

Project 1

①

a) $R = \sqrt{-2 \log(1-U)}$

$$P(R \leq r) = P(\sqrt{-2 \log(1-U)} \leq r) = P(U \leq 1 - e^{-r/2})$$

$$= \int_0^{1-e^{-r/2}} \sqrt{-2 \log(1-U)} dU$$

$$\Theta = 2\pi V$$

$$P(\Theta \leq x) = P(2\pi V \leq x) = P(V \leq x/2\pi)$$

$$= \int_0^{x/2\pi} 2\pi V dV = \frac{x^2}{4\pi}$$

b) $X = R \cos \Theta$ and $Y = R \sin \Theta$

$$Y = f(\theta) \rightarrow \theta = f^{-1}(Y) \rightarrow \theta = 2\pi n - \sin^{-1}(Y/R) + \pi \quad n \in \mathbb{Z}$$

$$\frac{1}{\det(\frac{\partial f}{\partial x}(f^{-1}(Y)))} P_X(f^{-1}(Y)) \rightarrow P_X = P_{R\Theta} = P(R)P(\Theta) \rightarrow$$

$$= P(-X)P(2\pi n + \pi)$$

②

a) $D_{X, X'} = \frac{1}{8} (X - X')^T \sigma^{-1} (X - X') + \frac{1}{2} \ln\left(\frac{\sigma}{\sigma_1 \sigma_2}\right) \quad \sigma = \frac{\sigma_1 + \sigma_2}{2}$

Since $X = X'$ and $\sigma_1 = \sigma_2 = \sigma^2 I_m$ here

$$D_{X, X'} = \frac{1}{2} \ln(1) = 0$$

2c) Since intra-class is 0, ratio will be 0, so as n increases the ratio will remain the same, implying that the accuracy is good.

b) In this case $\sigma_1 = \sigma_2 = \sigma^2 I_m$ but $X \neq X'$

$$D_{X, X'} = \frac{1}{8} (X - X')^T (\sigma^2 I_m)^{-1} (X - X') + \frac{1}{2} \ln(1)$$

③

a) $P(X_i, \lambda) = \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}$ show $\hat{\lambda} = \frac{1}{n} \sum_{i=1}^n X_i$ is MLE of λ

$$L(P(X_i, \lambda)) = \prod_{i=1}^n \frac{\lambda^{x_i} e^{-\lambda}}{x_i!} \rightarrow \log(L) = \log\left(\prod_{i=1}^n \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}\right) \rightarrow$$

$$= \sum_{i=1}^n \ln\left(\frac{\lambda^{x_i} e^{-\lambda}}{x_i!}\right) = \sum_{i=1}^n (\ln(e^{-\lambda}) + \ln(\lambda^{x_i}) - \ln(x_i!)) \rightarrow$$

$$= -n\lambda + \sum \ln(\lambda^{x_i}) - \sum \ln(x_i!)$$

$$\text{MLE: set } \frac{d}{d\lambda} (\log(L)) = 0 \rightarrow$$

$$-n + \frac{1}{\lambda} \sum x_i = 0 \rightarrow \lambda = \frac{1}{n} \sum x_i$$

$$b) P(\lambda | \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda}$$

$$\left(\frac{\beta}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} \right) \underbrace{\left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right)}_{\text{Likelihood Poisson}} = \left(\frac{\beta}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} \right) \left(\frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod x_i!} \right)$$

$$= \frac{\beta^\alpha}{\prod x_i! \Gamma(\alpha)} \left(\lambda^{\alpha-1 + \sum x_i} e^{-(\beta+n)\lambda} \right)$$

Project 1

Second part is Gamma distribution with

$$\hat{\alpha} = \alpha + \sum_{i=1}^n x_i \quad \text{and} \quad \hat{\beta} = \beta + n$$

$$P(\lambda | y) = \left(\lambda | \alpha + \sum_{i=1}^n x_i, \beta + n \right) = \Gamma(\hat{\alpha}, \hat{\beta})$$

- c) MAP of a Gamma function where the distribution has the highest probability is

$$\Gamma(\alpha, \beta) = \frac{\alpha-1}{\beta} \rightarrow \text{MAP} = \frac{\sum x_i + \alpha - 1}{N + \beta}$$

d) $\hat{\eta} = e^{-2x}$

$$\text{MLE} \rightarrow X = \lambda(\eta) \rightarrow e^{-2\lambda} = \eta \rightarrow \lambda = -\frac{1}{2} \ln(\eta) = \lambda(\eta)$$

$$\lambda(\eta) \text{ into Poisson } P(X|\lambda) = \frac{\lambda^x e^{-\lambda}}{x!} \quad \text{where } \lambda = \lambda(\eta) \rightarrow$$

$$P(X|\lambda(\eta)) = \frac{\lambda(\eta)^x e^{-\lambda(\eta)}}{x!} = \frac{1}{x!} \left(-\frac{1}{2} \ln(\eta) \right)^x e^{\frac{1}{2} \ln(\eta)} \rightarrow$$

$$\ln(P(X|\lambda(\eta))) = X \ln\left(-\frac{1}{2} \ln(\eta)\right) + \frac{1}{2} \ln(\eta) - \ln(x!) \rightarrow$$

$$\frac{\partial \ln(P(X|\lambda(\hat{\eta})))}{\partial \hat{\eta}} = 0 \rightarrow X \left(\frac{1}{-\frac{1}{2} \ln(\hat{\eta})} \right) \left(\frac{-1}{2\hat{\eta}} \right) + \frac{1}{2\hat{\eta}} = 0 \rightarrow$$

$$\hat{\eta} = e^{-2x}$$

e) Bias of $\hat{\eta} = e^{-2\lambda} - e^{\lambda(1/e^2-1)}$ using $e^+ = \sum_{n=0}^{\infty} t^n/n!$

$$\begin{aligned} \text{Bias}(\hat{\eta}) &= E[\hat{\eta}] - \eta \rightarrow E[\hat{\eta}] = \sum \hat{\eta} P(X) = \sum e^{-2\lambda} \frac{\lambda^x e^{-\lambda}}{x!} \\ &= e^{-\lambda} \sum \frac{(\lambda e^{-2})^x}{x!} = e^{-\lambda} e^{\lambda e^{-2}} = e^{(e^{-2}-1)\lambda} \\ \rightarrow \text{Bias}(\hat{\eta}) &= e^{(e^{-2}-1)\lambda} - e^{-2\lambda} \end{aligned}$$

f) $(-1)^x$ is the only unbiased estimator of η

$$\begin{aligned} E[\hat{\eta}] &= \sum \hat{\eta} P(X) = \sum (-1)^x \frac{\lambda^x e^{-\lambda}}{x!} = e^{-\lambda} \sum \frac{(-\lambda)^x}{x!} \\ &= e^{-\lambda} e^{-\lambda} = e^{-2\lambda} \end{aligned}$$

$$\text{Bias}(\hat{\eta}) = E[\hat{\eta}] - \eta = e^{-2\lambda} - e^{-2\lambda} = 0$$

Since Bias = 0 this is indeed unbiased

This Bias is bad because it will either be positive or negative based on X , it will never approach a true value for $\hat{\eta}$