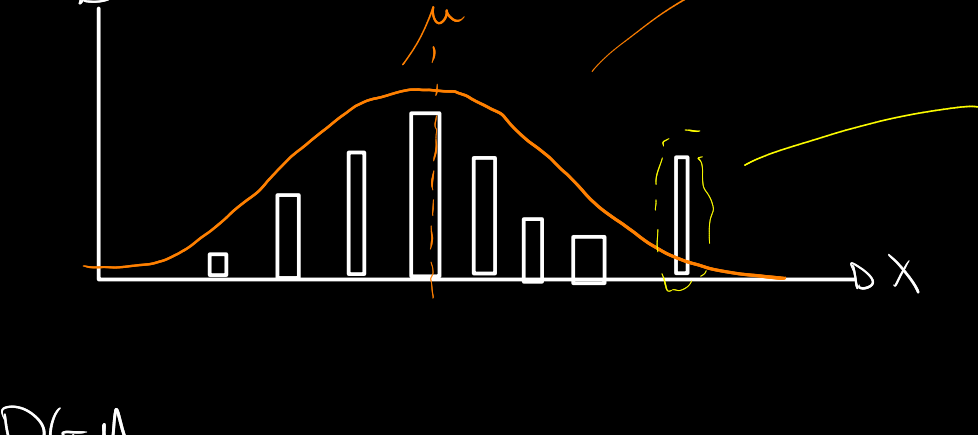


# Posterior & MAP for (univariate) Normal with unknown precision

drilling holes

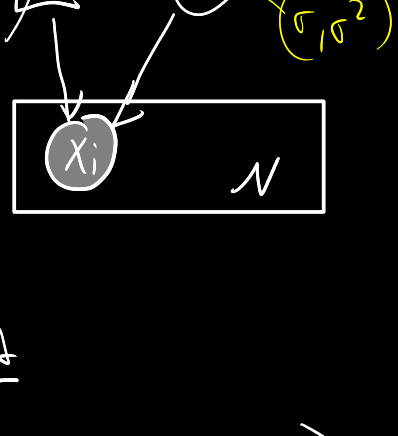


fix  $\mu$ ... you know how wide the holes are



$\sigma, \sigma^2, \tau$  unknown  
 $\rightarrow MLE?$   
 $\rightarrow$  robust estimate?  
 $\rightarrow$  prior knowledge

DGM



$$\tau \sim \text{Gamma}(\tau; \alpha_0, \beta_0)$$

$$x_i \sim \mathcal{N}(x_i | \mu, \tau^{-1})$$

joint

$$p(\tau, \mathbf{X} = \mathbf{D}) = p(\tau) p(\mathbf{X} = \mathbf{D} | \tau)$$

$$p(\tau | \mathbf{D}) \stackrel{\text{i.i.d.}}{=} p(\tau) \cdot \prod_{i=0}^{N-1} p(x_i = x^{L,i} | \tau)$$

$$= \text{Gamma}(\tau; \alpha_0, \beta_0) \prod_{i=0}^{N-1} \mathcal{N}(x_i = x^{L,i} | \mu, \tau^{-1})$$

$$= \frac{\beta_0^{\alpha_0}}{\Gamma(\alpha_0)} \tau^{\alpha_0-1} e^{-\beta_0 \tau} \prod_{i=0}^{N-1} \sqrt{\frac{\tau}{2\pi}} \exp\left(-\frac{\tau}{2} (x^{L,i} - \mu)^2\right)$$

$$\sim \tau^{\alpha_0-1} e^{-\beta_0 \tau} \tau^{N/2} \exp\left(-\frac{\tau}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right)$$

Posterior

$$p(\tau | \mathbf{D}) \stackrel{\text{Bayes' rule}}{=} \frac{p(\mathbf{D} | \tau) p(\tau)}{p(\mathbf{D})} \sim p(\mathbf{D} | \tau) p(\tau) = p(\tau | \mathbf{D})$$

Conditional is proportional to the joint

$$p(\tau | \mathbf{D}) \sim \tau^{\alpha_0-1} e^{-\beta_0 \tau} \tau^{N/2} \exp\left(-\frac{\tau}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right)$$

$$= \tau^{\alpha_0 + \frac{N}{2} - 1} \exp\left(-\beta_0 \tau - \frac{\tau}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right)$$

$$= \tau^{\alpha_N - 1} \exp\left(-\left(\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right) \tau\right)$$

$\alpha_N$

$\beta_N$

it's another Gamma

$$\Rightarrow p(\tau | \mathbf{D}) = \text{Gamma}(\tau; \alpha_N, \beta_N)$$

$$\alpha_N = \alpha_0 + \frac{N}{2}$$

$$\beta_N = \beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2$$

$$\int \sigma_{MLE}^2 = \frac{1}{N} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2 = \frac{1}{\tau_{MLE}}$$

$$\beta_N = \beta_0 + \frac{N}{2} \sigma_{MLE}^2$$

$$= \beta_0 + \frac{N}{2 \tau_{MLE}}$$

MAP-Estimate

$\rightarrow$  Mode of the posterior

$$\tau_{MAP} = \underset{\tau > 0}{\text{argmax}} (p(\tau | \mathbf{D}))$$

take derivative and set to zero

$$\frac{\partial p(\tau | \mathbf{D})}{\partial \tau} = (\alpha_0 + \frac{N}{2} - 1) \tau^{\alpha_0 + \frac{N}{2} - 2} \exp\left(-\left(\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right) \tau\right)$$

$$- \tau^{\alpha_0 + \frac{N}{2} - 1} \left(\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right) \exp\left(-\left(\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right) \tau\right)$$

$$\cdot \exp\left(-\left(\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2\right) \tau\right)$$

$$= 0$$

$$\Leftrightarrow (\alpha_0 + \frac{N}{2} - 1) \cdot \frac{1}{\tau} - \beta_0 - \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2 = 0$$

$$(\alpha_0 + \frac{N}{2} - 1) \cdot \frac{1}{\tau} = \beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2$$

$$\tau_{MAP} = \frac{\alpha_0 + \frac{N}{2} - 1}{\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2}$$

Mode of the posterior gamma

$$\tau_{MAP} = \frac{\alpha_0 + \frac{N}{2} - 1}{\beta_0 + \frac{N}{2} \sigma_{MLE}^2}$$

$$\tau := \frac{1}{\sigma^2}$$

$$\tau_{MAP} = \frac{\alpha_0 + \frac{N}{2} - 1}{\beta_0 + \frac{1}{2} \sum_{i=0}^{N-1} (x^{L,i} - \mu)^2}$$

"pseudo-count"

high  $\beta_0 \rightarrow$  high variance, std low precision

high  $\alpha_0 \rightarrow$  low variance, std high precision