

Bayesian statistics

Chapter 8

⑤ X discrete random variable with $P(X=1) = \theta$ and $P(X=2) = 1-\theta$

Data: $x_1=1, x_2=2, x_3=2$

$$\hat{\theta}_{\text{mom}} = \frac{1}{3} \quad \hat{\theta}_{\text{MLE}} = \frac{1}{3}$$

d) If $\theta \sim U[0,1]$ what's the posterior density?

Posterior density $\propto$ Likelihood $\cdot$ Prior density

likelihood function: $L(\theta) = \prod_{i=1}^n P(x_i|\theta) = \theta(1-\theta)^2$

$$f_{\theta|x}(\theta|x) \propto \theta(1-\theta)^2 \cdot 1 = \theta^{2-1}(1-\theta)^{3-1} \Rightarrow f_{\theta|x}(\theta|x) = \frac{1}{B(2,3)} \theta(1-\theta)^2$$

or For $X \sim \text{Bin}(3, p)$ and $\theta \sim U[0,1] = B(1,1)$

the posterior distribution is $B(1+1, 1+3-1) = B(2,3)$ ($x = \#$ successes)

$$\hat{\theta}_{\text{PME}} = E(\theta|X=x) = \frac{2}{2+3} = \frac{2}{5}$$

Normal conjugates

● Data sample of size n : $X_i \sim N(\mu, \sigma^2)$ $i=1, \dots, n$

Prior for $\mu \sim N(\mu_0, \sigma_0^2)$ (variance known). $\mu = \theta$ random variable
 $\Rightarrow \theta \sim N(\theta_0, \sigma_0^2)$

$$f_{\theta|x}(\theta|x) \propto f_{x|\theta}(x|\theta) \cdot f_{\theta}(\theta)$$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2} \frac{(x_i - \theta)^2}{\sigma^2}\right\} \cdot \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left\{-\frac{1}{2} \frac{(\theta - \theta_0)^2}{\sigma_0^2}\right\}$$

$$= \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{n}{2}} \left(\frac{1}{2\pi\sigma_0^2}\right)^{\frac{1}{2}} \prod_{i=1}^n \exp\left\{-\frac{1}{2} \frac{(x_i - \theta)^2}{\sigma^2}\right\} \exp\left\{-\frac{1}{2} \frac{(\theta - \theta_0)^2}{\sigma_0^2}\right\}$$

$$\propto \exp\left\{-\frac{1}{2} \left[\frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \theta)^2 + \frac{1}{\sigma_0^2} (\theta - \theta_0)^2 \right]\right\}$$

$$\lceil \sum (x_i - \theta)^2 = \sum (x_i - \bar{x})^2 + n(\theta - \bar{x})^2 \rceil$$

$$= \exp \left\{ -\frac{1}{2} \left[\frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2 + n(\theta - \bar{x})^2 + \frac{1}{\sigma_0^2} (\theta - \theta_0)^2 \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[\frac{n}{\sigma^2} (\theta - \bar{x})^2 + \frac{1}{\sigma_0^2} (\theta - \theta_0)^2 \right] \right\}$$

$$= \exp \left\{ -\frac{1}{2} \left[\frac{n}{\sigma^2} (\theta^2 - 2\theta\bar{x} + \bar{x}^2) + \frac{1}{\sigma_0^2} (\theta^2 - 2\theta\theta_0 + \theta_0^2) \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[\left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \theta^2 - \left(\frac{n}{\sigma^2} \bar{x} + \frac{1}{\sigma_0^2} \theta_0 \right) 2\theta \right] \right\}$$

$$= \exp \left\{ -\frac{1}{2} \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \left[\theta^2 - \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right)^{-1} \left(\frac{n}{\sigma^2} \bar{x} + \frac{1}{\sigma_0^2} \theta_0 \right) 2\theta \right] \right\}$$

$$= \exp \left\{ -\frac{1}{2} \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \left[\theta^2 - 2\theta \left(\frac{n\sigma_0^2 \bar{x} + \sigma^2 \theta_0}{n\sigma_0^2 + \sigma^2} \right) \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \left(\theta - \frac{n\sigma_0^2 \bar{x} + \sigma^2 \theta_0}{n\sigma_0^2 + \sigma^2} \right)^2 \right\} \text{ looks like } \exp \left\{ -\frac{1}{2} \sigma_p^{-1} (\theta - \theta_p)^2 \right\}$$

$$\rightarrow N \left(\frac{n\sigma_0^2 \bar{x} + \sigma^2 \theta_0}{n\sigma_0^2 + \sigma^2}, \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right)^{-1} \right) = N \left(\frac{\sigma^2}{n\sigma_0^2 + \sigma^2} \theta_0 + \left(1 - \frac{\sigma^2}{n\sigma_0^2 + \sigma^2} \right) \bar{x}, \frac{\sigma^2}{n\sigma_0^2 + \sigma^2} \sigma_0^2 \right)$$

$$= N(c_n \theta_0 + (1 - c_n) \bar{x}, c_n \sigma_0^2) \quad c_n = \frac{\sigma^2}{n\sigma_0^2 + \sigma^2} \quad \text{if } n=1 \quad c_1 = \frac{\sigma^2}{\sigma_0^2 + \sigma^2}$$

If $\frac{1}{\sigma_0^2}$ is very small (large σ_0^2 and therefore a non-informative prior)

then $\theta \sim N \left(\bar{x}, \frac{\sigma^2}{n} \right)$ as in MLE

Confidence interval for a normal population mean is given by

$$\bar{X} \pm z(d/2)\sigma_{\bar{X}}$$

Credibility interval is constructed on the same fashion but following the posterior distribution (the Bayes estimator of the mean would be the mean value of the posterior distribution)