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,Ridge,Elasti
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/madrid_2009
df
```

Out[2]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25
0	2009-10-01 01:00:00	NaN	0.27	NaN	NaN	NaN	39.889999	48.150002	NaN	50.680000	18.260000	NaN
1	2009-10-01 01:00:00	NaN	0.22	NaN	NaN	NaN	21.230000	24.260000	NaN	55.880001	10.580000	NaN
2	2009-10-01 01:00:00	NaN	0.18	NaN	NaN	NaN	31.230000	34.880001	NaN	49.060001	25.190001	NaN
3	2009-10-01 01:00:00	0.95	0.33	1.43	2.68	0.25	55.180000	81.360001	1.57	36.669998	26.530001	6.82
4	2009-10-01 01:00:00	NaN	0.41	NaN	NaN	0.12	61.349998	76.260002	NaN	38.090000	23.760000	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...
215683	2009-06-01 00:00:00	0.50	0.22	0.39	0.75	0.09	22.000000	24.510000	1.00	82.239998	10.830000	7.15
215684	2009-06-01 00:00:00	NaN	0.31	NaN	NaN	NaN	76.110001	101.099998	NaN	41.220001	9.920000	NaN
215685	2009-06-01 00:00:00	0.13	NaN	0.86	NaN	0.23	81.050003	99.849998	NaN	24.830000	12.460000	6.77
215686	2009-06-01 00:00:00	0.21	NaN	2.96	NaN	0.10	72.419998	82.959999	NaN	NaN	13.030000	NaN
215687	2009-06-01 00:00:00	0.37	0.32	0.99	1.36	0.14	54.290001	64.480003	1.06	56.919998	15.360000	11.61

215688 rows × 17 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 215688 entries, 0 to 215687
Data columns (total 17 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     215688 non-null  object 
 1   BEN      60082 non-null   float64
 2   CO       190801 non-null  float64
 3   EBE      60081 non-null   float64
 4   MXY      24846 non-null   float64
 5   NMHC     74748 non-null   float64
 6   NO_2     214562 non-null  float64
 7   NOx      214565 non-null  float64
 8   OXY      24854 non-null   float64
 9   O_3      204482 non-null  float64
 10  PM10     196331 non-null  float64
 11  PM25     55822 non-null   float64
 12  PXY      24854 non-null   float64
 13  SO_2     212671 non-null  float64
 14  TCH      75213 non-null   float64
 15  TOL      59920 non-null   float64
 16  station  215688 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 28.0+ MB
```

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

Out[4]:

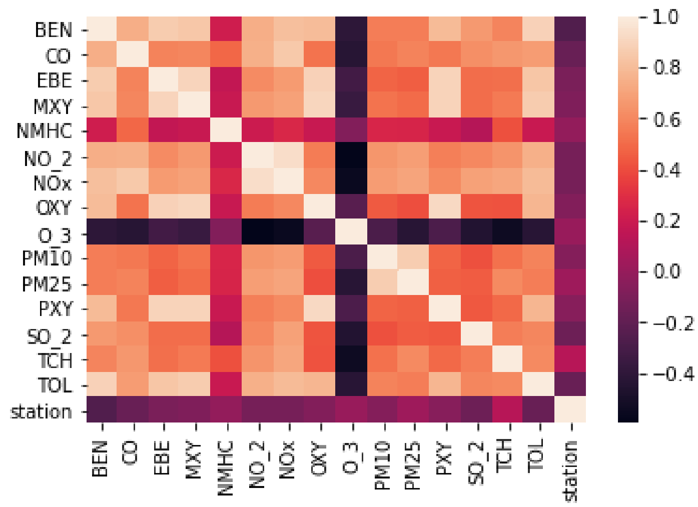
	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25
3	2009-10-01 01:00:00	0.95	0.33	1.43	2.68	0.25	55.180000	81.360001	1.57	36.669998	26.530001	6.82
20	2009-10-01 01:00:00	0.38	0.32	0.32	0.89	0.01	17.969999	19.240000	1.00	65.870003	10.520000	7.01
24	2009-10-01 01:00:00	0.55	0.24	0.65	1.79	0.18	36.619999	43.919998	1.28	48.070000	19.150000	9.33
28	2009-10-01 02:00:00	0.65	0.21	1.20	2.04	0.18	37.169998	48.869999	1.21	26.950001	32.200001	6.94
45	2009-10-01 02:00:00	0.38	0.30	0.50	1.15	0.00	17.889999	19.299999	1.00	60.009998	12.260000	8.46
...	...	...	...	...	...	...	...	...	...	...	...	...
215659	2009-05-31 23:00:00	0.54	0.27	1.00	0.69	0.09	28.280001	29.490000	0.86	78.750000	15.170000	10.21
215663	2009-05-31 23:00:00	0.74	0.35	1.13	1.65	0.15	56.410000	69.870003	1.26	56.799999	11.800000	9.63
215667	2009-06-01 00:00:00	0.78	0.29	0.99	1.96	0.04	64.870003	82.629997	1.13	58.000000	12.670000	6.57
215683	2009-06-01 00:00:00	0.50	0.22	0.39	0.75	0.09	22.000000	24.510000	1.00	82.239998	10.830000	7.15
215687	2009-06-01 00:00:00	0.37	0.32	0.99	1.36	0.14	54.290001	64.480003	1.06	56.919998	15.360000	11.61

24717 rows × 17 columns

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

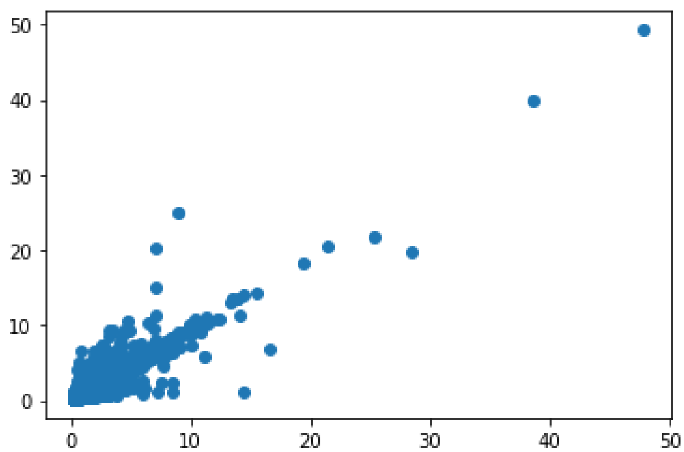
In [6]:
```
sns.heatmap(df1.corr())
```

Out[6]: <AxesSubplot:>



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

Out[7]: [<matplotlib.lines.Line2D at 0x23c87847160>]



In [8]:
```
data=df[["EBE","PXY"]]
```

In [9]:
```
# sns.stripplot(x=df["EBE"],y=df["PXY"],jitter=True,marker='o',color='blue')
```

In [10]:
```
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)
```

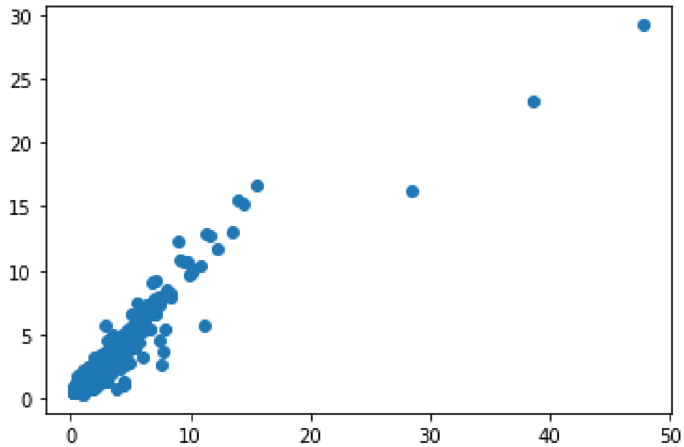
Linear

In [11]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[11]: LinearRegression()

In [12]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[12]: <matplotlib.collections.PathCollection at 0x23c8790c130>



In [13]:
```
lis=li.score(x_test,y_test)
```

In [14]:
```
df1["TCH"].value_counts()
```

Out[14]:
```
1.39    1091
1.36    1056
1.38    1046
1.40    1018
1.37    1017
        ...
2.52       1
1.16       1
2.41       1
1.13       1
2.79       1
Name: TCH, Length: 169, dtype: int64
```

In [15]:
```
df1.loc[df1["TCH"]<1.40,"TCH"]=1
df1.loc[df1["TCH"]>1.40,"TCH"]=2
df1["TCH"].value_counts()
```

Out[15]:
```
1.0    12963
2.0    11754
Name: TCH, dtype: int64
```

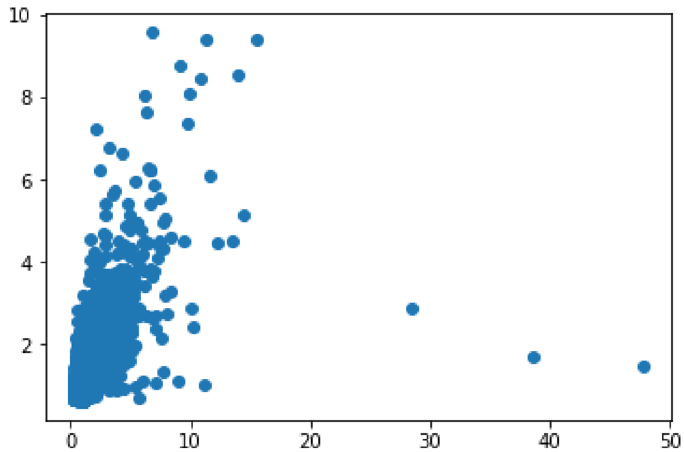
Lasso

In [16]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[16]: Lasso(alpha=5)

In [17]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[17]: <matplotlib.collections.PathCollection at 0x23c88533880>



In [18]:
```
las=la.score(x_test,y_test)
```

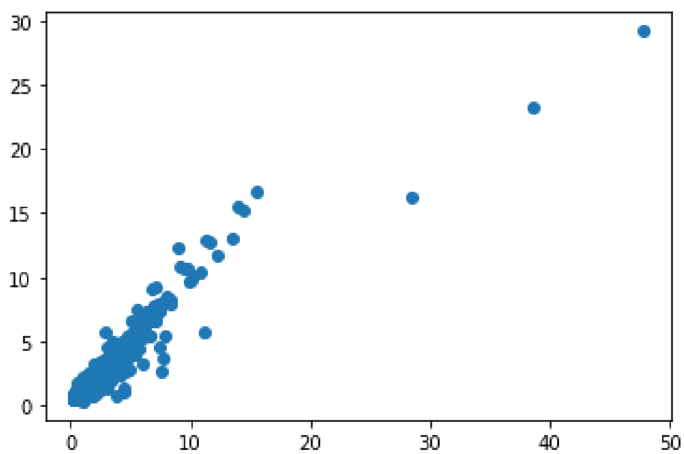
Ridge

In [19]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[19]: Ridge(alpha=1)

In [20]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[20]: <matplotlib.collections.PathCollection at 0x23c871da250>



In [21]:
```
rrs=rr.score(x_test,y_test)
```

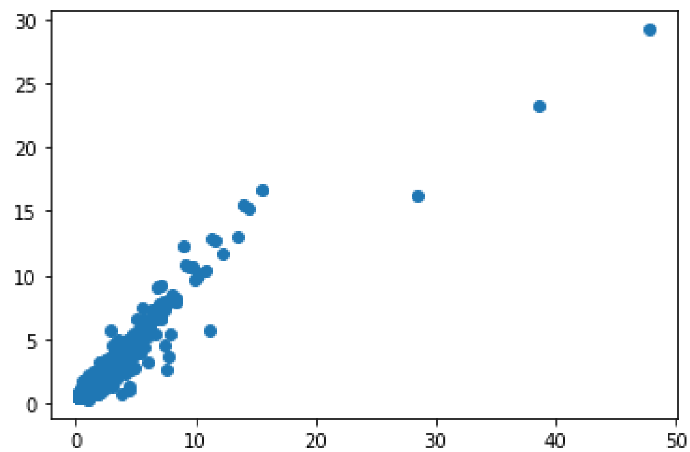
ElasticNet

In [22]:
```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[22]:
```
ElasticNet()
```

In [23]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[23]:
```
<matplotlib.collections.PathCollection at 0x23c885beca0>
```



In [24]:
```
ens=en.score(x_test,y_test)
```

In [25]:
```
print(rr.score(x_test,y_test))
rr.score(x_train,y_train)
```

```
0.8783497693150732
```

Out[25]:
```
0.8864182797143654
```

Logistic

In [26]:
```
g={"TCH":{1.0:"Low",2.0:"High"}}
df1=df1.replace(g)
df1["TCH"].value_counts()
```

Out[26]:
```
Low     12963
High    11754
Name: TCH, dtype: int64
```

In [27]:
```
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 [28]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[28]:
```
LogisticRegression()
```

In [29]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[29]: <matplotlib.collections.PathCollection at 0x23c88602520>

In [30]:
```
los=lo.score(x_test,y_test)
```

Random Forest

In [31]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [32]:
```
g1={"TCH":{"Low":1.0,"High":2.0}}
df1=df1.replace(g1)
```

In [33]:
```
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 [34]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[34]: RandomForestClassifier()

In [35]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [36]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

Out[36]:
```
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 [37]:
```
rfcs=grid_search.best_score_
```

In [38]:
```
rfc_best=grid_search.best_estimator_
```

In [39]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes',"No"],fill
```

Out[39]:
```
[Text(2232.0, 2019.0857142857144, 'O_3 <= 36.105\ngini = 0.499\nsamples = 10931\nval
ue = [9061, 8240]\nclass = Yes'),
 Text(1116.0, 1708.457142857143, 'PM25 <= 10.105\ngini = 0.35\nsamples = 4675\nvalue
= [1681, 5753]\nclass = No'),
 Text(558.0, 1397.8285714285716, 'NMHC <= 0.175\ngini = 0.499\nsamples = 1175\nvalue
= [912, 974]\nclass = No'),
 Text(279.0, 1087.2, 'EBE <= 0.585\ngini = 0.445\nsamples = 580\nvalue = [620, 311]
\nclass = Yes'),
 Text(139.5, 776.5714285714287, 'NOx <= 37.82\ngini = 0.262\nsamples = 116\nvalue =
[153, 28]\nclass = Yes'),
 Text(69.75, 465.9428571428573, 'BEN <= 0.565\ngini = 0.104\nsamples = 46\nvalue =
[69, 4]\nclass = Yes'),
 Text(34.875, 155.3142857142857, 'gini = 0.0\nsamples = 36\nvalue = [60, 0]\nclass =
Yes'),
 Text(104.625, 155.3142857142857, 'gini = 0.426\nsamples = 10\nvalue = [9, 4]\nclass
= Yes'),
 Text(209.25, 465.9428571428573, 'SO_2 <= 10.58\ngini = 0.346\nsamples = 70\nvalue =
[84, 24]\nclass = Yes'),
 Text(174.375, 155.3142857142857, 'gini = 0.041\nsamples = 31\nvalue = [47, 1]\nclas
```

In [40]:
```
print("Linear:",lis)
print("Lasso:",las)
print("Ridge:",rrs)
print("ElasticNet:",ens)
print("Logistic:",los)
print("Random Forest:",rfcs)
```

```
Linear: 0.8783680625661898
Lasso: 0.37328599597971324
Ridge: 0.8783497693150732
ElasticNet: 0.575045121851463
Logistic: 0.5225188781014024
Random Forest: 0.8625513973793
```

Best Model is Linear Regression

In [41]:
```
df2=pd.read_csv("C:/Users/user/Downloads/FP1_air/csvs_per_year/csvs_per_year/madrid_201
df2
```

Out[41]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	P
0	2010-03-01 01:00:00	NaN	0.29	NaN	NaN	NaN	25.090000	29.219999	NaN	68.930000	NaN	
1	2010-03-01 01:00:00	NaN	0.27	NaN	NaN	NaN	24.879999	30.040001	NaN	NaN	NaN	
2	2010-03-01 01:00:00	NaN	0.28	NaN	NaN	NaN	17.410000	20.540001	NaN	72.120003	NaN	
3	2010-03-01 01:00:00	0.38	0.24	1.74	NaN	0.05	15.610000	21.080000	NaN	72.970001	19.410000	7.87
4	2010-03-01 01:00:00	0.79	NaN	1.32	NaN	NaN	21.430000	26.070000	NaN	NaN	24.670000	22.03
...	...	...	...	...	...	...	...	...	...	...	...	
209443	2010-08-01 00:00:00	NaN	0.55	NaN	NaN	NaN	125.000000	219.899994	NaN	25.379999	NaN	
209444	2010-08-01 00:00:00	NaN	0.27	NaN	NaN	NaN	45.709999	47.410000	NaN	NaN	51.259998	
209445	2010-08-01 00:00:00	NaN	NaN	NaN	NaN	0.24	46.560001	49.040001	NaN	46.250000	NaN	
209446	2010-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	46.770000	50.119999	NaN	77.709999	NaN	
209447	2010-08-01 00:00:00	0.92	0.43	0.71	NaN	0.25	76.330002	88.190002	NaN	52.259998	47.150002	26.86

209448 rows × 17 columns

In [42]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209448 entries, 0 to 209447
Data columns (total 17 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     209448 non-null  object 
 1   BEN      60268 non-null   float64
 2   CO       94982 non-null   float64
 3   EBE      60253 non-null   float64
 4   MXY      6750 non-null    float64
 5   NMHC     51727 non-null   float64
 6   NO_2     208219 non-null  float64
 7   NOx      208210 non-null  float64
 8   OXY      6750 non-null    float64
 9   O_3      126684 non-null  float64
 10  PM10     106186 non-null  float64
 11  PM25     55514 non-null   float64
 12  PXY      6740 non-null    float64
 13  SO_2     93184 non-null   float64
 14  TCH      51730 non-null   float64
 15  TOL      60171 non-null   float64
 16  station  209448 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 27.2+ MB
```

In [43]:
```
df3=df2.dropna()
df3
```

Out[43]:

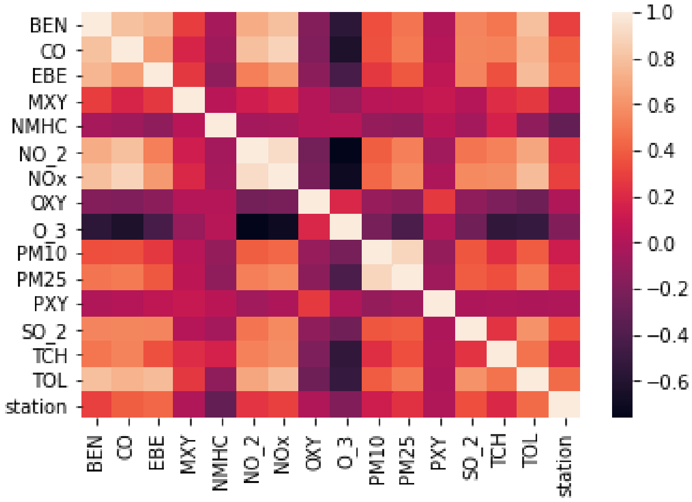
	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25	F
11	2010-03-01 01:00:00	0.78	0.18	0.84	0.73	0.28	10.420000	11.900000	1.0	90.309998	18.370001	11.30	(
23	2010-03-01 01:00:00	0.70	0.23	1.00	0.73	0.18	17.820000	22.290001	1.0	70.550003	23.639999	13.15	(
35	2010-03-01 02:00:00	0.58	0.17	0.84	0.73	0.28	3.500000	4.950000	1.0	68.849998	5.600000	5.25	(
47	2010-03-01 02:00:00	0.33	0.21	0.84	0.73	0.17	10.810000	14.900000	1.0	74.750000	7.890000	5.54	(
59	2010-03-01 03:00:00	0.38	0.16	0.64	1.00	0.26	2.750000	4.200000	1.0	93.629997	5.130000	4.90	(
...	...	...	...	...	...	...	...	...	...	...	...	...	
191879	2010-05-31 22:00:00	0.60	0.26	0.82	0.13	0.16	33.360001	43.779999	1.0	38.459999	20.340000	12.31	'
191891	2010-05-31 23:00:00	0.41	0.16	0.71	0.19	0.10	24.299999	26.059999	1.0	50.290001	14.380000	8.53	'
191903	2010-05-31 23:00:00	0.57	0.28	0.64	0.19	0.18	35.540001	44.590000	1.0	34.020000	22.840000	11.25	'
191915	2010-06-01 00:00:00	0.34	0.16	0.69	0.22	0.10	23.559999	25.209999	1.0	45.930000	10.770000	6.28	'
191927	2010-06-01 00:00:00	0.43	0.25	0.79	0.22	0.18	34.910000	42.369999	1.0	29.540001	15.350000	8.97	'

6666 rows × 17 columns

In [44]:
```
df3=df3.drop(["date"],axis=1)
```

In [45]:
```
sns.heatmap(df3.corr())
```

Out[45]: <AxesSubplot:>



In [46]:
```
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

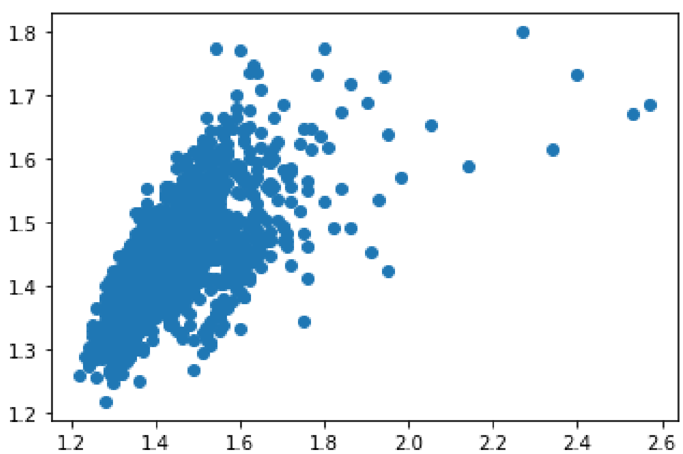
In [47]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[47]: LinearRegression()

In [ ]:

In [48]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[48]: <matplotlib.collections.PathCollection at 0x23c8864f190>



In [49]:
```
lis=li.score(x_test,y_test)
```

In [50]:
```
df3["TCH"].value_counts()
```

Out[50]:
```
1.36    364
1.38    351
1.39    324
1.35    323
1.37    321
       ...
2.07      1
2.17      1
2.53      1
2.12      1
2.05      1
Name: TCH, Length: 100, dtype: int64
```

In [51]:
```
df3.loc[df3["TCH"]<1.40,"TCH"]=1
df3.loc[df3["TCH"]>1.40,"TCH"]=2
df3["TCH"].value_counts()
```

Out[51]:
```
1.0    3340
2.0    3326
Name: TCH, dtype: int64
```

In [ ]:

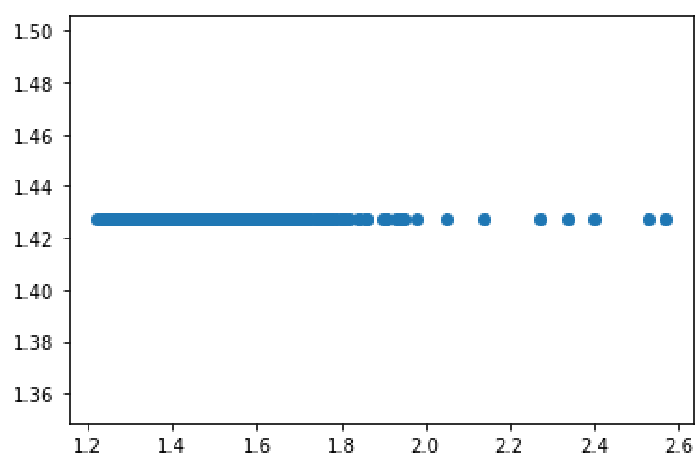
Lasso

In [52]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[52]:
```
Lasso(alpha=5)
```

In [53]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[53]:
```
<matplotlib.collections.PathCollection at 0x23c886ac280>
```



In [54]:
```
las=la.score(x_test,y_test)
```

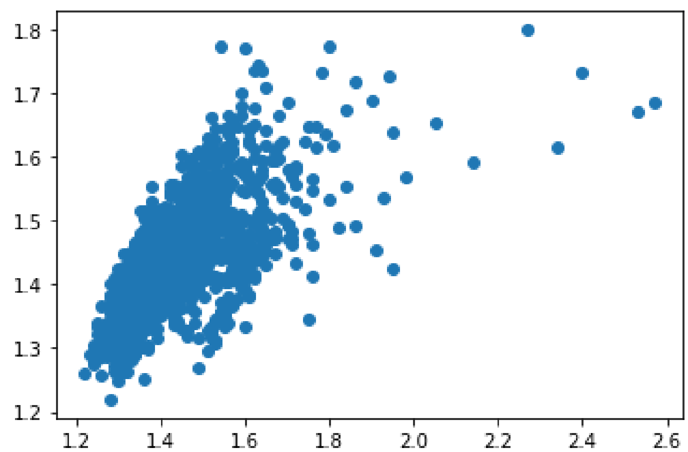
Ridge

In [55]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[55]: Ridge(alpha=1)

In [56]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[56]: <matplotlib.collections.PathCollection at 0x23c8870a310>



In [57]:
```
rrs=rr.score(x_test,y_test)
```

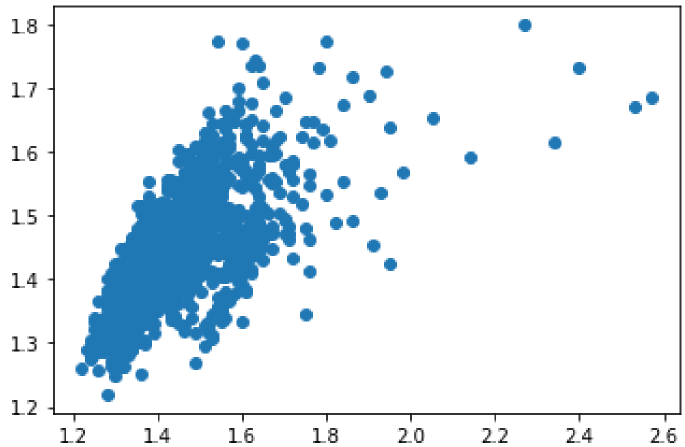
ElasticNet

In [58]:
```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[58]: ElasticNet()

In [59]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[59]: <matplotlib.collections.PathCollection at 0x23c88762e20>



In [60]:
```
ens=en.score(x_test,y_test)
```

In [61]:
```
print(rr.score(x_test,y_test))
rr.score(x_train,y_train)
```

0.4590393479321705

Out[61]: 0.44781912704161386

Logistic

In [62]:
```
g={"TCH":{1.0:"Low",2.0:"High"}}
df3=df3.replace(g)
df3["TCH"].value_counts()
```

Out[62]:
```
Low     3340
High    3326
Name: TCH, dtype: int64
```

In [63]:
```
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 [64]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[64]: LogisticRegression()

In [65]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[65]: <matplotlib.collections.PathCollection at 0x23c8813aac0>

In [66]:
```
los=lo.score(x_test,y_test)
```

Random Forest

In [67]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [68]:
```
g1={"TCH":{"Low":1.0,"High":2.0}}
df3=df3.replace(g1)
```

In [69]:
```
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 [70]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[70]: RandomForestClassifier()

In [71]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [72]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

Out[72]:
```
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 [73]:
```
rfcs=grid_search.best_score_
```

In [74]:
```
rfc_best=grid_search.best_estimator_
```

In [75]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes',"No"],fill
```

```
21]\nclass = No'),
 Text(390.05825242718447, 1087.2, 'PM10 <= 9.235\ngini = 0.308\nsamples = 629\nvalue
= [800, 188]\nclass = Yes'),
 Text(216.6990291262136, 776.5714285714287, 'NMHC <= 0.385\ngini = 0.39\nsamples = 2
51\nvalue = [298, 108]\nclass = Yes'),
 Text(130.01941747572818, 465.9428571428573, 'CO <= 0.215\ngini = 0.317\nsamples = 1
74\nvalue = [224, 55]\nclass = Yes'),
 Text(86.67961165048544, 155.3142857142857, 'gini = 0.113\nsamples = 101\nvalue = [1
41, 9]\nclass = Yes'),
 Text(173.35922330097088, 155.3142857142857, 'gini = 0.459\nsamples = 73\nvalue = [8
3, 46]\nclass = Yes'),
 Text(303.37864077669906, 465.9428571428573, 'BEN <= 0.265\ngini = 0.486\nsamples =
77\nvalue = [74, 53]\nclass = Yes'),
 Text(260.03883495145635, 155.3142857142857, 'gini = 0.226\nsamples = 34\nvalue = [4
7, 7]\nclass = Yes'),
 Text(346.71844660194176, 155.3142857142857, 'gini = 0.466\nsamples = 43\nvalue = [2
7, 46]\nclass = No'),
 Text(563.4174757281554, 776.5714285714287, 'NOx <= 19.02\ngini = 0.237\nsamples = 3
78\nvalue = [502, 80]\nclass = Yes'),
 Text(476.73786407766994, 465.9428571428573, 'CO <= 0.225\ngini = 0.11\nsamples = 20
```

In [76]:
```
print("Linear:",lis)
print("Lasso:",las)
print("Ridge:",rrs)
print("ElasticNet:",ens)
print("Logistic:",los)
print("Random Forest:",rfcs)
```

```
Linear: 0.45865884208093644
Lasso: -0.0002593585325185721
Ridge: 0.4590393479321705
ElasticNet: 0.35747558851830485
Logistic: 0.4895
Random Forest: 0.7788255465066438
```

Best model is Random Forest

In [ ]: