Deep Learning for Computer Vision

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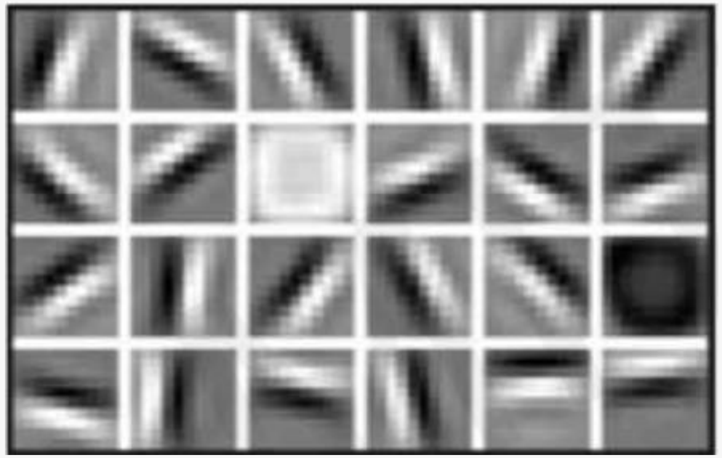
Deep Learning:
ConvNets

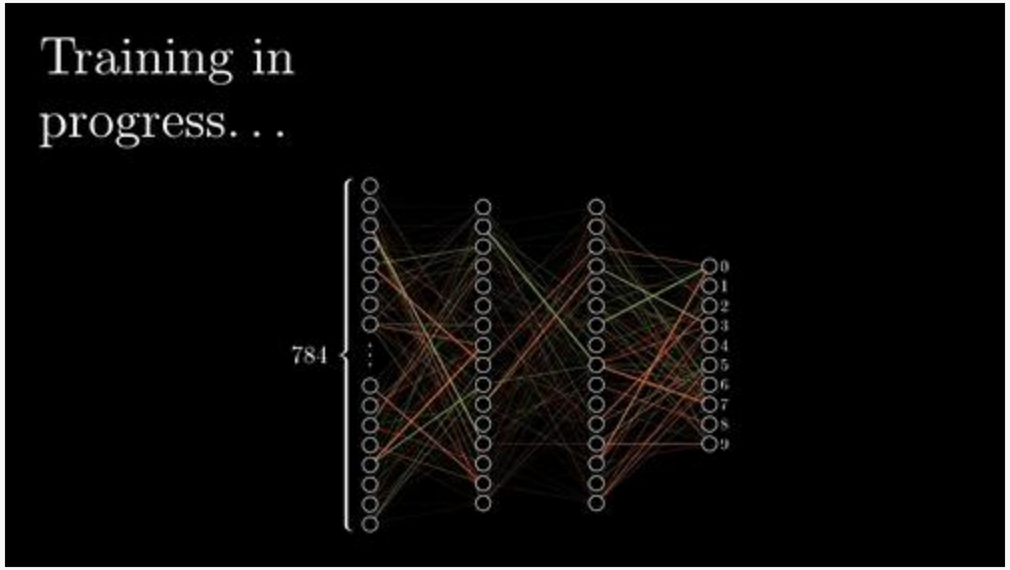
Feature Representations

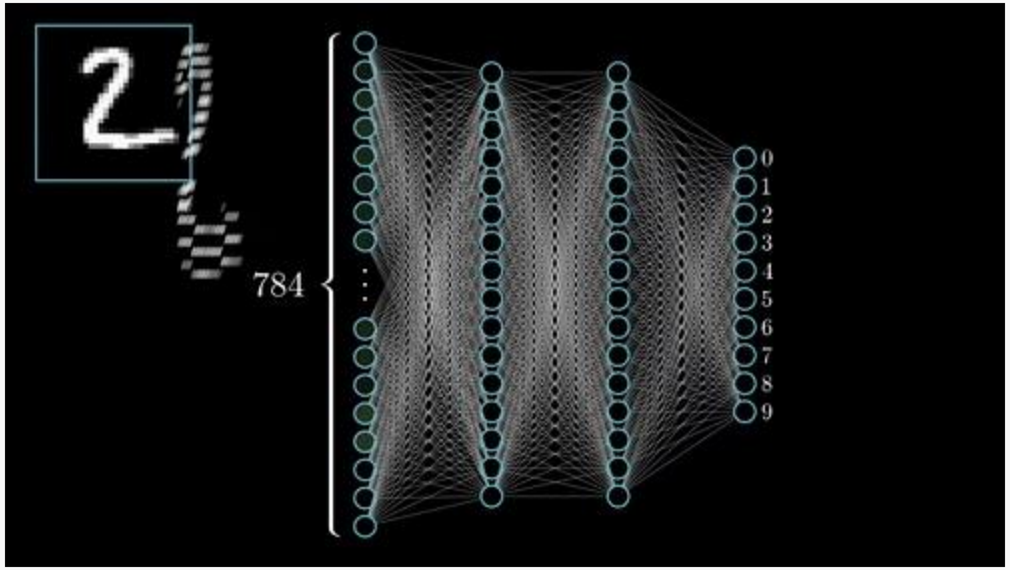
Hand engineered features are time consuming, brittle, and not scalable in practice

Can we learn the **underlying features** directly from data?

Low Level Features	Mid Level Features	High Level Features
		
Lines & Edges	Eyes & Nose & Ears	Facial Structure

Fully Connected Neural Networks





Input: 2D Image

- Vector of pixel values

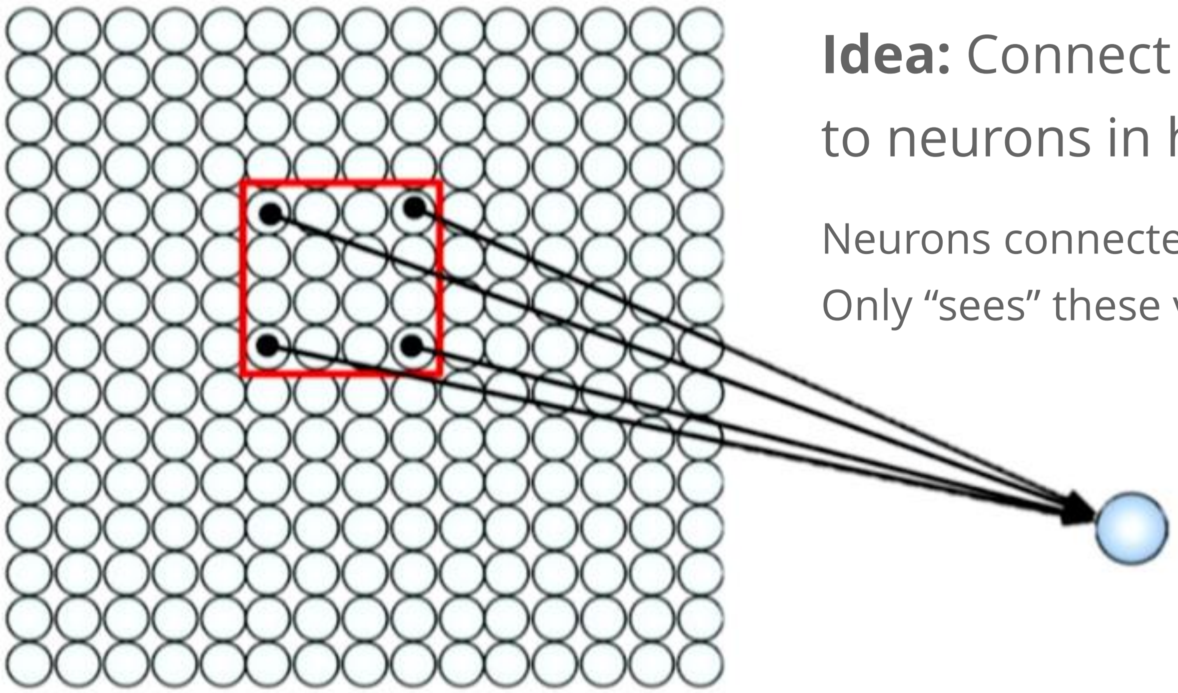
Fully Connected: Connect neurons in hidden layer to all neurons in input

- No spatial information!
- And many, many parameters.

Using Spatial Structure

Input: 2D Image

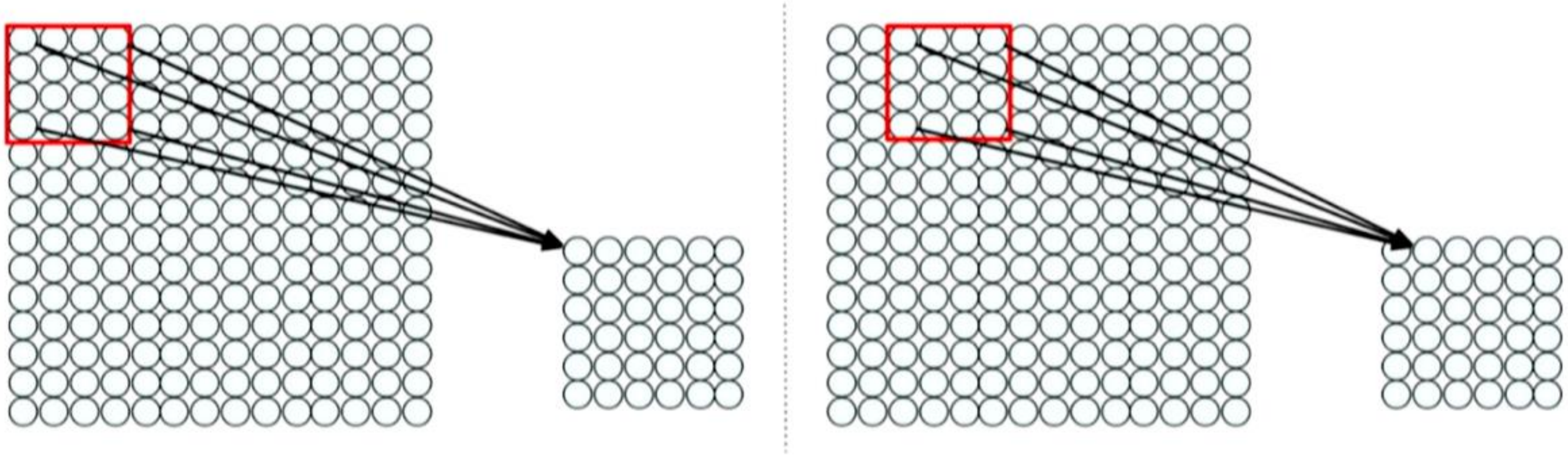
- Array of pixel values



Idea: Connect patches of input to neurons in hidden layer.

Neurons connected to region of input. Only "sees" these values.

Using Spatial Structure

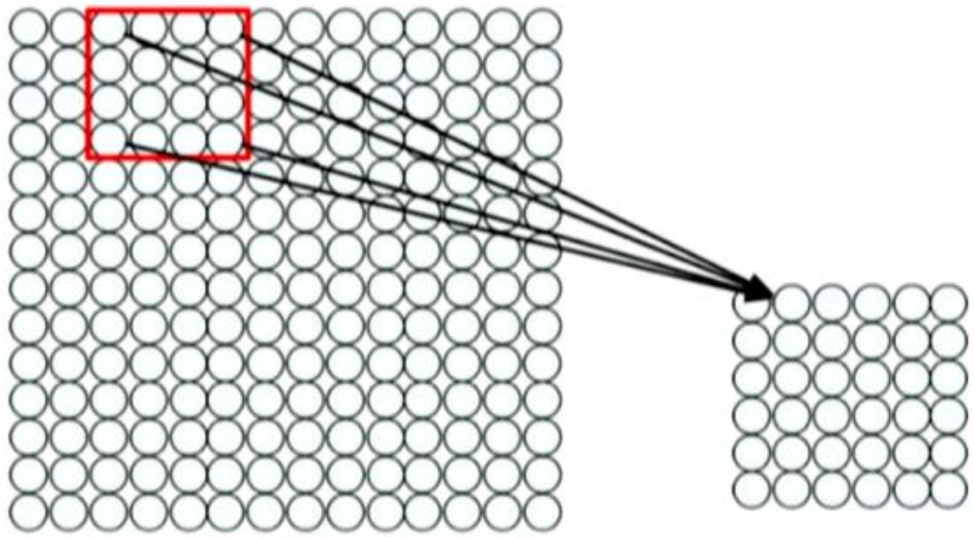


Connect patch in input layer to a single neuron in subsequent layer.

Use sliding window to define connections.

How can we **weight** the patch to detect particular features?

Using Spatial Structure



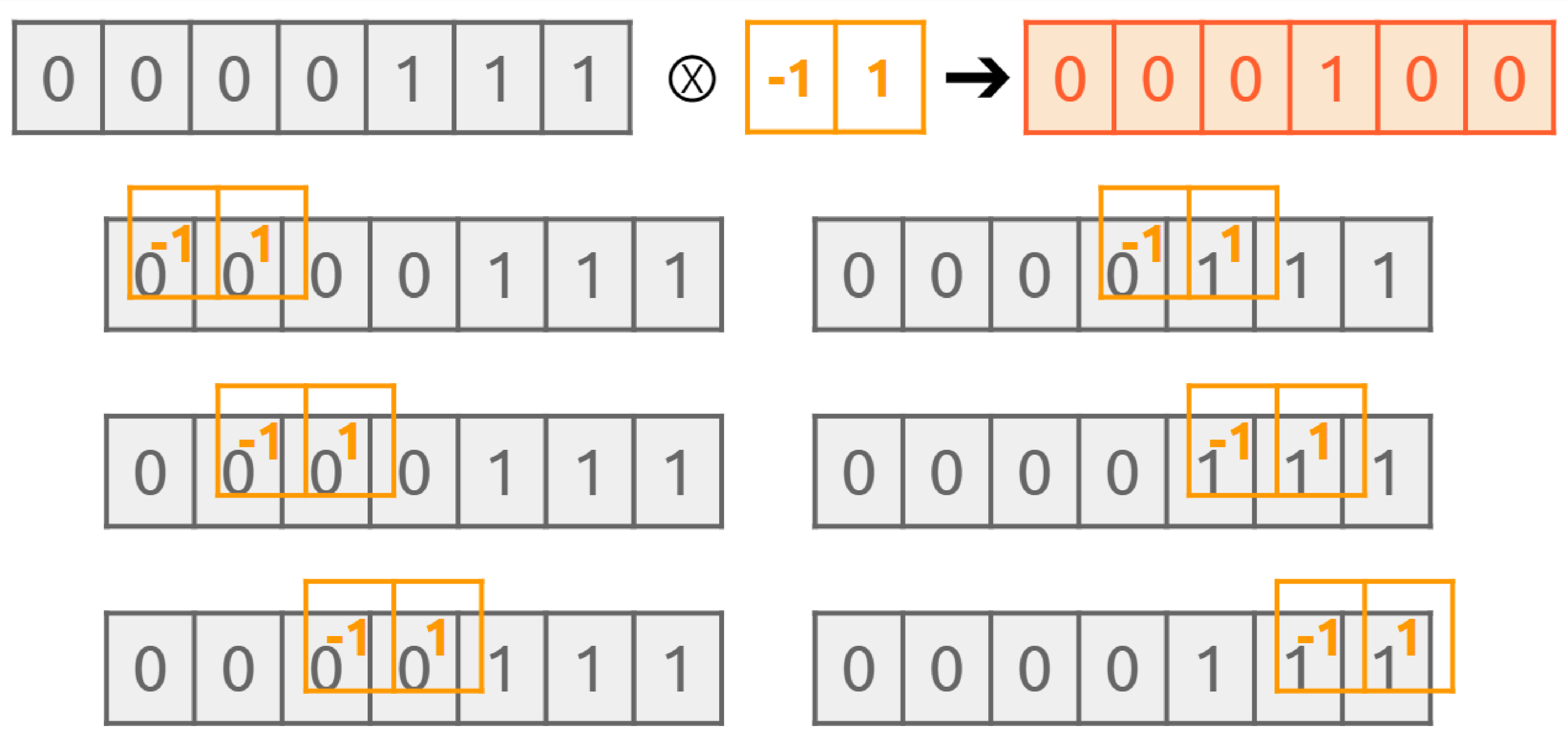
- Filter of size 4x4: 16 different weights
- Apply this same filter to 4x4 patches in input
- Shift by 2 pixels for next patch

This "patchy" operation is **convolution**

1. Apply a set of weights – a filter – to extract local features
2. Use **multiple filters** to extract different features
3. **Spatially share** parameters of each filter

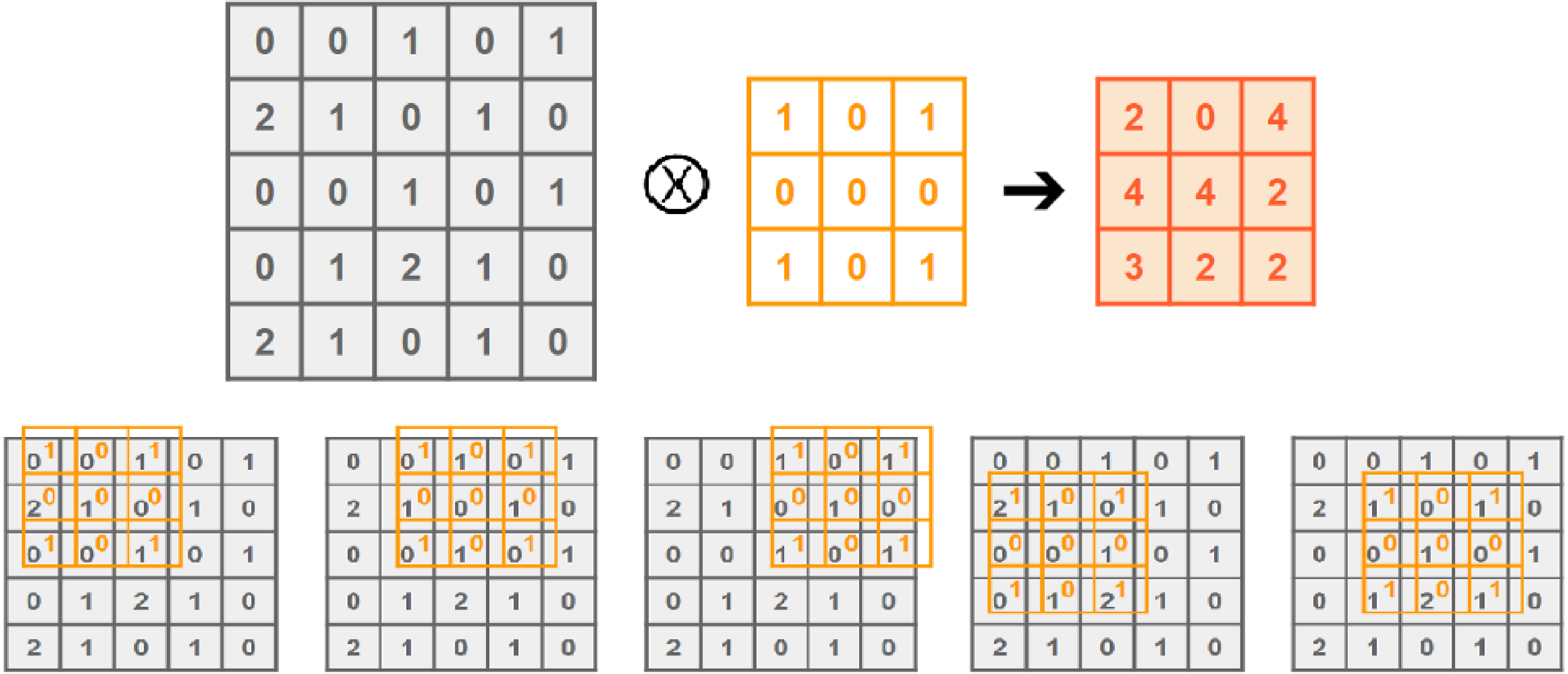
So what is Convolution?

Let’s try to understand the concept of convolution with a simple **1-dimensional** case first.



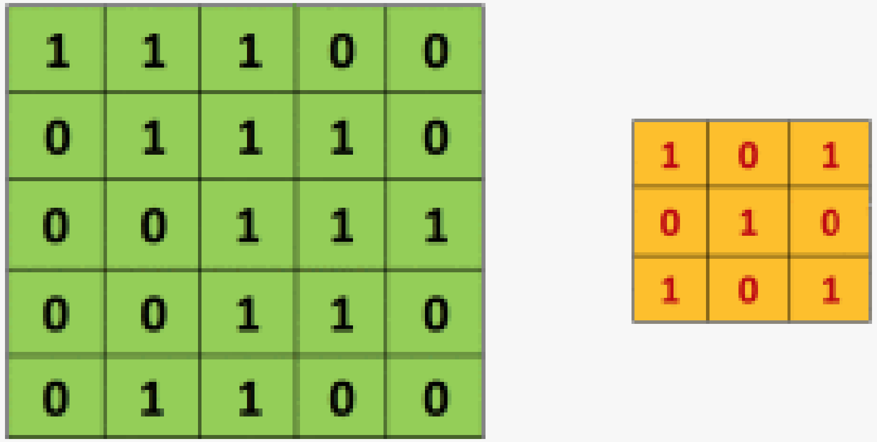
So what is Convolution?

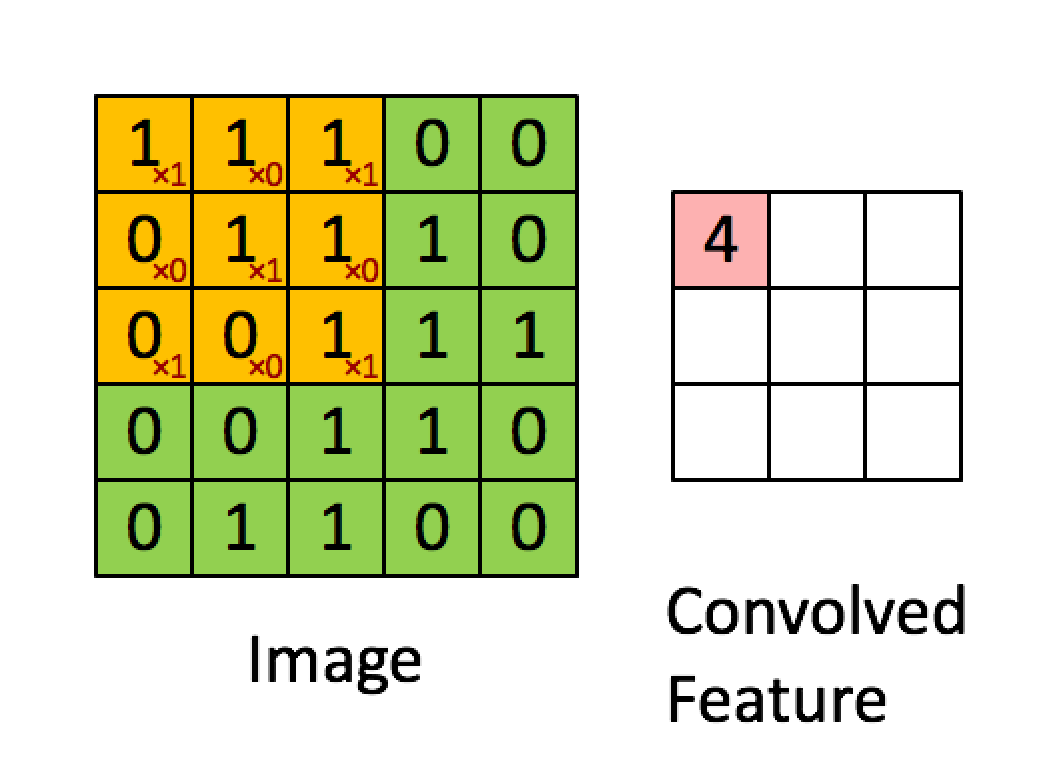
Then let's try a **2-dimensional** case.



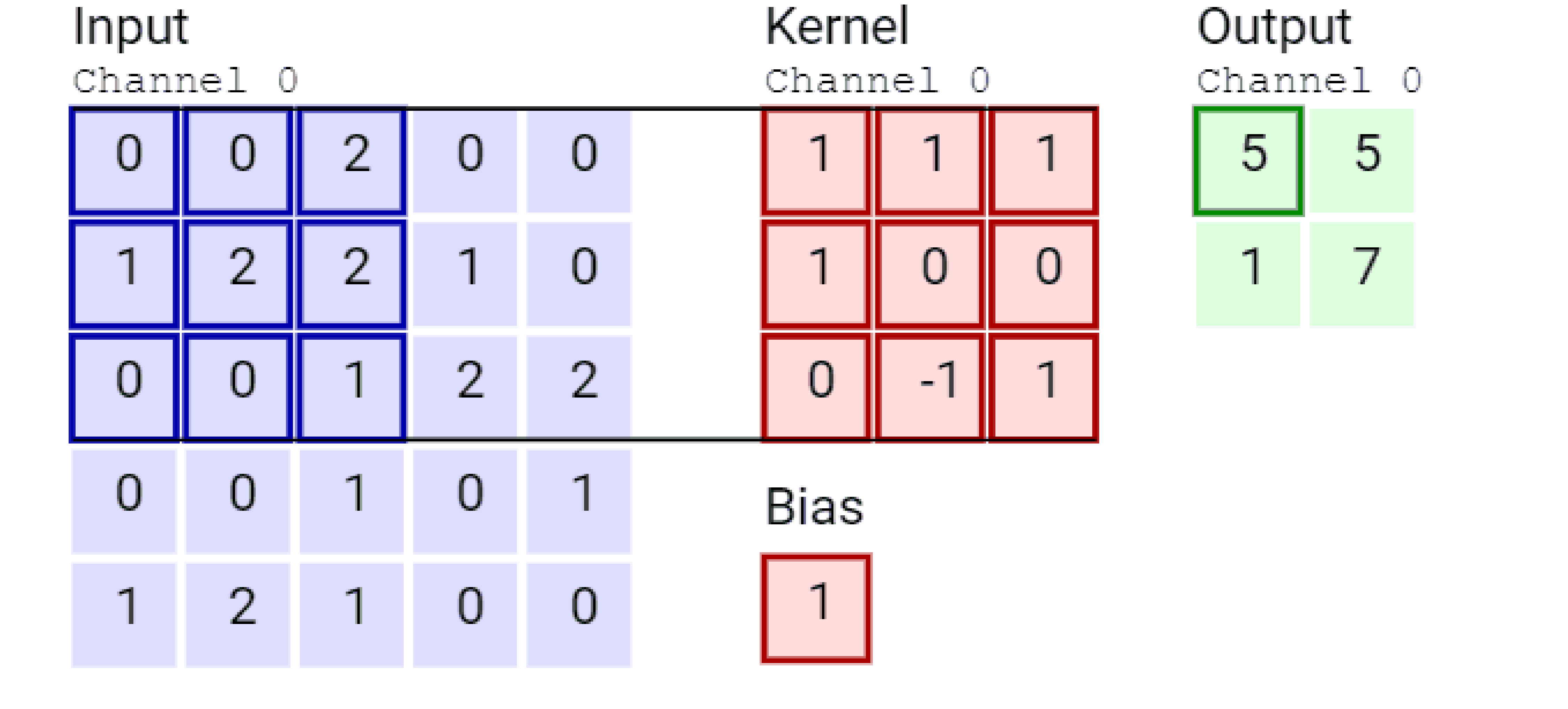
So what is Convolution?

Then let’s try a **2-dimensional** case.

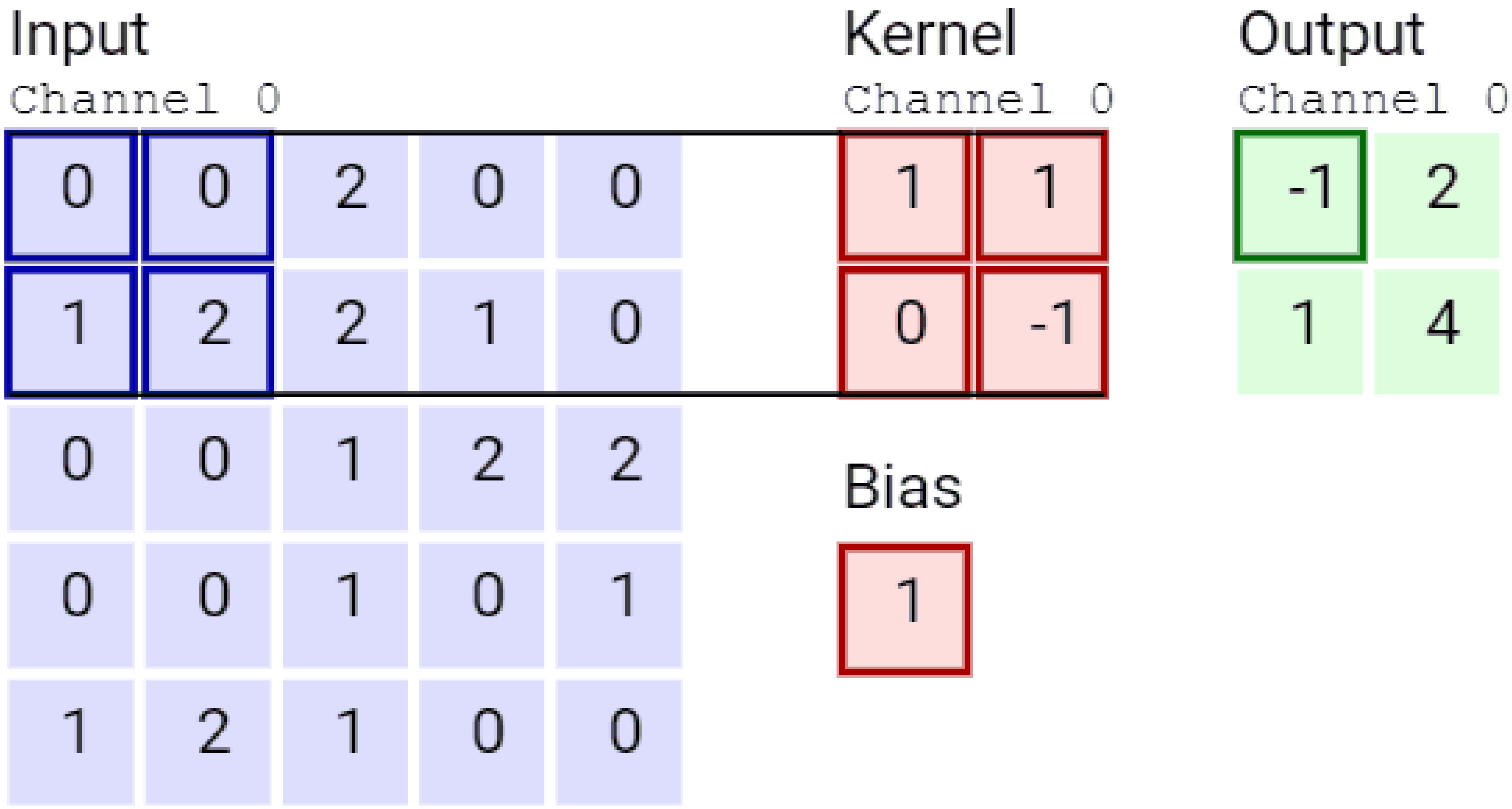




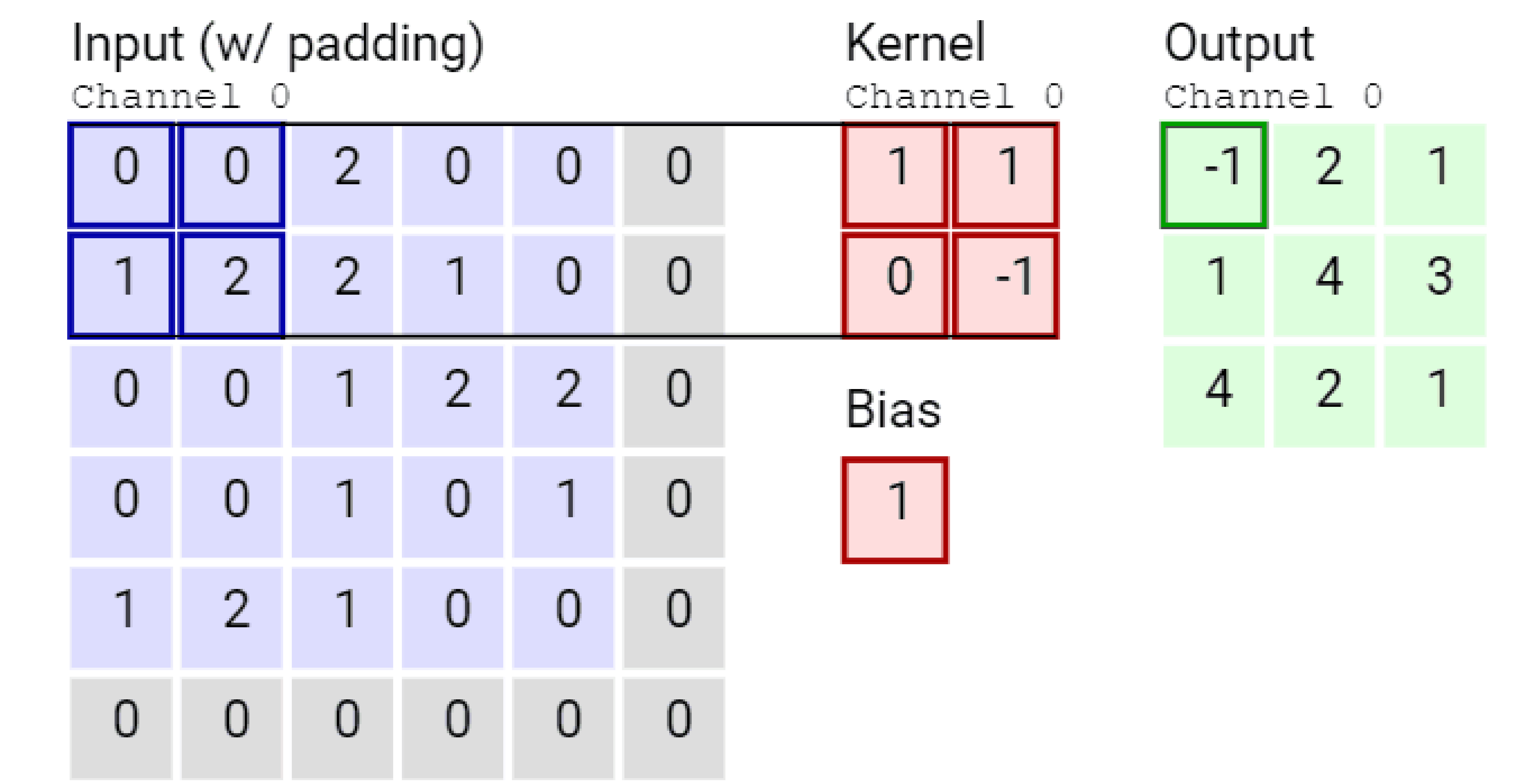
So what is Convolution?

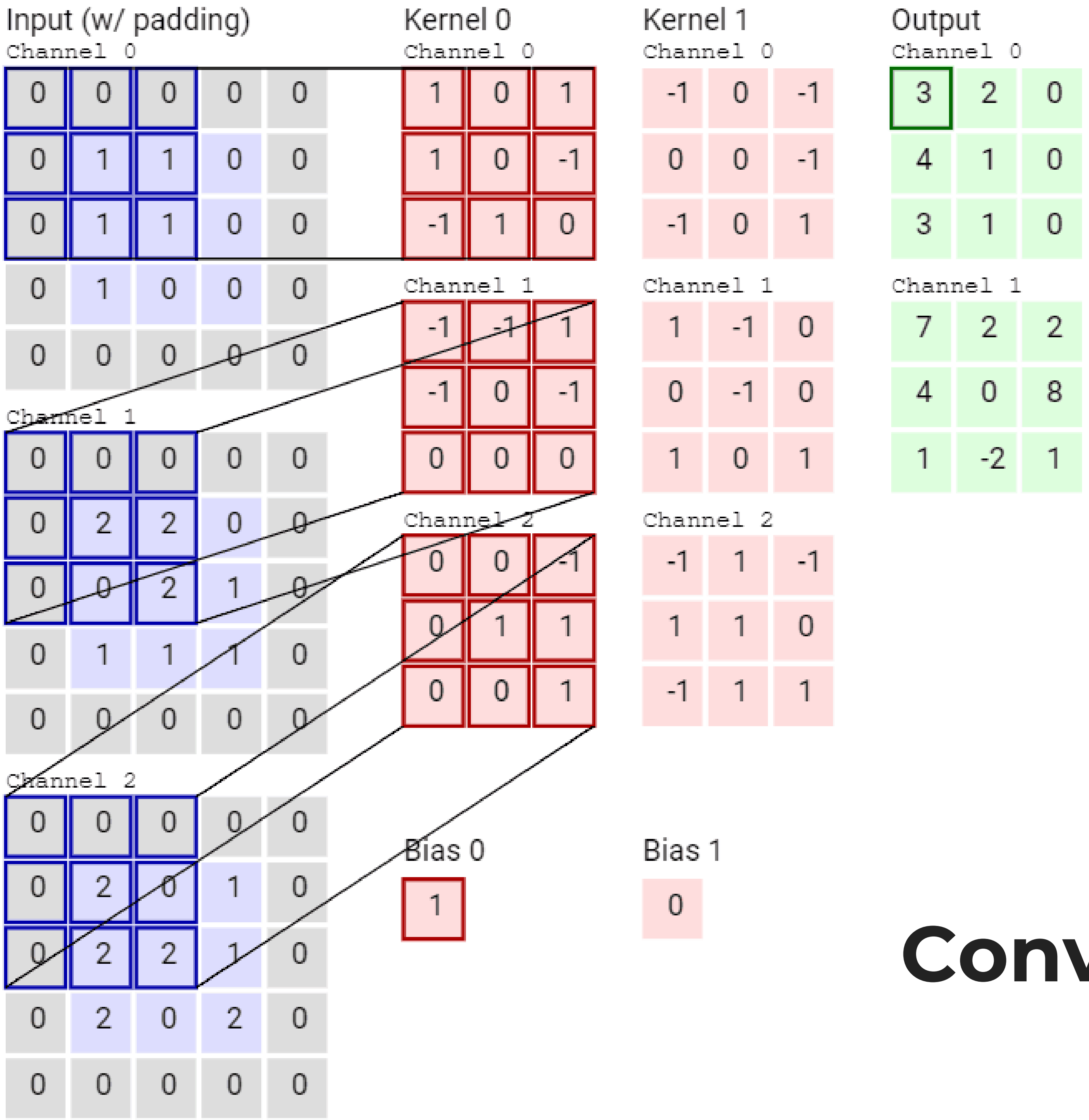


Convolution Edge Pixels Problem



Convolution with Padding

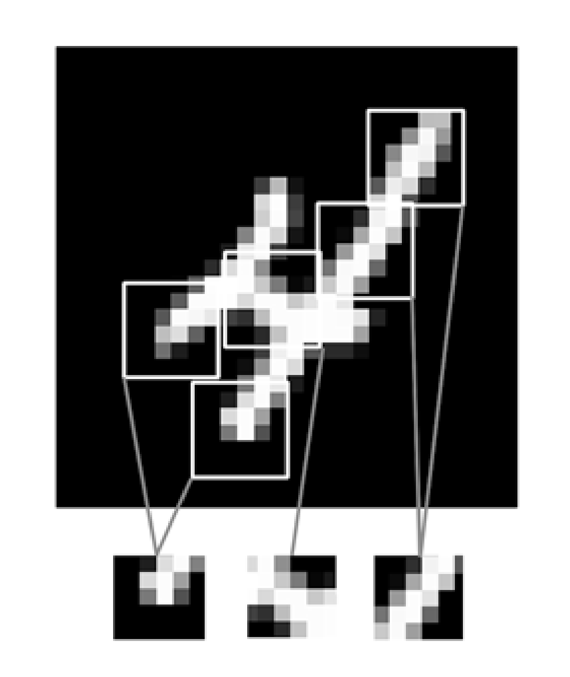




Convolution layer

The Convolution Operation - Why?

Densely connected layers learn **global** patterns in their input feature space (for example, for a MNIST digit, patterns involving all pixels), whereas **convolution layers** learn **local** patterns.



Key Convolution Properties:

1. The patterns they learn are Translation Invariant

For example, in the upper-left corner. A **densely** connected network would have to learn the pattern **anew** if it appeared at a new location.

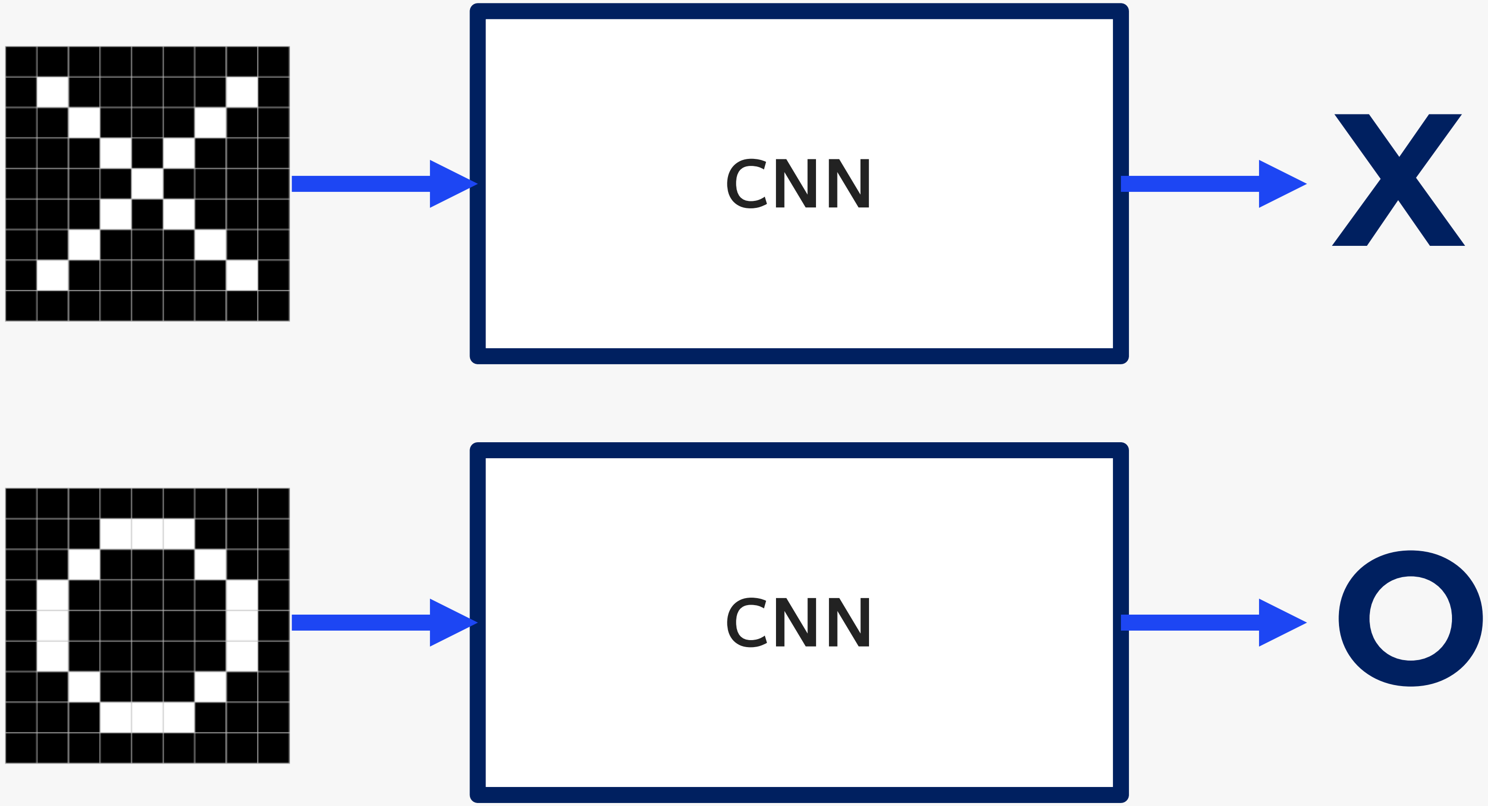
After learning a certain pattern in the lower-right corner of a picture, a **convnet** can recognize it **anywhere**: this makes convnets data efficient, they need fewer training samples to learn representations that have generalization power.

Feature Extraction & Convolution
A Case Study

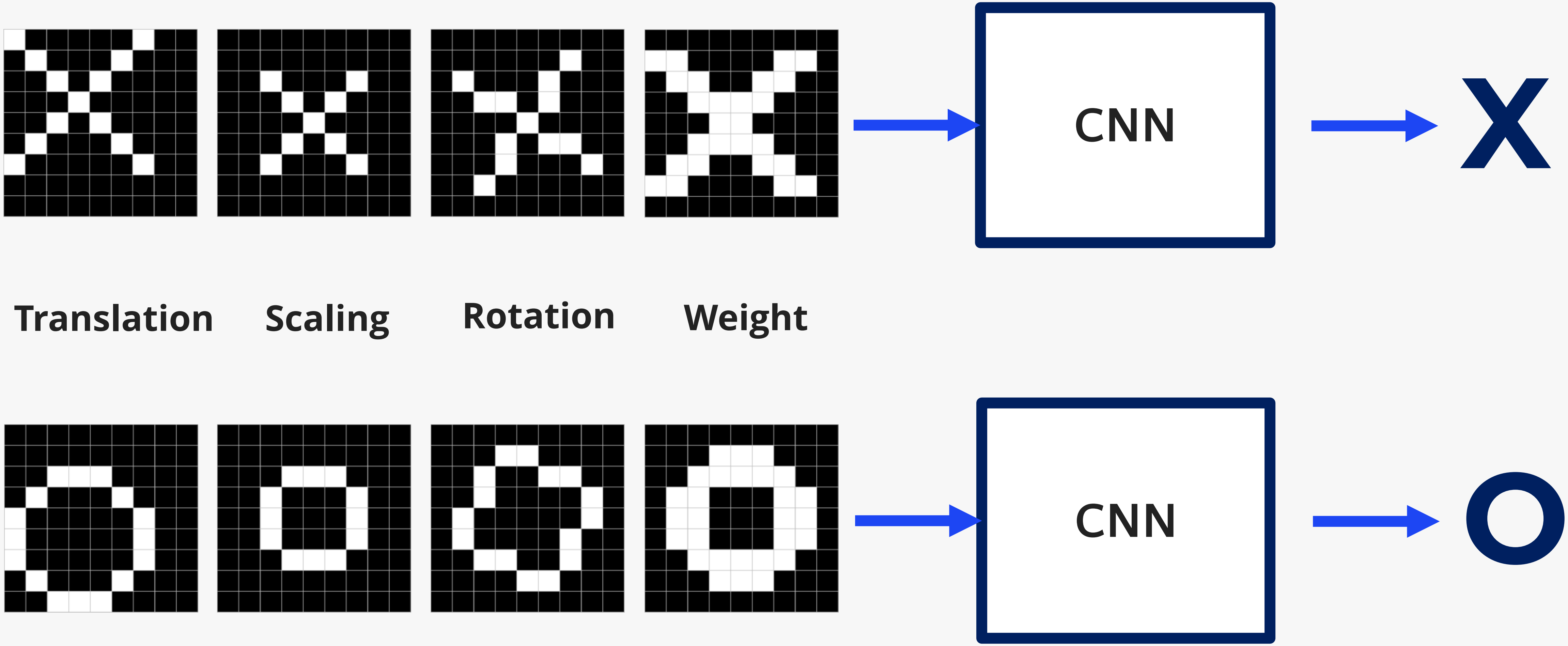
A toy ConvNet: X's and O's

Says whether a picture is of an X or an O

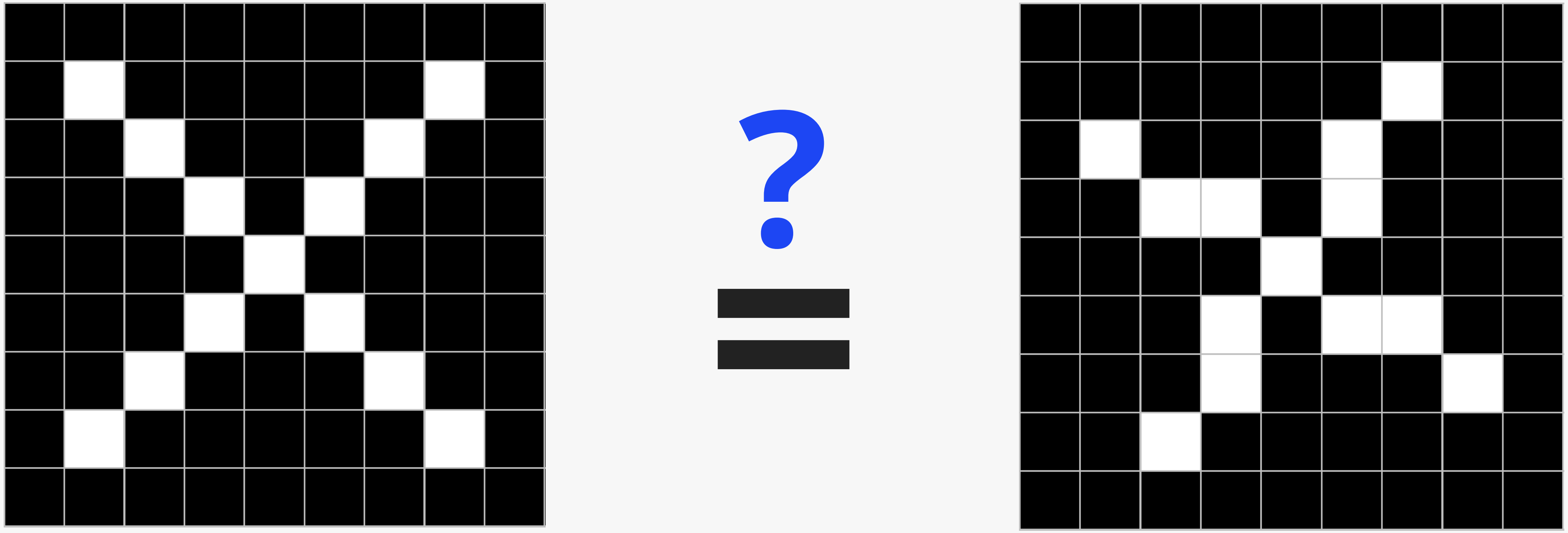
A toy ConvNet: X's and O's



X’s and O’s: Trickier Cases



X or X?



What Computers See

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

? =

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

What Computers See

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

? =

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

What Computers See

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	X	-1	-1	-1	-1	X	X	-1
-1	X	X	-1	-1	X	X	-1	-1
-1	-1	X	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	X	-1	-1
-1	-1	X	X	-1	-1	X	X	-1
-1	X	X	-1	-1	-1	-1	X	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

What Computers **See**

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

X

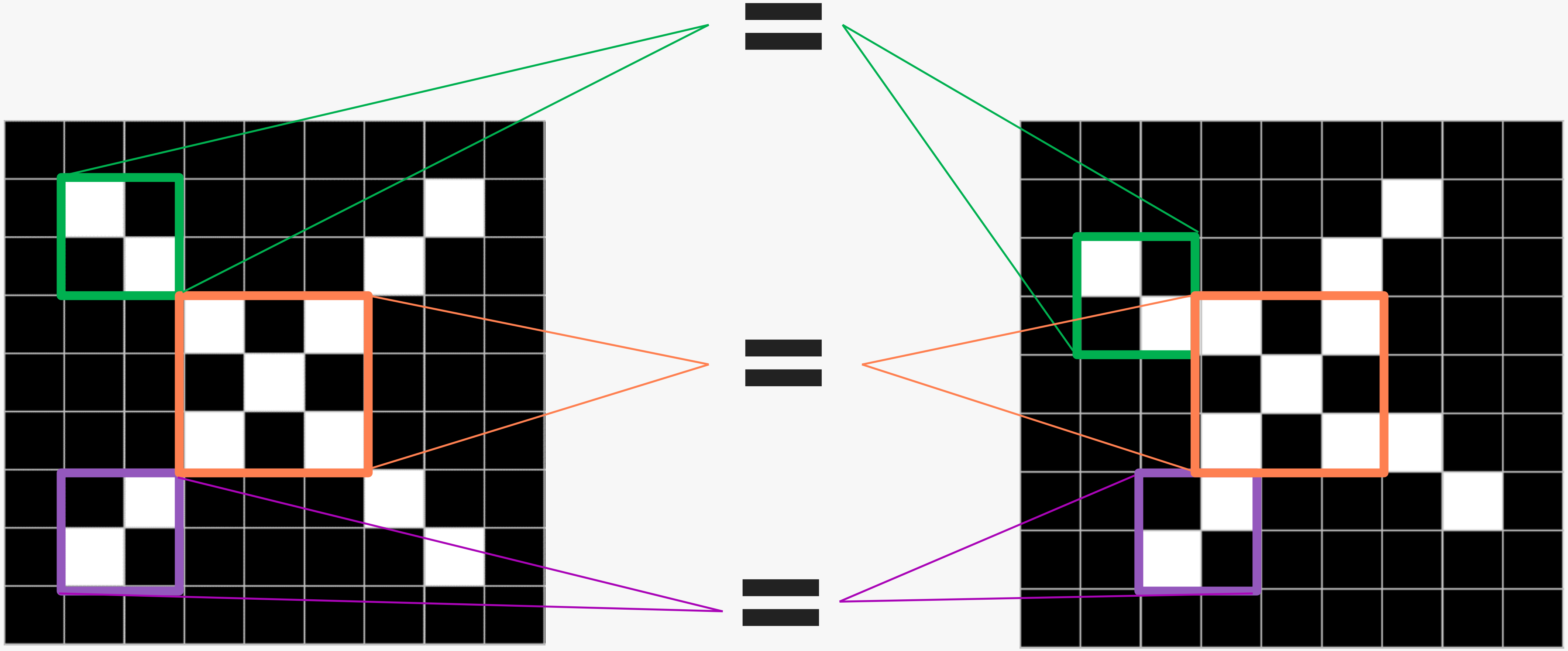
=

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Image is represented as matrix of pixel values... and computers are **literal**!

We want to be able to classify an X as an X even if it's shifted, shrunk, rotated, deformed.

Features of X

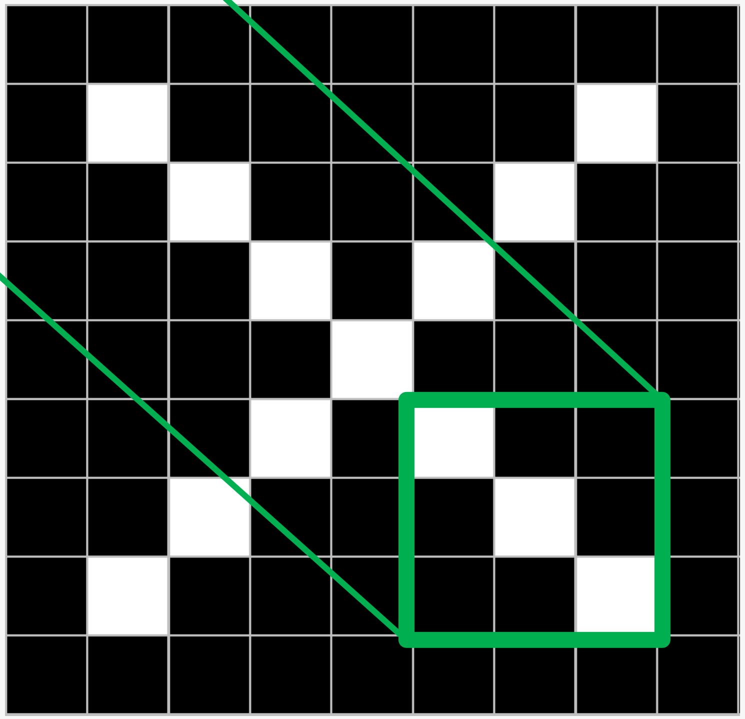


Filters to Detect X Features

1	-1	-1
-1	1	-1
-1	-1	1

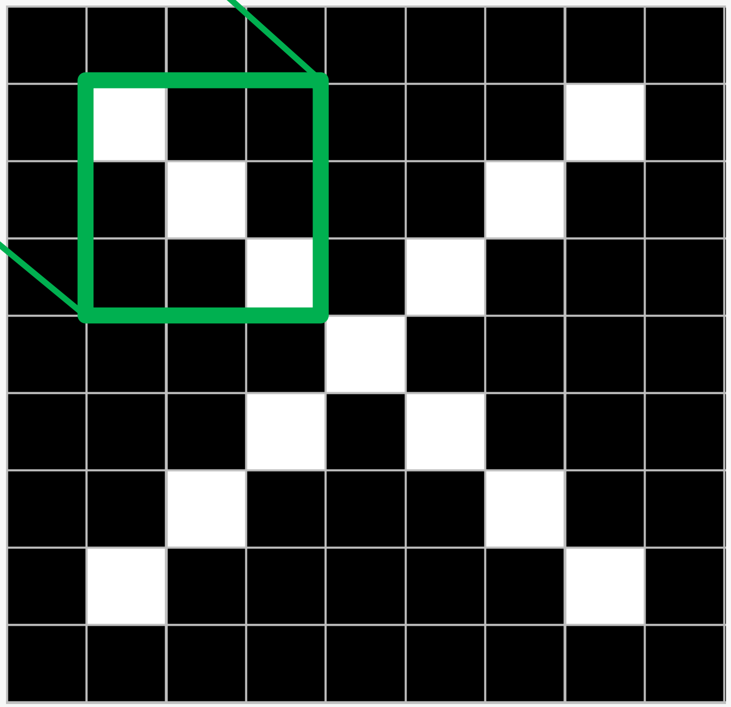
1	-1	1
-1	1	-1
1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1



Filters to Detect X Features

$$\begin{bmatrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \end{bmatrix} \qquad \begin{bmatrix} 1 & -1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & -1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & -1 \end{bmatrix}$$

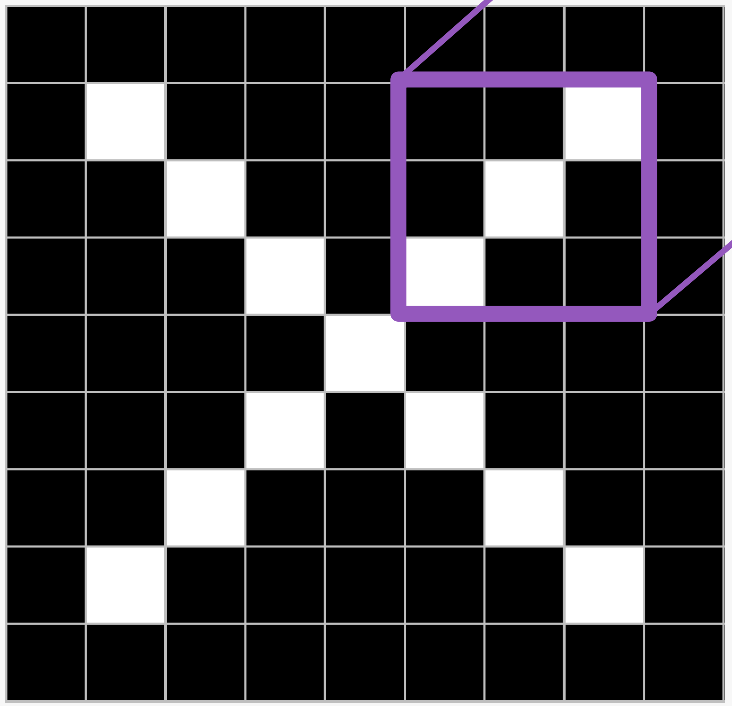


Filters to Detect X Features

1	-1	-1
-1	1	-1
-1	-1	1

1	-1	1
-1	1	-1
1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

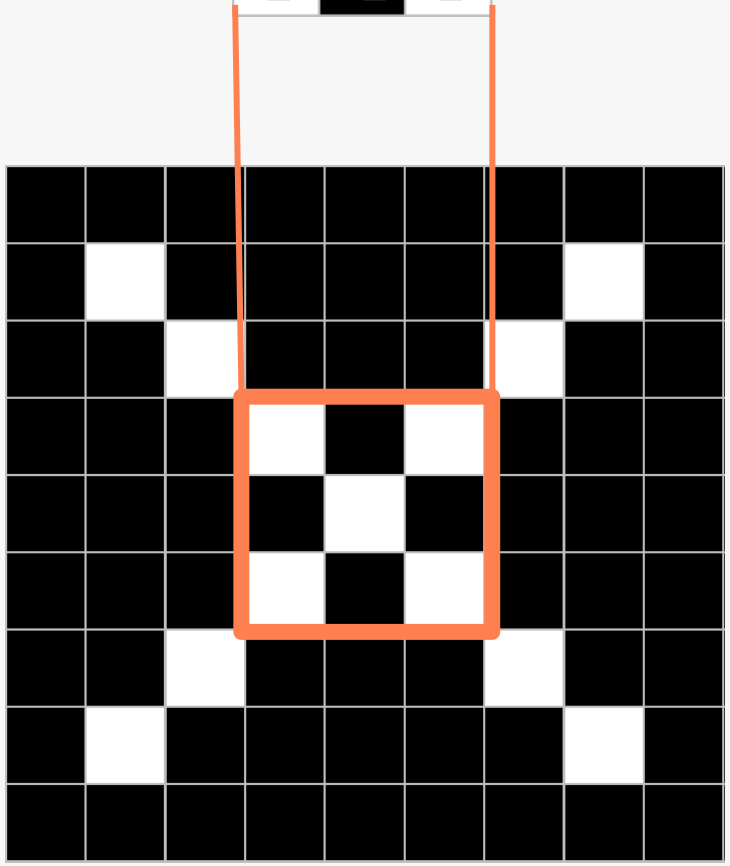


Filters to Detect X Features

1	-1	-1
-1	1	-1
-1	-1	1

1	-1	1
-1	1	-1
1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

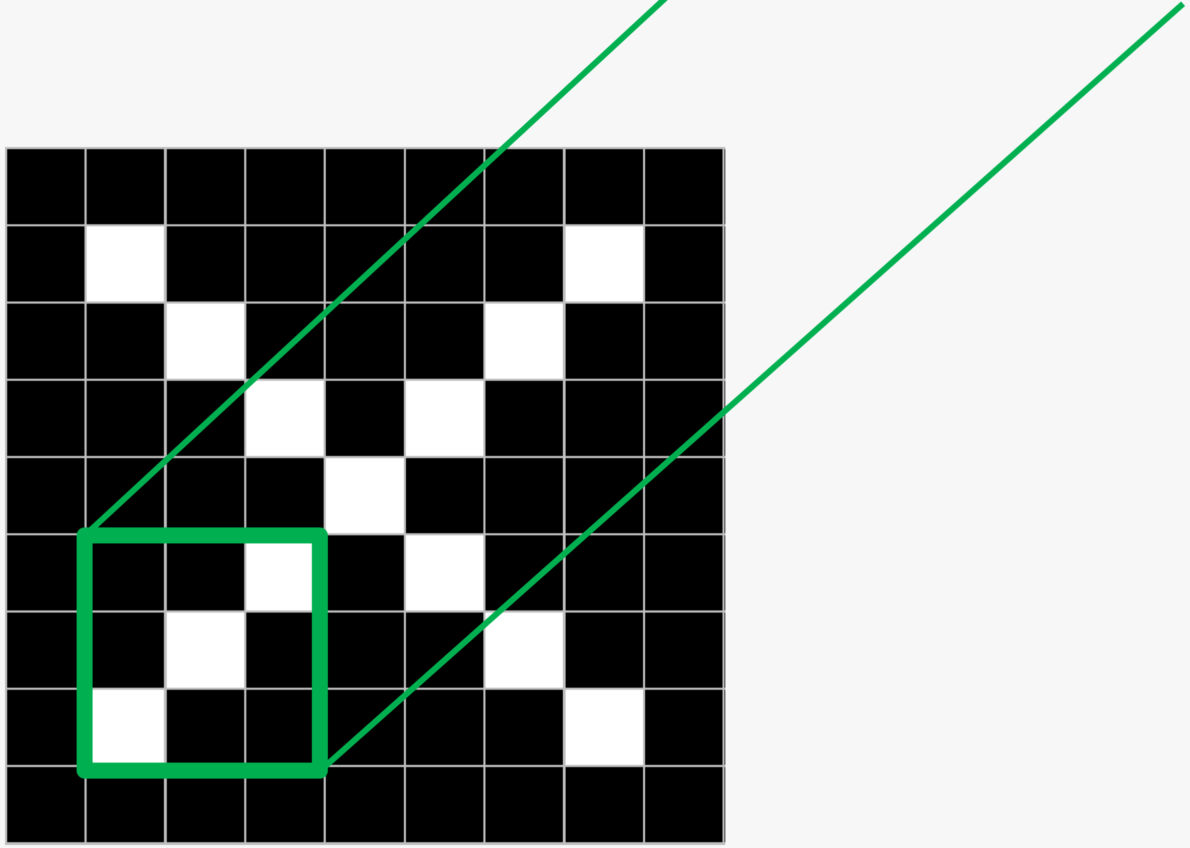


Filters to Detect X Features

1	-1	-1
-1	1	-1
-1	-1	1

1	-1	1
-1	1	-1
1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1



Filtering: The math behind the match

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
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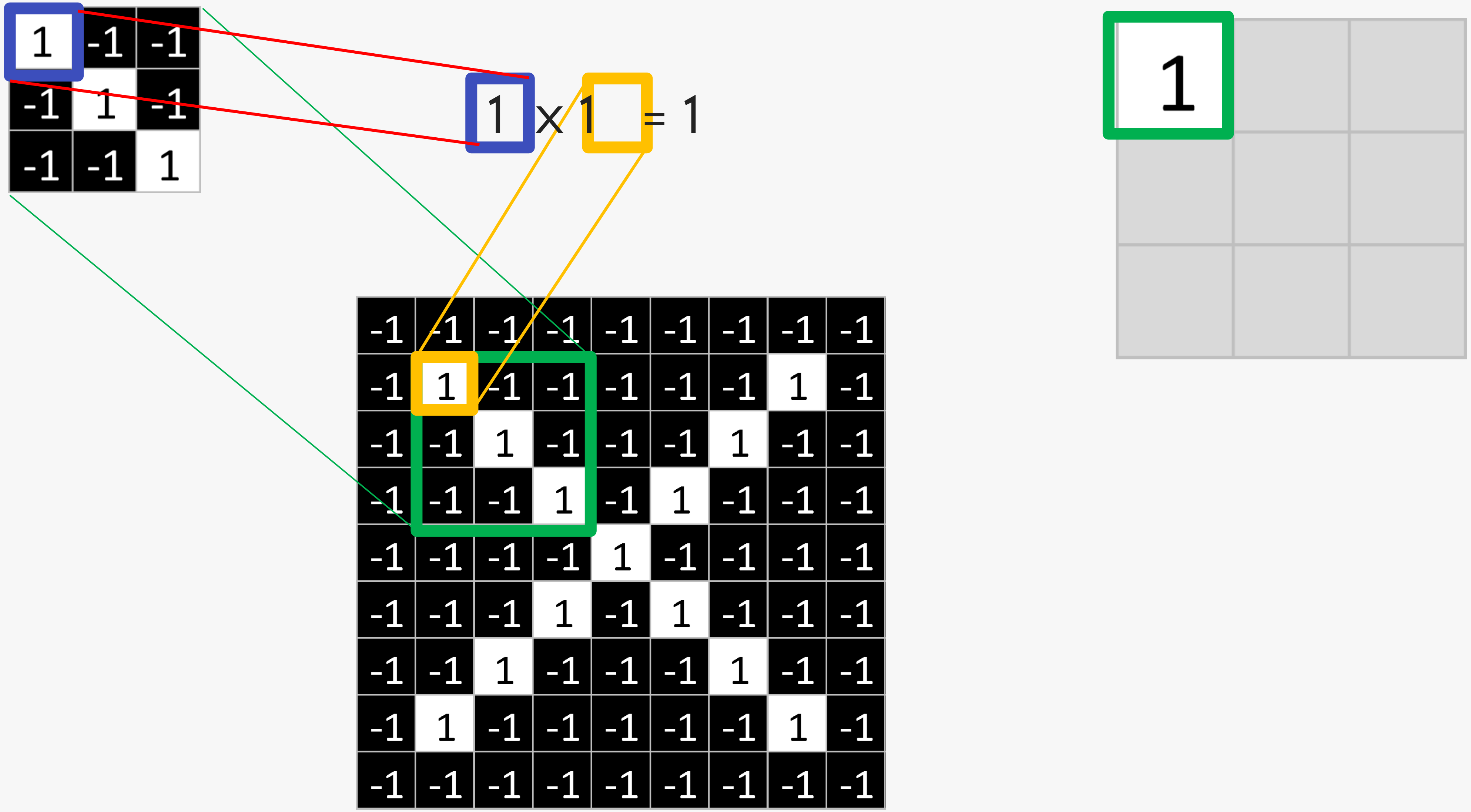
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Filtering: The math behind the match



Filtering: The math behind the match

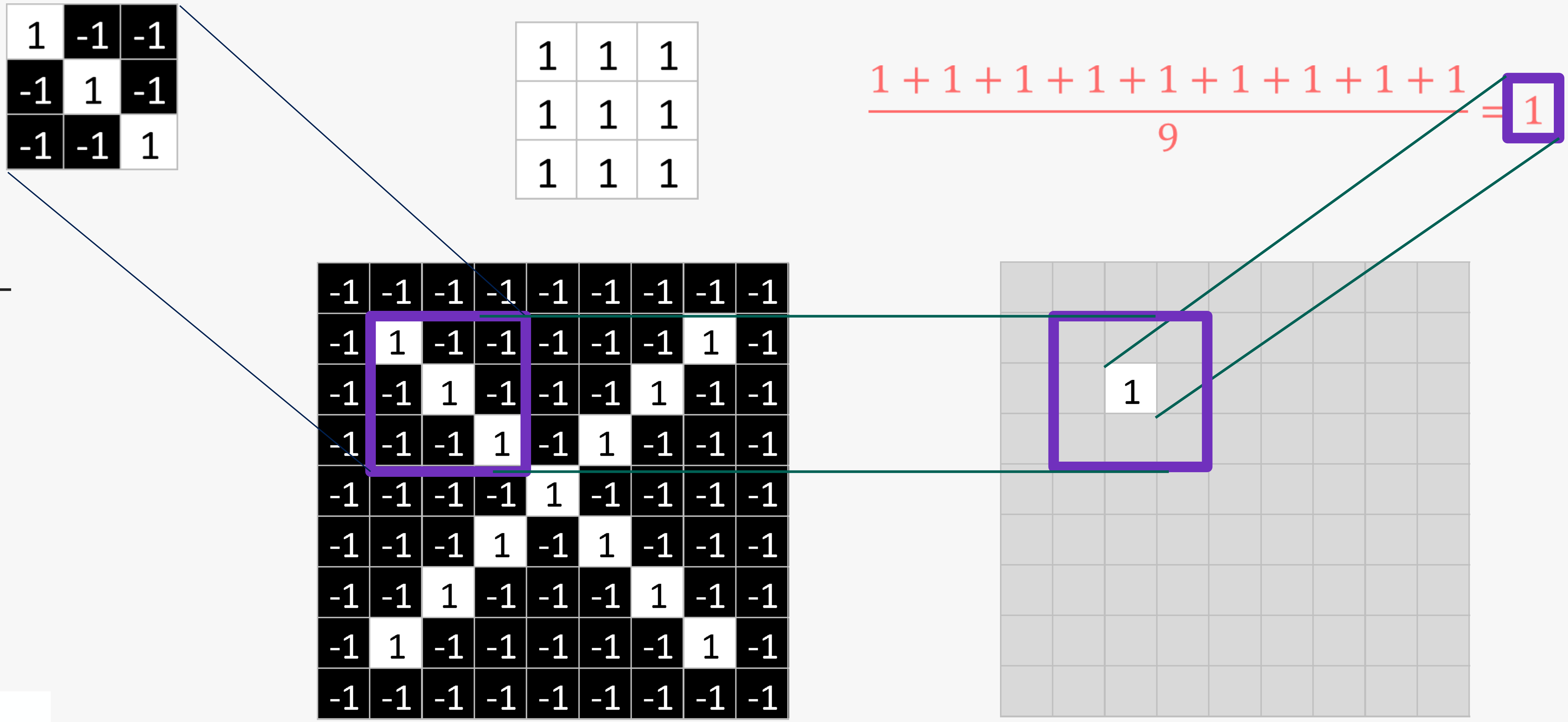
1	-1	-1
-1	1	-1
-1	-1	1

$1 \times 1 = 1$

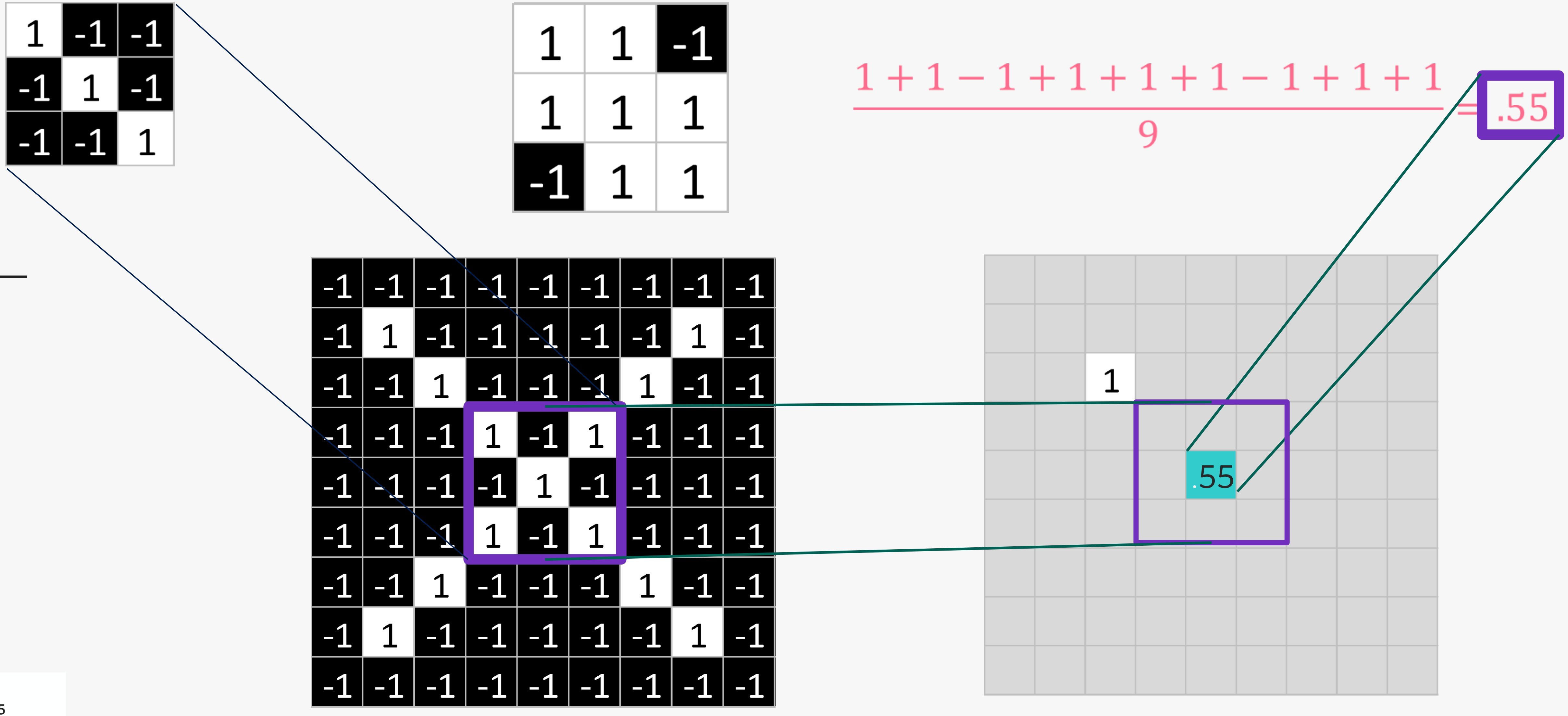
1	1	1
1	1	1
1	1	1

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Filtering: The math behind the match



Filtering: The math behind the match



Trying Every Possible **Match**

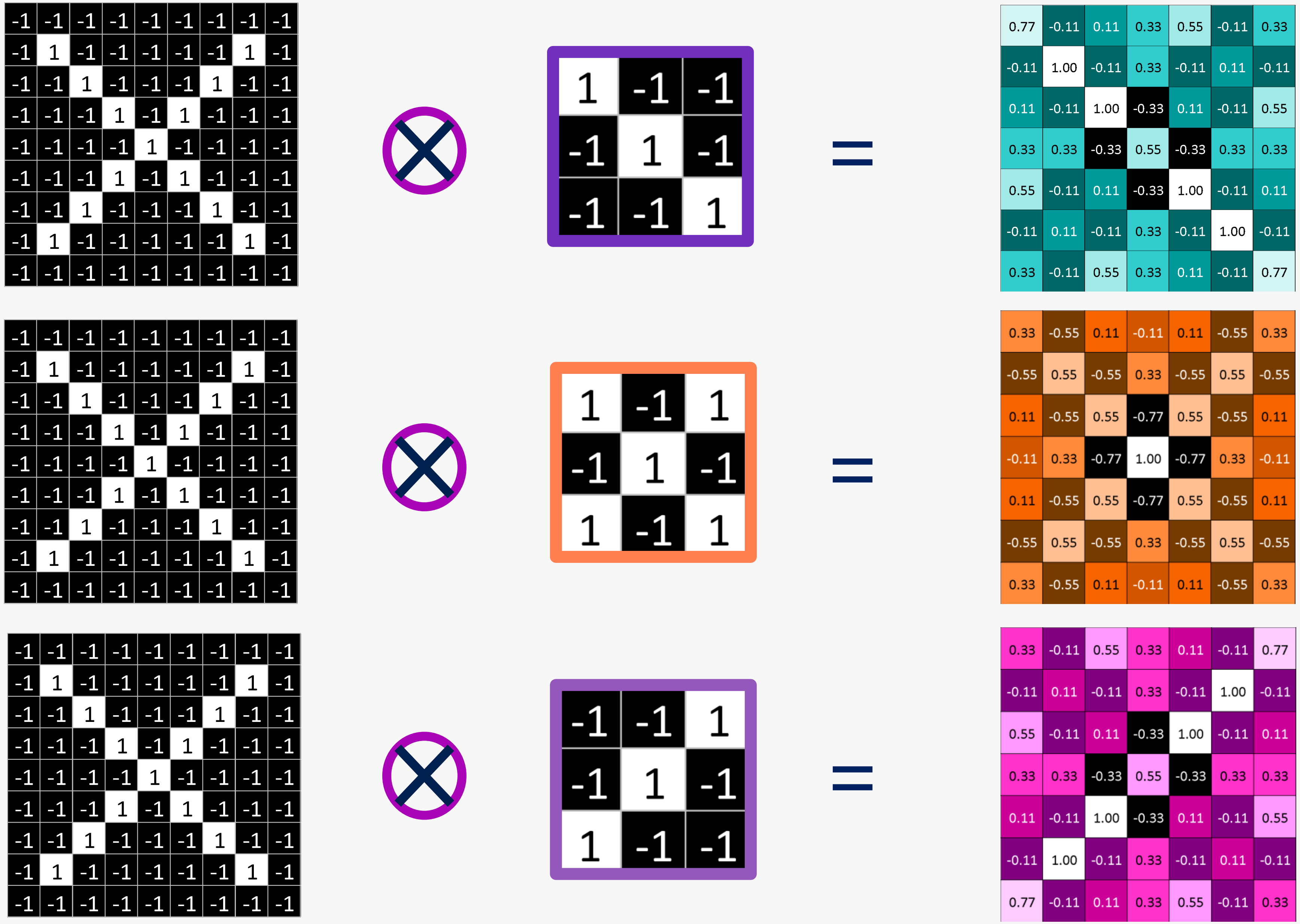
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

$\otimes$

1	-1	-1
-1	1	-1
-1	-1	1

$=$

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77


-1 -1 -1 -1 -1 -1 -1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 -1 -1 1 -1 -1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 -1 -1 -1 -1 -1 -1 -1
1 -1 -1
-1 1 -1
-1 -1 1
=
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
-1 -1 -1 -1 -1 -1 -1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 -1 -1 1 -1 -1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 -1 -1 -1 -1 -1 -1 -1
1 -1 1
-1 1 -1
1 -1 1
=
0.33 -0.55 0.11 -0.11 0.11 -0.55 0.33
-0.55 0.55 -0.55 0.33 -0.55 0.55 -0.55
0.11 -0.55 0.55 -0.77 0.55 -0.55 0.11
-0.11 0.33 -0.77 1.00 -0.77 0.33 -0.11
0.11 -0.55 0.55 -0.77 0.55 -0.55 0.11
-0.55 0.55 -0.55 0.33 -0.55 0.55 -0.55
0.33 -0.55 0.11 -0.11 0.11 -0.55 0.33
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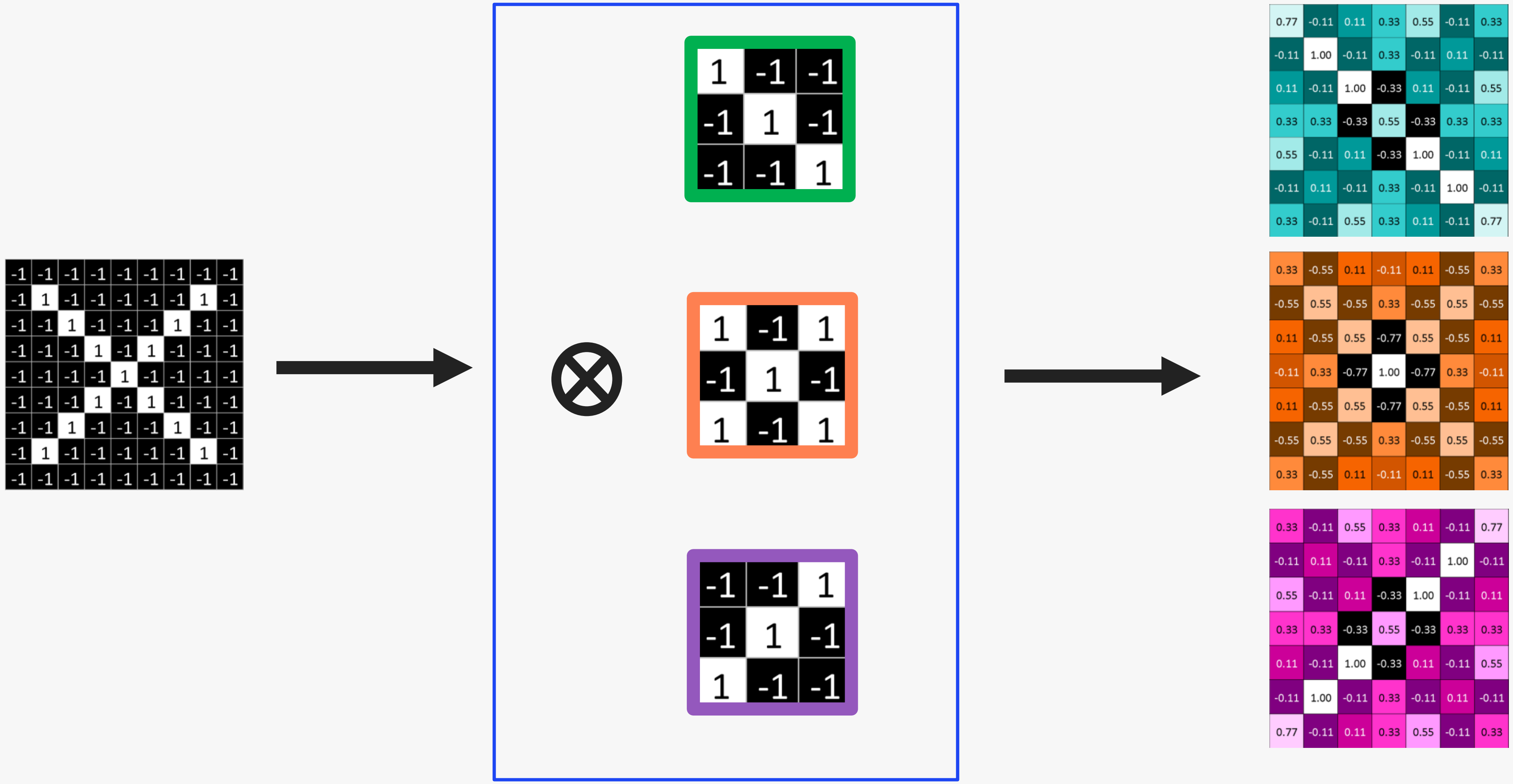
-1 -1 1 -1 -1 -1 1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 -1 -1 1 -1 -1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 -1 -1 -1 -1 -1 -1 -1
-1 -1 1
-1 1 -1
1 -1 -1
=
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33

Convolution layer

One image becomes a stack of filtered images



Producing Feature Maps

The Convolution Operation - Why?

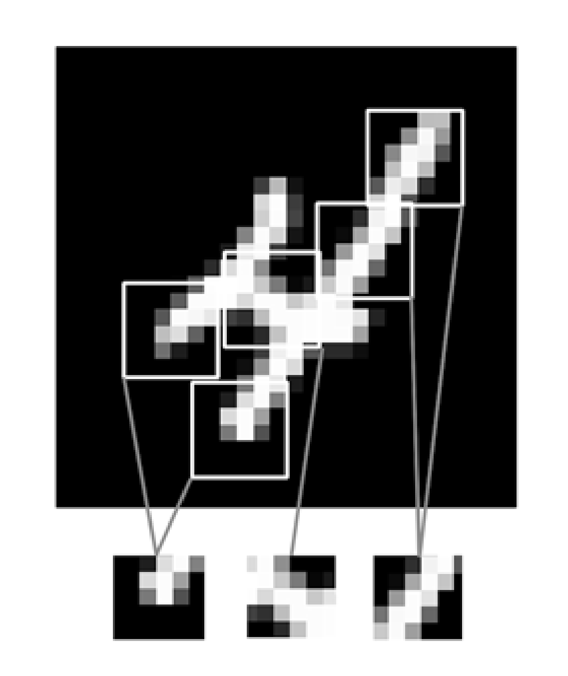
Densely connected layers learn **global** patterns in their input feature space (for example, for a MNIST digit, patterns involving all pixels), whereas **convolution layers** learn **local** patterns.

Key Convolution Properties:

1. The patterns they learn are Translation Invariant

For example, in the upper-left corner. A **densely** connected network would have to learn the pattern **anew** if it appeared at a new location.

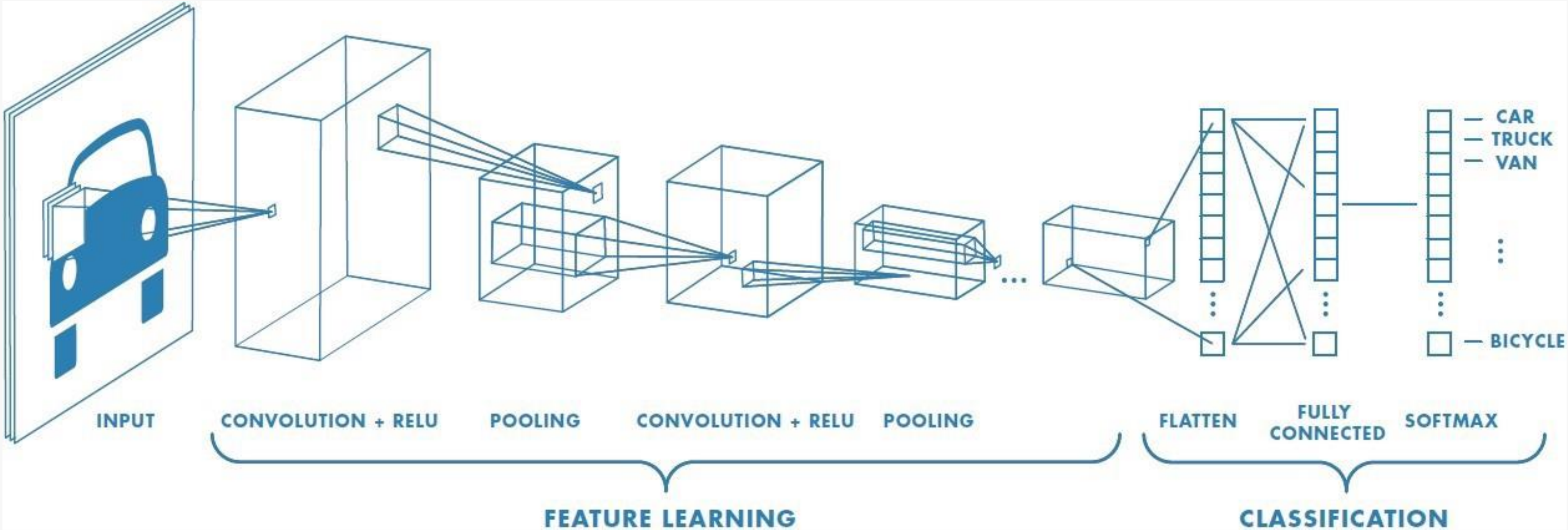
After learning a certain pattern in the lower-right corner of a picture, a **convnet** can recognize it **anywhere**: this makes convnets data efficient, they need fewer training samples to learn representations that have generalization power.



Convolutional Neural Networks

CNNs

CNNs for Classification



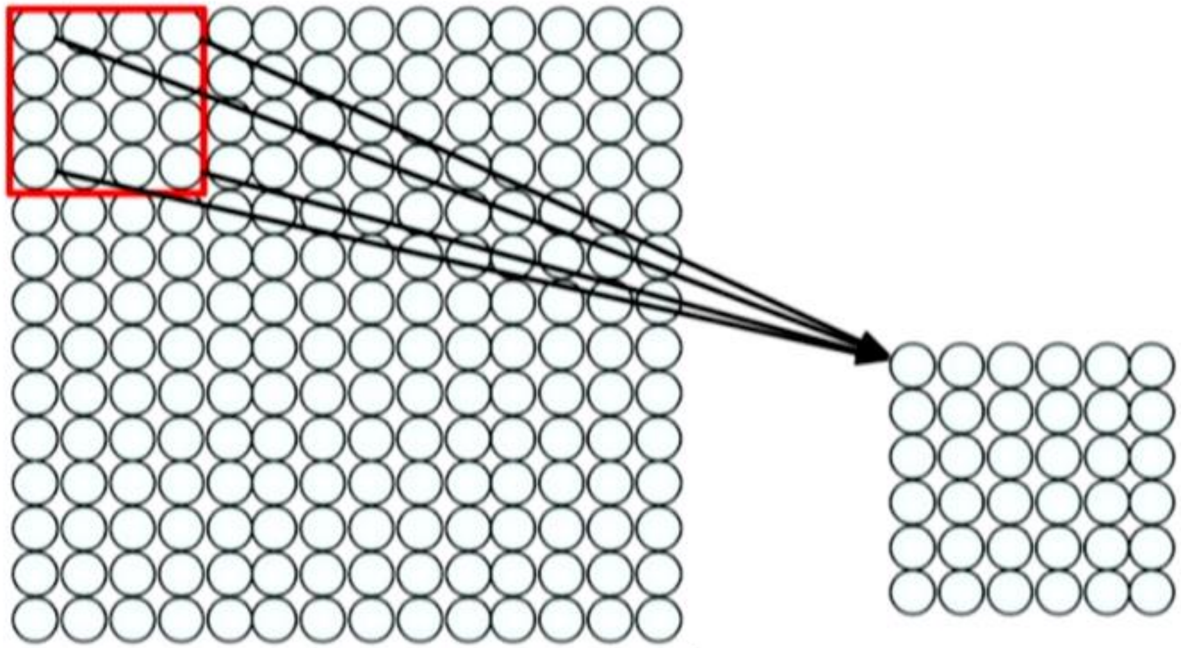
1. **Convolution**: Apply filters to generate feature maps.
2. **Non-linearity**: Often ReLU.
3. **Pooling**: Down-sampling operation on each feature map.

Train the model with image data.

Learn weights of filters in convolution layers.

Convolutional layer: Local Connectivity

`tf.keras.layers.Conv2D`



4x4 filter: matrix of weights w_{ij}

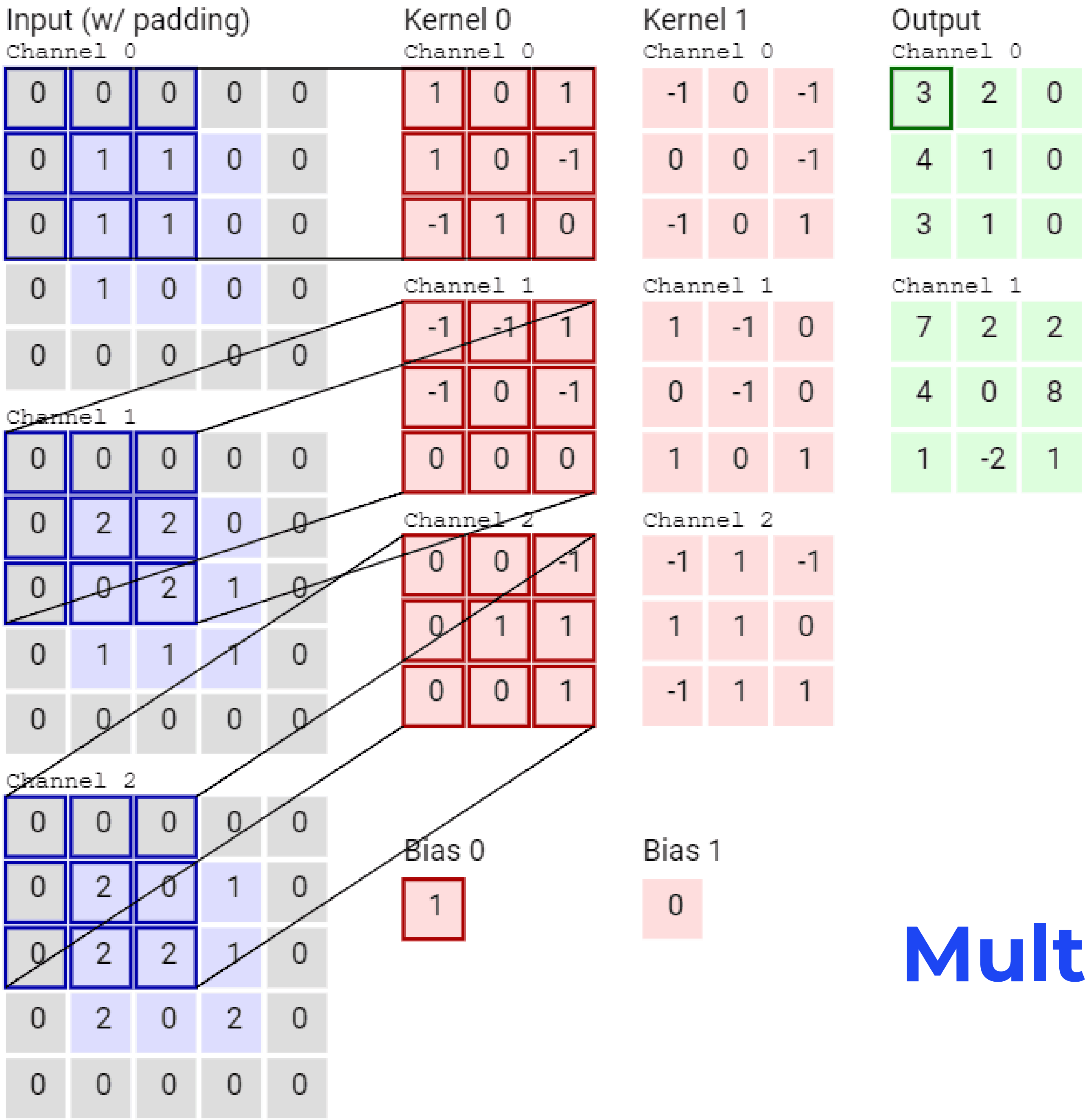
$$\sum_{i=1}^{4}\sum_{j=1}^{4} w_{ij}\, x_{i+p,j+q} + b$$

for neuron (p,q) in hidden layer

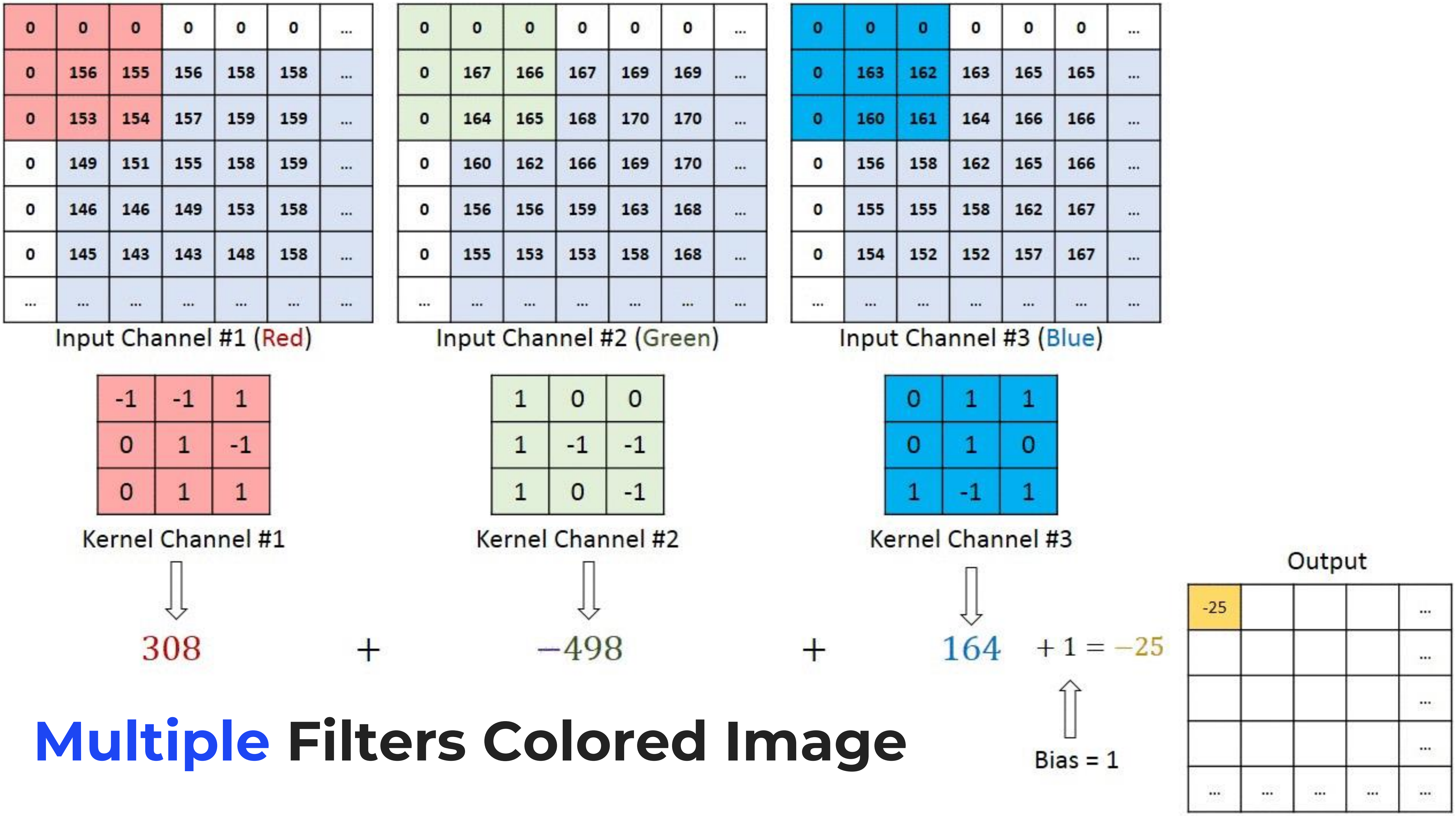
For a neuron in hidden layer:

- Take inputs from patch
- Compute weighted sum
- Apply bias

1) applying a window of weights
2) computing linear combinations
3) activating with non-linear function

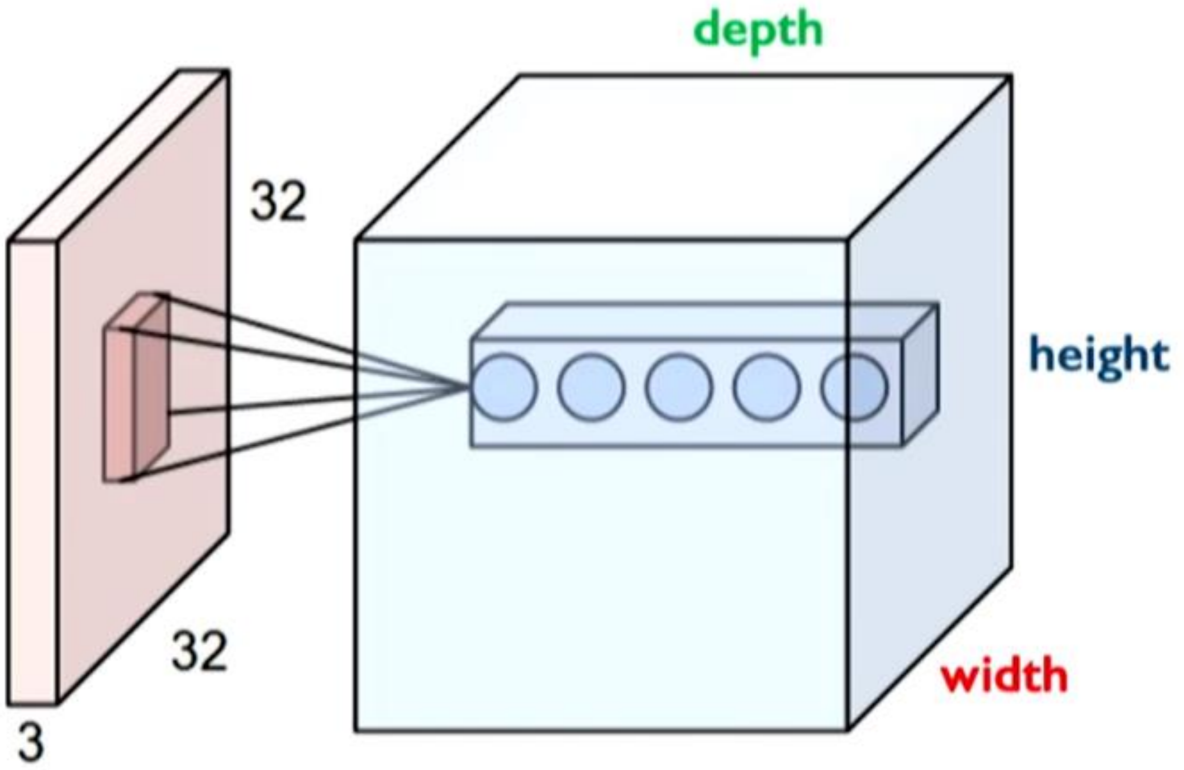


Multiple Filters



Multiple Filters Colored Image

CNNs: Spatial Arrangement of Output Volume



Layer Dimensions:

$h \ x \ w \ x \ d$

where h and w are spatial dimensions
d (depth) = number of filters

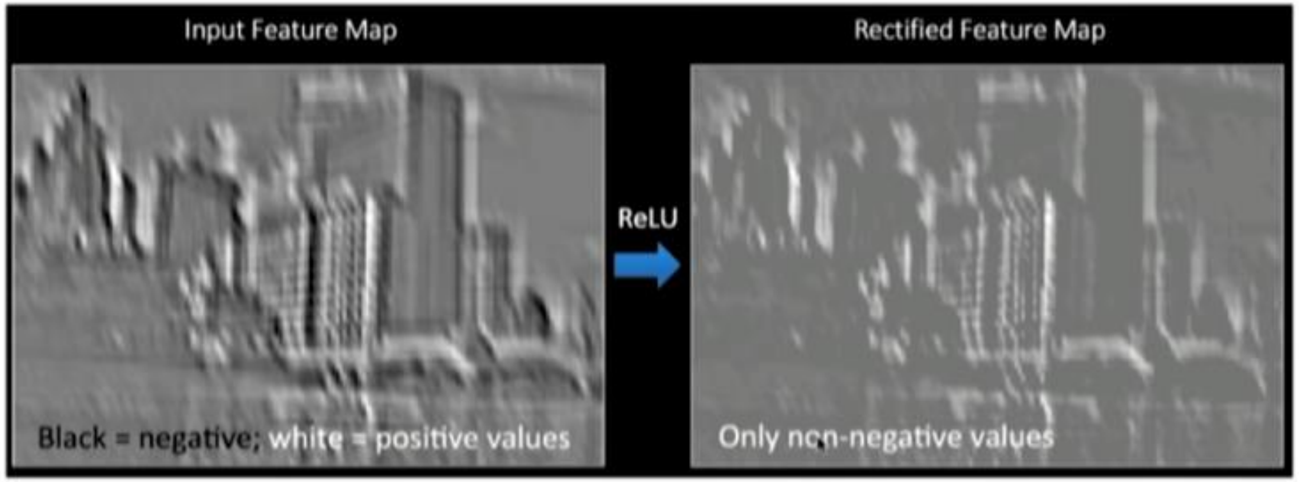
Stride:
Filter step size

Receptive Field:
Locations in input image that
a node is path connected to

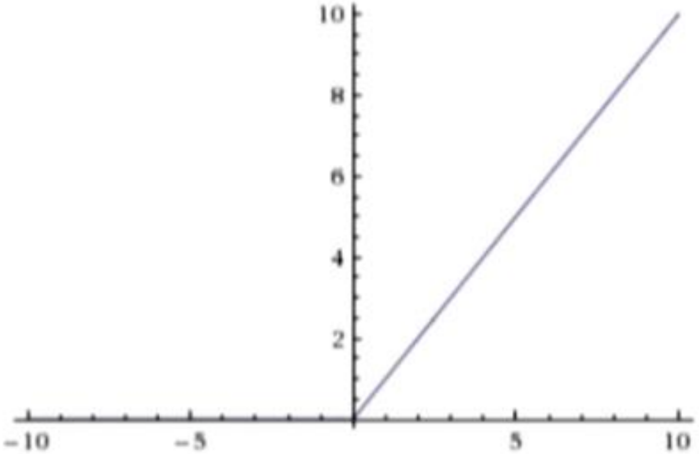
```
tf.keras.layers.Conv2D( filters=d, kernel_size=(h,w), strides=s )
```

CNNs: Introducing Non-Linearity

- Apply after every convolution operation (i.e., after convolutional layers)
- ReLU: pixel-by-pixel operation that replaces all negative values by zero. **Non-linear operation!**



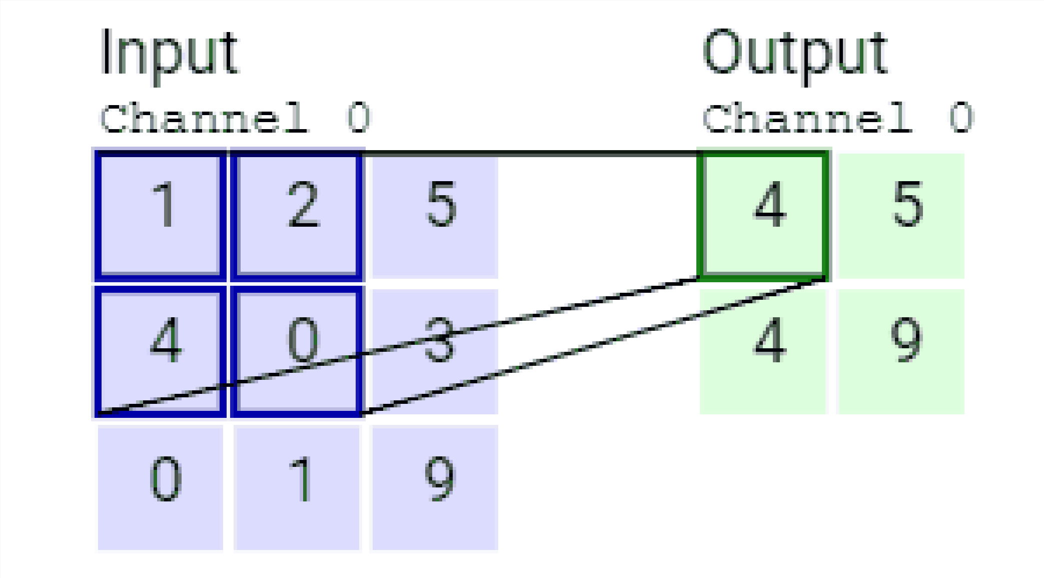
Rectified Linear Unit (ReLU)



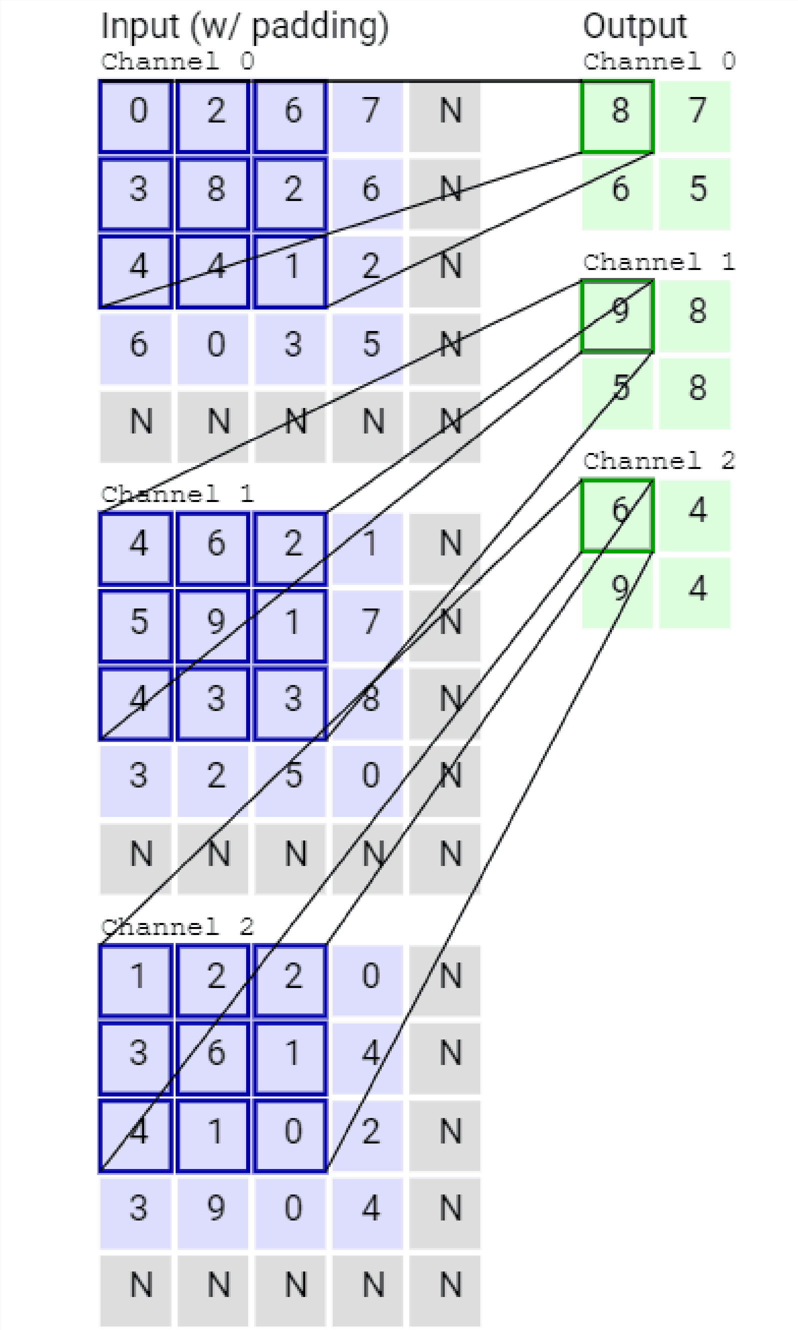
$$g(z) = \max(0, z)$$

`tf.keras.layers.ReLU`

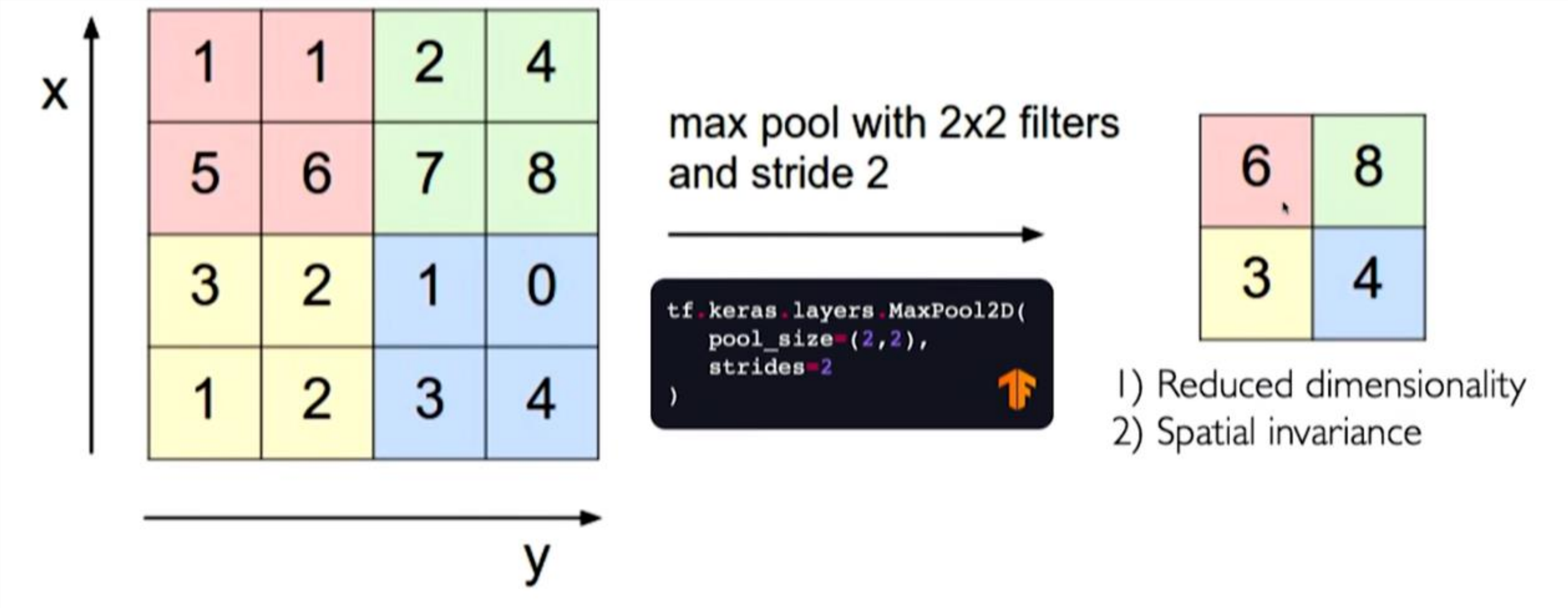
CNNs: Pooling



Max Pooling



CNNs: Pooling



How else can we down-sample and preserve spatial invariance?

Back to The Case Study

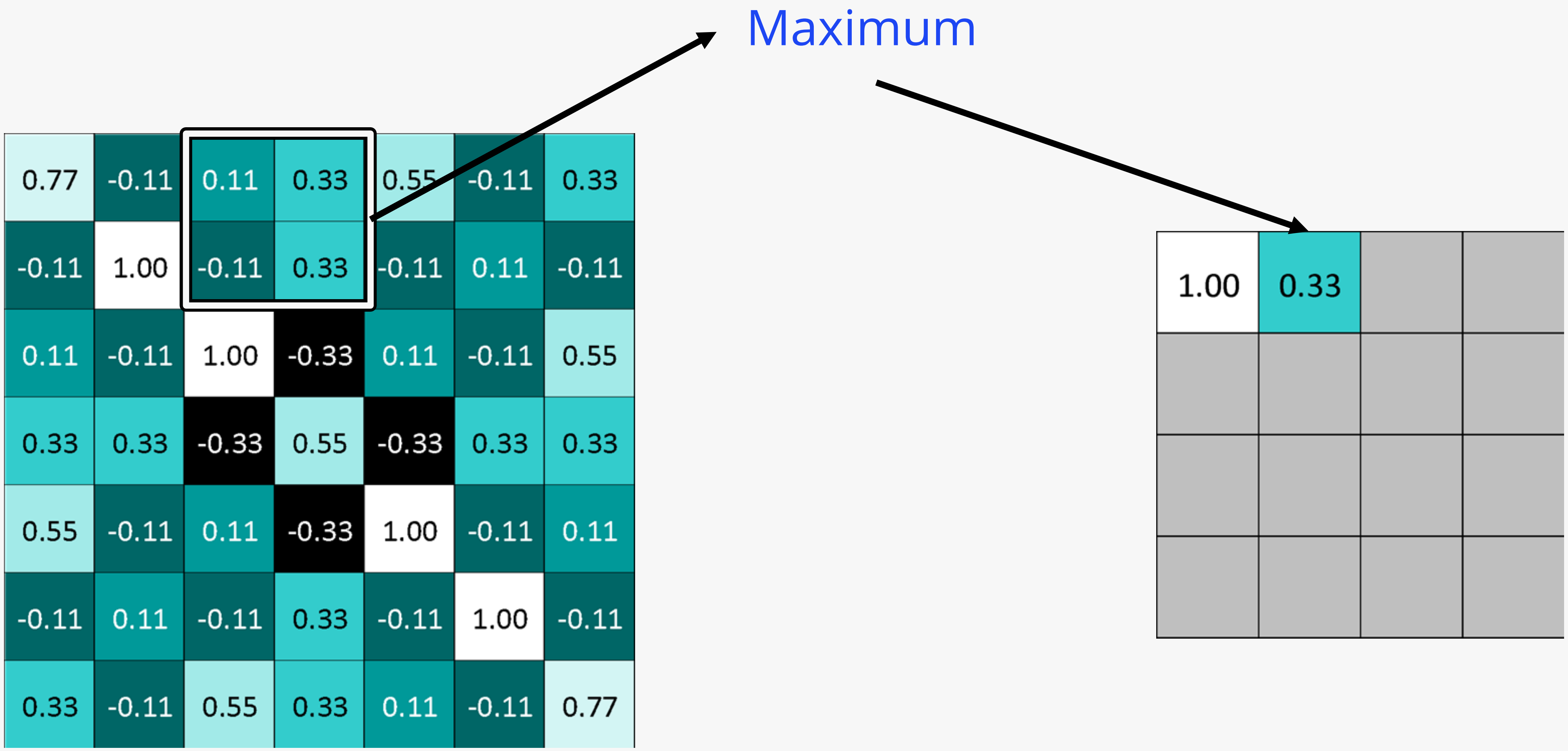
Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Maximum

1.00			

Pooling


Maximum
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1.00 0.33

Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Maximum

1.00	0.33	0.55	0.33

Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Max Pooling

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

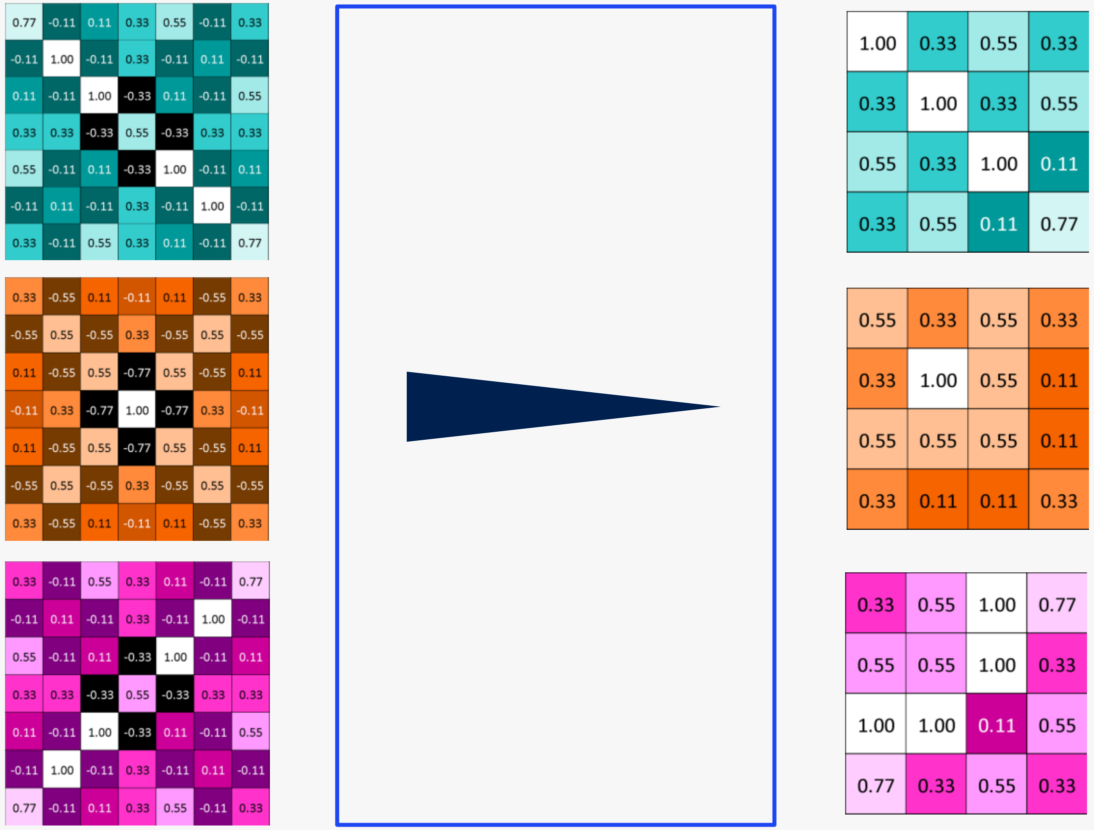
0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

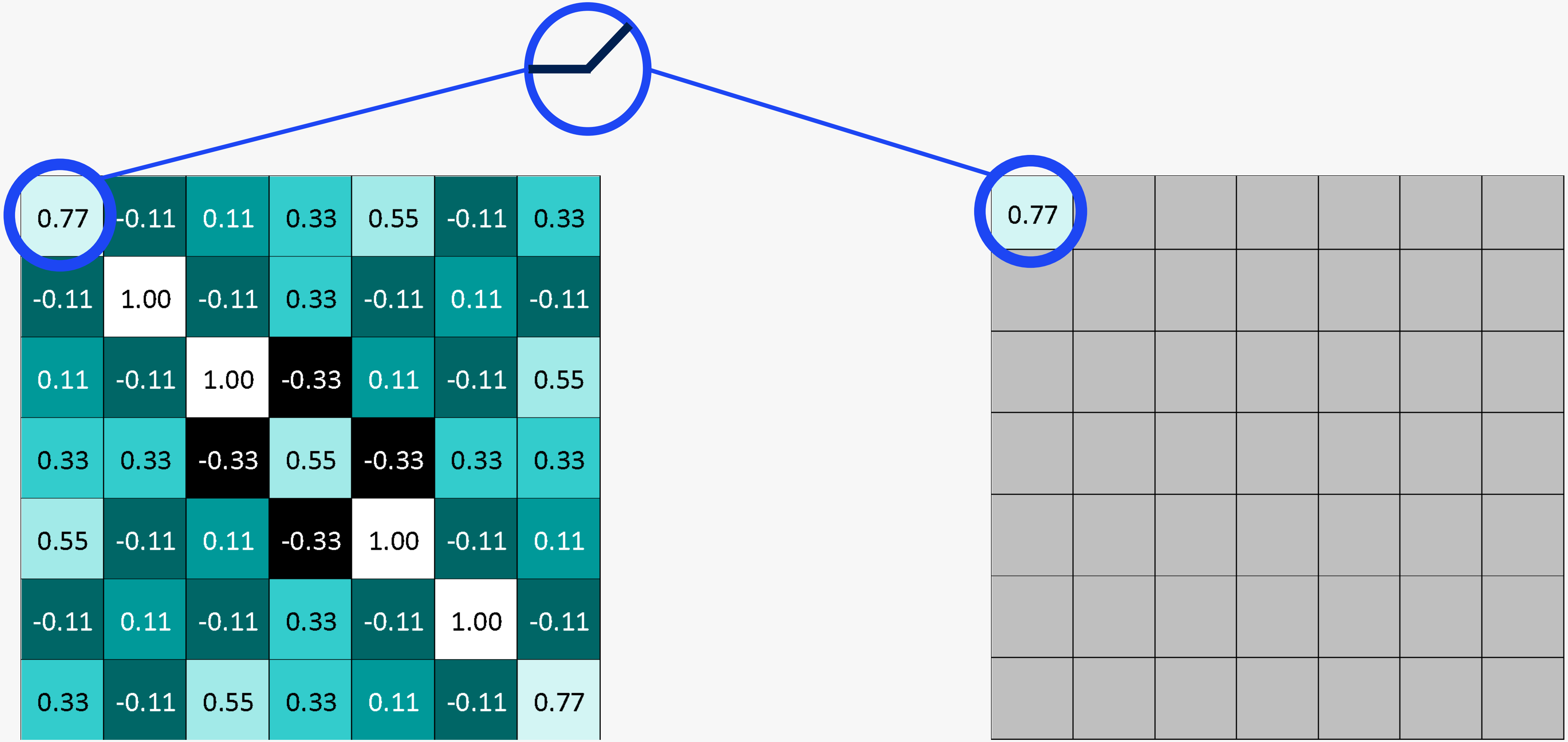
0.33	0.55	1.00	0.77
0.55	0.55	1.00	0.33
1.00	1.00	0.11	0.55
0.77	0.33	0.55	0.33

Pooling **Layer**

A stack of images becomes a stack of smaller images.



Rectified Linear Units (ReLUs)



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

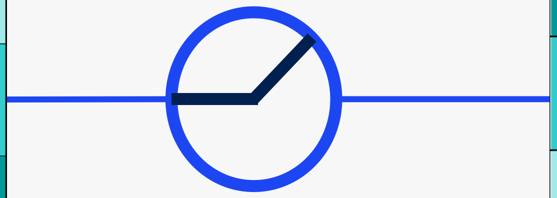
Rectified Linear Units (ReLUs)

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.77	0					

Rectified Linear Units (ReLUs)

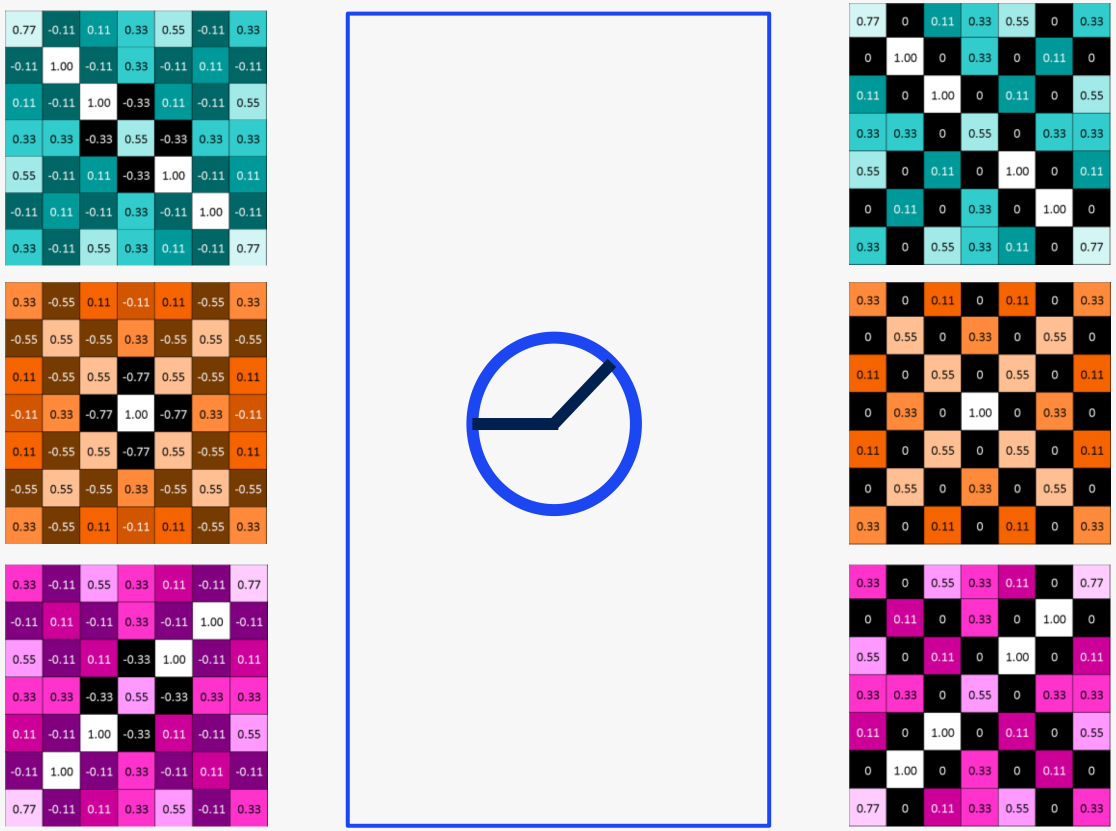
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77



0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	0.77

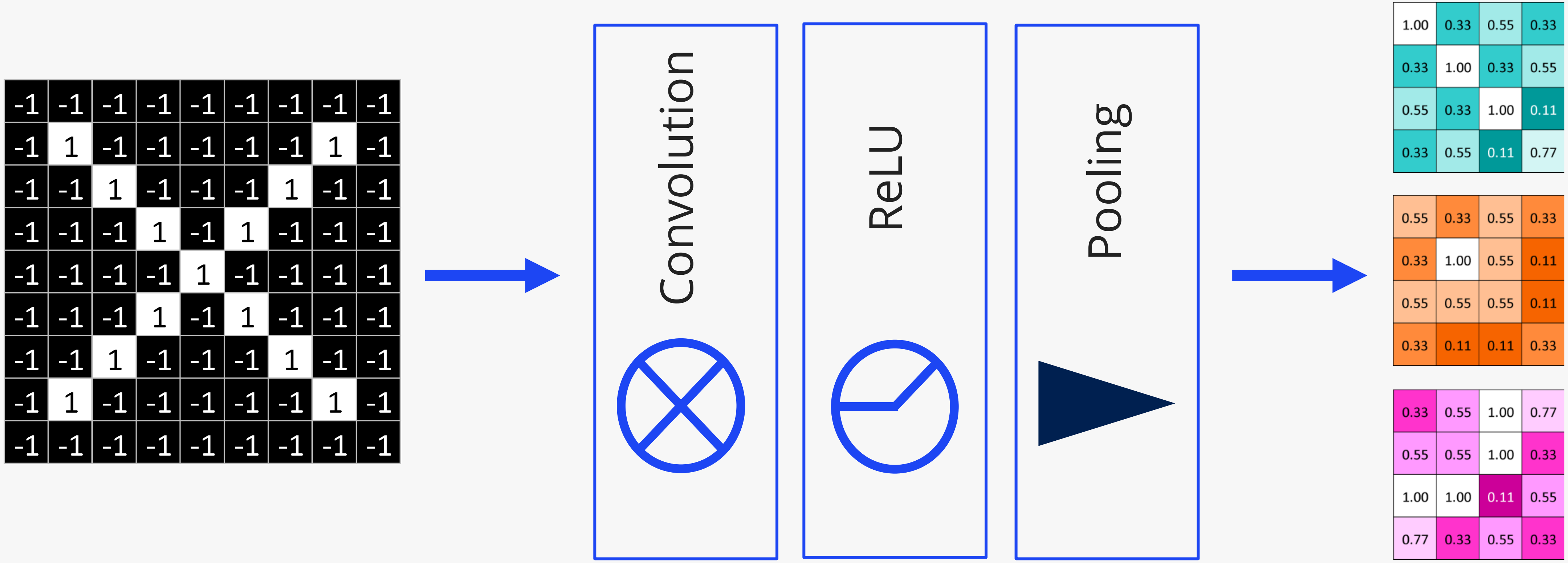
ReLU Layer

A stack of images becomes a stack of images with no negative values.



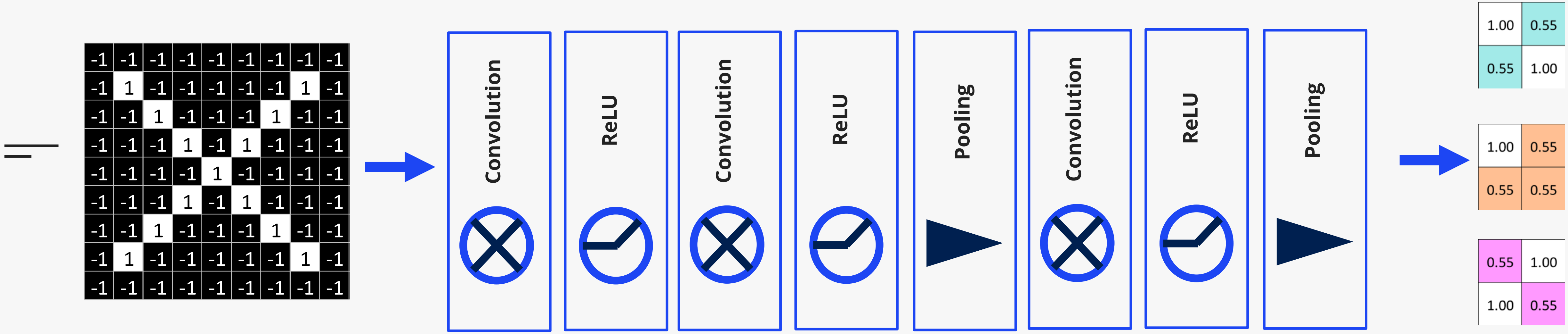
Layers Get **Stacked**

The output of one becomes the input of the next.

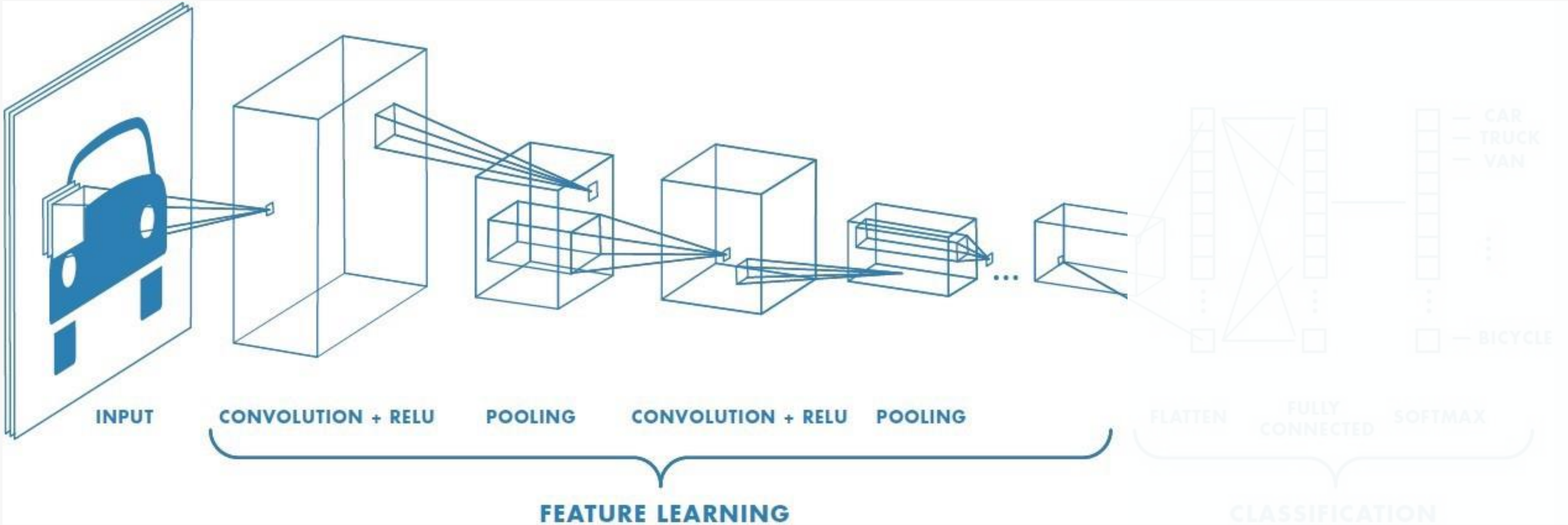


Deep Stacking

Layers can be repeated several (or many) times.



CNNs for Classification: Feature Learning

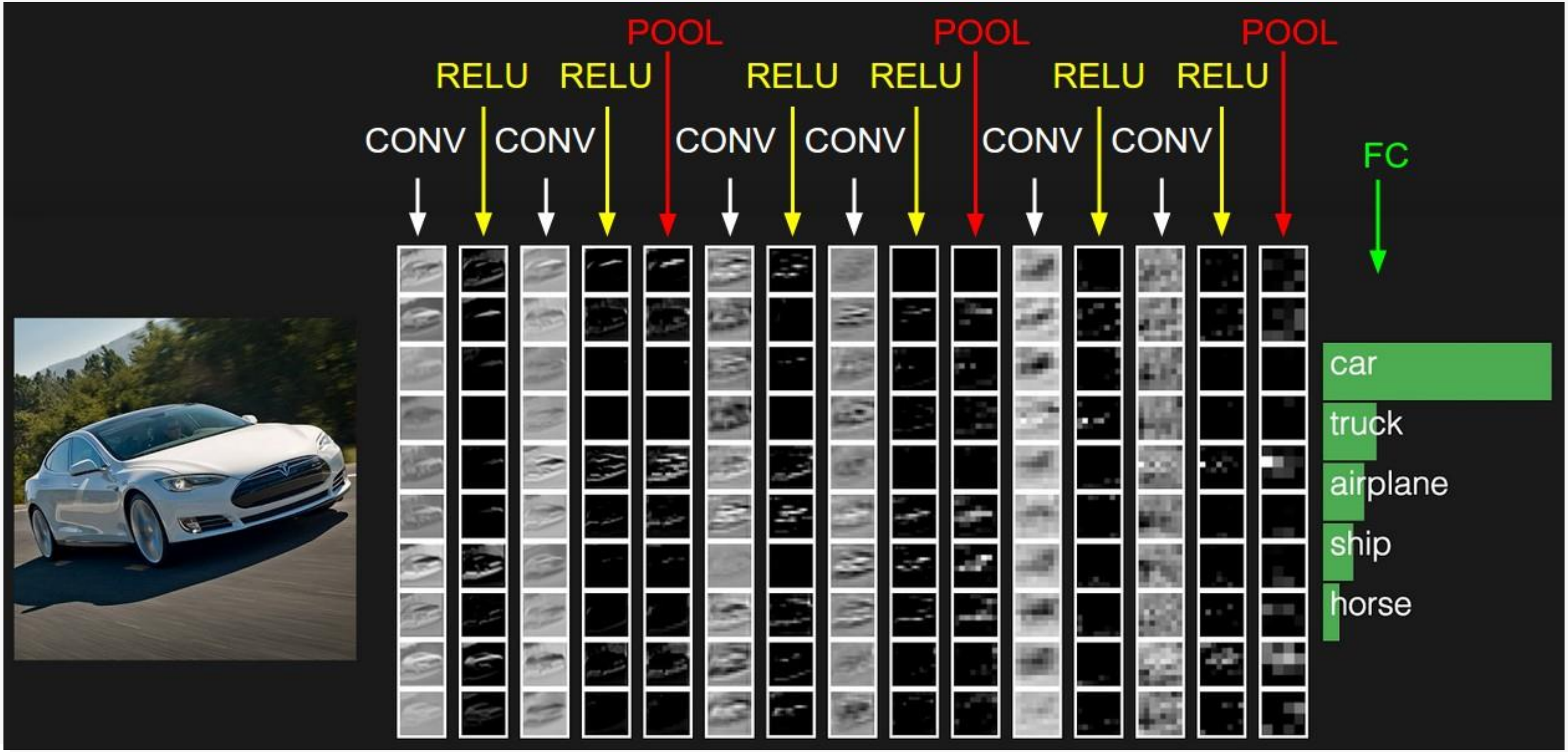


1. Learn features in input image through **convolution.**
2. Introduce **Non-linearity** through activation function (real-world data is non-linear).
3. Reduce dimensionality and preserve spatial invariance with **Pooling.**

CNNs for Classification: Class Probabilities

1. CONV and Pool layers output high-level feature of input
2. Fully connected layer uses these features for classifying input image.
3. Express output as **Probability** of image belonging to a particular class.

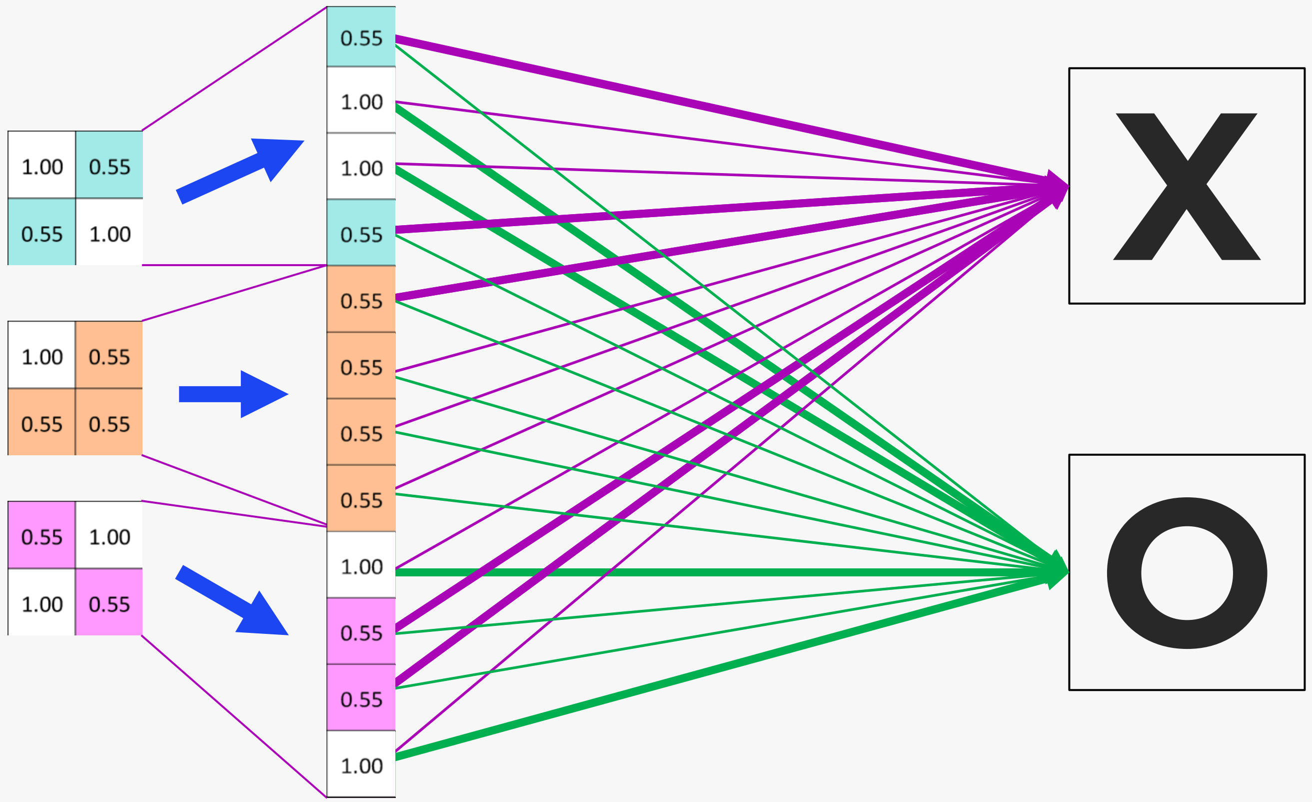
CNNs: Example



Back to
The Case Study again!

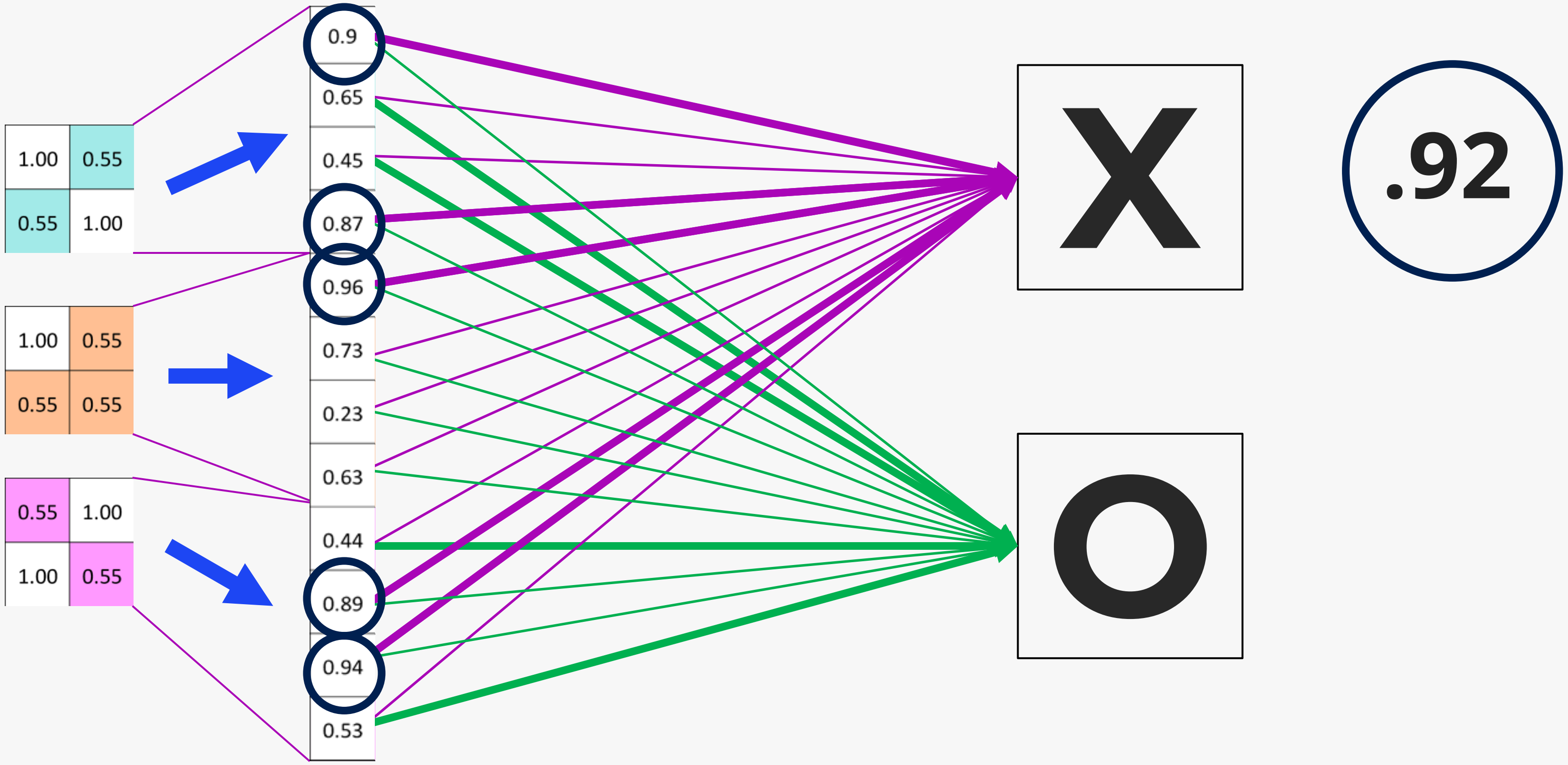
Fully Connected layer

Every value gets a vote depends on how strongly a value predicts X or O



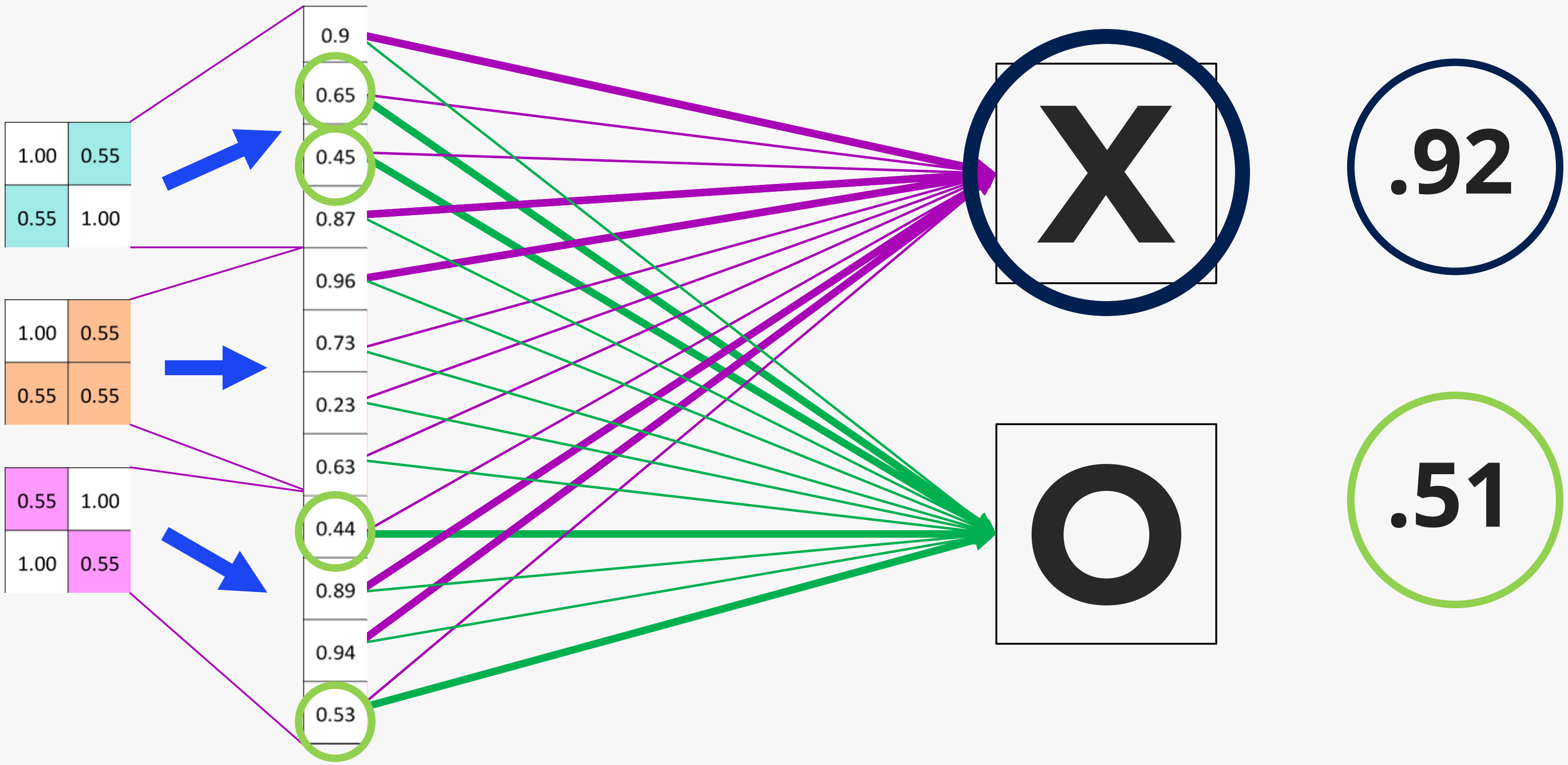
Fully Connected layer

Vote Values on X or O



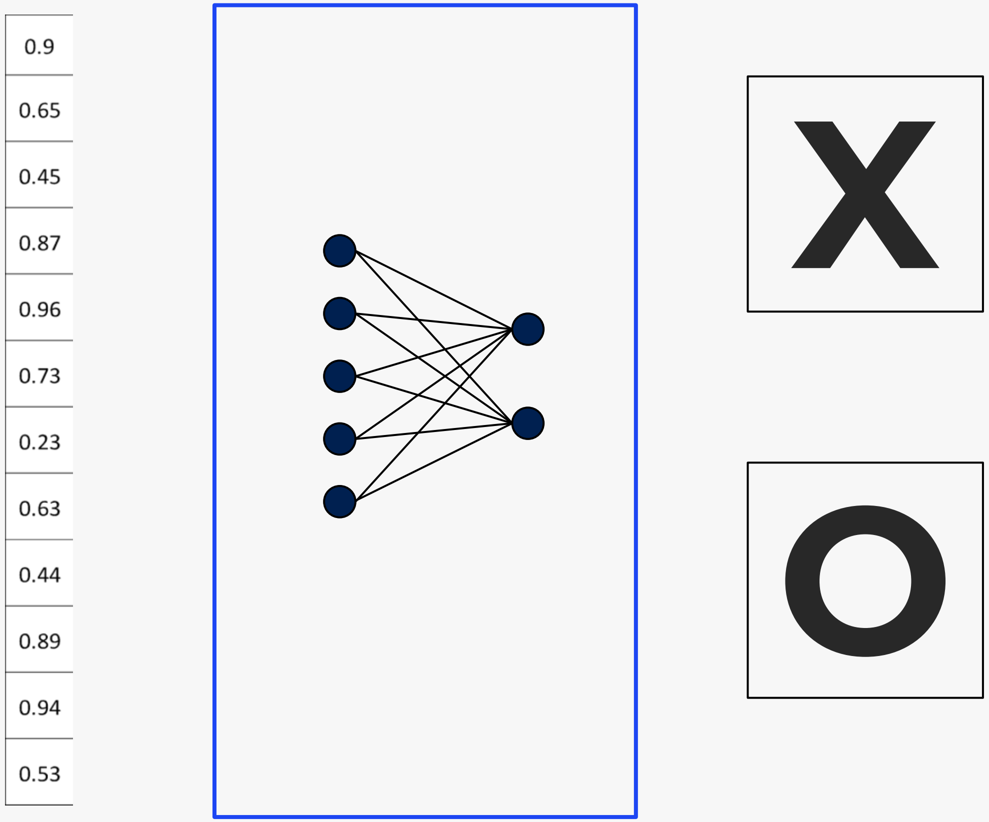
Fully Connected layer

Vote Values on X or O



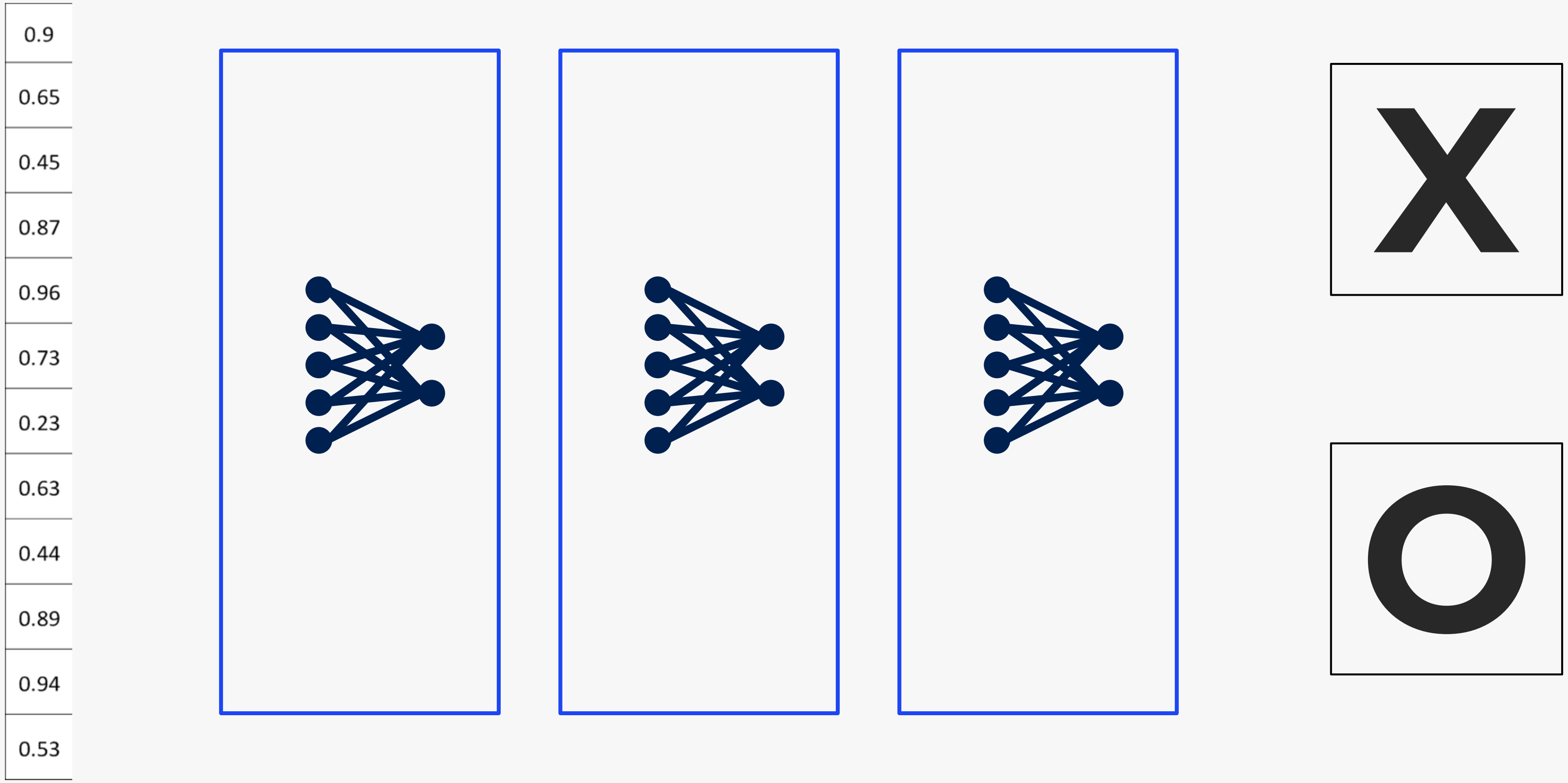
Fully Connected layer

A list of feature values becomes a list of votes.



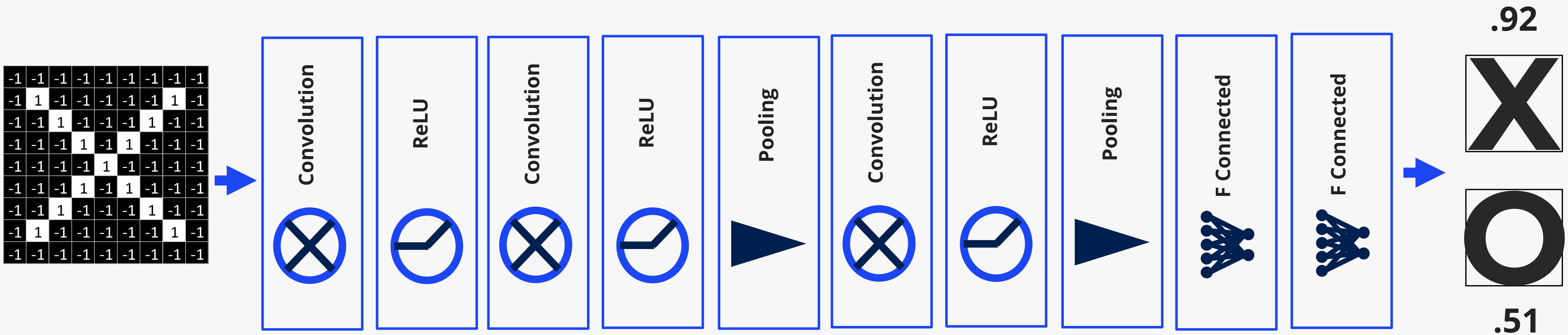
Fully Connected layer

These can also be stacked.



Backprop

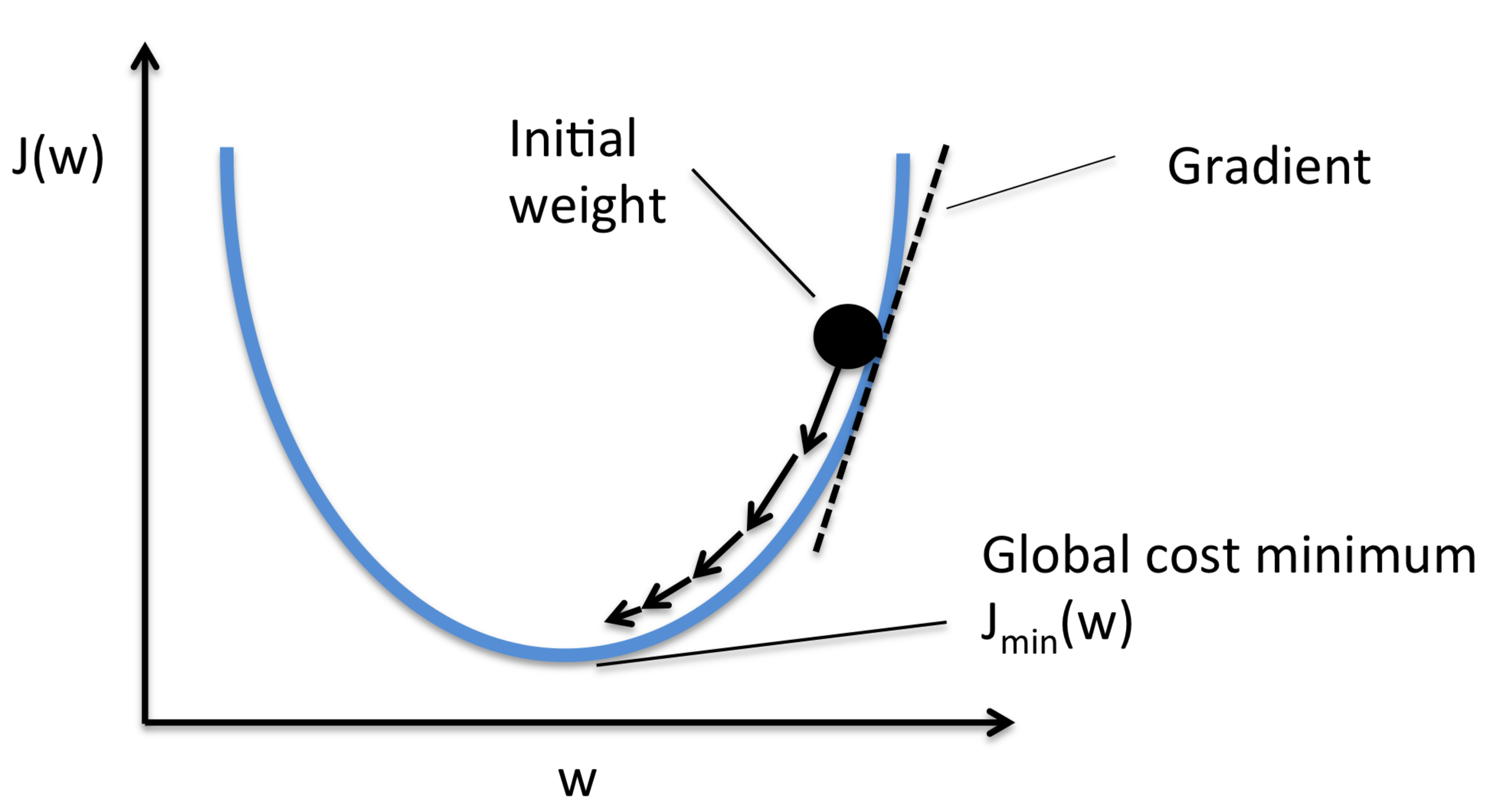
Error = right answer – actual answer



	Right answer	Actual answer	Error
X	1	0.92	0.08
O	0	0.51	0.49
		Total	0.57

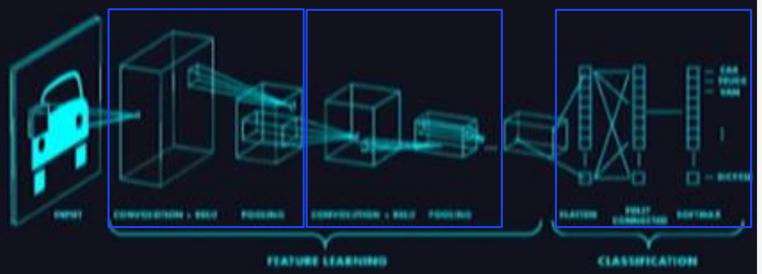
Gradient Descent

For each feature pixel and voting weight, adjust it up and down a bit and see how the error changes.



Putting it all together

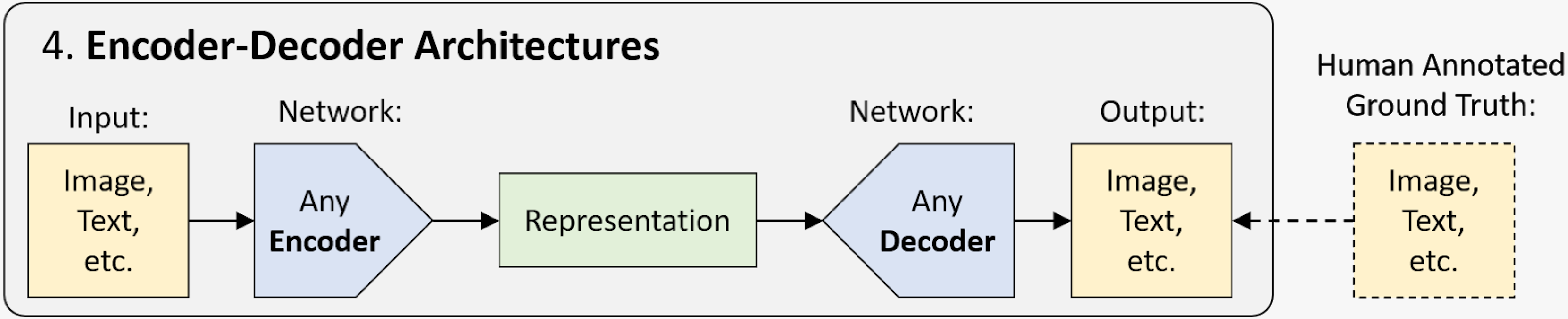
```python
import tensorflow as tf

def generate_model():
    model = tf.keras.Sequential([
        # first convolutional layer
        tf.keras.layers.Conv2D(32, filter_size=3, activation='relu'),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),

        # second convolutional layer
        tf.keras.layers.Conv2D(64, filter_size=3, activation='relu'),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),

        # fully connected classifier
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(1024, activation='relu'),
        tf.keras.layers.Dense(10, activation='softmax')  # 10 outputs
    ])
    return model
```



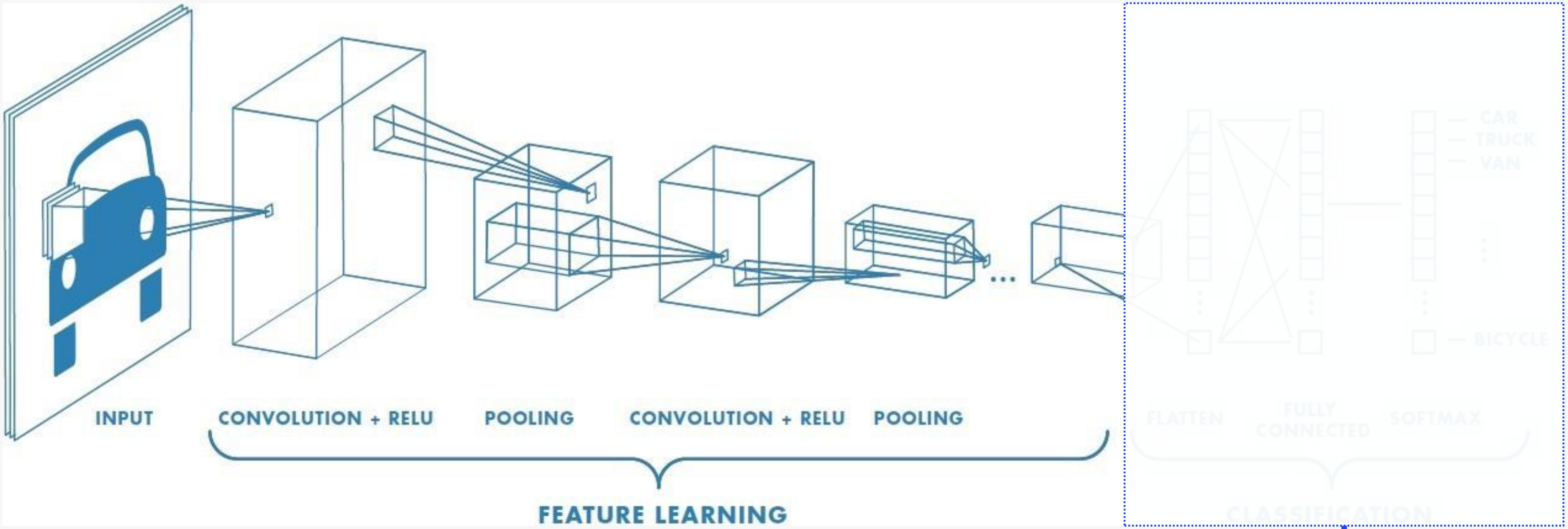
Encoder-Decoder Architectures (Pattern)

At a high-level, neural networks are either encoders, decoders, or a combination of both:

- **Encoders** find patterns in raw data to form compact, useful representations.
- **Decoders** generate high-resolution data from those representations. The generated data is either new examples or descriptive knowledge.



An Architecture for Many Applications



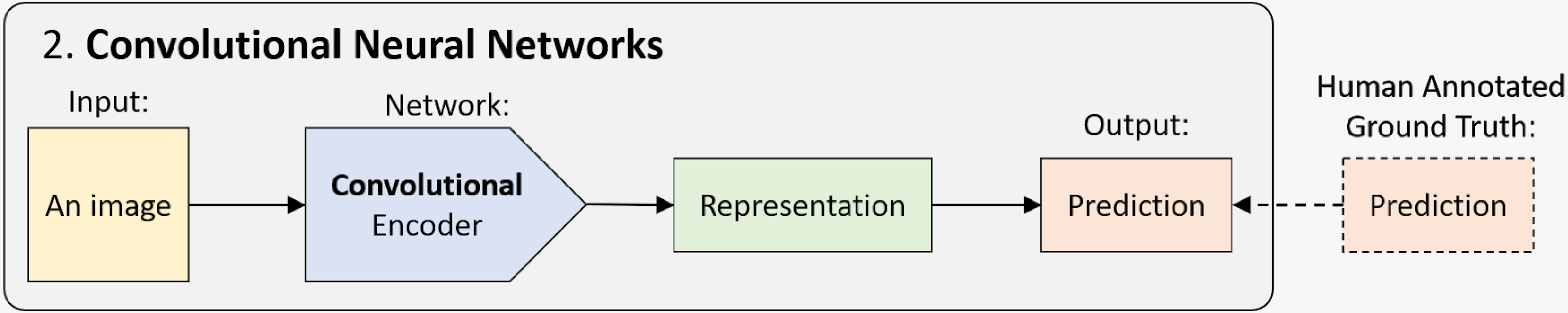
Classification

Object Detection

Segmentation

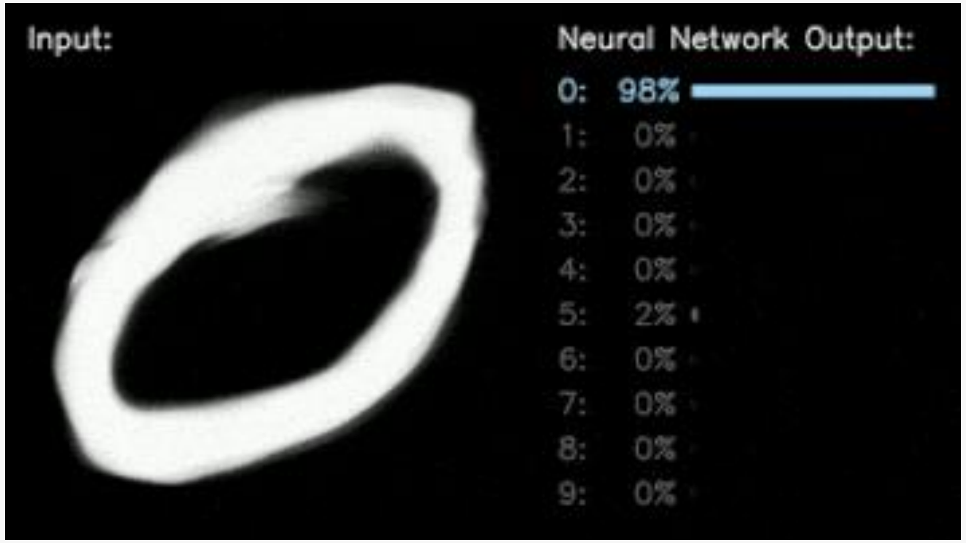
...

Convolutional Neural Networks (CNNs)



Instead of using only densely-connected layers, they use convolutional layers (**convolutional encoder**).

These networks are used for image classification, object detection, video action recognition, and any data that has some spatial invariance in its structure (e.g., speech audio).



Thank You!