Answer

Samples: [34, 21, 56, 76, 98]

new range [10, 20]

Equation for min-max normalization is

$$v' = \frac{v - min}{max - min}[newmax - newmin] + newmin$$

Here, $min = 21$, $max = 98$.
$newmax = 20$, $newmin = 10$

for $v = 34$

$$v' = \frac{34-21}{98-21}(20-10) + 10 = \frac{13}{77}(10) + 10$$
$$= 1.69 + 10 = 11.69$$

for $v = 21$

$$v' = \frac{21-21}{98-21}(20-10) + 10 = 0 + 10 = 10$$

for $v = 56$

$$v' = \frac{56-21}{98-21}(20-10) + 10 = \frac{35}{77}(10) + 10$$
$$= 4.55 + 10 = 14.55$$

for $v = 76$

$$v' = \frac{76-21}{98-21}(20-10) + 10 = 7.14 + 10 = 17.14$$

for $v = 98$ $\quad v' = \frac{98-21}{98-21}(20-10) + 10 = 10 + 10 = 20$

(Ans)

Answer

Item	frequency
CSI 123	4
CSI 221	2
CSI 231	2
CSE 213	1
CSI 223	1
CSI 483	1

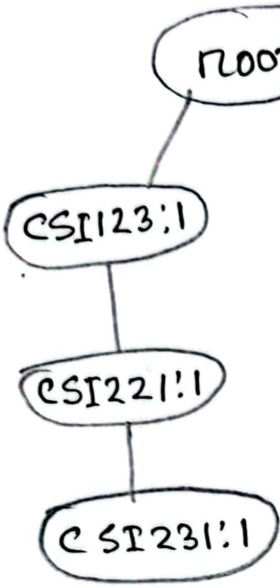
frequency pattern set

$L = \{(CSI\ 123 : 4), (CSI\ 221 : 2), (CSI\ 231 : 2)\}$

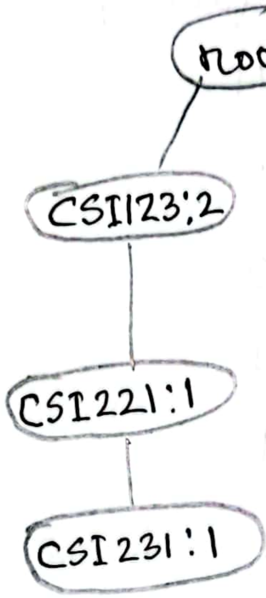
ID	(ordered) frequent Items
1	CSI123, CSI221, CSI231
2	CSI123
3	CSI123, CSI221, CSI231
4	CSI123

Now, creating frequent pattern tree:

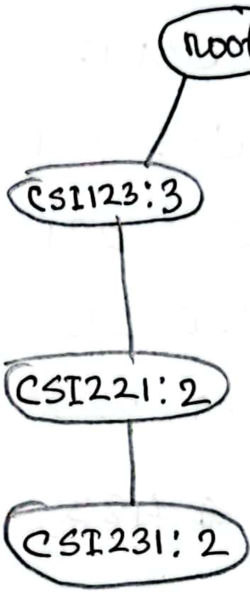
ID=1



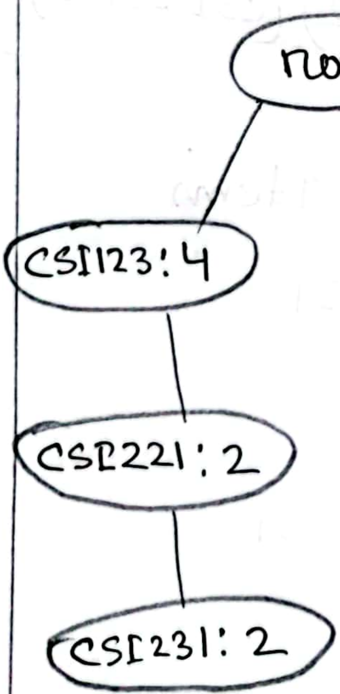
ID=2



ID=3



ID=4



Now, from the tree, we will be generating Conditional pattern base, Conditional FP tree, and frequent patterns.

Courses	Conditional Pattern base	Conditional FP tree	frequent pattern generated
CSI 231	{CSI123, CSI221 : 2}	{CSI123, CSI221 : 2}	{CSI123, CSI221, CSI 231 : 2}
CSI221	{CSI 123 : 2}	{CSI 123 : 2}	{<CSI123, CSI221 : 2>}
CSI123	ϕ	ϕ	{ }

Now given that confidence = 60%,

$$\text{equation} = \frac{(X \cup Y)\ \text{count}}{X\ \text{count}}$$

Generating rules for {<CSI 123, CSI 221, CSI 231 : 2>} and {<CSI 123, CSI 221 : 2>}

Rule	Support	Confidence	Confidence
{CSI 123, CSI 221} → {CSI 231}	2	2/2 = 1	100% ≥ 60%
{CSI123, CSI 231} → {CSI 221}	2	2/2 = 1	100% > 60%
{CSI 221, CSI 231} → {CSI 123}	2	2/2 = 1	100% > 60%
{CSI 231} → {CSI123, CSI 221}	2	2/2 = 1	100% > 60%
{CSI 221} → {CSI123, CSI 231}	2	2/2 = 1	100% > 60%
{CSI123} → {CSI 221, CSI 231}	2	2/4 = 0.5	50% < 60%
{CSI123} → {CSI221}	2	2/4 = 0.5	50% < 60%
{CSI 221} → {CSI123}	2	2/2 = 1	100 > 60%

so, we found the following Rule:

$\{CSI\,123, CSI\,221\} \rightarrow \{CSI\,231\}$

$\{CSI\,123, CSI\,231\} \rightarrow \{CSI\,221\}$

$\{CSI\,221, CSI\,231\} \rightarrow \{CSI\,123\}$

$\{CSI\,231\} \rightarrow \{CSI\,123, CSI\,221\}$

$\{CSI\,221\} \rightarrow \{CSI\,123, CSI\,231\}$

$\{CSI\,221\} \rightarrow \{CSI\,123\}$

Answer

<u>figure - A</u>: Under-fiting (too simple to explain the variance)

<u>figure - B</u>: Appropriate fitting

<u>figure - C</u>: Over-fiting (force fiting to good to be tune).

Answer

The ways to avoid over fiting in decision trees are:

I) Prepruning: Halt tree construction early, do not split a node if this would result in the goodness measure falling below a threshold.

→ Difficult to choose an appropriate threshold.

II) Postpruning: Remove branches from "a fully grown" tree; get a sequence of progressively pruned trees.

→ Use a set of data different from the training data to decide which is the "best pruned tree"

Answer

Here we assume city names as

Florence ⇒ a, Milan → b, Bologna → c

Naples → d, Rome → e, Trento → f

As it is a distance matrix, we will only consider upper right diagonal values for our math.

Dist	a	b	c	d	e	f
a	0	316	120	473	274	474
b		0	213	770	571	771
c			0	572	375	575
d				0	223	23
e					0	226
f						0

Here d_{df} distance is minimal (23)

$d_{df} \to a = \min(d_{da}, d_{fa}) = \min(473, 474) = 473$

$d_{df} \to b = \min(d_{db}, d_{fb}) = \min(770, 771) = 770$

$d_{df} \to c = \min(d_{dc}, d_{fc}) = \min(572, 575) = 572$

$d_{df} \to e = \min(d_{de}, d_{fe}) = \min(223, 226) = 223$

Dist	a	b	c	df	e
a	0	316	120	473	274
b		0	213	770	571
c			0	572	375
df				0	223
e					0

Now, dac distance is minimal 120

$d_{ac} \to b = \min(d_{ab}, d_{cb}) = \min(316, 213) = 213$

$d_{ac} \to e = \min(d_{ae}, d_{ce}) = \min(274, 375) = 274$

$d_{ac} \to df = \min(d_{ad}, d_{af}, d_{cd}, d_{cf})$

$= \min(473, 474, 572, 575) = 473$

Dist	b	e	df	ac
b	0	571	770	213
e		0	223	274
df			0	473
ac				0

Now, d_{ac} is minimum distance 213

$d_{bac} \to e = \min(d_{be}, d_{ae}, d_{ce})$

$= \min(571, 274, 375) = 274$

$d_{bac} \to df = \min(d_{bd}, d_{bf}, d_{ad}, d_{af}, d_{cd}, d_{ef})$

$= \min(770, 771, 473, 474, 572, 575)$

$= 473$

Dist	e	df	bac
e	0	223	274
df		0	473
bac			0

Now, d_{df} is minimum distance 223

$d_{dfe} \to bac = \min(d_{db}, d_{da}, d_{fb}, d_{fa}, d_{fc}, d_{be}, d_{ea}, d_{ec})$

$= \min(770, 473, 572, 771, 474, 577, 571, 274, 375) = 274$

Distance	bac	dfe
bac	0	274
dfe		0

Answer

True positive (TP) = 4
True Negative (TN) = 3
False positive (FP) = 1
False Negative (FN) = 2

Confusion matrix:

		Actual Level 1	Actual Level 0
Predicted Level	1	TP (4)	FP (1)
	0	FN (2)	TN (3)

$$\text{Accuracy} = \frac{TN + TP}{TN+FP+TP+FN} = \frac{3+4}{3+1+4+2} = \frac{7}{10}$$

$$= 0.7$$

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{4}{4+1} = \frac{4}{5} = 0.8$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{4}{4+2} = \frac{4}{6} = 0.67$$

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$= 2 * \frac{0.8 * 0.67}{0.8 + 0.67}$$

$$= 0.73$$

Answer

Calculating Entropy using ID3 algorithm

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

Species	
G	O
5	5

Entropy (species)

$$= -\frac{5}{10}\log_2\left(\frac{5}{10}\right) - \frac{5}{10}\left(\log_2 \frac{5}{10}\right)$$

$$= -(0.5)(-1) - (0.5)(-1) = 1$$

Engines	Species		Number of Instances
	G	O	
3	2	4	6
4	3	1	4

$$\text{Entropy (Engine, 3)} = \frac{-2}{6}\log(2/6) - \frac{4}{6}\log_2(4/6)$$

$$= (-0.33)(-1.6) - (0.67)(-0.58)$$

$$= 0.53 + 0.39 = 0.92$$

$$\text{Entropy (Engine, 4)} = -\frac{3}{4}\log_2(3/4) - \frac{1}{4}\log_2\frac{1}{4}$$

$$= -0.75(-0.42) - (0.25)(-2)$$

$$= 0.32 + 0.5 = 0.82$$

$$\text{Entropy (Species, Engine)} = \cancel{E\text{Species}}$$

$$= P(3)\,E(2,4) + P(4)\,E(3,1)$$

$$= 6/10\,(0.92) + \cancel{6}\ 4/10\,(0.82)$$

$= 0.552 + 0.33 = 0.88$

Information Gain = (species, Engine)

$= E(\text{species}) - E(\text{species, engine})$

$= 1 - 0.88 = 0.12$

Tanks	Species		Number of Instances
	G	O	
2	2	5	7
3	3	0	3

$\text{Entropy}(\text{Tanks}, 2) = \frac{-2}{7}\log_2\left(\frac{2}{7}\right) - \frac{5}{7}\log_2\left(\frac{5}{7}\right)$

$= -(0.29)(-1.79) - (0.71)(-0.49)$

$= 0.52 + 0.35 = 0.87$

$\text{Entropy}(\text{Tanks}, 3) = -\frac{3}{3}\log_2\left(\frac{3}{3}\right) - 0$

$= -1(0) = 0$

$\text{Entropy}(\text{species, Tanks}) = P(2)\ \text{Entropy}(2,5) + P(3)\ E(3,0)$

$= \frac{7}{10}(0.87) + \frac{3}{10} \times 0$

$= 0.61$

Information gain = (species, Tanks)

$= E(\text{species}) - E(\text{species, Tanks})$

$= 1 - 0.61 = 0.39$

Height	Species		Number of Instances
	G	O	
S	2	2	4
M	3	3	6

$$\text{Entropy}(\text{Height}, S) = -\frac{2}{4}\log_2\left(\frac{2}{4}\right) - \frac{2}{4}\log_2\frac{2}{4}$$

$$= -(0.5)(-1) - (0.5)(-1)$$

$$= 0.5 + 0.5 = 1$$

$$\text{Entropy}(\text{Height}, M) = -\frac{3}{6}\log_2\left(\frac{3}{6}\right) - \frac{3}{6}\log_2\frac{3}{6}$$

$$= -(0.5)(-1) - (0.5)(-1)$$

$$= 0.5 + 0.5 = 1$$

$$\text{Entropy}(\text{species}, \text{Height}) = P(S)\,\text{Entropy}(2,2) + P(M)\,\text{Entropy}(3,3)$$

$$= \frac{4}{10}(1) + \frac{6}{10}(1)$$

$$= 0.4 + 0.6 = 1$$

Information gain = (species, Height)

$$= E(\text{Species}) - E(\text{Species}, \text{Height})$$

$$= 1 - 1 = 0$$

Smell	Species		Number of Instances
	G	O	
7	2	2	4
5	3	3	6

$$\text{Entropy}(\text{Smell},7) = -\frac{2}{4}\log_2\left(\frac{2}{4}\right) - \frac{2}{4}\log_2\left(\frac{2}{4}\right)$$
$$= -(0.5)(-1) - (0.5) - 1$$
$$= 0.5 + 0.5 = 1$$

$$\text{Entropy}(\text{Smell},5) = -\frac{3}{6}\log_2\left(\frac{3}{6}\right) - \frac{3}{6}\log_2\left(\frac{3}{6}\right)$$
$$= -(0.5)(-1) - (0.5)(-1)$$
$$= 0.5 + 0.5 = 1$$

Entropy(Species, smell)

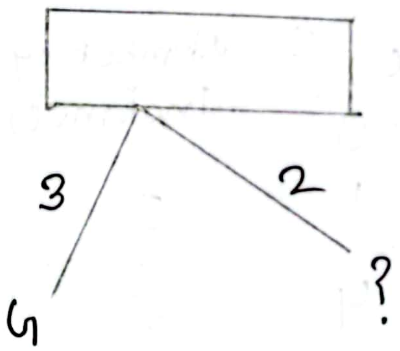
$$= P(7)\,E(2,2) + P(5)\,E(3,3)$$
$$= \frac{4}{10}(1) + \frac{6}{10}(1)$$
$$= 0.4 + 0.6 = 1$$

Information gain = (Species, smell)

$$= E(\text{Species}) - E(\text{Species, smell})$$
$$= 1 - 1 = 0$$

Feature	Information Gain
Engines	0.12
Tanks	0.39
Height	0
Smell	0

Tanks feature produce highest score, so Tanks will be ~~con~~ considered as the root node



Our condition is max-depth = 1, So, we need to check attributes for Tanks = 2, But for Tanks = 3, we see that all the values of species are G, this have reached a decision.

We will apply same principle to these sub dataset in the following steps. Focus of the sub dataset for Tanks = 2

Species	Engines	Tanks	Height	Smell
G	4	2	M	5
G	3	2	S	7
O	3	2	M	7
O	3	2	S	5
O	3	2	M	5
O	4	2	S	5
O	3	2	M	7

Engine	Species		Number of Instances
	G	O	
4	1	1	2
3	1	4	5

$$\text{Entropy}(\text{Tanks } 2 \mid \text{Engine } 3) = -\frac{1}{5}\log_2\left(\frac{1}{5}\right) - \frac{4}{5}\log_2\left(\frac{4}{5}\right)$$
$$= -(0.2)(-2.32) - (0.8)(-0.32)$$
$$= 0.464 + 0.28$$
$$= 0.744$$

$$\text{Entropy}(\text{Tanks } 2 \mid \text{Engine } 4) = -\frac{1}{2}\log_2\left(\frac{1}{2}\right) - \frac{1}{2}\log_2\left(\frac{1}{2}\right)$$
$$= (0.5)(-1) - (0.5)(-1)$$
$$= 0.5 + 0.5 = 1$$

$$\text{Entropy}(\text{Tanks } 2 \mid \text{species, Engine}) = \frac{5}{7}(0.744) + \frac{2}{7}(1)$$
$$= 0.53 + 0.29$$
$$= 0.82$$

Information gain = (Tanks 2 | species, Engine)

$$= E(\text{species}) - E(\text{Tanks2} \mid \text{species, Engine})$$

$$= 1 - 0.82 = 0.18$$

Height	Species		Number of Instances
	G	O	
M	1	3	4
S	1	2	3

$$\text{Entropy}(\text{Tanks 2} \mid \text{Height M}) = -\frac{1}{4}\log_2\left(\frac{1}{4}\right) - \frac{3}{4}\log_2(3/4)$$

$$= -(0.25)(-2) - (0.75)(-0.42)$$

$$= 0.5 + \cancel{\log}\ 0.315 = 0.82$$

Entropy (Tanks 2 | Height S)

$$\cancel{= -\frac{1}{4}\log_2\left(\frac{1}{3}\right)}$$

$$= -\frac{1}{3}\log_2\left(\frac{1}{3}\right) - \frac{2}{3}\log_2(2/3)$$

$$= -(0.33)(-1.6) - (0.67)(-0.58)$$

$$= 0.53 + 0.39 = 0.92$$

$$\text{Entropy}(\text{Tanks2} \mid \text{species, Height}) = \frac{3}{7}(0.92) + \frac{4}{7}(0.82)$$

$$= 0.39 + 0.47$$

$$= 0.86$$

Gain = (Tanks 2 | Species, Height)

$$= E(\text{species}) - E(\text{Tanks2} \mid \text{species, Height})$$

$$= 1 - 0.86 = 0.14$$

SMELL	Species		Number of Instances
	G	O	
5	1	3	4
7	1	2	3

Entropy (Tanks 2 | smell 5) $= -\frac{1}{4}\log_2\left(\frac{1}{4}\right) - \frac{3}{4}\log_2\left(\frac{3}{4}\right)$

$= -(0.25)(-2) - (0.75)(-0.42)$

$= 0.5 + 0.32 = 0.82$

Entropy (Tanks 2 | smell 7) $= -\frac{1}{3}\log_2\left(\frac{1}{3}\right) - \frac{2}{3}\log_2\left(\frac{2}{3}\right)$

$= -(0.33)(-1.6) - (0.67)(-0.58)$

$= 0.53 + 0.39 = 0.92$

Entropy (Tanks 2 | species, smell)

$= \frac{3}{7}(0.92) + \frac{4}{7}(0.82)$

$= \cancel{0.87}\ 0.4 + \cancel{0.4}\ 0.47$

$= 0.87$

~~Entropy (Tanks 2 | species, smell)~~

gain = (Tanks 2 | species, smell)

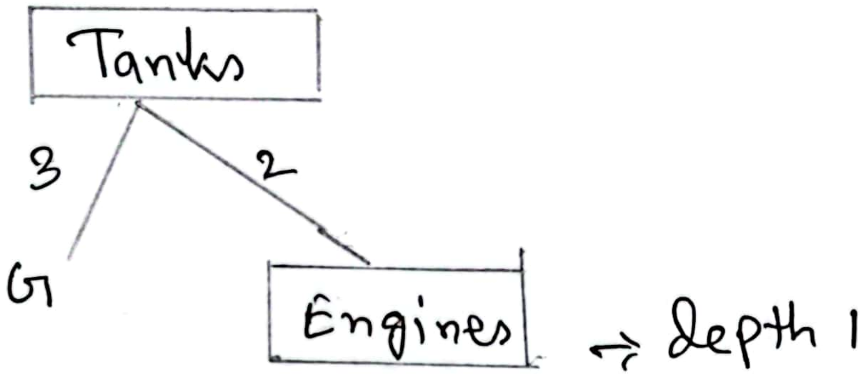
= E(species) − E(Tanks 2 | secies smell)

= 1 − 0.87 = 0.13

Feature	Information Gain
Engines	0.18
Height	0.14
Smell	0.13

The feature Engines produced ~~hight~~ highest score. so it will be selected in the tree as next attribute for tanks =2

∴ So the tree is



We have reached our max-depth =1, so tree generation is stopped.

Answer

Here we calculate the total net input for h_1

$$net_{h_1} = i_1 * w_1 + i_2 w_3 + i_3 w_5$$

$$= 0.8 * 0.04 + 0.09 * 0.07 + 0.49 * 0.89$$

$$= 0.32 + 0.0063 + 0.44 = 0.4744$$

Now, we then squash it using the logistic function to get the output of ~~k~~ h_1

$$Out_{h_1} = \frac{1}{1+e^{-net_{h_1}}} = \frac{1}{1+e^{-0.4744}} = \cancel{\frac{1}{1+0.62}}$$

$$= \frac{1}{1+0.62} = 0.62$$

Carrying out the same process for h_2

$$net_{h_2} = i_1 * w_2 + i_2 * w_4 + i_3 w_6$$

$$= 0.8 * 0.5 + 0.09 * 0.63 + 0.49 * 0.12$$

$$= 0.4 + 0.06 + 0.059 = 0.52$$

$$Out_{h_2} = \frac{1}{1+e^{-0.52}} = \frac{1}{1+0.6} = \frac{1}{1.6} = 0.63$$

Now we repeat this process for the output layer neurons using the output from the hidden layer neurons as input

$$net_{O_1} = w_7 * Out_{h_1} + w_9 * Out_{h_2}$$

$$= \cancel{0.07} * 0.34 * 0.62 + 0.44 * 0.63$$

$$= 0.21 + 0.28 = 0.49$$

$$Out_{O_1} = \frac{1}{1+e^{-net_{O_1}}} = \frac{1}{1+e^{-0.49}} = \frac{1}{1+0.61} = 0.62$$

$$net_{O_2} = w_8 * Out_{h_1} + w_{10} * Out_{h_2}$$

$$= 0.03 * 0.62 + 0.59 * 0.63$$

$$= 0.02 + 0.37 = 0.39$$

$$Out_{O_2} = \frac{1}{1+e^{-0.39}} = \frac{1}{1+0.68} = 0.595$$

Answer

Using the backpropagation technique, we have to update the weight of w_7, Given that $O_1 = 0.8$, $O_2 = 0.2$, learning rat $\eta = 0.5$ and information from previous answer

$$\frac{\partial E_{total}}{\partial w_7} = \frac{\partial E_{total}}{\partial Out_{o_1}} * \frac{\partial Out_{o_1}}{\partial net_{o_1}} * \frac{\partial net_{o_1}}{\partial w_7}$$

$$E_{total} = -\frac{1}{2}(target_{o_1} - Out_{o_1})^2 + \frac{1}{2}(target_{o_2} - Out_{o_2})^2$$

$$\frac{\partial E_{total}}{\partial Out_{o_1}} = 2 * \frac{1}{2}(target_{o_1} - Out_{o_1})^{2-1} * -1 + 0$$

$$= -(target_{o_1} - out_{o_1})$$

$$= -(0.8 - 0.62) = -0.18$$

Now, $$Out_{o_1} = \frac{1}{1+e^{-net_{o_1}}}$$

$$\frac{\partial out_{o_1}}{\partial net_{o_1}} = Out_{o_1}(1 - Out_{o_1}) = \{0.62(1-0.62)$$

$$= 0.2356$$

$$net_{o_1} = w_7 * Out_{h_1} + w_8 * Out_{h_2}$$

$$\frac{\partial net_{o_1}}{\partial w_7} = 1 * Out_{h_1} * w_7^{(1-1)} + 0 = Out_{h_1} = 0.62$$

$$\therefore \frac{\partial E_{total}}{\partial w_7} = (-0.18)(0.2356)(0.62) = -0.026$$

Now, Updating the ennor using leanningnate

$\eta = 0.5$

$$W_7^+ = W_7 - \eta \frac{\partial E_{total}}{\partial W_7}$$

$= 0.34 - 0.5\,(-0.026)$

$= 0.357$