## Homework 2

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## 1 Problem 1: Backpropagation

## 1.1 case 1

Sol:

Given  $x_i = g(y_j) = \frac{1}{1 + e^{-\sum_j w_{ji}y_j}}$ , and  $\sum_i \frac{\partial E}{\partial x_i} = -\sum_i (\frac{t_i}{x_i} - \frac{1 - t_i}{1 - x_i})$  apply the chain rule, first take  $x_i$  and  $y_j$  as fixed to compute the gradient for  $w_{ji}$ , then take  $z_k$  and  $y_j$  as fixed to compute the gradient for  $w_{kj}$  we have

$$\begin{split} \frac{\partial E}{\partial w_{ji}} &= \frac{\partial E}{\partial x_i} \frac{\partial x_i}{\partial w_{ji}} \\ &= (\frac{1 - t_i}{1 - x_i} - \frac{t_i}{x_i}) \frac{\partial g(w_{ji}, y_j)}{\partial w_{ji}} \\ &= (\frac{1 - t_i}{1 - x_i} - \frac{t_i}{x_i}) x_i^2 y_j e^{-\sum_j w_{ji} y_j} \\ &= (\frac{1 - t_i}{1 - x_i} - \frac{t_i}{x_i}) x_i y_j (1 - x_i) \\ &= (x_i - t_i) y_j \end{split}$$

$$\frac{\partial E}{\partial w_{kj}} = \sum_{i} \left(\frac{\partial E}{\partial x_{i}} \frac{\partial x_{i}}{\partial y_{j}}\right) \frac{\partial y_{j}}{\partial w_{kj}}$$

$$= \sum_{i} \frac{\partial E}{\partial x_{i}} (-w_{ji}) x_{i} (1 - x_{i}) (-z_{k}) y_{j} (1 - y_{j})$$

$$= \sum_{i} \frac{x_{i} - x_{i} t_{i} - t_{i} + x_{i} t_{i}}{(1 - x_{i}) x_{i}} (-(-w_{ji}) x_{i} (1 - x_{i})) (-(-z_{k}) y_{j} (1 - y_{j}))$$

$$= \sum_{i} (x_{i} - t_{i}) w_{ji} y_{j} (1 - y_{j}) z_{k}$$

Thus, we have  $\sum_{i} \frac{\partial E}{\partial w_{ji}} = \sum_{i} \delta_{j}^{i} y_{j}, \qquad \sum_{j} \frac{\partial E}{\partial w_{kj}} = \sum_{j} \delta_{k}^{j} z_{k}.$ 

## 1.2 case 2

Sol:

Given the cross-entropy 
$$E = -\sum_{i} t_{i} \log(x_{i})$$
 and softmax activation function  $x_{i} = \frac{e^{\sum_{j} w_{ji}y_{j}}}{\sum_{i} e^{\sum_{j} w_{ji}y_{j}}} = f(w_{11}, \dots, w_{j1}, \dots, w_{ji}, \dots, w_{jm}, \dots, y_{j}, \dots)$ , we have 
$$\frac{\partial E}{\partial x_{i}} = -\frac{t_{i}}{x_{i}}$$

$$\frac{\partial x_{m}}{\partial w_{ji}} = \frac{y_{j}(\delta(i-m)e^{\sum_{j} w_{jm}y_{j}}(\sum_{i} e^{\sum_{j} w_{ji}y_{j}}) - e^{\sum_{j} w_{jm}y_{j}}e^{\sum_{j} w_{ji}y_{j}})}{(\sum_{i} e^{\sum_{j} w_{ji}y_{j}})^{2}}$$

$$= y_{j}x_{m}(\delta(i-m) - x_{i})$$

$$\frac{\partial E}{\partial w_{ji}} = \sum_{m} \frac{\partial E}{\partial x_{m}} \frac{\partial x_{m}}{\partial w_{ji}}$$

$$= \sum_{m} y_{j}(-\frac{t_{m}}{x_{m}})x_{m}(\delta(i-m) - x_{i})$$

$$= y_{j}(\sum_{j} t_{m} \cdot x_{i} - t_{i})$$

$$\frac{\partial E}{\partial w_{kj}} = \sum_{i} \left( \sum_{m} \left( \frac{\partial E}{\partial x_{m}} \frac{\partial x_{m}}{\partial y_{j}} \right) \frac{\partial y_{j}}{\partial w_{kj}} \right)$$

$$= \sum_{i} \left( w_{ji} \left( \sum_{m} t_{m} x_{i} - t_{i} \right) \right) y_{j} (1 - y_{j}) z_{k}$$

$$= \sum_{i} \left( \sum_{m} t_{m} x_{i} - t_{i} \right) \left( w_{ji} y_{j} (1 - y_{j}) \right) z_{k}$$

Here 
$$\delta_j^i = \sum_m t_m \cdot x_i - t_i$$
,  $\delta_k^j = \sum_i (\sum_m t_m x_i - t_i) (w_{ji} y_j (1 - y_j))$ .