

(Lecture Notes part 6 pp. 77+)

DD AM
discussion section

$$z = (0, 1, \dots, 6) \quad n = 14 \quad \text{A histogram from } \textcircled{R} \textcircled{1}$$

full days in the hospital

shows (using the creating approach) that a Poisson sampling model is reasonable

for $\lambda > 0$

Poisson here

$$p(y_i | \lambda \text{ P.B.}) = \frac{\lambda^{y_i} e^{-\lambda}}{y_i!} \cdot I(y_i = 0 \text{ or } 1 \text{ or } \dots)$$

~~$z = (y_1, \dots, y_n)$
 $(z_i | \lambda \text{ P.B.}) \stackrel{?}{=} \text{Poisson}(\lambda)$ (assume = 1 here)~~

joint PMF

$$p(z | \lambda \text{ P.B.}) = \prod_{i=1}^n p(y_i | \lambda \text{ P.B.})$$

$$= \prod_{i=1}^n \frac{\lambda^{y_i} e^{-\lambda}}{y_i!} = \frac{\lambda^{y_1 + \dots + y_n} e^{-n\lambda}}{\prod_{i=1}^n y_i!} = \frac{\lambda^s e^{-n\lambda}}{\prod_{i=1}^n y_i!}$$

with

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

likelihood function:

$$L(\lambda | \mathcal{Z}, P, \mathcal{B}) = c \cdot \lambda^s e^{-n\lambda} \quad \text{for } \lambda > 0 \quad (2)$$

\uparrow $\prod_{i=1}^n z_i!$ $(c=1)$

(4) ~~log~~ likelihood

$$Q(\lambda | \mathcal{Z}, P, \mathcal{B}) = s \log \lambda - n\lambda$$

(5) MLE
& Suff. Stat

$$\frac{d}{d\lambda} Q(\lambda | \mathcal{Z}, P, \mathcal{B}) = \frac{s}{\lambda} - n = 0 \quad \text{if}$$

$$\lambda = \hat{\lambda}_{MLE} = \frac{s}{n} = \bar{y} = 2.1 \text{ here}$$

(6) visualize

Q and ll over an interesting range of λ values

sanity check on Poisson assumption

let's let λ grid go from (0.1, 517) to (517, 2.1) $\bar{y} = 4.2$

from 131

$$(\mathcal{Z} | \lambda) \sim \text{Poisson}(\lambda) \rightarrow$$

$$E(\mathcal{Z}) = V(\mathcal{Z}) = \lambda$$

so the sample mean and variance of \mathcal{Z} should be close:

$$\left\{ \begin{array}{l} \bar{y} = 2.07 \\ s^2 = 2.38 \end{array} \right\}$$

(looks reasonable)

* note that both s and $\bar{y} = \frac{s}{h}$ are minimal sufficient for λ in this sampling model (also n , of course)

⑥ observed information and standard error

$$\frac{d^2}{d\lambda^2} \ell(\lambda | \mathcal{Z}, \mathcal{P}, \mathcal{D}) = -\frac{s}{\lambda^2}$$

so the observed information is

$$\hat{I}(\hat{\lambda}_{MLE}) = \left[-\frac{d^2}{d\lambda^2} \ell(\lambda | \mathcal{Z}, \mathcal{P}, \mathcal{D}) \right]_{\lambda = \hat{\lambda}_{MLE}}$$

$$= \frac{s}{\hat{\lambda}_{MLE}^2} = \frac{s}{\left(\frac{s}{h}\right)^2} = \frac{h^2}{s} = \frac{h}{s/h} = \frac{h}{\hat{\lambda}_{MLE}} = O(h) \checkmark$$

and the estimate standard error is then

$$\hat{\sigma}_E(\hat{\lambda}_{MLE}) = \sqrt{\hat{V}(\hat{\lambda}_{MLE})} = \sqrt{\hat{I}^{-1}(\hat{\lambda}_{MLE})}$$

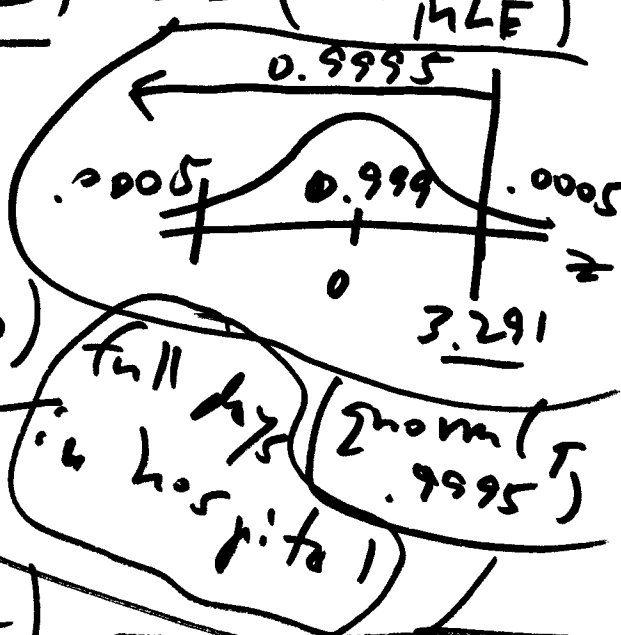
$$= \sqrt{\frac{\hat{\lambda}_{MLE}}{h}} = O\left(\frac{1}{\sqrt{h}}\right) \checkmark$$

⑦
 $100(1-\alpha)\%$
 $= 99.9\%$ CI for λ

CI:
CLT
approx.
(larger)

$$\hat{\lambda}_{MLE} \pm \underline{z}^{-1}(1 - \frac{\alpha}{2}) \cdot SE(\hat{\lambda}_{MLE}) \quad (4)$$

$$2.071 \pm (3.291) \cdot (0.384)$$



$$= (0.81, 3.34)$$

(could have gone negative with smaller α "incoherent")

Bayesian analysis

③ some as likelihood algorithm

$$L(\lambda | \mathcal{D}) = c \lambda^5 e^{-4\lambda}$$

④ conjugate prior?

Q: familiar PDF?

Gelman et al. Appendix A

Yes It's the family of Gamma(α, β) PDFs with ($\alpha > 0, \beta > 0$)

$$p(\lambda | \Gamma) = c \lambda^{\alpha-1} e^{-\beta\lambda} I(\lambda > 0)$$

product of 2 = another one? we have our conjugate prior Yes

⑤ Graphically explore conjugate family ⑤

(R) d governs shape & center β governs spread

$\Gamma(1, \beta) = \text{Exponential}(\beta)$

in an inverse way:

$\lambda \sim \Gamma(d, \beta) \rightarrow$ as $\beta \uparrow$, $SD[\Gamma(d, \beta)] \downarrow$

$E(\lambda) = \frac{d}{\beta}$

$V(\lambda) = \frac{d}{\beta^2}$

$SD(\lambda) = \frac{\sqrt{d}}{\beta}$

⑥ work out conjugate updating (posterior)

$p(\lambda | z, P, B) =$
 (constant) \cdot (prior) \cdot (likelihood)
 $c \cdot \Gamma(\lambda | \underline{P}, \underline{B}) \cdot \ell(\lambda | z, P, B)$

$= c \left(\lambda^{d-1} e^{-\beta \lambda} \right) \left(\lambda^s e^{-h \lambda} \right)$

$= c \lambda^{(d+s)-1} e^{-(\beta+h)\lambda} = \Gamma(d+s, \beta+h)$

PDF prior is $\Gamma(d, \beta)$

likelihood PDF is $\lambda^{(s+1)-1} e^{-h \lambda} = \Gamma(s+1, h)$

Poisson (λ)
family
($\lambda > 0$)

as $\lambda \uparrow$

conjugate
updating
rule

center \uparrow
spread \uparrow
shape becomes
less skewed

$(\lambda | \mathcal{B}) \sim \Gamma(\alpha, \beta)$
 $(\Sigma_i | \lambda \text{ i.i.d. } \mathcal{P} \mathcal{B}) \sim \text{Poisson}(\lambda)$
($i = 1, \dots, n$)

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

$z = (\gamma_1, \dots, \gamma_n)$

$(\lambda | z \text{ i.i.d. } \mathcal{P} \mathcal{B}) \sim \underline{\underline{\Gamma(\alpha + s, \beta + n)}}$

we're not forced to use a conj.
prior (if it exists), but if a
member of this family can be
found that matches context $(\mathcal{C}, \mathcal{B})$,

it's convenient to use it | ex. LI ⁽⁷⁾

$$\begin{aligned}
 & \text{(posterior)} \\
 & \text{(mean)} = \left(w_1 \right) \left(\text{prior} \right) + \left(\frac{w_2}{w_1 + w_2} \right) \left(\text{data} \right) \\
 & \text{(mean)}
 \end{aligned}$$

$$= \left(w_1 \right) + \left(w_2 \right)$$

$$\begin{aligned}
 \frac{d+s}{\beta+h} &= \left(\frac{d}{\beta} \right) \left(\frac{s}{h} \right) + \left(h \right) \left(\frac{s}{h} \right) \\
 &= \left(\frac{d}{\beta} \right) + s
 \end{aligned}$$

$$\left(\beta \right) + \left(h \right)$$

prior sample size = $h_{\text{prior}} = \beta$
 data = h

LI $I(a, \beta)$: take $\beta = \underset{=}{\epsilon} > 0$ small positive ($\beta > 0$)

How specify α ?
for LI prior

$$\text{prior mean} = \frac{\alpha}{\beta} = \frac{\alpha}{\epsilon}$$

if ϵ is close enough to 0, α could be just about any positive number

$$\frac{\alpha}{\epsilon} = 5 \rightarrow \alpha = 5\epsilon = .005 \quad (\epsilon = 0.001) \quad (h=14)$$

This will be a LI prior

sensitivity analysis:

vary $\frac{\alpha}{\epsilon}$ from $\{0.1, 1, 2, 5, 10\}$

& superimpose all resulting posterior

PDFs : should all be about same;

\therefore precise specification of α with

$\epsilon = 0.001$ doesn't matter much

$$\text{utah} \quad \frac{\alpha}{\epsilon} = 16$$

$$\text{class} \quad \frac{\alpha}{\epsilon} = 5$$