ASSIGNMENT 3 - SOLUTIONS

Exercise 1 (Guessing, Huffman)**.** There are 6 bottles of wine, one of which you know has gone bad. You do not know which bottle contains the bad wine, but you know that the probability of each bottle being bad is $(8/23, 6/23, 4/23, 2/23, 2/23, 1/23)$. The bad wine has a distinctive taste. To find the bad wine your friend suggests you to taste a little bit of each wine until you find the bad wine.

a. To have the least number of tastings on average, what should your strategy be? Which bottle should be tasted first?

b. What is the average number of tastings to find the bad wine?

c. Calculate the minimum average number of tastings if you are allowed to taste a mixture of different wines and detect a bad wine's taste inside (the distinctive taste is retained even when mixed with other good wines).

d. Is the strategy studied in (a) optimal if you are allowed to mix wines?

Solution. a. A guessing strategy for a random variable X can be written as a vector $G = (g_1, g_2, \ldots)$ with $g_i \in \mathcal{X}$ being the i-th guess of X. With this notation, the expected number of guesses is given by $\mathbb{E}(G) = \sum_i iPr(X = g_i)$. Now assume that for some $i < j$ we have $Pr(X = g_j) > Pr(X = g_i)$, and consider the new strategy G' where g_i and g_j are swapped. It then follows that $E(G) - E(G') = (j-i)(Pr(X = g_j) - Pr(X = g_i)) > 0$. It follows that the strategy that guesses the values of X in decreasing order of proabilities minimizes the expected number of guesses.

b. $56/23$

c. A sequence of questions is equivalent to a code. Indeed, any question depends on the sequence of answers to the questions before it. Since the sequence of answers uniquely determines a particular sample of X, if we represent the sequence of yes-no answers by 0 and 1, each sample of X is associated to a codeword. Conversely, from a binary code for each possible sample of X, we can find a sequence of questions that corresponds to the code. The i-th question is "Is the i-th bit bit equal to 1?" or, more specifically, "Does the X belongs to the set of samples whose codewords have the i-th bit equal to 1?"

Therefore, from the equivalence between quessing strategy and code, finding a quessing strategy that minimizes the number of questions is equivalent to finding a code whose average length is minimal. An optimal strategy to identify the bad bottle is thus obtained via the construction of the Huffman code of the bad bottle probability distribution. Note that we use here the fact that we are allowed to mix wines, hence we can ask, at each step, whether the bad wine belongs to some particular subset of bottles or not.

□

Exercise 2 (Entropy and Yes/No questions)**.** We are asked to determine an object by asking yes-no questions. The object is drawn randomly from a finite set according to a certain distribution. Playing optimally, we need 38.5 questions on the average to find the object. At least how many elements does the finite set have?

Solution. An optimal yes/no scheme corresponds to an optimal source code whose expected length is at most $H(X)+1$, where X is the hidden object. Hence $H(X)+1 \geq 38.5$. On the other hand we have $\log|\mathcal{X}| \geq H(X)$. These two yield that $\log|\mathcal{X}| \geq 37.5$, and so $n \geq \lceil 2^{37.5} \rceil$. □

Exercise 3. (Mixing increases entropy) Show that the entropy of the probability distribution, $(p_1, \ldots, p_i, \ldots, p_j, \ldots, p_m)$ is less than that of the distribution $\left(p_1, \ldots, \frac{p_i+p_j}{2}, \ldots, \frac{p_i+p_j}{2}, \ldots, p_m\right)$.

Solution. Let $P \equiv (p_1, \ldots, p_i, \ldots, p_j, \ldots, p_m)$ and $Q \equiv \left(p_1, \ldots, \frac{p_i+p_j}{2}, \ldots, \frac{p_i+p_j}{2}, \ldots, p_m\right)$. Then,

$$\begin{aligned} H(Q) - H(P) &= 2\left(\frac{p_i+p_j}{2}\right)\log\left(\frac{2}{p_i+p_j}\right) - p_i \log\frac{1}{p_i} - p_j\log\frac{1}{p_j} \\ &= p_i \log\frac{2p_i}{(p_i+p_j)} + p_j\log\frac{2p_j}{p_i+p_j} \\ &= (p_i+p_j)\left[\frac{p_i}{p_i+p_j}\log\frac{p_i/(p_i+p_j)}{1/2} + \frac{p_j}{p_i+p_j}\log\frac{p_j/(p_i+p_j)}{1/2}\right]. \end{aligned}$$

Identify the expression on the right side as (p_i+p_j) times the KL divergence between Bernoulli distributions $\left(\frac{p_i}{p_i+p_j}, \frac{p_j}{p_i+p_j}\right)$ and $\left(\frac{1}{2}, \frac{1}{2}\right)$, which is non-negative. □

Exercise 4. (Entropy of common distributions) Calculate the entropy of X where

a. X is the output of n independent tosses of a coin which shows heads with probability p.

b. X is a $Geo(p)$ random variable. That is, $\mathbb{P}[X=k] = (1-p)^{k-1}p$.

Solution. a. $H(X) = H(X_1, X_2, ..., X_n)$ where $X_i \sim$ i.i.d. $Ber(p)$. Therefore,

$$H(X) = nH(X_1) = n[-p\log p - (1-p)\log(1-p)].$$

b. $X \sim Geo(p)$. We know that for $X \sim Geo(p), \mathbb{E}[X] = \frac{1}{p}$. Let $h(X) = -\log P(X)$ where $P(k) = (1-p)^{k-1}p$. Then,

$$\begin{aligned} H(X) &= \mathbb{E}[h(X)] \\ &= \mathbb{E}[-\log\{(1-p)^{X-1}p\}] \\ &= \mathbb{E}[(1-X)\log(1-p) - \log p] \\ &= \left(1-\frac{1}{p}\right)\log(1-p) - \log p \\ &= \frac{-(1-p)\log(1-p) - p\log p}{p} \end{aligned}$$

□

Exercise 5. (KL divergence) Calculate the KL divergence (relative entropy) between P and Q where

a. $P \equiv Geo(p)$ and $Q \equiv Geo(q)$.

b. $P \equiv \mathcal{N}(\mu_1, \sigma^2)$ and $Q \equiv \mathcal{N}(\mu_2, \sigma^2)$

Solution. a. $P \equiv Geo(p), Q \equiv Geo(q)$.

$$\begin{aligned} D(P||Q) &= \mathbb{E}_P\left[\log \frac{(1-p)^{X-1}p}{(1-q)^{X-1}q}\right] \\ &= \mathbb{E}_P\left[(X-1)\log\left(\frac{1-p}{1-q}\right) + \log\left(\frac{p}{q}\right)\right] \\ &= \left(\frac{1}{p}-1\right)\log\left(\frac{1-p}{1-q}\right) + \log\left(\frac{p}{q}\right) \end{aligned}$$

a. $P \equiv \mathcal{N}(\mu_1, \sigma^2), Q \equiv \mathcal{N}(\mu_2, \sigma^2)$.

$$\begin{aligned} D(P||Q) &= \int_{\mathbb{R}} \frac{e^{\frac{-(x-\mu_1)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}\Big[\frac{(x-\mu_1)^2-(x-\mu_2)^2}{2\sigma^2}\Big]dx \\ &= \int_{\mathbb{R}} \frac{e^{\frac{-(x-\mu_1)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}\Big[\frac{2x(\mu_2-\mu_1)+\mu_2^2-\mu_1^2}{2\sigma^2}\Big]dx \\ &= \frac{2(\mu_2-\mu_1)}{2\sigma^2}\int_{\mathbb{R}} \frac{e^{\frac{-(x-\mu_1)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}\cdot x\cdot dx + \frac{(\mu_2^2-\mu_1^2)}{2\sigma^2}\int_{\mathbb{R}} \frac{e^{\frac{-(x-\mu_1)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}\cdot dx \\ &= \frac{2(\mu_2-\mu_1)\mu_1+\mu_2^2-\mu_1^2}{2\sigma^2} \\ &= \frac{(\mu_1-\mu_2)^2}{2\sigma^2}. \end{aligned}$$

□

Exercise 6 (Mutual information)**.** a. Let X be a uniform random variable over $\{1,2,3,4\}$. Let

$$Y = \begin{cases} 0 \text{ if } X \text{ is odd} \\ 1 \text{ otherwise.} \end{cases} \qquad Z = \begin{cases} 0 \text{ if } X \text{ is even} \\ 1 \text{ otherwise.} \end{cases}$$

Find $I(Y;Z)$.

b. We roll a fair die which has six sides (opposite sides of a die add up to 7). What is the mutual information between the top side and the one facing you?

Solution. a. Note that always $Y \neq Z$, which means knowing Z lets us know Y, *i.e.* $H(Y|Z) = 0$.

$$I(Y;Z) = H(Y) - H(Y|Z) = 1 - 0 = 1.$$

b. Top side X_T can take any of $\{1,2,3,4,5,6\}$ with same probability. Moreover, knowing the one facing us, X_F, X_T can take four values with same probability, so

$$I(X_T;X_F) = H(X_T) - H(X_T|X_F) = \log(6) - \log(4).$$

□

Exercise 7 (Entropy and Mutual Information)**.** Prove the following inequalities:

a. $H(X,Y|Z) \geq H(X|Z)$,

b. $I(X,Y;Z) \geq I(X;Z)$,

c. $H(X,Y,Z) - H(X,Y) \leq H(X,Z) - H(X)$.

Solution. a.

$$\begin{aligned} H(X,Y|Z) &\overset{(a)}{=} H(X|Z) + H(Y|X,Z) \\ &\overset{(b)}{\geq} H(X|Z) \end{aligned}$$

where (a) holds by the chain rule for entropy and where (b) follows by the non-negativity of entropy.

b.

$$\begin{aligned} I(X,Y|Z) &\overset{(a)}{=} I(X;Z) + I(Y;Z|X) \\ &\overset{(b)}{\geq} I(X;Z) \end{aligned}$$

where (a) holds by the chain rule for mutual information and where (b) holds by the non-negativity of mutual information.

c.

$$\begin{aligned} H(X,Y,Z) - H(X,Y) &\overset{(a)}{=} (H(X,Z) + H(Y|X,Z)) - (H(X) + H(Y|X)) \\ &\overset{(b)}{\leq} H(X,Z) - H(X) \end{aligned}$$

where (a) is due to the chain rule for entropy and where (b) holds since conditioning cannot increase entropy.

□

Exercise 8 (Conditioning for mutual information)**.** Give examples of joint random variables X, Y, and Z such that

a. $I(X;Y|Z) < I(X;Y)$.

b. $I(X;Y|Z) > I(X;Y)$.

Solution. a. Let X be Bernoulli$\left(\frac{1}{2}\right)$ random variable and $Z = Y = X$. Then,

$$I(X;Y|Z) = H(X|Z) - H(X|Y,Z) = H(X|X) - H(X|X) = 0 - 0 = 0$$

$$I(X;Y) = H(X) - H(X|Y) = H(X) - H(X|X) = H(X) - 0 = 1.$$

b. Let X and Y be independent Bernoulli$\left(\frac{1}{2}\right)$ random variables and $Z = X + Y$. Then,

$$I(X;Y|Z) = H(X|Z) - H(X|Y,Z) = H(X) - H(X|X,Y) = 1 - 0 = 1$$

$$I(X;Y) = H(X) - H(X|Y) = H(X) - H(X) = 0.$$

□

Exercise 9 (Entropy and pairwise independence)**.** Let X, Y, Z be three binary Bernoulli($\frac{1}{2}$) random variables that are pairwise independent; that is, $I(X;Y) = I(X;Z) = I(Y;Z) = 0$.

a. Under this constraint, what is the minimum value for $H(X,Y,Z)$?

b. Give an example achieving this minimum.

Solution. a.

$$\begin{aligned} H(X,Y,Z) &= H(X) + H(Y|X) + H(Z|Y,X) \\ &= H(X) + H(Y) + H(Z|Y,X) \\ &\geq H(X) + H(Y) \\ &= 2 \end{aligned}$$

b. Let $Z = X \oplus Y$. Verify that $I(X;Z) = I(Y;Z) = 0$.

□

Exercise 10. (Conditioning and sub additivity) Prove the following.

a.
$$H(X_1,X_2,X_3) \leq \frac{1}{2}\left[H(X_1,X_2) + H(X_2,X_3) + H(X_3,X_1)\right].$$

b.
$$H(X_1,X_2,X_3) \geq \frac{1}{2}\left[H(X_1,X_2|X_3) + H(X_2,X_3|X_1) + H(X_3,X_1|X_2)\right].$$

Solution. a. Using chain rule, $H(X_1,X_2,X_3)$ can be expanded in the following two ways.

$$\begin{aligned} 2H(X_1,X_2,X_3) &= H(X_1,X_2) + H(X_3|X_1,X_2) + H(X_2,X_3) + H(X_1|X_2,X_3) \\ &= H(X_1,X_2) + H(X_2,X_3) + H(X_3|X_1,X_2) + H(X_1|X_2,X_3) \\ &\leq H(X_1,X_2) + H(X_2,X_3) + H(X_3|X_1,X_2) + H(X_1) \\ &\leq H(X_1,X_2) + H(X_2,X_3) + H(X_3|X_1) + H(X_1) \\ &= H(X_1,X_2) + H(X_2,X_3) + H(X_3,X_1). \end{aligned}$$

b. Add and subtract $H(X_1) + H(X_2) + H(X_3)$.

$$\begin{aligned} &H(X_1,X_2|X_3) + H(X_2,X_3|X_1) + H(X_3,X_1|X_2) \\ &= H(X_1,X_2|X_3) + H(X_3) + H(X_2,X_3|X_1) + H(X_1) + H(X_3,X_1|X_2) + H(X_2) \\ &\quad - \left[H(X_1) + H(X_2) + H(X_3)\right] \\ &= 3H(X_1,X_2,X_3) - \left[H(X_1) + H(X_2) + H(X_3)\right] \\ &\leq 3H(X_1,X_2,X_3) - H(X_1,X_2,X_3) \\ &= 2H(X_1,X_2,X_3). \end{aligned}$$

□

Exercise 11. Show that among all $\mathbb{N}$-valued random variables X with $\mathbb{E}[X] = \mu$, the $Geo(1/\mu)$ random variable has the maximum value of Shannon entropy.
Hint – Consider random variables X and Y with mean μ and taking values in $\mathbb{N}$ with $X \sim P_X$ and $Y \sim P_Y$ where P_Y is Geometric, and calculate $D(P_X||P_Y)$.

Solution. Let X be a r.v. such that $X = i$ with probability $P_X(i), i \in \mathbb{N}$ and $\mathbb{E}[X] = \mu$. Let $Y \sim P_Y \equiv Geo\left(\frac{1}{\mu}\right)$. Therefore, $\mathbb{E}[Y] = \mu$. Then,

$$\begin{aligned} D(P_X||P_Y) &= \sum_{i=1}^{\infty} P_X(i) \log \frac{P_X(i)}{P_Y(i)} \\ &= \sum_{i=1}^{\infty} P_X(i) \log P_X(i) - P_Y(i) \log P_Y(i) + P_Y(i) \log P_Y(i) - P_X(i) \log P_Y(i) \\ &= H(Y) - H(X) + \sum_{i=1}^{\infty} \Big[P_Y(i) \log P_Y(i) - P_X(i) \log P_Y(i) \Big]. \end{aligned} \tag{1}$$

Since $P_Y(i) = \left(1 - \frac{1}{\mu}\right)^{i-1} \left(\frac{1}{\mu}\right)$,

$$\begin{aligned} \sum_{i=1}^{\infty} P_X(i) \log P_Y(i) &= \sum_{i=1}^{\infty} P_X(i) \cdot (i-1) \log(\mu - 1) - \sum_{i=1}^{\infty} P_X(i) \cdot i \cdot \log \mu \\ &= (\mu - 1) \log(\mu - 1) - \mu \log \mu. \end{aligned} \tag{2}$$

From the entropy calculation of a Geometric r.v. (Exer. 2*b*), we know that

$$\begin{aligned} \sum_{i=1}^{\infty} P_Y(i) \log P_Y(i) &= \frac{\left(1 - \frac{1}{\mu}\right) \log \left(1 - \frac{1}{\mu}\right) + \left(\frac{1}{\mu}\right) \log \left(\frac{1}{\mu}\right)}{1/\mu} \\ &= (\mu - 1) \log(\mu - 1) - \mu \log \mu. \end{aligned} \tag{3}$$

Substituting (2) and (3) in (1), we get

$$\begin{aligned} H(Y) - H(X) &= D(P_X||P_Y) \\ &\geq 0. \end{aligned}$$

Therefore, for any r.v. $X \in \mathbb{N}$ with $\mathbb{E}[X] = \mu$, $H(X) \leq H(Y)$ where $Y \sim Geo\left(\frac{1}{\mu}\right)$.

□

Exercise 12 (Conditional mutual information)**.** Consider a sequence of n binary random variables $X_1, X_2, \cdots, X_n$. Each sequence with an even number of 1's has probability $2^{-(n-1)}$, and each sequence with an odd number of 1's has probability 0. Find the mutual informations $I(X_1; X_2)$, $I(X_2; X_3|X_1), \ldots, I(X_{n-1}; X_n|X_1, \ldots, X_{n-2})$.

Proof. We always have $X_n = X_1 \oplus X_2 \oplus \cdots \oplus X_{n-1}$,[1] since the sequences with odd number of ones have zero probability, and since each sequence with even number of 1s is equiprobable, X_1, X_2, $\cdots$, X_n are independent Bernoulli$\left(\frac{1}{2}\right)$ random variables. So, for $2 \leq i \leq n-2$,

$$\begin{aligned} I(X_i; X_{i+1}|X_1, \cdots, X_{i-1}) &= H(X_{i+1}|X_1, \cdots, X_{i-1}) - H(X_{i+1}|X_1, \cdots, X_{i-1}, X_i) \\ &= H(X_{i+1}) - H(X_{i+1}) = 0 \end{aligned}$$

[1] $\oplus$ is sum modulo 2.

and for $i = n - 1$,

$$\begin{aligned} I(X_{n-1};X_n|X_1,\cdots,X_{n-2}) &= H(X_n|X_1,\cdots,X_{n-2}) - H(X_n|X_1,\cdots,X_{n-2},X_{n-1}) \\ &= H(X_1 \oplus X_2 \oplus \cdots \oplus X_{n-1}|X_1,\cdots,X_{n-2}) - H(X_1 \oplus X_2 \oplus \cdots \oplus X_{n-1}|X_1,\cdots,X_{n-2},X_{n-1}) \\ &= H(X_{n-1}|X_1,\cdots,X_{n-2}) - 0 \\ &= H(X_{n-1}) = 1 \end{aligned}$$

□