

1) Suppose $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$ satisfies the OLS CLT. Let $r_i = Y_i - \hat{Y}_i$ be the i th OLS residual for $i = 1, \dots, n$ where a constant is in the model. The residual bootstrap draws the residuals with replacement to form the model $\mathbf{Y}^* = \mathbf{X}\hat{\boldsymbol{\beta}} + \mathbf{r}^*$. ~~\mathbf{Z}~~ ~~\mathbf{U}~~ ~~\mathbf{N}~~ ~~\mathbf{P}~~ .

Suppose that for some large fixed m , OLS is fit to find $\hat{\boldsymbol{\beta}}_m$ and the m OLS residuals. Then as $n \rightarrow \infty$, the m residuals are drawn with replacement to form $\mathbf{Y}^* = \mathbf{X}\hat{\boldsymbol{\beta}}_m + \mathbf{r}^*$ where $Y_i^* = \mathbf{x}_i^T \hat{\boldsymbol{\beta}}_m + r_i^*$ for $i = 1, \dots, m$. This model satisfies the OLS CLT with the r_i^* iid with respect to the bootstrap distribution, $E(r_i^*) = 0$, and $V(r_i^*) = \sigma_m^2 = \frac{1}{m} \sum_{i=1}^m r_i^2 = \frac{m-1}{m} \text{MSE}(m)$ where $\text{MSE}(m) \xrightarrow{P} \sigma^2 = V(e_i)$ as $m \rightarrow \infty$. The bootstrap estimator $\hat{\boldsymbol{\beta}}^*$ is found by fitting OLS to the model $\mathbf{Y}^* = \mathbf{X}\hat{\boldsymbol{\beta}}_m + \mathbf{r}^*$. By the OLS CLT,

$$\sqrt{n}(\hat{\boldsymbol{\beta}}^* - \hat{\boldsymbol{\beta}}_m) \xrightarrow{D} \mathbf{u}.$$

What is the distribution of \mathbf{u} ?

$$\sim N_p(\mathbf{0}, \sigma_m^2 \mathbf{W})$$

2) Show that $\sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})(Y_i - \bar{Y}) = \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})Y_i$.

$$\begin{aligned} \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})(Y_i - \bar{Y}) &= \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})Y_i - \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})\bar{Y} \\ &= \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})Y_i - \bar{Y} \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}}) \\ &= \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})Y_i - \bar{Y} (n\bar{\mathbf{x}} - n\bar{\mathbf{x}}) \\ &= \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})Y_i - \bar{Y} n\bar{\mathbf{x}} + n\bar{Y}\bar{\mathbf{x}} \\ &= \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})Y_i \end{aligned}$$

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3) Let Σ_i be the nonsingular population covariance matrix of the i th treatment group or population. To simplify the large sample theory, assume $n_i = \pi_i n$ where $0 < \pi_i < 1$ and $\sum_{i=1}^3 \pi_i = 1$. Let T_i be a multivariate location estimator such that

$\sqrt{n_i}(T_i - \mu_i) \xrightarrow{D} N_m(\mathbf{0}, \Sigma_i)$, and $\sqrt{n}(T_i - \mu_i) \xrightarrow{D} N_m\left(\mathbf{0}, \frac{\Sigma_i}{\pi_i}\right)$ for $i = 1, 2, 3$. Assume the T_i are independent.

Then

$$\sqrt{n} \begin{bmatrix} T_1 - \mu_1 \\ T_2 - \mu_2 \\ T_3 - \mu_3 \end{bmatrix} \xrightarrow{D} \mathbf{u}.$$

a) Find the distribution of \mathbf{u} .

$$N_{3m} \left[\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} \frac{\Sigma_1}{\pi_1} & 0 & 0 \\ 0 & \frac{\Sigma_2}{\pi_2} & 0 \\ 0 & 0 & \frac{\Sigma_3}{\pi_3} \end{pmatrix} \right]$$

b) Suggest an estimator $\hat{\pi}_i$ of π_i .

$$\hat{\pi}_i = \frac{n_i}{n}$$

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