

## MTH 207A: Assignment 4

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**P 1.** Consider the one-way ANOVA model

$$y_{ij} = \mu + \alpha_i + \epsilon_{ij}, \quad i = 1, \dots, K, \quad j = 1, \dots, n_i \quad (1)$$

where  $\epsilon_{ij}$  are i.i.d.  $N(0, \sigma^2)$ .

(a) Find the residual sum of squares ( $RSS$ ) for the model (1).

(b) Find the distribution of  $RSS/\sigma^2$ .

**Solution:** For the model (1), the design matrix  $X$  is

$$X = \begin{bmatrix} \mathbf{1}_{n_1} & \mathbf{1}_{n_1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{1}_{n_2} & \mathbf{0} & \mathbf{1}_{n_2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{1}_{n_K} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{1}_{n_K} \end{bmatrix}_{n \times (K+1)}.$$

where  $n = \sum_{i=1}^K n_i$ .

Since  $X$  is not a full rank matrix, the least square estimator of  $\beta = (\mu, \alpha_1, \dots, \alpha_K)'$  is given by

$$\hat{\beta} = (X'X)^- X'y.$$

First we shall compute  $\hat{\beta}$ .

$$X'X = \begin{bmatrix} n & n_1 & n_2 & \cdots & n_K \\ n_1 & n_1 & 0 & \cdots & 0 \\ n_2 & 0 & n_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ n_K & 0 & 0 & \cdots & n_K \end{bmatrix}.$$

It can be shown that

$$(X'X)^- = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 1/n_1 & 0 & \cdots & 0 \\ 0 & 0 & 1/n_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1/n_K \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{0}' \\ \mathbf{0}' & D^{-1} \end{bmatrix}.$$

where

$$D = \begin{bmatrix} n_1 & 0 & \cdots & 0 \\ 0 & n_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & n_K \end{bmatrix}.$$

Also,

$$X'y = \begin{bmatrix} \sum_{i=1}^K \sum_{j=1}^{n_i} y_{ij} \\ \sum_{j=1}^{n_1} y_{1j} \\ \vdots \\ \sum_{j=1}^{n_K} y_{Kj} \end{bmatrix}.$$

Therefore,

$$\hat{\beta} = (X'X)^- X'y = \begin{bmatrix} 0 \\ \sum_{j=1}^{n_1} y_{1j}/n_1 \\ \vdots \\ \sum_{j=1}^{n_K} y_{Kj}/n_K \end{bmatrix} = \begin{bmatrix} 0 \\ \bar{y}_1 \\ \vdots \\ \bar{y}_K \end{bmatrix}.$$

Thus  $\hat{\mu} = 0$  and  $\hat{\alpha} = \bar{y}_i$  for  $i = 1, \dots, K$ . Now

$$\begin{aligned} RSS &= \sum_{i=1}^K \sum_{j=1}^{n_i} (y_{ij} - \hat{\alpha})^2 = \sum_{i=1}^K \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_i)^2 \\ &= \sum_{i=1}^K \sum_{j=1}^{n_i} (y_{ij}^2 + (\bar{y}_i)^2 - 2y_{ij}\bar{y}_i) = \sum_{i=1}^K \left( \sum_{j=1}^{n_i} y_{ij}^2 - n_i (\bar{y}_i)^2 \right) \end{aligned}$$

Now observe that

$$\begin{aligned} n_i (\bar{y}_i)^2 &= n_i (\bar{y}_i)' (\bar{y}_i) \\ &= \left[ (1/n_i) \begin{bmatrix} \mathbf{0}'_{n_1} & \cdots & \mathbf{0}'_{n_{i-1}} & \mathbf{1}'_{n_i} & \mathbf{0}'_{n_{i+1}} & \cdots & \mathbf{0}'_{n_K} \end{bmatrix} \mathbf{y} \right]' \\ &\quad \times \left[ (1/n_i) \begin{bmatrix} \mathbf{0}'_{n_1} & \cdots & \mathbf{0}'_{n_{i-1}} & \mathbf{1}'_{n_i} & \mathbf{0}'_{n_{i+1}} & \cdots & \mathbf{0}'_{n_K} \end{bmatrix} \mathbf{y} \right] \\ &= \frac{1}{n_i} \mathbf{y}' \begin{bmatrix} \mathbf{0}_{n_1} \\ \vdots \\ \mathbf{0}_{n_{i-1}} \\ \mathbf{1}_{n_i} \\ \mathbf{0}_{n_{i+1}} \\ \vdots \\ \mathbf{0}_{n_K} \end{bmatrix} \begin{bmatrix} \mathbf{0}'_{n_1} & \cdots & \mathbf{0}'_{n_{i-1}} & \mathbf{1}'_{n_i} & \mathbf{0}'_{n_{i+1}} & \cdots & \mathbf{0}'_{n_K} \end{bmatrix} \mathbf{y} \\ &= \mathbf{y}' \mathbf{E}_{n_i} \mathbf{y} \end{aligned}$$

where

$$\mathbf{E}_{n_i} = \begin{bmatrix} Z_{n_1 \times n_1} & Z_{n_1 \times n_2} & \cdots & Z_{n_1 \times n_i} & \cdots & Z_{n_1 \times n_K} \\ Z_{n_2 \times n_1} & Z_{n_2 \times n_2} & \cdots & Z_{n_2 \times n_i} & \cdots & Z_{n_2 \times n_K} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ Z_{n_{i-1} \times n_1} & Z_{n_{i-1} \times n_2} & \cdots & Z_{n_{i-1} \times n_i} & \cdots & Z_{n_{i-1} \times n_K} \\ Z_{n_i \times n_1} & Z_{n_i \times n_2} & \cdots & (1/n_i) \mathbf{J}_{n_i \times n_i} & \cdots & Z_{n_i \times n_K} \\ Z_{n_{i+1} \times n_1} & Z_{n_{i+1} \times n_2} & \cdots & Z_{n_{i+1} \times n_i} & \cdots & Z_{n_{i+1} \times n_K} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \\ Z_{n_K \times n_1} & Z_{n_K \times n_2} & \cdots & Z_{n_K \times n_i} & \cdots & Z_{n_K \times n_K} \end{bmatrix}$$

$Z_{n_i \times n_j}$  is  $n_i \times n_j$  matrix of all zeros and  $\mathbf{J}_{n_i \times n_j}$  is  $n_i \times n_j$  matrix of all ones.

Thus

$$RSS = \mathbf{y}' \mathbf{y} - \sum_{i=1}^K \mathbf{y}' \mathbf{E}_{n_i} \mathbf{y} = \mathbf{y}' \mathbf{y} - \mathbf{y}' \mathbf{J}_n \mathbf{y} = \mathbf{y}' [\mathbf{I} - \mathbf{J}_n] \mathbf{y},$$

where

$$\mathbf{J}_n = \begin{bmatrix} (1/n_1) \mathbf{J}_{n_1 \times n_1} & Z_{n_1 \times n_2} & \cdots & Z_{n_1 \times n_i} & \cdots & Z_{n_1 \times n_K} \\ Z_{n_2 \times n_1} & (1/n_2) \mathbf{J}_{n_2 \times n_2} & \cdots & Z_{n_2 \times n_i} & \cdots & Z_{n_2 \times n_K} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ Z_{n_{i-1} \times n_1} & Z_{n_{i-1} \times n_2} & \cdots & Z_{n_{i-1} \times n_i} & \cdots & Z_{n_{i-1} \times n_K} \\ Z_{n_i \times n_1} & Z_{n_i \times n_2} & \cdots & (1/n_i) \mathbf{J}_{n_i \times n_i} & \cdots & Z_{n_i \times n_K} \\ Z_{n_{i+1} \times n_1} & Z_{n_{i+1} \times n_2} & \cdots & Z_{n_{i+1} \times n_i} & \cdots & Z_{n_{i+1} \times n_K} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \\ Z_{n_K \times n_1} & Z_{n_K \times n_2} & \cdots & Z_{n_K \times n_i} & \cdots & (1/n_K) \mathbf{J}_{n_K \times n_K} \end{bmatrix}$$

Next, it can be shown that  $[\mathbf{I} - \mathbf{J}_n] \mathbf{X} = \mathbf{0}$ . Hence

$$RSS = \mathbf{y}' \mathbf{y} - \sum_{i=1}^K \mathbf{y}' \mathbf{E}_{n_i} \mathbf{y} = \mathbf{y}' \mathbf{y} - \mathbf{y}' \mathbf{J}_n \mathbf{y} = \mathbf{y}' [\mathbf{I} - \mathbf{J}_n] \mathbf{y} = (\mathbf{y} - \mathbf{X} \boldsymbol{\beta})' [\mathbf{I} - \mathbf{J}_n] (\mathbf{y} - \mathbf{X} \boldsymbol{\beta}),$$

Also,  $[I - J_n]$  is symmetric and idempotent.  $\text{Rank}[I - J_n] = \text{trace}[I - J_n] = n - K$ . Therefore by Cochran Theorem

$$\frac{RSS}{\sigma^2} = \frac{(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'[I - J_n](\mathbf{y} - \mathbf{X}\boldsymbol{\beta})}{\sigma^2} \sim \chi_{n-K}^2.$$

**P 2.** Consider the ANOVA model (1). The regression sum of squares  $SS_{\text{Reg}}$  is defined as

$$SS_{\text{Reg}} = \sum_{i=1}^K \sum_{j=1}^{n_i} (\hat{y}_{ij} - \bar{y})^2, \quad (2)$$

where  $\hat{y}_{ij} = \hat{\mu} + \hat{\alpha}_i$ ,  $\hat{\mu}$  and  $\hat{\alpha}_i$  are least squares estimators of  $\mu$  and  $\alpha_i$ ,  $\bar{y} = \sum_{i=1}^K n_i \bar{y}_i / \sum_{i=1}^K n_i$  and  $\bar{y}_i = \sum_{j=1}^{n_i} y_{ij} / n_i$  for  $i = 1, \dots, K$ . Find the distribution of  $SS_{\text{Reg}}/\sigma^2$ .

**Solution:** From **P 1**,

$$\begin{aligned} SS_{\text{Reg}} &= \sum_{i=1}^K \sum_{j=1}^{n_i} (\hat{y}_{ij} - \bar{y})^2 = \sum_{i=1}^K \sum_{j=1}^{n_i} (\bar{y}_i - \bar{y})^2 \\ &= \sum_{i=1}^K n_i (\bar{y}_i - \bar{y})^2 = \sum_{i=1}^K n_i (\bar{y}_i)^2 - n(\bar{y})^2 \\ &= \mathbf{y}' J_n \mathbf{y} - (1/n) \mathbf{y}' W_n \mathbf{y} = \mathbf{y}' [J_n - (1/n) W_n] \mathbf{y} \end{aligned}$$

Where  $W_n$  is  $n \times n$  matrix of all ones.

Next, it can be shown that  $[J_n - (1/n) W_n] \mathbf{X} = 0$ . Thus,

$$SS_{\text{Reg}} = \mathbf{y}' [J_n - (1/n) W_n] \mathbf{y} = (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})' [J_n - (1/n) W_n] (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}).$$

Also,  $[J_n - (1/n) W_n]$  is symmetric and idempotent.  $\text{Rank}[J_n - (1/n) W_n] = \text{trace}[J_n - (1/n) W_n] = K - 1$ . Therefore by Cochran Theorem

$$\frac{SS_{\text{Reg}}}{\sigma^2} = \frac{(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})' [J_n - (1/n) W_n] (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})}{\sigma^2} \sim \chi_{K-1}^2.$$

**Remark:** The hypothesis

$$H_0 : \alpha_1 = \dots = \alpha_K \text{ versus } H_1 : \alpha_i \neq \alpha_j \text{ for at least one pair of } (i, j)$$

can be tested using the statistics

$$F = \frac{SS_{\text{Reg}}/df_1}{RSS/df_2} \sim F_{df_1, df_2},$$

where  $df_1$  and  $df_2$  are degrees of freedoms associated to the distributions of  $SS_{\text{Reg}}$  and  $RSS$  respectively.

Note that it can be shown that  $[J_n - (1/n) W_n] [I - J_n] = 0$ . Thus,  $RSS$  and  $SS_{\text{Reg}}$  both are independent. Thus,

$$F = \frac{SS_{\text{Reg}}/(K-1)}{RSS/(n-K)} \sim F_{K-1, n-K}.$$

**P 3.** Consider the model  $y_1 = \theta_1 + \theta_2 + \epsilon_1$ ,  $y_2 = 2\theta_1 + \epsilon_2$ ,  $y_3 = \theta_1 - \theta_2 + \epsilon_3$ , where  $\epsilon_i$ ,  $i = 1, 2, 3$ , are i.i.d.  $N(0, \sigma^2)$ . Derive the  $F$ -statistics for testing  $\theta_1 = \theta_2$ .

## R: Assignment

**P 4.** Three teaching methods, A, B, C, are to be compared. Each method was administered to a group of 4 students, and the scores obtained by the students on a test are given below. Carry out an F -test at level of significance 0.01 to decide whether the mean scores under the three methods are significantly different.

Table 1: Data.

Method		
A	B	C
75	82	78
79	93	81
71	86	76
69	88	81

### Solution

Comment: Data Import from a CSV file named *Score\_Data.csv*

Comment: ANOVA Method

```
Score.Data <- read.csv("/Users/satya/Desktop/MTH207A/Score_Data.csv")
```

```
one.way <- aov(Score ~ Method, data = Score.Data)
```

```
summary(one.way)
```

Comment: Regression method

```
y <- c(75, 79, 71, 69, 82, 93, 86, 88, 78, 81, 76, 81)
```

```
x1 <- c(rep(1, 4), rep(0, 4), rep(0, 4))
```

```
x2 <- c(rep(0, 4), rep(1, 4), rep(0, 4))
```

```
x3 <- c(rep(0, 4), rep(0, 4), rep(1, 4))
```

```
model.lm.P1 <- lm(y ~ x1 + x2 + x3)
```

```
summary(model.lm.P1)
```

**P 5.** Consider the model  $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$  with the usual assumptions. Test the following hypotheses: **(a)**  $H_0 : \beta_2 = 0$  versus  $H_1 : \beta_2 \neq 0$ , **(b)**  $H_0 : \beta_3 = 0$  versus  $H_1 : \beta_3 \neq 0$  using the data given below.

Table 2: Data.

$y$	$x_1$	$x_2$	$y$	$x_1$	$x_2$
10	21	2.67	13	48	7.20
12	32	3.12	21	81	9.12
6	46	2.11	14	93	3.21
14	91	4.21	11	88	4.87
20	20	6.43	18	46	5.38
5	65	1.76	17	24	8.71
8	26	2.88	27	11	8.11
15	74	6.15			

### Solution:

Comment: Problem P5

```
P5.Data <- read.csv("/Users/satya/Desktop/MTH207A/P5.Data.csv")
```

```
model.lm.P2 <- lm(y ~ x1 + x2, data = P5.Data)
summary(model.lm.P2)
linearHypothesis(model.lm.P2, c("x1 = 0"), test = "F")
linearHypothesis(model.lm.P2, c("x1 - x2 = 0"), test = "F")
```