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	2015-10-01 01:00:00	NaN	0.8	NaN	NaN	90.0	82.0	NaN	NaN	NaN	10.0	NaN	NaN
1	2015-10-01 01:00:00	2.0	0.8	1.6	0.33	40.0	95.0	4.0	37.0	24.0	12.0	1.83	8.3
2	2015-10-01 01:00:00	3.1	NaN	1.8	NaN	29.0	97.0	NaN	NaN	NaN	NaN	NaN	7.1
3	2015-10-01 01:00:00	NaN	0.6	NaN	NaN	30.0	103.0	2.0	NaN	NaN	NaN	NaN	NaN
4	2015-10-01 01:00:00	NaN	NaN	NaN	NaN	95.0	96.0	2.0	NaN	NaN	9.0	NaN	NaN
210091	2015-08-01 00:00:00	NaN	0.2	NaN	NaN	11.0	33.0	53.0	NaN	NaN	NaN	NaN	NaN
210092	2015-08-01 00:00:00	NaN	0.2	NaN	NaN	1.0	5.0	NaN	26.0	NaN	10.0	NaN	NaN
210093	2015-08-01 00:00:00	NaN	NaN	NaN	NaN	1.0	7.0	74.0	NaN	NaN	NaN	NaN	NaN
210094	2015-08-01 00:00:00	NaN	NaN	NaN	NaN	3.0	7.0	65.0	NaN	NaN	NaN	NaN	NaN
210095	2015-08-01 00:00:00	NaN	NaN	NaN	NaN	1.0	9.0	54.0	29.0	NaN	NaN	NaN	NaN

210096 rows × 14 columns

### In [3]:

<class 'pandas.core.frame.DataFrame'> RangeIndex: 210096 entries, 0 to 210095 Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
0	date	210096 non-null	object
1	BEN	51039 non-null	float64
2	CO	86827 non-null	float64
3	EBE	50962 non-null	float64
4	NMHC	25756 non-null	float64
5	NO	208805 non-null	float64
6	NO_2	208805 non-null	float64
7	0_3	121574 non-null	float64
8	PM10	102745 non-null	float64
9	PM25	48798 non-null	float64
10	S0_2	86898 non-null	float64
11	TCH	25756 non-null	float64
12	TOL	50626 non-null	float64
13	station	210096 non-null	int64
dtype	es: float	64(12), int64(1),	object(1)

.)

memory usage: 22.4+ MB

In [4]: b=a.fillna(value=257)

Out[4]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	ТСН
0	2015-10-01 01:00:00 257.0 0.8 257.0 25		257.00	90.0	82.0	257.0	257.0	257.0	10.0	257.00		
1	2015-10-01 01:00:00	2.0	0.8	1.6	0.33	40.0	95.0	4.0	37.0	24.0	12.0	1.83
2	2015-10-01 01:00:00	3.1	257.0	1.8	257.00	29.0	97.0	257.0	257.0	257.0	257.0	257.00
3	2015-10-01 01:00:00	257.0	0.6	257.0	257.00	30.0	103.0	2.0	257.0	257.0	257.0	257.00
4	2015-10-01 01:00:00	257.0	257.0	257.0	257.00	95.0	96.0	2.0	257.0	257.0	9.0	257.00
210091	2015-08-01 00:00:00	257.0	0.2	257.0	257.00	11.0	33.0	53.0	257.0	257.0	257.0	257.00
210092	2015-08-01 00:00:00	257.0	0.2	257.0	257.00	1.0	5.0	257.0	26.0	257.0	10.0	257.00
210093	2015-08-01 00:00:00	257.0	257.0	257.0	257.00	1.0	7.0	74.0	257.0	257.0	257.0	257.00
210094	2015-08-01 00:00:00	257.0	257.0	257.0	257.00	3.0	7.0	65.0	257.0	257.0	257.0	257.00
210095	2015-08-01 00:00:00	257.0	257.0	257.0	257.00	1.0	9.0	54.0	29.0	257.0	257.0	257.00

210096 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	то
0	2015-10-01 01:00:00	257.0	0.8	257.0	257.00	90.0	82.0	257.0	257.0	257.0	10.0	257.00	257.
1	2015-10-01 01:00:00	2.0	0.8	1.6	0.33	40.0	95.0	4.0	37.0	24.0	12.0	1.83	8.
2	2015-10-01 01:00:00	3.1	257.0	1.8	257.00	29.0	97.0	257.0	257.0	257.0	257.0	257.00	7.
3	2015-10-01 01:00:00	257.0	0.6	257.0	257.00	30.0	103.0	2.0	257.0	257.0	257.0	257.00	257.
4	2015-10-01 01:00:00	257.0	257.0	257.0	257.00	95.0	96.0	2.0	257.0	257.0	9.0	257.00	257.
5	2015-10-01 01:00:00	0.7	0.4	0.3	257.00	35.0	104.0	1.0	26.0	257.0	3.0	257.00	3.
6	2015-10-01 01:00:00	0.5	0.3	0.3	0.12	6.0	83.0	1.0	19.0	12.0	3.0	1.29	4.
7	2015-10-01 01:00:00	257.0	257.0	257.0	257.00	54.0	94.0	1.0	257.0	257.0	257.0	257.00	257.
8	2015-10-01 01:00:00	257.0	0.5	257.0	257.00	38.0	114.0	16.0	257.0	257.0	257.0	257.00	257.
9	2015-10-01 01:00:00	257.0	0.7	257.0	257.00	64.0	97.0	257.0	34.0	257.0	6.0	257.00	257.
10	2015-10-01 01:00:00	0.3	257.0	0.4	257.00	16.0	69.0	257.0	18.0	12.0	3.0	257.00	3.

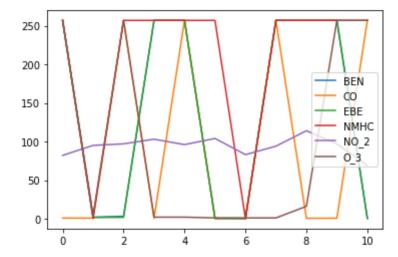
# In [7]: d=c[['BEN','CO','EBE','NMHC','NO\_2','O\_3']]

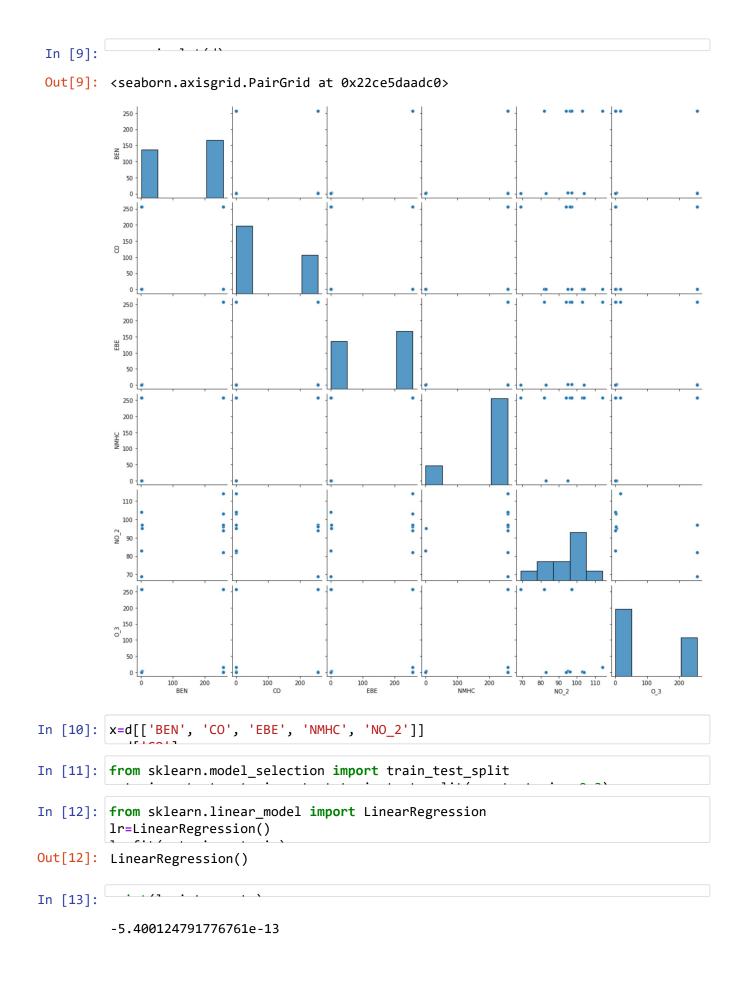
# Out[7]:

	BEN	CO	EBE	NMHC	NO_2	O_3
0	257.0	0.8	257.0	257.00	82.0	257.0
1	2.0	8.0	1.6	0.33	95.0	4.0
2	3.1	257.0	1.8	257.00	97.0	257.0
3	257.0	0.6	257.0	257.00	103.0	2.0
4	257.0	257.0	257.0	257.00	96.0	2.0
5	0.7	0.4	0.3	257.00	104.0	1.0
6	0.5	0.3	0.3	0.12	83.0	1.0
7	257.0	257.0	257.0	257.00	94.0	1.0
8	257.0	0.5	257.0	257.00	114.0	16.0
9	257.0	0.7	257.0	257.00	97.0	257.0
10	0.3	257.0	0.4	257.00	69.0	257.0

In [8]:

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





```
In [14]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[14]:
                   Co-efficient
            BEN -6.722470e-14
             CO 1.000000e+00
            EBE 6.672053e-14
           NMHC
                 1.198311e-15
           NO_2 2.334646e-15
In [15]: prediction=lr.predict(x_test)
Out[15]: <matplotlib.collections.PathCollection at 0x22ce6f7f670>
           0.70
           0.65
           0.60
           0.55
           0.50
           0.45
           0.40
           0.35
           0.30
                    0.35 0.40 0.45 0.50
               0.30
                                         0.55
                                               0.60 0.65
                                                         0.70
In [16]:
          1.0
In [17]:
In [18]: rr=Ridge(alpha=10)
Out[18]: Ridge(alpha=10)
In [19]:
Out[19]: 0.9680380043101725
In [20]: la=Lasso(alpha=10)
Out[20]: Lasso(alpha=10)
In [21]: -
Out[21]: 0.619677082719316
```

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	2015-10-01 01:00:00	257.0	0.8	257.0	257.00	90.0	82.0	257.0	257.0	257.0	10.0	257.00	2!
	1	2015-10-01 01:00:00	2.0	0.8	1.6	0.33	40.0	95.0	4.0	37.0	24.0	12.0	1.83	
	2	2015-10-01 01:00:00	3.1	257.0	1.8	257.00	29.0	97.0	257.0	257.0	257.0	257.0	257.00	
	3	2015-10-01 01:00:00	257.0	0.6	257.0	257.00	30.0	103.0	2.0	257.0	257.0	257.0	257.00	2!
	4	2015-10-01 01:00:00	257.0	257.0	257.0	257.00	95.0	96.0	2.0	257.0	257.0	9.0	257.00	2!
	5995	2015-10-11 10:00:00	257.0	0.2	257.0	257.00	15.0	38.0	33.0	257.0	257.0	257.0	257.00	2!
	5996	2015-10-11 10:00:00	257.0	0.2	257.0	257.00	3.0	17.0	257.0	17.0	257.0	12.0	257.00	2!
	5997	2015-10-11 10:00:00	257.0	257.0	257.0	257.00	1.0	10.0	50.0	257.0	257.0	257.0	257.00	2!
	5998	2015-10-11 10:00:00	257.0	257.0	257.0	257.00	6.0	12.0	40.0	257.0	257.0	257.0	257.00	2!
	5999	2015-10-11 10:00:00	257.0	257.0	257.0	257.00	2.0	23.0	28.0	21.0	257.0	257.0	257.00	2!
	6000 r	ows × 14 co	olumns											
In [23]:	e=a1[	['BEN', '(	0', '	EBE',	'NMHC'	, 'NO_	2','0	_3',						
In [24]:	f=e.i	loc[:,0:14	<b>!</b> ]											
In [25]:			/\ _	•		(6)								
In [26]:	logr=	LogisticRe	gress	ion(ma	ax_ite	r=1000	a)							
Out[26]:	Logis	ticRegress	sion(m	ax_it	er=100	00)								
In [27]:	from	sklearn.mo	del_s	elect:	ion im	port t	rain_ ·	test_s	split					
In [28]:		0 00 00 44			22-22	44	•							
In [29]:	predi	ction=logr	.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]: 0.94277777777778
In [34]: from sklearn.linear_model import ElasticNet
        en=ElasticNet()
Out[34]: ElasticNet()
In [35]:
        [-1.67116145e-01 9.99910493e-01 1.66647893e-01 1.77658477e-04
         0.00000000e+00]
In [36]:
        0.0812472450688233
In [37]: prediction=en.predict(x_test)
        0.9320694755487613
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 [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]: 0.99
In [42]:
In [43]: | from sklearn.tree import plot_tree
                                        plt.figure(figsize=(80,50))
Out[43]: [Text(1918.125, 2491.5, 'X[7] <= -0.126\ngini = 0.958\nsamples = 2654\nvalue
                                         = [187, 184, 177, 160, 208, 178, 158, 180, 185, 166\n166, 179, 179, 188, 178,
                                         151, 187, 182, 165, 194\n151, 170, 180, 147]'),
                                             Text(976.5, 2038.5, 'X[10] <= -1.803 \setminus = 0.899 \setminus = 1092 \setminus = 1092
                                         [186, 184, 0, 0, 208, 176, 158, 0, 171, 164, 166\n0, 179, 0, 0, 0, 0, 0, 0,
                                         0, 151, 0, 0, 0]'),
                                             Text(837.0, 1585.5, 'gini = 0.0\nsamples = 113\nvalue = [186, 0, 0, 0, 0, 0,
                                         0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                             Text(1116.0, 1585.5, 'X[0] <= -0.577\ngini = 0.888\nsamples = 979\nvalue =
                                          151, 0, 0, 0]'),
                                             Text(558.0, 1132.5, X[3] <= -1.148 = 0.749 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 415 = 4
                                         0]'),
                                             Text(279.0, 679.5, X[1] <= -1.187 = 0.498 = 208 = 208 = [0, 1.187]
                                         Text(139.5, 226.5, 'gini = 0.153\nsamples = 87\nvalue = [0, 12, 0, 0, 0, 0, 0, 0]
                                         132, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                             Text(418.5, 226.5, 'gini = 0.23\nsamples = 121\nvalue = [0, 170, 0, 0, 0, 0,
```

# From this observation I had observe that the RIDGE is a highest accuracy of 0.9680380043101725

```
In [ ]:
```