

Problem 1

Biến đổi lại posterior trên lớp ra latex, từ $p(w|D) \propto w = (X^T X + \alpha I)^{-1} X^T t$

Solution

Bayes theorem

$$\begin{aligned} p(w|D) &= \frac{p(D|w) * p(w)}{p(D)} \\ \Leftrightarrow \text{posterior} &= \frac{\text{likelihood} * \text{prior}}{\text{evidence}} \\ \Rightarrow p(w|x, t, \alpha, \beta) &= \frac{p(t|x, w, \beta) * p(w|\alpha)}{p(x, t, \alpha, \beta)} \end{aligned}$$

Suppose $p(w|\alpha)$ is a normal distribution. We have:

$$\begin{aligned} p(w|\alpha) &= N(w|0, \alpha^{-1}I) \\ p(t|x, w) &= \prod_{i=1}^N N(t_i|y(x_i, w), \beta^{-1}) \end{aligned}$$

Then we take:

$$p(w|\alpha) * p(t|x, w)$$

And maximize we get:

$$\begin{aligned} &= \log(p(t|x, w)) + \ln(p(w|\alpha)) \\ &= \sum_{i=1}^N \log(N(y(x_i, w), \beta^{-1}) + \log(p(w|\alpha^{-1}I)) \\ &= \sum_{i=1}^N \log\left(\frac{1}{\beta^{-1}\sqrt{2\pi}} e^{-\frac{(t_i - y(x_i, w))^2 \beta}{2}}\right) + \log\left(\frac{1}{\sqrt{(2\pi)^D |\alpha^{-1}I|}} e^{-\frac{1}{2} w^T (\alpha^{-1}I)^{-1} w}\right) \\ &= \frac{-\beta}{2} \sum_{i=1}^N (t_i - y(x_i, w))^2 + \frac{-1}{2} \alpha w^T w \\ \Leftrightarrow \text{minimize} : &\sum_{i=1}^N (t_i - y(x_i, w))^2 + \frac{\alpha}{\beta} w^T w \end{aligned}$$

Let:

$$\frac{\alpha}{\beta} = \lambda (\lambda > 0)$$

and then :

$$\begin{aligned} L &= \sum_{i=1}^N (t_i - y(x_i, w))^2 + \lambda w^T w \\ X, w, t \rightarrow L &= \|Xw - t\|_2^2 + \lambda \|w\|_2^2 \\ \frac{\partial L}{\partial w} &= 2X^T(Xw - t) + 2\lambda w = 0 \end{aligned}$$

$$\Leftrightarrow w(X^T X + \lambda I) = X^T t$$

$$\Leftrightarrow w = (X^T X + \lambda I)^{-1} X^T t$$