

Neural network

A gentle introduction: Neural network for supervised learning

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Chain rule in differentiation

⇒ We review the chain rule. Assume that

$$f = f(a)$$

$$a = a(\theta)$$

⇒ Then, the chain rule says

$$\frac{\partial f}{\partial \theta} = \frac{\partial f}{\partial a} \frac{\partial a}{\partial \theta}$$

Reasoning for back propagation

⇒ Let us consider one neural network with single hidden layer

$$\mathbf{z}^{[1]} = \mathbf{a}^{[2]} \mathbf{W}^{[1]T} + \mathbf{b}^{[1]}$$

$$\mathbf{a}^{[1]} = g(\mathbf{z}^{[1]})$$

$$\mathbf{z}^{[2]} = \mathbf{a}^{[1]} \mathbf{W}^{[2]T} + \mathbf{b}^{[2]}$$

$$\mathbf{a}^{[2]} = g^{\mathbf{z}^{[2]}}$$

⇒ We have the following series of mappings

$$\mathbf{a}^{[0]} \mapsto \text{Linear Mapping} \mapsto \mathbf{z}^{[1]} \mapsto \text{Activation Function} \mapsto \mathbf{a}^{[1]}$$

$$\mapsto \text{Linear Mapping} \mapsto \mathbf{z}^{[2]} \mapsto \text{Activation Function} \mapsto \mathbf{a}^{[2]} \mapsto \mathcal{L}(\mathbf{a}^{[2]}; y)$$

⇒ Our goal: compute the gradient of the loss function w.r.t. the learnable/model parameters

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[1]}} \quad \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[1]}} \quad \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[2]}} \quad \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[2]}}$$

Computation of gradient of loss function

⇒ Let us start with

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[1]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{W}^{[1]}} = \sum_k \frac{\partial \mathcal{L}}{\partial z_k^{[1]}} \frac{\partial z_k^{[1]}}{\partial \mathbf{W}^{[1]}}$$

The true formulation is more complex due to:

- $\mathbf{W}^{[1]}$ is a matrix, so the derivative is done w.r.t. each component $W_{ij}^{[1]}$
- $\mathbf{z}^{[1]}$ is a vector, so the derivative is done w.r.t. each component $z_k^{[1]}$
- The chain rule in differentiation is actually carried out in the above formula.

$$\frac{\partial \mathcal{L}}{\partial W_{ij}^{[1]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{W}^{[1]}} = \sum_k \frac{\partial \mathcal{L}}{\partial z_k^{[1]}} \frac{\partial z_k^{[1]}}{\partial W_{ij}^{[1]}}$$

for all i and j running in the set of parameters in $\mathbf{W}^{[1]}$

⇒ We shall focus on the “reduced” writing notation

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[1]}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{W}^{[1]}}}_{\text{easy}}$$

Computation of gradient of loss function

⇒ We shall try to compute the derivatives $\partial\mathcal{L}/\partial\mathbf{W}^{[1]}$ by chain rule

$$\frac{\partial\mathcal{L}}{\partial\mathbf{W}^{[1]}} = \underbrace{\frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[1]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial\mathbf{z}^{[1]}}{\partial\mathbf{W}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[1]}} = \underbrace{\frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial\mathbf{z}^{[2]}}{\partial\mathbf{a}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[1]}} = \underbrace{\frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[1]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial\mathbf{a}^{[1]}}{\partial\mathbf{z}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}} = \underbrace{\frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[2]}}}_{\text{FINALLY EASY}} \underbrace{\frac{\partial\mathbf{a}^{[2]}}{\partial\mathbf{z}^{[2]}}}_{\text{easy}}$$

⇒ In summary, we compute the derivative in the order

$$\begin{aligned} \frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[2]}} &\rightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial\mathbf{a}^{[2]}}{\partial\mathbf{z}^{[2]}}}_{\text{easy}} \rightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial\mathbf{z}^{[2]}}{\partial\mathbf{a}^{[1]}}}_{\text{easy}} \rightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial\mathbf{a}^{[1]}}{\partial\mathbf{z}^{[1]}}}_{\text{easy}} \\ &\rightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{W}^{[1]}} \text{ using } \underbrace{\frac{\partial\mathbf{z}^{[1]}}{\partial\mathbf{W}^{[1]}}}_{\text{easy}} \end{aligned}$$

Computation of gradient of loss function

⇒ Similarly, replacing $\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{W}^{[1]}}$ with $\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{b}^{[1]}} \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[1]}}$, we arrive at

$$\frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[1]}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{b}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}}}_{\text{FINALLY EASY}} \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}}$$

⇒ In summary, we compute the derivative in the order

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} &\longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \\ &\longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{b}^{[1]}}}_{\text{easy}} \end{aligned}$$

Computation of gradient of loss function

⇒ Let us now compute the derivative $\partial\mathcal{L}/\partial\mathbf{W}^{[2]}$ by chain rule

$$\frac{\partial\mathcal{L}}{\partial\mathbf{W}^{[2]}} = \underbrace{\frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}}}_{\text{NOT EASY}} \underbrace{\frac{\partial\mathbf{z}^{[2]}}{\partial\mathbf{W}^{[2]}}}_{\text{easy}}$$

$$\frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}} = \underbrace{\frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[2]}}}_{\text{ALSO EASY}} \underbrace{\frac{\partial\mathbf{a}^{[2]}}{\partial\mathbf{z}^{[2]}}}_{\text{easy}}$$

⇒ In summary, we compute the derive in the order

$$\frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[2]}} \longrightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial\mathbf{a}^{[2]}}{\partial\mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{W}^{[2]}} \text{ using } \underbrace{\frac{\partial\mathbf{z}^{[2]}}{\partial\mathbf{W}^{[2]}}}_{\text{easy}}$$

$$\frac{\partial\mathcal{L}}{\partial\mathbf{a}^{[2]}} \longrightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial\mathbf{a}^{[2]}}{\partial\mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial\mathcal{L}}{\partial\mathbf{b}^{[2]}} \text{ using } \underbrace{\frac{\partial\mathbf{z}^{[2]}}{\partial\mathbf{b}^{[2]}}}_{\text{easy}}$$

Computation of gradient of loss function

Back propagation process

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{W}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \mathbf{b}^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{W}^{[2]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{b}^{[2]}}}_{\text{easy}}$$

Back propagation process

⇒ Repeat the formulation above

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \Theta^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \Theta^{[2]}}}_{\text{easy}}$$

where Θ can play the role of \mathbf{W} or \mathbf{b}

⇒ To compute the derivative $\frac{\partial \mathcal{L}}{\partial \Theta^{[1]}}$, we need to go through the **exactly same process** for computing $\frac{\partial \mathcal{L}}{\partial \Theta^{[2]}}$ but then continue one layer more.

Back propagation process

⇒ Repeat the formulation above

$$\begin{array}{ccccccc}
 \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} & \text{using} & \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} & \text{using} & \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} & \text{using} & \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[1]}} & \text{using} & \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \Theta^{[1]}}}_{\text{easy}} \\
 & & & & \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} & \text{using} & \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[2]}} & \text{using} & \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \Theta^{[2]}}}_{\text{easy}}
 \end{array}$$

⇒ **Backpropagation process:** Let us combinet two equations in one as follows

$$\begin{array}{ccccccc}
 \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} & \text{using} & \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} & \text{using} & \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} & \text{using} & \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[1]}} & \text{using} & \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \Theta^{[1]}}}_{\text{easy}} \\
 \Downarrow & \Downarrow & \Downarrow & \Downarrow & \Downarrow & & & & \\
 \frac{\partial \mathcal{L}}{\partial \Theta^{[2]}} & \text{using} & \frac{\partial \mathbf{z}^{[2]}}{\partial \Theta^{[2]}} & & & & & &
 \end{array}$$

Backpropagation process

- ⇒ To compute the derivative $\frac{\partial \mathcal{L}}{\partial \Theta^{[1]}}$, we need to go through the **exactly same process** for computing $\frac{\partial \mathcal{L}}{\partial \Theta^{[2]}}$ but then continue one layer more.
- ⇒ What to expect?
To compute the derivative $\frac{\partial \mathcal{L}}{\partial \Theta^{[l-1]}}$, we need to go through the **exactly same process** for computing $\frac{\partial \mathcal{L}}{\partial \Theta^{[l]}}$ but then continue one layer more.

Backpropagation for L -layer network

Let us repeat the backpropagation for a shallow neural network

$$\begin{array}{ccccccc} \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \Theta^{[1]}}}_{\text{easy}} \\ \Downarrow \quad \Downarrow \quad \Downarrow \quad \Downarrow \quad \Downarrow \\ \frac{\partial \mathcal{L}}{\partial \Theta^{[2]}} \text{ using } \frac{\partial \mathbf{z}^{[2]}}{\partial \Theta^{[2]}} \end{array}$$

Backpropagation for L -layer network

By computing carefully for 4-layer network, we arrive at

$$\frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[4]}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[4]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[4]}}{\partial \mathbf{z}^{[4]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[3]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[4]}}{\partial \mathbf{a}^{[3]}}}_{\text{easy}}$$

$$\longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[3]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[3]}}{\partial \mathbf{z}^{[3]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[3]}}{\partial \mathbf{a}^{[2]}}}_{\text{easy}}$$

$$\longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[2]}}{\partial \mathbf{z}^{[2]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[1]}}}_{\text{easy}}$$

$$\longrightarrow \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{a}^{[1]}}{\partial \mathbf{z}^{[1]}}}_{\text{easy}} \longrightarrow \frac{\partial \mathcal{L}}{\partial \Theta^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \Theta^{[1]}}}_{\text{easy}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[4]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[4]}}{\partial \Theta^{[4]}}}_{\text{easy}} \implies \frac{\partial \mathcal{L}}{\partial \Theta^{[4]}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[3]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[3]}}{\partial \Theta^{[3]}}}_{\text{easy}} \implies \frac{\partial \mathcal{L}}{\partial \Theta^{[3]}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[2]}}{\partial \Theta^{[2]}}}_{\text{easy}} \implies \frac{\partial \mathcal{L}}{\partial \Theta^{[2]}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[1]}} \text{ using } \underbrace{\frac{\partial \mathbf{z}^{[1]}}{\partial \Theta^{[1]}}}_{\text{easy}} \implies \frac{\partial \mathcal{L}}{\partial \Theta^{[1]}}$$