Dense)	(None, 1)	17
<pre># fit network history = model.fit(X_train, validation_split=0.1, callba shuffle=False) Epoch 1/150 1232/1232 [===================================</pre>	cks=[early_stopping, checks= =========] - 15s 6ms, error: 0.0861 - val_loss: 0.1071 =========] - 7s 5ms/s	/step - loss: 0.0115 - step - loss:
0.0067 - root_mean_squared_e val_root_mean_squared_error: Epoch 3/150 1232/1232 [===================================	0.1043 ======] - 7s 5ms/s	step - loss:
<pre>val_root_mean_squared_error: Epoch 4/150</pre>		

0.0063 - root_mean_squared_error: 0.0794 - val_loss: 0.0109 -

0.0062 - root mean squared error: 0.0785 - val loss: 0.0110 -

0.0061 - root mean squared error: 0.0778 - val loss: 0.0099 -

val_root_mean_squared_error: 0.1043

val root mean squared error: 0.1049

val root mean squared error: 0.0993

Epoch 5/150

Epoch 6/150

```
Epoch 7/150
0.0059 - root mean squared error: 0.0767 - val loss: 0.0098 -
val root mean squared error: 0.0989
Epoch 8/150
0.0058 - root mean squared error: 0.0759 - val loss: 0.0107 -
val root mean squared error: 0.1036
Epoch 9/150
0.0057 - root mean squared error: 0.0757 - val loss: 0.0093 -
val root mean squared error: 0.0964
Epoch 10/150
0.0057 - root mean squared error: 0.0755 - val loss: 0.0084 -
val root mean squared error: 0.0914
Epoch 11/150
0.0057 - root mean squared error: 0.0753 - val loss: 0.0076 -
val root mean squared error: 0.0872
Epoch 12/150
0.0056 - root mean squared error: 0.0750 - val loss: 0.0070 -
val root mean squared error: 0.0839
Epoch 13/150
0.0056 - root mean squared error: 0.0749 - val loss: 0.0065 -
val root mean squared error: 0.0808
Epoch 14/150
0.0056 - root mean squared error: 0.0746 - val loss: 0.0063 -
val root mean squared error: 0.0791
Epoch 15/150
0.0056 - root mean squared error: 0.0745 - val loss: 0.0063 -
val root mean squared error: 0.0792
Epoch 16/150
0.0055 - root mean squared error: 0.0743 - val loss: 0.0060 -
val root mean squared error: 0.0774
Epoch 17/150
0.0055 - root mean squared error: 0.0741 - val loss: 0.0059 -
val root mean squared error: 0.0769
Epoch 18/150
0.0055 - root_mean_squared error: 0.0741 - val loss: 0.0057 -
val root mean squared error: 0.0757
Epoch 19/150
```

```
0.0055 - root mean squared error: 0.0740 - val loss: 0.0057 -
val root mean squared error: 0.0753
Epoch 20/150
0.0054 - root mean squared error: 0.0738 - val loss: 0.0056 -
val root mean squared error: 0.0750
Epoch 21/150
0.0054 - root mean squared error: 0.0738 - val loss: 0.0055 -
val root mean squared error: 0.0740
Epoch 22/150
0.0054 - root mean squared error: 0.0737 - val loss: 0.0054 -
val root mean squared error: 0.0735
Epoch 23/150
0.0054 - root mean squared error: 0.0736 - val loss: 0.0054 -
val root mean squared error: 0.0732
Epoch 24/150
0.0054 - root mean squared error: 0.0736 - val loss: 0.0053 -
val root mean squared error: 0.0727
Epoch 25/150
0.0054 - root mean squared error: 0.0735 - val loss: 0.0053 -
val_root_mean_squared error: 0.0727
Epoch 26/150
0.0054 - root mean squared error: 0.0734 - val loss: 0.0051 -
val root mean squared error: 0.0715
Epoch 27/150
0.0054 - root mean squared error: 0.0732 - val loss: 0.0051 -
val root mean squared error: 0.0716
Epoch 28/150
0.0054 - root mean squared error: 0.0732 - val loss: 0.0051 -
val root mean squared error: 0.0713
Epoch 29/150
0.0053 - root mean squared error: 0.0731 - val loss: 0.0050 -
val root mean squared error: 0.0711
Epoch 30/150
0.0053 - root mean squared error: 0.0731 - val loss: 0.0050 -
val root mean squared error: 0.0709
Epoch 31/150
```

```
0.0053 - root mean squared error: 0.0731 - val loss: 0.0050 -
val root mean squared error: 0.0708
Epoch 32/150
0.0053 - root mean squared error: 0.0730 - val loss: 0.0050 -
val root mean squared error: 0.0704
Epoch 33/150
0.0053 - root mean squared error: 0.0729 - val loss: 0.0050 -
val root mean squared error: 0.0706
Epoch 34/150
0.0053 - root mean squared error: 0.0729 - val loss: 0.0049 -
val root mean squared error: 0.0700
Epoch 35/150
0.0053 - root mean squared error: 0.0728 - val loss: 0.0049 -
val root mean squared error: 0.0698
Epoch 36/150
0.0053 - root mean squared error: 0.0727 - val loss: 0.0049 -
val root mean squared error: 0.0701
Epoch 37/150
0.0053 - root mean squared error: 0.0728 - val loss: 0.0049 -
val root mean squared error: 0.0699
Epoch 38/150
0.0053 - root mean squared error: 0.0727 - val loss: 0.0048 -
val root mean squared error: 0.0696
Epoch 39/150
0.0053 - root mean squared error: 0.0725 - val loss: 0.0048 -
val root mean squared error: 0.0691
Epoch 40/150
0.0053 - root mean squared error: 0.0726 - val loss: 0.0048 -
val root mean squared error: 0.0690
Epoch 41/150
0.0053 - root mean squared error: 0.0725 - val loss: 0.0048 -
val root mean squared error: 0.0694
Epoch 42/150
0.0053 - root mean squared error: 0.0725 - val loss: 0.0047 -
val root mean squared error: 0.0689
Epoch 43/150
0.0052 - root mean squared error: 0.0724 - val loss: 0.0047 -
```

```
val root mean squared error: 0.0689
Epoch 44/150
0.0052 - root mean squared error: 0.0724 - val loss: 0.0047 -
val root mean squared error: 0.0686
Epoch 45/150
0.0052 - root mean squared error: 0.0723 - val loss: 0.0047 -
val root mean squared error: 0.0686
Epoch 46/150
0.0052 - root mean squared error: 0.0723 - val loss: 0.0046 -
val root mean squared error: 0.0681
Epoch 47/150
0.0052 - root mean squared error: 0.0722 - val loss: 0.0046 -
val root mean squared error: 0.0681
Epoch 48/150
0.0052 - root_mean_squared_error: 0.0721 - val loss: 0.0046 -
val root mean squared error: 0.0681
Epoch 49/150
0.0052 - root mean squared error: 0.0722 - val loss: 0.0046 -
val root mean squared error: 0.0679
Epoch 50/150
0.0052 - root mean squared error: 0.0720 - val loss: 0.0046 -
val root mean squared error: 0.0677
Epoch 51/150
0.0052 - root mean squared error: 0.0719 - val loss: 0.0046 -
val root mean squared error: 0.0676
Epoch 52/150
0.0052 - root mean squared error: 0.0719 - val loss: 0.0046 -
val root mean squared error: 0.0676
Epoch 53/150
0.0052 - root mean squared error: 0.0718 - val loss: 0.0045 -
val root mean squared error: 0.0673
Epoch 54/150
0.0051 - root mean squared error: 0.0716 - val loss: 0.0045 -
val root mean squared error: 0.0675
Epoch 55/150
0.0051 - root mean squared error: 0.0716 - val loss: 0.0045 -
val root mean squared error: 0.0673
```

```
Epoch 56/150
0.0051 - root mean squared error: 0.0717 - val loss: 0.0045 -
val root mean squared error: 0.0673
Epoch 57/150
0.0051 - root mean squared error: 0.0715 - val loss: 0.0045 -
val root mean squared error: 0.0672
Epoch 58/150
0.0051 - root mean squared error: 0.0714 - val loss: 0.0045 -
val root mean squared error: 0.0674
Epoch 59/150
0.0051 - root mean squared error: 0.0714 - val loss: 0.0045 -
val root mean squared error: 0.0672
Epoch 60/150
0.0051 - root mean squared error: 0.0714 - val loss: 0.0045 -
val root mean squared error: 0.0672
Epoch 61/150
0.0051 - root mean squared error: 0.0714 - val loss: 0.0045 -
val root mean squared error: 0.0668
Epoch 62/150
0.0051 - root mean squared error: 0.0712 - val loss: 0.0045 -
val root mean squared error: 0.0672
Epoch 63/150
0.0051 - root mean squared error: 0.0713 - val loss: 0.0045 -
val root mean squared error: 0.0668
Epoch 64/150
0.0050 - root mean squared error: 0.0710 - val loss: 0.0045 -
val root mean squared error: 0.0671
Epoch 65/150
0.0051 - root mean squared error: 0.0711 - val loss: 0.0045 -
val root mean squared error: 0.0669
Epoch 66/150
0.0050 - root mean squared error: 0.0709 - val loss: 0.0045 -
val root mean squared error: 0.0668
Epoch 67/150
0.0050 - root mean squared error: 0.0708 - val loss: 0.0044 -
val root mean squared error: 0.0667
Epoch 68/150
```

```
0.0050 - root mean squared error: 0.0709 - val loss: 0.0044 -
val root mean squared error: 0.0667
Epoch 69/150
0.0050 - root mean squared error: 0.0708 - val loss: 0.0044 -
val root mean squared error: 0.0665
Epoch 70/150
0.0050 - root mean squared error: 0.0709 - val loss: 0.0044 -
val root mean squared error: 0.0664
Epoch 71/150
0.0050 - root_mean_squared error: 0.0708 - val loss: 0.0044 -
val root mean squared error: 0.0663
Epoch 72/150
0.0050 - root mean squared_error: 0.0707 - val_loss: 0.0044 -
val root mean squared error: 0.0664
Epoch 73/150
0.0050 - root mean squared error: 0.0706 - val loss: 0.0044 -
val root mean squared error: 0.0664
Epoch 74/150
0.0050 - root mean squared error: 0.0704 - val loss: 0.0044 -
val_root_mean_squared error: 0.0662
Epoch 75/150
0.0049 - root mean squared error: 0.0704 - val loss: 0.0044 -
val root mean squared error: 0.0661
Epoch 76/150
0.0050 - root mean squared error: 0.0704 - val loss: 0.0044 -
val root mean squared error: 0.0661
Epoch 77/150
0.0049 - root mean squared error: 0.0703 - val loss: 0.0044 -
val root mean squared error: 0.0660
Epoch 78/150
0.0049 - root mean squared error: 0.0703 - val loss: 0.0044 -
val root mean squared error: 0.0660
Epoch 79/150
0.0049 - root mean squared error: 0.0701 - val loss: 0.0043 -
val root mean squared error: 0.0659
Epoch 80/150
```

```
0.0049 - root mean squared error: 0.0702 - val loss: 0.0043 -
val root mean squared error: 0.0658
Epoch 81/150
0.0049 - root mean squared error: 0.0700 - val loss: 0.0044 -
val root mean squared error: 0.0660
Epoch 82/150
0.0049 - root mean squared error: 0.0700 - val loss: 0.0043 -
val root mean squared error: 0.0659
Epoch 83/150
0.0049 - root mean squared error: 0.0700 - val loss: 0.0044 -
val root mean squared error: 0.0660
Epoch 84/150
0.0049 - root mean squared error: 0.0698 - val loss: 0.0043 -
val root mean squared error: 0.0659
Epoch 85/150
0.0049 - root mean squared error: 0.0697 - val loss: 0.0043 -
val root mean squared error: 0.0657
Epoch 86/150
0.0048 - root mean squared error: 0.0696 - val loss: 0.0043 -
val root mean squared error: 0.0655
Epoch 87/150
0.0049 - root mean squared error: 0.0697 - val loss: 0.0043 -
val root mean squared error: 0.0654
Epoch 88/150
0.0048 - root mean squared error: 0.0696 - val loss: 0.0043 -
val root mean_squared_error: 0.0654
Epoch 89/150
0.0048 - root mean squared error: 0.0694 - val loss: 0.0043 -
val root mean squared error: 0.0656
Epoch 90/150
0.0048 - root mean squared error: 0.0694 - val loss: 0.0043 -
val root mean squared error: 0.0654
Epoch 91/150
0.0048 - root mean squared error: 0.0693 - val loss: 0.0043 -
val root mean squared error: 0.0655
Epoch 92/150
0.0048 - root mean squared error: 0.0694 - val loss: 0.0043 -
```

```
val root mean squared error: 0.0653
Epoch 93/150
0.0048 - root mean squared error: 0.0692 - val loss: 0.0043 -
val root mean squared error: 0.0655
Epoch 94/150
0.0048 - root mean squared error: 0.0691 - val loss: 0.0043 -
val root mean squared error: 0.0652
Epoch 95/150
0.0047 - root mean squared error: 0.0689 - val loss: 0.0043 -
val root mean squared error: 0.0652
Epoch 96/150
0.0047 - root mean squared error: 0.0689 - val loss: 0.0043 -
val root mean squared error: 0.0653
Epoch 97/150
0.0047 - root_mean_squared_error: 0.0688 - val loss: 0.0043 -
val root mean squared error: 0.0652
Epoch 98/150
0.0047 - root mean squared error: 0.0686 - val loss: 0.0043 -
val root mean squared error: 0.0653
Epoch 99/150
0.0047 - root mean squared error: 0.0684 - val loss: 0.0042 -
val root mean_squared_error: 0.0651
Epoch 100/150
0.0047 - root mean squared error: 0.0684 - val loss: 0.0043 -
val_root_mean_squared_error: 0.0653
Epoch 101/150
0.0047 - root mean squared error: 0.0683 - val loss: 0.0042 -
val root mean squared error: 0.0652
Epoch 102/150
0.0047 - root mean squared error: 0.0682 - val loss: 0.0042 -
val root mean squared error: 0.0650
Epoch 103/150
0.0046 - root mean squared error: 0.0681 - val loss: 0.0043 -
val root mean squared error: 0.0654
Epoch 104/150
0.0046 - root mean squared error: 0.0681 - val loss: 0.0042 -
val root mean squared error: 0.0651
```

```
Epoch 105/150
0.0046 - root mean squared error: 0.0679 - val loss: 0.0043 -
val root mean squared error: 0.0653
Epoch 106/150
0.0046 - root mean squared error: 0.0680 - val loss: 0.0042 -
val root mean squared error: 0.0649
Epoch 107/150
0.0046 - root mean squared error: 0.0677 - val loss: 0.0042 -
val root mean squared error: 0.0649
Epoch 108/150
0.0046 - root mean squared error: 0.0679 - val loss: 0.0042 -
val root mean squared error: 0.0650
Epoch 109/150
0.0046 - root mean squared error: 0.0677 - val loss: 0.0042 -
val root mean squared error: 0.0647
Epoch 110/150
0.0046 - root mean squared error: 0.0676 - val loss: 0.0041 -
val root mean squared error: 0.0644
Epoch 111/150
0.0046 - root mean squared error: 0.0675 - val loss: 0.0041 -
val root mean squared error: 0.0643
Epoch 112/150
0.0045 - root mean squared error: 0.0671 - val loss: 0.0041 -
val root mean squared error: 0.0644
Epoch 113/150
0.0045 - root mean squared error: 0.0673 - val loss: 0.0042 -
val root mean squared error: 0.0647
Epoch 114/150
0.0045 - root mean squared error: 0.0670 - val loss: 0.0041 -
val root mean squared error: 0.0643
Epoch 115/150
0.0045 - root mean squared error: 0.0671 - val loss: 0.0041 -
val root mean squared error: 0.0642
Epoch 116/150
0.0045 - root mean squared error: 0.0669 - val loss: 0.0042 -
val root mean squared error: 0.0645
Epoch 117/150
```

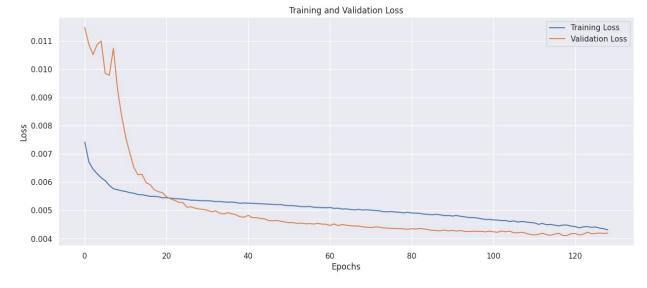
```
0.0045 - root mean squared error: 0.0667 - val loss: 0.0042 -
val root mean squared error: 0.0647
Epoch 118/150
0.0045 - root mean squared error: 0.0669 - val loss: 0.0041 -
val root mean squared error: 0.0641
Epoch 119/150
0.0045 - root mean squared error: 0.0669 - val loss: 0.0041 -
val root mean squared error: 0.0641
Epoch 120/150
0.0044 - root mean squared error: 0.0667 - val loss: 0.0042 -
val root mean squared error: 0.0646
Epoch 121/150
0.0044 - root mean squared error: 0.0665 - val loss: 0.0042 -
val root mean squared error: 0.0647
Epoch 122/150
0.0044 - root mean squared error: 0.0662 - val loss: 0.0041 -
val root mean squared error: 0.0643
Epoch 123/150
0.0044 - root mean squared error: 0.0664 - val loss: 0.0042 -
val_root_mean squared error: 0.0645
Epoch 124/150
0.0044 - root mean squared error: 0.0665 - val loss: 0.0042 -
val root mean squared error: 0.0650
Epoch 125/150
0.0044 - root mean squared error: 0.0663 - val loss: 0.0042 -
val root mean squared error: 0.0646
Epoch 126/150
0.0044 - root mean squared error: 0.0664 - val loss: 0.0042 -
val root mean_squared_error: 0.0647
Epoch 127/150
0.0044 - root mean squared error: 0.0661 - val loss: 0.0042 -
val_root_mean_squared_error: 0.0648
Epoch 128/150
0.0044 - root_mean_squared_error: 0.0660 - val_loss: 0.0042 -
val_root_mean_squared error: 0.0647
Epoch 129/150
```

```
0.0043 - root_mean_squared_error: 0.0656 - val_loss: 0.0042 - val_root_mean_squared_error: 0.0648
```

Evaluate the Model

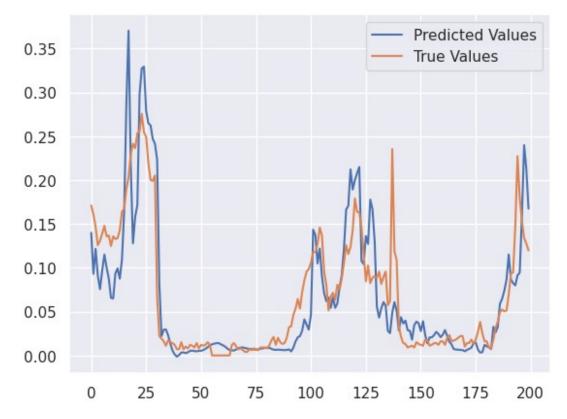
```
# Load the best model
best_model = load_model('best_model.h5')

plt.figure(figsize=(15,6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
test predictions = best model.predict(X test).flatten()
test results = pd.DataFrame(data={'Train Predictions':
test predictions,
                                'Actual':y_test.flatten()})
test_results.head()
11/11 [=======] - 1s 2ms/step
  Train Predictions
                      Actual
0
           0.139874 0.171026
1
           0.093021 0.160966
2
           0.121613 0.146881
3
           0.091181 0.125755
4
           0.075569 0.130785
```

```
plt.plot(test_results['Train Predictions'][:200], label='Predicted
Values')
plt.plot(test_results['Actual'][:200], label='True Values')
plt.legend()
plt.show()
```



```
rmse = sqrt(mse(y_test, test_predictions))
print('Test RMSE: %.5f' % rmse)
Test RMSE: 0.06954
```

Experementing with variables

```
# design network

model_2 = Sequential()
model_2.add(LSTM(64, input_shape=(X_train.shape[1], X_train.shape[2]),
return_sequences=True))
model_2.add(Dropout(0.2))
model_2.add(LSTM(32, return_sequences=False))
model_2.add(Dense(y_train.shape[1]))

# Compile the model
model_2.compile(loss='mse', optimizer=Adam(learning_rate=0.0005),
```

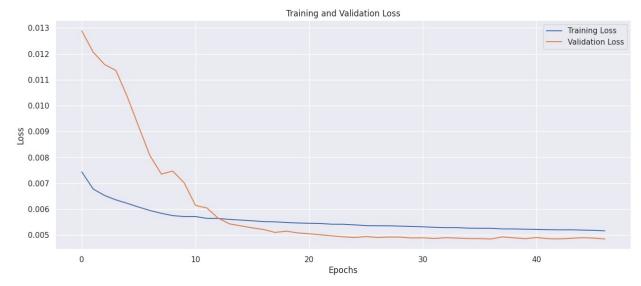
```
metrics=[RootMeanSquaredError()])
# Define callbacks for avoiding overfitting
early stopping = EarlyStopping(monitor='val loss', patience=10,
restore best weights=True)
checkpoint = ModelCheckpoint('best model.h5', monitor='val loss',
save best only=True)
model 2.summary()
Model: "sequential"
Layer (type)
                         Output Shape
                                               Param #
lstm (LSTM)
                         (None, 11, 32)
                                               5120
dropout (Dropout)
                         (None, 11, 32)
                                               0
lstm 1 (LSTM)
                         (None, 16)
                                               3136
dense (Dense)
                         (None, 1)
                                               17
Total params: 8,273
Trainable params: 8,273
Non-trainable params: 0
# fit network
history = model 2.fit(X train, y train, epochs=150, batch size=32,
validation split=0.1, callbacks=[early stopping, checkpoint],
shuffle=False)
Epoch 1/150
1232/1232 [============= ] - 11s 6ms/step - loss:
0.0074 - root mean squared error: 0.0862 - val loss: 0.0129 -
val root mean squared error: 0.1135
Epoch 2/150
0.0068 - root mean squared error: 0.0823 - val loss: 0.0121 -
val root mean squared error: 0.1098
Epoch 3/150
0.0065 - root mean squared error: 0.0808 - val loss: 0.0116 -
val root mean squared error: 0.1077
Epoch 4/150
0.0064 - root mean squared error: 0.0797 - val loss: 0.0114 -
val_root_mean_squared_error: 0.1066
Epoch 5/150
```

```
0.0062 - root mean squared error: 0.0789 - val loss: 0.0103 -
val root mean squared error: 0.1017
Epoch 6/150
0.0061 - root mean squared error: 0.0780 - val loss: 0.0092 -
val root mean squared error: 0.0959
Epoch 7/150
0.0059 - root mean squared error: 0.0771 - val loss: 0.0081 -
val root mean squared error: 0.0898
Epoch 8/150
0.0058 - root mean squared error: 0.0764 - val loss: 0.0074 -
val root mean squared error: 0.0857
Epoch 9/150
0.0057 - root mean squared error: 0.0758 - val loss: 0.0075 -
val root mean squared error: 0.0864
Epoch 10/150
0.0057 - root mean squared error: 0.0756 - val loss: 0.0070 -
val root mean squared error: 0.0838
Epoch 11/150
0.0057 - root mean squared error: 0.0756 - val loss: 0.0061 -
val root mean squared error: 0.0784
Epoch 12/150
0.0056 - root mean squared error: 0.0751 - val loss: 0.0060 -
val root mean squared error: 0.0777
Epoch 13/150
0.0056 - root mean squared error: 0.0751 - val loss: 0.0056 -
val root mean squared error: 0.0751
Epoch 14/150
0.0056 - root mean squared error: 0.0748 - val loss: 0.0054 -
val root mean_squared_error: 0.0737
Epoch 15/150
0.0056 - root mean squared error: 0.0747 - val loss: 0.0054 -
val root mean squared error: 0.0731
Epoch 16/150
0.0055 - root_mean_squared_error: 0.0745 - val_loss: 0.0053 -
val root mean squared error: 0.0726
Epoch 17/150
```

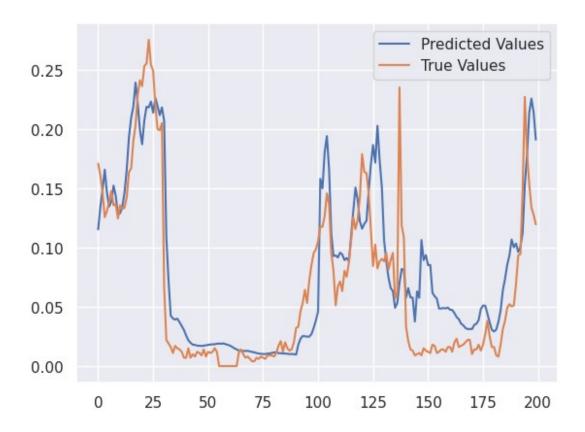
```
0.0055 - root mean squared error: 0.0743 - val loss: 0.0052 -
val root mean squared error: 0.0722
Epoch 18/150
0.0055 - root mean squared error: 0.0742 - val loss: 0.0051 -
val root mean squared error: 0.0714
Epoch 19/150
0.0055 - root mean squared error: 0.0740 - val loss: 0.0051 -
val root mean squared error: 0.0717
Epoch 20/150
0.0055 - root mean squared error: 0.0739 - val loss: 0.0051 -
val root mean squared error: 0.0713
Epoch 21/150
0.0055 - root mean squared error: 0.0738 - val loss: 0.0050 -
val root mean squared error: 0.0710
Epoch 22/150
0.0054 - root mean squared error: 0.0738 - val loss: 0.0050 -
val root mean squared error: 0.0708
Epoch 23/150
0.0054 - root mean squared error: 0.0736 - val loss: 0.0050 -
val root mean squared error: 0.0705
Epoch 24/150
0.0054 - root mean squared error: 0.0736 - val loss: 0.0049 -
val root mean squared error: 0.0702
Epoch 25/150
0.0054 - root mean squared error: 0.0734 - val loss: 0.0049 -
val root mean squared error: 0.0700
Epoch 26/150
0.0054 - root mean squared error: 0.0732 - val loss: 0.0049 -
val root mean squared error: 0.0703
Epoch 27/150
0.0054 - root mean squared error: 0.0732 - val loss: 0.0049 -
val root mean squared error: 0.0700
Epoch 28/150
0.0054 - root mean squared error: 0.0732 - val loss: 0.0049 -
val root mean squared error: 0.0701
Epoch 29/150
0.0053 - root mean squared error: 0.0731 - val loss: 0.0049 -
```

```
val root mean squared error: 0.0701
Epoch 30/150
0.0053 - root mean squared error: 0.0730 - val loss: 0.0049 -
val root mean squared error: 0.0699
Epoch 31/150
0.0053 - root mean squared error: 0.0729 - val loss: 0.0049 -
val root mean squared error: 0.0699
Epoch 32/150
0.0053 - root mean squared error: 0.0728 - val loss: 0.0049 -
val root mean squared error: 0.0697
Epoch 33/150
0.0053 - root mean squared error: 0.0727 - val loss: 0.0049 -
val root mean squared error: 0.0700
Epoch 34/150
0.0053 - root_mean_squared_error: 0.0727 - val loss: 0.0049 -
val root mean squared error: 0.0698
Epoch 35/150
0.0053 - root mean squared error: 0.0725 - val loss: 0.0049 -
val root mean squared error: 0.0697
Epoch 36/150
0.0053 - root mean squared error: 0.0725 - val loss: 0.0049 -
val root mean squared error: 0.0697
Epoch 37/150
0.0053 - root mean squared error: 0.0725 - val loss: 0.0048 -
val root mean squared error: 0.0696
Epoch 38/150
0.0052 - root mean squared error: 0.0723 - val loss: 0.0049 -
val root mean squared error: 0.0702
Epoch 39/150
0.0052 - root mean squared error: 0.0723 - val loss: 0.0049 -
val root mean squared error: 0.0699
Epoch 40/150
0.0052 - root mean squared error: 0.0723 - val loss: 0.0049 -
val root mean squared error: 0.0697
Epoch 41/150
0.0052 - root mean squared error: 0.0722 - val loss: 0.0049 -
val root mean squared error: 0.0700
```

```
Epoch 42/150
0.0052 - root mean squared error: 0.0721 - val loss: 0.0049 -
val root mean squared error: 0.0697
Epoch 43/150
0.0052 - root_mean_squared_error: 0.0721 - val loss: 0.0048 -
val root mean squared error: 0.0696
Epoch 44/150
0.0052 - root mean squared error: 0.0721 - val loss: 0.0049 -
val root mean squared error: 0.0698
Epoch 45/150
0.0052 - root mean squared error: 0.0720 - val loss: 0.0049 -
val root mean squared error: 0.0700
Epoch 46/150
0.0052 - root mean squared error: 0.0720 - val loss: 0.0049 -
val root mean squared error: 0.0699
Epoch 47/150
0.0052 - root mean squared error: 0.0718 - val loss: 0.0048 -
val root mean squared error: 0.0696
# Load the best model
best model = load model('best model.h5')
plt.figure(figsize=(15,6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
test predictions = best model.predict(X test).flatten()
test results = pd.DataFrame(data={'Train Predictions':
test_predictions,
                                'Actual':y test.flatten()})
test results.head()
Train Predictions
                      Actual
0
           0.115494 0.171026
1
           0.134319 0.160966
2
           0.149019
                   0.146881
3
           0.165917
                    0.125755
           0.146514 0.130785
rmse = sqrt(mse(y_test, test_predictions))
print('Test RMSE: %.5f' % rmse)
Test RMSE: 0.06896
plt.plot(test_results['Train Predictions'][:200], label='Predicted
Values')
plt.plot(test results['Actual'][:200], label='True Values')
plt.legend()
plt.show()
```



ARIMA

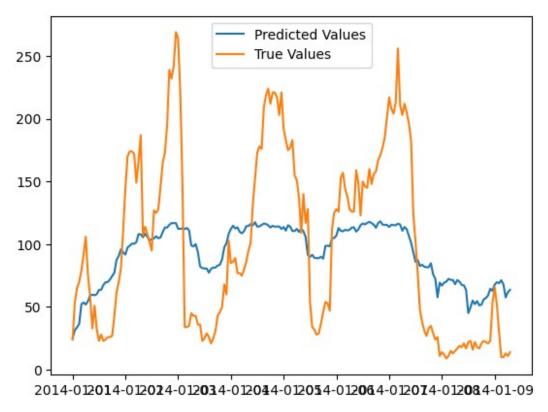
```
! pip install statsmodels
! pip install pandas
Requirement already satisfied: statsmodels in
/opt/conda/lib/python3.10/site-packages (0.14.0)
Requirement already satisfied: numpy>=1.18 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (1.23.5)
Requirement already satisfied: scipy!=1.9.2,>=1.4 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (1.11.2)
Requirement already satisfied: pandas>=1.0 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (2.0.2)
Requirement already satisfied: patsy>=0.5.2 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (0.5.3)
Requirement already satisfied: packaging>=21.3 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/opt/conda/lib/python3.10/site-packages (from packaging>=21.3-
>statsmodels) (3.0.9)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.10/site-packages (from pandas>=1.0-
>statsmodels) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
```

ARIMA

```
! pip install statsmodels
! pip install pandas
Requirement already satisfied: statsmodels in
/opt/conda/lib/python3.10/site-packages (0.14.0)
Requirement already satisfied: numpy>=1.18 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (1.23.5)
Requirement already satisfied: scipy!=1.9.2,>=1.4 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (1.11.2)
Requirement already satisfied: pandas>=1.0 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (2.0.2)
Requirement already satisfied: patsy>=0.5.2 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (0.5.3)
Requirement already satisfied: packaging>=21.3 in
/opt/conda/lib/python3.10/site-packages (from statsmodels) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/opt/conda/lib/python3.10/site-packages (from packaging>=21.3-
>statsmodels) (3.0.9)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.10/site-packages (from pandas>=1.0-
>statsmodels) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/opt/conda/lib/python3.10/site-packages (from pandas>=1.0-
>statsmodels) (2023.3)
Requirement already satisfied: tzdata>=2022.1 in
/opt/conda/lib/python3.10/site-packages (from pandas>=1.0-
>statsmodels) (2023.3)
Requirement already satisfied: six in /opt/conda/lib/python3.10/site-
packages (from patsy>=0.5.2->statsmodels) (1.16.0)
Requirement already satisfied: pandas in
/opt/conda/lib/python3.10/site-packages (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2.8.2)
Requirement already satisfied: pvtz>=2020.1 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2023.3)
Requirement already satisfied: tzdata>=2022.1 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2023.3)
Requirement already satisfied: numpy>=1.21.0 in
/opt/conda/lib/python3.10/site-packages (from pandas) (1.23.5)
Requirement already satisfied: six>=1.5 in
/opt/conda/lib/python3.10/site-packages (from python-dateutil>=2.8.2-
>pandas) (1.16.0)
import pandas as pd
# Assuming df is your DataFrame
df_arima = pd.read_csv('/kaggle/input/lstm-datasets-multivariate-
univariate/LSTM-Multivariate pollution.csv')
```

```
df arima['date'] = pd.to datetime(df arima['date'])
df arima.set index('date', inplace=True)
train size = int(len(df arima) * 0.8)
train, test = df arima[:train size], df arima[train size:]
from statsmodels.tsa.statespace.sarimax import SARIMAX
# Order and seasonal order depend on the characteristics of your data
(you may need to tune them)
order = (1, 1, 1)
seasonal order = (1, 1, 1, 30) # Example: 24 for daily seasonality
model = SARIMAX(train['pollution'], exog=train[['dew', 'temp',
'press', 'wnd spd', 'snow', 'rain']],
                order=order, seasonal order=seasonal order)
results = model.fit()
/opt/conda/lib/python3.10/site-packages/statsmodels/tsa/base/
tsa model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency H will be used.
  self. init dates(dates, freq)
/opt/conda/lib/python3.10/site-packages/statsmodels/tsa/base/tsa model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency H will be used.
  self. init dates(dates, freq)
RUNNING THE L-BFGS-B CODE
Machine precision = 2.220D-16
N =
               11
                  M =
                                    10
At X0
             O variables are exactly at the bounds
             0 	 f = 4.88599D + 00
At iterate
                                      |proj g| = 6.74344D-02
This problem is unconstrained.
At iterate 5 f = 4.84571D + 00
                                      |proj g| = 1.49889D-02
At iterate
            10
                f= 4.75210D+00
                                      |proj g| = 6.87411D-03
At iterate
                  f= 4.75143D+00
                                      |proj g| = 3.27156D-03
            15
At iterate
            20
                   f= 4.75085D+00
                                      |proj g| = 6.12194D-03
At iterate
            25
                   f= 4.74692D+00
                                      |proj g| = 1.68066D-02
At iterate
            30
                  f = 4.74019D + 00
                                      |proj g| = 2.02246D-03
```

```
At iterate 35 f= 4.73929D+00
                                     |proj g| = 5.63497D-03
At iterate
            40
                  f = 4.73884D + 00
                                      |proj g| = 1.72796D-03
At iterate
                                      |proj g| = 6.97092D-04
            45
                  f= 4.73865D+00
At iterate
            50 f= 4.73860D+00
                                     |proj g| = 2.13787D-04
           * * *
Tit
     = total number of iterations
     = 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
               Tnf Tnint Skip
  N
                                 Nact
                                          Projq
                                                    4.739D+00
  11
          50
                58
                              0 0
                                        2.138D-04
  F =
        4.7385993161891964
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT
/opt/conda/lib/python3.10/site-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to
converge. Check mle retvals
 warnings.warn("Maximum Likelihood optimization failed to "
forecast = results.get forecast(steps=len(test), exog=test[['dew',
'temp', 'press', 'wnd_spd', 'snow', 'rain']])
predicted_values = forecast.predicted mean
from sklearn.metrics import mean squared error
import numpy as np
mse = mean squared error(test['pollution'], predicted values)
rmse = np.sqrt(mse)
print(f"Root Mean Squared Error (RMSE): {rmse}")
Root Mean Squared Error (RMSE): 104.1033718150482
import matplotlib.pyplot as plt
plt.plot(predicted values[:200], label='Predicted Values')
plt.plot(test['pollution'][:200], label='True Values')
plt.legend()
plt.show()
```



```
### experiment
from statsmodels.tsa.statespace.sarimax import SARIMAX
# Order and seasonal order depend on the characteristics of your data
(you may need to tune them)
order = (1, 1, 1)
seasonal order = (1, 1, 1, 7) # Example: 24 for daily seasonality
model = SARIMAX(train['pollution'], exog=train[['dew', 'temp',
'press', 'wnd_spd', 'snow', 'rain']],
                order=order, seasonal_order=seasonal order)
results = model.fit()
/opt/conda/lib/python3.10/site-packages/statsmodels/tsa/base/
tsa model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency H will be used.
  self. init dates(dates, freq)
/opt/conda/lib/python3.10/site-packages/statsmodels/tsa/base/tsa model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency H will be used.
  self. init dates(dates, freq)
This problem is unconstrained.
RUNNING THE L-BFGS-B CODE
```

```
Machine precision = 2.220D-16
                                   10
              11
                     M =
At XO
             O variables are exactly at the bounds
At iterate
             0 f= 4.88985D+00
                                     |proj g| = 7.45723D-02
At iterate
             f = 4.84262D + 00
                                     |proj g| = 6.63395D-02
            10 f= 4.75308D+00
                                     |proj g| = 1.93635D-03
At iterate
            15 f= 4.75305D+00
At iterate
                                     |proj g| = 2.61986D-03
At iterate
                  f= 4.75206D+00
                                     |proj g| = 1.65841D-02
            20
At iterate
            25
               f= 4.74987D+00
                                     |proj g| = 8.62406D-03
                  f= 4.74539D+00
At iterate
            30
                                     |proj g| = 1.66471D-02
                                     |proj g| = 5.86799D-03
At iterate
            35
               f= 4.74292D+00
At iterate
            40
                  f= 4.74055D+00
                                     |proj g| = 3.56983D-03
At iterate
            45
               f= 4.74017D+00
                                     |proj g| = 1.06264D-03
/opt/conda/lib/python3.10/site-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to
converge. Check mle retvals
 warnings.warn("Maximum Likelihood optimization failed to "
            f = 4.73993D + 00 | proj g | = 5.56225D - 03
At iterate
     = total number of iterations
Tit
     = 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
                56
  11
         50
                                        5.562D-03
                                                   4.740D+00
                              0
                                   0
       4.7399333063875160
  F =
```

```
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT

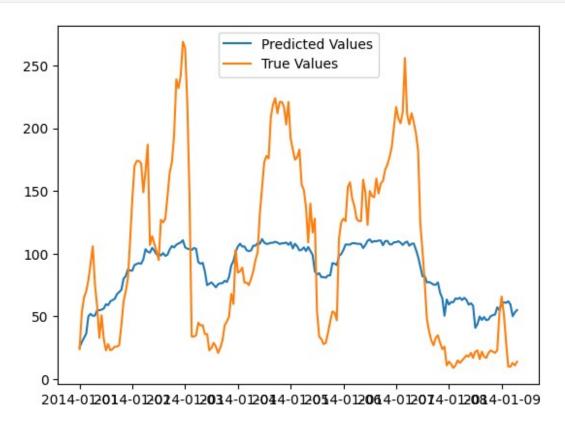
forecast = results.get_forecast(steps=len(test), exog=test[['dew', 'temp', 'press', 'wnd_spd', 'snow', 'rain']])
predicted_values = forecast.predicted_mean

from sklearn.metrics import mean_squared_error
import numpy as np

mse = mean_squared_error(test['pollution'], predicted_values)
rmse = np.sqrt(mse)
print(f"Root Mean Squared Error (RMSE): {rmse}")

Root Mean Squared Error (RMSE): 105.14277656039751
import matplotlib.pyplot as plt

plt.plot(predicted_values[:200], label='Predicted Values')
plt.plot(test['pollution'][:200], label='True Values')
plt.legend()
plt.show()
```



Temporal Convolutional Networks

```
! pip install keras-tcn
Collecting keras-tcn
  Downloading keras_tcn-3.5.0-py3-none-any.whl (13 kB)
Requirement already satisfied: numpy in
/opt/conda/lib/python3.10/site-packages (from keras-tcn) (1.23.5)
Requirement already satisfied: tensorflow in
/opt/conda/lib/python3.10/site-packages (from keras-tcn) (2.12.0)
Requirement already satisfied: tensorflow-addons in
/opt/conda/lib/python3.10/site-packages (from keras-tcn) (0.21.0)
Requirement already satisfied: absl-py>=1.0.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(1.6.3)
Requirement already satisfied: flatbuffers>=2.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(23.5.26)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(0.4.0)
Requirement already satisfied: google-pasta>=0.1.1 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(1.51.1)
Requirement already satisfied: h5py>=2.9.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(3.9.0)
Requirement already satisfied: jax>=0.3.15 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(0.4.13)
Requirement already satisfied: keras<2.13,>=2.12.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(2.12.0)
Requirement already satisfied: libclang>=13.0.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(16.0.0)
Requirement already satisfied: opt-einsum>=2.3.2 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(3.3.0)
Requirement already satisfied: packaging in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(21.3)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!
```

```
=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(3.20.3)
Requirement already satisfied: setuptools in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(68.0.0)
Requirement already satisfied: six>=1.12.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
Requirement already satisfied: tensorboard<2.13,>=2.12 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
Requirement already satisfied: tensorflow-estimator<2.13,>=2.12.0
in /opt/conda/lib/python3.10/site-packages (from tensorflow->keras-
tcn) (2.12.0)
Requirement already satisfied: termcolor>=1.1.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(2.3.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(4.6.3)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
(1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
/opt/conda/lib/python3.10/site-packages (from tensorflow->keras-tcn)
Requirement already satisfied: typeguard<3.0.0,>=2.7 in
/opt/conda/lib/python3.10/site-packages (from tensorflow-addons-
>keras-tcn) (2.13.3)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/opt/conda/lib/python3.10/site-packages (from astunparse>=1.6.0-
>tensorflow->keras-tcn) (0.40.0)
Requirement already satisfied: ml-dtypes>=0.1.0 in
/opt/conda/lib/python3.10/site-packages (from jax>=0.3.15->tensorflow-
>keras-tcn) (0.2.0)
Requirement already satisfied: scipy>=1.7 in
/opt/conda/lib/python3.10/site-packages (from jax>=0.3.15->tensorflow-
>keras-tcn) (1.11.2)
Requirement already satisfied: google-auth<3,>=1.6.3 in
/opt/conda/lib/python3.10/site-packages (from tensorboard<2.13,>=2.12-
>tensorflow->keras-tcn) (2.20.0)
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in
/opt/conda/lib/python3.10/site-packages (from tensorboard<2.13,>=2.12-
>tensorflow->keras-tcn) (1.0.0)
Requirement already satisfied: markdown>=2.6.8 in
/opt/conda/lib/python3.10/site-packages (from tensorboard<2.13,>=2.12-
>tensorflow->keras-tcn) (3.4.3)
Requirement already satisfied: requests<3,>=2.21.0 in
```

```
/opt/conda/lib/python3.10/site-packages (from tensorboard<2.13,>=2.12-
>tensorflow->keras-tcn) (2.31.0)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0
in /opt/conda/lib/python3.10/site-packages (from
tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (0.7.1)
Requirement already satisfied: werkzeug>=1.0.1 in
/opt/conda/lib/python3.10/site-packages (from tensorboard<2.13,>=2.12-
>tensorflow->keras-tcn) (2.3.7)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/opt/conda/lib/python3.10/site-packages (from packaging->tensorflow-
>keras-tcn) (3.0.9)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in
/opt/conda/lib/python3.10/site-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (4.2.4)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/opt/conda/lib/python3.10/site-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (0.2.7)
Requirement already satisfied: rsa<5,>=3.1.4 in
/opt/conda/lib/python3.10/site-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (4.9)
Requirement already satisfied: urllib3<2.0 in
/opt/conda/lib/python3.10/site-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (1.26.15)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/opt/conda/lib/python3.10/site-packages (from google-auth-
oauthlib<1.1,>=0.5->tensorboard<2.13,>=2.12->tensorflow->keras-tcn)
(1.3.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/opt/conda/lib/python3.10/site-packages (from reguests<3,>=2.21.0-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (3.1.0)
Requirement already satisfied: idna<4,>=2.5 in
/opt/conda/lib/python3.10/site-packages (from requests<3,>=2.21.0-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (3.4)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.10/site-packages (from requests<3,>=2.21.0-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (2023.7.22)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/opt/conda/lib/python3.10/site-packages (from werkzeug>=1.0.1-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (2.1.3)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/opt/conda/lib/python3.10/site-packages (from pyasn1-modules>=0.2.1-
>google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow->keras-
tcn) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in
/opt/conda/lib/python3.10/site-packages (from requests-
oauthlib>=0.7.0->google-auth-oauthlib<1.1,>=0.5-
>tensorboard<2.13,>=2.12->tensorflow->keras-tcn) (3.2.2)
Installing collected packages: keras-tcn
Successfully installed keras-tcn-3.5.0
```

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tcn import TCN
# Load your data
df = pd.read csv('/kaggle/input/lstm-datasets-multivariate-
univariate/LSTM-Multivariate pollution.csv')
# Feature scaling
scaler = MinMaxScaler()
scaled data = scaler.fit transform(df[['pollution', 'dew', 'temp',
'press', 'wnd spd', 'snow', 'rain']])
# Prepare data for TCN
X, y = [], []
for i in range(len(df) - 24): # Adjust the look-back window size (24)
hours in this example)
   X.append(scaled data[i:(i+24), :])
   y.append(scaled data[i+24, 0]) # Assuming 'pollution' is the
target variable
X, y = np.array(X), np.array(y)
model = Sequential([
   TCN(input shape=(X.shape[1], X.shape[2])),
   Dense(units=1)
1)
model.compile(optimizer='adam', loss='mean squared error')
model.fit(X, y, epochs=50, batch size=32)
Epoch 1/50
0.0571
Epoch 2/50
0.0015
Epoch 3/50
0.0013
Epoch 4/50
0.0013
Epoch 5/50
0.0012
Epoch 6/50
```

1368/1368 [====================================
0.0011
Epoch 7/50
1368/1368 [====================================
9.2349e-04
Epoch 8/50
1368/1368 [====================================
9.0949e-04
Epoch 9/50
1368/1368 [====================================
8.6504e-04
Epoch 10/50
1368/1368 [====================================
8.1356e-04
Epoch 11/50
1368/1368 [====================================
7.9250e-04
Epoch 12/50
1368/1368 [====================================
7.6921e-04
Epoch 13/50
1368/1368 [====================================
7.5185e-04
Epoch 14/50
1368/1368 [====================================
7.3601e-04
Epoch 15/50
1368/1368 [====================================
7.2050e-04
Epoch 16/50
1368/1368 [====================================
7.0817e-04
Epoch 17/50
1368/1368 [====================================
7.0625e-04
Epoch 18/50
1368/1368 [====================================
6.9781e-04
Epoch 19/50
1368/1368 [====================================
6.8820e-04
Epoch 20/50
1368/1368 [====================================
6.8039e-04
Epoch 21/50
1368/1368 [====================================
6.7806e-04
Epoch 22/50 1368/1368 [====================================
1300/1300 [

6.7349e-04			
Epoch 23/50			_
1368/1368 [===========] -	10s	7ms/step	- loss:
6.6601e-04			
Epoch 24/50			_
1368/1368 [============] -	10s	7ms/step	- loss:
6.6400e-04			
Epoch 25/50			
1368/1368 [============] -	10s	7ms/step	- loss:
6.5986e-04			
Epoch 26/50			_
1368/1368 [============] -	10s	8ms/step	- loss:
6.3882e-04			
Epoch 27/50			_
1368/1368 [====================================	10s	7ms/step	- loss:
6.4464e-04			
Epoch 28/50			_
1368/1368 [===========] -	10s	7ms/step	- loss:
6.3846e-04			
Epoch 29/50		_	_
1368/1368 [============] -	10s	8ms/step	- loss:
6.3939e-04			
Epoch 30/50			_
1368/1368 [====================================	10s	7ms/step	- loss:
6.3633e-04			
Epoch 31/50			_
1368/1368 [============] -	10s	7ms/step	- loss:
6.3672e-04			
Epoch 32/50			
1368/1368 [====================================	10s	/ms/step	- loss:
6.3061e-04			
Epoch 33/50	1.0	- , .	-
1368/1368 [====================================	10s	/ms/step	- loss:
6.3201e-04			
Epoch 34/50	1.0	7 / 1	-
1368/1368 [====================================	105	/ms/step	- LOSS:
6.2916e-04			
Epoch 35/50	10-	7 /	1
1368/1368 [====================================	105	/ms/step	- LOSS:
6.3025e-04			
Epoch 36/50	10-	7/	1
1368/1368 [====================================	105	/ms/step	- LOSS:
6.2190e-04			
Epoch 37/50	10 -	7	1
1368/1368 [====================================	105	/ms/step	- LOSS:
6.2117e-04			
Epoch 38/50	1.0	7 ()	1
1368/1368 [====================================	108	/ms/step	- loss:
6.1875e-04			

```
Epoch 39/50
6.2507e-04
Epoch 40/50
6.1726e-04
Epoch 41/50
6.1524e-04
Epoch 42/50
6.1613e-04
Epoch 43/50
6.1631e-04
Epoch 44/50
6.1415e-04
Epoch 45/50
6.0810e-04
Epoch 46/50
6.0630e-04
Epoch 47/50
1368/1368 [============= ] - 10s 7ms/step - loss:
6.0427e-04
Epoch 48/50
5.9589e-04
Epoch 49/50
5.9983e-04
Epoch 50/50
5.9156e-04
<keras.callbacks.History at 0x7a795484ad10>
# # Assume you have a test set X test
# predicted values = model.predict(X)
# # Inverse transform predictions to the original scale
# predicted values =
scaler.inverse transform(np.concatenate([np.zeros((24, 1)),
predicted values]))
# Make predictions on the training data
predicted values = model.predict(X)
```

```
# Inverse transform predictions to the original scale
predicted values =
scaler.inverse transform(np.concatenate([np.zeros((predicted values.sh
ape[0], 6)), predicted values], axis=1))
# Inverse transform the true values to the original scale
true values =
scaler.inverse transform(np.concatenate([np.zeros((y.shape[0], 6)),
y.reshape(-1, 1)], axis=1))
# Inverse transform the true values to the original scale
# true values = scaler.inverse transform(np.concatenate([np.zeros((24,
1)), y.reshape(-1, 1)]))
from sklearn.metrics import mean squared error, mean absolute error,
r2 score
# Calculate performance metrics
mse = mean squared error(true values, predicted values)
mae = mean absolute error(true values, predicted values)
r2 = r2_score(true_values, predicted_values)
print(f'Mean Squared Error (MSE): {mse:.5f}')
print(f'Mean Absolute Error (MAE): {mae:.5f}')
print(f'R-squared (R2): {r2:.5f}')
Mean Squared Error (MSE): 0.11026
Mean Absolute Error (MAE): 0.06790
R-squared (R2): 0.99013
```