## Get underatanding about data set

Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, maretial status, Education, Number of dependants, income, loan eligibility, Credit history and others.

- 1.Customer\_ID
- 2.Gender
- 3.Married
- 4.Dependents
- 5.Education
- 6.Self\_Employed
- 7.Applicant\_Income
- 8.Coapplicant\_Income
- 9.Loan\_Amount
- 10.Loan\_Amount\_Term
- 11.Credit\_History
- 12.Property\_Area
- 13.Loan Status

#### Import Library

```
import pandas as pd
```

import numpy as np

Double-click (or enter) to edit

#### Import CSV as DataFrame

df = pd.read\_csv(r'https://github.com/YBI-Foundation/Dataset/raw/main/Loan%20Eligibi

#### → Get the first five rows of DataFrame

df.head()

	Customer_ID	Gender	Married	Dependents	Education	Self_Employed	Applicant_Inc
0	569	Female	No	0	Graduate	No	2:
1	15	Male	Yes	2	Graduate	No	1:
2	95	Male	No	0	Not Graduate	No	30
3	134	Male	Yes	0	Graduate	Yes	34
4	556	Male	Yes	1	Graduate	No	54
4							<b>&gt;</b>

#### → Get Information of DataFrame

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):

#	Column	Non-Null Count	Dtype					
0	Customer_ID	614 non-null	int64					
1	Gender	614 non-null	object					
2	Married	614 non-null	object					
3	Dependents	614 non-null	int64					
4	Education	614 non-null	object					
5	Self_Employed	614 non-null	object					
6	Applicant_Income	614 non-null	int64					
7	Coapplicant_Income	614 non-null	float64					
8	Loan_Amount	614 non-null	int64					
9	Loan_Amount_Term	614 non-null	int64					
10	Credit_History	614 non-null	int64					
11	Property_Area	614 non-null	object					
12	Loan_Status	614 non-null	object					
dtyp	dtypes: float64(1), int64(6), object(6)							

# Get the summary Statistics

memory usage: 62.5+ KB

df.describe()

Customer_ID	Dependents	Applicant_Income	Coapplicant_Income	Loan_Amount	L
614.000000	614.000000	614.000000	614.000000	614.000000	
307.500000	0.856678	5403.459283	1621.245798	142.022801	
177.390811	1.216651	6109.041673	2926.248369	87.083089	
1.000000	0.000000	150.000000	0.000000	9.000000	
154.250000	0.000000	2877.500000	0.000000	98.000000	
307.500000	0.000000	3812.500000	1188.500000	125.000000	
	614.000000 307.500000 177.390811 1.000000 154.250000	614.000000 614.000000 307.500000 0.856678 177.390811 1.216651 1.000000 0.000000 154.250000 0.000000	614.000000       614.000000         307.500000       0.856678       5403.459283         177.390811       1.216651       6109.041673         1.000000       0.000000       150.000000         154.250000       0.000000       2877.500000	614.000000       614.000000       614.000000         307.500000       0.856678       5403.459283       1621.245798         177.390811       1.216651       6109.041673       2926.248369         1.000000       0.000000       150.000000       0.000000         154.250000       0.000000       2877.500000       0.000000	614.000000       614.000000       614.000000       614.000000       614.000000         307.500000       0.856678       5403.459283       1621.245798       142.022801         177.390811       1.216651       6109.041673       2926.248369       87.083089         1.000000       0.000000       150.000000       0.000000       9.000000         154.250000       0.000000       2877.500000       0.000000       98.000000

#### → Get Column Names

```
df.shape
(614, 13)
```

### Get the shape of the data Frame

```
df.shape
(614, 13)
```

# → Get the Unique values(Class or Lavel) in y Variable

	Customer_ID	Dependents	Applicant_Income	Coapplicant_Income	Loan_Amo
Loan_Status					
N	304.406250	0.864583	5446.078125	1877.807292	143.869
<b>Y</b>	308.907583	0.853081	5384.068720	1504.516398	141.182

# Get catagories and counts of catagorical variables

```
df['Gender'].value_counts()
               499
     Male
     Female
               115
     Name: Gender, dtype: int64
df['Married'].value counts()
     Yes
            399
            215
     Name: Married, dtype: int64
df['Education'].value_counts()
     Graduate
                     480
     Not Graduate
                     134
     Name: Education, dtype: int64
df['Self_Employed'].value_counts()
     No
            523
     Yes
             91
     Name: Self_Employed, dtype: int64
df['Property_Area'].value_counts()
     Semiurban
                  233
     Urban
                  202
     Rural
                  179
     Name: Property_Area, dtype: int64
```

#### Get Encoding of Catagorical Features

```
df.replace({'Gender':{'Male':0,
    'Female':1}},inplace = True)

df.replace({'Married':{'Yes':1,
    'No':0}},inplace = True)

df.replace({'Education':{'Graduate':1,
    'Not Graduate':0}},inplace = True)

df.replace({'Self_Employed':{'Yes':1,
    'No':0}},inplace = True)

df.replace({'Property_Area':{'Urban':1,
    'Semiurban':1.'Rural':0}},inplace = True)

https://colab.research.google.com/drive/1ZJnd_TNVLhm9J_vklN5nVLgluamy-jrT#printMode=true
```

# Define y (Dependent or label or target variable) and X (independent or features or attribute Variables)

```
y = df ['Loan_Status']
y.shape
    (614,)
У
          N
    609
         N
    610
    611
          N
    612
          Υ
    613
    Name: Loan_Status, Length: 614, dtype: object
df.columns
    'Loan_Amount', 'Loan_Amount_Term', 'Credit_History', 'Property_Area',
          'Loan_Status'],
         dtype='object')
X = df[[ 'Gender', 'Married', 'Dependents', 'Education',
      'Self_Employed', 'Applicant_Income', 'Coapplicant_Income',
      'Loan Amount', 'Loan Amount Term', 'Credit History', 'Property Area']]
Χ
```

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coappl
0	1	0	0	1	0	2378	
1	0	1	2	1	0	1299	
2	0	0	0	0	0	3620	
3	0	1	0	1	1	3459	
4	0	1	1	1	0	5468	
609	0	1	2	1	0	2947	
040	^	^	^	4	^	4000	

# Get train\_test\_split

from sklearn.model\_selection import train\_test\_split 014 rows × 11 columns

X\_train,X\_test,y\_train,y\_test = train\_test\_split(X,y,test\_size=0.3,random\_state =254

X\_train

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coappl
1	0	1	2	1	0	1299	
238	0	1	1	1	0	3750	
438	0	1	0	0	1	2609	
210	0	1	2	1	0	9703	
388	0	1	2	1	0	3340	
328	0	0	0	0	1	5800	
308	0	1	4	0	1	3333	
200	0	0	0	0	0	3833	
611	0	1	2	1	1	6633	
351	0	1	0	1	0	3087	

429 rows × 11 columns

#### Standardization of Train and test features

```
X_train_std = X_train[['Applicant_Income','Coapplicant_Income','Loan_Amount','Loan_A
X_test_std = X_test[['Applicant_Income','Coapplicant_Income','Loan_Amount','Loan_Amo
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
X_train_std = ss.fit_transform(X_train_std)
X_test_std = ss.fit_transform(X_test_std)
X_train_std
     array([[-0.80571566, -0.19393576, -1.57777937, -3.19876573],
            [-0.30020187, -0.61240927, -0.33240483, 0.30729073],
            [-0.53553081, 0.71661022, 0.28399266, -2.32225162],
            [-0.28308328, -0.61240927, -0.40788208, 0.30729073],
            [0.29441106, -0.61240927, -1.47714304, 0.30729073],
            [-0.43694428, 0.23918048, -0.08081402, 0.30729073]])
X test std
     array([[-4.47541939e-01, 4.31781875e-01, 3.60655789e-01,
             2.93944575e-01],
            [-3.51366900e-01, -8.77897020e-03, -6.94690237e-01,
             -2.19293407e+00],
            [-3.04846142e-01, 8.53268429e-02, -4.11310286e-01,
              2.93944575e-01],
            [-1.84326044e-01, 3.23923230e-02, 1.84764785e-01,
             2.93944575e-01],
            [-2.23736116e-01, -4.74295720e-02, 2.62938565e-01,
              2.93944575e-01],
            [-3.95236216e-01, 1.77752195e-01, -1.57245502e-01,
              2.93944575e-01],
            [-2.34462405e-01, -4.74826806e-01, -1.67017224e-01,
             2.93944575e-01],
            [-3.24129358e-01, 3.71285281e-01, -3.99848319e-02,
              2.93944575e-01],
            [-2.18433232e-01, 1.01014052e+00, -3.02131095e-02,
              2.93944575e-01],
            [ 8.16618128e-02, -4.74826806e-01, 6.24492296e-01,
              2.93944575e-01],
            [-3.17380233e-01, 2.92303616e-01, -3.03821339e-01,
              2.93944575e-01],
            [-5.36822576e-02, -4.74826806e-01, 2.62938565e-01,
              2.93944575e-01],
            [-4.63812152e-01, 6.54413883e-02, -6.55603347e-01,
```

```
2.93944575e-01],
[-1.90352049e-01,
                  1.92596267e-01, -1.37702057e-01,
  2.93944575e-01],
[-3.45581936e-01, -4.74826806e-01, -7.92407462e-01,
  2.93944575e-01],
[-2.76041839e-01, 6.77409250e-01, 1.06591005e-01,
 2.93944575e-01],
[-3.05689783e-01, -2.19116665e-01, -3.52679951e-01,
 -3.51926934e+00],
[-4.06203545e-01, 1.90355652e-01, -1.08555914e+00,
  2.93944575e-01],
[-2.93155693e-01, -1.24730776e-01, -1.27930334e-01,
 2.93944575e-01],
[-3.70650116e-01, 6.20804664e-02, 4.79606703e-02,
  2.93944575e-01],
[-5.32749648e-01, -4.74826806e-01, -1.03670052e+00,
 2.93944575e-01],
[ 8.91797913e-01, -4.74826806e-01, -9.87841911e-01,
 2.93944575e-01],
[-4.70561278e-01, 2.07440338e-01, -9.86151667e-02,
 2.93944575e-01],
[ 1.77234251e-01, 1.85905337e+00, 3.31340622e-01,
 -5.35014973e-01],
[-3.43774134e-01, 4.03494116e-01, -1.13441775e+00,
  2.93944575e-01],
[-2.41452571e-01, 4.49426715e-01, 8.87378040e-03,
-2.19293407e+00],
[ 4.17671847e-01, -4.74826806e-01, 4.58373014e-01,
-2.19293407e+00],
[ 8.74715330e-03, -4.74826806e-01, -7.90717218e-02,
  2.93944575e-01],
[-4.05239384e-01, 5.12670968e+00, -3.72223396e-01,
```

X\_train[['Applicant\_Income','Coapplicant\_Income','Loan\_Amount','Loan\_Amount\_Term']]=

X\_train

		Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coappl	
	1	0	1	2	1	0	-0.300202		
<pre>X_train = X_train.fillna(0)</pre>									
	438	U	1	U	U	1	NaN		
X_tra	ain								

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coappl
1	0	1	2	1	0	-0.300202	
238	0	1	1	1	0	-0.166141	
438	0	1	0	0	1	0.000000	
210	0	1	2	1	0	0.638226	
388	0	1	2	1	0	-0.436532	
328	0	0	0	0	1	-0.351764	
308	0	1	4	0	1	0.043614	
200	0	0	0	0	0	-0.002999	
611	0	1	2	1	1	0.000000	
351	0	1	0	1	0	-0.058273	

429 rows × 11 columns

X\_test[['Applicant\_Income','Coapplicant\_Income','Loan\_Amount','Loan\_Amount\_Term']]=p

X\_test

		Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coappl
	464	1	1	0	0	0	NaN	
	52	0	1	4	0	0	1.085112	
	136	0	1	2	0	0	9.055588	
X_tes	st = 2	X_test.f	illna(0)					
		^		^		•		
X_tes	st							

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coappl
464	1	1	0	0	0	0.000000	
52	0	1	4	0	0	1.085112	
136	0	1	2	0	0	9.055588	
424	0	1	4	1	0	0.000000	
443	0	1	2	1	0	0.000000	
177	1	1	0	1	0	-0.540463	
570	0	1	1	1	0	0.000000	
240	1	0	0	1	0	0.000000	
315	0	1	2	1	0	0.000000	
280	0	1	0	0	0	0.000000	

185 rows × 11 columns

#### → Get the model train

#### → Get model Prediction

```
y_pred = dt.predict(X_test)
y_pred.shape
     (185,)
y pred
                                  'Υ',
                                       'Υ',
                                                       'Υ',
     array(['N', 'N', 'Y', 'N',
                                            'N', 'Y',
                                        'N',
                                             'N',
                                                        'N',
                                        'Y'
                                                  'N'
                                                        'N'
                                                        'Y'
                                                  'N'
                                  'N'
                                                  'N',
                                                  'N',
                                             'Y',
                                                       'N',
                                       'Υ',
                                  'Y'
                                             'N', 'Y', 'N', 'Y', 'N',
                             'Y'
                       'N',
                                             'Y', 'Y',
                       'Y', 'N', 'Y',
                                       'N',
                                                       'Y', 'Y', 'N',
             'Y', 'Y', 'N'], dtype=object)
```

# Get Probability of each predicted value

```
dt.predict_proba(X_test)
             [0.
                        , 1.
             [1.
                         , 0.
             [0.35294118, 0.64705882],
             [0.
                       , 1.
             [0.
                        , 1.
             [0.
                        , 1.
             [0.
             [1.
             [1.
             [1.
                        , 0.
             [0.
             [0.
                        , 1.
             [0.
             [1.
                        , 0.
             [1.
                        , 1.
             [0.35294118, 0.64705882],
             [0.
                         , 1.
                                      ],
                         , 1.
             [0.
                                      ],
```

```
[0.42857143, 0.57142857],
            , 0.5
[0.5
[0.5
             0.5
                         ],
[0.
[0.
[1.
[1.
٢1.
[1.
[0.5
             0.5
[0.33333333, 0.66666667],
[0.
            , 1.
[0.4
             0.6
[1.
             0.
[0.
[1.
[0.
[1.
[0.
[1.
[0.
[0.
[0.
[1.
[0.30769231, 0.69230769],
[0.5
           , 0.5
           , 1.
[0.
[0.35294118, 0.64705882],
[0.07692308, 0.92307692],
[0.35294118, 0.64705882],
           , 0.
           , 1.
[0.
[0.30769231, 0.69230769],
         , 0.75
[0.25
[0.07692308, 0.92307692],
            , 0.
                         ]])
```

#### → Get model evaluation

```
from sklearn.metrics import confusion_matrix,classification_report
confusion_matrix(y_pred,y_test)
     array([[33, 28],
            [25, 99]])
print(classification_report(y_test,y_pred))
                   precision
                               recall f1-score
                                                  support
                        0.54
                                 0.57
                                           0.55
                                                       58
                N
                Υ
                        0.80
                                 0.78
                                           0.79
                                                      127
```

accuracy			0.71	185
macro avg	0.67	0.67	0.67	185
weighted avg	0.72	0.71	0.72	185

# Get Decission\_tree\_plot

from sklearn.tree import plot\_tree

import matplotlib.pyplot as plt
plt.figure(figsize=(30,30))
plot\_tree(dt,filled = True)

```
[Text(0.24828890489913544, 0.9736842105263158, 'X[9] \leftarrow 0.5 \text{ ngini} = 0.43 \text{ nsamples} = 4
    \label{eq:total_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_control_cont
    Text(0.069164265129683, 0.8157894736842105, 'X[6] <= 0.117\ngini = 0.165\nsamples =
    \label{text} Text(0.05763688760806916,\ 0.7631578947368421,\ 'X[6] <= 0.106 \\ logini = 0.238 \\ logini = 0.191 \\ logini = 0.
    \label{text} Text(0.0345821325648415,\ 0.6578947368421053,\ 'gini = 0.0 \ nsamples = 9 \ nvalue = [9, \ \ell ] \\ Text(0.05763688760806916,\ 0.6578947368421053,\ 'X[6] <= 0.04 \ ngini = 0.266 \ nsamples = 10.04 \ ngini = 10.04 \
    Text(0.0345821325648415, 0.6052631578947368, 'X[2] <= 0.5 \times 10^{-10} = 0.208 \ \text{nsamples} = 1
    Text(0.023054755043227664, 0.5526315789473685, 'gini = 0.0\nsamples = 7\nvalue = [7]
    Text(0.04610951008645533, 0.5526315789473685, 'X[3] <= 0.5\ngini = 0.32\nsamples = 1
    Text(0.023054755043227664, 0.5, 'X[1] \leftarrow 0.5 = 0.5 = 2 = 2 = [1, 1]
    Text(0.011527377521613832, 0.4473684210526316, 'gini = 0.0\nsamples = 1\nvalue = [1,
    Text(0.0345821325648415, 0.4473684210526316, 'gini = 0.0\nsamples = 1\nvalue = [0, 1
    Text(0.069164265129683, 0.5, X[1] <= 0.5 \text{ ngini} = 0.219 \text{ nsamples} = 8 \text{ nvalue} = [7, 1]
    Text(0.05763688760806916, 0.4473684210526316, 'gini = 0.0 \nsamples = 1 \nvalue = [0, 1]
    \label{text} Text(0.08069164265129683, 0.4473684210526316, 'gini = 0.0 \nsamples = 7 \nvalue = [7, Text(0.08069164265129683, 0.6052631578947368, 'X[6] <= 0.076 \ngini = 0.5 \nsamples = (7, Text(0.08069164265129683, 0.6052631578947368, 'X[6] <= 0.076 \ngini = 0.5 \nsamples = (7, Text(0.08069164265129683, 0.6052631578947368, 'X[6] <= 0.076 \ngini = 0.5 \nsamples = (7, Text(0.08069164265129683, 0.6052631578947368, 'X[6] <= 0.076 \ngini = 0.5 \nsamples = (7, Text(0.08069164265129683, 0.6052631578947368, 'X[6] <= 0.076 \ngini = 0.5 \nsamples = (7, Text(0.08069164265129683, 0.6052631578947368, 'X[6] <= 0.076 \ngini = (7, Text(0.0806916426512968, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947368, 0.6052631578947894, 0.6052631578947894, 0.6052631578947894, 0.605263157894, 0.605263157894, 0.605263157894, 0.605263157894, 0.605263157894, 0.605263157894, 0.605263157894, 0.60526315794, 0.605263157894, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526315794, 0.60526414, 0.60526414, 0.60526414, 0.60526414, 0.60526414, 
    Text(0.069164265129683, 0.5526315789473685, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]
    Text(0.09221902017291066, 0.5526315789473685, 'gini = 0.0\nsamples = 1\nvalue = [1,
    Text(0.069164265129683, 0.7105263157894737, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]
    Text(0.08069164265129683, 0.7631578947368421, 'gini = 0.0\nsamples = 15\nvalue = [15]
    Text(0.1037463976945245, 0.868421052631579, 'X[7] <= -0.88 \ngini = 0.444 \nsamples = -0.444 \nsamples = -
    Text(0.09221902017291066, 0.8157894736842105, 'gini = 0.0\nsamples = 1\nvalue = [1,
    Text(0.11527377521613832, 0.8157894736842105, 'gini = 0.0 \nsamples = 2 \nvalue = [0, 1.0]
    Text(0.4158861671469741, 0.9210526315789473, 'X[5] <= -0.53 \ngini = 0.319 \nsamples = -0.53 \ngini = -0.53 \ngi
    Text(0.14985590778097982, 0.868421052631579, 'X[3] <= 0.5\ngini = 0.085\nsamples = 4
    Text(0.138328530259366, 0.8157894736842105, 'X[4] <= 0.5 \neq 0.245 = 14
    Text(0.12680115273775217, 0.7631578947368421, 'X[5] <= -0.622\ngini = 0.142\nsamples
    Text(0.11527377521613832, 0.7105263157894737, 'X[5] <= -0.664 \ngini = 0.444 \nsamples
    Text(0.1037463976945245, 0.6578947368421053, 'gini = 0.0\nsamples = 2\nvalue = [0, 2
    Text(0.12680115273775217, 0.6578947368421053, 'gini = 0.0\nsamples = 1\nvalue = [1,
    Text(0.138328530259366, 0.7105263157894737, 'gini = 0.0 \nsamples = 10 \nvalue = [0, 1, 1, 1, 1] 
    Text(0.14985590778097982,\ 0.7631578947368421,\ 'gini = 0.0 \ nsamples = 1 \ nvalue = [1, 1]
    Text(0.16138328530259366, 0.8157894736842105, 'gini = 0.0\nsamples = 31\nvalue = [0,
    Text(0.6819164265129684, 0.868421052631579, 'X[5] <= 0.1 \setminus gini = 0.345 \setminus gini = 31
    Text(0.45605187319884727, 0.8157894736842105, 'X[5] <= -0.097 \setminus ini = 0.378 \setminus ini = 
    Text(0.138328530259366, 0.6052631578947368, X[7] <= -0.735  in = 0.159  in =
    Text(0.12680115273775217, 0.5526315789473685, 'X[0] <= 0.5 \ngini = 0.444 \nsamples =
    Text(0.11527377521613832, 0.5, 'gini = 0.0 \nsamples = 4 \nvalue = [0, 4]'),
    Text(0.138328530259366, 0.5, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
    Text(0.207492795389049, 0.6578947368421053, 'X[6] <= 0.636 \setminus ini = 0.486 \setminus ini =
    Text(0.1844380403458213, 0.6052631578947368, 'X[4] <= 0.5 \ngini = 0.278 \nsamples = 6
    Text(0.1729106628242075, 0.5526315789473685, 'gini = 0.0\nsamples = 5\nvalue = [5, 6]
    Text(0.19596541786743515, 0.5526315789473685, 'gini = 0.0\nsamples = 1\nvalue = [0,
    Text(0.23054755043227665, 0.6052631578947368, 'X[5] <= -0.524\ngini = 0.444\nsamples
    Text(0.21902017291066284, 0.5526315789473685, 'gini = 0.0\nsamples = 2\nvalue = [2,
    Text(0.2420749279538905, 0.5526315789473685, 'gini = 0.0\nsamples = 4\nvalue = [0, 4
    Text(0.2881844380403458, 0.6578947368421053, 'X[5] <= -0.355 \ngini = 0.062 \nsamples
    Text(0.276657060518732, 0.6052631578947368, 'X[5] <= -0.359 \ngini = 0.153 \nsamples = -0.453 \nsamples = 
    Text(0.26512968299711814, 0.5526315789473685, 'gini = 0.0\nsamples = 11\nvalue = [0,
    \label{text} Text(0.2881844380403458,\ 0.5526315789473685,\ 'gini = 0.0 \\ \ nsamples = 1 \\ \ nvalue = [1, \ \ell ] \\ \ Text(0.29971181556195964,\ 0.6052631578947368,\ 'gini = 0.0 \\ \ nsamples = 19 \\ \ nvalue = [0, \ \ell ] \\ \ nvalue
```