

Bayesian Lasso

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$$\begin{bmatrix} 1 \times p \\ \vdots \\ p \times 1 \end{bmatrix}$$

$j=1, \dots, 100$

1 Problems Week 2

1. Simulate a dataset according to the model

$$y_i = \beta^T \mathbf{x}_i + \varepsilon_i,$$

with, say, $\mathbf{x}_i \in \mathbb{R}^p$ with $p = 5$ being the number of covariates, $n = 100$ samples, the vector $\beta \in \mathbb{R}^p$ being a sparse vector, and $\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$ for some known σ^2 .

2. Fit the dataset using some R package that implements lasso regression. Choose a value of λ (the penalty parameter) so that some of the regression coefficients are fitted to be zero.

3. Calculate the full conditional distributions for the model

$$y_i | \beta, \sigma^2 \stackrel{\text{ind}}{\sim} N(\mathbf{x}_i^T \beta, \sigma^2), \quad \beta_j | \sigma^2, a_j \sim N\left(0, \frac{\sigma^2 a_j}{\lambda^2}\right), \quad a_j \stackrel{\text{iid}}{\sim} \text{Gamma}(1, 1/2), \quad 1 \leq j \leq p,$$

with priors $\sigma^2 \sim \text{IG}(a, b)$ and $\lambda > 0$ being the fixed constant chosen in 2, i.e., $p(\beta | \mathcal{D}, \sigma^2, \mathbf{a})$, $p(\sigma^2 | \mathcal{D}, \beta, \mathbf{a})$, and $p(a_j | \mathcal{D}, \beta, \sigma^2)$.

$$\lambda = 2$$

\mathbf{x}, \mathbf{y}

\mathbf{x}, \mathbf{y}

4. Implement a Gibbs sampler Set $\mathbf{a}^{(1)} = \mathbf{1}_n$, $\sigma^{2(1)} = 1$, $\lambda^2 > 0$, $A > 0$, $B > 0$, and $t = 1$. Iterate:

$$\bullet \beta^{(t+1)} \sim p(\beta | \mathcal{D}, \sigma^{2(t)}, \mathbf{a}^{(t)}) \longrightarrow$$

$$\bullet \sigma^{2(t+1)} \sim p(\sigma^2 | \mathcal{D}, \beta^{(t+1)}, \mathbf{a}^{(t)})$$

$$\bullet \text{For } j = 1, \dots, p$$

$$a_j^{(t+1)} \sim p(a_j | \mathcal{D}, \beta^{(t+1)}, \sigma^{2(t+1)})$$

$$\bullet t \leftarrow t + 1.$$

Run the sampler until $t = 10^5$ recording all values of $\beta^{(t)}$, $\mathbf{a}^{(t)}$ and $\sigma^{2(t)}$.

5. Plot density plots for each β_j and compare with the fitted values in 2.

2 Problems Week 7

1. The Bayesian EM algorithm iteratively calculates

$$\theta_1^{(t+1)} = \arg \max_{\theta_1} \left[\mathbb{E}_{\theta_2 | \mathbf{y}, \theta_1^{(t)}} [\log p(\mathbf{y}, \theta_1, \theta_2)] \right]$$

Apply the EM algorithm to the Bayesian Lasso model with $\theta_1 = (\beta, \sigma^2)$ and $\theta_2 = \mathbf{a}$.

$$\hat{\beta}, \hat{\sigma}^2, \hat{\mathbf{a}}$$