

STAT 510 HW#6

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Ex 15.7.1

1(a) Size = $\sup_{\theta \in T_0} P_{\theta}[T(X) > c]$

$$T(X) = |X-1|, \quad c = 3/4$$

$$\text{Size} = \sup_{\lambda > 0} P_{\lambda}[|X-1| > 3/4]$$

$$= \sup_{\lambda > 0} (P_{\lambda}[X < 1/4] + P_{\lambda}[X > 5/4])$$

$$= 1 - e^{-\frac{1}{4}\lambda} + 1 - (1 - e^{-\frac{3}{4}\lambda})$$

$$= \boxed{0.3949}$$

1.(b) Power $\lambda = 1 - P_{\lambda}(\text{Type II error})$

$$= 1 - P_{\lambda}[|X-1| \leq 3/4]$$

$$= 1 - P_{\lambda}[1/4 \leq X \leq 5/4]$$

$$= 1 - (P_{\lambda}[X \leq 5/4] - P_{\lambda}[X \leq 1/4])$$

$$= 1 - (1 - e^{-\frac{3}{4}\lambda} - (1 - e^{-\frac{1}{4}\lambda}))$$

$$= \underline{1 - e^{-\frac{1}{4}\lambda} + e^{-\frac{3}{4}\lambda}}$$

1.(c) $\frac{d\text{Power}}{d\lambda} = \frac{1}{4}e^{-\frac{1}{4}\lambda} - \frac{3}{4}e^{-\frac{3}{4}\lambda} = 0$

$$\Rightarrow \lambda = \frac{2}{3} \ln 7 \approx 1.297$$

When $\lambda = \frac{2}{3} \ln 7$,

$$\text{Power} = 1 - e^{-\frac{1}{4}\lambda} + e^{-\frac{3}{4}\lambda}$$

$$= 1 - \frac{6}{7\sqrt[3]{7}}$$

$$\approx \boxed{0.3802}$$

Since $0.3802 < 0.3949$, Power is less than Size.

Yes, it is a problem. Since Size refers to Type I error where we reject H_0 when H_0 is true and Power refers to the situation where we reject H_0 when H_0 is true. Larger size indicates that we are rejecting more than we should.



Ex 15.7.2 2. $X_1, \dots, X_n \stackrel{iid}{\sim} U(0, \theta)$, $T = \max \{X_1, \dots, X_n\}$

$$P(T < c)$$

$$= P(X_1 < c, X_2 < c, \dots, X_n < c)$$

$$= \prod_{i=1}^n P(X_i < c) \quad \text{due to iid.}$$

$$= \prod_{i=1}^n \frac{c}{\theta} \quad \text{Since cdf} = \frac{c}{\theta}.$$

$$= \left(\frac{c}{\theta}\right)^n$$

$$\text{Since Size} = \sup_{0 < \theta \leq \frac{1}{2}} P_{\theta}[T > c] = 0.05$$

$$\sup_{0 < \theta \leq \frac{1}{2}} (1 - P_{\theta}[T < c]) = 0.05$$

$$\sup_{0 < \theta \leq \frac{1}{2}} \left(1 - \left(\frac{c}{\theta}\right)^n\right) = 0.05$$

$$(2c)^n = 0.95$$

$$c = \boxed{0.95^{\frac{1}{n}} \cdot \frac{1}{2}}$$

when $n = 10$

$$c = 0.95^{0.1} \cdot \frac{1}{2}$$

$$= \boxed{0.4974}$$



Ex 16.7.2

3. (a) Under Null hypothesis: $\mu_x = \mu_y$

$$\text{Then, } \hat{\mu} = \frac{1}{n+m} \left(\sum_{i=1}^n x_i + \sum_{i=1}^m y_i \right)$$

$$= \frac{1}{n+m} (n\bar{x} + m\bar{y})$$

$$\hat{\sigma}_0^2 = \frac{1}{n+m} \left(\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{i=1}^m (y_i - \hat{\mu})^2 \right)$$

(b). Under Alternative: $\mu_x \neq \mu_y$.

$$\text{Then, } \hat{\mu}_x = \bar{x}, \quad \hat{\mu}_y = \bar{y}$$

$$\hat{\sigma}_A^2 = \frac{1}{n+m} \left(\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{i=1}^m (y_i - \bar{y})^2 \right)$$

$$\begin{aligned} \text{(c). } LRT &= \frac{f(x|\hat{\theta}_A)}{f(x|\hat{\theta}_0)} \\ &= \frac{\hat{\sigma}_0^{\frac{n+m}{2}} e^{-\frac{1}{2\hat{\sigma}_0^2} \left(\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{i=1}^m (y_i - \bar{y})^2 \right)}}{\hat{\sigma}_A^{\frac{n+m}{2}} e^{-\frac{1}{2\hat{\sigma}_A^2} \left(\sum_{i=1}^n (x_i - \hat{\mu})^2 + \sum_{i=1}^m (y_i - \hat{\mu})^2 \right)}} \\ &= \left(\frac{\hat{\sigma}_0^2}{\hat{\sigma}_A^2} \right)^{\frac{n+m}{2}} \end{aligned}$$

$$\text{(d). } (n+m)(\hat{\sigma}_0^2 - \hat{\sigma}_A^2)$$

$$= \frac{n+m}{n+m} \left(\sum_{i=1}^n ((x_i - \hat{\mu})^2 - (x_i - \bar{x})^2) + \sum_{i=1}^m ((y_i - \hat{\mu})^2 - (y_i - \bar{y})^2) \right)$$

$$= \sum_{i=1}^n ((x_i^2 - 2x_i\hat{\mu} + \hat{\mu}^2) - (x_i^2 - 2x_i\bar{x} + \bar{x}^2)) + \dots$$

$$= \sum_{i=1}^n (-2x_i(\hat{\mu} - \bar{x}) + \hat{\mu}^2 - \bar{x}^2) + \sum_{i=1}^m (-2y_i(\hat{\mu} - \bar{y}) + \hat{\mu}^2 - \bar{y}^2)$$

$$= -2n\bar{x}(\hat{\mu} - \bar{x}) + n(\hat{\mu}^2 - \bar{x}^2) - 2m\bar{y}(\hat{\mu} - \bar{y}) + m(\hat{\mu}^2 - \bar{y}^2)$$

$$= n(\hat{\mu} - \bar{x})^2 + m(\hat{\mu} - \bar{y})^2$$

$$= \frac{n m^2 (\bar{x} - \bar{y})^2}{(n+m)^2} + \frac{m n^2 (\bar{x} - \bar{y})^2}{(n+m)^2}$$

$$= \frac{nm}{n+m} (\bar{x} - \bar{y})^2$$

$$\boxed{k_{n,m} = \frac{nm}{n+m}}$$



3. (e) It is t_{n+m-2} distribution.

(f) Since $(n+m)(\hat{\sigma}_0^2 - \hat{\sigma}_A^2) = \frac{nm}{n+m}(\bar{x} - \bar{y})^2$
 $(\bar{x} - \bar{y})^2 = \frac{(n+m)^2}{nm}(\hat{\sigma}_0^2 - \hat{\sigma}_A^2)$

$$\begin{aligned} T^2 &= \frac{(\bar{x} - \bar{y})^2}{S_{\text{pooled}}^2 \left(\frac{n+m}{nm} \right)} \\ &= \frac{(n+m)(\hat{\sigma}_0^2 - \hat{\sigma}_A^2)}{(n+m)\hat{\sigma}_A^2 - \frac{1}{n+m-2}} \\ &= \frac{\hat{\sigma}_0^2 - \hat{\sigma}_A^2}{\hat{\sigma}_A^2} (n+m-2) \end{aligned}$$

$$\frac{\hat{\sigma}_0^2}{\hat{\sigma}_A^2} = \frac{T^2}{n+m-2} + 1$$

Since $LRT = \left(\frac{\hat{\sigma}_0^2}{\hat{\sigma}_A^2} \right)^{\frac{n+m}{2}}$

$$LRT = \left(\frac{T^2}{n+m-2} + 1 \right)^{\frac{n+m}{2}}$$

Hence, LRT is increasing function of T^2 .

Ex 16.7.8

4. (a) Under H_0 , $\rho = 0$, $\sigma^2 > 0$

$$\begin{pmatrix} x_1 \\ y_1 \end{pmatrix} \dots \begin{pmatrix} x_n \\ y_n \end{pmatrix} \stackrel{iid}{\sim} N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right)$$

$$\begin{aligned} \text{Hence, } \hat{\sigma}^2 &= \frac{1}{n} (\sum (x_i - 0)^2 + \sum (y_i - 0)^2) \\ &= \frac{1}{2n} (\sum x_i^2 + \sum y_i^2) \\ &= \boxed{T_1 / 2n} \end{aligned}$$



Ex 16.7.8.

4(b) $U_i = (X_i + Y_i)/\sqrt{2}$, $V_i = (X_i - Y_i)/\sqrt{2}$

$\Rightarrow X_i = \frac{1}{\sqrt{2}}(U_i + V_i)$ $Y_i = \frac{1}{\sqrt{2}}(U_i - V_i)$

$|J| = \begin{vmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{vmatrix} = 1$

for $\Sigma = \sigma^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$

$|\Sigma| = \sigma^4(1 - \rho^2)$ $\Sigma^{-1} = \frac{1}{\sigma^4(1 - \rho^2)} \begin{pmatrix} 1 & -\rho \\ -\rho & 1 \end{pmatrix}$

$$f(u_i, v_i) = \frac{1}{2\pi} \frac{1}{\sqrt{\sigma^4(1 - \rho^2)}} e^{-\frac{1}{2\sigma^4(1 - \rho^2)} \begin{pmatrix} (u_i + v_i)/\sqrt{2} \\ (u_i - v_i)/\sqrt{2} \end{pmatrix}^T \begin{pmatrix} 1 & -\rho \\ -\rho & 1 \end{pmatrix} \begin{pmatrix} (u_i + v_i)/\sqrt{2} \\ (u_i - v_i)/\sqrt{2} \end{pmatrix}}$$

$$= \frac{1}{2\pi} \frac{1}{\sigma^2 \sqrt{1 - \rho} \sqrt{1 + \rho}} e^{-\frac{1}{2\sigma^4(1 - \rho^2)} ((\rho + 1)v_i^2 - (\rho - 1)u_i^2)}$$

Since the joint pdf of u_i, v_i can be factored to two pdf with only u_i and v_i ,

i.e. pdf of $N(0, \sigma^2(1 + \rho)) \cdot$ pdf of $N(0, \sigma^2(1 - \rho))$

Hence, u_i and v_i are independent.

Also, $u_i \sim N(0, \theta_1)$, $v_i \sim N(0, \theta_2)$

where $\theta_1 = \sigma^2(1 + \rho)$, $\theta_2 = \sigma^2(1 - \rho)$

(c). $\hat{\theta}_1 = \frac{\sum u_i^2}{n}$ $\hat{\theta}_2 = \frac{\sum v_i^2}{n}$

(d) $\hat{\theta}_1 = \hat{\sigma}^2(1 + \hat{\rho}) = \frac{\sum u_i^2}{n} = \frac{\sum (X_i + Y_i)^2}{2n}$

$\hat{\theta}_2 = \hat{\sigma}^2(1 - \hat{\rho}) = \frac{\sum v_i^2}{n} = \frac{\sum (X_i - Y_i)^2}{2n}$

$\hat{\theta}_1 + \hat{\theta}_2 = 2\hat{\sigma}^2 = \frac{1}{2n} \sum ((X_i + Y_i)^2 + (X_i - Y_i)^2)$

$\hat{\theta}_1 - \hat{\theta}_2 = 2\hat{\sigma}^2\hat{\rho} = \frac{1}{2n} \sum ((X_i + Y_i)^2 - (X_i - Y_i)^2)$

$\Rightarrow \hat{\sigma}^2 = \frac{T_1}{2n}$, $\hat{\rho} = \frac{2T_2}{T_1}$



Ex. 16.7.8. 4. (e) Under H_0 , $\rho = 0$, $\sigma^2 > 0$.

$$\Sigma_0 = \sigma^2 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}.$$

$$|\Sigma_0| = \sigma^4, \quad \Sigma_0^{-1} = \frac{1}{\sigma^4} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Under H_A , $\rho \neq 0$, $\sigma^2 > 0$

$$|\Sigma_A| = \sigma^4(1 - \rho^2), \quad \Sigma_A^{-1} = \frac{1}{\sigma^4(1 - \rho^2)} \begin{pmatrix} 1 & -\rho \\ -\rho & 1 \end{pmatrix}$$

$$LRT = \left(\frac{\sigma^4(1 - \rho^2)}{\sigma^4} \right)^{-n/2} \frac{e^{-\frac{1}{\sigma^4(1 - \rho^2)} \cdot \sum (x_i^2 + y_i^2 - 2\rho^2 x_i y_i)}}{e^{-\frac{1}{\sigma^4} \cdot \sum (x_i^2 + y_i^2)}}$$

$$= (1 - \rho^2)^{-n/2}$$

$$= \left(1 - \left(\frac{T_2}{T_1} \right)^2 \right)^{-n/2}$$

Hence, it is equivalent to rejecting H_0
when $2(T_2/T_1)^2 > c$

