ML - Lab Assignment 6
Decision Tree

class sklearn.tree.DecisionTreeClassifier(*, criterion='gini', splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, class_weight=None, ccp_alpha=0.0, monotonic_cst=None)[source]

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import mutual_info_classif
from sklearn.preprocessing import StandardScaler, OrdinalEncoder
from sklearn.tree import DecisionTreeClassifier
```

[2]:
```
df = pd.read_csv("D:\MIT ADT\Third Year - Sem 2\ML LAB\Assgin 6 - Decision␣
↪Tree\\autism_screening.csv")
```

[3]:
```
df.head()
```

[3]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	\
0	1	1	1	1	0	0	1	
1	1	1	0	1	0	0	0	
2	1	1	0	1	1	0	1	
3	1	1	0	1	0	0	1	
4	1	0	0	0	0	0	0	

	A8_Score	A9_Score	A10_Score	…	gender	ethnicity	jundice	austim	\
0	1	0	0	…	f	White-European	no	no	
1	1	0	1	…	m	Latino	no	yes	
2	1	1	1	…	m	Latino	yes	yes	
3	1	0	1	…	f	White-European	no	yes	
4	1	0	0	…	f	?	no	no	

	contry_of_res	used_app_before	result	age_desc	relation	Class/ASD
0	United States	no	6.0	18 and more	Self	NO
1	Brazil	no	5.0	18 and more	Self	NO
2	Spain	no	8.0	18 and more	Parent	YES

```
3  United States              no    6.0  18 and more     Self        NO
4          Egypt              no    2.0  18 and more        ?        NO

[5 rows x 21 columns]
```

[4]:
```
df.isna().sum()
```

[4]:
```
A1_Score           0
A2_Score           0
A3_Score           0
A4_Score           0
A5_Score           0
A6_Score           0
A7_Score           0
A8_Score           0
A9_Score           0
A10_Score          0
age                2
gender             0
ethnicity          0
jundice            0
austim             0
contry_of_res      0
used_app_before    0
result             0
age_desc           0
relation           0
Class/ASD          0
dtype: int64
```

[5]:
```
df = df.replace('?', np.nan)
```

[6]:
```
df.isin(['?']).sum()
```

[6]:
```
A1_Score           0
A2_Score           0
A3_Score           0
A4_Score           0
A5_Score           0
A6_Score           0
A7_Score           0
A8_Score           0
A9_Score           0
A10_Score          0
age                0
gender             0
ethnicity          0
```

```
jundice             0
austim              0
contry_of_res       0
used_app_before     0
result              0
age_desc            0
relation            0
Class/ASD           0
dtype: int64
```

[7]:
```
df.isna().sum()
```

[7]:
```
A1_Score            0
A2_Score            0
A3_Score            0
A4_Score            0
A5_Score            0
A6_Score            0
A7_Score            0
A8_Score            0
A9_Score            0
A10_Score           0
age                 2
gender              0
ethnicity          95
jundice             0
austim              0
contry_of_res       0
used_app_before     0
result              0
age_desc            0
relation           95
Class/ASD           0
dtype: int64
```

[8]:
```
df
```

[8]:
```
     A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
0           1         1         1         1         0         0         1
1           1         1         0         1         0         0         0
2           1         1         0         1         1         0         1
3           1         1         0         1         0         0         1
4           1         0         0         0         0         0         0
..        ...       ...       ...       ...       ...       ...       ...
699         0         1         0         1         1         0         1
700         1         0         0         0         0         0         0
701         1         0         1         1         1         0         1
```

```
702         1         0         0         1         1         0         1
703         1         0         1         1         1         0         1

     A8_Score  A9_Score  A10_Score  …  gender       ethnicity jundice  \
0           1         0          0  …       f  White-European      no
1           1         0          1  …       m          Latino      no
2           1         1          1  …       m          Latino     yes
3           1         0          1  …       f  White-European      no
4           1         0          0  …       f             NaN      no
..        …       …        …  …     …             …     …
699         1         1          1  …       f  White-European      no
700         1         0          1  …       m        Hispanic      no
701         1         0          1  …       f             NaN      no
702         0         1          1  …       m     South Asian      no
703         1         1          1  …       f  White-European      no

    austim  contry_of_res used_app_before result     age_desc relation  \
0       no  United States              no    6.0  18 and more     Self
1      yes         Brazil              no    5.0  18 and more     Self
2      yes          Spain              no    8.0  18 and more   Parent
3      yes  United States              no    6.0  18 and more     Self
4       no          Egypt              no    2.0  18 and more      NaN
..     …            …              …    …          …       …
699     no         Russia              no    7.0  18 and more     Self
700     no         Mexico              no    3.0  18 and more   Parent
701     no         Russia              no    7.0  18 and more      NaN
702     no       Pakistan              no    6.0  18 and more     Self
703     no         Cyprus              no    8.0  18 and more     Self

    Class/ASD
0          NO
1          NO
2         YES
3          NO
4          NO
..        …
699       YES
700        NO
701       YES
702        NO
703       YES

[704 rows x 21 columns]
```

[9]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='most_frequent', missing_values=np.nan)
df['age'] = imputer.fit_transform(df[['age']]).ravel()
```

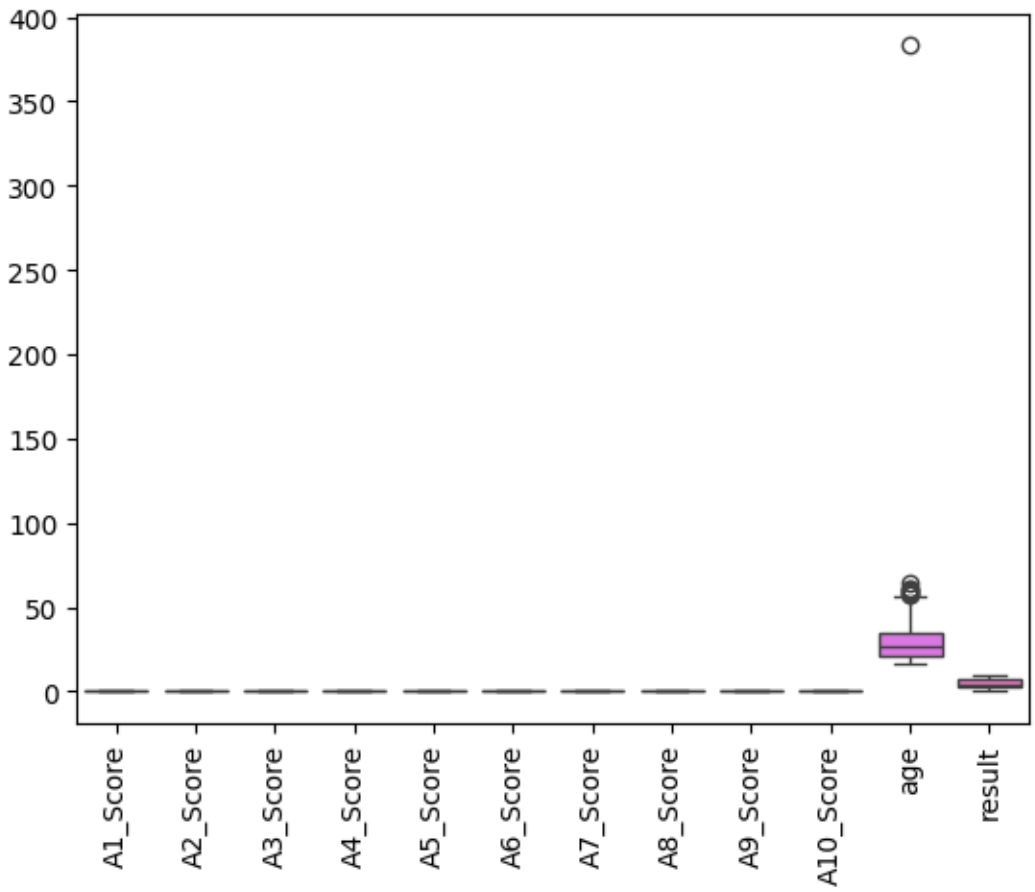
```
df['ethnicity'] = imputer.fit_transform(df[['ethnicity']]).ravel()
df['relation'] = imputer.fit_transform(df[['relation']]).ravel()
```

[10]:
```
df.isna().sum()
```

[10]:
```
A1_Score           0
A2_Score           0
A3_Score           0
A4_Score           0
A5_Score           0
A6_Score           0
A7_Score           0
A8_Score           0
A9_Score           0
A10_Score          0
age                0
gender             0
ethnicity          0
jundice            0
austim             0
contry_of_res      0
used_app_before    0
result             0
age_desc           0
relation           0
Class/ASD          0
dtype: int64
```

[11]:
```
sns.boxplot(df)

plt.xticks(rotation=90)
```

[11]:
```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11],
 [Text(0, 0, 'A1_Score'),
  Text(1, 0, 'A2_Score'),
  Text(2, 0, 'A3_Score'),
  Text(3, 0, 'A4_Score'),
  Text(4, 0, 'A5_Score'),
  Text(5, 0, 'A6_Score'),
  Text(6, 0, 'A7_Score'),
  Text(7, 0, 'A8_Score'),
  Text(8, 0, 'A9_Score'),
  Text(9, 0, 'A10_Score'),
  Text(10, 0, 'age'),
  Text(11, 0, 'result')])
```

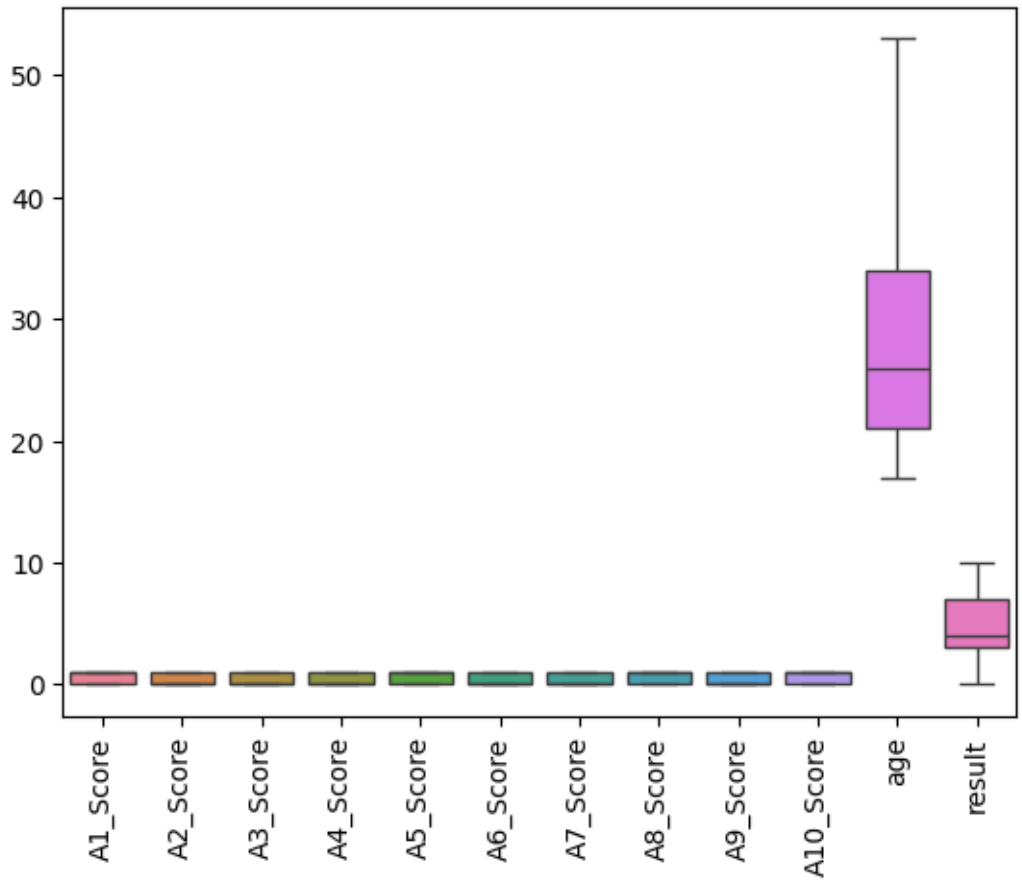


[14]:
```
Q1 = df['age'].quantile(0.25)
Q3 = df['age'].quantile(0.75)

IQR = Q3 - Q1

lower_bound = Q1-(1.5*IQR)
upper_bound = Q3+(1.5*IQR)

df = df[df["age"]<=upper_bound]
```

[15]:
```
sns.boxplot(df)

plt.xticks(rotation=90)
```

[15]:
```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11],
 [Text(0, 0, 'A1_Score'),
  Text(1, 0, 'A2_Score'),
  Text(2, 0, 'A3_Score'),
  Text(3, 0, 'A4_Score'),
```

```
Text(4, 0, 'A5_Score'),
Text(5, 0, 'A6_Score'),
Text(6, 0, 'A7_Score'),
Text(7, 0, 'A8_Score'),
Text(8, 0, 'A9_Score'),
Text(9, 0, 'A10_Score'),
Text(10, 0, 'age'),
Text(11, 0, 'result')])
```



[16]:
```
df.columns.values
```

[16]:
```
array(['A1_Score', 'A2_Score', 'A3_Score', 'A4_Score', 'A5_Score',
       'A6_Score', 'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score', 'age',
       'gender', 'ethnicity', 'jundice', 'austim', 'contry_of_res',
       'used_app_before', 'result', 'age_desc', 'relation', 'Class/ASD'],
      dtype=object)
```

[17]:
```
labels=df['Class/ASD'].unique().tolist()
labels
```

[17]:
```
['NO', 'YES']
```

[18]:
```
col_names = ['gender', 'austim', 'contry_of_res','used_app_before','age_desc',␣
 ↪'age_desc', 'ethnicity','relation', 'jundice','Class/ASD' ]

lbl_enc = OrdinalEncoder()
for i in col_names:
    df[i] = lbl_enc.fit_transform(df[[i]])
```

[19]:
```
df.head(20)
```

[19]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	\
0	1	1	1	1	0	0	1	
1	1	1	0	1	0	0	0	
2	1	1	0	1	1	0	1	
3	1	1	0	1	0	0	1	
4	1	0	0	0	0	0	0	
5	1	1	1	1	1	0	1	
6	0	1	0	0	0	0	0	
8	1	1	0	0	1	0	0	
9	1	1	1	1	0	1	1	
10	1	1	1	1	1	1	1	
11	0	1	0	1	1	1	1	
12	0	1	1	1	1	1	0	
13	1	0	0	0	0	0	1	
14	1	0	0	0	0	0	1	
15	1	1	0	1	1	0	0	
16	1	0	0	0	0	0	1	
17	0	0	0	0	0	0	0	
18	0	0	1	0	1	1	0	
19	0	0	0	0	0	0	1	
20	0	1	1	1	0	0	0	

	A8_Score	A9_Score	A10_Score	…	gender	ethnicity	jundice	austim	\
0	1	0	0	…	0.0	9.0	0.0	0.0	
1	1	0	1	…	1.0	3.0	0.0	1.0	
2	1	1	1	…	1.0	3.0	1.0	1.0	
3	1	0	1	…	0.0	9.0	0.0	1.0	
4	1	0	0	…	0.0	9.0	0.0	0.0	
5	1	1	1	…	1.0	5.0	1.0	0.0	
6	1	0	0	…	0.0	1.0	0.0	0.0	
8	1	1	1	…	1.0	9.0	0.0	0.0	
9	1	1	0	…	1.0	0.0	1.0	1.0	
10	1	1	1	…	1.0	9.0	0.0	0.0	
11	0	0	1	…	0.0	4.0	0.0	0.0	
12	0	1	0	…	0.0	9.0	0.0	0.0	
13	1	0	1	…	1.0	9.0	0.0	0.0	

```
14          1          0          1  …      0.0        9.0       0.0      0.0
15          1          0          1  …      1.0        4.0       0.0      1.0
16          1          1          1  …      1.0        4.0       0.0      0.0
17          1          0          1  …      1.0        9.0       0.0      0.0
18          0          0          0  …      0.0        4.0       0.0      1.0
19          1          0          1  …      1.0        9.0       1.0      0.0
20          0          0          0  …      1.0        9.0       0.0      0.0

    contry_of_res  used_app_before  result  age_desc  relation  Class/ASD
0            63.0              0.0     6.0       0.0       4.0        0.0
1            13.0              0.0     5.0       0.0       4.0        0.0
2            55.0              0.0     8.0       0.0       2.0        1.0
3            63.0              0.0     6.0       0.0       4.0        0.0
4            22.0              0.0     2.0       0.0       4.0        0.0
5            63.0              0.0     9.0       0.0       4.0        1.0
6            63.0              0.0     2.0       0.0       4.0        0.0
8            63.0              0.0     6.0       0.0       4.0        0.0
9             9.0              0.0     8.0       0.0       0.0        1.0
10           63.0              0.0    10.0       0.0       3.0        1.0
11           14.0              0.0     6.0       0.0       2.0        0.0
12            9.0              0.0     6.0       0.0       4.0        0.0
13            7.0              0.0     4.0       0.0       4.0        0.0
14            3.0              0.0     4.0       0.0       4.0        0.0
15           42.0              0.0     6.0       0.0       2.0        0.0
16           35.0              0.0     5.0       0.0       4.0        0.0
17           32.0              0.0     2.0       0.0       4.0        0.0
18           61.0              0.0     3.0       0.0       4.0        0.0
19           61.0              0.0     3.0       0.0       4.0        0.0
20           61.0              0.0     3.0       0.0       4.0        0.0

[20 rows x 21 columns]
```

[20]:
```
# labels=df['Class/ASD'].unique().tolist()
# labels
```

[21]:
```
X = df.drop("Class/ASD", axis=1)
y = df['Class/ASD']
```

[22]:
```
df.corr()
```

[22]:
```
            A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  \
A1_Score    1.000000  0.004984  0.076751  0.118994  0.165989  0.106592
A2_Score    0.004984  1.000000  0.217244  0.162360  0.147018  0.171173
A3_Score    0.076751  0.217244  1.000000  0.414296  0.270040  0.262514
A4_Score    0.118994  0.162360  0.414296  1.000000  0.312108  0.296689
A5_Score    0.165989  0.147018  0.270040  0.312108  1.000000  0.386015
A6_Score    0.106592  0.171173  0.262514  0.296689  0.386015  1.000000
```

```
A7_Score          0.212785 -0.051622  0.079008  0.153749  0.228512  0.168992
A8_Score          0.156850  0.040985  0.022488  0.005744  0.102419  0.109721
A9_Score          0.137956  0.195129  0.314221  0.327173  0.392156  0.473507
A10_Score         0.110649  0.059587  0.172243  0.215233  0.258771  0.290304
age               0.002898  0.078342  0.069629  0.087362  0.032037  0.072144
gender           -0.069148 -0.049371 -0.008340 -0.060659 -0.038129 -0.093303
ethnicity         0.050733  0.126341  0.109394  0.141510  0.010671  0.100452
jundice          -0.024586  0.105800  0.056467  0.069601  0.022634  0.068337
austim            0.091231  0.067644  0.111653  0.186297  0.089771  0.103918
contry_of_res     0.015319  0.138175  0.042152  0.036844 -0.026314 -0.026443
used_app_before  -0.040654 -0.009445  0.057582  0.024577 -0.000778  0.090190
result            0.393576  0.383773  0.555770  0.590176  0.637032  0.625069
age_desc               NaN       NaN       NaN       NaN       NaN       NaN
relation          0.015196 -0.037321  0.039904 -0.001411  0.038151 -0.085697
Class/ASD         0.293734  0.303555  0.442877  0.472834  0.531395  0.581464

                  A7_Score  A8_Score  A9_Score  A10_Score  …    gender  \
A1_Score          0.212785  0.156850  0.137956   0.110649  … -0.069148
A2_Score         -0.051622  0.040985  0.195129   0.059587  … -0.049371
A3_Score          0.079008  0.022488  0.314221   0.172243  … -0.008340
A4_Score          0.153749  0.005744  0.327173   0.215233  … -0.060659
A5_Score          0.228512  0.102419  0.392156   0.258771  … -0.038129
A6_Score          0.168992  0.109721  0.473507   0.290304  … -0.093303
A7_Score          1.000000  0.091659  0.180485   0.235253  …  0.061974
A8_Score          0.091659  1.000000  0.111823   0.100837  …  0.062197
A9_Score          0.180485  0.111823  1.000000   0.274221  … -0.002284
A10_Score         0.235253  0.100837  0.274221   1.000000  … -0.058624
age              -0.001090 -0.029547  0.128602   0.070784  … -0.066665
gender            0.061974  0.062197 -0.002284  -0.058624  …  1.000000
ethnicity        -0.001188 -0.034275  0.071901   0.063644  … -0.099497
jundice           0.019604  0.010849  0.046397   0.042978  … -0.026257
austim           -0.012414  0.036240  0.159100   0.113314  … -0.087856
contry_of_res    -0.026189 -0.035113 -0.086492   0.019054  … -0.021291
used_app_before  -0.023001 -0.043811  0.050781  -0.043377  … -0.026923
result            0.447863  0.332892  0.656617   0.530284  … -0.048646
age_desc               NaN       NaN       NaN        NaN  …       NaN
relation          0.021793  0.044719 -0.046814   0.025578  … -0.065043
Class/ASD         0.347100  0.247520  0.631436   0.380570  … -0.087113

                  ethnicity   jundice    austim  contry_of_res  \
A1_Score           0.050733 -0.024586  0.091231       0.015319
A2_Score           0.126341  0.105800  0.067644       0.138175
A3_Score           0.109394  0.056467  0.111653       0.042152
A4_Score           0.141510  0.069601  0.186297       0.036844
A5_Score           0.010671  0.022634  0.089771      -0.026314
A6_Score           0.100452  0.068337  0.103918      -0.026443
A7_Score          -0.001188  0.019604 -0.012414      -0.026189
```

```
A8_Score         -0.034275  0.010849  0.036240      -0.035113
A9_Score          0.071901  0.046397  0.159100      -0.086492
A10_Score         0.063644  0.042978  0.113314       0.019054
age               0.113248  0.139307  0.182631       0.061768
gender           -0.099497 -0.026257 -0.087856      -0.021291
ethnicity         1.000000  0.072071  0.109965       0.086617
jundice           0.072071  1.000000  0.154981       0.044462
austim            0.109965  0.154981  1.000000      -0.034783
contry_of_res     0.086617  0.044462 -0.034783       1.000000
used_app_before  -0.025410  0.031013  0.015976      -0.016099
result            0.124459  0.082148  0.183515       0.011828
age_desc               NaN       NaN       NaN            NaN
relation          0.111607 -0.109283 -0.094955       0.098468
Class/ASD         0.139515  0.091474  0.167864       0.000472

                 used_app_before    result  age_desc  relation  Class/ASD
A1_Score               -0.040654  0.393576       NaN  0.015196   0.293734
A2_Score               -0.009445  0.383773       NaN -0.037321   0.303555
A3_Score                0.057582  0.555770       NaN  0.039904   0.442877
A4_Score                0.024577  0.590176       NaN -0.001411   0.472834
A5_Score               -0.000778  0.637032       NaN  0.038151   0.531395
A6_Score                0.090190  0.625069       NaN -0.085697   0.581464
A7_Score               -0.023001  0.447863       NaN  0.021793   0.347100
A8_Score               -0.043811  0.332892       NaN  0.044719   0.247520
A9_Score                0.050781  0.656617       NaN -0.046814   0.631436
A10_Score              -0.043377  0.530284       NaN  0.025578   0.380570
age                    -0.028926  0.099550       NaN -0.037319   0.124653
gender                 -0.026923 -0.048646       NaN -0.065043  -0.087113
ethnicity              -0.025410  0.124459       NaN  0.111607   0.139515
jundice                 0.031013  0.082148       NaN -0.109283   0.091474
austim                  0.015976  0.183515       NaN -0.094955   0.167864
contry_of_res          -0.016099  0.011828       NaN  0.098468   0.000472
used_app_before         1.000000  0.011357       NaN -0.006486   0.045745
result                  0.011357  1.000000       NaN  0.004326   0.819825
age_desc                     NaN       NaN       NaN       NaN        NaN
relation               -0.006486  0.004326       NaN  1.000000   0.019438
Class/ASD               0.045745  0.819825       NaN  0.019438   1.000000

[21 rows x 21 columns]
```

[23]:
```
from sklearn.feature_selection import mutual_info_classif

mic = mutual_info_classif(X,y)
mic
```

[23]:
```
array([0.05606626, 0.01284231, 0.09914888, 0.12318655, 0.17877799,
       0.16483519, 0.0898205 , 0.0583742 , 0.21151768, 0.14207761,
```

```
       0.02852108, 0.        , 0.05534973, 0.        , 0.00293629,
       0.08968916, 0.        , 0.5792637 , 0.03060468, 0.00745336])
```

[24]:
```
mic = pd.Series(mic)
mic.index = X.columns
mic.sort_values(ascending=False)
```

[24]:
```
result             0.579264
A9_Score           0.211518
A5_Score           0.178778
A6_Score           0.164835
A10_Score          0.142078
A4_Score           0.123187
A3_Score           0.099149
A7_Score           0.089821
contry_of_res      0.089689
A8_Score           0.058374
A1_Score           0.056066
ethnicity          0.055350
age_desc           0.030605
age                0.028521
A2_Score           0.012842
relation           0.007453
austim             0.002936
jundice            0.000000
used_app_before    0.000000
gender             0.000000
dtype: float64
```

[25]:
```
X = X.drop(['gender', 'age_desc'],axis=1)
```

[26]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33,␣
 ↪random_state = 42)
```

[27]:
```
#Scale the Data

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

Xtrain_std = scaler.fit_transform(X_train)
Xtest_std = scaler.transform(X_test)
```

[40]:
```
entropy_clf = DecisionTreeClassifier(criterion='entropy',max_depth=5,␣
 ↪random_state=42)
```

```
entropy_clf.fit(X_train, y_train)
```

[40]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=5, random_state=42)
```

[41]:
```
print('Training Accuracy:', entropy_clf.score(X_train,y_train))
print('Test Accuracy:', entropy_clf.score(X_test,y_test))
```

```
Training Accuracy: 1.0
Test Accuracy: 1.0
```

[42]:
```
entropy_clf.fit(Xtrain_std, y_train)
```

[42]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=5, random_state=42)
```

[43]:
```
print('Training Accuracy scale:', entropy_clf.score(Xtrain_std,y_train))
print('Test Accuracy scale:', entropy_clf.score(Xtest_std,y_test))
```

```
Training Accuracy scale: 1.0
Test Accuracy scale: 1.0
```

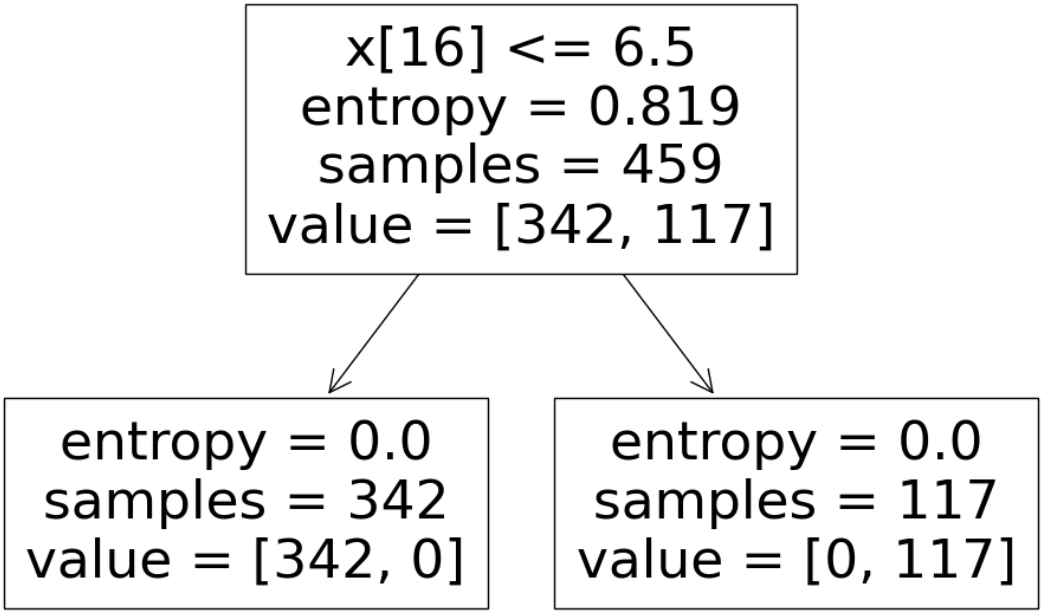
[38]:
```

```

```
Training Accuracy: 0.2788671023965142
Test Accuracy: 0.29955947136563876
```

```
c:\Users\nilesh\anaconda3\envs\mllab\lib\site-packages\sklearn\base.py:458:
UserWarning: X has feature names, but DecisionTreeClassifier was fitted without
feature names
  warnings.warn(
c:\Users\nilesh\anaconda3\envs\mllab\lib\site-packages\sklearn\base.py:458:
UserWarning: X has feature names, but DecisionTreeClassifier was fitted without
feature names
  warnings.warn(
```

[44]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,8))

from sklearn import tree

tree.plot_tree(entropy_clf.fit(X_train, y_train))
```

[44]:
```
[Text(0.5, 0.75, 'x[16] <= 6.5\nentropy = 0.819\nsamples = 459\nvalue = [342,
117]'),
 Text(0.25, 0.25, 'entropy = 0.0\nsamples = 342\nvalue = [342, 0]'),
 Text(0.75, 0.25, 'entropy = 0.0\nsamples = 117\nvalue = [0, 117]')]
```


x[16] <= 6.5
entropy = 0.819
samples = 459
value = [342, 117]
entropy = 0.0
samples = 342
value = [342, 0]
entropy = 0.0
samples = 117
value = [0, 117]