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STAT 2132

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### Homework 5

- a)  $Y_{ij} = \mu_i + \epsilon_{ij}$  for  $i = 1, \dots, r$  ( $r$  treatments)  
 $j = 1, \dots, n_i$  (each treatment  $i$  has  $n_i$  levels)

$$Y = X\beta + E, \quad Y = \begin{bmatrix} Y_{11} \\ \vdots \\ Y_{1n_1} \\ \vdots \\ Y_{r1} \\ \vdots \\ Y_{rn_r} \end{bmatrix}, \quad \beta = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_r \end{bmatrix}, \quad E = \begin{bmatrix} \epsilon_{11} \\ \vdots \\ \epsilon_{1n_1} \\ \vdots \\ \epsilon_{r1} \\ \vdots \\ \epsilon_{rn_r} \end{bmatrix}$$

$\Rightarrow X$  must be

$$\underbrace{\begin{bmatrix} 1 & 0 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \end{bmatrix}}_{r \text{ columns}} \left. \begin{array}{l} \left. \begin{array}{l} \dots \\ \dots \\ \dots \end{array} \right\} n_1 \text{ rows} \\ \left. \begin{array}{l} \dots \\ \dots \end{array} \right\} n_2 \text{ rows} \\ \dots \\ \left. \begin{array}{l} \dots \\ \dots \end{array} \right\} n_r \text{ rows} \end{array} \right\}$$

This is a  $n \times r$  matrix, where  $n = \sum_{i=1}^r n_i$

- b) With  $X$  given above,  $X^T X$  must be a diagonal matrix
- $$X^T X = \begin{bmatrix} n_1 & 0 & \dots & 0 \\ 0 & n_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & n_r \end{bmatrix}, \quad \text{which is a } r \times r \text{ matrix}$$
- $(X^T X)_{ii} = n_i$

$\Rightarrow (X^T X)^{-1}$  is also a diagonal matrix with dimension  $r \times r$

$$(X^T X)^{-1} = \begin{bmatrix} 1/n_1 & 0 & \dots & 0 \\ 0 & 1/n_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1/n_r \end{bmatrix} \quad \text{where } (X^T X)^{-1}_{ii} = 1/n_i$$

$$\Rightarrow \underset{n \times r}{X} (\underset{r \times r}{X^T X})^{-1} \underset{r \times 1}{X^T} = \begin{bmatrix} n_1^{-1} & 0 & \dots & 0 \\ n_1^{-1} & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ n_1^{-1} & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & n_r^{-1} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & n_r^{-1} \end{bmatrix} \left. \begin{array}{l} \vdots \\ \vdots \end{array} \right\} \begin{array}{l} n_1 \text{ rows} \\ n_r \text{ rows} \end{array}$$

$\underbrace{\hspace{10em}}_{r \text{ columns}}$

$$\Rightarrow H = X(X^T X)^{-1} X^T$$

$$= \begin{bmatrix} n_1^{-1} & \dots & n_1^{-1} & 0 & \dots & 0 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ n_1^{-1} & \dots & n_1^{-1} & 0 & \dots & 0 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & \dots & \dots & \dots & n_r^{-1} & \dots & n_r^{-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & n_r^{-1} & \dots & n_r^{-1} \\ 0 & \dots & \dots & \dots & \dots & n_r^{-1} & \dots & n_r^{-1} \end{bmatrix} \left. \begin{array}{l} \vdots \\ \vdots \end{array} \right\} \begin{array}{l} n_1 \text{ rows} \\ n_r \text{ rows} \end{array}$$

$\underbrace{\hspace{2em}}_{n_1 \text{ cols}} \quad \underbrace{\hspace{2em}}_{n_2 \text{ cols}} \quad \dots \quad \underbrace{\hspace{2em}}_{n_r \text{ cols}}$

$H$  is a  $n \times n$  matrix

$$c) \underset{n \times n}{H} \underset{n \times 1}{Y} = \begin{bmatrix} n_1^{-1} & \dots & n_1^{-1} & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ n_1^{-1} & \dots & n_1^{-1} & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & \dots & n_r^{-1} & \dots & n_r^{-1} \\ 0 & \dots & 0 & \dots & n_r^{-1} & \dots & n_r^{-1} \end{bmatrix} \begin{bmatrix} y_{11} \\ \vdots \\ y_{1n_1} \\ \vdots \\ y_{r1} \\ \vdots \\ y_{rn_r} \end{bmatrix}$$

$$= \left[ \frac{1}{n_1} (y_{11} + \dots + y_{1n_1}) \quad \dots \quad \frac{1}{n_1} (y_{1n_1} + \dots + y_{1n_1}) \quad \dots \quad \frac{1}{n_r} (y_{r1} + \dots + y_{rn_r}) \quad \dots \quad \frac{1}{n_r} (y_{r1} + \dots + y_{rn_r}) \right]^T$$

$$= \left[ \underbrace{\bar{y}_1 \dots \bar{y}_1}_{n_1 \text{ elements}} \quad \bar{y}_2 \dots \bar{y}_2 \quad \dots \quad \underbrace{\bar{y}_r \dots \bar{y}_r}_{n_r \text{ elements}} \right]^T = \left[ \bar{y}_1 \cdot \frac{1}{n_1} \quad \dots \quad \bar{y}_r \cdot \frac{1}{n_r} \right]^T$$



$$d) \quad H = \begin{bmatrix} n_1^{-1} J_{n_1} & \dots & \\ \vdots & \ddots & \\ & & n_r^{-1} J_{n_r} \end{bmatrix}_{n \times r} \quad \text{where } J_{n_i} = \begin{bmatrix} 1 & \dots & 1 \\ \vdots & & \vdots \\ 1 & \dots & 1 \end{bmatrix}_{n_i \times n_i}$$

We already defined  $n = \sum_{i=1}^r n_i$  previously, hence  $n = n_T$

$$i) \quad Y^T (H - L) Y = Y^T H Y - Y^T L Y = Y^T (HY) - Y^T L Y$$

$$HY = (\bar{y}_1, 1_{n_1}, \dots, \bar{y}_r, 1_{n_r})^T$$

$$\Rightarrow Y^T H Y = y_{11} \bar{y}_1 + \dots + y_{1n_1} \bar{y}_1 + \dots + y_{r1} \bar{y}_r + \dots + y_{rn_r} \bar{y}_r$$

$$= \sum_{i=1}^r \bar{y}_i (y_{i1} + \dots + y_{in_i}) = \sum_{i=1}^r n_i \bar{y}_i^2$$

$$LY = (n^{-1} 1_n 1_n^T) Y = \begin{bmatrix} n^{-1} y_{11} + \dots + n^{-1} y_{rn_r} \\ \vdots \\ n^{-1} y_{11} + \dots + n^{-1} y_{rn_r} \end{bmatrix}$$

$$= \begin{bmatrix} n^{-1} \sum_{i=1}^r \sum_{j=1}^{n_i} y_{ij} \\ \vdots \\ n^{-1} \sum_{i=1}^r \sum_{j=1}^{n_i} y_{ij} \end{bmatrix} = \begin{bmatrix} \bar{y}_{..} \\ \vdots \\ \bar{y}_{..} \end{bmatrix} = \bar{y}_{..} 1_n$$

$$\Rightarrow Y^T L Y = y_{11} \bar{y}_{..} + \dots + y_{1n_1} \bar{y}_{..} + y_{r1} \bar{y}_{..} + \dots + y_{rn_r} \bar{y}_{..}$$

$$= \bar{y}_{..} (y_{11} + \dots + y_{in_i}) = \bar{y}_{..}^2 n$$

$$\Rightarrow Y^T (H - L) Y = Y^T H Y - Y^T L Y = \sum_{i=1}^r n_i \bar{y}_i^2 - \bar{y}_{..}^2 n \quad (1)$$

On the other hand, we have

$$SS_{TR} = \sum_i n_i (\bar{y}_i - \bar{y}_{..})^2 = \sum_i n_i (\bar{y}_i^2 + \bar{y}_{..}^2 - 2 \bar{y}_i \bar{y}_{..})$$

$$= \sum_i n_i \bar{y}_i^2 + \bar{y}_{..}^2 \sum_i n_i - 2 \bar{y}_{..} \sum_i n_i \bar{y}_i$$

$$= \sum_i n_i \bar{y}_i^2 + \bar{y}_{..}^2 n - 2 \bar{y}_{..} \sum_i \sum_j y_{ij}$$

$$\Rightarrow SSTR = \sum_i n_i \bar{y}_i^2 + \bar{y}_{..}^2 n - 2n \bar{y}_{..} \left( \frac{\sum_i \sum_j y_{ij}}{n} \right)$$

$$= \sum_i n_i \bar{y}_i^2 + \bar{y}_{..}^2 n - 2n \bar{y}_{..}^2$$

$$\Rightarrow SSTR = \sum_i n_i \bar{y}_i^2 - \bar{y}_{..}^2 n \quad (2)$$

From (1) and (2)

$$\Rightarrow SSTR = Y^T (H - L) Y$$

From last semester, we learned  $H = X(X^T X)^{-1} X^T$  is symmetric and idempotent  $\Rightarrow H^2 = H, H^T = H$

We have  $L = n^{-1} \mathbf{1}_n \mathbf{1}_n^T$

$$\Rightarrow L^T = n^{-1} (\mathbf{1}_n^T)^T \mathbf{1}_n^T = n^{-1} \mathbf{1}_n \mathbf{1}_n^T = L$$

$$L^2 = L \cdot L = n^{-1} \mathbf{1}_n \mathbf{1}_n^T n^{-1} \mathbf{1}_n \mathbf{1}_n^T$$

$$= n^{-2} J_n J_n = n^{-2} (J_n^2) = n^{-2} n^1 J_n$$

$$= n^{-1} J_n = n^{-1} \mathbf{1}_n \mathbf{1}_n^T = L$$

( $J_n$  is  $n \times n$  matrix of ones, it has property  $J_n^k = n^{k-1} J_n$  for  $k = 1, 2, \dots$ )

$\Rightarrow L$  is also symmetric and idempotent

Now look at  $H - L$

$$(H - L)^T = H^T - L^T = H - L \Rightarrow H - L \text{ is symmetric}$$

$$(H - L)^2 = H^2 - HL - LH + L^2 = H - HL - LH + L$$

$$HL = \begin{bmatrix} \frac{1}{n_1} & \dots & \frac{1}{n_1} \\ \vdots & & \vdots \\ \frac{1}{n_2} & \dots & \frac{1}{n_2} \\ \vdots & & \vdots \\ \frac{1}{n_r} & \dots & \frac{1}{n_r} \\ \vdots & & \vdots \\ \frac{1}{n_r} & \dots & \frac{1}{n_r} \end{bmatrix} \begin{bmatrix} 1/n & \dots & 1/n \\ \vdots & & \vdots \\ 1/n & \dots & 1/n \end{bmatrix} = \begin{bmatrix} n_1 \frac{1}{n_1} n^{-1} & \dots & n_1 \frac{1}{n_1} n^{-1} \\ \vdots & & \vdots \\ n_r \frac{1}{n_r} n^{-1} & \dots & n_r \frac{1}{n_r} n^{-1} \end{bmatrix}$$

$$= \begin{bmatrix} n^{-1} & \dots & n^{-1} \\ \vdots & & \vdots \\ n^{-1} & \dots & n^{-1} \end{bmatrix} = L \quad ; \quad \text{Similarly } LH = L$$

$$\Rightarrow (H - L)^2 = H - L - L + L = H - L \Rightarrow H - L \text{ is idempotent}$$

1) d)

$$(ii) \quad \text{rank}(H) = r \\ \text{rank}(L) = 1$$

$$\Rightarrow \text{rank}(H - L) = r - 1$$

$$(iii) \quad \text{Let } \vec{a} \in \text{Im}(H - L)$$

$$\Rightarrow \vec{a}_{n_T \times 1} = \underbrace{(H - L)}_{n_T \times n_T} \vec{v}_1_{n_T \times 1}$$

$$\text{Let } \vec{b} \in \text{Im}(I_n - H)$$

$$\Rightarrow \vec{b}_{n_T \times 1} = \underbrace{(I_n - H)}_{n_T \times n_T} \vec{v}_2_{n_T \times 1}$$

$$\begin{aligned} \vec{a}^T \cdot \vec{b} &= \vec{v}_1^T (H - L)^T (I_n - H) \vec{v}_2 \\ &= \vec{v}_1^T (H - L) (I_n - H) \vec{v}_2 \quad (H - L \text{ is symmetric}) \\ &= \vec{v}_1^T (H - H - L + LH) \vec{v}_2 \\ &= \vec{v}_1^T (H - H - L + L) \vec{v}_2 \\ &= 0 \end{aligned}$$

$\Rightarrow \text{Im}(H - L)$  is orthogonal to  $\text{Im}(I_n - H)$

(iv) From last semester,  $Y \sim N$ ,  $A$  &  $B$  are symmetric and idempotent,  $A$  &  $B$  orthogonal

$\Rightarrow$  Quadratic forms  $Y^T A Y$  and  $Y^T B Y$  are independent

In this case  $Y \sim N$

$$\begin{aligned} \text{SSTR} &= Y^T (H - L) Y \\ \text{SSE} &= Y^T (I_n - H) Y \end{aligned} \quad \left. \vphantom{\begin{aligned} \text{SSTR} &= Y^T (H - L) Y \\ \text{SSE} &= Y^T (I_n - H) Y \end{aligned}} \right\} \text{quadratic forms}$$

And we proved  $(H - L)$  and  $(I_n - H)$  to be orthogonal  
 $(H - L)$  and  $(I_n - H)$  are symmetric and idempotent

$\Rightarrow$  SSTR and SSE are independent



$$2) \quad Z_{n \times 1} \in \mathbb{R}^n, \quad E(Z) = \mu, \quad \text{Var}(Z) = V$$

$$A_{n \times n}$$

$$\begin{aligned} a) \quad E(Z^T A Z) &= E(Z^T A Z) + \mu^T A \mu - \mu^T A \mu \\ &= E(Z^T A Z) - \mu^T A \mu + \mu^T A \mu \\ &= E[(Z^T - \mu^T) A (Z - \mu)] + \mu^T A \mu \\ &= E \left[ \underbrace{(Z - \mu)^T}_{1 \times n} \underbrace{A}_{n \times n} \underbrace{(Z - \mu)}_{n \times 1} \right] + \mu^T A \mu \\ &\quad \leftarrow \text{this whole expectation is a scalar} \\ &= E[\text{Tr}(A (Z - \mu)(Z - \mu)^T)] + \mu^T A \mu \\ &= \text{Tr}[E(A (Z - \mu)(Z - \mu)^T)] + \mu^T A \mu \\ &= \text{Tr}(A E[(Z - \mu)(Z - \mu)^T]) + \mu^T A \mu \\ &= \text{Tr}(A \text{Var}(Z)) + \mu^T A \mu \end{aligned}$$

$$\Rightarrow E(Z^T A Z) = \text{Tr}(A V) + \mu^T A \mu$$

$$(\text{because } E[(Z - \mu)(Z - \mu)^T] = \text{Cov}(Z) = \text{Var}(Z))$$

$$b) \quad \text{MSE} = \frac{1}{n-r} \text{SSE} = \frac{1}{n-r} Y^T (I_n - H) Y$$

$$\Rightarrow E(\text{MSE}) = \frac{1}{n-r} E(Y^T (I_n - H) Y)$$

$$= \frac{1}{n-r} [\text{Tr}(I_n - H) \text{Var}(Y) + (X\beta)^T (I_n - H) X\beta]$$

$$= \frac{1}{n-r} [(n-r) \sigma^2 + 0] \quad \left( \begin{array}{l} \text{because} \\ HX = X \\ I_n X = X \end{array} \right)$$

$$= \sigma^2$$

$$\text{MSTR} = \frac{\text{SSTR}}{r-1} = \frac{1}{r-1} Y^T (H - L) Y$$

$$\Rightarrow E(MSTR) = \frac{1}{r-1} E(Y^T(H-L)Y)$$

$$= \frac{1}{r-1} \left( \text{Tr}(H-L) \text{Var}(Y) + (X\beta)^T(H-L)X\beta \right)$$

$$= \frac{1}{r-1} \left( (r-1) \sigma^2 + \beta^T X^T H X \beta - \beta^T X^T L X \beta \right)$$

$$= \sigma^2 + \frac{1}{r-1} \left( \beta^T X^T X \beta - \beta^T X^T L X \beta \right) \quad (1)$$

$$\sum_i n_i (\mu_i - \mu_{..})^2 = \sum_i n_i (\mu_i^2 + \mu_{..}^2 - 2\mu_i \mu_{..})$$

$$= \sum_i n_i \mu_i^2 + \sum_i n_i \mu_{..}^2 - 2 \sum_i n_i \mu_i \mu_{..}$$

$$= \sum_i n_i \mu_i^2 + \frac{(\sum_i n_i \mu_i)^2}{\sum_i n_i} - 2 \mu_{..} \sum_i n_i \mu_i$$

$$= \sum_i n_i \mu_i^2 + \frac{(\sum_i n_i \mu_i)^2}{\sum_i n_i} - 2 \frac{(\sum_i n_i \mu_i)^2}{\sum_i n_i}$$

$$= \sum_i n_i \mu_i^2 - n^{-1} (\sum_i n_i \mu_i)^2$$

$$= \mu^T \mu - \mu^T L \mu = \beta^T X^T X \beta - \beta^T X^T L X \beta \quad (2)$$

From (1) and (2)

$$\Rightarrow E(MSTR) = \sigma^2 + \frac{1}{r-1} \cdot \sum_{i=1}^r n_i (\mu_i - \mu_{..})^2$$