

2. $Y_1, Y_2, \dots, Y_n \sim N(\mu, \sigma^2)$
 $\hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$ $\underbrace{\mu, \sigma^2}_{\text{both unknown}}$

a) Likelihood:
 $P(Y|\mu, \sigma^2) = \prod_{i=1}^n P(y_i|\mu, \sigma^2)$
 $\propto \frac{1}{\sigma^n} \exp\left\{-\frac{\sum_{i=1}^n (y_i - \mu)^2}{2\sigma^2}\right\}$

• Case-1: 'Standard' non-informative prior $\pi(\mu, \sigma^2) \propto \frac{1}{\sigma^2}$ ($\sigma^2 > 0$)

Joint Posterior (un-normalized)

$$P(\mu, \sigma^2|y) \propto P(y|\mu, \sigma^2) \cdot \pi(\mu, \sigma^2)$$

$$\propto \frac{1}{\sigma^n} \exp\left\{-\frac{\sum_{i=1}^n (y_i - \mu)^2}{2\sigma^2}\right\} \cdot \frac{1}{\sigma^2}$$

$$\propto \frac{1}{\sigma^{n+2}} \exp\left\{-\frac{(n-1)s^2 + n(\bar{y} - \mu)^2}{2\sigma^2}\right\}$$

This is a special case of normal inverse chi-squared distribution

Marginal Posterior

$$P(\mu|y) = \int_0^\infty P(\mu, \sigma^2|y) d\sigma^2$$

$$\propto \int_0^\infty \frac{1}{\sigma^{n+2}} \exp\left\{-\frac{(n-1)s^2 + n(\bar{y} - \mu)^2}{2\sigma^2}\right\} d\sigma^2$$

[Density of inverted chi-squared distribution is:

$$p(\sigma^2) = \frac{(\nu_0/2)^{\nu_0/2}}{\Gamma(\nu_0/2)} \cdot (\sigma_0^2)^{\nu_0/2} \cdot (\sigma^2)^{-(\nu_0/2+1)} \cdot \exp\left(-\frac{\nu_0 \sigma_0^2}{2\sigma^2}\right), \sigma^2 > 0$$

where $\nu_0 = n$,
 $\sigma_0^2 = \left(\frac{n-1}{n}\right)s^2 + (\bar{y} - \mu)^2$]

$$\propto (\sigma_0^2)^{-n/2} \int_0^\infty \frac{(nb)^{-n/2}}{\Gamma(n/2)} (\sigma_0^2)^{n/2} \cdot (\sigma^2)^{-(\frac{n}{2}+1)} \cdot \exp\left\{-\frac{n\sigma_0^2}{2\sigma^2}\right\} d\sigma^2$$

$$\propto \left(\frac{(n-1)s^2}{n} + (\bar{y} - \mu)^2\right)^{-n/2}$$

$$\propto \left(1 + \frac{1}{(n-1)} \left(\frac{\mu - \bar{y}}{s/\sqrt{n}}\right)^2\right)^{-\frac{(n-1)+1}{2}}$$

$\Rightarrow P(\mu|y)$ is the kernel of the non-std t-distribution with df = n-1

$$\mu|y = \bar{y} \sim t_{n-1}(\bar{y}, \frac{s^2}{n})$$

\Rightarrow Scaled & shifted μ follows std. t-distribution with df = n-1

$$\frac{\mu - \bar{y}}{s/\sqrt{n}} | Y = y \sim t_{n-1}(0, 1)$$

95% credible interval for μ

$$95\% \text{ CI for } \mu = \bar{y} \pm t_{0.025, n-1} \cdot \frac{s}{\sqrt{n}}$$

• Case-2 Jeffreys' Prior $\pi(\mu, \sigma^2) \propto \frac{1}{(\sigma^2)^{3/2}}, \sigma^2 > 0$

JP is an improper prior. For the scenario when there are atleast 2 distinct observed values of y , we obtain a proper posterior.

Under those conditions, the posterior turns out to be proper & is actually normal-inverse gamma:

$$\mu | \sigma^2, y \sim \text{Normal}(\bar{y}, \sigma^2/n)$$

$$\sigma^2 | y \sim \text{InvGamma}\left(\frac{n}{2}, \frac{n-1}{2} s^2 = \frac{n\hat{\sigma}^2}{2}\right)$$

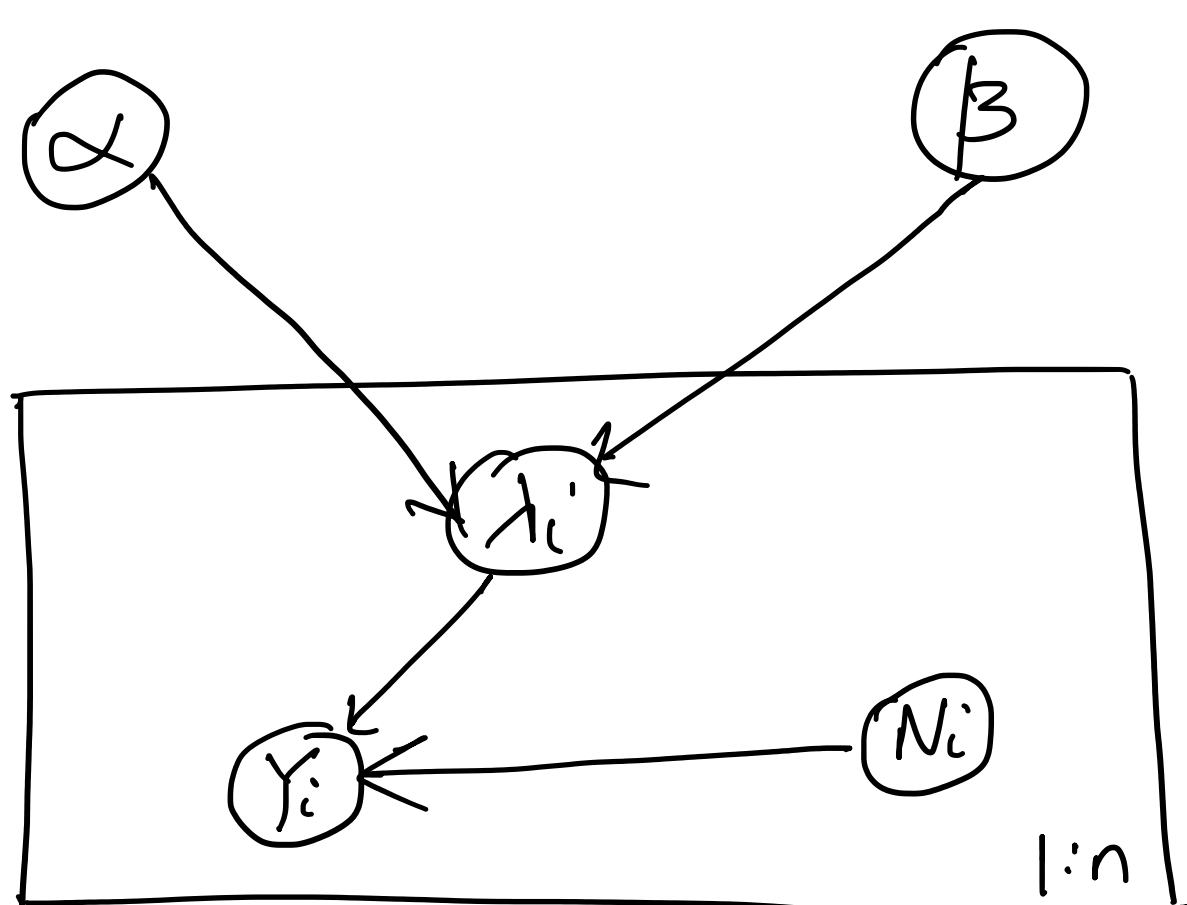
It follows that the marginal posterior for μ is

$$\mu | y \sim t_n(\bar{y}, \hat{\sigma}^2/n)$$

which gives the following 95% credible interval for μ :

$$\bar{y} \pm t_{0.025, n} \cdot \frac{\hat{\sigma}}{\sqrt{n}}$$

i) a)



Here,
 $n = \text{length}(y)$