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,ElasticNet
from sklearn.model_selection import train_test_split
```

In [2]:
```python
df=pd.read_csv("/Users/bhoomish/Downloads/FP1_air/csvs_per_year/csvs_per_year/madrid_2007.csv")
df
```

Out[2]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25	PXY	SO_2	TCH
0	2007-12-01 01:00:00	NaN	2.86	NaN	NaN	NaN	282.200012	1054.000000	NaN	4.030000	156.199997	97.43	NaN	64.519997	NaN
1	2007-12-01 01:00:00	NaN	1.82	NaN	NaN	NaN	86.419998	354.600006	NaN	3.260000	80.809998	NaN	NaN	35.419998	NaN
2	2007-12-01 01:00:00	NaN	1.47	NaN	NaN	NaN	94.639999	319.000000	NaN	5.310000	53.099998	NaN	NaN	19.080000	NaN
3	2007-12-01 01:00:00	NaN	1.64	NaN	NaN	NaN	127.900002	476.700012	NaN	4.500000	105.300003	NaN	NaN	17.670000	NaN
4	2007-12-01 01:00:00	4.64	1.86	4.26	7.98	0.57	145.100006	573.900024	3.49	52.689999	106.500000	15.90	3.56	40.230000	1.94
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
225115	2007-03-01 00:00:00	0.30	0.45	1.00	0.30	0.26	8.690000	11.690000	1.00	42.209999	6.760000	5.14	1.00	7.420000	1.44
225116	2007-03-01 00:00:00	NaN	0.16	NaN	NaN	NaN	46.820000	51.480000	NaN	22.150000	5.700000	NaN	NaN	7.130000	NaN
225117	2007-03-01 00:00:00	0.24	NaN	0.20	NaN	0.09	51.259998	66.809998	NaN	18.540001	13.010000	6.95	NaN	8.740000	1.30
225118	2007-03-01 00:00:00	0.11	NaN	1.00	NaN	0.05	24.240000	36.930000	NaN	NaN	6.610000	NaN	NaN	9.890000	1.29
225119	2007-03-01 00:00:00	0.53	0.40	1.00	1.70	0.12	32.360001	47.860001	1.37	24.150000	10.260000	7.08	1.23	9.890000	1.32

225120 rows × 17 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 225120 entries, 0 to 225119
Data columns (total 17 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     225120 non-null  object 
 1   BEN      68885 non-null   float64
 2   CO       206748 non-null  float64
 3   EBE      68883 non-null   float64
 4   MXY      26061 non-null   float64
 5   NMHC     86883 non-null   float64
 6   NO_2     223985 non-null  float64
 7   NOx      223972 non-null  float64
 8   OXY      26062 non-null   float64
 9   O_3      211850 non-null  float64
 10  PM10     222588 non-null  float64
 11  PM25     68870 non-null   float64
 12  PXY      26062 non-null   float64
 13  SO_2     224372 non-null  float64
 14  TCH      87026 non-null   float64
 15  TOL      68845 non-null   float64
 16  station  225120 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 29.2+ MB
```

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

Out[4]:

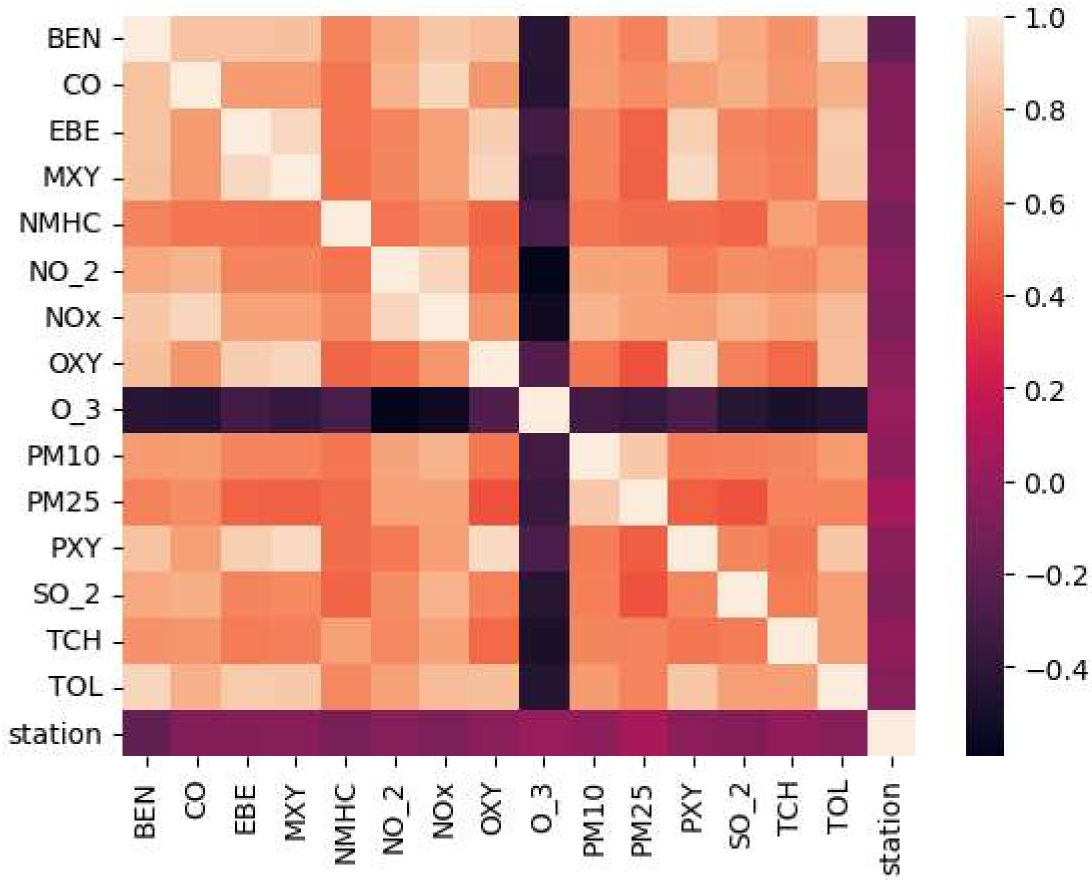
	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25	PXY	SO_2	TCH
4	2007-12-01 01:00:00	4.64	1.86	4.26	7.98	0.57	145.100006	573.900024	3.49	52.689999	106.500000	15.900000	3.56	40.230000	1.9
21	2007-12-01 01:00:00	1.98	0.31	2.56	6.06	0.35	76.059998	208.899994	1.70	1.000000	37.799999	25.580000	1.78	11.310000	1.5
25	2007-12-01 01:00:00	2.82	1.42	3.15	7.02	0.49	123.099998	402.399994	2.60	7.160000	70.809998	37.009998	2.67	25.670000	1.8
30	2007-12-01 02:00:00	4.65	1.89	4.41	8.21	0.65	151.000000	622.700012	3.55	58.080002	117.099998	17.049999	3.57	36.459999	2.2
47	2007-12-01 02:00:00	1.97	0.30	2.15	5.08	0.33	78.760002	189.800003	1.62	1.000000	34.740002	24.730000	1.59	10.500000	1.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
225073	2007-02-28 23:00:00	2.12	0.47	2.51	4.99	0.05	43.560001	83.889999	2.57	13.090000	21.860001	9.380000	2.32	21.780001	1.2
225094	2007-02-28 23:00:00	0.87	0.45	1.19	2.66	0.13	40.000000	61.959999	1.79	20.440001	15.070000	9.220000	1.66	10.310000	1.3
225098	2007-03-01 00:00:00	0.95	0.41	1.55	3.11	0.05	36.090000	63.349998	1.74	17.160000	9.210000	5.100000	1.45	20.690001	1.2
225115	2007-03-01 00:00:00	0.30	0.45	1.00	0.30	0.26	8.690000	11.690000	1.00	42.209999	6.760000	5.140000	1.00	7.420000	1.4
225119	2007-03-01 00:00:00	0.53	0.40	1.00	1.70	0.12	32.360001	47.860001	1.37	24.150000	10.260000	7.080000	1.23	9.890000	1.3

25443 rows × 17 columns

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

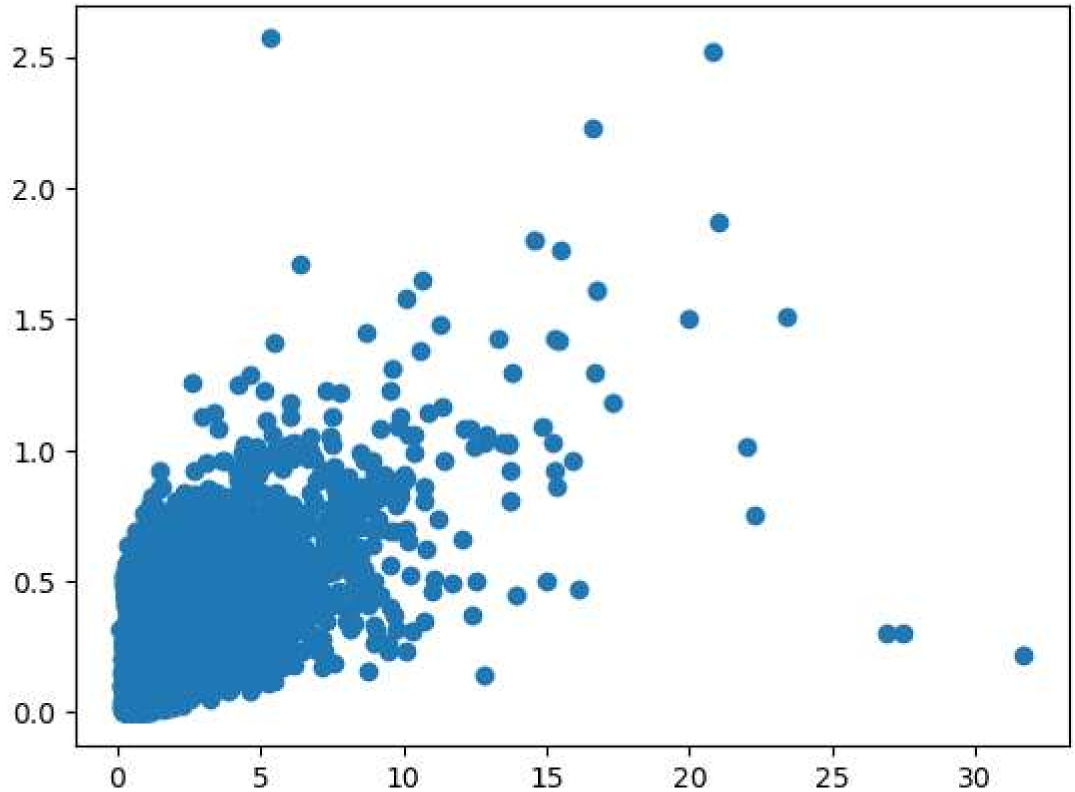
In [6]:
```
sns.heatmap(df1.corr())
```

Out[6]: <Axes: >



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

Out[7]: [<matplotlib.lines.Line2D at 0x7fd5495b9150>]



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

In [9]:
```
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

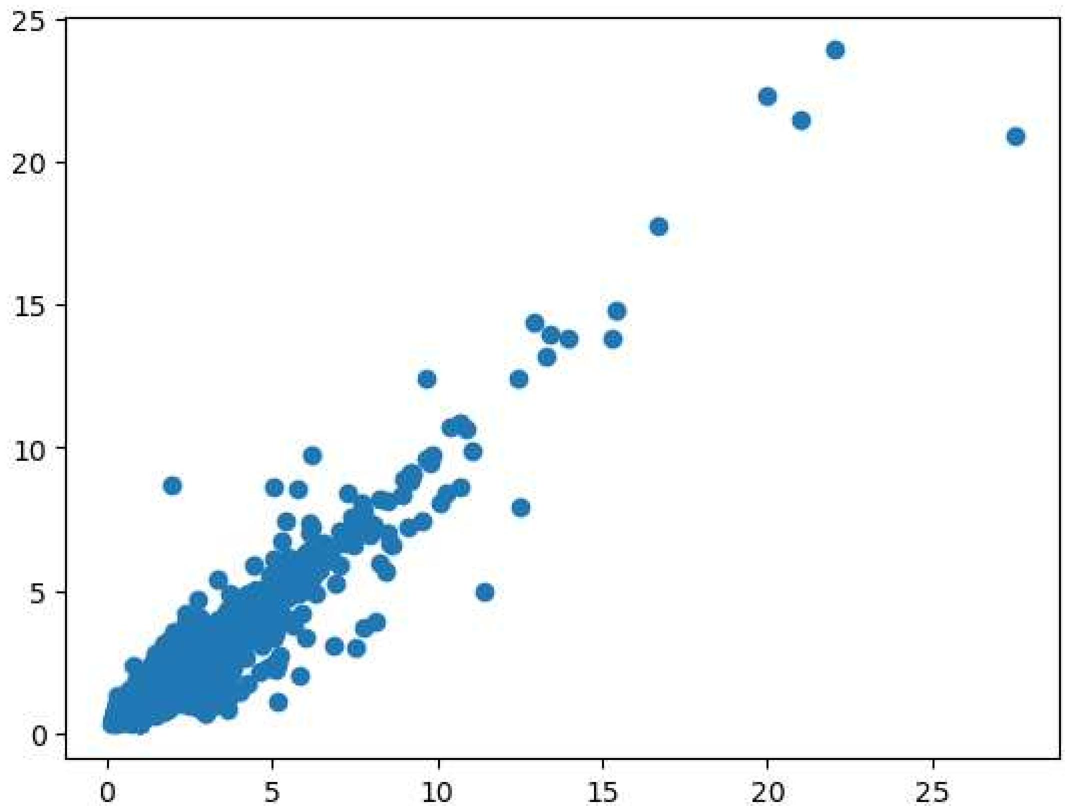
In [10]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[10]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [11]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[11]:
```
<matplotlib.collections.PathCollection at 0x7fd5437eb850>
```



In [12]:
```
lis=li.score(x_test,y_test)
```

In [13]:
```
df1["TCH"].value_counts()
```

Out[13]:
```
1.34    1130
1.33    1067
1.35    1037
1.36    1002
1.32     991
        ...
3.03       1
4.07       1
3.70       1
2.52       1
0.58       1
Name: TCH, Length: 250, dtype: int64
```

In [14]:
```
df1.loc[df1["TCH"]<1.40,"TCH"]=1
df1.loc[df1["TCH"]>1.40,"TCH"]=2
df1["TCH"].value_counts()
```

Out[14]:
```
1.0    14025
2.0    11418
Name: TCH, dtype: int64
```

Lasso

In [15]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[15]:
```
Lasso(alpha=5)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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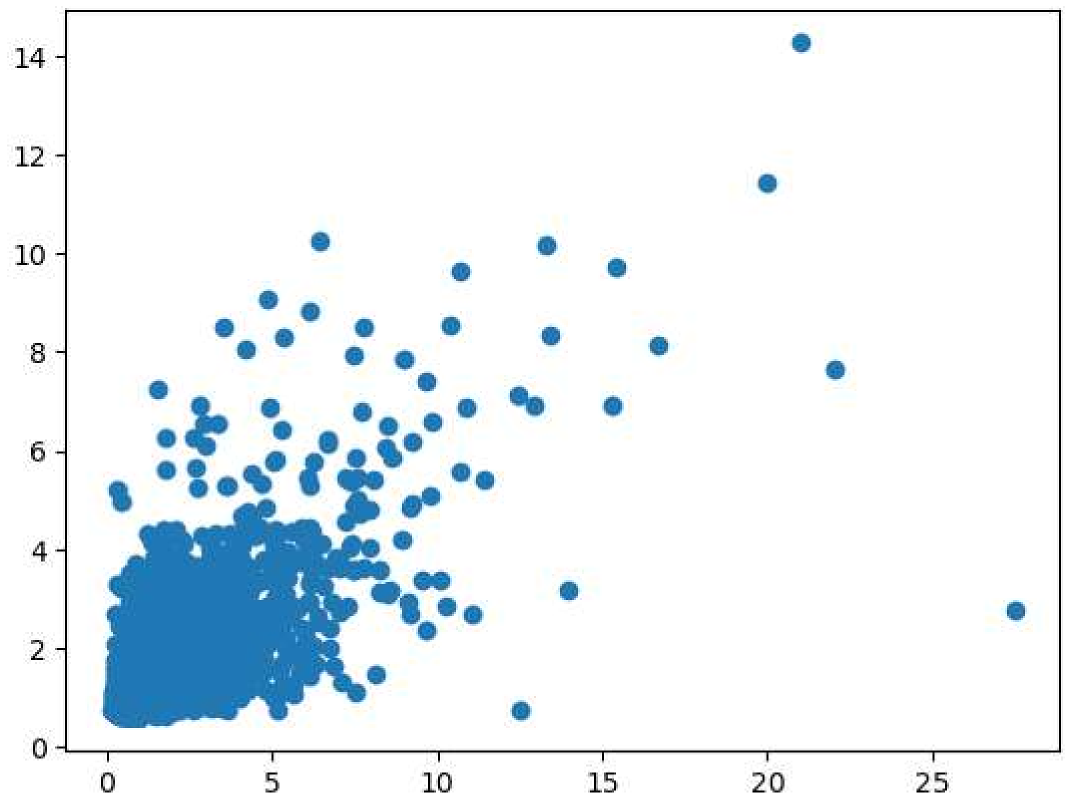
In [16]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[16]: <matplotlib.collections.PathCollection at 0x7fd543867dc0>



In [17]:
```
las=la.score(x_test,y_test)
```

Ridge

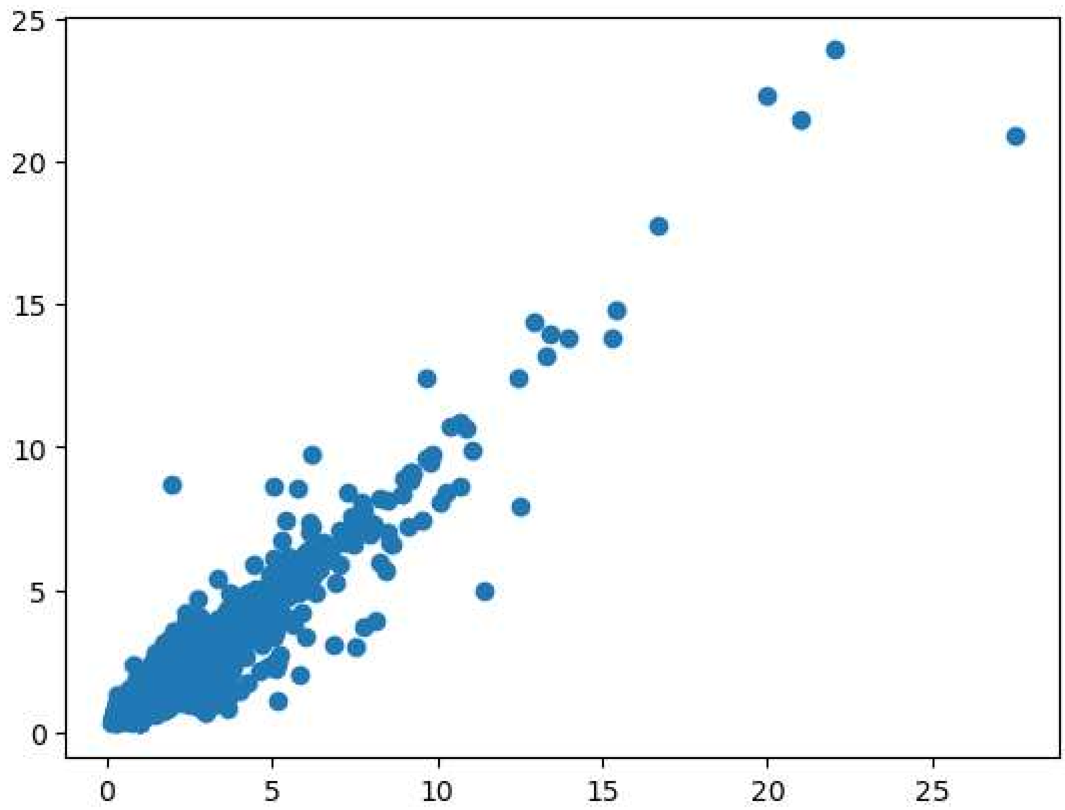
In [18]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[18]:
```
Ridge(alpha=1)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [19]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[19]:
```
<matplotlib.collections.PathCollection at 0x7fd54384bee0>
```



In [20]:
```
rrs=rr.score(x_test,y_test)
```

ElasticNet

In [21]:
```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[21]:
```
ElasticNet()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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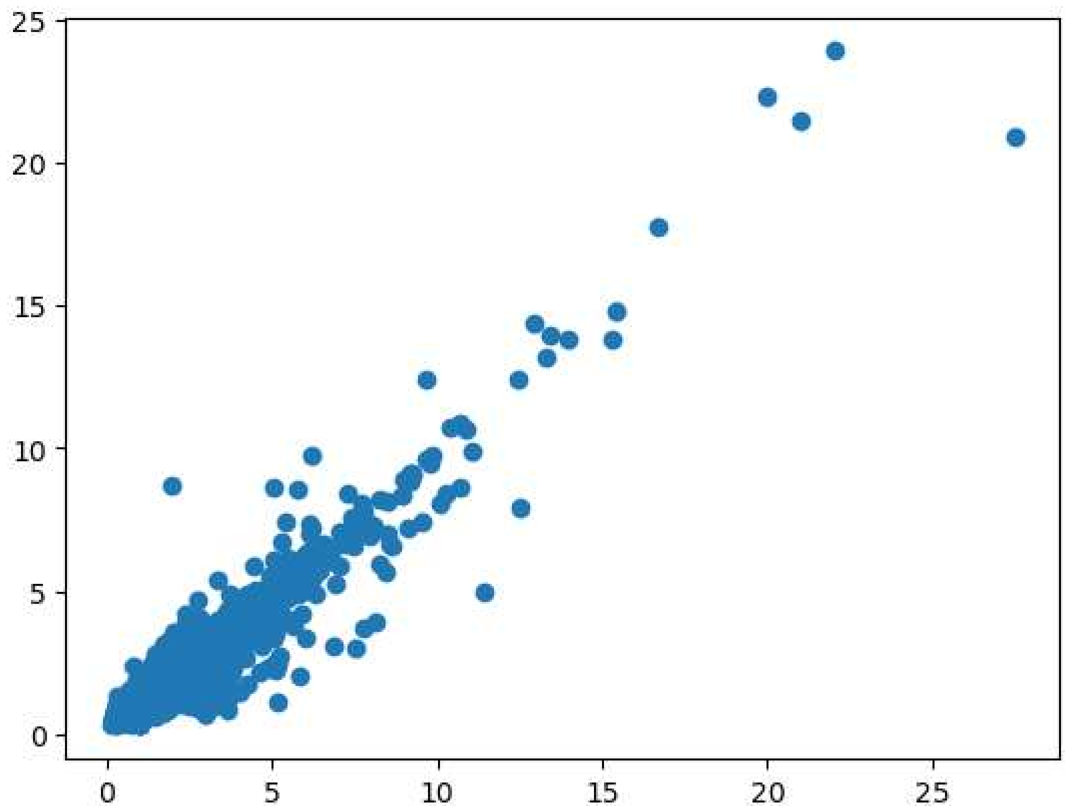
In [22]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[22]: <matplotlib.collections.PathCollection at 0x7fd5313f3010>



In [23]:
```
ens=en.score(x_test,y_test)
```

In [24]:
```
print(rr.score(x_test,y_test))
rr.score(x_train,y_train)
```

```
0.9031092096516402
```

Out[24]: 0.8640132513733083

Logistic

In [25]:
```
g={"TCH":{1.0:"Low",2.0:"High"}}
df1=df1.replace(g)
df1["TCH"].value_counts()
```

Out[25]:
```
Low     14025
High    11418
Name: TCH, dtype: int64
```

In [26]:
```
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 [27]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[27]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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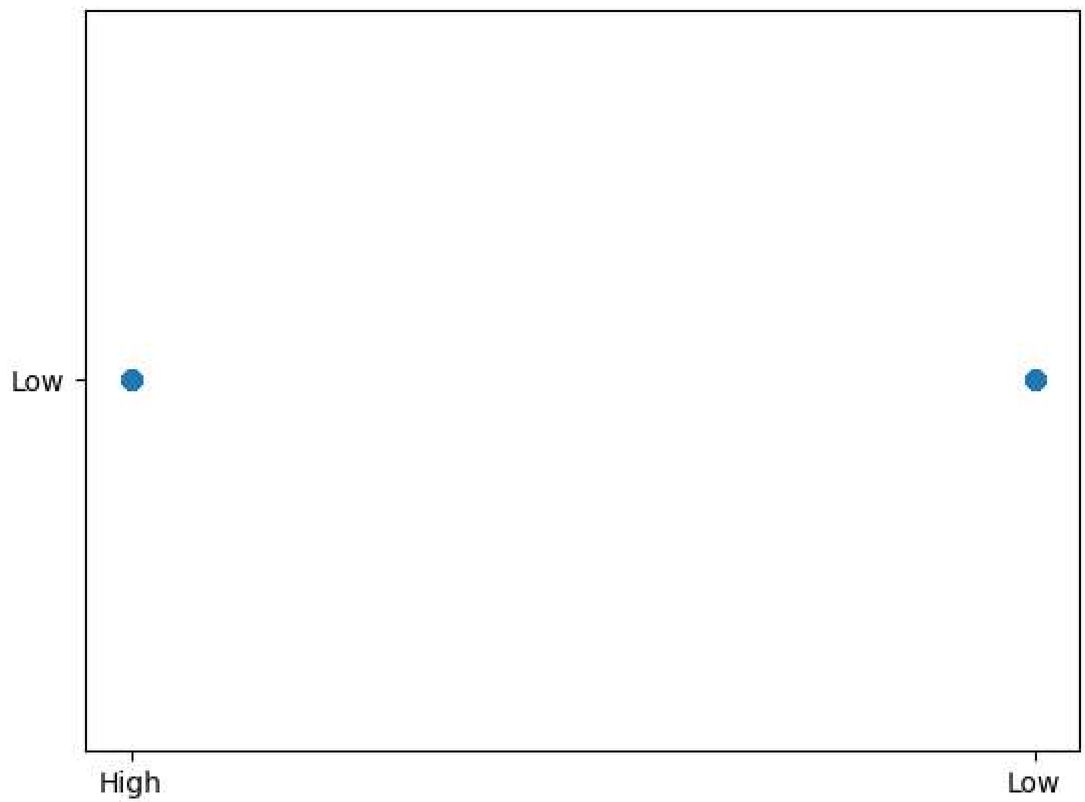
In [28]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[28]: <matplotlib.collections.PathCollection at 0x7fd5314f5a50>



In [29]:
```
los=lo.score(x_test,y_test)
```

Random Forest

In [30]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [31]:
```
g1={"TCH":{"Low":1.0,"High":2.0}}
df1=df1.replace(g1)
```

In [32]:
```
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 [33]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[33]:
```
RandomForestClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [34]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [35]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

Out[35]:
```
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 a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [36]:
```
rfcs=grid_search.best_score_
```

In [37]:
```python
rfc_best=grid_search.best_estimator_
```

In [38]:
```python
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"],filled=True)
```

Out[38]:
```
[Text(0.5206473214285714, 0.9285714285714286, 'O_3 <= 18.185\ngini = 0.493\nsamples = 11219\nvalue = [994
6, 7864]\nclass = Yes'),
 Text(0.26674107142857145, 0.7857142857142857, 'NMHC <= 0.225\ngini = 0.27\nsamples = 3787\nvalue = [972,
5075]\nclass = No'),
 Text(0.140625, 0.6428571428571429, 'NO_2 <= 91.22\ngini = 0.496\nsamples = 1005\nvalue = [740, 878]\ncla
ss = No'),
 Text(0.07142857142857142, 0.5, 'station <= 28079015.0\ngini = 0.5\nsamples = 844\nvalue = [701, 670]\ncl
ass = Yes'),
 Text(0.03571428571428571, 0.35714285714285715, 'NO_2 <= 76.305\ngini = 0.377\nsamples = 395\nvalue = [46
5, 157]\nclass = Yes'),
 Text(0.017857142857142856, 0.21428571428571427, 'NOx <= 182.4\ngini = 0.332\nsamples = 306\nvalue = [39
4, 105]\nclass = Yes'),
 Text(0.008928571428571428, 0.07142857142857142, 'gini = 0.314\nsamples = 294\nvalue = [387, 94]\nclass =
Yes'),
 Text(0.026785714285714284, 0.07142857142857142, 'gini = 0.475\nsamples = 12\nvalue = [7, 11]\nclass = N
o'),
 Text(0.05357142857142857, 0.21428571428571427, 'PM10 <= 44.9\ngini = 0.488\nsamples = 89\nvalue = [71, 5
2]\nclass = Yes'),
 Text(0.044642857142857144, 0.07142857142857142, 'gini = 0.428\nsamples = 66\nvalue = [60, 27]\nclass = Y
```

In [39]:
```
print("Linear:",lis)
print("Lasso:",las)
print("Ridge:",rrs)
print("ElasticNet:",ens)
print("Logistic:",los)
print("Random Forest:",rfcs)
```

```
Linear: 0.9031059082734888
Lasso: 0.49881871289711766
Ridge: 0.9031092096516402
ElasticNet: 0.8369295468530789
Logistic: 0.5470981265557447
Random Forest: 0.8717012914093206
```

Best Model is Random Forest

In [40]:
```python
df2=pd.read_csv("/Users/bhoomish/Downloads/FP1_air/csvs_per_year/csvs_per_year/madrid_2008.csv")
df2
```

Out[40]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25	PXY	SO_2	TCH	TOL	
0	2008-06-01 01:00:00	NaN	0.47	NaN	NaN	NaN	83.089996	120.699997	NaN	16.990000	16.889999	10.40	NaN	8.98	NaN	NaN	2
1	2008-06-01 01:00:00	NaN	0.59	NaN	NaN	NaN	94.820000	130.399994	NaN	17.469999	19.040001	NaN	NaN	5.85	NaN	NaN	2
2	2008-06-01 01:00:00	NaN	0.55	NaN	NaN	NaN	75.919998	104.599998	NaN	13.470000	20.270000	NaN	NaN	6.95	NaN	NaN	2
3	2008-06-01 01:00:00	NaN	0.36	NaN	NaN	NaN	61.029999	66.559998	NaN	23.110001	10.850000	NaN	NaN	5.96	NaN	NaN	2
4	2008-06-01 01:00:00	1.68	0.80	1.70	3.01	0.30	105.199997	214.899994	1.61	12.120000	37.160000	21.90	1.43	10.92	1.53	6.67	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
226387	2008-11-01 00:00:00	0.48	0.30	0.57	1.00	0.31	13.050000	14.160000	0.91	57.400002	5.450000	5.15	1.86	9.68	1.23	2.05	2
226388	2008-11-01 00:00:00	NaN	0.30	NaN	NaN	NaN	41.880001	48.500000	NaN	35.830002	15.020000	NaN	NaN	8.90	NaN	NaN	2
226389	2008-11-01 00:00:00	0.25	NaN	0.56	NaN	0.11	83.610001	102.199997	NaN	14.130000	17.540001	13.91	NaN	7.00	1.56	0.60	2
226390	2008-11-01 00:00:00	0.54	NaN	2.70	NaN	0.18	70.639999	81.860001	NaN	NaN	11.910000	NaN	NaN	8.02	1.57	2.97	2
226391	2008-11-01 00:00:00	0.75	0.36	1.20	2.75	0.16	58.240002	74.239998	1.64	31.910000	12.690000	11.42	1.98	8.74	1.43	4.15	2

226392 rows × 17 columns

In [41]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 226392 entries, 0 to 226391
Data columns (total 17 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     226392 non-null  object 
 1   BEN      67047 non-null   float64
 2   CO       208109 non-null  float64
 3   EBE      67044 non-null   float64
 4   MXY      25867 non-null   float64
 5   NMHC     85079 non-null   float64
 6   NO_2     225315 non-null  float64
 7   NOx      225311 non-null  float64
 8   OXY      25878 non-null   float64
 9   O_3      215716 non-null  float64
 10  PM10     220179 non-null  float64
 11  PM25     67833 non-null   float64
 12  PXY      25877 non-null   float64
 13  SO_2     225405 non-null  float64
 14  TCH      85107 non-null   float64
 15  TOL      66940 non-null   float64
 16  station  226392 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 29.4+ MB
```

In [42]:
```
df3=df2.dropna()
df3
```

Out[42]:

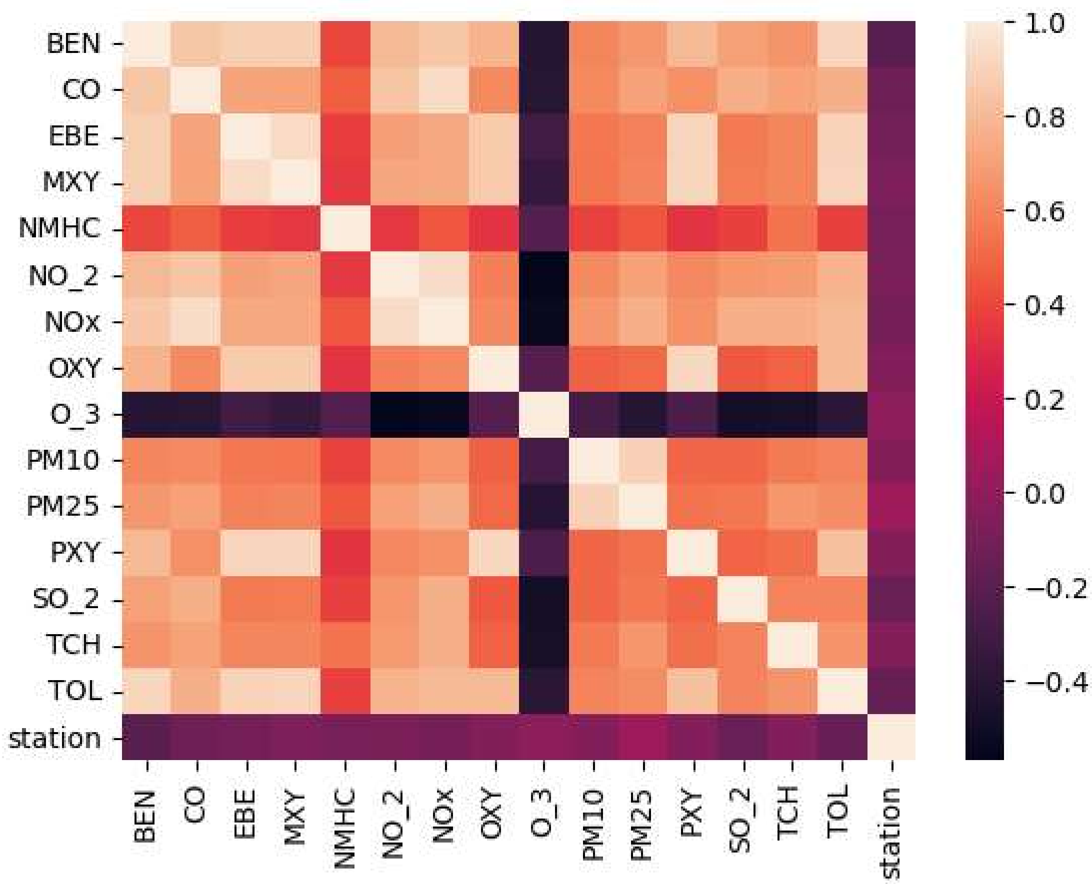
	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PM25	PXY	SO_2	TCH	TO
4	2008-06-01 01:00:00	1.68	0.80	1.70	3.01	0.30	105.199997	214.899994	1.61	12.120000	37.160000	21.900000	1.43	10.92	1.53	6.6
21	2008-06-01 01:00:00	0.32	0.37	1.00	0.39	0.33	21.580000	22.180000	1.00	35.770000	7.900000	6.140000	1.00	5.39	1.41	0.9
25	2008-06-01 01:00:00	0.73	0.39	1.04	1.70	0.18	64.839996	86.709999	1.31	23.379999	14.760000	9.840000	1.22	6.82	1.37	2.8
30	2008-06-01 02:00:00	1.95	0.51	1.98	3.77	0.24	79.750000	143.399994	2.03	18.090000	31.139999	18.410000	1.81	8.97	1.46	8.5
47	2008-06-01 02:00:00	0.36	0.39	0.39	0.50	0.34	26.790001	27.389999	1.00	33.029999	7.620000	6.250000	0.38	5.59	1.42	1.1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
226362	2008-10-31 23:00:00	0.47	0.35	0.65	1.00	0.33	22.480000	25.020000	1.00	33.509998	10.200000	7.680000	1.84	9.47	1.26	2.4
226366	2008-10-31 23:00:00	0.92	0.46	1.21	2.75	0.19	78.440002	106.199997	1.70	18.320000	14.140000	10.590000	1.98	9.66	1.44	4.7
226371	2008-11-01 00:00:00	1.83	0.53	2.22	4.51	0.17	93.260002	158.399994	2.38	18.770000	20.750000	18.620001	2.10	12.27	1.42	9.1
226387	2008-11-01 00:00:00	0.48	0.30	0.57	1.00	0.31	13.050000	14.160000	0.91	57.400002	5.450000	5.150000	1.86	9.68	1.23	2.0
226391	2008-11-01 00:00:00	0.75	0.36	1.20	2.75	0.16	58.240002	74.239998	1.64	31.910000	12.690000	11.420000	1.98	8.74	1.43	4.1

25631 rows × 17 columns

In [43]:
```
df3=df3.drop(["date"],axis=1)
```

In [44]:
```
sns.heatmap(df3.corr())
```

Out[44]: <Axes: >



In [45]:
```
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

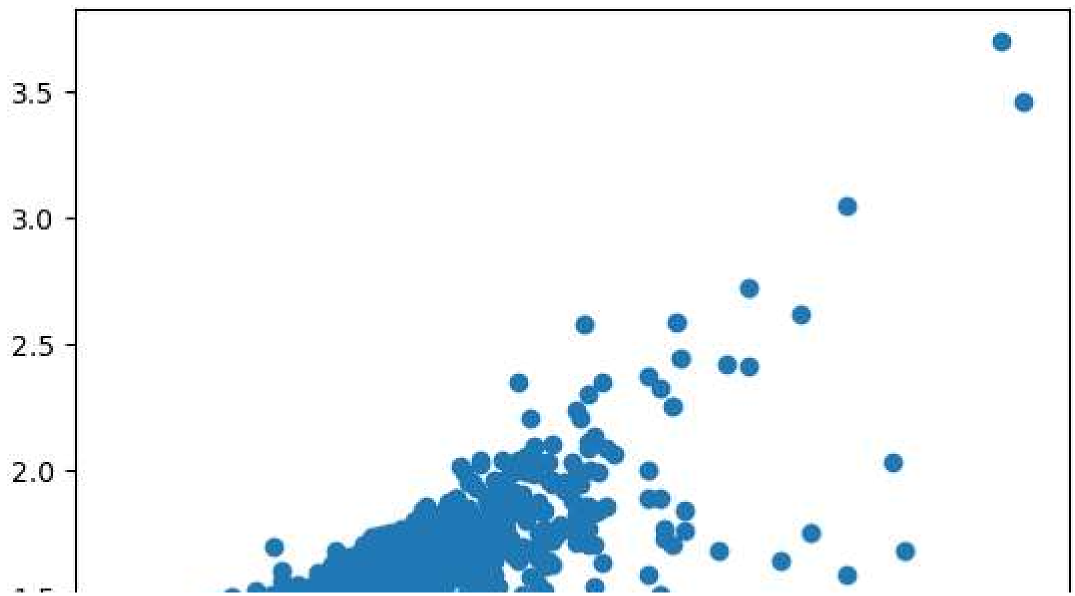
In [46]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[46]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [47]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[47]:
```
<matplotlib.collections.PathCollection at 0x7fd54aacd2a0>
```



In [48]:
```
lis=li.score(x_test,y_test)
```

In [49]:
```
df3["TCH"].value_counts()
```

Out[49]:
```
1.38    1274
1.37    1246
1.36    1243
1.39    1242
1.35    1209
        ...
3.30       1
2.95       1
3.38       1
2.51       1
1.02       1
Name: TCH, Length: 177, dtype: int64
```

In [50]:
```
df3.loc[df3["TCH"]<1.40,"TCH"]=1
df3.loc[df3["TCH"]>1.40,"TCH"]=2
df3["TCH"].value_counts()
```

Out[50]:
```
2.0    12904
1.0    12727
Name: TCH, dtype: int64
```

Lasso

In [51]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[51]:
```
Lasso(alpha=5)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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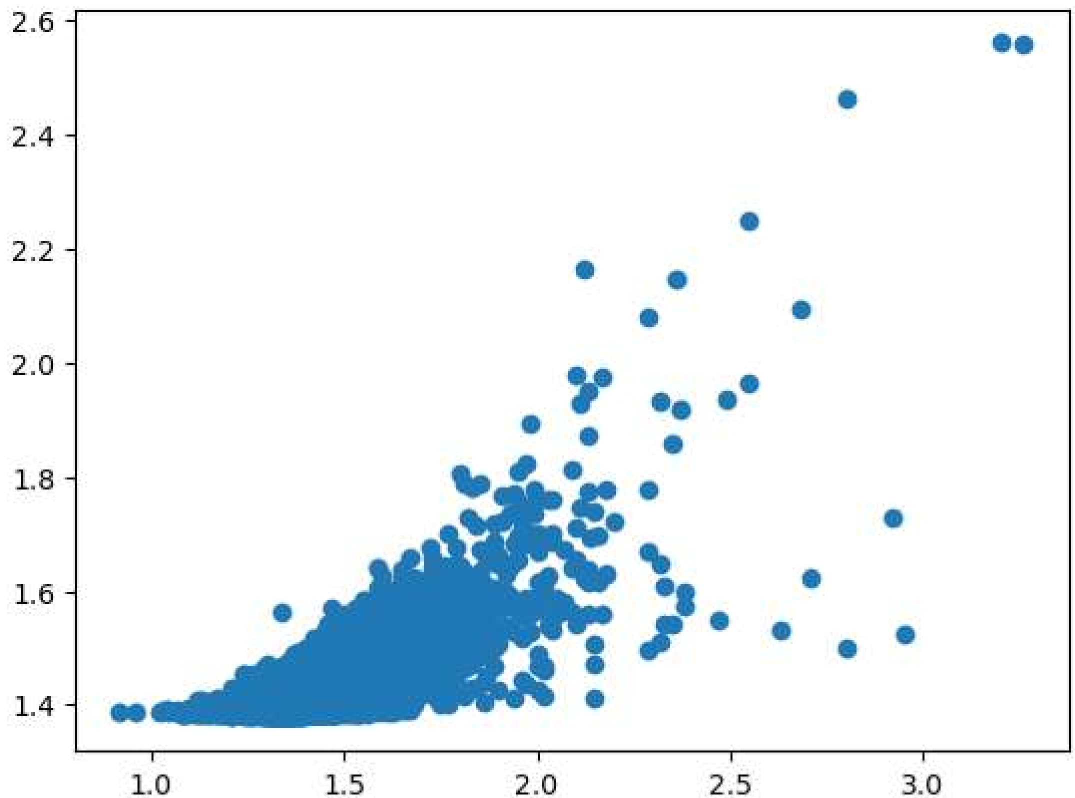
In [52]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[52]: <matplotlib.collections.PathCollection at 0x7fd55143e290>



In [53]:
```
las=la.score(x_test,y_test)
```

Ridge

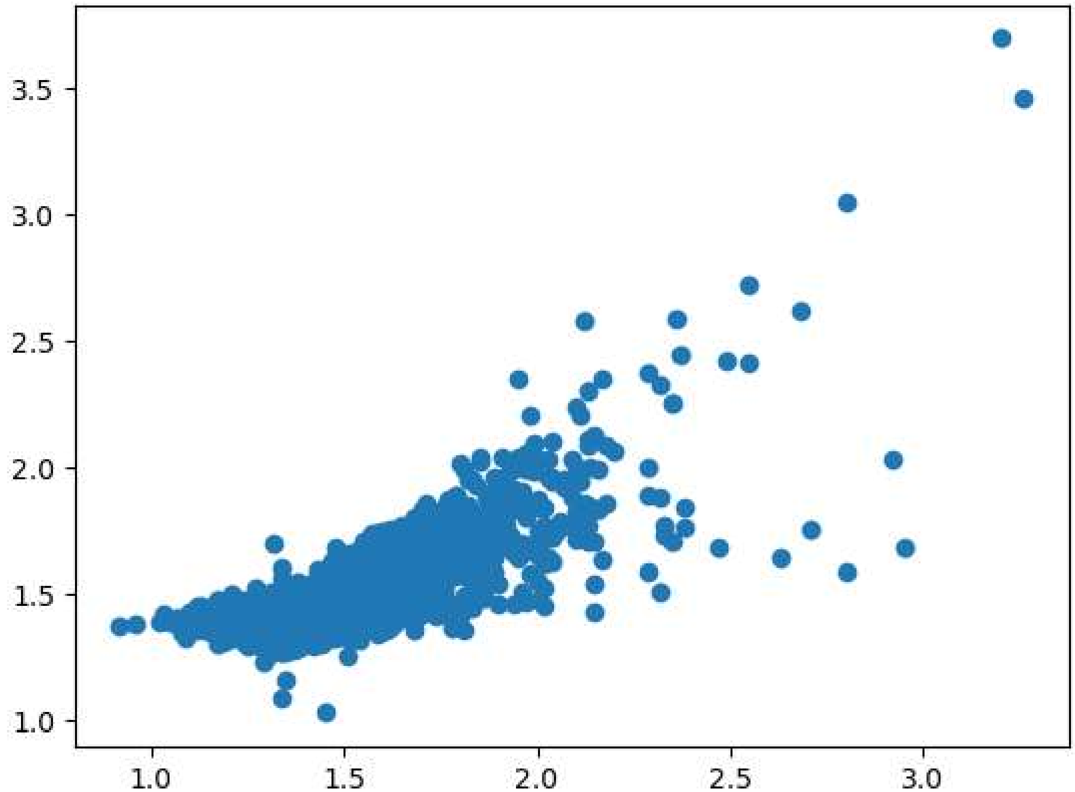
In [54]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[54]: `Ridge(alpha=1)`

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [55]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[55]: `<matplotlib.collections.PathCollection at 0x7fd54457dea0>`



In [56]:
```
rrs=rr.score(x_test,y_test)
```

ElasticNet

In [57]:
```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[57]:
```
ElasticNet()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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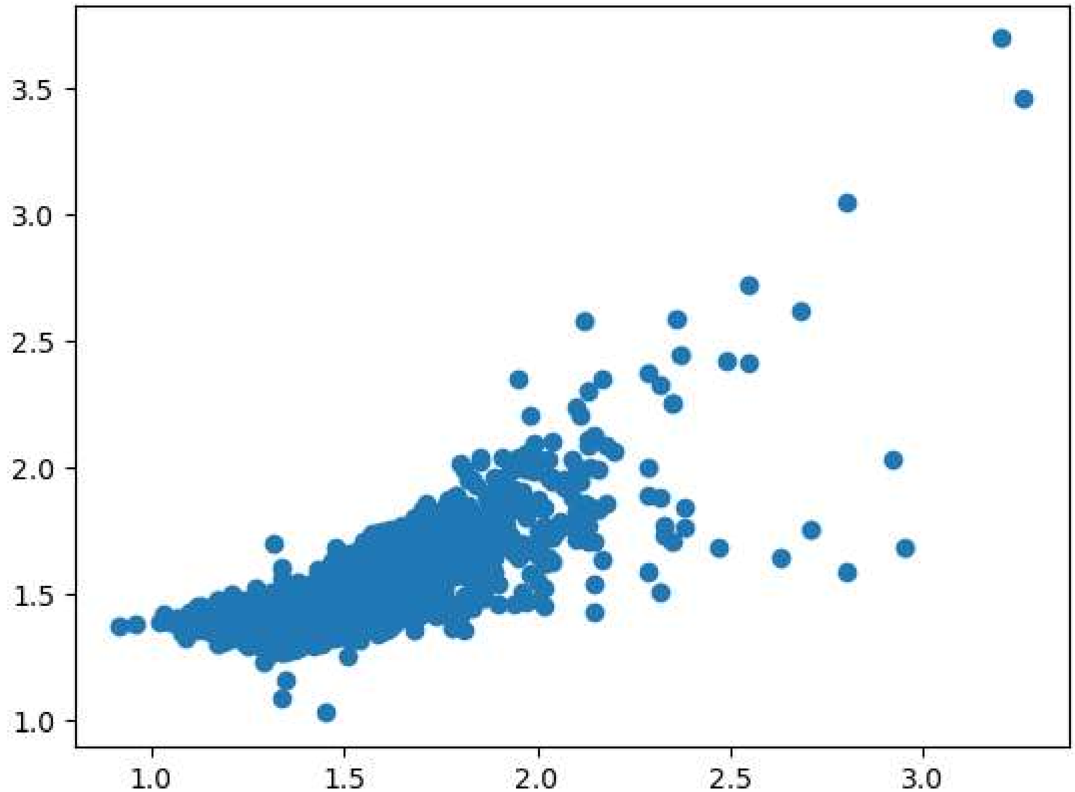
In [58]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[58]: <matplotlib.collections.PathCollection at 0x7fd5445fc940>



In [59]:
```
ens=en.score(x_test,y_test)
```

In [60]:
```
print(rr.score(x_test,y_test))
rr.score(x_train,y_train)
```

0.6686325972014862

Out[60]: 0.6552401520013147

Logistic

In [61]:
```
g={"TCH":{1.0:"Low",2.0:"High"}}
df3=df3.replace(g)
df3["TCH"].value_counts()
```

Out[61]:
```
High    12904
Low     12727
Name: TCH, dtype: int64
```

In [62]:
```
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 [63]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[63]:
```
LogisticRegression()
```

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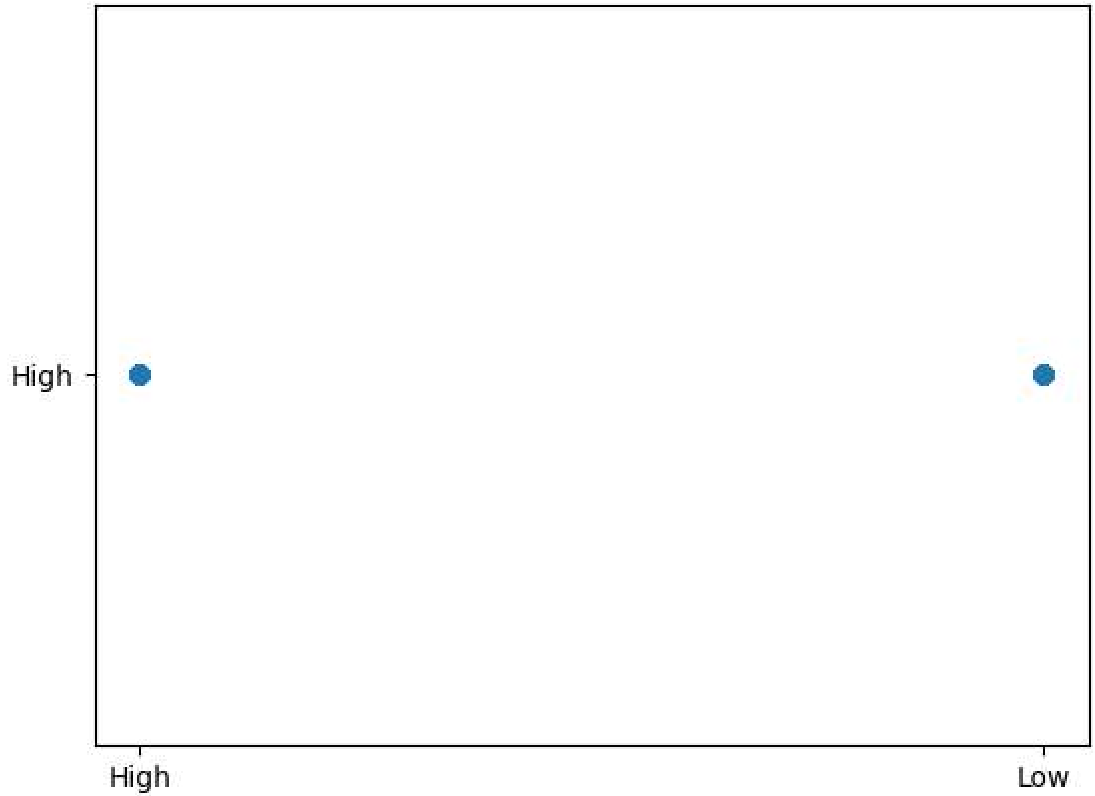
In [64]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[64]: <matplotlib.collections.PathCollection at 0x7fd5449f6890>



In [65]:
```
los=lo.score(x_test,y_test)
```

Random Forest

In [66]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [67]:
```
g1={"TCH":{"Low":1.0,"High":2.0}}
df3=df3.replace(g1)
```

In [68]:
```
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 [69]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[69]:
```
RandomForestClassifier()
```

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In [70]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [71]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

Out[71]:
```
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 a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [72]:
```
rfcs=grid_search.best_score_
```

In [73]:
```
rfc_best=grid_search.best_estimator_
```

In [74]:
```
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"],filled=True)
```

Out[74]:
```
[Text(0.5114583333333333, 0.9285714285714286, 'TOL <= 4.835\ngini = 0.5\nsamples = 11347\nvalue = [8960,
8981]\nclass = No'),
 Text(0.26666666666666666, 0.7857142857142857, 'O_3 <= 26.165\ngini = 0.436\nsamples = 7485\nvalue = [804
7, 3809]\nclass = Yes'),
 Text(0.13333333333333333, 0.6428571428571429, 'SO_2 <= 11.4\ngini = 0.435\nsamples = 1795\nvalue = [914,
1945]\nclass = No'),
 Text(0.06666666666666667, 0.5, 'MXY <= 1.325\ngini = 0.474\nsamples = 1055\nvalue = [647, 1029]\nclass =
No'),
 Text(0.03333333333333333, 0.35714285714285715, 'TOL <= 3.185\ngini = 0.499\nsamples = 516\nvalue = [437,
410]\nclass = Yes'),
 Text(0.016666666666666666, 0.21428571428571427, 'EBE <= 0.605\ngini = 0.496\nsamples = 451\nvalue = [40
4, 335]\nclass = Yes'),
 Text(0.008333333333333333, 0.07142857142857142, 'gini = 0.497\nsamples = 229\nvalue = [176, 204]\nclass
= No'),
 Text(0.025, 0.07142857142857142, 'gini = 0.463\nsamples = 222\nvalue = [228, 131]\nclass = Yes'),
 Text(0.05, 0.21428571428571427, 'NMHC <= 0.135\ngini = 0.424\nsamples = 65\nvalue = [33, 75]\nclass = N
o'),
 Text(0.041666666666666664, 0.07142857142857142, 'gini = 0.43\nsamples = 12\nvalue = [11, 5]\nclass = Ye
s'),
```

In [75]:
```
print("Linear:",lis)
print("Lasso:",las)
print("Ridge:",rrs)
print("ElasticNet:",ens)
print("Logistic:",los)
print("Random Forest:",rfcs)
```

```
Linear: 0.6686214896300879
Lasso: 0.4702435204100489
Ridge: 0.6686325972014862
ElasticNet: 0.5832313700304619
Logistic: 0.5042912873862159
Random Forest: 0.8318935211402727
```

Best model is Random Forest