1. The following questions all related to a random variable *y* which is distributed according to the Poisson distribution with density

$$f(y, \theta_o) = \frac{\theta_o^y e^{-\theta_o}}{y!}$$

(a) Write down the log-likelihood function $\ell(\theta, y)$ corresponding to a single observation drawn from a Poisson population.

For a single observation:

$$L(\theta) = \int (y, \theta) = \frac{\theta^{y} e^{-\theta}}{y!}$$

$$L_{N}(\Theta) = \frac{N}{11} \frac{\Theta^{4i} e^{-\Theta}}{y_{i!}}$$

$$\ell(\theta) = |n[L(\theta)]| = |n(\theta^{u}) + |n(e^{-\theta})| - |n(y!)$$

$$= y |n(\theta) - \Theta| - |n(y!)$$

$$\begin{aligned} \mathcal{L}(0) &= \ln \prod_{y_{120}}^{N} \frac{\theta^{3} e^{-\theta}}{y_{1}!} \\ &= \sum_{y_{120}}^{N} \left[y_{1} | n(0) - \theta - \ln (y_{1}!) \right] \end{aligned}$$

(b) Compute the expected log-likelihood and show that it's optimized at $\theta = \theta_o$ by examining the necessary first order condition

For a single observation

$$\begin{split} & E[\mathcal{U}(\theta)] = \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0}) \, \mathcal{U}(\theta) \\ & \frac{\partial E[\mathcal{U}(\theta)]}{\partial \theta} = \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{U}(\theta) \\ & = \frac{1}{16} \sum_{y=0}^{\infty} \int \mathcal{U}_{y}, \theta_{0} \, \mathcal{$$

(c) Show that the optimum from the prior part is a maximum by showing that

$$\frac{\partial \mathcal{B}_{z}}{\partial_{z} E[f(\theta, \lambda)]} \bigg|_{\theta = \theta^{0}} < 0$$

Since
$$\frac{\Im E[f(\theta)]}{\Im \theta} = \frac{\Theta_0}{\Theta} - 1$$

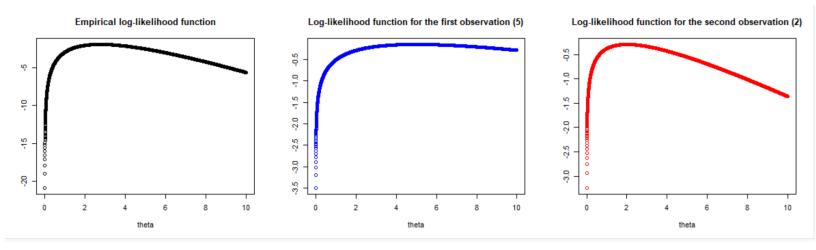
SOC $[\Theta] = \frac{\Theta_0}{\Theta^2}$ because it is evaluated at $\Theta = \Theta_0 = \frac{\Theta_0}{\Theta^2} = -\frac{1}{\Theta_0} < 0$

In Poisson Distribution, the parameter $0 \cdot$, which is also the mean, is strictly positive.

(d) Derive an expression for the empirical expectation.

and
$$\ell(0, y) = y \ln(0) - \theta - \ln(y!)$$

(e) Using the data, plot the expected log-likehood of the sample and likelihood functions corresponding to the first two observations.



(f) Show that $\hat{\theta}_{\text{\tiny ML}}$ is the sample mean by solving the necessary first order condition.

$$\begin{split} \frac{\partial \hat{E}_{N}[\mathcal{L}(\Theta, y)]}{\partial \Theta} \bigg|_{\Theta = \hat{\Theta}_{ML}} &= 0 \\ \text{Since } \hat{E}_{1000}[\mathcal{L}(\Theta, y)] = \frac{1}{y=0} \hat{F}_{1000}(y) \cdot \mathcal{L}(\Theta, y) \quad \text{and} \quad \mathcal{L}(\Theta, y) = y \ln(\Theta) - \Theta - \ln(y!) \\ \text{FOC } [\Theta] \quad \frac{1}{y=0} \hat{F}_{1000}(y) \cdot (\frac{y}{\Theta} - 1) \\ &= \frac{1}{\Theta} \frac{1}{y=0} \hat{F}_{1000}(y) \cdot (y - \Theta) \\ &= \frac{1}{\Theta} \hat{E}_{1000}(y) \cdot y - \frac{1}{\Theta} \frac{1}{y=0} \hat{F}_{1000}(y) \cdot \Theta \\ &= \frac{1}{\Theta} \hat{E}_{1000}(y) - 1 \quad \text{(be cause } \frac{1}{y=0} \hat{F}_{1000}(y) \cdot y = \hat{E}_{1000}(y)) \\ \text{Set the above equation to Zero produces} \quad \frac{\hat{E}_{1000}(y)}{\Theta} = 1 \quad \Rightarrow \hat{\Theta}_{ML} = \hat{E}_{1000}(y) \end{split}$$

(g) Show that the optimization problem is particularly well-behaved (globally concave) by showing that

$$\frac{\partial^2 \hat{E}_N [l(\theta, y)]}{\partial \theta^2} \bigg|_{\theta = \hat{\theta}_{ML}} < 0$$

Since the first order condition with respect to
$$\Theta$$
 is $\frac{1}{D} \hat{E}_{lood}(y) = 1$
SOC $[0] \Rightarrow -\frac{1}{\Theta} \cdot \hat{E}_{lood}(y) = -\frac{1}{\hat{E}_{lood}(y)} = -\frac{1}{2.747} \angle O(\hat{E}_{lood}(y) = 2.747 \text{ calculated in } R)$

(h) Write a function to compute the expected log-likelihood function for the sample and use an optimization routine to solve its maximizer, confirming your results in (f).