MADRID 2014

In [2]: 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,Rid
from sklearn.model_selection import train_test_split

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 | NMHC | NO | NO_2 | O_3 | PM10 | PM25 | SO_2 | тсн | TOL | |
|--------|----------------------------|-----|-----|-----|------|------|------|------|------|------|------|------|-----|----|
| 0 | 2014- 06-01 01:00:00 | NaN | 0.2 | NaN | NaN | 3.0 | 10.0 | NaN | NaN | NaN | 3.0 | NaN | NaN | 28 |
| 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 | 28 |
| 2 | 2014- 06-01 01:00:00 | 0.3 | NaN | 0.1 | NaN | 2.0 | 6.0 | NaN | NaN | NaN | NaN | NaN | 1.1 | 28 |
| 3 | 2014- 06-01 01:00:00 | NaN | 0.2 | NaN | NaN | 1.0 | 6.0 | 79.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| 4 | 2014- 06-01 01:00:00 | NaN | NaN | NaN | NaN | 1.0 | 6.0 | 75.0 | NaN | NaN | 4.0 | NaN | NaN | 28 |
| | | | | | | | | | | | | | | |
| 210019 | 2014- 09-01 00:00:00 | NaN | 0.5 | NaN | NaN | 20.0 | 84.0 | 29.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| 210020 | 2014- 09-01 00:00:00 | NaN | 0.3 | NaN | NaN | 1.0 | 22.0 | NaN | 15.0 | NaN | 6.0 | NaN | NaN | 28 |
| 210021 | 2014- 09-01 00:00:00 | NaN | NaN | NaN | NaN | 1.0 | 13.0 | 70.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| 210022 | 2014- 09-01 00:00:00 | NaN | NaN | NaN | NaN | 3.0 | 38.0 | 42.0 | NaN | NaN | NaN | NaN | NaN | 28 |
| 210023 | 2014- 09-01 00:00:00 | NaN | NaN | NaN | NaN | 1.0 | 26.0 | 65.0 | 11.0 | NaN | NaN | NaN | NaN | 28 |

210024 rows × 14 columns

localhost:8888/notebooks/Downloads/madrid_data(2013_14) (2).ipynb#Best-Model-is-Random-Forest

```
In [4]: 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 |

dtypes: float64(12), int64(1), object(1)

memory usage: 22.4+ MB

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

Out[5]:

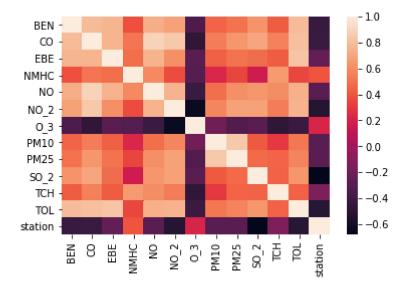
| | date | BEN | со | EBE | NMHC | NO | NO_2 | O_3 | PM10 | PM25 | SO_2 | тсн | TOL | |
|--------|----------------------------|-----|-----|-----|------|------|-------|------|------|------|------|------|-----|-----|
| 1 | 2014- 06-01 01:00:00 | 0.2 | 0.2 | 0.1 | 0.11 | 3.0 | 17.0 | 68.0 | 10.0 | 5.0 | 5.0 | 1.36 | 1.3 | 280 |
| 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 | 280 |
| 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 | 280 |
| 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 | 280 |
| 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 | 280 |
| | | | | | | | | | | | | | | |
| 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 | 280 |
| 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 | 280 |
| 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 | 280 |
| 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 | 280 |
| 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 | 280 |

13946 rows × 14 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

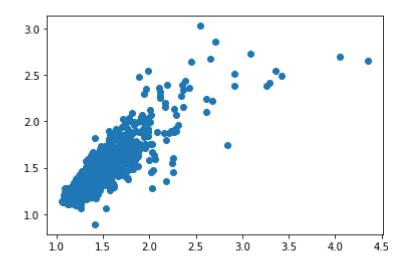
```
In [9]: li=LinearRegression()
li.fit(x_train,y_train)
```

Out[9]: LinearRegression()

```
In [ ]:
```

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

Out[10]: <matplotlib.collections.PathCollection at 0x23e34647b20>



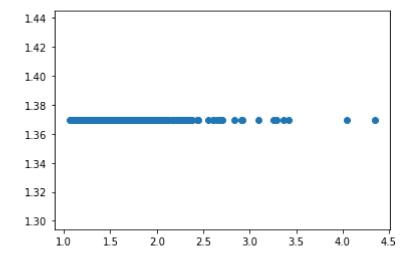
```
In [11]: lis=li.score(x_test,y_test)
In [12]: df3["TCH"].value_counts()
Out[12]: 1.37
                  601
          1.36
                  598
         1.34
                  529
          1.35
                  528
          1.38
                  515
         2.50
                    1
         2.86
                    1
         2.70
                    1
         3.04
                    1
         4.37
         Name: TCH, Length: 184, 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
                 9997
          2.0
                 3949
         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 0x23e34da5b50>



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

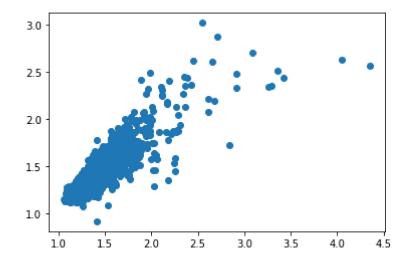
Ridge

```
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 0x23e34e097f0>



```
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 0x23e34d86fa0>
           3.0
           2.5
           2.0
           1.5
           1.0
                    1.5
                           2.0
                                 2.5
                                        3.0
                                              3.5
                                                     4.0
              1.0
                                                           4.5
In [22]:
         ens=en.score(x_test,y_test)
In [23]:
         print(rr.score(x_test,y_test))
          rr.score(x_train,y_train)
          0.7200667721423921
Out[23]: 0.7012758788869609
```

Logistic

```
In [24]:
         g={"TCH":{1.0:"Low",2.0:"High"}}
         df3=df3.replace(g)
         df3["TCH"].value_counts()
Out[24]: Low
                  9997
         High
                  3949
         Name: TCH, dtype: int64
```

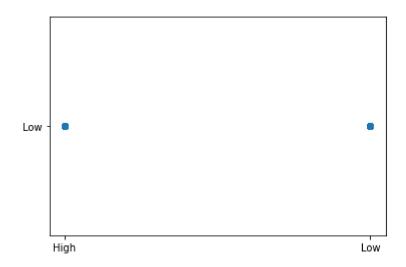
```
In [25]: x=df3.drop(["TCH"],axis=1)
    y=df3["TCH"]
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

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 0x23e34043e50>



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',"
Out[37]: [Text(2469.446808510638, 2019.0857142857144, 'NMHC <= 0.275\ngini = 0.408\n
                                                    samples = 6178\nvalue = [6972, 2790]\nclass = Yes'),
                                                          Text(1489.9787234042553, 1708.457142857143, 'BEN <= 0.35\ngini = 0.295\nsa
                                                    mples = 5152\nvalue = [6711, 1473]\nclass = Yes'),
                                                          Text(759.8297872340426, 1397.8285714285716, 'NO 2 <= 20.5 \neq 0.177 \neq 0.17
                                                     amples = 3659\nvalue = [5221, 569]\nclass = Yes'),
                                                          Text(379.9148936170213, 1087.2, 'NO <= 3.5 \neq 0.054 = 0.054 = 2367 = 0.054
                                                    value = [3644, 104]\nclass = Yes'),
                                                          Text(189.95744680851064, 776.5714285714287, 'NMHC <= 0.245 \neq 0.045 = 0.045
                                                     samples = 2198\nvalue = [3413, 81]\nclass = Yes'),
                                                          Text(94.97872340425532, 465.9428571428573, '0 3 <= 31.5 \setminus injury = 0.028 \setminus injury = 0.028
                                                     ples = 1640\nvalue = [2541, 36]\nclass = Yes'),
                                                          Text(47.48936170212766, 155.3142857142857, 'gini = 0.272\nsamples = 26\nva
                                                     lue = [31, 6]\nclass = Yes'),
                                                          Text(142.46808510638297, 155.3142857142857, 'gini = 0.023\nsamples = 1614
                                                     \nvalue = [2510, 30] \nclass = Yes'),
                                                          Text(284.93617021276594, 465.9428571428573, 'NO 2 <= 16.5 \neq 0.093 \neq 0.09
                                                     amples = 558\nvalue = [872, 45]\nclass = Yes'),
                                                          Text(237.4468085106383, 155.3142857142857, 'gini = 0.068 \nsamples = 500 \nv
                                                                                             [702 203) ]
```

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

Linear: 0.7193673186557659 Lasso: -2.9617947867599526e-06 Ridge: 0.7200667721423921 ElasticNet: 0.4410938925779051 Logistic: 0.7050669216061185 Random Forest: 0.8899815611555009

Best model is Random Forest

In []: