

SI Report

Name :- Abhinav Gudipati

Roll Number :- 2019227

Assignment 1

Question 1

### Question 1

Proof for Gamma Distribution

(shape =  $n$ ) and (rate =  $\lambda$ )

$$f(x) = \frac{\lambda^n}{\Gamma(n)} x^{n-1} e^{-\lambda x}$$

where  $f(x)$  is the PDF of the gamma distribution

likelihood function

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

$$L(\theta) = \prod_{i=1}^n \left\{ \frac{\lambda^n}{\Gamma(n)} x_i^{n-1} e^{-\lambda x_i} \right\}$$

$$= \left\{ \frac{\lambda^n}{\Gamma(n)} \right\}^n \times \prod_{i=1}^n x_i^{n-1} e^{-n\lambda x}$$

explanation

~~we are taking product and hence~~

the product for  $\prod_{i=1}^n e^{-\lambda x_i}$  is  $e^{-n\lambda x}$

which is because we take summation of all  $\left\{ \sum_{i=1}^n (x_i) \right\}$

$$L(\theta) = \left( \frac{\lambda^n}{\Gamma(n)} \right) \times \prod_{i=1}^n x_i^{(n-1)} \times e^{-n\lambda}$$

taking log on both sides we get

$$\log L(\theta) = \log \left( \frac{\lambda^n}{\Gamma(n)} \right) \times \prod_{i=1}^n x_i^{(n-1)} \times e^{-n\lambda}$$

$$\log L(\theta) = \left\{ \log \lambda^n - \log(\Gamma(n)) + \log \left( \prod_{i=1}^n x_i^{(n-1)} \right) + \log e^{-n\lambda} \right\}$$

$$= n \log(\lambda) - n \log \Gamma(n)$$

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

$$= n \log \lambda + n \log \Gamma(n) + (n-1) \log x_i$$

$$= n \log \lambda + n \log \Gamma(n) + (n-1) \log x_i - \bar{x} \lambda$$



Q. 2 (b) we took  $\log \prod_{i=1}^n x_i^{(\lambda-1)}$  to be.

$(\log x_i)$  and not as  $\bar{x}_i \lambda$ .

$$\log L(\theta) = n \log \lambda + n \log [(\lambda)] + (\lambda - 1) \log x_i - \bar{x}_i \lambda$$

(i) we use this log likelihood function for our graphs.

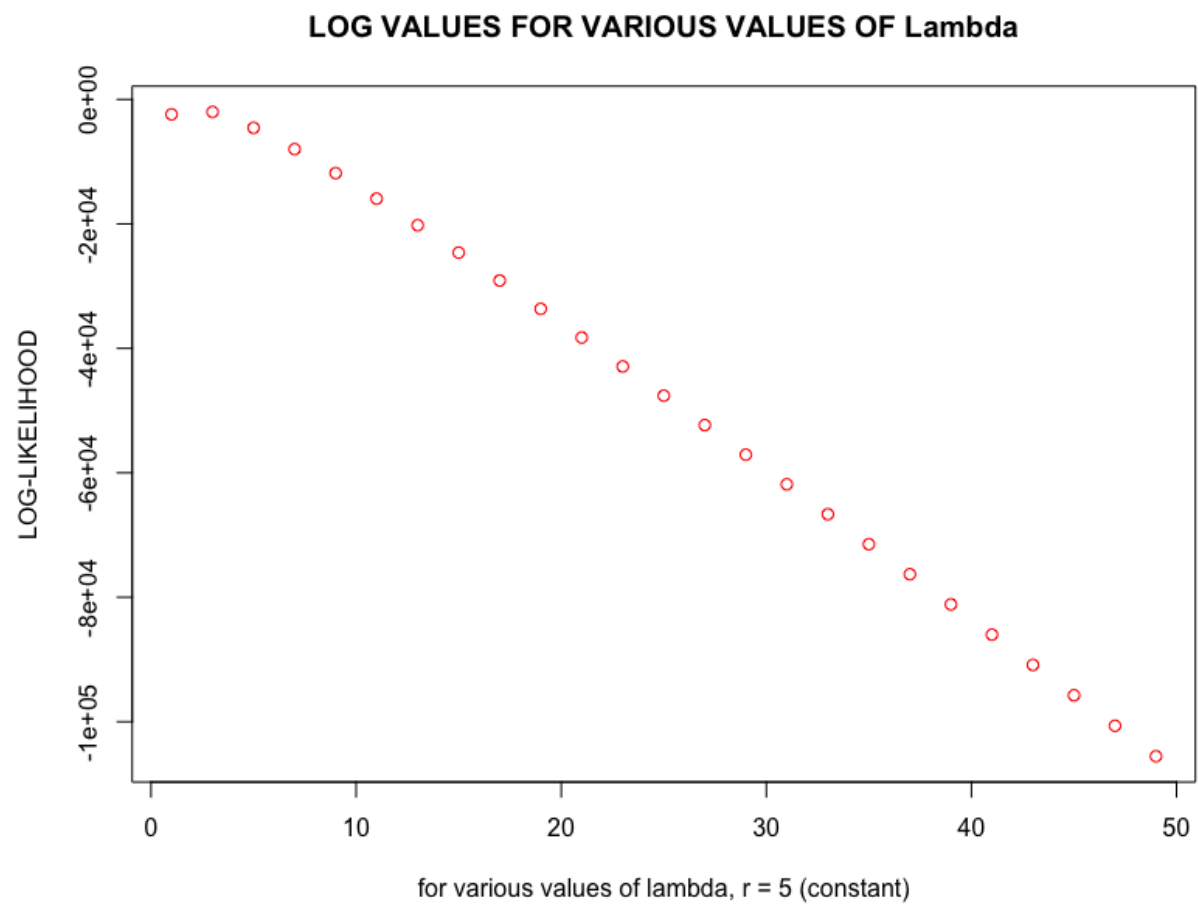
$$\begin{array}{|c|} \hline n = 5 \\ \hline \lambda = 2 \\ \hline \end{array}$$

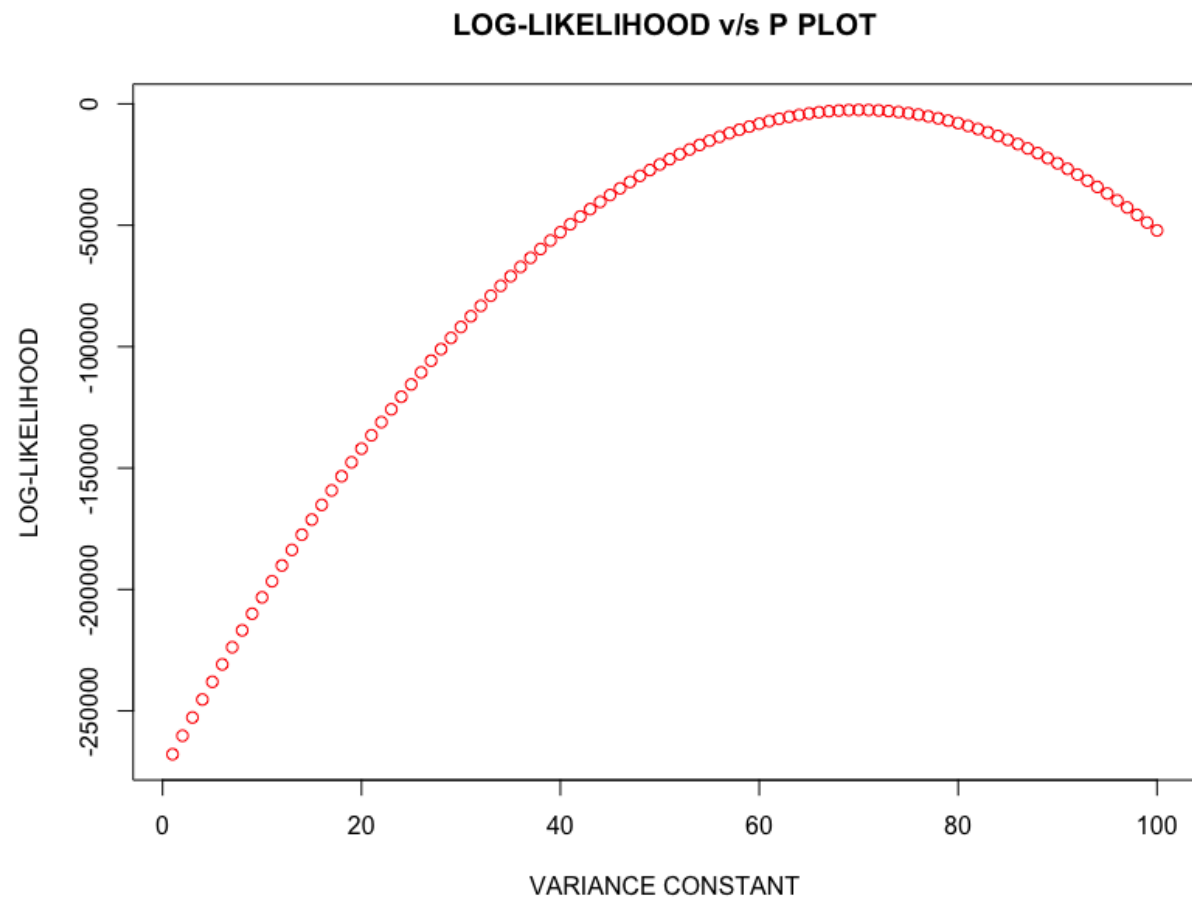
$$\begin{aligned} \log L(\theta) &= 1000 \times 2.5 \times \log(2) \\ &+ 1000 \times \log[5] \\ &+ (5 - 1) \log x_i - 1000 \times 2 \times 2 \end{aligned}$$

taking  $L(\theta)$  w.r.t  $\lambda$ .

we get

$$\frac{1}{\lambda} = \frac{\bar{x}}{n}$$





Question 2

## Normal Distribution

classmate

Date

Page

$$(2) \quad x_i \stackrel{iid}{\sim} N(\mu, \sigma^2)$$

$$\theta = (\mu, \sigma^2)$$

$$\downarrow \quad \downarrow$$
$$\theta_1 \quad \theta_2$$

MLE of  $\theta$  likelihood functions

$$L(\theta) = \frac{1}{(2\pi\theta_2)^{n/2}} \exp\left\{-\frac{1}{2} \frac{\sum (x_i - \theta_1)^2}{\theta_2}\right\}$$

$$l(\theta) = -\frac{n}{2} \log(2\pi\theta_2) - \frac{1}{2} \frac{\sum (x_i - \theta_1)^2}{\theta_2}$$

$$= c - \frac{n}{2} \log \theta_2 - \frac{1}{2} \frac{\sum (x_i - \theta_1)^2}{\theta_2}$$

$$\frac{dl}{d\theta_1} = 0$$

$$\frac{dl}{d\theta_2} = 0$$

$$\frac{dl}{d\theta_1} = \frac{\sum (x_i - \theta_1)}{\theta_2} = 0$$

$$\frac{dl}{d\theta_2} = -\frac{n}{2} \frac{1}{\theta_2} + \frac{1}{2} \frac{\sum (x_i - \theta_1)^2}{\theta_2^2} = 0$$

$$\hat{\theta}_1 = \bar{x} \quad ; \quad \hat{\theta}_2 = \frac{\sum (x_i - \hat{\theta}_1)^2}{n}$$



$$\hat{\theta}_2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$

$$a \quad \left. \frac{d^2 l}{d\theta_1^2} \right|_{\hat{\theta}_1, \hat{\theta}_2} < 0$$

$$a \quad \left. \frac{d^2 l}{d\theta_2^2} \right|_{\hat{\theta}_1, \hat{\theta}_2} < 0$$

and (b)

$$\left. \frac{d^2 l}{d\theta_1^2} \right|_{\hat{\theta}_1, \hat{\theta}_2} > 0$$

$$\left. \frac{d^2 l}{d\theta_1 d\theta_2} \right|_{\hat{\theta}_1, \hat{\theta}_2} > 0$$

$$\left. \frac{d^2 l}{d\theta_1^2} \right|_{\hat{\theta}_1, \hat{\theta}_2} = \frac{-n}{\hat{\theta}_2^2} = \frac{-n^2}{\sum (x_i - \bar{x})^2} < 0$$

$$\left. \frac{d^4 l}{d\theta_1^2} \right|_{\hat{\theta}_1, \hat{\theta}_2} = \frac{n^3}{2\hat{\theta}_2^3} < 0$$



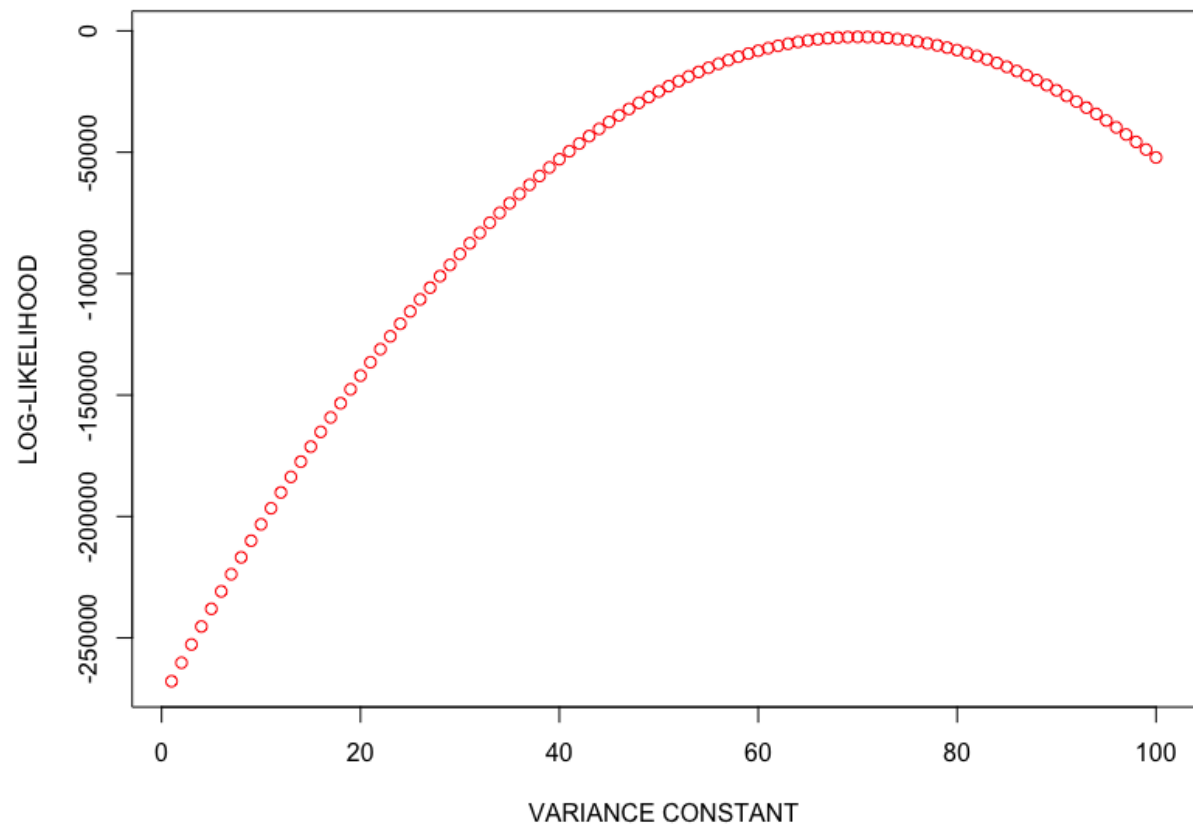
$$\left. \frac{d^2 l}{d\theta_1 d\theta_2} \right|_{\hat{\theta}_1, \hat{\theta}_2} = 0$$

$$[J] > 0$$

$$\text{Hence } \hat{\theta}_1 = \bar{x} \quad \& \quad \hat{\theta}_2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$

are MLEs for  $\theta_1, \theta_2$

## PART A



**PART B**

