

This part is overridden by the following parts!

Lab 3: Theory: Parameters of Gamma disto. are

- α : shape parameters
- β : rate parameters

NOTE: $\alpha, \beta > 0$

PDF of $\text{Gamma}(\alpha, \beta)$ is

$$\text{Gamma}(\alpha, \beta)(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$$

χ^2 distribution is a special case of Gamma, wherein $\alpha = k/2$ & $\beta = 1/2$

PDF of $\chi^2(k)$ is

$$\chi^2(k)(x) = \frac{1}{2^{k/2} \Gamma(k/2)} x^{k/2-1} e^{-x/2}$$

NOTE: Gamma can be parameterised in 2 ways:

- shape parameter α , rate parameters β
 - shape parameters α , scale parameters θ
- Here, note that $\beta = 1/\theta$

In the question, Gamma is parameterised in the 2nd way. Hence, PDF of Gamma is

$\text{Gamma}(\alpha, \theta)$

$$\text{Gamma}(\alpha, \theta)(x) = \frac{1}{\theta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\theta}$$

if $x > 0$, (else $\text{Gamma}(\alpha, \theta)(x) = 0$)

χ^2 distribution is a special case of Gamma wherein ~~$\alpha = \theta =$~~

$$\alpha = k/2, \theta = 2$$

Hence, PDF of $\chi^2(k)$ is

$$\chi^2(k)(x) = \frac{1}{2^{k/2} \Gamma(k/2)} x^{k/2-1} e^{-x/2}$$

Now, χ^2 has additivity i.e.

$$\chi^2(k_1) + \chi^2(k_2) + \dots + \chi^2(k_n) = \chi^2(k_1 + \dots + k_n)$$

All parameters are positive
hence $\theta > 0$

(provided each distribution is independent).

$$\therefore \sum_{i=1}^N \chi^2(k) = \chi^2(Nk)$$

Hence, consider $\frac{1}{N} \chi^2(Nk)$

In essence $\frac{1}{N} \chi^2(Nk)$ is the push-forward measure

$$g_* \chi^2(Nk) \text{ where } g: \mathbb{R} \rightarrow \mathbb{R}, x \mapsto \frac{x}{N}$$

Hence, for any $x > 0$,

$$g_* \chi^2(Nk)((-\infty, x])$$

This is the CDF, which gives the probability mass of a subset and is hence a measure (probability measure to be exact)

$$= \chi^2(Nk)(\{x_0 \mid \frac{x_0}{N} \in (-\infty, x], x_0 \in \mathbb{R}\})$$

(by definition of pushforward)

$$= \chi^2(Nk)((-\infty, Nx])$$

Now, by the fundamental theorem of calculus, we have that if $F: \mathbb{R} \rightarrow [0, 1]$ is the CDF of a probability distribution, then the corresponding PDF is given by f is given by

$$f(x) = \frac{dF(x)}{dx}$$

$$\therefore \frac{d}{dx} g_* \chi^2(Nk)((-\infty, x])$$

$$= \frac{d}{dx} \chi^2(Nk)((-\infty, Nx])$$

$$= \chi^2(Nk)(Nx)$$

$$= \frac{1}{2^{Nk/2} \Gamma(Nk/2)} x^{Nk/2 - 1} e^{-Nx/2}$$

$$= \text{Gamma}\left(\frac{Nk}{2}, \frac{x^2}{N}\right)(x)$$

NOTE:

Alternatively, you could just use the CDF of χ^2 & Gamma, but in case you knew only PDF, you could do this

2) a) Let $g: \mathbb{R} \rightarrow \mathbb{R}$, $x \mapsto x - \mu$

Then, for any interval $[a, b]$,

$$g_* \text{Norm}(\mu, \sigma)([a, b])$$

$$= \text{Norm}(\mu, \sigma)(\{x \mid g(x) \in [a, b], x \in \mathbb{R}\})$$

$$= \text{Norm}(\mu, \sigma) \xrightarrow{\substack{\text{by definition of} \\ \text{pushforward}}} \boxed{[a, b]}$$

$$= \text{Norm}(\mu, \sigma)(\{x \mid x - \mu \in [a, b], x \in \mathbb{R}\})$$

$$= \text{Norm}(\mu, \sigma)([a + \mu, b + \mu])$$

lower bound upper bound
of x of x

Now note that $g_* \text{Norm}(\mu, \sigma)$

$$= \text{Norm}(\mu, \sigma) - \mu$$

(i.e. shifting the distribution to the left (toward the origin) by μ)

$$= \text{Norm}(0, \sigma) \quad \begin{array}{l} \text{(since shifting the} \\ \text{disto. mean by } k \text{ changes} \\ \text{disto. mean by } k \text{ also)} \end{array}$$

$$\therefore \textcircled{1} \Rightarrow \text{Norm}(0, \sigma)([a, b])$$

$$= \text{Norm}(\mu, \sigma)([a + \mu, b + \mu])$$

$$\Rightarrow \text{Norm}(0, \sigma)([a - \mu, b - \mu])$$

$$= \text{Norm}(\mu, \sigma)([a, b])$$

b) Let $h: \mathbb{R} \rightarrow \mathbb{R}$, $x \mapsto \frac{x}{\sigma}$

Then, for any interval $[a, b]$,

$$h_* \text{Norm}(0, \sigma)([a, b])$$

$$= \text{Norm}(0, \sigma)(\{x \mid h(x) \in [a, b], x \in \mathbb{R}\})$$

$$= \text{Norm}(0, \sigma) \xrightarrow{\substack{\text{by definition of} \\ \text{pushforward}}} \boxed{[a\sigma, b\sigma]}$$

$$= \text{Norm}(0, \sigma)([a\sigma, b\sigma])$$

$$= \text{Norm}(0, \sigma)([\sigma a, \sigma b])$$

... $\textcircled{2}$

Now, note that $h * \text{Norm}(0, \sigma)$

$$= \frac{1}{\sigma} \text{Norm}(0, \sigma) = \text{Norm}(0, 1)$$

$$\therefore (2) \Rightarrow \text{Norm}(0, 1)([a, b])$$

$$= \text{Norm}(0, \sigma)([\sigma a, \sigma b])$$

$$\Rightarrow \text{Norm}(0, 1)\left(\left[\frac{a}{\sigma}, \frac{b}{\sigma}\right]\right)$$

$$= \text{Norm}(0, \sigma)([a, b])$$

c) Given h & g defined in (a) & (b), we have that

$$\text{Norm}(0, 1) = h * (g * \text{Norm}(\mu, \sigma))$$

~~$= h * g * \text{Norm}(\mu, \sigma)$~~ Hence, using results of (a) & (b), we get...

$$\text{Norm}(0, 1)\left(\left[\frac{a-\mu}{\sigma}, \frac{b-\mu}{\sigma}\right]\right)$$

$$= \text{Norm}(0, 1)([h(g(a)), h(g(b))])$$

$$= h * (g * \text{Norm}(\mu, \sigma))([h(g(a)), h(g(b))])$$

~~\therefore~~ Note that ~~Norm~~ $g * \text{Norm}(\mu, \sigma)$

$$= \text{Norm}(0, \sigma) \quad (\text{as seen in (a)})$$

Hence, from (b), we get:

$$= h * g * \text{Norm}(\mu, \sigma)([g(a), g(b)])$$

$$= \text{Norm}(\mu, \sigma)([a, b])$$

(from (a))

TIP: It might have been easier to relate to results of (a) & (b) if h & g were written out as expressions rather than symbolically
i.e. if $h(g(a))$ was written as $\frac{a-\mu}{\sigma}$

& $g(a)$ as $a - \mu$
(same for b)

$$\therefore \text{Norm}(0, 1)\left(\left[\frac{a-\mu}{\sigma}, \frac{b-\mu}{\sigma}\right]\right)$$

$$= \text{Norm}(\mu, \sigma)([a, b])$$

If Φ is the CDF of $\text{Norm}(0, 1)$,
then $\text{Norm}(0, 1)([\frac{a-\mu}{\sigma}, \frac{b-\mu}{\sigma}]) =$

$$\Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)$$

d) The weak law of large numbers states that the spread of ~~n-sized~~ sample means of n-sized sample sets taken from a distribution IP converges to an arbitrarily small interval ~~around~~ around the mean of IP, as $n \rightarrow \infty$.

i.e. $\lim_{n \rightarrow \infty} \overline{P}_n([\mu(P) - \varepsilon, \mu(P) + \varepsilon]) = 1$
 $\forall \varepsilon > 0$

If IP is the normal distribution ~~Norm~~ Norm (μ, σ), then

$$\overline{P}_n = \text{Norm}(\mu, \frac{\sigma}{\sqrt{n}}), \mu(P) = \mu$$

(This is given in the question, & obtained in lab 2's theory)
 questions

Hence, consider the probability mass

$$\overline{P}_n ([\mu(P) - \varepsilon, \mu(P) + \varepsilon]) = \text{Norm}(\mu, \frac{\sigma}{\sqrt{n}})([\mu - \varepsilon, \mu + \varepsilon]), \varepsilon > 0$$

Let $\delta > 0$ s.t., for a fixed $\varepsilon > 0$,

$$\text{Norm}(\mu, \frac{\sigma}{\sqrt{n}})([\mu - \varepsilon, \mu + \varepsilon]) > 1 - \delta$$

Now, note that from (c), we get

$$\begin{aligned} & \text{Norm}(\mu, \frac{\sigma}{\sqrt{n}})([\mu - \varepsilon, \mu + \varepsilon]) \\ &= \text{Norm}(0, 1)\left(\left[\frac{(\mu - \varepsilon) - \mu}{\sigma/\sqrt{n}}, \frac{(\mu + \varepsilon) - \mu}{\sigma/\sqrt{n}} \right] \right) \\ &= \text{Norm}(0, 1)\left(\left[-\frac{\sqrt{n}\varepsilon}{\sigma}, \frac{\sqrt{n}\varepsilon}{\sigma} \right] \right) \\ &= \Phi(+\sqrt{n}\varepsilon/\sigma) - \Phi(-\sqrt{n}\varepsilon/\sigma) \end{aligned}$$

$$\therefore \Phi(\sqrt{n}\varepsilon/\sigma) - \Phi(-\sqrt{n}\varepsilon/\sigma) > 1 - \delta$$

Now, note that since ~~normal~~ Norm (0, 1) is symmetric about 0,

$$\Phi(\sqrt{n}\varepsilon/\sigma) - \Phi(-\sqrt{n}\varepsilon/\sigma)$$

$$= 1 - 2\Phi(-\sqrt{n}\varepsilon/\sigma)$$

$$\begin{aligned} \therefore 1 - 2\Phi(-\sqrt{\epsilon/2}) &> 1 - \delta \\ \Rightarrow \Phi(-\sqrt{\epsilon/2}) &< \delta/2 \\ \Rightarrow -\sqrt{\epsilon/2} &< \Phi^{-1}(\delta/2) \end{aligned}$$

(we can do the above holds because any CDF is monotonic increasing, and CDF of a normal distribution is strictly monotonic increasing)

$$\begin{aligned} \Rightarrow -\sqrt{n} &< -\sigma\Phi^{-1}(\delta/2)/\epsilon \\ \Rightarrow \sqrt{n} &> -\sigma\Phi^{-1}(\delta/2)/\epsilon \\ \Rightarrow n &> (\sigma\Phi^{-1}(\delta/2)/\epsilon)^2 \quad \text{--- (1)} \end{aligned}$$

Now, since

NOT NECESSARY

- $\sigma > 0$
- $\epsilon > 0$
- $\Phi^{-1}(\delta/2) \neq 0$ if $\delta \neq 1$

we have that if $\cancel{-\sqrt{n}} + \delta \neq 1$,

$$(\sigma\Phi^{-1}(\delta/2)/\epsilon)^2 > 0$$

~~$\therefore \exists n \rightarrow 0$ s.t.~~ For any n above a certain non-negative quantity, we have that for an arbitrary $\delta > 0$ and $\epsilon > 0$,

$$\text{Norm}(\mu, \frac{\sigma}{\sqrt{n}})([\mu - \epsilon, \mu + \epsilon]) > 1 - \delta$$

~~Furthermore, inequality (1) implies that for smaller values of δ , since $\Phi^{-1}(\delta/2) \rightarrow -\infty$.~~

~~Furthermore, since $\Phi^{-1}(\delta/2) \rightarrow -\infty$ as $\delta \rightarrow 0$, the inequality in (1) implies that ~~as $n \rightarrow \infty$ as~~ as $\delta \rightarrow 0$, $n \rightarrow \infty$.~~

$$\Rightarrow \lim_{n \rightarrow \infty} \text{Norm}(\mu, \frac{\sigma}{\sqrt{n}})([\mu - \epsilon, \mu + \epsilon]) = 1$$

Thus proving the weak law of large numbers for normal distribution.