

Machine Learning 1 - Homework week 3: Linear Regression

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1 Problem 1. Biến đổi:

We assume that the target variable t is given by a deterministic function $y(x, w)$ with additive Gaussian noise so that

$$t = y(x, w) + \epsilon \quad (1)$$

Let

$$\epsilon = N(\mu, \sigma^2) \quad (2)$$

Set

$$\epsilon \sim N(\mu, \sigma^2) \quad (3)$$

$$\Rightarrow t = y(x, w) + \epsilon \sim N(y(x, w), \sigma^2) \quad (4)$$

$$\Rightarrow p(t) = N(t|y(x, w), \sigma^2) \quad (5)$$

We want:

$$t_n \approx y(x_n, w) \quad (6)$$

Then, $p(\mathbf{t}_n)$ could be maximized

Now consider a data set of inputs $X = \{x_1, \dots, x_N\}$ with corresponding target values t_1, \dots, t_N . We group the target variables $\{t_n\}$ into a column vector that we denote by \mathbf{t} where the typeface is chosen to distinguish it from a single observation of a multivariate target, which would be denoted t . We obtain the following expression for the likelihood function, which is a function of the adjustable parameters w and β , in the form

$$p(\mathbf{t}|\mathbf{X}, \mathbf{w}, \beta) = \prod_{n=1}^n \mathcal{N}(t_n|y(x_n, w), \beta^{-1}) \quad (7)$$

Let maximize (7) to find the model, i.e find the w :

$$\log \prod_{n=1}^n \mathcal{N}(t_n | y(x_n, w), \beta^{-1}) = \log \prod_{n=1}^n \frac{1}{\sqrt{2\pi\beta^{-1}}} e^{-(t_n - y(x_n, w))^2 \cdot \frac{\beta}{2}} \quad (8)$$

$$= \sum_{n=1}^n \log \left(\frac{1}{\sqrt{2\pi\beta^{-1}}} e^{-(t_n - y(x_n, w))^2 \cdot \frac{\beta}{2}} \right) \quad (9)$$

$$= \sum_{n=1}^n \frac{-1}{2} \log(2\pi\beta^{-1}) - (t_n - y(x_n, w))^2 \cdot \frac{\beta}{2} \quad (10)$$

$$= \text{const} - \sum_{n=1}^n (t_n - y(x_n, w))^2 \quad (11)$$

To maximize (11), we minimize:

$$\sum_{n=1}^n (t_n - y(x_n, w))^2 \quad (12)$$

In other words, we minimize the loss function:

$$L = \frac{1}{N} \sum_{n=1}^N (\hat{y}_i - y_i)^2 \quad (13)$$

with $\hat{y}_i = w_1 x_i + w_0$

$$\text{We have: } w = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}, X = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \dots & \dots \\ 1 & x_n \end{bmatrix}, y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}, \hat{y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \dots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} w_0 + w_1 x_1 \\ w_0 + w_1 x_2 \\ \dots \\ w_0 + w_1 x_n \end{bmatrix} = Xw.$$

So that, $L = \|\hat{y} - y\|^2 = \|Xw - y\|^2 = (Xw - y)^T (Xw - y)$

$$\frac{\partial L}{\partial w} = 2X^T(Xw - y) = 0 \quad (14)$$

$$\Leftrightarrow X^T Xw = X^T y \quad (15)$$

$$\Leftrightarrow w = (X^T X)^{-1} X^T y \quad (16)$$

2 Problem 4. Chứng minh:

$X^T X$ is invertible when X full rank.

Answer:

Assume X is an $m \times n$ size, with rank m ($n \geq m$).

Let $X^T X v = 0$, for some $v \in R^M$

$$\Rightarrow v^T X^T X v = 0 \tag{17}$$

$$\Rightarrow (Xv)^T Xv = 0 \tag{18}$$

$$\Rightarrow Xv = 0 \tag{19}$$

If the rank of X is m , this means that X is one-to-one when acting on R^M . Then, $X^T X$ is one-to-one too, and because it is a square matrix, it is invertible.