

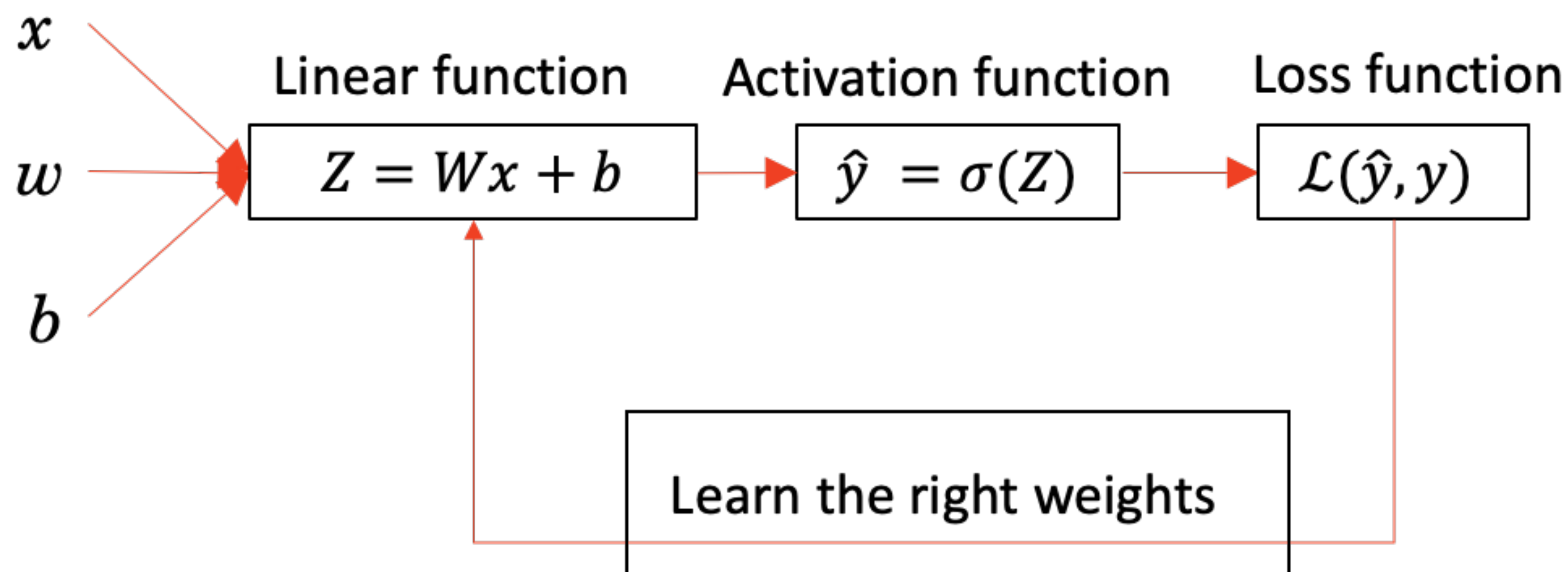
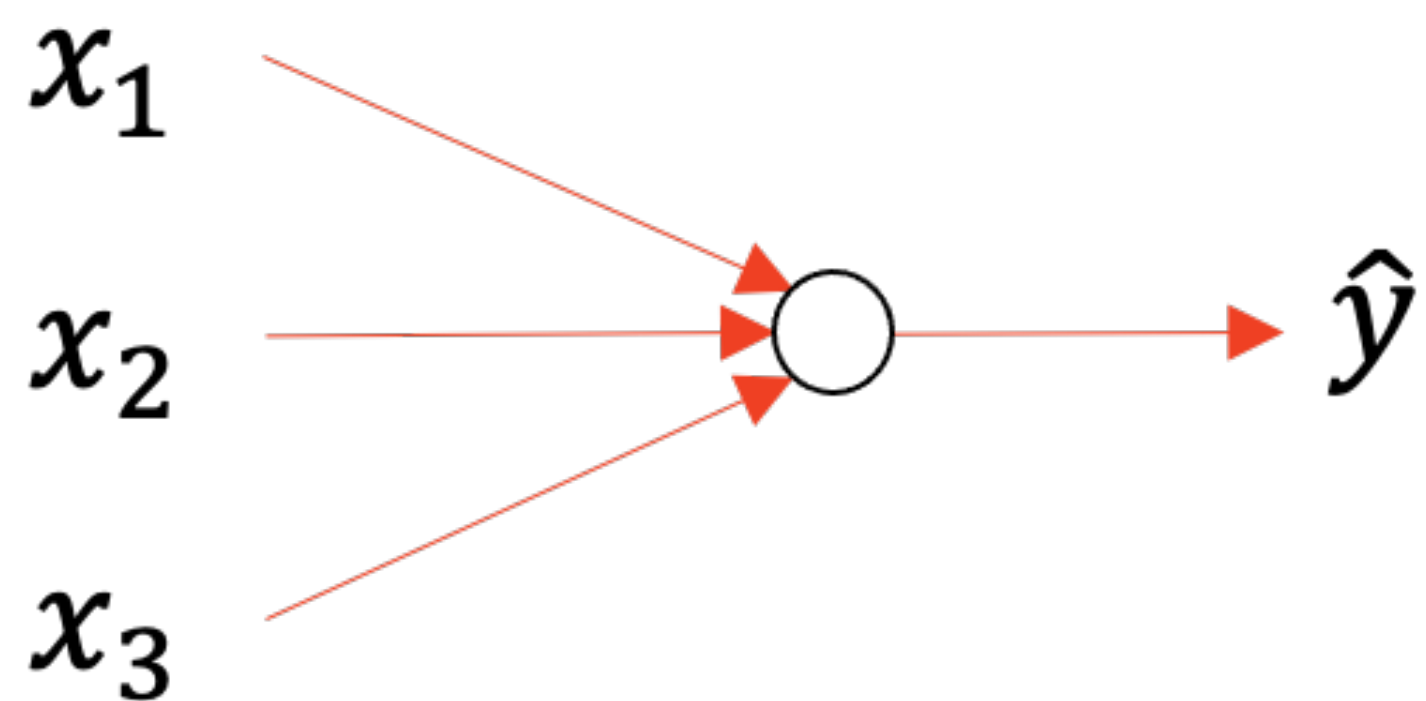
# **Image recognition**

**deep learning 2**

**R.Grouls, 5 mei 2022**

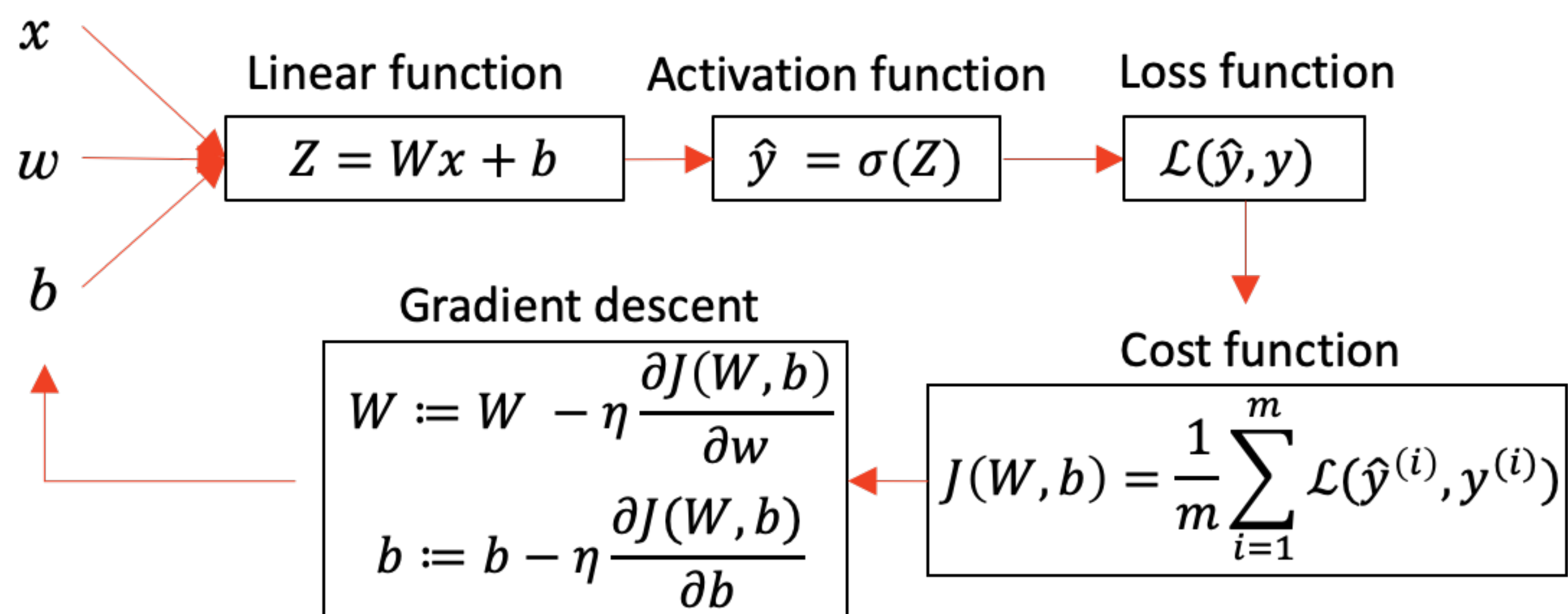
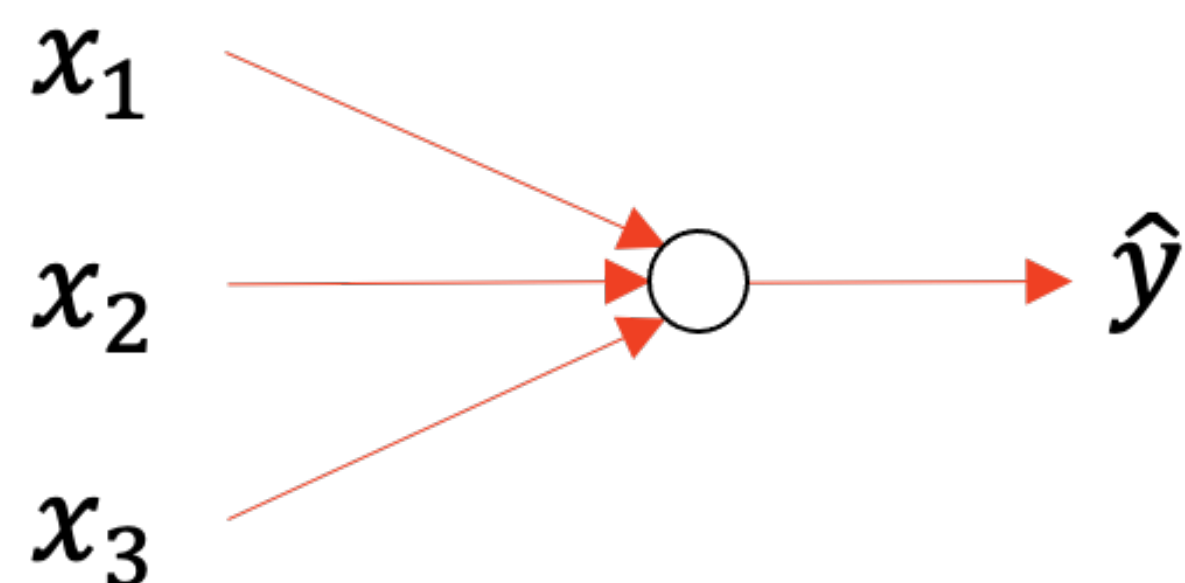
# Neural networks

recap



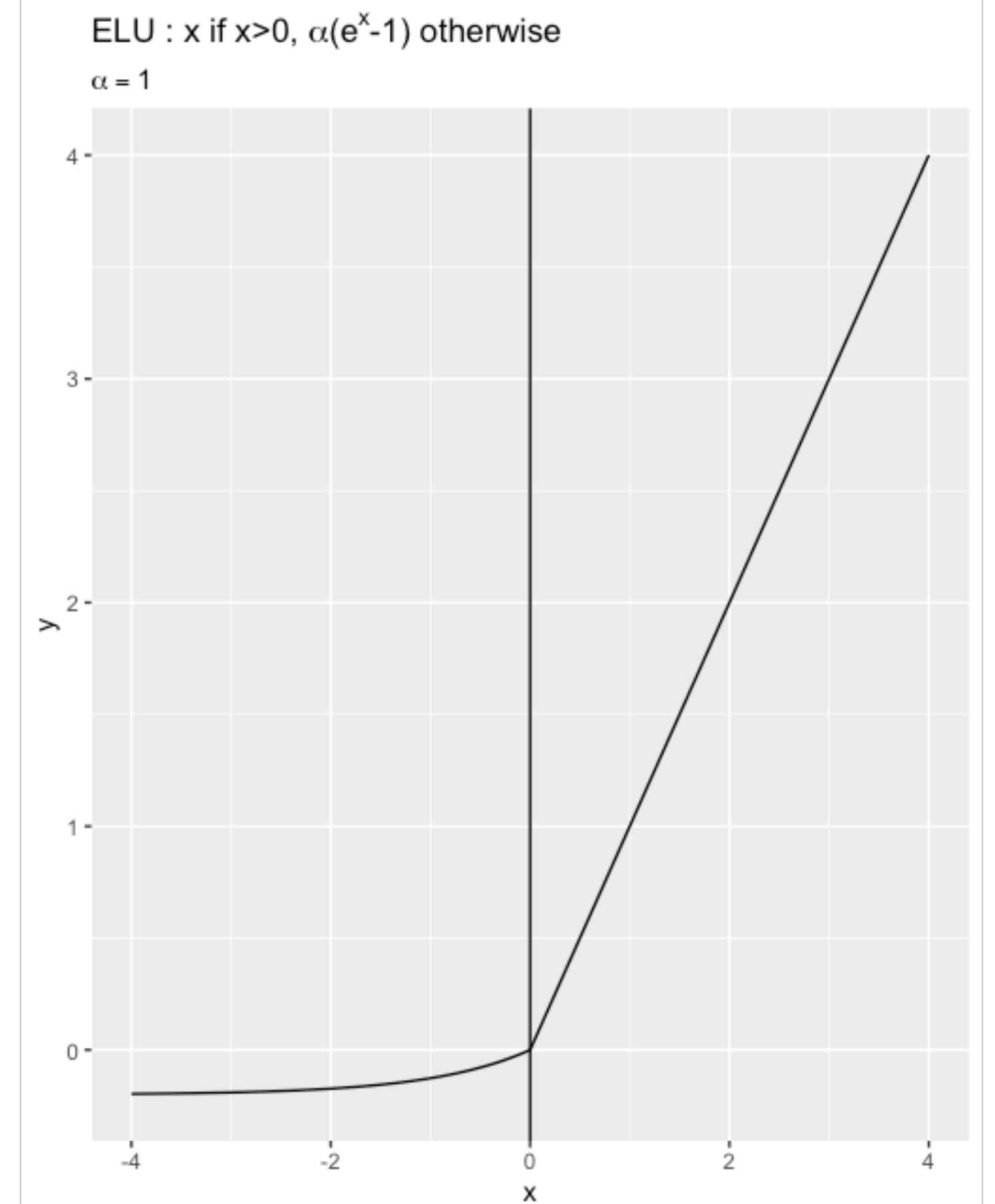
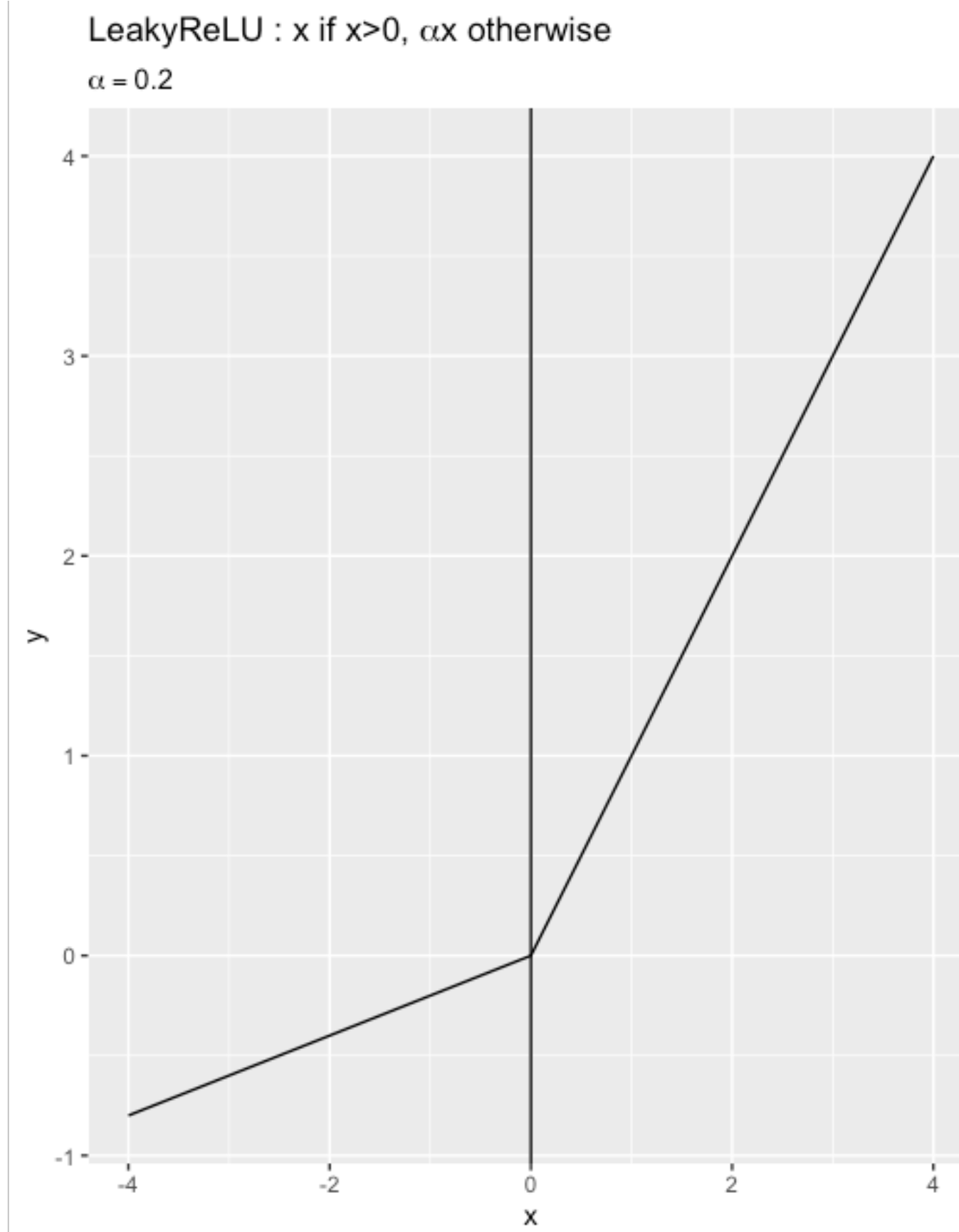
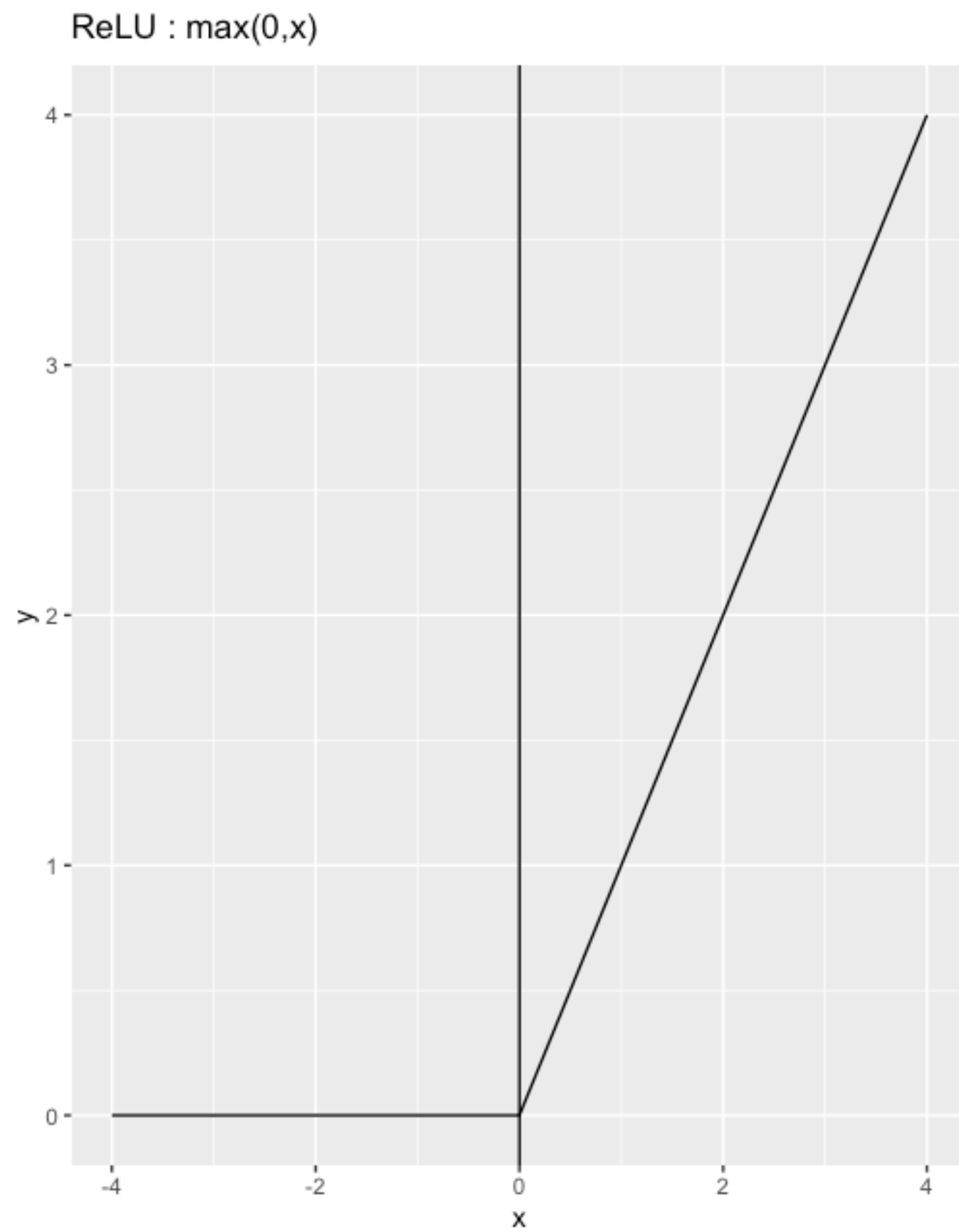
# Neural Networks

recap



# Activations

## non-linearities



# Convolutions - the motivation

## The curse of dimensionality

An image of size 28x28 has 784 pixels

With 256x256 you are already at 65536 pixels

Treating every pixels as a feature will blow up the amount of parameters for your model:

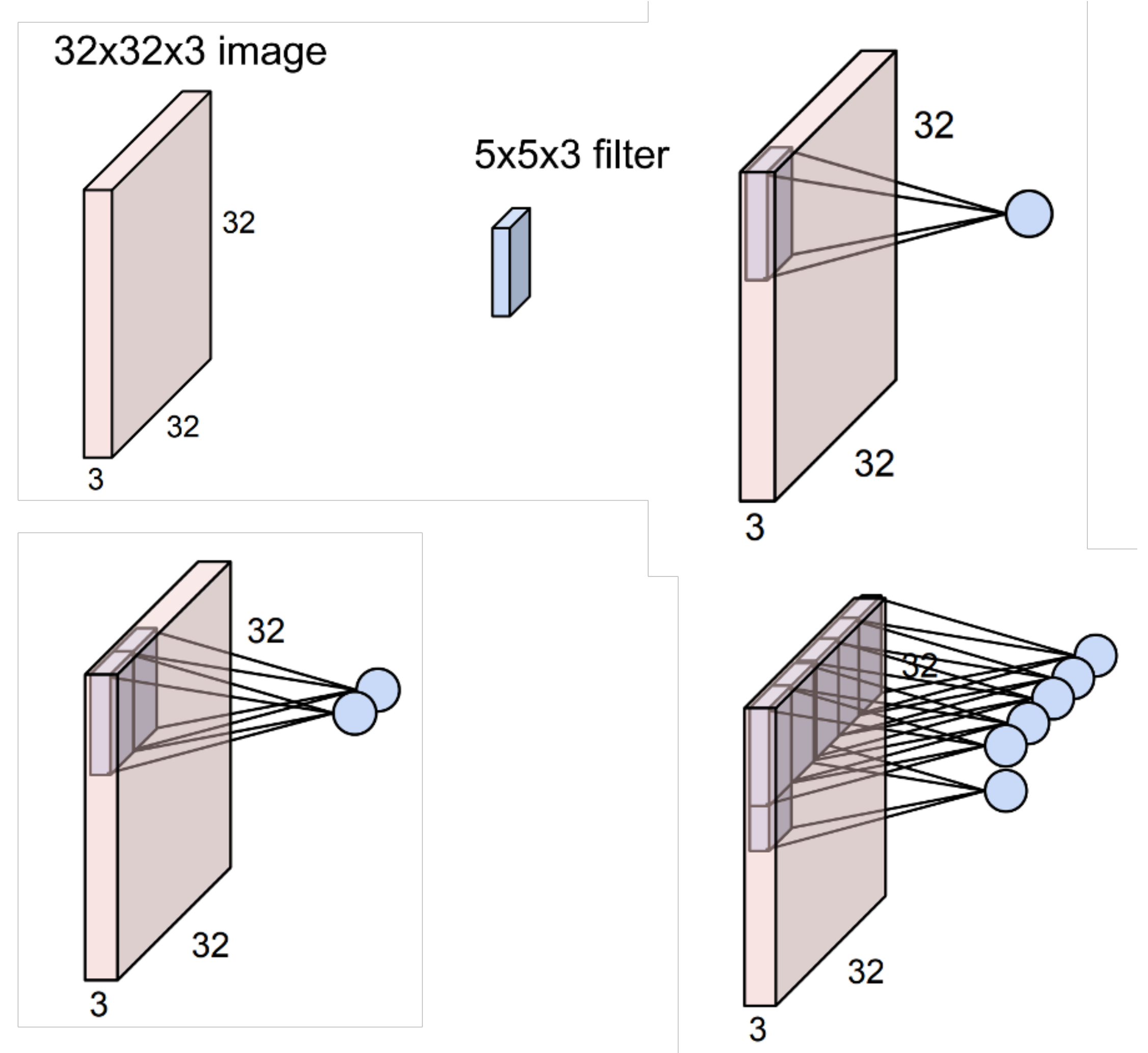
Assuming you halve the dimension, a batch with dimensions (32, 65536) will need a (65536, 32000) weight matrix.

That are over  $2 \times 10^9$  parameters, just for the first layer...

# Convolutions

## Divide and conquer

- Take a filter of size (5x5x3)
- This needs just 75 parameters
- Slide it over the image, like a scanner



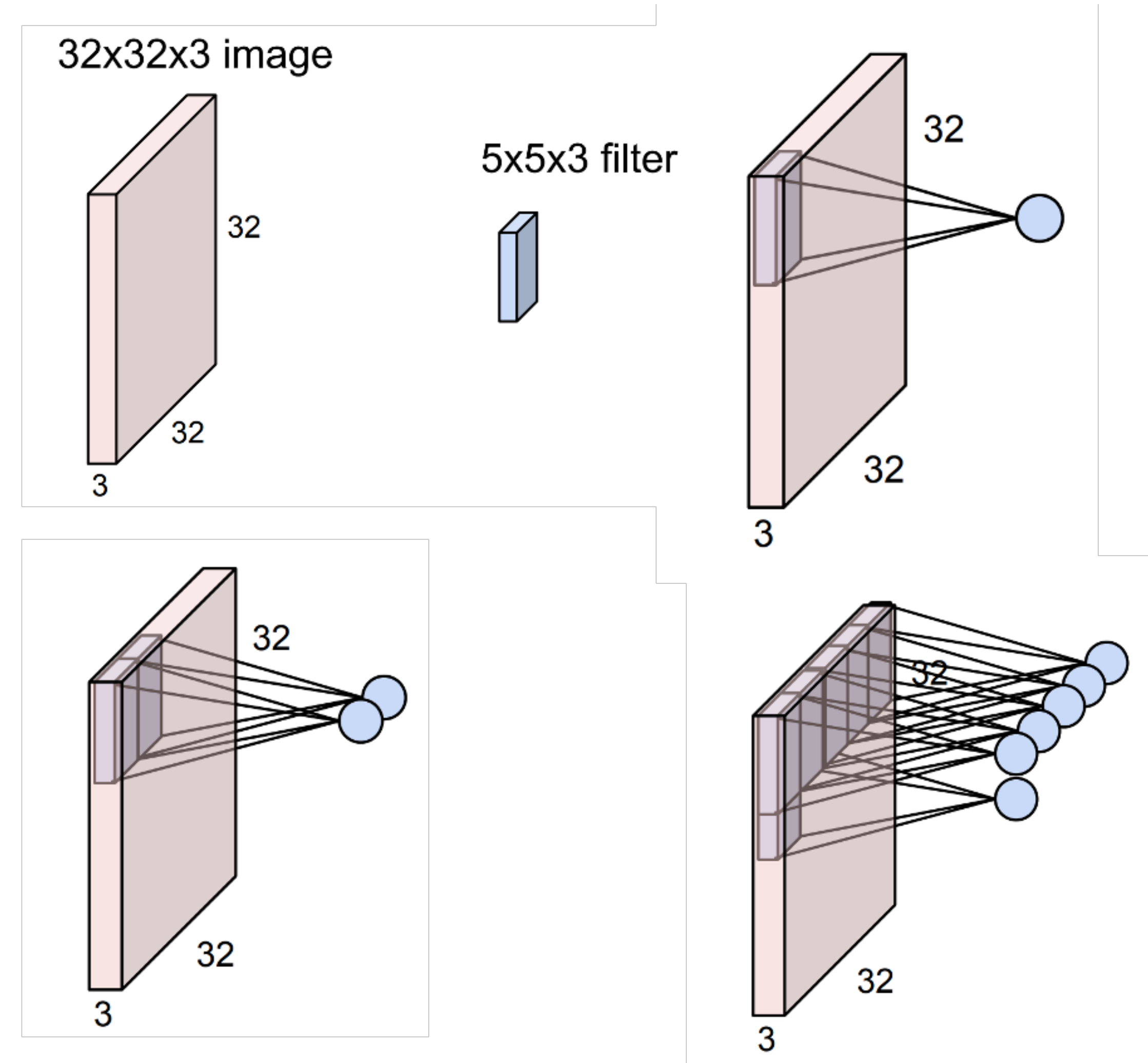
# Convolutions

## Divide and conquer

- Calculate the dot product between the filter and the image
- E.g.,

$$\begin{bmatrix} 1 & 10 \\ 2 & 20 \end{bmatrix} \cdot \begin{bmatrix} 1 & 2 \\ 2 & 0 \end{bmatrix} =$$

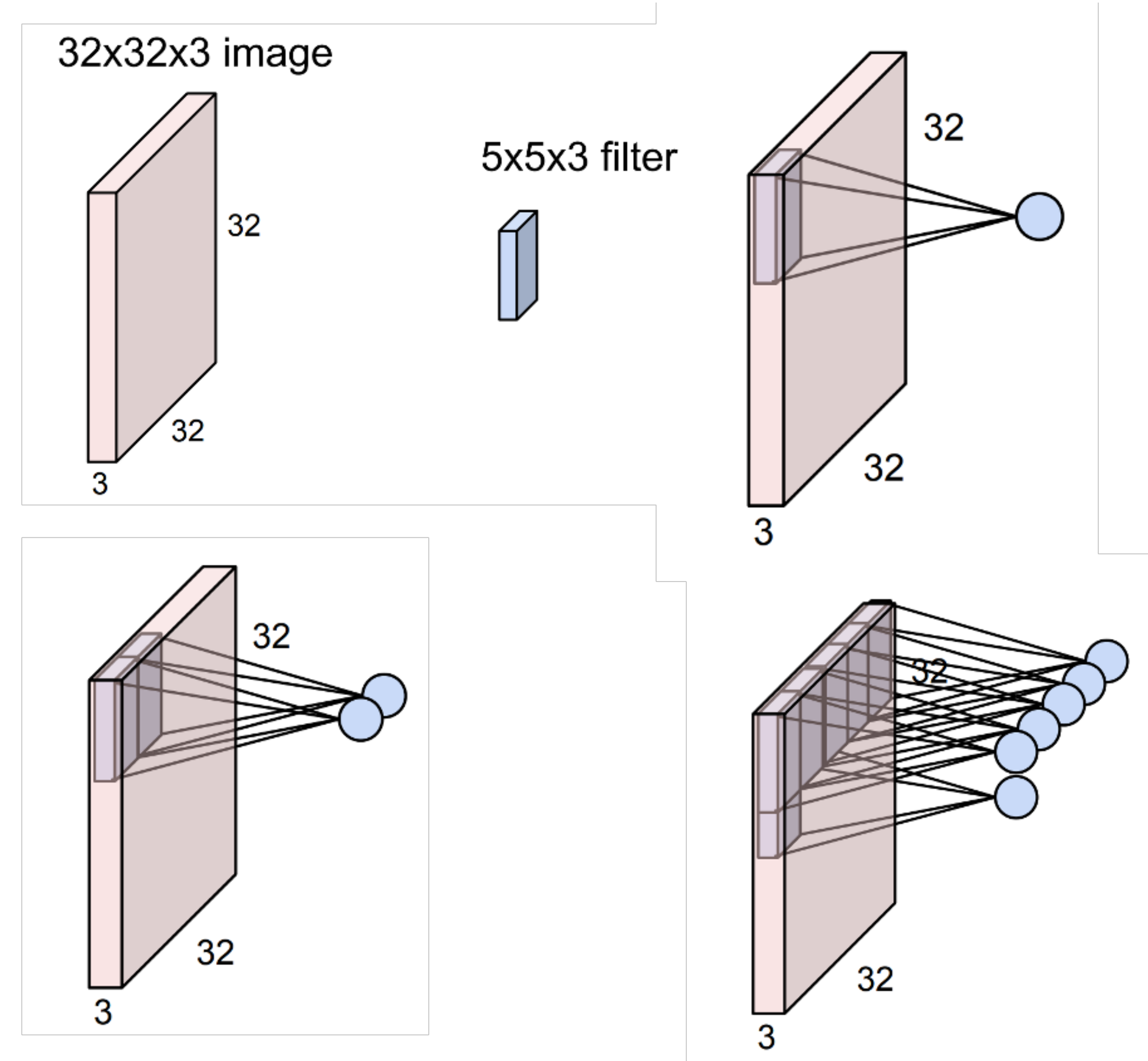
$$(1 * 1) + (10 * 2) + (2 * 2) + 0 = 25$$



# Convolutions

## Divide and conquer

- So, with a 5x5 filter, every 5x5 image slice is reduced to a single number
- This number contains weighted information about it's neighborhood
- We call the result an activation map.

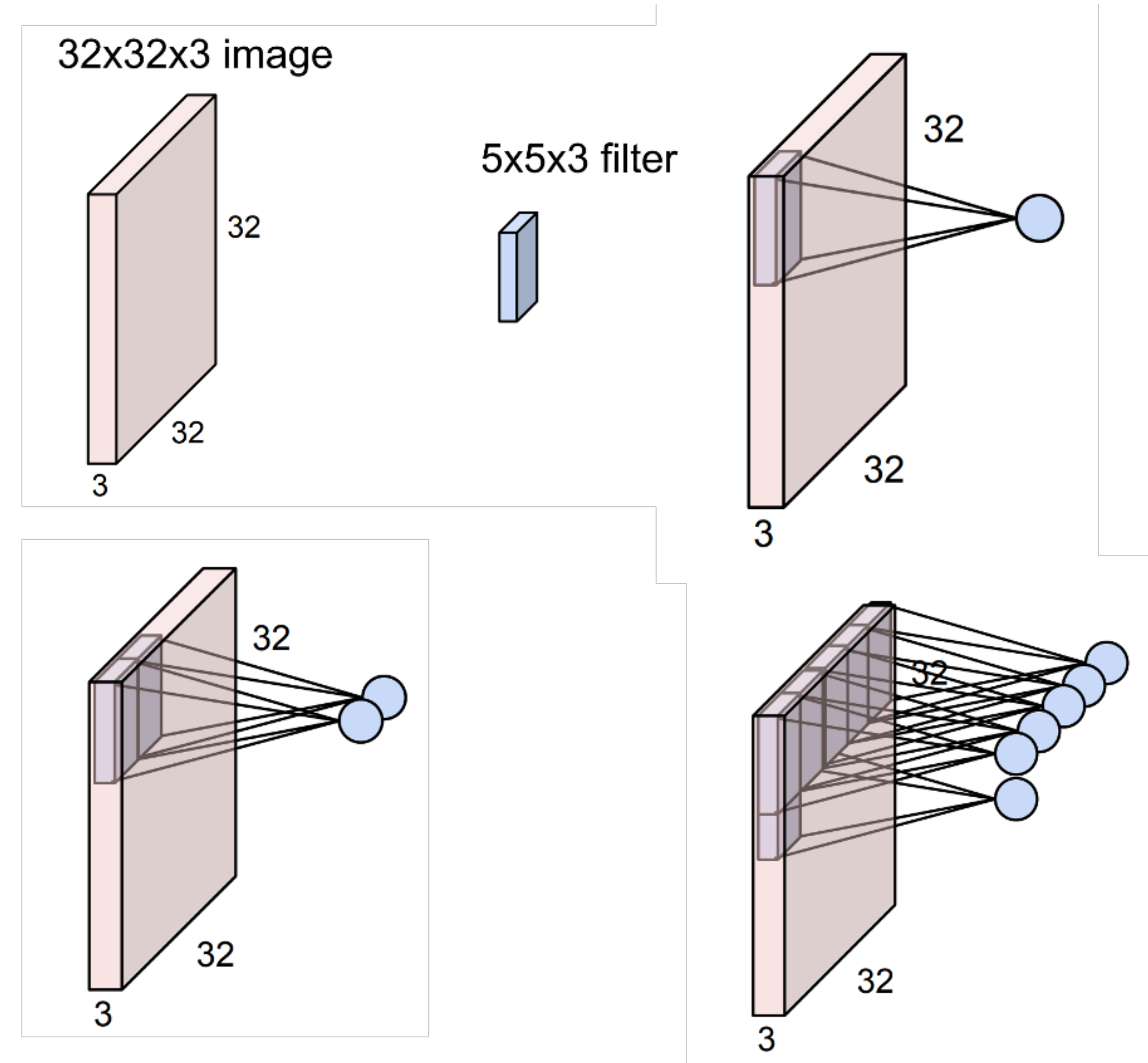




# Convolutions

## Divide and conquer

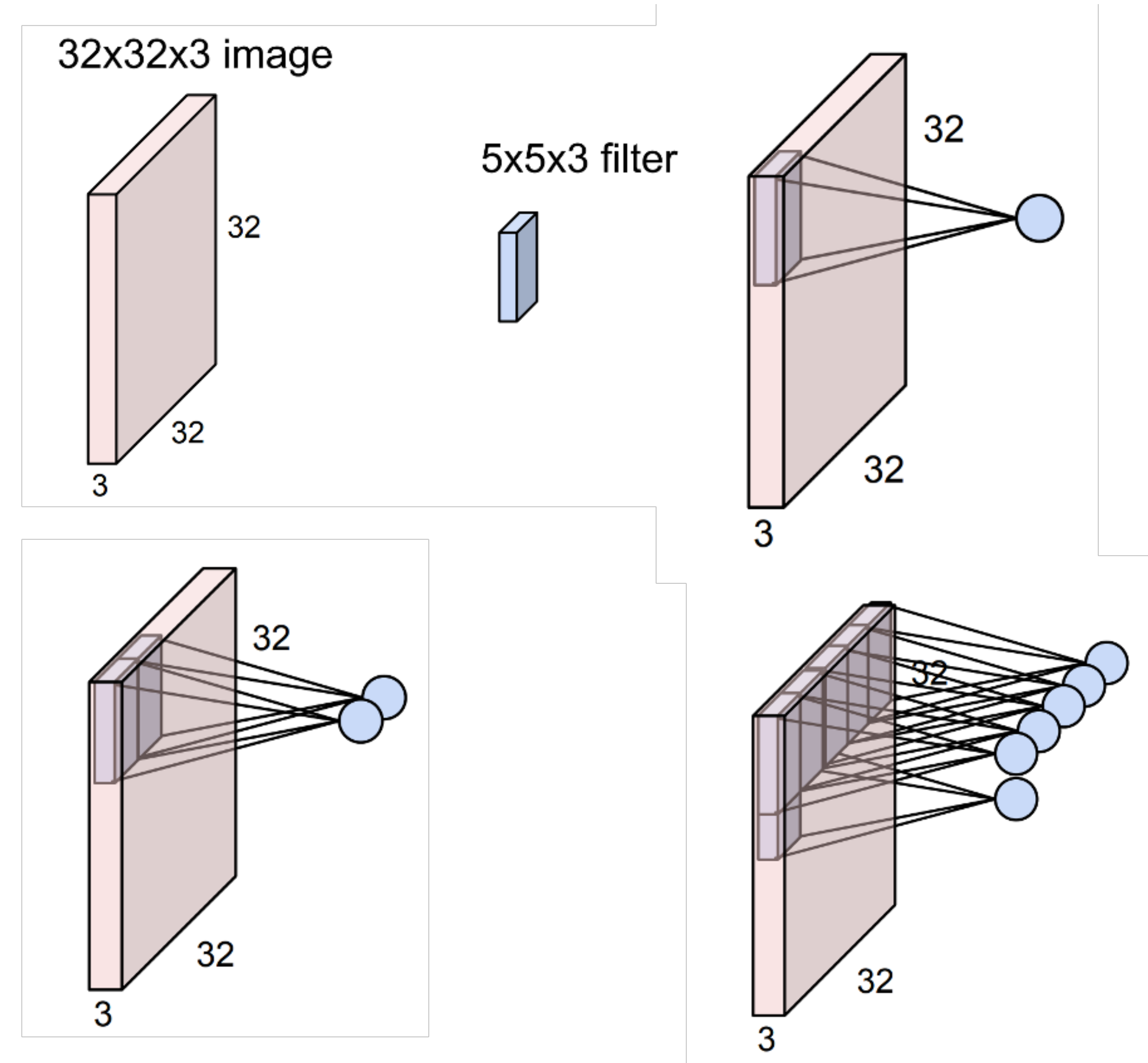
- The filter goes through the depth of the input
- Parameters of the filter are: width, height, depth
- In the first case, the depth is 3, representing the RGB colors



# Convolutions

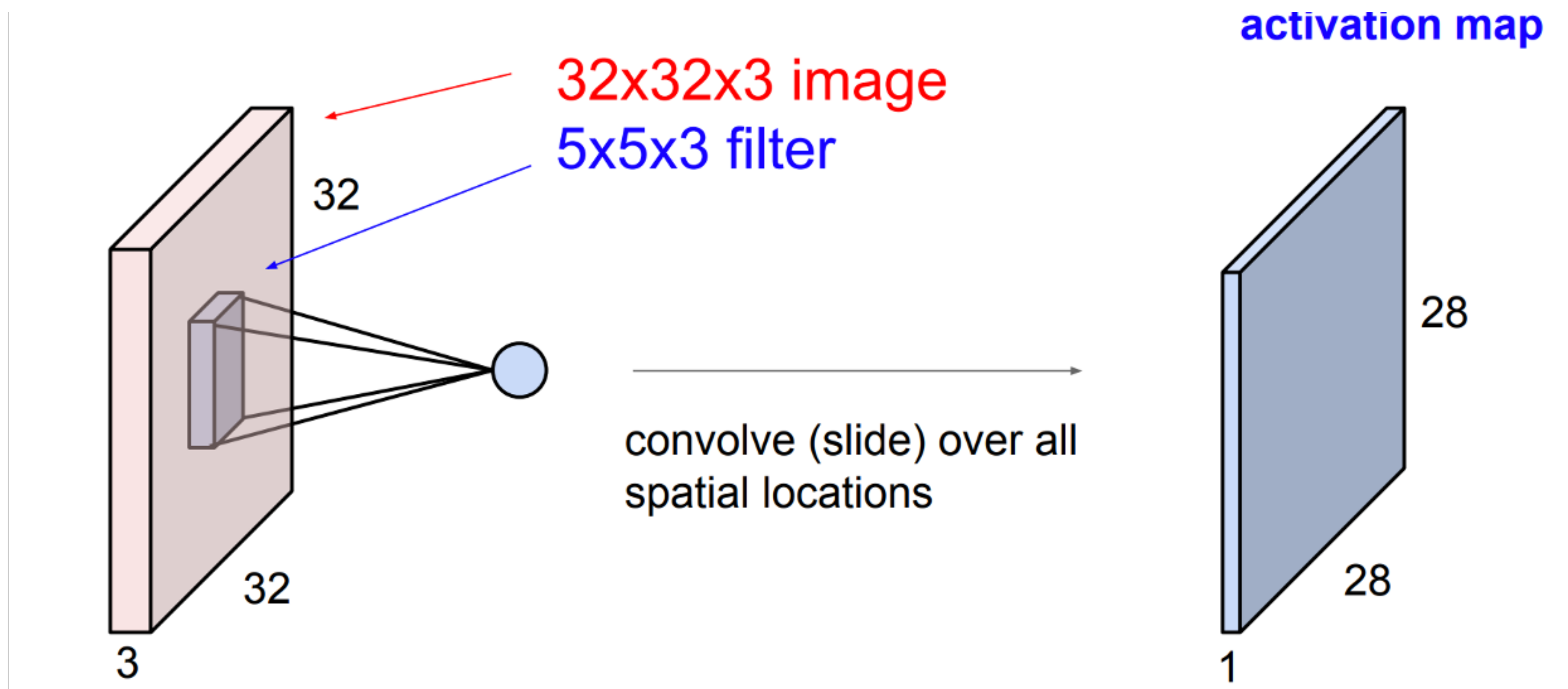
## Divide and conquer

- Later on, the channel represents the amount of filters the model has available.
- Typically, you might start with a matrix with dimensions like (256, 256, 3)
- After a few layers of convolutions, you end up with dimensions like (5, 5, 512) which means there are 512 activation maps



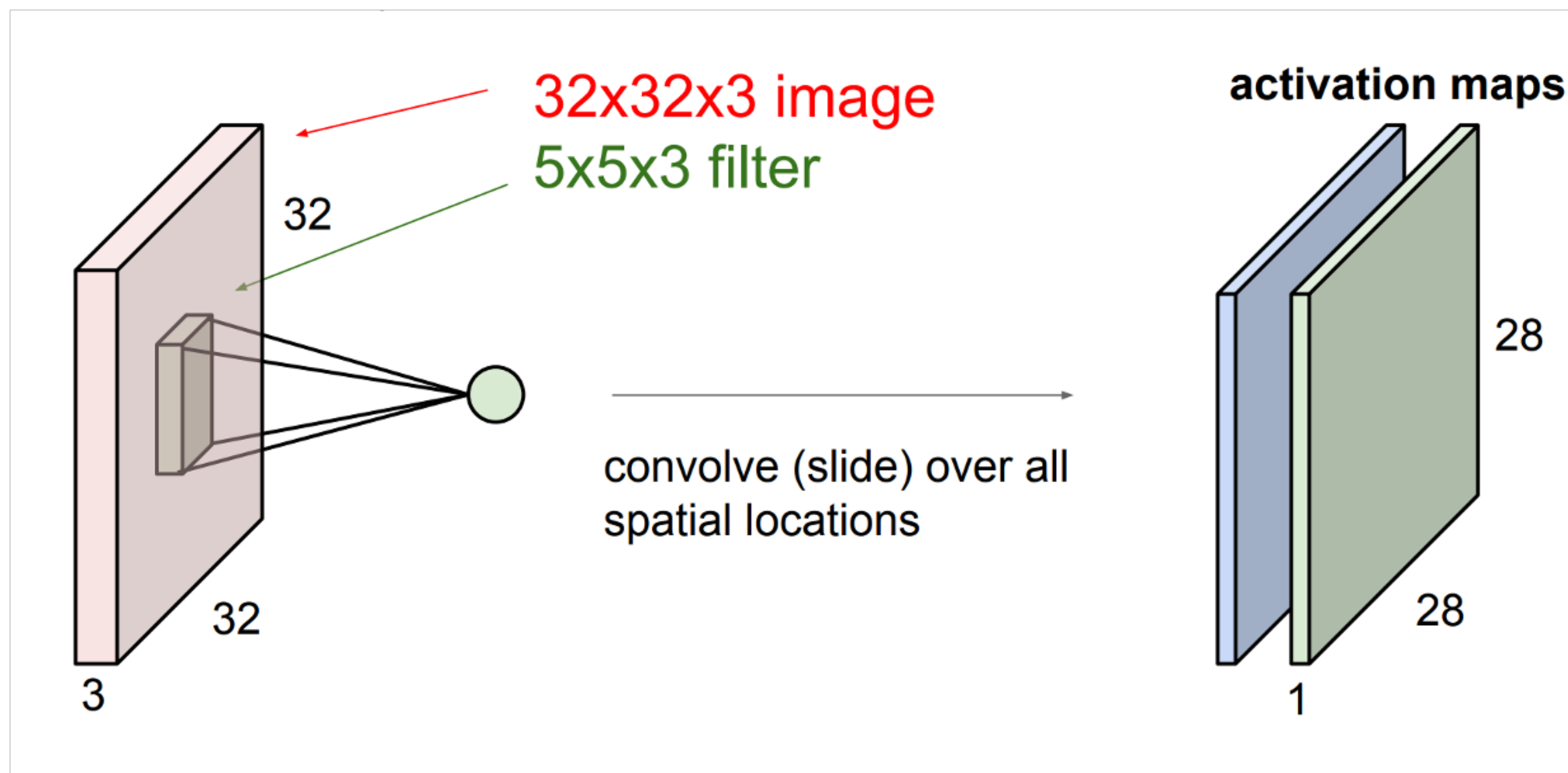
# Convolutions

Divide and conquer



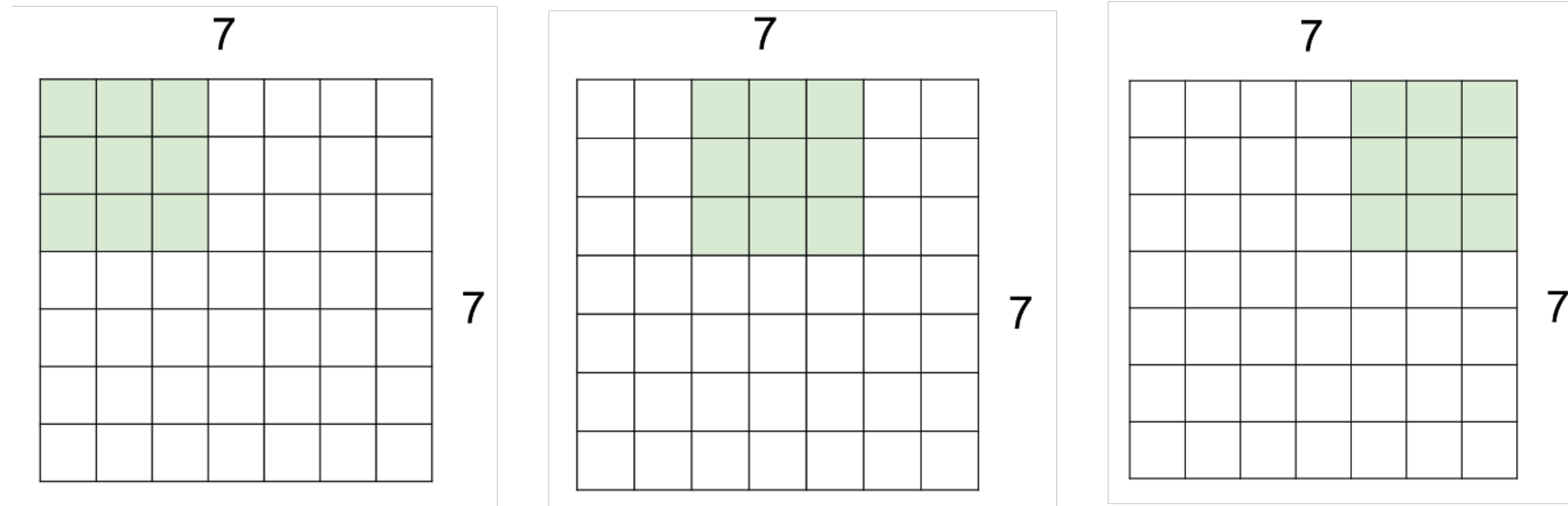
# Convolutions

Divide and conquer



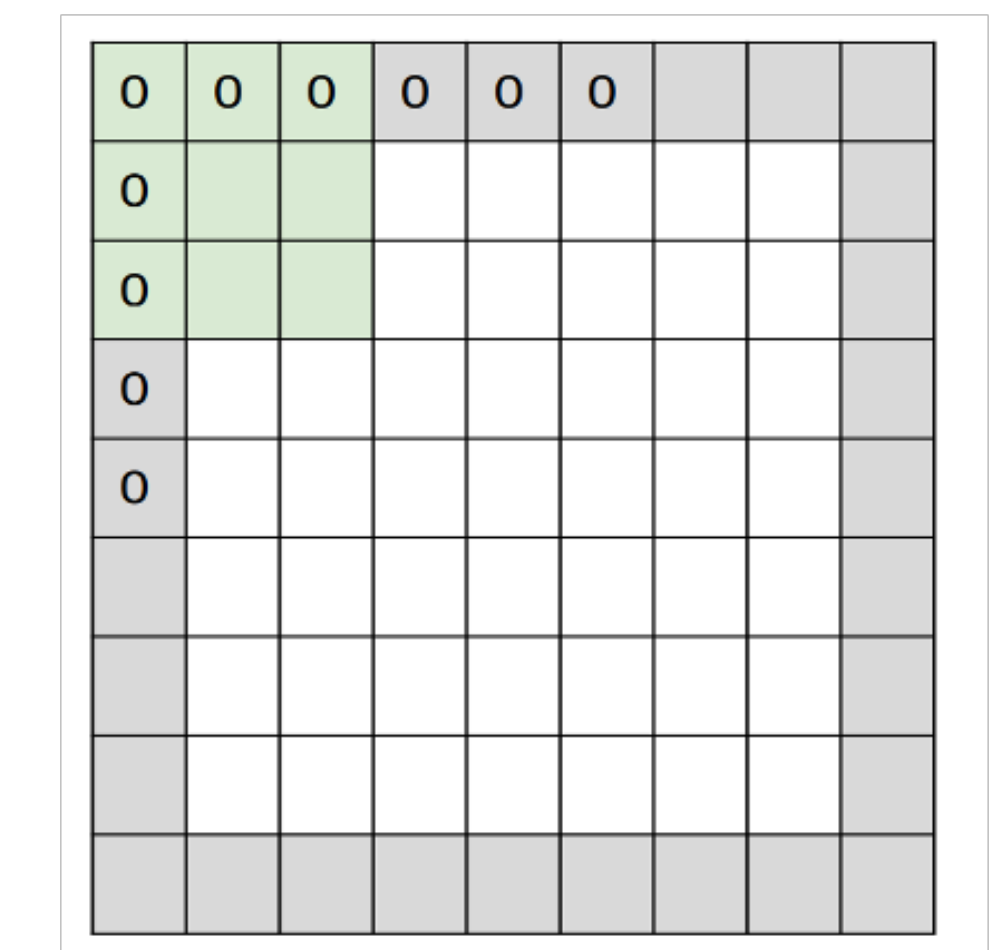
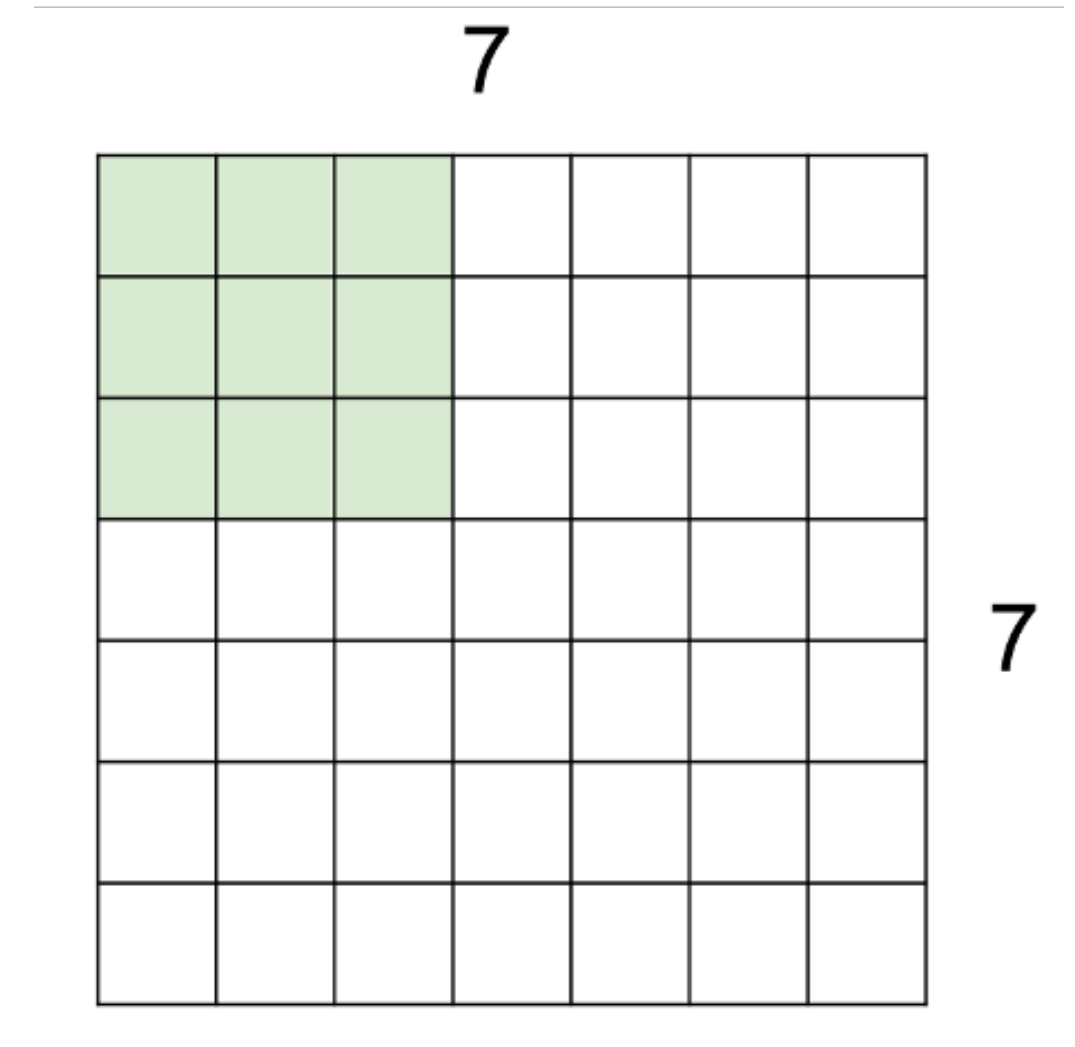
# Stride

- How many pixels to step while sliding the filter
- Note that this shrinks the size if stride  $> 1$



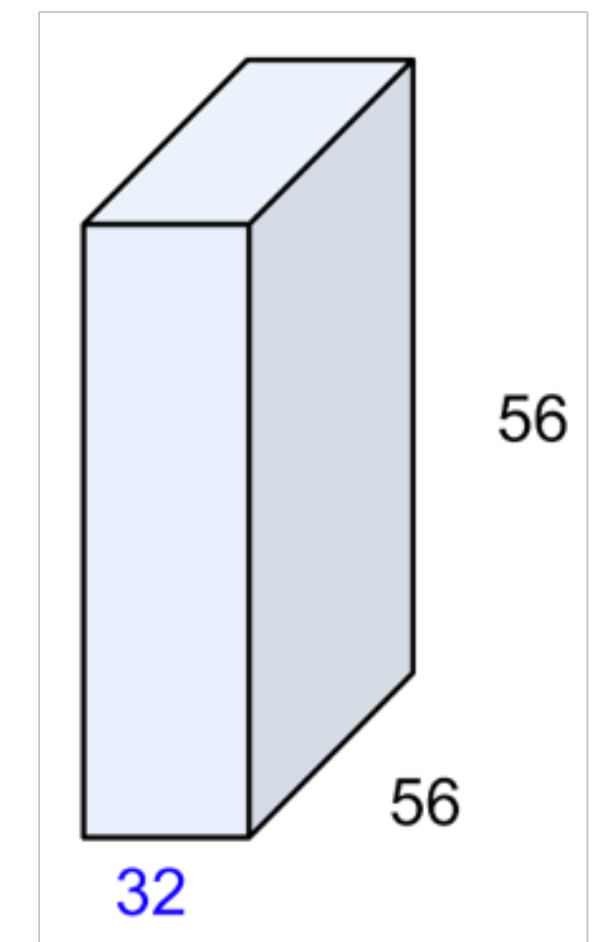
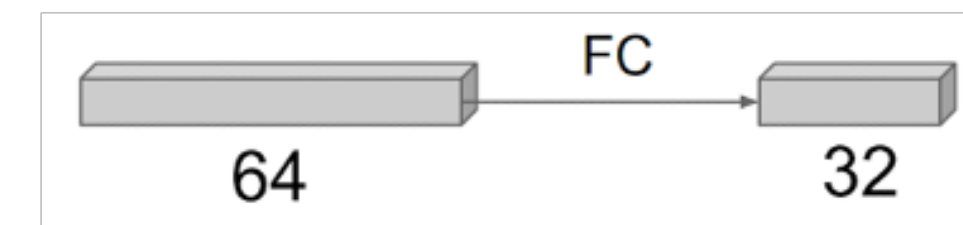
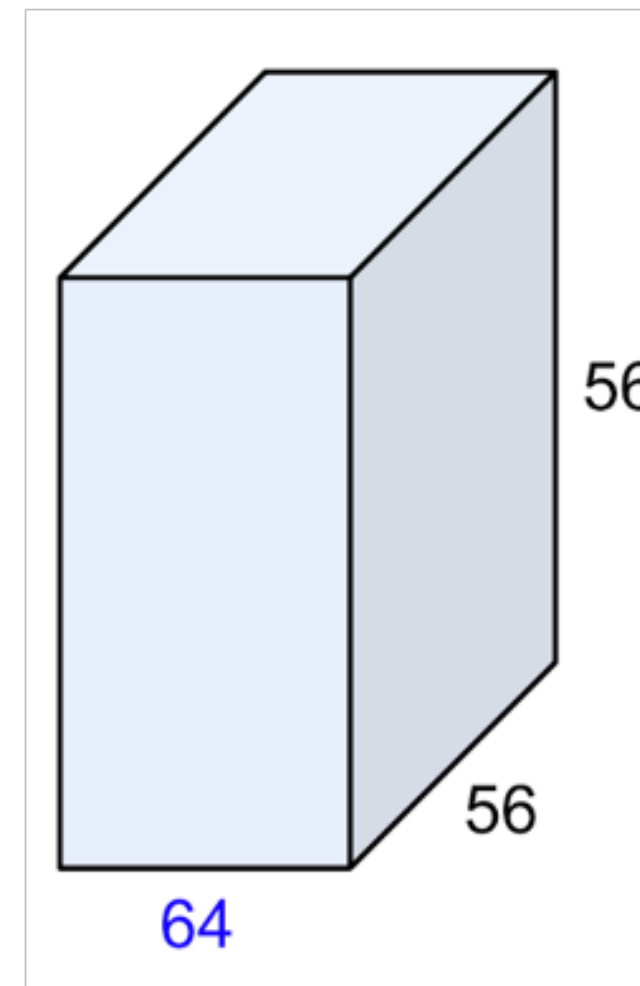
# Padding

- no padding: ignore the last pixel if the filter does not fit
- add a row of zeros to make the slide fit.



# 1x1 convolutions

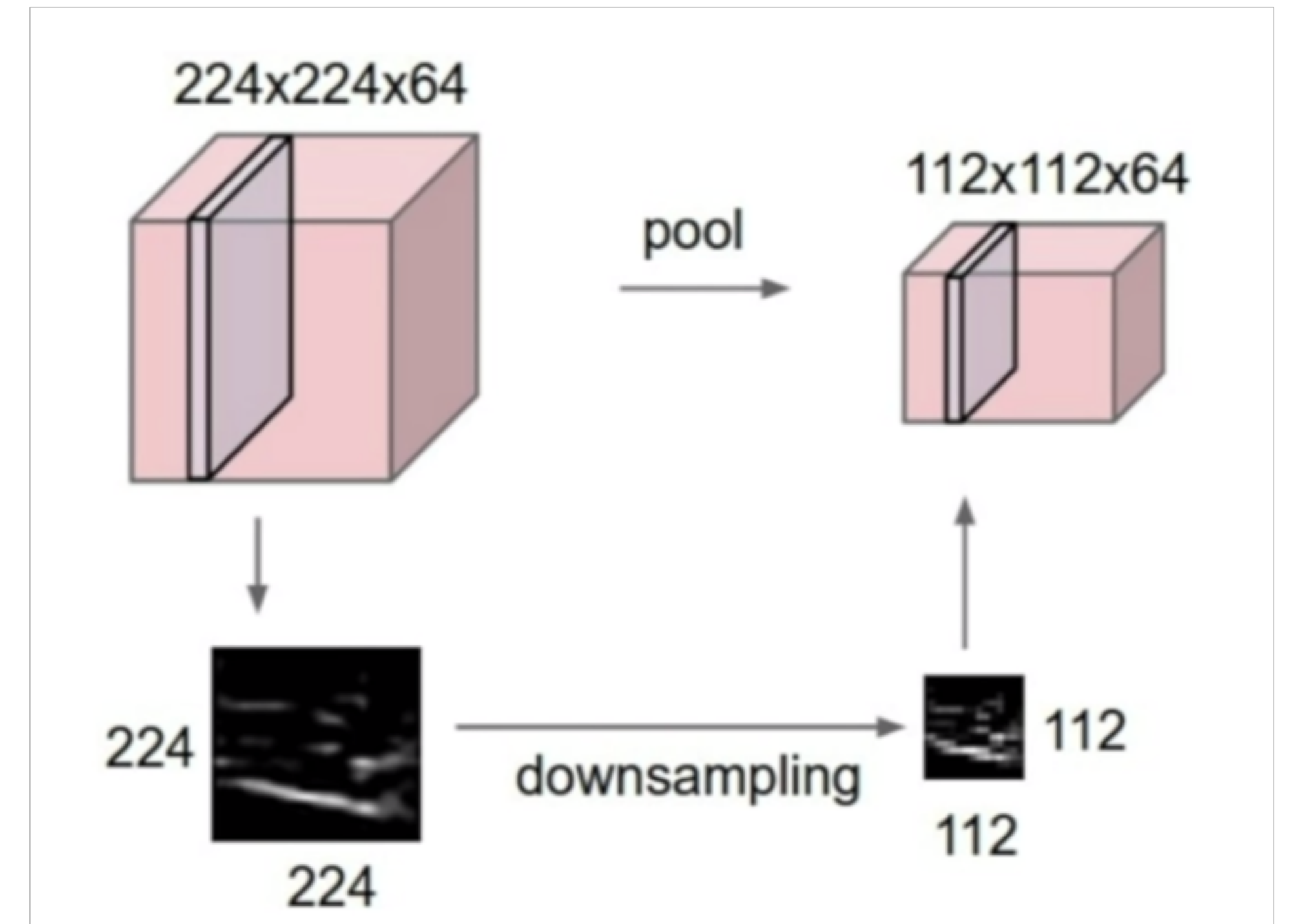
- While they can not capture spatial patterns, they will capture patterns along the **depth dimension**
- When configured to reduce the depth, they **reduce dimensionality**
- We can add extra activations, adding more **non-linearities**.





# Pooling

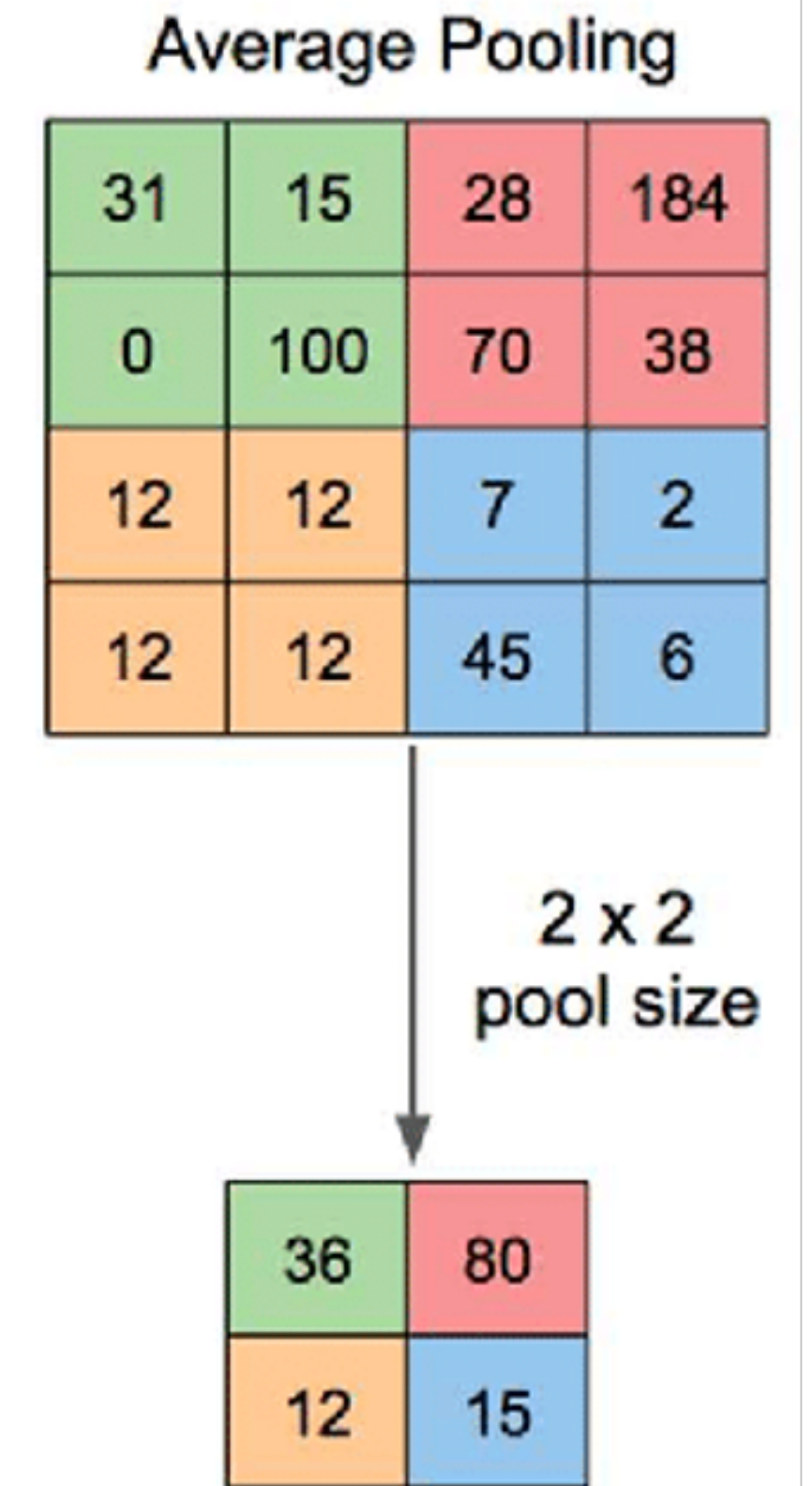
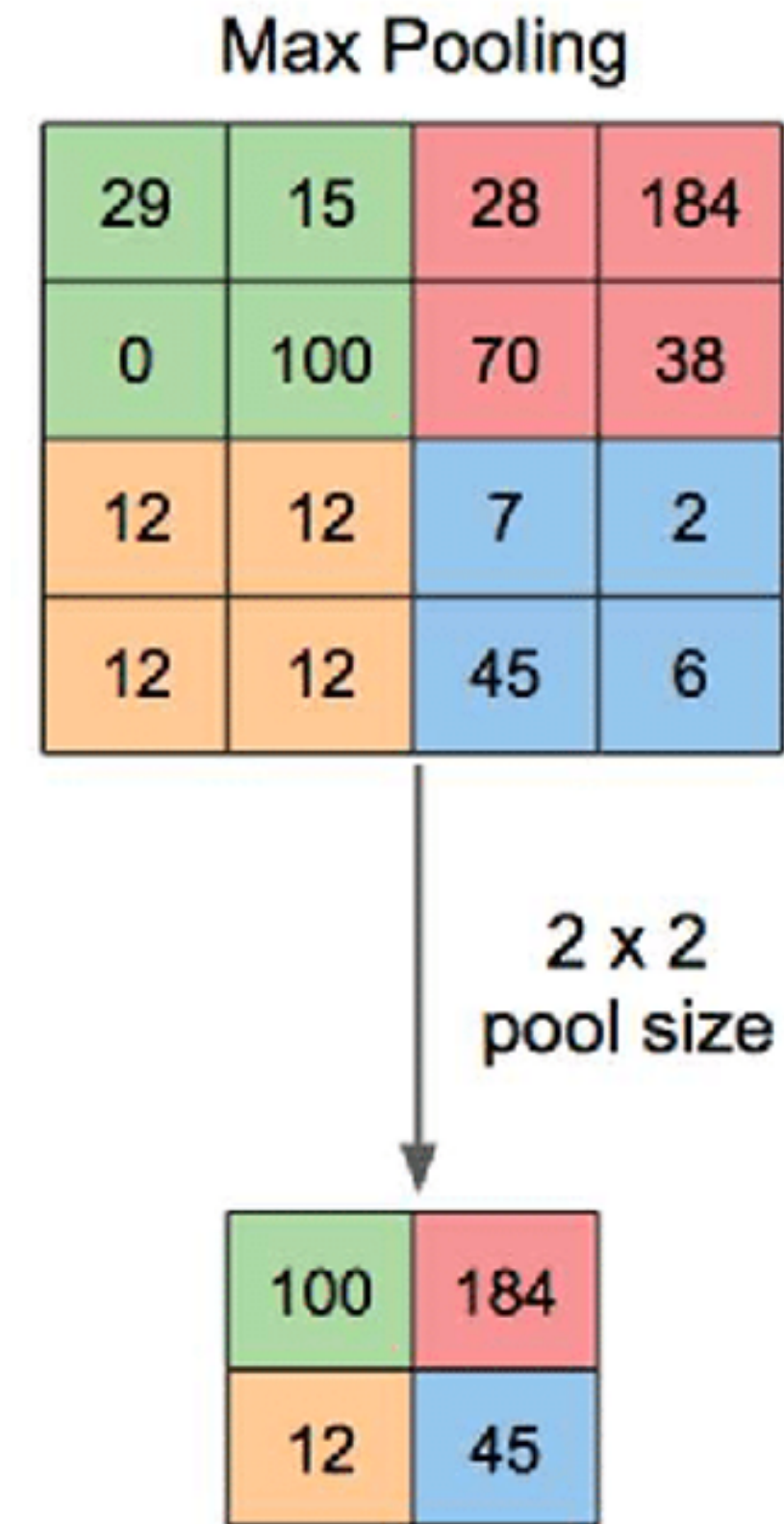
- A way to downsample the input
- Convolutions with stride 2 also downsample, but pooling has no learnable parameters





# Pooling

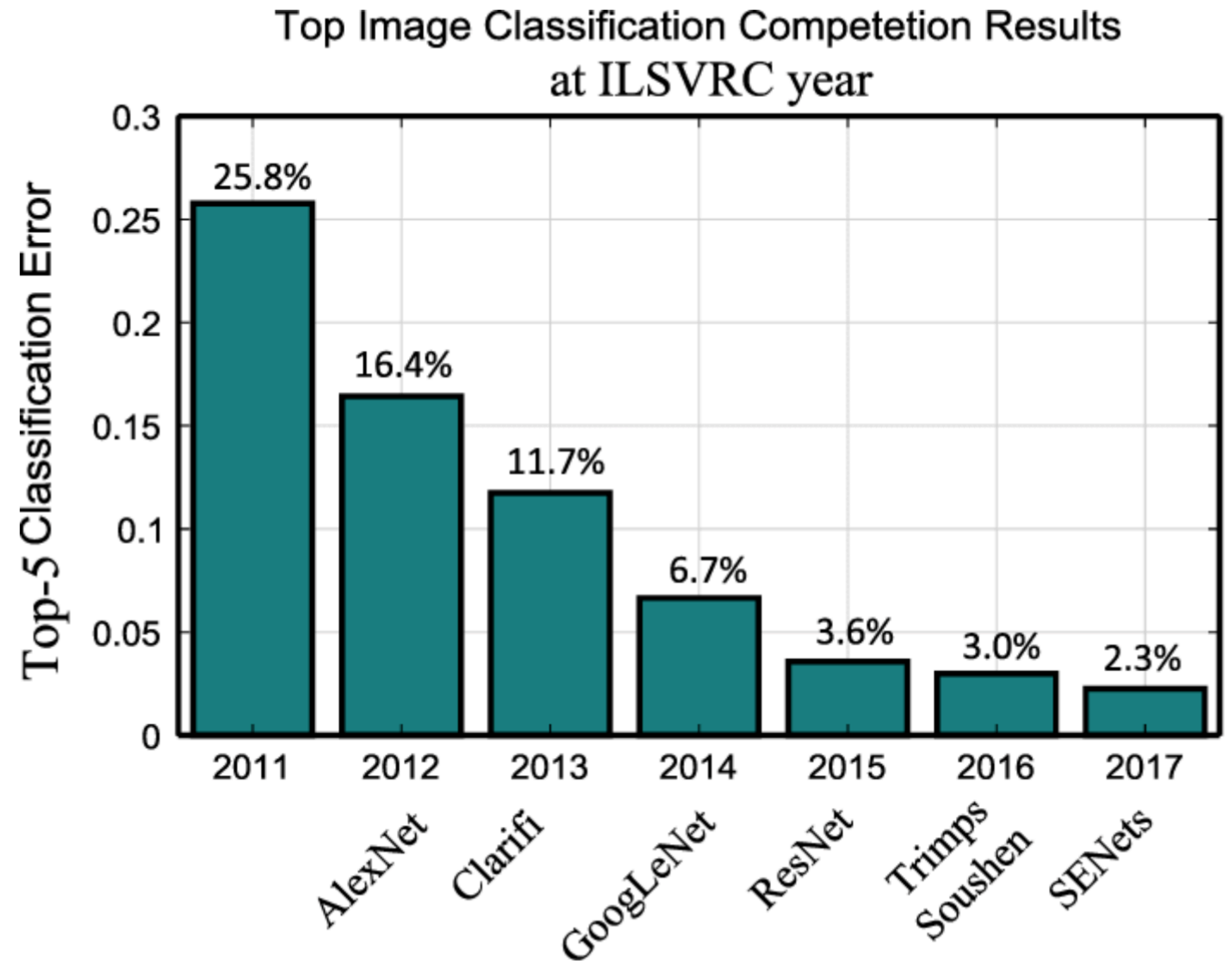
- max pooling: focus on the highest value
- average pooling: smooth the pixels



# Imagenet Challenge

## Superhuman performance

- Human performance is about 5%



Performance of winning entries in the ILSVRC competitions from 2011 to 2017 in the image classification task

# AlexNet

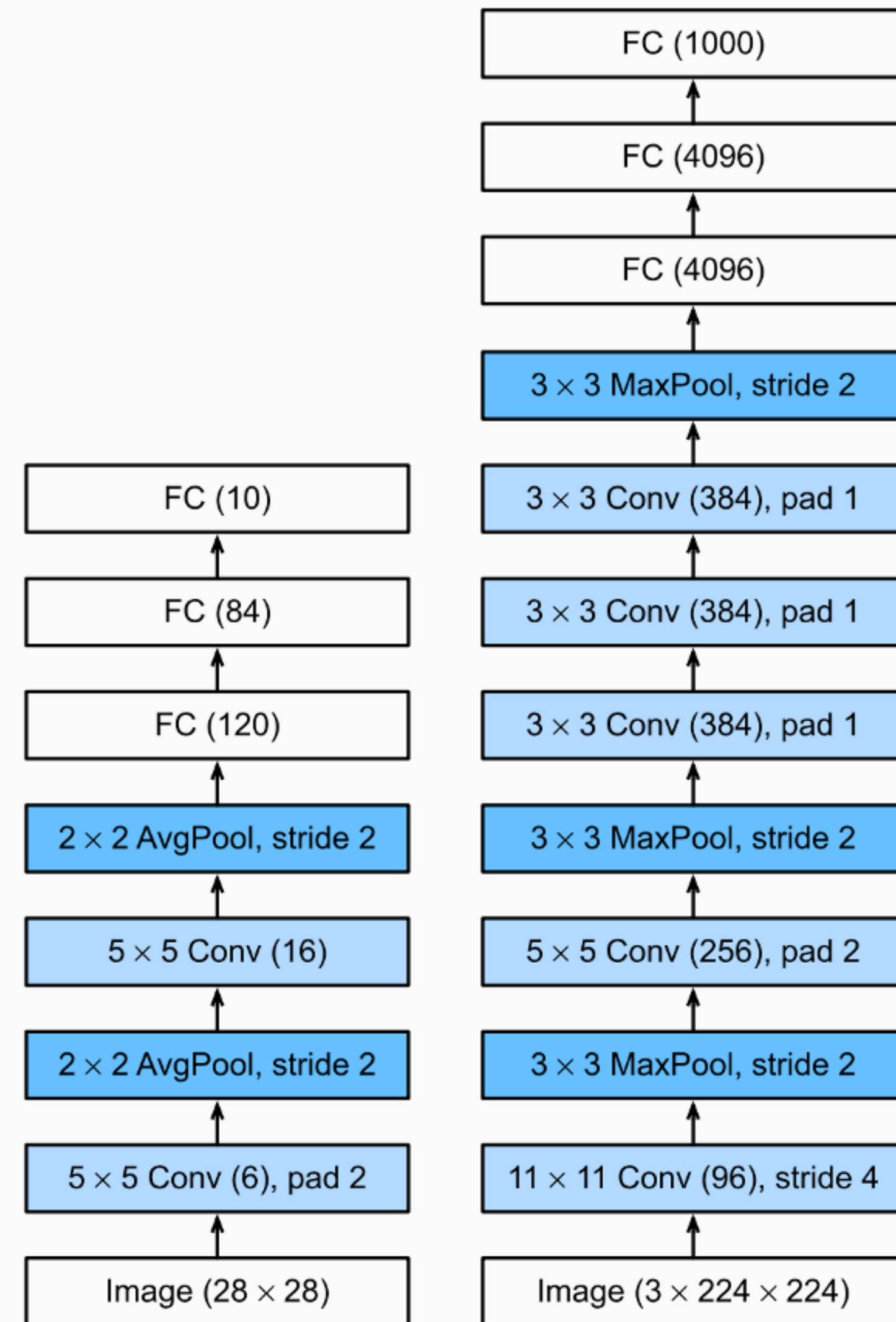


Fig. 7.1.2 From LeNet (left) to AlexNet (right).

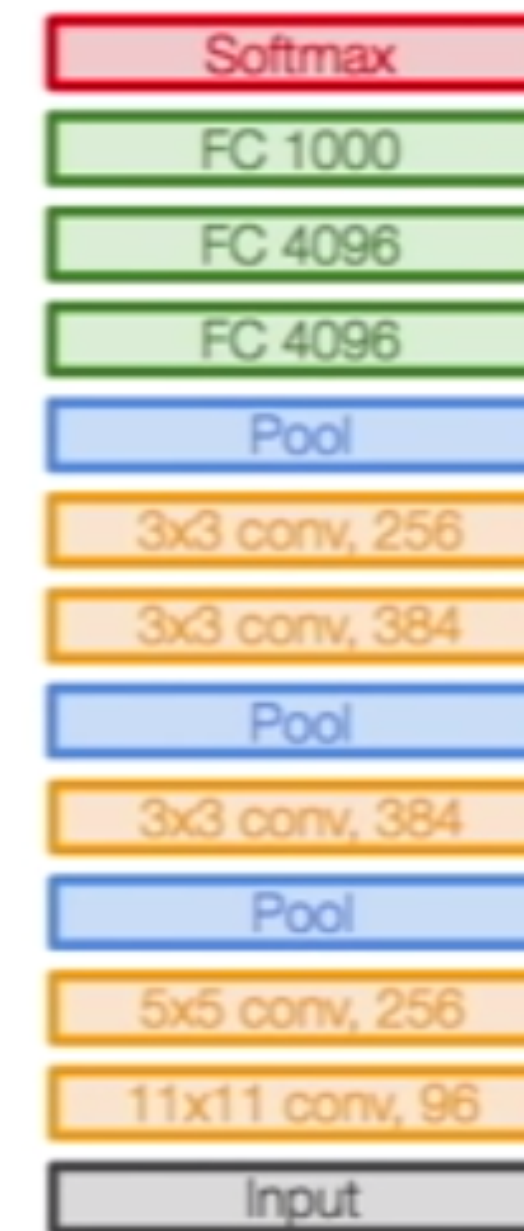


# VGG

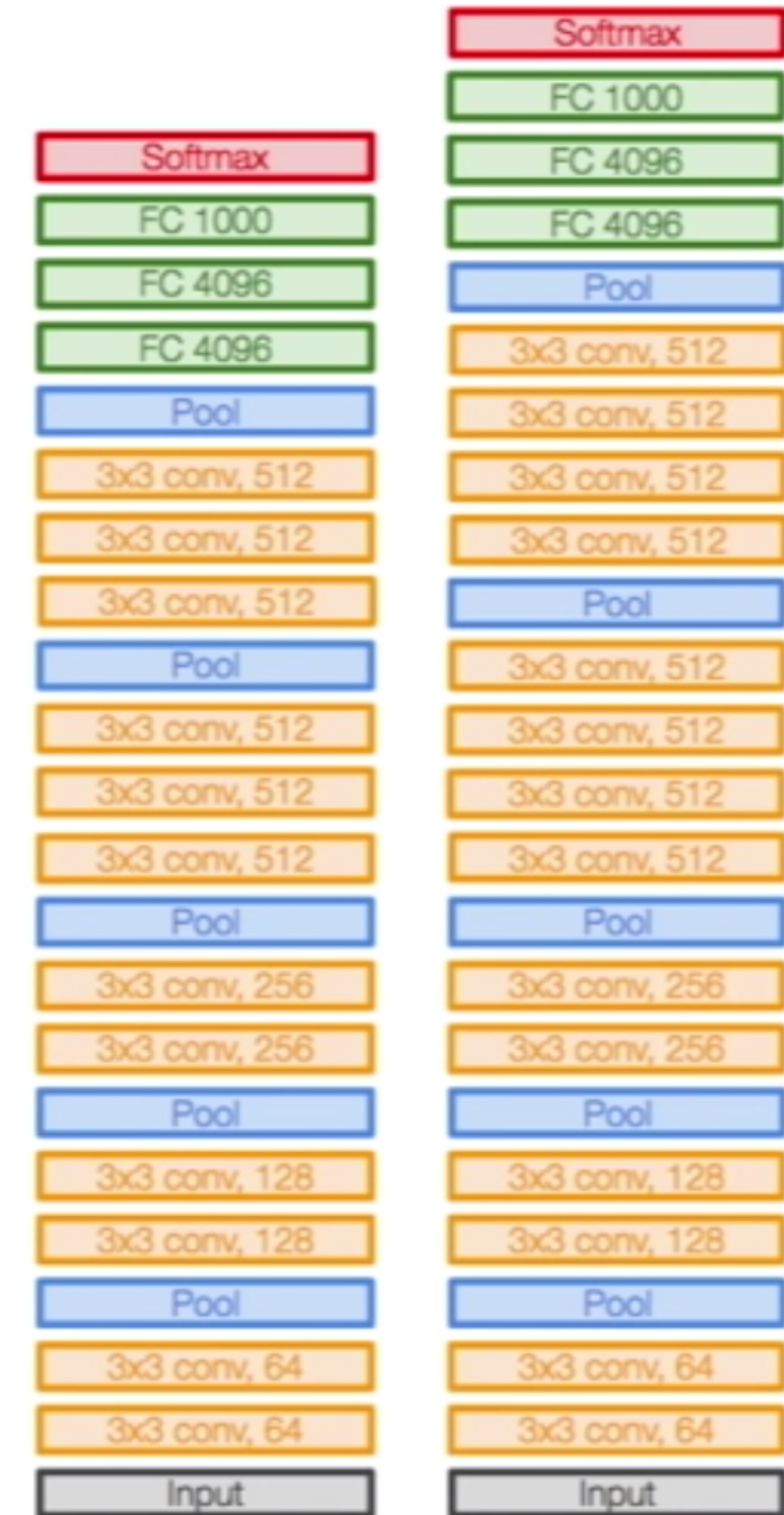
Changes in:

- Filter size
- channel numbers
- depth

138 million parameters



AlexNet



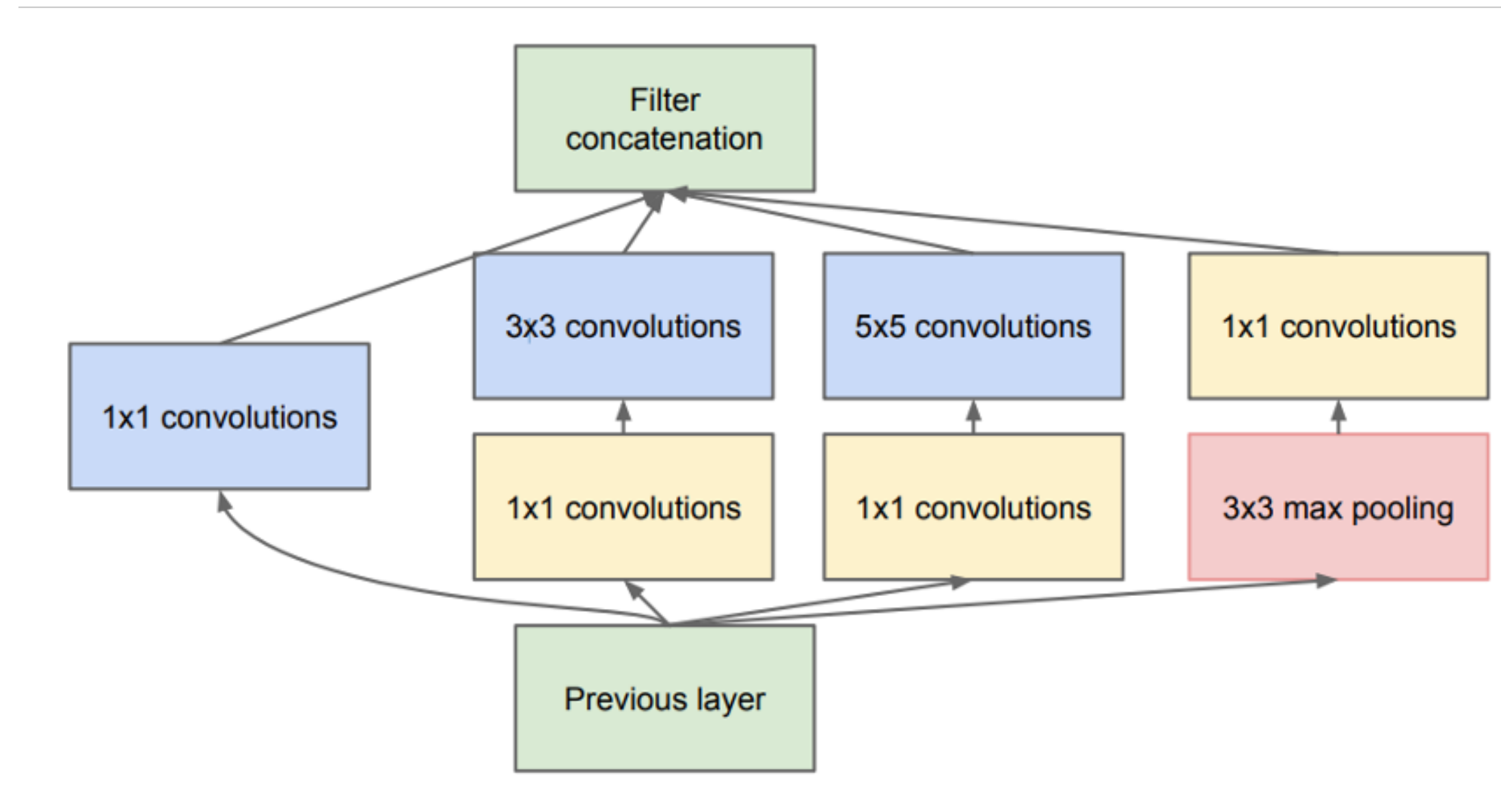
VGG16

VGG19

# GoogleNet

- Parallel filters
- Bottleneck layers

6.7 million parameters

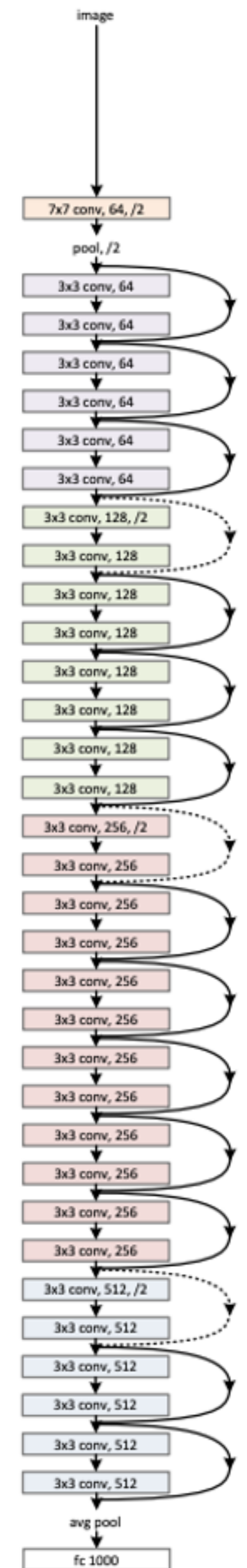


# ResNet

- batch normalisation
- Residual blocks

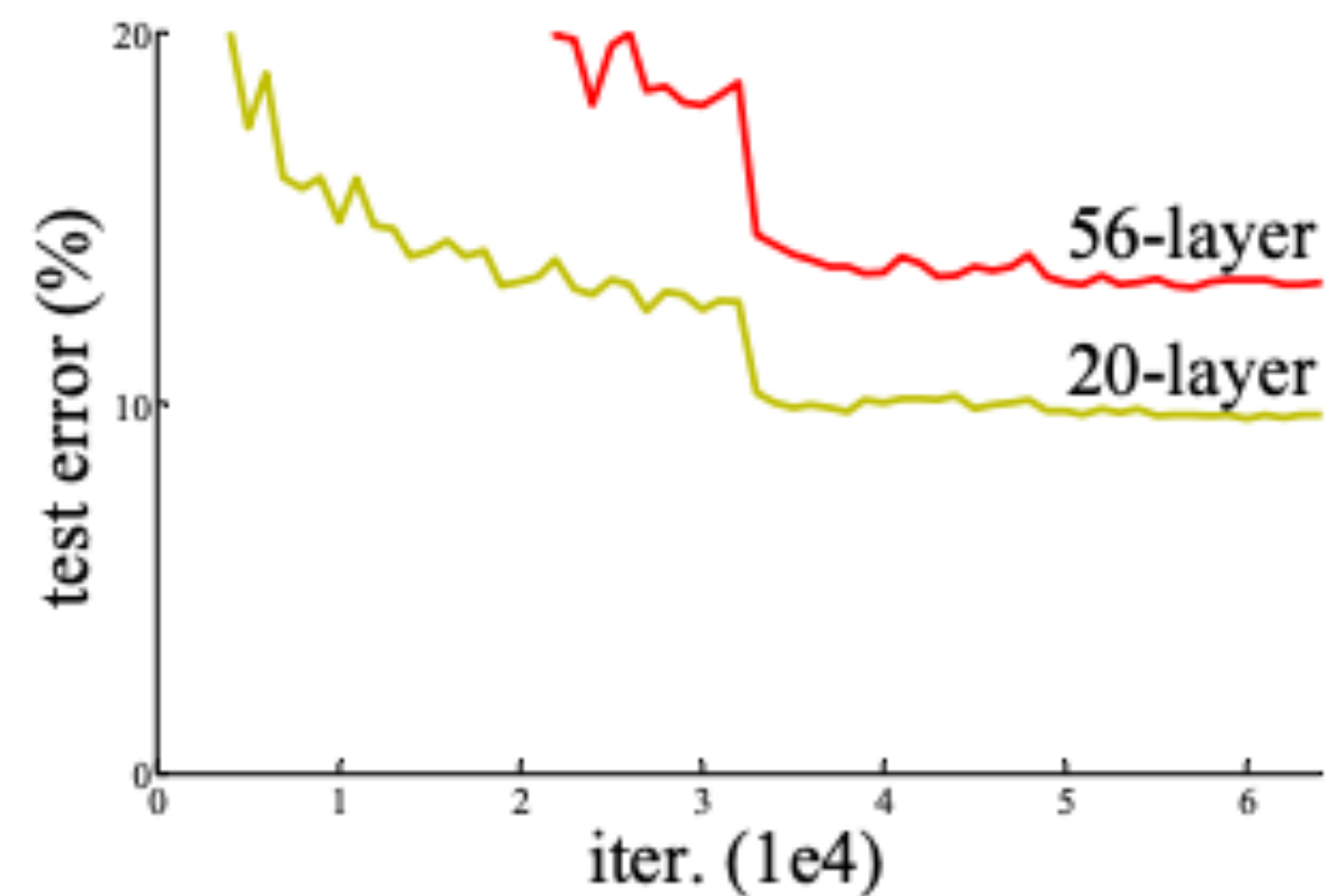
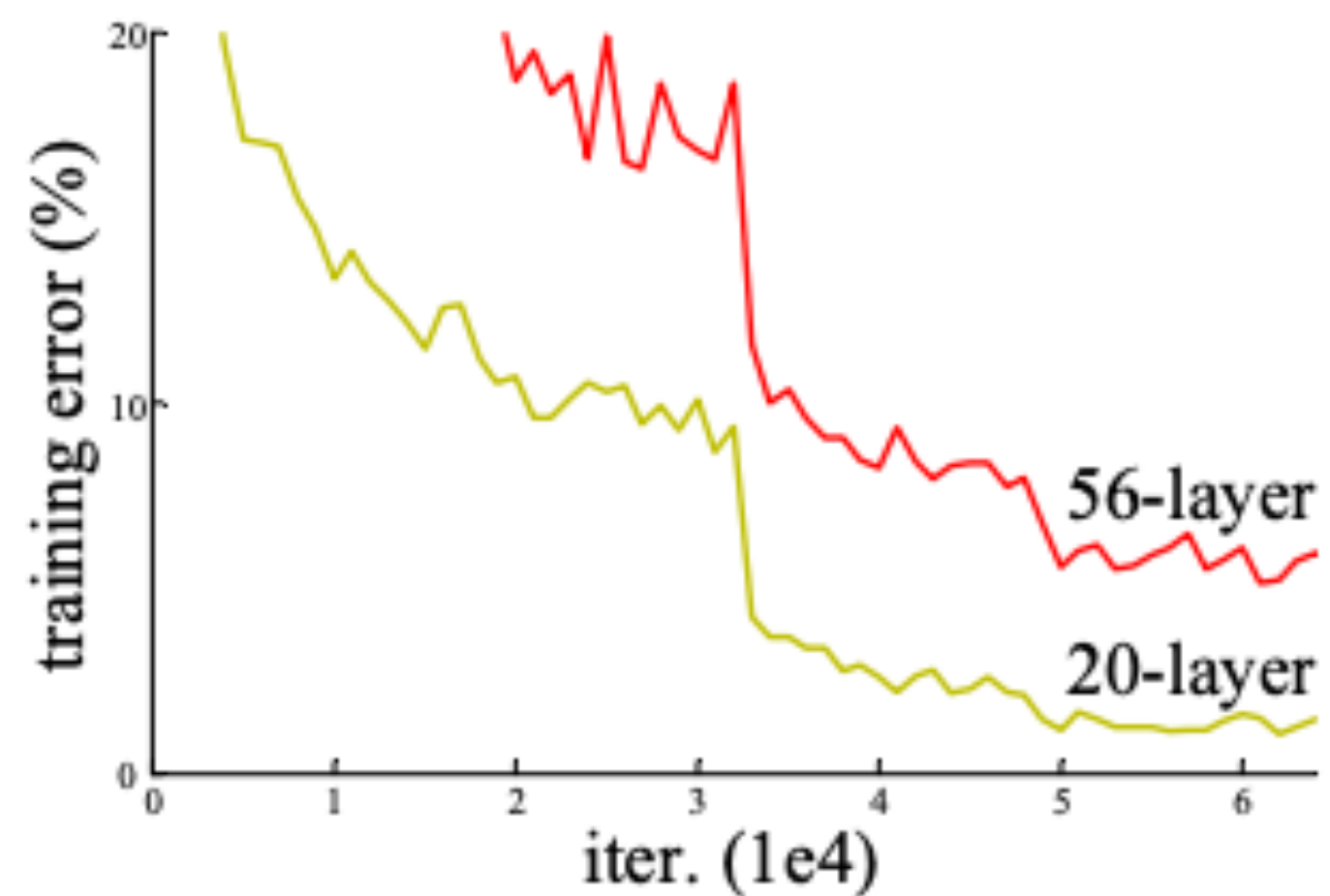
11 million parameters  
for ResNet18

34-layer residual



# ResNet

- **What they noticed:** a deeper net (56 layers) was performing worse than a shallower net (20 layers), but not because of overfitting
- **Hypothesis:** a deeper net is harder
- **Idea:** don't learn the mapping, but learn the residual
- **Residual:** what you need to change from the previous representation to achieve the mapping



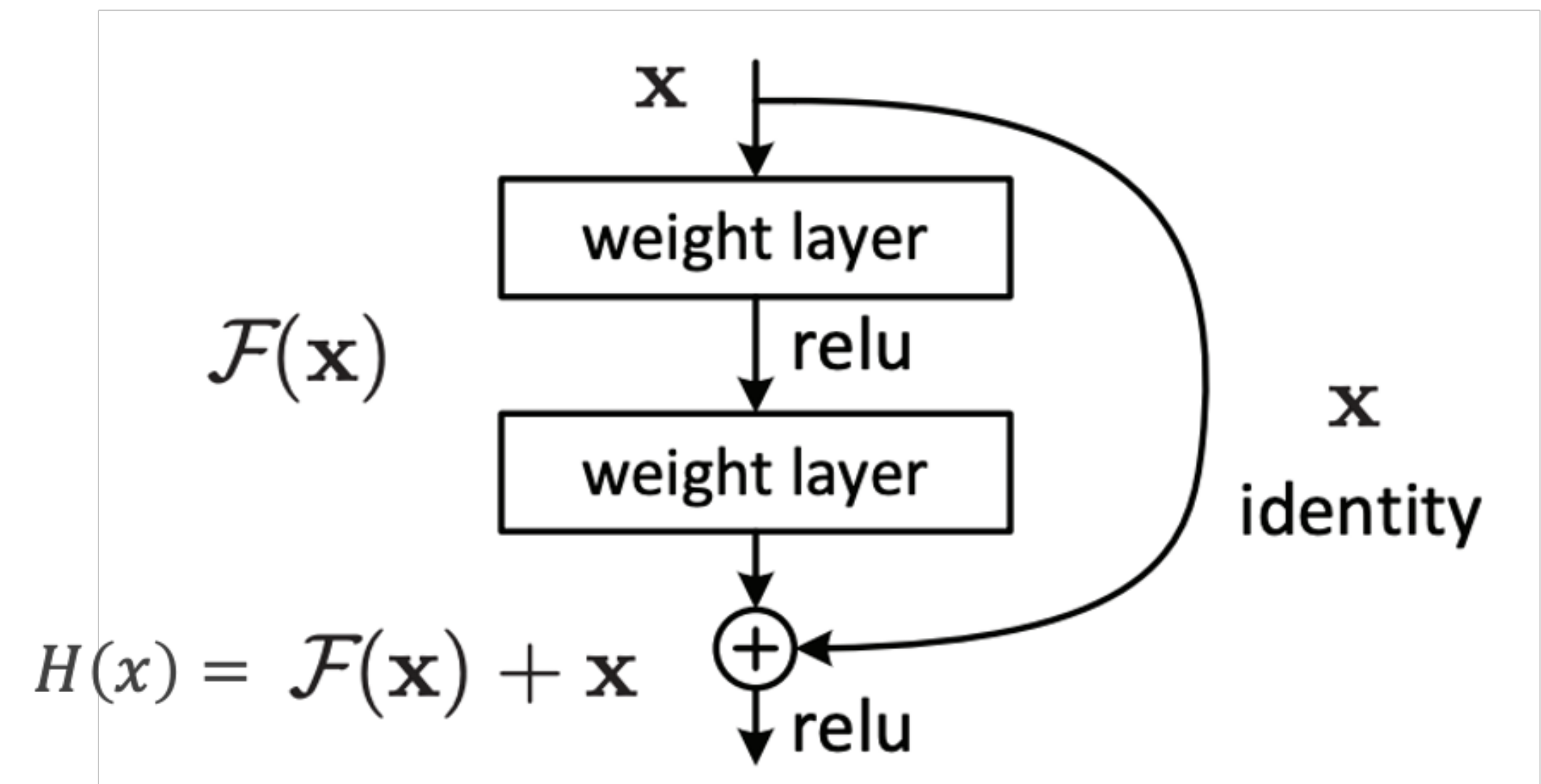


# ResNet

Learn the residual, instead of the full mapping

E.g., “use the same settings, but just change  $x$ ” is easier than starting from scratch.

It is easier for the gradient to flow back

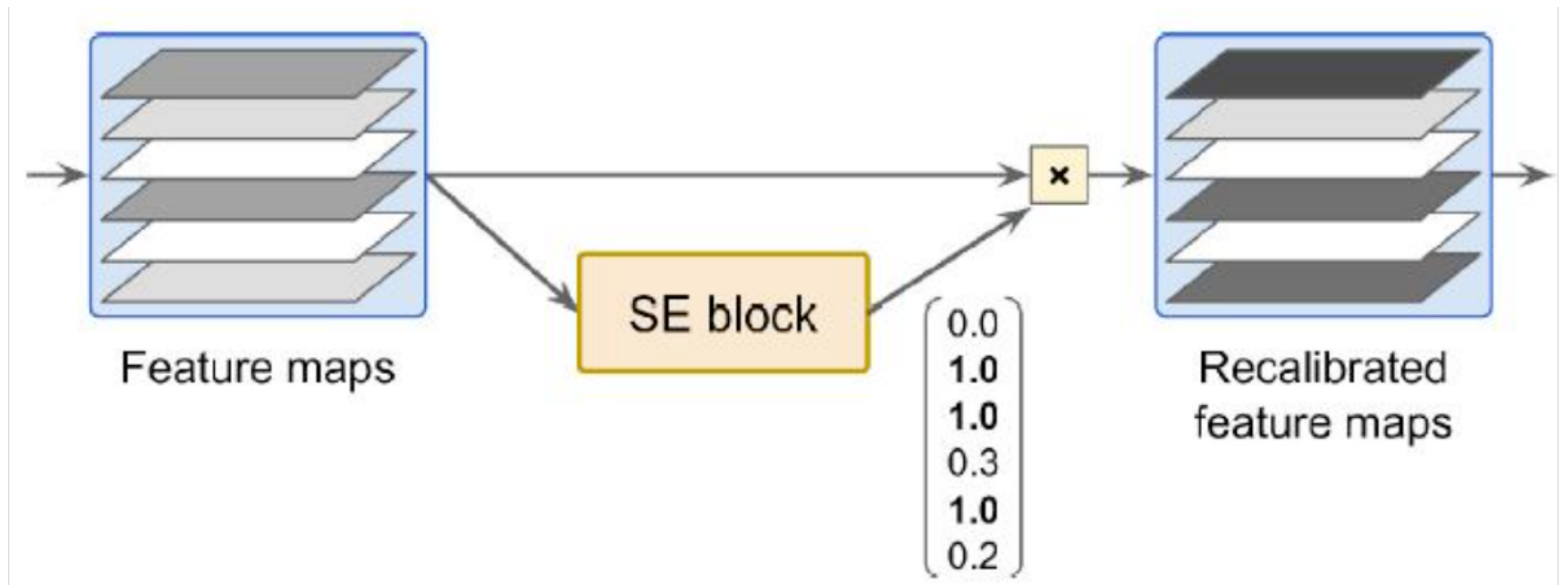




# SEnet

## Squeeze and excite

- Which features are most likely to be activated together?
- E.g., if you see a left eye, you expect a right eye. Even if it is hidden in the image.



# SEnet

## Squeeze and excite

- **global average pool:** calculates the average of each activation map
- **Squeeze:** reduce dimensionality, typically by a fraction of 16
- **Excite:** restore the amount of dimensions.

The process can be compared to writing an abstract of a text.

