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	2016-11-01 01:00:00	NaN	0.7	NaN	NaN	153.0	77.0	NaN	NaN	NaN	7.0	NaN	NaN
1	2016-11-01 01:00:00	3.1	1.1	2.0	0.53	260.0	144.0	4.0	46.0	24.0	18.0	2.44	14.4
2	2016-11-01 01:00:00	5.9	NaN	7.5	NaN	297.0	139.0	NaN	NaN	NaN	NaN	NaN	26.0
3	2016-11-01 01:00:00	NaN	1.0	NaN	NaN	154.0	113.0	2.0	NaN	NaN	NaN	NaN	NaN
4	2016-11-01 01:00:00	NaN	NaN	NaN	NaN	275.0	127.0	2.0	NaN	NaN	18.0	NaN	NaN
209491	2016-07-01 00:00:00	NaN	0.2	NaN	NaN	2.0	29.0	73.0	NaN	NaN	NaN	NaN	NaN
209492	2016-07-01 00:00:00	NaN	0.3	NaN	NaN	1.0	29.0	NaN	36.0	NaN	5.0	NaN	NaN
209493	2016-07-01 00:00:00	NaN	NaN	NaN	NaN	1.0	19.0	71.0	NaN	NaN	NaN	NaN	NaN
209494	2016-07-01 00:00:00	NaN	NaN	NaN	NaN	6.0	17.0	85.0	NaN	NaN	NaN	NaN	NaN
209495	2016-07-01 00:00:00	NaN	NaN	NaN	NaN	2.0	46.0	61.0	34.0	NaN	NaN	NaN	NaN

209496 rows × 14 columns

In [3]:

<class 'pandas.core.frame.DataFrame'> RangeIndex: 209496 entries, 0 to 209495 Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype		
0	date	209496 non-null	object		
1	BEN	50755 non-null	float64		
2	CO	85999 non-null	float64		
3	EBE	50335 non-null	float64		
4	NMHC	25970 non-null	float64		
5	NO	208614 non-null	float64		
6	NO_2	208614 non-null	float64		
7	0_3	121197 non-null	float64		
8	PM10	102892 non-null	float64		
9	PM25	52165 non-null	float64		
10	S0_2	86023 non-null	float64		
11	TCH	25970 non-null	float64		
12	TOL	50662 non-null	float64		
13	station	209496 non-null	int64		
dtype	es: float	54(12), int64(1),	object(1)		

.)

memory usage: 22.4+ MB

In [4]: b=a.fillna(value=192)

Out[4]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн
0	2016-11-01 01:00:00	192.0	0.7	192.0	192.00	153.0	77.0	192.0	192.0	192.0	7.0	192.00
1	2016-11-01 01:00:00	3.1	1.1	2.0	0.53	260.0	144.0	4.0	46.0	24.0	18.0	2.44
2	2016-11-01 01:00:00	5.9	192.0	7.5	192.00	297.0	139.0	192.0	192.0	192.0	192.0	192.00
3	2016-11-01 01:00:00	192.0	1.0	192.0	192.00	154.0	113.0	2.0	192.0	192.0	192.0	192.00
4	2016-11-01 01:00:00	192.0	192.0	192.0	192.00	275.0	127.0	2.0	192.0	192.0	18.0	192.00
209491	2016-07-01 00:00:00	192.0	0.2	192.0	192.00	2.0	29.0	73.0	192.0	192.0	192.0	192.00
209492	2016-07-01 00:00:00	192.0	0.3	192.0	192.00	1.0	29.0	192.0	36.0	192.0	5.0	192.00
209493	2016-07-01 00:00:00	192.0	192.0	192.0	192.00	1.0	19.0	71.0	192.0	192.0	192.0	192.00
209494	2016-07-01 00:00:00	192.0	192.0	192.0	192.00	6.0	17.0	85.0	192.0	192.0	192.0	192.00
209495	2016-07-01 00:00:00	192.0	192.0	192.0	192.00	2.0	46.0	61.0	34.0	192.0	192.0	192.00

209496 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	
0	2016-11-01 01:00:00	192.0	0.7	192.0	192.00	153.0	77.0	192.0	192.0	192.0	7.0	192.00	192
1	2016-11-01 01:00:00	3.1	1.1	2.0	0.53	260.0	144.0	4.0	46.0	24.0	18.0	2.44	1∠
2	2016-11-01 01:00:00	5.9	192.0	7.5	192.00	297.0	139.0	192.0	192.0	192.0	192.0	192.00	26
3	2016-11-01 01:00:00	192.0	1.0	192.0	192.00	154.0	113.0	2.0	192.0	192.0	192.0	192.00	192
4	2016-11-01 01:00:00	192.0	192.0	192.0	192.00	275.0	127.0	2.0	192.0	192.0	18.0	192.00	192
5	2016-11-01 01:00:00	0.9	0.5	0.5	192.00	66.0	82.0	1.0	27.0	192.0	8.0	192.00	(
6	2016-11-01 01:00:00	0.7	0.8	0.4	0.13	57.0	66.0	3.0	23.0	15.0	4.0	1.35	Ę
7	2016-11-01 01:00:00	192.0	192.0	192.0	192.00	52.0	78.0	1.0	192.0	192.0	192.0	192.00	192
8	2016-11-01 01:00:00	192.0	1.2	192.0	192.00	205.0	85.0	6.0	192.0	192.0	192.0	192.00	192
9	2016-11-01 01:00:00	192.0	0.7	192.0	192.00	114.0	91.0	192.0	37.0	192.0	6.0	192.00	192
10	2016-11-01 01:00:00	2.5	192.0	3.3	192.00	166.0	114.0	192.0	45.0	27.0	8.0	192.00	16

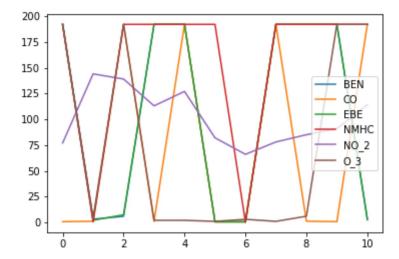
In [7]: d=c[['BEN','CO','EBE','NMHC','NO_2','O_3']]

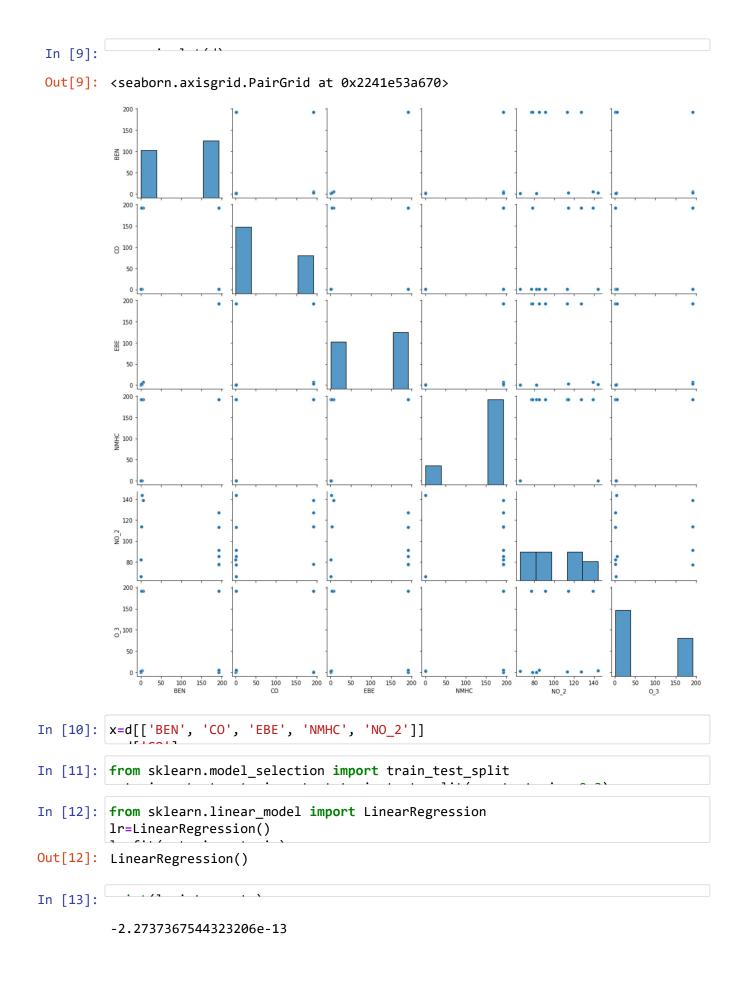
Out[7]:

	BEN	СО	EBE	NMHC	NO_2	O_3
0	192.0	0.7	192.0	192.00	77.0	192.0
1	3.1	1.1	2.0	0.53	144.0	4.0
2	5.9	192.0	7.5	192.00	139.0	192.0
3	192.0	1.0	192.0	192.00	113.0	2.0
4	192.0	192.0	192.0	192.00	127.0	2.0
5	0.9	0.5	0.5	192.00	82.0	1.0
6	0.7	8.0	0.4	0.13	66.0	3.0
7	192.0	192.0	192.0	192.00	78.0	1.0
8	192.0	1.2	192.0	192.00	85.0	6.0
9	192.0	0.7	192.0	192.00	91.0	192.0
10	2.5	192.0	3.3	192.00	114.0	192.0

In [8]:

Out[8]: <AxesSubplot:>





```
In [14]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[14]:
                  Co-efficient
            BEN 5.344282e-14
            CO 1.000000e+00
            EBE -5.238483e-14
          NMHC 4.579437e-17
           NO_2 8.577800e-16
In [15]: prediction=lr.predict(x_test)
Out[15]: <matplotlib.collections.PathCollection at 0x2241f710370>
          200
          175
          150
          125
          100
           75
           50
           25
In [16]:
         1.0
In [17]: -
In [18]: rr=Ridge(alpha=10)
Out[18]: Ridge(alpha=10)
In [19]:
Out[19]: 0.9999905418232936
In [20]: la=Lasso(alpha=10)
Out[20]: Lasso(alpha=10)
In [21]:
Out[21]: 0.9999978712598887
```

In [22]:	a1=b.head(6000)													
Out[22]:		date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	
	0	2016-11-01 01:00:00	192.0	0.7	192.0	192.00	153.0	77.0	192.0	192.0	192.0	7.0	192.00	
	1	2016-11-01 01:00:00	3.1	1.1	2.0	0.53	260.0	144.0	4.0	46.0	24.0	18.0	2.44	
	2	2016-11-01 01:00:00	5.9	192.0	7.5	192.00	297.0	139.0	192.0	192.0	192.0	192.0	192.00	
	3	2016-11-01 01:00:00	192.0	1.0	192.0	192.00	154.0	113.0	2.0	192.0	192.0	192.0	192.00	1
	4	2016-11-01 01:00:00	192.0	192.0	192.0	192.00	275.0	127.0	2.0	192.0	192.0	18.0	192.00	1
	5995	2016-11-11 10:00:00	192.0	1.1	192.0	192.00	203.0	111.0	8.0	192.0	192.0	192.0	192.00	1
	5996	2016-11-11 10:00:00	192.0	0.5	192.0	192.00	192.0	192.0	192.0	18.0	192.0	192.0	192.00	1
	5997	2016-11-11 10:00:00	192.0	192.0	192.0	192.00	18.0	15.0	13.0	192.0	192.0	192.0	192.00	1
	5998	2016-11-11 10:00:00	192.0	192.0	192.0	192.00	62.0	40.0	12.0	192.0	192.0	192.0	192.00	,
	5999	2016-11-11 10:00:00	192.0	192.0	192.0	192.00	132.0	86.0	7.0	36.0	192.0	192.0	192.00	,
	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	1]											
In [25]:		1 10 1	· · · ·	•••		(6)								
In [26]:	logr=	LogisticRe	gress	ion(ma	ax_ite	r=1000	0)							
Out[26]:	Logis	ticRegress	sion(m	ax_it	er=100	000)								
In [27]:	from	sklearn.mo	odel_s	elect:	ion im	port t	rain_t	est_s	plit					
In [28]:		22224		^ 44 /	22.22	44 553	7							
In [29]:	predi	ction=logr	r.pred	ict(i)									
	[2807	9059]												

```
In [301: -
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]: 2.42973207230404e-310
In [32]:
Out[32]: 0.0
In [33]:
Out[33]: 0.945555555555556
In [34]: | from sklearn.linear_model import ElasticNet
        en=ElasticNet()
        C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_d
        escent.py:530: ConvergenceWarning: Objective did not converge. You might want
        to increase the number of iterations. Duality gap: 7.271092215353746, toleran
        ce: 5.223610856756517
          model = cd_fast.enet_coordinate_descent(
Out[34]: ElasticNet()
In [35]:
        [-3.32031653e-01 9.97103512e-01 3.31185864e-01 1.84669016e-04
         -0.00000000e+00]
In [36]:
        0.12048587498125585
In [37]: prediction=en.predict(x_test)
        0.9999809298885648
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]: 0.9776190476190476
In [42]:
In [43]: | from sklearn.tree import plot_tree
        plt.figure(figsize=(80,50))
Out[43]: [Text(1639.125, 2491.5, 'X[3] <= -1.132\ngini = 0.958\nsamples = 2622\nvalue
        = [166, 191, 146, 161, 195, 210, 195, 182, 162, 181 \n155, 139, 178, 175, 194,
        186, 175, 152, 175, 161\n169, 188, 186, 178]'),
         Text(558.0, 2038.5, X[8] <= -2.649  ngini = 0.666 \nsamples = 340 \nvalue =
         [0, 191, 0, 0, 0, 0, 194, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 175, 0, 0, 0, 0,
         Text(279.0, 1585.5, 'X[10] <= 0.099\ngini = 0.493\nsamples = 201\nvalue =
         [0, 0, 0, 0, 0, 0, 189, 0, 0, 0, 0, 0, 0, 0]
        0]'),
         Text(139.5, 1132.5, 'gini = 0.0\nsamples = 114\nvalue = [0, 0, 0, 0, 0, 0, 1]
        89, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
         Text(418.5, 1132.5, 'gini = 0.0\nsamples = 87\nvalue = [0, 0, 0, 0, 0, 0, 0, 0]
         0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 148, 0, 0, 0, 0]'),
         Text(837.0, 1585.5, X[10] <= -1.235 = 0.251 = 0.251 = 139 = 139
         [0, 191, 0, 0, 0, 0, 5, 0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 0, 27, 0, 0, 0, 0, 0]
        0]'),
         0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
         Text(976.5, 1132.5, 'gini = 0.264\nsamples = 19\nvalue = [0, 0, 0, 0, 0, 0, 0, 0]
```

From this observation I had observe that the LASSO is a highest accuracy of 0.9999978712598887

```
In [ ]:
```