

# Appendix A

## A.1 Proof of Proposition 7.2.1

*Proof* Given  $P_F = P_{F_i}$  and  $P_M = P_{M_i}$  for all  $i \in \{1, \dots, K\}$ , false alarm and miss detection probabilities resulting from  $\gamma^K$  are  $P_{F_0} = 1 - B(K/2; K, P_F)$  and  $P_{M_0} = B(K/2; K, 1 - P_M)$ , respectively, where  $B(t_0; K, P)$  is a binomial cumulative distribution function with at most  $t_0$  successes out of  $K$  trials each having a success probability  $P$ . Let  $X \sim B(K, P)$  and  $Y \sim B(K, 1 - P)$  be two Binomial r.v.s with  $K$  trials each having a success probability  $P$  and  $1 - P$ , respectively. Then, for two disjoint events  $E_1 = X \leq K/2$  and  $E_2 = (K - X) \leq K/2$ ,

$$P(E_1 \cup E_2) = P(E_1) + P(E_2) = 1.$$

Now, by noting that  $Y = K - X$  in distribution, we have

$$\begin{aligned} P(E_1) + P(E_2) &= P(X \leq K/2) + P(Y \leq K/2) \\ &= B(K/2; K, P) + B(K/2; K, 1 - P) = 1 \end{aligned}$$

which implies that  $P_{F_0}$  and  $P_{M_0}$  own the same polynomial function  $f$  s.t.  $P_{F_0} = f(P_F)$  and  $P_{M_0} = f(P_M)$ . From Proposition 7.4.1,  $f$  is monotonically increasing, hence  $P_{M_0} = P_{F_0}$  iff  $P_M = P_F$ .  $\square$

## A.2 Proof of Proposition 7.2.2

*Proof* Using the substitution  $j = i + 1$ , we have

$$\begin{aligned}
P_F P_{F_0}^{2K-1} &= \sum_{i=K}^{2K-1} \binom{2K-1}{i} P_F^{i+1} (1-P_F)^{2K-1-i} \\
&= \sum_{j=K+1}^{2K} \binom{2K-1}{j-1} P_F^j (1-P_F)^{2K-j} \\
&= \left( \sum_{j=K+1}^{2K-1} \binom{2K-1}{j-1} P_F^j (1-P_F)^{2K-j} \right) + P_F^{2K} \quad (\text{A.1})
\end{aligned}$$

and

$$\begin{aligned}
(1-P_F) P_{F_0}^{2K-1} &= \sum_{i=K}^{2K-1} \binom{2K-1}{i} P_F^i (1-P_F)^{2K-i} \\
&= \binom{2K-1}{K} P_F^K (1-P_F)^K \\
&\quad + \sum_{i=K+1}^{2K-1} \binom{2K-1}{i} P_F^i (1-P_F)^{2K-i}. \quad (\text{A.2})
\end{aligned}$$

Adding up (A.1) and (A.2), we get

$$\begin{aligned}
(1-P_F) P_{F_0}^{2K-1} + P_F P_{F_0}^{2K-1} &= \binom{2K-1}{K} P_F^K (1-P_F)^K \\
&\quad + \sum_{i=K+1}^{2K-1} \left( \binom{2K-1}{i-1} + \binom{2K-1}{i} \right) P_F^i (1-P_F)^{2K-i} + P_F^{2K} \\
&= \frac{1}{2} \binom{2K}{K} P_F^K (1-P_F)^K + \sum_{i=K+1}^{2K} \binom{2K}{i} P_F^i (1-P_F)^{2K-i} \\
&= P_{F_0}^{2K}
\end{aligned}$$

using the identities

$$\binom{2K-1}{K} = \frac{1}{2} \binom{2K}{K}, \quad \binom{2K-1}{i} + \binom{2K-1}{i-1} = \binom{2K}{i}$$

and

$$P_F^{2K} = \binom{2K}{2K} P_F^{2K} (1-P_F)^{2K-2K}.$$

□

### A.3 Proof of Lemma 7.3.2

*Proof* By definition,  $P_F$  and  $P_M$  are probabilities, hence  $(P_F, P_M) \in [0, 1]^2$ . Evaluating  $P_F = 1 - P_0[l(Y) \leq t]$  and  $P_M = P_1[l(Y) \leq t]$  for  $\lim_{t \rightarrow 0}$  and  $\lim_{t \rightarrow \infty}$  shows that  $r_t$  passes through the points  $(1, 0)$  and  $(0, 1)$ . Let  $p_{0,l}$  and  $p_{1,l}$  be the density functions of  $l(Y)$  for  $Y \sim P_0$  and  $Y \sim P_1$ , respectively. Since  $r_t$  is differentiable for every  $t$ , i.e.

$$\frac{dP_M}{dP_F} = \frac{dP_M}{dt} \frac{dt}{dP_F} = -\frac{p_{1,l}(t)}{p_{0,l}(t)} \quad (\text{A.3})$$

exists,  $r_t$  is continuous. The miss detection probability can also be written as

$$P_M = \int_{\{y:l(y) \leq t\}} p_1(y) dy = \int_{\{y:l(y) \leq t\}} l(y) p_0(y) dy = \int_0^t x p_{0,l}(x) dx,$$

where the last equality follows from

$$p_{0,l}(x) = \left| \frac{dl^{-1}(x)}{dx} \right| p_0(l^{-1}(x))$$

with the change of variable  $x = l(y)$ . Hence,

$$\frac{dP_M}{dt} = t p_{0,l}(t) \stackrel{(\text{A.3})}{\implies} \frac{dP_M}{dP_F} = -t.$$

As a result,

$$\frac{d^2 P_M}{dP_F^2} = \frac{d}{dP_F} \left( \frac{dP_M}{dP_F} \right) = -\frac{dt}{dP_F} = \frac{1}{p_{0,l}(t)} \geq 0$$

proves that  $r_t$  is convex. □

### A.4 Proof of Proposition 7.4.1

Letting  $p = p(\theta) = 1 - \theta$  and  $q = q(\theta) = \frac{1-2\theta}{1-\theta}$ , showing that  $L_\infty^K$  is negative for sufficiently large  $K$  is equivalent to showing that

$$\sum_{i=0}^{K/2} \binom{K}{i} p^i (1-p)^{K-i} < \frac{1}{2} \sum_{i=0}^{K/2} \binom{K}{i} q^i (1-q)^{K-i} \quad (\text{A.4})$$

for sufficiently large  $K$ . There are two possible cases:

- Trivial case: For  $1/3 \leq \theta < 1/2$ , the sum on the left converges to zero and the sum on the right converges to a positive number, so the inequality (A.4) is true for large  $K$ .
- Remaining case: Suppose  $0 < \theta < 1/3$ . The inequality of the sums can be proven working term by term. It suffices to show that

$$p^i (1-p)^{K-i} < \frac{1}{2} q^i (1-q)^{K-i} \quad (\text{A.5})$$

for all  $0 \leq i \leq K/2$ , when  $K$  is large enough. Note that  $\frac{p(1-q)}{q(1-p)} = \frac{1-\theta}{1-2\theta} > 1$  and  $\frac{p(1-p)}{q(1-q)} = \frac{(1-\theta)^3}{1-2\theta} < 1$ . Therefore,

$$\left(\frac{1-p}{1-q}\right)^K \left(\frac{p(1-q)}{q(1-p)}\right)^i \leq \left(\frac{1-p}{1-q}\right)^K \left(\frac{p(1-q)}{q(1-p)}\right)^{K/2} = \left(\frac{p(1-p)}{q(1-q)}\right)^{K/2}. \quad (\text{A.6})$$

The right hand side of (A.6) can be made less than  $1/2$  by taking  $K$  sufficiently large, giving the inequality (A.5) and hence the inequality (A.4).

## A.5 Proof of Proposition 7.5.1

*Proof* To prove that  $P_{F_0}(P_F, K, t_0)$  and  $P_{M_0}(P_M, K, t_0)$  are increasing functions of  $P_F$  and  $P_M$ , respectively, it is sufficient to prove it only for  $P_{F_0}(P_F, K, t_0)$ . Because

$$\frac{\partial P_{M_0}(P_M, K, t_0)}{\partial P_M} = \frac{\partial P_{F_0}(P_F, K, t_0)}{\partial P_F} \Big|_{P_F := 1 - P_M}. \quad (\text{A.7})$$

Noting that (A.7) is zero for  $P_F = 0$ , we have

$$\begin{aligned} P_{F_0} &= \sum_{i=t_0}^K \binom{K}{i} P_F^i (1-P_F)^{K-i} = \sum_{i=t_0}^K \binom{K-1}{i-1} P_F^i (1-P_F)^{K-i} \\ &\quad + \sum_{i=t_0}^K \binom{K-1}{i} P_F^i (1-P_F)^{K-i}. \end{aligned} \quad (\text{A.8})$$

Since in the second sum, the term is zero when  $i = K$ , we get

$$\begin{aligned} \sum_{i=t_0}^K \binom{K-1}{i} P_F^i (1-P_F)^{K-i} &= \sum_{i=t_0}^{K-1} \binom{K-1}{i} P_F^i (1-P_F)^{K-i} \\ &< \sum_{i=t_0-1}^{K-1} \binom{K-1}{i} P_F^i (1-P_F)^{K-i}. \end{aligned} \quad (\text{A.9})$$

Changing the variable  $j = i + 1$ ,

$$\sum_{i=t_0-1}^{K-1} \binom{K-1}{i} P_F^i (1-P_F)^{K-i} = \sum_{j=t_0}^K \binom{K-1}{j-1} P_F^{j-1} (1-P_F)^{K-j+1} \quad (\text{A.10})$$

and writing (A.10) in (A.8) with (A.9), it follows that

$$\begin{aligned} \sum_{i=t_0}^K \binom{K}{i} P_F^i (1-P_F)^{K-i} &< \sum_{i=t_0}^K \binom{K-1}{i-1} P_F^i (1-P_F)^{K-i} \\ &+ \sum_{j=t_0}^K \binom{K-1}{j-1} P_F^{j-1} (1-P_F)^{K-j+1}. \end{aligned} \quad (\text{A.11})$$

Using

$$P_F^i (1-P_F)^{K-i} + P_F^{i-1} (1-P_F)^{K-i+1} = P_F^{i-1} (1-P_F)^{K-i}$$

rewrite (A.11),

$$\sum_{i=t_0}^K \binom{K}{i} P_F^i (1-P_F)^{K-i} < \sum_{i=t_0}^K \binom{K-1}{i-1} P_F^{i-1} (1-P_F)^{K-i}. \quad (\text{A.12})$$

Multiplying (A.12) with  $K/(1-P_F)$  and noting that

$$i \binom{K}{i} = K \binom{K-1}{i-1}$$

we finally get

$$\sum_{i=t_0}^K \binom{K}{i} P_F^{i-1} (1-P_F)^{K-i-1} (i - K P_F) = \frac{\partial P_{F_0}(P_F, K, t_0)}{\partial P_F} > 0.$$

□

## A.6 Proof of Proposition 7.5.2

*Proof* The claim will be proven for odd  $t_0$ , while its extension to even  $t_0$  can be accomplished following the same line of arguments. Let the threshold be  $t_0 \in \{0, \lfloor K/2 \rfloor - 1\}$  for some  $K$ . If  $t_0 = \lfloor K/2 \rfloor$ , then clearly

$$P_{F_0}(x, K, \lfloor K/2 \rfloor) = P_{M_0}(x, K, \lfloor K/2 \rfloor), \quad \forall x \in [0, 1].$$

One can also see that, cf. Remark 7.4.1,

$$P_{F_0}(x, K, \lfloor K/2 \rfloor - 1) > P_{F_0}(x, K, \lfloor K/2 \rfloor), \quad \forall x \in (0, 1),$$

and

$$P_{M_0}(x, K, \lfloor K/2 \rfloor - 1) < P_{M_0}(x, K, \lfloor K/2 \rfloor), \quad \forall x \in (0, 1).$$

Hence,

$$P_{F_0}(x, K, \lfloor K/2 \rfloor - 1) > P_{M_0}(x, K, \lfloor K/2 \rfloor - 1), \quad \forall x \in (0, 1). \quad (\text{A.13})$$

For a pair  $(P_F, P_M)$  to be valid, it should be in  $(\mathcal{F} \times \mathcal{M})_{t_0}^K$ , i.e.

$$P_{F_0}(P_F, K, \lfloor K/2 \rfloor - 1) = P_{M_0}(P_M, K, \lfloor K/2 \rfloor - 1). \quad (\text{A.14})$$

Assume that (A.14) holds for some  $(P_F^*, P_M^*)$  with  $P_M^* = P_F^*$  or with  $P_M^* < P_F^*$ . Then, both cases are obviously a contradiction with (A.13), since both  $P_{F_0}$  and  $P_{M_0}$  are monotonically increasing functions of  $P_F$  and  $P_M$ , respectively, cf. Proposition 7.4.1. Therefore,  $P_M^* > P_F^*$  must be true for all pairs  $(P_F^*, P_M^*) \in (\mathcal{F} \times \mathcal{M})_{t_0}^K$ . This proves that  $h_{t_0}^K(P_F) > P_F$  for all  $P_F \in (0, 1)$ . Clearly, when  $t_0 \in \{\lfloor K/2 \rfloor + 1, K\}$ , due to symmetry, e.g.,  $P_{M_0}(x, K, \lfloor K/2 \rfloor + 1) = P_{F_0}(x, K, \lfloor K/2 \rfloor - 1)$ , the inequalities above change direction and we get  $h_{t_0}^K(P_F) < P_F$  for all  $P_F \in (0, 1)$ . Next, assume that  $(P_F^*, P_M^*), (P_F^*, P_M^*) \neq (1, 1)$  is a valid pair that satisfies (A.14) and fix a small positive number  $\delta$ . Since  $P_{F_0}$  is increasing,

$$P_{F_0}(P_F^* + \delta, K, \lfloor K/2 \rfloor - 1) > P_{F_0}(P_F^*, K, \lfloor K/2 \rfloor - 1), \quad \forall P_F^* \in [0, 1).$$

This suggests that the left hand side of (A.14) increases by adding  $\delta$  to  $P_F^*$ . In order (A.14) to hold, its right hand side must also increase, which implies an increase of  $P_M^*$  by some positive number  $\epsilon$ , since  $P_{M_0}$  is also an increasing function. Then,  $(P_F^* + \delta, P_M^* + \epsilon) \in (\mathcal{F} \times \mathcal{M})_{t_0}^K$  for all  $(P_F^*, P_M^*) \neq (1, 1)$  implies that  $h_{t_0}^K$  is a monotonically increasing function.  $\square$

## A.7 Proof of (7.18)

*Proof* Introducing a random variable  $X_K$  with a binomial distribution  $B(K, \theta)$ , it can be shown that

$$\mathcal{L}^K(\theta) = P[X_K > \lfloor K/2 \rfloor] - \frac{1}{1 + \hat{\theta}(\theta)^{-K}}.$$

For every  $\theta \leq \frac{1}{2}$ ,  $P[X_K > \lfloor K/2 \rfloor] \leq \frac{1}{2}$  hence  $P[X_K > \lfloor K/2 \rfloor] < \frac{1}{2}$ . Assume that  $\theta = \theta_K(x)$  where  $\theta_K(x) = \frac{1}{2} \left(1 - \frac{x}{\sqrt{K}}\right)$ , for some fixed positive  $x$ . Then,  $\lfloor K/2 \rfloor = E[X_K] + x_K \sigma(X_K)$  with  $x_K = x / \sqrt{4\theta_K(x)(1 - \theta_K(x))} \sim x$ . The central limit theorem implies that

$$\begin{aligned} P[X_K > \lfloor K/2 \rfloor] &= P[X_K > E[X_K] + x_K \sigma(X_K)] \\ &= P\left[\frac{X_K - E[X_K]}{\sigma(X_K)} > x_K\right] \\ &= P[X'_K > x] = 1 - F(x) \text{ when } K \rightarrow \infty \end{aligned}$$

where  $X'_K \sim \mathcal{N}(0, \sigma^2)$ . Since  $\hat{\theta}(\theta_K(x))^{-K} \rightarrow \infty$  when  $K \rightarrow \infty$ , we get,

$$\lim_{K \rightarrow \infty} \sup_{\theta \leq 1/2} \mathcal{L}^K(\theta) \geq \lim_{K \rightarrow \infty} \mathcal{L}^K(\theta_K(x)) = 1 - F(x).$$

As  $F(x) \rightarrow \frac{1}{2}$  when  $x \rightarrow 0^+$ , this proves the claim.  $\square$