```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.linear_model import LogisticRegression
    from sklearn.preprocessing import StandardScaler
    import re
    from sklearn.datasets import load_digits
```

In [2]: a=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs_per_year\ma

Out[2]:

| | date | BEN | СО | EBE | MXY | NMHC | NO_2 | NOx | OXY | O_3 | |
|--------|------------------------|------|------|------|-----|------|------------|------------|-----|-----------|-----|
| 0 | 2010-03-01 01:00:00 | NaN | 0.29 | NaN | NaN | NaN | 25.090000 | 29.219999 | NaN | 68.930000 | |
| 1 | 2010-03-01 01:00:00 | NaN | 0.27 | NaN | NaN | NaN | 24.879999 | 30.040001 | NaN | NaN | |
| 2 | 2010-03-01 01:00:00 | NaN | 0.28 | NaN | NaN | NaN | 17.410000 | 20.540001 | NaN | 72.120003 | |
| 3 | 2010-03-01 01:00:00 | 0.38 | 0.24 | 1.74 | NaN | 0.05 | 15.610000 | 21.080000 | NaN | 72.970001 | 19. |
| 4 | 2010-03-01 01:00:00 | 0.79 | NaN | 1.32 | NaN | NaN | 21.430000 | 26.070000 | NaN | NaN | 24. |
| | | | | | | | | | | | |
| 209443 | 2010-08-01 00:00:00 | NaN | 0.55 | NaN | NaN | NaN | 125.000000 | 219.899994 | NaN | 25.379999 | |
| 209444 | 2010-08-01 00:00:00 | NaN | 0.27 | NaN | NaN | NaN | 45.709999 | 47.410000 | NaN | NaN | 51. |
| 209445 | 2010-08-01 00:00:00 | NaN | NaN | NaN | NaN | 0.24 | 46.560001 | 49.040001 | NaN | 46.250000 | |
| 209446 | 2010-08-01 00:00:00 | NaN | NaN | NaN | NaN | NaN | 46.770000 | 50.119999 | NaN | 77.709999 | |
| 209447 | 2010-08-01 00:00:00 | 0.92 | 0.43 | 0.71 | NaN | 0.25 | 76.330002 | 88.190002 | NaN | 52.259998 | 47. |

209448 rows × 17 columns

In [3]:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209448 entries, 0 to 209447
Data columns (total 17 columns):

| 4 |
|-----|
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| 4 |
| |
| (1) |
| |
| |

In [4]: b=a.fillna(value=111)

Out[4]:

| | date | BEN | СО | EBE | MXY | NMHC | NO_2 | NOx | OXY | Ο. |
|--------|------------------------|--------|--------|--------|-------|--------|------------|------------|-------|----------|
| 0 | 2010-03-01 01:00:00 | 111.00 | 0.29 | 111.00 | 111.0 | 111.00 | 25.090000 | 29.219999 | 111.0 | 68.9300 |
| 1 | 2010-03-01 01:00:00 | 111.00 | 0.27 | 111.00 | 111.0 | 111.00 | 24.879999 | 30.040001 | 111.0 | 111.0000 |
| 2 | 2010-03-01 01:00:00 | 111.00 | 0.28 | 111.00 | 111.0 | 111.00 | 17.410000 | 20.540001 | 111.0 | 72.1200 |
| 3 | 2010-03-01 01:00:00 | 0.38 | 0.24 | 1.74 | 111.0 | 0.05 | 15.610000 | 21.080000 | 111.0 | 72.9700 |
| 4 | 2010-03-01 01:00:00 | 0.79 | 111.00 | 1.32 | 111.0 | 111.00 | 21.430000 | 26.070000 | 111.0 | 111.0000 |
| | | | | | | | | | | |
| 209443 | 2010-08-01 00:00:00 | 111.00 | 0.55 | 111.00 | 111.0 | 111.00 | 125.000000 | 219.899994 | 111.0 | 25.3799 |
| 209444 | 2010-08-01 00:00:00 | 111.00 | 0.27 | 111.00 | 111.0 | 111.00 | 45.709999 | 47.410000 | 111.0 | 111.0000 |
| 209445 | 2010-08-01 00:00:00 | 111.00 | 111.00 | 111.00 | 111.0 | 0.24 | 46.560001 | 49.040001 | 111.0 | 46.2500 |
| 209446 | 2010-08-01 00:00:00 | 111.00 | 111.00 | 111.00 | 111.0 | 111.00 | 46.770000 | 50.119999 | 111.0 | 77.7099 |
| 209447 | 2010-08-01 00:00:00 | 0.92 | 0.43 | 0.71 | 111.0 | 0.25 | 76.330002 | 88.190002 | 111.0 | 52.2599 |

209448 rows × 17 columns

In [6]: c=b.head(11)

Out[6]:

| | date | BEN | СО | EBE | MXY | NMHC | NO_2 | NOx | OXY | 0_3 | |
|----|------------------------|--------|--------|--------|-------|--------|-----------|-----------|-------|------------|-----|
| 0 | 2010-03-01 01:00:00 | 111.00 | 0.29 | 111.00 | 111.0 | 111.00 | 25.090000 | 29.219999 | 111.0 | 68.930000 | 111 |
| 1 | 2010-03-01 01:00:00 | 111.00 | 0.27 | 111.00 | 111.0 | 111.00 | 24.879999 | 30.040001 | 111.0 | 111.000000 | 111 |
| 2 | 2010-03-01 01:00:00 | 111.00 | 0.28 | 111.00 | 111.0 | 111.00 | 17.410000 | 20.540001 | 111.0 | 72.120003 | 111 |
| 3 | 2010-03-01 01:00:00 | 0.38 | 0.24 | 1.74 | 111.0 | 0.05 | 15.610000 | 21.080000 | 111.0 | 72.970001 | 19 |
| 4 | 2010-03-01 01:00:00 | 0.79 | 111.00 | 1.32 | 111.0 | 111.00 | 21.430000 | 26.070000 | 111.0 | 111.000000 | 24 |
| 5 | 2010-03-01 01:00:00 | 0.56 | 111.00 | 0.58 | 111.0 | 111.00 | 21.370001 | 25.870001 | 111.0 | 111.000000 | 111 |
| 6 | 2010-03-01 01:00:00 | 111.00 | 111.00 | 111.00 | 111.0 | 111.00 | 16.660000 | 25.230000 | 111.0 | 111.000000 | 35 |
| 7 | 2010-03-01 01:00:00 | 111.00 | 0.23 | 111.00 | 111.0 | 111.00 | 17.799999 | 21.639999 | 111.0 | 55.880001 | 111 |
| 8 | 2010-03-01 01:00:00 | 111.00 | 111.00 | 111.00 | 111.0 | 111.00 | 12.050000 | 14.870000 | 111.0 | 57.369999 | 111 |
| 9 | 2010-03-01 01:00:00 | 1.48 | 0.18 | 0.51 | 111.0 | 111.00 | 16.780001 | 21.680000 | 111.0 | 78.660004 | 21 |
| 10 | 2010-03-01 01:00:00 | 111.00 | 0.22 | 111.00 | 111.0 | 111.00 | 21.450001 | 40.029999 | 111.0 | 111.000000 | 23 |

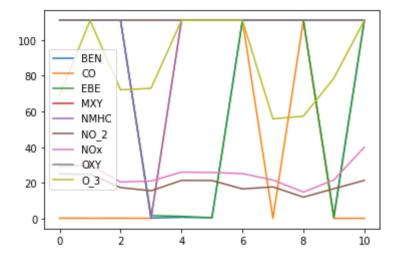
In [7]: d=c[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3']]

Out[7]:

| | BEN | СО | EBE | MXY | NMHC | NO_2 | NOx | OXY | O_3 |
|----|--------|--------|--------|-------|--------|-----------|-----------|-------|------------|
| 0 | 111.00 | 0.29 | 111.00 | 111.0 | 111.00 | 25.090000 | 29.219999 | 111.0 | 68.930000 |
| 1 | 111.00 | 0.27 | 111.00 | 111.0 | 111.00 | 24.879999 | 30.040001 | 111.0 | 111.000000 |
| 2 | 111.00 | 0.28 | 111.00 | 111.0 | 111.00 | 17.410000 | 20.540001 | 111.0 | 72.120003 |
| 3 | 0.38 | 0.24 | 1.74 | 111.0 | 0.05 | 15.610000 | 21.080000 | 111.0 | 72.970001 |
| 4 | 0.79 | 111.00 | 1.32 | 111.0 | 111.00 | 21.430000 | 26.070000 | 111.0 | 111.000000 |
| 5 | 0.56 | 111.00 | 0.58 | 111.0 | 111.00 | 21.370001 | 25.870001 | 111.0 | 111.000000 |
| 6 | 111.00 | 111.00 | 111.00 | 111.0 | 111.00 | 16.660000 | 25.230000 | 111.0 | 111.000000 |
| 7 | 111.00 | 0.23 | 111.00 | 111.0 | 111.00 | 17.799999 | 21.639999 | 111.0 | 55.880001 |
| 8 | 111.00 | 111.00 | 111.00 | 111.0 | 111.00 | 12.050000 | 14.870000 | 111.0 | 57.369999 |
| 9 | 1.48 | 0.18 | 0.51 | 111.0 | 111.00 | 16.780001 | 21.680000 | 111.0 | 78.660004 |
| 10 | 111.00 | 0.22 | 111.00 | 111.0 | 111.00 | 21.450001 | 40.029999 | 111.0 | 111.000000 |

In [8]:

Out[8]: <AxesSubplot:>



```
In [9]:
Out[9]: <seaborn.axisgrid.PairGrid at 0x2cfb0147460>
          114
          110
         x=d[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY']]
In [10]:
         from sklearn.model_selection import train_test_split
In [11]:
In [12]: from sklearn.linear_model import LinearRegression
         lr=LinearRegression()
Out[12]: LinearRegression()
In [13]:
         -3.197442310920451e-14
```

```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[14]:
                   Co-efficient
            BEN -9.267861e-16
             CO
                  1.214265e-16
             EBE
                  7.827542e-16
            MXY 0.000000e+00
           NMHC 0.000000e+00
           NO_2 7.440214e-16
            NOx 1.000000e+00
            OXY 0.000000e+00
In [15]: prediction=lr.predict(x_test)
Out[15]: <matplotlib.collections.PathCollection at 0x2cfb358ae20>
           30
           28
           26
           24
           22
                             24
                                       26
                                                 28
                    22
                                                           30
In [16]:
          1.0
In [17]:
In [18]: rr=Ridge(alpha=10)
Out[18]: Ridge(alpha=10)
In [19]:
Out[19]: 0.998143642386348
In [20]: la=Lasso(alpha=10)
la.fit(x_train,y_train)
Out[20]: Lasso(alpha=10)
```

```
In [21]:
Out[21]: 0.8953654254807312
In [22]: a1=b.head(7000)
Out[22]:
                                     CO
                                           EBE
                                                                                     OXY
                      date
                             BEN
                                                  MXY
                                                       NMHC
                                                                   NO_2
                                                                              NOx
                                                                                                O_3
                 2010-03-01
                            111.00
                                    0.29 111.00 111.00 25.090000 29.219999 111.00
                                                                                           68.930000
                   01:00:00
                 2010-03-01
                            111.00
                                         111.00 111.00 111.00 24.879999 30.040001 111.00 111.000000
                   01:00:00
                 2010-03-01
                            111.00
                                         111.00 111.00 111.00 17.410000 20.540001 111.00
                                    0.28
                   01:00:00
                 2010-03-01
                              0.38
                                    0.24
                                           1.74
                                                111.00
                                                          0.05 15.610000 21.080000 111.00
                   01:00:00
                 2010-03-01
                             0.79 111.00
                                           1.32 111.00 111.00 21.430000 26.070000 111.00 111.000000
                   01:00:00
                 2010-03-13
           6995
                              0.69
                                    0.26
                                            0.47
                                                   0.53
                                                          0.23 40.490002 42.220001
                                                                                     0.84
                                                                                           22.170000
                   06:00:00
                 2010-03-13
           6996
                            111.00 111.00 111.00 111.00
                                                          0.09 52.590000 66.339996 111.00
                                                                                           23.850000
                   06:00:00
                 2010-03-13
           6997
                            111.00 111.00 111.00 111.00 111.00 41.950001 44.310001 111.00 111.000000
                   06:00:00
                 2010-03-13
           6998
                            111.00 111.00 111.00 111.00 27.459999 30.540001 111.00
                                                                                          47.369999
                   06:00:00
                 2010-03-13
           6999
                            111.00 111.00 111.00 111.00 111.00 36.830002 42.049999 111.00 111.000000
                   06:00:00
          7000 rows × 17 columns
          e=a1[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
In [23]:
          f=e.iloc[:,0:14]
In [24]:
In [25]:
In [26]: logr=LogisticRegression(max_iter=10000)
Out[26]: LogisticRegression(max_iter=10000)
In [27]: from sklearn.model_selection import train_test_split
```

```
In [29]: prediction=logr.predict(i)
         [28079004]
In [30]: ___
Out[30]: array([28079003, 28079004, 28079008, 28079011, 28079016, 28079017,
               28079018, 28079024, 28079027, 28079036, 28079038, 28079039,
               28079040, 28079047, 28079049, 28079050, 28079054, 28079055,
               28079056, 28079057, 28079058, 28079059, 28079060, 28079099],
              dtype=int64)
In [31]:
Out[31]: 5.006307963717743e-221
In [32]:
Out[32]: 0.999999999999998
In [33]:
Out[33]: 0.8609523809523809
In [34]: | from sklearn.linear_model import ElasticNet
        en=ElasticNet()
Out[34]: ElasticNet()
In [351: \
        [ 2.91057726e-04 -1.25597362e-03 5.05219264e-04 0.00000000e+00
          0.00000000e+00 0.00000000e+00 9.78104467e-01 0.00000000e+00]
In [36]:
        0.5059785186362546
In [37]: | prediction=en.predict(x_test)
        0.9978374272653505
In [38]: from sklearn.ensemble import RandomForestClassifier
        rfc=RandomForestClassifier()
         Out[38]: RandomForestClassifier()
In [39]: parameters={'max_depth':[1,2,3,4,5],
         'min_samples_leaf':[5,10,15,20,25],
          'n_estimators':[10,20,30,40,50]
```

```
In [40]: from sklearn.model selection import GridSearchCV
                           grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="acc
Out[40]: 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 [41]:
Out[41]: 0.8322448979591837
In [42]:
In [43]: from sklearn.tree import plot_tree
                           plt.figure(figsize=(80,50))
Out[43]: [Text(2346.1363636363635, 2491.5, 'X[9] <= 0.652\ngini = 0.958\nsamples = 309
                           4\nvalue = [220, 164, 194, 189, 195, 195, 185, 216, 201, 194\n232, 211, 226,
                           190, 187, 225, 210, 198, 218, 225\n212, 211, 201, 201]'),
                             Text(1268.1818181818182, 2038.5, 'X[2] <= -0.39 \setminus i = 0.916 \setminus i = 154
                           0\nvalue = [0, 0, 194, 0, 0, 0, 185, 213, 0, 194, 232, 0\n226, 190, 0, 225,
                           0, 198, 0, 225, 0, 0, 201, 201]'),
                              Text(760.9090909090909, 1585.5, 'X[1] <= -0.098 \setminus i = 0.832 \setminus samples = 76
                           7\ value = [0, 0, 194, 0, 0, 0, 185, 213, 0, 0, 232, 0, 0\n0, 0, 0, 0, 198,
                           0, 0, 0, 0, 0, 201]'),
                             Text(405.8181818181818, 1132.5, 'X[3] <= -1.516\ngini = 0.749\nsamples = 49
                           1\nvalue = [0, 0, 194, 0, 0, 0, 185, 213, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0,
                           0, 0, 0, 201]'),
                              Text(202.9090909090909, 679.5, 'X[0] <= -1.56 \setminus ini = 0.499 \setminus ini = 248 \setminus ini = 0.499 \setminus ini = 0.49
                           value = [0, 0, 0, 0, 0, 0, 0, 213, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
                           0, 195]'),
                              Text(101.45454545454545, 226.5, 'gini = 0.361\nsamples = 122\nvalue = [0, 0,
                           0, 0, 0, 0, 0, 158, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 49]'),
                              Text(304.3636363636364, 226.5, 'gini = 0.398\nsamples = 126\nvalue = [0, 0, 0]
                           0, 0, 0, 0, 0, 55, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 146]'),
```

From this observation I had observe that the RIDGE is a highest accuracy of 0.998143642386348

```
In [ ]:
```