

# ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

School of Computer and Communication Sciences

## Handout 9

Principles of Digital Communications

Solutions to Problem Set 4

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**SOLUTION 1.** If  $H = 0$ , we have  $Y_2 = Z_1 Z_2 = Y_1 Z_2$ , and if  $H = 1$ , we have  $Y_2 = -Z_1 Z_2 = Y_1 Z_2$ . Therefore,  $Y_2 = Y_1 Z_2$  in all cases. Now since  $Z_2$  is independent of  $H$ , we clearly have  $H \rightarrow Y_1 \rightarrow (Y_1, Y_1 Z_2)$ . Hence,  $Y_1$  is a sufficient statistic.

**SOLUTION 2.**

(a) The MAP decoder  $\hat{H}(y)$  is given by

$$\hat{H}(y) = \arg \max_i P_{Y|H}(y|i) = \begin{cases} 0 & \text{if } y = 0 \text{ or } y = 1 \\ 1 & \text{if } y = 2 \text{ or } y = 3. \end{cases}$$

$T(Y)$  takes two values with the conditional probabilities

$$P_{T|H}(t|0) = \begin{cases} 0.7 & \text{if } t = 0 \\ 0.3 & \text{if } t = 1 \end{cases} \quad P_{T|H}(t|1) = \begin{cases} 0.3 & \text{if } t = 0 \\ 0.7 & \text{if } t = 1. \end{cases}$$

Therefore, the MAP decoder  $\hat{H}(T(y))$  is

$$\hat{H}(T(y)) = \arg \max_i P_{T(Y)|H}(t|i) = \begin{cases} 0 & \text{if } t = 0 \quad (y = 0 \text{ or } y = 1) \\ 1 & \text{if } t = 1 \quad (y = 2 \text{ or } y = 3). \end{cases}$$

Hence, the two decoders are equivalent.

(b) We have

$$\Pr\{Y = 0 | T(Y) = 0, H = 0\} = \frac{\Pr\{Y = 0, T(Y) = 0 | H = 0\}}{\Pr\{T(Y) = 0 | H = 0\}} = \frac{0.4}{0.7} = \frac{4}{7}$$

and

$$\Pr\{Y = 0 | T(Y) = 0, H = 1\} = \frac{\Pr\{Y = 0, T(Y) = 0 | H = 1\}}{\Pr\{T(Y) = 0 | H = 1\}} = \frac{0.1}{0.3} = \frac{1}{3}.$$

Thus  $\Pr\{Y = 0 | T(Y) = 0, H = 0\} \neq \Pr\{Y = 0 | T(Y) = 0, H = 1\}$ , hence  $H \rightarrow T(Y) \rightarrow Y$  is not true, although the MAP decoders are equivalent.

**SOLUTION 3.**

(a) The MAP decision rule can always be written as

$$\begin{aligned} \hat{H}(y) &= \arg \max_i f_{Y|H}(y|i) P_H(i) \\ &= \arg \max_i g_i(T(y)) h(y) P_H(i) \\ &= \arg \max_i g_i(T(y)) P_H(i). \end{aligned}$$

The last step is valid because  $h(y)$  is a non-negative constant which is independent of  $i$  and thus does not give any further information for our decision.

(b) Let us define the event  $\mathcal{B} = \{y : T(y) = t\}$ . Then,

$$\begin{aligned} f_{Y|H,T(Y)}(y|i, t) &= \frac{f_{Y,T(Y)|H}(y, t|i)P_H(i)}{f_{T(Y)|H}(t|i)P_H(i)} \\ &= \frac{\Pr\{Y = y, T(Y) = t|H = i\}}{\Pr\{T(Y) = t|H = i\}} = \frac{\Pr\{Y = y, Y \in \mathcal{B}|H = i\}}{\Pr\{Y \in \mathcal{B}|H = i\}} \\ &= \frac{f_{Y|H}(y|i)\mathbb{1}_{\mathcal{B}}(y)}{\int_{\mathcal{B}} f_{Y|H}(y|i)dy}. \end{aligned}$$

If  $f_{Y|H}(y|i) = g_i(T(y))h(y)$ , then

$$\begin{aligned} f_{Y|H,T(Y)}(y|i, t) &= \frac{g_i(T(y))h(y)\mathbb{1}_{\mathcal{B}}(y)}{\int_{\mathcal{B}} g_i(T(y))h(y)dy} \\ &= \frac{g_i(t)h(y)\mathbb{1}_{\mathcal{B}}(y)}{g_i(t)\int_{\mathcal{B}} h(y)dy} \\ &= \frac{h(y)\mathbb{1}_{\mathcal{B}}(y)}{\int_{\mathcal{B}} h(y)dy}. \end{aligned}$$

Hence, we see that  $f_{Y|H,T(Y)}(y|i, t)$  does not depend on  $i$ , so  $H \rightarrow T(Y) \rightarrow Y$ .

(c) Note that  $P_{Y_k|H}(1|i) = p_i$ ,  $P_{Y_k|H}(0|i) = 1 - p_i$  and

$$P_{Y_1, \dots, Y_n|H}(y_1, \dots, y_n|i) = P_{Y_1|H}(y_1|i) \cdots P_{Y_n|H}(y_n|i).$$

Thus, we have

$$P_{Y_1, \dots, Y_n|H}(y_1, \dots, y_n|i) = p_i^t (1 - p_i)^{(n-t)},$$

where  $t = \sum_k y_k$ .

Choosing  $g_i(t) = p_i^t (1 - p_i)^{(n-t)}$  and  $h(y) = 1$ , we see that  $P_{Y_1, \dots, Y_n|H}(y_1, \dots, y_n|i)$  fulfills the condition in the question.

(d) Because  $Y_1, \dots, Y_n$  are independent,

$$\begin{aligned} f_{Y_1, \dots, Y_n|H}(y_1, \dots, y_n|i) &= \prod_{k=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{(y_k - m_i)^2}{2}} \\ &= \frac{1}{(2\pi)^{\frac{n}{2}}} e^{-\sum_{k=1}^n \frac{(y_k - m_i)^2}{2}} \\ &= \frac{1}{(2\pi)^{\frac{n}{2}}} e^{-\frac{\sum_{k=1}^n y_k^2}{2}} e^{nm_i(\frac{1}{n} \sum_{k=1}^n y_k - \frac{m_i}{2})}. \end{aligned}$$

Choosing  $g_i(t) = e^{nm_i(t - \frac{m_i}{2})}$  and  $h(y_1, \dots, y_n) = \frac{1}{(2\pi)^{\frac{n}{2}}} e^{-\frac{\sum_{k=1}^n y_k^2}{2}}$ , we see that

$$f_{Y_1, \dots, Y_n|H}(y_1, \dots, y_n|i) = g_i(T(y_1, \dots, y_n))h(y_1, \dots, y_n).$$

Hence the condition in the question is fulfilled.

SOLUTION 4.

(a) Since the  $X_i$  are i.i.d, the joint probability density (or mass) function is

$$p(x_1, x_2, \dots, x_n) = \left[ \prod_{i=1}^n h(x_i) \right] \exp \left[ c(\theta) \sum_{i=1}^n T(x_i) - nB(\theta) \right].$$

By the Fisher-Neyman factorization theorem,  $\sum_{i=1}^n T(x_i)$  is a sufficient statistic, where  $T(x_i)$  is a sufficient statistic for the random variable  $X_i$ .

(b) It's easier to work with single random variables and use the result from (a):

- $p_X(x) = \lambda \exp(-\lambda x) = \exp(-\lambda x - \log \frac{1}{\lambda})$   
 $h(x) = 1, c(\theta) = -\theta, T(x) = x, B(\theta) = \log \frac{1}{\theta}$   
 By (a),  $\sum_{i=1}^n x_i$  is a sufficient statistic for  $(X_1, X_2, \dots, X_n)$
- $p_X(x) = \frac{1}{2\sigma} \exp \left( -\frac{|x - \mu|}{\sigma} \right) = \exp \left( (-\frac{1}{\sigma})|x - \mu| - (\log(2\sigma)) \right)$   
 $h(x) = 1, c(\theta) = -\frac{1}{\theta}, T(x) = |x - \mu|, B(\theta) = \log(2\theta)$   
 By (a),  $\sum_{i=1}^n |x_i - \mu|$  is a sufficient statistic for  $(X_1, X_2, \dots, X_n)$
- $p_X(x) = \frac{\lambda^x \exp(-\lambda)}{x!} = \frac{1}{x!} \exp(\log(\lambda)x - \lambda)$   
 $h(x) = \frac{1}{x!}, c(\theta) = \log \theta, T(x) = x, B(\theta) = \theta$   
 By (a),  $\sum_{i=1}^n x_i$  is a sufficient statistic for  $(X_1, X_2, \dots, X_n)$
- $p_X(x) = \binom{n}{x} p^x (1-p)^{n-x} = \binom{n}{x} \exp(\log(\frac{p}{1-p})x - n \log \frac{1}{1-p})$   
 $h(x) = \binom{n}{x}, c(\theta) = \log \frac{p}{1-p}, B(\theta) = n \log \frac{1}{1-p}$   
 By (a),  $\sum_{i=1}^n x_i$  is a sufficient statistic for  $(X_1, X_2, \dots, X_n)$

SOLUTION 5.

(a) Inequality (a) follows from the *Bhattacharyya Bound*.

Using the definition of DMC, it is straightforward to see that

$$P_{Y|X}(y|c_0) = \prod_{i=1}^n P_{Y|X}(y_i|c_{0,i}) \quad \text{and}$$

$$P_{Y|X}(y|c_1) = \prod_{i=1}^n P_{Y|X}(y_i|c_{1,i}).$$

(b) follows by substituting the above values in (a).

Equality (c) is obtained by observing that  $\sum_y$  is the same as  $\sum_{y_1, \dots, y_n}$  (the first one being a vector notation for the sum over all possible  $y_1, \dots, y_n$ ).

In (c), we see that we want the sum of all possible products. This is the same as summing over each  $y_i$  and taking the product of the resulting sum for all  $y_i$ . This results in equality (d). We obtain (e) by writing (d) in a more concise form.

When  $c_{0,i} = c_{1,i}$ ,  $\sqrt{P_{Y|X}(y|c_{0,i})P_{Y|X}(y|c_{1,i})} = P_{Y|X}(y|c_{0,i})$ . Therefore,

$$\sum_y \sqrt{P_{Y|X}(y|c_{0,i})P_{Y|X}(y|c_{1,i})} = \sum_y P_{Y|X}(y|c_{0,i}) = 1.$$

This does not affect the product, so we are only interested in the terms where  $c_{0,i} \neq c_{1,i}$ . We form the product of all such sums where  $c_{0,i} \neq c_{1,i}$ . We then look out for terms where  $c_{0,i} = a$  and  $c_{1,i} = b, a \neq b$ , and raise the sum to the appropriate power. (Eg. If we have the product  $prpqrpqrr$ , we would write it as  $p^3q^2r^4$ ). Hence equality (f).

(b) For a binary input channel, we have only two source symbols  $\mathcal{X} = \{a, b\}$ . Thus,

$$\begin{aligned} P_e &\leq z^{n(a,b)} z^{n(b,a)} \\ &= z^{n(a,b)+n(b,a)} \\ &= z^{d_H(c_0, c_1)}. \end{aligned}$$

(c) The value of  $z$  is:

(i) For a binary input Gaussian channel,

$$\begin{aligned} z &= \int_y \sqrt{f_{Y|X}(y|0)f_{Y|X}(y|1)} dy \\ &= \exp\left(-\frac{E}{2\sigma^2}\right). \end{aligned}$$

(ii) For the Binary Symmetric Channel (BSC),

$$\begin{aligned} z &= \sqrt{\Pr\{y=0|x=0\}\Pr\{y=0|x=1\}} + \sqrt{\Pr\{y=1|x=0\}\Pr\{y=1|x=1\}} \\ &= 2\sqrt{\delta(1-\delta)}. \end{aligned}$$

(iii) For the Binary Erasure Channel (BEC),

$$\begin{aligned} z &= \sqrt{\Pr\{y=0|x=0\}\Pr\{y=0|x=1\}} + \sqrt{\Pr\{y=E|x=0\}\Pr\{y=E|x=1\}} \\ &\quad + \sqrt{\Pr\{y=1|x=0\}\Pr\{y=1|x=1\}} \\ &= 0 + \delta + 0 \\ &= \delta. \end{aligned}$$

SOLUTION 6.

$$\begin{aligned} P_{00} &= \Pr\{(N_1 \geq -a) \cap (N_2 \geq -a)\} \\ &= \Pr\{(N_1 \leq a)\} \Pr\{(N_2 \leq a)\} \\ &= \left[1 - Q\left(\frac{a}{\sigma}\right)\right]^2. \end{aligned}$$

By symmetry:

$$\begin{aligned} P_{01} &= P_{03} = \Pr\{(N_1 \leq -(2b-a)) \cap (N_2 \geq -a)\} \\ &= \Pr\{N_1 \geq 2b-a\} \Pr\{N_2 \leq a\} \\ &= Q\left(\frac{2b-a}{\sigma}\right) \left[1 - Q\left(\frac{a}{\sigma}\right)\right]. \end{aligned}$$

$$\begin{aligned} P_{02} &= \Pr\{(N_1 \leq -(2b-a)) \cap (N_2 \leq -(2b-a))\} \\ &= \Pr\{N_1 \geq 2b-a\} \Pr\{N_2 \geq 2b-a\} \\ &= \left[Q\left(\frac{2b-a}{\sigma}\right)\right]^2. \end{aligned}$$

$$\begin{aligned}
P_{0\delta} &= 1 - \Pr\{(Y \in \mathcal{R}_0) \cup (Y \in \mathcal{R}_1) \cup (Y \in \mathcal{R}_2) \cup (Y \in \mathcal{R}_3) | c_0 \text{ was sent}\} \\
&= 1 - P_{00} - P_{01} - P_{02} - P_{03} \\
&= 1 - \left[1 - Q\left(\frac{a}{\sigma}\right)\right]^2 - 2Q\left(\frac{2b-a}{\sigma}\right) \left[1 - Q\left(\frac{a}{\sigma}\right)\right] - \left[Q\left(\frac{2b-a}{\sigma}\right)\right]^2 \\
&= 1 - \left[1 - Q\left(\frac{a}{\sigma}\right) + Q\left(\frac{2b-a}{\sigma}\right)\right]^2.
\end{aligned}$$

Equivalently,

$$\begin{aligned}
P_{0\delta} &= \Pr\{(N_1 \in [a, 2b-a]) \cup (N_2 \in [a, 2b-a])\} \\
&= \Pr\{N_1 \in [a, 2b-a]\} + \Pr\{N_2 \in [a, 2b-a]\} - \Pr\{(N_1 \in [a, 2b-a]) \cap (N_2 \in [a, 2b-a])\} \\
&= 2 \left[Q\left(\frac{a}{\sigma}\right) - Q\left(\frac{2b-a}{\sigma}\right)\right] - \left[Q\left(\frac{a}{\sigma}\right) - Q\left(\frac{2b-a}{\sigma}\right)\right]^2,
\end{aligned}$$

which gives the same result as before.