```
In [1]: import pandas as pd
   import numpy as np
   import matplotlib.pyplot as plt
   import seaborn as sns
   from sklearn.model_selection import train_test_split
   from sklearn.linear_model import LinearRegression
   from sklearn.linear_model import Ridge,Lasso
   from sklearn.linear_model import ElasticNet
   from sklearn import metrics
   from sklearn.linear_model import LogisticRegression
   from sklearn.preprocessing import StandardScaler
   from sklearn.ensemble import RandomForestClassifier
   from sklearn.model_selection import GridSearchCV
   from sklearn.tree import plot_tree
```

Out[2]:

	date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	
0	2013- 11-01 01:00:00	NaN	0.6	NaN	NaN	135.0	74.0	NaN	NaN	NaN	7.0	NaN	NaN	2
1	2013- 11-01 01:00:00	1.5	0.5	1.3	NaN	71.0	83.0	2.0	23.0	16.0	12.0	NaN	8.3	2
2	2013- 11-01 01:00:00	3.9	NaN	2.8	NaN	49.0	70.0	NaN	NaN	NaN	NaN	NaN	9.0	2
3	2013- 11-01 01:00:00	NaN	0.5	NaN	NaN	82.0	87.0	3.0	NaN	NaN	NaN	NaN	NaN	2
4	2013- 11-01 01:00:00	NaN	NaN	NaN	NaN	242.0	111.0	2.0	NaN	NaN	12.0	NaN	NaN	2
209875	2013- 03-01 00:00:00	NaN	0.4	NaN	NaN	8.0	39.0	52.0	NaN	NaN	NaN	NaN	NaN	2
209876	2013- 03-01 00:00:00	NaN	0.4	NaN	NaN	1.0	11.0	NaN	6.0	NaN	2.0	NaN	NaN	2
209877	2013- 03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	4.0	75.0	NaN	NaN	NaN	NaN	NaN	2
209878	2013- 03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	11.0	52.0	NaN	NaN	NaN	NaN	NaN	2
209879	2013- 03-01 00:00:00	NaN	NaN	NaN	NaN	1.0	10.0	75.0	3.0	NaN	NaN	NaN	NaN	2

209880 rows × 14 columns

localhost:8888/notebooks/F13.ipynb

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209880 entries, 0 to 209879
Data columns (total 14 columns):
```

#	Column	Non-Null Count	Dtype
0	date	209880 non-null	object
1	BEN	50462 non-null	float64
2	CO	87018 non-null	float64
3	EBE	50463 non-null	float64
4	NMHC	25935 non-null	float64
5	NO	209108 non-null	float64
6	NO_2	209108 non-null	float64
7	0_3	121858 non-null	float64
8	PM10	104339 non-null	float64
9	PM25	51980 non-null	float64
10	S0_2	86970 non-null	float64
11	TCH	25935 non-null	float64
12	TOL	50317 non-null	float64
13	station	209880 non-null	int64
		/>/->	

dtypes: float64(12), int64(1), object(1)

memory usage: 22.4+ MB

In [4]: df=df.dropna()
df

Out[4]:

	date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	st
17286	2013- 08-01 01:00:00	0.4	0.2	0.8	0.28	1.0	24.0	79.0	35.0	8.0	3.0	1.49	1.3	2807
17310	2013- 08-01 02:00:00	0.5	0.2	0.9	0.28	1.0	16.0	93.0	60.0	18.0	3.0	1.61	4.0	2807
17334	2013- 08-01 03:00:00	0.5	0.2	1.1	0.29	1.0	14.0	90.0	38.0	12.0	3.0	1.71	2.8	2807
17358	2013- 08-01 04:00:00	0.6	0.2	1.2	0.26	1.0	12.0	84.0	30.0	8.0	3.0	1.44	2.8	2807
17382	2013- 08-01 05:00:00	0.3	0.2	0.8	0.25	1.0	15.0	72.0	25.0	7.0	3.0	1.40	1.7	2807
209622	2013- 02-28 14:00:00	1.1	0.3	0.3	0.27	3.0	17.0	64.0	5.0	5.0	2.0	1.41	0.9	2807
209646	2013- 02-28 15:00:00	1.3	0.4	0.3	0.27	2.0	16.0	66.0	6.0	5.0	1.0	1.40	0.9	2807
209670	2013- 02-28 16:00:00	1.1	0.3	0.3	0.27	1.0	17.0	65.0	5.0	4.0	1.0	1.40	0.7	2807
209694	2013- 02-28 17:00:00	1.0	0.3	0.4	0.27	1.0	18.0	64.0	5.0	5.0	1.0	1.39	0.7	2807
209718	2013- 02-28 18:00:00	1.0	0.3	0.4	0.27	1.0	22.0	62.0	6.0	6.0	1.0	1.39	0.7	2807

7315 rows × 14 columns

```
In [5]: df.isnull().sum()
Out[5]: date
                       0
                       0
          BEN
          CO
                       0
          EBE
                       0
          NMHC
                       0
                       0
          NO
          NO 2
                       0
          0_3
                       0
          PM10
                       0
          PM25
                       0
          SO_2
                       0
          TCH
                       0
          TOL
                       0
                       0
          station
          dtype: int64
In [6]: df.describe()
Out[6]:
                         BEN
                                       CO
                                                   EBE
                                                              NMHC
                                                                              NO
                                                                                         NO_2
                                                                                                        O_
           count 7315.000000 7315.000000
                                            7315.000000 7315.000000
                                                                      7315.000000 7315.000000
                                                                                               7315.00000
           mean
                     0.501928
                                  0.236008
                                               0.753247
                                                            0.255133
                                                                         7.486808
                                                                                     19.742584
                                                                                                  62.65399
                     0.275264
                                  0.092865
                                               0.386968
                                                            0.046754
                                                                        18.386879
                                                                                     20.984539
                                                                                                  35.82244
             std
            min
                     0.100000
                                  0.100000
                                               0.100000
                                                            0.170000
                                                                         1.000000
                                                                                      1.000000
                                                                                                   2.00000
            25%
                     0.300000
                                  0.200000
                                               0.500000
                                                            0.230000
                                                                         1.000000
                                                                                      5.000000
                                                                                                  38.00000
            50%
                     0.400000
                                  0.200000
                                               0.700000
                                                            0.240000
                                                                         1.000000
                                                                                                  63.00000
                                                                                     12.000000
                                                                                                  85.00000
            75%
                     0.600000
                                  0.200000
                                               1.000000
                                                            0.270000
                                                                         3.000000
                                                                                     27.000000
                     2.600000
                                  0.900000
                                               3.600000
                                                            0.810000
                                                                       234.000000
                                                                                    124.000000
                                                                                                 215.00000
            max
```

```
In [7]: df.columns
Out[7]: Index(['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM2
```

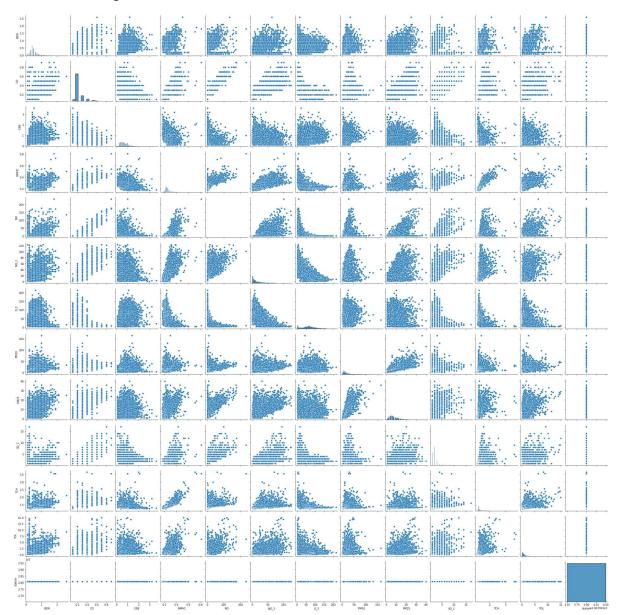
5',

'SO_2', 'TCH', 'TOL', 'station'],

dtype='object')

In [8]: | sns.pairplot(df)

Out[8]: <seaborn.axisgrid.PairGrid at 0x229665aa9a0>

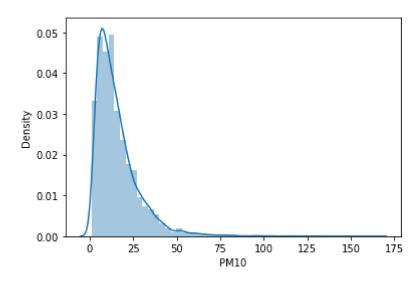


In [9]: sns.distplot(df['PM10'])

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 hi stograms).

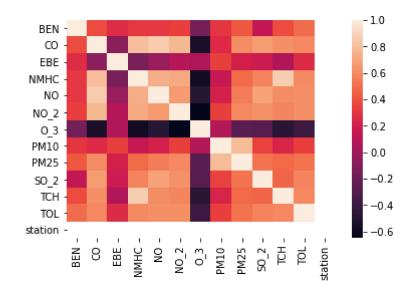
warnings.warn(msg, FutureWarning)

Out[9]: <AxesSubplot:xlabel='PM10', ylabel='Density'>



In [10]: sns.heatmap(df.corr())

Out[10]: <AxesSubplot:>



C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\indexing.py:1720: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

self. setitem single column(loc, value, pi)

C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\indexing.py:1720: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

self._setitem_single_column(loc, value, pi)
<ipython-input-11-e3d36a273982>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

df['TCH']=df['TCH'].astype(int)

Out[11]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	st
17286	2013- 08-01 01:00:00	0.4	0.2	0.8	0.28	1.0	24.0	79.0	35.0	8.0	3.0	0	1.3	2807
17310	2013- 08-01 02:00:00	0.5	0.2	0.9	0.28	1.0	16.0	93.0	60.0	18.0	3.0	0	4.0	2807
17334	2013- 08-01 03:00:00	0.5	0.2	1.1	0.29	1.0	14.0	90.0	38.0	12.0	3.0	0	2.8	2807
17358	2013- 08-01 04:00:00	0.6	0.2	1.2	0.26	1.0	12.0	84.0	30.0	8.0	3.0	0	2.8	2807
17382	2013- 08-01 05:00:00	0.3	0.2	0.8	0.25	1.0	15.0	72.0	25.0	7.0	3.0	0	1.7	2807
209622	2013- 02-28 14:00:00	1.1	0.3	0.3	0.27	3.0	17.0	64.0	5.0	5.0	2.0	0	0.9	2807
209646	2013- 02-28 15:00:00	1.3	0.4	0.3	0.27	2.0	16.0	66.0	6.0	5.0	1.0	0	0.9	2807
209670	2013- 02-28 16:00:00	1.1	0.3	0.3	0.27	1.0	17.0	65.0	5.0	4.0	1.0	0	0.7	2807
209694	2013- 02-28 17:00:00	1.0	0.3	0.4	0.27	1.0	18.0	64.0	5.0	5.0	1.0	0	0.7	2807
209718	2013- 02-28 18:00:00	1.0	0.3	0.4	0.27	1.0	22.0	62.0	6.0	6.0	1.0	0	0.7	2807

7315 rows × 14 columns

LogisticRegression

Out[12]: LogisticRegression()

```
In [13]: |lgr.predict(x_test)
Out[13]: array([0, 0, 0, ..., 0, 0, 0])
In [14]: |lgr.score(x_test,y_test)
Out[14]: 0.9931662870159453
In [15]: | fs=StandardScaler().fit_transform(x)
         logr=LogisticRegression()
         logr.fit(fs,y)
Out[15]: LogisticRegression()
In [17]: o=[[1,2,3,4,5,6,7,8,9,10,11,12]]
         prediction=logr.predict(o)
         print(prediction)
         [0]
In [18]: logr.classes_
Out[18]: array([0, 1, 2])
In [19]: logr.predict_proba(o)[0][0]
Out[19]: 0.999965076528319
In [20]: logr.predict_proba(o)[0][1]
Out[20]: 3.492292250767436e-05
```

LinearRegression

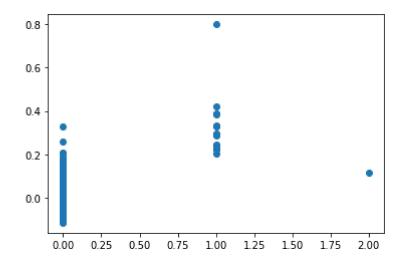
```
In [23]: coeff = pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[23]:

	Co-efficient
BEN	-0.004576
СО	-0.428683
EBE	0.035687
NMHC	1.830873
NO	0.000592
NO_2	-0.000606
O_3	0.000235
PM10	0.000776
PM25	-0.001487
SO_2	-0.006708
TOL	0.002402
station	0.000000

```
In [24]: prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[24]: <matplotlib.collections.PathCollection at 0x22973e395b0>



```
In [25]: print(lr.score(x_test,y_test))
```

0.2173651816259501

Ridge,Lasso

```
In [26]: rr=Ridge(alpha=10)
    rr.fit(x_train,y_train)
Out[26]: Ridge(alpha=10)
In [27]: rr.score(x_test,y_test)
Out[27]: 0.12953059882910944
In [28]: la=Lasso(alpha=10)
    la.fit(x_train,y_train)
Out[28]: Lasso(alpha=10)
In [29]: la.score(x_test,y_test)
Out[29]: -0.000533938669069034
```

ElasticNet

```
In [30]:
         en=ElasticNet()
         en.fit(x_train,y_train)
Out[30]: ElasticNet()
In [31]: |print(en.coef_)
                   0. 0. 0. 0. -0.
                                       0.
                                           0.
                                               0. 0.
                                                       0.1
In [32]:
         print(en.intercept_)
         0.009375
In [33]: |print(en.predict(x_train))
         [0.009375 0.009375 0.009375 ... 0.009375 0.009375 0.009375]
In [34]: |print(en.score(x_train,y_train))
         0.0
         print("Mean Absolytre Error:",metrics.mean_absolute_error(y_test,prediction))
In [35]:
         Mean Absolytre Error: 0.03533414583388424
In [36]: print("Mean Square Error:",metrics.mean_squared_error(y_test,prediction))
         Mean Square Error: 0.006376377698425174
```

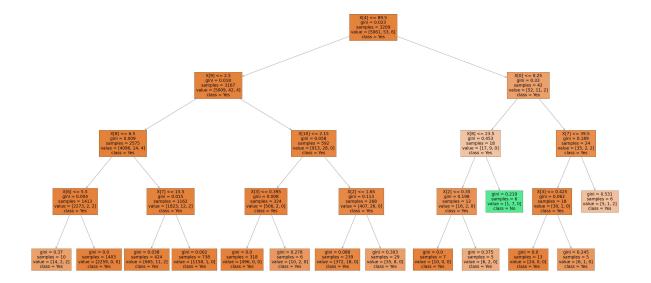
```
In [37]: print("Root Mean Square Error:",np.sqrt(metrics.mean_absolute_error(y_test,pregreen))
Root Mean Square Error: 0.18797379028440173
```

RandomForest

```
rfc=RandomForestClassifier()
In [38]:
         rfc.fit(x_train,y_train)
Out[38]: RandomForestClassifier()
In [39]: parameters={'max_depth':[1,2,3,4,5],
                      'min_samples_leaf':[5,10,15,20,25],
                      'n estimators':[10,20,30,40,50]}
In [40]: grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="acc
         grid_search.fit(x_train,y_train)
Out[40]: 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 [41]: grid search.best score
Out[41]: 0.99296875
In [42]: rfc_best=grid_search.best_estimator_
```

```
In [43]: plt.figure(figsize=(80,40))
    plot_tree(rfc_best.estimators_[5],class_names=['Yes','No','Yes','No'],filled=T
```

```
Out[43]: [Text(2589.12, 1956.96, 'X[4] <= 89.5\ngini = 0.023\nsamples = 3209\nvalue =
                [5061, 53, 6]\nclass = Yes'),
                 \nvalue = [5009, 42, 4] \setminus (135)
                 Text(714.24, 1087.2, 'X[8] <= 6.5\ngini = 0.009\nsamples = 2575\nvalue = [40
               96, 14, 4]\nclass = Yes'),
                 Text(357.12, 652.3200000000002, X[6] \le 5.5 = 0.004 = 0.004 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 1413 = 14
                value = [2273, 2, 2]\nclass = Yes'),
                 Text(178.56, 217.44000000000000, 'gini = 0.37\nsamples = 10\nvalue = [14, 2,
                2]\nclass = Yes'),
                 Text(535.680000000001, 217.4400000000005, 'gini = 0.0\nsamples = 1403\nval
                ue = [2259, 0, 0]\nclass = Yes'),
                 Text(1071.360000000001, 652.320000000002, 'X[7] <= 15.5\ngini = 0.015\nsam
               ples = 1162\nvalue = [1823, 12, 2]\nclass = Yes'),
                 Text(892.8, 217.44000000000005, 'gini = 0.038\nsamples = 424\nvalue = [665,
                11, 2]\nclass = Yes'),
                 Text(1249.92, 217.44000000000005, 'gini = 0.002\nsamples = 738\nvalue = [115
                8, 1, 0]\nclass = Yes'),
                 Text(2142.7200000000003, 1087.2, 'X[10] <= 2.15\ngini = 0.058\nsamples = 592
                \nvalue = [913, 28, 0] \setminus class = Yes'),
                 Text(1785.6, 652.320000000000, 'X[3] <= 0.395\ngini = 0.008\nsamples = 324
                \nvalue = [506, 2, 0]\nclass = Yes'),
                 Text(1607.04, 217.4400000000005, 'gini = 0.0\nsamples = 318\nvalue = [496,
                0, 0]\nclass = Yes'),
                 Text(1964.16, 217.4400000000000, 'gini = 0.278\nsamples = 6\nvalue = [10,
               2, 0]\nclass = Yes'),
                 Text(2499.84, 652.3200000000002, X[2] <= 1.65 \cdot ngini = 0.113 \cdot nsamples = 268
                \nvalue = [407, 26, 0] \setminus s = Yes'),
                 Text(2321.28, 217.44000000000005, 'gini = 0.088\nsamples = 239\nvalue = [37
                2, 18, 0]\nclass = Yes'),
                 Text(2678.4, 217.4400000000000, 'gini = 0.303\nsamples = 29\nvalue = [35,
                8, 0]\nclass = Yes'),
                 Text(3749.76, 1522.0800000000000, X[0] <= 0.25  ngini = 0.33  nsamples = 42 
               value = [52, 11, 2]\nclass = Yes'),
                 7, 9, 0]\nclass = Yes'),
                 Text(3214.08, 652.3200000000002, 'X[2] \le 0.35 \neq 0.198 = 12 
               value = [16, 2, 0]\nclass = Yes'),
                 Text(3035.52, 217.44000000000005, 'gini = 0.0\nsamples = 7\nvalue = [10, 0,
               0]\nclass = Yes'),
                 Text(3392.64, 217.44000000000005, 'gini = 0.375\nsamples = 5\nvalue = [6, 2, 1]
                0]\nclass = Yes'),
                 Text(3571.2, 652.3200000000002, 'gini = 0.219\nsamples = 6\nvalue = [1, 7,
                0] \nclass = No'),
                 Text(4106.88, 1087.2, 'X[7] <= 39.5 \ngini = 0.189 \nsamples = 24 \nvalue = [3]
                5, 2, 2]\nclass = Yes'),
                 Text(3928.32, 652.3200000000002, X[3] \le 0.425  gini = 0.062\nsamples = 18
                \nvalue = [30, 1, 0]\nclass = Yes'),
                 Text(3749.76, 217.4400000000000, 'gini = 0.0\nsamples = 13\nvalue = [24, 0,
               0]\nclass = Yes'),
                 Text(4106.88, 217.44000000000000, 'gini = 0.245\nsamples = 5\nvalue = [6, 1, 1]
               0]\nclass = Yes'),
                 Text(4285.4400000000005, 652.3200000000002, 'gini = 0.531\nsamples = 6\nvalu
                e = [5, 1, 2] \setminus nclass = Yes')
```



Best model:LogisticRegression

(
Tm F Ta	
In :	