```
In [1]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.model_selection import train_test_split
    from sklearn.linear_model import LinearRegression
    from sklearn.linear_model import Ridge,Lasso
    from sklearn.linear_model import ElasticNet
    from sklearn import metrics
    from sklearn.linear_model import LogisticRegression
    from sklearn.preprocessing import StandardScaler
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.model_selection import GridSearchCV
    from sklearn.tree import plot_tree
```

In [2]: df=pd.read\_csv(r"C:\Users\user\Downloads\csvs\_per\_year\csvs\_per\_year\madrid\_200
df

Out[2]:

date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	ОХҮ	O_3	Р
2004- 08-01 01:00:00	NaN	0.66	NaN	NaN	NaN	89.550003	118.900002	NaN	40.020000	39.99(
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(
2004- 08-01 01:00:00	NaN	1.02	NaN	NaN	NaN	93.389999	138.600006	NaN	20.860001	49.48(
2004- 08-01 01:00:00	NaN	0.53	NaN	NaN	NaN	87.290001	105.000000	NaN	36.730000	31.07(
2004- 08-01 01:00:00	NaN	0.17	NaN	NaN	NaN	34.910000	35.349998	NaN	86.269997	54.08(
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
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
2004- 06-01 00:00:00	NaN	NaN	NaN	NaN	0.13	102.699997	132.600006	NaN	17.809999	22.84(
2004- 06-01 00:00:00	NaN	NaN	NaN	NaN	0.09	82.599998	102.599998	NaN	NaN	45.63(
2004- 06-01 00:00:00	3.01	0.67	2.78	5.12	0.20	92.550003	141.000000	2.60	11.460000	24.38
	2004- 08-01 01:00:00 2004- 08-01 01:00:00 2004- 08-01 01:00:00 2004- 08-01 01:00:00 2004- 06-01 00:00:00 2004- 06-01 00:00:00 2004- 06-01 00:00:00	2004- 08-01	2004- 08-01	2004- 08-01	2004- 08-01 01:00:00       NaN       0.66       NaN       NaN         2004- 08-01 01:00:00       2.66       0.54       2.99       6.08         2004- 08-01 01:00:00       NaN       1.02       NaN       NaN         2004- 08-01 01:00:00       NaN       0.53       NaN       NaN         2004- 08-01 01:00:00       NaN       0.17       NaN       NaN         2004- 08-01 01:00:00       0.75       0.21       0.85       1.55         2004- 06-01 00:00:00       2.49       0.75       2.44       4.57         2004- 06-01 00:00:00       NaN       NaN       NaN       NaN         2004- 06-01 00:00:00       NaN       NaN       NaN       NaN	2004- 08-01	2004- 08-01 01:00:00         NaN         0.66         NaN         NaN         NaN         89.550003           2004- 08-01 01:00:00         2.66         0.54         2.99         6.08         0.18         51.799999           2004- 08-01 01:00:00         NaN         1.02         NaN         NaN         NaN         93.389999           2004- 08-01 01:00:00         NaN         0.53         NaN         NaN         NaN         87.290001           2004- 08-01 01:00:00         NaN         0.17         NaN         NaN         NaN         NaN         34.910000           2004- 06-01 00:00:00         0.75         0.21         0.85         1.55         0.07         59.580002           2004- 06-01 00:00:00         NaN         NaN         NaN         NaN         97.139999           2004- 06-01 00:00:00         NaN         NaN         NaN         NaN         NaN         102.699997           2004- 06-01 00:00:00         NaN         NaN         NaN         NaN         NaN         0.09         82.599998           2004- 06-01 00:00:00         3.01         0.67         2.78         5.12         0.20         92.550003	2004- 08-01 01:00:00         NaN         0.66         NaN         NaN         NaN         89.550003         118.900002           2004- 08-01 01:00:00         2.66         0.54         2.99         6.08         0.18         51.799999         53.860001           2004- 08-01 01:00:00         NaN         1.02         NaN         NaN         NaN         93.389999         138.600006           2004- 08-01 01:00:00         NaN         0.53         NaN         NaN         NaN         87.290001         105.000000           2004- 08-01 01:00:00         NaN         0.17         NaN         NaN         NaN         34.910000         35.349998           01:00:00	2004- 08-01 01:00:00         NaN         0.66         NaN         NaN         NaN         89.550003         118.900002         NaN           2004- 08-01 01:00:00         2.66         0.54         2.99         6.08         0.18         51.799999         53.860001         3.28           2004- 08-01 01:00:00         NaN         1.02         NaN         NaN         NaN         93.389999         138.600006         NaN           2004- 08-01 01:00:00         NaN         0.53         NaN         NaN         NaN         87.290001         105.000000         NaN           2004- 08-01 01:00:00         NaN         0.17         NaN         NaN         NaN         34.910000         35.349998         NaN           2004- 06-01 00:00:00         0.75         0.21         0.85         1.55         0.07         59.580002         64.389999         0.66           2004- 06-01 00:00:00         0.75         2.44         4.57         NaN         97.139999         146.899994         2.34           2004- 06-01 00:00:00         NaN         NaN         NaN         NaN         0.13         102.699997         132.600006         NaN           2004- 06-01 00:00:00         NaN         NaN         NaN         NaN <td< th=""><th>2004- 08-01 01:00:00         NaN         0.66         NaN         NaN         NaN         89.550003         118.900002         NaN         40.020000           2004- 08-01 01:00:00         2.66         0.54         2.99         6.08         0.18         51.799999         53.860001         3.28         51.689999           2004- 08-01 01:00:00         NaN         1.02         NaN         NaN         NaN         93.389999         138.600006         NaN         20.860001           2004- 08-01 01:00:00         NaN         0.53         NaN         NaN         NaN         87.290001         105.00000         NaN         36.730000           2004- 08-01 01:00:00         NaN         0.17         NaN         NaN         NaN         34.910000         35.349998         NaN         86.269997                       .004- 08-01 00:00:00         0.75         0.21         0.85         1.55         0.07         59.580002         64.389999         0.66         33.029999           2004- 06-01 00:00:00         1.00         1.00         1.00         1.00         1.00         1.00         1.00</th></td<>	2004- 08-01 01:00:00         NaN         0.66         NaN         NaN         NaN         89.550003         118.900002         NaN         40.020000           2004- 08-01 01:00:00         2.66         0.54         2.99         6.08         0.18         51.799999         53.860001         3.28         51.689999           2004- 08-01 01:00:00         NaN         1.02         NaN         NaN         NaN         93.389999         138.600006         NaN         20.860001           2004- 08-01 01:00:00         NaN         0.53         NaN         NaN         NaN         87.290001         105.00000         NaN         36.730000           2004- 08-01 01:00:00         NaN         0.17         NaN         NaN         NaN         34.910000         35.349998         NaN         86.269997                       .004- 08-01 00:00:00         0.75         0.21         0.85         1.55         0.07         59.580002         64.389999         0.66         33.029999           2004- 06-01 00:00:00         1.00         1.00         1.00         1.00         1.00         1.00         1.00

245496 rows × 17 columns

#### In [3]: df.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 float64 NMHC 107630 non-null 6 243280 non-null float64 NO\_2 7 NOx 243283 non-null float64 8 0XY 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 243402 non-null float64 SO\_2 14 TCH 107650 non-null float64 15 TOL float64 64914 non-null

16 station 245496 non-null int64 dtypes: float64(15), int64(1), object(1)

memory usage: 31.8+ MB

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

### Out[4]:

	date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	ОХҮ	0_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

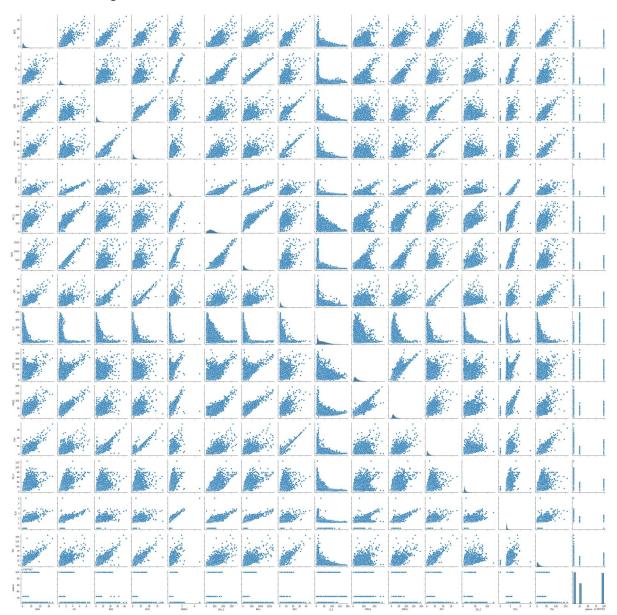
```
F4 - Jupyter Notebook
In [5]: df.isnull().sum()
Out[5]: date
                       0
                       0
          BEN
          CO
                       0
          EBE
                       0
          MXY
                       0
          NMHC
                       0
                       0
          NO 2
          NOx
                       0
          OXY
                       0
          0_3
                       0
          PM10
                       0
          PM25
                       0
          PXY
                       0
          SO_2
                       0
          TCH
                       0
          TOL
                       0
          station
          dtype: int64
In [6]: df.describe()
Out[6]:
                                         CO
                                                     EBE
                                                                   MXY
                                                                               NMHC
                          BEN
                                                                                              NO_2
           count 19397.000000
                               19397.000000
                                             19397.000000
                                                          19397.000000 19397.000000
                      2.250781
                                   0.675347
                                                 2.775913
                                                               5.424809
                                                                             0.151024
                                                                                          62.887023
           mean
                      2.184724
                                   0.591026
                                                 2.729622
                                                               5.554358
                                                                             0.158603
                                                                                          37.952255
             std
                                                                             0.000000
                      0.000000
                                   0.000000
                                                 0.000000
                                                               0.000000
                                                                                           0.090000
            min
            25%
                      0.870000
                                   0.320000
                                                 1.020000
                                                               1.780000
                                                                             0.060000
                                                                                          35.150002
            50%
                      1.620000
                                   0.520000
                                                 1.970000
                                                               3.800000
                                                                             0.110000
                                                                                          58.310001
```

```
19397.000000 193
                                                                                                1
                                                                                                1
75%
          2.910000
                         0.860000
                                       3.580000
                                                      7.260000
                                                                     0.200000
                                                                                  85.730003
                                                                                                1
         34.180000
                         8.900000
                                      41.880001
                                                     91.599998
                                                                     4.810000
                                                                                 355.100006
                                                                                               17
max
```

```
In [7]: | df.columns
Out[7]: Index(['date', 'BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_
        3',
                'PM10', 'PM25', 'PXY', 'SO_2', 'TCH', 'TOL', 'station'],
              dtype='object')
```

In [8]: sns.pairplot(df)

Out[8]: <seaborn.axisgrid.PairGrid at 0x1f8d84b0c70>

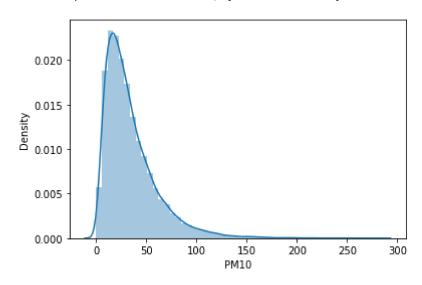


#### In [9]: sns.distplot(df['PM10'])

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fut ureWarning: `distplot` is a deprecated function and will be removed in a futu re version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for hi stograms).

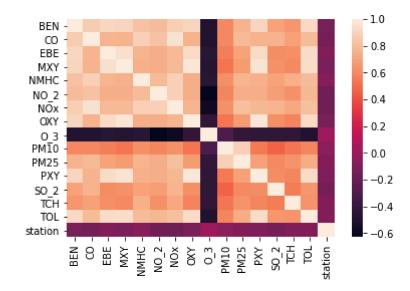
warnings.warn(msg, FutureWarning)

Out[9]: <AxesSubplot:xlabel='PM10', ylabel='Density'>



In [10]: sns.heatmap(df.corr())

#### Out[10]: <AxesSubplot:>



```
In [11]: | df.loc[df['NMHC']<1,'NMHC']=0</pre>
         df.loc[df['NMHC']>1,'NMHC']=1
         df['NMHC']=df['NMHC'].astype(int)
         C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\indexing.py:1720: Sett
         ingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row_indexer,col_indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
         table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
         s.pydata.org/pandas-docs/stable/user guide/indexing.html#returning-a-view-ver
         sus-a-copy)
           self. setitem single column(loc, value, pi)
         C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\indexing.py:1720: Sett
         ingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row_indexer,col_indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
         table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
         s.pydata.org/pandas-docs/stable/user guide/indexing.html#returning-a-view-ver
         sus-a-copy)
           self. setitem single column(loc, value, pi)
         <ipython-input-11-c5145d14383f>:3: SettingWithCopyWarning:
```

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s table/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy)

df['NMUC']\_df['NMUC']\_astwo(int)

df['NMHC']=df['NMHC'].astype(int)

## LogisticRegression

```
In [15]: fs=StandardScaler().fit_transform(x)
    logr=LogisticRegression()

Out[15]: LogisticRegression()

In [16]: o=[[1,2,3,4,5,6,7,8,9,10,11,12,13,14]]
    prediction=logr.predict(o)
    print(prediction)
    [1]

In [17]: logr.classes_
Out[17]: array([0, 1])

In [18]: logr.predict_proba(o)[0][0]

Out[18]: 1.2229580181877253e-07

In [19]: logr.predict_proba(o)[0][1]

Out[19]: 0.9999998777041982
```

# LinearRegression

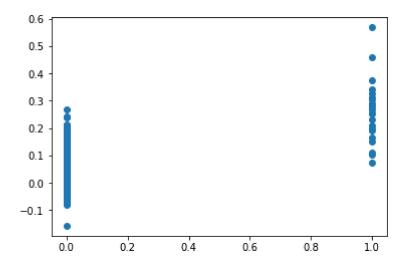
```
In [22]: coeff = pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

#### Out[22]:

Co-efficient
-0.002369
0.031898
-0.005493
0.001408
-0.000597
0.000320
0.004470
0.000380
0.000030
-0.003739
-0.000747
0.039217
0.000005
0.000054

```
In [23]: prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[23]: <matplotlib.collections.PathCollection at 0x1f8e41dee80>



```
In [24]: print(lr.score(x_test,y_test))
```

0.22426765937058513

# Ridge,Lasso

```
In [25]: rr=Ridge(alpha=10)
    rr.fit(x_train,y_train)
Out[25]: Ridge(alpha=10)
In [26]: rr.score(x_test,y_test)
Out[26]: 0.2251016207877765
In [27]: la=Lasso(alpha=10)
    la.fit(x_train,y_train)
Out[27]: Lasso(alpha=10)
In [28]: la.score(x_test,y_test)
Out[28]: -1.9487786558247677e-05
```

## **ElasticNet**

```
In [29]:
         en=ElasticNet()
         en.fit(x_train,y_train)
Out[29]: ElasticNet()
In [30]: |print(en.coef_)
          [ 0.
                        0.
                                   -0.
                                                 0.
                                                            -0.
                                                                         0.00018651
           0.
                                                 0.
                                                             0.
                                                                         0.
                        0.
                                    0.
           0.
                        0.
In [31]: print(en.intercept )
          -0.019955314751395007
In [32]:
         print(en.predict(x_train))
          [-0.00696309 -0.01493262 -0.01212007 ... -0.0058832
                                                                 0.0128703
          -0.01508743]
         print(en.score(x_train,y_train))
In [33]:
         0.1896264668946248
In [34]: print("Mean Absolytre Error:",metrics.mean_absolute_error(y_test,prediction))
         Mean Absolytre Error: 0.020022805597023283
In [35]: print("Mean Square Error:",metrics.mean_squared_error(y_test,prediction))
         Mean Square Error: 0.002921237185476247
```

```
In [36]: print("Root Mean Square Error:",np.sqrt(metrics.mean_absolute_error(y_test,pre
```

## RandomForest

```
In [37]: rfc=RandomForestClassifier()
         rfc.fit(x_train,y_train)
Out[37]: RandomForestClassifier()
In [38]: parameters={'max_depth':[1,2,3,4,5],
                      'min_samples_leaf':[5,10,15,20,25],
                      'n estimators':[10,20,30,40,50]}
In [39]: grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="acc
         grid_search.fit(x_train,y_train)
Out[39]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
                      param_grid={'max_depth': [1, 2, 3, 4, 5],
                                   'min samples leaf': [5, 10, 15, 20, 25],
                                   'n estimators': [10, 20, 30, 40, 50]},
                      scoring='accuracy')
In [40]: grid search.best score
Out[40]: 0.9987479204158205
In [41]: rfc_best=grid_search.best_estimator_
```

```
plt.figure(figsize=(80,40))
In [42]:
           plot_tree(rfc_best.estimators_[5],class_names=['Yes','No','Yes','No'],filled=Ti
Out[42]: [Text(3348.0, 1956.96, 'X[0] <= 15.055\ngini = 0.007\nsamples = 8586\nvalue =
           [13526, 51]\nclass = Yes'),
            Text(2790.0, 1522.0800000000002, 'X[5] <= 740.15\ngini = 0.004\nsamples = 85
           64\nvalue = [13511, 28]\nclass = Yes'),
            Text(2232.0, 1087.2, 'X[4] <= 173.0\ngini = 0.001\nsamples = 8542\nvalue =
           [13493, 10] \setminus class = Yes'),
            Text(1116.0, 652.3200000000000, X[11] <= 2.315 \setminus gini = 0.001 \setminus gsamples = 849
           7\nvalue = [13433, 7]\nclass = Yes'),
            Text(558.0, 217.44000000000005, 'gini = 0.0\nsamples = 8476\nvalue = [13415,
           0]\nclass = Yes'),
            Text(1674.0, 217.4400000000000, 'gini = 0.403\nsamples = 21\nvalue = [18,
           7]\nclass = Yes'),
            Text(3348.0, 652.3200000000000, X[4] <= 181.8 \text{ ngini} = 0.091 \text{ nsamples} = 45 \text{ ngini}
           value = [60, 3]\nclass = Yes'),
            Text(2790.0, 217.4400000000000, 'gini = 0.185\nsamples = 20\nvalue = [26,
           3]\nclass = Yes'),
            Text(3906.0, 217.4400000000005, 'gini = 0.0\nsamples = 25\nvalue = [34, 0]
           \nclass = Yes'),
            Text(3348.0, 1087.2, 'gini = 0.5\nsamples = 22\nvalue = [18, 18]\nclass = Ye
           s'),
            Text(3906.0, 1522.0800000000002, 'gini = 0.478 \nsamples = 22 \nvalue = [15, 2]
           31\nclass = No')1
                                                                           X[0] \le 15.055
                                                                             gini = 0.007
                                                                           samples = 8586
                                                                          value = [13526, 51]
                                                                                        gini = 0.478
                                                                 gini = 0.004
                                                                                        samples = 22
                                                                samples = 8564
                                                                                       value = [15, 23]
                                                              value = [13511, 28]
                                                                                         class = No
                                                                 class = Yes
                                                     X[4] \le 173.0
                                                                             gini = 0.5
                                                     aini = 0.001
                                                                            samples = 22
                                                    samples = 8542
                                                                           value = [18, 18]
                                                   value = [13493, 10]
                                                                             class = Yes
                                                      class = Yes
                             X[11] \le 2.315
                                                                            X[4] \le 181.8
                              gini = 0.001
                                                                            gini = 0.091
                             samples = 8497
                                                                            samples = 45
                                                                            value = [60, 3]
                            value = [13433, 7]
                              class = Yes
                                                                             class = Yes
                 samples = 8476
                                                                 samples = 20
                                         samples = 21
                                                                                        samples = 25
                value = [13415, 0]
                                         value = [18, 7]
                                                                value = [26, 3]
                   class = Yes
                                          class = Yes
                                                                 class = Yes
                                                                                         class = Yes
```

#### Best model:RandomForest

```
In [ ]:
```