

(b) Monotone Likelihood Ratio

- assume  $\{f_{\theta} : \theta \in \Theta\}$  is st.  $\Theta \subseteq \mathbb{R}^1$  and  $\mathbb{R}$  MSS  $T(x) \in \mathbb{R}$ , so suppose  $x \in \mathbb{R}^1$

-  $\{f_{\theta} : \theta \in \Theta\}$  has monotone likelihood ratio (MLR) form if whenever  $\theta_1 < \theta_2$ , the  $f_{\theta_2}(x)/f_{\theta_1}(x)$  is a monotone (increasing or decreasing) fn of  $x$  always in the same direction.

Theorem 3 If  $\{f_{\theta} : \theta \in \Theta\}$  has strictly increasing MLR form, then a UMP size  $\alpha$  test exists for  $H_0 : \theta \leq \theta_0$  vs  $H_a : \theta > \theta_0$  and is of the form

$$\phi(x) = \begin{cases} 1 & x \geq x_0 \\ \delta & = \\ 0 & < \end{cases}$$

where  $x_0, \delta$  are determined to give exact size  $\alpha$ .

Proof: Let  $\theta_0 < \theta_1$ . Then by the FL the MP size  $\alpha$  test of  $\theta_0$  vs  $\theta_1$  is of the form

$$\phi(x) = \begin{cases} 1 & f_{\theta_1}(x)/f_{\theta_0}(x) > k_0 \\ \delta & = k_0 \\ 0 & < k_0 \end{cases}$$

Since the model is of strict increasing MLR form  $\exists$  at most one  $x_0$  st.  $f_{\theta_1}(x_0)/f_{\theta_0}(x_0) = k_0$  and so  $\phi_1 = \phi$ .

Since it is independent  $\alpha$ ,  $\alpha$  is also MP size  $\alpha$  for  $\theta_0$  vs  $\theta_1$  for  $\theta_1 > \theta_0$  and thus UMP size  $\alpha$  for  $\theta = \theta_0$  vs  $\theta > \theta_0$ .

For any  $\theta_0' < \theta_0$  we have that  $\alpha$  is MP size  $\alpha$  for  $\theta_0'$  vs  $\theta_0$  and so

$E_{\theta_0'}(\alpha) \leq E_{\theta_0}(\alpha) = \alpha$  by the Corollary

to the FL so  $\alpha$  is size  $\alpha$  for  $H_0: \theta \leq \theta_0$  vs  $H_a: \theta > \theta_0$ . If  $\alpha'$  is size  $\alpha$  for  $H_0: \theta = \theta_0$  vs  $H_a: \theta > \theta_0$  so  $E_{\theta_0}(\alpha') \leq E_{\theta_0}(\alpha) \leq \alpha$  so  $\alpha'$  is UMP size  $\alpha$  for  $H_0: \theta \leq \theta_0$  vs  $H_a: \theta > \theta_0$ .

Corollary 4  $E_{\theta_0}(\alpha)$  is monotone increasing.

Proof: We have shown that for any  $\theta_1 < \theta_2$  then  $\alpha$  is MP size  $\alpha$  for  $\theta_1$  vs  $\theta_2$

and so by the Corollary to the FL

$$E_{\theta_1}(\alpha) \leq E_{\theta_2}(\alpha)$$

Corollary 5 For  $\theta \leq \theta_0$ ,  $E_{\theta_0}(\alpha)$  is minimal among all size  $\alpha$  tests for  $\theta \leq \theta_0$  vs  $\theta > \theta_0$ .

note

can weaken to just increasing or decreasing but then boundary becomes an interval.

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Proof: Reverse the FL to  $\min E_{\theta_0}(\alpha)$  subject to  $E_{\theta_0}(\alpha) \geq \alpha$  and note that this will just reverse the roles of 1 and 0 in definition of  $\alpha$ .

- note - if  $\{f_{\theta} : \theta \in \Theta\}$  is MLR strictly decreasing then the UMP size  $\alpha$  for  $\theta \leq \theta_0$  vs  $\theta > \theta_0$  is of the form

$$Q(x) = \begin{cases} 1 & x < x_0 \\ \gamma & = \\ 0 & > \end{cases}$$

- similar results for  $H_0: \theta \geq \theta_0$  vs  $H_a: \theta < \theta_0$ .

eg

1-parameter exponential family

-  $f_{\theta}(x) = \exp\{\theta t(x) - A(\theta)\}$

so  $\frac{f_{\theta_2, T}(t)}{f_{\theta_1, T}(t)} = \exp\{(t_2 - t_1)t - (A(t_2) - A(t_1))\}$

$\therefore$  model for MSS,  $t(x)$  is of MLR form (increasing)

- Poisson  $(\lambda)$ , Binomial  $(n, p)$ ,  $N(\mu, \sigma^2)$

## (c) Generalized Fundamental Lemma

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### Theorem 6 (Generalized Fundamental Lemma)

Let  $f_0, f_1, \dots, f_m$  be  $\mu$ -integrable on  $\mathcal{X}$   
For fixed positive  $k_1, \dots, k_m$  and  $\delta \in [0, 1]$  define

$$a_0(x) = \begin{cases} 1 & \text{if } f_0(x) > \sum_{i=1}^m k_i f_i(x) \\ \delta & \text{if } f_0(x) = \sum_{i=1}^m k_i f_i(x) \\ 0 & \text{if } f_0(x) < \sum_{i=1}^m k_i f_i(x) \end{cases}$$

Then  $a_0$  maximizes  $\int_{\mathcal{X}} a(x) f_0(x) \mu(dx)$   
among all test fns satisfying

$$\int_{\mathcal{X}} a(x) f_i(x) \mu(dx) \leq \int_{\mathcal{X}} a_0(x) f_i(x) \mu(dx)$$

for  $i=1, \dots, m$ .

- note Neyman-Pearson  $m=1$ ,  $f_0 = f_0$ ,  $f_1 = f_0$

Corollary 7 If  $k_1, \dots, k_m, \delta$  are chosen s.t.

$\int_{\mathcal{X}} a_0(x) f_i(x) \mu(dx) = \alpha$  for  $i=1, \dots, m$  and  $f_0, \dots, f_m$

are pdfs

then  $\int_{\mathcal{X}} a_0(x) f_0(x) \mu(dx) \geq \alpha$ .

- note the  $f_i$  need not be pdf's

Proof of Theorem 6

Let  $\alpha = \{\alpha_i\}_{i=1}^m \in [0, 1]^m$  satisfy  $\int_{\mathbb{X}} \alpha_i(x) f_i(x) \mu(dx)$

$\leq \int_{\mathbb{X}} \alpha_{i0}(x) f_i(x) \mu(dx)$  for  $i=1, \dots, m$  and

suppose  $\int_{\mathbb{X}} \alpha(x) f_0(x) \mu(dx) > \int_{\mathbb{X}} \alpha_0(x) f_0(x) \mu(dx)$ .

Then  $0 \leq \int_{\mathbb{X}} (\alpha(x) - \alpha_0(x)) f_0(x) \mu(dx)$

$$= \int_{\{\alpha(x) - \alpha_0(x) \neq 0\}} (\alpha(x) - \alpha_0(x)) f_0(x) \mu(dx)$$

$$= \int_{\{f_0(x) \geq \sum_{k=1}^m k_i f_i(x), \alpha(x) - \alpha_0(x) < 0\}}$$

$$+ \int_{\{f_0(x) \leq \sum_{k=1}^m k_i f_i(x), \alpha(x) - \alpha_0(x) > 0\}}$$

$$\leq \int_{\{ \}} (\alpha(x) - \alpha_0(x)) \sum_{k=1}^m k_i f_i(x) \mu(dx)$$

$$+ \int_{\{ \}} (\alpha(x) - \alpha_0(x)) \sum_{k=1}^m k_i f_i(x) \mu(dx)$$

$$= \sum_{k=1}^m k_i \int_{\mathbb{X}} (\alpha(x) - \alpha_0(x)) f_i(x) \mu(dx)$$

$$= \sum_{k=1}^m k_i \int_{\mathbb{X}} \alpha_i(x) f_i(x) \mu(dx) - \sum_{k=1}^m k_i \int_{\mathbb{X}} \alpha_{i0}(x) f_i(x) \mu(dx)$$

$\leq 0$  since  $\alpha$  satisfies the inequalities and so

$$\int_{\mathbb{X}} \alpha(x) f_0(x) \mu(dx) = \int_{\mathbb{X}} \alpha_0(x) f_0(x) \mu(dx).$$

Proof of Corollary 2 The fn  $\varphi_\alpha(x) \equiv \alpha$  satisfies

$$\int_{-\infty}^{\infty} \varphi_\alpha(x) f(x) \mu(dx) = \alpha \int_{-\infty}^{\infty} f(x) \mu(dx)$$

result follows.

eg locally most powerful tests

- suppose we want to test  $H_0: \theta \leq \theta_0$  vs  $H_a: \theta > \theta_0$   
and we don't have MLR so it is unlikely  
that a UMP test exists

- relax to finding a test good near  $\theta_0$

$$- \frac{\partial}{\partial \theta} E_{\theta}(\alpha) \stackrel{\text{under}}{=} \int_{\mathcal{X}} \alpha(x) \frac{\partial f_{\theta}(x)}{\partial \theta} \mu(dx)$$
  
$$= E_{\theta_0}(\alpha(x) S(\theta|x))$$

→ so we want a st.  $E_{\theta_0}(\alpha) = \alpha$  and

$E_{\theta_0}(\alpha(x) S(\theta|x))$  is maximized

(maximizing the slope of the power fn at  $\theta_0$ )

called a locally most powerful size  $\alpha$  test  
(when it exists)

- put  $P_0 = S(\theta_0|\cdot) f_{\theta_0}$ ,  $P_1 = P_{\theta_0}$  is  $\in FL$   
and look for size  $\alpha$  test of the form

$$\alpha_0(x) = \begin{cases} 1 & S(\theta_0|x) > k_0 \\ \gamma & = \\ 0 & < k_0 \end{cases}$$

### eg Location Cauchy

-  $x = (x_1, \dots, x_n)$  iid  $\frac{1}{\pi(1+x^2-\theta)^2}$   $\theta \in \mathbb{R}$

- test  $H_0: \theta = \theta_0$  vs  $H_a: \theta = \theta_1$ , where  $\theta_1 > \theta_0$

- FL says MP size  $\alpha$  is of the form

$$g(x) = \frac{\sum_{i=1}^n (1+(x_i-\theta_0)^2)}{\sum_{i=1}^n (1+(x_i-\theta_1)^2)} \geq k_0$$

for some  $k_0$  (simulate under  $\theta_0$  to find  $k_0$ )

- but dependent on  $\theta_1$ , so not UMP

-  $l(\theta|x) = -n \log \pi - \sum_{i=1}^n \log(1+(x_i-\theta)^2)$

$$S(\theta|x) = 2 \sum_{i=1}^n \frac{x_i - \theta}{1+(x_i-\theta)^2}$$

- find  $k_0$  st  $\alpha = P_{\theta_0} \left( \sum_{i=1}^n \frac{x_i - \theta_0}{1+(x_i-\theta_0)^2} \geq k_0 \right)$

$$= P_0 \left( \sum_{i=1}^n \frac{x_i}{1+x_i^2} \geq k_0 \right)$$

- simulation when  $n=20$ ,  $k_0 = 2.55$