

## Module 5

### Hypothesis Testing

Let  $X$  be a random observation having pdf/pmf  $b \in \mathcal{P}$ , where  $\mathcal{P}$  is a given family of pdfs/pmfs.

Let  $\mathcal{P}_0$  and  $\mathcal{P}_1$  be subfamilies of  $\mathcal{P}$  such that  $\mathcal{P}_0 \cap \mathcal{P}_1 = \emptyset$  and  $\mathcal{P}_0 \cup \mathcal{P}_1 = \mathcal{P}$ .

Problem: Based on observed sample (say  $\underline{x} = \underline{z}$ ) to decide which of the following <sup>two</sup> statements <sup>(hypotheses)</sup> is true?

$$H_0: b \in \mathcal{P}_0$$

$$H_1: b \in \mathcal{P}_1$$

$H_0$  is called the null hypothesis and  $H_1$  is called the alternative hypothesis

$\mathcal{X}$ : Sample space of  $X$

Two possible actions after observing  $\underline{x} = \underline{z}$ :

$a_0$ : do not reject  $H_0$

$a_1$ : reject  $H_0$

Randomized Test Function: After observing  $\underline{x} = \underline{z}$ , another random experiment is conducted to decide in favor of  $a_0$  or  $a_1$ . Then a test function is a function

$$\phi: \mathcal{X} \rightarrow [0, 1]$$

Such that

$\phi(\underline{z}) =$  Conditional prob. of rejecting  $H_0$  <sup>(i.e. taking action  $a_1$ )</sup> given that  $\underline{x} = \underline{z}$   
 $1 - \phi(\underline{z}) =$  Conditional prob. of not rejecting  $H_0$  <sup>(i.e. taking action  $a_0$ )</sup> given that  $\underline{x} = \underline{z}$

Remark If  $\forall x \in X, \phi(x) \in \{0, 1\}$ , then after observing the sample  $\underline{x} = x$  no further randomization is necessary to choose from actions  $a_0$  or  $a_1$ . Such test functions are called non-randomized test functions. Such tests are of the form

$$\phi(x) = \begin{cases} 1 & \text{if } x \in C \\ 0 & \text{otherwise;} \end{cases}$$

where

$C = \{x \in X : \phi(x) = 1\}$  =  
 $\wedge$  rejection region or critical region of  $\phi$  for testing  $H_0$

Goal: To find a reasonable test function  $\phi$ .

Any test function  $\phi$  may lead to two possible errors:

Type I error: rejecting  $H_0$  when  $H_0$  is true

Type II error: not rejecting  $H_0$  when  $H_0$  is wrong.

For  $b \in \mathcal{P}$ , define

$$P_\phi(b) = E_b(\phi(x)) \rightarrow \text{Expected probability of rejecting } H_0 \text{ when } b \in \mathcal{P} \text{ is the true distribution}$$

For  $b \in \mathcal{P}$ ,  $P_\phi(b)$  is called the power function of test  $\phi$ .

For  $b \in \mathcal{P}_0$ ,

$P_\phi(b)$ : Expected prob. of type-I error at  $b \in \mathcal{P}_0$

For  $b \in \mathcal{P}_1$ ,

$$1 - P_\phi(b) = E_b[1 - \phi(x)] \rightarrow \text{Expected prob. of type-II error at } b \in \mathcal{P}_1$$

For  $b \in \theta_1$ ,  $\beta_\phi(b)$  is called the power of the test at  $b \in \theta_1$

An ideal thing would be to find a test (function)  $\phi_0$  which uniformly minimizes  $\beta_\phi(b)$ ,  $\forall b \in \theta_0$  and  $1 - \beta_\phi(b)$ ,  $\forall b \in \theta_1$ .

Unfortunately  $\beta_\phi(b)$ ,  $\forall b \in \theta_0$ , and  $1 - \beta_\phi(b)$ ,  $\forall b \in \theta_1$ , can not be minimized simultaneously.

Example Consider test functions  $\phi_0$  and  $\phi_1$  such that

$$\phi_0(z) = 0, \quad \forall z \in \mathcal{X} \quad \text{and} \quad \phi_1(z) = 1, \quad \forall z \in \mathcal{X}.$$

Note that  $\phi_0$  and  $\phi_1$  are no-data test functions where  $\phi_0$  never rejects  $H_0$  and  $\phi_1$  always rejects  $H_0$ . Here, for  $\phi_0$

$$\text{prob. of type-I error} = \beta_{\phi_0}(b) = 0, \quad \forall b \in \theta_0$$

$$\text{prob. of type-II error} = 1 - \beta_{\phi_0}(b) = 1, \quad \forall b \in \theta_1$$

Whereas for the test  $\phi_1$

$$\text{prob. of type-I error} = \beta_{\phi_1}(b) = 1, \quad \forall b \in \theta_0$$

$$\text{prob. of type-II error} = 1 - \beta_{\phi_1}(b) = 0, \quad \forall b \in \theta_1.$$

Clearly the test  $\phi_0$  is the best test as far as minimization of type-I error is concerned and the worst possible test for minimizing type-II error. Similarly the test  $\phi_1$  is the best test for minimizing type-II error and the worst test for minimizing type-I error.

Example Let  $X \sim \text{Bin}(n, \theta)$  where  $\theta \in (0, 1)$  is unknown and  $n > 1$  is a known integer. Consider testing

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

$$\text{against } H_1: \theta > \theta_0,$$

where  $\theta_0 \in (0, 1)$  is a fixed value.

Since larger values of  $\theta$  (prob. of success) are captured in the data through larger values of  $\frac{X}{n}$  or  $\bar{X}$  (proportion of success) or

number of successes), a class of reasonable test functions is

$$\mathcal{D}_0 = \{ \phi_j : j = 0, 1, 2, \dots, n-1 \}$$

where

$$\phi_j(x) = \begin{cases} 1, & \text{if } x \in \{j+1, \dots, n\} \\ 0, & \text{if } x \in \{0, \dots, j\} \end{cases}, \quad j = 0, 1, \dots, n-1.$$

Consider minimizing the risk function (w.r.t.  $\phi$ )

$$R_\phi(\theta) = E_\theta(\beta_\phi(\theta)) \pm E_{\theta_0}(\beta_\phi(\theta)) + E_\theta((1-\beta_\phi(\theta)) \mathbb{1}_{\{\theta \geq \theta_0\}})$$

For  $0 \leq k < j \leq n-1$

$$R_{\phi_j}(\theta) = \begin{cases} E_\theta(\beta_{\phi_j}(\theta)) = P_\theta(X \geq j+1), & \text{if } 0 < \theta \leq \theta_0 \\ E_\theta(1 - \beta_{\phi_j}(\theta)) = P_\theta(X \leq j), & \text{if } \theta_0 < \theta < 1 \end{cases}$$

For  $0 \leq k < j \leq n-1$

$$R_{\phi_j}(\theta) - R_{\phi_k}(\theta) = \begin{cases} -P_\theta(k < X \leq j) < 0, & \text{if } 0 < \theta \leq \theta_0 \\ P_\theta(k < X \leq j) > 0, & \text{if } \theta_0 < \theta < 1 \end{cases}$$

hence neither  $\phi_j$  nor  $\phi_k$  is better than the other.

Thus controlling the two errors simultaneously does not seem feasible.

### A Common Approach

Assign a small upper bound  $\alpha \in (0, 1)$  to one of the error probabilities (say prob. of type-I error  $P_\phi(b), b \in \mathcal{B}_0$ ) and then attempt to minimize the other error prob. (say prob. of type-II error  $1 - \beta_\phi(b), b \in \mathcal{B}_1$ ) <sup>(maximize)</sup> <sup>(power)</sup> <sup>(other error prob.)</sup> <sup>(say  $P_\phi(b), b \in \mathcal{B}_1$ )</sup> <sup>For a fixed</sup>

$\alpha \in (0, 1)$  let

$$\mathcal{Y} = \{ \phi : \phi: \mathcal{X} \rightarrow [0, 1], P_\phi(b) \leq \alpha, \forall b \in \mathcal{B}_0 \}$$

The goal is to find a  $\phi^* \in \mathcal{T}$  such that for any other  $\phi \in \mathcal{T}$

$$P_{\phi^*}(b) \geq P_{\phi}(b) \quad \forall b \in \rho_1, \dots \quad (I)$$

or equivalently  $1 - P_{\phi^*}(b) \leq 1 - P_{\phi}(b) \quad \forall b \in \rho_1$

The bound  $\alpha$  is called the level of significance. The size of a test  $\phi$  is the quantity

$$\sup_{b \in \rho_0} P_{\phi}(b)$$

Note: (a) The level of significance  $\alpha$  should lie in the interval  $[0, 1]$ . If  $\alpha = 0$ , then

$$P_{\phi}(b) \leq 0 \quad \forall b \in \rho_0$$

$$\Rightarrow E_b(\phi(X)) = 0 \quad \forall b \in \rho_0$$

$$\Rightarrow P_b(\phi(X) = 0) = 1 \quad \forall b \in \rho_0$$

Such a test is generally undetectable.

(b) We frame our null and alternative hypothesis in such a way that the error of wrongly rejecting the null hypothesis  $H_0$  is considered to be more serious than the error of wrongly not rejecting  $H_0$ . By doing so we guarantee that the probability of the error which is more serious is bounded above a derived level  $\alpha$ . Note that the above formulation does not guarantee upper bound on the probability of Type II error, which may be large. Thus one should be very careful in the use of the test which is optimal under the above formulation, as it does not guarantee upper bound on Type-II error probability. Thus if such an <sup>optimal</sup> test rejects  $H_0$  one may actually conclude the rejection of  $H_0$ , however if it does not reject  $H_0$  one would not like to accept  $H_0$ . At the best one would conclude that there is not enough evidence to reject  $H_0$ . In short, under the above formulation, if the optimal test does not reject  $H_0$  then one must make sure that the probability of Type II error

(or the power) ... are not large (small) before actually accepting  $H_0$ .

Example Let  $X_1, \dots, X_n$  be i.i.d.  $N(\theta, 1)$  where  $\theta \in \mathbb{R}$  is unknown. Consider testing

$$H_0: \theta \leq 0$$

$$\text{against } H_1: \theta > 0$$

Note that  $\bar{X}$  is a Complete and Sufficient (and hence minimal Sufficient) Statistic for  $\theta$ . It is reasonable to consider the class

$$\Theta_\alpha = \{ \phi_\alpha: \alpha \in (0, 1) \}$$

of tests, where

$$\phi_\alpha(x) = \begin{cases} 1 & \text{if } \bar{x} > c_\alpha \\ 0 & \text{if } \bar{x} \leq c_\alpha \end{cases}$$

where  $c_\alpha$  is chosen so that the test has level of significance  $\alpha$ . We want a test with  $\alpha$ -level of significance, i.e.

$$P_\theta(\phi) = E_\theta[\phi_c(\bar{X})]$$

$$= P_\theta(\bar{X} > c)$$

$$\leq \alpha \quad \forall \theta \leq 0$$

$$\Rightarrow \Phi(\sqrt{n}(c-\theta)) \geq 1-\alpha \quad \forall \theta \leq 0$$

$$\Rightarrow \Phi(\sqrt{n}c) \geq 1-\alpha \Leftrightarrow c_\alpha \geq \frac{1}{\sqrt{n}} \Phi^{-1}(1-\alpha)$$

The best choice is

$$c^* \equiv c_\alpha^* = \frac{1}{\sqrt{n}} \Phi^{-1}(1-\alpha)$$

For  $n=25$  and  $\alpha=0.05$

$$c_\alpha^* = c_{0.05}^* = \frac{1}{5} \Phi^{-1}(0.95) = \frac{1.65}{5} = 0.33 = c^*, \text{ say}$$

Thus a UMP (0.05) test is

$$\phi_{\alpha}^*(z) = \hat{\phi}_{c^*}^*(z) = \begin{cases} 1, & \text{if } \bar{x} > 0.33 \\ 0, & \text{if } \bar{x} \leq 0.33 \end{cases}$$

The power of the test is

$$\begin{aligned} \beta_{\phi_{c^*}^*}(\theta) &= P_{\theta}(\bar{x} > 0.33) \\ &= 1 - \Phi(\sqrt{n}(0.33 - \theta)), \quad \theta > 0 \\ &= 1 - \Phi(5(0.33 - \theta)), \quad \theta > 0 \\ &\in [0.05, 1) \end{aligned}$$

Near  $\theta = 0$  power is very low but for  $\theta$  far away from 0 power is large. For example the power at  $\theta = 0.4$

$$\beta_{\phi_{c^*}^*}(0.4) = 1 - \Phi(-0.35) = \Phi(0.35) = 0.6368$$

p-value of a test  $\phi$  It is the smallest possible level of significance  $\hat{\alpha} \equiv \hat{\alpha}(z)$  at which  $H_0$  would be rejected for computed  $\phi_{\alpha}(z)$  (based on the observed sample  $\underline{x} = z$ ).

Thus the p-value of a test  $\phi$  is

$$\hat{\alpha}(z) \equiv \inf\{\alpha \in (0, 1) : \phi_{\alpha}(z) = 1\},$$

where  $z$  is the observed sample

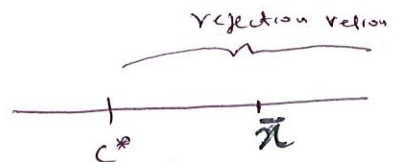
Example (Continued) In the last example the p-value of the

test is

$$\phi_{\alpha}^*(z) = \begin{cases} 1, & \text{if } \bar{x} > c_{\alpha} \\ 0, & \text{otherwise} \end{cases} \quad (c_{\alpha} \geq \frac{1}{\sqrt{n}} \Phi^{-1}(1-\alpha))$$

is

$$\hat{\alpha}(z) = \inf\{\alpha \in (0, 1) : \phi_{\alpha}(z) = 1\}$$



$$\alpha \geq \sup_{\text{beta}} E_{\beta}(\phi_{\alpha}(z))$$

$$\Rightarrow \hat{\alpha}(z) = \sup_{H_0} P_{\beta}(\bar{x} > \bar{x}) = \sup_{\theta \leq 0} [1 - \Phi(\sqrt{n}(\bar{x} - \theta))] = 1 - \Phi(\sqrt{n}\bar{x})$$

With the additional information provided by p-values, using p-values is typically more appropriate than using fixed level tests.

In the example discussed above the level of the test  $\hat{\phi}_{\text{crit}} = \text{size of the test}$ . This may not be true always, especially in situations where the distributions of the statistic involved in the test function  $\phi$  is discrete.

Example  $X \sim \text{Bin}(2, \theta)$ ,  $\theta \in \Theta = \{\frac{1}{2}, \frac{1}{4}\}$ .

Consider testing

$$H_0: \theta = \frac{1}{2}$$

$$\text{against } H_1: \theta = \frac{1}{4}$$

A reasonable class of test procedures is  $\mathcal{D}_0 = \{\phi_j: j=0, 1, 2\}$

$$\phi_j(x) = \begin{cases} 1 & \text{if } x \geq j \\ 0 & \text{otherwise} \end{cases}$$

For test  $\phi_0$

$$P_{\phi_0}(\geq 1) = P(X \geq 0) = 1$$

For test  $\phi_1$

$$P_{\phi_1}(x) = P(X \geq 1) = 1 - (1-\theta)^2$$

$$\sup_{H_0} P_{\phi_1}(0) = \frac{3}{4}$$

For test  $\phi_2$

$$P_{\phi_2}(\geq 1) = P(X \geq 2) = \theta^2$$

$$\sup_{H_0} P_{\phi_2}(\geq 1) = \frac{1}{4}$$

Thus

level = size  
is possible only for levels  $\alpha \in \{1, \frac{1}{4}, \frac{3}{4}\}$ .



Example

$X \sim \text{Bin}(2, \theta)$  where  $\theta \in \Theta = \{0, 1\}$  is unknown and  $n > 1$  is a known integer. Consider testing

$H_0: \theta \leq \frac{1}{2}$

against  $H_1: \theta > \frac{1}{2}$

Consider following class of randomized tests

$$\phi_{\delta, \nu}(x) = \begin{cases} 1, & \text{if } x > \delta \\ 0, & \text{if } x = \delta \\ 0, & \text{if } x < \delta \end{cases}$$

$\delta = 0, 1, 2$

Suppose we want

Size = level  $\alpha$

Then

$$P_{\phi_{\delta, \nu}}(1) = P_0(X > \delta) + \nu P_0(X = \delta)$$

It can be shown that  $P_{\phi_{\delta, \nu}}(1)$  is an increasing function of  $\delta$ . Thus

$$\text{Sup }_{H_0} P_{\phi_{\delta, \nu}}(1) = P_{\phi_{\delta, \nu}}(\frac{1}{2}) = P_{\theta = \frac{1}{2}}(X > \delta) + \nu P_{\theta = \frac{1}{2}}(X = \delta)$$

Suppose level  $\alpha = 0.90$ . We have  $P_{\theta = \frac{1}{2}}(X > -1) = 1$

$$P_{\theta = \frac{1}{2}}(X > 0) = 1 - (1 - \frac{1}{2})^2 = \frac{3}{4}$$

$$P_{\theta = \frac{1}{2}}(X > 1) = 1 - (1 - \frac{1}{2})^2 - 2 \cdot \frac{1}{2} (1 - \frac{1}{2}) = \frac{1}{4}$$

$$P_{\theta = \frac{1}{2}}(X > 2) = 0$$

Thus we take  $\delta = 0$ , and

$$\frac{3}{4} + \nu P_{\theta = \frac{1}{2}}(X = 0) = 0.95$$

$$\nu (1 - \frac{1}{2})^2 = 0.20$$

$$\Rightarrow \nu = 0.80$$

Thus a test for which  $\text{Size} = \alpha$

$$\phi^*(x) = \begin{cases} 1 \\ 0.8 \end{cases} \quad \begin{cases} \text{if } x = 1, 2 \\ \text{if } x = 0 \end{cases}$$

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## Uniformly Most Powerful Tests

Consider testing

$$H_0: b \in P_0 \\ \text{vs } H_1: b \in P_1$$

where  $P_0 \cap P_1 = \emptyset$  and  $P_0 \cup P_1 = P$ .

Let  $\alpha \in (0, 1)$  be given level of significance.

Goal: To find a test funct  $\phi^*$  for which

$$\sup_{b \in P_0} \beta_{\phi^*}(b) \leq \alpha \quad \dots \quad (1) \quad (\text{level of significance} = \alpha)$$

and for any other test  $\phi$  satisfying (1) (i.e.

$$\sup_{b \in P_0} \beta_{\phi}(b) \leq \alpha)$$

$$\beta_{\phi^*}(b) \geq \beta_{\phi}(b), \quad \forall b \in P_1 \quad (\text{maximum power among tests having level of significance } \alpha)$$

Such a test  $\phi^*$  is called uniformly most powerful test at level of significance  $\alpha$  (UMP( $\alpha$ ) test).

Remark: (1) Suppose that the statistic  $T$  is sufficient for  $b \in P$ . Then, given any test function  $\phi$ , consider the test

$$\phi^*(T) = E_b(\phi(X) | T).$$

Clearly  $\phi^*$  depends on  $T$  alone and by virtue of sufficiency of  $T$  does not depend on  $b$ . Thus  $\phi^*$  is a valid test function depending on sufficient statistic  $T$  alone.

Also

$$\begin{aligned} \beta_{\phi^*}(b) &= E_b(\phi^*(T)) = E_b(E_b(\phi(X) | T)) \\ &= E_b(\phi(X)) = \beta_{\phi}(b), \end{aligned}$$

i.e.  $\phi^*$  and  $\phi$  have the same power function.

Therefore, to find an UMP( $\alpha$ ) test one may consider

tests that are functions of minimal sufficient statistic  $T$ .

### Simple and Composite Hypotheses:

A hypothesis  $H_0$  (or  $H_1$ ) is said to be simple iff  $\mathcal{P}_0$  (or  $\mathcal{P}_1$ ) contains exactly one pdf/pmf. A hypothesis which is not simple is called a composite hypothesis.

#### Example

Let

$$\underline{X} = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim N_2 \left( \begin{pmatrix} \mu \\ \mu \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right),$$

where  $\underline{\theta} = (\mu, \rho) \in \Theta = \mathbb{R} \times (-1, 1)$ . Then

$$H_0: \mu = 0$$

is a simple hypothesis iff  $\rho$  is known.

### The Neyman Pearson Lemma

Consider testing simple null hypothesis  $H_0: b = b_0$  against simple alternative hypothesis  $H_1: b = b_1$ ; here  $b_0$  and  $b_1$  are known pdfs/pmf;  $\mathcal{P} = \{b_0, b_1\}$ ,  $\mathcal{P}_0 = \{b_0\}$  and  $\mathcal{P}_1 = \{b_1\}$ .

Theorem (The Neyman-Pearson Lemma) Consider testing the simple null hypothesis

$$H_0: b = b_0$$

against simple alternative hypothesis

$$H_1: b = b_1$$

(i) (Existence of UNP( $\alpha$ ) test). For any  $\alpha \in [0, 1]$ , there exists a UNP( $\alpha$ ) test given by

$$\phi^*(x) = \begin{cases} 1, & \text{if } b_1(x) > c b_0(x) \\ \alpha, & \text{if } b_1(x) = c b_0(x) \\ 0, & \text{if } b_1(x) < c b_0(x) \end{cases} \quad (A)$$

where  $\alpha \in [0, 1]$  and  $c \geq 0$  are constants satisfying

$$E_{b_0}(\phi^*(x)) = \alpha \quad (c = 0 \text{ is allowed})$$

(ii) (Uniqueness). *Let  $\phi^*$  be the UNP test defined in (i) above.* If  $\phi^{**}$  is a UNP( $\alpha$ ) test then

$$\phi^{**}(x) = \begin{cases} 1, & \text{if } b_1(x) > c b_0(x) \\ 0, & \text{if } b_1(x) < c b_0(x), \end{cases} \quad \text{a.s. } \beta$$

i.e. UNP( $\alpha$ ) tests can essentially differ only on the set  $\{x: b_1(x) = c b_0(x)\}$ ,  $c \geq 0$ .

Proof. (i) We provide the proof for the case  $\alpha \in (0, 1)$  as the proof for  $\alpha \in \{0, 1\}$  follows trivially.

Claim I: There exist  $\alpha \in [0, 1]$  and  $c \geq 0$  such that

$$E_{b_0}(\phi^*(x)) = \alpha.$$

Let

$$\beta(t) = P_{b_0}(b_1(x) > t b_0(x)) = 1 - P_{b_0}(b_1(x) \leq t b_0(x))$$

Then  $\beta(t) \downarrow$  in  $t \in [0, \infty)$ ,  $\beta(t)$  is right continuous,  $\beta(+\infty) = \lim_{t \rightarrow \infty} \beta(t) = 0$  and  $\beta(0) = \lim_{t \rightarrow 0} \beta(t) = 1$ .

Thus there exists a  $c \in [0, \infty)$  such that

$$\beta(c) \leq \alpha \leq \beta(c-).$$

Set

$$\alpha = \begin{cases} \frac{\alpha - \beta(c)}{\beta(c-) - \beta(c)}, & \text{if } \beta(c-) \neq \beta(c) \\ 0, & \text{if } \beta(c-) = \beta(c) \end{cases}$$

Then

$$P(c) - P(c) = P_{b_0} (b_1(x) = c b_0(x))$$

and

$$E_{b_0}(\phi^*(x)) = P_{b_0}(b_1(x) > c b_0(x)) + 0 P_{b_0}(b_1(x) = c b_0(x)) \\ = \alpha.$$

Claim II:  $\phi^*$  is (A) U UNP( $\alpha$ ) test.

Let  $\phi(\cdot)$  be any other test at level of significance  $\alpha$ ,  
i.e. let

$$E_{b_0}(\phi(x)) \leq \alpha.$$

Consider

$$\Delta(x) = [\phi^*(x) - \phi(x)] [b_1(x) - c b_0(x)]$$

Then  $\Delta(x) \geq 0$ , a.s.  $\beta$  and thus

$$\int [(\phi^*(x) - \phi(x)) (b_1(x) - c b_0(x))] dx \geq 0$$

$$\Rightarrow E_{b_1}(\phi^*(x) - \phi(x)) \geq c E_{b_0}(\phi^*(x) - \phi(x))$$

$$\Rightarrow P_{\phi^*}(b_1) - P_{\phi}(b_1) \geq c [ \underbrace{P_{\phi^*}(b_0)}_{=\alpha} - \underbrace{P_{\phi}(b_0)}_{\leq \alpha} ]$$

$$\geq 0.$$

$$\Rightarrow P_{\phi^*}(b_1) \geq P_{\phi}(b_1)$$

$$\Rightarrow \phi^* \text{ is UNP}(\alpha).$$

Then prove (i)

(ii) Let  $\phi^{**}$  be a UNP( $\alpha$ ) test, and let  $\phi^*$  be as in (i). Consider

$$\Delta(x) = [\phi^*(x) - \phi^{**}(x)] [b_1(x) - c b_0(x)]$$

Then

$$\Delta(x) > 0 \quad \text{on } A = \{x : \phi^*(x) - \phi^{**}(x) \neq 0, b_1(x) \neq c b_0(x)\}$$
$$\Delta(x) = 0 \quad \text{on } A^c$$

Also

$$\int [\phi^*(x) - \phi^{**}(x)] [b_1(x) - c b_0(x)] dx$$

$$= -c \int [\phi^*(x) - \phi^{**}(x)] b_0(x) dx$$

(both  $\phi^*$  and  $\phi^{**}$  have the same power)

$$\leq 0$$

$$\Rightarrow \int_A \underbrace{[\phi^*(x) - \phi^{**}(x)] [b_1(x) - c b_0(x)]}_{\geq 0 \text{ on } A} dx \leq 0$$

$\Rightarrow$  Set  $A$  is negligible

$\Rightarrow$  For almost all values of  $\lambda$ ,  $\phi^*(x) = \phi^{**}(x)$  or  $b_1(x) = c b_0(x)$ .

Remark: (i) If the set  $B = \{\lambda: b_1(x) = c b_0(x)\}$  is negligible then we have a unique UMP( $\alpha$ ) test; otherwise UMP( $\alpha$ ) tests are randomized on the set  $B$ .

(ii) There always exists a UMP( $\alpha$ ) test for which  $\lambda_{size} = \alpha$ . (the level of significance).

Example Let  $b_0 \equiv U(0,1)$  and  $b_1 \equiv U(0,2)$ . For testing

$$H_0: b \equiv b_0$$

$$\text{vs } H_1: b \equiv b_1$$

Show that the test

$$Q(x) = \begin{cases} \alpha, & \text{if } 0 < x < 1 \\ 1, & \text{if } 1 < x < 2 \end{cases}$$

is UMP( $\alpha$ ).

Example. Let  $b_0 \equiv U(0,1)$  and  $b_1 \equiv U(0,2)$ . For testing

$$H_0: b \equiv b_0$$

$$\text{vs } H_1: b \equiv b_1$$

Show that any test of the following form is UMP( $\alpha$ )

$$\phi(x) = \begin{cases} 0, & \text{if } 0 < x < 1 \\ 1, & \text{if } 1 < x < 2 \end{cases}$$

where  $\forall t \in [0, \alpha]$ . Show that power of each of these tests is 1. Among these UMP( $\alpha$ ) test find the test with smallest Type-I error.

Example

$X =$  Sample of size one from  $\theta = \{\theta_0, \theta_1\}$ ,

where  $f_{\theta_0}(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad -\infty < x < \infty \quad (N(0, 1))$

$f_{\theta_1}(x) = \frac{1}{4} e^{-\frac{|x|}{2}}, \quad -\infty < x < \infty \quad (DE(0, 2))$

Here

$P_{\theta} (b_1(x) < c < b_0(x)) = 0, \quad \forall b \in \theta.$

Thus the unique UMP( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1, & \text{if } b_1(x) > c < b_0(x) \\ 0, & \text{if } b_1(x) < c < b_0(x) \end{cases}$$

Note that

$\phi^*(x) = 1 \Leftrightarrow \frac{b_1(x)}{b_0(x)} > c$

$\Leftrightarrow |x|^2 - |x| > d, \quad \text{for some } d \in (-\infty, \infty)$

$\Leftrightarrow |x| < \frac{1 - \sqrt{1+4d}}{2} \quad \text{or} \quad |x| > \frac{1 + \sqrt{1+4d}}{2} \quad (1+4d > 0)$

$\Leftrightarrow |x| < 1-t \quad \text{or} \quad |x| > t, \quad \text{for some } t > \frac{1}{2}.$

Case I.  $\frac{1}{2} < t \leq 1$

$E_{\theta_0}(\phi^*(x)) = P_{\theta_0}(|x| < 1-t) + P_{\theta_0}(|x| > t) \downarrow t$

$\in [P_{\theta_0}(|x| > 1), P_{\theta_0}(|x| < \frac{1}{2}) + P_{\theta_0}(|x| > \frac{1}{2})]$

$= [0.3379, 1)$

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Thus choice  $t \in (\frac{1}{2}, 1)$  can be used only when  $\alpha \in [0.3374, 1)$

Case I  $t \geq \frac{1}{2}$  (i.e.  $\alpha \in (0, 0.3374)$ )

$$\phi^*(x) = \begin{cases} 1, & |x| < t \text{ or } |x| > 1 \\ 0, & \text{o.w.} \end{cases}$$

$$\phi^*(x) = \begin{cases} 1, & |x| > t \\ 0, & \text{o.w.} \end{cases}$$

$$P_{\theta_0}(|X| > t) = \alpha$$

$$2(1 - \Phi(t)) = \alpha$$

$$t = \Phi^{-1}(1 - \alpha/2)$$

Example

Let  $x_1, \dots, x_n$  be iid  $\text{Bin}(1, \theta)$ ,  $\theta \in \Theta = (0, 1)$

Consider testing

$$H_0: \theta = \theta_0$$

$$H_1: \theta = \theta_1$$

where  $0 < \theta_0 < \theta_1 < 1$  are fixed constants.

A UMP( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1, & \lambda(x) > c \\ 0, & \lambda(x) < c \\ \text{arbitrary}, & \lambda(x) = c \end{cases}$$

where  $Y = \sum_{i=1}^n X_i \sim \text{Bin}(n, \theta)$

and

$$\lambda(Y) = \frac{b_{\theta_1}(Y)}{b_{\theta_0}(Y)} = \frac{\prod_{i=1}^n \theta_1^{x_i} (1-\theta_1)^{n-x_i}}{\prod_{i=1}^n \theta_0^{x_i} (1-\theta_0)^{n-x_i}}$$

$$= \left( \frac{\theta_1(1-\theta_0)}{\theta_0(1-\theta_1)} \right)^Y \left( \frac{1-\theta_1}{1-\theta_0} \right)^n$$

Clearly  $\lambda(Y) \uparrow$  in  $Y$ . Thus, for some  $m \geq 0$

$$\phi^*(x) = \begin{cases} 1, & Y > m \\ 0, & Y < m \\ \text{arbitrary}, & Y = m \end{cases}$$

$$\begin{cases} Y > m \\ Y = m \\ Y < m \end{cases}$$

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where  $m$  and  $\delta$  satisfy

$$E_{b_0}(\phi^*(Y)) = \alpha$$

$$P_{b_0}(Y > m) + \delta P_{b_0}(Y = m) = \alpha$$

$$\Rightarrow \sum_{j=m+1}^n \binom{n}{j} \theta_0^j (1-\theta_0)^{n-j} + \delta \binom{n}{m} \theta_0^m (1-\theta_0)^{n-m} = \alpha$$

If for some  $m \geq 0$ ,

$$\sum_{j=m+1}^n \binom{n}{j} \theta_0^j (1-\theta_0)^{n-j} = \alpha,$$

then  $\delta = 0$  and  $\phi^*$  is non-randomized.

In general  $m$  is such that

$$\sum_{j=m+1}^n \binom{n}{j} \theta_0^j (1-\theta_0)^{n-j} \leq \alpha \leq \sum_{j=m}^n \binom{n}{j} \theta_0^j (1-\theta_0)^{n-j}$$

and

$$\delta = \frac{\alpha - \sum_{j=m+1}^n \binom{n}{j} \theta_0^j (1-\theta_0)^{n-j}}{\binom{n}{m} \theta_0^m (1-\theta_0)^{n-m}},$$

provided  $P_{b_0}(X=m) > 0$ .

Remark: The above test  $\phi^*$  does not depend on  $\theta_1$  as long as  $\theta_1 > \theta_0$ . Therefore by definition of UMP( $\alpha$ ) test  $\phi^*$  is in fact UMP( $\alpha$ ) test even for testing

$$H_0: \theta = \theta_0$$

$$H_1: \theta > \theta_0$$

$\forall \theta$

Lemma Suppose that for every  $b_1 \in \beta_1$ , a test  $\phi^*$  is UMP( $\alpha$ ) for testing  $H_0: b = b_0$  vs  $H_1: b = b_1$ . Then  $\phi^*$  is UMP( $\alpha$ ) for testing  $H_0: b = b_0$  vs  $H_1: b \in \beta_1$ .

Proof Let  $\phi$  be some test of  $\alpha$  level of significance for testing  $H_0: b = b_0$  vs  $H_1: b \in \beta_1$ . Then

$$E_{b_0}(\phi^*(Y)) = E_{b_0}(\phi(Y)) \leq \alpha.$$

Let  $b_i \in \mathcal{P}_1$ . Then, since  $\phi^*$  is UMP( $\alpha$ ) test for testing  $H_0: b \equiv b_0$  vs  $H_1: b \equiv b_1$ , it follows that

$$P_{\phi^*}(b_1) \geq P_{\phi}(b_1)$$

Since  $b_i \in \mathcal{P}_1$  was arbitrary, we have

$$P_{\phi^*}(b_i) \geq P_{\phi}(b_i), \quad \forall b_i \in \mathcal{P}_1.$$

$\Rightarrow \phi^*$  is UMP( $\alpha$ ) test for testing

$$\begin{aligned} H_0: b \equiv b_0 \\ \text{vs} \\ H_1: b \in \mathcal{P}_1. \end{aligned}$$

Lemma (Generalized Neyman Pearson Lemma). Let  $b_1, \dots, b_{m+1}$  be real-valued functions on  $\mathbb{R}^p$ . For given constants  $\alpha_1, \dots, \alpha_m$ , let

$$\mathcal{D} = \left\{ \phi: \mathbb{R}^p \rightarrow [0, 1], \int \phi(x) b_i(x) dx \leq \alpha_i, \quad i=1, \dots, m \right\}$$

and

$$\mathcal{D}_0 = \left\{ \phi: \mathbb{R}^p \rightarrow [0, 1], \int \phi(x) b_i(x) dx = \alpha_i, \quad i=1, \dots, m \right\}.$$

If there are constants  $c_1, \dots, c_m$  such that

$$\phi^*(x) = \begin{cases} 1, & \text{if } b_{m+1}(x) > \sum_{i=1}^m c_i b_i(x) \\ 0, & \text{if } b_{m+1}(x) < \sum_{i=1}^m c_i b_i(x) \end{cases}$$

is a member of  $\mathcal{D}_0$ , then  $\phi^*$  maximizes  $\int \phi(x) b_{m+1}(x) dx$  over  $\phi \in \mathcal{D}_0$ . If  $c_i \geq 0, \quad i=1, \dots, m$ , then  $\phi^*$  maximizes  $\int \phi b_{m+1} dx$  over  $\phi \in \mathcal{D}$ .

Proof. Case 1 General  $c_i$ 's

Let  $\phi \in \mathcal{D}_0$ . Consider

$$\Delta(x) = \left[ \phi^*(x) - \phi(x) \right] \left[ b_{m+1}(x) - \sum_{i=1}^m c_i b_i(x) \right]$$

Then

$$\Delta(x) \geq 0, \quad \forall x$$

$$\Rightarrow \int (\phi^*(x) - \phi(x)) [b_{m+1}(x) - \sum_{i=1}^m c_i b_i(x)] dx \geq 0$$

$$\Rightarrow \int (\phi^*(x) - \phi(x)) b_{m+1}(x) dx \geq \sum_{i=1}^m c_i \left[ \int \phi^*(x) b_i(x) dx - \int \phi(x) b_i(x) dx \right] \quad \dots \text{(I)}$$

$$\Rightarrow \int \phi^*(x) b_{m+1}(x) dx - \int \phi(x) b_{m+1}(x) dx$$

$$\geq \sum_{i=1}^m c_i (\alpha - \alpha) \quad [\text{Since } \phi, \phi^* \in \mathcal{T}_0]$$

$$= 0$$

Case II  $c_i \geq 0, \quad \forall i=1, \dots, m$

Let  $\phi \in \mathcal{D}$ . Then again (I) yields

$$\int \phi^*(x) b_{m+1}(x) dx - \int \phi(x) b_{m+1}(x) dx \geq \sum_{i=1}^m c_i (\alpha - \alpha) = 0.$$

Lemma (Existence of  $C(\Omega)$ ): Under the notation of above lemma

the set  $C = \{ (\int \phi b_1 dx, \dots, \int \phi b_m dx) : \phi; \mathbb{R}^1 \rightarrow [0,1] \}$  is a closed and convex set. If  $(\alpha_1, \dots, \alpha_m)$  is an interior point of  $C$ , then there exist constants  $c_1, \dots, c_m$  such that  $\phi^*$  defined in above lemma is in  $\mathcal{D}_0$ .

Monotone Likelihood Ratio Property: A family  $\mathcal{P} = \{ p_{\theta} : \theta \in \Theta \}$  (II) of  $p_{\theta}$  is said to have the monotone likelihood ratio (MLRP) property in a statistic  $T(x)$  if for any  $\theta_1 < \theta_2$  ( $\theta_1, \theta_2 \in \Theta$ ),  $\frac{p_{\theta_2}(x)}{p_{\theta_1}(x)}$  is a non-decreasing function of  $T(x)$  for all  $x \in \{t: p_{\theta_1}(t) > 0\} \cup \{t: p_{\theta_2}(t) > 0\}$ .

Lemma Suppose that the family  $\mathcal{P} = \{p_{\theta}; \theta \in \Theta\}$  ( $\Theta \subseteq \mathbb{R}$ ) of pdfs has mhr in  $T(x)$ . If  $\psi(\cdot)$  is a non-decreasing function of  $T$ , then  $g(\theta) = E_{\theta}(\psi(T))$  is a non-decreasing function of  $\theta \in \Theta$ .

Proof. Let  $\theta_1, \theta_2 \in \Theta$  be such that  $\theta_1 < \theta_2$ . Define

$$A = \{x: b_{\theta_1}(x) > b_{\theta_2}(x)\}, \quad B = \{x: b_{\theta_1}(x) < b_{\theta_2}(x)\}$$

$$C = \{x: b_{\theta_1}(x) = b_{\theta_2}(x)\}$$

$$a = \inf_{x \in A} \psi(T(x)), \quad b = \inf_{x \in B} \psi(T(x)).$$

Since  $b_{\theta_2}(x)/b_{\theta_1}(x) \uparrow$  and  $\psi(\cdot) \uparrow$ , it follows that  $b \geq a$ . Thus

$$g(\theta_2) - g(\theta_1) = \int \psi(T(x)) [b_{\theta_2}(x) - b_{\theta_1}(x)] dx$$

$$= \int_A \underbrace{\psi(T(x))}_{\leq a} \underbrace{[b_{\theta_2}(x) - b_{\theta_1}(x)]}_{< 0} dx + \int_{B \cup C} \underbrace{\psi(T(x))}_{\geq b} \underbrace{[b_{\theta_2}(x) - b_{\theta_1}(x)]}_{\geq 0} dx$$

$$\geq a \int_A [b_{\theta_2}(x) - b_{\theta_1}(x)] dx + b \int_B [b_{\theta_2}(x) - b_{\theta_1}(x)] dx$$

$$= (b-a) \int_B [b_{\theta_2}(x) - b_{\theta_1}(x)] dx \quad \left[ \int_A [b_{\theta_2}(x) - b_{\theta_1}(x)] dx = 0 \right]$$

$$\geq 0.$$

Example Let  $\Theta \subseteq \mathbb{R}$  and let  $\eta(\theta) \uparrow$  in  $\theta \in \Theta$ . Then the one-parameter exponential family with pdf

$$p_{\theta}(x) = \exp\{\eta(\theta)T(x) - \xi(\theta)\}h(x) \quad \dots \quad (*)$$

has mhr in  $T(x)$ .

Solution For  $\theta_2 > \theta_1$

$$\frac{p_{\theta_2}(x)}{p_{\theta_1}(x)} = e^{-(\xi(\theta_2) - \xi(\theta_1))} e^{\underbrace{(\eta(\theta_2) - \eta(\theta_1))}_{\geq 0} T(x)} \uparrow \text{ in } T(x)$$

Examples of (\*) are; when  $x_1, \dots, x_n$  is a random sample from

- (i)  $\text{Bin}(n, \theta)$ ,  $\theta \in \Theta \subseteq (0, 1)$ ,  $n \in \{1, 2, \dots\}$  is known/fixed;
- (ii)  $\text{Poisson}(\theta)$ ,  $\theta \in \Theta \subseteq (0, \infty)$ ;
- (iii)  $\text{NB}(r, \theta)$ ,  $\theta \in \Theta \subseteq (0, 1)$ ,  $r \in \{1, 2, \dots\}$  is known/fixed
- (iv)  $\text{N}(\theta, \sigma_0^2)$ ,  $\theta \in \Theta \subseteq \mathbb{R}$ ,  $\sigma_0^2$  is known/fixed
- (v)  $\text{N}(\mu_0, \theta)$ ,  $\theta \in \Theta \subseteq (0, \infty)$ ,  $\mu_0 \in \mathbb{R}$  is known/fixed
- (vi)  $\text{Exp}(\mu_0, \theta)$ ,  $\theta \in \Theta \subseteq (0, \infty)$ ,  $\mu_0 \in \mathbb{R}$  is known/fixed
- (vii)  $\text{Exp}(\theta, \sigma_0)$ ,  $\theta \in \Theta \subseteq \mathbb{R}$ ,  $\sigma_0 > 0$  is known/fixed
- (viii)  $\text{Gamma}(\alpha_0, \theta)$ , with scale parameter  $\theta \in \Theta \subseteq \mathbb{R}$ ,  $\alpha_0 > 0$  is known/fixed
- (ix)  $\text{DE}(\mu_0, \theta)$ ,  $\theta \in \Theta \subseteq (0, \infty)$ ,  $\mu_0 \in \mathbb{R}$  is known/fixed;

Example Let  $x_1, \dots, x_n$  be iid  $U(0, \theta)$ ,  $\theta > 0$ .

Then

$$b_{\theta}(z) = \frac{1}{\theta^n} \mathbb{1}_{(0, \theta)}(z_{(n)})$$

For  $\theta_2 > \theta_1$ ,

$$\frac{b_{\theta_2}(z)}{b_{\theta_1}(z)} = \begin{cases} \frac{\theta_1^n}{\theta_2^n} & 0 < z_{(n)} < \theta_1 \\ \infty & \theta_1 < z_{(n)} < \theta_2 \end{cases} \quad \uparrow \text{ in } z_{(n)}$$

$\Rightarrow \{b_{\theta}: \theta > 0\}$  has mlr in  $X_{(n)}$ .

Example Let  $x_1, \dots, x_n$  be iid  $\text{Exp}(\theta, \sigma_0)$ ,  $\theta \in \mathbb{R}$ ,  $\sigma_0 > 0$  is fixed. Show that the family  $\{b_{\theta}: \theta \in \mathbb{R}\}$  has MLR in  $T(x) = X_{(1)}$ .

Example Consider a random sample  $x$  of size 1 from the Cauchy pdf

$$f_{\theta}(x) = \frac{1}{\pi} \cdot \frac{1}{1+(x-\theta)^2}, \quad -\infty < x < \infty, \quad \theta \in \mathbb{R}$$

For  $\theta_2 > \theta_1$

$$\frac{f_{\theta_2}(x)}{f_{\theta_1}(x)} = \frac{1+(x-\theta_1)^2}{1+(x-\theta_2)^2} \rightarrow 1, \quad \text{as } x \rightarrow \pm \infty$$

$$\rightarrow \frac{1+\theta_1^2}{1+\theta_2^2} \quad \text{at } x=0$$

$\Rightarrow$  the family  $\{f_{\theta}: \theta \in \mathbb{R}\}$  does not have MLR in  $x$ .

### UMP( $\alpha$ ) Tests for One Sided Hypotheses

One-Sided Hypotheses: Hypotheses of the form

$$H_0: \theta \leq \theta_0 \quad (\text{or } H_0: \theta \geq \theta_0)$$

$$\text{vs } H_1: \theta > \theta_0 \quad (\text{or } H_1: \theta < \theta_0)$$

are called one-sided hypotheses for any fixed constant  $\theta_0$ .

Theorem. Suppose that the distribution of  $x$  has the p.d.f./p.m.f.  $f_{\theta}(x)$  that has MLR in  $T(x)$ . <sup>(in the p.d.f./p.m.f.  $f_{\theta}(x)$  have MLR in  $T(x)$ )</sup> Consider testing  $H_0: \theta \leq \theta_0$  vs  $H_1: \theta > \theta_0$ , where  $\theta_0$  is a given constant.

(a) There exist a UMP( $\alpha$ ) test, given by

$$\phi^*(x) = \begin{cases} 1 & \text{if } T(x) > c \\ \nu & \text{if } T(x) = c \\ 0 & \text{if } T(x) < c \end{cases}$$

where  $c$  and  $\nu \in [0, 1]$  are determined by  $\beta_{\phi^*}(\theta_0) = \alpha$

(b)  $\beta_{\phi^*}(\theta)$  is strictly increasing for all  $\theta$ 's for which  $0 < \beta_{\phi^*}(\theta) < 1$ .

(c) For any  $\theta < \theta_0$   $\phi^*$  minimizes  $\beta_{\phi}(\theta)$  (Type I error prob. of  $\phi$ ) among all tests  $\phi$  satisfying  $\beta_{\phi}(\theta_0) = \alpha$ .

(d) For any  $\delta_1 \in \mathbb{R}$ ,  $\phi^*$  is UMP( $\alpha$ ) for testing  $H_0: \theta \leq \theta_0$ ,  
 $\forall \theta_1: \theta > \theta_0$ , with  $\alpha^* = \beta_{\phi^*}(\theta_1)$ .

Proof. (a) First consider testing

$$H_0^*: \theta = \theta_0$$

$$\forall \theta_1^*: \theta = \theta_1$$

where  $\theta_1 > \theta_0$ . Then a UMP( $\alpha$ ) test is

$$\phi^* = \begin{cases} 1 & \text{if } b_{\theta_1}(x) > k b_{\theta_0}(x) \\ 0 & \text{if } b_{\theta_1}(x) = k b_{\theta_0}(x) \\ 0 & \text{if } b_{\theta_1}(x) < k b_{\theta_0}(x) \end{cases}$$

Since  $\frac{b_{\theta_1}(x)}{b_{\theta_0}(x)}$  is ~~strictly~~  $\uparrow$  in  $T(x)$ , the UMP( $\alpha$ ) test is

$$\phi^* = \begin{cases} 1 & \text{if } T(x) > c \\ 0 & \text{if } T(x) = c \\ 0 & \text{if } T(x) < c \end{cases}$$

as long as  $\int_{\mathcal{X}} \phi^* dP_{\theta_0} = \alpha$  and  $c$  satisfies

$$\beta_{\phi^*}(\theta_1) = \alpha$$

$$= P_{\theta_0}(T(x) > c) + \int_{T(x)=c} \phi^* dP_{\theta_0} = \alpha$$

Since  $\phi^*$  does not depend on  $\delta_1$  (as long as  $\theta_1 > \theta_0$ ), it is UMP( $\alpha$ ) for testing

$$H_0^*: \theta = \theta_0$$

$$\forall \theta_1^*: \theta > \theta_0$$

To show that  $\phi^*$  is UMP( $\alpha$ ) for testing  $H_0: \theta \leq \theta_0$  vs  $H_1: \theta > \theta_0$ , it suffices to show that  $\sup_{\theta \leq \theta_0} \beta_{\phi^*}(\theta) \leq \alpha$ . We have

$$\beta_{\phi^*}(\theta) = E_{\theta}(\phi^*(x)), \theta \in \mathbb{R}$$

But  $\phi^*(x)$  is an increasing function of  $T(x)$  and the part of  $x$  that increases in  $T(x)$ . Therefore

$$\Rightarrow \beta_{\phi^*}(\theta) = E_{\theta}(\phi^*(x)) \uparrow \theta$$

$$\Rightarrow \beta_{\phi^*}(\theta) \leq \beta_{\phi^*}(\theta_0) = \alpha, \forall \theta \leq \theta_0$$

$$\Rightarrow \sup_{\theta \leq \theta_0} \beta_{\phi^*}(\theta) \leq \alpha$$

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(b) Let  $\theta_1 < \theta_2$  be such that  $\beta_{\phi^*}(\theta_i) \in (0, 1)$ ,  $i=1, 2$ .

Consider test

$$h_0: \theta = \theta_1$$

$$v_1 \quad h_1: \theta = \theta_2$$

(A)

Then  $\phi^*$  is UMP( $\alpha^*$ ) test of level  $\alpha^* = E_{\theta_1}(\phi^*) \in (0, 1)$ .

Consider the no-data test

$$Q_0(\Delta) = \alpha^* \quad \forall \Delta$$

Then,  $E_{\theta_1}(Q_0) = \alpha^*$  and thus we have (since  $\phi^*$  is UMP( $\alpha^*$ ) for  $\mathcal{A}$ )

$$E_{\theta_2}(Q_0) \leq E_{\theta_2}(\phi^*) \Leftrightarrow \alpha^* \leq E_{\theta_2}(\phi^*)$$

$$\Rightarrow E_{\theta_1}(\phi^*) = \alpha^* \leq E_{\theta_2}(\phi^*)$$

Moreover,

$$E_{\theta_1}(Q^*) = E_{\theta_2}(Q^*) \Leftrightarrow E_{\theta_1}(Q_0) = E_{\theta_2}(Q^*)$$

$\Rightarrow Q_0$  is also UMP( $\alpha^*$ ).

By uniqueness of UMP( $\alpha^*$ ) test

$$Q_0(\Delta) = \begin{cases} 1 \\ 0 \end{cases}$$

$$\parallel$$

$$\alpha^* \in (0, 1)$$

$$b_{\theta_1}(\Delta) > k b_{\theta_2}(\Delta)$$

$$b_{\theta_1}(\Delta) < k b_{\theta_2}(\Delta)$$

$$\Rightarrow P_{\theta} (b_{\theta_1}(\Delta) = k b_{\theta_2}(\Delta)) = 1 \quad \forall \Delta \in \{\theta_1, \theta_2\}$$

$$\Rightarrow k=1 \quad \text{and} \quad b_{\theta_1}(\Delta) = b_{\theta_2}(\Delta) \rightarrow \text{Contradiction}$$

(c)

Let  $\theta_{00} < \theta_0$ .

Consider test

$$h_0: \theta = \theta_0$$

$$v_1 \quad h_1: \theta = \theta_{00}$$

UMP( $1-\alpha$ ) test

$$\phi^{**} = \begin{cases} 1 \\ 1-\alpha \\ 0 \end{cases}$$

$$T(X) < c^*$$

$$T(X) = c^*$$

$$T(X) > c^*$$

where  $E_{\theta_0}(Q^{**}) = 1-\alpha$

$$1-Q^{**} = \begin{cases} 1 \\ 1-\alpha \\ 0 \end{cases}$$

$$T(X) > c^*$$

$$T(X) = c^*$$

$$T(X) < c^*$$



level  $E_{\theta_0}(1 - \phi_{\alpha}) = \alpha$

Comparing with  $\phi^*$  we observe that  $\phi^* = 1 - \phi$  is UMP  $(1 - \alpha)$  test for testing the above hypothesis.

Let  $\phi_0$  be any test of level  $\alpha$  for testing

$H_0: \theta \leq \theta_0$

$H_1: \theta > \theta_0$

Then  $1 - \phi_0$  is a valid test for testing  $H_0: \theta \leq \theta_0$  vs  $H_1: \theta > \theta_0$ . Also  $E_{\theta_0}(1 - \phi_0) \geq 1 - \alpha$ . Since  $\phi^* = 1 - \phi$  is UMP  $(1 - \alpha)$  test for  $H_0: \theta \leq \theta_0$  vs  $H_1: \theta > \theta_0$  we have

$$E_{\theta_0}(1 - \phi^*) \geq E_{\theta_0}(1 - \phi_0)$$

$$\Leftrightarrow E_{\theta_0}(\phi_0) \geq E_{\theta_0}(\phi^*)$$

(or) Similarly  $\Rightarrow$  (a)

Remark: Under the set-up of last theorem consider testing  $H_0: \theta \geq \theta_0$  vs  $H_1: \theta < \theta_0$ . An in last theorem, it can be shown that the test

$$\phi^*(T) = \begin{cases} 1 & \text{if } T < c \\ 0 & \text{if } T \geq c \end{cases}$$

where  $\delta$  and  $c$  are chosen so that  $E_{\theta_0}(\phi^*(T)) = \alpha$ , is UMP  $(\alpha)$  for testing the above hypothesis.

Covollary Suppose that  $X$  has p.d.f/p.m.f.

$$f_{\theta}(x) = \frac{1}{c} \eta(|T(x) - \theta|) h(x), \quad x \in X, \theta \in \Theta \subseteq \mathbb{R} \text{ and } c(\theta) = 1$$

where  $\eta(|\cdot|)$  is an increasing function of  $\theta$ . Let  $\theta_0 \in \Theta$  be fixed. Then a UMP  $(\alpha)$  test for testing  $H_0: \theta \leq \theta_0$  ( $\theta > \theta_0$ ) vs  $H_1: \theta > \theta_0$  ( $\theta < \theta_0$ ) is

$$\phi^*(T) = \begin{cases} 1 & \text{if } T(x) > c \\ 0 & \text{if } T(x) \leq c \end{cases}$$

where  $c$  and  $\delta$  are such that  $\beta_{\theta_0}(\theta_0) = \alpha$ .

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If  $\eta(\theta)$  is  $\uparrow$ , decreasing or  $\eta(\theta)$  is strictly increasing but  $H_0: \theta \geq \theta_0$   
 ( $\forall \theta: \theta < \theta_0$ ) the result is still valid by reversing inequalities  
 in  $\phi^*$ .

Example Let  $X_1, \dots, X_n$  be iid  $N(\theta, \sigma_0^2)$  where  $\theta \in \Theta = \mathbb{R}$  is unknown  
 and  $\sigma_0 > 0$  is known. Consider testing

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

$$\forall \theta: \theta > \theta_0$$

where  $\theta_0 \in \mathbb{R}$  is a fixed constant at  $\alpha$ -level of significance.

We have

$$f_{\theta}(x) = \exp \left[ \frac{n\theta}{\sigma_0^2} \bar{x} - \left\{ \frac{n\theta^2}{2\sigma_0^2} + \frac{n}{2} \ln(2\pi\sigma_0^2) \right\} \right] e^{-\frac{1}{2\sigma_0^2} \sum_{i=1}^n x_i^2}$$

$h(x)$        $g(\theta)$

$$= \exp [ \eta(\theta) T(x) - g(\theta) ] h(x), \quad x \in \mathcal{X} = \mathbb{R}^n$$

where  $\eta(\theta) = \frac{n\theta}{\sigma_0^2}$  is strictly increasing in  $\theta$ . Then  $u(\theta)$

test is

$$\phi^* = \begin{cases} 1 & \text{if } \bar{x} > c \\ 0 & \text{o.w.} \end{cases}$$

where  $c$  is chosen so that

$$E_{\theta_0}(\phi^*) = \alpha$$

$$\Rightarrow P_{\theta_0}(\bar{x} > c) = \alpha$$

$$\Phi \left( \frac{\sqrt{n}(c - \theta_0)}{\sigma_0} \right) = \alpha$$

$$\Rightarrow c = \frac{\sigma_0}{\sqrt{n}} \Phi^{-1}(1 - \alpha) + \theta_0$$

**Note:**

The above test is also UMP( $\alpha$ ) test for testing

$$H_0: \theta = \theta_0$$

$$\forall \theta: \theta > \theta_0$$

**Example**

Let  $x_1, \dots, x_n$  be a random sample from  $\text{Bin}(1, \theta)$ ,  $\theta \in \Theta = (0, 1)$ .

$f_{\theta}(x)$  belongs to the parameter exponential family with

$T(x) = \sum_{i=1}^n x_i$  and  $\eta(\theta) = \ln \frac{\theta}{1-\theta} \uparrow$  as  $\theta \in (0, 1)$

UMP( $\alpha$ ) test for testing

$H_0: \theta \geq \theta_0$   
 $\forall H_1: \theta < \theta_0$

is given by

$$\phi^*(x) = \begin{cases} 1, & \text{if } \sum_{i=1}^n x_i < c \\ 0, & \text{if } \sum_{i=1}^n x_i = c \\ 0, & \text{if } \sum_{i=1}^n x_i > c \end{cases}$$

where  $c$  and  $\nu \in [0, 1]$  are determined by

$$E_{\theta_0}(\phi^*(x)) = \alpha$$

$$\sum_{j=0}^{c-1} \binom{n}{j} \theta_0^j (1-\theta_0)^{n-j} + \nu \binom{n}{c} \theta_0^c (1-\theta_0)^{n-c} = \alpha.$$

Obviously this test is also UMP( $\alpha$ ) for testing  $H_0: \theta = \theta_0$  vs  $H_1: \theta < \theta_0$ .

**Example**

Let  $x_1, \dots, x_n$  be i.i.d.  $\text{Poisson}(\theta)$ ,  $\theta > 0$

$f_{\theta}(x)$  belongs to exponential family with

$T(x) = \sum_{i=1}^n x_i$  and  $\eta(\theta) = \ln \theta \uparrow$  as  $\theta \in (0, \infty)$ ,  
 $\sim \text{Poisson}(n\theta)$

For testing

$H_0: \theta \leq \theta_0$   
 $\forall H_1: \theta > \theta_0$

a UMP( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1, & \text{if } \sum_{i=1}^n x_i > c \\ 0, & \text{if } \sum_{i=1}^n x_i = c \\ 0, & \text{if } \sum_{i=1}^n x_i < c \end{cases}$$

where  $c$  and  $\alpha \in (0, 1)$  satisfy

$$E_{\theta_0}[\phi^*(x)] = \alpha$$

$$\Rightarrow P_{\theta_0}(T(x) > c) + 0 \cdot P_{\theta_0}(T(x) = c) = \alpha$$

$$\Rightarrow \sum_{j=c+1}^{\infty} \frac{e^{-n\theta_0} (n\theta_0)^j}{j!} = \alpha \quad \frac{e^{-n\theta_0} (n\theta_0)^c}{c!} = \alpha$$

### Example

Let  $x_1, \dots, x_n$  be a random sample from a fixed  $U(0, \theta)$  where  $\theta \in \mathbb{R}^+ = (0, \infty)$ .

Consider testing

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

$$\text{against } H_1: \theta > \theta_0$$

$f_{\theta}(x)$  has MLR in  $T(x) = x_{(n)}$

$$f_{x_{(n)}}(x|\theta) = \frac{n x^{n-1}}{\theta^n}, \quad 0 < x < \theta.$$

UMP( $\alpha$ ) test for testing  $H_0$  against  $H_1$  is

$$\phi^*(x) = \begin{cases} 1, & x_{(n)} > c \\ 0, & x_{(n)} < c \end{cases}$$

where  $c$  is given by

$$E_{\theta_0}[\phi^*(x)] = \alpha$$

$$P_{\theta_0}(x_{(n)} > c) = \alpha$$

$$\Rightarrow \frac{1}{\theta_0^n} (\theta_0^n - c^n) = \alpha, \quad \text{ie } c = \theta_0 (1 - \alpha)^{1/n}$$

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The power function is

$$\beta_{\phi^*}(\theta) = P_{\theta}(X_{(n)} > c) = 1 - \left(\frac{c}{\theta}\right)^n = 1 - \left(\frac{\theta_0}{\theta}\right)^n (1 - \alpha).$$

Another UMP( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1, & x_{(n)} > \theta_0 \\ \alpha, & x_{(n)} \leq \theta_0 \end{cases}$$

Obviously above tests are also UMP( $\alpha$ ) tests for testing  
 $H_0: \theta = \theta_0$  v.  $H_1: \theta > \theta_0$ .

### UMP Tests For Two Sided Hypotheses

The following hypotheses are referred to as two-sided hypotheses

- $H_0: \theta \leq \theta_1$  or  $\theta \geq \theta_2$  v.  $H_1: \theta_1 < \theta < \theta_2 \dots (1)$
- $H_0: \theta_1 \leq \theta \leq \theta_2$  v.  $H_1: \theta < \theta_1$  or  $\theta > \theta_2 \dots (2)$
- $H_0: \theta = \theta_0$  v.  $H_1: \theta \neq \theta_0, \dots (3)$

where  $\theta_0, \theta_1$  and  $\theta_2$  ( $\theta_1 < \theta_2$ ) are fixed constants.

Suppose that  $\underline{X}$  has p.d.f. belonging to one parameter exponential family with p.d.f.

$$f_{\theta}(x) = \exp\{\eta(\theta)T(x) - B(\theta)\} h(x); \dots (4)$$

$$\theta \in \Theta \subseteq \mathbb{R}$$

The p.d.f. of  $T \equiv T(x)$  is given by

$$g_{\theta}(t) = \exp\{\eta(\theta)t - B(\theta)\} m(t), \quad \text{--- (Lehmann (1961))} \dots (5)$$

for some function  $m(\cdot)$ ;  $\theta \in \Theta$ .

Clearly  $T \equiv T(X)$  is a sufficient statistic for  $\theta \in \Theta$  and, for any test function  $\phi(\cdot)$ ,

$$\phi^*(T) = E_{\theta}(\phi(X) | T)$$

is a proper test function ( $0 \leq \phi^* \leq 1$  and it does not depend on  $\theta \in \Theta$  by virtue of sufficiency of  $T$ ). Moreover  $\phi^*$  has the same power function as  $\phi$ , i.e.

$$\beta_{\phi^*}(\theta) = E_{\theta}(E_{\theta}(\phi(X) | T))$$

$$= E_{\theta}(\phi(X)) = \beta_{\phi}(\theta), \quad \forall \theta \in \Theta$$

and thus it suffices to consider only those test functions that depend on observations only through sufficient statistic  $T$ .

The following lemma will be useful in deriving UMP tests for two-sided alternatives.

**Lemma** Suppose that a r.v.  $T$  has a p.d.f. / p.m.f. in the family of p.d.f.s / p.m.f.s  $\mathcal{P} = \{g_{\theta} : \theta \in \Theta\}$ , where  $\Theta \subseteq \mathbb{R}$ . Suppose that the family  $\mathcal{P}$  has MLR in  $T$ .

Let  $\psi(\cdot)$  be a function with single sign change, i.e. there exists  $\lambda_0 \in \mathbb{R}$  such that  $\psi(\lambda) \leq 0 \quad \forall \lambda < \lambda_0$  and  $\psi(\lambda) \geq 0 \quad \forall \lambda \geq \lambda_0$ . Then there exists  $\theta_0 \in \Theta$  such that  $E_{\theta}(\psi(T)) \leq 0 \quad \forall \theta < \theta_0$  and  $E_{\theta}(\psi(T)) \geq 0 \quad \forall \theta > \theta_0$ , unless  $E_{\theta}(\psi(T))$  is either positive for all  $\theta \in \Theta$  or negative for all  $\theta \in \Theta$ .

(ii) Suppose that  $g_{\theta}(\lambda) > 0$  for all  $\lambda \in \mathbb{R}$  and  $\theta \in \Theta$ , that  $g_{\theta_2}(t) / g_{\theta_1}(t)$  is strictly increasing in  $t$ , whenever  $\theta_2 > \theta_1$ , and that  $P_{\theta}(\psi(T) \neq 0) > 0 \quad \forall \theta \in \Theta$ .

If  $E_{\theta_0}(\psi(T)) = 0$ , then  $E_{\theta}(\psi(T)) < 0$  for  $\theta < \theta_0$   
 and  $E_{\theta}(\psi(T)) > 0$  for  $\theta > \theta_0$ .

**Proof.** (i) Suppose that there exists  $\lambda_0 \in \mathbb{R}$  such that  
 $\psi(x) \leq 0$  for  $x < \lambda_0$  and  $\psi(x) \geq 0$  for  $x > \lambda_0$ .  
 Let  $\theta_1, \theta_2 \in \Theta$  and  $\theta_1 < \theta_2$ .

Claim  $E_{\theta_1}(\psi(T)) > 0 \Rightarrow E_{\theta_2}(\psi(T)) > 0$   
 Suppose that  $E_{\theta_1}(\psi(T)) > 0$  and  $\theta_1 < \theta_2$ .

If  $\frac{g_{\theta_2}(x)}{g_{\theta_1}(x)} = 0$ , then  $g_{\theta_1}(t) \geq 0$  for  $t \geq \lambda_0$  and

hence  $E_{\theta_1}(\psi(T)) = \int_{-\infty}^{\lambda_0} \psi(t) g_{\theta_1}(t) dt \leq 0$ , which

is not true. Thus  $g_{\theta_2}(\lambda_0) / g_{\theta_1}(\lambda_0) = c < \infty$  ( $0 \leq c < \infty$ )

Then  $g_{\theta_2}(t) / g_{\theta_1}(t) \leq c$ , for  $t < \lambda_0$  and  $g_{\theta_2}(t) / g_{\theta_1}(t) \geq c$ , for  $t \geq \lambda_0$ ;

$\psi(t) \geq 0$  on the set  $A = \{t: g_{\theta_1}(t) > 0 \text{ and } g_{\theta_2}(t) > 0\}$

(as on the set  $g_{\theta_2}(t) / g_{\theta_1}(t) = 0$  and  $g_{\theta_2}(t) / g_{\theta_1}(t) \geq c$  implying that  
 for every  $t \in A$ ,  $t \geq \lambda_0$ )

Thus

$$E_{\theta_2}(\psi(X)) = \int_A \psi(t) g_{\theta_2}(t) dt + \int_{A^c} \psi(t) g_{\theta_2}(t) dt$$

$$\geq \int_{A^c} \psi(t) g_{\theta_2}(t) dt$$

$$= \int_{\{t: g_{\theta_1}(t) > 0\} \cup \{t: g_{\theta_2}(t) > 0\}} \psi(t) g_{\theta_2}(t) dt$$

$$= \int_{\{t: g_{\theta_1}(t) > 0\}} \psi(t) g_{\theta_2}(t) dt$$

$$= \int_{\{t: g_{\theta_1}(t) > 0, t < \lambda_0\}} \psi(t) \frac{g_{\theta_2}(t)}{g_{\theta_1}(t)} g_{\theta_1}(t) dt + \int_{\{t: g_{\theta_1}(t) > 0, t \geq \lambda_0\}} \psi(t) \frac{g_{\theta_2}(t)}{g_{\theta_1}(t)} g_{\theta_1}(t) dt$$

$$\geq \int_{\{t: g_{\theta_1}(t) > 0, t < \tau_0\}} c \psi(t) g_{\theta_1}(t) dt + \int_{\{t: g_{\theta_1}(t) > 0, t \geq \tau_0\}} c \psi(t) g_{\theta_1}(t) dt$$

$$= c \left[ \int \psi(t) g_{\theta_1}(t) dt \right] = c E_{\theta_1}(\psi(\tau)) \geq 0$$

The result now follows by letting

$$\theta_0 = \inf \{ \theta \in \Theta : E_{\theta}(\psi(\tau)) > 0 \}$$

(ii) Similar to proof of (i) by noting that  $g_{\theta_2}(t) / g_{\theta_1}(t)$  is strictly increasing in  $t$ , whenever  $\theta_1 < \theta_2$ .

Now let us recall the Generalized Neyman Pearson Lemma stated on page 18

**Theorem** Suppose that  $X$  has p.d.f./p.m.f. belonging one-parameter exponential family given by (4), where  $\eta(\cdot)$  is a strictly increasing function of  $\theta \in \Theta$ .

(i) For testing  $H_0: \theta \leq \theta_0$  or  $\theta \geq \theta_1$  (i.e.  $\theta_0 < \theta_1$ ) against  $H_1: \theta \in (\theta_0, \theta_1)$  a UMP( $\alpha$ ) test is

$$\phi^*(T) = \begin{cases} 1, & \text{if } c_1 < T < c_2 \\ D_i, & \text{if } T = c_i, \quad i=1, 2 \\ 0, & \text{if } T < c_1 \text{ or } T > c_2 \end{cases} \quad \dots (6)$$

where  $c_1 < c_2$  and  $D_i$ 's are determined by

$$P_{\phi^*}(\theta_0) = P_{\phi^*}(\theta_1) = \alpha \quad \dots (7)$$



(b) The test  $\phi^*$  defined in (a) minimizes  $\beta_\phi(\theta)$  over all  $\theta < \theta_1, \theta > \theta_2$  among all  $\phi$  satisfying  $\beta_\phi(\theta_1) = \beta_\phi(\theta_2) = \alpha$ .

(c) If  $\phi_1$  and  $\phi_2$  are two tests of the form (6) (with  $\theta_1$  different  $\theta_1$ , or  $\theta_2$  or  $\alpha$ ) and  $\beta_{\phi_1}(\theta_1) = \beta_{\phi_2}(\theta_1)$  and the region  $\{\phi_2 = 1\}$  is to the right of  $\{\phi_1 = 1\}$  then  $\beta_{\phi_1}(\theta) < \beta_{\phi_2}(\theta) \forall \theta > \theta_0$  and  $\beta_{\phi_1}(\theta) > \beta_{\phi_2}(\theta) \forall \theta < \theta_0$ .  
 If  $\phi_1$  and  $\phi_2$  both satisfy (6) and (7) then  $\phi_1 \equiv \phi_2$  a.s.  $\mathcal{P}$ .

We consider  $\alpha \in (0, 1)$ , as the proof for  $\alpha \in \{0, 1\}$  follows trivially. It suffices to consider tests based on sufficient statistic  $T \equiv T(X)$ . The p.d.f. of  $T$  is

**Proof.**

$$g_\theta(t) = \exp\{\eta(\theta)t - B(\theta)\} m(t)$$

Let  $\theta_3 \in (\theta_1, \theta_2)$ . Consider problem of maximizing  $\beta_\phi(\theta_3)$  subject to  $\beta_\phi(\theta_1) = \beta_\phi(\theta_2) = \alpha$ .

By generalized NP Lemma maximizer  $\phi^*$  is of the form

$$\phi^*(t) = \begin{cases} 1, & g_{\theta_3}(t) > c_1 g_{\theta_1}(t) + c_2 g_{\theta_2}(t) \\ 0, & g_{\theta_3}(t) < c_1 g_{\theta_1}(t) + c_2 g_{\theta_2}(t) \end{cases}$$

Note that

$$g_{\theta_3}(t) > c_1 g_{\theta_1}(t) + c_2 g_{\theta_2}(t)$$

$$\Rightarrow \exp\{\eta(\theta_3)t - B(\theta_3)\} m(t) > c_1 \exp\{\eta(\theta_1)t - B(\theta_1)\} m(t) + c_2 \exp\{\eta(\theta_2)t - B(\theta_2)\} m(t)$$

$$\Leftrightarrow a_1 e^{b_1 t} + a_2 e^{b_2 t} < 1, \quad \text{where } b_1 < 0 < b_2, \\ a_1 = c_1 e^{B_1(0_1) + B_1(0_2)}, \quad a_2 = c_2 e^{-B_1(0_2) + B_1(0_3)}$$

Case I:  $a_1 \leq 0, \quad a_2 \leq 0$

$$\phi^*(t) = 1, \quad \forall t$$

$\rightarrow$  can not have  $\mathbb{1} \times \alpha \in (0, 1)$

Case II:  $a_1 \leq 0, \quad a_2 > 0$  (or  $a_1 > 0, \quad a_2 < 0$ )

$$a_1 e^{b_1 t} + a_2 e^{b_2 t} \uparrow (\downarrow) \text{ in } t$$

$$\text{Thus } a_1 e^{b_1 t} + a_2 e^{b_2 t} < 1 \Leftrightarrow t < (>) T,$$

$$\phi^*(x) = \begin{cases} 1, \\ 0, \end{cases}$$

$$T < (>) T$$

$$T > (<) T$$

$\downarrow$   $\begin{matrix} (T) \\ T \end{matrix}$

$\exists \beta \mathbb{E}_{\theta_1}[\phi^*(x)] = \alpha$  (i.e.  $\mathbb{E}_{\theta_1}[\phi^*(T) - \alpha] = 0$ ), then  $\mathbb{E}_{\theta_2}[\phi^*(x) - \alpha] < (>) 0$   
(by last lemma, part (iii))

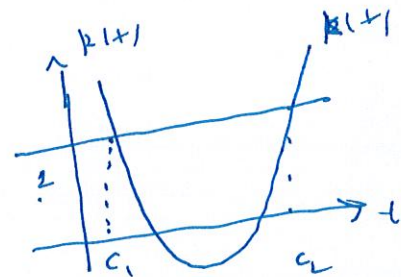
Thus  $\beta_{\theta_1}(\alpha) = \beta_{\theta_2}(\alpha) = \alpha$  can not be satisfied.

Case III:  $a_1 > 0, \quad a_2 > 0$

$$\text{let } k(t) = a_1 e^{b_1 t} + a_2 e^{b_2 t} \\ k'(t) = a_1 b_1 e^{b_1 t} + a_2 b_2 e^{b_2 t}$$

$$k'(t) > (<) 0 \Leftrightarrow (b_2 - b_1) t > \ln \left( -\frac{a_1 b_1}{a_2 b_2} \right)$$

$$\Leftrightarrow t > (<) \frac{1}{b_2 - b_1} \ln \left( -\frac{a_1 b_1}{a_2 b_2} \right)$$



Thus

$$\phi^*(x) = \begin{cases} 1, \\ 0, \end{cases}$$

$$\begin{cases} 1, \\ 0, \\ 0 \end{cases}$$

$$c_1 < T < c_2$$

$$T = c_1$$

$$T < c_1 \text{ or } T > c_2$$

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where  $v_i \in [0, 1]$ ,  $i=1, 2$ , and  $c_i$  are real constants

$$E_{\theta_1}[\phi^*(x)] = E_{\theta_2}[\phi^*(x)] = \alpha$$

~~The second part of generalized NP lemma guarantees that~~

Thus  $\phi^*$  is in fact <sup>most powerful</sup> ~~the~~ test for testing

$$H_0: \theta \in \{\theta_1, \theta_2\}$$

among all tests  $\phi$  satisfying  $E_{\theta_i}[\phi] = \alpha$ ,  $i=1, 2$ . (as long as  $\theta_2 \in (\theta_1, \theta_2)$ )

Since  $\phi^*$  does not depend on  $\theta_2$  for testing

$\phi^*$  is also UMP test of size  $\alpha$  for testing

$$H_0: \theta \in \{\theta_1, \theta_2\}$$

among all tests  $\phi$  satisfying  $E_{\theta_i}[\phi] = \alpha$ ,  $i=1, 2$ .  
 Now comparing  $\phi^*$  with the no-data test  $\phi_0(x) = \alpha$ ,  $\forall x$

and using (b), we conclude that

$$P_{\phi^*}(\theta) \leq P_{\phi_0}(\theta) = \alpha, \quad \forall \theta \in (\theta_1, \theta_2) \cup (\theta_2, \theta_1)$$

$$\Rightarrow P_{\phi^*}(\theta) \leq \alpha, \quad \forall \theta < \theta_1 \text{ or } \theta > \theta_2$$

$$\Rightarrow \sup_{\theta \in (\theta_1, \theta_2) \cup (\theta_2, \theta_1)} P_{\phi^*}(\theta) = \alpha, \quad \text{i.e. } \phi^* \text{ is size } \alpha \text{ test for}$$

$$H_0: \theta \leq \theta_1 \text{ or } \theta \geq \theta_2$$

Consequently,  $\phi^*$  is UMP test of size  $\alpha$  for testing

$$H_0: \theta \leq \theta_1 \text{ or } \theta \geq \theta_2 \quad \text{vs} \quad H_1: \theta \in (\theta_1, \theta_2)$$

(b) Let  $\theta_4 < \theta_1$ . Consider minimizing  $P_{\phi}(\theta_4) = E_{\theta_4}[\phi]$  (or maximizing  $E_{\theta_4}(1-\phi)$ ) among all  $\phi$ 's s.t.  $E_{\theta_1}(\phi) = E_{\theta_2}(\phi) = \alpha$ . (or  $E_{\theta_1}(1-\phi) = E_{\theta_2}(1-\phi) = 1-\alpha$ ). By generalized NP lemma the minimized  $\phi^{**}$  is UMP test that

$$1 - \phi^{**} = 1 \Leftrightarrow g_{\theta_4}(t) > c, \quad g_{\theta_1}(t) + c_2 g_{\theta_2}(t)$$

$$1 - \phi^{**} = 0 \Leftrightarrow g_{\theta_4}(t) < c, \quad g_{\theta_1}(t) + c_2 g_{\theta_2}(t)$$

$$g_{\theta_1}(t) < c_1 g_{\theta_1}(t) + c_2 g_{\theta_2}(t)$$

$$\Leftrightarrow e^{(\eta(\theta_1) - \eta(\theta_1))t + b(\theta_1) - b(\theta_2)} - c_2 e^{(\eta(\theta_1) - \eta(\theta_1))t + b(\theta_1) - b(\theta_2)} < c_1$$

$$\Leftrightarrow a_1 e^{b_1 t} + a_2 e^{b_2 t} < c_1 \quad \text{where} \quad a_1 = e^{b(\theta_1) - b(\theta_2)} > 0,$$

$$b_1 = \eta(\theta_1) - \eta(\theta_1) < 0$$

$$a_2 = -c_2 e^{b(\theta_1) - b(\theta_2)} \in \mathbb{R}$$

$$b_2 = \eta(\theta_2) - \eta(\theta_1) > 0.$$

An in (a), the only possibility is  $a_1 > 0, a_2 > 0, c_1 > 0$ , in which case  $\phi^{**} = \phi^*$ .

Similarly one may minimize  $P_p(\theta_5)$  for  $\theta_5 > \theta_L$ , and get  $\phi^*$  as the derived test.

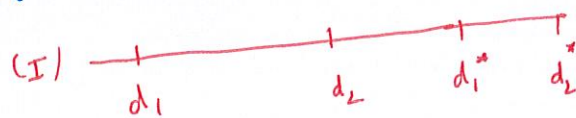
(c) Let

$$\phi_1(t) = \begin{cases} 1 & d_1 < t < d_L \\ v_i & t = d_i, i=1,2 \\ 0 & t < d_1 \text{ or } t > d_2 \end{cases}$$

$$\phi_2(t) = \begin{cases} 1 & d_1^* < t < d_2^* \\ v_i^* & t = d_i^*, i=1,2 \\ 0 & t < d_1^* \text{ or } t > d_2^* \end{cases}$$

$$\beta_{\phi_1}(\theta_0) = P_{\theta_2}(\theta_0)$$

And the vector  $\{\theta_2 = 1\}$  is to right of the vector  $\{\theta_1 = 1\}$



The following two cases I and II arise. Consider

$$\phi_2(t) - \phi_1(t) = \begin{cases} 0 & (0) \\ \leq 0 & (-) \\ - & (-) \\ \leq 0 & (-) \\ - & (0) \\ \geq 0 & (+) \\ + & (+) \\ \geq 0 & (+) \\ 0 & (0) \end{cases} \quad [36]$$

$$t < d_1$$

$$t = d_1$$

$$d_1 < t < d_L \quad (d_1 < t < d_1^*)$$

$$t = d_L \quad (t = d_1^*)$$

$$d_L < t < d_1^* \quad (d_1^* < t < d_2)$$

$$t = d_1^* \quad (t = d_L)$$

$$d_1^* < t < d_2^* \quad (d_L < t < d_2^*)$$

$$t = d_2^* \quad ($$

$$t > d_2^*$$

$\Rightarrow \phi_2(t+1) - \phi_1(t+1)$  has ~~at most~~ one change in sign (from - to +)  
 $\Rightarrow E_0[\phi_2(t+1) - \phi_1(t+1)]$  has ~~at most one change in sign~~  
 (from - to +).

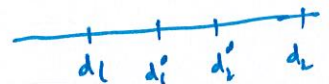
Since  $E_0[\phi_2(t+1) - \phi_1(t+1)] = 0$ , we get from last lemma

$$\begin{aligned}
 E_0[\phi_2 - \phi_1] &< 0, & \forall \theta < \theta_0 \\
 E_0[\phi_2 - \phi_1] &> 0, & \forall \theta > \theta_0 \\
 \Rightarrow P_{\phi_2}(\theta) &< P_{\phi_1}(\theta), & \forall \theta < \theta_0 \\
 \text{or } P_{\phi_2}(\theta) &> P_{\phi_1}(\theta), & \forall \theta > \theta_0
 \end{aligned}$$

Now suppose  $E_0[\phi_1] = E_0[\phi_2] = \alpha, \alpha \in \mathbb{R}$ .

$$E_0[\phi_1] = E_0[\phi_2]$$

$\Rightarrow$  the vector  $\{\phi_2 = 1\}$  lies either to the left or to the right of  $\{\phi_1 = 1\}$  (as the possibility  $\phi_2 = 1$  is ruled out)



Suppose  $\{\phi_2 = 1\}$  lies to the right of  $\{\phi_1 = 1\}$ . Then  $\phi_2 - \phi_1$  has at most one change in sign (from - to +) and  $E_0[\phi_2 - \phi_1] = 0$ . This implies that

$$\begin{aligned}
 E_0[\phi_2 - \phi_1] &< 0, & \forall \theta < \theta_1 \\
 E_0[\phi_2 - \phi_1] &> 0, & \forall \theta > \theta_1
 \end{aligned}$$

a contradiction.

Thus  $\phi_2 = \phi_1$  a.s.  $P$

Remark: (a) From part (c) of above theorem we conclude that  $c_i$ 's and  $d_i$ 's are uniquely determined.

(b) One can start with a trial test  $\phi_1^{(0)}$  with trial values  $c_1^{(0)}$  and  $d_1^{(0)}$ . Then find  $c_2^{(0)}$  and  $d_2^{(0)}$  s.t.  $\beta_{\phi_1^{(0)}}(\theta_1) = \alpha = \beta_{\phi_2^{(0)}}(\theta_1)$  and compute  $\beta_{\phi_1^{(1)}}(\theta_2)$ . If  $\beta_{\phi_1^{(1)}}(\theta_2) < \alpha = \beta_{\phi_2^{(0)}}(\theta_2)$ , then  $\phi_1^{(0)}$  is to the left of  $\phi_2^*$  (i.e.  $\phi_2^*$  is to the right of  $\phi_1^{(0)}$ ). Therefore one should try  $c_1^{(1)} > c_1^{(0)}$  or  $c_1^{(1)} = c_1^{(0)}$  and  $d_1^{(1)} > d_1^{(0)}$ . The converse holds if  $\beta_{\phi_1^{(1)}}(\theta_2) > \alpha$ .

(c) When the distribution of  $X$  does not belong to exponential family, UMP tests for testing  $H_0: \theta \leq \theta_1$  or  $\theta \geq \theta_2$  vs  $H_1: \theta_1 < \theta < \theta_2$  exist in some cases. (Ex:  $h(x) = \theta f_0(x) + (1-\theta) f_1(x)$ ,  $-1 < x < 1$ ,  $\theta \in (0,1) = \Theta$ , where  $f_0$  and  $f_1$  are given pdfs. In this case it can be shown that  $\phi^*(x) = \alpha$  is a UMP( $\alpha$ ) test for testing  $H_0: \theta \leq \theta_1$  or  $\theta \geq \theta_2$  vs  $H_1: \theta_1 < \theta < \theta_2$ .)

(d) UMP tests, in general, do not exist for testing  
 $H_0: \theta_1 \leq \theta \leq \theta_2$  vs  $H_1: \theta < \theta_1$  or  $\theta > \theta_2$   
 or  $H_0: \theta = \theta_0$  vs  $H_1: \theta \neq \theta_0$ .

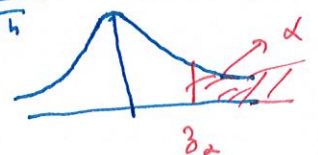
Example (Non-Existence of UMP test)

Let  $X_1, \dots, X_n$  be a random sample from  $N(\theta, 1)$ , where  $\theta \in \mathbb{R} = \Theta$ . Show that UMP( $\alpha$ ) test does not exist for testing

$H_0: \theta = 0$   
 vs  $H_1: \theta \neq 0$

**Solution**

On the contrary suppose that there exists a UMP( $\alpha$ ) test,  $\phi^*$ , is a fixed constant. Consider testing  $H_0: \theta = 0$  vs  $H_1: \theta = \theta_1$ , where  $\theta_1 > 0$ . The UMP( $\alpha$ ) test is  $\bar{X} > \frac{z_{1-\alpha/2}}{\sqrt{n}}$  or  $\bar{X} < -\frac{z_{1-\alpha/2}}{\sqrt{n}}$  o.w.



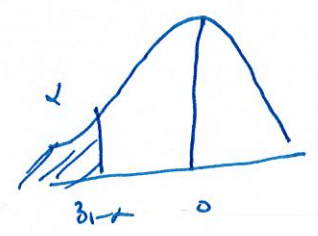
and  $P_{\theta_1 | \theta_1} = P_{\theta^* | \theta_1}$

By uniqueness of  $\pi(x)$  test we have  $\phi_1 \equiv \phi^*$ , a.e.

Now consider testing  $H_0: \theta = \theta_0$  vs  $H_1: \theta = \theta_2$ , where  $\theta_2 < \theta_0$ .

A  $\pi(x)$  test is

$$\phi_2(x) = \begin{cases} 1, & \bar{x} < \frac{\theta_2 - \alpha}{\sqrt{n}} \\ 0 & \text{o.w.} \end{cases}$$



and  $P_{\theta_2 | \theta_2} = P_{\theta^* | \theta_2}$ .

By uniqueness of  $\pi(x)$  test we have

$$\phi_2 \equiv \phi^* \text{ a.e.}$$

Thus we have

$$\phi^* = \phi_1 = \phi_2, \text{ a.e.}$$

leading to contradiction

Remark: (1) One can carry out the analysis of above example using completeness of  $\{N(\theta, 1): \theta > 0\}$  and consider testing problems (a)  $H_0: \theta = 0$  vs  $H_1: \theta > 0$ ; (b)  $H_0: \theta = 0$  vs  $H_1: \theta < 0$ . In the above analysis completeness of families  $\{N(\theta, 1): \theta > 0\}$  or  $\{N(\theta, 1): \theta < 0\}$  is crucial and the analysis will break down if any of these subfamilies is not complete, as the following example illustrates.

Example Let  $x_1, \dots, x_n$  be a random sample from  $N(\theta, 1)$  where  $\theta \in \mathbb{R} = \mathbb{R}$ . Let  $\theta_1$  and  $\theta_2$  be fixed real constants.

Consider testing

$$H_0: \theta \leq \theta_1 \text{ or } \theta \geq \theta_2$$

$$\text{vs } H_1: \theta_1 < \theta < \theta_2.$$

A  $\pi(x)$  test of size  $\alpha$  is

$$\phi_{\pi}(x) = \begin{cases} 1, & c_1 < \bar{x} < c_2 \\ 0, & \text{otherwise} \end{cases}$$

where  $c_1 < c_2$  is determined by  $E_{\theta_1}(\phi_{\pi}(x)) = E_{\theta_2}(\phi_{\pi}(x)) = \alpha \Leftrightarrow$

$$\begin{aligned} \Phi(\sqrt{n}(c_2 - \theta_1)) - \Phi(\sqrt{n}(c_1 - \theta_1)) &= \alpha \\ \Phi(\sqrt{n}(c_2 - \theta_2)) - \Phi(\sqrt{n}(c_1 - \theta_2)) &= \alpha \end{aligned}$$

# Uniformly Most Powerful Unbiased (UMPU) Tests

When the UMP test does not exist, we may restrict to a smaller class of reasonable tests to find optimal test in this class of tests. One such restricted class of tests is the class of unbiased tests.

Note that a UMP( $\alpha$ ) test  $\phi^*$  for testing  $H_0: \theta \in \theta_0$  vs  $H_1: \theta \in \theta_1$ , has the  $\beta$ -test

$$P_{\phi^*}(b) \leq \alpha, \quad \forall b \in \theta_0 \quad \text{and} \quad P_{\phi^*}(b) \geq \alpha, \quad \forall b \in \theta_1 \quad \dots (I)$$

The later inequality above follows on comparing  $\phi^*$  with no-data test  $\phi_0(x) \geq \alpha, \quad \forall x$ .

Note that (I) is equivalent to saying that  $\phi^*$  is at least as good as no-data test  $\phi_0$ . (or power  $\geq$  level of significance or size of the test)

## Definition

Consider testing

$$H_0: \theta \in \theta_0$$

$$\vee H_1: \theta \in \theta_1$$

at  $\alpha$  ( $\alpha \in (0,1)$ ) level of significance, nonempty where  $\theta_0$  and  $\theta_1$  are classes of p.d.f.s and  $\theta_0 \cup \theta_1 = \theta$ .

..... (A)

such that  $\theta_0 \cap \theta_1 = \emptyset$

(i) A test  $\phi$  is said to be unbiased if  $P_{\phi}(b) \leq \alpha, \quad \forall b \in \theta_0$  and  $P_{\phi}(b) \geq \alpha, \quad \forall b \in \theta_1$ .

(ii) A test of level  $\alpha$  is called a uniformly most powerful unbiased (UMPU) test if it is UMP within the class of unbiased tests of level  $\alpha$ .

Let  $\theta = \{ \theta_i : i \in \mathbb{N} \}$  where  $\mathbb{N} \subseteq \mathbb{R}^k$ . Let  $\theta_0 \subseteq \theta$  and  $\theta_1 \subseteq \theta$  be such that  $\theta_i \neq \emptyset, \quad i \geq 1, \quad \theta_0 \cap \theta_1 = \emptyset$  and  $\theta_0 \cup \theta_1 = \theta$ .

Consider testing

$$H_0: \theta \in \theta_0$$

$$\vee H_1: \theta \in \theta_1$$

at  $\alpha$  ( $\alpha \in (0,1)$ ) level of significance. .... (II)



Definition: Consider the testing problem (II). Let  $\alpha \in (0, 1)$  be a given level of significance and let  $\overline{\Theta}_{01}$  be the common boundary of  $\Theta_0$  and  $\Theta_1$ , i.e. the set of points that are ~~points~~ or limit points of both  $\Theta_0$  and  $\Theta_1$ . A test  $\phi$  is said to be similar (or  $\alpha$ -similar) on the boundary  $\overline{\Theta}_{01}$  iff

$$\beta_\phi(\theta) = \alpha, \quad \forall \theta \in \overline{\Theta}_{01}$$

(b) For a given test  $\phi$ , the power function  $\beta_\phi(\theta) = E_\theta(\phi(X))$  is said to be continuous in  $\theta \in \Theta$  iff for any sequence  $\{\theta_m\}_{m \geq 1} \in \Theta$  with  $\theta_m \rightarrow \theta_0$  as  $m \rightarrow \infty$  (where  $\theta_0 \in \Theta$ ), we have  $\beta_\phi(\theta_m) \rightarrow \beta_\phi(\theta_0)$ .

Define

$$\mathcal{E}_\alpha = \text{class of } \alpha\text{-similar tests} \\ = \{ \phi : 0 \leq \phi \leq 1, \beta_\phi(\theta) = \alpha, \forall \theta \in \overline{\Theta}_{01} \}$$

$$\mathcal{E}_U = \text{class of all unbiased tests} \\ = \{ \phi : 0 \leq \phi \leq 1, \beta_\phi(\theta) \leq \alpha, \forall \theta \in \Theta_0 \text{ and } \beta_\phi(\theta) \geq \alpha, \forall \theta \in \Theta_1 \}$$

Lemma If for every test function  $\phi$ ,  $\beta_\phi(\theta)$  is continuous in  $\theta \in \Theta$ , then  $\mathcal{E}_U \subseteq \mathcal{E}_\alpha$ .

Proof. Let  $\phi \in \mathcal{E}_U$ . Then  $\beta_\phi(\theta) \leq \alpha, \forall \theta \in \Theta_0$  and  $\beta_\phi(\theta) \geq \alpha, \forall \theta \in \Theta_1$ .

Let  $\theta_0 \in \overline{\Theta}_{01}$ . Then  $\theta_0$  is a limit point of  $\Theta_0$  and  $\Theta_1$  both.

Thus there exist sequences  $\{\theta_m^{(0)}\}_{m \geq 1} \in \Theta_0$  and  $\{\theta_m^{(1)}\}_{m \geq 1} \in \Theta_1$  such that

$$\lim_{m \rightarrow \infty} \theta_m^{(0)} = \lim_{m \rightarrow \infty} \theta_m^{(1)} = \theta_0$$

Then  $\beta_\phi(\theta_m^{(0)}) \leq \alpha, \forall m \geq 1$  and  $\beta_\phi(\theta_m^{(1)}) \geq \alpha, \forall m \geq 1$  ( $\phi$  is unbiased)

$$\lim_{m \rightarrow \infty} \beta_\phi(\theta_m^{(0)}) \leq \alpha \quad \text{and} \quad \lim_{m \rightarrow \infty} \beta_\phi(\theta_m^{(1)}) \geq \alpha$$

$$\Rightarrow \beta_{\phi}(\theta_0) \leq \alpha \quad \text{and} \quad \beta_{\phi}(\theta_1) \geq \alpha \quad (\text{Continuity of } \beta_{\phi}(\theta))$$

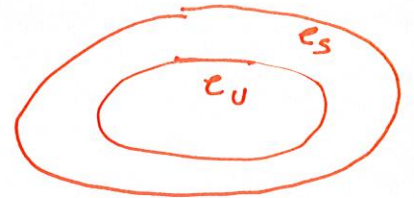
$$\Rightarrow \beta_{\phi}(\theta_0) = \alpha$$

Since  $\theta_0 \in \overline{\Theta}_0$  was arbitrary, we have

$$\beta_{\phi}(\theta) = \alpha, \quad \forall \theta \in \overline{\Theta}_0$$

$$\Rightarrow \phi \in e_s.$$

Consequently  $e_U \subseteq e_s$ .



Theorem Consider testing

$$H_0: \theta \in \Theta_0$$

$$\text{vs } H_1: \theta \in \Theta,$$

at  $\alpha$  ( $\alpha \in (0, 1)$ ) level of significance. Suppose that, for every test function  $\phi$ ,  $\beta_{\phi}(\theta) = E_{\theta}(Q(X))$  is a continuous function of  $\theta \in \Theta$ . Let  $\phi^*$  be a UMP test among all tests  $\phi$  satisfying  $\beta_{\phi}(\theta) = \alpha, \forall \theta \in \overline{\Theta}_0$  and has level  $\alpha$ .

(i.e.  $\phi^*$  is UMP( $\alpha$ ) test among all  $\alpha$ -Nuisance tests)  
Then  $\phi^*$  is UMP( $\alpha$ ) test.

Proof By the last lemma  $e_U \subseteq e_s$ . Thus it suffices to show that  $\phi^* \in e_U$ . Consider the no-data test  $\phi_0(z) \equiv \alpha, \forall z$ . Then  $\phi_0 \in e_s$  and therefore

$$\beta_{\phi^*}(\theta) \geq \beta_{\phi_0}(\theta), \quad \forall \theta \in \Theta, \quad (\phi^* \text{ is UMP within } e_s)$$

$$\beta_{\phi^*}(\theta) \geq \alpha, \quad \forall \theta \in \Theta, \quad \dots (A)$$

Since  $\phi^*$  has level  $\alpha$ , we have

$$\beta_{\phi^*}(\theta) \leq \alpha, \quad \forall \theta \in \Theta, \quad \dots (B)$$

$$(A) + (B) \Rightarrow \phi^* \in e_U.$$

Hence the result follows.

Remark Continuity of  $\beta_{\phi}(\theta)$ , for any test function  $\phi$ , is satisfied for distributions belonging to exponential family (to be discussed later)

a Sufficient Statistic for  $\Theta \in \overline{\Theta}_{01}$ . Define, for a test function  $\phi$ ,  
~~for a Sufficient Statistic (under  $\Theta \in \overline{\Theta}_{01}$ )~~

$$K_\phi(U) = E_\Theta(\phi(X)|U), \quad \Theta \in \overline{\Theta}_{01}. \quad (\text{does not depend on } \Theta \in \overline{\Theta}_{01})$$

= family of distributions of  $U$  as  $\Theta$  varies over  $\overline{\Theta}_{01}$ .

$K_\phi(U)$  does not depend on  $\Theta \in \overline{\Theta}_{01}$  (as  $U$  is sufficient for  $\Theta \in \overline{\Theta}_{01}$ )

~~$\phi$  be a test function satisfying~~ let  $\phi$  be a test function  
~~satisfying~~ a.s.  $P_U$

$$E_\Theta(\phi(X)|U) = \alpha, \quad \dots \dots \dots (c)$$

Then

$$E_\Theta(K_\phi(U)) = \alpha, \quad \forall \Theta \in \overline{\Theta}_{01},$$

i.e.  $\phi$  is  $\alpha$ -level on  $\overline{\Theta}_{01}$

A test  $\phi$  satisfying (c) is said to have Neyman Structure w.r.t.  $U$ . Define

$\mathcal{E}_\alpha$  = class of all tests having Neyman Structure. Then

$$\mathcal{E}_\alpha \subseteq \mathcal{E}_\alpha$$

Thus if all  $\alpha$ -level tests on  $\overline{\Theta}_{01}$  have Neyman Structure (i.e.  $\mathcal{E}_\alpha \subseteq \mathcal{E}_\alpha$ ) wrt  $U$ , then  $\mathcal{E}_\alpha = \mathcal{E}_\alpha$  and working with  $\mathcal{E}_\alpha$  is the same as working with  $\mathcal{E}_\alpha$ .

Theorem Let  $U(X)$  be a Sufficient Statistic for  $\Theta \in \overline{\Theta}_{01}$ . Then a necessary and sufficient condition for  $\mathcal{E}_\alpha = \mathcal{E}_\alpha$  is that  $U$  is boundedly complete for  $\overline{\Theta}_{01}$ .

Proof. First suppose that  $U$  is sufficient and boundedly complete for  $\Theta \in \overline{\Theta}_{01}$ . Let  $\phi \in \mathcal{E}_\alpha$ . Then

$$E_\Theta(\phi(X)) = \alpha, \quad \forall \Theta \in \overline{\Theta}_{01}$$

$$\Rightarrow E_\Theta(\phi(X) - \alpha) = 0, \quad \forall \Theta \in \overline{\Theta}_{01}$$

Consider

$$\psi(U) = E_\Theta((\phi(X) - \alpha)|U) = E_\Theta(\phi(X)|U) - \alpha, \quad \forall \Theta \in \overline{\Theta}_{01}$$

$$= K_\phi(U) - \alpha$$

Then  $\psi$  is bounded ( $-\alpha \leq \psi \leq 1 - \alpha$ ) and

$$E_\Theta(\psi(U)) = E_\Theta(E_\Theta(\phi(X) - \alpha)|U) = 0, \quad \forall \Theta \in \overline{\Theta}_{01}$$

$$\Rightarrow P_\Theta(\psi(U) = 0) = 1, \quad \forall \Theta \in \overline{\Theta}_{01}$$

$$\Rightarrow \psi(U) = \alpha, \text{ a.s. } \bar{\mathcal{P}}_U, P_\theta(K_\phi(U) = \alpha) = 1, \forall \theta \in \bar{\Theta}_1$$

$$\Rightarrow E_\theta[\phi(X)|U] = \alpha, \text{ a.s. } \bar{\mathcal{P}}_U$$

$$\Rightarrow \phi \in \mathcal{E}_r$$

$$\Rightarrow \mathcal{E}_s \subseteq \mathcal{E}_r \text{ and } \mathcal{E}_s = \mathcal{E}_r$$

Conversely suppose that  $\mathcal{E}_s \subseteq \mathcal{E}_r$ . On contrary suppose that  $U$  is not boundedly complete for  $\Theta \in \bar{\Theta}_1$ . Then there exists a function  $B$  s.t.  $|B(U)| \leq c < \infty$  for some constant  $0 < c < \infty$ ,  $E_\theta(B|U) = 0, \forall \theta \in \bar{\Theta}_1$  and  $P_\theta(B|U) \neq 0 > 0$ , for some  $\theta \in \bar{\Theta}_1$ .

Define

$$\phi(X) = \alpha + d B(U),$$

where  $d = \frac{\min(\alpha, 1-\alpha)}{c}$ . Then  $0 \leq \phi \leq 1$  and

$$E_\theta(\phi(X)) = \alpha, \forall \theta \in \bar{\Theta}_1,$$

i.e.  $\phi \in \mathcal{E}_s$ . By hypothesis, then  $\phi \in \mathcal{E}_r$  i.e.  $\bar{\mathcal{P}}_U$ .  
 $P_\theta(K_\phi(U) = \alpha) = 1, \forall \theta \in \bar{\Theta}_1 \Rightarrow P_\theta(B(U) = 0) = 1, \forall \theta \in \bar{\Theta}_1$   
 $\Rightarrow E_\theta(\phi(X)|U) = \alpha, \text{ a.s. } \bar{\mathcal{P}}_U \Rightarrow$

But, we have  $E_\theta(\phi(X)|U) = \alpha + d B(U) \neq \alpha, \text{ a.s. } \bar{\mathcal{P}}_U$

leading to a contradiction.  
 Hence  $U$  is boundedly complete for  $\Theta \in \bar{\Theta}_1$ .

Theorem Let  $X$  be a random vector having ~~Canonical~~ <sup>prob/pmf</sup> form belonging to exponential family having

$$f_\eta(x) = \exp\left\{ \sum_{i=1}^p \eta_i T_i(x) - \psi(\eta) \right\} h(x), \quad \eta \in \Theta_\eta,$$

where  $\Theta_\eta$  is the natural parameter space.

(a) The s.v.  $T = (T_1(X), \dots, T_p(X))$  has the following p.d.f. in an exponential family  $\eta \in \Theta_\eta$

$$g_\eta(t) = \exp\left\{ \sum_{i=1}^p \eta_i t_i - \psi(\eta) \right\} m(t),$$

Where  $w(\xi)$  is a non-negative function

(ii) If  $\eta_0$  is an interior point of natural parameter space  $\mathbb{R}^k$  and  $K$  is a  $\mathbb{R}$  function such that  $E_{\eta_0}(K(\xi)) \in (-\infty, \infty)$ , then the function  $E_{\eta}(K(\xi))$  is infinitely differentiable in a neighborhood of  $\eta_0$  and the derivatives may be computed by differentiating under the Integral sign.

### UMPV Tests For Exponential Family

Suppose that  $X$  has a p.d.f. / p.m.f. belonging to multiparameter exponential family with p.d.f. of  $X$  as

$$f_{\theta, \psi}(x) = \exp\{\theta \gamma(x) + \sum_{i=1}^k \psi_i u_i(x) - \xi(\theta, \psi)\} h(x) \dots (A)$$

where  $\theta$  and  $\gamma$  are real-valued,  $\psi = (\psi_1, \dots, \psi_k)^t$  and  $\underline{u} = (u_1, \dots, u_k)^t$  are vector-valued. *Let the range of  $\psi = (\psi_1, \dots, \psi_k)$  contain a fixed  $\psi = (\psi_1, \dots, \psi_k)$  is a c.s. statistic*

Clearly  $(\underline{y}, \underline{u})$  is a sufficient statistic with p.d.f. of

$$h_{\theta, \psi}(\underline{y}, \underline{u}) = \exp\{\theta \gamma + \sum_{i=1}^k \psi_i u_i - \xi(\theta, \psi)\} w(\underline{y}, \underline{u})$$

and the conditional p.d.f. of  $\gamma$  given  $\underline{u} = \underline{y}$  has p.d.f.

$$g_{\theta}(\gamma | \underline{y}) = e^{\theta \gamma} l(\gamma | \underline{y})$$

*Also, note that, for any fixed  $\theta$ ,  $\underline{u} = (u_1, \dots, u_k)$  is sufficient for  $\psi$ .*

For exponential family, continuity assumption of any test function  $\phi$  holds and thus  $\mathcal{L}_S = \mathcal{L}_N$ , i.e. working with  $\mathcal{L}_S$  is the same as working with  $\mathcal{L}_N$ .

Theorem Suppose that the distribution of  $X$  is in multiparameter natural exponential family with pdf/pmf

$$f_{\theta, \eta}(x) = \exp\{\theta \eta(x) + \sum_{i=1}^k \psi_i v_i(x) - \xi(\theta, \psi)\} h(x) \dots (A)$$

where  $\theta$  and  $\eta$  are real-valued,  $\psi = (\psi_1, \dots, \psi_k)^t$  and  $v = (v_1, \dots, v_k)^t$  are vector-valued and for any fixed  $\theta$ , the range of  $\psi = (\psi_1, \dots, \psi_k)$  contains a  $k$ -dimensional rectangle in  $\mathbb{R}^k$ . Let  $\theta_0, \theta_1, \theta_2$  be fixed constants.

(a) For testing  $H_0: \theta \leq \theta_0$  vs  $H_1: \theta > \theta_0$ , a UMPV( $\alpha$ ) test  $\phi_1^*$  having size  $\alpha$

$$\phi_1^*(T, v) = \begin{cases} 1 & T > c(v) \\ \gamma & T > c_1(v) \\ 0 & T < c_2(v) \end{cases}$$

where  $c(v)$  and  $\gamma$  are functions determined by

$$E_{\theta_0}(\phi_1^*(T, v) | v = \underline{v}) = \alpha,$$

for every  $\underline{v}$ , and  $E_{\theta_0}(\cdot)$  is the expectation wrt  $\theta_0, \psi$

(b) For testing  $H_0: \theta \leq \theta_1$  or  $\theta \geq \theta_2$  vs  $H_1: \theta_1 < \theta < \theta_2$ , a UMPV( $\alpha$ ) test, having size  $\alpha$ , is

$$\phi_2^*(T, v) = \begin{cases} 1 & \text{if } c_1(v) < T < c_2(v) \\ v_i(v) & \text{if } T > c_1(v) \quad c_1 < c_2 \\ 0 & \text{if } T < c_1(v) \text{ or } T > c_2(v) \end{cases}$$

where  $c_1(v)$  and  $c_2(v)$  are determined by

$$E_{\theta_1}(\phi_2^*(T, v) | v = \underline{v}) = E_{\theta_2}(\phi_2^*(T, v) | v = \underline{v}) = \alpha,$$

for every  $\underline{v}$

(c) For testing  $H_0: \theta_1 \leq \theta \leq \theta_2$  vs  $H_1: \theta < \theta_1$  or  $\theta > \theta_2$ , a UMP( $\alpha$ ) test, having size  $\alpha$ , is

$$\phi_{\alpha}^*(Y, \underline{u}) = \begin{cases} 1, & \text{if } \gamma < c_1(\underline{u}) \text{ or } \gamma > c_2(\underline{u}) \\ 0, & \text{if } \gamma > c_1(\underline{u}), \\ 0, & \text{if } c_1(\underline{u}) < \gamma < c_2(\underline{u}) \end{cases} \quad \dots (B)$$

where  $c_1(\underline{u})$ 's and  $c_2(\underline{u})$ 's are determined by

$$E_{\theta_0}(\phi_{\alpha}^*(Y, \underline{u}) | \underline{u} = \underline{u}) = E_{\theta_0}(\phi_{\alpha}^*(Y, \underline{u}) | \underline{u} = \underline{u}) = \alpha,$$

for every  $\underline{u}$ .

(d) For testing  $H_0: \theta = \theta_0$  vs  $H_1: \theta \neq \theta_0$ , a UMP( $\alpha$ ) test, having size  $\alpha$ , is given by (B) where  $c_1(\underline{u})$ 's and  $c_2(\underline{u})$ 's are determined by

$$E_{\theta_0}(\phi_{\alpha}^*(Y, \underline{u}) | \underline{u} = \underline{u}) = \alpha$$

$$\text{and } E_{\theta_0}(\phi_{\alpha}^*(Y, \underline{u}) | \underline{u} = \underline{u}) = \alpha E_{\theta_0}(\gamma | \underline{u} = \underline{u}),$$

for every  $\underline{u}$ .

Proof. Note that  $(Y, \underline{u})$  is a sufficient statistic for  $(\theta, \underline{u})$ . Thus it suffices to consider only those test functions that depend on  $\underline{x}$  only through  $(Y, \underline{u})$ .

(a) We have  $\bar{\Theta}_{\theta_0} = \{(\theta, \underline{u}) : \theta = \theta_0\}$ . Clearly  $\underline{u}$  is C-S for  $\theta \in \bar{\Theta}_{\theta_0}$  and consequently  $e_S = e_{\theta}$  and power functions of all tests are continuous functions of  $\theta$ .

Thus if  $\phi^*$  is UMP  $\alpha$ -similar test and has level  $\alpha$ , then  $\phi^*$  is UMP( $\alpha$ ) test. It is enough to show that  $\phi^*$  is UMP among all tests having Neyman structure w.r.t.  $\underline{u}$ . Conditional f.d.f. of  $Y$  given  $\underline{u} = \underline{u}$  is

$$g_{\theta}(\underline{y} | \underline{u}) = e^{\theta \underline{y}} h(\underline{y} | \underline{u})$$

The assertion follows from a result done before.

(b) Let  $\bar{\Theta}_{01} = \{\theta, \psi\}: \theta \in \{\theta_1, \theta_2\}\}$ , let  $\bar{\Theta}_1^* = \{\theta, \psi\}: \theta = \theta_1\}$   
 and  $\bar{\Theta}_2^* = \{\theta, \psi\}: \theta = \theta_2\}$ . Then  $\underline{U}$  is C-S under  $\bar{\Theta}_1^*$  and  $\bar{\Theta}_2^*$ .  
 And it suffices to find UMP test based among tests having Neyman structure. Using the result done before the assertion follows.

(c) From a result done before we know that  $\phi_2^*$  (b) minimizes  $E_{\theta}[\phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}]$  over all  $\alpha < \alpha_1, \alpha > \alpha_2$   
 and  $\phi$  satisfying  $E_{\theta_1}[\phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] = E_{\theta_2}[\phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] = 1 - \alpha$  (replace using (b) with  $\alpha$  replaced by  $1 - \alpha$ ). Also  $E_{\theta}[\phi_2^*(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] \geq 1 - \alpha, \forall \theta_1 < \alpha < \theta_2$   
 $\Rightarrow 1 - \phi_2^*(\underline{Y}, \underline{U})$  maximizes  $E_{\theta}[1 - \phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}]$  over all  $\alpha < \alpha_1, \alpha > \alpha_2$  and  $\phi$  satisfying  $E_{\theta_1}[1 - \phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] = E_{\theta_2}[1 - \phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] = \alpha$ . Also  $E_{\theta}[1 - \phi_2^*(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] \leq \alpha, \forall \theta_1 < \alpha < \theta_2$

Since  $\{\phi: 0 \leq \phi \leq 1\} = \{1 - \phi: 0 \leq \phi \leq 1\}$ , we conclude that the test in (c) maximizes  $E_{\theta}[\phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}]$  over all  $\alpha < \alpha_1, \alpha > \alpha_2$  and  $\phi$  satisfying

$$E_{\theta_1}[\phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] = E_{\theta_2}[\phi(\underline{Y}, \underline{U}) | \underline{U} = \underline{u}] = \alpha.$$

Also  $\phi_2^*$  has level  $\alpha$ .

(d) Let us first derive conditions for a test  $\phi$  to be unbiased for testing  $H_0: \theta = \theta_0$  vs  $H_1: \theta \neq \theta_0$ . Here  $\bar{\Theta}_{01} = \{\theta, \psi\}: \theta = \theta_0\}$   
 and  $\underline{U}$  is C-S for  $\bar{\Theta}_{01}$ . ~~Any unbiased test  $\phi$  satisfies~~ ~~A test  $\phi$  is unbiased iff~~

$$E_{\theta_0, \psi}[\phi(\underline{Y}, \underline{U})] \geq \alpha \geq E_{\theta_1, \psi}[\phi(\underline{Y}, \underline{U})], \quad \forall \theta_1 \neq \theta_0, \forall \psi$$

~~$\theta_0, \psi \in \bar{\Theta}_{01}, \theta_1, \psi \in \bar{\Theta}_{01}$~~

By continuity of power function, we have, a test  $\phi$  is unbiased iff

$$E_{\theta_0, \psi}[\phi(\underline{Y}, \underline{U})] = \alpha, \quad \forall \theta_0, \psi \in \bar{\Theta}_{01}$$

and

$$E_{\theta_1, \psi}[\phi(\underline{Y}, \underline{U})] \geq E_{\theta_2, \psi}[\phi(\underline{Y}, \underline{U})] = \alpha, \quad \forall \theta_1 > \theta_0, \forall \psi$$

~~$\theta_0, \psi \in \bar{\Theta}_{01}$~~   
~~and  $\theta_1, \psi \in \bar{\Theta}_{01}$~~



$\Rightarrow$   $E_{\theta_0, \psi}(\phi(\gamma, \underline{y})) = \alpha, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$  even if  $(\theta_0, \psi) \in \bar{\Theta}_\alpha$   
 $\Leftarrow$  and  $E_{\theta_0, \psi}(\phi(\gamma, \underline{y}))$  has a local minimum at  $\theta_0 = \theta_0, \forall \psi$ .  
 Thus ~~any unbiased estimator  $\phi$  is inadmissible~~  
 a test  $\phi$  is unbiased iff

$$E_{\theta_0, \psi}(\phi(\gamma, \underline{y})) = \alpha, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\text{and } \frac{\partial}{\partial \theta} E_{\theta_0, \psi}(\phi(\gamma, \underline{y})) = 0, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\Rightarrow \frac{\partial}{\partial \theta} \int \phi(\gamma, \underline{y}) e^{\theta \gamma + \sum_{i=1}^k \psi_i u_i - \xi(\theta, \psi)} h(\underline{y}) d\underline{y} = 0, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\Rightarrow \int \frac{\partial}{\partial \theta} [ \phi(\gamma, \underline{y}) e^{\theta \gamma + \sum_{i=1}^k \psi_i u_i - \xi(\theta, \psi)} h(\underline{y}) ] d\underline{y} = 0, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\Rightarrow \int \phi(\gamma, \underline{y}) e^{\theta \gamma + \sum_{i=1}^k \psi_i u_i - \xi(\theta, \psi)} h(\underline{y}) \left[ \gamma - \frac{\partial}{\partial \theta} \xi(\theta, \psi) \right] d\underline{y} = 0, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\Rightarrow E_{\theta_0, \psi}[\gamma \phi(\gamma, \underline{y})] = \alpha \frac{\partial}{\partial \theta} \xi(\theta, \psi), \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

We have

$$\int e^{\theta \gamma + \sum_{i=1}^k \psi_i u_i - \xi(\theta, \psi)} h(\underline{y}) \lambda \gamma = 1, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\Rightarrow \frac{\partial}{\partial \theta} \int [ \dots ] = 0, \quad "$$

$$\Rightarrow \int \frac{\partial}{\partial \theta} [ \dots ] = 0, \quad "$$

$$\Rightarrow \int e^{\theta \gamma + \sum_{i=1}^k \psi_i u_i - \xi(\theta, \psi)} h(\underline{y}) \left[ \gamma - \frac{\partial}{\partial \theta} \xi(\theta, \psi) \right] d\underline{y} = 0, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

$$\Rightarrow E(\gamma) = \frac{\partial}{\partial \theta} \xi(\theta, \psi), \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha$$

Thus, for (a), any unbiased test of level  $\alpha$  with restriction

$$\left\{ \begin{array}{l} \text{and } E_{\theta_0, \psi}(\phi(\gamma, \underline{y})) = \alpha, \forall (\theta_0, \psi) \in \bar{\Theta}_\alpha \\ E_{\theta_0, \psi}(\gamma \phi(\underline{y}, \underline{y})) = \alpha E_{\theta_0, \psi}(\gamma), \forall \theta \in \bar{\Theta}_\alpha \end{array} \right.$$

$$\Leftrightarrow \begin{cases} E_{\theta_0, \psi} ( E_{\theta_0, \psi} ( \phi(\gamma, \underline{y}) - \alpha | \underline{y} ) ) = 0 & \forall \theta_0 \in \Theta_{01} \\ E_{\theta_0, \psi} ( E ( \gamma \phi(\gamma, \underline{y}) - \alpha \gamma | \underline{y} ) ) = 0 & \forall \theta_0 \in \Theta_{01} \end{cases}$$

By virtue of completeness of  $\underline{y}$ , it follows that

$$\begin{cases} E_{\theta_0, \psi} ( \phi(\gamma, \underline{y}) | \underline{y} ) = \alpha \\ \text{or } E_{\theta_0, \psi} ( \gamma \phi(\gamma, \underline{y}) | \underline{y} ) = \alpha E_{\theta_0, \psi} ( \gamma | \underline{y} ) \end{cases}$$

does not depend on  $(\theta_0, \psi) \in \Theta_{01}$

Thus, for (a) it suffices to show that  $\phi_3^*$  is UMP among all tests satisfying (\*)

~~Under conditional distribution (given  $\underline{y}$ ) the power function of any test  $\phi(\gamma, \underline{y})$  is~~

$$P_\phi(\theta_0, \psi) = E_{\theta_0, \psi} ( E_{\theta_0, \psi} ( \phi(\gamma, \underline{y}) | \underline{y} ) )$$

and thus it suffices to show that for any  $(\theta_0, \psi) \in \Theta_{01}$ , and any fixed  $\underline{y}$ ,  $\phi_3^*$  maximizes

$$E_{\theta_0, \psi} ( \phi(\gamma, \underline{y}) | \underline{y} )$$

over all  $\phi$  satisfying (\*)

Now the conditional p.d.f. of  $\gamma$  given  $\underline{y} = \underline{y}$  is

$$g_{\theta_0}(\gamma | \underline{y}) = e^{\theta_0 \gamma} l(\underline{y}, \underline{y})$$

Clearly  $\{g_{\theta_0} : \theta_0 \in \Theta\}$  has MLR in  $\gamma$ , for every fixed  $\underline{y}$ .

We now omit  $\underline{y}$  in the following discussion, as whole discussion is in reference to conditional dist. of  $\gamma$  given  $\underline{y}$ , for fixed  $\underline{y}$ .

Consider testing  $H_0: \theta = \theta_0$  vs  $H_1: \theta = \theta_1$ . Then the rejection region of UMP test satisfying (\*) is

$$g_{\theta_1}(\gamma | \underline{y}) > k_1 e^{\theta_0 \gamma} + k_2 e^{\theta_1 \gamma}$$

$$g_{01}(y|u) > k_1 e^{g_{01}(y)} + k_2 y g_{01}(y)$$

$$\Leftrightarrow e^{\delta_1 y} > k_1 e^{\delta_0 y} + k_2 y e^{\delta_0 y}$$

where  $k_1, k_2$  are constants.

$$\Leftrightarrow a_1 + a_2 y < e^{by} \quad (a_1 = k_1, a_2 = k_2, b = \delta_1 - \delta_0)$$

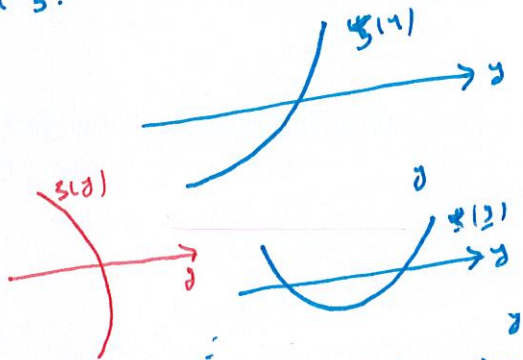
for some constants  $a_1, a_2$  and  $b$ .

Consider

$$s(y) = e^{by} - a_2 y - a_1$$

$$s'(y) = b e^{by} - a_2$$

$$s''(y) = b^2 e^{by} > 0$$



Thus the C.R.  $\{y: s(y) > 0\}$  is either one-sided or two outside an interval. But a one-sided test has strictly monotone power function and therefore can not be unbiased. Thus this test must have the form of the test given in (c). Since this test does not depend on  $\theta_1$ , it is UMP among all tests satisfying the unbiased condition.

Lemma: Suppose that  $X$  has  $pab/pmb$

$f_{\theta_0, \psi}(z) = \exp\{\theta Y(z)\} + \sum_{i=1}^k w_i U_i(z) - S(\theta, \psi) h(z)$ ,  
 as defined in (A) let  $\theta_0, \theta_1$  and  $\theta_2$  are fixed constants as defined in the hypotheses of (a)-(c) last theorem. Let  $V(Y, \underline{u})$  be a statistic such that  $V(Y, \underline{u})$  and  $\underline{u}$  are independent when  $(\theta, \psi) \in \overline{\Theta}_{\theta_1}$ .

(a) If  $V(Y, \underline{u})$  is increasing in  $Y$ , for each  $\underline{u}$ , then UMPU tests in (a)-(c) of above theorem are equivalent to those in (a)-(c) with  $Y$  and  $V(Y, \underline{u})$  replaced by  $V$  and  $W$  with

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$c_i(u)$ 's and  $d_i(u)$ 's replaced by  $c_i$ 's and  $d_i$ 's (independent of  $u$ ).

(b) If there are functions  $a(u) > 0$  and  $b(u)$  such that  $V(\gamma, u) = a(u)\gamma + b(u)$ , then the UMPU test in (d) of above theorem is equivalent to the one obtained by replacing  $\gamma$  at  $(\gamma, u)$  by  $v$  and  $c_i(u)$ 's and  $d_i(u)$ 's replaced by  $c_i$ 's and  $d_i$ 's.

Proof (a) Since, for every fixed  $u$ ,  $V(\gamma, u) \uparrow \gamma > c_i(u) \Leftrightarrow v > d_i(u)$ , for some  $d_i(u)$ .  
 The assertion now follows from the fact that  $V$  and  $u$  are statistically independent. No that  $d_i$ 's and  $c_i$ 's do not depend on  $u$ , when  $\gamma$  is replaced by  $v$ .

(b) (a) Since  $V = a(u)\gamma + b(u)$ , the UMPU test of (d) is the same as

$$\phi_{\gamma}^*(V, u) = \begin{cases} 1, & \\ d_1(u), & \\ 0, & \end{cases}$$

$$\begin{aligned} &v < d_1(u) \text{ or } v > d_2(u) \\ &v = d_1(u), \quad c_1 < v < d_2(u) \end{aligned}$$

Subject to

$$\begin{cases} E_{\theta_0, \psi}(\phi^*(V, u) | u) = \alpha, & \forall (\theta_0, \psi) \in \overline{\Theta}_{\alpha} \\ \text{or } E_{\theta_0, \psi}(\phi^*(V, u) \frac{v - b(u)}{a(u)} | u) = \alpha E_{\theta_0} \left( \frac{v - b(u)}{a(u)} | u \right) \\ & \forall (\theta_0, \psi) \in \overline{\Theta}_{\alpha} \end{cases}$$

$$\Leftrightarrow \begin{cases} E_{\theta_0, \psi}(\phi^*(V, u) | u) = \alpha, & \forall (\theta_0, \psi) \in \overline{\Theta}_{\alpha} \\ \text{or } E_{\theta_0}(\phi^*(V, u) V | u) = \alpha E_{\theta_0}(V | u), & \forall (\theta_0, \psi) \in \overline{\Theta}_{\alpha} \end{cases}$$

Since  $V$  and  $u$  are independent,  $c_i(u)$ 's and  $d_i(u)$ 's do not depend on  $u$  and therefore  $\phi_{\gamma}^*$  does not depend on  $u$ .

## One Sample Problem From Normal Family

Let  $x_1, \dots, x_n$  be a random sample from  $N(\mu, \sigma^2)$ , where  $n \geq 2$  and  $\mu \in (-\infty, \infty)$  and  $\sigma > 0$  are unknown parameters

Case I: Hypothesis concerning  $\mu$  with  $\sigma = \sigma_0$  known

$$H_0: \mu = \mu_0 \\ \forall H_1: \mu \neq \mu_0,$$

for known  $\mu_0 \in \mathbb{R}$ .

$$f_{\theta}(x) = \frac{1}{(2\pi\sigma_0^2)^{\frac{n}{2}}} e^{-\frac{n}{2\sigma_0^2}(\mu - \mu_0)\bar{x}}$$

$$e^{-\frac{n}{2\sigma_0^2}(\mu - \mu_0)\bar{x}} = e^{-\frac{n\mu_0\bar{x}}{2\sigma_0^2} - \frac{1}{2\sigma_0^2} \sum x_i^2 + \frac{n\mu_0^2}{2\sigma_0^2}}$$

$$\theta = \frac{n}{\sigma_0^2}(\mu - \mu_0),$$

$$H_0: \theta = 0 \\ \forall H_1: \theta \neq 0$$

$$T = \bar{X}$$

There are no nuisance parameters  $\psi'$  and  $\underline{U}'$  no one should use the above results with condition distribution of  $\underline{Y}$  given  $\underline{U} = \underline{u}$  just replaced by distribution of  $\underline{Y}$ .

The UMPU(x) test is

$$\phi^*(x) = \begin{cases} 1, \\ 0, \end{cases}$$

$$T < c_1 \text{ or } T > c_2$$

$$c_1 < T < c_2$$

When  $E_{\theta=0}(\phi^*(x)) = \alpha$

and  $E_{\theta=0}(\phi^*(x)T) = \alpha E_{\theta=0}(T)$

$$P_{\mu_0}(\bar{X} < c_1) + P_{\mu_0}(\bar{X} > c_2) = \alpha$$

$$E_{\mu_0}(\bar{X} I(\bar{X} < c_1)) + E_{\mu_0}(\bar{X} I(\bar{X} > c_2)) = \alpha E_{\mu_0}(\bar{X})$$

Let  $Z = \frac{\sqrt{n}(\bar{X} - \mu_0)}{\sigma_0} \sim N(0, 1)$ , under  $\mu = \mu_0$

$$(a) \quad \Phi\left(\frac{\sqrt{n}(c_1 - \mu_0)}{\sigma_0}\right) + 1 - \Phi\left(\frac{\sqrt{n}(c_2 - \mu_0)}{\sigma_0}\right) = \alpha \quad \dots (a)$$

and  $E\left[\left(\frac{\sigma_0 Z}{\sqrt{n}} + \mu_0\right) I\left(Z < \frac{\sqrt{n}(c_1 - \mu_0)}{\sigma_0}\right)\right] + E\left[\left(\frac{\sigma_0 Z}{\sqrt{n}} + \mu_0\right) I\left(Z > \frac{\sqrt{n}(c_2 - \mu_0)}{\sigma_0}\right)\right] = \alpha \mu_0 \quad \dots (b)$

$$(b) \Leftrightarrow \frac{\sigma_0}{\sqrt{n}} \left[ E\left[Z I\left(Z < \frac{\sqrt{n}(c_1 - \mu_0)}{\sigma_0}\right)\right] + E\left[Z I\left(Z > \frac{\sqrt{n}(c_2 - \mu_0)}{\sigma_0}\right)\right] \right] = 0 \quad \dots (c)$$

Since  $Z \stackrel{d}{=} -Z$ , we have

$$E\left[Z I\left(Z > \frac{\sqrt{n}(c_2 - \mu_0)}{\sigma_0}\right)\right] = -E\left[Z I\left(Z < -\frac{\sqrt{n}(c_2 - \mu_0)}{\sigma_0}\right)\right]$$

Then by taking  $\frac{\sqrt{n}(c_2 - \mu_0)}{\sigma_0} = -\frac{\sqrt{n}(c_1 - \mu_0)}{\sigma_0}$ , (c) (and hence (b))

is satisfied. Putting this in (a) we get

$$\Phi\left(\frac{\sqrt{n}(c_1 - \mu_0)}{\sigma_0}\right) = \frac{\alpha}{2}$$

$$\Rightarrow c_1 = \mu_0 + \frac{\sigma_0}{\sqrt{n}} \Phi^{-1}\left(\frac{\alpha}{2}\right) = \mu_0 - \frac{\sigma_0}{\sqrt{n}} \Phi^{-1}(1 - \alpha/2)$$

$$c_2 = \mu_0 + \frac{\sigma_0}{\sqrt{n}} \Phi^{-1}(1 - \alpha/2)$$

(Note that  $\Phi^{-1}(\alpha/2) < 0$  and  $\Phi^{-1}(1 - \alpha/2) > 0$ )

and Unpooled test

$$\phi(\bar{X}) = \begin{cases} 1, \\ 0, \end{cases}$$

$$\bar{X} < \mu_0 - \frac{\sigma_0}{\sqrt{n}} \Phi^{-1}(1 - \alpha/2) \text{ or } \bar{X} > \mu_0 + \frac{\sigma_0}{\sqrt{n}} \Phi^{-1}(1 - \alpha/2)$$

0-0

$$= \begin{cases} 1, \\ 0, \end{cases} \quad \left| \frac{\sqrt{n}(\bar{X} - \mu_0)}{\sigma_0} \right| > \Phi^{-1}(1 - \alpha/2)$$

otherwise.

Under Case (I), now consider test  $\rightarrow$

$$H_0: \mu \leq \mu_1 \text{ or } \mu \geq \mu_2$$

$$\vee H_1: \mu < \mu_1 \text{ or } \mu > \mu_2$$

where  $\mu_1$  and  $\mu_2$  ( $\mu_1 < \mu_2$ ) are pre-specified.

UMP( $\alpha$ ) test is

$$\phi^*(X) = \begin{cases} 1, & Y < c_1 \text{ or } Y > c_2 \\ 0, & c_1 < Y < c_2 \end{cases}$$

where  $E_{\mu_1}(\phi^*(X)) = E_{\mu_2}(\phi^*(X)) = \alpha$

$$P_{\mu_1}(X < c_1) + P_{\mu_2}(X > c_2) = \alpha, \quad i=1, 2$$

$$\Phi\left(\frac{\sqrt{n}(c_1 - \mu_1)}{\sigma}\right) + 1 - \Phi\left(\frac{\sqrt{n}(c_2 - \mu_2)}{\sigma}\right) = \alpha, \quad i=1, 2$$

i.e.

$$\Phi\left(\frac{\sqrt{n}(c_2 - \mu_1)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(c_1 - \mu_1)}{\sigma}\right) = 1 - \alpha, \quad i=1, 2$$

$\Rightarrow$

$$\Phi\left(\frac{\sqrt{n}(c_2 - \mu_1)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(c_1 - \mu_1)}{\sigma}\right) = 1 - \alpha$$

and

$$\Phi\left(\frac{\sqrt{n}(c_2 - \mu_2)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(c_1 - \mu_2)}{\sigma}\right) = 1 - \alpha$$

Note: For test  $H_0: |\mu| \leq \mu_0$  (where  $\mu_0 > 0$  is pre-specified)  $\vee H_1: |\mu| > \mu_0$  (i.e.  $\mu = \mu_0$  and  $\mu = -\mu_0$ ), we get

$$\Phi\left(\frac{\sqrt{n}(c_2 + \mu_0)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(c_1 + \mu_0)}{\sigma}\right) = 1 - \alpha$$

$$\Phi\left(\frac{\sqrt{n}(c_2 - \mu_0)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(c_1 - \mu_0)}{\sigma}\right) = 1 - \alpha$$

$$\Rightarrow \Phi\left(\frac{\sqrt{n}(-c_1 + \mu_0)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(-c_2 + \mu_0)}{\sigma}\right) = 1 - \alpha$$

**PSS**

$$\Rightarrow c_1 = -c_2 \text{ and } \Phi\left(\frac{\sqrt{n}(c_2 + \mu_0)}{\sigma}\right) - \Phi\left(\frac{\sqrt{n}(-c_1 + \mu_0)}{\sigma}\right) = 1 - \alpha \quad \text{--- (*)}$$

Clearly, LHS of (4) is a strictly increasing function of  $c_2$  and LHS  $e(0, \infty)$  as  $c_2$  varies from 0 to  $\infty$ . Thus there is unique  $c_2$  satisfying (4)

Case II:  $\sigma > 0$  is unknown.

$$H_0: \mu \leq \mu_0$$

$$H_1: \mu > \mu_0$$

$$f_{\theta, \psi}(x) = e^{-\frac{n(\mu - \mu_0)(\bar{x} - \mu_0)}{\sigma^2}} \frac{1}{2\sigma^2} \sum (x_i - \mu_0)^2 \dots$$

$$\theta = \frac{n(\mu - \mu_0)}{\sigma^2}, \quad \psi = -\frac{1}{2\sigma^2} = \gamma = \bar{x} - \mu_0, \quad U = \sum_{i=1}^n (x_i - \mu_0)^2$$

By Basu's Theorem  $\gamma$  and  $U$  are independent under  $\mu = \mu_0$ .

Take  $V(\gamma, U) = V = \frac{\sqrt{n}(\bar{x} - \mu_0)}{\sqrt{\frac{\sum (x_i - \mu_0)^2}{n}}}$   $\uparrow \gamma = \bar{x}$  for every fixed  $U$ .

UMP(U) test is

$$\phi^*(x) = \begin{cases} 1, & V > c \\ 0, & \text{o.w.} \end{cases}$$

where

$$E_{\mu_0}(\phi^*(x)) = \alpha$$

$$= P_{\mu_0, \sigma} (V > c) = \alpha$$

Under  $H_0: \mu = \mu_0$  and  $\sigma > 0$ ,  $V \sim t_n$  (Student's  $t$  dist with  $n$  d.f.)

$\Rightarrow c = (1 - \alpha)^{1/n}$  quantile of  $t$  dist with  $n$  d.f.

Note:  $\frac{V}{\sqrt{n}} = \frac{\sqrt{n}(\bar{x} - \mu_0)}{\sqrt{\frac{\sum (x_i - \mu_0)^2}{n}}} = \frac{\sqrt{n}(\bar{x} - \mu_0)}{\sqrt{(n-1) \frac{S^2}{n} + n(\bar{x} - \mu_0)^2}} = \frac{T_{n-1}}{\sqrt{n-1 + T_{n-1}^2}}$



Where  $T_{n-1} = \frac{\sqrt{n}(\bar{X} - \mu_0)}{S_{n-1}}$  (  $S_{n-1} = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$  )

$\sim t_{n-1}$  ( Student t-dist with  $(n-1)$  d.f )  
 Under  $\mu = \mu_0$

$\frac{V}{\sqrt{h}} \uparrow T_{n-1}$  [  $\frac{d}{dx} \frac{\lambda}{\sqrt{n+\lambda^2}} = \frac{n-1}{(n-1+\lambda^2)^{3/2}} > 0$  ]

An equivalent UMP( $\alpha$ ) test is

$\phi_1^*(X) = \begin{cases} 1, & T_{n-1} > c^* \\ 0, & \text{o.w.} \end{cases}$

Where  $E_{\mu_0, \sigma}(\phi_1^*(X)) = \alpha$   
 $P_{\mu_0, \sigma}(T_{n-1} > c^*) = \alpha$

$\Rightarrow c^* = (1-\alpha)$ th quantile of t-distribution with  $(n-1)$  d.f.

Now Consider

$H_0: \mu = \mu_0$   $\Leftrightarrow$   $H_0: \theta = 0$   
 $V \cap H_1: \mu \neq \mu_0$   $\Leftrightarrow$   $V \cap H_1: \theta \neq 0$

$V = V(\gamma, U) = \frac{\sqrt{n}(\bar{X} - \mu_0)}{\sqrt{\sum_{i=1}^n (X_i - \mu_0)^2 / n}} = \frac{n\bar{X} - n\mu_0}{\sqrt{U}}$

Under  $\mu = \mu_0$ ,  $V \sim T_n$  ( Student t-dist with  $n$  d.f )  
 UMP( $\alpha$ ) test is  $a(U) \gamma + b(U)$ ,  $a(U) > 0$   
 $V < c_1$  or  $V > c_2$   
 $c_1 < \bar{X} < c_2$

$\phi^*(X) = \begin{cases} 1, \\ 0, \end{cases}$

... (a)

Where

$E_{\mu_0, \sigma}(\phi^*) = \alpha$

$E_{\mu_0, \sigma}(\phi^* V) = \alpha E_{\mu_0, \sigma}(V)$  ... (b)

(P57)

$$\Rightarrow P(T_n < c_1) + P(T_n > c_2) = \alpha$$

$$E(T_n I(T_n < c_1)) + E(T_n I(T_n > c_2)) = \alpha$$

$$T_n \stackrel{d}{=} -T_n \Rightarrow c_1 = -c_2$$

The Unbiased test is

$$\phi(x) = \begin{cases} 1, & |T_n| > c \\ 0, & \text{o.w.} \end{cases}$$

Where

$$P(T_n \leq c) = 1 - \frac{\alpha}{2}$$

$\Rightarrow c = (1 - \frac{\alpha}{2})^{\text{th}}$  quantile of  $t$  dist. with  $n$  d.f.

An earlier an equivalent test is

$$\phi_1^*(x) = \begin{cases} 1, & \text{if } |T_{n-1}| > c^* \\ 0, & \text{o.w.} \end{cases}$$

Where  $T_{n-1} = \frac{\sqrt{n}(\bar{X} - \mu_0)}{S_{n-1}}$  and  $c^* = (1 - \frac{\alpha}{2})^{\text{th}}$  quantile of

Student  $t$ -distribution with  $(n-1)$  d.f.

Case III hypothesis concerning  $\sigma^2$

Case IIIA:  $\mu = \mu_0$  is known

$$H_0: \sigma^2 = \sigma_0^2$$

$$H_1: \sigma^2 \neq \sigma_0^2$$

$$f_{\sigma^2}(x) = e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_0)^2} \cdot \frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2$$

$$\theta = -\frac{1}{2\sigma^2}, \quad Y = \sum_{i=1}^n (x_i - \mu_0)^2 \sim \sigma^2 \chi_n^2 \text{ under } H_0$$

$\rightarrow$  has NLR in  $Y$ .

UMPV( $\alpha$ ) test is

$$\phi^*(|Z|) = \begin{cases} 1, & \gamma < c_1 \text{ or } \gamma > c_2 \\ 0, & c_1 < \gamma < c_2 \end{cases}$$

Where  $E_{\sigma_0}(\phi^*) = \alpha$  and  $E_{\sigma_0}(\phi^*V) = \alpha E_{\sigma_0}(V)$   
 and  $E_{\sigma_0}((1-\phi^*)V) = (1-\alpha)E_{\sigma_0}(V)$

$\Rightarrow P_{\sigma_0}(c_1 < \gamma < c_2) = 1 - \alpha$

$$\Rightarrow \int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} \frac{e^{-y/2} y^{\frac{n}{2}-1}}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} dy = 1 - \alpha \quad \text{and} \quad \int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} \frac{e^{-y/2} y^{\frac{n}{2}-1}}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} dy = (1-\alpha) \quad (\text{Under } \frac{\gamma}{\sigma_0^2} \sim \chi_n^2)$$

$$\int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} \chi_n^2(y) dy = 1 - \alpha \quad \text{and} \quad \int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} \chi_{n+2}^2(y) dy = 1 - \alpha$$

i.e.  $\int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} \chi_n^2(y) dy = \int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} \chi_{n+2}^2(y) dy = 1 - \alpha$

When  $n$  is large (i.e.  $n-1 \approx n+1$ ) then  $\frac{c_1}{\sigma_0^2}$  and  $\frac{c_2}{\sigma_0^2}$  are heavily  $(\frac{\alpha}{2})^{\text{th}}$  and  $(1 - \frac{\alpha}{2})^{\text{th}}$  quantiles of  $\chi_n^2$  distribution

Similarity for tested

$H_0: \sigma_1^2 \leq \sigma_2^2 \leq \sigma_3^2$

$\vee H_1: \sigma_1^2 < \sigma_1^2 \text{ or } \sigma_1^2 > \sigma_2^2$

When  $0 < a_1 < a_2 < a_3$  are fixed constants and

$$\phi_1^*(|Z|) = \begin{cases} 1, \\ 0, \end{cases} \quad \text{Otherwise}$$

Where  $E_{\sigma_1}(\phi_1^*(|Z|)) = \alpha$ ,  $c_2 \leq 2$

$\Rightarrow E_{\sigma_1}((1-\phi_1^*(|Z|))) = 1 - \alpha$ ,  $c_2 \leq 2$

$$\Leftrightarrow \int_{\frac{d_1}{\sigma_1^2}}^{\frac{d_2}{\sigma_2^2}} f_{X_{n-1}^L}(y) dy = \int_{\frac{d_1}{\sigma_1^2}}^{\frac{d_2}{\sigma_2^2}} f_{X_{n-1}^L}(y) dy = 1 - \alpha.$$

Case II B:  $\mu$  is unknown

$$H_0: \sigma^2 = \sigma_0^2 \\ \text{vs } H_1: \sigma^2 \neq \sigma_0^2$$

$$f_{\theta, \psi}(\lambda) = e^{-\frac{1}{2\sigma^2} \sum x_i^2 + \frac{n\mu}{\sigma^2} \bar{x} - \frac{n\mu^2}{2\sigma^2} - \frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2}$$

$$\theta = -\frac{1}{2\sigma^2}, \quad \gamma = \sum_{i=1}^n x_i^2, \quad \psi = \frac{n\mu}{\sigma^2}, \quad U = \bar{x}$$

By Basu's Theorem

$V = (n-1)S^2$  and  $U = \bar{x}$  are independent

$$V = \gamma - nU^2 = a(U)\gamma + b(U), \quad a(U) > 0.$$

Under  $H_0$   $\frac{V}{\sigma_0^2} \sim X_{n-1}^2$

$$H_0: \sigma^2 = \sigma_0^2 \\ \text{vs } H_1: \sigma^2 \neq \sigma_0^2$$

$$\Leftrightarrow H_0: \theta = \theta_0 \\ \text{vs } H_1: \theta \neq \theta_0$$

UMP(U) test is

$$\phi^*(X) = \begin{cases} 1, & V < c_1 \text{ or } V > c_2 \\ 0, & \text{o.w.} \end{cases}$$

where  $E_{\sigma_0^2}(\phi^*) = \alpha$  and  $E_{\sigma_0^2}(\phi^* V) = \alpha E_{\sigma_0^2}(V)$

As before we get

$$\int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} f_{X_{n-1}^2}(y) dy = \int_{\frac{c_1}{\sigma_0^2}}^{\frac{c_2}{\sigma_0^2}} f_{X_{n-1}^2}(y) dy = 1 - \alpha.$$

When  $n-1 \approx n$  (i.e.  $n$  is large), then  $\frac{c_1}{\sigma_0^2}$  and  $\frac{c_2}{\sigma_0^2}$  are heavily  $(\frac{\alpha}{2})^{th}$

and  $(1 - \frac{\alpha}{2})^{th}$  quantiles of  $\chi^2_n$  distribution.

The hypothesis testing of

$$H_0: \sigma_1^2 \leq \sigma^2 \leq \sigma_2^2$$

$$\forall H_1: \sigma^2 < \sigma_1^2 \text{ or } \sigma^2 > \sigma_2^2$$

can be dealt with similarly.

### The Sample Problems

$$\begin{aligned} x_{11}, \dots, x_{1n_1} &\stackrel{iid}{\sim} N(\mu_1, \sigma_1^2) \\ x_{21}, \dots, x_{2n_2} &\stackrel{iid}{\sim} N(\mu_2, \sigma_2^2) \end{aligned} \quad \left. \vphantom{\begin{aligned} x_{11}, \dots, x_{1n_1} \\ x_{21}, \dots, x_{2n_2} \end{aligned}} \right\} \text{independent, } n_1 \geq 2, n_2 \geq 2$$

Consider testing

$$H_0: \frac{\sigma_2^2}{\sigma_1^2} \leq \Delta_0$$

$$\forall H_1: \frac{\sigma_2^2}{\sigma_1^2} > \Delta_0$$

$$H_0: \frac{\sigma_2^2}{\sigma_1^2} = \Delta_0$$

$$\forall H_1: \frac{\sigma_2^2}{\sigma_1^2} \neq \Delta_0$$

Where  $\Delta_0 > 0$  is a fixed constant

$$f_{\theta, \psi}(\lambda) = \exp \left\{ -\frac{1}{2\sigma_1^2} \sum_{j=1}^{n_1} x_{1j}^2 - \frac{1}{2\sigma_2^2} \sum_{j=1}^{n_2} x_{2j}^2 + \frac{n_1 \mu_1 \bar{x}_1}{\sigma_1^2} + \frac{n_2 \mu_2 \bar{x}_2}{\sigma_2^2} - \frac{n_1 \mu_1^2}{\sigma_1^2} - \frac{n_2 \mu_2^2}{\sigma_2^2} - \frac{n_1 + n_2}{2} \ln 2\pi - \frac{n_1}{2} \ln \sigma_1^2 - \frac{n_2}{2} \ln \sigma_2^2 \right\}$$

$$= \exp \left\{ -\frac{1}{2} \sum_{j=1}^{n_2} x_{2j}^2 \left\{ \frac{1}{\sigma_2^2} - \frac{1}{\Delta_0 \sigma_1^2} \right\} - \frac{1}{2\sigma_1^2} \left\{ \sum_{j=1}^{n_1} x_{1j}^2 + \frac{\sum_{j=1}^{n_2} x_{2j}^2}{\Delta_0} \right\} + \frac{n_1 \mu_1 \bar{x}_1}{\sigma_1^2} + \frac{n_2 \mu_2 \bar{x}_2}{\sigma_2^2} - \frac{n_1 \mu_1^2}{\sigma_1^2} - \frac{n_2 \mu_2^2}{\sigma_2^2} - \frac{n_1 + n_2}{2} \ln 2\pi - \frac{n_1}{2} \ln \sigma_1^2 - \frac{n_2}{2} \ln \sigma_2^2 \right\}$$

$$\theta = \frac{1}{2} \left( \frac{1}{\Delta_0 \sigma_{1L}^2} - \frac{1}{\sigma_{2L}^2} \right), \quad \gamma = \sum_{j=1}^{n_L} X_{2j}^2$$

$$\underline{\Psi} = \left( -\frac{1}{2\sigma_{1L}^2}, \frac{n_1 \mu_1}{\sigma_{1L}^2}, \frac{n_2 \mu_2}{\sigma_{2L}^2} \right)$$

$$\underline{U} = \left( \sum_{j=1}^{n_1} x_{1j}^2 + \frac{1}{\Delta_0} \sum_{j=1}^{n_2} x_{2j}^2, \bar{x}_1, \bar{x}_2 \right) = (U_1, U_2, U_3)$$

Define

$$V(\underline{\gamma}, \underline{u}) = \frac{(n_2 - 1) S_2^2 / \Delta_0}{(n_1 - 1) S_1^2 + (n_2 - 1) S_2^2 / \Delta_0} = \frac{\gamma - n_2 U_3^2}{U_1 - n_1 U_2^2 - n_2 U_3^2 / \Delta_0} \uparrow \gamma$$

By Basu's Theorem  $V$  and  $\underline{U}$  are independent under  $\sigma_{1L}^2 = \Delta_0 \sigma_{2L}^2$ . Thus a UMPUCR test for

$$H_0: \frac{\sigma_{1L}^2}{\sigma_{2L}^2} \leq \Delta_0$$

$$H_1: \frac{\sigma_{1L}^2}{\sigma_{2L}^2} > \Delta_0$$

$$H_0: \theta \leq 0$$

$$H_1: \theta > 0$$

is

$$\phi^*(X) = \begin{cases} 1, \\ 0, \end{cases}$$

$$V > c_1$$

otherwise

where

$$E_{\sigma_{1L}^2 = \sigma_{2L}^2 \Delta_0}(\phi^*) = \alpha$$

$$P_{\sigma_{1L}^2 = \sigma_{2L}^2 \Delta_0}(V > c_1) = \alpha$$

Under  $\sigma_{1L}^2 = \sigma_{2L}^2 \Delta_0$

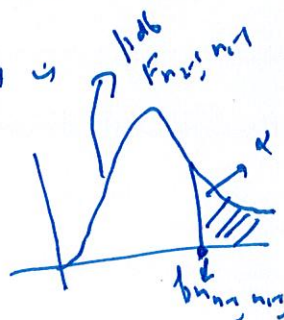
$$V = \frac{(n_2 - 1) F}{(n_1 - 1) + (n_2 - 1) F}, \quad \text{where } F = \frac{S_1^2 / \Delta_0}{S_2^2 / \Delta_0} \sim F_{n_2 - 1, n_1 - 1}$$

Since  $V \uparrow$  as  $F \uparrow$ , an equivalent UMPUCR test is

$$Q_1^*(X) = \begin{cases} 1, \\ 0, \end{cases}$$

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if  $F > b_{n_2 - 1, n_1 - 1, \alpha}$   
if  $F < b_{n_2 - 1, n_1 - 1, \alpha}$



Where  $b_{a,b,\alpha} = (1-\alpha)^{\alpha}$  quantile for  $F_{a,b}$

Now consider testing

$$H_0: \frac{\sigma_1^2}{\sigma_2^2} = \Delta_0 \quad \Leftrightarrow \quad H_0: \delta = 0$$

$$V \wedge H_1: \frac{\sigma_1^2}{\sigma_2^2} \neq \Delta_0 \quad \Leftrightarrow \quad V \wedge H_1: \delta \neq 0$$

Here

$$V = a(\underline{Y}) + b(\underline{U})$$

Then a UMPUC( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1, & \text{if } V < c_1 \text{ or } V > c_2 \\ 0, & \text{if } c_1 < V < c_2 \end{cases}$$

Where  $E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(\phi^*) = \alpha$  and  $E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(\phi^* V) = \alpha E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(V)$

Under  $\sigma_1^2 = \sigma_1^2 \Delta_0$ ,  $V \sim \text{Beta}(\frac{n_2-1}{2}, \frac{n_1-1}{2})$

$$E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(V) = \frac{n_2-1}{n_1+n_2-2}$$

$$E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(\phi^* V) = \alpha E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(V)$$

$$\Leftrightarrow E_{\sigma_1^2 = \sigma_1^2 \Delta_0}((1-\phi^*)V) = (1-\alpha) E_{\sigma_1^2 = \sigma_1^2 \Delta_0}(V)$$

$$\Leftrightarrow \int_{c_1}^{c_2} v \cdot b_{\frac{n_2-1}{2}, \frac{n_1-1}{2}}(v) dv = \frac{(1-\alpha)(n_2-1)}{n_1+n_2-2}$$

Where  $b_{a,b}$  is the p.d.f. of  $\text{Beta}(a,b)$

$$v \cdot b_{\frac{n_2-1}{2}, \frac{n_1-1}{2}}(v) = \frac{n_2-1}{n_1+n_2-2} b_{\frac{n_2-1}{2}, \frac{n_1-1}{2}}(v)$$

Thus, we have

$$\int_{c_1}^{c_2} b_{\frac{n_2-1}{2}, \frac{n_1-1}{2}}(v) dv = 1-\alpha = \int_{c_1}^{c_2} b_{\frac{n_2-1}{2}, \frac{n_1-1}{2}}(v) dv$$

If  $n_2 - 1 \approx n_2 + 1$  (i.e. if  $n_2$  is large) then equal tail test can be used.

Now consider testing

$$H_0: \mu_1 \geq \mu_2 \quad \text{or} \quad H_0: \mu_1 = \mu_2$$

$$\text{vs } H_1: \mu_1 < \mu_2 \quad \text{or} \quad \text{vs } H_1: \mu_1 \neq \mu_2$$

Case I  $\sigma_1^2 \neq \sigma_2^2$

→ Behrens/Fisher Problem and is not acremible by UMPU test method.  
→ Two Sample procedure (Stein)

Case II:  $\sigma_1^2 = \sigma_2^2 = \sigma^2$ ,  $N(\mu, \sigma^2)$

$$b_{\sigma, \psi}(\underline{x}) = \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^2 \sum_{j=1}^{n_i} x_{ij}^2 + \frac{n_1 \mu_1}{\sigma^2} \bar{x}_1 + \frac{n_2 \mu_2}{\sigma^2} \bar{x}_2 - \frac{n_1 \mu_1}{\sigma^2} - \frac{n_2 \mu_2}{\sigma^2} - \frac{n_1 + n_2}{2} \ln(2\pi) - \frac{n_1 + n_2}{2} \ln \sigma^2 \right\}$$

$$= \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^2 \sum_{j=1}^{n_i} x_{ij}^2 + \left( \frac{\mu_2}{\frac{\sigma^2}{n_2} + \frac{\sigma^2}{n_1}} - \frac{\mu_1}{\frac{\sigma^2}{n_2} + \frac{\sigma^2}{n_1}} \right) (\bar{x}_2 - \bar{x}_1) + \frac{n_1 \mu_1 + n_2 \mu_2}{(n_1 + n_2) \sigma^2} (n_1 \bar{x}_1 + n_2 \bar{x}_2) - \frac{n_1 \mu_1}{\sigma^2} - \frac{n_2 \mu_2}{\sigma^2} - \frac{n_1 + n_2}{2} \ln(2\pi) - \frac{n_1 + n_2}{2} \ln \sigma^2 \right\}$$

$$\theta = \frac{\mu_2 - \mu_1}{\sigma^2 \left( \frac{1}{n_1} + \frac{1}{n_2} \right)}, \quad \gamma = \bar{x}_2 - \bar{x}_1, \quad \psi = \left( \frac{n_1 \mu_1 + n_2 \mu_2}{(n_1 + n_2) \sigma^2}, -\frac{1}{2\sigma^2} \right)$$

$$\underline{U} = \left( n_1 \bar{x}_1 + n_2 \bar{x}_2, \sum_{i=1}^2 \sum_{j=1}^{n_i} x_{ij} \right)$$

$$(\bar{x}_2 - \bar{x}_1) / \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

$$\sqrt{\frac{(\bar{x}_2 - \bar{x}_1) / \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}{\frac{\sum_{i=1}^2 \sum_{j=1}^{n_i} (x_{ij} - \frac{n_1 \bar{x}_1 + n_2 \bar{x}_2}{n_1 + n_2})^2}{n_1 + n_2 - 2}}} \quad \uparrow \gamma$$

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$\sim T_{n_1+n_2-1}$  (Student's t distribution with  $n_1+n_2-1$  d.f.)

Under  $H_0: (\sigma_1 = \sigma_2)$

Also,  $\mu_1 = \mu_2$ ,  $V(\bar{Y}, \bar{V})$  and  $\underline{U}$  are independent by Basu's theorem.

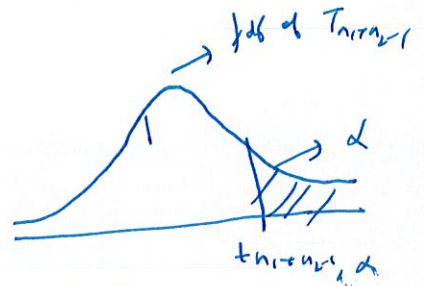
Case II A:  $H_0: \mu_1 \geq \mu_2$   $\Leftrightarrow \forall \theta: \theta \leq 0$   
 $\forall \theta: \mu_1 < \mu_2$   $\Leftrightarrow \forall \theta: \theta > 0$

UMPV( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1 \\ 0 \end{cases}$$

$v > c$

o.w.



Where  $E_{\theta=0}(\phi^*(x)) = \alpha \Rightarrow c = t_{n_1+n_2-1, \alpha}$

Case II B:  $H_0: \mu_1 = \mu_2$   $\Leftrightarrow \forall \theta: \theta = 0$   
 $\forall \theta: \mu_1 \neq \mu_2$   $\Leftrightarrow \forall \theta: \theta \neq 0$

UMPV( $\alpha$ ) test is

$$\phi^*(x) = \begin{cases} 1 \\ 0 \end{cases}$$

$v < c_1$  or  $v > c_2$

o.w.

Where  $E_{\mu_1=\mu_2}(\phi^*(x)) = \alpha$ , &  $E_{\mu_1=\mu_2}(\phi^*(x|v)) = \alpha E_{\mu_1=\mu_2}(v)$   
 $\Leftrightarrow E_{\mu_1=\mu_2}(1-\phi^*(x)) = 1-\alpha$ , &  $E_{\mu_1=\mu_2}((1-\phi^*(x))v) = (1-\alpha)E_{\mu_1=\mu_2}(v)$

As before we will have  $c_2 = -c_1 = t_{n_1+n_2-1, 1-\alpha/2}$

### Testing for Independence in the Bivariate Normal Model

Let  $X_j = \begin{pmatrix} x_{1j} \\ x_{2j} \end{pmatrix}$ ,  $j=1, 2, \dots, n$  be a random sample from

$$N_2 \left( \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \right)$$

Where  $\theta = (\mu_1, \mu_2, \sigma_1, \sigma_2, \rho) \in \Theta = \mathbb{R}^2 \times (0, \infty)^2 \times (-1, 1)$  a vector of unknown parameters.

Consider test of

$$\forall H_0: \rho \leq 0 \\ \forall H_1: \rho > 0$$

or

$$H_0: \rho = 0 \\ \forall H_1: \rho \neq 0$$

We have

$$f_{\theta, \psi}(\underline{x}) = (2\pi \sigma_1 \sigma_2 \sqrt{1-\rho^2})^{-n} \times \\ \exp \left[ -\frac{1}{2(1-\rho^2)} \left[ \frac{\sum_{j=1}^n (x_{1j} - \mu_1)^2}{\sigma_1^2} + \frac{\sum_{j=1}^n (x_{2j} - \mu_2)^2}{\sigma_2^2} - \frac{2\rho}{\sigma_1 \sigma_2} \sum_{j=1}^n (x_{1j} - \mu_1)(x_{2j} - \mu_2) \right] \right]$$

$$\theta = \frac{\rho}{\sigma_1 \sigma_2 (1-\rho^2)}, \quad \gamma = \sum_{j=1}^n x_{1j} x_{2j}, \quad \underline{U} = \left( \sum_{j=1}^n x_{1j}^2, \sum_{j=1}^n x_{2j}^2, \sum_{j=1}^n x_{1j}, \sum_{j=1}^n x_{2j} \right)$$

Consider

$$V(\underline{\gamma}, \underline{U}) = R = \frac{\sum_{j=1}^n (x_{1j} - \bar{x}_1)(x_{2j} - \bar{x}_2)}{\sqrt{\left\{ \sum_{j=1}^n (x_{1j} - \bar{x}_1)^2 \right\} \left\{ \sum_{j=1}^n (x_{2j} - \bar{x}_2)^2 \right\}}}$$

Under  $H_0$ ,  $V$  and  $\underline{U}$  are independent and

$$T = \frac{\sqrt{n-2} R}{\sqrt{1-R^2}} \sim T_{n-2} \quad \left( \text{Student } t\text{-distribution with } n-2 \text{ d.f.} \right)$$

Thus one can construct a  $t$  test based on Statistic  $T$ .