

Q1)
ans) a)

Mudit Balogja
2019258

CLASSTEAM	Page No.
Date	/ /

SI - Assignment - 1

Q.
ans)

x_i iid Gamma(r, λ) ($r=5, \lambda=2$)

Now if $X \sim \text{Gamma}(r, \lambda)$
then

$$f(x) = \frac{\lambda^r x^{r-1} \exp(-\lambda x)}{\Gamma(r)}$$

$$\Rightarrow L(\theta) = \prod_{i=1}^n \frac{\lambda^r x_i^{r-1} \exp(-\lambda x_i)}{\Gamma(r)}$$

(Likelihood function)

$$\Rightarrow L(\theta) = \frac{(\lambda^{nr}) \cdot \left(\prod_{i=1}^n x_i \right)^{r-1} \exp(-\lambda \sum_{i=1}^n x_i)}{(\Gamma(r))^n}$$

Now,
log-likelihood \rightarrow $l(\theta) = \log(L(\theta))$
function

$$= n \cdot r \cdot \log \lambda + (r-1) \cdot \sum_{i=1}^n \log(x_i) - n \log(\Gamma(r)) - \lambda \cdot \sum_{i=1}^n x_i$$

For maximum,

$$\frac{dL(\theta)}{dr} = 0 \quad \text{and} \quad \frac{dl(\theta)}{d\lambda} = 0$$

$$\rightarrow \text{firstly } \frac{dl(\theta)}{d\lambda} = 0$$

$$\Rightarrow \frac{n\gamma}{\lambda} + 0 - 0 - \sum_{i=1}^n x_i = 0$$

$$\Rightarrow \lambda = \frac{n\gamma}{\sum_{i=1}^n x_i}$$

$$\Rightarrow \boxed{\lambda = \frac{n}{\bar{x}}}$$

Now, for $\frac{dL(\theta)}{d\theta} = 0$

$$\Rightarrow n \log \lambda + \sum_{i=1}^n x_i - \frac{n}{\Gamma(r)} \frac{d\Gamma(r)}{dr} = 0$$

To check maximum

$$\Rightarrow \frac{d^2 L(\theta)}{d\lambda^2} = \frac{-n\gamma}{\lambda^2} = \frac{-n(\bar{x})^2}{n}$$

n, \bar{x}, γ are +ve so $\frac{d^2 L(\theta)}{d\lambda^2} < 0$

$$\text{Now, } \frac{dL(\theta)}{dr} = 0$$

$$\Rightarrow n \log \lambda + \sum_{i=1}^n x_i - \frac{n}{\Gamma(r)} \frac{d\Gamma(r)}{dr} = 0$$

Sub λ & diff further leads to \rightarrow

$$\ln(r) - \underbrace{\psi(r)}_{\text{digamma}} = \ln(\bar{x}) - \frac{\sum_{i=1}^n \ln(x_i)}{n}$$

b)

The eqⁿ can only be solved iteratively using complex numerical analysis, beyond the scope of our purview, so we leave the solution at this point.

→ Now + method of moments estimation

$$X_i \sim \text{Gamma}(r, \lambda) \quad \rightarrow \text{Var}(x) = (E(x))^2$$

$$E[X] = \frac{r}{\lambda} \quad E[X^2] = \frac{r(r+1)}{\lambda}$$

$$\frac{\sum_{i=1}^n x_i}{n} = \frac{r}{\lambda} \quad \frac{\sum_{i=1}^n x_i^2}{n} = \frac{r(r+1)}{\lambda} \quad \text{--- (1)}$$

Put $r = \lambda \frac{\sum x}{n}$ in (2)

$$\lambda \bar{X} (\lambda \bar{X} + 1) = \frac{\sum x_i^2}{n}$$

$$\Rightarrow \boxed{\hat{\lambda} = \frac{\bar{x}}{\frac{\sum x_i^2}{n} - \bar{x}^2}}$$

$$\Rightarrow \boxed{\hat{r} = \hat{\lambda} \bar{x} = \frac{\bar{x}^2}{\frac{\sum x_i^2}{n} - \bar{x}^2}}$$

For the maximum likelihood estimate, R routine 'optim()' is used to maximise the log likelihood of the random sample drawn from the Gamma distribution.

The following Maximum likelihood estimates for $r = 5$ and $\lambda = 2$ were obtained:

$$\hat{r}_{MLE} = 5.018516$$

$$\hat{\lambda}_{MLE} = 2.061471$$

The value of log-likelihood at this value of r and λ is $L(r, \lambda) = -1432.231$

The MLE using Method of Moments where $r = (\text{mean})^2/\text{variance}$ and $\lambda = \text{mean}/\text{variance}$

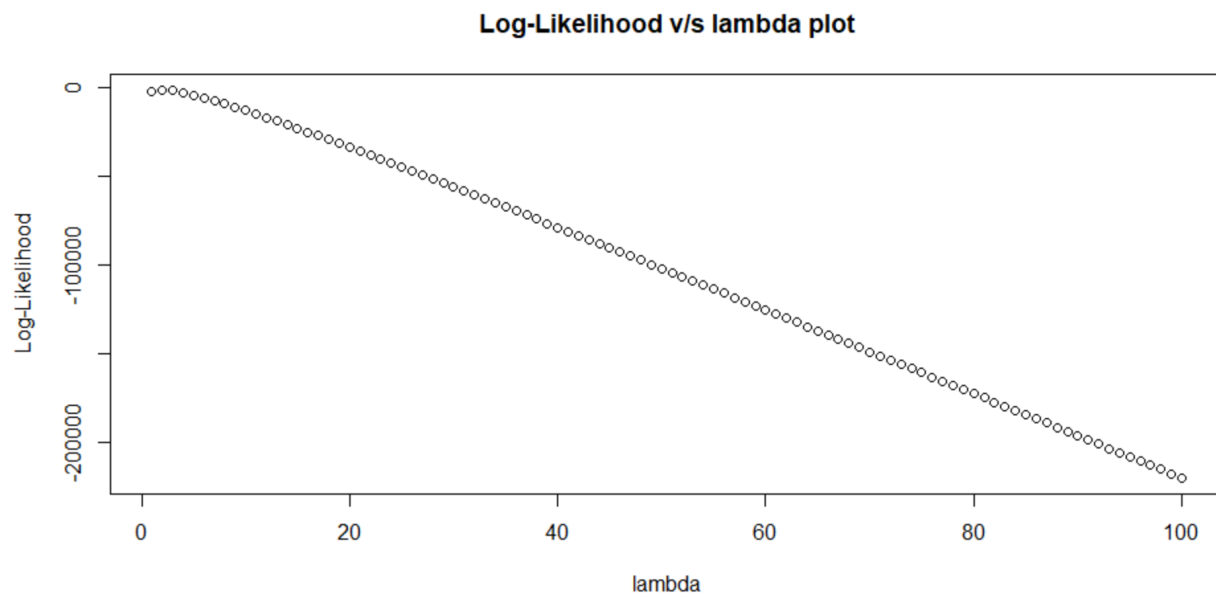
$$\hat{r}_{MLE} = 5.018560$$

$$\hat{\lambda}_{MLE} = 2.061468$$

The value of log-likelihood at this value of r and λ is $L(r, \lambda) = -1432.231$

c) Below is the plot of Log-Likelihood with varied λ and constant $r = 5$. We observe that the log-likelihood function value is maximum at $\lambda \approx 2$, which agrees with the theoretical value and the value obtained using the optimiser function (optim()).

Log-Likelihood value is plotted on the y-axis. While the x-axis contains various values of λ from 1 to 100 with a jump of 1.

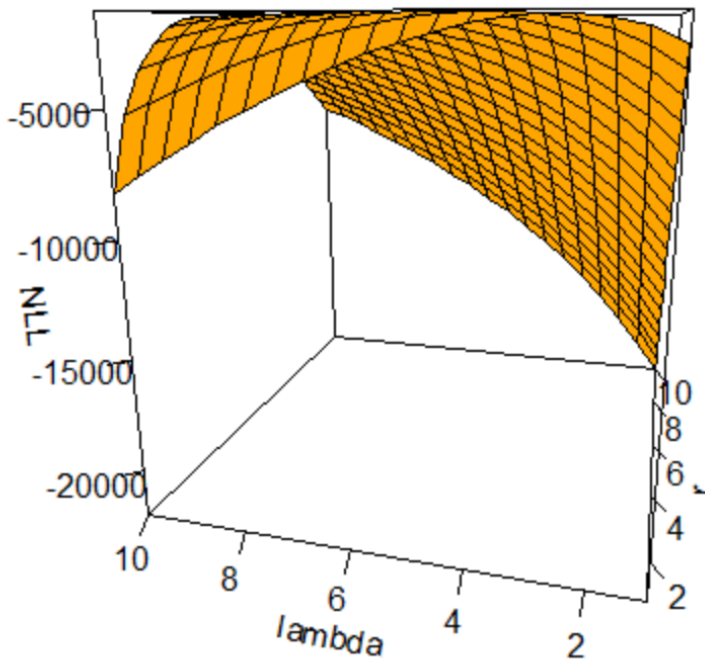


Conclusion: The maximum likelihood estimate of the unknown parameter λ (i.e 2.061468) calculated using the R routine 'optim()' is nearly the same as the given value (≈ 2) which is also verified using the above plot.

d) Below is a 3-d plot of NLL with various values of lambda and r. We observe that the below plot reaches the maximum value at $\lambda \approx 2$ and $r \approx 5$ which is consistent with theoretically obtained values.

NLL is plotted on the z-axis, r is plotted on the x-axis and lambda is plotted on the y-axis both varying between 1 to 10 at a step = 0.5

Plot NLL vs lambda vs r



Conclusion: Maximum reached graphically using R routines 'optim()' and 'persp()' gives us approximately the same value of $r (\approx 5)$ and $\lambda (\approx 2)$ as theoretically obtained.

Q2)

ans) a)

Q2.
ans) a) X iid Normal (μ, σ)

then

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \frac{(x_i - \mu)^2}{\sigma^2}\right)$$

$\mu \rightarrow \text{mean}$
 $\sigma^2 \rightarrow \text{variance}$

$$L(\theta) = \prod_{i=1}^n f(x_i)$$

(Likelihood function)

$$= \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2} \sum_{i=1}^n \frac{(x_i - \mu)^2}{\sigma^2}\right)$$

2)

$$l(\theta) = \log(L(\theta))$$

LLF

$$= -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2$$

$$= -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2$$

$$\text{At max, } \frac{dl(\theta)}{d\mu} = 0 \quad \text{and} \quad \frac{dl(\theta)}{d\sigma} = 0$$

\rightarrow firstly $\frac{dl(\theta)}{d\sigma} = 0$

2)

$$0 = -\frac{n}{\sigma} + \frac{1}{\sigma^3} \sum_{i=1}^n (x_i - \mu)^2 = 0$$

3)

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (x_i - \mu)^2}{n}}$$

To check θ maxima

$$\frac{d^2 l(\theta)}{d^2 \sigma} = \frac{n}{\sigma^2} - \frac{3}{\sigma^4} (\sum (x_i - \mu)^2)$$

substituting

$$= \frac{n^2}{\sum (x_i - \mu)^2} - \frac{3n^2}{\sum (x_i - \mu)^2}$$

$$= \frac{-2n^2}{\sum (x_i - \mu)^2} < 0$$

\therefore maxima achieved.

So,

$$\sigma_{MLE}^2 = \frac{\sum (x_i - \mu)^2}{n}$$

Now, $\frac{dl(\theta)}{d\mu} = 0$

1) first substituting σ_{MLE}^2 in $l(\theta)$ & then differentiating w.r.t μ

2) we'll get $\mu = \frac{\sum x_i}{n}$

$$\mu = \frac{\sum x_i}{n}$$

To check max,

$$\frac{d^2 l(\theta)}{d\mu^2} = -\frac{n}{\sigma^2} < 0$$

So, max attained.

$$\mu_{MLE} = \frac{\sum x_i}{n}$$

For the maximum likelihood estimate, R routine 'optim()' is used to maximise the log likelihood of the random sample drawn from the Normal distribution.

The following Maximum likelihood estimates for μ and σ^2 were obtained:

$$\hat{\mu}_{MLE} = 70.109648$$

$$\hat{\sigma}^2_{MLE} = 8.898797$$

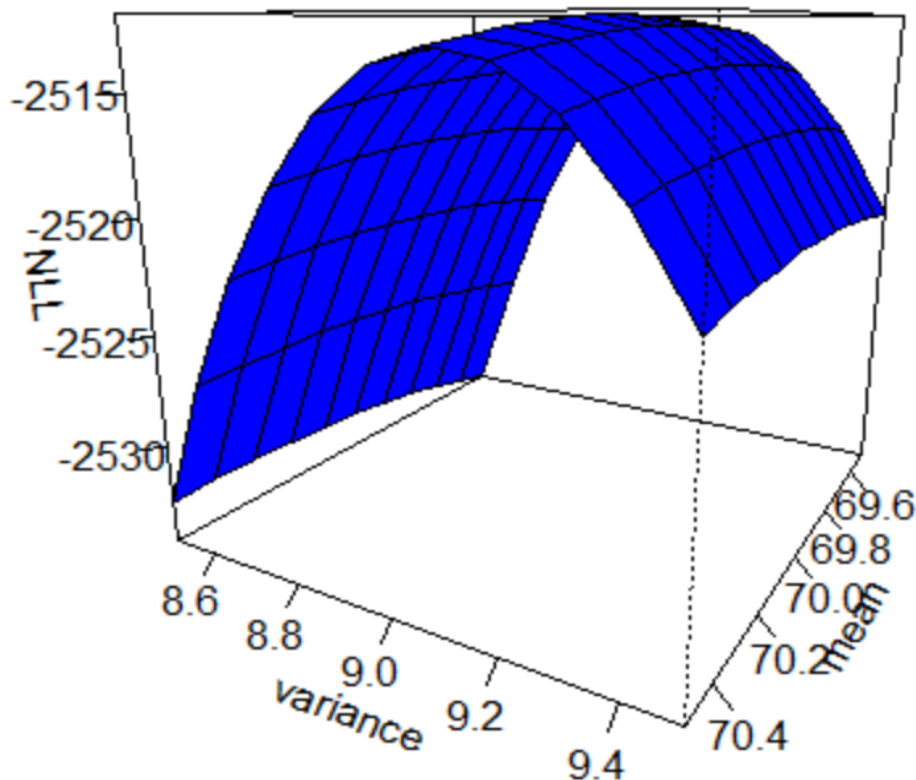
The value of log-likelihood at this value of μ and σ^2 is $L(\mu, \sigma^2) = -2512.004$

b) In the below 3-d plot, NLL is plotted against varied values of μ and σ^2 .

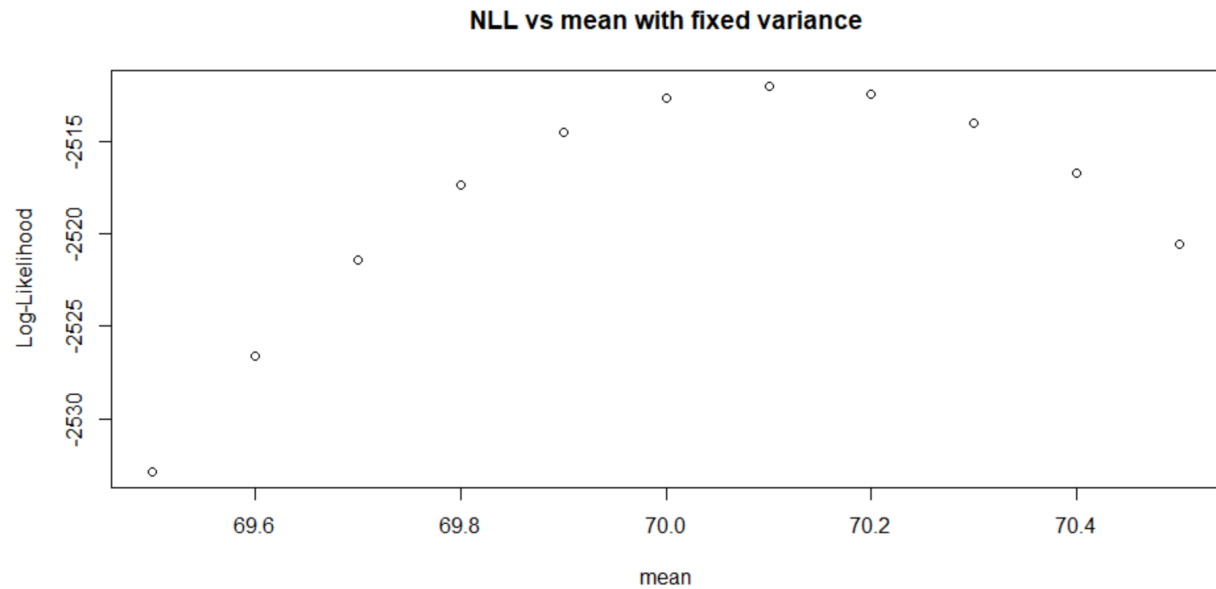
We observe that the below plot reaches the maximum value at $\mu \approx 70.10$ and $\sigma^2 \approx 8.89$ which is consistent with theoretically obtained values.

NLL is plotted on the z-axis, μ is plotted on the x-axis varying between 69.5 and 70.5 with step = 0.1 and σ^2 is plotted on the y-axis varying between 8.5 and 9.5 with step = 0.1

Plot of NLL vs mean vs variance

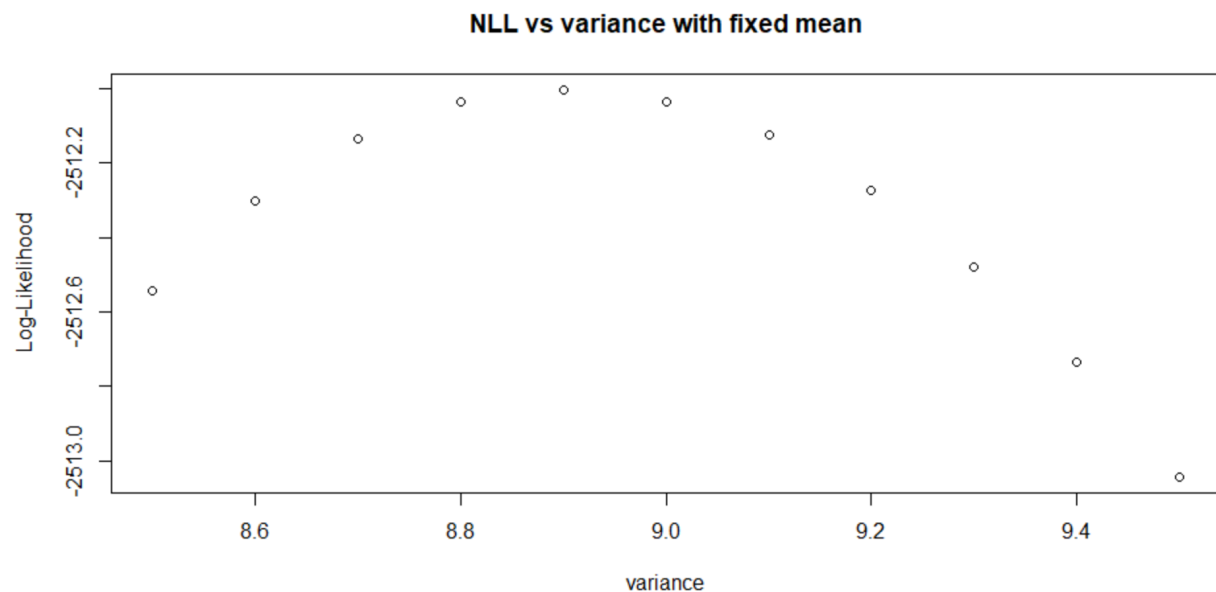


For a deeper explanation, I have provided two 2-d plots providing a clearer picture of maximum. In the first plot, variance is fixed at the estimated value and mean is varied -



As we can see, we attain maximum at $\mu \approx 70.10$, consistent with the theoretical value.

Similarly, in the second plot, the mean is fixed at the estimated value, and variance is varied.



As we can see, we attain maximum at $\sigma^2 \approx 8.89$, consistent with the theoretical value.

Conclusion: Maximum reached graphically using R routines ‘optim()’ and ‘persp()’ gives us approximately the same value of $\mu (\approx 70.10)$ and $\sigma^2 (\approx 8.89)$ as theoretically obtained.