

2.1  $X = \text{one child}$ ,  $Y = \text{other child}$

$X$	$Y$	$P(X, Y)$
G	G	$1/4$
G	B	$1/4$
B	G	$1/4$
B	B	$1/4$

(a) Let  $N_g = \text{numbers of girls}$ ,  $N_b = \text{number of boys with constraint } N_g + N_b = 2$

(2 Point)

$$P(N_g = 1 | N_b \geq 1) = \frac{P(N_b \geq 1 | N_g = 1) P(N_g = 1)}{P(N_b \geq 1)} = \frac{1 \times 1/2}{3/4} = 2/3$$

(b) Let  $Y = \text{the identity of the observed child}$

(2 Point)  $X = \text{identity of the other child}$

Then  $P(X = g | Y = b) = \frac{P(Y = b | X = g) P(X = g)}{P(Y = b)} = \frac{1/2 \times 1/2}{1/2} = 1/2$

2.3 Variance of a Sum

(2 points)

$$\begin{aligned} \text{Var}[X+Y] &= E[(X+Y)^2] - (E[X+Y])^2 \quad (\because \text{Var}(Z) = E[Z^2] - (E[Z])^2) \\ &= E[X^2 + Y^2 + 2XY] - (E[X] + E[Y])^2 \quad (\because \text{Expectation is linear}) \\ &= E[X^2] + E[Y^2] + 2E[XY] - (E[X])^2 - (E[Y])^2 - 2E[X]E[Y] \\ &= \underbrace{E[X^2] - (E[X])^2}_{\text{Var}[X]} + \underbrace{E[Y^2] - (E[Y])^2}_{\text{Var}[Y]} + \underbrace{2E[XY] - 2E[X]E[Y]}_{2 \text{Cov}[X,Y]} \\ &= \text{Var}[X] + \text{Var}[Y] + 2 \text{Cov}[X, Y] \end{aligned}$$

2.6

(a) Baye's rule gives

(3 points)

$$P(H | E_1 = e_1, E_2 = e_2) = \frac{P(E_1 = e_1, E_2 = e_2 | H) P(H)}{P(E_1, E_2)}$$

Hence (ii) is sufficient (we even don't need  $P(e_1, e_2)$ )

(i), (iii) are insufficient

(b) If  $E_1 \perp E_2 | H$  ( $E_1$  and  $E_2$  are conditionally independent given  $H$ )

(3 points)

$$\text{then } P(H | E_1 = e_1, E_2 = e_2) = \frac{P(E_1 = e_1 | H) P(E_2 = e_2 | H) P(H)}{P(E_1 \neq e_1, E_2 = e_2)}$$

(i) and (ii) are obviously sufficient

(iii) is also sufficient, because we can compute  $P(E_1, E_2)$  for normalization

(2)

2.12  
= Expressing mutual information in terms of entropies

(2 points)

$$\begin{aligned}
 I[X, Y] &= \sum_{x, y} P(x, y) \log \frac{P(x, y)}{P(x)P(y)} \\
 &= \sum_{x, y} P(x, y) \log \frac{P(x|y)P(y)}{P(x)P(y)} \\
 &= - \sum_{x, y} P(x, y) \log P(x) + \sum_{x, y} P(x, y) \log (x|y) \\
 &\quad \swarrow \text{marginalization} \\
 &= - \sum_x P(x) \log P(x) - \left( - \sum_{x, y} P(x, y) \log (x|y) \right) \\
 &= H[X] - \left( - \sum_y P(y) \sum_x P(y|x) \log (x|y) \right) \\
 &= H[X] - H[X|Y]
 \end{aligned}$$

and  $I[X, Y] = H(Y) - H[Y|X]$  by symmetry

2.16  
(2 points)

Beta( $x|a, b$ ) =  $\frac{1}{B(a, b)} x^{a-1} (1-x)^{b-1}$

mode =  $x$  where Beta( $x|a, b$ ) has maximum value

Hence using simple calculus we have

$$\begin{aligned}
 \frac{d \text{Beta}(x|a, b)}{dx} &= \frac{1}{B(a, b)} \left[ -x^{(a-1)}(b-1)(1-x)^{b-2} + (a-1)x^{a-2}(1-x)^{b-1} \right] = 0 \\
 &\Rightarrow \frac{x^{a-2}(1-x)^{b-2}}{B(a, b)} \left[ -(b-1)x + (a-1)(1-x) \right] = 0
 \end{aligned}$$

$$\Rightarrow [(a-1) - (b-1+a-1)x] = 0$$

$$\Rightarrow x = \frac{a-1}{a+b-2}$$

mean  
(2 points)

$$E[X] = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_0^1 x^{a-1} (1-x)^{b-1} dx = \frac{\Gamma(a+b)\Gamma(a+1)\Gamma(b)}{\Gamma(a)\Gamma(b)\Gamma(a+b)} = \frac{a}{a+b}$$

For variance first observe that  $E[X^2] = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_0^1 x^2 (x^{a-1} (1-x)^{b-1}) dx$

$$= \frac{\Gamma(a+b)\Gamma(a+2)\Gamma(b)}{\Gamma(a)\Gamma(b)\Gamma(a+b)}$$

(3)

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(a+2)\Gamma(b)}{\Gamma(a+2+b)} = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(b)}{\Gamma(a+2+b)}$$

$$= \frac{(a+1)a}{(a+b)(a+b)}$$

$\because \Gamma(z+1) = z \Gamma(z)$   
 note gamma function behave like factorial with its argument shifted down by 1

Hence  $\text{Var}[x] = E[x^2] - (E[x])^2 = \frac{(a+1)a}{(a+b)(a+b)} - \left(\frac{a}{a+b}\right)^2$   
 (2 points)

$$= \frac{ab}{(a+b)(a+b+1)}$$

Total Points =  $(2+2) + (2) + (3+3) + (2+2+2)$   
 $= 4 + 2 + 6 + 6$   
 $= 18 + 2 = 20$