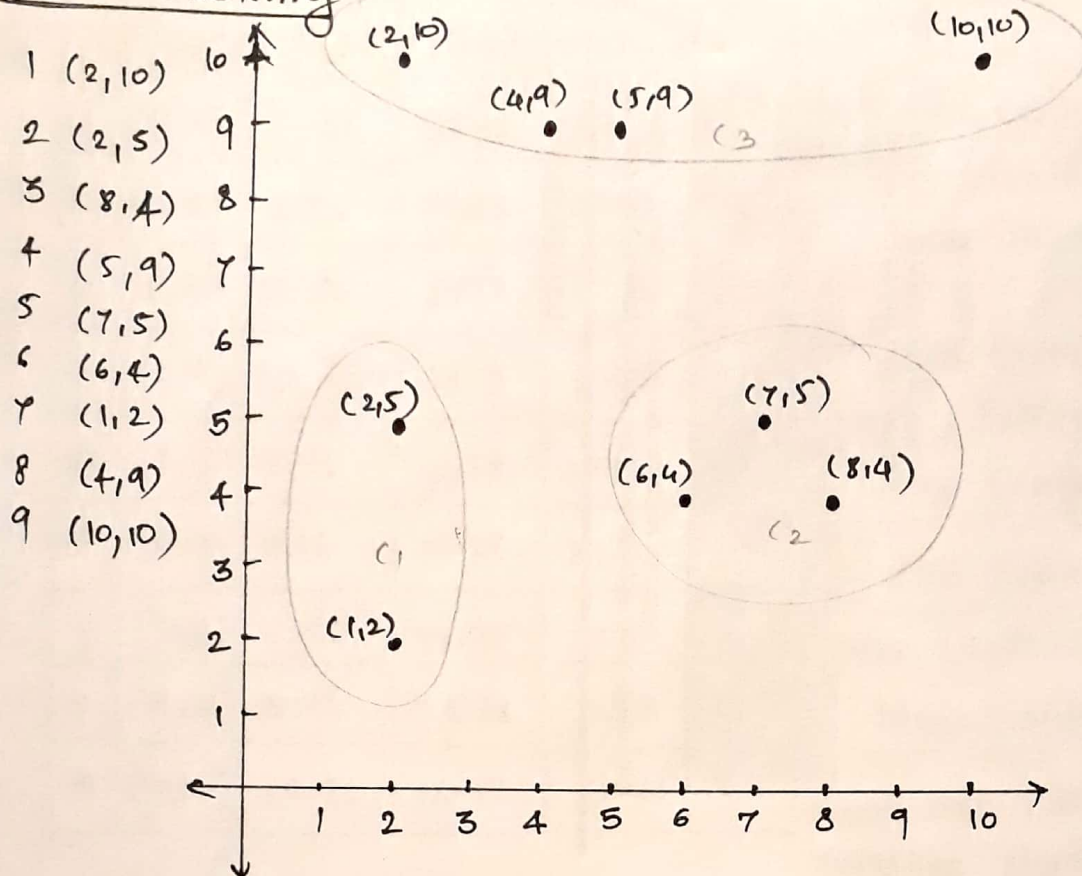


Part 1. Clustering



11) Beginning point: (2,5) (5,8) (4,9) as initial cluster centers

	Points	C1 (2,5)	C2 (5,8)	C3 (4,9)	
1	(2,10)	25	13	5	C3
2	(2,5)	0	18	20	C1
3	(8,4)	37	25	41	C2
4	(5,9)	25	1	1	C3
5	(7,5)	25	13	25	C2
6	(6,4)	17	17	21	C1
7	(1,2)	10	52	58	C1
8	(4,9)	20	2	0	C3
9	(10,10)	89	29	37	C2

[C1] Old Centroid: (2,5)
Points: (2,5), (6,4) (1,2)
New Centroid: (3,3.6)

[C2] Old Centroid (5,8).
Points: (8,4) (7,5) (10,10)
New Centroid: (8.3, 6.3)

[C3]: Old Centroid: (4,9)
Points: (4,9) (2,10) (5,9)
New Centroid: (3.6, 9.3)

(Euclidean distance)² is used, between cluster center and point to min distance is cluster belonging

III)

	Points	$C_1(3, 3.6)$	$C_2(8.3, 6.3)$	$C_3(3.6, 9.3)$	
1	(2, 10)	41.96	53.38	3.05	C_3
2	(2, 5)	2.96	41.38	21.05	C_1
3	(8, 4)	25.16	5.38	47.45	C_2
4	(5, 9)	33.16	18.18	2.05	C_3
5	(7, 5)	17.96	3.38	30.05	C_2
6	(6, 4)	9.16	10.58	33.85	C_1
7	(1, 2)	6.56	71.78	60.05	C_1
8	(4, 9)	30.16	25.78	0.25	C_3
9	(10, 10)	89.96	16.58	41.45	C_2

C_1 Old Centroid: (3, 3.6)

Points: (2, 5) (6, 4) (1, 2)

New Centroid: (3, 3.6)

C_2 Old Centroid (8.3, 6.3)

Points: (8, 4) (7, 5) (10, 10)

New Centroid: (8.3, 6.3)

C_3 Old Centroid: (3.6, 9.3)

Points: (2, 10) (5, 9) (4, 9)

New Centroid: (3.6, 9.3)

Above are resulting centers and resulting clusters → final

Question B

	P1	P2	P3	P4	P5
P1	1				
P2	0.10	1			
P3	0.41	0.64	1		
P4	0.55	0.47	0.44	1	
P5	0.35	0.98	0.85	0.76	1

Single (max) $\rightarrow (P_2, P_5)$ (minimum)

	P1	P3	P4	(P_2, P_5)
P1	1			
P3	0.41	1		
P4	0.55	0.44	1	
(P_2, P_5)	0.35	0.85	0.76	1

$((P_2, P_5), P_3)$

	P1	P4	$((P_2, P_5), P_3)$
P1	1		
P4	0.55	1	
$((P_2, P_5), P_3)$	0.41	0.76	1

$((P_2, P_5), P_3), P_4)$

	P1	$((P_2, P_5), P_3), P_4)$
P1	1	
$((P_2, P_5), P_3), P_4)$	0.41	1

Complete (minimum)

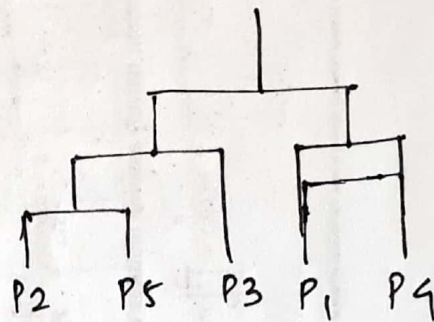
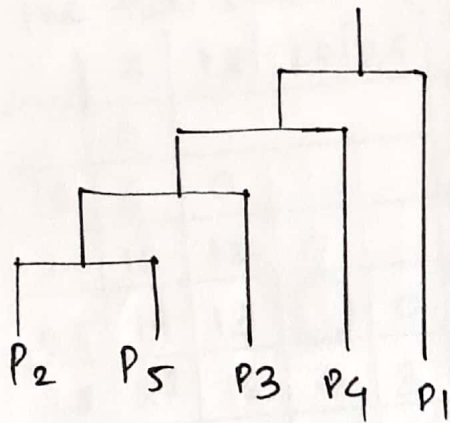
	P1	P3	P4	(P_2, P_5)
P1	1			
P3	0.41	1		
P4	0.55	0.44	1	
(P_2, P_5)	0.35	0.64	0.44	1

$((P_2, P_5), P_3)$

	P1	P4	$((P_2, P_5), P_3)$
P1	1		
P4	0.55	1	
$((P_2, P_5), P_3)$	0.35	0.44	1

$((P_2, P_5), P_3), (P_1, P_4)$

	(P_1, P_4)	$((P_2, P_5), P_3)$
(P_1, P_4)	1	
$((P_2, P_5), P_3)$	0.35	1



Question

One-dimensional: $\{6, 12, 18, 24, 25, 28, 30, 42, 48\}$

1) Center $(5, 7.5)$

C1: 5	C2: 7.5
6	- 12
	- 18
	- 24
	- 25
	- 28
	- 30
	- 42
	- 48

2) Center $(15, 25)$

C1: 15	C2: 25
- 6	- 24
- 12	- 25
- 18	- 28
	- 30
	- 42
	- 48

$$\textcircled{1} WSS = (6-5)^2 + (12-7.5)^2 + (18-7.5)^2 + (24-7.5)^2 + (25-7.5)^2 + \dots = 4467$$

$$BSS = 14 \cdot 0625$$

$$TSS = 4481 \cdot 0625$$

$$\textcircled{2} WSS = (6-15)^2 + (12-15)^2 + \dots = 943$$

$$BSS = 3 \cdot (20-15)^2 + 6 \cdot (20-25)^2 = 225$$

$$TSS = 943 + 225 = 1168$$

b)

Centeroids

C1 $(5, 7.5) \Rightarrow k\text{means}$

C1: 5 (6)

C2: 7.5 (12, 18, 24, 25, 28, 30, 42, 48)

C1: 6.56 (6, 12, 18)

C2: 28.375 (18, 24, 25, 28, 30, 42, 48)

C1: 9 (6, 12, 18)

C2: 30.71 (24, 25, 28, 30, 42, 48)

In this way centeroids of the both clusters keep moving until both the clusters are stable.

c) Single link clustering

The two clusters produced are $[((28, 30), 25), ((6, 12), (18, 24))]$

	6	12	24	25	28	30	42	48	18
6	0								
12	6	0							
24	18	12	0						
25	19	13	①	0					
28	22	16	4	3	0				
30	24	18	6	5	2	0			
42	36	30	18	17	14	12	0		
48	42	36	24	28	20	18	6	0	
18	12	6	6	7	10	12	24	30	0

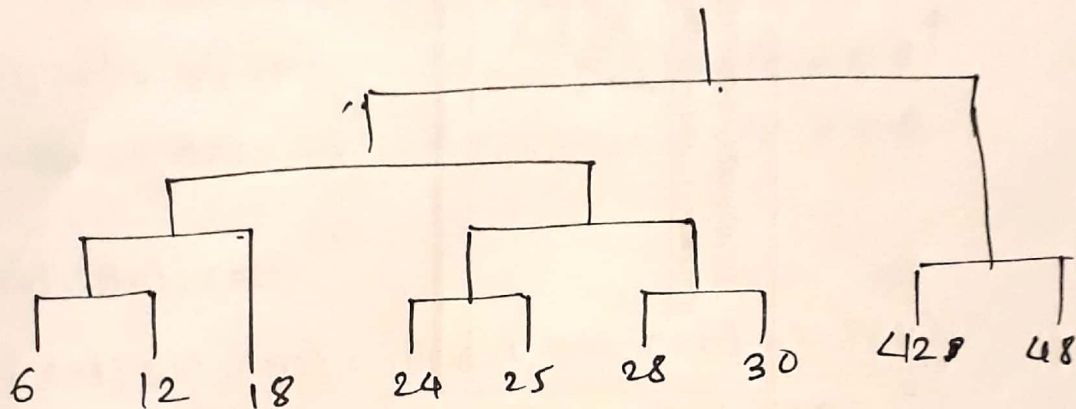
	6	12	18	28	30	42	48	(24, 25)
6	0							
12	6	0						
18	12	6	0					
28 (24, 25)	22	16	10	0				
30	24	18	¹² 12	②	0			
42	36	30	24	14	12	0		
48	42	36	30	20	18	36	0	
(24, 25)	18	13	6	3	5	17	23	0

	6	12	18	42	48	(24,25)	(28,30)
6	0						
12	6	0					
18	12	6	0				
42	36	30	24	0			
48	42	36	30	6	0		
(24,25)	18	13	6	17	23	0	
(28,30)	22	16	10	12	18	(3)	0

	6	12	18	42	48	((24,25),(28,30))
6	0					
12	(6)	0				
18	12	(6)	0			
42	36	30	24	0		
48	42	36	30	(6)	0	
((24,25),(28,30))	18	13	6	12	18	0

	((6,12),18)	(42,48)	((24,25),(28,30))
((6,12),18)	0		
(42,48)	24	0	
((24,25),(28,30))	(6)	12	0

	$(42, 48)$	\times
$(42, 48)$	0	
$\left[\begin{array}{l} (6, 12), 18, \\ (24, 25), \\ (28, 30) \end{array} \right]$	12	0



- d) ~~Min~~ ^{kmeans} produced more natural clustering in this case
- e) k means tries to stabilize the clusters by constantly shifting centroid and changing clusters to reduce errors and become stable.

Part II

Question D

1. Naive Bayes

$$\begin{aligned} \textcircled{a} \quad & P(A=1|-) = 2/5 = 0.4 & P(A=0|-) = 3/5 = 0.6 & P(+)=\frac{5}{10}=0.5 \\ \textcircled{1} \quad & P(B=1|+) = 2/5 = 0.4 & P(B=0|-) = 3/5 = 0.6 & P(-)=\frac{5}{10}=0.5 \\ & P(C=1|-) = 1 & P(C=0|-) = 0 & \end{aligned}$$

$$\begin{aligned} P(A=1|+) &= 3/5 = 0.6 & P(A=0|+) &= 2/5 = 0.4 \\ P(B=1|+) &= 1/5 = 0.2 & P(B=0|+) &= 4/5 = 0.8 \\ P(C=1|+) &= 4/5 = 0.8 & P(C=0|+) &= 1/5 = 0.2 \end{aligned}$$

$$\textcircled{b} \quad P(A=1, B=1, C=0)$$

$$\begin{aligned} \textcircled{2} \quad P(+|A=1, B=1, C=0) &= \frac{P(A=1, B=1, C=0|+) \cdot P(+)}{P(A=1, B=1, C=0)} \\ &= \frac{P(A=1|+) \cdot P(B=1|+) \cdot P(C=0|+) \cdot P(+)}{P(A=1, B=1, C=0)} \\ &= \frac{0.6 * 0.2 * 0.2 * 0.5}{P(A=1, B=1, C=0)} = 0.012 / P(A=1, B=1, C=0) \end{aligned}$$

$$\begin{aligned} P(-|A=1, B=1, C=0) &= \frac{P(A=1, B=1, C=0|-) \cdot P(-)}{P(A=1, B=1, C=0)} \\ &= \frac{P(A=1|-) \cdot P(B=1|-) \cdot P(C=0|-) \cdot P(-)}{P(A=1, B=1, C=0)} \\ &= 0.4 * 0.4 * 0 = 0. \end{aligned}$$

We label the it with +ve

$$c) P(A=1|+) = (3+2)/(5+4) = 5/9 = 0.55$$

$$b) P(A=1|-) = (2+2)/(5+4) = 4/9 = 0.44$$

$$P(A|B) = \frac{n_{c+mp}}{n+c}$$

$$P(B=1|+) = (1+2)/(5+4) = 3/9 = 0.33$$

$$P(B=1|-) = (2+2)/(5+4) = 4/9 = 0.44$$

$$P(C=0|+) = (1+2)/(5+4) = 3/9 = 0.33$$

$$P(C=0|-) = (0+2)/(5+4) = 2/9 = 0.22$$

$$d) P(A=1, B=1, C=0) = 0$$

$$u) P(+|A=1, B=1, C=0) = \frac{P(A=1, B=1, C=0|+) \cdot P(+)}{P(A=1, B=1, C=0)}$$

$$= \frac{P(A=1|+) \cdot P(B=1|+) \cdot P(C=0|+) \cdot P(+)}{P(A=1, B=1, C=0)}$$

$$= \frac{0.55 * 0.33 * 0.33 * 0.5}{0} = 0.0311 / 0 = 0.03/k$$

$$P(-|A=1, B=1, C=0) = \frac{P(A=1, B=1, C=0|-) \cdot P(-)}{P(A=1, B=1, C=0)}$$

$$= \frac{P(A=1|-) \cdot P(B=1|-) \cdot P(C=0|-) \cdot P(-)}{P(A=1, B=1, C=0)}$$

$$= \frac{0.44 * 0.44 * 0.22 * 0.5}{0} = 0.042592 * 0.5 = 0.021296/k$$

This belongs to class +ve

- e) When one of the conditional probabilities is zero, the estimate for conditional probabilities using maximum probability approach is better, since we don't want the entire expression to become zero.

① AdaBoosting

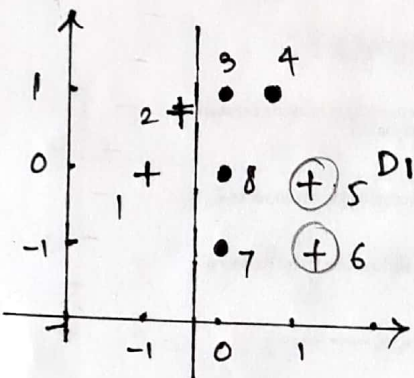
$$\epsilon = \frac{1}{n} \sum_{i=1}^n \mathbb{1}(h(x_i) \neq y_i)$$

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right)$$

$$Z_t = 2 \sqrt{\epsilon_t (1 - \epsilon_t)}$$

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \begin{cases} e^{-\alpha_t} & \text{if } h(x_i) = y_i \\ e^{+\alpha_t} & \text{if } h(x_i) \neq y_i \end{cases}$$

$$\text{final classifier } H = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) \right)$$



1	2	3	4	5	6	7	8	ϵ_1	α_1	Z_1
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.25	0.55	0.866

$$\epsilon_1 = \frac{2}{8} = 0.25 \quad \alpha_1 = \frac{1}{2} \ln \left(\frac{1 - \epsilon_1}{\epsilon_1} \right) = 0.55$$

$$D_2 = \frac{D_1}{Z_1} \begin{cases} e^{-\alpha_1} & \text{if } h(x_i) = y_i \\ e^{+\alpha_1} & \text{if } h(x_i) \neq y_i \end{cases}$$

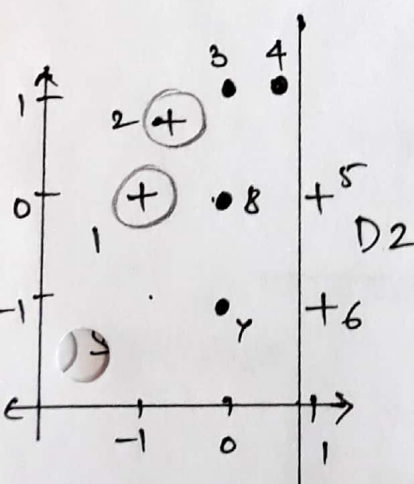
$$Z_1 = 2 \sqrt{\epsilon_1 (1 - \epsilon_1)} = 0.866 =$$

$$D_2 = \frac{D_1}{Z_1} e^{+\alpha_1} = \frac{0.125}{0.866} e^{0.55} = 0.25$$

(invalid classification) (1, 2, 3, 4, 7, 8) (5, 6)

$$D_2' = \frac{D_1}{Z_1} e^{-\alpha_1} = \frac{0.125}{0.866} e^{-0.55} = 0.083$$

(valid classification) (5, 2, 3, 4, 7, 8)



1	2	3	4	5	6	7	8	ϵ_2	α_2	Z_2
0.083	0.083	0.083	0.083	0.25	0.25	0.083	0.083	0.1666	1.066	0.8156

misclassified points are 1, 2.

$$\epsilon_2 = \frac{0.083 + 0.083}{1} = 0.1666 \quad \alpha_2 = \frac{1}{2} \ln \left(\frac{1 - \epsilon_2}{\epsilon_2} \right) = 1.066$$

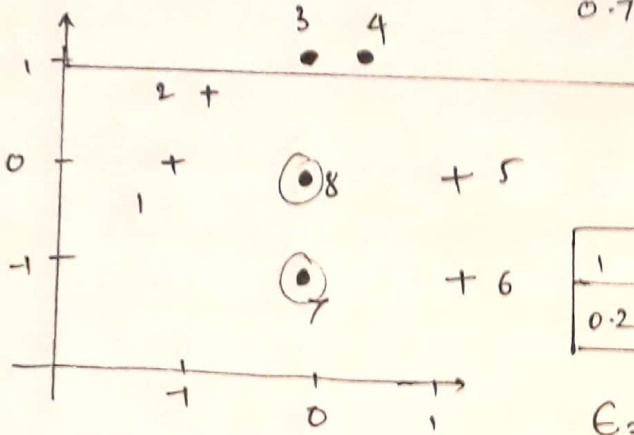
$$Z_2 = 2 \sqrt{\epsilon_2 (1 - \epsilon_2)} = 0.8156$$

$$D_3 = \frac{D_2}{\sum_2} e^{-\alpha_2}$$

$$D_{3,4,7,8} = \frac{0.083}{0.744} \times e^{-0.166} = 0.049$$

$$D_{5,6} = \frac{0.05}{0.744} \times e^{-0.166} = 0.1498$$

$$D_{1,2} = \frac{0.083}{0.744} \times e^{0.166} = 0.25$$



1	2	3	4	5	6	7	8	ϵ	α	z
0.25	0.25	0.049	0.049	0.1498	0.1498	0.049	0.049	0.099	1.1019	0.598

$$\epsilon_3 = \frac{0.049 + 0.049}{0.994} = 0.099$$

$$\alpha_3 = \frac{1}{2} \ln \left(\frac{1 - \epsilon_3}{\epsilon_3} \right) = 1.1019$$

$$z_3 = 2 \sqrt{\epsilon_3 (1 - \epsilon_3)} = 0.598$$

$$H = \text{Sign} \left(0.55 \begin{array}{|c|c|} \hline \text{shaded} & \text{white} \\ \hline \end{array} + 0.807 \begin{array}{|c|c|} \hline \text{white} & \text{shaded} \\ \hline \end{array} + 1.1019 \begin{array}{|c|c|} \hline \text{shaded} & \text{shaded} \\ \hline \end{array} \right) = \begin{array}{|c|c|} \hline \text{shaded} & \text{shaded} \\ \hline \end{array}$$

(b) Training Error:

$$P_{\text{train}}[H(x_i) \neq y] = \frac{1}{N} \sum_i \sqrt{1 - 4\gamma_i^2}$$

$$\text{T.E} = \sqrt{1 - 4(0.25)^2} + \sqrt{1 - 4(0.334)^2} + \sqrt{1 - 4(0.426)^2} = 0.866 + 0.7512 + 0.5235$$

$$\gamma_t = \frac{1}{2} - \epsilon_t$$

$$\gamma_1 = \frac{1}{2} - 0.25 = 0.25$$

$$\gamma_2 = \frac{1}{2} - 0.334 = 0.166$$

$$\gamma_3 = \frac{1}{2} - 0.426 = 0.074$$

$$\text{TE} = 0.34$$

* Ada Boost uses multiple decision stumps instead of single decision stumps and giving each decision stump different weight according to output is better than classifying just by single decision stump

* In Ada Boosting misclassified points are focused more on given more weights

Q5. Decision Tree.

Information Gain Heuristics Using Entropy.

X1	X2	X3	Y
a	c	k	-1
a	w	k	-1
b	w	v	+1
a	c	v	+1
b	w	k	-1
a	c	s	+1
b	w	s	+1
a	v	v	-1
b	c	v	-1
b	c	s	+1
b	g	v	-1

$$E_X[I(x)] = - \sum_{x \in X} p(x) \cdot \log p(x)$$

$$E(\text{Target}) = - [P(+1) \cdot \log P(+1) + P(-1) \cdot \log P(-1)]$$

$$E(\text{Target}) = - \left[\left(\frac{5}{11} \right) \log_2 \left(\frac{5}{11} \right) + \left(\frac{6}{11} \right) \cdot \log_2 \left(\frac{6}{11} \right) \right]$$

$$E(\text{Target}) = 0.994$$

Information Gain for X1:

$$IG(X_1) = E(\text{Target}) - E(\text{Target}, X_1)$$

$$E(\text{Target}, X_1) = P(a) \cdot E(a) + P(b) \cdot E(b)$$

$$\begin{aligned} E(a) &= - [P(+1) \log P(+1) + P(-1) \log P(-1)] \\ &= - \left[\left(\frac{3}{5} \right) \cdot \log_2 \left(\frac{3}{5} \right) + \left(\frac{2}{5} \right) \log_2 \left(\frac{2}{5} \right) \right] \\ &= 0.97 \end{aligned}$$

$$\begin{aligned} E(b) &= - [P(+1) \log P(+1) + P(-1) \log P(-1)] \\ &= - \left[\left(\frac{3}{6} \right) \log_2 \left(\frac{3}{6} \right) + \left(\frac{3}{6} \right) \cdot \log_2 \left(\frac{3}{6} \right) \right] \\ &= 1 \end{aligned}$$

$$\begin{aligned} E(\text{Target}, X_1) &= P(a) \cdot E(a) + P(b) \cdot E(b) \\ &= \frac{5}{11} \times 0.97 + \frac{6}{11} \times 1 \\ &= 0.986 \end{aligned}$$

$$\begin{aligned} IG(X_1) &= E(\text{Target}) - E(\text{Target}, X_1) \\ &= 0.994 - 0.986 = 8.5 \times 10^{-3} = 0.85 \times 10^{-2} \end{aligned}$$

Information Gain for X_2

$$IG(X_2) = E(\text{Target}) - E(\text{Target}, X_2)$$

$$E(\text{Target}, X_2) = P(c) \cdot E(c) + P(g) \cdot E(g) + P(u) \cdot E(u) + P(w) \cdot E(w)$$

$$E(c) = -[P_{+re}(c) \cdot \log_2 P_{+re}(c) + P_{-re}(c) \cdot \log_2 P_{-re}(c)]$$

$$= -\left[\frac{3}{5} \cdot \log_2 \frac{3}{5} + \frac{2}{5} \log_2 \frac{2}{5}\right] = 0.961$$

$$E(g) = -[P_{+re}(g) \cdot \log_2 P_{+re}(g) + P_{-re}(g) \cdot \log_2 P_{-re}(g)]$$

$$= -\left[0 + \frac{1}{1} \log_2 \frac{1}{1}\right] = 0$$

$$E(u) = -[P_{+re}(u) \cdot \log_2 P_{+re}(u) + P_{-re}(u) \cdot \log_2 P_{-re}(u)]$$

$$= -\left[0 + \frac{1}{1} \log_2 \frac{1}{1}\right] = 0$$

$$E(w) = -[P_{+re}(w) \cdot \log_2 P_{+re}(w) + P_{-re}(w) \cdot \log_2 P_{-re}(w)]$$

$$= -\left[\frac{2}{4} \log_2 \frac{2}{4} + \frac{2}{4} \log_2 \frac{2}{4}\right] = 1$$

$$E(\text{Target}, X_2) = \frac{5}{11} \cdot (0.961) + 0 + 0 + \frac{4}{11} \cdot (1) = 0.800 = 80 \times 10^{-2}$$

$$IG(X_2) = 0.994 - 0.800 = 0.193 = 19.3 \times 10^{-2}$$

Information Gain for X_3

$$IG(X_3) = E(\text{Target}) - E(\text{Target}, X_3)$$

$$E(\text{Target}, X_3) = P(k) \cdot E(k) + P(s) \cdot E(s) + P(v) \cdot E(v)$$

$$E(k) = -[P_{+re}(k) \cdot \log_2 P_{+re}(k) + P_{-re}(k) \cdot \log_2 P_{-re}(k)] = -\left[\frac{0}{3} + \frac{3}{3} \log_2 \frac{3}{3}\right] = 0$$

$$E(s) = -[P_{+re}(s) \cdot \log_2 P_{+re}(s) + P_{-re}(s) \cdot \log_2 P_{-re}(s)] = -\left[\frac{0}{3} \log_2 \frac{0}{3} + 0\right] = 0$$

$$E(v) = -[P_{+re}(v) \cdot \log_2 P_{+re}(v) + P_{-re}(v) \cdot \log_2 P_{-re}(v)] = -\left[\frac{2}{5} \log_2 \frac{2}{5} + \frac{3}{5} \log_2 \frac{3}{5}\right] = 0.961$$

$$E(\text{Target}, X_3) = 0 + 0 + 0.961 \cdot \frac{5}{11} = 0.436$$

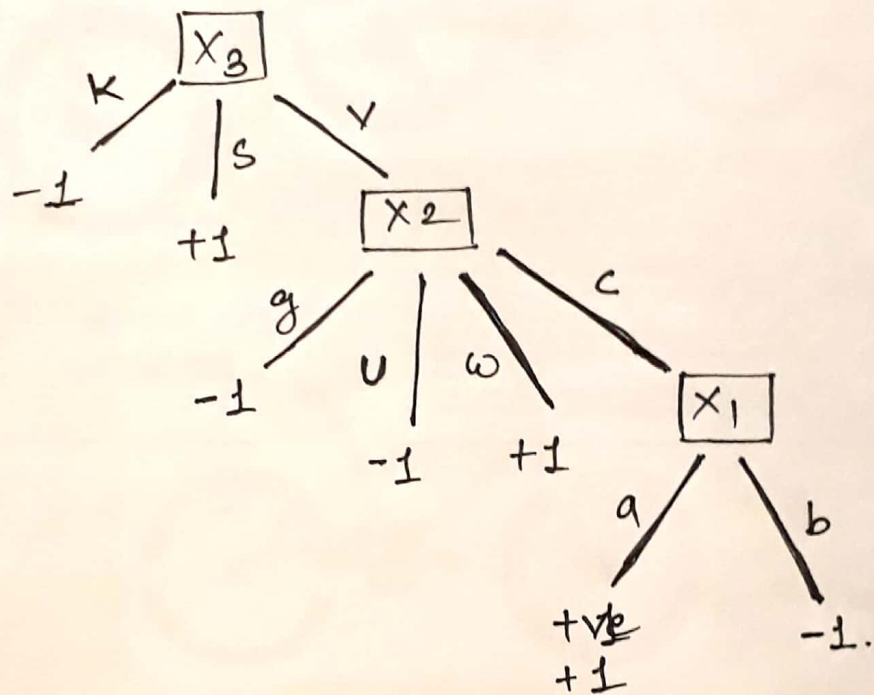
$$IG(X_3) = E(\text{Target}) - E(\text{Target}, X_3) = 0.994 - 0.436 = 0.557 = 55.7 \times 10^{-2}$$

$$IG(X_1) = 0.85 \times 10^{-2}$$

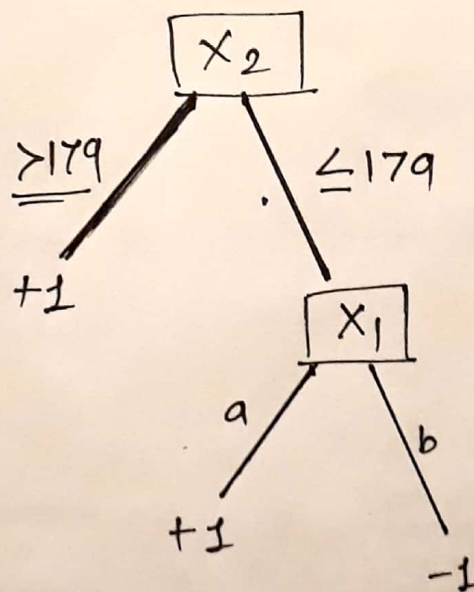
$$IG(X_2) = 19.3 \times 10^{-2}$$

$$IG(X_3) = 55.7 \times 10^{-2}$$

X_3 is highest Information Gain. Hence, it will be the head of Decision tree.



(b) $IG(X_1) = 0.2$
 (i) $IG(X_2) = 0.46$
 $IG(X_3) = 0.2$
 $IG(X_4) = 0$



(ii)

X_1	X_2	X_3	X_4	Y	Pred
b	170	f	d	-1	-1
a	150	f	d	+1	+1
b	60	f	d	+1	-1

$$\text{Accuracy} = \frac{2}{3} \times 100 = \underline{\underline{0.75}} @ \underline{\underline{66\%}}$$

Accuracy is 66%