

Dec 1, 2023

Newmann
Pearson
Lemma

$$\begin{aligned} H_0: \{f_0\} \\ H_1: \{f_1\} \\ f_1(x_1, \dots, x_n) &= \frac{1}{(2\pi)^{n/2}} e^{-1/2 \sum_{i=1}^n (x_i - \mu_1)^2} \end{aligned}$$

$$\frac{f_1(x_1, \dots, x_n)}{f_0(x_1, \dots, x_n)} = e^{(\mu_1 - \mu_0) \sum_{i=1}^n x_i + \frac{n}{2} (\mu_0^2 - \mu_1^2)} \geq k$$

sufficient statistics

$$\sum_{i=1}^n x_i > x^* n$$

$$\bar{x} > x^* \quad x^* = \mu_0 - \frac{\sigma}{\sqrt{n}} z_\alpha$$

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

Definition: Family of distributions $\mathcal{P} = \{f_\theta, \theta \in \Theta\}$ has monotone likelihood ratio, if for $\theta < \theta_0$
 $f_{\theta_0}(x)/f_\theta(x)$ is a monotone, increasing function of $T(x)$
 $T(x)$ is a sufficient statistic from the data to test the hypothesis

Theorem: Suppose that \mathcal{P} is the distribution family with monotone likelihood ratio.
 For testing $H_0: \theta \leq \theta_0$ vs. $H_1: \theta > \theta_0$.

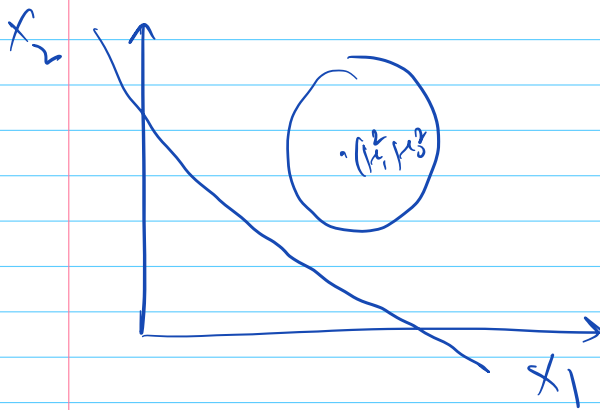
(i) There exist uniformly most powerful (UMP) test

$$\phi(x) = \begin{cases} 1, & \text{if } T(x) > c \\ 0, & \text{if } T(x) < c \end{cases} \quad \therefore \text{(reject)} \quad \text{(accept)}$$
 (you have to randomize them).

$$\text{where } E_{\theta_0}[\phi(x)] = \alpha$$

(ii) $\beta(\theta)$ is strictly increasing whenever $0 < \beta(\theta) < 1$

(iii) for any θ' , test $\phi(\cdot)$ is UMP test for $H_0: \theta \leq \theta'$ vs $H_1: \theta > \theta'$ but with size $\alpha' = \beta(\theta')$



Multi dimensional
optimization
problems

$$H_0: E[X_1] = \mu_1^0$$

$$E[X_2] = \mu_2^0$$

$$H_1: E[X_1] \neq \mu_1^0$$

$$E[X_2] \neq \mu_2^0$$

Very difficult to calculate & this is why
2-dimensional. What is usually done
is heuristic models.

$$H_0: \theta \leq \theta_0$$

$$H_1: \theta \neq \theta_0$$

Joint probability

to note X_i independent: —

$$\sum \frac{1}{n} \frac{1}{n} = \Sigma \rightarrow \text{covariance matrix}$$

$$\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, \Sigma) \quad \text{still tough to evaluate}$$

$$\sqrt{n} \Sigma^{-1/2}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, I) \quad \begin{array}{l} \text{Normal dist'n} \\ \text{diagonal} \\ \text{matrix} \end{array}$$

$$\sqrt{n}(\hat{\theta} - \theta_0) \Sigma^{-1}(\hat{\theta} - \theta_0) \xrightarrow{d} \chi^2_1$$

Allows us to use single dimensional dist'n.

