

Comments:

L: I think, the notation is still way from optimal since we always need additional parenthesis when your layer index meets an exponent: $(o_i^{(0)})^2$

L: I was talking with Bhiksha this morning. He pointed out, where the recursion actually is. I am not sure, I understood this completely, but we should work on this together tonight. I am as well curious, what your parenthesis down there explain. :P

Name and network definitions:

$$E = \sum_{i} (o_i^{(0)} - t_i)^2 \qquad o_i^{(0)} = \sigma(x_0^{(i)})$$
 (1)

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$$x_i^{(0)} = \sum_{j} w_{ji}^{(0)} o_j^{(1)} \qquad c_{ji}^{(0)} = w_{ji}^{(0)} o_j^{(1)} \qquad (2)$$

$$c_{ji}^{(0)} = w_{ji}^{(0)} o_j^{(1)} c_{ji}^{(0)} = w_{ji}^{(0)} o_j^{(1)} (3)$$

Derivatives with respect to network output:

$$\frac{\partial E}{\partial o_i^{(0)}} = o_i^{(0)} - t_i \qquad \frac{\partial^2 E}{\partial (o_i^{(0)})^2} = 1 \tag{4}$$

First and second derivative of the sigmoid function:

$$\sigma' = \sigma(1 - \sigma) \qquad \qquad \sigma'' = \sigma'(1 - 2\sigma) \tag{5}$$

Derivative with respect to last layer output:

$$\frac{\partial E}{\partial x_i^{(0)}} = \frac{\partial E}{\partial o_i^{(0)}} \frac{\partial o_i^{(0)}}{\partial x_i^{(0)}} \tag{6}$$

$$= (o_i^{(0)} - t_i)(o_i^{(0)}(1 - o_i^{(0)}))$$
(7)

Second derivative with respect to last layer output:

$$\frac{\partial^2 E}{\partial (x_i^{(0)})^2} = \frac{\partial}{\partial x_i^{(0)}} \left(\frac{\partial E}{\partial o_i^{(0)}} \frac{\partial o_i^{(0)}}{\partial x_i^{(0)}} \right) \tag{8}$$

$$= \frac{\partial^2 x_i^{(0)}}{\partial (o_i^{(0)})^2} \frac{\partial o_i^{(0)}}{\partial x_i^{(0)}} + \frac{\partial E}{\partial o_i^{(0)}} \frac{\partial^2 o_i^{(0)}}{\partial (x_i^{(0)})^2}$$
(9)

$$= \frac{\partial^2 x_i^{(0)}}{\partial (o_i^{(0)})^2} o_i^{(0)} (1 - o_i^{(0)}) + (o_i^{(0)} - t_i) \frac{\partial o_i^{(0)}}{\partial x_i^{(0)}}$$
(10)

$$= \sigma'(x_i^{(0)})o_i^{(0)}(1 - o_i^{(0)}) + (o_i^{(0)} - t_i)\sigma'(x_i^{(0)})(1 - 2o_i^{(0)})$$
(11)

First derivative with respect to single input contribution:

$$\frac{\partial E}{\partial c_{ij}^{(0)}} = \frac{\partial E}{\partial o_i^{(0)}} \frac{\partial o_i^{(0)}}{\partial x_i^{(0)}} \cdot \dots \cdot \frac{\partial x_i^{(0)}}{\partial c_{ji}^{(0)}}$$
(12)

$$= \left(o_i^{(0)} - t_i\right) \underbrace{\left(o_i^{(0)} \left(1 - o_i^{(0)}\right)\right)}_{z'} \tag{13}$$

Where we use:

$$\frac{\partial x_i^{(0)}}{\partial c_{ji}^{(0)}} = \frac{\partial}{\partial c_{ji}^{(0)}} \left(\sum w_{ji}^{(0)} o_j^{(1)} \right) = \frac{\partial}{\partial c_{ji}^{(0)}} \left(c_{ji}^{(0)} + k \right) = 1 \tag{14}$$

(15)

Second derivative with respect to single input contribution:

$$\begin{split} & \cdot \frac{\partial x_{i}^{(0)}}{\partial (((c_{ji}^{(0)})} + \ldots \\ & \frac{\partial E}{\partial o_{i}^{(0)}} \cdot \ldots \cdot \frac{\partial o_{i}^{(0)}}{\partial x_{i}^{(0)}} \\ & \cdot \frac{\partial x_{i}^{(0)}}{\partial ((((((((((c_{ji}^{(0)})))))))))} \end{split}$$

Term is just zero, of course. Then, plugging in...

$$= \left(\frac{\partial o_i^{(0)}}{\partial x_i^{(0)}}\right)^2 + \left(o_i^{(0)} - t_i\right)\sigma''\left(x_i^{(0)}\right) \tag{17}$$

$$= \left(\sigma'\left(x_i^{(0)}\right)\right)^2 + \left(o_i^{(0)} - t_i\right)\sigma''\left(x_i^{(0)}\right) \tag{18}$$

Moving on to the next layer, we have:

$$\frac{\partial E}{\partial o_{j}^{(1)}} = \frac{\partial E}{\partial o_{i}^{(0)}} \cdot \dots \cdot \frac{\partial o_{i}^{(0)}}{\partial x_{i}^{(0)}} \cdot \dots \cdot \frac{\partial x_{i}^{(0)}}{\partial c_{ji}^{(0)}} \cdot \frac{\partial c_{ji}^{(0)}}{\partial o_{j}^{(1)}} = \left(o_{i}^{(0)} - t_{i}\right) \sigma'(x_{i}^{(0)}) w_{ji}^{(0)} \tag{19}$$