

Quantum Information, Lecture 4 HW

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1 Let $(X^n, Y^n) \sim p(x^n, y^n)$

We can prove it, by separating the original expression into:

$$\begin{aligned}\sum_{i=1}^n I(X_{i+1}^n; Y_i | Y_1^{i-1}) &= \sum_{i=1}^n [I(X_{i+1}^n; Y_1^i) - I(X_{i+1}^n; Y_1^{i-1})] \\ &=^* \sum_{i=1}^n [I(X_{i+1}^n; Y_1^i) - I(X_i^n; Y_1^{i-1}) + I(X_i; Y_1^{i-1} | X_{i+1}^n)] \\ &=^{**} \sum_{i=1}^n I(X_i; Y_1^{i-1} | X_{i+1}^n)\end{aligned}$$

where in $=^*$, we have used the second provided Hint for the application of the chain rule of mutual information, on the right term:

$$-I(X_{i+1}^n; Y_1^{i-1}) = -I(X_i^n; Y_1^{i-1}) + I(X_i; Y_1^{i-1} | X_{i+1}^n)$$

and in $=^{**}$, for canceling the two left terms, we have moved the sum index of the second one, obtaining:

$$\begin{aligned}\sum_{i=1}^n [I(X_{i+1}^n; Y_1^i) - I(X_i^n; Y_1^{i-1})] &= \sum_{i=1}^n I(X_{i+1}^n; Y_1^i) - \sum_{i=0}^{n-1} I(X_{i+1}^n; Y_1^i) \\ &= I(X_{n+1}^n; Y_1^n) - I(X_1^n; Y_1^0) \\ &= I(\emptyset; Y_1^n) - I(X_1^n; \emptyset) = 0\end{aligned}$$

2 Inequalities

a) **Answer:** \leq

$$H(X | Z) \leq H(X, Y | Z) = H(X | Y, Z) + H(Y | Z) \leq H(X | Y) + H(Y | Z)$$

b) **Answer:** \geq

If X, Y are independent:

$$H(X + Y) \geq H(X + Y | Y) = H(X | Y) + H(Y | Y) = H(X)$$

c) **Answer:** \leq

From the given expression:

$$p(y_1, y_2 \mid x_1, x_2) = p(y_1 \mid x_1) p(y_2 \mid x_2)$$

we can easily see that X_1 to X_2 to Y_2 or that Y_1 to X_1 to X_2 form Markov chains. Therefore:

$$\begin{aligned} I(X_1, X_2; Y_1, Y_2) &= I(X_1, X_2; Y_1) + I(X_1, X_2; Y_2 \mid Y_1) \\ &= I(X_1; Y_1) + I(X_2; Y_1 \mid X_1) + I(X_2; Y_2 \mid Y_1) + I(X_1; Y_2 \mid Y_1, X_2) \\ &\leq I(X_1; Y_1) + I(X_2; Y_1 \mid X_1) + I(X_2; Y_2) + I(X_1; Y_2 \mid X_2) \\ &= I(X_1; Y_1) + I(X_2; Y_2) \end{aligned}$$

where at the first and last inequalities, we used that Y_1 to X_1 to X_2 to Y_2 is a Markov chain!

d) **Answer:** \geq

From the given expression $p(x_1, x_2) = p(x_1) p(x_2)$, we see that X_1 and X_2 are independent. Therefore:

$$\begin{aligned} I(X_1, X_2; Y_1, Y_2) &= I(X_1; Y_1, Y_2) + I(X_2; Y_1, Y_2 \mid X_1) \\ &= I(X_1; Y_1) + I(X_1; Y_2 \mid Y_1) + I(X_2; Y_2 \mid X_1) + I(X_2; Y_1 \mid X_1, Y_2) \\ &\geq I(X_1; Y_1) + I(X_1; Y_2 \mid Y_1) + I(X_2; Y_2) + I(X_2; Y_1 \mid Y_2) \\ &\geq I(X_1; Y_1) + I(X_2; Y_2) \end{aligned}$$

where at the first inequality we used the independence of X_1 and X_2 .

3 Z channel

The Z channel has a conditional PMF $p(y \mid x)$:

$$p(0 \mid 0) = 1 \quad p(1 \mid 1) = \frac{1}{2} \quad \text{and} \quad p(0 \mid 1) = \frac{1}{2}$$

which if we define the probability of $p(x = 1)$ as p , gets us:

$$p(0, 0) = 1 - p \quad p(1, 0) = 0 \quad p(1, 1) = \frac{p}{2} \quad \text{and} \quad p(0, 1) = \frac{p}{2}$$

now, using $I(y \mid x) = -p(y, x) \log \frac{p(y, x)}{p(x)}$ we obtain:

$$I(0 \mid 0) = I(1 \mid 0) = 0 \quad \text{and} \quad I(0 \mid 1) = I(1 \mid 1) = \frac{p}{2}$$

and so $H(Y \mid X) = \sum I(y \mid x) = p$. On the other hand, $p(y) = \sum_x p(y \mid x) p(x)$ is:

$$p(0) = 1(1 - p) + \frac{1}{2}p = 1 - \frac{p}{2} \quad \text{and} \quad p(1) = \frac{1}{2}p = \frac{p}{2}$$

This means that the mutual information is:

$$I(X; Y) = H(Y) - H(Y \mid X) = H\left(\frac{p}{2}\right) - p = -\frac{p}{2} \log \frac{p}{2} - \left(1 - \frac{p}{2}\right) \log \left(1 - \frac{p}{2}\right) - p$$

Finally, the channel capacity will be the maximum of this quantity:

$$0 = \frac{dI(X; Y)}{dp} = \frac{\log\left(\frac{1}{2} - \frac{p}{4}\right) - \log(p)}{\log(4)} = \frac{1}{2} \log\left(\frac{1}{2p} - \frac{1}{4}\right) \Rightarrow p = \frac{2}{5}$$

which is:

$$C = I(X; Y)|_{p=\frac{2}{5}} \simeq 0.3219 \text{ bits}$$

4 The Noisy typewriter channel

Now, in the Noisy Typewriter channel we have a conditional PDF given by:

$$p(y | x) = \frac{1}{2}\delta_{x,y} + \frac{1}{2}\delta_{x-1,y} \quad x, y = 1, 2, \dots, N$$

And then the joint probability will be:

$$p(y, x) = p(y | x)p_X(x) = \frac{1}{2}\delta_{x,y}p_X(x) + \frac{1}{2}\delta_{x-1,y}p_X(x)$$

from where we can obtain:

$$p_Y(y) = \sum_x p(y, x) = \sum_x \left(\frac{1}{2}\delta_{x,y}p_X(x) + \frac{1}{2}\delta_{x-1,y}p_X(x) \right) = \frac{1}{2}(p_X(y) + p_X(y+1))$$

Now, the entropy of Y will then be:

$$H(Y) = - \sum_y \frac{1}{2}(p_X(y) + p_X(y+1)) \log \left(\frac{1}{2}(p_X(y) + p_X(y+1)) \right)$$

We can also evaluate the conditional entropy now:

$$\begin{aligned} H(Y | X) &= - \sum_{x,y} p(y, x) \log p(y | x) \\ &= - \sum_y \sum_x \left(\frac{1}{2}\delta_{x,y}p_X(x) + \frac{1}{2}\delta_{x-1,y}p_X(x) \right) \log \left(\frac{1}{2}\delta_{x,y} + \frac{1}{2}\delta_{x-1,y} \right) \\ &= - \frac{1}{2} \sum_y (p_X(y) + p_X(y+1)) \log \frac{1}{2} = \sum_y p_X(y) = 1 \end{aligned}$$

and the mutual information of X and Y is:

$$I(X; Y) = H(Y) - H(Y | X) = H(Y) - 1$$

So, we now only need to find the maximums of $H(Y)$, which at first sight, one would guess that a homogenous distribution, with $p(x) = 1/26$ for the 26 cases would do the trick, and evaluating it, we get:

$$H(Y) = - \sum_0^{26} \frac{\frac{1}{26} + \frac{1}{26}}{2} \log \left(\frac{\frac{1}{26} + \frac{1}{26}}{2} \right) = - \sum_0^{26} \frac{1}{26} \log \left(\frac{1}{26} \right) = \log_2(26)$$

which is the maximum entropy for a random variable with 26 outcomes, so we have found our first maximum!

For the second one, we can also think that given the symmetry that the system has, a probability with only the odd or even x having $p(x) = 2/26$ and the others $p(x) = 0$, would also maximize it! And its also easy to evaluate this, by:

$$H(Y) = - \sum_0^{26} \frac{0 + \frac{2}{26}}{2} \log \left(\frac{0 + \frac{2}{26}}{2} \right) = - \sum_0^{26} \frac{1}{26} \log \left(\frac{1}{26} \right) = \log_2(26)$$

finding our other maximums!

To end, let's compute the channel capacity:

$$C = \max_{p(x)} I(X; Y) = \max_{p(x)} H(Y) - 1 = \log_2 26 - 1 = \log_2 13$$