

\* Write a program to demonstrate the working of the decision tree based IO3 algorithms. Use an appropriate dataset for building the decision tree & apply this knowledge to classify new scope.

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import pandas as pd
from pandas import DataFrame
df_tennis = pd.read_csv('C:/User/Mili/OneDrive/Desktop/Mili/4MT17CS058_Mili/PlayTennis.csv')
attribute_name = list(df_tennis.columns)
attribute_name.remove('Play Tennis')
print(attribute_name)

def entropy_of_list(lst):
    from collections import Counter
    count = Counter(x for x in lst)
    num_instances = len(lst) * 1
    probs = [x / num_instances for x in count.values()]
    return entropy(probs)

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

total_entropy = entropy_of_list(df_tennis['Play Tennis'])
```

Teacher's Signature \_\_\_\_\_

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def information_gain(df, split_attribute_name, target_attribute_name,
                    trace=0):
    df_split = df.groupby(split_attribute_name)
    nobs = len(df.index) * 1
    df_agg_ent = df_split.agg({target_attribute_name:
                               [entropy_of_list, lambda x: len(x)/nobs]})
    df_agg_ent.columns = ['Entropy', 'proportions']
    new_entropy = sum(df_agg_ent['Entropy'] * df_agg_ent
                      ['proportions'])
    old_entropy = entropy_of_list(df[target_attribute_name])
    print(split_attribute_name, 'IG', old_entropy - new_entropy)
    return old_entropy - new_entropy

```

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def id3(df, target_attribute_name, attribute_name, default_class=None):
    from collections import Counter
    count = Counter(x for x in df[target_attribute_name])
    if len(count) == 1:
        return next(iter(count))
    elif df.empty or (not attribute_name):
        return default_class
    else:
        default_class = max(count.keys())
        gain = [information_gain(df, attr, target_attribute_name) for
                attr in attribute_name]
        index_of_max = gain.index(max(gain))
        best_attr = attribute_name[index_of_max]
        tree = {best_attr: {}}

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remaining attribute-names = [i for i is attribute-name if  
i != best-attr]

for attr\_val, data\_subset in df.groupby(best-attr):

subtree = id3(data\_subset, target\_attribute\_name, remaining\_  
attribute\_name, default\_class)

tree[best-attr][attr\_val] = subtree

return tree

from pprint import pprint

tree = id3(df\_tennis, 'Play Tennis', attribute\_name)

print("\n The Resultant Decision Tree is : \n")

pprint(tree)

Teacher's Signature \_\_\_\_\_

output

['outlook', 'Temperature', 'Humidity', 'wind']

outlook IG : 0.2467498 197744391

Temperature IG = 0.0299222565658954647

Humidity IG: 0.15183550136234136

wind IG: 0.09812703040826927

Temperature IG: 0.01997309402197489

Humidity: 0.01997309402197489

wind IG: 0.01997309402197489

The Resultant Decision tree is:

{ 'outlook' : { 'overcast' : 'yes',

'Rain' : { 'wind' : { 'strongly' : 'No', 'weak' : 'yes' } },

'Sunny' : { 'Humidity' : { 'High' : 'No', 'Normal' : 'yes' } } ] }