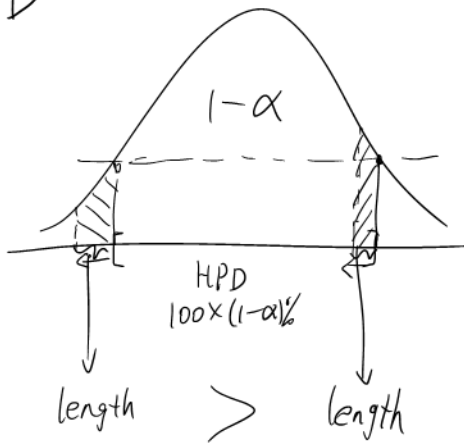


HPD



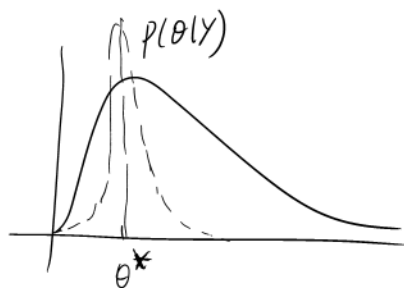
HPD has the shortest length among all C.I.  
with coverage  $100 \times (1-\alpha)\%$ .

Poisson model

posterior:  $\text{Gamma}(a_0 + \sum y_i, b_0 + n)$

$$E(\theta|y) = \frac{a_0 + \sum y_i}{b_0 + n}$$

$\leadsto \theta^*$



$$\text{Var}(\theta|y) = \frac{a_0 + \sum y_i}{(b_0 + n)^2}$$

If  $y_1, \dots, y_n | \theta^* \sim \text{Poisson}(\theta^*)$

by law of large numbers.  $\frac{\sum y_i}{n} \Rightarrow E(y) = \theta^*$

If  $n$  is big,  $\text{Var}(\theta|y) \approx \frac{\sum y_i}{n^2} \approx \frac{\theta^*}{n} (\approx \frac{\text{Var}(y)}{n})$

central limit theorem

$$\sqrt{n}(\bar{X} - \mu) \rightarrow N(0, \sigma^2)$$

$$\bar{X} \stackrel{\text{approx}}{\sim} N(\mu, \frac{\sigma^2}{n})$$

$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} F$

$E X_i = \mu, \text{Var}(X_i) = \sigma^2$

Gamma densities

$$\frac{b^a}{\Gamma(a)} x^{a-1} e^{-bx}$$

$$P(\tilde{Y} = \tilde{y} | y)$$

$$= \int_0^\infty \frac{b^a}{\Gamma(a) \tilde{y}!} \cdot \theta^{\tilde{y}+a-1} e^{-(b+1)\theta} d\theta$$

$$= \frac{b^a}{\Gamma(a) \tilde{y}!} \cdot \frac{1}{\frac{(b+1)^{\tilde{y}+a}}{\Gamma(\tilde{y}+a)}} \int_0^\infty \theta^{\tilde{y}+a-1} e^{-(b+1)\theta} d\theta$$

= 1

$$p(Y_1, \dots, Y_n | \theta), \quad p(\theta)$$

$$p(\theta | Y_1, \dots, Y_n) \quad \text{posterior of } \theta$$



uncertainty  $\downarrow$  as  $n \rightarrow \infty$

$$p(\tilde{y} | \theta) = \frac{\theta^{\tilde{y}}}{\tilde{y}!} e^{-\theta}$$

$$\text{Var}(\tilde{y} | \theta) = \theta$$

$$\text{Var}(\tilde{y} | \theta^*) = \theta^* \quad \text{"truth"}$$

uncertainty (remains the same)

$$p(\tilde{y} | Y_1, \dots, Y_n)$$

$$\text{Var}(\tilde{y} | Y_1, \dots, Y_n) = \text{Var}(\theta | y) (b_0 + n + 1)$$

$$= \frac{(a_0 + \sum y_i)}{(b_0 + n)^2} \cdot (b_0 + n + 1)$$

$$n \text{ is big} \approx \frac{\sum y_i}{n} \approx \theta^* = \text{Var}(\tilde{y} | \theta^*)$$

tails of densities

$$f(x) = \frac{c}{(1+x)^2}, \quad x > 0 \quad \text{heavy-tailed}$$

$$g(x) = e^{-x}, \quad x > 0$$

$$h(x) = C \cdot e^{-x^2}, \quad x > 0 \quad \text{light-tailed}$$

← prior 1

$$\frac{p(y|\theta) \cdot p_1(\theta)}{\int p(y|\theta') p_1(\theta') d\theta'} = p_1(\theta|y) \quad \Rightarrow \quad \underline{p(y|\theta) p_1(\theta)} = m_1(y) p_1(\theta|y)$$

$m_1(y)$