03/08/2023 (P14)

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
df=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs_per_year\madrid_201
df
```

Out[2]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	station
0	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	3.0	10.0	NaN	NaN	NaN	3.0	NaN	NaN	28079004
1	2014-06-01 01:00:00	0.2	0.2	0.1	0.11	3.0	17.0	68.0	10.0	5.0	5.0	1.36	1.3	28079008
2	2014-06-01 01:00:00	0.3	NaN	0.1	NaN	2.0	6.0	NaN	NaN	NaN	NaN	NaN	1.1	28079011
3	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	1.0	6.0	79.0	NaN	NaN	NaN	NaN	NaN	28079016
4	2014-06-01 01:00:00	NaN	NaN	NaN	NaN	1.0	6.0	75.0	NaN	NaN	4.0	NaN	NaN	28079017
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
210019	2014-09-01 00:00:00	NaN	0.5	NaN	NaN	20.0	84.0	29.0	NaN	NaN	NaN	NaN	NaN	28079056
210020	2014-09-01 00:00:00	NaN	0.3	NaN	NaN	1.0	22.0	NaN	15.0	NaN	6.0	NaN	NaN	28079057
210021	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	13.0	70.0	NaN	NaN	NaN	NaN	NaN	28079058
210022	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	3.0	38.0	42.0	NaN	NaN	NaN	NaN	NaN	28079059
210023	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	26.0	65.0	11.0	NaN	NaN	NaN	NaN	28079060

210024 rows × 14 columns

In [3]:
```
df=df.dropna()
```

In [4]:
```
df.columns
```

Out[4]:
```
Index(['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
       'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [5]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13946 entries, 1 to 210006
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     13946 non-null  object 
 1   BEN      13946 non-null  float64
 2   CO       13946 non-null  float64
 3   EBE      13946 non-null  float64
 4   NMHC     13946 non-null  float64
 5   NO       13946 non-null  float64
 6   NO_2     13946 non-null  float64
 7   O_3      13946 non-null  float64
 8   PM10     13946 non-null  float64
 9   PM25     13946 non-null  float64
 10  SO_2     13946 non-null  float64
 11  TCH      13946 non-null  float64
 12  TOL      13946 non-null  float64
 13  station  13946 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.6+ MB
```

In [6]:
```
1 data=df[['BEN', 'TOL', 'TCH']]
2 data
```

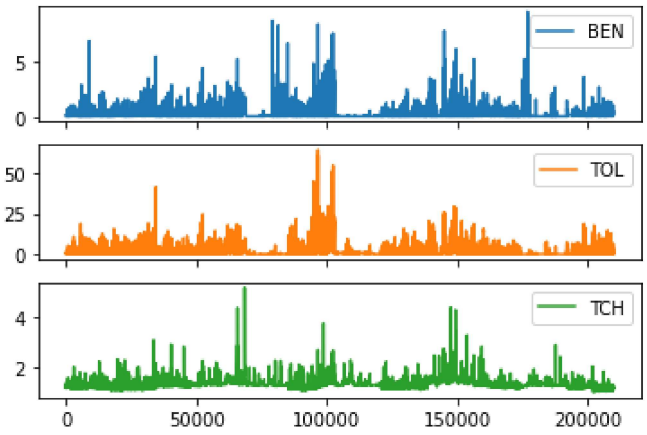
Out[6]:

	BEN	TOL	TCH
1	0.2	1.3	1.36
6	0.1	0.1	1.21
25	0.2	0.8	1.36
30	0.2	0.1	1.21
49	0.1	0.9	1.36
...	...	...	...
209958	0.2	0.1	1.28
209977	1.1	6.5	1.27
209982	0.2	0.2	1.27
210001	0.6	4.1	1.19
210006	0.2	0.1	1.30

13946 rows × 3 columns

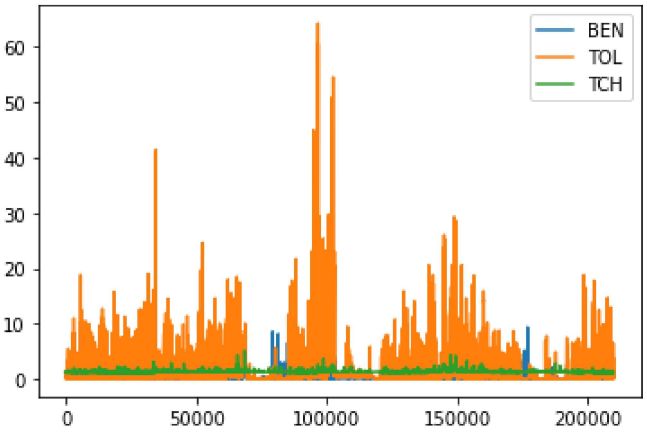
In [7]:
```
1 data.plot.line(subplots=True)
```

Out[7]:
```
array([<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>], dtype=object)
```



In [8]:
```
1 data.plot.line()
```

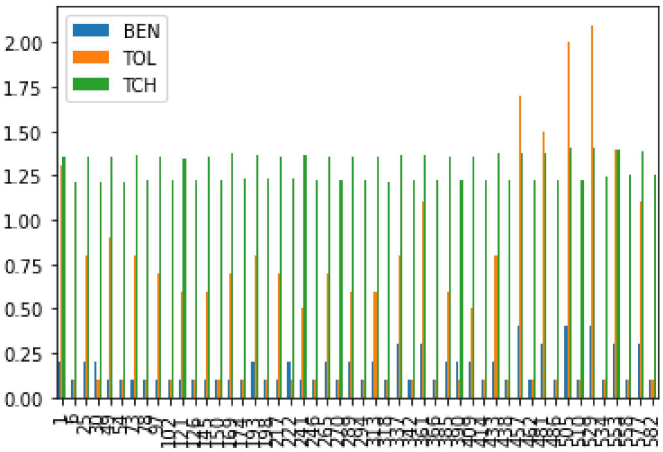
Out[8]:
```
<AxesSubplot:>
```



In [9]:
```
1 b=data[0:50]
```

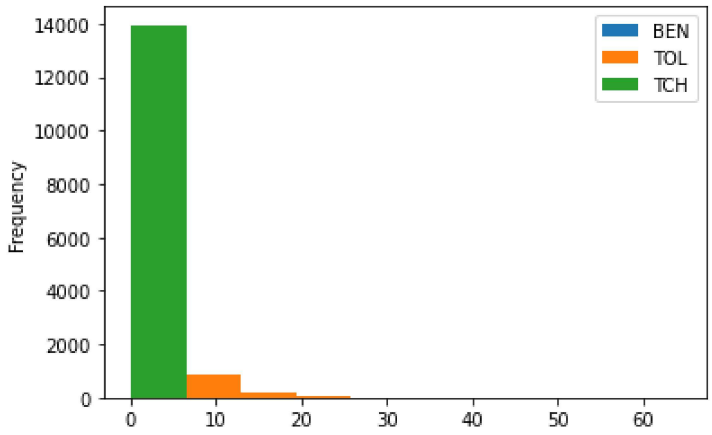
In [10]:
```
1 b.plot.bar()
```

Out[10]:
```
<AxesSubplot:>
```



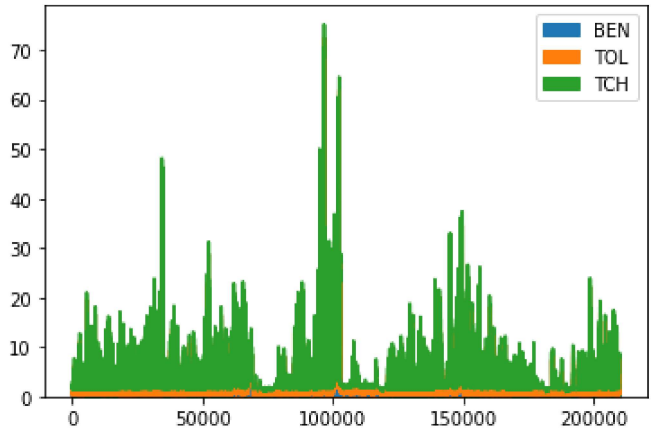
In [11]:
```
1 data.plot.hist()
```

Out[11]: <AxesSubplot:ylabel='Frequency'>



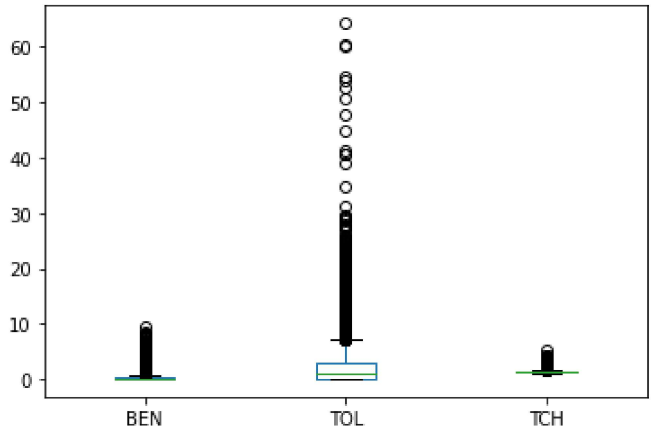
In [12]:
```
1 data.plot.area()
```

Out[12]: <AxesSubplot:>



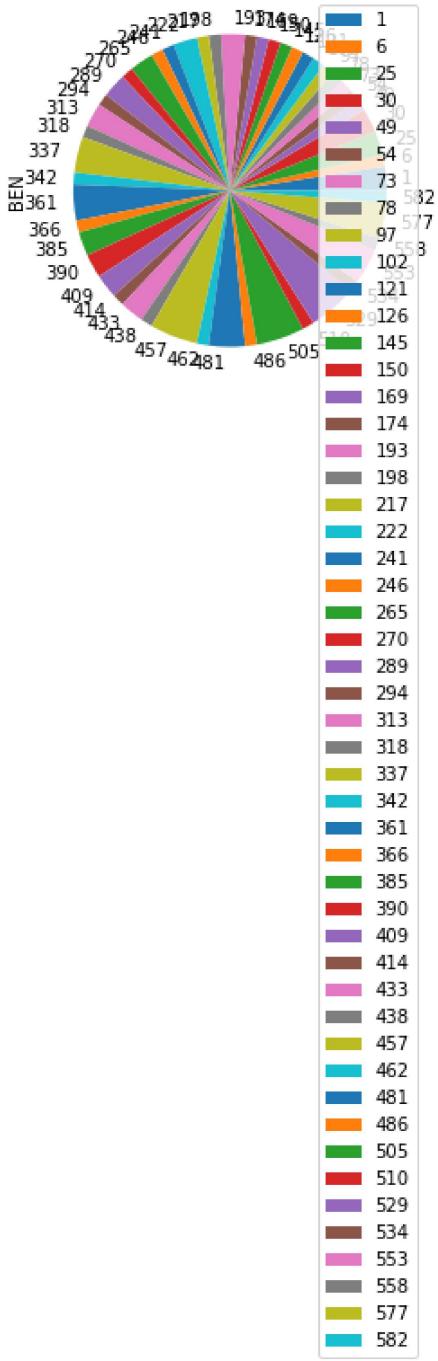
In [13]:
```
1 data.plot.box()
```

Out[13]: <AxesSubplot:>



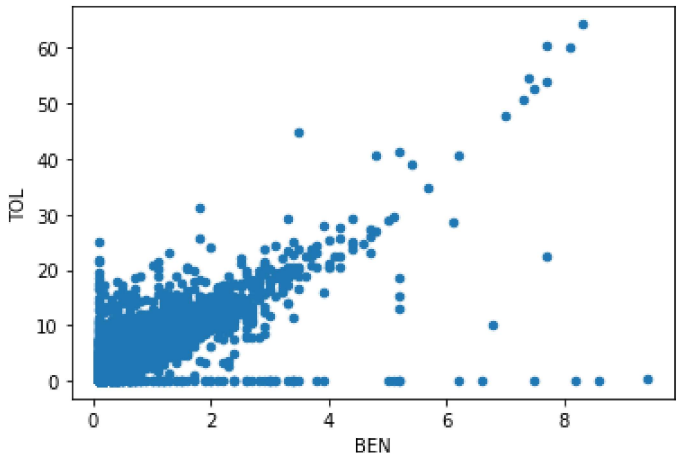
In [14]:
```
1 b.plot.pie(y='BEN' )
```

Out[14]: <AxesSubplot:ylabel='BEN'>



In [15]:
```
1 data.plot.scatter(x='BEN' ,y='TOL')
```

Out[15]: <AxesSubplot:xlabel='BEN', ylabel='TOL'>



In [16]:
```
1 df.describe()
```

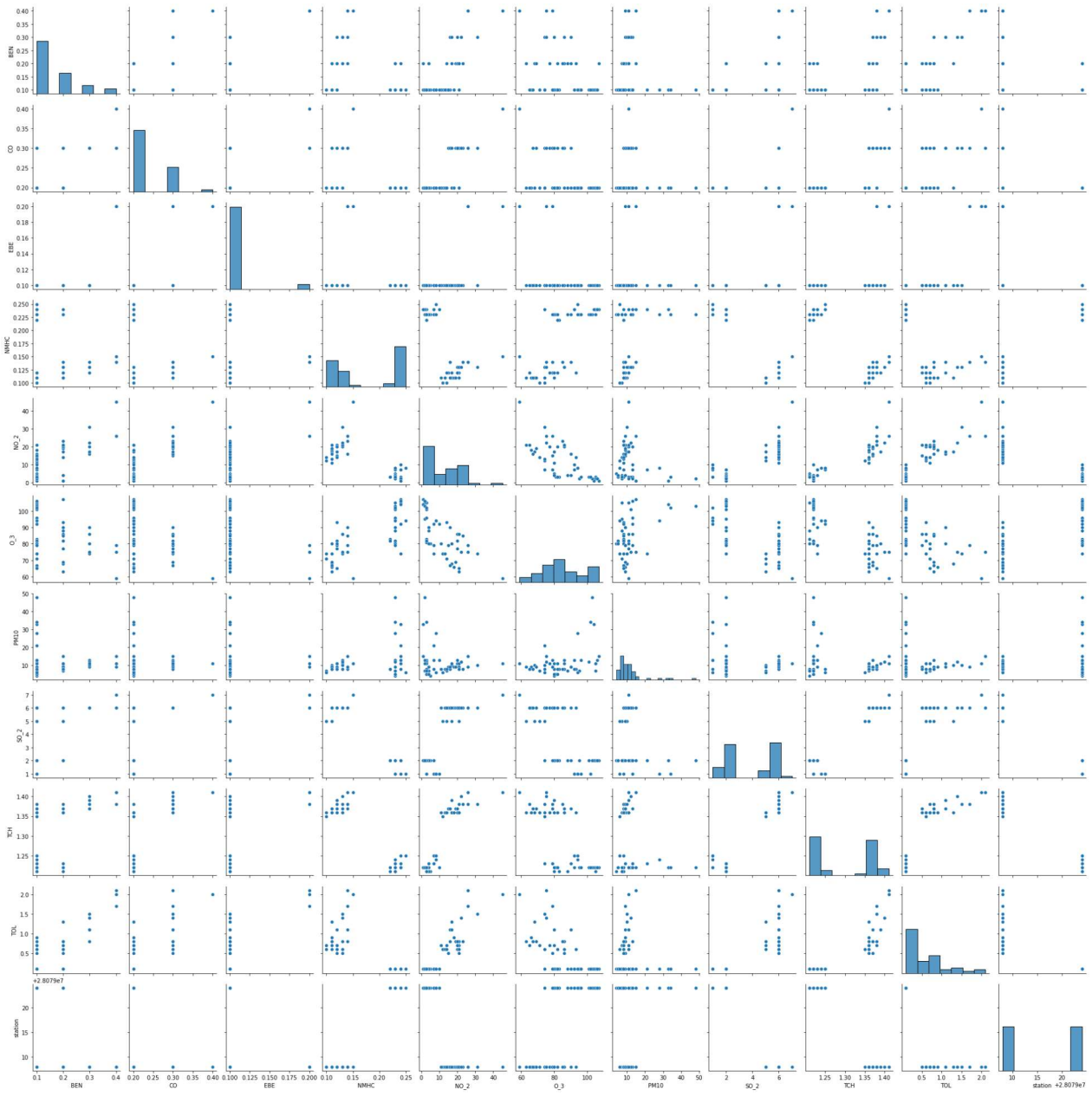
Out[16]:

	BEN	CO	EBE	NMHC	NO	NO_2	O_3	
count	13946.000000	13946.000000	13946.000000	13946.000000	13946.000000	13946.000000	13946.000000	13946
mean	0.375921	0.314793	0.306016	0.222302	17.589129	34.240929	53.082389	19
std	0.555093	0.207375	0.635475	0.082403	39.432216	30.654229	33.488167	15
min	0.100000	0.100000	0.100000	0.060000	1.000000	1.000000	1.000000	1
25%	0.100000	0.200000	0.100000	0.160000	1.000000	10.000000	25.000000	10
50%	0.200000	0.300000	0.100000	0.230000	4.000000	27.000000	53.000000	16
75%	0.400000	0.400000	0.300000	0.260000	18.000000	51.000000	75.000000	25
max	9.400000	4.400000	16.200001	1.290000	725.000000	346.000000	220.000000	197

In [17]:
```
1 df1=df[['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'O_3', 'PM10',
2 'SO_2', 'TCH', 'TOL', 'station']]
```

In [18]:
```
1 sns.pairplot(df1[0:50])
```

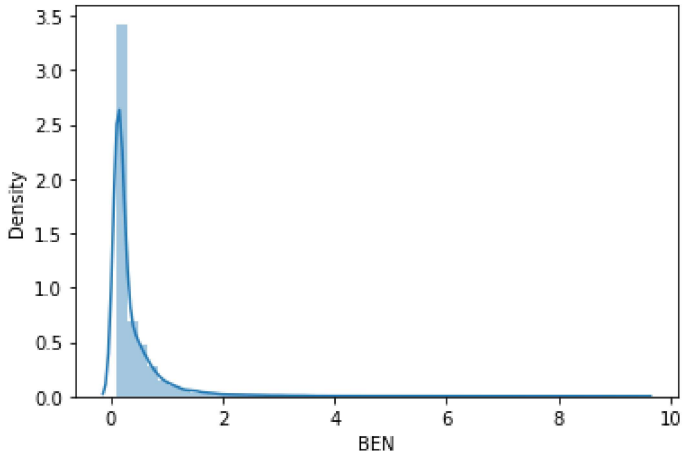
Out[18]: <seaborn.axisgrid.PairGrid at 0x1c1a6d61070>



In [19]:
```
1 sns.distplot(df1['BEN'])
```

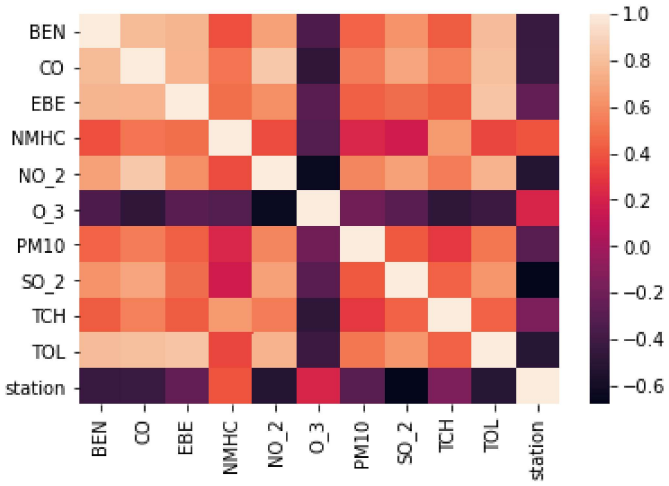
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `
distplot` is a deprecated function and will be removed in a future version. Please adapt y
our code to use either `displot` (a figure-level function with similar flexibility) or `hi
stplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[19]: <AxesSubplot:xlabel='BEN', ylabel='Density'>



In [20]:
```
1 sns.heatmap(df1.corr())
```

Out[20]: <AxesSubplot:>



In [21]:
```
1 x=df[['BEN', 'CO', 'EBE', 'NMHC','NO_2', 'O_3', 'PM10',
2 'SO_2', 'TCH', 'TOL']]
3 y=df['station']
```

In [22]:
```
1 from sklearn.model_selection import train_test_split
2 x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [23]:
```
1 from sklearn.linear_model import LinearRegression
2 lr=LinearRegression()
3 lr.fit(x_train,y_train)
```

Out[23]: LinearRegression()

In [24]:
```
1 lr.intercept_
```

Out[24]: 28079022.4478457

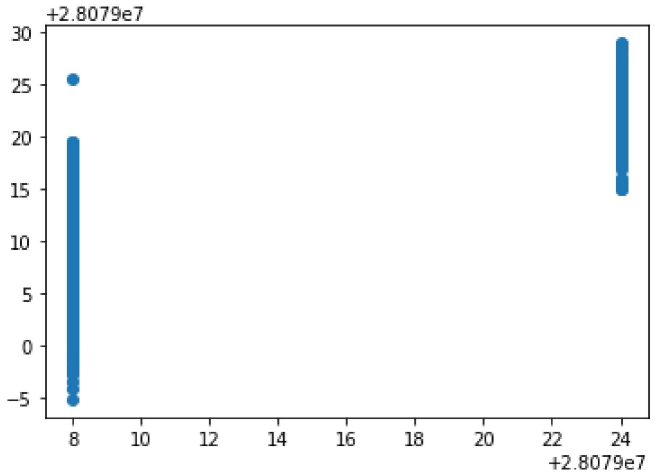
In [25]:
```
1 coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
2 coeff
```

Out[25]:

	Co-efficient
BEN	-1.293950
CO	-5.809428
EBE	0.424667
NMHC	83.373217
NO_2	-0.033397
O_3	0.002186
PM10	0.017884
SO_2	-0.879364
TCH	-11.780202
TOL	-0.441750

In [26]:
```
1 prediction =lr.predict(x_test)
2 plt.scatter(y_test,prediction)
```

Out[26]: <matplotlib.collections.PathCollection at 0x1c1b0363400>



In [27]:
```
1 lr.score(x_test,y_test)
```

Out[27]: 0.8895083402137607

In [28]:
```
1 lr.score(x_train,y_train)
```

Out[28]: 0.881893030415985

In [29]:
```
1 from sklearn.linear_model import Ridge,Lasso
```

In [30]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[30]:
```
Ridge(alpha=10)
```

In [31]:
```
rr.score(x_test,y_test)
```

Out[31]:
```
0.8677110519288443
```

In [32]:
```
rr.score(x_train,y_train)
```

Out[32]:
```
0.8588863738901591
```

In [33]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[33]:
```
Lasso(alpha=10)
```

In [34]:
```
la.score(x_test,y_test)
```

Out[34]:
```
0.28025128201289573
```

In [35]:
```
la.score(x_train,y_train)
```

Out[35]:
```
0.26893317064861
```

In [36]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[36]:
```
ElasticNet()
```

In [37]:
```
en.coef_
```

Out[37]:
```
array([ 0.        ,  0.        ,  0.22449093,  0.        , -0.04441306,
       -0.0113182 ,  0.02390173, -1.24163916,  0.        , -0.16995639])
```

In [38]:
```
en.intercept_
```

Out[38]:
```
28079024.652497325
```

In [39]:
```
prediction=en.predict(x_test)
```

In [40]:
```
en.score(x_test,y_test)
```

Out[40]:
```
0.4895268914063027
```

In [41]:
```
from sklearn import metrics
print(metrics.mean_absolute_error(y_test,prediction))
print(metrics.mean_squared_error(y_test,prediction))
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
4.994734441387836
32.32841206961237
5.685807952227402
```

In [42]:
```
from sklearn.linear_model import LogisticRegression
```

In [43]:
```
feature_matrix=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'O_3',
'PM10', 'SO_2', 'TCH', 'TOL']]
target_vector=df[ 'station']
```

In [44]:
```
feature_matrix.shape
```

Out[44]: (13946, 10)

In [45]:
```
target_vector.shape
```

Out[45]: (13946,)

In [46]:
```
from sklearn.preprocessing import StandardScaler
```

In [47]:
```
fs=StandardScaler().fit_transform(feature_matrix)
```

In [48]:
```
logr=LogisticRegression(max_iter=10000)
logr.fit(fs,target_vector)
```

Out[48]: LogisticRegression(max_iter=10000)

In [49]:
```
observation=[[1,2,3,4,5,6,7,8,9,10]]
```

In [50]:
```
prediction=logr.predict(observation)
print(prediction)
```

```
[28079008]
```

In [51]:
```
logr.classes_
```

Out[51]: array([28079008, 28079024], dtype=int64)

In [52]:
```
logr.score(fs,target_vector)
```

Out[52]: 0.9926143697117453

In [53]:
```
logr.predict_proba(observation)[0][0]
```

Out[53]: 1.0

In [54]:
```
logr.predict_proba(observation)
```

Out[54]: array([[1.00000000e+00, 5.27113072e-18]])

In [55]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [56]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[56]: RandomForestClassifier()

In [57]:
```
parameters={'max_depth':[1,2,3,4,5],
'min_samples_leaf':[5,10,15,20,25],
'n_estimators':[10,20,30,40,50]
}
```

In [58]:
```
from sklearn.model_selection import GridSearchCV
grid_search =GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

Out[58]:
```
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 [59]:
```
grid_search.best_score_
```

Out[59]:
```
0.99580004097521
```

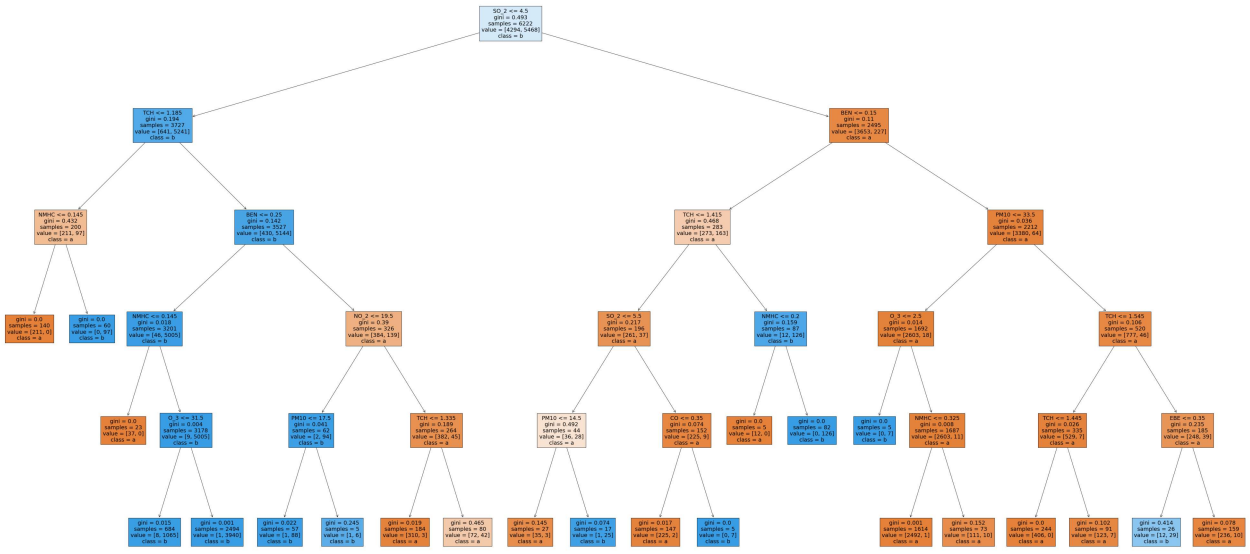
In [60]:
```
rfc_best=grid_search.best_estimator_
```

In [61]:

```
from sklearn.tree import plot_tree
plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['a','b','c','d']
```

Out[61]:
```
[Text(1827.4499999999998, 1993.2, 'SO_2 <= 4.5\ngini = 0.493\nsamples = 6222\nvalue = [4294, 5468]\nclass = b'),
 Text(585.9, 1630.8000000000002, 'TCH <= 1.185\ngini = 0.194\nsamples = 3727\nvalue = [641, 5241]\nclass = b'),
 Text(223.2, 1268.4, 'NMHC <= 0.145\ngini = 0.432\nsamples = 200\nvalue = [211, 97]\nclass = a'),
 Text(111.6, 906.0, 'gini = 0.0\nsamples = 140\nvalue = [211, 0]\nclass = a'),
 Text(334.79999999999995, 906.0, 'gini = 0.0\nsamples = 60\nvalue = [0, 97]\nclass = b'),
 Text(948.5999999999999, 1268.4, 'BEN <= 0.25\ngini = 0.142\nsamples = 3527\nvalue = [430, 5144]\nclass = b'),
 Text(558.0, 906.0, 'NMHC <= 0.145\ngini = 0.018\nsamples = 3201\nvalue = [46, 5005]\nclass = b'),
 Text(446.4, 543.5999999999999, 'gini = 0.0\nsamples = 23\nvalue = [37, 0]\nclass = a'),
 Text(669.5999999999999, 543.5999999999999, 'O_3 <= 31.5\ngini = 0.004\nsamples = 3178\nvalue = [9, 5005]\nclass = b'),
 Text(558.0, 181.19999999999982, 'gini = 0.015\nsamples = 684\nvalue = [8, 1065]\nclass = b'),
 Text(781.1999999999999, 181.19999999999982, 'gini = 0.001\nsamples = 2494\nvalue = [1, 3940]\nclass = b'),
 Text(1339.1999999999998, 906.0, 'NO_2 <= 19.5\ngini = 0.39\nsamples = 326\nvalue = [384, 139]\nclass = a'),
 Text(1116.0, 543.5999999999999, 'PM10 <= 17.5\ngini = 0.041\nsamples = 62\nvalue = [2, 94]\nclass = b'),
 Text(1004.4, 181.19999999999982, 'gini = 0.022\nsamples = 57\nvalue = [1, 88]\nclass = b'),
 Text(1227.6, 181.19999999999982, 'gini = 0.245\nsamples = 5\nvalue = [1, 6]\nclass = b'),
 Text(1562.3999999999999, 543.5999999999999, 'TCH <= 1.335\ngini = 0.189\nsamples = 264\nvalue = [382, 45]\nclass = a'),
 Text(1450.8, 181.19999999999982, 'gini = 0.019\nsamples = 184\nvalue = [310, 3]\nclass = a'),
 Text(1674.0, 181.19999999999982, 'gini = 0.465\nsamples = 80\nvalue = [72, 42]\nclass = a'),
 Text(3069.0, 1630.8000000000002, 'BEN <= 0.15\ngini = 0.11\nsamples = 2495\nvalue = [3653, 227]\nclass = a'),
 Text(2511.0, 1268.4, 'TCH <= 1.415\ngini = 0.468\nsamples = 283\nvalue = [273, 163]\nclass = a'),
 Text(2232.0, 906.0, 'SO_2 <= 5.5\ngini = 0.217\nsamples = 196\nvalue = [261, 37]\nclass = a'),
 Text(2008.8, 543.5999999999999, 'PM10 <= 14.5\ngini = 0.492\nsamples = 44\nvalue = [36, 28]\nclass = a'),
 Text(1897.1999999999998, 181.19999999999982, 'gini = 0.145\nsamples = 27\nvalue = [35, 3]\nclass = a'),
 Text(2120.4, 181.19999999999982, 'gini = 0.074\nsamples = 17\nvalue = [1, 25]\nclass = b'),
 Text(2455.2, 543.5999999999999, 'CO <= 0.35\ngini = 0.074\nsamples = 152\nvalue = [225, 9]\nclass = a'),
 Text(2343.6, 181.19999999999982, 'gini = 0.017\nsamples = 147\nvalue = [225, 2]\nclass = a'),
 Text(2566.7999999999997, 181.19999999999982, 'gini = 0.0\nsamples = 5\nvalue = [0, 7]\nclass = b'),
 Text(2790.0, 906.0, 'NMHC <= 0.2\ngini = 0.159\nsamples = 87\nvalue = [12, 126]\nclass = b'),
 Text(2678.3999999999996, 543.5999999999999, 'gini = 0.0\nsamples = 5\nvalue = [12, 0]\nclass = a'),
 Text(2901.6, 543.5999999999999, 'gini = 0.0\nsamples = 82\nvalue = [0, 126]\nclass = b'),
 Text(3627.0, 1268.4, 'PM10 <= 33.5\ngini = 0.036\nsamples = 2212\nvalue = [3380, 64]\nclass = a'),
 Text(3236.3999999999996, 906.0, 'O_3 <= 2.5\ngini = 0.014\nsamples = 1692\nvalue = [2603, 18]\nclass = a'),
 Text(3124.7999999999997, 543.5999999999999, 'gini = 0.0\nsamples = 5\nvalue = [0, 7]\nclass = b'),
 Text(3348.0, 543.5999999999999, 'NMHC <= 0.325\ngini = 0.008\nsamples = 1687\nvalue = [2603, 11]\nclass = a'),
```

```
 Text(3236.3999999999996, 181.19999999999982, 'gini = 0.001\nsamples = 1614\nvalue = [249
2, 1]\nclass = a'),
 Text(3459.6, 181.19999999999982, 'gini = 0.152\nsamples = 73\nvalue = [111, 10]\nclass =
a'),
 Text(4017.6, 906.0, 'TCH <= 1.545\ngini = 0.106\nsamples = 520\nvalue = [777, 46]\nclass
= a'),
 Text(3794.3999999999996, 543.5999999999999, 'TCH <= 1.445\ngini = 0.026\nsamples = 335\nv
alue = [529, 7]\nclass = a'),
 Text(3682.7999999999997, 181.19999999999982, 'gini = 0.0\nsamples = 244\nvalue = [406, 0]
\nclass = a'),
 Text(3906.0, 181.19999999999982, 'gini = 0.102\nsamples = 91\nvalue = [123, 7]\nclass =
a'),
 Text(4240.8, 543.5999999999999, 'EBE <= 0.35\ngini = 0.235\nsamples = 185\nvalue = [248,
39]\nclass = a'),
 Text(4129.2, 181.19999999999982, 'gini = 0.414\nsamples = 26\nvalue = [12, 29]\nclass =
b'),
 Text(4352.4, 181.19999999999982, 'gini = 0.078\nsamples = 159\nvalue = [236, 10]\nclass =
a')]
```



Conclusion

Linear Regression=0.8069102549582842

Ridge Regression=0.709408577546153

Lasso Regression=0.4113700257643299

ElasticNet Regression=0.4901906715101415

Logistic Regression=0.9888206926786497

Random Forest=0.9921700776675565

Random Forest is suitable for this dataset