

# Neural Networks

Dr. Jameel Malik

[muhammad.jameel@seecs.edu.pk](mailto:muhammad.jameel@seecs.edu.pk)

# Backpropagation in Neural Networks

*Training data*

**Features**                      **class**

1.4 2.7 1.9                      0

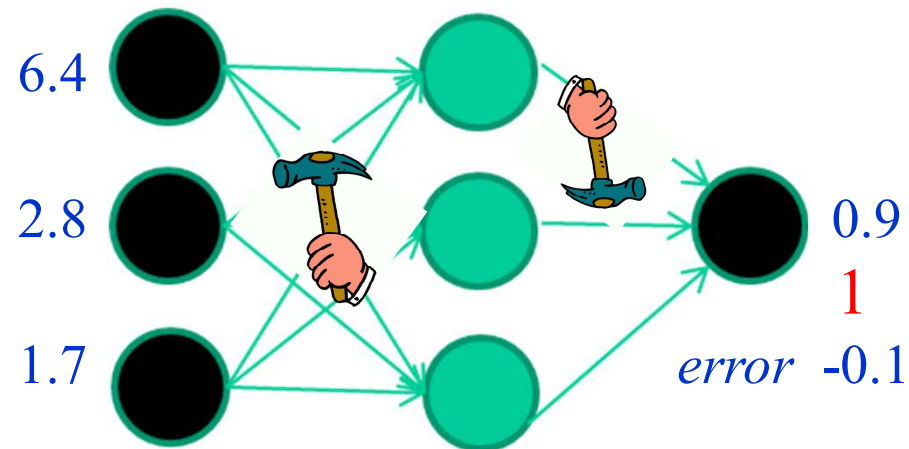
3.8 3.4 3.2                      0

6.4 2.8 1.7                      1

4.1 0.1 0.2                      0

etc ...

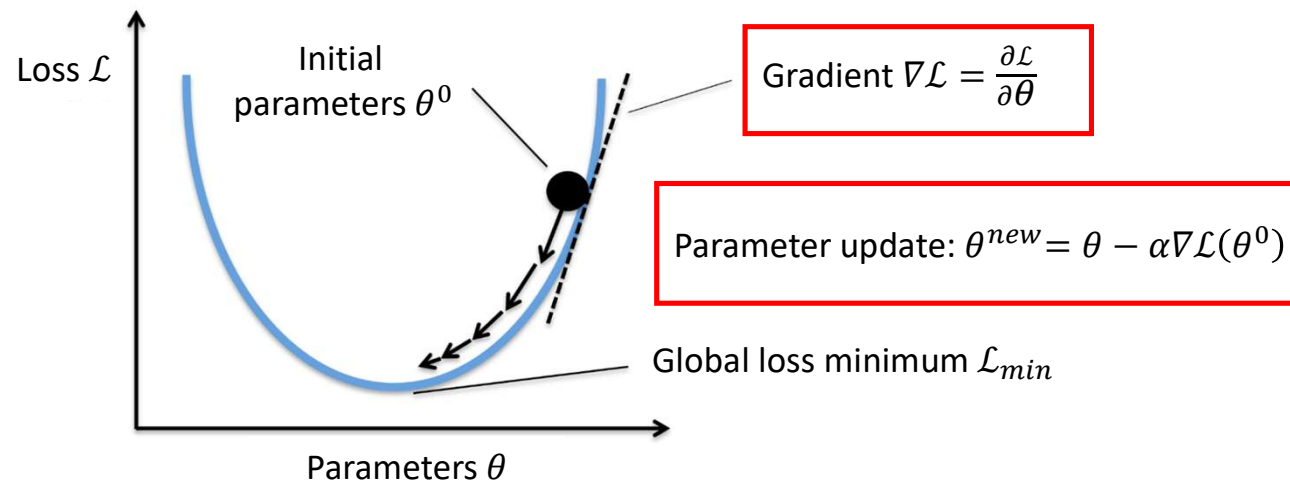
Adjust weights based on error



Neural Network

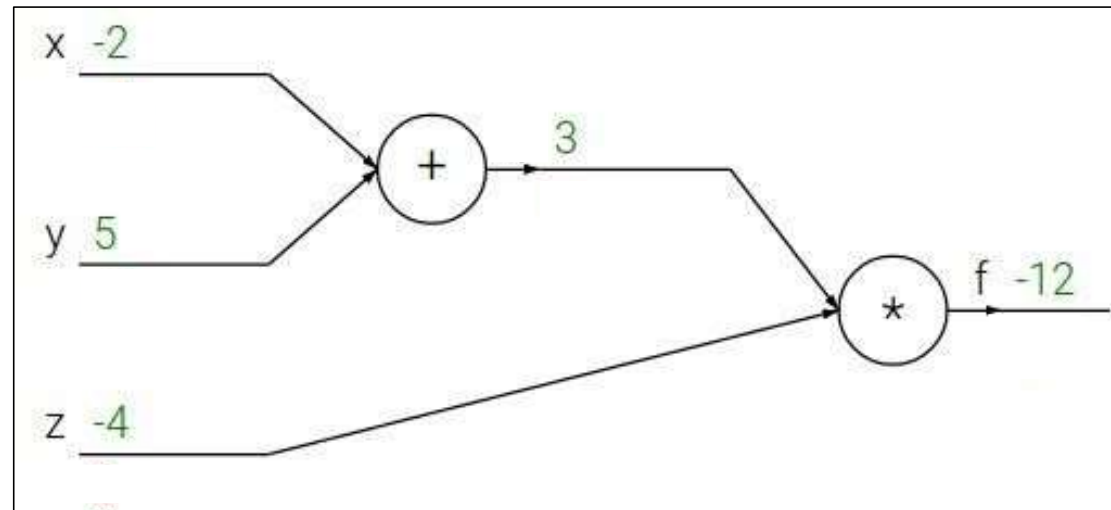
# Gradient Descent Algorithm -- Recap

- Steps in the *gradient descent algorithm*:
  1. Randomly initialize the model parameters,  $\theta^0$
  2. Compute the gradient of the loss function at the initial parameters  $\theta^0$ :  $\nabla\mathcal{L}(\theta^0)$
  3. Update the parameters as:  $\theta^{new} = \theta^0 - \alpha\nabla\mathcal{L}(\theta^0)$ 
    - Where  $\alpha$  is the learning rate
  4. Go to step 2 and repeat (until a terminating criterion is reached)



$$f(x, y, z) = (x + y)z$$

e.g.  $x = -2, y = 5, z = -4$



A simple Computational Graph / Circuit

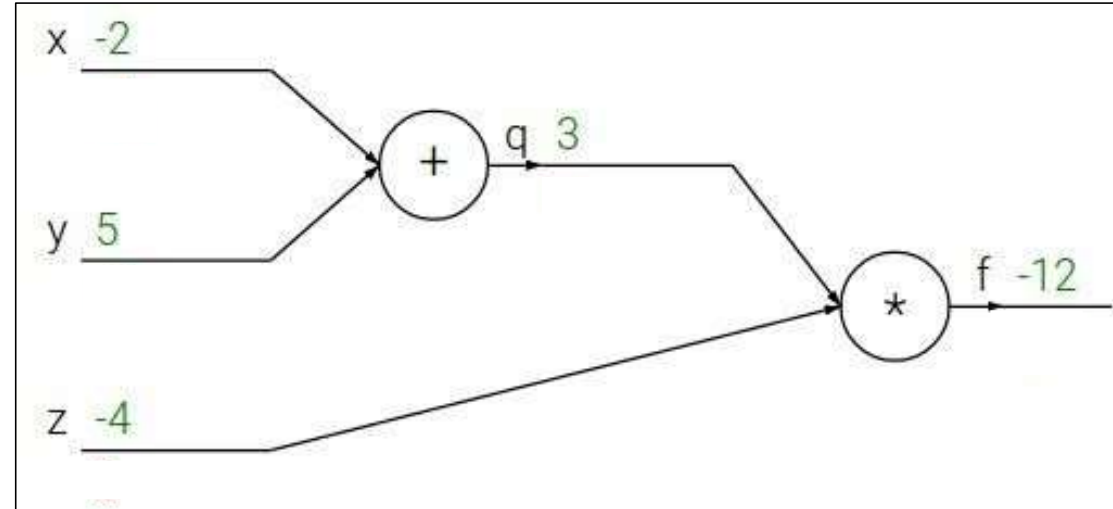
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Want:  $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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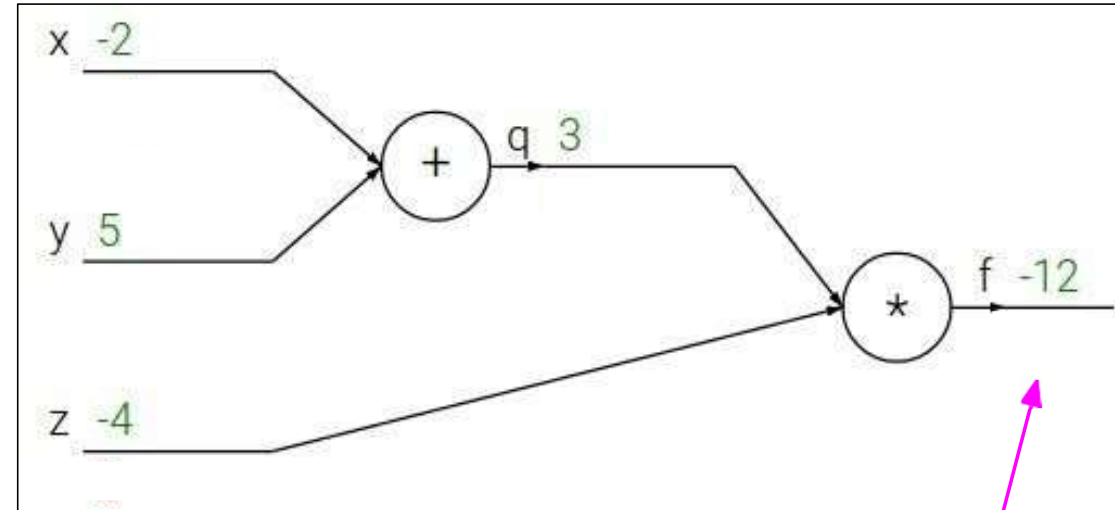
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$$\frac{\partial f}{\partial f}$$

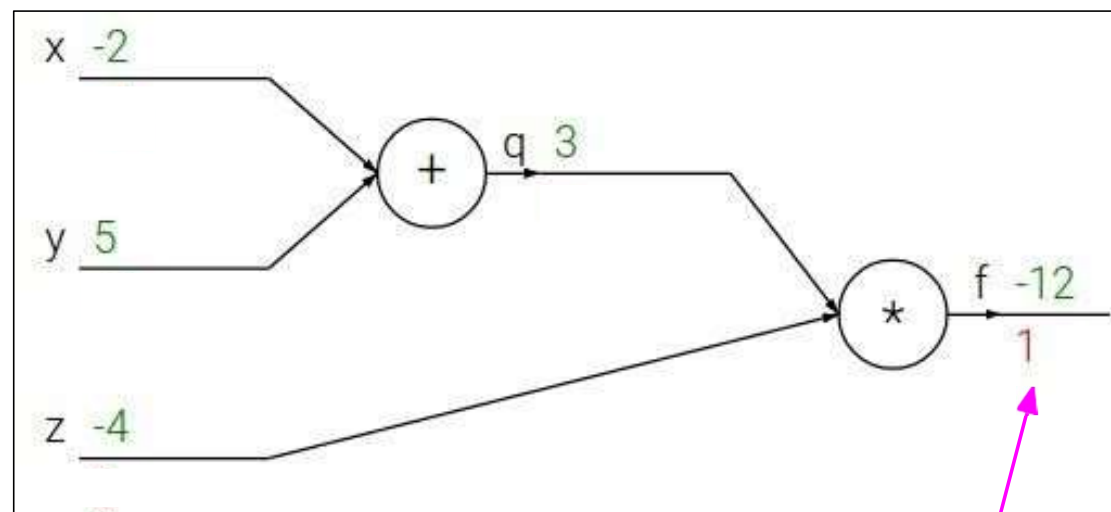
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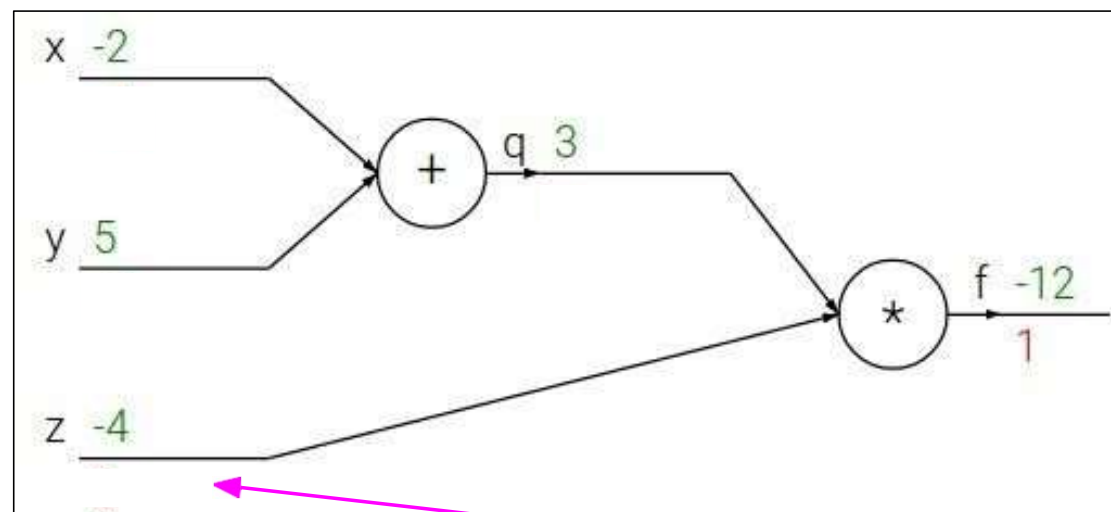
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$$\frac{\partial f}{\partial z}$$



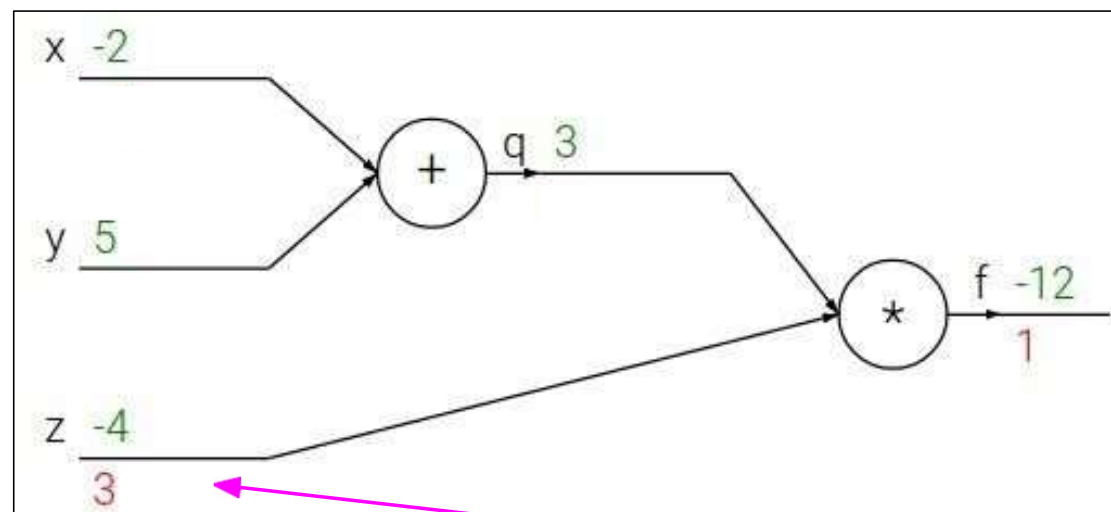
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$$\frac{\partial f}{\partial z}$$

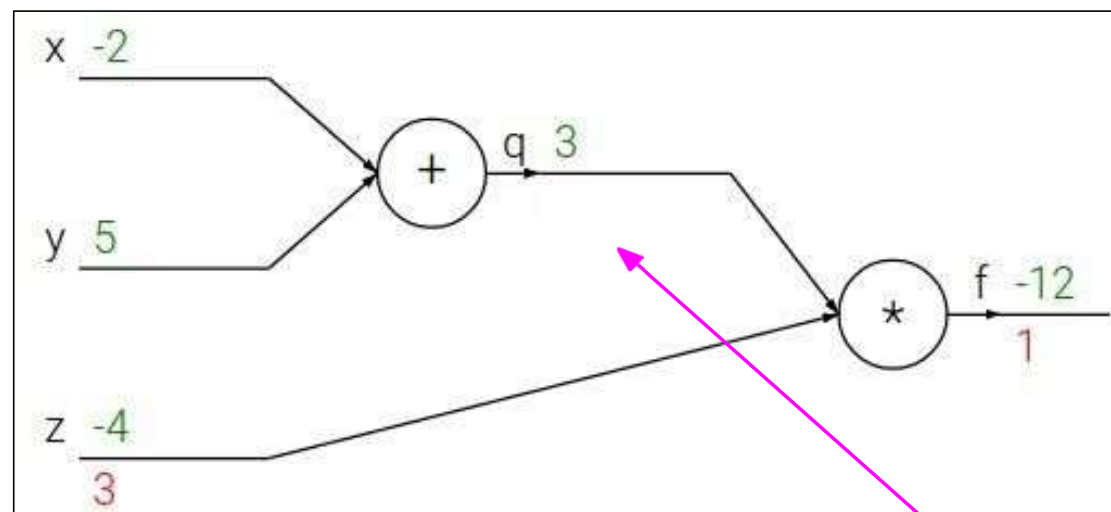
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$$\frac{\partial f}{\partial q}$$

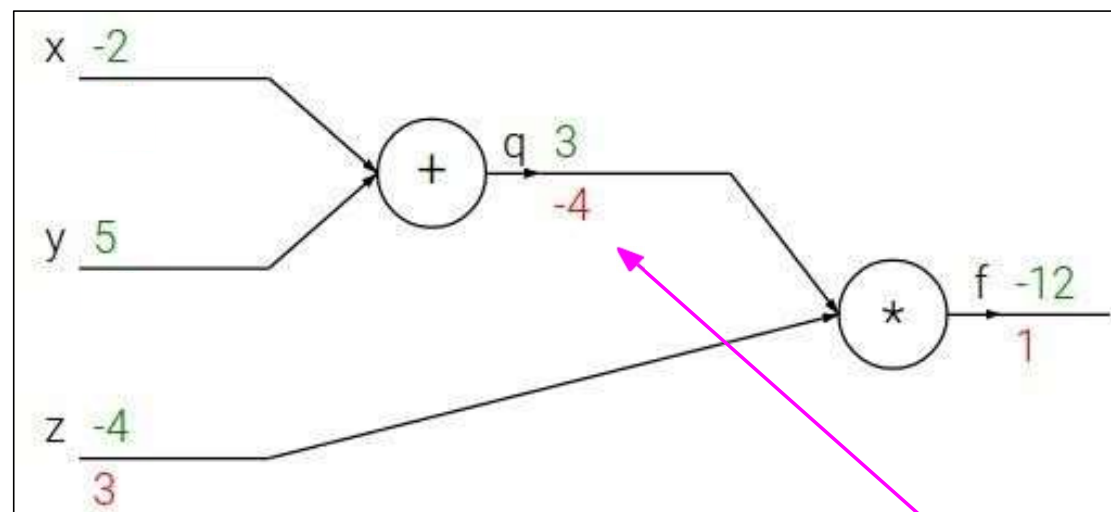
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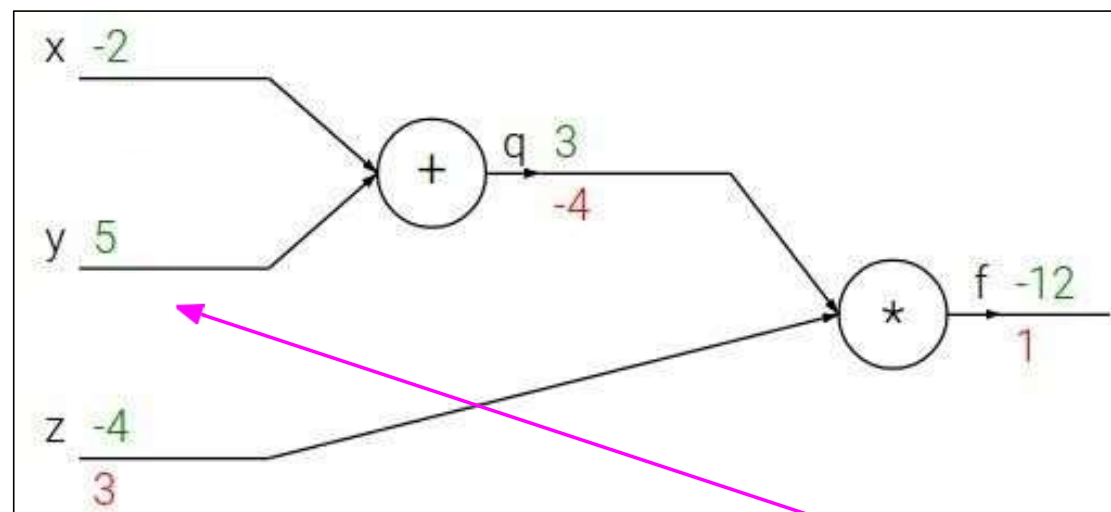
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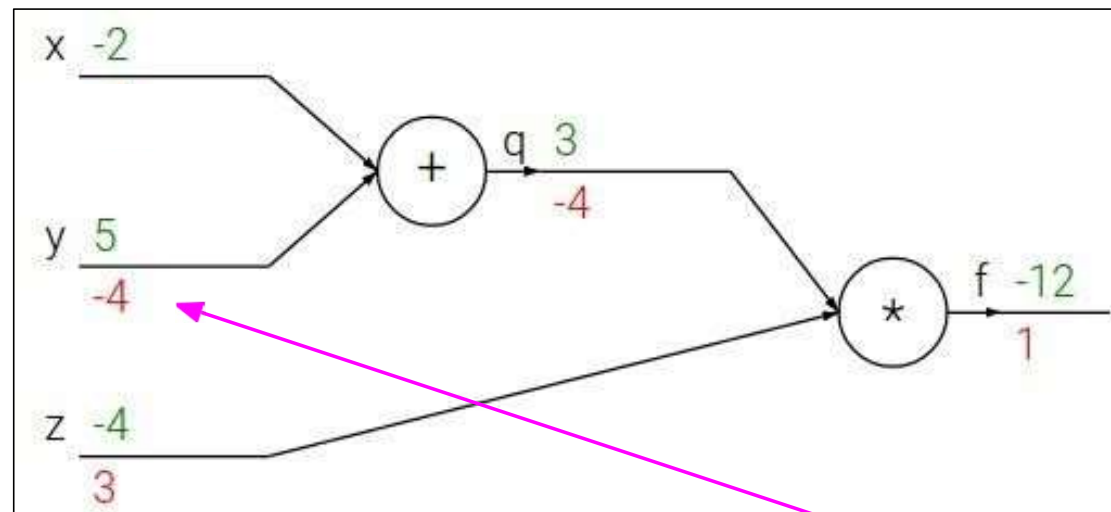
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Want:  $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



Chain rule:

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

$$\frac{\partial f}{\partial y}$$

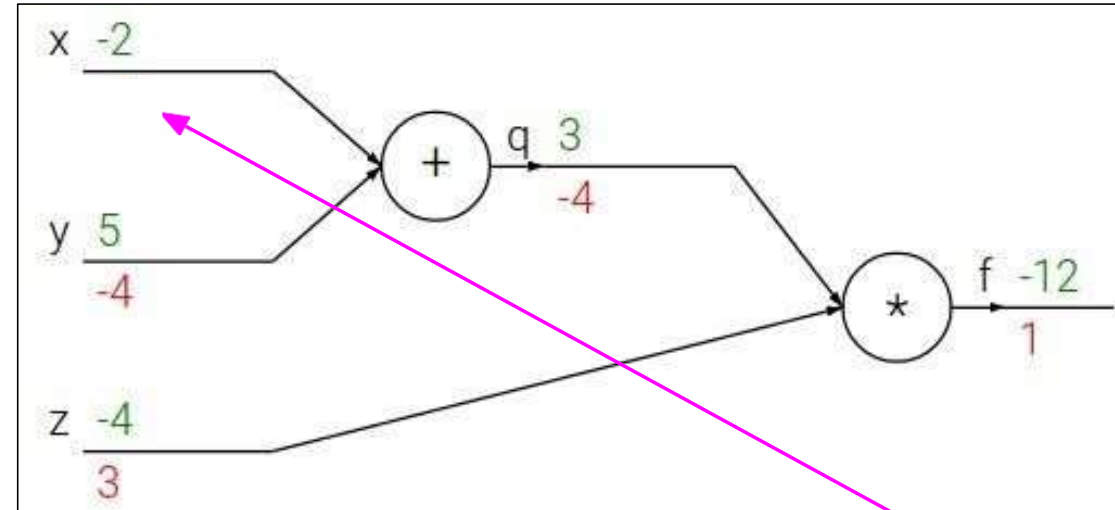
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$$\frac{\partial f}{\partial x}$$

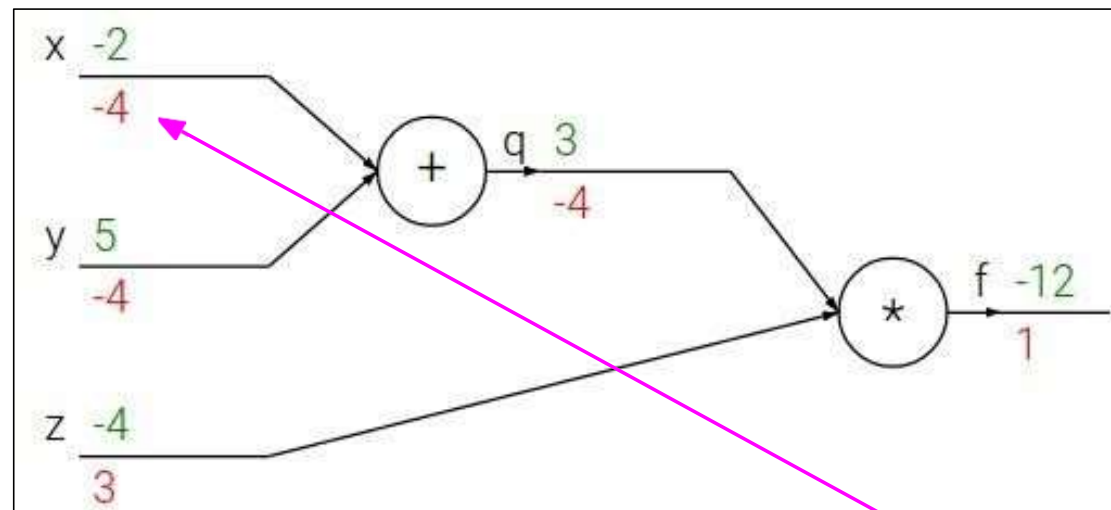
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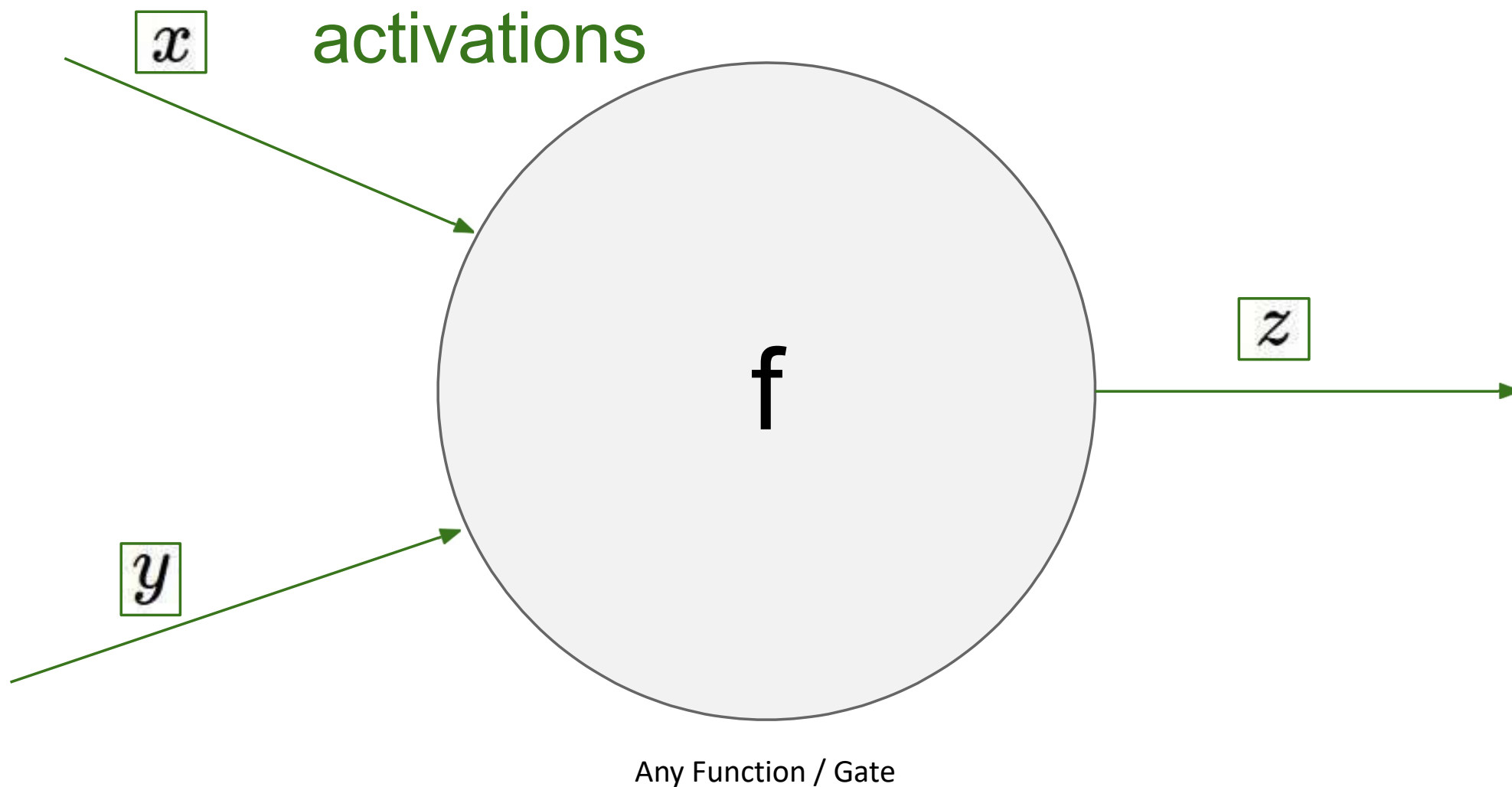
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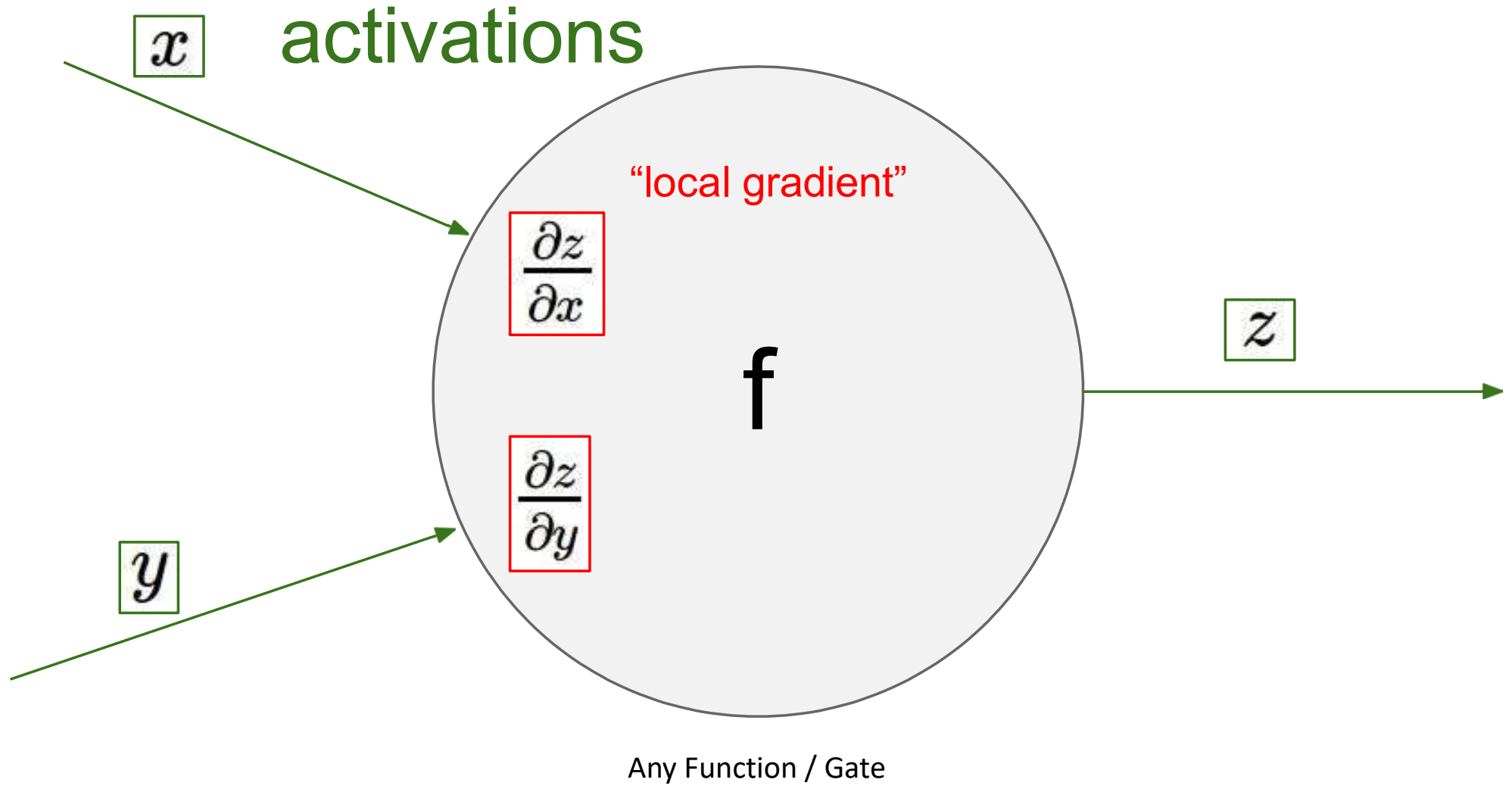
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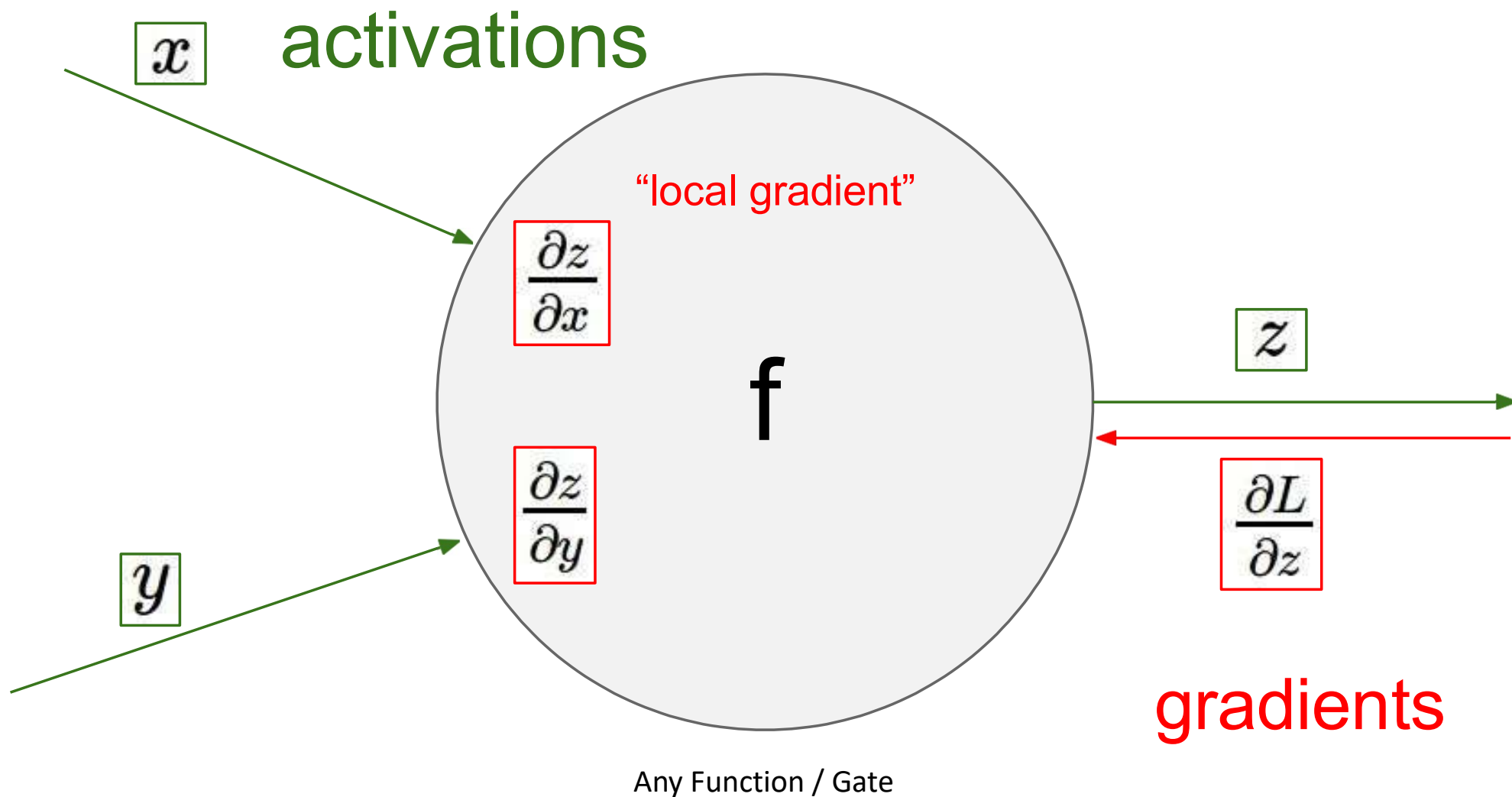
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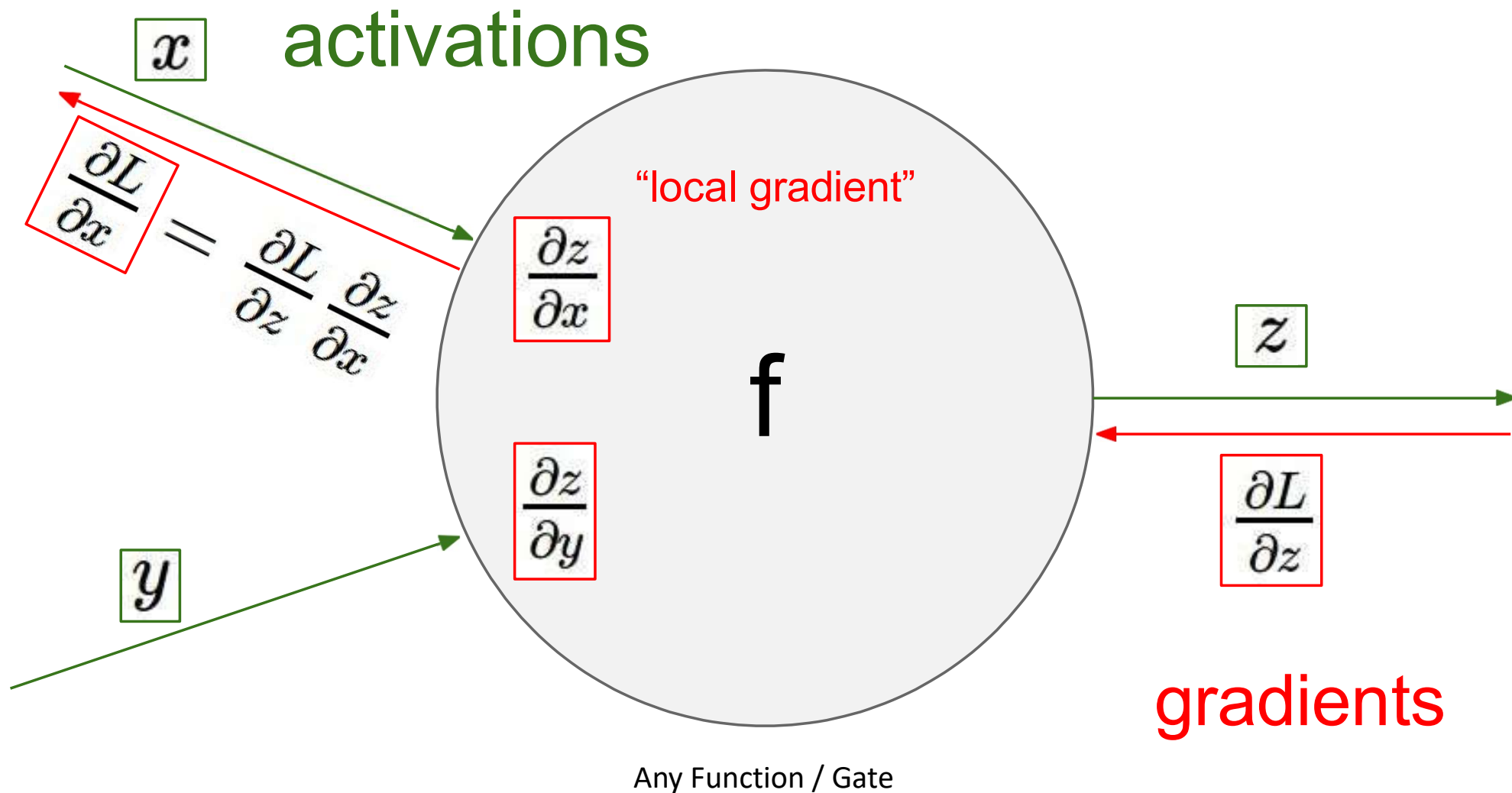
$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}$$

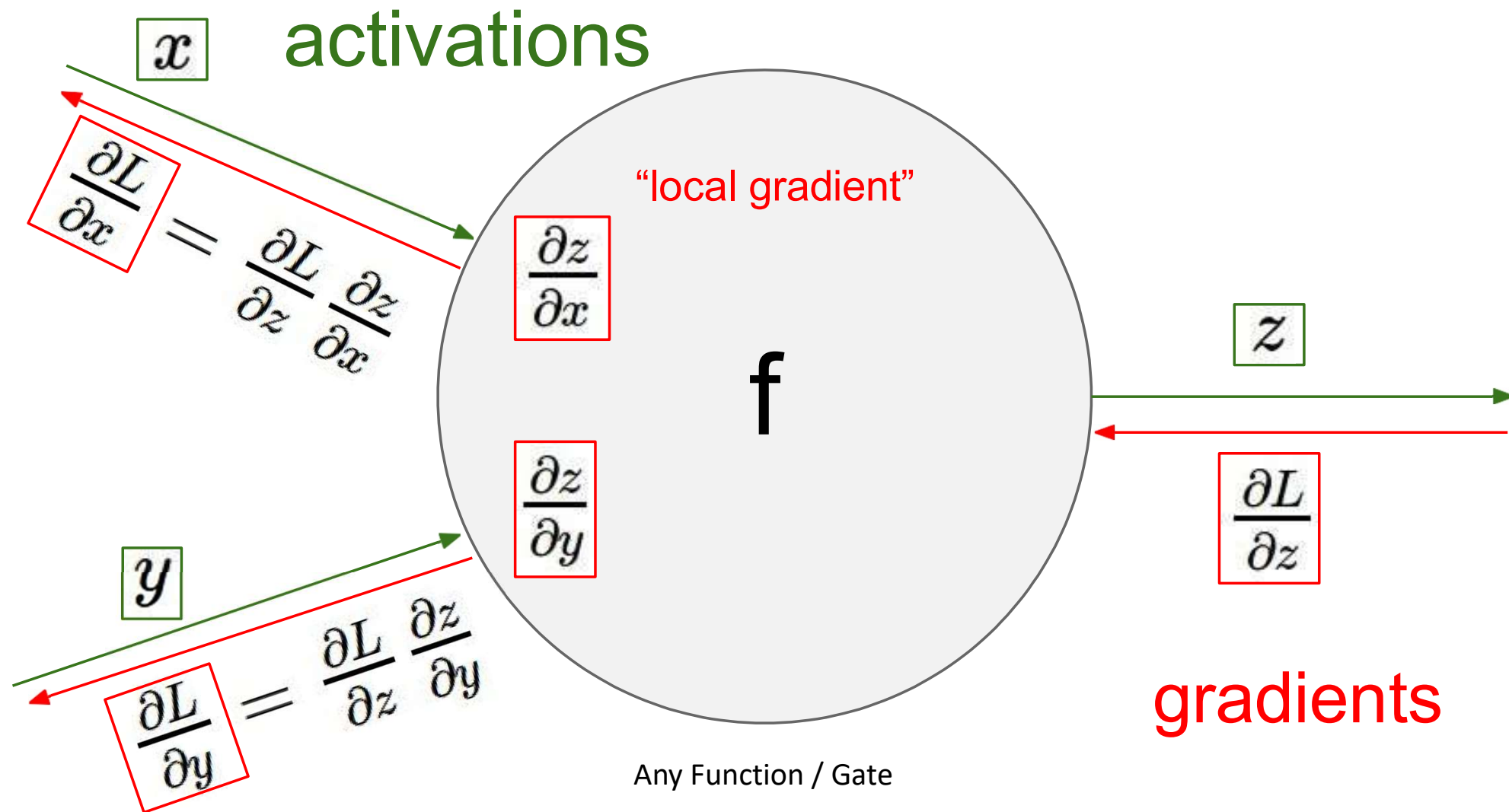


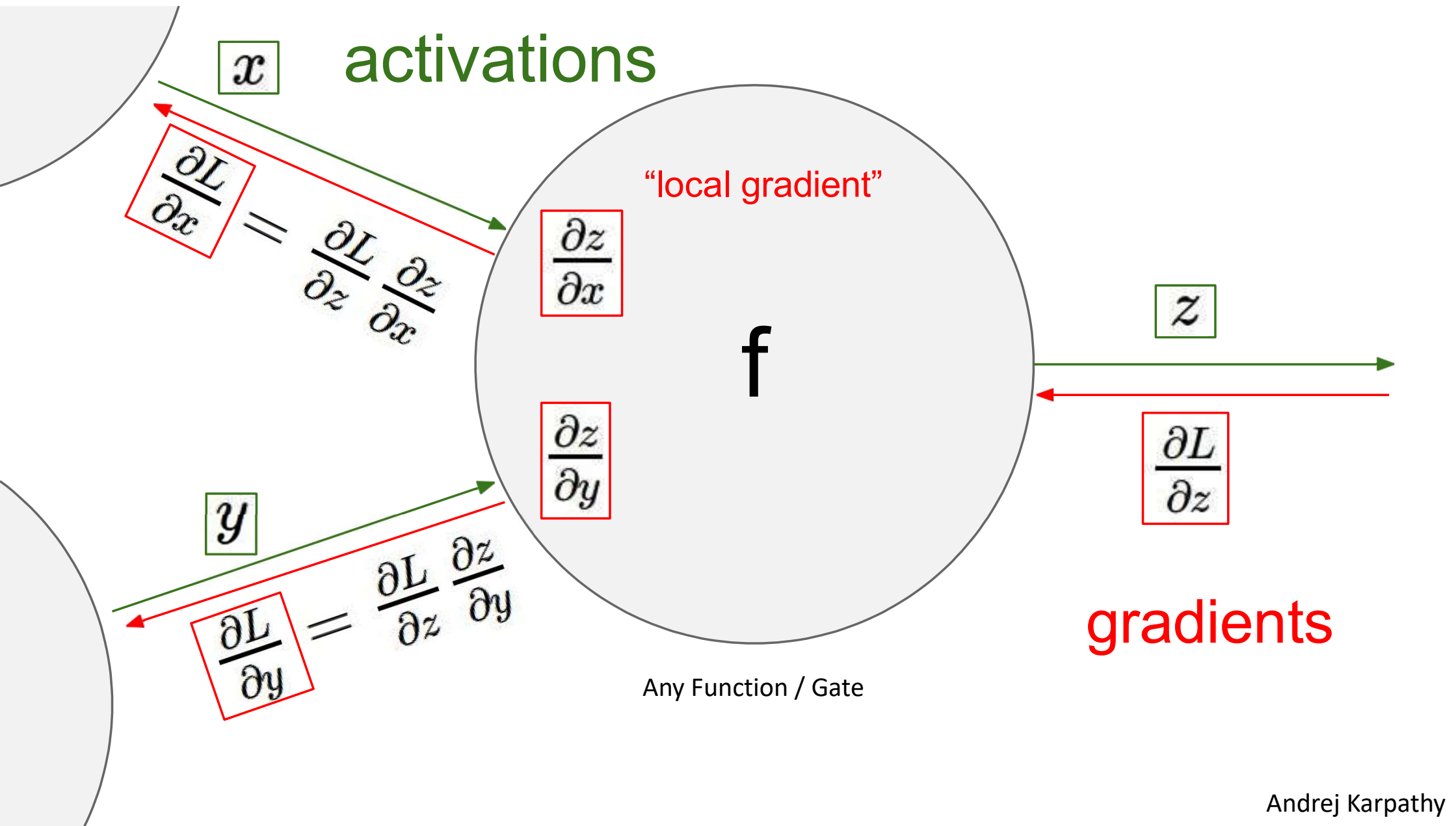




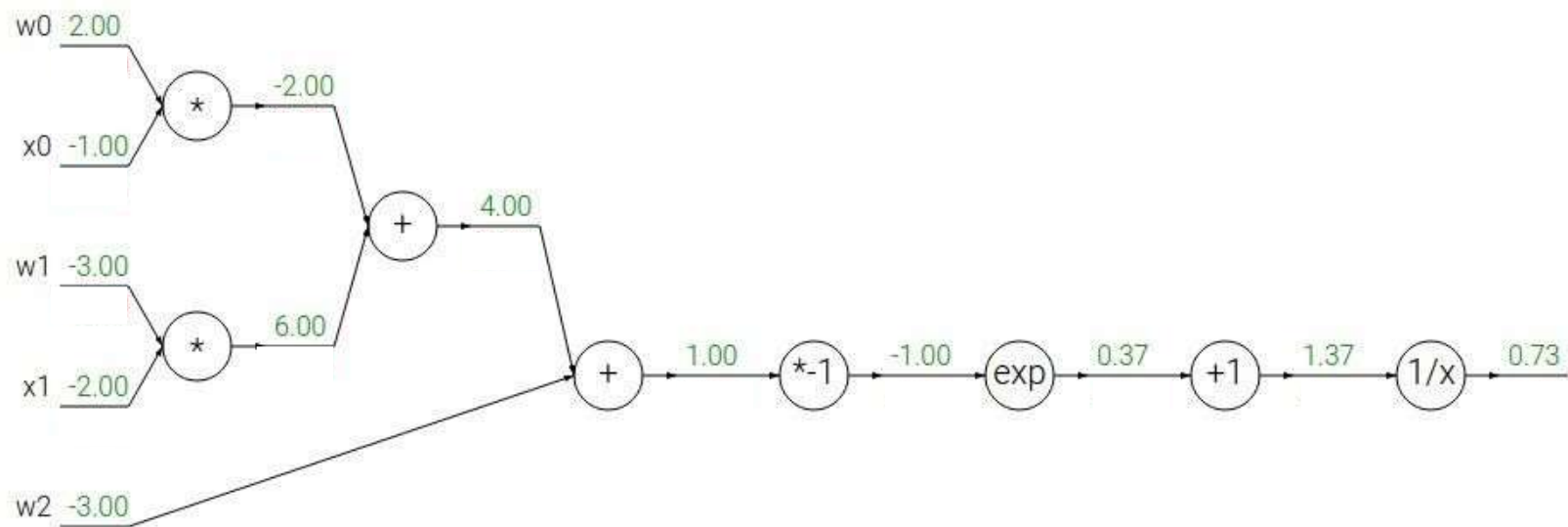






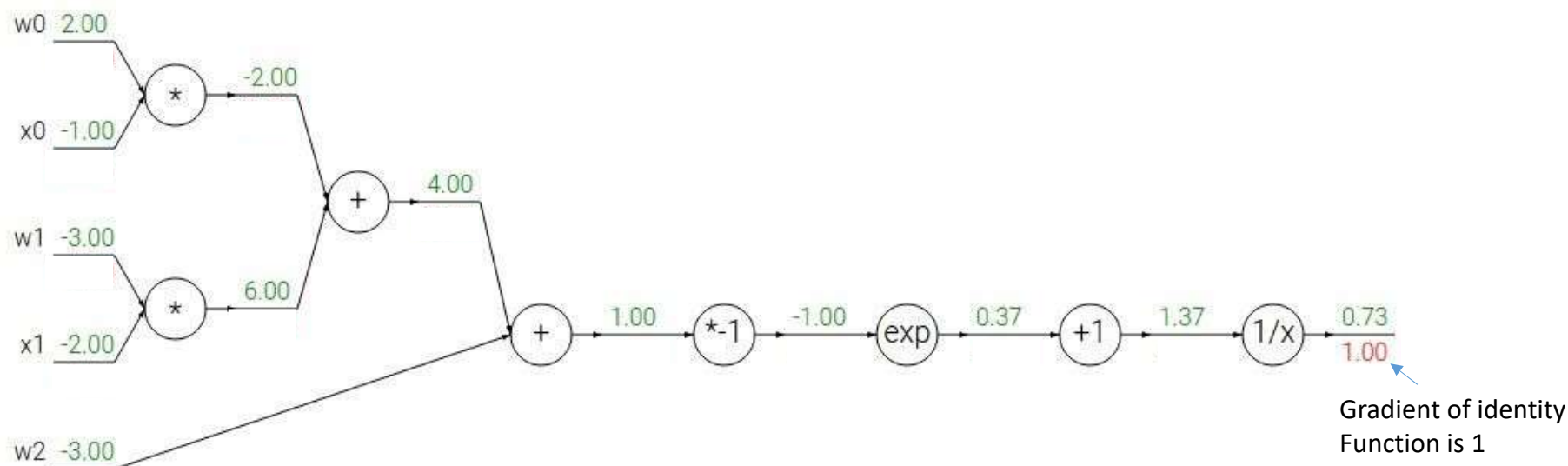


Another example:  $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



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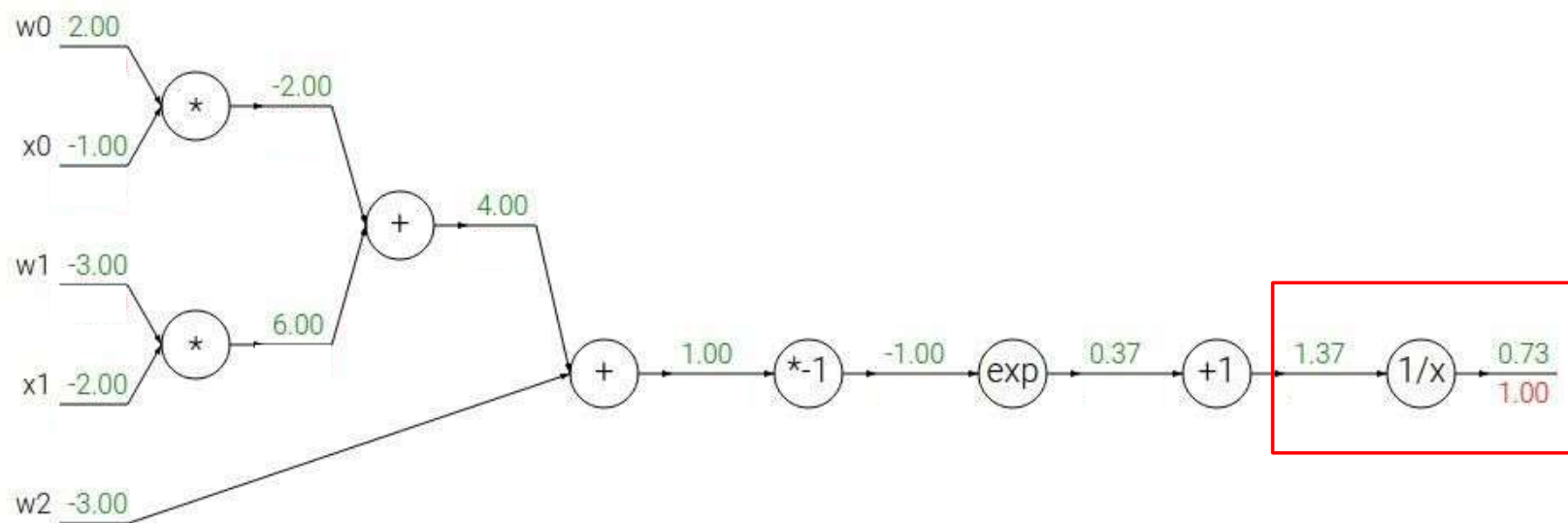
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$f(x) = e^x$	$\rightarrow$	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	$\rightarrow$	$\frac{df}{dx} = -1/x^2$
$f_a(x) = ax$	$\rightarrow$	$\frac{df}{dx} = a$		$f_c(x) = c + x$	$\rightarrow$	$\frac{df}{dx} = 1$

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$\rightarrow$

$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

$\rightarrow$

$$\frac{df}{dx} = a$$

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$\rightarrow$

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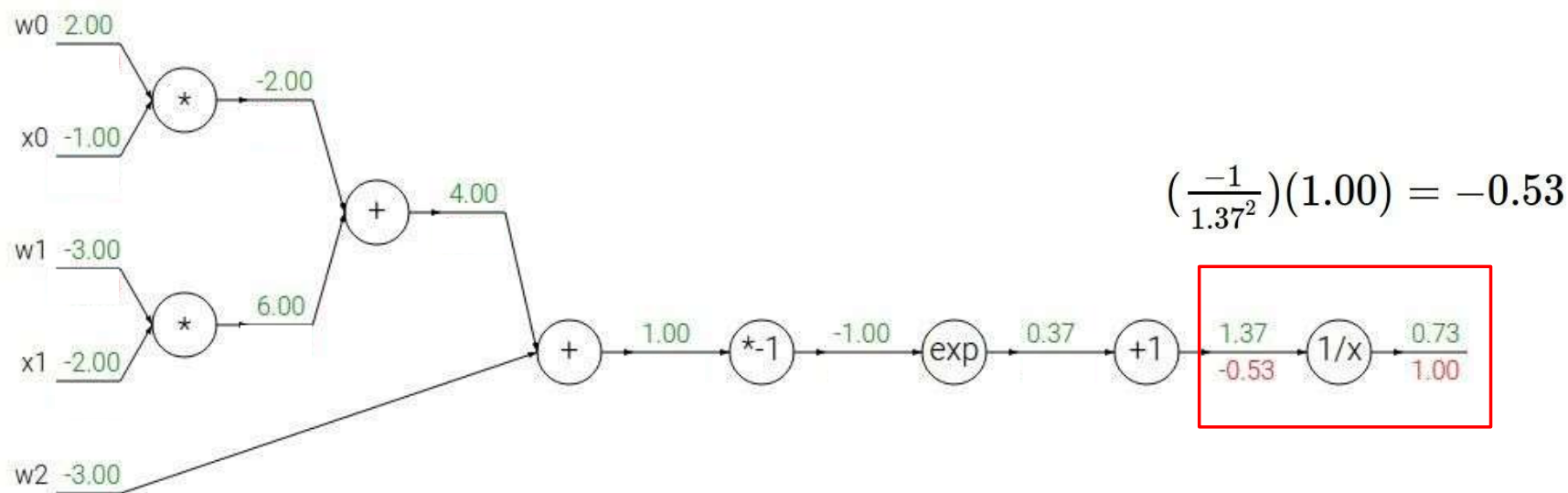
$\rightarrow$

$$\frac{df}{dx} = 1$$



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$$f(w, x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$$



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→

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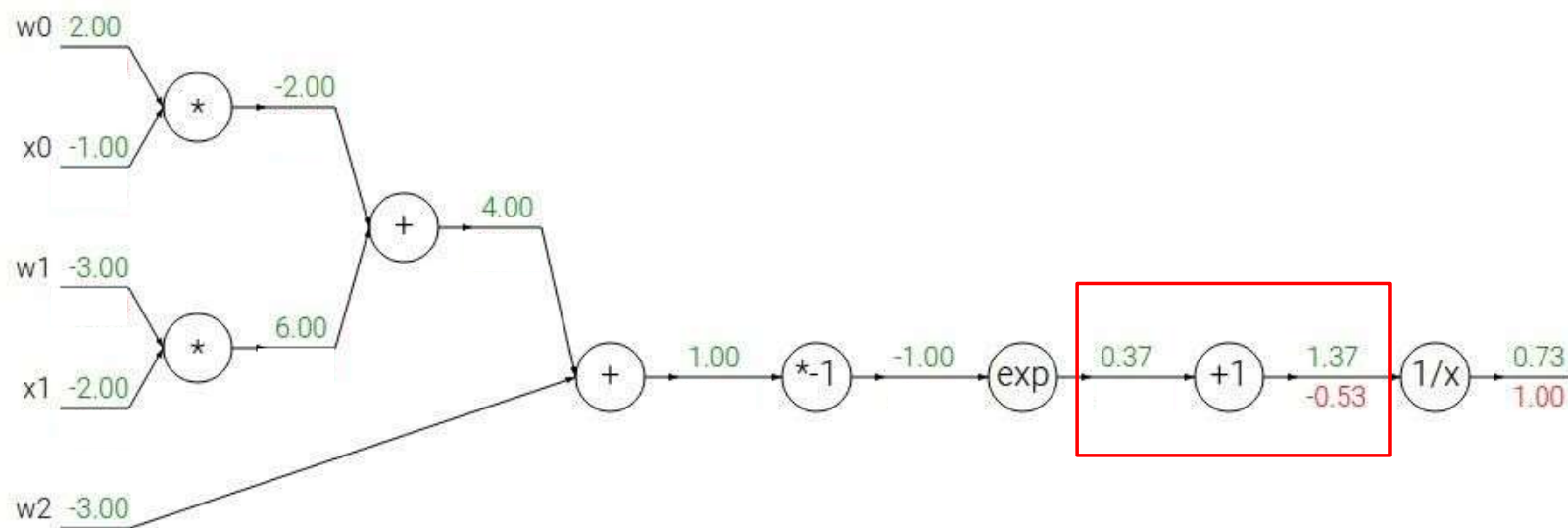
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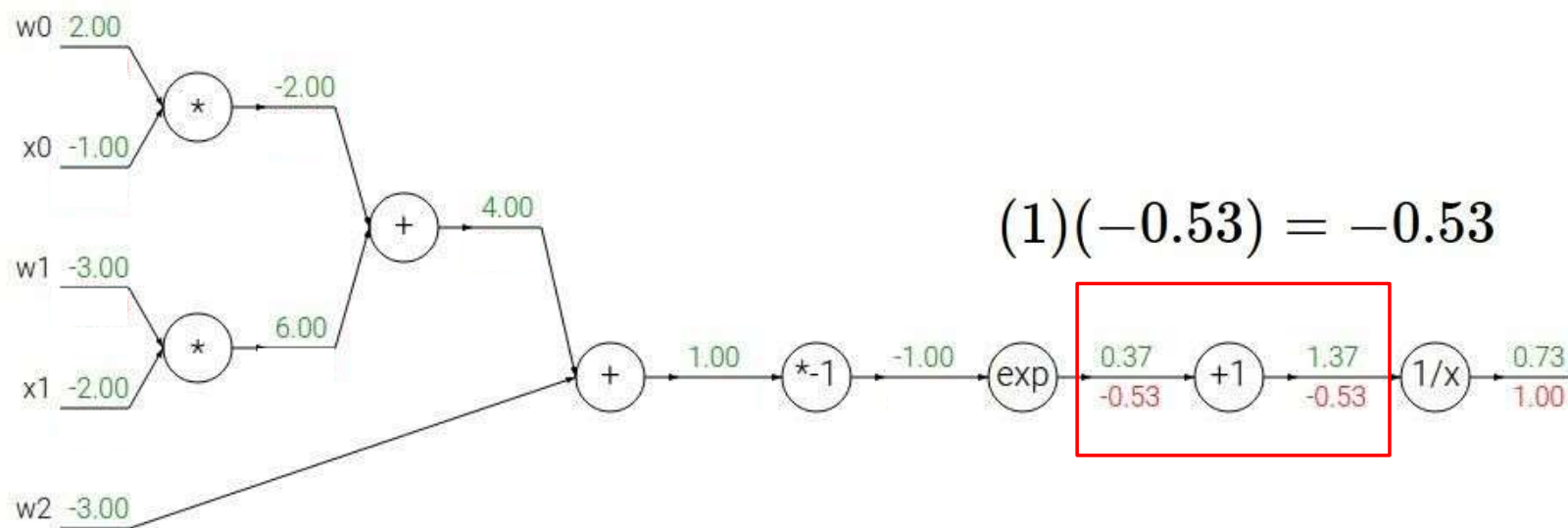
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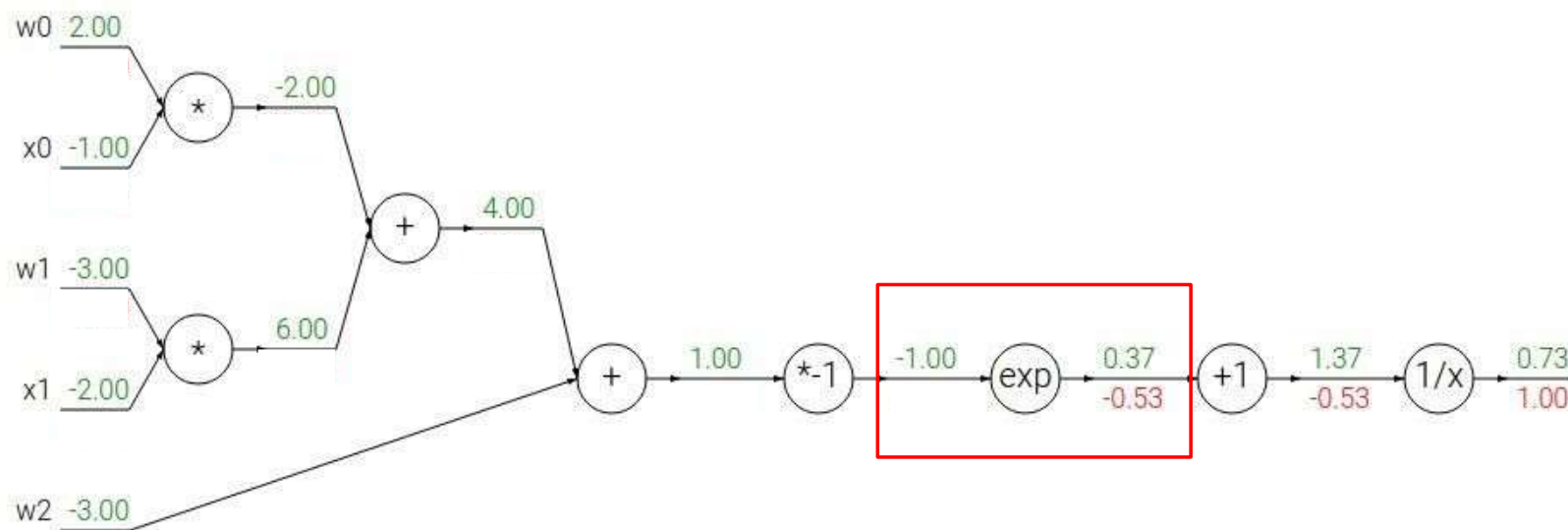
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$$f(x) = e^x \rightarrow \frac{df}{dx} = e^x$$

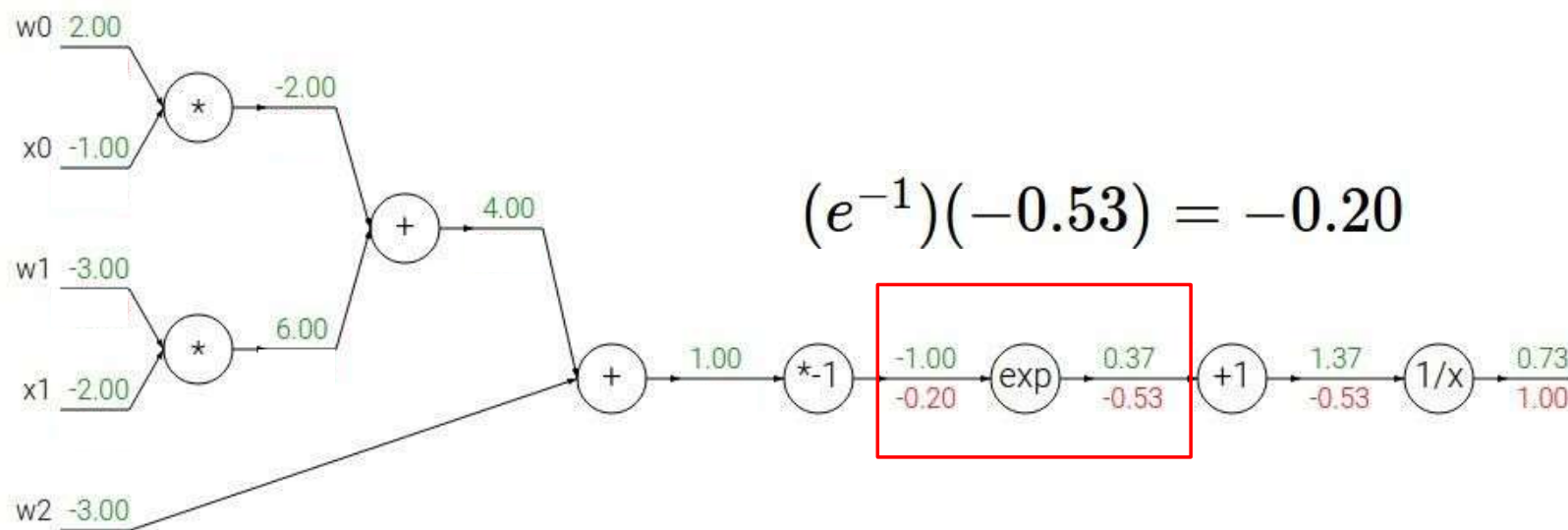
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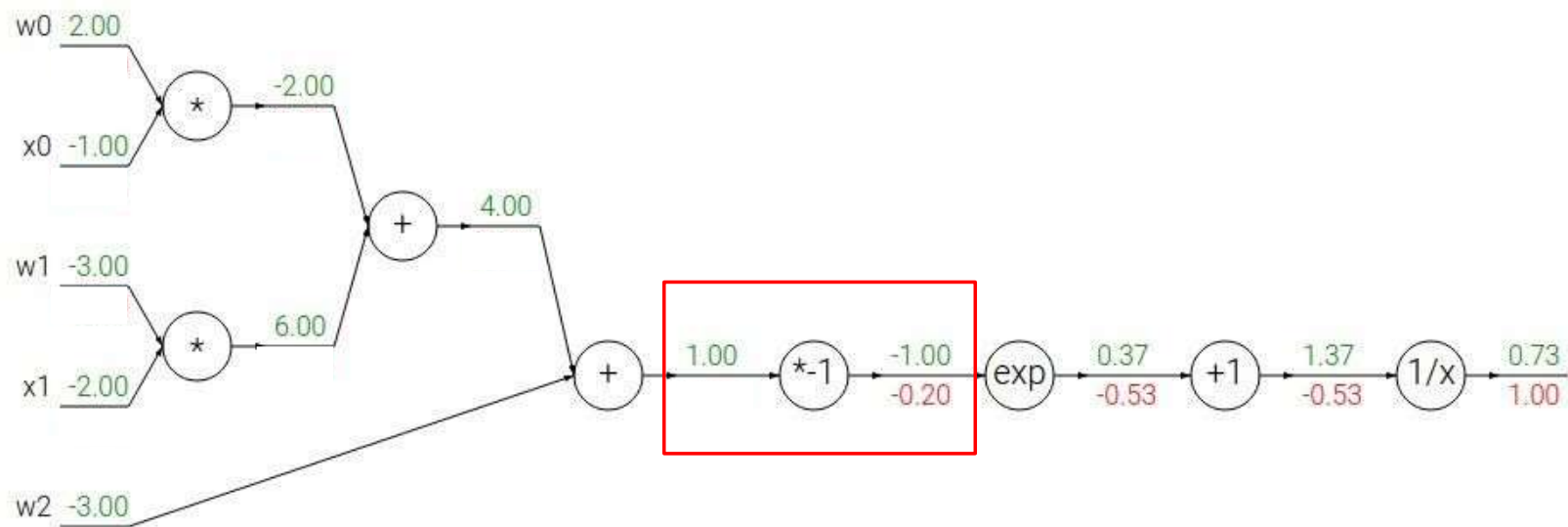
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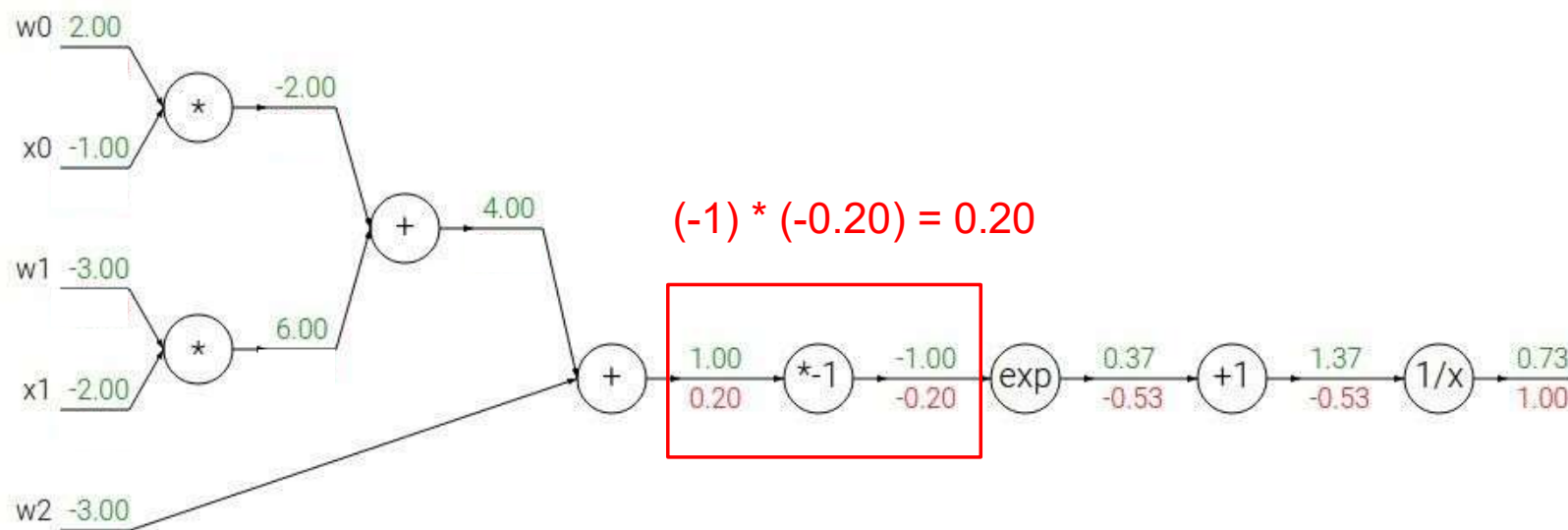
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$$f(x) = e^x \rightarrow \frac{df}{dx} = e^x$$

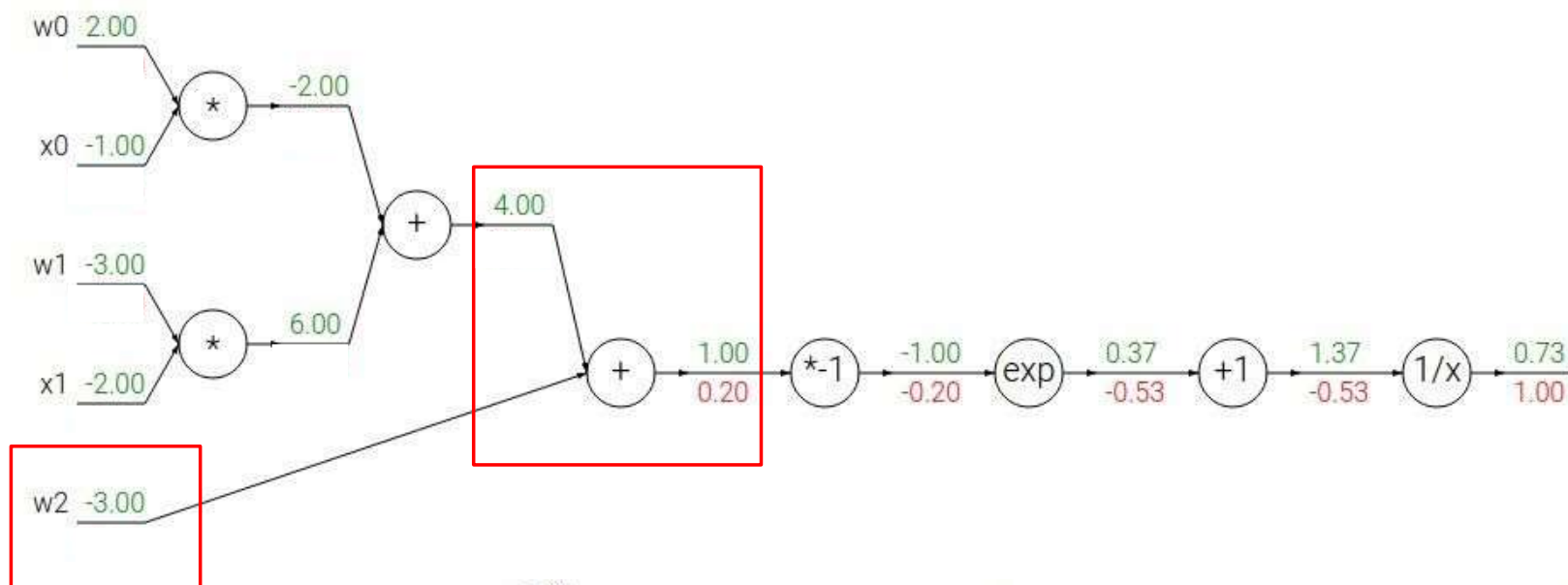
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$$f(w, x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$$



$$f(x) = e^x$$

→

$$\frac{df}{dx} = e^x$$

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→

$$\frac{df}{dx} = a$$

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$$\frac{df}{dx} = -1/x^2$$

$$f_c(x) = c + x$$

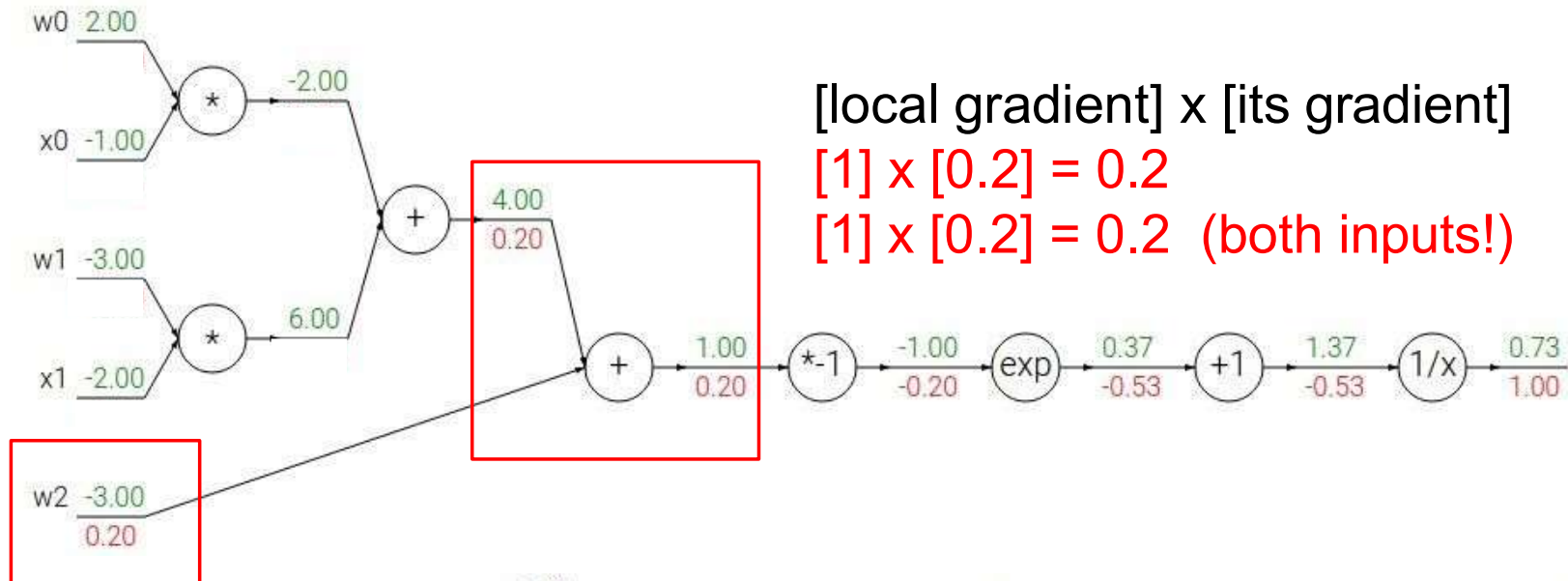
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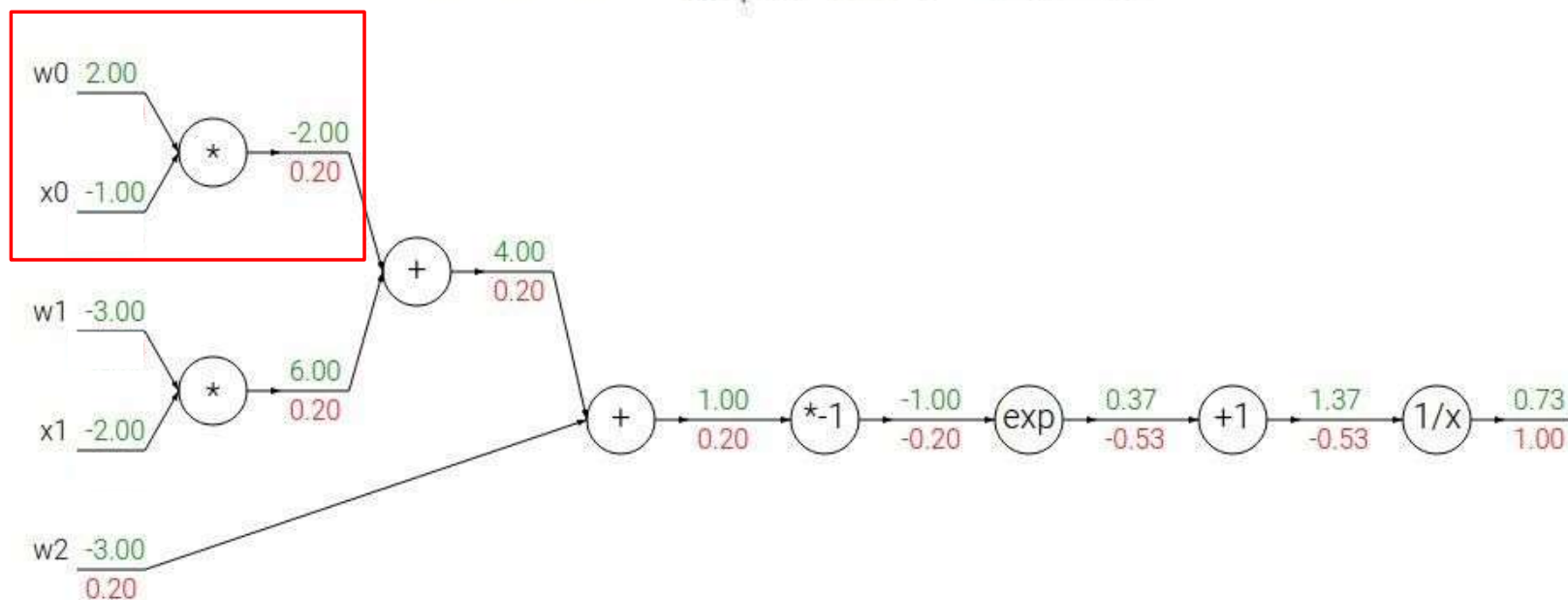
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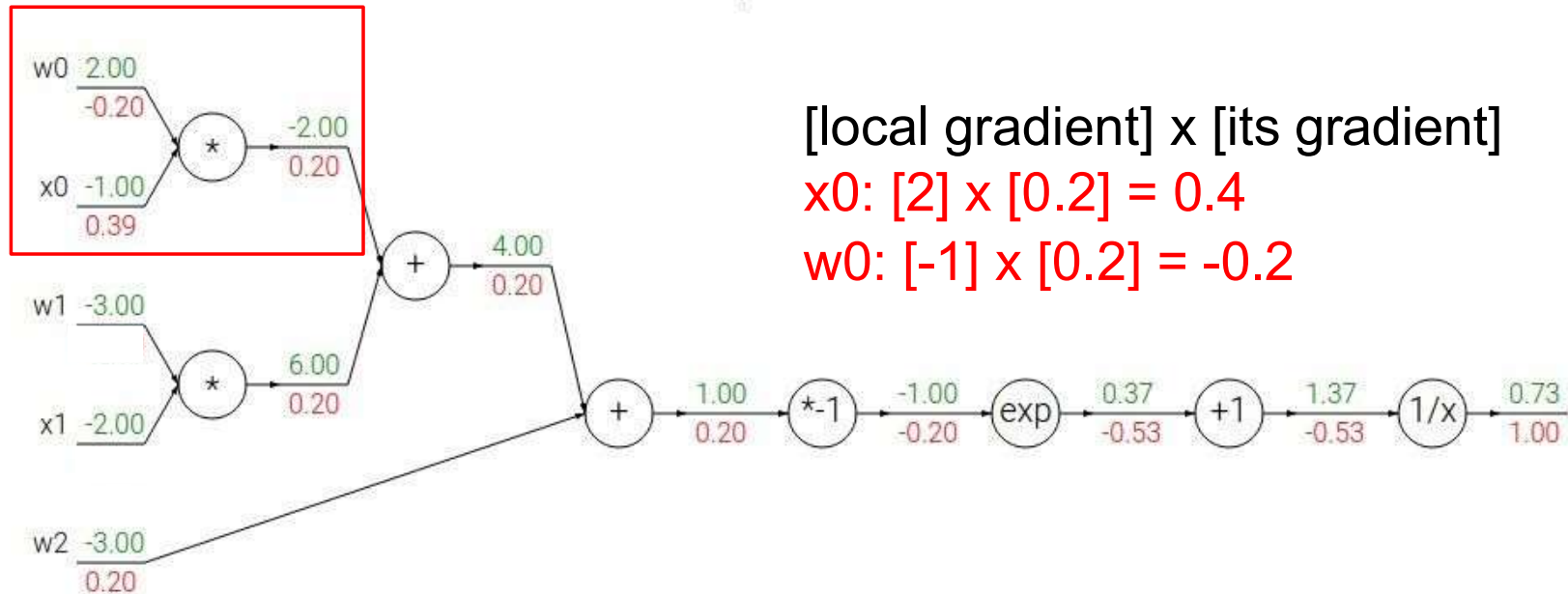
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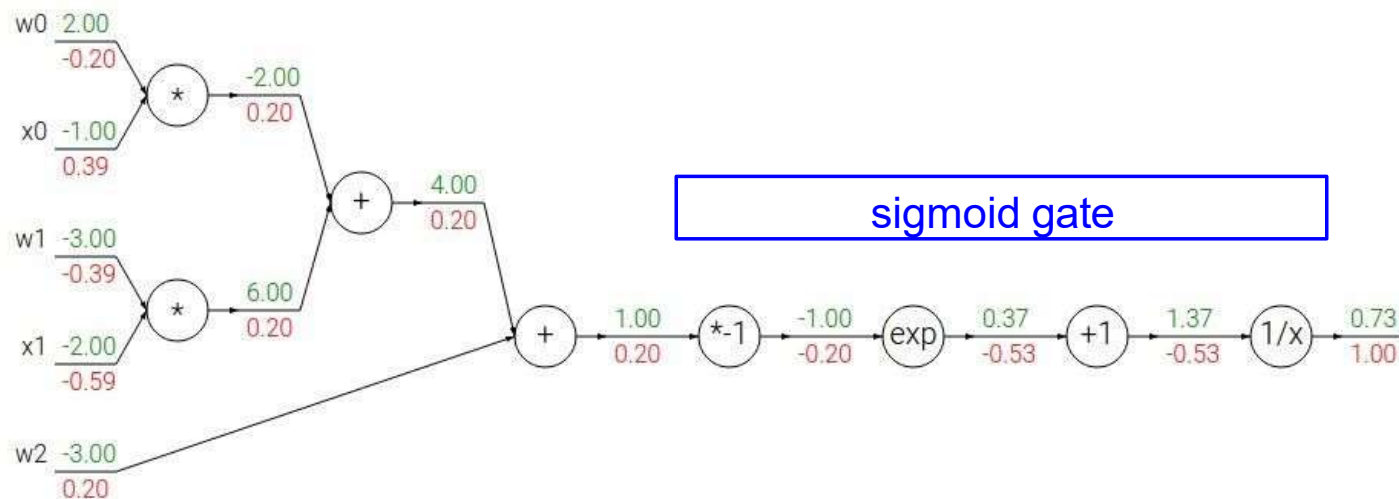
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$$f(w, x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

sigmoid function

$$\frac{d\sigma(x)}{dx} = \frac{e^{-x}}{(1 + e^{-x})^2} = \left( \frac{1 + e^{-x} - 1}{1 + e^{-x}} \right) \left( \frac{1}{1 + e^{-x}} \right) = (1 - \sigma(x)) \sigma(x)$$



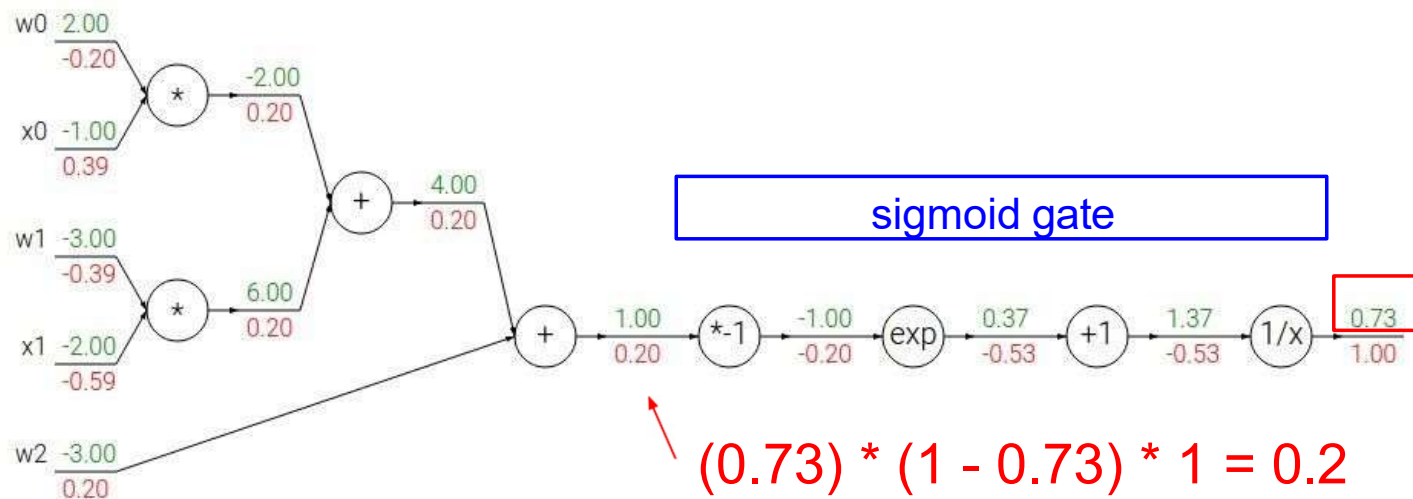
sigmoid gate

$$f(w, x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$$

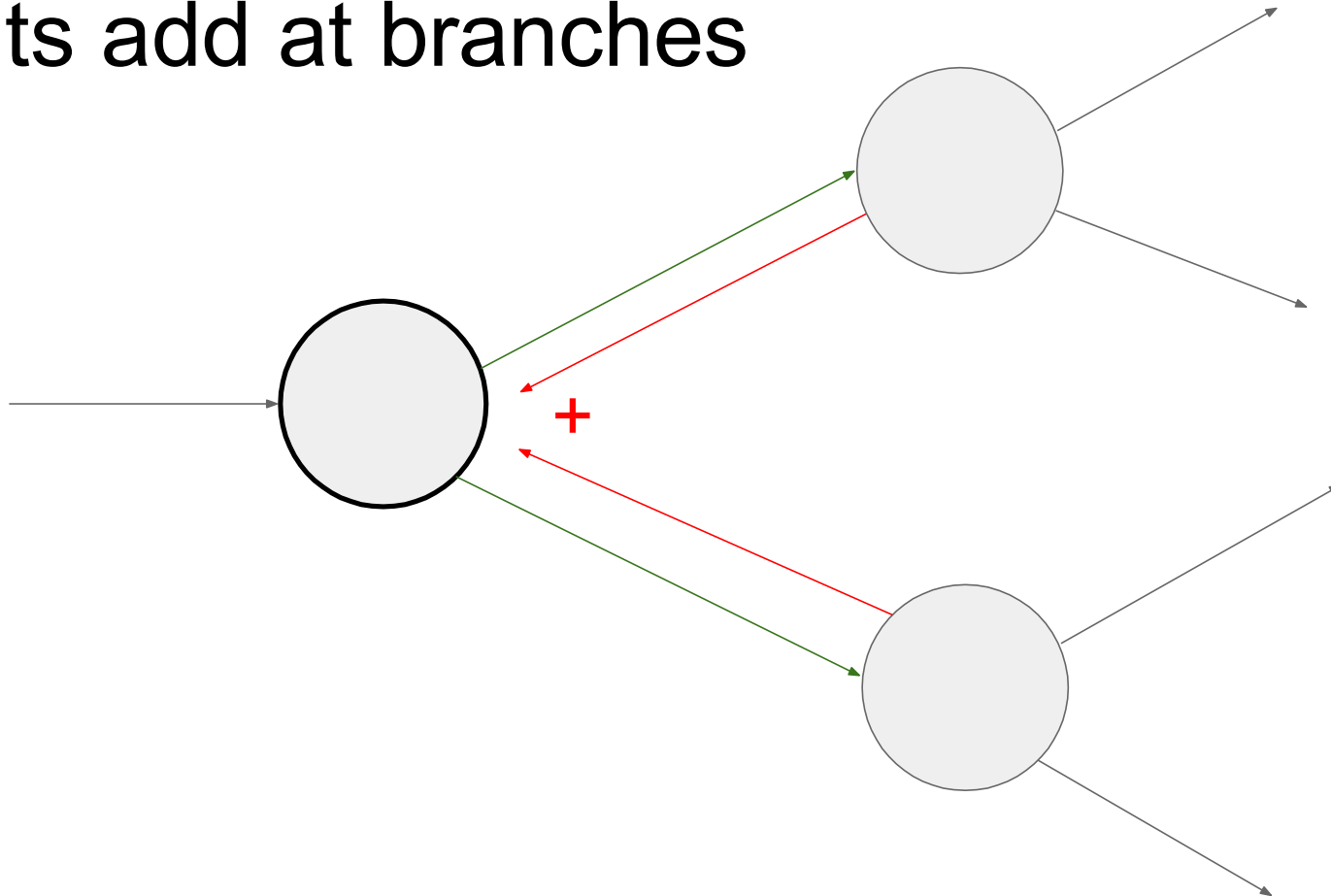
$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

sigmoid function

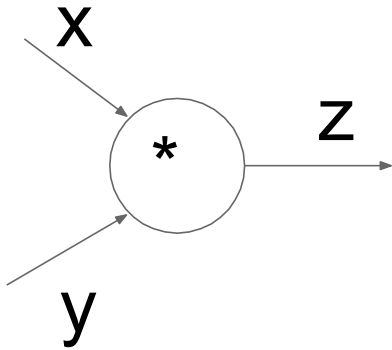
$$\frac{d\sigma(x)}{dx} = \frac{e^{-x}}{(1 + e^{-x})^2} = \left( \frac{1 + e^{-x} - 1}{1 + e^{-x}} \right) \left( \frac{1}{1 + e^{-x}} \right) = (1 - \sigma(x)) \sigma(x)$$



# Gradients add at branches



# Implementation: forward/backward API



```
class MultiplyGate(object):  
    def forward(x,y):  
        z = x*y  
        self.x = x # must keep these around!  
        self.y = y  
        return z  
    def backward(dz):  
        dx = self.y * dz # [dz/dx * dL/dz]  
        dy = self.x * dz # [dz/dy * dL/dz]  
        return [dx, dy]
```

(x,y,z are scalars)



# Implementation: forward/backward

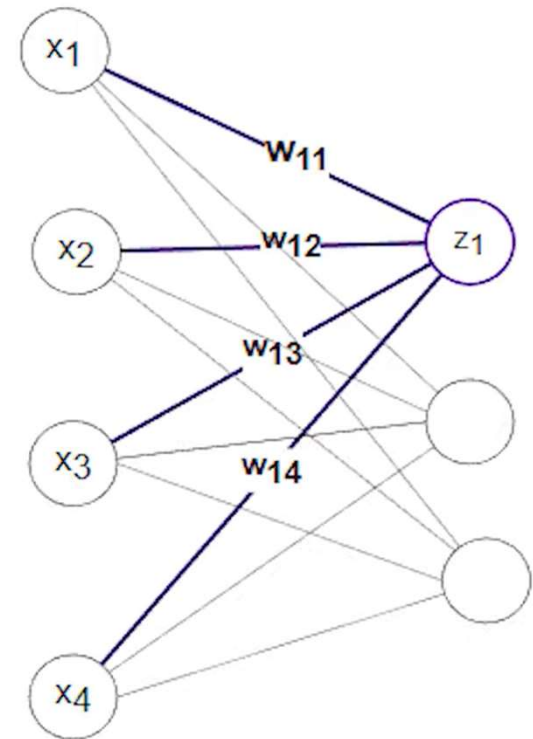
**1- Find generic equations for forward and backward propagation**

**2- Find gradient values for the following weights**

```
weights = numpy.array([0.80, 0.87, 0.16, 0.96, 0.89, 0.87, 0.31, 0.08, 0.09, 0.69, 0.03, 0.42])
```

```
inputs = numpy.array([0.75, 0.98, 0.74, 0.28])
```

```
biases = numpy.array([0.68, 0.83, 0.01])
```



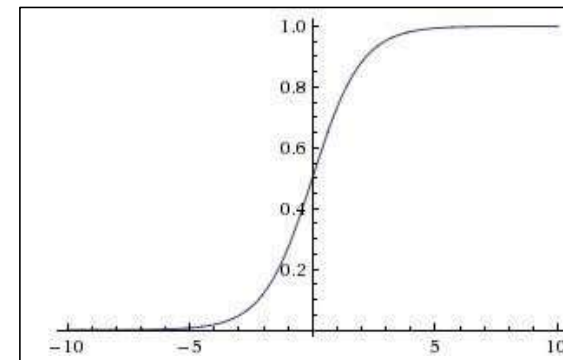
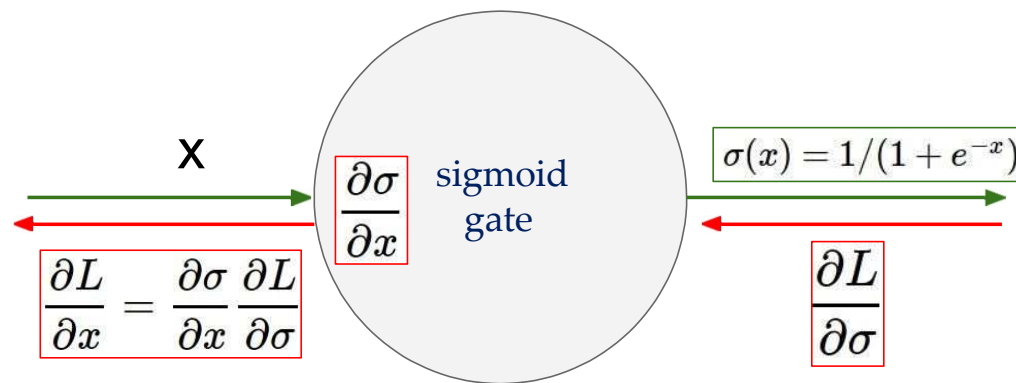


# Backpropagation Summary

- Modern NNs employ the *backpropagation* method for calculating the gradients of the loss function  $\nabla \mathcal{L}(\theta) = \partial \mathcal{L} / \partial \theta_i$ 
  - Backpropagation is short for “backward propagation”
- For training NNs, **forward propagation** (forward pass) refers to passing the inputs  $x$  through the hidden layers to obtain the model outputs (predictions)  $y$ 
  - The loss  $\mathcal{L}(y, \hat{y})$  function is then calculated
  - **Backpropagation** traverses the network in reverse order, from the outputs  $y$  backward toward the inputs  $x$  to calculate the gradients of the loss  $\nabla \mathcal{L}(\theta)$
  - The chain rule is used for calculating the partial derivatives of the loss function with respect to the parameters  $\theta$  in the different layers in the network
- Each update of the model parameters  $\theta$  during training takes one forward and one backward pass (e.g., of a batch of inputs)
- Automatic calculation of the gradients (**automatic differentiation**) is available in all current deep learning libraries
  - It significantly simplifies the implementation of deep learning algorithms, since it avoids deriving the partial derivatives of the loss function by hand

# Vanishing Gradient Problem

- In some cases, during training, the gradients can become either very small (vanishing gradients) or very large (exploding gradients)
  - They result in very small or very large update of the parameters
  - Solutions: change learning rate, ReLU activations, regularization

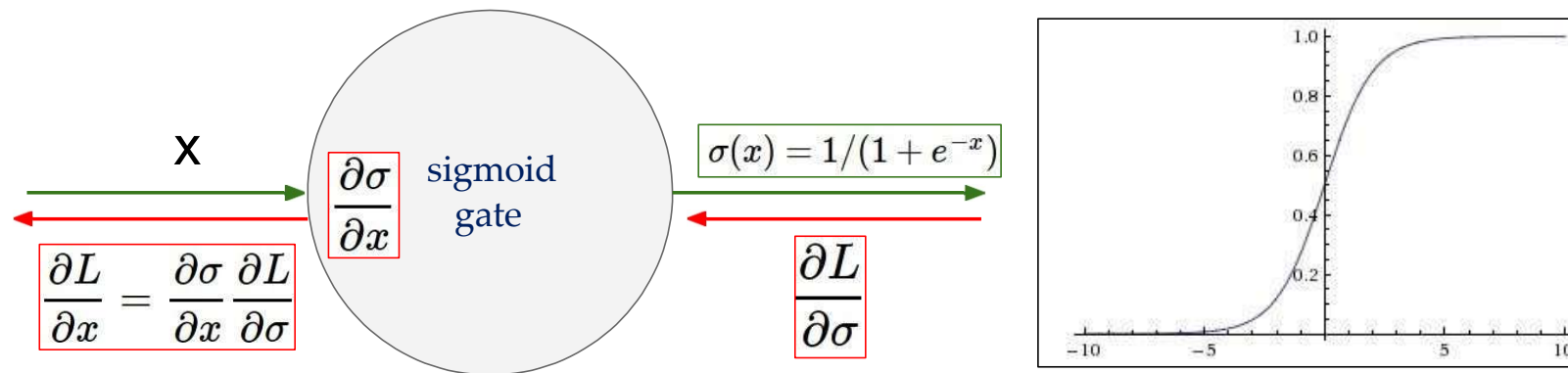


What happens when  $x = -10$ ?

What happens when  $x = 0$ ?

What happens when  $x = 10$ ?

# Vanishing Gradient Problem



What happens when  $x = -10$ ? (almost zero)

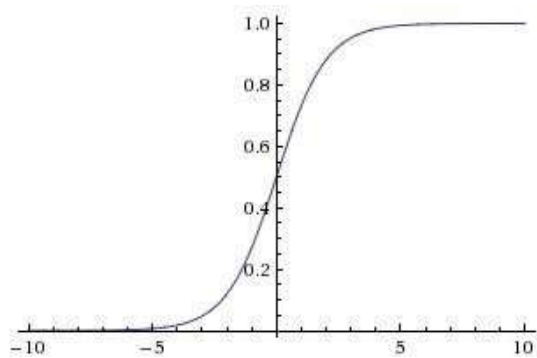
What happens when  $x = 0$ ? (small value)

What happens when  $x = 10$ ? (almost zero)

# Vanishing Gradient Problem

---

## Activation Functions



**Sigmoid**

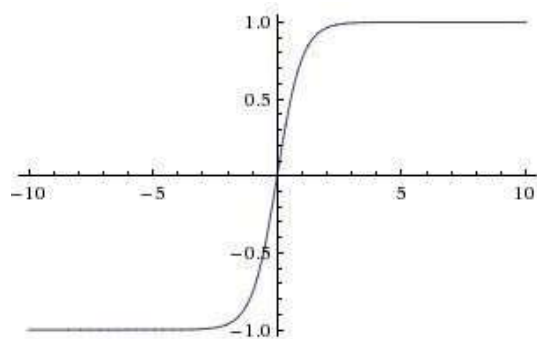
$$\sigma(x) = 1/(1 + e^{-x})$$

- Squashes numbers to range [0,1]
- 3 problems:
  1. Saturated neurons “kill” the gradients
  2.  $\exp()$  is a bit compute expensive

# Vanishing Gradient Problem

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## Activation Functions



**$\tanh(x)$**

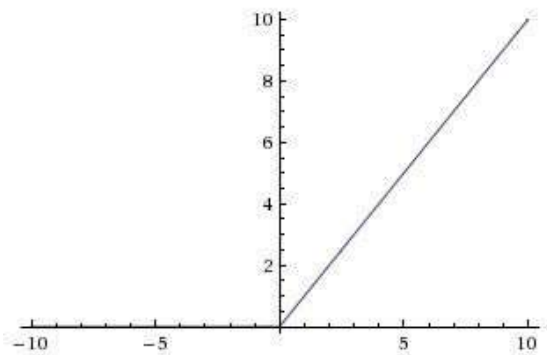
- Squashes numbers to range  $[-1,1]$
- zero centered (nice)
- still kills gradients when saturated :(

[LeCun et al., 1991]

# Vanishing Gradient Problem

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## Activation Functions



## ReLU (Rectified Linear Unit)

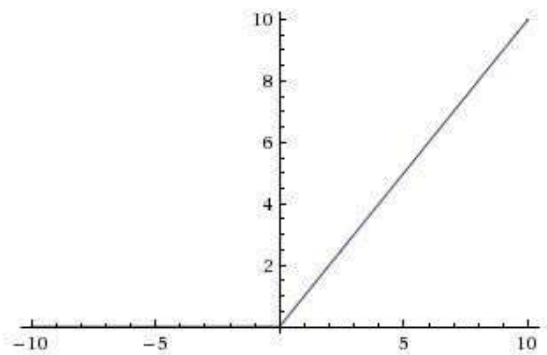
- Computes  $f(x) = \max(0, x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)
- What happens when input is less than zero ?

[Krizhevsky et al., 2012]

# Vanishing Gradient Problem

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## Activation Functions



**ReLU**  
(Rectified Linear Unit)

- Computes  $f(x) = \max(0, x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)
- What happens when input is less than zero ?
  - Gradients are zero

[Krizhevsky et al., 2012]

# Vanishing Gradient Problem

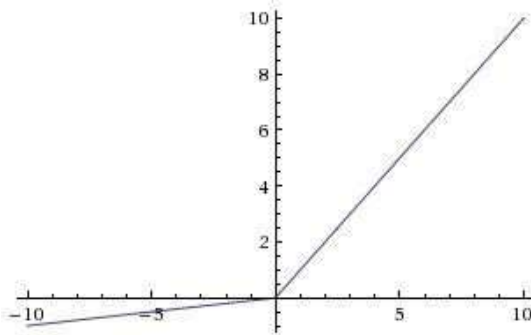
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## Activation Functions

[Mass et al., 2013]

[He et al., 2015]

- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- **will not “die”**.



### Leaky ReLU

$$f(x) = \max(0.01x, x)$$



# Vanishing Gradient Problem

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In Practice,

- Use **ReLU**. Be careful with your learning rates
- Try out **Leaky ReLU**
- Try out **tanh** but don't expect much
- **Don't use sigmoid**