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## 12. Solution Sheet

## 1. Back propagation: Theory

Go through the proof of Theorem 5.3.8 and check that the gradient $\nabla_{w} F_{w}(x)$ is computed by $\frac{\partial}{\partial w_{i, j}^{l}} F_{w}(x)_{m}=\delta_{i, j}^{l} V_{i}^{l}$ with $\delta_{j, m}^{L}=\Phi^{\prime}\left(h_{j}^{L}\right)$ if $j=m$ and zero else and $\delta_{j, m}^{l}=\sigma^{\prime}\left(h_{j}^{l-1}\right) w_{j, m}^{l+1} \delta_{m, m}^{l+1}$. Hint: Note that $\nabla_{w} F_{w}(x) \in R^{k}$, i.e. $\delta_{j, m}$ is with respect to the $m$-th koordinate of $\nabla_{w} F_{w}(x)$.
Solution:
First, note that $\nabla_{w} F_{w}(x) \in \mathbb{R}^{k}$, i.e. we have to consider the derivatives in each dimension.
Output layer: To compute the partial derivative with respect to the final weights $w_{i, j}^{L}$ we proceed as follows:

$$
\begin{aligned}
\frac{\partial}{\partial w_{i, j}^{L}} F_{w}(x)_{j} & =\frac{\partial}{\partial w_{i, j}^{L}} \Phi(\underbrace{\sum_{k=1}^{N_{L-1}} w_{k, j}^{L} V_{k}^{L-1}}_{=h_{j}^{L}}) \\
& =\Phi^{\prime}\left(h_{j}^{L}\right) V_{i}^{L-1} \\
& =: \delta_{j, j}^{L} V_{i}^{L-1}
\end{aligned}
$$

Note that the derivative of $F_{w}(x)_{m}$ with respect to $w_{i, j}^{L}$ is 0 for $j \neq m$.
In the last hidden layer we have

$$
\begin{aligned}
& \frac{\partial}{\partial w_{i, j}^{L-1}} F_{w}(x)_{m} \\
= & \frac{\partial}{\partial w_{i, j}^{L-1}} \Phi\left(\sum_{t=1}^{N_{L-1}} w_{t, m}^{L} \sigma\left(\sum_{r=1}^{N_{l-2}} w_{r, t}^{L-1} V_{r}^{L-2}\right)\right) \\
= & \Phi^{\prime}\left(h_{m}^{L}\right) \frac{\partial}{\partial w_{i, j}^{L-1}} \sum_{t=1}^{N_{L-1}} w_{t, m}^{L} \sigma\left(\sum_{r=1}^{N_{l-2}} w_{r, t}^{L-1} V_{r}^{L-2}\right) \\
= & \Phi^{\prime}\left(h_{m}^{L}\right) \sum_{t=1}^{N_{L-1}} w_{t, m}^{L} \sigma^{\prime}\left(\sum_{r=1}^{N_{l-2}} w_{r, t}^{L-1} V_{r}^{L-2}\right) \frac{\partial}{\partial w_{i, j}^{L-1}} \sum_{r=1}^{N_{l-2}} w_{r, t}^{L-1} V_{r}^{L-2} \\
= & \Phi^{\prime}\left(h_{m}^{L}\right) w_{j, m}^{L} \sigma^{\prime}\left(h_{j}^{L-2}\right) V_{i}^{L-2} \\
= & \delta_{m, m}^{L} w_{j, m}^{L} \sigma^{\prime}\left(h_{j}^{L-2}\right) V_{i}^{L-2} \\
= & \delta_{j, m}^{L-1} V_{i}^{L-2} .
\end{aligned}
$$

And so on...

## 2. Back propagation: Praxis

Consider a neural network with two inputs, two hidden neurons, two output neurons:


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The blue numbers are the training inputs/outputs, the red numbers are the weights and the orange numbers the biases. Calculate the forward passes and backward passes from Algorithm 33 in the lecture and update the weights.
Solution:
See https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example net $_{h_{l}} \equiv \delta^{l}$ and out $h_{l} \equiv V^{l}$ from Algorithm 33 in the lecture notes.

