

MATH 308 Assignment 16:

Exercises 6.4

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We know that $X \sim \mathcal{B}(n, p) \implies f_X(x) = \binom{n}{x} p^x (1-p)^{n-x}$. Thus, the probability of obtaining the value X can be written as a function of the parameter p :

$$\begin{aligned} L(p) &= \binom{n}{X} p^X (1-p)^{n-X} \\ \implies L'/\binom{n}{X} &= X p^{X-1} (1-p)^{n-X} \\ &\quad - p^X (n-X) (1-p)^{n-X-1} \end{aligned}$$

We can then obtain the MLE \hat{p} by setting $L' = 0$:

$$\begin{aligned} X p^{X-1} (1-p)^{n-X} &= p^X (n-X) (1-p)^{n-X-1} \\ \implies \hat{p}(n-X) &= X(1-\hat{p}) \\ \implies \hat{p}n - \hat{p}X &= X - X\hat{p} \\ \implies \hat{p} &= X/n \quad \square \end{aligned}$$

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$X \sim \mathcal{P}(\lambda) \implies f_X = \frac{\lambda^x e^{-\lambda}}{x!}$. So, the likelihood of obtaining the sample $\{x_1, x_2, \dots, x_n\}$ is $L(\lambda) = \prod_{i=1}^n f_X(x_i)$, since the elements of the sample are i.i.d.

$$\begin{aligned} L &= \prod_{i=1}^n \frac{\lambda^{x_i} e^{-\lambda}}{x_i!} \\ &= \frac{\lambda^{\sum x_i} e^{-n\lambda}}{\prod (x_i!)} \end{aligned}$$

$$\begin{aligned} \implies L'/\prod (x_i!) &= (\lambda^{\sum x_i} e^{-n\lambda})' \\ &= \sum x_i \lambda^{\sum x_i - 1} e^{-n\lambda} + \lambda^{\sum x_i} e^{-n\lambda} (-n) \\ &= e^{-n\lambda} \lambda^{\sum x_i - 1} (\sum x_i - n\lambda) \end{aligned}$$

Setting $L' = 0$, we get $\hat{\lambda}$:

$$\begin{aligned} 0 &= \sum x_i - n\hat{\lambda} \\ \implies \hat{\lambda} &= \sum x_i / n = \bar{x} \quad \square \end{aligned}$$

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As in the previous problem,

$$\begin{aligned} L(\theta) &= \prod_{i=1}^n \frac{x_i^3 e^{-x_i/\theta}}{6\theta^4} \\ &= \frac{(\prod x_i)^3 e^{-\sum x_i/\theta}}{6^n \theta^{4n}} \\ &= k e^{-\sum x_i/\theta} \theta^{-4n} \end{aligned}$$

$$\begin{aligned} \implies L'/k &= e^{-\sum x_i/\theta} (\sum x_i/\theta^2) \theta^{-4n} \\ &\quad + e^{-\sum x_i/\theta} (-4n) \theta^{-4n-1} \\ &= e^{-\sum x_i/\theta} \theta^{-4n-1} \left(\frac{\sum x_i}{\theta} - 4n \right) \end{aligned}$$

Setting $L' = 0$:

$$\begin{aligned} 0 &= \frac{\sum x_i}{\hat{\theta}} - 4n \\ \implies \hat{\theta} &= \frac{\sum x_i}{4n} \\ &= \bar{x}/4 \end{aligned}$$

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a)

$$\begin{aligned}
L(\mu) &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\
&= \mathcal{C} \prod_{i=1}^n e^{-\frac{x_i^2 + \mu^2 - 2x_i\mu}{2\sigma^2}} \\
&= \mathcal{C} \prod_{i=1}^n (e^{\frac{x_i\mu}{\sigma^2}} / e^{\frac{\mu^2}{2\sigma^2}}) \\
&= \mathcal{C} e^{\frac{\mu\Sigma x}{\sigma^2}} / e^{\frac{n\mu^2}{2\sigma^2}} \\
&= \mathcal{C} e^{\frac{2\mu\Sigma x - n\mu^2}{2\sigma^2}} \\
\Rightarrow \log L - \log \mathcal{C} &= \frac{2\mu\Sigma x - n\mu^2}{2\sigma^2} \\
\Rightarrow L'/L &= \frac{2\Sigma x - 2n\mu}{2\sigma^2} \\
\Rightarrow 0 &= \Sigma x - n\hat{\mu} \\
\Rightarrow \hat{\mu} &= \Sigma x/n = \bar{x}
\end{aligned}$$

b)

$$\begin{aligned}
L(\sigma) &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\
&= \frac{\mathcal{C}}{\sigma^n} \prod_{i=1}^n e^{-\frac{x_i^2 - \mu^2 + 2x_i\mu}{2\sigma^2}} \\
&= \frac{\mathcal{C}}{\sigma^n} e^{\frac{-\Sigma x^2 - n\mu^2 + 2\mu\Sigma x}{2\sigma^2}} \\
\Rightarrow L/\mathcal{C} &= e^{\frac{-\Sigma x^2 - n\mu^2 + 2\mu\Sigma x}{2\sigma^2}} / \sigma^n \\
\Rightarrow \log L - \log \mathcal{C} &= \frac{-\Sigma x^2 - n\mu^2 + 2\mu\Sigma x}{2\sigma^2} - n \log \sigma \\
\Rightarrow L'/L &= (\Sigma x^2 + n\mu^2 - 2\mu\Sigma x)/\sigma^3 - n/\sigma \\
\Rightarrow 0 &= (\Sigma x^2 + n\mu^2 - 2\mu\Sigma x)/\hat{\sigma}^2 - n
\end{aligned}$$

$$\begin{aligned}
\Rightarrow \hat{\sigma}^2 &= (\Sigma x^2 + n\mu^2 - 2\mu\Sigma x)/n \\
&= \frac{\Sigma x^2}{n} + \mu^2 - 2\mu\bar{x} \\
\Rightarrow \hat{\sigma} &= \sqrt{\frac{\Sigma x^2}{n} + \mu^2 - 2\mu\bar{x}}
\end{aligned}$$

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$$\begin{aligned}
L(\mu) &= \frac{1}{\sigma_X\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma_X^2}} \frac{1}{\sigma_Y\sqrt{2\pi}} e^{-\frac{(y-1.3\mu)^2}{2\sigma_Y^2}} \\
&= \mathcal{C} e^{-\frac{(x-\mu)^2}{2\sigma_X^2} - \frac{(y-1.3\mu)^2}{2\sigma_Y^2}} \\
\Rightarrow \log L - \log \mathcal{C} &= -\frac{(x-\mu)^2}{2\sigma_X^2} - \frac{(y-1.3\mu)^2}{2\sigma_Y^2} \\
\Rightarrow L'/L &= \frac{(x-\mu)}{\sigma_X^2} + \frac{(y-1.3\mu)}{\sigma_Y^2} \\
\Rightarrow 0 &= \frac{95 - \hat{\mu}}{15^2} + \frac{130 - 1.3\hat{\mu}}{20^2} \\
\Rightarrow \hat{\mu} &\approx 97.1
\end{aligned}$$

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$$\begin{aligned}
L(r, \lambda) &= \prod_{i=1}^n \frac{\lambda^r}{\Gamma(r)} x_i^{r-1} e^{-\lambda x_i} \\
&= \frac{\lambda^{nr}}{\Gamma^n(r)} (\Pi x)^{r-1} e^{-\lambda \Sigma x} \\
\log L &= nr \log \lambda + (r-1) \log(\Pi x) \\
&\quad - \lambda \Sigma x - n \log \Gamma(r) \\
\Rightarrow \frac{\partial \log L}{\partial r} &= n \log \lambda + \log(\Pi x)
\end{aligned}$$

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