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

Out[2]:		date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	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 Dtype Non-Null Count ---------0 date 209880 non-null object 50462 non-null float64 1 BEN 87018 non-null float64 2 C0 50463 non-null float64 3 EBE NMHC 25935 non-null float64 NO 209108 non-null float64 5 NO_2 209108 non-null float64 0 3 7 121858 non-null float64 8 PM10 104339 non-null float64 PM25 51980 non-null float64 10 SO 2 86970 non-null float64 11 TCH 25935 non-null float64 50317 non-null float64 12 TOL station 209880 non-null int64 13 dtypes: float64(12), int64(1), object(1)

memory usage: 22.4+ MB

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

Out[4]:

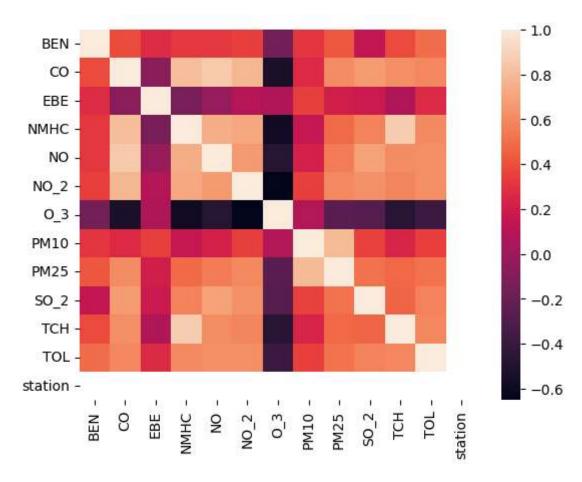
	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	station
17286	2013-08-01 01:00:00	0.4	0.2	8.0	0.28	1.0	24.0	79.0	35.0	8.0	3.0	1.49	1.3	28079024
17310	2013-08-01 02:00:00	0.5	0.2	0.9	0.28	1.0	16.0	93.0	60.0	18.0	3.0	1.61	4.0	28079024
17334	2013-08-01 03:00:00	0.5	0.2	1.1	0.29	1.0	14.0	90.0	38.0	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	8.0	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)

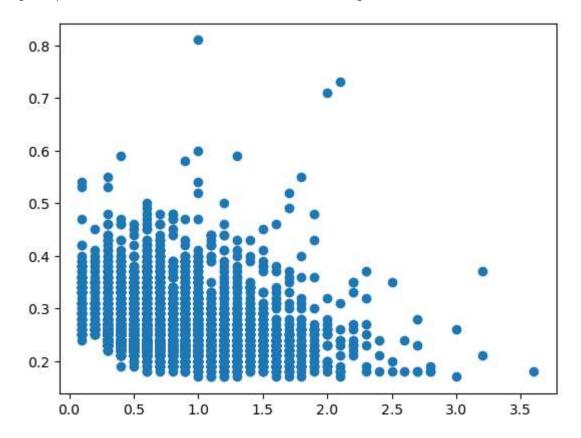
```
In [6]: sns.heatmap(df1.corr())
```

Out[6]: <Axes: >



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

Out[7]: [<matplotlib.lines.Line2D at 0x7f9d822f5150>]



```
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

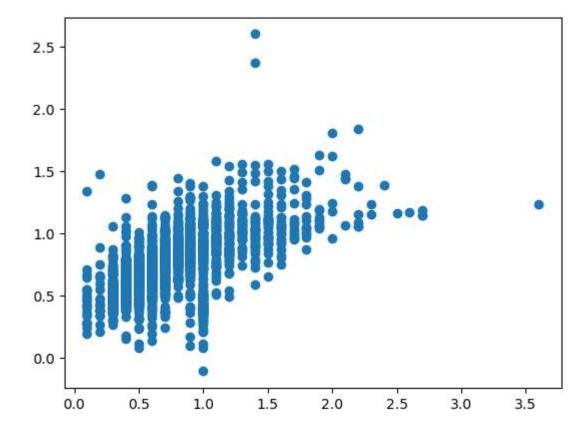
```
In [10]: li=LinearRegression()
li.fit(x_train,y_train)
```

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 0x7f9d92470940>



```
In [12]: lis=li.score(x_test,y_test)
In [13]: df1["TCH"].value counts()
Out[13]: 1.32
                  888
         1.33
                  843
         1.34
                 729
         1.31
                 719
         1.35
                  556
         2.39
                    1
         2.22
                    1
         2.29
                    1
         2.38
                    1
         2.80
                    1
         Name: TCH, Length: 114, dtype: int64
In [14]: df1.loc[df1["TCH"]<1.40,"TCH"]=1</pre>
         df1.loc[df1["TCH"]>1.40,"TCH"]=2
         df1["TCH"].value counts()
Out[14]: 1.0
                 5718
         2.0
                1597
         Name: TCH, dtype: int64
```

Lasso

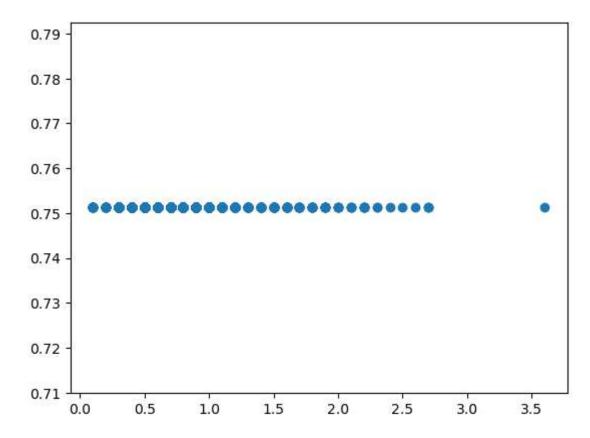
```
In [15]: la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[15]: Lasso(alpha=5)

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

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

Out[16]: <matplotlib.collections.PathCollection at 0x7f9d924dab30>



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

Ridge

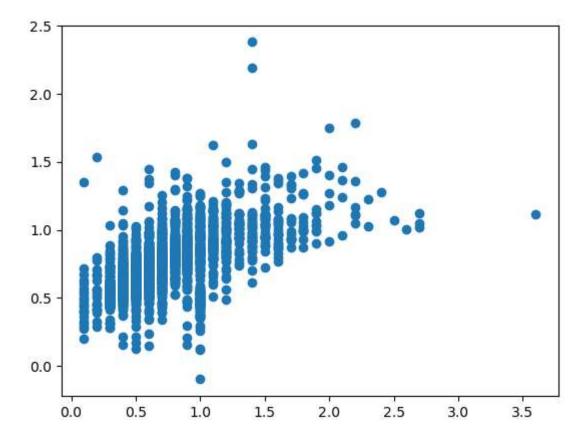
```
In [18]: rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

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 0x7f9d9256b550>



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

ElasticNet

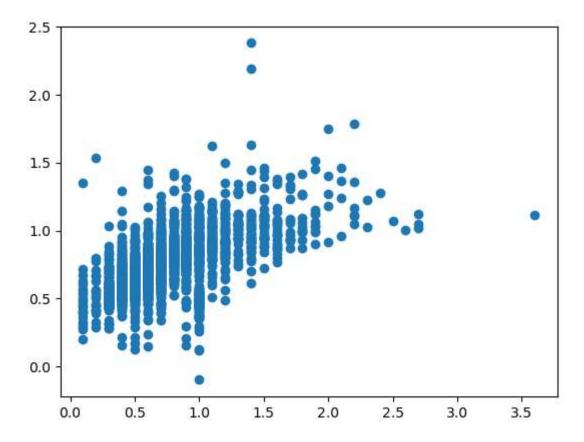
```
In [21]: en=ElasticNet()
    en.fit(x_train,y_train)
```

Out[21]: ElasticNet()

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

```
In [22]: prediction2=rr.predict(x_test)
    plt.scatter(y_test,prediction2)
```

Out[22]: <matplotlib.collections.PathCollection at 0x7f9d9240b4f0>



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

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

0.3923674796819595

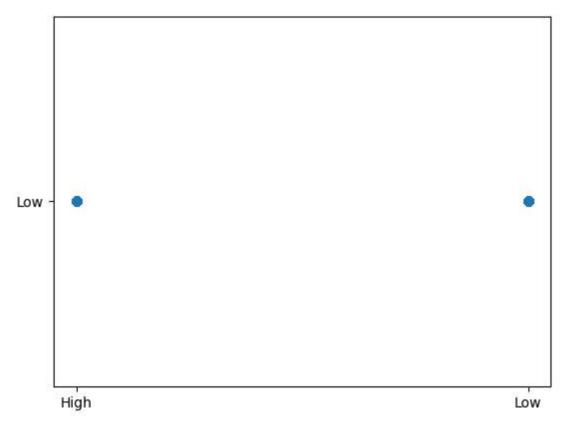
Out[24]: 0.3927671300897322

Logistic

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [28]: prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[28]: <matplotlib.collections.PathCollection at 0x7f9d30433c70>



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

Random Forest

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

```
g1={"TCH":{"Low":1.0,"High":2.0}}
In [31]:
         df1=df1.replace(g1)
In [32]: x=df1.drop(["TCH"],axis=1)
         v=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.
          On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
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]
         grid search=GridSearchCV(estimator=rfc,param grid=parameter,cv=2,scoring="accuracy")
In [35]:
         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.
          On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
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 names=['Yes',"No"],filled=True)
Out[38]: [Text(0.5375, 0.9285714285714286, 'NMHC <= 0.275\ngini = 0.328\nsamples = 3238\nvalue = [4060, 1060]\ncla</pre>
         ss = Yes'),
          Text(0.3390625, 0.7857142857142857, 'TOL <= 1.05\ngini = 0.09\nsamples = 2599\nvalue = [3927, 194]\nclas
         s = Yes'),
          Text(0.196875, 0.6428571428571429, 'O 3 <= 45.5\ngini = 0.031\nsamples = 1960\nvalue = [3090, 50]\nclass
         = Yes'),
          Text(0.1, 0.5, 'PM10 <= 17.5\ngini = 0.174\nsamples = 215\nvalue = [309, 33]\nclass = Yes'),
          Text(0.05, 0.35714285714285715, '0 3 <= 20.5\ngini = 0.123\nsamples = 191\nvalue = [283, 20]\nclass = Ye
         s'),
          Text(0.025, 0.21428571428571427, 'SO 2 <= 1.5\ngini = 0.335\nsamples = 30\nvalue = [37, 10]\nclass = Ye
         s'),
          Text(0.0125, 0.07142857142857142, 'gini = 0.497\nsamples = 9\nvalue = [7, 6]\nclass = Yes'),
          Text(0.0375, 0.07142857142857142, 'gini = 0.208\nsamples = 21\nvalue = [30, 4]\nclass = Yes'),
          Text(0.075, 0.21428571428571427, 'PM10 <= 5.5\ngini = 0.075\nsamples = 161\nvalue = [246, 10]\nclass = Y
         es'),
          Text(0.0625, 0.07142857142857142, 'gini = 0.0 \nsamples = 46 \nvalue = [75, 0] \nclass = Yes'),
          Text(0.0875, 0.07142857142857142, 'gini = 0.104\nsamples = 115\nvalue = [171, 10]\nclass = Yes'),
          Text(0.15, 0.35714285714285715, '0.3 <= 37.5 \ngini = 0.444 \nsamples = 24 \nvalue = [26, 13] \nclass = Ye
         s'),
```

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

Linear: 0.40767907025541705 Lasso: -0.00029951584872067727 Ridge: 0.3923674796819595

ElasticNet: 0.10978052070818145 Logistic: 0.7890660592255125 Random Forest: 0.946484375

Best Model is Random Forest

In [40]: df2=pd.read_csv("/Users/bob/Downloads/FP1_air/csvs_per_year/csvs_per_year/madrid_2014.csv")
df2

0u	t	۲4	0	1:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	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 [41]: 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	0_3	121681 non-null	float64
8	PM10	104311 non-null	float64
9	PM25	51954 non-null	float64
10	S0_2	87141 non-null	float64
11	TCH	25021 non-null	float64
12	TOL	46570 non-null	float64
13	station	210024 non-null	int64
dtype	es: floate	54(12), int64(1),	object(1)
memoi	rv usage:	22 4+ MB	

memory usage: 22.4+ MB

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

Out[42]:

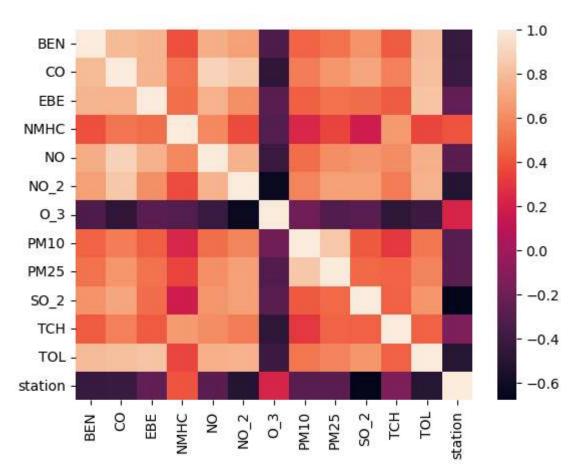
	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	station
1	2014-06-01 01:00:00	0.2	0.2	0.1	0.11	3.0	17.0	68.0	10.0	5.0	5.0	1.36	1.3	28079008
6	2014-06-01 01:00:00	0.1	0.2	0.1	0.23	1.0	5.0	80.0	4.0	3.0	2.0	1.21	0.1	28079024
25	2014-06-01 02:00:00	0.2	0.2	0.1	0.11	4.0	21.0	63.0	9.0	6.0	5.0	1.36	8.0	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 [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

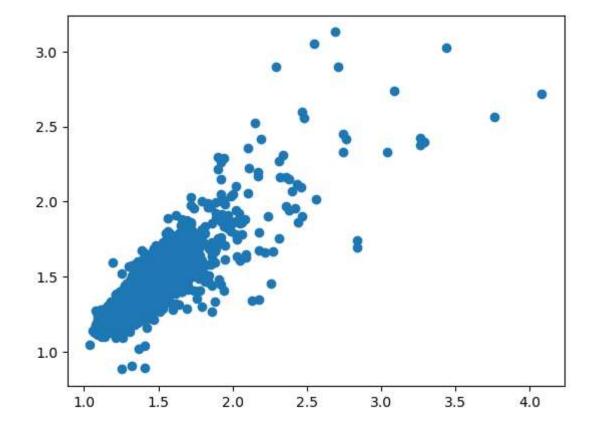
In [46]: li=LinearRegression()
li.fit(x_train,y_train)

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 0x7f9d82aff730>



```
In [48]: lis=li.score(x_test,y_test)
In [49]: df3["TCH"].value counts()
Out[49]: 1.37
                  601
                  598
         1.36
         1.34
                  529
         1.35
                  528
         1.38
                  515
         4.39
                    1
         4.08
                    1
         3.42
                    1
         2.98
                    1
         2.69
                    1
         Name: TCH, Length: 184, 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]: 1.0
                 9997
         2.0
                 3949
         Name: TCH, dtype: int64
 In [ ]:
```

Lasso

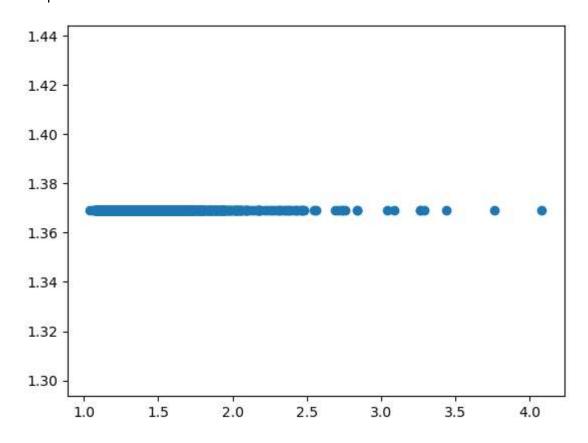
```
In [51]: la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

Out[51]: Lasso(alpha=5)

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

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

Out[52]: <matplotlib.collections.PathCollection at 0x7f9d8297ceb0>



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

Ridge

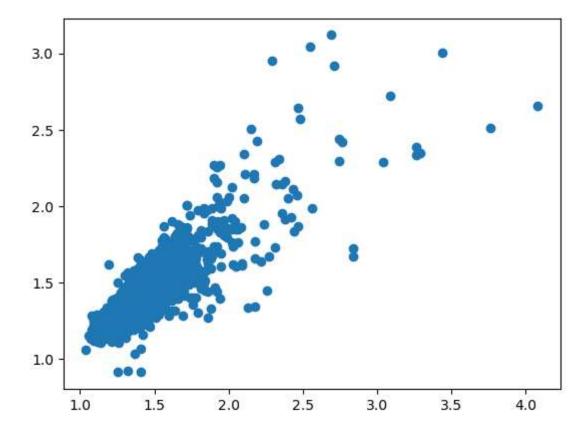
```
In [54]: rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

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 0x7f9d829cc9d0>



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

ElasticNet

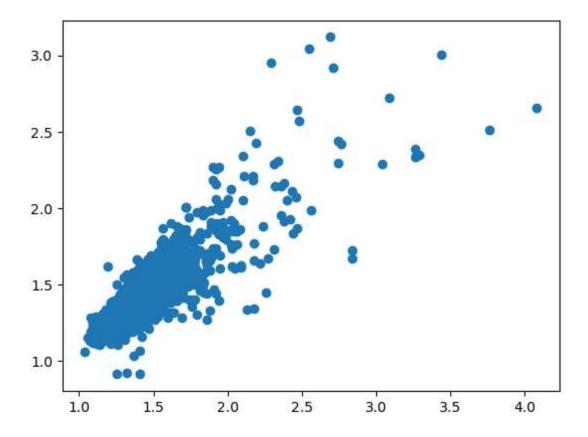
```
In [57]: en=ElasticNet()
en.fit(x_train,y_train)
```

Out[57]: ElasticNet()

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

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

Out[58]: <matplotlib.collections.PathCollection at 0x7f9d82b49030>



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

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

0.7091386251261051

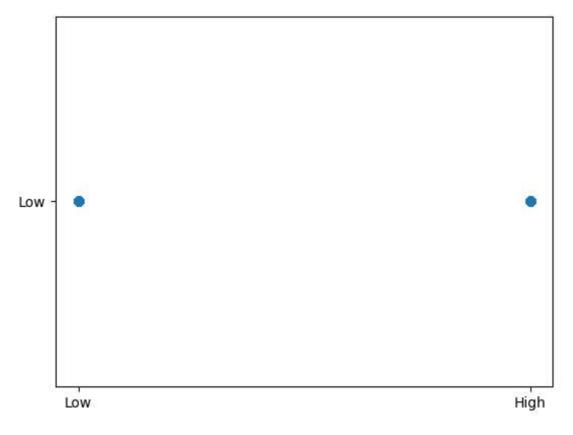
Out[60]: 0.7047426795616607

Logistic

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

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

Out[64]: <matplotlib.collections.PathCollection at 0x7f9d3046cb80>



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

Random Forest

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

```
g1={"TCH":{"Low":1.0,"High":2.0}}
In [67]:
         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()
          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 [70]: parameter={
              'max_depth':[1,2,4,5,6],
              'min_samples_leaf':[5,10,15,20,25],
              'n estimators':[10,20,30,40,50]
         grid search=GridSearchCV(estimator=rfc,param grid=parameter,cv=2,scoring="accuracy")
In [71]:
         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.
         On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
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(0.5191326530612245, 0.9285714285714286, 'PM25 <= 12.5\ngini = 0.402\nsamples = 6171\nvalue = [7045,</pre>
         2717 \\nclass = Yes'),
          Text(0.2755102040816326, 0.7857142857142857, 'NMHC <= 0.285\ngini = 0.289\nsamples = 4464\nvalue = [583
         6, 1237]\nclass = Yes'),
          Text(0.14540816326530612, 0.6428571428571429, 'SO 2 <= 8.5\ngini = 0.233\nsamples = 4206\nvalue = [5776,
         898\nclass = Yes'),
          Text(0.08163265306122448, 0.5, 'NO 2 <= 25.5\ngini = 0.211\nsamples = 4094\nvalue = [5722, 779]\nclass =
         Yes'),
          Text(0.04081632653061224, 0.35714285714285715, 'NO 2 <= 11.5\ngini = 0.084\nsamples = 2607\nvalue = [395]
         3, 182\nclass = Yes'),
          Text(0.02040816326530612, 0.21428571428571427, 'NO 2 <= 4.5\ngini = 0.023\nsamples = 1603\nvalue = [253]
         6, 301\nclass = Yes'),
          Text(0.01020408163265306, 0.07142857142857142, 'gini = 0.008\nsamples = 800\nvalue = [1275, 5]\nclass =
         Yes'),
          Text(0.030612244897959183, 0.07142857142857142, 'gini = 0.038\nsamples = 803\nvalue = [1261, 25]\nclass
         = Yes'),
          Text(0.061224489795918366, 0.21428571428571427, 'NMHC <= 0.135\ngini = 0.175\nsamples = 1004\nvalue = [1
         417, 152]\nclass = Yes'),
          Text(0.05102040816326531, 0.07142857142857142, 'gini = 0.05\nsamples = 279\nvalue = [418, 11]\nclass = Y
```

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

Linear: 0.7105902856424091 Lasso: -0.0001259044549823951 Ridge: 0.7091386251261051

ElasticNet: 0.43942661468297217 Logistic: 0.7127151051625239 Random Forest: 0.8929522638803524

Best model is Random Forest