

I reordered!

Solution to ST 793 Midterm Exam, 2018

4a. $r = f(\hat{\sigma}_x^2, \hat{\sigma}_y^2, \hat{\sigma}_{12}) = \frac{\hat{\sigma}_{12}}{\sqrt{\hat{\sigma}_x^2 \hat{\sigma}_y^2}}$ which is a continuous fu. for $\hat{\sigma}_x^2 > 0, \hat{\sigma}_y^2 > 0$

$$\hat{\sigma}_{12} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y}) - (\bar{X} - \mu_x)(\bar{Y} - \mu_y)$$

\downarrow P by WLLN \downarrow P by $o_p(1) o_p(1) = o_p(1)$ and WLLN for $(\bar{X} - \mu_x) + (\bar{Y} - \mu_y)$

$$\hat{\sigma}_x^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 - (\bar{X} - \mu_x)^2$$

\downarrow P by WLLN \downarrow P since $\bar{X} - \mu_x \xrightarrow{P} 0$ by WLLN
 $\xrightarrow{P} \sigma_x^2$ \downarrow P since $(\)^2$ is a cont. fu.

So by the cont. theorem, $r \xrightarrow{P} \rho = \frac{\sigma_{12}}{\sigma_x \sigma_y}$.

4b. $s^2 \xrightarrow{P} \text{Var}(X_1 - Y_1) = \sigma_1^2$ by same arg. as above along with $\frac{1}{\sqrt{n}}(\bar{X} - \bar{Y}) = \frac{1}{\sqrt{n}} \sum_{i=1}^n (X_i - Y_i)$ with $\frac{(n-1)}{n} \rightarrow 1$

$\xrightarrow{d} N(0, \sigma_1^2)$ by CLT applied to $\Delta_i = X_i - Y_i$ under H_0

thus $\frac{\frac{1}{\sqrt{n}}(\bar{X} - \bar{Y})}{s} = \frac{\frac{1}{\sqrt{n}}(\bar{X} - \bar{Y})}{\sigma} \left(\frac{\sigma}{s} \right) \xrightarrow{d} N(0, 1)$ by Slutsky since $\frac{\sigma}{s} \xrightarrow{P} 1$ by cont. theorem

5a. $L(p) = \frac{n!}{n_1! n_2! n_3!} p^{N_1} p^{N_2} (1-2p)^{n-N_1-N_2} \log L = C + (N_1 + N_2) \log p + (n - N_1 - N_2) \log(1-2p)$

$$\frac{d}{dp} (\log L) = \frac{N_1 + N_2}{p} - \frac{2(n - N_1 - N_2)}{1-2p} = 0$$

$$N_1 + N_2 - 2p(N_1 + N_2) - 2np + 2p(N_1 + N_2) = 0$$

$$\hat{p} = \frac{N_1 + N_2}{2n} \quad \text{so} \quad \hat{p}_1 = \hat{p}_2 = \hat{p}$$

$$\hat{p}_3 = 1 - \hat{p}_1 - \hat{p}_2 = 1 - 2\hat{p}$$

5b. To get score \underline{S} , we need $\log L(p_1, p_2 | N) = C + N_1 \log p_1 + N_2 \log p_2 + (n - N_1 - N_2) \log(1 - p_1 - p_2)$

$$S_1(p_1, p_2) = \frac{\partial}{\partial p_1} (\log L) = \frac{N_1}{p_1} - \frac{(n - N_1 - N_2)}{1 - p_1 - p_2} \text{ or } \frac{N_1}{p_1} - \frac{N_3}{p_3}$$

$$S_2(p_1, p_2) = \frac{\partial}{\partial p_2} (\log L) = \frac{N_2}{p_2} - \frac{N_3}{p_3}$$

Thus

$$T_{\underline{S}} = \left(\frac{N_1 - N_3}{\bar{p}} \quad \frac{N_2 - N_3}{1 - 2\bar{p}} \right) \frac{1}{n} \begin{pmatrix} \bar{p}(1 - \bar{p}) & -\bar{p}^2 \\ -\bar{p}^2 & \hat{p}(\hat{p}) \end{pmatrix} \begin{pmatrix} \frac{N_1 - N_3}{\bar{p}} & \frac{N_2 - N_3}{1 - 2\bar{p}} \\ \frac{N_2 - N_3}{\bar{p}} & \frac{N_2 - N_3}{1 - 2\bar{p}} \end{pmatrix}$$

5c. $h(p_1, p_2) = p_1 - p_2$ $H(p_1, p_2) = (1, -1)$

$$T_W = (\hat{p}_1 - \hat{p}_2) \left\{ (1, -1) \frac{1}{n} \begin{pmatrix} \hat{p}_1(1 - \hat{p}_1) & -\hat{p}_1\hat{p}_2 \\ -\hat{p}_1\hat{p}_2 & \hat{p}_2(1 - \hat{p}_2) \end{pmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\}^{-1} (\hat{p}_1 - \hat{p}_2)$$

$$= \frac{n(\hat{p}_1 - \hat{p}_2)^2}{\hat{p}_1(1 - \hat{p}_1) + \hat{p}_2(1 - \hat{p}_2) + 2\hat{p}_1\hat{p}_2} \quad \hat{p}_1 = \frac{N_1}{n} \quad \hat{p}_2 = \frac{N_2}{n}$$

1. $Y_n = O_p(1)$ means "For each $\epsilon > 0$, there exists $M_\epsilon + n_\epsilon$ such that $P(|Y_n| > M_\epsilon) < \epsilon$ for all $n \geq n_\epsilon$."

2. $\prod_{i=1}^n f_{\epsilon} \left(\frac{Y_i - X_i^T \beta}{\sqrt{g(X_i; \gamma)}} \right) \frac{1}{g(X_i; \gamma)}$

3. only b is true

- a. never put an n on the rhs of a limit
- c. AN says nothing about moments