

# COMP9417 – Machine Learning

## Tutorial: Regression I

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### Question 1.

(b) Because  $L(w_0, w_1) = \frac{1}{n} \sum_{i=1}^n (y_i - (w_0 + w_1 x_i))^2$

Then  $\frac{\partial L(w_0, w_1)}{\partial w_0} = \frac{1}{n} \sum_{i=1}^n (2w_0 + 2w_1 x_i - 2y_i)$   $\frac{\partial L(w_0, w_1)}{\partial w_1} = \frac{1}{n} \sum_{i=1}^n (2w_1 x_i^2 + 2w_0 x_i - 2x_i y_i)$

Let  $\frac{\partial L(w_0, w_1)}{\partial w_0} = 0$  and  $\frac{\partial L(w_0, w_1)}{\partial w_1} = 0$

Then  $w_0 = \frac{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i - \sum_{i=1}^n x_i \sum_{i=1}^n x_i y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$  ..... ①  $w_1 = \frac{n \sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i \sum_{i=1}^n y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$  ..... ②

Because  $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$  ..... ③ and  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  ..... ④

Substituting equation ①②③④ into  $y = w_0 + w_1 x$

$$\frac{1}{n} \sum_{i=1}^n y_i = \frac{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i - \sum_{i=1}^n x_i \sum_{i=1}^n x_i y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2} + \frac{1}{n} \sum_{i=1}^n x_i \frac{n \sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i \sum_{i=1}^n y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$\frac{1}{n} \sum_{i=1}^n y_i = \frac{1}{n} \left( \frac{n \sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i - n \sum_{i=1}^n x_i \sum_{i=1}^n x_i y_i + n \sum_{i=1}^n x_i \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)^2 \sum_{i=1}^n y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2} \right)$$

$$\frac{1}{n} \sum_{i=1}^n y_i = \frac{\sum_{i=1}^n y_i (n \sum_{i=1}^n x_i - (\sum_{i=1}^n x_i)^2)}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2} = \frac{1}{n} \sum_{i=1}^n y_i$$

Therefore, the point  $(\bar{x}, \bar{y})$  is always on the least squares regression line.

(c) Because  $L(w_0, w_1) = \frac{1}{n} \sum_{i=1}^n (y_i - (w_0 + w_1 x_i))^2 + \lambda w_1^2$

Then  $\frac{\partial L(w_0, w_1)}{\partial w_0} = \frac{1}{n} \sum_{i=1}^n (2w_0 + 2w_1 x_i - 2y_i)$  and

$\frac{\partial L(w_0, w_1)}{\partial w_1} = \frac{1}{n} \sum_{i=1}^n (2w_1 x_i^2 + 2w_0 x_i - 2x_i y_i) + 2\lambda w_1$

Let  $\frac{\partial L(w_0, w_1)}{\partial w_0} = 0$  and  $\frac{\partial L(w_0, w_1)}{\partial w_1} = 0$

Then  $w_0 = \frac{1}{n} \sum_{i=1}^n y_i - \frac{(1 - \frac{1}{n})(\sum_{i=1}^n x_i)^2 \sum_{i=1}^n y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2 + n^2 \lambda}$  and

$$w_1 = \frac{(1 - \frac{1}{n}) \sum_{i=1}^n x_i \sum_{i=1}^n y_i}{\sum_{i=1}^n x_i^2 - \frac{1}{n} (\sum_{i=1}^n x_i)^2 + n \lambda}$$

### Question 2.

(g) (i) This is true.

$$MSE(w) = \frac{1}{n} \|y - Xw\|_2^2 = \frac{1}{n} (y - Xw)^T (y - Xw)$$

$$SSE(w) = \|y - Xw\|_2^2 = (y - Xw)^T (y - Xw)$$

$$\begin{aligned}
\text{Because } \frac{\partial MSE(w)}{\partial w} &= \frac{\partial \frac{1}{n}(y-Xw)^T(y-Xw)}{\partial w} = \frac{\partial \frac{1}{n}(y^T y - y^T Xw - w^T X^T y + w^T X^T Xw)}{\partial w} \\
&= \frac{1}{n} \left( \frac{\partial y^T y}{\partial w} - 2 \frac{\partial (x^T y)w}{\partial w} + \frac{\partial w^T x^T Xw}{\partial w} \right) \\
&= \frac{1}{n} (-2x^T y + 2x^T Xw) \quad \dots\dots\dots (a) \text{ Hint1 \& Hint2}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial SSE(w)}{\partial w} &= \frac{\partial (y-Xw)^T(y-Xw)}{\partial w} = \frac{\partial (y^T y - y^T Xw - w^T X^T y + w^T X^T Xw)}{\partial w} \\
&= \frac{\partial y^T y}{\partial w} - 2 \frac{\partial (x^T y)w}{\partial w} + \frac{\partial w^T x^T Xw}{\partial w} \\
&= -2x^T y + 2x^T Xw \quad \dots\dots\dots (a) \text{ Hint1 \& Hint2}
\end{aligned}$$

$$\text{Then } \frac{\partial SSE(w)}{\partial w} = n \frac{\partial MSE(w)}{\partial w}$$

Therefore, both MSE and SSE are minimized at point  $w = (X^T X)^{-1} X^T y$

(ii) False.

Because both MSE and SSE are minimized at point  $w = (X^T X)^{-1} X^T y$ .

$$\text{But } MSE(w) = \frac{1}{n} SSE(w)$$

$$\text{Therefore, } \min_{w \in R^p} MSE(w) \neq \min_{w \in R^p} SSE(w)$$