

Excercise 1

1. (a) For $f_{p,\theta} = 0$ to be a pdf, we must show that;

$$\int_{-\infty}^{\infty} f_{p,\theta} = 1$$

$$\int_{-\infty}^{\infty} f_{p,\theta} = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise.} \end{cases}$$

$$\int_0^{\infty} \frac{\theta^p}{\Gamma(p)} e^{-\theta x} x^{p-1} dx$$

We know that $\Gamma(p) = \int_0^{\infty} x^{p-1} e^{-x} dx$

Let $t = \theta x$; $x = \frac{t}{\theta}$; $\frac{dx}{dt} = \frac{1}{\theta}$; $dx = \frac{dt}{\theta}$

$$= \int_0^{\infty} \frac{\theta^p}{\Gamma(p)} e^{-t} \left(\frac{t}{\theta}\right)^{p-1} \frac{dt}{\theta}$$

$$= \int_0^{\infty} \frac{\theta^{p-1}}{\Gamma(p)} e^{-t} \frac{t^{p-1}}{\theta^{p-1}} dt$$

$$= \frac{1}{\Gamma(p)} \int_0^{\infty} e^{-t} t^{p-1} dt$$

$$= \frac{\Gamma(p)}{\Gamma(p)}$$

$$= 1$$

(b)

$$E(X^n) = \int_0^{\infty} x^n \frac{\theta^p}{\Gamma(p)} x^{p-1} e^{-\theta x} dx$$

$$\frac{\theta^p}{\Gamma(p)} \int_0^{\infty} x^{n+p-1} e^{-\theta x} dx$$

$$\frac{\theta^p}{\Gamma(p)} \times \frac{\Gamma(n+p)}{\theta^{n+p}} = \frac{\Gamma(n+p)}{\Gamma(p)\theta^n}$$

$$E(X^n) = \frac{\Gamma(n+p)}{\theta^n \Gamma(p)}$$

2. (a) $U=X+Y$ where $X \sim \Gamma(p, \theta)$ and $Y \sim \Gamma(q, \theta)$

$$f_{X+Y}(u) = \int_0^u f_X(x)f_Y(u-x)dx$$

$$f_{X+Y}(u) = \int_0^u \frac{\theta^p}{\Gamma(p)}e^{-\theta x}x^{p-1} \cdot \frac{\theta^q}{\Gamma(q)}e^{-\theta(u-x)}(u-x)^{q-1}dx$$

Recall that

$$\beta(p, q) = \int_0^1 u^{p-1}(1-u)^{q-1}du = \frac{\Gamma(p)\Gamma(q)}{\Gamma(p+q)}$$

so,

$$f_{X+Y}(u) = \int_0^u \frac{\theta^p}{\Gamma(p)}x^{p-1} \frac{\theta^q}{\Gamma(q)}(u-x)^{q-1}e^{-\theta u}dx$$

Let $x = ut$; $dx = udt$

$$\begin{aligned} f(u) &= \int_0^{\frac{u}{\theta}} \frac{\theta^p}{\Gamma(p)}(ut)^{p-1} \frac{\theta^q}{\Gamma(q)}(u-ut)^{q-1}e^{-\theta u}udt \\ &= \frac{e^{-\theta u}\theta^p\theta^q}{\Gamma(p)\Gamma(q)}(u)^{q-1}(u)^p \int_0^1 (t)^{p-1}(1-t)^{q-1}dt \\ &= \frac{e^{-\theta u}\theta^p\theta^q}{\Gamma(p)\Gamma(q)}(u)^{q-1}(u)^p \cdot \frac{\Gamma(p)\Gamma(q)}{\Gamma(p+q)} \\ &= \frac{e^{-\theta u}\theta^p\theta^q}{\Gamma(p+q)}(u)^{p+q-1} \\ &= \frac{e^{-\theta u}\theta^{p+q}}{\Gamma(p+q)}u^{(p+q)-1} \sim \Gamma(p+q, \theta) \end{aligned}$$

- (b) $V = aX$; $X = \frac{v}{a}$; $\frac{dx}{dv} = \frac{1}{a}$. Using jacobian, we get

$$\begin{aligned} f_{ax}(v) &= \left| \frac{dx}{dv} \right| f_x \frac{v}{a} = \frac{1}{a} f_x \frac{v}{a} \\ &= \frac{1}{a} \frac{\theta^p}{\Gamma(p)} e^{-\theta \frac{v}{a}} \left(\frac{v}{a} \right)^{p-1} \\ &= \frac{a^{-p}\theta^p}{\Gamma(p)} e^{-\frac{\theta}{a}v} v^{p-1} \\ &= \frac{(\frac{\theta}{a})^p}{\Gamma(p)} e^{-\frac{\theta}{a}v} v^{p-1} \sim \Gamma(p, \frac{\theta}{a}) \end{aligned}$$

(c) $Z = \frac{X}{Y}$; $U = Y$; $X = \frac{Z}{U}$

$$J \begin{bmatrix} z & u \\ 1 & 0 \end{bmatrix} = u$$

$$\begin{aligned} f_{U,Z}(u, z) &= \int_0^\infty \frac{\theta^p}{\Gamma(p)} e^{-\theta zu} (zu)^{p-1} \cdot \frac{\theta^q}{\Gamma(q)} e^{-\theta(u)} (u)^{q-1} u du \\ &= \frac{\theta^p}{\Gamma(p)} \frac{\theta^q}{\Gamma(q)} (z)^{p-1} \int_0^\infty e^{-\theta u(z+1)} (u)^{(p+q)-1} du \end{aligned}$$

$$v = \theta u(z+1); \quad u = \frac{v}{\theta(z+1)}; \quad dv = \theta(z+1) du; \quad du = \frac{dv}{\theta(z+1)};$$

$$\begin{aligned} &= \frac{\theta^p}{\Gamma(p)} \frac{\theta^q}{\Gamma(q)} (z)^{p-1} \int_0^\infty e^{-v} \frac{(v)^{(p+q)-1}}{(\theta(z+1))^{q+p}} dv \\ &= \frac{\theta^p}{\Gamma(p)} \frac{\theta^q}{\Gamma(q)} (z)^{p-1} \frac{1}{\theta(z+1)^{q+p}} \int_0^\infty e^{-v} (v)^{(p+q)-1} dv \\ &= \frac{\theta^p}{\Gamma(p)} \frac{\theta^q}{\Gamma(q)} (z)^{p-1} \frac{1}{\theta(z+1)^{q+p}} \Gamma(p+q) \\ &= \frac{\theta^{p+q}}{\beta} \times \frac{z^{p-1}}{\theta(z+1)^{q+p}} \sim \beta(p, q) \text{ type II} \end{aligned}$$

3.

$$S_n = \sum_{i=1}^n X_i$$

$$X_i \leq i \leq n \sim \Gamma(1, 0)$$

Using its characteristic function,

$$\Psi_{1,0}(t) = \Pi_{i=1}^n \left(\frac{\theta}{\theta - it} \right) = \left(\frac{\theta}{\theta - it} \right)^n$$

This resulting characteristic function follows the probability law $\sim \Gamma(n, \theta)$

4. If X follows the standard normal distribution law, then $X^2 \sim \chi^2$ with one degree of freedom

5. (a) $Z_n = \sum_{i=1}^n X_i^2$ which follows $X^2 \sim (v)$, and the probability density function of Z_n is ;

$$f(x) = \frac{e^{-\frac{x}{2}} X^{\frac{v}{2}-1}}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} \quad x \geq 0$$

$$E(Z_n) = E(X) = \int_0^{\infty} X f(x) dx$$

$$= \frac{e^{-\frac{x}{2}} X^{\frac{v}{2}-1}}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} dx$$

$$= \frac{1}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} \int_0^{\infty} X^{\frac{v}{2}} e^{-\frac{x}{2}} dx = \frac{1}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} \int_0^{\infty} X^{\frac{v}{2}+1-1} e^{-\frac{x}{2}} dx$$

$$= \frac{2^{\frac{v}{2}} \cdot 2 \cdot \frac{v}{2} \Gamma(\frac{v}{2})}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} = 2 \cdot \frac{v}{2}$$

$$E(X) = v = \mathbf{E}(Z_n)$$

$$\mathbf{E}(X^2) = \int_0^{\infty} \frac{X^2 X^{\frac{v}{2}-1} e^{-\frac{x}{2}}}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} dx = \frac{1}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} \int_0^{\infty} X^{\frac{v}{2}+2-1} e^{-\frac{x}{2}} dx$$

$$\frac{1}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})} \cdot 2^{\frac{v}{2}+2} \Gamma(\frac{v}{2} + 2)$$

$$\frac{2^{\frac{v}{2}} \cdot 2^2 \cdot (\frac{v}{2} + 1) (\frac{v}{2}) \Gamma(\frac{v}{2})}{2^{\frac{v}{2}} \Gamma(\frac{v}{2})}$$

$$= 2^3 \cdot (\frac{v}{2} + 1) (\frac{v}{2}) = 2^2 (\frac{v^2}{4} + \frac{v}{2}) = 4 (\frac{v^2}{4} + \frac{v}{2})$$

$$E(x^2) = v^2 + 2v \text{var}(Z_n) = \text{var}(X) = E(x^2) - [E(x)^2] v^2 + 2v - v^2 = 2v$$

Therefore, $\text{var}(Z_n) = 2v$ and $\mathbf{E}(Z_n) = v$

(b)

$$F = \frac{\frac{1}{n} \sum_i^n X_i^2}{\frac{1}{m} \sum_i^n Y_i^2} \sim f - \text{distribution}(n, m)$$

with the *pdf* given by (probability law).

$$F_{n,m}(X) = \frac{\Gamma(\frac{n+m}{2}) m^{\frac{m}{2}} n^{\frac{n}{2}}}{\Gamma(\frac{n}{2}) \Gamma(\frac{m}{2})} \frac{X^{\frac{m}{2}} - 1}{(m + nx)^{\frac{n+m}{2}}}$$

$$\begin{aligned} \text{let } U' &= \sum X_i^2 \sim X_{(n)^2} \\ V' &= \sum Y_i^2 \sim X_{(m)^2} \end{aligned}$$

$$F = \frac{U'}{V'}$$

$U \sim X_{(n)^2}$ and $V \sim X_{(m)^2}$ and U and V are independent.

$$\begin{aligned} E(f) &= E\left(\frac{U'}{V'}\right) = EU'EU' \\ &= \frac{1}{n}E(U) \cdot mE\frac{1}{v} = \frac{m}{n}E(U)E\left(\frac{1}{v}\right) \end{aligned}$$

We know that $\mathbf{E}(U) = n$

$$E(f) = \frac{m}{n}nE\left(\frac{1}{v}\right) = mE\left(\frac{1}{v}\right)$$

$$E\left(\frac{1}{v}\right) = \int_0^\infty \frac{1}{v} f(v) dv$$

where $f(v)$ is the X_m^2 density

$$\begin{aligned} f(v) &= \frac{1}{2^{\frac{m}{2}} \Gamma(\frac{m}{2})} v^{\frac{m}{2}-1} e^{-\frac{v}{2}} dv \\ &= \frac{1}{\Gamma(\frac{m}{2})} \int_0^\infty \frac{1}{v} \left(\frac{v}{2}\right)^{\frac{m}{2}-1} e^{-\frac{v}{2}} \frac{dv}{2} \end{aligned}$$

let $w = \frac{v}{2}$; $dw = \frac{dv}{2}$. $v = 2w$ we have

$$\begin{aligned}
&= \frac{1}{\Gamma(\frac{m}{2})} \int_0^\infty \frac{1}{2w} w^{\frac{m}{2}-1} e^{-w} dw \\
&= \frac{1}{2\Gamma(\frac{m}{2})} \int_0^\infty w^{\frac{m}{2}-2} e^{-w} dw \\
&= \frac{1}{2\Gamma(\frac{m}{2})} \int_0^\infty w^{(\frac{m}{2}-1)-1} e^{-w} dw \\
&= \frac{\Gamma(\frac{m}{2} - 1)}{2\Gamma(\frac{m}{2})} \\
&= E\left(\frac{1}{v}\right) = \frac{\Gamma(\frac{m}{2} - 1)}{2\Gamma(\frac{m}{2} - 1)\Gamma(\frac{m}{2} - 1)} = \frac{1}{2(\frac{m}{2} - 1)}
\end{aligned}$$

$$E\left(\frac{1}{v}\right) = \frac{1}{m-2}$$

$$\therefore \mathbf{E}(F) = m\mathbf{E}\left(\frac{1}{v}\right) \Rightarrow m\left(\frac{1}{m-2}\right)$$

$$\text{So, } E(F) = \frac{m}{m-2}$$

Exercise 2

1. The likelihood of the Lebesgue measure it follows is;

$$L(\theta; x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{\theta} 1_{x_i \leq \theta} = 1_{\max\{X_i\} \leq \theta} \theta^{-n}$$

From the above equation, there exists a maximum likelihood because the function $\theta \rightarrow \theta^{-n}$ decreases. Therefore, we conclude that $\hat{\theta} = \max\{X_i\}$

2. Let $t \in \mathbb{R}^+$. For find the law, we have;

$$\mathbb{P}_\theta(\hat{\theta} \leq t) = \mathbb{P}_\theta(\forall i \in [1, n], X_i \leq t) = \mathbb{P}_\theta(X_1 \leq t)^n = \left(\frac{t}{\theta}\right)^n 1_{t \leq \theta} + 1_{t > \theta}$$

From this, we deduced that the density is θ given by;

$$f_n(t) = \frac{n}{\theta} \left(\frac{t}{\theta}\right)^{n-1} 1_{[0, \theta]}(t)$$

So the bias is;

$$E_\theta[\hat{\theta}] = \int_{\mathbb{R}} t f_n(t) dt = \frac{n}{\theta^n} \int_0^\theta t^n dt = \frac{n}{n+1} \theta$$

3. We fix $t \in \mathbb{R}^+$ and we let $n \geq \frac{t}{\theta}$. We get;

$$\begin{aligned} \mathbb{P}_\theta(n(\theta - \hat{\theta}) \geq t) &= \mathbb{P}_\theta(\hat{\theta} \leq \theta - \frac{t}{n}) = \left(\frac{\theta - \frac{t}{n}}{\theta}\right)^n \\ &= \left(1 - \frac{t}{n\theta}\right)^n \rightarrow e^{-\frac{t}{\theta}} \text{ as } n \rightarrow \infty \end{aligned}$$

Therefore,

$$\mathbb{P}_\theta(n|\theta - \hat{\theta}|) \rightarrow 1 - e^{-\frac{t}{\theta}} = -Y$$

.The speed of convergence follows an exponential law $\frac{1}{\theta}$

4. The quadratic risk is as thus;

$$\begin{aligned} E_\theta[(\hat{\theta} - \theta)^2] &= E_\theta[(\hat{\theta})^2] - 2\theta E_\theta[\hat{\theta}] + \theta^2 \\ &= \frac{n}{\theta^n} \int_0^\theta t^{n+1} dt - \frac{2n\theta^2}{n+1} + \theta^2 \\ &= \left(\frac{n}{n+2} - \frac{2n}{n+1} + 1\right)\theta^2 \\ &= \frac{2\theta^2}{(n+1)(n+2)} \end{aligned}$$