_data_modelling

July 10, 2023

[ ]:
```python
import warnings
warnings.filterwarnings('ignore')

# visuals
import tensorflow as tf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
plt.style.use('seaborn')
%matplotlib inline

# models
import tensorflow as tf
from tensorflow import keras
from keras.wrappers.scikit_learn import KerasClassifier
from tensorflow.keras import Sequential, layers, callbacks
from tensorflow.keras.layers import Dense, LSTM, Dropout, GRU, Bidirectional

# validation
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import MinMaxScaler, StandardScaler

# metrics & evaluation
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import␣
↪mean_squared_error,mean_absolute_error,explained_variance_score, r2_score,␣
↪mean_absolute_percentage_error
from scipy import stats

print('Imports Complete')
```

```
Imports Complete
```

```
Using TensorFlow backend.
```

Data Exploration

This dataset has already been cleaned and preprocessed for modelling. This was done in the Data Preparation Notebook.

[ ]:
```
# fix random seed for reproducibility
tf.random.set_seed(42)
```

[ ]:
```
# load the dataset
df = pd.read_csv('mod_dec21_dec22_prepared_.csv')
# df = dataframe.values
df.head()
```

[ ]:
```
             timestamp  hour  sensor_id    P1   P2  pressure  temperature  \
0  2021-12-01 11:13:48    11    67959.0  6.80  1.0       NaN          NaN
1  2021-12-01 11:16:16    11    67959.0  6.15  0.8       NaN          NaN
2  2021-12-01 11:18:45    11    67959.0  5.97  0.8       NaN          NaN
3  2021-12-01 11:23:44    11    67959.0  6.20  1.3       NaN          NaN
4  2021-12-01 11:26:15    11    67959.0  4.65  0.8       NaN          NaN

   humidity  day  month    year
0       NaN  1.0   12.0  2021.0
1       NaN  1.0   12.0  2021.0
2       NaN  1.0   12.0  2021.0
3       NaN  1.0   12.0  2021.0
4       NaN  1.0   12.0  2021.0
```

[ ]:
```
df.tail()
```

[ ]:
```
                   timestamp  hour  sensor_id      P1     P2   pressure  \
1316743  2022-12-06 23:58:29    23    67961.5  19.250  10.93  101580.81
1316744  2022-12-06 23:58:43    23    67955.5  18.270   8.65  101676.44
1316745  2022-12-06 23:59:29    23    67959.0  33.670  15.60  101576.00
1316746  2022-12-06 23:59:30    23    67960.0  23.485  11.50  101475.56
1316747  2022-12-06 23:59:49    23    67993.5  13.300   7.40  101658.63

         temperature  humidity  day  month    year
1316743        3.950    100.00  6.0   12.0  2022.0
1316744        2.750    100.00  6.0   12.0  2022.0
1316745        2.835    100.00  6.0   12.0  2022.0
1316746        2.920    100.00  6.0   12.0  2022.0
1316747        7.510     74.25  6.0   12.0  2022.0
```

[ ]:
```
df.shape
```

[ ]:
```
(1316748, 11)
```

[ ]:
```
# df["timestamp"] = pd.to_datetime(df[['year', 'month', 'day', 'hour']])

df['timestamp'] = pd.to_datetime(df['timestamp'],infer_datetime_format=True)

df.sort_values(by=['timestamp'], inplace=False)
```

[ ]:
```
                  timestamp  hour  sensor_id      P1     P2   pressure  \
0       2021-12-01 11:13:48    11    67959.0   6.800   1.00        NaN
1       2021-12-01 11:16:16    11    67959.0   6.150   0.80        NaN
2       2021-12-01 11:18:45    11    67959.0   5.970   0.80        NaN
3       2021-12-01 11:23:44    11    67959.0   6.200   1.30        NaN
4       2021-12-01 11:26:15    11    67959.0   4.650   0.80        NaN
…                       …   …         …      …     …        …
1316743 2022-12-06 23:58:29    23    67961.5  19.250  10.93  101580.81
1316744 2022-12-06 23:58:43    23    67955.5  18.270   8.65  101676.44
1316745 2022-12-06 23:59:29    23    67959.0  33.670  15.60  101576.00
1316746 2022-12-06 23:59:30    23    67960.0  23.485  11.50  101475.56
1316747 2022-12-06 23:59:49    23    67993.5  13.300   7.40  101658.63

         temperature  humidity  day  month    year
0                NaN       NaN  1.0   12.0  2021.0
1                NaN       NaN  1.0   12.0  2021.0
2                NaN       NaN  1.0   12.0  2021.0
3                NaN       NaN  1.0   12.0  2021.0
4                NaN       NaN  1.0   12.0  2021.0
…                  …       …   …     …       …
1316743        3.950    100.00  6.0   12.0  2022.0
1316744        2.750    100.00  6.0   12.0  2022.0
1316745        2.835    100.00  6.0   12.0  2022.0
1316746        2.920    100.00  6.0   12.0  2022.0
1316747        7.510     74.25  6.0   12.0  2022.0

[1316748 rows x 11 columns]
```

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

[ ]:
```
            timestamp  hour  sensor_id    P1   P2  pressure  temperature  \
0 2021-12-01 11:13:48    11    67959.0  6.80  1.0       NaN          NaN
1 2021-12-01 11:16:16    11    67959.0  6.15  0.8       NaN          NaN
2 2021-12-01 11:18:45    11    67959.0  5.97  0.8       NaN          NaN
3 2021-12-01 11:23:44    11    67959.0  6.20  1.3       NaN          NaN
4 2021-12-01 11:26:15    11    67959.0  4.65  0.8       NaN          NaN

   humidity  day  month    year
0       NaN  1.0   12.0  2021.0
1       NaN  1.0   12.0  2021.0
2       NaN  1.0   12.0  2021.0
```

```
3       NaN  1.0   12.0  2021.0
4       NaN  1.0   12.0  2021.0
```

[ ]:
```
df.tail()
```

[ ]:
```
                  timestamp  hour  sensor_id      P1     P2   pressure  \
1316743 2022-12-06 23:58:29    23    67961.5  19.250  10.93  101580.81
1316744 2022-12-06 23:58:43    23    67955.5  18.270   8.65  101676.44
1316745 2022-12-06 23:59:29    23    67959.0  33.670  15.60  101576.00
1316746 2022-12-06 23:59:30    23    67960.0  23.485  11.50  101475.56
1316747 2022-12-06 23:59:49    23    67993.5  13.300   7.40  101658.63

         temperature  humidity  day  month    year
1316743        3.950    100.00  6.0   12.0  2022.0
1316744        2.750    100.00  6.0   12.0  2022.0
1316745        2.835    100.00  6.0   12.0  2022.0
1316746        2.920    100.00  6.0   12.0  2022.0
1316747        7.510     74.25  6.0   12.0  2022.0
```

Overall, the data set has over a million records of measurements per minute with 11 columns.

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1316748 entries, 0 to 1316747
Data columns (total 11 columns):
 #   Column       Non-Null Count    Dtype
---  ------       --------------    -----
 0   timestamp    1316748 non-null  datetime64[ns]
 1   hour         1316748 non-null  int64
 2   sensor_id    1316748 non-null  float64
 3   P1           1316748 non-null  float64
 4   P2           1316748 non-null  float64
 5   pressure     1316255 non-null  float64
 6   temperature  1316255 non-null  float64
 7   humidity     1316255 non-null  float64
 8   day          1316748 non-null  float64
 9   month        1316748 non-null  float64
 10  year         1316748 non-null  float64
dtypes: datetime64[ns](1), float64(9), int64(1)
memory usage: 110.5 MB
```

Below we set the group the data by hour. By doing that, we shrink the data to just over 8K rows.

[ ]:
```
# print info to check conversion
df = df.set_index('timestamp').resample('H').mean() # set date as index or␣
↪rest_index() .resample('5min').mean()
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8893 entries, 2021-12-01 11:00:00 to 2022-12-06 23:00:00
Freq: H
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   hour         8330 non-null   float64
 1   sensor_id    8330 non-null   float64
 2   P1           8330 non-null   float64
 3   P2           8330 non-null   float64
 4   pressure     8309 non-null   float64
 5   temperature  8309 non-null   float64
 6   humidity     8309 non-null   float64
 7   day          8330 non-null   float64
 8   month        8330 non-null   float64
 9   year         8330 non-null   float64
dtypes: float64(10)
memory usage: 764.2 KB
```

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

[ ]:
```
                     hour  sensor_id         P1        P2  pressure  \
timestamp
2021-12-01 11:00:00  11.0    67959.0   5.918750  0.921250       NaN
2021-12-01 12:00:00  12.0    67959.0   6.340000  0.891176       NaN
2021-12-01 13:00:00  13.0    67959.0   7.080000  0.987000       NaN
2021-12-01 14:00:00  14.0    67959.0  11.604091  1.667273       NaN
2021-12-01 15:00:00  15.0    67959.0  13.948500  2.034500       NaN

                     temperature  humidity  day  month    year
timestamp
2021-12-01 11:00:00          NaN       NaN  1.0   12.0  2021.0
2021-12-01 12:00:00          NaN       NaN  1.0   12.0  2021.0
2021-12-01 13:00:00          NaN       NaN  1.0   12.0  2021.0
2021-12-01 14:00:00          NaN       NaN  1.0   12.0  2021.0
2021-12-01 15:00:00          NaN       NaN  1.0   12.0  2021.0
```

[ ]:
```
df.tail()
```

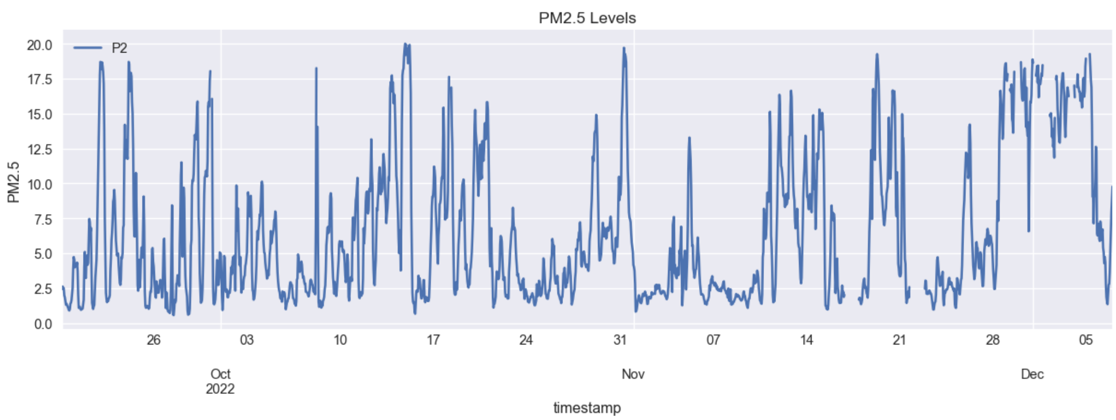
[ ]:
```
                     hour     sensor_id         P1        P2       pressure  \
timestamp
2022-12-06 19:00:00  19.0  67966.827114   9.824515  5.174757  101612.213190
2022-12-06 20:00:00  20.0  67967.959732  12.462634  6.818859  101621.297785
2022-12-06 21:00:00  21.0  68968.278523  14.505705  7.973121  101606.998859
2022-12-06 22:00:00  22.0  67967.442029  16.657174  8.854710  101611.657500
```

```
2022-12-06 23:00:00  23.0  67967.000000  18.115521  9.781424  101604.348264

                     temperature   humidity  day  month    year
timestamp
2022-12-06 19:00:00     5.828451  92.733433  6.0   12.0  2022.0
2022-12-06 20:00:00     5.795403  92.526711  6.0   12.0  2022.0
2022-12-06 21:00:00     5.779866  92.406711  6.0   12.0  2022.0
2022-12-06 22:00:00     5.242500  92.941957  6.0   12.0  2022.0
2022-12-06 23:00:00     4.554861  93.283785  6.0   12.0  2022.0
```

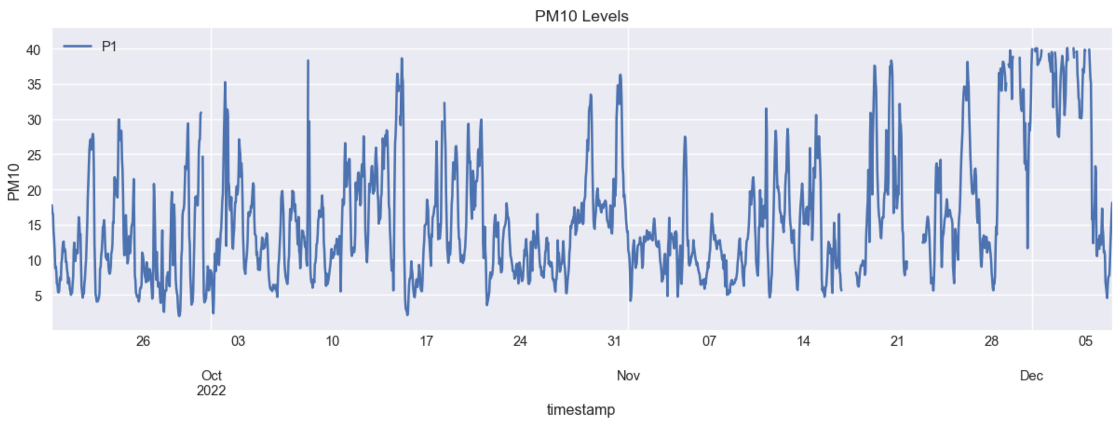
[ ]:
```
df.shape
```

[ ]:
```
(8893, 10)
```

[ ]:
```
plt.figure(dpi=105,figsize=(14,4))
df["P2"].iloc[7000:8893].plot(legend=True)
# df["P2"].iloc[1300000:1316748].plot(legend=True)
# plt.legend(['Training set (40000 Hours)','Test set'])
plt.title('PM2.5 Levels')
plt.ylabel("PM2.5")
plt.show()
```



[ ]:
```
plt.figure(dpi=105,figsize=(14,4))
df["P1"].iloc[7000:8893].plot(legend=True)
# df["P1"].iloc[1300000:1316748].plot(legend=True)
plt.title('PM10 Levels')
plt.ylabel("PM10")
plt.show()
```

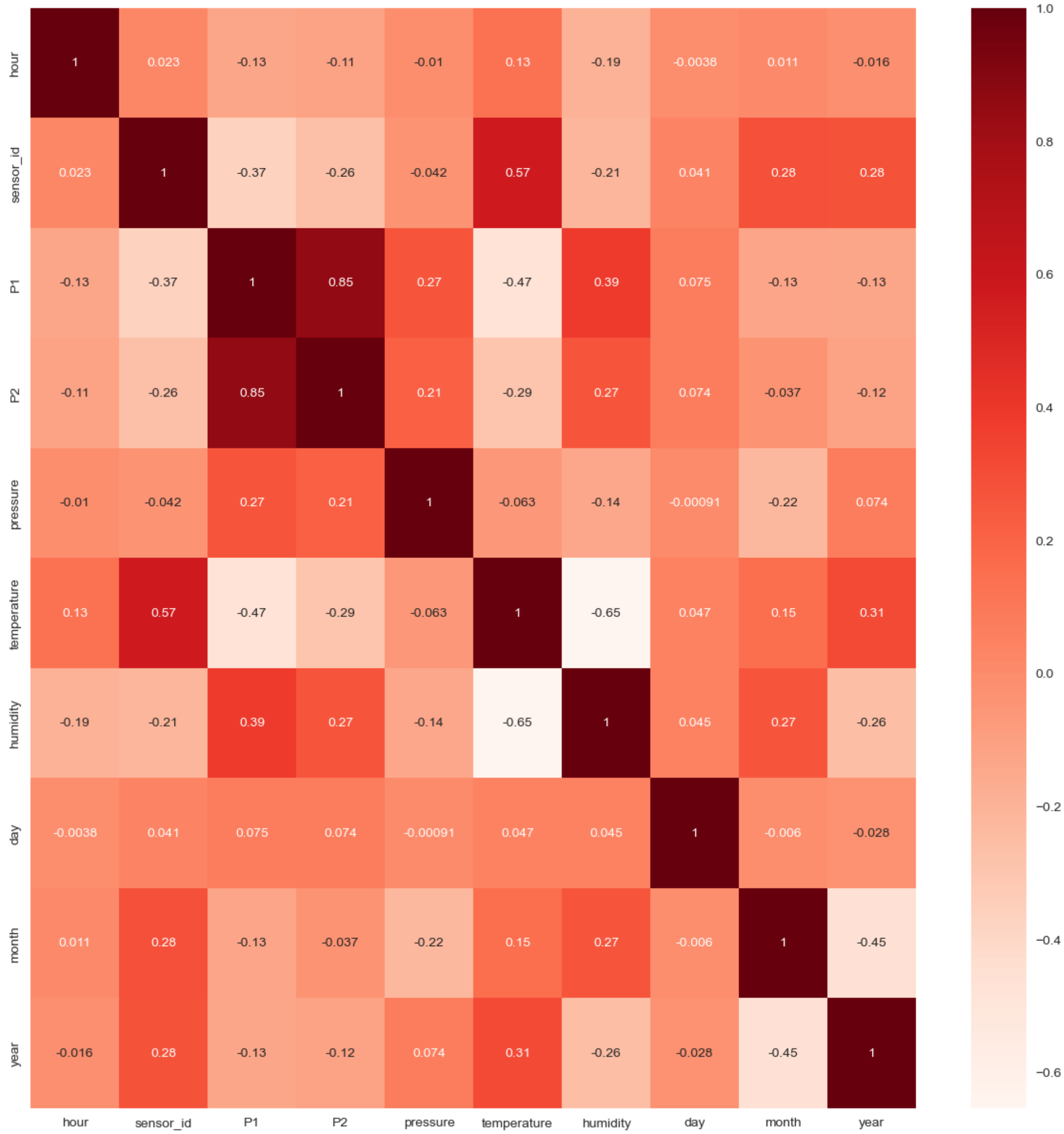


Above we see the plot of PM2.5 and PM10. Looks very similar but still slightly different.

[ ]:
```python
fig = px.histogram(df, x=df["P1"])

fig.update_layout(
    title={
        'text': "Distribution of PM10 values registered by sensors in various␣
 ↪location in Eindhoven",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})
fig.update_yaxes(showgrid=False)  # turning off the grid
fig.show()

# ----------

fig2 = px.histogram(df, x=df["P2"])

fig2.update_layout(
    title={
        'text': "Distribution of PM2.5 values registered by sensors in various␣
 ↪location in Eindhoven",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'})
fig2.update_yaxes(showgrid=False)  # turning off the grid
fig2.show()
```

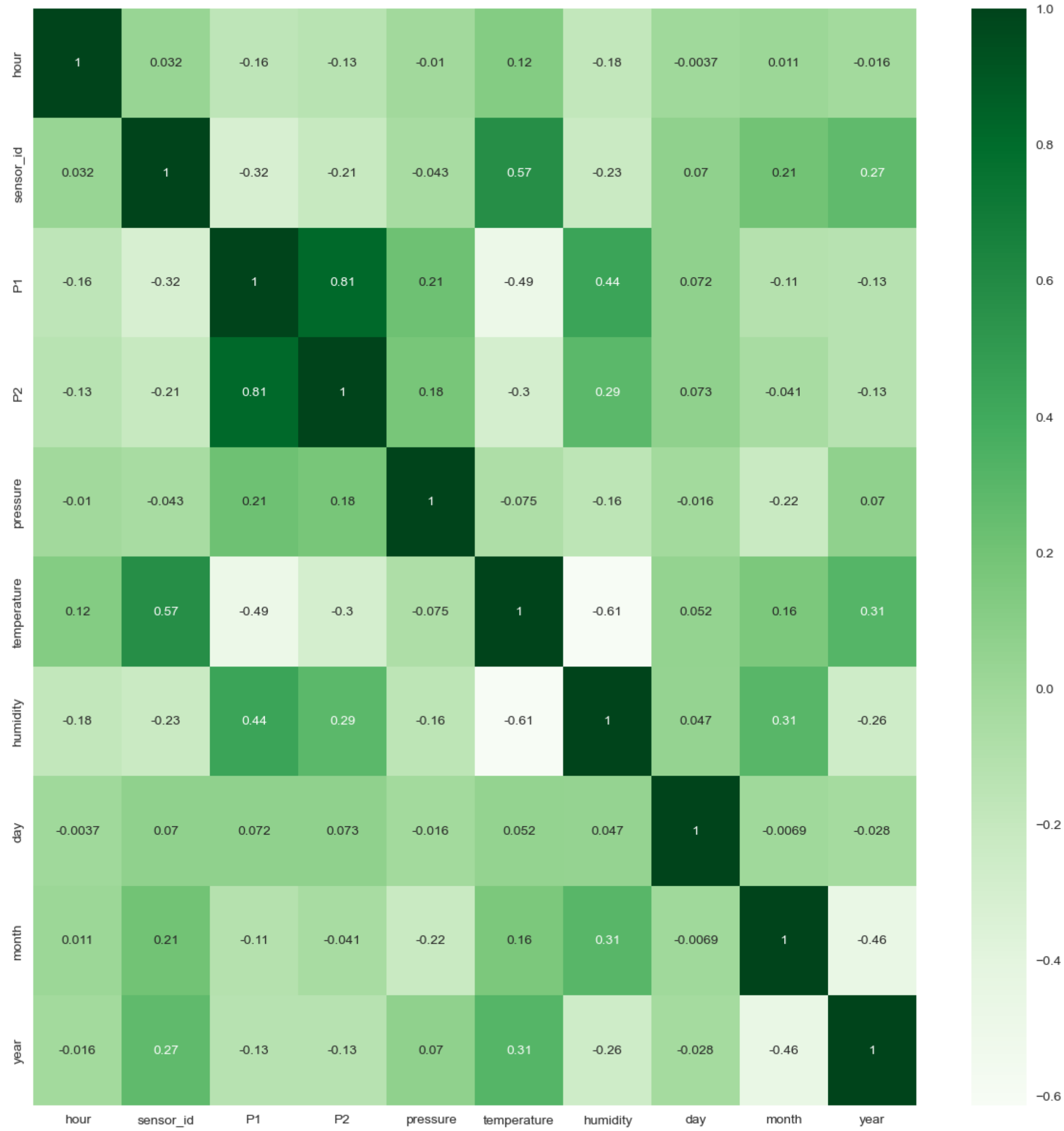
Below we will use a heatmap to have a overview of the correlation between the fetaures. The darker the color, the more correlation.

[ ]:
```python
plt.figure(figsize=(15,15))
cor = df.corr(method='pearson')
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```

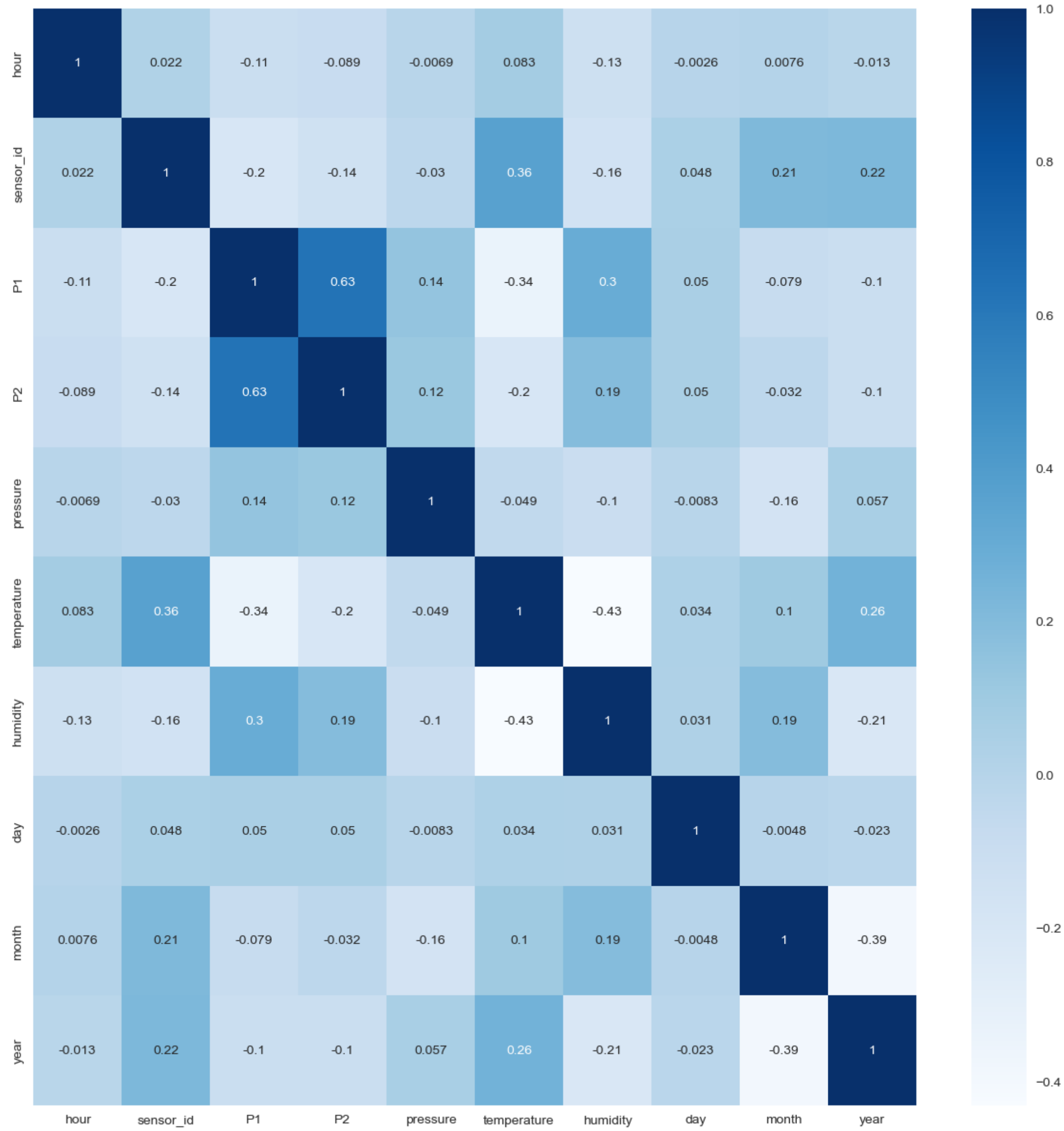


	hour	sensor_id	P1	P2	pressure	temperature	humidity	day	month	year
hour	1	0.023	-0.13	-0.11	-0.01	0.13	-0.19	-0.0038	0.011	-0.016
sensor_id	0.023	1	-0.37	-0.26	-0.042	0.57	-0.21	0.041	0.28	0.28
P1	-0.13	-0.37	1	0.85	0.27	-0.47	0.39	0.075	-0.13	-0.13
P2	-0.11	-0.26	0.85	1	0.21	-0.29	0.27	0.074	-0.037	-0.12
pressure	-0.01	-0.042	0.27	0.21	1	-0.063	-0.14	-0.00091	-0.22	0.074
temperature	0.13	0.57	-0.47	-0.29	-0.063	1	-0.65	0.047	0.15	0.31
humidity	-0.19	-0.21	0.39	0.27	-0.14	-0.65	1	0.045	0.27	-0.26
day	-0.0038	0.041	0.075	0.074	-0.00091	0.047	0.045	1	-0.006	-0.028
month	0.011	0.28	-0.13	-0.037	-0.22	0.15	0.27	-0.006	1	-0.45
year	-0.016	0.28	-0.13	-0.12	0.074	0.31	-0.26	-0.028	-0.45	1

[ ]:
```python
plt.figure(figsize=(15,15))
cor = df.corr(method='spearman')
sns.heatmap(cor, annot=True, cmap=plt.cm.Greens)
plt.show()
```



[ ]:
```
plt.figure(figsize=(15,15))
cor = df.corr(method='kendall')
sns.heatmap(cor, annot=True, cmap=plt.cm.Blues)
plt.show()
```



The PM values are heavily correlated with each other, as expected.

Splitting datasets

[ ]:
```
df.columns
```

[ ]:
```
Index(['hour', 'sensor_id', 'P1', 'P2', 'pressure', 'temperature', 'humidity',
       'day', 'month', 'year'],
      dtype='object')
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8893 entries, 2021-12-01 11:00:00 to 2022-12-06 23:00:00
Freq: H
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   hour         8330 non-null   float64
 1   sensor_id    8330 non-null   float64
 2   P1           8330 non-null   float64
 3   P2           8330 non-null   float64
 4   pressure     8309 non-null   float64
 5   temperature  8309 non-null   float64
 6   humidity     8309 non-null   float64
 7   day          8330 non-null   float64
 8   month        8330 non-null   float64
 9   year         8330 non-null   float64
dtypes: float64(10)
memory usage: 764.2 KB
```

[ ]:
```
df.shape
```

[ ]:
```
(8893, 10)
```

Scale the dataset for LSTM

[ ]:
```
min_max_scaler = MinMaxScaler(feature_range=(0,1))
for col in df.columns:
    if col == 'P2' and col == 'P1':
        continue
    else:
        df[col] = min_max_scaler.fit_transform(df[[col]])
```

[ ]:
```
# convert multiple records into 1 record having history of last n hours of data␣
 ↪as attributes
def transform_data_many_to_one (data, columns, time_steps=1):
    n_vars = data.shape[1]
    dataset = pd.DataFrame(data)
    cols, names = list(), list()
    for i in range(time_steps, 0, -1):
        cols.append(dataset.shift(i))
        names += [('{}(t-{})'.format(columns[j], i)) for j in range(n_vars)]
    cols.append(dataset.shift(-0))
    names += [('{}(t)'.format(columns [j])) for j in range(n_vars)]
    new_df = pd.concat(cols, axis=1)
    new_df.columns = names
    new_df. dropna(inplace=True)
```

```
    return new_df
```

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

[ ]:
```
                         hour  sensor_id        P1        P2  pressure  \
timestamp
2021-12-01 11:00:00  0.478261   0.002918  0.100451  0.021469       NaN
2021-12-01 12:00:00  0.521739   0.002918  0.111201  0.019940       NaN
2021-12-01 13:00:00  0.565217   0.002918  0.130084  0.024811       NaN
2021-12-01 14:00:00  0.608696   0.002918  0.245531  0.059394       NaN
2021-12-01 15:00:00  0.652174   0.002918  0.305356  0.078062       NaN

                     temperature  humidity  day  month  year
timestamp
2021-12-01 11:00:00          NaN       NaN  0.0    1.0   0.0
2021-12-01 12:00:00          NaN       NaN  0.0    1.0   0.0
2021-12-01 13:00:00          NaN       NaN  0.0    1.0   0.0
2021-12-01 14:00:00          NaN       NaN  0.0    1.0   0.0
2021-12-01 15:00:00          NaN       NaN  0.0    1.0   0.0
```

[ ]:
```
# remove unused columns.
df.drop(['sensor_id', 'day', 'month', 'year', 'hour', 'pressure',␣
 ↪'temperature', 'humidity'], axis=1, inplace=True)
```

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

[ ]:
```
                           P1        P2
timestamp
2021-12-01 11:00:00  0.100451  0.021469
2021-12-01 12:00:00  0.111201  0.019940
2021-12-01 13:00:00  0.130084  0.024811
2021-12-01 14:00:00  0.245531  0.059394
2021-12-01 15:00:00  0.305356  0.078062
```

[ ]:
```
values = df.values
values = values.astype('float32')
n_hours = 1
transformed_df = transform_data_many_to_one (values, df.columns, n_hours)
transformed_df.drop(['P1(t)', 'P2(t)'], axis=1, inplace=True)
transformed_df.reset_index (drop=True, inplace=True)
```

[ ]:
```
transformed_df.shape
```

[ ]:
```
(8237, 2)
```

[ ]:
```
transformed_df.head()
```

```
[ ]:     P1(t-1)   P2(t-1)
     0  0.100451  0.021469
     1  0.111201  0.019940
     2  0.130084  0.024811
     3  0.245531  0.059394
     4  0.305356  0.078062
```

```
[ ]: values = transformed_df.values
     n_features = transformed_df.shape[1]
     n_train_hours = int(len(transformed_df)*0.8)
     n_attributes = n_hours * n_features

     train = values[:n_train_hours, :]
     # validate = values[n_train_hours:, :] #kept 1 year data for validation
     test = values[n_train_hours:, :] # 1 year data for test

     train_X, train_y = train[:,:n_attributes], train[:,-1]
     test_X, test_y = test[:,:n_attributes], test[:,-1]
     # validate_X, validate_y = validate[:,:n_attributes], validate[:,-1]

     train_X = train_X.reshape((train_X.shape[0], n_hours, n_features))
     # validate_X = validate_X.reshape((validate_X.shape[0], n_hours, n_features))
     test_X = test_X.reshape((test_X.shape[0], n_hours, n_features))

     # Print data shape
     print('number of attributes: ', n_attributes)
     print('number of features: ', n_features)
     print('number of hours;/window/lookback: ', n_hours)
     print('train_X.shape: ', train_X.shape)
     print('train_y.shape: ', train_y.shape)
     print('test_X.shape: ', test_X.shape)
     print('test_y.shape: ', test_y.shape)
     # print('validate_X.shape: ', validate_X.shape)
     # print('validate_y.shape: ', validate_y.shape)
```

```
number of attributes:  2
number of features:  2
number of hours;/window/lookback:  1
train_X.shape:  (6589, 1, 2)
train_y.shape:  (6589,)
test_X.shape:  (1648, 1, 2)
test_y.shape:  (1648,)
```

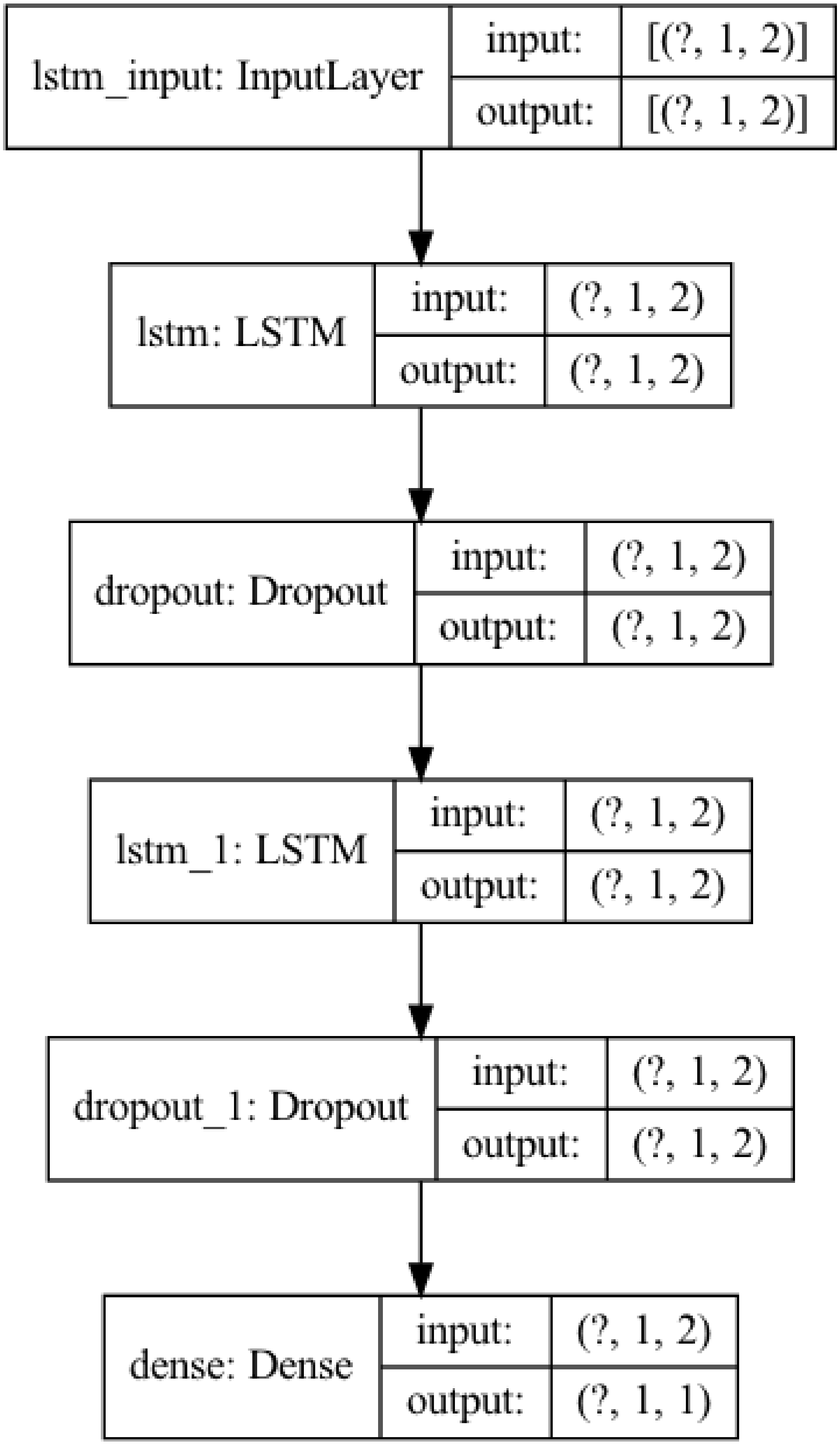
Model

```
[ ]: model = Sequential()
     model.add(LSTM(2, return_sequences = True, input_shape=(n_hours, n_features)))
     model.add(Dropout(0.2))
```

```python
model.add(LSTM(2, return_sequences = True))
model.add(Dropout(0.2))
model.add(Dense(1))
model.compile(optimizer = 'adam', loss='mse')

tf.keras.utils.plot_model(model=model, show_shapes=True)
```

```
2023-01-11 15:46:18.153146: I tensorflow/core/platform/cpu_feature_guard.cc:145]
This TensorFlow binary is optimized with Intel(R) MKL-DNN to use the following
CPU instructions in performance critical operations:  SSE4.1 SSE4.2
To enable them in non-MKL-DNN operations, rebuild TensorFlow with the
appropriate compiler flags.
2023-01-11 15:46:18.153636: I
tensorflow/core/common_runtime/process_util.cc:115] Creating new thread pool
with default inter op setting: 8. Tune using inter_op_parallelism_threads for
best performance.
```

[ ]:


lstm_input: InputLayer
input:
[(?, 1, 2)]
output:
[(?, 1, 2)]
lstm: LSTM
input:
(?, 1, 2)
output:
(?, 1, 2)
dropout: Dropout
input:
(?, 1, 2)
output:
(?, 1, 2)
lstm_1: LSTM
input:
(?, 1, 2)
output:
(?, 1, 2)
dropout_1: Dropout
input:
(?, 1, 2)
output:
(?, 1, 2)
dense: Dense
input:
(?, 1, 2)
output:
(?, 1, 1)

Train model and plot evaluation results

```
[ ]: def model_train_evaluation(X, y, model, model_name):
         #Model run

         # early_stop = EarlyStopping(monitor='val_loss', mode='min', verbose=1,␣
      ↪patience=3)
         # lr_monitor = tf.keras.callbacks.ReduceLROnPlateau(monitor="val_loss",␣
      ↪patience=3, factor=0.5, cooldown=1)
         history = model.fit(train_X, train_y, epochs=5, batch_size=16,␣
      ↪validation_split=0.2, verbose=1, shuffle=False)
         history_frame = pd.DataFrame(history.history)
         print('\n \n')

         # Model Evaluation metrics
         ypred = model.predict(X).flatten()
         print("LSTM Model Evaluation Report: ")
         print('Mean Absolute Error(MAE) of', model_name,':', mean_absolute_error(y,␣
      ↪ypred))
         print('Mean Absolute Percentage Error (MAPE) of', model_name,':',␣
      ↪mean_absolute_percentage_error(y, ypred))
         print('Mean Squared Error(MSE) of', model_name,':', mean_squared_error(y,␣
      ↪ypred))
         print('Root Mean Squared Error (RMSE) of', model_name,':',␣
      ↪mean_squared_error(y, ypred, squared = False))
         # print('Explained Variance Score (EVS) of', model_name,':',␣
      ↪explained_variance_score(y, ypred))
         print('R2 Score of', model_name,':', (r2_score(y, ypred)).round(2))
         print('\n \n')

         # model performance plot
         plt.figure(figsize=(20,5),dpi=100)
         plt.plot(history.history['loss'], label='training loss')
         plt.plot(history.history['val_loss'], label='validation loss')
         plt.ylabel('loss')
         plt.xlabel('epoch')
         plt.legend(loc='best')
         plt.title(model_name + ' Performance Loss')
         plt.show()
         print('\n \n')

         # Actual vs Predicted Plot
         f, ax = plt.subplots(figsize=(12,6),dpi=100);
         plt.scatter(y, ypred, label="Actual vs Predicted")
         # predictions
```

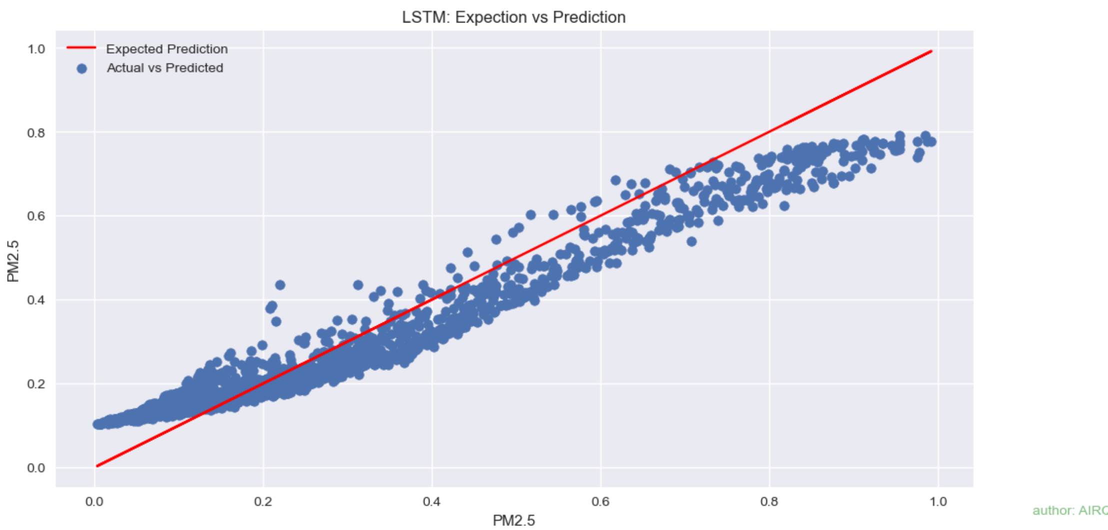
```python
    plt.xlabel('PM2.5')
    plt.ylabel('PM2.5')
    plt.title('LSTM: Expection vs Prediction')
    plt.plot(y,y,'r', label="Expected Prediction")
    plt.legend()
    f.text(0.95, 0.06, 'author: AIRQ',
    fontsize=10, color='green',
    ha='left', va='bottom', alpha=0.5);
    print('\n \n')

    # Plot test data vs prediction
    plt.figure(dpi=100, figsize = (11, 7))
    range_future = len(ypred)
    plt.plot(np.arange(range_future), np.array(ypred),label='Predicted values')
    plt.plot(np.arange(range_future), np.array(y), label='Actual values')
    plt.title('Prediction vs Actual for ' + model_name)
    plt.legend(['Predicted', 'Actual'], loc='upper right')
    plt.ylabel('Values')
    print('\n \n')

model_train_evaluation(test_X, test_y, model, 'LSTM Model')
```

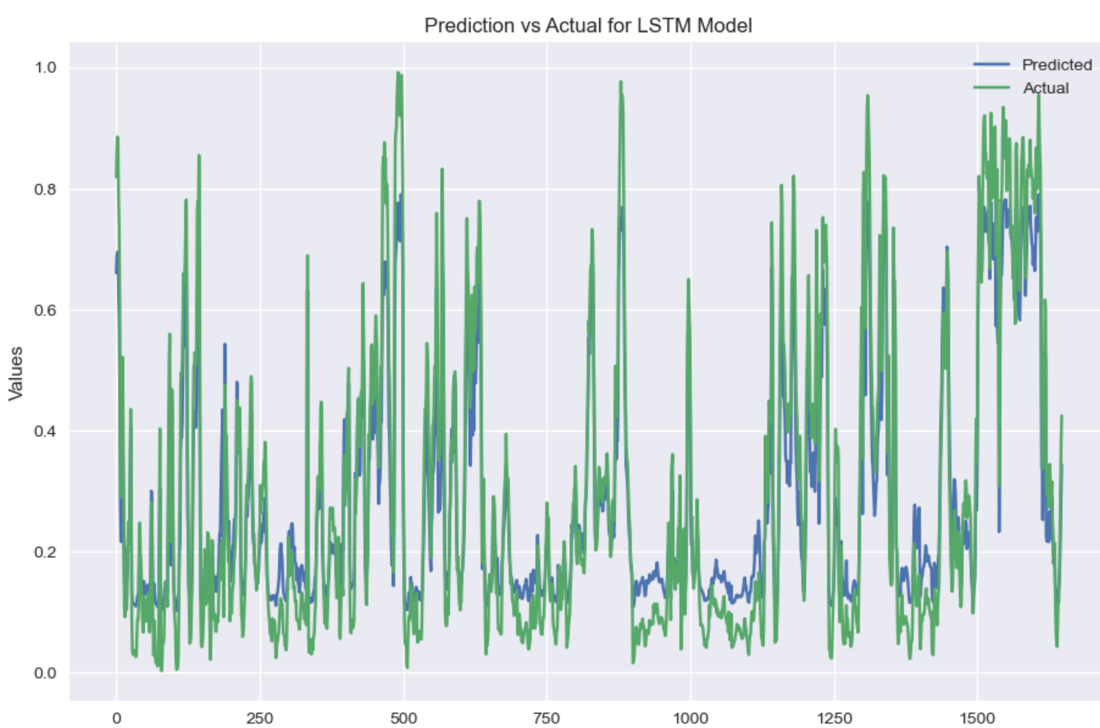
```
Train on 5271 samples, validate on 1318 samples
Epoch 1/5

2023-01-11 15:46:21.686615: W
tensorflow/core/grappler/optimizers/implementation_selector.cc:310] Skipping
optimization due to error while loading function libraries: Invalid argument:
Functions '__inference___backward_standard_lstm_4880_5365_specialized_for_Statef
ulPartitionedCall_at___inference_distributed_function_6006' and
'__inference___backward_cudnn_lstm_with_fallback_4525_4707' both implement
'lstm_6c52b04a-11ea-4ede-8c99-4b38f62d430d' but their signatures do not match.

5264/5271 [============================>.] - ETA: 0s - loss: 0.0878

2023-01-11 15:46:26.873905: W
tensorflow/core/grappler/optimizers/implementation_selector.cc:310] Skipping
optimization due to error while loading function libraries: Invalid argument:
Functions '__inference_cudnn_lstm_with_fallback_6967' and '__inference_standard_
lstm_6856_specialized_for_sequential_lstm_StatefulPartitionedCall_at___inference
_distributed_function_7680' both implement
'lstm_9bc4594b-4523-4918-b321-b85eeb838da8' but their signatures do not match.

5271/5271 [==============================] - 9s 2ms/sample - loss: 0.0878 -
val_loss: 0.0344
Epoch 2/5
5271/5271 [==============================] - 2s 446us/sample - loss: 0.0493 -
val_loss: 0.0263
Epoch 3/5
```

```
5271/5271 [==============================] - 2s 447us/sample - loss: 0.0357 -
val_loss: 0.0156
Epoch 4/5
5271/5271 [==============================] - 2s 448us/sample - loss: 0.0257 -
val_loss: 0.0081
Epoch 5/5
5271/5271 [==============================] - 2s 442us/sample - loss: 0.0189 -
val_loss: 0.0050
```

```
2023-01-11 15:46:37.664784: W
tensorflow/core/grappler/optimizers/implementation_selector.cc:310] Skipping
optimization due to error while loading function libraries: Invalid argument:
Functions '__inference_standard_lstm_11396' and '__inference_standard_lstm_11396
_specialized_for_sequential_lstm_StatefulPartitionedCall_at___inference_distribu
ted_function_12193' both implement 'lstm_7aaa2bc5-9f60-49d0-af4f-fd7a2757ca2d'
but their signatures do not match.
```

```
LSTM Model Evaluation Report:
Mean Absolute Error(MAE) of LSTM Model : 0.060889676
Mean Absolute Percentage Error (MAPE) of LSTM Model : 0.51925695
Mean Squared Error(MSE) of LSTM Model : 0.00510778
Root Mean Squared Error (RMSE) of LSTM Model : 0.07146873
R2 Score of LSTM Model : 0.92
```





Save model

[ ]:
```
model.save("lstm_model_v5.h5")
```

Load model and check values. This block of code can also be used on a validation set to check the predicted value against the actual values.

```
[ ]: loaded_model = tf.keras.models.load_model('lstm_model_v3.h5')
     train_predictions = loaded_model.predict(train_X).flatten()
     train_results = pd.DataFrame(data={'Train Predictions': train_predictions,␣
      ↪'Actual':train_y})
     train_results.head()
```

```
[ ]:    Train Predictions    Actual
     0           0.810553  0.899267
     1           0.801528  0.854910
     2           0.799165  0.835224
     3           0.791139  0.792853
     4           0.775569  0.746143
```