

STA207 Discussion 3

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January 2023

One-way ANOVA model:

$$Y_{ij} = \mu_i + \epsilon_{ij}; i = 1, \dots, k, j = 1, \dots, n_k$$

or

$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij}; i = 1, \dots, k, j = 1, \dots, n_k$$

where $\epsilon_{ij} \sim_{iid} N(0, \sigma^2)$. Suppose we have constraints $\sum_{i=1}^k n_i \alpha_i = 0$. $N = \sum_{i=1}^k n_i$. Then LS estimation gives

$$\hat{\mu}_i = \bar{Y}_{i.}, \hat{\mu} = \bar{Y}_{..}, \hat{\alpha}_i = \hat{\mu}_i - \hat{\mu} = \bar{Y}_{i.} - \bar{Y}_{..}, \hat{\sigma}^2 = \frac{SSE}{N - k}$$

1 Properties

(1) **Proof:** $\hat{\sigma}^2$ is an unbiased estimator of σ^2

$$SSE = \sum_{i=1}^k \sum_{j=1}^{n_i} (Y_{ij} - \bar{Y}_{i.})^2$$

We just need to calculate $E[(Y_{ij} - \bar{Y}_{i.})^2]$:

$$\begin{aligned} E[(Y_{ij} - \bar{Y}_{i.})^2] &= Var(Y_{ij} - \bar{Y}_{i.}) = Var\left(\left(1 - \frac{1}{n_i}\right)Y_{ij} - \frac{1}{n_i} \sum_{l \neq j} Y_{il}\right) \\ &= \left(1 - \frac{1}{n_i}\right)^2 Var(Y_{ij}) + \frac{1}{n_i^2} \sum_{l \neq j} Var(Y_{il}) \\ &= \left(1 - \frac{1}{n_i}\right)^2 \sigma^2 + \frac{1}{n_i^2} (n_i - 1) \sigma^2 \\ &= \left(1 - \frac{1}{n_i}\right) \sigma^2 \end{aligned}$$

Then we have

$$E[SSE] = \sum_{i=1}^k \sum_{j=1}^{n_i} \left(1 - \frac{1}{n_i}\right) \sigma^2 = (N - k) \sigma^2$$

(2) **Proof:** $E[MSTR] = \sigma^2 \sum_{i=1}^k n_i (\mu_i - \mu)^2 / (k - 1)$ **where** $\mu = \frac{\sum_{i=1}^k n_i \mu_i}{N}$

$$MSTR = \frac{\sum_{i=1}^k n_i (\bar{Y}_{i.} - \bar{Y}_{..})^2}{k - 1}$$

We just need to calculate $E[(\bar{Y}_{i.} - \bar{Y}_{..})^2]$. Notice that $E[(\bar{Y}_{i.} - \bar{Y}_{..})^2] = Var(\bar{Y}_{i.} - \bar{Y}_{..}) + [E(\bar{Y}_{i.} - \bar{Y}_{..})]^2$ where

$E(\bar{Y}_{i.} - \bar{Y}_{..}) = \mu_i - \mu$. And

$$\begin{aligned}
Var(\bar{Y}_{i.} - \bar{Y}_{..}) &= Var\left(\bar{Y}_{i.} - \frac{\sum_{s=1}^k n_s \bar{Y}_{s.}}{N}\right) = Var\left(\left(1 - \frac{n_i}{N}\right)\bar{Y}_{i.} - \frac{\sum_{s \neq i} n_s \bar{Y}_{s.}}{N}\right) \\
&= \left(1 - \frac{n_i}{N}\right)^2 Var(\bar{Y}_{i.}) + \sum_{s \neq i} \frac{n_s^2}{N^2} Var(\bar{Y}_{s.}) \\
&= \left(1 - \frac{n_i}{N}\right)^2 \frac{\sigma^2}{n_i} + \sum_{s \neq i} \frac{n_s^2}{N^2} \frac{\sigma^2}{n_s} \\
&= \left(\frac{1}{n_i} - \frac{1}{N}\right) \sigma^2
\end{aligned}$$

Then we have

$$E[SSTR] = E\left[\sum_{i=1}^k n_i (\bar{Y}_{i.} - \bar{Y}_{..})^2\right] = \sum_{i=1}^k n_i \left[\left(\frac{1}{n_i} - \frac{1}{N}\right) \sigma^2 + (\mu_i - \mu)^2\right] = (k-1) \sigma^2 + \sum_{i=1}^k n_i (\mu_i - \mu)^2$$

(3) Moment properties of the estimation

$$E(\hat{\mu}) = \mu, Var(\hat{\mu}) = \frac{\sigma^2}{N}$$

$$E(\hat{\mu}_i) = \mu_i, Var(\hat{\mu}_i) = \frac{\sigma^2}{n_i}$$

$$E(\hat{\alpha}_i) = E(\hat{\mu}_i - \hat{\mu}) = \mu_i - \mu = \alpha_i, Var(\hat{\alpha}_i) = Var(\hat{\mu}_i - \hat{\mu}) = Var(\bar{Y}_{i.} - \bar{Y}_{..}) = \left(\frac{1}{n_i} - \frac{1}{N}\right) \sigma^2$$