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_2013
df
```

Out[2]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	station
0	2013-11-01 01:00:00	NaN	0.6	NaN	NaN	135.0	74.0	NaN	NaN	NaN	7.0	NaN	NaN	28079004
1	2013-11-01 01:00:00	1.5	0.5	1.3	NaN	71.0	83.0	2.0	23.0	16.0	12.0	NaN	8.3	28079008
2	2013-11-01 01:00:00	3.9	NaN	2.8	NaN	49.0	70.0	NaN	NaN	NaN	NaN	NaN	9.0	28079011
3	2013-11-01 01:00:00	NaN	0.5	NaN	NaN	82.0	87.0	3.0	NaN	NaN	NaN	NaN	NaN	28079016
4	2013-11-01 01:00:00	NaN	NaN	NaN	NaN	242.0	111.0	2.0	NaN	NaN	12.0	NaN	NaN	28079017
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
209875	2013-03-01 00:00:00	NaN	0.4	NaN	NaN	8.0	39.0	52.0	NaN	NaN	NaN	NaN	NaN	28079056
209876	2013-03-01 00:00:00	NaN	0.4	NaN	NaN	1.0	11.0	NaN	6.0	NaN	2.0	NaN	NaN	28079057
209877	2013-03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	4.0	75.0	NaN	NaN	NaN	NaN	NaN	28079058
209878	2013-03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	11.0	52.0	NaN	NaN	NaN	NaN	NaN	28079059
209879	2013-03-01 00:00:00	NaN	NaN	NaN	NaN	1.0	10.0	75.0	3.0	NaN	NaN	NaN	NaN	28079060

209880 rows × 14 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209880 entries, 0 to 209879
Data columns (total 14 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     209880 non-null  object 
 1   BEN      50462 non-null   float64
 2   CO       87018 non-null   float64
 3   EBE      50463 non-null   float64
 4   NMHC     25935 non-null   float64
 5   NO       209108 non-null  float64
 6   NO_2     209108 non-null  float64
 7   O_3      121858 non-null  float64
 8   PM10     104339 non-null  float64
 9   PM25     51980 non-null   float64
 10  SO_2     86970 non-null   float64
 11  TCH      25935 non-null   float64
 12  TOL      50317 non-null   float64
 13  station  209880 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 22.4+ MB
```

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

Out[4]:

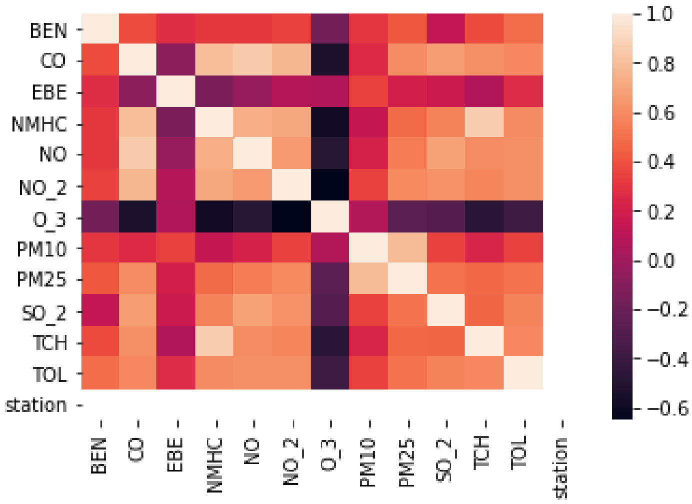
	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	station
17286	2013-08-01 01:00:00	0.4	0.2	0.8	0.28	1.0	24.0	79.0	35.0	8.0	3.0	1.49	1.3	28079024
17310	2013-08-01 02:00:00	0.5	0.2	0.9	0.28	1.0	16.0	93.0	60.0	18.0	3.0	1.61	4.0	28079024
17334	2013-08-01 03:00:00	0.5	0.2	1.1	0.29	1.0	14.0	90.0	38.0	12.0	3.0	1.71	2.8	28079024
17358	2013-08-01 04:00:00	0.6	0.2	1.2	0.26	1.0	12.0	84.0	30.0	8.0	3.0	1.44	2.8	28079024
17382	2013-08-01 05:00:00	0.3	0.2	0.8	0.25	1.0	15.0	72.0	25.0	7.0	3.0	1.40	1.7	28079024
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
209622	2013-02-28 14:00:00	1.1	0.3	0.3	0.27	3.0	17.0	64.0	5.0	5.0	2.0	1.41	0.9	28079024
209646	2013-02-28 15:00:00	1.3	0.4	0.3	0.27	2.0	16.0	66.0	6.0	5.0	1.0	1.40	0.9	28079024
209670	2013-02-28 16:00:00	1.1	0.3	0.3	0.27	1.0	17.0	65.0	5.0	4.0	1.0	1.40	0.7	28079024
209694	2013-02-28 17:00:00	1.0	0.3	0.4	0.27	1.0	18.0	64.0	5.0	5.0	1.0	1.39	0.7	28079024
209718	2013-02-28 18:00:00	1.0	0.3	0.4	0.27	1.0	22.0	62.0	6.0	6.0	1.0	1.39	0.7	28079024

7315 rows × 14 columns

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

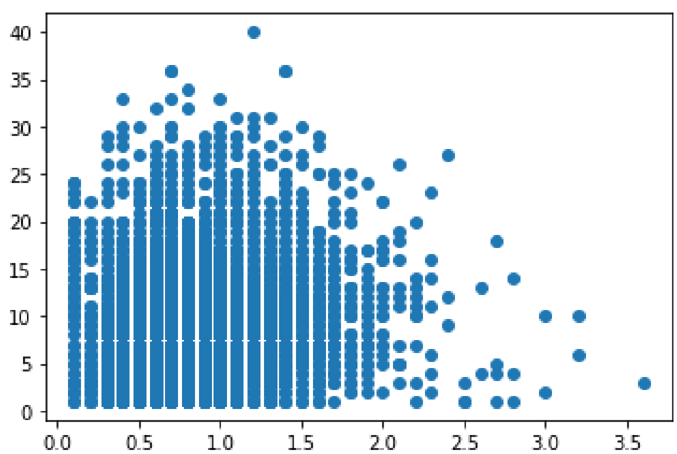
In [6]:
```
sns.heatmap(df1.corr())
```

Out[6]: <AxesSubplot:>



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

Out[7]: [<matplotlib.lines.Line2D at 0x25a0674f250>]



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)
```

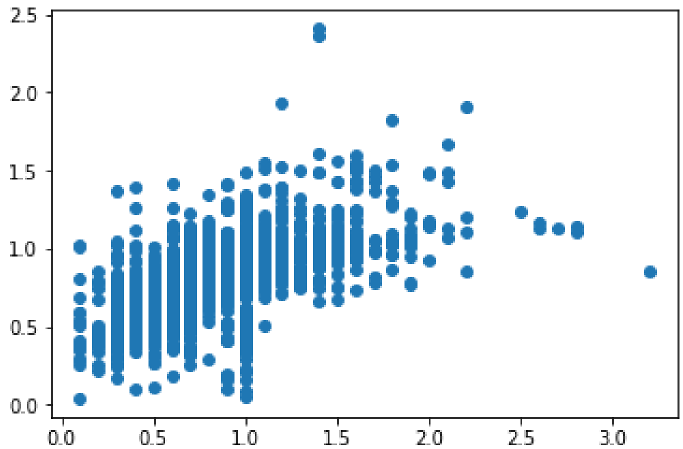
Linear

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 0x25a06816790>



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

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

Out[12]:
```
1.32    888
1.33    843
1.34    729
1.31    719
1.35    556
       ...
1.23      1
2.09      1
1.84      1
2.25      1
2.29      1
Name: TCH, Length: 114, 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    5718
2.0    1597
Name: TCH, dtype: int64
```

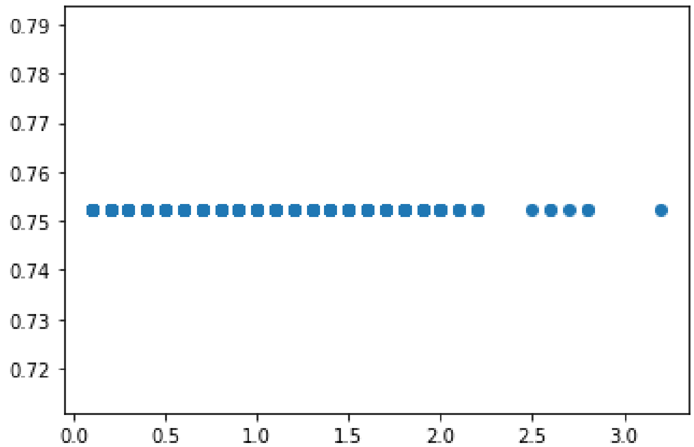
Lasso

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 0x25a0687ed90>



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

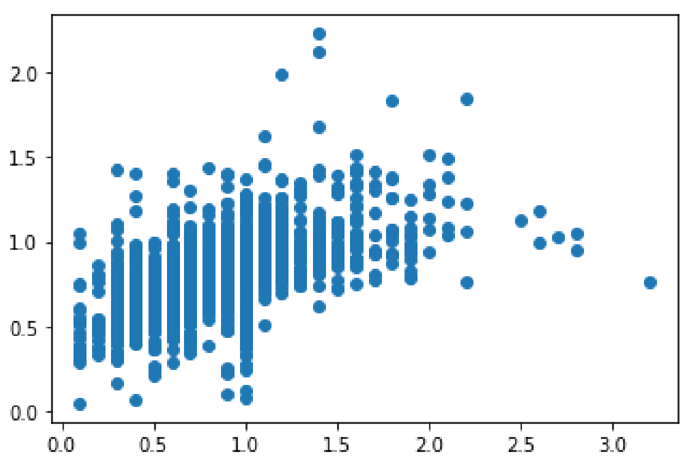
Ridge

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 0x25a066009d0>



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

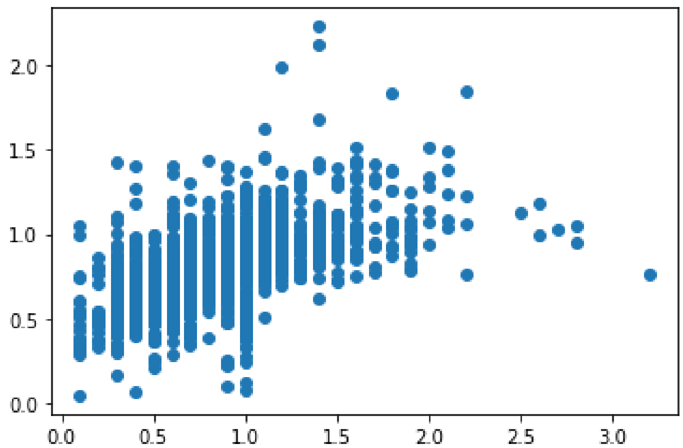
ElasticNet

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 0x25a07126cd0>



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

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

```
0.38794864124666883
```

Out[23]: 0.391803939842712

Logistic

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

Out[24]:
```
Low     5718
High    1597
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 0x25a07187280>

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="accuracy")
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',"No"],fill
```

Out[37]:
```
[Text(2305.4210526315787, 2019.0857142857144, 'TOL <= 1.75\ngini = 0.337\nsamples =
3228\nvalue = [4020, 1100]\nclass = Yes'),
 Text(1204.1052631578948, 1708.457142857143, 'O_3 <= 26.5\ngini = 0.195\nsamples = 2
605\nvalue = [3677, 453]\nclass = Yes'),
 Text(469.89473684210526, 1397.8285714285716, 'NMHC <= 0.265\ngini = 0.436\nsamples
= 262\nvalue = [124, 262]\nclass = No'),
 Text(234.94736842105263, 1087.2, 'PM10 <= 19.5\ngini = 0.266\nsamples = 59\nvalue =
[80, 15]\nclass = Yes'),
 Text(176.21052631578948, 776.5714285714287, 'TOL <= 1.55\ngini = 0.217\nsamples = 5
4\nvalue = [78, 11]\nclass = Yes'),
 Text(117.47368421052632, 465.9428571428573, 'EBE <= 1.15\ngini = 0.147\nsamples = 4
6\nvalue = [69, 6]\nclass = Yes'),
 Text(58.73684210526316, 155.3142857142857, 'gini = 0.215\nsamples = 31\nvalue = [4
3, 6]\nclass = Yes'),
 Text(176.21052631578948, 155.3142857142857, 'gini = 0.0\nsamples = 15\nvalue = [26,
0]\nclass = Yes'),
 Text(234.94736842105263, 465.9428571428573, 'gini = 0.459\nsamples = 8\nvalue = [9,
5]\nclass = Yes'),
 Text(293.6842105263158, 776.5714285714287, 'gini = 0.444\nsamples = 5\nvalue = [2,
```

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

```
Linear: 0.4114978071131482
Lasso: -6.234443005292967e-05
Ridge: 0.38794864124666883
ElasticNet: 0.09906134120330623
Logistic: 0.7831435079726652
Random Forest: 0.9505859375000001
```

Best Model is Random Forest

In [39]:
```
df2=pd.read_csv("C:/Users/user/Downloads/FP1_air/csvs_per_year/csvs_per_year/madrid_2014
df2
```

Out[39]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	station
0	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	3.0	10.0	NaN	NaN	NaN	3.0	NaN	NaN	28079004
1	2014-06-01 01:00:00	0.2	0.2	0.1	0.11	3.0	17.0	68.0	10.0	5.0	5.0	1.36	1.3	28079008
2	2014-06-01 01:00:00	0.3	NaN	0.1	NaN	2.0	6.0	NaN	NaN	NaN	NaN	NaN	1.1	28079011
3	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	1.0	6.0	79.0	NaN	NaN	NaN	NaN	NaN	28079016
4	2014-06-01 01:00:00	NaN	NaN	NaN	NaN	1.0	6.0	75.0	NaN	NaN	4.0	NaN	NaN	28079017
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
210019	2014-09-01 00:00:00	NaN	0.5	NaN	NaN	20.0	84.0	29.0	NaN	NaN	NaN	NaN	NaN	28079056
210020	2014-09-01 00:00:00	NaN	0.3	NaN	NaN	1.0	22.0	NaN	15.0	NaN	6.0	NaN	NaN	28079057
210021	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	13.0	70.0	NaN	NaN	NaN	NaN	NaN	28079058
210022	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	3.0	38.0	42.0	NaN	NaN	NaN	NaN	NaN	28079059
210023	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	26.0	65.0	11.0	NaN	NaN	NaN	NaN	28079060

210024 rows × 14 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210024 entries, 0 to 210023
Data columns (total 14 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     210024 non-null  object 
 1   BEN      46703 non-null   float64
 2   CO       87023 non-null   float64
 3   EBE      46722 non-null   float64
 4   NMHC     25021 non-null   float64
 5   NO       209154 non-null  float64
 6   NO_2     209154 non-null  float64
 7   O_3      121681 non-null  float64
 8   PM10     104311 non-null  float64
 9   PM25     51954 non-null   float64
 10  SO_2     87141 non-null   float64
 11  TCH      25021 non-null   float64
 12  TOL      46570 non-null   float64
 13  station  210024 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 22.4+ MB
```

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

Out[41]:

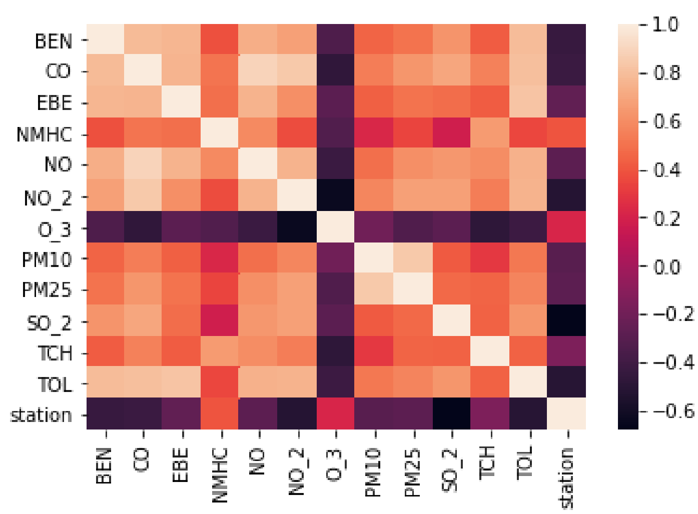
	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	station
1	2014-06-01 01:00:00	0.2	0.2	0.1	0.11	3.0	17.0	68.0	10.0	5.0	5.0	1.36	1.3	28079008
6	2014-06-01 01:00:00	0.1	0.2	0.1	0.23	1.0	5.0	80.0	4.0	3.0	2.0	1.21	0.1	28079024
25	2014-06-01 02:00:00	0.2	0.2	0.1	0.11	4.0	21.0	63.0	9.0	6.0	5.0	1.36	0.8	28079008
30	2014-06-01 02:00:00	0.2	0.2	0.1	0.23	1.0	4.0	88.0	7.0	5.0	2.0	1.21	0.1	28079024
49	2014-06-01 03:00:00	0.1	0.2	0.1	0.11	4.0	18.0	66.0	9.0	7.0	6.0	1.36	0.9	28079008
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
209958	2014-08-31 22:00:00	0.2	0.2	0.1	0.22	1.0	28.0	96.0	61.0	15.0	3.0	1.28	0.1	28079024
209977	2014-08-31 23:00:00	1.1	0.7	0.7	0.19	36.0	118.0	23.0	60.0	25.0	9.0	1.27	6.5	28079008
209982	2014-08-31 23:00:00	0.2	0.2	0.1	0.21	1.0	17.0	90.0	28.0	14.0	3.0	1.27	0.2	28079024
210001	2014-09-01 00:00:00	0.6	0.4	0.4	0.12	6.0	63.0	41.0	26.0	15.0	8.0	1.19	4.1	28079008
210006	2014-09-01 00:00:00	0.2	0.2	0.1	0.23	1.0	30.0	69.0	18.0	13.0	3.0	1.30	0.1	28079024

13946 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

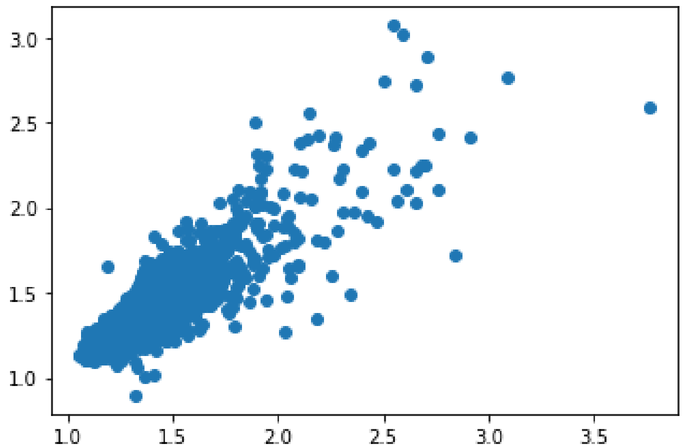
In [45]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[45]:
```
LinearRegression()
```

In [ ]:

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

Out[46]:
```
<matplotlib.collections.PathCollection at 0x25a0b165d60>
```



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

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

Out[48]:
```
1.37    601
1.36    598
1.34    529
1.35    528
1.38    515
       ...
2.50      1
2.86      1
2.70      1
3.04      1
4.37      1
Name: TCH, Length: 184, 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    9997
2.0    3949
Name: TCH, dtype: int64
```

In [ ]:

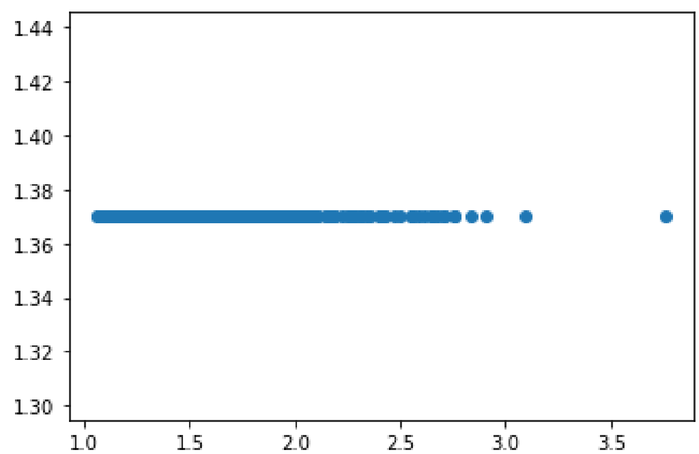
Lasso

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 0x25a0b1bca90>



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

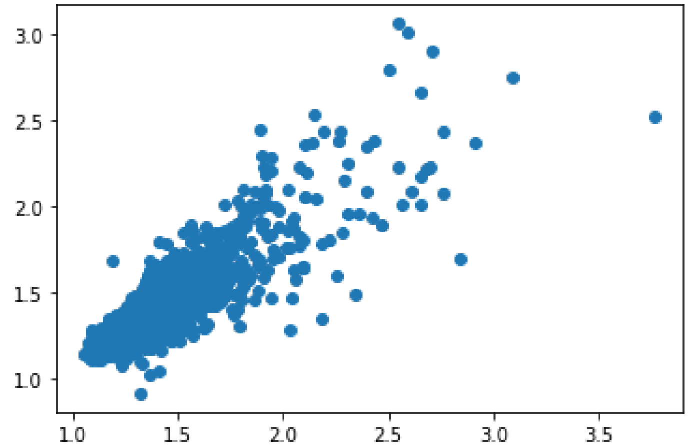
Ridge

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 0x25a0b21f100>



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

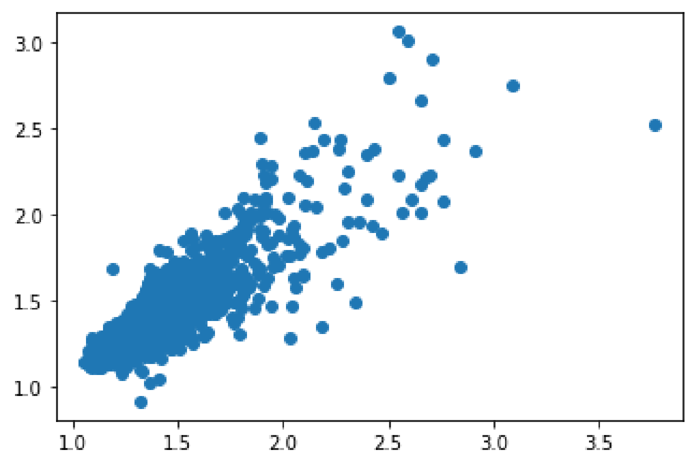
ElasticNet

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 0x25a0b26e6a0>



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

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

```
0.7037488127556343
```

Out[59]:
```
0.7081013643502528
```

Logistic

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

Out[60]:
```
Low     9997
High    3949
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 0x25a0b2a06a0>
```

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="accuracy")
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',"No"],fill
```

```
367\nvalue = [197, 363]\nclass = No'),
 Text(474.8936170212766, 465.9428571428573, 'BEN <= 0.35\ngini = 0.407\nsamples = 81
\nvalue = [88, 35]\nclass = Yes'),
 Text(427.40425531914894, 155.3142857142857, 'gini = 0.256\nsamples = 59\nvalue = [7
9, 14]\nclass = Yes'),
 Text(522.3829787234042, 155.3142857142857, 'gini = 0.42\nsamples = 22\nvalue = [9,
21]\nclass = No'),
 Text(664.8510638297872, 465.9428571428573, 'CO <= 0.25\ngini = 0.374\nsamples = 286
\nvalue = [109, 328]\nclass = No'),
 Text(617.3617021276596, 155.3142857142857, 'gini = 0.478\nsamples = 67\nvalue = [4
3, 66]\nclass = No'),
 Text(712.3404255319149, 155.3142857142857, 'gini = 0.321\nsamples = 219\nvalue = [6
6, 262]\nclass = No'),
 Text(1139.7446808510638, 1087.2, 'O_3 <= 52.5\ngini = 0.16\nsamples = 3774\nvalue =
[5439, 523]\nclass = Yes'),
 Text(949.7872340425532, 776.5714285714287, 'CO <= 0.25\ngini = 0.299\nsamples = 100
8\nvalue = [1299, 291]\nclass = Yes'),
 Text(854.8085106382979, 465.9428571428573, 'PM25 <= 11.5\ngini = 0.251\nsamples = 5
68\nvalue = [766, 132]\nclass = Yes'),
 Text(807.3191489361702, 155.3142857142857, 'gini = 0.216\nsamples = 483\nvalue = [6
```

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

```
Linear: 0.6984961782299648
Lasso: -0.00010435529624808204
Ridge: 0.7037488127556343
ElasticNet: 0.45599972417723134
Logistic: 0.7194072657743786
Random Forest: 0.8882401147305881
```

Best model is Random Forest

In [ ]: