MADRID 2004

In [3]: df2=pd.read_csv(r"C:\Users\user\Downloads\FP1_air\csvs_per_year\csvs_per_year\r
df2

Out[3]:

	date	BEN	со	EBE	MXY	NМНС	NO_2	NOx	ОХҮ	O_3	Р
0	2004- 08-01 01:00:00	NaN	0.66	NaN	NaN	NaN	89.550003	118.900002	NaN	40.020000	39.99(
1	2004- 08-01 01:00:00	2.66	0.54	2.99	6.08	0.18	51.799999	53.860001	3.28	51.689999	22.95(
2	2004- 08-01 01:00:00	NaN	1.02	NaN	NaN	NaN	93.389999	138.600006	NaN	20.860001	49.48(
3	2004- 08-01 01:00:00	NaN	0.53	NaN	NaN	NaN	87.290001	105.000000	NaN	36.730000	31.07(
4	2004- 08-01 01:00:00	NaN	0.17	NaN	NaN	NaN	34.910000	35.349998	NaN	86.269997	54.080
								***		***	
245491	2004- 06-01 00:00:00	0.75	0.21	0.85	1.55	0.07	59.580002	64.389999	0.66	33.029999	30.900
245492	2004- 06-01 00:00:00	2.49	0.75	2.44	4.57	NaN	97.139999	146.899994	2.34	7.740000	37.689
245493	2004- 06-01 00:00:00	NaN	NaN	NaN	NaN	0.13	102.699997	132.600006	NaN	17.809999	22.84(
245494	2004- 06-01 00:00:00	NaN	NaN	NaN	NaN	0.09	82.599998	102.599998	NaN	NaN	45.63(
245495	2004- 06-01 00:00:00	3.01	0.67	2.78	5.12	0.20	92.550003	141.000000	2.60	11.460000	24.389

245496 rows × 17 columns

```
In [4]: df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 245496 entries, 0 to 245495
Data columns (total 17 columns):
```

#	Column	Non-Null Count	Dtype		
0	date	245496 non-null	object		
1	BEN	65158 non-null	float64		
2	CO	226043 non-null	float64		
3	EBE	56781 non-null	float64		
4	MXY	39867 non-null	float64		
5	NMHC	107630 non-null	float64		
6	NO_2	243280 non-null	float64		
7	NOx	243283 non-null	float64		
8	OXY	39882 non-null	float64		
9	0_3	233811 non-null	float64		
10	PM10	234655 non-null	float64		
11	PM25	58145 non-null	float64		
12	PXY	39891 non-null	float64		
13	S0_2	243402 non-null	float64		
14	TCH	107650 non-null	float64		
15	TOL	64914 non-null	float64		
16	station	245496 non-null	int64		
dtype	object(1)				

In [5]: df3=df2.dropna()
 df3

Out[5]:

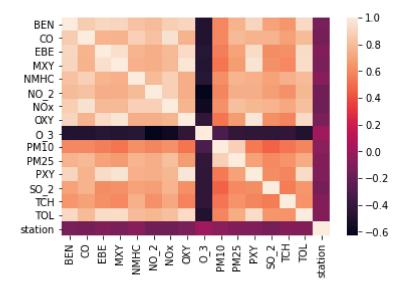
	date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	ОХҮ	O_3	Р
5	2004- 08-01 01:00:00	3.24	0.63	5.55	9.72	0.06	103.800003	144.800003	5.04	32.480000	59.11(
22	2004- 08-01 01:00:00	0.55	0.36	0.54	0.86	0.07	31.980000	32.799999	0.50	79.040001	43.549
26	2004- 08-01 01:00:00	1.80	0.46	2.28	4.62	0.21	62.259998	75.470001	2.47	54.419998	46.630
32	2004- 08-01 02:00:00	1.94	0.67	3.14	4.91	0.06	113.500000	165,800003	2.56	26.980000	86.930
49	2004- 08-01 02:00:00	0.29	0.30	0.47	0.76	0.07	33.919998	34.840000	0.46	75.570000	48.959
245463	2004- 05-31 23:00:00	0.62	0.08	0.54	0.70	0.04	44.360001	45.450001	0.42	43.419998	19.29(
245467	2004- 05-31 23:00:00	2.39	0.67	2.49	3.92	0.20	89.809998	132.800003	2.09	14.740000	31.809
245473	2004- 06-01 00:00:00	3.72	1.12	4.33	8.79	0.24	113.900002	253.600006	4.51	9.380000	21.219
245491	2004- 06-01 00:00:00	0.75	0.21	0.85	1.55	0.07	59.580002	64.389999	0.66	33.029999	30.900
245495	2004- 06-01 00:00:00	3.01	0.67	2.78	5.12	0.20	92.550003	141.000000	2.60	11.460000	24.389

19397 rows × 17 columns

In [6]: df3=df3.drop(["date"],axis=1)

```
In [7]: sns.heatmap(df3.corr())
```

Out[7]: <AxesSubplot:>



```
In [8]: 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

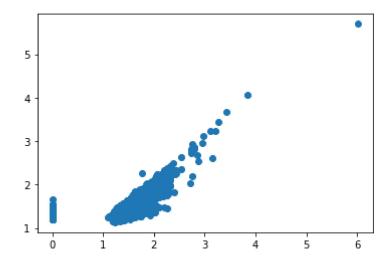
```
In [9]: li=LinearRegression()
li.fit(x_train,y_train)
```

Out[9]: LinearRegression()

```
In [ ]:
```

In [10]: prediction=li.predict(x_test)
plt.scatter(y_test,prediction)

Out[10]: <matplotlib.collections.PathCollection at 0x238e4beb220>



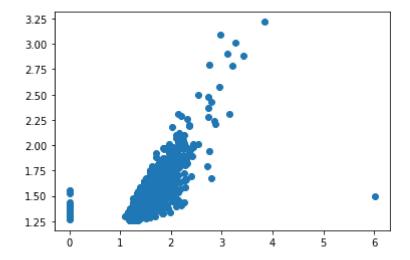
```
In [11]: lis=li.score(x_test,y_test)
In [12]: df3["TCH"].value_counts()
Out[12]: 1.34
                  740
          1.33
                  714
         1.35
                  708
         1.37
                  688
         1.36
                  679
         2.95
                    1
         3.65
                    1
         3.59
                    1
         2.58
                    1
         3.86
         Name: TCH, Length: 191, dtype: int64
In [13]: |df3.loc[df3["TCH"]<1.40,"TCH"]=1</pre>
         df3.loc[df3["TCH"]>1.40,"TCH"]=2
         df3["TCH"].value_counts()
Out[13]: 1.0
                 11861
          2.0
                  7536
         Name: TCH, dtype: int64
In [ ]:
```

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 0x238e4ca3e50>



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

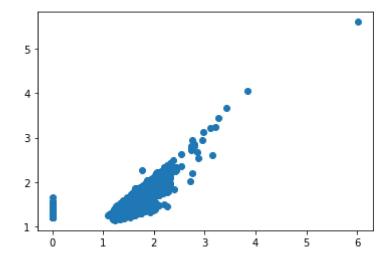
Ridge

```
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 0x238e5393f70>



```
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 0x238e4c587c0>
```

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

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

0.5859990677228715

Out[23]: 0.5914128037722362

2

Logistic

t[24]: Low 11861 High 7536

Name: TCH, dtype: int64

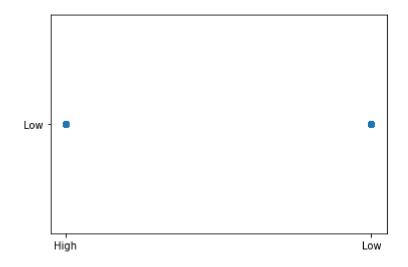
```
In [25]: x=df3.drop(["TCH"],axis=1)
    y=df3["TCH"]
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

In [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 0x238e4ab94f0>



```
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}}
    df3=df3.replace(g1)

In [31]: 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 [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]
                   grid search=GridSearchCV(estimator=rfc,param grid=parameter,cv=2,scoring="accur")
In [34]:
                    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',
                    841\nvaiue = [424/, 205]\nciass = Yes ),
                      Text(175.05882352941177, 776.5714285714287, '0_3 <= 7.99\ngini = 0.043\nsa
                    mples = 2337\nvalue = [3587, 80]\nclass = Yes'),
                      Text(87.52941176470588, 465.9428571428573, 'NO_2 <= 44.605 \ngini = 0.406 \ngin
                    samples = 43\nvalue = [43, 17]\nclass = Yes'),
                      Text(43.76470588235294, 155.3142857142857, 'gini = 0.0\nsamples = 22\nvalu
                    e = [29, 0]\nclass = Yes'),
                      Text(131.29411764705884, 155.3142857142857, 'gini = 0.495\nsamples = 21\nv
                    alue = [14, 17] \setminus nclass = No'),
                      Text(262.5882352941177, 465.9428571428573, 'NO 2 <= 34.065 \ngini = 0.034 \n
                    samples = 2294\nvalue = [3544, 63]\nclass = Yes'),
                      Text(218.8235294117647, 155.3142857142857, 'gini = 0.011\nsamples = 1558\n
                    value = [2415, 14]\nclass = Yes'),
                      Text(306.3529411764706, 155.3142857142857, 'gini = 0.08\nsamples = 736\nva
                    lue = [1129, 49] \setminus (129, 49] \setminus (129, 49]
                      Text(525.1764705882354, 776.5714285714287, 'NMHC <= 0.135\ngini = 0.268\ns
                    amples = 504\nvalue = [660, 125]\nclass = Yes'),
                      Text(437.6470588235294, 465.9428571428573, 'OXY <= 1.465\ngini = 0.201\nsa
                    mples = 461\nvalue = [641, 82]\nclass = Yes'),
                      Text(393.88235294117646, 155.3142857142857, 'gini = 0.191\nsamples = 443\n -
```

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

Linear: 0.5861025371823241 Lasso: 0.46524945960663167 Ridge: 0.5859990677228715

ElasticNet: 0.4893278610828047 Logistic: 0.6001718213058419 Random Forest: 0.8934226616021463

BEST MODEL IS RANDOM FOREST

In []: