

**TEMA 7: Contraste de hipótesis**

- 7.1. Planteamiento del problema y conceptos básicos.
- 7.2. Test de Neyman-Pearson.
- 7.3. Test de la razón de verosimilitudes.
- 7.4. Contrastes sobre los parámetros de una población normal.
- 7.5. Contrastes sobre los parámetros de dos poblaciones normales.
- 7.6. Dualidad entre estimación por intervalos y contraste de hipótesis.

## 7.1. PLANTEAMIENTO DEL PROBLEMA Y CONCEPTOS BÁSICOS

$(X_1, \dots, X_n) \in \chi^n$  muestra aleatoria simple de  $X \rightarrow \{P_\theta; \theta \in \Theta\}$ ,  $\Theta = \Theta_0 \cup \Theta_1$

$H_0 : \theta \in \Theta_0$  Hipótesis nula

$H_1 : \theta \in \Theta_1$  Hipótesis alternativa

**Test de hipótesis:** Es un estadístico,  $\varphi(X_1, \dots, X_n)$ , con valores en  $[0,1]$ , que especifica la probabilidad de rechazar  $H_0$  a partir de  $X_1, \dots, X_n$ .

- *Test no aleatorizado:*  $\varphi : \chi^n \rightarrow \{0, 1\}$ .

$$\varphi(X_1, \dots, X_n) = \begin{cases} 1 & (X_1, \dots, X_n) \in C \\ 0 & (X_1, \dots, X_n) \notin C \end{cases} \quad \begin{array}{l} C \subseteq \chi^n \text{ región crítica o de rechazo} \\ C^c = \chi^n - C \text{ región de aceptación.} \end{array}$$

- *Test aleatorizado:* Toma algún valor distinto de 0, 1.

**Tipos de errores asociados a un test de hipótesis:**

- *Error de tipo 1:* Rechazar  $H_0$  siendo cierta.
- *Error de tipo 2:* Aceptar  $H_0$  siendo falsa.

**Función de potencia de  $\varphi(X_1, \dots, X_n)$ :**

$$\begin{aligned} \beta_\varphi : \Theta &\rightarrow [0, 1] \\ \theta &\mapsto \beta_\varphi(\theta) = E_\theta [\varphi(X_1, \dots, X_n)] \quad (\text{probabilidad media de rechazar } H_0 \text{ bajo } P_\theta.) \end{aligned}$$

**Tamaño de  $\varphi(X_1, \dots, X_n)$ :**  $\sup_{\theta \in \Theta_0} \beta_\varphi(\theta)$  (máxima probabilidad media de cometer un error de tipo 1).

**Nivel de significación de un test:**  $\varphi(X_1, \dots, X_n)$  tiene nivel de significación  $\alpha$  ( $\in [0, 1]$ ) si su tamaño es menor o igual que  $\alpha$  (cota superior de las probabilidades medias de cometer error de tipo 1):

$$\forall \theta \in \Theta_0, \beta_\varphi(\theta) = E_\theta [\varphi(X_1, \dots, X_n)] \leq \alpha.$$

**Test uniformemente más potente:** Un test  $\varphi(X_1, \dots, X_n)$  con nivel de significación  $\alpha$  es uniformemente más potente a dicho nivel si para cualquier otro test,  $\varphi'(X_1, \dots, X_n)$ , con nivel de significación  $\alpha$ , se tiene:

$$\beta_{\varphi'}(\theta) \leq \beta_\varphi(\theta), \quad \forall \theta \in \Theta_1.$$

**Resolución de un problema de contraste:** *fijado un nivel de significación, encontrar el test uniformemente más potente a dicho nivel.*

## 7.2. LEMA DE NEYMAN-PEARSON ( $H_0, H_1$ simples)

Sea  $X \rightarrow \{P_\theta; \theta \in \{\theta_0, \theta_1\}\}$  y  $(X_1, \dots, X_n)$  una muestra aleatoria simple con funciones de densidad (o funciones masa de probabilidad)  $f_0^n(x_1, \dots, x_n)$  ( $\theta = \theta_0$ ) y  $f_1^n(x_1, \dots, x_n)$  ( $\theta = \theta_1$ ). Consideremos el problema de contraste

$$\begin{aligned} H_0 : \theta &= \theta_0 \\ H_1 : \theta &= \theta_1. \end{aligned}$$

a) Sea  $\varphi(X_1, \dots, X_n)$  un test de la forma

$$\varphi(X_1, \dots, X_n) = \begin{cases} 1, & \text{si } f_1^n(X_1, \dots, X_n) > k f_0^n(X_1, \dots, X_n) \\ \gamma(X_1, \dots, X_n), & \text{si } f_1^n(X_1, \dots, X_n) = k f_0^n(X_1, \dots, X_n) \\ 0, & \text{si } f_1^n(X_1, \dots, X_n) < k f_0^n(X_1, \dots, X_n), \end{cases}$$

con  $k \in \mathbb{R}^+ \cup \{0\}$  y  $\gamma(X_1, \dots, X_n) \in [0, 1]$ . Si  $\varphi(X_1, \dots, X_n)$  tiene tamaño  $\alpha$ , es de máxima potencia a nivel de significación  $\alpha$ . Un test de esta forma se denomina test de Neyman-Pearson.

b) Para todo  $\alpha \in (0, 1]$  existe un test de Neyman-Pearson de tamaño  $\alpha$ , con  $\gamma(X_1, \dots, X_n) = \gamma$  constante.

c) Si  $\varphi'(X_1, \dots, X_n)$  es un test de tamaño  $\alpha$  y es de máxima potencia a nivel de significación  $\alpha$ ,  $\varphi'(X_1, \dots, X_n)$  es un test de Neyman-Pearson.

d) El test de máxima potencia entre todos los de nivel de significación 0 (tamaño 0) es:

$$\varphi_0(X_1, \dots, X_n) = \begin{cases} 1, & \text{si } f_0^n(X_1, \dots, X_n) = 0 \\ 0, & \text{si } f_0^n(X_1, \dots, X_n) > 0 \end{cases}$$

## 7.3. TEST DE LA RAZÓN DE VEROSIMILITUDES ( $H_0, H_1$ arbitrarias)

Sea  $(X_1, \dots, X_n) \in \chi^n$  una muestra aleatoria simple de  $X \rightarrow \{P_\theta; \theta \in \Theta = \Theta_0 \cup \Theta_1\}$ . El test de razón de verosimilitudes para el problema de contraste

$$\begin{aligned} H_0 : \theta &\in \Theta_0 \\ H_1 : \theta &\in \Theta_1 \end{aligned}$$

se define como:

$$\varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \lambda(X_1, \dots, X_n) < c \\ 0 & \text{si } \lambda(X_1, \dots, X_n) \geq c \end{cases} \quad \text{con } \lambda(x_1, \dots, x_n) = \frac{\sup_{\theta \in \Theta_0} L_{x_1, \dots, x_n}(\theta)}{\sup_{\theta \in \Theta} L_{x_1, \dots, x_n}(\theta)}, \quad \forall (x_1, \dots, x_n) \in \chi^n,$$

siendo  $L_{x_1, \dots, x_n}$  la función de verosimilitud asociada a  $(x_1, \dots, x_n)$ , y  $c \in (0, 1]$  una constante que se determina imponiendo el tamaño o nivel de significación requerido.

## 7.4. CONTRASTES SOBRE LOS PARÁMETROS DE UNA NORMAL

### Contrastes sobre la media con varianza conocida

$(X_1, \dots, X_n)$  muestra aleatoria simple de  $X \longrightarrow \{\mathcal{N}(\mu, \sigma_0^2); \mu \in \mathbb{R}\}$

*Función de verosimilitud:*

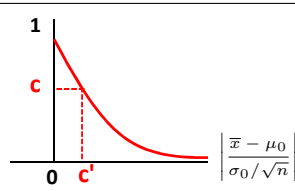
$$(x_1, \dots, x_n) \in \mathbb{R}^n \longrightarrow L_{x_1, \dots, x_n}(\mu) = \frac{1}{(\sigma_0^2)^{n/2} (2\pi)^{n/2}} e^{-\sum_{i=1}^n (x_i - \mu)^2 / 2\sigma_0^2}, \quad \mu \in \mathbb{R}$$

$$\sup_{\mu \in \mathbb{R}} L_{x_1, \dots, x_n}(\mu) = L_{x_1, \dots, x_n}(\bar{x})$$

$$\sup_{\mu \leq \mu_0} L_{x_1, \dots, x_n}(\mu) = \begin{cases} L_{x_1, \dots, x_n}(\bar{x}), & \bar{x} \leq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \leq 0 \right) \\ L_{x_1, \dots, x_n}(\mu_0), & \bar{x} \geq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq 0 \right) \end{cases}$$

$$\sup_{\mu \geq \mu_0} L_{x_1, \dots, x_n}(\mu) = \begin{cases} L_{x_1, \dots, x_n}(\mu_0), & \bar{x} \leq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \leq 0 \right) \\ L_{x_1, \dots, x_n}(\bar{x}), & \bar{x} \geq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq 0 \right) \end{cases}$$

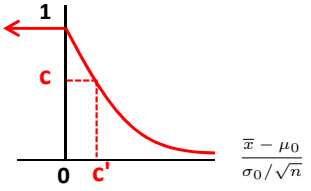
$$\begin{matrix} H_0 : \mu = \mu_0 \\ H_1 : \mu \neq \mu_0 \end{matrix} \quad \text{TRV de tamaño } \alpha \in [0, 1] \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \left| \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} \right| > z_{\alpha/2} \\ 0 & \text{si } \left| \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} \right| \leq z_{\alpha/2} \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu = \mu_0} L_{x_1, \dots, x_n}(\mu)}{\sup_{\mu \in \mathbb{R}} L_{x_1, \dots, x_n}(\mu)} = \frac{L_{x_1, \dots, x_n}(\mu_0)}{L_{x_1, \dots, x_n}(\bar{x})} = \exp \left\{ \frac{-n(\bar{x} - \mu_0)^2}{2\sigma_0^2} \right\}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (\in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \quad \Leftrightarrow \quad \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \left| \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \right| > c' \quad (\geq 0) \\ 0, & \left| \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \right| \leq c' \end{cases}$$

$$\alpha = P_{\mu_0} \left( \left| \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} \right| > c' \right) = [Z \rightarrow \mathcal{N}(0, 1)] = P(|Z| > c') \Rightarrow c' = z_{\alpha/2} \geq 0, \quad \forall \alpha \in [0, 1].$$

$$\boxed{\begin{array}{l} H_0 : \mu \leq \mu_0 \\ H_1 : \mu > \mu_0 \end{array}} \quad \text{TRV de tamaño } \alpha \leq 1/2 \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} > z_\alpha \\ 0 & \text{si } \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} \leq z_\alpha \end{cases}$$

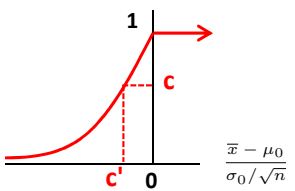
$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \leq \mu_0} L_{x_1, \dots, x_n}(\mu)}{L_{x_1, \dots, x_n}(\bar{x})} = \begin{cases} 1, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \leq 0 \\ \frac{L_{x_1, \dots, x_n}(\mu_0)}{L_{x_1, \dots, x_n}(\bar{x})}, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq 0 \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} > c' \quad (c' \geq 0) \\ 0, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \leq c' \end{cases}$$

$$\alpha = \sup_{\mu \leq \mu_0} P_\mu \left( \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} > c' \right) = \sup_{\mu \leq \mu_0} P_\mu \left( \bar{X} > \mu_0 + c' \frac{\sigma_0}{\sqrt{n}} \right) = \sup_{\mu \leq \mu_0} P_\mu \left( \frac{\bar{X} - \mu}{\sigma_0/\sqrt{n}} > \frac{\mu_0 - \mu}{\sigma_0/\sqrt{n}} + c' \right) =$$

$$\left[ Z \rightarrow \mathcal{N}(0, 1) \right] = \sup_{\mu \leq \mu_0} P \left( Z > \frac{\mu_0 - \mu}{\sigma_0/\sqrt{n}} + c' \right) = P(Z > c') = \alpha \Rightarrow c' = z_\alpha \quad (\geq 0 \Leftrightarrow \alpha \leq 1/2)$$

$$\boxed{\begin{array}{l} H_0 : \mu \geq \mu_0 \\ H_1 : \mu < \mu_0 \end{array}} \quad \text{TRV de tamaño } \alpha \leq 1/2 \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} < z_{1-\alpha} \\ 0 & \text{si } \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} \geq z_{1-\alpha} \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \geq \mu_0} L_{x_1, \dots, x_n}(\mu)}{L_{x_1, \dots, x_n}(\bar{x})} = \begin{cases} \frac{L_{x_1, \dots, x_n}(\mu_0)}{L_{x_1, \dots, x_n}(\bar{x})}, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \leq 0 \\ 1, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq 0 \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} < c' \quad (c' \leq 0) \\ 0, & \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq c' \end{cases}$$

$$\alpha = \sup_{\mu \geq \mu_0} P_\mu \left( \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} < c' \right) = \sup_{\mu \geq \mu_0} P_\mu \left( \bar{X} < \mu_0 + c' \frac{\sigma_0}{\sqrt{n}} \right) = \sup_{\mu \geq \mu_0} P_\mu \left( \frac{\bar{X} - \mu}{\sigma_0/\sqrt{n}} < \frac{\mu_0 - \mu}{\sigma_0/\sqrt{n}} + c' \right) =$$

$$\left[ Z \rightarrow \mathcal{N}(0, 1) \right] = \sup_{\mu \geq \mu_0} P \left( Z < \frac{\mu_0 - \mu}{\sigma_0/\sqrt{n}} + c' \right) = P(Z < c') = \alpha \Rightarrow c' = z_{1-\alpha} \quad (\leq 0 \Leftrightarrow \alpha \leq 1/2)$$

# Contrastes sobre la media con varianza desconocida

$(X_1, \dots, X_n)$  muestra aleatoria simple de  $X \rightarrow \{\mathcal{N}(\mu, \sigma^2); \mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+\}$

*Función de verosimilitud:*

$$(x_1, \dots, x_n) \in \mathbb{R}^n \rightarrow L_{x_1, \dots, x_n}(\mu, \sigma^2) = \frac{1}{(\sigma^2)^{n/2} (2\pi)^{n/2}} e^{-\sum_{i=1}^n (x_i - \mu)^2 / 2\sigma^2}, \quad \mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+$$

$$\sup_{\mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2) = L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2), \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$$

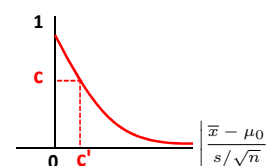
$$\sup_{\mu = \mu_0, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2) = L_{x_1, \dots, x_n}(\mu_0, \hat{\sigma}_0^2), \quad \hat{\sigma}_0^2 = \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{n}$$

$$\sup_{\mu \leq \mu_0, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2) = \begin{cases} L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2), & \bar{x} \leq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \leq 0 \right) \\ L_{x_1, \dots, x_n}(\mu_0, \hat{\sigma}_0^2), & \bar{x} \geq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \geq 0 \right) \end{cases}$$

$$\sup_{\mu \geq \mu_0, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2) = \begin{cases} L_{x_1, \dots, x_n}(\mu_0, \hat{\sigma}_0^2), & \bar{x} \leq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \leq 0 \right) \\ L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2), & \bar{x} \geq \mu_0 \left( \Leftrightarrow \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \geq 0 \right) \end{cases}$$

$$\begin{matrix} H_0 : \mu = \mu_0 \\ H_1 : \mu \neq \mu_0 \end{matrix} \quad \text{TRV de tamaño } \alpha \in [0, 1] \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \left| \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \right| > t_{n-1; \alpha/2} \\ 0 & \text{si } \left| \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \right| \leq t_{n-1; \alpha/2} \end{cases}$$

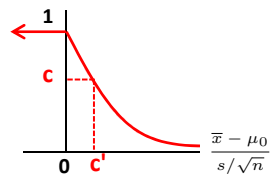
$$\begin{aligned} \lambda(x_1, \dots, x_n) &= \frac{\sup_{\mu = \mu_0, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2)}{\sup_{\mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2)} = \frac{L_{x_1, \dots, x_n}(\mu_0, \hat{\sigma}_0^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)} = \\ &= \left[ \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{\sum_{i=1}^n (x_i - \mu_0)^2} \right]^{n/2} = \left[ \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2} \right]^{n/2} = \left[ \frac{1}{1 + \frac{n(\bar{x} - \mu_0)^2}{(n-1)s^2}} \right]^{n/2} \end{aligned}$$



$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (\in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \quad \Leftrightarrow \quad \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \left| \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \right| > c' \quad (c' \geq 0) \\ 0, & \left| \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \right| \leq c'. \end{cases}$$

$$\alpha = \sup_{\sigma^2 \in \mathbb{R}^+} P_{\mu_0, \sigma^2} \left( \left| \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \right| > c' \right) = [T \rightarrow t(n-1)] = P(|T| > c') \Rightarrow c' = t_{n-1; \alpha/2} \geq 0, \quad \forall \alpha \in [0, 1].$$

$$\begin{array}{l}
 H_0 : \mu \leq \mu_0 \\
 H_1 : \mu > \mu_0
 \end{array}
 \quad \text{TRV de tamaño } \alpha \leq 1/2 \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\bar{X} - \mu_0}{S/\sqrt{n}} > t_{n-1; \alpha} \\ 0 & \text{si } \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \leq t_{n-1; \alpha} \end{cases}$$

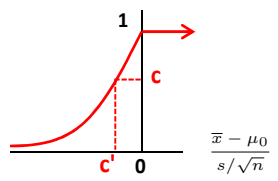
$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \leq \mu_0, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)} = \begin{cases} 1, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \leq 0 \\ \frac{L_{x_1, \dots, x_n}(\mu_0, \hat{\sigma}_0^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)}, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \geq 0 \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} > c' \quad (c' \geq 0) \\ 0, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \leq c'. \end{cases}$$

$$\alpha = \sup_{\mu \leq \mu_0, \sigma^2 \in \mathbb{R}^+} P_{\mu, \sigma^2} \left( \frac{\bar{X} - \mu_0}{S/\sqrt{n}} > c' \right) = \sup_{\mu \leq \mu_0, \sigma^2 \in \mathbb{R}^+} P_{\mu, \sigma^2} \left( \bar{X} > \mu_0 + c' \frac{S}{\sqrt{n}} \right) = \sup_{\mu \leq \mu_0, \sigma^2 \in \mathbb{R}^+} P_{\mu, \sigma^2} \left( \frac{\bar{X} - \mu}{S/\sqrt{n}} > \frac{\mu_0 - \mu}{S/\sqrt{n}} + c' \right) =$$

$$[T \rightarrow t(n-1)] = \sup_{\mu \leq \mu_0} P \left( T > \frac{\mu_0 - \mu}{S/\sqrt{n}} + c' \right) = P(T > c') = \alpha \Rightarrow c' = t_{n-1; \alpha} \quad (\alpha \geq 0 \Leftrightarrow \alpha \leq 1/2)$$

$$\begin{array}{l}
 H_0 : \mu \geq \mu_0 \\
 H_1 : \mu < \mu_0
 \end{array}
 \quad \text{TRV de tamaño } \alpha \leq 1/2 \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\bar{X} - \mu_0}{S/\sqrt{n}} < t_{n-1; 1-\alpha} \\ 0 & \text{si } \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \geq t_{n-1; 1-\alpha} \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \geq \mu_0, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)} = \begin{cases} \frac{L_{x_1, \dots, x_n}(\mu_0, \hat{\sigma}_0^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)}, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \leq 0 \\ 1, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \geq 0 \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} < c' \quad (c' \leq 0) \\ 0, & \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \geq c'. \end{cases}$$

$$\alpha = \sup_{\mu \geq \mu_0, \sigma^2 \in \mathbb{R}^+} P_{\mu, \sigma^2} \left( \frac{\bar{X} - \mu_0}{S/\sqrt{n}} < c' \right) = \sup_{\mu \geq \mu_0, \sigma^2 \in \mathbb{R}^+} P_{\mu, \sigma^2} \left( \bar{X} < \mu_0 + c' \frac{S}{\sqrt{n}} \right) = \sup_{\mu \geq \mu_0, \sigma^2 \in \mathbb{R}^+} P_{\mu, \sigma^2} \left( \frac{\bar{X} - \mu}{S/\sqrt{n}} < \frac{\mu_0 - \mu}{S/\sqrt{n}} + c' \right) =$$

$$[T \rightarrow t(n-1)] = \sup_{\mu \geq \mu_0} P \left( T < \frac{\mu_0 - \mu}{S/\sqrt{n}} + c' \right) = P(T < c') = \alpha \Rightarrow c' = t_{n-1; 1-\alpha} \quad (\alpha \geq 0 \Leftrightarrow \alpha \leq 1/2)$$

# Contrastes sobre la varianza con media conocida

$(X_1, \dots, X_n)$  muestra aleatoria simple de  $X \longrightarrow \{\mathcal{N}(\mu_0, \sigma^2); \sigma^2 \in \mathbb{R}^+\}$

Función de verosimilitud:

$$(x_1, \dots, x_n) \in \mathbb{R}^n \longrightarrow L_{x_1, \dots, x_n}(\sigma^2) = \frac{1}{(\sigma^2)^{n/2} (2\pi)^{n/2}} e^{-\sum_{i=1}^n (x_i - \mu_0)^2 / 2\sigma^2}, \quad \sigma^2 \in \mathbb{R}^+$$

$$\begin{aligned} \blacksquare \sup_{\sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\sigma^2) &= L_{x_1, \dots, x_n}(\hat{\sigma}_0^2), \quad \hat{\sigma}_0^2 = \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{n} \\ \blacksquare \sup_{\sigma^2 \leq \sigma_0^2} L_{x_1, \dots, x_n}(\sigma^2) &= \begin{cases} L_{x_1, \dots, x_n}(\hat{\sigma}_0^2), & \hat{\sigma}_0^2 \leq \sigma_0^2 \left( \Leftrightarrow \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \leq n \right) \\ L_{x_1, \dots, x_n}(\sigma_0^2), & \hat{\sigma}_0^2 \geq \sigma_0^2 \left( \Leftrightarrow \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \geq n \right) \end{cases} \\ \blacksquare \sup_{\sigma^2 \geq \sigma_0^2} L_{x_1, \dots, x_n}(\sigma^2) &= \begin{cases} L_{x_1, \dots, x_n}(\sigma_0^2), & \hat{\sigma}_0^2 \leq \sigma_0^2 \left( \Leftrightarrow \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \leq n \right) \\ L_{x_1, \dots, x_n}(\hat{\sigma}_0^2), & \hat{\sigma}_0^2 \geq \sigma_0^2 \left( \Leftrightarrow \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \geq n \right) \end{cases} \end{aligned}$$

$$\begin{aligned} H_0 : \sigma^2 &= \sigma_0^2 \\ H_1 : \sigma^2 &\neq \sigma_0^2 \end{aligned}$$

$$\text{TRV}(\approx) \text{ de tamaño } \alpha \in [0, 1] \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} < \chi_{n; 1-\alpha/2}^2 \text{ ó } > \chi_{n; \alpha/2}^2 \\ 0 & \text{si } \chi_{n; 1-\alpha/2}^2 \leq \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} \leq \chi_{n; \alpha/2}^2. \end{cases}$$

$$\begin{aligned} \lambda(x_1, \dots, x_n) &= \frac{\sup_{\sigma^2 = \sigma_0^2} L_{x_1, \dots, x_n}(\sigma^2)}{\sup_{\sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\sigma^2)} = \frac{L_{x_1, \dots, x_n}(\sigma_0^2)}{L_{x_1, \dots, x_n}(\hat{\sigma}_0^2)} = \left( \frac{\hat{\sigma}_0^2}{\sigma_0^2} \right)^{n/2} \exp \left\{ \frac{-n\hat{\sigma}_0^2}{2\sigma_0^2} + \frac{n}{2} \right\} \\ \varphi(x_1, \dots, x_n) &= \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} < c_1 \text{ ó } \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} > c_2 \\ 0, & c_1 \leq \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \leq c_2 \end{cases} \end{aligned}$$

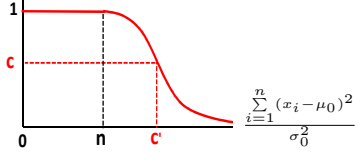
donde  $c_1 \leq n$  y  $c_2 \geq n$  son tales que  $(c_1/n)^{n/2} e^{-c_1/2+n/2} = (c_2/n)^{n/2} e^{-c_2/2+n/2}$  y

$$\alpha = P_{\sigma_0^2} \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} < c_1 \right) + P_{\sigma_0^2} \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} > c_2 \right) = P(Y < c_1) + P(Y > c_2), \text{ con } Y \rightarrow \chi^2(n).$$

En la práctica, se toma el test de colas iguales,  $c_1 = \chi_{n; 1-\alpha/2}^2$ ,  $c_2 = \chi_{n; \alpha/2}^2$  ( $\forall \alpha \in [0, 1]$ ,  $\chi_{n; 1-\alpha/2}^2 \leq \chi_{n; \alpha/2}^2$ ).



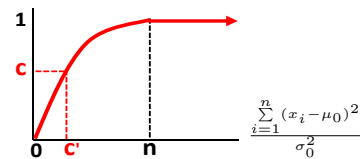
$$\begin{array}{l}
 H_0 : \sigma^2 \leq \sigma_0^2 \\
 H_1 : \sigma^2 > \sigma_0^2
 \end{array}
 \quad
 \text{TRV de tamaño } \alpha \leq P(Y > n) \ (Y \rightarrow \chi^2(n)) \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} > \chi_{n; \alpha}^2 \\ 0 & \text{si } \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} \leq \chi_{n; \alpha}^2 \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\sigma^2 \leq \sigma_0^2} L_{x_1, \dots, x_n}(\sigma^2)}{L_{x_1, \dots, x_n}(\hat{\sigma}_0^2)} = \begin{cases} 1, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \leq n \\ \frac{L_{x_1, \dots, x_n}(\sigma_0^2)}{L_{x_1, \dots, x_n}(\hat{\sigma}_0^2)}, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \geq n \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \ (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} > c' \ (c' \geq n) \\ 0, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \leq c' \end{cases}$$

$$\alpha = \sup_{\sigma^2 \leq \sigma_0^2} P_{\sigma^2} \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} > c' \right) = \sup_{\sigma^2 \leq \sigma_0^2} P_{\sigma^2} \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma^2} > c' \frac{\sigma_0^2}{\sigma^2} \right) = [Y \rightarrow \chi^2(n)] = \sup_{\sigma^2 \leq \sigma_0^2} P(Y > c' \frac{\sigma_0^2}{\sigma^2}) = P(Y > c') \Rightarrow c' = \chi_{n; \alpha}^2 \ (\geq n \Leftrightarrow P(Y > n) \geq \alpha).$$

$$\begin{array}{l}
 H_0 : \sigma^2 \geq \sigma_0^2 \\
 H_1 : \sigma^2 < \sigma_0^2
 \end{array}
 \quad
 \text{TRV de tamaño } \alpha \leq P(Y \leq n) \ (Y \rightarrow \chi^2(n)) \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} < \chi_{n; 1-\alpha}^2 \\ 0 & \text{si } \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} \geq \chi_{n; 1-\alpha}^2 \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\sigma^2 \geq \sigma_0^2} L_{x_1, \dots, x_n}(\sigma^2)}{L_{x_1, \dots, x_n}(\hat{\sigma}_0^2)} = \begin{cases} \frac{L_{x_1, \dots, x_n}(\sigma_0^2)}{L_{x_1, \dots, x_n}(\hat{\sigma}_0^2)}, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \leq n \\ 1, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \geq n \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \ (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} < c' \ (c' \leq n) \\ 0, & \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{\sigma_0^2} \geq c' \end{cases}$$

$$\alpha = \sup_{\sigma^2 \geq \sigma_0^2} P_{\sigma^2} \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} < c' \right) = \sup_{\sigma^2 \geq \sigma_0^2} P_{\sigma^2} \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma^2} < c' \frac{\sigma_0^2}{\sigma^2} \right) = [Y \rightarrow \chi^2(n)] = \sup_{\sigma^2 \geq \sigma_0^2} P(Y < c' \frac{\sigma_0^2}{\sigma^2}) = P(Y < c') \Rightarrow c' = \chi_{n; 1-\alpha}^2 \ (\leq n \Leftrightarrow P(Y < n) \geq \alpha).$$

## Contrastes sobre la varianza con media desconocida

$(X_1, \dots, X_n)$  muestra aleatoria simple de  $X \longrightarrow \{\mathcal{N}(\mu, \sigma^2); \mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+\}$

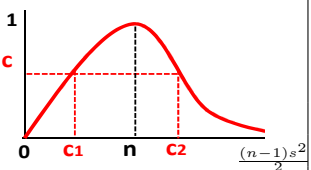
Función de verosimilitud:

$$(x_1, \dots, x_n) \in \mathbb{R}^n \longrightarrow L_{x_1, \dots, x_n}(\mu, \sigma^2) = \frac{1}{(\sigma^2)^{n/2} (2\pi)^{n/2}} e^{-\sum_{i=1}^n (x_i - \mu)^2 / 2\sigma^2}, \quad \mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+$$

$$\begin{aligned} \blacksquare \quad \sup_{\mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2) &= L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2), \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} = \frac{(n-1)s^2}{n}. \\ \blacksquare \quad \sup_{\mu \in \mathbb{R}, \sigma^2 = \sigma_0^2} L_{x_1, \dots, x_n}(\mu, \sigma^2) &= L_{x_1, \dots, x_n}(\bar{x}, \sigma_0^2) \\ \blacksquare \quad \sup_{\mu \in \mathbb{R}, \sigma^2 \leq \sigma_0^2} L_{x_1, \dots, x_n}(\mu, \sigma^2) &= \begin{cases} L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2), & \hat{\sigma}^2 \leq \sigma_0^2 \left( \Leftrightarrow \frac{(n-1)s^2}{\sigma_0^2} \leq n \right) \\ L_{x_1, \dots, x_n}(\bar{x}, \sigma_0^2), & \hat{\sigma}^2 \geq \sigma_0^2 \left( \Leftrightarrow \frac{(n-1)s^2}{\sigma_0^2} \geq n \right) \end{cases} \\ \blacksquare \quad \sup_{\mu \in \mathbb{R}, \sigma^2 \geq \sigma_0^2} L_{x_1, \dots, x_n}(\mu, \sigma^2) &= \begin{cases} L_{x_1, \dots, x_n}(\bar{x}, \sigma_0^2), & \hat{\sigma}^2 \leq \sigma_0^2 \left( \Leftrightarrow \frac{(n-1)s^2}{\sigma_0^2} \leq n \right) \\ L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2), & \hat{\sigma}^2 \geq \sigma_0^2 \left( \Leftrightarrow \frac{(n-1)s^2}{\sigma_0^2} \geq n \right) \end{cases} \end{aligned}$$

$$\begin{aligned} H_0 : \sigma^2 &= \sigma_0^2 \\ H_1 : \sigma^2 &\neq \sigma_0^2 \end{aligned}$$

$$\text{TRV}(\approx) \text{ de tamaño } \alpha \in [0, 1] \rightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{(n-1)S^2}{\sigma_0^2} < \chi_{n-1; 1-\alpha/2}^2 \text{ ó } > \chi_{n-1; \alpha/2}^2 \\ 0 & \text{si } \chi_{n-1; 1-\alpha/2}^2 \leq \frac{(n-1)S^2}{\sigma_0^2} \leq \chi_{n-1; \alpha/2}^2. \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \in \mathbb{R}, \sigma^2 = \sigma_0^2} L_{x_1, \dots, x_n}(\mu, \sigma^2)}{\sup_{\mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+} L_{x_1, \dots, x_n}(\mu, \sigma^2)} = \frac{L_{x_1, \dots, x_n}(\bar{x}, \sigma_0^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)} = \left( \frac{\hat{\sigma}^2}{\sigma_0^2} \right)^{n/2} \exp \left\{ \frac{-n\hat{\sigma}^2}{2\sigma_0^2} + \frac{n}{2} \right\}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1 & \text{si } \frac{(n-1)s^2}{\sigma_0^2} < c_1 \text{ ó } \frac{(n-1)s^2}{\sigma_0^2} > c_2 \\ 0 & \text{si } c_1 \leq \frac{(n-1)s^2}{\sigma_0^2} \leq c_2 \end{cases}$$

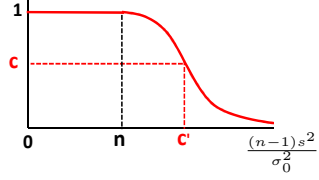
donde  $c_1 \leq n$ ,  $c_2 \geq n$ ,  $(c_1/n)^{n/2} e^{-c_1/2+n/2} = (c_2/n)^{n/2} e^{-c_2/2+n/2}$  son tales que

$$\alpha = \sup_{\mu \in \mathbb{R}} P_{\mu, \sigma_0^2} \left( \frac{(n-1)S^2}{\sigma_0^2} < c_1 \right) + \sup_{\mu \in \mathbb{R}} P_{\mu, \sigma_0^2} \left( \frac{(n-1)S^2}{\sigma_0^2} > c_2 \right) = [Y \rightarrow \chi^2(n-1)] = P(Y < c_1) + P(Y > c_2)$$

En la práctica, se toma el test de colas iguales,  $c_1 = \chi_{n-1; 1-\alpha/2}^2$ ,  $c_2 = \chi_{n-1; \alpha/2}^2$  ( $\forall \alpha \in [0, 1]$ ,  $\chi_{n-1; 1-\alpha/2}^2 \leq \chi_{n-1; \alpha/2}^2$ ).

$$\begin{aligned} H_0 : \sigma^2 &\leq \sigma_0^2 \\ H_1 : \sigma^2 &> \sigma_0^2 \end{aligned}$$

$$\text{TRV de tamaño } \alpha \leq P(Y > n) \quad (Y \rightarrow \chi^2(n-1)) \longrightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{(n-1)S^2}{\sigma_0^2} > \chi_{n-1; \alpha}^2 \\ 0 & \text{si } \frac{(n-1)S^2}{\sigma_0^2} \leq \chi_{n-1; \alpha}^2 \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \in \mathbb{R}, \sigma^2 \leq \sigma_0^2} L_{x_1, \dots, x_n}(\mu, \sigma^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)} = \begin{cases} 1, & \frac{(n-1)s^2}{\sigma_0^2} \leq n \\ \frac{L_{x_1, \dots, x_n}(\bar{x}, \sigma_0^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)}, & \frac{(n-1)s^2}{\sigma_0^2} \geq n \end{cases}$$


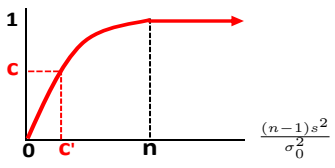
$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1 & \text{si } \frac{(n-1)s^2}{\sigma_0^2} > c' \quad (c' \geq n) \\ 0 & \text{si } \frac{(n-1)s^2}{\sigma_0^2} \leq c'. \end{cases}$$

$$\alpha = \sup_{\mu \in \mathbb{R}, \sigma^2 \leq \sigma_0^2} P_{\mu, \sigma^2} \left( \frac{(n-1)S^2}{\sigma_0^2} > c' \right) = \sup_{\mu \in \mathbb{R}, \sigma^2 \leq \sigma_0^2} P_{\mu, \sigma^2} \left( \frac{(n-1)S^2}{\sigma^2} > c' \frac{\sigma_0^2}{\sigma^2} \right) = [Y \rightarrow \chi^2(n-1)] =$$

$$= \sup_{\sigma^2 \leq \sigma_0^2} P \left( Y > c' \frac{\sigma_0^2}{\sigma^2} \right) = P(Y > c') \Rightarrow c' = \chi_{n-1; \alpha}^2 \quad (\geq n \Leftrightarrow P(Y > n) \geq \alpha).$$

$$\begin{aligned} H_0 : \sigma^2 &\geq \sigma_0^2 \\ H_1 : \sigma^2 &< \sigma_0^2 \end{aligned}$$

$$\text{TRV de tamaño } \alpha \leq P(Y \leq n) \quad (Y \rightarrow \chi^2(n-1)) \longrightarrow \varphi(X_1, \dots, X_n) = \begin{cases} 1 & \text{si } \frac{(n-1)S^2}{\sigma_0^2} < \chi_{n-1; 1-\alpha}^2 \\ 0 & \text{si } \frac{(n-1)S^2}{\sigma_0^2} \geq \chi_{n-1; 1-\alpha}^2 \end{cases}$$

$$\lambda(x_1, \dots, x_n) = \frac{\sup_{\mu \in \mathbb{R}, \sigma^2 \geq \sigma_0^2} L_{x_1, \dots, x_n}(\mu, \sigma^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)} = \begin{cases} \frac{L_{x_1, \dots, x_n}(\bar{x}, \sigma_0^2)}{L_{x_1, \dots, x_n}(\bar{x}, \hat{\sigma}^2)}, & \frac{(n-1)s^2}{\sigma_0^2} \leq n \\ 1, & \frac{(n-1)s^2}{\sigma_0^2} \geq n \end{cases}$$


$$\varphi(x_1, \dots, x_n) = \begin{cases} 1, & \lambda(x_1, \dots, x_n) < c \quad (c \in (0, 1]) \\ 0, & \lambda(x_1, \dots, x_n) \geq c \end{cases} \Leftrightarrow \varphi(x_1, \dots, x_n) = \begin{cases} 1 & \text{si } \frac{(n-1)s^2}{\sigma_0^2} < c' \quad (c' \leq n) \\ 0 & \text{si } \frac{(n-1)s^2}{\sigma_0^2} \geq c'. \end{cases}$$

$$\alpha = \sup_{\mu \in \mathbb{R}, \sigma^2 \geq \sigma_0^2} P_{\mu, \sigma^2} \left( \frac{(n-1)S^2}{\sigma_0^2} < c' \right) = \sup_{\mu \in \mathbb{R}, \sigma^2 \geq \sigma_0^2} P_{\mu, \sigma^2} \left( \frac{(n-1)S^2}{\sigma^2} < c' \frac{\sigma_0^2}{\sigma^2} \right) = [Y \rightarrow \chi^2(n-1)] =$$

$$= \sup_{\sigma^2 \geq \sigma_0^2} P \left( Y < c' \frac{\sigma_0^2}{\sigma^2} \right) = P(Y < c') \Rightarrow c' = \chi_{n-1; 1-\alpha}^2 \quad (\geq n \Leftrightarrow P(Y < n) \geq \alpha).$$

**TESTS E INTERVALOS EN POBLACIONES NORMALES**

Contraste	Región de rechazo $\sigma^2 = \sigma_0^2$ conocida	Región de rechazo $\sigma^2$ desconocida
$H_0 : \mu = \mu_0$ $H_1 : \mu \neq \mu_0$	$\left  \frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} \right  > z_{\alpha/2}$ $\mu_0 \notin \left( \bar{X} - z_{\alpha/2} \frac{\sigma_0}{\sqrt{n}}, \bar{X} + z_{\alpha/2} \frac{\sigma_0}{\sqrt{n}} \right)$	$\left  \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \right  > t_{n-1; \alpha/2}$ $\mu_0 \notin \left( \bar{X} - t_{n-1; \alpha/2} \frac{S}{\sqrt{n}}, \bar{X} + t_{n-1; \alpha/2} \frac{S}{\sqrt{n}} \right)$
$H_0 : \mu \leq \mu_0$ $H_1 : \mu > \mu_0$	$\frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} > z_{\alpha}$ $\mu_0 \notin \left( \bar{X} - z_{\alpha} \frac{\sigma_0}{\sqrt{n}}, +\infty \right)$	$\frac{\bar{X} - \mu_0}{S/\sqrt{n}} > t_{n-1; \alpha}$ $\mu_0 \notin \left( \bar{X} - t_{n-1; \alpha} \frac{S}{\sqrt{n}}, +\infty \right)$
$H_0 : \mu \geq \mu_0$ $H_1 : \mu < \mu_0$	$\frac{\bar{X} - \mu_0}{\sigma_0/\sqrt{n}} < z_{1-\alpha}$ $\mu_0 \notin \left( -\infty, \bar{X} + z_{\alpha} \frac{\sigma_0}{\sqrt{n}} \right)$	$\frac{\bar{X} - \mu_0}{S/\sqrt{n}} < t_{n-1; 1-\alpha}$ $\mu_0 \notin \left( -\infty, \bar{X} + t_{n-1; \alpha} \frac{S}{\sqrt{n}} \right)$

Contraste	Región de rechazo $\mu = \mu_0$ conocida	Región de rechazo $\mu$ desconocida
$H_0 : \sigma^2 = \sigma_0^2$ $H_1 : \sigma^2 \neq \sigma_0^2$	$\frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} < \chi_{n; 1-\alpha/2}^2 \text{ ó } > \chi_{n; \alpha/2}^2$ $\sigma_0^2 \notin \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\chi_{n; \alpha/2}^2}, \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\chi_{n; 1-\alpha/2}^2} \right)$	$\frac{(n-1)S^2}{\sigma_0^2} < \chi_{n-1; 1-\alpha/2}^2 \text{ ó } > \chi_{n-1; \alpha/2}^2$ $\sigma_0^2 \notin \left( \frac{(n-1)S^2}{\chi_{n-1; \alpha/2}^2}, \frac{(n-1)S^2}{\chi_{n-1; 1-\alpha/2}^2} \right)$
$H_0 : \sigma^2 \leq \sigma_0^2$ $H_1 : \sigma^2 > \sigma_0^2$	$\frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} > \chi_{n; \alpha}^2$ $\sigma_0^2 \notin \left( \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\chi_{n; \alpha}^2}, +\infty \right)$	$\frac{(n-1)S^2}{\sigma_0^2} > \chi_{n-1; \alpha}^2$ $\sigma_0^2 \notin \left( \frac{(n-1)S^2}{\chi_{n-1; \alpha}^2}, +\infty \right)$
$H_0 : \sigma^2 \geq \sigma_0^2$ $H_1 : \sigma^2 < \sigma_0^2$	$\frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sigma_0^2} < \chi_{n; 1-\alpha}^2$ $\sigma_0^2 \notin \left( 0, \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\chi_{n; 1-\alpha}^2} \right)$	$\frac{(n-1)S^2}{\sigma_0^2} < \chi_{n-1; 1-\alpha}^2$ $\sigma_0^2 \notin \left( 0, \frac{(n-1)S^2}{\chi_{n-1; 1-\alpha}^2} \right)$



7.5. TESTS DE HIPÓTESIS E INTERVALOS DE CONFIANZA PARA LOS PARÁMETROS DE DOS POBLACIONES NORMALES		
Contraste	Región de rechazo, $\sigma_1^2, \sigma_2^2$ conocidas	Región de rechazo, $\sigma_1^2 = \sigma_2^2$ desconocida
$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	$\frac{ \bar{X} - \bar{Y} }{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} > z_{\alpha/2}$ $0 \notin \left( \bar{X} - \bar{Y} \mp z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} \right)$	$\frac{ \bar{X} - \bar{Y} }{\sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}} > t_{n_1+n_2-2; \alpha/2}$ $0 \notin \left( \bar{X} - \bar{Y} \mp t_{n_1+n_2-2; \alpha/2} \sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right)$
$H_0 : \mu_1 \leq \mu_2$ $H_1 : \mu_1 > \mu_2$	$\frac{\bar{X} - \bar{Y}}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} > z_{\alpha}$ $0 \notin \left( \bar{X} - \bar{Y} - z_{\alpha} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}, +\infty \right)$	$\frac{\bar{X} - \bar{Y}}{\sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}} > t_{n_1+n_2-2; \alpha}$ $0 \notin \left( \bar{X} - \bar{Y} - t_{n_1+n_2-2; \alpha} \sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, +\infty \right)$
Contraste	Región de rechazo, $\mu_1, \mu_2$ conocidas	Región de rechazo, $\mu_1, \mu_2$ desconocidas
$H_0 : \sigma_1^2 = \sigma_2^2$ $H_1 : \sigma_1^2 \neq \sigma_2^2$	$\frac{\sum_{i=1}^{n_1} (X_i - \mu_1)^2 / n_1}{\sum_{i=1}^{n_2} (Y_i - \mu_2)^2 / n_2} < F_{n_1, n_2; 1-\alpha/2} \text{ ó } > F_{n_1, n_2; \alpha/2}$ $1 \notin \left( F_{n_2, n_1; 1-\alpha/2} \frac{\sum_{i=1}^{n_1} (X_i - \mu_1)^2 / n_1}{\sum_{i=1}^{n_2} (Y_i - \mu_2)^2 / n_2}, F_{n_2, n_1; \alpha/2} \frac{\sum_{i=1}^{n_1} (X_i - \mu_1)^2 / n_1}{\sum_{i=1}^{n_2} (Y_i - \mu_2)^2 / n_2} \right)$	$\frac{S_1^2}{S_2^2} < F_{n_1-1, n_2-1; 1-\alpha/2} \text{ ó } > F_{n_1-1, n_2-1; \alpha/2}$ $1 \notin \left( F_{n_2-1, n_1-1; 1-\alpha/2} \frac{S_1^2}{S_2^2}, F_{n_2-1, n_1-1; \alpha/2} \frac{S_1^2}{S_2^2} \right)$
$H_0 : \sigma_1^2 \leq \sigma_2^2$ $H_1 : \sigma_1^2 > \sigma_2^2$	$\frac{\sum_{i=1}^{n_1} (X_i - \mu_1)^2 / n_1}{\sum_{i=1}^{n_2} (Y_i - \mu_2)^2 / n_2} > F_{n_1, n_2; \alpha}$ $1 \notin \left( F_{n_2, n_1; 1-\alpha} \frac{\sum_{i=1}^{n_1} (X_i - \mu_1)^2 / n_1}{\sum_{i=1}^{n_2} (Y_i - \mu_2)^2 / n_2}, +\infty \right)$	$\frac{S_1^2}{S_2^2} > F_{n_1-1, n_2-1; \alpha}$ $1 \notin \left( F_{n_2-1, n_1-1; 1-\alpha} \frac{S_1^2}{S_2^2}, +\infty \right)$



## 7.6. DUALIDAD ENTRE TESTS DE HIPÓTESIS Y REGIONES DE CONFIANZA

Sea  $X \rightarrow \{P_\theta; \theta \in \Theta\}$  y  $(X_1, \dots, X_n)$  una muestra aleatoria simple de  $X$ . Para cada  $\theta_0 \in \Theta$  consideramos un conjunto  $A(\theta_0) \subseteq \chi^n$  y, para cada realización muestral,  $(x_1, \dots, x_n) \in \chi^n$ , definimos:

$$\varphi_{\theta_0}(x_1, \dots, x_n) = \begin{cases} 1 & \text{si } (x_1, \dots, x_n) \notin A(\theta_0) \\ 0 & \text{si } (x_1, \dots, x_n) \in A(\theta_0) \end{cases}$$

$$S(x_1, \dots, x_n) = \{\theta \in \Theta / (x_1, \dots, x_n) \in A(\theta)\} \subseteq \Theta.$$

Cada uno de los tests  $\varphi_{\theta_0}(X_1, \dots, X_n)$  aplicado al problema de contrastar  $H_0 : \theta = \theta_0$  frente a  $H_1 : \theta \neq \theta_0$  tiene nivel de significación  $\alpha$  si, y sólo si,  $S(X_1, \dots, X_n)$  es una región de confianza para  $\theta$  al nivel de confianza  $1 - \alpha$ .



## DEMOSTRACIÓN LEMA DE NEYMAN-PEARSON

Sea  $X \rightarrow \{P_\theta; \theta \in \{\theta_0, \theta_1\}\}$  y  $(X_1, \dots, X_n)$  una muestra aleatoria simple con funciones de densidad (o funciones masa de probabilidad)  $f_0^n(x_1, \dots, x_n)$  ( $\theta = \theta_0$ ) y  $f_1^n(x_1, \dots, x_n)$  ( $\theta = \theta_1$ ). Consideremos el problema de contraste

$$\begin{aligned} H_0 : \theta &= \theta_0 \\ H_1 : \theta &= \theta_1. \end{aligned}$$

a) Sea  $\varphi(X_1, \dots, X_n)$  un test de la forma

$$\varphi(X_1, \dots, X_n) = \begin{cases} 1, & \text{si } f_1^n(X_1, \dots, X_n) > k f_0^n(X_1, \dots, X_n) \\ \gamma(X_1, \dots, X_n), & \text{si } f_1^n(X_1, \dots, X_n) = k f_0^n(X_1, \dots, X_n) \\ 0, & \text{si } f_1^n(X_1, \dots, X_n) < k f_0^n(X_1, \dots, X_n), \end{cases}$$

con  $k \in \mathbb{R}^+ \cup \{0\}$  y  $\gamma(X_1, \dots, X_n) \in [0, 1]$ . Si  $\varphi(X_1, \dots, X_n)$  tiene tamaño  $\alpha$ , es de máxima potencia a nivel de significación  $\alpha$ .

**Demostración:** Supondremos que  $X$  es de tipo continuo y, para simplificar, notaremos  $\mathbf{X} = (X_1, \dots, X_n)$  a la muestra aleatoria simple y  $\mathbf{x} = (x_1, \dots, x_n) \in \chi^n$  a las realizaciones muestrales. Así,

$$\beta_\varphi(\theta_i) = E_{\theta_i}[\varphi(\mathbf{X})] = \int_{\chi^n} \varphi(\mathbf{x}) f_i^n(\mathbf{x}) d\mathbf{x}, \quad i = 0, 1.$$

Una demostración totalmente similar puede hacerse con variables discretas, sustituyendo las densidades por las funciones masa de probabilidad y las integrales por sumas.

Consideremos la siguiente integral:

$$I = \int_{\chi^n} h(\mathbf{x}) d\mathbf{x}, \quad h(\mathbf{x}) = [\varphi(\mathbf{x}) - \varphi'(\mathbf{x})][f_1^n(\mathbf{x}) - k f_0^n(\mathbf{x})], \quad \mathbf{x} \in \chi^n.$$

Teniendo en cuenta la forma de  $\varphi$  y que  $\varphi' \in [0, 1]$  tenemos:

- $f_1^n(\mathbf{x}) > k f_0^n(\mathbf{x}) \Rightarrow h(\mathbf{x}) = [1 - \varphi'(\mathbf{x})][f_1^n(\mathbf{x}) - k f_0^n(\mathbf{x})] \geq 0.$
- $f_1^n(\mathbf{x}) < k f_0^n(\mathbf{x}) \Rightarrow h(\mathbf{x}) = [-\varphi'(\mathbf{x})][f_1^n(\mathbf{x}) - k f_0^n(\mathbf{x})] \geq 0.$
- $f_1^n(\mathbf{x}) = k f_0^n(\mathbf{x}) \Rightarrow h(\mathbf{x}) = 0.$

Esto es,  $h \geq 0$  y, consecuentemente,  $I \geq 0$ . Entonces, desarrollando  $h$  tenemos:

$$\begin{aligned} I &= \int_{\chi^n} \varphi(\mathbf{x}) f_1^n(\mathbf{x}) d\mathbf{x} - \int_{\chi^n} \varphi'(\mathbf{x}) f_1^n(\mathbf{x}) d\mathbf{x} - k \left( \int_{\chi^n} \varphi(\mathbf{x}) f_0^n(\mathbf{x}) d\mathbf{x} - \int_{\chi^n} \varphi'(\mathbf{x}) f_0^n(\mathbf{x}) d\mathbf{x} \right) \\ &= \beta_\varphi(\theta_1) - \beta_{\varphi'}(\theta_1) - k(\alpha - E_{\theta_0}[\varphi'(\mathbf{X})]) \geq 0 \Rightarrow \beta_\varphi(\theta_1) - \beta_{\varphi'}(\theta_1) \geq k(\alpha - E_{\theta_0}[\varphi'(\mathbf{X})]). \end{aligned}$$

Por tanto, como  $k \geq 0$  y  $E_{\theta_0}[\varphi'(\mathbf{X})] \leq \alpha$ , el segundo miembro es no negativo y, por tanto, el primero también. Esto es,  $\beta_\varphi(\theta_1) \geq \beta_{\varphi'}(\theta_1)$ .

**b)** Para todo  $\alpha \in (0, 1]$  existe un test de Neyman-Pearson de tamaño  $\alpha$ , con  $\gamma(\mathbf{X}) = \gamma$  constante.

**Demostración:** Dado  $\alpha \in (0, 1]$ , hacemos  $\gamma(\mathbf{X}) = \gamma$  en el test de Neyman-Pearson,  $\varphi(\mathbf{X})$ , y probamos que existen  $k \geq 0$  y  $\gamma \in [0, 1]$  tales que el test tiene tamaño  $\alpha$ . Esto es:

$$\begin{aligned}\alpha &= E_{\theta_0}[\varphi(\mathbf{X})] = P_{\theta_0}(f_1^n(\mathbf{X}) > k f_0^n(\mathbf{X})) + \gamma P_{\theta_0}(f_1^n(\mathbf{X}) = k f_0^n(\mathbf{X}))^1 \\ &= P_{\theta_0}\left(\frac{f_1^n(\mathbf{X})}{f_0^n(\mathbf{X})} > k\right) + \gamma P_{\theta_0}\left(\frac{f_1^n(\mathbf{X})}{f_0^n(\mathbf{X})} = k\right).\end{aligned}$$

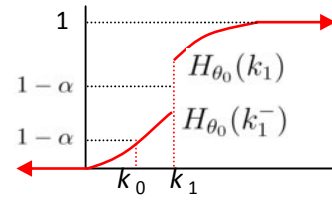
Equivalentemente, notando  $H_{\theta_0}$  la función de distribución de  $f_1^n(\mathbf{X})/f_0^n(\mathbf{X}) \geq 0$  bajo  $P_{\theta_0}$ , dado  $\alpha \in (0, 1]$ , debemos encontrar  $k \geq 0$  y  $\gamma \in [0, 1]$  tales que:

$$1 - \alpha = H_{\theta_0}(k) - \gamma(H_{\theta_0}(k) - H_{\theta_0}(k^-)).$$

Existen dos posibilidades:

$$a) \exists k_0 \geq 0 / H_{\theta_0}(k_0) = 1 - \alpha \rightarrow k = k_0, \gamma = 0.$$

$$\begin{aligned}b) \exists k_1 \geq 0 / H_{\theta_0}(k_1^-) \leq 1 - \alpha < H_{\theta_0}(k_1) \\ \rightarrow k = k_1, \gamma = \frac{H_{\theta_0}(k_1) - (1 - \alpha)}{H_{\theta_0}(k_1) - H_{\theta_0}(k_1^-)} \in (0, 1).\end{aligned}$$



**c)** Si  $\varphi'(\mathbf{X})$  es un test de tamaño  $\alpha$  y es de máxima potencia a nivel de significación  $\alpha$ ,  $\varphi(\mathbf{X})$  es un test de Neyman-Pearson.

**Demostración:** Por b), dado  $\alpha = E_{\theta_0}[\varphi'(\mathbf{X})]$ , podemos encontrar un test de Neyman-Pearson de tamaño  $\alpha$ ,  $\varphi(\mathbf{X})$ . Puesto que  $\varphi(\mathbf{X})$  y  $\varphi'(\mathbf{X})$  son de máxima potencia, ésta debe ser la misma, y ambos tests tienen el mismo tamaño y la misma potencia. Por tanto:

$$I = \int_{\chi^n} [\varphi(\mathbf{x}) - \varphi'(\mathbf{x})] [f_1^n(\mathbf{x}) - k f_0^n(\mathbf{x})] d\mathbf{x} = \beta_{\varphi}(\theta_1) - \beta_{\varphi'}(\theta_1) - k(\beta_{\varphi}(\theta_0) - \beta_{\varphi'}(\theta_0)) = 0.$$

Ya que, según se probó en el apartado a), el integrando es una función no negativa,  $I = 0$  significa que el integrando es nulo (salvo, quizás, en conjuntos con medida de Lebesgue nula, que tienen probabilidades nulas). Esto es:

- $f_1^n(\mathbf{x}) > k f_0^n(\mathbf{x}) \Rightarrow \varphi'(\mathbf{x}) = \varphi(\mathbf{x}) = 1.$
- $f_1^n(\mathbf{x}) < k f_0^n(\mathbf{x}) \Rightarrow \varphi'(\mathbf{x}) = \varphi(\mathbf{x}) = 0.$

Por tanto:

$$\varphi'(\mathbf{X}) = \begin{cases} 1, & f_1^n(\mathbf{X}) > k f_0^n(\mathbf{X}) \\ \gamma(\mathbf{X}), & f_1^n(\mathbf{X}) = k f_0^n(\mathbf{X}) \\ 0, & f_1^n(\mathbf{X}) < k f_0^n(\mathbf{X}). \end{cases}$$

$$^1 P_{\theta_0}(f_0^n(\mathbf{X}) = 0) = \int_{\{\mathbf{x} \in \chi^n / f_0^n(\mathbf{x}) = 0\}} f_0^n(\mathbf{x}) d\mathbf{x} = 0.$$

*d) El test de máxima potencia entre todos los de nivel de significación 0 (tamaño 0) es:*

$$\varphi_0(\mathbf{X}) = \begin{cases} 1, & f_0^n(\mathbf{X}) = 0 \\ 0, & f_0^n(\mathbf{X}) > 0. \end{cases}$$

*Demostración:* Puesto que  $P_{\theta_0}(f_0^n(\mathbf{X}) = 0)$ , es inmediato que el test  $\varphi_0(\mathbf{X})$  tiene tamaño 0.

Si  $\varphi'_0(\mathbf{X})$  es cualquier otro test de tamaño cero,  $E_{\theta_0}[\varphi'_0(\mathbf{X})] = 0$ , y al ser una función no negativa, debe anularse en  $\{\mathbf{x} \in \chi^n / f_0^n(\mathbf{x}) > 0\}$ . Esto es:

$$\varphi'_0(\mathbf{X}) = \begin{cases} \gamma(\mathbf{X}), & f_0^n(\mathbf{X}) = 0, \\ 0, & f_0^n(\mathbf{X}) > 0, \end{cases} \quad \gamma(\mathbf{X}) \in [0, 1].$$

Por tanto,  $\varphi'_0(\mathbf{X}) \leq \varphi_0(\mathbf{X})$  y, consecuentemente:

$$\beta_{\varphi'_0}(\theta_1) = E_{\theta_1}[\varphi'_0(\mathbf{X})] \leq E_{\theta_1}[\varphi_0(\mathbf{X})] = \beta_{\varphi_0}(\theta_1). \quad \square$$

**Expresión del test para su resolución en diferentes situaciones prácticas:**

$$\chi_0 = \{x / f_0(x) > 0\}; \quad \chi_1 = \{x / f_1(x) > 0\}.$$

- $\chi_0 \supseteq \chi_1 \Rightarrow \chi^n = \chi_0^n = \{(x_1, \dots, x_n) / f_0^n(x_1, \dots, x_n) \neq 0\}$ .

En esta situación, se puede dividir siempre por  $f_0^n(x_1, \dots, x_n)$  y la función test queda:

$$\varphi(x_1, \dots, x_n) = \begin{cases} 1 & \text{si } \lambda(x_1, \dots, x_n) > k \\ \gamma & \text{si } \lambda(x_1, \dots, x_n) = k \\ 0 & \text{si } \lambda(x_1, \dots, x_n) < k, \end{cases} \quad \text{con } \lambda(x_1, \dots, x_n) = \frac{f_1^n(x_1, \dots, x_n)}{f_0^n(x_1, \dots, x_n)}.$$

- $\chi_0 \subset \chi_1 \Rightarrow \chi^n = \chi_1^n = \{(x_1, \dots, x_n) / f_1^n(x_1, \dots, x_n) \neq 0\}$ .

Existen realizaciones muestrales para las que  $f_0^n(x_1, \dots, x_n) = 0$  y no se puede dividir. Sin embargo, en estos casos es obvio que,  $f_1^n(x_1, \dots, x_n) > k f_0^n(x_1, \dots, x_n)$ ,  $\forall k \geq 0$ , lo que significa que tales realizaciones conducen al rechazo de  $H_0$  en cualquier test de Neyman-Pearson, y éste se expresa como:

$$\varphi(x_1, \dots, x_n) = \begin{cases} 1 & \text{si } f_0^n(x_1, \dots, x_n) = 0 \\ 1 & \text{si } f_0^n(x_1, \dots, x_n) \neq 0 \text{ y } \lambda(x_1, \dots, x_n) > k \\ \gamma & \text{si } f_0^n(x_1, \dots, x_n) \neq 0 \text{ y } \lambda(x_1, \dots, x_n) = k \\ 0 & \text{si } f_0^n(x_1, \dots, x_n) \neq 0 \text{ y } \lambda(x_1, \dots, x_n) < k. \end{cases} \quad \lambda(x_1, \dots, x_n) = \frac{f_1^n(x_1, \dots, x_n)}{f_0^n(x_1, \dots, x_n)}.$$