

# Math 741 Assignment 2 (Hand-In)

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February 10, 2019

5.2.4

solution: Given  $L(\theta) = \prod_{i=1}^n p_X(k_i; \theta)$  for discrete. i.e.

$$L(\theta) = \prod_{i=0}^n \frac{\theta^{2k_i} e^{-\theta^2}}{k_i!} = \frac{\theta^{2\sum_{i=0}^n k_i} e^{-n\theta^2}}{\prod_{i=0}^n k_i!}$$

$$\ln(L(\theta)) = \ln \theta^{2\sum_{i=0}^n k_i} + \ln e^{-n\theta^2} - \ln \prod_{i=0}^n k_i! = 2 \sum_{i=0}^n k_i \ln \theta - n\theta^2 - \sum_{i=0}^n (\ln k_i!)$$

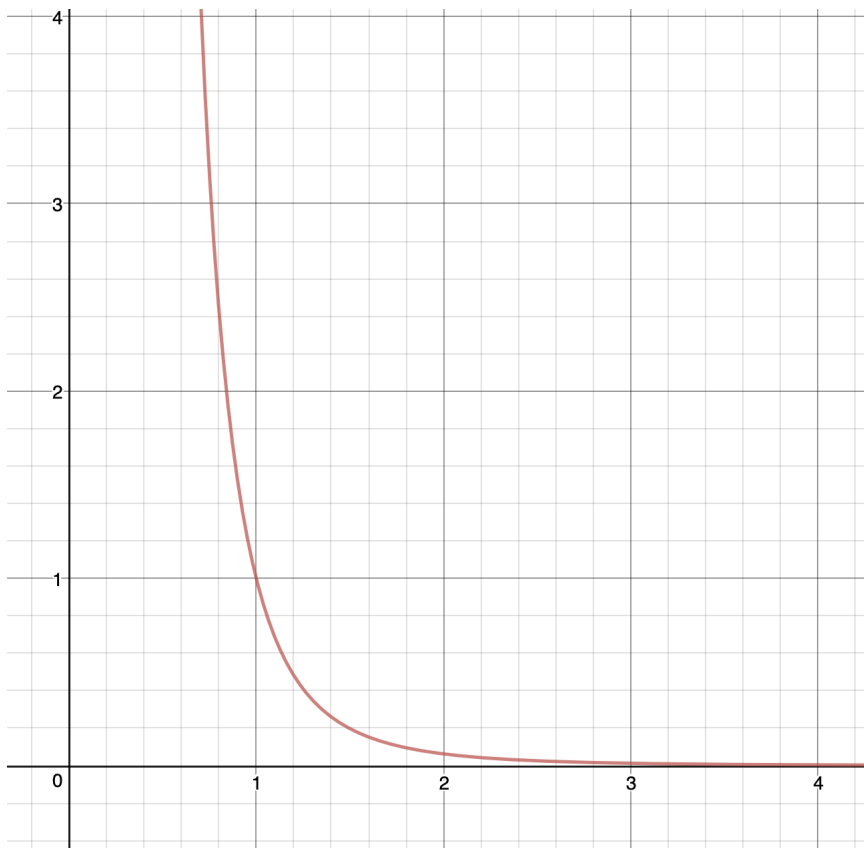
$$\frac{d}{d\theta}(\ln(L(\theta))) = \frac{2\sum_{i=0}^n k_i}{\theta} - 2n\theta$$

$$\begin{aligned} \text{Let } \frac{d}{d\theta}(\ln(L(\theta))) = 0 &\Rightarrow \frac{2\sum_{i=0}^n k_i}{\hat{\theta}} - 2n\hat{\theta} = 0 \Rightarrow \hat{\theta}^2 = \frac{\sum_{i=0}^n k_i}{n} \\ &\Rightarrow \hat{\theta} = \sqrt{\frac{\sum_{i=0}^n k_i}{n}} \end{aligned}$$

5.2.10

solution: Given  $L(\theta) = \prod_{i=1}^n f_Y(y_i; \theta)$  for continuous. Then

(a) By observation that  $L(\theta) = \frac{1}{\theta^4}$  and  $\theta \geq 0$ . The graph is showing below



We can just look at the  $L(\theta)$  directly.  $L(\theta)$  is maximum when  $\theta$  is the smallest. Moreover the inequality  $0 \leq y \leq \theta$  must hold. Therefore  $\theta$  must not less than all  $y$ . Hence  $\hat{\theta} = y_{\max} = 14.2$ .

(b) By observation that  $L(\theta_1, \theta_2) = \frac{1}{(\theta_2 - \theta_1)^4}$  and  $\theta_2 \geq \theta_1 \Rightarrow \theta_2 - \theta_1 \geq 0$ . Let  $\theta = \theta_2 - \theta_1$ , then  $L(\theta)$  is the same as part a). Therefore, we can look at the function directly to find maximum.

In order to get  $L(\theta_1, \theta_2)$  maximized,  $\theta_2 - \theta_1$  must be minimized as well as the inequality  $\theta_1 \leq y \leq \theta_2$  must hold. We want  $\theta_2$  as small as possible and  $\theta_1$  as large as possible. Hence  $\hat{\theta}_2 = y_{\max} = 14.2, \hat{\theta}_1 = y_{\min} = 1.8$ .

5.2.15

solution: Given the normal pdf and  $\mu$ , then

$$L(\sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{1}{2} \frac{(y_i - \mu)^2}{\sigma^2}} = (2\pi\sigma^2)^{-n/2} e^{\frac{1}{2} \frac{\sum_{i=1}^n (y_i - \mu)^2}{\sigma^2}}$$

$$\begin{aligned}
\ln(L(\sigma^2)) &= -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \cdot \sum_{i=1}^n (y_i - \mu)^2 \\
&= -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} \cdot \sum_{i=1}^n (y_i - \mu)^2 \\
\frac{d}{d\sigma^2}(\ln(L(\sigma^2))) &= -\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - \mu)^2
\end{aligned}$$

Let  $\frac{d}{d\sigma^2}(\ln(L(\sigma^2))) = 0$ , then

$$\begin{aligned}
-\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - \mu)^2 &= 0 \Rightarrow -n\hat{\sigma}^2 + \sum_{i=1}^n (y_i - \mu)^2 = 0 \\
\hat{\sigma}^2 &= \frac{\sum_{i=1}^n (y_i - \mu)^2}{n}
\end{aligned}$$

They are almost identical. In example 5.2.4,  $\mu$  is not given. Therefore, In the estimator  $\hat{\sigma}^2$ ,  $\hat{\mu}$  is there. In this case,  $\mu$  is given, we only need to estimate  $\hat{\sigma}^2$ .

5.2.17

solution: This is a continuous pdf, therefore by definition 5.2.3.

$$\begin{aligned}
E(Y) &= \int_{-\infty}^{+\infty} y f_Y(y) dy = \int_0^1 (\theta^2 + \theta) y^\theta (1 - y) dy = (\theta^2 + \theta) \int_0^1 (y^\theta - y^{\theta+1}) dy \\
&= (\theta^2 + \theta) \left( \frac{y^{\theta+1}}{\theta+1} - \frac{y^{\theta+2}}{\theta+2} \right) \Big|_0^1 = (\theta^2 + \theta) \left( \frac{1}{\theta+1} - \frac{1}{\theta+2} \right) = \frac{\theta}{\theta+2}
\end{aligned}$$

Since  $\hat{\mu} = \bar{y}$ , therefore

$$\frac{\hat{\theta}}{\hat{\theta} + 2} = \bar{y} \Rightarrow \hat{\theta} = (\hat{\theta} + 2)\bar{y} \Rightarrow \hat{\theta} - \hat{\theta}\bar{y} = 2\bar{y} \Rightarrow \hat{\theta} = \frac{2\bar{y}}{1 - \bar{y}}$$