

BASIC PHD WRITTEN EXAMINATION
THEORY, SECTION 1
(9:00 AM–1:00 PM, July 26, 2017)

INSTRUCTIONS:

- (a) This is a **CLOSED-BOOK** examination.
- (b) The time limit for this examination is four hours.
- (c) Answer both questions that follow.
- (d) Put the answers to different questions on separate sets of paper.
- (e) Put your exam code, **NOT YOUR NAME**, on each page. The same code is used for Section 1 and Section 2 of the PhD Theory Exam. Please keep the code confidential and do not share this information with any students or faculty. Sharing your code with either students or faculty is viewed as a violation of the UNC honor code.
- (f) Return the examination with a signed statement of the UNC honor pledge, separately from your answers. The pledge statement is given on the last page of the exam handout.
- (g) In the questions to follow, you are required to answer only what is asked, and not to tell all you know about the topics involved.

1. (25 points) Let N be Poisson distributed with parameter $0 < \lambda < \infty$, and let X_1, X_2, \dots be an i.i.d. sequence of positive random variables, independent of N , with $E \log(X_1) = \mu$, $\text{var}[\log(X_1)] = \sigma^2$, $|\mu| < \infty$, $0 < \sigma^2 < \infty$, and $M(\delta) = EX_1^\delta < \infty$ for some $\delta > 0$. Let $Y = \prod_{i=1}^N X_i$, where $\prod_{i=1}^0$ is defined as 1. Do the following:

- (a) (4 points) Show that $E \log Y = \lambda\mu$ and $\text{var}[\log Y] = \lambda(\sigma^2 + \mu^2)$.
- (b) (5 points) Show that $EY^t = \exp(\lambda[M(t) - 1])$, for all $0 \leq t \leq \delta$.
- (c) (7 points) Show that $Y^{1/\lambda} \rightarrow_p e^\mu$, as $\lambda \rightarrow \infty$.
- (d) (9 points) Letting $\tau^2 = \lambda(\sigma^2 + \mu^2)$, show that

$$(e^{-\lambda\mu}Y)^{1/\tau} \rightarrow_d e^Z,$$

as $\lambda \rightarrow \infty$, where $Z \sim N(0, 1)$.

2. (25 points) Let F and G be two distinct known cumulative distribution functions on the real line and X be a single observation from the cumulative distribution function $\theta F(x) + (1 - \theta)G(x)$, where $\theta \in [0, 1]$ is unknown.
- (a) (4 points) Given $0 < \theta_0 < 1$, derive a Uniformly Most Powerful (UMP) test of size α for testing $H_0 : \theta \leq \theta_0$ versus $H_1 : \theta > \theta_0$. You need to specify how the rejection region can be calculated .
 - (b) (6 points) Given $0 < \theta_1 < \theta_2 < 1$, derive a UMP test of size α for testing $H_0 : \theta \in [0, \theta_1] \cup [\theta_2, 1]$ versus $H_1 : \theta \in (\theta_1, \theta_2)$.
 - (c) (6 points) Show that a UMP test does not exist for testing $H_0 : \theta \in [\theta_1, \theta_2]$ versus $\theta \notin [\theta_1, \theta_2]$.
 - (d) (5 points) Obtain a Uniformly Most Powerful Unbiased (UMPU) test of size α for the problem in part (c).
 - (e) (4 points) Given $0 < \theta_1 < \theta_2 < 1$, derive the likelihood ratio test statistic for testing $H_0 : \theta \in [\theta_1, \theta_2]$ versus $\theta \notin [\theta_1, \theta_2]$.

2017 PhD Theory Exam, Section 1

Statement of the UNC honor pledge:

"In recognition of and in the spirit of the honor code, I certify that I have neither given nor received aid on this examination and that I will report all Honor Code violations observed by me."

(Signed) _____
NAME

(Printed) _____
NAME

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Q1.

$N \sim \text{Poi}(\lambda)$. $X_i > 0$, $E \log X_i = \mu$, $\text{Var} \log X_i = \sigma^2$. $M(f) = E X_i^f < \infty$, $\exists f > 0$. $Y = \prod_{i=1}^N X_i$

$$(a) \log Y = \sum_{i=1}^N \log X_i$$

$$\begin{aligned} E(\log Y | N=n) &= E\left(\sum_{i=1}^n \log X_i | N=n\right) \\ &= E\left(\sum_{i=1}^n \log X_i\right) \quad (\because X_1, \dots, X_n \text{ i.i.d.}) \\ &= \sum_{i=1}^n E \log X_i \\ &= n\mu \end{aligned}$$

$$\Rightarrow E(\log Y) = E[E(\log Y | N)] = E[N\mu] = \mu \cdot E[N] = \lambda\mu.$$

$$\text{Var}(\log Y | N=n) = \text{Var}\left(\sum_{i=1}^n \log X_i | N=n\right)$$

$$\begin{aligned} &= \text{Var}\left(\sum_{i=1}^n \log X_i\right) \\ &= \sum_{i=1}^n \text{Var}(\log X_i) \\ &= n\sigma^2 \end{aligned}$$

$$\begin{aligned} \Rightarrow \text{Var}(\log Y) &= E[\text{Var}(\log Y | N)] + \text{Var}(E[\log Y | N]) \\ &= E[N\sigma^2] + \text{Var}(N\mu) \\ &= \lambda\sigma^2 + \mu^2\lambda = \lambda(\sigma^2 + \mu^2) \end{aligned}$$

$$(b) E(Y^t | N=n) = E\left(\prod_{i=1}^n X_i^t | N=n\right)$$

$$= E\left(\prod_{i=1}^n X_i^t\right)$$

$$= \prod_{i=1}^n E X_i^t$$

$$\begin{aligned} \text{Here, Hölder inequality : } &\left[\int_{\mathbb{R}} f(x)^p dP(x) \right]^{\frac{1}{p}} \left[\int_{\mathbb{R}} g(x)^q dP(x) \right]^{\frac{1}{q}} \geq \left[\int_{\mathbb{R}} f(x)g(x) dP(x) \right] \\ &\frac{1}{p} + \frac{1}{q} = 1. \text{ Assume } 0 < t < f. \text{ Then, } p < \frac{f}{t}, q < \left(1 - \frac{t}{f}\right)^{-1}, f < x^t, g < \\ &\left[\int_{\mathbb{R}} x^f dP(x) \right]^{\frac{1}{f}} \geq \left[\int_{\mathbb{R}} x^t dP(x) \right] \\ &\Rightarrow (E X^f)^{\frac{1}{f}} \geq (E X^t)^{\frac{1}{t}} \end{aligned}$$

Thus, $E X_i^f < \infty \Rightarrow E X_i^t < \infty$ for $0 < t < f$. When $t=0, f$ also holds.

$$\text{Then, } E(Y^t | N=n) = \prod_{i=1}^n M(t) = M(t)^n$$

$$\text{Then, } E Y^t = E[E(Y^t | N)] = E(M(t)^N) = \sum_{n=0}^{\infty} M(t)^n \cdot \frac{e^{-\lambda} \lambda^n}{n!} = \sum_{n=0}^{\infty} e^{-\lambda} \cdot \frac{(M(t) \cdot \lambda)^n}{n!} = e^{-\lambda} \cdot e^{M(t) \cdot \lambda}$$

(c) $\langle \text{WTS} \rangle \frac{1}{N} \log Y \rightarrow_p \mu$ by Continuous Mapping Thm.

Lemma) $\frac{N}{\lambda} \rightarrow_p 1$. as $\lambda \rightarrow \infty$

(Pf)

$$\text{Let } \varepsilon > 0. \quad P(|\frac{N}{\lambda} - 1| > \varepsilon) = P(|N - \lambda| > \lambda \varepsilon) \leq \frac{\mathbb{E}(|N - \lambda|^2)}{(\lambda \varepsilon)^2} \quad \text{Chebyshev}$$

$$= \frac{\text{Var}(N)}{\lambda^2 \varepsilon^2} = \frac{1}{\lambda^2 \varepsilon^2} \xrightarrow{\lambda \rightarrow \infty} 0.$$

$\langle \text{WTS} \rangle \frac{1}{N} \log Y \rightarrow_p \mu \quad (\text{so}) \text{ Slutsky: } \frac{N}{\lambda} \cdot \frac{1}{N} \log Y \rightarrow_p 1 \cdot \mu = \mu \text{ will hold if it is true.}$

$\langle \text{WTS} \rangle P(|\frac{1}{N} \log Y - \mu| > \varepsilon) \xrightarrow{\lambda \rightarrow \infty} 0, \forall \varepsilon > 0.$

Let $\varepsilon > 0$.

$$P(|\frac{1}{N} \log Y - \mu| > \varepsilon | N=n) = P\left(|\frac{1}{n} \sum_{i=1}^n \log X_i - \mu| > \varepsilon | N=n\right)$$

$$= P\left(|\frac{1}{n} \sum_{i=1}^n \log X_i - \mu| > \varepsilon\right) = p_n$$

As $\text{var}[\log(X_1)] = \sigma^2 < \infty$,

WLLN: $\frac{1}{n} \sum_{i=1}^n \log X_i \xrightarrow{P} \mathbb{E}[\log X_1] = \mu. \text{ as } n \rightarrow \infty$

$$\Rightarrow P\left(|\frac{1}{n} \sum_{i=1}^n \log X_i - \mu| > \varepsilon\right) \xrightarrow{n \rightarrow \infty} 0.$$

Thus, $p_n \xrightarrow{n \rightarrow \infty} 0$.

$$\begin{aligned} \text{Now, } P\left(|\frac{1}{N} \log Y - \mu| > \varepsilon\right) &= \mathbb{E}[P(|\frac{1}{N} \log Y - \mu| > \varepsilon | N)] \\ &= \sum_{n=0}^{\infty} P\left(|\frac{1}{n} \log Y - \mu| > \varepsilon | N=n\right) \cdot P(N=n) \\ &= \sum_{n=0}^{\infty} p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} \end{aligned}$$

Now, let $\psi > 0$.

Since $p_n \xrightarrow{n \rightarrow \infty} 0$, $\exists M$ s.t. $n > M \Rightarrow p_n < \psi$

$$\begin{aligned} \text{Then, } \sum_{n=0}^{\infty} p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} &= \sum_{n=0}^M p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} + \sum_{n=M+1}^{\infty} p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} \\ &\leq \sum_{n=0}^M 1 \cdot \frac{e^{-\lambda} \lambda^n}{n!} + \sum_{n=M+1}^{\infty} \psi \cdot \frac{e^{-\lambda} \lambda^n}{n!} \\ &= e^{-\lambda} \left(\sum_{n=0}^M \frac{1}{n!} \lambda^n \right) + \psi (1 - e^{-\lambda} \cdot \sum_{n=0}^M \frac{1}{n!} \lambda^n) \\ &\xrightarrow{\lambda \rightarrow \infty} 0 + \psi (1 - 0) = \psi \quad (\text{as } \frac{p_n(\lambda)}{e^{-\lambda}} \xrightarrow{\lambda \rightarrow \infty} 0) \end{aligned}$$

It implies that $\lim_{\lambda \rightarrow \infty} \sum_{n=0}^{\infty} p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} \leq \psi, \forall \psi > 0$, thus $0 \leq \lim_{\lambda \rightarrow \infty} \sum_{n=0}^{\infty} p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} \leq 0$

$$\therefore \sum_{n=0}^{\infty} p_n \cdot \frac{e^{-\lambda} \lambda^n}{n!} \xrightarrow{\lambda \rightarrow \infty} 0..$$

Chebyshev "Easy solution"

$$\begin{aligned} P\left(|\frac{1}{N} \log Y - \mu| > \varepsilon\right) &= P\left(|\log Y - \lambda \mu| > \lambda \varepsilon\right) \\ &\leq \frac{\mathbb{E}(|\log Y - \lambda \mu|^2)}{(\lambda \varepsilon)^2} = \frac{\text{Var}(\log Y)}{\lambda^2 \varepsilon^2} \\ &= \frac{\lambda(\sigma^2 + \mu^2)}{\lambda^2 \varepsilon^2} \\ &\xrightarrow{\lambda \rightarrow \infty} 0 \end{aligned}$$

(d) $\langle \text{WTS} \rangle = \frac{1}{\lambda}(-\lambda\mu + \log \gamma) \rightarrow_d N(0,1)$ as $\lambda \rightarrow \infty$ by CMT.

$\langle \text{WTS} \rangle = \log \mathbb{E} \exp \left(t - \frac{1}{\lambda}(-\lambda\mu + \log \gamma) \right) \rightarrow \frac{1}{2}t^2$ as $\lambda \rightarrow \infty$ by 1-1 property of mgf and distⁿ

$$\mathbb{E} \left[\exp \left(t - \frac{1}{\lambda}(-\lambda\mu + \log \gamma) \right) \middle| N=n \right] = \mathbb{E} \left[\exp \left(-\frac{\lambda\mu}{\lambda}t \right) \cdot \exp \left(\frac{t}{\lambda} \sum_{i=1}^n \log X_i \right) \middle| N=n \right]$$

$$= \exp \left(-\frac{\lambda\mu}{\lambda}t \right) \cdot \mathbb{E} \exp \left(\frac{t}{\lambda} \sum_{i=1}^n \log X_i \right)$$

$$= \exp \left(-\frac{\lambda\mu}{\lambda}t \right) \cdot \left\{ \mathbb{E} \exp \left(\frac{t}{\lambda} \cdot \log X_1 \right) \right\}^n$$

Let $Z_1 = \log X_1$.

$$= \dots \cdot \left\{ M_{Z_1} \left(\frac{t}{\lambda} \right) \right\}^n$$

$$\text{Then, } \mathbb{E} \left[\exp \left(t - \frac{1}{\lambda}(-\lambda\mu + \log \gamma) \right) \right] = \sum_{n=0}^{\infty} \exp \left(-\frac{\lambda\mu}{\lambda}t \right) \cdot \left\{ M_{Z_1} \left(\frac{t}{\lambda} \right) \right\}^n \cdot \frac{e^{-\lambda} \lambda^n}{n!}$$

$$= \exp \left(-\frac{\lambda\mu}{\lambda}t - \lambda \right) \cdot \exp \left(\lambda M_{Z_1} \left(\frac{t}{\lambda} \right) \right)$$

Since $\lim_{x \rightarrow \infty} \frac{(\log x)^k}{x^k} = 0$, $\forall k \in \mathbb{N}$, $\exists M$ s.t. $x > M \Rightarrow \frac{(\log x)^k}{x^k} < 1$.

$$\Rightarrow \mathbb{E} Z_1^k = \mathbb{E} Z_1^k I(X_1 \leq M) + \mathbb{E} Z_1^k I(X_1 > M)$$

$$\leq (\log M)^k + \mathbb{E} X_1^k < \infty, \forall k \in \mathbb{N}.$$

$$\begin{aligned} \text{Thus, } M_{Z_1} \left(\frac{t}{\lambda} \right) &= 1 + m_1 \frac{t}{\lambda} + \frac{m_2}{2!} \left(\frac{t}{\lambda} \right)^2 + \frac{m_3}{3!} \left(\frac{t}{\lambda} \right)^3 + \dots & (m_k := \mathbb{E} Z_1^k = \mathbb{E} ((\log X_1)^k)) \\ &= 1 + \mu \frac{t}{\sqrt{\lambda(\mu^2 + \sigma^2)}} + \frac{\frac{6\mu^2 + \mu^4}{2!}}{\lambda(\mu^2 + \sigma^2)} \frac{t^2}{\lambda} + o(t^2) \end{aligned}$$

$$\begin{aligned} \therefore \mathbb{E} \left[\exp \left(t - \frac{1}{\lambda}(-\lambda\mu + \log \gamma) \right) \right] &= \exp \left(-\frac{\lambda\mu}{\lambda}t - \cancel{\lambda} + \cancel{\lambda} + \lambda\mu \cancel{\frac{t}{\sqrt{\lambda(\mu^2 + \sigma^2)}}} + \frac{1}{2}t^2 + o(t^2) \right) \\ &= \exp \left(\frac{1}{2}t^2 + o(t^2) \right) \\ &= \exp \left(\frac{1}{2}t^2 \right) + o(t^2) \end{aligned}$$

$$\therefore \lim_{\lambda \rightarrow \infty} \dots = \exp \left(\frac{1}{2}t^2 \right) : \text{mgf of } N(0,1).$$

Q2.

(a) Given the dominating measure $F+G$,

$$P_X(x; \theta) = \frac{d}{d(F+G)} (\theta F(x) + (1-\theta) G(x)) = \theta f(x) + (1-\theta) g(x), \quad f(x) = \frac{dF}{d(F+G)}, \quad g(x) = \frac{dG}{d(F+G)}$$

$$= \theta(f(x) - g(x)) + g(x)$$

Then, for $\theta_1 < \theta_2$,

$$\frac{P_X(x; \theta_2)}{P_X(x; \theta_1)} = \frac{\theta_2(f(x) - g(x)) + g(x)}{\theta_1(f(x) - g(x)) + g(x)} = \frac{\theta_2\left(\frac{f(x)}{g(x)} - 1\right) + 1}{\theta_1\left(\frac{f(x)}{g(x)} - 1\right) + 1} \stackrel{\text{MLR in } \frac{f(x)}{g(x)}}{\approx}$$

\therefore UMP \propto test for $H_0: \theta \leq \theta_0$ vs $H_1: \theta > \theta_0$ is

$$\phi(x) = \begin{cases} 1 & , \frac{f(x)}{g(x)} < c \\ \gamma & , \quad = c \\ 0 & , \quad > c \end{cases} \quad \text{where } P_{\theta_0}\left(\frac{f(x)}{g(x)} < c\right) + \gamma \cdot P_{\theta_0}\left(\frac{f(x)}{g(x)} = c\right) = \alpha,$$

$$\Rightarrow c \text{ & } \gamma \in [0, 1].$$

(b) ϕ : arbitrary test at size α

$$\sup_{\theta \in [\theta_1, \theta_2] \cup [\theta_2, 1]} \theta \cdot \underbrace{\left(\int \phi dF - \int \phi dG \right)}_{\text{linear in } \theta} + \int \phi dG \leq \alpha \Rightarrow \int \phi dF \leq \alpha, \quad \int \phi dG \leq \alpha \text{ hold.}$$

\Rightarrow power at $\theta_* \in (\theta_1, \theta_2)$:

$$E_{\theta_*} \phi(x) = \theta_* \left(\int \phi dF - \int \phi dG \right) + \int \phi dG \leq \max \left\{ \int \phi dF, \int \phi dG \right\} \leq \alpha \text{ hold.}$$

$\therefore \phi(x) \equiv \alpha$ is a UMP test of size α .

(c) Assume. ϕ : UMP test $\boxed{\text{of size } \alpha}$ for $H_0: \theta \in [\theta_1, \theta_2]$ vs $H_1: \theta \notin [\theta_1, \theta_2]$.

$$\sup_{\theta \in [\theta_1, \theta_2]} \theta \cdot \underbrace{\left(\int \phi dF - \int \phi dG \right)}_{a_1} + \underbrace{\int \phi dG}_{a_2} \leq \alpha \Leftrightarrow a_1 \theta_1 + a_2 \leq \alpha$$

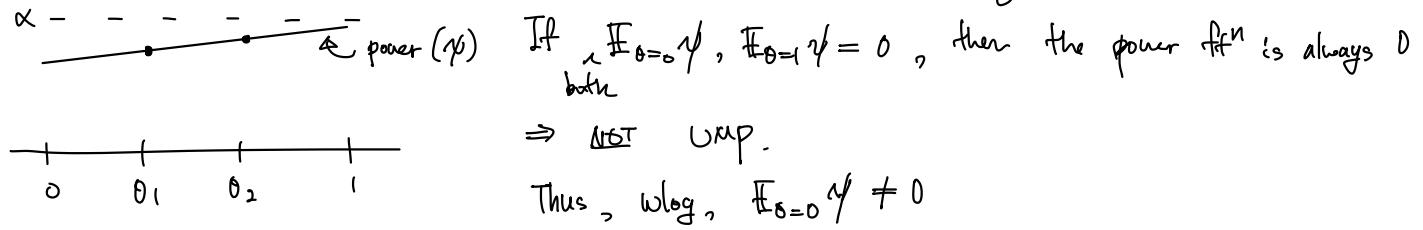
$$a_1 \theta_2 + a_2 \leq \alpha.$$

For any arbitrary ϕ s.t. $\sup_{\theta \in [\theta_1, \theta_2]} \theta \cdot \left(\int \phi dF - \int \phi dG \right) + \int \phi dG \leq \alpha$,

$$b_1 \theta + b_2 \leq a_1 \theta + a_2, \quad \forall \theta \notin [\theta_1, \theta_2]$$

We know that the power at $\theta = \theta_1, \theta_2$ fully determines a test's power function, which is linear in θ .

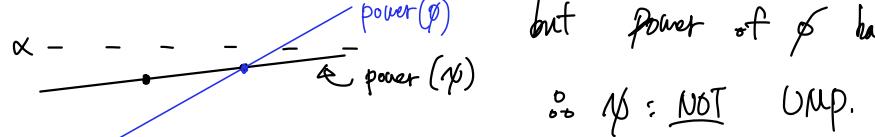
Thus, $\forall \phi$: UMP \Leftrightarrow the line corresponds to the power $f(\theta)$ of ϕ is always upper than other line " " " " " arbitrary test ϕ .



Now, consider a test set $E_{\theta=0} \phi = 0$ and $E_{\theta>0} \phi = E_{\theta>1} \phi \leq \alpha$.

Then, $E_{\theta=1} \phi = \frac{\theta_1}{\theta_2} E_{\theta>1} \phi < \alpha$ holds. $\Rightarrow \phi$: size α test.

However, it is obvious that $E_{\theta=1} \phi > E_{\theta=0} \phi$ because two line intersects at $\theta=\theta_2$, but power of ϕ has a larger slope.



Final step is to construct such test ϕ s.t $E_{\theta=0} \phi = 0$, $E_{\theta>1} \phi = E_{\theta>2} \phi \leq \alpha$.

This is done by letting \leftarrow Showing the existence of such ϕ is Really hard ~~hard~~

Instead, use the fact that $\sup_{\theta \in [\theta_1, \theta_2]} E_{\theta} \phi \leq E_{\theta>2} \phi, \forall \theta_3 \notin [\theta_1, \theta_2]$

\because property of UMP. ("power \geq size")

It is only true when $E_{\theta=1} \phi = E_{\theta=2} \phi$. (zero slope ..)

(d) ψ : UMPU test of size α

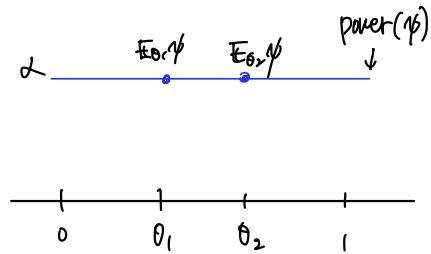
$$\Leftrightarrow \textcircled{1} \psi: \text{unbiased. i.e. } \sup_{\theta \in [\theta_1, \theta_2]} \mathbb{E}_\theta \psi \leq \mathbb{E}_{\theta_0} \psi, \forall \theta_0 \notin [\theta_1, \theta_2]$$

$$\textcircled{2} \text{ If } \psi: \text{unbiased, then } \mathbb{E}_{\theta_1} \psi \geq \mathbb{E}_{\theta_2} \psi, \forall \theta_2 \notin [\theta_1, \theta_2]$$

$$\textcircled{3} \sup_{\theta \in [\theta_1, \theta_2]} \mathbb{E}_\theta \psi \leq \alpha$$

ψ is determined by the value of $\mathbb{E}_{\theta_1} \psi$ and $\mathbb{E}_{\theta_2} \psi$. (linear in θ)

ψ 's power $f(\psi)$



Similarly, for any test ϕ , its power $f(\phi)$ is determined by the value of $\mathbb{E}_{\theta_1} \phi$, $\mathbb{E}_{\theta_2} \phi$.

Note that if ϕ 's power $f(\phi)$'s slope is NOT zero, then $\mathbb{E}_{\theta=0} \phi < \mathbb{E}_{\theta_1} \phi$ (slope > 0)

or $\mathbb{E}_{\theta=1} \phi < \mathbb{E}_{\theta_2} \phi$ (slope < 0) occurs

\Rightarrow NOT unbiased.

$\therefore \phi$: unbiased \Leftrightarrow slope = 0 $\Leftrightarrow \mathbb{E}_\theta \phi = \mathbb{E}_{\theta_1} \phi, \forall \theta \in [0, 1]$

Thus, by setting $\psi(x) = \alpha$, it is a UMPU size α test.

(e) Assume $f(x), g(x)$: density of F, G distⁿ

Then X 's density is $\theta f(x) + (1-\theta)g(x) =: L(\theta)$

1. Without restriction

$$\sup_{\theta \in [0, 1]} L(\theta) = \max \{f(x), g(x)\}$$

2. Under H_0

$$\sup_{\theta \in [\theta_1, \theta_2]} L(\theta) = \begin{cases} \theta_2 f(x) + (1-\theta_2) g(x) & \text{if } f(x) \geq g(x) \\ \theta_1 f(x) + (1-\theta_1) g(x) & \text{if } f(x) < g(x) \end{cases}$$

$$\text{Thus, } \lambda = \frac{\sup_{\theta \in [\theta_1, \theta_2]} L(\theta)}{\sup_{\theta \in [0, 1]} L(\theta)} = \begin{cases} \frac{\theta_2 f + (1-\theta_2) g}{f(x)} & , f(x) \geq g(x) \\ \frac{\theta_1 f + (1-\theta_1) g}{g(x)} & , f(x) < g(x) \end{cases}$$

Rejection Region: $\lambda < c \Leftrightarrow \text{i) } f(x) \geq g(x): \theta_2 + (1-\theta_2) \frac{g}{f} < c \Leftrightarrow \frac{g}{f} < k_1,$

(Note that $\lambda \leq 1$ always) $\text{ii) } f(x) < g(x): \theta_1 \frac{f}{g} + (1-\theta_1) < c \Leftrightarrow \frac{f}{g} < k_2$

\therefore Reject H_0 if $k_3 < \frac{g}{f} < k_1, \exists k_3 \leq 1 \leq k_1$.