

EM Lasso

$$E \sim N(0, s^2)$$

$$y = Xb + E$$

$$b_j | s_j^2 \sim N(0, s_j^2)$$

$$s_j^2 \sim \text{Exp}\left(\frac{1}{\eta}\right)$$

rate, so $m = \eta$

$$\Rightarrow p(b_j) = \frac{1}{2} \sqrt{\frac{2}{\eta}} \exp\left(-\sqrt{\frac{2}{\eta}} |b_j|\right)$$

$$(E(b_j | s_j) = \sqrt{\frac{\eta}{2}})$$

$$\log p(y, b, s^2) = -\frac{1}{2s^2} \|y - Xb\|_2^2 - \frac{1}{2} \log(2\pi s^2)$$

$$- \sum_i \frac{b_j^2}{2s_j^2} - \sum_i \frac{1}{2} \log 2\pi s_j^2$$

$$+ p \log \frac{1}{\eta} - \frac{1}{\eta} \sum_j s_j^2 \quad \leftarrow \text{prior on } s_j^2$$

$$p(s_j^2 | b_j) \propto \exp\left(-\frac{s_j^2}{\eta}\right) \frac{1}{\sqrt{s_j^2}} \exp\left(-\frac{b_j^2}{2s_j^2}\right)$$

$$= \frac{1}{\sqrt{s_j^2}} \exp\left[-\frac{s_j^2}{\eta} - \frac{b_j^2}{2s_j^2}\right]$$

let $w = s_j^2$

$$p(w | b) \propto \frac{1}{w} \exp\left[-\frac{w}{\eta} - \frac{b^2}{2w}\right]$$

$$E_q(\log p(y, b, s^2)) + E_q(\log q(b)) + E_q(\log q(s))$$

$$\hat{q}(b) = \text{ridge}, \quad \text{prior precision} = E\left(\frac{1}{s_j^2}\right)$$

...

$\hat{\theta}_j(s_j) = \text{posterior given data } \mathcal{D}(s_j) \sim \mathcal{N}(0, s_j)$
 so for losses, posterior mean, just replace $|b|$ w/ $\sqrt{E(s_j)}$

$$E_q \left[\log p(y|b) + \log \frac{p(b|s)}{q(s)} + \log \frac{p(s|y)}{q(s)} \right] \quad \text{--- } \log q(b)$$

Optimize over q

$$F(q) = p \log \frac{1}{q} - \frac{1}{q} \sum_j E_q(s_{b_j}^2)$$

$$F'(q) = p \frac{1}{(q^2)} - \sum_j E_q(s_{b_j}^2)$$

$$\Rightarrow \hat{q} = \frac{1}{p} \sum_j E_q(s_{b_j}^2) \quad \left[\text{iteration } \rightarrow \text{mean } \hat{q} \right]$$

(Figure zero $E_q(\frac{1}{s_{b_j}^2})$, so we need $E(s_{b_j}^2) = E(\tau)$ in Fig notation)

In Figure 0's notation:

$$E(\tau) = \frac{\int_0^\infty \tau N(\beta; 0, \varepsilon) \exp(-\frac{\delta}{2}\tau) d\tau}{\int N(\beta; 0, \varepsilon) \exp(-\frac{\delta}{2}\tau) d\tau}$$

($\delta = \frac{1}{\hat{q}}$)

$$\begin{aligned} \text{top} &= \int_0^\infty \tau \frac{1}{\sqrt{2\pi\varepsilon}} \exp\left(-\frac{\beta^2 + \delta\tau^2}{2\varepsilon}\right) \\ &= \int_0^\infty \tau^2 \left[\frac{1}{\sqrt{2\pi\varepsilon^3}} \exp\left(-\frac{\beta^2 + \delta\tau^2}{2\varepsilon}\right) \right] d\tau \end{aligned}$$

$$\text{IG distr: } = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left[-\frac{\lambda(x-y)^2}{2y^2x}\right]$$

$$= \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left[-\frac{\lambda x}{2y^2} - \frac{\lambda y^2}{2x}\right] \exp\left[+\frac{\lambda 2xy}{2y^2x}\right]$$

$E = \mu$
 $V = \mu^2/\lambda$
 (denom's)

$$= \sqrt{\lambda} \exp\left(\frac{\lambda}{\nu}\right) \left(\frac{1}{\sqrt{2\pi\lambda\nu}} \exp\left[-\frac{\lambda x}{2\nu^2} - \frac{\lambda}{2\nu}\right] \right)$$

We have: $\int_0^\infty \tau^2 \left(\frac{1}{\sqrt{2\pi\tau^2}} \exp\left[-\frac{\delta\tau}{2} - \frac{\beta^2}{2\tau}\right] \right) d\tau$

$\begin{cases} \frac{\lambda}{\nu^2} = \delta \\ \lambda = \beta^2 \\ \Rightarrow \nu = \sqrt{\frac{\lambda}{\delta}} = \frac{\beta}{\sqrt{\delta}} \end{cases}$
 $\lambda = \beta^2, \nu = \frac{|\beta|}{\sqrt{\delta}}$
 $\left(\frac{\delta}{2} = \frac{1}{\nu}\right)$

Bottom = $\int \frac{1}{\sqrt{2\pi\tau^2}} \exp\left(-\frac{\beta^2 + \delta\tau^2}{2\tau}\right)$

$= \int \tau \left(\frac{1}{\sqrt{2\pi\tau^2}} \exp(\dots) \right) d\tau$

$= \frac{1}{\sqrt{\lambda}} \exp\left(-\frac{\lambda}{\nu}\right) [\nu]$

Ratio: $\nu + \frac{\nu^2}{\lambda} = \frac{|\beta|}{\sqrt{\delta}} + \frac{1}{\delta}$

$= |\beta| \sqrt{\frac{\nu}{2}} + \frac{\nu}{2}$

So $\hat{\nu}_{\text{ML}} = \frac{1}{p} \sum_i \left(|\beta_j| \sqrt{\frac{\nu}{2}} + \frac{\nu}{2} \right)$

$\sqrt{E(B^2)}$

$\left[\text{note } \beta_j \sim \text{Exp}\left(\frac{\nu}{2}\right) \right]$

$E(|\beta_j|) = \sqrt{\frac{\nu}{2}}$

consistent with (33) in his notes, but inconsistent with his (9) which says $\frac{\delta}{|\beta|} = \frac{2}{\nu|\beta|}$ [recall $\gamma = E(s^{-1})$]

$$\hat{S}^2 = \frac{1}{n} E((y - Xb)^T (y - Xb))$$

$$= \frac{1}{n} [y^T y - 2b^T X^T y + b^T X^T X b]$$

$$E(bb^T) = \Sigma + \mu\mu^T$$

$$b^T X^T X b = \sum_{ij} b_i (X^T X)_{ij} b_j \\ = \sum_{ijk} b_i b_j X_{ki} X_{kj}$$