

# COMP2610: INFORMATION THEORY

Week 3 Tutorial



Australian  
National  
University

# SOME KEY CONCEPTS:

- Binomial and Bernoulli distribution
- Likelihood function

$$\mathcal{L}(\theta) = p(\mathcal{D} \mid \theta) = \prod_{i=1}^N p(x_i \mid \theta)$$

- Maximum likelihood estimate

Maximising  $p(\mathcal{D} \mid \theta)$  is same as  $\max \log$  of  $\mathcal{L}$

$$\text{ie. } \max \log p(\mathcal{D} \mid \theta) = \sum_{i=1}^N \log p(x_i \mid \theta)$$

- Information content of a random variable outcome

$$h(x) = \log_2 \left( \frac{1}{p(x)} \right) = -\log_2 p(x)$$

- Entropy of a RV

$$\begin{aligned} H(X) &= \mathbb{E}_x(h(x)) \\ &= \sum p(x) \cdot h(x) \\ &= - \sum p(x) \log_2 p(x) \end{aligned}$$

- Conditional entropy

$$\begin{aligned} H(Y \mid X = x) &= - \sum p(y \mid X = x) \log p(y \mid X = x) \\ H(Y \mid X) &= \sum p(x) H(Y \mid X = x) \\ &= - \sum p(x) \sum p(y \mid x) \log p(y \mid x) \end{aligned}$$

- Joint entropy and chain rule

$$\begin{aligned} H(X, Y) &= - \sum_x \sum_y p(x, y) \log(p(x, y)) \\ H(X, Y) &= H(X) + H(Y \mid X) = H(Y) + H(X \mid Y) \end{aligned}$$



1. Let  $X$  be a random variable with possible outcomes  $\{1, 2, 3\}$ . Let the probabilities of the outcomes be

$$p(X = 1) = \frac{\theta}{2}$$

$$p(X = 2) = \frac{\theta}{2}$$

$$p(X = 3) = 1 - \theta$$

for some parameter  $\theta \in [0, 1]$ .

Suppose we see  $N$  observations of the random variable,  $\{x_1, \dots, x_N\}$ . Let  $n_i$  denote the number of times that we observe the outcome  $X = i$ , i.e.

$$n_i = \sum_{k=1}^N \begin{cases} 1 & \text{if } x_k = i \\ 0 & \text{else.} \end{cases}$$

- (a) Write down the likelihood function of  $\theta$  given the observations  $\{x_1, \dots, x_N\}$  in terms of  $n_1, n_2, n_3$ .

- (b) Suppose the observations are

$$\{3, 3, 1, 2, 3, 2, 2, 1, 3, 1\}.$$

Compute the maximum likelihood estimate of  $\theta$ . (*Hint: Compute the log-likelihood function, and check when the derivative is zero.*)



(a) Write down the likelihood function of  $\theta$  given the observations  $\{X_1, \dots, X_N\}$  in terms of  $n_1, n_2, n_3$ .

**Solution:** 1. (a) Let  $n_i$  denote the number of times that we observe outcome  $X = i$ . The likelihood is

$$\begin{aligned} L(\theta) &= \prod_{i=1}^N p(X = x_i | \theta) \\ &= \prod_{i: x_i=1} \left(\frac{\theta}{2}\right) \cdot \prod_{i: x_i=2} \left(\frac{\theta}{2}\right) \cdot \prod_{i: x_i=3} (1 - \theta) \\ &= \left(\frac{\theta}{2}\right)^{n_1} \cdot \left(\frac{\theta}{2}\right)^{n_2} \cdot (1 - \theta)^{n_3} \\ &= \left(\frac{\theta}{2}\right)^{n_1+n_2} \cdot (1 - \theta)^{n_3}. \end{aligned}$$



(b) Suppose the observations are

$$\{3,3,1,2,3,2,2,1,3,1\}.$$

Compute the maximum likelihood estimate of  $\theta$ . (Hint: Compute the log-likelihood function, and check when the derivative is zero.)

**Solution:** (b) The log-likelihood is

$$\mathcal{L}(\theta) = (n_1 + n_2) \cdot \log \frac{\theta}{2} + n_3 \cdot \log(1 - \theta).$$

The derivative is

$$\mathcal{L}'(\theta) = \frac{n_1 + n_2}{\ln 2} \cdot \frac{1/2}{\theta/2} + \frac{n_3}{\ln 2} \cdot \frac{-1}{1 - \theta}.$$

We have that  $n_1 = 3, n_2 = 3, n_3 = 4$ . So, we need

$$\frac{6}{\theta} = \frac{4}{1 - \theta}$$

for which the solution may be checked to be  $\theta = 0.6$ . Observe then that we estimate

$$p(X = 1) = 0.3$$

$$p(X = 2) = 0.3$$

$$p(X = 3) = 0.4,$$

matching the frequencies of observations of each outcome.



2. Consider the following joint distribution over  $X, Y$ :

$p(X,Y)$		$X$			
		1	2	3	4
$Y$	1	0	0	1/8	1/8
	2	1/8	1/16	1/16	0
	3	1/8	1/8	0	0
	4	0	1/16	1/16	1/8

(a) Show that  $X$  and  $Y$  are not statistically independent. (*Hint: You need only show that for at least one specific  $x,y$  pair,  $p(X=x, Y=y)$  not equal to  $p(X=x)p(Y=y)$ .)*)

(b) Compute the following quantities:

- (i)  $H(X)$
- (ii)  $H(Y)$
- (iii)  $H(X|Y)$
- (iv)  $H(Y|X)$
- (v)  $H(X,Y)$



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- (a) Show that  $X$  and  $Y$  are not statistically independent. (*Hint: You need only show that for at least one specific  $x,y$  pair,  $p(X=x,Y=y)$  not equal to  $p(X=x)p(Y=y)$ .)*)

**Solution:** 2. (a) We can show that  $X$  and  $Y$  are not statistically independent by showing that  $p(x,y) \neq p(x)p(y)$  for at least one value of  $x$  and  $y$ . For example:  $p(X=1) = 1/8 + 1/8 = 1/4$  and  $p(Y=2) = 1/8 + 1/16 + 1/16 = 1/4$ . From the given table we see that:  
 $p(X=1, Y=2) = 1/8$  which is different from  $p(X=1)p(Y=2) = 1/16$ .



$p(X,Y)$		$X$			
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$Y$	1	0	0	1/8	1/8
	2	1/8	1/16	1/16	0
	3	1/8	1/8	0	0
	4	0	1/16	1/16	1/8

## Solution:

(b) First, we find the marginal probabilities using the sum rule:

$$\mathbf{p}^{(X)} = (P(X=1), P(X=2), P(X=3), P(X=4)) = (1/4, 1/4, 1/4, 1/4)$$

$$\mathbf{p}^{(Y)} = (P(Y=1), P(Y=2), P(Y=3), P(Y=4)) = (1/4, 1/4, 1/4, 1/4).$$

We see that both  $p(X)$  and  $p(Y)$  are uniform distributions with 4 possible states. Hence:

$$H(X) = H(Y) = \log_2 4 = 2 \text{ bits.}$$

To compute the conditional entropy  $H(X|Y)$  we need the conditional distributions

$p(X|Y)$  which can be computed by using the definition of conditional probability  $p(X=x|Y=y) = p(X=x, Y=y)/p(Y=y)$ . In other words, we divide the rows of the given table by the corresponding marginal.

$$\begin{aligned} \mathbf{p}(X|Y=1) &= (0, 0, 1/2, 1/2) \quad \mathbf{p}(X|Y=2) = (1/2, 1/4, 1/4, 0) \\ \mathbf{p}(X|Y=3) &= (1/2, 1/2, 0, 0) \quad \mathbf{p}(X|Y=4) = (0, 1/4, 1/4, 1/2). \end{aligned}$$

(b) Compute the following quantities:

(i)  $H(X)$

(ii)  $H(Y)$

(iii)  $H(X|Y)$

(iv)  $H(Y|X)$

(v)  $H(X,Y)$





$p(X,Y)$		$X$			
		1	2	3	4
$Y$	1	0	0	1/8	1/8
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(b) Compute the following quantities:

- (i)  $H(X)$
- (ii)  $H(Y)$
- (iii)  $H(X|Y)$
- (iv)  $H(Y|X)$
- (v)  $H(X,Y)$

## Solution:

b) continued

Hence the conditional entropy  $H(X|Y)$  is given by:

$$\begin{aligned}
 H(X|Y) &= \sum_{i=1}^4 p(Y=i)H(X|Y=i) \\
 &= (1/4)H(0, 0, 1/2, 1/2) + (1/4)H(1/2, 1/4, 1/4, 0) \\
 &\quad + (1/4)H(1/2, 1/2, 0, 0) + (1/4)H(0, 1/4, 1/4, 1/2) \\
 &= 1/4 \times 1 + 1/4 \times 3/2 + 1/4 \times 1 + 1/4 \times 3/2 \\
 &= 5/4 \text{ bits.}
 \end{aligned}$$

Here we note that conditioning has indeed decreased entropy. We can compute the joint entropy by using the chain rule:

$$H(X,Y) = H(X|Y) + H(Y) = 5/4 + 2 = 13/4 \text{ bits.}$$

Additionally, we know that by the chain rule  $H(X,Y) = H(Y|X) + H(X)$ , hence:

$$H(Y|X) = H(X,Y) - H(X) = 13/4 - 2 = 5/4 \text{ bits.}$$



3. A standard deck of cards contains 4 *suits* — ♥, ♦, ♣, ♠ (“hearts”, “diamonds”, “clubs”, “spades”) — each with 13 *values* — A, 2, 3, 4, 5, 6, 7, 8, 9, 10, J, Q, K (The A, J, Q, K are called “Ace”, “Jack”, “Queen”, “King”). Each card has a *colour*: hearts and diamonds are coloured red; clubs and spades are black. Cards with values J, Q, K are called *face cards*.

Each of the 52 cards in a deck is identified by its value  $v$  and suit  $s$  and denoted  $vs$ . For example,  $2♥$ ,  $J♣$ , and  $7♠$  are the “two of hearts”, “Jack of clubs”, and “7 of spades”, respectively. The variable  $c$  will be used to denote a card’s colour. Let  $f = 1$  if a card is a face card and  $f = 0$  otherwise.

A card is drawn at random from a thoroughly shuffled deck. Calculate:

- (a) The information in observing a red King, i.e.,  $h(c = \text{red}, v = K)$
- (b) The conditional information in observing a King given a face card was drawn, i.e.,  $h(v = K | f = 1)$
- (c) The entropies  $H(S)$  and  $H(V, S)$ .



- (a) The information in observing a red King, i.e.,  $h(c = \text{red}, v = K)$
- (b) The conditional information in observing a King given a face card was drawn, i.e.,  $h(v = K | f = 1)$
- (c) The entropies  $H(S)$  and  $H(V, S)$ .

**Solution:**

3. (a)  $h(c = \text{red}, v = K) = \log_2 \frac{1}{P(c=\text{red}, v=K)} = \log_2 \frac{1}{1/26} = 4.7004 \text{ bits.}$

(b)  $h(v = K | f = 1) = \log_2 \frac{1}{p(v = K | f = 1)} = \log_2 \frac{1}{1/3} = 1.585 \text{ bits}$

(c) We have

i.  $H(S) = \sum_s p(s) \log_2 \frac{1}{p(s)} = 4 \times \frac{1}{4} \times \log_2 \frac{1}{1/4} = 2 \text{ bits.}$

ii.  $H(V, S) = \sum_{v,s} p(v, s) \log_2 \frac{1}{p(v,s)} = 52 \times \frac{1}{52} \log_2 \frac{1}{1/52} = 5.7 \text{ bits.}$



4. Let  $X$  be a random variable taking on a finite number of values. What is the (general) inequality relationship of  $H(X)$  and  $H(Y)$  if
- a.  $Y = 2^X$  ?
  - b.  $Y = \cos X$  ?



Q4

By chain rule we have  $H(X) + H(Y | X) = H(Y) + H(X | Y)$ . If we can find whether  $H(Y | X)$  &  $H(X | Y)$  are zero or  $> 0$ , then we can find the inequality relationship of  $H(X)$  and  $H(Y)$ .

**Solution:** a) Let's first consider  $Y = 2^X$ . We know this is a 1 to 1 mapping expression, i.e., for every unique value of  $X$ , we can find a unique  $Y$ .

$$\therefore \text{ if } p(X = x_i) = \theta, \text{ then } p(Y = 2^{x_i}) = \theta.$$

We also have

$$p(Y = 2^{x_i} | X = x_i) = 1 \text{ and } p(Y = y_i | X = x_i) = 0 \text{ for } y_i \neq 2^{x_i},$$

which can be generalised as

$$p(Y = y_i | X = x_i) = \begin{cases} 1 & y_i = f(x_i), \\ 0 & \text{otherwise.} \end{cases}$$



**Solution:** 4a) continued

$$p(Y = y_i | X = x_i) = \begin{cases} 1 & y_i = f(x_i), \\ 0 & \text{otherwise.} \end{cases}$$

The conditional entropy formula

$$H(Y | X) = - \sum p(x) \sum p(y | x) \log p(y | x),$$

When  $p(Y = y_i | X = x_i) = 1, \log(p(Y = y_i | X = x_i)) = 0$

$$p(Y = y_i | X = x_i) = 0, p(Y = y_i | X = x_i) \log(p(Y = y_i | X = x_i)) = 0.$$

$$\therefore H(Y | X) = 0.$$

We can further generalise to:

$$\text{if } B = f(A), H(B | A) = 0. \quad (1)$$

Using (1), we can conclude

$$H(Y | X) = 0 \text{ since } Y = 2^X = f(X)$$

$$\text{Also } H(X | Y) = 0 \text{ since } X = \log_2(Y) = g(Y).$$

$$\therefore H(X) = H(Y).$$



## Solution:

b)  $Y = \cos(X)$

We can conclude

$$H(Y | X) = 0, \text{ since } Y = \cos(X) = f(X).$$

But we cannot express  $X$  as a function of  $Y$ , since  $Y = \cos(X)$  is a many to 1 mapping expression.

$$\therefore H(X | Y) \neq 0$$

$$\therefore H(X) + \cancel{H(Y|X)}^{\rightarrow 0} = H(Y) + \cancel{H(X|Y)}^{\rightarrow \neq 0}$$

$$\therefore H(X) = H(Y) + H(X | Y)$$

$$\therefore H(X) > H(Y).$$



# THANK YOU

## Contact Details:

***Office:*** B137B, Brian Anderson Building (Ground Floor)

***Email:*** [yile.zhang@anu.edu.au](mailto:yile.zhang@anu.edu.au)



Australian  
National  
University