# MADRID 2015

In [ ]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression,LogisticRegression,Lasso,Rid
from sklearn.model_selection import train_test_split
```

In [2]:
```
df=pd.read_csv("C:/Users/user/Downloads/FP1_air/csvs_per_year/csvs_per_year/ma
df
```

Out[2]:

| | date | BEN | CO | EBE | NMHC | NO | NO_2 | O_3 | PM10 | PM25 | SO_2 | TCH | TOL | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2015-10-01 01:00:00 | NaN | 0.8 | NaN | NaN | 90.0 | 82.0 | NaN | NaN | NaN | 10.0 | NaN | NaN | 28 |
| **1** | 2015-10-01 01:00:00 | 2.0 | 0.8 | 1.6 | 0.33 | 40.0 | 95.0 | 4.0 | 37.0 | 24.0 | 12.0 | 1.83 | 8.3 | 28 |
| **2** | 2015-10-01 01:00:00 | 3.1 | NaN | 1.8 | NaN | 29.0 | 97.0 | NaN | NaN | NaN | NaN | NaN | 7.1 | 28 |
| **3** | 2015-10-01 01:00:00 | NaN | 0.6 | NaN | NaN | 30.0 | 103.0 | 2.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| **4** | 2015-10-01 01:00:00 | NaN | NaN | NaN | NaN | 95.0 | 96.0 | 2.0 | NaN | NaN | 9.0 | NaN | NaN | 28 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **210091** | 2015-08-01 00:00:00 | NaN | 0.2 | NaN | NaN | 11.0 | 33.0 | 53.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| **210092** | 2015-08-01 00:00:00 | NaN | 0.2 | NaN | NaN | 1.0 | 5.0 | NaN | 26.0 | NaN | 10.0 | NaN | NaN | 28 |
| **210093** | 2015-08-01 00:00:00 | NaN | NaN | NaN | NaN | 1.0 | 7.0 | 74.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| **210094** | 2015-08-01 00:00:00 | NaN | NaN | NaN | NaN | 3.0 | 7.0 | 65.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| **210095** | 2015-08-01 00:00:00 | NaN | NaN | NaN | NaN | 1.0 | 9.0 | 54.0 | 29.0 | NaN | NaN | NaN | NaN | 28 |

210096 rows × 14 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210096 entries, 0 to 210095
Data columns (total 14 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     210096 non-null  object 
 1   BEN      51039 non-null   float64
 2   CO       86827 non-null   float64
 3   EBE      50962 non-null   float64
 4   NMHC     25756 non-null   float64
 5   NO       208805 non-null  float64
 6   NO_2     208805 non-null  float64
 7   O_3      121574 non-null  float64
 8   PM10     102745 non-null  float64
 9   PM25     48798 non-null   float64
 10  SO_2     86898 non-null   float64
 11  TCH      25756 non-null   float64
 12  TOL      50626 non-null   float64
 13  station  210096 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 22.4+ MB
```

In [4]:
```
df1=df.dropna()
df1
```

Out[4]:

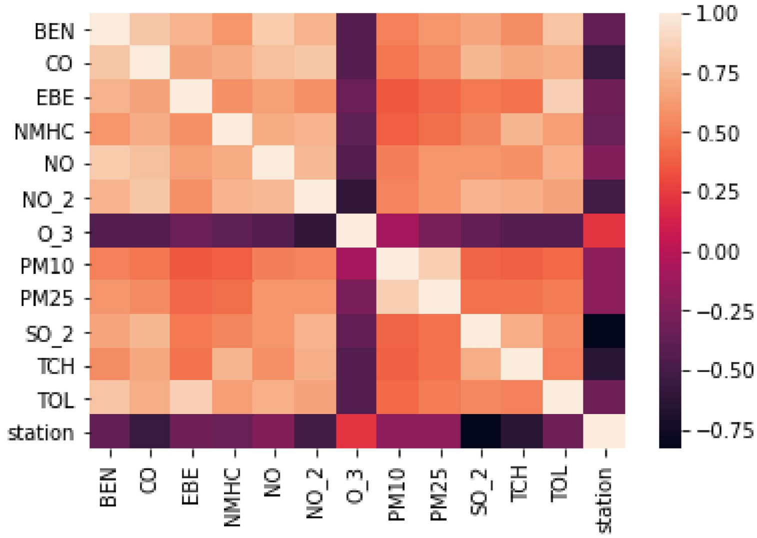
| | date | BEN | CO | EBE | NMHC | NO | NO_2 | O_3 | PM10 | PM25 | SO_2 | TCH | TOL | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2015-10-01 01:00:00 | 2.0 | 0.8 | 1.6 | 0.33 | 40.0 | 95.0 | 4.0 | 37.0 | 24.0 | 12.0 | 1.83 | 8.3 | 28 |
| **6** | 2015-10-01 01:00:00 | 0.5 | 0.3 | 0.3 | 0.12 | 6.0 | 83.0 | 1.0 | 19.0 | 12.0 | 3.0 | 1.29 | 4.8 | 28 |
| **25** | 2015-10-01 02:00:00 | 1.6 | 0.7 | 1.3 | 0.38 | 81.0 | 105.0 | 4.0 | 36.0 | 19.0 | 13.0 | 1.93 | 6.9 | 28 |
| **30** | 2015-10-01 02:00:00 | 0.4 | 0.3 | 0.3 | 0.11 | 5.0 | 72.0 | 2.0 | 16.0 | 10.0 | 2.0 | 1.27 | 7.8 | 28 |
| **49** | 2015-10-01 03:00:00 | 2.2 | 0.8 | 1.8 | 0.41 | 111.0 | 104.0 | 4.0 | 35.0 | 20.0 | 14.0 | 2.05 | 13.9 | 28 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **210030** | 2015-07-31 22:00:00 | 0.1 | 0.1 | 0.1 | 0.06 | 1.0 | 10.0 | 69.0 | 10.0 | 3.0 | 2.0 | 1.18 | 0.2 | 28 |
| **210049** | 2015-07-31 23:00:00 | 0.4 | 0.3 | 0.1 | 0.12 | 3.0 | 28.0 | 56.0 | 15.0 | 7.0 | 12.0 | 1.45 | 1.2 | 28 |
| **210054** | 2015-07-31 23:00:00 | 0.1 | 0.1 | 0.1 | 0.06 | 1.0 | 10.0 | 63.0 | 5.0 | 1.0 | 2.0 | 1.18 | 0.2 | 28 |
| **210073** | 2015-08-01 00:00:00 | 0.1 | 0.3 | 0.1 | 0.11 | 2.0 | 23.0 | 59.0 | 5.0 | 2.0 | 11.0 | 1.44 | 0.6 | 28 |
| **210078** | 2015-08-01 00:00:00 | 0.1 | 0.1 | 0.1 | 0.06 | 1.0 | 8.0 | 65.0 | 7.0 | 1.0 | 2.0 | 1.18 | 0.4 | 28 |

16026 rows × 14 columns

In [5]:
```
df1=df1.drop(["date"],axis=1)
```

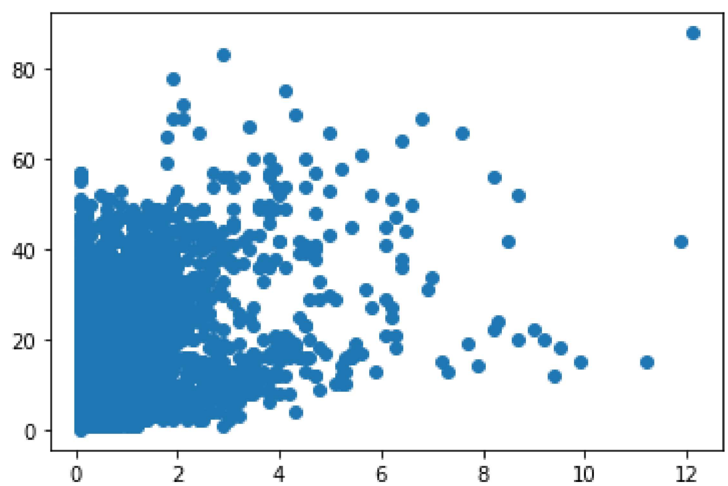
In [6]:
```
sns.heatmap(df1.corr())
```

Out[6]: <AxesSubplot:>




In [7]:
```
plt.plot(df1["EBE"],df1["PM25"],"o")
```

Out[7]: [<matplotlib.lines.Line2D at 0x23a1638ebb0>]




In [8]:
```
x=df1.drop(["EBE"],axis=1)
y=df1["EBE"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

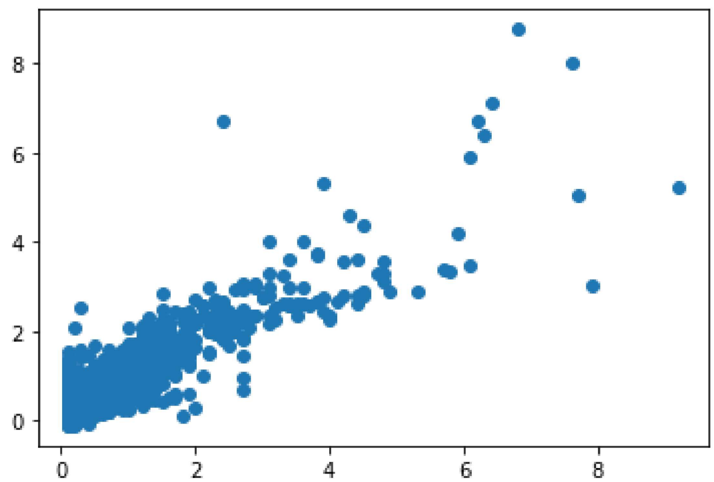
# Linear

In [9]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[9]: LinearRegression()

In [10]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[10]: <matplotlib.collections.PathCollection at 0x23a16575700>



In [11]:
```
lis=li.score(x_test,y_test)
```

In [12]:
```
df1["TCH"].value_counts()
```

Out[12]:
```
1.20    905
1.19    873
1.21    793
1.22    638
1.18    465
       ...
2.79      1
4.46      1
2.48      1
3.43      1
2.63      1
Name: TCH, Length: 184, dtype: int64
```

In [13]:
```
df1.loc[df1["TCH"]<1.40,"TCH"]=1
df1.loc[df1["TCH"]>1.40,"TCH"]=2
df1["TCH"].value_counts()
```

Out[13]:
```
2.0    8290
1.0    7736
Name: TCH, dtype: int64
```

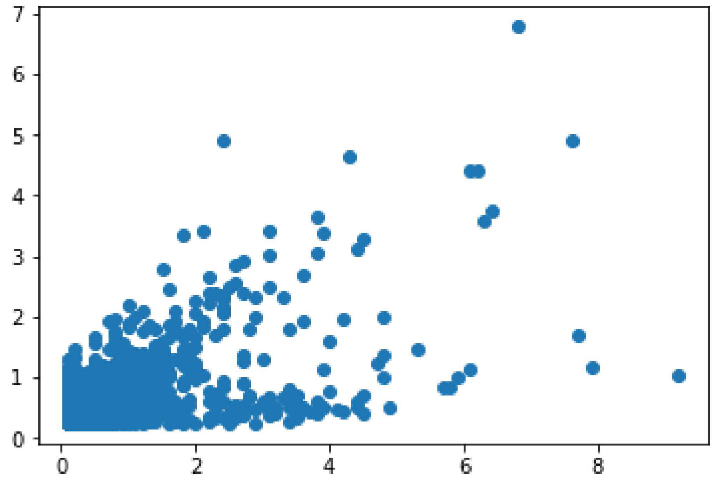
# Lasso

In [14]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[14]: Lasso(alpha=5)

In [15]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[15]: <matplotlib.collections.PathCollection at 0x23a165d8e50>




In [16]:
```
las=la.score(x_test,y_test)
```

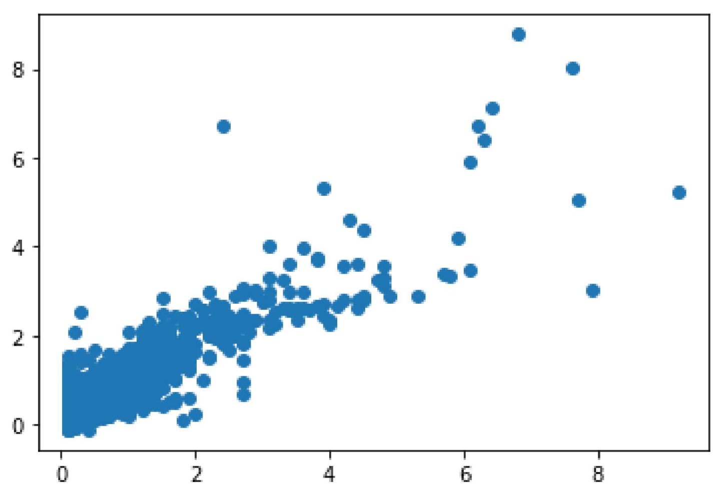
# Ridge

In [17]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[17]: Ridge(alpha=1)

In [18]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[18]: <matplotlib.collections.PathCollection at 0x23a163df9a0>



In [19]:
```
rrs=rr.score(x_test,y_test)
```

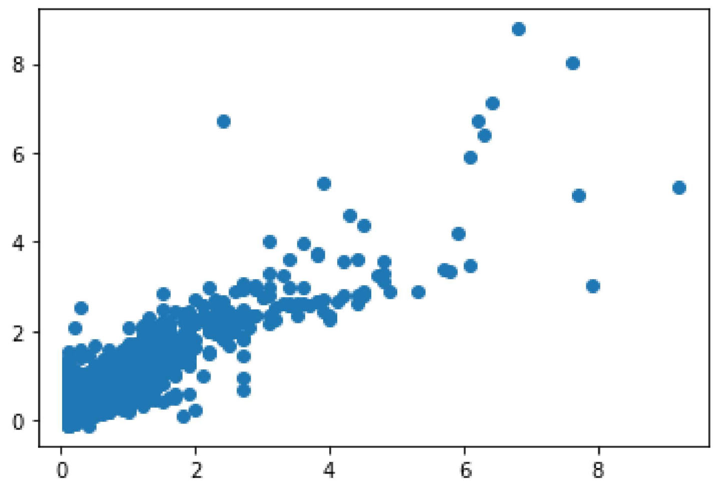
# ElasticNet

In [20]:
```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[20]:
```
ElasticNet()
```

In [21]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[21]:
```
<matplotlib.collections.PathCollection at 0x23a16657ee0>
```




In [22]:
```
ens=en.score(x_test,y_test)
```

In [23]:
```
print(rr.score(x_test,y_test))
rr.score(x_train,y_train)
```

```
0.8030115171965686
```

Out[23]:
```
0.7576572353945755
```

# Logistic

In [24]:
```
g={"TCH":{1.0:"Low",2.0:"High"}}
df1=df1.replace(g)
df1["TCH"].value_counts()
```

Out[24]:
```
High    8290
Low     7736
Name: TCH, dtype: int64
```

In [25]:
```
x=df1.drop(["TCH"],axis=1)
y=df1["TCH"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [26]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[26]: LogisticRegression()

In [27]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[27]: <matplotlib.collections.PathCollection at 0x23a16414a60>


In [28]:
```
los=lo.score(x_test,y_test)
```

# Random Forest

In [29]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [30]:
```
g1={"TCH":{"Low":1.0,"High":2.0}}
df1=df1.replace(g1)
```

In [31]:
```
x=df1.drop(["TCH"],axis=1)
y=df1["TCH"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [32]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[32]: RandomForestClassifier()

In [33]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [34]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accu
grid_search.fit(x_train,y_train)
```

Out[34]:
```
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 2, 4, 5, 6],
                         'min_samples_leaf': [5, 10, 15, 20, 25],
                         'n_estimators': [10, 20, 30, 40, 50]},
             scoring='accuracy')
```

In [35]:
```
rfcs=grid_search.best_score_
```

In [36]:
```
rfc_best=grid_search.best_estimator_
```

In [37]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes',"
```

Out[37]:
```
[Text(2200.56338028169, 2019.0857142857144, 'SO_2 <= 5.5\ngini = 0.5\nsampl
es = 7059\nvalue = [5445, 5773]\nclass = No'),
 Text(1257.4647887323945, 1708.457142857143, 'CO <= 0.35\ngini = 0.168\nsam
ples = 3458\nvalue = [4990, 509]\nclass = Yes'),
 Text(723.0422535211268, 1397.8285714285716, 'NO <= 2.5\ngini = 0.109\nsamp
les = 3159\nvalue = [4720, 291]\nclass = Yes'),
 Text(345.80281690140845, 1087.2, 'CO <= 0.25\ngini = 0.065\nsamples = 2303
\nvalue = [3540, 123]\nclass = Yes'),
 Text(125.74647887323944, 776.5714285714287, 'CO <= 0.15\ngini = 0.048\nsam
ples = 2164\nvalue = [3359, 84]\nclass = Yes'),
 Text(62.87323943661972, 465.9428571428573, 'gini = 0.0\nsamples = 368\nval
ue = [588, 0]\nclass = Yes'),
 Text(188.61971830985917, 465.9428571428573, 'O_3 <= 50.5\ngini = 0.057\nsa
mples = 1796\nvalue = [2771, 84]\nclass = Yes'),
 Text(125.74647887323944, 155.3142857142857, 'gini = 0.169\nsamples = 366\n
value = [544, 56]\nclass = Yes'),
 Text(251.49295774647888, 155.3142857142857, 'gini = 0.025\nsamples = 1430
\nvalue = [2227, 28]\nclass = Yes'),
 Text(565.8591549295775, 776.5714285714287, 'BEN <= 0.15\ngini = 0.292\nsam
```

In [38]:
```
print("Linear:",lis)
print("Lasso:",las)
print("Ridge:",rrs)
print("ElasticNet:",ens)
print("Logistic:",los)
print("Random Forest:",rfcs)
```

```
Linear: 0.8029944802406465
Lasso: 0.4077775855828065
Ridge: 0.8030115171965686
ElasticNet: 0.7001824428916614
Logistic: 0.5187188019966722
Random Forest: 0.9561419147798181
```

# Best Model is Random Forest

In [39]:

Out[39]:

| | date | BEN | CO | EBE | NMHC | NO | NO_2 | O_3 | PM10 | PM25 | SO_2 | TCH | TOL | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2016-11-01 01:00:00 | NaN | 0.7 | NaN | NaN | 153.0 | 77.0 | NaN | NaN | NaN | 7.0 | NaN | NaN | 2 |
| **1** | 2016-11-01 01:00:00 | 3.1 | 1.1 | 2.0 | 0.53 | 260.0 | 144.0 | 4.0 | 46.0 | 24.0 | 18.0 | 2.44 | 14.4 | 2 |
| **2** | 2016-11-01 01:00:00 | 5.9 | NaN | 7.5 | NaN | 297.0 | 139.0 | NaN | NaN | NaN | NaN | NaN | 26.0 | 2 |
| **3** | 2016-11-01 01:00:00 | NaN | 1.0 | NaN | NaN | 154.0 | 113.0 | 2.0 | NaN | NaN | NaN | NaN | NaN | 2 |
| **4** | 2016-11-01 01:00:00 | NaN | NaN | NaN | NaN | 275.0 | 127.0 | 2.0 | NaN | NaN | 18.0 | NaN | NaN | 2 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **209491** | 2016-07-01 00:00:00 | NaN | 0.2 | NaN | NaN | 2.0 | 29.0 | 73.0 | NaN | NaN | NaN | NaN | NaN | 2 |
| **209492** | 2016-07-01 00:00:00 | NaN | 0.3 | NaN | NaN | 1.0 | 29.0 | NaN | 36.0 | NaN | 5.0 | NaN | NaN | 2 |
| **209493** | 2016-07-01 00:00:00 | NaN | NaN | NaN | NaN | 1.0 | 19.0 | 71.0 | NaN | NaN | NaN | NaN | NaN | 2 |
| **209494** | 2016-07-01 00:00:00 | NaN | NaN | NaN | NaN | 6.0 | 17.0 | 85.0 | NaN | NaN | NaN | NaN | NaN | 2 |
| **209495** | 2016-07-01 00:00:00 | NaN | NaN | NaN | NaN | 2.0 | 46.0 | 61.0 | 34.0 | NaN | NaN | NaN | NaN | 2 |

209496 rows × 14 columns

# MADRID 2016

In [ ]:

```
df2=pd.read_csv("C:/Users/user/Downloads/FP1_air/csvs_per_year/csvs_per_year/ma
df2
```

In [40]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209496 entries, 0 to 209495
Data columns (total 14 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     209496 non-null  object 
 1   BEN      50755 non-null   float64
 2   CO       85999 non-null   float64
 3   EBE      50335 non-null   float64
 4   NMHC     25970 non-null   float64
 5   NO       208614 non-null  float64
 6   NO_2     208614 non-null  float64
 7   O_3      121197 non-null  float64
 8   PM10     102892 non-null  float64
 9   PM25     52165 non-null   float64
 10  SO_2     86023 non-null   float64
 11  TCH      25970 non-null   float64
 12  TOL      50662 non-null   float64
 13  station  209496 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 22.4+ MB
```

In [41]:
```
df3=df2.dropna()
df3
```

Out[41]:

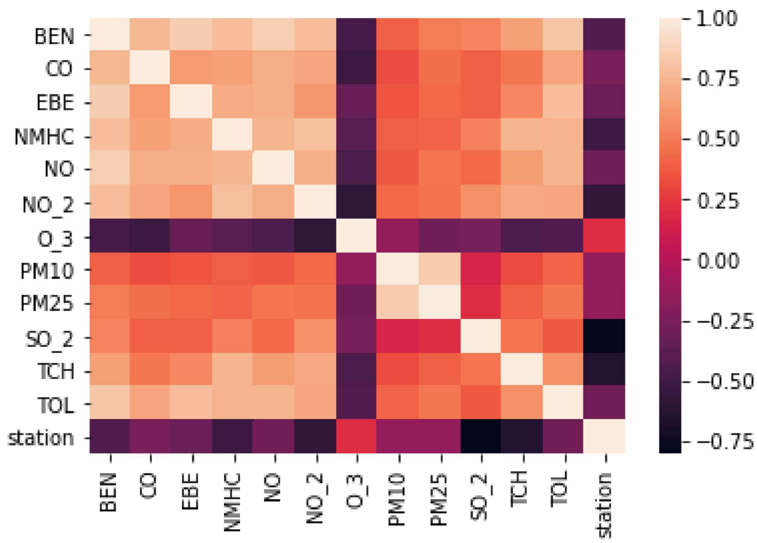
| | date | BEN | CO | EBE | NMHC | NO | NO_2 | O_3 | PM10 | PM25 | SO_2 | TCH | TOL | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2016-11-01 01:00:00 | 3.1 | 1.1 | 2.0 | 0.53 | 260.0 | 144.0 | 4.0 | 46.0 | 24.0 | 18.0 | 2.44 | 14.4 | 28 |
| **6** | 2016-11-01 01:00:00 | 0.7 | 0.8 | 0.4 | 0.13 | 57.0 | 66.0 | 3.0 | 23.0 | 15.0 | 4.0 | 1.35 | 5.0 | 28 |
| **25** | 2016-11-01 02:00:00 | 2.7 | 1.0 | 2.1 | 0.40 | 139.0 | 114.0 | 4.0 | 37.0 | 21.0 | 14.0 | 2.30 | 15.0 | 28 |
| **30** | 2016-11-01 02:00:00 | 0.7 | 0.7 | 0.4 | 0.13 | 48.0 | 59.0 | 3.0 | 23.0 | 15.0 | 3.0 | 1.35 | 5.0 | 28 |
| **49** | 2016-11-01 03:00:00 | 1.7 | 0.8 | 1.4 | 0.25 | 53.0 | 90.0 | 4.0 | 31.0 | 19.0 | 10.0 | 1.95 | 10.7 | 28 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **209430** | 2016-06-30 22:00:00 | 0.1 | 0.2 | 0.1 | 0.02 | 1.0 | 5.0 | 97.0 | 19.0 | 12.0 | 2.0 | 1.15 | 0.2 | 28 |
| **209449** | 2016-06-30 23:00:00 | 0.6 | 0.4 | 0.3 | 0.15 | 14.0 | 63.0 | 54.0 | 29.0 | 13.0 | 16.0 | 1.48 | 1.9 | 28 |
| **209454** | 2016-06-30 23:00:00 | 0.1 | 0.2 | 0.1 | 0.02 | 1.0 | 7.0 | 91.0 | 16.0 | 9.0 | 2.0 | 1.15 | 0.3 | 28 |
| **209473** | 2016-07-01 00:00:00 | 0.6 | 0.4 | 0.3 | 0.16 | 11.0 | 68.0 | 45.0 | 24.0 | 14.0 | 16.0 | 1.50 | 1.9 | 28 |
| **209478** | 2016-07-01 00:00:00 | 0.1 | 0.2 | 0.1 | 0.02 | 1.0 | 6.0 | 89.0 | 16.0 | 9.0 | 2.0 | 1.15 | 0.2 | 28 |

16932 rows × 14 columns

In [42]:
```
df3=df3.drop(["date"],axis=1)
```

In [43]:
```
sns.heatmap(df3.corr())
```

Out[43]: <AxesSubplot:>




In [44]:
```
x=df3.drop(["TCH"],axis=1)
y=df3["TCH"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

## Linear

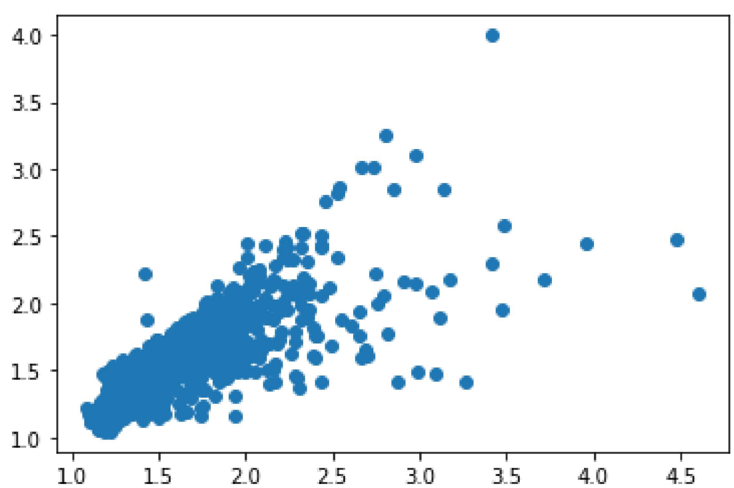
In [45]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[45]: LinearRegression()

In [ ]:

In [46]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[46]: <matplotlib.collections.PathCollection at 0x23a1724cd60>



In [47]:
```
lis=li.score(x_test,y_test)
```

In [48]:
```
df3["TCH"].value_counts()
```

Out[48]:
```
1.16    757
1.18    701
1.17    683
1.19    618
1.15    577
       ...
4.82      1
2.78      1
3.59      1
3.10      1
4.07      1
Name: TCH, Length: 217, dtype: int64
```

In [49]:
```
df3.loc[df3["TCH"]<1.40,"TCH"]=1
df3.loc[df3["TCH"]>1.40,"TCH"]=2
df3["TCH"].value_counts()
```

Out[49]:
```
1.0    10002
2.0     6930
Name: TCH, dtype: int64
```

In [ ]:

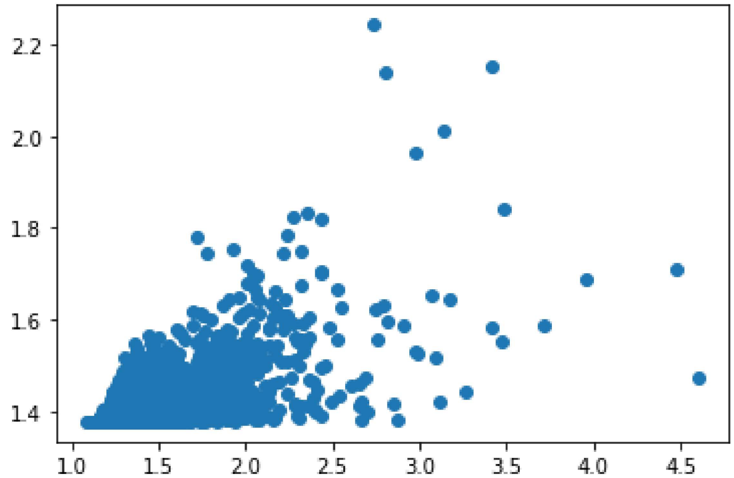
# Lasso

In [50]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[50]:
```
Lasso(alpha=5)
```

In [51]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[51]: <matplotlib.collections.PathCollection at 0x23a16fa9e80>




In [52]:
```
las=la.score(x_test,y_test)
```

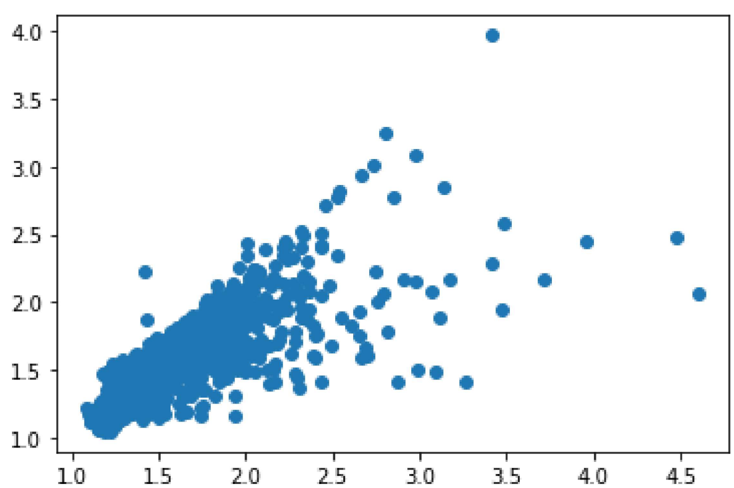
# Ridge

In [53]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[53]: Ridge(alpha=1)

In [54]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[54]: <matplotlib.collections.PathCollection at 0x23a16ffef40>




In [55]:
```
rrs=rr.score(x_test,y_test)
```

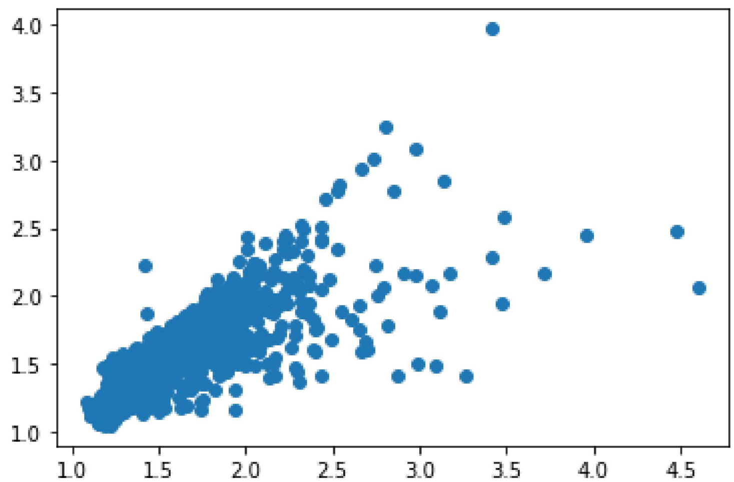
# ElasticNet

In [56]:
```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[56]:
```
ElasticNet()
```

In [57]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[57]:
```
<matplotlib.collections.PathCollection at 0x23a17022f40>
```




In [58]:
```
ens=en.score(x_test,y_test)
```

In [59]:
```
print(rr.score(x_test,y_test))
rr.score(x_train,y_train)
```

```
0.7500531919104193
```

Out[59]:
```
0.7540860619941899
```

# Logistic

In [60]:
```
g={"TCH":{1.0:"Low",2.0:"High"}}
df3=df3.replace(g)
df3["TCH"].value_counts()
```

Out[60]:
```
Low     10002
High     6930
Name: TCH, dtype: int64
```

In [61]:
```
x=df3.drop(["TCH"],axis=1)
y=df3["TCH"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [62]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[62]: LogisticRegression()

In [63]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[63]: <matplotlib.collections.PathCollection at 0x23a170c0ca0>


In [64]:
```
los=lo.score(x_test,y_test)
```

# Random Forest

In [65]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [66]:
```
g1={"TCH":{"Low":1.0,"High":2.0}}
df3=df3.replace(g1)
```

In [67]:
```
x=df3.drop(["TCH"],axis=1)
y=df3["TCH"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [68]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[68]: RandomForestClassifier()

In [69]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [70]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accu
grid_search.fit(x_train,y_train)
```

Out[70]:
```
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 2, 4, 5, 6],
                         'min_samples_leaf': [5, 10, 15, 20, 25],
                         'n_estimators': [10, 20, 30, 40, 50]},
             scoring='accuracy')
```

In [71]:
```
rfcs=grid_search.best_score_
```

In [72]:
```
rfc_best=grid_search.best_estimator_
```

In [73]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes',"
```

Out[73]:
```
[Text(2187.8019801980195, 2019.0857142857144, 'NO_2 <= 37.5\ngini = 0.484\n
samples = 7481\nvalue = [6970, 4882]\nclass = Yes'),
 Text(999.980198019802, 1708.457142857143, 'TOL <= 0.55\ngini = 0.283\nsamp
les = 4079\nvalue = [5368, 1102]\nclass = Yes'),
 Text(453.02970297029697, 1397.8285714285716, 'SO_2 <= 3.5\ngini = 0.075\ns
amples = 1882\nvalue = [2887, 117]\nclass = Yes'),
 Text(220.99009900990097, 1087.2, 'TOL <= 0.35\ngini = 0.01\nsamples = 1702
\nvalue = [2710, 13]\nclass = Yes'),
 Text(88.39603960396039, 776.5714285714287, 'NO_2 <= 11.5\ngini = 0.003\nsa
mples = 1243\nvalue = [2015, 3]\nclass = Yes'),
 Text(44.198019801980195, 465.9428571428573, 'gini = 0.0\nsamples = 1100\nv
alue = [1803, 0]\nclass = Yes'),
 Text(132.59405940594058, 465.9428571428573, 'TOL <= 0.25\ngini = 0.028\nsa
mples = 143\nvalue = [212, 3]\nclass = Yes'),
 Text(88.39603960396039, 155.3142857142857, 'gini = 0.0\nsamples = 67\nvalu
e = [105, 0]\nclass = Yes'),
 Text(176.79207920792078, 155.3142857142857, 'gini = 0.053\nsamples = 76\nv
alue = [107, 3]\nclass = Yes'),
 Text(353.58415841584156, 776.5714285714287, 'NO_2 <= 29.5\ngini = 0.028\ns
```

In [74]:
```
print("Linear:",lis)
print("Lasso:",las)
print("Ridge:",rrs)
print("ElasticNet:",ens)
print("Logistic:",los)
print("Random Forest:",rfcs)
```

```
Linear: 0.7499272637946903
Lasso: 0.19751618918213187
Ridge: 0.7500531919104193
ElasticNet: 0.5703555451049473
Logistic: 0.5938976377952756
Random Forest: 0.9190010124873439
```

# Best model is Random Forest

In [ ]: