

Answer Key 10

1.

(1) Consider $\hat{\mu} = c_1 \bar{Y}_1 + c_2 \bar{Y}_2$. Then $E(\hat{\mu}) = (c_1 + c_2)\mu$. For $\hat{\mu}$ to be unbiased, we require

$$c_1 + c_2 = 1. \quad V(\hat{\mu}) = \frac{\sigma_1^2}{n_1} c_1^2 + \frac{\sigma_2^2}{n_2} c_2^2.$$

For $\hat{\mu}$ to be MVUE, minimize $V(\hat{\mu})$ s.t. $c_1 + c_2 = 1$.

$$\text{The answer will be } c_1^* = \frac{\sigma_2^2/n_2}{\sigma_1^2/n_1 + \sigma_2^2/n_2}, \quad c_2^* = \frac{\sigma_1^2/n_1}{\sigma_1^2/n_1 + \sigma_2^2/n_2}.$$

(2) Let $A = \frac{\sigma_1^2}{n_1}$, $B = \frac{\sigma_2^2}{n_2}$. Then $A, B > 0$, and

$$V(T) = \left(\frac{B}{A+B} \right)^2 A + \left(\frac{A}{A+B} \right)^2 B = \frac{AB}{A+B} < A = \frac{A(A+B)}{(A+B)} = V(\bar{Y}_1).$$

$$\text{And } V(T) = \frac{AB}{A+B} < B = \frac{B(A+B)}{(A+B)} = V(\bar{Y}_2).$$

$$2. \quad T = \hat{P}(Y \leq c) = \frac{\# \text{ of } Y_i \leq c}{n}.$$

$$(1) \quad X = \# \text{ of } Y_i \leq c = \sum_{i=1}^n Z_i, \text{ where } Z_i = \begin{cases} 1 & \text{for } Y_i \leq c \\ 0 & \text{otherwise} \end{cases}.$$

Then $X \sim B(n, \theta)$ and $Z_i \sim \text{Bernoulli}(\theta)$.

Note that $E(X) = n\theta$, $V(X) = n\theta(1-\theta)$.

Therefore, $E(T) = \frac{1}{n} E(X) = \theta$; unbiased.

$$(2) \quad V(T) = \frac{1}{n^2} V(X) = \frac{\theta(1-\theta)}{n}.$$

(3) Note that $T = \frac{1}{n} \sum_{i=1}^n Z_i = \bar{Z} \xrightarrow{p} E(Z) = \theta$, since $V(T) \rightarrow 0$.

(4) From Central Limit Theorem, $T \stackrel{a}{\sim} N(\theta, \theta(1-\theta)/n)$.

(5) From (4), $Asy.V(T) = \frac{\theta(1-\theta)}{n}$.

Since T is a consistent estimator of θ , propose $\hat{Asy.V}(T) = \frac{T(1-T)}{n}$.

Then, since $p\lim T = \theta$, $\hat{Asy.V}(T) = \frac{T(1-T)}{n} \xrightarrow{p} \frac{\theta(1-\theta)}{n} = Asy.V(T)$.

(6) From (4) and (5), 95% asymptotic confidence interval of θ is $\left[T \pm 1.96 \sqrt{\frac{T(1-T)}{n}} \right]$.