19075153_O'Leary_PartB

October 24, 2021

[1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import warnings
from pandas.plotting import scatter_matrix
import seaborn as sns
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import tree
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from numpy import set_printoptions
from sklearn.decomposition import PCA
from sklearn import preprocessing
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import RANSACRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from scipy.stats import pearsonr
import sklearn.metrics as metrics

warnings.filterwarnings('ignore')
```

1 Data load and pre-processing

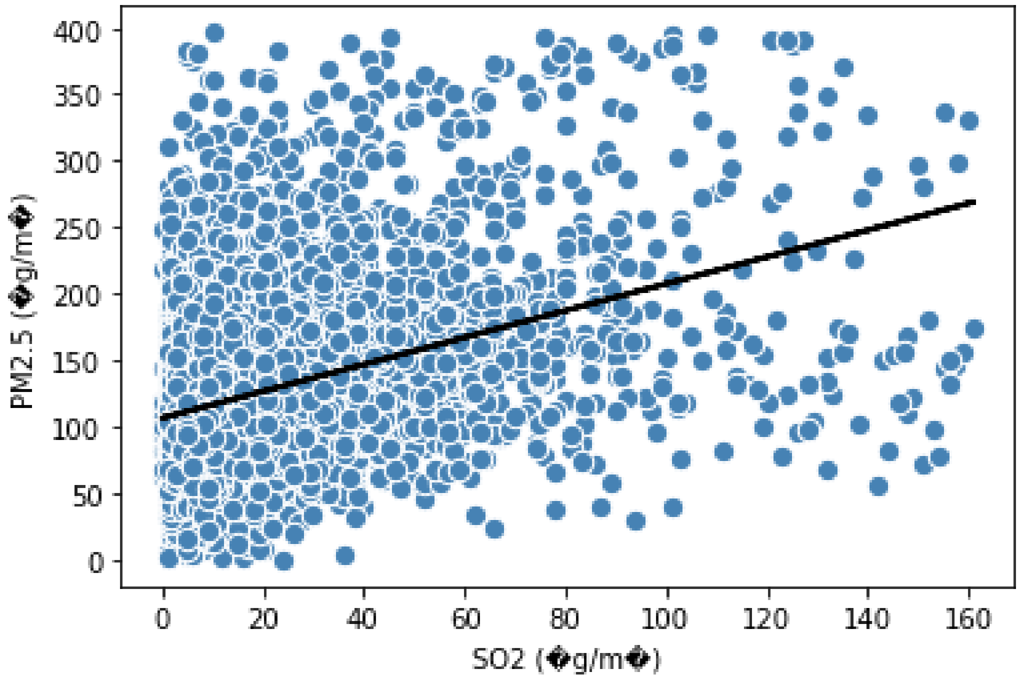
[2]:
```
min_max_scaler = preprocessing.MinMaxScaler()

#################
# load Penrose data
#################
path = "/mnt/c/Users/T828808/Study/AUT/COMP809/Ass2/
↪Penrose_Hourly_AggregateData_Jan2016Dec2020.csv"
rawdata = pd.read_csv(path)
```

```
# Rearrange Timestamp column
# Remove incorrect values or outliers
rawdata = rawdata[rawdata['Relative Humidity (%)'] <= 100]
rawdata = rawdata[rawdata['Air Temp ( C)'] <= 40]
rawdata = rawdata.dropna(how='any',axis=0)
rawdata['Timestamp (UTC+12:00)'] = pd.to_datetime(rawdata['Timestamp (UTC+12:
 ↪00)'])
rawdata = rawdata.set_index('Timestamp (UTC+12:00)')
rawdata['Hour'] = rawdata.index.hour
rawdata['Day'] = rawdata.index.day
rawdata['Month'] = rawdata.index.month
rawdata['Year'] = rawdata.index.year

# categorise everything and create array
list_of_columns = rawdata.columns
rawdata[list_of_columns] = rawdata[list_of_columns].apply(lambda col:pd.
 ↪Categorical(col).codes)
```

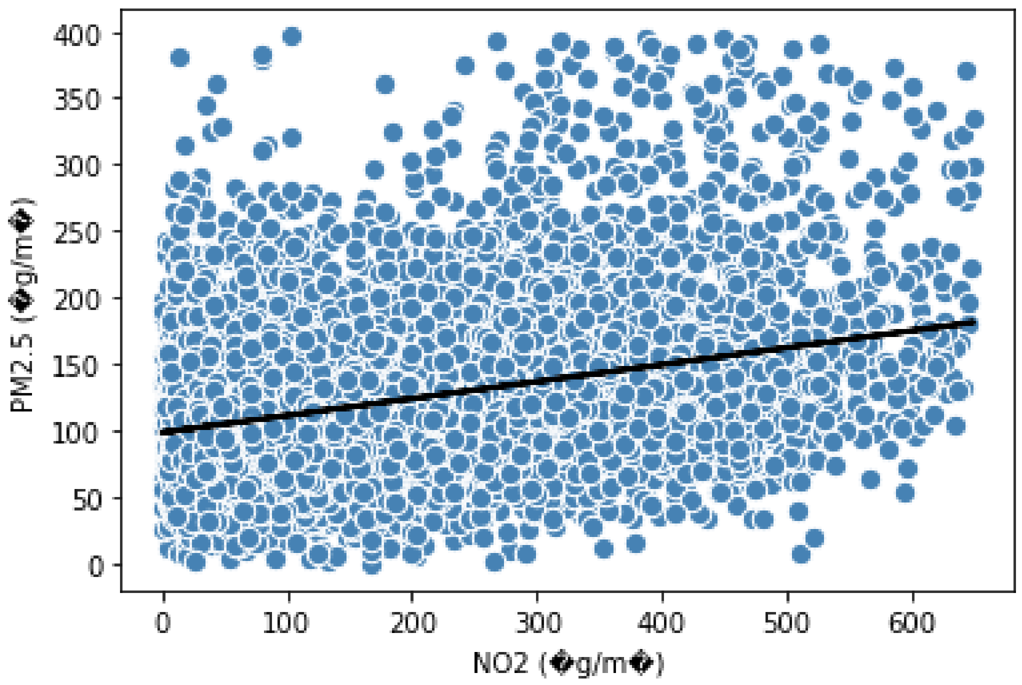
2 Inspecting outliers

[3]:
```
# A function that will plot a scatterplot of the training samples and add the␣
 ↪regression line
def lin_reg_plot(x_name):

    # Create the model
    slr = LinearRegression()
    slr.fit(X, y)

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y, slr.predict(X))
    mean_absolute_error=metrics.mean_absolute_error(y, slr.predict(X))
    mse=metrics.mean_squared_error(y, slr.predict(X))
    median_absolute_error=metrics.median_absolute_error(y, slr.predict(X))
    r2=metrics.r2_score(y, slr.predict(X))
    corr, _ = pearsonr(rawdata[x_name], y)

    # Print stats
    print('==================================== ' + x_name + '␣
 ↪====================================')
    print('Slope: %.3f' % slr.coef_[0])
    print('Intercept: %.3f' % slr.intercept_)
    print('explained_variance: ', round(explained_variance,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))
    print('Pearsons correlation: ', round(corr,4)) # Over 0.5 or less than -0.5␣
↪signifies strongest correlation

    # Chart
    plt.scatter(X, y, c='steelblue', edgecolor='white', s=70)
    plt.plot(X, slr.predict(X), color='black', lw=2)
    plt.xlabel(x_name)
    plt.ylabel('PM2.5 ( g/m )')
    plt.show()

# Starting point X and y
X = rawdata[['Hour','Air Temp ( C)','Relative Humidity (%)','Solar Radiation (W/
↪m )','Wind Direction ( )','Wind Speed (m/s)','NO ( g/m )','NO2 ( g/m )','SO2 ( g/
↪m )']].values
y = rawdata['PM2.5 ( g/m )'].values

# Display data in 2D
x_name = 'SO2 ( g/m )'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'NO2 ( g/m )'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'NO ( g/m )'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'Wind Speed (m/s)'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'Wind Direction ( )'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'Solar Radiation (W/m )'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'Relative Humidity (%)'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'Air Temp ( C)'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
x_name = 'Hour'
X = rawdata[[x_name]].values
lin_reg_plot(x_name)
```

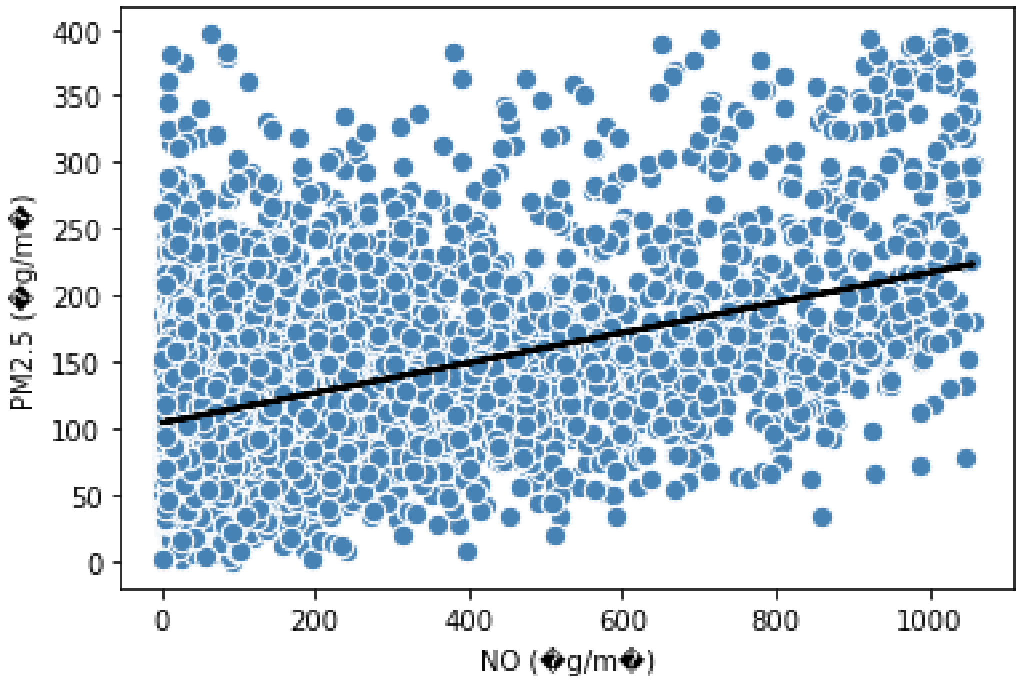
```
==================================== SO2 ( g/m )
====================================
Slope: 1.011
Intercept: 106.215
explained_variance:  0.1236
r2:  0.1236
MAE:  36.4505
MSE:  2458.9511
RMSE:  49.5878
Pearsons correlation:  0.3515
```



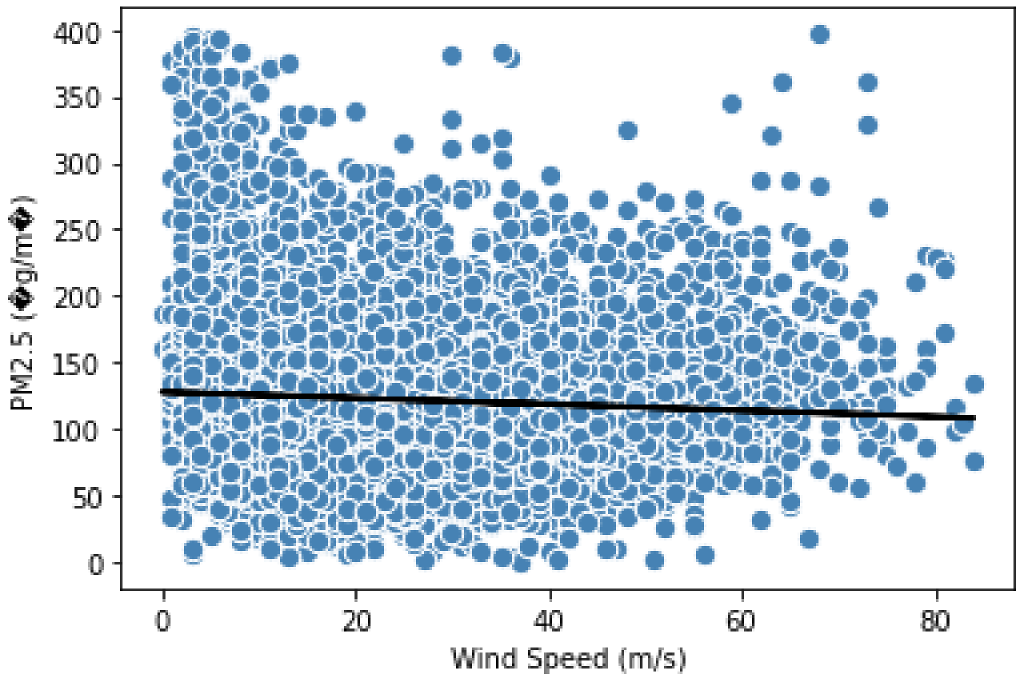
```
==================================== NO2 ( g/m )
====================================
Slope: 0.128
Intercept: 98.190
explained_variance:  0.1137
r2:  0.1137
MAE:  36.438
MSE:  2486.5994
RMSE:  49.8658
Pearsons correlation:  0.3372
```



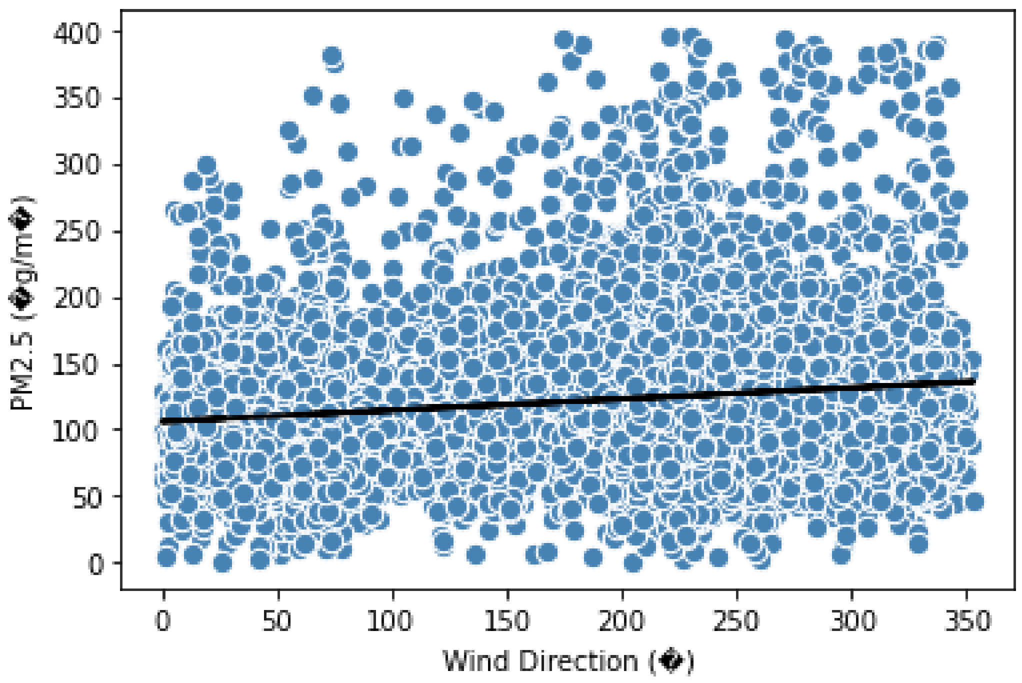
```
==================================== NO ( g/m )
====================================
Slope: 0.113
Intercept: 103.757
explained_variance:  0.1904
r2:  0.1904
MAE:  35.2568
MSE:  2271.5162
RMSE:  47.6604
Pearsons correlation:  0.4363
```



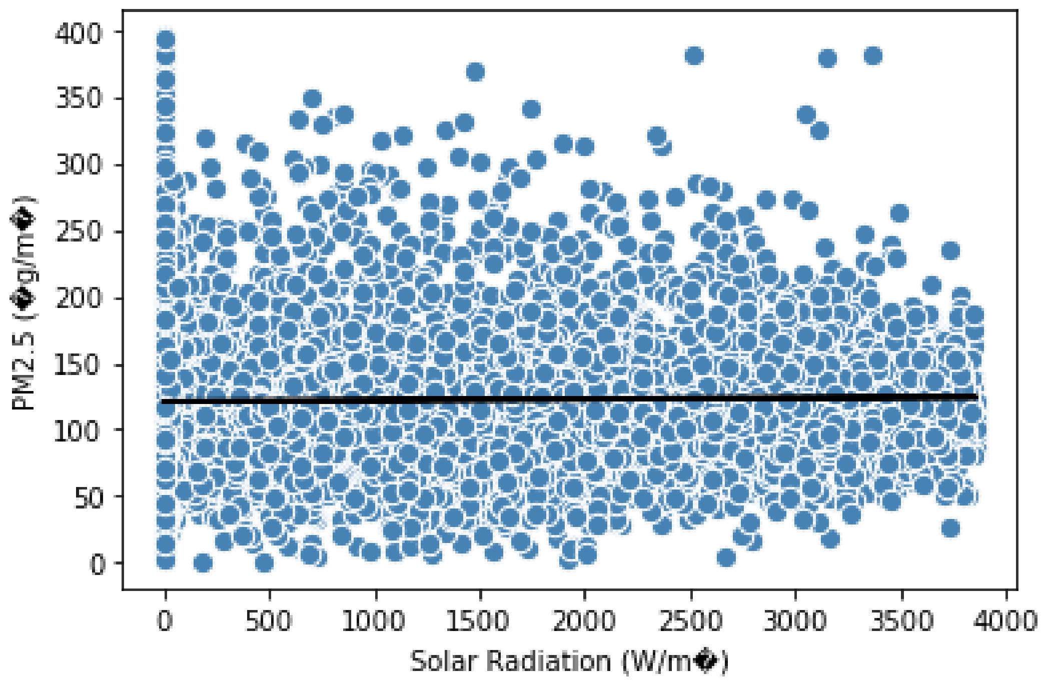
```
==================================== Wind Speed (m/s)
====================================
Slope: -0.233
Intercept: 127.722
explained_variance:  0.0045
r2:  0.0045
MAE:  38.6166
MSE:  2792.8766
RMSE:  52.8477
Pearsons correlation:  -0.0673
```



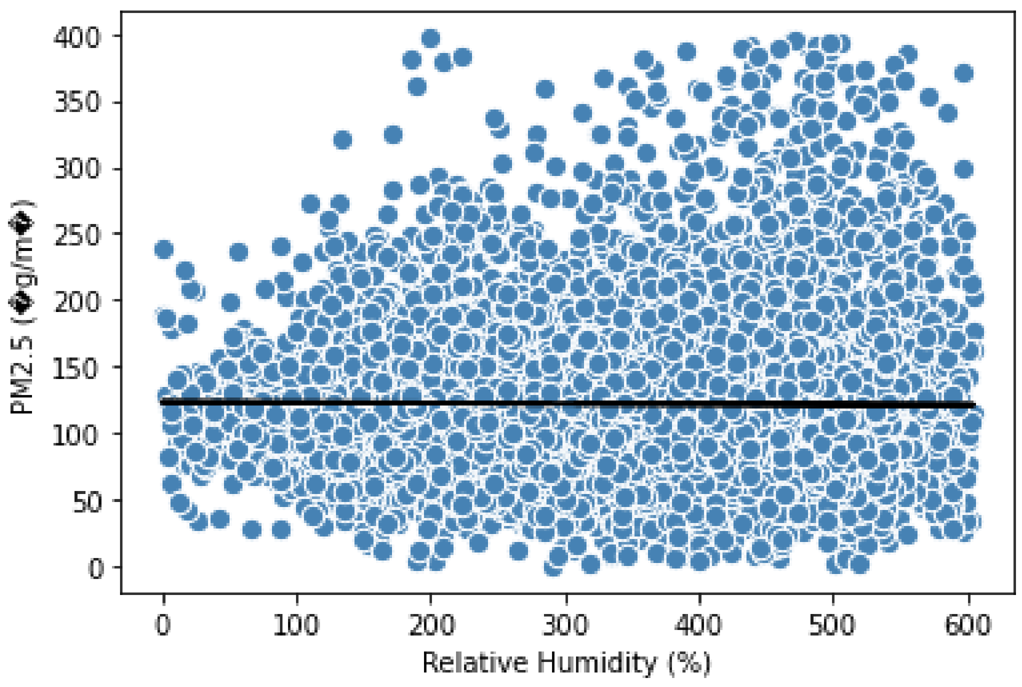
```
==================================== Wind Direction ( )
====================================
Slope: 0.085
Intercept: 106.028
explained_variance:  0.0211
r2:  0.0211
MAE:  38.016
MSE:  2746.4533
RMSE:  52.4066
Pearsons correlation:  0.1452
```



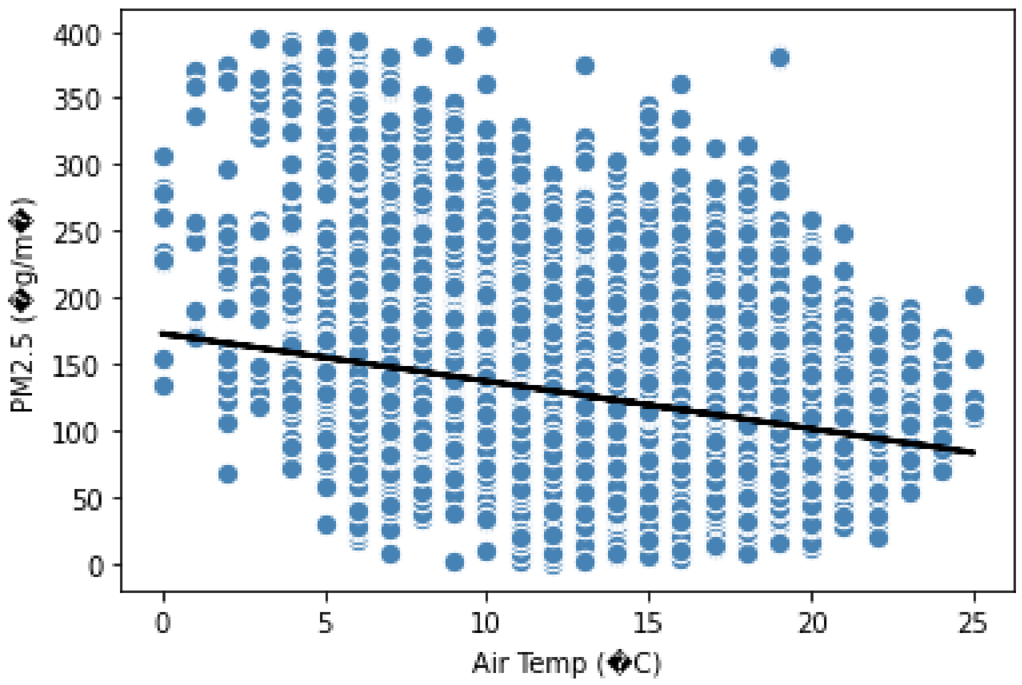
```
===================================== Solar Radiation (W/m )
=====================================
Slope: 0.001
Intercept: 121.037
explained_variance:  0.0004
r2:  0.0004
MAE:  38.47
MSE:  2804.466
RMSE:  52.9572
Pearsons correlation:  0.02
```



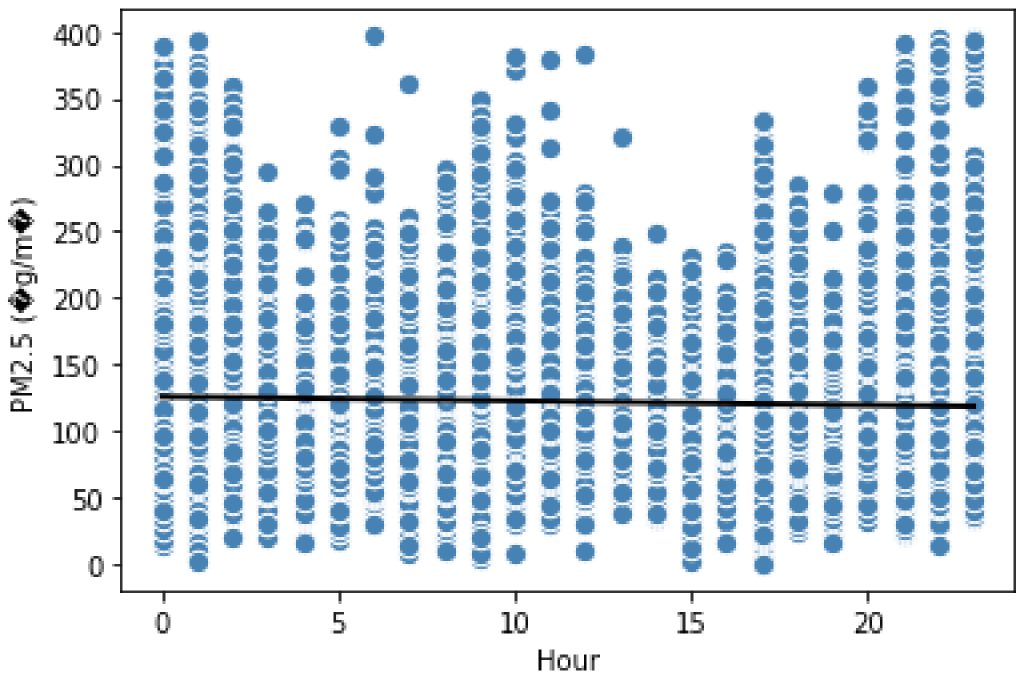
```
==================================== Relative Humidity (%)
====================================
Slope: -0.003
Intercept: 123.050
explained_variance:  0.0001
r2:  0.0001
MAE:  38.4961
MSE:  2805.3804
RMSE:  52.9658
Pearsons correlation:  -0.0086
```



```
==================================== Air Temp ( C)
====================================
Slope: -3.581
Intercept: 172.655
explained_variance:  0.0722
r2:  0.0722
MAE:  37.9256
MSE:  2603.0704
RMSE:  51.0203
Pearsons correlation:  -0.2687
```

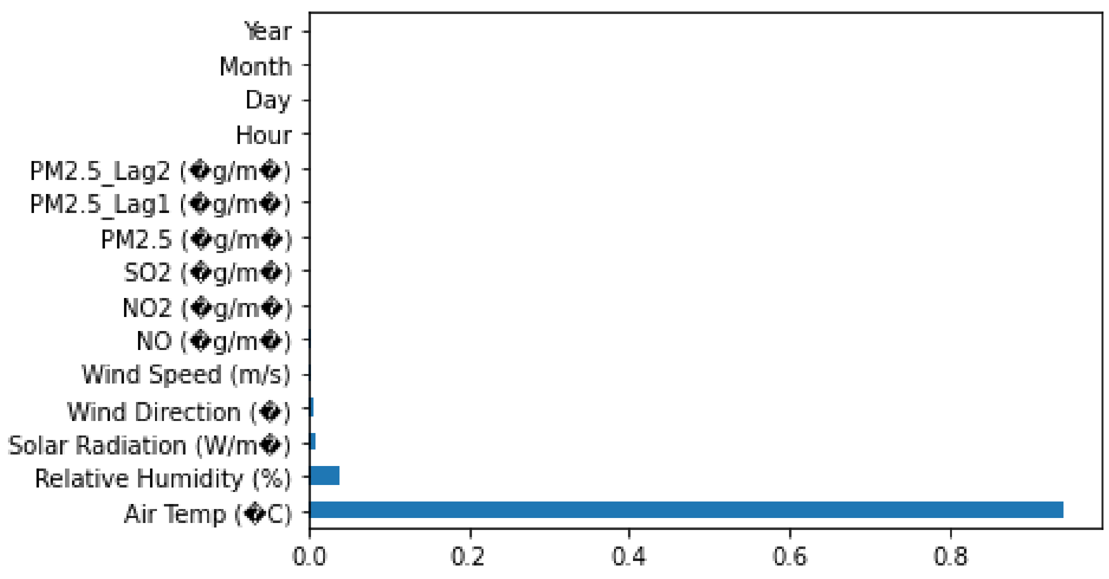


```
==================================== Hour ====================================
Slope: -0.318
Intercept: 125.667
explained_variance:  0.0017
r2:  0.0017
MAE:  38.4984
MSE:  2800.7835
RMSE:  52.9224
Pearsons correlation:  -0.0414
```



3 Feature importance

[4]:
```
# Run PCA
pca = PCA()
pca_fit = pca.fit(rawdata)
# summarize components
feat_importances = pd.Series(pca_fit.explained_variance_ratio_, index=rawdata.
 ↪columns)
feat_importances.nlargest(20).plot(kind='barh')
# Get only the first two components as they explain almost all of the variance
pca = PCA(n_components=2)
pca_fit = pca.fit(rawdata)
```



4 Summary stats for PM2.5 (g/m)

[5]:
```
rawdata['PM2.5 ( g/m )'].describe()
```

[5]:
```
count    10313.000000
mean       121.846310
std         52.970365
min          0.000000
25%         88.000000
50%        113.000000
75%        145.000000
max        397.000000
Name: PM2.5 ( g/m ), dtype: float64
```

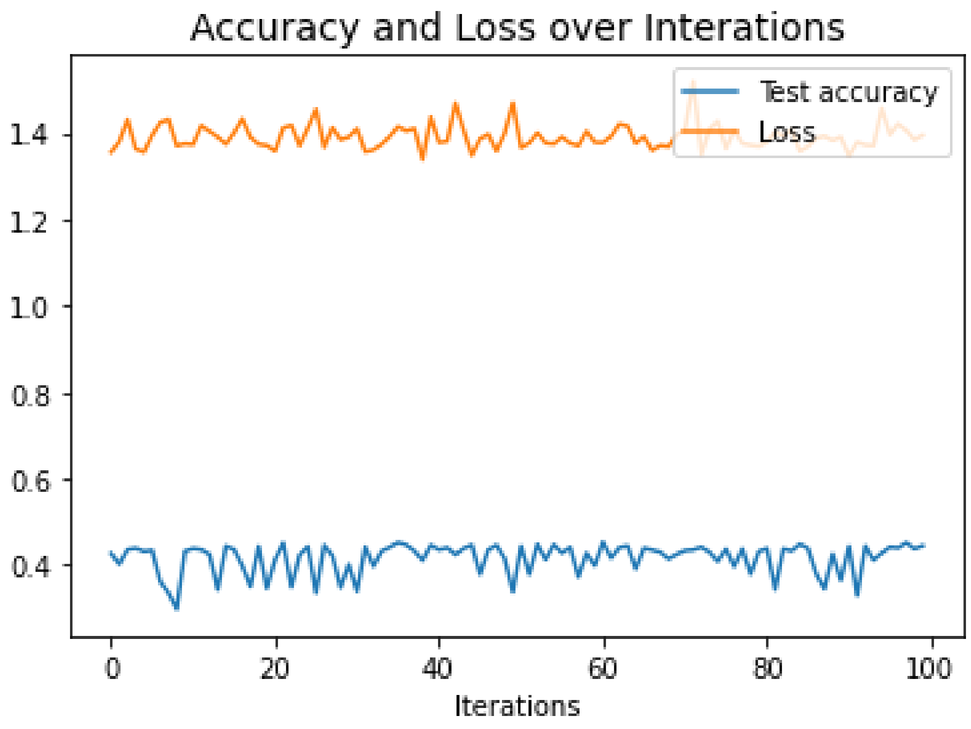
5 Do the train/test split

[9]:
```
# Get final X and y - we want to keep the top five attributes based on Pearsons␣
↪correlation
# Five topmost correlated varaiables are 'Air Temp ( C)','Wind Direction␣
↪( )','NO ( g/m )','NO2 ( g/m )','SO2 ( g/m )'
X = rawdata[['Air Temp ( C)','Wind Direction ( )','NO ( g/m )','NO2 ( g/m )','SO2␣
↪( g/m )']].values
y = rawdata['PM2.5 ( g/m )'].values
```

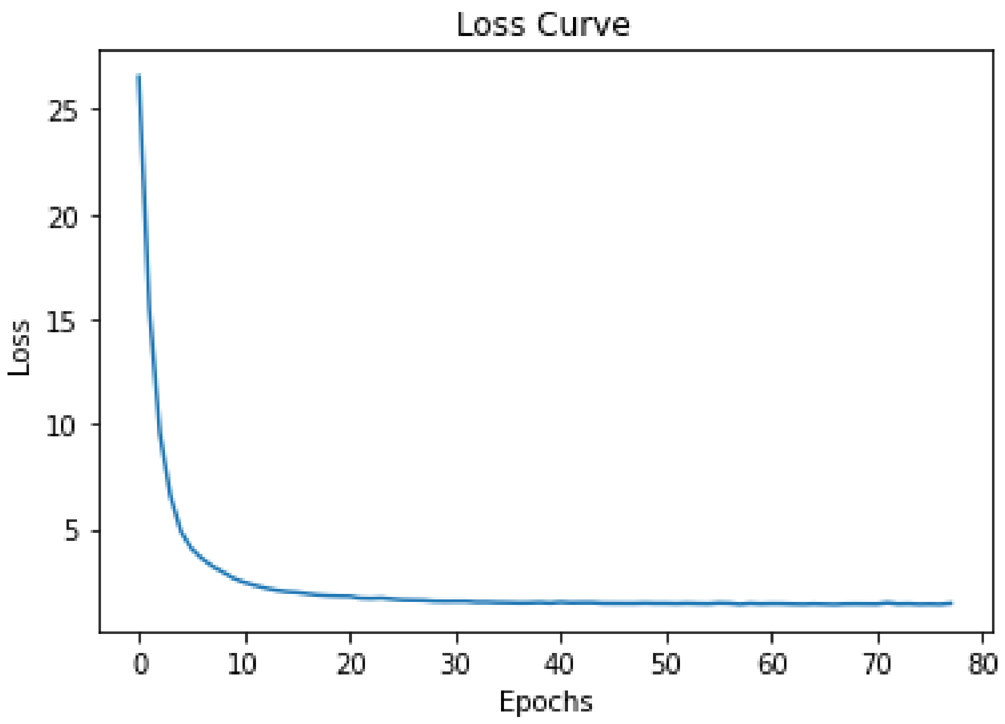
```
# We need to reduce the number of categories for y - max is 397, we can␣
↪probably start with 7 categories
# In this case we get about 0.45 accuracy score
# If we reduce the categories to 4, we get about 0.6 accuracy score
y = np.digitize(y,bins=[50,100,150,200,250,300,350])

# Do the train/test split
pred_train, pred_test, tar_train, tar_test = train_test_split(X, y, test_size=.
↪3, random_state=4)
```

6 MLP classifier

[10]:
```
import pandas
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.neural_network import MLPClassifier
import matplotlib.pyplot as plt

#A function to see some of the attributes of NN
def NN_properties(model):
    loss_values = model.loss_
    print("Loss", loss_values)
    iterations = model.n_iter_
    print("iterations",iterations)
    classes_assigned= model.classes_
    print("Assigned classes", classes_assigned)

#Displaying loss curve using loss_curve method.Note that this only works with␣
↪the MLP default solver "adam"
def make_plots_default(model):
    plt.plot(model.loss_curve_)
    plt.title('Loss Curve')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.show()

#A generic function to display training loss and testing accuracy of␣
↪MLPClassifier
def make_plots_all(mlp, target_train, target_test,␣
↪predictors_test,predictors_train):
    max_iter = 100
    accuracy = []
    losses = []
    for i in range(max_iter):
        mlp.fit(predictors_train, target_train)
        iter_acc = mlp.score(predictors_test, target_test)
        accuracy.append(iter_acc)
        losses.append(mlp.loss_)
    plt.plot(accuracy, label='Test accuracy')
    plt.plot(losses, label='Loss')
    plt.title("Accuracy and Loss over Interations", fontsize=14)
    plt.xlabel('Iterations')
    plt.legend(loc='upper right')
    plt.show()

#A function for model building and calculating accuracy
def get_accuracy(target_train, target_test, predictors_test, predictors_train):
    # Two hidden layers with 10 and 5 neurons - NN
    clf = MLPClassifier(hidden_layer_sizes=(25), max_iter=100)
    #Calling the make_plots_allfunction with unfitted model
    make_plots_all(clf, target_train, target_test, predictors_test,␣
 ↪predictors_train)
    clf.fit(predictors_train, np.ravel(target_train, order='C'))
    predictions = clf.predict(predictors_test)
    NN_properties(clf) ##Calling NN_properties to see the model attributes
    make_plots_default(clf) ##Calling make_plots function to see the error plots
    return accuracy_score(target_test, predictions)

#train-test split
pred_train, pred_test, tar_train, tar_test = train_test_split(X, y, test_size=.
 ↪3, random_state=4)

#Calling get_accuracy function which also invoke other functions NN_properties,␣
 ↪make_plots, make_plots_all
print("Accuracy score: %.2f" % get_accuracy(tar_train, tar_test, pred_test,␣
 ↪pred_train))
```



```
Loss 1.44612704682277754
iterations 78
Assigned classes [0 1 2 3 4 5 6 7]
```



```
Accuracy score: 0.44
```

7 2-Layer MLP

```
[11]: #train-test split
pred_train, pred_test, tar_train, tar_test = train_test_split(X, y, test_size=.
 ↪3, random_state=4)

def two_layer_mlp(num_l1):
    tlmlp = MLPClassifier(hidden_layer_sizes=(num_l1, 25-num_l1,), max_iter=84)
    fit_tlmlp = tlmlp.fit(pred_train, np.ravel(tar_train, order='C'))
    pred_tlmlp = tlmlp.predict(pred_test)
    prob_tlmlp = tlmlp.predict_proba(pred_test)
    accuracy_tlmlp = accuracy_score(tar_test, pred_tlmlp)
    return accuracy_tlmlp

results = pd.DataFrame(columns=["Combination of neurons", "Accuracy"])
for i in range(1,25):
    new_row = {"Combination of neurons": str(i)+","+str(25-i), "Accuracy":␣
 ↪str(two_layer_mlp(i))}
    results = results.append(new_row, ignore_index=True)

# Drop results out to a table
```

```
results
```

```
[11]:    Combination of neurons             Accuracy
      0                    1,24  0.43956043956043955
      1                    2,23  0.38978668390433097
      2                    3,22   0.4188752424046542
      3                    4,21  0.41047188106011634
      4                    5,20   0.3784744667097608
      5                    6,19   0.4460245636716225
      6                    7,18  0.43956043956043955
      7                    8,17   0.4253393665158371
      8                    9,16   0.4414996767937944
      9                   10,15   0.4411764705882353
      10                  11,14   0.4434389140271493
      11                  12,13   0.4137039431157078
      12                  13,12   0.4308338720103426
      13                  14,11  0.43244990303813835
      14                  15,10   0.4114414996767938
      15                   16,9  0.44505494505494503
      16                   17,8   0.4502262443438914
      17                   18,7   0.4204912734324499
      18                   19,6  0.44182288299935357
      19                   20,5   0.4175824175824176
      20                   21,4  0.41952165481577247
      21                   22,3   0.4230769230769231
      22                   23,2   0.4191984486102133
      23                   24,1   0.4191984486102133
```

```
[ ]:
```