

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 $Y = \text{the identity of the observed child}$

$X = \text{identity of the other child}$

(2 Point)

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

2.3 Variance of a Sum

(2 points)

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

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

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(a+2)\Gamma(b)}{\Gamma(a+2)\Gamma(b)} = \frac{a(a+1)}{a(a+b)}$$

(3)

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(a+2)\Gamma(b)}{\Gamma(a+2+b)} = \frac{(a+1)a}{(a+b+1)(a+b)}$$

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

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

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

(2.4) (1 Point)

Denote test by binary discrete random variable $T = 1$ test is positive
 $= 0$ test is negative

Similarly

Disease present by binary random variable $D = 1$ disease present
 $= 0$ disease not present

Then we know that

$$P(T=1|D=1) = P(T=0|D=0) = 0.99$$

$$\Rightarrow P(T=0|D=1) = P(T=1|D=0) = 0.01$$

$$\text{and } P(D=1) = 10^{-4} = 0.0001$$

$$\Rightarrow P(D=0) = 0.9999$$

hence

$$P(D=1 | T=1) = \frac{P(T=1 | D=1) P(D=1)}{P(T=1)}$$

$$= \frac{P(T=1 | D=1) P(D=1)}{\sum_{D=\{0,1\}} P(T=1, D)}$$

$$D = \{0, 1\}$$

$$= \frac{P(T=1 | D=1) P(D=1)}{\sum_{D=\{0,1\}} P(T=1 | D) P(D)}$$

$$= \frac{P(T=1 | D=1) P(D=1)}{P(T=1 | D=1) P(D=1) + P(T=1 | D=0) P(D=0)}$$

$$= \frac{0.99 \times 0.0001}{0.99 \times 0.0001 + 0.01 \times 0.9999}$$

$$= 0.009804$$

so given that you have tested positive than a random person in the population, probability of you having it is still unlikely