Decision Tree Homework

Decision Tree Analysis

Given Data:

Instance	Meat	Crust	Veg	Quality
1	Υ	Thin	N	Great
2	N	Deep	N	Bad
3	N	Stuffed	Y	Good
4	Υ	Stuffed	Y	Great
5	Υ	Deep	N	Good
6	Υ	Deep	Y	Great
7	N	Thin	Y	Good
8	Υ	Deep	N	Good
9	N	Thin	N	Bad

Calculating Entropy at the Root Node:

Step 1: Compute Info(S)

We have three classes: Bad (B), Good (G), Great (Gr).

Count of each class in the dataset:

Bad: 2

Good: 4

Great: 3

Total instances: 9

Compute probabilities:

$$ullet \ p_{
m Bad}=rac{2}{9}$$

$$ullet \ p_{
m Good} = rac{4}{9}$$

•
$$p_{ ext{Great}} = rac{3}{9}$$

Compute entropy:

$$egin{aligned} Info(S) &= -\left(p_{ ext{Bad}} \log_2 p_{ ext{Bad}} + p_{ ext{Good}} \log_2 p_{ ext{Good}} + p_{ ext{Great}} \log_2 p_{ ext{Great}}
ight) \ &= -\left(rac{2}{9} \log_2 rac{2}{9} + rac{4}{9} \log_2 rac{4}{9} + rac{3}{9} \log_2 rac{3}{9}
ight) \ &pprox - \left(0.2222 imes (-2.1699) + 0.4444 imes (-1.1699) + 0.3333 imes (-1.5849)
ight) \ &pprox 1.529 \end{aligned}$$

Calculating Information Gain for Each Attribute:

Attribute: Meat

Possible values: Y, N

Splitting Data by Meat:

• **Meat = Y** (Instances: 1, 4, 5, 6, 8)

Class counts: Good = 2, Great = 3

• Meat = N (Instances: 2, 3, 7, 9)

• Class counts: Bad = 2, Good = 2

Entropy for Each Subset:

ullet $Info(S_{
m Meat=Y})$

$$Info(S_{ ext{Meat}= ext{Y}}) = -\left(0 imes \log_2 0 + rac{2}{5} \log_2 rac{2}{5} + rac{3}{5} \log_2 rac{3}{5}
ight) \ = -\left(0 + 0.4 imes (-1.3219) + 0.6 imes (-0.7369)
ight) \ pprox 0.971$$

ullet $Info(S_{
m Meat=N})$

$$egin{split} Info(S_{
m Meat=N}) &= -\left(rac{2}{4}{
m log_2}rac{2}{4} + rac{2}{4}{
m log_2}rac{2}{4} + 0 imes{
m log_2}\,0
ight) \ &= -\left(0.5 imes(-1) + 0.5 imes(-1) + 0
ight) \ &= 1.0 \end{split}$$

Weighted Entropy After Split:

$$Info_{
m Meat}(S) = rac{5}{9} imes 0.971 + rac{4}{9} imes 1.0 pprox 0.984$$

Information Gain:

$$Gain(S, \mathrm{Meat}) = Info(S) - Info_{\mathrm{Meat}}(S) \approx 1.529 - 0.984 = 0.545$$

Attribute: Crust

Possible values: Thin, Deep, Stuffed

[Detailed calculations omitted for brevity]

Information Gain:

$$Gain(S, \text{Crust}) \approx 0.112$$

Attribute: Veg

Possible values: Y, N

[Detailed calculations omitted for brevity]

Information Gain:

$$Gain(S, \mathrm{Veg}) pprox 0.239$$

Best Attribute at Root Node:

Meat has the highest information gain.

Splitting on Meat:

Root Node: Split on Meat (Y/N)

Second Level - Leftmost Node (Meat = Y):

Remaining Attributes: Crust, Veg

Entropy at Node $S_{\mathrm{Meat}=Y}$:

$$Info(S_{
m Meat=Y}) pprox 0.971$$

Calculating Information Gain for Remaining Attributes:

Attribute: Crust

Possible values: Thin, Deep, Stuffed

Splitting Data by Crust:

• Crust = Thin (Instance: 1)

· Class: Great

Crust = Deep (Instances: 5, 6, 8)

Class counts: Good = 2, Great = 1

Crust = Stuffed (Instance: 4)

Class: Great

Entropy for Each Subset:

• $Info(S_{
m Crust=Thin})=0$ (Pure node)

• $Info(S_{\text{Crust}=\text{Deep}})$

$$Info(S_{ ext{Crust=Deep}}) = -\left(rac{2}{3} ext{log}_2\,rac{2}{3} + rac{1}{3} ext{log}_2\,rac{1}{3}
ight) \ pprox 0.918$$

• $Info(S_{ ext{Crust}= ext{Stuffed}})=0$ (Pure node)

Weighted Entropy After Split:

$$Info_{ ext{Crust}}(S_{ ext{Meat}= ext{Y}}) = rac{1}{5} imes 0 + rac{3}{5} imes 0.918 + rac{1}{5} imes 0 pprox 0.551$$

Information Gain:

$$Gain(S_{\mathrm{Meat=Y}}, \mathrm{Crust}) = Info(S_{\mathrm{Meat=Y}}) - Info_{\mathrm{Crust}}(S_{\mathrm{Meat=Y}}) pprox 0.971 - 0.551 = 0.420$$

Attribute: Veg

Information Gain:

$$Gain(S_{
m Meat=Y}, {
m Veg}) pprox 0.420$$

Best Attribute at This Node:

Crust (Alphabetically first among attributes with equal gain)

Splitting on Crust at Meat = Y Node:

- Crust = Thin: Leaf node labeled Great
- Crust = Stuffed: Leaf node labeled Great
- Crust = Deep: Leaf node labeled Good (Majority class)

Final Decision Tree (Up to Second Level):

- 1. Root Node: Meat
 - Meat = Y:
 - Split on Crust
 - Crust = Deep: Good
 - Crust = Stuffed: Great
 - Crust = Thin: Great
 - Meat = N:
 - [Further splitting can be done for practice]

Leaf Node Labels:

Nodes are labeled with their majority class if not pure.