

# 1 Deriving the BatchNorm Gradients

The goal is to derive the gradient across the whole batch normalization process for a batch B of size m.

Assume we already have gradient w.r.t logits:  $\frac{\partial L}{\partial y_i}$

Going backwards, we will find  $\frac{\partial L}{\partial \hat{x}_i}$ ,  $\frac{\partial L}{\partial \sigma_B^2}$ ,  $\frac{\partial L}{\partial \mu_B}$ , and finally  $\frac{\partial L}{\partial x_i}$ .

**Finding gradient for normalized unshifted logits:**

$$\frac{\partial L}{\partial \hat{x}_i} = \frac{\partial L}{\partial y_i} \frac{\partial y_i}{\partial \hat{x}_i} = \frac{\partial L}{\partial y_i} \gamma$$

**Finding gradient for variance across batch:**

$$\begin{aligned} \frac{\partial L}{\partial \sigma_b^2} &= \sum_j \frac{\partial L}{\partial \hat{x}_j} \frac{\partial \hat{x}_j}{\partial \sigma_b^2} \Rightarrow \sum_j \frac{\partial \hat{x}_j}{\partial \sigma_b^2} = \frac{\partial}{\partial \sigma_b^2} \left( \sum_j (x_j - \mu_B)(\sigma_b^2 + \epsilon)^{-\frac{1}{2}} \right) \\ &= -\frac{1}{2} \sum_j (x_j - \mu_B)(\sigma_b^2 + \epsilon)^{-\frac{3}{2}} \Rightarrow \frac{\partial L}{\partial \sigma_b^2} = -\gamma \frac{1}{2} (\sigma_b^2 + \epsilon)^{-\frac{3}{2}} \sum_j (x_j - \mu_B) \frac{\partial L}{\partial y_j} \end{aligned}$$

**Finding gradient for mean across batch:**

$$\begin{aligned} \frac{\partial L}{\partial \mu_b} &= \sum_j \frac{\partial L}{\partial \hat{x}_j} \frac{\partial \hat{x}_j}{\partial \mu_B} + \frac{\partial L}{\partial \sigma_b^2} \frac{\partial \sigma_b^2}{\partial \mu_B} \\ \sum_j \frac{\partial L}{\partial \hat{x}_j} \frac{\partial \hat{x}_j}{\partial \mu_B} &= -\gamma (\sigma_B + \epsilon)^{-\frac{1}{2}} \sum_j \frac{\partial L}{\partial y_j} \\ \frac{\partial \sigma_b^2}{\partial \mu_B} &= \frac{\partial}{\partial \mu_B} \left( \frac{1}{m-1} \sum_j (x_j - \mu_B)^2 \right) = \frac{2}{m-1} \sum_j (x_j - \mu_B) = \frac{2}{m-1} \left( \sum_j x_j - \sum_j \mu_B \right) \\ &= \frac{2}{m-1} (m\mu_B - m\mu_B) = 0 \Rightarrow \frac{\partial L}{\partial \sigma_b^2} \frac{\partial \sigma_b^2}{\partial \mu_B} = 0 \Rightarrow \frac{\partial L}{\partial \mu_B} = -\gamma (\sigma_B + \epsilon)^{-\frac{1}{2}} \sum_j \frac{\partial L}{\partial y_j} \end{aligned}$$

**Finding total gradient for BatchNorm input:**

$$\begin{aligned} \frac{\partial L}{\partial x_i} &= \frac{\partial L}{\partial \hat{x}_i} \frac{\partial \hat{x}_i}{\partial x_i} + \frac{\partial L}{\partial \mu_B} \frac{\partial \mu_B}{\partial x_i} + \frac{\partial L}{\partial \sigma_b^2} \frac{\partial \sigma_b^2}{\partial x_i} \\ \frac{\partial \hat{x}_i}{\partial x_i} &= \frac{\partial}{\partial x_i} ((x_i - \mu_B)(\sigma_B^2 + \epsilon)^{-\frac{1}{2}}) = (\sigma_B^2 + \epsilon)^{-\frac{1}{2}} \Rightarrow \frac{\partial L}{\partial \hat{x}_i} \frac{\partial \hat{x}_i}{\partial x_i} = \gamma \frac{\partial L}{\partial y_i} (\sigma_B^2 + \epsilon)^{-\frac{1}{2}} \\ \frac{\partial \mu_B}{\partial x_i} &= \frac{1}{m} \Rightarrow \frac{\partial L}{\partial \mu_B} \frac{\partial \mu_B}{\partial x_i} = -\frac{\gamma}{m} (\sigma_B^2 + \epsilon)^{\frac{1}{2}} \sum_j \frac{\partial L}{\partial y_j} \\ \frac{\partial \sigma_b^2}{\partial x_i} &= \frac{2}{m-1} (x_i - \mu_B) \Rightarrow \frac{\partial L}{\partial \sigma_b^2} \frac{\partial \sigma_b^2}{\partial x_i} = -\frac{\gamma}{m-1} (x_i - \mu_B)(\sigma_B^2 + \epsilon)^{-\frac{3}{2}} \sum_j (x_j - \mu_B) \frac{\partial L}{\partial y_j} \\ \frac{\partial L}{\partial x_i} &= \gamma \frac{\partial L}{\partial y_i} (\sigma_B^2 + \epsilon)^{-\frac{1}{2}} - \frac{\gamma}{m} (\sigma_B^2 + \epsilon)^{\frac{1}{2}} \sum_j \frac{\partial L}{\partial y_j} - \frac{\gamma}{m-1} (x_i - \mu_B)(\sigma_B^2 + \epsilon)^{-\frac{3}{2}} \sum_j (x_j - \mu_B) \frac{\partial L}{\partial y_j} \\ &= \gamma (\sigma_B^2 + \epsilon)^{-\frac{1}{2}} \left( \frac{\partial L}{\partial y_i} - \frac{1}{m} \sum_j \frac{\partial L}{\partial y_j} - \frac{\hat{x}_i}{m-1} \sum_j (x_j - \mu_B) \frac{\partial L}{\partial y_j} \right) \end{aligned}$$