인공지능 심화학습 프로그램
Convolution Neural Network
Computer vision

Vision and Learning laboratory
김민지
2023.11.06 ~ 2023.11.09

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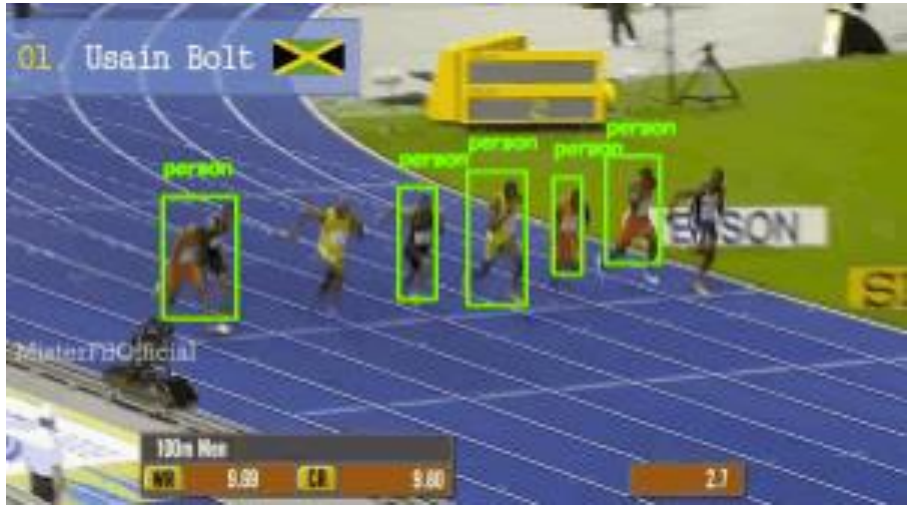
- More Tasks
- Backpropagation
- Reminding: Convolution neural network
- Receptive Field
- Other Convolution layers
- QnA

More Tasks

- MOT (Multiple Object Tracking)



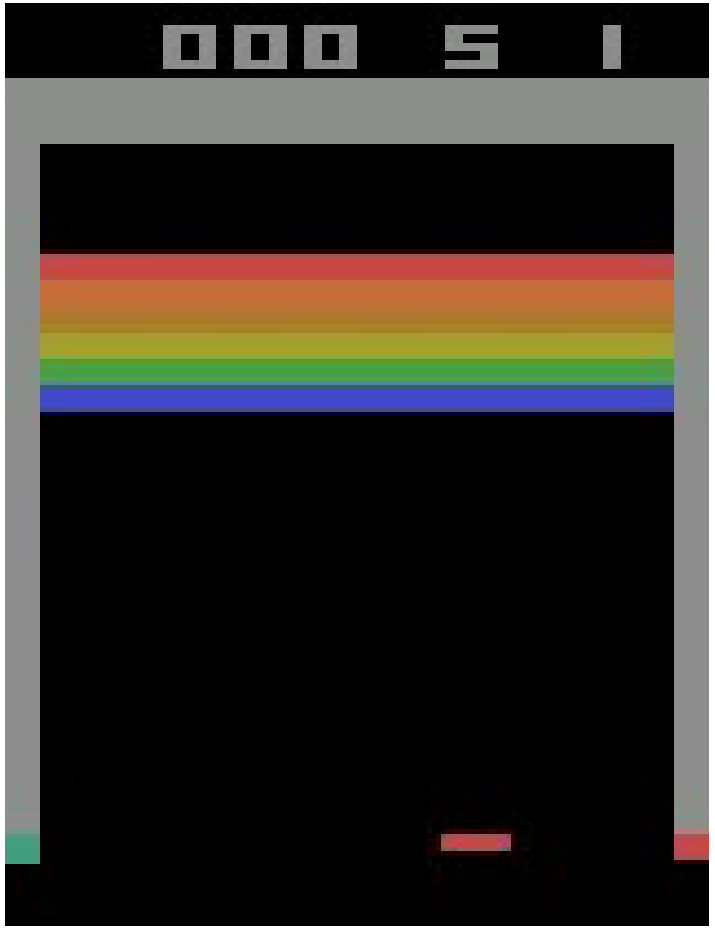
More Tasks

- MOT (Multiple Object Tracking)

Tracking vs **Detection** vs **Recognition**

More Tasks

- Deep Reinforcement Learning

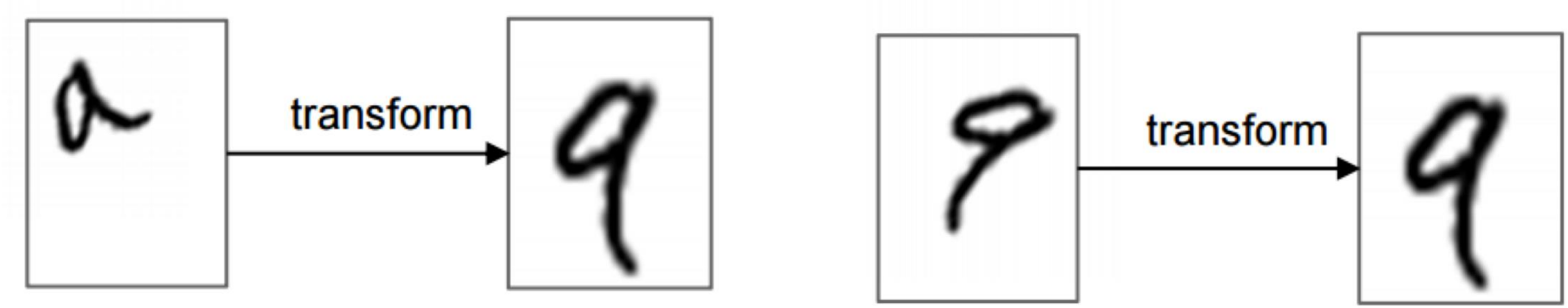


More Tasks

- Deep Reinforcement Learning

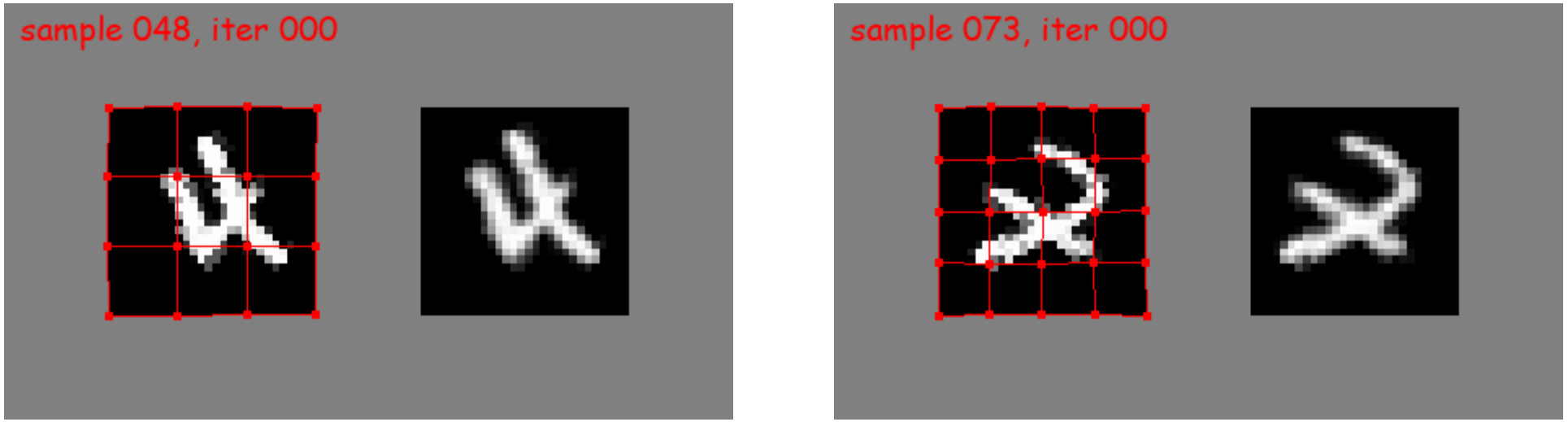
More Tasks

- Image Alignment



More Tasks

- Image Alignment



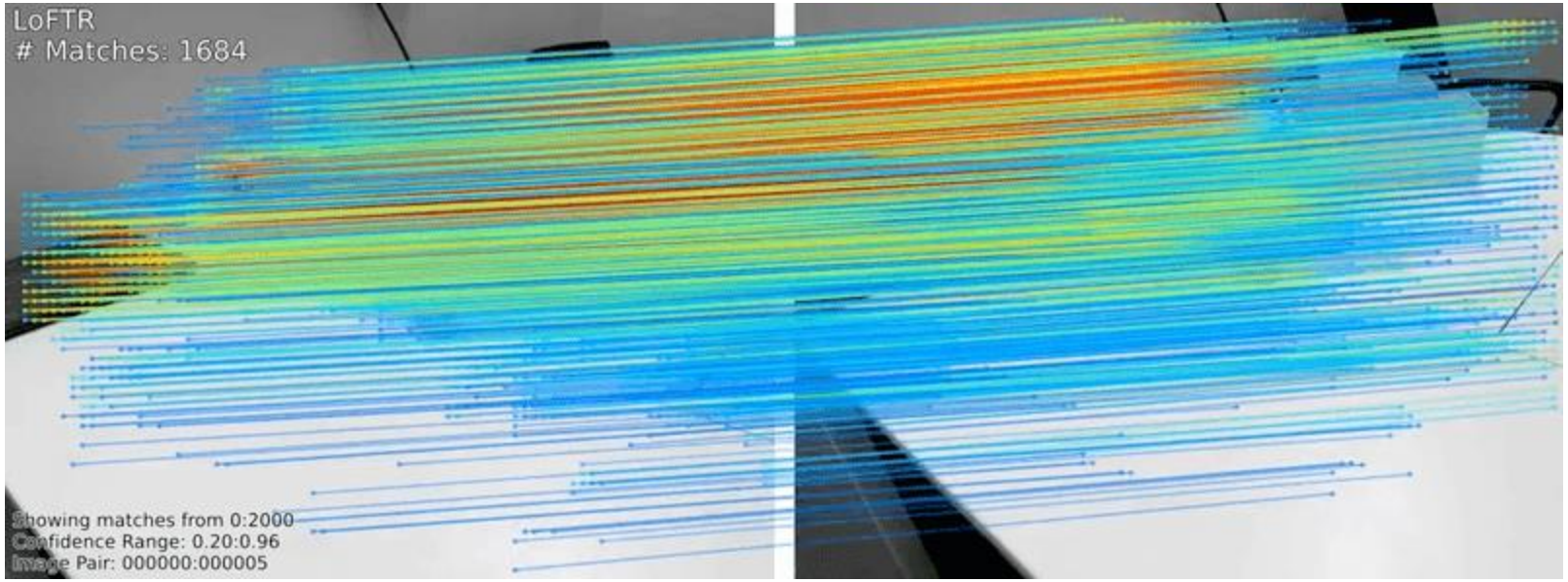
Source: https://github.com/WarBean/tps_stn_pytorch

More Tasks

- Image Alignment (Keypoint matching)

More Tasks

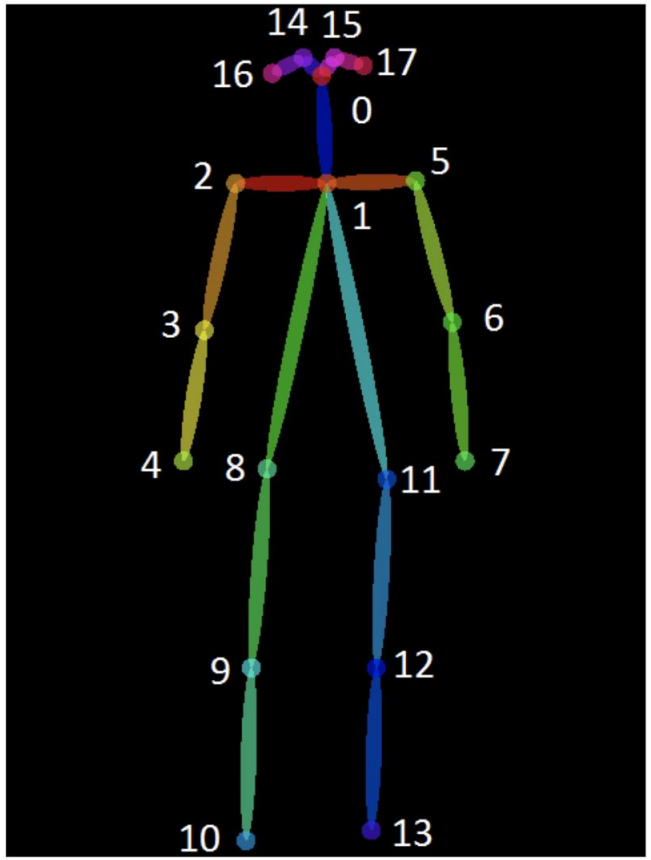
- Image Alignment (Keypoint matching)



Source: https://github.com/zju3dv/LoFTR

More Tasks

- Human Pose Estimation



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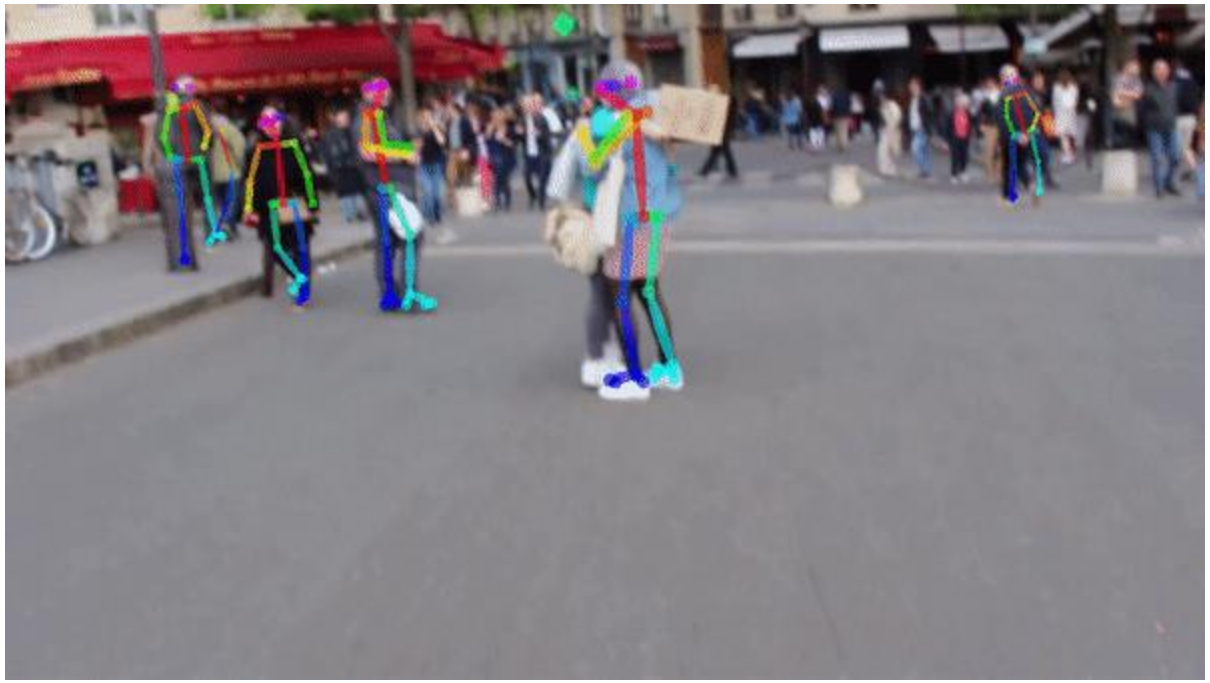
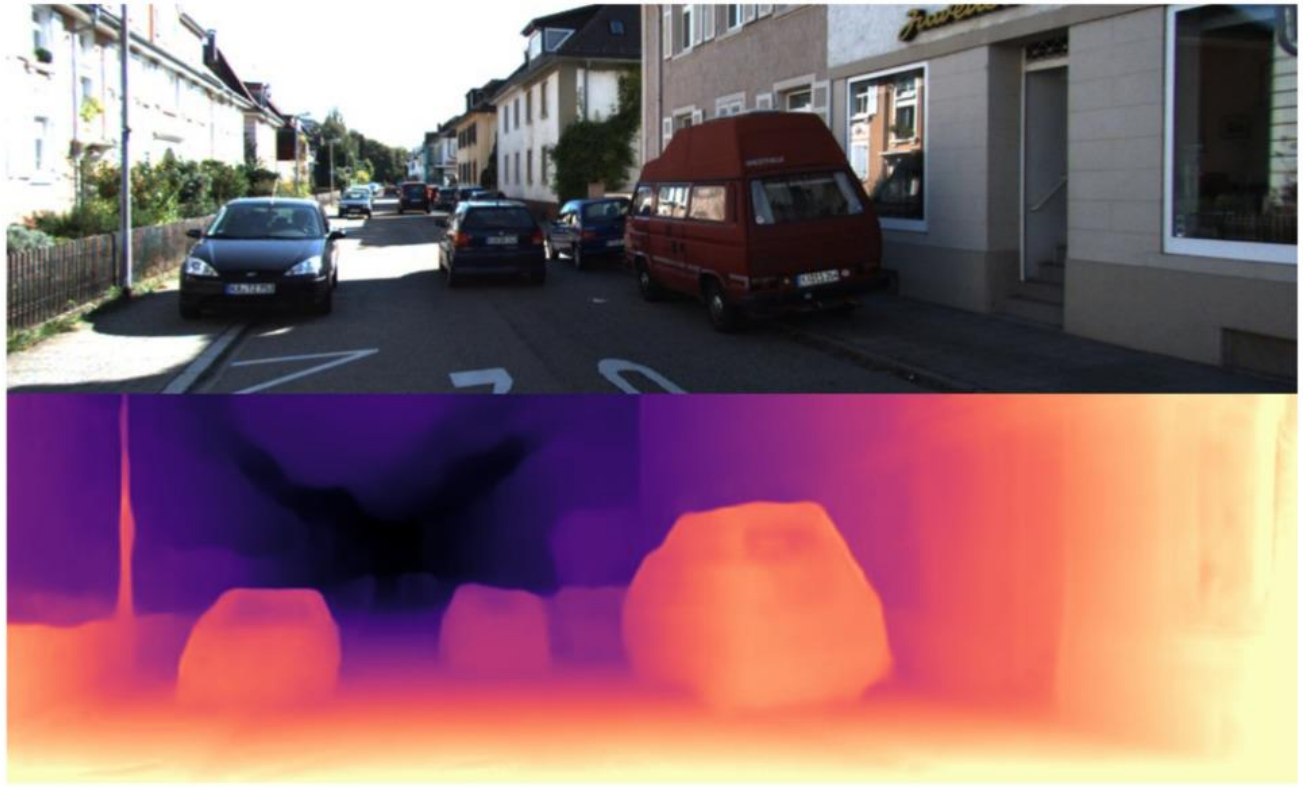
- Human Pose Estimation



More Tasks

- Depth Estimation



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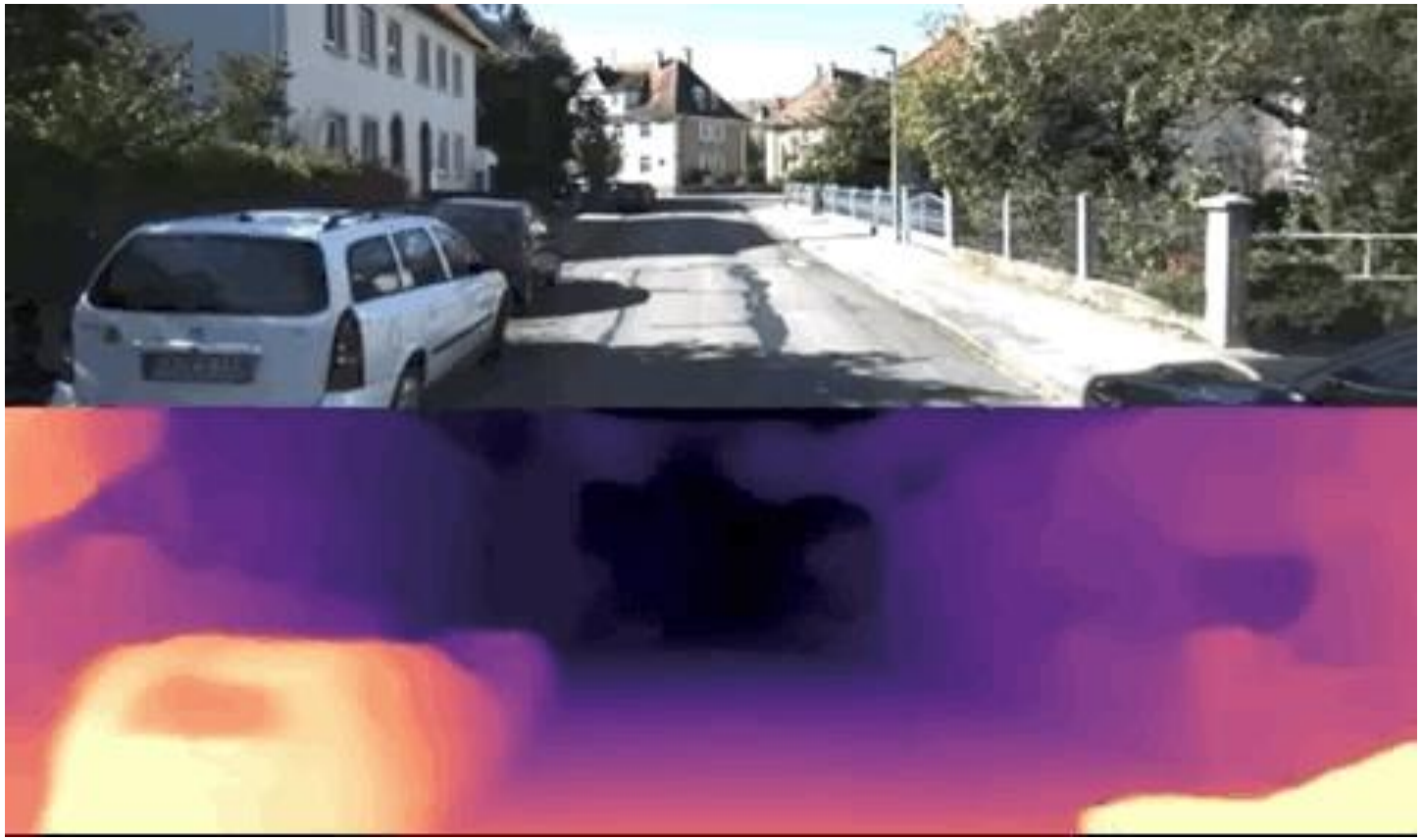
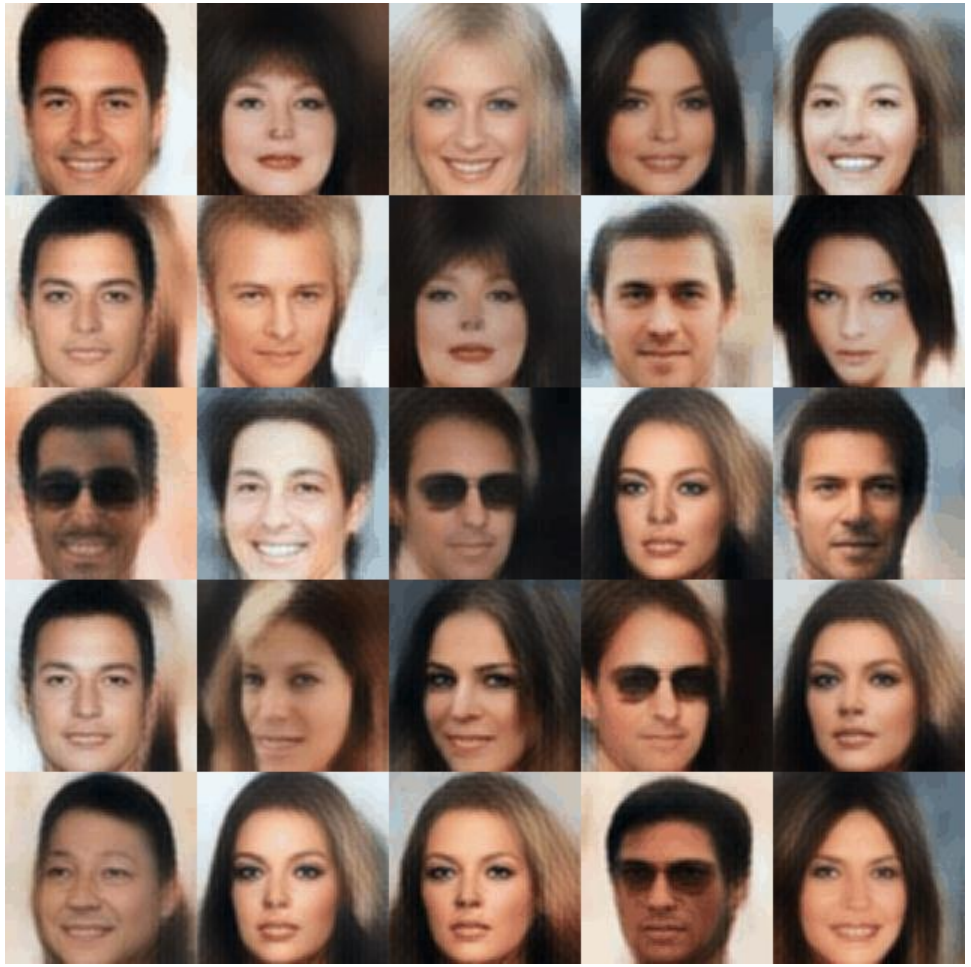


More Tasks

- Generative model



More Tasks

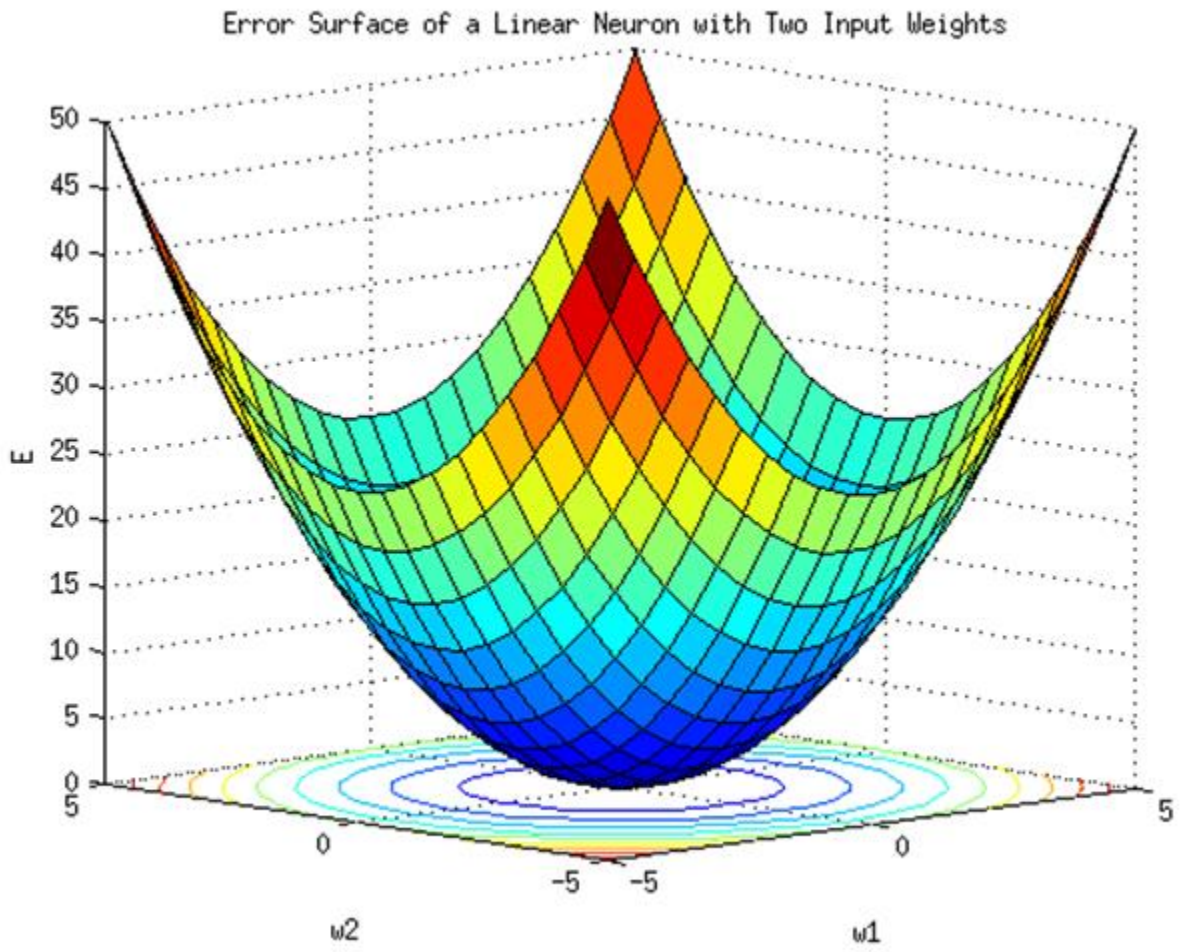
- Explainable AI

Grad-CAM for "Cat"

Grad-CAM for "Dog"

Backpropagation

- What is backpropagation?



Backpropagation

- What is Differentiation?
  - 미분은 쉽게 말해 미세한 부분을 뜻함
  - 미세한 변화를 연구하는 분야

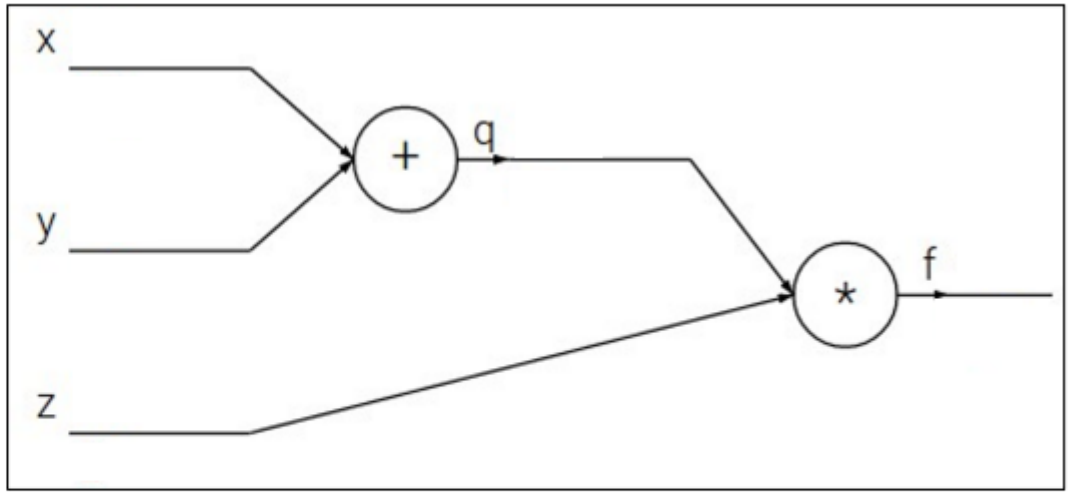
$$f'(a) = \lim_{x \to a} \frac{f(x) - f(a)}{x - a}$$

$$= \lim_{\Delta x \to 0} \frac{f(a + \Delta x) - f(a)}{\Delta x}$$

Backpropagation

Backpropagation:
Simple Example

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



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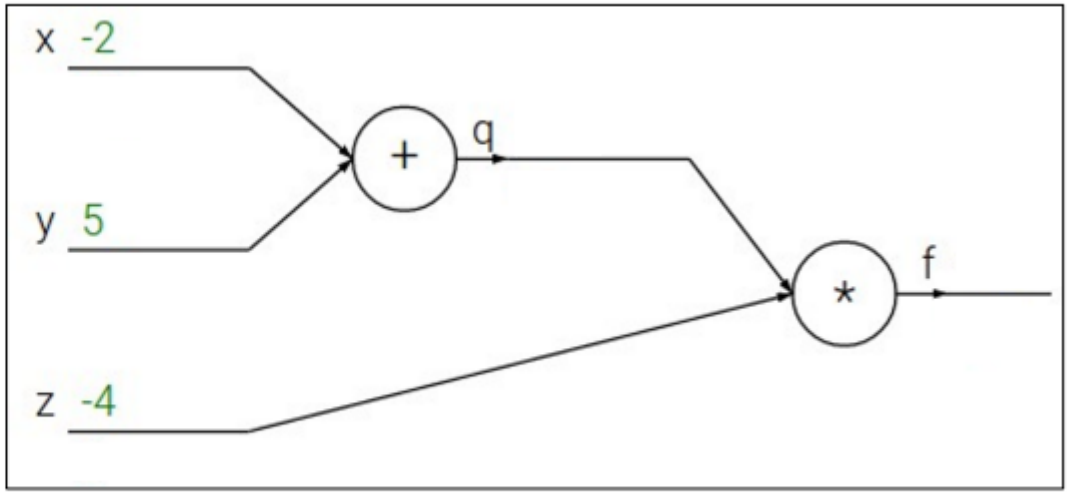
$$f(x, y, z) = (x + y) \cdot z$$

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



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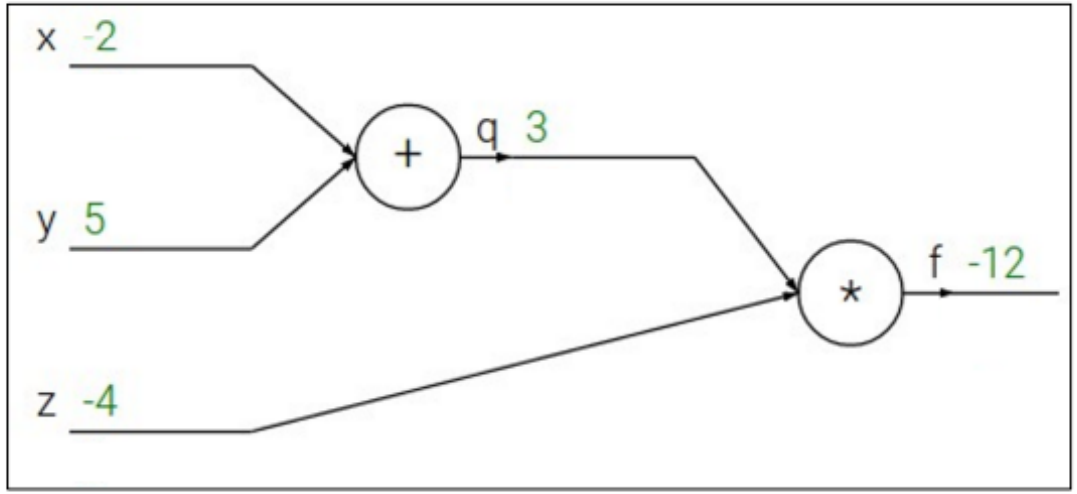

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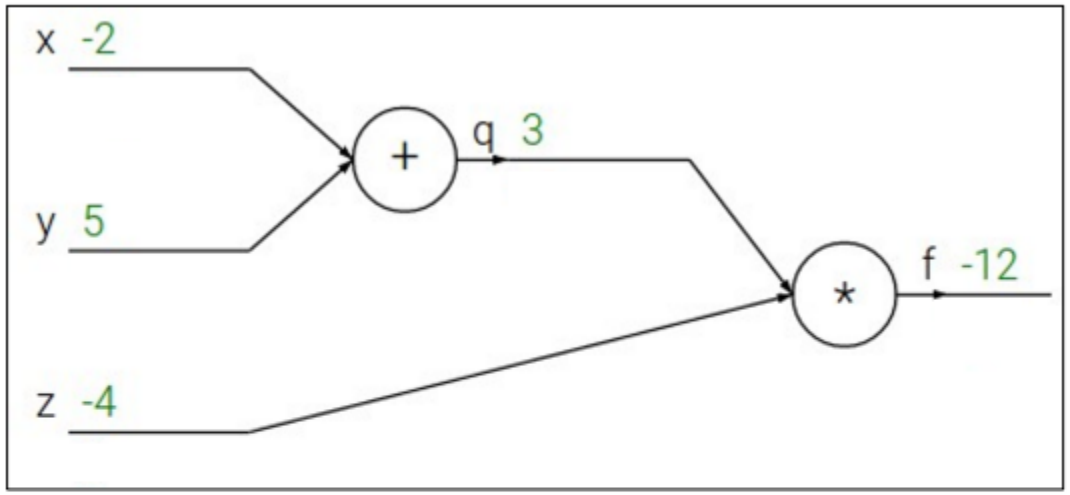

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2. Backward pass: Compute derivatives

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

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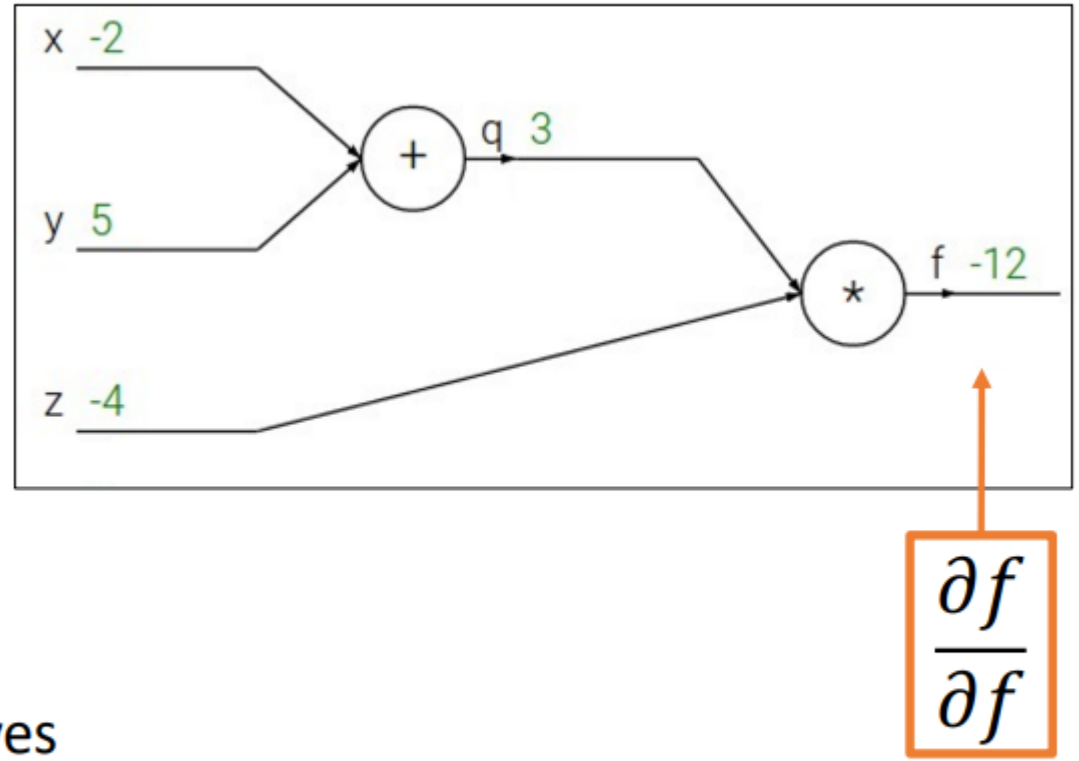

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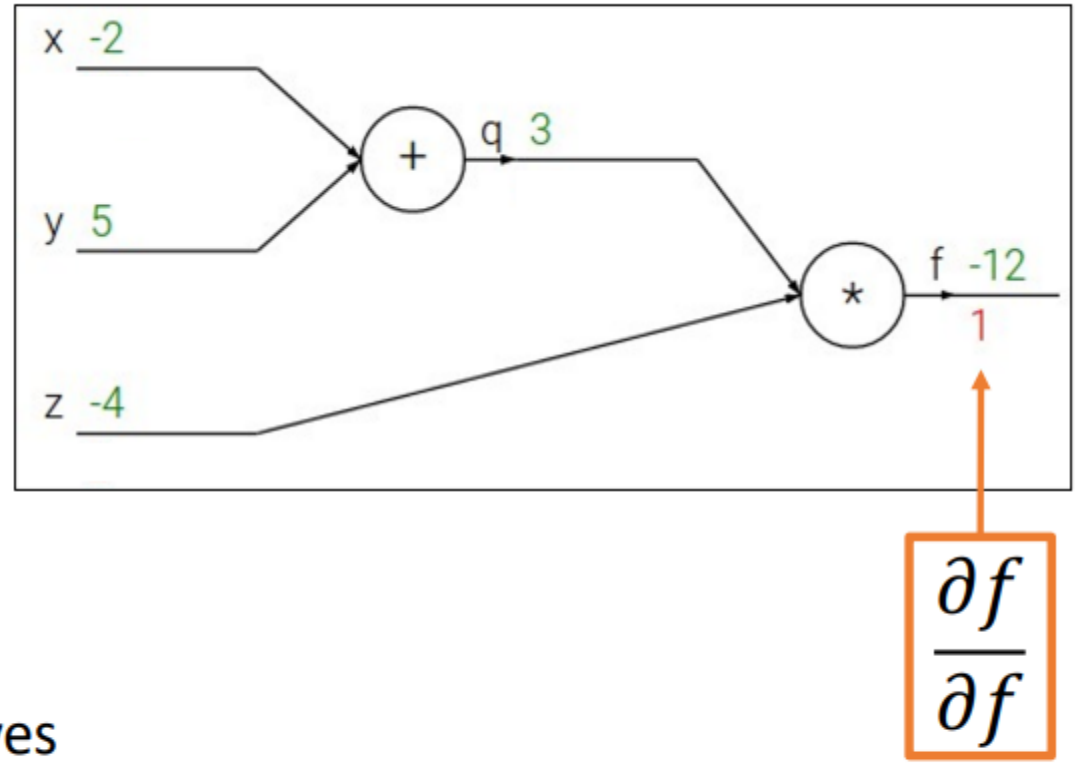

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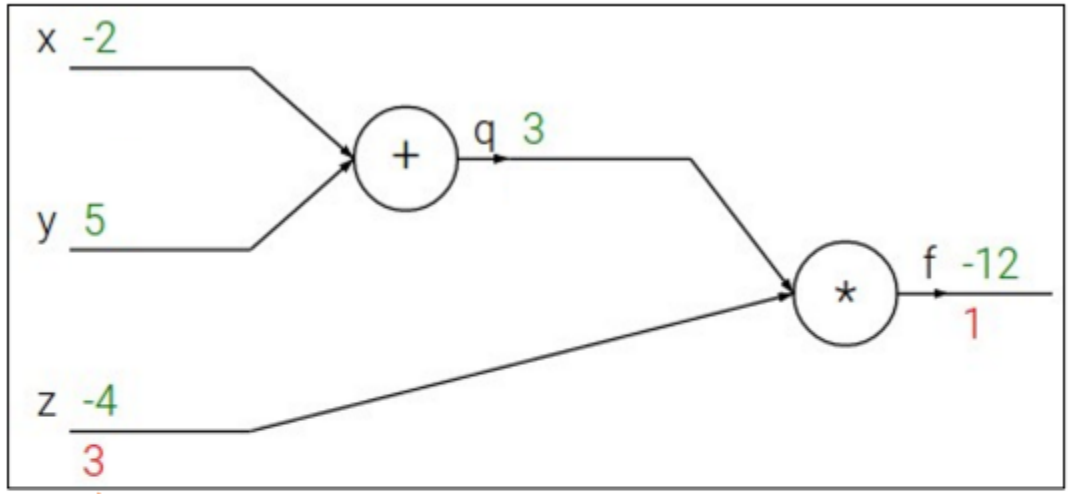

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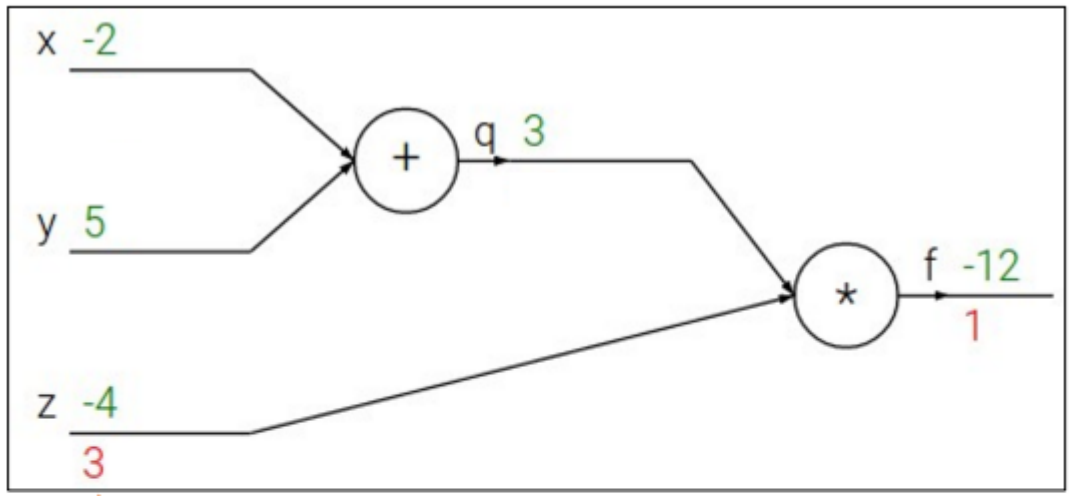

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2. Backward pass: Compute derivatives

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

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

Backpropagation

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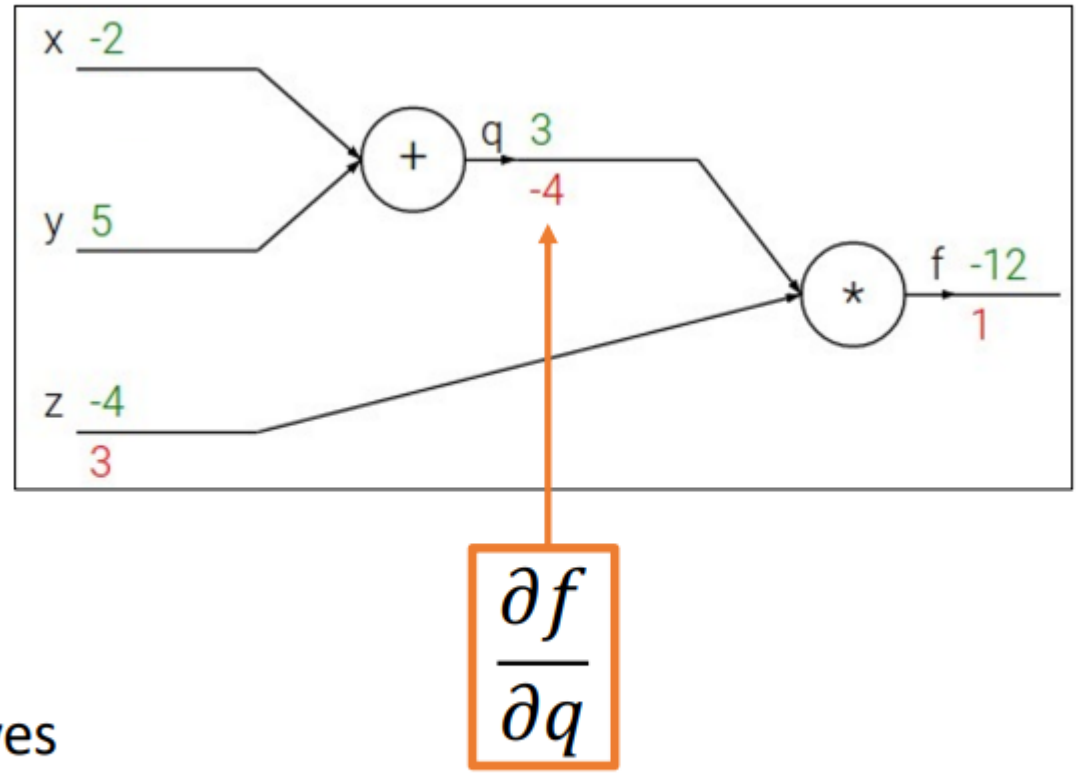

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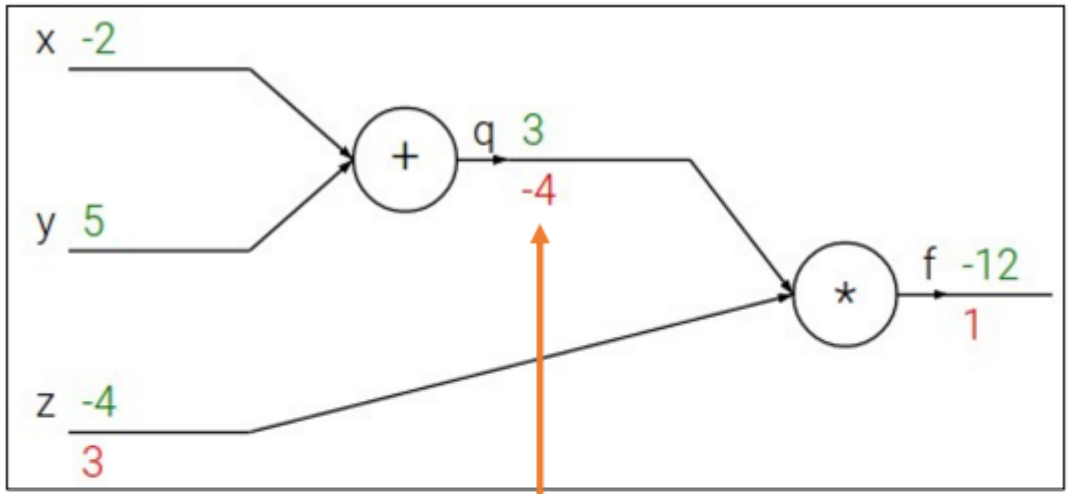

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$$q = x + y \qquad f = q \cdot z$$

2. Backward pass: Compute derivatives

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

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

Backpropagation

Backpropagation:
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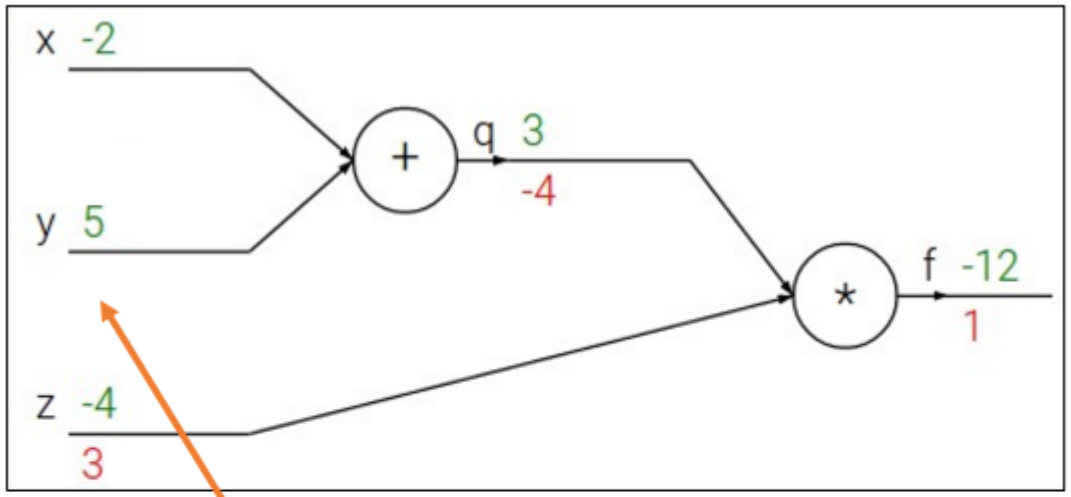

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$\frac{\partial f}{\partial y}$

Backpropagation

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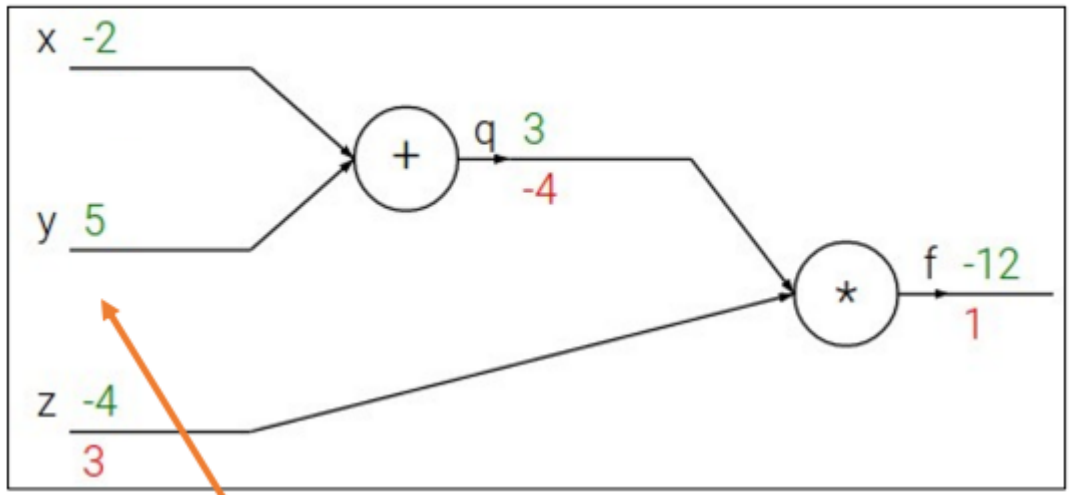

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$$q = x + y \qquad f = q \cdot z$$

2. Backward pass: Compute derivatives

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

Chain Rule

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

Backpropagation

Backpropagation:
Simple Example

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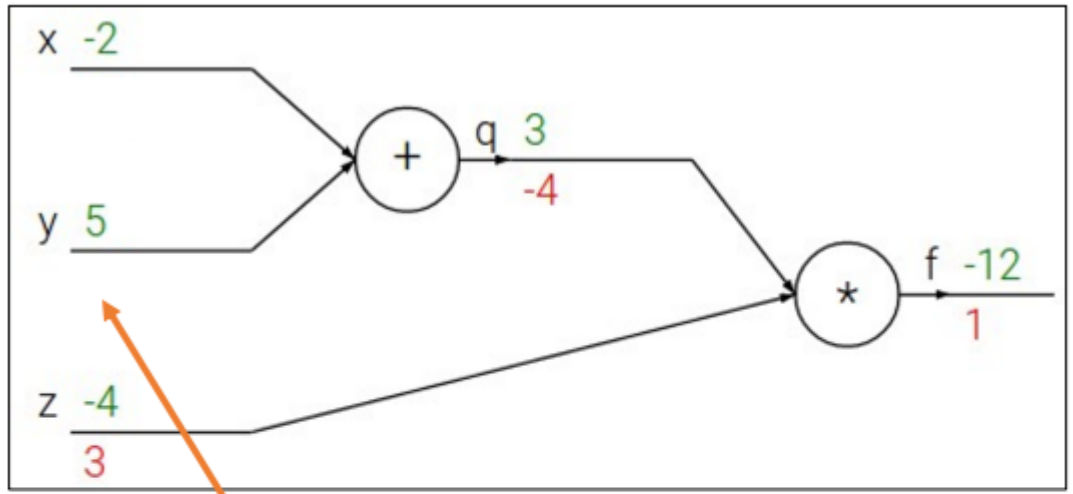

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Downstream Gradient **Local Gradient** **Upstream Gradient**

Backpropagation

Backpropagation:
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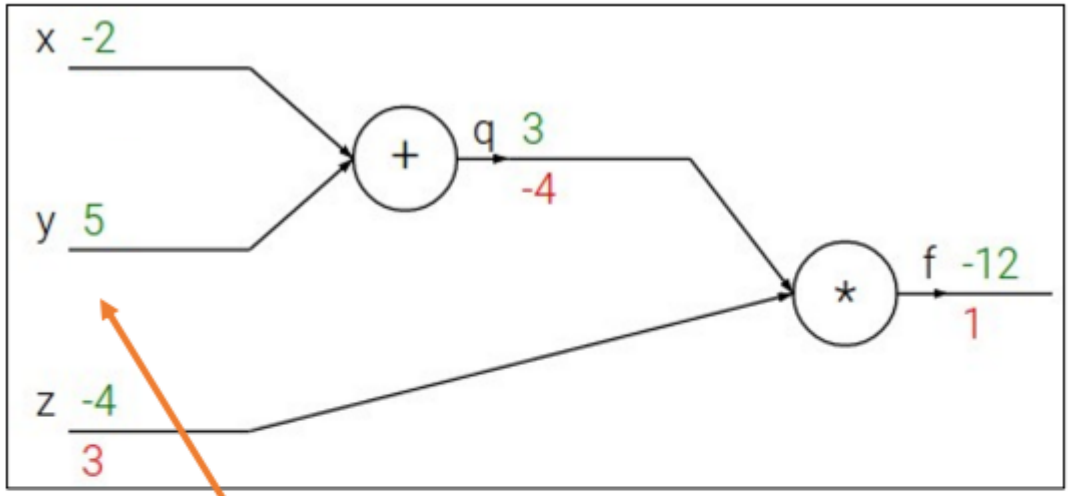

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Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Chain Rule

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

$$\frac{\partial q}{\partial y} = 1$$

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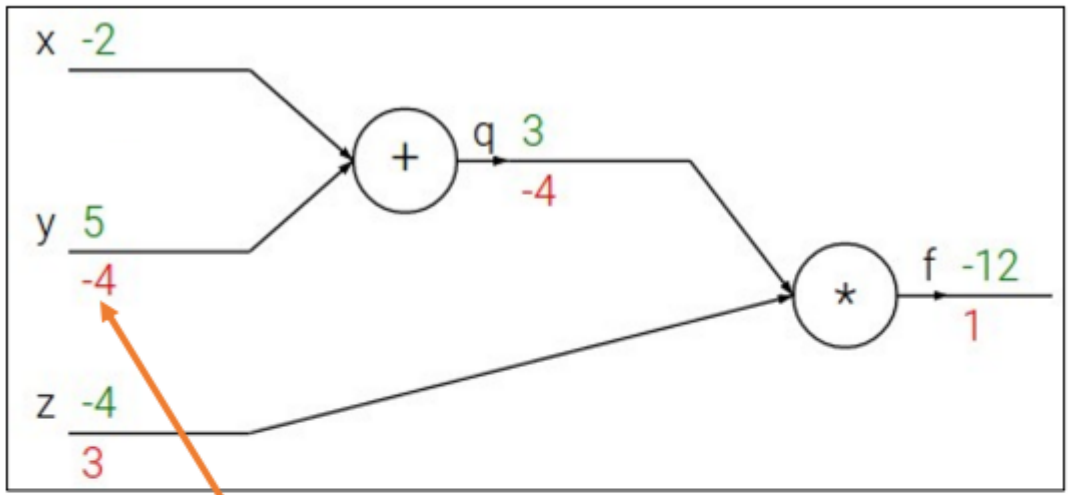

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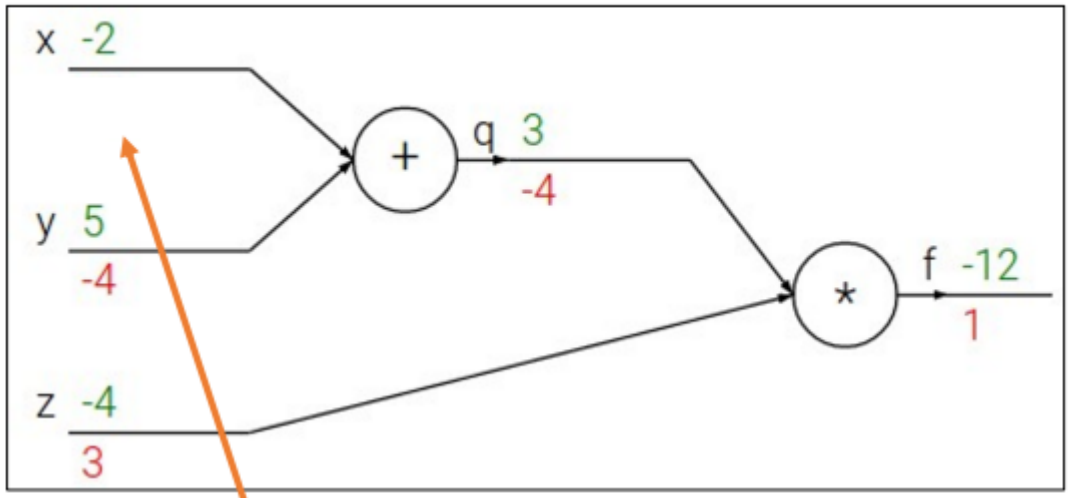

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Backpropagation:
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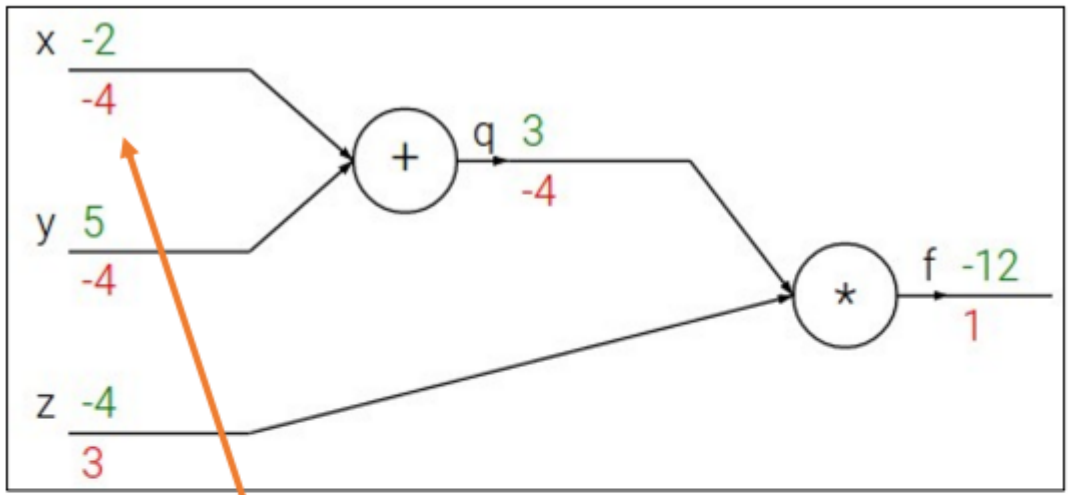

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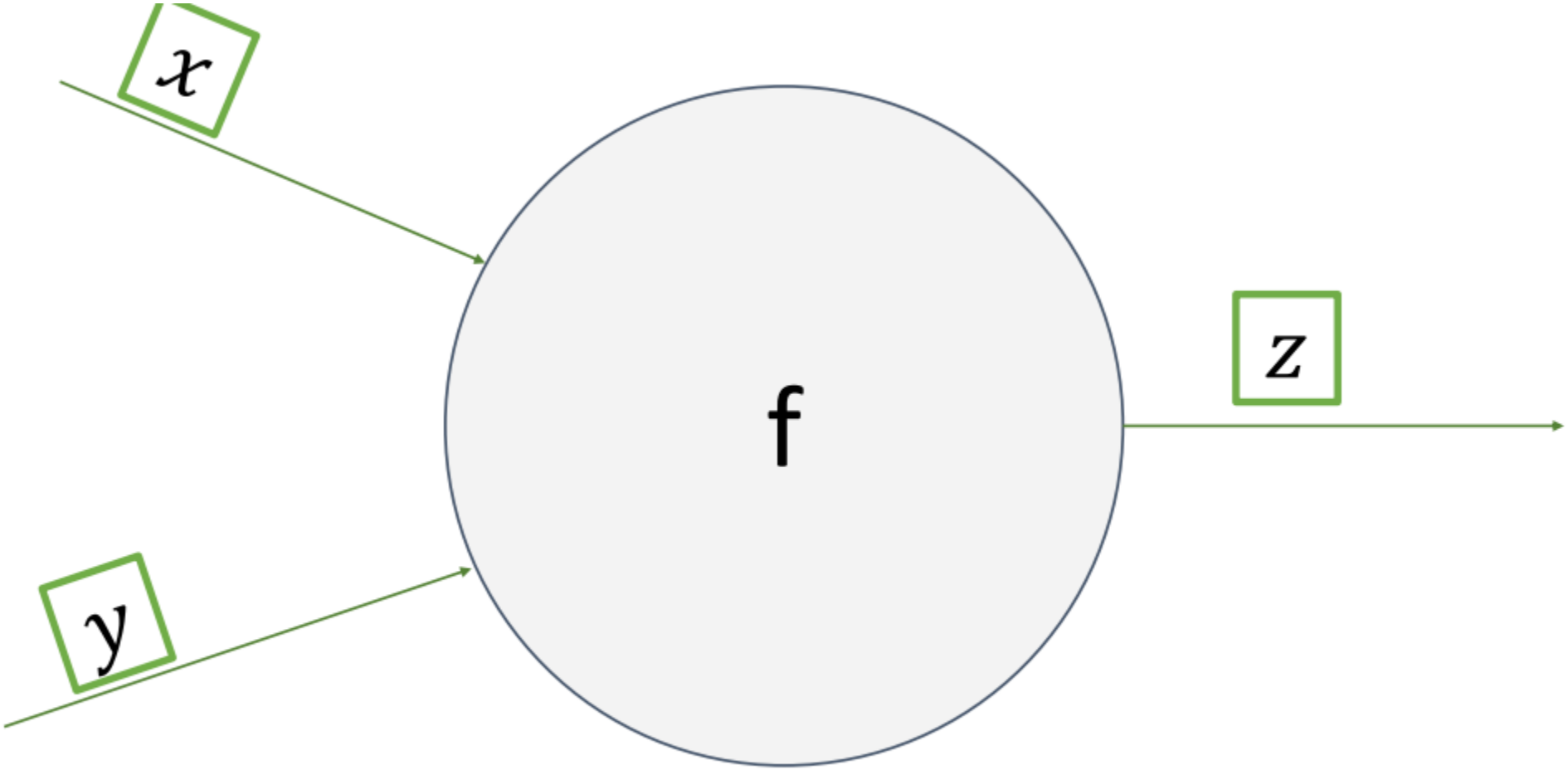
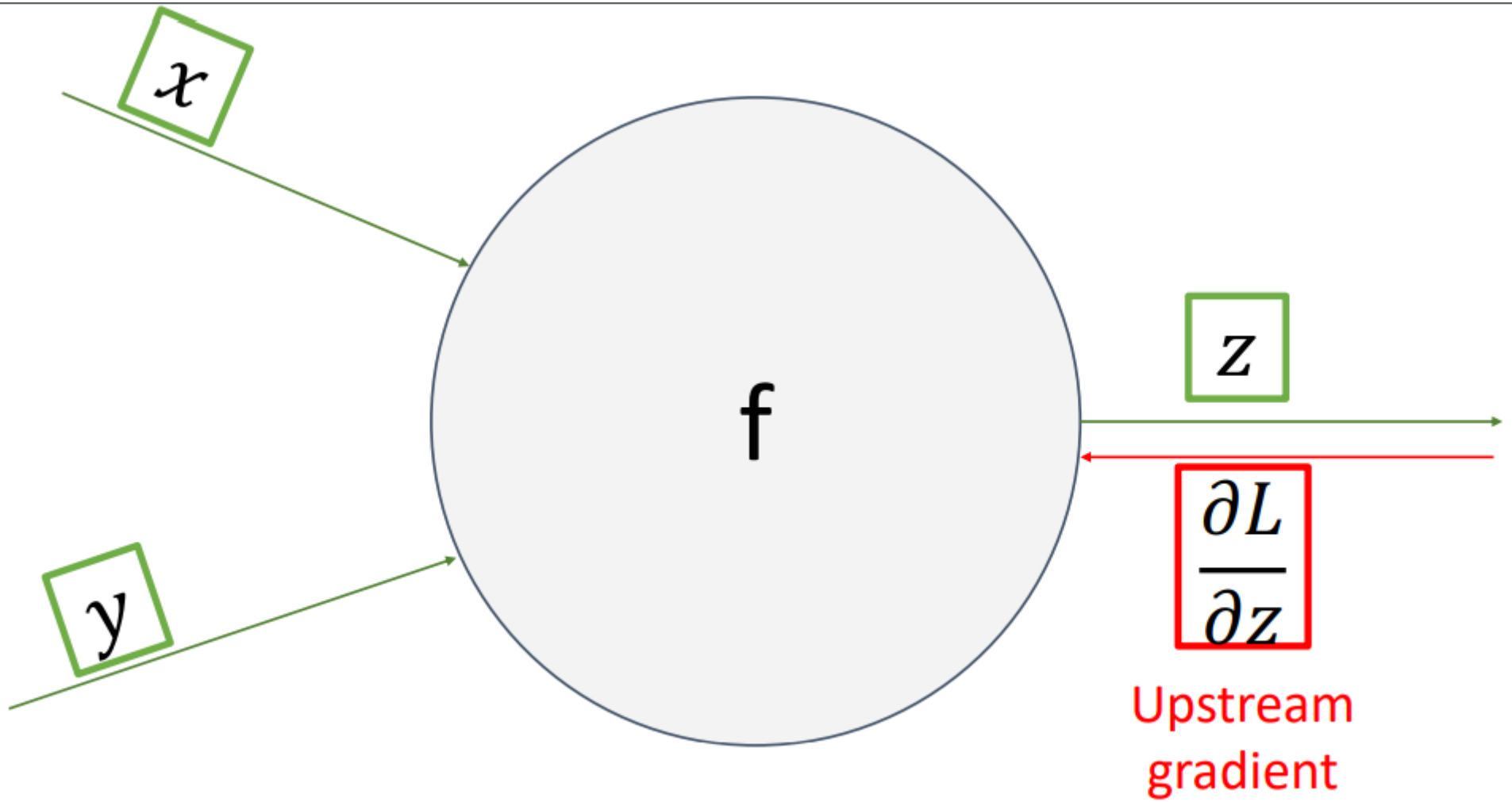


Backpropagation



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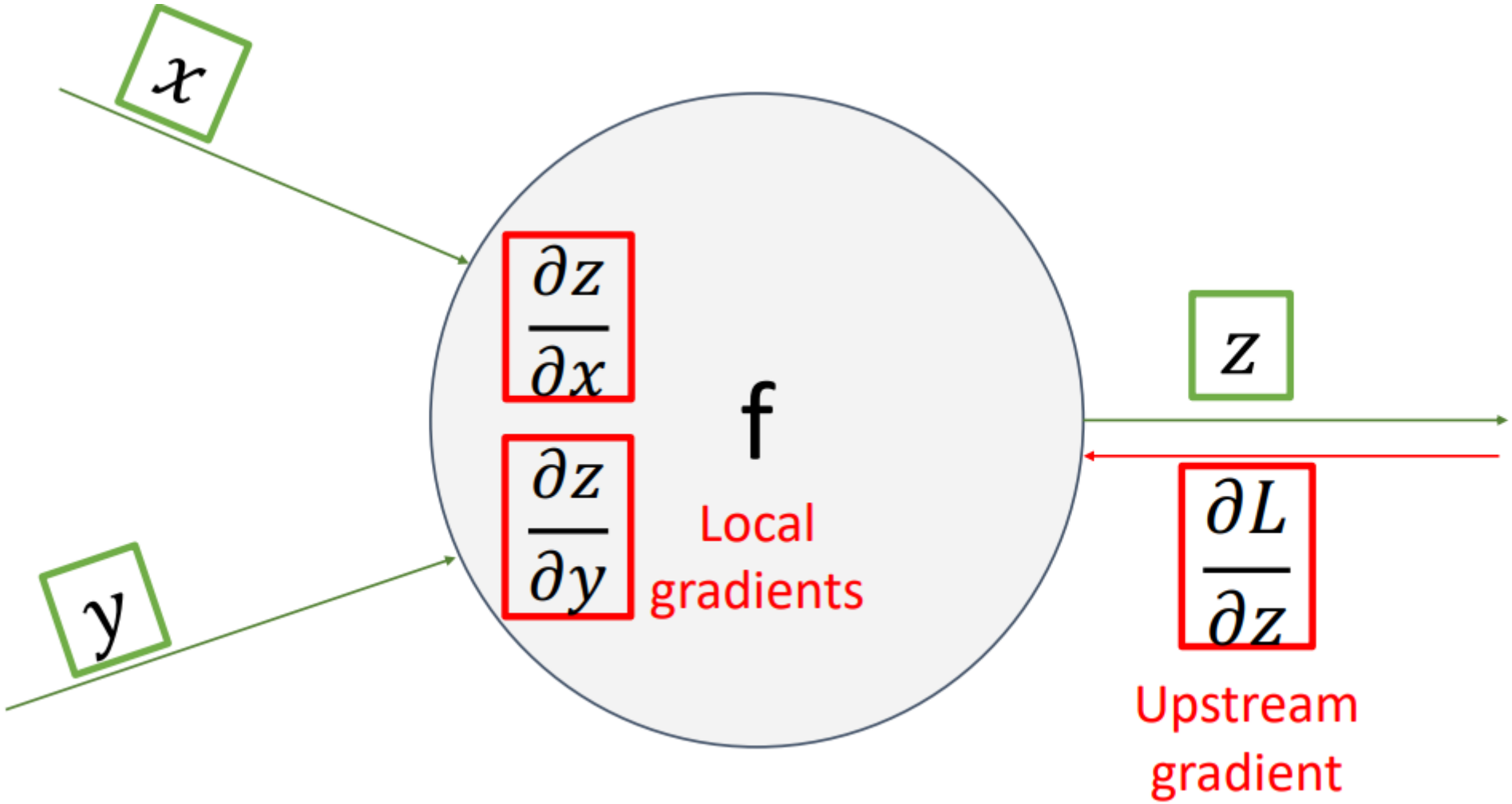

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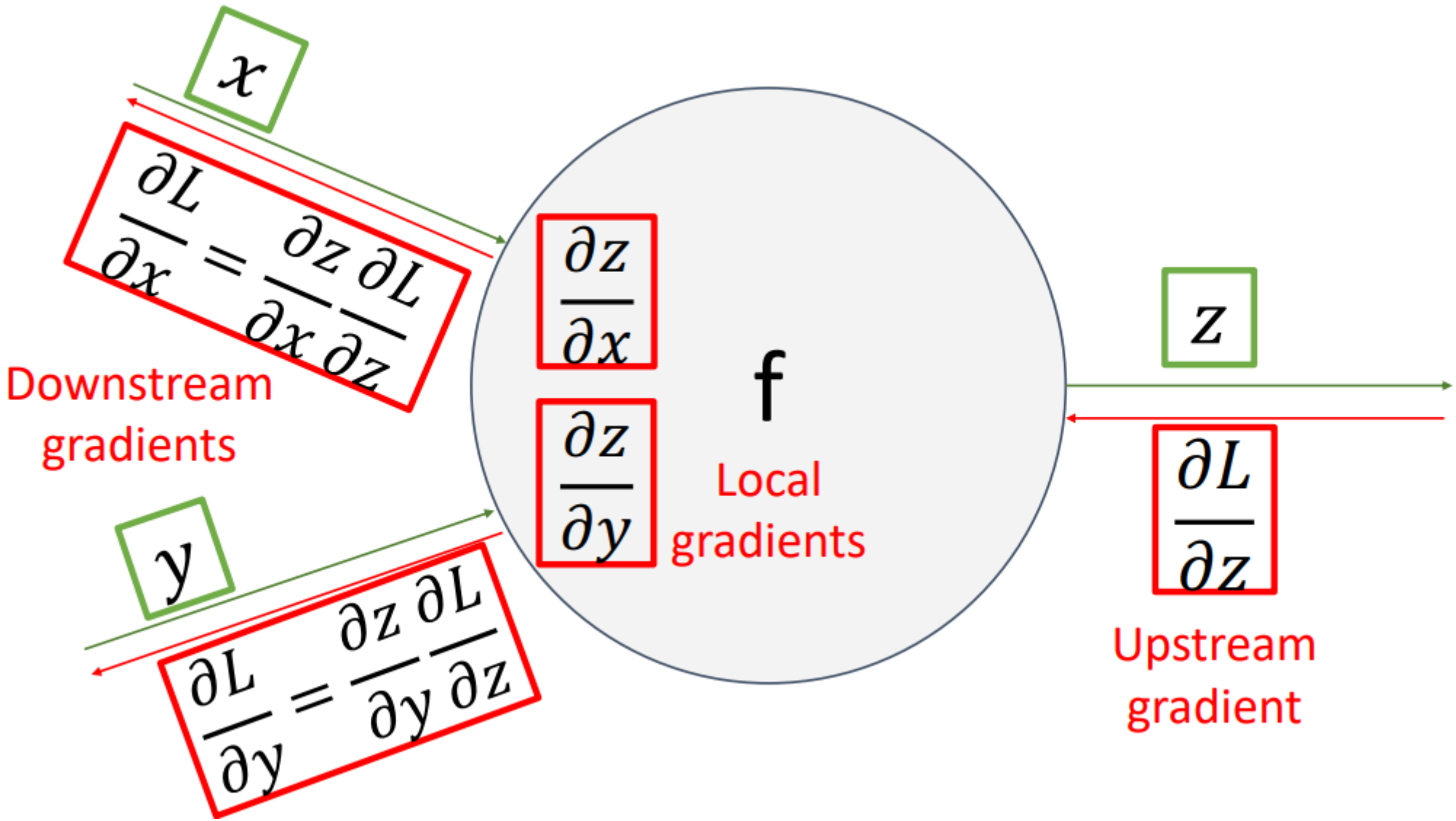

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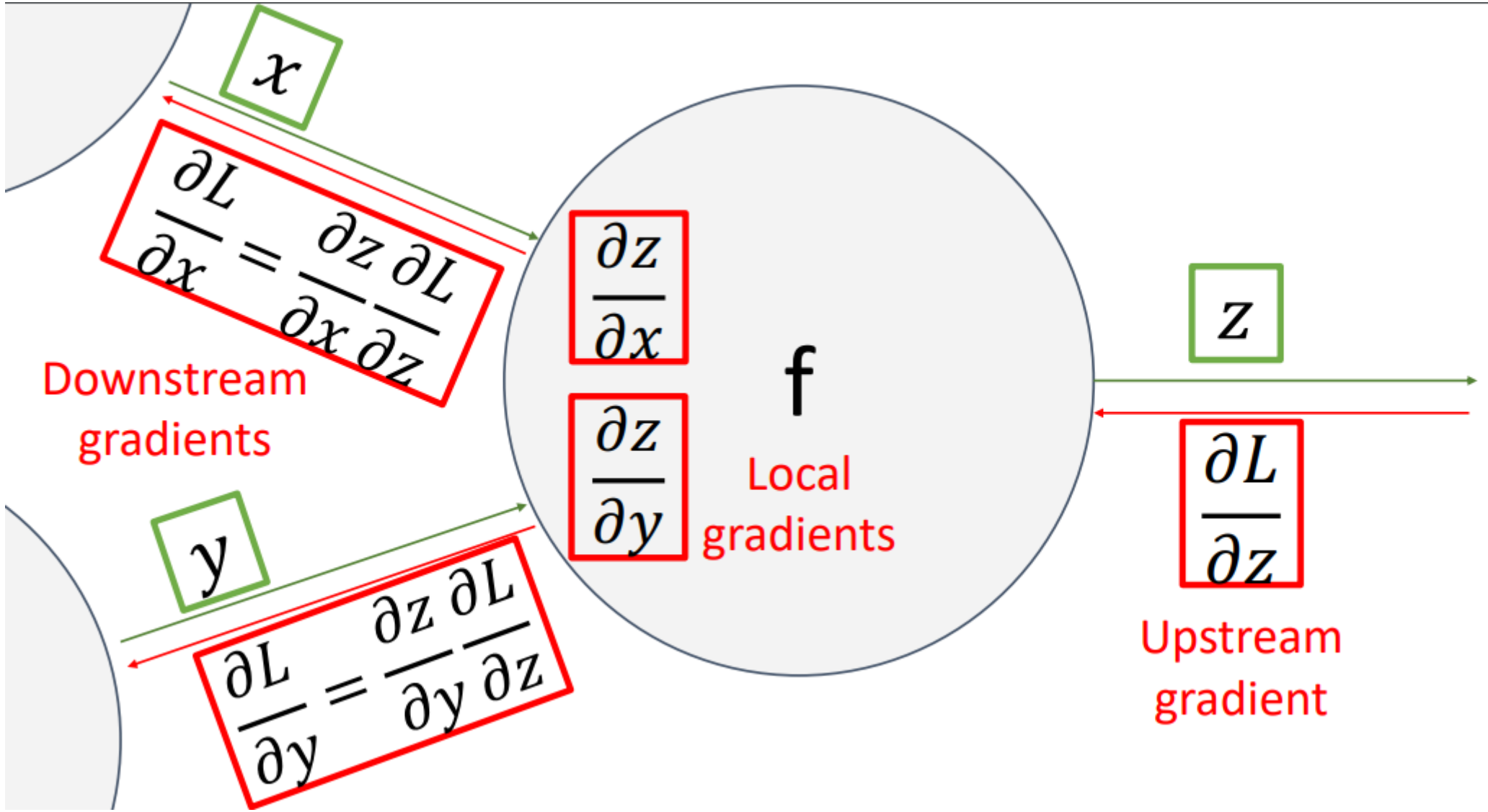
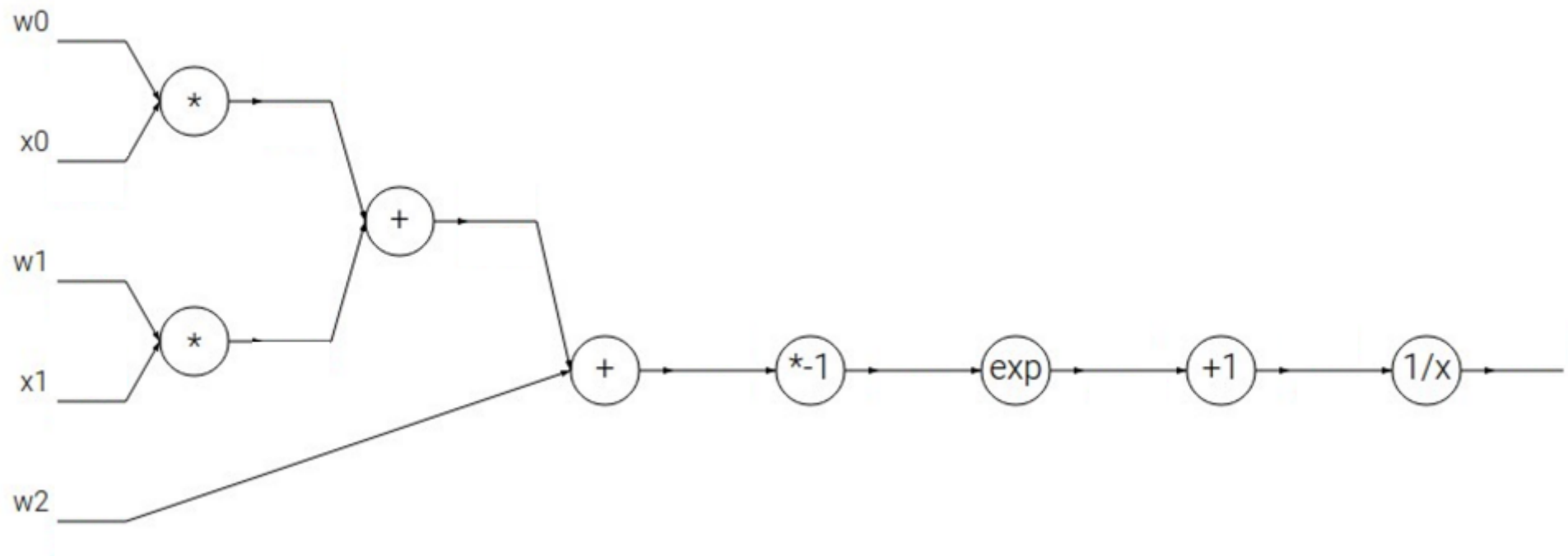


Backpropagation

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



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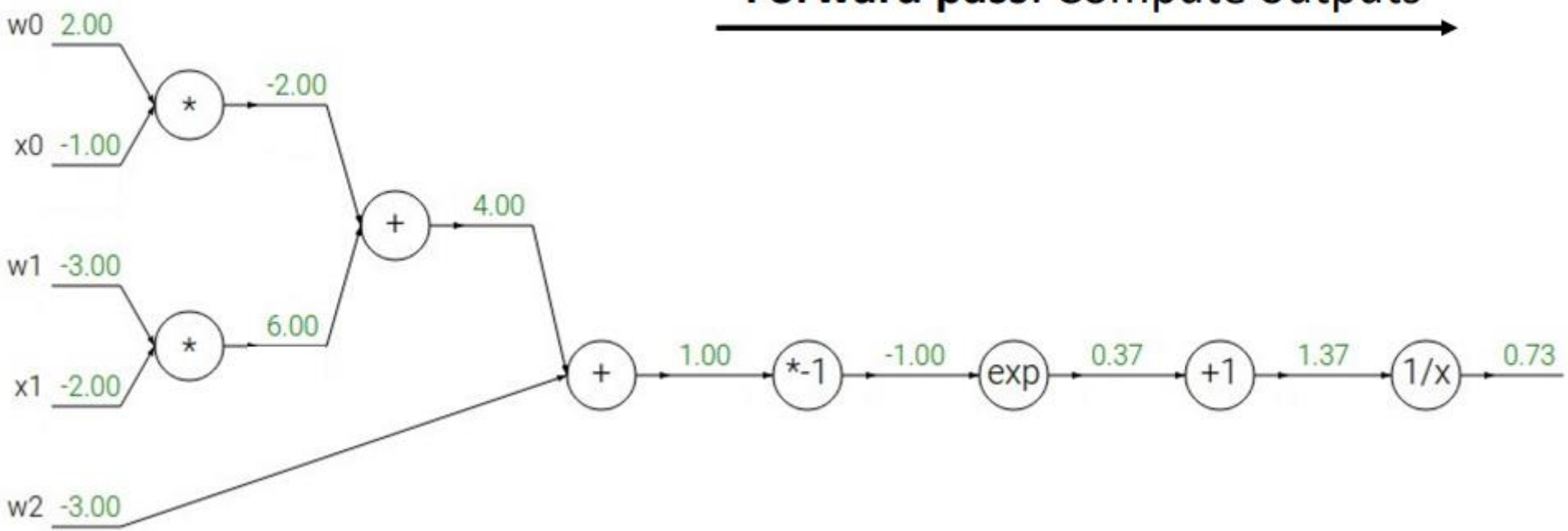
Forward pass: Compute outputs



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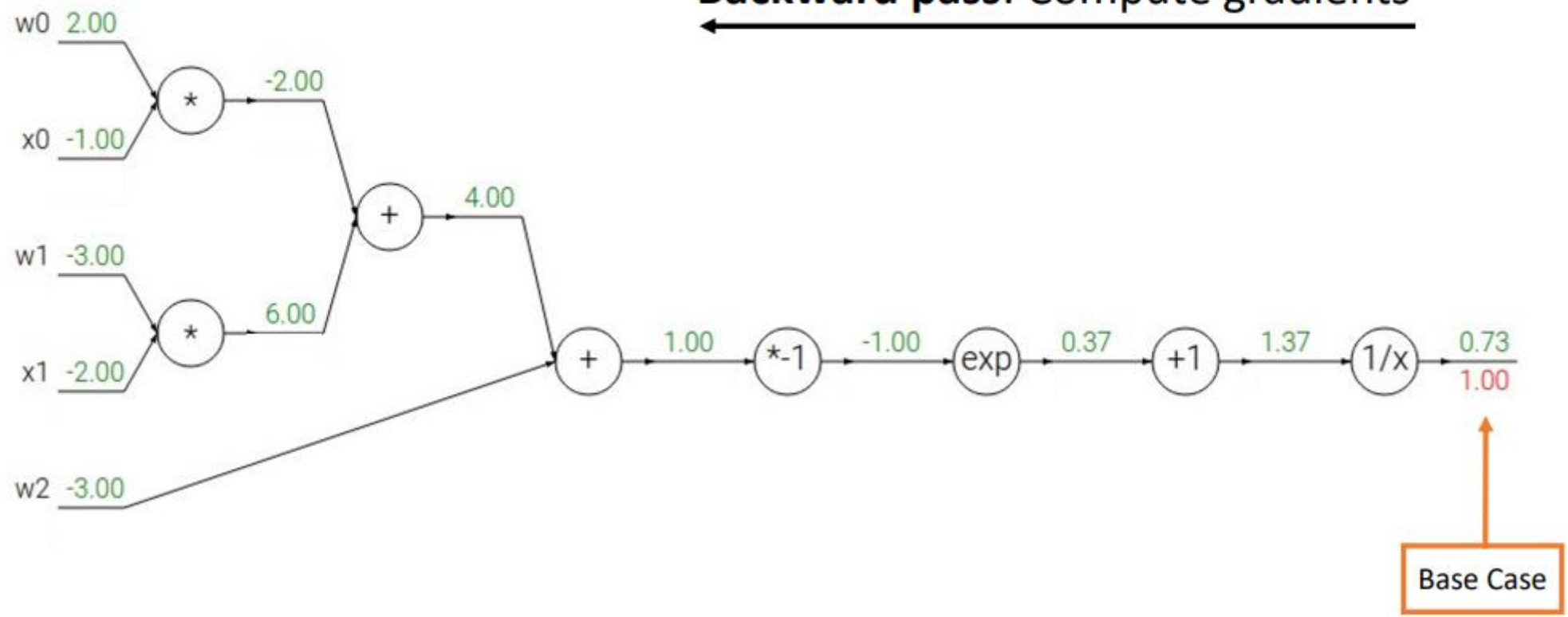
Backward pass: Compute gradients



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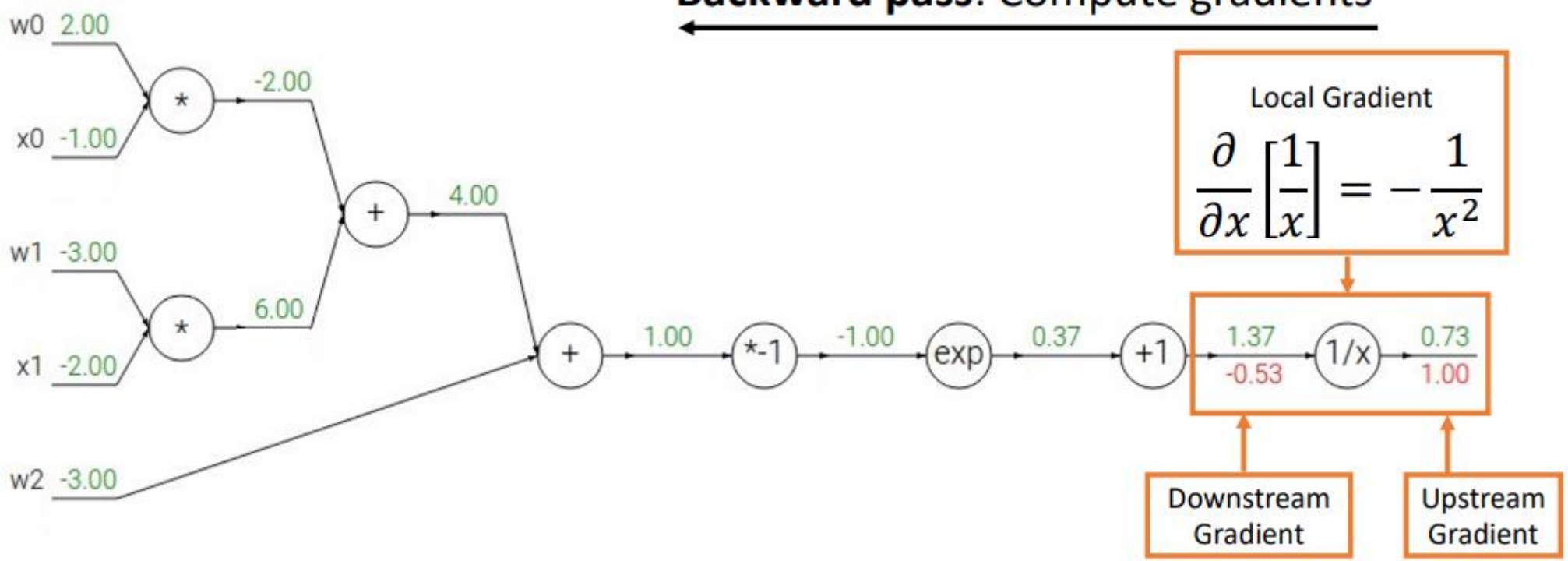

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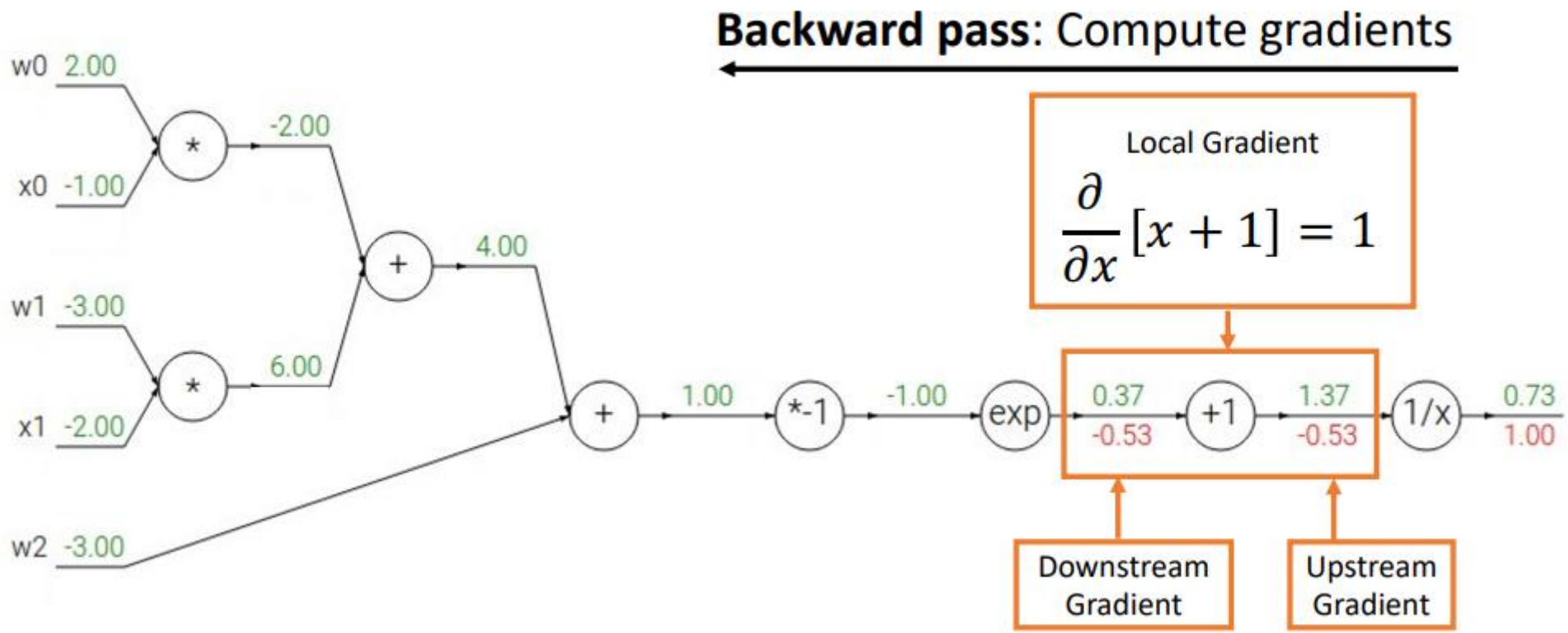

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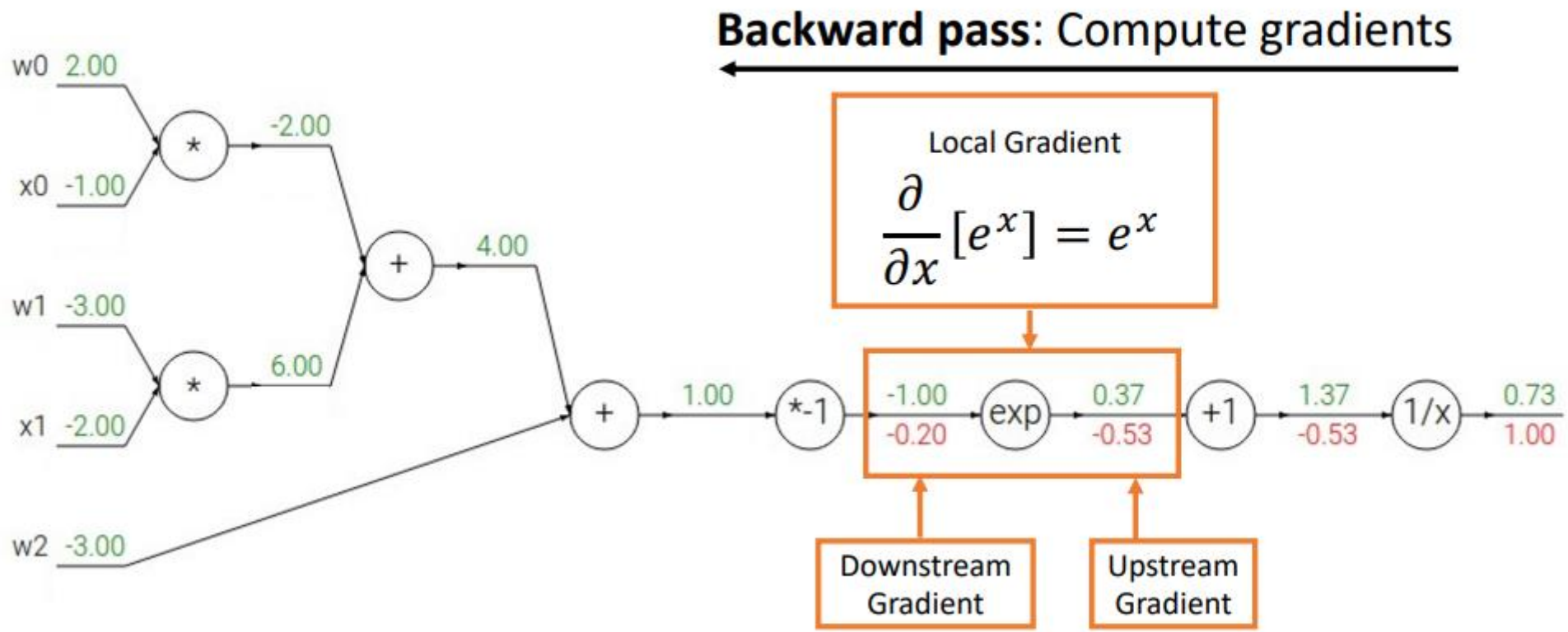
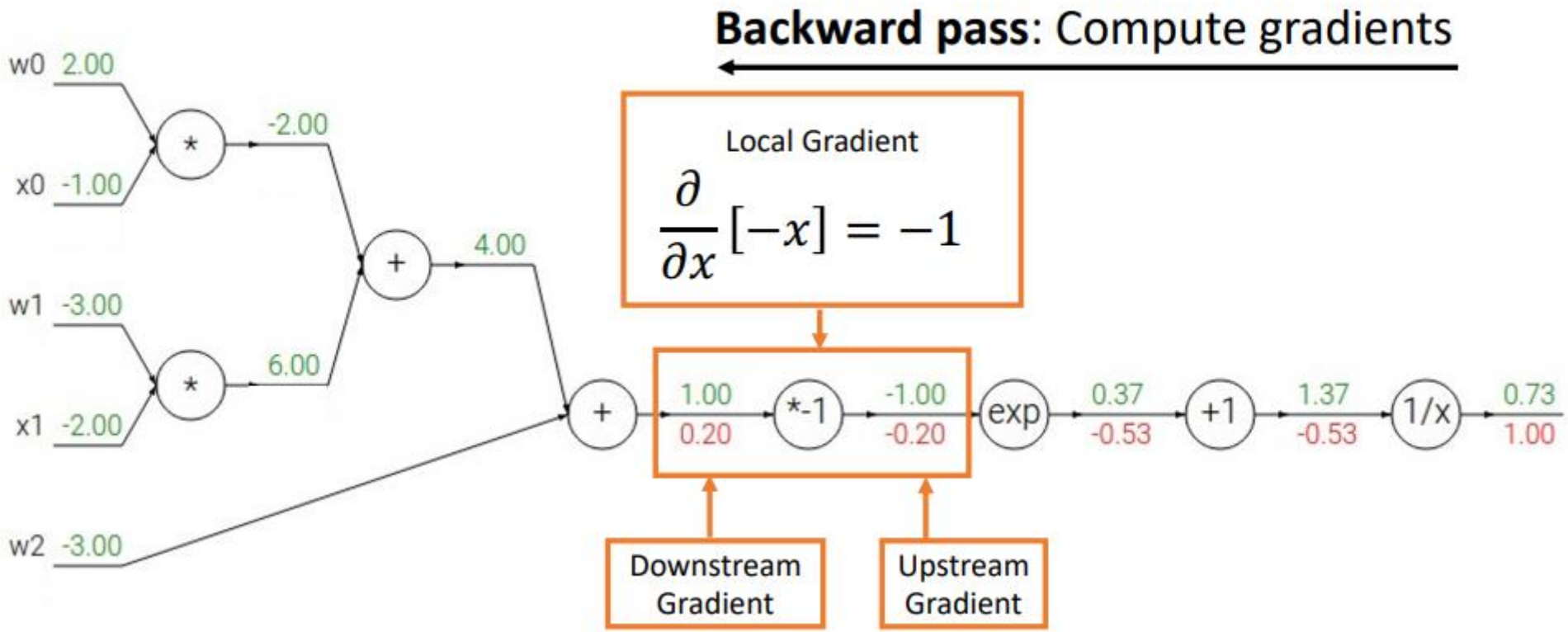


Backpropagation

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



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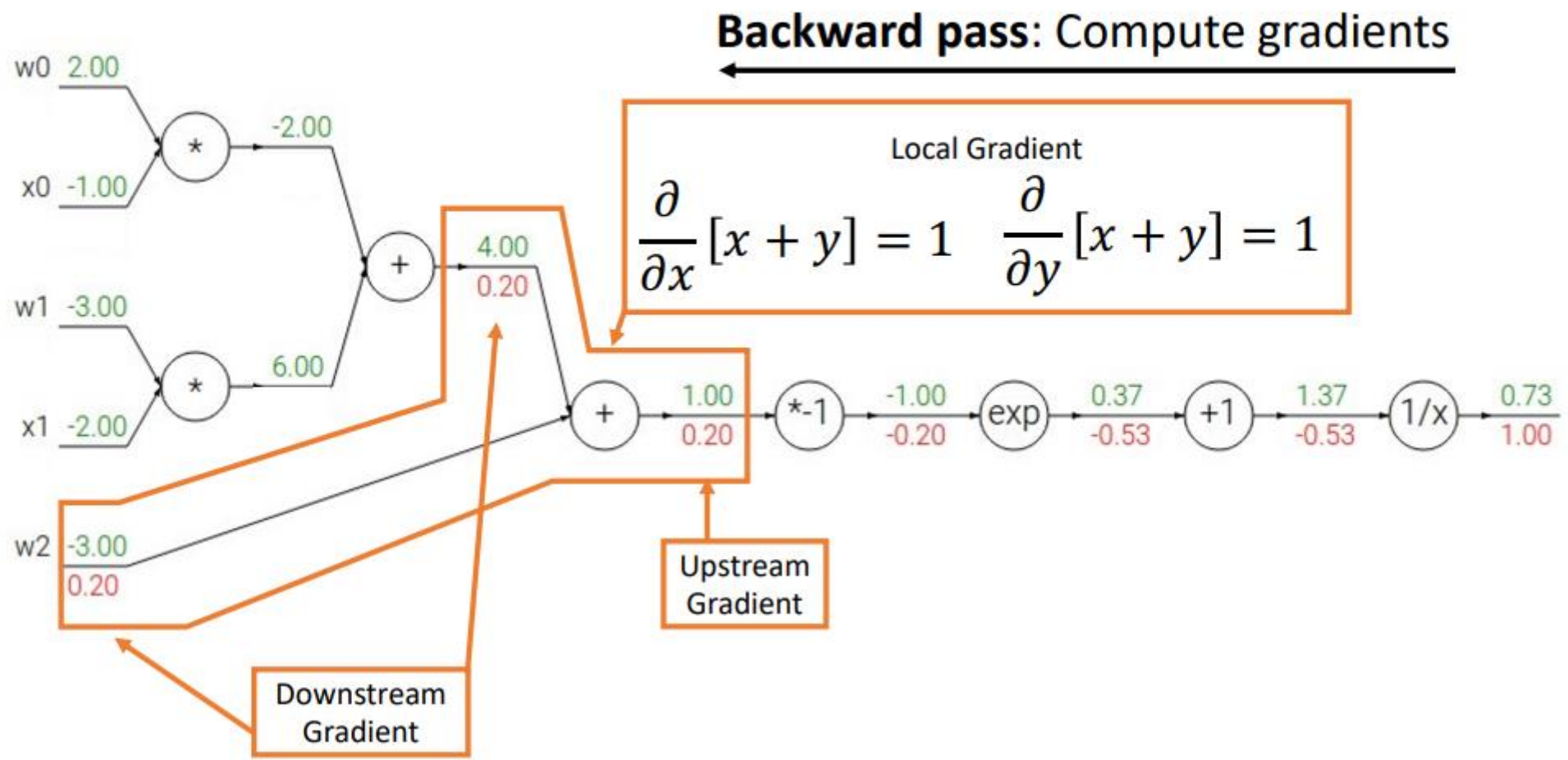

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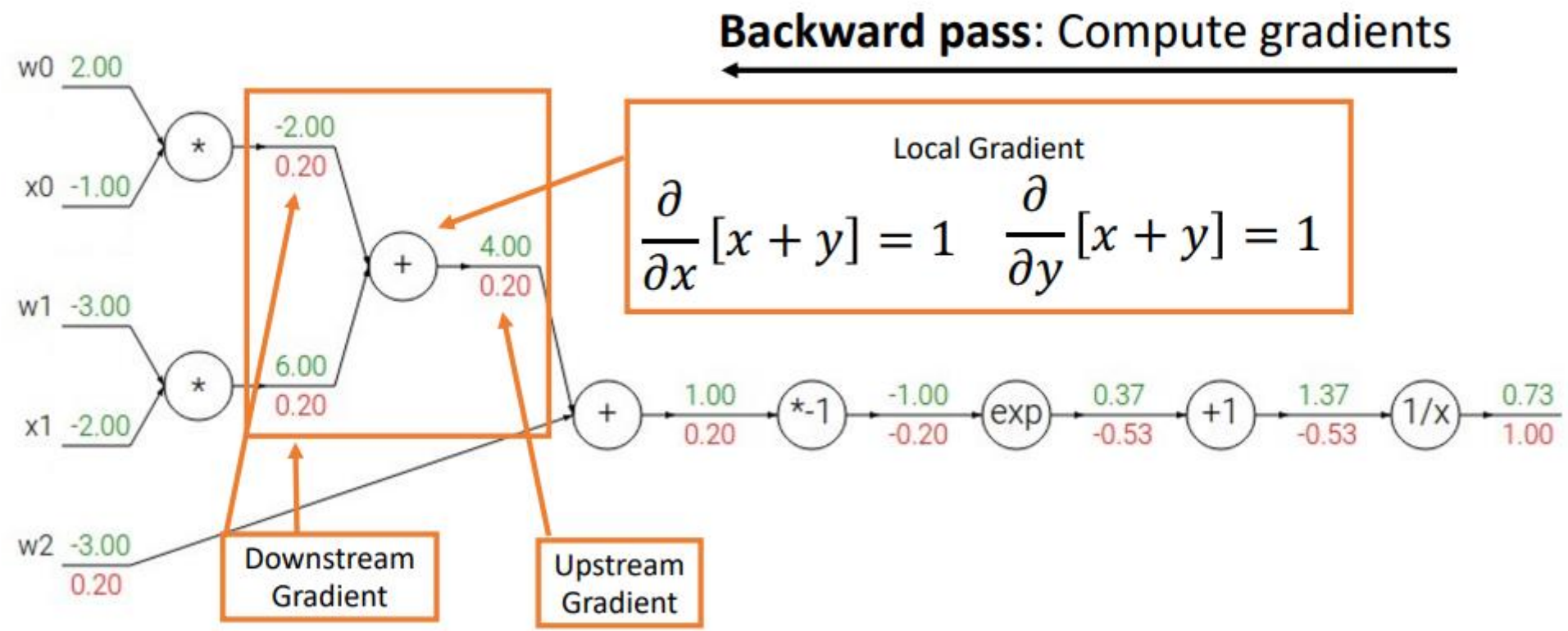
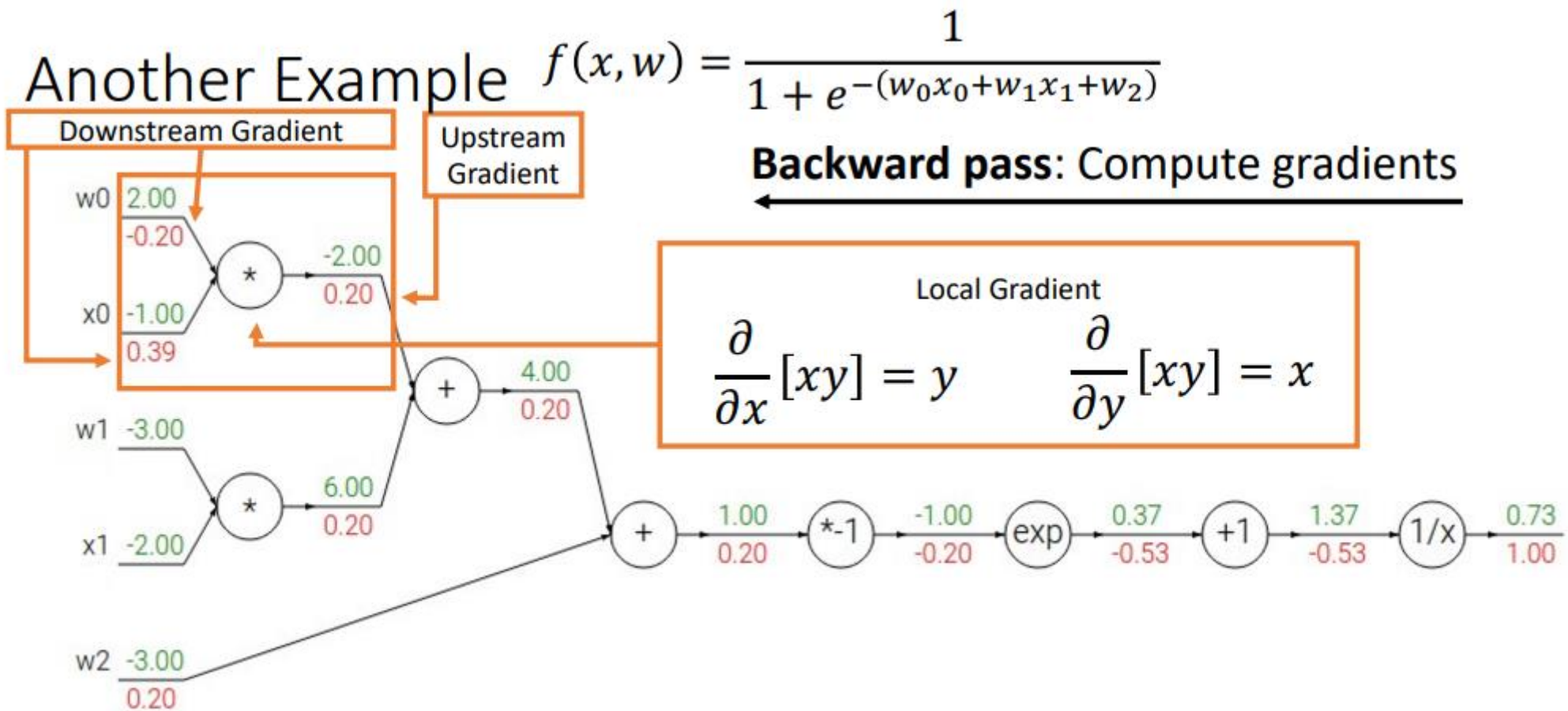
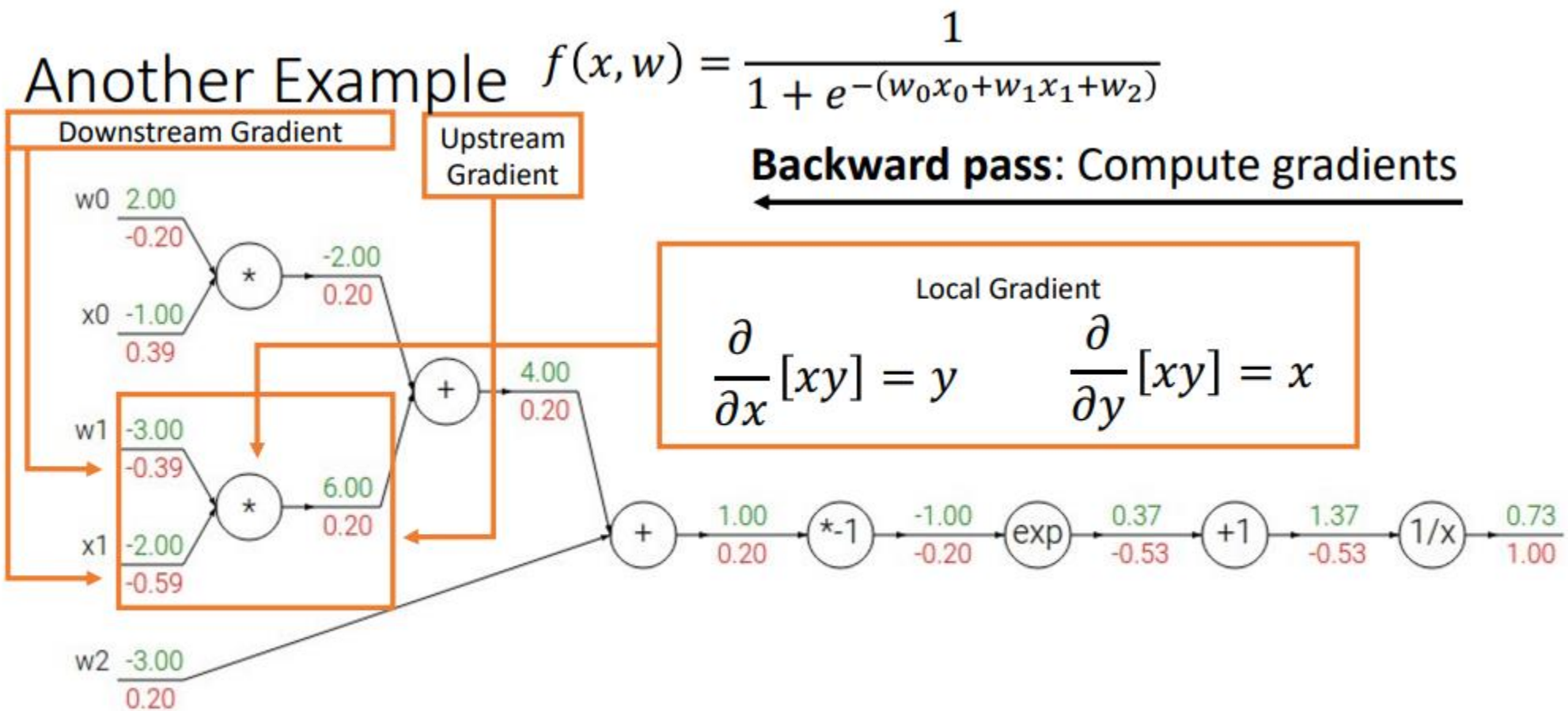


Backpropagation



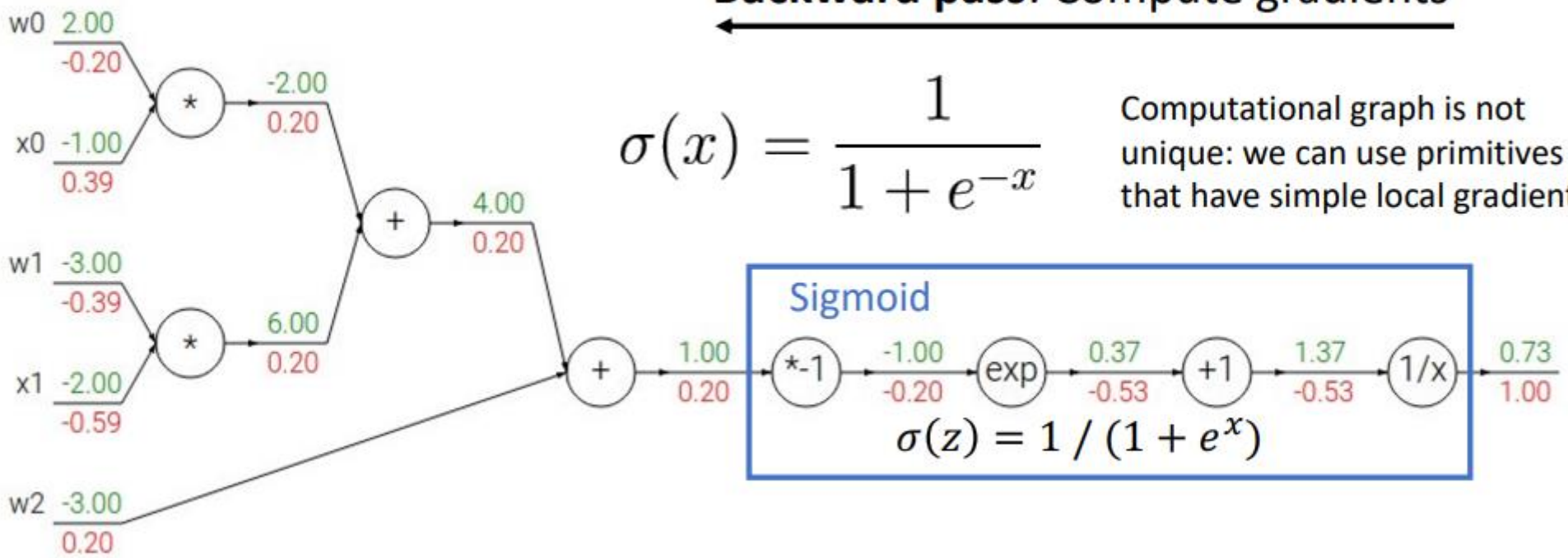
Backpropagation



Backpropagation

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

Backward pass: Compute gradients



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

Computational graph is not unique: we can use primitives that have simple local gradients

Backpropagation

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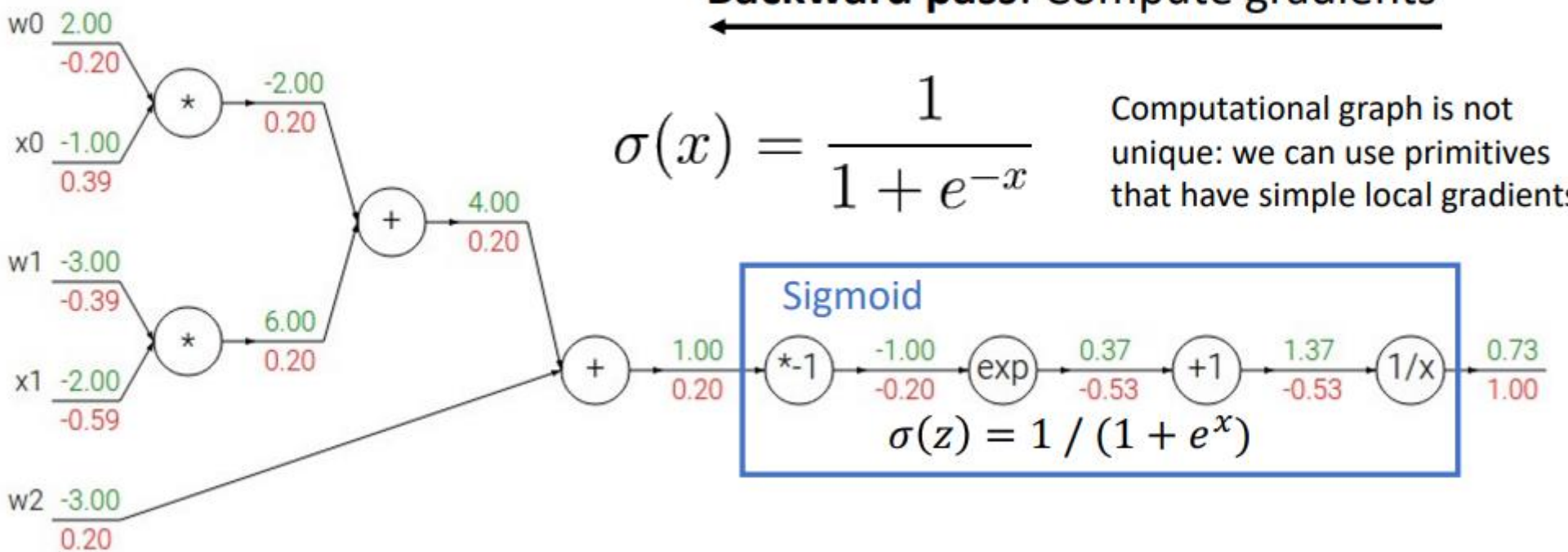

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Sigmoid local gradient: $$\frac{\partial}{\partial x}[\sigma(x)] = \frac{e^{-x}}{(1+e^{-x})^2} = \left(\frac{1+e^{-x}-1}{1+e^{-x}}\right)\left(\frac{1}{1+e^{-x}}\right) = \big(1-\sigma(x)\big)\sigma(x)$$

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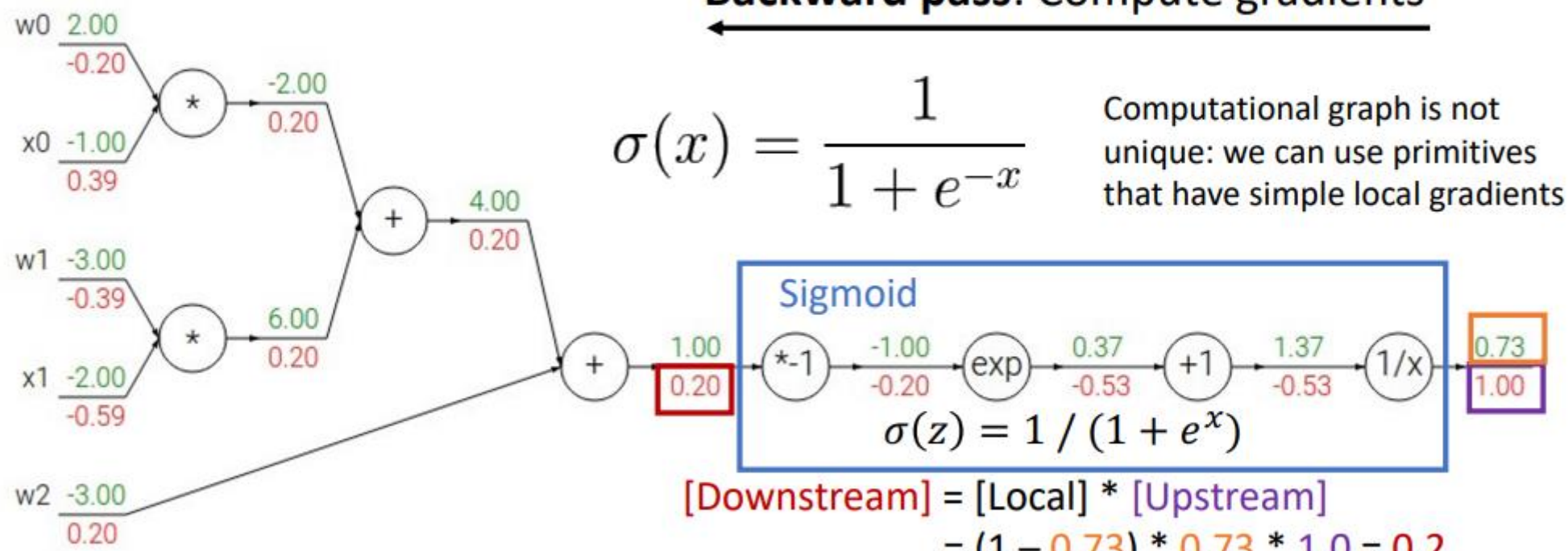


$$\sigma(x) = \frac{1}{1+e^{-x}}$$

Computational graph is not unique: we can use primitives that have simple local gradients

[Downstream] = [Local] * [Upstream]

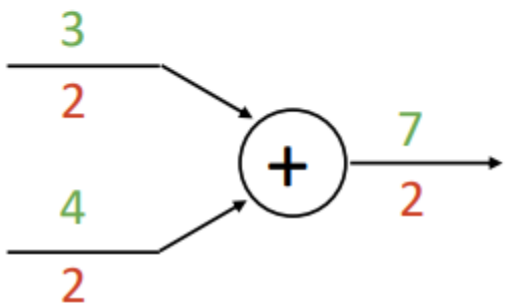
= (1 – 0.73) * 0.73 * 1.0 = 0.2

Sigmoid local gradient: $\frac{\partial}{\partial x}[\sigma(x)] = \frac{e^{-x}}{(1+e^{-x})^2} = \left(\frac{1+e^{-x}-1}{1+e^{-x}}\right)\left(\frac{1}{1+e^{-x}}\right) = \big(1-\sigma(x)\big)\sigma(x)$

Backpropagation

Patterns in Gradient Flow

add gate: gradient distributor



Backpropagation

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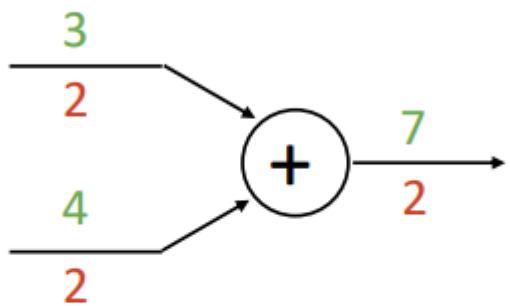
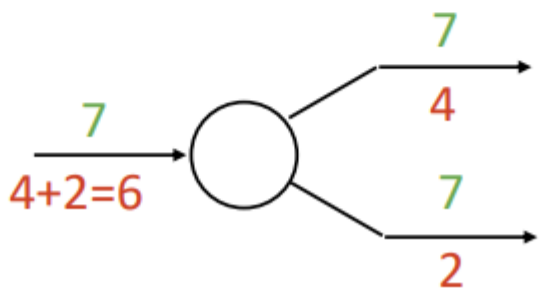


copy gate: gradient adder



Backpropagation

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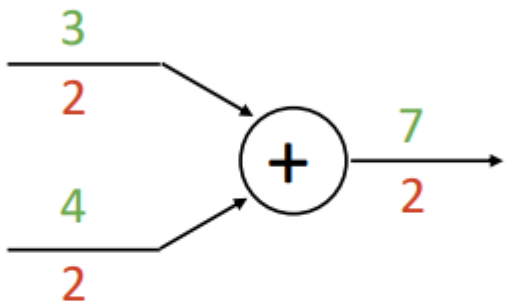
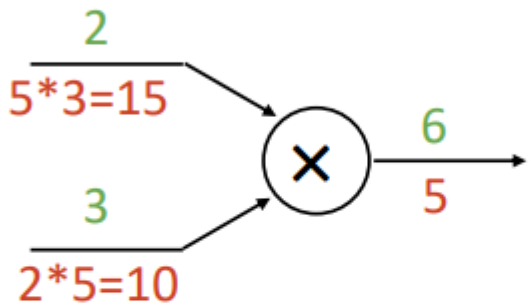


mul gate: "swap multiplier"



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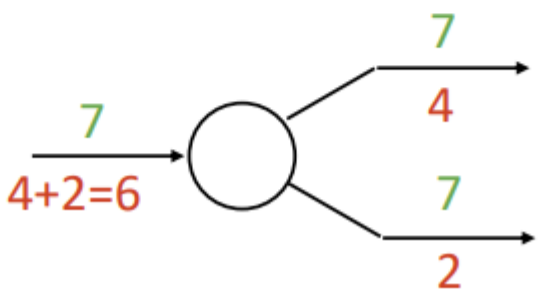

Backpropagation

Patterns in Gradient Flow

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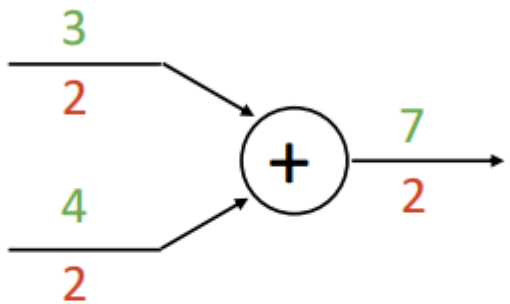

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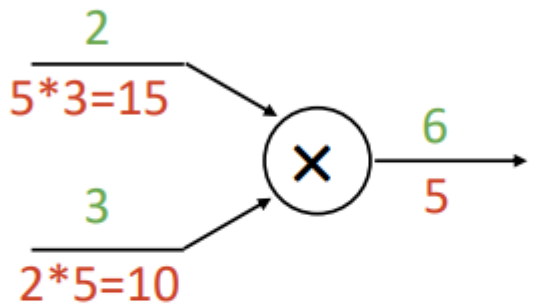
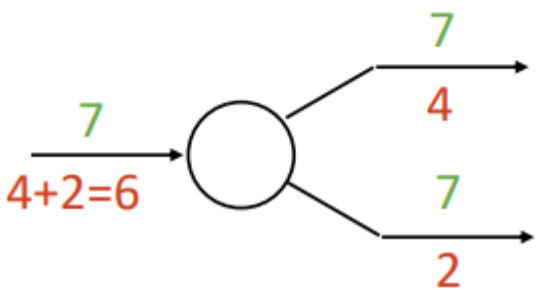
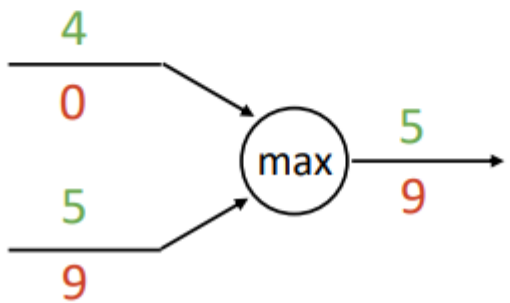


copy gate: gradient adder



max gate: gradient router



Backpropagation

So far: backprop with scalars

What about vector-valued functions?

Recap: Vector derivatives

Scalar to Scalar

$$x \in \mathbb{R}, y \in \mathbb{R}$$

Regular derivative:

$$\frac{\partial y}{\partial x} \in \mathbb{R}$$

If x changes by a small amount, how much will y change?

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Vector to Scalar

$$x \in \mathbb{R}^N, y \in \mathbb{R}$$

Derivative is **Gradient**:

$$\frac{\partial y}{\partial x} \in \mathbb{R}^N \quad \left(\frac{\partial y}{\partial x}\right)_n = \frac{\partial y}{\partial x_n}$$

For each element of x, if it changes by a small amount then how much will y change?

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Vector to Vector

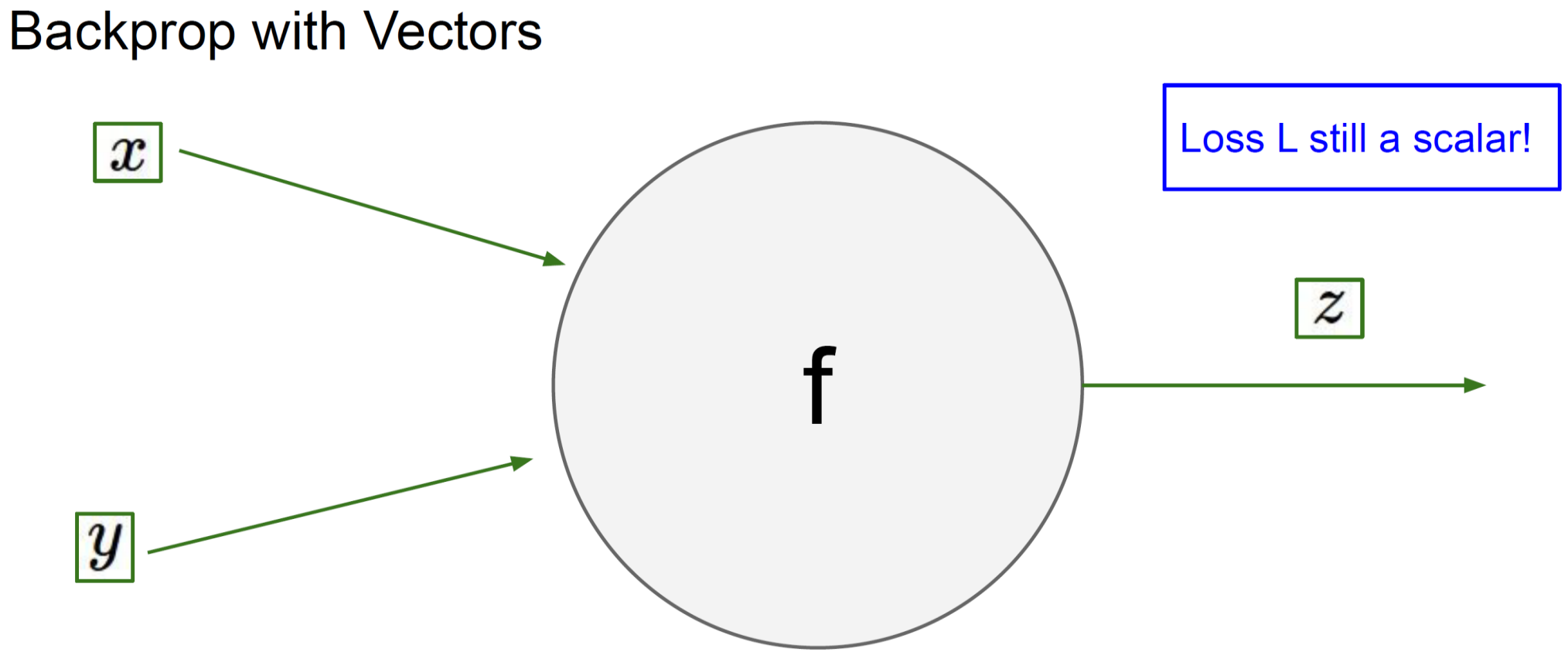
$$x \in \mathbb{R}^N, y \in \mathbb{R}^M$$

Derivative is **Jacobian**:

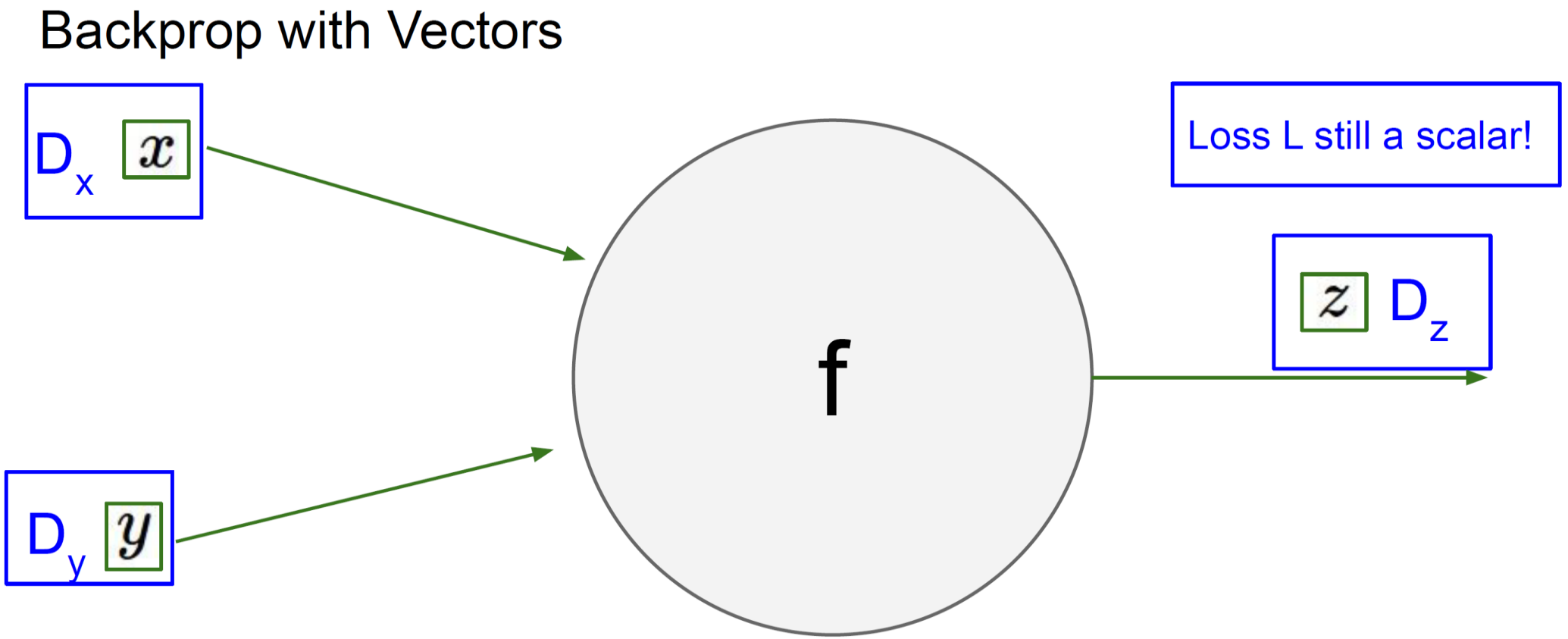
$$\frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M} \quad \left(\frac{\partial y}{\partial x}\right)_{n,m} = \frac{\partial y_m}{\partial x_n}$$

For each element of x, if it changes by a small amount then how much will each element of y change?

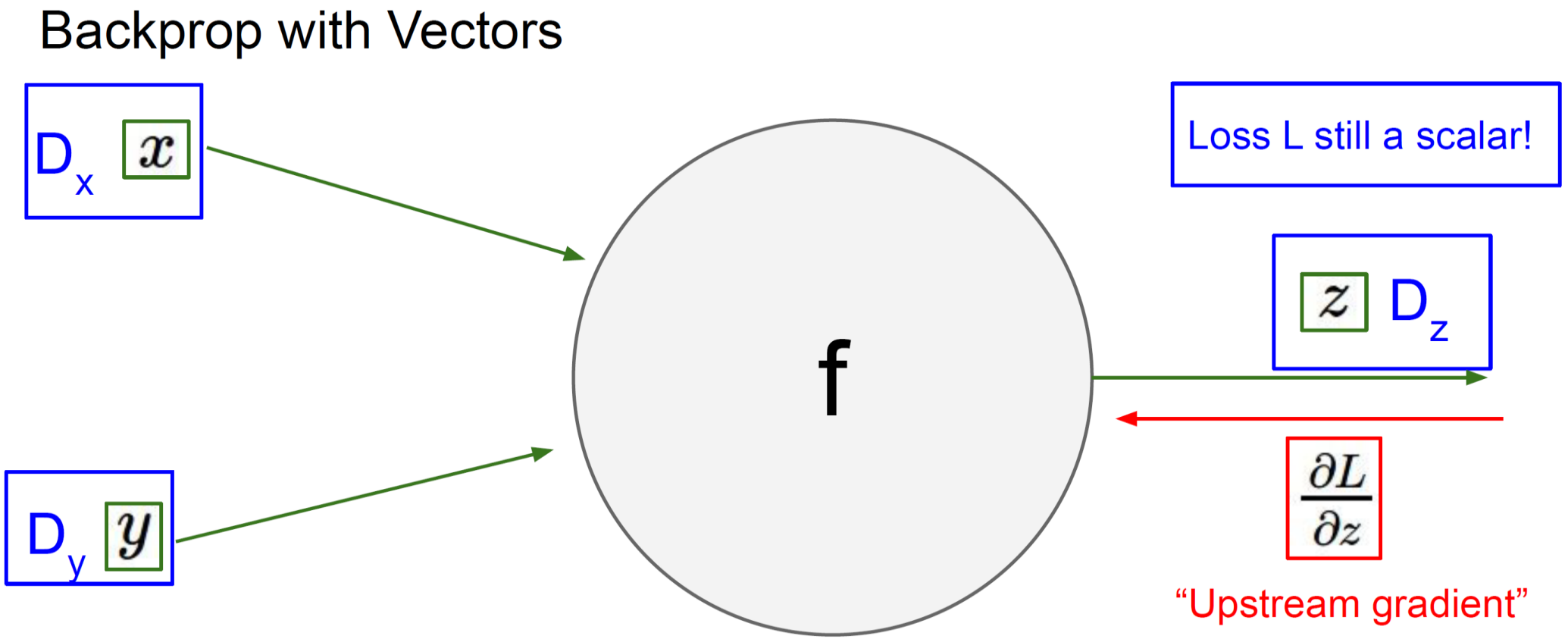
Backpropagation



Backpropagation



Backpropagation



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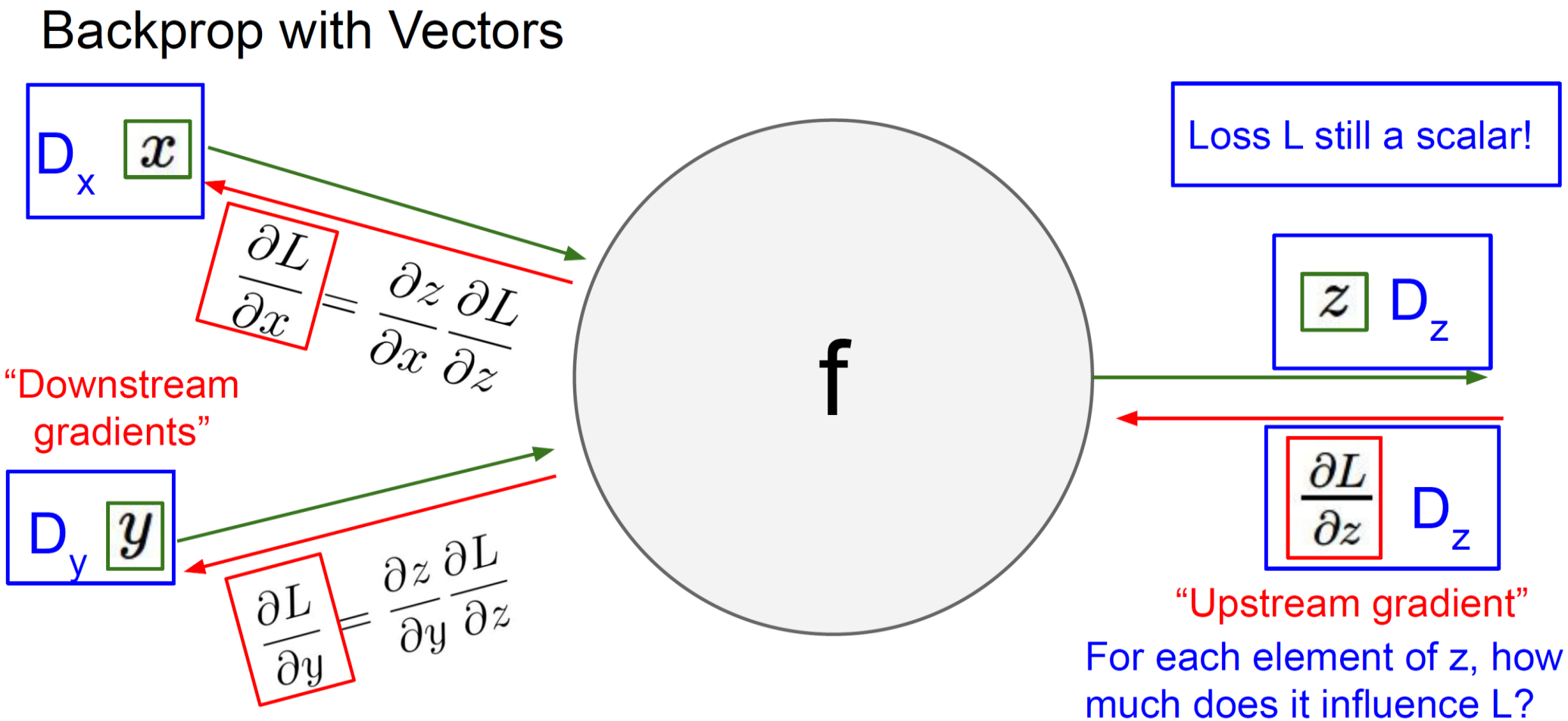

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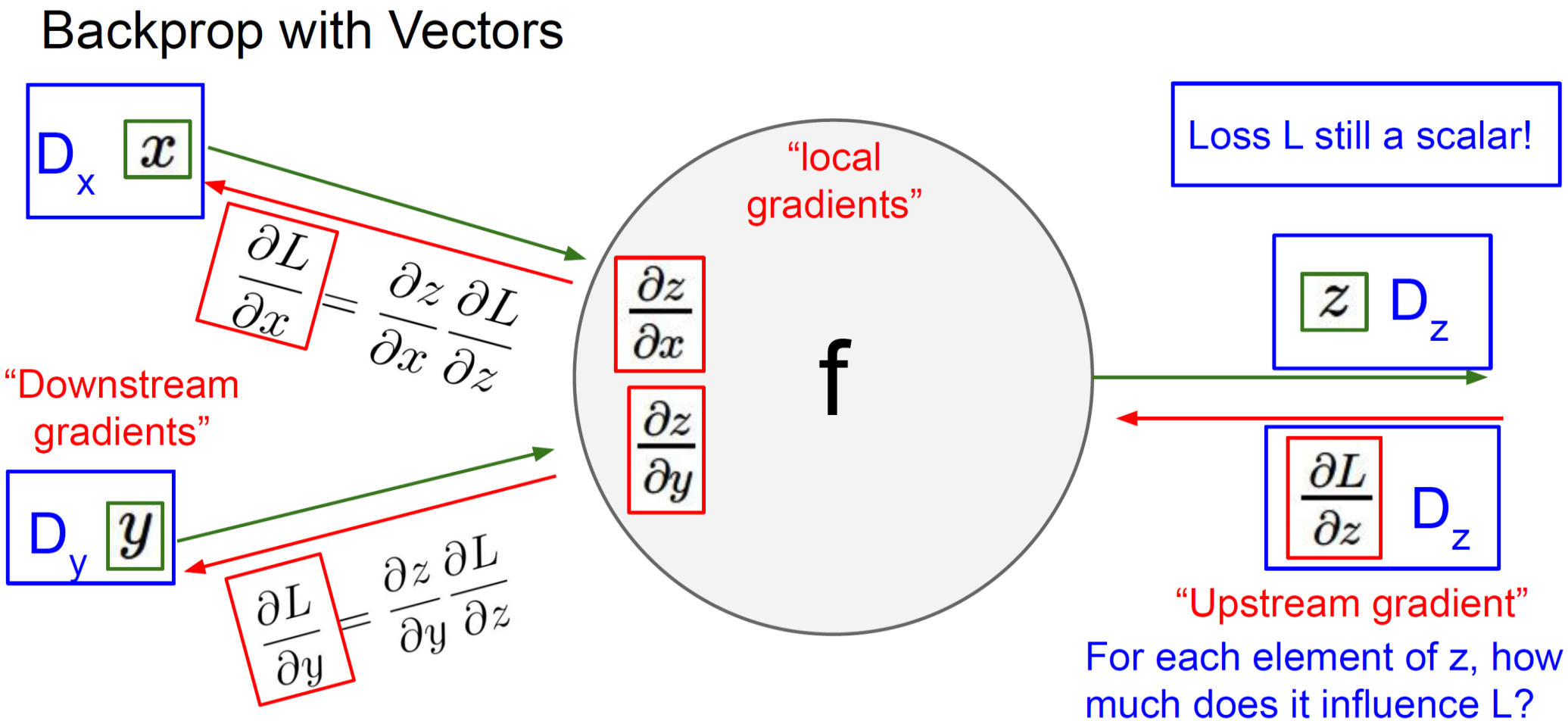

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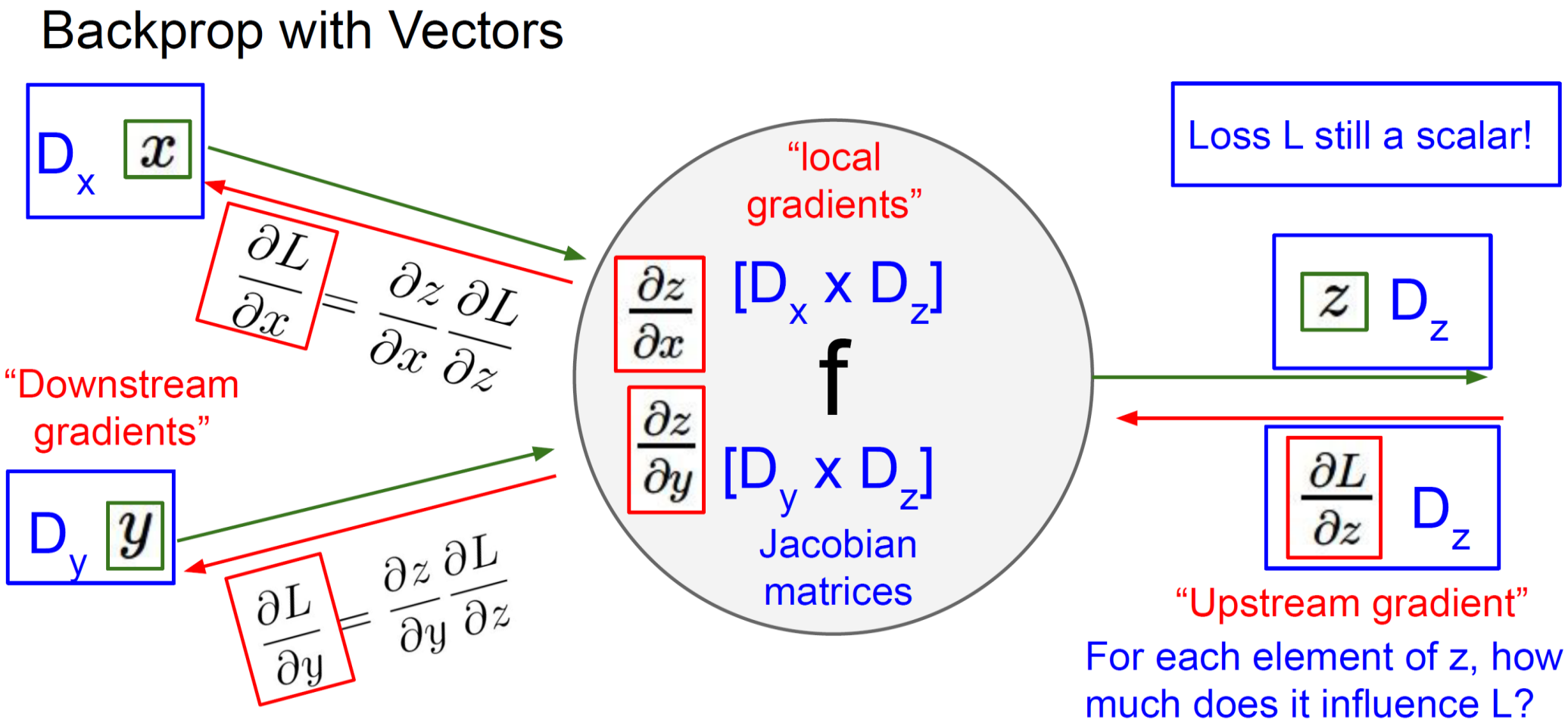

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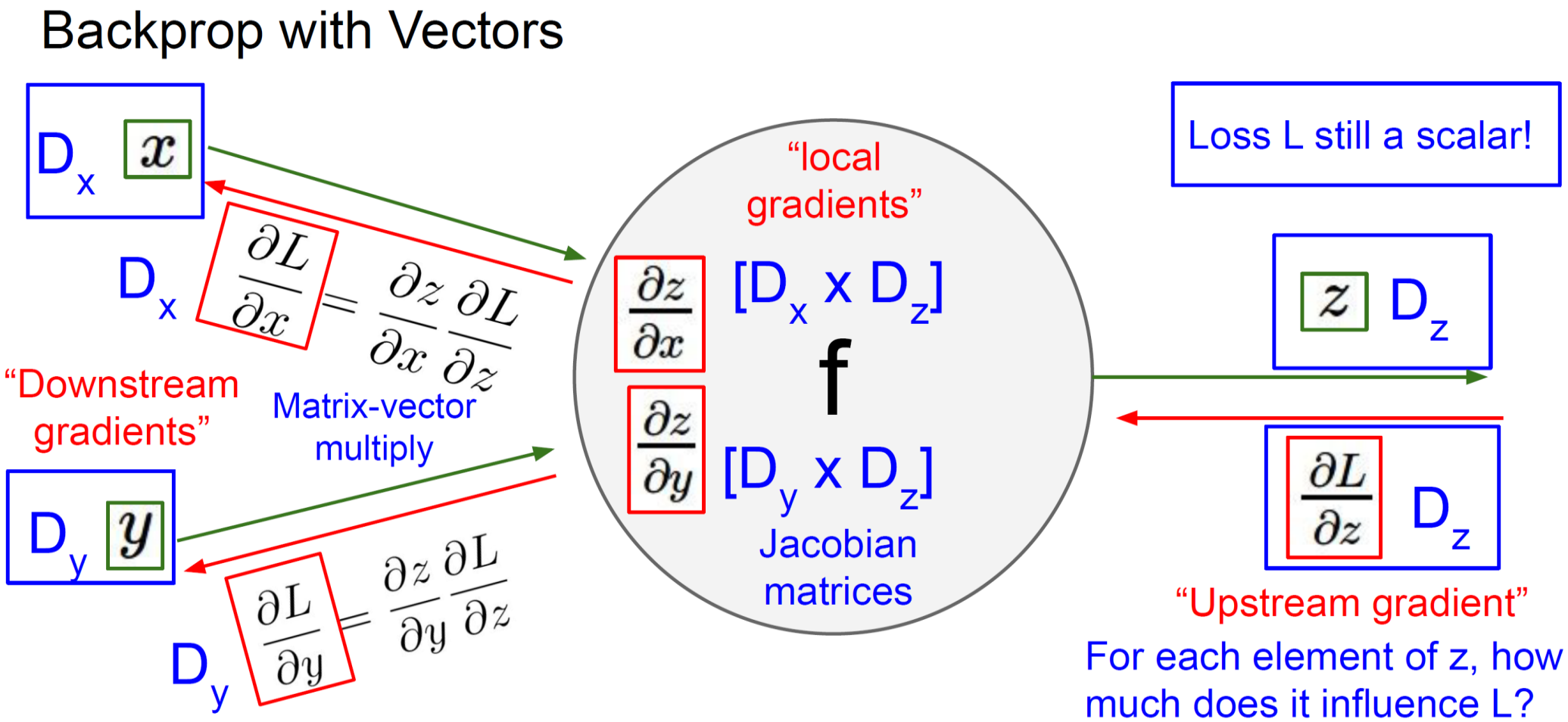
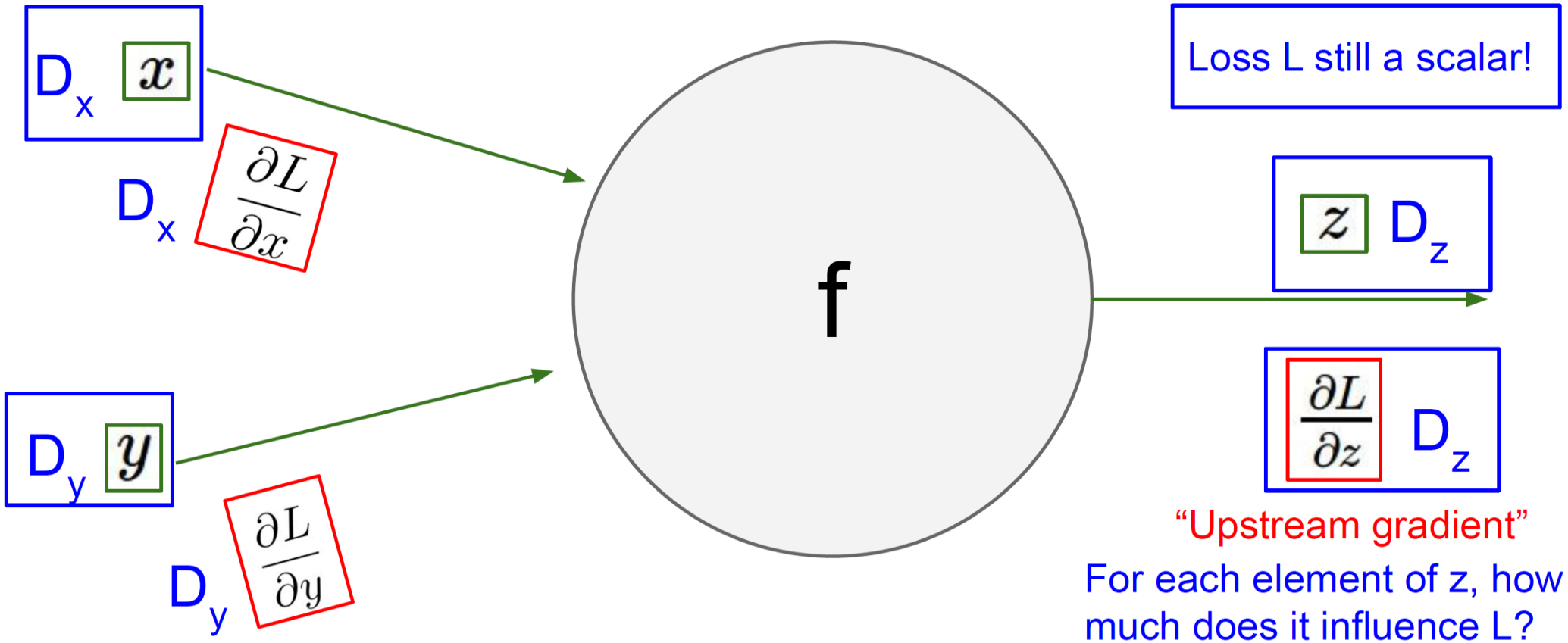


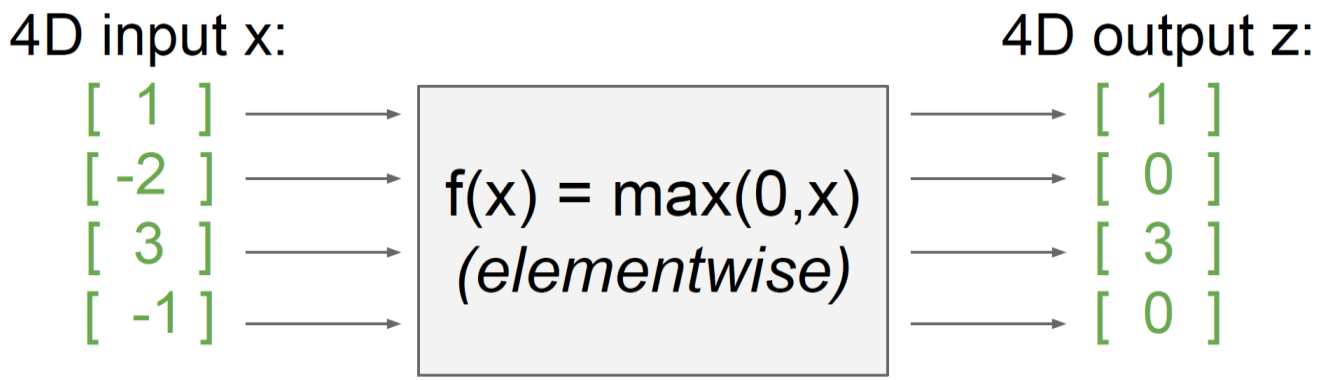
Backpropagation

Gradients of variables wrt loss have same dims as the original variable



Backpropagation

Backprop with Vectors



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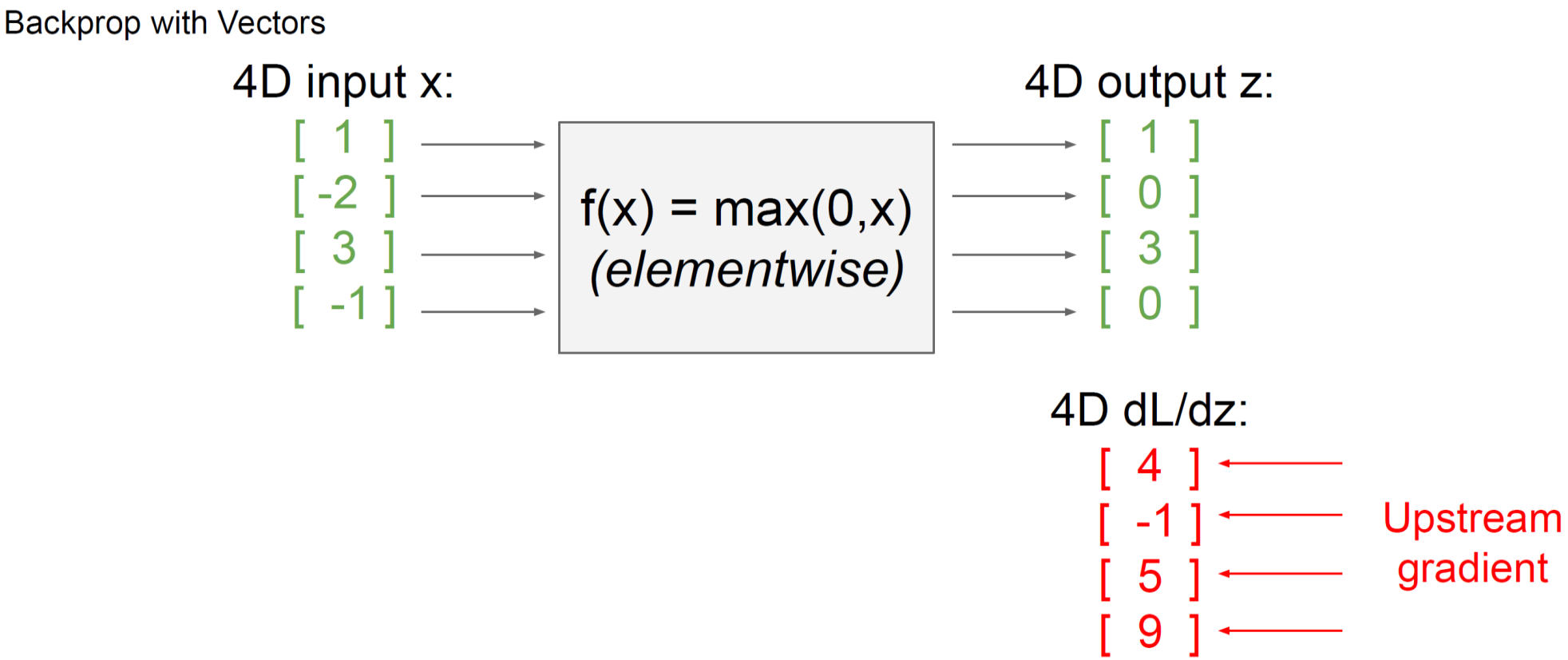

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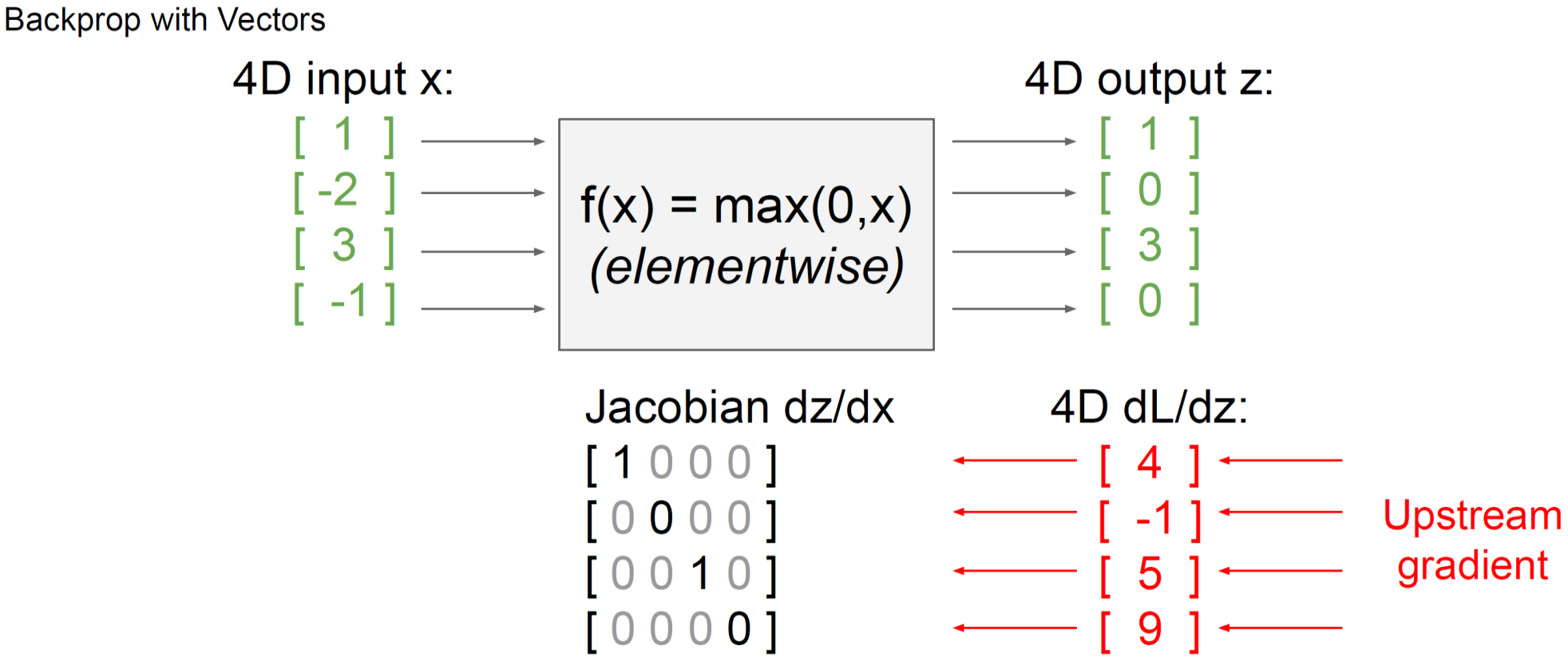

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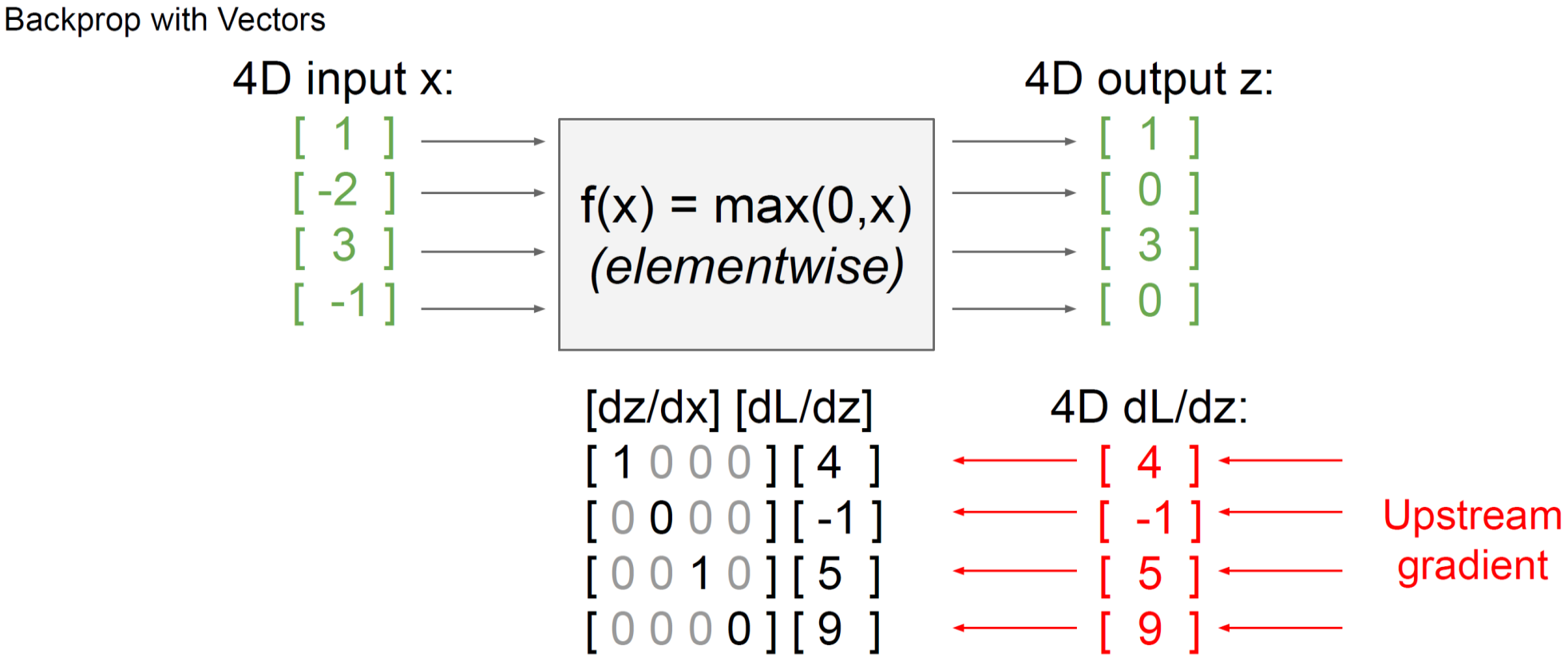

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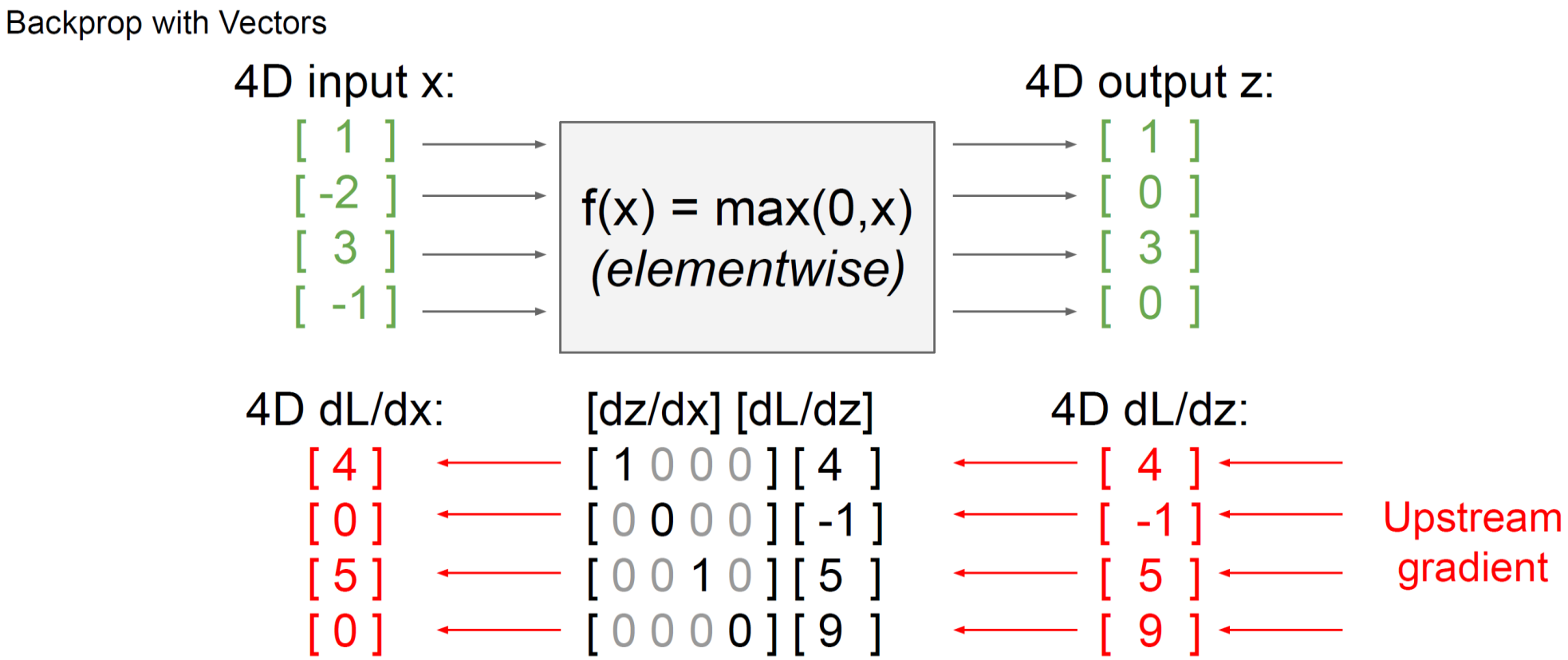
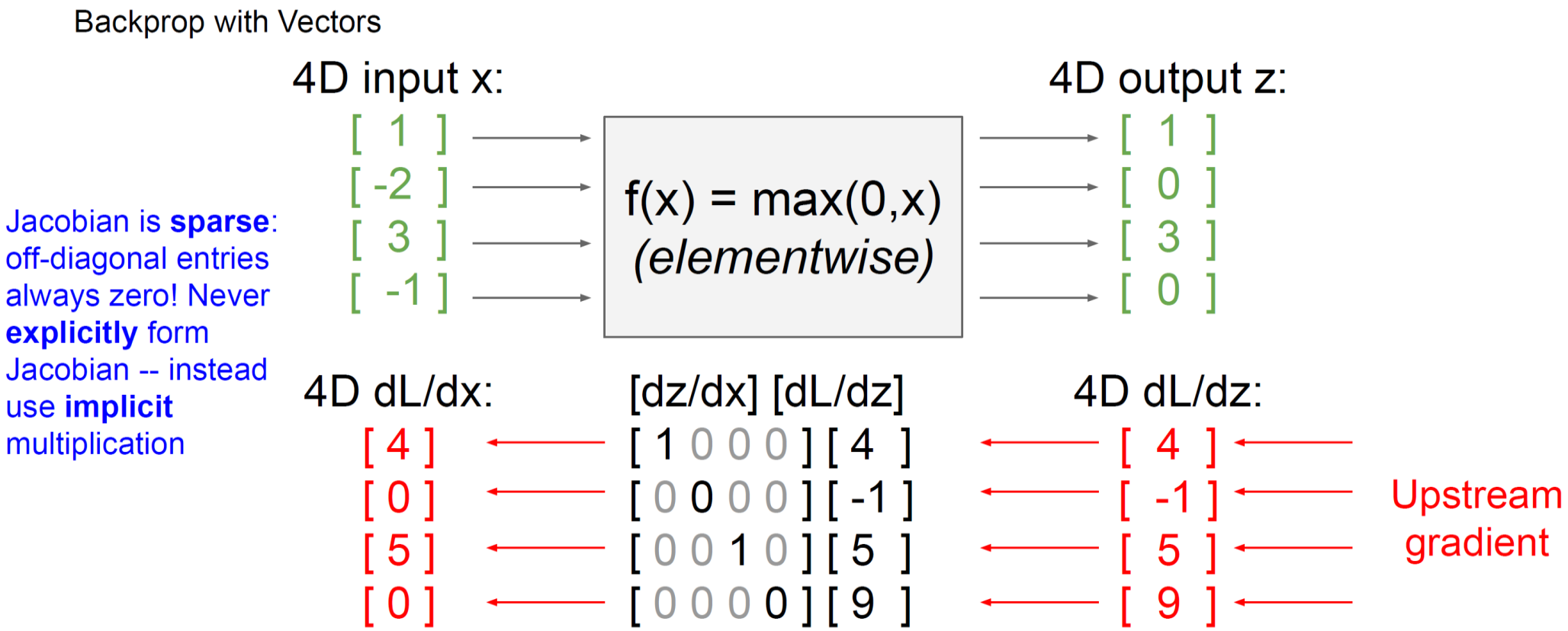
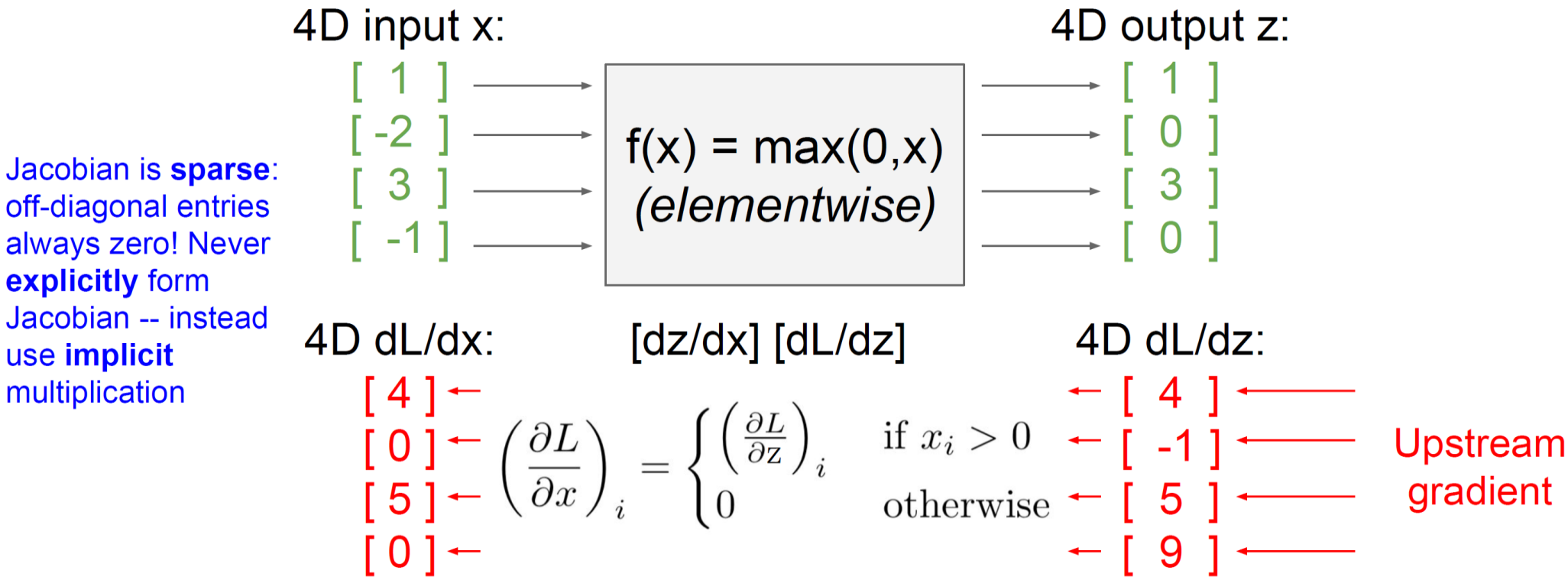


Backpropagation



Backpropagation

Backprop with Vectors



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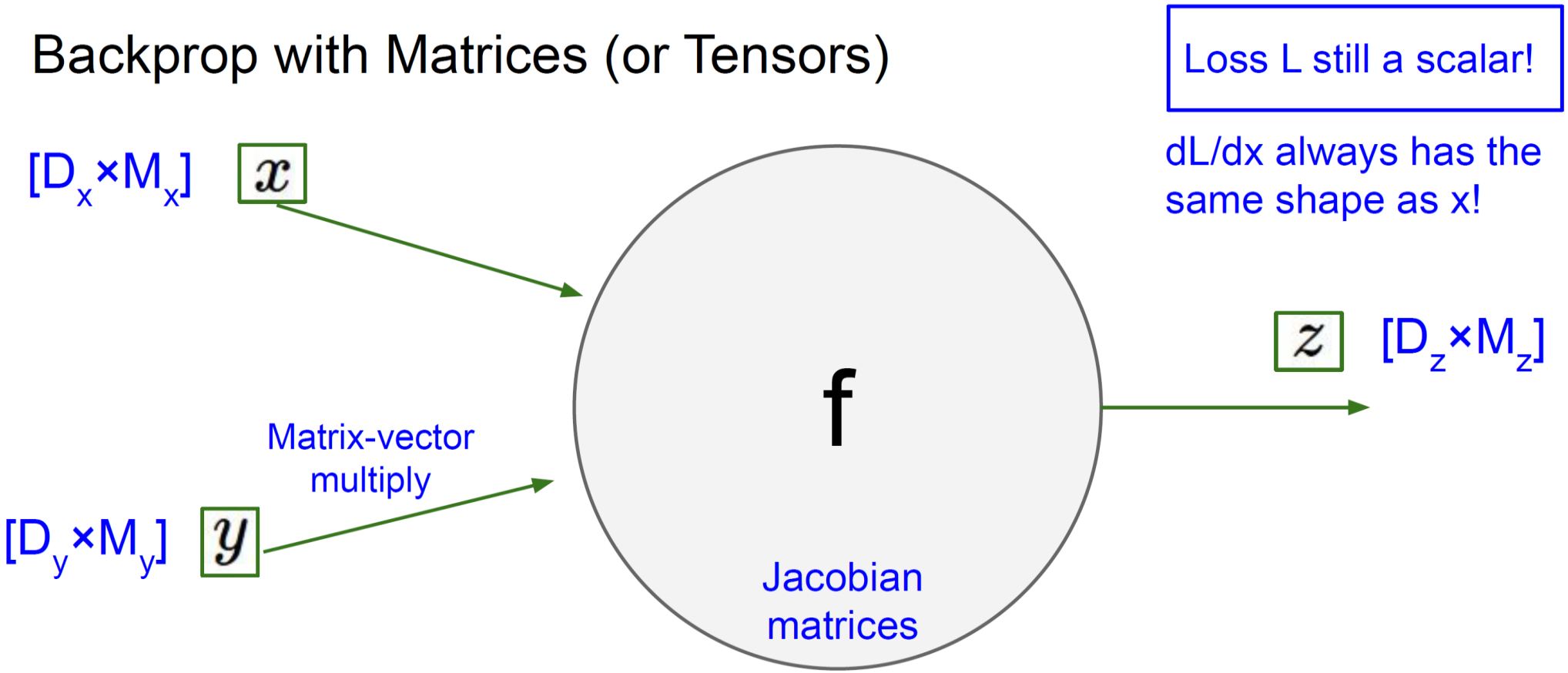

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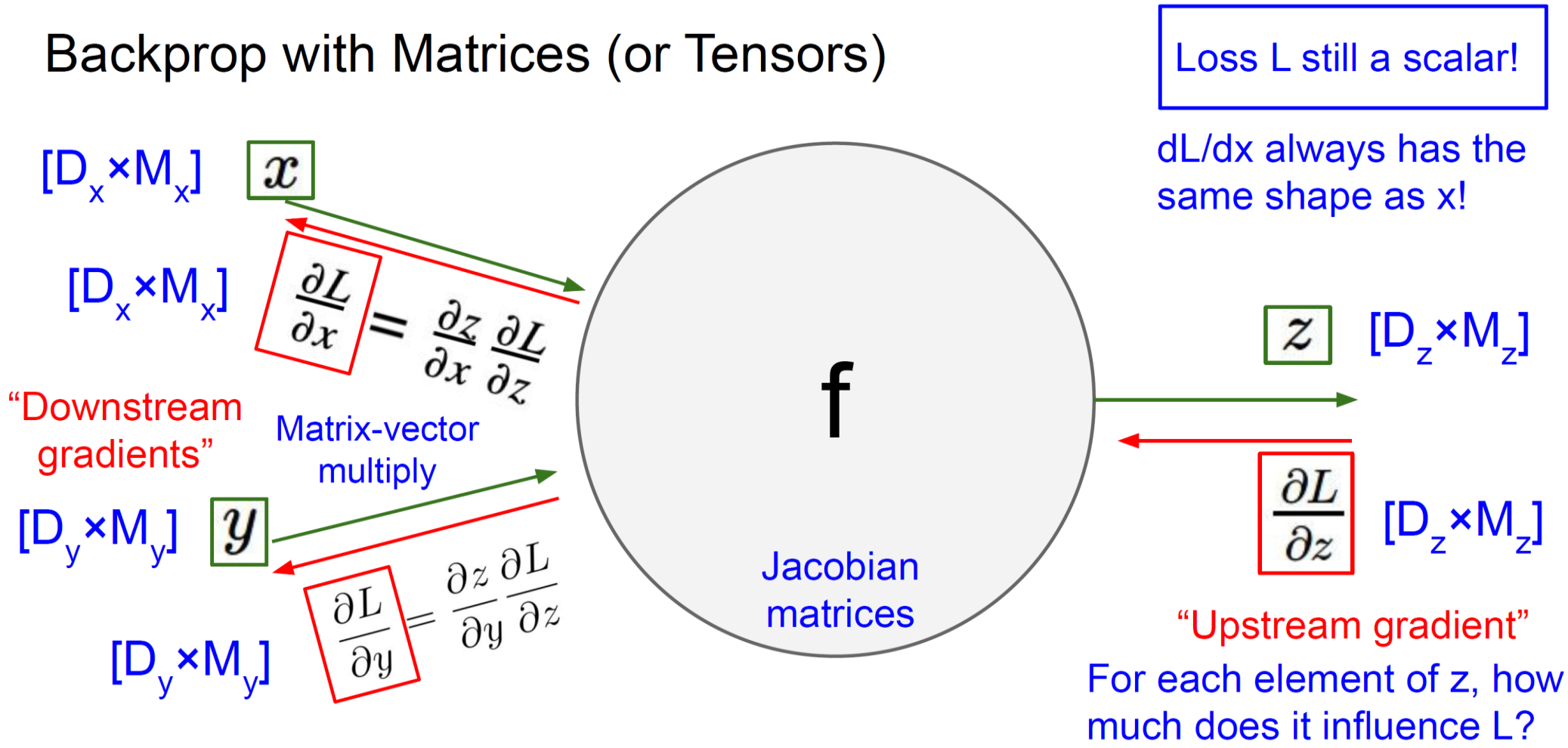

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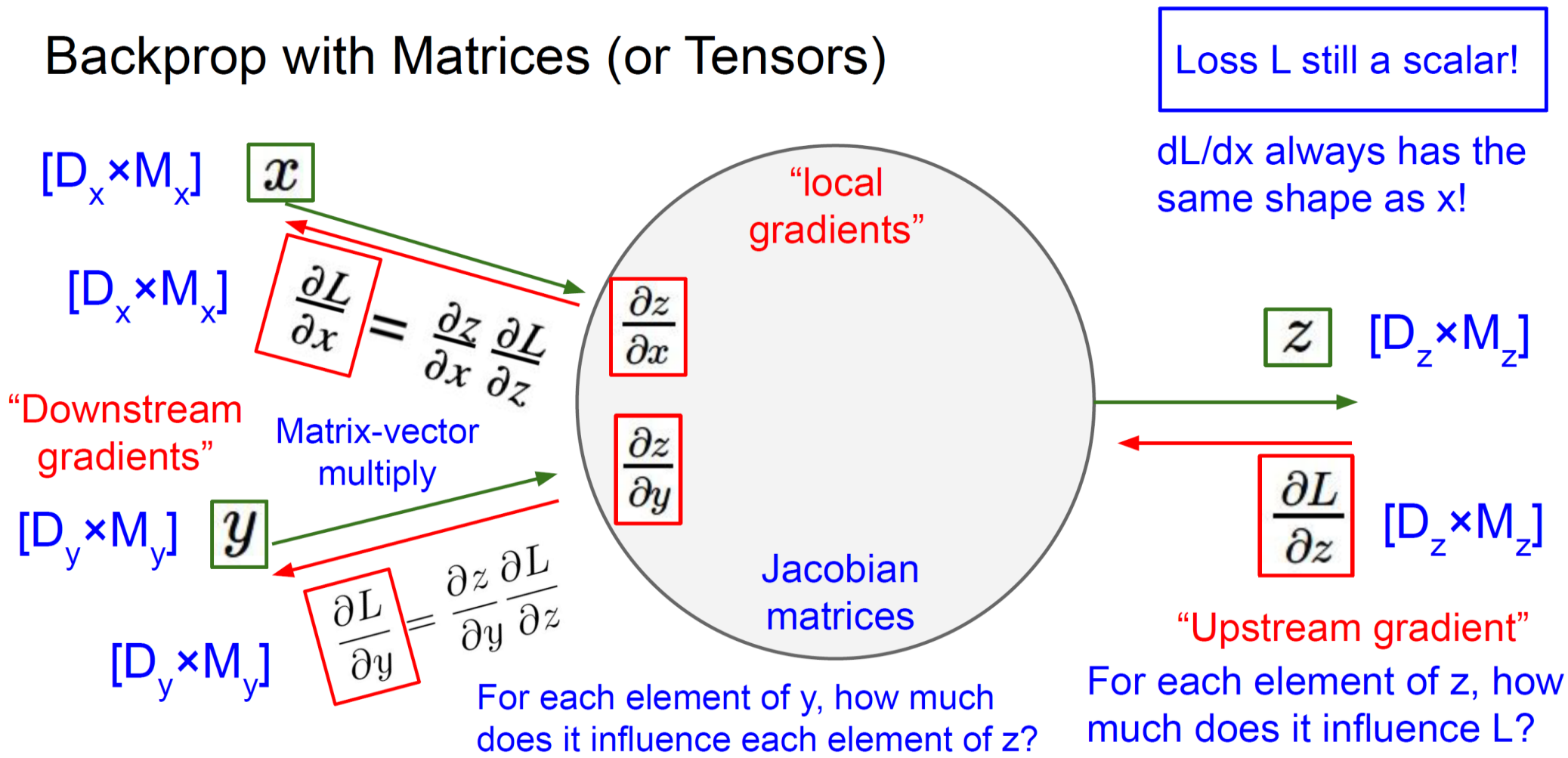
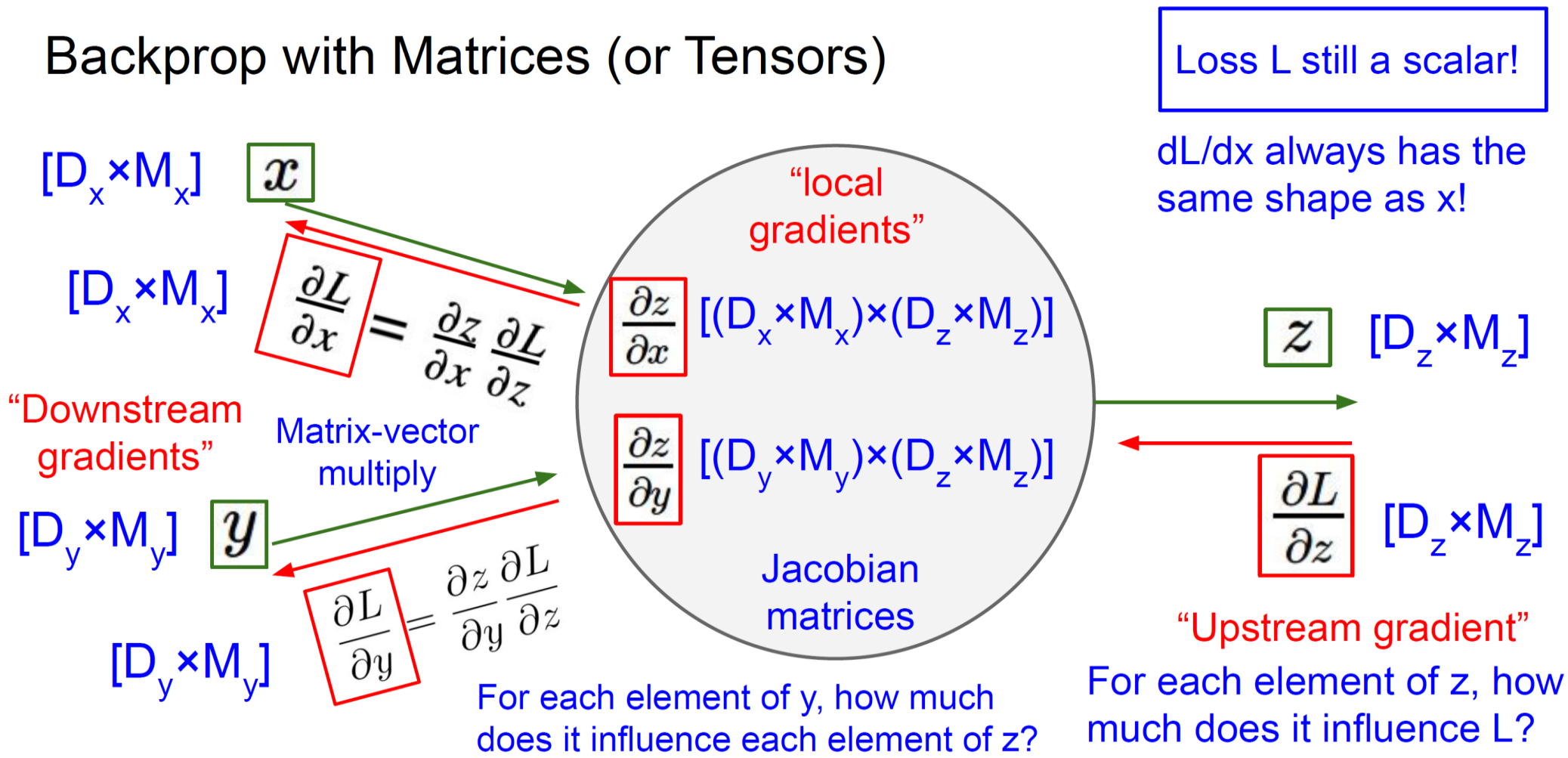


Backpropagation



Backpropagation

Example: Matrix Multiplication

x: [N×D]

[2 1 -3]
[-3 4 2]

w: [D×M]

[3 2 1 -1]
[2 1 3 2]
[3 2 1 -2]

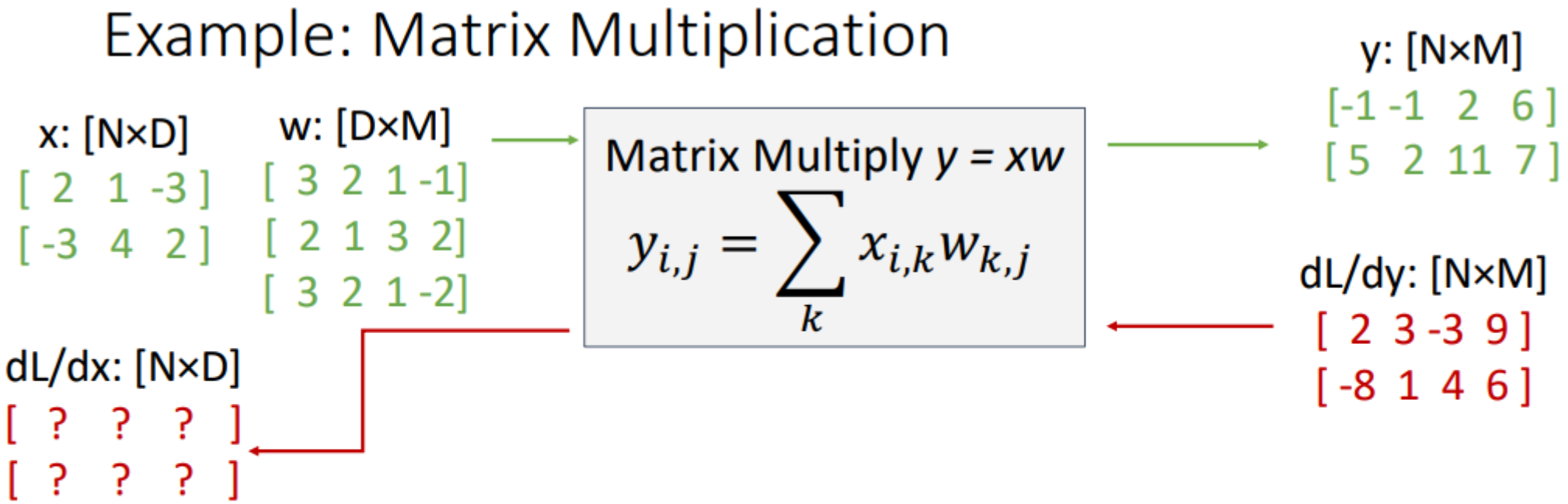
Matrix Multiply $y = xw$

$$y_{i,j} = \sum_k x_{i,k} w_{k,j}$$

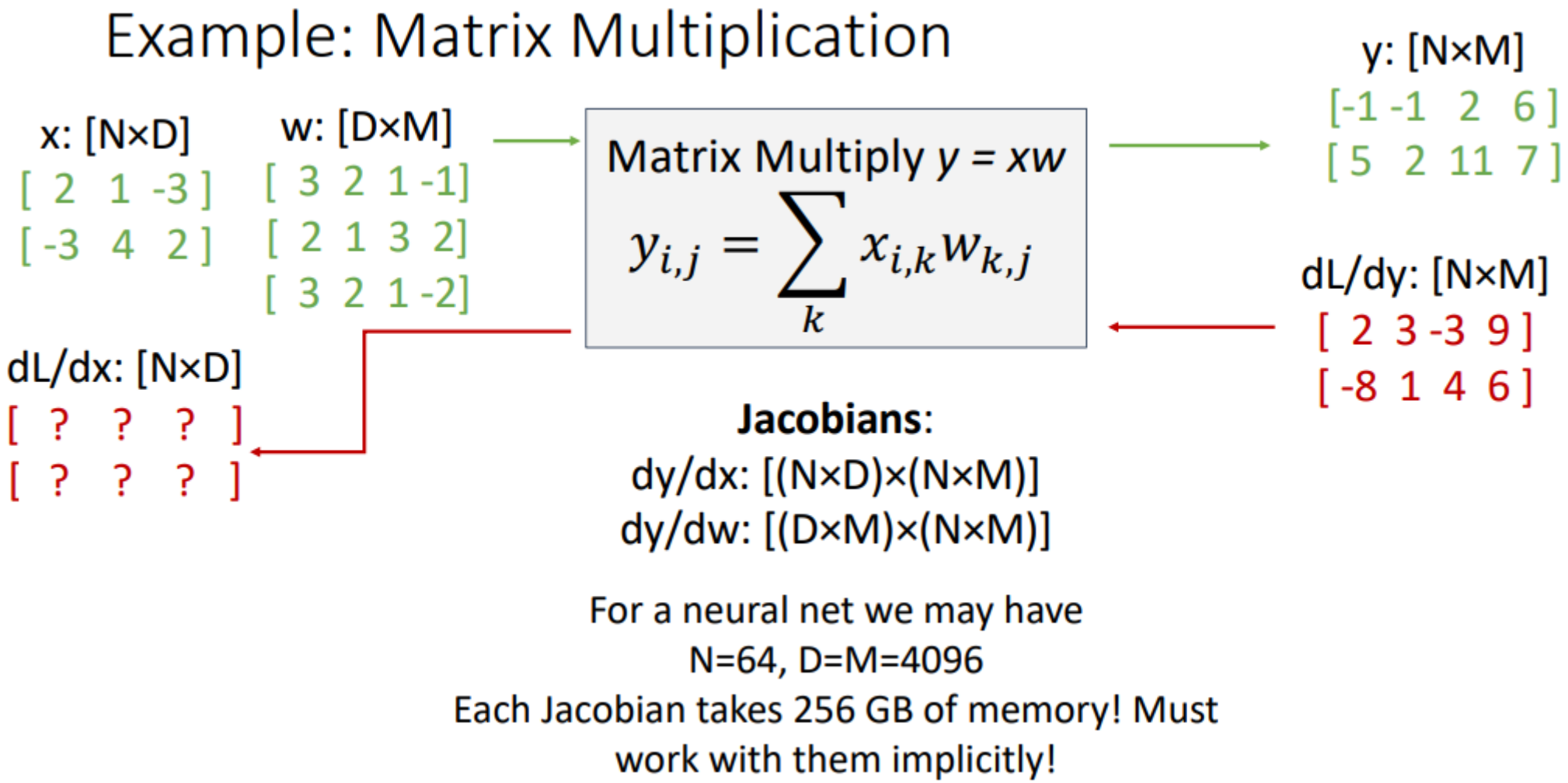
y: [N×M]

[-1 -1 2 6]
[5 2 11 7]

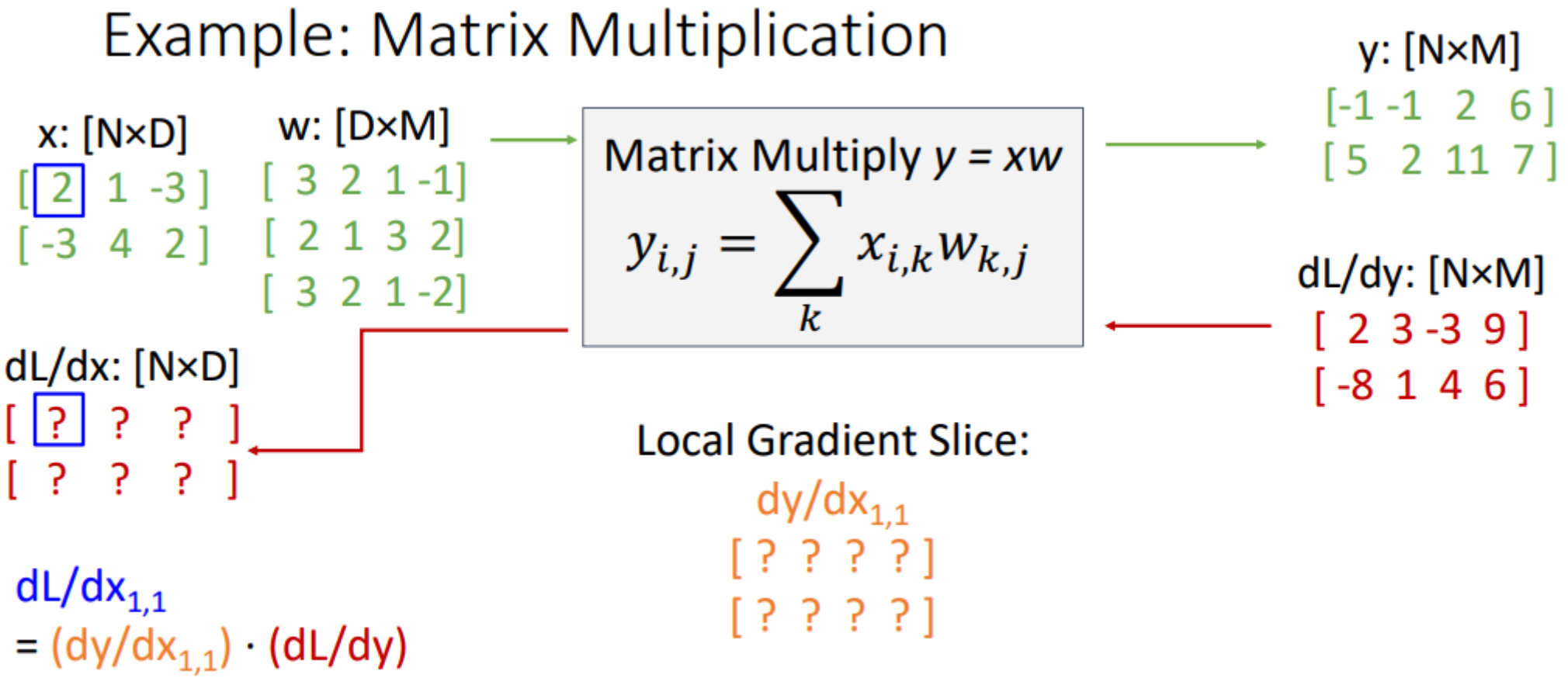
Backpropagation



Backpropagation



Backpropagation



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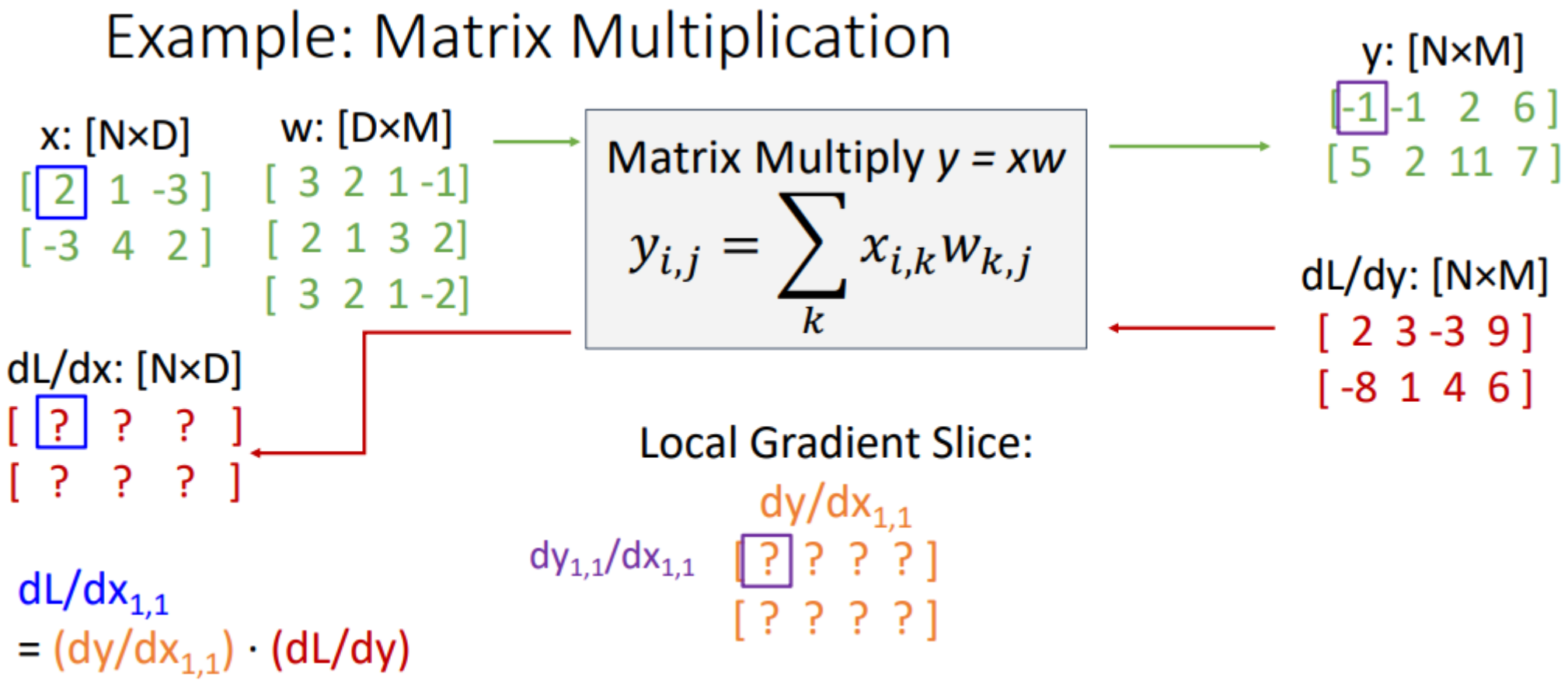

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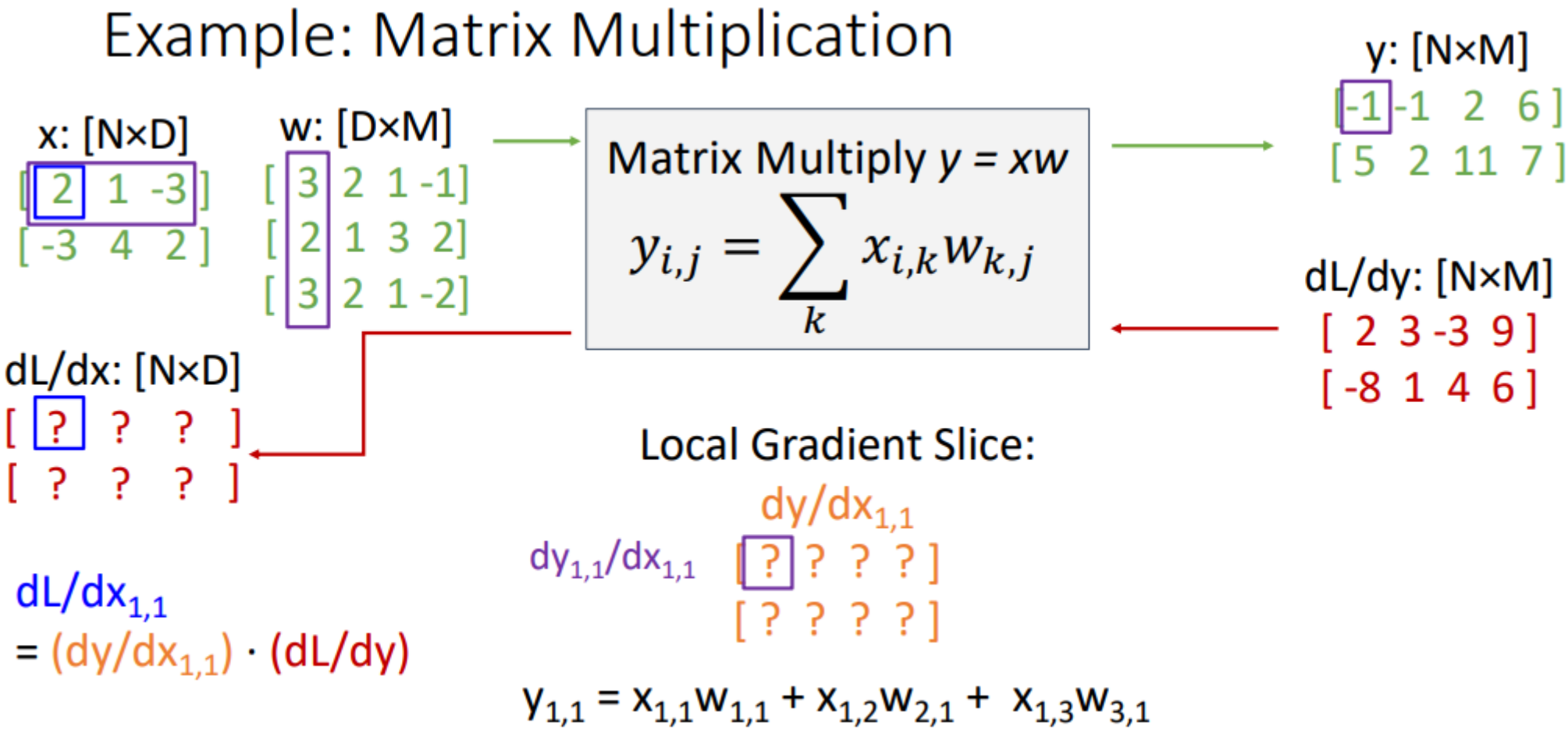
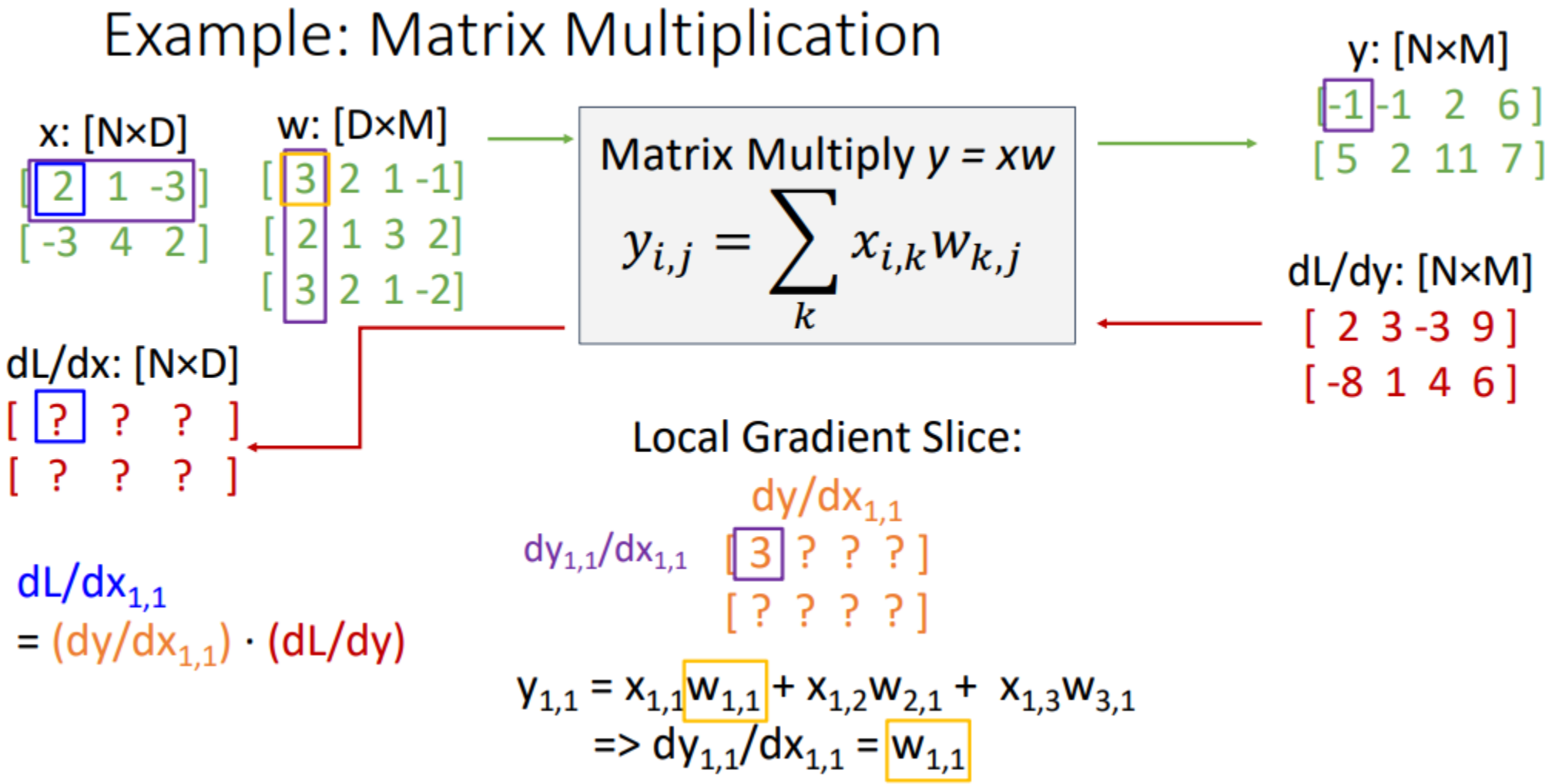
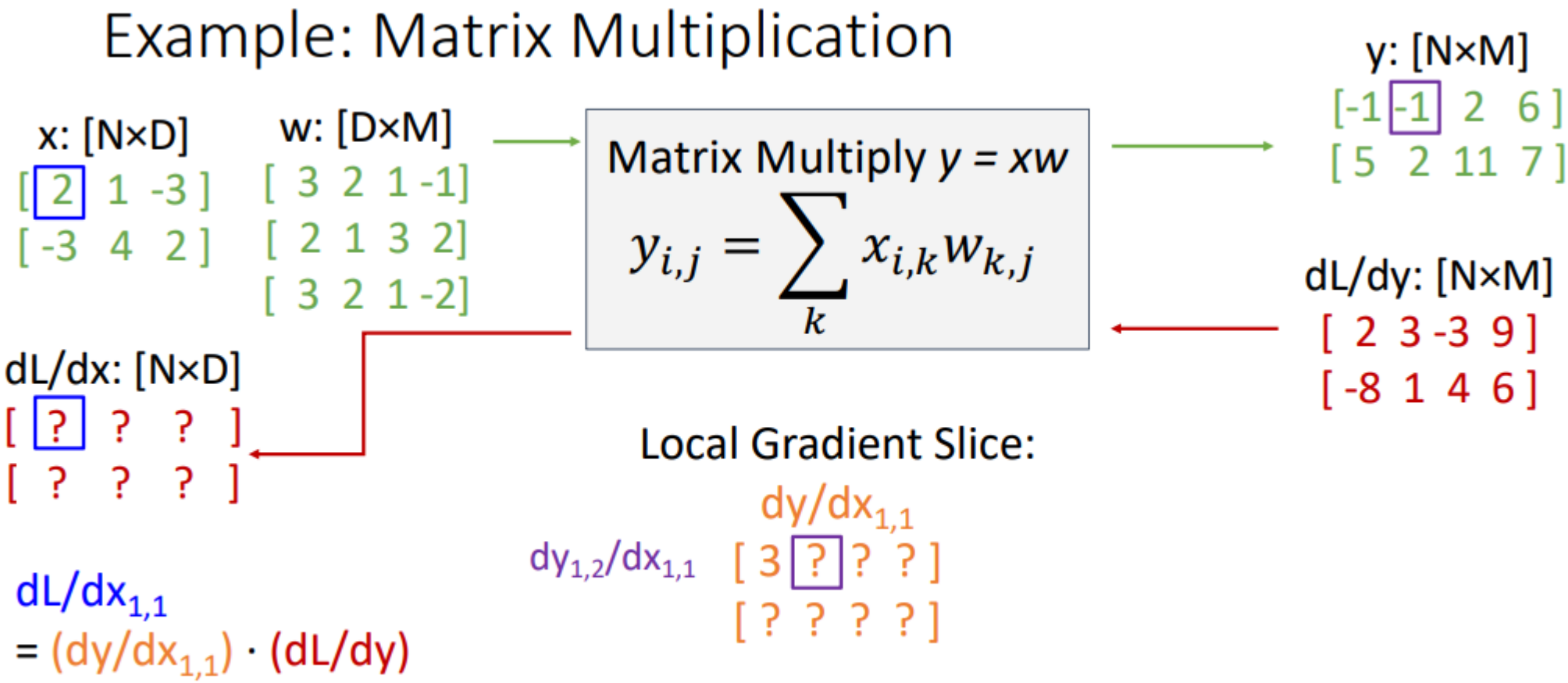


Backpropagation



Backpropagation



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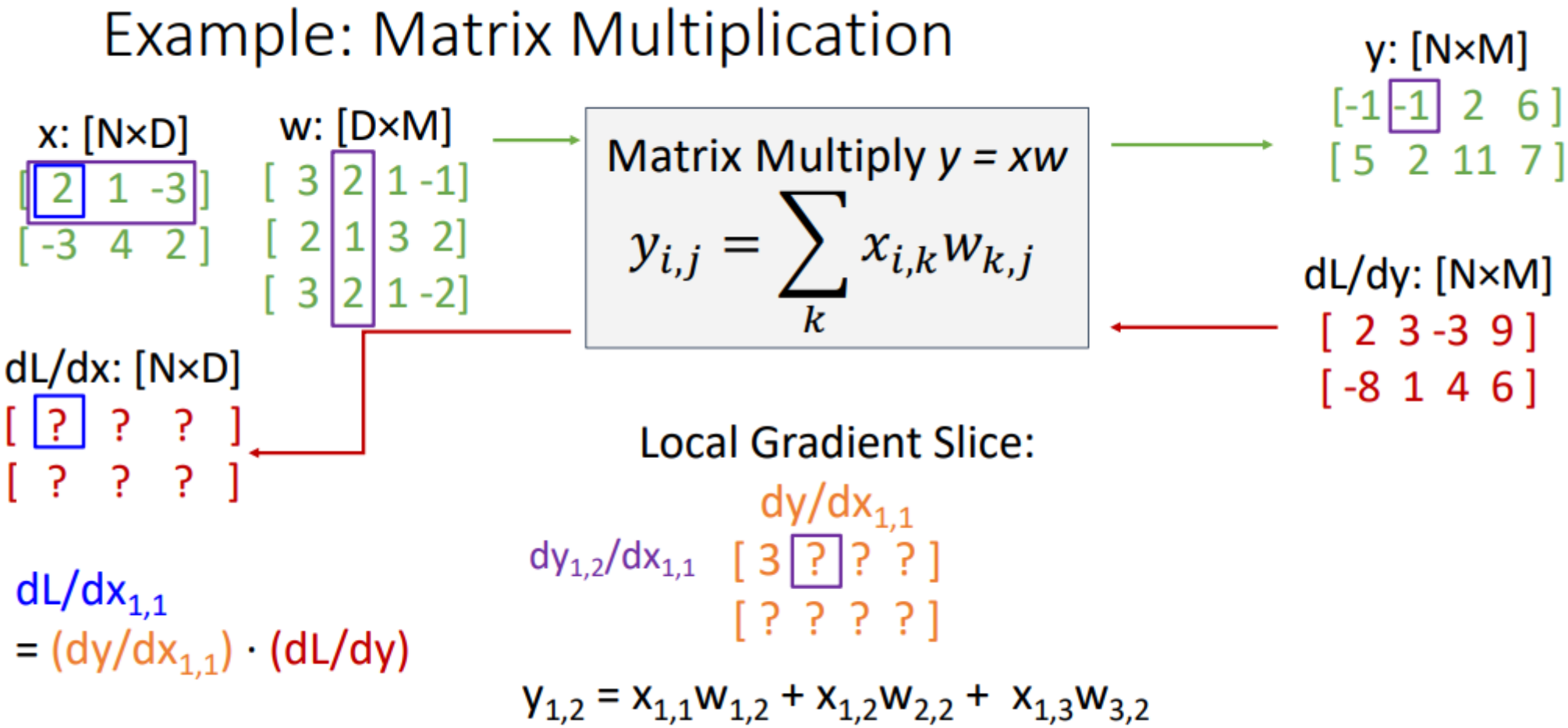

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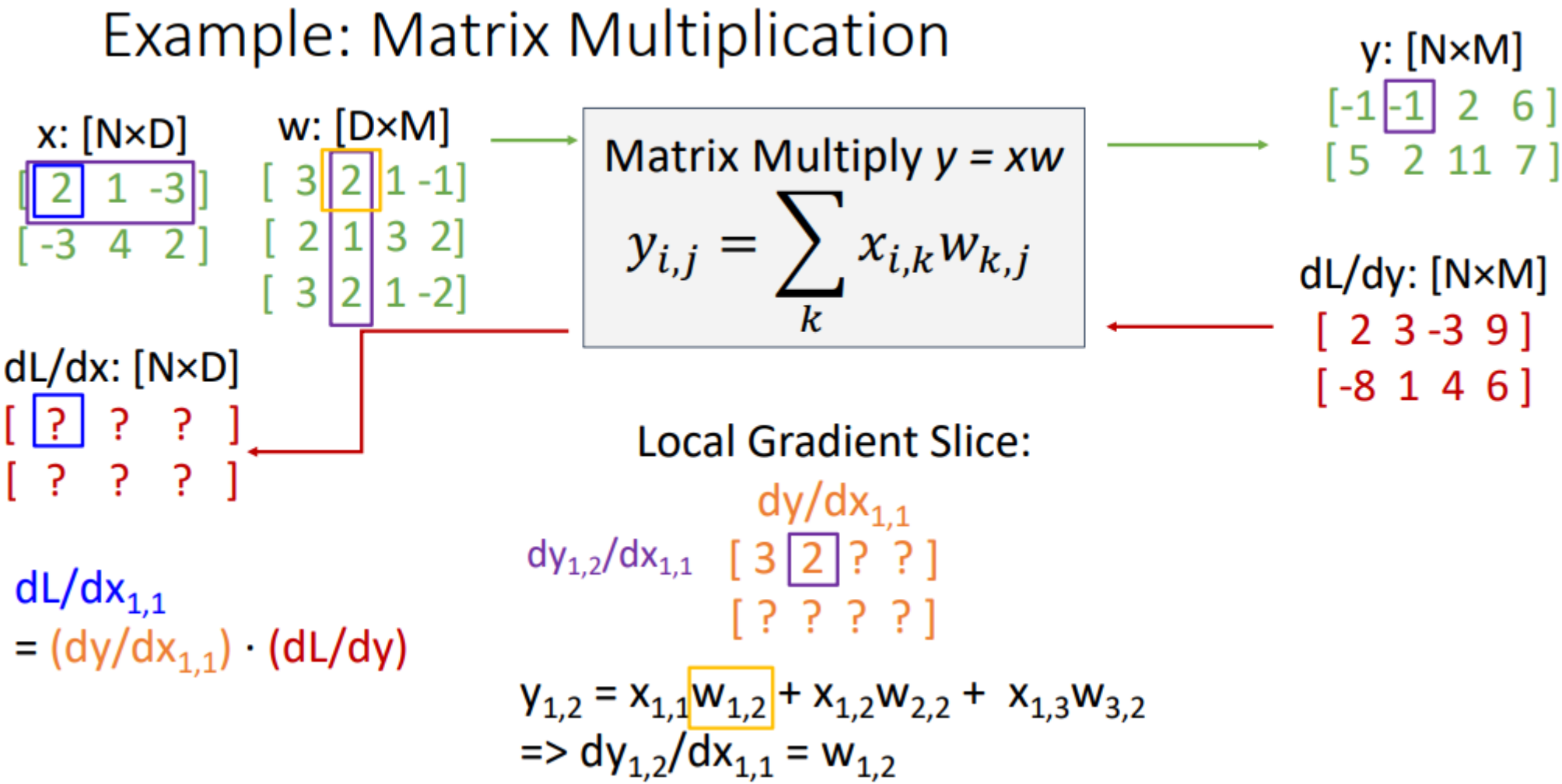

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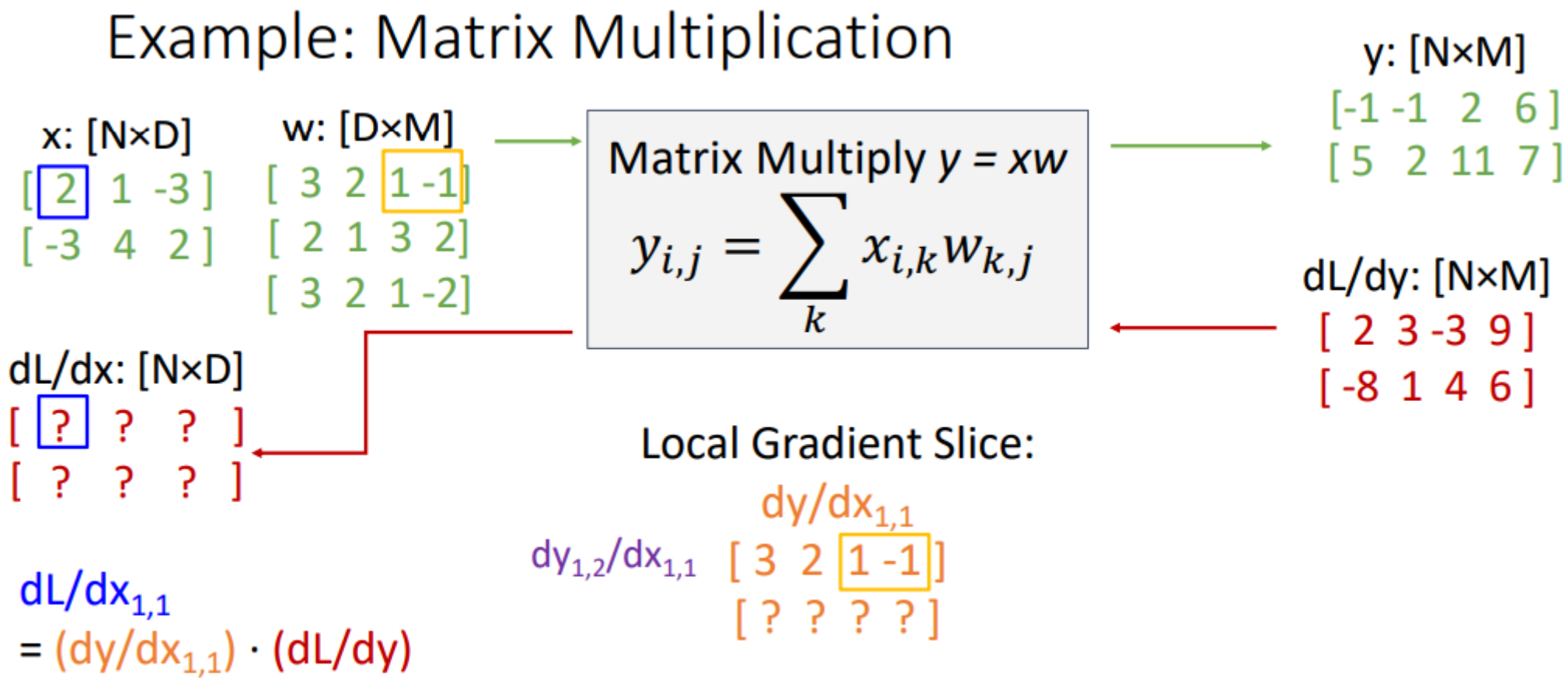
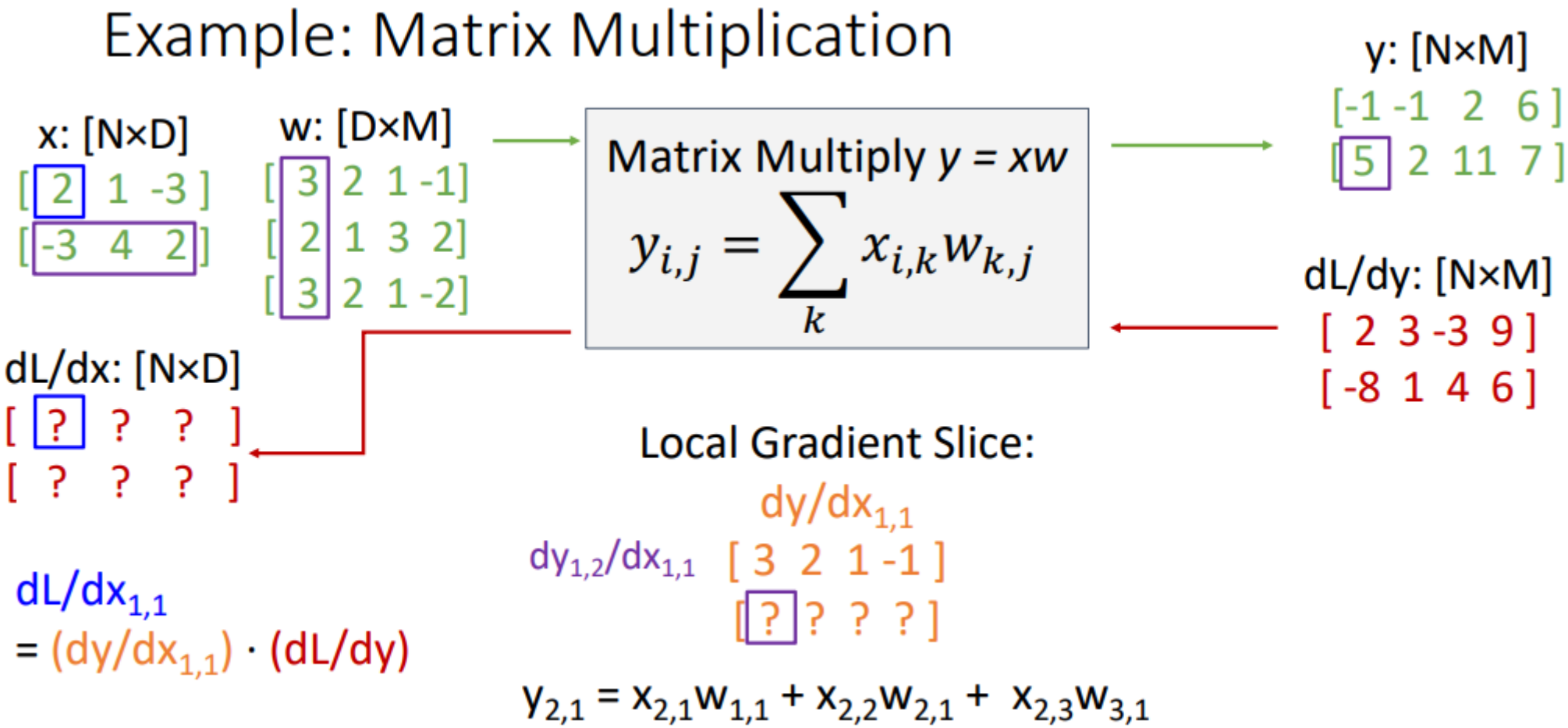
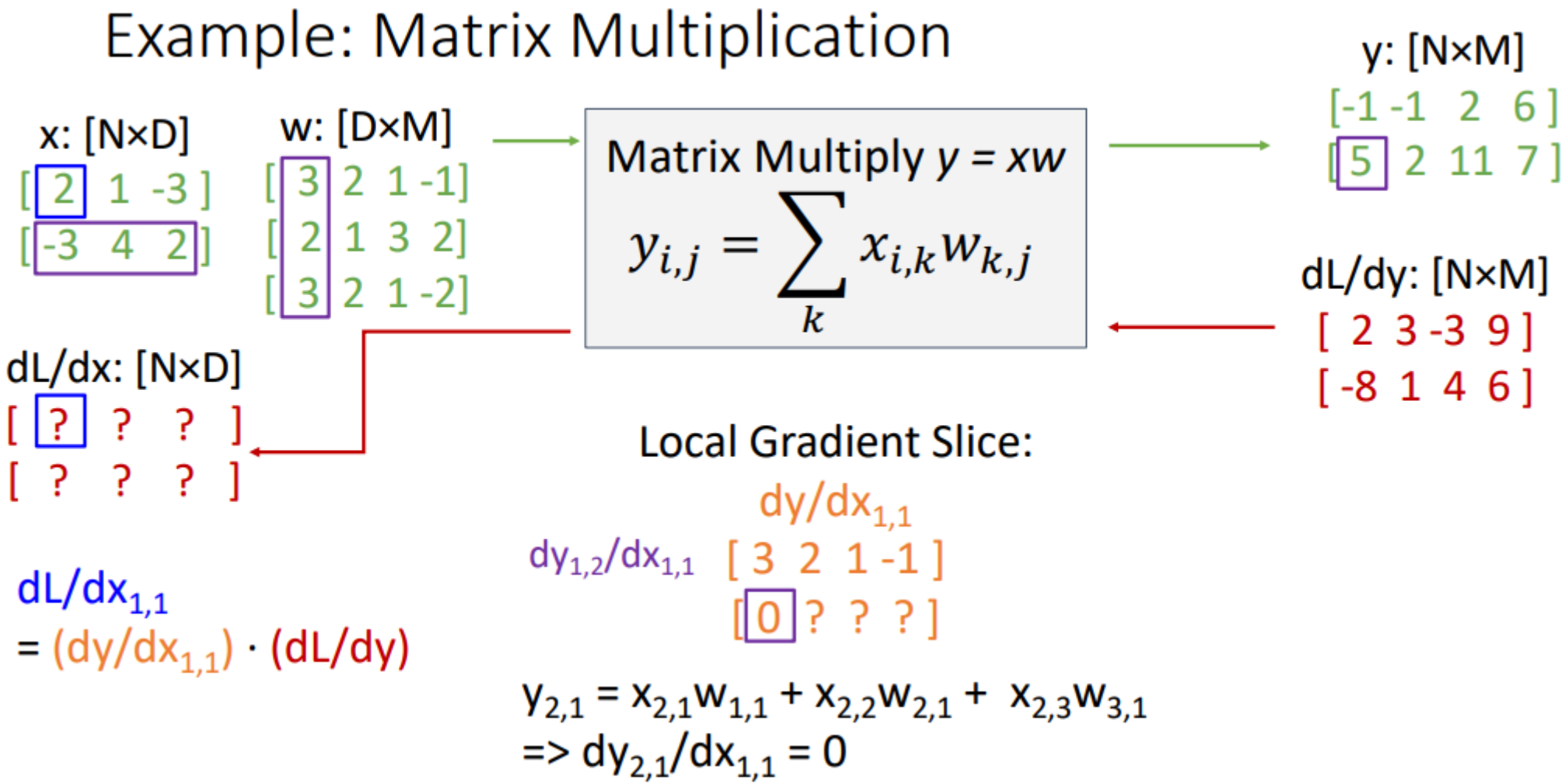


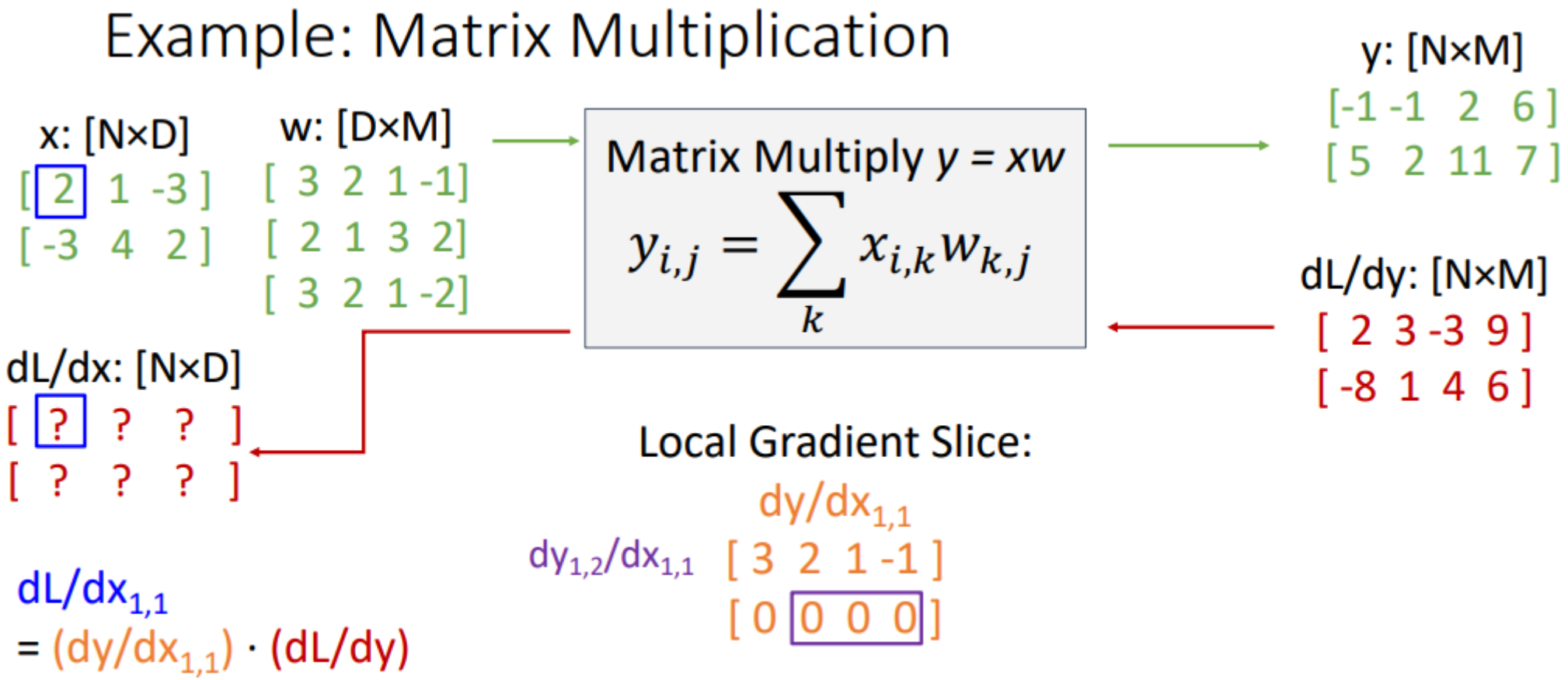
Backpropagation



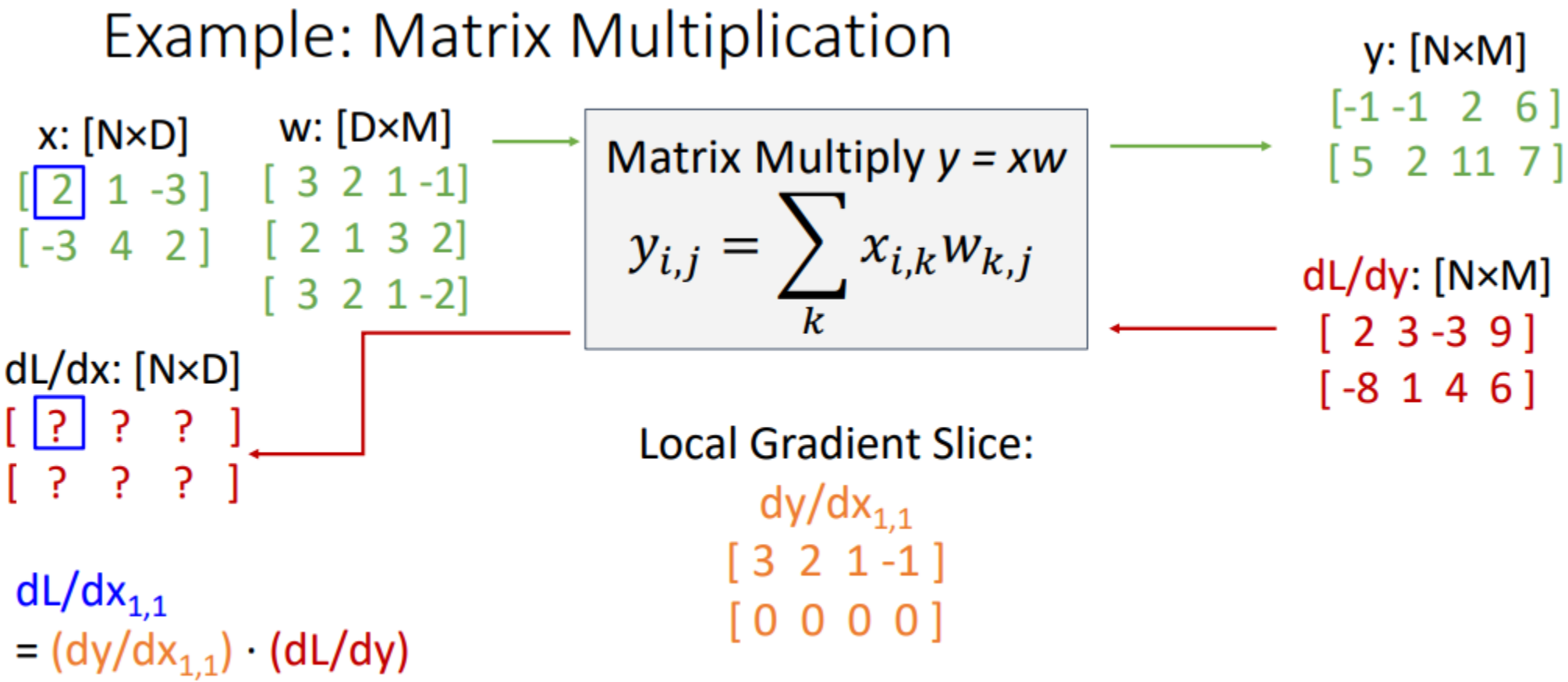
Backpropagation



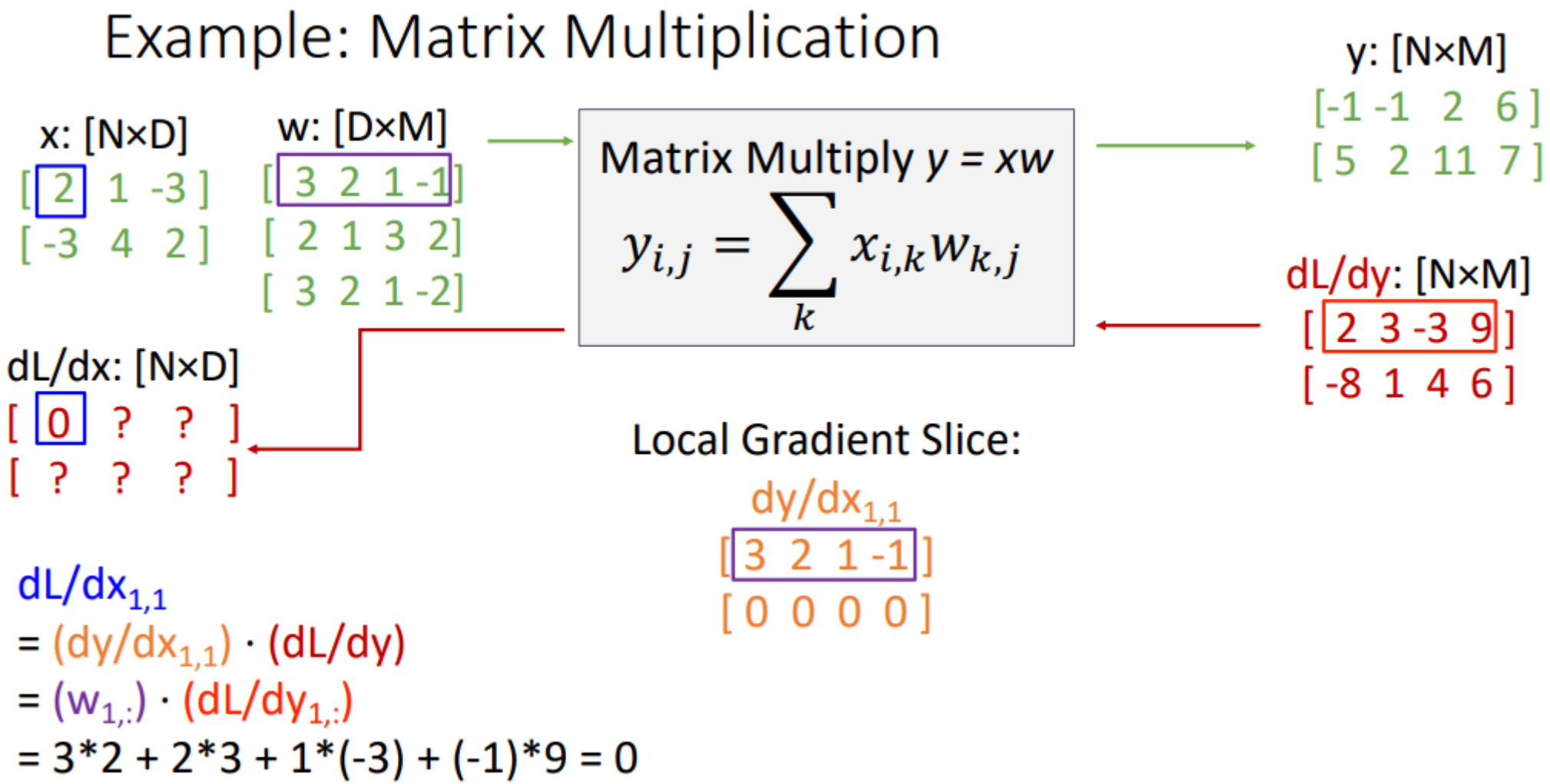
Backpropagation



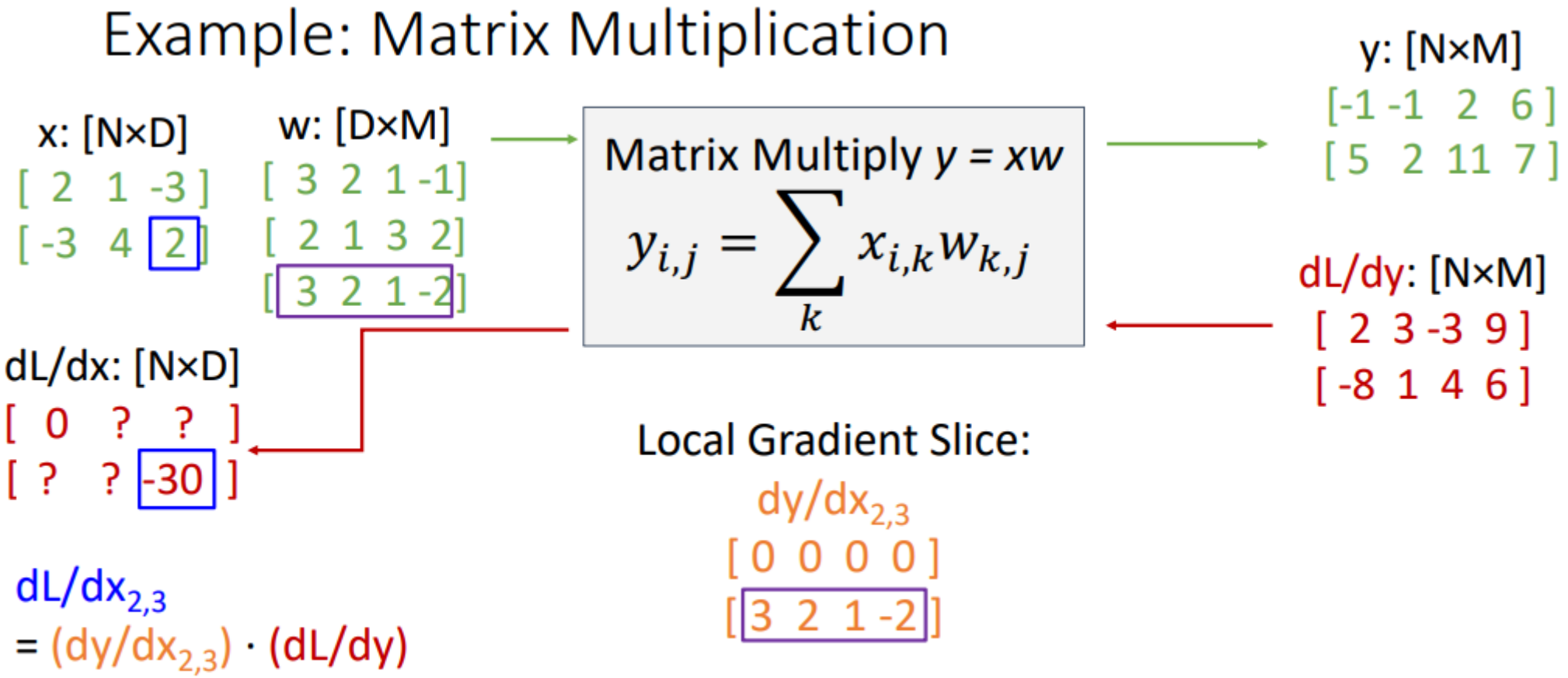
Backpropagation



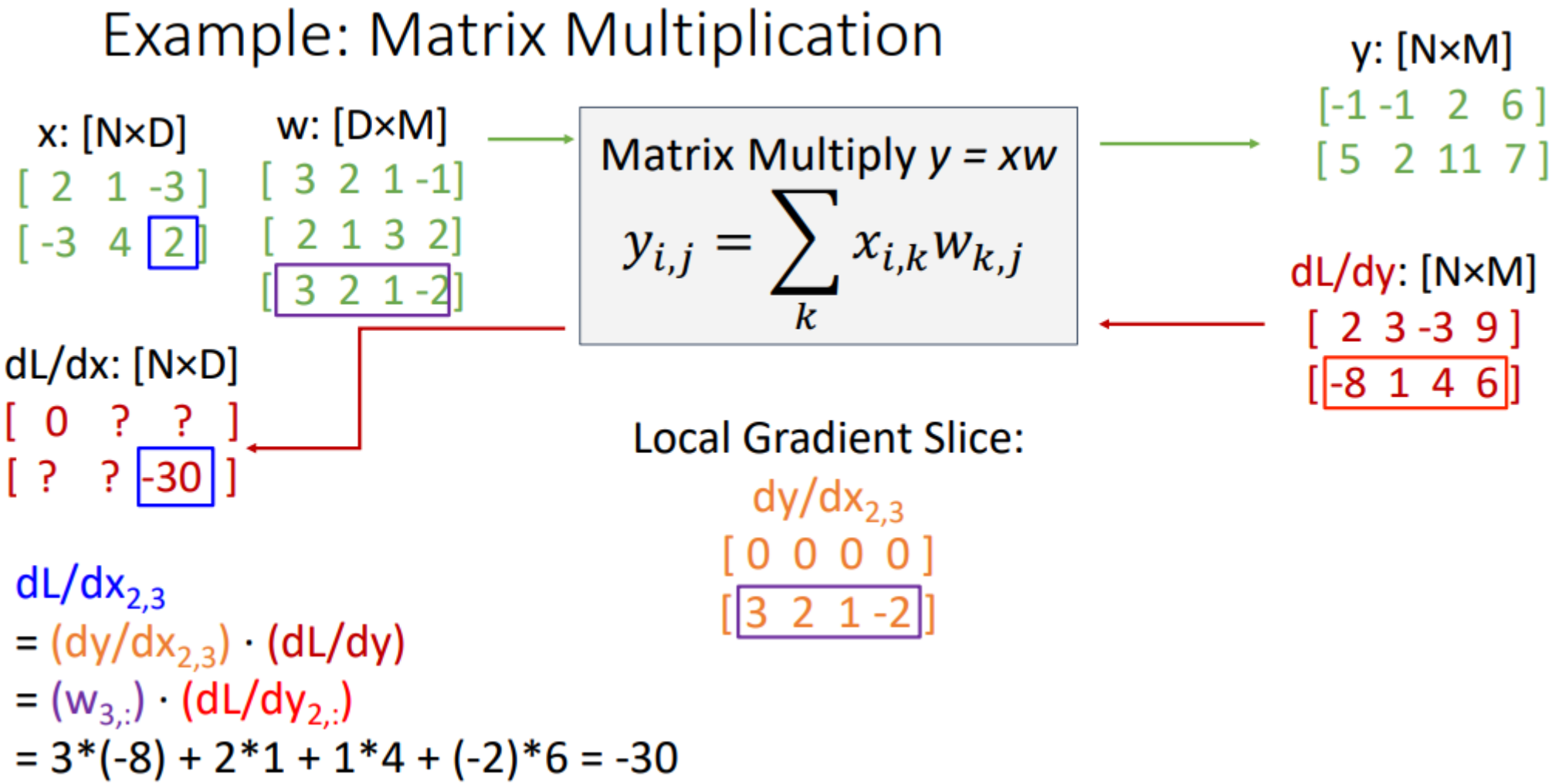
Backpropagation



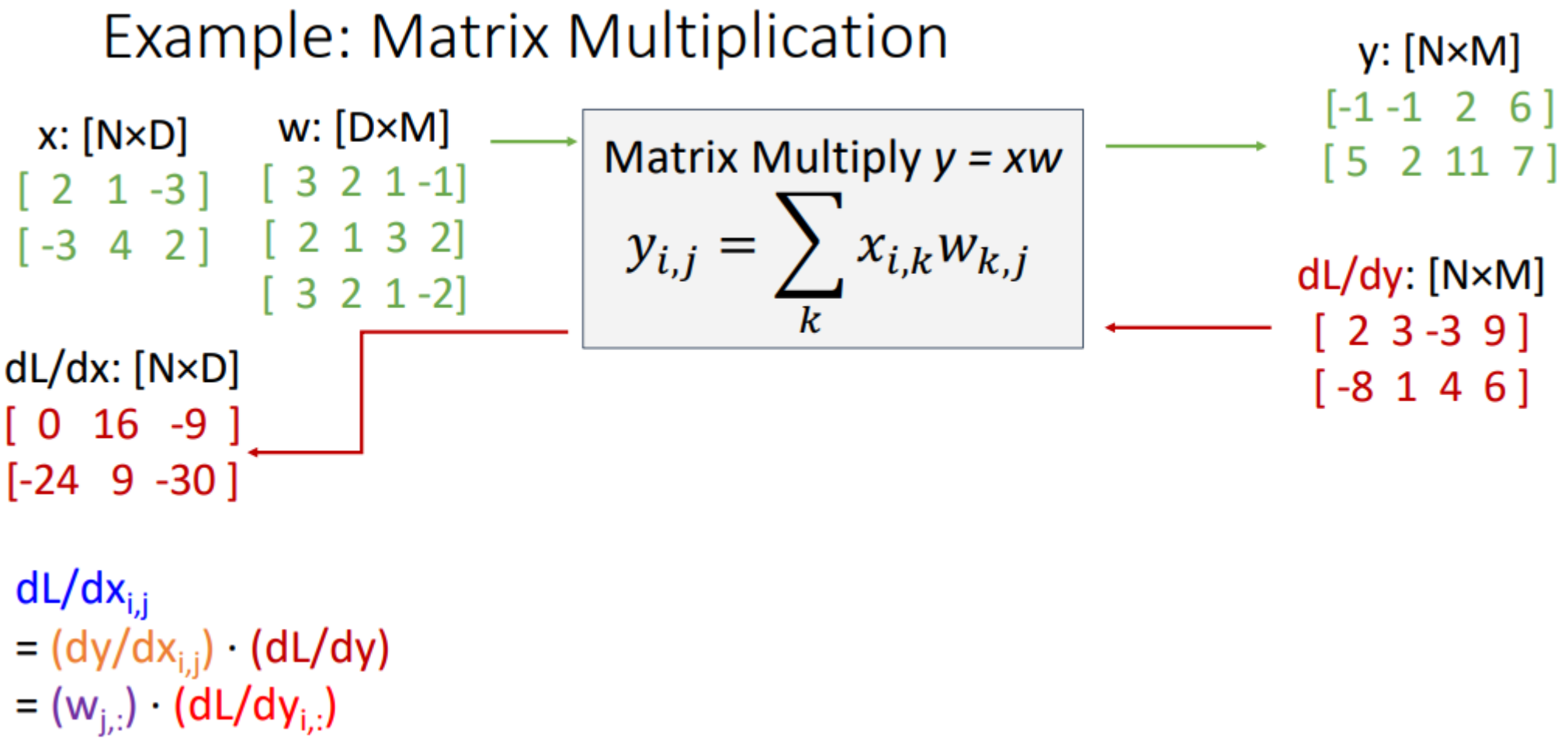
Backpropagation



Backpropagation

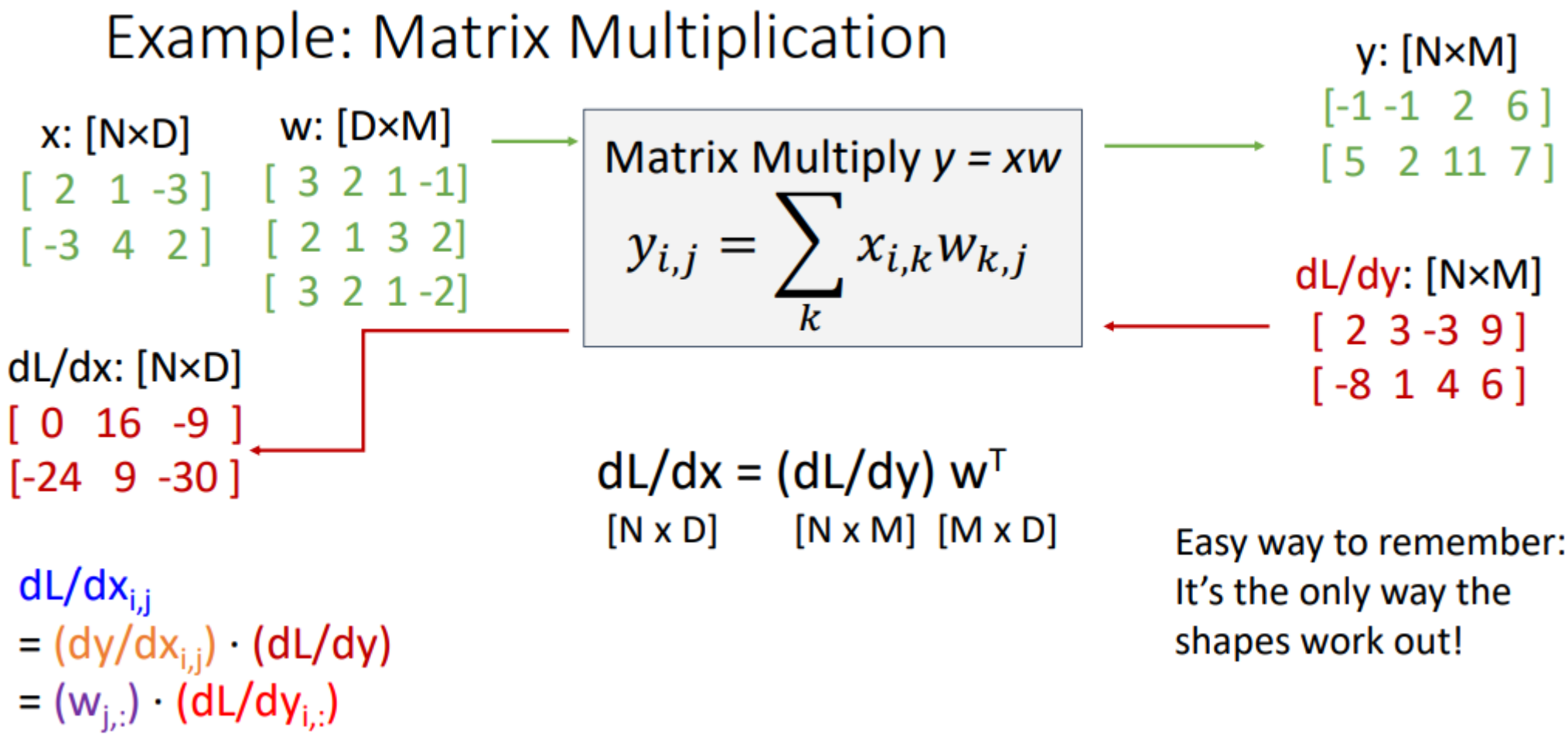


Backpropagation

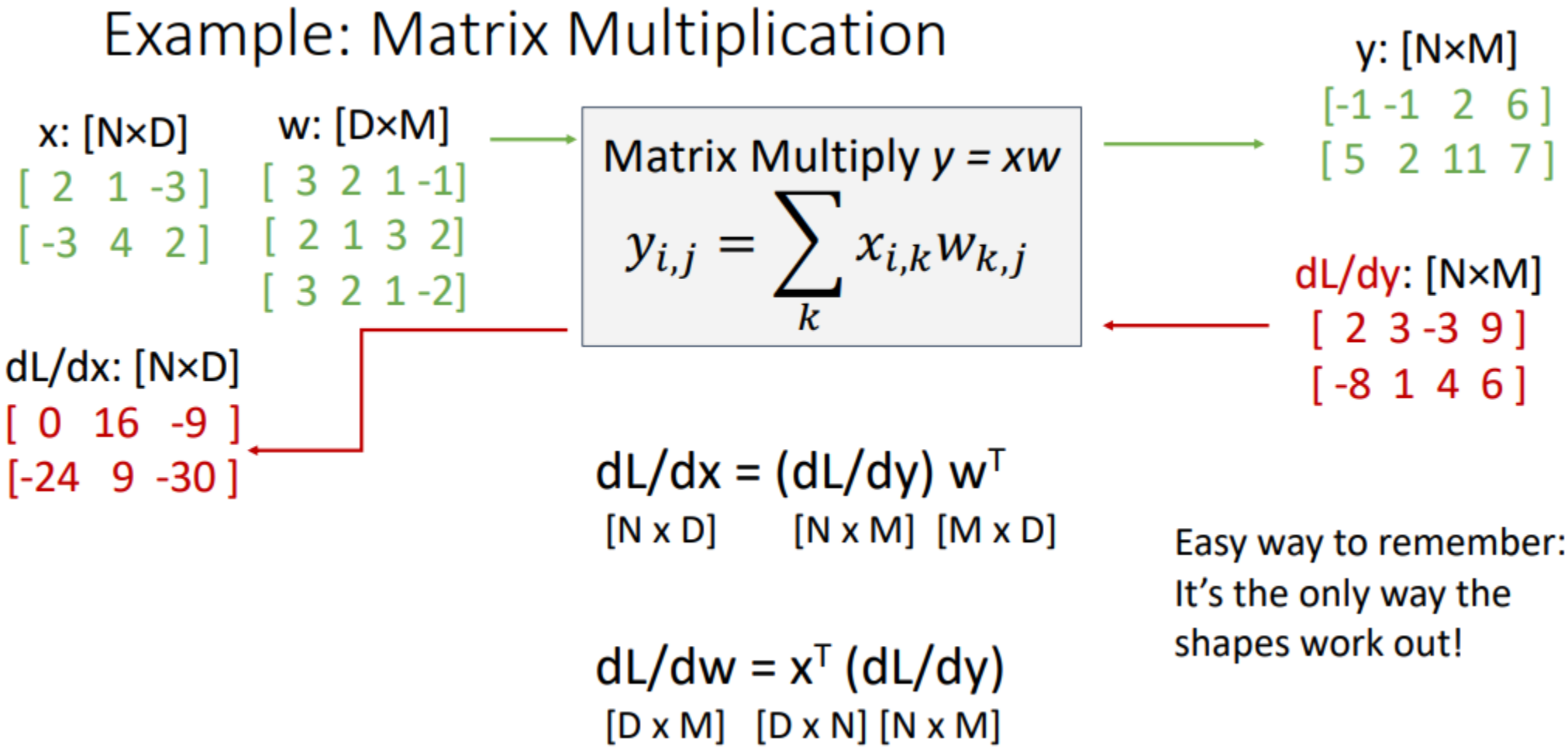


$dL/dx_{i,j}$
$= (dy/dx_{i,j}) \cdot (dL/dy)$
$= (w_{j,:}) \cdot (dL/dy_{i,:})$

Backpropagation



Backpropagation



Choosing Hyperparameters: Grid Search

Choose several values for each hyperparameter
(Often space choices log-linearly)

Example:
Weight decay: [$1x10^{-4}$, $1x10^{-3}$, $1x10^{-2}$, $1x10^{-1}$]
Learning rate: [$1x10^{-4}$, $1x10^{-3}$, $1x10^{-2}$, $1x10^{-1}$]

Evaluate all possible choices on this
hyperparameter grid

Choosing Hyperparameters: Random Search

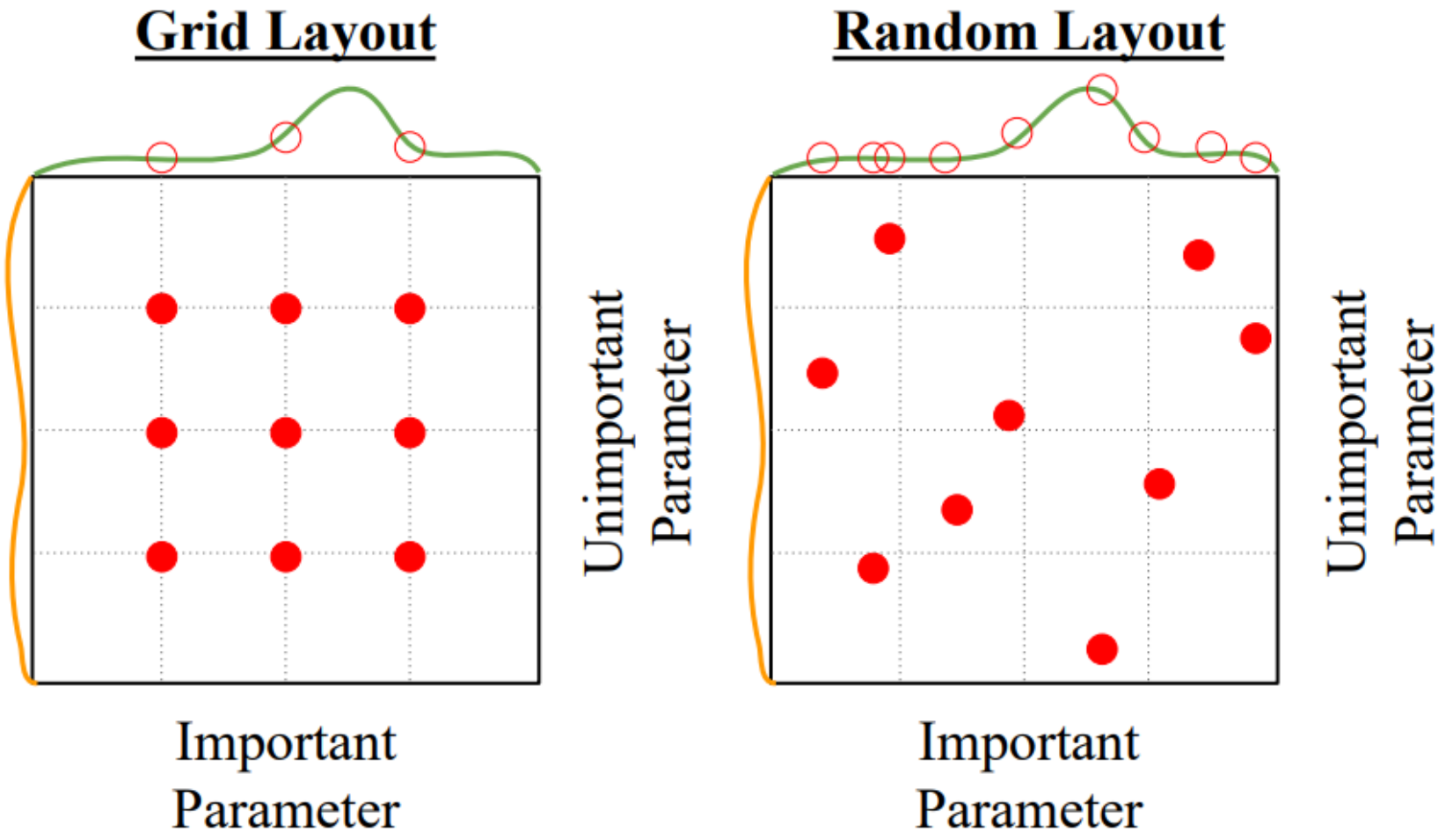
Choose several values for each hyperparameter
(Often space choices log-linearly)

Example:
Weight decay: log-uniform on $[1x10^{-4}, 1x10^{-1}]$
Learning rate: log-uniform on $[1x10^{-4}, 1x10^{-1}]$

Run many different trials

Choosing hyperparameters

Hyperparameters: Random vs Grid Search



Choosing hyperparameters

Choosing Hyperparameters

Step 1: Check initial loss

Turn off weight decay, sanity check loss at initialization
e.g. log(C) for softmax with C classes

Choosing hyperparameters

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample

Try to train to 100% training accuracy on a small sample of training data (~5-10 minibatches); fiddle with architecture, learning rate, weight initialization. Turn off regularization.

Loss not going down? LR too low, bad initialization
Loss explodes to Inf or NaN? LR too high, bad initialization

Choosing hyperparameters

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down

Use the architecture from the previous step, use all training data, turn on small weight decay, find a learning rate that makes the loss drop significantly within ~100 iterations

Good learning rates to try: 1e-1, 1e-2, 1e-3, 1e-4

Choosing hyperparameters

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs

Choose a few values of learning rate and weight decay around what worked from Step 3, train a few models for ~1-5 epochs.

Good weight decay to try: 1e-4, 1e-5, 0

Choosing hyperparameters

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer

Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay

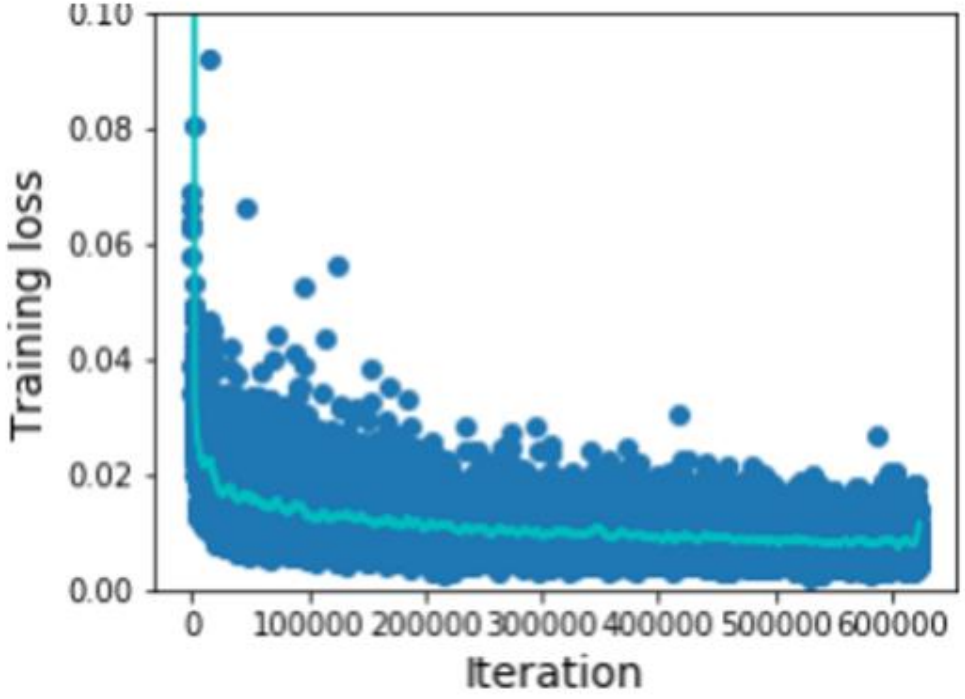
Choosing hyperparameters

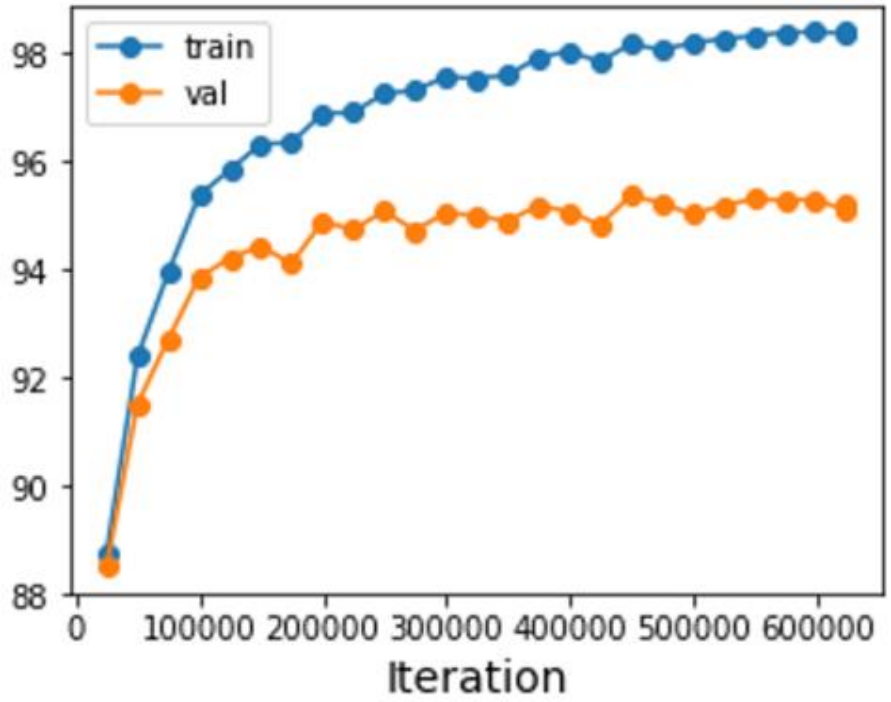
Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at learning curves

Choosing hyperparameters

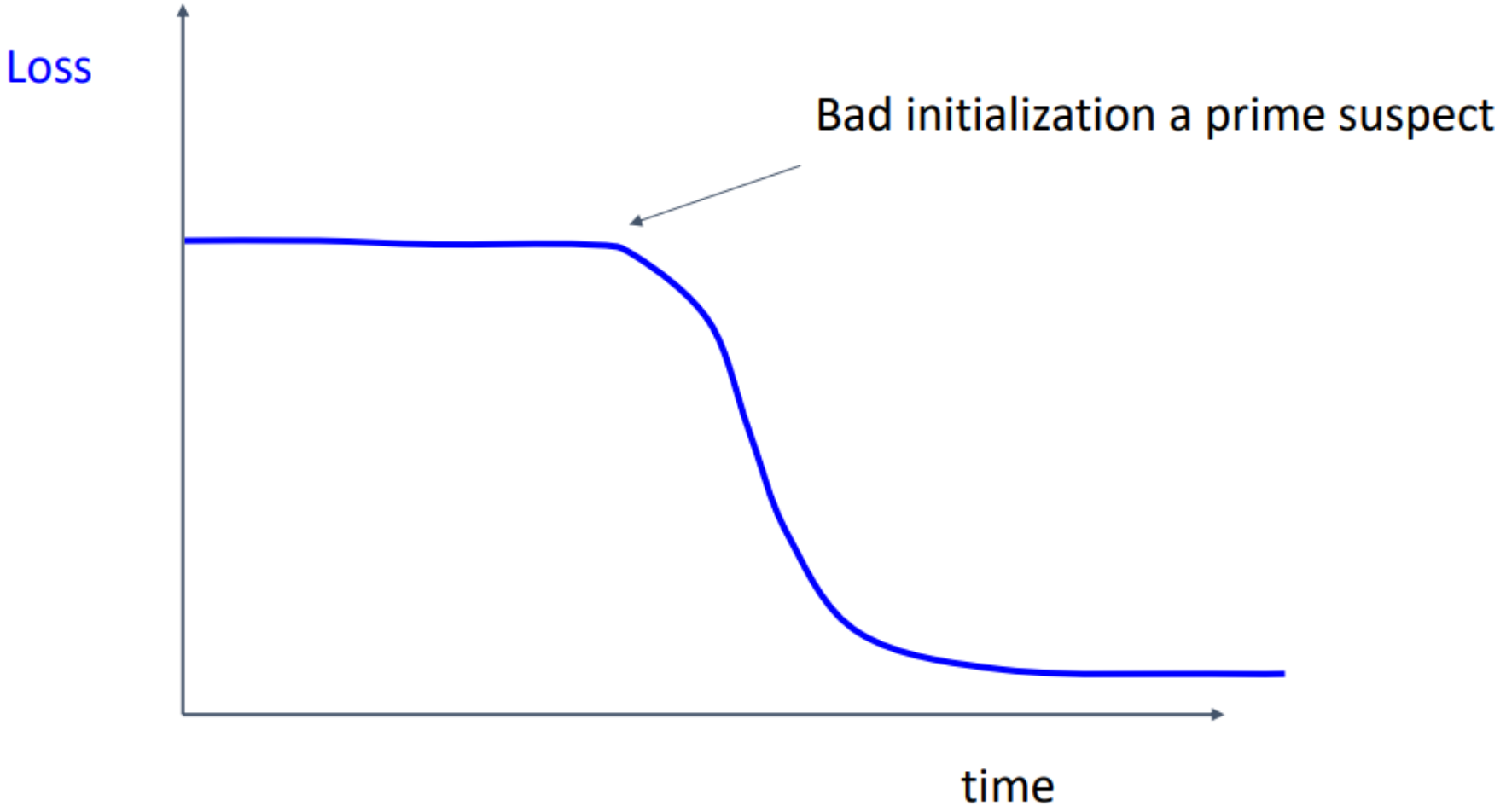
Look at Learning Curves!



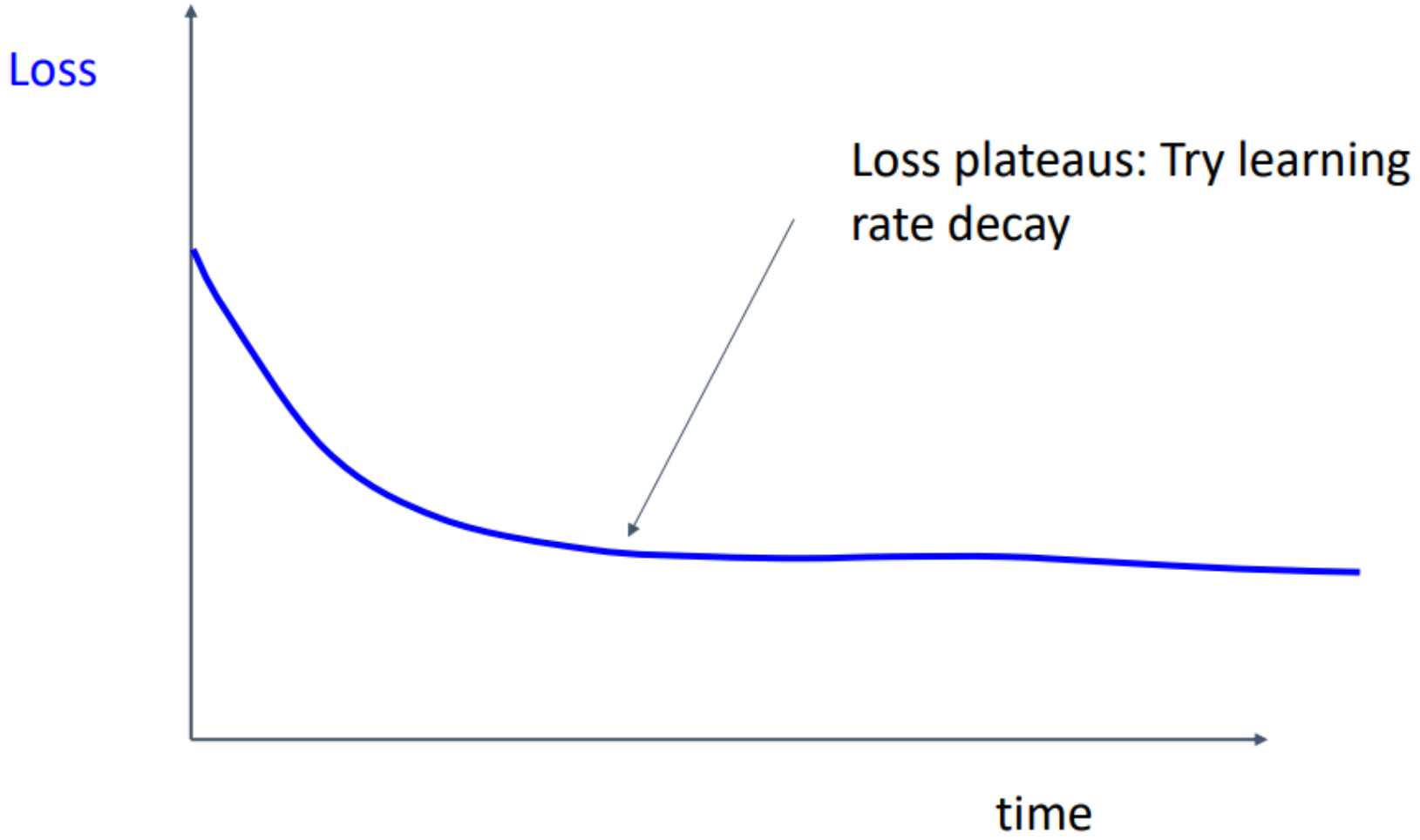


Losses may be noisy, use a scatter plot and also plot moving average to see trends better

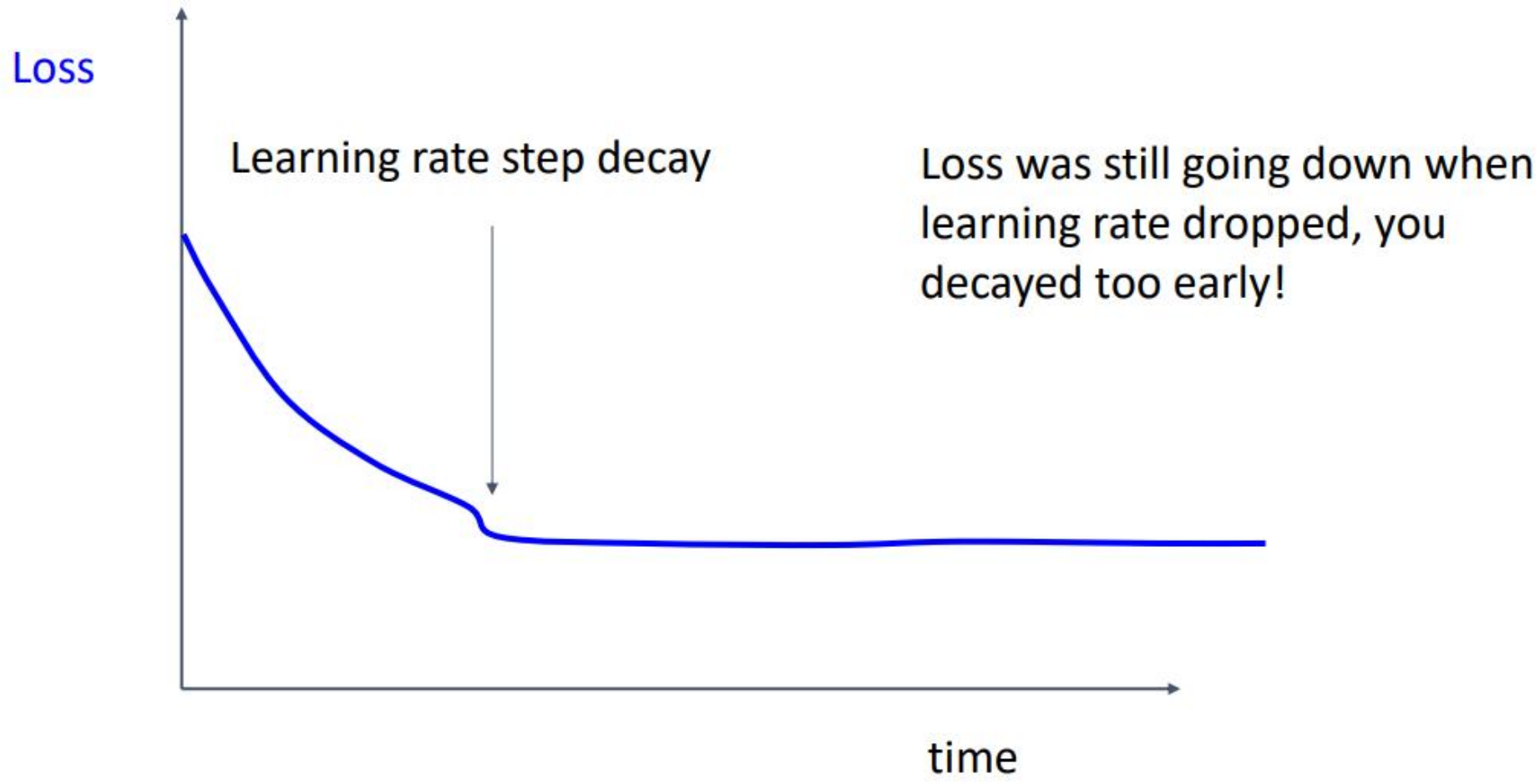
Choosing hyperparameters



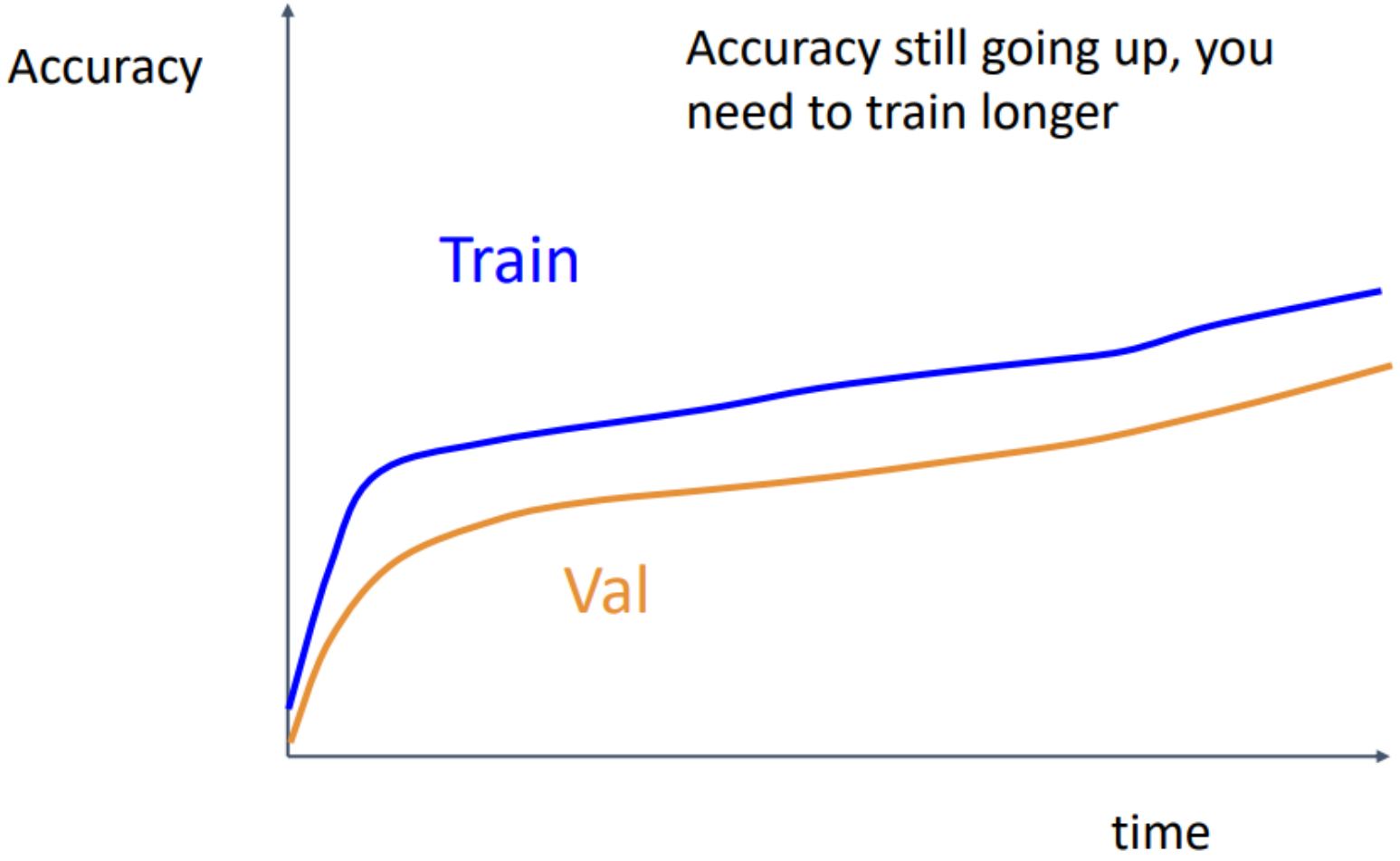
Choosing hyperparameters



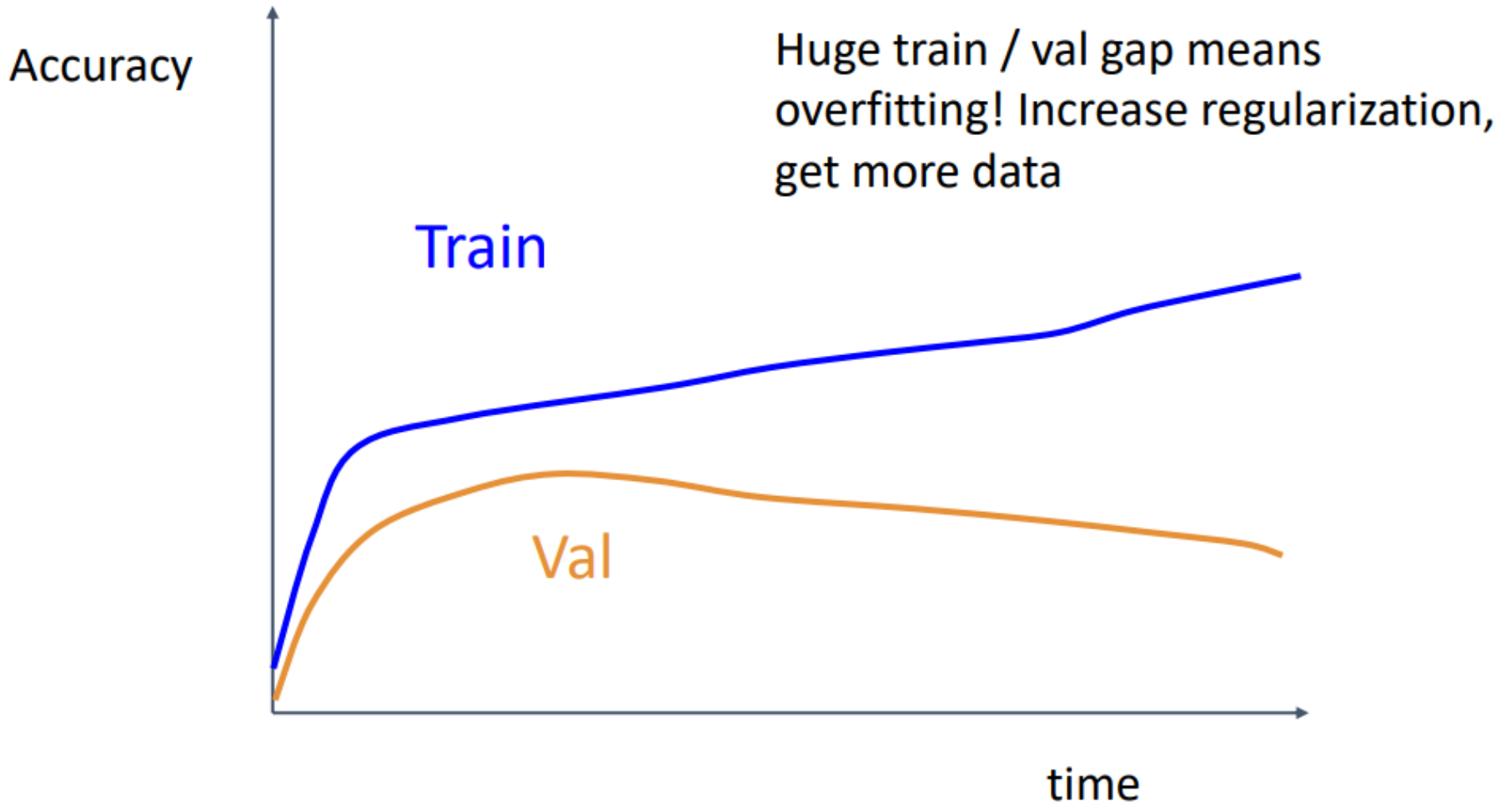
Choosing hyperparameters



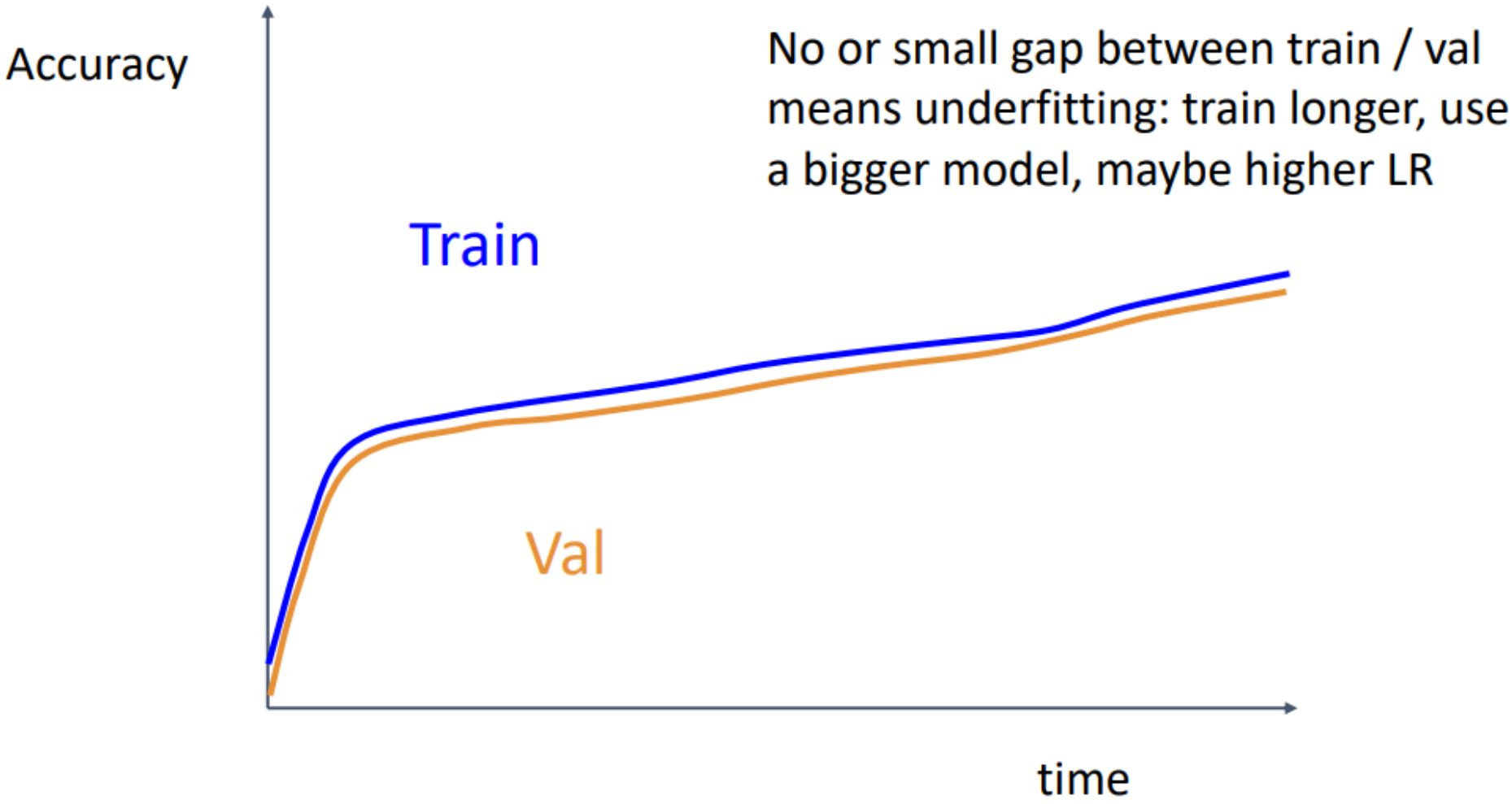
Choosing hyperparameters



Choosing hyperparameters



Choosing hyperparameters



Choosing hyperparameters

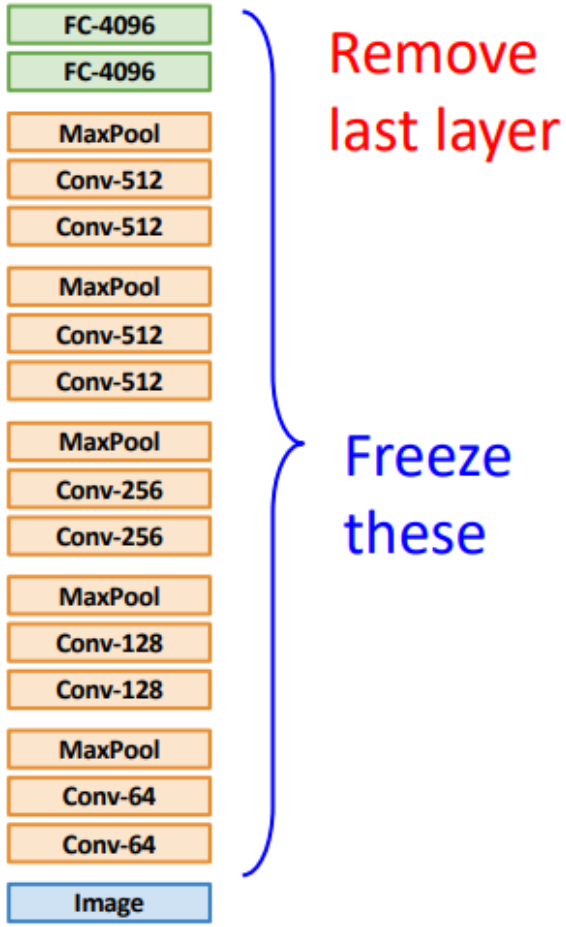
Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at loss curves
Step 7: GOTO step 5

Transfer learning

1. Train on ImageNet

2. Use CNN as a feature extractor



Remove last layer

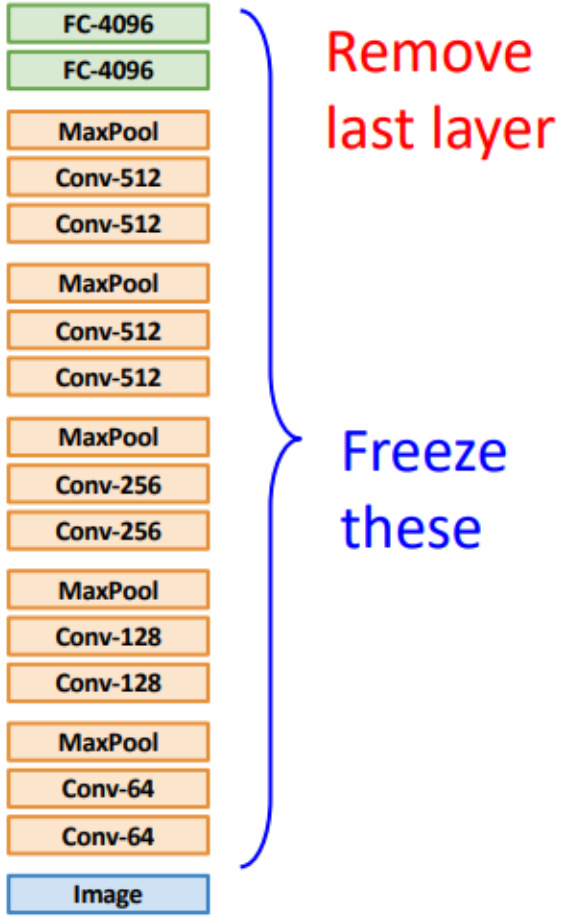
Freeze these

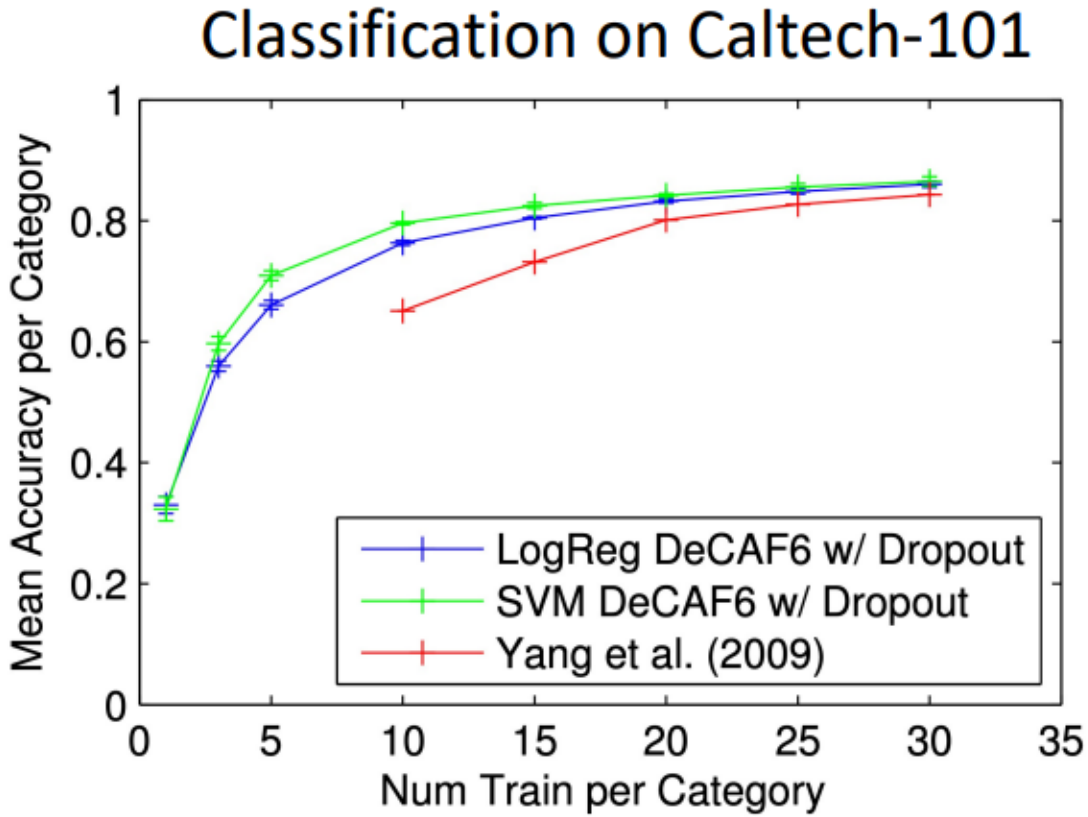
Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

Transfer learning

1. Train on ImageNet

2. Use CNN as a feature extractor





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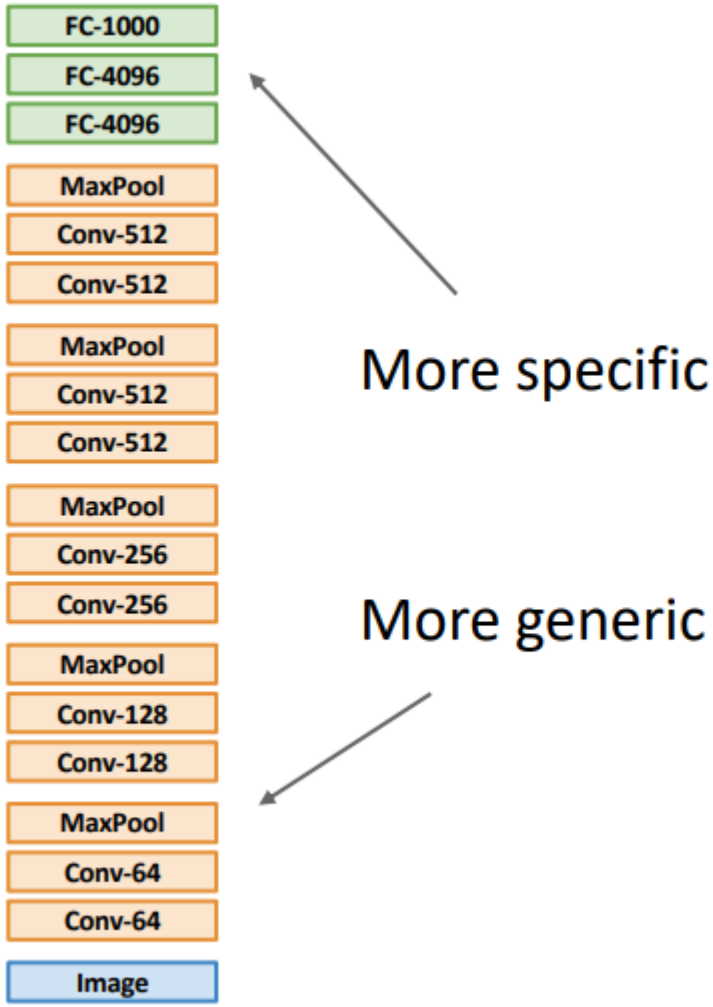
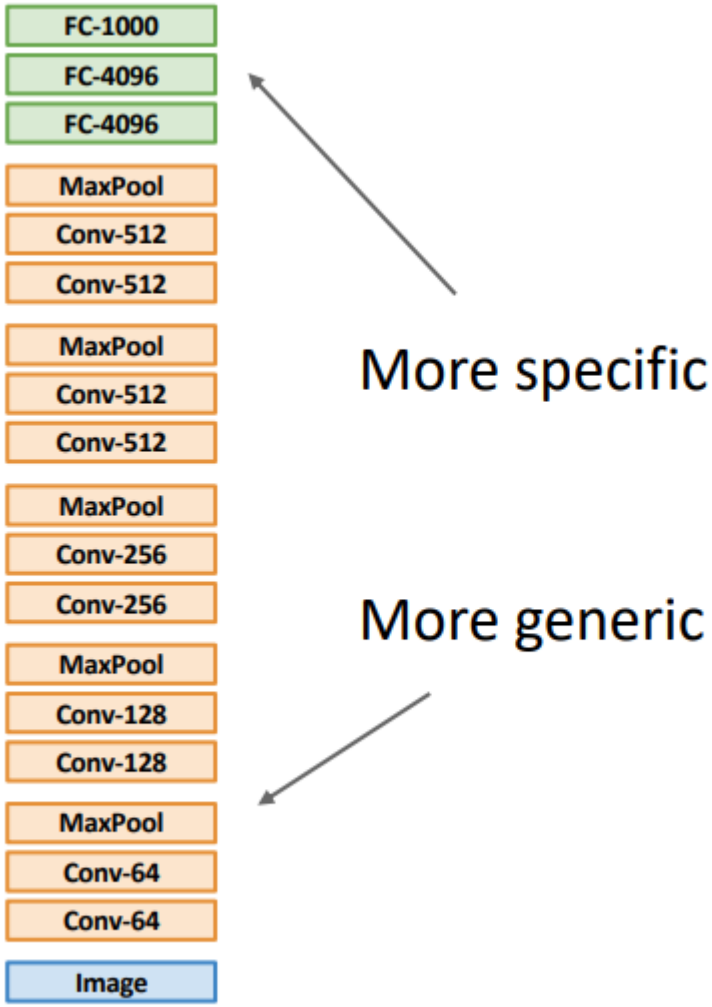
Transfer learning



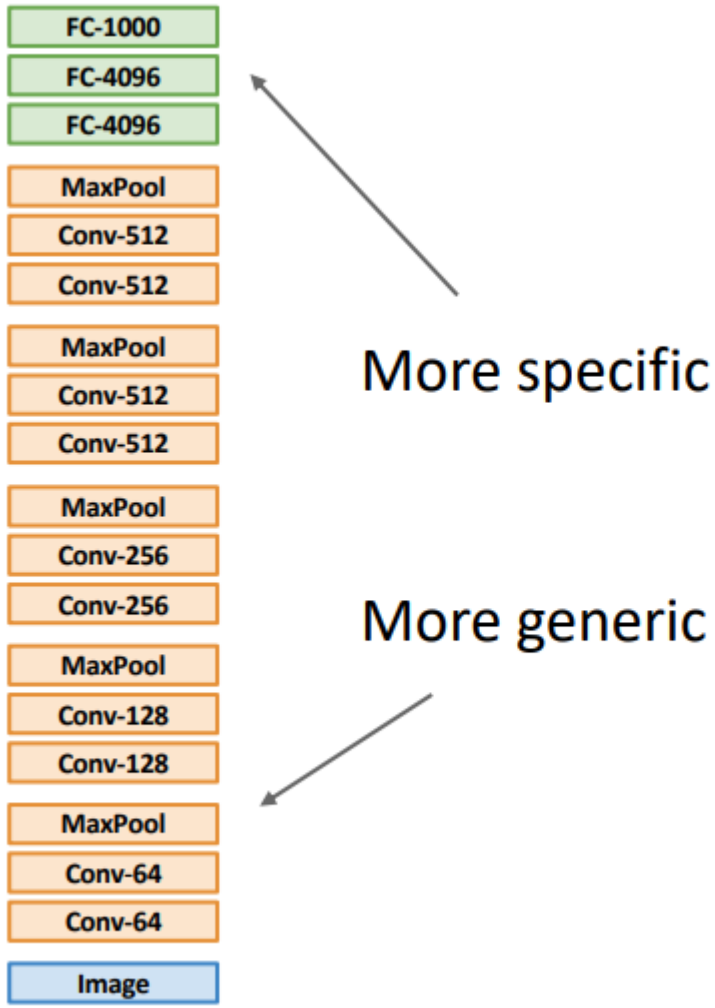
	Dataset similar to ImageNet	Dataset very different from ImageNet
very little data (10s to 100s)	?	?
quite a lot of data (100s to 1000s)	?	?

Transfer learning



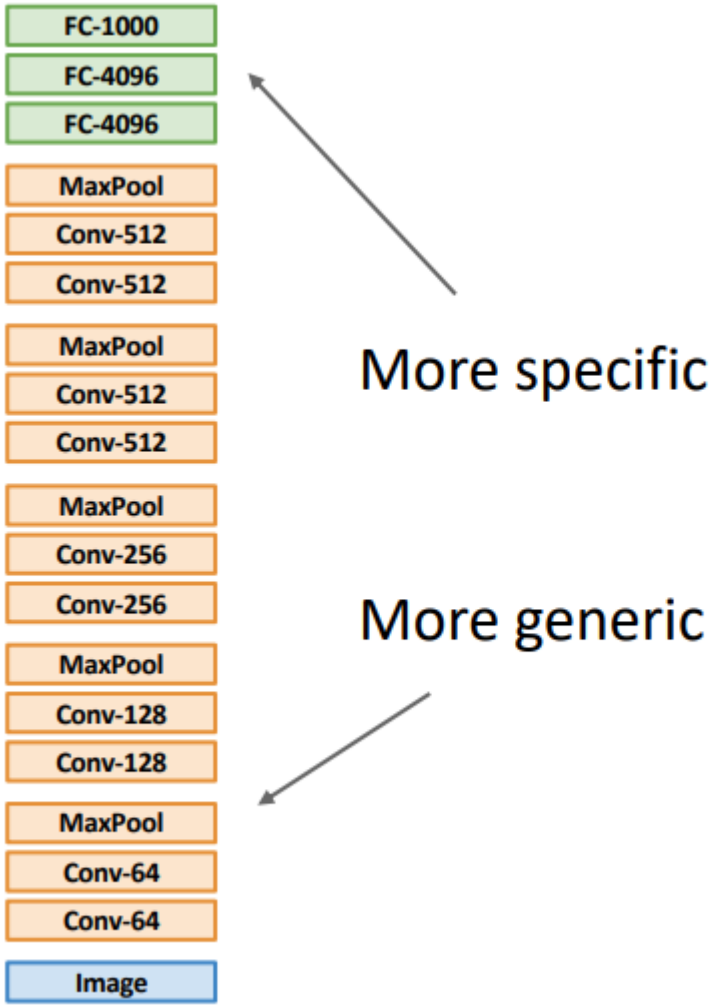
	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	Use Linear Classifier on top layer	?
quite a lot of data (100s to 1000s)	Finetune a few layers	?

Transfer learning



	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	Use Linear Classifier on top layer	?
quite a lot of data (100s to 1000s)	Finetune a few layers	Finetune a larger number of layers

Transfer learning



	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data (100s to 1000s)	Finetune a few layers	Finetune a larger number of layers

Reference and Readings

Reference

- http://cs231n.stanford.edu

Readings

- “Computing Receptive Fields of Convolutional Neural Networks” In Distill 2019.
- https://naokishibuya.medium.com/up-sampling-with-transposed-convolution-9ae4f2df52d0

Thank You!!