## Derivative of BatchNorm operation w.r.t X

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Let  $Y = \gamma \hat{X} + \beta$ , where  $\hat{X} \in \mathbb{R}^{N \times D}$ ,  $\gamma \in \mathbb{R}^{D}$ ,  $\beta \in \mathbb{R}^{D}$ ,  $\hat{X} = \frac{X - \mu}{\sigma}$ ,  $\mu = \frac{1}{N} \sum_{i=1}^{N} x_{i}$ ,  $\sigma = \sqrt{v + \epsilon}$ ,  $v = \frac{1}{N} \sum_{i=1}^{N} (x_{i} - \mu)^{2}$ ,  $\epsilon \in \mathbb{R}$  is a small scalar to omit zero division. Let  $f : \mathbb{R}^{N \times D} \to \mathbb{R}$  is a differentiable scalar function. We also know  $\frac{\partial f}{\partial Y}$ . Derive  $\frac{\partial f}{\partial X}$ . Notice that

- $y_i$  depends on  $x_j$ , where  $1 \le j \le N$
- there is only per-column dependency:  $y_{ij}$  depends on  $x_{kj}$ , where  $1 \leq i$ k < N

Consider first column of X as x.

$$y = \gamma \hat{x} + \beta$$
$$y, x, \hat{x} \in \mathbb{R}^{N}$$
$$\gamma, \beta, \mu, v, \sigma \in \mathbb{R}$$

Let's consider j-th element of x as  $x_j$ .

$$\frac{\partial f}{\partial x_j} = \sum_{i=1}^{N} \frac{\partial f}{\partial y_i} \frac{\partial y_i}{\partial \hat{x}_i} \frac{\partial \hat{x}_i}{\partial x_j}$$

Let's derive expressions for building blocks:

$$\frac{\partial y}{\partial x_i} = \gamma$$

$$\frac{\partial x_i}{\partial x_j} = \frac{\partial (x_i - \mu)}{\partial x_j} (v + \epsilon)^{-\frac{1}{2}} + (x_i - \mu)(-\frac{1}{2})(v + \epsilon)^{-\frac{3}{2}} \frac{\partial (v + \epsilon)}{\partial x_j}$$

$$\frac{\partial \mu}{\partial x_j} = \frac{1}{N}$$

$$\frac{\partial x_i}{\partial x_j} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$

Let's derive  $\frac{\partial v}{\partial x_i}$ .

Consider *i*-th component of sum in v as  $y_i$ .

$$\frac{\partial y_i}{\partial x_j} = \begin{cases} 2(x_i - \mu)(1 - \frac{1}{N}) = -\frac{2}{N}(x_i - \mu) + 2(x_i - \mu) & i = j \\ -\frac{2}{N}(x_i - \mu) & i = j \end{cases}$$

So, 
$$\frac{\partial v}{\partial x_j} = \frac{1}{N} \left( -\frac{2}{N} \sum_{i=1}^{N} (x_i - \mu) + 2(x_j - \mu) \right).$$

Note, that 
$$\sum_{i=1}^{N} (x_i - \mu) = \sum_{i=1}^{N} x_i - N\mu = N\mu - N\mu = 0$$
.  
So,  $\frac{\partial v}{\partial x_j} = \frac{2}{N} (x_j - \mu)$ .

Now we can expand  $\frac{\partial \hat{x_i}}{\partial x_i}$ . Let's do it in case  $i \neq j$ :

$$\frac{\partial \hat{x}_i}{\partial x_j} = -\frac{1}{N} (v + \epsilon)^{-\frac{1}{2}} + (x_i - \mu)(-\frac{1}{2})(v + \epsilon)^{-\frac{3}{2}} \frac{2}{N} (x_j - \mu) = -\frac{1}{N} (v + \epsilon)^{-\frac{1}{2}} (1 + (x_i - \mu)(x_j - \mu)(v + \epsilon)^{-1})$$

Note that the only difference of case i = j is the first multiplier of the first term: it's  $1 - \frac{1}{N}$  instead of  $-\frac{1}{N}$ .

Now we have all to derive  $\frac{\partial f}{\partial x_i}$ :

$$\frac{\partial f}{\partial x_j} = \sum_{i=1}^N \frac{\partial f}{\partial y_i} \frac{\partial y_i}{\partial x_i} \frac{\partial \hat{x}_i}{\partial x_j} = \gamma \sum_{i=1}^N \frac{\partial f}{\partial y_i} \frac{\partial \hat{x}_i}{\partial x_j} =$$

$$\gamma \left( \sum_{i=1}^N -\frac{1}{N} (v+\epsilon)^{-\frac{1}{2}} (1 + (x_i - \mu)(x_j - \mu)(v+\epsilon)^{-1}) \frac{\partial f}{\partial y_i} + (v+\epsilon)^{-\frac{1}{2}} \frac{\partial f}{\partial y_j} \right) =$$

$$\gamma (v+\epsilon)^{-\frac{1}{2}} \left( -\frac{1}{N} \sum_{i=1}^N (1 + (x_i - \mu)(x_j - \mu)(v+\epsilon)^{-1}) \frac{\partial f}{\partial y_i} + \frac{\partial f}{\partial y_j} \right) =$$

$$\gamma (v+\epsilon)^{-\frac{1}{2}} \left( -\frac{1}{N} \sum_{i=1}^N \frac{\partial f}{\partial y_i} - (x_j - \mu)(v+\epsilon)^{-1} \frac{1}{N} \sum_{i=1}^N (x_i - \mu) \frac{\partial f}{\partial y_i} + \frac{\partial f}{\partial y_j} \right)$$

Knowing that, it's easy to write expression in matrix form:

$$\frac{\partial f}{\partial X} = \gamma (v + \epsilon)^{-\frac{1}{2}} \left( -\frac{1}{N} \sum_{i=1}^{N} \frac{\partial f}{\partial y_i} - (X - \mu)(v + \epsilon)^{-1} \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu) \frac{\partial f}{\partial y_i} + \frac{\partial f}{\partial Y} \right)$$

Here  $x, y, v, \mu, \gamma \in \mathbb{R}^D$ .