

THT 1 2(B)(ii)(b) Mr. Fisher's
MLE algorithm

STAT 208
8 Feb 21

① marginal PDF of \underline{Y}_i :
(for $\lambda > 0$)

DD 0 H

$$p(y_i | \lambda \in \mathcal{B}) = \frac{1}{\lambda} \exp\left(-\frac{y_i}{\lambda}\right) \mathbf{I}(y_i > 0) \quad \textcircled{1}$$

$\underline{y} = (y_1, \dots, y_n)$

② joint PDF of $\underline{Y} = (Y_1, \dots, Y_n)$:

$$p(\underline{y} | \lambda \in \mathcal{B}) = \prod_{i=1}^n p(y_i | \lambda \in \mathcal{B})$$

$$= \prod_{i=1}^n \frac{1}{\lambda} \exp\left(-\frac{y_i}{\lambda}\right) \mathbf{I}(y_i > 0)$$

$\mathbf{I}(\dots)$
assume $\lambda = 1$

$$= \lambda^{-n} \exp\left(-\frac{1}{\lambda} \sum_{i=1}^n y_i\right) \mathbf{I}(\text{all } y_i > 0)$$

$$= \left[\frac{1}{\lambda} \exp\left(-\frac{y_1}{\lambda}\right) \right] \left[\frac{1}{\lambda} \exp\left(-\frac{y_2}{\lambda}\right) \right]$$

$$\dots \left[\frac{1}{\lambda} \exp\left(-\frac{y_n}{\lambda}\right) \right]$$

$$s = \sum_{i=1}^n y_i$$

$$p(z | \lambda \in \mathcal{B}) = \lambda^{-n} \exp\left(-\frac{s}{\lambda}\right)$$

$$\textcircled{3} \quad \mathcal{L}(\lambda | z \in \mathcal{B}) = c \lambda^{-n} \exp\left(-\frac{s}{\lambda}\right)$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i = \frac{s}{n} \quad \mathcal{L}(\lambda | z \in \mathcal{B}) = c \lambda^{-n} \exp\left(-\frac{n\bar{y}}{\lambda}\right)$$

$$s = n\bar{y}$$

$\theta =$ vector of unknowns
 $= (\lambda)$

$$\dim(\theta) = k = 1$$

in nice problems

$\dim(\underbrace{\text{minimal sufficient statistic}}_{\leftarrow \text{MSS}})$

$$= k = 1$$

here s and \bar{y} are both MSSs

Bayesian

(Mr. Fisher) $\textcircled{4}$

$$\textcircled{4} \quad p(\lambda | z \in \mathcal{B}) =$$

$$\mathcal{L}(\lambda | z \in \mathcal{B}) =$$

$$c \cdot p(\lambda | \mathcal{B}) \cdot \mathcal{L}(\lambda | z \in \mathcal{B}) = n \log \lambda - \frac{n\bar{y}}{\lambda}$$

$$p(\lambda | \mathcal{Z}, \mathbb{B}) = c \left[p(\lambda | \mathbb{B}) \times \lambda^{-n} \exp\left(-\frac{n\bar{z}}{\lambda}\right) \right] \quad (3)$$

$$c_x \cdot c_x = c_x$$

$(x > 0)$

(5) see if a conjugate prior exists with this sampling model / likelihood PDF

Exponential to the likelihood $p(\lambda | \mathbb{B})$ is conjugate to the likelihood $\lambda^{-n} \exp\left(-\frac{n\bar{z}}{\lambda}\right)$

n unnormalized

- iff
- (1) does this PDF match a known family of parametric PDFs?
 - (2) is the product of 2 such PDFs in (1) another PDF of the same form?

Gelman et al. Appendix A

Examples of parametric families of Θ

PDFs

① Beta(α, β): $\boxed{C} \theta^{\alpha-1} (1-\theta)^{\beta-1}$ (PDF)

($\alpha > 0, \beta > 0$)

② Normal(μ, σ^2): $I(\theta \in \mathbb{R})$

($-\infty < \mu < +\infty$
 $\sigma^2 > 0$)

③ $\frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\theta - \mu}{\sigma}\right)^2\right] I(-\infty < \theta < +\infty)$

dim 2 = k

③ Exponential(λ): ($\lambda > 0$)

$\frac{1}{\lambda} \exp\left(-\frac{\theta}{\lambda}\right) I(\theta > 0)$

dim k = 1

$p(\lambda | \mathcal{B})$

$p(\lambda | \gamma \in \mathcal{B}) = c \lambda^{-(\alpha+1)} \exp\left(-\frac{\beta}{\lambda}\right)$

(*)

$\lambda^{-n} \exp\left(-\frac{n\gamma}{\lambda}\right)$

$$\textcircled{*} p(\lambda | \bar{x}, EB) = c \lambda^{-[(\alpha+n)+1]} \cdot \exp\left(-\frac{\beta+s}{\lambda}\right) \textcircled{*}$$

$$= \Gamma^{-1}\left(\frac{\alpha+n}{\bar{y}}, \beta+s\right)$$

\uparrow
 $n\bar{y}$