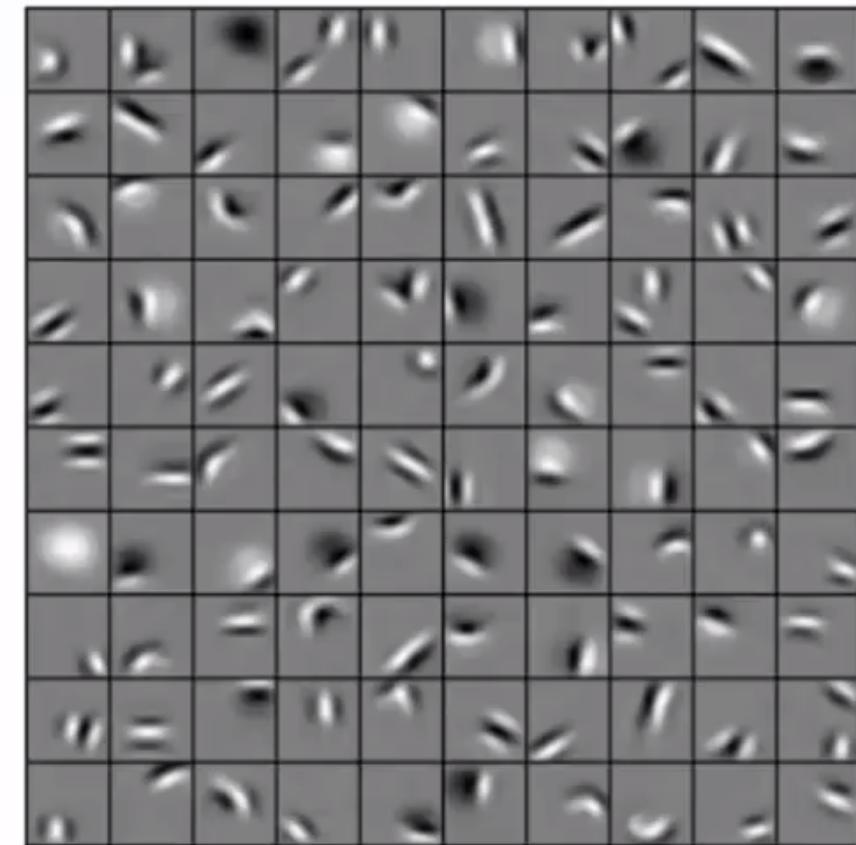
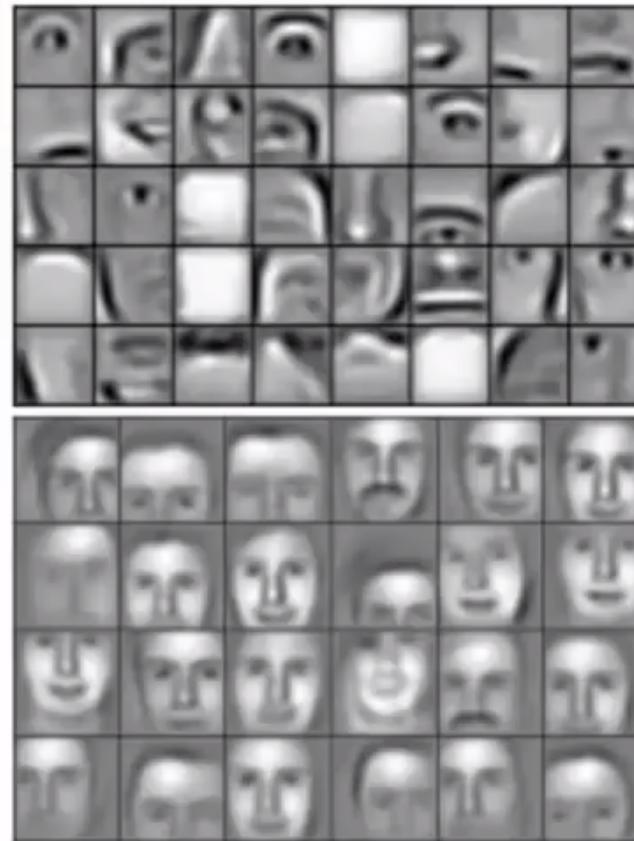


How Convolutional Neural Networks Work

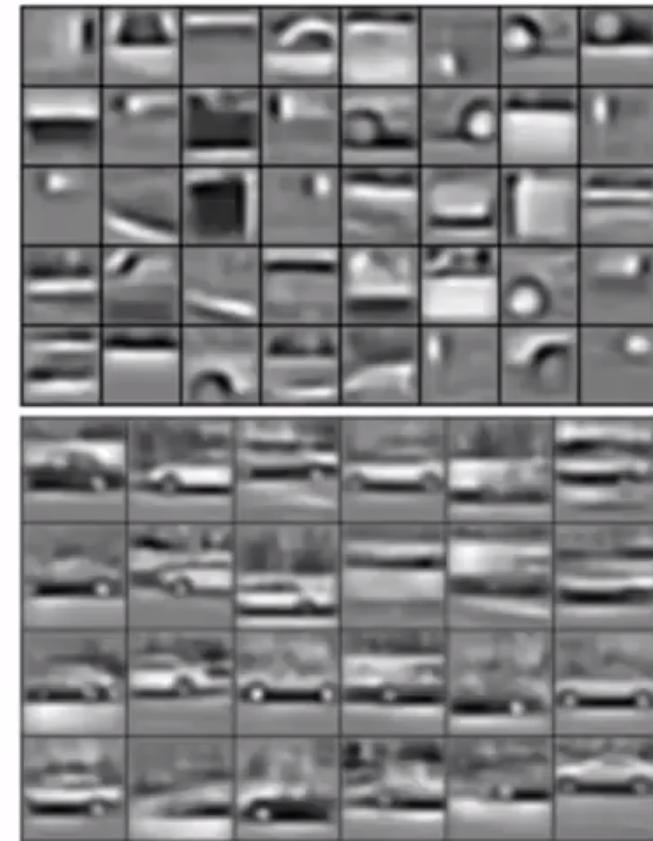




faces



cars

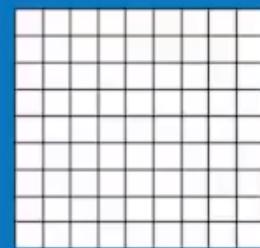


Convolutional Deep Belief Networks for Scalable
Unsupervised Learning of Hierarchical Representations
Honglak Lee, Roger Grosse, Rajesh Ranganath,
Andrew Y. Ng

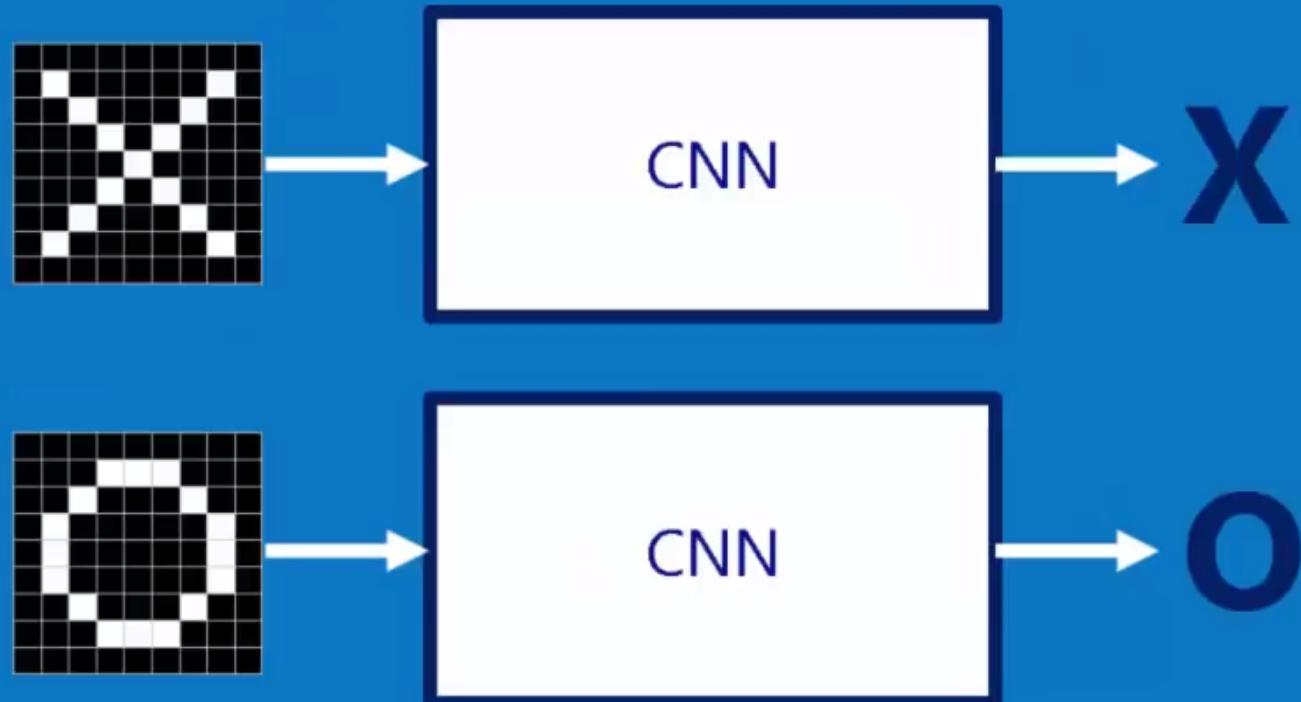
A toy ConvNet: X's and O's

Says whether a picture is of an X or an O

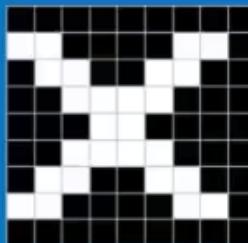
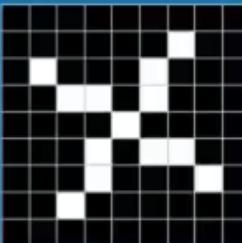
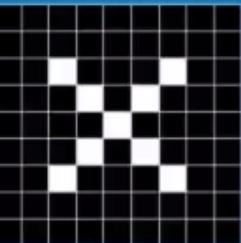
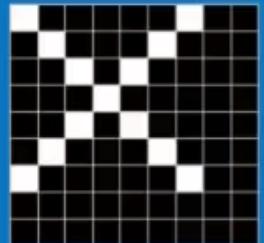
A two-dimensional
array of pixels



For example



Trickier cases

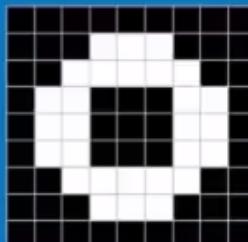
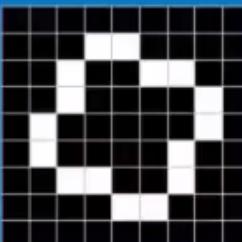
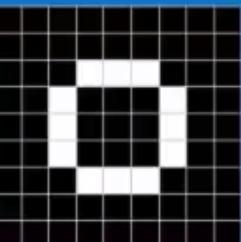


translation

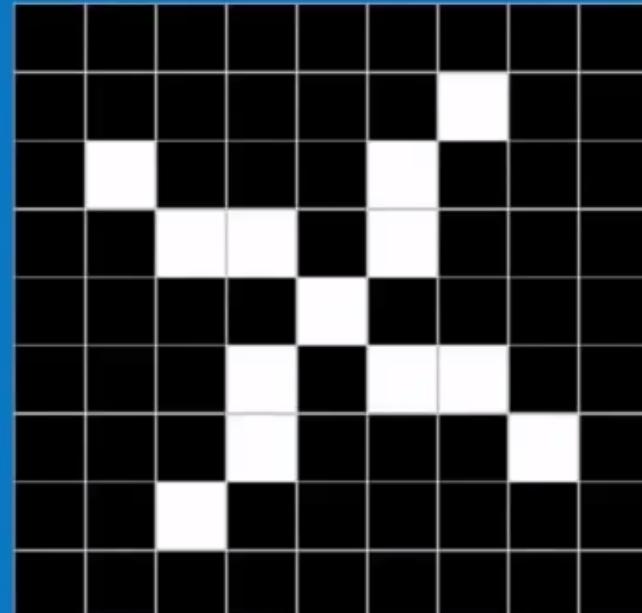
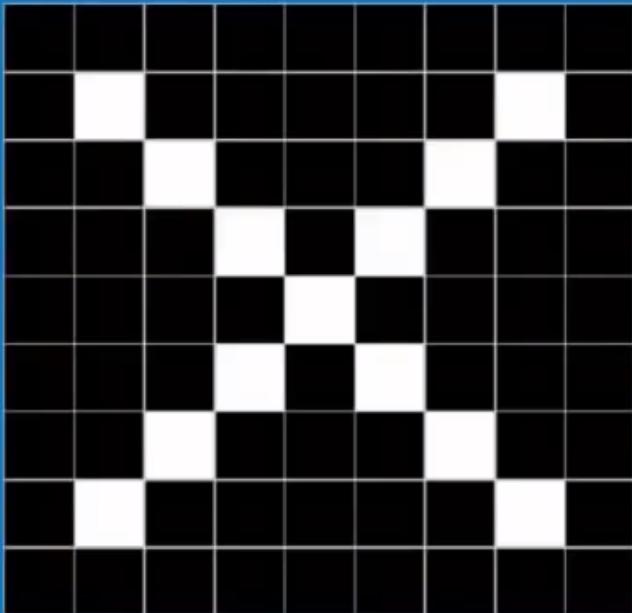
scaling

rotation

weight



Deciding is hard



What computers see

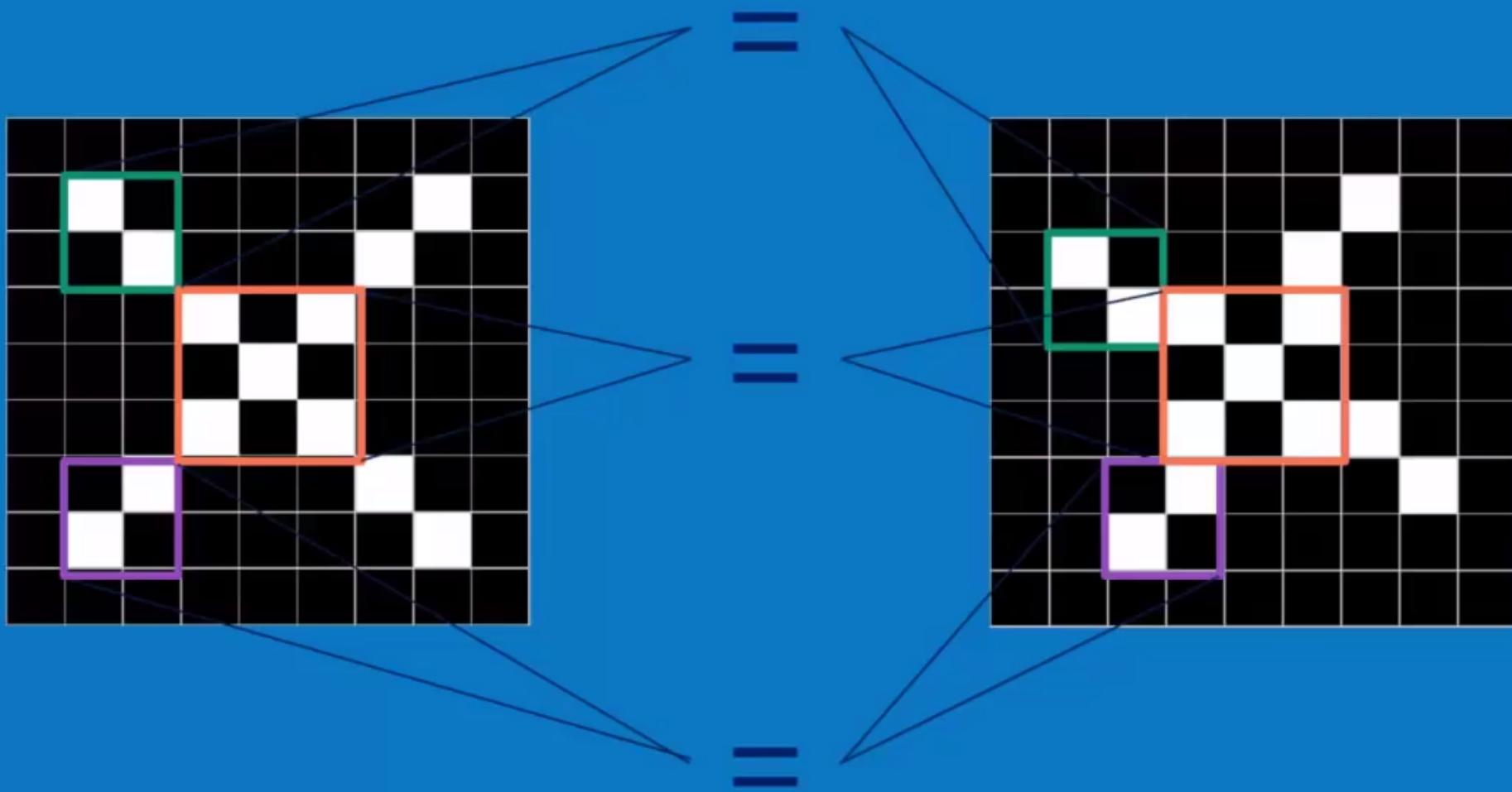
?

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

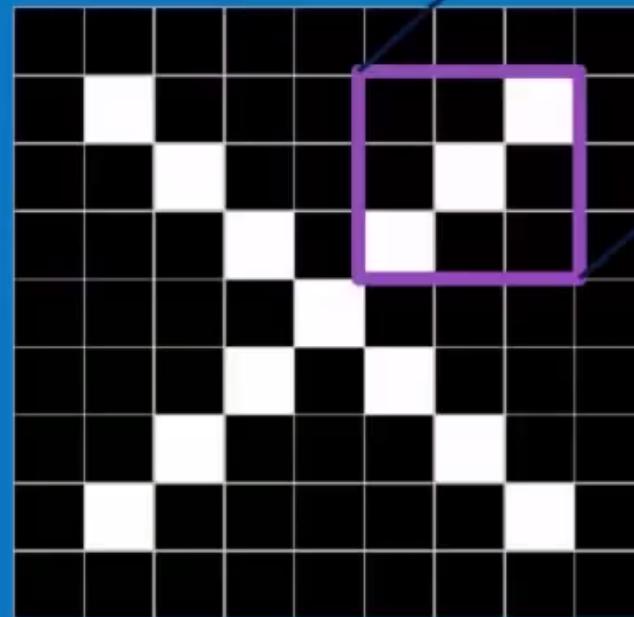
1	-1	1
-1	1	-1
1	-1	1

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

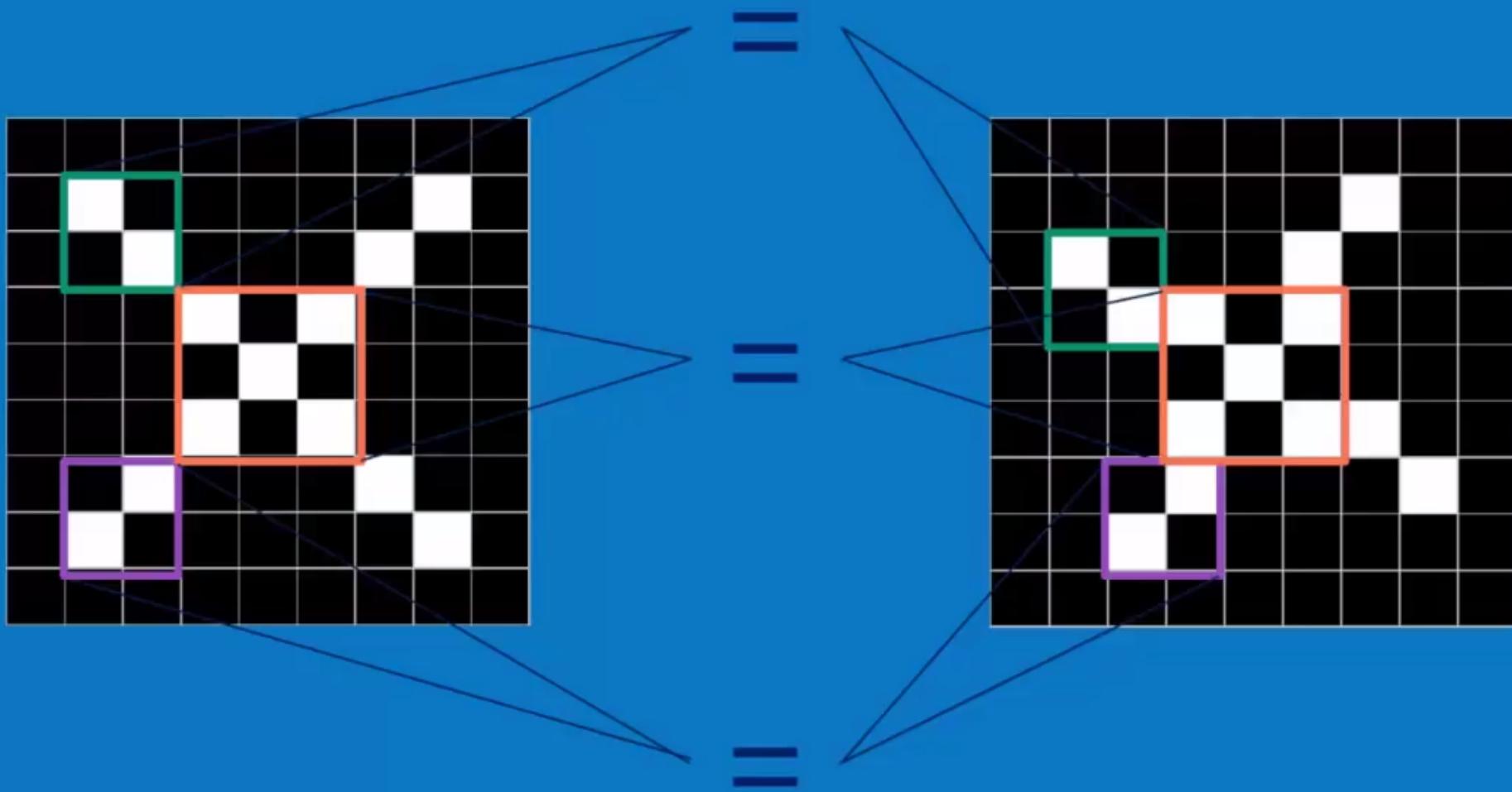
1	-1	-1
-1	1	-1
-1	-1	1

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

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



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

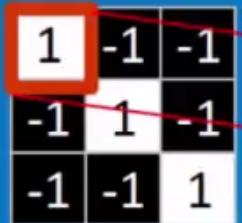
Filtering: The math behind the match

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

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



$$1 \times 1 = 1$$

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	

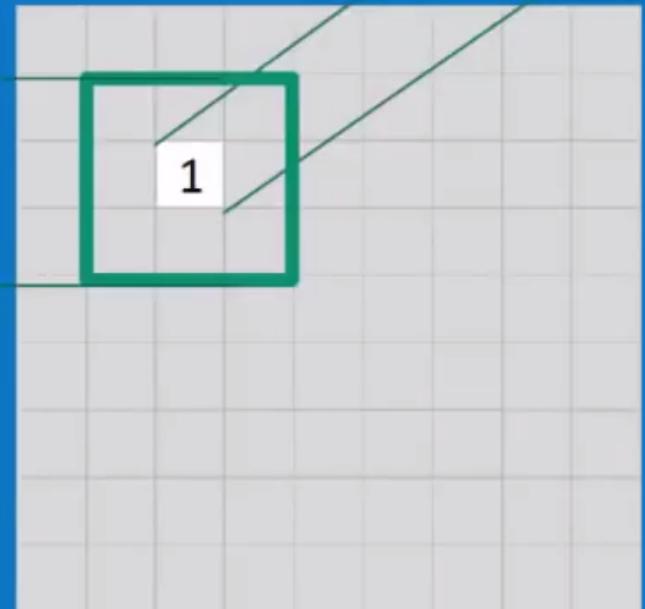
Filtering: The math behind the match

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

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

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

1	1	-1
1	1	1
-1	1	1

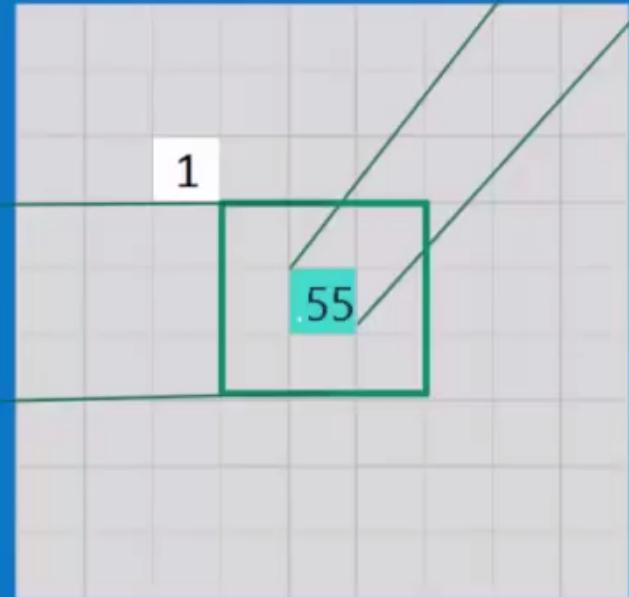
Filtering: The math behind the match

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



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

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



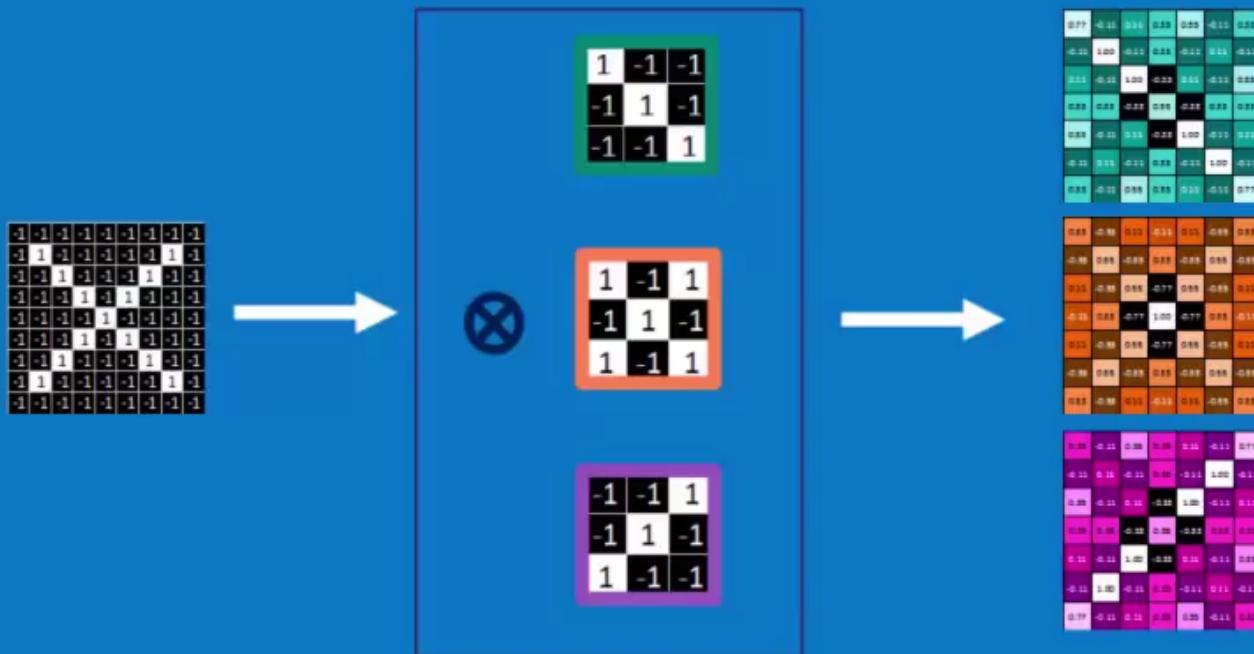
-1	-1	1
-1	1	-1
1	-1	-1

=

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



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

0.77	-0.11	0.11	0.35	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



Pooling



Pooling



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

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

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

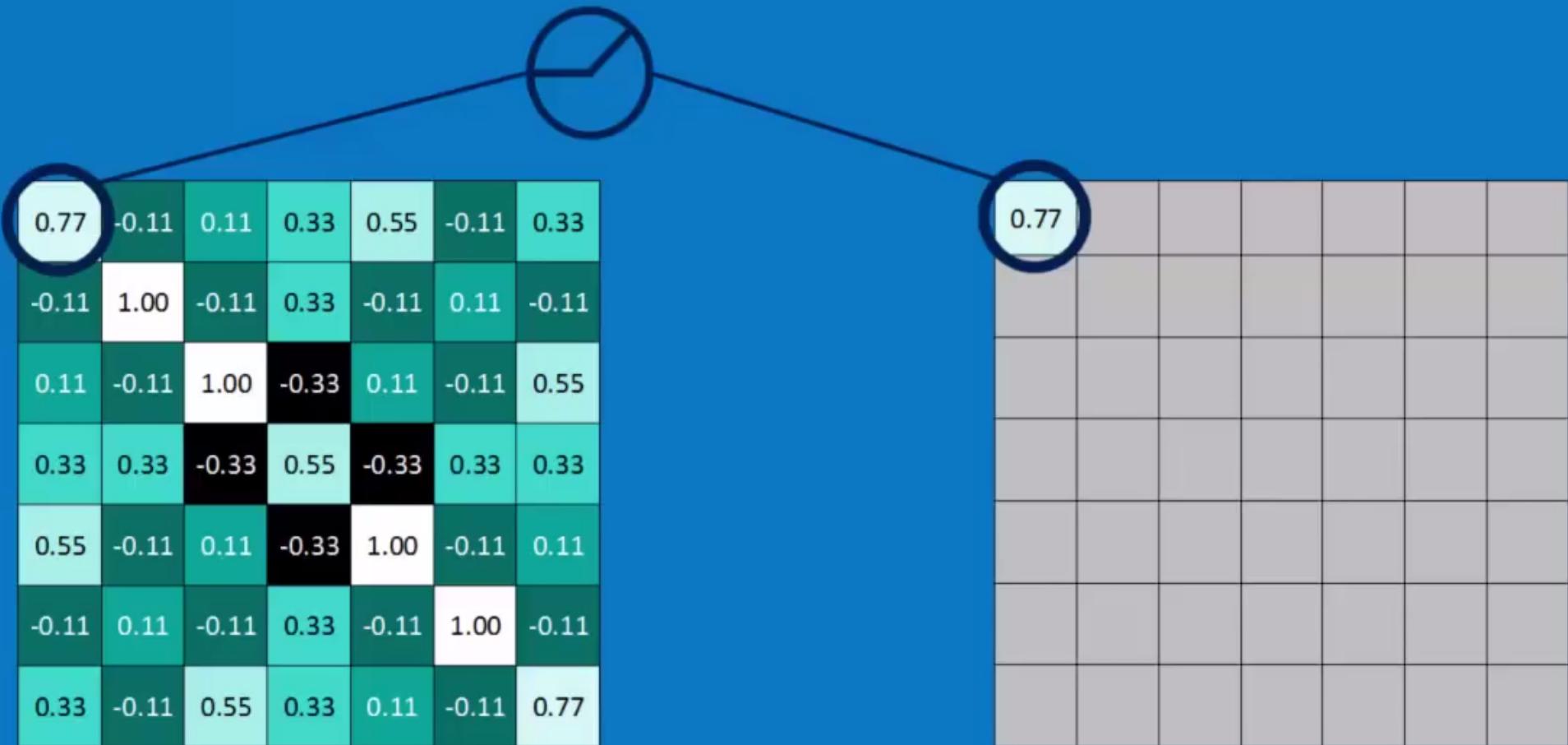
0.33	0.55	1.00	0.77
0.55	0.55	1.00	0.33
1.00	1.00	0.11	0.55
0.77	0.33	0.55	0.33

Normalization

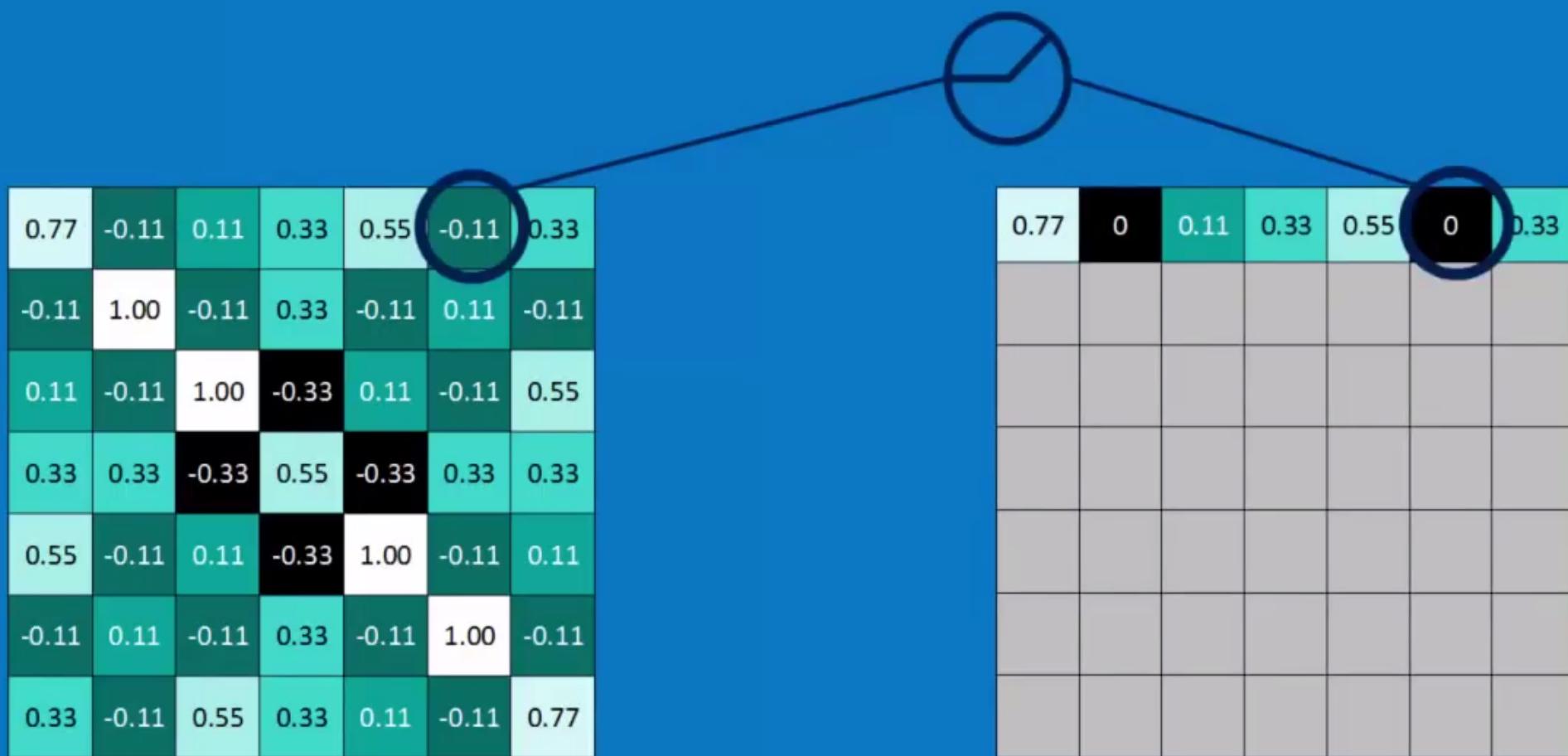
Keep the math from breaking by tweaking each of the values just a bit.

Change everything negative to zero.

Rectified Linear Units (ReLUs)



Rectified Linear Units (ReLUs)



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	0.31	0.38	-0.11	0.34
-0.11	1.00	-0.11	0.31	-0.11	0.34	-0.11
0.11	-0.11	1.00	-0.31	0.31	-0.11	0.38
0.31	0.38	-0.31	0.31	-0.31	0.34	0.31
0.38	-0.31	0.11	-0.31	1.00	-0.11	0.31
-0.11	0.11	-0.11	0.31	-0.11	1.00	-0.11
0.38	-0.11	0.38	0.31	0.31	-0.11	0.77

0.11	-0.33	0.11	-0.11	0.11	-0.33	0.11
-0.33	0.33	-0.33	0.33	-0.33	0.33	-0.33
0.11	-0.55	0.33	-0.77	0.55	-0.55	0.31
-0.33	0.33	-0.77	1.00	-0.77	0.11	0.33
0.11	-0.55	0.33	-0.77	0.33	-0.55	0.11
-0.33	0.33	-0.55	0.48	-0.33	0.57	-0.33
0.11	-0.33	0.11	0.11	0.11	-0.33	0.11

0.11	-0.11	0.33	0.11	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.23	-0.11	1.00	0.11
0.33	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.11	0.11	-0.33	0.23	-0.33	0.33	0.11
0.11	-0.11	1.00	0.23	0.11	-0.11	0.23
-0.11	1.00	-0.11	0.23	-0.11	0.11	0.11
0.77	-0.11	0.11	0.33	0.33	-0.11	0.11



0.77	0	0.11	0.23	0.38	0	0.33
0	1.00	0	0.33	0	0.31	0
0.11	0	1.00	0	0.11	0	0.33
0.23	0.33	0	0.23	0	0.33	0.23
0.38	0	0.31	0	1.00	0	0.11
0	0.33	0	0.33	0	1.00	0
0.33	0	0.34	0.23	0.33	0	0.77

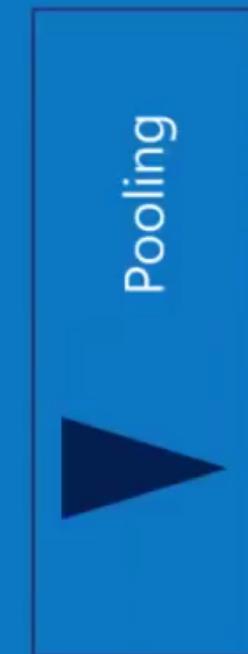
0.23	0	0.11	0	0.11	0	0.23
0	0.39	0	0.33	0	0.39	0
0.11	0	0.33	0	0.39	0	0.11
0.23	0	0.33	0	0.33	0	1.00
0.11	0	0.33	0	0.39	0	0.11
0	0.33	0	0.33	0	0.39	0
0.23	0	0.11	0	0.11	0	0.23

0.11	0	0.11	0.11	0.11	0	0.77
0	0.11	0	0.11	0	1.00	0
0.11	0	0.11	0	0.11	0	0.11
0.11	0.11	0	0.11	0	0.11	0.11
0.11	0	1.00	0	0.11	0	0.11
0	1.00	0	0.11	0	0.11	0
0.77	0	0.11	0.11	0.11	0	0.11

Layers get stacked

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	



1.00	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

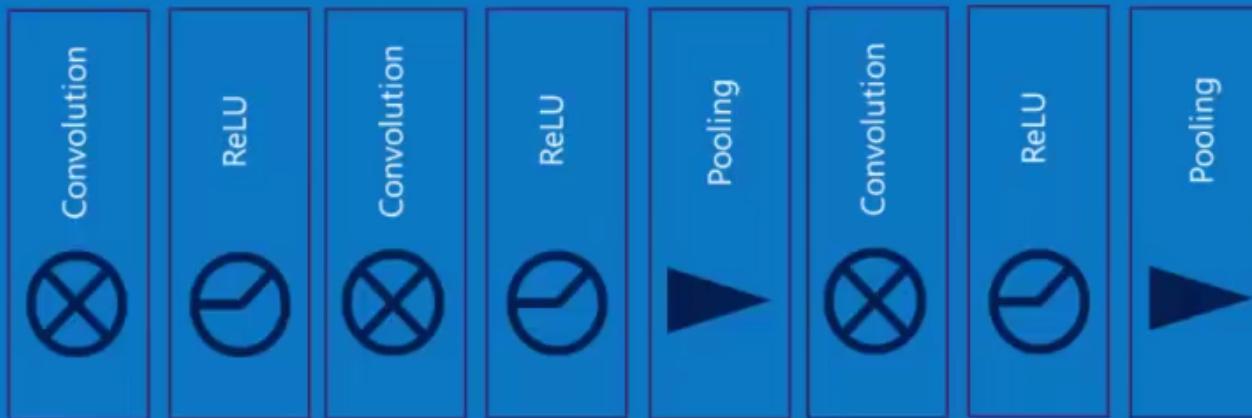
0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

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.

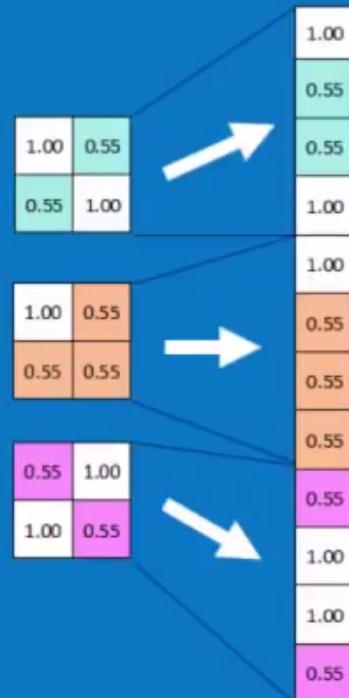
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1



1.00	0.55
0.55	1.00
1.00	0.55
0.55	0.55
0.55	1.00
1.00	0.55

Fully connected layer

Every value gets a vote



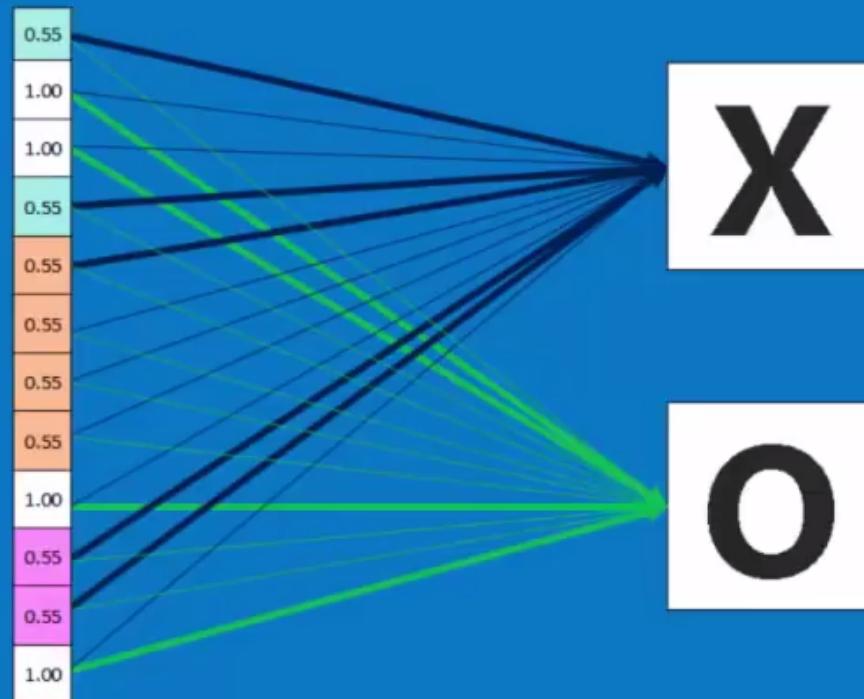
Fully connected layer

Vote depends on how strongly a value predicts X or O



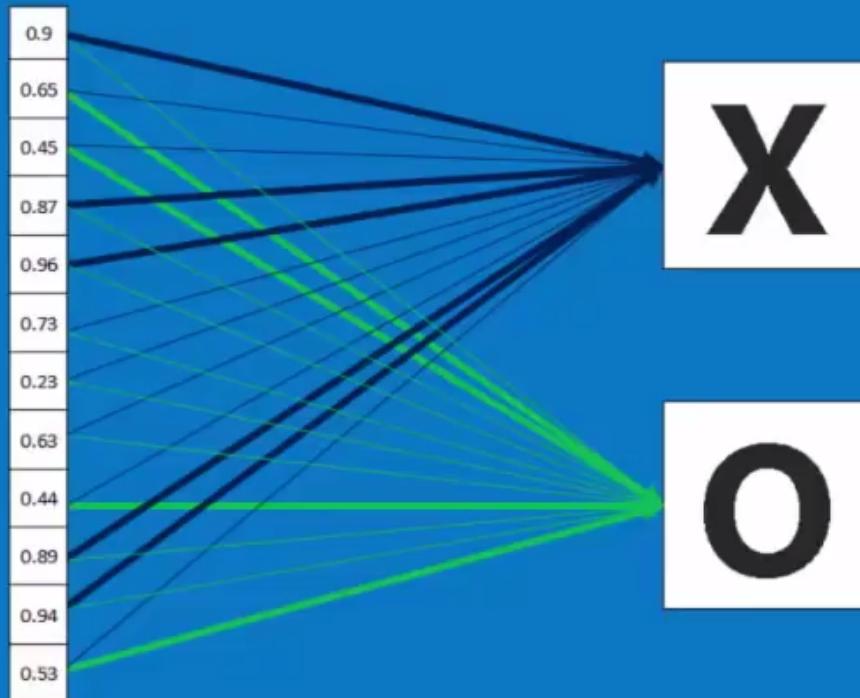
Fully connected layer

Vote depends on how strongly a value predicts X or O



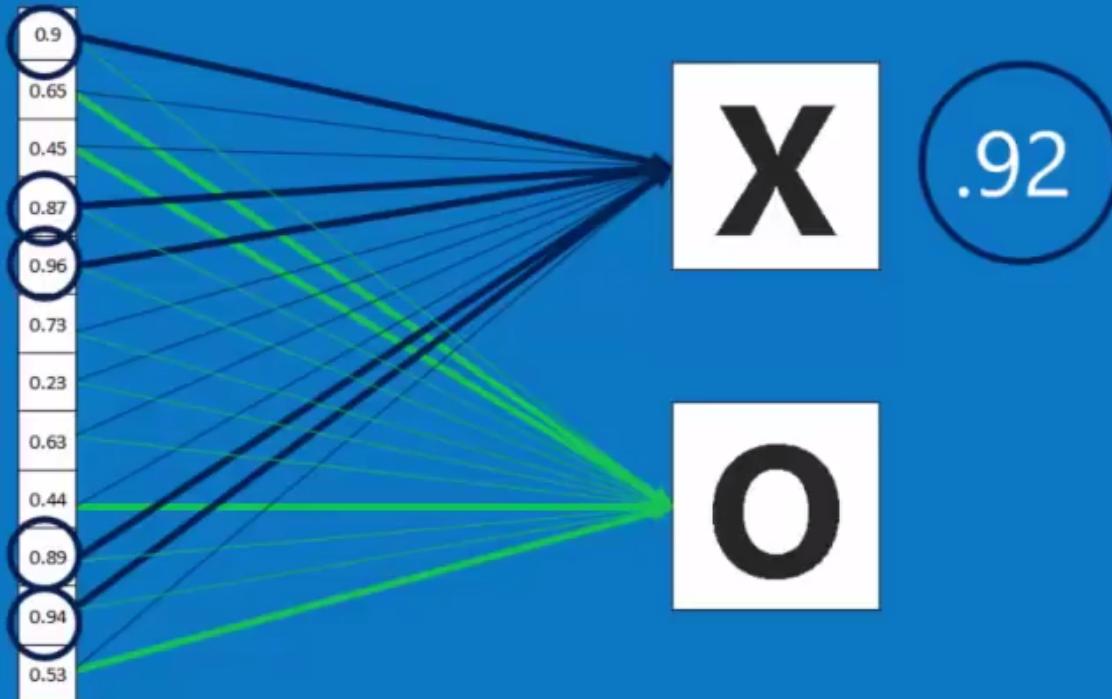
Fully connected layer

Future values vote on X or O



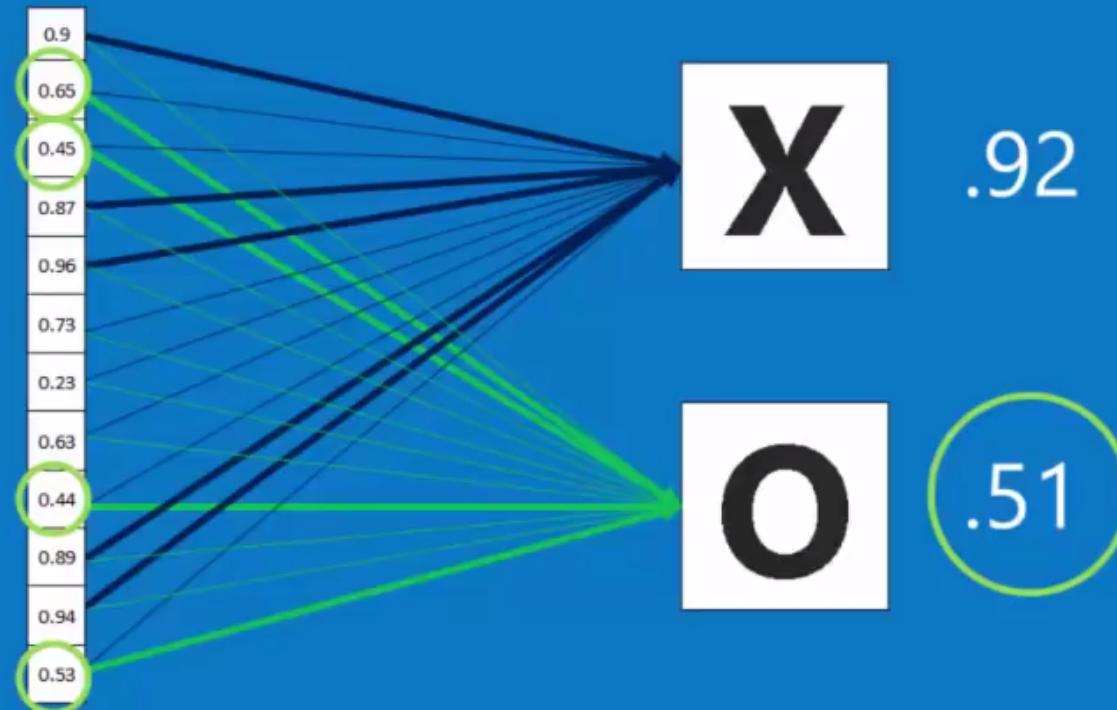
Fully connected layer

Future values vote on X or O



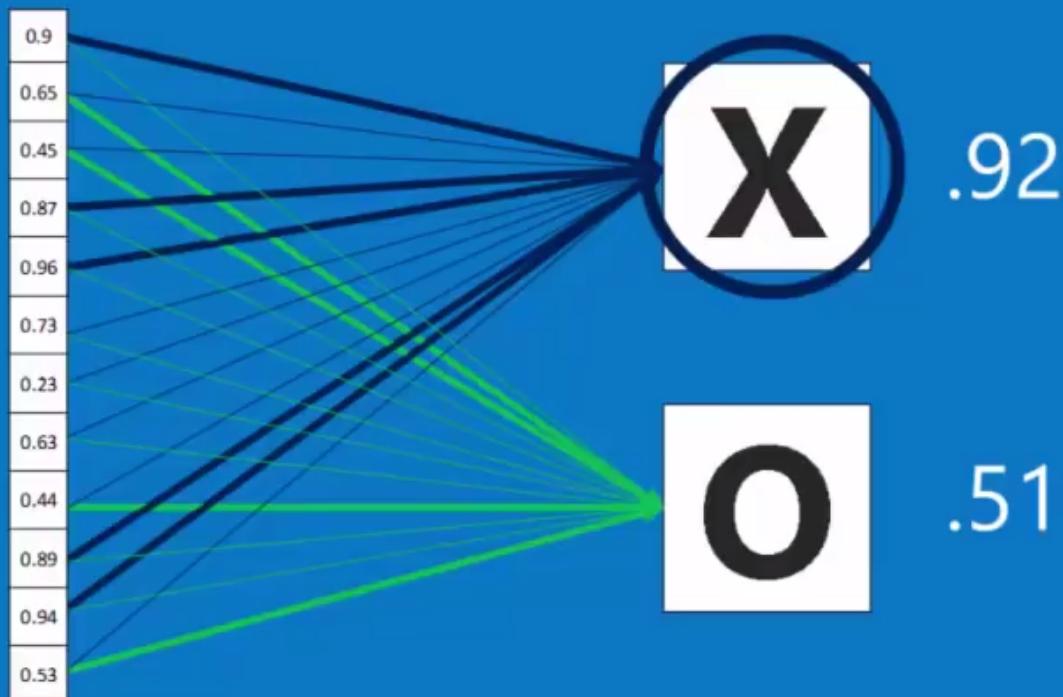
Fully connected layer

Future values vote on X or O



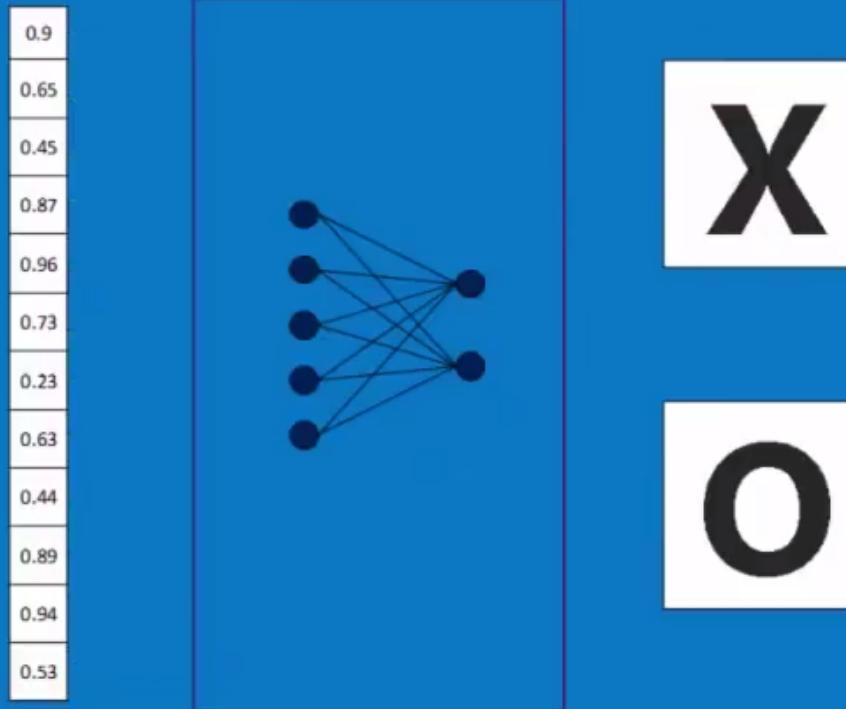
Fully connected layer

Future values vote on X or O



Fully connected layer

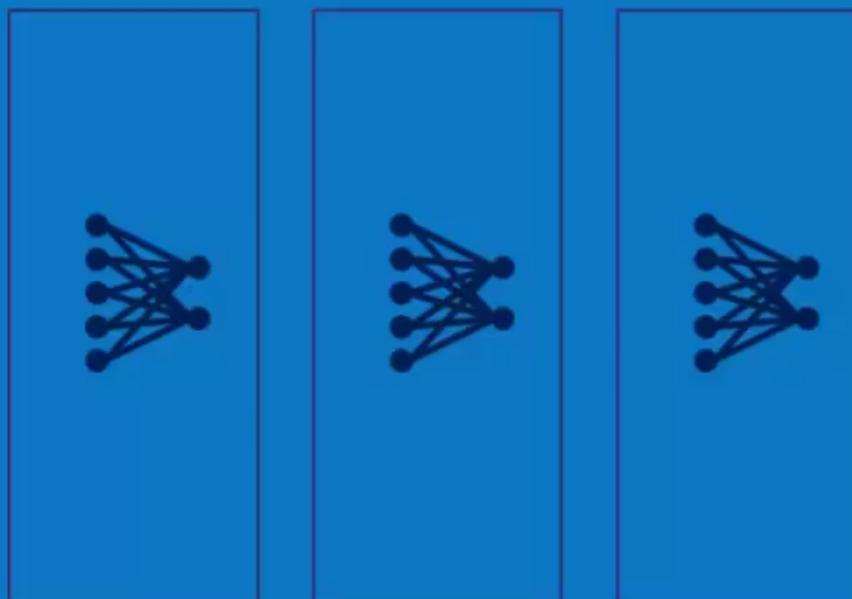
A list of feature values becomes a list of votes.



Fully connected layer

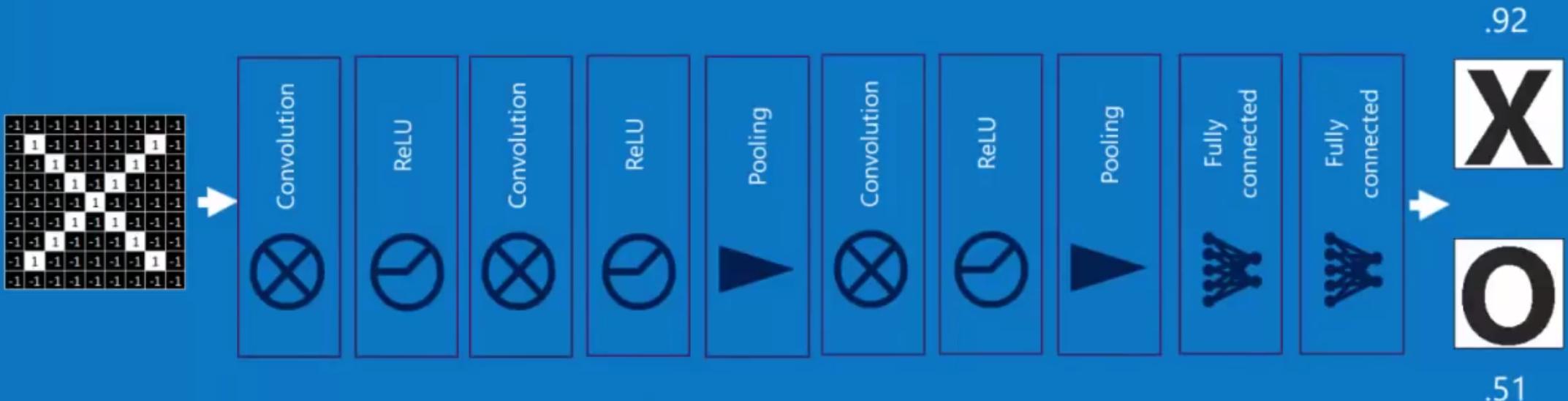
These can also be stacked.

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



Putting it all together

A set of pixels becomes a set of votes.



Learning

Q: Where do all the magic numbers come from?

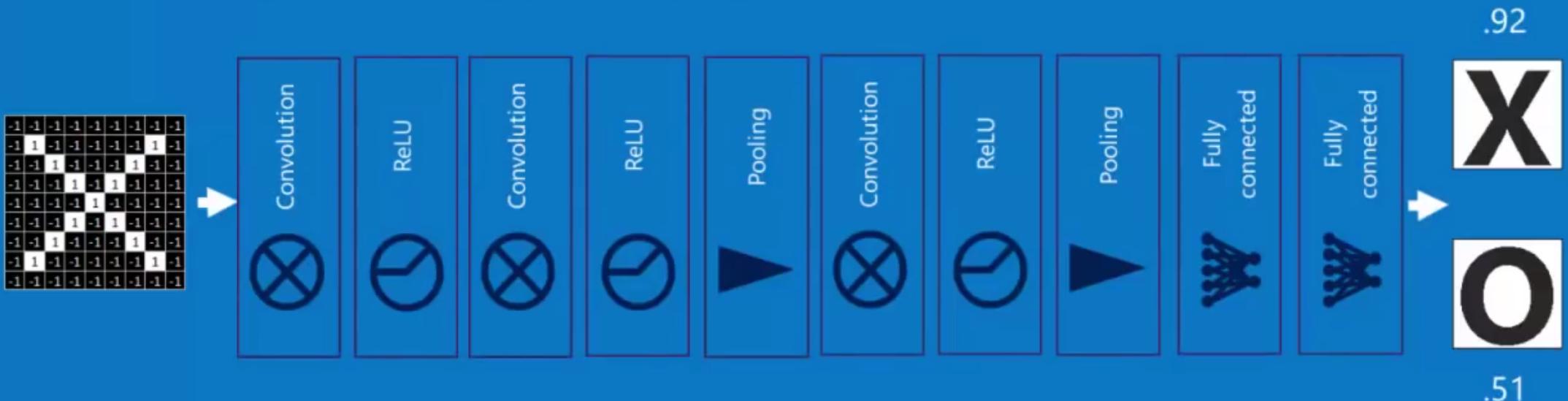
Features in convolutional layers

Voting weights in fully connected layers

A: Backpropagation

Backprop

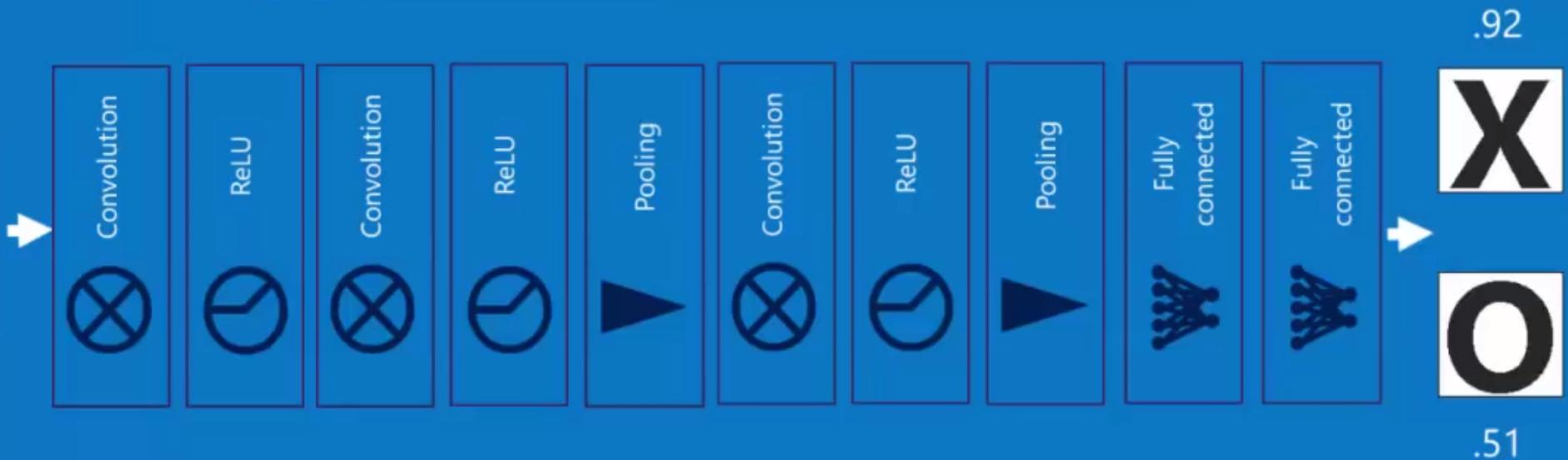
Error = right answer – actual answer



Backprop

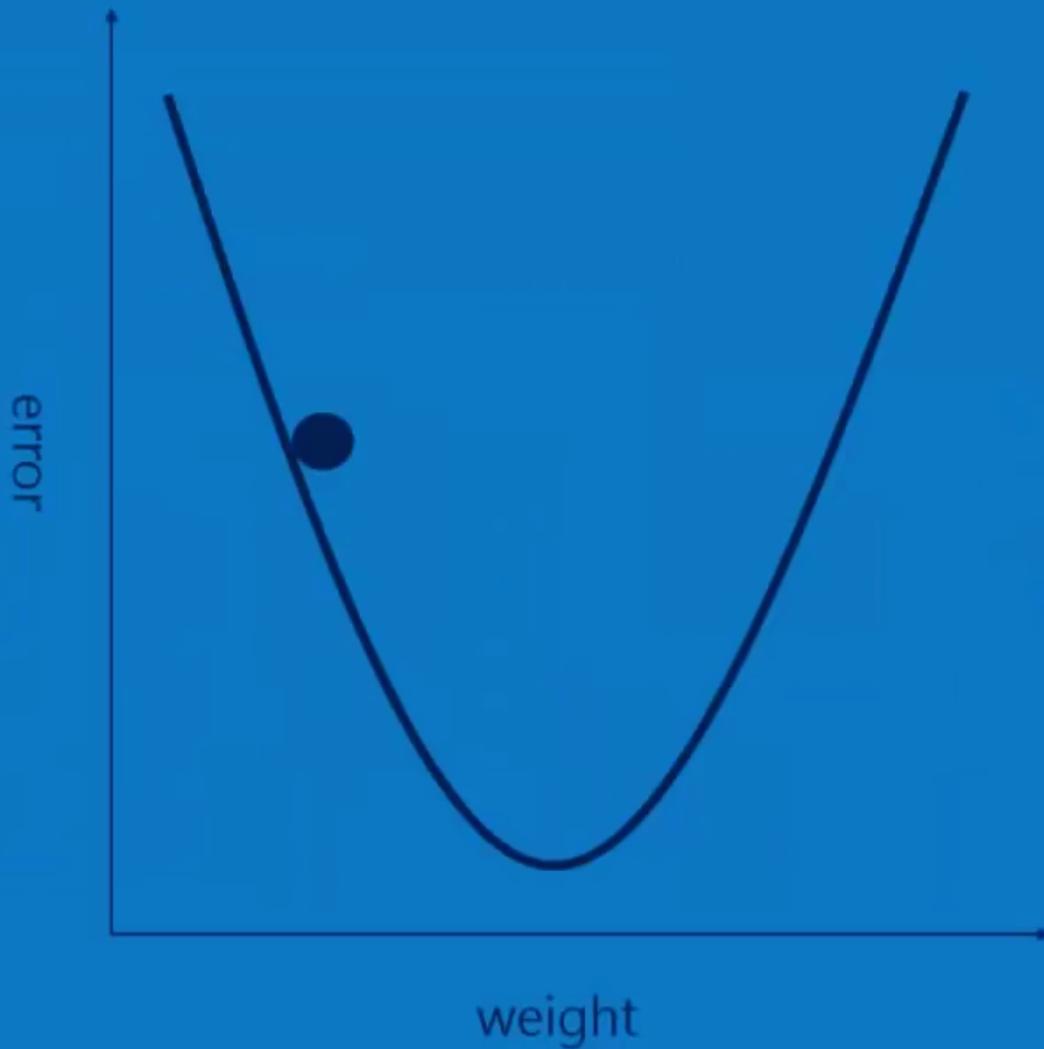
	Right answer	Actual answer	Error
X	1	0.92	0.08
O	0	0.51	0.49
Total			0.57

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



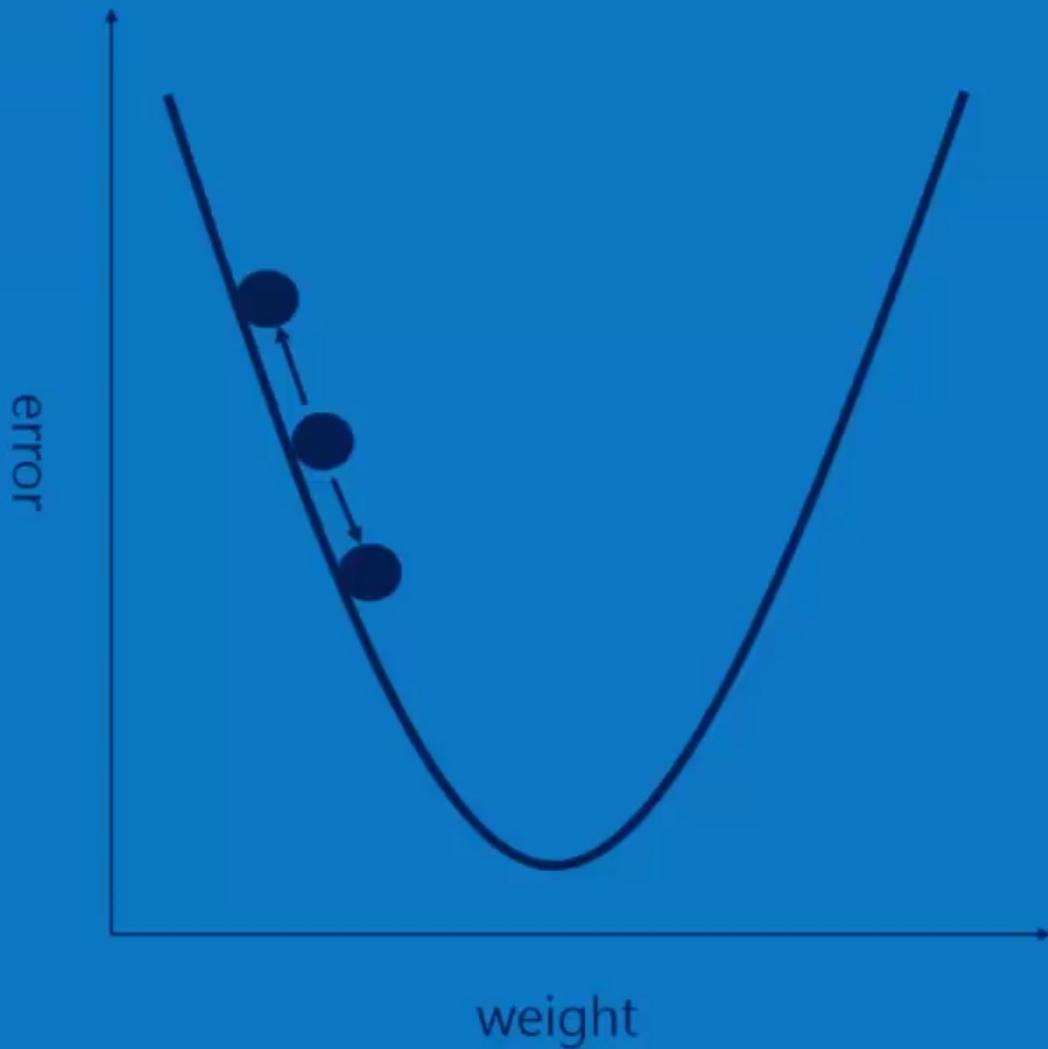
Gradient descent

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



Gradient descent

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



Hyperparameters (knobs)

Convolution

Number of features

Size of features

Pooling

Window size

Window stride

Fully Connected

Number of neurons

Architecture

How many of each type of layer?

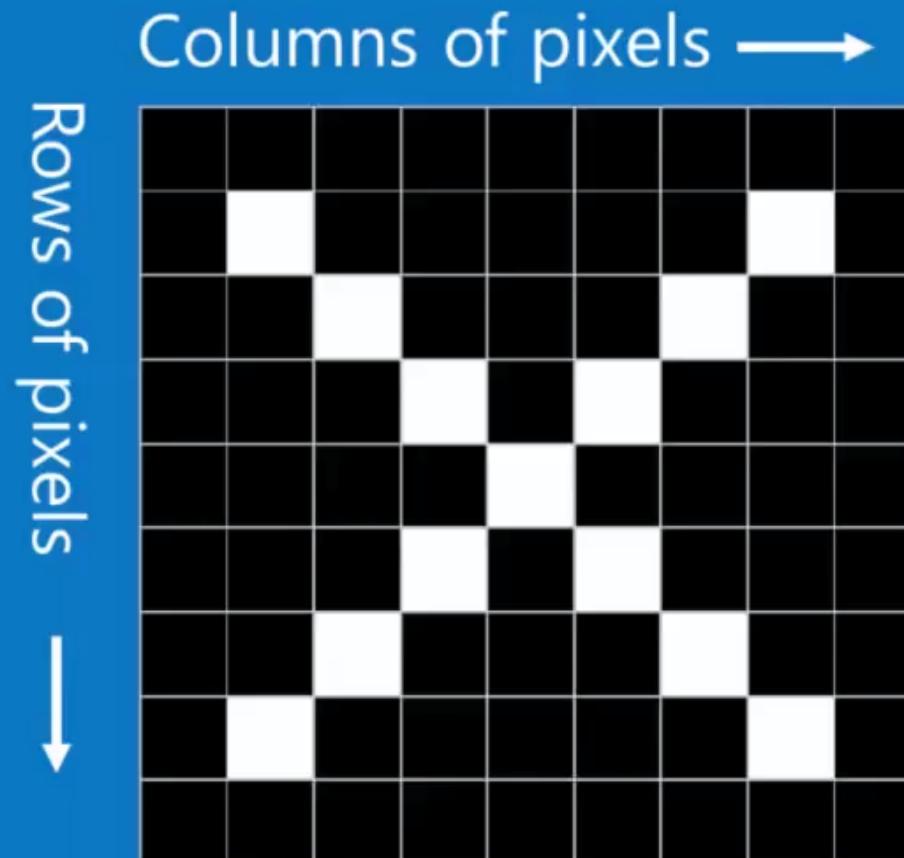
In what order?

Not just images

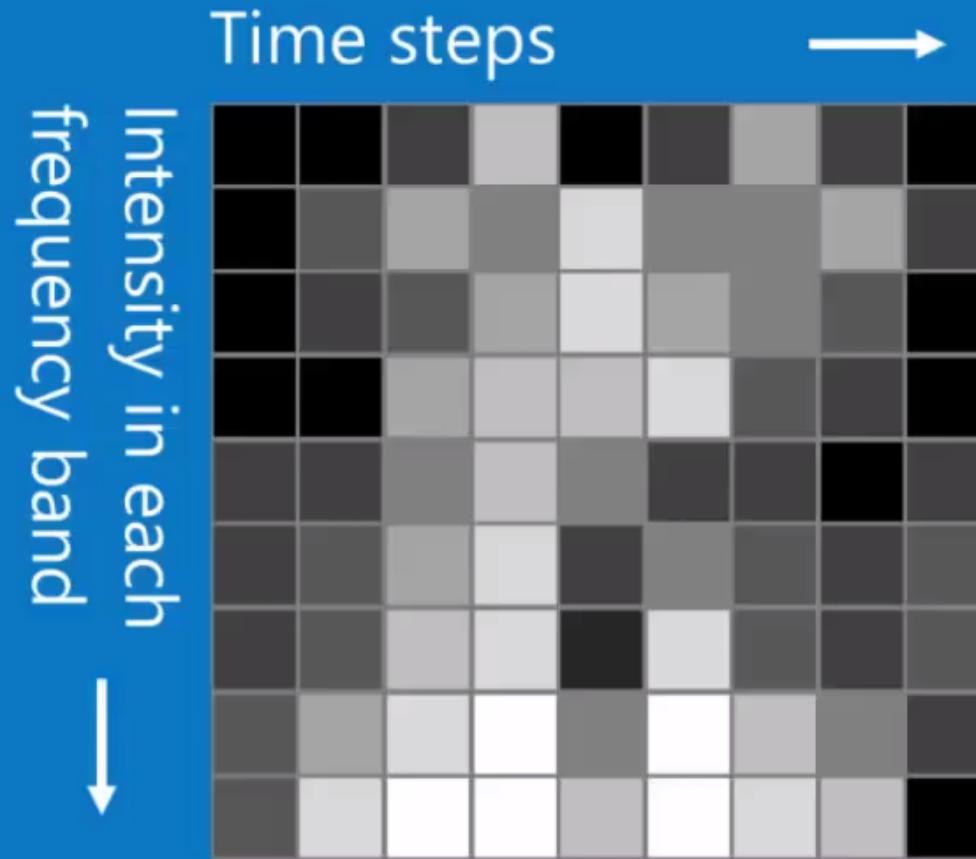
Any 2D (or 3D) data.

Things closer together are more closely related than things far away.

Images



Sound

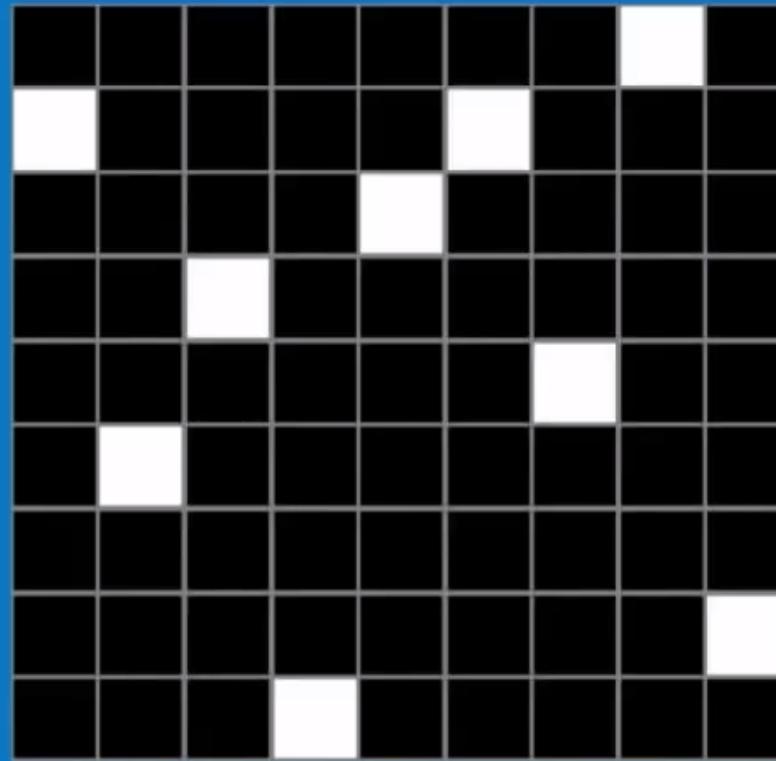


Text

Position in sentence



Words in dictionary



Limitations

ConvNets only capture local “spatial” patterns in data.
If the data can’t be made to look like an image,
ConvNets are less useful.

Customer data

Name, age,
address, email,
purchases,
browsing activity,...



Customers



A	22	1A	a@a	1	aa	a1.a	123	aa1
B	33	2B	b@b	2	bb	b2.b	234	bb2
C	44	3C	c@c	3	cc	c3.c	345	cc3
D	55	4D	d@d	4	dd	d4.d	456	dd4
E	66	5E	e@e	5	ee	e5.e	567	ee5
F	77	6F	f@f	6	ff	f6.f	678	ff6
G	88	7G	g@g	7	gg	g7.g	789	gg7
H	99	8H	h@h	8	hh	h8.h	890	hh8
I	111	9I	i@i	9	ii	i9.i	901	ii9

Rule of thumb

If your data is just as useful after swapping any of your columns with each other, then you can't use Convolutional Neural Networks.

In a nutshell

ConvNets are great at finding patterns and using them to classify images.

<https://www.youtube.com/watch?v=FmpDIaiM1eA&index=3&list=PLVZqlMpoM6kbaeySxhdhgQPFEc5nV7Faa>