

Assignment of Data Mining (1) April 12, 2022

Name: 階戸 弾

ID: 1124525046

1.

A linear regression model of multi-dimensional input $\mathbf{x} \in \mathbb{R}^D$ and output $y \in \mathbb{R}$ is defined as

$$f(\mathbf{x}, \mathbf{w}) = w_0 + \sum_{d=1}^D w_d x_d = \mathbf{w}^T \mathbf{x},$$

where $\mathbf{w} = (w_0, w_1, \dots, w_D)^T$ is a parameter vector and $\mathbf{x} = (1, x_1, \dots, x_D)^T$ is an input vector. Given N samples $(\mathbf{x}_n, y_n), n = 1, \dots, N$, find the optimum \mathbf{w} minimizing the squared error:

$$\begin{aligned} J(\mathbf{w}) &= \frac{1}{2} \sum_{n=1}^N \{f(\mathbf{x}_n, \mathbf{w}) - y_n\}^2 \\ &= \frac{1}{2} (\mathbf{X}\mathbf{w} - \mathbf{y})^T (\mathbf{X}\mathbf{w} - \mathbf{y}), \end{aligned}$$

where $\mathbf{y} = (y_1, \dots, y_N)^T$ and data matrix

$$\mathbf{X} = \begin{pmatrix} \mathbf{x}_1^T \\ \mathbf{x}_2^T \\ \vdots \\ \mathbf{x}_N^T \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1D} \\ 1 & x_{21} & \cdots & x_{2D} \\ 1 & \vdots & \ddots & \vdots \\ 1 & x_{N1} & \cdots & x_{ND} \end{pmatrix}$$

Answer:

$$J(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N \{f(\mathbf{x}_n, \mathbf{w}) - y_n\}^2 = \frac{1}{2} (\mathbf{X}\mathbf{w} - \mathbf{y})^T (\mathbf{X}\mathbf{w} - \mathbf{y})$$

より,

$$\begin{aligned} J(\mathbf{w}) &= \frac{1}{2} \{(\mathbf{X}\mathbf{w})^T \mathbf{X}\mathbf{w} - (\mathbf{X}\mathbf{w})^T \mathbf{y} - \mathbf{y}^T \mathbf{X}\mathbf{w} + \mathbf{y}^T \mathbf{y}\} \\ &= \frac{1}{2} \{(\mathbf{X}\mathbf{w})^T \mathbf{X}\mathbf{w} - ((\mathbf{X}\mathbf{w})^T \mathbf{y})^T - (\mathbf{y}^T \mathbf{X}\mathbf{w})^T + \mathbf{y}^T \mathbf{y}\} \\ &= \frac{1}{2} \{(\mathbf{X}\mathbf{w})^T \mathbf{X}\mathbf{w} - 2(\mathbf{X}\mathbf{w})^T \mathbf{y} + \mathbf{y}^T \mathbf{y}\} \\ &= \frac{1}{2} \{\mathbf{X}^T \mathbf{w}^T \mathbf{X}\mathbf{w} - 2\mathbf{X}^T \mathbf{w}^T \mathbf{y} + \mathbf{y}^T \mathbf{y}\} \end{aligned}$$

ここで最適化パラメータ \mathbf{w} は、 $J(\mathbf{w})$ を最小とする値であるため、

$$\frac{\partial}{\partial \mathbf{w}} J(\mathbf{w}) = 0$$

とする。

$$\begin{aligned}
\frac{\partial}{\partial \mathbf{w}} J(\mathbf{w}) &= -\mathbf{X}^T \mathbf{y} + \frac{1}{2} (\mathbf{X}^T \mathbf{X} + (\mathbf{X}^T \mathbf{X})^T) \mathbf{w} \\
&= -\mathbf{X}^T \mathbf{y} + \frac{1}{2} (\mathbf{X}^T \mathbf{X} + \mathbf{X}^T \mathbf{X}) \mathbf{w} \\
&= -\mathbf{X}^T \mathbf{y} + \mathbf{X}^T \mathbf{X} \mathbf{w} \\
&= 0
\end{aligned}$$

よって、 $\mathbf{X}^T \mathbf{X} \mathbf{w} = \mathbf{X}^T \mathbf{y}$ となるため、多重回帰分析の最適化パラメータは

$$\mathbf{w} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

となる。