

# 1 Pen-and-Paper

- Given an input vector  $\mathbf{x} \in \mathbb{R}^{n \times 1}$ , a linear layer with weights  $W = [w_0, w_1, \dots, w_{n-1}] \in \mathbb{R}^{n \times 1}$ , and a forward calculation  $\hat{y} = W^T \mathbf{x}$ . Smooth- $L_1$  loss is defined as:

$$\mathcal{L} = \begin{cases} 0.5(\hat{y} - y)^2 / \beta & |\hat{y} - y| \leq \beta \\ |\hat{y} - y| - 0.5 \cdot \beta & \text{else} \end{cases}$$

where  $\beta$  is a predefined positive threshold.

Your task is to compute the derivative of the loss with respect to each weight  $w_i$ , which is  $\frac{\partial \mathcal{L}}{\partial w_i}$ .

**Hint:** The derivative of piecewise functions can be computed separately for each case, and then recombined as a single function. You can express the piecewise function as a single formula by multiplying by an indicator function  $\mathbf{1}(\text{condition})$ , where  $\mathbf{1}(\text{condition}) = 1$  if the condition holds, and 0 otherwise. For example,  $x \cdot \mathbf{1}(c > 5) = x$  if  $c > 5$ , otherwise 0.

$$\mathcal{L} = \begin{cases} \frac{1}{2}(W^T \mathbf{x} - y)^2 / \beta & |W^T \mathbf{x} - y| \leq \beta \\ |W^T \mathbf{x} - y| - \frac{1}{2}\beta & \text{else} \end{cases}$$

$$\frac{\partial \mathcal{L}}{\partial W} = \begin{cases} a & |W^T \mathbf{x} - y| \leq \beta \\ b & \text{else} \end{cases}$$

$$a := \frac{(W^T \mathbf{x} - y)^2}{2\beta} \cdot \frac{\partial}{\partial W} = \frac{1}{\beta} \cdot (W^T \mathbf{x} - y) \cdot \mathbf{x} \\ = \frac{(W^T \mathbf{x} - y) \cdot \mathbf{x}}{\beta}$$

$$b := (|W^T \mathbf{x} - y| - \frac{\beta}{2}) \cdot \frac{\partial}{\partial W} \\ = \frac{\partial |W^T \mathbf{x} - y|}{\partial W} + \frac{\partial (-\beta/2)}{\partial W \cdot 2} \quad \mathbf{x} \cdot \text{sign}(W^T \mathbf{x} - y) \\ = \begin{matrix} x & , & W^T \mathbf{x} \geq y \\ -x & , & W^T \mathbf{x} < y \end{matrix} = x \cdot (1 - 2\mathbf{1}(W^T \mathbf{x} < y))$$

$$\frac{\partial \mathcal{L}}{\partial W} = (x \cdot (W^T \mathbf{x} - y) \cdot \frac{1}{\beta}) \cdot \mathbf{1}(|W^T \mathbf{x} - y| \leq \beta) \\ + (x \cdot \text{sign}(W^T \mathbf{x} - y)) \cdot \mathbf{1}(|W^T \mathbf{x} - y| > \beta) \\ = (x \cdot (\hat{y} - y) \cdot \frac{1}{\beta}) \cdot \mathbf{1}(|\hat{y} - y| \leq \beta) \\ + (x \cdot \text{sign}(\hat{y} - y)) \cdot \mathbf{1}(|\hat{y} - y| > \beta)$$

