In [1]:
```
import numpy as np
import pandas as pd
from numpy import log2 as log
```

In [2]:
```
dataset = [
    ['<21', 'High', 'Male', 'Single', 'No'],
    ['<21', 'High', 'Male', 'Married', 'No'],
    ['21-35', 'High', 'Male', 'Single', 'Yes'],
    ['>35', 'Medium', 'Male', 'Single', 'Yes'],
    ['>35', 'Low', 'Female', 'Single', 'Yes'],
    ['>35', 'Low', 'Female', 'Married', 'No'],
    ['21-35', 'Low', 'Female', 'Married', 'Yes'],
    ['<21', 'Medium', 'Male', 'Single', 'No'],
    ['<21', 'Low', 'Female', 'Married', 'Yes'],
    ['>35', 'Medium', 'Female', 'Single', 'Yes'],
    ['<21', 'Medium', 'Female', 'Married', 'Yes'],
    ['21-35', 'Medium', 'Male', 'Married', 'Yes'],
    ['21-35', 'High', 'Female', 'Single', 'Yes'],
    ['>35', 'Medium', 'Male', 'Married', 'No']
]
```

In [3]:
```
columns = ['Age', 'Income', 'Gender', 'Marital Status', 'Buys']
df = pd.DataFrame(dataset,columns=columns)
df
```

Out[3]:

	Age	Income	Gender	Marital Status	Buys
0	<21	High	Male	Single	No
1	<21	High	Male	Married	No
2	21-35	High	Male	Single	Yes
3	>35	Medium	Male	Single	Yes
4	>35	Low	Female	Single	Yes
5	>35	Low	Female	Married	No
6	21-35	Low	Female	Married	Yes
7	<21	Medium	Male	Single	No
8	<21	Low	Female	Married	Yes
9	>35	Medium	Female	Single	Yes
10	<21	Medium	Female	Married	Yes
11	21-35	Medium	Male	Married	Yes
12	21-35	High	Female	Single	Yes
13	>35	Medium	Male	Married	No

In [4]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in range(5):
    df[columns[i]] = le.fit_transform(df[columns[i]])
df
```

Out[4]:

	Age	Income	Gender	Marital Status	Buys
0	1	0	1	1	0
1	1	0	1	0	0
2	0	0	1	1	1
3	2	2	1	1	1
4	2	1	0	1	1
5	2	1	0	0	0
6	0	1	0	0	1
7	1	2	1	1	0
8	1	1	0	0	1
9	2	2	0	1	1
10	1	2	0	0	1
11	0	2	1	0	1
12	0	0	0	1	1
13	2	2	1	0	0

In [5]:
```
test_data=[[1, 1, 0, 0]]
test = pd.DataFrame(test_data,columns=['Age', 'Income', 'Gender', 'Marital Status'])
test
```

Out[5]:

	Age	Income	Gender	Marital Status
0	1	1	0	0

In [6]:
```
eps = np.finfo(float).eps
```

$$E(S) = \sum_{i=1}^{c} - p_i \log_2 p_i$$

In [7]:
```
# Calculate the Cost Function that is Entropy
def find_entropy(df):
    Class = df.keys()[-1]
    entropy = 0
    values = df[Class].unique()
    for value in values:
        fraction = df[Class].value_counts()[value]/len(df[Class])
        entropy += -fraction*np.log2(fraction)
        print("Class: ", Class, " E(S): ", entropy)
    return entropy
```

$$E(T,X)=\sum_{c\in X}P(c)E(c)$$

In [8]:
```
#Find entropy of the attribute (Each Columns)
def find_entropy_attribute(df,attribute):
    Class = df.keys()[-1]
    target_variables = df[Class].unique()
    variables = df[attribute].unique()
    entropy2 = 0
    for variable in variables:
        entropy = 0
        for target_variable in target_variables:
            num = len(df[attribute][df[attribute]==variable][df[Class]==target_variable])
            den = len(df[attribute][df[attribute]==variable])
            fraction = num/(den+eps)
            entropy += -fraction*log(fraction+eps)
        fraction2 = den/len(df)
        entropy2 += -fraction2*entropy
        print("Class: ", Class, " E(T,X): ", entropy2)
    return abs(entropy2)
```

$$Gain(T,X)=Entropy(T)-Entropy(T,X)$$

In [9]:
```
#Find Root Node
def find_winner(df):
    IG = []
    for key in df.keys()[:-1]:
        IG.append(find_entropy(df)-find_entropy_attribute(df,key))
        print(np.argmax(IG))
    return df.keys()[:-1][np.argmax(IG)]
```

In [10]:
```
def get_subtable(df, node,value):
    return df[df[node] == value].reset_index(drop=True)
```

In [11]:
```
def buildTree(df,tree=None):
    Class = df.keys()[-1]
    #Build Decision Tree

    #Get attribute with maximum information gain
    node = find_winner(df)
    print("node with max info gain: ",node)

    #Get distinct value of that attribute
    attValue = np.unique(df[node])
    print("distinct values found: ", attValue)

    #Create an empty dictionary to create tree
    if tree is None:
        tree={}
        tree[node] = {}

    #Check if the subset is pure and stops if it is.
    for value in attValue:
        subtable = get_subtable(df,node,value)
        print("subtable: ", subtable)
        clValue,counts = np.unique(subtable['Buys'],return_counts=True)
        print("clValue: ", clValue)
        print("counts: ", counts)

        if(len(counts)==1): #Checking purity of subset
            tree[node][value] = clValue[0]
        else:
            tree[node][value] = buildTree(subtable) #Calling the function recursively

    return tree
```

In [12]:
```
dtree = buildTree(df)
dtree
```

```
Class:  Buys  E(S):  0.5305095811322292
Class:  Buys  E(S):  0.9402859586706311
Class:  Buys  E(T,X):  -0.34676806944809574
Class:  Buys  E(T,X):  -0.34676806944809563
Class:  Buys  E(T,X):  -0.6935361388961914
0
Class:  Buys  E(S):  0.5305095811322292
Class:  Buys  E(S):  0.9402859586706311
Class:  Buys  E(T,X):  -0.28571428571428553
Class:  Buys  E(T,X):  -0.6792696431662093
Class:  Buys  E(T,X):  -0.9110633930116756
0
Class:  Buys  E(S):  0.5305095811322292
Class:  Buys  E(S):  0.9402859586706311
Class:  Buys  E(T,X):  -0.49261406801712543
Class:  Buys  E(T,X):  -0.7884504573082889
0
Class:  Buys  E(S):  0.5305095811322292
Class:  Buys  E(S):  0.9402859586706311
Class:  Buys  E(T,X):  -0.43156028428331517
Class:  Buys  E(T,X):  -0.9241743523004406
0
node with max info gain:  Age
distinct values found:  [0 1 2]
subtable:     Age  Income  Gender  Marital Status  Buys
0    0       0       1               1     1
1    0       1       0               0     1
2    0       2       1               0     1
3    0       0       0               1     1
clValue:  [1]
counts:  [4]
subtable:     Age  Income  Gender  Marital Status  Buys
0    1       0       1               1     0
1    1       0       1               0     0
2    1       2       1               1     0
3    1       1       0               0     1
4    1       2       0               0     1
clValue:  [0 1]
counts:  [3 2]
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
```

```
Class:  Buys  E(T,X):  -0.970950594454668
0
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  1.281370601525967e-16
Class:  Buys  E(T,X):  -0.39999999999999963
Class:  Buys  E(T,X):  -0.39999999999999963
1
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  1.9220559022889502e-16
Class:  Buys  E(T,X):  3.203426503814917e-16
2
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  1.281370601525967e-16
Class:  Buys  E(T,X):  -0.5509775004326932
2
node with max info gain:  Gender
distinct values found:  [0 1]
subtable:     Age  Income  Gender  Marital Status  Buys
0    1       1       0               0     1
1    1       2       0               0     1
clValue:  [1]
counts:  [2]
subtable:     Age  Income  Gender  Marital Status  Buys
0    1       0       1               1     0
1    1       0       1               0     0
2    1       2       1               1     0
clValue:  [0]
counts:  [3]
subtable:     Age  Income  Gender  Marital Status  Buys
0    2       2       1               1     1
1    2       1       0               1     1
2    2       1       0               0     0
3    2       2       0               1     1
4    2       2       1               0     0
clValue:  [0 1]
counts:  [2 3]
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  -0.970950594454668
0
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  -0.5509775004326933
Class:  Buys  E(T,X):  -0.950977500432693
1
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  -0.39999999999999974
Class:  Buys  E(T,X):  -0.950977500432693
1
Class:  Buys  E(S):  0.44217935649972373
Class:  Buys  E(S):  0.9709505944546686
Class:  Buys  E(T,X):  1.9220559022889502e-16
Class:  Buys  E(T,X):  3.203426503814917e-16
3
node with max info gain:  Marital Status
distinct values found:  [0 1]
subtable:     Age  Income  Gender  Marital Status  Buys
0    2       1       0               0     0
1    2       2       1               0     0
clValue:  [0]
counts:  [2]
subtable:     Age  Income  Gender  Marital Status  Buys
0    2       2       1               1     1
1    2       1       0               1     1
2    2       2       0               1     1
clValue:  [1]
counts:  [3]
```

Out[12]:
```
{'Age': {0: 1,
  1: {'Gender': {0: 1, 1: 0}},
  2: {'Marital Status': {0: 0, 1: 1}}}}
```

In [13]:
```python
def predict(inst,tree):
    #Recursively we going through the tree that built earlier
    for nodes in tree.keys():
        value = inst[nodes]
        tree = tree[nodes][value]
        prediction = 0

        if type(tree) is dict:
            prediction = predict(inst, tree)
        else:
            prediction = tree
            break;

    return prediction
```

In [14]:
```python
tester = test.iloc[0]
Prediction = predict(tester,dtree)
```

In [15]:
```python
Prediction
```

Out[15]:
```
1
```

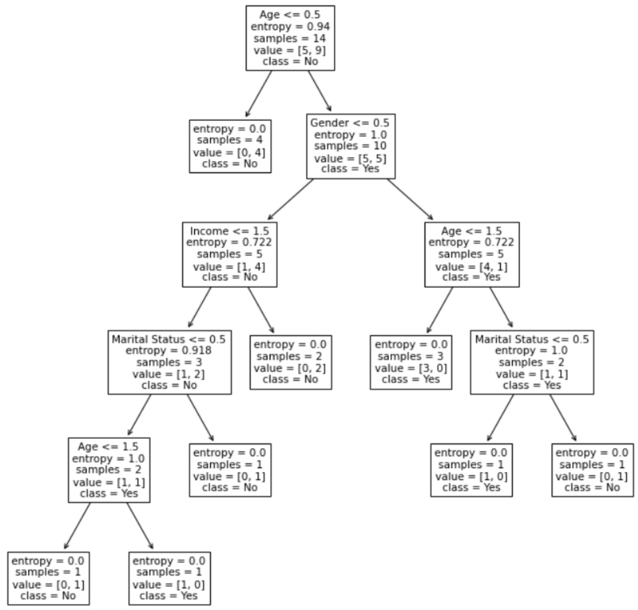
In [16]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.tree import plot_tree
sklearn_dtree=DecisionTreeClassifier(criterion="entropy")
```

In [17]:
```python
df1 = df.copy()
df1.drop('Buys', axis=1, inplace=True)
X=df1
```

In [18]:
```python
sklearn_dtree.fit(X, df['Buys'])
sklearn_dtree.predict(test)
```

Out[18]:
```
array([1])
```

In [19]:
```python
import matplotlib.pyplot as plt
plt.figure(figsize=(12,12))
dec_tree = plot_tree(decision_tree=sklearn_dtree, feature_names = df.columns, class_names =["Yes", "No"])
plt.show()
```



In [20]:
```
dtree
```

Out[20]:
```
{'Age': {0: 1,
  1: {'Gender': {0: 1, 1: 0}},
  2: {'Marital Status': {0: 0, 1: 1}}}}
```

In [ ]: