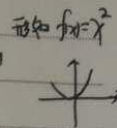


## ① 求解偏置 $b$ 的公式推导

推导思路: 由最小二乘法导出损失函数  $E(w, b)$

↓  
证明损失函数  $E(w, b)$  是关于  $w$  和  $b$  的 凸函数



↓  
对损失函数  $E(w, b)$  关于  $b$  求一阶偏导数

↓  
令一阶偏导数等于 0 解出  $b$

由最小二乘法导出损失函数  $E(w, b)$ :

$$\begin{aligned} E(w, b) &= \sum_{i=1}^m (y_i - f(x_i))^2 \quad \text{均方误差, 平方损失} \quad \text{令 } f(x_i) = wx_i + b \\ &= \sum_{i=1}^m (y_i - (wx_i + b))^2 \\ &= \sum_{i=1}^m (y_i - wx_i - b)^2 \end{aligned}$$

二元函数判断凹凸性:

设  $f(x, y)$  在区域  $D$  上具有二阶连续偏导数, 记  $A = f''_{xx}(x, y)$ ,  $B = f''_{xy}(x, y)$ ,  $C = f''_{yy}(x, y)$

则:

(1) 在  $D$  上恒有  $A > 0$ , 且  $AC - B^2 > 0$  时,  $f(x, y)$  在区域  $D$  上是凸函数;

(2) 在  $D$  上恒有  $A < 0$ , 且  $AC - B^2 > 0$  时,  $f(x, y)$  在区域  $D$  上是凹函数。

二元凹凸函数求最值:

设  $f(x, y)$  是在开区域  $D$  内具有连续偏导数的凸(或凹)函数,  $(x_0, y_0) \in D$  且  $f'_x(x_0, y_0) = 0$ ,  $f'_y(x_0, y_0) = 0$  则  $f(x_0, y_0)$  必为  $f(x, y)$  在  $D$  内的最小值或最大值。

②

证明损失函数  $E(w, b)$  是关于  $w$  和  $b$  的凸函数 —— 求  $A = f''_{xx}(x, y)$ :

$$\begin{aligned}\frac{\partial E(w, b)}{\partial w} &= \frac{\partial}{\partial w} \left[ \sum_{i=1}^m (y_i - wx_i - b)^2 \right] \\ &= \sum_{i=1}^m \frac{\partial}{\partial w} (y_i - wx_i - b)^2 \\ &= \sum_{i=1}^m 2(y_i - wx_i - b) \cdot (-x_i) \\ &= 2 \left( w \sum_{i=1}^m x_i^2 - \sum_{i=1}^m (y_i - b) x_i \right)\end{aligned}$$

$$\begin{aligned}\frac{\partial^2 E(w, b)}{\partial w^2} &= \frac{\partial}{\partial w} \left( \frac{\partial E(w, b)}{\partial w} \right) \\ &= \frac{\partial}{\partial w} \left[ 2 \left( w \sum_{i=1}^m x_i^2 - \sum_{i=1}^m (y_i - b) x_i \right) \right] \\ &= \frac{\partial}{\partial w} \left[ 2w \sum_{i=1}^m x_i^2 \right] \\ &= 2 \sum_{i=1}^m x_i^2, \text{ 此即为 } A = f''_{xx}(x, y)\end{aligned}$$

证明损失函数  $E(w, b)$  是关于  $w$  和  $b$  的凸函数 —— 求  $B = f''_{xy}(x, y)$

$$\begin{aligned}\frac{\partial^2 E(w, b)}{\partial w \partial b} &= \frac{\partial}{\partial b} \left( \frac{\partial E(w, b)}{\partial w} \right) \\ &= \frac{\partial}{\partial b} \left[ 2 \left( w \sum_{i=1}^m x_i^2 - \sum_{i=1}^m (y_i - b) x_i \right) \right] \\ &= \frac{\partial}{\partial b} \left[ -2 \sum_{i=1}^m (y_i - b) x_i \right] \\ &= \frac{\partial}{\partial b} \left( -2 \sum_{i=1}^m y_i x_i + 2 \sum_{i=1}^m b x_i \right) \\ &= \frac{\partial}{\partial b} \left( 2 \sum_{i=1}^m b x_i \right) \\ &= 2 \sum_{i=1}^m x_i, \text{ 此即为 } B = f''_{xy}(x, y)\end{aligned}$$

证明损失函数  $E(w, b)$  是关于  $w$  和  $b$  的凸函数——求  $C = f''_{yy}(x, y)$ :

$$\begin{aligned}\frac{\partial E(w, b)}{\partial b} &= \frac{\partial}{\partial b} \left[ \sum_{i=1}^m (y_i - wx_i - b)^2 \right] \\ &= \sum_{i=1}^m \frac{\partial}{\partial b} (y_i - wx_i - b)^2 \\ &= \sum_{i=1}^m 2(y_i - wx_i - b) \cdot (-1) \\ &= 2 \left( mb - \sum_{i=1}^m (y_i - wx_i) \right)\end{aligned}$$

$$\begin{aligned}\frac{\partial^2 E(w, b)}{\partial b^2} &= \frac{\partial}{\partial b} \left( \frac{\partial E(w, b)}{\partial b} \right) \\ &= \frac{\partial}{\partial b} \left[ 2 \left( mb - \sum_{i=1}^m (y_i - wx_i) \right) \right] \\ &= \frac{\partial}{\partial b} (2mb) \\ &= 2m \quad \text{此即为 } C = f''_{yy}(x, y)\end{aligned}$$

$$A = 2 \sum_{i=1}^m x_i^2 > 0 \quad B = 2 \sum_{i=1}^m x_i \quad C = 2m \quad AC - B^2 \geq 0, A > 0$$

$$\begin{aligned}AC - B^2 &= 2m \cdot 2 \sum_{i=1}^m x_i^2 - \left( 2 \sum_{i=1}^m x_i \right)^2 \\ &= 4m \sum_{i=1}^m x_i^2 - 4 \left( \sum_{i=1}^m x_i \right)^2 \\ &= 4m \sum_{i=1}^m x_i^2 - 4m \cdot \frac{1}{m} \left( \sum_{i=1}^m x_i \right)^2 \\ &= 4m \sum_{i=1}^m x_i^2 - 4m \cdot \bar{x} \cdot \sum_{i=1}^m x_i \\ &= 4m \left( \sum_{i=1}^m x_i^2 - \sum_{i=1}^m x_i \bar{x} \right) \\ &= 4m \sum_{i=1}^m (x_i^2 - x_i \bar{x})\end{aligned}$$

$$\frac{1}{m} \sum_{i=1}^m x_i = \bar{x}$$

$$\begin{aligned}\text{又: } \sum_{i=1}^m x_i \bar{x} &= \bar{x} \sum_{i=1}^m x_i = \bar{x} \cdot m \cdot \frac{1}{m} \sum_{i=1}^m x_i = m \bar{x}^2 = \sum_{i=1}^m \bar{x}^2 \\ &= 4m \sum_{i=1}^m (x_i^2 - x_i \bar{x} - x_i \bar{x} + \bar{x}^2) = 4m \sum_{i=1}^m (x_i^2 - x_i \bar{x} - x_i \bar{x} + \bar{x}^2) \\ &= 4m \sum_{i=1}^m (x_i - \bar{x})^2\end{aligned}$$



④ 令一阶偏导数等于0解出b:

$$\frac{\partial E(w,b)}{\partial b} = 2 \left( mb - \sum_{i=1}^m (y_i - wx_i) \right) = 0$$

$$mb - \sum_{i=1}^m (y_i - wx_i) = 0$$

$$b = \frac{1}{m} \sum_{i=1}^m (y_i - wx_i)$$

$$b = \frac{1}{m} \sum_{i=1}^m y_i - w \cdot \frac{1}{m} \sum_{i=1}^m x_i$$

$$= \bar{y} - w\bar{x}$$

二. 求解权重w的公式推导

推导思路: 由最小二乘法导出损失函数  $E(w,b)$

↓  
证明损失函数  $E(w,b)$  是关于w和b的凸函数

↓  
对损失函数  $E(w,b)$  关于w求一阶偏导数

↓  
令一阶偏导数等于0解出w.

令一阶偏导数等于0解出w:

$$\frac{\partial E(w,b)}{\partial w} = 2 \left( w \sum_{i=1}^m x_i^2 - \sum_{i=1}^m (y_i - b) x_i \right) = 0$$

$$w \sum_{i=1}^m x_i^2 - \sum_{i=1}^m (y_i - b) x_i = 0$$

$$w \sum_{i=1}^m x_i^2 = \sum_{i=1}^m y_i x_i - \sum_{i=1}^m b x_i \quad \text{将 } b = \bar{y} - w\bar{x} \text{ 代入}$$

$$w \sum_{i=1}^m x_i^2 = \sum_{i=1}^m y_i x_i - \sum_{i=1}^m (\bar{y} - w\bar{x}) x_i$$

$$w \sum_{i=1}^m x_i^2 = \sum_{i=1}^m y_i x_i - \bar{y} \sum_{i=1}^m x_i + w\bar{x} \sum_{i=1}^m x_i$$

$$w \left( \sum_{i=1}^m x_i^2 - \bar{x} \sum_{i=1}^m x_i \right) = \sum_{i=1}^m y_i x_i - \bar{y} \sum_{i=1}^m x_i$$

$$w = \frac{\sum_{i=1}^m y_i x_i - \bar{y} \sum_{i=1}^m x_i}{\sum_{i=1}^m x_i^2 - \bar{x} \sum_{i=1}^m x_i}$$

$$\bar{y} \sum_{i=1}^m x_i = \frac{1}{m} \sum_{i=1}^m y_i \sum_{i=1}^m x_i$$

$$= \bar{x} \sum_{i=1}^m y_i$$

$$\bar{x} \sum_{i=1}^m x_i = \frac{1}{m} \sum_{i=1}^m x_i \sum_{i=1}^m x_i$$

$$= \frac{1}{m} \left( \sum_{i=1}^m x_i \right)^2$$

$$w = \frac{\sum_{i=1}^n y_i x_i - \bar{y} \sum_{i=1}^n x_i}{\sum_{i=1}^n x_i^2 - \frac{1}{n} \left( \sum_{i=1}^n x_i \right)^2} = \frac{\sum_{i=1}^n y_i (x_i - \bar{x})}{\sum_{i=1}^n x_i^2 - \frac{1}{n} \left( \sum_{i=1}^n x_i \right)^2} \quad (3)$$

将  $w$  向量化. Vectorize  $w$

$$w = \frac{\sum_{i=1}^n y_i (x_i - \bar{x})}{\sum_{i=1}^n x_i^2 - \frac{1}{n} \left( \sum_{i=1}^n x_i \right)^2} \quad \text{将 } \frac{1}{n} \left( \sum_{i=1}^n x_i \right)^2 = \bar{x} \sum_{i=1}^n x_i = \sum_{i=1}^n \bar{x} x_i \text{ 代入:}$$

$$\begin{aligned} w &= \frac{\sum_{i=1}^n y_i (x_i - \bar{x})}{\sum_{i=1}^n x_i^2 - \sum_{i=1}^n x_i \bar{x}} \\ &= \frac{\sum_{i=1}^n (y_i x_i - y_i \bar{x})}{\sum_{i=1}^n (x_i^2 - x_i \bar{x})} \end{aligned}$$

$$\text{由于 } \begin{cases} \sum_{i=1}^n y_i \bar{x} = \bar{x} \sum_{i=1}^n y_i = \frac{1}{n} \sum_{i=1}^n x_i \sum_{i=1}^n y_i = \sum_{i=1}^n x_i \cdot \frac{1}{n} \sum_{i=1}^n y_i = \sum_{i=1}^n x_i \bar{y} \\ \sum_{i=1}^n y_i \bar{x} = \bar{x} \sum_{i=1}^n y_i = \bar{x} \cdot n \cdot \frac{1}{n} \sum_{i=1}^n y_i = n \bar{x} \bar{y} = \sum_{i=1}^n \bar{x} \bar{y} \\ \sum_{i=1}^n x_i \bar{x} = \bar{x} \sum_{i=1}^n x_i = \bar{x} \cdot n \cdot \frac{1}{n} \sum_{i=1}^n x_i = n \bar{x}^2 = \sum_{i=1}^n \bar{x}^2 \end{cases}$$

$$\begin{aligned} w &= \frac{\sum_{i=1}^n (y_i x_i - y_i \bar{x})}{\sum_{i=1}^n (x_i^2 - x_i \bar{x})} = \frac{\sum_{i=1}^n (y_i x_i - y_i \bar{x} - y_i \bar{x} + y_i \bar{x})}{\sum_{i=1}^n (x_i^2 - x_i \bar{x} - x_i \bar{x} + x_i \bar{x})} \\ &= \frac{\sum_{i=1}^n (y_i x_i - y_i \bar{x} - x_i \bar{y} + \bar{x} \bar{y})}{\sum_{i=1}^n (x_i^2 - x_i \bar{x} - x_i \bar{x} + \bar{x}^2)} \\ &= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \end{aligned}$$

⑥

将  $w$  向量化

$$x = (x_1, x_2, \dots, x_m)^T$$

$$x_d = (x_1 - \bar{x}, x_2 - \bar{x}, \dots, x_m - \bar{x})^T$$

$$y = (y_1, y_2, \dots, y_m)^T$$

$$y_d = (y_1 - \bar{y}, y_2 - \bar{y}, \dots, y_m - \bar{y})^T$$

$$w = \frac{\sum_{i=1}^m (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^m (x_i - \bar{x})^2} = \frac{x_d^T y_d}{x_d^T x_d}$$