

We are starting at 13:00!

Grab a seat and get ready



Saturdays.AI  
Kigali

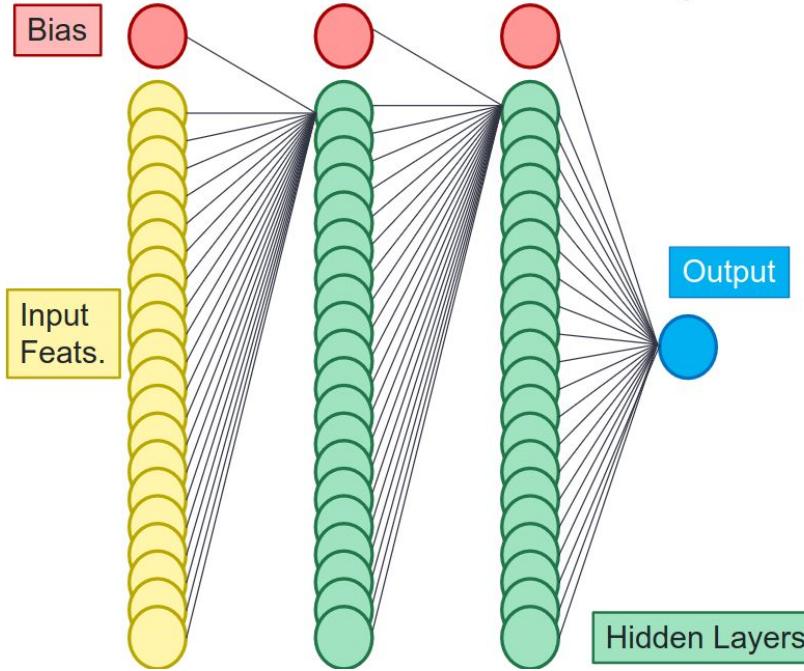
## #7 CNNs

AI Saturdays Kigali

# Today: Parameter Sharing: CNNs and RNNs

- Convolutional Neural Networks (CNNs) operate on images
  - Parameter share over space
  - CIFAR 10 images are  $32 \times 32 = 1024$  pixels, 1024 input features
  - ImageNet often pre-processed to be  $256 \times 256 = \sim 64K$  pixels,  $\sim 64k$  input features 😱

# An MLP can have many many params



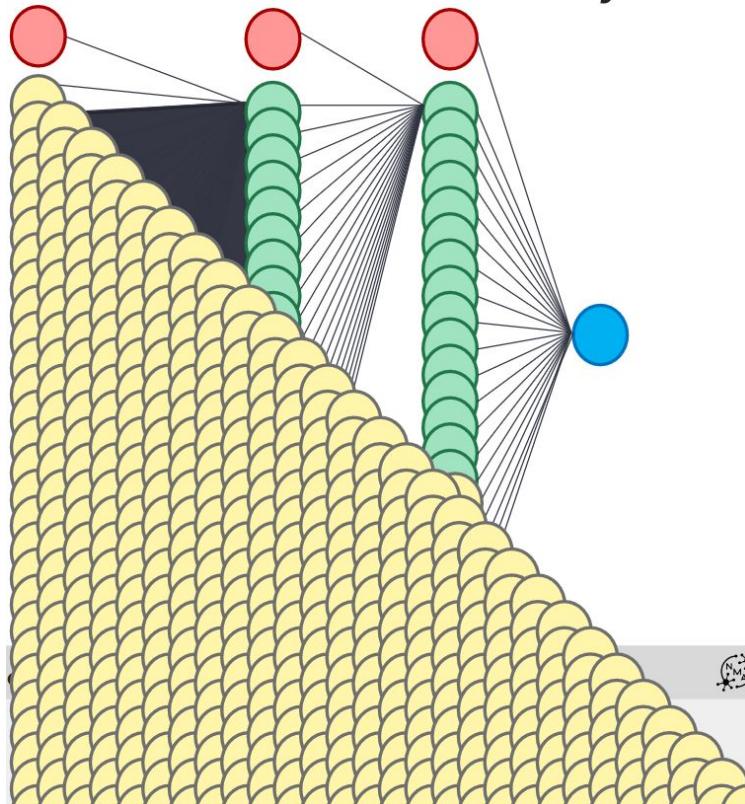
Data: 20 input features, single binary label

- 1 input layer with 20 nodes,
- 2 fully connected layers, 20 nodes each
- 1 final prediction node

How many weights is that?

$$(20+1)*20+(20+1)*20+(20+1)*1=861 \text{ params}$$

# An MLP can have many many params



1 input layer with  $256 \times 256$  nodes,  
2 fully connected layers, 20 nodes each  
1 final prediction node

How many weights is that?

$$(256 \times 256 + 1) \times 20 + (20 + 1) \times 20 + (20 + 1) \times 1 = \sim 1.3M \text{ params}$$

And that's with only two fairly small hidden layers!  
Modern CNNs have many more layers! 50-100 or more!

# Translation invariance in images

- At the same time that the number of parameters grows very quickly, we are missing an opportunity



JOSH HAROLDSON VIA [FLICKR // CC BY-NC 2.0](#)

# Representations & Visual processing in the brain

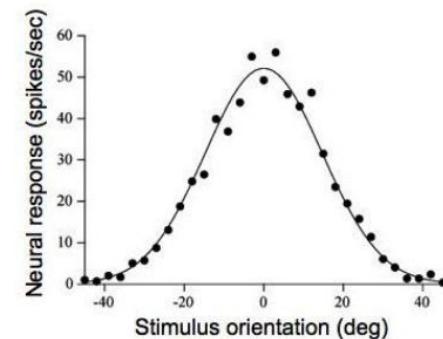
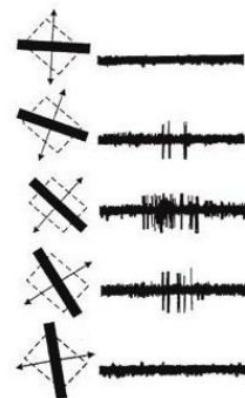
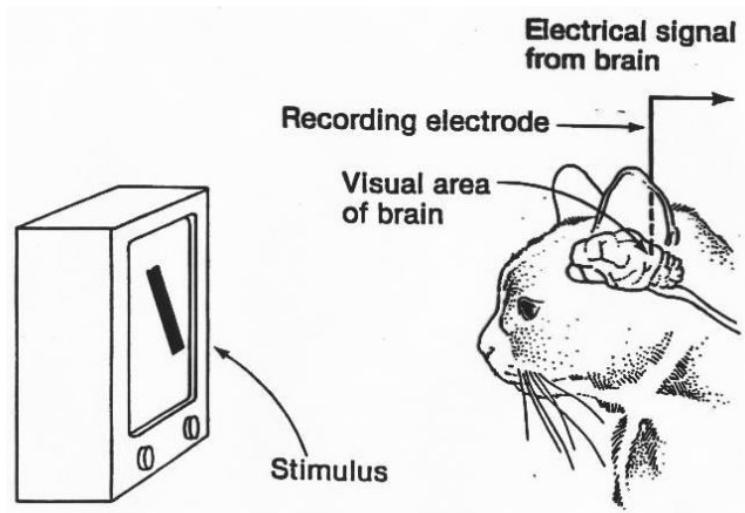


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# Visual Processing in the Brain

- The brain is an efficient machine
- How does it “solve” vision?

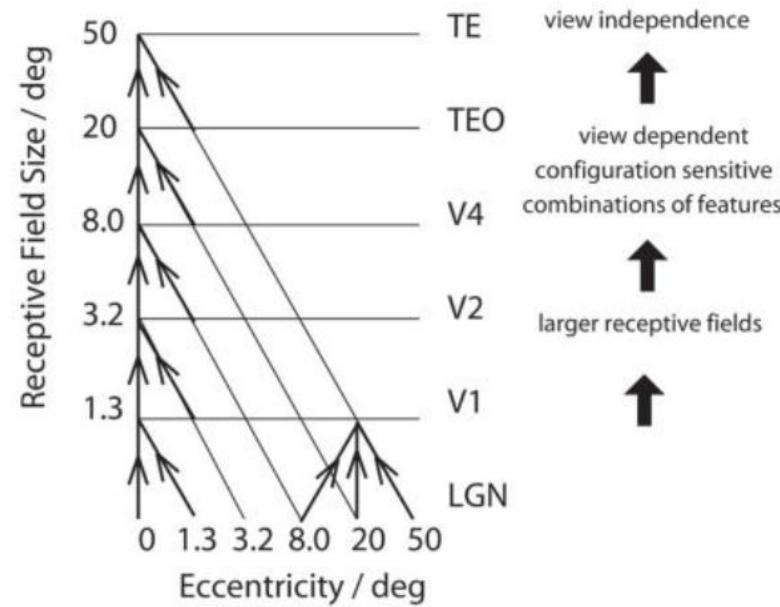
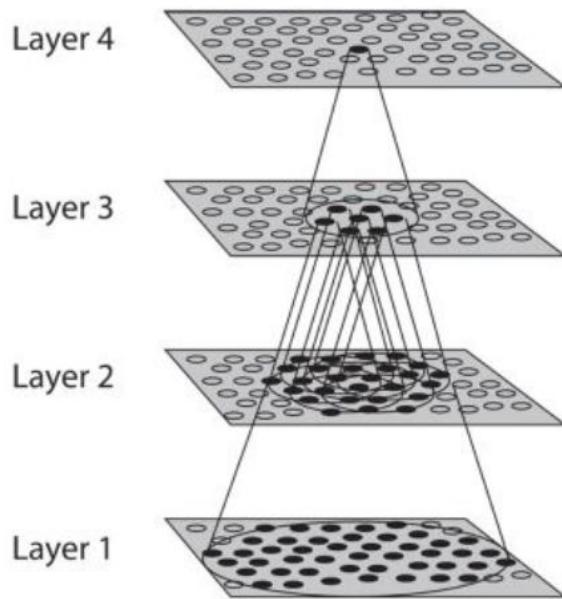
# Hubel and Wiesel



Hubel & Wiesel, 1968



# A hierarchy of processing



# Invariances



JOSH HAROLDSON VIA [FLICKR](#) // CC BY-NC 2.0

Translation Invariance



Rotation/Viewpoint Invariance



Size Invariance



Illumination Invariance



Matt Krause  
matthkrause

# What is a CNN? Convolution?

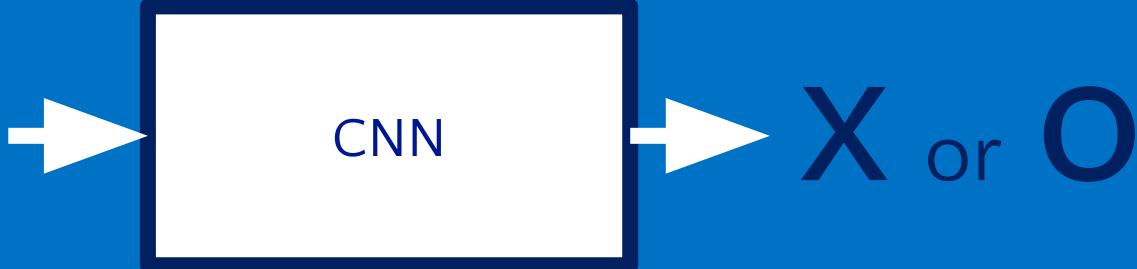
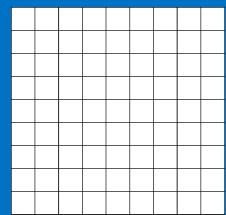


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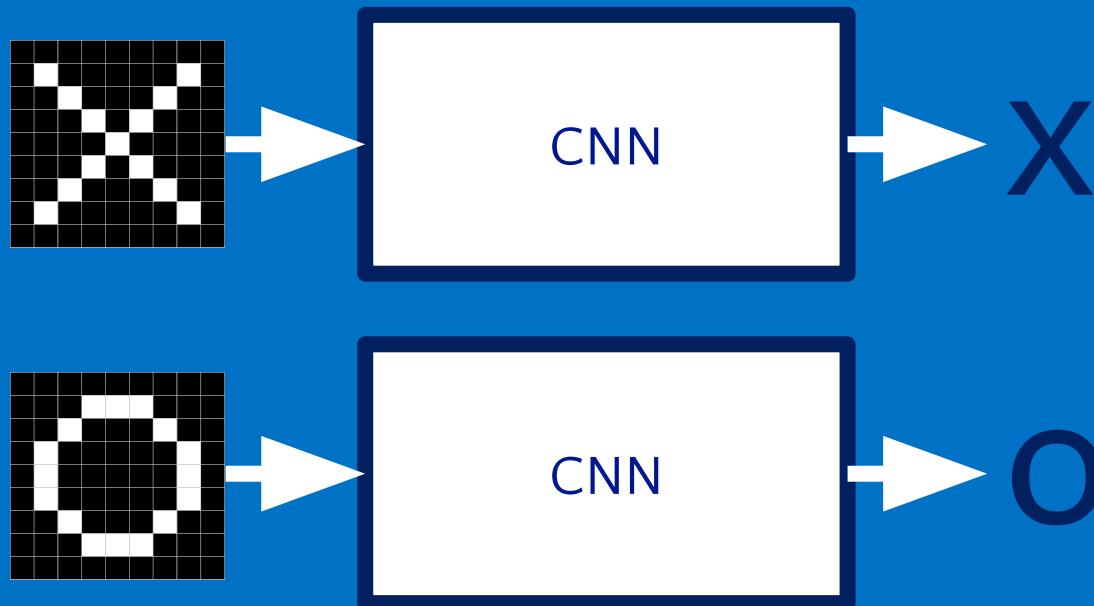
# A toy ConvNet: X's and O's

Says whether a picture is of an X or an O

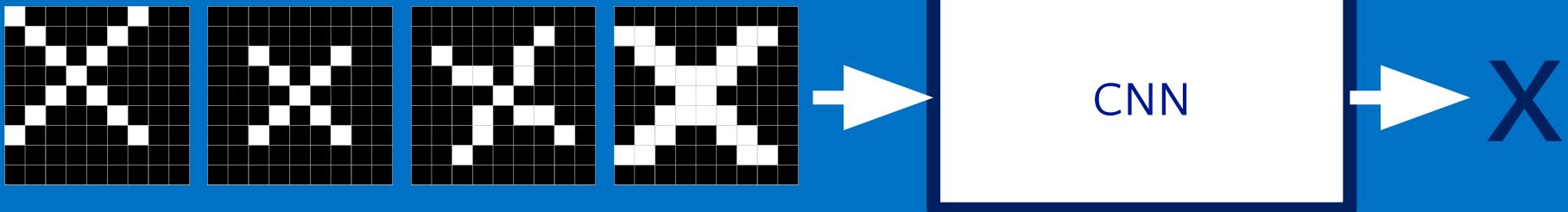
A two-dimensional  
array of pixels



For example



# Trickier cases

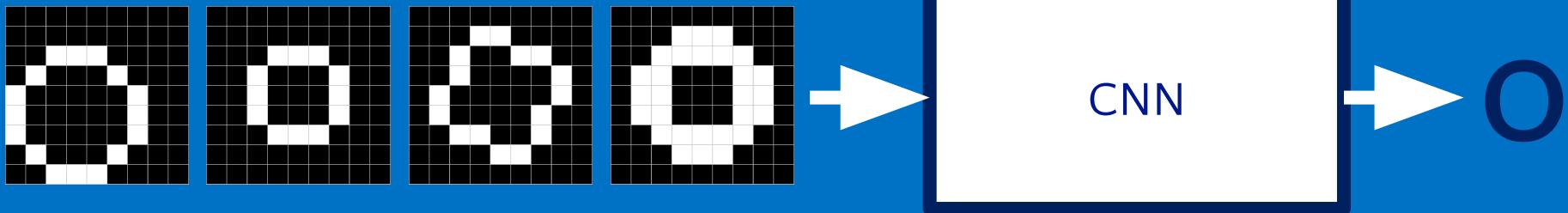


translation

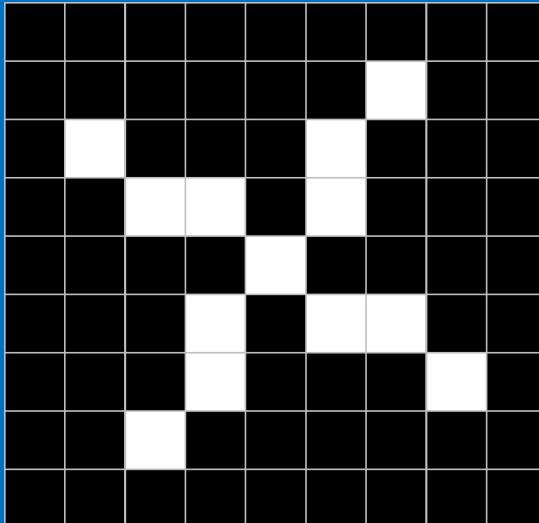
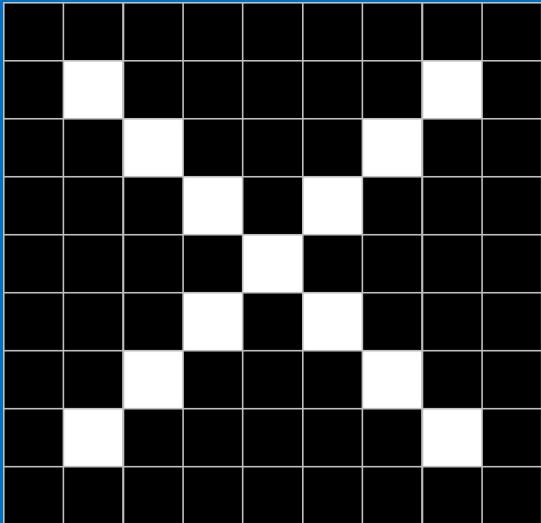
scaling

rotation

weight



# Deciding is hard



# What computers see

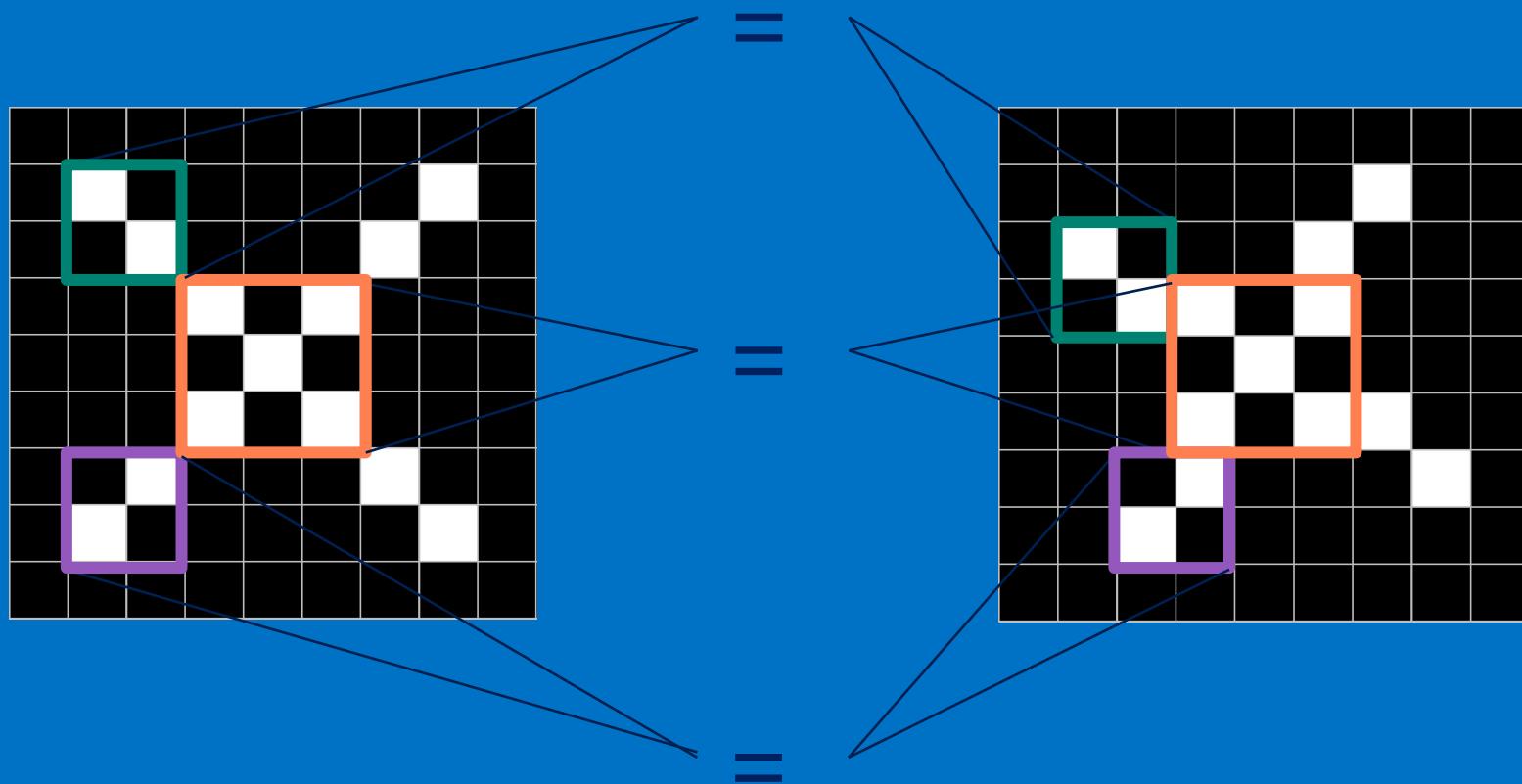


# What computers see

# Computers are literal



# ConvNets match pieces of the image



# Features match pieces of the image

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

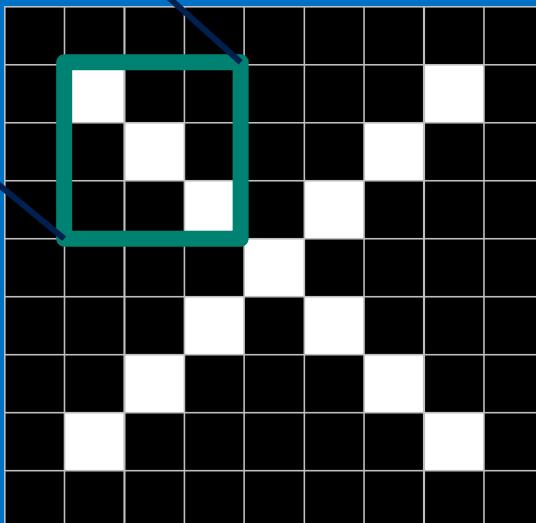
1	-1	1
-1	1	-1
1	-1	1

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

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

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

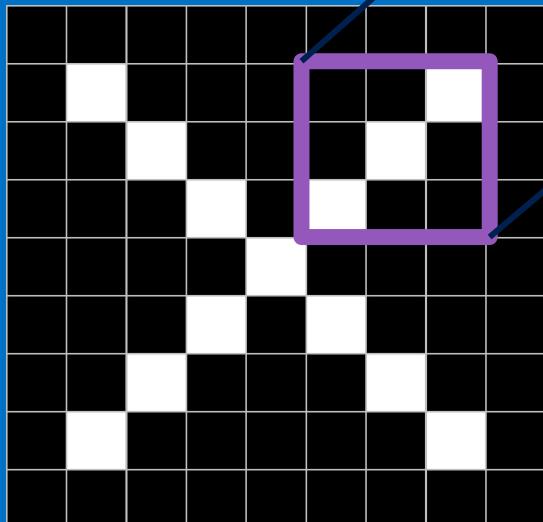
-1	-1	1
-1	1	-1
1	-1	-1



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

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

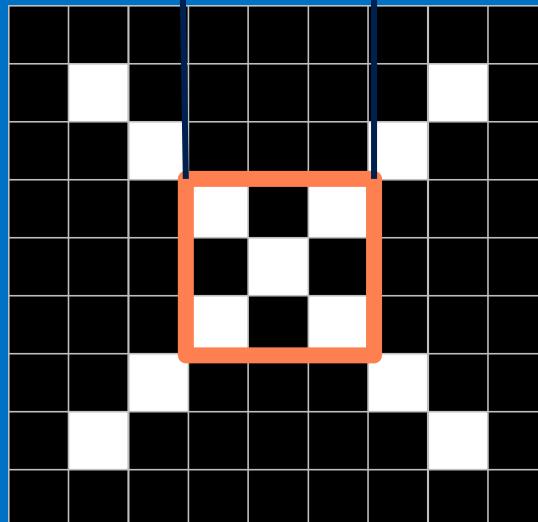
-1	-1	1
-1	1	-1
1	-1	-1



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

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

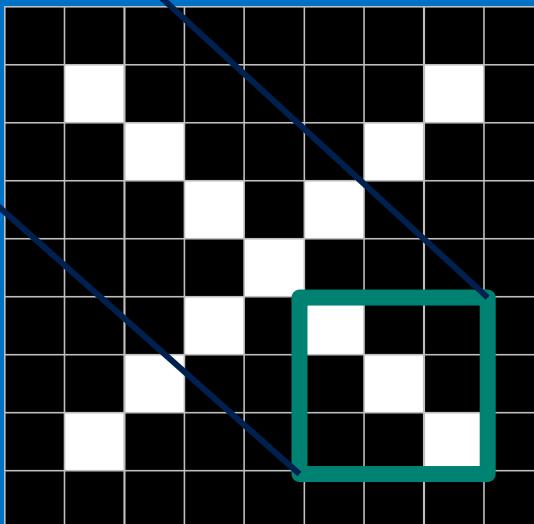
-1	-1	1
-1	1	-1
1	-1	-1



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

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

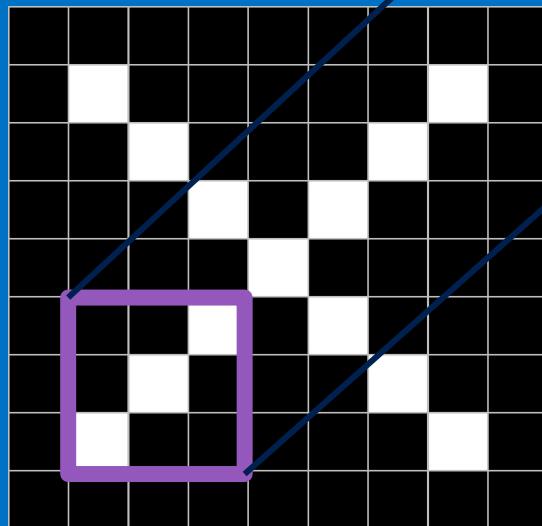
-1	-1	1
-1	1	-1
1	-1	-1



1	-1	-1
-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

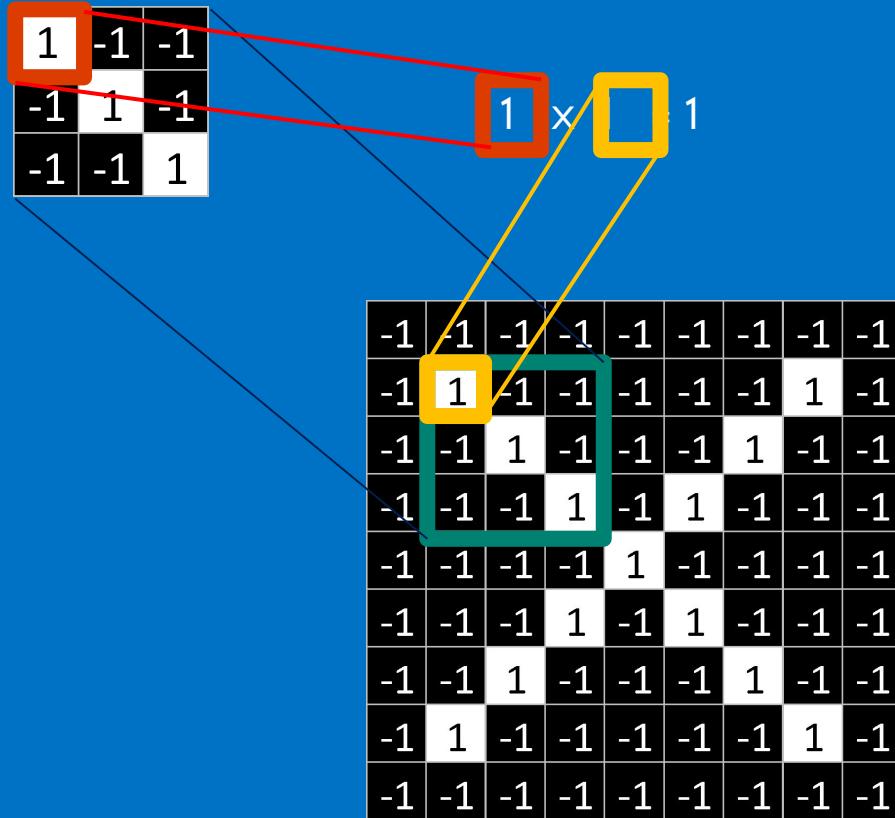
1	-1	-1
-1	1	-1
-1	-1	1

**DON'T  
PANIC**

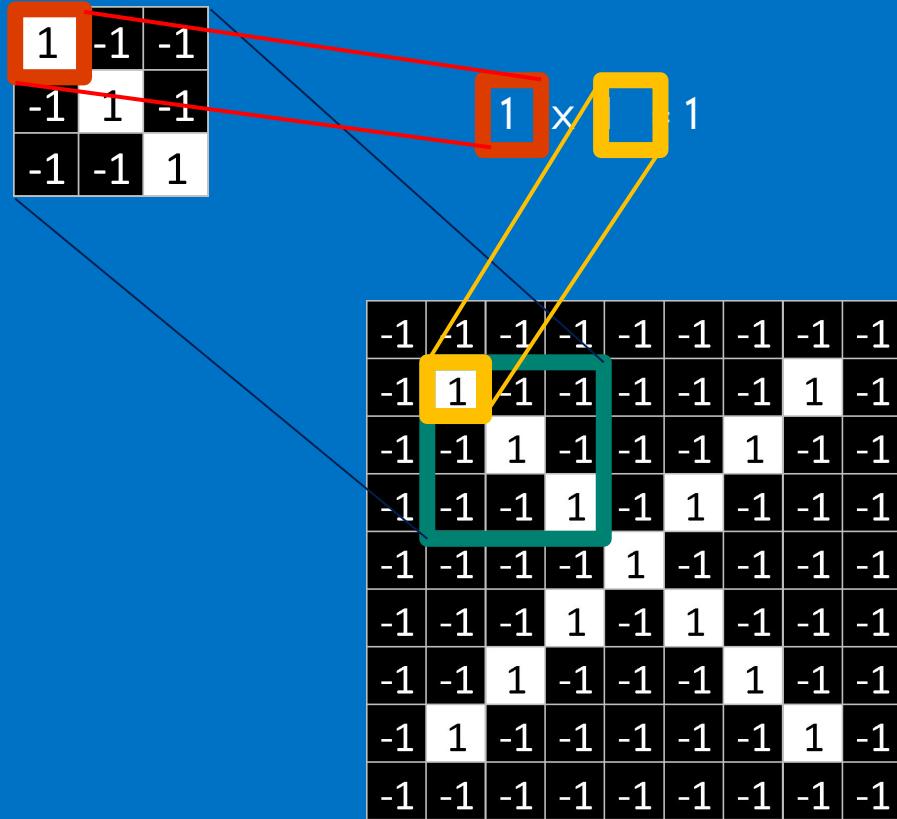
# Filtering: The math behind the match

1. Line up the feature and the image patch.
2. Multiply each image pixel by the corresponding feature pixel.
3. Add them up.
4. Divide by the total number of pixels in the feature.

# Filtering: The math behind the match



# 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	

# 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

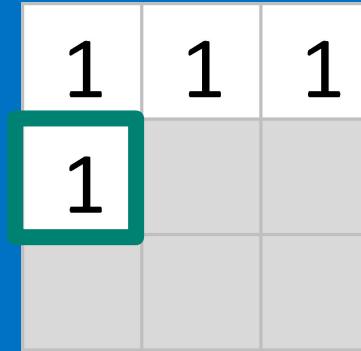
1	1	1

# Filtering: The math behind the match

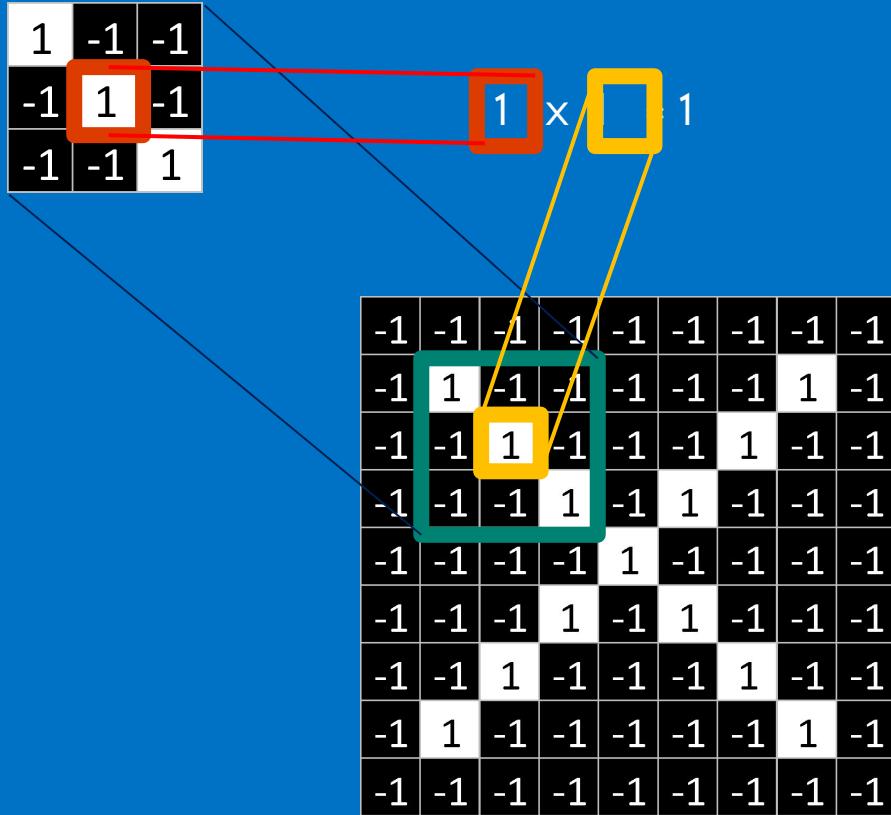
$$\begin{matrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \end{matrix}$$

$-1 \times -1 = 1$

-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



# Filtering: The math behind the match



# Filtering: The math behind the match

$$\begin{array}{|c|c|c|} \hline 1 & -1 & -1 \\ \hline -1 & 1 & -1 \\ \hline -1 & -1 & 1 \\ \hline \end{array}$$

$-1 \times -1 = 1$

$$\begin{array}{cccccccccc} -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & 1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\ -1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & -1 & 1 & -1 & -1 \\ -1 & 1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{array}$$

$$\begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

# 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		

# Filtering: The math behind the match

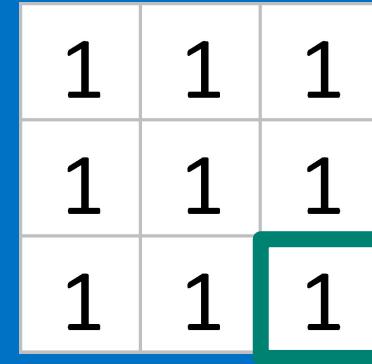
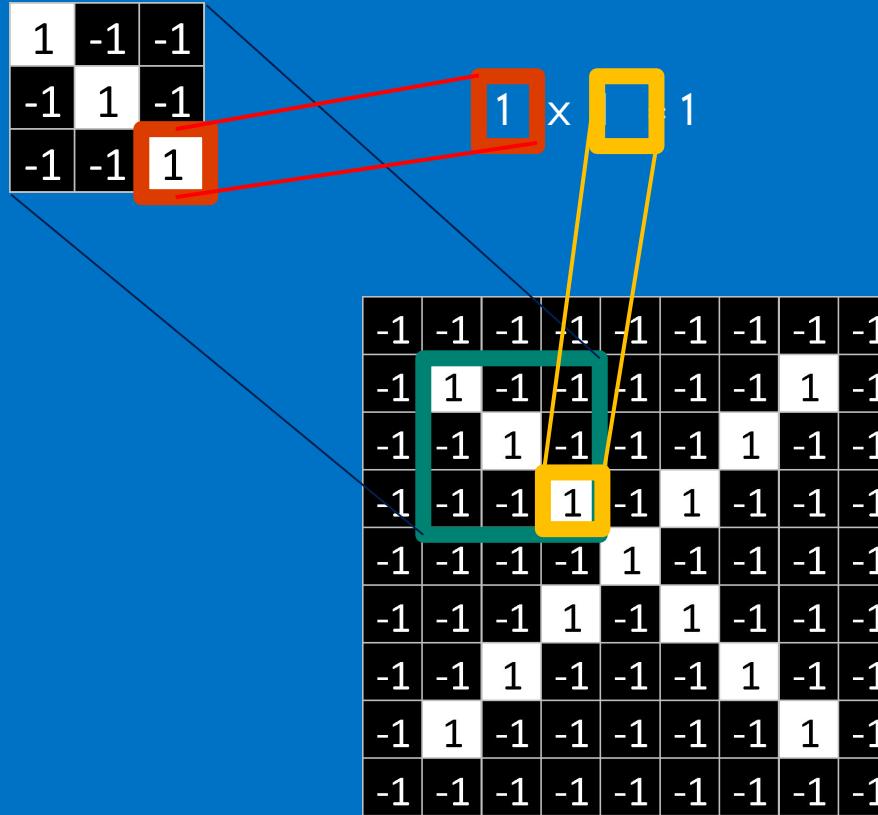
1	-1	-1
-1	1	-1
-1	-1	1

$$-1 \times -1 = 1$$

-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	

# Filtering: The math behind the match



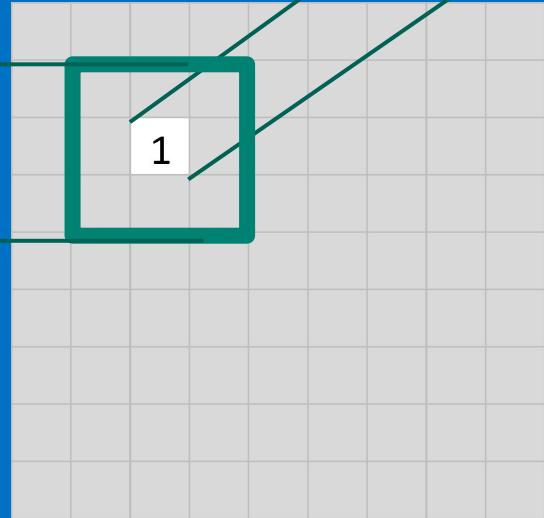
# Filtering: The math behind the match

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

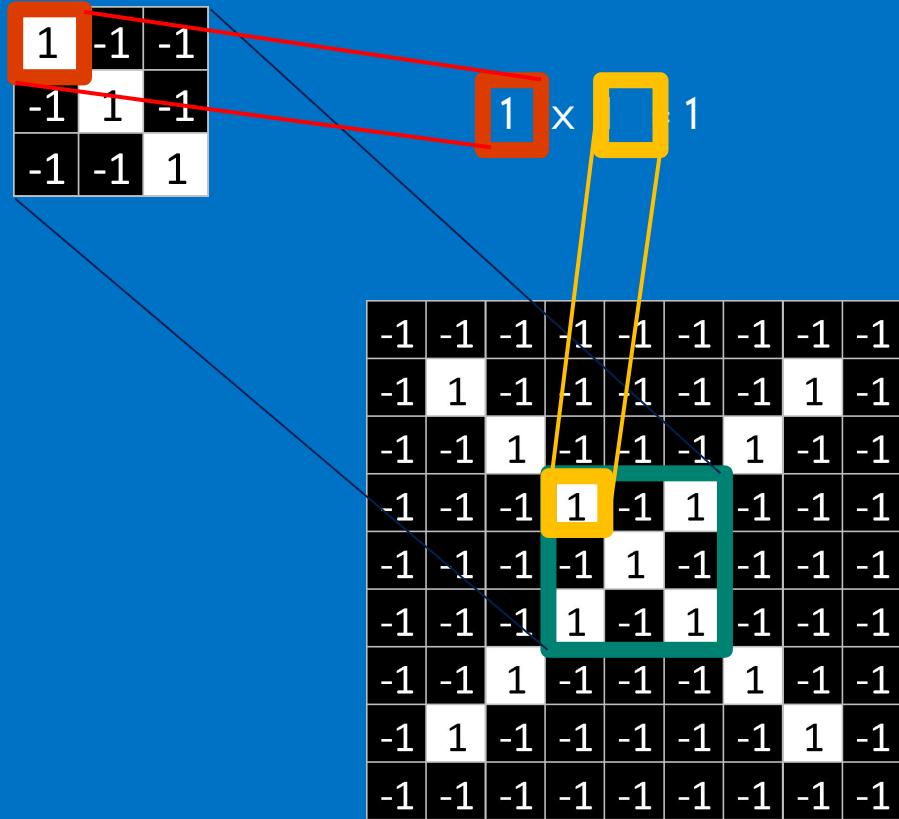
1	1	1
1	1	1
1	1	1

$$\frac{1 + 1 + 1 + 1 + 1 + 1 + 1 + 1}{9} = 1$$

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

# 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
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

1	1	-1
1	1	1
-1	1	1

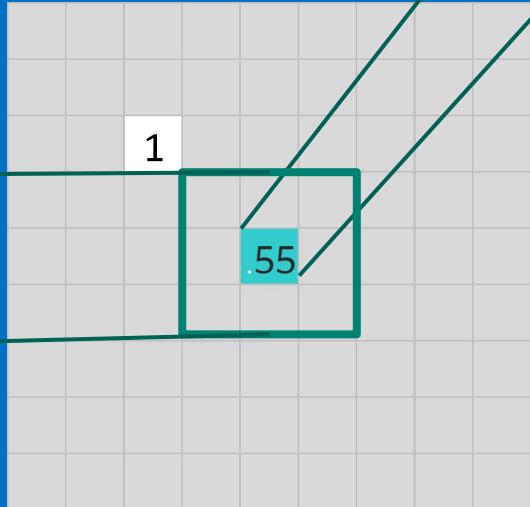
# Filtering: The math behind the match

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

1	1	-1
1	1	1
-1	1	1

$$\frac{1 + 1 - 1 + 1 + 1 + 1 - 1 + 1 + 1}{9} = .55$$

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



# Convolution: 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
-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

# Convolution: 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	-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

# This is 2D convolution

- Convolution can also be 1D and 3D
- Convolutions can be used in other application areas
  - Whenever there's predictable correlation over time/space
  - Language, protein or DNA sequences

*Practice*

*Do a convolution by hand*

Input	Kernel													
<table border="1" style="margin: auto;"><tr><td>0</td><td>1</td><td>2</td></tr><tr><td>3</td><td>4</td><td>5</td></tr><tr><td>6</td><td>7</td><td>8</td></tr></table>	0	1	2	3	4	5	6	7	8	<table border="1" style="margin: auto;"><tr><td>0</td><td>1</td></tr><tr><td>2</td><td>3</td></tr></table>	0	1	2	3
0	1	2												
3	4	5												
6	7	8												
0	1													
2	3													
*														
	=													



## Practice

*Do a convolution by hand*

Input	Kernel	Output													
<table border="1" style="display: inline-table; vertical-align: middle;"><tr><td>0</td><td>1</td><td>2</td></tr><tr><td>3</td><td>4</td><td>5</td></tr><tr><td>6</td><td>7</td><td>8</td></tr></table>	0	1	2	3	4	5	6	7	8	$*$	<table border="1" style="display: inline-table; vertical-align: middle;"><tr><td>0</td><td>1</td></tr><tr><td>2</td><td>3</td></tr></table>	0	1	2	3
0	1	2													
3	4	5													
6	7	8													
0	1														
2	3														
	=	<table border="1" style="display: inline-table; vertical-align: middle;"><tr><td>19</td><td>25</td></tr><tr><td>37</td><td>43</td></tr></table>	19	25	37	43									
19	25														
37	43														

$$\begin{aligned}0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 &= 19, \\1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 &= 25, \\3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 &= 37, \\4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 &= 43.\end{aligned}$$

# Details about Convolution?

# What about the edges of an image?



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# Padding

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

# Padding

# Padding, Stride = 2

# Padding, Stride = 3

# Padding, Stride = 4

# Motivation: conv for edge detection

-1	-1	-1
2	2	2
-1	-1	-1

Horizontal lines

-1	2	-1
-1	2	-1
-1	2	-1

Vertical lines

-1	-1	2
-1	2	-1
2	-1	-1

45 degree lines

2	-1	-1
-1	2	-1
-1	-1	2

135 degree lines

Horizontal lines:



# Feature detection - edges

Filters give us global translation invariance

Run a filter across an image

How could that be useful for image recognition?

# Pooling and Subsampling



Saturdays.AI  
Kigali

# Multiple Filters and ReLU

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

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



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

=

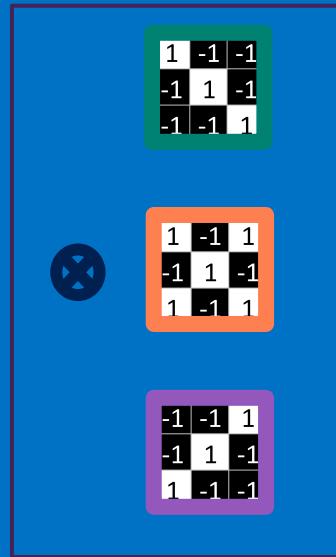
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

# Convolution layer

One image becomes a stack of filtered images



$$\begin{array}{cccc} 1 & -1 & 1 & -1 \\ -1 & 1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ -1 & 1 & -1 & -1 \end{array}$$



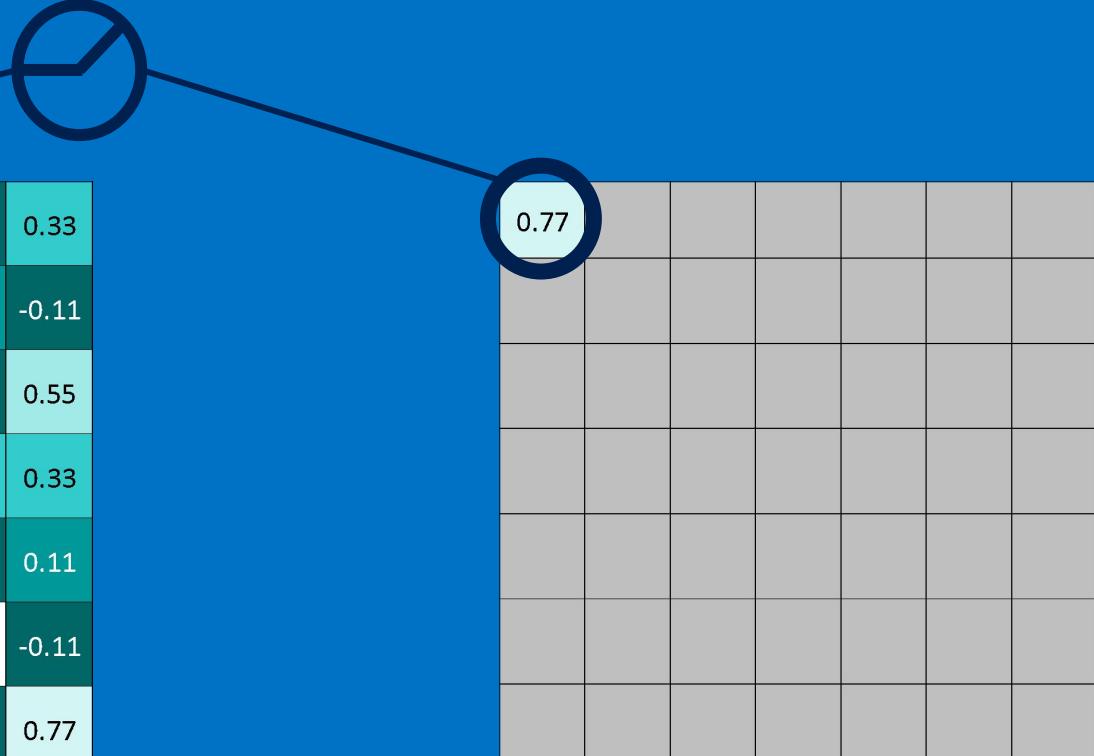
A 5x5 grid of numerical values representing the output of the convolution layer. The values range from -0.77 to 0.77, with higher values in the center and lower values towards the edges.

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	1.00	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.55	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)

$$\text{ReLU}(x) = \max(0, x)$$

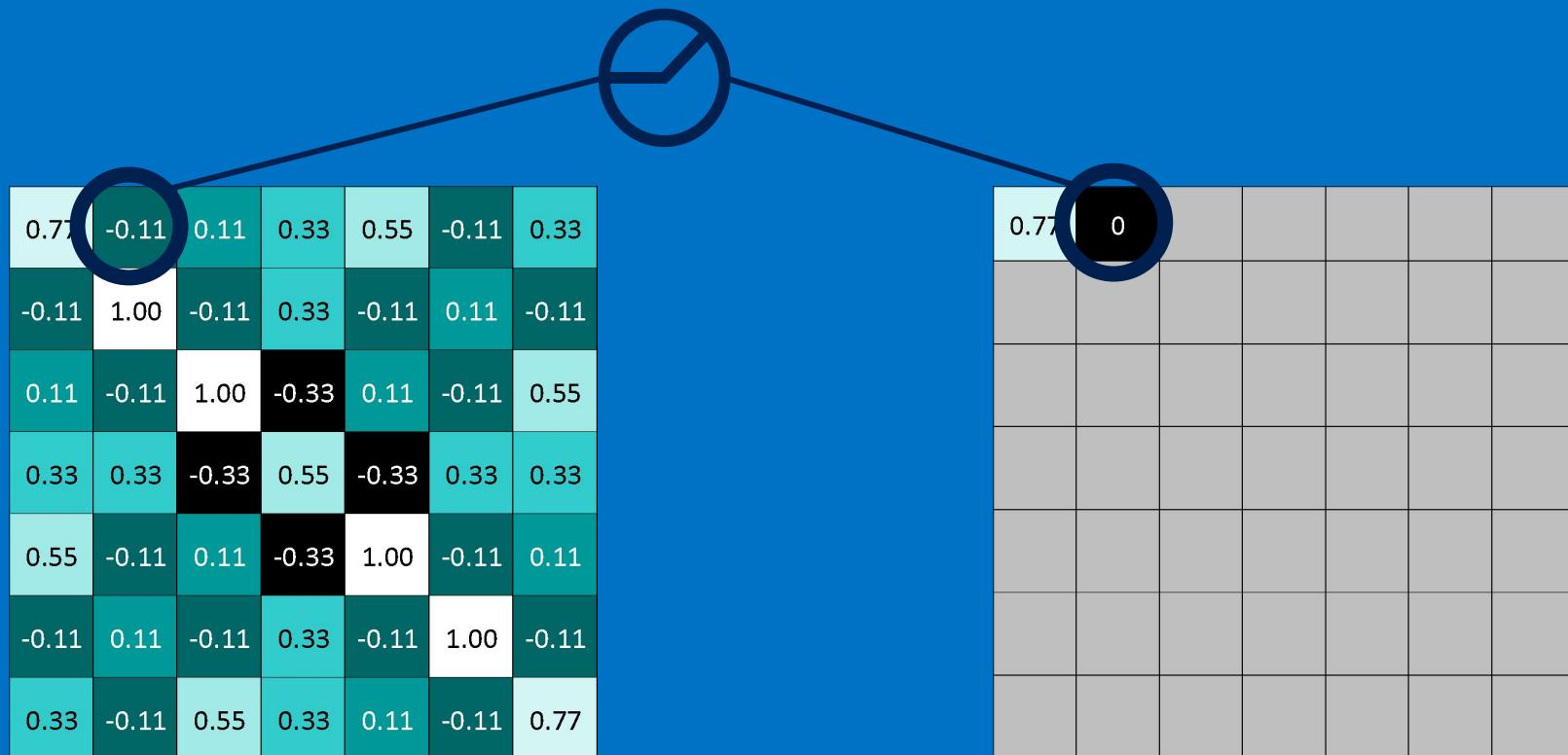


A 7x7 matrix representing input data. The values range from -0.11 to 1.00. The matrix is visualized with a color gradient where darker shades represent negative values and lighter shades represent positive values. A thick black border surrounds the entire matrix.

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

# Rectified Linear Units (ReLUs)



# Rectified Linear Units (ReLUs)

0.77	-0.11	0.11	0.33	0.55	<b>-0.11</b>	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	<b>0</b>	0.33

# 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

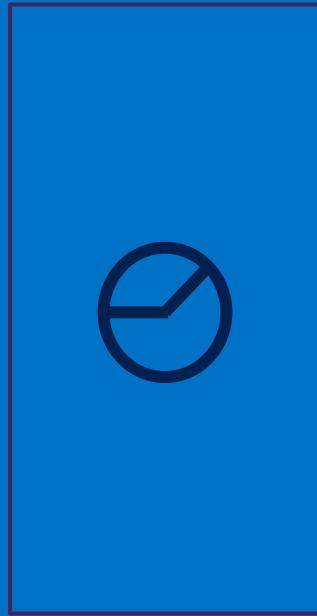
# ReLU layer

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

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

0.33	-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

0.33	-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



0.77	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	0.11	0
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

0.35	0	0.11	0	0.11	0	0.33
0	0.55	0	0.33	0	0.55	0
0.11	0	0.55	0	0.55	0	0.11
0	0.33	0	1.00	0	0.33	0
0.11	0	0.55	0	0.55	0	0.11
0	0.55	0	0.33	0	0.55	0
0.35	0	0.11	0	0.11	0	0.33

0.35	0	0.55	0.33	0.11	0	0.77
0	0.11	0	0.33	0	1.00	0
0.55	0	0.11	0	1.00	0	0.11
0.35	0.35	0	0.55	0	0.33	0.33
0.11	0	0.55	0	0.55	0	0.11
0	0.55	0	0.33	0	0.55	0
0.35	0	0.11	0	0.11	0	0.33

0.35	0	0.55	0.33	0.11	0	0.77
0	0.11	0	0.33	0	1.00	0
0.55	0	0.11	0	1.00	0	0.11
0.35	0.35	0	0.55	0	0.33	0.33
0.11	0	0.55	0	0.55	0	0.11
0	0.55	0	0.33	0	0.55	0
0.35	0	0.11	0	0.11	0	0.33

# Pooling

# Pooling = Local invariance

- Recall: filters give us global invariance
- Pooling gives local invariance

# The need for some invariance

Features may appear in (slightly)  
different places

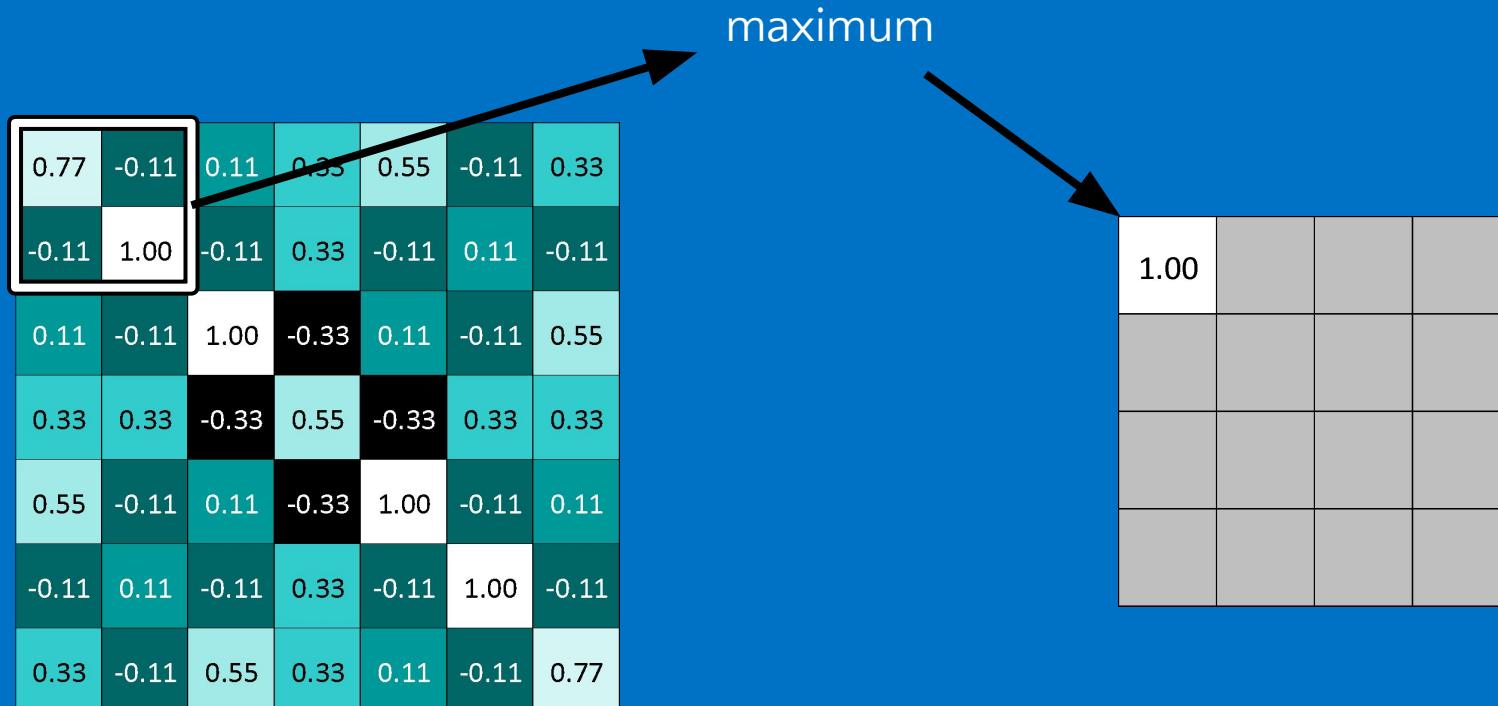


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# Pooling: Shrinking the image stack

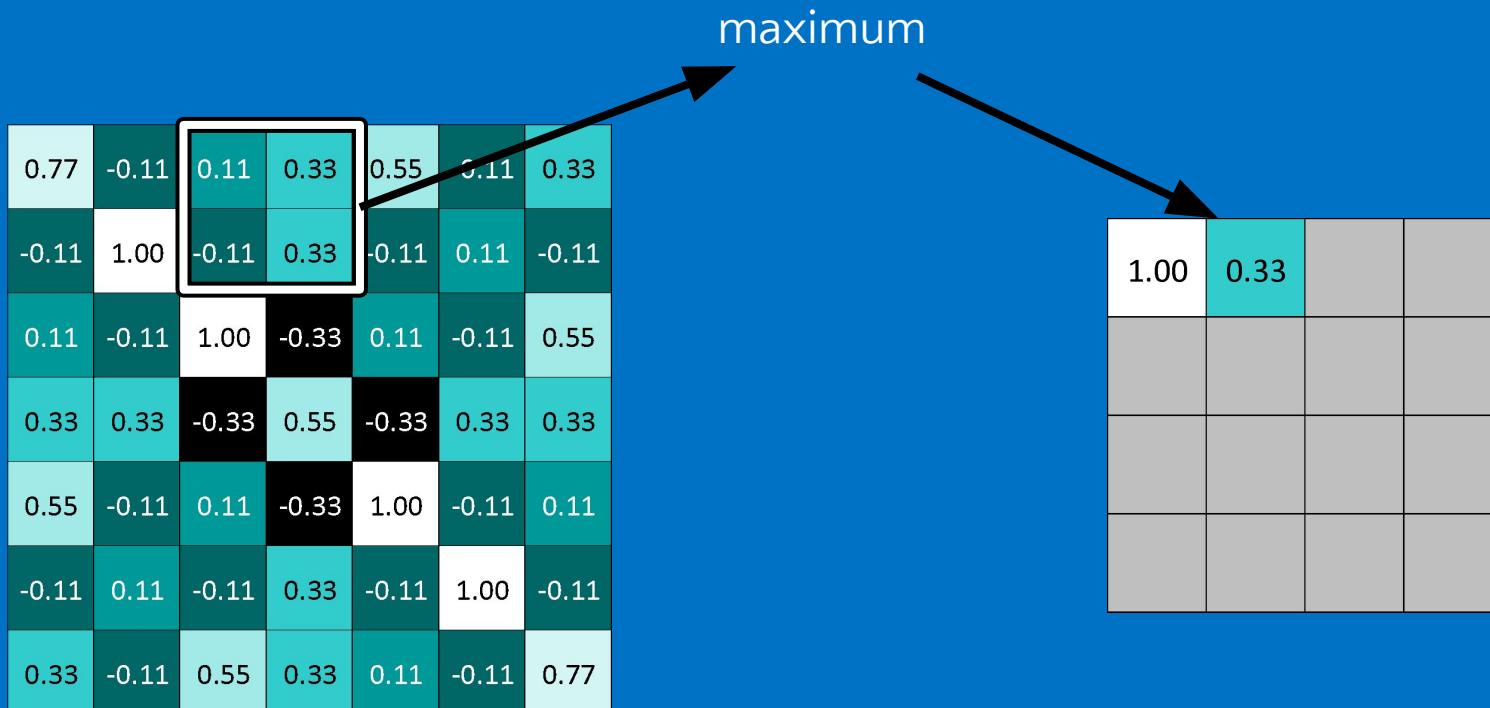
1. Pick a window size (usually 2 or 3).
2. Pick a stride (usually 2).
3. Walk your window across your filtered images.
4. From each window, take the maximum value.

# Pooling (max pooling)



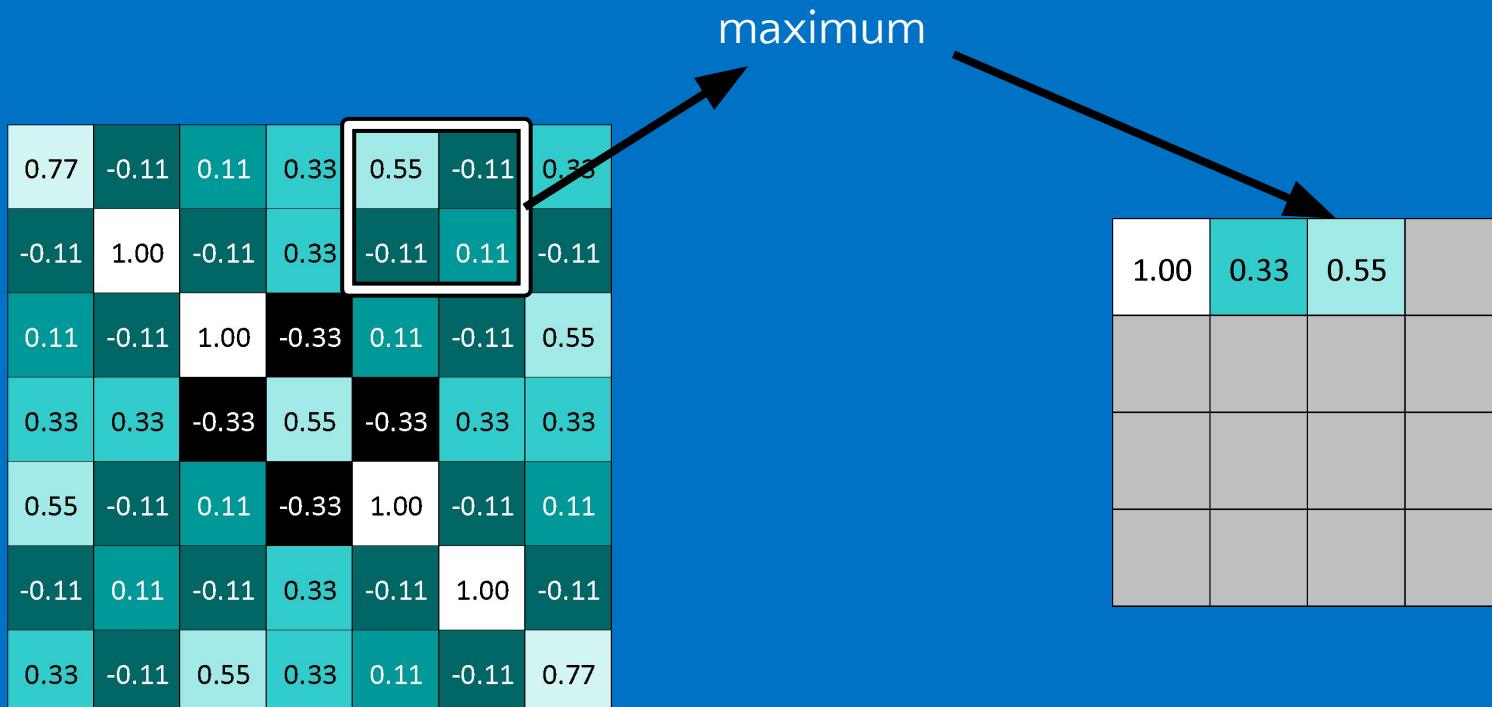
$2 \times 2$ , Stride=2

# Pooling (max pooling)



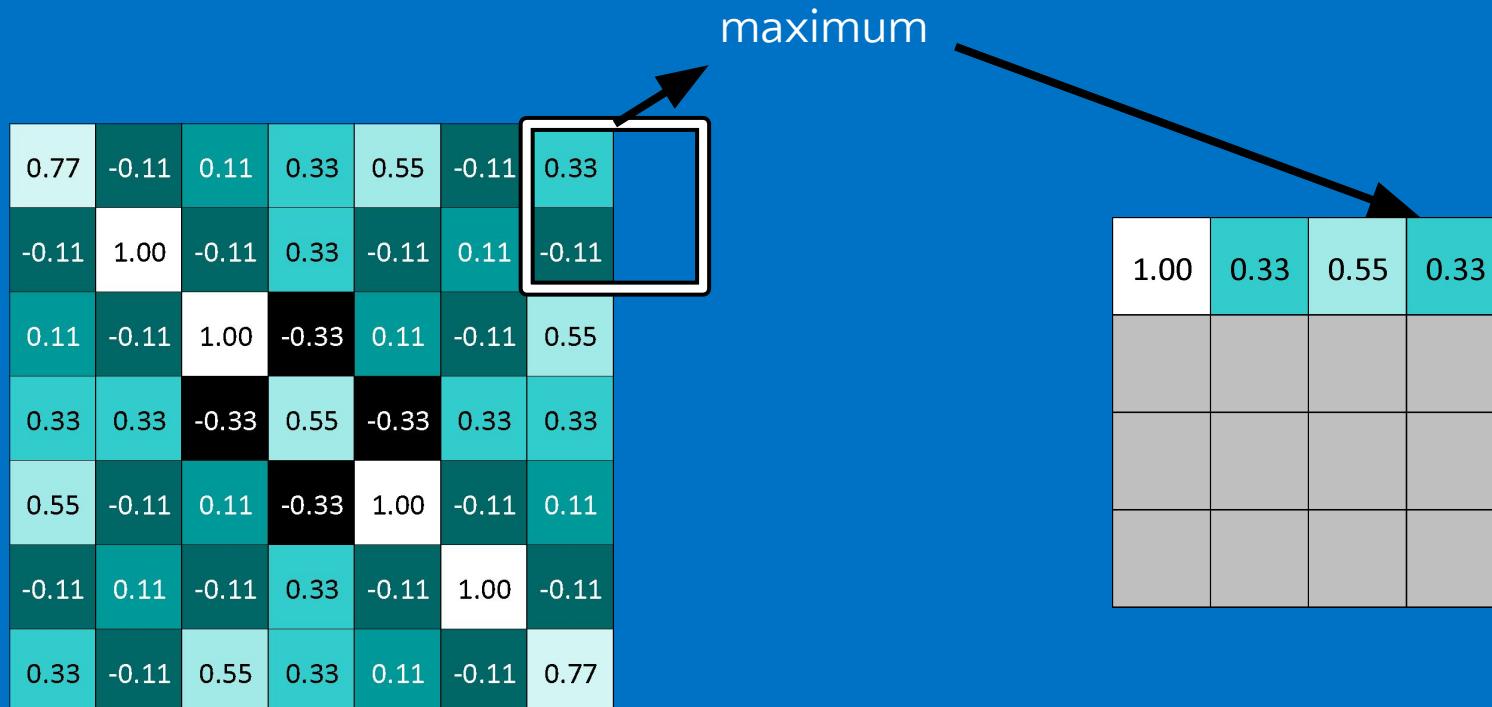
$2 \times 2$ , Stride=2

# Pooling (max pooling)



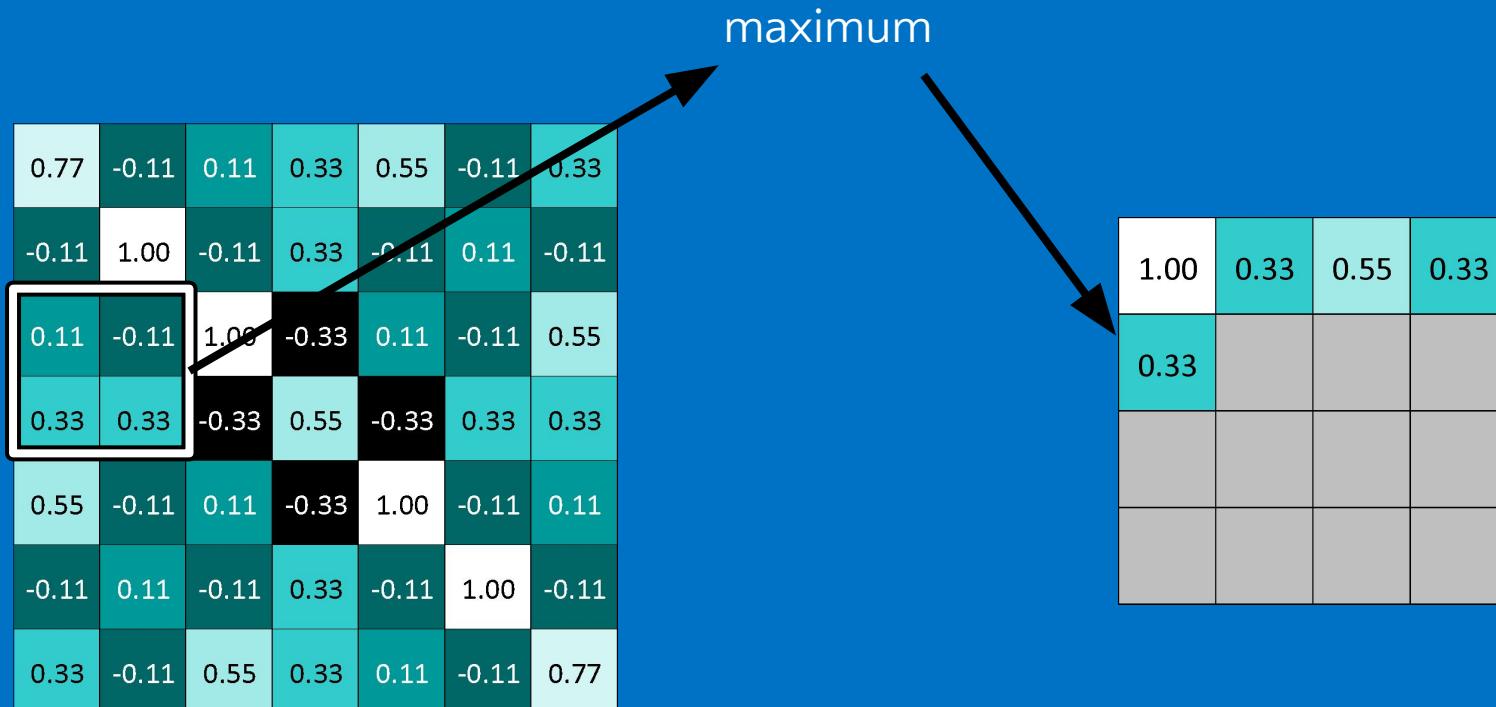
$2 \times 2$ , Stride=2

# Pooling



$2 \times 2$ , Stride=2

# Pooling



$2 \times 2$ , Stride=2

# And a whole max pooling operation

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

2\*2, Stride=2

# Hold up, how does this reduce the # of params?

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

Next layer has  
fewer  
connections!

$2^2$ , Stride=2

# Multiple Filters

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

0.33	-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

0.33	-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

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

0.55	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	0.55	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 layers

- Want to:
  - Reduce dimensions of data, without additional parameters
  - Introduce some local translation invariance
- Pooling operation can be  $\max(0,x)$  or  $\text{average}(x)$

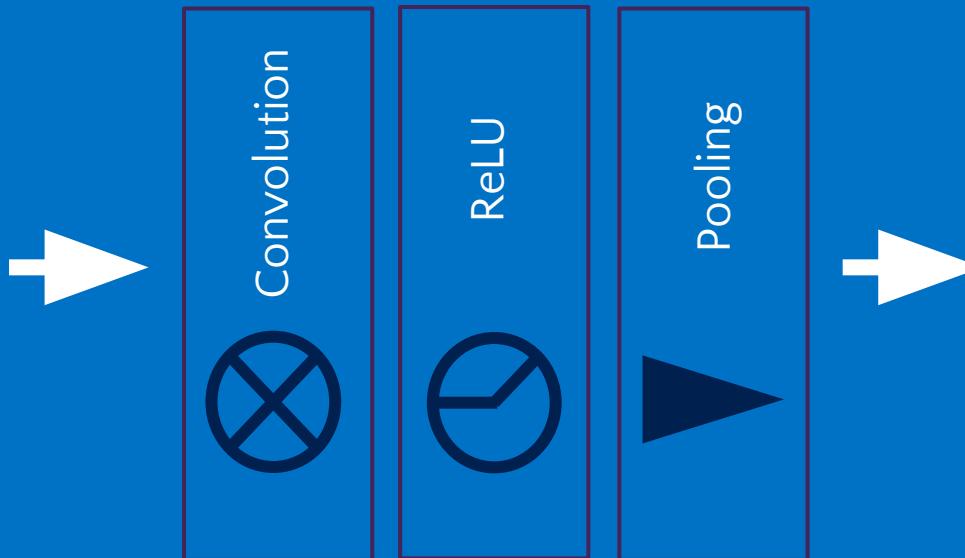
# Putting it all together

# Layers get stacked

So far: not much of a hierarchy

The output of one becomes the input of the next.

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



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

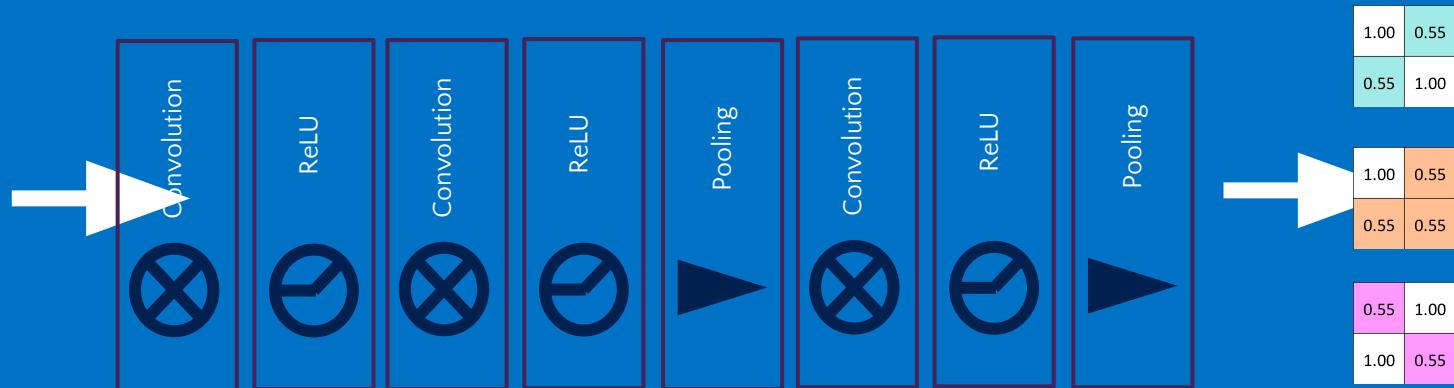
0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

0.33	0.55	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

# Deep stacking

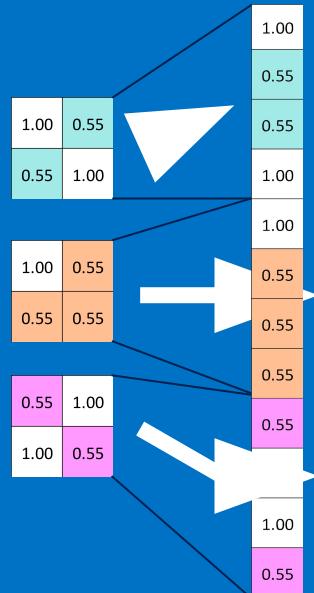
Layers can be repeated several (or many) times.

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



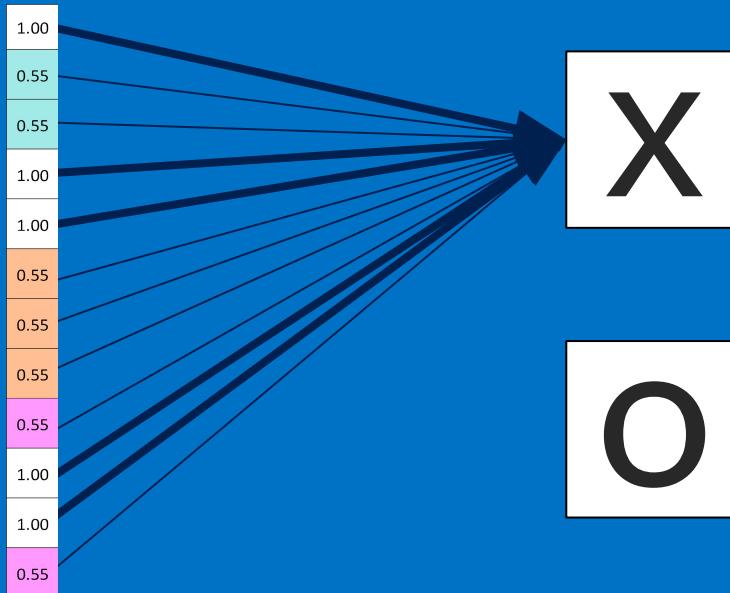
# How to transition to Fully connected layer

Every value gets a vote



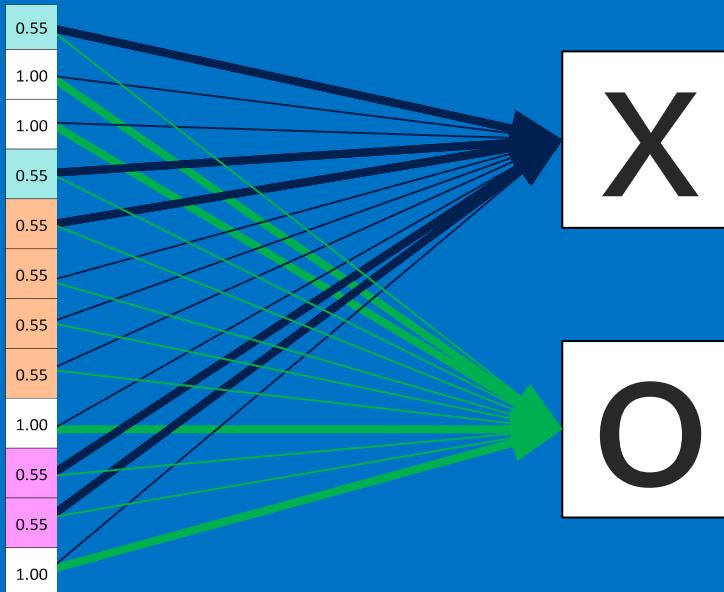
# Fully connected layer

Vote depends on how strongly a value predicts X or O



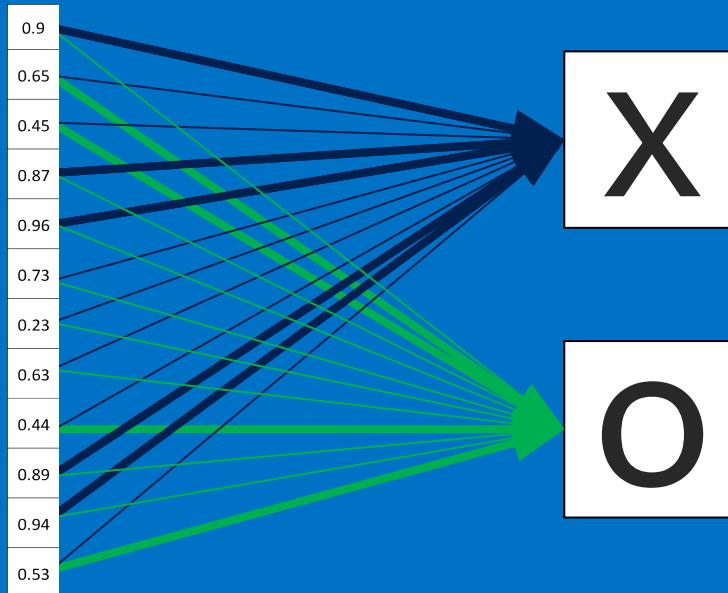
# Fully connected layer

Vote depends on how strongly a value predicts X or O



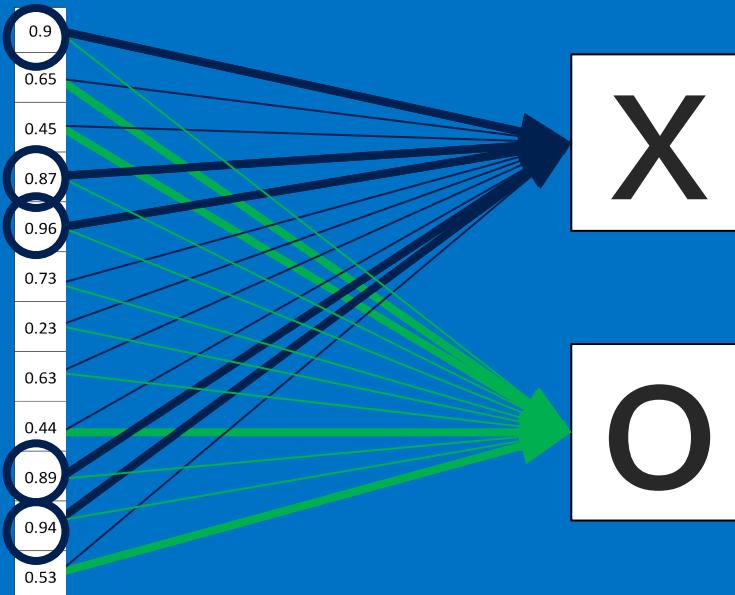
# Fully connected layer

Future values vote on X or O



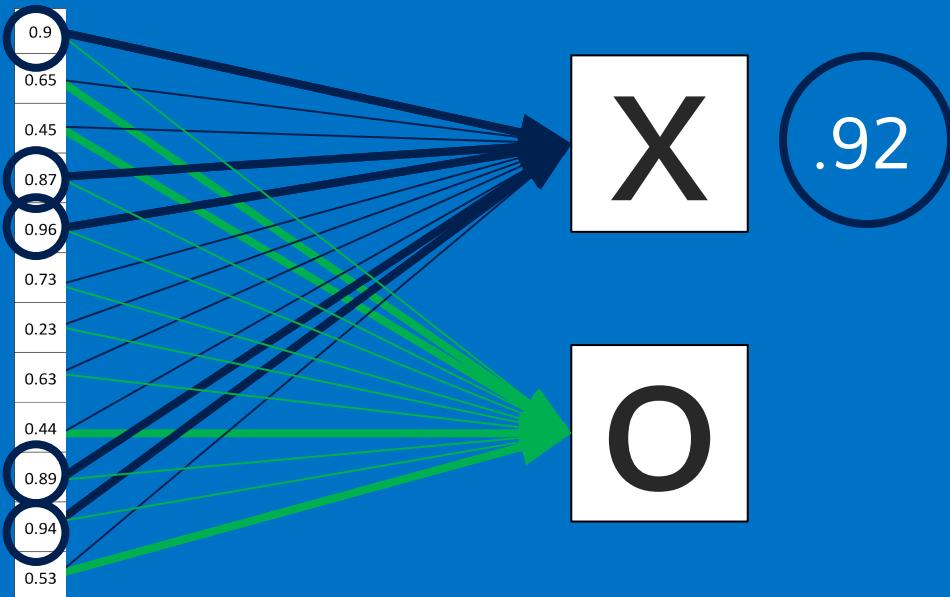
# Fully connected layer

Future values vote on X or O



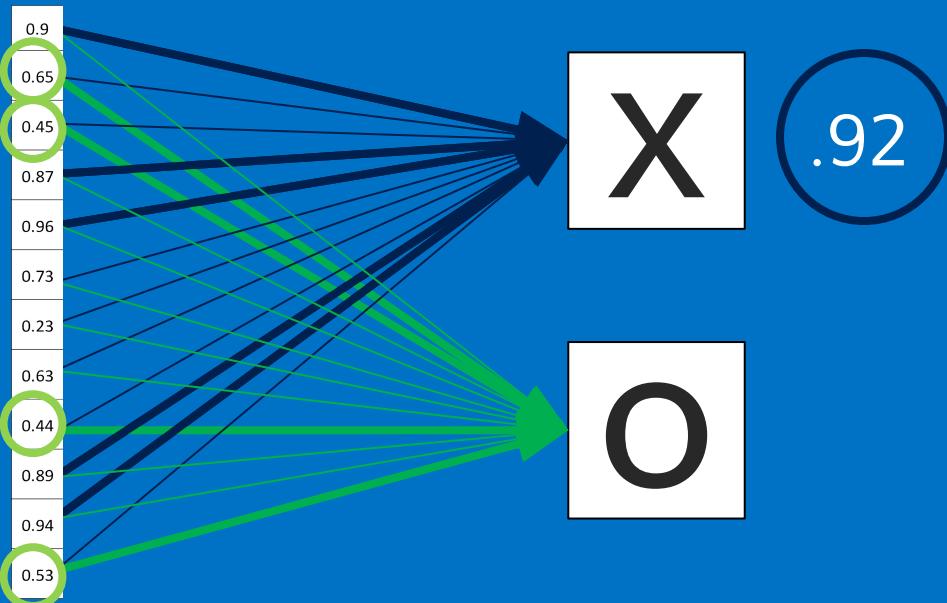
# Fully connected layer

Future values vote on X or O



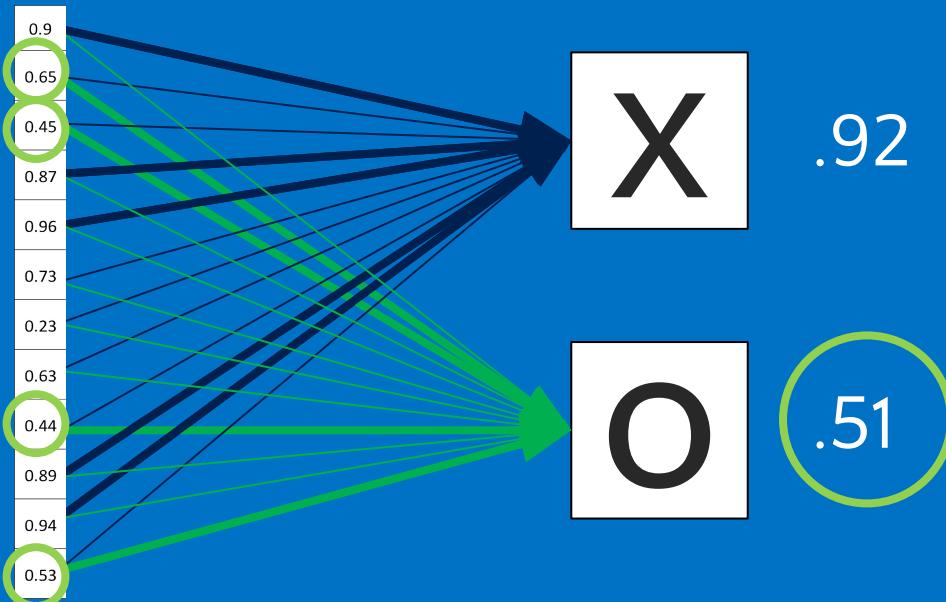
# Fully connected layer

Future values vote on X or O



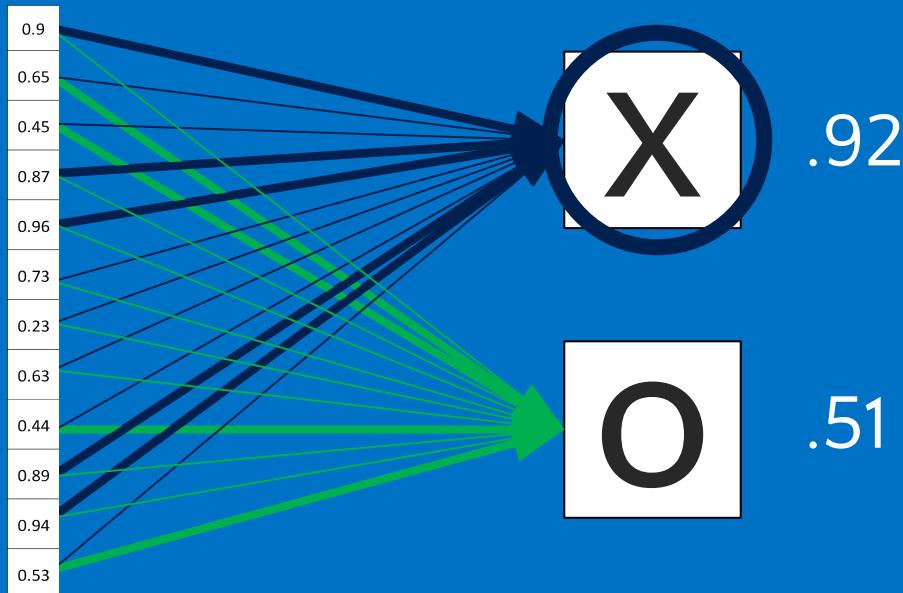
# Fully connected layer

Future values vote on X or O



# Fully connected layer

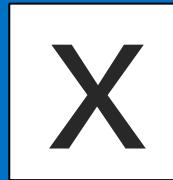
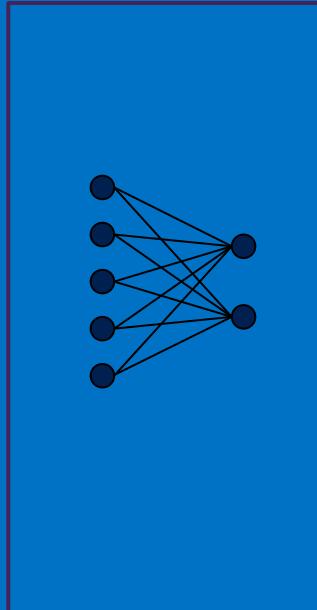
Future values vote on X or O



# Fully connected layer

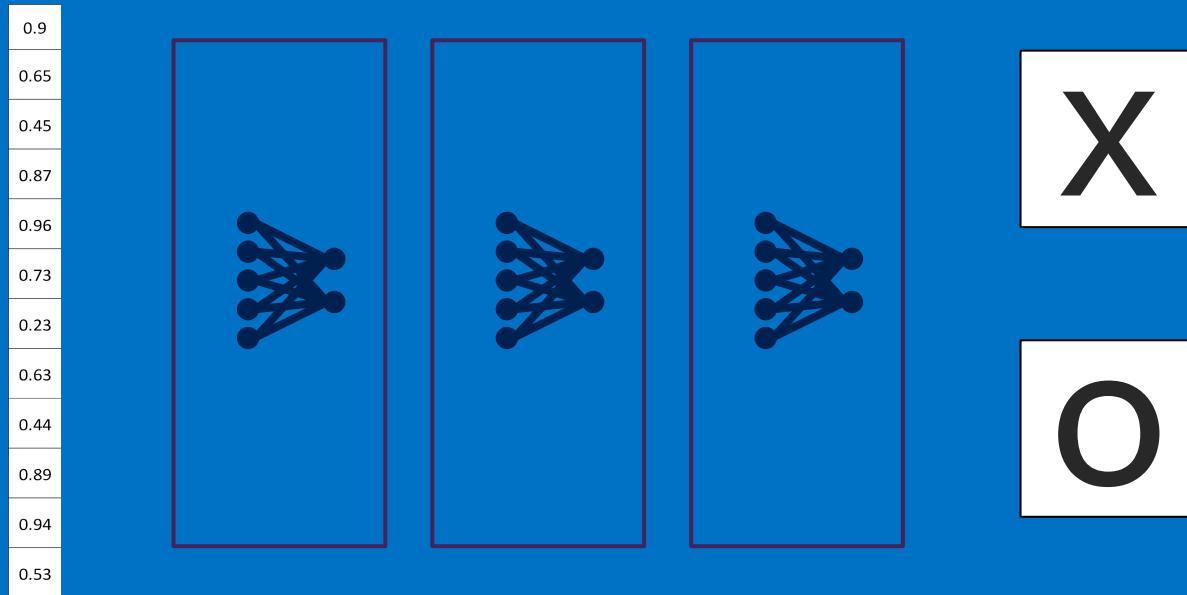
A list of feature values becomes a list of votes.

0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53



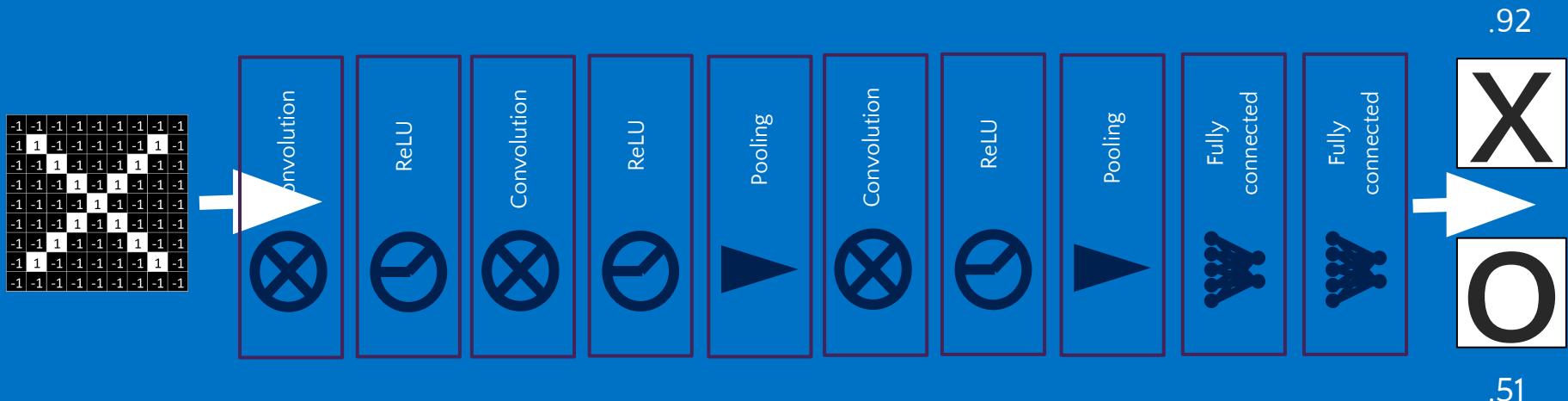
# Fully connected layer

These can also be stacked.

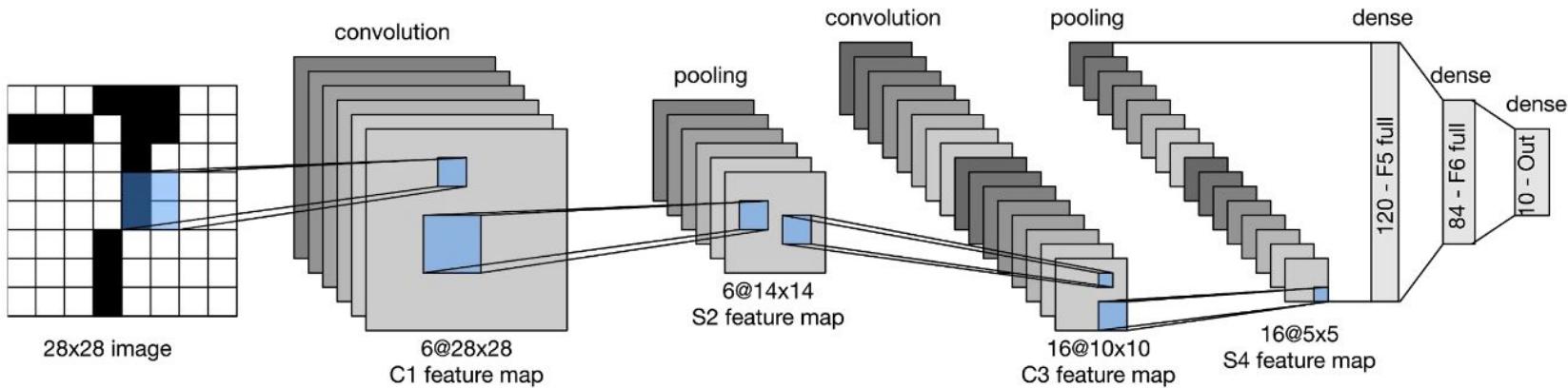


# Putting it all together

A set of pixels becomes a set of votes.



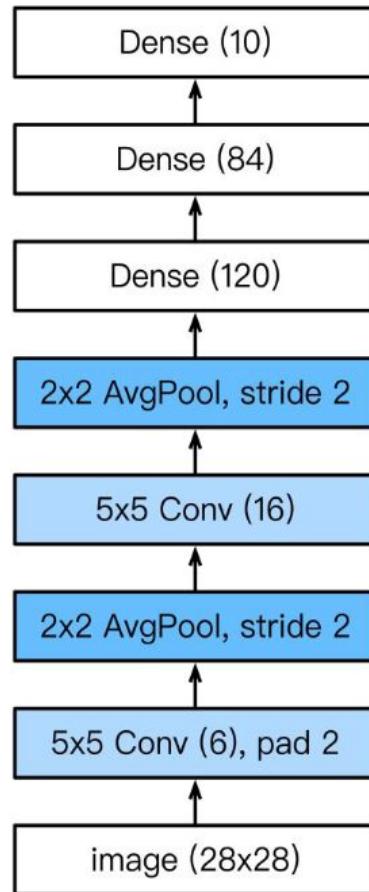
# Putting things together



Input → (Conv → ReLU → Pooling) → ... → Fully connected



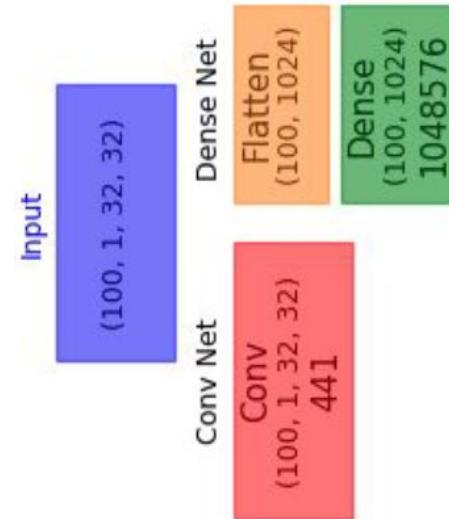
# Another way of visualizing the same network



# Dense vs conv layers

- Now you'll compare the number of parameters in networks that use dense (fully connected) vs convolutional layers

Total Parameters in Dense Layer 1,048,576  
Total Parameters in Conv Layer 441



# Let's implement a CNN!

# Make a network

Now we're going to chain together the components of CNNs that we've been talking about.

- Convolution
- Convolution
- Pool Layer
  - Flatten the output here!
- Fully Connected Layer
- Fully Connected layer

*Practice*  
*Train a CNN*  
*CNN for smile classification*  
*CNN*

# Break

*Practice*

*We give you code. What happens?*

*Run. Learn. Repeat.*



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# Challenges & Next steps!



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# Best part of the day!



**Kahoot!**  
[kahoot.it](https://kahoot.it)



**Any  
questions?**



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Kigali

# THANKS



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*coming soon*



*coming soon*