Midterm Exam 2022

Instructor: Brian M. Kurkoski and Lei Liu May 20, 2022 13:30–15:10

SOLUTIONS

 $\mathit{Exam\ Policy}.$ This is a $\mathit{closed\ book}$ exam. You may use:

• One page of notes, A4-sized paper, double-sided OK.

You may not use anything else:

- No printed materials, including books, lecture notes and slides
- No notes (except as above)
- No internet-connected devices
- $\bullet\,$ No calculators. Answers such as "log 3" are acceptable.

Question	Points	Score
1	25	
2	20	
3	25	
4	30	
Total:	100	

This exam has 10 pages.

- 1. What is the correct relationship, =, \geq , \leq or ? (for unknown) for each pair below.
 - (a) (2 points) I(X;Y) = 0.

Solution: Mutual information is non-negative, so $I(X;Y) \ge 0$.

(b) (2 points) $H(X, Y) _{----} H(X) + H(Y)$

Solution: \leq Chain rule of entropy and conditioning reduces entropy.

(c) (2 points) $I(X;Y) + H(X|Y) \underline{\hspace{1cm}} H(X)$.

Solution: Variation on the definition of mutual information, so =.

(d) (2 points) I(X;X)_____H(X).

Solution: I(X;X) = H(X) since H(X|X) = 0.

(e) (2 points) I(X;Y) = H(X) - H(g(Y)|Y).

Solution: By conditional entropy of functions, H(g(Y)|Y) = 0. From the definition of mutual information I(X;Y) = H(X) - H(X|Y), we have $I(X;Y) \le H(X)$.

(f) (2 points) H(X|Y)_____H(X) + H(Y)

Solution: Conditioning reduces entropy: $H(X|Y) \leq H(X)$ and non-negativity of entropy: $0 \leq H(Y)$, correct answer is \leq .

(g) (2 points) H(2X) = H(X)

Solution: For a discrete random variable X, the probability vectors of 2X and X are the same, so correct answer is H(2X) = H(X).

(h) (2 points) $H(X^2) \longrightarrow H(X)$

Solution: The correct answer is $H(X^2) \leq H(X)$, because

$$H(\mathsf{X}^2,\mathsf{X}^2) = H(\mathsf{X}^2) + \underbrace{H(\mathsf{X}|\mathsf{X}^2)}_{\geq 0}$$
$$= H(\mathsf{X}) + \underbrace{H(\mathsf{X}^2|\mathsf{X})}_{=0}.$$

(i) (2 points) $H(X_2|X_1)$ _____ $H(X_2|X_1,X_0)$

Solution: Conditioning reduces entropy, so correct answer is $H(X_2|X_1) \ge H(X_2|X_1,X_0)$.

(j) (3 points) $H(X,Y) + I(X;Y) ___ H(X) + H(Y)$

Solution:

$$\begin{split} H(\mathsf{X},\mathsf{Y}) + I(\mathsf{X};\mathsf{Y}) &= \underbrace{H(\mathsf{X}) + H(\mathsf{Y}|\mathsf{X})}_{=H(\mathsf{X},\mathsf{Y}) \text{ (chain rule)}} + \underbrace{H(\mathsf{Y}) - H(\mathsf{Y}|\mathsf{X})}_{I(\mathsf{X};\mathsf{Y})} \\ &= I(\mathsf{X}) + H(\mathsf{Y}). \end{split}$$

(k) (4 points) H(X,Y)_____H(X|Y) + H(Y|X) + I(X;Y)

Solution:

$$\begin{split} H(\mathsf{X},\mathsf{Y}) &= H(\mathsf{X}) + H(\mathsf{Y}|\mathsf{X}) \\ &= \underbrace{H(\mathsf{X}) - H(\mathsf{X}|\mathsf{Y})}_{=I(\mathsf{X};\mathsf{Y})} + H(\mathsf{X}|\mathsf{Y}) + H(\mathsf{Y}|\mathsf{X}) \\ &= I(\mathsf{X};\mathsf{Y}) + H(\mathsf{X}|\mathsf{Y}) + H(\mathsf{Y}|\mathsf{X}). \end{split}$$

- 2. Let X be defined on $\mathcal{X} = \{-1, 0, 1\}$ with $p_{\mathsf{X}}(x) = [\frac{1}{4}, \frac{1}{2}, \frac{1}{4}]$. Let $g(x) = x^2$ and let $\mathsf{Y} = g(\mathsf{X})$, so that $\mathcal{Y} = \{0, 1\}$ and $p_{\mathsf{Y}}(0) = \frac{1}{2}$ and $p_{\mathsf{Y}}(1) = \frac{1}{2}$.
 - (a) (4 points) Compute E[X] and E[g(X)].
 - (b) (4 points) What is H(Y|X)? It is easily found without computations.
 - (c) (4 points) Find $p_{XY}(x,y)$. Find $p_{X|Y}(x|y)$.
 - (d) (4 points) Compute H(X|Y=0) and H(X|Y=1).
 - (e) (4 points) Compute H(X|Y).

Solution: (a)

$$\begin{split} E[\mathsf{X}] &= \sum_{x \in \mathcal{X}} x p_{\mathsf{X}}(x) \\ &= (-1)\frac{1}{4} + 0\frac{1}{2} + 1\frac{1}{4} = 0 \\ E[g(\mathsf{X})] &= \sum_{x \in \mathcal{X}} g(x) p_{\mathsf{X}}(x) \\ &= (-1)^2 \frac{1}{4} + 0\frac{1}{2} + 1^2 \frac{1}{4} \\ &= \frac{1}{2} \end{split}$$

- (b) H(Y|X) = 0 because if you know X, you can always compute Y, that is H(g(X)|X) = 0.
- (c) Note it is easy to find $p_{\mathsf{Y}|\mathsf{X}}(y|x)$ from the problem statement:

$$p_{\mathsf{Y}|\mathsf{X}}(y|x) = \begin{bmatrix} 0 & 1\\ 1 & 0\\ 0 & 1 \end{bmatrix},$$

since $y = x^2$. Since $p_{XY}(x, y) = p_{Y|X}(y|x)p_X(x)$,

$$p_{XY}(x,y) = \begin{bmatrix} 0 & 1/4 \\ 1/2 & 0 \\ 0 & 1/4 \end{bmatrix},$$

Since $p_{Y|X}(y|x)$, $p_X(x)$ and $p_Y(y)$ are all known, use Bayes rule to find $p_{X|Y}(x|y)$:

$$p_{X|Y}(x|y) = \frac{p_{Y|X}(y|x)p_{X}(x)}{p_{Y}(y)}$$

$$p_{X|Y}(-1|0) = \frac{p_{Y|X}(0|-1)p_{X}(-1)}{p_{Y}(0)} = \frac{0 \cdot 1/4}{1/2} = 0$$

$$p_{X|Y}(0|0) = \frac{p_{Y|X}(0|0)p_{X}(0)}{p_{Y}(0)} = \frac{1 \cdot 1/2}{1/2} = 1$$

$$p_{X|Y}(-1|1) = \frac{p_{Y|X}(1|-1)p_{X}(-1)}{p_{Y}(1)} = \frac{1 \cdot 1/4}{1/2} = \frac{1}{2} \cdots$$

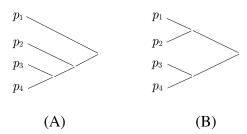
$$\cdots \text{ so that } p_{X|Y}(x|y) = \begin{bmatrix} 0 & 1 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix}.$$

(d)
$$H(\mathsf{X}|\mathsf{Y}=0) = -\sum_{x \in \mathcal{X}} p_{\mathsf{X}|\mathsf{Y}}(x|0) \log p_{\mathsf{X}|\mathsf{Y}}(x|0) = -0 \log 0 - 1 \log 1 - 0 \log 0 = 0$$

$$H(\mathsf{X}|\mathsf{Y}=1) = -\sum_{x \in \mathcal{X}} p_{\mathsf{X}|\mathsf{Y}}(x|1) \log p_{\mathsf{X}|\mathsf{Y}}(x|1) = -\frac{1}{2} \log \frac{1}{2} - 0 \log 0 - \frac{1}{2} \log \frac{1}{2} = 1 \text{ bit }$$

(e)
$$H(\mathsf{X}|\mathsf{Y}) = p_{\mathsf{Y}}(0)H(\mathsf{X}|\mathsf{Y}=1) + p_{\mathsf{Y}}(1)H(\mathsf{X}|\mathsf{Y}=1) = \frac{1}{2} \cdot 0 + \frac{1}{2} \cdot 1 = \frac{1}{2} \text{ bit}$$

3. Huffman code trees Consider a source with $\mathcal{X} = \{1, 2, 3, 4\}$ and $p_1 > p_2 > p_3 > p_4$ and $p_1 + p_2 + p_3 + p_4 = 1$. There are only two possible binary Huffman codes for this source, with corresponding trees (A) and (B):



- (a) (5 points) Let $(p_1, p_2, p_3, p_4) = (0.39, 0.21, 0.2, 0.2)$. Give a binary Huffman code for this source. What is the expected codeword length?
- (b) (5 points) Give a ternary Huffman code for the source in part (a). What is the expected codeword length?
- (c) (5 points) Give an inequality using p_1, p_3 and p_4 such that tree (A) is always obtained.
- (d) (5 points) Show that if $p_1 > \frac{2}{5}$ then $p_3 + p_4 < \frac{2}{5}$.
- (e) (5 points) Show that if $p_1 > \frac{2}{5}$, then the length of the corresponding Huffman codeword for "x = 1" is 1.

Solution:

(a) There are many possible codes. One code is below, but all codes have expected length 2.



(b) There are many possible codes. One code is below.

c(x)	р					$p_{X}(x)$	code
0	0.39		0	┑.		0.39	0
1	0.21	0	1	1	_	0.21	1
20	0.2	1	0.4 2			0.20	20
21 Dumn	0.2 av 0	2		_		0.20	21

The expected length is 0.6 * 1 + 0.4 * 2 = 1.4.

- (c) Note that symbol 3 and symbol 4 are always combined first. Tree (B) will be obtained only when $p_3 + p_4$ is greater than p_1 (which is greater than p_2). So, tree (A) is obtained when $p_3 + p_4 \le p_1$.
- (d) Assume that $p_3 + p_4 \ge 2/5$.
 - (1) From $p_3 + p_4 \ge 2/5$ and $p_3 > p_4$, we have $p_3 > 1/5$. Since $p_2 > p_3$, we then have $p_2 > 1/5$.
 - (2) From $p_3 + p_4 \ge 2/5$, $p_1 > \frac{2}{5}$ and $p_1 + p_2 + p_3 + p_4 = 1$, we then have $p_2 = 1 (p_2 + p_3 + p_4) < 1/5$, which contradicts the result in point (1).

Therefore, $p_3 + p_4 \ge 2/5$ does not hold. That is, $p_3 + p_4 < 2/5$.

(e) If $p_1 > \frac{2}{5}$, then by part (d), we have that $p_3 + p_4 < \frac{2}{5}$. Then, $p_1 > p_3 + p_4$, so by the condition in part (c), we must have Tree (A), which has the codeword for "x = 1" with length 1.

4. Consider a two-state Markov chain $\mathbf{X} = [X_1, X_2, \cdots]$ with probability transition matrix:

$$\begin{array}{c|cccc} \mathbf{P}_{\mathsf{X}_{n}|\mathsf{X}_{n-1}} & x_{n-1} = 0 & x_{n-1} = 1 \\ \hline x_{n} = 0 & 4/5 & 1/2 \\ x_{n} = 1 & 1/5 & 1/2 \\ \hline \end{array}$$

(a) (3 points) What is the stationary distribution \mathbf{p}_{X} ?

Solution:

$$\begin{split} \mathbf{Q} &= \left[\begin{array}{c} 1 & 1 \\ \{\mathbf{P} - \mathbf{I}\}_{\backslash \mathbf{r_1}} \end{array} \right] = \left[\begin{array}{c} 1 & 1 \\ 1/5 & -1/2 \end{array} \right], \\ \mathbf{p_X} &= \mathbf{Q}^{-1} \left[\begin{array}{c} 1 \\ 0 \end{array} \right] = \frac{1}{-1/2 - 1/5} \left[\begin{array}{c} -1/2 & -1 \\ -1/5 & 1 \end{array} \right] \left[\begin{array}{c} 1 \\ 0 \end{array} \right] = \left[\begin{array}{c} 5/7 \\ 2/7 \end{array} \right] \approx \left[\begin{array}{c} 0.714 \\ 0.286 \end{array} \right]. \end{split}$$

(b) (3 points) What is the entropy rate $H(\mathcal{X})$?

Solution:
$$H(\mathcal{X}) = H(X_n | X_{n-1}) = \frac{5}{7}h(1/5) + \frac{2}{7}h(1/2) = \frac{5}{7}h(1/5) + \frac{2}{7} \approx 0.801$$
 bits.

(c) (3 points) What is the (single-variable) entropy $\lim_{n\to\infty} H(\mathsf{X}_n)$?

Solution:
$$\lim_{n\to\infty} H(X_n) = h(\mathbf{p}_X) = h(2/7) \approx 0.863$$
 bits.

(d) (3 points) Which has lower compression rate, compression using the Markov property, or single-variable compression?

Solution: Since $\lim_{n\to\infty} H(X_n) > H(\mathcal{X})$, compression using the Markov property has lower compression rate.

- Let $\mathbf{Y} = [Y_1, Y_2, ...]$ and $Y_n = [X_{2n-1}, X_{2n}]$. Then $Y_1 = [X_1, X_2], Y_2 = [X_3, X_4], ...$ is a four-state Markov chain.
- (e) (4 points) What is the probability transition matrix $\mathbf{P}_{\mathsf{Y}_n|\mathsf{X}_{2n-2}}$? What is the probability transition matrix $\mathbf{P}_{\mathsf{Y}_n|\mathsf{Y}_{n-1}}$?

Solution: Following the Markov property, we have

$$P_{\mathsf{Y}_n|\mathsf{X}_{2n-2}} = P_{\mathsf{X}_{2n-1},\mathsf{X}_{2n}|\mathsf{X}_{2n-2}} = P_{\mathsf{X}_{2n-1}|\mathsf{X}_{2n-2}} P_{\mathsf{X}_{2n}|\mathsf{X}_{2n-1}},$$

$$\begin{array}{c|ccccc} \mathbf{P}_{\mathsf{Y}_n|\mathsf{X}_{2n-2}} & x_{2n-2} = 0 & x_{2n-2} = 1 \\ \hline y_n = 00 & 16/25 & 2/5 \\ y_n = 01 & 4/25 & 1/10 \\ y_n = 10 & 1/10 & 1/4 \\ y_n = 11 & 1/10 & 1/4 \\ \end{array}.$$

Similarly,

$$P_{\mathsf{Y}_n|\mathsf{Y}_{n-1}} = P_{\mathsf{X}_{2n-1},\mathsf{X}_{2n}|\mathsf{X}_{2n-3},\mathsf{X}_{2n-2}} = P_{\mathsf{X}_{2n-1},\mathsf{X}_{2n}|\mathsf{X}_{2n-2}} = P_{\mathsf{Y}_n|\mathsf{X}_{2n-2}},$$

$\mathbf{P}_{Y_n Y_{n-1}}$	$y_{n-1} = 00$	$y_{n-1} = 01$	$y_{n-1} = 10$	$y_{n-1} = 11$
$y_n = 00$	16/25	2/5	16/25	2/5
$y_n = 01$	4/25	1/10	4/25	1/10 .
$y_n = 10$	1/10	1/4	1/10	1/4
$y_n = 11$	1/10	1/4	1/10	1/4

(f) (2 points) What is the stationary distribution \mathbf{p}_{Y} ? (Hint: Matrix inverse is not necessary. You can utilize the stationary distribution \mathbf{p}_{X} .)

Solution:

$$\mathbf{p}_{\mathsf{Y}} = \mathbf{P}_{\mathsf{Y}_n | \mathsf{X}_{2n-2}} * \mathbf{P}_{\mathsf{X}} = \left[egin{array}{c} 4/7 \\ 1/7 \\ 1/7 \\ 1/7 \end{array}
ight].$$

(g) (3 points) What is the entropy rate $H(\mathcal{Y})$?

Solution: $H(\mathcal{Y}) = 2H(\mathcal{X}) = \frac{10}{7}h(1/5) + \frac{4}{7} \approx 1.602$.

(h) (3 points) Which has lower compression rate per symbol, compression using the Markov property of \mathbf{Y} , or compression using the Markov property of \mathbf{X} ?

Solution: Since $H(\mathcal{Y}) = 2H(\mathcal{X})$, both of them are optimal. Compression using the Markov property of **Y** has the same compression rate per symbol as that of **X**.

(i) (3 points) What is the (two-variable) entropy $\lim_{n\to\infty} H(Y_n)$?

Solution: $\lim_{n\to\infty} H(\mathsf{Y}_n) = h(\mathbf{p}_{\mathsf{Y}}) = -\frac{4}{7}\log_2\frac{4}{7} - 3*\frac{1}{7}\log_2\frac{1}{7} = \log_27 - \frac{8}{7} \approx 1.665 \text{ bits.}$

(j) (3 points) Which has lower compression rate per symbol, two-variable compression, or single-variable compression?

Solution: $\lim_{n\to\infty} H(\mathsf{Y}_n) \approx 1.665 \text{ bits } < 2*\lim_{n\to\infty} H(\mathsf{X}_n) \approx 1.726 \text{ bits.}$ Hence, two-variable compression has lower compression rate per symbol than single-variable compression.

Notes: $\log_2 5 \approx 2.3219, \log_2 7 \approx 2.8074$, and you may use the binary entropy function $h(p) \equiv -p \log p - (1-p) \log (1-p)$ for the questions above.