

High-dimensional data analysis HW#1

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1. In one-way ANOVA:

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij}, i = 1, 2, 3; j = 1, \dots, n \text{ where } \alpha_1 + \alpha_2 + \alpha_3 = 0.$$

$$\text{Matrix form: } \mathbf{y} = \begin{bmatrix} y_{11} \\ \vdots \\ y_{1n} \\ y_{21} \\ \vdots \\ y_{2n} \\ y_{31} \\ \vdots \\ y_{3n} \end{bmatrix}, \mathbf{X} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 1 \end{bmatrix}, \boldsymbol{\beta} = \begin{bmatrix} \mu \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix}, \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{1n} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{2n} \\ \varepsilon_{31} \\ \vdots \\ \varepsilon_{3n} \end{bmatrix}.$$

Compute $\text{rank}(\mathbf{X})$, $\mathbf{X}^T \mathbf{y}$, $\mathbf{X}^T \mathbf{X}$ and find a LSE $\hat{\boldsymbol{\beta}}$.

Solution:

(1)

$$\text{rank}(\mathbf{X}) = 3 \quad (x_0 = x_1 + x_2 + x_3)$$

(2)

$$\mathbf{X}^T \mathbf{y} = \begin{bmatrix} y_{\cdot} \\ y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

(3)

$$\mathbf{X}^T \mathbf{X} = n \begin{bmatrix} 3 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

(4)

$$\text{LSE} \Rightarrow \text{satisfy } \mathbf{X}^T \mathbf{y} = \mathbf{X}^T \mathbf{X} \hat{\boldsymbol{\beta}}$$

Consider the estimator of $\boldsymbol{\beta}$ by method of moments:

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij}, i = 1, 2, 3; j = 1, \dots, n$$

$$\begin{aligned}
\Rightarrow \sum_{i=1}^3 \sum_{j=1}^n y_{ij} &= \sum_{i=1}^3 \sum_{j=1}^n (\mu + \alpha_i + \varepsilon_{ij}) \\
\Rightarrow y_{..} &= 3n\mu + 0 + \sum_{i=1}^3 \sum_{j=1}^n \varepsilon_{ij} \quad (\because \sum_{i=1}^3 \alpha_i = 0) \\
\Rightarrow E(y_{..}) &= 3n\mu \\
\Rightarrow E(\bar{y}_{..}) &= \mu \\
\Rightarrow \hat{\mu} &= \bar{y}_{..}
\end{aligned}$$

Similarly, $y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$, $i = 1, 2, 3$; $j = 1, \dots, n$

$$\begin{aligned}
\Rightarrow \sum_{j=1}^n y_{ij} &= \sum_{j=1}^n (\mu + \alpha_i + \varepsilon_{ij}) \\
\Rightarrow y_{i.} &= n\mu + n\alpha_i + \sum_{j=1}^n \varepsilon_{ij} \\
\Rightarrow y_{i.} &= n\mu + n\alpha_i + \sum_{j=1}^n \varepsilon_{ij} \\
\Rightarrow E(\bar{y}_{i.}) &= \mu + \alpha_i \\
\Rightarrow \hat{\alpha}_i &= \bar{y}_{i.} - \hat{\mu} = \bar{y}_{i.} - \bar{y}_{..}
\end{aligned}$$

Thus, by method of moments, estimators $\begin{cases} \hat{\mu} = \bar{y}_{..} \\ \hat{\alpha}_i = \bar{y}_{i.} - \bar{y}_{..} \end{cases}$, take $\hat{\boldsymbol{\beta}} = \begin{bmatrix} \hat{\mu} \\ \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \hat{\alpha}_3 \end{bmatrix} = \begin{bmatrix} \bar{y}_{..} \\ \bar{y}_{1.} - \bar{y}_{..} \\ \bar{y}_{2.} - \bar{y}_{..} \\ \bar{y}_{3.} - \bar{y}_{..} \end{bmatrix}$,

which satisfy the equal $\mathbf{X}^T \mathbf{y} = \mathbf{X}^T \mathbf{X} \hat{\boldsymbol{\beta}}$.

2. Show that the F statistic (3.13) for dropping a single coefficient from a model is equal to the square of the corresponding z-score (3.12).

Solution:

Assume that RSS_1 is from full model and RSS_j is from model dropping β_j .

Our goal is to show that $F = \frac{(RSS_j - RSS_1)/(p - p_j)}{RSS_1/(N - p - 1)}$ and $z_j^2 = \frac{\hat{\beta}_j^2}{\hat{\sigma}^2 v_j}$ have same

distribution.

The numerator of F is $\chi_{df=1}^2$ because $p - p_j = 1$ in our setting. The denominator

of F is $\frac{\chi_{df=N-p-1}^2}{N - p - 1}$.

The component $z_j = \frac{\hat{\beta}_j}{\hat{\sigma}\sqrt{v_j}}$ can be written as

$\frac{\hat{\beta}_j - \beta_j}{\sigma\sqrt{v_j}} \bigg/ \sqrt{\frac{\hat{\sigma}^2(N-p-1)}{\sigma^2}} \bigg/ (N-p-1)$ where the numerator is standard

normal and the denominator is $\sqrt{\frac{\chi_{df=N-p-1}^2}{N-p-1}}$. Thus, $z_j^2 \sim \frac{\chi_{df=1}^2}{\chi_{df=N-p-1}^2}$ where is the

same as F.