

**Solutions to Homework Set #2**  
**Properties of Entropy and Mutual Information**

**1. The value of a question.**

Let  $X \sim p(x)$ ,  $x = 1, 2, \dots, m$ .

We are given a set  $S \subseteq \{1, 2, \dots, m\}$ . We ask whether  $X \in S$  and receive the answer

$$Y = \begin{cases} 1, & \text{if } X \in S \\ 0, & \text{if } X \notin S. \end{cases}$$

Suppose  $\Pr\{X \in S\} = \alpha$ .

- (a) Find the decrease in uncertainty  $H(X) - H(X|Y)$ .
- (b) Is it true that any set  $S$  with a given probability  $\alpha$  is as good as any other.

**Solution: The value of a question.**

- (a) Consider

$$H(X) - H(X|Y) = H(Y) - H(Y|X) = H(Y) = H_b(\alpha) \quad (1)$$

- (b) Yes, since the answer depends only on  $\alpha$ .

**2. Relative entropy is not symmetric**

Let the random variable  $X$  have three possible outcomes  $\{a, b, c\}$ . Consider two distributions on this random variable

Symbol	$p(x)$	$q(x)$
a	1/2	1/3
b	1/4	1/3
c	1/4	1/3

Calculate  $H(p)$ ,  $H(q)$ ,  $D(p \parallel q)$  and  $D(q \parallel p)$ .

Verify that in this case  $D(p \parallel q) \neq D(q \parallel p)$ .

**Solution: Relative entropy is not symmetric.**

- (a)  $H(p) = 1/2 \log 2 + 2 \times 1/4 \log 4 = 1.5$  bits.
- (b)  $H(q) = 3 \times 1/3 \log 3 = \log 3 = 1.585$  bits.
- (c)  $D(p||q) = 1/2 \log 3/2 + 2 \times 1/4 \log 3/4 = \log 3 - 3/2 = 0.0850$  bits.
- (d)  $D(q||p) = 1/3 \log 2/3 + 2 \times 1/3 \log 4/3 = 5/3 - \log 3 = 0.0817$  bits.

$D(p||q) \neq D(q||p)$  as expected.

### 3. True or False

- (a) If  $H(X|Y) = H(X)$  then  $X$  and  $Y$  are independent.

**True:**

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

If  $I(X; Y) = 0$  then  $H(X) = H(X|Y)$ . We can write:

$$I(X; Y) = D(P_{X,Y} || P_X P_Y) = 0$$

$D(Q||P) = 0$  iff  $P(x) = Q(x) \forall x$ , therefore  $P_{X,Y}(x, y) = P_X(x)P_Y(y)$  for every  $x, y$  and as result  $X \perp Y$ .

- (b) For any two probability mass functions (pmf)  $P, Q$ ,

$$D\left(\frac{P+Q}{2} || Q\right) \leq \frac{1}{2}D(P||Q),$$

where  $D(||)$  is a divergence between two pmfs.

**True:**

Using the concave property of the divergence function:

$$D(\lambda P + (1 - \lambda)Q || Q) \leq \lambda D(P || Q) + (1 - \lambda)D(Q || Q)$$

Assigning  $\lambda = \frac{1}{2}$ , and since  $D(Q||Q) = 0$ :

$$D\left(\frac{1}{2}P + \frac{1}{2}Q || Q\right) \leq \frac{1}{2}D(P||Q)$$

(c) Let  $X$  and  $Y$  be two independent random variables. Then

$$H(X + Y) \geq H(X).$$

**True:**

$$H(X + Y) \geq H(X + Y|Y) \stackrel{(a)}{=} H(X)$$

(a) - since  $X$  is independent of  $Y$ .

(d)  $I(X; Y) - I(X; Y|Z) \leq H(Z)$

**True:**

$$\begin{aligned} I(X; Y) - I(X; Y|Z) &= H(X) - H(X|Y) - [H(X|Z) - H(X|Y, Z)] \\ &= \underbrace{H(X) - H(X|Z)}_{I(X; Z)} - \underbrace{[H(X|Y) - H(X|Y, Z)]}_{\geq 0} \\ &\leq I(X; Z) \\ &= H(Z) - \underbrace{H(Z|X)}_{\geq 0} \\ &\leq H(Z) \end{aligned}$$

#### 4. Random questions.

One wishes to identify a random object  $X \sim p(x)$ . A question  $Q \sim r(q)$  is asked at random according to  $r(q)$ . This results in a deterministic answer  $A = A(x, q) \in \{a_1, a_2, \dots\}$ . Suppose the object  $X$  and the question  $Q$  are independent. Then  $I(X; Q, A)$  is the uncertainty in  $X$  removed by the question-answer  $(Q, A)$ .

(a) Show  $I(X; Q, A) = H(A|Q)$ . Interpret.

(b) Now suppose that two i.i.d. questions  $Q_1, Q_2 \sim r(q)$  are asked, eliciting answers  $A_1$  and  $A_2$ . Show that two questions are less valuable than twice the value of a single question in the sense that  $I(X; Q_1, A_1, Q_2, A_2) \leq 2I(X; Q_1, A_1)$ .

**Solution: Random questions.**

- (a) Since  $A$  is a deterministic function of  $(Q, X)$ ,  $H(A|Q, X) = 0$ . Also since  $X$  and  $Q$  are independent,  $H(Q|X) = H(Q)$ . Hence,

$$\begin{aligned}
 I(X; Q, A) &= H(Q, A) - H(Q, A, |X) \\
 &= H(Q) + H(A|Q) - H(Q|X) - H(A|Q, X) \\
 &= H(Q) + H(A|Q) - H(Q) \\
 &= H(A|Q).
 \end{aligned}$$

The interpretation is as follows. The uncertainty removed in  $X$  given  $(Q, A)$  is the same as the uncertainty in the answer given the question.

- (b) Using the result from part (a) and the fact that questions are independent, we can easily obtain the desired relationship.

$$\begin{aligned}
 I(X; Q_1, A_1, Q_2, A_2) &\stackrel{(a)}{=} I(X; Q_1) + I(X; A_1|Q_1) + I(X; Q_2|A_1, Q_1) \\
 &\quad + I(X; A_2|A_1, Q_1, Q_2) \\
 &\stackrel{(b)}{=} I(X; A_1|Q_1) + H(Q_2|A_1, Q_1) - H(Q_2|X, A_1, Q_1) \\
 &\quad + I(X; A_2|A_1, Q_1, Q_2) \\
 &\stackrel{(c)}{=} I(X; A_1|Q_1) + I(X; A_2|A_1, Q_1, Q_2) \\
 &= I(X; A_1|Q_1) + H(A_2|A_1, Q_1, Q_2) - H(A_2|X, A_1, Q_1, Q_2) \\
 &\stackrel{(d)}{=} I(X; A_1|Q_1) + H(A_2|A_1, Q_1, Q_2) \\
 &\stackrel{(e)}{\leq} I(X; A_1|Q_1) + H(A_2|Q_2) \\
 &\stackrel{(f)}{=} 2I(X; A_1|Q_1)
 \end{aligned}$$

- (a) Chain rule.  
 (b)  $X$  and  $Q_1$  are independent.  
 (c)  $Q_2$  are independent of  $X$ ,  $Q_1$ , and  $A_1$ .  
 (d)  $A_2$  is completely determined given  $Q_2$  and  $X$ .  
 (e) Conditioning decreases entropy.  
 (f) Result from part (a).

## 5. Entropy bounds.

Let  $X \sim p(x)$ , where  $x$  takes values in an alphabet  $\mathcal{X}$  of size  $m$ . The

entropy  $H(X)$  is given by

$$\begin{aligned} H(X) &\equiv -\sum_{x \in \mathcal{X}} p(x) \log p(x) \\ &= E_p \log \frac{1}{p(X)}. \end{aligned}$$

Use Jensen's inequality ( $Ef(X) \leq f(EX)$ , if  $f$  is concave) to show

- (a)  $H(X) \leq \log E_p \frac{1}{p(X)}$   
 $= \log m$ .
- (b)  $-H(X) \leq \log(\sum_{x \in \mathcal{X}} p^2(x))$ , thus establishing a lower bound on  $H(X)$ .
- (c) Evaluate the upper and lower bounds on  $H(X)$  when  $p(x)$  is uniform.
- (d) Let  $X_1, X_2$  be two independent drawings of  $X$ . Find  $\Pr\{X_1 = X_2\}$  and show  $\Pr\{X_1 = X_2\} \geq 2^{-H}$ .

**Solution: Entropy Bounds.**

To prove (a) observe that

$$\begin{aligned} H(X) &= E_p \log \frac{1}{p(X)} \\ &\leq \log E_p \frac{1}{p(X)} \\ &= \log \sum_{x \in \mathcal{X}} p(x) \frac{1}{p(x)} \\ &= \log m \end{aligned}$$

where the first inequality follows from Jensen's, and the last step follows since the size of  $\mathcal{X}$  is  $m$ .

To prove (b) proceed

$$\begin{aligned} -H(X) &= E_p \log p(X) \\ &\leq \log E_p p(X) \\ &= \log \left( \sum_{x \in \mathcal{X}} p^2(x) \right) \end{aligned}$$

where the second step again follows from Jensen's and the third step is just the definition of  $E_p(p(X))$ . Thus, we have the lower bound

$$H(X) \geq -\log \left( \sum_{x \in \mathcal{X}} p^2(x) \right) .$$

The upper bound is  $m$  irrespective of the distribution. Now,  $p(x) = 1/m$  for the uniform distribution, and therefore

$$\begin{aligned} -\log \sum_{x \in \mathcal{X}} p^2(x) &= -\log \sum_{x \in \mathcal{X}} \frac{1}{m^2} \\ &= -\log \frac{1}{m} \end{aligned}$$

and therefore the upper and lower bounds agree, and are  $\log m$ . A direct calculation of the entropy yields the same result immediately.

The derivation of (d) follows from

$$\begin{aligned} \Pr\{X_1 = X_2\} &= \sum_{x, y \in \mathcal{X}} \Pr\{X_1 = x, X_2 = y\} \delta_{xy} \\ &= \sum_{x \in \mathcal{X}} p^2(x) \end{aligned}$$

where the second step follows from the independence of  $X_1, X_2$ , and the fact that they are identically distributed  $X_1, X_2 \sim p(x)$ . Here  $\delta_{xy}$  is Kronecker's delta function.

## 6. Bottleneck.

Suppose a (non-stationary) Markov chain starts in one of  $n$  states, necks down to  $k < n$  states, and then fans back to  $m > k$  states. Thus  $X_1 \rightarrow X_2 \rightarrow X_3$ ,  $X_1 \in \{1, 2, \dots, n\}$ ,  $X_2 \in \{1, 2, \dots, k\}$ ,  $X_3 \in \{1, 2, \dots, m\}$ , and  $p(x_1, x_2, x_3) = p(x_1)p(x_2|x_1)p(x_3|x_2)$ .

- (a) Show that the dependence of  $X_1$  and  $X_3$  is limited by the bottleneck by proving that  $I(X_1; X_3) \leq \log k$ .
- (b) Evaluate  $I(X_1; X_3)$  for  $k = 1$ , and conclude that no dependence can survive such a bottleneck.

**Solution: Bottleneck.**

- (a) From the data processing inequality, and the fact that entropy is maximum for a uniform distribution, we get

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

Thus, the dependence between  $X_1$  and  $X_3$  is limited by the size of the bottleneck. That is  $I(X_1; X_3) \leq \log k$ .

- (b) For  $k = 1$ ,  $0 \leq I(X_1; X_3) \leq \log 1 = 0$  so that  $I(X_1, X_3) = 0$ . Thus, for  $k = 1$ ,  $X_1$  and  $X_3$  are independent.