

Hypothesis Test

① H_0 & H_1

α -mistake : reject H_0 But H_0 is true $P(\text{reject } H_0 | H_0)$

β -mistake : accept H_0 But H_0 is false $P(\text{accept } H_0 | H_1)$

$$t \geq \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}} \text{ or something}$$

② aim: control α -mistake $P(\text{reject } H_0 | H_0 \text{ is true}) \leq \alpha$

③ For example: a) $H_0: \mu \leq \mu_0$, $H_1: \mu > \mu_0$, $\alpha = 0.05$

b) construct statistics

$$t = \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}} \sim t(n-1) \rightarrow \text{r.v.}$$

consider $P(t_{n-1} \geq \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}})$

Quantity

c) if $P(t_{n-1} \geq *) < 0.05$, then reject H_0

Understanding of reject region for one-side hypothesis test

→ when $H_0: \mu = \mu_0$, the accept region is (a_μ, b_μ)

→ when $H_0: \mu \leq \mu_0$, the accept region is $\bigcup_{\mu \leq \mu_0} (a_\mu, b_\mu)$

$$\Rightarrow \text{reject region} = \bigcap_{\mu \leq \mu_0} (a_\mu, b_\mu)^c$$

$$= \bigcap_{\mu \leq \mu_0} \text{reject region}_\mu$$

2022.09.28

Hypothesis testing

① $H_0: \theta \in \Theta_0$

$H_1: \theta \in \Theta_0^c$

② if $x \in R$, then reject H_0

$$R := \{x: W(x) \leq c\} \rightarrow \text{reject region}$$

if $x \in R^c$, then accept H_0 1) Likelihood Ratio Test (LRT) \leftarrow same reasonable method to choose Reject Region

Reject Region

$$R := \{x: \lambda(x) \leq c\}$$

$\lambda(x) := \frac{\sup_{\theta \in \Theta_0} L(\theta|x)}{\sup_{\theta \in \Theta} L(\theta|x)}$

\rightarrow a reasonable choice intuitively

[E.g.] Normal LRT $N(\theta, \sigma^2)$
 $\Theta_0 = \{\theta_0\}$

$$\lambda(x) = \frac{C \cdot \exp(-\frac{1}{2\sigma^2} \sum (x_i - \theta_0)^2)}{C \cdot \exp(-\frac{1}{2\sigma^2} \sum (x_i - \bar{x})^2)}$$

$$= \exp(-\frac{1}{2\sigma^2} (\sum (x_i - \bar{x} + \bar{x} - \theta_0)^2 - \sum (x_i - \bar{x})^2))$$

$$= \exp(-\frac{n}{2\sigma^2} (\bar{x} - \theta_0)^2)$$

$$\Rightarrow \text{Reject Region } R = \{x: \left| \frac{\bar{x} - \theta_0}{\sigma} \right| \geq \sqrt{\frac{-2 \log c}{n}}\}$$

Property !!the reject region only depends onsufficient statistic of θ $f(x_1, \dots, x_n | T)$ 与 θ 无关2) union-intesection method

$$H_0: \theta \in \bigcap_{r \in \Gamma} \Theta_r$$

$$\Rightarrow R = \bigcup_{r \in \Gamma} R_r$$

[E.g.] if $R_r = \{x: T_r(x) > c\}$

$$\text{then } \bigcup_{r \in \Gamma} R_r = \{x: \sup_{r \in \Gamma} T_r(x) > c\}$$

★ If R_r is simple, then we can simplify

intersect - union method

$$H_0: \theta \in \bigcap_{r \in \mathcal{R}} \mathcal{U}_r \Rightarrow R = \bigcap_{r \in \mathcal{R}} R_r$$

$$(A \cup B) \cap (C \cup D)$$

[Application]

LRT Normal (θ, σ^2)

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

$$H_1: \theta > \theta_0$$

$$R_\theta = \left\{ x: \left| \frac{\bar{x} - \theta}{\sigma} \right| \geq \sqrt{\frac{-2 \log c}{n}} \right\} \Rightarrow R = \bigcap_{\theta \leq \theta_0} R_\theta = \left\{ x: \frac{\bar{x} - \theta_0}{\sigma} \geq \sqrt{\frac{-2 \log c}{n}} \right\}$$

3) Evaluate Method for Hypothesis Testing

$$H_0: \theta \in \mathcal{U}_0$$

$$H_1: \theta \in \mathcal{U}_0^c$$

$$\left\{ \begin{array}{l} \text{Type I Error: } P(X \in R | \theta \in \mathcal{U}_0) \end{array} \right.$$

$$\left\{ \begin{array}{l} \text{Type II Error: } P(X \in R^c | \theta \in \mathcal{U}_0^c) = 1 - P(X \in R | \theta \in \mathcal{U}_0^c) \end{array} \right.$$

Defn: Power Function

$$\Rightarrow \text{define } \beta(\theta) = P_\theta(X \in R) := P(X \in R | \theta), \quad \theta \in \mathcal{U}$$

$$\text{then } \left\{ \begin{array}{l} \text{Type I Error Prob.} = \beta(\theta) \quad \theta \in \mathcal{U}_0 \end{array} \right.$$

$$\left\{ \begin{array}{l} \text{Type II Error Prob.} = 1 - \beta(\theta) \quad \theta \in \mathcal{U}_0^c \end{array} \right.$$

Example: Power function for Normal LRT

$$X \sim N(\theta, \sigma^2)$$

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

$$H_1: \theta > \theta_0$$

$$\text{LRT} \Rightarrow R = \left\{ x: \frac{\bar{x} - \theta_0}{\frac{\sigma}{\sqrt{n}}} > c \right\}$$

$$\frac{1}{\sqrt{2\pi}\sigma}$$

$$(2\pi)^{\frac{n}{2}} (\sigma^2)^{-\frac{n}{2}}$$

when σ^2 unknown,

$$\text{then } \lambda(x) = \frac{\sup_{\theta \in \mathcal{U}_0} L(\theta|x)}{\sup_{\theta \in \mathcal{U}} L(\theta|x)}$$

$$\textcircled{1} \hat{\mu}_1 = \theta_0 \quad \hat{\sigma}_1^2 = \frac{1}{n} \sum (x_i - \theta_0)^2$$

$$\textcircled{2} \hat{\mu}_2 = \bar{x} \quad \hat{\sigma}_2^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$

$$\beta(\theta) = P_{\theta}(X \in R) = P_{\theta}\left(\frac{\bar{X} - \theta}{\frac{\sigma}{\sqrt{n}}} > c + \frac{\theta_0 - \theta}{\frac{\sigma}{\sqrt{n}}}\right)$$

X is r.v.

$$= P_{\theta}\left(Z > c + \frac{\theta_0 - \theta}{\frac{\sigma}{\sqrt{n}}}\right)$$

$$= 1 - \Phi\left(c + \frac{\theta_0 - \theta}{\frac{\sigma}{\sqrt{n}}}\right)$$

$$\lambda(x) = \left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2}\right)^{-\frac{n}{2}} = \left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2}\right)^{\frac{n}{2}}$$

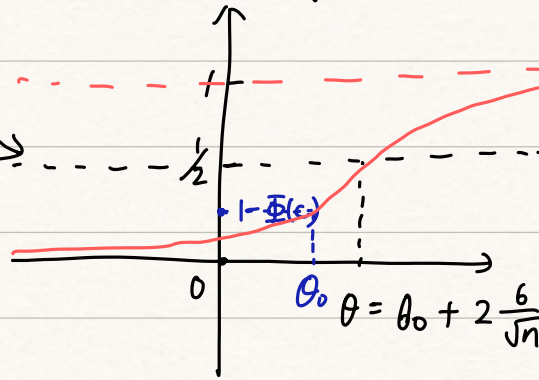
$$\begin{aligned}\hat{\sigma}_1^2 &= \frac{1}{n} \sum (x_i - \bar{x} + \bar{x} - \theta_0)^2 \\ &= \frac{1}{n} (\sum (x_i - \bar{x})^2 + \sum (\bar{x} - \theta_0)^2) \\ &= \frac{1}{n} \sum (x_i - \bar{x})^2 + (\bar{x} - \theta_0)^2\end{aligned}$$

$$\Rightarrow \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2} = 1 + \frac{n(\bar{x} - \theta_0)^2}{\sum (x_i - \bar{x})^2}$$

$$= 1 + \frac{t(x)}{n-1}$$

$$\text{where } t(x) = \frac{\sqrt{n}(\bar{x} - \theta_0)}{\sqrt{\frac{1}{n-1} \sum (x_i - \bar{x})^2}}$$

$$= \frac{\sqrt{n}(\bar{x} - \theta_0)}{\sqrt{S_{n-1}}}$$



Hypothesis Test
Neyman-Pearson

显著水平

Use Power Function to determine R

Therefore $\{x: \lambda(x) \geq c\}$

$$= \{x: |t(x)| \geq d\} = R$$

where $t(x) \sim t_{n-1}$

\Rightarrow we can calculate $P_{\theta}(X \in R) := \beta(\theta)$

\Rightarrow let $\alpha = \sup_{\theta \in \Theta_0} \beta(\theta)$ to decide the reject region R

This α is called size α

Distinguish with significance test

Fisher Significance Test

Interpretation of such experiment:

\rightarrow If H_0 is true, then when we do N experiments (in each experiment we sample n example), the frequency of we reject H_0 converges to $N \cdot \alpha$ (at most when Θ_0 is not singleton)

\rightarrow large $\alpha \Rightarrow$ bigger reject region \Rightarrow easier to reject H_0

犯第一类错误概率大

Then, it is followed by Neyman-Pearson Lemma, which dives into the details of Hypothesis Testing. \rightarrow only works for SIMPLE vs SIMPLE test

(Uniform Most Powerful class (test))

UMP

Sufficient & Necessary Condition

Leave for future

① p-value definition

\rightarrow for sample $X = (X_1, \dots, X_n)$, construct statistic $p(X)$

s.t ① $0 \leq p(X) \leq 1$

② $p(X)$ small \Rightarrow evidence for reject H_0

② valid p-value defn

\rightarrow for $\theta \in \Theta_0$ and $0 \leq \alpha \leq 1$,

we have $P_\theta(X: \underline{p(X) \leq \alpha}) \leq \alpha$

can be viewed as $R = \{x: p(x) \leq \alpha\}$

One construction for $p(X)$

\rightarrow then $p(x)$ is the probability of view data x

[E.g.]

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0,1)$$

$$P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < z\right) = \alpha$$

$$\textcircled{1} \{x: p(x) \leq \alpha\} = \{x: |\bar{x} - \mu| \geq z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}\}$$

$$\textcircled{2} p: x \mapsto P(|Z| \geq \left| \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}} \right|) \Rightarrow \text{X is random variable} \Rightarrow p(x) \text{ also r.v.}$$

$$\Rightarrow \textcircled{3} \{x: p(x) \leq \alpha\} = \{x: P(|Z| \geq \left| \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}} \right|) \leq \alpha\}$$

$$= \{x: |\bar{x} - \mu| \geq z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}\}$$

$$\Rightarrow P_{\theta}(p(x) \leq \alpha) = \alpha$$

Consider CI with Bootstrap:

$\theta_0 \rightarrow$ ground-truth

ideally

sample $\rightarrow X_i = \{X_{i1}, \dots, X_{in}\} \quad i=1, 2, \dots, B$

$$\Rightarrow \text{for each } i, \text{ consider } \hat{\theta}(X_{i1}, \dots, X_{in}) = \hat{\theta}_i$$

$$\Rightarrow \{\hat{\theta}_1, \dots, \hat{\theta}_B\} \rightarrow \text{approximate the sampling distribution } \hat{\theta}$$

$$\hat{\theta} - \theta \sim \text{some distribution}$$

$$\Rightarrow \text{consider quantile in } \{\hat{\theta}_1 - \theta, \dots, \hat{\theta}_B - \theta\}, \text{ namely } \underline{s}, \bar{s}$$

$$\text{then } P(\underline{s} \leq \hat{\theta} - \theta \leq \bar{s}) \approx 1 - \alpha$$



$$P(\theta \in [\hat{\theta} - \bar{s}, \hat{\theta} - \underline{s}]) \approx 1 - \alpha$$

Real World

$$\begin{cases} \theta = T(F) \\ \hat{\theta} = T(\hat{F}_n) \\ X \sim F \end{cases}$$

Bootstrap World

But we don't know $\theta_0! \Rightarrow \hat{\theta}_{MLE} \approx \theta_0$

Then, the framework is:

① $\hat{\theta} \approx \theta_0 \Rightarrow$ generate $\{x_{i1}, \dots, x_{in}\}$

② compute $\theta^*(x_{i1}, \dots, x_{in}) = \theta_i^*$

③ $P(\underline{\delta} \leq \hat{\theta} - \theta_0 \leq \bar{\delta})$

$\approx P(\underline{\delta} \leq \theta^* - \hat{\theta} \leq \bar{\delta})$

$\approx 1 - \alpha$

④ $P(\theta_0 \in [\hat{\theta} - \bar{\delta}, \hat{\theta} - \underline{\delta}]) \approx 1 - \alpha$

$[\underline{\delta} \& \bar{\delta}]$ is the quantile for $\{\theta_1^* - \hat{\theta}, \dots, \theta_B^* - \hat{\theta}\}$

$$\begin{cases} \hat{\theta} = T(\bar{F}_n) \\ \theta^* = T(F_n^*) \\ X \sim \bar{F}_n \\ \downarrow \\ \text{fixed} \end{cases}$$

The duality between CI & Hypothesis Testing

→ From Bootstrap

$$\hat{\theta} = \hat{\theta}(X_1, \dots, X_n)$$

$P(\theta_0 \in [\hat{\theta} - \bar{\delta}, \hat{\theta} - \underline{\delta}]) \approx 1 - \alpha$ CI

⇒ Construct Hypothesis Testing Thru Reversing the CI

① 从参数估计角度构造

Hypothesis Testing $\begin{cases} \text{exact} \\ \text{MLE asymptotic} \\ \text{Bootstrap} \end{cases}$

$X_1, \dots, X_n \rightarrow$ observation

$\hat{\theta}$

generate samples and achieve

$\{\theta_1^*, \dots, \theta_B^*\}$

② $\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t_{n-1} \Rightarrow$ 从统计量角度

$(\underline{\delta}, \bar{\delta}) \rightarrow \theta_i^* - \hat{\theta}$

Accept Region

$\{X: \hat{\theta}(X) \in [\theta_0 + \underline{\delta}, \theta_0 + \bar{\delta}]\}$