

## Example Sheet 3 (of 3)

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1. Consider the simple linear regression model

$$Y_i = \alpha + \beta x_i + \epsilon_i$$

where  $\epsilon_1, \dots, \epsilon_n \stackrel{iid}{\sim} N(0, \sigma^2)$  and  $\sum_{i=1}^n x_i = 0$ . Derive from first principles explicit expressions for the MLEs  $\hat{\alpha}$ ,  $\hat{\beta}$  and  $\hat{\sigma}^2$ . Let  $A$  be an  $n \times n$  orthogonal matrix where the entries in the first row are all equal to  $1/\sqrt{n}$ , and where the  $j$ th entry in the second row is  $x_j/\sqrt{S_{xx}}$ . By considering the distribution of  $Z = AY$ , derive the joint distribution of  $\hat{\alpha}$ ,  $\hat{\beta}$  and  $\hat{\sigma}^2$ .

2. The relationship between the range in metres,  $Y$ , of a howitzer with muzzle velocity  $v$  metres per second fired at angle of elevation  $\alpha$  degrees is assumed to be

$$Y = \frac{v^2}{g} \sin(2\alpha) + \epsilon,$$

where  $g = 9.81$  and where  $\epsilon \sim N(0, \sigma^2)$ . Estimate  $v$  from the following independent observations made on 9 shells, and provide a 95% confidence interval for  $v$ .

$\alpha$ (deg)	5	10	15	20	25	30	35	40	45
$\sin 2\alpha$	0.1736	0.3420	0.5	0.6428	0.7660	0.8660	0.9397	0.9848	1
range (m)	4860	9580	14080	18100	21550	24350	26400	27700	28300

3. Let  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ . By considering the distribution of the random vector

$$(\bar{X}, X_1 - \bar{X}, X_2 - \bar{X}, \dots, X_n - \bar{X}),$$

where  $\bar{X} = n^{-1} \sum_{i=1}^n X_i$ , show that  $\bar{X}$  and  $(X_1 - \bar{X}, \dots, X_n - \bar{X})$  are independent. Hence give an alternative proof to the one from lectures of the fact that  $\bar{X}$  and  $S_{XX} = \sum_{i=1}^n (X_i - \bar{X})^2$  are independent.

4. Consider the linear model  $Y = X\beta + \epsilon$ , where  $\mathbb{E}(\epsilon) = 0$  and  $\text{Cov}(\epsilon) = \sigma^2 \Sigma$ , for some unknown parameter  $\sigma > 0$  and known positive definite matrix  $\Sigma$ . Derive the form of the Generalised Least Squares estimator  $\tilde{\beta}^{GLS}$ , defined by

$$\tilde{\beta}^{GLS} = \text{argmin}_{\beta} (Y - X\beta)^T \Sigma^{-1} (Y - X\beta).$$

State and prove a version of the Gauss–Markov theorem for  $\tilde{\beta}^{GLS}$ .

5. Suppose  $X_1, \dots, X_m, Y_1, \dots, Y_n$  are independent, with  $X_1, \dots, X_m \sim N(\mu_X, \sigma^2)$  and  $Y_1, \dots, Y_n \sim N(\mu_Y, \sigma^2)$ , where  $\sigma$  is unknown. Derive the likelihood ratio test of size  $\alpha$  of  $H_0 : \mu_X = \mu_Y$  against  $H_1 : \mu_X \neq \mu_Y$ , showing in particular that it can be expressed in terms of

$$T = \frac{(\bar{X} - \bar{Y})}{\sqrt{\frac{S_{XX} + S_{YY}}{m+n-2} \left( \frac{1}{m} + \frac{1}{n} \right)}}.$$

**6.** Download the ‘Mobile phone data’ at <http://www.statslab.cam.ac.uk/~rjs57/Teaching.html>, and read the description that accompanies the data. Explain why, if each student carries out the task both with and without a mobile phone, we should consider a single sample  $t$ -test based on the matched paired differences, whereas if students are assigned only to one group or the other, we should consider a two sample  $t$ -test. Carry out both tests at the 5% level.

**7.** Suppose  $X_1, \dots, X_m, Y_1, \dots, Y_n$  are independent, with  $X_1, \dots, X_m \sim N(\mu_X, \sigma_X^2)$  and  $Y_1, \dots, Y_n \sim N(\mu_Y, \sigma_Y^2)$ , and we wish to test  $H_0 : \sigma_X^2 = \sigma_Y^2$  against  $H_1 : \sigma_X^2 > \sigma_Y^2$  with  $\mu_X, \mu_Y$  unknown. Show that for  $S_{XX}/S_{YY} > m/n$ , the likelihood ratio is an increasing function of  $S_{XX}/S_{YY}$ , and derive a size  $\alpha$  test.

**8.** Download the ‘Cars data demo’ at <http://www.statslab.cam.ac.uk/~rjs57/Teaching.html> and work through the commands in **R**. Carry out the exercise at the end.

**9.** Derive from first principles the form of the size  $\alpha$  likelihood ratio test of equality of means in a one-way Analysis of Variance model.

**10.** If  $X_1, \dots, X_n$  are independent with  $X_i \sim N(\mu_i, 1)$ , we say  $X = \sum_{i=1}^n X_i^2$  has a *non-central chi-squared distribution* with  $n$  degrees of freedom and non-centrality parameter  $\lambda = \sum_{i=1}^n \mu_i^2$  and write  $X \sim \chi_n^2(\lambda)$ . In this case  $X$  has probability density function

$$f(x; n, \lambda) = \sum_{r=0}^{\infty} \frac{e^{-\lambda/2} \lambda^r}{2^r r!} \frac{x^{\frac{n}{2}+r-1} e^{-x/2}}{2^{\frac{n}{2}+r} \Gamma(\frac{n}{2}+r)}, \quad x \in (0, \infty).$$

Show that if  $R \sim \text{Poi}(\lambda/2)$  and the conditional distribution of  $X$  given  $R$  is  $\chi_{n+2R}^2$ , then  $X \sim \chi_n^2(\lambda)$ . Hence or otherwise compute  $\mathbb{E}(X)$  and  $\text{Var}(X)$ .

**11.\* (Extension of Cochran’s theorem)** Let  $Y \sim N_n(\mu, \sigma^2 I)$ , and let  $A_1, \dots, A_k$  be  $n \times n$  symmetric matrices with  $\text{rank}(A_i) = r_i$  and  $A_1 + \dots + A_k = I$ . Suppose that  $r_1 + \dots + r_k = n$ . Write down expressions for  $A_i^2$  and  $A_j A_i$  for  $j \neq i$ . Hence show that we have the orthogonal direct sum decomposition  $\mathbb{R}^n = \text{Im}(A_1) \oplus \dots \oplus \text{Im}(A_k)$ , where  $\text{Im}(A_i) = \{A_i x : x \in \mathbb{R}^n\}$  denotes the image of  $A_i$ . Deduce that there exists an  $n \times n$  orthogonal matrix  $Q$  such that

$$Q^T A_i Q = \begin{pmatrix} 0 & 0 & 0 \\ 0 & I_{r_i} & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

for all  $i = 1, \dots, k$ , where the ones occur in diagonal entries  $\sum_{l=1}^{i-1} r_l + 1, \dots, \sum_{l=1}^i r_l$ . Finally, show that  $Y^T A_1 Y, \dots, Y^T A_k Y$  are independent, with  $Y^T A_i Y \sim \sigma^2 \chi_{r_i}^2(\frac{1}{\sigma^2} \mu^T A_i \mu)$ .

**12.** Let  $Y = X\beta + \epsilon$ , where  $X$  and  $\beta$  are partitioned as  $X = (X_0 \ X_1)$  and  $\beta^T = (\beta_0^T, \beta_1^T)$  (where  $\beta_0$  has  $p_0$  components and  $\beta_1$  has  $p - p_0$  components). Recall that the likelihood ratio statistic for testing  $H_0 : \beta_1 = 0$  against  $H_1 : \beta_1 \neq 0$  is  $\|PY - P_0 Y\|^2 / \|Y - PY\|^2$ , where  $P = X(X^T X)^{-1} X^T$  and  $P_0 = X_0(X_0^T X_0)^{-1} X_0^T$ . Determine the joint distribution of  $\|PY - P_0 Y\|^2$  and  $\|Y - PY\|^2$  under  $H_1$ .