

Problem

Transform back posterior on the class to latex, from $p(w|D) \propto w = (X^T X + \alpha I)^{-1} X^T t$

Solution

$$p(w | x, t, \alpha, \beta) \propto p(t | x, w, \beta) p(w | \alpha) \\ \Rightarrow \log(p(w | x, t, \alpha, \beta)) \propto \log(p(t | x, w, \beta) p(w | \alpha))$$

We have:

$$p(t | x, w, \beta) = \prod_{n=1}^N N(t_n | y(x_n, w), \beta^{-1}) \\ p(t | x, w, \beta) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi\beta^{-1}}} \times e^{\frac{-(t - y(x_n, w))^2}{2\beta^{-1}}} \\ \log(p(t | x, w, \beta)) = \frac{-\beta}{2} \sum_{n=1}^N (t - y(x_n, w))^2 + noise$$

And:

$$p(w | \alpha) = N(w | 0, \alpha^{-1} I) \\ = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} e^{\frac{-(w - 0)^T \Sigma^{-1} (w - 0)}{2}} \\ \log(p(w | \alpha)) = \frac{-1}{2} w^T w + noise$$

So:

$$\log(p(w | x, t, \alpha, \beta)) \propto \frac{-\beta}{2} \sum_{n=1}^N (t - y(x_n, w))^2 + \frac{-1}{2} w^T w$$

The maximum of the posterior is given by the minimum of:

$$\frac{\beta}{2} \sum_{n=1}^N (t - y(x_n, w))^2 + \frac{1}{2} w^T w$$

or we minimize:

$$Q = \|Xw - t\|_2^2 + \lambda w^T w \\ \nabla Q_w = 2X^T(Xw - t) + 2\lambda w \\ So w = (X^T X + \lambda I)^{-1} X^T t$$