

# Machine Learning Homework Week 4

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## 1 Question 1: Linear regression model

We have:

+ Set an observation

$$x = (x_1, x_2, \dots, x_N)^T \quad (1)$$

+ Total observations N

+ Target values

$$t = (t_1, t_2, \dots, t_N)^T \quad (2)$$

Suppose that the observations are drawn independently from a Gaussian distribution.

$$t = y(x, w) + N(0, \beta^{-1}) \quad (3)$$

with  $\beta = \frac{1}{\sigma^2}$

$$p(t | x, w, \beta) = N(t | y(x, w), \beta^{-1})$$

We now use the training data  $x, t$  to determine the values of the unknown parameters  $w$  by maximum likelihood function. If the data are assumed to be drawn independently from the distribution, then the likelihood function:

$$p(t | x, w, \beta) = \prod_{n=1}^N N(t | y(x, w), \beta^{-1}) \quad (4)$$

We have to maximise the logarithm of the likelihood function:

$$\log p(t | x, w, \beta) = \prod_{n=1}^N \log(N(t | y(x, w), \beta^{-1})) \quad (5)$$

$$\log p(t | x, w, \beta) = \sum_{n=1}^N \log \left( \frac{1}{\sqrt{2\pi\beta^{-1}}} e^{-\frac{(t_n - y(x_n, w))^2}{2}} \right) \quad (6)$$

$$\log p(t|x, w, \beta) = \sum_{n=1}^N \left[ \frac{1}{2} \log(2\pi\beta^{-1}) - t_n - y(x_n, w)^2 - \frac{\beta}{2} \right] \quad (7)$$

$$\log p(t|x, w, \beta) = - \sum_{n=1}^N (t_n - y(x_n, w)^2) \quad (8)$$

We eliminate  $\frac{1}{2}\log(2\pi\beta^{-1})$  and  $\frac{\beta}{2}$  because they are not elements that we want to optimize. We have to minimize  $(t_n - y(x_n, w)^2)$   
Set

$$L = \frac{1}{2N} \sum_{n=1}^N (t_n - y(x_n, w)^2) \quad (9)$$

with

$$x = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \dots & \dots \\ 1 & x_n \end{bmatrix}, w = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}, y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} w_1 x_1 + w_0 \\ w_1 x_2 + w_0 \\ w_1 x_3 + w_0 \\ \dots \\ w_1 x_n + w_0 \end{bmatrix} = xw \quad (10)$$

we have

$$\frac{\partial L}{\partial w} = \begin{bmatrix} \frac{\partial L}{\partial w_0} \\ \frac{\partial L}{\partial w_1} \end{bmatrix} = \begin{bmatrix} t - xw \\ x(t - xw) \end{bmatrix} = x^T(t - xw) = 0 \quad (11)$$

$$\iff x^T t = x^T x w$$

$$\iff w = (x^T x)^{-1} x^T t$$

## 2 Question 2: Proof $X^T X$ is invertible when $X$ full rank

Suppose  $X^T v = 0$ , then  $XX^T v = 0$  too.

On the other hand, suppose  $XX^T v = 0$ , then  $v^T XX^T v = 0$  too. Therefore,  $(X^T v)^T (X^T v) = 0$ . It also means  $X^T v = 0$

Hence, we also know that  $X^T v = 0 \iff v$  is in the nullspace of  $X^T X$

But  $X^T v = 0$  and  $v \neq 0 \iff X$  has linearly dependent rows.

Therefore,  $X^T X$  is invertible when  $X$  has full row rank.