

## 1 Review

$H_0 : \theta = \theta_0$  vs  $H_1 : \theta = \theta_1$ . LRT is MP.

$H_0 : \theta \leq \theta_0$  vs  $H_1 : \theta > \theta_0$  MLR in  $T(X) \implies$  UMP test rejects when  $T(x)$  large.

$H_0 : \theta = \theta_0$  vs  $H_1 : \theta \neq \theta_0$ . Exponential families  $\implies$  UMPU rejects when  $T(x)$  extreme

## 2 Confidence sets/intervals

Model  $\mathcal{P} = \{P_\theta : \theta \in \Theta\}$

**Definition 2.1.**  $C(X)$  is a  $1 - \alpha$  confidence set for  $g(\theta)$  if  $\forall \theta$

$$P_\theta(g(\theta) \in C(X)) \geq 1 - \alpha \quad (2.1)$$

## 3 Duality of tests and intervals

Suppose we have a level- $\alpha$  test  $\phi_{\theta_0}(x)$  of  $H_0 : \theta = \theta_0$  vs  $H_1 : \theta \neq \theta_0$  for each  $\theta_0 \in \Theta$ . Assume non-randomized.

Let  $C(x) = \{\theta : \phi_\theta(x) = 0\}$ .  $C(x)$  is a  $1 - \alpha$  confidence set for  $\theta$ .

$$P_\theta(\theta \notin C(x)) = P_\theta(\underbrace{\phi_\theta(x)}_{\text{level-}\alpha \text{ test}} = 1) \leq \alpha \quad (3.1)$$

Alternatively, suppose  $C(x)$  is a  $1 - \alpha$  confidence set for  $\theta$ . To test  $H_0 : \theta = \theta_0$  vs  $H_1 : \theta \neq \theta_0$

$$\phi(x) = 1_{\theta_0 \notin C(x)} \quad (3.2)$$

**Example 3.1.**  $X \sim \text{Exp}(\theta) = \theta^{-1}e^{-x/\theta}$ . CDF is  $1 - \exp^{-x/\theta}$ ,  $x > 0$ .

Equal tailed test:  $\phi_\theta(x)$  rejects  $\theta$  unless

$$-\theta \log(1 - \alpha/2) \leq X \leq -\theta \log(\alpha/2) \quad (3.3)$$

$\iff$  reject  $\theta$  unless

$$-x^{-1} \log(1 - \alpha/2) \leq \theta^{-1} \leq -x^{-1} \log(\alpha/2) \quad (3.4)$$

Hence

$$C(x) = x \left( \frac{-1}{\log(\alpha/2)}, \frac{-1}{\log(1 - \alpha/2)} \right) \quad (3.5)$$

## 4 Testing with nuisance parameters

$\mathcal{P} = \{P_{\theta, \zeta} : (\theta, \zeta) \in \Omega \subset \mathbb{R}^{r+s}\}. \theta \in \mathbb{R}^s, \zeta \in \mathbb{R}^r.$

$H_0 : \theta \in \Theta_0$  vs  $H_1 : \theta \in \Theta_1.$

Presence of  $\zeta$  affects the distribution of the data, so power of test  $\phi(\theta)$  depends on  $\zeta$ .  
Goal is to control the dependence of the power of the test on the parameter  $\zeta$ .

**Example 4.1.**  $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu, \sigma^2). \sigma^2 > 0$  unknown.

$H_0 : \mu = 0$  vs  $H_1 : \mu \neq 0$ . Nuisance parameter in this case is  $\sigma^2$ .

**Example 4.2.**

$$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu, \sigma^2) \quad (4.1)$$

$$Y_1, \dots, Y_n \stackrel{\text{iid}}{\sim} \mathcal{N}(\nu, \sigma^2) \quad (4.2)$$

$H_0 : \mu \leq \nu$  vs  $H_1 : \mu > \nu$

$\theta = \mu - \nu (\implies H_0 : \theta \leq 0). \zeta = (\mu + \nu, \sigma^2)$

**Example 4.3.**  $X_i \stackrel{\text{indep}}{\sim} \text{Pois}(\lambda_i), i = 1, 2.$

$H_0 : \lambda_1 \leq \lambda_2$  vs  $H_1 : \lambda_1 > \lambda_2.$

$\theta = \lambda_1 / \lambda_2. H_0 : \theta \leq 1.$  Nuisance  $\lambda_1$  or  $\lambda_1 \lambda_2$  or ...

**Example 4.4.**  $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} P. Y_1, \dots, Y_m \stackrel{\text{iid}}{\sim} Q.$

$H_0 : P = Q$  vs  $H_1 : P \neq Q.$

### 4.1 Multi-parameter exponential families

**Model:**

$$p_{\theta, \zeta}(x) = e^{\theta T(x) + \zeta' U(x) - A(\theta, \zeta)} h(x)$$

. (4.3)

$H_0 : \theta = \theta_0$  or  $H_1 : \theta \leq \theta_0.$

Under the null hypothesis,  $e^{\theta T(x)}$  is constant so only  $e^{\zeta' U(x)}$  is the complete sufficient statistic; the power of the test does not depend on  $\zeta$ :

$$p_{\theta, \zeta}(x \mid U(x) = u) = \frac{e^{\theta T(x) + \zeta' U(x) - A(\theta, \zeta)} h(x) 1_{U(x)=u}}{\int_{U(z)=u} e^{\theta T(z) + \zeta' U(z) - A(\theta, \zeta)} h(z) dz} \quad (4.4)$$

$$= e^{\theta T(x) - \tilde{A}_u(\theta)} h(x) 1_{U=u} \quad (4.5)$$

**Example 4.5.**

$$p_{\lambda}(x) = \lambda_1^{x_1} \lambda_2^{x_2} e^{-\lambda_1 - \lambda_2} \frac{1}{x_1! x_2!} \quad (4.6)$$

$$= e^{x_1 \log \lambda_1 + x_2 \log \lambda_2 - \lambda_1 - \lambda_2} \frac{1}{x_1! x_2!} \quad (4.7)$$

$$\propto \underbrace{e^{(X_1 - X_2)}}_{T(X)} \underbrace{e^{\left(\frac{\log \lambda_1 - \log \lambda_2}{2}\right)}}_{\theta} \underbrace{e^{(X_1 + X_2)}}_{U(x)} \underbrace{e^{\left(\frac{\log \lambda_1 + \log \lambda_2}{2}\right)}}_{\zeta} e^{\frac{1}{x_1! x_2!}} \quad (4.8)$$

Condition on  $X_1 + X_2 = u$ :

$$p_{\theta}(x \mid x_1 + x_2 = u) \propto e^{(x_1 - x_2)\theta} \frac{u!}{x_1! x_2!} \quad (4.9)$$

$$p_{\theta}(x \mid x_2 = u - x_1) = e^{(2x_1 - u)\theta} \binom{u}{x_1} \quad (4.10)$$

$$\propto e^{x_1 \log \frac{\lambda_1}{\lambda_2}} \binom{u}{x_1} \quad (4.11)$$

$$= \text{Binom}(u, \frac{\lambda_1}{\lambda_1 + \lambda_2}) \quad (4.12)$$

Reject when  $T(X) = X_1 - X_2$  large  $\iff$  Reject when  $X_1$  large (conditioned on  $U$ ).

For  $H_0 : \lambda_1 \leq \lambda_2$  reject if  $X_1$  large compared to  $\text{Binom}(u, 1/2)$ .

For a composite null, conditioning on a sufficient statistic can reduce composite null to a simple null.

## 4.2 UMPU Tests with nuisance parameters

**Theorem 4.6.** Consider testing

(a)  $H_0 : \theta = \theta_0$  vs  $\theta \neq \theta_0$

(b)  $H_0 : \theta \leq \theta_0$  vs  $\theta > \theta_0$

in model  $\mathcal{P}$  of the form section 4.1.

$\Omega$  open,  $\mathcal{P}$  full rank.

There is a UMPU test of the form  $\phi^*(x) = \psi(T(x), U(x))$  where

$$\psi(t, u) = \begin{cases} 1, & \text{if } t < c_1(u) \text{ or } t > c_2(u) \\ 0, & \text{if } t \in (c_1(u), c_2(u)) \\ \gamma_i, & \text{if } t = c_i(u) \end{cases} \quad (4.13)$$

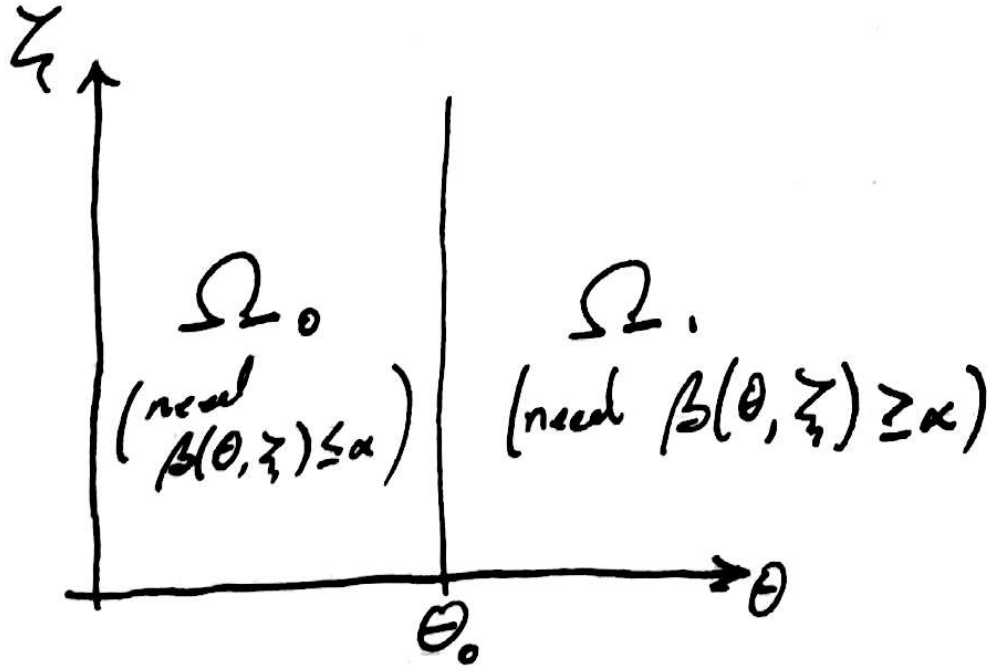
for (a), and

$$\psi(t, u) = \begin{cases} 1, & \text{if } t > c(u) \\ 0, & \text{if } t < c(u) \\ \gamma_i, & \text{if } t = c(u) \end{cases} \quad (4.14)$$

for (b), where  $c(\cdot)$ ,  $\gamma(\cdot)$  chosen so

$$\mathbb{E}_{\theta_0}[\phi(x) \mid U(x) = u] = \alpha \quad \forall u \text{ for (a), (b)} \quad (4.15)$$

$$\mathbb{E}_{\theta_0}[T(x)(\phi(x) - \alpha) \mid U(x) = u] = 0 \quad \forall u \text{ for (a)} \quad (4.16)$$



*Proof.* (1)  $\phi^*$  is unbiased, level  $\alpha$

(2) Any unbiased test has  $\beta(\theta_0, \zeta) = \alpha \quad \forall \zeta$  (by continuity of  $\beta$ )

(3) Power  $\equiv \alpha$  on boundary  $\implies \mathbb{E}[\phi(X) \mid U(X) = u] \stackrel{\text{a.s.}}{=} \alpha$  (by completeness of  $U(X)$ )

(4)  $\phi^*(X)$  optimal among all unbiased tests with  $E_{\theta_0}[\phi \mid U] \stackrel{\text{a.s.}}{=} \alpha$  (by reduction to 1-param problem)

□