

Deep Learning

Big Data & Machine Learning Bootcamp - Keep Coding



Outline

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5. Simple convolutional network
6. Pooling layers
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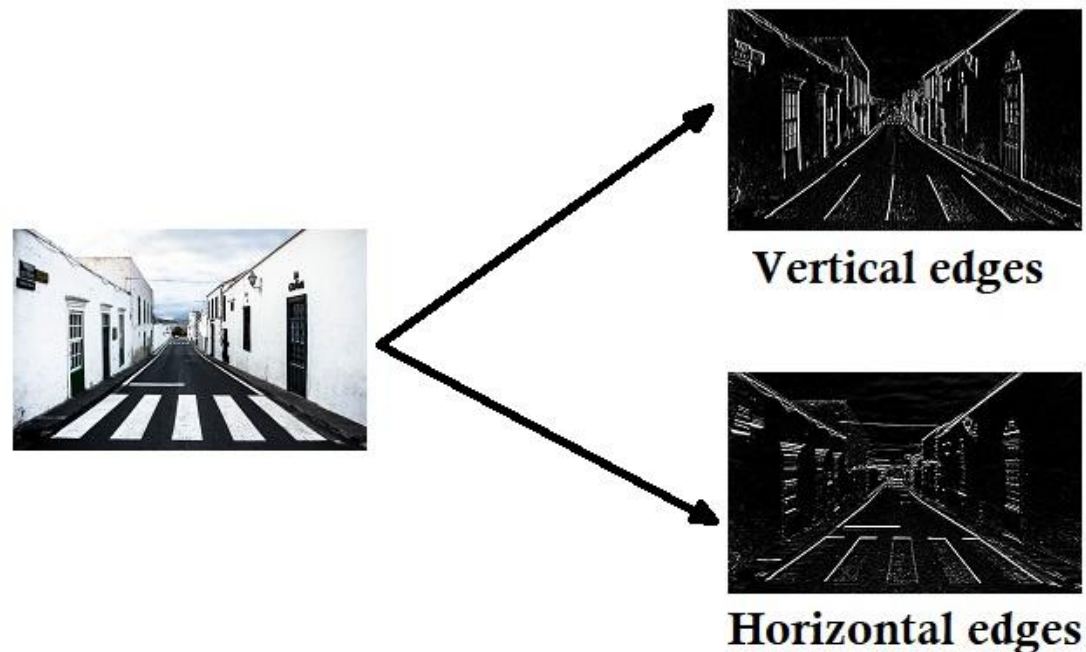


Edge detection

We've previously talked about how the neural networks extract different features at different layers.



But how the CNN detect edges?



Edge detection

First, how convolution works:

| | | | | |
|---|---|---|---|---|
| 7 | 2 | 3 | 3 | 8 |
| 4 | 5 | 3 | 8 | 4 |
| 3 | 3 | 2 | 8 | 4 |
| 2 | 8 | 7 | 2 | 7 |
| 5 | 4 | 4 | 5 | 4 |

*

| | | |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |
| 1 | 0 | -1 |

=

| | | |
|---|--|--|
| 6 | | |
| | | |
| | | |

$$\begin{aligned} &7 \times 1 + 4 \times 1 + 3 \times 1 + \\ &2 \times 0 + 5 \times 0 + 3 \times 0 + \\ &3 \times -1 + 3 \times -1 + 2 \times -1 \\ &= 6 \end{aligned}$$



Padding

Padding is a modification made to the basic convolutional operation that solves two problems:

- Shrinking output
- Throwing away information from edge

This modification allows us to have **same size of image after convolution** and also **process more than one time the edge pixels** by just adding zeros around the input image.

In this image padding = 1

| | | | | | |
|---|----|----|----|----|---|
| 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 35 | 19 | 25 | 6 | 0 |
| 0 | 13 | 22 | 16 | 53 | 0 |
| 0 | 4 | 3 | 7 | 10 | 0 |
| 0 | 9 | 8 | 1 | 3 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 |



Padding

There are two common choices on how much to pad:

- **Valid convolutions** -> NO PADDING.

The output image will be $(n - f + 1) \times (n - f + 1)$ where n is the size on the input image and f the size of the filter/kernel

- **Same convolution** -> Pad so that output size is the same as the input size

$$\text{Padding} = (\text{filter size} - 1) / 2$$

As as side note, the size of the filter is usually odd! i.e. 3, 5, 7



Strided convolutions

Stride is another modification of the basic convolution operation.

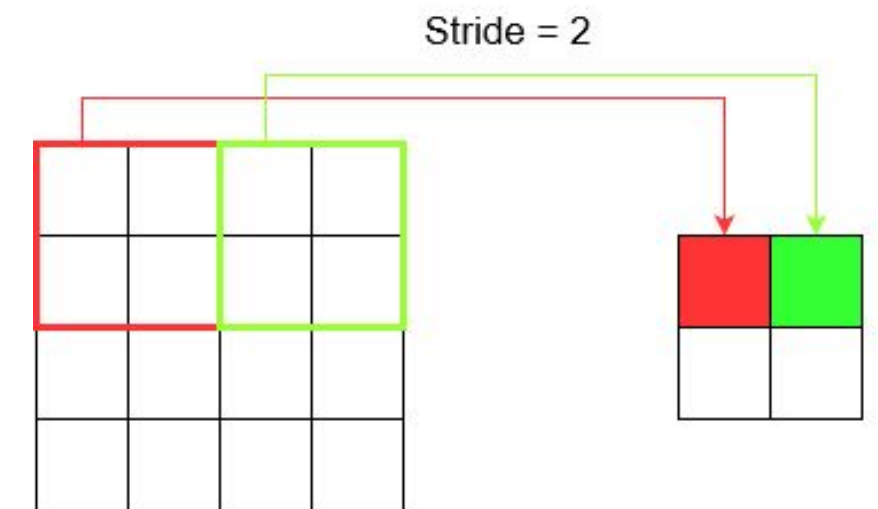
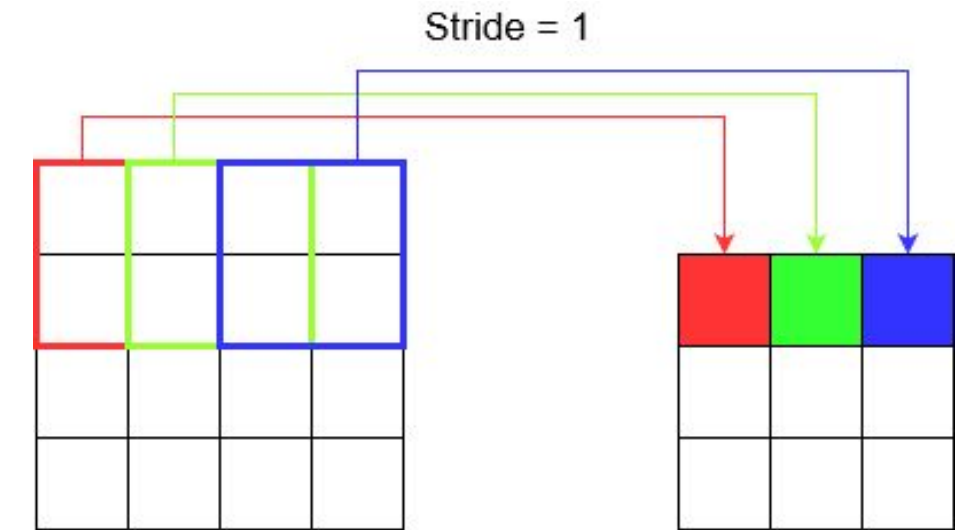
Basically, stride is the **number of rows and columns we traverse per slide** when doing the convolution.

The output width and height are specified by these equations:

$$\text{output width} = \frac{W - F_w + 2P}{S_w} + 1$$

$$\text{output height} = \frac{H - F_h + 2P}{S_h} + 1$$

When the output values are not integers, we take the floor operation. This means we round the values down

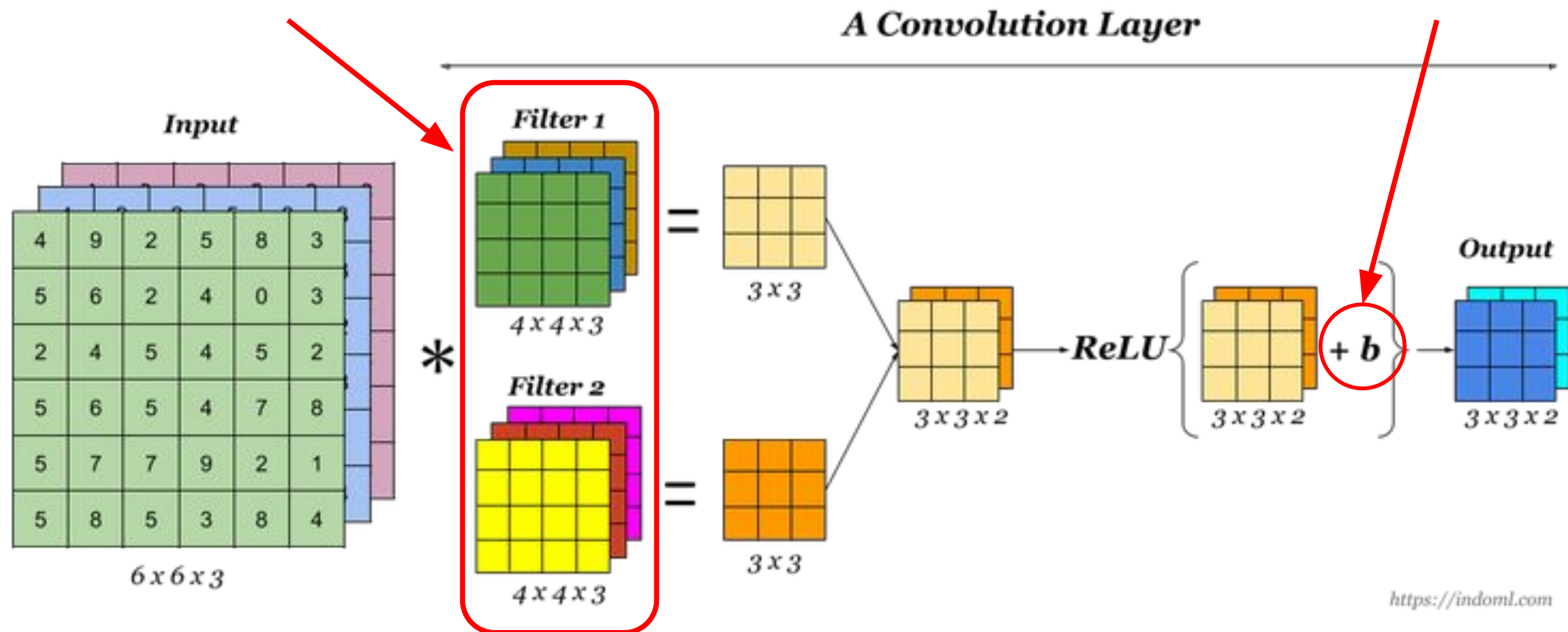


5. One layer of a convolutional network

Convolution is a linear operation

*This play the role of W
Remember the linear equation?*

*We add the bias before
the activation function!*



<https://indoml.com>



Sources:

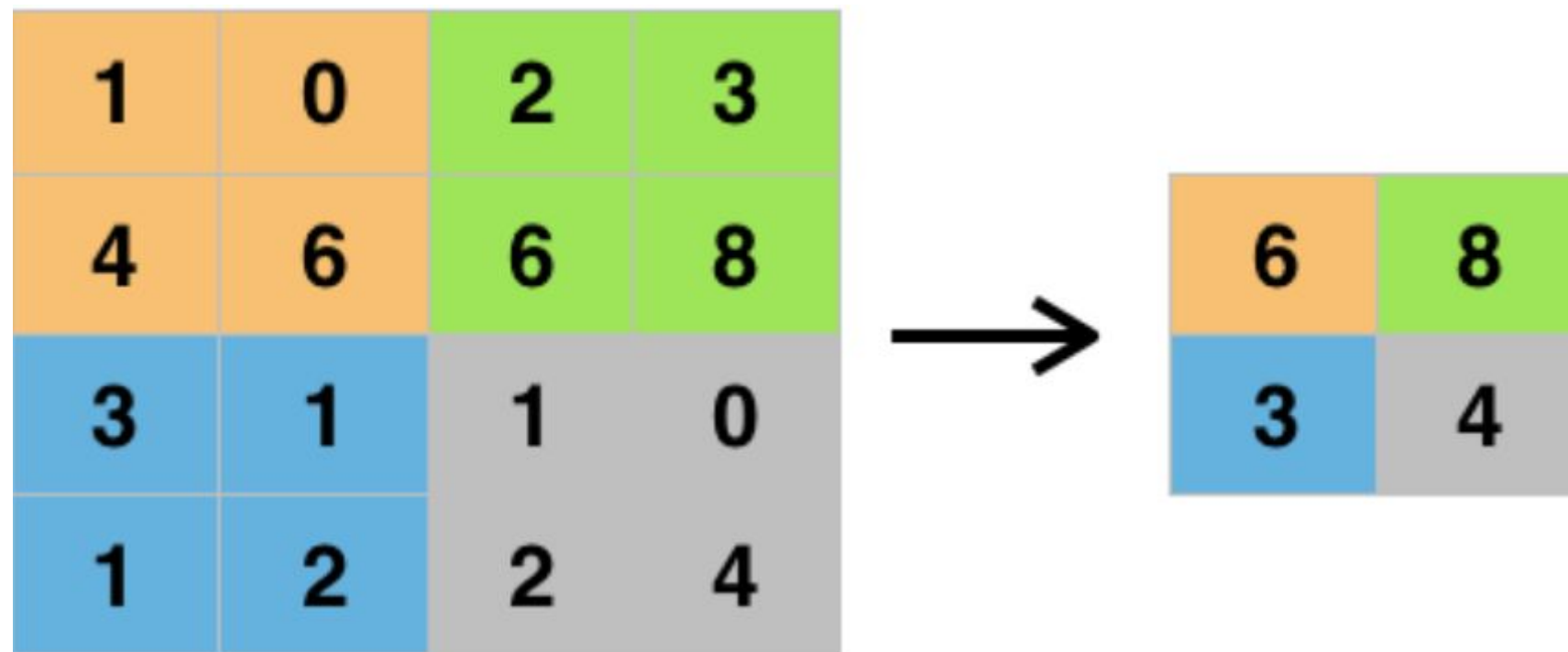
- Coursera

- <https://indoml.com/2018/03/07/student-notes-convolutional-neural-networks-cnn-introduction/>

Pooling layers

Pooling layers are used to **reduce the size of the representation**, to speed up the computation and to make the features detected a bit more robust.

There are different types of pooling. One of the most commonly used is the max pooling:



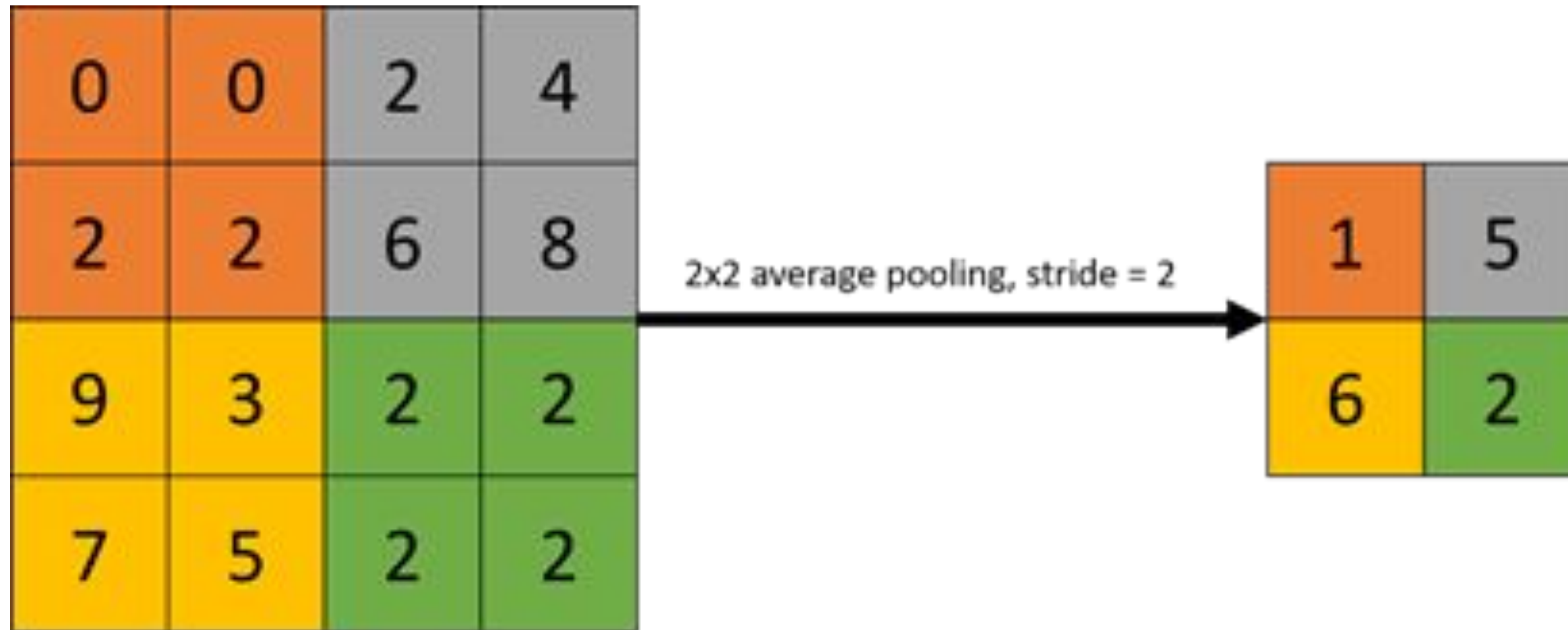
Hyperparameters:
Filter size = 2
Stride = 2

- Pooling **doesn't have parameters to learn**
- Pooling is applied to a single slice and it doesn't change the number of slices



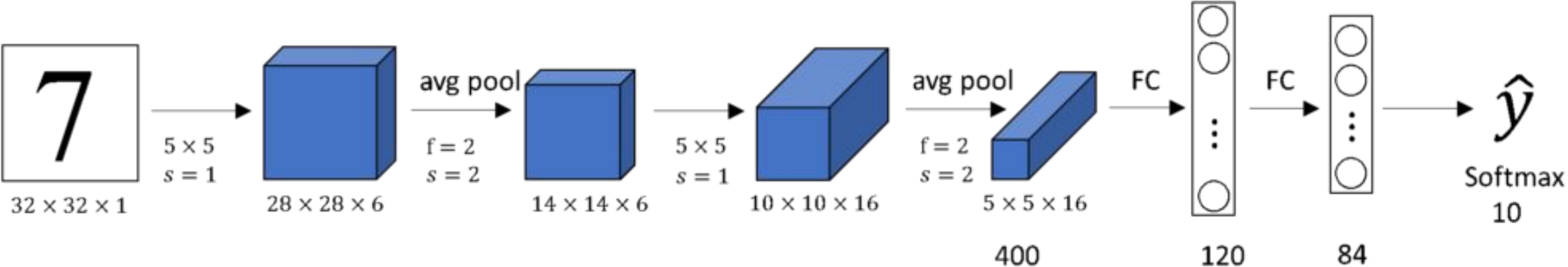
Pooling layers

There is a less used type of pooling called **average pooling**:



CNN example

Let's count the number of parameters



| | Activation Shape | Activation Size | # Parameters |
|------------------|------------------|-----------------|--------------|
| Input | (32,32,1) | 1.024 | 0 |
| CONV1 (f=5, s=1) | (28,28,6) | 4.704 | 156 |
| POOL1 | (14,14,6) | 1.176 | 0 |
| CONV2 (f=5, s=1) | (10,10,16) | 1.600 | 2416 |
| POOL2 | (5,5,16) | 400 | 0 |
| FC | (120,1) | 120 | 48.120 |
| FC | (84,1) | 84 | 10.164 |
| FC + Softmax | (10,1) | 10 | 850 |

How can we compute this value???

You can see that most of the parameters come from the FC layers



Why convolutions?

Parameters sharing: A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

Sparsity of connections: In each layer, each output value depends only on a small number of input.

Translation invariance: A cat that is shifted or mirrored it is still cat in convolution neural networks

AND we still can use gradient descent to train it



Sources:
- Coursera

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