

Problem 1

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

Solution

$$\begin{aligned} p(w \mid x, t, \alpha, \beta) &\propto p(t \mid x, w, \beta) p(w \mid \alpha) \\ \Rightarrow \log(p(w \mid x, t, \alpha, \beta)) &\propto \log(p(t \mid x, w, \beta) p(w \mid \alpha)) \end{aligned}$$

We have:

$$\begin{aligned} p(t \mid x, w, \beta) &= \prod_{n=1}^N N(t_n \mid y(x_n, w), \beta^{-1}) \\ \Rightarrow p(t \mid x, w, \beta) &= \prod_{n=1}^N \frac{1}{\sqrt{2\pi\beta^{-1}}} e^{-\frac{(t - y(x_n, w))^2}{2\beta^{-1}}} \\ \log(p \mid x, w, \beta) &= \frac{-\beta}{2} \sum_{n=1}^N ((t - y(x_n, w))^2) + noise \end{aligned}$$

And:

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

So:

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

The maximum of the posterior is given by minimum of:

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

Or we minimize:

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