

## The Solutions

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

1.

a)

$$\text{i)} \quad I(\mathcal{Y}; \mathcal{X}) = H(\mathcal{X}) + H(\mathcal{Y}) - H(\mathcal{X}, \mathcal{Y}) = E \log \frac{p(\mathcal{X}, \mathcal{Y})}{p(\mathcal{X})p(\mathcal{Y})} = \sum p(\mathcal{X}, \mathcal{Y}) \log \frac{p(\mathcal{X}, \mathcal{Y})}{p(\mathcal{X})p(\mathcal{Y})}$$

Mutual information is the average amount of information that you get about  $x$  from observing the value of  $y$ . In particular, in communications, mutual information is the amount of information transmitted through a noisy channel. [3B]

- ii) Max  $I(\mathcal{Y}; \mathcal{X})$  = channel capacity, achieved by a capacity-achieving input distribution.  
 Min  $I(\mathcal{Y}; \mathcal{X}) = 0$ , achieved by a trivial input distribution with 0 entropy. [3B]

iii) [3A]

$$\begin{aligned} \mathbf{p} &= \left[ \frac{1}{6} \quad \frac{1}{6} \quad \frac{1}{6} \quad \frac{1}{6} \quad \frac{1}{6} \quad \frac{1}{6} \right] \Rightarrow H(\mathbf{p}) = 2.585 \\ \mathbf{q} &= \left[ \frac{1}{10} \quad \frac{1}{10} \quad \frac{1}{10} \quad \frac{1}{10} \quad \frac{1}{10} \quad \frac{1}{2} \right] \Rightarrow H(\mathbf{q}) = 2.161 \\ D(\mathbf{p} \parallel \mathbf{q}) &= E_{\mathbf{p}}(-\log q_x) - H(\mathbf{p}) = 2.935 - 2.585 = 0.35 \\ D(\mathbf{q} \parallel \mathbf{p}) &= E_{\mathbf{q}}(-\log p_x) - H(\mathbf{q}) = 2.585 - 2.161 = 0.424 \end{aligned}$$

iv) It is NOT a distance, since it is not symmetric. [3A]

$$\text{v)} \quad I(\mathcal{Y}; \mathcal{X}) = \sum p(\mathcal{X}, \mathcal{Y}) \log \frac{p(\mathcal{X}, \mathcal{Y})}{p(\mathcal{X})p(\mathcal{Y})} = D(p(\mathcal{X}, \mathcal{Y}) \parallel p(\mathcal{X})p(\mathcal{Y}))$$

[3B]

b)

i) To find the stationary distribution, we write [3A]

$$\begin{aligned} T^T \begin{pmatrix} a \\ 1-a \end{pmatrix} &= \begin{pmatrix} 1-p & p \\ p & 1-p \end{pmatrix} \begin{pmatrix} a \\ 1-a \end{pmatrix} = \begin{pmatrix} a \\ 1-a \end{pmatrix} \\ \Rightarrow (1-p)a + p(1-a) &= (1-2p)a + p = a \\ \Rightarrow a &= 1/2 \end{aligned}$$

which is a uniform distribution. [2A]

It follows that the entropy rate is given by  
 $H(\mathcal{X}) = aH(p) + (1-a)H(p) = H(p)$  [3A]

ii) Obviously,  $H(\mathcal{X})$  is maximized when  $p = 1/2$ . [2A]

2.

a) 11000011010100000110101

location	parsing	encoding
0000		
0001	1	(0000,1)
0010	10	(0001,0)
0011	0	(0000,0)
0100	00	(0011,0)
0101	11	(0001,1)
0110	01	(0011,1)
0111	010	(0110,0)
1000	000	(0100,0)
1001	011	(0110,1)
1010	0101	(0111,1)
1011		
1100		
1101		
1110		
1111		

[10E, 1 each step]

b)

Obviously, both  $x$  and  $y$  are uniform, with entropy  $H(x) = H(y) = 1$ .

i)  $H(x) = 1$

The probability of a particular sequence  $x$  is given by

$$p(x) = \left(\frac{1}{2}\right)^m \left(\frac{1}{2}\right)^{n-m} = \left(\frac{1}{2}\right)^n \quad m: \text{the number of ones}$$

Thus,

$$-\frac{1}{n} \log p(x) = -\frac{1}{n} \log \left(\frac{1}{2}\right)^n = 1 = H(x)$$

Therefore, all  $2^n$  sequences are in the typical set.

[3A]

ii)  $H(Y) = 1$

Similarly, all  $2^n$  sequences  $y$  are in the typical set

[2A]

iii)  $H(X, Y) = H(X) + H(Y|X) = 1 + H(0.2) = 1.72$

From the joint distribution, we deduce

$$p(x, y) = 0.4^{n-k} 0.1^k = 2^{-n} 0.8^{n-k} 0.2^k$$

where  $k$  is the number of positions where they differ.

[3A]

We also have

$$-\frac{1}{n} \log p(x, y) = 1 - \frac{1}{n} \log(0.8^{n-k} 0.2^k)$$

Joint typicality requires

$$\left| -\frac{1}{n} \log p(x, y) - H(X, Y) \right| = \left| -\frac{1}{n} \log(0.8^{n-k} 0.2^k) - 0.72 \right| < \varepsilon = 0.1$$

From the following table, only the case  $k=2$  is eligible. The size of the typical set is 45, while the probability is 0.302.

[3A]

$k$	$\binom{n}{k}$	$0.8^{n-k} 0.2^k$	$-\frac{1}{n} \log(0.8^{n-k} 0.2^k)$	probability
0	1	0 . 1 0 7	0 . 3 2 2	0 . 1 0 7
1	1 0	0 . 0 2 6 8	0 . 5 2 2	0 . 2 6 8
2	4 5	0 . 0 0 6 7 1	0 . 7 2 2	0 . 3 0 2
3	1 2 0	0 . 0 0 1 6 8	0 . 9 2 2	0 . 2 0 1
	...			

[4A]

3.

a)

- (1) definition of mutual info [1B]
- (2) conditional entropy = average row entropy  $H(Y|X) = \sum_i H(Y|X = i)$  [1B]
- (3) algebra [1B]
- (4)  $H(X) \leq 1$  [1B]
- (5) definition of capacity, = is achieved by uniform input distribution [1B]

b) Erasure probability of  $W^-$ :

$$1 - (1 - f)^2 = 2f - f^2 \quad [2E]$$

$$\mathcal{C}(W^-) = (1 - f)^2 = \left(1 - \frac{3}{4}\right)^2 = \frac{1}{16}$$

[3E]

Erasure probability of  $W^+$ :

$$f^2 \quad [2E]$$

$$\mathcal{C}(W^+) = 1 - f^2 = 1 - \left(\frac{3}{4}\right)^2 = \frac{7}{16}$$

[3E]

c) Input (0 0 0 1 0 1 1 1)

[1E]

First level (0 0 1 1 1 1 0 1)

[3E]

Second level (1 1 1 1 1 0 0 1)

[3E]

Third level (0 1 1 0 1 0 0 1)  $\leftarrow$  codeword

[3E]

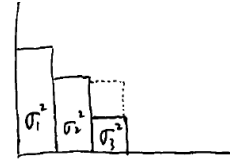
4. a)

i) Single channel is when

$$3P \leq \sigma_1^2 - \sigma_3^2$$

Capacity

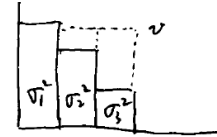
$$C = \frac{1}{2} \log \left( 1 + \frac{3P}{\sigma_1^2} \right)$$



[5A]

ii) A pair of channel is when

$$\sigma_1^2 - \sigma_3^2 < 3P \leq \sigma_1^2 - \sigma_2^2 + \sigma_2^2 - \sigma_3^2 \\ = 2\sigma_1^2 - \sigma_2^2 - \sigma_3^2$$



$$3P = \nu - \sigma_1^2 + \nu - \sigma_3^2 \Rightarrow \nu = \frac{3P + \sigma_1^2 + \sigma_3^2}{2}$$

$$P_2 = \nu - \sigma_2^2 = \frac{3P - \sigma_2^2 + \sigma_3^2}{2}$$

$$P_3 = \nu - \sigma_3^2 = \frac{3P + \sigma_1^2 - \sigma_3^2}{2}$$

$$C = \frac{1}{2} \log \left( 1 + \frac{P_2}{\sigma_2^2} \right) + \frac{1}{2} \log \left( 1 + \frac{P_3}{\sigma_3^2} \right) \\ = \frac{1}{2} \log \left( 1 + \frac{3P - \sigma_2^2 + \sigma_3^2}{2\sigma_2^2} \right) + \frac{1}{2} \log \left( 1 + \frac{3P + \sigma_1^2 - \sigma_3^2}{2\sigma_3^2} \right)$$

[5A]

iii) Three channels is when

$$3P > 2\sigma_1^2 - \sigma_2^2 - \sigma_3^2$$

$$3P = \nu - \sigma_1^2 + \nu - \sigma_2^2 + \nu - \sigma_3^2$$

$$\Rightarrow \nu = \frac{3P + \sigma_1^2 + \sigma_2^2 + \sigma_3^2}{3} = P + \frac{\sigma_1^2 + \sigma_2^2 + \sigma_3^2}{3}$$

$$P_1 = \nu - \sigma_1^2 = P + \frac{\sigma_2^2 + \sigma_3^2 - 2\sigma_1^2}{3}$$

$$P_2 = \nu - \sigma_2^2 = P + \frac{\sigma_1^2 + \sigma_3^2 - 2\sigma_2^2}{3}$$

$$P_3 = \nu - \sigma_3^2 = P + \frac{\sigma_1^2 + \sigma_2^2 - 2\sigma_3^2}{3}$$

$$C = \frac{1}{2} \log \left( 1 + \frac{P_1}{\sigma_1^2} \right) + \frac{1}{2} \log \left( 1 + \frac{P_2}{\sigma_2^2} \right) + \frac{1}{2} \log \left( 1 + \frac{P_3}{\sigma_3^2} \right)$$

[5A]

b)

We can expand the mutual information

$$I(X; Y) = h(Y) - h(Y | X) = h(Y) - h(Z)$$

and  $h(Z) = \log 2$ , since  $Z$  is uniform over  $[-1, 1]$ .

[1T]

The output  $Y$  is a sum of a discrete and a continuous random variable, and if the probabilities of  $X$  are  $p_{-1}, p_0, p_1$ , then the output distribution of  $Y$  has piecewise constant distribution

uniform with weight  $\frac{p_{-1}}{2}$  for  $-2 \leq y \leq -1$ ,

[1T]

uniform with weight  $\frac{p_{-1}+p_0}{2}$  for  $-1 \leq y \leq 0$ ,

[1T]

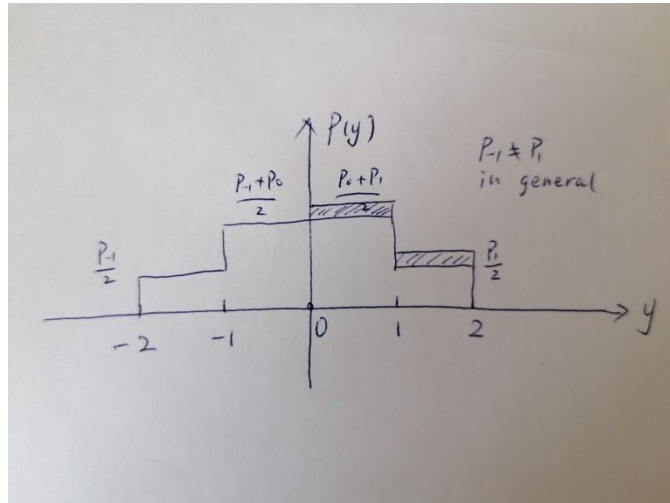
uniform with weight  $\frac{p_0+p_1}{2}$  for  $0 \leq y \leq 1$ ,

[1T]

uniform with weight  $\frac{p_1}{2}$  for  $1 \leq y \leq 2$ .

[1T]

See the following sketch:



Given that  $Y$  ranges from  $-2$  to  $2$ , the maximum entropy that it can have is a uniform over this range.

[2T]

This can be achieved if the distribution of  $X$  is  $(1/2, 0, 1/2)$ .

[1T]

Then  $h(Y) = \log 4$  and the capacity of this channel is

[2T]

$$C = \log 4 - \log 2 = \log 2 \text{ bits.}$$