

Question 3

Show that $\text{Cov}(X) = E(XX') - \mu\mu'$
 $\mu = E(X)$

$$\text{Var}(X) = E((X - \mu)^2) = \text{Cov}(X, X)$$

$$\text{Var}(X) = E(X^2) - \mu^2$$

$$\text{Cov}(X) = E((X - \mu)(X' - \mu'))$$

$$= E(XX' - \mu X' - X\mu + \mu\mu')$$

$$= E(XX') - \mu E(X') - E(X)\mu + \mu\mu'$$

$$= \underline{E(XX') - \mu\mu'}$$

Question 4

Show that (i, j) th term of $H = X(X'X)^{-1}X'$

$$h_{ij} = \frac{1}{n} + \frac{(x_i - \bar{x})(x_j - \bar{x})}{S_{xx}}$$

$$Y = X\beta + e$$

$$X'X\beta = X'Y$$

$$\hat{\beta} = (X'X)^{-1}X'Y$$

$$\hat{Y} = X\hat{\beta} = X(X'X)^{-1}X'Y$$

$$\text{var}(Y_i) = \sigma^2 \sum_{j=1}^n h_{ij}^2$$

$$= \sigma^2 \sum_{j=1}^n \left(\frac{1}{n} + \frac{(x_i - \bar{x})(x_j - \bar{x})}{\sum_{k=1}^n (x_k - \bar{x})^2} \right)^2$$

$$\sqrt{\sigma^2} = \frac{\sigma^2}{\sigma^2} \sqrt{\sum_{j=1}^n \left(\frac{1}{n} + \frac{(x_i - \bar{x})(x_j - \bar{x})}{\sum_{k=1}^n (x_k - \bar{x})^2} \right)^2} \quad S_{xx} = \sum_{k=1}^n (x_k - \bar{x})^2$$

$$= \frac{1}{n} + \frac{(x_i - \bar{x})(x_j - \bar{x})}{S_{xx}}$$

Show that the trace of H is 2

If X is $i \times j$ with $j \leq i$ and has a full rank, then $\text{rank}(X) = \min(i, j) = j$ and we know that $(X'X)^{-1}$ exists

By commutativity of the trace operator

$$\text{tr}(H) = \text{tr}(X(X'X)^{-1}X')$$

$$= \text{tr}(X'X(X'X)^{-1}) = \text{tr}(I_m) = m$$

but H is 2×2 matrix hence $m=2$

$$\text{tr}(I_2) = 2$$

Question 5(a)

$$Y = AX \quad X = (X_1, X_2)' \quad A \text{ is } 2 \times 2 \text{ matrix of constants}$$

(a) Derive the elements of the vector $Y = (Y_1, Y_2)'$ by matrix multiplication.

$$Cov(Y) = Cov(Y_1, Y_2)$$

$$\equiv \begin{pmatrix} Var(Y_1) & Cov(Y_1, Y_2) \\ Cov(X_2, Y_1) & Var(Y_2) \end{pmatrix}$$

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix} = \begin{pmatrix} a_1 & \dots & a_n \\ \vdots & \ddots & \vdots \\ a_n & \dots & a_n \end{pmatrix} \begin{pmatrix} X_1 \dots X_n \\ \vdots \\ X_n \dots X_{n+2} \end{pmatrix}$$

$$= \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{matrix} a_{11}X_1 + \dots + a_{1n}X_n \\ a_{21}X_1 + \dots + a_{2n}X_n \end{matrix}$$

$$\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} a_{11}X_1 & \dots & a_{1n}X_n \\ a_{21}X_1 & \dots & a_{2n}X_n \end{pmatrix}$$

Question 5b

$$\text{Cov}(Y) = \begin{pmatrix} \text{Var}(Y_1) & \text{Cov}(Y_1, Y_2) \\ \text{Cov}(Y_1, Y_2) & \text{Cov}(Y_2) \end{pmatrix}$$

$$\text{VAR}[Y] = E[YY'] - E(Y) \cdot E(Y)'$$

Let Y is a 2×1 random vector with components (Y_1, Y_2)

$$\text{Let } \text{Var}(Y_1) = 2$$

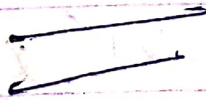
$$\text{Var}(Y_2) = 4$$

$$\text{Cov}(Y_1, Y_2) = 1$$

By the symmetry of covariance it must also be

$$\text{Cov}(Y_1, Y_2) = \text{Cov}(Y_2, Y_1) = 1$$

$$\text{Cov}(Y) = \begin{bmatrix} 2 & 1 \\ 1 & 4 \end{bmatrix}$$



Question 3 (c)

Show by matrix multiplication

$$\text{Cov}(Y) = A \text{Cov}(X) A'$$

$$\text{Cov}(Y) = A \text{Cov}(X) A'$$

Proof.

$$\begin{aligned} \text{Cov}(Y) &= E[(AY - E[AY])(AY - E[AY])'] \\ &= E[(AY - E[AY])(AY - E[AY])'] \\ &= A E[(X - E[X])(X - E[X])'] A' \\ &= A \text{Cov}(X) A' \end{aligned}$$

Question 7 (a)

X_1, \dots, X_n are iid g.r.v with parameter p .

$$f(x) = (1-p)^{x-1} p \quad \text{for } x=1, 2, \dots$$

Find maximum likelihood estimator for p .

$$L(p) = \prod_{i=1}^n p(1-p)^{x_i-1}$$

$$L(p) = p^n (1-p)^{\sum x_i - n}$$

Taking \ln both sides

$$\ln L(p) = n \ln p + \sum (x_i - n) \ln(1-p)$$

Differentiate with respect to p

$$\frac{d}{dp} \ln L(p) = n \frac{d}{dp} \ln p + (\sum x_i - n) \frac{d}{dp} \ln(1-p)$$

$$\frac{d}{dp} \ln L(p) = \frac{n}{p} - \frac{1}{1-p} (\sum x_i - n) \quad \dots (i)$$

$$\text{Put } \frac{d}{dp} \ln L(p) = 0$$

$$\frac{n}{p} - \frac{1}{1-p} (\sum x_i - n) = 0$$

$$n(1-p) = p(\sum x_i - n)$$

$$p = \frac{n}{\sum x_i}$$

(7d)

find 2nd derivative with respect to p

$$\frac{d^2}{dp^2} \ln L(p) = \frac{-n}{p^2} - \frac{(\sum x - n)}{(1-p)^2}$$

$$\frac{d^2}{dp^2} \ln L(p) = \frac{-n(1-p)^2 - p^2(\sum x - n)}{p^2(1-p)^2}$$

$$= \frac{-n + np}{p^2(1-p)^2}$$

$$= \frac{-n}{p^2(1-p)} < 0 \text{ as } 0 < p < 1$$

So Maximum Likelihood Estimator of p

$$\hat{p} = \frac{n}{\sum x} = \frac{1}{\frac{\sum x}{n}} = \frac{1}{\bar{x}}$$

$$= \frac{1}{\bar{x}}$$

$$= \frac{-n + np}{p^2(1-p)^2}$$

$$= \frac{-n}{p^2(1-p)} \quad \text{L.O. as } 0 < p < 1$$

So Maximum Likelihood Estimator of p

$$\begin{aligned} \hat{p} &= \frac{n}{\sum x} = \frac{1}{\frac{\sum x}{n}} = \frac{1}{\bar{x}} \\ &= \frac{1}{\bar{x}} \end{aligned}$$

(7) (b) Show that this is not equal to the moment estimator of p .

Moment Generating function.

$$\begin{aligned} M(t) &= E(e^{tx}) \\ &= \sum_{x=1}^{\infty} e^{tx} (1-p)^{x-1} p \\ &= p \sum_{x=1}^{\infty} e^{tx} e^{-t} e^{-t(x-1)} (1-p)^{x-1} \\ &= p e^t \sum_{x=1}^{\infty} e^{t(x-1)} (1-p)^{x-1} \end{aligned}$$

(7b)

$$= p e^t (1 + \theta + \theta^2 + \dots)$$

$$= \frac{p e^t}{1 - \theta} \quad \text{if } |\theta| < 1$$

$$= \frac{p e^t}{1 - q e^t}$$

$$= \frac{1}{p}$$

hence $\frac{1}{x} = \frac{1}{p}$
