

Intro

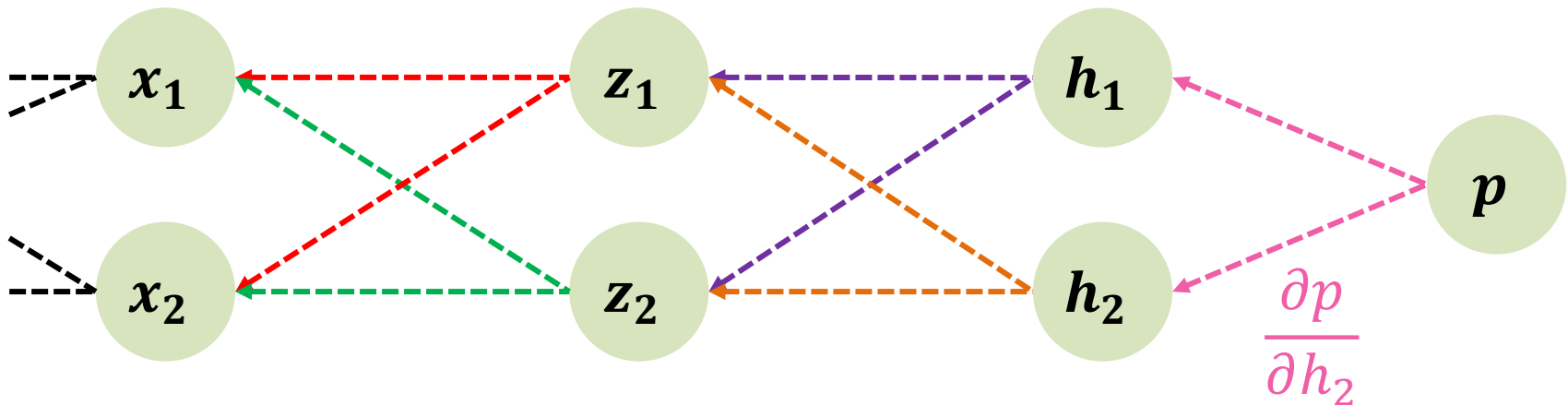
- In this video we will find out how to apply a chain rule **efficiently**!

Let's look at MLP with 3 hidden layers

Let's drill down to an actual parameter of MLP:

$$h_2 = \sigma(\mathbf{w}_0 + \mathbf{w}_1 z_1 + \mathbf{w}_2 z_2)$$

Gradient
Descent: $\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial p} \frac{\partial p}{\partial w_1} = \frac{\partial L}{\partial p} \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial w_1}$



We need to do this efficiently!

3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

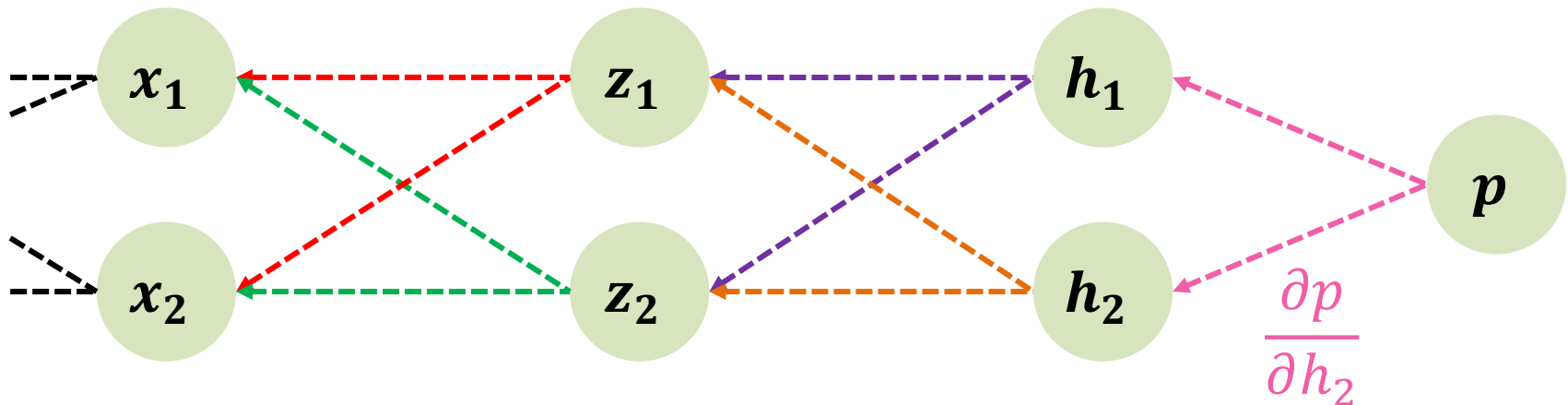
We will need these for GD

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$

$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$

1: $\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$

$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$



We can reuse previous computations

3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

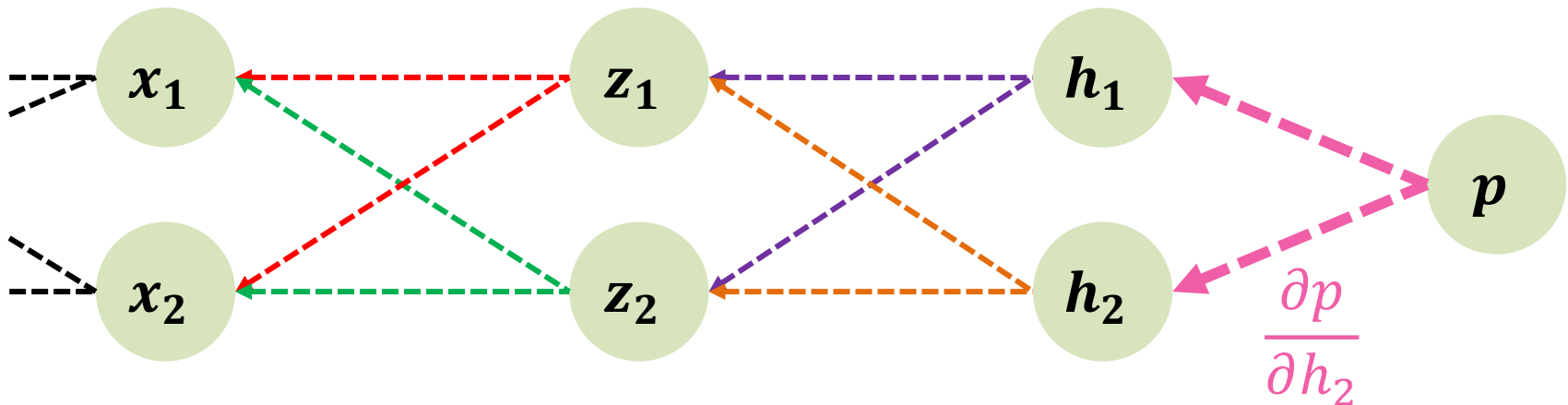
We will need these for GD

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$

$$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$$

1: $\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$

$$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$$



We can reuse previous computations

3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

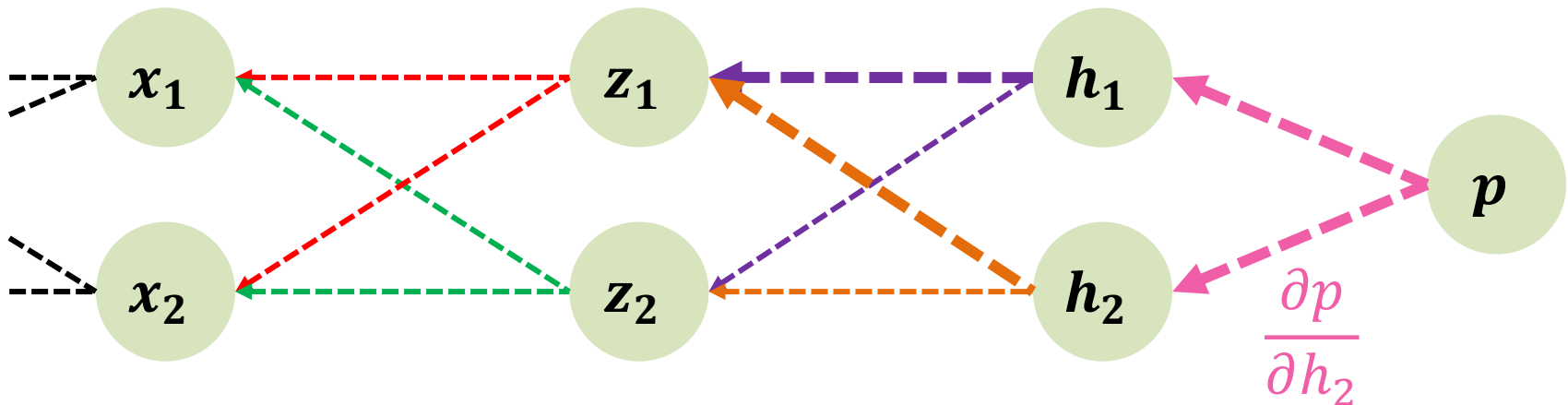
We will need these for GD

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$

$$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$$

1: $\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$

$$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$$



We can reuse previous computations

3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

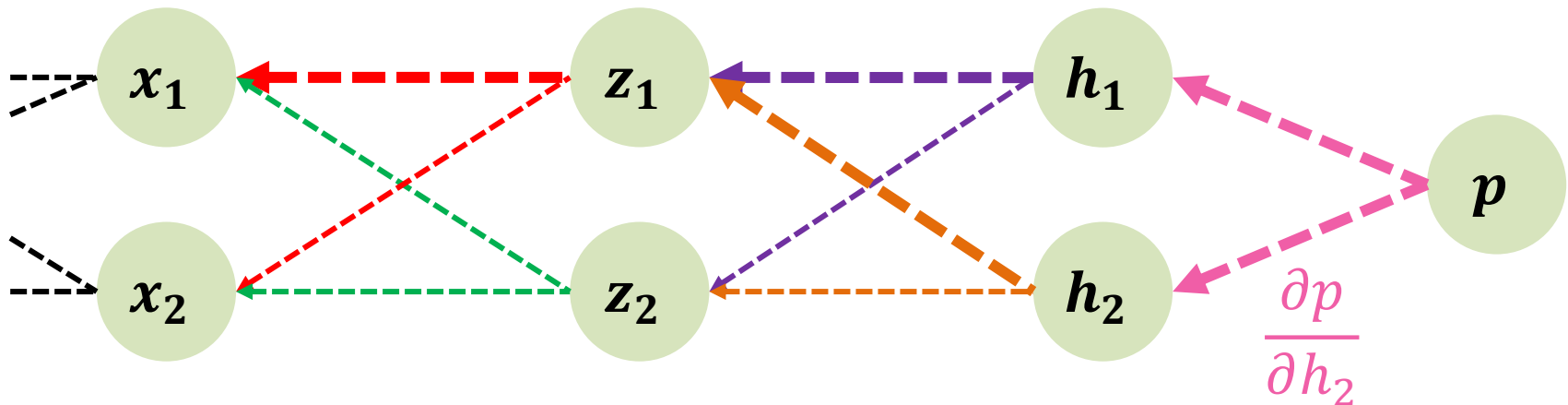
We will need these for GD

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$

$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$

1: $\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$

$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$



We can reuse previous computations

3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

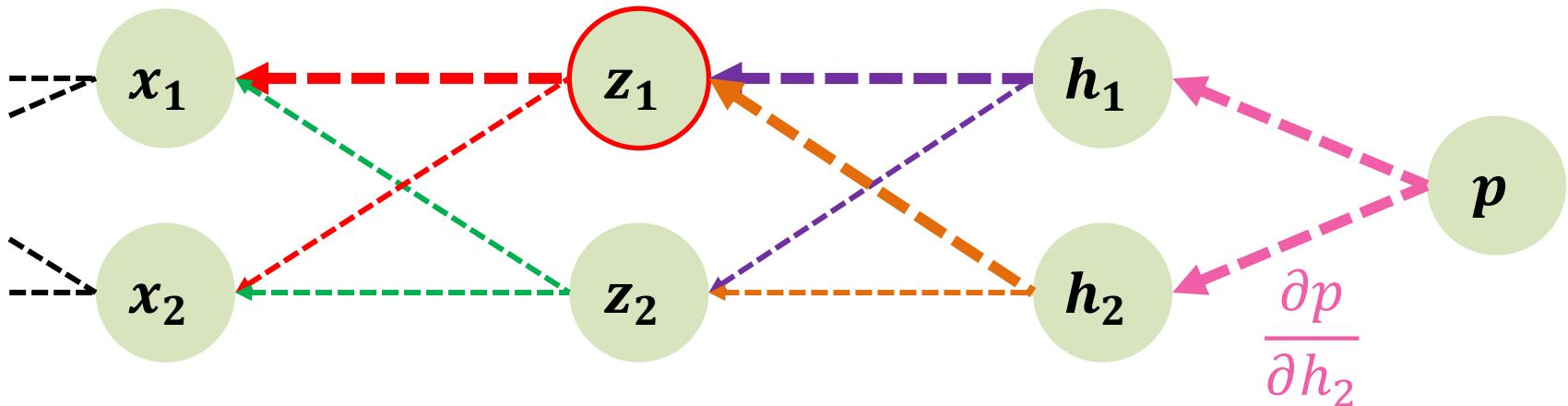
We will need these for GD

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$

$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$

1: $\frac{\partial p}{\partial x_1} = \left(\frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \right) \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$

$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$



We can reuse previous computations

$$3: \frac{\partial p}{\partial h_1} \quad \frac{\partial p}{\partial h_2}$$

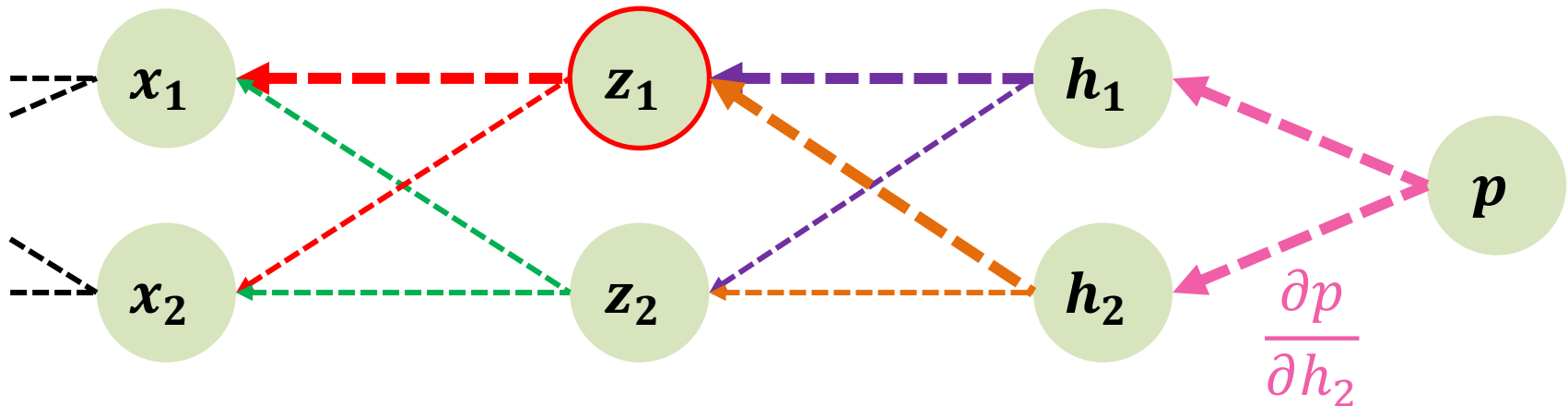
We will need these for GD

$$2: \frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$$

$$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$$

$$1: \frac{\partial p}{\partial x_1} = \left(\frac{\partial p}{\partial z_1} \right) \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

$$\frac{\partial p}{\partial x_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$$



We can reuse previous computations

3: $\frac{\partial p}{\partial h_1}$ $\frac{\partial p}{\partial h_2}$

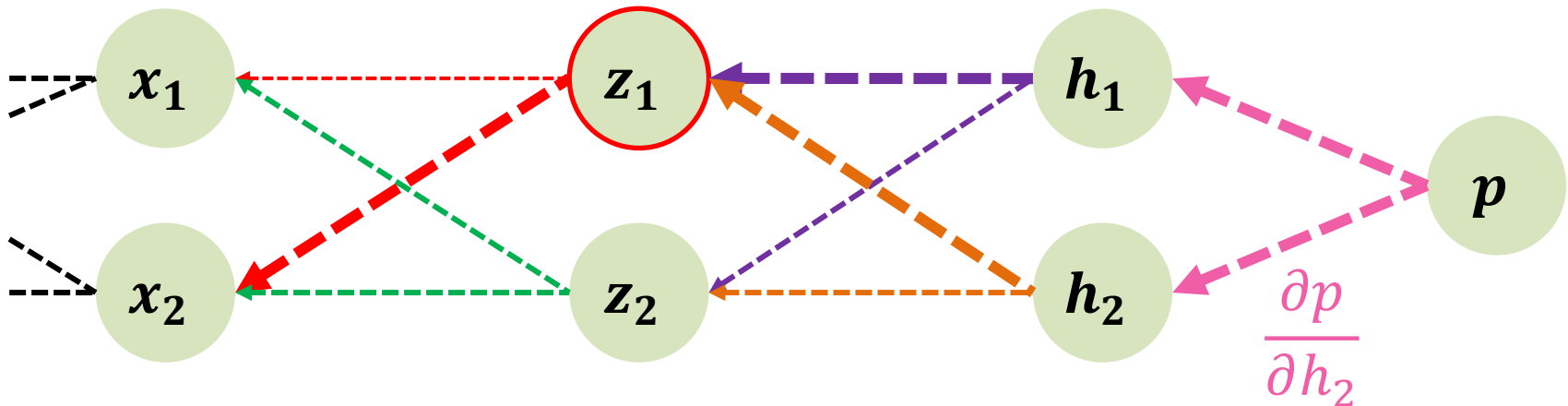
We will need these for GD

2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_1}$

$$\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2}$$

1: $\frac{\partial p}{\partial x_1} = \left(\frac{\partial p}{\partial z_1} \right) \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$

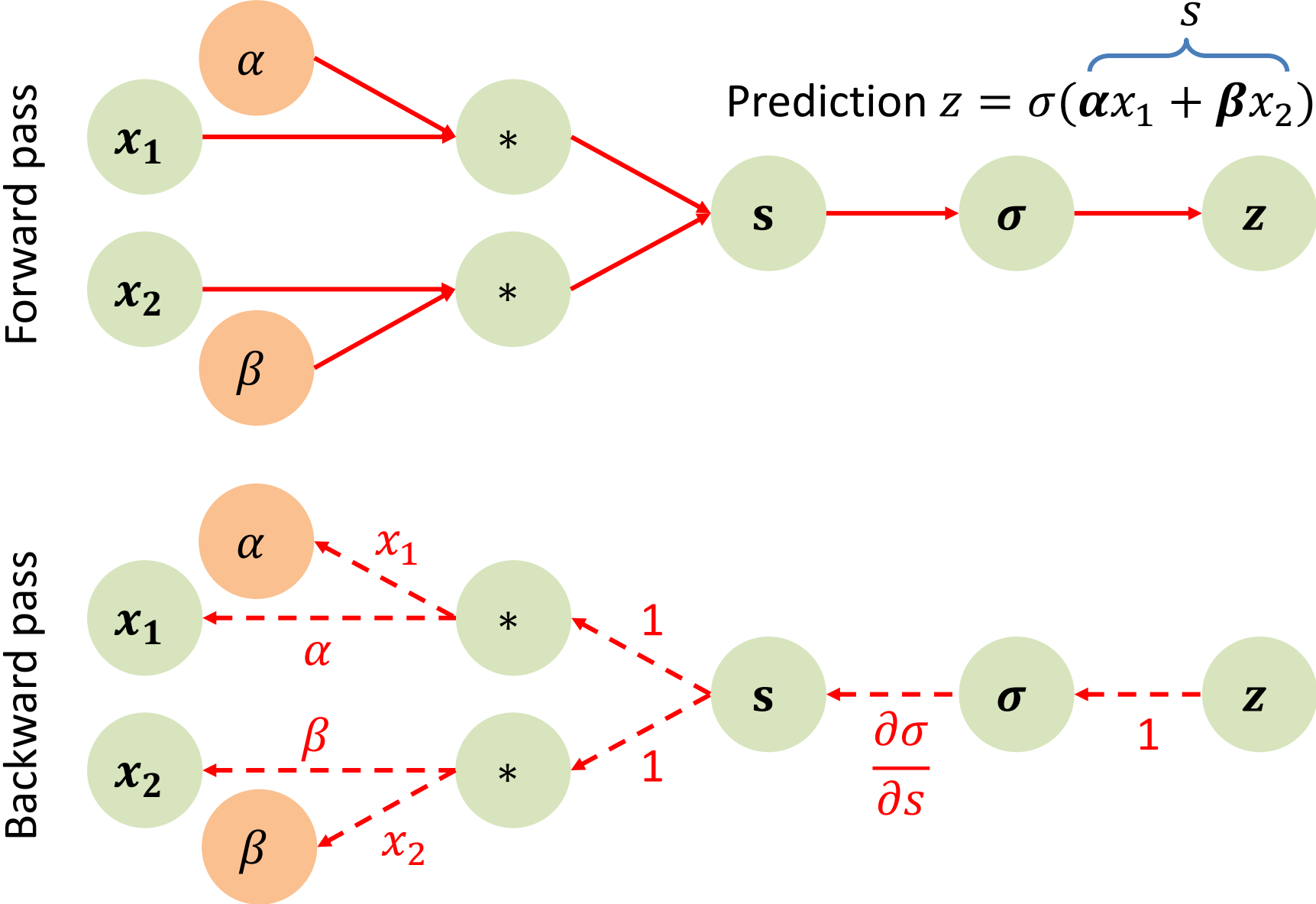
1: $\frac{\partial p}{\partial x_2} = \left(\frac{\partial p}{\partial z_1} \right) \frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_2}$



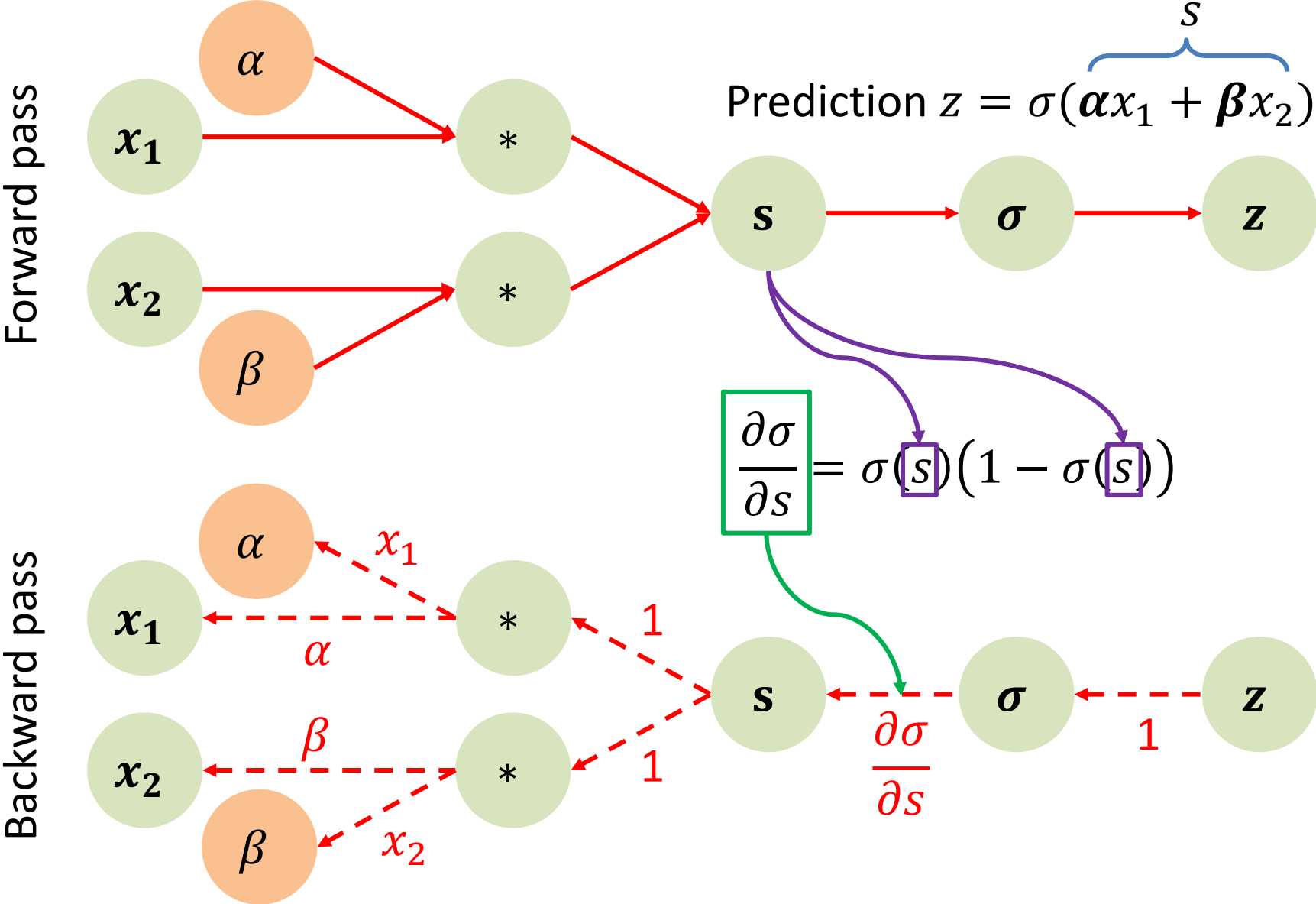
This is called reverse-mode differentiation

- In application to neural networks it has one more name: **back-propagation**.
- It works **fast**, because we reuse computations from previous steps.
- In fact, for each edge we compute its value only once. And multiply by its value exactly once.

Back-propagation (Back-prop)

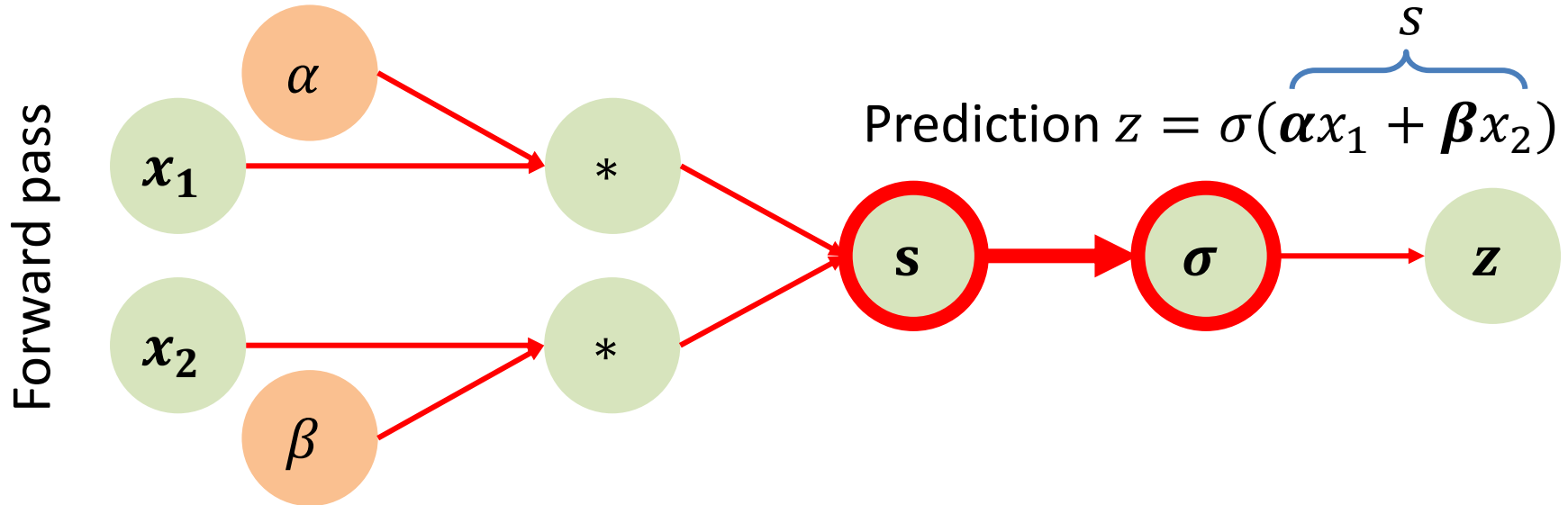


Back-propagation (Back-prop)



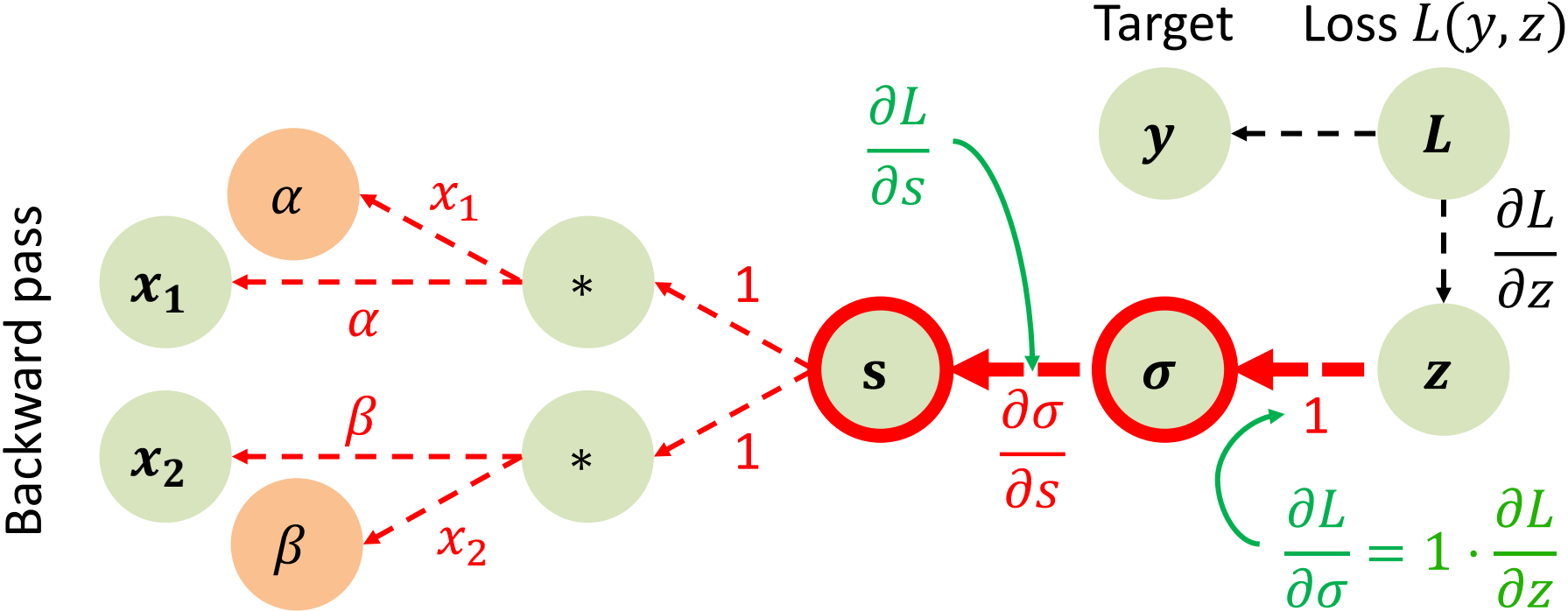
Forward pass interface

Let's implement a sigmoid activation node!

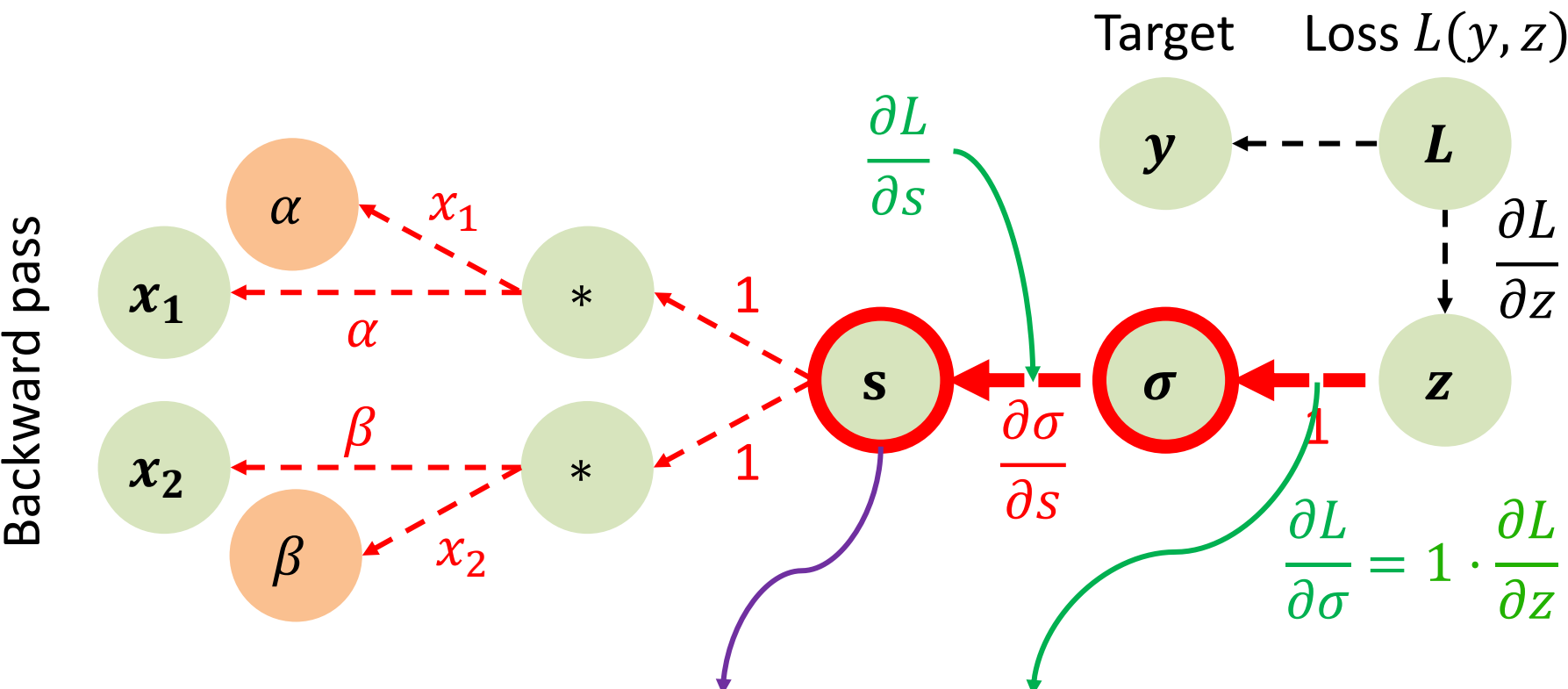


```
def forward_pass(inputs):  
    return 1. / (1 + np.exp(-inputs))
```

Backward pass interface



Backward pass interface



```
def backward_pass(inputs, incoming_gradient):  
    sigmoid = 1. / (1 + np.exp(-inputs))  
    return sigmoid * (1 - sigmoid) * incoming_gradient
```

$\frac{\partial L}{\partial s} = \underbrace{\text{sigmoid} * (1 - \text{sigmoid})}_{\frac{\partial \sigma}{\partial s}} \cdot \frac{\partial L}{\partial \sigma}$

Summary

- Back-propagation is a name for an **automatic** reverse-mode differentiation
- Back-propagation is **fast**
- And this is how neural nets are trained today
- In the next video we will look at MLP implementation details