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

Out[2]:		date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY
	0	2010- 03-01 01:00:00	NaN	0.29	NaN	NaN	NaN	25.090000	29.219999	NaN
	1	2010- 03-01 01:00:00	NaN	0.27	NaN	NaN	NaN	24.879999	30.040001	NaN
	2	2010- 03-01 01:00:00	NaN	0.28	NaN	NaN	NaN	17.410000	20.540001	NaN
	3	2010- 03-01 01:00:00	0.38	0.24	1.74	NaN	0.05	15.610000	21.080000	NaN
	4	2010- 03-01 01:00:00	0.79	NaN	1.32	NaN	NaN	21.430000	26.070000	NaN
	209443	2010- 08-01 00:00:00	NaN	0.55	NaN	NaN	NaN	125.000000	219.899994	NaN
	209444	2010- 08-01 00:00:00	NaN	0.27	NaN	NaN	NaN	45.709999	47.410000	NaN
	209445	2010- 08-01 00:00:00	NaN	NaN	NaN	NaN	0.24	46.560001	49.040001	NaN
	209446	2010- 08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	46.770000	50.119999	NaN
	209447	2010- 08-01 00:00:00	0.92	0.43	0.71	NaN	0.25	76.330002	88.190002	NaN

209448 rows × 17 columns

In [3]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209448 entries, 0 to 209447
Data columns (total 17 columns):
     Column
             Non-Null Count
                              Dtype
     -----
             -----
 0
     date
             209448 non-null object
 1
     BEN
             60268 non-null
                              float64
 2
     C0
             94982 non-null
                              float64
 3
             60253 non-null
                              float64
     EBE
 4
    MXY
             6750 non-null
                              float64
 5
    NMHC
             51727 non-null
                              float64
 6
    NO 2
             208219 non-null float64
 7
    N0x
             208210 non-null float64
 8
     0XY
             6750 non-null
                              float64
 9
     0 3
             126684 non-null float64
 10
    PM10
             106186 non-null float64
             55514 non-null
                              float64
 11
    PM25
 12 PXY
             6740 non-null
                              float64
 13 S0 2
             93184 non-null
                              float64
 14
    TCH
             51730 non-null
                              float64
 15
    T0L
             60171 non-null
                              float64
 16 station 209448 non-null int64
dtypes: float64(15), int64(1), object(1)
memory usage: 27.2+ MB
```

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

Out[4]:		date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	ОХҮ
	0	2010- 03-01 01:00:00	0.00	0.29	0.00	0.0	0.00	25.090000	29.219999	0.0
	1	2010- 03-01 01:00:00	0.00	0.27	0.00	0.0	0.00	24.879999	30.040001	0.0
	2	2010- 03-01 01:00:00	0.00	0.28	0.00	0.0	0.00	17.410000	20.540001	0.0
	3	2010- 03-01 01:00:00	0.38	0.24	1.74	0.0	0.05	15.610000	21.080000	0.0
	4	2010- 03-01 01:00:00	0.79	0.00	1.32	0.0	0.00	21.430000	26.070000	0.0
	209443	2010- 08-01 00:00:00	0.00	0.55	0.00	0.0	0.00	125.000000	219.899994	0.0
	209444	2010- 08-01 00:00:00	0.00	0.27	0.00	0.0	0.00	45.709999	47.410000	0.0
	209445	2010- 08-01 00:00:00	0.00	0.00	0.00	0.0	0.24	46.560001	49.040001	0.0
	209446	2010- 08-01 00:00:00	0.00	0.00	0.00	0.0	0.00	46.770000	50.119999	0.0
	209447	2010- 08-01 00:00:00	0.92	0.43	0.71	0.0	0.25	76.330002	88.190002	0.0

 $209448 \text{ rows} \times 17 \text{ columns}$

In [5]: df1.info()

```
<class 'pandas.core.frame.DataFrame'>
      RangeIndex: 209448 entries, 0 to 209447
      Data columns (total 17 columns):
           Column
                    Non-Null Count
                                    Dtype
           -----
                    -----
       0
                    209448 non-null object
           date
           BEN
                    209448 non-null float64
       1
       2
           C0
                    209448 non-null float64
       3
                    209448 non-null float64
           EBE
       4
           MXY
                    209448 non-null float64
       5
                    209448 non-null float64
           NMHC
       6
           NO 2
                    209448 non-null float64
       7
                    209448 non-null float64
           N0x
       8
           0XY
                    209448 non-null float64
       9
           0 3
                    209448 non-null float64
                    209448 non-null float64
       10 PM10
                    209448 non-null float64
       11 PM25
                    209448 non-null float64
       12 PXY
       13 S0 2
                    209448 non-null float64
       14 TCH
                    209448 non-null float64
       15 T0L
                    209448 non-null float64
       16 station 209448 non-null int64
       dtypes: float64(15), int64(1), object(1)
      memory usage: 27.2+ MB
In [6]: df1.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
```

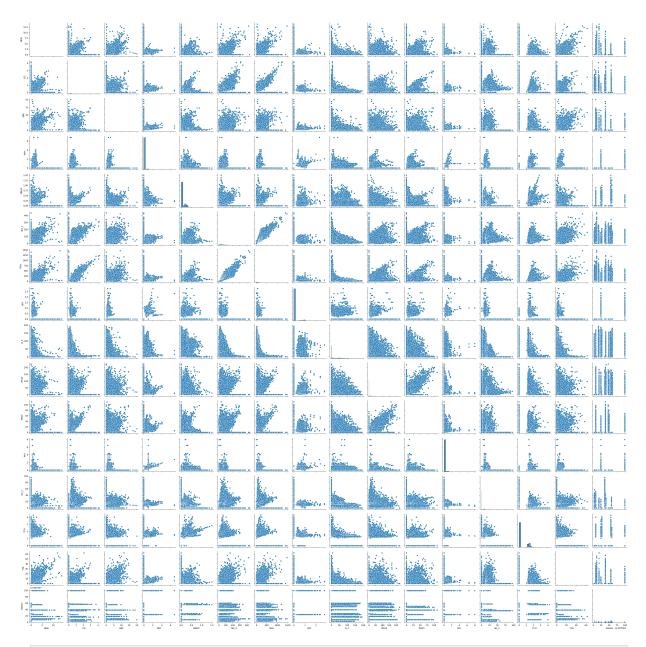
Out[7]:		BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	0_3
	0	0.00	0.29	0.00	0.0	0.00	25.090000	29.219999	0.0	68.930000
	1	0.00	0.27	0.00	0.0	0.00	24.879999	30.040001	0.0	0.000000
	2	0.00	0.28	0.00	0.0	0.00	17.410000	20.540001	0.0	72.120003
	3	0.38	0.24	1.74	0.0	0.05	15.610000	21.080000	0.0	72.970001
	4	0.79	0.00	1.32	0.0	0.00	21.430000	26.070000	0.0	0.000000
	209443	0.00	0.55	0.00	0.0	0.00	125.000000	219.899994	0.0	25.379999
	209444	0.00	0.27	0.00	0.0	0.00	45.709999	47.410000	0.0	0.000000
	209445	0.00	0.00	0.00	0.0	0.24	46.560001	49.040001	0.0	46.250000
	209446	0.00	0.00	0.00	0.0	0.00	46.770000	50.119999	0.0	77.709999
	209447	0.92	0.43	0.71	0.0	0.25	76.330002	88.190002	0.0	52.259998

 $209448 \text{ rows} \times 16 \text{ columns}$

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 0x224b9fb7050>



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

C:\Users\HP\AppData\Local\Temp\ipykernel_12480\1070072814.py:1: UserWarning:

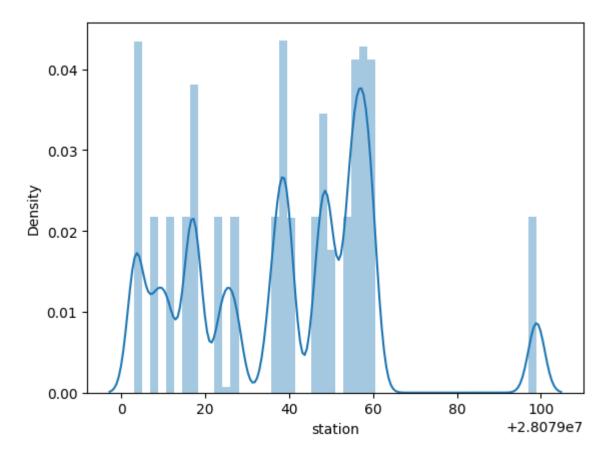
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

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

```
In [12]: from sklearn.linear_model import LinearRegression
In [13]: lr=LinearRegression()
lr.fit(x_train,y_train)
Out[13]: v LinearRegression
LinearRegression()
In [14]: coeff =pd.DataFrame(lr.coef_,x.columns,columns=["Co-efficient"])
coeff
```

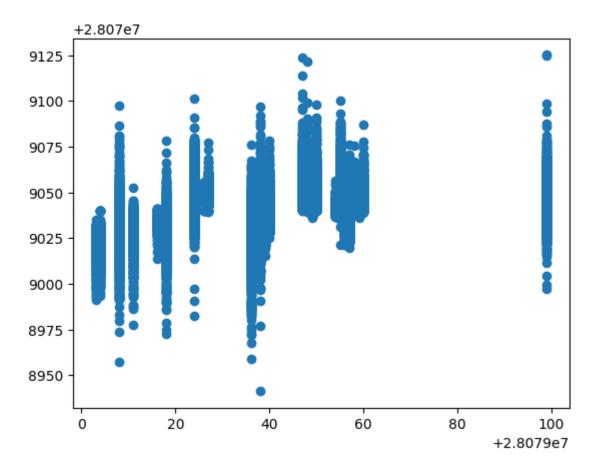
Out[14]:		Co-efficient
	BEN	-3.675069
	СО	-13.393441
	EBE	-5.093590
	MXY	5.385968
	NMHC	32.325774
	NO_2	-0.076891
	NOx	0.044861
	OXY	15.656012
	0_3	0.024323
	PM10	0.285897
	PM25	0.189816
	PXY	3.531780
	SO_2	-0.916592
	тсн	1.002794
	TOL	0.633842

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

28079039.760603778

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

Out[16]: <matplotlib.collections.PathCollection at 0x2248f7cf3d0>



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

0.22524695026649333

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

0.2198822349850672

Ridge

Out[21]: 0.22522514571473184

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]: 0.11260673000732624
         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.
                                -1.03442475
                                             0.20003777
                                                                    -0.07837882
          0.01520194 0.29743903 0.03318777
                                             0.29556583  0.25905033  0.13878282
         -1.07099494 1.93662963 -0.655199681
In [26]: print(en.intercept_)
        28079040.872002963
In [27]: print(en.predict(x test))
        [28079027.02765574 28079035.2384622 28079043.83452355 ...
         28079045.45205421 28079027.19544104 28079031.6041041 ]
In [28]: print(en.score(x_test,y_test))
        0.15060496110645605
         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]: (209448, 15)
In [32]: target vector.shape
Out[32]: (209448,)
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([28079003, 28079004, 28079008, 28079011, 28079016, 28079017,
                28079018, 28079024, 28079026, 28079027, 28079036, 28079038,
                28079039, 28079040, 28079047, 28079048, 28079049, 28079050,
                28079054, 28079055, 28079056, 28079057, 28079058, 28079059,
                28079060, 28079099], dtype=int64)
In [39]: logr.score(fs,target vector)
Out[39]: 0.7488398074939842
```

Loading [MathJax]/extensions/Safe.js

```
In [40]: logr.predict proba(observation)[0][0]
  Out[40]: 2.8940987299868526e-170
  In [41]: logr.predict proba(observation)[0][1]
  Out[41]: 3.553838813539422e-201
           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)
  Out[48]:
                         GridSearchCV
            ▶ estimator: RandomForestClassifier
                  ▶ RandomForestClassifier
  In [49]: grid search.best score
  Out[49]: 0.7313397205334691
  In [50]: rfc best=grid search.best estimator
  In [51]: py.figure(figsize=(80,50))
           plot tree(rfc best.estimators [5],filled=True)
Loading [MathJax]/extensions/Safe.js
```

```
Out[51]: [Text(0.5023148148148148, 0.91666666666666, 'x[10] <= 0.28 \ngini = 0.96 \n
        samples = 39653\nvalue = [2700, 2650, 2653, 2595, 2752, 1880, 2674, 2525, 8
        0\n2598, 2625, 2749, 2658, 2645, 2647, 1503, 2546, 2016\n2616, 2554, 2537,
        2490, 2529, 2603, 2318, 2691]'),
         Text(0.27314814814814814, 0.75, 'x[6] \le 32.565 \setminus gini = 0.945 \setminus gini = 2
        9145\nvalue = [2700, 2650, 13, 2595, 2752, 1880, 2674, 60, 80, 2598\n2625,
        11, 2658, 2645, 22, 0, 2546, 42, 2616, 2554\n2537, 2490, 2529, 2603, 2318,
        0]'),
         Text(0.14814814814814814, 0.5833333333333334, 'x[9] <= 0.665 \ngini = 0.935
        \n in samples = 10273\n value = [433, 482, 2, 516, 927, 795, 877, 60, 22, 610, 4
        54\n6, 904, 1027, 8, 0, 1175, 42, 1167, 859, 222, 1238\n1744, 1593, 1041,
        0]'),
         \nsamples = 6838\nvalue = [433, 482, 2, 516, 927, 795, 7, 60, 3, 610, 0, 4
        \n904, 18, 0, 0, 1175, 38, 1167, 8, 222, 11, 1744\n1593, 35, 0]'),
         Text(0.037037037037037035, 0.25, 'x[4] \le 0.025 \cdot gini = 0.842 \cdot gini = 4
        966\nvalue = [0, 8, 2, 516, 3, 795, 3, 60, 3, 610, 0, 4, 2\n18, 0, 0, 1175,
        38, 1167, 8, 9, 11, 1744, 1593\n35, 0]'),
         Text(0.018518518518518517, 0.0833333333333333, 'gini = 0.792\nsamples = 3
        480\nvalue = [0, 8, 2, 516, 3, 795, 3, 60, 3, 1, 0, 4, 2\n18, 0, 0, 1175, 3
        8, 1167, 8, 9, 11, 7, 1593, 35\n0]'),
         86\nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 609, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0,
        0, 0, 1737, 0, 0, 0]'),
         \nvalue = [433, 474, 0, 0, 924, 0, 4, 0, 0, 0, 0, 0, 902\n0, 0, 0, 0, 0, 0, 0]
        0, 213, 0, 0, 0, 0, 0]'),
         Text(0.09259259259259259, 0.08333333333333333, 'gini = 0.0 \nsamples = 306
        \nvalue = [0, 474, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0]'),
         Text(0.12962962962962962, 0.0833333333333333, 'gini = 0.69 \nsamples = 156
        6\nvalue = [433, 0, 0, 0, 924, 0, 4, 0, 0, 0, 0, 0, 902\n0, 0, 0, 0, 0, 0,
        0, 213, 0, 0, 0, 0, 0]'),
         samples = 3435\nvalue = [0, 0, 0, 0, 0, 0, 870, 0, 19, 0, 454, 2, 0 \n1009,
        8, 0, 0, 4, 0, 851, 0, 1227, 0, 0, 1006\n0]'),
         Text(0.18518518518518517, 0.25, 'x[13] \le 0.61 \cdot gini = 0.672 \cdot gsamples = 18
        12\nvalue = [0, 0, 0, 0, 0, 0, 0, 19, 0, 0, 2, 0, 1009\n8, 0, 0, 4, 0, 8
        51, 0, 0, 0, 0, 1006, 0]'),
         5\nvalue = [0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 2, 0, 1009\n8, 0, 0, 4, 0, 6,
        0, 0, 0, 0, 1006, 0]'),
         Text(0.2037037037037037, 0.0833333333333333, 'gini = 0.041 \nsamples = 537
        \nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 18, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 845,
        0, 0, 0, 0, 0, 0]'),
         Text(0.25925925925925924, 0.25, 'x[14] \le 0.055 \setminus gini = 0.621 \setminus gini = 1
        623\nvalue = [0, 0, 0, 0, 0, 0, 870, 0, 0, 454, 0, 0, 0\n0, 0, 0, 0, 0,
        0, 0, 1227, 0, 0, 0, 0]'),
         Text(0.24074074074074073, 0.0833333333333333, 'gini = 0.401\nsamples = 10
        64\nvalue = [0, 0, 0, 0, 0, 0, 10, 0, 0, 0, 454, 0, 0, 0\n0, 0, 0, 0, 0, 0,
        0, 1227, 0, 0, 0, 0]'),
         Text(0.27777777777778, 0.083333333333333333, 'qini = 0.0 \nsamples = 559 \n
        0, 0, 0, 0, 0]'),
         Text(0.39814814814814814, 0.5833333333333334, 'x[9] \le 0.74
```

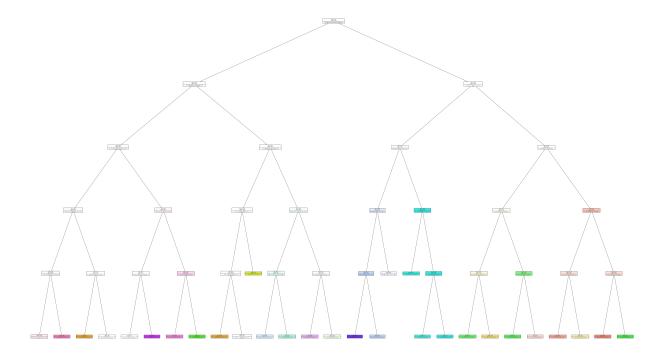
```
1988\n2171, 5, 1754, 1618, 14, 0, 1371, 0, 1449, 1695\n2315, 1252, 785, 101
0, 1277, 0]'),
Text(0.35185185185185186, 0.416666666666667, 'x[14] <= 0.055 \ngini = 0.90
9\nsamples = 12666\nvalue = [2267, 2168, 2, 2079, 1825, 1085, 2, 0, 0, 198
8, 0 \setminus n0, 1754, 11, 0, 0, 1371, 0, 1449, 1, 2315, 0 \setminus n785, 1010, 2, 0]'),
\nvalue = [2267, 2168, 2, 36, 1825, 1085, 0, 0, 0, 1988, 0\n0, 1754, 11, 0,
0, 1371, 0, 1449, 0, 2315, 0\n785, 1010, 2, 0]'),
Text(0.3148148148148148, 0.0833333333333333, 'gini = 0.101\nsamples = 143
1\nvalue = [7, 2168, 0, 36, 2, 32, 0, 0, 0, 18, 0, 0, 0\n11, 0, 0, 1, 0, 0,
0, 2, 0, 8, 2, 0, 0]'),
Text(0.35185185185185186, 0.08333333333333333, 'gini = 0.89 \nsamples = 997
2\nvalue = [2260, 0, 2, 0, 1823, 1053, 0, 0, 0, 1970, 0, 0\n1754, 0, 0, 0,
1370, 0, 1449, 0, 2313, 0, 777\n1008, 2, 0]'),
Text(0.37037037037037035, 0.25, 'gini = 0.003 \setminus samples = 1263 \setminus samples = [0, 120]
0, 0, 2043, 0, 0, 2, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0]'),
 samples = 6206 \cdot \text{nvalue} = [0, 0, 9, 0, 0, 0, 1795, 0, 58, 0, 2171, 5, 0 \cdot 160]
7, 14, 0, 0, 0, 0, 1694, 0, 1252, 0, 0, 1275\n0]'),
Text(0.4074074074074074, 0.25, 'x[1] \le 0.03 \cdot gini = 0.74 \cdot gini = 4027

    \text{Invalue} = [0, 0, 0, 0, 0, 0, 20, 0, 0, 0, 2171, 0, 0 \\
    \text{Invalue} = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

17, 0, 1252, 0, 0, 1275\n0]'),
Text(0.38888888888888889, 0.0833333333333333, 'qini = 0.504\nsamples = 182
3\nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1607\n14, 0, 0, 0, 1
7, 0, 1, 0, 0, 1275, 0]'),
Text(0.42592592592592593, 0.08333333333333333, 'qini = 0.47 \nsamples = 220
4\nvalue = [0, 0, 0, 0, 0, 0, 20, 0, 0, 2171, 0, 0, 0\n0, 0, 0, 0, 0, 0,
0, 1251, 0, 0, 0, 0]'),
Text(0.48148148148148145, 0.25, 'x[9] \le 5.575 \cdot equiv = 0.52 \cdot equiv = 217
9\nvalue = [0, 0, 9, 0, 0, 0, 1775, 0, 58, 0, 0, 5, 0, 0\n0, 0, 0, 0, 16
77, 0, 0, 0, 0, 0, 0]'),
Text(0.46296296296297, 0.083333333333333, 'gini = 0.508\nsamples = 21
5\nvalue = [0, 0, 0, 0, 0, 0, 110, 0, 14, 0, 0, 1, 0, 0\n0, 0, 0, 0, 19
6, 0, 0, 0, 0, 0, 0]
0, 9, 0, 0, 0, 1665, 0, 44, 0, 0, 4, 0, 0\n0, 0, 0, 0, 0, 1481, 0, 0, 0,
0, 0]'),
Text(0.7314814814814815, 0.75, 'x[1] \le 0.055 \cdot ngini = 0.852 \cdot nsamples = 105
08\nvalue = [0, 0, 2640, 0, 0, 0, 0, 2465, 0, 0, 0, 2738, 0\n0, 2625, 1503,
0, 1974, 0, 0, 0, 0, 0, 0\n2691]'),
samples = 5592\nvalue = [0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 2738, 0, 0\n2625,
1503, 0, 1974, 0, 0, 0, 0, 0, 0, 0, 0]'),
Text(0.5740740740740741, 0.4166666666666667, 'x[5] \le 33.015 \cdot ngini = 0.65
nsamples = 3919 \quad [0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 4, 0, 0]
1503, 0, 1974, 0, 0, 0, 0, 0, 0, 0, 0]'),
Text(0.5555555555555556, 0.25, 'x[5] \le 5.14 \cdot qini = 0.631 \cdot nsamples = 1438
\nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0 \ndots 571, 0, 569, 0,
0, 0, 0, 0, 0, 0, 0]
Text(0.5370370370370371, 0.08333333333333333, 'qini = 0.0 \nsamples = 15 \nv
0, 0, 0, 0]'),
 Text(0.5740740740740741, 0.0833333333333333, 'gini = 0.628\nsamples = 142
3\nvalue = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, \dots, \dots,
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Text(0.5925925925925926, 0.25, 'gini = 0.654 \nsamples = 2481 \nvalue = [0, 0.5925925925925925925]
0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0\n1530, 932, 0, 1405, 0, 0, 0, 0, 0,
0, 0, 0]'),
 Text(0.6481481481481481, 0.4166666666666667, 'x[6] \le 127.15 \cdot equiv = 0.001
nsamples = 1673 nvalue = [0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 2734, 0, 0]
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
Text(0.6296296296296297, 0.25, 'qini = 0.0 \land samples = 1364 \land value = [0, 0, 0]
0, 0, 0, 0, 0, 0, 0, 0, 2250, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0]'),
 Text(0.6666666666666666, 0.25, 'x[5] \le 72.695 \text{ ngini} = 0.008 \text{ nsamples} = 30
9\nvalue = [0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 484, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0]'),
 Text(0.6481481481481481, 0.08333333333333333, 'qini = 0.142\nsamples = 18
0, 0, 0, 0, 0]'),
 Text(0.6851851851851852, 0.08333333333333333, 'qini = 0.0\nsamples = 291\n
value = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 460, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0]'),
nsamples = 4916 \quad [0, 0, 2637, 0, 0, 0, 0, 2465, 0, 0, 0, 0, 0]
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2691]'),
Text(0.77777777777778, 0.416666666666667, 'x[7] \le 0.1 \neq 0.548 
amples = 1882\nvalue = [0, 0, 1434, 0, 0, 0, 0, 1346, 0, 0, 0, 0, 0\n0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 156]'),
Text(0.7407407407407407, 0.25, 'x[14] \le 1.385 \cdot gini = 0.52 \cdot gini = 169
5\nvalue = [0, 0, 1434, 0, 0, 0, 0, 1134, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 74]'),
 \nvalue = [0, 0, 166, 0, 0, 0, 0, 745, 0, 0, 0, 0, 0, 0 \n0, 0, 0, 0, 0, 0, 0]
0, 0, 0, 0, 0, 33]'),
 Text(0.7592592592592593, 0.0833333333333333, 'gini = 0.389 \ nsamples = 109
3\nvalue = [0, 0, 1268, 0, 0, 0, 0, 389, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 41]'),
Text(0.8148148148148148, 0.25, 'x[0] \le 0.595  ngini = 0.402 \ nsamples = 187
0, 0, 0, 0, 82]'),
 Text(0.7962962962963, 0.0833333333333333, 'qini = 0.272 \setminus nsamples = 136
0, 0, 0, 0, 34]'),
\nvalue = [0, 0, 0, 0, 0, 0, 0, 37, 0, 0, 0, 0, 0, 0 \n0, 0, 0, 0, 0, 0, 0, 0]
0, 0, 0, 0, 48]'),
 Text(0.9259259259259259, 0.4166666666666667, 'x[7] \le 0.15 \cdot ngini = 0.613 \cdot 
samples = 3034\nvalue = [0, 0, 1203, 0, 0, 0, 1119, 0, 0, 0, 0, 0 \n0, 0, 0]
0, 0, 0, 0, 0, 0, 0, 0, 0, 2535]'),
Text(0.888888888888888888, 0.25, 'x[12] \le 9.575 \text{ ngini} = 0.585 \text{ nsamples} = 19
32\nvalue = [0, 0, 1203, 0, 0, 0, 0, 339, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 1547]'),
Text(0.8703703703703703, 0.0833333333333333, 'gini = 0.498 \nsamples = 113
1\nvalue = [0, 0, 468, 0, 0, 0, 0, 156, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 1175]'),
 Text(0.9074074074074074, 0.08333333333333333, 'gini = 0.572\nsamples = 801
\nvalue = [0, 0, 735, 0, 0, 0, 0, 183, 0, 0, 0, 0, 0, 0 \setminus n0, 0, 0, 0, 0, 0, 0]
0, 0, 0, 0, 0, 372]'),
 Text(0.9629629629629629, 0.25, 'x[4] \le 0.275 \text{ ngini} = 0.493 \text{ nsamples} = 110
```

0, 0, 0, 0, 0, 988]'),



concusion

The bestfit model is logistic Regression with score of 0.7488398074939842

In []: