Convolutional Neural Networks (CNNs)

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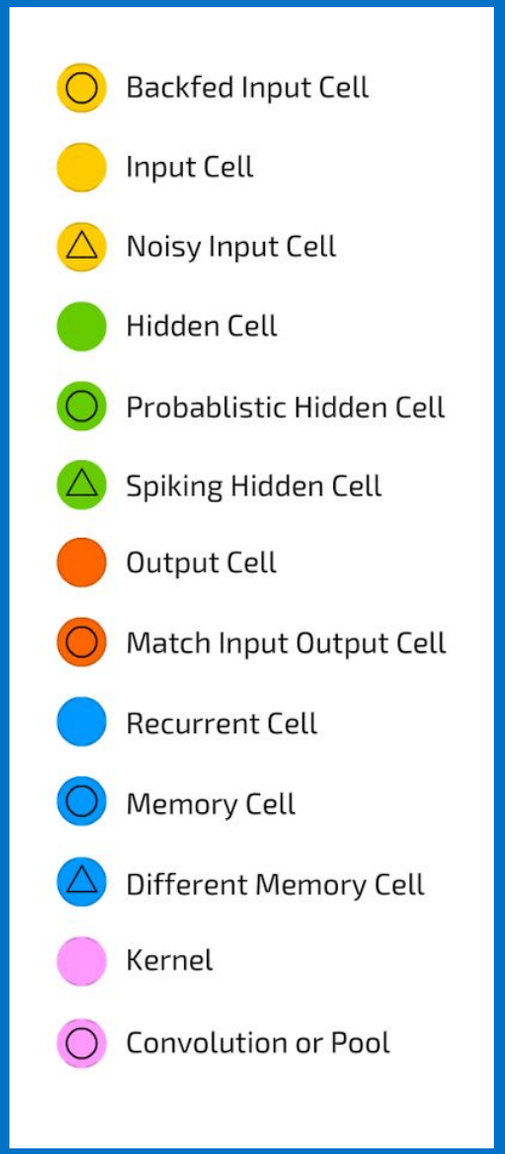
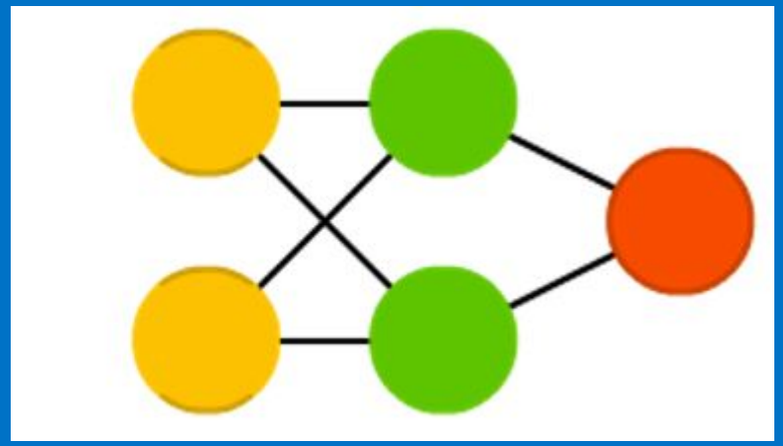
Original content from:
https://brohrer.github.io/how_convolutional_neural_networks_work.html
http://cs231n.github.io/convolutional-networks/

Learning Objectives

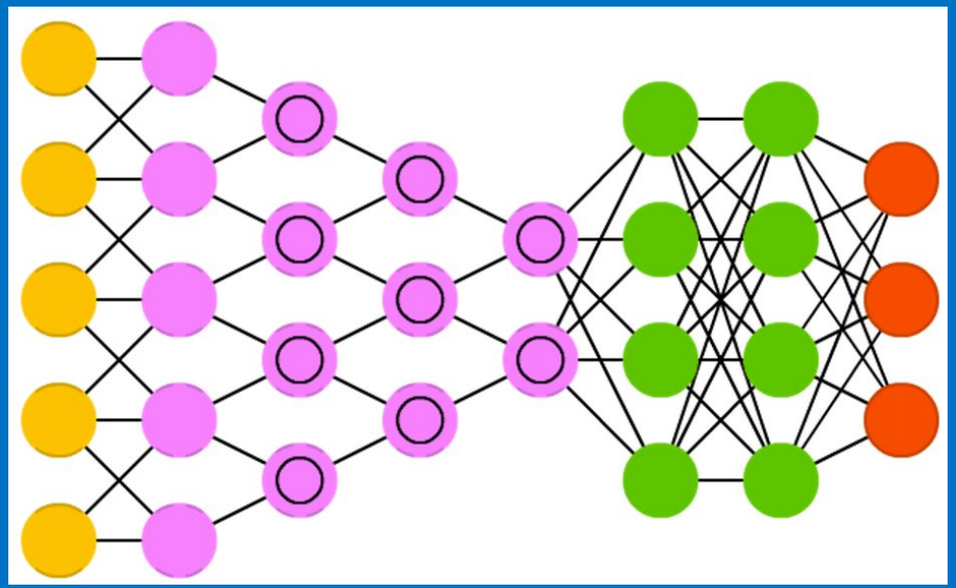
- Identify the layers in CNNs.
- Describe the process of convolution.
- Understand how the process of pooling works.



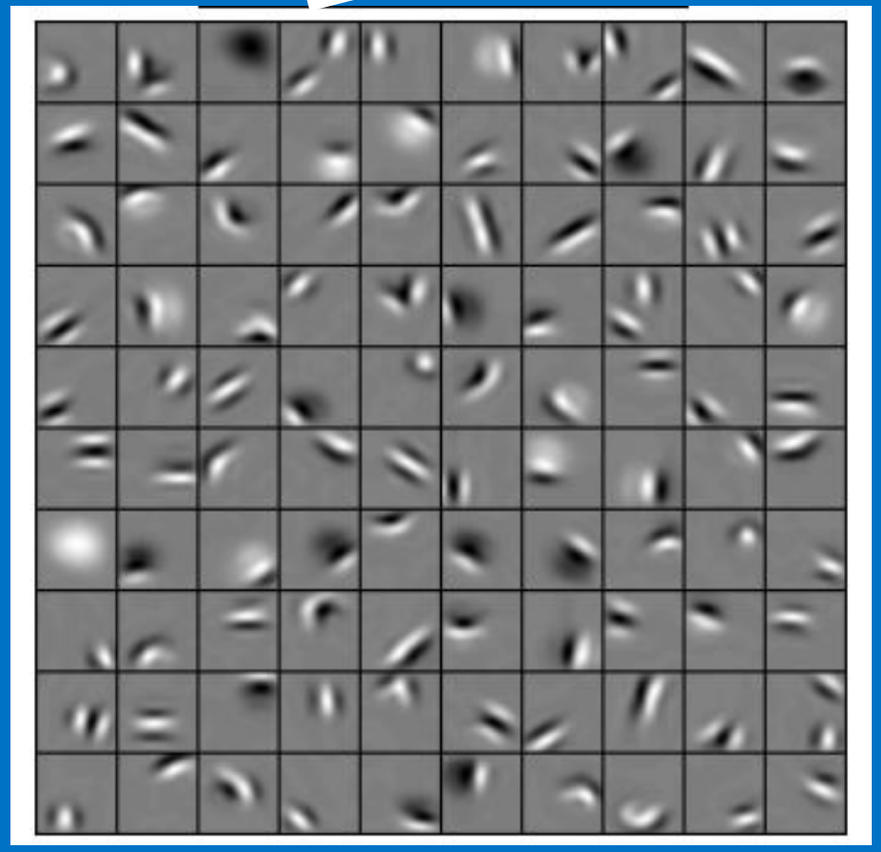
Previously: Multilayer Perceptrons (MLP)



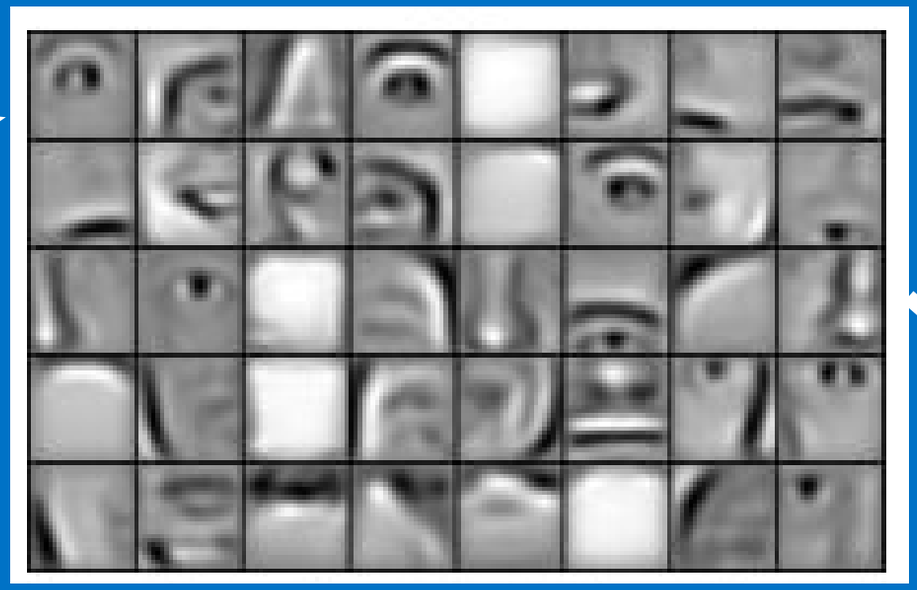
Now: Convolutional Neural Networks (CNN)



Original (larger) chart comparing structures of many more neural networks:
http://www.asimovinstitute.org/neural-network-zoo/



First Layer After Activation



Second Layer After Activation

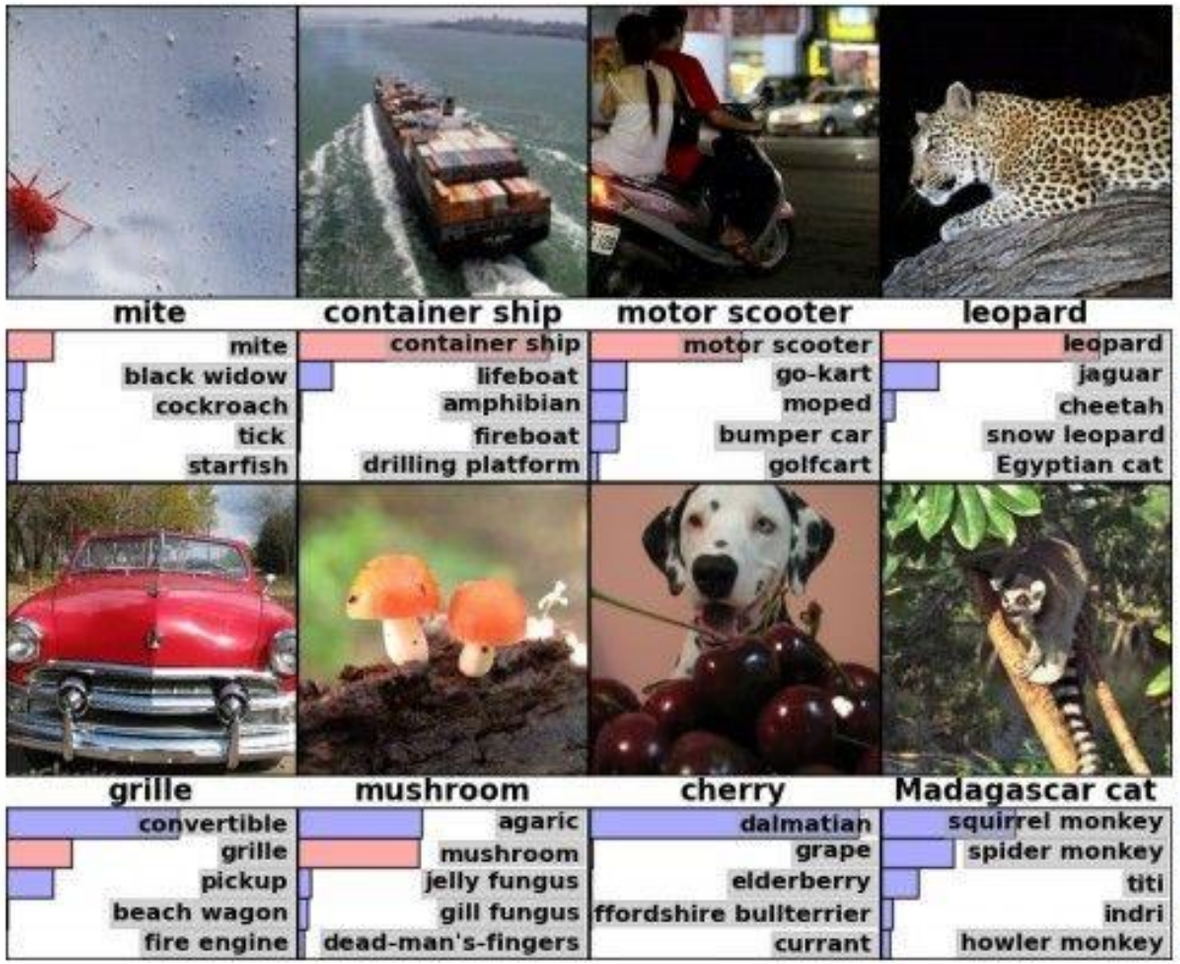
Third Layer After Activation

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

Functions of CNNs

Classification

Retrieval



Functions of CNNs

Detection

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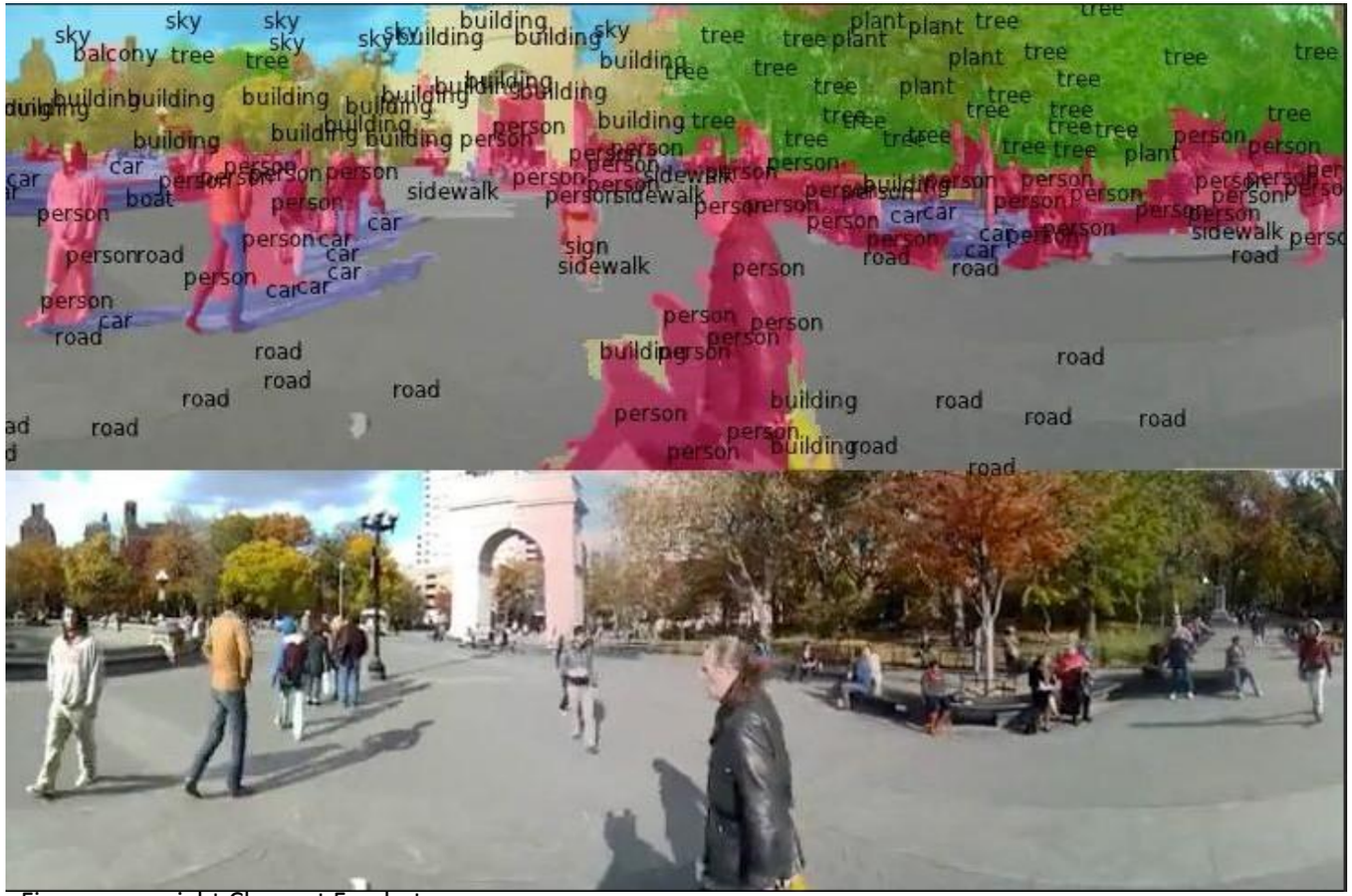
[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Segmentation



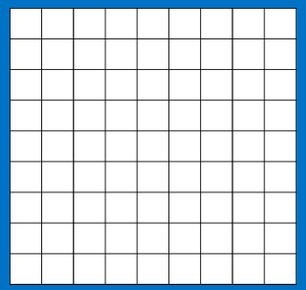
Figures copyright Clement Farabet, 2012. Reproduced with permission.

[Farabet et al., 2012]

An example CNN: X's and O's

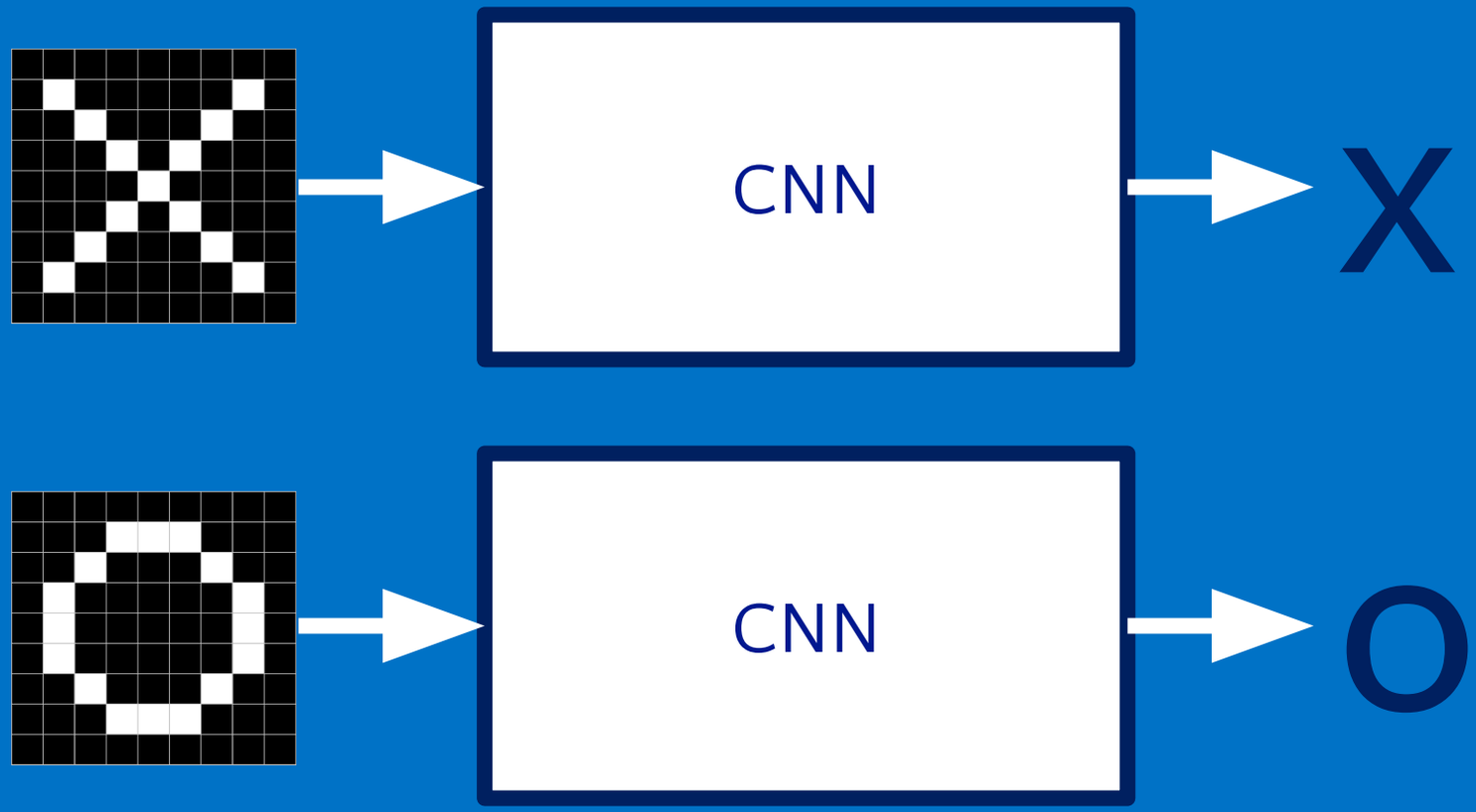
Says whether a picture is of an X or an O

A two-dimensional array of pixels

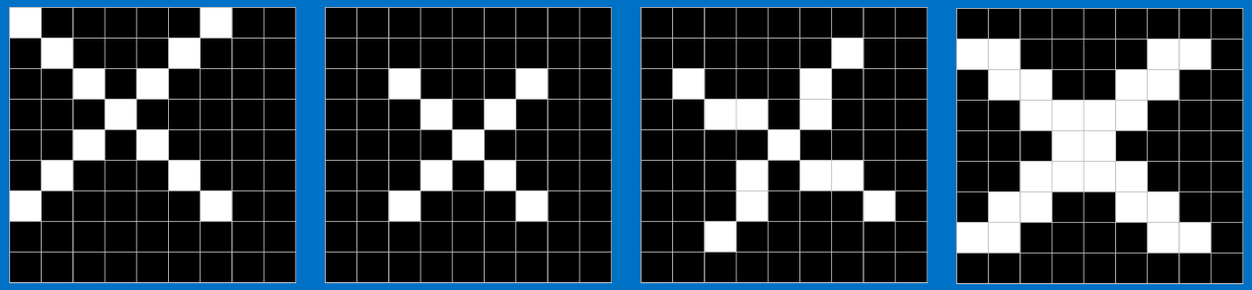


X or **O**

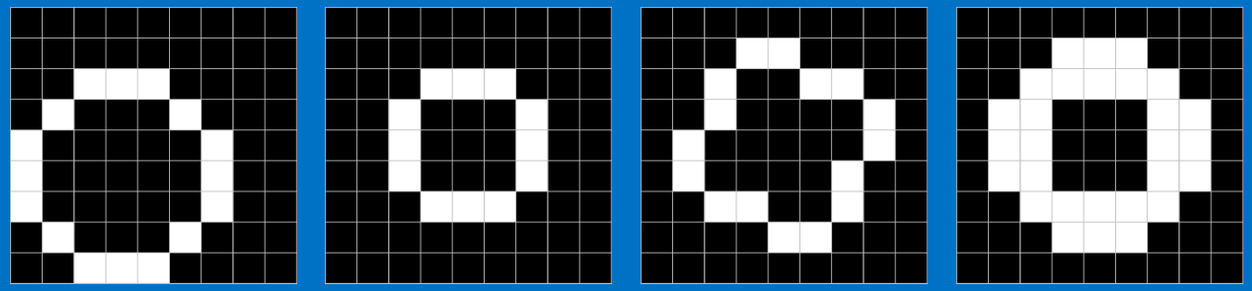
CNN: Identifying X's and O's



Trickier cases



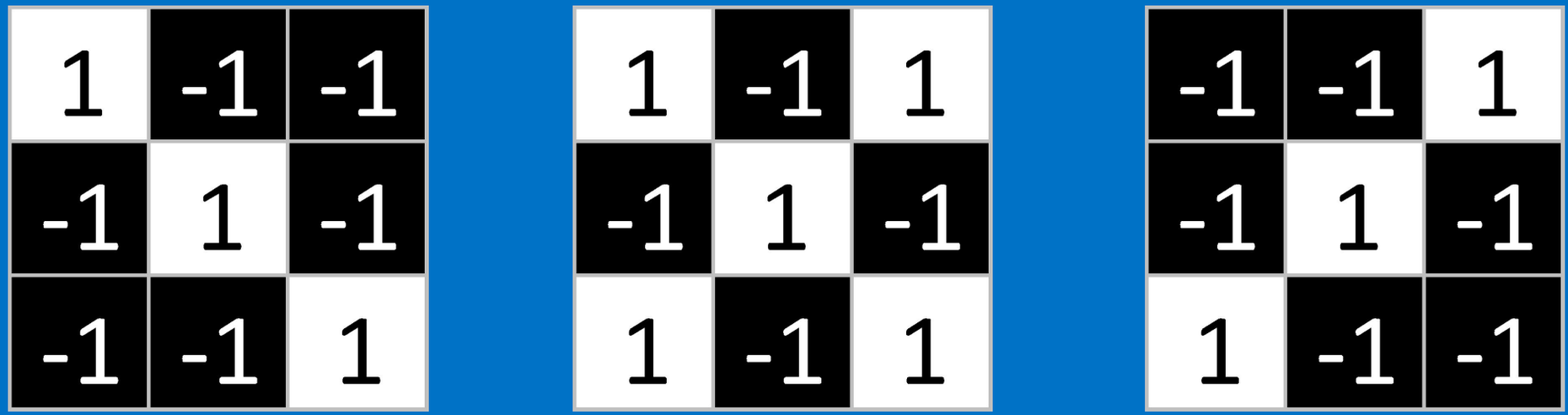
translation scaling rotation weight

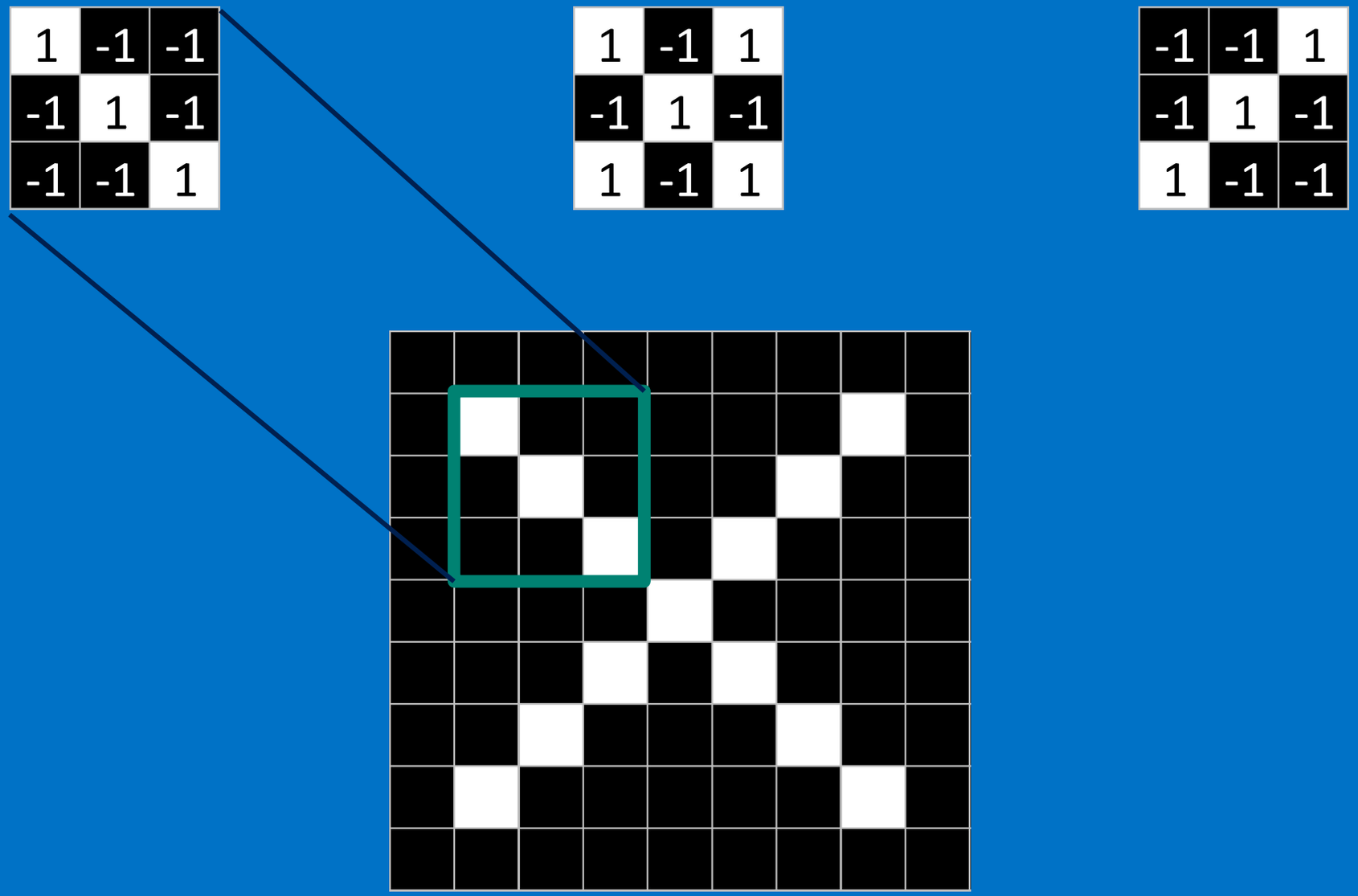


What computers see

-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

Filters/kernels match pieces of the image

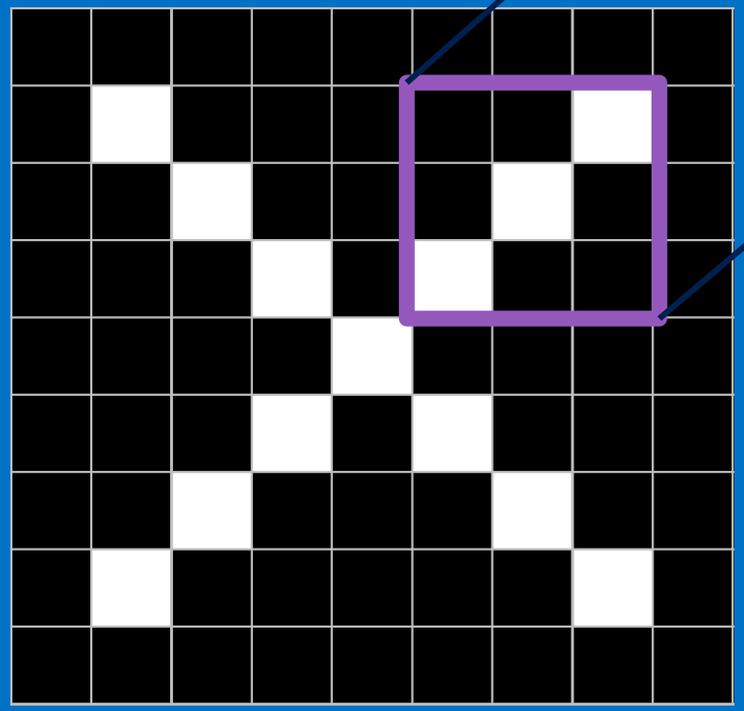



1 -1 -1
-1 1 -1
-1 -1 1
1 -1 1
-1 1 -1
1 -1 1
-1 -1 1
-1 1 -1
1 -1 -1

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

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

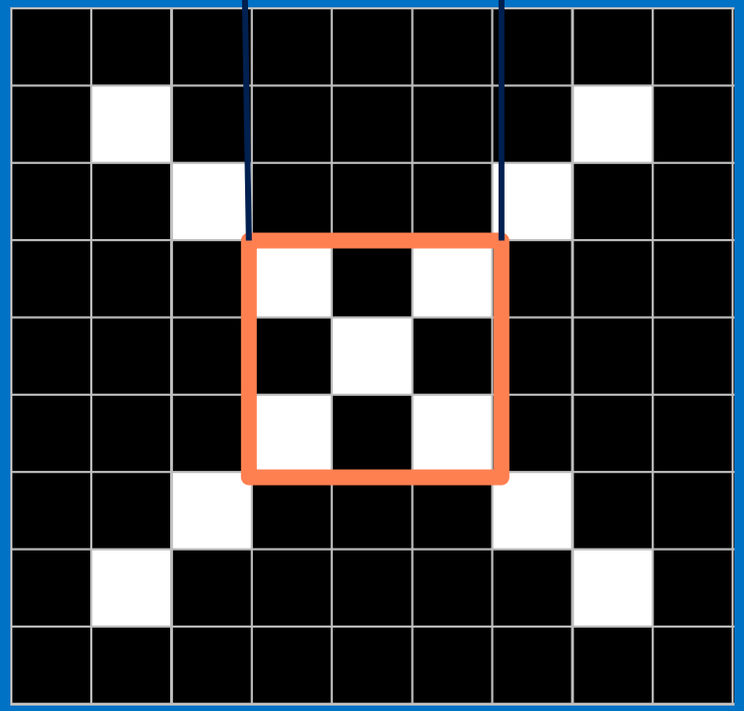
-1	-1	1
-1	1	-1
1	-1	-1



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

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

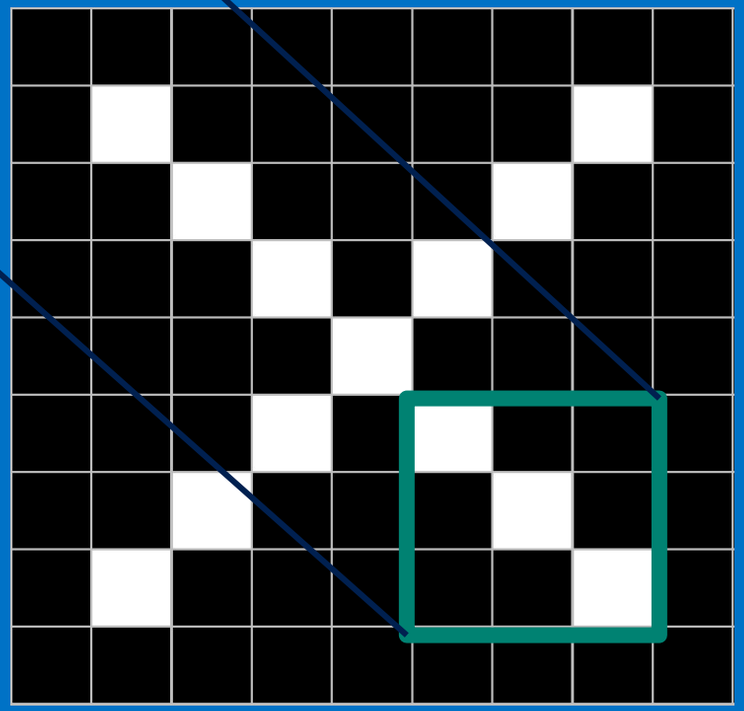
-1	-1	1
-1	1	-1
1	-1	-1



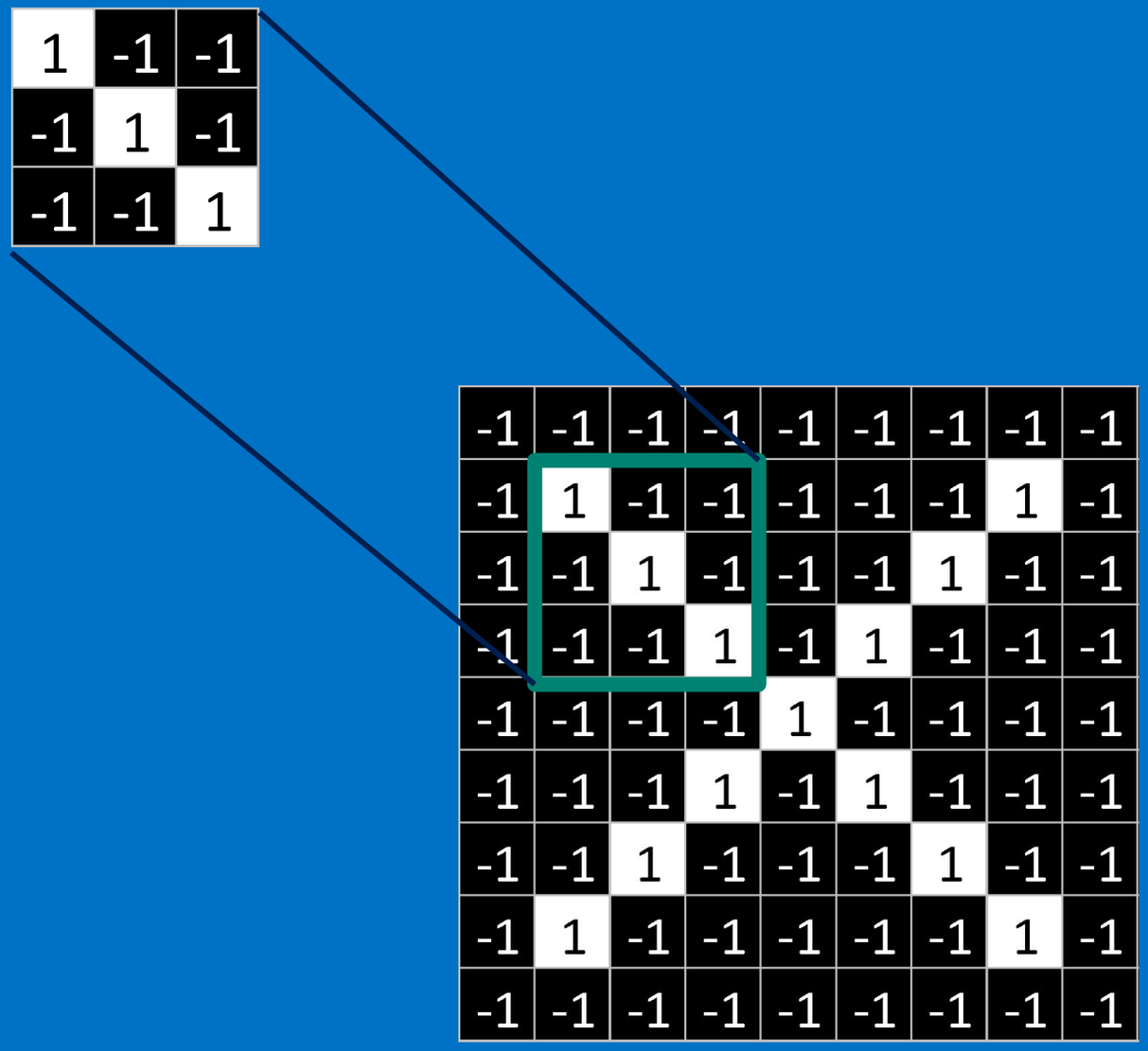
1	-1	-1
-1	1	-1
-1	-1	1

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

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



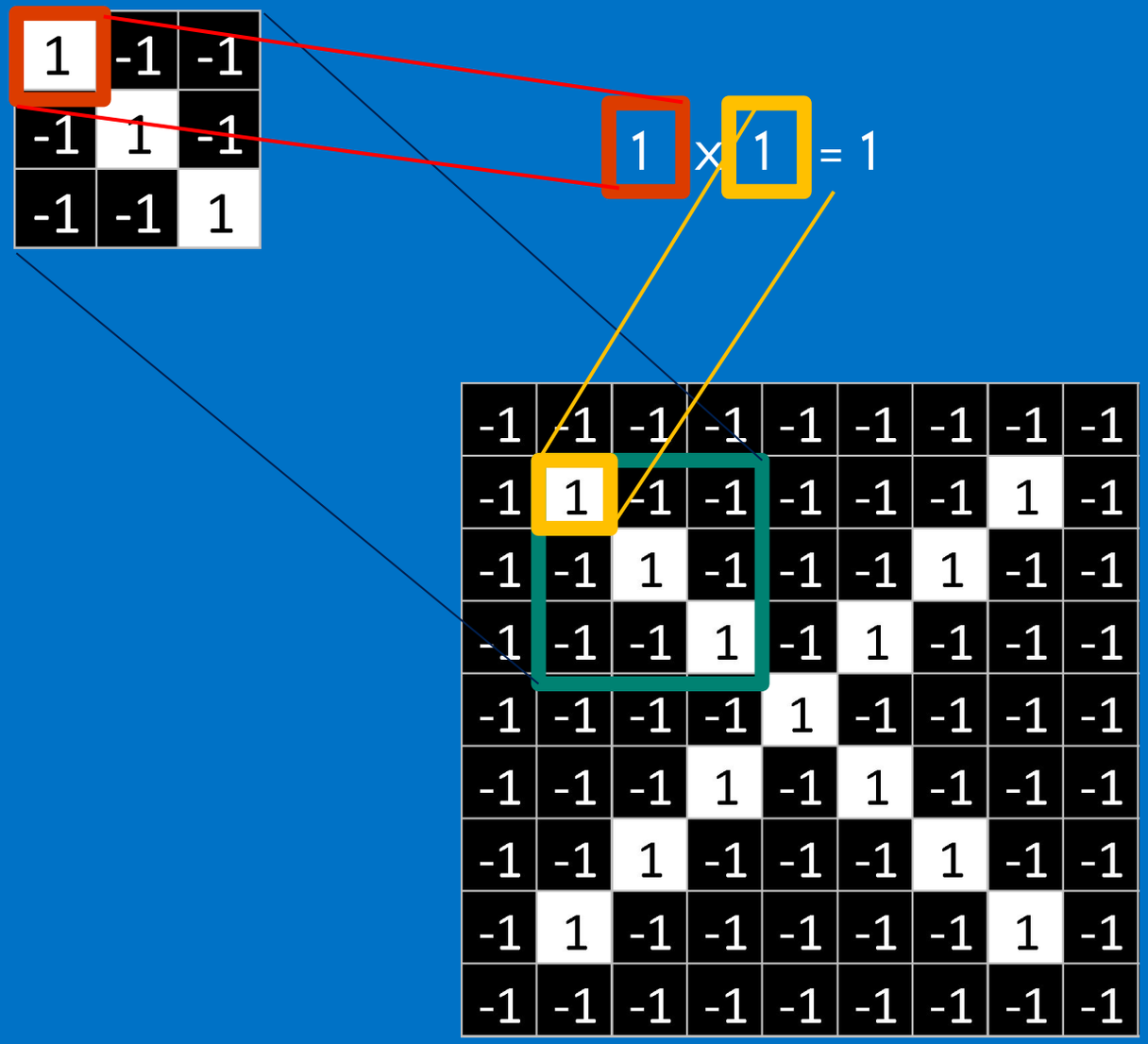
Convolution Layer – Filtering Our Image

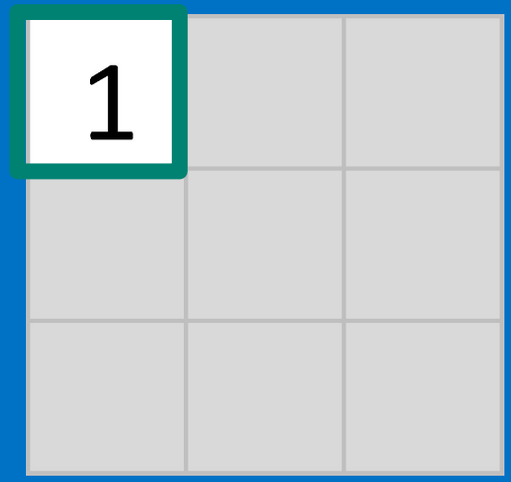


Convolution Layer – Filtering Our Image

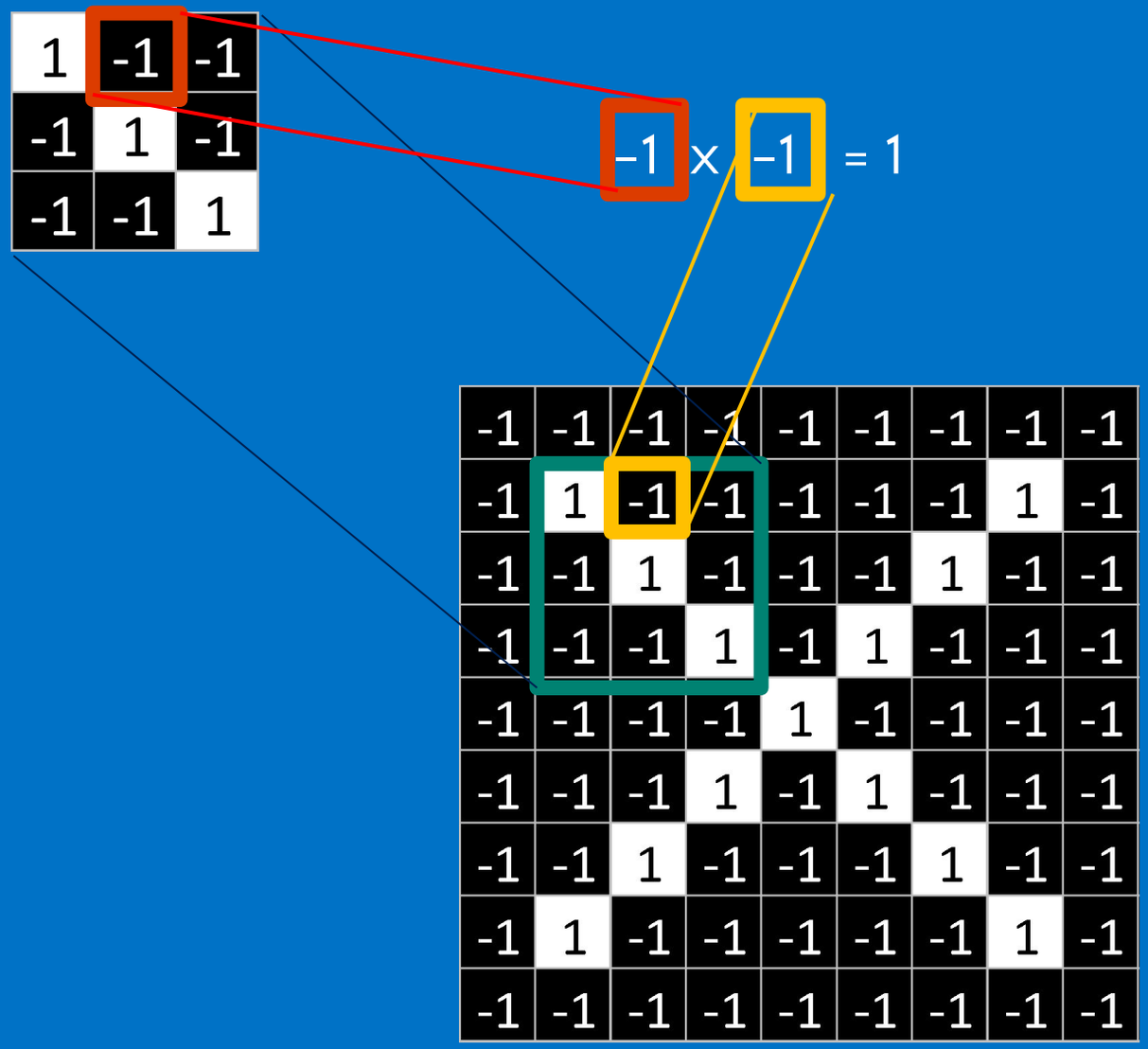
1. Line up the filter (i.e., mini piece of the image) and the original image.
2. Go through each pixel in the original image one by one and multiply it by the corresponding pixel in the filter
3. Find the total sum of all of these pixel multiplications
4. Divide this sum by the total number of pixels in the filter to determine its value for the activation map.

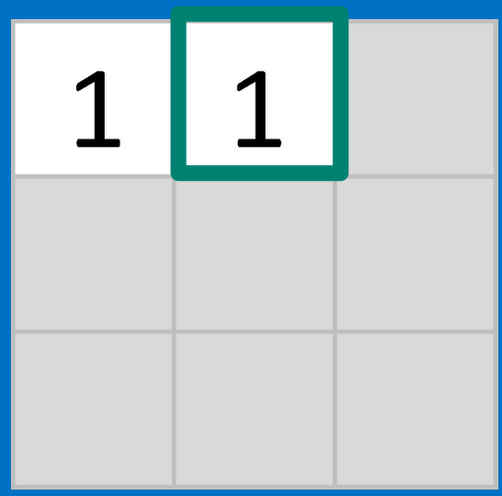
Convolution Layer – Filtering Our Image



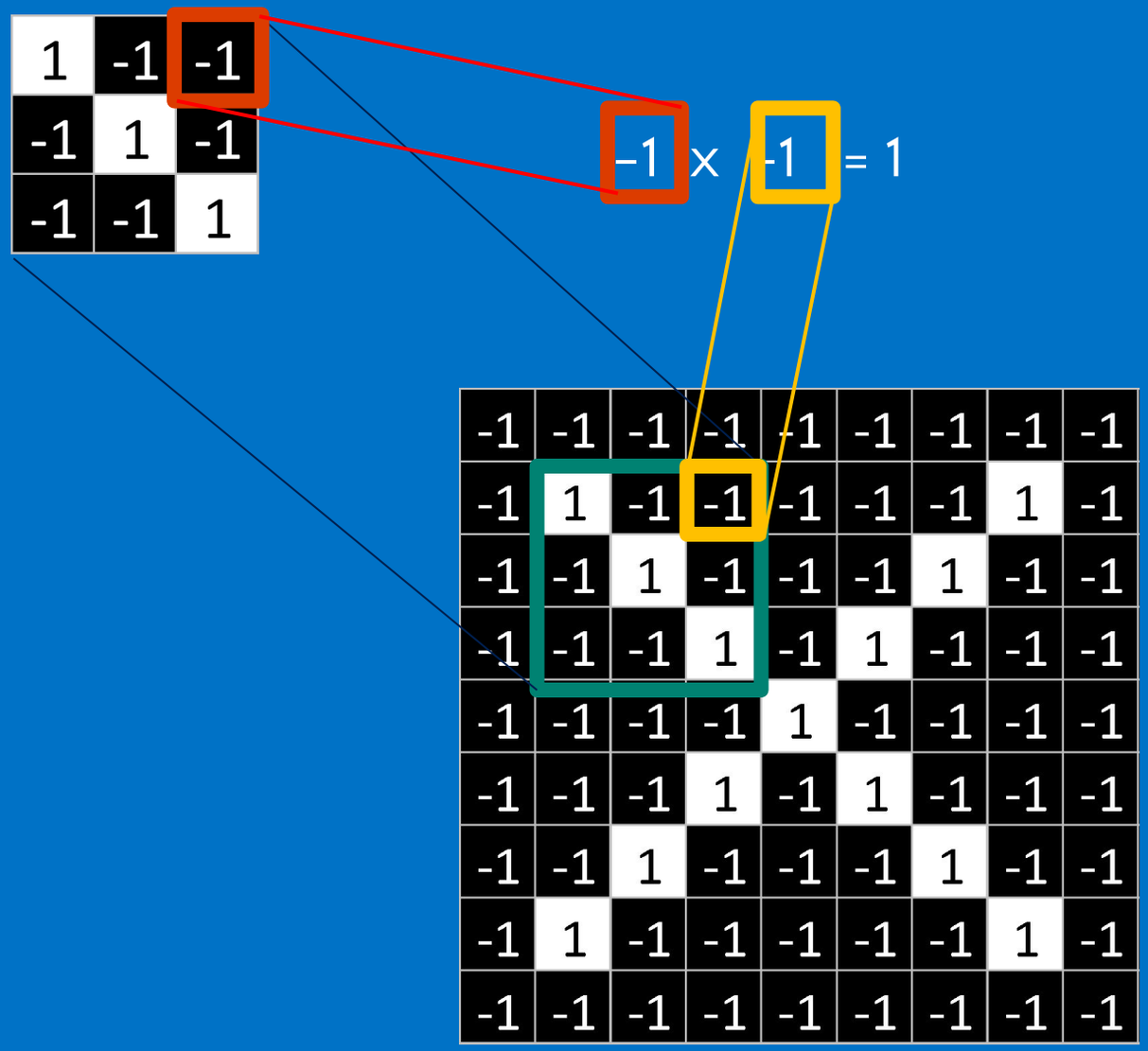


Convolution Layer – Filtering Our Image

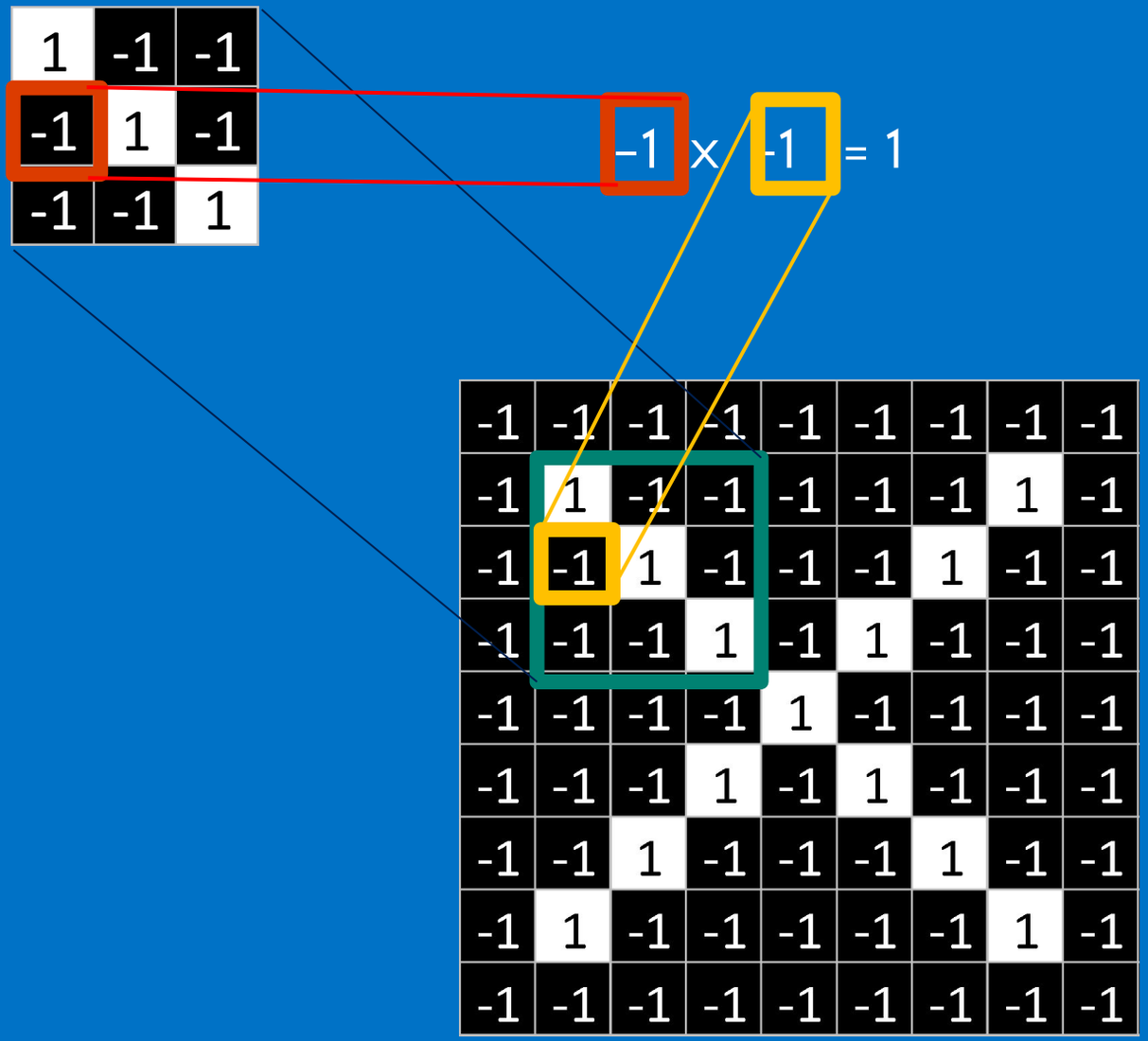


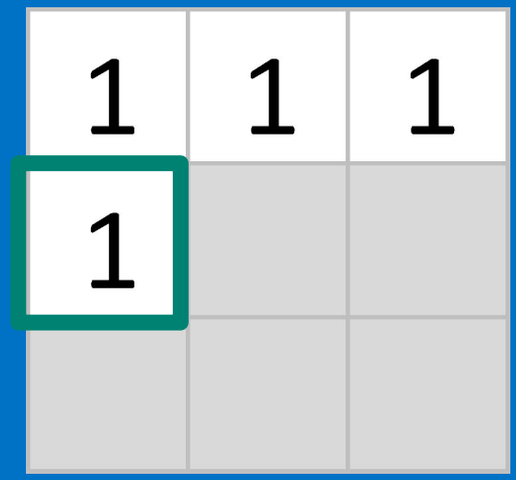


Convolution Layer – Filtering Our Image

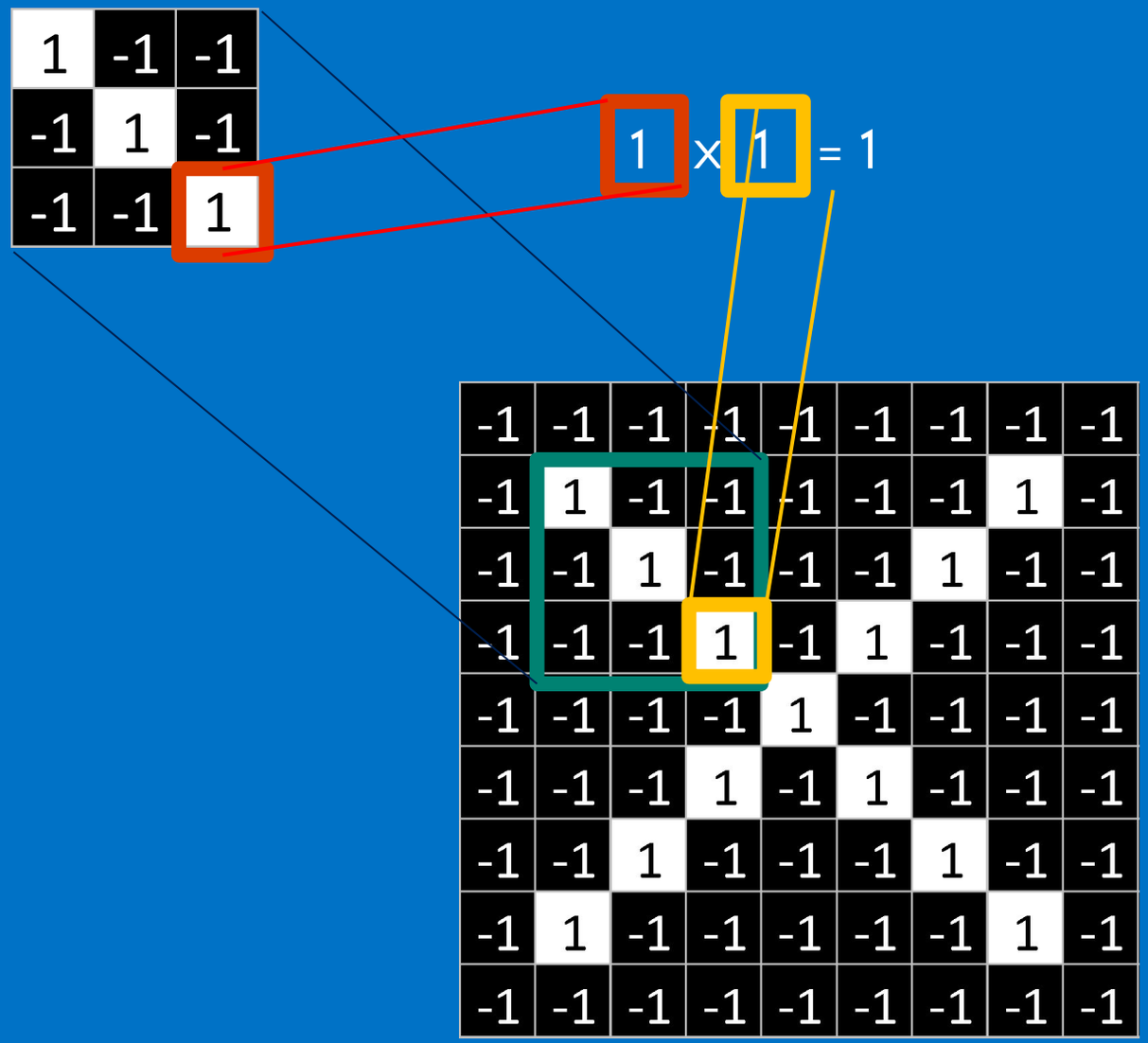


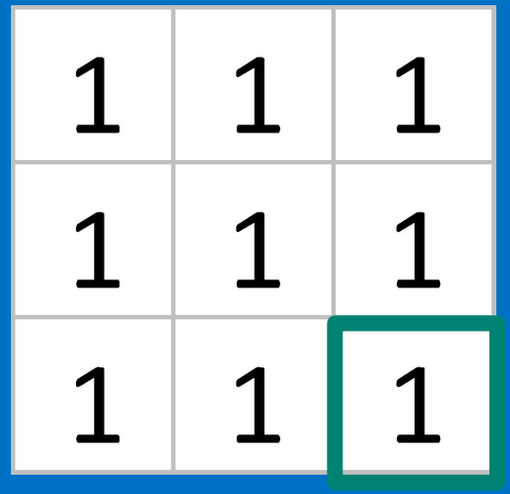
Convolution Layer – Filtering Our Image



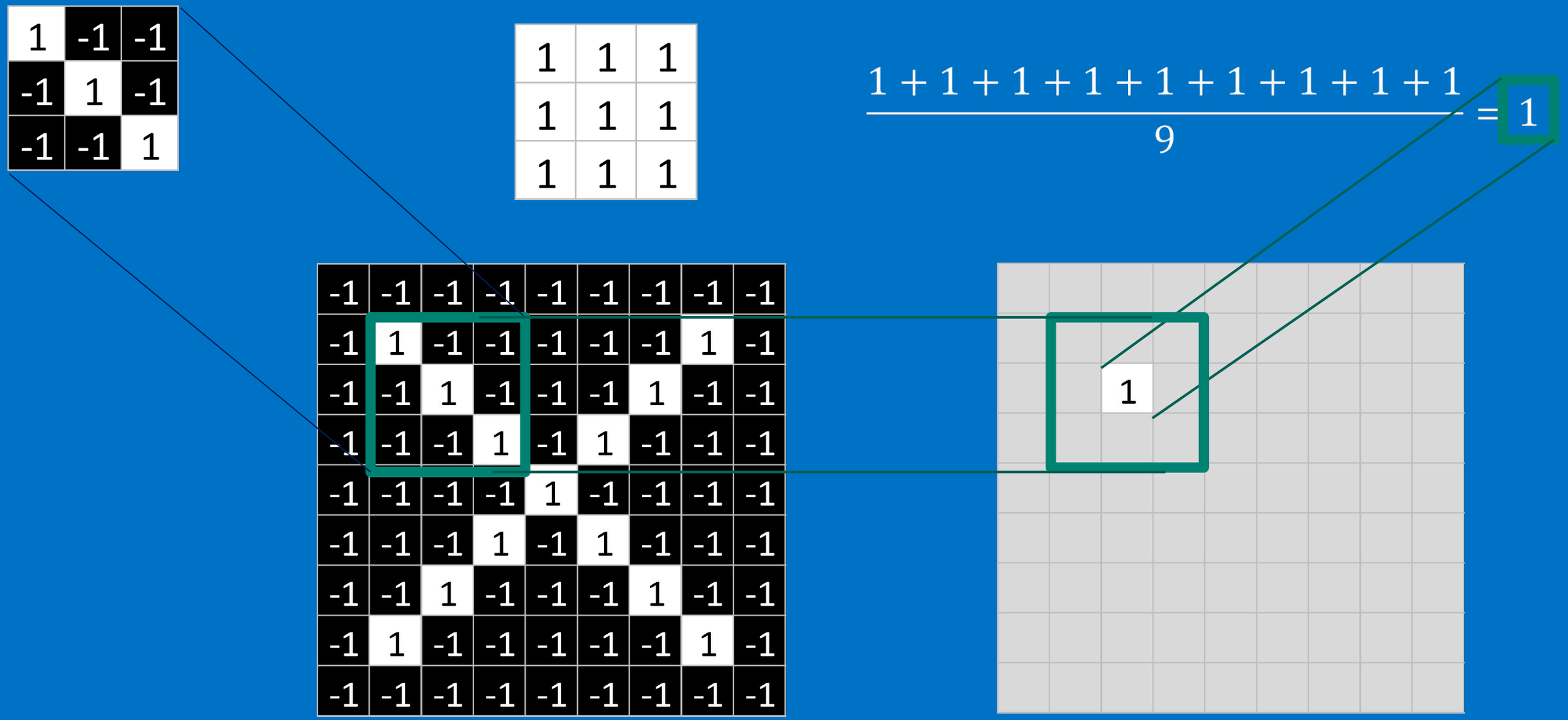


Convolution Layer – Filtering Our Image





Convolution Layer – Filtering Our Image

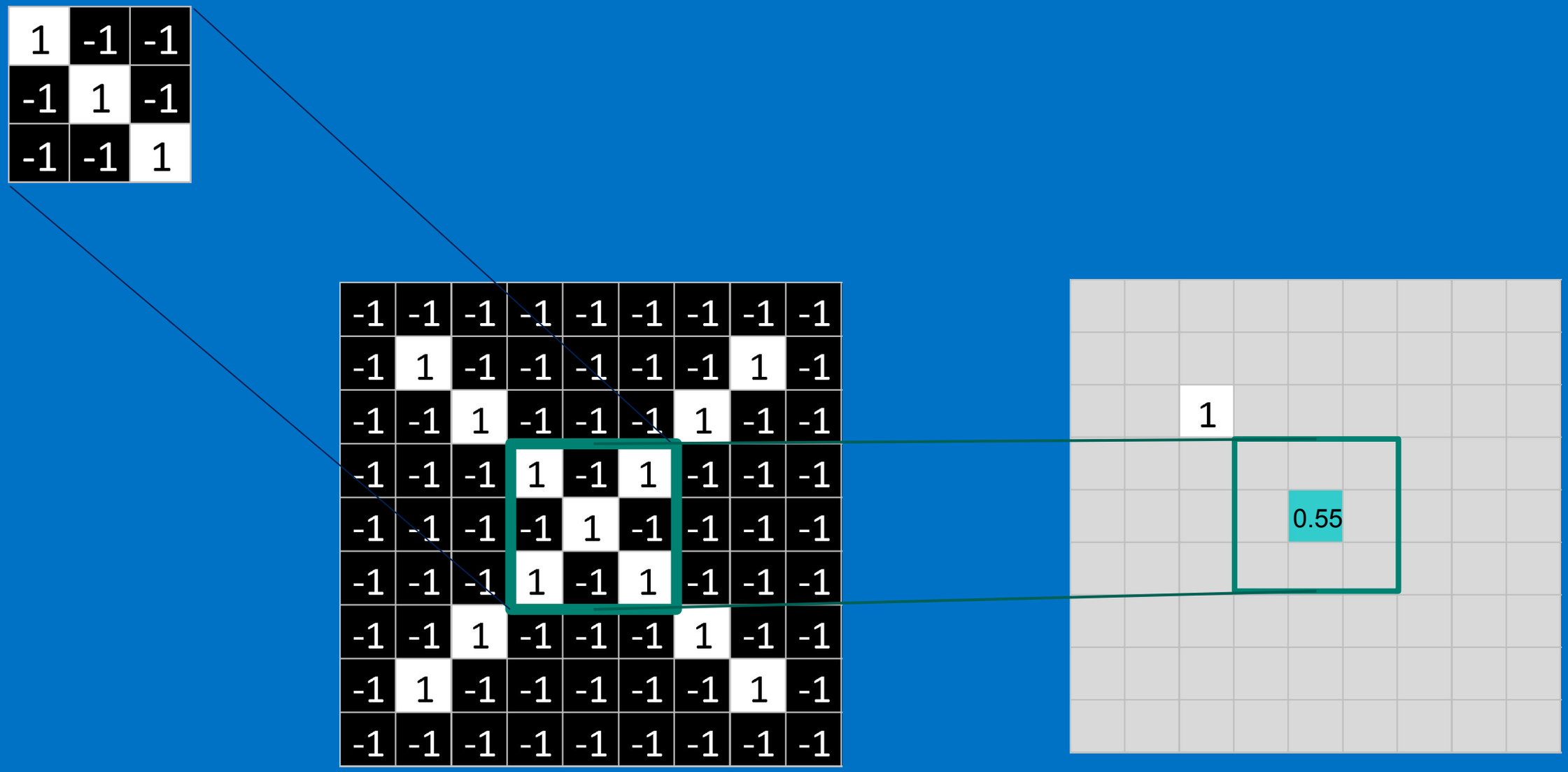


Breakout: Apply Filter to Another Location

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

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

Breakout: Apply Filter to Another Location



Convolution Layer – Filtering Our 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

=

Activation Map

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

After the convolution layer, we went from a 9x9 image to a 7x7 filtered image – how?

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

⊗

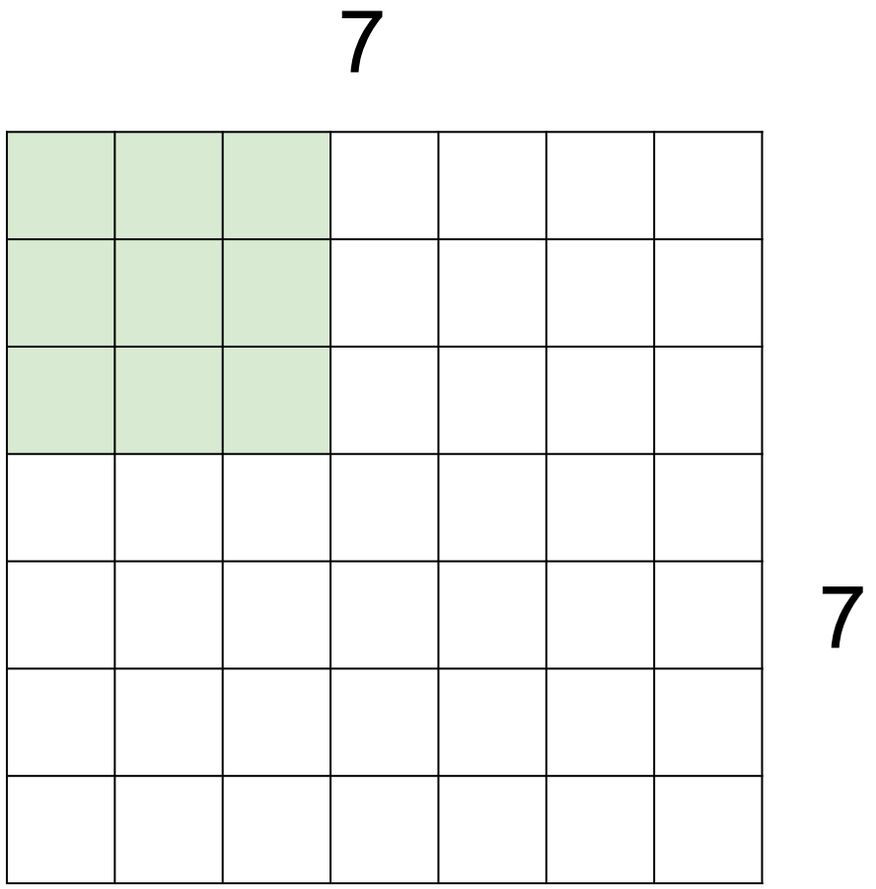
1	-1	-1
-1	1	-1
-1	-1	1

=

Activation Map

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

A closer look at spatial dimensions:

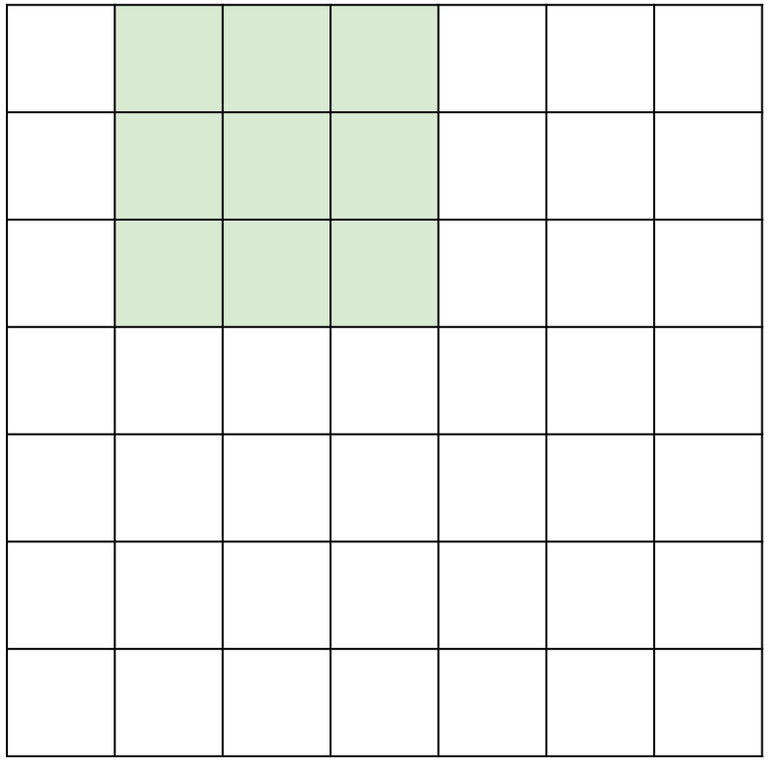


7x7 image input

Using a 3x3 filter

A closer look at spatial dimensions:

7

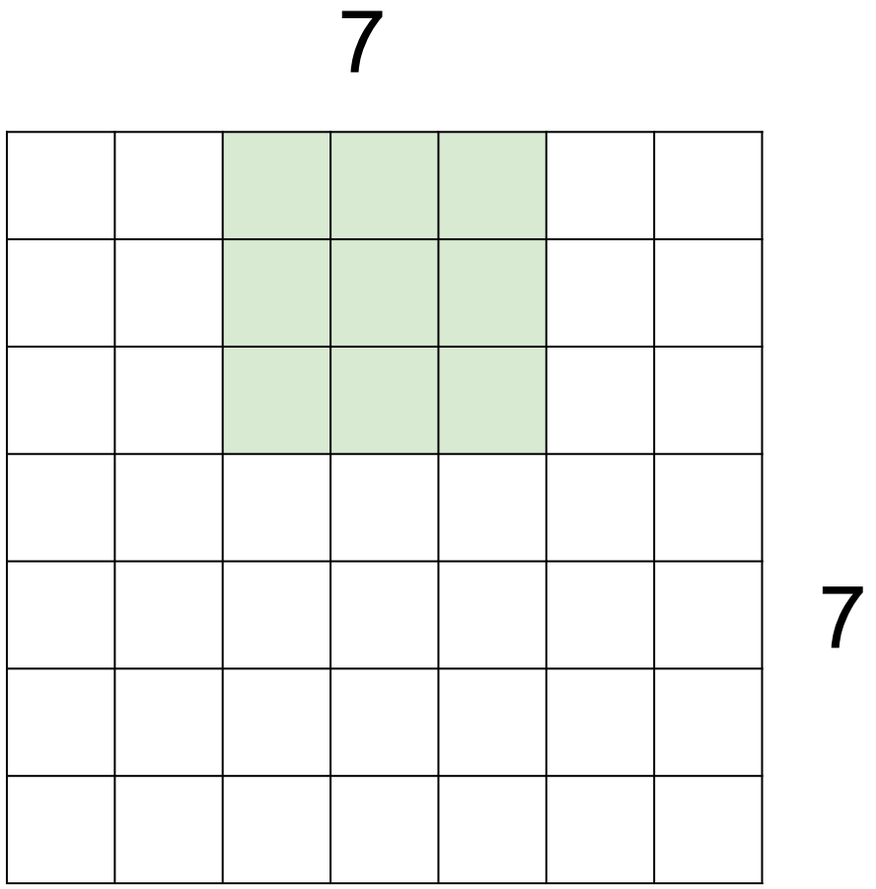


7

7x7 image input

Using a 3x3 filter

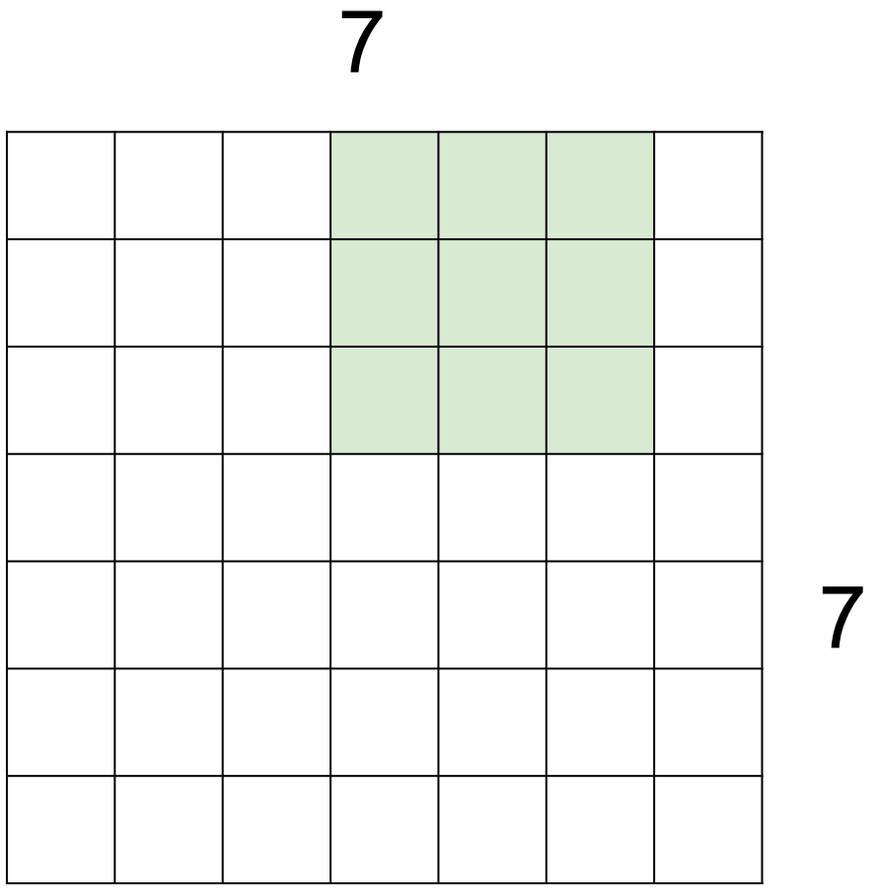
A closer look at spatial dimensions:



7x7 image input

Using a 3x3 filter

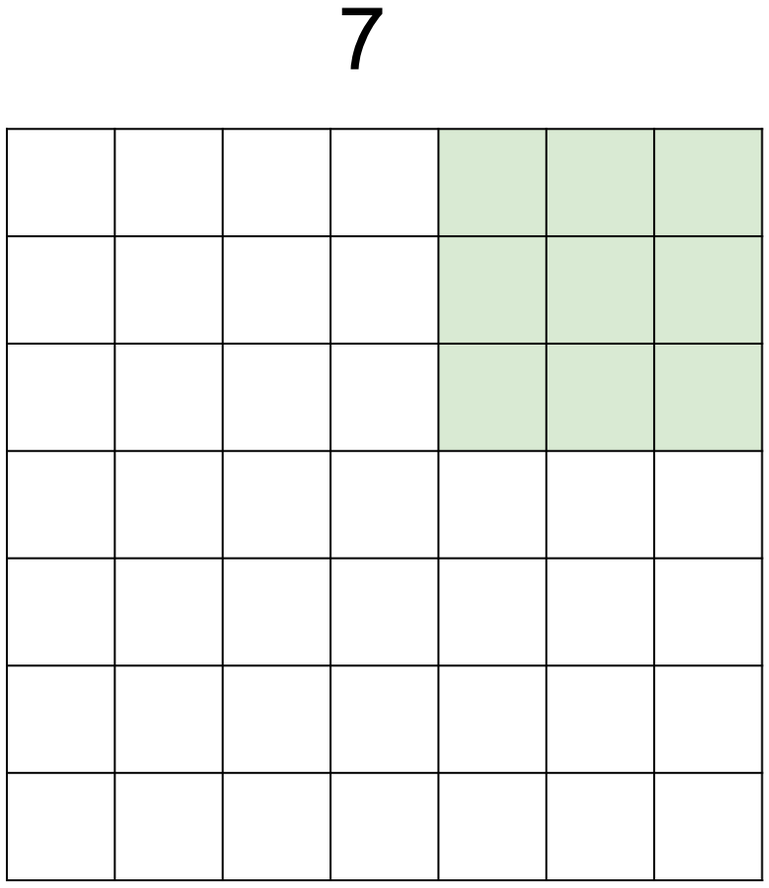
A closer look at spatial dimensions:



7x7 image input

Using a 3x3 filter

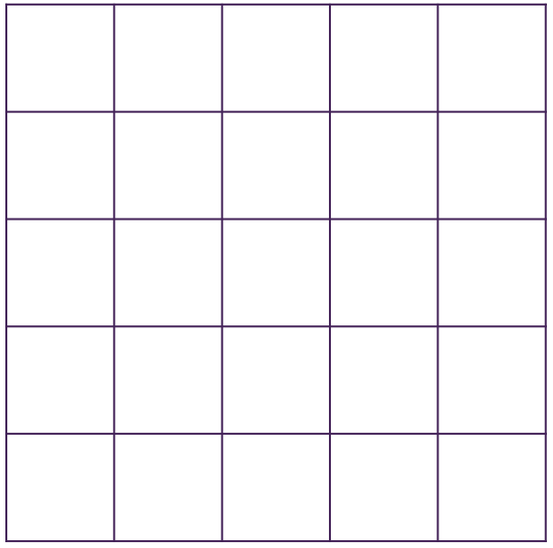
A closer look at spatial dimensions:



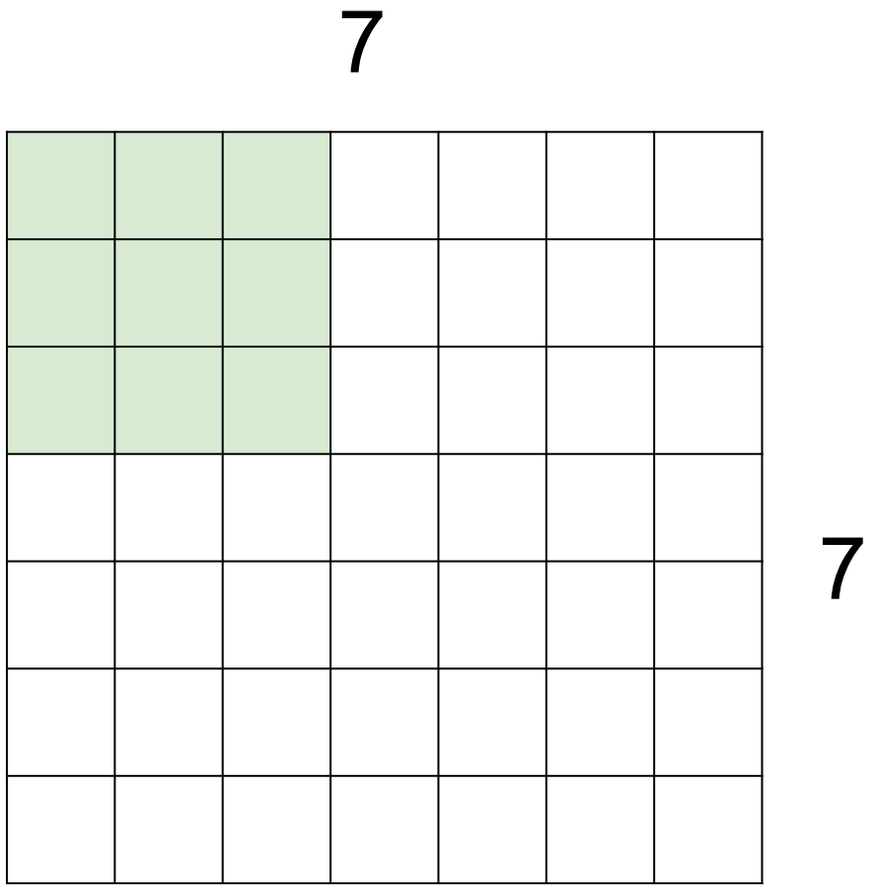
7x7 image input

Using a 3x3 filter

=> 5x5 output



A closer look at spatial dimensions:

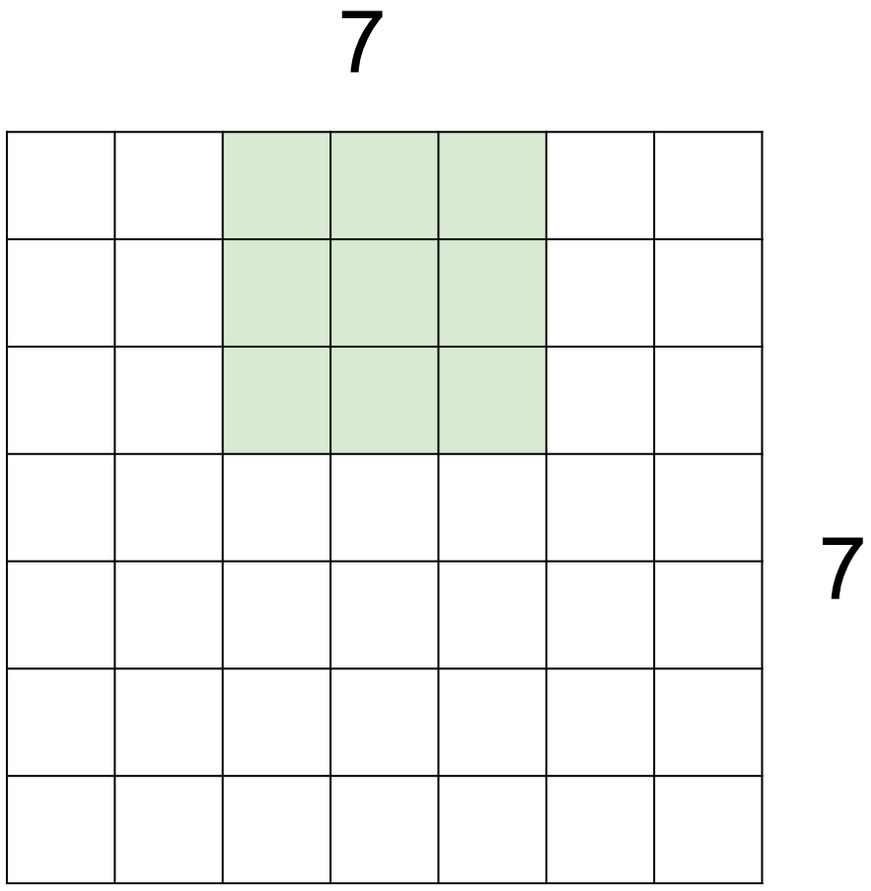


7x7 image input

Using a 3x3 filter

Applied **with stride 2**

A closer look at spatial dimensions:

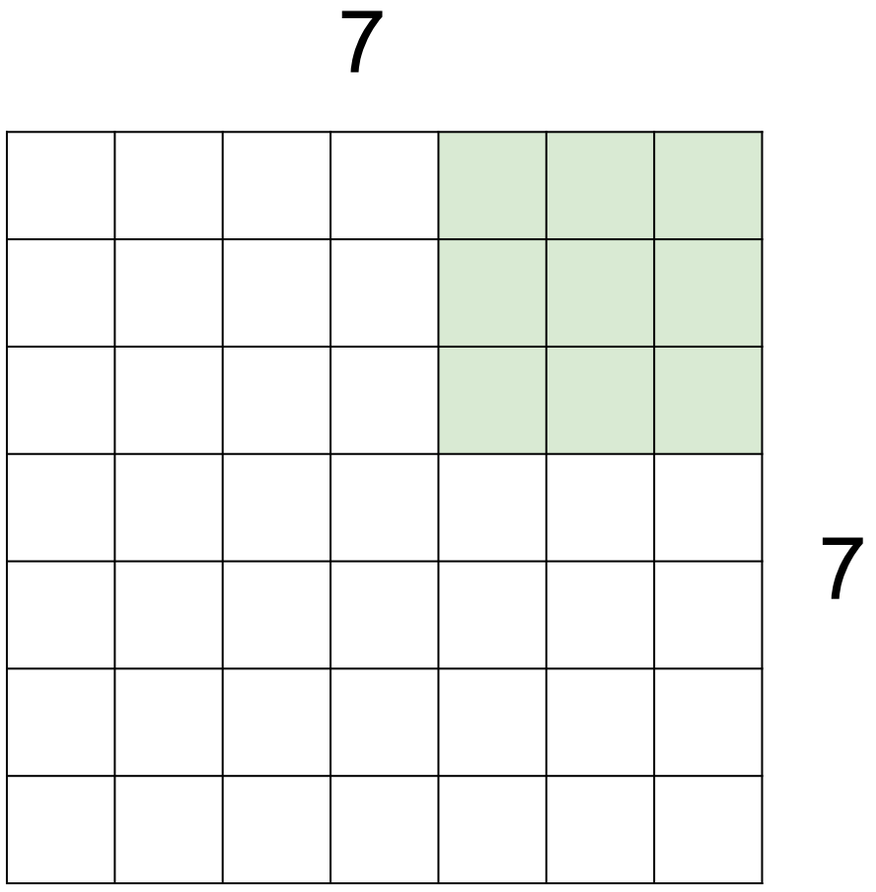


7x7 image input

Using a 3x3 filter

Applied **with stride 2**

A closer look at spatial dimensions:

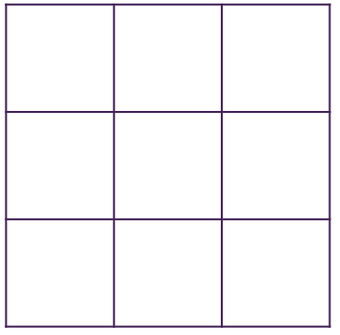


7x7 image input Using a

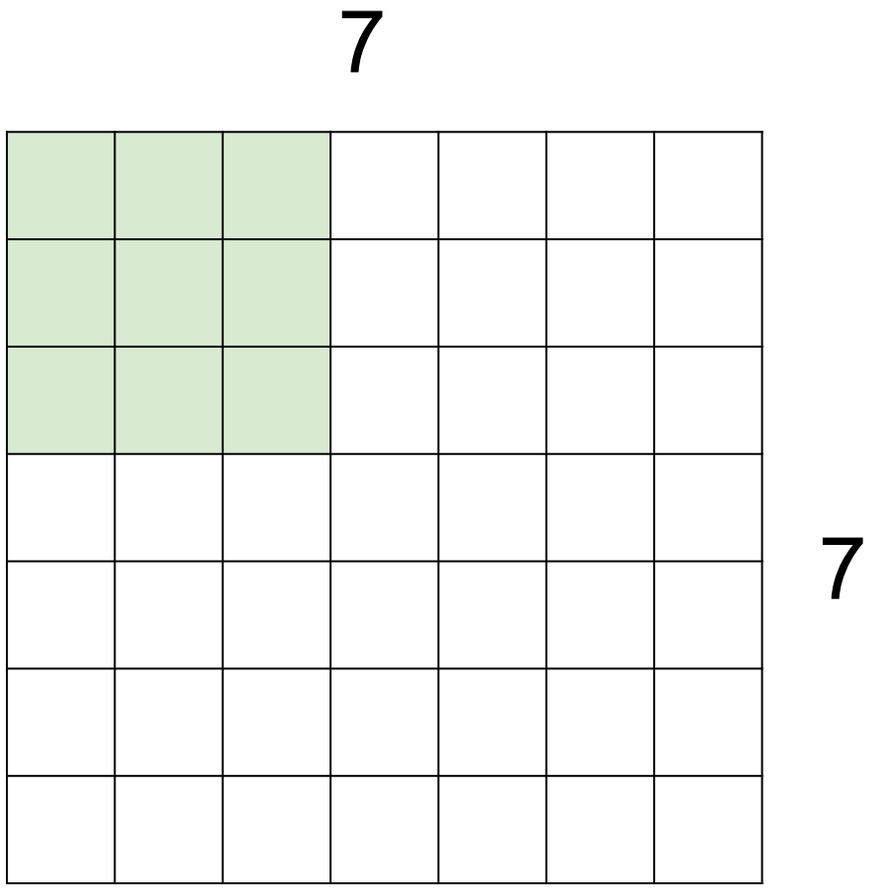
3x3 filter

Applied **with stride 2**

=> 3x3 output!



A closer look at spatial dimensions:



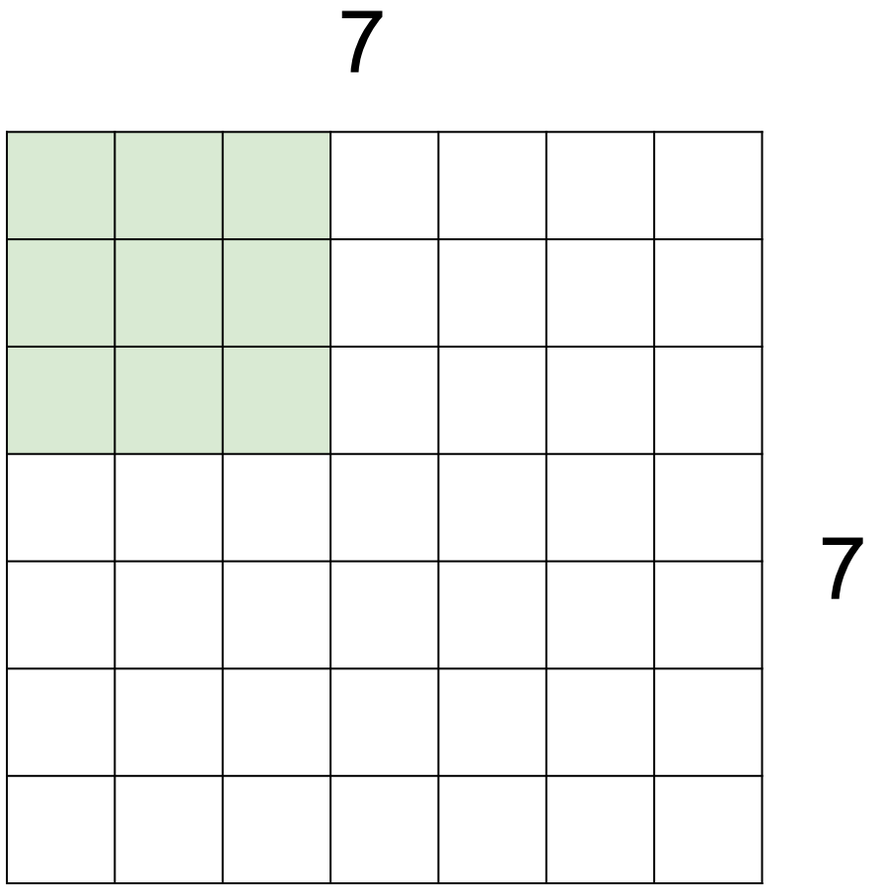
7x7 image input

What is the output of

3x3 filter applied

with stride 3?

A closer look at spatial dimensions:



7x7 image input

What is the output of

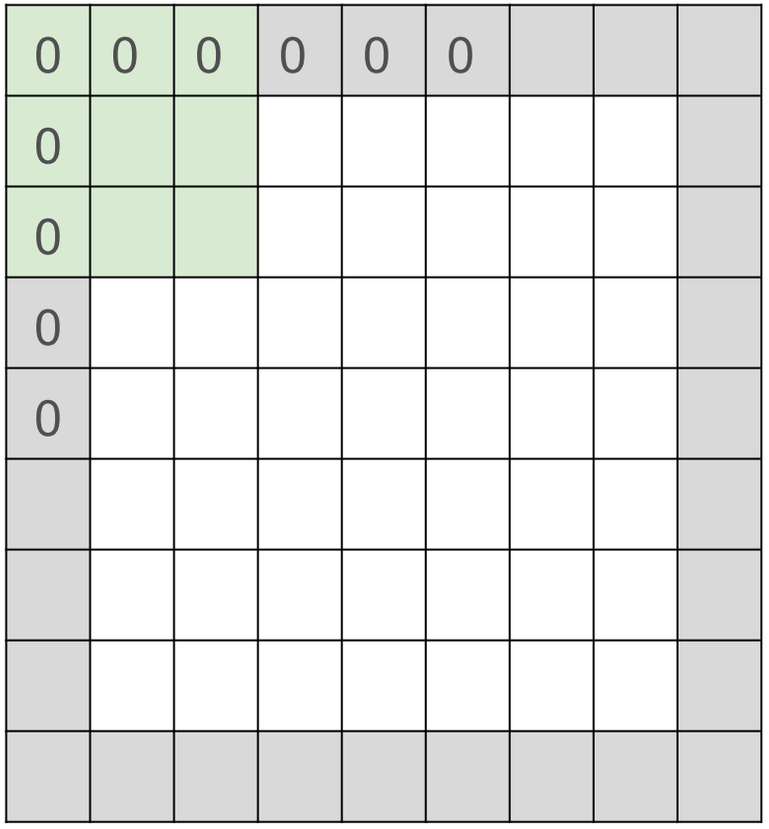
3x3 filter applied

with stride 3?

Doesn't fit!

For the convolution layer, you cannot apply a filter with a stride that does not fit cleanly.

In practice: Common to zero pad the border



7x7 image input

What is the output of 3x3 filter applied

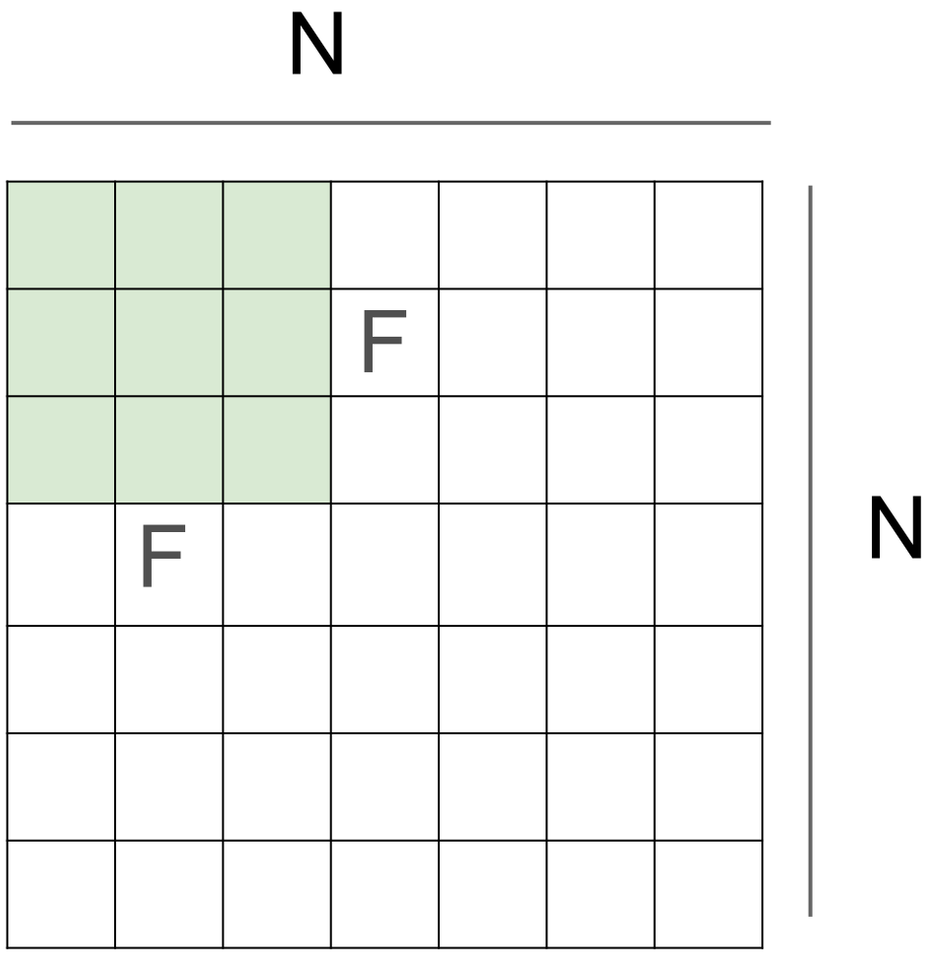
with stride 1 and padded with a **1 pixel border?**

Answer: **7x7 output** (i.e., same as the original)

It's common to see convolutional layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2 (this will preserve the original size spatially).

e.g. F = 3 => zero pad with 1 F = 5 => zero pad with 2 F = 7 => zero pad with 3

Calculating Output Size



N - original image dimension

F - filter dimension

S - stride

P - padding

Output size = ((N - F + 2P) / S) + 1

e.g. N = 7, F = 3:

stride 1 => (7 - 3)/1 + 1 = 5

stride 2 => (7 - 3)/2 + 1 = 3

stride 3 => (7 - 3)/3 + 1 = 2.33

Breakout: Compute Output Sizes

Input volume: 32x32
5x5 filter
Stride 1
Pad 2
Output volume size = ?

Input volume: 50x50
2x2 filter
Stride 2
Output volume size = ?

N - original image dimension

F - filter dimension

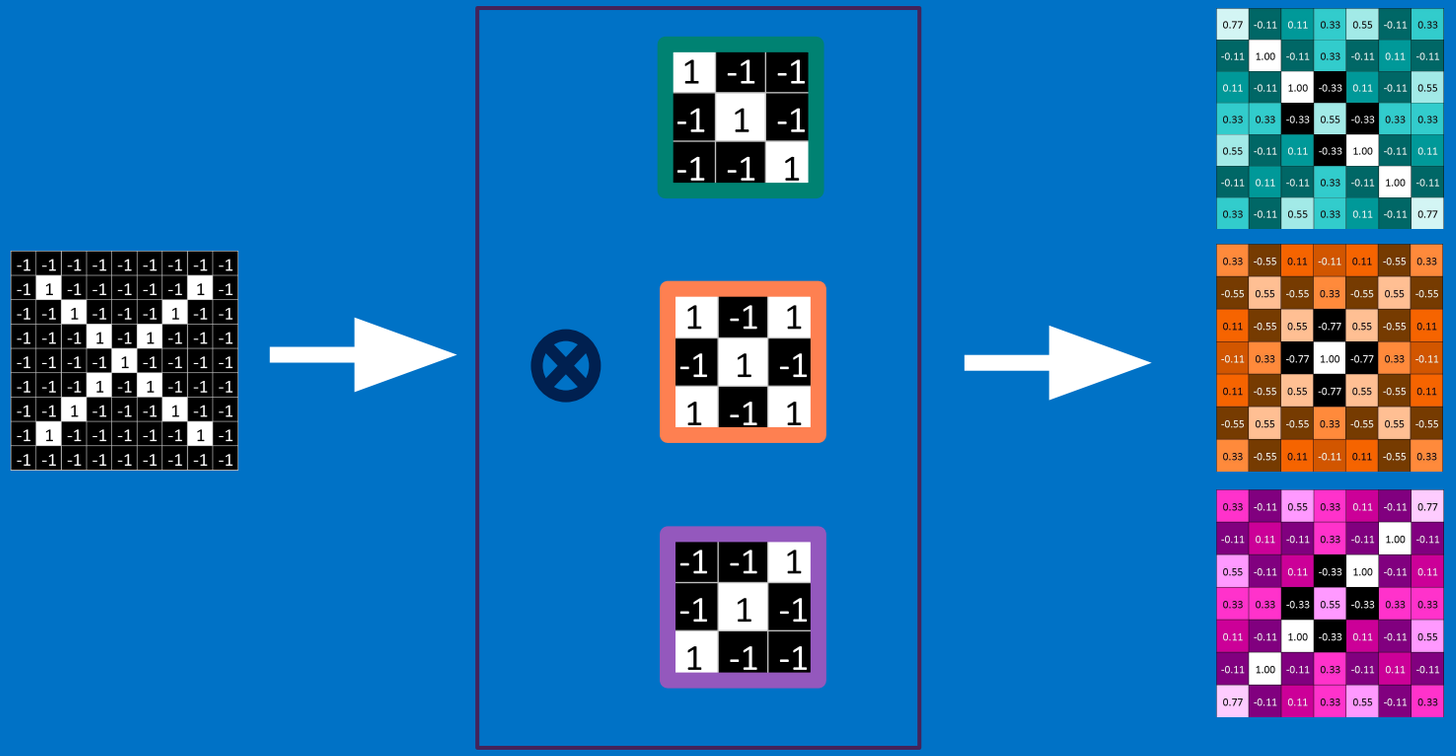
S - stride

P - padding

Output size = ((N - F + 2P) / S) + 1

Convolution layer

One image becomes a stack of filtered images



Convolutional Layer: Summary

galvanize

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Common settings:

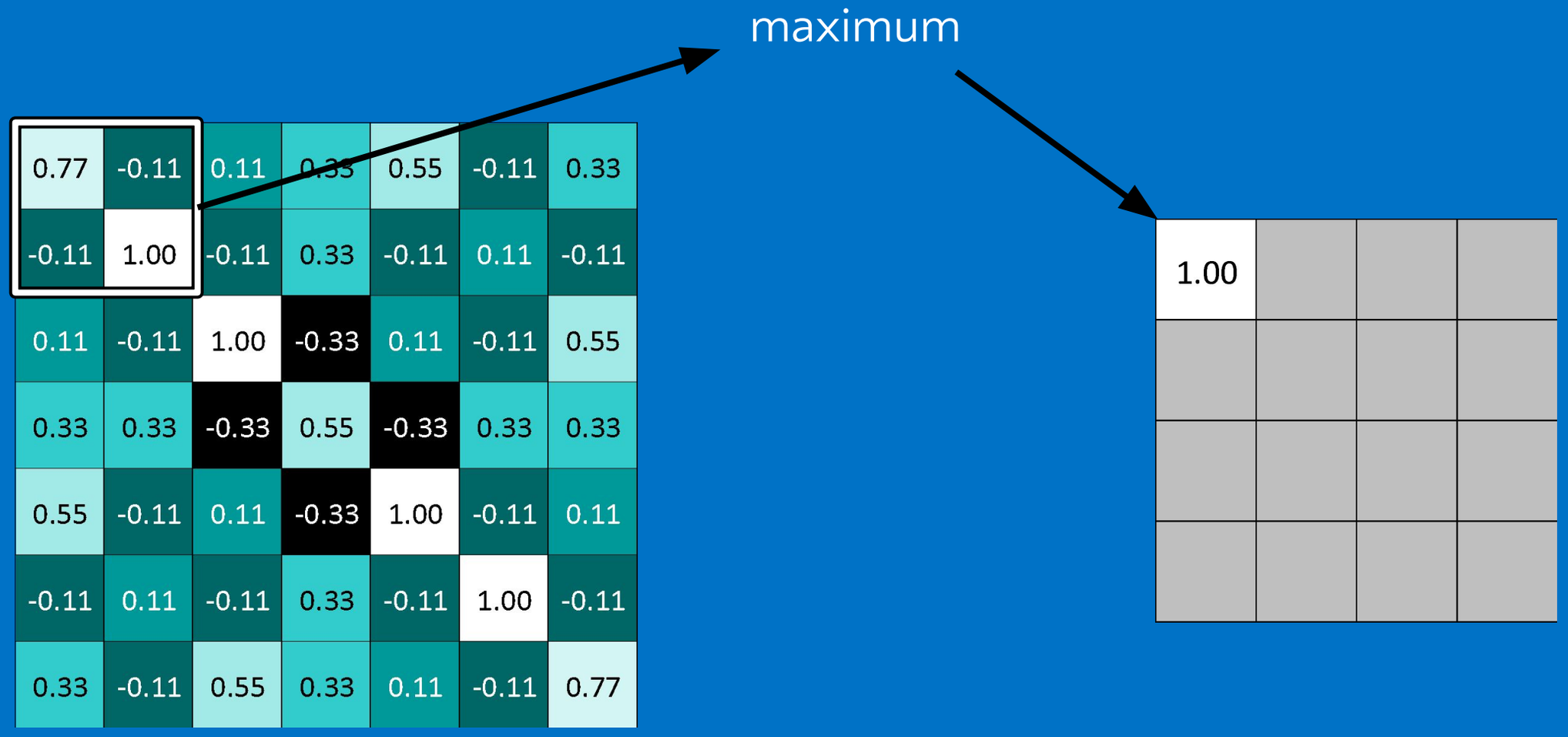
K = (powers of 2, e.g. 32, 64, 128, 512)

- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = ? (whatever fits)
- F = 1, S = 1, P = 0

Pooling: Shrinking the image stack

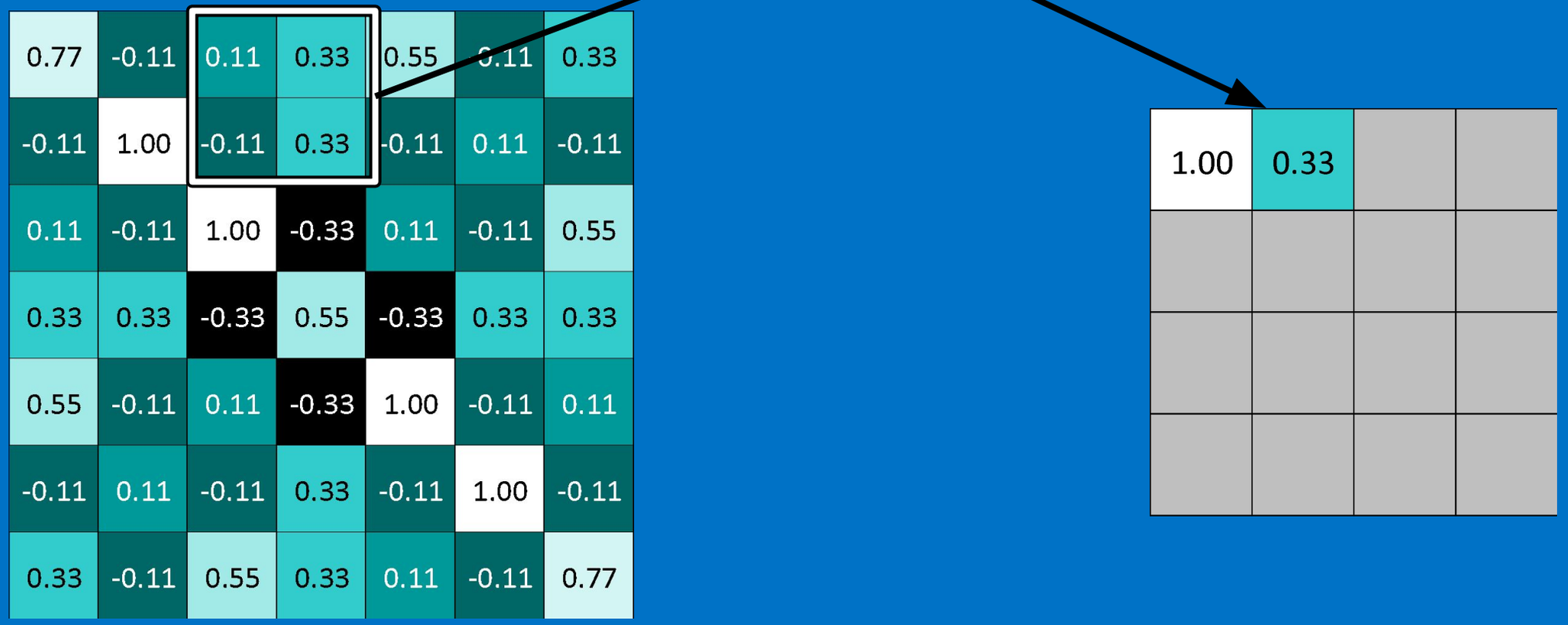
1. Pick a window size (usually 2x2 or 3x3 pixels).
2. Pick a stride (usually 2 pixels).
3. Walk your window in strides across your filtered images.
4. From each window, take the maximum value.

Pooling (2x2 window / stride of 2)



Pooling (2x2 window / stride of 2)

maximum



Pooling (2x2 window / stride of 2) Breakout: Calculate the Next 3 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

1.00	0.33		

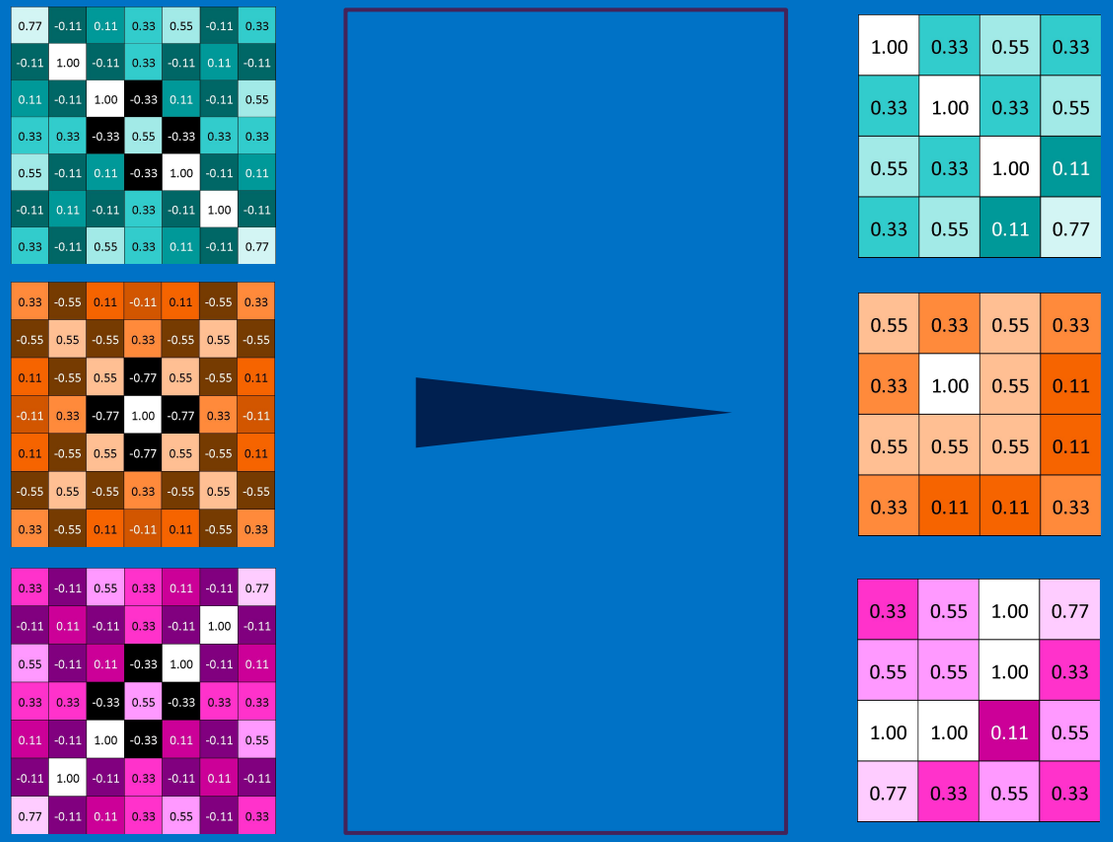
Pooling (2x2 window / stride of 2)

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

Pooling layer

A stack of images becomes a stack of smaller images.



Pooling Layers – Technical Summary

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

Common settings:

F = 2, S = 2

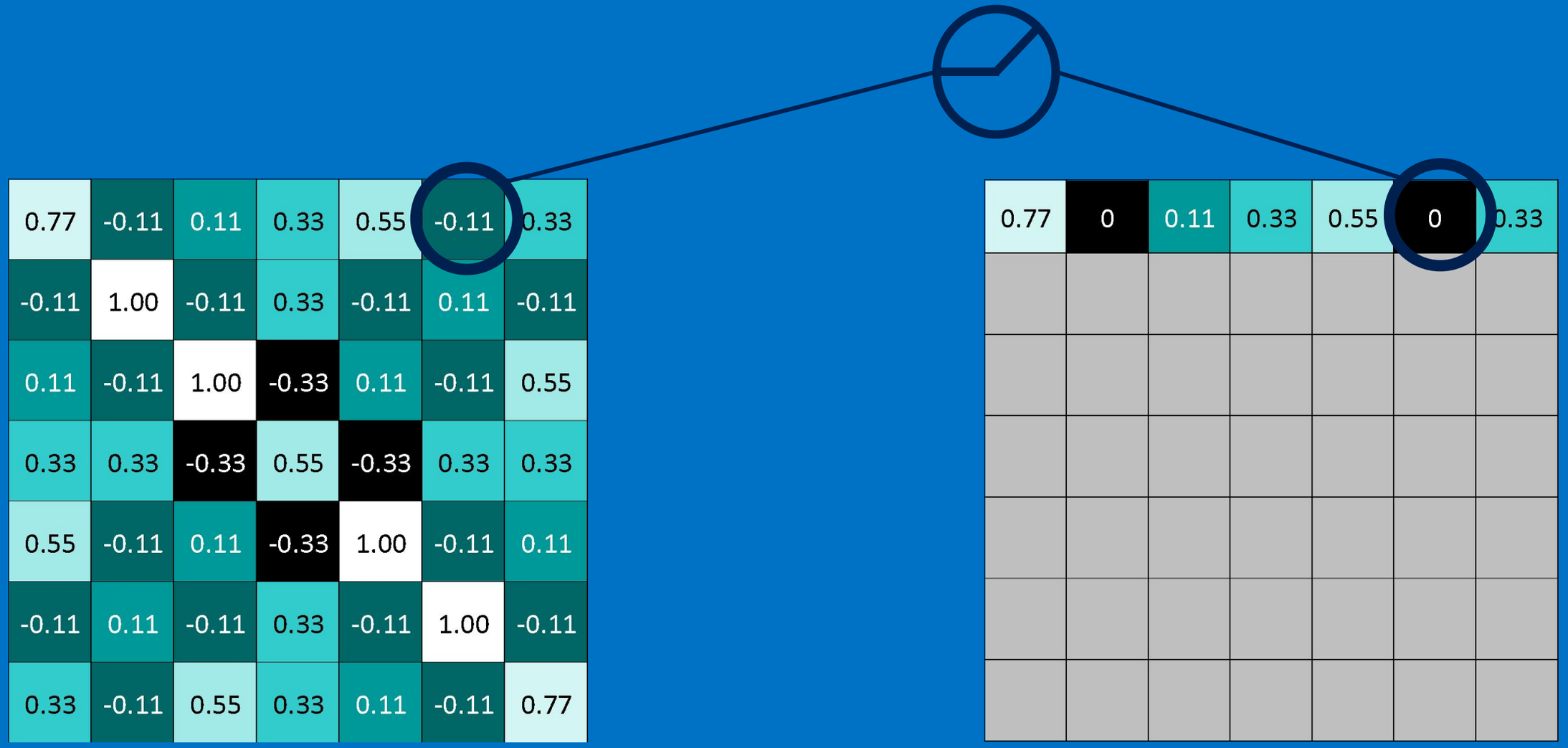
F = 3, S = 2

Concept Review: Activation Layer

- CNNs use activation function(s) just like MLPs
- Types of activation functions in this layer:
  - ReLU – maps all values between 0 and ∞
  - Leaky ReLU – instead of mapping all negative values to 0, these values have a small negative slope of about 0.01
  - Tanh – maps all values between -1 and 1
  - Sigmoid – maps all values between 0 and 1
- Keeps the math from breaking by tweaking each of the values just a bit.

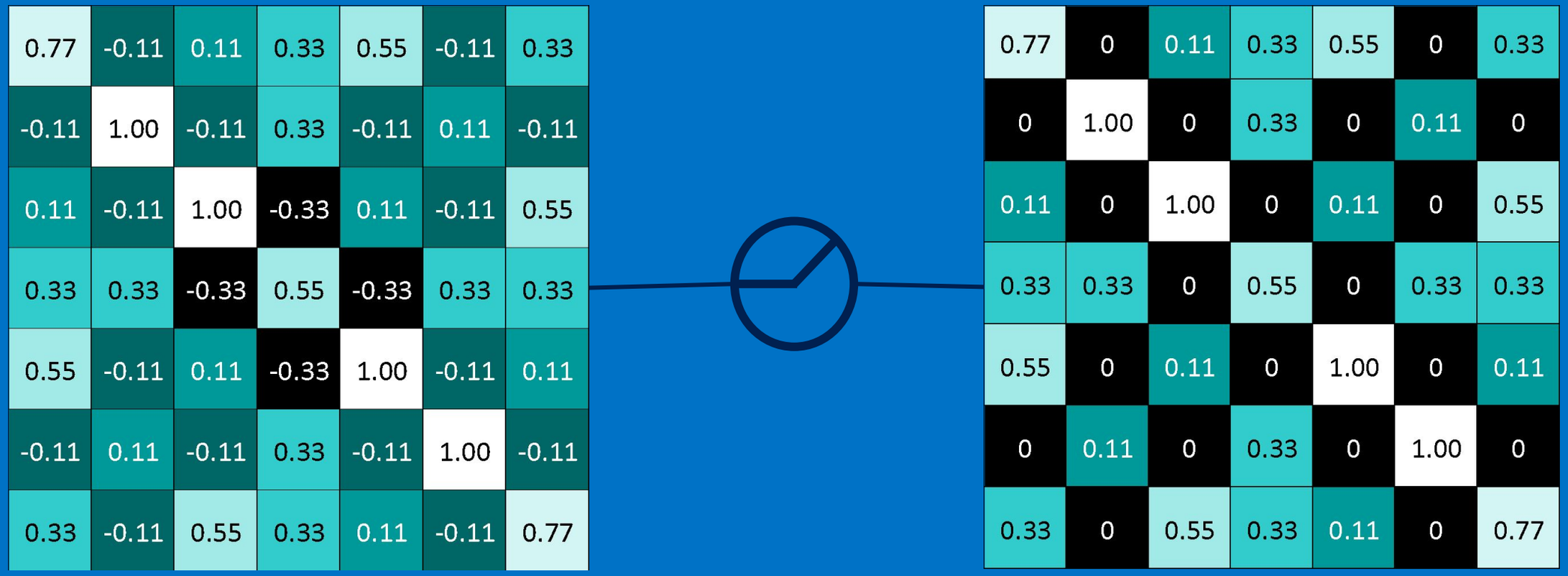
Rectified Linear Units (ReLUs)

Computational units that perform the process of normalization



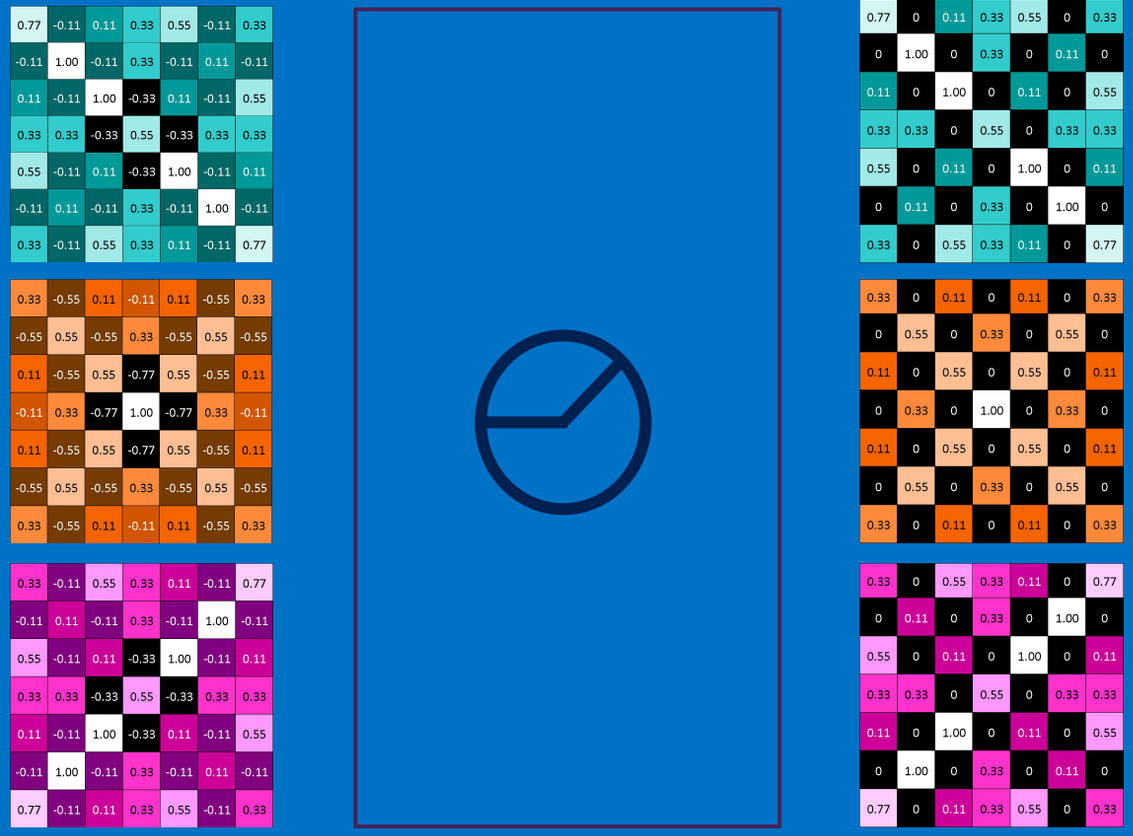
Rectified Linear Units (ReLUs)

Computational units that perform the process of normalization



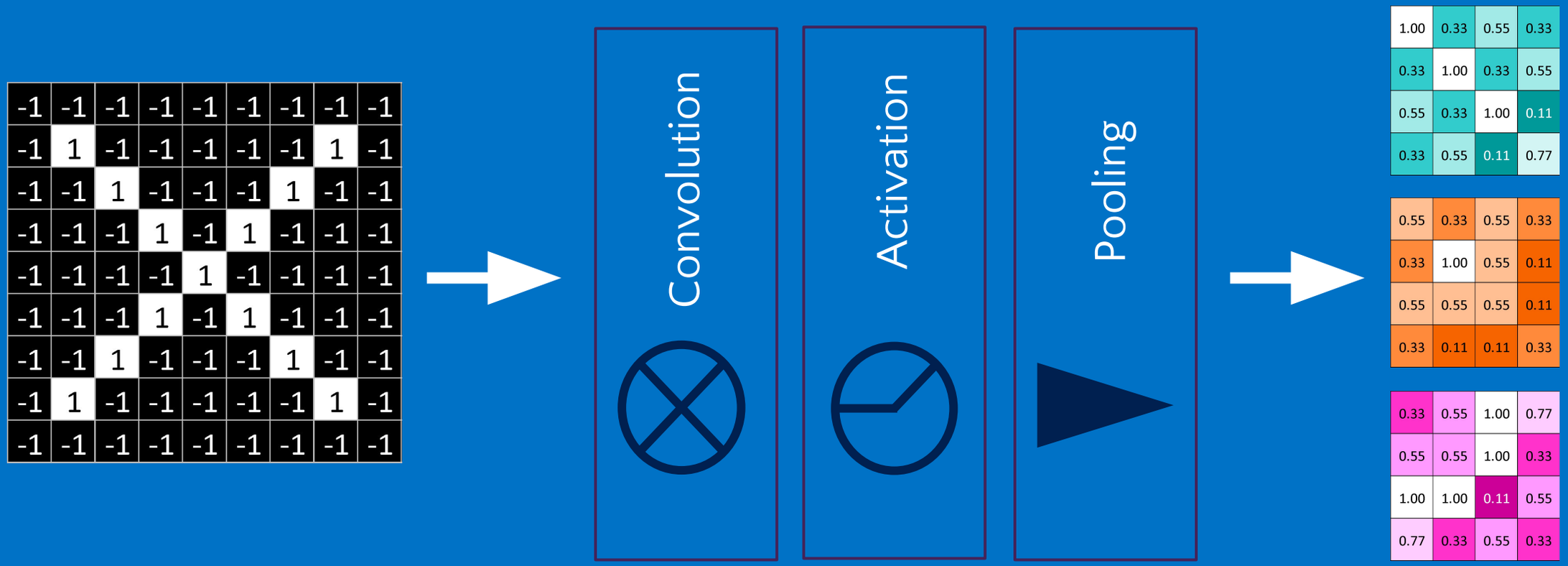
Activation Layer

A stack of images becomes a stack of images with adjusted values.



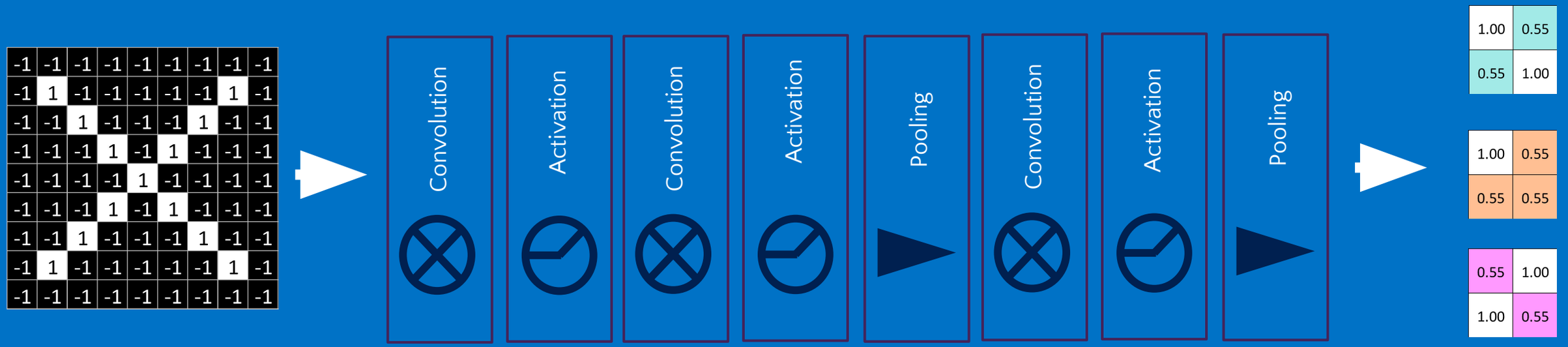
Layers get stacked

The output of one becomes the input of the next.



Deep stacking

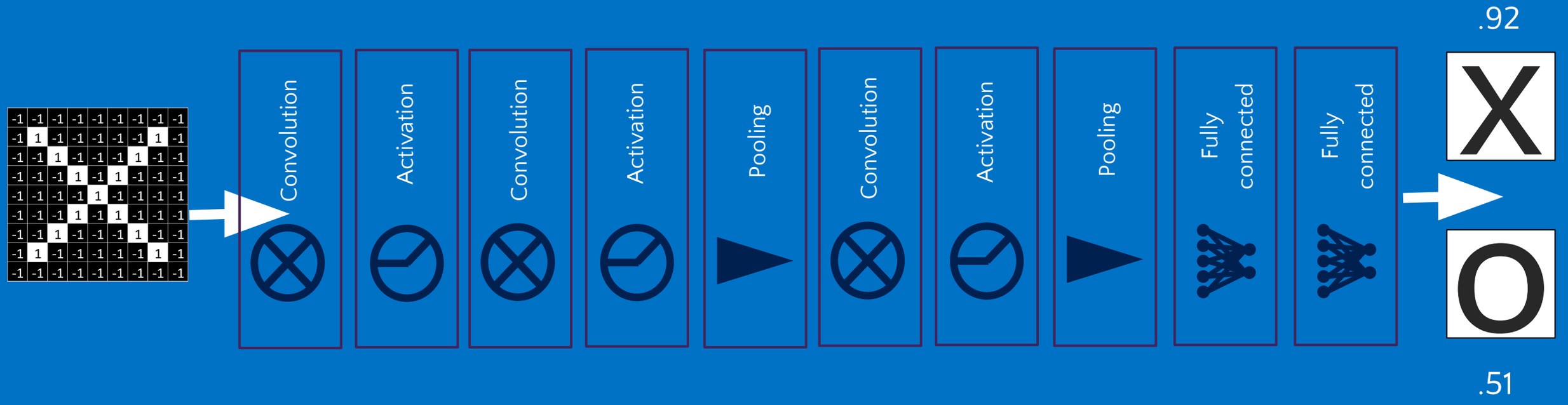
Layers can be repeated several (or many) times.



Concept Review: Fully Connected Layer

- Computing our votes for X & O through feed forward calculations
- Doing the summation of the dot products between the activations & the weights
- We classify the image as an X or O depending on which has the higher value for a vote
- The filters used (e.g., the 3x3 diagonal line images) are updated through backpropagation
- You can think of this as an MLP just stuck onto the end of the CNN

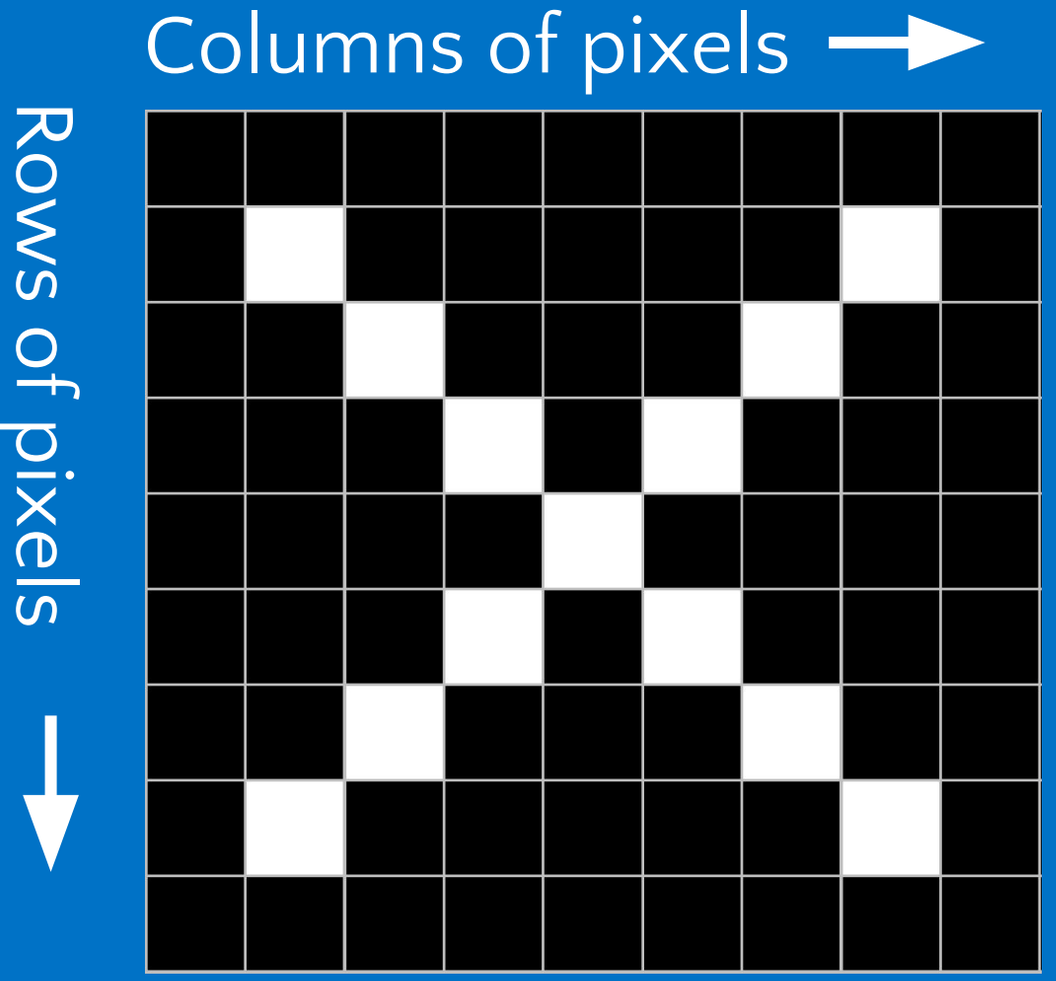
Putting it all together



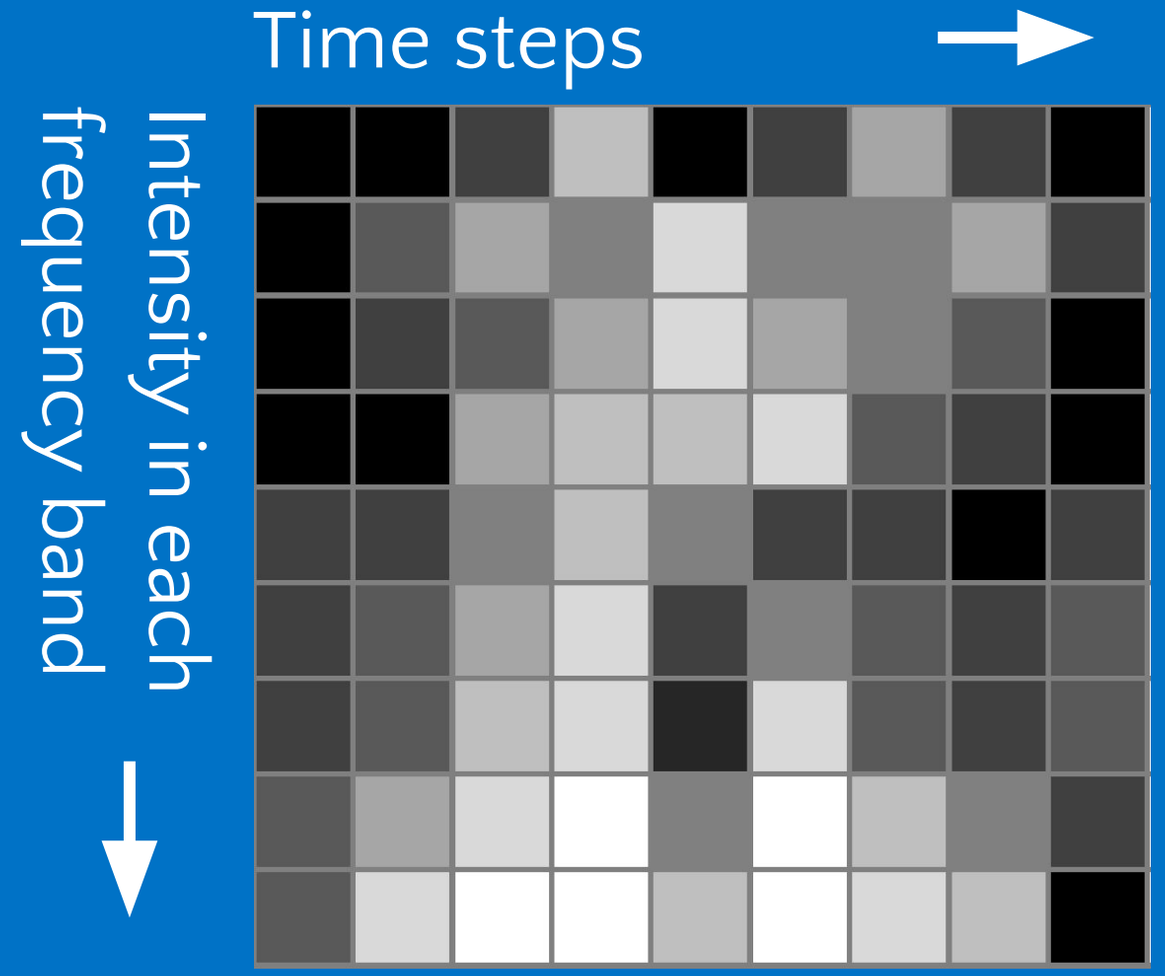
Available Hyperparameters

- Convolution
  - Number of filters
  - Size of filters (dimensions in pixels)
  - Length of stride
  - Size of padding
- Pooling
  - Window size
  - Window stride
- Fully Connected
  - Number of intermediate/hidden neurons
- The number of each type of layer
- The order of your layers

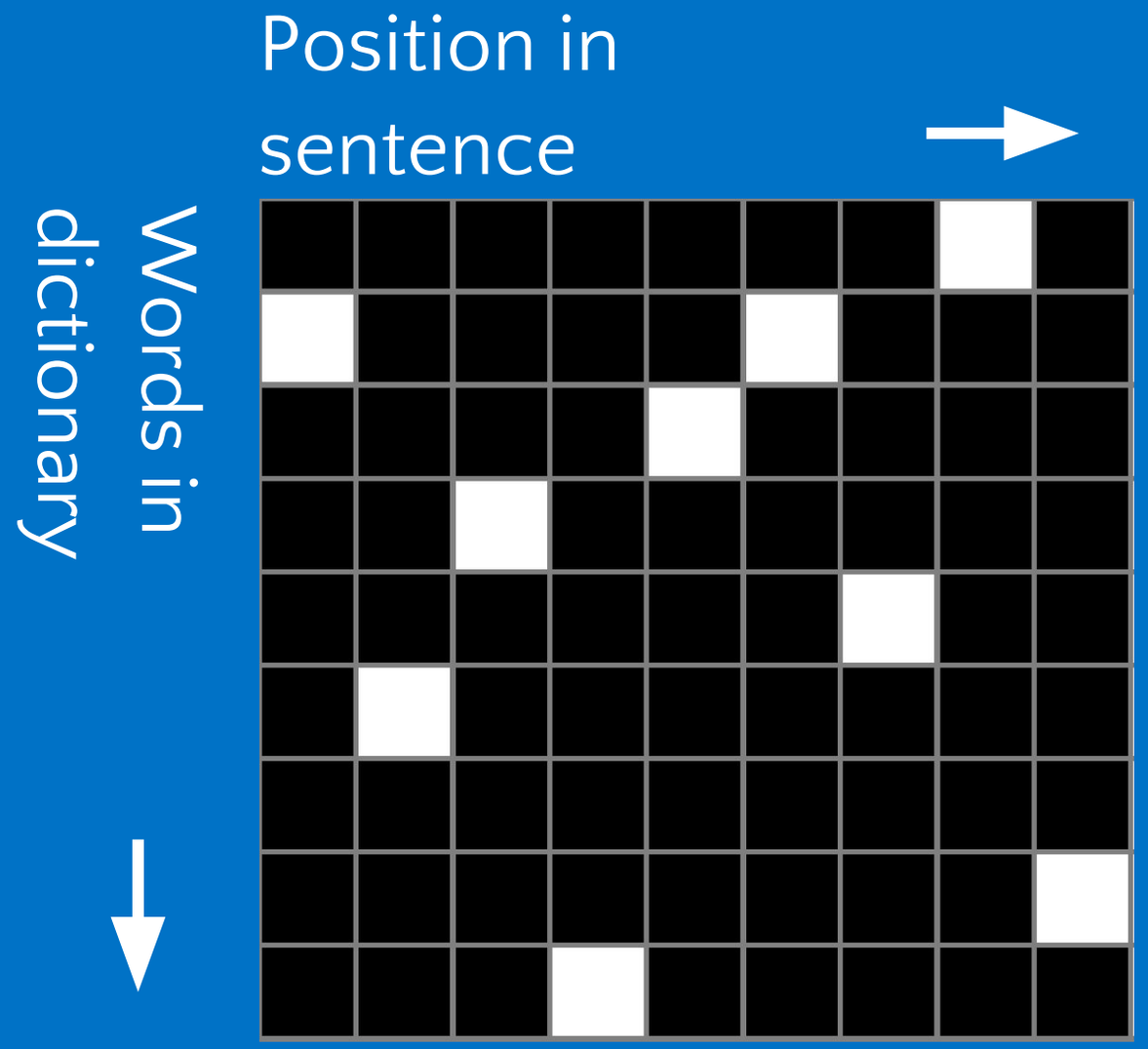
Order in Images



Order in Sound Data



Order in Text Data



Customer Data (Not good for CNNs)

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

Advantages & Disadvantages of CNNs

Advantages:

- CNNs are great at finding patterns and using these patterns to classify images.
- If you can make your data look like images, then they are super useful!
- You can use any 2D, 3D, or even higher dimensional data in a CNN.

Disadvantages:

- CNNs only capture local “spatial” patterns in data.
- If your data is just as useful after swapping any of your columns with each other, then you can’t use CNNs.

Check in Questions

- What are the four types of layers in CNNs?
- How does convolution work?
- How does pooling work?

Additional Resources

- Visual Explanation of Image Kernels/Filters – http://setosa.io/ev/image-kernels/
- Convolution Demo – http://cs231n.github.io/convolutional-networks/ (note the 'Case Studies' and 'Computational Considerations' sections)
- Another explanation of CNNs – https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/
- Working with images in Python
  - Skimage – http://scikit-image.org/docs/dev/api/skimage.html
  - PIL – http://www.pythonware.com/products/pil/