

1

a) $\left\{ x^1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^2 = \begin{pmatrix} 2 \\ 2 \end{pmatrix}, x^3 = \begin{pmatrix} 0 \\ -1 \end{pmatrix}, x^4 = \begin{pmatrix} -1 \\ 0 \end{pmatrix} \right\}$ \rightarrow Bias

$\{ t^1 = 1, t^2 = 1, t^3 = -1, t^4 = -1 \}$

$\eta = 1, W = \begin{pmatrix} 1 \\ 1 \end{pmatrix}; W = W + \eta \underbrace{(t - \sigma)}_{\delta} x$

1st Epoch

- $x^1: \sigma^1 = \text{sign}(W x^1) = \text{sign}(1 \cdot 1 + 1 \cdot 1) = +1$
As $t^1 = \sigma^1$, no mistake was made
- $x^2: \sigma^2 = \text{sign}(W x^2) = \text{sign}(1 \cdot 2 + 1 \cdot 2) = +1$
As $t^2 = \sigma^2$, no mistake was made
- $x^3: \sigma^3 = \text{sign}(W x^3) = \text{sign}(1 \cdot 0 + 1 \cdot (-1)) = \text{sign}(0) = +1$
 $W^{\text{new}} = W + \eta \cdot (t - \sigma) x \Rightarrow W = (1 \ 1)^T + 1 \cdot (1 \ 0)^T (-1 - 1)$
 $\Rightarrow W = (1 \ 1)^T + (-2 \ 0)^T = (-1 \ 1)$
- $x^4: \sigma^4 = \text{sign}(W x^4) = \text{sign}(1 \cdot (-1) + 1 \cdot 0) = \text{sign}(-1) = -1$
As $t^4 = \sigma^4$, no mistake was made

2nd Epoch

- $x^1: \sigma^1 = \text{sign}(W x^1) = \text{sign}((-1) \cdot 1 + 1 \cdot 1) = +1$
As $t^1 = \sigma^1$, no mistake was made
- $x^2: \sigma^2 = \text{sign}(W x^2) = \text{sign}((-1) \cdot 2 + 1 \cdot 2) = +1$
As $t^2 = \sigma^2$, no mistake was made
- $x^3: \sigma^3 = \text{sign}(W x^3) = \text{sign}((-1) \cdot 0 + 1 \cdot (-1)) = -1$
As $t^3 = \sigma^3$, no mistake was made
- $x^4: \sigma^4 = \text{sign}(W x^4) = \text{sign}((-1) \cdot (-1) + 1 \cdot 0) = +1$
As $t^4 = \sigma^4$, no mistake was made

We have converged. $W = \begin{pmatrix} -1 \\ 1 \end{pmatrix}$

1

b) $\left\{ x^1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^2 = \begin{pmatrix} 2 \\ 2 \end{pmatrix}, x^3 = \begin{pmatrix} 0 \\ -1 \end{pmatrix}, x^4 = \begin{pmatrix} -1 \\ 0 \end{pmatrix} \right\}$ → Bias

$\{ t^1 = 1, t^2 = 1, t^3 = -1, t^4 = -1 \}$

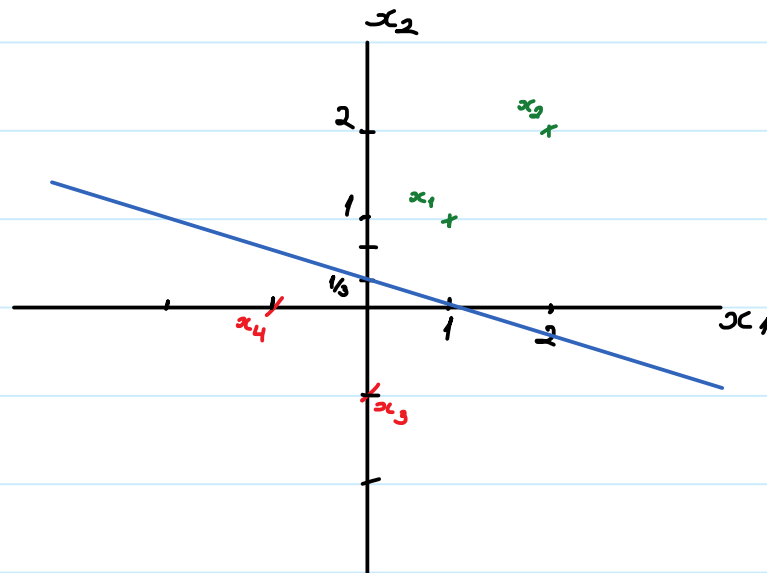
$m = 1, w = \begin{pmatrix} -1 \\ 3 \end{pmatrix}$

Separation Hypothesis

$$w \cdot x = 0 \Leftrightarrow w_0 \cdot x_0 + w_1 \cdot x_1 + w_2 \cdot x_2 = 0$$

$$\Leftrightarrow (-1) \cdot 1 + 1 \cdot x_1 + 3 \cdot x_2 = 0 \Leftrightarrow x_1 + 3x_2 = 1$$

$$\Leftrightarrow x_2 = \frac{1}{3} - \frac{1}{3} x_1$$



2

a)

F_1	F_2	F_3	F_4	Output
c	a	b	x	m
a	a	c	a	t
a	b	b	a	t
c	b	c	x	m
a	b	b	c	f

1st - Compute initial entropy

$$E_{\text{start}} = E\left(\frac{\#\{O=f\}}{\sum_o \#\{O=o\}}, \frac{\#\{O=m\}}{\sum_o \#\{O=o\}}, \frac{\#\{O=m\}}{\sum_o \#\{O=o\}}, \frac{\#\{O=t\}}{\sum_o \#\{O=o\}}\right)$$

$$= E\left(\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{2}{5}\right) = -\left(\frac{1}{5} \log_2 \frac{1}{5} + \frac{1}{5} \log_2 \frac{1}{5} + \frac{1}{5} \log_2 \frac{1}{5} + \frac{2}{5} \cdot \log_2 \frac{2}{5}\right)$$

$$= -\left(\frac{3}{5} \log_2 \frac{1}{5} + \frac{2}{5} \log_2 \frac{2}{5}\right) = -(-1.39 + (-0.53)) = 1.92 \text{ Bits}$$

2nd - Test each attribute

• F_1 :

$$\begin{array}{l} F_1 = a \\ \hline \#\{O=f\} = 1 \\ \#\{O=m\} = 0 \\ \#\{O=m\} = 0 \\ \#\{O=t\} = 2 \end{array}$$

$$E\left(\frac{1}{3}, \frac{2}{3}\right) = -\left(\frac{1}{3} \log_2 \frac{1}{3} + \frac{2}{3} \log_2 \frac{2}{3}\right)$$

$$= 0.92 \text{ Bits}$$

$$\begin{array}{l} F_1 = c \\ \hline \#\{O=f\} = 0 \\ \#\{O=m\} = 1 \\ \#\{O=m\} = 1 \\ \#\{O=t\} = 0 \end{array}$$

$$E\left(\frac{1}{2}, \frac{1}{2}\right) = -\left(\frac{1}{2} \log_2 \frac{1}{2} + \frac{1}{2} \log_2 \frac{1}{2}\right)$$

$$= 1 \text{ Bit}$$

$$E_{F_1} = \frac{3}{5} \cdot E\left(\frac{1}{3}, \frac{2}{3}\right) + \frac{2}{5} \cdot E\left(\frac{1}{2}, \frac{1}{2}\right) = 0.952 \text{ Bits}$$

$$\underline{G_1(F_1)} = E_{\text{start}} - E_{F_1} = 1.92 - 0.95 \approx 0.97 \text{ Bits}$$

2

a cont.) $2^{n!}$ - Test each attribute (cont)

• F_2

$$\begin{array}{l} F_2 = a \\ \hline \#\{0=j\} = 0 \\ \#\{0=m\} = 0 \\ \#\{0=n\} = 1 \\ \#\{0=t\} = 1 \end{array}$$

$$\begin{array}{l} F_2 = b \\ \hline \#\{0=j\} = 0 \\ \#\{0=m\} = 1 \\ \#\{0=n\} = 1 \\ \#\{0=t\} = 1 \end{array}$$

$$E(1/2, 1/2) = -(1/2 \log_2 1/2 + 1/2 \log_2 1/2) = 1 \text{ Bit}$$

$$E(1/3, 1/3, 1/3) = -(1/3 \log_2 1/3 + 1/3 \log_2 1/3 + 1/3 \log_2 1/3) = 1.58 \text{ Bits}$$

$$E_{F_2} = 3/5 \cdot E(1/3, 1/3, 1/3) + 2/5 \cdot E(1/2, 1/2) = 1.348 \text{ Bits}$$

$$\underline{G_1(F_2)} = E_{\text{start}} - E_{F_2} = 1.92 - 1.35 \approx 0.57 \text{ Bits}$$

• F_3

$$\begin{array}{l} F_3 = b \\ \hline \#\{0=j\} = 1 \\ \#\{0=m\} = 0 \\ \#\{0=n\} = 1 \\ \#\{0=t\} = 1 \end{array}$$

$$\begin{array}{l} F_3 = c \\ \hline \#\{0=j\} = 0 \\ \#\{0=m\} = 1 \\ \#\{0=n\} = 0 \\ \#\{0=t\} = 1 \end{array}$$

$$E(1/3, 1/3, 1/3) = -(1/3 \log_2 1/3 + 1/3 \log_2 1/3 + 1/3 \log_2 1/3) = 1.58 \text{ Bits}$$

$$E(1/2, 1/2) = -(1/2 \log_2 1/2 + 1/2 \log_2 1/2) = 1 \text{ Bit}$$

$$E_{F_3} = 3/5 \cdot E(1/3, 1/3, 1/3) + 2/5 \cdot E(1/2, 1/2) = 1.348 \text{ Bits}$$

$$\underline{G_1(F_3)} = E_{\text{start}} - E_{F_3} = 1.92 - 1.35 \approx 0.57 \text{ Bits}$$

• F_4

$$\begin{array}{l} F_4 = a \\ \hline \#\{0=j\} = 0 \\ \#\{0=m\} = 1 \\ \#\{0=n\} = 1 \\ \#\{0=t\} = 0 \end{array}$$

$$\begin{array}{l} F_4 = a \\ \hline \#\{0=j\} = 0 \\ \#\{0=m\} = 0 \\ \#\{0=n\} = 0 \\ \#\{0=t\} = 2 \end{array}$$

$$\begin{array}{l} F_4 = c \\ \hline \#\{0=j\} = 1 \\ \#\{0=m\} = 0 \\ \#\{0=n\} = 0 \\ \#\{0=t\} = 0 \end{array}$$

$$E(1/2, 1/2) = -(1/2 \log_2 1/2 + 1/2 \log_2 1/2) = 1 \text{ Bit}$$

$$E(2/2) = -(1 \log_2 1) = 0 \text{ Bits}$$

$$E(1/1) = -(1 \log_2 1) = 0 \text{ Bits}$$

$$E_{F_4} = 2/5 \cdot E(1/2, 1/2) + 3/5 \cdot E(2/2) + 1/5 \cdot E(1/1) = 2/5 \text{ Bits}$$

$$\underline{G_1(F_4)} = E_{\text{start}} - E_{F_4} = 1.92 - 2/5 \approx 1.52 \text{ Bits}$$

2

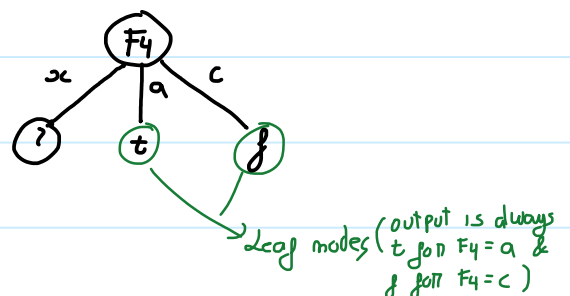
a cont.) 3rd - Pick root

$$\left. \begin{array}{l} G(F_1) = 0,97 \\ G(F_2) = G(F_3) = 0,57 \\ G(F_4) = 1,52 \end{array} \right\} \begin{array}{l} \text{Since } F_4 \text{ has the highest} \\ \text{info gain, } (F_4) \text{ is picked as} \\ \text{root} \end{array}$$

b) Picking F_4 as our root, we have the following partitions

$F_4 = x$				$F_4 = a$				$F_4 = c$			
F_1	F_2	F_3	θ	F_1	F_2	F_3	θ	F_1	F_2	F_3	θ
c	a	b	m	a	a	c	t	a	b	b	f
c	b	c	m	a	b	b	t				

- Right now we have the tree.
- So we need to pick which feature to test on node (?)



Following the same logic as in exercise 2 a), we have

1st - Initial Entropy

$$E_{\text{start}} = E(1/2, 1/2) = 1 \text{ Bit}$$

2nd - Test each feature

$$\begin{array}{l} \bullet F_1 \\ \quad \begin{array}{l} \frac{F_1 = c}{\# \{ \theta = m \} = 1} \\ \# \{ \theta = m \} = 1 \end{array} \end{array} \quad \begin{array}{l} E_{F_1} = 1 \cdot E(1/2, 1/2) = 1 \text{ Bit} \\ \underline{G_{F_1}} = E_{\text{start}} - E_{F_1} = 0 \end{array}$$

2

b cont.) 2nd - Test each feature (cont)

• F_2

$$\begin{array}{l} F_2 = a \\ \# \{0=m\} = 1 \\ \# \{0=m\} = 0 \end{array}$$

$$E(1/1) = 0 \text{ Bit}$$

$$\begin{array}{l} F_2 = b \\ \# \{0=m\} = 0 \\ \# \{0=m\} = 1 \end{array}$$

$$E(1/1) = 0 \text{ Bit}$$

$$E_{F_2} = 1/2 \cdot 0 + 1/2 \cdot 0 = 0$$

$$\underline{G_{F_2}} = E_{\text{start}} - E_{F_2} = 1 \text{ Bit (MAX!)}$$

• F_3

$$\begin{array}{l} F_3 = a \\ \# \{0=m\} = 0 \\ \# \{0=m\} = 1 \end{array}$$

$$E(1/1) = 0 \text{ Bit}$$

$$\begin{array}{l} F_3 = b \\ \# \{0=m\} = 1 \\ \# \{0=m\} = 0 \end{array}$$

$$E(1/1) = 0 \text{ Bit}$$

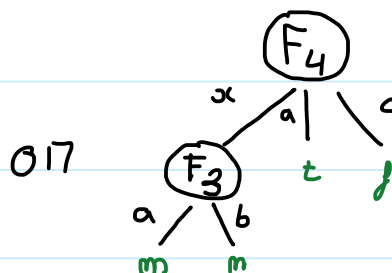
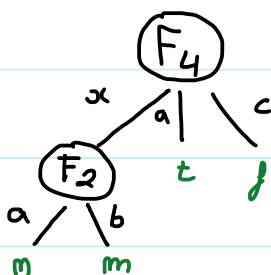
$$E_{F_3} = 1/2 \cdot 0 + 1/2 \cdot 0 = 0$$

$$\underline{G_{F_3}} = E_{\text{start}} - E_{F_3} = 1 \text{ Bit (MAX!)}$$

3rd - Pick Feature to test

Both F_2 & F_3 have maximum info. gain whilst F_1 has minimum

So, we can pick between either of these 2 features.

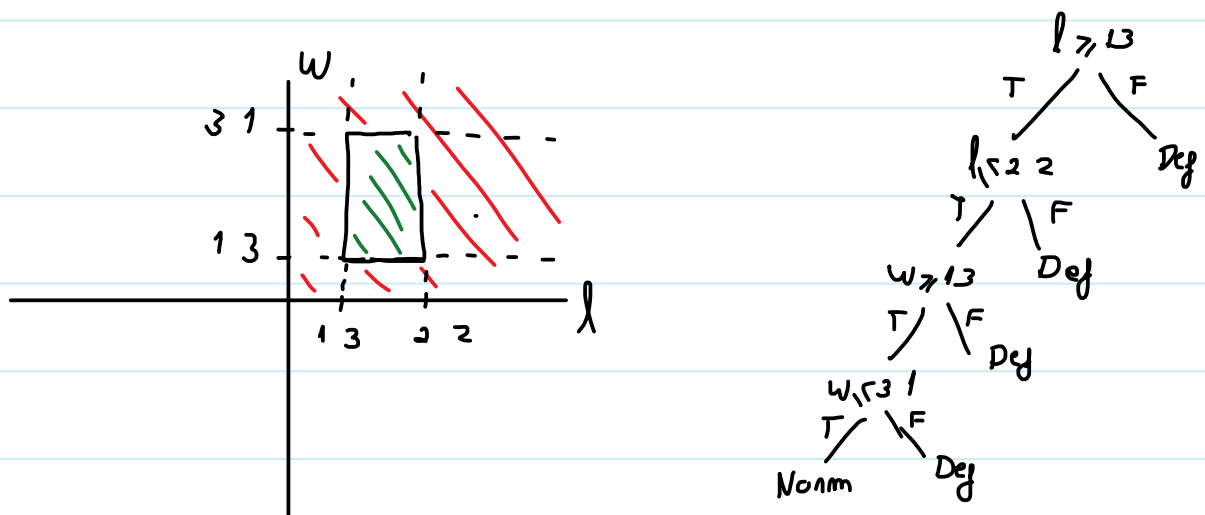


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3

Only the Decision Tree. This problem demands a classifier able to represent joint conditions across multiple dimensions. By this we mean that the condition to classify a piece as defective or not can be written as a conjunction of AND statements ($l < 2.2$ AND $l > 1.3$ AND $w < 3.1$ AND $w > 1.3$), which would be too complex for a single perceptron (which can only classify linearly separable points). Decision trees, however, have no problem dealing with conjunctions such as this one.



4

a)

x_1	x_2	Class
0	10	A
0	20	A
10	10	A
5	20	A
30	30	B
40	40	B
50	30	B
50	50	B

$$x = \begin{pmatrix} 5 \\ 10 \end{pmatrix}$$

$$N = \frac{\sum_{x=x_i} x}{N} \quad \sigma = \sqrt{\frac{\sum_{x=x_i} (x-N)^2}{N}}$$

Teacher Note: Assume for standard deviation and covariance that we have population, use N instead of N-1 (divide by N and not N-1)

- ① Prior

$$P(A) = \frac{\#A}{\#Examples} = \frac{4}{8} = \frac{1}{2}$$

$$P(B) = \frac{\#B}{\#Examples} = \frac{4}{8} = \frac{1}{2}$$

- ② Estimate likelihoods

$$\begin{aligned} & \bullet p(x_1 | \text{Class} = A) \\ N & \frac{0+0+10+5}{4} = 3.75 \\ \sigma & \sqrt{\frac{(0-3.75)^2 + (0-3.75)^2 + (10-3.75)^2 + (5-3.75)^2}{4}} = 4.15 \end{aligned}$$

$$\begin{aligned} & \bullet p(x_1 | \text{Class} = B) \\ N & \frac{30+40+50+50}{4} = 42.5 \\ \sigma & \sqrt{\frac{(30-42.5)^2 + (40-42.5)^2 + (50-42.5)^2 + (50-42.5)^2}{4}} = 8.29 \end{aligned}$$

4

Teacher Note: Assume for standard deviation and covariance that we have population, use N instead of N-1 (divide by N and not N-1)

a cont.)

x_1	x_2	Class
0	10	A
0	20	A
10	10	A
5	20	A
30	30	B
40	40	B
50	30	B
50	50	B

$$x = \begin{pmatrix} 5 \\ 10 \end{pmatrix}$$

$$\mu = \frac{\sum x}{N} \quad \sigma = \sqrt{\frac{\sum (x - \mu)^2}{N}}$$

$$p(x|N, \sigma^2) = \mathcal{N}(x|N, \sigma^2) = \frac{1}{\sqrt{2 \cdot \pi} \sigma} \exp\left(-\frac{1}{2 \cdot \sigma^2} (x - \mu)^2\right)$$

② Estimate likelihoods

$$p(x_2 | \text{Class} = A)$$

$$\mu = \frac{10 + 20 + 10 + 5}{4} = 15.0$$

$$\sigma = \sqrt{\frac{(10-15)^2 + (20-15)^2 + (10-15)^2 + (5-15)^2}{4}} = 5$$

$$p(x_2 | \text{Class} = B)$$

$$\mu = \frac{30 + 40 + 30 + 50}{4} = 37.5$$

$$\sigma = \sqrt{\frac{(30-37.5)^2 + (40-37.5)^2 + (30-37.5)^2 + (50-37.5)^2}{4}} = 8.29$$

$$p(\text{Class} = A | x_1 = 5, x_2 = 10) = \frac{p(\text{Class} = A) p(x_1 = 5, x_2 = 10 | \text{Class} = A)}{p(x_1 = 5, x_2 = 10)}$$

$$= \frac{1/2 \cdot p(x_1 = 5 | \text{Class} = A) p(x_2 = 10 | \text{Class} = A)}{p(x_1 = 5, x_2 = 10)} = \frac{1/2 \mathcal{N}(5 | \mu = 15, \sigma = 5) \cdot \mathcal{N}(10 | \mu = 15, \sigma = 5)}{p(x_1 = 5, x_2 = 10)}$$

$$= \frac{1/2 \cdot \frac{1}{\sqrt{2\pi \cdot 25}} \cdot \exp\left(-\frac{1}{2 \cdot 25} \cdot (5-15)^2\right) \cdot \frac{1}{\sqrt{2\pi \cdot 25}} \cdot \exp\left(-\frac{1}{2 \cdot 25} \cdot (10-15)^2\right)}{p(x_1 = 5, x_2 = 10)} = \frac{1/2 \cdot 0.002 \cdot 0.008}{p(x_1 = 5, x_2 = 10)}$$

$$= \frac{0.002}{p(x_1 = 5, x_2 = 10)}$$

$$p(\text{Class} = B | x_1 = 5, x_2 = 10) = \frac{p(\text{Class} = B) p(x_1 = 5, x_2 = 10 | \text{Class} = B)}{p(x_1 = 5, x_2 = 10)}$$

$$= \frac{1/2 \cdot p(x_1 = 5 | \text{Class} = B) p(x_2 = 10 | \text{Class} = B)}{p(x_1 = 5, x_2 = 10)} = \frac{1/2 \mathcal{N}(5 | \mu = 37.5, \sigma = 8.29) \cdot \mathcal{N}(10 | \mu = 37.5, \sigma = 8.29)}{p(x_1 = 5, x_2 = 10)}$$

$$= \frac{1/2 \cdot \frac{1}{\sqrt{2\pi \cdot 68.72}} \cdot \exp\left(-\frac{1}{2 \cdot 68.72} \cdot (5-37.5)^2\right) \cdot \frac{1}{\sqrt{2\pi \cdot 68.72}} \cdot \exp\left(-\frac{1}{2 \cdot 68.72} \cdot (10-37.5)^2\right)}{p(x_1 = 5, x_2 = 10)} = \frac{1/2 \cdot 1.73 \cdot 10^{-6} \cdot 0.00019}{p(x_1 = 5, x_2 = 10)}$$

$$= \frac{1.64 \times 10^{-10}}{p(x_1 = 5, x_2 = 10)}$$

As $0.002 > 1.64 \times 10^{-6}$, this query vector will be classified as A

$$= \frac{1.64 \times 10^{-10}}{P(x_1=5, x_2=10)} \quad \checkmark$$

As $0.002 > 1.64 \times 10^{-6}$, this query vector will be Classified as A \checkmark

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Teacher Note: Assume for standard deviation and covariance that we have population, use N instead of N-1 (divide by N and not N-1)

b)

x_1	x_2	Class
0	10	A
0	20	A
10	10	A
5	20	A
30	30	B
40	40	B
50	30	B
50	50	B

$$x = \begin{pmatrix} 5 \\ 10 \end{pmatrix}$$

$$\mu = \frac{\sum_{i=1}^N x_i}{N} \quad \bar{X} = \frac{1}{N} \sum_{i=1}^N (x_i - \mu_i) (x_i - \mu_i)^T$$

$$p(x|N, \sigma^2) = \prod_{i=1}^N p(x_i|N, \bar{X}) = \frac{1}{(2\pi)^{D/2}} \cdot \frac{1}{|\bar{X}|^{1/2}} \exp\left(-\frac{1}{2} \cdot (x - \mu)^T \bar{X}^{-1} \cdot (x - \mu)\right)$$

$$D=2$$

① Prior

$$P(A) = \frac{\#A}{\#Examples} = \frac{4}{8} = \frac{1}{2}$$

$$P(B) = \frac{\#B}{\#Examples} = \frac{4}{8} = \frac{1}{2}$$

② Estimate likelihoods

$$p(x_1, x_2 | \text{Class} = A)$$

$$N \cdot \begin{bmatrix} \frac{0+0+10+5}{4} \\ \frac{10+20+10+20}{4} \end{bmatrix} = \begin{bmatrix} 3.75 \\ 15 \end{bmatrix}$$

$$\bar{X} = \begin{bmatrix} \frac{(0-3.75)^2 + (0-3.75)^2 + (10-3.75)^2 + (5-3.75)^2}{4} & \frac{(0-3.75) \cdot (10-15) + (0-3.75) \cdot (20-15) + (10-3.75) \cdot (10-15) + (5-3.75) \cdot (20-15)}{4} \\ \frac{(0-3.75) \cdot (10-15) + (0-3.75) \cdot (20-15) + (10-3.75) \cdot (10-15) + (5-3.75) \cdot (20-15)}{4} & \frac{(10-15)^2 + (20-15)^2 + (10-15)^2 + (20-15)^2}{4} \end{bmatrix} = \begin{bmatrix} 17.19 & -6.25 \\ -6.25 & 25 \end{bmatrix}$$

$$p(x_1, x_2 | \text{Class} = B)$$

$$N \cdot \begin{bmatrix} \frac{30+40+50+50}{4} \\ \frac{30+40+30+50}{4} \end{bmatrix} = \begin{bmatrix} 42.5 \\ 37.5 \end{bmatrix}$$

$$\bar{X} = \begin{bmatrix} \frac{(30-42.5)^2 + (40-42.5)^2 + (50-42.5)^2 + (50-42.5)^2}{4} & \frac{(30-42.5)(30-37.5) + (40-42.5)(30-37.5) + (50-42.5)(30-37.5) + (50-42.5)(30-37.5)}{4} \\ \frac{(30-42.5)(30-37.5) + (40-42.5)(30-37.5) + (50-42.5)(30-37.5) + (50-42.5)(30-37.5)}{4} & \frac{(30-37.5)^2 + (40-37.5)^2 + (50-37.5)^2 + (50-37.5)^2}{4} \end{bmatrix} = \begin{bmatrix} 68.75 & 31.25 \\ 31.25 & 68.75 \end{bmatrix}$$

$$\left| \frac{(30-42,5)(30-37,5) + (40-42,5)(40-37,5) + (50-42,5)(50-37,5)}{4} \quad \frac{(30-37,5)^2 + (40-37,5)^2 + (50-37,5)^2}{4} \right|$$

4

b cont.)

• ② Estimate likelihoods

$$\begin{aligned} & \bullet P(X_2 | \text{Class} = A) \\ \mu & \frac{10 + 20 + 10 + 20}{4} = 15.0 \\ \sigma & \sqrt{\frac{(10-15)^2 + (20-15)^2 + (10-15)^2 + (20-15)^2}{4}} = 5 \end{aligned}$$

$$\begin{aligned} & \bullet P(X_2 | \text{Class} = B) \\ \mu & \frac{30 + 40 + 30 + 50}{4} = 37.5 \\ \sigma & \sqrt{\frac{(30-37.5)^2 + (40-37.5)^2 + (30-37.5)^2 + (50-37.5)^2}{4}} = 8.29 \end{aligned}$$

$$\bullet P(\text{Class} = A | X_1 = 5, X_2 = 10) = \frac{P(\text{Class} = A) P(X_1 = 5, X_2 = 10 | \text{Class} = A)}{P(X_1 = 5, X_2 = 10)}$$

$$= \frac{1}{2} N\left(\begin{bmatrix} 5 \\ 10 \end{bmatrix} \mid \mu = \begin{bmatrix} 15 \\ 15 \end{bmatrix}, \Sigma = \begin{bmatrix} 17.19 & -6.25 \\ -6.25 & 25 \end{bmatrix}\right) =$$

$$= \frac{1}{2} \left(\frac{1}{2\pi} \right)^{\frac{1}{2}} \frac{1}{|\Sigma|^{1/2}} \exp\left(-\frac{1}{2} \left(\begin{bmatrix} 5 \\ 10 \end{bmatrix} - \begin{bmatrix} 15 \\ 15 \end{bmatrix}\right)^T \Sigma^{-1} \left(\begin{bmatrix} 5 \\ 10 \end{bmatrix} - \begin{bmatrix} 15 \\ 15 \end{bmatrix}\right)\right) = \frac{1}{2} \frac{0.0049}{P(X_1 = 5, X_2 = 10)}$$

$$\bullet P(\text{Class} = B | X_1 = 5, X_2 = 10) = \frac{P(\text{Class} = B) P(X_1 = 5, X_2 = 10 | \text{Class} = B)}{P(X_1 = 5, X_2 = 10)}$$

$$= \frac{1}{2} N\left(\begin{bmatrix} 5 \\ 10 \end{bmatrix} \mid \mu = \begin{bmatrix} 42.5 \\ 37.5 \end{bmatrix}, \Sigma = \begin{bmatrix} 68.75 & 31.25 \\ 31.25 & 68.75 \end{bmatrix}\right) =$$

$$= \frac{1}{2} \left(\frac{1}{2\pi} \right)^{\frac{1}{2}} \frac{1}{|\Sigma|^{1/2}} \exp\left(-\frac{1}{2} \left(\begin{bmatrix} 5 \\ 10 \end{bmatrix} - \begin{bmatrix} 42.5 \\ 37.5 \end{bmatrix}\right)^T \Sigma^{-1} \left(\begin{bmatrix} 5 \\ 10 \end{bmatrix} - \begin{bmatrix} 42.5 \\ 37.5 \end{bmatrix}\right)\right) = \frac{1}{2} \frac{3.45 \cdot 10^{-8}}{P(X_1 = 5, X_2 = 10)}$$

As $0.0049 > 3.45 \cdot 10^{-8}$, this query vector will be Classified as A

