

Intro

- In this video we will learn how to compute the gradients for MLP **automatically**.

Chain rule

- We know derivatives for simple functions:

$$\frac{dx^2}{dx} = 2x \qquad \frac{de^x}{dx} = e^x \qquad \frac{d\ln(x)}{dx} = \frac{1}{x}$$

- Let's take a composite function:

$$z_1 = z_1(\textcolor{red}{x}_1, x_2)$$

$$z_2 = z_2(\textcolor{green}{x}_1, x_2) \qquad \text{where } z_1, z_2, p \text{ are differentiable}$$

$$p = p(\textcolor{violet}{z}_1, \textcolor{brown}{z}_2)$$

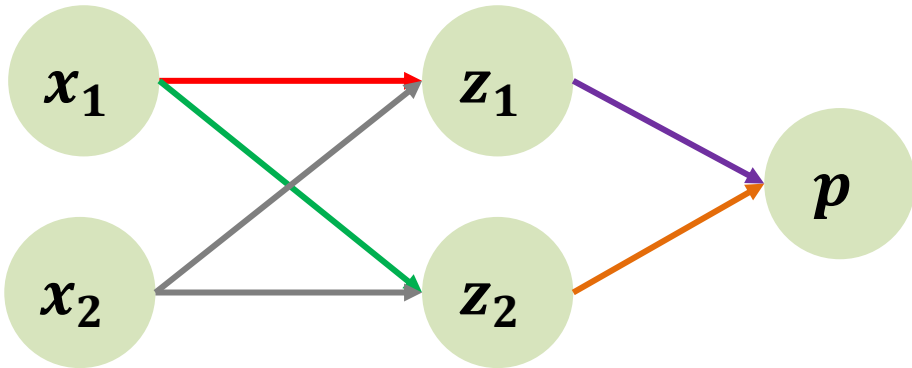
$$\text{Chain rule: } \frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial \textcolor{violet}{z}_1} \frac{\partial \textcolor{red}{z}_1}{\partial \textcolor{red}{x}_1} + \frac{\partial p}{\partial \textcolor{brown}{z}_2} \frac{\partial \textcolor{green}{z}_2}{\partial \textcolor{green}{x}_1}$$

Example for $h(x) = f(x)g(x)$:

$$\frac{\partial h}{\partial x} = \frac{\partial h}{\partial \textcolor{blue}{f}} \frac{\partial \textcolor{blue}{f}}{\partial x} + \frac{\partial h}{\partial \textcolor{pink}{g}} \frac{\partial \textcolor{pink}{g}}{\partial x} = \textcolor{blue}{g} \frac{\partial f}{\partial x} + \textcolor{pink}{f} \frac{\partial g}{\partial x}$$

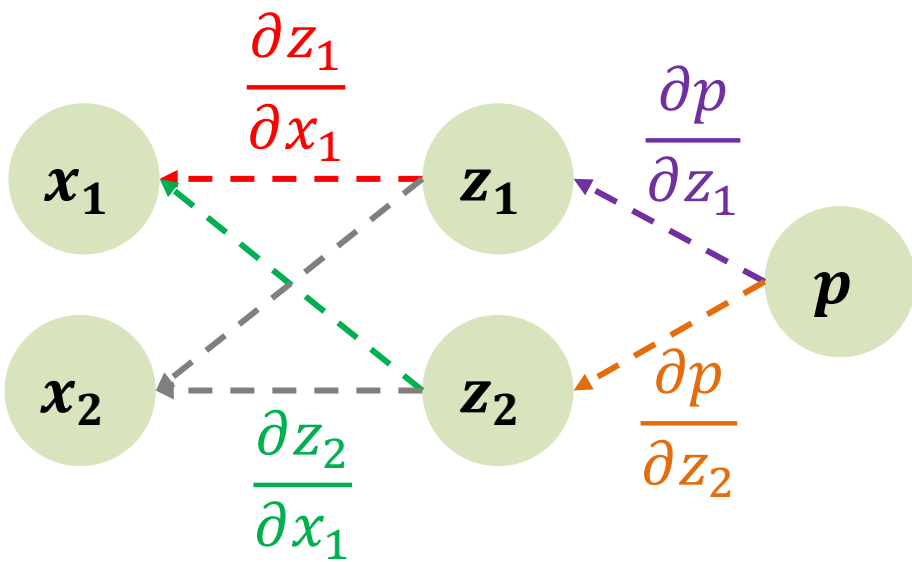
Derivatives computation graph

- Let's take our simple computation graph:



$z_1 = z_1(x_1, x_2)$
 $z_2 = z_2(x_1, x_2)$
 $p = p(z_1, z_2)$

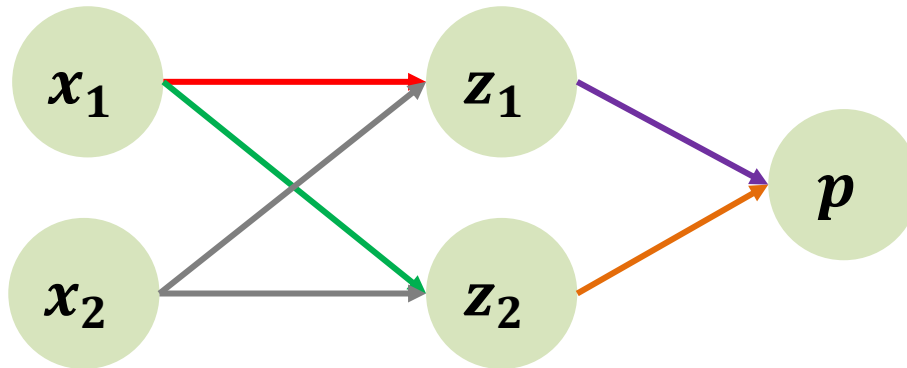
- And construct a new graph of derivatives:



Each edge is assigned to derivative of origin w.r.t. destination

Derivatives computation graph

- Let's take our simple computation graph:

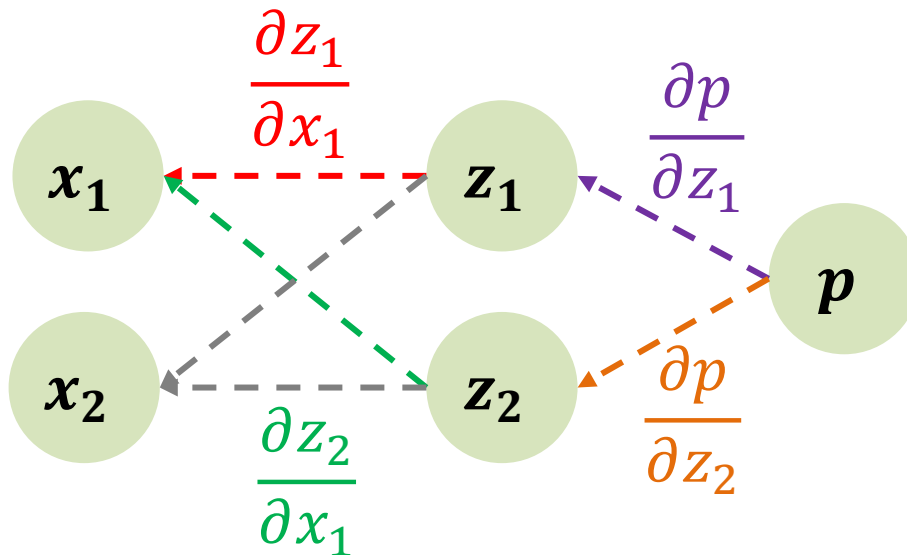


$$z_1 = z_1(x_1, x_2)$$

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- And construct a new graph of derivatives:

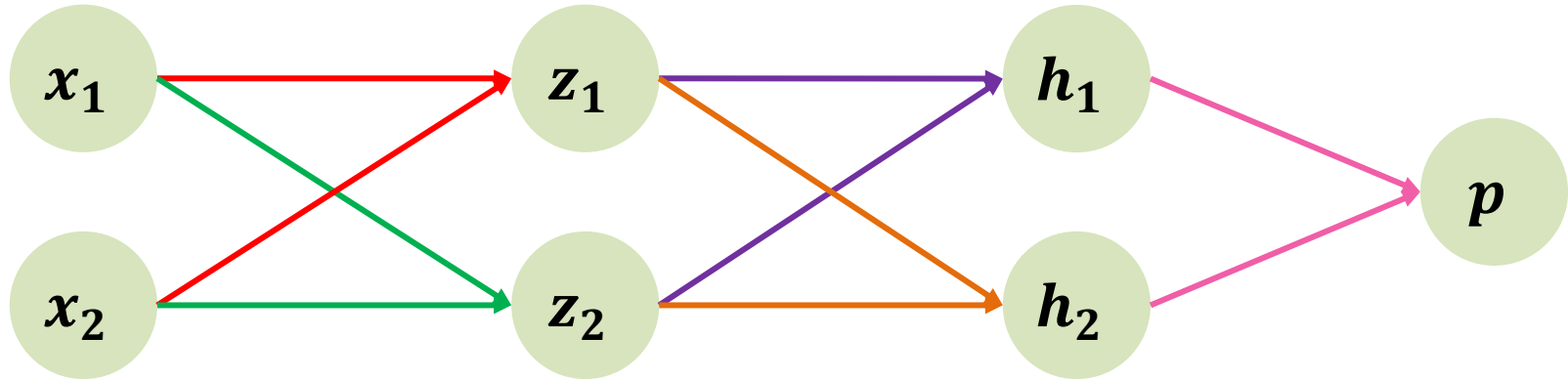


$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

You can see how
a **chain rule** works

Let's go deeper

- A little bit more composite function:



$$z_1 = z_1(\textcolor{red}{x}_1, \textcolor{red}{x}_2)$$

$$h_1 = h_1(\textcolor{purple}{z}_1, \textcolor{purple}{z}_2)$$

$$z_2 = z_2(\textcolor{green}{x}_1, \textcolor{green}{x}_2)$$

$$h_2 = h_2(\textcolor{orange}{z}_1, \textcolor{orange}{z}_2)$$

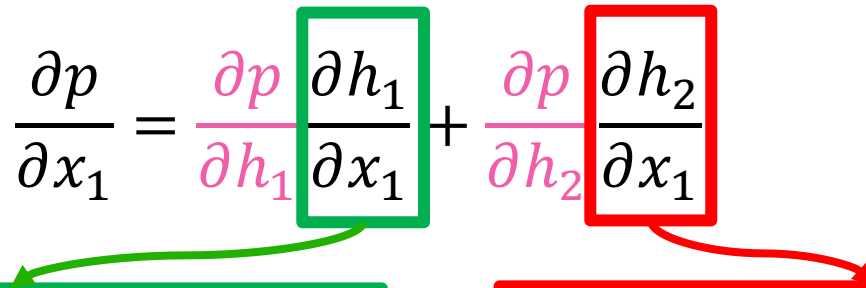
$$p = p(\textcolor{pink}{h}_1, \textcolor{pink}{h}_2)$$

Let's go deeper

Chain rule:
$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial x_1}$$

Let's go deeper

Chain rule: $\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial x_1}$



$$\frac{\partial h_1}{\partial x_1} = \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

$$\frac{\partial h_2}{\partial x_1} = \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

Let's go deeper

Chain rule: $\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial x_1}$

$$\frac{\partial h_1}{\partial x_1} = \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

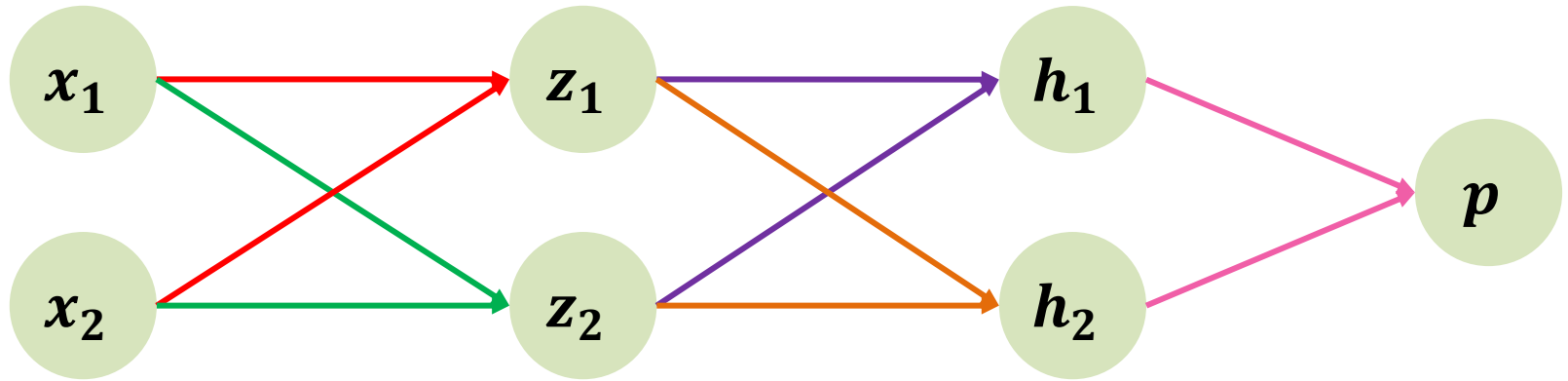
$$\frac{\partial h_2}{\partial x_1} = \frac{\partial h_2}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial h_2}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

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

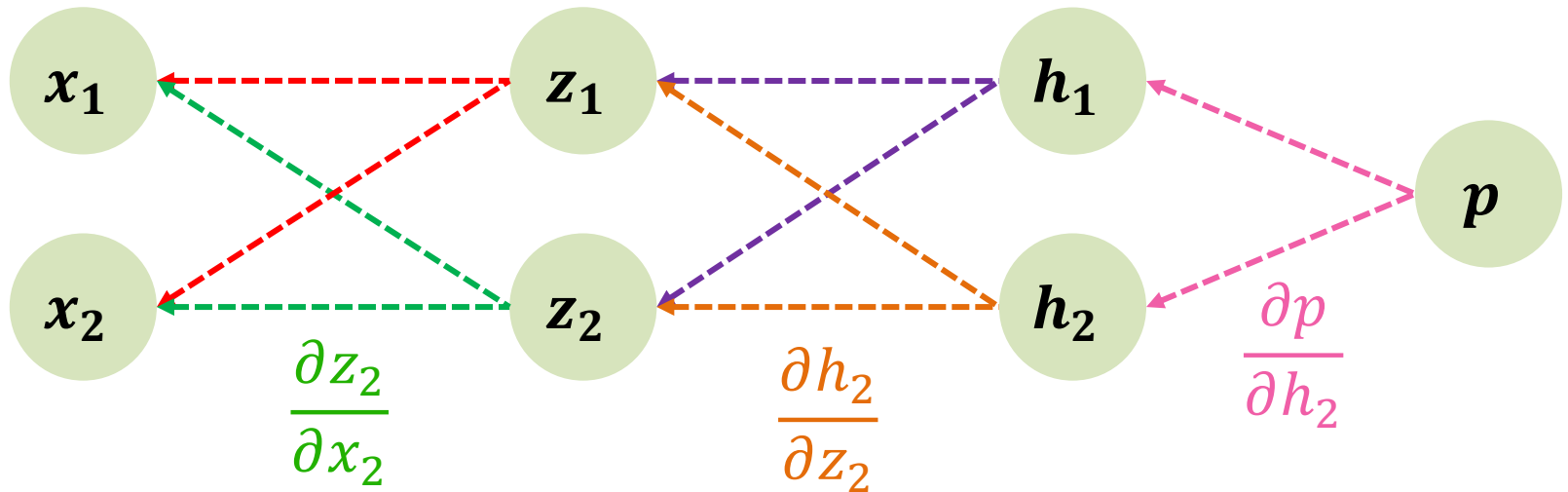
$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial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

Let's check out the derivatives graph!

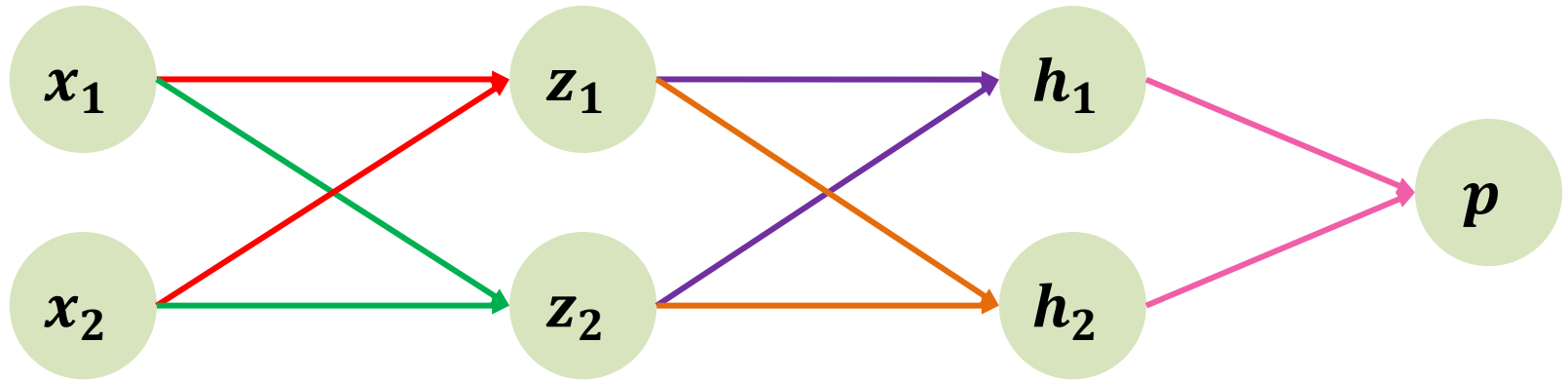
Let's go deeper



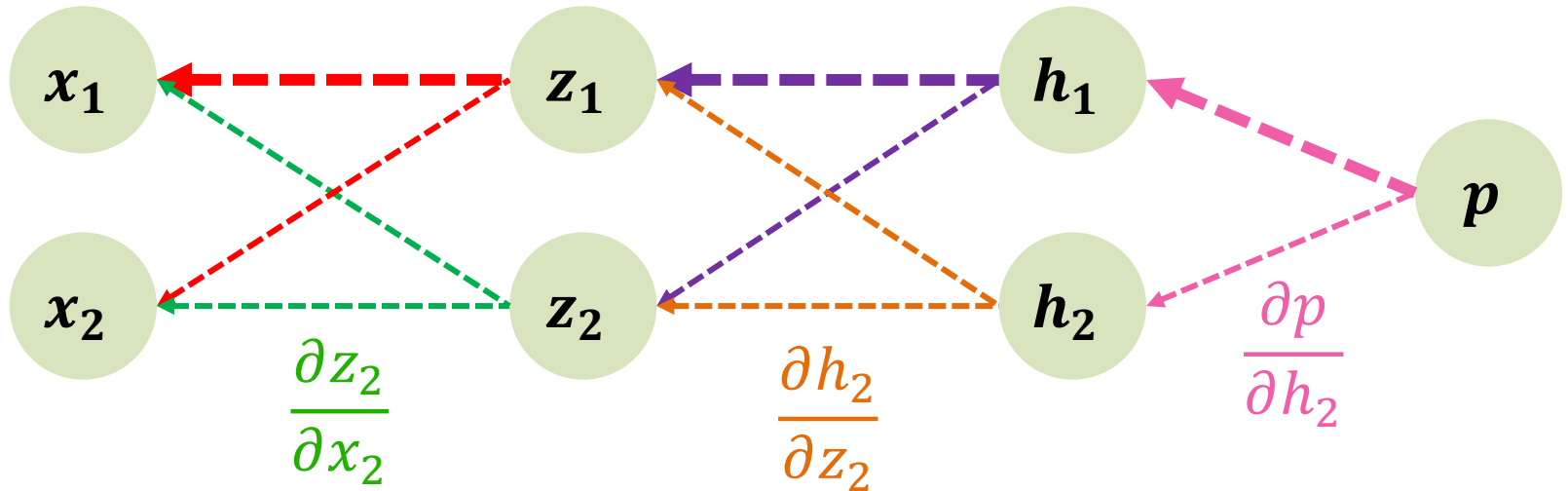
$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial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



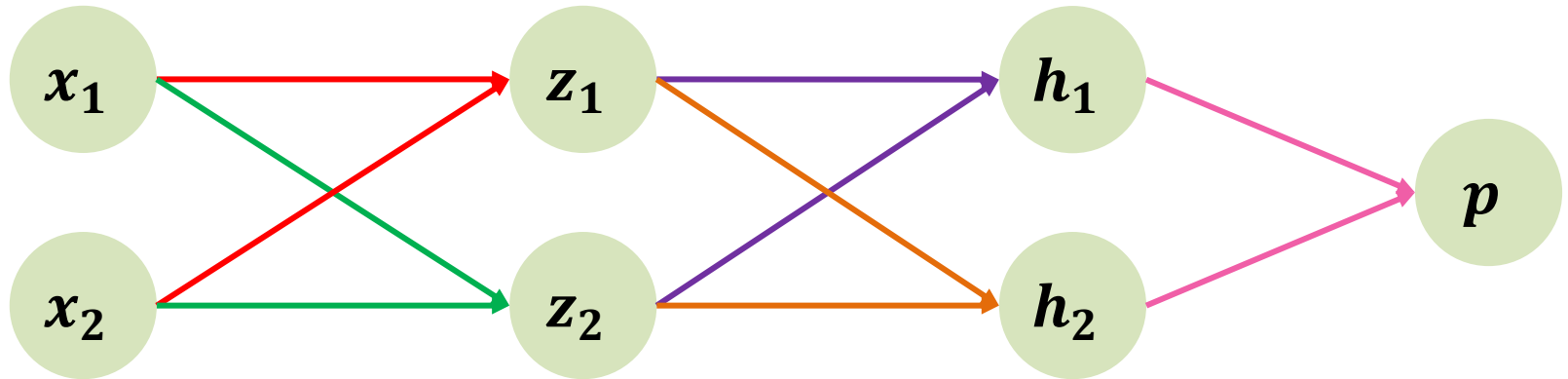
Let's go deeper



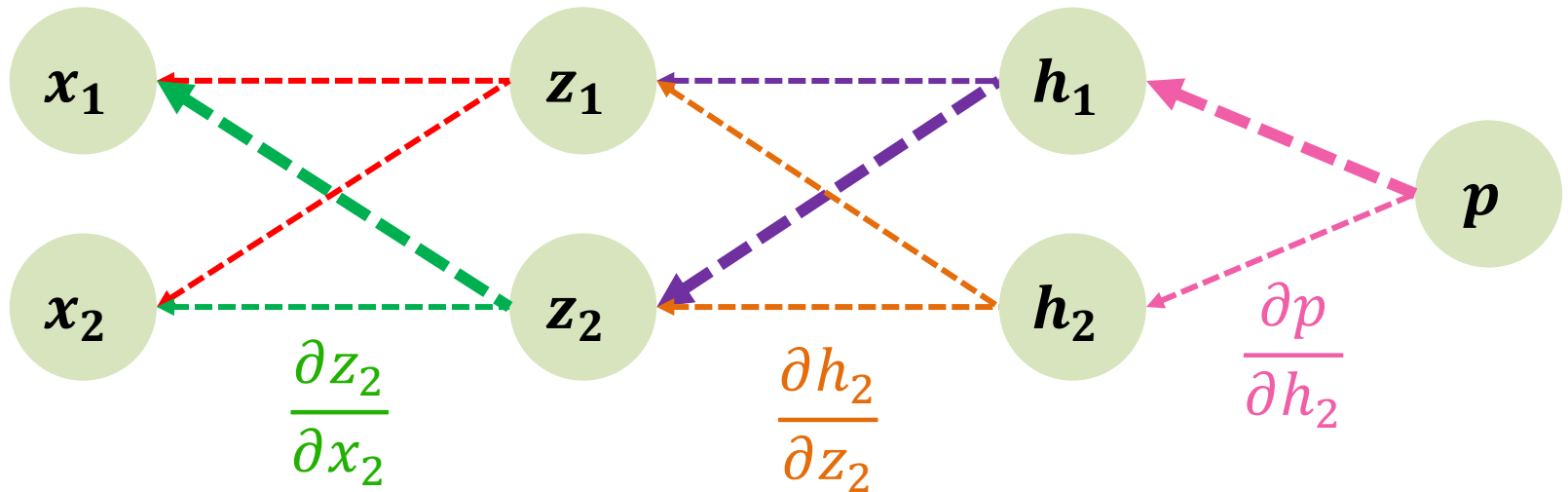
$$\frac{\partial p}{\partial x_1} = \boxed{\frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1}} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial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



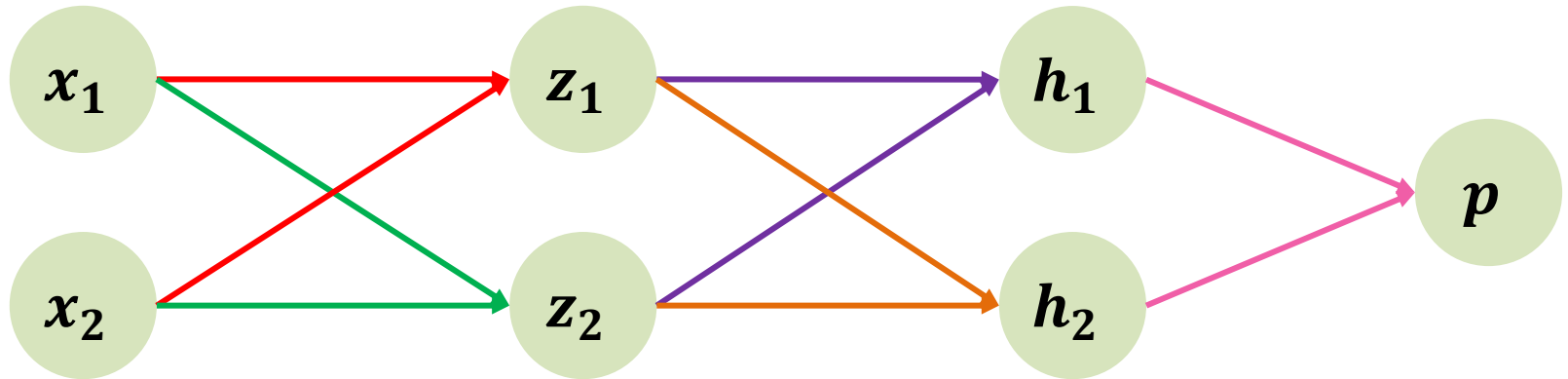
Let's go deeper



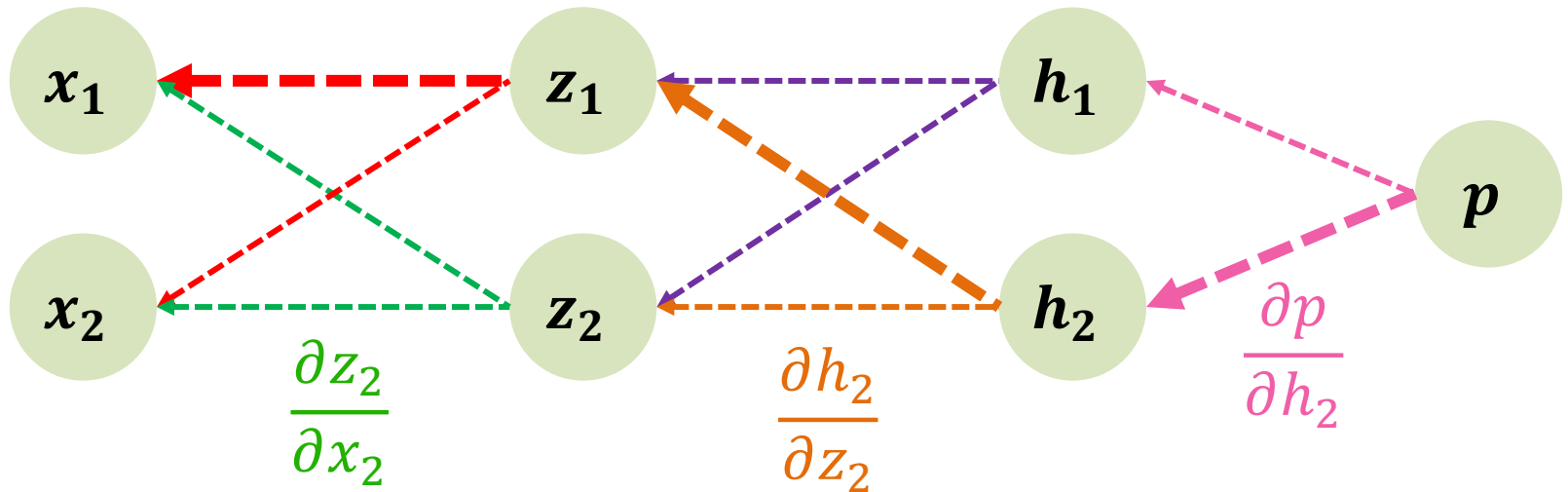
$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \boxed{\frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1}} + \frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial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



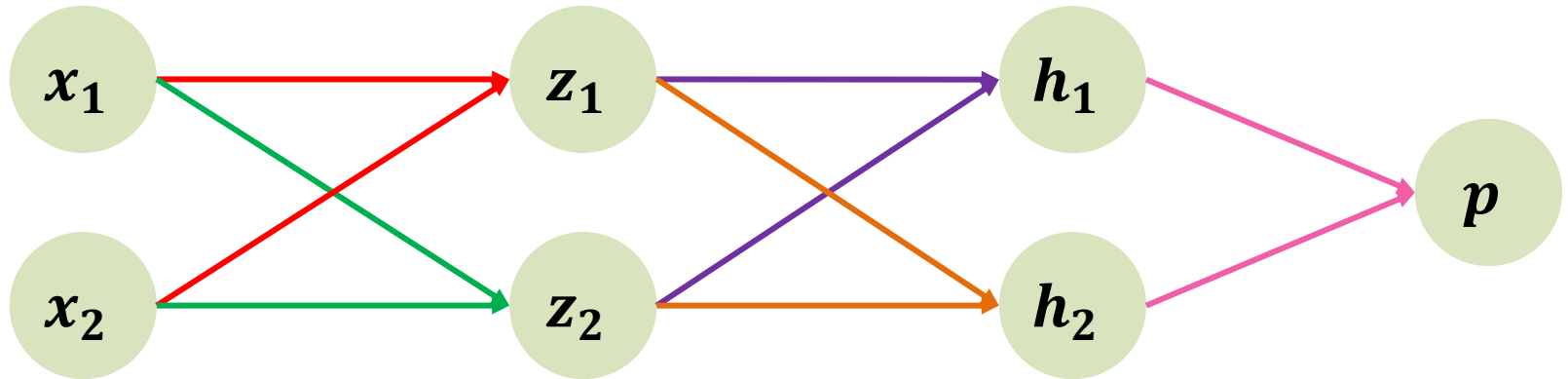
Let's go deeper



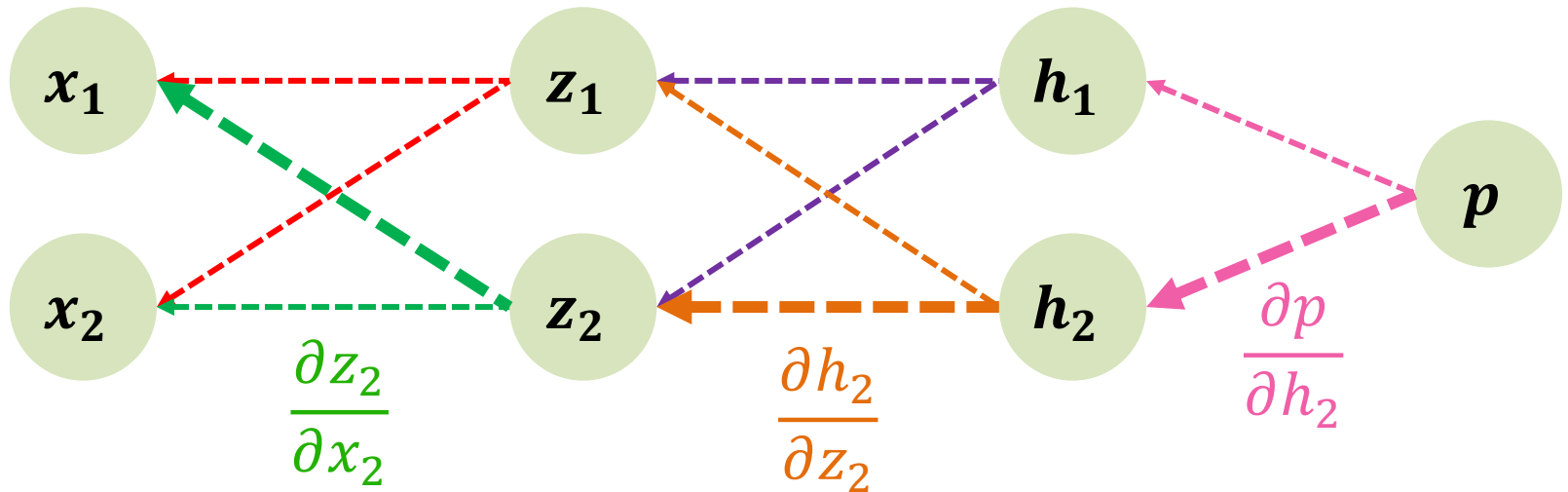
$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1} \frac{\partial h_1}{\partial z_2} \frac{\partial z_2}{\partial x_1} + \boxed{\frac{\partial p}{\partial h_2} \frac{\partial h_2}{\partial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



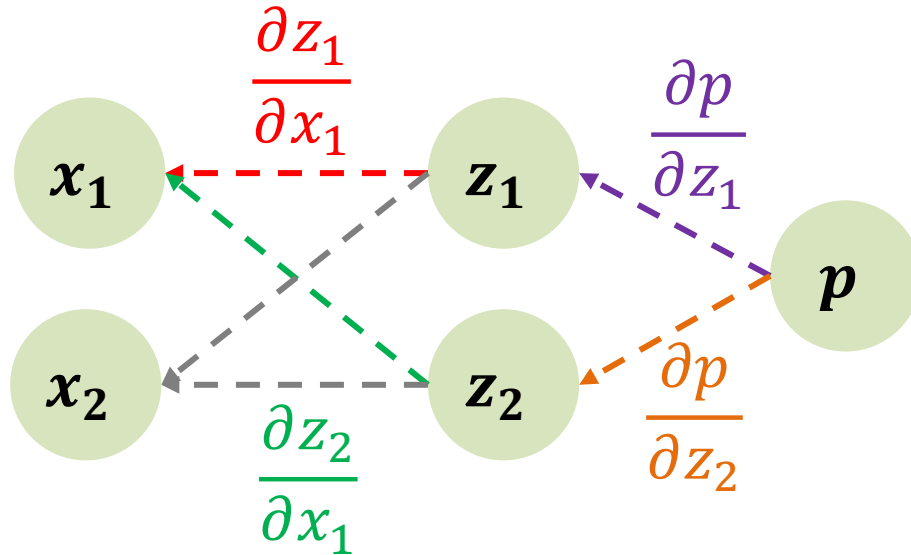
Let's go deeper



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



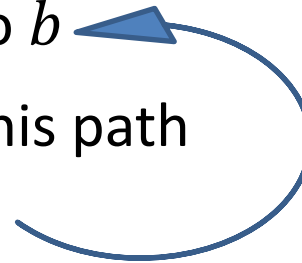
How this graph of derivatives helps



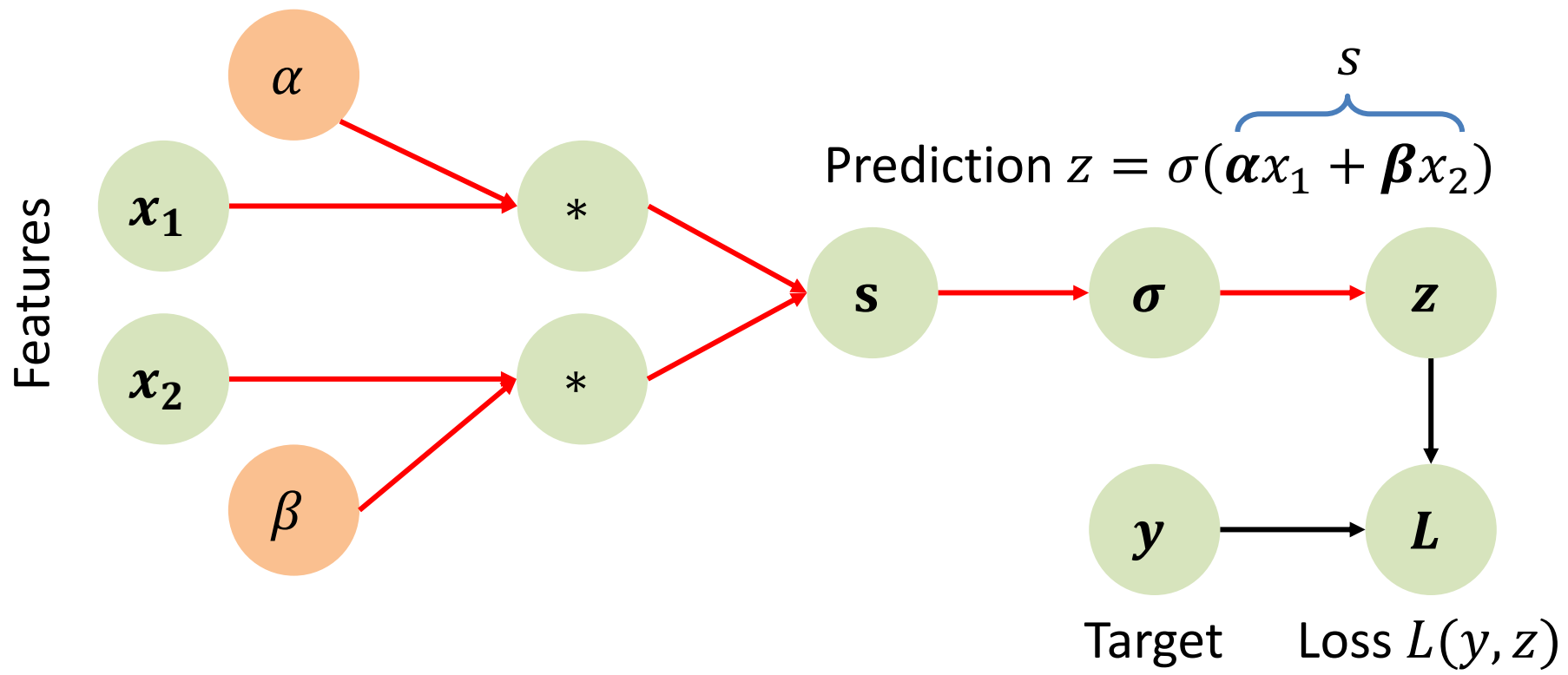
$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial z_1} \frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial z_2} \frac{\partial z_2}{\partial x_1}$$

How to calculate a derivative of node a w.r.t. node b :

- Find an unvisited path from a to b
- Multiply all edge values along this path
- Add to the resulting derivative

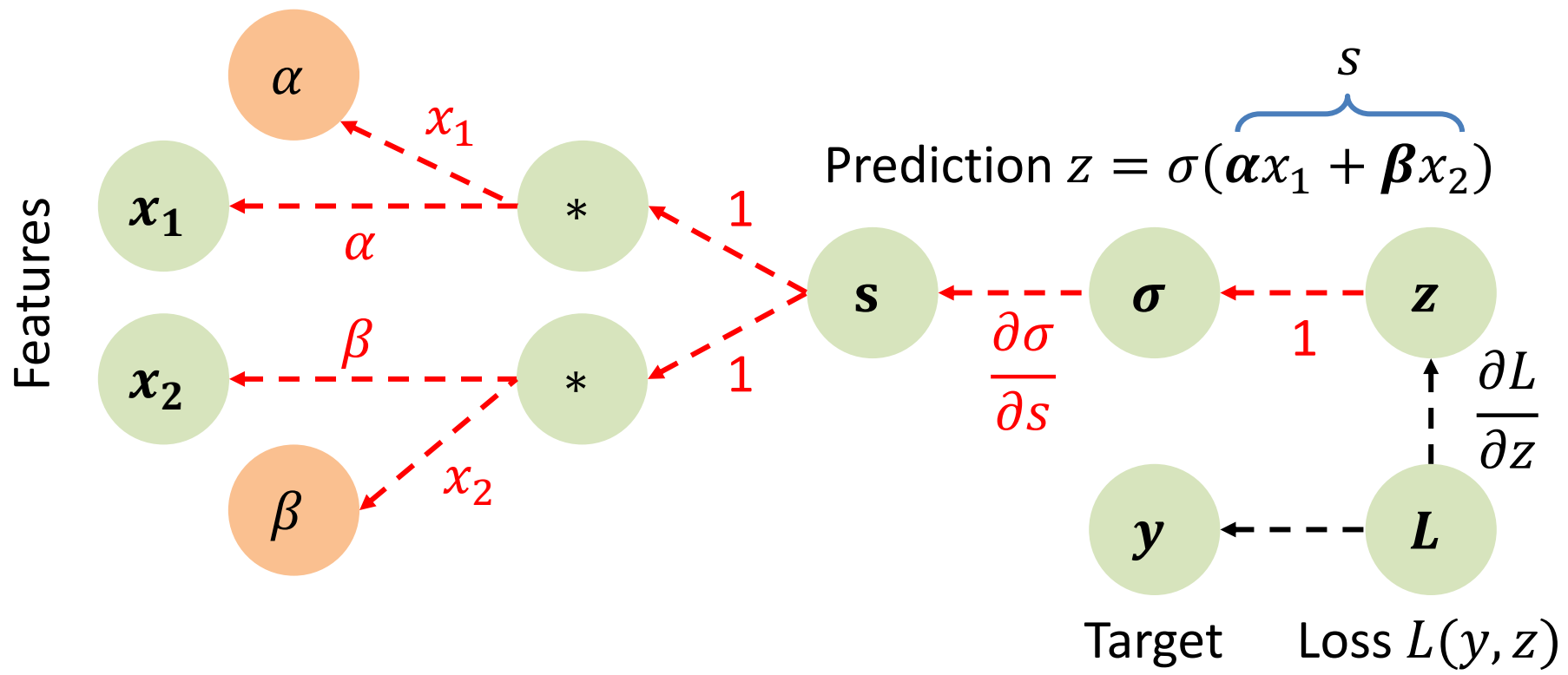


How chain rule helps to train a neuron



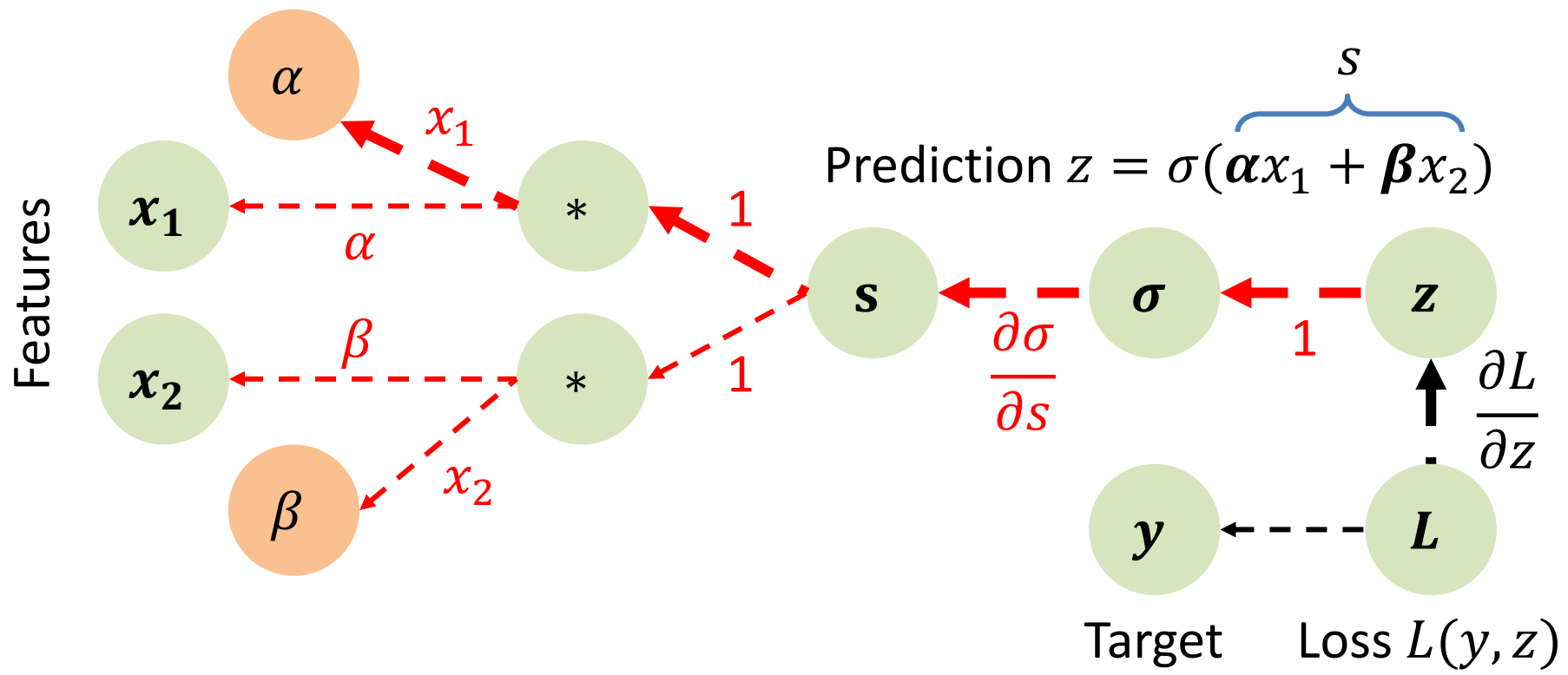
For SGD to work we need $\frac{\partial L}{\partial \alpha}, \frac{\partial L}{\partial \beta}$

Derivatives computation graph



For SGD to work we need $\frac{\partial L}{\partial \alpha}, \frac{\partial L}{\partial \beta}$

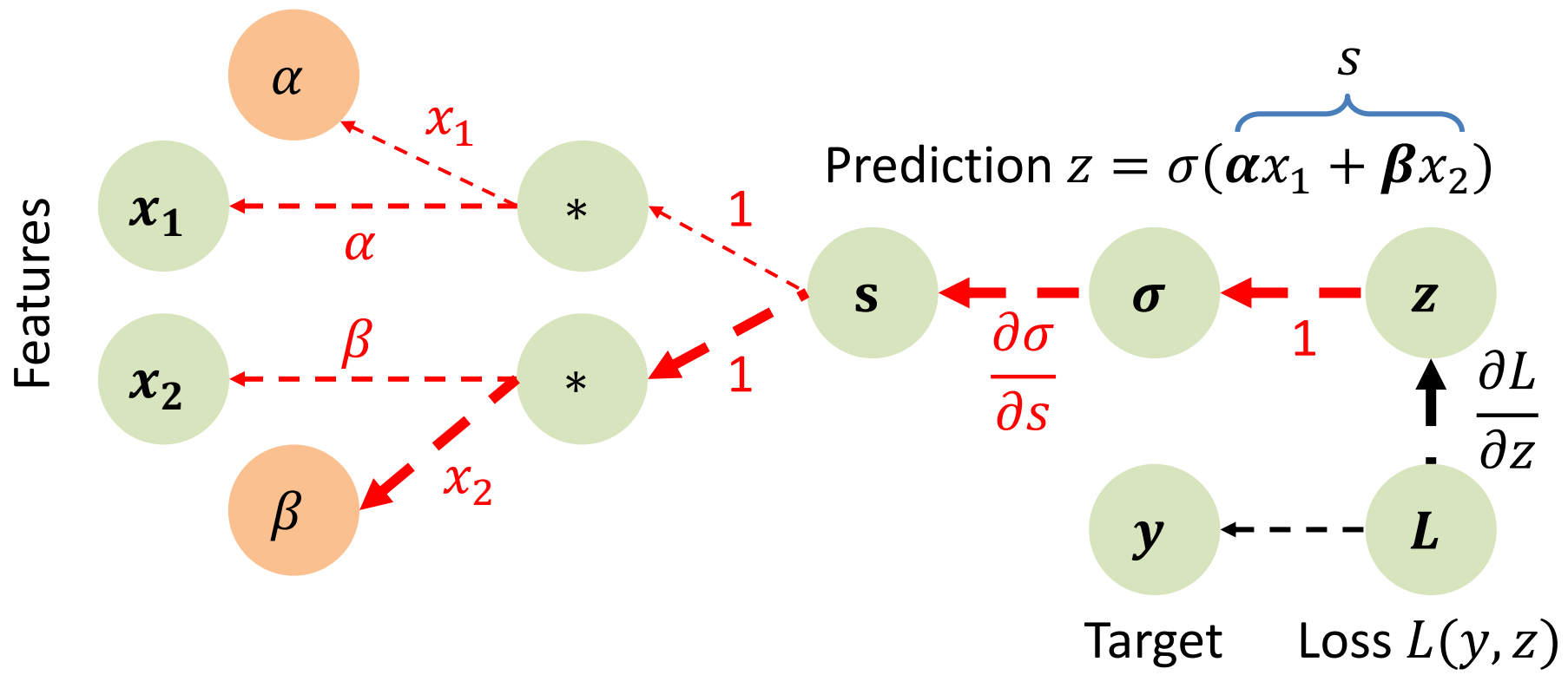
Derivatives computation graph



For SGD to work we need $\frac{\partial L}{\partial \alpha}, \frac{\partial L}{\partial \beta}$

$$\frac{\partial L}{\partial \alpha} = \frac{\partial L}{\partial z} \frac{\partial \sigma}{\partial s} x_1$$

Derivatives computation graph



For SGD to work we need $\frac{\partial L}{\partial \alpha}, \frac{\partial L}{\partial \beta}$

$$\frac{\partial L}{\partial \alpha} = \frac{\partial L}{\partial z} \frac{\partial \sigma}{\partial s} x_1$$

$$\frac{\partial L}{\partial \beta} = \frac{\partial L}{\partial z} \frac{\partial \sigma}{\partial s} x_2$$

Summary

- We can use chain rule to compute derivatives of composite functions
- We can use a computation graph of derivatives to compute them **automatically**
- In the next video we will find out how to do this **fast!**