Backpropagation

Hung-yi Lee

李宏毅

Gradient Descent

Network parameters
$$\theta = \{w_1, w_2, \dots, b_1, b_2, \dots\}$$

$$\theta^0 \longrightarrow \theta^1 \longrightarrow \theta^2 \longrightarrow \dots$$

Parameters
$$\nabla L(\theta)$$

$$= \begin{bmatrix} \partial L(\theta)/\partial w_1 \\ \partial L(\theta)/\partial w_2 \\ \vdots \\ \partial L(\theta)/\partial b_1 \\ \vdots \\ \partial L(\theta)/\partial b_2 \\ \vdots \end{bmatrix}$$
 Compute
$$\nabla L(\theta^0)$$

$$\theta^1 = \theta^0 - \eta \nabla L(\theta^0)$$

$$\theta^2 = \theta^1 - \eta \nabla L(\theta^1)$$

$$\theta^2 = \theta^1 - \eta \nabla L(\theta^1)$$
 Millions of parameters

To compute the gradients efficiently, we use backpropagation.

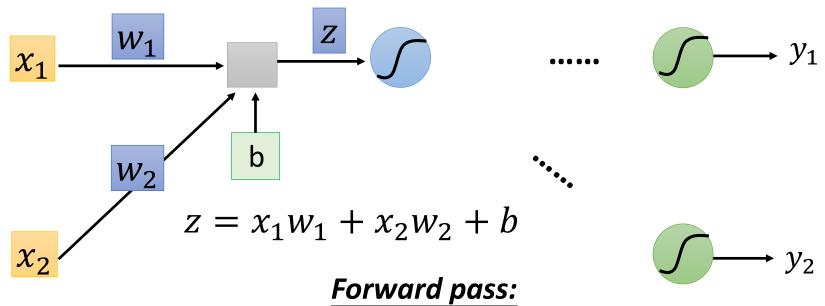
Compute
$$\nabla L(\theta^0)$$

$$\theta^1 = \theta^0 - \eta \nabla L(\theta^0)$$

Compute
$$\nabla L(\theta^1)$$

$$\theta^2 = \theta^1 - \eta \nabla L(\theta^1)$$

Backpropagation



$$\frac{\partial l}{\partial w} = ? \quad \frac{\partial z}{\partial w} \frac{\partial l}{\partial z}$$
(Chain rule)

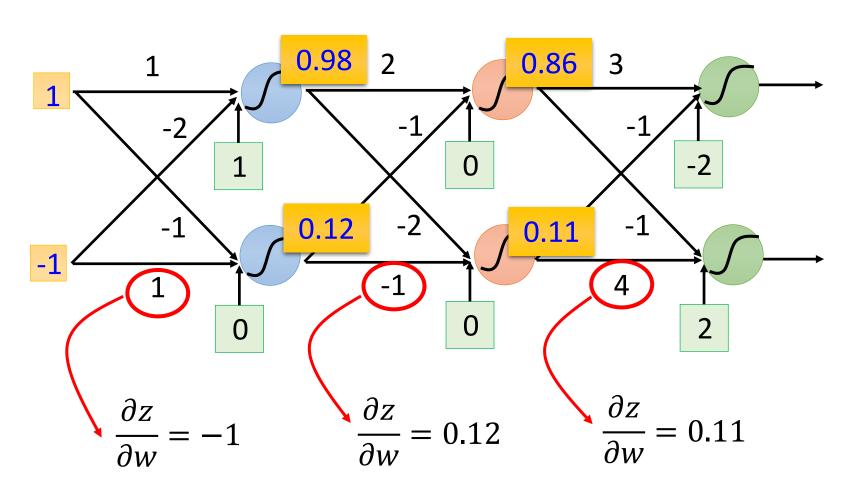
Compute $\partial z/\partial w$ for all parameters

Backward pass:

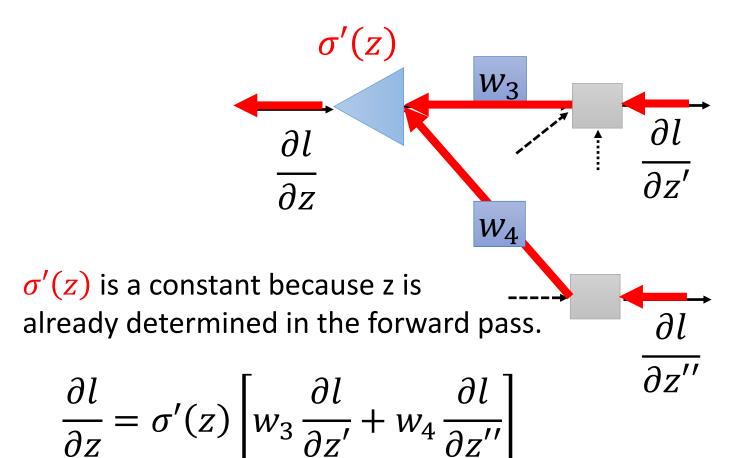
Compute $\partial l/\partial z$ for all activation function inputs z

Backpropagation – Forward pass

Compute $\partial z/\partial w$ for all parameters

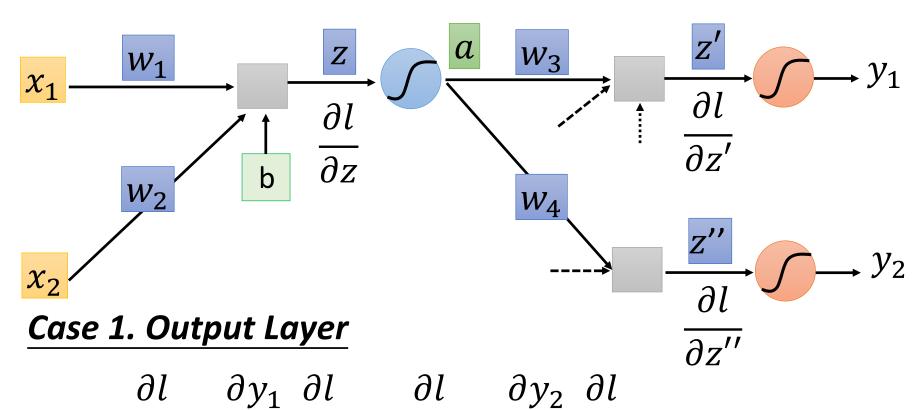


Backpropagation – Backward pass



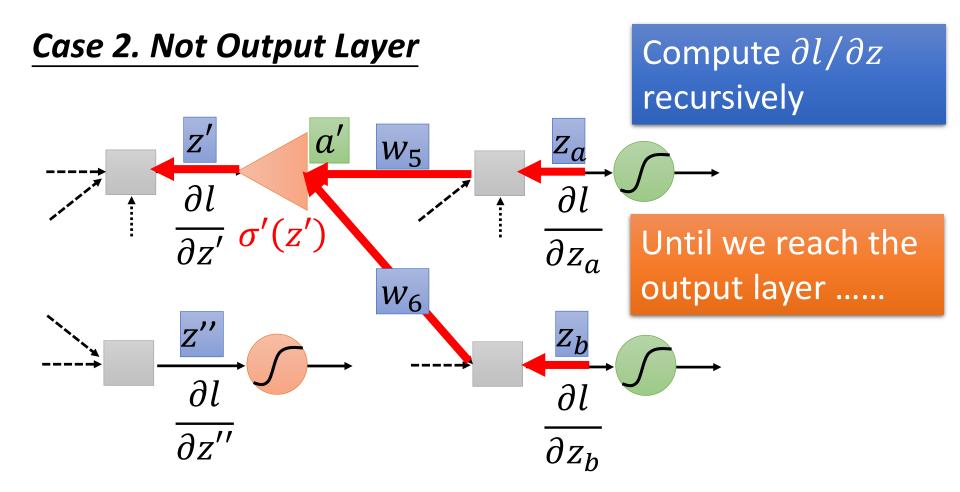
Backpropagation – Backward pass

Compute $\partial l/\partial z$ for all activation function inputs z



Backpropagation – Backward pass

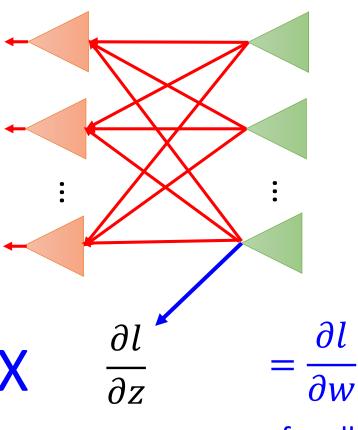
Compute $\partial l/\partial z$ for all activation function inputs z



Backpropagation – Summary

Forward Pass

Backward Pass



for all w