

Problem Set 4

MATH 778C, Spring 2009, Austin Mohr (with John Boozar)

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1. Two n -sided dice with sides labeled 1 through n are rolled, resulting in the i.i.d. random variables X and Y . Let $Z = X + Y$. Compute $H(X)$, $H(X, Y)$, $H(Z)$, $H(X|Z)$, $I(X; Y)$ and $I(X; Y|Z)$.

We compute the entropy of X , we compute directly.

$$\begin{aligned} H(X) &= - \sum_{i=1}^n \mathbf{P}(X = i) \log(\mathbf{P}(X = i)) \\ &= - \sum_{i=1}^n \frac{1}{n} \log\left(\frac{1}{n}\right) \\ &= \log(n) \end{aligned}$$

We compute the the joint entropy of X and Y directly.

$$\begin{aligned} H(X, Y) &= H(X) + H(Y | X) \\ &= H(X) + H(Y) \quad (\text{since } X \text{ and } Y \text{ are independent}) \\ &= 2 \log(n) \end{aligned}$$

To determine the entropy of $Z = X + Y$, observe that there are a total of n^2 possible outcomes. There is no way to get $Z = 1$. For $2 \leq k \leq n + 1$, there are $k - 1$ ways to achieve $Z = k$ (for a given k , we have the results $(1, k - 1), (2, k - 2), \dots, (k - 1, 1)$). For $n + 2 \leq k \leq 2n - 1$, we see by a similar argument that there are $2n - (k - 1)$ ways. Observe that for sums other than $n + 1$, there is a kind of parity (both 2 and $2n$ have

1 possibility, 3 and $2n - 1$ have 2 possibilities, etc.). Combining this information, we have

$$\begin{aligned}
H(Z) &= - \sum_{i=2}^{2n} \mathbf{P}(Z = i) \log(\mathbf{P}(Z = i)) \\
&= -2 \sum_{i=2}^{n+1} \mathbf{P}(Z = i) \log(\mathbf{P}(Z = i)) + \mathbf{P}(Z = n+1) \log(\mathbf{P}(Z = n+1)) \\
&= -2 \sum_{i=2}^{n+1} \frac{i-1}{n^2} \log\left(\frac{i-1}{n^2}\right) + \frac{n}{n^2} \log\left(\frac{n}{n^2}\right) \\
&= -\frac{2}{n^2} \sum_{i=1}^n i \log\left(\frac{i}{n^2}\right) + \frac{1}{n} \log\left(\frac{1}{n}\right) \\
&= -\frac{2}{n^2} \sum_{i=1}^n i (\log(i) - \log(n^2)) + \frac{1}{n} \log\left(\frac{1}{n}\right) \\
&= -\frac{2}{n^2} \left(\sum_{i=1}^n i \log(i) - \sum_{i=1}^n i \log(n^2) \right) + \frac{1}{n} \log\left(\frac{1}{n}\right) \\
&= -\frac{2}{n^2} \sum_{i=1}^n i \log(i) + \frac{2}{n^2} \cdot \frac{n(n+1) \log(n^2)}{2} + \frac{1}{n} \log\left(\frac{1}{n}\right) \\
&= -\frac{2}{n^2} \sum_{i=1}^n i \log(i) + \frac{(2n+1) \log(n)}{n}
\end{aligned}$$

To determine the entropy of X given the value of Z , we employ a similar parity argument to obtain

$$\begin{aligned}
H(X | Z) &= - \sum_{i=2}^{2n} \left(\sum_{j=1}^n \mathbf{P}(X = j | Z = i) \log(\mathbf{P}(X = j | Z = i)) \right) \\
&= -2 \sum_{i=2}^{n+1} \left(\frac{i-1}{n^2} \sum_{j=1}^{i-1} \frac{1}{i-1} \log\left(\frac{1}{i-1}\right) \right) + \frac{1}{n} \sum_{j=1}^n \frac{1}{n} \log\left(\frac{1}{n}\right) \\
&= -2 \sum_{i=2}^{n+1} \left(\frac{i-1}{n^2} \log\left(\frac{1}{i-1}\right) \right) + \frac{1}{n} \log\left(\frac{1}{n}\right) \\
&= \frac{2}{n^2} \sum_{i=1}^n i \log(i) - \frac{1}{n} \log(n)
\end{aligned}$$

We compute the mutual information of X and Y directly.

$$\begin{aligned} I(X; Y) &= H(X) - H(X | Y) \\ &= H(X) - H(X) \quad (\text{since } X \text{ and } Y \text{ independent}) \\ &= 0 \end{aligned}$$

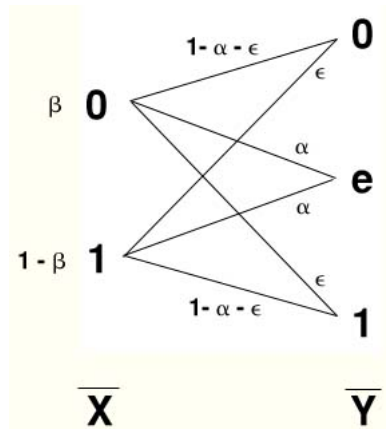
We compute the mutual information of X and Y given the value of Z directly.

$$\begin{aligned} I(X; Y | Z) &= H(X | Z) - H(X | (Y, Z)) \\ &= H(X | Z) \end{aligned}$$

since knowing both Y and Z completely determines X .

2. Consider a channel with binary inputs that has both erasures and errors. Let the probability of error be ϵ and the probability of erasure be α . (Hence, the probability of correct transmission is $1 - \alpha - \epsilon$.) What is the capacity of this channel?

We can visualize the channel in the following way



where e denotes erasure and we write the probability distribution of the input in terms of β . The capacity of the channel is given by

$$\max_{\mathbf{P}(X)} I(X; Y) = \max_{\mathbf{P}(X)} [H(Y) - H(Y | X)]$$

Now

$$\begin{aligned}
H(Y) &= - \sum_{y \in Y} \mathbf{P}(Y = y) \log(\mathbf{P}(Y = y)) \\
&= -[\mathbf{P}(Y = 0) \log(\mathbf{P}(Y = 0)) \\
&\quad + \mathbf{P}(Y = e) \log(\mathbf{P}(Y = e)) \\
&\quad + \mathbf{P}(Y = 1) \log(\mathbf{P}(Y = 1))] \\
&= -[(\beta(1 - \alpha - \epsilon) + (1 - \beta)\epsilon) \log(\beta(1 - \alpha - \epsilon) + (1 - \beta)\epsilon) \\
&\quad + (\beta\alpha + (1 - \beta)\alpha) \log(\beta\alpha + (1 - \beta)\alpha) \\
&\quad + (\beta\epsilon + (1 - \beta)(1 - \alpha - \epsilon)) \log(\beta\epsilon + (1 - \beta)(1 - \alpha - \epsilon))] \\
&= -[(\beta(1 - \alpha - \epsilon) + (1 - \beta)\epsilon) \log(\beta(1 - \alpha - \epsilon) + (1 - \beta)\epsilon) \\
&\quad + \alpha \log(\alpha) \\
&\quad + (\beta\epsilon + (1 - \beta)(1 - \alpha - \epsilon)) \log(\beta\epsilon + (1 - \beta)(1 - \alpha - \epsilon))]
\end{aligned}$$

and

$$\begin{aligned}
H(Y | X) &= - \sum_{x \in X} \mathbf{P}(X = x) \left(\sum_{y \in Y} \mathbf{P}(Y = y | X = x) \log(\mathbf{P}(Y = y | X = x)) \right) \\
&= -\mathbf{P}(X = 0)[\mathbf{P}(Y = 0 | X = 0) \log(\mathbf{P}(Y = 0 | X = 0)) \\
&\quad + \mathbf{P}(Y = e | X = 0) \log(\mathbf{P}(Y = e | X = 0)) \\
&\quad + \mathbf{P}(Y = 1 | X = 0) \log(\mathbf{P}(Y = 1 | X = 0))] \\
&\quad -\mathbf{P}(X = 1)[\mathbf{P}(Y = 0 | X = 1) \log(\mathbf{P}(Y = 0 | X = 1)) \\
&\quad + \mathbf{P}(Y = e | X = 1) \log(\mathbf{P}(Y = e | X = 1)) \\
&\quad + \mathbf{P}(Y = 1 | X = 1) \log(\mathbf{P}(Y = 1 | X = 1))] \\
&= -\beta[(1 - \alpha - \epsilon) \log(1 - \alpha - \epsilon) \\
&\quad + \alpha \log(\alpha) \\
&\quad + \epsilon \log(\epsilon)] \\
&\quad - (1 - \beta)[\epsilon \log(\epsilon) \\
&\quad + \alpha \log(\alpha) \\
&\quad + (1 - \alpha - \epsilon) \log(1 - \alpha - \epsilon)] \\
&= -(\epsilon \log(\epsilon) + \alpha \log(\alpha) + (1 - \alpha - \epsilon) \log(1 - \alpha - \epsilon))
\end{aligned}$$

Since $H(Y | X)$ does not depend on β , we need only to maximize $H(Y)$, which occurs at $\beta = \frac{1}{2}$. So

$$\begin{aligned} \max_{\mathbf{P}(X)} I(X; Y) &= \max_{\mathbf{P}(X)} [H(Y) - H(Y | X)] \\ &= -(1 - \alpha) \log\left(\frac{1}{2}(1 - \alpha)\right) + \epsilon \log(\epsilon) + \alpha \log(\alpha) + (1 - \alpha - \epsilon) \log(1 - \alpha - \epsilon) \end{aligned}$$

3. Let $s_t(n)$ denote the number of graphs on n vertices not containing a K_t , $t \geq 3$. Show that

$$1 - \frac{1}{t-1} + o(1) \leq \frac{\log s_t(n)}{\log N} \leq 1 - \epsilon_t,$$

where $N = 2^{\binom{n}{2}}$ is the number of total graphs on n vertices and

$$\epsilon_t = \frac{1}{\binom{t}{2} 2^{\binom{t}{2}}}.$$

Hint: Shearer's Inequality.

Proof. Let Y be the random variable representing choosing a random graph on n vertices without a K_t . Let X_i represent the i th edge of that graph.

$$\log(S_t(n)) = H(Y) = H(X_1 \dots X_{\binom{n}{2}})$$

Let G_i be the set of possible edges in a t -vertex subgraph. This is a $\binom{n-2}{t-2}$ covering of the edges. So by Shearer's inequality:

$$\begin{aligned} H(X_1 \dots X_{\binom{n}{2}}) &\leq \frac{1}{\binom{n-2}{t-2}} \sum_{G_i} H(X_{G_i}) \\ &\leq \frac{1}{\binom{n-2}{t-2}} \sum_{G_i} \log(2^{\binom{t}{2}} - 1) \\ &= \frac{\binom{n}{t}}{\binom{n-2}{t-2}} \log(2^{\binom{t}{2}} - 1) \end{aligned}$$

$$= \frac{\binom{n}{2}}{\binom{t}{2}} \log(2^{\binom{t}{2}} - 1)$$

Now a little calculus tells us $\log(2^{\binom{t}{2}} - 1) \leq \binom{t}{2} - \frac{1}{\ln(2)2^{\binom{t}{2}}}$, since the derivative of $\log(x)$ is $\frac{1}{\ln(2)x}$ and $\log(x)$ is concave down. Also $\binom{t}{2} - \frac{1}{\ln(2)2^{\binom{t}{2}}} \leq \binom{t}{2} - \frac{1}{2^{\binom{t}{2}}}$. Thus

$$\begin{aligned} \log(S_t(n)) &\leq \frac{\binom{n}{2}}{\binom{t}{2}} \binom{t}{2} - \frac{1}{2^{\binom{t}{2}}} \\ \frac{\log(S_t(n))}{\log(2^{\binom{n}{2}})} &\leq 1 - \frac{1}{\binom{t}{2}2^{\binom{t}{2}}} \end{aligned}$$

□

4. Find the capacity C of the union of two channels $(\mathcal{X}_1, p_1(y_1|x_1), \mathcal{Y}_1)$ and $(\mathcal{X}_2, p_2(y_2|x_2), \mathcal{Y}_2)$, where at each time, one can send a symbol over channel 1 or channel 2 but not both. Assume that the output alphabets are disjoint. Express your answer as a function of the two channel capacities C_1 and C_2 .

Since the output alphabets are disjoint, we can assume without loss of generality that the input alphabets are also disjoint (for any letter $x \in \mathcal{X}_1 \cap \mathcal{X}_2$, remove it and add a letter x_1 to \mathcal{X}_1 only and x_2 to \mathcal{X}_2 only). Now,

$$P(x) = \begin{cases} \lambda P_1(x) & : x \in \mathcal{X}_1 \\ (1 - \lambda) P_2(x) & : x \in \mathcal{X}_2 \end{cases}$$

where $\lambda \in [0, 1]$ is the probability of choosing to send through channel 1 (and so $(1 - \lambda)$ is the probability of sending through channel 2). To determine C , we need

$$\begin{aligned} H(Y) &= - \sum_{y \in \mathcal{Y}} P(y) \log(P(y)) \\ &= - \sum_{y \in \mathcal{Y}_1} P(y) \log(P(y)) - \sum_{y \in \mathcal{Y}_2} P(y) \log(P(y)) \end{aligned}$$

$$\begin{aligned}
&= -\sum_{y \in \mathcal{Y}_1} \frac{\lambda P(y)}{\lambda} \log\left(\frac{\lambda P(y)}{\lambda}\right) - \sum_{y \in \mathcal{Y}_2} \frac{(1-\lambda)P(y)}{1-\lambda} \log\left(\frac{(1-\lambda)P(y)}{1-\lambda}\right) \\
&= -\lambda \sum_{y \in \mathcal{Y}_1} P_1(y) \log(P_1(y)) - \lambda \sum_{y \in \mathcal{Y}_1} P_1(y) \log(\lambda) \\
&\quad - (1-\lambda) \sum_{y \in \mathcal{Y}_2} P_2(y) \log(P_2(y)) - (1-\lambda) \sum_{y \in \mathcal{Y}_2} P_2(y) \log(1-\lambda) \\
&= \lambda H(Y_1) + (1-\lambda)H(Y_2) + \lambda \log\left(\frac{1}{\lambda}\right) + (1-\lambda) \log\left(\frac{1}{1-\lambda}\right)
\end{aligned}$$

and

$$\begin{aligned}
H(Y | X) &= -\sum_{x \in \mathcal{X}} P(x) \left(\sum_{y \in \mathcal{Y}} P(y | x) \log(P(y | x)) \right) \\
&= -\left(\sum_{x \in \mathcal{X}_1} P(x) + \sum_{x \in \mathcal{X}_2} P(x) \right) \left(\sum_{y \in \mathcal{Y}} P(y | x) \log(P(y | x)) \right) \\
&= -\left(\lambda \sum_{x \in \mathcal{X}_1} \frac{P(x)}{\lambda} + (1-\lambda) \sum_{x \in \mathcal{X}_2} \frac{P(x)}{1-\lambda} \right) \left(\sum_{y \in \mathcal{Y}} P(y | x) \log(P(y | x)) \right) \\
&= -\left(\lambda \sum_{x \in \mathcal{X}_1} \frac{P(x)}{\lambda} \right) \left(\sum_{y \in \mathcal{Y}} P(y | x) \log(P(y | x)) \right) \\
&\quad - \left((1-\lambda) \sum_{x \in \mathcal{X}_2} \frac{P(x)}{1-\lambda} \right) \left(\sum_{y \in \mathcal{Y}} P(y | x) \log(P(y | x)) \right) \\
&= -\left(\lambda \sum_{x \in \mathcal{X}_1} \frac{P(x)}{\lambda} \right) \left(\sum_{y \in \mathcal{Y}_1} P(y | x) \log(P(y | x)) \right) \\
&\quad - \left((1-\lambda) \sum_{x \in \mathcal{X}_2} \frac{P(x)}{1-\lambda} \right) \left(\sum_{y \in \mathcal{Y}_2} P(y | x) \log(P(y | x)) \right) \\
&= \lambda H(Y_1 | X_1) + (1-\lambda)H(Y_2 | X_2)
\end{aligned}$$

Now,

$$\begin{aligned}
C &= \max_{P(X)} I(X; Y) \\
&= \max_{P(X)} H(X) - H(Y | X)
\end{aligned}$$

$$\begin{aligned} &= \max_{\lambda} \lambda H(Y_1) + (1 - \lambda)H(Y_2) + \lambda \log \left(\frac{1}{\lambda} \right) + (1 - \lambda) \log \left(\frac{1}{1 - \lambda} \right) \\ &\quad - (\lambda H(Y_1 | X_1) - (1 - \lambda)H(Y_2 | X_2)) \\ &= \max_{\lambda} \lambda C_1 + (1 - \lambda)C_2 + \lambda \log \left(\frac{1}{\lambda} \right) + (1 - \lambda) \log \left(\frac{1}{1 - \lambda} \right) \end{aligned}$$

Using calculus, we determine that this expression is maximized when $\lambda = \frac{1}{2^{b-a}+1}$.