

Example: $X_1, \dots, X_n \sim \text{iid } N(\theta, 1)$

Stat 563
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$$H_0: \theta = \theta_0$$

①

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

Let θ_1 be any value of $\theta \neq \theta_0$

$$\Lambda = \frac{L(\theta_0)}{L(\theta_1)} = \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2}\sum (x_i - \theta_0)^2}}{\left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2}\sum (x_i - \theta_1)^2}} \stackrel{\text{xt}}{\leq} c$$
$$e^{-\frac{1}{2}[\sum x_i^2 - 2\theta_0 \sum x_i + n\theta_0^2 - (\sum x_i^2 - 2\theta_1 \sum x_i + n\theta_1^2)]} \leq c$$

$$-2\theta_0 \sum x_i + n\theta_0^2 + 2\theta_1 \sum x_i - n\theta_1^2 \geq c' \quad (2)$$

$$2\bar{x}(\theta_1 - \theta_0) + \theta_0^2 - \theta_1^2 \geq c''$$

$$\bar{x}(\theta_1 - \theta_0) \geq c'''$$

Our reject region is $\bar{x} \geq k$ if $\theta_1 > \theta_0$

or $\bar{x} \leq k$ if $\theta_1 < \theta_0$

\therefore There is no single rejection region that gives a most powerful test $\forall \theta_1$.

That is, there is no UMP test.

Defn: $L(\theta)$ has monotone likelihood ratio (MLR) in $T = g(x_1, \dots, x_n)$ if (3)

$$\forall \theta_1 < \theta_2, \quad \frac{L(\theta_2)}{L(\theta_1)} \text{ is a monotone function of } T.$$

Some families of distributions with this property:
Normal (σ known), Poisson, Binomial,
most exponential families

Assume that T is a sufficient statistic for θ .
and that $L(\theta)$ has MLR in T

Consider $H_0: \theta = \theta_0$ (4)
 $H_1: \theta = \theta_1$ where $\theta_1 > \theta_0$

Neyman-Pearson theorem says that the MP test is the one which rejects H_0 when

$$\Lambda = \frac{L(\theta_1)}{L(\theta_0)} \leq c$$

But our additional assumption says

$$\frac{L(\theta_1)}{L(\theta_0)} = g(t), \text{ which is } \uparrow \text{ or } \downarrow$$

(5)

Case 1: $g(t) \uparrow$ Then Λ is \downarrow in t

$$\text{So } \Lambda \leq c \Leftrightarrow \frac{1}{g(t)} \leq c$$

$$\Leftrightarrow g(t) \geq c''$$

$$\Leftrightarrow t \geq c'''$$

Case 2: $g(t) \downarrow$ Then Λ is \uparrow in t

$$\Lambda \leq c \Leftrightarrow \frac{1}{g(t)} \leq c$$

$$g(t) \geq c''$$

$$t \leq c'''$$

(6)

This is the Karlin-Rubin Theorem,
which is a corollary to the Neyman-Pearson
Theorem.

Summary: If $L(\theta)$ has MLR in T (sufficient),

then the MP test of $H_0: \theta = \theta_0$
 $H_1: \theta = \theta_1$

will be of the form $T \leq c$ or $T \geq c$

($g(t) \downarrow$)

($g(t) \uparrow$)

Bayesian Hypothesis Tests

(7)

We now assume that θ is a random variable whose distribution is known,

And θ is independent of X_1, \dots, X_n .

Example (normal-normal)

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

known

$$\theta \sim N(\mu, \tau^2)$$

both known

Prior distribution

$$h(\theta) = \frac{1}{\tau\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\theta-\mu}{\tau}\right)^2}$$

(8)

$$\begin{aligned} L(\theta) &= f(x_1, \dots, x_n | \theta) \\ &= \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n e^{-\frac{1}{2}\sum_{i=1}^n \left(\frac{x_i - \theta}{\sigma}\right)^2} \end{aligned}$$

The joint distr. of $(x_1, \dots, x_n, \theta)$ is $L(\theta)h(\theta)$

Recall that the posterior distribution of $\theta | \vec{x}$

is proportional to $L(\theta)h(\theta)$

$$L(\theta)h(\theta) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \frac{1}{n\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}\sum(x_i-\theta)^2} e^{-\frac{1}{2\tau^2}(\theta-\mu)^2} \quad (9)$$

This is proportional to a normal density

with mean $\frac{n\tau^2\bar{x} + \sigma^2\mu}{n\tau^2 + \sigma^2}$ and

variance $\frac{\sigma^2\tau^2}{n\tau^2 + \sigma^2}$

Decision rule: Reject H_0 if

$$P(\theta \in \Omega_0^c | \bar{x}) \geq P(\theta \in \Omega_0 | \bar{x})$$

Suppose that we were testing

$$H_0: \theta \leq \theta_0 \quad \text{vs} \quad H_1: \theta > \theta_0$$

Rule: reject H_0 if

$$P(\theta > \theta_0 | \bar{x}) \geq .5$$

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$$P\left(\frac{\theta - \frac{n\tau^2\bar{x} + \sigma^2\mu}{n\tau^2 + \sigma^2}}{\sqrt{\frac{\sigma^2\tau^2}{n\tau^2 + \sigma^2}}} > \frac{\theta_0 - \dots}{\dots} \mid \bar{x}\right)$$

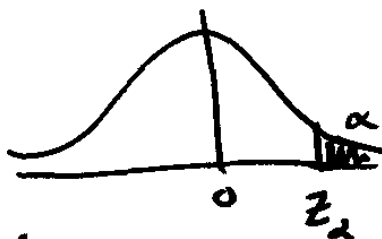
$$P(Z > \frac{\theta_0 - \dots}{\dots}) \geq .5$$

$$\Rightarrow \frac{\theta_0 - \frac{n\tau^2 \bar{x} + \sigma^2 \mu}{n\tau^2 + \sigma^2}}{\sqrt{\frac{\sigma^2 \tau^2}{n\tau^2 + \sigma^2}}} \leq 0 \quad (11)$$

$$\Rightarrow \bar{x} \geq \theta_0 + \frac{\sigma^2(\theta_0 - \mu)}{n\tau^2}$$

Compare this to the LRT, where we would have rejected H_0 if $\bar{x} \geq c$

$$\text{Under } H_0: \frac{\bar{x} - \theta_0}{\sigma/\sqrt{n}} \sim N(0,1)$$



Reject H_0 if

$$\frac{\bar{x} - \theta_0}{\sigma/\sqrt{n}} \geq z_\alpha$$

$$\bar{x} \geq \theta_0 + z_\alpha \frac{\sigma}{\sqrt{n}} \quad (12)$$