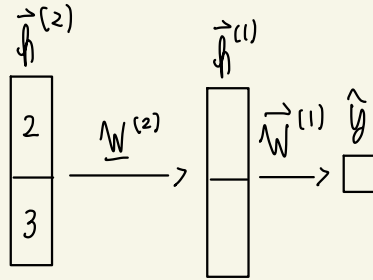


Which can be rewritten into Martha's version, which I'll be using here:



Our network is initialized with:

$y$  True value of the labeled input

$$y = 1$$

$\hat{y}$  Model output

$$\hat{y} = 0.2533$$

$\vec{x}^{(1)}$  Input values for our labeled input

$$\vec{x}^{(1)} = [0.93 \ 0.56]^T$$

$\vec{x}^{(2)}$  Input values for our labeled input

$$\vec{x}^{(2)} = [2 \ 3]^T$$

$\vec{w}^{(1)}$  Weights of the linear model at the end

$$\vec{w}^{(1)} = [0.17 \ 0.17]$$

$\underline{W}^{(2)}$  Weights in the input layer

$$\underline{W}^{(2)} = \begin{bmatrix} 0.12 & 0.13 \\ 0.23 & 0.10 \end{bmatrix}$$

$\alpha$  The learning rate we use for backprop

$$\alpha = 0.05$$

$\mathcal{L} : \mathbb{R}^2 \rightarrow \mathbb{R}$  Loss function for training

$$\mathcal{L}(\hat{y}, y) = \frac{1}{2} (\hat{y} - y)^2$$

Since we'll need it later, we should write out our prediction  $\hat{y}$  in terms of the inputs

$$\hat{y} = \vec{w}^{(1)} \vec{h}^{(1)}$$

$$= \vec{w}^{(1)} \underline{w}^{(2)} \vec{h}^{(2)}$$

$$= \begin{bmatrix} w_1^{(1)} & w_2^{(1)} \end{bmatrix} \begin{bmatrix} w_1^{(2)} & w_3^{(2)} \\ w_2^{(2)} & w_4^{(2)} \end{bmatrix} \begin{bmatrix} h_1^{(2)} \\ h_2^{(2)} \end{bmatrix}$$

$$= \begin{bmatrix} w_1^{(1)} & w_2^{(1)} \end{bmatrix} \begin{bmatrix} w_1^{(2)} h_1^{(2)} + w_3^{(2)} h_2^{(2)} \\ w_2^{(2)} h_1^{(2)} + w_4^{(2)} h_2^{(2)} \end{bmatrix}$$

$$= w_1^{(1)} (w_1^{(2)} h_1^{(2)} + w_3^{(2)} h_2^{(2)}) + w_2^{(1)} (w_2^{(2)} h_1^{(2)} + w_4^{(2)} h_2^{(2)})$$

$$= w_1^{(1)} w_1^{(2)} h_1^{(2)} + w_1^{(1)} w_3^{(2)} h_2^{(2)} + w_2^{(1)} w_2^{(2)} h_1^{(2)} + w_2^{(1)} w_4^{(2)} h_2^{(2)}$$

$$\begin{aligned}
\vec{w}_*^{(1)} &= \vec{w}^{(1)} - a \frac{\partial l(\hat{y}, y)}{\partial \vec{w}^{(1)}} \\
&= \vec{w}^{(1)} - a \frac{\partial l(\hat{y}, y)}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \vec{w}^{(1)}} \\
&= \vec{w}^{(1)} - a \frac{\partial l(\hat{y}, y)}{\partial \hat{y}} \left[ \frac{\partial \hat{y}}{\partial w_1^{(1)}} \quad \frac{\partial \hat{y}}{\partial w_2^{(1)}} \right]^T \\
&= \vec{w}^{(1)} - a (\hat{y} - y) \left[ w_1^{(2)} h_1^{(2)} + w_3^{(2)} h_2^{(2)} \quad w_2^{(2)} h_1^{(2)} + w_4^{(2)} h_2^{(2)} \right]^T \\
&= \vec{w}^{(1)} - 0.05 (-0.7467) [0.1581 \quad 0.0952]^T \\
&= \begin{bmatrix} 0.17 \\ 0.17 \end{bmatrix} + 0.0373 \begin{bmatrix} 0.1581 \\ 0.0952 \end{bmatrix} \\
&= \begin{bmatrix} 0.1759 \\ 0.1736 \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
\underline{w}_*^{(2)} &= \underline{w}^{(2)} - a \frac{\partial l(\hat{y}, y)}{\partial \underline{w}^{(2)}} \\
&= \underline{w}^{(2)} - a \frac{\partial l(\hat{y}, y)}{\partial (\vec{w}^{(1)} \vec{h}^{(1)})} \frac{\partial (\vec{w}^{(1)} \vec{h}^{(1)})}{\partial \underline{w}^{(2)}} \\
&= \underline{w}^{(2)} - a \frac{\partial l(\hat{y}, y)}{\partial (\vec{w}^{(1)} \vec{h}^{(1)})} \frac{\partial (\vec{w}^{(1)} \vec{h}^{(1)})}{\partial \underline{w}^{(2)}}
\end{aligned}$$

$$\begin{aligned}
&= \underline{W}^{(2)} - \alpha (\hat{y} - y) \begin{bmatrix} \partial \hat{y} / \partial w_1^{(2)} & \partial \hat{y} / \partial w_3^{(2)} \\ \partial \hat{y} / \partial w_2^{(2)} & \partial \hat{y} / \partial w_4^{(2)} \end{bmatrix} \\
&= \underline{W}^{(2)} - \alpha (\hat{y} - y) \begin{bmatrix} w_1^{(1)} h_1^{(2)} & w_3^{(1)} h_2^{(2)} \\ w_2^{(1)} h_1^{(2)} & w_4^{(1)} h_2^{(2)} \end{bmatrix} \\
&= \begin{bmatrix} 0.12 & 0.13 \\ 0.23 & 0.10 \end{bmatrix} + 0.0373 \begin{bmatrix} 0.34 & 0.51 \\ 0.34 & 0.51 \end{bmatrix} \\
&= \begin{bmatrix} 0.1327 & 0.1490 \\ 0.2427 & 0.1190 \end{bmatrix}
\end{aligned}$$

Now we do a forward pass with these new weights

$$\vec{h}^{(2)} = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \quad y = 1$$

$$\hat{y} = \underline{w}_*^{(1)} \underline{w}_*^{(2)} \vec{h}^{(2)}$$

$$= \begin{bmatrix} 0.1759 \\ 0.1736 \end{bmatrix} \begin{bmatrix} 0.1327 & 0.1490 \\ 0.2427 & 0.1190 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \end{bmatrix}$$

$$= 0.2715$$

This is about 7% better than our previous output of 0.2533, so the backpropagation update clearly is working