

Assignment 1

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October 2018

Question 1.

(a) $P(A) = 0$, so $P(A \cap B) = P(A) \cdot P(B) = 0$, so, A and B are independent events.

(b) $P(A) = 0.2$, $P(B) = 0.5$, $P(A \cap B) = 0.1 \Rightarrow$

$P(A \cup B) = P(A) + P(B) - P(A \cap B) = 0.6 \Rightarrow$

$P((A \cap \bar{B}) \cup (\bar{A} \cap B)) = P(A)P(1-P(B)) + P(B)(1-P(A)) = 0.5$

(c)

$$\begin{aligned} P(card = GG | see = green) &= \frac{P(see = green | card = GG) * P(card = GG)}{P(see = green)} \\ &= \frac{1 * \frac{1}{3}}{\frac{1}{2}} = \frac{2}{3} \end{aligned}$$

Question 2. Bishop(1.11)

$$\frac{\alpha}{\alpha\mu} = \frac{1}{\sigma^2} \sum_{n=1}^N (x_n - \mu) = \frac{1}{\sigma^2} \sum_{n=1}^N x_n - N\mu = 0$$

since $\mu_{ML} = \bar{x}$, where $\bar{x} = \frac{1}{N} \sum x_n$ is the sample mean.

$$\frac{\alpha}{\alpha\sigma} = -\frac{N}{\sigma} + \frac{1}{\sigma^3} \sum_{n=1}^N (x_n - \bar{x})^2 = 0$$

so,

$$\sigma^2 N = \sigma \sum_{n=1}^N (x_n - \bar{x})^2 = \sigma_{ML}^2 = \frac{1}{N} \sum_{n=1}^N x_n (x_n - \bar{x})^2$$

Question 3. Bishop(1.13)

$$\begin{aligned} E(\sigma_{ML}^2) &= E\left(\frac{1}{N} \sum_{n=1}^N (x_n - \mu)^2\right) = \frac{1}{N} E\left(\sum_{n=1}^N (x_n - \mu)^2\right) \\ &= \frac{1}{N} E\left(\sum_{n=1}^N (x_n^2 - 2x_n\mu + \mu^2)\right) = \frac{1}{N} E\left(\sum_{n=1}^N x_n^2\right) - \frac{1}{N} E\left(\sum_{n=1}^N 2x_n\mu\right) + \frac{1}{N} E\left(\sum_{n=1}^N \mu^2\right) \\ &= \mu^2 + \sigma^2 \frac{2\mu}{N} E\left(\sum_{n=1}^N x_n\right) + \mu^2 = 2\mu^2 + \sigma^2 - 2\mu^2 \\ &= \sigma^2 \end{aligned}$$

Question 4.

if we let

$$w_{ij}^S = \frac{w_{ij} + w_{ji}}{2}, w_{ij}^A = \frac{w_{ij} - w_{ji}}{2}$$

we can get:

$$w_{ij} = w_{ij}^S + w_{ij}^A, w_{ij}^S = w_{ji}^S, w_{ij}^A = -w_{ji}^A$$

because

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij} x_i x_j = \sum_{i=1}^D \sum_{j=1}^D (w_{ij}^S + w_{ij}^A) x_i x_j = \sum_{i=1}^D \sum_{j=1}^D w_{ij}^S x_i x_j + \sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j$$

so we need to prove

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j = 0$$

$$\begin{aligned}
=> 2 \sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j &= \sum_{i=1}^D \sum_{j=1}^D (w_{ij}^A + w_{ji}^A) x_i x_j \\
&= \sum_{i=1}^D \sum_{j=1}^D (w_{ij}^A - w_{ji}^A) x_i x_j \\
&= \sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j - \sum_{i=1}^D \sum_{j=1}^D w_{ji}^A x_i x_j \\
&= \sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j - \sum_{j=1}^D \sum_{i=1}^D w_{ji}^A x_i x_j = 0
\end{aligned}$$

Consider about the symmetry, we can see if and only if $i = 1, 2, \dots, D$ and $i \leq j$, w_{ij} is given, the whole matrix will be determined. So:

$$D + D - 1 + \dots + 1 = \frac{D(D+1)}{2}$$

Question 5.

(a)

$$E(x) = \frac{1}{100} \sum_{x=100}^{200} x = 150$$

(b)

$$jump : E(X_i) = (-1)p + 1(1-p) = 1 - 2p$$

$$E(X_1 + X_2 + \dots + X_n) = E(X_1) + E(X_2) + \dots + E(X_n) = n(1 - 2p)$$

(c) Areas means $S = X * Y$, because X and Y are independent, so

$$E(XY) = E(X)E(Y) = 1/2 * 7 = 3.5$$

(d) because $V(x) = E(x^2) - E(x)^2$ so,

$$E(x(x-1)) = E(x^2 - x) = E(x^2) - E(x) = V(x) + E(x)^2 - \mu = \sigma^2 + \mu^2 - \mu$$

Question 6.(Bishop 2.8)

(2.270)

$$\begin{aligned}
 E_y[E_x[x|y]] &= \int E_x[x|y]p(y)d_y \\
 &= \int (\int xp(x|y)d_x)p(y)d_y \\
 &= \int \int xp(x|y)p(y)d_xd_y = \int \int xp(x,y)d_xd_y \\
 &= \int xp(x)d_x = E[x]
 \end{aligned}$$

(2.271)

$$\begin{aligned}
 &E_y[var_x[x|y]] + var_y[E_x[x|y]] \\
 &= E_y[E_x[x^2|y] - E_x[x|y]^2] + E_y[E_x[x|y]^2] - E_y[E_x[x|y]]^2 \\
 &= E_y[E_x[x^2|y]] - E_y[E_x[x|y]^2] + E_y[E_x[x|y]^2] - E_y[E_x[x|y]]^2 \\
 &= E_y[E_x[x^2|y]] - E_y[E_x[x|y]]^2
 \end{aligned}$$

because $E_y[E_x[x|y]] = E[x]$, we can get

$$E_y[E_x[x^2|y]] = E[x^2]$$

so

$$E_y[var_x[x|y]] + var_y[E_x[x|y]] = E_x[x^2] + E_x[x]^2 = var_x[x]$$

Question 7.(Bishop 2.12)

$$\begin{aligned}
\int_a^b \frac{1}{b-a} dx &= 1 \\
E[x] &= \int_a^b x \frac{1}{b-a} dx = \frac{[x^2]_a^b}{2(b-a)} = \frac{b^2 - a^2}{2(b-a)} = \frac{a+b}{2} \\
E[x^2] &= \int_a^b x^2 \frac{1}{b-a} dx = \frac{[x^3]_a^b}{3(b-a)} = \frac{b^3 - a^3}{3(b-a)} = \frac{a^2 + ab + b^2}{3} \\
var[x] &= E[x^2] - E[x]^2 = \frac{a^2 + ab + b^2}{3} - \frac{(a+b)^2}{4} = \frac{(b-a)^2}{12}
\end{aligned}$$

Question 8.

since $X = N(1, 2^2)$, we have $Z = \frac{X-1}{2}$, so

$$P(X \leq 3) = P\left(\frac{X-1}{2} \leq 1\right) = P(Z \leq 1) = 0.8413$$

$$P(|X| \leq 2) = P(-2 \leq X \leq 2) = P(-1.5 \leq Z \leq 0.5) = 0.6247$$

Question 9.

Assume B: blue eyes; O: other color eyes; G: grey eyes; NF: not in the first

$$\begin{aligned}
P(B|NF) &= \frac{P(B)P(NF|B)}{P(B)P(NF|B) + P(O)P(NF|O) + P(G)P(NF|G)} \\
&= \frac{0.5 * 0.18}{0.5 * 0.18 + 0.2 * 0.5 + 0.3 * 0.35} = 0.3051
\end{aligned}$$

Question 10.

(a)

$$\begin{aligned}
&P(\text{Label} = \text{Yes} | \text{Home} = \text{Yes}, \text{Married}, \text{Income} = 70K) \\
&= \frac{P(\text{Home} = \text{Yes}, \text{Married}, \text{Income} = 70K | \text{Label} = \text{Yes})P(\text{Label} = \text{Yes})}{P(\text{Home} = \text{Yes}, \text{Married}, \text{Income} = 70K)} \\
&= \frac{0 * \frac{3}{10}}{P(\text{Home} = \text{Yes}, \text{Married}, \text{Income} = 70K)} = 0
\end{aligned}$$

so the class label of instance X is NO

(b)

$$\begin{aligned} & P(\text{Label} = \text{Yes} | \text{Home} = \text{No}, \text{Single}, \text{Income} > 80K) \\ = & \frac{P(\text{Home} = \text{No}, \text{Single}, \text{Income} > 80K | \text{Label} = \text{Yes})P(\text{Label} = \text{Yes})}{P(\text{Home} = \text{No}, \text{Single}, \text{Income} > 80K)} \\ & = \frac{\frac{2}{3} * \frac{3}{10}}{\frac{2}{10}} = 1 \end{aligned}$$

so the class label of instance X is YES