

Example: Large Scale Bayesian variable selection

data: $y \in \mathbb{R}^n$ $X \in \mathbb{R}^{n \times p}$, $p \gg n$

model: $Y = X\beta + \varepsilon$, $\varepsilon \sim N(0, \sigma^2 I_n)$

Prior info: β is sparse

effective approach: spike + slab prior

Given $\delta = (\delta_1, \dots, \delta_p) \in \mathbb{R}^p$ $\delta_j \in \{0, 1\}$

$$\beta_j | \delta_j \sim \begin{cases} N(0, \delta_j) & \delta_j = 1 \\ N(0, \delta_0) & \delta_j = 0 \end{cases} \quad \delta_j \sim \text{Bern}(\alpha)$$

marginally $\beta_j \propto \alpha N(0, \delta_j) + (1-\alpha) N(0, \delta_0)$

Typically we take $\delta_1 \gg \delta_0$

Then we change the model $Y = X\beta_\delta + \varepsilon$; $\beta_\delta \equiv \beta \cdot \delta$

To summarize the hierarchical model

$$Y = X\beta_\delta + \varepsilon$$

$$g \stackrel{iid}{\sim} \text{Bern}(\alpha)$$

$$\beta_j | \delta_j \sim \begin{cases} N(0, \sigma_1) & \delta_j = 1 \\ N(0, \sigma_0) & \delta_j = 0 \end{cases}$$

$$\pi(o^2) = 1 \quad (\text{improper prior})$$

Variation 1 Leave first level and include

$\beta_j \sim N(0, \tau_0)$ to obtain an approx. sparse solution

$$\pi(\theta^2, \beta, \delta | y) \propto \left(\frac{1}{\sigma^2}\right)^{n/2} e^{-\frac{1}{2\sigma^2} \|y - X\beta_\delta\|_2^2} \prod_{j=1}^p \alpha^{\delta_j} (1-\alpha)^{1-\delta_j} f_1(\beta_j)^{\delta_j} f_0(\beta_j)^{1-\delta_j}$$

$$f_i(x) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{x_i^2}{2\sigma_i^2}}$$

Rmk: We could also use an IG prior on σ^2

MCMC: Given $(\beta, \delta) \Rightarrow \sigma^2 \sim \text{Inv-}\chi^2\left(\frac{D-1}{2}, \frac{\|y - X\beta\|^2}{2}\right)$

Given (σ^2, δ) linear regression

$$\text{Model} \left\{ \begin{array}{l} Y \sim XD_S(\beta + \varepsilon) \\ \quad \quad \quad \hat{L} \quad D_S = \text{diag}(\vec{\delta}) \\ \beta \sim N(0, m_S) \quad m_S = \begin{cases} \sigma_1 & \delta_1 = 1 \\ \sigma_0 & \delta_0 = 0 \end{cases} \end{array} \right.$$

Posterior

$$\beta | \sigma^2, \delta, Y \sim N(m_\delta, \sigma^2 \Sigma_\delta)$$

$$m_g = \sum_g D_g x^T y$$

$$- \frac{1}{2} \frac{1}{1-1}$$

$$\Sigma'_f = (D_f X^T X D_f + \sigma^2 M_f^{-1})^{-1}$$

Given: (σ^2, β) update each δ_j

$$\|y - X\beta\|_2^2 \Rightarrow \delta_j \beta_j^2 \|x_j\|_2^2 - 2\delta_j \beta_j \langle x_j, y - X(\beta - \delta)_j \rangle$$

$$\delta_j | \sigma^2, \beta, y \sim \text{Bern}(\alpha_j) \quad \alpha_j = \frac{1}{1 + c_j}$$

$$c_j = \frac{1-\alpha}{\alpha} \sqrt{\frac{\sigma_1}{\sigma_0}} \exp \left\{ \frac{1}{2\sigma^2} (\beta_j^2 \|x_j\|_2^2 - 2\beta_j \langle x_j, y - X(\beta - \delta)_j \rangle - \frac{\beta_j^2}{2} \left(\frac{1}{\sigma_0} - \frac{1}{\sigma_1} \right)) \right\}$$

Issues: {expensive: need to invert $D_f X^T X D_f + \sigma^2 M_f^{-1}$ }

Variational Approximation:

$$q(\sigma^2, \delta, \beta) = \text{Ih}(\sigma^2; \sigma_1, \sigma_2) \prod_{j=1}^P \text{Bern}(\delta_j, \alpha_j) N(\beta_j; \mu_j, \sigma_j^2)$$

Search $(\sigma, \alpha, \mu, \sigma^2)$ that minimize $KL(\pi, q(\sigma, \alpha, \mu, \sigma^2))$

$$\begin{aligned} \text{ELBO}(\sigma, \alpha, \mu, \sigma^2) = & \int \left[\frac{n}{2} \log \frac{1}{\sigma^2} - \frac{\|y - X\beta\|_2^2}{2\sigma^2} + \sum_{j=1}^P \delta_j \log \alpha + (1 - \delta_j) \log(1 - \alpha_j) \right. \\ & \left. + \delta_j \log f_1(\beta_j) + (1 - \delta_j) \log f_0(\beta_j) \right] \end{aligned}$$

$$-\log q_{(-\mu)}(\sigma^2, \delta, \beta) \Big] q_{(-\mu)}(\sigma^2, \delta, \beta)$$

Idea: Fix (α, μ, σ^2)

$$ELB(\gamma) = \int \left[\frac{n}{2} \log\left(\frac{1}{\sigma^2}\right) - \frac{\mathbb{E}[\|Y - X\beta\|_2^2]}{2\sigma^2} - \log q_\delta(\sigma^2) \right] q(\gamma)$$

$$\Rightarrow r_1 = \frac{n}{2} \quad r_2 = \mathbb{E}_q \left[\frac{\|Y - X\beta\|_2^2}{2} \right]$$

because $\Gamma_h(x; c, d) \propto \left(\frac{1}{x}\right)^{c+1} e^{-d/x}$

$$\log \Gamma_h(x; c, d) = \text{const.} + (c+1) \log \frac{1}{x} - \frac{d}{x}$$

$$\mathbb{E}_q[\|Y - X\beta\|_2^2] = \mathbb{E}_q[\|Y\|_2^2 + \beta_\delta^\top X^\top X \beta_\delta - 2 \langle Y, X\beta_\delta \rangle]$$

$$= \|y\|_2^2 + \mathbb{E}_q[\text{Tr}(X^\top X \beta_\delta \beta_\delta^\top)] - 2 \langle y, X\beta_\delta \rangle$$

$$= \|y\|_2^2 + \sum_{j=1}^p \alpha_j \|x_j\|_2^2 (\mu_j^2 + \sigma^2) + \sum_{j \neq i} \langle x_i, x_j \rangle \mu_i \mu_j \alpha_i \alpha_j \\ - 2 \langle y, X(\mu - \alpha) \rangle$$

$$= \|y - X(\mu - \alpha)\|_2^2 + \sum_{j=1}^p (*)$$