In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as py
import seaborn as sns
from sklearn.linear_model import LogisticRegression
```

In [2]:
```python
df=pd.read_csv(r"D:\New folder\madrid_2012.csv")
df
```

Out[2]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10
0	2002-04-01 01:00:00	NaN	1.39	NaN	NaN	NaN	145.100006	352.100006	NaN	6.54	41.990002
1	2002-04-01 01:00:00	1.93	0.71	2.33	6.20	0.15	98.150002	153.399994	2.67	6.85	20.980000
2	2002-04-01 01:00:00	NaN	0.80	NaN	NaN	NaN	103.699997	134.000000	NaN	13.01	28.440001
3	2002-04-01 01:00:00	NaN	1.61	NaN	NaN	NaN	97.599998	268.000000	NaN	5.12	42.180000
4	2002-04-01 01:00:00	NaN	1.90	NaN	NaN	NaN	92.089996	237.199997	NaN	7.28	76.330002
...	...	...	...	...	...	...	...	...	...	...	...
217291	2002-11-01 00:00:00	4.16	1.14	NaN	NaN	NaN	81.080002	265.700012	NaN	7.21	36.750000
217292	2002-11-01 00:00:00	3.67	1.73	2.89	NaN	0.38	113.900002	373.100006	NaN	5.66	63.389999
217293	2002-11-01 00:00:00	1.37	0.58	1.17	2.37	0.15	65.389999	107.699997	1.30	9.11	9.640000
217294	2002-11-01 00:00:00	4.51	0.91	4.83	10.99	NaN	149.800003	202.199997	1.00	5.75	NaN
217295	2002-11-01 00:00:00	3.11	1.17	3.00	7.77	0.26	80.110001	180.300003	2.25	7.38	29.240000

217296 rows × 16 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 217296 entries, 0 to 217295
Data columns (total 16 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     217296 non-null  object 
 1   BEN      66747 non-null   float64
 2   CO       216637 non-null  float64
 3   EBE      58547 non-null   float64
 4   MXY      41255 non-null   float64
 5   NMHC     87045 non-null   float64
 6   NO_2     216439 non-null  float64
 7   NOx      216439 non-null  float64
 8   OXY      41314 non-null   float64
 9   O_3      216726 non-null  float64
 10  PM10     209113 non-null  float64
 11  PXY      41256 non-null   float64
 12  SO_2     216507 non-null  float64
 13  TCH      87115 non-null   float64
 14  TOL      66619 non-null   float64
 15  station  217296 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 26.5+ MB
```

In [4]:
```
df1=df.fillna(value=0)
df1
```

Out[4]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10
0	2002-04-01 01:00:00	0.00	1.39	0.00	0.00	0.00	145.100006	352.100006	0.00	6.54	41.990002
1	2002-04-01 01:00:00	1.93	0.71	2.33	6.20	0.15	98.150002	153.399994	2.67	6.85	20.980000
2	2002-04-01 01:00:00	0.00	0.80	0.00	0.00	0.00	103.699997	134.000000	0.00	13.01	28.440001
3	2002-04-01 01:00:00	0.00	1.61	0.00	0.00	0.00	97.599998	268.000000	0.00	5.12	42.180000
4	2002-04-01 01:00:00	0.00	1.90	0.00	0.00	0.00	92.089996	237.199997	0.00	7.28	76.330002
...	...	...	...	...	...	...	...	...	...	...	...
217291	2002-11-01 00:00:00	4.16	1.14	0.00	0.00	0.00	81.080002	265.700012	0.00	7.21	36.750000
217292	2002-11-01 00:00:00	3.67	1.73	2.89	0.00	0.38	113.900002	373.100006	0.00	5.66	63.389999
217293	2002-11-01 00:00:00	1.37	0.58	1.17	2.37	0.15	65.389999	107.699997	1.30	9.11	9.640000
217294	2002-11-01 00:00:00	4.51	0.91	4.83	10.99	0.00	149.800003	202.199997	1.00	5.75	0.000000
217295	2002-11-01 00:00:00	3.11	1.17	3.00	7.77	0.26	80.110001	180.300003	2.25	7.38	29.240000

217296 rows × 16 columns

In [5]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 217296 entries, 0 to 217295
Data columns (total 16 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   date     217296 non-null  object 
 1   BEN      217296 non-null  float64
 2   CO       217296 non-null  float64
 3   EBE      217296 non-null  float64
 4   MXY      217296 non-null  float64
 5   NMHC     217296 non-null  float64
 6   NO_2     217296 non-null  float64
 7   NOx      217296 non-null  float64
 8   OXY      217296 non-null  float64
 9   O_3      217296 non-null  float64
 10  PM10     217296 non-null  float64
 11  PXY      217296 non-null  float64
 12  SO_2     217296 non-null  float64
 13  TCH      217296 non-null  float64
 14  TOL      217296 non-null  float64
 15  station  217296 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 26.5+ MB
```

In [6]:
```
df1.columns
```

Out[6]:
```
Index(['date', 'BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_
3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [7]:
```
df2=df1[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station']]
df2
```

Out[7]:

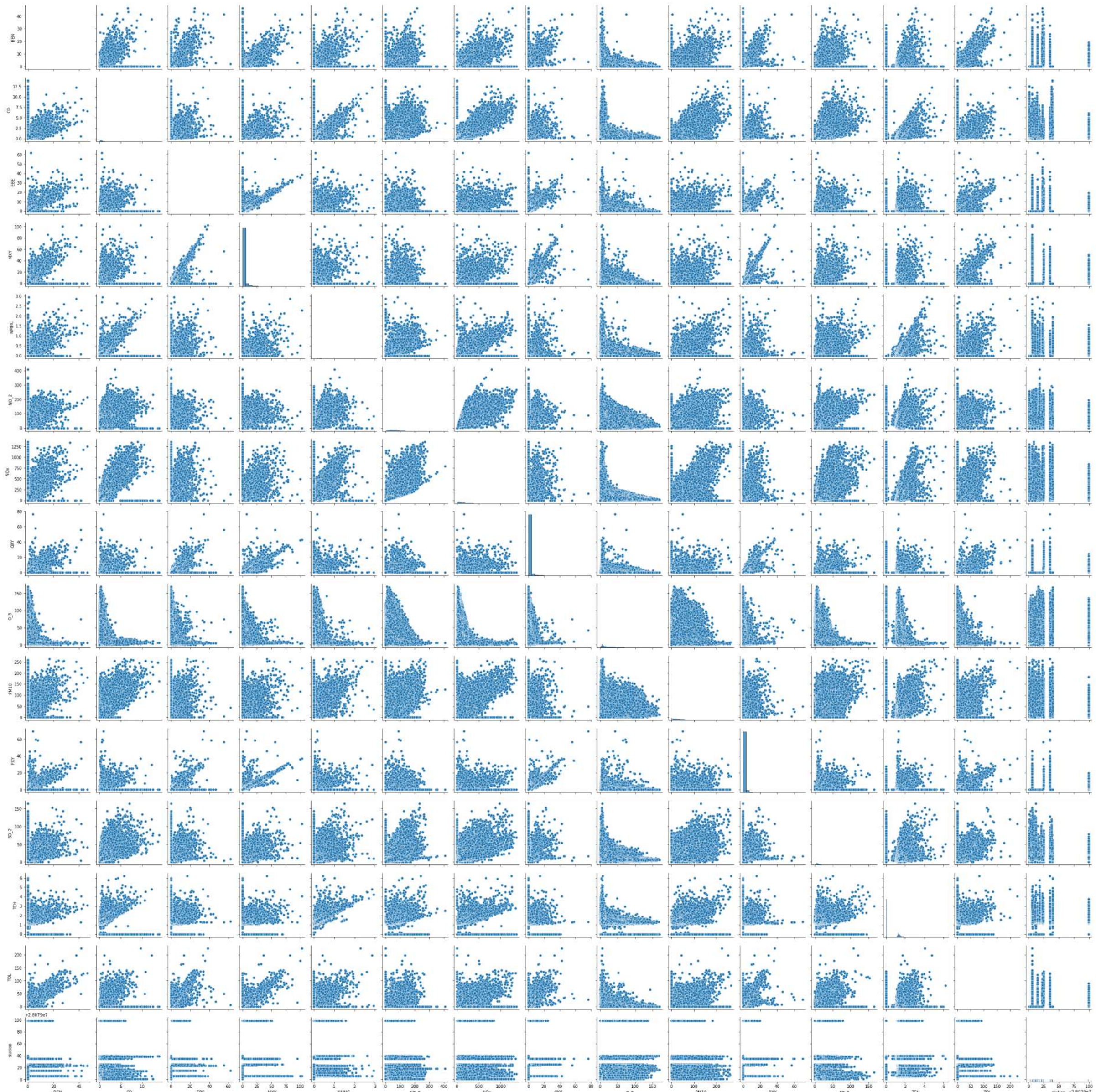
	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PXY
0	0.00	1.39	0.00	0.00	0.00	145.100006	352.100006	0.00	6.54	41.990002	0.00
1	1.93	0.71	2.33	6.20	0.15	98.150002	153.399994	2.67	6.85	20.980000	2.53
2	0.00	0.80	0.00	0.00	0.00	103.699997	134.000000	0.00	13.01	28.440001	0.00
3	0.00	1.61	0.00	0.00	0.00	97.599998	268.000000	0.00	5.12	42.180000	0.00
4	0.00	1.90	0.00	0.00	0.00	92.089996	237.199997	0.00	7.28	76.330002	0.00
...	...	...	...	...	...	...	...	...	...	...	...
217291	4.16	1.14	0.00	0.00	0.00	81.080002	265.700012	0.00	7.21	36.750000	0.00
217292	3.67	1.73	2.89	0.00	0.38	113.900002	373.100006	0.00	5.66	63.389999	0.00
217293	1.37	0.58	1.17	2.37	0.15	65.389999	107.699997	1.30	9.11	9.640000	0.94
217294	4.51	0.91	4.83	10.99	0.00	149.800003	202.199997	1.00	5.75	0.000000	5.52
217295	3.11	1.17	3.00	7.77	0.26	80.110001	180.300003	2.25	7.38	29.240000	3.35

In [8]:

```
sns.pairplot(df2)
```

Out[8]:

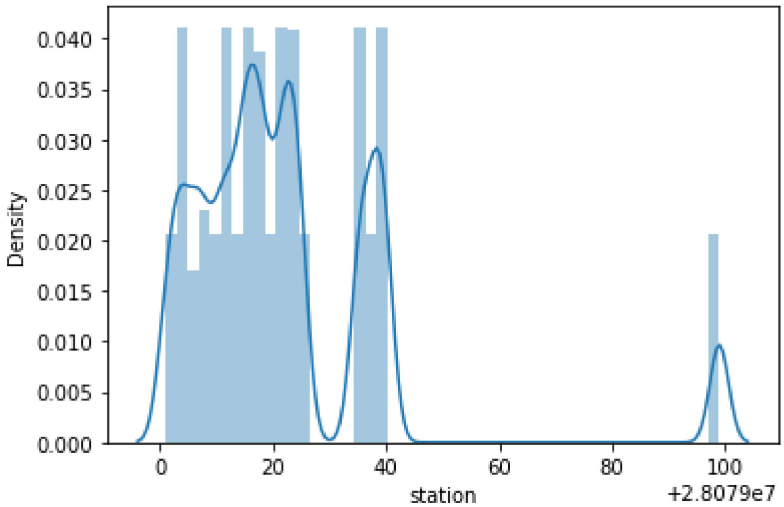
```
<seaborn.axisgrid.PairGrid at 0x20a881eaa90>
```



In [9]:
```
sns.distplot(df2['station'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fut
ureWarning: `distplot` is a deprecated function and will be removed in a futu
re version. Please adapt your code to use either `displot` (a figure-level fu
nction with similar flexibility) or `histplot` (an axes-level function for hi
stograms).
  warnings.warn(msg, FutureWarning)
```

Out[9]: <AxesSubplot:xlabel='station', ylabel='Density'>



In [10]:
```
x=df2[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'O_3','PM10', 'PXY', '
y=df2['station']
```

In [24]:
```
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)
```

linear

In [12]:
```
from sklearn.linear_model import LinearRegression
```

In [13]:
```
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[13]: LinearRegression()

In [14]:
```
coeff =pd.DataFrame(lr.coef_,x.columns,columns=["Co-efficient"])
coeff
```

Out[14]:

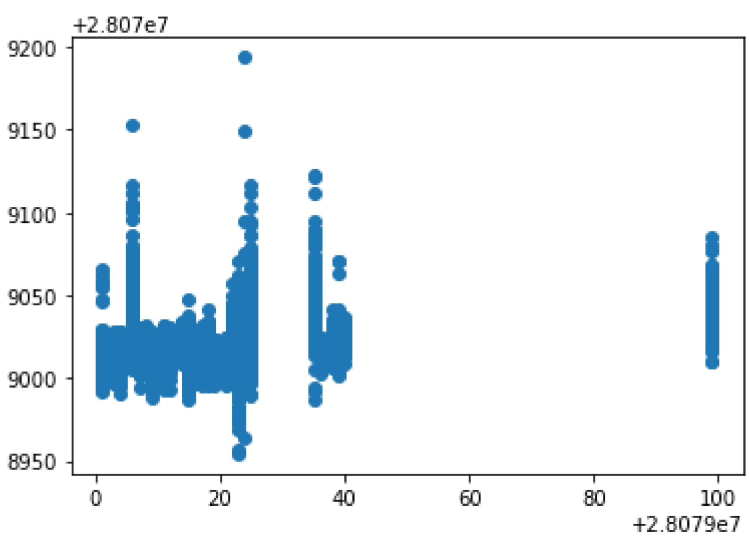
	Co-efficient
BEN	2.833498
CO	4.218625
EBE	-1.896436
MXY	0.996361
NMHC	-11.596930
NO_2	-0.044724
NOx	-0.038944
O_3	-0.014382
PM10	0.032646
PXY	4.152622
SO_2	-0.108335
TCH	6.355155
TOL	-0.418133
OXY	-2.160064

In [15]:
```
print(lr.intercept_)
```

```
28079023.010687977
```

In [16]:
```
prediction =lr.predict(x_test)
py.scatter(y_test,prediction)
```

Out[16]: <matplotlib.collections.PathCollection at 0x20aa0591eb0>



In [17]:
```
print(lr.score(x_test,y_test))
```

```
0.13971016103643064
```

In [18]:
```
print(lr.score(x_train,y_train))
```

```
0.1377927917601448
```

Ridge

In [19]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [20]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[20]:
```
Ridge(alpha=10)
```

In [21]:
```
rr.score(x_test,y_test)
```

Out[21]:
```
0.13971942807063387
```

Lasso

In [22]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[22]:
```
Lasso(alpha=10)
```

In [23]:
```
la.score(x_test,y_test)
```

Out[23]:
```
0.05961311096197963
```

elasticnet

In [24]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[24]:
```
ElasticNet()
```

In [25]:
```
print(en.coef_)
```

```
[ 0.52192221  0.06008224 -0.          0.79420303  0.         -0.05650403
 -0.0175735  -0.01514683  0.04193206  0.86416339 -0.09613152  1.46701895
 -0.02315909  0.        ]
```

In [26]:
```
print(en.intercept_)
```

```
28079025.64837437
```

In [27]:
```
print(en.predict(x_test))
```

```
[28079022.98173612 28079021.18830581 28079020.94239793 ...
 28079040.90115401 28079016.84820627 28079026.37385159]
```

In [28]:
```
print(en.score(x_test,y_test))
```

```
0.10679846191048736
```

logistic

In [8]:
```
feature_matrix=df2.iloc[:,0:14]
target_vector=df2.iloc[:,-1]
```

In [9]:
```
feature_matrix=df2[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'O_3','PM
y=df2['station']
```

In [10]:
```
feature_matrix.shape
```

Out[10]:
```
(217296, 14)
```

In [11]:
```
target_vector.shape
```

Out[11]:
```
(217296,)
```

In [12]:
```
from sklearn.preprocessing import StandardScaler
```

In [13]:
```
fs=StandardScaler().fit_transform(feature_matrix)
```

In [14]:
```
logr =LogisticRegression()
logr.fit(fs,target_vector)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:
763: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://sciki
t-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regr
ession)
  n_iter_i = _check_optimize_result(
```

Out[14]:
```
LogisticRegression()
```

In [15]:
```
observation=[[1.4,2.3,5.0,11,12,13,14,15,4,5,7,6,7,13]]
```

In [16]:
```
prediction=logr.predict(observation)
print(prediction)
```

```
[28079099]
```

In [17]:
```
logr.classes_
```

Out[17]:
```
array([28079001, 28079003, 28079004, 28079006, 28079007, 28079008,
       28079009, 28079011, 28079012, 28079014, 28079015, 28079016,
       28079017, 28079018, 28079019, 28079021, 28079022, 28079023,
       28079024, 28079025, 28079035, 28079036, 28079038, 28079039,
       28079040, 28079099], dtype=int64)
```

In [18]:
```
logr.score(fs,target_vector)
```

Out[18]:
```
0.9224836168176128
```

In [19]:
```
logr.predict_proba(observation)[0][0]
```

Out[19]:
```
0.0
```

In [20]:
```
logr.predict_proba(observation)[0][1]
```

Out[20]:
```
0.0
```

random forest

In [21]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import plot_tree
```

In [22]:
```
x=df2.drop('station',axis=1)
y=df2['station']
```

In [25]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.70)
```

In [26]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[26]:
```
RandomForestClassifier()
```

In [27]:
```
parameters = {'max_depth':[1,2,3,4,5],
             'min_samples_leaf':[5,10,15,20,25],
              'n_estimators':[10,20,30,40,50]}
```

In [28]:
```
from sklearn.model_selection import GridSearchCV
```

In [29]:
```
grid_search = GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring='ac
grid_search.fit(x_train,y_train)
```

Out[29]:
```
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 [30]:
```
grid_search.best_score_
```

Out[30]:
```
0.46224765294225933
```

In [31]:
```
rfc_best =grid_search.best_estimator_
```

In [32]:
```
py.figure(figsize=(80,50))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,filled=True)
```

Out[32]:
```
[Text(2317.846153846154, 2491.5, 'BEN <= 0.08\ngini = 0.96\nsamples = 41186
\nvalue = [2613, 2648, 2619, 2168, 2497, 320, 2540, 2737, 2575\n2576, 2686,
2622, 2476, 2383, 2628, 2641, 2616, 2607\n2667, 2543, 2591, 2678, 2659, 272
0, 2751, 2627]'),
 Text(1373.5384615384614, 2038.5, 'CO <= 0.685\ngini = 0.943\nsamples = 285
22\nvalue = [2613, 2648, 2619, 16, 2497, 320, 2540, 2737, 2575\n2576, 44, 2
622, 2476, 2383, 2628, 2641, 155, 10, 179\n41, 72, 2678, 2659, 2720, 2751,
25]'),
 Text(686.7692307692307, 1585.5, 'NMHC <= 0.005\ngini = 0.939\nsamples = 17
000\nvalue = [778, 1645, 1812, 16, 1245, 83, 935, 2041, 1386, 767\n32, 200
8, 1895, 1726, 1675, 1960, 106, 10, 146, 37\n57, 1910, 930, 1801, 1893, 1
9]'),
 Text(343.38461538461536, 1132.5, 'CO <= 0.205\ngini = 0.919\nsamples = 125
54\nvalue = [778, 1645, 1812, 16, 70, 2, 935, 10, 1269, 767, 18\n2008, 189
5, 56, 1675, 1960, 106, 9, 9, 37, 24\n1910, 930, 1801, 90, 4]'),
 Text(171.69230769230768, 679.5, 'TCH <= 1.205\ngini = 0.886\nsamples = 222
7\nvalue = [59, 137, 428, 16, 20, 2, 22, 10, 508, 77, 2, 291\n575, 53, 58,
658, 20, 9, 3, 12, 14, 134, 177\n223, 25, 2]'),
 Text(85.84615384615384, 226.5, 'gini = 0.884\nsamples = 2169\nvalue = [59,
```

conclusion

The bestfit model is Logistic Regression with score of 0.9224836168176128

In [ ]: