

STAT610 - HWK Solution 12

5.3.8 (a) $H : \sigma_1^2 = \sigma_2^2 (= \sigma^2)$ vs. $H : \sigma_1^2 \neq \sigma_2^2$

Under Θ_0 , MLEs are $\hat{\mu}_1 = \bar{X}$, $\hat{\mu}_2 = \bar{Y}$, $\hat{\sigma}^2 = \frac{\sum(X_i - \bar{X})^2 + \sum(Y_i - \bar{Y})^2}{n_1 + n_2}$.

Under Θ , MLEs are $\hat{\mu}_1 = \bar{X}$, $\hat{\mu}_2 = \bar{Y}$, $\hat{\sigma}_1^2 = \frac{1}{n_1} \sum(X_i - \bar{X})^2$, $\hat{\sigma}_2^2 = \frac{1}{n_2} \sum(Y_i - \bar{Y})^2$.

$$\begin{aligned} \lambda &= \frac{\sup_{\Theta} p(x, y; \mu_1, \mu_2, \sigma_1^2, \sigma_2^2)}{\sup_{\Theta_0} p(x, y; \mu_1, \mu_2, \sigma^2)} = \frac{p(x, y; \hat{\mu}_1, \hat{\mu}_2, \hat{\sigma}_1^2, \hat{\sigma}_2^2)}{p(x, y; \hat{\mu}_1, \hat{\mu}_2, \hat{\sigma}^2)} \\ &= \frac{(\hat{\sigma}^2)^{\frac{n_1+n_2}{2}} \exp\left(-\frac{\sum(x_i - \bar{x})^2}{2\hat{\sigma}_1^2} - \frac{\sum(y_i - \bar{y})^2}{2\hat{\sigma}_2^2}\right)}{(\hat{\sigma}_1^2)^{\frac{n_1}{2}} (\hat{\sigma}_2^2)^{\frac{n_2}{2}} \exp\left(-\frac{\sum(x_i - \bar{x})^2 + \sum(y_i - \bar{y})^2}{2\hat{\sigma}^2}\right)} \\ &\propto \frac{\left(\frac{\sum(x_i - \bar{x})^2}{\sum(y_i - \bar{y})^2} + 1\right)^{\frac{n_1+n_2}{2}}}{\left(\frac{\sum(x_i - \bar{x})^2}{\sum(y_i - \bar{y})^2}\right)^{\frac{n_1}{2}}} \propto \frac{\left(\frac{s_1^2}{s_2^2} + \frac{n_2-1}{n_1-1}\right)^{\frac{n_1+n_2}{2}}}{\left(\frac{s_1^2}{s_2^2}\right)^{\frac{n_1}{2}}} \end{aligned}$$

(b) Since $(n_1 - 1)s_1^2/\sigma_1^2 \sim \chi_{n_1-1}^2$, $(n_2 - 1)s_2^2/\sigma_2^2 \sim \chi_{n_2-1}^2$, and they are independent,

$$\frac{s_1^2/\sigma_1^2}{s_2^2/\sigma_2^2} \sim F_{n_1-1, n_2-1}.$$

(c) $P(s_1^2/s_2^2 \leq c_{k,m}) = P\left(\sqrt{\frac{km}{\kappa(k+m)}} \left(\frac{s_1^2}{s_2^2} - 1\right) \leq z_{1-\alpha}\right).$

$$\begin{aligned} \sqrt{\frac{km}{\kappa(k+m)}} \left(\frac{s_1^2}{s_2^2} - 1\right) &= \sqrt{\frac{km}{\kappa(k+m)}} \left(\frac{(s_1^2 - \sigma_1^2) - (s_2^2 - \sigma_1^2)}{s_2^2}\right) \\ &= \frac{1}{s_2^2} \left(\sqrt{\frac{m}{\kappa(k+m)}} \sqrt{k}(s_1^2 - \sigma_1^2) - \sqrt{\frac{k}{\kappa(k+m)}} \sqrt{m}(s_2^2 - \sigma_1^2) \right) \quad (1) \end{aligned}$$

Under H , $E(s_1^2) = E(s_2^2) = \sigma_1^2$. By CLT and Slutsky's Theorem

$$\begin{aligned} \sqrt{k}(s_1^2 - \sigma_1^2) &\rightarrow \sqrt{n_1} \left(\frac{1}{n_1} \sum [(X_i - \mu)^2 - (\bar{X} - \mu)^2] - \sigma_1^2 \right) \\ &\rightarrow \sigma_1^2 \sqrt{n_1} \left(\frac{1}{n_1} \sum \left(\frac{X_i - \mu}{\sigma_1} \right)^2 - 1 \right) - \sqrt{n_1} (\bar{X} - \mu)^2 \\ &\rightarrow \sigma_1^2 N(0, \kappa), \end{aligned}$$

$$\text{similarly } \sqrt{m}(s_2^2 - \sigma_1^2) \rightarrow \sigma_1^2 N(0, \kappa)$$

Together with $s_2^2 \rightarrow \sigma_1^2$ by LLN, plug-into (1),

$$\sqrt{\frac{km}{\kappa(k+m)}} \left(\frac{s_1^2}{s_2^2} - 1\right) \rightarrow \frac{\sigma_1^2}{s_2^2} \left(\sqrt{\frac{m}{\kappa(k+m)}} + \frac{k}{\kappa(k+m)} \right) N(0, \kappa) = N(0, 1)$$

Therefore, $P(s_1^2/s_2^2 \leq c_{k,m}) \rightarrow 1 - \alpha$.

(d) By LLN, the moment estimate is consistent, as long as the moment exists. Thus, $\hat{c}_{k,m} \rightarrow c_{k,m}$, by LLN. Therefore, from (c), $P\left(\frac{s_1^2}{s_2^2} \leq \hat{c}_{k,m}\right) \rightarrow 1 - \alpha$.

5.3.17 $EX = 2(1 - \theta)$, $Var(X) = 2\theta(1 - \theta)$.

(a) By CLT,

$$\frac{\sqrt{n}(\bar{X} - 2(1 - \theta))}{\sqrt{2\theta(1 - \theta)}} \rightarrow N(0, 1).$$

$$P(\bar{X} \leq t) = P\left(\frac{\sqrt{n}(\bar{X} - 2(1 - \theta))}{\sqrt{2\theta(1 - \theta)}} \leq \frac{\sqrt{n}(t - 2(1 - \theta))}{\sqrt{2\theta(1 - \theta)}}\right) \sim \Phi\left(\frac{\sqrt{n}(t - 2(1 - \theta))}{\sqrt{2\theta(1 - \theta)}}\right)$$

(b) By delta method,

$$\begin{aligned} \frac{\sqrt{n}(\sqrt{\bar{X}} - \sqrt{2(1 - \theta)})}{\sqrt{2\theta(1 - \theta)}} &\rightarrow \left[\frac{1}{2\sqrt{x}} \Big|_{x=2(1-\theta)} \right] N(0, 1) \\ &\Rightarrow \sqrt{n}\left(\sqrt{\bar{X}} - \sqrt{2(1 - \theta)}\right) \rightarrow N\left(0, \frac{\theta}{4}\right) \end{aligned}$$

(c) By LLN, $\bar{X} \rightarrow \mu$. By continuous mapping theorem, $\bar{X}^2 \rightarrow \mu^2$. By Slutsky's theorem, $\sqrt{n}(\bar{X} - \mu) + \bar{X}^2 \rightarrow N(0, 2\theta(1 - \theta)) + \mu^2 = M(\mu^2, 2\theta(1 - \theta))$.

5.3.22 $S_n \sim \Gamma(n/2, 1/2)$. By B.2.4., $E(\sqrt{S_n}) = \frac{\Gamma(1/2 + n/2)}{(1/2)^{1/2} \Gamma(n/2)}$.

By Stirling's approximation, $\Gamma(p + 1) \sim \sqrt{2\pi} e^{-p} p^{p + \frac{1}{2}}$,

$$\begin{aligned} E(\sqrt{S_n}) &= \sqrt{2} \Gamma\left(\frac{n+1}{2}\right) / \Gamma\left(\frac{n}{2}\right) \\ &\sim \sqrt{2} \frac{\sqrt{2\pi} \exp\left(-\frac{n-1}{2}\right) \left(\frac{n-1}{2}\right)^{\frac{n}{2}}}{\sqrt{2\pi} \exp\left(-\frac{n-2}{2}\right) \left(\frac{n}{2} - 1\right)^{\frac{n-1}{2}}} \\ &= \sqrt{2} e^{-\frac{1}{2}} \left(\frac{n-1}{n-2}\right)^{\frac{n-2}{2}} \left(\frac{n-1}{2}\right) \left(\frac{n-2}{2}\right)^{-1/2} \\ &\sim \frac{n-1}{\sqrt{n-2}} \sim \frac{n+1}{\sqrt{n}} = \sqrt{n} + 1/\sqrt{n} \end{aligned}$$

Hence, $E(\sqrt{S_n}) = \sqrt{n} + R_n$ where $R_n = O(1/\sqrt{n})$.

5.3.28 (a) $E(\bar{Y} - \bar{X}) = \mu_2 - \mu_1 = \Delta$, $s^2 = \frac{(n-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}$, $T(\Delta) = \sqrt{\frac{n_1 n_2}{n}} \left(\frac{\bar{Y} - \bar{X} - \Delta}{s}\right)$.

By CLT,

$$\begin{aligned} \sqrt{\frac{n_1 n_2}{n}}(\bar{X} - \mu_1) &= \sqrt{\frac{n_2}{n}} \sqrt{n_1}(\bar{X} - \mu_1) \rightarrow \sqrt{(1 - \lambda)} N(0, \sigma_1^2) = N(0, (1 - \lambda)\sigma_1^2) \\ \sqrt{\frac{n_1 n_2}{n}}(\bar{Y} - \mu_2) &= \sqrt{\frac{n_1}{n}} \sqrt{n_2}(\bar{Y} - \mu_2) \rightarrow \sqrt{\lambda} N(0, \sigma_2^2) = N(0, \lambda\sigma_2^2) \end{aligned}$$

Hence,

$$\sqrt{\frac{n_1 n_2}{n}}(\bar{Y} - \bar{X} - \Delta) \rightarrow N(0, \lambda\sigma_2^2 + (1 - \lambda)\sigma_1^2).$$

Since $s^2 \rightarrow \lambda\sigma_1^2 + (1-\lambda)\sigma_2^2$, by Slutsky's theorem,

$$T(\Delta) \rightarrow N\left(0, \frac{\lambda\sigma_2^2 + (1-\lambda)\sigma_1^2}{\lambda\sigma_1^2 + (1-\lambda)\sigma_2^2}\right) \quad (2)$$

Therefore $P[T(\Delta) \leq t] \rightarrow \Phi\left(t\sqrt{\frac{\lambda\sigma_1^2 + (1-\lambda)\sigma_2^2}{\lambda\sigma_2^2 + (1-\lambda)\sigma_1^2}}\right)$.

- (b) If $\lambda = \frac{1}{2}$ or $\sigma_1 = \sigma_2$, $T(\Delta) \rightarrow N(0, 1)$. Also $t_{n-2} \rightarrow N(0, 1)$. Therefore, (4.9.3) has correct asymptotic probability of coverage.
- (c) If $\sigma_2^2 > \sigma_1^2$ and $\lambda > 1 - \lambda$, then $T(\Delta) \rightarrow N(0, \Sigma)$ in (2) with $\Sigma > 1$. Therefore, (4.9.3) has asymptotic probability of coverage $< 1 - \alpha$. Similarly if $\sigma_2^2 < \sigma_1^2$ and $\lambda > 1 - \lambda$, then $\Sigma < 1$, and (4.9.3) has asymptotic probability of coverage $> 1 - \alpha$.
- (d) The asymptotic length of the interval (4.9.3) is given by

$$l_1 = 2t_{n-2}\left(1 - \frac{\alpha}{2}\right) s\sqrt{\frac{n}{n_1n_2}} \rightarrow 2\Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \sqrt{\frac{\sigma_1^2}{1-\lambda} + \frac{\sigma_2^2}{\lambda}} \cdot n^{-\frac{1}{2}}$$

In section (4.9.4), $S_D^2 = \frac{s_1^2}{n_1} + \frac{s_2^2}{n_2} \rightarrow \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$. By CLT and Slutsky's theorem,

$$(\bar{Y} - \bar{X} - \Delta)/S_D \rightarrow N(0, 1).$$

So the asymptotic length of the interval based on $|D - \Delta|/s_D$ is given by

$$l_2 = 2\Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2} = 2\Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \sqrt{\frac{\sigma_1^2}{\lambda} + \frac{\sigma_2^2}{1-\lambda}} \cdot n^{-\frac{1}{2}}.$$