DEEP LEARNING 2: CONVOLUTIONS

Keith Butler

CONVOLUTIONAL NEURAL NETS: THE POWER OF INDUCTIVE BIAS

The Need for Biases in Learning Generalizations

Tom M. Mitchell

The **inductive bias** (also known as **learning bias**) of a learning algorithm is the set of assumptions that the learner uses to predict outputs of given inputs that it has not encountered.

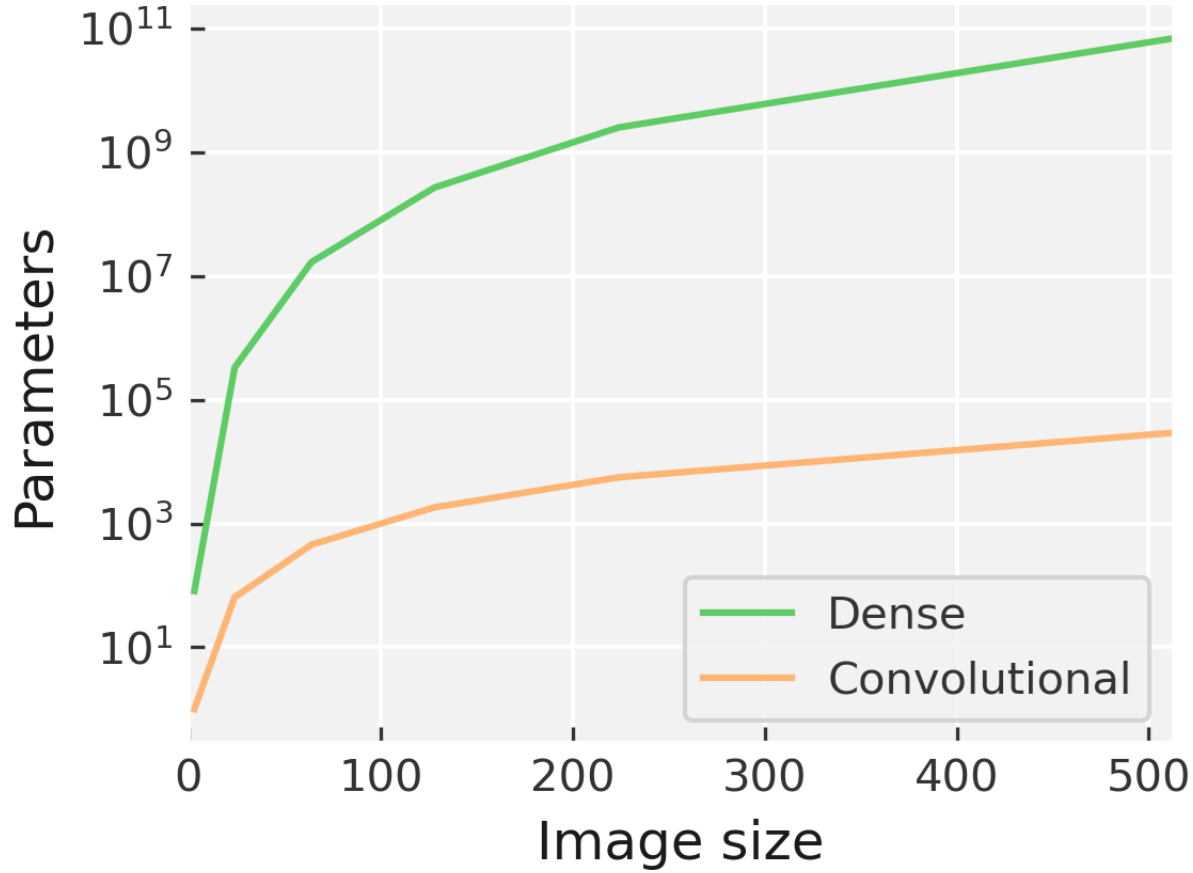
The need for biases in learning generalizations, CBM-TR 5-110, New Brunswick, New Jersey, USA: Rutgers University

OVERVIEW

- Intro to convolutional neural networks
- Building blocks of CNNs
- Deep CNNs
- Advanced CNNs – Residual blocks

DRAWBACKS OF MLPS

MLPs have **no spatial awareness** and also suffer from **parametric explosions** as the input gets larger



EARLY CNNS

LeCun – restricting the number of parameters in a NN leads to **better generalisation**

Generalization and Network Design Strategies

Y. le Cun
Department of Computer Science
University of Toronto

Technical Report CRG-TR-89-4
June 1989

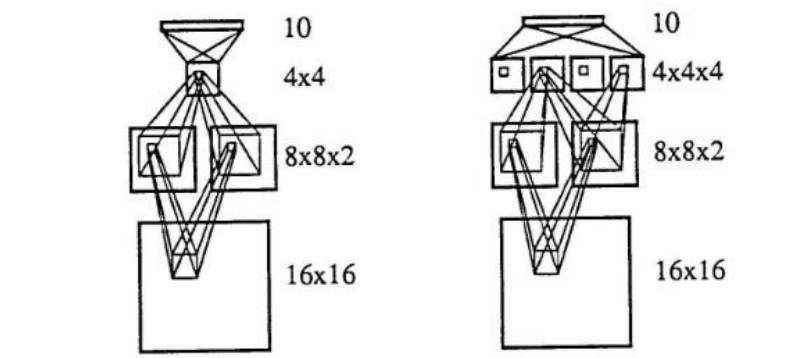
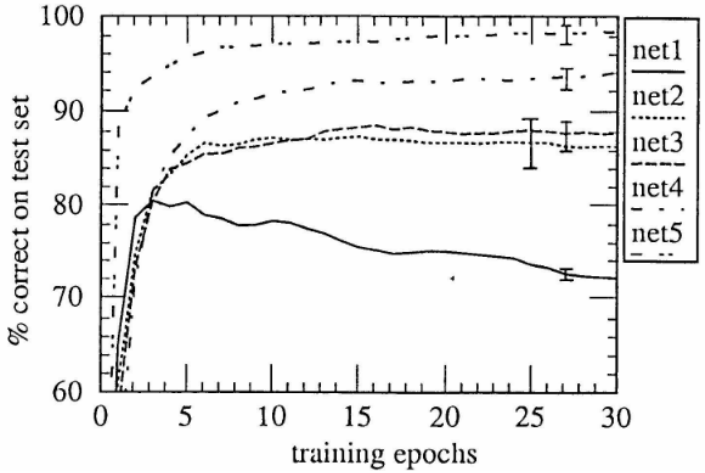


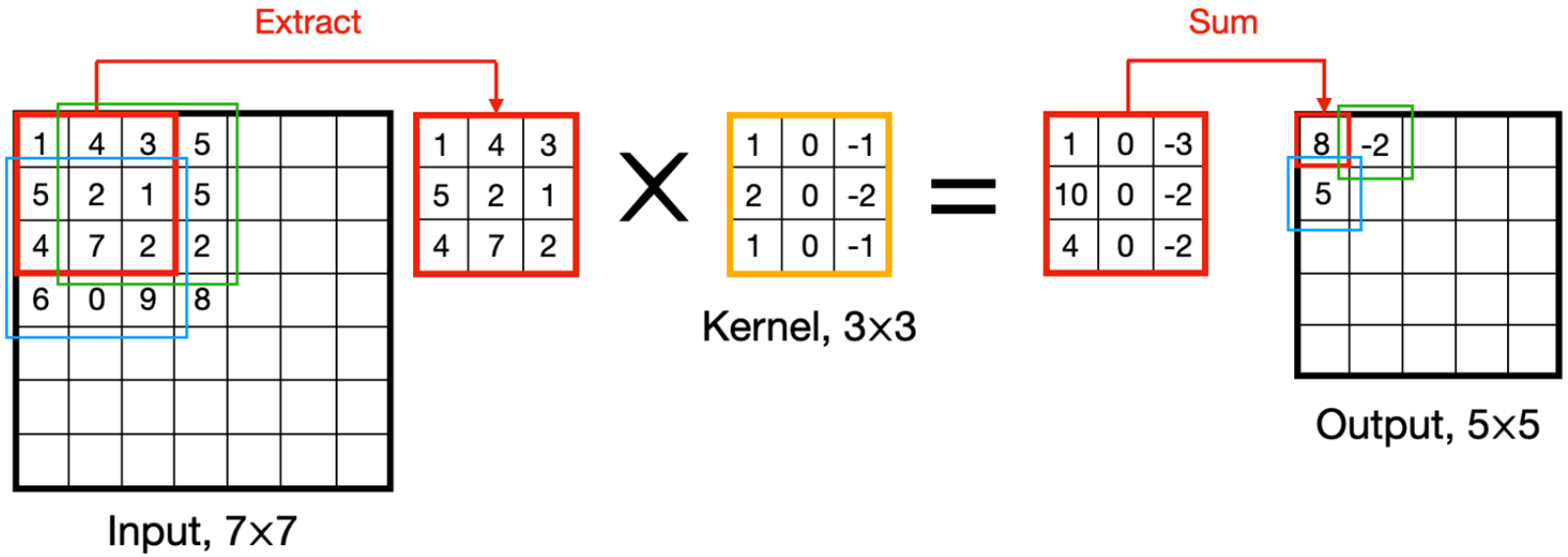
Figure 5 two network architectures with shared weights: Net-4 and Net-5



STRUCTURE OF A CONVOLUTIONAL LAYER

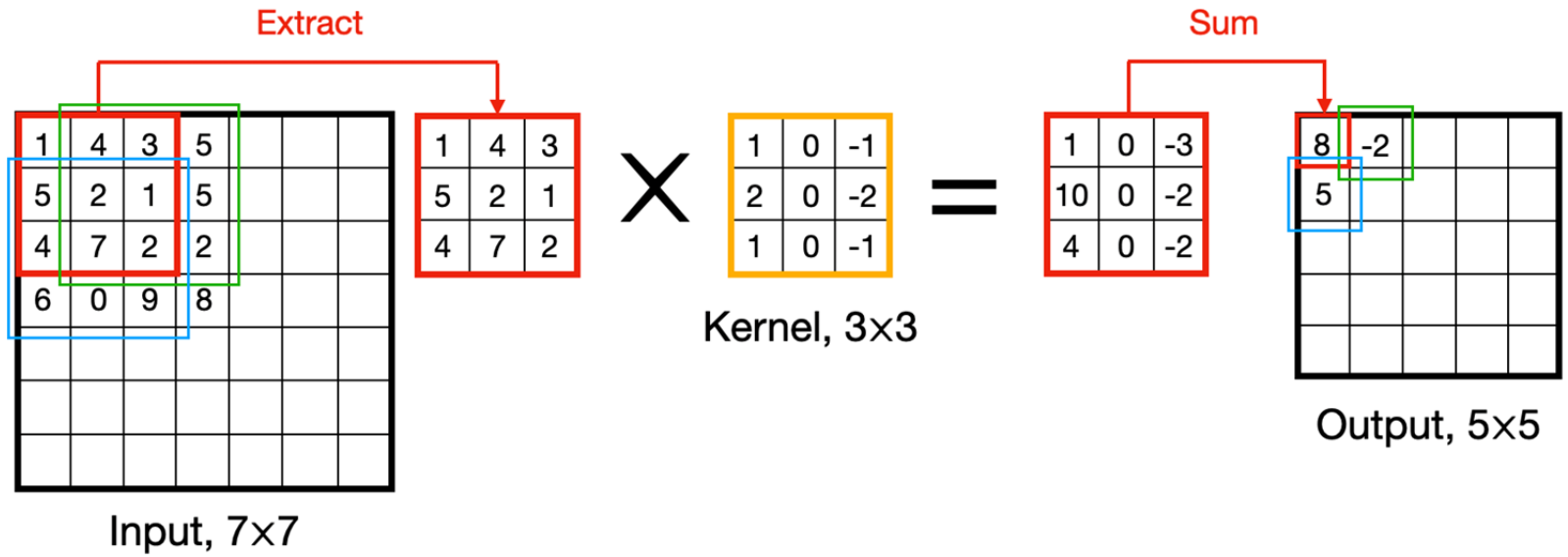
Typical convolutional layers have three main ingredients:

- Kernel
- Pooling
- Activation



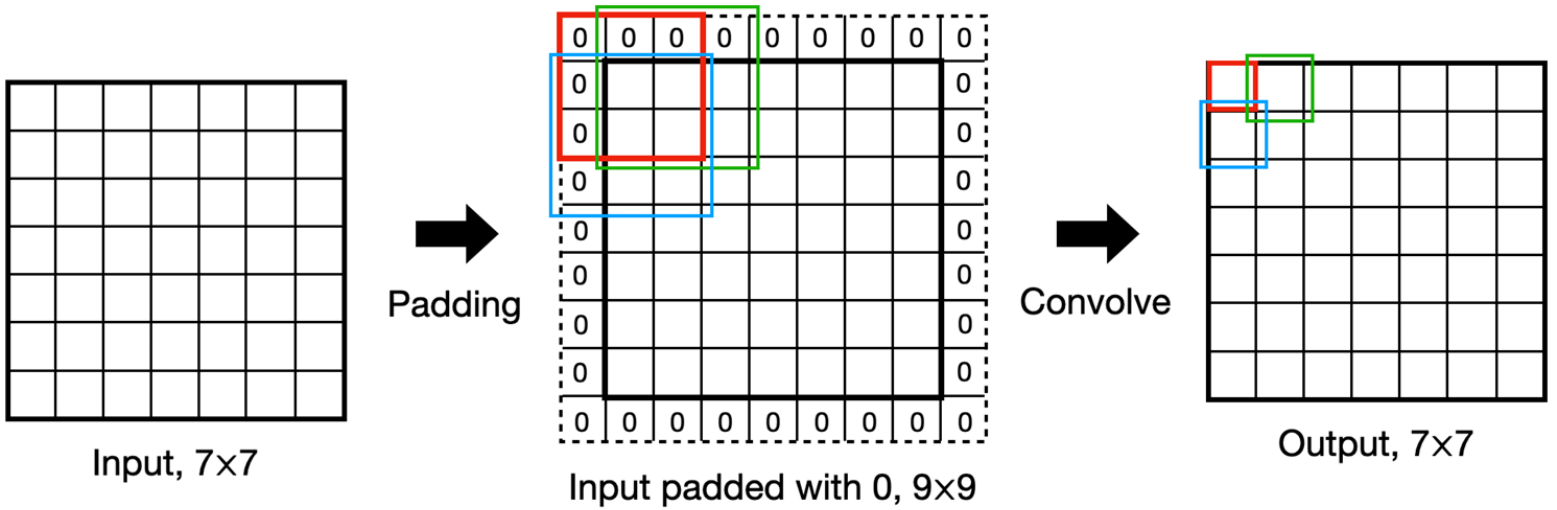
CONVOLUTION IN ACTION: KERNEL

- Input + kernel -> activation map



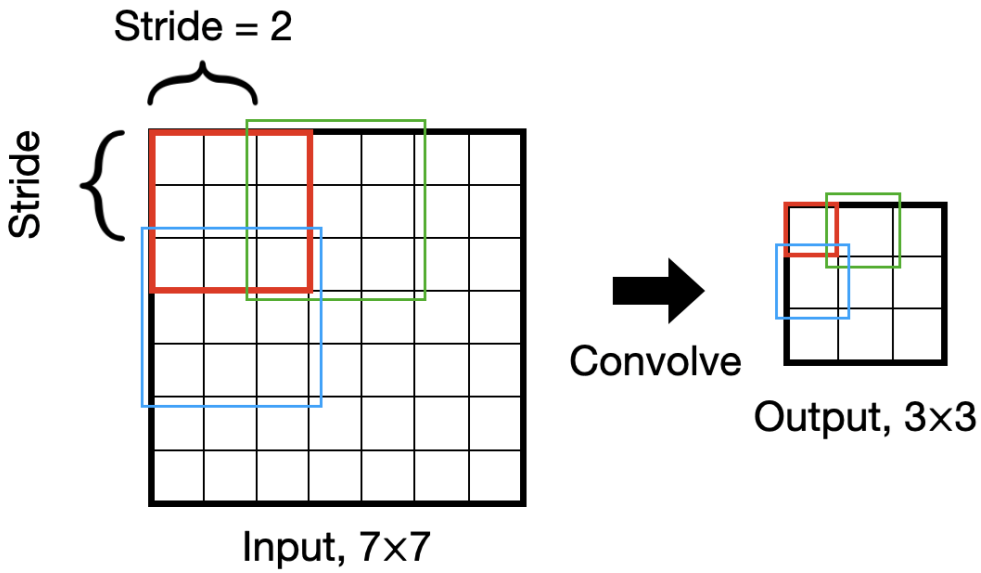
CONVOLUTION IN ACTION: PADDING

- Padding around the outside of images
  - Zero pad: pad with zeros to make `torch.nn.ZeroPad2d(padding)`
  - No padding `output.shape < input.shape`



CONVOLUTION IN ACTION: STRIDING

Controls how the filter slides across the image



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

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

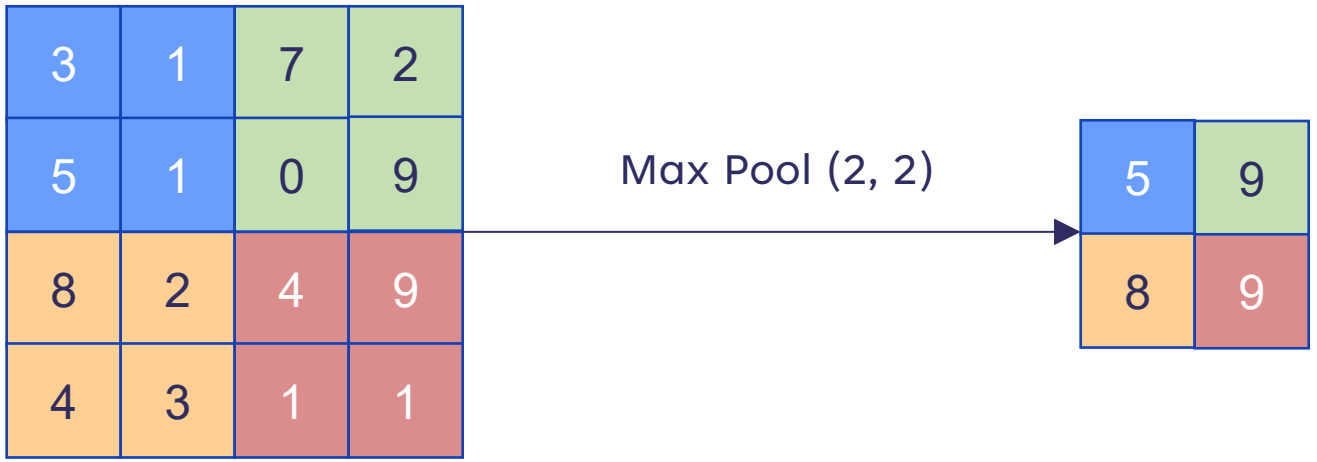
GO TO NOTEBOOK

Let’s try building and understanding some filters

```python
# a 2D convolutonal filter
def convolve2D(input_image, kernel, padding=1, stride=1):
    # padding
    nx = input_image.shape[0]
    ny = input_image.shape[1]
    nchannel = input_image.shape[2]
    if padding > 0:
        padded_image = np.zeros((nx + padding * 2, ny + padding * 2, nchannel))
        padded_image[padding:-padding, padding:-padding, :] = input_image
    else:
        padded_image = input_image

    # allocate output
    k = kernel.shape[0]
    nx_out = (nx + padding * 2 - k) // stride + 1 # must use // instead of /
    ny_out = (ny + padding * 2 - k) // stride + 1
    output_image = np.zeros((nx_out, ny_out, nchannel))

    # compute output pixel by pixel
    for ix_out in np.arange(nx_out):
        for iy_out in np.arange(ny_out):
            ix_in = ix_out * stride
            iy_in = iy_out * stride
            # the inner product
            output_image[ix_out, iy_out, :] = \
            np.tensordot(kernel, padded_image[ix_in:(ix_in + k), iy_in:(iy_in + k), :], axes=2)

    # truncate to [0, 1]
    output_image = np.maximum(output_image, 0)
    output_image = np.minimum(output_image, 1)
    return output_image
```

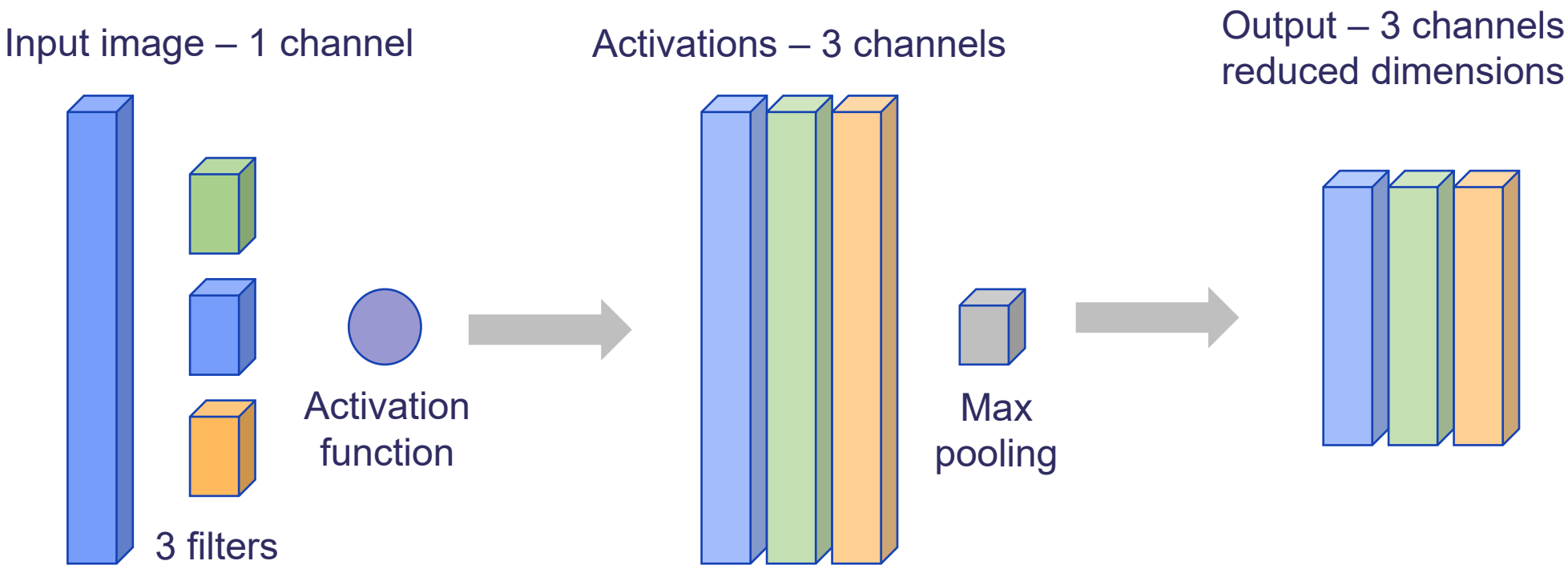
CONVOLUTION IN ACTION: POOLING

Pooling **compresses information** content between layers



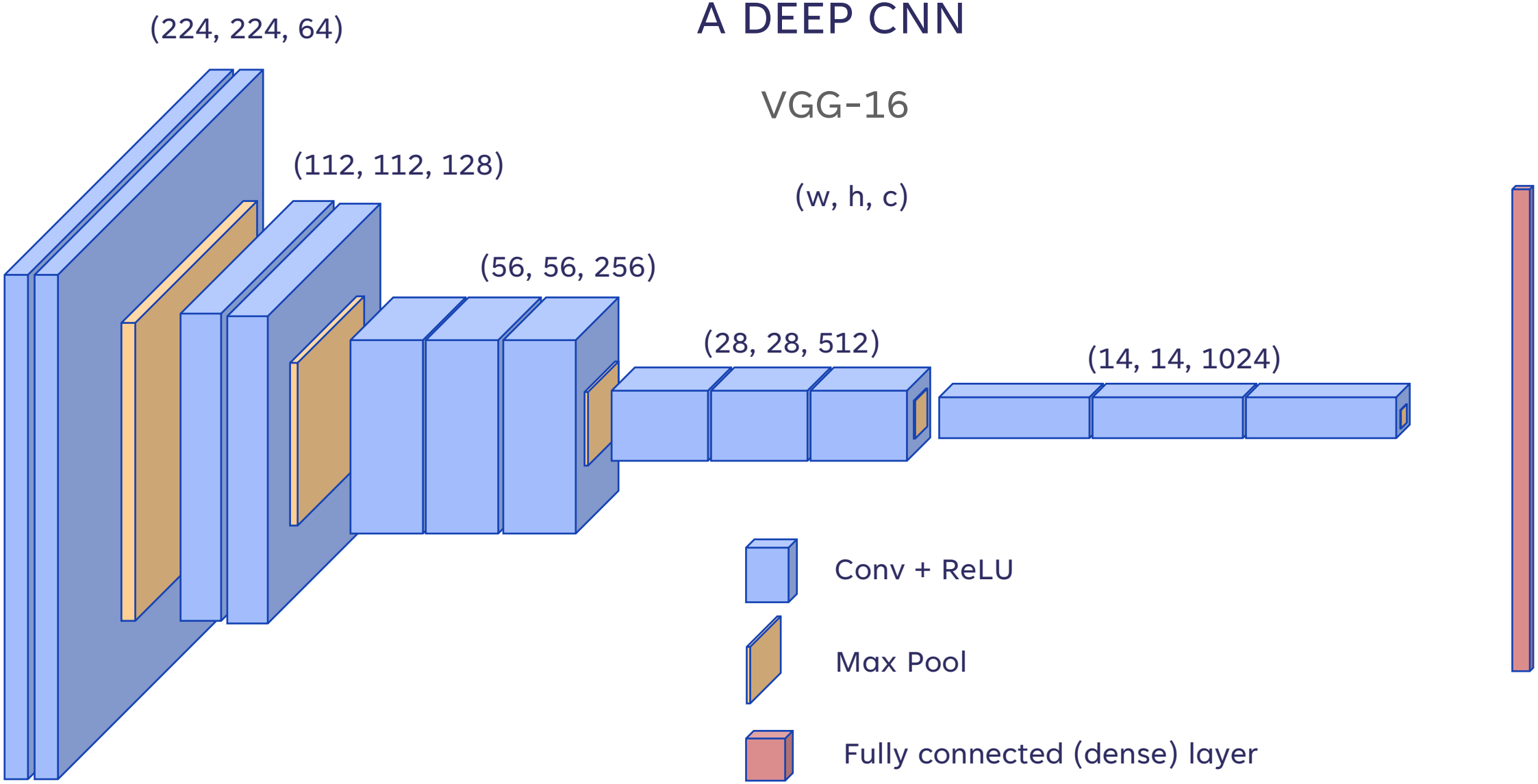
The most commonly used pooling is choosing the maximum value patchwise; **max pooling**

CONVOLUTION IN ACTION: PUTTING IT TOGETHER



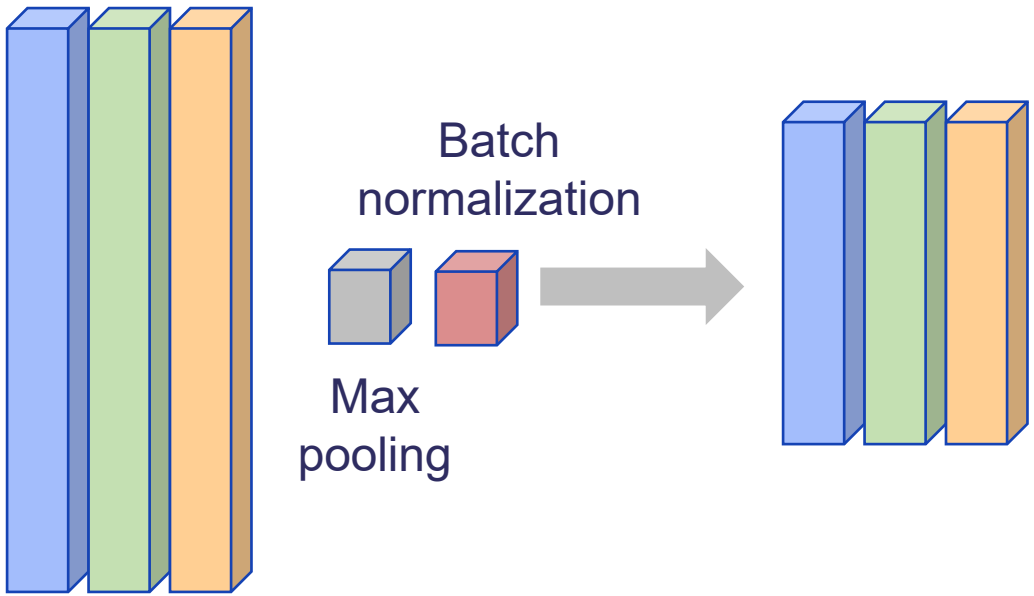
A DEEP CNN

VGG-16



BATCH NORMALISATION

Normalise the outputs from intermediate layers



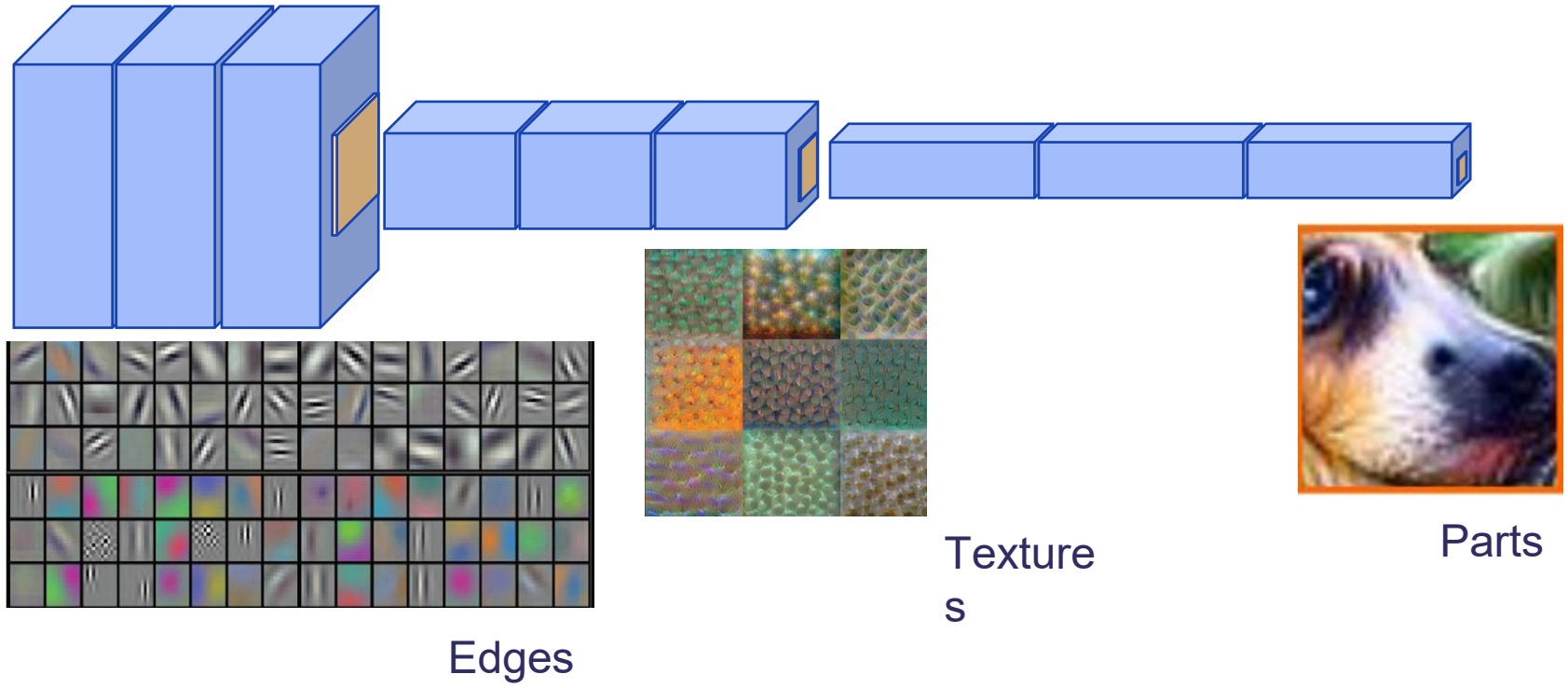
Makes weights deep in the NN more robust to changes early in the NN

BUILDING BLOCKS: CONVOLUTION BLOCK

```
import torch
import torch.nn as nn
import torch.nn.functional as F

nn.Conv2d(in_channels=1, out_channels=6,kernel_size=5)
F.max_pool2d(x, kernel_size=2)
```

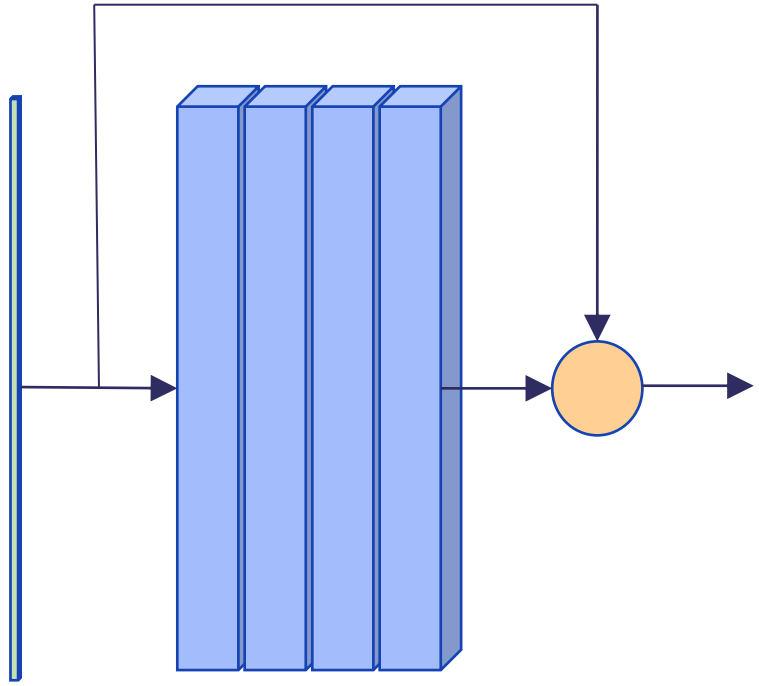
Hierarchy of filters

- Stacking deep networks means that different levels of features are learned at different depths



Advanced CNNs: Residual blocks

- A connection that passes the input over a block of convolutions
- Useful in very deep architectures
- Allows network to learn to skip blocks
- Allows gradient to pass back through the network more effectively in backprop



CONCEPT CHECKLIST

Origins of convolutional neural networks

Building blocks of CNNs – kernel, padding, stride

Max pooling

Deep CNNs

Batch normalisation

Feature detection in different layers

Residual blocks

THANK YOU

mdi-group.github.com