

The Solutions

B—bookwork, A—application, E—new example, T—new theory

1.

a)

$$\text{i) } H(\mathcal{Y}) = 0.81 \quad [3E]$$

$$\text{ii) } I(X_1; \mathcal{Y}) = 0.31 \quad [3E]$$

$$\text{iii) } I(X_{1:2}; \mathcal{Y}) = 0.81 \quad [3E]$$

b)

$$D(\mathbf{p}||\mathbf{q}) = \sum p_i \log \frac{p_i}{q_i} = \frac{1}{3} \log \frac{2}{3} + \frac{2}{3} \log \frac{4}{3} = 0.0817 \quad [3E]$$

$$D(\mathbf{q}||\mathbf{p}) = \sum q_i \log \frac{q_i}{p_i} = \frac{1}{2} \log \frac{3}{2} + \frac{1}{2} \log \frac{3}{4} = 0.085 \quad [3E]$$

c) i) Firstly note that the output distributions are given by

$$p'_y = \sum_{x \in X} p_x W(y|x)$$

$$q'_y = \sum_{x \in X} q_x W(y|x)$$

Thus,

$$D(\mathbf{p}'||\mathbf{q}') = \sum_{y \in Y} p'_y \log \frac{p'_y}{q'_y} = \sum_{y \in Y} \sum_{x \in X} p_x W(y|x) \cdot \log \frac{\sum_{x \in X} p_x W(y|x)}{\sum_{x \in X} q_x W(y|x)} \quad [2T]$$

Now, using the log-sum inequality, the inner sum [2T]

$$\begin{aligned} & \sum_{x \in X} p_x W(y|x) \cdot \log \frac{\sum_{x \in X} p_x W(y|x)}{\sum_{x \in X} q_x W(y|x)} \\ & \leq \sum_{x \in X} p_x W(y|x) \log \frac{p_x W(y|x)}{q_x W(y|x)} = \sum_{x \in X} p_x W(y|x) \log \frac{p_x}{q_x} \end{aligned}$$

Substituting this back to $D(\mathbf{p}'||\mathbf{q}')$, we obtain [3T]

$$\begin{aligned} D(\mathbf{p}'||\mathbf{q}') & \leq \sum_{y \in Y} \sum_{x \in X} p_x W(y|x) \log \frac{p_x}{q_x} \\ & = \sum_{x \in X} p_x \sum_{y \in Y} W(y|x) \log \frac{p_x}{q_x} = \sum_{x \in X} p_x \log \frac{p_x}{q_x} = D(\mathbf{p}||\mathbf{q}) \end{aligned}$$

where we use the fact that

$$\sum_{y \in Y} W(y|x) = 1 \quad [3T]$$

2.

- a) (1) chain rule [1B]
 (2) chain rule in another way [1B]
 (3) $H(e|x, y) \geq 0$ entropy is non-negative [1B]
 $H(e|y) \leq H(e)$ conditioning reduces entropy [1B]
 (4) total probability theorem
 (5) $H(e) = H(p_e)$ [2B]
 Given y and $e=0$, $X=y$, so entropy = 0.
 Given y and $e=1$, $X \neq y$ but can take any of the $|X|-1$ values, so entropy $\leq \log(|X|-1)$
 (6) algebra [1B]
 (7) $H(p_e) \leq 1$ [1B]

b) The optimum estimator is given by [3E]

$$\hat{x} = \begin{cases} 1 & y = a \\ 2 & y = b \end{cases}$$

Then the error probability is given by [2E]

$$P_e = \frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12} = \frac{1}{3}$$

To apply Fano's inequality, we need to calculate conditional entropy [3E]

$$H(Y|X) = \frac{1}{2} H\left(\frac{1}{3}, \frac{1}{12}, \frac{1}{12}\right) + \frac{1}{2} H\left(\frac{1}{12}, \frac{1}{3}, \frac{1}{12}\right) = H\left(\frac{1}{3}, \frac{1}{12}, \frac{1}{12}\right) = 1.252$$

Then Fano's inequality gives [2E]

$$\frac{H(Y|X) - 1}{\log 2} = 0.252$$

which is smaller than $1/3$.

c) If $|X|$ is infinity, then Fano's inequality is vacuous, namely, it only says $P_e \geq 0$. [2T]

To get a meaningful bound, one may modify step (5) to get

[3T]

$$\begin{aligned}
 & \stackrel{(4)}{=} H(e) + H(X|Y, e=0)(1-p_e) + H(X|Y, e=1)p_e \\
 & \stackrel{(5)}{\leq} H(p_e) + 0 \times (1-p_e) + H(X)p_e \\
 & \stackrel{(6)}{\Rightarrow} p_e \geq \frac{(H(X|Y) - H(p_e))}{H(X)} \stackrel{(7)}{\geq} \frac{(H(X|Y) - 1)}{H(X)}
 \end{aligned}$$

where we use conditioning reduces entropy:

[1T]

$$H(X|Y, e=1) \leq H(X)$$

Then, the bound is meaningful as long as X has finite entropy.

[1T]

(Solution is not unique; student will get credit as long as it makes sense.)

3.

a)

- (1) definition of Gaussian pdf [1B]
- (2) definition of differential entropy [1B]
- (3) algebra, definition of mean [1B]
- (4) $\text{tr}(AB) = \text{tr}(BA)$ [1B]
- (5) since trace is linear, E and tr can exchange order [1B]
- (6) definition of covariance matrix K [1B]
- (7) $\text{tr}(KK^{-1}) = \text{tr}(I) = n$ [1B]
- (8) algebra [1B]
- (9) identity $|cA| = c^n|A|$ [1B]
- (10) same [1B]

b) Using the chain rule of mutual information, [3A]

$$I(X; Y, V) = I(X; V) + I(X; Y|V) = I(X; Y) + I(X; V|Y).$$

But $I(X; V) = 0$ due to independence, and $I(X; V|Y) \geq 0$ trivially, so [2A]

$$I(X; Y|V) = I(X; Y) + I(X; V|Y) \geq I(X; Y). \quad [3A]$$

c)

i) This is well known $C = \frac{1}{2} \log(1 + \frac{P}{N})$ [2B]

ii) This looks tricky but really is simple: you can just think of two noise terms, where one has variance N while the other has variance N1. [3A]

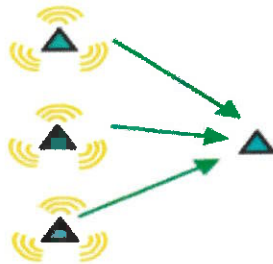
So

$$C = \frac{1}{2} \log(1 + \frac{P}{N+N_1}) \quad [2A]$$

4.

- a) i) Multi-access channel is a many-to-one channel where there are many senders but only one receiver. A typical example is the uplink of a cellular communication system.

[3B]



[2B]

ii)

$$R_1 \leq W \log \left(1 + \frac{P_1}{N W} \right)$$

$$R_2 \leq W \log \left(1 + \frac{P_2}{N W} \right)$$

[3B]

$$R_1 + R_2 \leq W \log \left(1 + \frac{P_1}{N W} \right) + W \log \left(1 + \frac{P_2}{N W} \right)$$

The capacity region is a pentagon. To achieve corner points, one may use onion peeling.

[2B]

iii) If W goes to infinity, then

$$R_1 \rightarrow \frac{P_1}{N}$$

$$R_2 \rightarrow \frac{P_2}{N}$$

[3T]

$$R_1 + R_2 \rightarrow \frac{P_1}{N} + \frac{P_2}{N}$$

where the unit is nat (there is an extra factor $\log(e)$ if the unit is bit). Therefore, senders can transmit as if there were no interference.

[2T]

b)

i) Let $Y = (Y_1, Y_2)$. Denote its covariance matrix by K_Y , which is given by

[2A]

$$K_Y = \begin{bmatrix} \alpha^2 P + N & \alpha(1 - \alpha)P \\ \alpha(1 - \alpha)P & (1 - \alpha)^2 P + N \end{bmatrix}$$

Its determinant

[1A]

$$\det(K_Y) = \alpha^2 P N + (1 - \alpha)^2 P N + N^2$$

Then, since $h(Y_1, Y_2)$ is maximized when X is Gaussian,

$$\begin{aligned} C = I(X; Y) &= h(Y_1, Y_2) - h(Z_1, Z_2) = \frac{1}{2} \log \left(\frac{\det K_Y}{N^2} \right) \\ &= \frac{1}{2} \log \left(1 + \frac{\alpha^2 P}{N} + \frac{(1-\alpha)^2 P}{N} \right) \end{aligned}$$

[2A]

ii) The problem is equivalent to a degraded broadcast channel

$$\begin{aligned} Y_1' &= X + Z_1/\alpha \\ Y_2' &= X + Z_2/(1-\alpha) \end{aligned}$$

The noise terms have variance $N_1 = N/\alpha^2$ and $N_2 = N/(1-\alpha)^2$, respectively.

[2A]

Assume $N_1 < N_2$, i.e., $\alpha < \frac{1}{2}$, its capacity region is given by

$$\begin{aligned} R_1 &\leq C \left(\frac{\beta P}{N_1} \right) \\ R_2 &\leq C \left(\frac{(1-\beta)P}{\beta P + N_2} \right) \end{aligned}$$

where $\beta \in [0,1]$.

[2A]

If $\alpha > \frac{1}{2}$, the rates are reversed

$$\begin{aligned} R_1 &\leq C \left(\frac{(1-\beta)P}{\beta P + N_1} \right) \\ R_2 &\leq C \left(\frac{\beta P}{N_2} \right) \end{aligned}$$

[1A]