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

	U. U. U.														
:		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	2
	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
	2	2016- 11-01 01:00:00	5.9	NaN	7.5	NaN	297.0	139.0	NaN	NaN	NaN	NaN	NaN	26.0	2
	3	2016- 11-01 01:00:00	NaN	1.0	NaN	NaN	154.0	113.0	2.0	NaN	NaN	NaN	NaN	NaN	2
	4	2016- 11-01 01:00:00	NaN	NaN	NaN	NaN	275.0	127.0	2.0	NaN	NaN	18.0	NaN	NaN	2
	•••														
	209491	2016- 07-01 00:00:00	NaN	0.2	NaN	NaN	2.0	29.0	73.0	NaN	NaN	NaN	NaN	NaN	2
	209492	2016- 07-01 00:00:00	NaN	0.3	NaN	NaN	1.0	29.0	NaN	36.0	NaN	5.0	NaN	NaN	2
	209493	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	1.0	19.0	71.0	NaN	NaN	NaN	NaN	NaN	2
	209494	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	6.0	17.0	85.0	NaN	NaN	NaN	NaN	NaN	2
	209495	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	2.0	46.0	61.0	34.0	NaN	NaN	NaN	NaN	2

209496 rows × 14 columns

In [3]: data.head(10)

Out[3]:		date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	stati
	0	2016- 11-01 01:00:00	NaN	0.7	NaN	NaN	153.0	77.0	NaN	NaN	NaN	7.0	NaN	NaN	280790
	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	280790
	2	2016- 11-01 01:00:00	5.9	NaN	7.5	NaN	297.0	139.0	NaN	NaN	NaN	NaN	NaN	26.0	280790
	3	2016- 11-01 01:00:00	NaN	1.0	NaN	NaN	154.0	113.0	2.0	NaN	NaN	NaN	NaN	NaN	280790
	4	2016- 11-01 01:00:00	NaN	NaN	NaN	NaN	275.0	127.0	2.0	NaN	NaN	18.0	NaN	NaN	280790
	5	2016- 11-01 01:00:00	0.9	0.5	0.5	NaN	66.0	82.0	1.0	27.0	NaN	8.0	NaN	6.0	280790
	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	5.0	280790
	7	2016- 11-01 01:00:00	NaN	NaN	NaN	NaN	52.0	78.0	1.0	NaN	NaN	NaN	NaN	NaN	280790
	8	2016- 11-01 01:00:00	NaN	1.2	NaN	NaN	205.0	85.0	6.0	NaN	NaN	NaN	NaN	NaN	280790
	9	2016- 11-01 01:00:00	NaN	0.7	NaN	NaN	114.0	91.0	NaN	37.0	NaN	6.0	NaN	NaN	280790
	4 1														

In [4]: data.tail(20)

Out[4]:		date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	
	209476	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	4.0	24.0	77.0	NaN	NaN	8.0	NaN	NaN	28
	209477	2016- 07-01 00:00:00	0.2	0.3	0.1	NaN	2.0	28.0	83.0	33.0	NaN	4.0	NaN	0.7	28
	209478	2016- 07-01 00:00:00	0.1	0.2	0.1	0.02	1.0	6.0	89.0	16.0	9.0	2.0	1.15	0.2	28
	209479	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	1.0	24.0	73.0	NaN	NaN	NaN	NaN	NaN	28
	209480	2016- 07-01 00:00:00	NaN	0.3	NaN	NaN	1.0	27.0	47.0	NaN	NaN	19.0	NaN	NaN	28
	209481	2016- 07-01 00:00:00	NaN	0.2	NaN	NaN	1.0	32.0	NaN	37.0	NaN	6.0	NaN	NaN	28
	209482	2016- 07-01 00:00:00	0.1	NaN	0.1	NaN	8.0	28.0	NaN	19.0	9.0	2.0	NaN	1.1	28
	209483	2016- 07-01 00:00:00	NaN	0.3	NaN	NaN	5.0	41.0	59.0	NaN	NaN	NaN	NaN	NaN	28
	209484	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	4.0	31.0	NaN	30.0	NaN	5.0	NaN	NaN	28
	209485	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	3.0	20.0	NaN	20.0	15.0	NaN	NaN	NaN	28
	209486	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	2.0	34.0	NaN	21.0	14.0	NaN	NaN	NaN	28
	209487	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	1.0	20.0	74.0	NaN	NaN	NaN	NaN	NaN	28
	209488	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	28.0	54.0	NaN	21.0	13.0	NaN	NaN	NaN	28
	209489	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	4.0	31.0	73.0	NaN	NaN	NaN	NaN	NaN	28
	209490	2016- 07-01 00:00:00	0.3	NaN	0.2	0.10	1.0	30.0	NaN	45.0	NaN	NaN	1.19	2.0	28
	209491	2016- 07-01 00:00:00	NaN	0.2	NaN	NaN	2.0	29.0	73.0	NaN	NaN	NaN	NaN	NaN	28
	209492	2016- 07-01 00:00:00	NaN	0.3	NaN	NaN	1.0	29.0	NaN	36.0	NaN	5.0	NaN	NaN	28

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	
209493	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	1.0	19.0	71.0	NaN	NaN	NaN	NaN	NaN	28
209494	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	6.0	17.0	85.0	NaN	NaN	NaN	NaN	NaN	28
209495	2016- 07-01 00:00:00	NaN	NaN	NaN	NaN	2.0	46.0	61.0	34.0	NaN	NaN	NaN	NaN	28

In [5]: data.describe()

Out[5]:

	BEN	со	EBE	NMHC	NO	NO_2
count	50755.000000	85999.000000	50335.000000	25970.000000	208614.000000	208614.000000 1
mean	0.632450	0.354954	0.374407	0.124340	22.058280	38.559248
std	0.857079	0.234792	0.684403	0.117454	46.518291	28.970459
min	0.100000	0.100000	0.100000	0.000000	1.000000	1.000000
25%	0.100000	0.200000	0.100000	0.070000	2.000000	17.000000
50%	0.300000	0.300000	0.200000	0.110000	6.000000	32.000000
75%	0.700000	0.400000	0.400000	0.150000	19.000000	54.000000
max	21.400000	4.500000	27.400000	9.070000	957.000000	324.000000
4						•

In [6]: np.shape(data)

Out[6]: (209496, 14)

In [7]: np.size(data)

Out[7]: 2932944

In [8]: data.isna()

Out[8]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL
0	False	True	False	True	True	False	False	True	True	True	False	True	True
1	False												
2	False	False	True	False	True	False	False	True	True	True	True	True	False
3	False	True	False	True	True	False	False	False	True	True	True	True	True
4	False	True	True	True	True	False	False	False	True	True	False	True	True
209491	False	True	False	True	True	False	False	False	True	True	True	True	True
209492	False	True	False	True	True	False	False	True	False	True	False	True	True
209493	False	True	True	True	True	False	False	False	True	True	True	True	True
209494	False	True	True	True	True	False	False	False	True	True	True	True	True
209495	False	True	True	True	True	False	False	False	False	True	True	True	True

209496 rows × 14 columns

In [9]: data.dropna()

2016- 1 11-01 01:00:00 6 11-01 01:00:00 2016- 25 11-01 02:00:00 2016- 30 11-01 02:00:00 49 11-01 03:00:00 2016- 430 06-30	0.7 2.7 0.7 1.7	1.1 0.8 1.0 0.7 0.8	2.0 0.4 2.1 0.4	0.13	260.0 57.0 139.0 48.0 53.0	144.0 66.0 114.0 59.0	3.0	46.0 23.0 37.0 23.0	24.0 15.0 21.0 15.0	4.0 14.0	2.441.352.301.35	5.0 15.0
6 11-01 01:00:00 2016- 25 11-01 02:00:00 2016- 30 11-01 02:00:00 2016- 49 11-01 03:00:00 2016- 430 06-30	2.7 0.7 1.7	1.0	2.1	0.40 0.13	139.0 48.0	114.0 59.0	4.0 3.0	37.0 23.0	21.0	14.0	2.30	15.0
25 11-01 02:00:00 2016- 30 11-01 02:00:00 2016- 49 11-01 03:00:00 2016- 430 06-30	0.7 1.7 	0.7	0.4	0.13	48.0	59.0	3.0	23.0				
30 11-01 02:00:00 2016- 49 11-01 03:00:00 2016- 430 06-30	1.7								15.0	3.0	1.35	5.0
49 11-01 03:00:00 2016- 430 06-30		0.8	1.4	0.25	53.0	90.0		24.0				
2016- 430 06-30							4.0	31.0	19.0	10.0	1.95	10.7
430 06-30			• • • • • • • • • • • • • • • • • • • •									
22:00:00	0.1	0.2	0.1	0.02	1.0	5.0	97.0	19.0	12.0	2.0	1.15	0.2
2016- 449 06-30 23:00:00	0.6	0.4	0.3	0.15	14.0	63.0	54.0	29.0	13.0	16.0	1.48	1.9
2016- 454 06-30 23:00:00	0.1	0.2	0.1	0.02	1.0	7.0	91.0	16.0	9.0	2.0	1.15	0.3
2016- 473 07-01 00:00:00	0.6	0.4	0.3	0.16	11.0	68.0	45.0	24.0	14.0	16.0	1.50	1.9
2016- 478 07-01 00:00:00	0.1	0.2	0.1	0.02	1.0	6.0	89.0	16.0	9.0	2.0	1.15	0.2
47	23:00:00 2016- 64 06-30 23:00:00 2016- 73 07-01 00:00:00 78 07-01 00:00:00	23:00:00 2016- 54 06-30 0.1 23:00:00 2016- 73 07-01 0.6 00:00:00 2016- 78 07-01 0.1 00:00:00	23:00:00 2016- 54 06-30 0.1 0.2 23:00:00 2016- 73 07-01 0.6 0.4 00:00:00 2016- 78 07-01 0.1 0.2	23:00:00 2016- 54 06-30 0.1 0.2 0.1 23:00:00 2016- 73 07-01 0.6 0.4 0.3 00:00:00 2016- 78 07-01 0.1 0.2 0.1 00:00:00	23:00:00 2016- 54 06-30 0.1 0.2 0.1 0.02 23:00:00 2016- 73 07-01 0.6 0.4 0.3 0.16 00:00:00 2016- 78 07-01 0.1 0.2 0.1 0.02 00:00:00	23:00:00 2016- 54 06-30 0.1 0.2 0.1 0.02 1.0 23:00:00 2016- 73 07-01 0.6 0.4 0.3 0.16 11.0 00:00:00 2016- 78 07-01 0.1 0.2 0.1 0.02 1.0 00:00:00	23:00:00 2016- 54 06-30 0.1 0.2 0.1 0.02 1.0 7.0 23:00:00 2016- 73 07-01 0.6 0.4 0.3 0.16 11.0 68.0 00:00:00 2016- 78 07-01 0.1 0.2 0.1 0.02 1.0 6.0 00:00:00	23:00:00 2016- 54 06-30	23:00:00 2016- 06-30 23:00:00 2016- 73 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00	23:00:00 2016- 54 06-30	23:00:00 2016- 54 06-30 0.1 0.2 0.1 0.02 1.0 7.0 91.0 16.0 9.0 2.0 23:00:00 2016- 73 07-01 0.6 0.4 0.3 0.16 11.0 68.0 45.0 24.0 14.0 16.0 00:00:00 2016- 78 07-01 0.1 0.2 0.1 0.02 1.0 6.0 89.0 16.0 9.0 2.0 00:00:00	23:00:00 2016- 06-30 23:00:00 2016- 73 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00 2016- 07-01 00:00:00

```
In [11]: sd=data[['BEN','CO', 'EBE', 'NMHC', 'NO_2']]
```

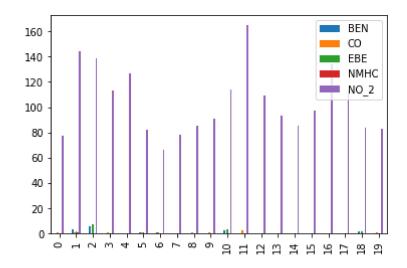
In [12]: dd=sd.head(20) dd

Out[12]:

	BEN	со	EBE	NMHC	NO_2
0	NaN	0.7	NaN	NaN	77.0
1	3.1	1.1	2.0	0.53	144.0
2	5.9	NaN	7.5	NaN	139.0
3	NaN	1.0	NaN	NaN	113.0
4	NaN	NaN	NaN	NaN	127.0
5	0.9	0.5	0.5	NaN	82.0
6	0.7	8.0	0.4	0.13	66.0
7	NaN	NaN	NaN	NaN	78.0
8	NaN	1.2	NaN	NaN	85.0
9	NaN	0.7	NaN	NaN	91.0
10	2.5	NaN	3.3	NaN	114.0
11	NaN	2.4	NaN	NaN	165.0
12	NaN	NaN	NaN	NaN	109.0
13	NaN	NaN	NaN	NaN	93.0
14	NaN	NaN	NaN	NaN	85.0
15	NaN	NaN	NaN	NaN	97.0
16	NaN	NaN	NaN	NaN	134.0
17	NaN	NaN	NaN	NaN	113.0
18	1.4	NaN	1.3	0.20	84.0
19	NaN	0.5	NaN	NaN	83.0

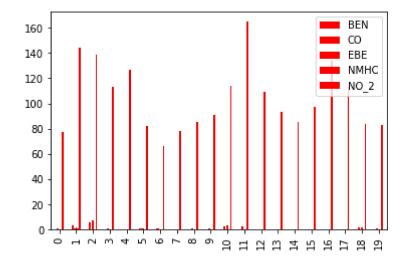
In [13]: dd.plot.bar()

Out[13]: <AxesSubplot:>



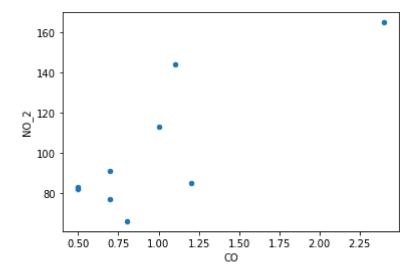
```
In [14]: dd.plot.bar(color='r')
```

Out[14]: <AxesSubplot:>



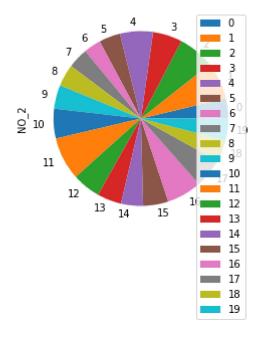
```
In [15]: dd.plot.scatter(x='CO',y='NO_2')
```

Out[15]: <AxesSubplot:xlabel='CO', ylabel='NO_2'>



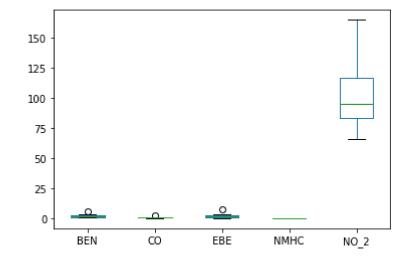
```
In [16]: dd.plot.pie(y='NO_2')
```

Out[16]: <AxesSubplot:ylabel='NO_2'>



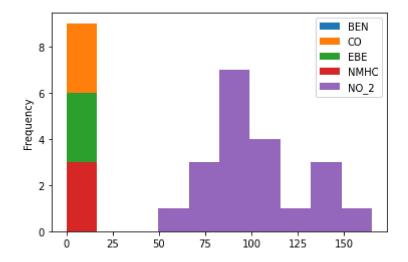
In [17]: dd.plot.box()

Out[17]: <AxesSubplot:>



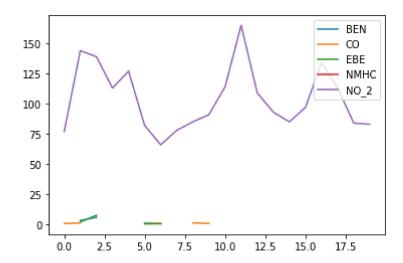
```
In [18]: dd.plot.hist()
```

Out[18]: <AxesSubplot:ylabel='Frequency'>



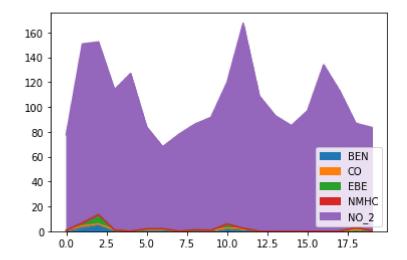
In [19]: | dd.plot.line()

Out[19]: <AxesSubplot:>



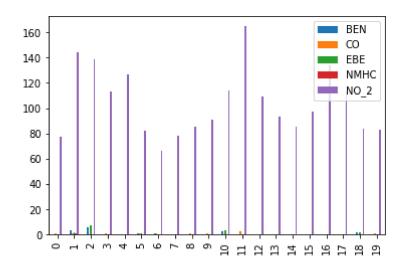
```
In [20]: dd.plot.area()
```

Out[20]: <AxesSubplot:>



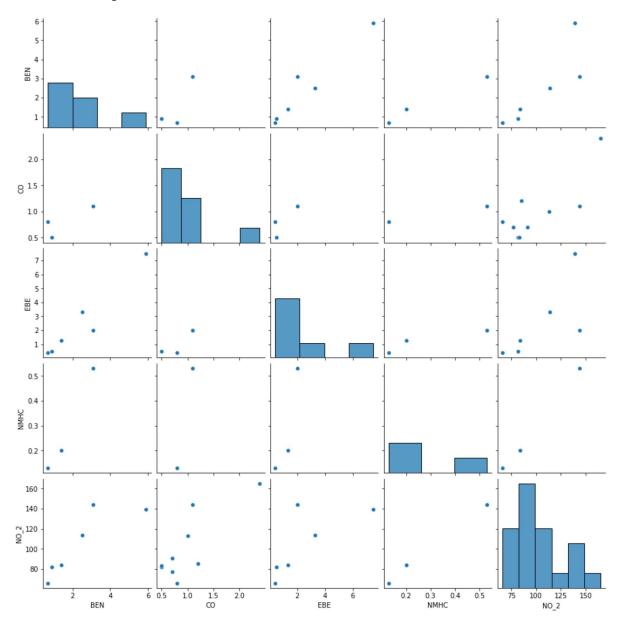
In [21]: dd.plot.bar()

Out[21]: <AxesSubplot:>



In [22]: sns.pairplot(dd)

Out[22]: <seaborn.axisgrid.PairGrid at 0x1caa2747c70>

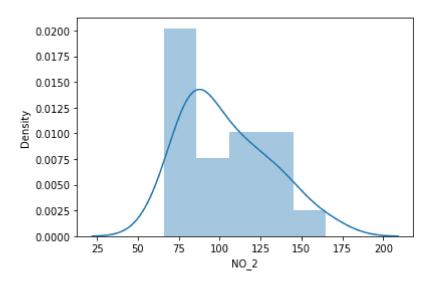


In [23]: sns.distplot(dd['NO_2'])

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 function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

Out[23]: <AxesSubplot:xlabel='NO_2', ylabel='Density'>



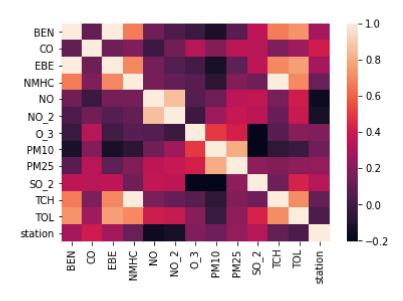
```
In [24]: ds=data.fillna(20)
```

In [25]: ssd=ds.head(20)

```
In [26]: sd1=ssd[['BEN','CO', 'EBE', 'NMHC', 'NO_2']]
```

In [27]: sns.heatmap(ssd.corr())

Out[27]: <AxesSubplot:>



```
In [28]: | x= ssd[['BEN','CO', 'EBE','NMHC', 'NO_2']]
         y=ssd['station']
In [29]: 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 [30]: from sklearn.linear_model import LinearRegression
         lr=LinearRegression()
         lr.fit(x_train,y_train)
Out[30]: LinearRegression()
In [31]:
         print(lr.intercept_)
         28079032.39849289
         coeff= pd.DataFrame(lr.coef ,x.columns,columns=['Co-efficient'])
In [32]:
         coeff
Out[32]:
                 Co-efficient
                 -18.062999
            BEN
             CO
                   0.543611
            EBE
                  18.459225
          NMHC
                  -0.762618
           NO_2
                   0.014609
         prediction = lr.predict(x_test)
In [33]:
         plt.scatter(y_test,prediction)
Out[33]: <matplotlib.collections.PathCollection at 0x1caa541eee0>
             +2.8079e7
          60
          55
          50
          45
          40
```

35

30

10

20

30

40

50 +2.8079e7

```
In [34]: |print(lr.score(x_test,y_test))
         -1.736951953080799
In [35]: |lr.score(x_test,y_test)
Out[35]: -1.736951953080799
In [36]: |lr.score(x_train,y_train)
Out[36]: 0.31143336104469654
In [37]: from sklearn.linear_model import Ridge,Lasso
In [38]: | dr=Ridge(alpha=10)
         dr.fit(x_train,y_train)
Out[38]: Ridge(alpha=10)
In [39]: |dr.score(x_test,y_test)
Out[39]: -0.060956239476947616
In [40]: |dr.score(x_train,y_train)
Out[40]: 0.23910889006323122
In [41]: la=Lasso(alpha=10)
         la.fit(x_train,y_train)
Out[41]: Lasso(alpha=10)
In [42]: la.score(x_test,y_test)
Out[42]: -0.19039613318274196
In [43]: la.score(x_train,y_train)
Out[43]: 0.22148355450604817
         ElasticNet
```

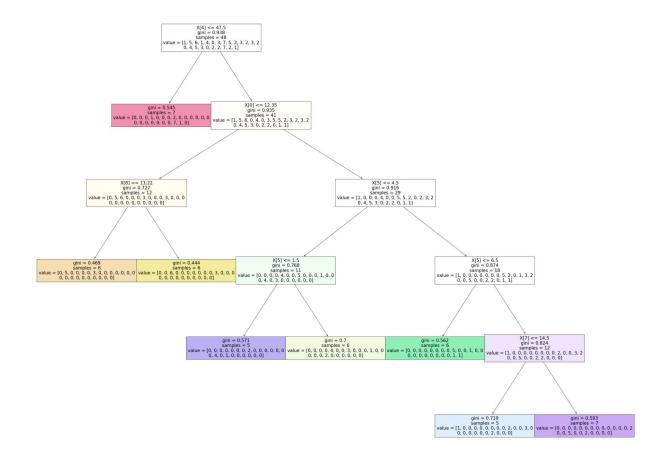
```
In [45]: |print(en.coef_)
         In [46]:
        print(en.intercept_)
         28079024.923744354
In [47]: prediction=en.predict(x_test)
In [48]: print(en.score(x_test,y_test))
         -0.025875730398854824
In [49]:
        import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
In [50]: | from sklearn.linear model import LogisticRegression
In [51]: feature_matrix = ssd[['BEN','CO', 'EBE','NMHC', 'NO_2']]
         target vector=ssd['station']
In [52]: | feature_matrix.shape
Out[52]: (20, 5)
In [53]: target_vector.shape
Out[53]: (20,)
In [54]: from sklearn.preprocessing import StandardScaler
In [55]: | fs=StandardScaler().fit_transform(feature_matrix)
In [56]: logr= LogisticRegression()
         logr.fit(fs,target_vector)
Out[56]: LogisticRegression()
In [57]: observation =[[1.2,2.3,3.3,4.3,5.3]]
In [58]: | prediction=logr.predict(observation)
         print(prediction)
         [28079039]
```

```
In [59]: logr.classes
Out[59]: array([28079004, 28079008, 28079011, 28079016, 28079017, 28079018,
                28079024, 28079027, 28079035, 28079036, 28079038, 28079039,
                28079040, 28079047, 28079048, 28079049, 28079050, 28079054,
                28079055, 28079056], dtype=int64)
In [60]: logr.predict_proba(observation)[0][0]
Out[60]: 6.359675284065992e-05
In [61]: | ged=data[['BEN','CO','EBE','NMHC','NO_2','O_3','PM10','SO_2','TCH','TOL','stati
In [62]: | d=ged.fillna(20)
In [63]: | dg=d.head(100)
In [64]: | x=dg[['BEN','CO','EBE','NMHC','NO 2','O 3','PM10','SO 2','TCH','TOL']]
         y=dg['station']
In [65]: from sklearn.model selection import train test split
         x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.70)
In [66]: from sklearn.ensemble import RandomForestClassifier
         rfc=RandomForestClassifier()
         rfc.fit(x_train,y_train)
Out[66]: RandomForestClassifier()
In [67]: paramets = {'max_depth':[1,2,3,4,5,6,7],
                        'min samples leaf':[5,10,15,20,25,30,35],
                        'n_estimators':[10,20,30,40,50,60,70]}
In [68]: from sklearn.model selection import GridSearchCV
         grid_search= GridSearchCV(estimator = rfc,param_grid=paramets,cv=2,scoring="ac
         grid_search.fit(x_train,y_train)
         C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:
         666: UserWarning: The least populated class in y has only 1 members, which is
         less than n splits=2.
           warnings.warn(("The least populated class in y has only %d"
Out[68]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
                      param_grid={'max_depth': [1, 2, 3, 4, 5, 6, 7],
                                   'min_samples_leaf': [5, 10, 15, 20, 25, 30, 35],
                                   'n_estimators': [10, 20, 30, 40, 50, 60, 70]},
                      scoring='accuracy')
In [69]: |grid_search.best_score_
Out[69]: 0.41428571428571426
```

In [70]: rfc_best=grid_search.best_estimator_

In [71]: from sklearn.tree import plot_tree
 plt.figure(figsize=(50,40))
 plot_tree(rfc_best.estimators_[5],filled=True)

Out[71]: [Text(813.75, 1993.2, 'X[4] <= 47.5\ngini = 0.938\nsamples = 48\nvalue = [1,</pre> $5, 6, 1, 4, 0, 3, 7, 5, 2, 3, 2, 3, 2 \setminus 0, 4, 5, 3, 0, 2, 2, 7, 2, 1]'),$ Text(581.25, 1630.80000000000002, 'gini = 0.545\nsamples = 7\nvalue = [0, 0, 0]0, 1, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 7, 1, 0]'), $Text(1046.25, 1630.8000000000000, 'X[0] <= 12.35 \ngini = 0.935 \nsamples = 41$ \nvalue = $[1, 5, 6, 0, 4, 0, 3, 5, 5, 2, 3, 2, 3, 2 \n0, 4, 5, 3, 0, 2, 2, 0,$ 1, 1]'), $Text(465.0, 1268.4, 'X[8] \le 11.22 = 0.727 = 0.727 = 12 = 12$ 5, 6, 0, 0, 0, 3, 0, 0, 0, 3, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'), Text(232.5, 906.0, 'gini = 0.469\nsamples = 6\nvalue = [0, 5, 0, 0, 0, 0, 3, $0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 0, 0, 0, 0, 0, 0]'),$ Text(697.5, 906.0, 'gini = 0.444\nsamples = 6\nvalue = [0, 0, 6, 0, 0, 0, 0, 0]0, 0, 0, 3, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0]'), Text(1627.5, 1268.4, $'X[5] \leftarrow 4.5$ | one in i = 0.916 | nsamples = 29 | nvalue = [1, 1.5] 0, 0, 0, 4, 0, 0, 5, 5, 2, 0, 2, 3, 2\n0, 4, 5, 3, 0, 2, 2, 0, 1, 1]'), Text(1162.5, 906.0, $'X[5] \leftarrow 1.5 \neq 0.768 = 11 \neq 0.768 =$ 0, 0, 4, 0, 0, 5, 0, 0, 0, 1, 0, 0\n0, 4, 0, 3, 0, 0, 0, 0, 0, 0]'), Text(930.0, 543.599999999999, 'gini = 0.571\nsamples = 5\nvalue = [0, 0, 0, 0]0, 0, 0, 0, 2, 0, 0, 0, 0, 0\n0, 4, 0, 1, 0, 0, 0, 0, 0]'), Text(1395.0, 543.59999999999, 'gini = 0.7\nsamples = 6\nvalue = [0, 0, 0, 0, 4, 0, 0, 3, 0, 0, 0, 1, 0, 0\n0, 0, 0, 2, 0, 0, 0, 0, 0, 0]'), $Text(2092.5, 906.0, 'X[5] \le 6.5 \le 0.874 \le 18 \le 18 \le [1, 0, 1]$ $0, 0, 0, 0, 0, 0, 5, 2, 0, 1, 3, 2 \setminus 0, 0, 5, 0, 0, 2, 2, 0, 1, 1]'),$ Text(1860.0, 543.59999999999, 'gini = 0.562\nsamples = 6\nvalue = [0, 0, $0, 0, 0, 0, 0, 0, 5, 0, 0, 1, 0, 0 \setminus 0, 0, 0, 0, 0, 0, 0, 1, 1]'),$ Text(2325.0, 543.59999999999, 'X[7] <= 14.5\ngini = 0.824\nsamples = 12\nv alue = [1, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 3, 2\n0, 0, 5, 0, 0, 2, 2, 0, 0, 0]'), Text(2092.5, 181.199999999999, 'gini = 0.719\nsamples = 5\nvalue = [1, 0, $0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 3, 0 \setminus 0, 0, 0, 0, 0, 0, 2, 0, 0]'),$ 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2\n0, 0, 5, 0, 0, 2, 0, 0, 0]')]



Conclusion : LogisticRegression() [28079039] HIGH RANGE

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Tu []:		