

Ch 12. Hypothesis Testing.

- Two competing hypotheses H_0 , H_1 .

$$X \sim P_\theta \quad \theta \in \Omega$$

$$H_0: \theta \in \Omega_0 \quad \text{vs.} \quad H_1: \theta \in \Omega_1$$

$$\Omega = \Omega_0 \cup \Omega_1 \quad \Omega_0 \cap \Omega_1 = \emptyset$$

focus on the case where θ is univariate.

- Critical region S : when $X \in S$, accept H_1
 $X \notin S$, accept H_0 .

- Power function $\beta(\cdot)$: $\beta(\theta) = P_\theta(X \in S)$.

The chance of rejecting H_0 as a function of $\theta \in \Omega$.

We hope: $\beta(\theta) = 0$ for $\theta \in \Omega_0$, $\beta(\theta) = 1$ for $\theta \in \Omega_1$
impossible!

- Significance level α : $\alpha = \sup_{\theta \in \Omega_0} P_\theta(X \in S)$.

The level α is the worst chance of falsely rejecting H_0 .

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- test or critical function $\varphi \in [0, 1]$.

Given $X=x$. $\varphi(x)$ is the chance of rejecting H_0 .

$$\beta(\theta) = P_{\theta}(\text{reject } H_0) = E_{\theta} P_{\theta}(\text{reject } H_0 | X) = E_{\theta} \varphi(X)$$

- Simple vs. Simple.

H_0, H_1 contain a single parameter θ_0, θ_1 resp.

$$\alpha = E_{\theta_0} \varphi = \int \varphi(x) p_{\theta_0}(x) d\mu(x)$$

$$E_{\theta_1} \varphi = \int \varphi(x) p_{\theta_1}(x) d\mu(x)$$

maximizing $E_{\theta_1} \varphi$ among all tests φ with $E_{\theta_0} \varphi = \alpha$.

Prop 12.1. suppose $\alpha > 0$. φ^* maximizes $E_{\theta_1} \varphi - K E_{\theta_0} \varphi$ among all critical functions and $E_{\theta_0} \varphi^* = \alpha$. Then φ^* maximizes $E_{\theta_1} \varphi$ over all φ with level at most α .

Pf. suppose $E_{\theta_0} \varphi \leq \alpha$. Then

$$\begin{aligned} E_{\theta_1} \varphi &\leq E_{\theta_1} \varphi - K E_{\theta_0} \varphi + K \alpha \\ &\leq E_{\theta_1} \varphi^* - K E_{\theta_0} \varphi^* + K \alpha \\ &= E_{\theta_1} \varphi^*. \end{aligned}$$

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- Maximize $E_1 \varphi - k E_0 \varphi$.

$$E_1 \varphi - k E_0 \varphi = \int [P_1(x) - k P_0(x)] \varphi(x) d\mu(x)$$

$$= \int |P_1(x) - k P_0(x)| \varphi(x) d\mu(x) - \int |P_1(x) - k P_0(x)| \varphi(x) d\mu(x)$$

$P_1(x) > k P_0(x)$ $P_1(x) < k P_0(x)$

$$\varphi^* = 1 \quad \text{when} \quad P_1(x) > k P_0(x)$$

$$\varphi^* = 0 \quad \text{when} \quad P_1(x) < k P_0(x)$$

likelihood ratio. $L(x) = \frac{P_1(x)}{P_0(x)}$

$$\varphi^*(x) = \begin{cases} 1 & L(x) > k \\ \text{any} & L(x) = k \\ 0 & L(x) < k \end{cases}$$

likelihood ratio test.

Prop 12.2 (Neyman-Pearson Lemma) Given any level $\alpha \in [0, 1]$, there exists a likelihood ratio test φ_α with level α , and any likelihood ratio test with level α maximizes $E_1 \varphi$ among all tests with level at most α .

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Prop 12.3. Fix $\alpha \in [0, 1]$. Let K be the critical value for a likelihood ratio test φ_α and $B = \{x : p_1(x) \neq K p_0(x)\}$.

If φ^* maximizes $E_I \varphi$ among all tests with level at most α , then φ^* and φ_α must agree on B .

→ If a test is optimal, it must be a likelihood ratio test.

→ If $p_0 \neq p_1$, $E_I \varphi_\alpha > \alpha$

$$\text{d}x \quad X \sim p_0(x) = \begin{cases} \theta e^{-\theta x} & x > 0 \\ 0 & \text{o.w.} \end{cases}$$

$H_0: \theta = 1$ vs. $H_1: \theta = \theta_1$, $\theta_1 > 1$, pre-specified

$$\varphi = 1 \text{ if } \frac{p_1(x)}{p_0(x)} = \frac{\theta_1 e^{-\theta_1 x}}{e^{-x}} > K \quad x < \frac{\ln \frac{\theta_1}{K}}{\theta_1 - 1} = k'$$

$$\varphi = 0 \text{ if } x > k' \quad \varphi = \text{anything in } [0, 1] \text{ if } x = k'$$

$$\alpha = p_0(X < k') = \int_0^{k'} e^{-x} dx = 1 - e^{-k'} \quad k' = -\ln(1-\alpha)$$

$$\varphi_\alpha(x) = \begin{cases} 1 & x < -\ln(1-\alpha) \\ 0 & x > -\ln(1-\alpha) \end{cases}$$

1. does not depend on θ_1
2. if φ is any test with level α , $E_{\theta_1} \varphi \leq E_{\theta_1} \varphi_\alpha$ for $\theta_1 > 1$

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Ex: $X \sim \text{Bin}(n=2, \theta)$.

$$H_0: \theta = \frac{1}{2} \quad \text{vs.} \quad H_1: \theta = \frac{3}{4}.$$

$$L(X) = \frac{P_1(X)}{P_0(X)} = \frac{\binom{2}{X} \left(\frac{3}{4}\right)^X \left(\frac{1}{4}\right)^{2-X}}{\binom{2}{X} \left(\frac{1}{2}\right)^X \left(\frac{1}{2}\right)^{2-X}} = \frac{3^X}{4}$$

Under H_0

$$L(X) = \begin{cases} \frac{1}{4} & \text{w.p. } \frac{1}{4} \\ \frac{3}{4} & \text{w.p. } \frac{1}{2} \\ \frac{9}{4} & \text{w.p. } \frac{1}{4}. \end{cases}$$

$$\text{if } K < \frac{9}{4}, \quad L(2) = \frac{9}{4} > K \quad \varphi(2) = 1$$

$$E_0 \varphi(X) \geq \varphi(2) P_0(X=2) = \frac{1}{4}$$

$$\text{if } K > \frac{9}{4} \quad \varphi = 0.$$

$$\text{so } K = \frac{9}{4}. \quad \varphi(0) = \varphi(1) = 0.$$

$$5\% = E_0 \varphi(X) = \frac{1}{4} \varphi(0) + \frac{1}{2} \varphi(1) + \frac{1}{4} \varphi(2) = \frac{1}{4} \varphi(2)$$

$$\varphi(2) = \frac{1}{5}.$$

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- Uniformly most powerful test: A test φ^* with level α ,
 $E_\theta \varphi^* \geq E_\theta \varphi \quad \forall \theta \in \Omega_1.$

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

- monotone likelihood ratio: there exists a statistic $T = T(x)$. s.t. when $\theta_1 < \theta_2$, $\frac{P_{\theta_2}(x)}{P_{\theta_1}(x)}$ is a nondecreasing function of T .
 $P_{\theta_1} \neq P_{\theta_2}$. whenever $\theta_1 \neq \theta_2$.

Ex. $P_\theta(x) = e^{\eta(\theta)T(x) - B(\theta)}$
 $h(x)$

$$\frac{P_{\theta_2}(x)}{P_{\theta_1}(x)} = e^{[\eta(\theta_2) - \eta(\theta_1)]T(x) + B(\theta_1) - B(\theta_2)} \rightarrow \text{in } T(x).$$

- Thm 12.9. Suppose the family of densities has a monotone likelihood ratio. Then 1. $\varphi^*(x) = \begin{cases} 1 & T(x) > c \\ r & T(x) = c \\ 0 & T(x) < c \end{cases}$ is UMP test for

$H_0: \theta \leq \theta_0$. vs. $H_1: \theta > \theta_0$. It has level $\alpha = E_{\theta_0} \varphi^*$. adjust c and r.

2. The power function $\beta(\theta) = E_\theta \varphi^*$ — nondecreasing and strictly increasing when $\beta(\theta) \in (0, 1)$.
3. if $\theta_1 < \theta_0$. φ^* minimizes $E_{\theta_1} \varphi$ among all tests with $E_{\theta_0} \varphi - \lambda = E_{\theta_1} \varphi^*$.

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Ex. $X_1 \dots X_n$ iid $\text{Unif}(0, \theta)$

$$M(x) = \min\{X_1, \dots, X_n\} > 0 \quad T(x) = \max\{X_1, \dots, X_n\} < \theta.$$

$$f_{\theta}(x) = \begin{cases} \frac{1}{\theta^n} & M(x) > 0, \quad T(x) < \theta \\ 0 & \text{o.w.} \end{cases}$$

Suppose $\theta_2 > \theta_1$. $M(x) > 0$. $T(x) < \theta_2$. Then

$$\frac{f_{\theta_2}(x)}{f_{\theta_1}(x)} = \begin{cases} \frac{\theta_1^n}{\theta_2^n} & T(x) < \theta_1 \\ +\infty & T(x) \geq \theta_1 \end{cases} \quad \text{monotone likelihood ratios}$$

Test $H_0: \theta \leq 1$. vs. $H_1: \theta > 1$.

$$\varphi = \begin{cases} 1 & T \geq c \\ 0 & \text{o.w.} \end{cases} \quad \text{uniformly m.p.}$$

$$P_1(T \geq c) = 1 - c^n \quad c = (1-\alpha)^{\frac{1}{n}}$$

$$\text{Power: } \beta_{\varphi}(\theta) = P_{\theta}(T \geq c) = \begin{cases} 0 & \theta < c \\ 1 - \frac{1-\alpha}{\theta^n} & \theta \geq c \end{cases}$$

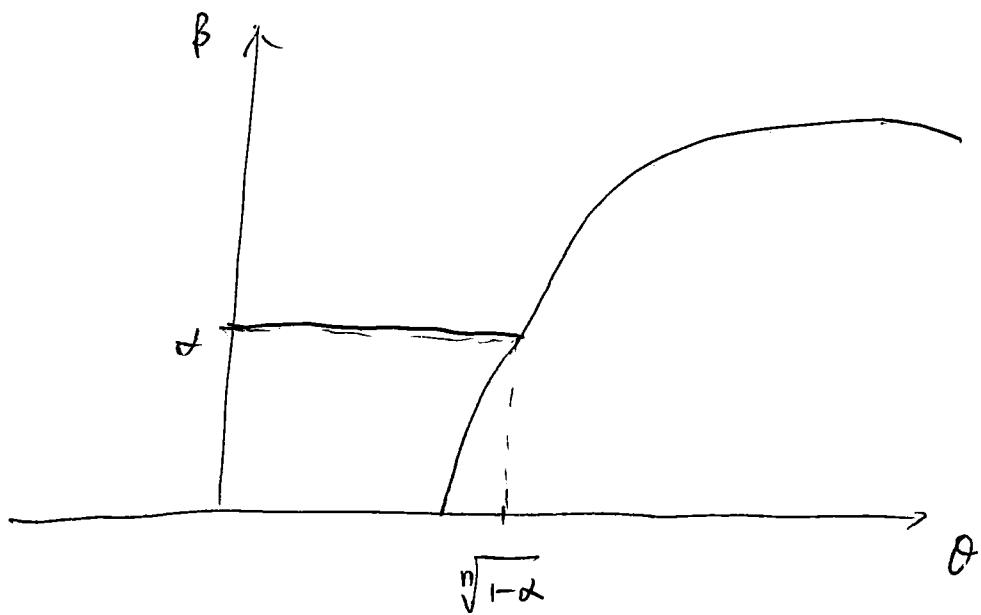
Competing one:

$$\tilde{\varphi} = \begin{cases} \alpha & T < 1 \\ 1 & T \geq 1 \end{cases} \quad E_{\theta} \tilde{\varphi} = \alpha \text{ for } \theta < 1$$

$$\begin{aligned} \text{For } \theta > 1. \quad \beta_{\tilde{\varphi}}(\theta) &= E_{\theta} \tilde{\varphi} = \alpha P_{\theta}(T < 1) \\ &= \frac{\alpha}{\theta^n} + 1 - \frac{1}{\theta^n} + P_{\theta}(T \geq 1) \\ &= \beta_{\varphi}(\theta) \end{aligned}$$

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The power function for $\tilde{\varphi}$ and φ are the same under H_0 ,
under H_1 the power function for φ is smaller than
the power function for $\tilde{\varphi}$. $\rightarrow \varphi$ is better.



$$\beta_{\varphi} \quad \text{and} \quad \beta_{\tilde{\varphi}}$$

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Duality Between Testing and Interval Estimation

- $S(x)$ — $1-\alpha$ confidence region for $\theta = \hat{\theta}(x)$
 if $P_\theta(\hat{\theta} \in S(x)) \geq 1-\alpha$ for $\forall \theta \in \Omega$.
- For every θ_0 . Let $A(\theta_0)$ — acceptance region for $H_0: \hat{\theta}(x) = \theta_0$ vs. $H_1: \hat{\theta}(x) \neq \theta_0$.

$$P_\theta[x \in A(\hat{\theta}(x))] \geq 1-\alpha \quad \forall \theta \in \Omega.$$
- Define $S(x) = \{\hat{\theta}: x \in A(\hat{\theta})\}$.
 $\hat{\theta}(x) \in S(x)$ iff $x \in A(\hat{\theta}(x))$
 $P_\theta(\hat{\theta}(x) \in S(x)) = P_\theta(x \in A(\hat{\theta}(x))) \geq 1-\alpha$.
 $S(x)$ — $1-\alpha$ confidence region for $\hat{\theta}$.
- Define $\varphi = \begin{cases} 1 & \theta_0 \notin S(x) \\ 0 & \text{o.w.} \end{cases}$
 then if $\hat{\theta}(x) = \theta_0$,
 $E_\theta \varphi = P_\theta(\theta_0 \notin S(x)) = P_\theta(\hat{\theta}(x) \neq \theta_0) \leq \alpha$.
 This test has level at most α . $H_0: \hat{\theta}(x) = \theta_0$ vs.
 $H_1: \hat{\theta}(x) \neq \theta_0$.

$$\varphi = \begin{cases} 1 & \theta_0 \notin S(x) \\ 0 & \text{o.w.} \end{cases} \quad \text{ump } H_0: \theta = \theta_0 \text{ vs. } H_1: \theta > \theta_0.$$

then for any $\theta > \theta_0$. $E_\theta \varphi \geq E_{\theta^*} \varphi^*$.

$$P_\theta(\theta_0 \in S(x)) \leq P_\theta(\theta_0 \in S^*(x))$$

\Rightarrow if θ is the true value, $S(x)$ has a smaller chance of containing any incorrect value $\theta_0 < \theta$.

Let $\Omega = (\underline{\omega}, \bar{\omega})$.

$$\begin{aligned} E_\theta \lambda(S(x) \cap (\underline{\omega}, \theta)) &= E_\theta \int_{\underline{\omega}}^\theta I(\theta_0 \in S(x)) d\theta_0 \\ &= \int_{\underline{\omega}} \int_{\underline{\omega}}^\theta I(\theta_0 \in S(x)) d\theta_0 dP_\theta(x) = \int_{\underline{\omega}}^\theta P_\theta(\theta_0 \in S(x)) d\theta_0 \end{aligned}$$

$$E_\theta \lambda(S^*(x) \cap (\underline{\omega}, \theta)) = \int_{\underline{\omega}}^\theta P_\theta(\theta_0 \in S^*(x)) d\theta_0$$

$$E_\theta \lambda(S(x) \cap (\underline{\omega}, \theta)) \leq E_\theta \lambda(S^*(x) \cap (\underline{\omega}, \theta)).$$

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Two-sided Hypotheses

- $H_0: \theta = \theta_0$, vs. $H_1: \theta \neq \theta_0$.

one parameter exponential family.

Theorem 12.17. T — sufficient $\mathcal{P} = \{P_\theta, \theta \in \mathcal{R}\}$. Then for any test $\varphi = \varphi(x)$, the test $\psi = \psi(T) = \bar{E}_\theta(\varphi(x)/T)$ has the same power function as φ , $\bar{E}_\theta \psi(T) = \bar{E}_\theta \varphi(x)$.

Lemma 12.18. $P_1 \ll P_0$. $\frac{dP_1}{dP_0} = L(x) = \frac{p_1(x)}{p_0(x)}$

$$\bar{E}_1 h(x) = \bar{E}_0 h(x)L(x). \quad P_1(B) = \bar{E}_0 \mathbb{1}_B(x)L(x).$$

Theorem 12.19. $X \sim f_\theta(x) = h(x) e^{\eta(\theta) \cdot T(x) - B(\theta)}$, $\theta \in \mathcal{R}$

$\Rightarrow T = T(x)$ has density $g_\theta(t) = e^{\eta(\theta) \cdot t - B(\theta)}$, $\theta \in \mathcal{R}$

Consider $H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$.

$X \sim h(x) e^{\eta(\theta) T(x) - B(\theta)}$, $\theta \in \mathcal{R}$. $\eta \nearrow$ and differentiable

$$\varphi_+ = \begin{cases} 1 & T > c_+ \\ r_+ & T = c_+ \\ 0 & T < c_+ \end{cases}$$

$$\varphi_- = \begin{cases} 1 & T < c_- \\ r_- & T = c_- \\ 0 & T > c_- \end{cases}$$

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These tests are most powerful for one-sided alternatives.

If $\theta_- < \theta_0 < \theta_+$, then φ_+ will have maximal power at θ_+ , and φ_- will have maximal power at θ_- .

Thm 12.20. If φ differentiable at θ and θ lies in the interior of Ω . then $\beta'(\theta) = \eta'(\theta) E_\theta T \varphi - B'(\theta) \beta(\theta)$.

$$\begin{aligned} \text{pf. } \beta'(\theta) &= \frac{\partial}{\partial \theta} \int \varphi(x) e^{\eta(\theta) T(x) - B(\theta)} h(x) d\mu(x) \\ &= \int \varphi(x) [\eta'(\theta) T(x) - B'(\theta)] e^{\eta(\theta) T(x) - B(\theta)} h(x) d\mu(x) \end{aligned}$$

- Because φ_+ has maximal power for $\theta > \theta_0$.

$$\beta_{\varphi_+}'(\theta_0) = \lim_{\varepsilon \downarrow 0} \frac{\beta_{\varphi_+}(\theta_0 + \varepsilon) - \beta_{\varphi_+}(\theta_0)}{\varepsilon} \leq \lim_{\varepsilon \downarrow 0} \frac{\beta_{\varphi_+}(\theta_0 + \varepsilon) - \beta_{\varphi_+}(\theta_0)}{\varepsilon} = \beta_{\varphi_+}'(\theta_0) \stackrel{\Delta}{=} m_+$$

$$\beta_{\varphi_-}'(\theta_0) > \beta_{\varphi_-}'(\theta_0) \stackrel{\Delta}{=} m_-$$

For $m \in [m_-, m_+]$, let C_m denote the class of all level α tests with $\beta_{\varphi}'(\theta_0) = m$.

- Def. φ is called two-sided if there are finite constants $t_1 \leq t_2$ s.t. $\varphi = \begin{cases} 1 & T < t_1 \text{ or } T > t_2 \\ 0 & T \in (t_1, t_2) \end{cases}$

In addition, the test should not be one-sided.

$E\varphi I(T \geq t_2)$ and $E\varphi I(T \leq t_1)$ should both be positive.

Theorem 12.22. θ_0 — interior of S_2 . $\lambda \in (0, 1)$. $X = P_\theta(x)$.

η — differentiable \nearrow . $0 < \eta'(\theta_0) < \infty$, then for $m \in (m_-, m_+)$

there is a two-sided test $\varphi^* \in C_m$. Any such test is uniformly m.p. in class C_m : For any $\varphi \in C_m$.

$$E_\theta \varphi \leq E_\theta \varphi^*. \quad \forall \theta \in S_2.$$

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Unbiased Tests.

- A test φ for $H_0: \theta \in \mathcal{S}_0$ vs. $H_1: \theta \in \mathcal{S}_1$, with level α is unbiased if its power $\beta_\varphi(\theta) = E_\theta \varphi$ satisfies

$$\beta_\varphi(\theta) \leq \alpha \quad \forall \theta \in \mathcal{S}_0$$

$$\beta_\varphi(\theta) \geq \alpha \quad \forall \theta \in \mathcal{S}_1$$
- If φ^* is UMP, it is automatically unbiased

$$\beta_{\varphi^*}(\theta) \geq \beta_\varphi(\theta) = \alpha \quad \text{for all } \theta \in \mathcal{S}_1$$

Thm 12.26. $\alpha \in (0, 1)$. $\theta_0 \in$ interior of \mathcal{S}_2 . X has density $h(x) e^{\eta(\theta) T(x) - B(\theta)}$, η - differentiable, strictly increasing
 $0 < \eta'(\theta_0) < \infty$

Then, there is a 2-sided, level α test φ^* with
 $\beta_{\varphi^*}'(\theta_0) = 0$. Any such test is UMP testing
 $H_0: \theta = \theta_0$, $H_1: \theta \neq \theta_0$ among all unbiased tests with level α .

Pf. θ_0 interior point. the power function for any unbiased test φ must have zero slope at θ_0 so $\varphi \in C_0 \rightarrow$ corollary Thm 12.22
 provided $\theta \in (m_-, m_+)$.

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$$d_x. \quad X \sim P_\theta(x) = \theta e^{-\theta x} \quad x > 0$$

$$H_0: \theta = 1 \quad \text{vs.} \quad H_1: \theta \neq 1$$

$$\varphi = \begin{cases} 0 & X \in (c_1, c_2) \\ 1 & X \leq c_1 \text{ or } X \geq c_2 \end{cases}$$

$$\varphi \text{ is AMP if } E_1 \varphi = 1 - \int_{c_1}^{c_2} e^{-x} dx = 1 - e^{-c_1} + e^{-c_2} = \alpha.$$

$$\text{and } E_1 X \varphi = E_1 X - E_1 X(1-\varphi) = 1 - \int_{c_1}^{c_2} x e^{-x} dx \\ = 1 - (1+c_1)e^{-c_1} + (1+c_2)e^{-c_2} = \alpha \quad E_1 X = \alpha.$$

$$c_1 e^{-c_1} = c_2 e^{-c_2} \Rightarrow c_2 = -\ln(e^{-c_1} - 1 + \alpha)$$

$$c_1 e^{-c_1} = -(\alpha - (e^{-c_1} - 1 + \alpha)) \ln(e^{-c_1} - 1 + \alpha)$$

$$\text{For } \alpha = 5\% \quad c_1 = 0.042 \quad c_2 = 4.705$$

or

$$P_1(X \leq c_1) = P_1(X \geq c_2) = \frac{\alpha}{2} \quad c_1 = -\ln(1 - \frac{\alpha}{2})$$

$$c_1 = 0.025 \quad c_2 = 3.689 \quad c_2 = -\ln(\frac{\alpha}{2})$$