

# Building Convolutional Neural Networks for Image Classification

---



**Janani Ravi**

CO-FOUNDER, LOONYCORN

[www.loonycorn.com](http://www.loonycorn.com)

# Overview

**Narrow and wide convolution**

**Zero-padding and the feature map sizes for convolutional layers**

**Calculating feature map dimensions**

**Batch normalization of input images**

**Building and training a CNN for image classification**

**Changing model hyperparameters**

# Convolutional Neural Networks

---

# Two Kinds of Layers in CNNs

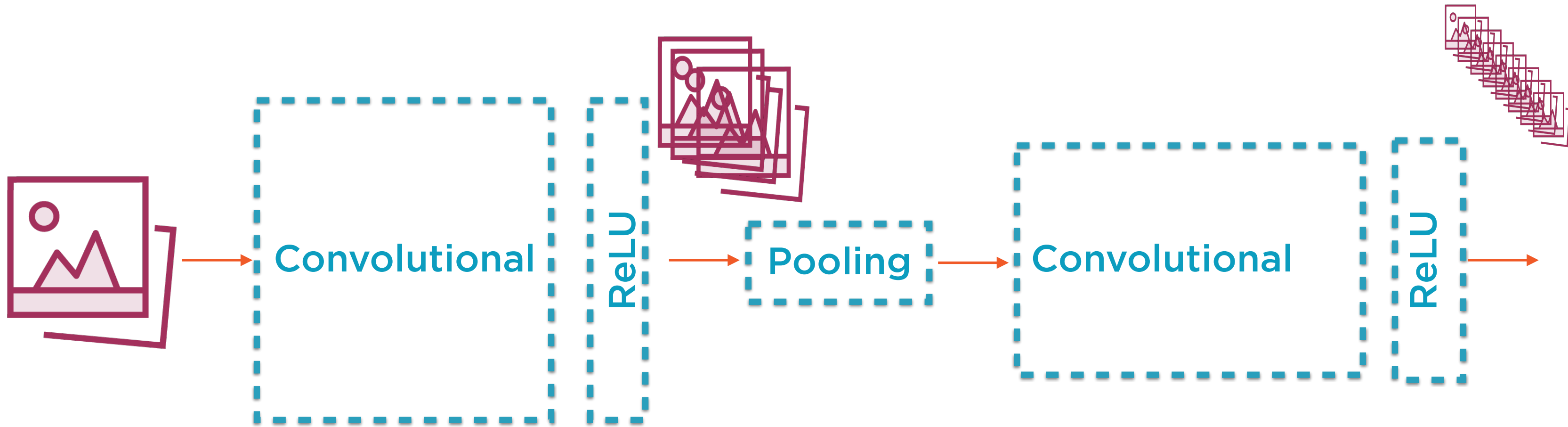
## Convolution

Local receptive field

## Pooling

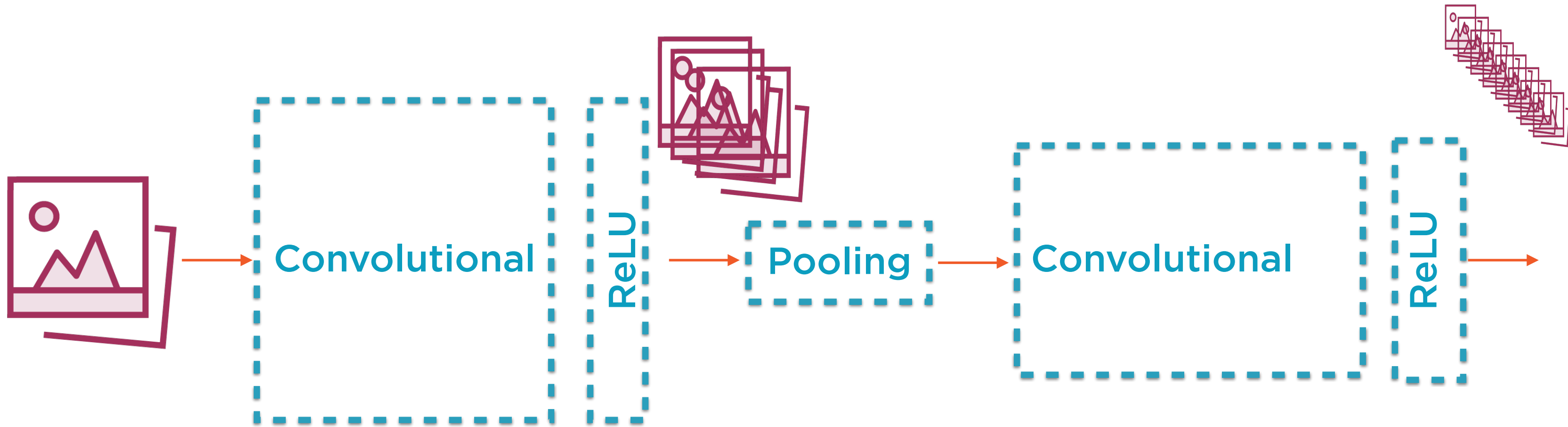
Subsampling of inputs

# Typical CNN Architecture



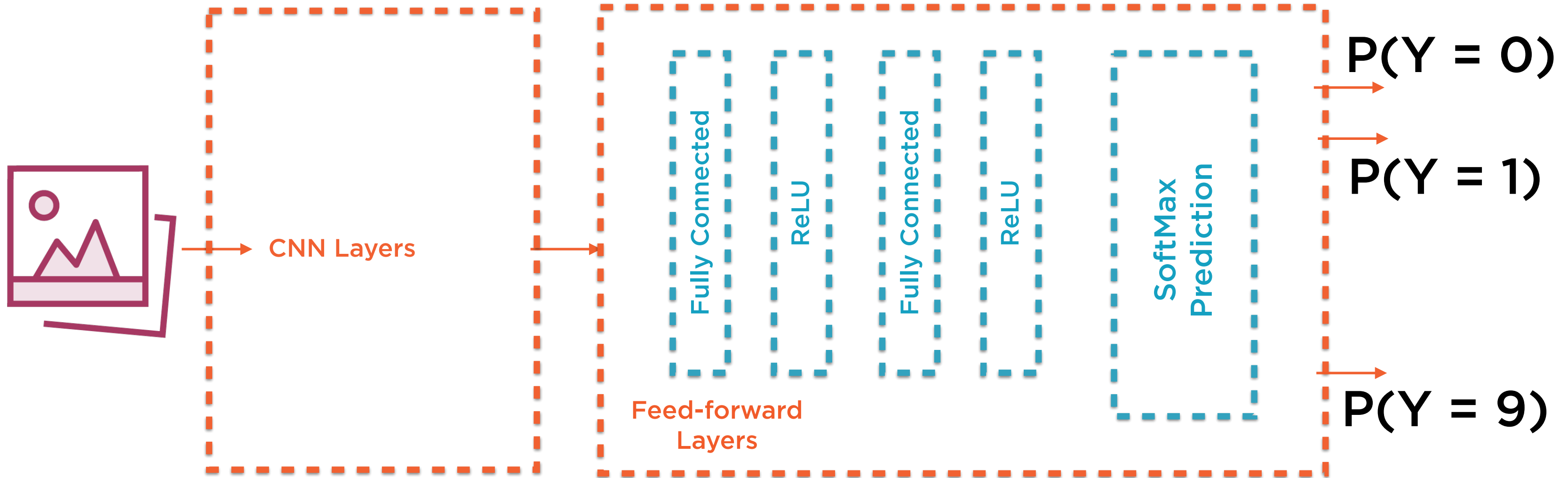
**Alternating convolutional and pooling layers**

# Typical CNN Architecture



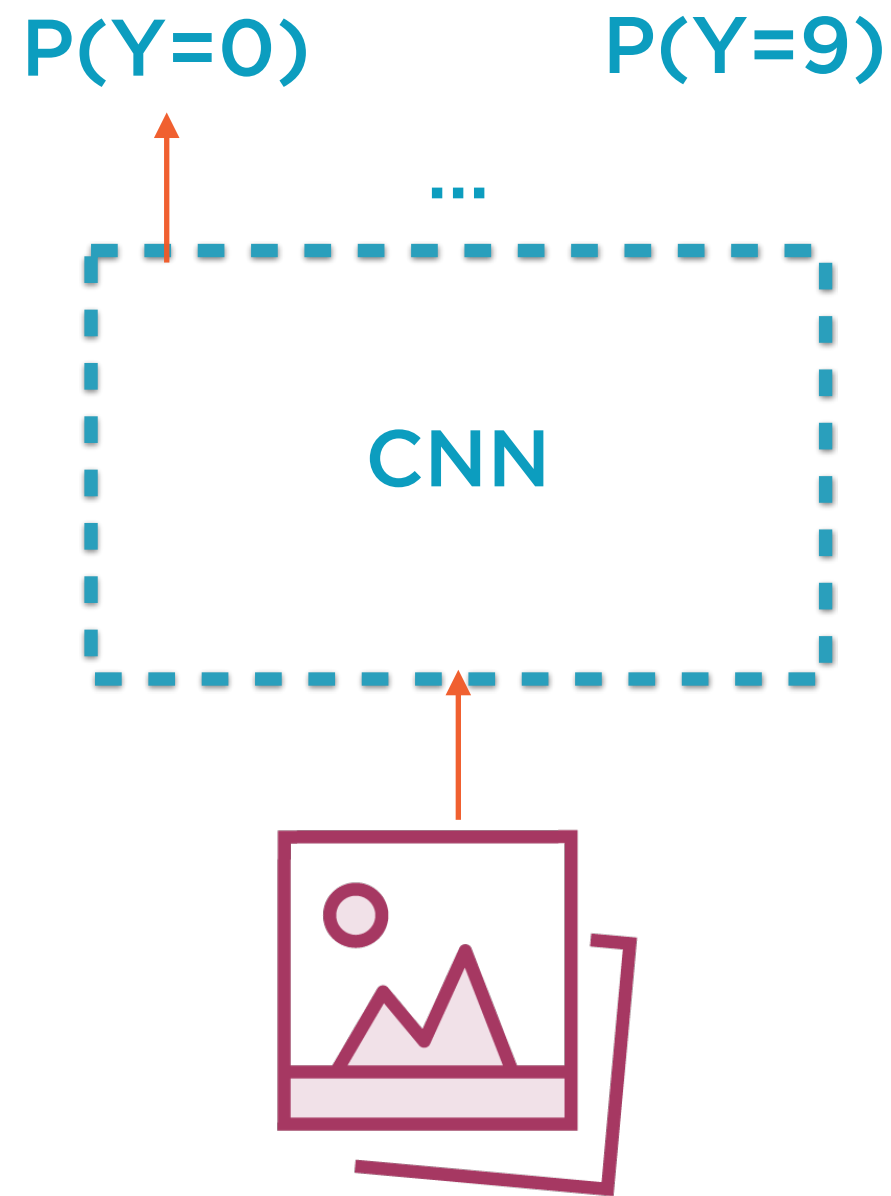
**This entire set of layers is then fed into a regular, feed-forward NN**

# Typical CNN Architecture



**This is the output layer, emitting probabilities**

# Typical CNN Architecture



**Input is an image**

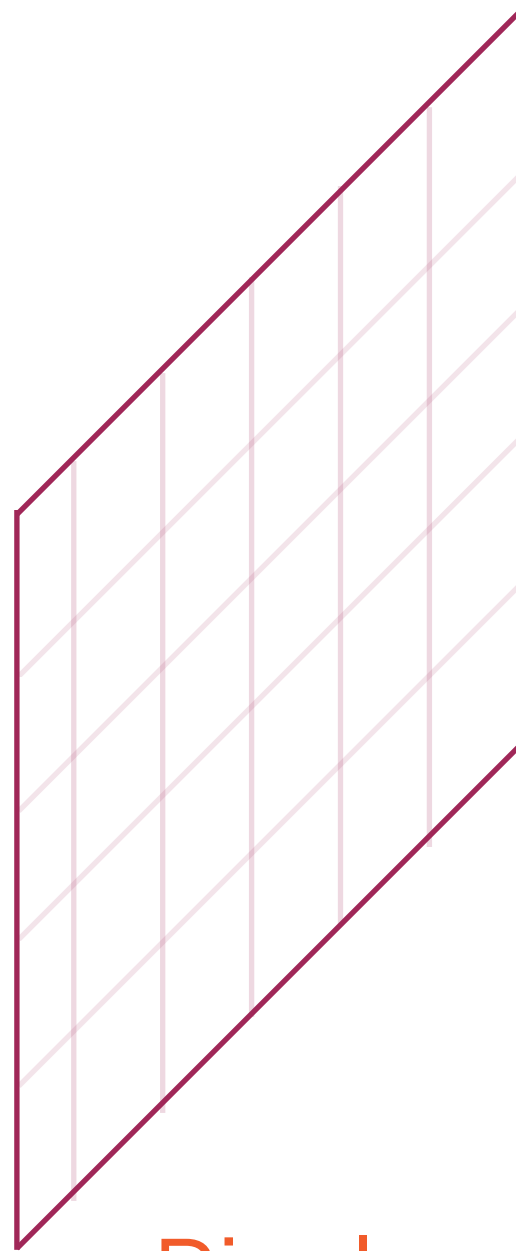
**Outputs are probabilities**



# Feature Maps

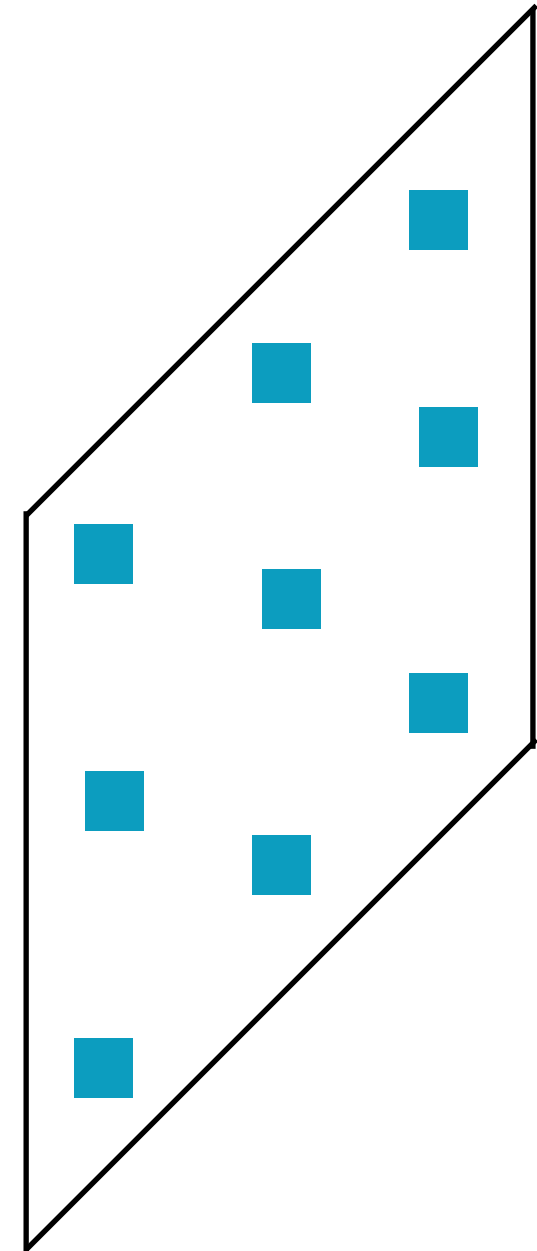


Image



Pixels

x1	x0	x1
x0	x1	x0
x1	x0	x1

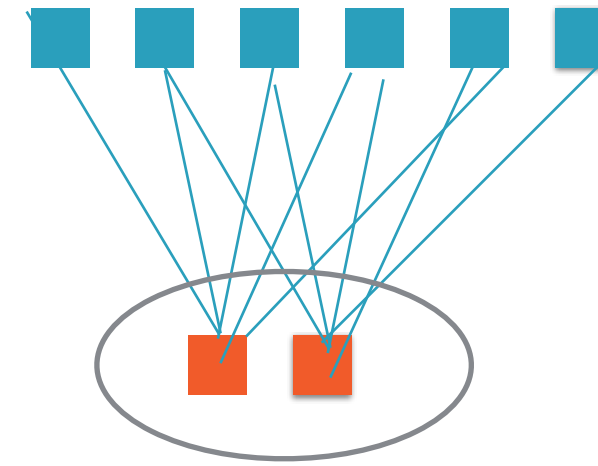
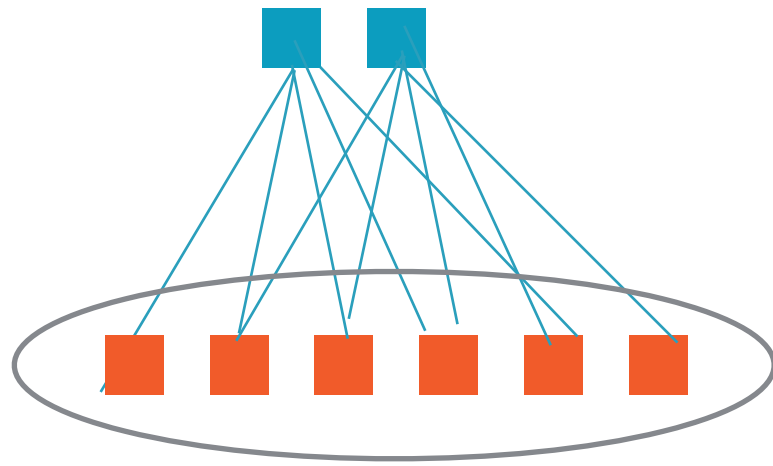


Feature  
Map

# Zero-padding, Stride Size

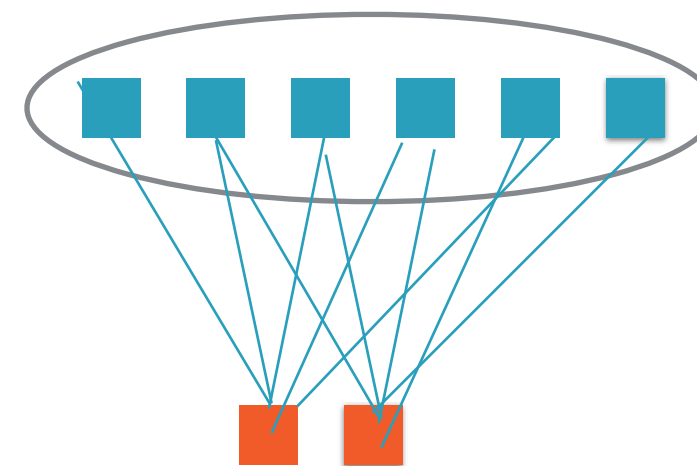
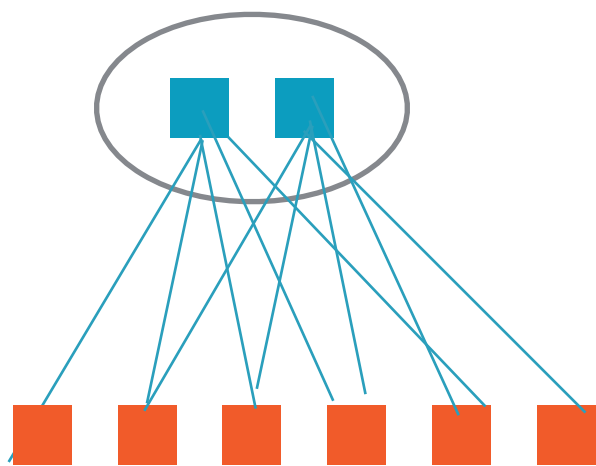
---

# Narrow vs. Wide Convolution



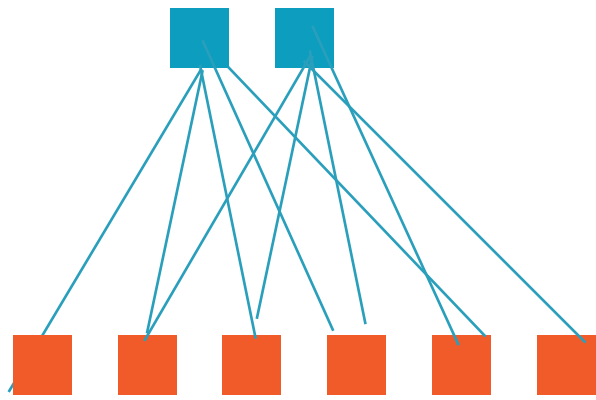
**Input matrix i.e. image**

# Narrow vs. Wide Convolution



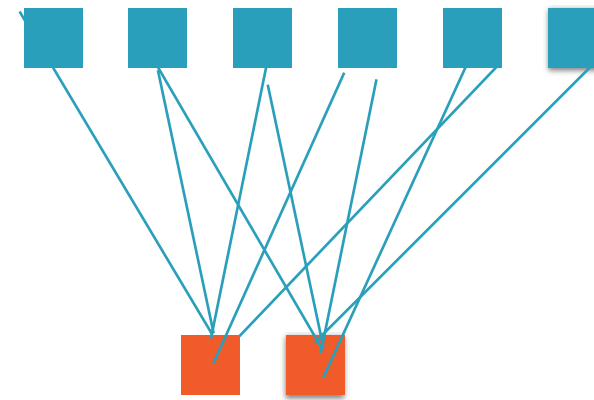
**Convolution result**

# Narrow vs. Wide Convolution



## Narrow Convolution

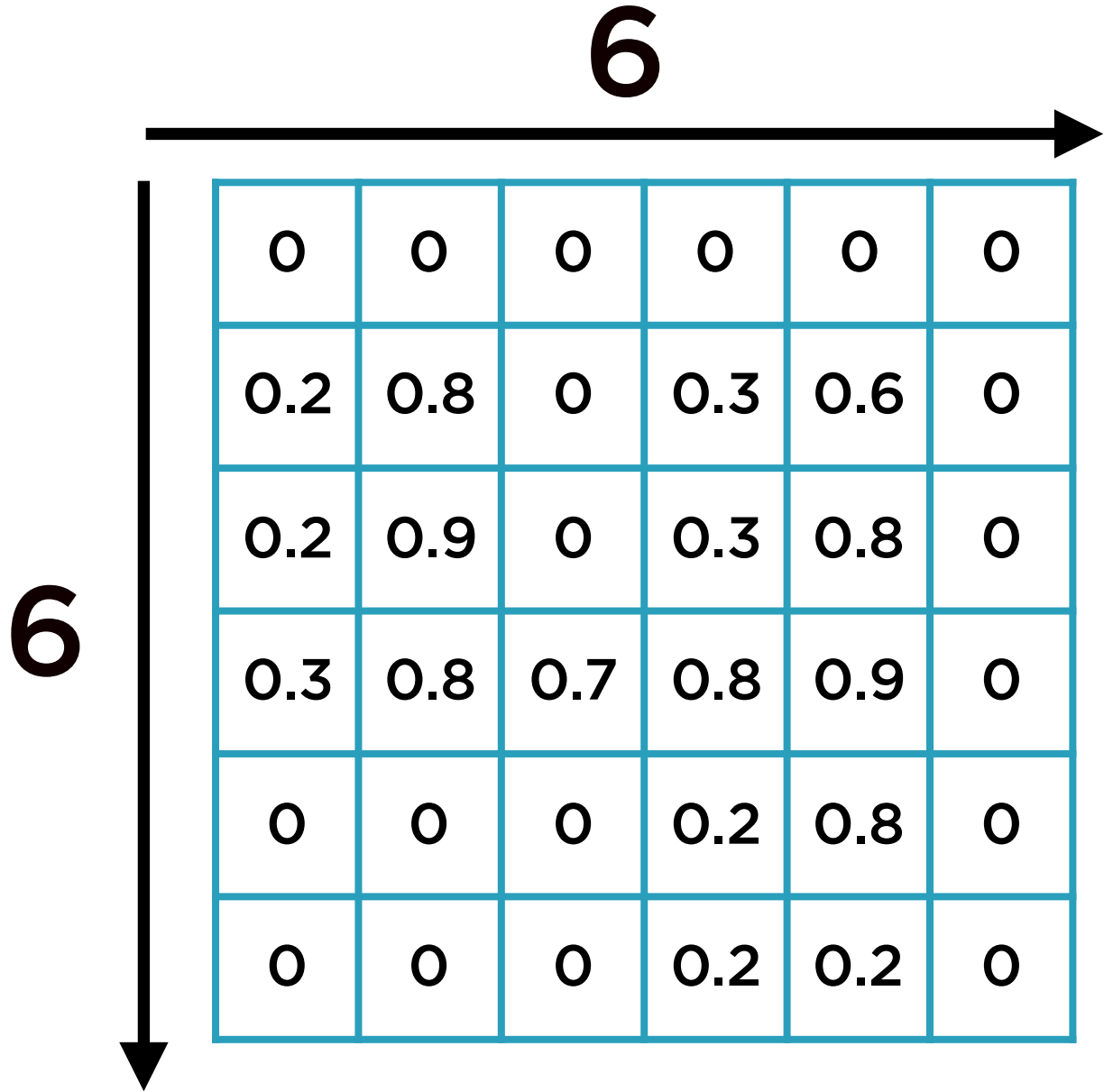
Little zero padding; output narrower than input



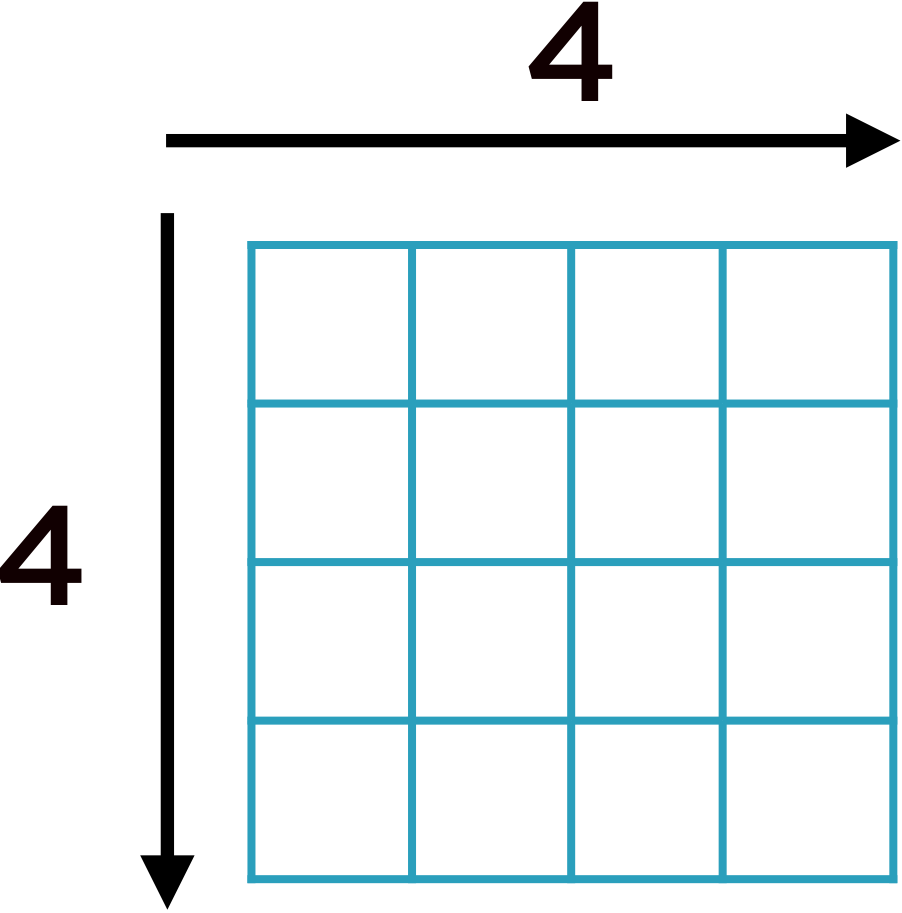
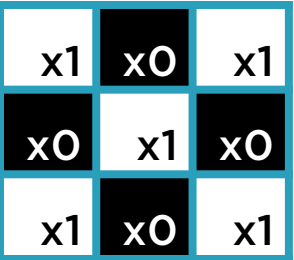
## Wide Convolution

Lots of zero padding; output wider than input

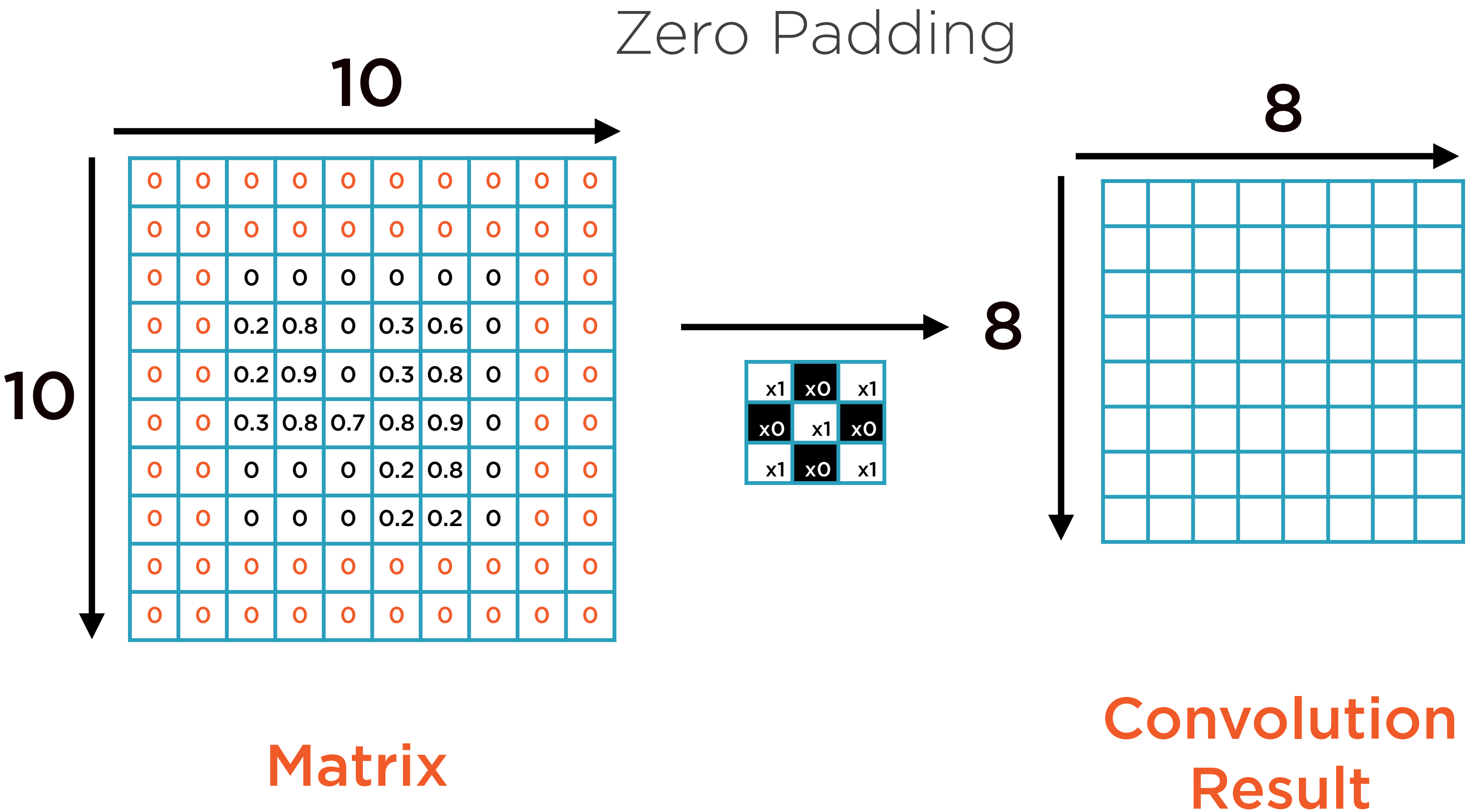
Without Zero Padding



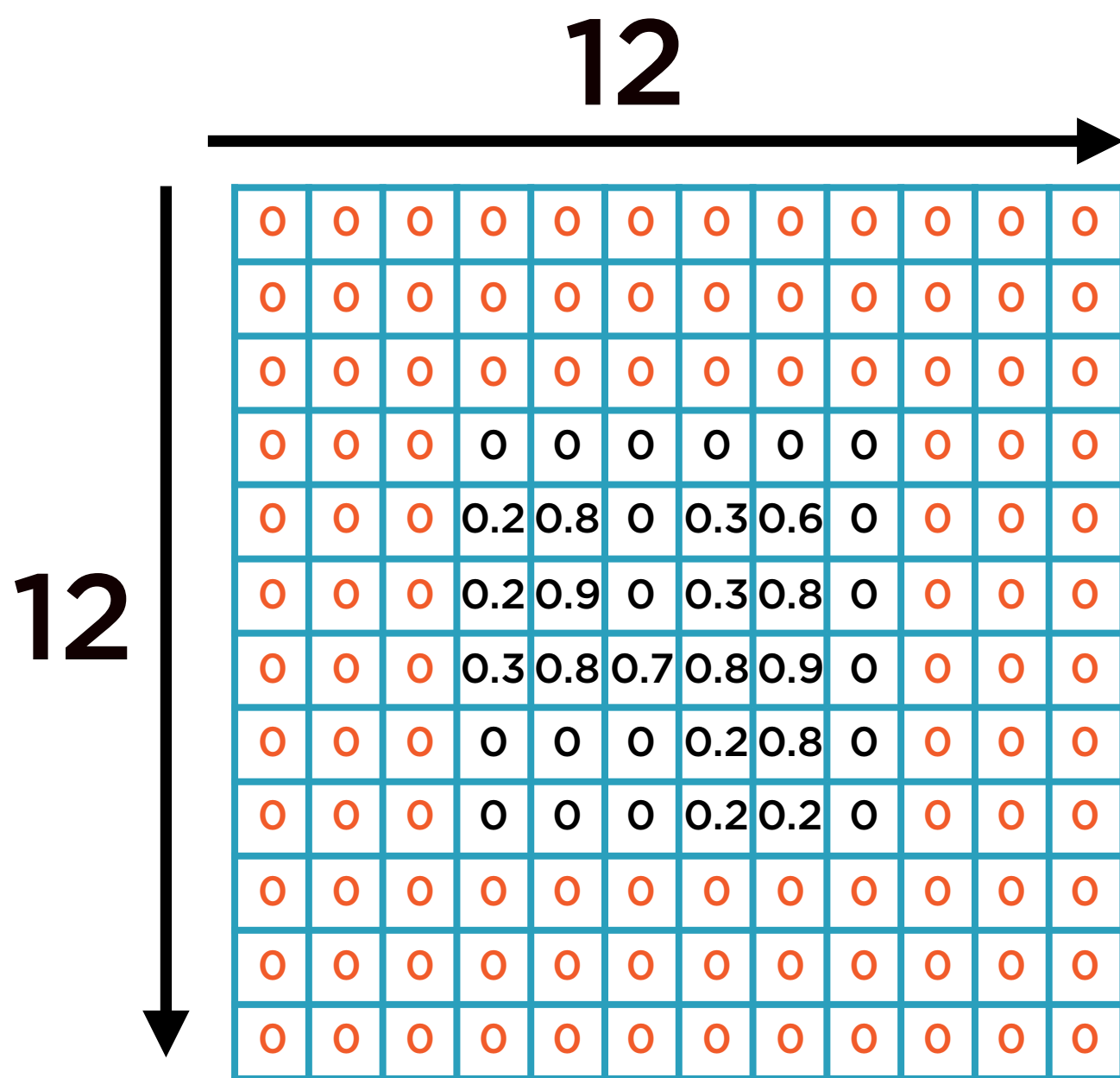
Matrix



Convolution  
Result



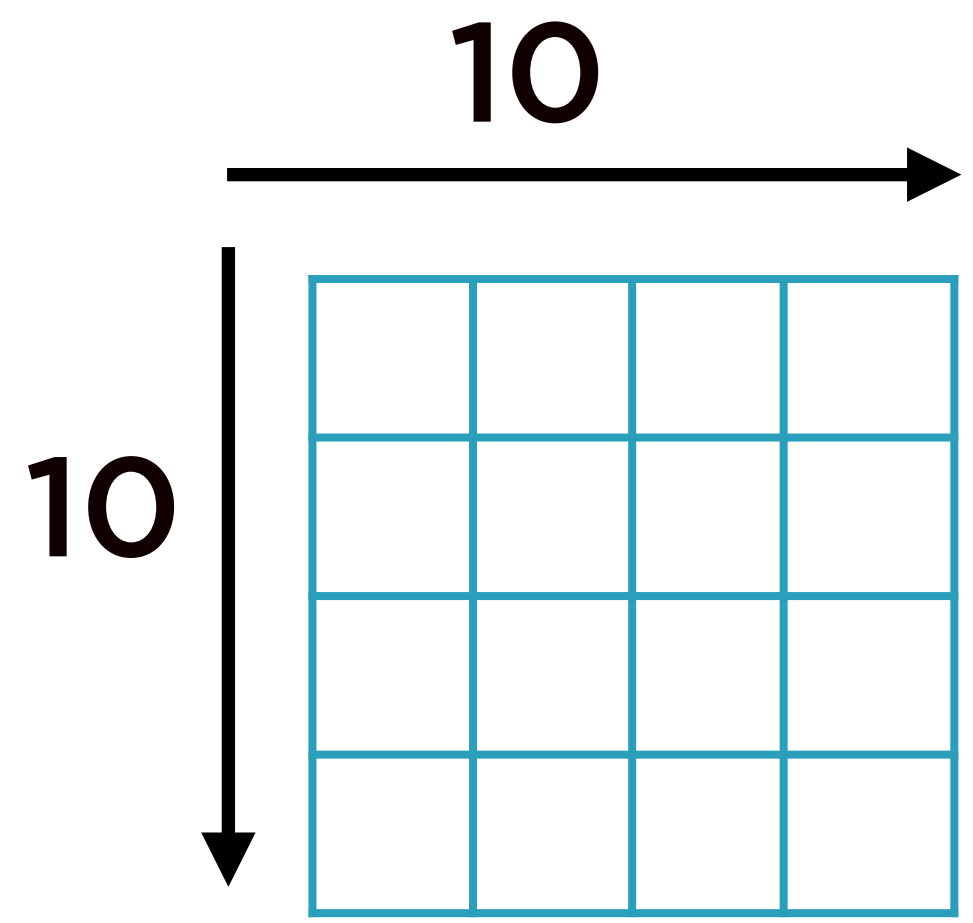
Zero Padding



Matrix



x1	x0	x1
x0	x1	x0
x1	x0	x1



Convolution  
Result



# Zero Padding

x0		x0	x0
x0	x1	x1	x0
x0	x1	x1	x0
x0	x1	x1	x0
x0			x0

**With zero-padding, every element of matrix will be passed into filter**

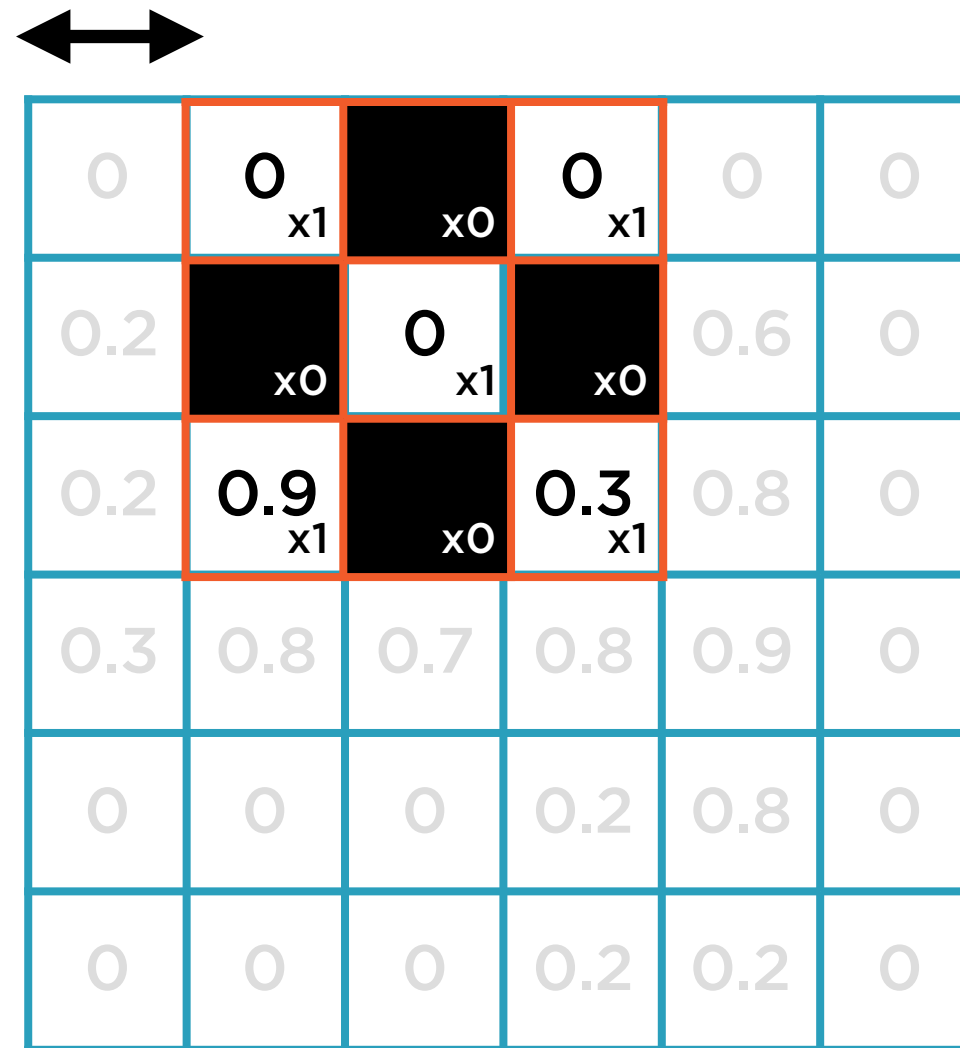
**Can decide number of zero columns to pad with**

**Use to get output larger than input**

# Stride Size

$0_{x1}$	$x0$	$0_{x1}$	0	0	0
$x0$	$0.8_{x1}$	$x0$	0.3	0.6	0
$0.2_{x1}$	$x0$	$0_{x1}$	0.3	0.8	0
0.3	0.8	0.7	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

# Stride Size



A 6x6 grid illustrating a convolution operation with a horizontal stride of 1. The grid contains numerical values, some of which are highlighted in black or red. A 3x3 kernel is highlighted in red, centered at row 3, column 2. The kernel values are 0, 0, 0 in the first row, 0, 0, 0 in the second row, and 0.9, 0, 0.3 in the third row. The values 0.9 and 0.3 are labeled x1, and the 0s are labeled x0. A double-headed arrow above the grid indicates the horizontal stride size.

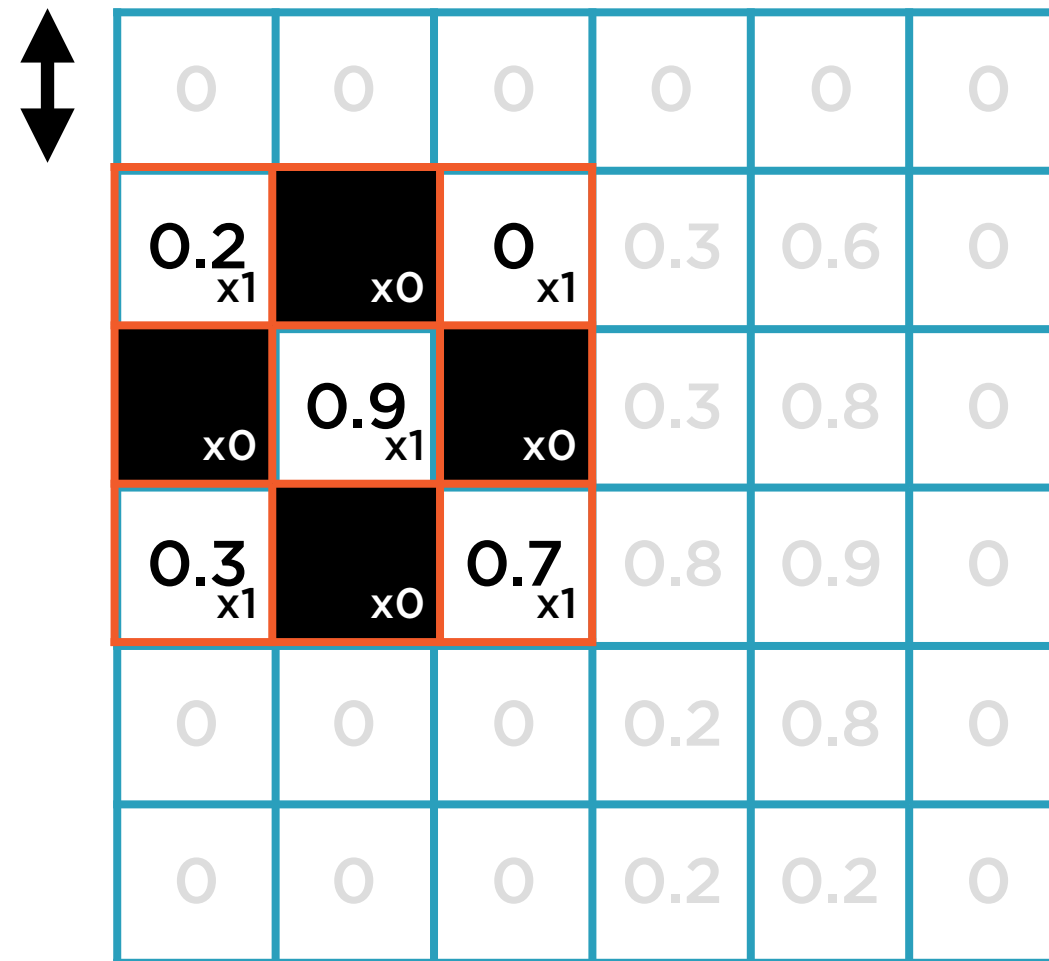
0	0 <sub>x1</sub>	0 <sub>x0</sub>	0 <sub>x1</sub>	0	0
0.2	0 <sub>x0</sub>	0 <sub>x1</sub>	0 <sub>x0</sub>	0.6	0
0.2	0.9 <sub>x1</sub>	0 <sub>x0</sub>	0.3 <sub>x1</sub>	0.8	0
0.3	0.8	0.7	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

**Horizontal stride of 1**

# Stride Size

$0_{x1}$	$x0$	$0_{x1}$	0	0	0
$x0$	$0.8_{x1}$	$x0$	0.3	0.6	0
$0.2_{x1}$	$x0$	$0_{x1}$	0.3	0.8	0
0.3	0.8	0.7	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

# Stride Size



A 6x6 grid illustrating a vertical stride of 1. The grid contains numerical values and labels  $x_0$  and  $x_1$ . A 3x3 subgrid is highlighted with an orange border, and a vertical double-headed arrow to its left indicates the stride size.

0	0	0	0	0	0
0.2 <sub>x1</sub>	$x_0$	0 <sub>x1</sub>	0.3	0.6	0
$x_0$	0.9 <sub>x1</sub>	$x_0$	0.3	0.8	0
0.3 <sub>x1</sub>	$x_0$	0.7 <sub>x1</sub>	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

**Vertical stride of 1**

# Stride Size

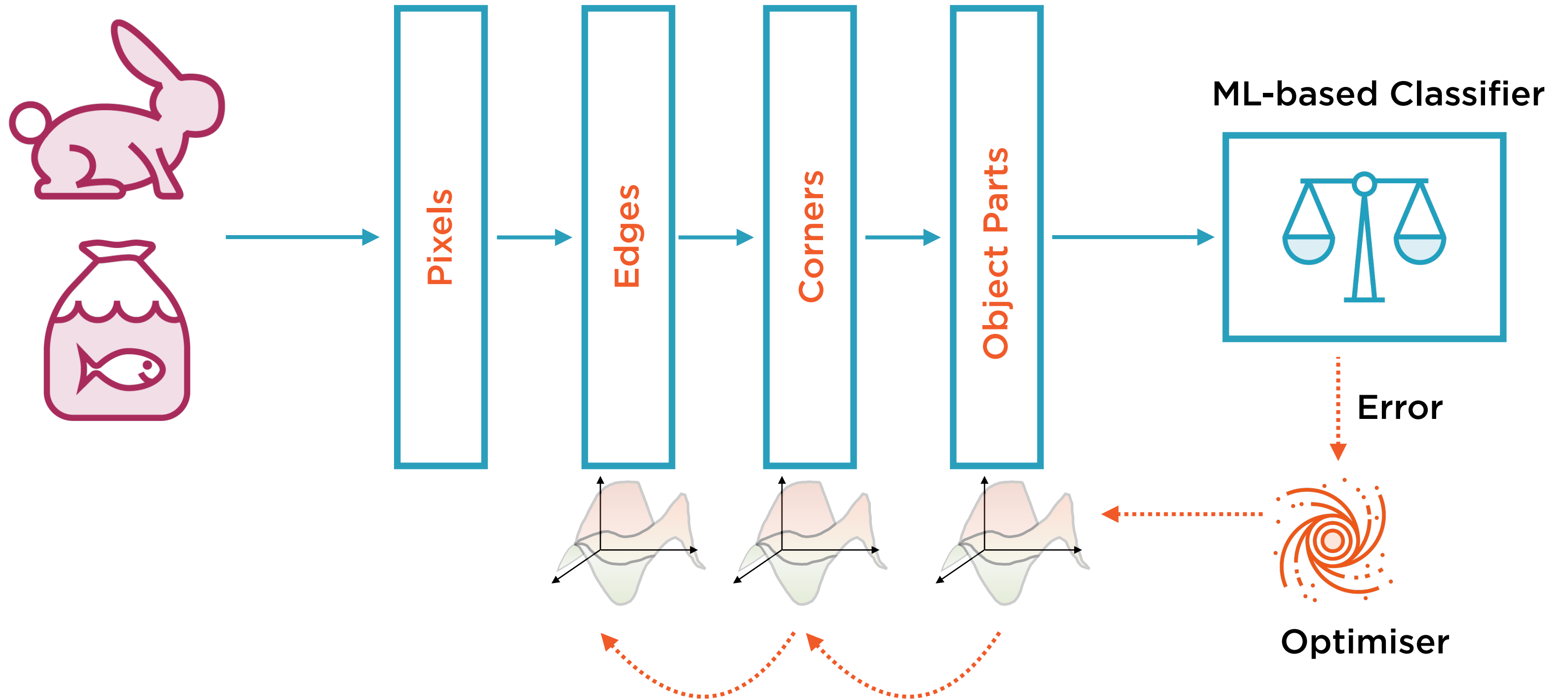
0	0	0	0	0	0
0.2 <sub>x1</sub>	0.9 <sub>x0</sub>	0.7 <sub>x1</sub>	0.3	0.6	0
0.3 <sub>x0</sub>	0.6 <sub>x1</sub>	0.8 <sub>x0</sub>	0.3	0.8	0
0.8 <sub>x1</sub>	0.9 <sub>x0</sub>	0.9 <sub>x1</sub>	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

**Stride size is an important hyperparameter in CNNs**

# Batch Normalization

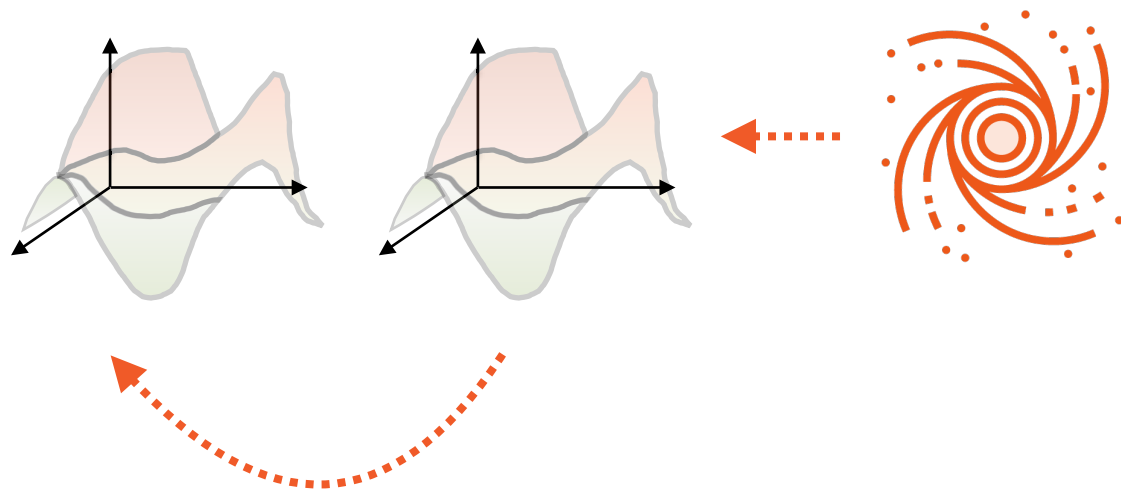
---

# Training via Back Propagation





# Vanishing and Exploding Gradients

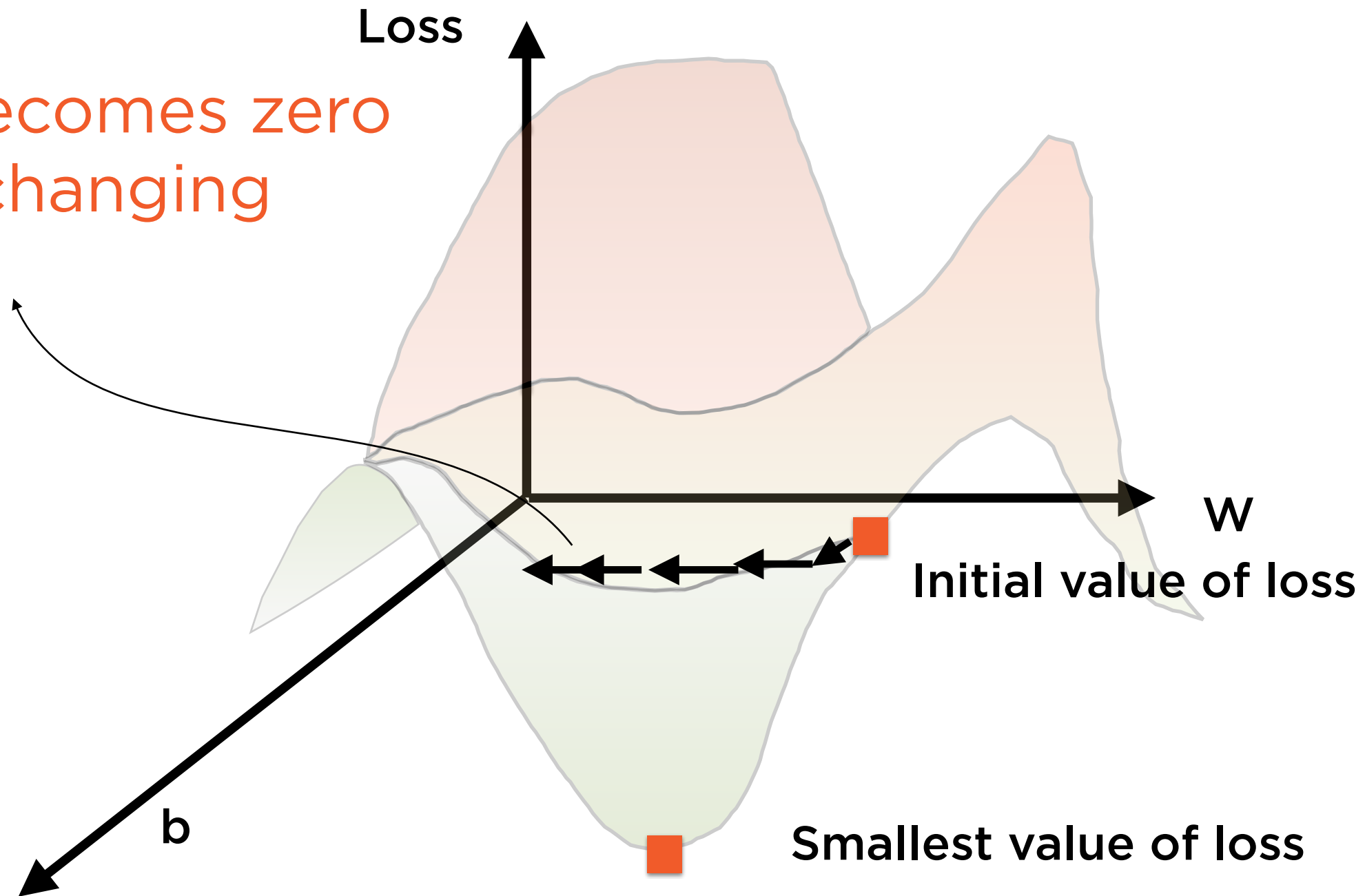


**Back propagation fails if**

- gradients are **vanishing**
- gradients are **exploding**

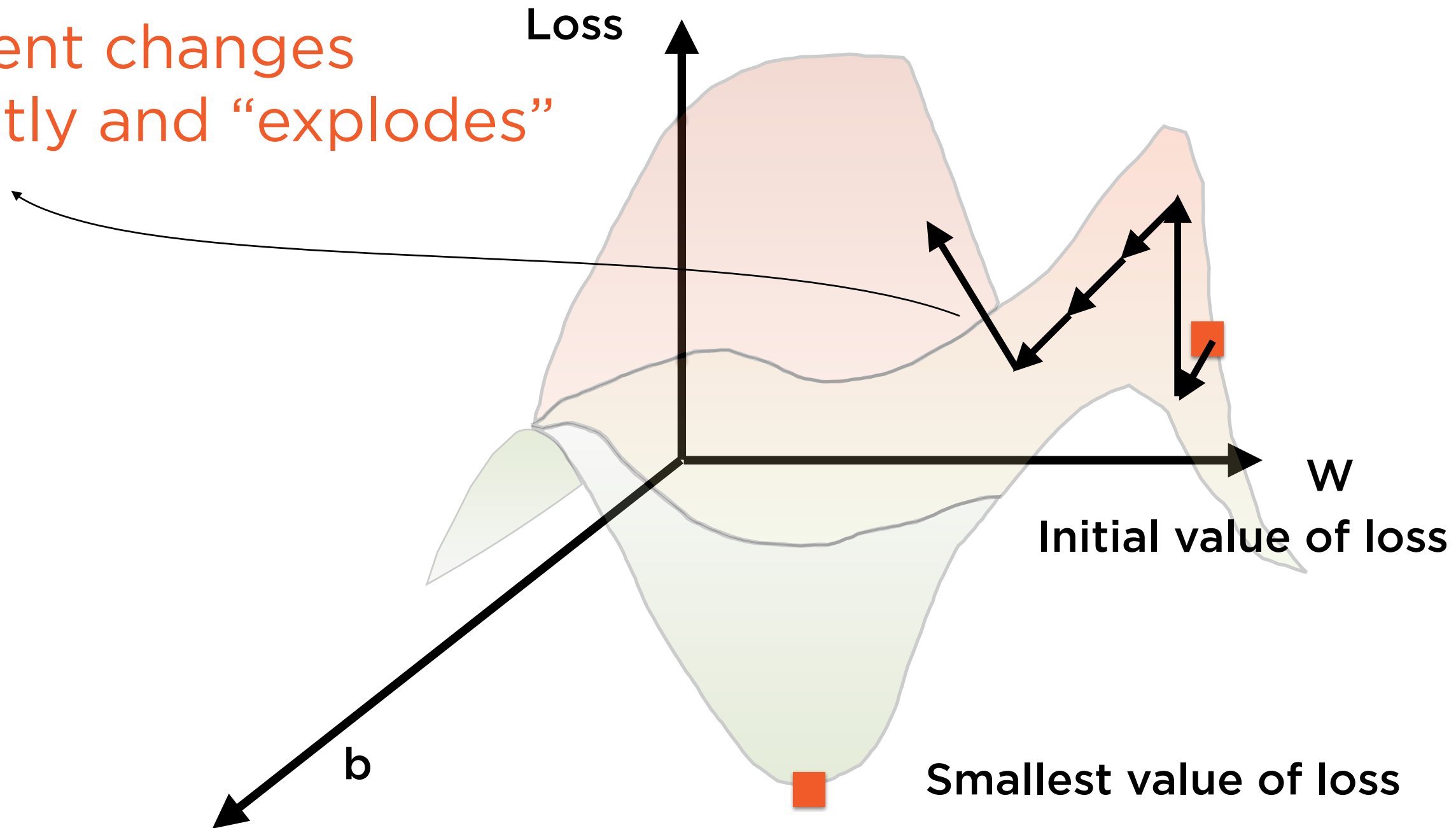
# Vanishing Gradient Problem

Gradient becomes zero  
and stops changing



# Exploding Gradient Problem

Gradient changes abruptly and “explodes”



# Coping with Vanishing/Exploding Gradients

**Proper initialization**

**Non-saturating activation  
function**

**Batch normalization**

**Gradient clipping**

# Coping with Vanishing/Exploding Gradients

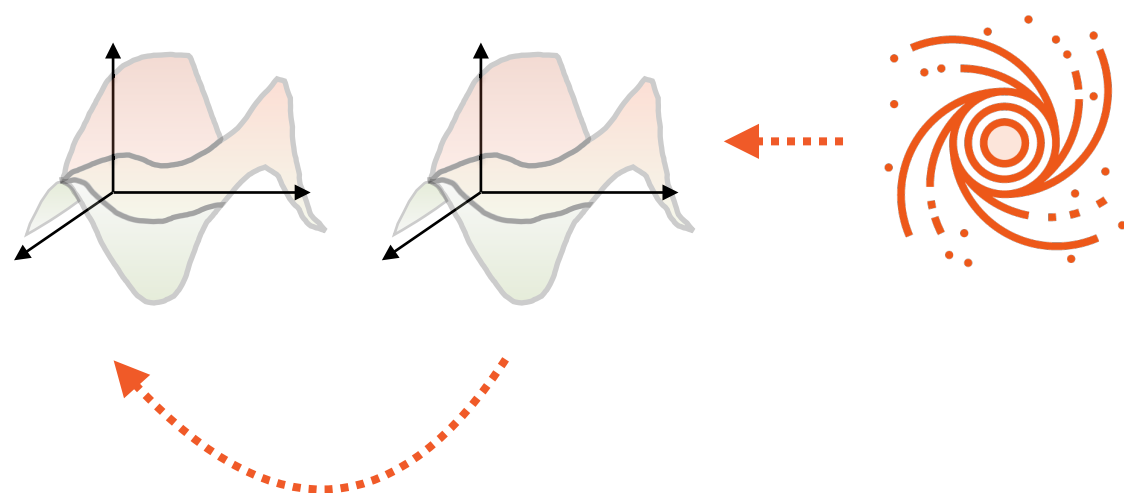
Proper initialisation

Non-saturating activation  
function

**Batch normalization**

Gradient clipping

# Batch Normalization

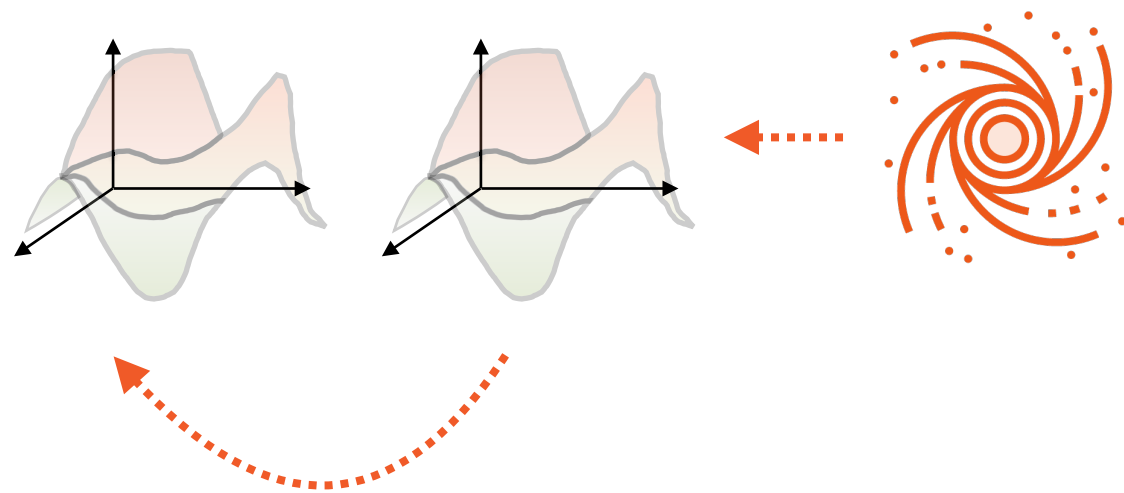


**Just before applying activation function**

**First, “normalize” inputs**

**Second, “scale and shift” inputs**

# Batch Normalization



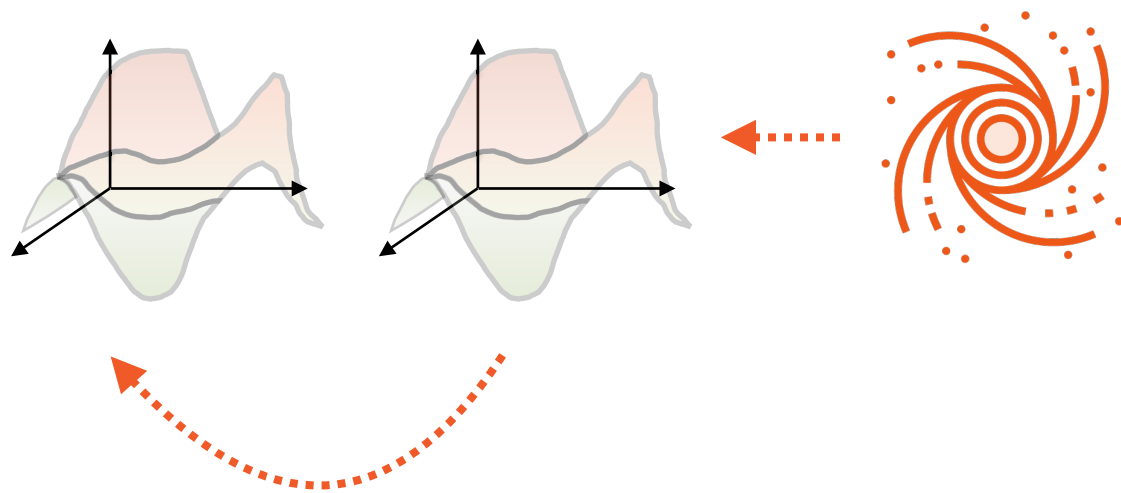
## “Normalize” inputs

- subtract mean
- divide by standard deviation

## “Scale and shift” inputs

- scale = multiply by constant
- shift = add constant

# Batch Normalization



**Supported in PyTorch**

**Many other benefits**

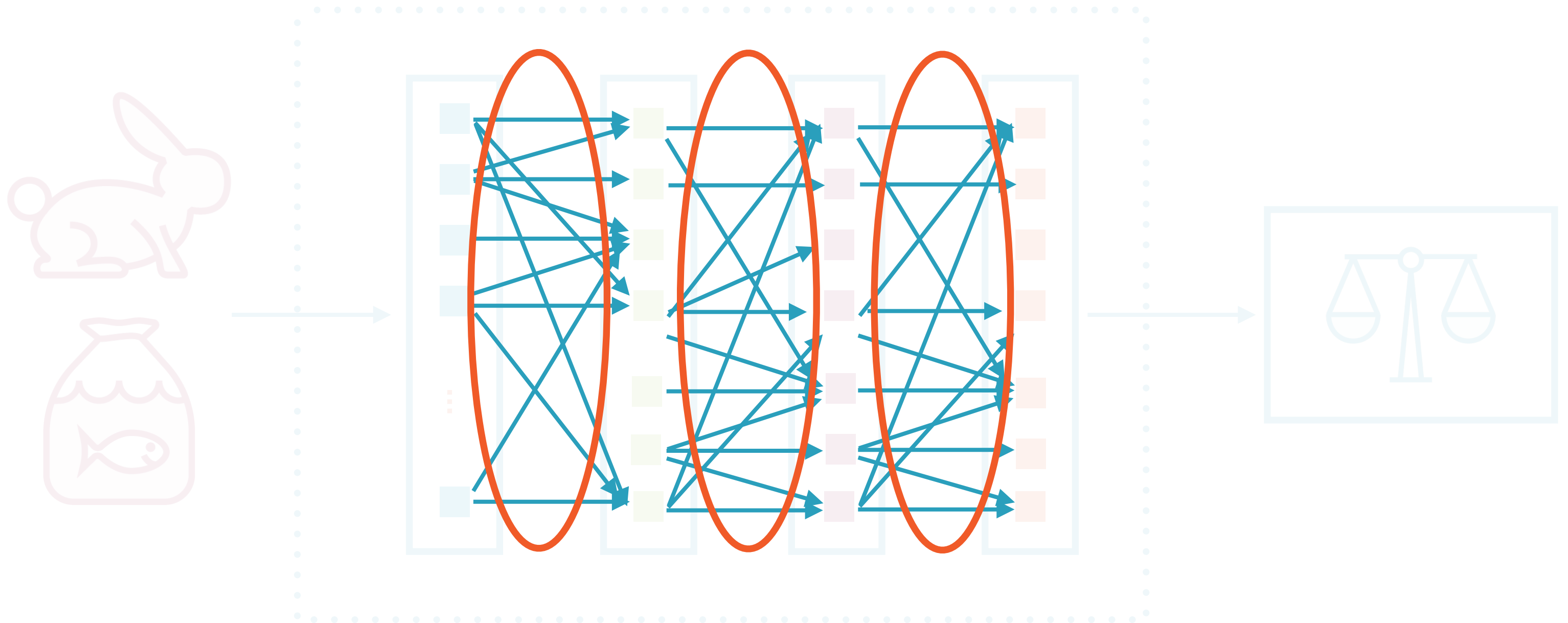
- allows much larger learn rate
- reduces overfitting
- speeds convergence of training



# Choice of Activation Function

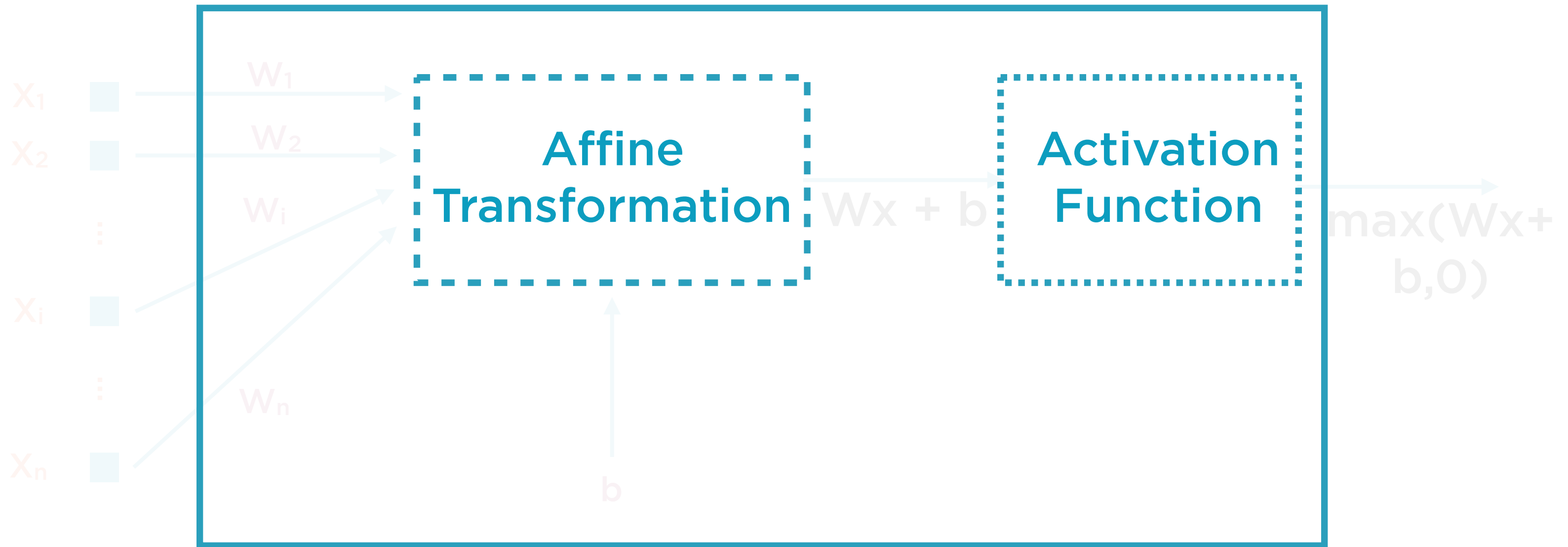
---

# A Neural Network



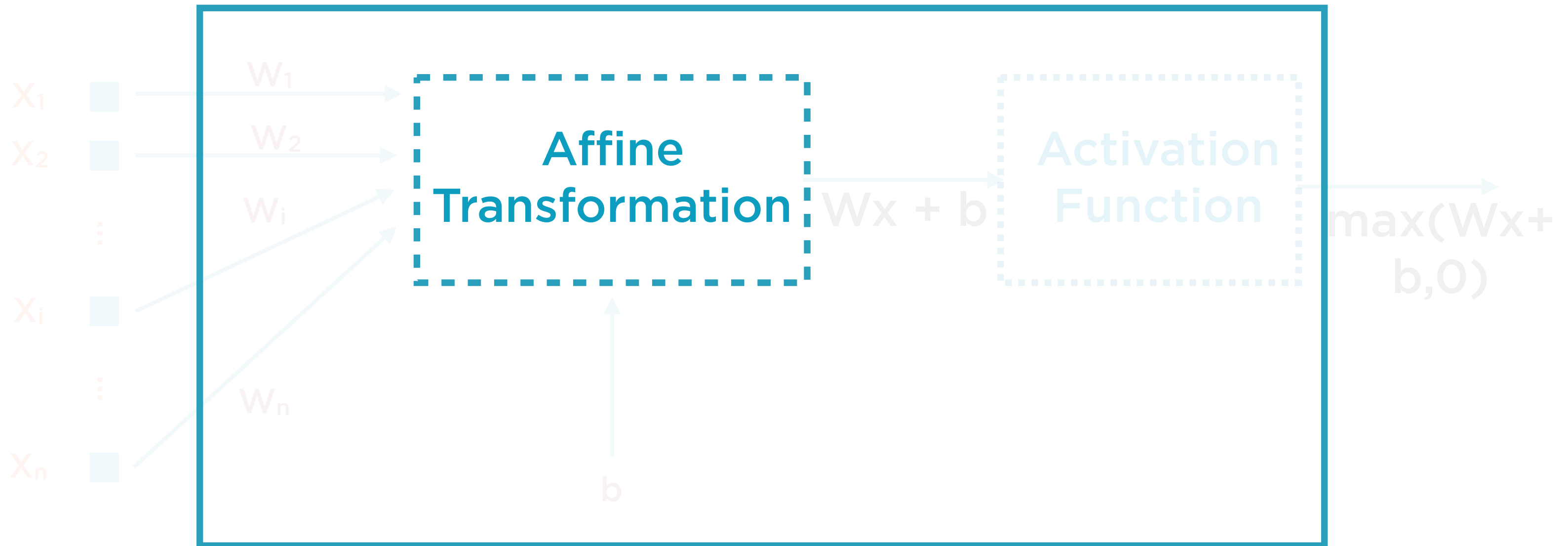
Once a neural network is **trained** all edges have weights which help it make predictions

# Operation of a Single Neuron



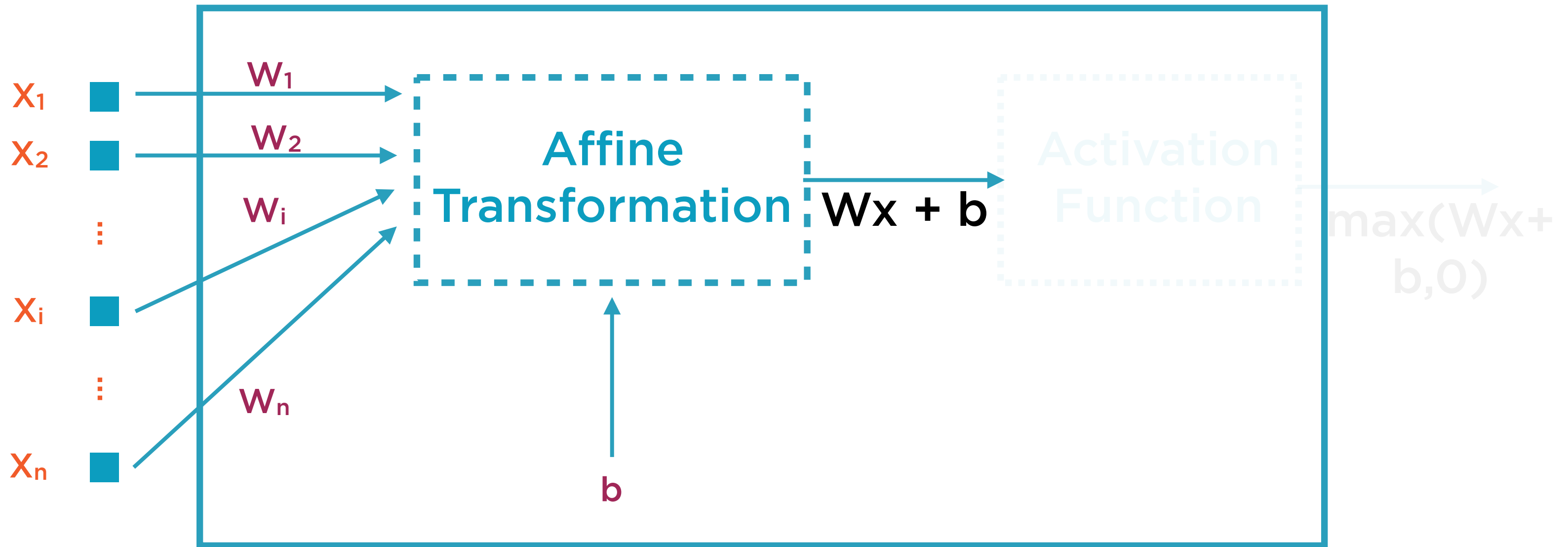
**Each neuron only applies two simple functions to its inputs**

# Operation of a Single Neuron



The affine transformation alone can **only** learn **linear** relationships between the inputs and the output

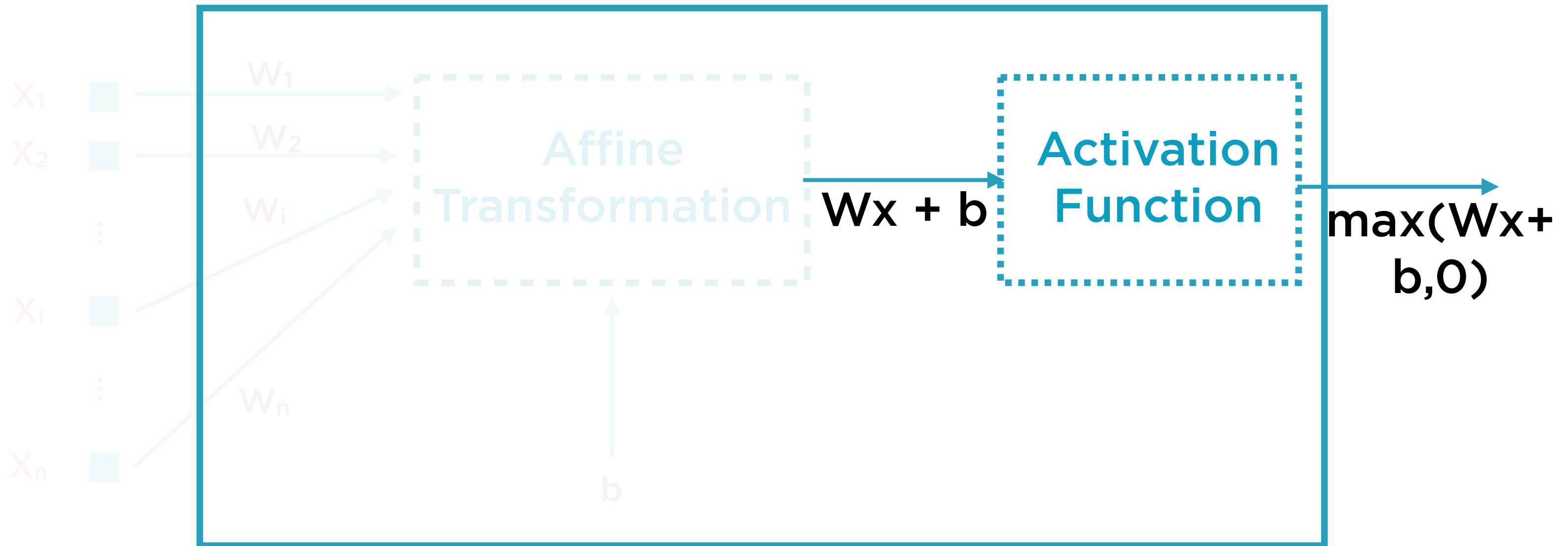
# Operation of a Single Neuron



The affine transformation is just a weighted sum with a bias added:  $W_1x_1 + W_2x_2 + \dots + W_nx_n + b$

The **weights** and **biases** of individual neurons are determined during the **training** process

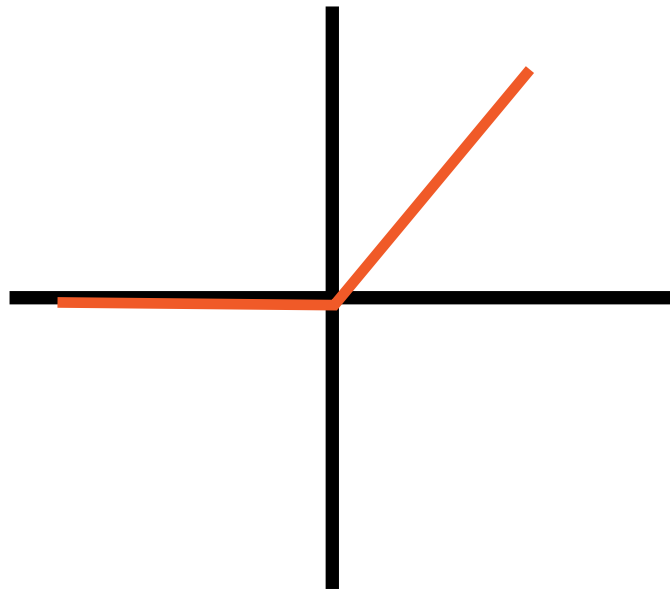
# Operation of a Single Neuron



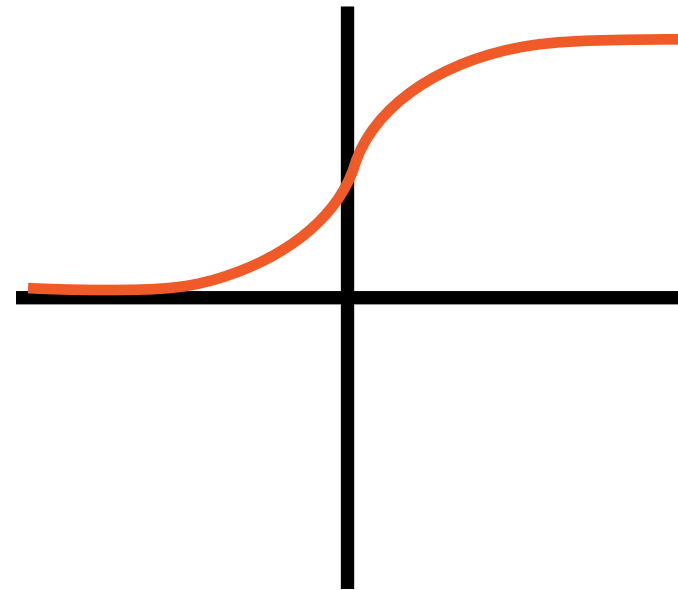
The **combination** of the affine transformation and the activation function can **learn any arbitrary relationship**

# Activation Function

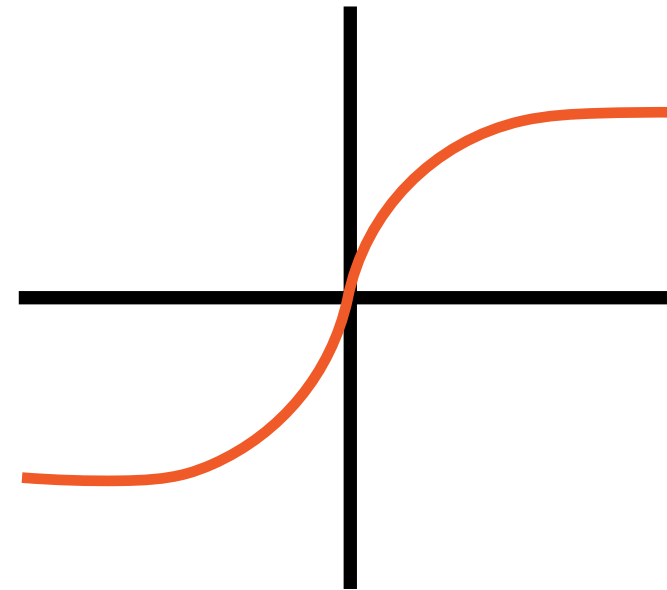
**ReLU**



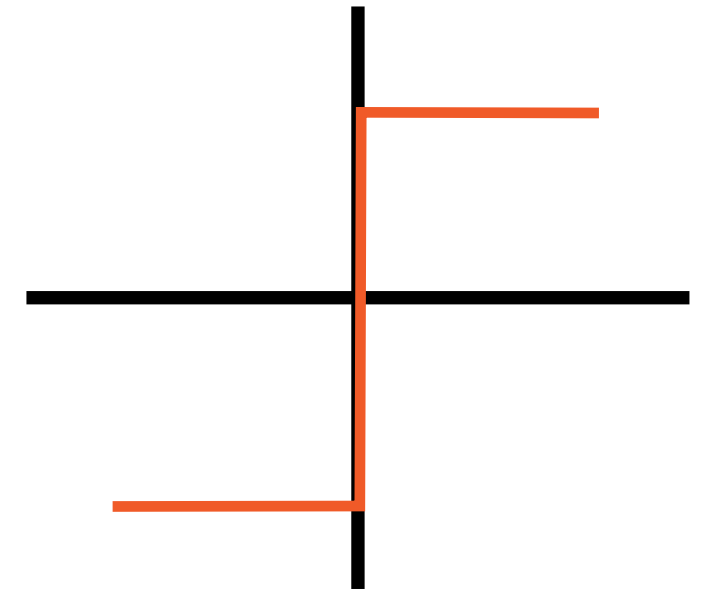
**logit**



**tanh**



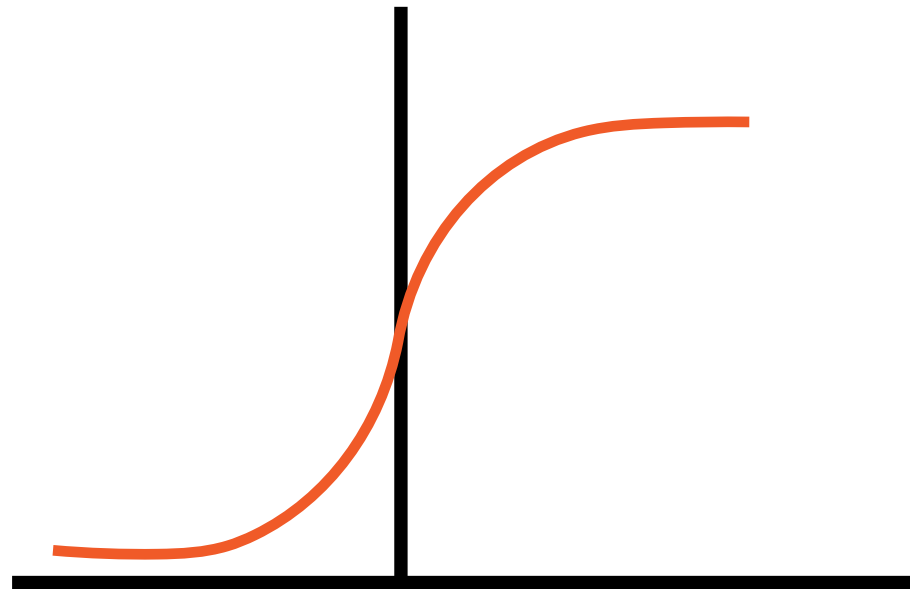
**step**



**Various choices of activation functions exist and drive the design of your neural network**



# Importance of Activation

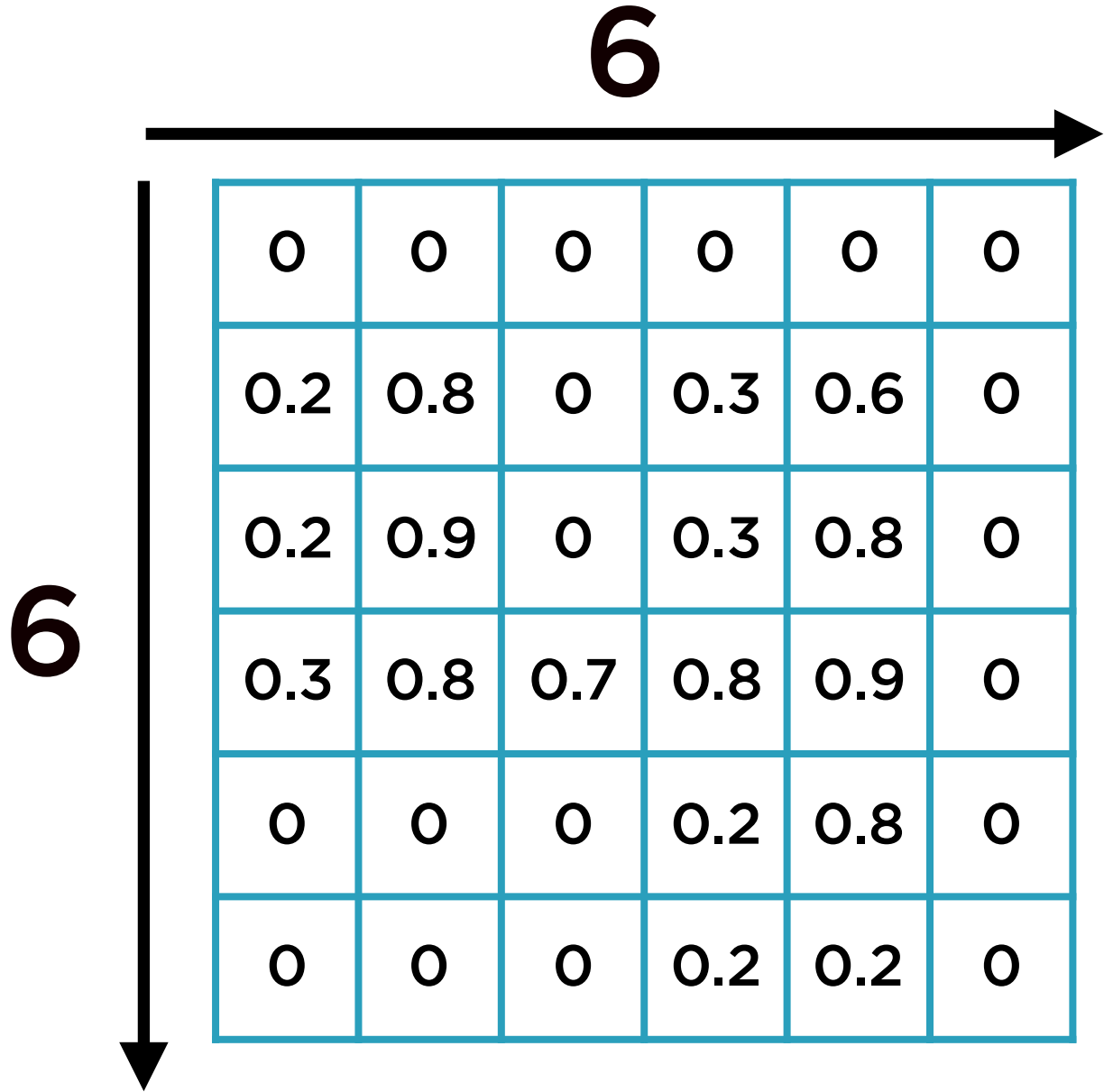


**The choice of activation function is crucial in determining performance**

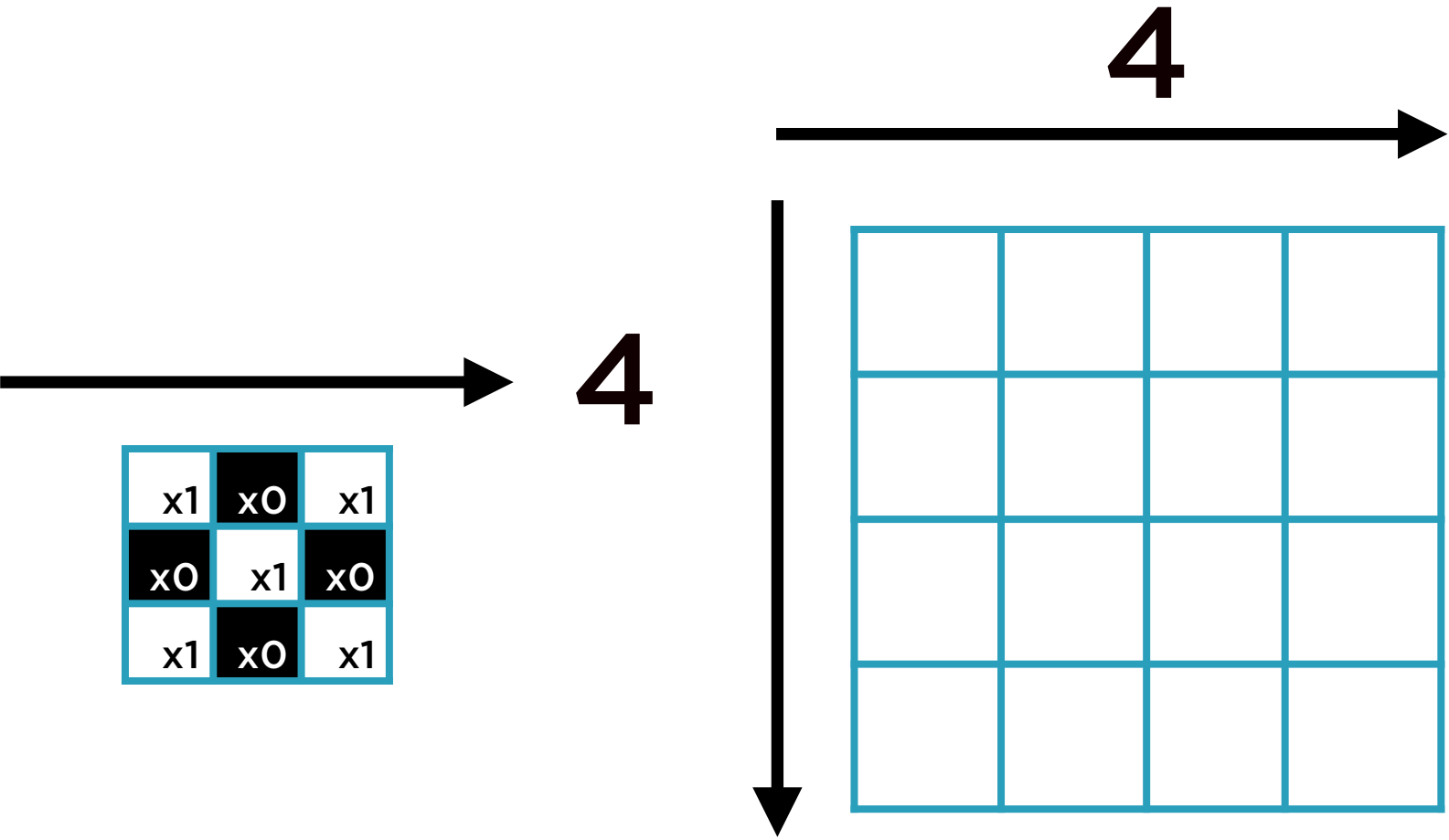
# Feature Map Size Calculations

---

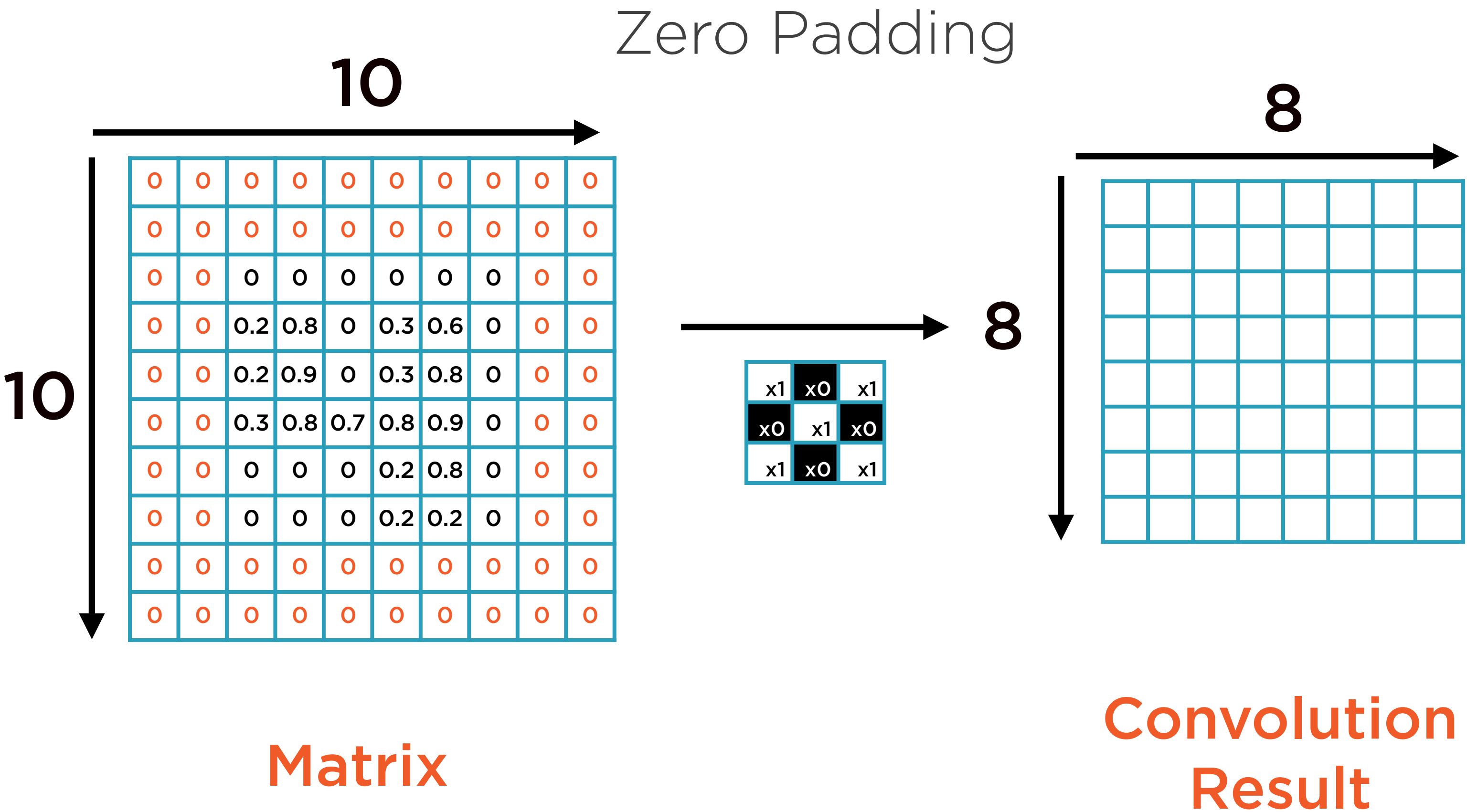
Without Zero Padding



Matrix



Convolution  
Result



$$O = \frac{W-K+2P}{S} + 1$$

---

Formula for dimension calculations

**Handy in getting dimensions of CNN layers right**

$$O = \frac{W-K+2P}{S} + 1$$

---

$O$  = Output dimension

**Height/width of output**

$$O = \frac{W - K + 2P}{S} + 1$$

---

$W$  = Input dimension

Height/width of input image

$$O = \frac{W-K+2P}{S} + 1$$

---

$K$  = Kernel size

**Height/width of kernel**



$$0 = \frac{W - K + 2P}{S} + 1$$

---

P = Padding (if any)

**Maybe zero**

$$0 = \frac{W-K+2P}{S} + 1$$

---

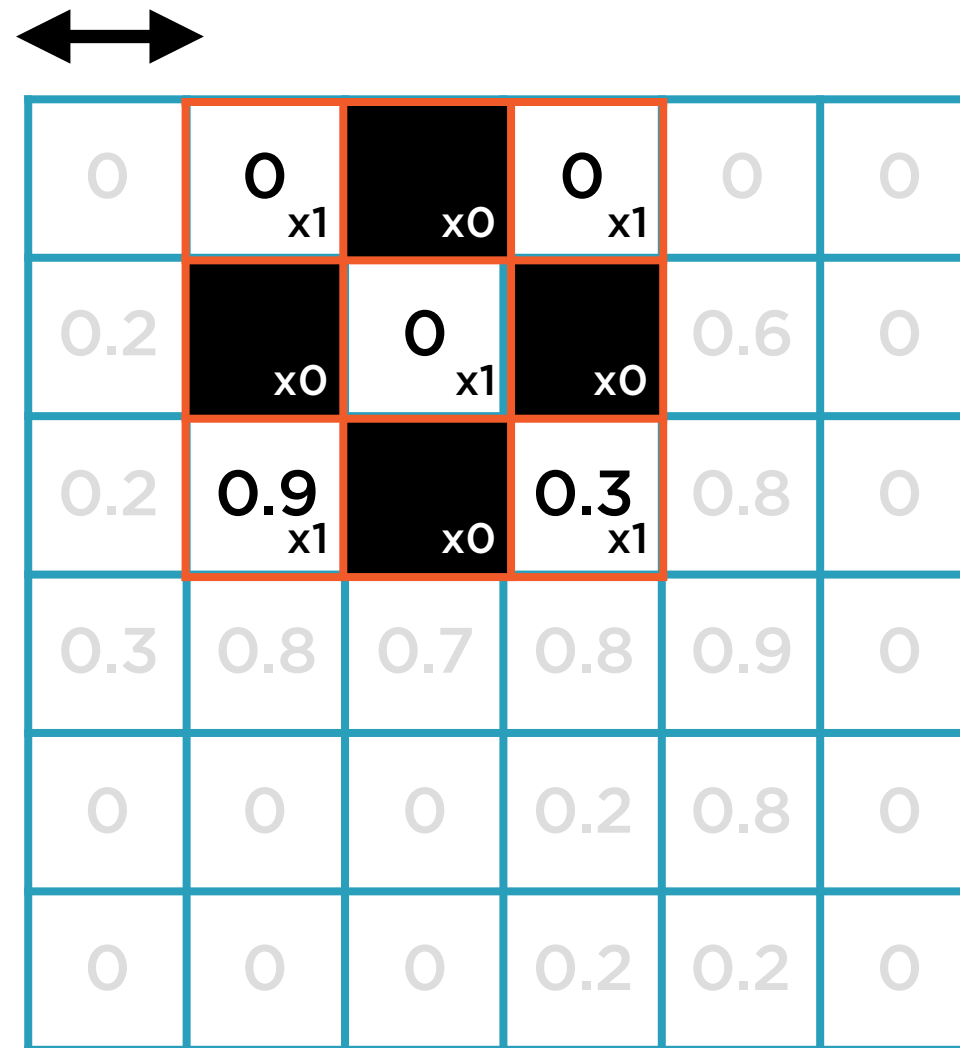
$S = \text{Stride}$

**How far the kernel advances in each step**

# Stride Size

0 <sub>x1</sub>	x0	0 <sub>x1</sub>	0	0	0
x0	0.8 <sub>x1</sub>	x0	0.3	0.6	0
0.2 <sub>x1</sub>	x0	0 <sub>x1</sub>	0.3	0.8	0
0.3	0.8	0.7	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

# Stride Size



A 6x6 grid illustrating a horizontal stride of 1. A 3x3 kernel is highlighted with a red border, and a double-headed arrow above it indicates the stride size. The grid contains numerical values, with some cells labeled as 'x0' or 'x1'.

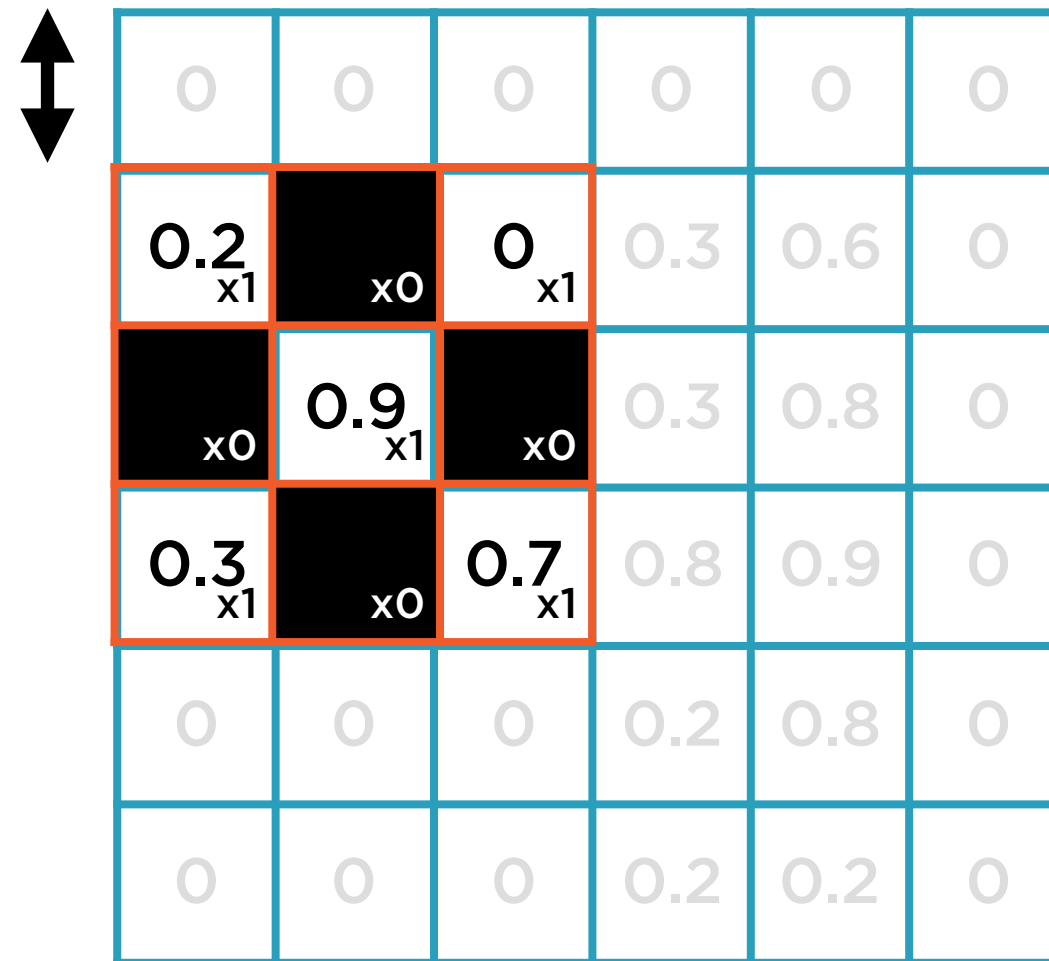
0	0 <sub>x1</sub>	x0	0 <sub>x1</sub>	0	0
0.2	x0	0 <sub>x1</sub>	x0	0.6	0
0.2	0.9 <sub>x1</sub>	x0	0.3 <sub>x1</sub>	0.8	0
0.3	0.8	0.7	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

**Horizontal stride of 1**

# Stride Size

0 <sub>x1</sub>	x0	0 <sub>x1</sub>	0	0	0
x0	0.8 <sub>x1</sub>	x0	0.3	0.6	0
0.2 <sub>x1</sub>	x0	0 <sub>x1</sub>	0.3	0.8	0
0.3	0.8	0.7	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

# Stride Size



A 6x6 grid illustrating a vertical stride of 1. The grid contains numerical values and labels  $x_0$  and  $x_1$ . A 3x3 subgrid is highlighted with an orange border, and a vertical double-headed arrow indicates the stride size.

0	0	0	0	0	0
0.2 <sub>x1</sub>	$x_0$	0 <sub>x1</sub>	0.3	0.6	0
$x_0$	0.9 <sub>x1</sub>	$x_0$	0.3	0.8	0
0.3 <sub>x1</sub>	$x_0$	0.7 <sub>x1</sub>	0.8	0.9	0
0	0	0	0.2	0.8	0
0	0	0	0.2	0.2	0

**Vertical stride of 1**

$$O = \frac{W-K+2P}{S} + 1$$

---

Formula for dimension calculations

**Handy in getting dimensions of CNN layers right**

# Demo

**Image classification using  
convolutional neural networks (CNNs)**

**Hyperparameter tuning**



# Summary

**Narrow and wide convolution**

**Zero-padding and the feature map sizes for convolutional layers**

**Calculating feature map dimensions**

**Batch normalization of input images**

**Building and training a CNN for image classification**

**Changing model hyperparameters**