

Q 7.1

a) $X \rightarrow Y \rightarrow \hat{Y}$

and using \hat{Y} to recover the message results in a capacity

$$\hat{C} = \max_{p(x)} I(x; \hat{Y})$$

but $I(x; \hat{Y}) \leq I(x; Y)$ by Data processing inequality.

$$\Rightarrow \hat{C} = \max_{p(x)} I(x; \hat{Y}) \leq \max_{p(x)} I(x; Y) = C$$

b) We have equality iff $X \rightarrow \hat{Y} \rightarrow Y$ is a Markov chain.

7.2

$$\text{Let } P_X(0) = \alpha, \quad P_X(1) = 1 - \alpha$$

$$\text{Let } \alpha = \frac{1}{2}$$

$$C = \max_{P_X} I(X; Y) = \max_{\alpha} H(Y) - H(Y|X)$$

$$= \max_{\alpha} H(X+Z) - H(X+Z|X)$$

$$= \max_{\alpha} H(X+Z) - H(Z|X)$$

$$= \max_{\alpha} H(X+Z) - H(Z)$$

$$= \max_{\alpha} H(X+Z) - 1$$

$$\text{Now, } P_Y(0) = \frac{1}{2}\alpha$$

$$P_Y(1) = \frac{1}{2}\alpha + \frac{1}{2}(1-\alpha) = \frac{1}{2}$$

$$P_Y(2) = \frac{1}{2}(1-\alpha)$$

$$\Rightarrow H(Y) = -\frac{\alpha}{2} \log \frac{\alpha}{2} - \frac{1}{2} \log \frac{1}{2} - \frac{1-\alpha}{2} \log \frac{1-\alpha}{2}$$

$$= -\frac{\alpha}{2} \log \frac{1}{2} - \frac{1}{2} \log \frac{1}{2} - \frac{1-\alpha}{2} \log \frac{1}{2}$$

$$+ \frac{1}{2} (-\alpha \log \alpha - (1-\alpha) \log (1-\alpha))$$

$$= 1 + \frac{1}{2} h(\alpha)$$

$$\Rightarrow C = \max_{\alpha} \left(1 + \frac{1}{2} h(\alpha) - 1 \right) = \frac{1}{2}$$

$$\text{When } \alpha = \frac{1}{2}.$$

- The calculation is essentially identical if $a = -1$, except that

$$P_Y(-1) = \frac{1}{2} \alpha$$

$$P_Y(0) = \frac{1}{2}$$

$$P_Y(1) = \frac{1}{2} (1 - \alpha).$$

- If $a \neq \pm 1$, then

$$X = 0, Z = 0 \Rightarrow Y = 0$$

$$X = 0, Z = a \Rightarrow Y = a$$

$$X = 1, Z = 0 \Rightarrow Y = 1$$

$$X = 1, Z = a \Rightarrow Y = 1 + a$$

results in 4 different values of Y , and thus X can be recovered without error from Y .

Then $X \rightarrow Y \rightarrow X$, and thus

$$I(X; Y) \stackrel{Z}{=} I(X; X) = 1$$

which can be achieved.

$$\underline{7.3} \quad Y_\ell = X_\ell \oplus Z_\ell, \quad \ell = 1, \dots, n$$

If noise Z_ℓ is iid, then capacity is $1 - h(p) = C$ which is achieved with X_1, \dots, X_n iid $\sim p_X$,

$$\text{i.e., } p(x_1, \dots, x_n) = \prod_{\ell=1}^n p_X(x_\ell)$$

Now

$$\max_{p(x_1, \dots, x_n)} I(x_1, \dots, x_n; Y_1, \dots, Y_n)$$

$$\geq I(x_1, \dots, x_n; Y_1, \dots, Y_n) \quad \text{for } X_1^n \sim \text{iid } p_X$$

$$= H(x_1, \dots, x_n) - H(x_1, \dots, x_n | Y_1, \dots, Y_n) \quad \text{for } X_1^n \sim \text{iid } p_X$$

$$= \sum_{\ell=1}^n H(x_\ell) - H(x_\ell | Y_1^n, x_1^{\ell-1}) \quad \text{for } X_1^n \sim \text{iid } p_X$$

$$\stackrel{(a)}{\geq} \sum_{\ell=1}^n H(x_\ell) - H(x_\ell | Y_\ell) \quad \text{for } X_1^n \sim \text{iid } p_X$$

$$= \sum_{\ell=1}^n I(x_\ell; Y_\ell) = nC$$

where (a) follows since conditioning reduces entropy.

Note that if Z_1, \dots, Z_n was memoryless then (a) would hold with equality.

7.4

$$a) C = \max_{P_X} I(X; Y)$$

$$= \max_{P_X} H(Y) - H(Y|X)$$

$$= \max_{P_X} H(X \oplus Z) - H(X \oplus Z | X)$$

$$= \max_{P_X} H(X \oplus Z) - H(Z | X)$$

$$= \max_{P_X} H(X \oplus Z) - H(Z)$$

$$\leq \log_2 11 - \log_2 3$$

with equality when P_X is uniform on $\{0, 1, \dots, 10\}$
Since then $Y = X \oplus Z$ is also.

7.5 Let $\bar{x} = (x_1, x_2)$
 $\bar{y} = (y_1, y_2)$

Then $C = \max_{P_{\bar{x}}} I(\bar{x}; \bar{y})$

$$= \max_{P_{x_1, x_2}} I(x_1, x_2; y_1, y_2)$$

$$= \max_{P_{x_1, x_2}} H(y_1, y_2) - H(y_1, y_2 | x_1, x_2)$$

$$\stackrel{(a)}{\leq} \max_{P_{x_1, x_2}} H(y_1) + H(y_2) - H(y_1, y_2 | x_1, x_2)$$

But $H(y_1, y_2 | x_1, x_2) = H(y_1 | x_1, x_2) + H(y_2 | x_1, x_2, y_1)$
 $= H(y_1 | x_1) + H(y_2 | x_2)$

Since $P_{y_1, y_2 | x_1, x_2}(y_1, y_2 | x_1, x_2) = P_{y_1 | x_1}(y_1 | x_1) P_{y_2 | x_2}(y_2 | x_2)$

$$\Rightarrow C \leq \max_{P_{x_1, x_2}} H(y_1) + H(y_2) - H(y_1 | x_1) - H(y_2 | x_2)$$

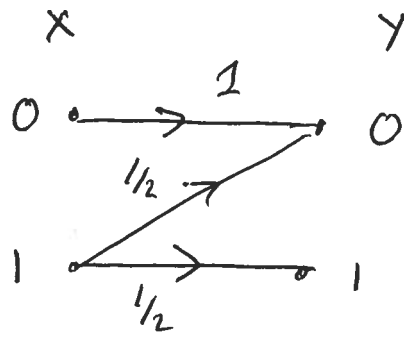
$$= \max_{P_{x_1, x_2}} I(x_1; y_1) + I(x_2; y_2)$$

$$= \max_{P_{x_1}} I(x_1; y_1) + \max_{P_{x_2}} I(x_2; y_2)$$

$$= C_1 + C_2$$

and we have equality in (a) when x_1 & x_2 are independent

7.8



$$C = \max_{P_x} H(Y) - H(Y|X)$$

$$\text{Let } P_x(0) = \alpha \quad P_x(1) = 1 - \alpha$$

$$\begin{aligned} H(Y|X) &= \sum_{x \in \{0,1\}} H(Y|X=x) P_x(x) \\ &= H(Y|X=0) P_x(0) + H(Y|X=1) P_x(1) \\ &= 0 \cdot \alpha + 1 \cdot (1 - \alpha) \end{aligned}$$

$$P_y(0) = 1 \cdot \alpha + \frac{1}{2}(1 - \alpha) = \frac{1}{2} + \frac{1}{2}\alpha$$

$$P_y(1) = \frac{1}{2}(1 - \alpha) = \frac{1}{2} - \frac{1}{2}\alpha$$

$$\begin{aligned} H(Y) &= -\frac{1}{2}(1 + \alpha) \log \frac{1 + \alpha}{2} - \frac{1}{2}(1 - \alpha) \log \frac{1 - \alpha}{2} \\ &= -\frac{1}{2}(1 + \alpha) \log \frac{1}{2} - \frac{1}{2}(1 - \alpha) \log \frac{1}{2} \\ &\quad + \frac{1}{2}[(1 + \alpha) \log(1 + \alpha) - (1 - \alpha) \log(1 - \alpha)] \\ &= 1 - \frac{1}{2}[(1 + \alpha) \log(1 + \alpha) + (1 - \alpha) \log(1 - \alpha)] \end{aligned}$$

$$I(x; \gamma) = 1 - \frac{1}{2} [(1+\alpha) \log_2(1+\alpha) + (1-\alpha) \log_2(1-\alpha)]$$

$$- (1-\alpha)$$

$$= \alpha - \frac{1}{2} [(1+\alpha) \log_2(1+\alpha) + (1-\alpha) \log_2(1-\alpha)]$$

$$\frac{d}{d\alpha} I(x; \gamma) = 1 - \frac{1}{2 \ln 2} \left[\frac{1+\alpha}{1+\alpha} + \ln(1+\alpha) + \frac{1-\alpha}{1-\alpha} - 1 - \ln(1-\alpha) \right]$$

$$= 1 - \frac{1}{2 \ln 2} \left[\ln \frac{1+\alpha}{1-\alpha} \right]$$

$$= 1 - \frac{1}{2} \log_2 \left(\frac{1+\alpha}{1-\alpha} \right) = 0$$

$$\log_2 \left(\frac{1+\alpha}{1-\alpha} \right) = 2$$

$$\frac{1+\alpha}{1-\alpha} = 4$$

$$1+\alpha = 4-4\alpha$$

$$5\alpha = 3$$

$$\alpha = 3/5$$

$$\Rightarrow C = \frac{3}{5} - \frac{4}{5} \log_2 \frac{8}{5} - \frac{2}{5} \log_2 \frac{2}{5}$$

$$\underline{7.11} \quad I(X_1^n; Y_1^n)$$

$$= H(Y_1^n) - H(Y_1^n | X_1^n)$$

$$= H(Y_1^n) - \sum_{l=1}^n H(Y_l | X_l)$$

$$\stackrel{(a)}{\leq} \sum_{l=1}^n H(Y_l) - H(Y_l | X_l)$$

$$= \sum_{l=1}^n I(X_l; Y_l) \quad (*)$$

Where we have equality in (a) when X_1, \dots, X_n are independent.

Now, maximizing (*) yields

$$\max_{p(X_1^n)} \sum_{l=1}^n I(X_l; Y_l) = \sum_{l=1}^n 1 - h(p_l)$$

Where the maximizing input distribution is

$$p(X_1^n) = \prod_{l=1}^n p_X(X_l) \quad \text{and} \quad p_X \text{ is uniform on } \{0, 1\}.$$

But since X_1, \dots, X_n are independent, we have equality in (a)

Thus, the upper bound $\sum_{l=1}^n [1 - h(p_l)]$ is achievable.

7.20 Note that $Y_1 \rightarrow X \rightarrow Y_2$ (*)

$$a) I(X; Y_1, Y_2) = I(X; Y_1) + I(X; Y_2 | Y_1)$$

also

$$\begin{aligned} I(Y_1; X) &= I(Y_2; X) && \text{since } P_{Y_1|X} = P_{Y_2|X} \\ &= I(Y_2; X | Y_1) && \text{by (*)} \\ &= I(Y_1; Y_2) + I(X; Y_2 | Y_1) \end{aligned}$$

$$\Rightarrow I(X; Y_2 | Y_1) = I(X; Y_1) - I(Y_1; Y_2)$$

$$\Rightarrow I(X; Y_1, Y_2) = 2I(X; Y_1) - I(Y_1; Y_2)$$

$$b) C = \max_{P_X} I(X; Y_1, Y_2)$$

$$= \max_{P_X} 2I(X; Y_1) - I(Y_1; Y_2)$$

$$\leq 2 \max_{P_X} I(X; Y_1)$$

7.25

$$C = \max_{P_x} I(x; Y)$$

$$\text{and } I(x; Y) \leq I(x; V)$$

$$\leq H(V)$$

$$\leq \log k$$

by data processing
inequality

$$\Rightarrow C \leq \max_{P_x} \log k = \log k$$

7.31

We need $H(V) < C$

$$\text{Here } H(V) = h(\alpha) = -\alpha \log \alpha - (1-\alpha) \log(1-\alpha)$$

$$C = \max_{P_x} I(x; Y)$$

$$= \max_{P_x} H(Y) - H(Y|X)$$

$$= \max_{P_x} H(Y) - h(p)$$

$$= 1 - h(p)$$

$$\Rightarrow h(\alpha) \leq 1 - h(p) \quad \text{or} \quad h(\alpha) + h(p) \leq 1.$$

7.34

$$a) C = \max_{P_X} I(X; Y)$$

$$I(X; Y) = H(Y) - H(Y|X)$$

$$H(Y|X) = \sum_{x=1}^4 H(Y|X=x) P_X(x)$$

$$= \sum_{x=1}^4 h(p) P_X(x)$$

$$= h(p)$$

$$\Rightarrow C = \max_{P_X} H(Y) - h(p)$$

$$\leq \log_2 4 - h(p) = 2 - h(p)$$

and we see that when P_X is uniform on $\{1, 2, 3, 4\}$
that Y is uniform on $\{1, 2, 3, 4\}$ so $H(Y) = 2$,
and therefore $C = 2 - h(p)$.

$$7.34b) \quad C = \max_{P_X} I(X; Y)$$

$$I(X; Y) = H(Y) - H(Y|X)$$

$$H(Y|X) = \sum_{x=1}^3 H(Y|X=x) P_X(x)$$

$$= h(p) \cdot P_X(1) + h(p) \cdot P_X(2) + 0 \cdot P_X(3)$$

$$= h(p) \cdot [1 - P_X(3)]$$

where we used the fact that $P_X(1) + P_X(2) + P_X(3) = 1$

$$\Rightarrow P_X(2) + P_X(1) = 1 - P_X(3)$$

$$\Rightarrow I(X; Y) = H(Y) - h(p) [1 - P_X(3)]$$

Now, let $P_Y = (P_Y(1) \ P_Y(2) \ P_Y(3))$

be the distribution on Y when $P_X = (P_X(1) \ P_X(2) \ P_X(3))$

Then, when distribution on X is $\bar{P}_X = (P_X(2) \ P_X(1) \ P_X(3))$

distribution on Y is $\bar{P}_Y = (P_Y(2) \ P_Y(1) \ P_Y(3))$

$$\Rightarrow H(P_Y) = H(\bar{P}_Y)$$

$$\text{Also, if } \hat{P}_X = \left(\frac{P_Y(1) + P_Y(2)}{2} \quad \frac{P_Y(1) + P_Y(2)}{2} \quad P_Y(3) \right)$$

$$= \frac{P_X + \bar{P}_X}{2}$$

$$\text{Then } \hat{P}_Y = \frac{1}{2}(P_Y + \bar{P}_Y) = \left(\frac{1 - P_Y(3)}{2} \quad \frac{1 - P_Y(3)}{2} \quad P_Y(3) \right)$$

But, by convexity of entropy,

$$H\left(\frac{1}{2}P_Y + \frac{1}{2}\bar{P}_Y\right) \geq \frac{1}{2}H(P_Y) + \frac{1}{2}H(\bar{P}_Y)$$

$$= H(P_Y)$$

and since $P_Y(3) = P_X(3)$,

$$H(Y) \geq -\frac{1 - P_X(3)}{2} \log \frac{1 - P_X(3)}{2} - \frac{1 - P_X(3)}{2} \log \frac{1 - P_X(3)}{2}$$

$$- P_X(3) \log P_X(3)$$

with equality when $P_X(1) = P_X(2) = \frac{1 - P_X(3)}{2}$.