Solutions of Chapter 2 Problems

Problem 2.1

a) Consider the binary hypothesis testing problem

$$H_0 : X = 0$$

 $H_1 : X = 1$,

where the a-priori probabilities of the two hypotheses are given by

$$\pi_0 = P[X = 0] = 1/4$$
 , $\pi_1 = P[X = 1] = 3/4$.

Since Y = X + V, under H_0 we have Y = V, whereas under H_1 Y = 1 + V, so that the probability mass distributions of Y under H_0 and H_1 are as sketched below.

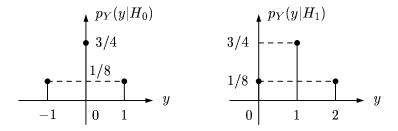


Figure 1: Probability mass distribution of Y under H_0 and H_1 .

The costs corresponding to the minimum probability of error risk function are given by $C_{ij} = 1 - \delta_{ij}$.

The likelihood ratio function is given by

$$L(y) = rac{p_Y(y|H_1)}{p_Y(y|H_0)} = \left\{ egin{array}{ll} \infty & y=2 \ 6 & y=1 \ 1/6 & y=0 \ 0 & y=-1 \ , \end{array}
ight.$$

and the LRT takes the form

$$L(y) \stackrel{H_1}{\underset{H_0}{\geq}} \tau = \frac{(C_{10} - C_{00})\pi_0}{(C_{01} - C_{11})\pi_1} = \frac{1}{3}.$$

The optimum decision rule can therefore be expressed as

$$\hat{X} = \begin{cases} 1 & \text{for } y \ge 1 \\ 0 & \text{for } y \le 0. \end{cases}$$

b) The probability of a correct decision is

$$\begin{split} P[\hat{X} = X] &= P[\hat{X} = X = 1] + P[\hat{X} = X = 0] \\ &= P[\hat{X} = 1|H_1]\pi_1 + P[\hat{X} = 0|H_0]\pi_0 \\ &= P[Y \ge 1|H_1]\pi_1 + P[Y \le 0|H_0]\pi_0 \\ &= (\frac{1}{8} + \frac{3}{4})\frac{1}{4} + (\frac{1}{8} + \frac{3}{4})\frac{3}{4} = \frac{7}{8} \,. \end{split}$$

Problem 2.2

a) Since Y = AX + V where X takes values 0 and 1 with probabilities $\pi_0 = 1/3$ and $\pi_1 = 2/3$, respectively, the hypothesis testing problem takes the Gaussian form

$$H_0$$
: $Y = V \sim N(0,1)$
 H_1 : $Y = A + V \sim N(1,4)$.

So the LRT is given by

$$L(y) = \frac{f_Y(y|H_1)}{f_Y(y|H_0)}$$

$$= \frac{1}{2} \frac{\exp(-(y-1)^2/8)}{\exp(-y^2/2)} \stackrel{H_1}{\underset{H_0}{\geq}} \tau, \qquad (2.1)$$

where since we seek to minimize the probability of error

$$\tau = \frac{\pi_0}{\pi_1} = \frac{1}{2} \,. \tag{2.2}$$

Substituting (2.2) inside (2.1), we obtain the test

$$\exp(-(y-1)^2/8) \stackrel{H_1}{\underset{H_0}{\geq}} \exp(-y^2/2)$$
.

Equivalently, since the logarithm function preserves ordering, we have

$$-(Y-1)^2/8 \underset{H_0}{\overset{H_1}{\geq}} -Y^2/2$$
,

and after some simple algebraic manipulations, we get

$$q(Y) \stackrel{\triangle}{=} 3Y^2 + 2Y - 1 \stackrel{H_1}{\underset{H_0}{\gtrless}} 0$$
.

The quadratic equation q(y) = 0 has for roots -1 and 1/3 so the Bayesian test is given by

$$\delta_{\mathrm{B}}(Y) = \left\{ egin{array}{ll} 0 & \mathrm{for} \ -1 < Y < 1/3 \\ 1 & \mathrm{otherwise} \ . \end{array}
ight.$$

Problem 2.3

a) Under H_1 , since Y = X + V with X and V independent, the probability density of Y is the convolution of the densities of X and V. This gives

$$\begin{split} f_Y(y|H_1) &= f_X(y) * f_V(y) \\ &= ab \Big[\int_0^y \exp(-a(y-v)) \exp(-bv) dv \Big] u(y) \\ &= ab \exp(-ay) u(y) \int_0^y \exp(-(b-a)v) dv \\ &= \frac{ab}{b-a} \exp(-ay) u(y) [1 - \exp(-(b-a)y)] \\ &= \frac{ab}{b-a} [\exp(-ay) - \exp(-by)] u(y) \;, \end{split}$$

where $u(\cdot)$ denotes the unit step function.

The likelihood ratio test (LRT) takes the form

$$L(y) = \frac{f_Y(y|H_1)}{f_Y(y|H_0)}$$

$$= \frac{ab}{b-a} \frac{[\exp(-ay) - \exp(-by)]}{b \exp(-by)} \stackrel{H_1}{\underset{H_0}{\geq}} \tau, \qquad (2.3)$$

which yields after simplifications

$$\frac{a}{b-a}[\exp((b-a)y)-1] \stackrel{H_1}{\underset{H_0}{\geq}} \tau.$$

Assuming without loss of generality that b > a, this gives

$$\exp((b-a)y) \underset{H_0}{\overset{H_1}{\geq}} \left(\frac{b}{a}-1\right)\tau + 1$$

or equivalently

$$Y \underset{H_0}{\overset{H_1}{\geq}} \eta \stackrel{\triangle}{=} \frac{1}{b-a} \log \left[\left(\frac{b}{a} - 1 \right) \tau + 1 \right]. \tag{2.4}$$

b) The cost function corresponding to the minimum probability of error criterion is given by $C_{ij} = 1 - \delta_{ij}$. If the two hypotheses are equally likely, $\pi_0 = \pi_1 = 1/2$, so that the threshold $\tau = 1$ Substituting in (2.4), we find that the threshold

$$\eta = \frac{1}{b-a}\log(b/a) \ .$$

Problem 2.4:

a) For the densities

$$f_Y(y|H_0) = \frac{1}{(2\pi)^{1/2}} \exp(-y^2/2)$$

 $f_Y(y|H_1) = \frac{1}{2} \exp(-|y|)$

the likelihood ratio function takes the form

$$L(y) = rac{f_Y(y|H_1)}{f_Y(y|H_0)} = \left(\pi/2
ight)^{1/2} \exp\left(rac{y^2}{2} - |y|
ight).$$

b) The function L(y) is plotted as a function of y in Fig. 2 below.

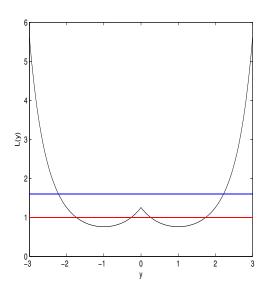


Figure 2: Plot of likelihood ratio function L(y).

The decision rule

$$L(y) \stackrel{H_1}{\underset{H_0}{\geq}} \tau$$

is implemented by drawing a horizontal line at $L(y) = \tau$ and choosing H_1 for all values of y for which L(y) is above the line. From this simple observation we deduce that if

$$\tau \leq (\pi/2)^{1/2} \exp(-1/2)$$
,

we always choose H_1 . If

$$(\pi/2)^{1/2} \exp(-1/2) < \tau \le (\pi/2)^{1/2}$$

there are two regions of identical width, centered about 1 and -1, for which H_0 is selected. If

$$\tau > \left(\pi/2\right)^{1/2}$$

there is only one region, centered about zero, where H_0 is selected. These last two cases are illustrated by red and blue horizontal lines in Fig. 2, which correspond respectively to the choices $\tau = 1$ and $\tau = 1.6$.

Problem 2.5

a) Consider the binary hypothesis testing problem

$$H_0$$
: $f_{Y_k}(y_k|H_0) = \frac{\lambda}{2} \exp(-\lambda|y_k|)$
 H_1 : $f_{Y_k}(y_k|H_1) = \frac{\lambda}{2} \exp(-\lambda|y_k - A|)$,

where the Y_k 's are independent for $1 \leq k \leq N$. The likelihood ratio function can be expressed as

$$L(\mathbf{y}) = \prod_{k=1}^{N} L(y_k) \tag{2.5}$$

with

$$L(y_k) = \exp[\lambda(|y_k| - |y_k - A|)].$$

Accordingly, by taking logarithms and dividing by N, the LR test can written as

$$S \overset{H_1}{\underset{H_0}{\gtrless}} \eta = rac{1}{N} \ln(au) \, ,$$

where

$$S = \frac{1}{N} \sum_{k=1}^{N} \ln L(Y_k) ,$$

with

$$\ln L(y) = c(y - A/2) = \begin{cases} -A & y \le 0 \\ 2y - A & 0 \le y \le A \\ A & y \ge A \end{cases}.$$

- b) When the two hypotheses are equally likely $(\pi_0 = \pi_1 = 1/2)$ and we seek to minimize the probability of error, so the Bayesian costs are given by $C_{ij} = 1 \delta_{ij}$, the Bayesian threshold $\tau = 1$, so $\eta = 0$.
- c) The clipping function $c(\cdot)$ truncates the high and low values of centered observations $Y_k A/2$ to prevent them from dominating the sum S.

Problem 2.6:

a) Since $f_Y(y|H_0)$ and $f_Y(y|H_1)$ are densities, we have

$$\int_{-\infty}^{\infty} f_Y(y|H_0)dy = A_0 \int_{-a}^{a} (a-|y|)dy = A_0 a^2 = 1$$
 $\int_{-\infty}^{\infty} f_Y(y|H_1)dy = A_1 \int_{-b}^{b} (b-|y|)dy = A_1 b^2 = 1$,

so that

$$A_0 = \frac{1}{a^2} \ , \ A_1 = \frac{1}{b^2} \, .$$

b) We have

$$L(y) = \frac{f_Y(y|H_1)}{f_Y(y|H_0)}$$

$$= \begin{cases} \infty & \text{for } a \le |y| \le b \\ \frac{a^2}{b^2} \frac{b - |y|}{a - |y|} & \text{for } 0 \le |y| < a. \end{cases}$$

Thus for $\tau < a/b$ we always choose H_1 , whereas for $\tau > a/b$, the LRT takes the form

$$rac{a^2}{b^2}rac{(b-|y|)}{(a-|y|)} \stackrel{H_1}{\underset{H_0}{ ides}} au \; ,$$

or equivalently

$$|Y| \stackrel{H_1}{\underset{H_0}{\geq}} \eta \stackrel{\triangle}{=} ba \frac{(b\tau - a)}{(b^2\tau - a^2)}$$
.

c) We have

$$P_{D}(\eta) = \int_{\eta}^{\infty} f_{Y}(y|H_{1})dy + \int_{-\infty}^{-\eta} f_{Y}(y|H_{1})dy$$
$$= \frac{2}{b^{2}} \int_{\eta}^{b} (b-y)dy = \frac{(b-\eta)^{2}}{b^{2}}.$$

Similarly

$$P_F(\eta) = \int_{\eta}^{\infty} f_Y(y|H_0)dy + \int_{-\infty}^{-\eta} f_Y(y|H_0)dy$$
$$= \frac{(a-\eta)^2}{a^2}.$$

Since

$$\eta = b(P_D^{1/2} - 1)
= a(P_F^{1/2} - 1),$$
(2.6)

the ROC takes theform

$$P_D = \left[1 + \frac{a}{b}(P_F^{1/2} - 1)\right]^2.$$

For b = 2a, this gives

$$P_D = \frac{(1 + P_F^{1/2})^2}{4} \,, \tag{2.7}$$

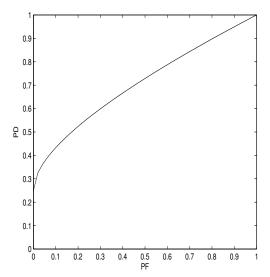


Figure 3: Plot of receiver operating characteristic (2.7).

which is sketched below.

Problem 2.7:

The minimum probability of error decision rule is the LRT

$$L(k) = \frac{P[K = k|H_1]}{P[K = k|H_0]} = \frac{q_1^k (1 - q_1)^{n-k}}{q_0^k (1 - q_0)^{n-k}} \stackrel{H_1}{\underset{H_0}{\geq}} \tau = \frac{\pi_0}{\pi_1},$$

where we have used the costs $C_{ij} = 1 - \delta_{ij}$ with i, j = 0, 1. This rule can be expressed as

$$K = k \underset{H_0}{\overset{H_1}{\geq}} \eta$$

with

$$\eta = \frac{\ln\left(\frac{\pi_0(1-q_0)^n}{\pi_1(1-q_1)^n}\right)}{\ln\left(\frac{q_1(1-q_0)}{q_0(1-q_1)}\right)}.$$

b) Since the random variable K is integer valued, the ROC is obtained by connecting linearly the discrete points $(P_F(m), P_D(m))$ corresponding to the test

$$K \underset{H_0}{\overset{H_1}{\geq}} m \tag{2.8}$$

for $-1 \leq m \leq n$. The probabilities of false alarm and of detection for test (2.8) can be

$$P_F(m) = \sum_{k=m+1}^n \binom{n}{k} q_0^k (1-q_0)^{n-k}$$

 $P_F(m) = \sum_{k=m+1}^n \binom{n}{k} q_1^k (1-q_1)^{n-k}$,

where

expressed as

$$\binom{n}{k} \stackrel{\triangle}{=} \frac{n!}{k!(n-k)!}$$
.

For n=2 we only need to consider $-1 \leq m \leq 2$, and in this case $(P_F(m), P_D(m))$ are specified by Table 1 shown below.

m	$P_F(m)$	$P_D(m)$
-1	1	1
0	$2q_0(1-q_0)+q_0^2$	$2q_1(1-q_1)+q_1^2$
1	q_0^2	q_1^2
2	0	0

Table 1: Probabilities $(P_F(m), P_D(m))$ for n = 2 and $-1 \le m \le 2$.

The ROC is plotted in Fig. 4 below for $q_0 = 0.2$ and $q_1 = 0.6$. Note that the linear segments connecting the four discrete points $(P_F(m), P_D(m))$ with $-1 \le m \le 2$ are obtained by randomization.

Problem 2.8:

a) The Bayesian test can be expressed as

$$L(y) = \frac{f_Y(y|H_1)}{f_Y(y|H_0)}$$

$$= 2\frac{\exp(-2|y|)}{\exp(-|y|)} = 2\exp(-|y|) \stackrel{H_1}{\underset{H_0}{\geq}} \tau,$$

or equivalently

$$|Y| \stackrel{H_0}{\underset{H_1}{\gtrless}} \eta \stackrel{\triangle}{=} - \ln(\tau/2) \; .$$

b) The probability of false alarm can be expressed as

$$P_{F}(\tau) = \int_{-\eta}^{\eta} f_{Y}(y|H_{0})dy$$

$$= 1 - 2\int_{\eta}^{\infty} f_{Y}(y|H_{0})dy$$

$$= 1 - \exp(-\eta) = 1 - \frac{\tau}{2}$$
(2.9)

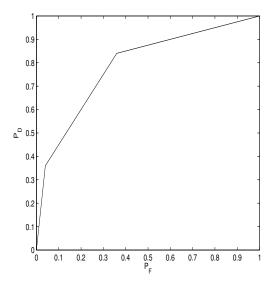


Figure 4: Plot of the ROC for $q_0 = 0.2$, $q_1 = 0.6$ and n = 2.

for $\tau \leq 2$ and $P_F(\tau) = 0$ for $\tau > 2$. Similarly

$$P_{D}(\tau) = \int_{-\eta}^{\eta} f_{Y}(y|H_{1})dy$$

$$= 1 - 2 \int_{\eta}^{\infty} f_{Y}(y|H_{1})dy$$

$$= 1 - \exp(-2\eta) = 1 - \frac{\tau^{2}}{4}$$
(2.10)

for $\tau \leq 2$ and $P_D(\tau) = 0$ for $\tau > 2$.

c) Eliminating η from identities (2.9) and (2.10) yields the ROC equation

$$P_D = 1 - (1 - P_F)^2 (2.11)$$

which is sketched below.

d) To design a Neyman-Pearson test with probability of false alarm less or equal to α , we must in fact select $P_F = \alpha$ which, after substitution in (2.9), yields

$$\tau = 2(1 - \alpha) .$$

Problem 2.9

a) For the Bayesian costs $C_{00} = C_{11} = 0$, $C_{10} = 1$, and $C_{01} = 2$, the minimax equation is given by

$$P_F = 2(1 - P_D) ,$$

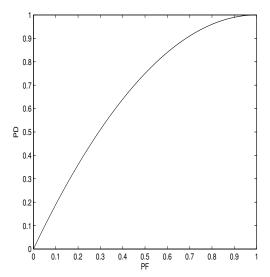


Figure 5: Plot of receiver operating characteristic (2.11).

or equivalently

$$P_D = 1 - \frac{P_F}{2} \,. \tag{2.12}$$

Eliminating P_D from equations (2.11) and (2.12) gives the quadratic equation

$$P_F^2 - \frac{5}{2}P_F + 1 = 0$$

whose roots are

$$P_F = \frac{1}{2} \left[\frac{5}{2} \pm \left(\frac{25}{4} - 4 \right)^{1/2} \right] = \frac{1}{2}, 2.$$

Since P_F must be less than 1, this gives $P_F = 1/2$, and backsubstituting inside (2.12), we obtain

$$P_D = 3/4$$
.

The slope of the ROC (2.11) is

$$\frac{dP_D}{dP_F} = 2(1 - P_F) \ .$$

Evaluating it at $P_F = 1/2$, we find that the threshold of the minimax test is

$$\tau_{\rm M}=1$$
 .

According to equation (2.96) of the book, we have therefore

$$\pi_{0M} = [1 + 1/2]^{-1} = \frac{2}{3}$$
.

This completes the specification of the minimax test.

b) For the given costs, the Bayesian risk of an arbitrary test δ is

$$R(\delta, \pi_0) = 2(1 - \pi_0)(1 - P_D(\delta)) + \pi_0 P_F(\delta)$$
(2.13)

for a fixed π_0 , the test δ that minimizes the risk $R(\delta, \pi_0)$ is the LRT with threshold

$$au = rac{\pi_0}{2(1-\pi_0)} \, .$$

Note that $\tau \leq 2$ as long as

$$\pi_0 \le \frac{4}{5} \ .$$

For $\pi_0 \leq 4/5$, the probability of false alarm and of a miss are given by

$$P_F = 1 - \frac{\tau}{2} = \frac{4 - 5\pi_0}{4(1 - \pi_0)}$$

 $1 - P_D = \frac{\tau^2}{4} = \frac{\pi_0^2}{16(1 - \pi_0)^2}$.

Substituting these values inside (2.13) yields

$$V(\pi_0) = \frac{\pi_0^2}{8(1-\pi_0)} + \pi_0 \frac{(4-5\pi_0)}{4(1-\pi_0)}$$

$$= \frac{8\pi_0 - 9\pi_0^2}{8(1-\pi_0)}$$
(2.14)

for $0 \le \pi_0 \le 4/5$, and observing that $P_F = P_D = 0$ for $\tau > 2$, or equivalently $\pi_0 > 4/$, we find

$$V(\pi_0) = 2(1 - \pi_0) \tag{2.15}$$

for $4/5 < \pi_0 \le 1$. The function $V(\pi_0)$ defined by (2.14)-(2.15) is skteched below in Fig. 6. Its maximum is obtained by setting the derivative of (2.14) equal to zero. We have

$$\frac{dV}{d\pi_0} = \frac{(8 - 18\pi_0)(1 - \pi_0) + (8\pi_0 - 9\pi_0^2)}{8(1 - \pi_0)^2}
= \frac{9(1 - \pi_0)^2 - 1}{8(1 - \pi_0)^2},$$

which is zero whenever

$$3(1-\pi_0)=1$$

or $\pi_{0M} = 2/3$, which verifies the result obtained earlier in part a) of this problem.

Problem 2.10

a) For the probability densities

$$f_Y(y|H_0) = \begin{cases} 1 & 0 \le y \le 1\\ 0 & \text{otherwise} \end{cases}$$

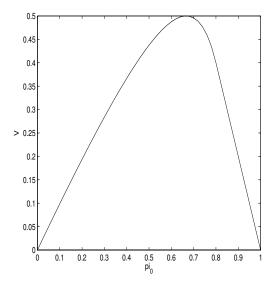


Figure 6: Plot of function $V(\pi_0)$.

and

$$f_Y(y|H_1) = \begin{cases} 4\left(\frac{1}{2} - \left|\frac{1}{2} - y\right|\right) & 0 \le y \le 1\\ 0 & \text{otherwise} \end{cases},$$

the LRT can be expressed as

$$L(y) = \frac{f_Y(y|H_1)}{f_Y(y|H_0)}$$

$$= 4(\frac{1}{2} - |\frac{1}{2} - y|) \underset{H_0}{\overset{H_1}{\geq}} \tau$$
(2.16)

for $0 \le y \le 1$. Since the maximum value of L(y) is 2, 2 cases occur. When $\tau > 2$, we always select H_0 . On the other hand when $\tau \le 2$, the test (2.16) can be rewritten as

$$\eta = rac{2- au}{4} \mathop{}_{\stackrel{ ext{$<$}}{ ext{$<$}}}^{H_1} \left| rac{1}{2} - y
ight|.$$

b) The probability of false alarm can be expressed as

$$P_{F}(\tau) = \int_{1/2-\eta}^{1/2+\eta} f_{Y}(y|H_{0})dy$$
$$= 2\eta = 1 - \frac{\tau}{2}. \qquad (2.17)$$