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	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL
0	2013-11-01 01:00:00	NaN	0.6	NaN	NaN	135.0	74.0	NaN	NaN	NaN	7.0	NaN	NaN
1	2013-11-01 01:00:00	1.5	0.5	1.3	NaN	71.0	83.0	2.0	23.0	16.0	12.0	NaN	8.3
2	2013-11-01 01:00:00	3.9	NaN	2.8	NaN	49.0	70.0	NaN	NaN	NaN	NaN	NaN	9.0
3	2013-11-01 01:00:00	NaN	0.5	NaN	NaN	82.0	87.0	3.0	NaN	NaN	NaN	NaN	NaN
4	2013-11-01 01:00:00	NaN	NaN	NaN	NaN	242.0	111.0	2.0	NaN	NaN	12.0	NaN	NaN
209875	2013-03-01 00:00:00	NaN	0.4	NaN	NaN	8.0	39.0	52.0	NaN	NaN	NaN	NaN	NaN
209876	2013-03-01 00:00:00	NaN	0.4	NaN	NaN	1.0	11.0	NaN	6.0	NaN	2.0	NaN	NaN
209877	2013-03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	4.0	75.0	NaN	NaN	NaN	NaN	NaN
209878	2013-03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	11.0	52.0	NaN	NaN	NaN	NaN	NaN
209879	2013-03-01 00:00:00	NaN	NaN	NaN	NaN	1.0	10.0	75.0	3.0	NaN	NaN	NaN	NaN

209880 rows × 14 columns

In [3]:

<class 'pandas.core.frame.DataFrame'> RangeIndex: 209880 entries, 0 to 209879 Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype		
0	date	209880 non-null	object		
1	BEN	50462 non-null	float64		
2	CO	87018 non-null	float64		
3	EBE	50463 non-null	float64		
4	NMHC	25935 non-null	float64		
5	NO	209108 non-null	float64		
6	NO_2	209108 non-null	float64		
7	0_3	121858 non-null	float64		
8	PM10	104339 non-null	float64		
9	PM25	51980 non-null	float64		
10	S0_2	86970 non-null	float64		
11	TCH	25935 non-null	float64		
12	TOL	50317 non-null	float64		
13	station	209880 non-null	int64		
dtype	es: float	64(12), int64(1),	object(1		

.)

memory usage: 22.4+ MB

In [4]: b=a.fillna(value=122)

Out[4]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн
0	2013-11-01 01:00:00	122.0	0.6	122.0	122.0	135.0	74.0	122.0	122.0	122.0	7.0	122.0
1	2013-11-01 01:00:00	1.5	0.5	1.3	122.0	71.0	83.0	2.0	23.0	16.0	12.0	122.0
2	2013-11-01 01:00:00	3.9	122.0	2.8	122.0	49.0	70.0	122.0	122.0	122.0	122.0	122.0
3	2013-11-01 01:00:00	122.0	0.5	122.0	122.0	82.0	87.0	3.0	122.0	122.0	122.0	122.0
4	2013-11-01 01:00:00	122.0	122.0	122.0	122.0	242.0	111.0	2.0	122.0	122.0	12.0	122.0
209875	2013-03-01 00:00:00	122.0	0.4	122.0	122.0	8.0	39.0	52.0	122.0	122.0	122.0	122.0
209876	2013-03-01 00:00:00	122.0	0.4	122.0	122.0	1.0	11.0	122.0	6.0	122.0	2.0	122.0
209877	2013-03-01 00:00:00	122.0	122.0	122.0	122.0	2.0	4.0	75.0	122.0	122.0	122.0	122.0
209878	2013-03-01 00:00:00	122.0	122.0	122.0	122.0	2.0	11.0	52.0	122.0	122.0	122.0	122.0
209879	2013-03-01 00:00:00	122.0	122.0	122.0	122.0	1.0	10.0	75.0	3.0	122.0	122.0	122.0

209880 rows × 14 columns

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

## Out[6]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	T(
0	2013-11-01 01:00:00	122.0	0.6	122.0	122.00	135.0	74.0	122.0	122.0	122.0	7.0	122.00	122
1	2013-11-01 01:00:00	1.5	0.5	1.3	122.00	71.0	83.0	2.0	23.0	16.0	12.0	122.00	8
2	2013-11-01 01:00:00	3.9	122.0	2.8	122.00	49.0	70.0	122.0	122.0	122.0	122.0	122.00	Ę
3	2013-11-01 01:00:00	122.0	0.5	122.0	122.00	82.0	87.0	3.0	122.0	122.0	122.0	122.00	122
4	2013-11-01 01:00:00	122.0	122.0	122.0	122.00	242.0	111.0	2.0	122.0	122.0	12.0	122.00	122
5	2013-11-01 01:00:00	1.0	0.6	0.8	122.00	70.0	70.0	2.0	24.0	122.0	6.0	122.00	Ę
6	2013-11-01 01:00:00	122.0	0.4	122.0	0.29	51.0	80.0	5.0	23.0	14.0	4.0	1.44	122
7	2013-11-01 01:00:00	122.0	122.0	122.0	0.23	29.0	60.0	4.0	122.0	122.0	122.0	1.51	122
8	2013-11-01 01:00:00	122.0	1.0	122.0	122.00	165.0	107.0	2.0	122.0	122.0	11.0	122.00	122
9	2013-11-01 01:00:00	122.0	0.6	122.0	122.00	63.0	93.0	122.0	11.0	122.0	8.0	122.00	122
10	2013-11-01 01:00:00	1.4	122.0	1.4	122.00	68.0	84.0	122.0	26.0	11.0	6.0	122.00	7

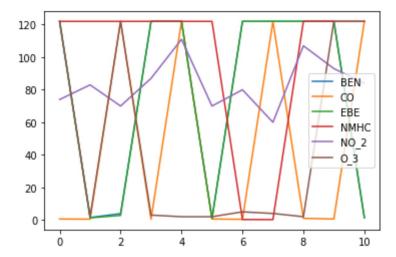
In [7]: d=c[['BEN','CO','EBE','NMHC','NO\_2','O\_3']]

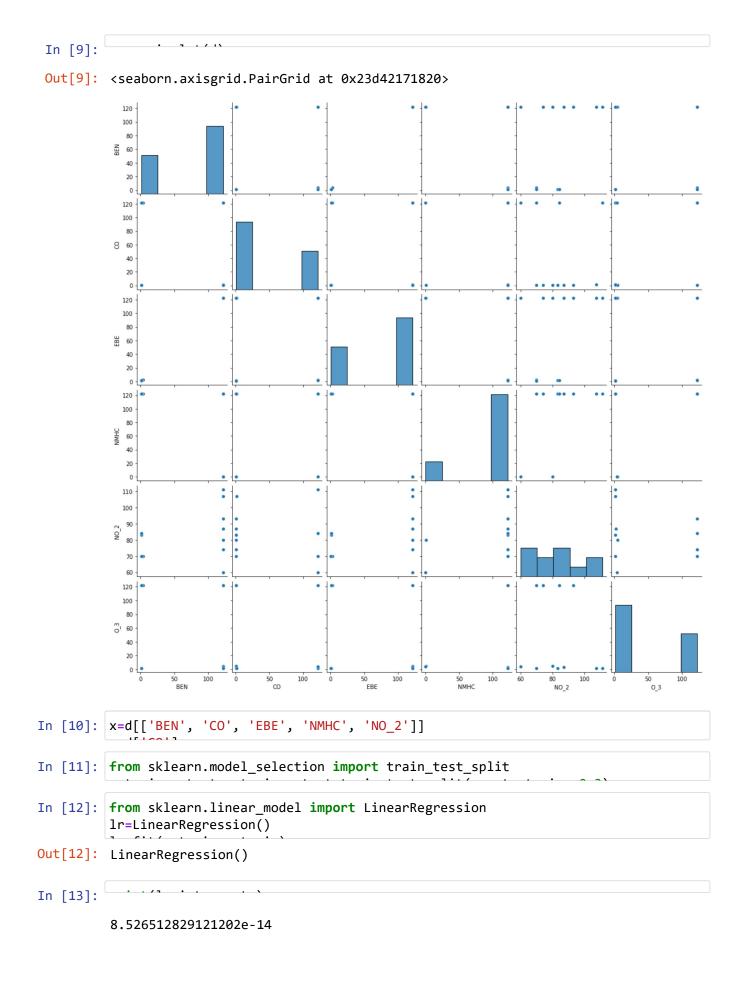
# Out[7]:

	BEN	СО	EBE	NMHC	NO_2	O_3
0	122.0	0.6	122.0	122.00	74.0	122.0
1	1.5	0.5	1.3	122.00	83.0	2.0
2	3.9	122.0	2.8	122.00	70.0	122.0
3	122.0	0.5	122.0	122.00	87.0	3.0
4	122.0	122.0	122.0	122.00	111.0	2.0
5	1.0	0.6	0.8	122.00	70.0	2.0
6	122.0	0.4	122.0	0.29	80.0	5.0
7	122.0	122.0	122.0	0.23	60.0	4.0
8	122.0	1.0	122.0	122.00	107.0	2.0
9	122.0	0.6	122.0	122.00	93.0	122.0
10	1.4	122.0	1.4	122.00	84.0	122.0

In [8]:

### Out[8]: <AxesSubplot:>





```
In [14]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[14]:
                   Co-efficient
            BEN 0.000000e+00
             CO 1.000000e+00
            EBE -1.256790e-16
           NMHC 4.884001e-18
           NO_2 -7.198288e-16
In [15]: prediction=lr.predict(x_test)
Out[15]: <matplotlib.collections.PathCollection at 0x23d45204a30>
           120
           100
            80
            40
            20
                      20
                             40
                                    60
                                                 100
                                                        120
In [16]:
          1.0
In [17]: -
In [18]: rr=Ridge(alpha=10)
Out[18]: Ridge(alpha=10)
In [19]:
Out[19]: 0.9999992236551154
In [20]: la=Lasso(alpha=10)
Out[20]: Lasso(alpha=10)
In [21]: -
Out[21]: 0.9999910068713143
```

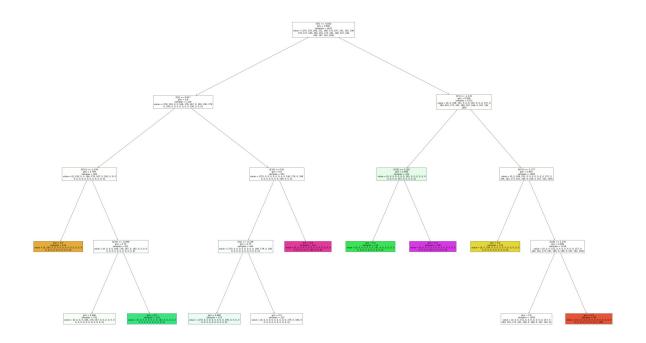
In [22]:	a1=b.	head(6000)	)											
Out[22]:		date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	7
	0	2013-11-01 01:00:00	122.0	0.6	122.0	122.0	135.0	74.0	122.0	122.0	122.0	7.0	122.0	12
	1	2013-11-01 01:00:00	1.5	0.5	1.3	122.0	71.0	83.0	2.0	23.0	16.0	12.0	122.0	
	2	2013-11-01 01:00:00	3.9	122.0	2.8	122.0	49.0	70.0	122.0	122.0	122.0	122.0	122.0	
	3	2013-11-01 01:00:00	122.0	0.5	122.0	122.0	82.0	87.0	3.0	122.0	122.0	122.0	122.0	12
	4	2013-11-01 01:00:00	122.0	122.0	122.0	122.0	242.0	111.0	2.0	122.0	122.0	12.0	122.0	12
	5995	2013-11-11 10:00:00	122.0	1.1	122.0	122.0	202.0	93.0	7.0	122.0	122.0	122.0	122.0	12
	5996	2013-11-11 10:00:00	122.0	0.8	122.0	122.0	170.0	100.0	122.0	44.0	122.0	12.0	122.0	12
	5997	2013-11-11 10:00:00	122.0	122.0	122.0	122.0	14.0	27.0	4.0	122.0	122.0	122.0	122.0	12
	5998	2013-11-11 10:00:00	122.0	122.0	122.0	122.0	78.0	50.0	9.0	122.0	122.0	122.0	122.0	12
	5999	2013-11-11 10:00:00	122.0	122.0	122.0	122.0	181.0	102.0	9.0	53.0	122.0	122.0	122.0	12
	6000 r	rows × 14 co	olumns											
In [23]:	e=a1[	['BEN', 'C	0', '	EBE',	'NMHC'	, 'NO_	2','0_	_3',						
In [24]:	f=e.i	loc[:,0:14	1]											
In [25]:						/ ( )								
In [26]:	logr=	LogisticRe	egress	ion(ma	ax_ite	r=1000	0)							
Out[26]:	Logis	ticRegress	sion(m	nax_it	er=100	900)								
In [27]:	from	sklearn.mo	odel_s	elect:	ion im	port t	rain_t	test_s	plit		2 21			
In [28]:		22224		0 44	22.22	44 1	7							
In [29]:	predi	ction=logr	r.pred	ict(i	)									
	[2807	9050]												

```
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]: 0.9511111111111111
In [34]: | from sklearn.linear_model import ElasticNet
        en=ElasticNet()
Out[34]: ElasticNet()
In [35]:
        [-0. 0.99972286 -0. -0.
                                                  -0.
                                                           ]
In [36]:
        0.014589219172414403
In [37]: | prediction=en.predict(x_test)
        0.9999999100936346
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 [43]: from sklearn.tree import plot tree
                plt.figure(figsize=(80,50))
Out[43]: [Text(2232.0, 2446.2, 'X[7] <= -0.042\ngini = 0.958\nsamples = 2637\nvalue =</pre>
                [170, 193, 208, 151, 166, 178, 167, 191, 182, 190\n179, 157, 180, 184, 161, 1
                73, 181, 168, 167, 166\n190, 167, 162, 169]'),
                 Text(1174.7368421052631, 1902.6, 'X[5] <= 0.617\ngini = 0.9\nsamples = 1126\
                nvalue = [170, 193, 0, 0, 166, 178, 167, 0, 182, 190, 179\n0, 180, 0, 0, 0,
                0, 0, 0, 0, 190, 0, 0, 0]'),
                  Text(469.89473684210526, 1359.0, X[10] <= -1.434 = 0.799 = 5
                65\nvalue = [0, 193, 0, 0, 166, 178, 167, 0, 182, 0, 0, 0\n0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0]'),
                 Text(234.94736842105263, 815.399999999999, 'gini = 0.0\nsamples = 114\nvalu
                0]'),
                  mples = 451\nvalue = [0, 0, 0, 0, 166, 178, 167, 0, 182, 0, 0, 0, 0\n0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0]'),
                  Text(469.89473684210526, 271.799999999997, 'gini = 0.666\nsamples = 332\nva
                0, 0, 0]'),
                 Text(939.7894736842105, 271.799999999997, 'gini = 0.0\nsamples = 119\nvalue
                0]'),
                 Text(1879.578947368421, 1359.0, 'X[10] <= 0.61 \setminus initial = 0.8 \setminus initial = 561 \setminus initial = 0.8 \setminus initial = 561 \setminus initial = 0.8 \setminus initial = 561 \setminus initial = 5
                alue = [170, 0, 0, 0, 0, 0, 0, 0, 190, 179, 0, 180 \ 0, 0, 0, 0, 0, 0, 1
                90, 0, 0, 0]'),
                 mples = 445\nvalue = [170, 0, 0, 0, 0, 0, 0, 0, 190, 179, 0, 180\n0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0]'),
                 Text(1409.6842105263158, 271.79999999997, 'gini = 0.498\nsamples = 223\nva
                lue = [170, 0, 0, 0, 0, 0, 0, 0, 190, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0]'),
                  Text(1879.578947368421, 271.799999999997, 'gini = 0.5\nsamples = 222\nvalue
                = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 179, 0, 180, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0]'),
                 Text(2114.5263157894738, 815.39999999999, 'gini = 0.0\nsamples = 116\nvalu
                0]'),
                 Text(3289.2631578947367, 1902.6, 'X[3] <= -1.133 \setminus = 0.928 \setminus = 15
                11\nvalue = [0, 0, 208, 151, 0, 0, 0, 191, 0, 0, 0, 157, 0\n184, 161, 173, 18
                1, 168, 167, 166, 0, 167, 162\n169]'),
                 Text(2819.3684210526317, 1359.0, 'X[10] <= 0.185 \setminus gini = 0.498 \setminus gini = 22
                2\nvalue = [0, 0, 0, 0, 0, 0, 0, 191, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 167, 0,
                0, 0, 0, 0]'),
                 Text(2584.4210526315787, 815.39999999999, 'gini = 0.0\nsamples = 114\nvalu
                Text(3054.315789473684, 815.399999999999, 'gini = 0.0\nsamples = 108\nvalue
                0]'),
                  Text(3759.157894736842, 1359.0, 'X[10] <= -1.377 \setminus gini = 0.916 \setminus gini = 12
                89\nvalue = [0, 0, 208, 151, 0, 0, 0, 0, 0, 0, 157, 0\n184, 161, 173, 181,
                168, 0, 166, 0, 167, 162, 169]'),
                 Text(3524.2105263157896, 815.39999999999, 'gini = 0.0\nsamples = 133\nvalu
```

0]'),

Text(3759.157894736842, 271.799999999997, 'gini = 0.9\nsamples = 1058\nvalue =  $[0, 0, 0, 151, 0, 0, 0, 0, 0, 0, 157, 0 \n184, 161, 173, 181, 168, 0, 166, 0, 167, 162, 0]')$ 



# From this observation I had observe that the ELASTICNET is a highest accuracy of 0.999999100936346

In [ ]: