Sipna College of Engineering & Technology, Amravati.
Department of Computer Science & Engineering
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Branch :- Computer Sci. & Engg. **Class :- Final Year**
Subject :-Artificial Intelligence and Machine Learning **Sem :- VIII**

Teacher Manual

PRACTICAL NO 7

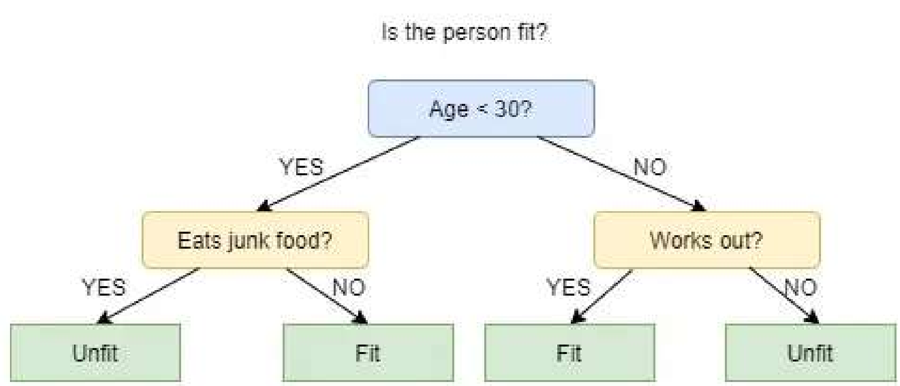
AIM: To Understand and implement the concept of decision tree using ID3 Algorithm

S/W REQUIRED: Python
DATA SET USED: `3-dataset.csv`

What are Decision Trees?

In simple words, a decision tree is a structure that contains nodes (rectangular boxes) and edges(arrows) and is built from a dataset (table of columns representing features/attributes and rows corresponds to records). Each node is either used to make a decision (known as decision node) or represent an outcome (known as leaf node).

Decision tree Example



ID3

ID3 stands for Iterative Dichotomiser 3 and is named such because the algorithm iteratively (repeatedly) dichotomizes(divides) features into two or more groups at each step.

Invented by Ross Quinlan, ID3 uses a top-down greedy approach to build a decision tree. In simple words, the top-down approach means that we start building the tree from the top and the greedy approach means that at each iteration we select the best feature at the present moment to create a node.

Most generally ID3 is only used for classification problems with nominal features only.

Decision tree using ID3 Step by Step Explanation

ID3(Examples, Target_attribute, Attributes)

Examples are the training examples.

Target_attribute is the attribute whose value is to be predicted by the tree.
Attributes is a list of other attributes that may be tested by the learned decision tree.
Returns a decision tree that correctly classifies the given Examples.

Create a Root node for the tree
If all Examples are positive, Return the single-node tree Root, with label = +
If all Examples are negative, Return the single-node tree Root, with label = -
If Attributes is empty, Return the single-node tree Root,
with label = most common value of Target_attribute in Examples

Otherwise Begin
  A ← the attribute from Attributes that best* classifies Examples
  The decision attribute for Root ← A
  For each possible value, vi, of A,
    Add a new tree branch below Root, corresponding to the test A = vi
    Let Examples vi, be the subset of Examples that have value vi for A
    If Examples vi , is empty
      Then below this new branch add a leaf node with
      label = most common value of Target_attribute in Examples
    Else
      below this new branch add the subtree
      ID3(Examples vi, Targe_tattribute, Attributes – {A}))
End
Return Root

Implementation:

```
#decision tree using ID3
import pandas as pd
import math
import numpy as np

data = pd.read_csv("/content/sample_data/3-dataset.csv")
features = [feat for feat in data]
features.remove("answer")

#Create a class named Node with four members children, value, isLeaf and pred.
class Node:
    def __init__(self):
        self.children = []
        self.value = ""
        self.isLeaf = False
        self.pred = ""

#Define a function called entropy to find the entropy oof the dataset.

def entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
```

```
            pos += 1
        else:
            neg += 1
    if pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))

#Define a function named ID3 to get the decision tree for the given dataset
def ID3(examples, attrs):
    root = Node()

    max_gain = 0
    max_feat = ""
    for feature in attrs:
        #print ("\n",examples)
        gain = info_gain(examples, feature)
        if gain > max_gain:
            max_gain = gain
            max_feat = feature
    root.value = max_feat
    #print ("\nMax feature attr",max_feat)
    uniq = np.unique(examples[max_feat])
    #print ("\n",uniq)
    for u in uniq:
        #print ("\n",u)
        subdata = examples[examples[max_feat] == u]
        #print ("\n",subdata)
        if entropy(subdata) == 0.0:
            newNode = Node()
            newNode.isLeaf = True
            newNode.value = u
            newNode.pred = np.unique(subdata["answer"])
            root.children.append(newNode)
        else:
            dummyNode = Node()
            dummyNode.value = u
            new_attrs = attrs.copy()
            new_attrs.remove(max_feat)
            child = ID3(subdata, new_attrs)
            dummyNode.children.append(child)
            root.children.append(dummyNode)

    return root

#Define a function named printTree to draw the decision tree
def printTree(root: Node, depth=0):
    for i in range(depth):
        print("\t", end="")
```

```
    print(root.value, end="")
    if root.isLeaf:
        print(" -> ", root.pred)
    print()
    for child in root.children:
        printTree(child, depth + 1)

#Define a function named classify to classify the new example

def classify(root: Node, new):
    for child in root.children:
        if child.value == new[root.value]:
            if child.isLeaf:
                print ("Predicted Label for new example", new," is:", child.pred)
                exit
            else:
                classify (child.children[0], new)

#Define a function named info_gain to find the gain of the attribute
def info_gain(examples, attr):
    uniq = np.unique(examples[attr])
    #print ("\n",uniq)
    gain = entropy(examples)
    #print ("\n",gain)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        #print ("\n",subdata)
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
        #print ("\n",gain)
    return gain

#Finally, call the ID3, printTree and classify functions
root = ID3(data, features)
print("Decision Tree is:")
printTree(root)
print ("------------------")

new = {"outlook":"sunny", "temperature":"hot", "humidity":"normal", "wind":"strong"
}
classify (root, new)
```

Output

```
Decision Tree is:
outlook
        overcast ->  ['yes']

        rain
                wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                humidity
                        high ->  ['no']

                        normal ->  ['yes']

------------------
Predicted Label for new example {'outlook': 'sunny', 'temperature': 'hot', 'humidity': 'normal', 'wind': 'strong'}  is: ['yes']
```

CONCLUSION: Thus we have implemented the concept of decision tree using ID3 Algorithm