

# HW ML 3

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## 1 We will prove that

$$t_n = y(x, w) + \epsilon \iff W = (X^T X)^{-1} X^T t$$

Suppose that the observations are drawn independently from a Gaussian distribution we have:

$$p(t_n) = \mathcal{N}(t_n | y(x, w), \epsilon^2) p(t | x, w, \beta) = \prod_{n=1}^N \mathcal{N}(t_n | y(x_n, w); \sigma^2)$$

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

Maximize the logarithm of the likelihood function:

$$\log \prod_{i=1}^N \mathcal{N}(t_n | y(x_n, w), \beta^{-1}) = \sum_{i=1}^N \log \left( \frac{1}{\sqrt{2\pi\beta^{-1}}} e^{(t_n - y(x_n, w))^2 \frac{\beta}{2}} \right) = \sum_{i=1}^N \left( \frac{-1}{2} \log(2\pi\beta^{-1}) - (t_n - y(x_n, w))^2 \frac{\beta}{2} \right)$$

Minimize:  $\sum_{i=1}^N (t_n - y(x_n, w))^2$

$$X = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \dots & \dots \\ 1 & x_n \end{bmatrix}, W = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}, t = \begin{bmatrix} t_1 \\ t_2 \\ \dots \\ t_n \end{bmatrix}, y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} w_1 x_1 + w_0 \\ w_1 x_2 + w_0 \\ \dots \\ w_1 x_n + w_0 \end{bmatrix} = XW, t - y = \begin{bmatrix} t_1 - y_1 \\ t_2 - y_2 \\ \dots \\ t_n - y_n \end{bmatrix}$$

$$\implies \|t - y\|_2^2 = \sum_{i=1}^n (t_i - y_i)^2 = \text{Loss Function} \implies L = \|t - y\|_2^2 = \|t - XW\|_2^2 \implies \frac{\partial L}{\partial W} = 2X^T(t - XW) = 0$$

## 2 Prove that $X^T X$ is invertible when $X$ full rank

### Solution

If  $X$  is full rank,  $X$  is linear independent.

$$\Rightarrow \vec{v}^T X^T X \vec{v} = \vec{v}^T \vec{0} = 0 \Rightarrow (X\vec{v})^T X\vec{v} = 0 \Rightarrow (X\vec{v}) \cdot (X\vec{v}) = 0 \Rightarrow X\vec{v} = \vec{0}$$

So we have: if  $\vec{v} \in N(X^T X) \Rightarrow \vec{v} \in N(X)$

$$\Rightarrow \vec{v} \text{ can only be } \vec{0} \Rightarrow N(X^T X) = N(X) = \{\vec{0}\}$$

$\Rightarrow X^T X$  is linearly independent; and  $X^T X$  is a square matrix  $\Rightarrow X^T X$  is invertible