

### Assign - 3

8.

①.

let  $p_i$   $\xrightarrow{\text{success probability}}$  probability of approve of HOV lane of County i

$n_i \rightarrow$  # commuters

$y_i \rightarrow$  no. of approve

This will

Data follow binomial

$$y_i | p_i \sim \text{Bin}(n_i, p_i)$$

Likelihood  $\rightarrow$

$$f(y_i | p_i) = {}^{n_i}C_{y_i} p_i^{y_i} (1-p_i)^{n_i-y_i}$$

$$l(f) = \log(f(y_i | p_i))$$

$$= \log {}^{n_i}C_{y_i} + y_i \log(p_i) + (n_i - y_i) \log(1-p_i)$$

\*

ⓐ for Jeffreys's priors.

$$\frac{\partial l}{\partial p_i} = \frac{y_i}{p_i} - \frac{n_i - y_i}{1-p_i}$$

$$\frac{\partial^2 l}{\partial p_i^2} = -\frac{y_i}{p_i^2} - \frac{(n_i - y_i)}{(1-p_i)^2}$$

$$I(p_i) = -E\left(\frac{\partial^2 l}{\partial p_i^2}\right)$$

$$= \frac{n_i p_i}{p_i^2} + \frac{1}{(1-p_i)^2} (n_i - n_i p_i)$$

$$= \frac{n_i}{p_i (1 - p_i)}$$

Jeffrey's prior.

$$\begin{aligned} \pi(p_i) &\propto \sqrt{I(p_i)} = \sqrt{\frac{1}{p_i(1-p_i)}} = p_i^{-1/2} (1-p_i)^{-1/2} \\ &\propto p_i^{-1/2} (1-p_i)^{-1/2} \\ &\rightarrow \text{Beta}\left(\frac{1}{2}, \frac{1}{2}\right) \end{aligned}$$

$$p_i | y_i \propto f(y_i | p_i) \pi(p_i)$$

$$\propto p_i^{y_i} (1-p_i)^{n_i - y_i} p_i^{-1/2} (1-p_i)^{-1/2}$$

$$\propto p_i^{y_i + \frac{1}{2} - 1} (1-p_i)^{n_i - y_i + \frac{1}{2} - 1}$$

$$\rightarrow \text{Beta}\left(y_i + \frac{1}{2}, n_i - y_i + \frac{1}{2}\right)$$

95% Credible interval for county i

$$(L, U)$$

$$L = \text{qbeta}(0.025, y_i + \frac{1}{2}, n_i - y_i + \frac{1}{2})$$



(b)

$$\hat{p} = 0.48$$

$$\text{var } p = 0.02$$

$$\frac{a}{a+b} = 0.48$$

$$\frac{ab}{(a+b)^2(a+b+1)} = 0.02$$

$$\Rightarrow a = c(a+b) = \left(\frac{c}{1-c}\right)b = c^*b$$

$$\Rightarrow \frac{c^*bb}{(c^*b+b)^2(c^*b+b+1)} = 0.02$$

$$\Rightarrow \frac{1}{(c^*+1)^2(c^*b+b+1)} = \frac{0.02}{c^*} \rightarrow e$$

$\rightarrow d$

$$\Rightarrow (c^*b+b+1) = \frac{1}{ed}$$

$$\Rightarrow b = \frac{\left(\frac{1}{ed} - 1\right)}{(c^*+1)} = \frac{f}{(c^*+1)}$$

$$a = 5.5104$$

$$b = 5.9696$$

$$c^* = \frac{c}{1-c}$$

$$e = \frac{0.02}{c^*}$$

$$d = (c^*+1)^2$$

$$f = \left(\frac{1}{ed} - 1\right)$$

2.2

$$(a) \hat{\mu}_{MAP} = \arg \max_{\mu} [\log(f(y|\mu) + \log(\pi(\mu)))]$$

log

$$f(y_1, \dots, y_n | \mu) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi} \sigma_i^2} e^{-\frac{(y_i - \mu)^2}{2\sigma_i^2}}$$

$$= \frac{1}{\prod_{i=1}^n \sqrt{2\pi} \sigma_i^2} \cdot e^{-\sum_{i=1}^n \frac{(y_i - \mu)^2}{2\sigma_i^2}}$$

$$= e^{-\sum_{i=1}^n \frac{(y_i - \mu)^2}{2\sigma_i^2}}$$

$$l = \log(f(y_1, \dots, y_n | \mu))$$

$$= \log c + \left( -\frac{1}{2} \sum_{i=1}^n \frac{(y_i - \mu)^2}{\sigma_i^2} \right)$$

$$\frac{dl}{d\mu} = \frac{1}{2} \sum_{i=1}^n \frac{(y_i - \mu)}{\sigma_i^2} \Rightarrow 0$$

$$\Rightarrow \sum_{i=1}^n \frac{y_i}{\sigma_i^2} = \sum_{i=1}^n \frac{\mu}{\sigma_i^2}$$

$$\Rightarrow \hat{\mu}_{MAP} = \frac{\sum_{i=1}^n \left( \frac{y_i}{\sigma_i^2} \right)}{\sum_{i=1}^n \frac{1}{\sigma_i^2}}$$



$$\pi(\mu | y_1, \dots, y_n) \propto f(y_1, \dots, y_n | \mu) \pi(\mu)$$

$$\begin{aligned} & \propto e^{-\frac{1}{2} \sum_{i=1}^n \frac{(y_i - \mu)^2}{\sigma_i^2}} \\ & \propto e^{-\frac{1}{2} \left( \mu^2 \sum_{i=1}^n \frac{1}{\sigma_i^2} - 2\mu \sum_{i=1}^n \frac{y_i}{\sigma_i^2} \right)} \\ & \propto e^{-\frac{1}{2} \mu^2 \left[ \sum_{i=1}^n \frac{1}{\sigma_i^2} \right]} e^{\mu \left[ \sum_{i=1}^n \frac{y_i}{\sigma_i^2} \right]} \end{aligned}$$

$$\rightarrow N \left( \frac{\sum_{i=1}^n \frac{y_i}{\sigma_i^2}}{\sum_{i=1}^n \frac{1}{\sigma_i^2}}, \frac{1}{\sum_{i=1}^n \frac{1}{\sigma_i^2}} \right)$$

⑧.  $y_i | \theta$  iid Laplace  $(\mu, \sigma)$ ,  $\theta = (\mu, \sigma)$

$$f(y | \mu, \sigma) = \frac{1}{2\sigma} e^{-\frac{|y - \mu|}{\sigma}}$$

$$\pi(\theta | y_1, \dots, y_n)$$

$$\mu \in \mathbb{R}$$

$$\propto f(y_1, \dots, y_n | \theta) \pi(\theta)$$

$$\propto \frac{1}{\sigma^n} e^{-\frac{\sum_{i=1}^n |y_i - \mu|}{\sigma}} \mathbb{I}(\sigma \in (0, 10^5), 1)$$

$$\theta_j^c \sim \text{Normal}(\theta_j^*, s_j^2)$$

$$R^2 = \min \left\{ 1, \frac{p(\theta_j^c | \theta_{-j}, y)}{p(\theta_j^* | \theta_{-j}, y)} \right\}$$

$$\frac{e^{-\frac{\sum_{i=1}^n |y_i - \mu^c|}{\sigma}}}{e^{-\frac{\sum_{i=1}^n |y_i - \mu^*|}{\sigma}}} = e^{\frac{\sum_{i=1}^n |y_i - \mu^*| - \sum_{i=1}^n |y_i - \mu^c|}{\sigma}}$$