

## Question 2

Red box  $\rightarrow$  3 apples, 4 oranges, 3 limes (r)

Green box  $\rightarrow$  3 apples, 3 oranges, 4 limes (g)

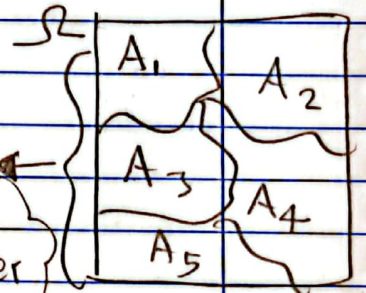
Blue box  $\rightarrow$  1 apple, 1 orange, 0 limes (b)

Probability of choosing each box:  $p(r) = 0.2$ ,  $p(g) = 0.6$   
 $p(b) = 0.2$

a) Probability of selecting an apple?

If  $\Omega$  is the sample space (i.e. all possible outcomes) and  $A_1, A_2, \dots, A_n$  are events that partition it, then:

$$P(X) = \sum_{i=1}^n P(X \cap A_i)$$



Also:

$$P(X \cap A_i) = P(X|A_i)P(A_i)$$

(definition of conditional probability)

exactly one of  $A_i$  occurs whenever  $X$  occurs

$$\Rightarrow P(X) = \sum_{i=1}^n P(X|A_i)P(A_i) \quad (\text{total probability theorem})$$

Let  $A =$  "We select an apple". Then, based on the above:

$$P(A) = P(A|r) \cdot P(r) + P(A|g)P(g) + P(A|b)P(b)$$

$P(A|r) \rightarrow$  given box  $r$  what is the probability of picking an apple?

$$P(A|r) = \frac{\text{number of apples in } r}{\text{number of fruit pieces in } r}$$

$$= \frac{3}{10} = 0.3$$

Similarly:  $P(A|g) = \frac{3}{10}$ ,  $P(A|b) = \frac{1}{2}$



$$\text{Then: } P(A) = \frac{3}{10} \cdot \frac{2}{10} + \frac{3}{10} \cdot \frac{6}{10} + \frac{1}{10} \cdot \frac{2}{10} \\ = \frac{6}{100} + \frac{18}{100} + \frac{2}{100} = \frac{26}{100} = 0.26$$

b) If we observe that the selected fruit is an orange what is the probability that it came from the green box?  
Let  $O$  = "The selected fruit is an orange"  
This is again conditional probability:

$P(g|O)$  → given that we picked an orange, what is the probability it came from  $g$ ?

Bayes' rule:  $P(g|O) = \frac{P(O|g) \cdot P(g)}{P(O)}$

$$P(O|g) = \frac{\text{number of oranges in } g}{\text{pieces of fruit in } g} = \frac{3}{10}$$

$$P(O) = P(O|g)P(g) + P(O|r)P(r) + P(O|b)P(b) =$$

$$= \frac{3}{10} \cdot \frac{6}{10} + \frac{4}{10} \cdot \frac{2}{10} + \frac{1}{10} \cdot \frac{2}{10} = \frac{18}{100} + \frac{8}{100} + \frac{2}{100} \\ = \frac{28}{100}$$

$$P(O|g) = \frac{\frac{3}{10} \cdot \frac{6}{10}}{\frac{28}{100}} = \frac{18}{28} = \frac{9}{14}$$



### Question 3

$C = \{C_1, \dots, C_N\} \rightarrow$  classes of the problem

$$L_{kj} = \begin{cases} 0, & \text{if } k=j \text{ (correct prediction)} \\ l_r, & \text{if } j=N+1 \text{ (rejection choice)} \\ l_s, & \text{otherwise (misclassification)} \end{cases}$$

a) Expected loss:  $E[L] = \sum_k \sum_j \int_{R_j} L_{kj} p(x, C_k) dx$

$\rightarrow R_j$  is the region of the input space where our classifier outputs <<class j>>

$\Rightarrow$  Sum over  $j$  examines each region, sum over  $k$  examines each ground truth class

Rewriting:  $E[L] = \sum_j \int_{R_j} \sum_k L_{kj} p(x, C_k) dx$   
 $= \sum_j \int_{R_j} \sum_k L_{kj} p(x) p(C_k | x) dx$

$\nabla$  Summation terms don't affect each other  $\Rightarrow$  to minimize the sum minimize each term  $\Rightarrow$  minimize "pointwise" over  $x \Rightarrow$  for each  $x$ , choose  $j$  so that:

$$\arg \min_j \left\{ \sum_k L_{kj} p(C_k | x) p(x) \right\} = \arg \min_j \left\{ \sum_k L_{kj} p(C_k | x) \right\}$$

doesn't change with  $j$

If  $j \neq N+1$ :

$$\begin{aligned} \sum_k L_{kj} p(C_k | x) &= \sum_{k \neq j} L_{kj} p(C_k | x) + \cancel{L_{jj} p(C_j | x)} \\ &= \sum_{k \neq j} l_s p(C_k | x) = l_s \sum_{k \neq j} p(C_k | x) = l_s (1 - p(C_j | x)) \end{aligned}$$

If  $j = N+1$  (reject), the cost is  $l_r$

$\Rightarrow$  Cost  $l_r$  when choosing reject, cost  $l_s (1 - p(C_j | x))$  when choosing  $j$



$\Rightarrow$  To minimize, we should choose <<reject>> if  $\neq$

$$l_r < l_s(1 - p(c_j|x)) \quad \forall j \Leftrightarrow l_s \neq 0$$

$$\frac{l_r}{l_s} < 1 - p(c_j|x) \Rightarrow p(c_j|x) < 1 - \frac{l_r}{l_s}$$

If  $p(c_j|x) \geq 1 - \frac{l_r}{l_s}$  then choose  $j$  so that  $l_s(1 - p(c_j|x))$  is minimum  $\Rightarrow p(c_j|x)$  is maximum

Therefore the optimal classifier is:

$$\text{classify}(x) = \begin{cases} c_j & \text{if } p(c_i|x) \leq p(c_j|x) \forall i \text{ and } p(c_j|x) \geq 1 - \frac{l_r}{l_s} \\ c_{\text{rej}} & \text{otherwise} \end{cases}$$

b) If  $l_r = 0$  then we always reject unless  $p(c_j|x) = 1$  (<<absolute certainty>>)

c) If  $l_r > l_s$  then  $1 - \frac{l_r}{l_s} < 0 \Rightarrow$  we never reject

#### Question 4

$$p(x|\theta) = \theta^2 x e^{-\theta x} g(x), \quad g(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

$N$  measurements  $x_1, x_2, \dots, x_N > 0$

What is  $\hat{\theta}$  MLE?

$\hat{\theta}$  is such that  $p(x_1, x_2, \dots, x_N|\hat{\theta})$  is maximum

$$\begin{aligned} p(x_1, x_2, \dots, x_N|\theta) &= p(x_1|\theta) p(x_2|\theta) \dots p(x_N|\theta) \\ &= \theta^2 x_1 e^{-\theta x_1} g(x_1) \theta^2 x_2 e^{-\theta x_2} g(x_2) \dots \theta^2 x_N e^{-\theta x_N} g(x_N) \end{aligned}$$

$\Rightarrow g(x_i) \geq 0$  since  $x_i > 0$ . Then:

$$p(x_1, \dots, x_N|\theta) = \theta^{2N} \prod_{i=1}^N x_i e^{-\theta \sum_{i=1}^N x_i}$$



To maximize wrt.  $\theta$  we need the derivative wrt.  $\theta$ ,  $\dots$

$$\begin{aligned} \frac{\partial}{\partial \theta} (p(x_1, \dots, x_N | \theta)) &= \frac{\partial}{\partial \theta} \left( \theta^{2N} \prod_{i=1}^N x_i e^{-\theta \sum_{i=1}^N x_i} \right) \\ &= \prod_{i=1}^N x_i \frac{\partial}{\partial \theta} \left( \theta^{2N} e^{-\theta \sum_{i=1}^N x_i} \right) = \left( \theta^{2N-1} e^{-\theta \sum_{i=1}^N x_i} \right) 2N \\ &\quad + \theta^{2N} e^{-\theta \sum_{i=1}^N x_i} \left( -\sum_{i=1}^N x_i \right) \cdot \prod_{i=1}^N x_i \end{aligned}$$

Set to 0:  $\prod_{i=1}^N x_i \left( 2N \theta^{2N-1} e^{-\theta \sum_{i=1}^N x_i} + \theta^{2N} e^{-\theta \sum_{i=1}^N x_i} \left( -\sum_{i=1}^N x_i \right) \right) = 0$

$\Rightarrow$  (Divide with  $\prod_{i=1}^N x_i \neq 0$ )  $(2N + \theta \left( -\sum_{i=1}^N x_i \right)) e^{-\theta \sum_{i=1}^N x_i} \theta^{2N-1} = 0$

$$\Rightarrow \theta = 0 \text{ or } 2N + \theta \left( -\sum_{i=1}^N x_i \right) = 0 \Rightarrow \theta = \frac{2N}{\sum_{i=1}^N x_i}$$

$\theta = 0$  is rejected as a possible maximum position since  $p(x|0) = 0 \forall x$  (definitely not maximum likelihood)

Therefore  $\boxed{\theta = \frac{2N}{\sum_{i=1}^N x_i}}$

Note: You can also do this by maximizing  $\log p(x_1, \dots, x_N | \theta)$ , as is common in many cases. In that case just note that this is not defined for  $\theta = 0$  and observe that the maximum is not achieved there, so it's not an issue