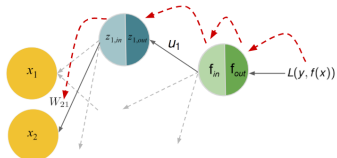


# Deep Learning

## Basic Backpropagation 2



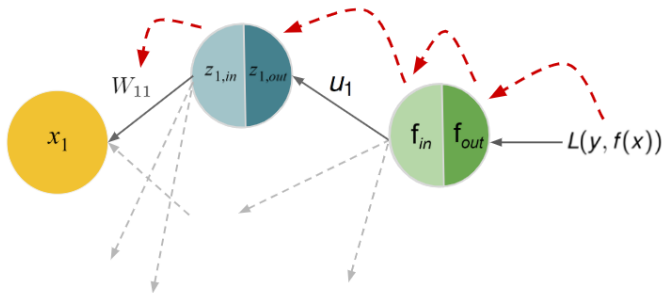
### Learning goals

- Backprop formalism and recursion

# BACKWARD COMPUTATION AND CACHING

In the XOR example, we computed:

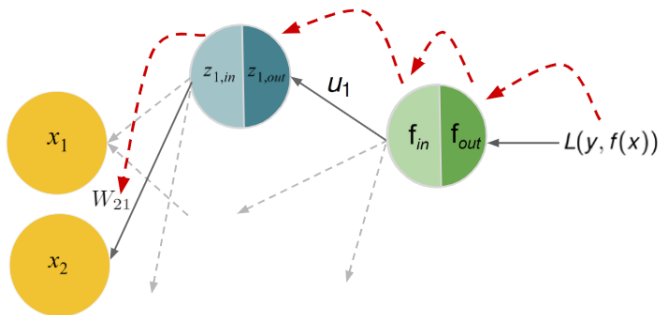
$$\frac{\partial L(y, f(\mathbf{x}))}{\partial W_{11}} = \frac{\partial L(y, f(\mathbf{x}))}{\partial f_{out}} \cdot \frac{\partial f_{out}}{\partial f_{in}} \cdot \frac{\partial f_{in}}{\partial z_{1,out}} \cdot \frac{\partial z_{1,out}}{\partial z_{1,in}} \cdot \frac{\partial z_{1,in}}{\partial W_{11}}$$



# BACKWARD COMPUTATION AND CACHING

Next, let us compute:

$$\frac{\partial L(y, f(\mathbf{x}))}{\partial W_{21}} = \frac{\partial L(y, f(\mathbf{x}))}{\partial f_{out}} \cdot \frac{\partial f_{out}}{\partial f_{in}} \cdot \frac{\partial f_{in}}{\partial z_{1,out}} \cdot \frac{\partial z_{1,out}}{\partial z_{1,in}} \cdot \frac{\partial z_{1,in}}{\partial W_{21}}$$



# BACKWARD COMPUTATION AND CACHING

- Examining the two expressions:

$$\frac{\partial L(y, f(\mathbf{x}))}{\partial W_{11}} = \frac{\partial L(y, f(\mathbf{x}))}{\partial f_{out}} \cdot \frac{\partial f_{out}}{\partial f_{in}} \cdot \frac{\partial f_{in}}{\partial z_{1,out}} \cdot \frac{\partial z_{1,out}}{\partial z_{1,in}} \cdot \frac{\partial z_{1,in}}{\partial W_{11}}$$

$$\frac{\partial L(y, f(\mathbf{x}))}{\partial W_{21}} = \frac{\partial L(y, f(\mathbf{x}))}{\partial f_{out}} \cdot \frac{\partial f_{out}}{\partial f_{in}} \cdot \frac{\partial f_{in}}{\partial z_{1,out}} \cdot \frac{\partial z_{1,out}}{\partial z_{1,in}} \cdot \frac{\partial z_{1,in}}{\partial W_{21}}$$

- Significant overlap / redundancy in the two expressions.
- Again:** Let's call this subexpression  $\delta_1$  and cache it.

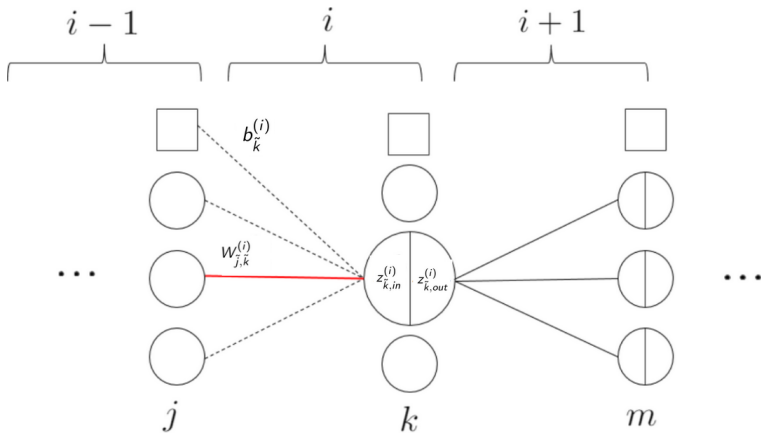
$$\delta_1 = \frac{\partial L(y, f(\mathbf{x}))}{\partial z_{1,in}} = \frac{\partial L(y, f(\mathbf{x}))}{\partial f_{out}} \cdot \frac{\partial f_{out}}{\partial f_{in}} \cdot \frac{\partial f_{in}}{\partial z_{1,out}} \cdot \frac{\partial z_{1,out}}{\partial z_{1,in}}$$

$$\frac{\partial L(y, f(\mathbf{x}))}{\partial W_{11}} = \delta_1 \cdot \frac{\partial z_{1,in}}{\partial W_{11}} \quad \text{and} \quad \frac{\partial L(y, f(\mathbf{x}))}{\partial W_{21}} = \delta_1 \cdot \frac{\partial z_{1,in}}{\partial W_{21}}$$

- $\delta_1$  can also be seen as an **error signal** that represents how much the loss  $L$  changes when the input  $z_{1,in}$  changes.

# BACKPROP: RECURSION

- Let us now derive a general formulation of backprop.
- The neurons in layers  $i - 1$ ,  $i$  and  $i + 1$  are indexed by  $j$ ,  $k$  and  $m$ , respectively.
- The output layer will be referred to as layer O.



Credit: Erik Hallström



# BACKPROP: RECURSION

Using

$$\begin{aligned}z_{\tilde{k},out}^{(i)} &= \sigma(z_{\tilde{k},in}^{(i)}) \\z_{m,in}^{(i+1)} &= \sum_k w_{k,m}^{(i+1)} z_{k,out}^{(i)} + b_m^{(i+1)}\end{aligned}$$

we get:

$$\begin{aligned}\delta_{\tilde{k}}^{(i)} &= \sum_m \left( \frac{\partial L}{\partial z_{m,in}^{(i+1)}} \frac{\partial z_{m,in}^{(i+1)}}{\partial z_{\tilde{k},out}^{(i)}} \right) \frac{\partial z_{\tilde{k},out}^{(i)}}{\partial z_{\tilde{k},in}^{(i)}} \\&= \sum_m \left( \frac{\partial L}{\partial z_{m,in}^{(i+1)}} \frac{\partial \left( \sum_k w_{k,m}^{(i+1)} z_{k,out}^{(i)} + b_m^{(i+1)} \right)}{\partial z_{\tilde{k},out}^{(i)}} \right) \frac{\partial \sigma(z_{\tilde{k},in}^{(i)})}{\partial z_{\tilde{k},in}^{(i)}} \\&= \sum_m \left( \frac{\partial L}{\partial z_{m,in}^{(i+1)}} w_{\tilde{k},m}^{(i+1)} \right) \sigma'(z_{\tilde{k},in}^{(i)}) = \sum_m \left( \delta_{\tilde{k}}^{(i+1)} w_{\tilde{k},m}^{(i+1)} \right) \sigma'(z_{\tilde{k},in}^{(i)})\end{aligned}$$

Therefore, we now have a **recursive definition** for the error signal of a neuron in layer  $i$  in terms of the error signals of the neurons in layer  $i + 1$  and, by extension, layers  $\{i+2, i+3 \dots, O\}$ !

# BACKPROP: RECURSION

- Given the error signal  $\delta_{\tilde{k}}^{(i)}$  of neuron  $\tilde{k}$  in layer  $i$ , the derivative of loss  $L$  w.r.t. to the weight  $W_{j,\tilde{k}}$  is simply:

$$\frac{\partial L}{\partial W_{j,\tilde{k}}^{(i)}} = \frac{\partial L}{\partial z_{\tilde{k},in}^{(i)}} \frac{\partial z_{\tilde{k},in}^{(i)}}{\partial W_{j,\tilde{k}}^{(i)}} = \delta_{\tilde{k}}^{(i)} z_{j,out}^{(i-1)}$$

because  $z_{\tilde{k},in}^{(i)} = \sum_j W_{j,\tilde{k}}^{(i)} z_{j,out}^{(i-1)} + b_{\tilde{k}}^{(i)}$

- Similarly, the derivative of loss  $L$  w.r.t. bias  $b_{\tilde{k}}^{(i)}$  is:

$$\frac{\partial L}{\partial b_{\tilde{k}}^{(i)}} = \frac{\partial L}{\partial z_{\tilde{k},in}^{(i)}} \frac{\partial z_{\tilde{k},in}^{(i)}}{\partial b_{\tilde{k}}^{(i)}} = \delta_{\tilde{k}}^{(i)}$$



# BACKPROP: RECURSION

- It is not hard to show that the error signal  $\delta^i$  for an entire layer  $i$  is ( $\odot$  = element-wise product):
  - $\delta^{(O)} = \nabla_{f_{out}} L \odot \tau'(f_{in})$
  - $\delta^{(i)} = W^{(i+1)} \delta^{(i+1)} \odot \sigma'(z_{in}^{(i)})$
- Therefore, backpropagation works by computing and storing the error signals **backwards**. That is, starting at the output layer and ending at the first hidden layer. This way, the error signals of later layers **propagate backwards** to the earlier layers.
- The derivative of the loss  $L$  w.r.t. a given weight is computed efficiently by plugging in the cached error signals, thereby avoiding expensive and redundant computations.