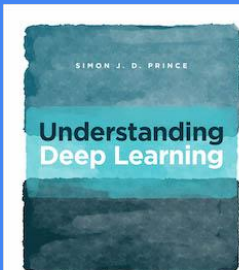
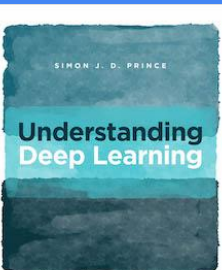
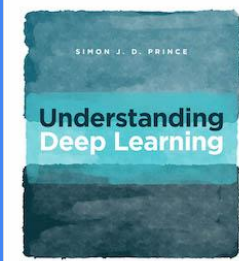
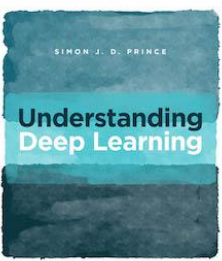
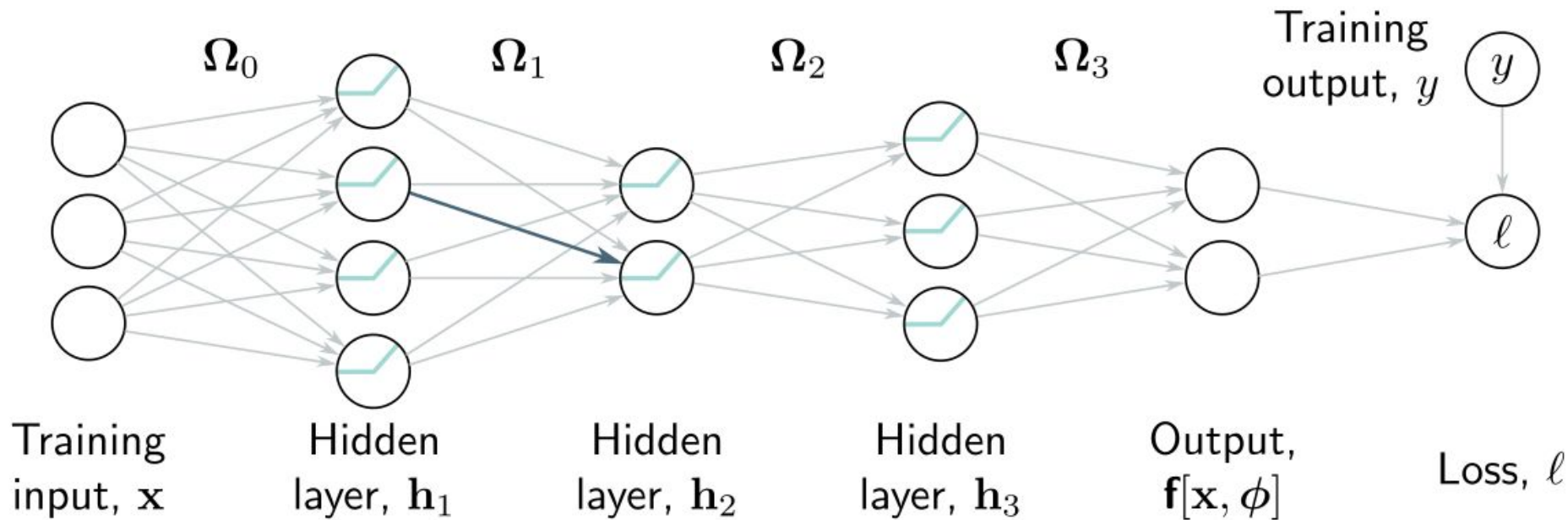


# Gradients and initialization

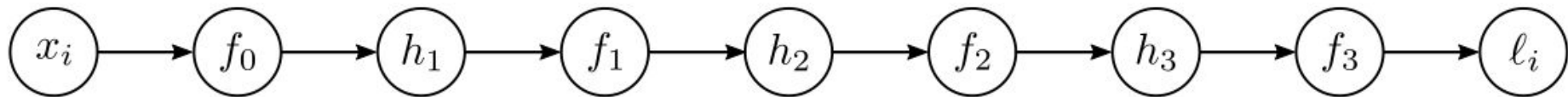
## Chapter 7



**Goal:** to compute the derivatives of the loss  $\ell$  with respect to each of the weights (arrows) and biases (not shown)

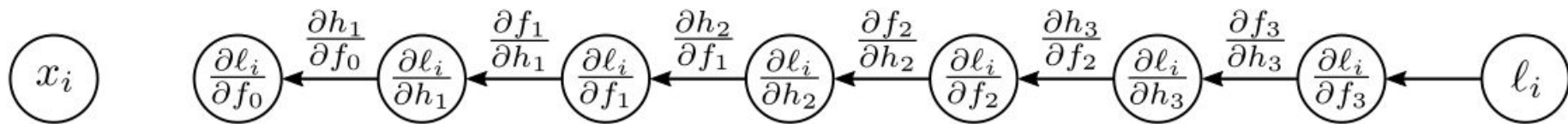


# Backpropagation forward pass

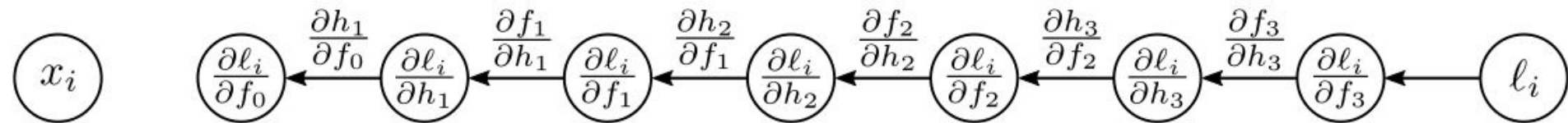


**Figure 7.3** Backpropagation forward pass. We compute and store each of the intermediate variables in turn until we finally calculate the loss.

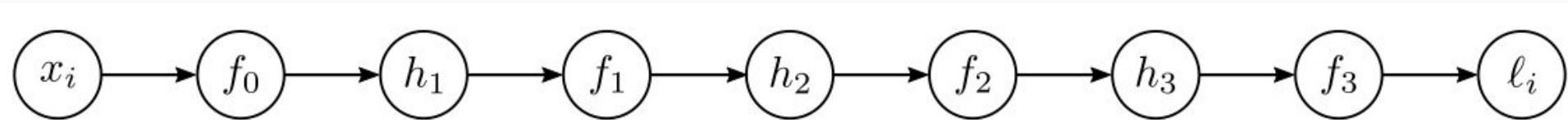
# Backpropagation backward pass



**Figure 7.4** Backpropagation backward pass #1. We work backward from the end of the function computing the derivatives  $\partial \ell_i / \partial f_\bullet$  and  $\partial \ell_i / \partial h_\bullet$  of the loss with respect to the intermediate quantities. Each derivative is computed from the previous one by multiplying by terms of the form  $\partial f_k / \partial h_k$  or  $\partial h_k / \partial f_{k-1}$ .

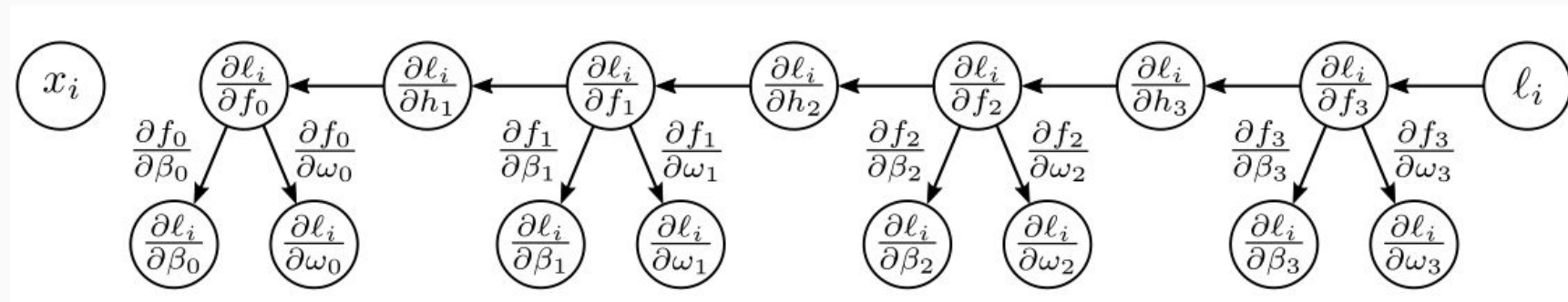


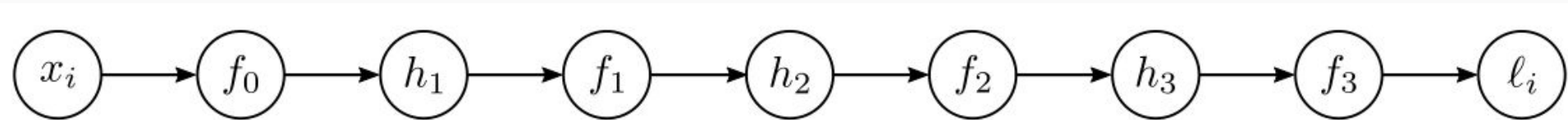
$$\begin{aligned}
 \frac{\partial l_i}{\partial f_2} &= \frac{\partial h_3}{\partial f_2} \left( \frac{\partial f_3}{\partial h_3} \frac{\partial l_i}{\partial f_3} \right) \\
 \frac{\partial l_i}{\partial h_2} &= \frac{\partial f_2}{\partial h_2} \left( \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial l_i}{\partial f_3} \right) \\
 \frac{\partial l_i}{\partial f_1} &= \frac{\partial h_2}{\partial f_1} \left( \frac{\partial f_2}{\partial h_2} \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial l_i}{\partial f_3} \right) \\
 \frac{\partial l_i}{\partial h_1} &= \frac{\partial f_1}{\partial h_1} \left( \frac{\partial h_2}{\partial f_1} \frac{\partial f_2}{\partial h_2} \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial l_i}{\partial f_3} \right) \\
 \frac{\partial l_i}{\partial f_0} &= \frac{\partial h_1}{\partial f_0} \left( \frac{\partial f_1}{\partial h_1} \frac{\partial h_2}{\partial f_1} \frac{\partial f_2}{\partial h_2} \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial l_i}{\partial f_3} \right)
 \end{aligned}$$



$$f_k = \beta_k + \omega_k \cdot h_k$$

$$\frac{\partial f_k}{\partial \beta_k} = 1 \quad \text{and} \quad \frac{\partial f_k}{\partial \omega_k} = h_k$$





$$\mathbf{f}_0 = \boldsymbol{\beta}_0 + \boldsymbol{\Omega}_0 \mathbf{x}_i$$

$$\mathbf{h}_1 = \mathbf{a}[\mathbf{f}_0]$$

$$\mathbf{f}_1 = \boldsymbol{\beta}_1 + \boldsymbol{\Omega}_1 \mathbf{h}_1$$

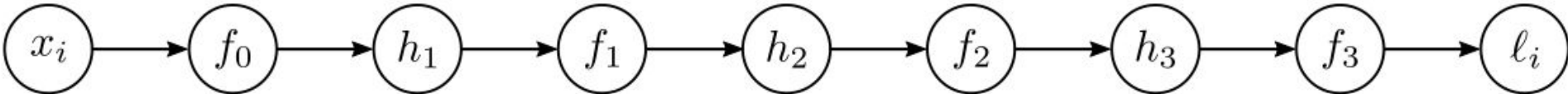
$$\mathbf{h}_2 = \mathbf{a}[\mathbf{f}_1]$$

$$\mathbf{f}_2 = \boldsymbol{\beta}_2 + \boldsymbol{\Omega}_2 \mathbf{h}_2$$

$$\mathbf{h}_3 = \mathbf{a}[\mathbf{f}_2]$$

$$\mathbf{f}_3 = \boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3$$

$$\ell_i = l[\mathbf{f}_3, y_i],$$



$$\frac{\partial \ell_i}{\partial \mathbf{f}_2} = \frac{\partial \mathbf{h}_3}{\partial \mathbf{f}_2} \frac{\partial \mathbf{f}_3}{\partial \mathbf{h}_3} \frac{\partial \ell_i}{\partial \mathbf{f}_3}$$

$$D_3 \times D_3, D_3 \times D_f, \text{ and } D_f \times 1$$

$$\mathbf{f}_0 = \boldsymbol{\beta}_0 + \boldsymbol{\Omega}_0 \mathbf{x}_i$$

$$\mathbf{h}_1 = \mathbf{a}[\mathbf{f}_0]$$

$$\mathbf{f}_1 = \boldsymbol{\beta}_1 + \boldsymbol{\Omega}_1 \mathbf{h}_1$$

$$\mathbf{h}_2 = \mathbf{a}[\mathbf{f}_1]$$

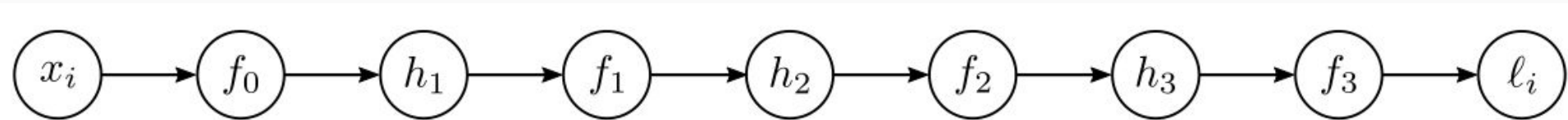
$$\mathbf{f}_2 = \boldsymbol{\beta}_2 + \boldsymbol{\Omega}_2 \mathbf{h}_2$$

$$\mathbf{h}_3 = \mathbf{a}[\mathbf{f}_2]$$

$$\mathbf{f}_3 = \boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3$$

$$\ell_i = l[\mathbf{f}_3, y_i],$$





$$\frac{\partial \ell_i}{\partial \mathbf{f}_2} = \frac{\partial \mathbf{h}_3}{\partial \mathbf{f}_2} \frac{\partial \mathbf{f}_3}{\partial \mathbf{h}_3} \frac{\partial \ell_i}{\partial \mathbf{f}_3}$$

$$D_3 \times D_3, D_3 \times D_f, \text{ and } D_f \times 1$$

$$\frac{\partial \ell_i}{\partial \mathbf{f}_1} = \frac{\partial \mathbf{h}_2}{\partial \mathbf{f}_1} \frac{\partial \mathbf{f}_2}{\partial \mathbf{h}_2} \left( \frac{\partial \mathbf{h}_3}{\partial \mathbf{f}_2} \frac{\partial \mathbf{f}_3}{\partial \mathbf{h}_3} \frac{\partial \ell_i}{\partial \mathbf{f}_3} \right)$$

$$\mathbf{f}_0 = \boldsymbol{\beta}_0 + \boldsymbol{\Omega}_0 \mathbf{x}_i$$

$$\mathbf{h}_1 = \mathbf{a}[\mathbf{f}_0]$$

$$\mathbf{f}_1 = \boldsymbol{\beta}_1 + \boldsymbol{\Omega}_1 \mathbf{h}_1$$

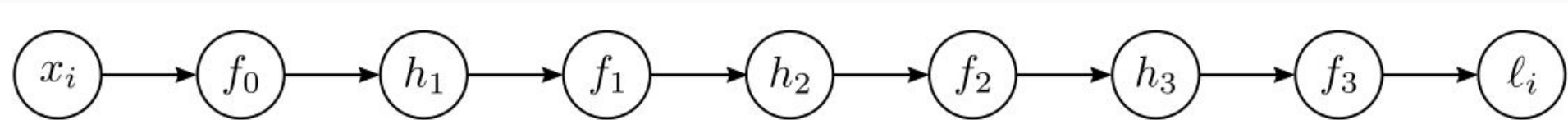
$$\mathbf{h}_2 = \mathbf{a}[\mathbf{f}_1]$$

$$\mathbf{f}_2 = \boldsymbol{\beta}_2 + \boldsymbol{\Omega}_2 \mathbf{h}_2$$

$$\mathbf{h}_3 = \mathbf{a}[\mathbf{f}_2]$$

$$\mathbf{f}_3 = \boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3$$

$$\ell_i = l[\mathbf{f}_3, y_i],$$



$$\frac{\partial \ell_i}{\partial \mathbf{f}_1} = \frac{\partial \mathbf{h}_2}{\partial \mathbf{f}_1} \frac{\partial \mathbf{f}_2}{\partial \mathbf{h}_2} \left( \frac{\partial \mathbf{h}_3}{\partial \mathbf{f}_2} \frac{\partial \mathbf{f}_3}{\partial \mathbf{h}_3} \frac{\partial \ell_i}{\partial \mathbf{f}_3} \right)$$

$$\frac{\partial \ell_i}{\partial \mathbf{f}_0} = \frac{\partial \mathbf{h}_1}{\partial \mathbf{f}_0} \frac{\partial \mathbf{f}_1}{\partial \mathbf{h}_1} \left( \frac{\partial \mathbf{h}_2}{\partial \mathbf{f}_1} \frac{\partial \mathbf{f}_2}{\partial \mathbf{h}_2} \frac{\partial \mathbf{h}_3}{\partial \mathbf{f}_2} \frac{\partial \mathbf{f}_3}{\partial \mathbf{h}_3} \frac{\partial \ell_i}{\partial \mathbf{f}_3} \right)$$

$$\mathbf{f}_0 = \boldsymbol{\beta}_0 + \boldsymbol{\Omega}_0 \mathbf{x}_i$$

$$\mathbf{h}_1 = \mathbf{a}[\mathbf{f}_0]$$

$$\mathbf{f}_1 = \boldsymbol{\beta}_1 + \boldsymbol{\Omega}_1 \mathbf{h}_1$$

$$\mathbf{h}_2 = \mathbf{a}[\mathbf{f}_1]$$

$$\mathbf{f}_2 = \boldsymbol{\beta}_2 + \boldsymbol{\Omega}_2 \mathbf{h}_2$$

$$\mathbf{h}_3 = \mathbf{a}[\mathbf{f}_2]$$

$$\mathbf{f}_3 = \boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3$$

$$\ell_i = l[\mathbf{f}_3, y_i],$$

The derivative  $\partial \ell_i / \partial \mathbf{f}_3$  of the loss  $\ell_i$  with respect to the network output  $\mathbf{f}_3$  will depend on the loss function but usually has a simple form.

The derivative  $\partial \mathbf{f}_3 / \partial \mathbf{h}_3$  of the network output with respect to hidden layer  $\mathbf{h}_3$  is:

$$\frac{\partial \mathbf{f}_3}{\partial \mathbf{h}_3} = \frac{\partial}{\partial \mathbf{h}_3} (\boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3) = \boldsymbol{\Omega}_3^T$$

$$\begin{aligned} \frac{\partial \ell_i}{\partial \boldsymbol{\beta}_k} &= \frac{\partial \mathbf{f}_k}{\partial \boldsymbol{\beta}_k} \frac{\partial \ell_i}{\partial \mathbf{f}_k} \\ &= \frac{\partial}{\partial \boldsymbol{\beta}_k} (\boldsymbol{\beta}_k + \boldsymbol{\Omega}_k \mathbf{h}_k) \frac{\partial \ell_i}{\partial \mathbf{f}_k} \\ &= \frac{\partial \ell_i}{\partial \mathbf{f}_k}, \end{aligned}$$

$$\begin{aligned} \mathbf{f}_0 &= \boldsymbol{\beta}_0 + \boldsymbol{\Omega}_0 \mathbf{x}_i \\ \mathbf{h}_1 &= \mathbf{a}[\mathbf{f}_0] \\ \mathbf{f}_1 &= \boldsymbol{\beta}_1 + \boldsymbol{\Omega}_1 \mathbf{h}_1 \\ \mathbf{h}_2 &= \mathbf{a}[\mathbf{f}_1] \\ \mathbf{f}_2 &= \boldsymbol{\beta}_2 + \boldsymbol{\Omega}_2 \mathbf{h}_2 \\ \mathbf{h}_3 &= \mathbf{a}[\mathbf{f}_2] \\ \mathbf{f}_3 &= \boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3 \\ \ell_i &= l[\mathbf{f}_3, y_i], \end{aligned}$$

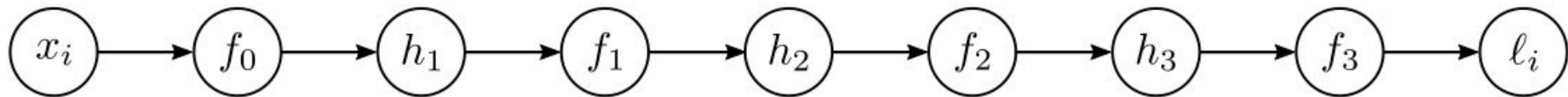
$$\begin{aligned}
\frac{\partial \ell_i}{\partial \boldsymbol{\beta}_k} &= \frac{\partial \mathbf{f}_k}{\partial \boldsymbol{\beta}_k} \frac{\partial \ell_i}{\partial \mathbf{f}_k} \\
&= \frac{\partial}{\partial \boldsymbol{\beta}_k} (\boldsymbol{\beta}_k + \boldsymbol{\Omega}_k \mathbf{h}_k) \frac{\partial \ell_i}{\partial \mathbf{f}_k} \\
&= \frac{\partial \ell_i}{\partial \mathbf{f}_k},
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \ell_i}{\partial \boldsymbol{\Omega}_k} &= \frac{\partial \mathbf{f}_k}{\partial \boldsymbol{\Omega}_k} \frac{\partial \ell_i}{\partial \mathbf{f}_k} \\
&= \frac{\partial}{\partial \boldsymbol{\Omega}_k} (\boldsymbol{\beta}_k + \boldsymbol{\Omega}_k \mathbf{h}_k) \frac{\partial \ell_i}{\partial \mathbf{f}_k} \\
&= \frac{\partial \ell_i}{\partial \mathbf{f}_k} \mathbf{h}_k^T.
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \ell_i}{\partial \beta_0} &= \frac{\partial \ell_i}{\partial \mathbf{f}_0} \\
\frac{\partial \ell_i}{\partial \boldsymbol{\Omega}_0} &= \frac{\partial \ell_i}{\partial \mathbf{f}_0} \mathbf{x}_i^T
\end{aligned}$$

$$\begin{aligned}
\mathbf{f}_0 &= \boldsymbol{\beta}_0 + \boldsymbol{\Omega}_0 \mathbf{x}_i \\
\mathbf{h}_1 &= \mathbf{a}[\mathbf{f}_0] \\
\mathbf{f}_1 &= \boldsymbol{\beta}_1 + \boldsymbol{\Omega}_1 \mathbf{h}_1 \\
\mathbf{h}_2 &= \mathbf{a}[\mathbf{f}_1] \\
\mathbf{f}_2 &= \boldsymbol{\beta}_2 + \boldsymbol{\Omega}_2 \mathbf{h}_2 \\
\mathbf{h}_3 &= \mathbf{a}[\mathbf{f}_2] \\
\mathbf{f}_3 &= \boldsymbol{\beta}_3 + \boldsymbol{\Omega}_3 \mathbf{h}_3 \\
\ell_i &= l[\mathbf{f}_3, y_i],
\end{aligned}$$

# Forward pass



An example:

$$f_0 = \beta_0 + \omega_0 \cdot x_i$$

$$h_1 = \sin[f_0]$$

$$f_1 = \beta_1 + \omega_1 \cdot h_1$$

$$h_2 = \exp[f_1]$$

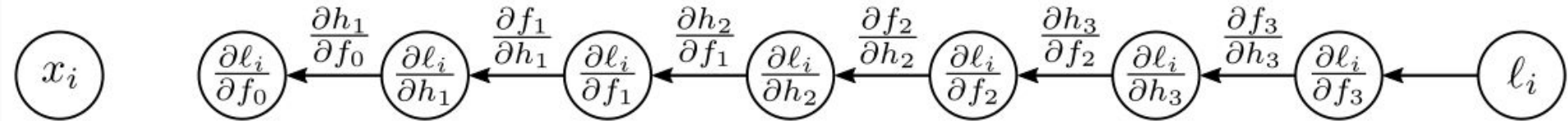
$$f_2 = \beta_2 + \omega_2 \cdot h_2$$

$$h_3 = \cos[f_2]$$

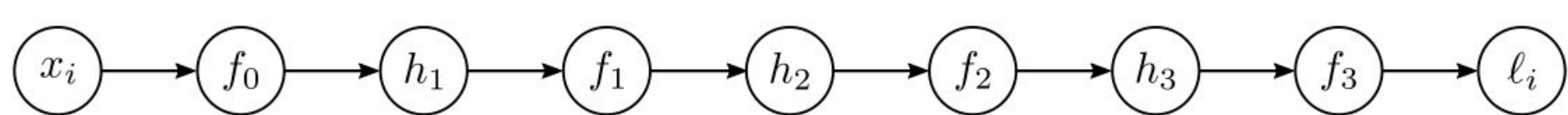
$$f_3 = \beta_3 + \omega_3 \cdot h_3$$

$$\ell_i = (f_3 - y_i)^2.$$

# Backward pass



$$\frac{\partial l_i}{\partial f_3}, \quad \frac{\partial l_i}{\partial h_3}, \quad \frac{\partial l_i}{\partial f_2}, \quad \frac{\partial l_i}{\partial h_2}, \quad \frac{\partial l_i}{\partial f_1}, \quad \frac{\partial l_i}{\partial h_1}, \quad \text{and} \quad \frac{\partial l_i}{\partial f_0}$$



$$f_k = \beta_k + \omega_k.h_k$$

$$\frac{\partial \ell_i}{\partial f_3} = 2(f_3 - y_i)$$

$$\frac{\partial \ell_i}{\partial h_3} = \frac{\partial f_3}{\partial h_3} \frac{\partial \ell_i}{\partial f_3}$$

$$\frac{\partial \ell_i}{\partial f_2} = \frac{\partial h_3}{\partial f_2} \left( \frac{\partial f_3}{\partial h_3} \frac{\partial \ell_i}{\partial f_3} \right)$$

$$\frac{\partial \ell_i}{\partial h_2} = \frac{\partial f_2}{\partial h_2} \left( \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial \ell_i}{\partial f_3} \right)$$

$$\frac{\partial \ell_i}{\partial f_1} = \frac{\partial h_2}{\partial f_1} \left( \frac{\partial f_2}{\partial h_2} \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial \ell_i}{\partial f_3} \right)$$

$$\frac{\partial \ell_i}{\partial h_1} = \frac{\partial f_1}{\partial h_1} \left( \frac{\partial h_2}{\partial f_1} \frac{\partial f_2}{\partial h_2} \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial \ell_i}{\partial f_3} \right)$$

$$\frac{\partial \ell_i}{\partial f_0} = \frac{\partial h_1}{\partial f_0} \left( \frac{\partial f_1}{\partial h_1} \frac{\partial h_2}{\partial f_1} \frac{\partial f_2}{\partial h_2} \frac{\partial h_3}{\partial f_2} \frac{\partial f_3}{\partial h_3} \frac{\partial \ell_i}{\partial f_3} \right)$$

$$\frac{\partial f_k}{\partial \beta_k} = 1 \quad \text{and} \quad \frac{\partial f_k}{\partial \omega_k} = h_k$$

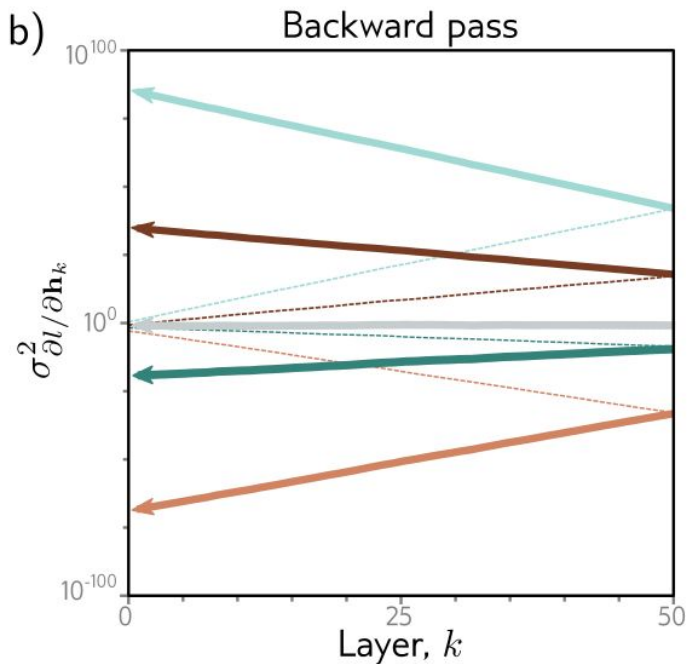
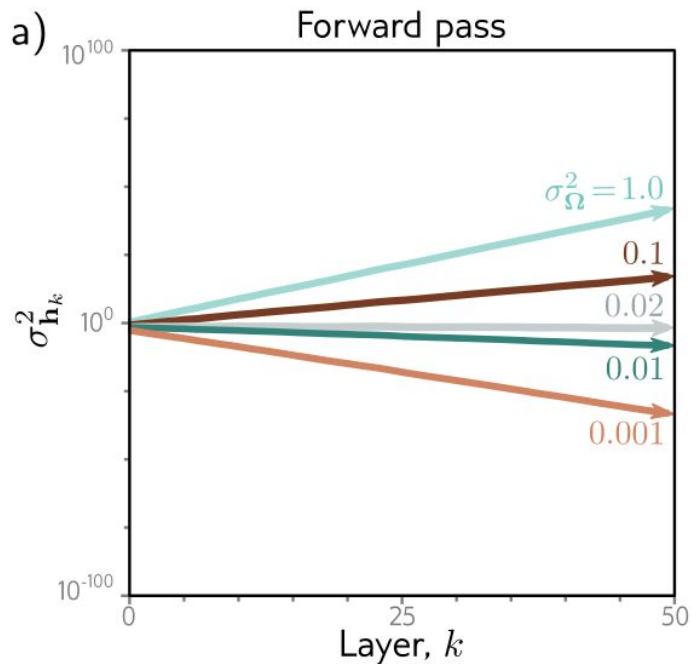
$$\frac{\partial f_0}{\partial \beta_0} = 1 \quad \text{and} \quad \frac{\partial f_0}{\partial \omega_0} = x_i$$



# Parameter initialization

$$\begin{aligned}\mathbf{f}_k &= \boldsymbol{\beta}_k + \boldsymbol{\Omega}_k \mathbf{h}_k \\ &= \boldsymbol{\beta}_k + \boldsymbol{\Omega}_k \mathbf{a}[\mathbf{f}_{k-1}]\end{aligned}$$

# vanishing gradient problem & exploding gradient problem



$$\begin{aligned}
\mathbb{E}[f'_i] &= \mathbb{E} \left[ \beta_i + \sum_{j=1}^{D_h} \Omega_{ij} h_j \right] \\
&= \mathbb{E} [\beta_i] + \sum_{j=1}^{D_h} \mathbb{E} [\Omega_{ij} h_j] \\
&= \mathbb{E} [\beta_i] + \sum_{j=1}^{D_h} \mathbb{E} [\Omega_{ij}] \mathbb{E} [h_j] \\
&= 0 + \sum_{j=1}^{D_h} 0 \cdot \mathbb{E} [h_j] = 0,
\end{aligned}$$

$$\begin{aligned}
\sigma_{f'}^2 &= \mathbb{E}[f_i'^2] - \mathbb{E}[f_i']^2 \\
&= \mathbb{E} \left[ \left( \beta_i + \sum_{j=1}^{D_h} \Omega_{ij} h_j \right)^2 \right] - 0 \\
&= \mathbb{E} \left[ \left( \sum_{j=1}^{D_h} \Omega_{ij} h_j \right)^2 \right] \\
&= \sum_{j=1}^{D_h} \mathbb{E} [\Omega_{ij}^2] \mathbb{E} [h_j^2] \\
&= \sum_{j=1}^{D_h} \sigma_{\Omega}^2 \mathbb{E} [h_j^2] = \sigma_{\Omega}^2 \sum_{j=1}^{D_h} \mathbb{E} [h_j^2] ,
\end{aligned}$$

$$\sigma^2 = \mathbb{E}[(z - \mathbb{E}[z])^2] = \mathbb{E}[z^2] - \mathbb{E}[z]^2$$

$$\sigma_{f'}^2 = \sigma_{\Omega}^2 \sum_{j=1}^{D_h} \frac{\sigma_f^2}{2} = \frac{1}{2} D_h \sigma_{\Omega}^2 \sigma_f^2$$

# He initialization (Kaiming Initialization)

$$\sigma_{\Omega}^2 = \frac{2}{D_h}$$



$$\sigma_{f'}^2 = \sigma_{\Omega}^2 \sum_{j=1}^{D_h} \frac{\sigma_f^2}{2} = \frac{1}{2} D_h \sigma_{\Omega}^2 \sigma_f^2$$

# Initialization for both forward and backward pass

$$\sigma_{\Omega}^2 = \frac{2}{D_{h'}}$$

# Initialization for both forward and backward pass

$$\sigma_{\Omega}^2 = \frac{4}{D_h + D_{h'}}$$

# Understanding Deep Learning

## **Chapter 8**