

Multiparameter Models

$$\Theta = (\Theta_1, \Theta_2)$$

$\swarrow \in \mathbb{R}^{d_1}$ $\searrow \in \mathbb{R}^{d_2}$
parameter of interest nuisance parameters

e.g. $y_i \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$

\downarrow \downarrow
poi nuisance parameters

• General Strategy: joint posterior $p(\Theta_1, \Theta_2 | \text{obs})$

$$\rightarrow \text{marginal } p(\Theta_1 | \text{obs}) = \int_{\mathbb{R}^{d_2}} p(\Theta_1, \Theta_2 | \text{obs}) d\Theta_2$$

Recall: in single parameter models; when σ^2 is known

\rightarrow inference for μ : Gaussian - Gra ... Conjugate model

Now: σ^2 is unknown,

but we still want to make inference for μ .

$$\begin{aligned} \text{prior: } p(\mu, \sigma^2) &= p(\sigma^2) p(\mu | \sigma^2) \\ &\stackrel{\text{or}}{=} p(\sigma^2) p(\mu) \quad (\text{we'll use this}) \\ &\propto \frac{1}{\sigma^2} \quad \text{non-informative prior} \end{aligned}$$

posterior (joint):

$$p(\mu, \sigma^2 | y_1, y_2, \dots, y_n) \propto p(\mu, \sigma^2) p(y_1, \dots, y_n | \mu, \sigma^2)$$

$$\propto 1/\sigma^2 \cdot \prod_{i=1}^N \left[\boxed{\frac{1}{\sigma}} \exp\left(-\frac{(y_i - \mu)^2}{2\sigma^2}\right) \right]$$

Since σ is also unknown

$$= \sigma^{-n-2} \exp\left(-\frac{1}{2\sigma^2}[(n-1)S_n^2 + n(\bar{y} - \mu)^2]\right)$$

Check?

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$$

Sample variance

Sample mean