

$$H_0: \mu = \mu_0 \text{ vs. } H_1: \mu \neq \mu_0$$

$$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu, \sigma^2)$$

Reject  $H_0$  if

$$\frac{\sup_{\mu, \sigma^2} \mathcal{L}(\mu, \sigma^2 | \underline{x}, H_1)}{\sup_{\sigma^2} \mathcal{L}(\sigma^2 | \mu_0, \underline{x}, H_0)} > k$$

Under  $H_1$ :

$$\mathcal{L}(\mu, \sigma^2 | \underline{X}) = (2\pi\sigma^2)^{-\frac{n}{2}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu)^2 \right\}$$

Log-likelihood function:

$$\begin{aligned} \ell(\mu, \sigma^2 | \underline{X}) &= -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 \\ &\quad - \frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu)^2 \end{aligned}$$

Get mles:

$$\frac{\partial \ell}{\partial \mu} \Big|_{\hat{\mu}, \hat{\sigma}^2} = 0 \quad \Rightarrow \quad \hat{\mu} = \bar{X}$$

$$\begin{aligned} \frac{\partial \ell}{\partial \sigma^2} \Big|_{\hat{\mu}, \hat{\sigma}^2} &= 0 \quad \Rightarrow \quad \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \hat{\mu})^2 \\ &= \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \end{aligned}$$

$$\begin{aligned}\sup_{\mu, \sigma^2} L(\mu, \sigma^2 | \underline{X}, H_1) &= (2\pi \hat{\sigma}^2)^{-\frac{n}{2}} \exp \left\{ -\frac{1}{2\hat{\sigma}^2} \sum_{i=1}^n (X_i - \hat{\mu})^2 \right\} \\ &= (2\pi \hat{\sigma}^2)^{-\frac{n}{2}} \exp \left\{ -\frac{n}{2} \right\}\end{aligned}$$

Under  $H_0$ :

$L(\mu_0, \sigma^2)$

$$L(\sigma^2 | \mu_0, \underline{X}, H_0) = (2\pi \sigma^2)^{-\frac{n}{2}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu_0)^2 \right\}$$

$$\begin{aligned}\ell(\sigma^2 | \mu_0, \underline{X}, H_0) &= -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 \\ &\quad - \frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu_0)^2\end{aligned}$$

$$\frac{\partial \ell}{\partial \sigma^2} \bigg|_{\tilde{\sigma}^2} = 0 \quad \Rightarrow \quad \tilde{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \mu_0)^2$$

$$\begin{aligned}\sup_{\sigma^2} L(\sigma^2 | \mu_0, \underline{X}, H_0) &= (2\pi \tilde{\sigma}^2)^{-\frac{n}{2}} \exp \left\{ -\frac{1}{2\tilde{\sigma}^2} \sum_{i=1}^n (X_i - \mu_0)^2 \right\} \\ &= (2\pi \tilde{\sigma}^2)^{-\frac{n}{2}} \exp \left\{ -\frac{n}{2} \right\}\end{aligned}$$

The likelihood ratio is:

$$\frac{(2\pi\hat{\sigma}^2)^{-n/2} e^{-n/2}}{(2\pi\tilde{\sigma}^2)^{-n/2} e^{-n/2}}$$

$$= \left( \frac{\tilde{\sigma}^2}{\hat{\sigma}^2} \right)^{n/2}$$

$\therefore$  Reject  $H_0$  if

$$\left[ \frac{\sum_{i=1}^n (X_i - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{n/2} > k$$

$$\left[ \frac{\sum_{i=1}^n (X_i - \bar{X} + \bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{n/2} > k$$

$$\left[ \frac{\sum_{i=1}^n (X_i - \bar{X})^2 + n(\bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{n/2} > k$$

$$\left[ 1 + \frac{n(\bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{n/2} > k$$

$$\bar{X} \sim N\left(\mu_0, \frac{\sigma^2}{n}\right)$$

$$[1 + f(X)]^{\frac{n}{2}}$$

As  $f(X) \rightarrow \infty$

$$[1 + f(X)]^{\frac{n}{2}} \rightarrow \infty.$$

$$\left[ 1 + \frac{n(\bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{\frac{n}{2}} \text{ is a monotonic increasing function of}$$

$$\frac{n(\bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

$$\frac{n(\bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} > c \iff \left[ 1 + \frac{n(\bar{X} - \mu_0)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \right]^{\frac{n}{2}} > k$$

for some  $c$ .

$$\frac{(\bar{X} - \mu_0)}{\sigma/\sqrt{n}} \sim N(0,1) \text{ under } H_0$$

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

$$\Rightarrow \text{If } Z \sim N(0,1)$$

$$U \sim \chi^2_v$$

Where  $Z$  and  $U$  are independent

$$\frac{Z}{\sqrt{\frac{U}{v}}} \sim t_{n-1}$$

$$\frac{\left[ \frac{\sqrt{n}(\bar{X} - \mu_0)}{\sigma} \right]}{\sqrt{\frac{(n-1)S^2}{(n-1)\sigma^2}}} \sim t_{n-1}$$

$$\frac{\sqrt{n}(\bar{X} - \mu_0)}{S} \sim t_{n-1}$$

$\therefore$  Likelihood ratio is

$$\left[ 1 + \frac{T^2}{n-1} \right]^{\frac{n}{2}}$$

∴ We reject  $H_0$  if  
 $|T|$  is large.

∴ Test is

Reject  $H_0$  if

$$|T| > k'$$

where

$$P(|T| > k' | H_0) = \alpha.$$

$T \sim t_{n-1}$  under  $H_0$ .

Critical region

$$C = \{ \underline{x} : |T| > k' \}$$

$$= \left\{ \underline{x} : \left| \frac{\sqrt{n}(\bar{x} - \mu_0)}{s} \right| > k' \right\}$$

$$s = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2,$$

Given  $X_1, \dots, X_n \stackrel{iid}{\sim} \mathcal{N}(\mu, \sigma^2)$

We know that

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2 \quad S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

$\therefore \frac{(n-1)S^2}{\sigma^2}$  is a pivotal quantity.

$$\mathbb{P}\left(\chi_{n-1}^2\left(1-\frac{\alpha}{2}\right) < \frac{(n-1)S^2}{\sigma^2} < \chi_{n-1}^2\left(\frac{\alpha}{2}\right)\right) = 1-\alpha$$

$$\mathbb{P}\left(\frac{1}{\chi_{n-1}^2\left(1-\frac{\alpha}{2}\right)} > \frac{\sigma^2}{(n-1)S^2} > \frac{1}{\chi_{n-1}^2\left(\frac{\alpha}{2}\right)}\right) = 1-\alpha$$

$$\mathbb{P}\left(\frac{(n-1)S^2}{\chi_{n-1}^2\left(1-\frac{\alpha}{2}\right)} > \sigma^2 > \frac{(n-1)S^2}{\chi_{n-1}^2\left(\frac{\alpha}{2}\right)}\right) = 1-\alpha$$

$$= \mathbb{P}\left(\left\{\frac{(n-1)S^2}{\chi_{n-1}^2\left(1-\frac{\alpha}{2}\right)} > \sigma^2\right\} \cap \left\{\frac{(n-1)S^2}{\chi_{n-1}^2\left(\frac{\alpha}{2}\right)} < \sigma^2\right\}\right) = 1-\alpha$$

$\therefore 100(1-\alpha)\%$  confidence interval for  $\sigma^2$  is:

$$\left[\frac{(n-1)S^2}{\chi_{n-1}^2\left(\frac{\alpha}{2}\right)}, \frac{(n-1)S^2}{\chi_{n-1}^2\left(1-\frac{\alpha}{2}\right)}\right]$$

$$X \sim \text{Bin}(n, \theta)$$

$$\begin{aligned} L(\theta | X) &= P(X = x; \theta) \\ &= \binom{n}{x} \theta^x (1-\theta)^{n-x} \end{aligned}$$

The log-likelihood function is

$$\ell(\theta | X) = \log \binom{n}{x} + X \log \theta + (n-x) \log(1-\theta)$$

$$\frac{\partial \ell}{\partial \theta} = \frac{X}{\theta} - \frac{(n-x)}{1-\theta}$$

MLE solve  $\left. \frac{\partial \ell}{\partial \theta} \right|_{\hat{\theta}} = 0 \Rightarrow \hat{\theta} = \frac{X}{n}$

$$\frac{\partial^2 \ell}{\partial \theta^2} = -\frac{X}{\theta^2} - \frac{(n-x)}{(1-\theta)^2}$$

$$\therefore \mathcal{I}(\theta) = \mathbb{E} \left[ -\frac{\partial^2 \ell}{\partial \theta^2} \right] = \frac{n}{\theta(1-\theta)}$$

100(1- $\alpha$ )% confidence interval for  $\theta$  is

$$\left[ \hat{\theta} - \frac{z_{\frac{\alpha}{2}}}{\sqrt{\mathcal{I}(\hat{\theta})}}, \hat{\theta} + \frac{z_{\frac{\alpha}{2}}}{\sqrt{\mathcal{I}(\hat{\theta})}} \right]$$



$$=, \left[ \hat{\theta} - z_{\frac{\alpha}{2}} \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}}, \hat{\theta} + z_{\frac{\alpha}{2}} \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}} \right]$$