

Regression: modeling conditional expectations

(1)

Ex:  $EY|X = X\beta$

$$\begin{aligned} Y &\in \mathbb{R}^n \\ X &\in \mathbb{R}^{n \times p} \\ \beta &\in \mathbb{R}^p \end{aligned}$$

Common model

$$Y|X, \beta, \sigma^2 \sim N(X\beta, \sigma^2 I)$$

$\beta$  &  $\sigma^2$  unknown.

We'll turn our attention to common priors for  $\beta$ .

Common prior setup: independent exp. power priors on  $\beta$  entries.

$$p(\beta) = \prod_{j=1}^p p(\beta_j)$$

$$p(\beta_j) \propto \exp\left\{-\frac{|\beta_j|^\alpha}{\tau}\right\}$$

$\alpha = 2 \Rightarrow$  normal  
 $\alpha = 1 \Rightarrow$  Laplace  
 $\alpha \in (0, 1) \Rightarrow$  "Bridge"

Following Ex 1: (considering  $\sigma^2$  fixed, unknown right now)

posterior of  $\beta$

$$p(\beta|Y, X) \propto p(Y|\beta, X) p(\beta)$$

$\hat{\beta}_{MAP} := \operatorname{argmax}_{\beta} p(\beta|Y, X)$  corresponds to many well known regularization procedures.

$$\hat{\beta}_{MAP} = \operatorname{argmax}_{\beta} \log p(\beta|Y, X)$$

$$= \operatorname{argmax}_{\beta} \left[ -\frac{1}{2} \|Y - X\beta\|_2^2 - \sum_j \frac{|\beta_j|^\alpha}{\tau} \right]$$

$$= \operatorname{argmin}_{\beta} \left[ \frac{1}{2} \|Y - X\beta\|_2^2 + \lambda \sum |\beta_j|^\alpha \right]; \quad \lambda = \frac{1}{\tau}$$

$\alpha = 2$  : ridge regression  
 $\alpha = 1$  : lasso  
 $\alpha = 0$  : best subset selection.

} well known regularization procedures

Mike West (1987): exp. power prior can be represented as scale mixture of normals. (2)

$$p(\theta) \propto e^{-|\theta|^\alpha} \Rightarrow \int_0^\infty e^{-s|\theta|^2/2} g(s) ds$$

for some mixing distr.  $g(s)$ .

often we parameterize:

$$\beta_j | \lambda_j, \tau \sim N(0, \lambda_j^2 \tau^2 I^2)$$

local shrinkage parameter  $\lambda_j$   
global shrinkage parameter  $\tau$

$$\lambda_j \sim g(\lambda)$$

$$\text{so } p(\beta_j | \tau) \propto \exp\left\{-\frac{|\beta_j|^2}{\tau^2}\right\} = \int \underbrace{p(\beta_j | \lambda_j, \tau)}_{\text{normal density}} g(\lambda) d\lambda$$

$$\text{when } \lambda_j \sim C^+(0, 1)$$

$\frac{1}{2}$  Cauchy  $\Rightarrow$  horseshoe prior

$$\text{when } \lambda_j \sim \exp(2) \Rightarrow \text{Laplace prior}$$

$$\lambda_j \sim \text{inverse-Gamma} \Rightarrow \text{student-t}$$

see Carvalho, Polson & Scott (2009)  
"Handling sparsity via the Horseshoe"  
for further reading.