

exercise6

8.

Consider the following distribution

$$f(x|k, \lambda) = \frac{\lambda^k x^{k-1} e^{-\lambda x}}{(k-1)!}$$

a.

Knowing that this distribution gives the density of the sum of k i.i.d. exponential random variables with rate λ , use the moment generating function method to derive analytical expressions for its mean and variance

we know this is a gamma distribution from the question

the mgf can be calculated with

$$\begin{aligned} M_x(t) &= \int_{-\infty}^{\infty} e^{tx} f(x|k, \lambda) dx \\ &= \int_{-\infty}^{\infty} e^{tx} \frac{\lambda^k x^{k-1} e^{-\lambda x}}{(k-1)!} dx \\ &= \int_0^{\infty} e^{tx} \frac{\lambda^k x^{k-1} e^{-\lambda x}}{(k-1)!} dx && f(x|k, \lambda) \text{ is only defined for } x \geq 0 \\ &= \int_0^{\infty} \frac{\lambda^k x^{k-1} e^{(t-\lambda)x}}{(k-1)!} dx \\ &= \frac{\lambda^k}{(k-1)!} \int_0^{\infty} x^{k-1} e^{(t-\lambda)x} dx \end{aligned}$$

at this point, for clarity, we focus on the integral part

$$\begin{aligned} \int_0^{\infty} x^{k-1} e^{(t-\lambda)x} dx &= \frac{1}{(t-\lambda)} \int_0^{\infty} x^{k-1} d e^{(t-\lambda)x} \\ &= \frac{1}{(t-\lambda)} \left(x^{k-1} e^{(t-\lambda)x} \Big|_0^{\infty} - \int_0^{\infty} e^{(t-\lambda)x} dx^{k-1} \right) \\ &= \frac{k-1}{(t-\lambda)} \left(x^{k-1} e^{(t-\lambda)x} \Big|_0^{\infty} - \int_0^{\infty} e^{(t-\lambda)x} x^{k-2} dx \right) \end{aligned}$$

to evaluate $x^{k-1} e^{(t-\lambda)x} \Big|_0^{\infty}$

we need to discuss in cases,

if $t - \lambda \geq 0$, $x^{k-1}e^{(t-\lambda)x} \Big|_0^\infty$ is obviously ∞ , which make the whole mgf ∞ and meaningless, therefore we assume this case would never happen, in other words, we enforce $\lambda > t$

we rewrite the formula

$$x^{k-1}e^{(t-\lambda)x} = \frac{x^{k-1}}{e^{(\lambda-t)x}}$$

notice that the numerator and the denominator have similar characteristics in the limit, or

if $x \rightarrow 0$, $x^{k-1} \rightarrow 0$ ($k \geq 1$), $e^{(\lambda-t)x} \rightarrow 1$

and if $x \rightarrow \infty$, $x^{k-1} \rightarrow \infty$ ($k \geq 1$), $e^{(\lambda-t)x} \rightarrow 0$ ($\lambda > t$)

also notice that in the general case, this also applies for all x^a , $x > 0$ and also apply when x^a is multiplied by any constant, since $C * 0 = 0$, $C * \infty = \infty$

therefore, by recursively applying L'hopital rule, we get

$$\lim_{x \rightarrow \infty} \frac{x^{k-1}}{e^{(\lambda-t)x}} = \lim_{x \rightarrow \infty} \frac{(k-1)x^{k-2}}{(\lambda-t)e^{(\lambda-t)x}} = \dots = \lim_{x \rightarrow \infty} C * \frac{1}{e^{(\lambda-t)x}} = 0$$

$$\text{and } \lim_{x \rightarrow 0} \frac{x^{k-1}}{e^{(\lambda-t)x}} = \frac{0}{1} = 0$$

$$\text{so } x^{k-1}e^{(t-\lambda)x} \Big|_0^\infty = 0$$

back to the integral, this gives

$$\begin{aligned} \int_0^\infty x^{k-1}e^{(t-\lambda)x} dx &= \frac{k-1}{(t-\lambda)} \left(x^{k-1}e^{(t-\lambda)x} \Big|_0^\infty - \int_0^\infty e^{(t-\lambda)x} x^{k-2} dx \right) \\ &= \frac{k-1}{\lambda-t} \int_0^\infty e^{(t-\lambda)x} x^{k-2} dx \\ &= \text{this iterates} \end{aligned}$$

if we denote $I_{k-1} = \int_0^\infty x^{k-1}e^{(t-\lambda)x} dx$ and so forth, then $I_{k-1} = \frac{k-1}{\lambda-t} I_{k-2}$

and actually $I_n = \frac{n}{\lambda-t} I_{n-1}$

$$\text{the final term } I_0 = \int_0^\infty e^{(t-\lambda)x} dx = \frac{1}{t-\lambda} e^{(t-\lambda)x} \Big|_0^\infty = \frac{1}{t-\lambda} e^u \Big|_{u=0}^{-\infty} = \frac{1}{\lambda-t} e^u \Big|_{u=-\infty}^0 = \frac{1}{\lambda-t}$$

so the integral can be evaluated as

$$\int_0^\infty x^{k-1}e^{(t-\lambda)x} dx = \frac{1}{(t-\lambda)} \int_0^\infty x^{k-1} de^{(t-\lambda)x} = \frac{1}{\lambda-t} \prod_{n=1}^{k-1} \left(\frac{n}{\lambda-t} \right) = \frac{(k-1)!}{(\lambda-t)^k}$$

therefore, finally,

$$M_x(t) = \frac{\lambda^k}{(k-1)!} \int_0^\infty x^{k-1}e^{(t-\lambda)x} dx = \frac{\lambda^k}{(k-1)!} \frac{(k-1)!}{(\lambda-t)^k} = \left(\frac{\lambda}{\lambda-t} \right)^k$$

therefore

$$\begin{aligned}\mu &= \frac{dM_x(t)}{dt} \Big|_{t=0} = \frac{d}{dt} \left(\frac{\lambda}{\lambda - t} \right)^k \Big|_{t=0} \\ &= k\lambda^k (\lambda - t)^{-(k+1)} \Big|_{t=0} \\ &= \frac{k}{\lambda}\end{aligned}$$

and

$$\begin{aligned}E[X^2] &= \frac{d^2 M_x(t)}{dt^2} \Big|_{t=0} \\ &= \frac{d(k\lambda^k (\lambda - t)^{-(k+1)})}{dt} \Big|_{t=0} \\ &= k(k+1)\lambda^k (\lambda - t)^{-(k+2)} \Big|_{t=0} \\ &= \frac{k(k+1)}{\lambda^2}\end{aligned}$$

therefore

$$Var(X) = E[X^2] - E[X]^2 = \frac{k(k+1)}{\lambda^2} - \left(\frac{k}{\lambda}\right)^2 = \frac{k}{\lambda^2}$$

b

Assume in this part that you collected the following $n = 10$ samples from the distribution

(2.846,3.445,4.376,0.402,2.893,2.522,0.458,3.742,3.156,1.030)

Give unbiased estimates for the mean and variance of this distribution. Using the results of part a., obtain estimates for k and λ , ensuring that the obtained values are admissible for this distribution.

the mean value of this sample is

$$\begin{aligned}&\frac{1}{n} \sum_{n=1}^{10} x_n \\ &= \frac{2.846 + 3.445 + 4.376 + 0.402 + 2.893 + 2.522 + 0.458 + 3.742 + 3.156 + 1.030}{10} \\ &= \frac{24.87}{10} = 2.487\end{aligned}$$

the variance of this sample is

$$\begin{aligned}
\sigma^2 &= \frac{1}{n-1} \sum_{n=1}^{10} (x_n - \mu)^2 \\
&= \frac{1}{9} \left((2.846 - 2.487)^2 + (3.445 - 2.487)^2 + \right. \\
&\quad (4.376 - 2.487)^2 + (0.402 - 2.487)^2 + \\
&\quad (2.893 - 2.487)^2 + (2.522 - 2.487)^2 + \\
&\quad (0.458 - 2.487)^2 + (3.742 - 2.487)^2 + \\
&\quad \left. (3.156 - 2.487)^2 + (1.030 - 2.487)^2 \right) \\
&= \frac{1}{9} \left(0.359^2 + 0.958^2 + 1.889^2 + (-2.085)^2 \right. \\
&\quad 0.406^2 + 0.035^2 + (-2.029)^2 + 1.255^2 \\
&\quad \left. 0.669^2 + (-1.457)^2 \right) \\
&= \frac{17.3905}{9} \approx 1.9323
\end{aligned}$$

therefore

$$\mu = \frac{k}{\lambda} = 2.487$$

$$\sigma^2 = \frac{k}{\lambda^2} = 1.9323$$

$$\text{so } \lambda = \frac{\mu}{\sigma^2} \approx \frac{2.487}{1.9323} = 1.287$$

$$k = \mu\lambda = 2.487 * 1.287 \approx 3.201$$

and since $\lambda > 0, k \geq 1$, this set of parameters is admissible

(c)

Assume in this part that k is known. Suppose now that you have collected n independent samples (x_1, x_2, \dots, x_n) from this distribution. Derive an analytical expression for the maximum likelihood estimate for λ based on these samples, expressing it as a function of the sample mean \bar{X} and the known value of k

(to be consistent with the notation in the lectures, the log in the following proof is actually \ln)

to get the MLE of this distribution, we first try to obtain the log-likelihood function of the distribution

$$\begin{aligned}
 \ell(\lambda) &= \log L(\lambda) = \log \prod_{i=1}^n f(x_i | \lambda, k) && k \text{ is known} \\
 &= \log \prod_{i=1}^n \frac{\lambda^k x_i^{k-1} e^{-\lambda x_i}}{(k-1)!} \\
 &= nk \log \lambda + (k-1) \sum_{i=1}^n \log x_i + -\lambda \sum_{i=1}^n x_i \log e - n \log(k-1)!
 \end{aligned}$$

we would want to maximize, or calculate the value of λ that make the derivative 0

$$\frac{d\ell(\lambda)}{d\lambda} = \frac{nk}{\lambda} - \sum_{i=1}^n x_i$$

$$\text{therefore } \lambda = \frac{nk}{\sum_{i=1}^n x_i} = \frac{k}{\bar{X}}$$