

Assignment 3

October 12, 2023

1 2.15

By the chain rule, we have

$$\begin{aligned} I(X_1; X_2, \dots, X_n) &= \sum_{i=2}^n I(X_1; X_i | X_2, X_3, \dots, X_{i-1}) \\ &= I(X_1; X_2) + I(X_1; X_3 | X_2) + \dots + I(X_1; X_n | X_2, \dots, X_{n-1}) \end{aligned}$$

For $X_1 \rightarrow X_2 \rightarrow \dots \rightarrow X_n$, by the Markov property, X_i and X_j with $j - i > 1$ are independent when given X_p with $p \in (i, j)$. Therefore, we have

$$\begin{aligned} I(X_1; X_2, \dots, X_n) &= I(X_1; X_2) + I(X_1; X_3 | X_2) + \dots + I(X_1; X_n | X_2, \dots, X_{n-1}) \\ &= I(X_1; X_2) \end{aligned}$$

2 2.16

1. By the data processing inequality, we have

$$\begin{aligned} I(X_1; X_3) &\leq I(X_1; X_2) \\ &= H(X_2) - H(X_2 | X_1) \\ &\leq H(X_2) \end{aligned}$$

Since $H(X_2) \leq \log |\mathcal{X}_2| = \log k$, we have $I(X_1; X_3) \leq \log k$.

2. From the above, we know that $I(X_1; X_3) \leq \log k$. For $k = 1$, we have $I(X_1; X_3) \leq 0$. Since $I(X_1; X_3) \geq 0$, we have $I(X_1; X_3) = 0$, i.e., X_1 and X_3 are independent.

3 2.32

1. From the table, we can see that $Pr[X = 1, Y = a]$ is the greatest among $Pr[X = x, Y = a]$ for $x \in \{1, 2, 3\}$, and so are the $Pr[X = 2, Y = b]$ and $Pr[X = 3, Y = c]$. Therefore, the minimum probability of error estimator is like below

$$\hat{X}(Y) = \begin{cases} 1, & y = a \\ 2, & y = b \\ 3, & y = c \end{cases}$$

and the associated $P_e = Pr[\hat{X} \neq X] = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{1}{2}$.

2. By Fano's inequality, we have

$$P_e \geq \frac{H(X|Y) - 1}{\log |\mathcal{X}| - 1}$$

We have

$$\begin{aligned} H(X|Y) &= \sum_{y \in \mathcal{Y}} Pr[Y = y] H(X|Y = y) \\ &= Pr[Y = a] H(X|Y = a) + Pr[Y = b] H(X|Y = b) + Pr[Y = c] H(X|Y = c) \end{aligned}$$

Since

$$H(X|Y = a) = H(X|Y = b) = H(X|Y = c) = -\frac{1}{2} \log \frac{1}{2} - \frac{1}{4} \log \frac{1}{4} - \frac{1}{4} \log \frac{1}{4} = \frac{3}{2} \log 2$$

we have

$$H(X|Y) = \frac{3}{2} \log 2 (Pr[Y = a] + Pr[Y = b] + Pr[Y = c]) = \frac{3}{2} \log 2$$

Therefore, we have

$$P_e \geq \frac{H(X|Y) - 1}{\log |\mathcal{X}| - 1} = \frac{\frac{3}{2} \log 2 - 1}{\log 2} = \frac{1}{2}$$

So the P_e we calculated before matches well with Fano's inequality.

4 2.34

By the data processing inequality, we have

$$I(X_0; X_{n-1}) \geq I(X_0; X_n)$$

Since $I(X_1; X_2) = H(X_1) - H(X_1|X_2)$, we have

$$\begin{aligned} H(X_0) - H(X_0|X_{n-1}) &\geq H(X_0) - H(X_0|X_n) \\ \implies H(X_0|X_{n-1}) &\leq H(X_0|X_n) \end{aligned}$$

Therefore, $H(X_0|X_n)$ is non-decreasing with n .