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	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
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
2	2014-06-01 01:00:00	0.3	NaN	0.1	NaN	2.0	6.0	NaN	NaN	NaN	NaN	NaN	1.1
3	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	1.0	6.0	79.0	NaN	NaN	NaN	NaN	NaN
4	2014-06-01 01:00:00	NaN	NaN	NaN	NaN	1.0	6.0	75.0	NaN	NaN	4.0	NaN	NaN
210019	2014-09-01 00:00:00	NaN	0.5	NaN	NaN	20.0	84.0	29.0	NaN	NaN	NaN	NaN	NaN
210020	2014-09-01 00:00:00	NaN	0.3	NaN	NaN	1.0	22.0	NaN	15.0	NaN	6.0	NaN	NaN
210021	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	13.0	70.0	NaN	NaN	NaN	NaN	NaN
210022	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	3.0	38.0	42.0	NaN	NaN	NaN	NaN	NaN
210023	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	26.0	65.0	11.0	NaN	NaN	NaN	NaN

210024 rows × 14 columns

In [3]:

<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: float	64(12), int64(1),	object(1)

.)

memory usage: 22.4+ MB

In [4]: b=a.fillna(value=222)

## Out[4]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH
0	2014-06-01 01:00:00	7771 117 7		222.0	222.00	3.0	10.0	222.0	222.0	222.0	3.0	222.00
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
2	2014-06-01 01:00:00	0.3	222.0	0.1	222.00	2.0	6.0	222.0	222.0	222.0	222.0	222.00
3	2014-06-01 01:00:00	222.0	0.2	222.0	222.00	1.0	6.0	79.0	222.0	222.0	222.0	222.00
4	2014-06-01 01:00:00	222.0	222.0	222.0	222.00	1.0	6.0	75.0	222.0	222.0	4.0	222.00
210019	2014-09-01 00:00:00	222.0	0.5	222.0	222.00	20.0	84.0	29.0	222.0	222.0	222.0	222.00
210020	2014-09-01 00:00:00	222.0	0.3	222.0	222.00	1.0	22.0	222.0	15.0	222.0	6.0	222.00
210021	2014-09-01 00:00:00	222.0	222.0	222.0	222.00	1.0	13.0	70.0	222.0	222.0	222.0	222.00
210022	2014-09-01 00:00:00	222.0	222.0	222.0	222.00	3.0	38.0	42.0	222.0	222.0	222.0	222.00
210023	2014-09-01 00:00:00	222.0	222.0	222.0	222.00	1.0	26.0	65.0	11.0	222.0	222.0	222.00

#### 210024 rows × 14 columns

```
In [5]:
```

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

## Out[6]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL
0	2014-06-01 01:00:00	222.0	0.2	222.0	222.00	3.0	10.0	222.0	222.0	222.0	3.0	222.00	222.0
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
2	2014-06-01 01:00:00	0.3	222.0	0.1	222.00	2.0	6.0	222.0	222.0	222.0	222.0	222.00	1.1
3	2014-06-01 01:00:00	222.0	0.2	222.0	222.00	1.0	6.0	79.0	222.0	222.0	222.0	222.00	222.0
4	2014-06-01 01:00:00	222.0	222.0	222.0	222.00	1.0	6.0	75.0	222.0	222.0	4.0	222.00	222.0
5	2014-06-01 01:00:00	0.1	0.4	0.1	222.00	1.0	10.0	83.0	7.0	222.0	2.0	222.00	0.2
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
7	2014-06-01 01:00:00	222.0	222.0	222.0	222.00	1.0	1.0	86.0	222.0	222.0	222.0	222.00	222.0
8	2014-06-01 01:00:00	222.0	0.3	222.0	222.00	5.0	22.0	68.0	222.0	222.0	4.0	222.00	222.0
9	2014-06-01 01:00:00	222.0	0.2	222.0	222.00	1.0	4.0	222.0	14.0	222.0	1.0	222.00	222.0
10	2014-06-01 01:00:00	0.1	222.0	0.1	222.00	6.0	18.0	222.0	8.0	5.0	2.0	222.00	0.7

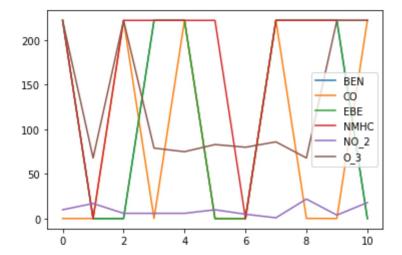
In [7]: d=c[['BEN','CO','EBE','NMHC','NO\_2','O\_3']]

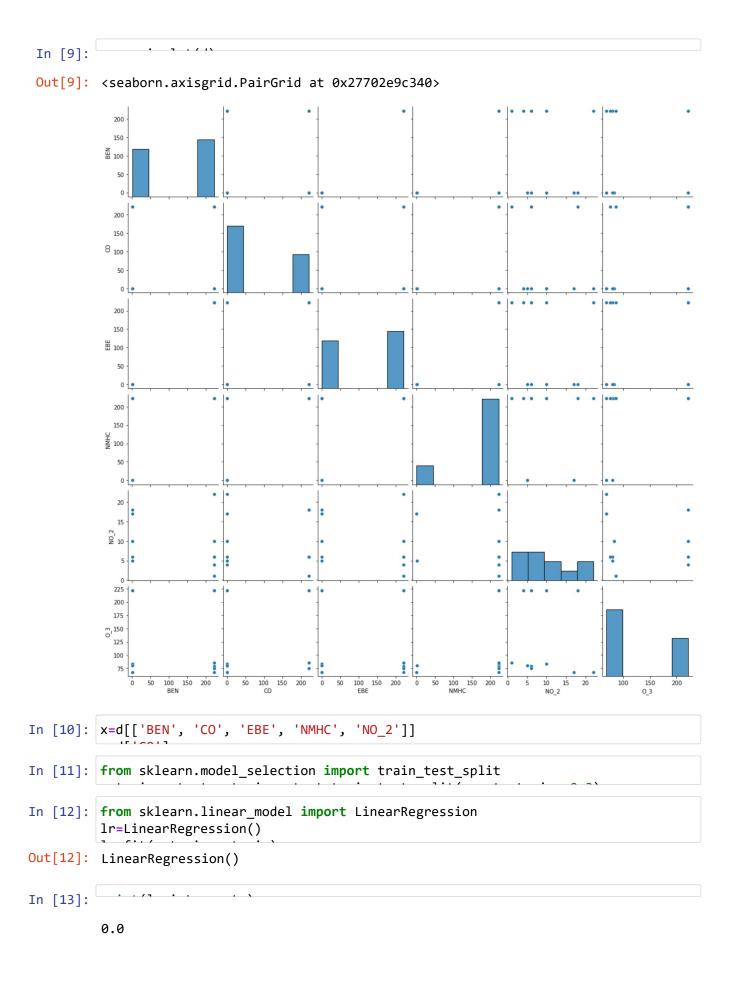
## Out[7]:

	BEN	СО	EBE	NMHC	NO_2	O_3
0	222.0	0.2	222.0	222.00	10.0	222.0
1	0.2	0.2	0.1	0.11	17.0	68.0
2	0.3	222.0	0.1	222.00	6.0	222.0
3	222.0	0.2	222.0	222.00	6.0	79.0
4	222.0	222.0	222.0	222.00	6.0	75.0
5	0.1	0.4	0.1	222.00	10.0	83.0
6	0.1	0.2	0.1	0.23	5.0	80.0
7	222.0	222.0	222.0	222.00	1.0	86.0
8	222.0	0.3	222.0	222.00	22.0	68.0
9	222.0	0.2	222.0	222.00	4.0	222.0
10	0.1	222.0	0.1	222.00	18.0	222.0

In [8]:

Out[8]: <AxesSubplot:>





```
In [14]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[14]:
                  Co-efficient
            BEN 1.888206e-13
             CO 1.000000e+00
            EBE -1.892682e-13
          NMHC 4.802573e-16
           NO_2 -1.703788e-15
In [15]: prediction=lr.predict(x_test)
Out[15]: <matplotlib.collections.PathCollection at 0x2770578e4c0>
           200
          150
          100
           50
                                 100
                                           150
                                                    200
In [16]:
          1.0
In [17]: -
In [18]: rr=Ridge(alpha=10)
Out[18]: Ridge(alpha=10)
In [19]:
Out[19]: 0.999999543984697
In [20]: la=Lasso(alpha=10)
Out[20]: Lasso(alpha=10)
In [21]: -
Out[21]: 0.9999991931063271
```

In [22]:	a1=b.head(6000)													
Out[22]:		date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	-
	0	2014-06-01 01:00:00	222.0	0.2	222.0	222.00	3.0	10.0	222.0	222.0	222.0	3.0	222.00	22
	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	
	2	2014-06-01 01:00:00	0.3	222.0	0.1	222.00	2.0	6.0	222.0	222.0	222.0	222.0	222.00	
	3	2014-06-01 01:00:00	222.0	0.2	222.0	222.00	1.0	6.0	79.0	222.0	222.0	222.0	222.00	22
	4	2014-06-01 01:00:00	222.0	222.0	222.0	222.00	1.0	6.0	75.0	222.0	222.0	4.0	222.00	22
	5995	2014-06-11 10:00:00	222.0	0.4	222.0	222.00	31.0	73.0	45.0	222.0	222.0	222.0	222.00	22
	5996	2014-06-11 10:00:00	222.0	0.3	222.0	222.00	8.0	24.0	222.0	24.0	222.0	6.0	222.00	22
	5997	2014-06-11 10:00:00	222.0	222.0	222.0	222.00	1.0	10.0	88.0	222.0	222.0	222.0	222.00	22
	5998	2014-06-11 10:00:00	222.0	222.0	222.0	222.00	7.0	17.0	70.0	222.0	222.0	222.0	222.00	22
	5999	2014-06-11 10:00:00	222.0	222.0	222.0	222.00	5.0	27.0	222.0	30.0	222.0	222.0	222.00	22
	6000 rows × 14 columns													
In [23]:	e=a1[	['BEN', '(	0', '	EBE',	'NMHC'	, 'NO_	2','0	_3',						
In [24]:	f=e.i	loc[:,0:14	1]											
In [25]:		1 16 7	· · · ·	•		(6)								
In [26]:	logr=	LogisticRe	gress	ion(ma	ax_ite	r=1000	ð)							
		ticRegress												
In [27]:	from	sklearn.mo	odel_s	elect:	ion im	port t	rain_	test_s	split					
In [28]:		0 00 00 40		0 44 /	22-22	44	1							
In [29]:	predi	ction=logr	r.pred	ict(i	)									
	[2807	9050]												

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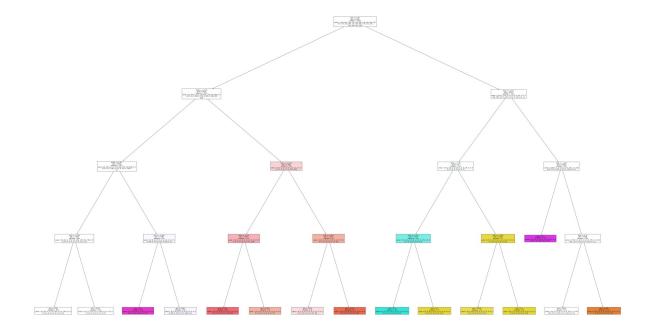
```
In [30]: -
Out[30]: array([28079004, 28079008, 28079011, 28079016, 28079017, 28079018,
              28079024, 28079027, 28079035, 28079036, 28079038, 28079039,
              28079040, 28079047, 28079048, 28079049, 28079050, 28079054,
              28079055, 28079056, 28079057, 28079058, 28079059, 28079060],
             dtype=int64)
In [31]:
Out[31]: 0.0
In [32]:
Out[32]: 0.0
In [33]:
Out[33]: 0.95
In [34]: | from sklearn.linear_model import ElasticNet
        en=ElasticNet()
Out[34]: ElasticNet()
In [35]:
        [-1.65763063e-01 9.99965212e-01 1.65669519e-01 6.09045377e-06
         -0.00000000e+00]
In [36]:
        0.015797123874477847
In [37]: prediction=en.predict(x_test)
        0.999999957832388
In [38]: from sklearn.ensemble import RandomForestClassifier
        rfc=RandomForestClassifier()
Out[38]: RandomForestClassifier()
        parameters={'max_depth':[1,2,3,4,5],
        'min_samples_leaf':[5,10,15,20,25],
         'n_estimators':[10,20,30,40,50]
```

```
In [43]: from sklearn.tree import plot tree
            plt.figure(figsize=(80,50))
Out[43]: [Text(2431.285714285714, 2446.2, 'X[5] <= 0.64\ngini = 0.958\nsamples = 2646\
            nvalue = [179, 161, 174, 172, 172, 166, 179, 154, 184, 155\n177, 173, 202, 19
            6, 171, 190, 202, 175, 172, 153\n162, 169, 203, 159]'),
             Text(1275.4285714285713, 1902.6, 'X[10] <= 1.178\ngini = 0.928\nsamples = 15
            35\nvalue = [0, 161, 0, 172, 172, 166, 179, 154, 184, 0, 0\n173, 0, 0, 0, 19
            0, 0, 175, 0, 153, 0, 169, 203\n158]'),
             Text(637.7142857142857, 1359.0, 'X[10] \le 0.355 \setminus i = 0.916 \setminus i = 130
            7\nvalue = [0, 161, 0, 172, 172, 166, 179, 154, 184, 0, 0\n173, 0, 0, 0, 190,
            0, 175, 0, 153, 0, 169, 0\n0]'),
             amples = 880\nvalue = [0, 161, 0, 172, 172, 166, 179, 154, 184, 0, 0\n173, 0,
            0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
             Text(159.42857142857142, 271.79999999997, 'gini = 0.799\nsamples = 544\nva
            0, 0, 0, 0]'),
             Text(478.2857142857142, 271.799999999997, 'gini = 0.675\nsamples = 336\nval
            0, 0]'),
             Text(956.5714285714284, 815.3999999999999, 'X[1] <= -0.166  ngini = 0.749  nsa
            5, 0, 153, 0, 169, 0, 0]'),
             Text(797.1428571428571, 271.799999999997, 'gini = 0.0\nsamples = 101\nvalue
            0]'),
             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0 \setminus 190, 0, 175, 0, 0, 0, 169, 0, 0]'),
             Text(1913.1428571428569, 1359.0, X[5] <= -0.514  | 0.492 | 1359.0, X[5] <= -0.514  | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 1359.0 | 135
            203, 158]'),
             0, 0, 0, 0, 176, 108]'),
             Text(1434.8571428571427, 271.79999999997, 'gini = 0.321\nsamples = 103\nva
            Text(1753.7142857142856, 271.799999999997, 'gini = 0.459\nsamples = 76\nval
            ue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 41, 7
            4]'),
             Text(2232.0, 815.399999999999, X[4] <= -0.679  ngini = 0.455 \ nsamples = 49\
            7, 50]'),
             Text(2072.5714285714284, 271.79999999997, 'gini = 0.495\nsamples = 26\nval
            9]'),
             Text(2391.428571428571, 271.799999999997, 'gini = 0.202\nsamples = 23\nvalu
            1]'),
             Text(3587.142857142857, 1902.6, X[2] <= -0.713  = 0.899  = 111
            1\nvalue = [179, 0, 174, 0, 0, 0, 0, 0, 155, 177, 0\n202, 196, 171, 0, 20
            2, 0, 172, 0, 162, 0, 0, 1]'),
```

0, 0, 0]'),

 $\label{eq:total_continuous_cont$ 

Text(3985.7142857142853, 271.799999999997, 'gini =  $0.832 \times 0.832 \times 0$ 



# From this observation I had observe that the ELASTICNET is a highest accuracy of 0.999999957832388

In [ ]: