2017

In [1]:
```
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("madrid_2017.csv")
df
```

Out[2]:

	date	BEN	CH4	CO	EBE	NMHC	NO	NO_2	NOx	O_3	PM10	PM25	SO_2	TC
0	2017-06-01 01:00:00	NaN	NaN	0.3	NaN	NaN	4.0	38.0	NaN	NaN	NaN	NaN	5.0	Na
1	2017-06-01 01:00:00	0.6	NaN	0.3	0.4	0.08	3.0	39.0	NaN	71.0	22.0	9.0	7.0	1.
2	2017-06-01 01:00:00	0.2	NaN	NaN	0.1	NaN	1.0	14.0	NaN	NaN	NaN	NaN	NaN	Na
3	2017-06-01 01:00:00	NaN	NaN	0.2	NaN	NaN	1.0	9.0	NaN	91.0	NaN	NaN	NaN	Na
4	2017-06-01 01:00:00	NaN	NaN	NaN	NaN	NaN	1.0	19.0	NaN	69.0	NaN	NaN	2.0	Na
...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
210115	2017-08-01 00:00:00	NaN	NaN	0.2	NaN	NaN	1.0	27.0	NaN	65.0	NaN	NaN	NaN	Na
210116	2017-08-01 00:00:00	NaN	NaN	0.2	NaN	NaN	1.0	14.0	NaN	NaN	73.0	NaN	7.0	Na
210117	2017-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	4.0	NaN	83.0	NaN	NaN	NaN	Na
210118	2017-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	11.0	NaN	78.0	NaN	NaN	NaN	Na
210119	2017-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	14.0	NaN	77.0	60.0	NaN	NaN	Na

210120 rows × 16 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210120 entries, 0 to 210119
Data columns (total 16 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     210120 non-null  object 
 1   BEN      50201 non-null   float64
 2   CH4      6410 non-null    float64
 3   CO       87001 non-null   float64
 4   EBE      49973 non-null   float64
 5   NMHC     25472 non-null   float64
 6   NO       209065 non-null  float64
 7   NO_2     209065 non-null  float64
 8   NOx      52818 non-null   float64
 9   O_3      121398 non-null  float64
 10  PM10     104141 non-null  float64
 11  PM25     52023 non-null   float64
 12  SO_2     86803 non-null   float64
 13  TCH      25472 non-null   float64
 14  TOL      50117 non-null   float64
 15  station  210120 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 25.6+ MB
```

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

Out[4]:

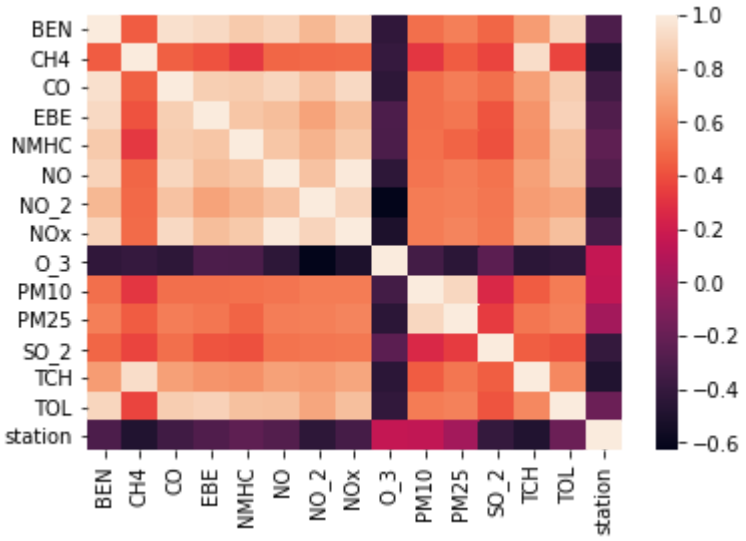
	date	BEN	CH4	CO	EBE	NMHC	NO	NO_2	NOx	O_3	PM10	PM25	SO_2	TCH
87457	2017-10-01 01:00:00	0.6	1.22	0.3	0.4	0.09	4.0	54.0	60.0	43.0	12.0	9.0	13.0	1.31
87462	2017-10-01 01:00:00	0.2	1.18	0.2	0.1	0.09	1.0	26.0	28.0	42.0	14.0	6.0	3.0	1.27
87481	2017-10-01 02:00:00	0.4	1.22	0.2	0.2	0.06	2.0	32.0	36.0	53.0	14.0	10.0	13.0	1.28
87486	2017-10-01 02:00:00	0.2	1.19	0.2	0.1	0.07	1.0	15.0	17.0	51.0	18.0	8.0	3.0	1.26
87505	2017-10-01 03:00:00	0.3	1.23	0.2	0.2	0.06	2.0	27.0	29.0	57.0	15.0	10.0	13.0	1.29
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
158238	2017-12-31 22:00:00	0.3	1.11	0.2	0.1	0.03	1.0	8.0	9.0	73.0	3.0	1.0	3.0	1.14
158257	2017-12-31 23:00:00	0.6	1.38	0.3	0.1	0.03	6.0	42.0	51.0	47.0	7.0	4.0	3.0	1.41
158262	2017-12-31 23:00:00	0.3	1.11	0.2	0.1	0.03	1.0	6.0	8.0	72.0	6.0	3.0	3.0	1.14
158281	2018-01-01 00:00:00	0.5	1.38	0.2	0.1	0.02	2.0	20.0	23.0	69.0	4.0	2.0	3.0	1.39
158286	2018-01-01 00:00:00	0.3	1.11	0.2	0.1	0.03	1.0	1.0	3.0	83.0	8.0	5.0	3.0	1.14

4127 rows × 16 columns

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

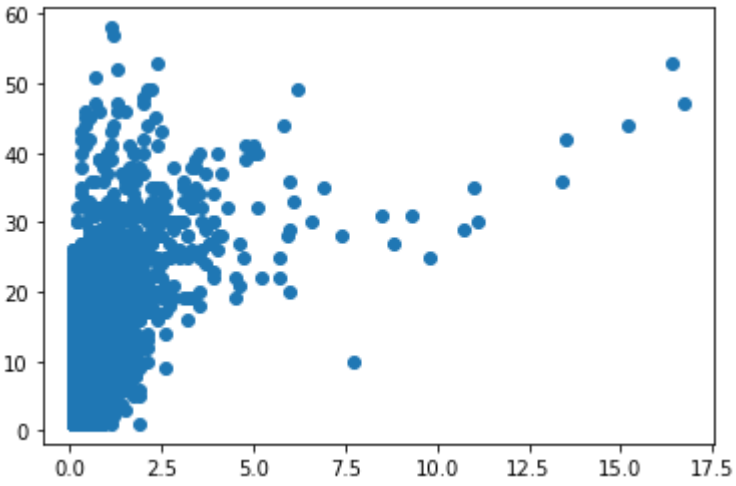
In [6]:
```
sns.heatmap(df1.corr())
```

Out[6]: <AxesSubplot:>



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

Out[7]: [<matplotlib.lines.Line2D at 0x25f5f6d7fd0>]



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)
```

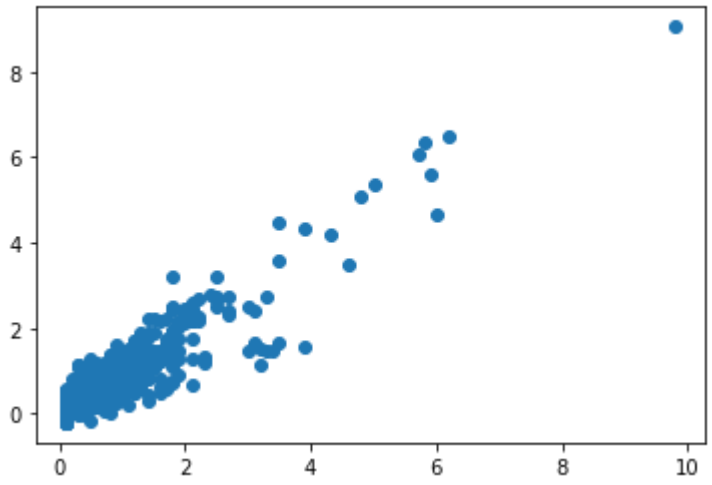
Linear

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 0x25f5f7a3c70>
```



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

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

Out[12]:
```
1.24    124
1.36    118
1.26    112
1.25    110
1.41    107
       ...
3.23      1
2.47      1
2.35      1
2.61      1
2.94      1
Name: TCH, Length: 164, 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]:
```
1.0    2428
2.0    1699
Name: TCH, dtype: int64
```

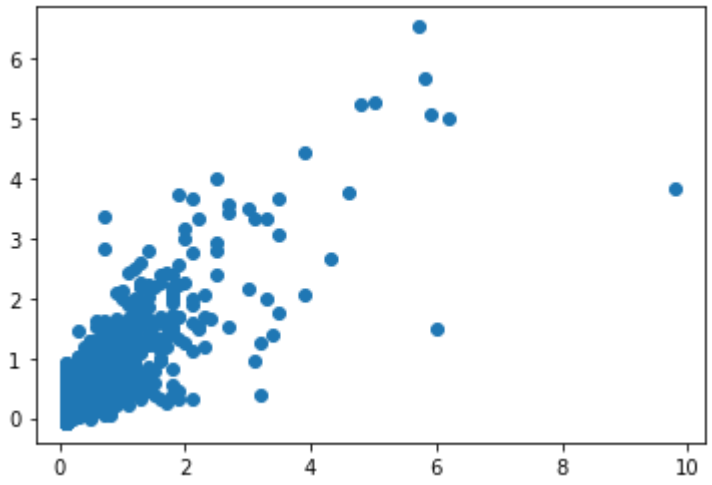
Lasso

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 0x25f5f80f820>



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

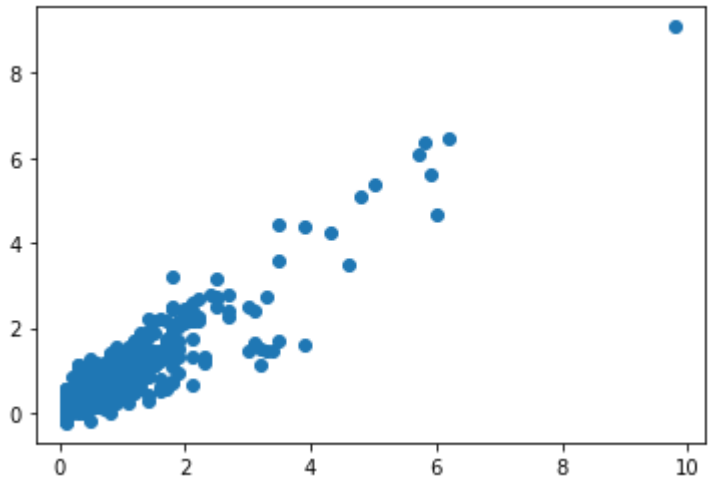
Ridge

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 0x25f5f64b2e0>



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

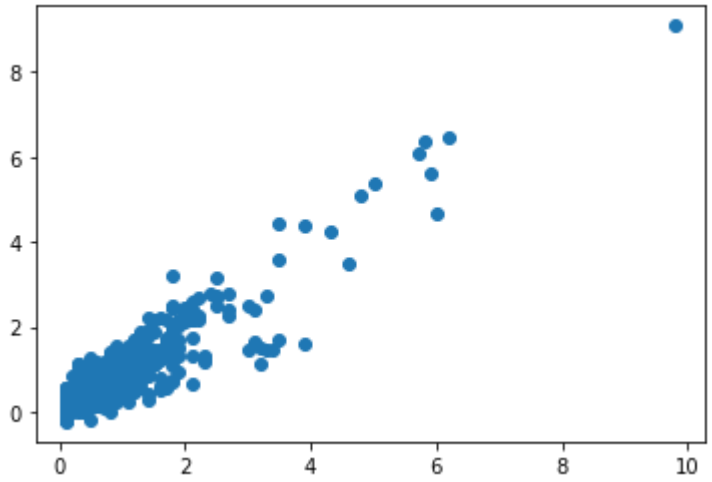
ElasticNet

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 0x25f60140640>
```



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

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

```
0.8446472469016151
```

Out[23]:
```
0.8976558488919304
```

Logistic

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

Out[24]:
```
Low     2428
High    1699
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 0x25f601ad700>
```

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_
```

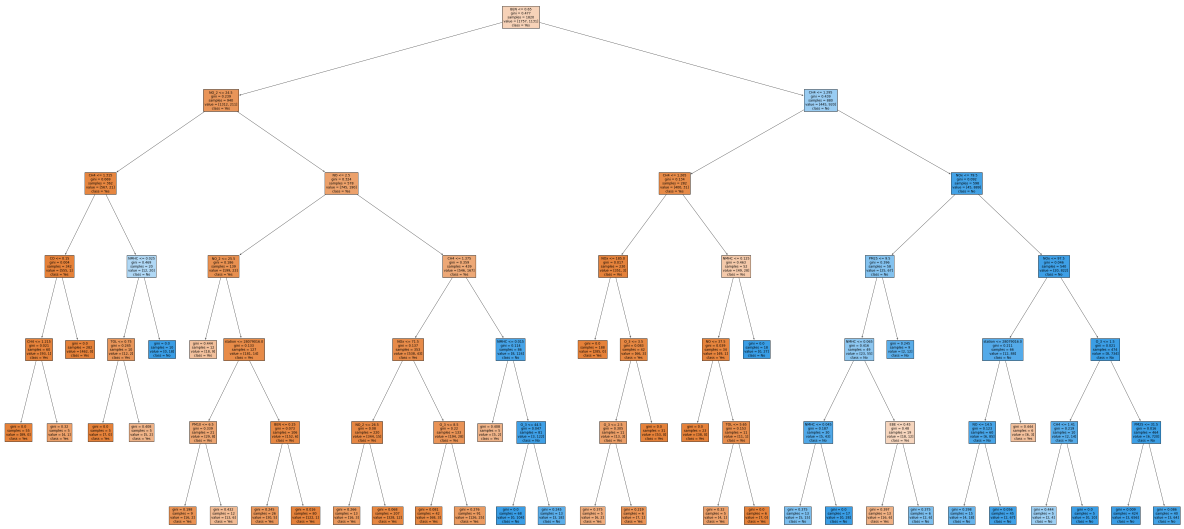
In [37]:
```
from sklearn.tree import plot_tree

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

Out[37]:
[Text(1962.6206896551726, 2019.0857142857144, 'BEN <= 0.65\ngini = 0.477\nsamples = 1820\nvalue = [1757, 1131]\nclass = Yes'),
 Text(837.0000000000001, 1708.457142857143, 'NO_2 <= 24.5\ngini = 0.239\nsamples = 940\nvalue = [1312, 211]\nclass = Yes'),
 Text(384.82758620689657, 1397.8285714285716, 'CH4 <= 1.315\ngini = 0.069\nsamples = 362\nvalue = [567, 21]\nclass = Yes'),
 Text(230.89655172413796, 1087.2, 'CO <= 0.15\ngini = 0.004\nsamples = 342\nvalue = [555, 1]\nclass = Yes'),
 Text(153.93103448275863, 776.5714285714287, 'CH4 <= 1.215\ngini = 0.021\nsamples = 60\nvalue = [93, 1]\nclass = Yes'),
 Text(76.96551724137932, 465.9428571428573, 'gini = 0.0\nsamples = 55\nvalue = [89, 0]\nclass = Yes'),
 Text(230.89655172413796, 465.9428571428573, 'gini = 0.32\nsamples = 5\nvalue = [4, 1]\nclass = Yes'),
 Text(307.86206896551727, 776.5714285714287, 'gini = 0.0\nsamples = 282\nvalue = [462, 0]\nclass = Yes'),
 Text(538.7586206896552, 1087.2, 'NMHC <= 0.025\ngini = 0.469\nsamples = 20\nvalue = [12, 20]\nclass = No'),
 Text(461.79310344827593, 776.5714285714287, 'TOL <= 0.75\ngini = 0.245\nsamples = 10\nvalue = [12, 2]\nclass = Yes'),
 Text(384.82758620689657, 465.9428571428573, 'gini = 0.0\nsamples = 5\nvalue = [7, 0]\nclass = Yes'),
 Text(538.7586206896552, 465.9428571428573, 'gini = 0.408\nsamples = 5\nvalue = [5, 2]\nclass = Yes'),
 Text(615.7241379310345, 776.5714285714287, 'gini = 0.0\nsamples = 10\nvalue = [0, 18]\nclass = No'),
 Text(1289.1724137931035, 1397.8285714285716, 'NO <= 2.5\ngini = 0.324\nsamples = 578\nvalue = [745, 190]\nclass = Yes'),
 Text(846.6206896551724, 1087.2, 'NO_2 <= 25.5\ngini = 0.186\nsamples = 139\nvalue = [199, 23]\nclass = Yes'),
 Text(769.6551724137931, 776.5714285714287, 'gini = 0.444\nsamples = 12\nvalue = [18, 9]\nclass = Yes'),
 Text(923.5862068965519, 776.5714285714287, 'station <= 28079016.0\ngini = 0.133\nsamples = 127\nvalue = [181, 14]\nclass = Yes'),
 Text(769.6551724137931, 465.9428571428573, 'PM10 <= 6.5\ngini = 0.339\nsamples = 21\nvalue = [29, 8]\nclass = Yes'),
 Text(692.6896551724138, 155.3142857142857, 'gini = 0.198\nsamples = 9\nvalue = [16, 2]\nclass = Yes'),
 Text(846.6206896551724, 155.3142857142857, 'gini = 0.432\nsamples = 12\nvalue = [13, 6]\nclass = Yes'),
 Text(1077.5172413793105, 465.9428571428573, 'BEN <= 0.25\ngini = 0.073\nsamples = 106\nvalue = [152, 6]\nclass = Yes'),
 Text(1000.5517241379312, 155.3142857142857, 'gini = 0.245\nsamples = 26\nvalue = [30, 5]\nclass = Yes'),
 Text(1154.4827586206898, 155.3142857142857, 'gini = 0.016\nsamples = 80\nvalue = [122, 1]\nclass = Yes'),
 Text(1731.7241379310346, 1087.2, 'CH4 <= 1.375\ngini = 0.359\nsamples = 439\nvalue = [546, 167]\nclass = Yes'),
 Text(1539.3103448275863, 776.5714285714287, 'NOx <= 71.5\ngini = 0.137\nsamples = 353\nvalue = [538, 43]\nclass = Yes'),
 Text(1385.3793103448277, 465.9428571428573, 'NO_2 <= 26.5\ngini = 0.08\nsamples = 220\nvalue = [344, 15]\nclass = Yes'),
 Text(1308.4137931034484, 155.3142857142857, 'gini = 0.266\nsamples = 13\nvalue = [16, 3]\nclass = Yes'),
 Text(1462.344827586207, 155.3142857142857, 'gini = 0.068\nsamples = 207\nvalue = [328, 12]\nclass = Yes'),
 Text(1693.2413793103449, 465.9428571428573, 'O_3 <= 8.5\ngini = 0.22\nsample

```
s = 133\nvalue = [194, 28]\nclass = Yes'),
 Text(1616.2758620689656, 155.3142857142857, 'gini = 0.081\nsamples = 42\nval
ue = [68, 3]\nclass = Yes'),
 Text(1770.2068965517242, 155.3142857142857, 'gini = 0.276\nsamples = 91\nval
ue = [126, 25]\nclass = Yes'),
 Text(1924.137931034483, 776.5714285714287, 'NMHC <= 0.015\ngini = 0.114\nsam
ples = 86\nvalue = [8, 124]\nclass = No'),
 Text(1847.1724137931037, 465.9428571428573, 'gini = 0.408\nsamples = 5\nvalu
e = [5, 2]\nclass = Yes'),
 Text(2001.1034482758623, 465.9428571428573, 'O_3 <= 44.5\ngini = 0.047\nsamp
les = 81\nvalue = [3, 122]\nclass = No'),
 Text(1924.137931034483, 155.3142857142857, 'gini = 0.0\nsamples = 68\nvalue
= [0, 104]\nclass = No'),
 Text(2078.0689655172414, 155.3142857142857, 'gini = 0.245\nsamples = 13\nval
ue = [3, 18]\nclass = No'),
 Text(3088.241379310345, 1708.457142857143, 'CH4 <= 1.295\ngini = 0.439\nsamp
les = 880\nvalue = [445, 920]\nclass = No'),
 Text(2539.8620689655177, 1397.8285714285716, 'CH4 <= 1.265\ngini = 0.134\nsa
mples = 282\nvalue = [400, 31]\nclass = Yes'),
 Text(2308.9655172413795, 1087.2, 'NOx <= 185.0\ngini = 0.017\nsamples = 230
\nvalue = [351, 3]\nclass = Yes'),
 Text(2232.0, 776.5714285714287, 'gini = 0.0\nsamples = 188\nvalue = [285, 0]
\nclass = Yes'),
 Text(2385.9310344827586, 776.5714285714287, 'O_3 <= 3.5\ngini = 0.083\nsampl
es = 42\nvalue = [66, 3]\nclass = Yes'),
 Text(2308.9655172413795, 465.9428571428573, 'O_3 <= 2.5\ngini = 0.305\nsampl
es = 11\nvalue = [13, 3]\nclass = Yes'),
 Text(2232.0, 155.3142857142857, 'gini = 0.375\nsamples = 5\nvalue = [6, 2]\n
class = Yes'),
 Text(2385.9310344827586, 155.3142857142857, 'gini = 0.219\nsamples = 6\nvalu
e = [7, 1]\nclass = Yes'),
 Text(2462.896551724138, 465.9428571428573, 'gini = 0.0\nsamples = 31\nvalue
= [53, 0]\nclass = Yes'),
 Text(2770.7586206896553, 1087.2, 'NMHC <= 0.125\ngini = 0.463\nsamples = 52
\nvalue = [49, 28]\nclass = Yes'),
 Text(2693.7931034482763, 776.5714285714287, 'NO <= 37.5\ngini = 0.039\nsampl
es = 34\nvalue = [49, 1]\nclass = Yes'),
 Text(2616.8275862068967, 465.9428571428573, 'gini = 0.0\nsamples = 23\nvalue
= [38, 0]\nclass = Yes'),
 Text(2770.7586206896553, 465.9428571428573, 'TOL <= 5.65\ngini = 0.153\nsamp
les = 11\nvalue = [11, 1]\nclass = Yes'),
 Text(2693.7931034482763, 155.3142857142857, 'gini = 0.32\nsamples = 5\nvalue
= [4, 1]\nclass = Yes'),
 Text(2847.724137931035, 155.3142857142857, 'gini = 0.0\nsamples = 6\nvalue =
[7, 0]\nclass = Yes'),
 Text(2847.724137931035, 776.5714285714287, 'gini = 0.0\nsamples = 18\nvalue
= [0, 27]\nclass = No'),
 Text(3636.6206896551726, 1397.8285714285716, 'NOx <= 79.5\ngini = 0.092\nsam
ples = 598\nvalue = [45, 889]\nclass = No'),
 Text(3309.5172413793107, 1087.2, 'PM25 <= 9.5\ngini = 0.396\nsamples = 58\nv
alue = [25, 67]\nclass = No'),
 Text(3232.551724137931, 776.5714285714287, 'NMHC <= 0.065\ngini = 0.416\nsam
ples = 49\nvalue = [23, 55]\nclass = No'),
 Text(3078.6206896551726, 465.9428571428573, 'NMHC <= 0.045\ngini = 0.187\nsa
mples = 30\nvalue = [5, 43]\nclass = No'),
 Text(3001.6551724137935, 155.3142857142857, 'gini = 0.375\nsamples = 13\nval
ue = [5, 15]\nclass = No'),
```

```
 Text(3155.586206896552, 155.3142857142857, 'gini = 0.0\nsamples = 17\nvalue
= [0, 28]\nclass = No'),
 Text(3386.4827586206898, 465.9428571428573, 'EBE <= 0.45\ngini = 0.48\nsampl
es = 19\nvalue = [18, 12]\nclass = Yes'),
 Text(3309.5172413793107, 155.3142857142857, 'gini = 0.397\nsamples = 13\nval
ue = [16, 6]\nclass = Yes'),
 Text(3463.4482758620693, 155.3142857142857, 'gini = 0.375\nsamples = 6\nvalu
e = [2, 6]\nclass = No'),
 Text(3386.4827586206898, 776.5714285714287, 'gini = 0.245\nsamples = 9\nvalu
e = [2, 12]\nclass = No'),
 Text(3963.724137931035, 1087.2, 'NOx <= 97.5\ngini = 0.046\nsamples = 540\nv
alue = [20, 822]\nclass = No'),
 Text(3771.3103448275865, 776.5714285714287, 'station <= 28079016.0\ngini =
0.211\nsamples = 66\nvalue = [12, 88]\nclass = No'),
 Text(3694.3448275862074, 465.9428571428573, 'NO <= 14.5\ngini = 0.123\nsampl
es = 60\nvalue = [6, 85]\nclass = No'),
 Text(3617.379310344828, 155.3142857142857, 'gini = 0.298\nsamples = 15\nvalu
e = [4, 18]\nclass = No'),
 Text(3771.3103448275865, 155.3142857142857, 'gini = 0.056\nsamples = 45\nval
ue = [2, 67]\nclass = No'),
 Text(3848.275862068966, 465.9428571428573, 'gini = 0.444\nsamples = 6\nvalue
= [6, 3]\nclass = Yes'),
 Text(4156.137931034483, 776.5714285714287, 'O_3 <= 1.5\ngini = 0.021\nsample
s = 474\nvalue = [8, 734]\nclass = No'),
 Text(4002.2068965517246, 465.9428571428573, 'CH4 <= 1.41\ngini = 0.219\nsamp
les = 10\nvalue = [2, 14]\nclass = No'),
 Text(3925.241379310345, 155.3142857142857, 'gini = 0.444\nsamples = 5\nvalue
= [2, 4]\nclass = No'),
 Text(4079.1724137931037, 155.3142857142857, 'gini = 0.0\nsamples = 5\nvalue
= [0, 10]\nclass = No'),
 Text(4310.068965517242, 465.9428571428573, 'PM25 <= 31.5\ngini = 0.016\nsamp
les = 464\nvalue = [6, 720]\nclass = No'),
 Text(4233.103448275862, 155.3142857142857, 'gini = 0.009\nsamples = 424\nval
ue = [3, 656]\nclass = No'),
 Text(4387.034482758621, 155.3142857142857, 'gini = 0.086\nsamples = 40\nvalu
e = [3, 64]\nclass = No')]
```



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

```
Linear: 0.8441268043977549
Lasso: 0.6393010463991731
Ridge: 0.8446472469016151
ElasticNet: 0.7899757472729623
Logistic: 0.579499596448749
Random Forest: 0.9681440443213296
```

Best Model is Random Forest

2018

In [39]:
```
df2=pd.read_csv("madrid_2018.csv")
df2
```

Out[39]:

	date	BEN	CH4	CO	EBE	NMHC	NO	NO_2	NOx	O_3	PM10	PM25	SO_2	T
0	2018-03-01 01:00:00	NaN	NaN	0.3	NaN	NaN	1.0	29.0	31.0	NaN	NaN	NaN	2.0	N
1	2018-03-01 01:00:00	0.5	1.39	0.3	0.2	0.02	6.0	40.0	49.0	52.0	5.0	4.0	3.0	1
2	2018-03-01 01:00:00	0.4	NaN	NaN	0.2	NaN	4.0	41.0	47.0	NaN	NaN	NaN	NaN	N
3	2018-03-01 01:00:00	NaN	NaN	0.3	NaN	NaN	1.0	35.0	37.0	54.0	NaN	NaN	NaN	N
4	2018-03-01 01:00:00	NaN	NaN	NaN	NaN	NaN	1.0	27.0	29.0	49.0	NaN	NaN	3.0	N
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
69091	2018-02-01 00:00:00	NaN	NaN	0.5	NaN	NaN	66.0	91.0	192.0	1.0	35.0	22.0	NaN	N
69092	2018-02-01 00:00:00	NaN	NaN	0.7	NaN	NaN	87.0	107.0	241.0	NaN	29.0	NaN	15.0	N
69093	2018-02-01 00:00:00	NaN	NaN	NaN	NaN	NaN	28.0	48.0	91.0	2.0	NaN	NaN	NaN	N
69094	2018-02-01 00:00:00	NaN	NaN	NaN	NaN	NaN	141.0	103.0	320.0	2.0	NaN	NaN	NaN	N
69095	2018-02-01 00:00:00	NaN	NaN	NaN	NaN	NaN	69.0	96.0	202.0	3.0	26.0	NaN	NaN	N

69096 rows × 16 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 69096 entries, 0 to 69095
Data columns (total 16 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     69096 non-null  object 
 1   BEN      16950 non-null  float64
 2   CH4      8440 non-null   float64
 3   CO       28598 non-null  float64
 4   EBE      16949 non-null  float64
 5   NMHC     8440 non-null   float64
 6   NO       68826 non-null  float64
 7   NO_2     68826 non-null  float64
 8   NOx      68826 non-null  float64
 9   O_3      40049 non-null  float64
 10  PM10     36911 non-null  float64
 11  PM25     18912 non-null  float64
 12  SO_2     28586 non-null  float64
 13  TCH      8440 non-null   float64
 14  TOL      16950 non-null  float64
 15  station  69096 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 8.4+ MB
```

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

Out[41]:

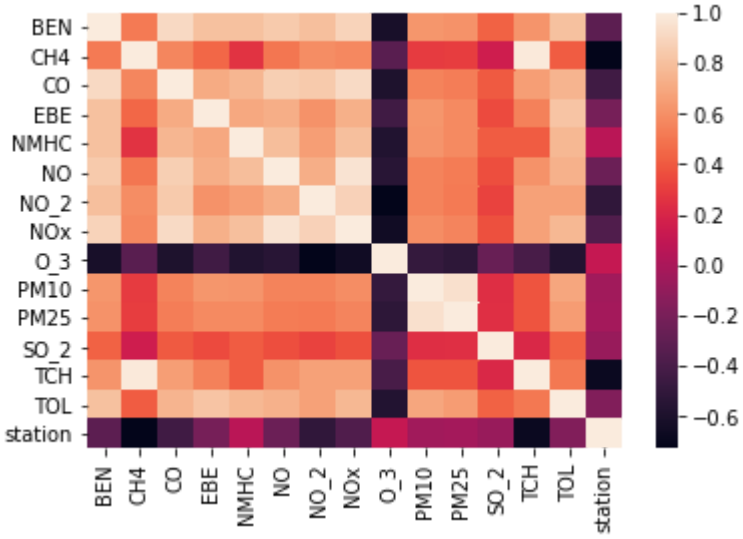
	date	BEN	CH4	CO	EBE	NMHC	NO	NO_2	NOx	O_3	PM10	PM25	SO_2	TC
1	2018-03-01 01:00:00	0.5	1.39	0.3	0.2	0.02	6.0	40.0	49.0	52.0	5.0	4.0	3.0	1.
6	2018-03-01 01:00:00	0.4	1.11	0.2	0.1	0.06	1.0	25.0	27.0	55.0	5.0	4.0	4.0	1.
25	2018-03-01 02:00:00	0.4	1.42	0.2	0.1	0.01	4.0	26.0	32.0	64.0	4.0	4.0	3.0	1.
30	2018-03-01 02:00:00	0.3	1.10	0.2	0.1	0.05	1.0	12.0	13.0	69.0	5.0	4.0	4.0	1.
49	2018-03-01 03:00:00	0.3	1.41	0.2	0.1	0.01	3.0	16.0	20.0	68.0	3.0	2.0	3.0	1.
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
69030	2018-01-31 22:00:00	1.8	1.21	0.7	1.7	0.19	151.0	129.0	361.0	1.0	45.0	26.0	11.0	1.
69049	2018-01-31 23:00:00	3.1	1.87	1.2	2.0	0.35	296.0	162.0	615.0	3.0	39.0	23.0	8.0	2.
69054	2018-01-31 23:00:00	1.6	1.17	0.6	1.4	0.15	127.0	106.0	301.0	1.0	43.0	25.0	8.0	1.
69073	2018-02-01 00:00:00	3.2	1.53	1.0	2.1	0.19	125.0	117.0	309.0	3.0	37.0	24.0	6.0	1.
69078	2018-02-01 00:00:00	1.3	1.14	0.4	0.8	0.10	54.0	73.0	155.0	1.0	27.0	16.0	5.0	1.

4562 rows × 16 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)
```

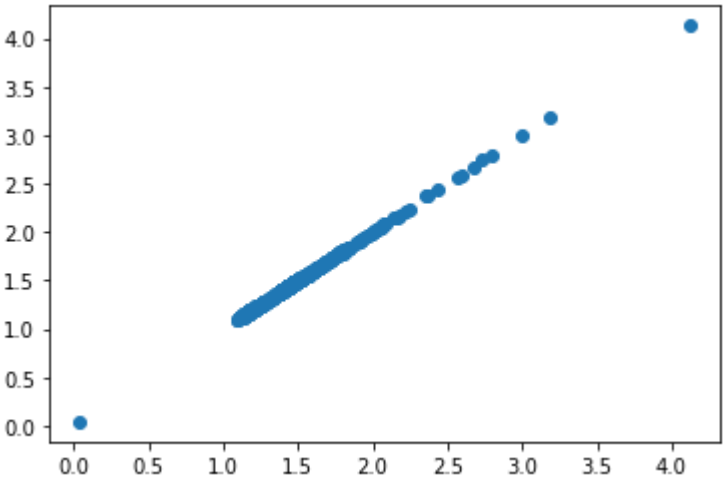
Linear

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

Out[45]: LinearRegression()

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

Out[46]: <matplotlib.collections.PathCollection at 0x25f605d5070>



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

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

Out[48]:
```
1.15    246
1.43    232
1.44    223
1.14    210
1.13    201
       ...
2.35      1
2.58      1
2.73      1
2.12      1
1.96      1
Name: TCH, Length: 143, 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]:
```
2.0    2477
1.0    2085
Name: TCH, dtype: int64
```

In [ ]:
```

```

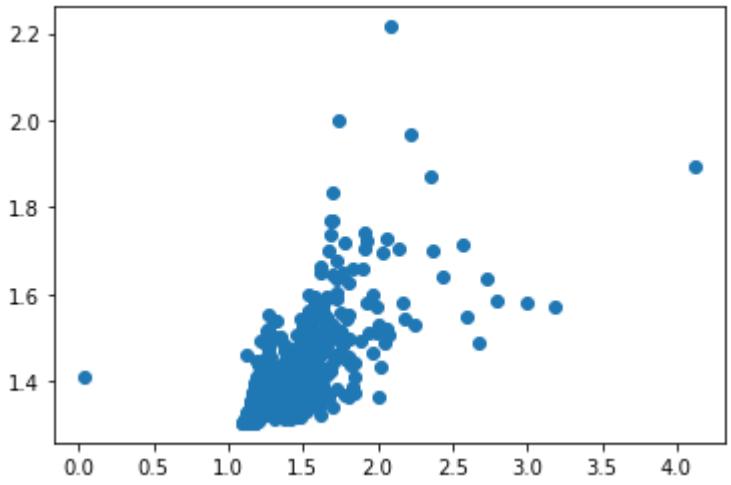
Lasso

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 0x25f60639190>



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

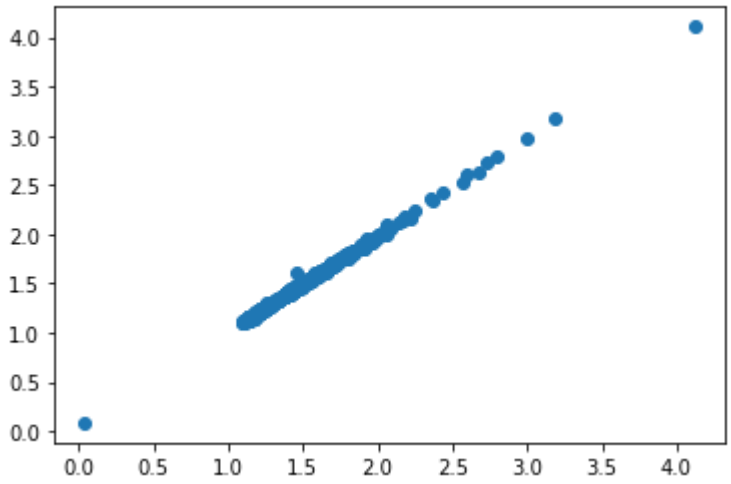
Ridge

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 0x25f6068d760>



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

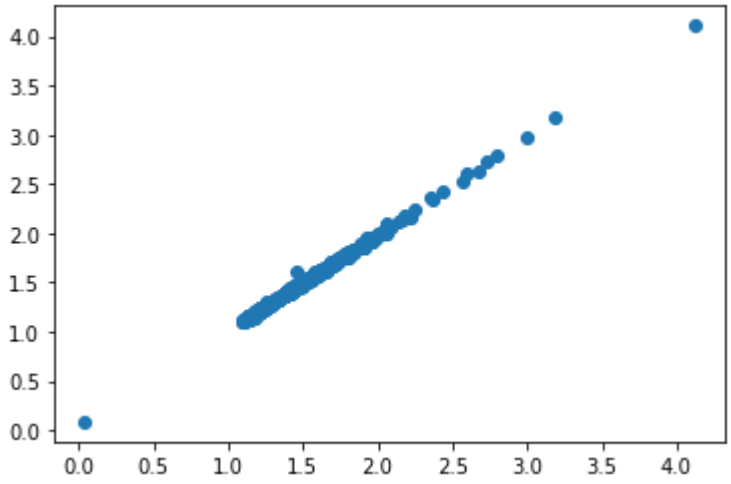
ElasticNet

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 0x25f606f32b0>
```



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

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

```
0.9979283454674264
```

Out[59]:
```
0.998113461617783
```

Logistic

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

Out[60]:
```
High    2477
Low     2085
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 0x25f6075c7f0>
```

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_
```

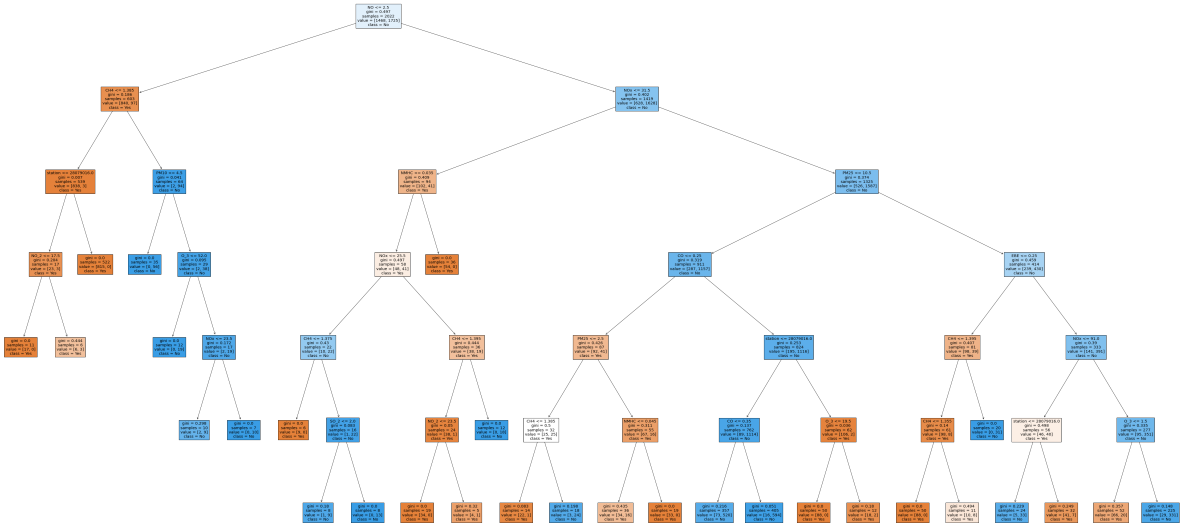
In [72]:
```
rfc_best=grid_search.best_estimator_
```

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(1435.6875, 2019.0857142857144, 'NO <= 2.5\ngini = 0.497\nsamples = 2022\nvalue = [1468, 1725]\nclass = No'),
 Text(465.0, 1708.457142857143, 'CH4 <= 1.385\ngini = 0.186\nsamples = 603\nvalue = [840, 97]\nclass = Yes'),
 Text(279.0, 1397.8285714285716, 'station <= 28079016.0\ngini = 0.007\nsamples = 539\nvalue = [838, 3]\nclass = Yes'),
 Text(186.0, 1087.2, 'NO_2 <= 17.5\ngini = 0.204\nsamples = 17\nvalue = [23, 3]\nclass = Yes'),
 Text(93.0, 776.5714285714287, 'gini = 0.0\nsamples = 11\nvalue = [17, 0]\nclass = Yes'),
 Text(279.0, 776.5714285714287, 'gini = 0.444\nsamples = 6\nvalue = [6, 3]\nclass = Yes'),
 Text(372.0, 1087.2, 'gini = 0.0\nsamples = 522\nvalue = [815, 0]\nclass = Yes'),
 Text(651.0, 1397.8285714285716, 'PM10 <= 4.5\ngini = 0.041\nsamples = 64\nvalue = [2, 94]\nclass = No'),
 Text(558.0, 1087.2, 'gini = 0.0\nsamples = 35\nvalue = [0, 56]\nclass = No'),
 Text(744.0, 1087.2, 'O_3 <= 52.0\ngini = 0.095\nsamples = 29\nvalue = [2, 38]\nclass = No'),
 Text(651.0, 776.5714285714287, 'gini = 0.0\nsamples = 12\nvalue = [0, 19]\nclass = No'),
 Text(837.0, 776.5714285714287, 'NOx <= 23.5\ngini = 0.172\nsamples = 17\nvalue = [2, 19]\nclass = No'),
 Text(744.0, 465.9428571428573, 'gini = 0.298\nsamples = 10\nvalue = [2, 9]\nclass = No'),
 Text(930.0, 465.9428571428573, 'gini = 0.0\nsamples = 7\nvalue = [0, 10]\nclass = No'),
 Text(2406.375, 1708.457142857143, 'NOx <= 31.5\ngini = 0.402\nsamples = 1419\nvalue = [628, 1628]\nclass = No'),
 Text(1581.0, 1397.8285714285716, 'NMHC <= 0.035\ngini = 0.409\nsamples = 94\nvalue = [102, 41]\nclass = Yes'),
 Text(1488.0, 1087.2, 'NOx <= 25.5\ngini = 0.497\nsamples = 58\nvalue = [48, 41]\nclass = Yes'),
 Text(1209.0, 776.5714285714287, 'CH4 <= 1.375\ngini = 0.43\nsamples = 22\nvalue = [10, 22]\nclass = No'),
 Text(1116.0, 465.9428571428573, 'gini = 0.0\nsamples = 6\nvalue = [9, 0]\nclass = Yes'),
 Text(1302.0, 465.9428571428573, 'SO_2 <= 2.0\ngini = 0.083\nsamples = 16\nvalue = [1, 22]\nclass = No'),
 Text(1209.0, 155.3142857142857, 'gini = 0.18\nsamples = 8\nvalue = [1, 9]\nclass = No'),
 Text(1395.0, 155.3142857142857, 'gini = 0.0\nsamples = 8\nvalue = [0, 13]\nclass = No'),
 Text(1767.0, 776.5714285714287, 'CH4 <= 1.395\ngini = 0.444\nsamples = 36\nvalue = [38, 19]\nclass = Yes'),
 Text(1674.0, 465.9428571428573, 'NO_2 <= 23.5\ngini = 0.05\nsamples = 24\nvalue = [38, 1]\nclass = Yes'),
 Text(1581.0, 155.3142857142857, 'gini = 0.0\nsamples = 19\nvalue = [34, 0]\nclass = Yes'),
 Text(1767.0, 155.3142857142857, 'gini = 0.32\nsamples = 5\nvalue = [4, 1]\nclass = Yes'),
 Text(1860.0, 465.9428571428573, 'gini = 0.0\nsamples = 12\nvalue = [0, 18]\nclass = No'),
 Text(1674.0, 1087.2, 'gini = 0.0\nsamples = 36\nvalue = [54, 0]\nclass = Yes'),
 Text(3231.75, 1397.8285714285716, 'PM25 <= 10.5\ngini = 0.374\nsamples = 132

```
5\nvalue = [526, 1587]\nclass = No'),
 Text(2604.0, 1087.2, 'CO <= 0.25\ngini = 0.319\nsamples = 911\nvalue = [287,
1157]\nclass = No'),
 Text(2232.0, 776.5714285714287, 'PM25 <= 2.5\ngini = 0.426\nsamples = 87\nva
lue = [92, 41]\nclass = Yes'),
 Text(2046.0, 465.9428571428573, 'CH4 <= 1.385\ngini = 0.5\nsamples = 32\nval
ue = [25, 25]\nclass = Yes'),
 Text(1953.0, 155.3142857142857, 'gini = 0.083\nsamples = 14\nvalue = [22, 1]
\nclass = Yes'),
 Text(2139.0, 155.3142857142857, 'gini = 0.198\nsamples = 18\nvalue = [3, 24]
\nclass = No'),
 Text(2418.0, 465.9428571428573, 'NMHC <= 0.045\ngini = 0.311\nsamples = 55\n
value = [67, 16]\nclass = Yes'),
 Text(2325.0, 155.3142857142857, 'gini = 0.435\nsamples = 36\nvalue = [34, 1
6]\nclass = Yes'),
 Text(2511.0, 155.3142857142857, 'gini = 0.0\nsamples = 19\nvalue = [33, 0]\n
class = Yes'),
 Text(2976.0, 776.5714285714287, 'station <= 28079016.0\ngini = 0.253\nsample
s = 824\nvalue = [195, 1116]\nclass = No'),
 Text(2790.0, 465.9428571428573, 'CO <= 0.35\ngini = 0.137\nsamples = 762\nva
lue = [89, 1114]\nclass = No'),
 Text(2697.0, 155.3142857142857, 'gini = 0.216\nsamples = 357\nvalue = [73, 5
20]\nclass = No'),
 Text(2883.0, 155.3142857142857, 'gini = 0.051\nsamples = 405\nvalue = [16, 5
94]\nclass = No'),
 Text(3162.0, 465.9428571428573, 'O_3 <= 19.5\ngini = 0.036\nsamples = 62\nva
lue = [106, 2]\nclass = Yes'),
 Text(3069.0, 155.3142857142857, 'gini = 0.0\nsamples = 50\nvalue = [88, 0]\n
class = Yes'),
 Text(3255.0, 155.3142857142857, 'gini = 0.18\nsamples = 12\nvalue = [18, 2]
\nclass = Yes'),
 Text(3859.5, 1087.2, 'EBE <= 0.25\ngini = 0.459\nsamples = 414\nvalue = [23
9, 430]\nclass = No'),
 Text(3627.0, 776.5714285714287, 'CH4 <= 1.395\ngini = 0.407\nsamples = 81\nv
alue = [98, 39]\nclass = Yes'),
 Text(3534.0, 465.9428571428573, 'CH4 <= 1.355\ngini = 0.14\nsamples = 61\nva
lue = [98, 8]\nclass = Yes'),
 Text(3441.0, 155.3142857142857, 'gini = 0.0\nsamples = 50\nvalue = [88, 0]\n
class = Yes'),
 Text(3627.0, 155.3142857142857, 'gini = 0.494\nsamples = 11\nvalue = [10, 8]
\nclass = Yes'),
 Text(3720.0, 465.9428571428573, 'gini = 0.0\nsamples = 20\nvalue = [0, 31]\n
class = No'),
 Text(4092.0, 776.5714285714287, 'NOx <= 91.0\ngini = 0.39\nsamples = 333\nva
lue = [141, 391]\nclass = No'),
 Text(3906.0, 465.9428571428573, 'station <= 28079016.0\ngini = 0.498\nsample
s = 56\nvalue = [46, 40]\nclass = Yes'),
 Text(3813.0, 155.3142857142857, 'gini = 0.229\nsamples = 24\nvalue = [5, 33]
\nclass = No'),
 Text(3999.0, 155.3142857142857, 'gini = 0.249\nsamples = 32\nvalue = [41, 7]
\nclass = Yes'),
 Text(4278.0, 465.9428571428573, 'O_3 <= 1.5\ngini = 0.335\nsamples = 277\nva
lue = [95, 351]\nclass = No'),
 Text(4185.0, 155.3142857142857, 'gini = 0.357\nsamples = 52\nvalue = [66, 2
0]\nclass = Yes'),
 Text(4371.0, 155.3142857142857, 'gini = 0.148\nsamples = 225\nvalue = [29, 3
31]\nclass = No')]
```



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

```
Linear: 0.9996222720077558
Lasso: 0.3728582371674869
Ridge: 0.9979283454674264
ElasticNet: 0.5889752318704515
Logistic: 0.5536888239590942
Random Forest: 0.9802696314989101
```

Best model is Linear Regression