

# Bayesian Statistics

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# Today's topics

- ▶ Hierarchical Bayes models
- ▶ Examples of hierarchical Bayes models

# Hierarchical Bayes models

# Hierarchical Bayes models

- ▶ In hierarchical models, the prior  $\pi(\theta \mid \xi)$  for  $\theta$  depends on other parameters  $\xi$ , called **hyperparameters**, which also have a prior distribution  $\pi(\xi)$
- ▶ This leads to a triple of random variables  $(\xi, \theta, x)$  with joint density

$$\pi(\xi)\pi(\theta \mid \xi)f(x \mid \theta)$$

# Hierarchical Bayes models

- ▶ By conditioning on the data  $x$ , we obtain the posterior  $\pi(\xi, \theta | x)$ 
  - ▶ For complex models,  $\pi(\xi, \theta | x)$  usually cannot be determined in closed form and some approximation is needed (see later in the course)
- ▶ Often, the primary interest is in the parameter  $\theta$ , i.e. the **marginal posterior**  $\pi(\theta | x)$
- ▶ There are two ways to compute it

# Marginal posterior: approach 1

1. In the first approach, one first computes the marginal prior

$$\pi(\theta) = \int \pi(\theta \mid \xi) \pi(\xi) d\xi$$

and then uses Bayes formula

$$\pi(\theta \mid \mathbf{x}) \propto \pi(\theta) f(\mathbf{x} \mid \theta)$$

# Marginal posterior: approach 2

2. In some situations, the approach based on the following formula is computationally easier:

$$\begin{aligned}\pi(\theta | x) &= \int \pi(\theta | x, \xi) \pi(\xi | x) d\xi \\ &\propto \int \pi(\theta | x, \xi) \pi(\xi) f(x | \xi) d\xi\end{aligned}$$

- One first needs to determine  $\pi(\theta | x, \xi)$  and  $\pi(\xi | x)$  or  $f(x | \xi)$

## Marginal posterior: approach 2

- ▶  $\pi(\xi | x)$  can be calculated either by marginalizing the joint posterior over  $\theta$

$$\pi(\xi | x) = \int \pi(\theta, \xi | x) d\theta$$

or by using

$$\pi(\xi | x) = \frac{\pi(\theta, \xi | x)}{\pi(\theta | x, \xi)}$$

- ▶ Analogously,  $f(x | \xi)$  can be obtained by marginalizing the joint distribution of  $x$  and  $\theta$  given  $\xi$

$$f(x | \xi) = \int \pi(x, \theta | \xi) d\theta = \int f(x | \theta) \pi(\theta | \xi) d\theta$$



## Marginal posterior: approach 2

- ▶ For conjugate priors, we have an explicit expression not only for  $\pi(\theta \mid x, \xi)$  but often also for  $f(x \mid \xi)$
- ▶ Usually, the final integration over  $\xi$  to obtain  $\pi(\theta \mid x)$  cannot be done in closed form, and some approximation is needed

# Examples of hierarchical models

- ▶ Normal means
- ▶ Hierarchical Poisson model
- ▶ One-way ANOVA model

# Normal means example

Assume the following model:

- ▶ Likelihood:  $X_1, \dots, X_n$  i.i.d.  $\sim \mathcal{N}(\theta, 1)$
- ▶ Hierarchical prior:
  - ▶  $\theta \sim \mathcal{N}(\mu, \tau^2)$ ,  $\mu$  fix
  - ▶  $\tau^{-2} \sim \text{Gamma}(\gamma, \lambda)$

*See blackboard for more details*

*Clicker question*

# Hierarchical Poisson model example

Assume the following model:

- ▶ Likelihood:  $X_j$  independent  $\sim \text{Poisson}(\theta_j)$ ,  $j = 1, 2, \dots, J$
- ▶ Hierarchical prior:
  - ▶  $\theta_j$  i.i.d.  $\sim \text{Gamma}(\gamma, \lambda)$
  - ▶ Some prior  $\pi(\gamma, \lambda)$

*See blackboard for more details*

*Clicker question*

# One-way ANOVA model example

Assume the following model:

- ▶ Likelihood:  $y_{ij} = \theta_i + \varepsilon_{ij}$ ,  $\varepsilon_{ij}$  i.i.d  $\sim \mathcal{N}(0, \sigma_\varepsilon^2)$ ,  
 $j = 1, \dots, n_i, i = 1, \dots, I$
- ▶ Hierarchical prior:
  - ▶  $\theta_i$  i.i.d  $\sim \mathcal{N}(\mu, \tau^2)$
  - ▶ For simplification,  $\sigma_\varepsilon$  is assumed to be known
  - ▶  $\pi(\mu, \tau^2) = \pi(\mu)\pi(\tau^2)$  (specified later)

*See blackboard for more details*

*Clicker question*