

$$H_0: \theta \in \Theta_0 \quad \text{vs} \quad H_1: \theta \in \Theta_1,$$

$$\lambda(x) = \frac{\sup_{\theta \in \Theta_0} L(\theta|x)}{\sup_{\theta \in \Theta_0 \cup \Theta_1} L(\theta|x)}$$

$$\frac{\sup_{\Theta_0} L(\theta|x)}{\sup_{\Theta_1} L(\theta|x)}$$

$$H_0: \theta \in \Theta_0 \quad \text{vs} \quad H_1: \theta \notin \Theta_0$$

Power function.

$$\begin{aligned} \beta(\theta) &= P_{\theta}(\text{reject } H_0) \\ &= P_{\theta}(x \in RR) \end{aligned}$$

$$\phi(x) = \begin{cases} 1 & x \in RR \\ 0 & x \notin RR \end{cases}$$

$$\beta(\theta) = E_{\theta}[\phi(x)]$$

Type I error : reject H_0 when H_0 is true
 $\beta(\theta)$ when $\theta \in \Theta_0$

Type II error : do not reject H_0 when H_1 is true
 $1 - \beta(\theta)$ when $\theta \in \Theta_1$

Level α test :

$$\sup_{\theta \in \Theta_0} \beta(\theta) \leq \alpha$$

Size α test :

$$\sup_{\theta \in \Theta_0} \beta(\theta) = \alpha$$

UMP: uniformly most powerful test.

A test with power function $\beta(\theta)$ is a UMP test.
if $\beta(\theta) \geq \beta^*(\theta)$ for all $\theta \in \Theta_1$,
where $\beta^*(\theta)$ is the power function of any other test.
restricted to a class of tests:
{ all level α tests }

$$H_0: \theta = \theta_0 \quad \text{versus} \quad H_1: \theta = \theta_1 \quad (*)$$

simple - versus - simply

denote by $f_{\underline{X}}(\underline{x} | \theta_0)$ the joint pdf of $\underline{X} = (X_1, \dots, X_n)$ at $\theta = \theta_0$

$f_{\underline{X}}(\underline{x} | \theta_1)$ the joint pdf of $\underline{X} = (X_1, \dots, X_n)$ at $\theta = \theta_1$

$$\text{Let } \phi(\underline{x}) = \begin{cases} 1 & \frac{f_{\underline{X}}(\underline{x} | \theta_1)}{f_{\underline{X}}(\underline{x} | \theta_0)} > k \\ 0 & \frac{f_{\underline{X}}(\underline{x} | \theta_1)}{f_{\underline{X}}(\underline{x} | \theta_0)} < k \end{cases}$$

for $k > 0$, where k is determined by

$$\alpha = P_{\theta_0}(X \in RR) = E_{\theta_0}[\phi(X)]$$

Theorem 8.3.12 (Neyman-Pearson Lemma)

This $\phi(\underline{x})$ gives us a (UMP) test for (*)

meaning: if you have another test $\phi^*(\underline{x})$, where $E_{\theta_0}[\phi^*(\underline{x})] \leq \alpha$,
Prob of Type I error

$$\text{then } E_{\theta_1}[\phi^*(\underline{x})] \leq E_{\theta_1}[\phi(\underline{x})]$$

1 - Prob of Type II error

Proof: $E_{\theta_0}[\phi(x)] = \alpha$

for any other level α $\phi^*(x)$

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

Goal: $E_{\theta_0}[\phi^*(x)] \leq E_{\theta_0}[\phi(x)]$

$$\Leftrightarrow E_{\theta_0}[\phi(x) - \phi^*(x)] \geq 0$$

Define $b(x) = [\phi(x) - \phi^*(x)] [f_x(x|\theta_1) - k f_x(x|\theta_0)]$

$b(x) \geq 0$

Case I: $f_x(x|\theta_1) - k f_x(x|\theta_0) > 0$

$$\phi(x) = 1 \geq \phi^*(x)$$

$$\phi(x) - \phi^*(x) \geq 0$$

Then $b(x) \geq 0$

Case II: $f_x(x|\theta_1) - k f_x(x|\theta_0) < 0$

$$\phi(x) = 0 \leq \phi^*(x)$$

$$\phi(x) - \phi^*(x) \leq 0$$

Then $b(x) \geq 0$

Case III: $f_x(x|\theta_1) - k f_x(x|\theta_0) = 0$

Then $b(x) = 0$

$\Rightarrow b(x) \geq 0$

$$b(x) = [\phi(x) - \phi^*(x)] [f_x(x|\theta_1) - k f_x(x|\theta_0)]$$

$$= [\phi(x) - \phi^*(x)] f_x(x|\theta_1) - k [\phi(x) - \phi^*(x)] f_x(x|\theta_0) \geq 0$$

for x

$$\begin{aligned} \text{Then } \int [\phi(x) - \phi^*(x)] f_x(x|\theta_1) dx \\ \geq k \int [\phi(x) - \phi^*(x)] f_x(x|\theta_0) dx \end{aligned}$$

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

$$\geq k \underbrace{E_{\theta_0} [\phi(x) - \phi^*(x)]}_{\geq 0}$$

$$\underbrace{E_{\theta_0} [\phi(x)]}_{\geq \alpha} - \underbrace{E_{\theta_0} [\phi^*(x)]}_{\leq \alpha} \geq 0 \quad \#$$

8.3.2 Most powerful tests

Definition: Let \mathcal{C} be a class of tests for testing

$$\begin{aligned} H_0 : \theta \in \Theta_0 \\ \text{versus} \\ H_1 : \theta \in \Theta_0^c, \end{aligned}$$

where $\Theta_0^c = \Theta \setminus \Theta_0$. A test in \mathcal{C} with power function $\beta(\theta)$ is a **uniformly most powerful (UMP) class \mathcal{C} test** if

$$\beta(\theta) \geq \beta^*(\theta) \quad \text{for all } \theta \in \Theta_0^c,$$

where $\beta^*(\theta)$ is the power function of any other test in \mathcal{C} . The “uniformly” part in this definition refers to the fact that the power function $\beta(\theta)$ is larger than (i.e., at least as large as) the power function of any other class \mathcal{C} test **for all** $\theta \in \Theta_0^c$.

Important: In this course, we will restrict attention to tests $\phi(\mathbf{x})$ that are level α tests. That is, we will take

$$\mathcal{C} = \{\text{all level } \alpha \text{ tests}\}.$$

This restriction is analogous to the restriction we made in the “optimal estimation problem” in Chapter 7. Recall that we restricted attention to unbiased estimators first; we then wanted to find the one with the smallest variance (uniformly, for all $\theta \in \Theta$). In the same spirit, we make the same type of restriction here by considering only those tests that are level α tests. This is done so that we can avoid having to consider “silly tests,” e.g.,

$$\phi(\mathbf{x}) = 1 \quad \text{for all } \mathbf{x} \in \mathcal{X}.$$

The power function for this test is $\beta(\theta) = 1$, for all $\theta \in \Theta$. This test cannot be beaten in terms of power when H_1 is true! Unfortunately, it is not a very good test when H_0 is true.

Recall: A test $\phi(\mathbf{x})$ with power function $\beta(\theta)$ is a **level α test** if

$$\sup_{\theta \in \Theta_0} \beta(\theta) \leq \alpha.$$

That is, $P(\text{Type I Error}|\theta)$ can be **no larger** than α for all $\theta \in \Theta_0$.

Starting point: We start by considering the **simple-versus-simple** test:

$$\begin{aligned} H_0 : \theta = \theta_0 \\ \text{versus} \\ H_1 : \theta = \theta_1. \end{aligned}$$

Both H_0 and H_1 specify exactly one probability distribution.

Remark: This type of test is rarely of interest in practice. However, it is the “building block” situation for more interesting problems.

Theorem 8.3.12 (Neyman-Pearson Lemma). Consider testing

$$\begin{aligned} H_0 : \theta = \theta_0 \\ \text{versus} \\ H_1 : \theta = \theta_1 \end{aligned}$$

and denote by $f_{\mathbf{X}}(\mathbf{x}|\theta_0)$ and $f_{\mathbf{X}}(\mathbf{x}|\theta_1)$ the pdfs (pmfs) of $\mathbf{X} = (X_1, X_2, \dots, X_n)$ corresponding to θ_0 and θ_1 , respectively. Consider the test function

$$\phi(\mathbf{x}) = \begin{cases} 1, & \frac{f_{\mathbf{X}}(\mathbf{x}|\theta_1)}{f_{\mathbf{X}}(\mathbf{x}|\theta_0)} > k \\ 0, & \frac{f_{\mathbf{X}}(\mathbf{x}|\theta_1)}{f_{\mathbf{X}}(\mathbf{x}|\theta_0)} < k, \end{cases}$$

for $k \geq 0$, where

$$\alpha = P_{\theta_0}(\mathbf{X} \in R) = E_{\theta_0}[\phi(\mathbf{X})]. \tag{8.1}$$

Sufficiency: Any test satisfying the definition of $\phi(\mathbf{x})$ above and Equation (8.1) is a **most powerful (MP) level α test**.

Remarks:

- The necessity part of the Neyman-Pearson (NP) Lemma is less important for our immediate purposes (see CB, pp 388).
- In a simple-versus-simple test, any MP level α test is obviously also UMP level α . Recall that the “uniformly” part in UMP refers to all $\theta \in \Theta_0^c$. However, in a simple H_1 , there is only one value of $\theta \in \Theta_0^c$. I choose to distinguish MP from UMP in this situation (whereas the authors of CB do not).

Example 8.13. Suppose that X_1, X_2, \dots, X_n are iid $\text{beta}(\theta, 1)$, where $\theta > 0$; i.e., the population pdf is

$$f_X(x|\theta) = \theta x^{\theta-1} I(0 < x < 1).$$

Derive the MP level α test for

$$\begin{aligned} H_0 : \theta = 1 & \quad \theta_0 = 1 & \text{where if } H_1 : \theta = \frac{1}{2} \\ \text{versus} & \\ H_1 : \theta = 2 & \quad \theta_1 = 2 & \text{If } H_1 : \theta = 3 \end{aligned}$$

Solution. The pdf of $\mathbf{X} = (X_1, X_2, \dots, X_n)$ is, for $0 < x_i < 1$,

$$f_{\mathbf{X}}(\mathbf{x}|\theta) \stackrel{\text{iid}}{=} \prod_{i=1}^n \theta x_i^{\theta-1} = \theta^n \left(\prod_{i=1}^n x_i \right)^{\theta-1}.$$

Form the ratio

$$\frac{f_{\mathbf{X}}(\mathbf{x}|\theta_1)}{f_{\mathbf{X}}(\mathbf{x}|\theta_0)} = \frac{f_{\mathbf{X}}(\mathbf{x}|2)}{f_{\mathbf{X}}(\mathbf{x}|1)} = \frac{2^n (\prod_{i=1}^n x_i)^{2-1}}{1^n (\prod_{i=1}^n x_i)^{1-1}} = 2^n \prod_{i=1}^n x_i$$

$(\frac{1}{2})^n (\prod_{i=1}^n x_i)^{-1}$
 NP
 Lemma

The NP Lemma says that the MP level α test uses the rejection region

$$R = \left\{ \mathbf{x} \in \mathcal{X} : 2^n \prod_{i=1}^n x_i > k \right\},$$

$R = \left\{ \mathbf{x} : 2^n \prod_{i=1}^n x_i > k \right\} \Leftrightarrow \left\{ \mathbf{x} : \prod_{i=1}^n x_i > k' \right\}$

where the constant k satisfies

$$\alpha = P_{\theta=1}(\mathbf{X} \in R) = P \left(2^n \prod_{i=1}^n X_i > k \mid \theta = 1 \right).$$

Distribution hard

Instead of finding the constant k that satisfies this equation, we rewrite the rejection rule $\{2^n \prod_{i=1}^n x_i > k\}$ in a way that makes our life easier. Note that

$$\begin{aligned} 2^n \prod_{i=1}^n x_i > k &\Leftrightarrow \prod_{i=1}^n x_i > \frac{k}{2^n} \Leftrightarrow \sum_{i=1}^n \ln x_i > k \\ &\Leftrightarrow \left(\sum_{i=1}^n -\ln x_i < -\ln \left(\frac{k}{2^n} \right) = k' \right) \text{ say.} \end{aligned}$$

We have rewritten the rejection rule $\{2^n \prod_{i=1}^n x_i > k\}$ as $\{\sum_{i=1}^n -\ln x_i < k'\}$. Therefore,

$$\alpha = P \left(2^n \prod_{i=1}^n X_i > k \mid \theta = 1 \right) = P \left(\sum_{i=1}^n -\ln X_i < k' \mid \theta = 1 \right).$$

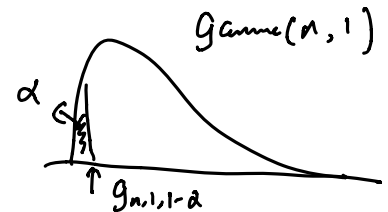
We have now changed the problem to choosing k' to solve this equation above.

Q: Why did we do this?

A: Because it is easier to find the distribution of $\sum_{i=1}^n -\ln X_i$ when $H_0 : \theta = 1$ is true.

Recall that

$$\begin{aligned} X_i \stackrel{H_0}{\sim} \mathcal{U}(0, 1) &\implies -\ln X_i \stackrel{H_0}{\sim} \text{exponential}(1) \\ &\implies \sum_{i=1}^n -\ln X_i \stackrel{H_0}{\sim} \text{gamma}(n, 1). \end{aligned}$$



Therefore, to satisfy the equation above, we take $k' = g_{n,1-\alpha}$, the (lower) α quantile of a $\text{gamma}(n, 1)$ distribution. This notation for quantiles is consistent with how CB have defined them on pp 386. Thus, the MP level α test of $H_0 : \theta = 1$ versus $H_1 : \theta = 2$ has rejection region

$$R = \left\{ \mathbf{x} \in \mathcal{X} : \sum_{i=1}^n -\ln x_i < g_{n,1-\alpha} \right\}$$

→ MP for

$\theta=1$ vs $\theta=2$
 $\theta=1$ vs $\theta=3$
 $\theta=1$ vs $\theta=4$
 ...

Special case: If $n = 10$ and $\alpha = 0.05$, then $g_{10,1,0.95} \approx 5.425$.

↓ VMP for

$H_0: \theta=1$ versus $H_1: \theta > 1$

Q: What is $\beta(2)$, the power of this MP test (when $n = 10$ and $\alpha = 0.05$)?

A: We calculate

$$\beta(2) = P \left(\sum_{i=1}^{10} -\ln X_i < 5.425 \mid \theta = 2 \right).$$

Recall that

$$\begin{aligned} X_i \stackrel{H_1}{\sim} \text{beta}(2, 1) &\implies -\ln X_i \stackrel{H_1}{\sim} \text{exponential}(1/2) \\ &\implies \sum_{i=1}^{10} -\ln X_i \stackrel{H_1}{\sim} \text{gamma}(10, 1/2). \end{aligned}$$

Therefore,

$$\beta(2) = \int_0^{5.425} \underbrace{\frac{1}{\Gamma(10) \left(\frac{1}{2}\right)^{10}} u^9 e^{-2u}}_{\text{gamma}(10, 1/2) \text{ pdf}} du \approx \underline{0.643}.$$

Proof of NP Lemma. We prove the sufficiency part only. Define the test function

$$\phi(\mathbf{x}) = \begin{cases} 1, & \frac{f_{\mathbf{X}}(\mathbf{x}|\theta_1)}{f_{\mathbf{X}}(\mathbf{x}|\theta_0)} > k \\ 0, & \frac{f_{\mathbf{X}}(\mathbf{x}|\theta_1)}{f_{\mathbf{X}}(\mathbf{x}|\theta_0)} < k, \end{cases}$$

where $k \geq 0$ and

$$\alpha = P_{\theta_0}(\mathbf{X} \in R) = E_{\theta_0}[\phi(\mathbf{X})];$$

i.e., $\phi(\mathbf{x})$ is a size α test. We want to show that $\phi(\mathbf{x})$ is MP level α . Therefore, let $\phi^*(\mathbf{x})$ be the test function for any other level α test of H_0 versus H_1 . Note that

$$\begin{aligned} E_{\theta_0}[\phi(\mathbf{X})] &= \alpha \\ E_{\theta_0}[\phi^*(\mathbf{X})] &\leq \alpha. \end{aligned}$$

Thus,

$$E_{\theta_0}[\phi(\mathbf{X}) - \phi^*(\mathbf{X})] = \underbrace{E_{\theta_0}[\phi(\mathbf{X})]}_{= \alpha} - \underbrace{E_{\theta_0}[\phi^*(\mathbf{X})]}_{\leq \alpha} \geq 0.$$

Define

$$b(\mathbf{x}) = [\phi(\mathbf{x}) - \phi^*(\mathbf{x})][f_{\mathbf{X}}(\mathbf{x}|\theta_1) - k f_{\mathbf{X}}(\mathbf{x}|\theta_0)].$$

We want to show that $b(\mathbf{x}) \geq 0$, for all $\mathbf{x} \in \mathcal{X}$.

- **Case 1:** Suppose $f_{\mathbf{X}}(\mathbf{x}|\theta_1) - k f_{\mathbf{X}}(\mathbf{x}|\theta_0) > 0$. Then, by definition, $\phi(\mathbf{x}) = 1$. Because $0 \leq \phi^*(\mathbf{x}) \leq 1$, we have

$$b(\mathbf{x}) = \underbrace{[\phi(\mathbf{x}) - \phi^*(\mathbf{x})]}_{\geq 0} \underbrace{[f_{\mathbf{X}}(\mathbf{x}|\theta_1) - k f_{\mathbf{X}}(\mathbf{x}|\theta_0)]}_{> 0} \geq 0.$$

- **Case 2:** Suppose $f_{\mathbf{X}}(\mathbf{x}|\theta_1) - kf_{\mathbf{X}}(\mathbf{x}|\theta_0) < 0$. Then, by definition, $\phi(\mathbf{x}) = 0$. Because $0 \leq \phi^*(\mathbf{x}) \leq 1$, we have

$$b(\mathbf{x}) = \underbrace{[\phi(\mathbf{x}) - \phi^*(\mathbf{x})]}_{\leq 0} \underbrace{[f_{\mathbf{X}}(\mathbf{x}|\theta_1) - kf_{\mathbf{X}}(\mathbf{x}|\theta_0)]}_{< 0} \geq 0.$$

- **Case 3:** Suppose $f_{\mathbf{X}}(\mathbf{x}|\theta_1) - kf_{\mathbf{X}}(\mathbf{x}|\theta_0) = 0$. It is then obvious that $b(\mathbf{x}) = 0$.

We have shown that $b(\mathbf{x}) = [\phi(\mathbf{x}) - \phi^*(\mathbf{x})][f_{\mathbf{X}}(\mathbf{x}|\theta_1) - kf_{\mathbf{X}}(\mathbf{x}|\theta_0)] \geq 0$. Therefore,

$$\begin{aligned} [\phi(\mathbf{x}) - \phi^*(\mathbf{x})]f_{\mathbf{X}}(\mathbf{x}|\theta_1) - k[\phi(\mathbf{x}) - \phi^*(\mathbf{x})]f_{\mathbf{X}}(\mathbf{x}|\theta_0) &\geq 0 \\ \iff [\phi(\mathbf{x}) - \phi^*(\mathbf{x})]f_{\mathbf{X}}(\mathbf{x}|\theta_1) &\geq k[\phi(\mathbf{x}) - \phi^*(\mathbf{x})]f_{\mathbf{X}}(\mathbf{x}|\theta_0). \end{aligned}$$

Integrating both sides, we get

$$\int_{\mathbb{R}^n} [\phi(\mathbf{x}) - \phi^*(\mathbf{x})]f_{\mathbf{X}}(\mathbf{x}|\theta_1)d\mathbf{x} \geq k \int_{\mathbb{R}^n} [\phi(\mathbf{x}) - \phi^*(\mathbf{x})]f_{\mathbf{X}}(\mathbf{x}|\theta_0)d\mathbf{x},$$

that is,

$$E_{\theta_1}[\phi(\mathbf{X}) - \phi^*(\mathbf{X})] \geq k \underbrace{E_{\theta_0}[\phi(\mathbf{X}) - \phi^*(\mathbf{X})]}_{\geq 0, \text{ shown above}} \geq 0.$$

Therefore, $E_{\theta_1}[\phi(\mathbf{X}) - \phi^*(\mathbf{X})] \geq 0$ and hence $E_{\theta_1}[\phi(\mathbf{X})] \geq E_{\theta_1}[\phi^*(\mathbf{X})]$. This shows that $\phi(\mathbf{x})$ is more powerful than $\phi^*(\mathbf{x})$. Because $\phi^*(\mathbf{x})$ is an arbitrary level α test, we are done. \square

Corollary 8.3.13 (NP Lemma with a sufficient statistic T). Consider testing

$$\begin{aligned} H_0 : \theta = \theta_0 \\ \text{versus} \\ H_1 : \theta = \theta_1, \end{aligned}$$

$$f_{\mathbf{X}}(\mathbf{x}|\theta) \approx h(\mathbf{x})g_T(t|\theta)$$

and suppose that $T = T(\mathbf{X})$ is a sufficient statistic. Denote by $g_T(t|\theta_0)$ and $g_T(t|\theta_1)$ the pdfs (pmfs) of T corresponding to θ_0 and θ_1 , respectively. Consider the test function

$$\phi(t) = \begin{cases} 1, & \frac{g_T(t|\theta_1)}{g_T(t|\theta_0)} > k \\ 0, & \frac{g_T(t|\theta_1)}{g_T(t|\theta_0)} < k, \end{cases}$$

for $k \geq 0$, where, with rejection region $S \subset \mathcal{T}$,

$$\alpha = P_{\theta_0}(T \in S) = E_{\theta_0}[\phi(T)].$$

The test that satisfies these specifications is a MP level α test.

Proof. See CB (pp 390).

Implication: In search of a MP test, we can immediately restrict attention to those tests based on a sufficient statistic.

Example 8.14. Suppose X_1, X_2, \dots, X_n are iid $\mathcal{N}(\mu, \sigma_0^2)$, where $-\infty < \mu < \infty$ and σ_0^2 is known. Find the MP level α test for

$$\begin{aligned} H_0 : \mu &= \mu_0 \\ \text{versus} \\ H_1 : \mu &= \mu_1, \end{aligned}$$

where $\mu_1 < \mu_0$.

Solution. The sample mean $T = T(\mathbf{X}) = \bar{X}$ is a sufficient statistic for the $\mathcal{N}(\mu, \sigma_0^2)$ family. Furthermore,

$$T \sim \mathcal{N}\left(\mu, \frac{\sigma_0^2}{n}\right) \implies g_T(t|\mu) = \frac{1}{\sqrt{2\pi\sigma_0^2/n}} e^{-\frac{n}{2\sigma_0^2}(t-\mu)^2},$$

for $t \in \mathbb{R}$. Form the ratio

$$\frac{g_T(t|\mu_1)}{g_T(t|\mu_0)} = \frac{\frac{1}{\sqrt{2\pi\sigma_0^2/n}} e^{-\frac{n}{2\sigma_0^2}(t-\mu_1)^2}}{\frac{1}{\sqrt{2\pi\sigma_0^2/n}} e^{-\frac{n}{2\sigma_0^2}(t-\mu_0)^2}} = e^{-\frac{n}{2\sigma_0^2}[(t-\mu_1)^2 - (t-\mu_0)^2]}.$$

Corollary 8.3.13 says that the MP level α test rejects H_0 when

$$e^{-\frac{n}{2\sigma_0^2}[(t-\mu_1)^2 - (t-\mu_0)^2]} > k \iff t < \frac{2\sigma_0^2 n^{-1} \ln k - (\mu_1^2 - \mu_0^2)}{2(\mu_0 - \mu_1)} = k', \text{ say.}$$

what if $\mu_1 > \mu_0$?

Therefore, the MP level α test uses the rejection region

$$S = \left\{ t \in \mathcal{T} : \frac{g_T(t|\theta_1)}{g_T(t|\theta_0)} > k \right\} = \{t \in \mathcal{T} : t < k'\},$$

where k' satisfies

$$\begin{aligned} \alpha = P_{\mu_0}(T < k') &= P\left(Z < \frac{k' - \mu_0}{\sigma_0/\sqrt{n}}\right) \\ &\implies \frac{k' - \mu_0}{\sigma_0/\sqrt{n}} = -z_\alpha \\ &\implies k' = \mu_0 - z_\alpha \sigma_0/\sqrt{n}. \end{aligned}$$

Therefore, the MP level α test rejects H_0 when $\bar{X} < \mu_0 - z_\alpha \sigma_0/\sqrt{n}$. This is the same test we would have gotten using $f_{\mathbf{X}}(\mathbf{x}|\mu_0)$ and $f_{\mathbf{X}}(\mathbf{x}|\mu_1)$ with the original version of the NP Lemma (Theorem 8.3.12).

UMP test for $H_0: \mu = \mu_0$ vs $H_1: \mu < \mu_0$