In [1]: 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]: df =pd.read_csv(r"D:\datasets\madrid_2009.csv")
 df

Out[2]:		date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	
	0	2009- 10-01 01:00:00	NaN	0.27	NaN	NaN	NaN	39.889999	48.150002	NaN	5
	1	2009- 10-01 01:00:00	NaN	0.22	NaN	NaN	NaN	21.230000	24.260000	NaN	5
	2	2009- 10-01 01:00:00	NaN	0.18	NaN	NaN	NaN	31.230000	34.880001	NaN	4
	3	2009- 10-01 01:00:00	0.95	0.33	1.43	2.68	0.25	55.180000	81.360001	1.57	3
	4	2009- 10-01 01:00:00	NaN	0.41	NaN	NaN	0.12	61.349998	76.260002	NaN	3
	215683	2009- 06-01 00:00:00	0.50	0.22	0.39	0.75	0.09	22.000000	24.510000	1.00	8
	215684	2009- 06-01 00:00:00	NaN	0.31	NaN	NaN	NaN	76.110001	101.099998	NaN	4
	215685	2009- 06-01 00:00:00	0.13	NaN	0.86	NaN	0.23	81.050003	99.849998	NaN	2
	215686	2009- 06-01 00:00:00	0.21	NaN	2.96	NaN	0.10	72.419998	82.959999	NaN	
	215687	2009- 06-01 00:00:00	0.37	0.32	0.99	1.36	0.14	54.290001	64.480003	1.06	5

215688 rows \times 17 columns

In [3]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 215688 entries, 0 to 215687
Data columns (total 17 columns):
     Column
             Non-Null Count
                              Dtype
     -----
              -----
 0
     date
             215688 non-null object
 1
     BEN
             60082 non-null
                              float64
 2
     C0
             190801 non-null float64
 3
             60081 non-null
     EBE
                              float64
 4
    MXY
             24846 non-null
                              float64
 5
             74748 non-null
    NMHC
                              float64
 6
    NO 2
             214562 non-null float64
 7
    N0x
             214565 non-null float64
 8
     0XY
             24854 non-null
                              float64
 9
     0 3
             204482 non-null float64
 10
    PM10
             196331 non-null float64
                              float64
 11
    PM25
             55822 non-null
 12
    PXY
             24854 non-null
                              float64
 13 S0 2
             212671 non-null float64
 14
    TCH
             75213 non-null
                              float64
 15
    T0L
             59920 non-null
                              float64
 16 station 215688 non-null int64
dtypes: float64(15), int64(1), object(1)
memory usage: 28.0+ MB
```

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

Out[4]:		date	BEN	СО	EBE	MXY	NМНС	NO_2	OXY		
	0	2009- 10-01 01:00:00	0.00	0.27	0.00	0.00	0.00	39.889999	48.150002	0.00	5
	1	2009- 10-01 01:00:00	0.00	0.22	0.00	0.00	0.00	21.230000	24.260000	0.00	5
	2	2009- 10-01 01:00:00	0.00	0.18	0.00	0.00	0.00	31.230000	34.880001	0.00	4
	3	2009- 10-01 01:00:00	0.95	0.33	1.43	2.68	0.25	55.180000	81.360001	1.57	3
	4	2009- 10-01 01:00:00	0.00	0.41	0.00	0.00	0.12	61.349998	76.260002	0.00	3
	215683	2009- 06-01 00:00:00	0.50	0.22	0.39	0.75	0.09	22.000000	24.510000	1.00	8
	215684	2009- 06-01 00:00:00	0.00	0.31	0.00	0.00	0.00	76.110001	101.099998	0.00	4
	215685	2009- 06-01 00:00:00	0.13	0.00	0.86	0.00	0.23	81.050003	99.849998	0.00	2
	215686	2009- 06-01 00:00:00	0.21	0.00	2.96	0.00	0.10	72.419998	82.959999	0.00	
	215687	2009- 06-01 00:00:00	0.37	0.32	0.99	1.36	0.14	54.290001	64.480003	1.06	5

215688 rows × 17 columns

In [5]: df1.info()

```
<class 'pandas.core.frame.DataFrame'>
      RangeIndex: 215688 entries, 0 to 215687
      Data columns (total 17 columns):
           Column
                    Non-Null Count
                                    Dtype
           -----
                    -----
       0
                    215688 non-null object
           date
           BEN
                    215688 non-null float64
       1
       2
           C0
                    215688 non-null float64
       3
                    215688 non-null float64
           EBE
       4
           MXY
                    215688 non-null float64
       5
                    215688 non-null float64
           NMHC
       6
           NO 2
                    215688 non-null float64
       7
                    215688 non-null float64
           N0x
       8
           0XY
                    215688 non-null float64
       9
                    215688 non-null float64
           0 3
       10 PM10
                    215688 non-null float64
                    215688 non-null float64
       11 PM25
                    215688 non-null float64
       12 PXY
       13 S0 2
                    215688 non-null float64
       14 TCH
                    215688 non-null float64
       15 T0L
                    215688 non-null float64
       16 station 215688 non-null int64
      dtypes: float64(15), int64(1), object(1)
      memory usage: 28.0+ MB
In [6]: dfl.columns
Out[6]: Index(['date', 'BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO 2', 'NOx', 'OXY', 'O
        3',
               'PM10', 'PM25', 'PXY', 'SO 2', 'TCH', 'TOL', 'station'],
              dtype='object')
In [7]: df2=df1[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
               'PM10', 'PM25', 'PXY', 'SO 2', 'TCH', 'TOL', 'station']]
        df2
```

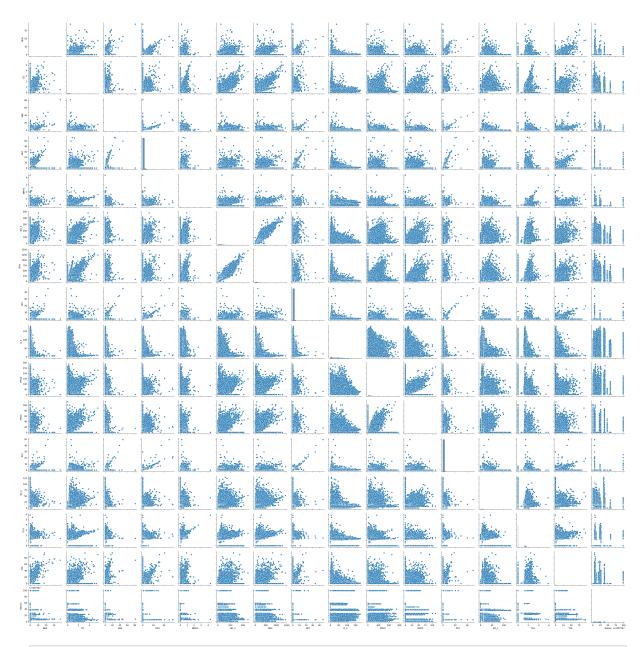
Out[7]:		BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	0_3
	0	0.00	0.27	0.00	0.00	0.00	39.889999	48.150002	0.00	50.680000
	1	0.00	0.22	0.00	0.00	0.00	21.230000	24.260000	0.00	55.880001
	2	0.00	0.18	0.00	0.00	0.00	31.230000	34.880001	0.00	49.060001
	3	0.95	0.33	1.43	2.68	0.25	55.180000	81.360001	1.57	36.669998
	4	0.00	0.41	0.00	0.00	0.12	61.349998	76.260002	0.00	38.090000
	215683	0.50	0.22	0.39	0.75	0.09	22.000000	24.510000	1.00	82.239998
	215684	0.00	0.31	0.00	0.00	0.00	76.110001	101.099998	0.00	41.220001
	215685	0.13	0.00	0.86	0.00	0.23	81.050003	99.849998	0.00	24.830000
	215686	0.21	0.00	2.96	0.00	0.10	72.419998	82.959999	0.00	0.000000
	215687	0.37	0.32	0.99	1.36	0.14	54.290001	64.480003	1.06	56.919998

215688 rows × 16 columns

In [8]: sns.pairplot(df2)

C:\Users\HP\AppData\Local\Programs\Python\Python311\Lib\site-packages\seabor
n\axisgrid.py:118: UserWarning: The figure layout has changed to tight
self._figure.tight_layout(*args, **kwargs)

Out[8]: <seaborn.axisgrid.PairGrid at 0x17d8ba9ebd0>



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

 $\label{local-loc$

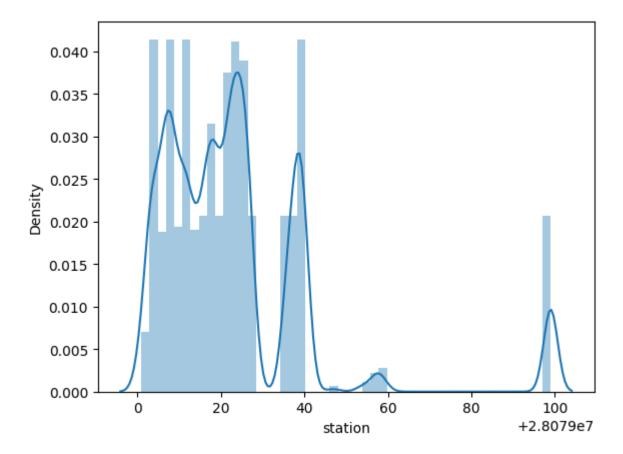
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df2['station'])

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



linear

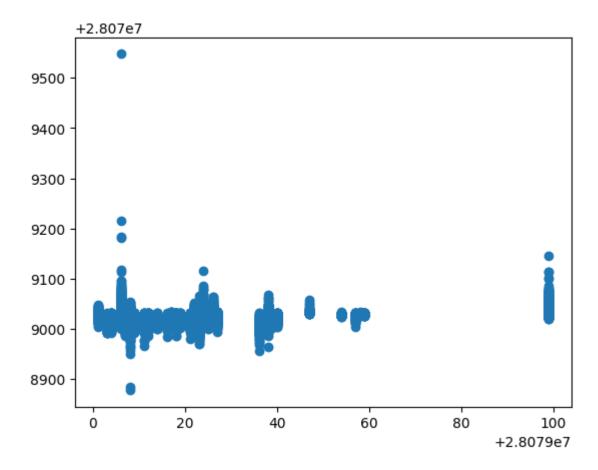
Out[14]:		Co-efficient
	BEN	-4.615807
	СО	-4.992281
	EBE	1.758629
	MXY	-3.154330
	NMHC	5.333756
	NO_2	-0.115052
	NOx	0.038630
	OXY	9.468954
	0_3	-0.048493
	PM10	-0.014585
	PM25	0.540350
	PXY	6.623647
	SO_2	-0.482322
	TCH	0.235949
	TOL	-0.331949

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

28079031.57755233

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

Out[16]: <matplotlib.collections.PathCollection at 0x17da7023fd0>



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

0.16164022524589827

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

0.16574919725540282

Ridge

Lasso

```
In [22]: la=Lasso(alpha=10)
         la.fit(x train,y train)
Out[22]: ▼
               Lasso
         Lasso(alpha=10)
In [23]: la.score(x_test,y_test)
Out[23]: 0.08330465988481084
         elasticnet
In [24]: from sklearn.linear model import ElasticNet
         en=ElasticNet()
         en.fit(x_train,y_train)
Out[24]: ▼ ElasticNet
         ElasticNet()
In [25]: print(en.coef_)
        [-0.
                                 0.25594261 1.44132117
                                                                    -0.10674645
                     1.08447441 -0.04738088 -0.00726588 0.62195308 0.90028299
         -0.50143208 0.28762132 -0.20115409]
In [26]: print(en.intercept_)
        28079031.76020447
In [27]: print(en.predict(x test))
        [28079022.11968691 28079017.58153
                                            28079024.58582972 ...
         28079033.68694673 28079021.0396411 28079021.17881544]
In [28]: print(en.score(x_test,y_test))
        0.13279398323860492
         logistic
In [29]: feature matrix =df2.iloc[:,0:15]
         target vector=df2.iloc[:,-1]
```

```
In [30]: feature matrix=df2[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO 2', 'NOx', 'OXY'
                'PM10', 'PM25', 'PXY', 'SO 2', 'TCH', 'TOL']]
         y=df2['station']
In [31]: feature matrix.shape
Out[31]: (215688, 15)
In [32]: target vector.shape
Out[32]: (215688,)
In [33]: from sklearn.preprocessing import StandardScaler
In [34]: fs=StandardScaler().fit transform(feature matrix)
In [35]: logr = LogisticRegression()
         logr.fit(fs,target vector)
        C:\Users\HP\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklear
        n\linear model\ logistic.py:460: ConvergenceWarning: lbfgs failed to converg
        e (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
        Please also refer to the documentation for alternative solver options:
            https://scikit-learn.org/stable/modules/linear model.html#logistic-regre
        ssion
          n iter i = check optimize result(
Out[35]: ▼ LogisticRegression
         LogisticRegression()
In [36]: observation=[[1,2,3,4,5,6,7,8,9,11,12,13,14,15,16]]
In [37]: prediction =logr.predict(observation)
         print(prediction)
        [280790991
In [38]: logr.classes
Out[38]: array([28079001, 28079003, 28079004, 28079006, 28079007, 28079008,
                28079009, 28079011, 28079012, 28079014, 28079016, 28079017,
                28079018, 28079019, 28079021, 28079022, 28079023, 28079024,
                28079025, 28079026, 28079027, 28079036, 28079038, 28079039,
                28079040, 28079047, 28079054, 28079057, 28079058, 28079059,
                28079099], dtype=int64)
In [39]: logr.score(fs,target vector)
```

```
In [40]: logr.predict proba(observation)[0][0]
Out[40]: 3.7014022758991974e-133
In [41]: logr.predict proba(observation)[0][1]
Out[41]: 1.9803684011074334e-191
         Random forest
In [42]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.tree import plot tree
In [43]: x=df2.drop('station',axis=1)
         y=df2['station']
In [44]: x train,x test,y train,y test=train test split(x,y,test size=0.70)
In [45]: rfc=RandomForestClassifier()
         rfc.fit(x_train,y_train)
Out[45]: ▼ RandomForestClassifier
         RandomForestClassifier()
In [46]:
         parameters={'max depth':[1,2,3,4,5],
                     'min_samples_leaf' :[6,7,8,9,10],
                     'n estimators':[11,12,13,14,15]}
In [47]: from sklearn.model selection import GridSearchCV
In [48]: grid search =GridSearchCV(estimator =rfc,param grid=parameters,cv=2,scoring=
         grid search.fit(x train,y train)
                      GridSearchCV
Out[48]:
          ▶ estimator: RandomForestClassifier
                ▶ RandomForestClassifier
In [49]: grid search.best score
Out[49]: 0.5005718171421506
         rfc best=grid search.best estimator
```

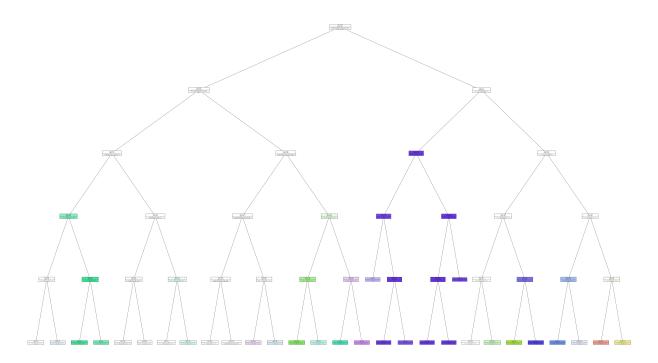
Out[39]: 0.5425522050369052

```
In [51]: py.figure(figsize=(80,50))
   plot_tree(rfc_best.estimators_[5],filled=True)
```

```
Out[51]: [Text(0.5178571428571429, 0.916666666666666, 'x[13] <= 0.305 \ngini = 0.961]
                \nsamples = 40817\nvalue = [869, 2706, 2665, 2334, 2727, 2672, 2475, 2510,
                2625\n2385, 2659, 1347, 2609, 2604, 2401, 2301, 2545, 2574\n2370, 2643, 264
                6, 2741, 2672, 2598, 2600, 76, 178\n292, 210, 122, 2550]'),
                 Text(0.2857142857142857, 0.75, 'x[5] \le 30.735 \setminus gini = 0.943 \setminus gini = 26
                685\nvalue = [869, 2706, 2665, 38, 273, 9, 2475, 476, 2625, 2385\n2659, 134
                7, 2609, 2604, 2401, 2301, 224, 23, 2370\n11, 4, 2741, 2672, 2598, 2600, 7
                6, 178, 292, 0\n122, 0]'),
                 Text(0.14285714285714285, 0.5833333333333334, 'x[9] \le 0.375 \setminus gini = 0.935
                \nsamples = 7722\nvalue = [98, 530, 616, 29, 50, 8, 428, 63, 375, 404, 1196
                \n738, 1122, 562, 449, 654, 33, 23, 682, 10, 4, 732\n895, 1098, 1173, 16, 5
                8, 104, 0, 53, 0]'),
                 Text(0.07142857142857142, 0.41666666666666667, 'x[12] \le 6.545 \setminus gini = 0.56
                7\nsamples = 745\nvalue = [3, 2, 12, 28, 16, 8, 28, 1, 20, 18, 3, 738, 31\n
                5, 6, 7, 33, 14, 9, 9, 2, 1, 3, 6, 4, 0, 58\n15, 0, 53, 0]'),
                 Text(0.03571428571428571, 0.25, 'x[1] \le 0.075 \cdot gini = 0.92 \cdot gini = 228
                \nvalue = [3, 0, 10, 28, 9, 8, 28, 1, 20, 5, 3, 5, 19\n5, 6, 7, 26, 14, 9,
                9, 2, 1, 3, 6, 4, 0, 58\n15, 0, 53, 0]'),
                 Text(0.017857142857142856, 0.08333333333333333, 'gini = 0.91\nsamples = 19
                9\nvalue = [3, 0, 10, 28, 9, 6, 15, 1, 20, 5, 2, 5, 16\n5, 6, 7, 10, 14, 7,
                9, 2, 1, 3, 1, 4, 0, 58 \ln 5, 0, 53, 0]'),
                 Text(0.05357142857142857, 0.08333333333333333, 'gini = 0.735\nsamples = 29
                0, 0, 5, 0, 0, 0, 0 \setminus n0, 0, 0]'),
                 Text(0.10714285714285714, 0.25, 'x[6] \le 47.36 \cdot gini = 0.107 \cdot gini = 51
                7\nvalue = [0, 2, 2, 0, 7, 0, 0, 0, 0, 13, 0, 733, 12, 0\n0, 0, 7, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0\n0, 0, 0]'),
                 Text(0.08928571428571429, 0.08333333333333333, 'gini = 0.101\nsamples = 50
                8\nvalue = [0, 2, 2, 0, 7, 0, 0, 0, 0, 13, 0, 723, 12, 0\n0, 0, 4, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0\n0, 0, 0]'),
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 10, 0, 0\n0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0\n0, 0, 0]'),
                 7\nsamples = 6977\nvalue = [95, 528, 604, 1, 34, 0, 400, 62, 355, 386, 1193
                \n0, 1091, 557, 443, 647, 0, 9, 673, 1, 2, 731\n892, 1092, 1169, 16, 0, 89,
                0, 0, 0]'),
                 Text(0.17857142857142858, 0.25, 'x[10] \le 0.3 \setminus i = 0.911 \setminus i = 468
                9\nvalue = [0, 93, 0, 0, 0, 0, 376, 5, 296, 367, 966, 0\n239, 510, 266, 63
                5, 0, 8, 589, 1, 2, 385, 657\n1048, 892, 16, 0, 89, 0, 0, 0]'),
                 Text(0.16071428571428573, 0.0833333333333333, 'gini = 0.891\nsamples = 38
                44\nvalue = [0, 93, 0, 0, 0, 0, 376, 5, 296, 367, 966, 0\n239, 510, 266, 2,
                0, 0, 589, 0, 2, 385, 0, 1048\n892, 0, 0, 89, 0, 0, 0]'),
                 Text(0.19642857142857142, 0.0833333333333333, 'gini = 0.518\nsamples = 84
                5\nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 633, 0, 8, 0, 1,
                0, 0, 657, 0, 0, 16, 0 \setminus n0, 0, 0, 0]
                 Text(0.25, 0.25, 'x[8] \le 70.87 \cdot gini = 0.875 \cdot g
                5, 435, 604, 1, 34, 0, 24, 57, 59, 19, 227, 0\n852, 47, 177, 12, 0, 1, 84,
                0, 0, 346, 235, 44\n277, 0, 0, 0, 0, 0, 0]'),
                 Text(0.23214285714285715, 0.08333333333333333, 'gini = 0.9\nsamples = 1445
                \nvalue = [74, 215, 284, 1, 34, 0, 24, 40, 45, 15, 205, 0\n341, 37, 141, 1
                1, 0, 1, 32, 0, 0, 340, 188, 31\n196, 0, 0, 0, 0, 0, 0]'),
                 Text(0.26785714285714285, 0.08333333333333333, 'gini = 0.774\nsamples = 84
                3\nvalue = [21, 220, 320, 0, 0, 0, 17, 14, 4, 22, 0\n511, 10, 36, 1, 0,
                0, 52, 0, 0, 6, 47, 13, 81\n0, 0, 0, 0, 0, 0]'),
```

```
\nsamples = 18963\nvalue = [771, 2176, 2049, 9, 223, 1, 2047, 413, 2250, 19]
81\n1463, 609, 1487, 2042, 1952, 1647, 191, 0, 1688, 1\n0, 2009, 1777, 150
0, 1427, 60, 120, 188, 0, 69, 0]'),
\nsamples = 18675\nvalue = [771, 2176, 2049, 0, 223, 0, 2047, 223, 2250, 19
81\n1463, 609, 1347, 2042, 1952, 1647, 176, 0, 1688, 0\n0, 2009, 1671, 150
0, 1427, 60, 120, 188, 0, 69, 0]'),
Text(0.32142857142857145, 0.25, 'x[12] \le 6.405 \cdot gini = 0.93 \cdot gini = 16
046\nvalue = [1, 2176, 2049, 0, 223, 0, 2047, 223, 2250, 1981\n1463, 609, 1
347, 2042, 1952, 20, 176, 0, 1688, 0\n0, 2009, 2, 1500, 1427, 0, 120, 188,
0, 69, 0]'),
Text(0.30357142857142855, 0.08333333333333333, 'qini = 0.818\nsamples = 23
23\nvalue = [0, 84, 0, 0, 0, 0, 945, 0, 848, 1, 54, 0, 91\n1, 167, 4, 15,
0, 867, 0, 0, 57, 0, 7, 413, 0\n120, 37, 0, 69, 0]'),
Text(0.3392857142857143, 0.08333333333333333, 'gini = 0.927 \ nsamples = 137
23\nvalue = [1, 2092, 2049, 0, 223, 0, 1102, 223, 1402, 1980\n1409, 609, 12
56, 2041, 1785, 16, 161, 0, 821, 0, 0\n1952, 2, 1493, 1014, 0, 0, 151, 0,
0, 0]'),
Text(0.39285714285714285, 0.25, 'x[5] \le 63.695  ngini = 0.646 \ nsamples = 2
629\nvalue = [770, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 1627, 0, 0, 0,
0, 0, 0, 1669, 0, 0, 60, 0\n0, 0, 0, 0]'),
14, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 816, 0, 0, 0, 0, 0, 1065,
0, 0, 48, 0\n0, 0, 0, 0]'),
Text(0.4107142857142857, 0.083333333333333333, 'qini = 0.653\nsamples = 120
3\nvalue = [456, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 811, 0, 0, 0,
0, 0, 604, 0, 0, 12, 0\n0, 0, 0, 0]'),
Text(0.5, 0.4166666666666667, 'x[2] \le 1.035 \setminus gini = 0.685 \setminus gini = 288
\nvalue = [0, 0, 0, 9, 0, 1, 0, 190, 0, 0, 0, 0, 140, 0\n0, 0, 15, 0, 0, 1,
0, 0, 106, 0, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.4642857142857143, 0.25, 'x[14] \le 3.385 \text{ ngini} = 0.524 \text{ nsamples} = 17
4\nvalue = [0, 0, 0, 4, 0, 1, 0, 186, 0, 0, 0, 0, 73, 0\n0, 0, 13, 0, 0, 1,
0, 0, 13, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.44642857142857145, 0.08333333333333333, 'gini = 0.359\nsamples = 11
4\nvalue = [0, 0, 0, 4, 0, 0, 0, 146, 0, 0, 0, 0, 10, 0\n0, 0, 11, 0, 0, 1,
0, 0, 12, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.48214285714285715, 0.08333333333333333, 'gini = 0.513\nsamples = 60
0, 1, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.5357142857142857, 0.25, 'x[8] \le 6.36 \cdot gini = 0.549 \cdot samples = 114
\nvalue = [0, 0, 0, 5, 0, 0, 0, 4, 0, 0, 0, 0, 67, 0\n0, 0, 2, 0, 0, 0, 0,
0, 93, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.5178571428571429, 0.08333333333333333, 'gini = 0.1\nsamples = 29\nv
2, 0, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.5535714285714286, 0.08333333333333333, 'gini = 0.475 \nsamples = 85
0, 91, 0, 0, 0, 0, 0\n0, 0, 0]'),
Text(0.75, 0.75, 'x[8] \le 0.3 \cdot = 0.89 \cdot = 14132 \cdot = [0, 0.75]
0, 0, 2296, 2454, 2663, 0, 2034, 0, 0, 0, 0\n0, 0, 0, 0, 2321, 2551, 0, 263
2, 2642, 0, 0, 0\n0, 0, 0, 0, 210, 0, 2550]'),
\label{eq:text} \texttt{Text}(0.6428571428571429,\ 0.58333333333333334,\ 'x[2] <= 0.565 \\ \texttt{ngini} = 0.019
\nsamples = 1679\nvalue = [0, 0, 0, 1, 0, 2, 0, 3, 0, 0, 0, 0, 0, 0 \n0, 0, 0]
0, 0, 0, 12, 2618, 0, 0, 0, 0, 0, 0\n7, 0, 0]'),
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0, 0, 0, 11, 371, 0, 0, 0, 0, 0, 0, 0 \setminus n7, 0, 0]
            Text(0.5714285714285714, 0.25, 'gini = 0.475 \nsamples = 9 \nvalue = [0, 0, 0]
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 11, 0, 0, 0, 0, 0, 0,
           0 \ n7, 0, 0]'),
            Text(0.6071428571428571, 0.25, 'x[4] \le 0.305 \setminus gini = 0.026 \setminus gini = 248
           \nvalue = [0, 0, 0, 0, 0, 2, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 371,
           0, 0, 0, 0, 0, 0, 0\n0, 0, 0]'),
            Text(0.5892857142857143, 0.08333333333333333, 'gini = 0.011 \ nsamples = 235
           0, 0, 0, 0, 0, 0\n0, 0, 0]'),
            0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 22, 0, 0, 0, 0,
           0, 0\n0, 0, 0]'),
            Text(0.6964285714285714, 0.4166666666666667, 'x[14] \le 13.7 \text{ ngini} = 0.002
           \nsamples = 1422\nvalue = [0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0,
           0, 0, 0, 1, 2247, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0]'),
            Text(0.6785714285714286, 0.25, 'x[14] \le 0.565 \text{ ngini} = 0.001 \text{ nsamples} = 14
           08\nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 1, 22
           28, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0]'),
            Text(0.6607142857142857, 0.08333333333333333, 'gini = 0.005 \nsamples = 238
           \nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 1, 384,
           0, 0, 0, 0, 0, 0, 0 \setminus n0, 0, 0]'),
            Text(0.6964285714285714, 0.08333333333333333, 'gini = 0.0 \nsamples = 1170
           4, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0]'),
            Text(0.7142857142857143, 0.25, 'gini = 0.095 \nsamples = 14 \nvalue = [0, 0, 0]
           0\n0, 0, 0]'),
            Text(0.8571428571428571, 0.5833333333333334, 'x[11] <= 0.105 \ngini = 0.877
           nsamples = 12453 nvalue = [0, 0, 0, 2295, 2454, 2661, 0, 2031, 0, 0, 0, 0]
           \n0, 0, 0, 0, 2321, 2551, 0, 2620, 24, 0, 0, 0\n0, 0, 0, 0, 203, 0, 255
           0]'),
            Text(0.7857142857142857, 0.4166666666666667, 'x[10] <= 0.365 \ngini = 0.809
           nsamples = 7872 nvalue = [0, 0, 0, 88, 2454, 2661, 0, 2031, 0, 0, 0, 0]
           0, 0, 0, 2321, 22, 0, 2620, 24, 0, 0, 0, 0\n0, 0, 0, 203, 0, 23]'),
            Text(0.75, 0.25, 'x[4] \le 0.315 \cdot ngini = 0.76 \cdot nsamples = 5735 \cdot nvalue = [0, 1.5]
           0, 0, 0, 2454, 1967, 0, 2031, 0, 0, 0, 0, 0\n0, 0, 0, 2321, 0, 0, 10, 24,
           0, 0, 0, 0, 0\n0, 0, 203, 0, 0]'),
            Text(0.7321428571428571, 0.08333333333333333, 'gini = 0.758 \ nsamples = 500
           2\nvalue = [0, 0, 0, 0, 2202, 1853, 0, 1477, 0, 0, 0, 0, 0\n0, 0, 0, 2122,
           0, 0, 7, 24, 0, 0, 0, 0, 0, 0 \setminus n0, 195, 0, 0]
            Text(0.7678571428571429, 0.08333333333333333, 'gini = 0.669\nsamples = 733
           3, 0, 0, 0, 0, 0, 0, 0\n0, 8, 0, 0]'),
            Text(0.8214285714285714, 0.25, 'x[9] \le 0.715 \cdot gini = 0.382 \cdot nsamples = 213
           7\nvalue = [0, 0, 0, 88, 0, 694, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 22, 0, 26]
           10, 0, 0, 0, 0, 0, 0, 0\n0, 0, 23]'),
            Text(0.8035714285714286, 0.08333333333333333, 'qini = 0.0 \nsamples = 422 \n
           value = [0, 0, 0, 0, 0, 679, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0,
           0, 0, 0, 0, 0, 0\n0, 0, 0]'),
            Text(0.8392857142857143, 0.08333333333333333, 'gini = 0.103\nsamples = 171
           5\nvalue = [0, 0, 0, 88, 0, 15, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 22, 0, 261]
           0, 0, 0, 0, 0, 0, 0, 0, 0 \setminus n0, 0, 23]
            \label{text} \texttt{Text}(0.9285714285714286,\ 0.41666666666666667,\ 'x[2] <= 1.005 \\ \texttt{ngini} = 0.665
           nsamples = 4581 nvalue = [0, 0, 0, 2207, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js 0, 0, 0, 0, 0\n0, 0, 2527]'),
```



concusion

The bestfit model is logistic Regression with score of 0.5425522050369052

In []: