In [478]: 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

from sklearn.model_selection import train_test_split

In [479]: | a=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs_per_year\madrid_2013

Out[479]:

	date	BEN	со	EBE	NМНС	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	station
0	2011-11- 01 01:00:00	NaN	1.0	NaN	NaN	154.0	84.0	NaN	NaN	NaN	6.0	NaN	NaN	28079004
1	2011-11- 01 01:00:00	2.5	0.4	3.5	0.26	68.0	92.0	3.0	40.0	24.0	9.0	1.54	8.7	28079008
2	2011-11- 01 01:00:00	2.9	NaN	3.8	NaN	96.0	99.0	NaN	NaN	NaN	NaN	NaN	7.2	28079011
3	2011-11- 01 01:00:00	NaN	0.6	NaN	NaN	60.0	83.0	2.0	NaN	NaN	NaN	NaN	NaN	28079016
4	2011-11- 01 01:00:00	NaN	NaN	NaN	NaN	44.0	62.0	3.0	NaN	NaN	3.0	NaN	NaN	28079017
209923	2011-09- 01 00:00:00	NaN	0.2	NaN	NaN	5.0	19.0	44.0	NaN	NaN	NaN	NaN	NaN	28079056
209924	2011-09- 01 00:00:00	NaN	0.1	NaN	NaN	6.0	29.0	NaN	11.0	NaN	7.0	NaN	NaN	28079057
209925	2011-09- 01 00:00:00	NaN	NaN	NaN	0.23	1.0	21.0	28.0	NaN	NaN	NaN	1.44	NaN	28079058
209926	2011-09- 01 00:00:00	NaN	NaN	NaN	NaN	3.0	15.0	48.0	NaN	NaN	NaN	NaN	NaN	28079059
209927	2011-09- 01 00:00:00	NaN	NaN	NaN	NaN	4.0	33.0	38.0	13.0	NaN	NaN	NaN	NaN	28079060

209928 rows × 14 columns

```
In [480]: a.info()
```

<class 'pandas.core.frame.DataFrame'> RangeIndex: 209928 entries, 0 to 209927 Data columns (total 14 columns): Column Non-Null Count Dtype --------------0 date 209928 non-null object BEN float64 1 51393 non-null 2 CO 87127 non-null float64 3 EBE 51350 non-null float64 float64 4 NMHC 43517 non-null 5 NO 208954 non-null float64 6 NO 2 208973 non-null float64 7 0 3 122049 non-null float64 8 PM10 103743 non-null float64 9 PM25 51079 non-null float64 float64 10 SO 2 87131 non-null 11 TCH 43519 non-null float64 12 TOL 51175 non-null float64 13 station 209928 non-null int64 dtypes: float64(12), int64(1), object(1) memory usage: 22.4+ MB

```
In [481]: b=a.fillna(value=55)
          b
```

Out[481]:

	date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	station
0	2011-11- 01 01:00:00	55.0	1.0	55.0	55.00	154.0	84.0	55.0	55.0	55.0	6.0	55.00	55.0	28079004
1	2011-11- 01 01:00:00	2.5	0.4	3.5	0.26	68.0	92.0	3.0	40.0	24.0	9.0	1.54	8.7	28079008
2	2011-11- 01 01:00:00	2.9	55.0	3.8	55.00	96.0	99.0	55.0	55.0	55.0	55.0	55.00	7.2	28079011
3	2011-11- 01 01:00:00	55.0	0.6	55.0	55.00	60.0	83.0	2.0	55.0	55.0	55.0	55.00	55.0	28079016
4	2011-11- 01 01:00:00	55.0	55.0	55.0	55.00	44.0	62.0	3.0	55.0	55.0	3.0	55.00	55.0	28079017
209923	2011- 09-01 00:00:00	55.0	0.2	55.0	55.00	5.0	19.0	44.0	55.0	55.0	55.0	55.00	55.0	28079056
209924	2011- 09-01 00:00:00	55.0	0.1	55.0	55.00	6.0	29.0	55.0	11.0	55.0	7.0	55.00	55.0	28079057
209925	2011- 09-01 00:00:00	55.0	55.0	55.0	0.23	1.0	21.0	28.0	55.0	55.0	55.0	1.44	55.0	28079058
209926	2011- 09-01 00:00:00	55.0	55.0	55.0	55.00	3.0	15.0	48.0	55.0	55.0	55.0	55.00	55.0	28079059
209927	2011- 09-01 00:00:00	55.0	55.0	55.0	55.00	4.0	33.0	38.0	13.0	55.0	55.0	55.00	55.0	28079060

209928 rows × 14 columns

```
In [482]: b.columns
dtype='object')
```

In [483]: c=b.head(20) c

Out[483]:

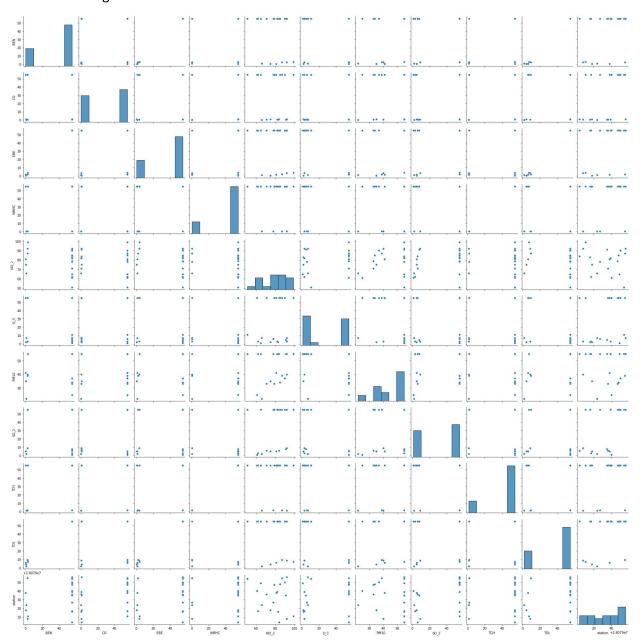
	date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	station
0	2011-11-01 01:00:00	55.0	1.0	55.0	55.00	154.0	84.0	55.0	55.0	55.0	6.0	55.00	55.0	28079004
1	2011-11-01 01:00:00	2.5	0.4	3.5	0.26	68.0	92.0	3.0	40.0	24.0	9.0	1.54	8.7	28079008
2	2011-11-01 01:00:00	2.9	55.0	3.8	55.00	96.0	99.0	55.0	55.0	55.0	55.0	55.00	7.2	28079011
3	2011-11-01 01:00:00	55.0	0.6	55.0	55.00	60.0	83.0	2.0	55.0	55.0	55.0	55.00	55.0	28079016
4	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	44.0	62.0	3.0	55.0	55.0	3.0	55.00	55.0	28079017
5	2011-11-01 01:00:00	0.5	0.8	0.3	55.00	102.0	75.0	2.0	35.0	55.0	5.0	55.00	4.3	28079018
6	2011-11-01 01:00:00	0.7	0.3	1.1	0.16	17.0	66.0	7.0	22.0	16.0	2.0	1.36	1.7	28079024
7	2011-11-01 01:00:00	55.0	55.0	55.0	0.36	83.0	78.0	6.0	55.0	55.0	55.0	1.80	55.0	28079027
8	2011-11-01 01:00:00	55.0	0.7	55.0	55.00	80.0	91.0	5.0	55.0	55.0	8.0	55.00	55.0	28079035
9	2011-11-01 01:00:00	55.0	0.6	55.0	55.00	63.0	71.0	55.0	33.0	55.0	6.0	55.00	55.0	28079036
10	2011-11-01 01:00:00	0.3	55.0	1.4	55.00	77.0	81.0	55.0	41.0	23.0	5.0	55.00	6.2	28079038
11	2011-11-01 01:00:00	55.0	0.6	55.0	55.00	57.0	82.0	3.0	55.0	55.0	55.0	55.00	55.0	28079039
12	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	9.0	61.0	55.0	25.0	55.0	1.0	55.00	55.0	28079040
13	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	58.0	79.0	55.0	33.0	22.0	55.0	55.00	55.0	28079047
14	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	60.0	85.0	55.0	34.0	20.0	55.0	55.00	55.0	28079048
15	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	57.0	65.0	1.0	55.0	55.0	55.0	55.00	55.0	28079049
16	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	85.0	90.0	55.0	37.0	12.0	55.0	55.00	55.0	28079050
17	2011-11-01 01:00:00	55.0	55.0	55.0	55.00	17.0	51.0	11.0	55.0	55.0	55.0	55.00	55.0	28079054
18	2011-11-01 01:00:00	2.3	55.0	1.9	0.27	110.0	87.0	55.0	39.0	55.0	55.0	1.80	9.5	28079055
19	2011-11-01 01:00:00	55.0	0.8	55.0	55.00	133.0	92.0	7.0	55.0	55.0	55.0	55.00	55.0	28079056

Out[520]:

	BEN	СО	EBE	NMHC	NO_2	O_3	PM10	SO_2	TCH	TOL	station
0	55.0	1.0	55.0	55.00	84.0	55.0	55.0	6.0	55.00	55.0	28079004
1	2.5	0.4	3.5	0.26	92.0	3.0	40.0	9.0	1.54	8.7	28079008
2	2.9	55.0	3.8	55.00	99.0	55.0	55.0	55.0	55.00	7.2	28079011
3	55.0	0.6	55.0	55.00	83.0	2.0	55.0	55.0	55.00	55.0	28079016
4	55.0	55.0	55.0	55.00	62.0	3.0	55.0	3.0	55.00	55.0	28079017
5	0.5	8.0	0.3	55.00	75.0	2.0	35.0	5.0	55.00	4.3	28079018
6	0.7	0.3	1.1	0.16	66.0	7.0	22.0	2.0	1.36	1.7	28079024
7	55.0	55.0	55.0	0.36	78.0	6.0	55.0	55.0	1.80	55.0	28079027
8	55.0	0.7	55.0	55.00	91.0	5.0	55.0	8.0	55.00	55.0	28079035
9	55.0	0.6	55.0	55.00	71.0	55.0	33.0	6.0	55.00	55.0	28079036
10	0.3	55.0	1.4	55.00	81.0	55.0	41.0	5.0	55.00	6.2	28079038
11	55.0	0.6	55.0	55.00	82.0	3.0	55.0	55.0	55.00	55.0	28079039
12	55.0	55.0	55.0	55.00	61.0	55.0	25.0	1.0	55.00	55.0	28079040
13	55.0	55.0	55.0	55.00	79.0	55.0	33.0	55.0	55.00	55.0	28079047
14	55.0	55.0	55.0	55.00	85.0	55.0	34.0	55.0	55.00	55.0	28079048
15	55.0	55.0	55.0	55.00	65.0	1.0	55.0	55.0	55.00	55.0	28079049
16	55.0	55.0	55.0	55.00	90.0	55.0	37.0	55.0	55.00	55.0	28079050
17	55.0	55.0	55.0	55.00	51.0	11.0	55.0	55.0	55.00	55.0	28079054
18	2.3	55.0	1.9	0.27	87.0	55.0	39.0	55.0	1.80	9.5	28079055
19	55.0	8.0	55.0	55.00	92.0	7.0	55.0	55.0	55.00	55.0	28079056

In [521]: sns.pairplot(d)

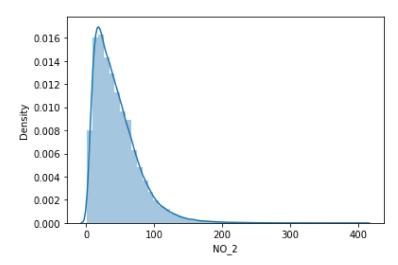
Out[521]: <seaborn.axisgrid.PairGrid at 0x1b700200f40>



```
In [523]: sns.distplot(a['NO_2'])
```

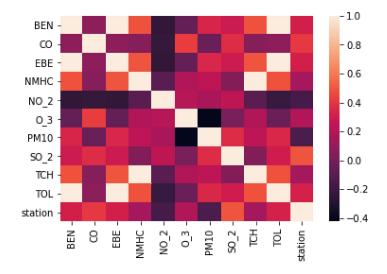
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarni ng: `distplot` is a deprecated function and will be removed in a future version. Plea se adapt your code to use either `displot` (a figure-level function with similar flex ibility) or `histplot` (an axes-level function for histograms). warnings.warn(msg, FutureWarning)

Out[523]: <AxesSubplot:xlabel='NO 2', ylabel='Density'>



In [524]: | sns.heatmap(d.corr())

Out[524]: <AxesSubplot:>



```
In [525]: x=d[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2']]
          y=d['TCH']
```

```
In [526]: | from sklearn.model selection import train test split
          x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

```
In [527]: from sklearn.linear model import LinearRegression
          lr=LinearRegression()
          lr.fit(x_train,y_train)
```

Out[527]: LinearRegression()

```
In [528]: print(lr.intercept_)
           1.368401196214812
In [529]: coeff=pd.DataFrame(lr.coef ,x.columns,columns=['Co-efficient'])
           coeff
Out[529]:
                    Co-efficient
                  4.146134e-01
             BEN
              CO -3.242159e-16
             EBE -4.130974e-01
           NMHC 9.736040e-01
            NO_2 -1.995580e-15
In [530]: | prediction=lr.predict(x_test)
          plt.scatter(y_test,prediction)
Out[530]: <matplotlib.collections.PathCollection at 0x1b70ac4f3d0>
            50
            40
            30
            20
           10
             0
                      10
                              20
                                      30
                                              40
                                                      50
In [531]: print(lr.score(x_test,y_test))
           0.9998419489187631
In [532]: | from sklearn.linear_model import Ridge,Lasso
In [533]: rr=Ridge(alpha=10)
          rr.fit(x_train,y_train)
Out[533]: Ridge(alpha=10)
In [534]: rr.score(x_test,y_test)
Out[534]: 0.9999752243404992
In [535]: la=Lasso(alpha=10)
          la.fit(x_train,y_train)
Out[535]: Lasso(alpha=10)
```

```
In [536]: la.score(x_test,y_test)
```

Out[536]: 0.9990877132711634

In [537]: a1=b.head(7000) a1

Out[537]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	station
0	2011-11- 01 01:00:00	55.0	1.0	55.0	55.00	154.0	84.0	55.0	55.0	55.0	6.0	55.00	55.0	28079004
1	2011-11- 01 01:00:00	2.5	0.4	3.5	0.26	68.0	92.0	3.0	40.0	24.0	9.0	1.54	8.7	28079008
2	2011-11- 01 01:00:00	2.9	55.0	3.8	55.00	96.0	99.0	55.0	55.0	55.0	55.0	55.00	7.2	28079011
3	2011-11- 01 01:00:00	55.0	0.6	55.0	55.00	60.0	83.0	2.0	55.0	55.0	55.0	55.00	55.0	28079016
4	2011-11- 01 01:00:00	55.0	55.0	55.0	55.00	44.0	62.0	3.0	55.0	55.0	3.0	55.00	55.0	28079017
6995	2011-11- 13 04:00:00	55.0	0.2	55.0	55.00	1.0	17.0	50.0	55.0	55.0	55.0	55.00	55.0	28079039
6996	2011-11- 13 04:00:00	55.0	55.0	55.0	55.00	1.0	6.0	55.0	11.0	55.0	1.0	55.00	55.0	28079040
6997	2011-11- 13 04:00:00	55.0	55.0	55.0	55.00	1.0	14.0	55.0	12.0	8.0	55.0	55.00	55.0	28079047
6998	2011-11- 13 04:00:00	55.0	55.0	55.0	55.00	2.0	16.0	55.0	8.0	4.0	55.0	55.00	55.0	28079048
6999	2011-11- 13 04:00:00	55.0	55.0	55.0	55.00	1.0	8.0	57.0	55.0	55.0	55.0	55.00	55.0	28079049

7000 rows × 14 columns

g=e.iloc[:,-1]

```
In [541]: e=a1[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'O_3',
           'PM10', 'SO_2', 'TCH', 'TOL', 'station']]
In [542]: f=e.iloc[:,0:14]
```

```
In [543]: h=StandardScaler().fit_transform(f)
```

```
In [544]: logr=LogisticRegression(max_iter=10000)
          logr.fit(h,g)
```

Out[544]: LogisticRegression(max_iter=10000)

```
In [545]: from sklearn.model selection import train test split
          h train,h test,g train,g test=train test split(h,g,test size=0.3)
In [549]: | i=[[10,20,30,40,50,60,15,26,37,47,58]]
In [550]: | prediction=logr.predict(i)
          print(prediction)
          [28079059]
In [551]: logr.classes
Out[551]: 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 [552]: logr.predict_proba(i)[0][0]
Out[552]: 0.0
In [553]: logr.predict_proba(i)[0][1]
Out[553]: 0.0
In [554]: logr.score(h_test,g_test)
Out[554]: 0.9742857142857143
In [555]: | from sklearn.linear model import ElasticNet
          en=ElasticNet()
          en.fit(x_train,y_train)
Out[555]: ElasticNet()
In [556]: print(en.coef_)
          [0.00213706 0.
                                  0.
                                             0.97049735 0.
                                                                   ]
In [557]: |print(en.intercept_)
          1.493859286726753
In [558]: prediction=en.predict(x_test)
          print(en.score(x_test,y_test))
          0.9999730240612734
In [559]: from sklearn.ensemble import RandomForestClassifier
          rfc=RandomForestClassifier()
          rfc.fit(h_train,g_train)
Out[559]: RandomForestClassifier()
```

```
In [560]: parameters={'max_depth':[1,2,3,4,5],
                                            'min samples leaf':[5,10,15,20,25],
                                            'n estimators':[10,20,30,40,50]
In [561]: from sklearn.model selection import GridSearchCV
                                       grid search=GridSearchCV(estimator=rfc,param grid=parameters,cv=2,scoring="accuracy")
                                      grid search.fit(h train,g train)
Out[561]: 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 [562]: grid_search.best_score_
Out[562]: 0.9987755102040816
In [563]: rfc_best=grid_search.best_estimator_
In [564]: from sklearn.tree import plot_tree
                                       plt.figure(figsize=(80,50))
                                       plot tree(rfc best.estimators [20],filled=True)
                                                                                                                                                                                              Mileton (1) (6)

gran = 1 (6) (6)

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mileton = 1000 (100, 100) (100 (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100)
```

Conclusion: from this data set i observed that the ridge has the highest accuracy of 0.9999752243404992

```
In [ ]:
```