

(1) SS42 Problem set 2

PAUL Emerick NGOUCHET

1.6

a) when two variables are independent

$$E(x \cdot y) = E(x) \cdot E(y)$$

$$\text{cov}(x, y) = E(x \cdot y) - E(x) \cdot E(y)$$

$$= E(x) \cdot E(y) - E(x) \cdot E(y)$$

$$\boxed{\text{cov}(x, y) = 0}$$

b) i. $P(+ | \text{has HIV}) = \frac{72}{75}$
ii. $P(- | \text{with HIV}) = \frac{3}{75}$

iii. $P(\text{has HIV} | +) = \frac{P(+ | \text{has HIV}) \cdot P(\text{has HIV})}{P(+)}$

$$P(+)=P(+|\text{HIV}) \cdot P(\text{HIV}) + P(+|\text{No HIV}) \cdot P(\text{No HIV})$$
$$=0.2424$$

$$P(\text{has HIV} | +) = \frac{P(\text{HIV}) \cdot P(+|\text{HIV})}{P(+)}$$

$$= \frac{0.12 \times 0.86}{0.2424}$$

$$\boxed{P(\text{has HIV} | +) = 0.475 = 47.5\%}$$

$$P(-) = P(-|HEV) \cdot P(HEV) + P(-|NoHEV) \cdot P(NoHEV) \\ = 0.7576$$

$$P(HEV|-) = 0.0063$$

2. Bayes Theorem

(a) $P(C) + \frac{1}{2}P(C) + \frac{1}{2}P(C) + \frac{1}{2}P(C) = 1$

$$\begin{aligned} P(A|B) &= \frac{3}{5} / 2 = 0.3 \\ P(D|B) &= \frac{3}{5} / 2 = 0.3 \\ P(C|B) &= \frac{2}{5} = 0.4 \end{aligned}$$

$$(1 + \frac{3}{2})P(C) = 1$$

$$P(C) = \frac{2}{5}$$

$$P(A) = \frac{1}{5} \quad P(B) = \frac{1}{5}$$

$$P(D) = \frac{1}{5}$$

$$P(A) + P(B) + P(D) = \frac{3}{5}$$

by opening the door B $P(B)$ and $P(A) \cdot P(D) \Rightarrow P(A)$ and $P(D) \Rightarrow \frac{3}{5}$

b)

	Suspected	Not suspected	Total
Cheating	1.8	0.2	2
Not cheating	14.6	58.4	73
Total	16.4	58.6	75

$$P(\text{cheating} | \text{Suspected}) = \frac{1.8}{16.4} = 0.1097 = 10.97\%$$

3. Linear Algebra

(2)

(a)

$$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}^T \Rightarrow \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}^{-1} \Rightarrow \frac{1}{1-4} \begin{bmatrix} 1 & -2 \\ -2 & 1 \end{bmatrix}$$

$$\Rightarrow \frac{1}{3} \begin{bmatrix} 1 & -2 \\ -2 & 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} \frac{1}{3} & -\frac{2}{3} \\ -\frac{2}{3} & \frac{1}{3} \end{bmatrix}$$

$$\begin{bmatrix} \frac{1}{3} & -\frac{2}{3} \\ -\frac{2}{3} & \frac{1}{3} \end{bmatrix}^T \Rightarrow \begin{bmatrix} \frac{1}{3} & -\frac{2}{3} \\ -\frac{2}{3} & \frac{1}{3} \end{bmatrix}$$


True, the inverse of a symmetric matrix is itself symmetric.

$$A = \begin{bmatrix} 3 & 4 & -2 \\ -2 & -2 & 1 \\ 3 & 9 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 3-\lambda & 4 & -1 \\ -1 & -1-\lambda & 1 \\ 0 & 9 & -2 \end{bmatrix}$$

$$3-\lambda \begin{bmatrix} -1-\lambda & 1 \\ 9 & -2 \end{bmatrix} - 4 \begin{bmatrix} -1 & 1 \\ 0 & -2 \end{bmatrix} - 1 \begin{bmatrix} -1 & -1-\lambda \\ 0 & 9 \end{bmatrix}$$

$$3-\lambda(-2\lambda+\lambda^2-9) - 4(\lambda-0) - 1(-9-0)$$

$$6\lambda + 3\lambda^2 - 27 - 2\lambda^2 - \lambda^3 + 9\lambda - 4\lambda + 9 + 12 - 6$$

$$-\lambda^3 + \lambda^2 + 12\lambda + 6$$

$$8\lambda + \lambda^2 - \lambda^3 - 22$$

$$-(\lambda^3 + \lambda^2 + 4 - 4\lambda)(\lambda + 3)$$

$$\boxed{\lambda = 2 \text{ and } \lambda = -3} \text{ eigenvalues.}$$

$\lambda = 2$ Eigenvectors

$$\left(\begin{array}{ccc|c} 1 & 4 & -1 & 0 \\ -1 & -1 & 1 & 0 \\ 3 & 9 & -2 & 0 \end{array} \right)$$

$$\Rightarrow \text{vector} \begin{pmatrix} -\frac{1}{3} \\ \frac{1}{3} \\ 1 \end{pmatrix}$$

$\lambda = -3$

$$\left(\begin{array}{ccc|c} 6 & 4 & -1 & 0 \\ -1 & 2 & 1 & 0 \\ 3 & 9 & 13 & 0 \end{array} \right)$$

$$\Rightarrow \text{vector} \begin{pmatrix} \frac{1}{2} \\ -\frac{1}{2} \\ 1 \end{pmatrix}$$

$\lambda = 2, \lambda = -3$
Not all the eigenvalues are positive. so

A is not positive definite

3. Probability distributions. (3)

Bishop.

2.2 Normalization

$$P(x=+1/\mu) + P(x=-1/\mu) = \left(\frac{1+\mu}{2}\right) + \left(\frac{1-\mu}{2}\right) = 1$$

The mean is given by

$$E(x) = \left(\frac{1+\mu}{2}\right) - \left(\frac{1-\mu}{2}\right) = \mu.$$

Variance.

$$E(x^2) = \left(\frac{1-\mu}{2}\right) + \left(\frac{1+\mu}{2}\right) = 1.$$

$$\text{Var}[x] = E[x^2] - E[x]^2 = 1 - \mu^2$$

Entropy.

$$H[x] = - \sum_{x=\pm 1} P(x/\mu) \ln P(x/\mu)$$

$$H[x] = - \left(\frac{1-\mu}{2}\right) \ln \left(\frac{1-\mu}{2}\right) - \left(\frac{1+\mu}{2}\right) \ln \left(\frac{1+\mu}{2}\right).$$

2.10

$$\int \prod_{k=1}^M u_k^{\alpha_k-1} du = \frac{\Gamma(\alpha_1) \cdots \Gamma(\alpha_M)}{\Gamma(\alpha_0)} \quad (88)$$

$$\begin{aligned} E[u_j] &= \frac{\Gamma(\alpha_0)}{\Gamma(\alpha_1) \cdots \Gamma(\alpha_M)} \int u_j \prod_{k=1}^M u_k^{\alpha_k-1} du \\ &= \frac{\Gamma(\alpha_0)}{\Gamma(\alpha_1) \cdots \Gamma(\alpha_M)} \cdot \frac{\Gamma(\alpha_1) \cdots \Gamma(\alpha_{j+1}) \cdots \Gamma(\alpha_M)}{\Gamma(\alpha_0 + 1)} \end{aligned}$$

$$E[u_j] = \frac{\alpha_j}{\alpha_0}$$

$$\text{Var}[u_j] = E[u_j^2] - E[u_j]^2 = \frac{\alpha_j(\alpha_j+1)}{\alpha_0(\alpha_0+1)} - \frac{\alpha_j^2}{\alpha_0^2}$$

$$\text{Var}[u_j] = \frac{\alpha_j(\alpha_0 - \alpha_j)}{\alpha_0^2(\alpha_0 + 1)}$$

$$\text{Cov}[u_j, u_L] = E[u_j u_L] - E[u_j] E[u_L]$$

$$\text{Cov}[u_j, u_L] = \frac{\alpha_j \alpha_L}{\alpha_0(\alpha_0+1)} - \frac{\alpha_j \alpha_L}{\alpha_0 \alpha_0} = -\frac{\alpha_j \alpha_L}{\alpha_0^2(\alpha_0+1)}$$

(4)

2.12.

$$\int_a^b \frac{1}{b-a} dx = \frac{b-a}{b-a} = 1 \quad \text{Normalization}$$

$$E(x) = \int_a^b \frac{1}{b-a} x dx = \left[\frac{x^2}{2(b-a)} \right]_a^b = \frac{b^2 - a^2}{2(b-a)} = \frac{a+b}{2}$$

$$E[x^2] = \int_a^b \frac{1}{b-a} x^2 dx = \left[\frac{x^3}{3(b-a)} \right]_a^b = \frac{b^3 - a^3}{3(b-a)} = \frac{a^2 + ab + b^2}{3}$$

$$\begin{aligned} \text{Var}[x] &= E[x^2] - E[x]^2 = \frac{a^2 + ab + b^2}{3} - \frac{(a+b)^2}{4} \\ &= \frac{(b-a)^2}{12} \end{aligned}$$

2.15.

$$H[x] = - \int N(x|\mu, \Sigma) \ln N(x|\mu, \Sigma) dx$$

$$= \int N(x|\mu, \Sigma) \frac{1}{2} (D \ln(2\pi) + \ln|\Sigma| + (x-\mu)^T$$

$$= \frac{1}{2} (D \ln(2\pi) + \ln|\Sigma| + \text{Tr}[\Sigma^{-1} \Sigma]) \int N(x|\mu, \Sigma) dx$$

$$H[x] = \frac{1}{2} (D \ln(2\pi) + \ln|\Sigma| + D)$$