In [2]:

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import pandas as pd
import math

df = pd.read_csv('PlayTennis.csv')
print("\n Input Data Set is:\n", df)

t = df.keys()[-1]
print('Target Attribute is: ', t)
# Get the attribute names from input dataset
attribute_names = list(df.keys())
#Remove the target attribute from the attribute names list
attribute_names.remove(t)
print('Predicting Attributes: ', attribute_names)

#Function to calculate the entropy of collection S

def entropy(probs):
    return sum( [-prob*math.log(prob, 2) for prob in probs])

#Function to calulate the entropy of the given Data Sets/List with
#respect to target attributes
def entropy_of_list(ls,value):
    from collections import Counter
    cnt = Counter(x for x in ls)# Counter calculates the propotion of class
    #print('Target attribute class count(Yes/No)=',dict(cnt))
    total_instances = len(ls)
    #print("Total no of instances/records associated with {0} is:
{1}".format(value,total_instances ))
    probs = [x / total_instances for x in cnt.values()]  # x means no of YES/NO
    #print("Probability of Class {0} is: {1:.4f}".format(min(cnt),min(probs)))
    #print("Probability of Class {0} is: {1:.4f}".format(max(cnt),max(probs)))
    return entropy(probs) # Call Entropy

def information_gain(df, split_attribute, target_attribute,battr):
    #print("\n\n-----Information Gain Calculation of ",split_attribute, " --------")
    df_split = df.groupby(split_attribute) # group the data based on attribute values
    glist=[]
    for gname,group in df_split:
        #print('Grouped Attribute Values \n',group)
        glist.append(gname)

    glist.reverse()
    nobs = len(df.index) * 1.0
    df_agg1=df_split.agg({target_attribute:lambda x:entropy_of_list(x, glist.pop())})
    df_agg2=df_split.agg({target_attribute :lambda x:len(x)/nobs})

    df_agg1.columns=['Entropy']
    df_agg2.columns=['Proportion']

    # Calculate Information Gain:
    new_entropy = sum( df_agg1['Entropy'] * df_agg2['Proportion'])
    if battr !='S':
        old_entropy = entropy_of_list(df[target_attribute],'S-'+df.iloc[0][df.columns.get_loc(battr
)])
    else:
        old_entropy = entropy_of_list(df[target_attribute],battr)
    return old_entropy - new_entropy

def id3(df, target_attribute, attribute_names, default_class=None,default_attr='S'):

    from collections import Counter
    cnt = Counter(x for x in df[target_attribute])# class of YES /NO

    ## First check: Is this split of the dataset homogeneous?
    if len(cnt) == 1:
        return next(iter(cnt))  # next input data set, or raises StopIteration when EOF is hit.

    ## Second check: Is this split of the dataset empty? if yes, return a default value
    elif df.empty or (not attribute_names):
        return default_class  # Return None for Empty Data Set

    ## Otherwise: This dataset is ready to be devied up!
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    else:
        # Get Default Value for next recursive call of this function:
        default_class = max(cnt.keys()) #No of YES and NO Class
        # Compute the Information Gain of the attributes:
        gainz=[]
        for attr in attribute_names:
            ig= information_gain(df, attr, target_attribute,default_attr)
            gainz.append(ig)
            #print('Information gain of ',attr,' is : ',ig)

        index_of_max = gainz.index(max(gainz))               # Index of Best Attribute
        best_attr = attribute_names[index_of_max]            # Choose Best Attribute to split on
        #print("\nAttribute with the maximum gain is: ", best_attr)
        # Create an empty tree, to be populated in a moment
        tree = {best_attr:{}} # Initiate the tree with best attribute as a node
        remaining_attribute_names =[i for i in attribute_names if i != best_attr]

        # Split dataset-On each split, recursively call this algorithm.Populate the empty tree
with subtrees, which
        # are the result of the recursive call
        for attr_val, data_subset in df.groupby(best_attr):
            subtree = id3(data_subset,target_attribute, remaining_attribute_names,default_class,bes
t_attr)
            tree[best_attr][attr_val] = subtree
        return tree

    from pprint import pprint
tree = id3(df,t,attribute_names)
print("\nThe Resultant Decision Tree is:")
print(tree)

def classify(instance, tree,default=None): # Instance of Play Tennis with Predicted
    attribute = next(iter(tree)) # Outlook/Humidity/Wind
    if instance[attribute] in tree[attribute].keys(): # Value of the attributs in  set of Tree
keys
        result = tree[attribute][instance[attribute]]
        if isinstance(result, dict): # this is a tree, delve deeper
            return classify(instance, result)
        else:
            return result # this is a label
    else:
        return default

df_new=pd.read_csv('PlayTennisTest.csv')
df_new['predicted'] = df_new.apply(classify, axis=1, args=(tree,'?'))
print(df_new)


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 Input Data Set is:
      Outlook Temperature Humidity    Wind PlayTennis
0       Sunny         Hot     High    Weak         No
1       Sunny         Hot     High  Strong         No
2    Overcast         Hot     High    Weak        Yes
3        Rain        Mild     High    Weak        Yes
4        Rain        Cool   Normal    Weak        Yes
5        Rain        Cool   Normal  Strong         No
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6   Overcast        Cool   Normal  Strong        Yes
7      Sunny        Mild     High    Weak         No
8      Sunny        Cool   Normal    Weak        Yes
9       Rain        Mild   Normal    Weak        Yes
10     Sunny        Mild   Normal  Strong        Yes
11  Overcast        Mild     High  Strong        Yes
12  Overcast         Hot   Normal    Weak        Yes
13      Rain        Mild     High  Strong         No
Target Attribute is:  PlayTennis
Predicting Attributes:  ['Outlook', 'Temperature', 'Humidity', 'Wind']

The Resultant Decision Tree is:
{'Outlook': {'Overcast': 'Yes', 'Rain': {'Wind': {'Strong': 'No', 'Weak': 'Yes'}}, 'Sunny':
{'Humidity': {'High': 'No', 'Normal': 'Yes'}}}}
  Outlook Temperature Humidity  Wind PlayTennis predicted
0   Sunny         Hot     High  Weak          ?        No
1    Rain        Mild     High  Weak          ?       Yes
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