

## M-ary Detection & the MAP Test

D-1

Let  $H$  be a  $\{0, \dots, M-1\}$ -valued RV with

$$p_i := P(H=i).$$

Let  $Y$  be an  $\mathbb{R}^d$ -valued random vector with conditional density  $f_i(y)$  so that

$$P(Y \in B | H=i) = \int_B f_i(y) dy.$$

Having observed  $Y$ , we would like to decide what the most likely value of  $H$  is. In other words, we want to find a function  $\psi(y)$  taking values in  $\{0, \dots, M-1\}$  so that

$$P(\psi(Y) \neq H)$$

is minimized.

Since  $\psi(y)$  takes only the values  $0, \dots, M-1$ ,  $\psi$  must have the form

$$\psi(y) = \sum_{i=0}^{M-1} i I_{D_i}(y)$$

where the sets  $D_i$  are disjoint and  $\bigcup_{i=0}^{M-1} D_i = \mathbb{R}^d$ .

So really, our goal is to find the decision regions  $D_0, \dots, D_{M-1}$ . To find the best ones, we proceed as follows:

Use the law of total probability to write

D-2

$$\begin{aligned} P(\Psi(Y)=H) &= \sum_{i=0}^{M-1} P(\Psi(Y)=H|H=i) p_i \\ &= \sum_{i=0}^{M-1} P(\Psi(Y)=i|H=i) p_i, \text{ by substitution} \end{aligned}$$

$$\begin{aligned} &= \sum_{i=0}^{M-1} P(Y \in D_i | H=i) p_i \\ &= \sum_{i=0}^{M-1} \left( \int_{D_i} f_i(y) dy \right) p_i \\ &= \sum_{i=0}^{M-1} \left( \int I_{D_i}(y) f_i(y) dy \right) p_i \\ &= \int \left[ \sum_{i=0}^{M-1} I_{D_i}(y) f_i(y) p_i \right] dy. \end{aligned}$$

For fixed  $y$ , only one term in the sum is nonzero since the  $D_i$  are disjoint. To maximize  $P(\Psi(Y)=H)$ , we should put  $y \in D_i \Leftrightarrow f_i(y) p_i \geq f_j(y) p_j$  for all  $j$ . This is the maximum a posteriori probability rule (MAP rule). If the  $p_i$  are all the same; i.e.,  $H$  is uniformly distributed with  $p_i = 1/M$ , then the rule of putting  $y \in D_i \Leftrightarrow f_i(y) \geq f_j(y)$  for all  $j$  is called the maximum likelihood (ML) rule.

Example. Suppose  $f_i(y) \sim N(m_i, C)$  and that  $p_i = 1/M$ . Then

$$f_i(y) \geq f_j(y)$$

if and only if

$$\frac{\exp[-(y-m_i)'C^{-1}(y-m_i)/2]}{(2\pi)^{d/2}\sqrt{\det C}} \geq \frac{\exp[-\frac{1}{2}(y-m_j)'C^{-1}(y-m_j)]}{(2\pi)^{d/2}\sqrt{\det C}}$$

$\Leftrightarrow$

$$-\frac{1}{2}(y-m_i)'C^{-1}(y-m_i) \geq -\frac{1}{2}(y-m_j)'C^{-1}(y-m_j) \quad (*)$$

$$\Leftrightarrow y'C^{-1}y - 2m_i'C^{-1}y + m_i'C^{-1}m_i \leq y'C^{-1}y - 2m_j'C^{-1}y + m_j'C^{-1}m_j \quad (**)$$

$$\Leftrightarrow (m_j - m_i)'C^{-1}y \leq \frac{1}{2}\{m_j'C^{-1}m_j - m_i'C^{-1}m_i\}.$$

If  $C = \sigma^2 I$ , then  $(*)$  is equivalent to

$$\|y - m_i\| \leq \|y - m_j\|, \quad (\#)$$

where here  $\|\cdot\|$  denote Euclidean distance. Thus, we choose  $i$  if  $y$  is closer to  $m_i$  than any other  $m_j$ . If  $C = \sigma^2 I$ , then  $(**)$  becomes

$$\|y\|^2 - 2m_i'y + \|m_i\|^2 \leq \|y\|^2 - 2m_j'y + \|m_j\|^2. \quad (\#\#)$$

Example. Let us repeat the preceding example, but instead of having the observation be a real-valued random vector, let us use a <sup>complex</sup> circularly symmetric Gaussian random vector  $\mathbf{z} \sim N(m_i, K)$ . Then  $f_i(\mathbf{z}) \geq f_j(\mathbf{z}) \Leftrightarrow$

$$\frac{e^{-(\mathbf{z}-m_i)^H K^{-1} (\mathbf{z}-m_i)}}{\pi^d \det K} \geq \frac{e^{-(\mathbf{z}-m_j)^H K^{-1} (\mathbf{z}-m_j)}}{\pi^d \det K}$$

$$\Leftrightarrow (\mathbf{z}-m_i)^H K^{-1} (\mathbf{z}-m_i) \leq (\mathbf{z}-m_j)^H K^{-1} (\mathbf{z}-m_j) \quad (*)$$

$$\begin{aligned} \Leftrightarrow \mathbf{z}^H K^{-1} \mathbf{z} - 2 \operatorname{Re} m_i^H K^{-1} \mathbf{z} + m_i^H K^{-1} m_i \\ \leq \mathbf{z}^H K^{-1} \mathbf{z} - 2 \operatorname{Re} m_j^H K^{-1} \mathbf{z} + m_j^H K^{-1} m_j \end{aligned} \quad (**)$$

$$\Leftrightarrow \operatorname{Re} (m_j - m_i)^H K^{-1} \mathbf{z} \leq \frac{1}{2} \{ m_j^H K^{-1} m_j - m_i^H K^{-1} m_i \}$$

If  $K = \sigma^2 \mathbf{I}$ , then  $(*)$  is equivalent to

$$\|\mathbf{z} - m_i\| \leq \|\mathbf{z} - m_j\|, \quad (\#)$$

and  $(**)$  becomes

$$\|\mathbf{z}\|^2 - 2 \operatorname{Re} m_i^H \mathbf{z} + \|m_i\|^2 \leq \|\mathbf{z}\|^2 - 2 \operatorname{Re} m_j^H \mathbf{z} + \|m_j\|^2. \quad (\#\#)$$

In this problem, given  $H=i$ ,  $Y(t)$  is a random process of the form

$$Y(t) = s_i(t) + Z(t)$$

where  $s_i(t)$  is a known, finite-energy waveform and  $Z(t)$  is AWGN. In the complex case,  $Z(t)$  is assumed circularly symmetric, i.e., any vector of the form  $[Z(t_1), \dots, Z(t_n)]'$  is circularly symmetric, and hence, so is any vector whose components have the form

$$\int \phi_k(t) Z_t dt.$$

### Plan of Analysis.

- 1) Let  $\mathcal{S} := \text{span}\{s_0, \dots, s_{M-1}\}$ . Thus, any  $x \in \mathcal{S}$  has the form  $x(t) = \sum_{i=0}^{M-1} x_i s_i(t)$  for suitable coefficients  $x_i$ .
- 2) Let  $\phi_1, \dots, \phi_N$  be orthonormal and such that  $\text{span}\{\phi_1, \dots, \phi_N\} = \mathcal{S}$ . Then  $N \leq M$ , with equality  $\Leftrightarrow s_0, \dots, s_{M-1}$  are linearly independent. The  $\phi_k$  can be found by the Gram-Schmidt procedure.

Notation. For any finite-energy waveforms  $x$  and  $y$ ,  $\langle x, y \rangle := \int x(t)y(t)^* dt$ . The energy of  $y$  is  $\|y\|^2$ , where  $\|y\| := \langle y, y \rangle^{1/2}$ . Thus  $\|y\|^2 = \int |y(t)|^2 dt$ .

We say  $x$  &  $y$  are orthogonal if  $\langle x, y \rangle = 0$ , and  $\uparrow$  (denoted by  $x \perp y$ )

We say  $x$  and  $y$  are orthonormal (o.n.) if they are orthogonal AND  $\|x\| = \|y\| = 1$ . (i.e., they have unit energy).

3) Every finite-energy waveform  $y$  can be written uniquely in the form

$$y = \hat{y} + \tilde{y},$$

where  $\hat{y} \in \mathcal{S}$  and  $\tilde{y}$  is orthogonal to every element of  $\mathcal{S}$ , including  $\hat{y}$ . To see this, put

$$\hat{y} := \sum_{k=1}^N \langle y, \phi_k \rangle \phi_k.$$

Then<sup>#</sup>

$$\langle \tilde{y}, \phi_l \rangle = \langle y - \hat{y}, \phi_l \rangle$$

$$= \langle y, \phi_l \rangle - \langle \hat{y}, \phi_l \rangle$$

$$= \langle y, \phi_l \rangle - \left\langle \sum_{k=1}^N \langle y, \phi_k \rangle \phi_k, \phi_l \right\rangle$$

$$= \langle y, \phi_l \rangle - \sum_{k=1}^N \langle y, \phi_k \rangle \underbrace{\langle \phi_k, \phi_l \rangle}_{= \delta_{kl}}$$

$$= \langle y, \phi_l \rangle - \langle y, \phi_l \rangle = 0. \quad (*)$$

The decomposition  $y = \hat{y} + \tilde{y}$  is unique, for if  $y = \hat{y}_1 + \tilde{y}_1$  as well, then from

$$\hat{y} + \tilde{y} = \hat{y}_1 + \tilde{y}_1$$

we would have

$$\hat{y} - \hat{y}_1 = \tilde{y}_1 - \tilde{y}$$

Then the LHS  $\in \mathcal{S}$ , but the RHS is  $\perp$  to  $\mathcal{S}$ . We

<sup>#</sup> Eq. (\*) shows that  $\langle y, \phi_k \rangle = \langle \hat{y}, \phi_k \rangle$

could then write

$$\begin{aligned}\|\hat{y} - \hat{y}_1\|^2 &= \langle \hat{y} - \hat{y}_1, \hat{y} - \hat{y}_1 \rangle \\ &= \langle \hat{y} - \hat{y}_1, (y - \tilde{y}) - (y - \tilde{y}_1) \rangle \\ &= \langle \hat{y} - \hat{y}_1, \tilde{y}_1 - \tilde{y} \rangle \\ &= 0.\end{aligned}$$

$\therefore \hat{y} = \hat{y}_1$ , and then  $\tilde{y} = \tilde{y}_1$  as well.

- 4) Since the above decomposition is unique, if  $s \in \mathcal{S}$ , then  $\hat{s} = s \in \mathcal{S}$  and  $\tilde{s} = 0$ ; i.e.,  $s = s + 0$ .
- 5) Take the received signal  $Y(t) = s_i(t) + Z(t)$  and write it as  $Y = \hat{Y} + \tilde{Y}$ , where  $\hat{Y} = \hat{s}_i + \hat{Z} = s_i + \hat{Z}$ , and  $\tilde{Y} = \tilde{s}_i + \tilde{Z} = \tilde{Z}$ . The first key observation is that  $\tilde{Y}$  does NOT contain any information about the signal  $s_i$ . However,  $\tilde{Y} = \tilde{Z}$  may contain information about the noise  $\hat{Z}$ . Fortunately, because the noise is Gaussian, we can show that  $\hat{Z}$  and  $\tilde{Z}$  are statistically independent. Because they are Gaussian, it is enough to show they are uncorrelated, which you will do in the HW. Because  $\tilde{Y}$  does not contain any information about the signal  $s_i$  or the noise term  $\hat{Z}$ , we can make our decision based on  $\hat{Y}$  instead of  $Y$  itself.
- 6) Our next key observation is that the waveform  $\hat{Y}(t)$  and the vector  $\underline{y} = [\langle Y, \phi_1 \rangle, \dots, \langle Y, \phi_N \rangle]'$  are

equivalent in that each is a function of the other. If we know  $\hat{Y}$ , then we know  $\langle \hat{Y}, \phi_k \rangle = \langle Y, \phi_k \rangle$  by the footnote on p. D-6, and so we can compute the vector  $\underline{Y}$  from the waveform  $\hat{Y}(t)$ . Conversely, since

$$\hat{Y}(t) := \sum_{k=1}^N \langle Y, \phi_k \rangle \phi_k(t),$$

we can compute the waveform  $\hat{Y}(t)$  from the column vector  $\underline{Y}$ .

7) We can write  $\underline{Y} = \underline{S}_i + \underline{Z}$ , where

$$(\underline{S}_i)_k = \langle S_i, \phi_k \rangle \quad \text{and} \quad Z_k = \langle Z, \phi_k \rangle.$$

Thus, given  $H=i$ ,  $\underline{Y}$  has density  $f_i(\underline{y}) = f(\underline{y} - \underline{S}_i)$

$$\text{where } f(\underline{z}) = \frac{e^{-\|\underline{z}\|^2/\sigma^2}}{\pi^N (\sigma^2)^N} \quad \text{in the complex case,}$$

$$\text{and } f(\underline{z}) = \frac{e^{-\frac{1}{2}\|\underline{z}\|^2/\sigma^2}}{(2\pi)^{N/2} \sigma^N} \quad \text{in the real case,}$$

$$\text{and where } \|\underline{z}\|^2 = \sum_{k=1}^N |z_k|^2.$$

We have from ~~##~~ on p. D-3 or p. D-4 that we should decide

i if

$$\|\underline{Y}\|^2 - 2\operatorname{Re} \underline{S}_i^H \underline{Y} + \|\underline{S}_i\|^2 \leq \|\underline{Y}\|^2 - 2\operatorname{Re} \underline{S}_j^H \underline{Y} + \|\underline{S}_j\|^2. \quad (*)$$

8) Since  $S_i \in \mathcal{S}$ ,  $S_i = \sum_{k=1}^N \langle S_i, \phi_k \rangle \phi_k$ , we have



for any waveform  $x$ ,

$$\begin{aligned}\langle x, s_i \rangle &= \langle x, \sum_{k=1}^N \langle s_i, \phi_k \rangle \phi_k \rangle \\ &= \sum_{k=1}^N \langle s_i, \phi_k \rangle^* \langle x, \phi_k \rangle \\ &= \underline{s}_i^H \begin{bmatrix} \langle x, \phi_1 \rangle \\ \vdots \\ \langle x, \phi_N \rangle \end{bmatrix}.\end{aligned}$$

Thus,  $\|s_i\|^2 = \langle s_i, s_i \rangle = \underline{s}_i^H \underline{s}_i = \|\underline{s}_i\|^2$ .

Also,

$$\langle y, s_i \rangle = \underline{s}_i^H \underline{y}.$$

Thus, after replacing  $\|\underline{y}\|^2$  by  $\|y\|^2$  in  $\textcircled{*}$  on p. D-8, and then changing  $\underline{s}_i^H \underline{y}$  to  $\langle y, s_i \rangle$  and  $\|\underline{s}_i\|^2$  to  $\|s_i\|^2$ , etc, we obtain

$$\|y - s_i\| \leq \|y - s_j\|.$$

Thus, the optimal decision can be expressed in terms of the received waveform  $y(t)$  and the signaling waveforms  $s_i(t)$ .

### Probability of Error for Binary Signaling

The false alarm probability is

$$P(\text{decode } i=1 | H=0) = P(\|(s_0 + z) - s_1\| \leq \|(s_0 + z) - s_0\| | H=0)$$

The required event can be rewritten as

$$\| (s_0 - s_1) + z \|^2 \leq \| z \|^2$$

or

$$\| s_0 - s_1 \|^2 + 2 \operatorname{Re} \langle s_0 - s_1, z \rangle + \| z \|^2 \leq \| z \|^2$$

or

$$2 \operatorname{Re} \langle s_1 - s_0, z \rangle \geq \| s_1 - s_0 \|^2$$

or

$$\operatorname{Re} \left\langle \frac{s_1 - s_0}{\| s_1 - s_0 \|}, z \right\rangle \geq \frac{1}{2} d,$$

where  $d := \| s_1 - s_0 \|$ .

Now, since  $(s_1 - s_0) / \| s_1 - s_0 \|^2$  has unit energy,

$$\left\langle \frac{s_1 - s_0}{\| s_1 - s_0 \|^2}, z \right\rangle \sim N(0, \sigma^2)$$

and its real part is  $N(0, \sigma^2/2)$ . Thus, in the complex case, the false-alarm prob. is

$$P_{FA} = Q\left(\frac{d/2}{\sigma/\sqrt{2}}\right) = Q\left(\frac{d}{\sqrt{2}\sigma}\right),$$

where  $Q(x) := \int_x^\infty \frac{e^{-\theta^2/2}}{\sqrt{2\pi}} d\theta$ . In the real case, we would have  $Q(d/(2\sigma))$ .

The total prob. of error is

$$P_e = P(\text{decide } i=1 | H=0) \frac{1}{2} + P(\text{decide } 0 | H=1) \frac{1}{2}$$

By symmetry,  $P_e = P_{FA}$ .

Examples

1) Antipodal Signaling (BPSK),  $s_1 = -s_0$ . Then

$$d = \|s_1 - (-s_1)\| = 2\|s_1\| = 2\sqrt{\mathcal{E}} \text{ if}$$

$$\mathcal{E} := \|s_1\|^2 = \text{energy in } s_1$$

In the complex case,

$$P_e = Q\left(\sqrt{\frac{2\mathcal{E}}{\sigma^2}}\right).$$

In the real case

$$P_e = Q\left(\sqrt{\mathcal{E}/\sigma^2}\right).$$

2) Orthogonal Signaling.  $s_1 \perp s_0$ . Then

$$\begin{aligned} d^2 &= \|s_1 - s_0\|^2 = \|s_1\|^2 - 2\operatorname{Re}\langle s_1, s_0 \rangle + \|s_0\|^2 \\ &= \|s_1\|^2 + \|s_0\|^2. \end{aligned}$$

For equal-energy signals,

$$d = \sqrt{2\mathcal{E}}.$$

In the complex case,  $P_e = Q\left(\sqrt{\mathcal{E}/\sigma^2}\right).$

In the real case,  $P_e = Q\left(\sqrt{\frac{\mathcal{E}}{2\sigma^2}}\right).$