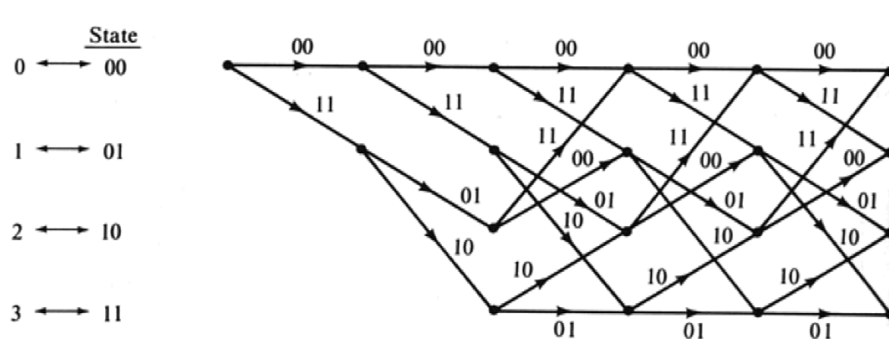


2016 Spring: The First Midterm of Digital Communications

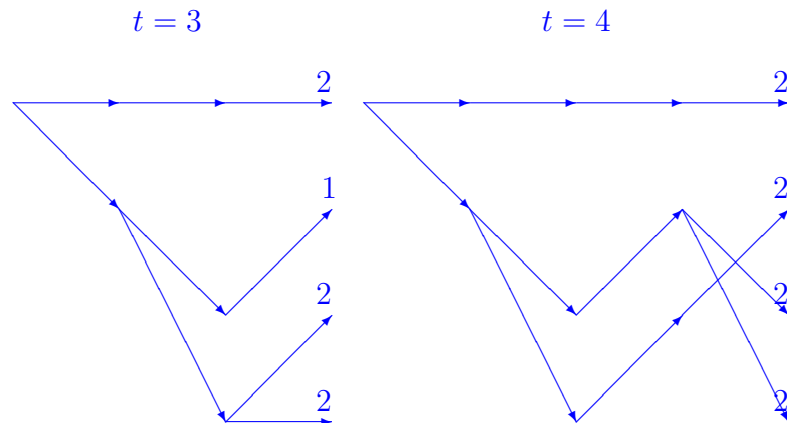
The total points of this exam is 108.

1. (12 pt)

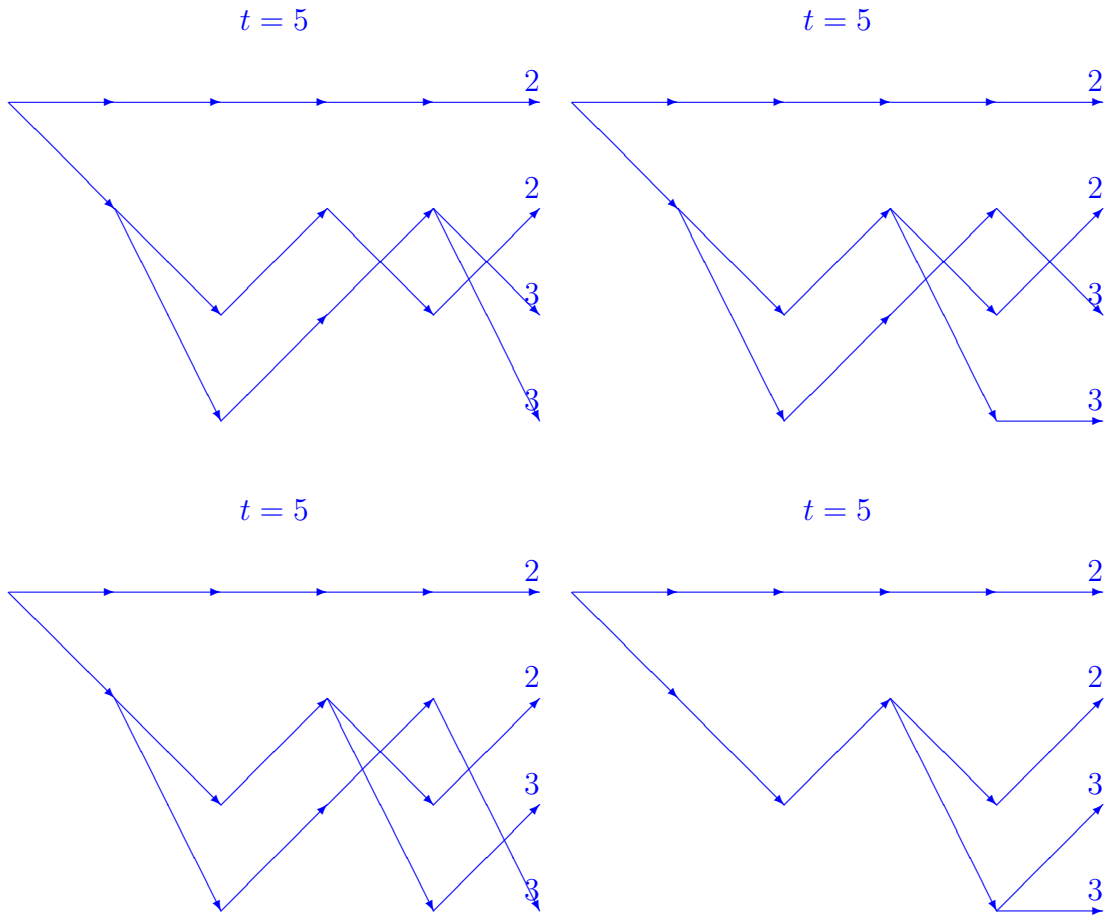


Based on the trellis above, draw the survivor paths at time instance 3, 4 and 5 if the received vector is 11 00 00 00 00 ... Please mark the accumulated Hamming metric of each survivor path.
Hint: See for example the bottom picture of Slide 4-207.

Solutions.



There are four possible choices of survivor paths at $t = 5$. Just pick one of them for your answer.



2. (a) (8 pt) The channel model for non-coherent transmission is given by

$$\mathbf{r}_\ell = e^{i\phi} \mathbf{s}_{m,\ell} + \mathbf{n}_\ell,$$

where ϕ is a random variable with probability density function $f_\phi(\phi)$, $\mathbf{s}_{m,\ell}$ is the m th channel symbol for transmission, and \mathbf{n}_ℓ is a zero-mean complex Gaussian random vector with i.i.d. components of variance $2N_0$. Prove that the MAP decision rule for a semiblind receiver is equal to

$$\hat{m} = \arg \max_{1 \leq m \leq M} \Pr \{ \mathbf{s}_{m,\ell} | \mathbf{r}_\ell \} = \arg \max_{1 \leq m \leq M} P_m e^{-\frac{\mathcal{E}_m}{N_0}} \int_0^{2\pi} e^{\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|}{N_0} \cos(\alpha_m + \phi)} f_\phi(\phi) d\phi$$

where P_m is the prior probability for symbol $\mathbf{s}_{m,\ell}$, $\mathcal{E}_m = \frac{1}{2} \|\mathbf{s}_{m,\ell}\|^2$, and $\alpha_m = \angle(\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell})$.

- (b) (8 pt) For equal-energy and equiprobable signaling, can the decision rule in (a) be simplified to

$$\hat{m} = \arg \max_{1 \leq m \leq M} |\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|$$

provided that $\Pr[\phi = \frac{\pi}{2}] = \Pr[\phi = -\frac{\pi}{2}] = \frac{1}{2}$. If your answer is positive, prove it; otherwise, determine the simplified decision rule corresponding to equal-energy and equiprobable signaling.

Hint: By "simplified decision rule," we mean one that requires no knowledge of N_0 .

- (c) (8 pt) For differential PSK modulation under non-coherent detection, the two consecutive symbols can be expressed as

$$\mathbf{s}_\ell^{(k-1)} = \sqrt{2\mathcal{E}_s} e^{i\phi_0} \quad \text{and} \quad \mathbf{s}_{m,\ell}^{(k)} = \sqrt{2\mathcal{E}_s} e^{i(\theta_m + \phi_0)}, \quad m = 1, 2, \dots, M$$

and the channel is modeled as

$$\vec{\mathbf{r}}_\ell = \begin{bmatrix} \mathbf{r}_\ell^{(k-1)} \\ \mathbf{r}_\ell^{(k)} \end{bmatrix} = e^{i\phi} \begin{bmatrix} \mathbf{s}_\ell^{(k-1)} \\ \mathbf{s}_{m,\ell}^{(k)} \end{bmatrix} + \begin{bmatrix} \mathbf{n}_\ell^{(k-1)} \\ \mathbf{n}_\ell^{(k)} \end{bmatrix} = e^{i\phi} \vec{\mathbf{s}}_{m,\ell} + \vec{\mathbf{n}}_\ell$$

where $\vec{\mathbf{n}}_\ell$ is a zero-mean Gaussian vector with i.i.d. components of variance $2N_0$. Then we immediately know from (a) that

$$\hat{m} = \arg \max_{1 \leq m \leq M} \Pr \{ \vec{\mathbf{s}}_{m,\ell} | \vec{\mathbf{r}}_\ell \} = \arg \max_{1 \leq m \leq M} P_m \int_0^{2\pi} e^{\frac{|\vec{\mathbf{r}}_\ell^\dagger \vec{\mathbf{s}}_{m,\ell}|}{N_0} \cos(\alpha_m + \phi)} f_\phi(\phi) d\phi,$$

where P_m is the prior probability for symbol $\mathbf{s}_{m,\ell}^{(k)}$, and $\alpha_m = \angle(\vec{\mathbf{r}}_\ell^\dagger \vec{\mathbf{s}}_{m,\ell})$. Now under equal prior probability, is the decision rule above equivalent to

$$\arg \max_{1 \leq m \leq M} \mathbf{Re} \left\{ \left(\mathbf{r}_\ell^{(k-1)} \right)^* \mathbf{r}_\ell^{(k)} e^{-i\theta_m} \right\}.$$

Justify your answer.

Hint: Check the decision rule in (b).

Solutions.

(a)

$$\begin{aligned} \hat{m} &= \arg \max_{1 \leq m \leq M} P_m \int_0^{2\pi} f_{\mathbf{n}_\ell}(\mathbf{r}_\ell - \mathbf{s}_{m,\ell} e^{i\phi}) f_\phi(\phi) d\phi \\ &= \arg \max_{1 \leq m \leq M} P_m \frac{1}{(2\pi N_0)^N} \int_0^{2\pi} e^{-\frac{\|\mathbf{r}_\ell - \mathbf{s}_{m,\ell} e^{i\phi}\|^2}{2N_0}} f_\phi(\phi) d\phi \\ &= \arg \max_{1 \leq m \leq M} P_m e^{-\frac{\varepsilon_m}{N_0}} \int_0^{2\pi} e^{\frac{\mathbf{Re}[\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell} e^{i\phi}]}{N_0}} f_\phi(\phi) d\phi \\ &= \arg \max_{1 \leq m \leq M} P_m e^{-\frac{\varepsilon_m}{N_0}} \int_0^{2\pi} e^{\frac{\mathbf{Re}[\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell} |e^{i\alpha_m} e^{i\phi}|]}{N_0}} f_\phi(\phi) d\phi \\ &= \arg \max_{1 \leq m \leq M} P_m e^{-\frac{\varepsilon_m}{N_0}} \int_0^{2\pi} e^{\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}| \cos(\alpha_m + \phi)}{N_0}} f_\phi(\phi) d\phi. \end{aligned}$$

- (b) For equal-energy and equiprobable signals and $\Pr[\phi = \pi/2] = \Pr[\phi = -\pi/2] = \frac{1}{2}$, the

decision rule in (a) can be simplified to

$$\begin{aligned}
\hat{m} &= \arg \max_{1 \leq m \leq M} \int_0^{2\pi} e^{\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|}{N_0} \cos(\alpha_m + \phi)} f_\phi(\phi) d\phi \\
&= \arg \max_{1 \leq m \leq M} \left\{ \frac{1}{2} e^{\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|}{N_0} \cos(\alpha_m + \pi/2)} + \frac{1}{2} e^{\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|}{N_0} \cos(\alpha_m - \pi/2)} \right\} \\
&= \arg \max_{1 \leq m \leq M} \left\{ e^{-\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|}{N_0} \sin(\alpha_m)} + e^{\frac{|\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}|}{N_0} \sin(\alpha_m)} \right\} \\
&= \arg \max_{1 \leq m \leq M} \left\{ e^{-\frac{\mathbf{Im}[\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}]}{N_0}} + e^{\frac{\mathbf{Im}[\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}]}{N_0}} \right\} \\
&= \arg \max_{1 \leq m \leq M} \cosh \left(\frac{1}{N_0} \mathbf{Im} [\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}] \right).
\end{aligned}$$

Since $\cosh(x)$ is monotonically increasing with respect to $|x|$,

$$\hat{m} = \arg \max_{1 \leq m \leq M} \frac{1}{N_0} \left| \mathbf{Im} [\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}] \right| = \arg \max_{1 \leq m \leq M} \left| \mathbf{Im} [\mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell}] \right|,$$

which is in general not equal to $\arg \max_{1 \leq m \leq M} \left| \mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell} \right|$. Hence, only for certain distributions of ϕ , we have $\hat{m} = \arg \max_{1 \leq m \leq M} \left| \mathbf{r}_\ell^\dagger \mathbf{s}_{m,\ell} \right|$.

(c) The answer is “Not necessary.” For certain distributions of ϕ , we may have

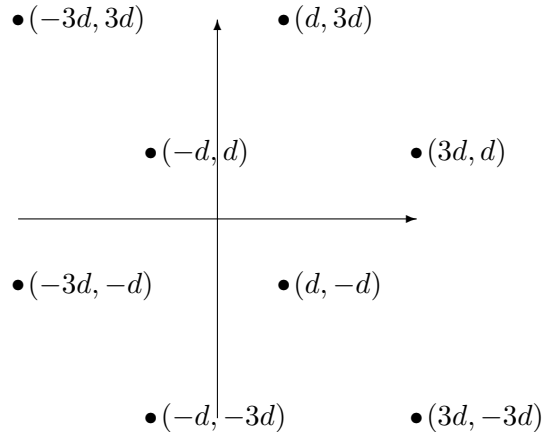
$$\hat{m} = \arg \max_{1 \leq m \leq M} \left| \mathbf{Im} [\vec{\mathbf{r}}_\ell^\dagger \vec{\mathbf{s}}_{m,\ell}] \right|$$

instead of

$$\hat{m} = \arg \max_{1 \leq m \leq M} \left| \vec{\mathbf{r}}_\ell^\dagger \vec{\mathbf{s}}_{m,\ell} \right| = \arg \max_{1 \leq m \leq M} \mathbf{Re} \left\{ \left(\mathbf{r}_\ell^{(k-1)} \right)^* \mathbf{r}_\ell^{(k)} e^{-i\theta_m} \right\}$$

as demonstrated in (b).

3. Below an equal-probable 8-ary QAM constellation is depicted for transmission over the AWGN channel, i.e., $\mathbf{r} = \mathbf{s}_m + \mathbf{n}$ for $1 \leq m \leq 8$ and \mathbf{n} is a two-dimensional Gaussian vector with i.i.d components of mean zero and variance $N_0/2$.



- (a) (8 pt) Determine the average transmission energy per information bit \mathcal{E}_b .
- (b) (8 pt) Draw the partitions for optimal detection at the receiver.
- (c) (8 pt) Determine the union bound for this constellation, where the union bound formula is given by

$$P_e \leq \frac{1}{M} \sum_{m=1}^M \sum_{\substack{1 \leq m' \leq M \\ m' \neq m}} Q \left(\sqrt{\frac{d_{m,m'}^2}{2N_0}} \right).$$

Please express the bound as a function of \mathcal{E}_b/N_0 .

Hint: Complete the $d_{m,m'}$ table below.

$d_{m,m'}$	$2\sqrt{2}d$	$4d$	$4\sqrt{2}d$	$2\sqrt{10}d$	$6\sqrt{2}d$
$(-3d, 3d), (3d, -3d)$					
$(d, 3d), (3d, d), (-3d, -d), (-d, -3d)$					
$(-d, d), (d, -d)$					
Sum					

- (d) (8 pt) One can actually improve the union bound in (b) by considering only those constellation points m' whose corresponding partition regions have shared borderlines with m . Determine the improved union bound.

Solutions.

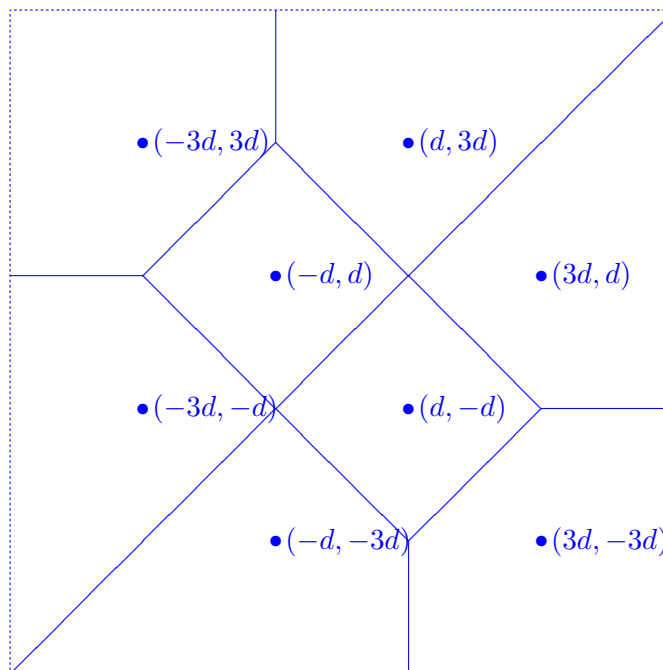
(a)

$$\mathcal{E}_s = E[|\mathbf{s}_m|^2] = \frac{2}{8}(9d^2 + 9d^2) + \frac{4}{8}(d^2 + 9d^2) + \frac{2}{8}(d^2 + d^2) = \frac{9}{2}d^2 + 5d^2 + \frac{1}{2}d^2 = 10d^2$$

Hence

$$\mathcal{E}_b = \frac{\mathcal{E}_s}{3} = \frac{10}{3}d^2.$$

(b)



(c) The table of $d_{m,m'}$ for $m \neq m'$ can be given below.

$d_{m,m'}$	$2\sqrt{2}d$	$4d$	$4\sqrt{2}d$	$2\sqrt{10}d$	$6\sqrt{2}d$
$(-3d, 3d), (3d, -3d)$	1	2	1	2	1
$(d, 3d), (3d, d), (-3d, -d), (-d, -3d)$	2	2	1	2	0
$(-d, d), (d, -d)$	4	2	1	0	0
sum	18	16	8	12	2

Hence

$$\begin{aligned}
P_e &\leq \frac{1}{M} \sum_{m=1}^M \sum_{\substack{1 \leq m' \leq M \\ m' \neq m}} Q \left(\sqrt{\frac{d_{m,m'}^2}{2N_0}} \right) \\
&= \frac{1}{8} \left(18 Q \left(\sqrt{\frac{4d^2}{N_0}} \right) + 16 Q \left(\sqrt{\frac{8d^2}{N_0}} \right) + 8 Q \left(\sqrt{\frac{16d^2}{N_0}} \right) \right. \\
&\quad \left. + 12 Q \left(\sqrt{\frac{20d^2}{N_0}} \right) + 2 Q \left(\sqrt{\frac{36d^2}{N_0}} \right) \right) \\
&= \frac{9}{4} Q \left(\sqrt{\frac{6\mathcal{E}_b}{5N_0}} \right) + 2Q \left(\sqrt{\frac{12\mathcal{E}_b}{5N_0}} \right) + Q \left(\sqrt{\frac{24\mathcal{E}_b}{5N_0}} \right) \\
&\quad + \frac{3}{2} Q \left(\sqrt{\frac{6\mathcal{E}_b}{N_0}} \right) + \frac{1}{4} Q \left(\sqrt{\frac{54\mathcal{E}_b}{5N_0}} \right).
\end{aligned}$$

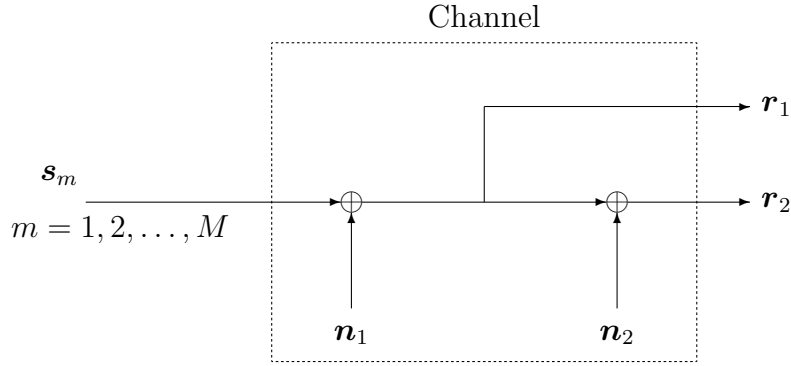
(d) The table of $d_{m,m'}$ for $m \neq m'$ can be refined below.

	$2\sqrt{2}d$	$4d$	$4\sqrt{2}d$	$2\sqrt{10}d$	$6\sqrt{2}d$
$(-3d, 3d), (3d, -3d)$	1	2	0	0	0
$(d, 3d), (3d, d), (-3d, -d), (-d, -3d)$	2	1	0	0	0
$(-d, d), (d, -d)$	4	0	0	0	0
sum	18	8	0	0	0

Hence

$$\begin{aligned}
P_e &\leq \frac{1}{8} \left(18 Q \left(\sqrt{\frac{4d^2}{N_0}} \right) + 8 Q \left(\sqrt{\frac{8d^2}{N_0}} \right) \right) \\
&\leq \frac{9}{4} Q \left(\sqrt{\frac{4d^2}{N_0}} \right) + Q \left(\sqrt{\frac{8d^2}{N_0}} \right) \\
&\leq \frac{9}{4} Q \left(\sqrt{\frac{6\mathcal{E}_b}{5N_0}} \right) + Q \left(\sqrt{\frac{12\mathcal{E}_b}{5N_0}} \right).
\end{aligned}$$

4. In the communication system below, the receiver receives two signals \mathbf{r}_1 and \mathbf{r}_2 .



(a) (8 pt) If the two additive noises \mathbf{n}_1 and \mathbf{n}_2 are independent, is \mathbf{r}_1 a sufficient statistics for optimal (i.e., MAP) detection? If the answer is YES, prove it; otherwise, give a counterexample.

Hint: The MAP decision of this system is $\hat{m} = \arg \max_{1 \leq m \leq M} \Pr\{\mathbf{s}_m | \mathbf{r}_1, \mathbf{r}_2\}$.

(b) (8 pt) If the two additive noises \mathbf{n}_1 and \mathbf{n}_2 are dependent, is \mathbf{r}_1 a sufficient statistics for optimal detection? If the answer is YES, prove it; otherwise, give a counterexample.

Hint: Think of the extreme case such as that \mathbf{n}_1 is a function of \mathbf{n}_2 .

Solutions.

(a) With

$$\begin{cases} \mathbf{r}_1 = \mathbf{s}_m + \mathbf{n}_1 \\ \mathbf{r}_2 = \mathbf{s}_m + \mathbf{n}_1 + \mathbf{n}_2 \end{cases} \quad \text{or equivalently} \quad \begin{cases} \mathbf{n}_1 = \mathbf{r}_1 - \mathbf{s}_m \\ \mathbf{n}_2 = \mathbf{r}_2 - \mathbf{r}_1 \end{cases}$$

the MAP decision of this system is

$$\begin{aligned} \hat{m} &= \arg \max_{1 \leq m \leq M} \Pr\{\mathbf{s}_m | \mathbf{r}_1, \mathbf{r}_2\} \\ &= \arg \max_{1 \leq m \leq M} P_m \mathbf{f}_{\mathbf{n}_1, \mathbf{n}_2}(\mathbf{r}_1 - \mathbf{s}_m, \mathbf{r}_2 - \mathbf{r}_1) \\ &= \arg \max_{1 \leq m \leq M} P_m \mathbf{f}_{\mathbf{n}_1}(\mathbf{r}_1 - \mathbf{s}_m) \mathbf{f}_{\mathbf{n}_2}(\mathbf{r}_2 - \mathbf{r}_1) \\ &= \arg \max_{1 \leq m \leq M} P_m \mathbf{f}_{\mathbf{n}_1}(\mathbf{r}_1 - \mathbf{s}_m), \end{aligned}$$

where the last equality holds because $\mathbf{f}_{\mathbf{n}_2}(\mathbf{r}_2 - \mathbf{r}_1)$ is irrelevant to m . Thus \mathbf{r}_1 is a sufficient statistic for optimal detection.

(b) The answer is NO. A quick counterexample is to have $\mathbf{n}_1 = -\mathbf{n}_2$, which gives $\mathbf{r}_2 = \mathbf{s}_m$ (while $\mathbf{r}_1 = \mathbf{s}_m + \mathbf{n}_1$). Another counterexample is to have $\mathbf{n}_1 = \mathbf{n}_2$, which gives $\mathbf{s}_m = 2\mathbf{r}_1 - \mathbf{r}_2$.

5. (a) (8 pt) Subject to a given channel transition probability density function $\mathbf{f}(\mathbf{r} | \mathbf{s}_m) = \frac{1}{2} e^{-|\mathbf{r} - \mathbf{s}_m|}$ for 4-ary channel input $\mathbf{s}_m = -3, -1, 1, 3$ respectively for $m = 1, 2, 3, 4$, and channel output \mathbf{r} , derive the maximum-likelihood (ML) decision rule $g_{\text{ML}}(\mathbf{r})$.

(b) (8 pt) Continue from (a). Let the bit patterns $b_1 b_0$ corresponding to $m = 1, 2, 3, 4$ be respectively 00, 01, 11, 10. Derive the ML decision rule $g_{\text{ML},i}(\mathbf{r})$ for the i th bit, where $i = 0, 1$.

Hint: (i)

$$g_{\text{ML},i}(\mathbf{r}) \triangleq \arg \max_{b \in \{0,1\}} \sum_{\mathbf{s}_m : b_i=b} \mathbf{f}(\mathbf{r}|\mathbf{s}_m)$$

and (ii) $\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4) < \mathbf{f}(\mathbf{r}|\mathbf{s}_2) + \mathbf{f}(\mathbf{r}|\mathbf{s}_3)$ if, and only if,

$$|\mathbf{r}| < \lambda \triangleq \frac{1}{2} \log(e^4 + e^2 - 1) \approx 2.0553.$$

(c) (8 pt) The bit error probability $P_{\text{BER},i}$ of the i th bit b_i can be derived through either *symbol-based ML decision maker* $g_{\text{ML}}(\mathbf{r})$ in (a)

or

bit-based ML decision maker $g_{\text{ML},i}(\mathbf{r})$ in (b).

The two bit error probabilities can be expressed as

$$P_{\text{BER},i}(g_{\text{ML}}) = \frac{1}{4} \sum_{b \in \{0,1\}} \sum_{\mathbf{s}_m : b_i=b} \int_{\{\mathbf{r} : g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_i^{(b)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r}, \quad i = 0, 1$$

and

$$P_{\text{BER},i}(g_{\text{ML},i}) = \frac{1}{4} \sum_{b \in \{0,1\}} \sum_{\mathbf{s}_m : b_i=b} \int_{\{\mathbf{r} : g_{\text{ML},i}(\mathbf{r}) \neq b\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r}, \quad i = 0, 1$$

where $\mathcal{U}_i^{(b)}$ is the set of symbol indices, of which the i th bit is equal to b . Specifically, $\mathcal{U}_0^{(0)} = \{1, 4\}$, $\mathcal{U}_0^{(1)} = \{2, 3\}$, $\mathcal{U}_1^{(0)} = \{1, 2\}$ and $\mathcal{U}_1^{(1)} = \{3, 4\}$.

Show that the two bit error probabilities for bit b_0 are equal to

$$P_{\text{BER},0}(g_{\text{ML}}) = \frac{1}{4}e^{-3}(e^2 - e^{-2}) + \frac{1}{4}(e + e^{-1})e^{-2}$$

and

$$P_{\text{BER},0}(g_{\text{ML},0}) = \frac{1}{4}e^{-3}(e^\lambda - e^{-\lambda}) + \frac{1}{4}(e + e^{-1})e^{-\lambda},$$

respectively, where the constant λ is defined in the Hint of (b).

Solutions.

(a)

$$g_{\text{ML}}(\mathbf{r}) \triangleq \arg \max_{1 \leq m \leq 4} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) = \arg \max_{1 \leq m \leq 4} \frac{1}{2}e^{-|\mathbf{r}-\mathbf{s}_m|} = \begin{cases} 1, & \mathbf{r} < -2 \\ 2, & -2 \leq \mathbf{r} < 0 \\ 3, & 0 \leq \mathbf{r} < 2 \\ 4, & \mathbf{r} \geq 2 \end{cases}$$

(b)

$$\begin{aligned} g_{\text{ML},0}(\mathbf{r}) &\triangleq \arg \max_{b \in \{0,1\}} \sum_{\mathbf{s}_m : b_0=b} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) \\ &= \arg \max_{b \in \{0,1\}} \left\{ \underbrace{\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4)}_{b=0}, \underbrace{\mathbf{f}(\mathbf{r}|\mathbf{s}_2) + \mathbf{f}(\mathbf{r}|\mathbf{s}_3)}_{b=1} \right\} \\ &= \begin{cases} 0, & \mathbf{r} < -3 \text{ or } \mathbf{r} \geq c \\ 1, & -c \leq \mathbf{r} < c \end{cases} \end{aligned}$$

and

$$\begin{aligned}
g_{\text{ML},1}(\mathbf{r}) &\triangleq \arg \max_{b \in \{0,1\}} \sum_{\mathbf{s}_m: b_1=b} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) \\
&= \arg \max_{b \in \{0,1\}} \left\{ \underbrace{\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_2)}_{b=0}, \underbrace{\mathbf{f}(\mathbf{r}|\mathbf{s}_3) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4)}_{b=1} \right\} \\
&= \begin{cases} 0, & \mathbf{r} < 0 \\ 1, & \mathbf{r} \geq 0 \end{cases}
\end{aligned}$$

(c)

$$\begin{aligned}
P_{\text{BER},0}(g_{\text{ML}}) &= \frac{1}{M} \sum_{b \in \{0,1\}} \sum_{\mathbf{s}_m: b_0=b} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_0^{(b)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{M} \sum_{m \in \mathcal{U}_0^{(0)}} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_0^{(0)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} + \frac{1}{M} \sum_{m \in \mathcal{U}_0^{(1)}} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_0^{(1)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{4} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \{1,4\}\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4)] d\mathbf{r} + \frac{1}{4} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \{2,3\}\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_2) + \mathbf{f}(\mathbf{r}|\mathbf{s}_3)] d\mathbf{r} \\
&= \frac{1}{4} \int_{-2 \leq r < 2} \frac{1}{2} (e^{-|r+3|} + e^{-|r-3|}) d\mathbf{r} + \frac{1}{4} \int_{r < -2 \text{ or } r \geq 2} \frac{1}{2} (e^{-|r+1|} + e^{-|r-1|}) d\mathbf{r} \\
&= \frac{1}{4} \int_{-2}^2 \frac{1}{2} e^{-3} (e^{-r} + e^r) d\mathbf{r} + \frac{1}{4} \int_{-\infty}^{-2} \frac{1}{2} \left(e + \frac{1}{e}\right) e^r d\mathbf{r} + \frac{1}{4} \int_2^{\infty} \frac{1}{2} \left(\frac{1}{e} + e\right) e^{-r} d\mathbf{r} \\
&= \frac{1}{4} \int_{-2}^2 e^{-3} e^r d\mathbf{r} + \frac{1}{4} \int_{-\infty}^{-2} \left(e + \frac{1}{e}\right) e^r d\mathbf{r} \\
&= \frac{1}{4} e^{-3} (e^2 - e^{-2}) + \frac{1}{4} (e + e^{-1}) e^{-2} \approx 0.1947
\end{aligned}$$

and

$$\begin{aligned}
P_{\text{BER},0}(g_{\text{ML},0}) &= \frac{1}{M} \sum_{b \in \{0,1\}} \sum_{\mathbf{s}_m: b_0=b} \int_{\{\mathbf{r}: g_{\text{ML},0}(\mathbf{r}) \neq b\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{M} \sum_{m \in \mathcal{U}_0^{(0)}} \int_{\{\mathbf{r}: g_{\text{ML},0}(\mathbf{r}) \neq 0\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} + \frac{1}{M} \sum_{m \in \mathcal{U}_0^{(1)}} \int_{\{\mathbf{r}: g_{\text{ML},0}(\mathbf{r}) \neq 1\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{M} \int_{\{\mathbf{r}: g_{\text{ML},0}(\mathbf{r}) \neq 0\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4)] d\mathbf{r} + \frac{1}{M} \int_{\{\mathbf{r}: g_{\text{ML},0}(\mathbf{r}) \neq 1\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_2) + \mathbf{f}(\mathbf{r}|\mathbf{s}_3)] d\mathbf{r} \\
&= \frac{1}{4} \int_{-\lambda \leq r < \lambda} \frac{1}{2} (e^{-|r+3|} + e^{-|r-3|}) d\mathbf{r} + \frac{1}{4} \int_{r < -\lambda \text{ or } r \geq \lambda} \frac{1}{2} (e^{-|r+1|} + e^{-|r-1|}) d\mathbf{r} \\
&= \frac{1}{4} \int_{-\lambda}^{\lambda} \frac{1}{2} e^{-3} (e^{-r} + e^r) d\mathbf{r} + \frac{1}{4} \int_{-\infty}^{-\lambda} \frac{1}{2} \left(e + \frac{1}{e}\right) e^r d\mathbf{r} + \frac{1}{4} \int_{\lambda}^{\infty} \frac{1}{2} \left(\frac{1}{e} + e\right) e^{-r} d\mathbf{r} \\
&= \frac{1}{4} \int_{-\lambda}^{\lambda} e^{-3} e^r d\mathbf{r} + \frac{1}{4} \int_{-\infty}^{-\lambda} \left(e + \frac{1}{e}\right) e^r d\mathbf{r} \\
&= \frac{1}{4} e^{-3} (e^{\lambda} - e^{-\lambda}) + \frac{1}{4} (e + e^{-1}) e^{-\lambda} \approx 0.1944
\end{aligned}$$

For your information, we can also obtain $\mathcal{U}_1^{(0)} = \{1, 2\}$ and $\mathcal{U}_0^{(1)} = \{3, 4\}$, and derive

$$\begin{aligned}
P_{\text{BER},1}(g_{\text{ML}}) &= \frac{1}{M} \sum_{b \in \{0,1\}} \sum_{\mathbf{s}_m: b_1=b} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_1^{(b)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{M} \sum_{m \in \mathcal{U}_1^{(0)}} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_1^{(0)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} + \frac{1}{M} \sum_{m \in \mathcal{U}_1^{(1)}} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \mathcal{U}_1^{(1)}\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{4} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \{1,2\}\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_2)] d\mathbf{r} + \frac{1}{4} \int_{\{\mathbf{r}: g_{\text{ML}}(\mathbf{r}) \notin \{3,4\}\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_3) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4)] d\mathbf{r} \\
&= \frac{1}{4} \int_0^\infty \frac{1}{2} (e^{-|\mathbf{r}+3|} + e^{-|\mathbf{r}+1|}) d\mathbf{r} + \frac{1}{4} \int_{-\infty}^0 \frac{1}{2} (e^{-|\mathbf{r}-1|} + e^{-|\mathbf{r}-3|}) d\mathbf{r} \\
&= \frac{1}{4} \int_0^\infty (e^{-|\mathbf{r}+3|} + e^{-|\mathbf{r}+1|}) d\mathbf{r} \\
&= \frac{1}{4} \int_0^\infty e^{-|\mathbf{r}+3|} d\mathbf{r} + \frac{1}{4} \int_0^\infty e^{-|\mathbf{r}+1|} d\mathbf{r} \\
&= \frac{1}{4} \int_3^\infty e^{-|\mathbf{r}|} d\mathbf{r} + \frac{1}{4} \int_1^\infty e^{-|\mathbf{r}|} d\mathbf{r} \\
&= \frac{1}{4} e^{-3} + \frac{1}{4} e^{-1} \approx 0.1044
\end{aligned}$$

and

$$\begin{aligned}
P_{\text{BER},1}(g_{\text{ML},1}) &= \frac{1}{M} \sum_{b \in \{0,1\}} \sum_{\mathbf{s}_m: b_1=b} \int_{\{\mathbf{r}: g_{\text{ML},1}(\mathbf{r}) \neq b\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{M} \sum_{m \in \mathcal{U}_1^{(0)}} \int_{\{\mathbf{r}: g_{\text{ML},1}(\mathbf{r}) \neq 0\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} + \frac{1}{M} \sum_{m \in \mathcal{U}_1^{(1)}} \int_{\{\mathbf{r}: g_{\text{ML},1}(\mathbf{r}) \neq 1\}} \mathbf{f}(\mathbf{r}|\mathbf{s}_m) d\mathbf{r} \\
&= \frac{1}{M} \int_{\{\mathbf{r}: g_{\text{ML},1}(\mathbf{r}) \neq 0\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_1) + \mathbf{f}(\mathbf{r}|\mathbf{s}_2)] d\mathbf{r} + \frac{1}{M} \int_{\{\mathbf{r}: g_{\text{ML},1}(\mathbf{r}) \neq 1\}} [\mathbf{f}(\mathbf{r}|\mathbf{s}_3) + \mathbf{f}(\mathbf{r}|\mathbf{s}_4)] d\mathbf{r} \\
&= \frac{1}{4} \int_0^\infty \frac{1}{2} (e^{-|\mathbf{r}+3|} + e^{-|\mathbf{r}+1|}) d\mathbf{r} + \frac{1}{4} \int_{-\infty}^0 \frac{1}{2} (e^{-|\mathbf{r}-1|} + e^{-|\mathbf{r}-3|}) d\mathbf{r} \\
&= P_{\text{BER},1}(g_{\text{ML}}).
\end{aligned}$$

Note that one can recover the transmitted channel symbol through the two bit-based ML decision rules as $(\hat{b}_1, \hat{b}_0) = (g_{\text{ML},1}(\mathbf{r}), g_{\text{ML},0}(\mathbf{r}))$. Hence, two kinds of symbol errors, $P_{\text{SER}}(g_{\text{ML}})$ and $P_{\text{SER}}(g_{\text{ML},1}, g_{\text{ML},0})$, will be resulted. Below we derive the symbol correction rates (SCR)

instead: i.e., $P_{\text{SCR}}(g_{\text{ML}}) = 1 - P_{\text{SER}}(g_{\text{ML}})$ and $P_{\text{SCR}}(g_{\text{ML},1}, g_{\text{ML},0}) = 1 - P_{\text{SER}}(g_{\text{ML},1}, g_{\text{ML},0})$.

$$\begin{aligned}
P_{\text{SCR}}(g_{\text{ML}}) &= \frac{1}{4} \int_{-\infty}^{-2} \mathbf{f}(\mathbf{r}|\mathbf{s}_1) d\mathbf{r} + \frac{1}{4} \int_{-2}^0 \mathbf{f}(\mathbf{r}|\mathbf{s}_2) d\mathbf{r} + \frac{1}{4} \int_0^2 \mathbf{f}(\mathbf{r}|\mathbf{s}_3) d\mathbf{r} + \frac{1}{4} \int_2^{\infty} \mathbf{f}(\mathbf{r}|\mathbf{s}_4) d\mathbf{r} \\
&= \frac{1}{4} \int_{-\infty}^{-2} \frac{1}{2} e^{-|r+3|} d\mathbf{r} + \frac{1}{4} \int_{-2}^0 \frac{1}{2} e^{-|r+1|} d\mathbf{r} + \frac{1}{4} \int_0^2 \frac{1}{2} e^{-|r-1|} d\mathbf{r} + \frac{1}{4} \int_2^{\infty} \frac{1}{2} e^{-|r-3|} d\mathbf{r} \\
&= \frac{1}{4} \int_{-\infty}^{-1} \frac{1}{2} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-1}^1 \frac{1}{2} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-1}^1 \frac{1}{2} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-1}^{\infty} \frac{1}{2} e^{-|r|} d\mathbf{r} \\
&= \frac{1}{4} \int_{-\infty}^{-1} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-1}^1 e^{-|r|} d\mathbf{r} \\
&= \frac{1}{4} (2 - e^{-1}) + \frac{1}{4} (2 - 2e^{-1}) \\
&= 1 - \frac{3}{4} e^{-1} \approx 0.7241
\end{aligned}$$

and

$$\begin{aligned}
P_{\text{SCR}}(g_{\text{ML},1}, g_{\text{ML},0}) &= \frac{1}{4} \int_{-\infty}^{-c} \mathbf{f}(\mathbf{r}|\mathbf{s}_1) d\mathbf{r} + \frac{1}{4} \int_{-c}^0 \mathbf{f}(\mathbf{r}|\mathbf{s}_2) d\mathbf{r} + \frac{1}{4} \int_0^c \mathbf{f}(\mathbf{r}|\mathbf{s}_3) d\mathbf{r} + \frac{1}{4} \int_c^{\infty} \mathbf{f}(\mathbf{r}|\mathbf{s}_4) d\mathbf{r} \\
&= \frac{1}{4} \int_{-\infty}^{-c} \frac{1}{2} e^{-|r+3|} d\mathbf{r} + \frac{1}{4} \int_{-c}^0 \frac{1}{2} e^{-|r+1|} d\mathbf{r} + \frac{1}{4} \int_0^c \frac{1}{2} e^{-|r-1|} d\mathbf{r} + \frac{1}{4} \int_c^{\infty} \frac{1}{2} e^{-|r-3|} d\mathbf{r} \\
&= \frac{1}{4} \int_{-\infty}^{-c+3} \frac{1}{2} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-c+1}^1 \frac{1}{2} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-1}^{c-1} \frac{1}{2} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{c-3}^{\infty} \frac{1}{2} e^{-|r|} d\mathbf{r} \\
&= \frac{1}{4} \int_{-\infty}^{-c+3} e^{-|r|} d\mathbf{r} + \frac{1}{4} \int_{-c+1}^1 e^{-|r|} d\mathbf{r} \\
&= \frac{1}{4} (2 - e^{-3+c}) + \frac{1}{4} (2 - e^{-1} - e^{1-c}) \\
&= 1 - \frac{1}{4} e^{-1} - \frac{1}{4} e \cdot e^{-c} - \frac{1}{4} e^{-3} e^c \\
&= 1 - \frac{1}{4} e^{-1} - \frac{1}{4} \frac{e}{\sqrt{e^4 + e^2 - 1}} - \frac{1}{4} e^{-3} \sqrt{e^4 + e^2 - 1} \approx 0.7238
\end{aligned}$$

In summary, we conclude that for the Gray mapping,

$$\begin{cases} P_{\text{BER},0}(g_{\text{ML}}) > P_{\text{BER},0}(g_{\text{ML},0}); \\ P_{\text{BER},1}(g_{\text{ML}}) = P_{\text{BER},1}(g_{\text{ML},1}); \\ P_{\text{SER}}(g_{\text{ML}}) < P_{\text{SER}}(g_{\text{ML},1}, g_{\text{ML},0}). \end{cases}$$