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,LogisticRegressio
from sklearn.model_selection import train_test_split

In [2]: df=pd.read_csv("/Users/bob/Downloads/FP1_air/csvs_per_year/csvs_per
 df

Out[2]:

	date	BEN	CH4	СО	EBE	NMHC	NO	NO_2	NOx	O_3	PM10	PM25	SO
0	2017- 06-01 01:00:00	NaN	NaN	0.3	NaN	NaN	4.0	38.0	NaN	NaN	NaN	NaN	5
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
2	2017- 06-01 01:00:00	0.2	NaN	NaN	0.1	NaN	1.0	14.0	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	Na
4	2017- 06-01 01:00:00	NaN	NaN	NaN	NaN	NaN	1.0	19.0	NaN	69.0	NaN	NaN	2
210115	2017- 08-01 00:00:00	NaN	NaN	0.2	NaN	NaN	1.0	27.0	NaN	65.0	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
210117	2017- 08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	4.0	NaN	83.0	NaN	NaN	Na
210118	2017- 08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	11.0	NaN	78.0	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	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	N0_2	209065 non-null	float64
8	N0x	52818 non-null	float64
9	0_3	121398 non-null	float64
10	PM10	104141 non-null	float64
11	PM25	52023 non-null	float64
12	S0_2	86803 non-null	float64
13	TCH	25472 non-null	float64
14	T0L	50117 non-null	float64
15	station	210120 non-null	int64
d+vn	ac: float	64(14) in+64(1)	object(1

dtypes: float64(14), int64(1), object(1)

memory usage: 25.6+ MB

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

Out[4]:

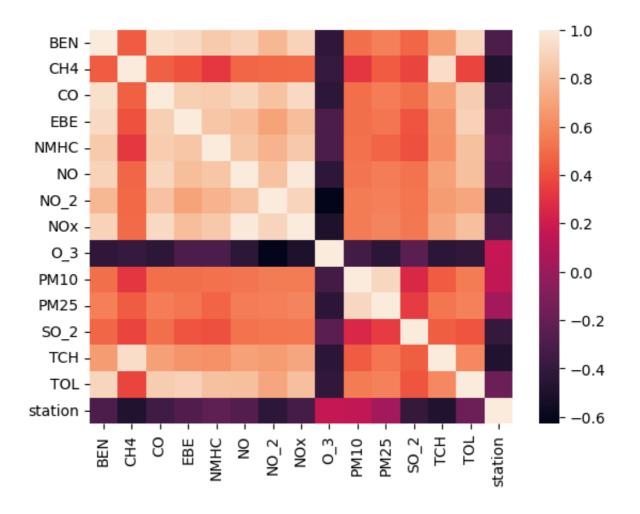
	date	BEN	CH4	СО	EBE	NMHC	NO	NO_2	NOx	0_3	PM10	PM25	SO_4
87457	2017- 10-01 01:00:00	0.6	1.22	0.3	0.4	0.09	4.0	54.0	60.0	43.0	12.0	9.0	13.(
87462	2017- 10-01 01:00:00	0.2	1.18	0.2	0.1	0.09	1.0	26.0	28.0	42.0	14.0	6.0	3.0
87481	2017- 10-01 02:00:00	0.4	1.22	0.2	0.2	0.06	2.0	32.0	36.0	53.0	14.0	10.0	13.(
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
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.(
	•••												
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
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
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
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
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

4127 rows × 16 columns

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

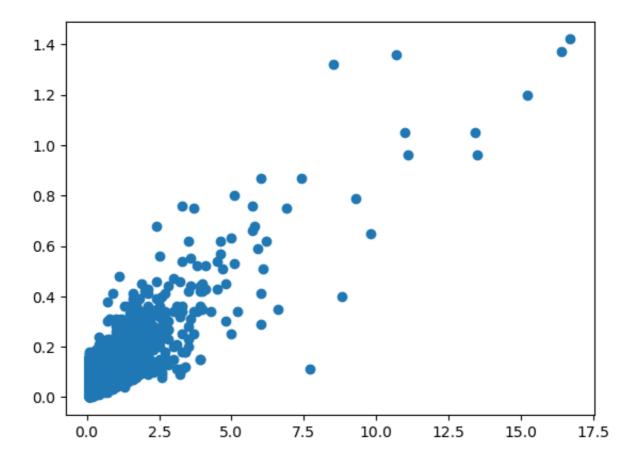
In [6]: sns.heatmap(df1.corr())

Out[6]: <Axes: >



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

Out[7]: [<matplotlib.lines.Line2D at 0x7fe3e8c2f910>]



```
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)
```

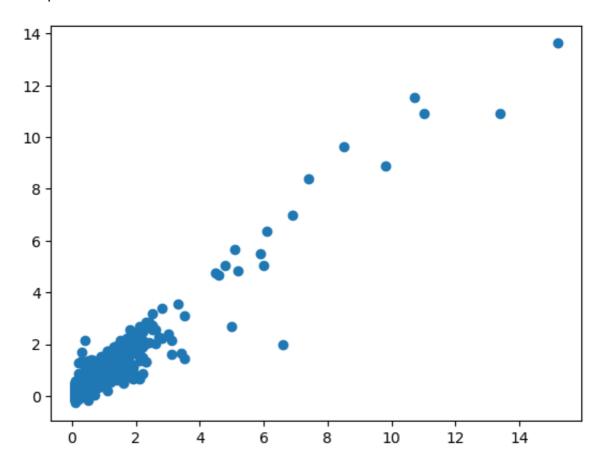
Linear

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

Out[10]: v LinearRegression LinearRegression()

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

Out[11]: <matplotlib.collections.PathCollection at 0x7fe409097e20>



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

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

```
Out[13]: 1.24
                   124
          1.36
                   118
          1.26
                   112
          1.25
                   110
          1.33
                   107
          3.17
                      1
          3.22
                      1
          3.02
                     1
          2.75
                      1
          2.71
```

Name: TCH, Length: 164, 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 2428

2.0 1699

Name: TCH, dtype: int64

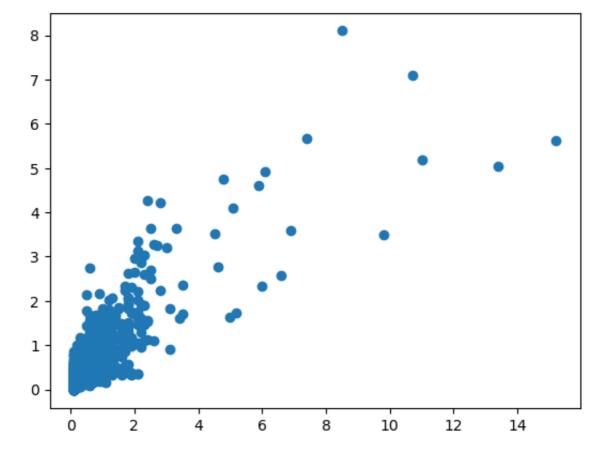
Lasso

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

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

```
In [16]: prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[16]: <matplotlib.collections.PathCollection at 0x7fe4097671f0>

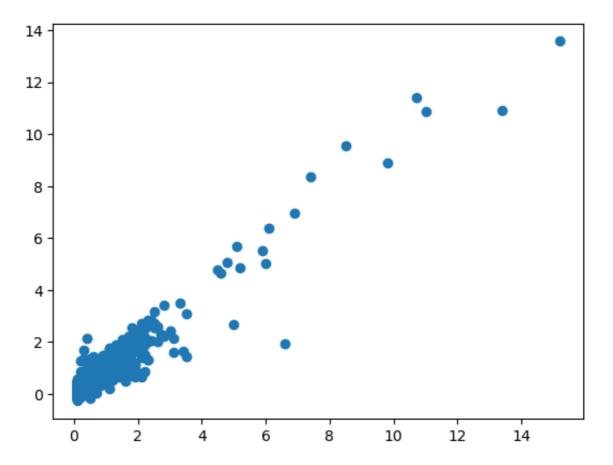


```
In [17]: las=la.score(x_test,y_test)
```

Ridge

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

Out[19]: <matplotlib.collections.PathCollection at 0x7fe4097fb3a0>



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

ElasticNet

```
In [21]: en=ElasticNet()
          en.fit(x_train,y_train)
Out [21]:
          ▼ ElasticNet
          ElasticNet()
In [22]: | prediction2=rr.predict(x_test)
         plt.scatter(y_test,prediction2)
Out[22]: <matplotlib.collections.PathCollection at 0x7fe409566980>
           14
           12
           10
            8
            6
            4
            2
            0
                0
                        2
                               4
                                       6
                                               8
                                                      10
                                                             12
                                                                     14
In [23]: ens=en.score(x_test,y_test)
```

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

0.9059346080236226

Out[24]: 0.8762721659976673

Logistic

```
In [25]: g={"TCH":{1.0:"Low",2.0:"High"}}
         df1=df1.replace(g)
         df1["TCH"].value_counts()
Out[25]: Low
                 2428
                 1699
         High
         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
          LogisticRegression()
In [28]: prediction3=lo.predict(x_test)
         plt.scatter(y_test,prediction3)
Out[28]: <matplotlib.collections.PathCollection at 0x7fe409609bd0>
          Low
                High
                                                                       Low
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]: |q1={"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
          RandomForestClassifier()
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,sc
         grid search.fit(x train,y train)
Out[35]:
                       GridSearchCV
           ▶ estimator: RandomForestClassifier
                ▶ RandomForestClassifier
In [36]: rfcs=grid_search.best_score_
In [37]: rfc_best=grid_search.best_estimator_
```

```
In [38]: from sklearn.tree import plot_tree
                              plt.figure(figsize=(80,40))
                              plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_nam
Out[38]: [Text(0.4816666666666667, 0.9285714285714286, 'EBE <= 0.25\ngini =</pre>
                              0.485\nsamples = 1802\nvalue = [1697, 1191]\nclass = Yes'),
                                 = 0.26\nsamples = 823\nvalue = [1115, 202]\nclass = Yes'),
                                 Text(0.143333333333333334, 0.6428571428571429, 'SO_2 <= 6.5 \ngini
                              = 0.392 \times = 409 \times = [485, 177] \times = Yes')
                                 s = 358 \setminus value = [462, 121] \setminus class = Yes'),
                                 Text(0.02666666666666667, 0.35714285714285715, 'BEN <= 0.45\ngini
                              = 0.46\nsamples = 28\nvalue = [14, 25]\nclass = No'),
                                 Text(0.013333333333333334, 0.21428571428571427, 'qini = 0.42 \nsam
                              ples = 7\nvalue = [7, 3]\nclass = Yes'),
                                 Text(0.04, 0.21428571428571427, 'CH4 <= 1.38 \setminus gini = 0.366 \setminus gi
                              es = 21\nvalue = [7, 22]\nclass = No'),
                                 Text(0.02666666666666667, 0.07142857142857142, 'qini = 0.0 \nsample
                              es = 7\nvalue = [7, 0]\nclass = Yes'),
                                 Text(0.05333333333333334, 0.07142857142857142, 'gini = 0.0\nsampl
                              es = 14\nvalue = [0, 22]\nclass = No'),
                                 Text(0.12, 0.35714285714285715, 'station <= 28079016.0 \cdot \text{ngini} = 0.021
In [39]: print("Linear:", lis)
print("Lasso:", las)
                              print("Ridge:", rrs)
                              print("ElasticNet:",ens)
                              print("Logistic:",los)
                              print("Random Forest:",rfcs)
```

Linear: 0.9056106323408553 Lasso: 0.6651452631235361 Ridge: 0.9059346080236226 ElasticNet: 0.8167044214155901 Logistic: 0.5819209039548022

Random Forest: 0.9639889196675899

Best Model is Random Forest

Out[40]:

	date	BEN	CH4	СО	EBE	NMHC	NO	NO_2	NOx	0_3	PM10	PM25	S
0	2018- 03-01 01:00:00	NaN	NaN	0.3	NaN	NaN	1.0	29.0	31.0	NaN	NaN	NaN	
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	
2	2018- 03-01 01:00:00	0.4	NaN	NaN	0.2	NaN	4.0	41.0	47.0	NaN	NaN	NaN	1
3	2018- 03-01 01:00:00	NaN	NaN	0.3	NaN	NaN	1.0	35.0	37.0	54.0	NaN	NaN	1
4	2018- 03-01 01:00:00	NaN	NaN	NaN	NaN	NaN	1.0	27.0	29.0	49.0	NaN	NaN	
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	1
69092	2018- 02-01 00:00:00	NaN	NaN	0.7	NaN	NaN	87.0	107.0	241.0	NaN	29.0	NaN	1
69093	2018- 02-01 00:00:00	NaN	NaN	NaN	NaN	NaN	28.0	48.0	91.0	2.0	NaN	NaN	1
69094	2018- 02-01 00:00:00	NaN	NaN	NaN	NaN	NaN	141.0	103.0	320.0	2.0	NaN	NaN	1
69095	2018- 02-01 00:00:00	NaN	NaN	NaN	NaN	NaN	69.0	96.0	202.0	3.0	26.0	NaN	1

69096 rows × 16 columns

In [41]: 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	C0	28598 non-null	float64
4	EBE	16949 non-null	float64
5	NMHC	8440 non-null	float64
6	NO	68826 non-null	float64
7	N0_2	68826 non-null	float64
8	N0×	68826 non-null	float64
9	0_3	40049 non-null	float64
10	PM10	36911 non-null	float64
11	PM25	18912 non-null	float64
12	S0_2	28586 non-null	float64
13	TCH	8440 non-null	float64
14	T0L	16950 non-null	float64
15	station	69096 non-null	int64
d+vn	oci float	64(14) in+64(1)	obioc+(1)

dtypes: float64(14), int64(1), object(1)

memory usage: 8.4+ MB

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

Out[42]:

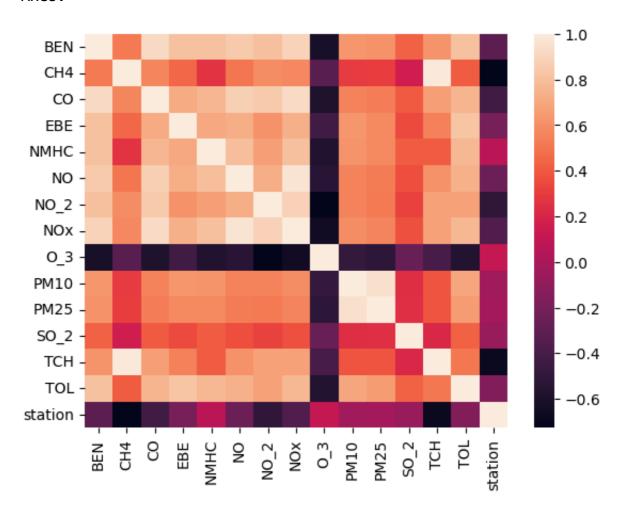
	date	BEN	CH4	СО	EBE	NMHC	NO	NO_2	NOx	0_3	PM10	PM25	so
1	2018- 03-01 01:00:00	0.5	1.39	0.3	0.2	0.02	6.0	40.0	49.0	52.0	5.0	4.0	:
6	2018- 03-01 01:00:00	0.4	1.11	0.2	0.1	0.06	1.0	25.0	27.0	55.0	5.0	4.0	2
25	2018- 03-01 02:00:00	0.4	1.42	0.2	0.1	0.01	4.0	26.0	32.0	64.0	4.0	4.0	:
30	2018- 03-01 02:00:00	0.3	1.10	0.2	0.1	0.05	1.0	12.0	13.0	69.0	5.0	4.0	4
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	:
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	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	{
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	{
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	(
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	ţ

4562 rows × 16 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

LinearRegression()

```
In [47]: prediction=li.predict(x_test)
          plt.scatter(y_test,prediction)
Out[47]: <matplotlib.collections.PathCollection at 0x7fe419825b70>
           4.0
           3.5
           3.0
           2.5
           2.0
           1.5
In [48]: lis=li.score(x_test,y_test)
In [49]: df3["TCH"].value_counts()
Out[49]: 1.15
                  246
          1.43
                  232
          1.44
                  223
          1.14
                  210
          1.13
                  201
          2.68
                    1
          2.43
                    1
          2.45
                    1
          2.12
          2.35
                    1
         Name: TCH, Length: 143, dtype: int64
In [50]: df3.loc[df3["TCH"]<1.40,"TCH"]=1</pre>
         df3.loc[df3["TCH"]>1.40,"TCH"]=2
         df3["TCH"].value_counts()
Out[50]: 2.0
                 2477
          1.0
                 2085
         Name: TCH, dtype: int64
 In [ ]:
```

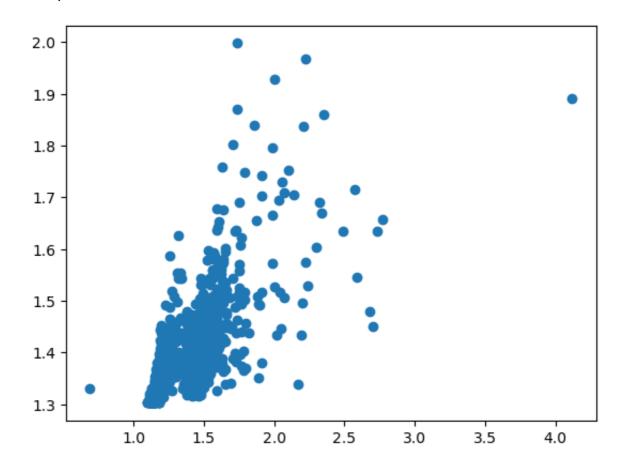
Lasso

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

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

In [52]: prediction1=la.predict(x_test)
 plt.scatter(y_test,prediction1)

Out[52]: <matplotlib.collections.PathCollection at 0x7fe419690670>



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

Ridge

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

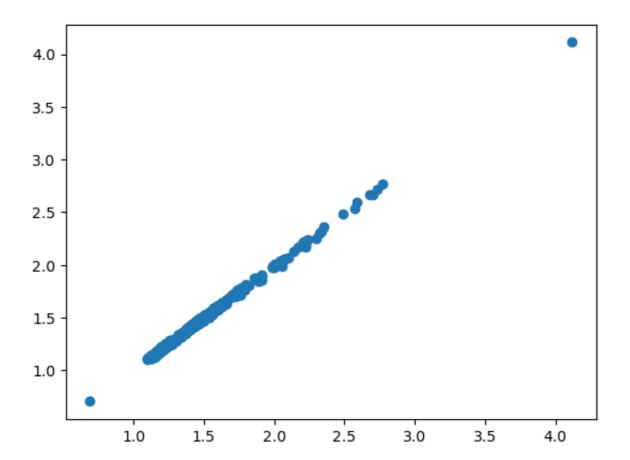
Out[54]:

▼ Ridge

Ridge(alpha=1)

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

Out[55]: <matplotlib.collections.PathCollection at 0x7fe3d852dde0>



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

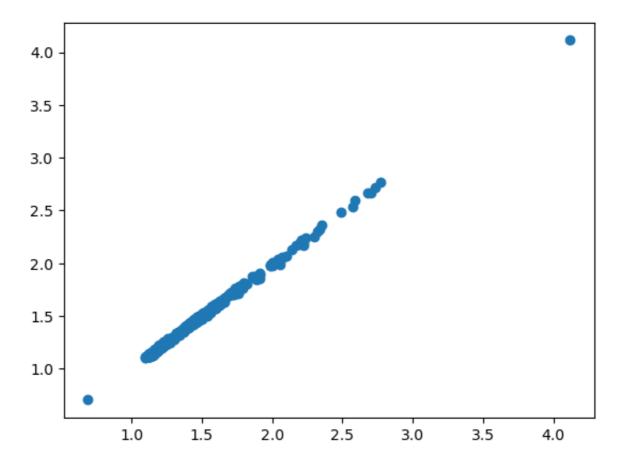
ElasticNet

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

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

```
In [58]: prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[58]: <matplotlib.collections.PathCollection at 0x7fe4198f1510>



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

0.9983120614140699

Out[60]: 0.9981277627436985

Logistic

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

Out[61]: High 2477 Low 2085

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()

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

Out[64]: <matplotlib.collections.PathCollection at 0x7fe419921510>
```

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

Random Forest

High

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

High

Low

```
In [67]: |g1={"TCH":{"Low":1.0,"High":2.0}}
                          df3=df3.replace(q1)
In [68]: x=df3.drop(["TCH"],axis=1)
                          v=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
                           RandomForestClassifier()
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,sc
                          grid_search.fit(x_train,y_train)
Out [71]:
                                                               GridSearchCV
                             ▶ estimator: RandomForestClassifier
                                             ▶ RandomForestClassifier
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_nam
0.496\nsamples = 2024\nvalue = [1450, 1743]\nclass = No'),
                            Text(0.1875, 0.75, 'NOx \leq 17.5\ngini = 0.252\nsamples = 704\nval
                          ue = [958, 166] \nclass = Yes'),
                            i = 0.056 \setminus samples = 395 \setminus samples = [612, 18] \setminus samples = Yes'),
                            Text(0.0416666666666664, 0.41666666666667, 'PM10 <= 3.5\ngini
                          = 0.497\nsamples = 20\nvalue = [13, 15]\nclass = No'),
                            Text(0.02083333333333332, 0.25, 'gini = 0.0\nsamples = 6\nvalue
                          = [0, 11] \setminus nclass = No'),
                            Text(0.0625, 0.25, 'NO \le 1.5 \le 0.36 \le 14 \le 1.5 \le 1.5
```

```
[13, 4] \setminus nclass = Yes'),
  Text(0.04166666666666664, 0.083333333333333, 'gini = 0.165\nsa
mples = 8\nvalue = [10, 1]\nclass = Yes'),
  es = 6\nvalue = [3, 3]\nclass = Yes'),
  Text(0.125, 0.416666666666667, 'NOx \leq 12.5\ngini = 0.01\nsample
s = 375 \setminus value = [599, 3] \setminus class = Yes'),
  Text(0.1041666666666667, 0.25, 'gini = 0.0\nsamples = 304\nvalue
= [484, 0] \setminus nclass = Yes'),
  Text(0.145833333333333334, 0.25, 'PM10 <= 1.5 \setminus injury = 0.05 \setminus injury = 0.0
s = 71 \setminus value = [115, 3] \setminus class = Yes'),
  e = [14, 3] \setminus class = Yes'),
  Text(0.16666666666666666, 0.083333333333333, 'gini = 0.0\nsampl
es = 63\nvalue = [101, 0]\nclass = Yes'),
  0.42\nsamples = 309\nvalue = [346, 148]\nclass = Yes'),
  Text(0.25, 0.416666666666667, 'station <= 28079016.0 \cdot \text{ngini} = 0.4
96\nsamples = 114\nvalue = [97, 82]\nclass = Yes'),
  es = 76\nvalue = [31, 82]\nclass = No'),
  ples = 49\nvalue = [16, 58]\nclass = No'),
  e = [15, 24] \setminus nclass = No'),
  Text(0.2708333333333333, 0.25, 'gini = 0.0\nsamples = 38\nvalue =
[66, 0] \setminus class = Yes'),
  = 0.331\nsamples = 195\nvalue = [249, 66]\nclass = Yes'),
  Text(0.3125, 0.25, 'gini = 0.496\nsamples = 6\nvalue = [6, 5]\ncl
ass = Yes'),
  Text(0.354166666666667, 0.25, 'NMHC <= 0.035 \ngini = 0.321 \nsamp
les = 189\nvalue = [243, 61]\nclass = Yes'),
  les = 80\nvalue = [84, 55]\nclass = Yes'),
  ue = [159, 6] \setminus class = Yes'),
  Text(0.723958333333334, 0.75, 'CH4 <= 1.375 \setminus gini = 0.362 \setminus gin
es = 1320\nvalue = [492, 1577]\nclass = No'),
  Text(0.5625, 0.58333333333333334, 'EBE <= 0.45 \setminus gini = 0.215 \setminus gini
les = 328\nvalue = [465, 65]\nclass = Yes'),
  Text(0.479166666666667, 0.41666666666667, 'station <= 2807901
6.0 \neq 0.166 = 277 = [407, 41] = Ye
s'),
  Text(0.4375, 0.25, 'NMHC \leq 0.045\ngini = 0.394\nsamples = 87\nva
lue = [100, 37]\nclass = Yes'),
  Text(0.4166666666666667, 0.08333333333333333, 'qini = 0.154\nsamp
les = 68\nvalue = [98, 9]\nclass = Yes'),
  les = 19\nvalue = [2, 28]\nclass = No'),
  Text(0.5208333333333334, 0.25, 'C0 \le 0.35 \neq 0.025 \land samples
= 190 \text{ nvalue} = [307, 4] \text{ nclass} = \text{Yes'},
```

 $= [233, 0] \setminus nclass = Yes'),$ les = 45\nvalue = [74, 4]\nclass = Yes'), Text(0.6458333333333334, 0.416666666666667, 'station <= 2807901 $6.0 \cdot 1 = 0.414 \cdot 1 = 51 \cdot 1$ = 11\nvalue = [3, 17]\nclass = No'), $Text(0.58333333333333334, 0.083333333333333, 'gini = 0.444 \nsamp$ les = 5\nvalue = [3, 6]\nclass = No'), $= [0, 11] \setminus nclass = No'),$ Text(0.6875, 0.25, 'CH4 \leq 1.29\ngini = 0.2\nsamples = 40\nvalue = $[55, 7] \setminus class = Yes'),$ Text(0.6666666666666666, 0.0833333333333333, 'gini = 0.0\nsample $s = 35 \setminus value = [55, 0] \setminus class = Yes'),$ $Text(0.7083333333333334, 0.083333333333333, 'gini = 0.0 \nsample$ $s = 5 \mid value = [0, 7] \mid value = No'),$ $= 0.034 \times = 992 \times = [27, 1512] \times = No'),$

 $Text(0.8125, 0.4166666666666667, 'TOL <= 1.15 \ngini = 0.358 \nsamp$ les = 70\nvalue = [25, 82]\nclass = No'),

 $Text(0.7708333333333334, 0.25, '0_3 \le 58.5 \setminus gini = 0.496 \setminus gini$ $s = 35 \setminus value = [24, 29] \setminus class = No'),$

 $e = [12, 27] \setminus nclass = No'),$

 $Text(0.7916666666666666, 0.083333333333333, 'gini = 0.245 \nsamp$ les = 13\nvalue = [12, 2]\nclass = Yes'),

les = 35\nvalue = [1, 53]\nclass = No'),

 $Text(0.833333333333334, 0.08333333333333, 'gini = 0.219\nsamp$ les = 6\nvalue = [1, 7]\nclass = No'),

 $= [0, 46] \setminus nclass = No'),$

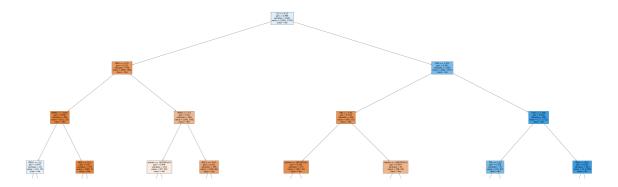
 $Text(0.95833333333333334, 0.4166666666666667, 'NOx <= 30.5 \ngini =$ 0.003\nsamples = 922\nvalue = [2, 1430]\nclass = No'),

 $Text(0.9375, 0.25, 'N0 \le 3.5 \le 0.089 \le 28 \le 28$ $= [2, 41] \setminus nclass = No'),$

 $s = 22 \setminus value = [0, 34] \setminus value = No'),$

 $Text(0.9583333333333334, 0.083333333333333, 'gini = 0.346 \nsamp$ les = 6\nvalue = [2, 7]\nclass = No'),

 $= [0, 1389] \setminus nclass = No')$





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

Linear: 0.9996090192033011 Lasso: 0.3875640304973138 Ridge: 0.9983120614140699 ElasticNet: 0.609503466089908 Logistic: 0.5507669831994156

Random Forest: 0.9793305665541436

Best model is Random Forest