

$$w = (X^T.X + \alpha * I_n)^{-1}X^T t$$

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1 Posterior

Bayes theorem

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

Vì $p(t|x, w)$ chưa biết phân phối nên giả sử nó phân phối chuẩn Ta có:

$$\begin{aligned} p(w|\alpha).p(t|x, w) &= N(w|0, \alpha^{-1}I) \cdot \prod_{i=1}^N N(t_i|y(x_i, w), B^{-1})(*) \\ \log(*) &= \log\left(\frac{1}{(2\pi)^{\frac{D}{2} \cdot |\alpha^{-1}.I|}} \cdot \exp\left\{\frac{-1}{2} \cdot w^T (\alpha^{-1}I)^{-1} \cdot w\right\} \cdot \prod_{i=1}^N \frac{1}{\sqrt{2\pi} \cdot \beta^{-1}} \cdot \exp\left(\frac{-(t_i - y(x, w))^2 \cdot \beta}{2}\right)\right) \\ &= \frac{-\beta}{2} \sum_{i=1}^N (t_i - y)^2 - \frac{1}{2} \cdot \alpha \cdot w^T \cdot w + \text{constant} \end{aligned}$$

Maximize: $\log(*) \Leftrightarrow \text{minimize}(\sum_{i=1}^N (t_i - y(x_i, w))^2 - \lambda \cdot w^T \cdot w)$ Đặt $L = \sum_{i=1}^N (t_i - y(x_i, w))^2 + \lambda w^T w$

$$L = \|Xw - t\|_2^2 + \lambda \|w\|_2^2$$

$$\frac{dL}{dw} = 2X^T \cdot (Xw - t) + 2\lambda I_n w = 0$$

$$\Leftrightarrow X^T Xw - X^T t + \lambda w = 0$$

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

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