

$$C = \frac{1}{2n} \sum_{i=1}^n \| \tilde{y}_i - \tilde{a}_i^L \|^2 \approx \underbrace{\frac{1}{2m} \sum_{i=1}^m \| \tilde{y}_i - \tilde{a}_i^L \|^2}_{\text{For Mini Batch}}$$

Let, p_j^L be a parameter of j th neuron in l th layer.

$$\therefore \frac{\partial C}{\partial p_j^L} \approx \frac{1}{2m} \sum_{i=1}^m \frac{\partial}{\partial p_j^L} \| \tilde{y}_i - \tilde{a}_i^L \|^2$$

Now, we do derivative for every data point in Mini Batch. So, we can drop the summation, index i when calculating derivative for a single data point. We also ignore the constant $\frac{1}{2m}$.

So, we get,

$$\frac{\partial}{\partial p_j^L} \| \tilde{y} - \tilde{a}^L \|^2 = \frac{\partial Q}{\partial p_j^L}$$

($Q = C$ if $m = 1$)

Now,

$$\frac{\partial Q}{\partial p_j^L} = \frac{\partial Q}{\partial z_j^L} \cdot \frac{\partial z_j^L}{\partial p_j^L} = \delta_j^L \cdot \frac{\partial z_j^L}{\partial p_j^L} \quad (*)$$

where, $\delta_j^L = \frac{\partial Q}{\partial z_j^L}$

$$z_j^L = w_{j1} a_1^{L-1} + w_{j2} a_2^{L-1} + w_{j3} a_3^{L-1} + \dots + w_{jN_{L-1}} a_{N_{L-1}}^{L-1} + b_j^L$$

We calculate δ_j^L for $L=1$, then using that calculate δ_t^{L-1} , so on.

For $L=1$

$$\begin{aligned}\delta_j^L &= \frac{\partial Q}{\partial z_j^L} = \frac{\partial Q}{\partial a_j^L} \cdot \frac{\partial a_j^L}{\partial z_j^L} \\ &= \frac{\partial}{\partial a_j^L} \| \tilde{y} - \tilde{a}^L \|^2 \cdot \frac{\partial}{\partial z_j^L} \sigma(z_j^L) \\ &= \frac{\partial}{\partial a_j^L} \sum_{s=1}^p (y_s - a_s^L)^2 \cdot \frac{\partial}{\partial z_j^L} \sigma(z_j^L) \\ &= (a_j^L - y_s) \sigma'(z_j^L)\end{aligned}$$

(In our case $p=10$)

$$\therefore \delta^L = (\tilde{a}^L - \tilde{y}) \circ \sigma'(z^L) \quad \text{--- (1)}$$

\circ is Hadamard product.

For any layer l ,

$$\begin{aligned}\delta_j^l &= \frac{\partial Q}{\partial z_j^l} \\ &= \sum_{t=1}^{N_{l+1}} \frac{\partial Q}{\partial z_t^{l+1}} \cdot \frac{\partial z_t^{l+1}}{\partial z_j^l} \\ &= \sum_{t=1}^{N_{l+1}} \delta_t^{l+1} \cdot \frac{\partial z_t^{l+1}}{\partial z_j^l} \quad \text{--- (* *)}\end{aligned}$$

$$\begin{aligned}z_t^{l+1} &= \sum_{s=1}^{N_l} w_{ts}^{l+1} a_s^l + b_t^{l+1} \\ &= \sum_{s=1}^{N_l} w_{ts}^{l+1} \sigma(z_s^l) + b_t^{l+1}\end{aligned}$$

$$\therefore \frac{\partial z_t^{l+1}}{\partial z_j^l} = w_{tj}^{l+1} \sigma'(z_j^l)$$

$$\therefore \text{From (* *)} \quad \delta_j^l = \sum_{t=1}^{N_{l+1}} \delta_t^{l+1} w_{tj}^{l+1} \sigma'(z_j^l)$$

$$\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l) \quad - (2)$$

Now, from (*)

$$\begin{aligned} \frac{\partial Q}{\partial p_j^l} &= \delta_j^l \cdot \frac{\partial z_j^l}{\partial p_j^l} \\ &= \delta_j^l \cdot \frac{\partial}{\partial p_j^l} (w_{j1} a_1^{l-1} + w_{j2} a_2^{l-1} + w_{j3} a_3^{l-1} + \dots \\ &\quad + w_{jN_{l-1}} a_{N_{l-1}}^{l-1} + b_j^l) \end{aligned}$$

$$\text{If, } p_j^l = b_j^l$$

$$\text{then, } \frac{\partial Q}{\partial b_j^l} = \delta_j^l \quad - (3)$$

$$\text{If, } p_j^l = w_{jr}^l$$

$$\text{then, } \frac{\partial Q}{\partial w_{jr}^l} = a_r^{l-1} \quad - (4)$$

In my code ~~Back~~ backpropagation function implements only (1) - (4), update function adds the derivatives and divide the sum by Mini Batch size.