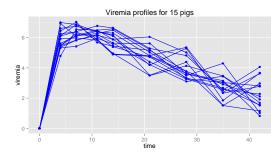


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Bayesian Inference for the parameters of the Woods function (Islam et al., 2013)



- Data were obtained from a in-vivo challenge study
- viremia profiles suggest different host responses to PRRSV infections

potential sources of variation

- within host variation (dynamic variation of each pig's viremia)
- between host variation (difference between pigs)

model first stage: within host variation

 $y_{i,j}$ viral load of pig *i* at time *j*

first stage: within host variation:

$$y_{i,j} = f(a_i, b_i, c_i, t_{i,j}) + \epsilon_{i,j}$$

•
$$f(a_i, b_i, c_i, t_{i,j}) = a_i t_{i,j}^{b_i} \exp(-c_i t_{i,j})$$
 (Woods function)

• $\epsilon \sim N(0, \sigma_{\epsilon}^2)$ - constant variance over time - strong assumption!

Distribution for the viremia profiles based on model first stage:

$$y_{i,j} \sim \mathsf{N}(f(a_i, b_i, c_i, t_{i,j}), \sigma_{\epsilon}^2)$$

model second stage: between host variation:

- problem: for the Woods function, a must be larger than 0 and both b and c must be between 0 and 1
- we can use transformations to allow the paramters to vary on the real line - makes inference easier

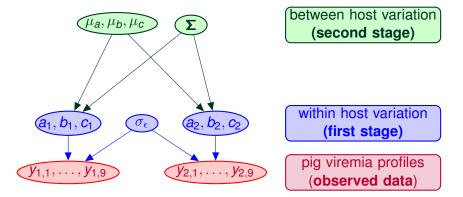
example: $\theta_i = [\log(a_i) \ \log(b_i) \ \log(c_i)]$

 a probability distribution can be considered to account for random variation in each parameter for each pig i

 $\begin{aligned} \log(a_i) &= \mu_a + e_{i,a} \\ \log(b_i) &= \mu_b + e_{i,b} \\ \log(c_i) &= \mu_c + e_{i,b} \end{aligned} \qquad \begin{array}{l} \boldsymbol{\theta}_i \sim \operatorname{MultiNormal}([\mu_a \ \mu_b \ \mu_c]^\top, \boldsymbol{\Sigma}) \\ \boldsymbol{\Sigma} \text{ is a variance-covariance matrix} \end{aligned}$

other covariates could be included to account for systematic variation (eg. pig's age)

what we have so far..



prior uncertainty about parameters (model 3 rd stage) and Bayesian inference

prior uncertainty about parameters of first and second stages

 $\boldsymbol{\mu} = [\mu_a \ \mu_b \ \mu_c]^\top \sim \mathsf{MultiNormal}(\mathbf{0}, \boldsymbol{\Sigma}_{\mu})$

 $(\Sigma_{\mu} \text{ components must be high values for a non-informative prior distribution})$ $\sigma_{\epsilon}^{2} \sim \text{InverseGamma}(a, b) \text{ and } \Sigma \sim \text{InverseWishart}(k, \mathbf{D})$

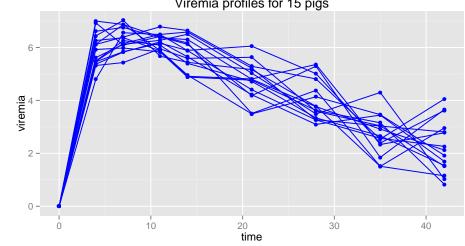
- parameters: $\boldsymbol{\theta}^{\top} = [\boldsymbol{\theta}_1^{\top}, \dots \ \boldsymbol{\theta}_k^{\top}], \sigma^2, \boldsymbol{\mu}, \boldsymbol{\Sigma}$
- data: viremia profiles of the pigs

Posterior distribution

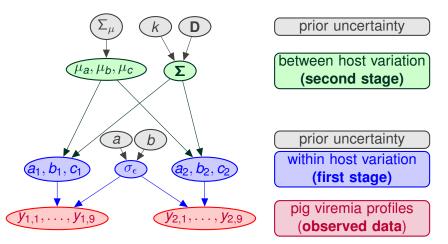
posterior \propto prior \times likelihood $g(\theta, \sigma^2, \mu, \Sigma | \text{data}) \propto g(\theta)g(\sigma^2)g(\mu)g(\Sigma)f(\text{data}|\theta, \sigma^2, \Sigma)$

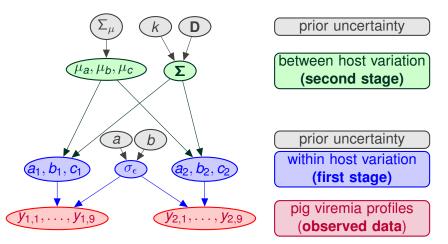
MCMC must be used to sample from this posterior

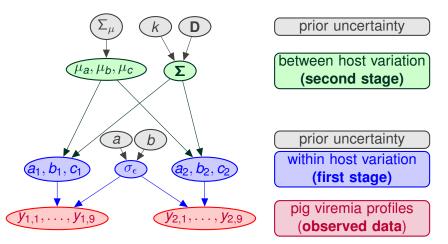
Now we have a model for this data

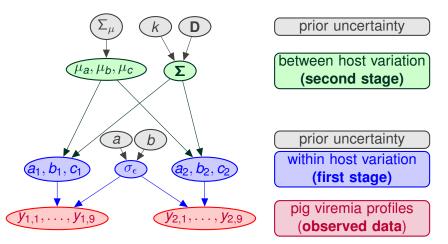


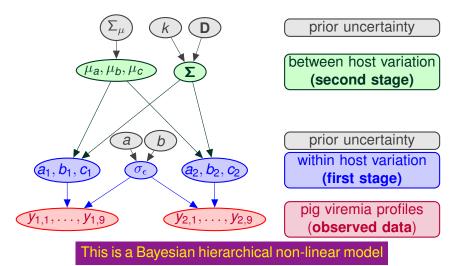
Viremia profiles for 15 pigs











Tutorial 12:

Estimating parameters of the Woods function

- Analyse results of the Hierarchical model fitted to the pigs viremia data
- compare estimates from different pigs