

Exercice 3.6

Ex. 3.6 Show that the ridge regression estimate is the mean (and mode) of the posterior distribution, under a Gaussian prior $\beta \sim N(0, \tau \mathbf{I})$, and Gaussian sampling model $\mathbf{y} \sim N(\mathbf{X}\beta, \sigma^2 \mathbf{I})$. Find the relationship between the regularization parameter λ in the ridge formula, and the variances τ and σ^2 .

By Bayes theorem:

$$p(\beta | \mathbf{y}) = \frac{p(\mathbf{y} | \beta) p(\beta)}{p(\mathbf{y})}$$

on $p(\mathbf{y} | \beta) = N(\mathbf{X}\beta, \sigma^2)$ est la vraisemblance

- $p(\beta) = N(0, \tau \mathbf{I})$ est le prior

- $p(\mathbf{y}) \Rightarrow$ cste de normalisation

En utilisant le log on obtient:

$$\ln(p(\beta | \mathbf{y})) = -\frac{1}{2} \left(\frac{(\mathbf{y} - \mathbf{X}\beta)^T (\mathbf{y} - \mathbf{X}\beta)}{\sigma^2} + \frac{\beta^T \beta}{\tau} \right) + c$$

On pose $\lambda = \frac{\sigma^2}{\tau}$, on sait que c est une cste indépendante de β , max sur β pour $p(\beta | \mathbf{y})$ revient à:

$$\min_{\beta} (\mathbf{y} - \mathbf{X}\beta)^T (\mathbf{y} - \mathbf{X}\beta) + \lambda \beta^T \beta$$

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