

Logistic Regression

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1 Problem 1:

$L = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$ in which $\hat{y} = \alpha(w_0 + w_1 x_1 + w_2 x_2)$

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w}$$

$$\begin{aligned} \frac{\partial L}{\partial \hat{y}} &= \frac{\partial [-y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]}{\partial \hat{y}} \\ &= -[y \frac{1}{\hat{y}} - (1 - y) \frac{1}{1 - \hat{y}}] \\ &= -\frac{y - \hat{y}}{\hat{y}(1 - \hat{y})} \end{aligned}$$

$$\begin{aligned} z &= e^{-W^T X} \\ \hat{y} &= \frac{1}{1 + z} = \frac{1}{1 + e^{-W^T X}} \end{aligned}$$

$$\begin{aligned} \frac{\partial \hat{y}}{\partial w} &= \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial w} \\ &= \frac{\partial \frac{1}{1+z}}{\partial z} \frac{\partial z}{\partial w} \\ &= -\frac{1}{(1+z)^2} (-zw) \\ &= \frac{zX}{(1+z)^2} \\ &= X\hat{y}(1 - \hat{y}) \end{aligned}$$

$$\begin{aligned} \frac{\partial L}{\partial w} &= -\frac{y - \hat{y}}{\hat{y}(1 - \hat{y})} X\hat{y}(1 - \hat{y}) \\ &= X(\hat{y} - y) \end{aligned}$$

Biểu diễn dưới dạng ma trận: $\frac{\partial L}{\partial w} = X^T(\hat{Y} - Y)$

2 Problem 2:

Chứng minh với model logistic thì loss binary crossentropy là convex function với W, loss mean square error không là convex function với W

a, Binary-crossentropy: Từ bài 1 ta có:

$$\frac{\partial L}{\partial w} = X(\hat{y} - y)$$

Do:

$$\frac{\partial \hat{y}}{\partial w} = X\hat{y}(1 - \hat{y})$$

Nên:

$$\begin{aligned}\frac{\partial^2 L}{\partial w^2} &= X \frac{\partial \hat{y}}{\partial w} \\ &= X^2 \hat{y}(1 - \hat{y}) \geq 0\end{aligned}$$

⇒ **The loss binary-crossentropy with logistic model is convex**

b,MSE:

$$L = \frac{1}{N} \sum_{i=1}^N (\hat{y} - y)^2$$

$$\begin{aligned}\frac{\partial L}{\partial w} &= \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} \\ &= -2(y - \hat{y})x\hat{y}(1 - \hat{y}) \\ &= -2x(y\hat{y} - \hat{y}^2)(1 - \hat{y}) \\ &= -2x(y\hat{y} - y\hat{y}^2 - \hat{y}^2 + \hat{y}^3)\end{aligned}$$

Second derivate:

$$\begin{aligned}\frac{\partial^2 L}{\partial w^2} &= -2x(y \frac{\partial \hat{y}}{\partial w} - y \frac{\partial \hat{y}^2}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} - \frac{\partial \hat{y}^2}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} + \frac{\partial \hat{y}^3}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w}) \\ &= -2x(y.x.\hat{y}(1 - \hat{y}) - y.2.\hat{y}.x.\hat{y}(1 - \hat{y}) - 2.\hat{y}.x.\hat{y}(1 - \hat{y}) + 3.\hat{y}^2.x.\hat{y}(1 - \hat{y})) \\ &= -2.x^2.\hat{y}.(1 - \hat{y}).(y - 2.y.\hat{y} - 2\hat{y} + 3\hat{y}^2)\end{aligned}$$

$$\forall x^2 y(1 - \hat{y}) \geq 0$$

$$\text{Khi } y = 0: \frac{\partial^2 L}{\partial w^2} = 4\hat{y} - 6\hat{y}^2 = 2\hat{y}(2\hat{y} - 3\hat{y}) \geq 0 \forall \hat{y} \in [\frac{2}{3}, 1]$$

Khi $y = 1$: $\frac{\partial^2 L}{\partial w^2} = -2(3\hat{y} - 1)(\hat{y} - 1) \geq 0 \forall \hat{y} \in [0, \frac{1}{3}]$

\Rightarrow **The loss MSE with logistic model is convex**