# INTRODUCTION TO DEEP LEARNING

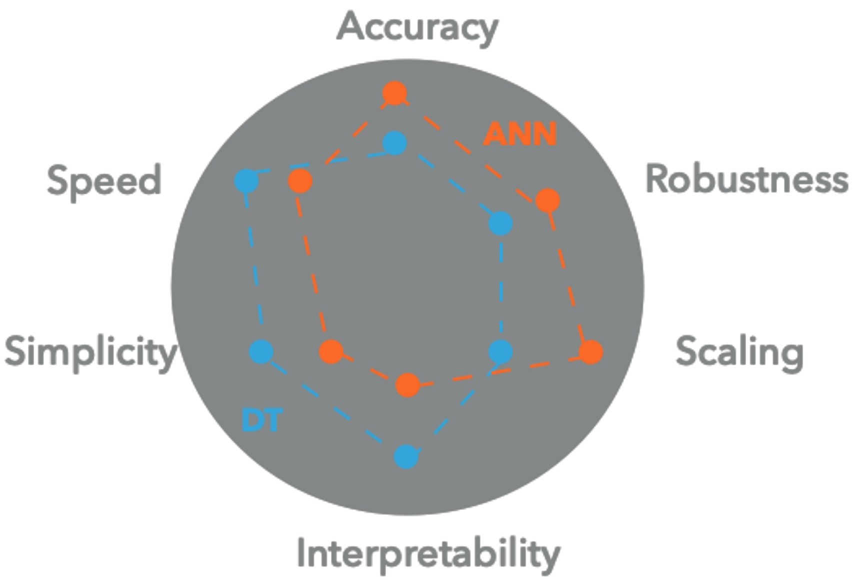
Keith Butler

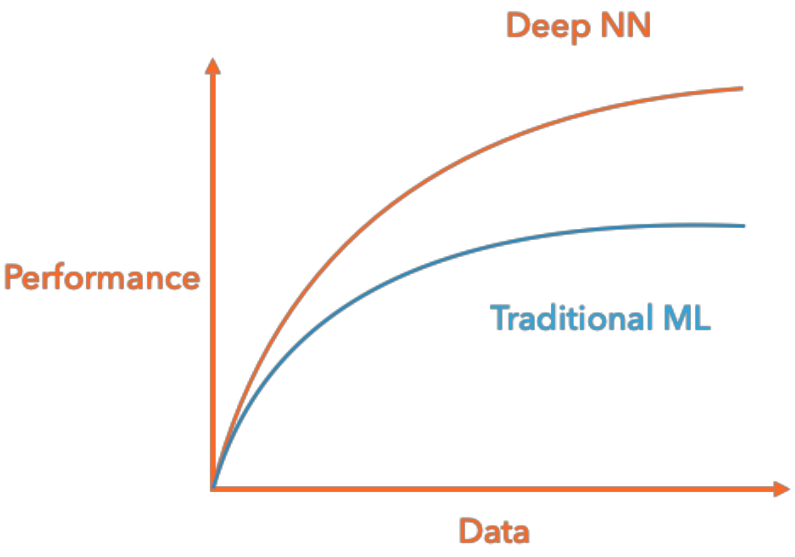
# WHAT WE WILL COVER

- The difference between deep and classical learning
- The concept of representation learning
- The structure of a simple multi-layer perceptron
- How to write an MLP in PyTorch
- How a NN learns – optimisation and backpropagation
- The power of inductive bias
- The structure of a simple convolutional neural network

# CLASSICAL/DEEP METHODS

- Classical: linear regression, trees etc..
- Deep: neural network type models



# DEEP LEARNING AS REPRESENTATION LEARNING

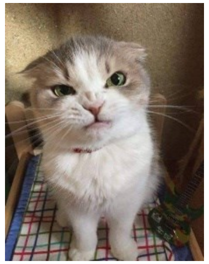
"Hand-crafted" features

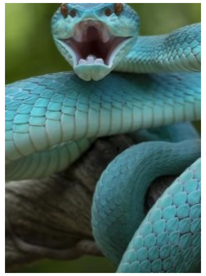
Classical ML $$f(x) = y$$

Deep learning $$f(f(\Theta)) = y$$

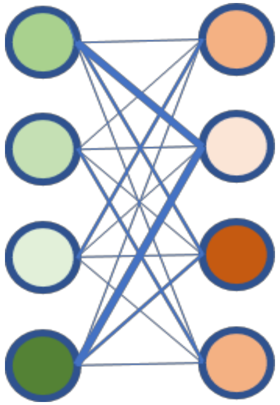
Unstructured data

# DEEP LEARNING AS REPRESENTATION LEARNING





Deep learning



Classical ML

| | |
|---|---|
| Number of eyes | 2 |
| Whiskers | N |
| Legs | N |
| ... | |
| Scales | Y |

Classification model

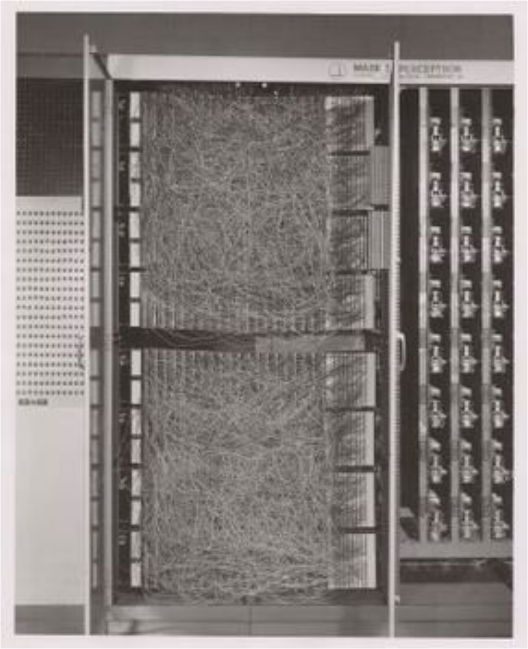
$$f(x) = y$$

Cat/Snake

# NEURAL NETWORKS

Originally an analogue device intended for binary classification

$$y = \phi(\sum_i w_i x_i + b) = \phi(\mathbf{w}^T \mathbf{x} + b)$$

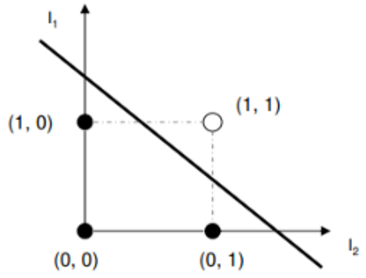


Produces a single output from a matrix of inputs, weights and biases

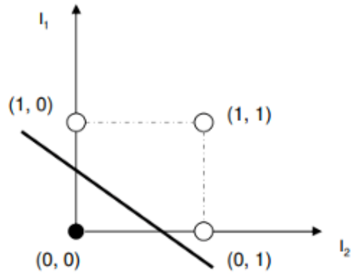
# NEURAL NETWORKS

Minsky and Papert showed they could not solve non-linear classification

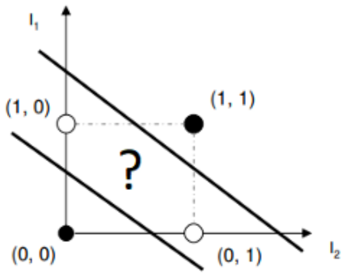
| AND | | |
|---|---|---|
| $I_1$ | $I_2$ | out |
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 1 | 1 | 1 |

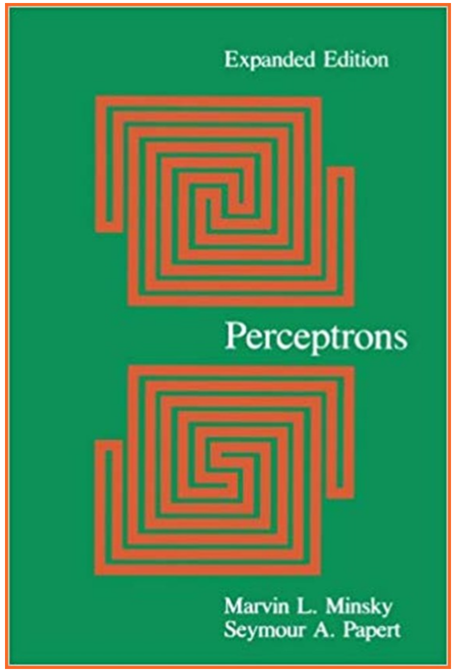



| OR | | |
|---|---|---|
| $I_1$ | $I_2$ | out |
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 1 |



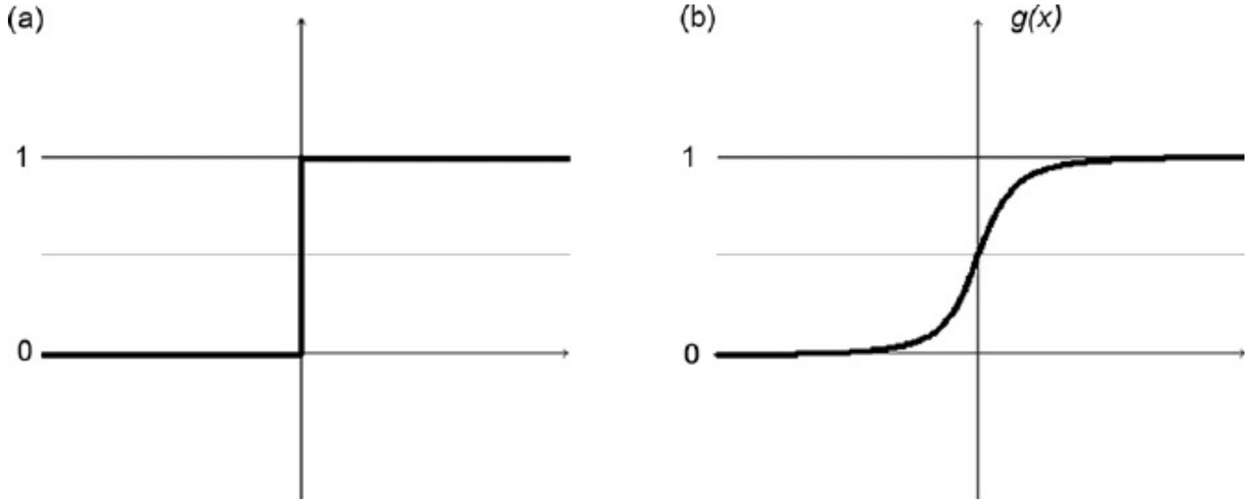

| XOR | | |
|---|---|---|
| $I_1$ | $I_2$ | out |
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |



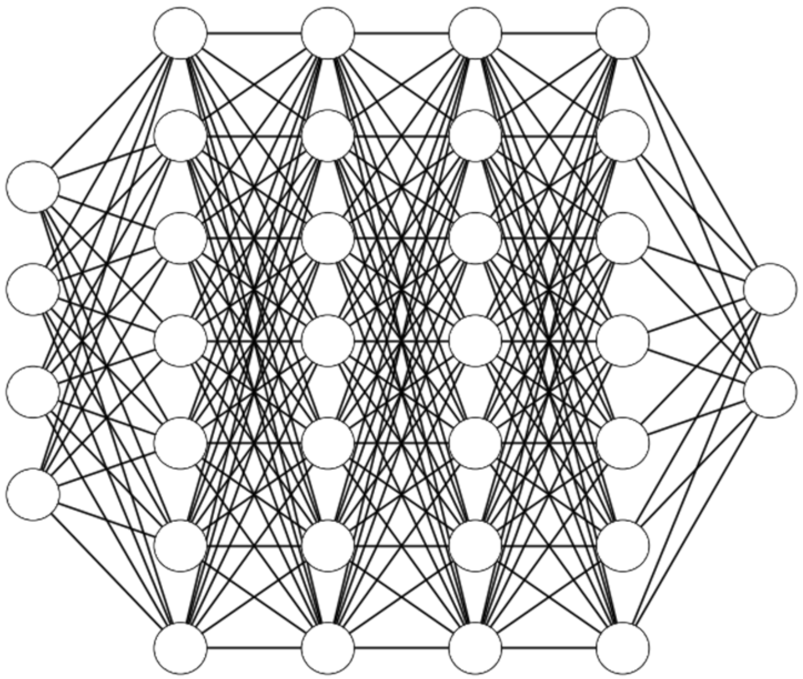
# CHANGE OF FUNCTION

$$y = \phi(\sum_i w_i x_i + b) = \phi(\mathbf{w}^T \mathbf{x} + b)$$



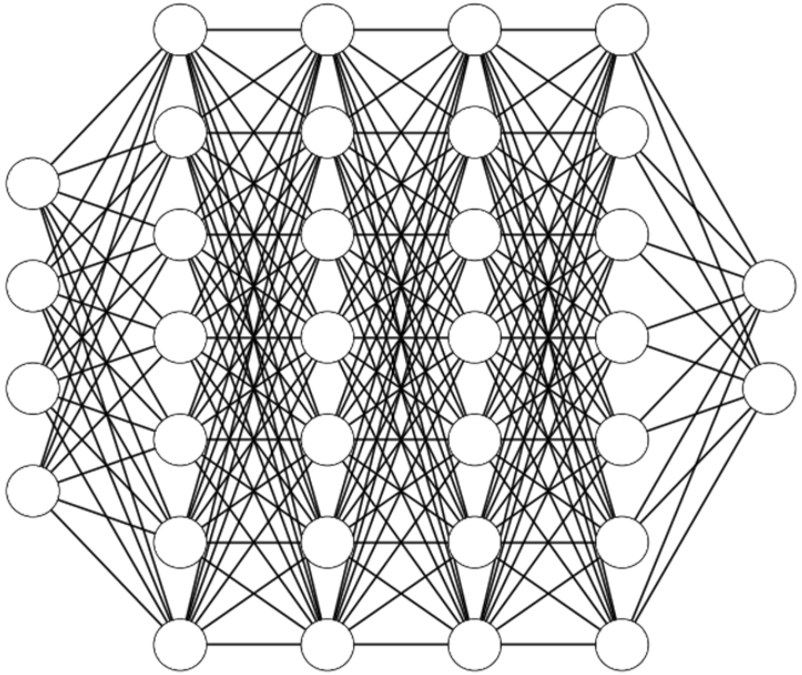
# SIGMOID NON-LINEARITY

A differentiable non-linearity allows for multiple layers



# DEEP NEURAL NETWORKS: MULTI LAYER PERCEPTRON

Input layer

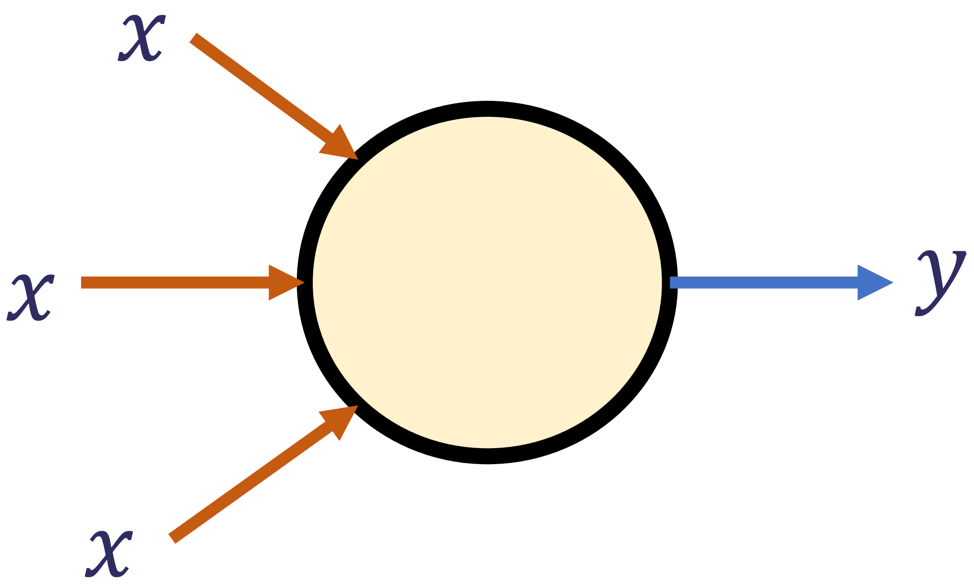


Output layer

Hidden layers

# DENSE LAYERS

Also called fully connected layers as each node is connected to each node in the previous layer




Activation function

Output signal $y = g(z)$

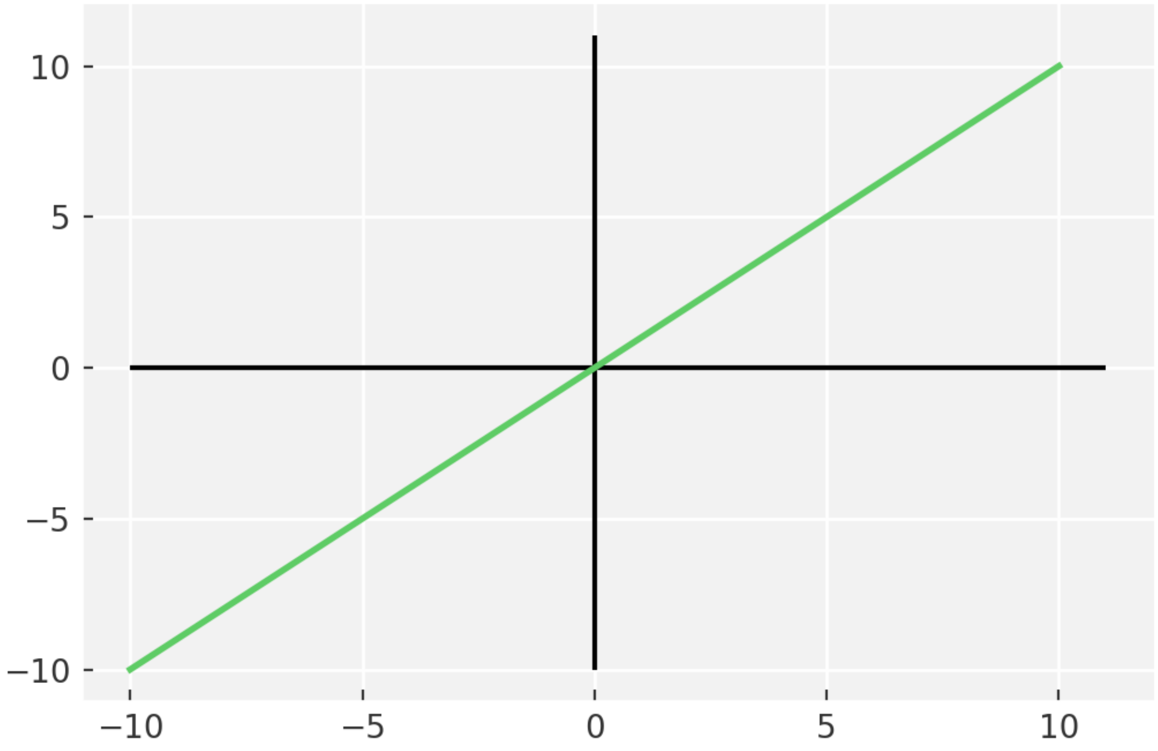
$z = \mathbf{w}^T . \mathbf{x} + b$ Bias

Weights

Input signals

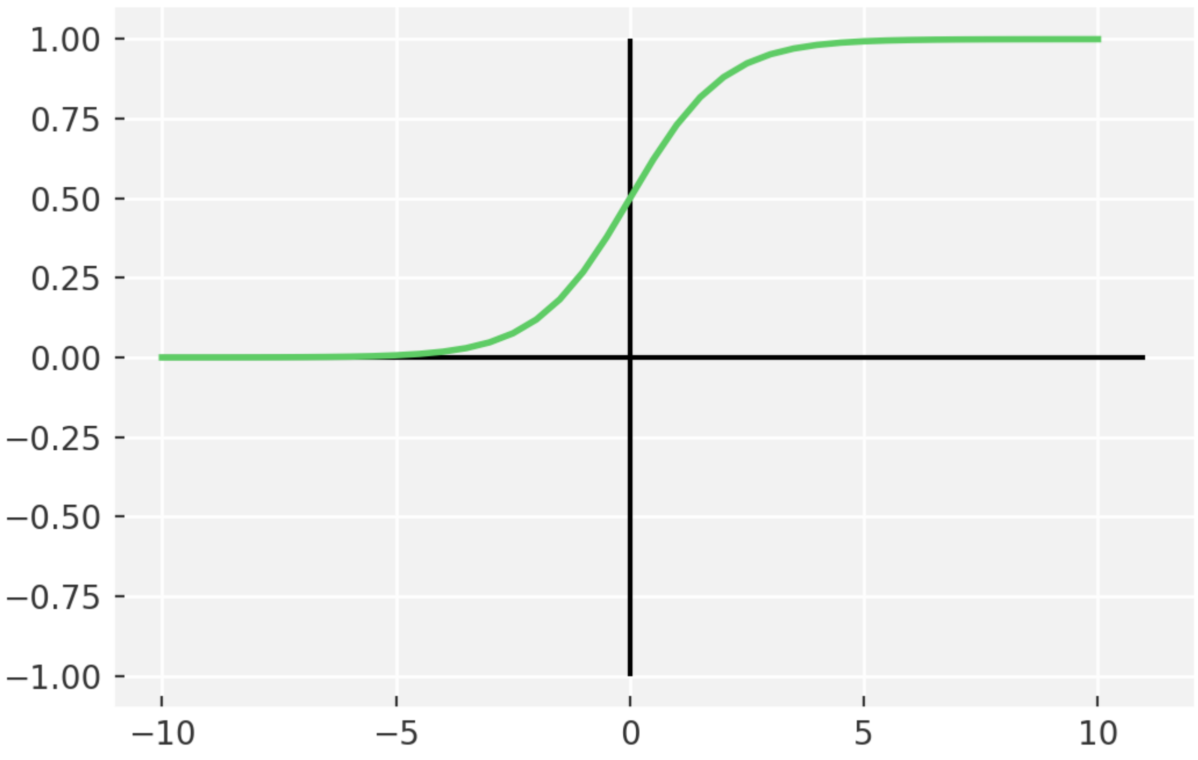
# ACTIVATION FUNCTION: LINEAR

The simplest activation is a linear transformation of the weights matrix



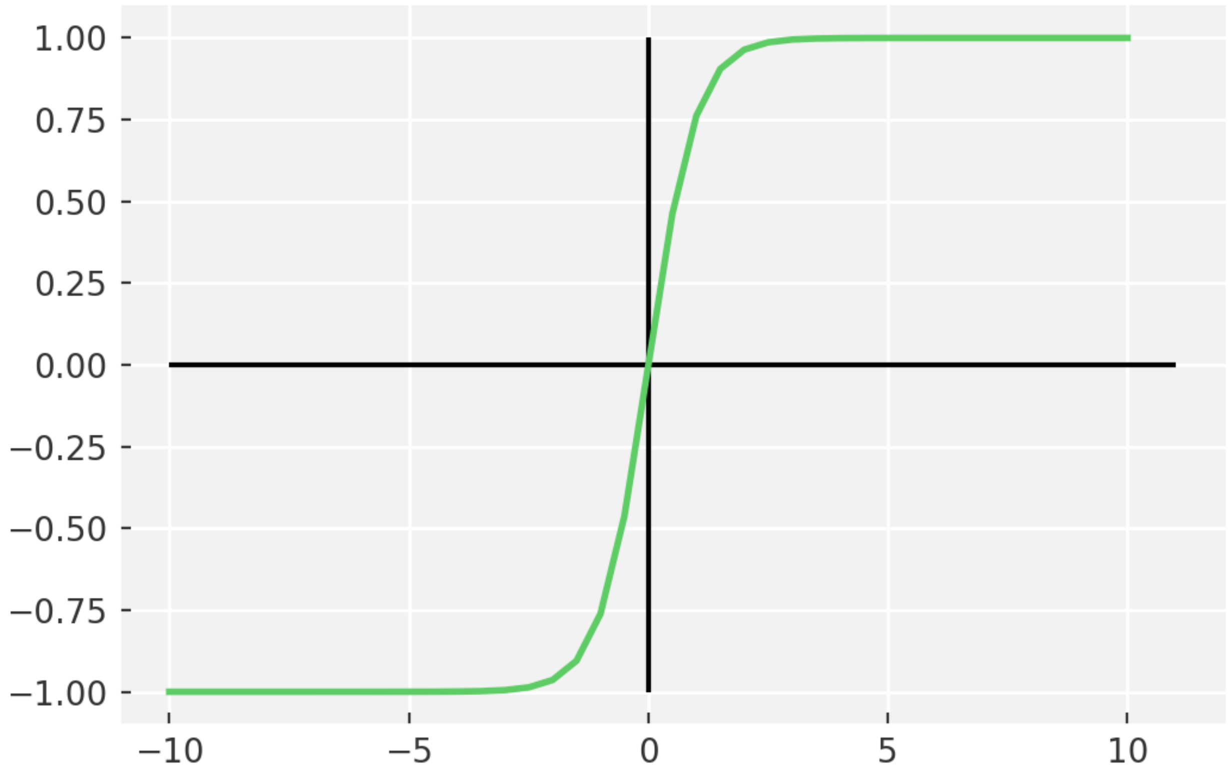
# ACTIVATION FUNCTION: SIGMOID

As we saw earlier sigmoid was the first non-linearity (after the step function)



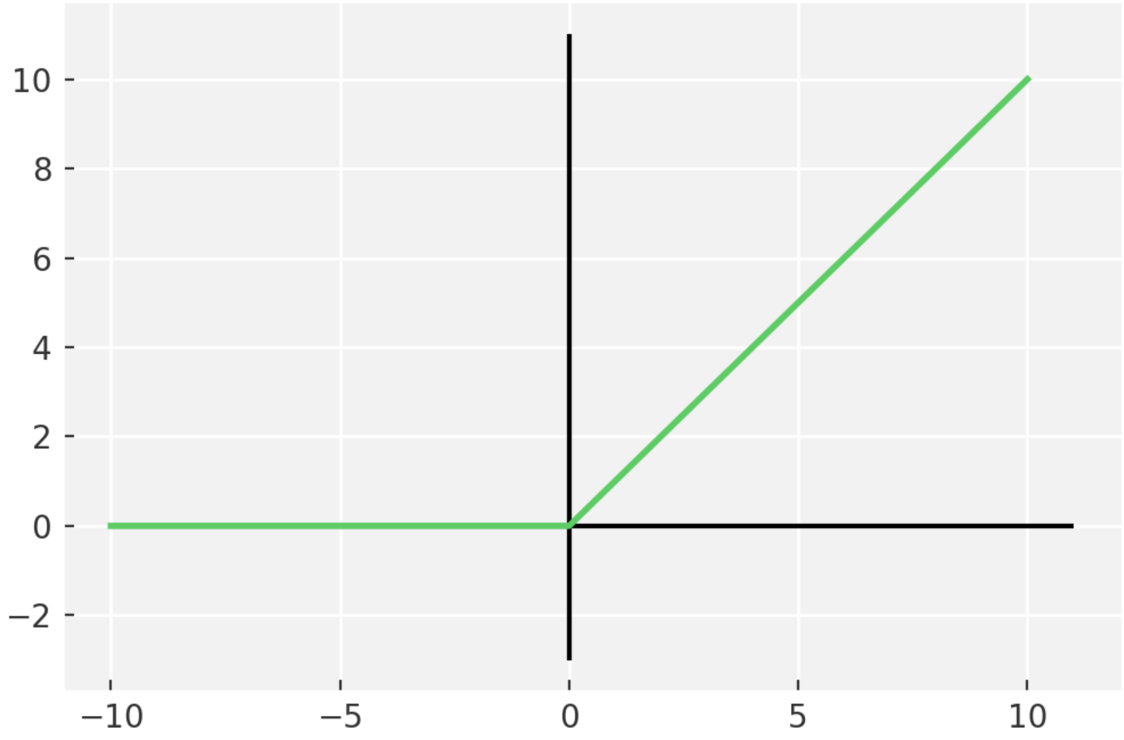
# ACTIVATION FUNCTION: TANH

Like sigmoid, but zero-centered, **converges better** than sigmoid



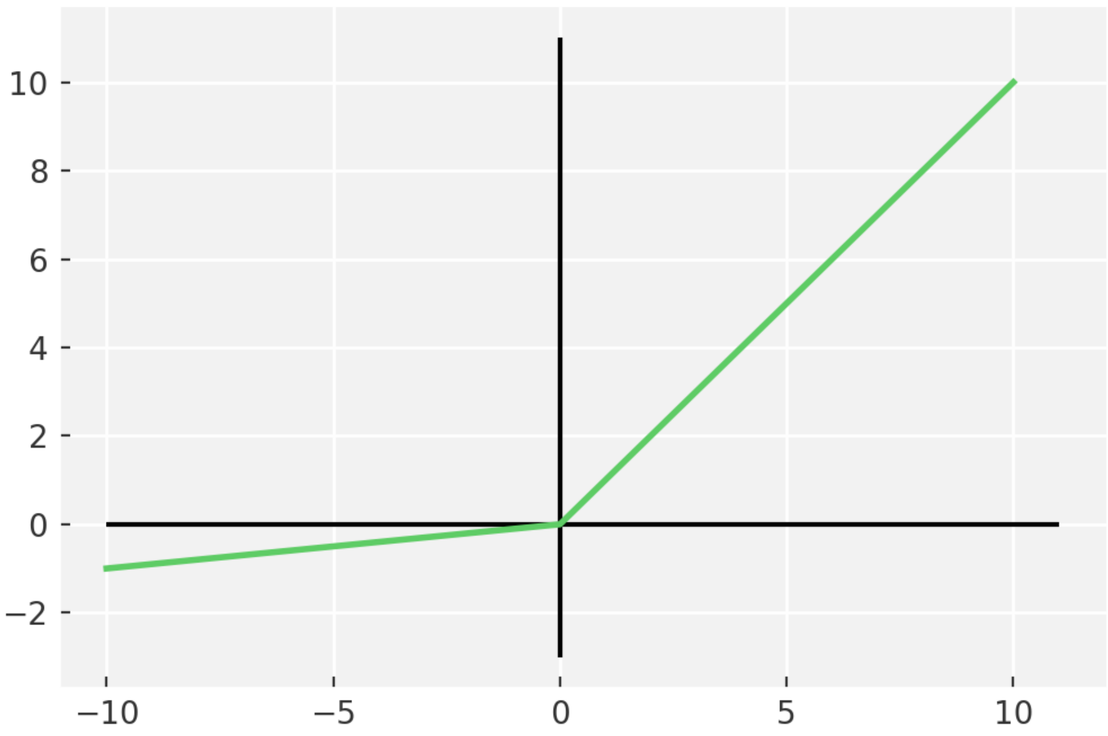
# ACTIVATION FUNCTION: RELU

The rectified linear unit (ReLU) has 6 x improvement in convergence from Tanh function



# ACTIVATION FUNCTION: LEAKYRELU

ReLU can still lead to vanisihing gradients, leaky ReLU attempts to circumvent this

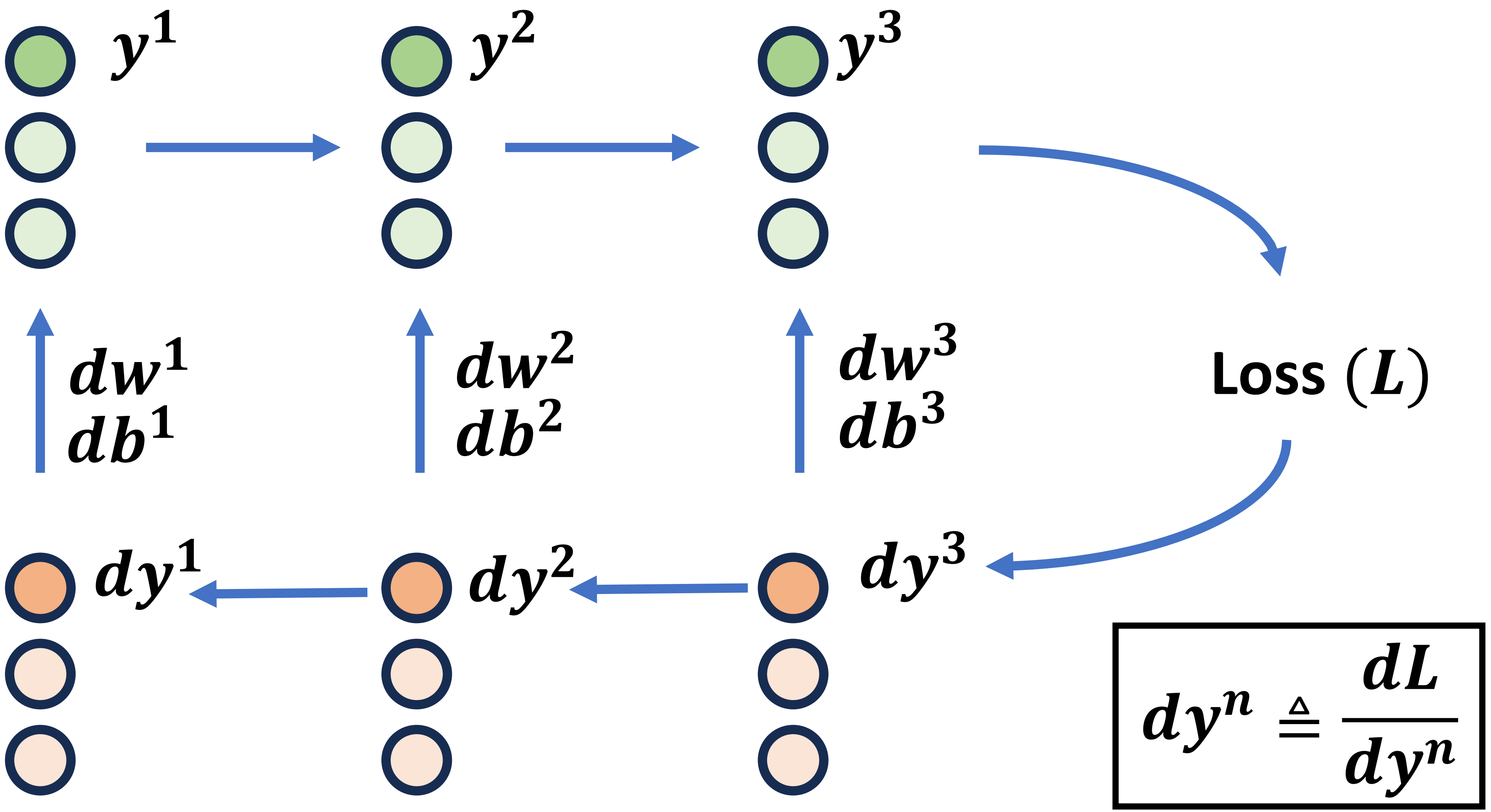


# WRITING A DNN IN PYTORCH

```
class MLP(nn.Module):
    def __init__(self, input_dim, output_dim):
        super().__init__()

        self.input_fc = nn.Linear(input_dim, 250)
        self.hidden_fc = nn.Linear(250, 100)
        self.output_fc = nn.Linear(100, output_dim)

    def forward(self, x):

        batch_size = x.shape[0]
        x = x.view(batch_size, -1)
        h_1 = F.relu(self.input_fc(x))
        h_2 = F.relu(self.hidden_fc(h_1))
        y_pred = self.output_fc(h_2)

        return y_pred, h_2
```

Go to notebook

BACK PROPAGATION



# OPTIMISATION STOCHASTIC GRADIENT DESCENT

- Gradient descent – calculate the gradient of the loss of the entire set with respect to parameters
- SGD – calculated per sample rather than on the entire batch
  - Much quicker to calculate, but can lead to high variance
- Mini-batch SGD – calculate loss gradient on batches of set size
  - Best of both worlds

# OPTIMISATION: ADAPTIVE METHODS

- Some parameters update much more often than others
- Therefore different learning rates can be appropriate for different parameters
- *Adagrad* modifies the learning rate η at each time step for every parameter based on the past gradients computed for that parameter

Current gradient

Old parameter

New parameter

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{G_t + \varepsilon}} g_t$$

Sum of previous gradients

# OPTIMISATION: ADAM

- Similar to Adagrad
- Add in information about the mean of the momentum of previous steps too
- Works very well in most situations

Mean of last n gradients

Old parameter

New parameter

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v} + \varepsilon} m$$

Variance of last n gradients

# BUILDING BLOCK: ADAM OPTIMIZER

```
import torch.optim as optim

optimizer = optim.Adam(model.parameters())
criterion = nn.CrossEntropyLoss()
```

# BUILDING BLOCK – A TRAINING LOOP

```
def train(model, iterator, optimizer, criterion, device):

    epoch_loss = 0
    epoch_acc = 0

    model.train()

    for (x, y) in tqdm(iterator, desc="Training", leave=False):

        x = x.to(device)
        y = y.to(device)

        optimizer.zero_grad()

        y_pred, _ = model(x)

        loss = criterion(y_pred, y)

        acc = calculate_accuracy(y_pred, y)

        loss.backward()

        optimizer.step()

        epoch_loss += loss.item()
        epoch_acc += acc.item()

    return epoch_loss / len(iterator), epoch_acc / len(iterator)
```

Go to notebook

# CONCEPT CHECKLIST

Deep learning is a qualitatively different process to classical ML

Deep learning generally requires more data than classical ML

Deep learning relies on representation learning

How to write and train a neural network in PyTorch

# THANK YOU

mdi-group.github.com

# 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.

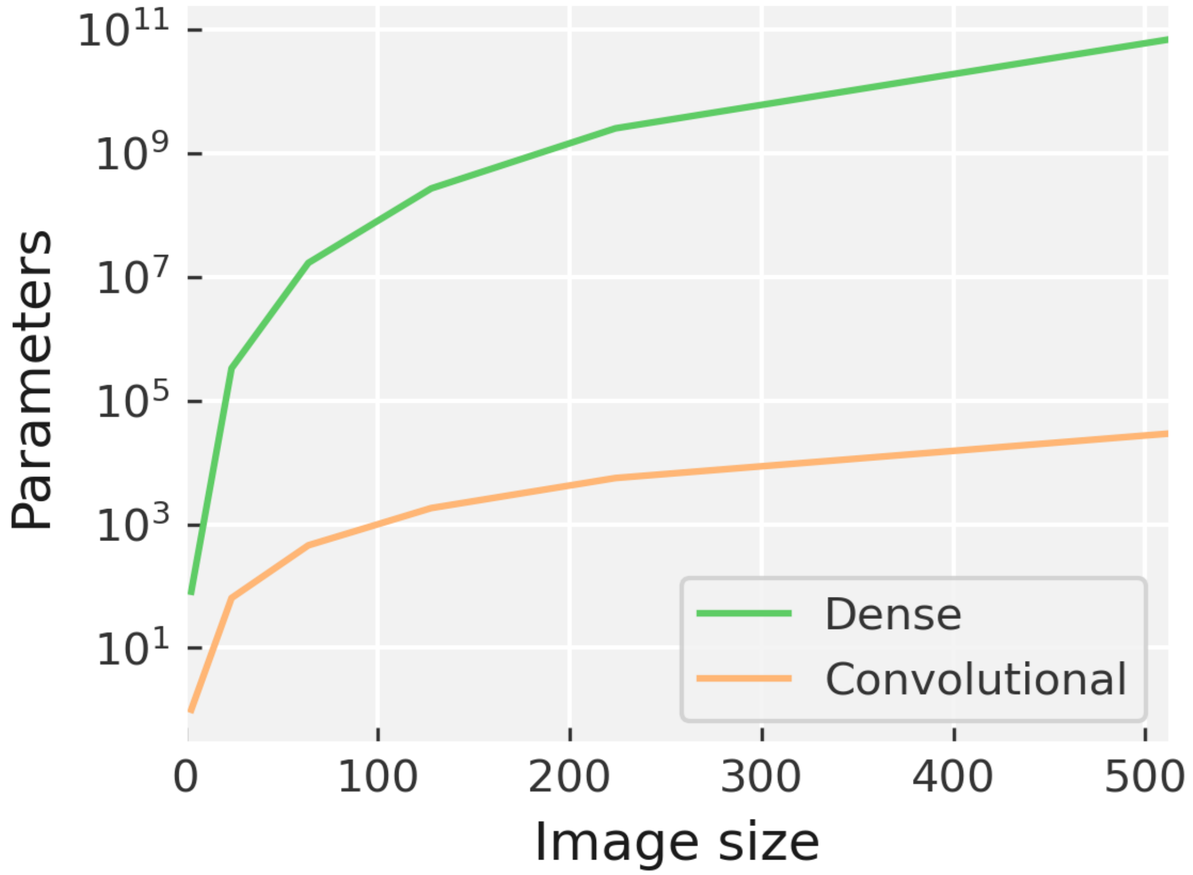
*The need for biases in learning generalizations, CBM-TR 5-110, New Brunswick, New Jersey, USA: Rutgers University*

# OVERVIEW

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

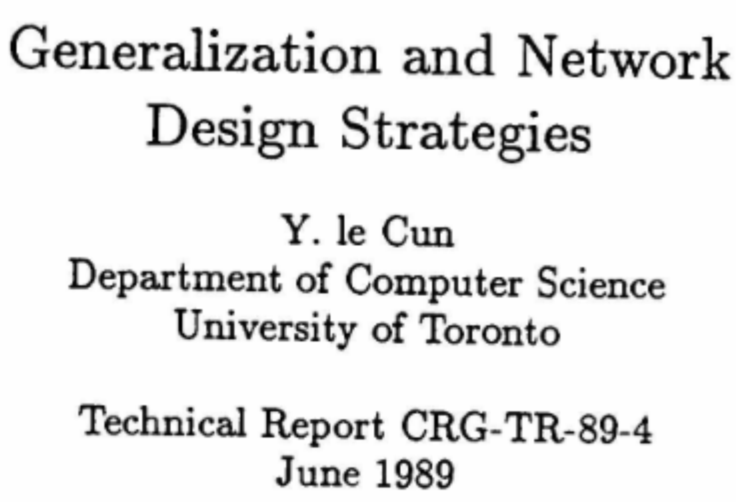
# DRAWBACKS OF MLPS

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

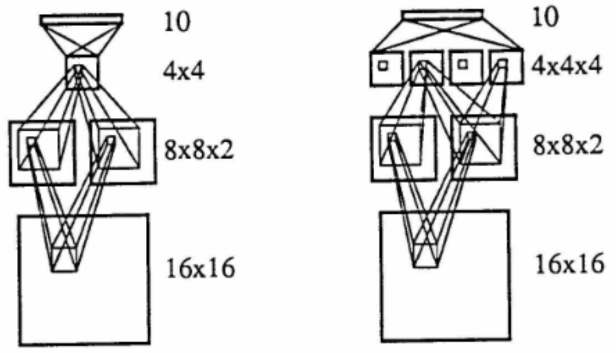
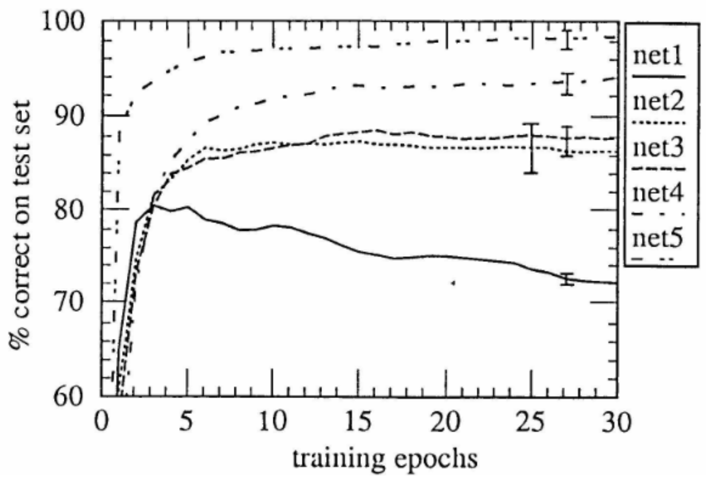


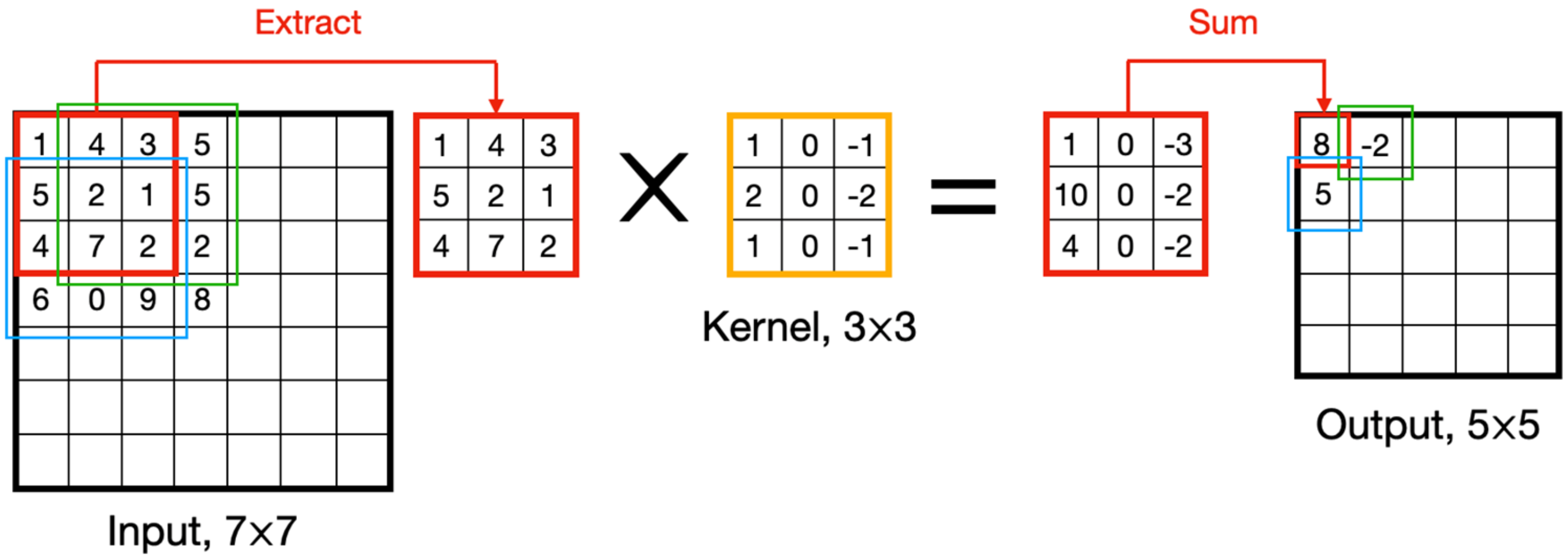

Figure 5 two network architectures with shared weights: Net-4 and Net-5



# STRUCTURE OF A CONVOLUTIONAL LAYER

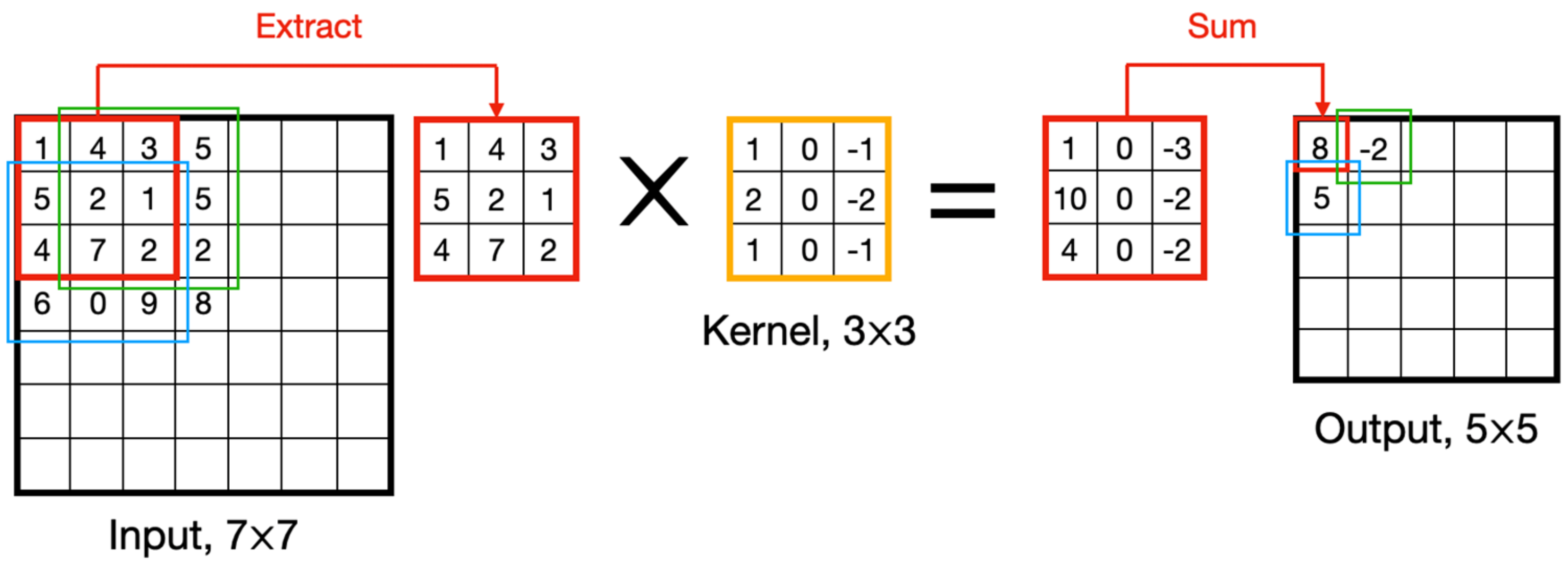
Typical convolutional layers have three main ingredients:

- Kernel
- Pooling
- Activation



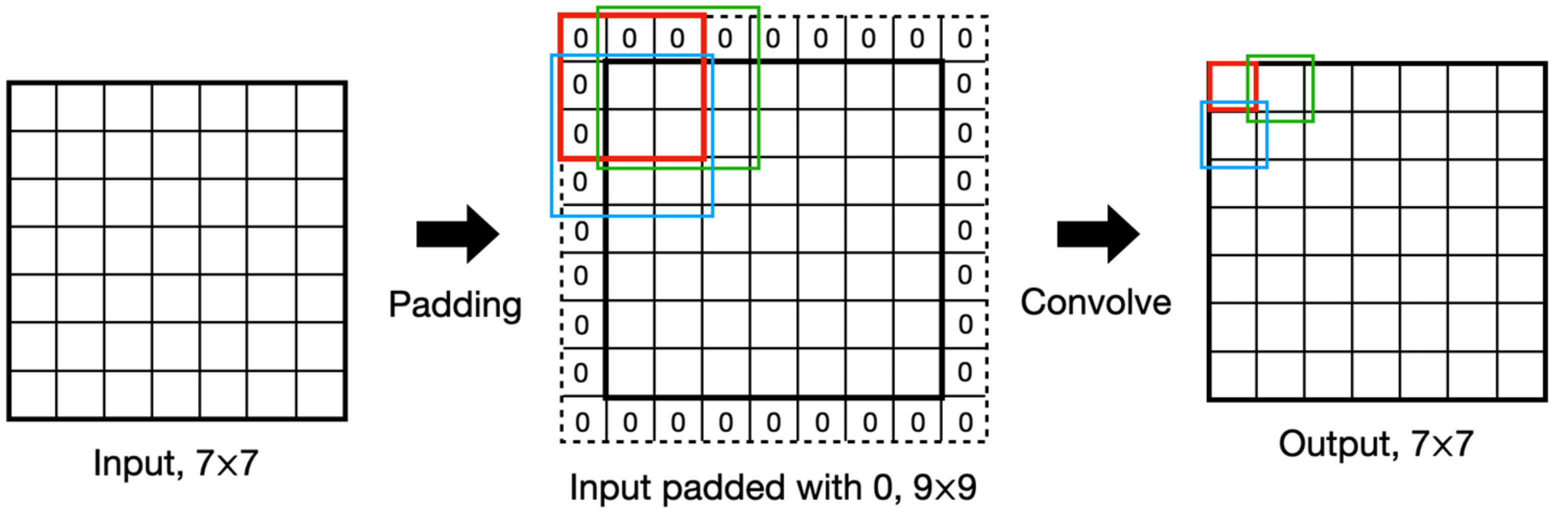
# CONVOLUTION IN ACTION: KERNEL

- Input + kernel -> activation map



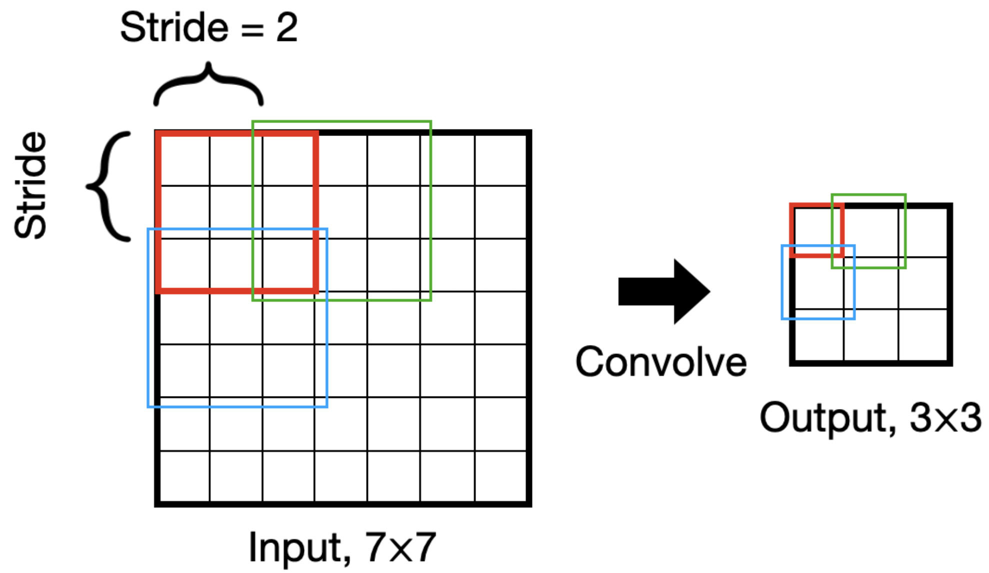
# CONVOLUTION IN ACTION: PADDING

- 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




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

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

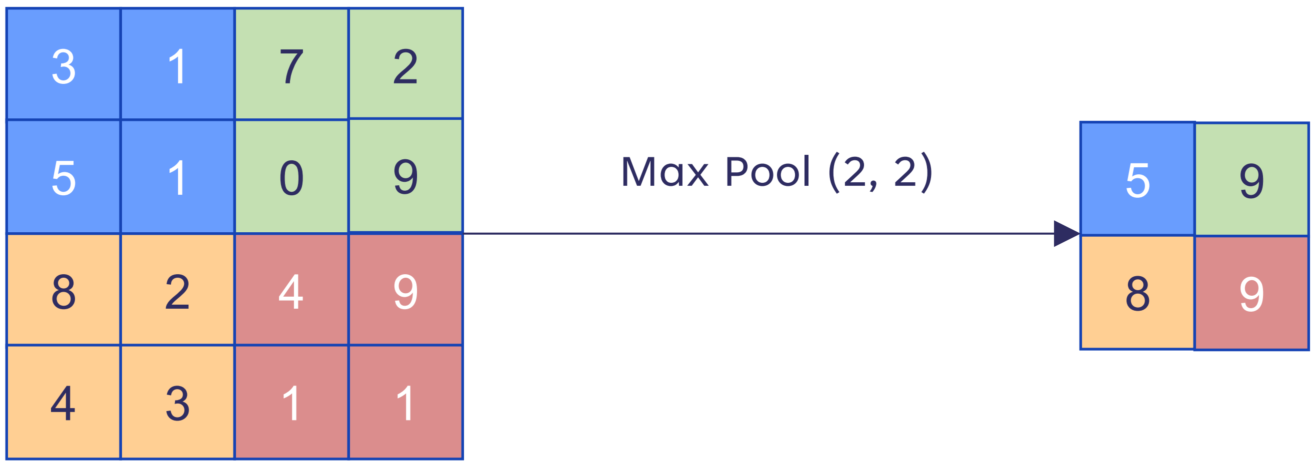
# GO TO NOTEBOOK

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
```

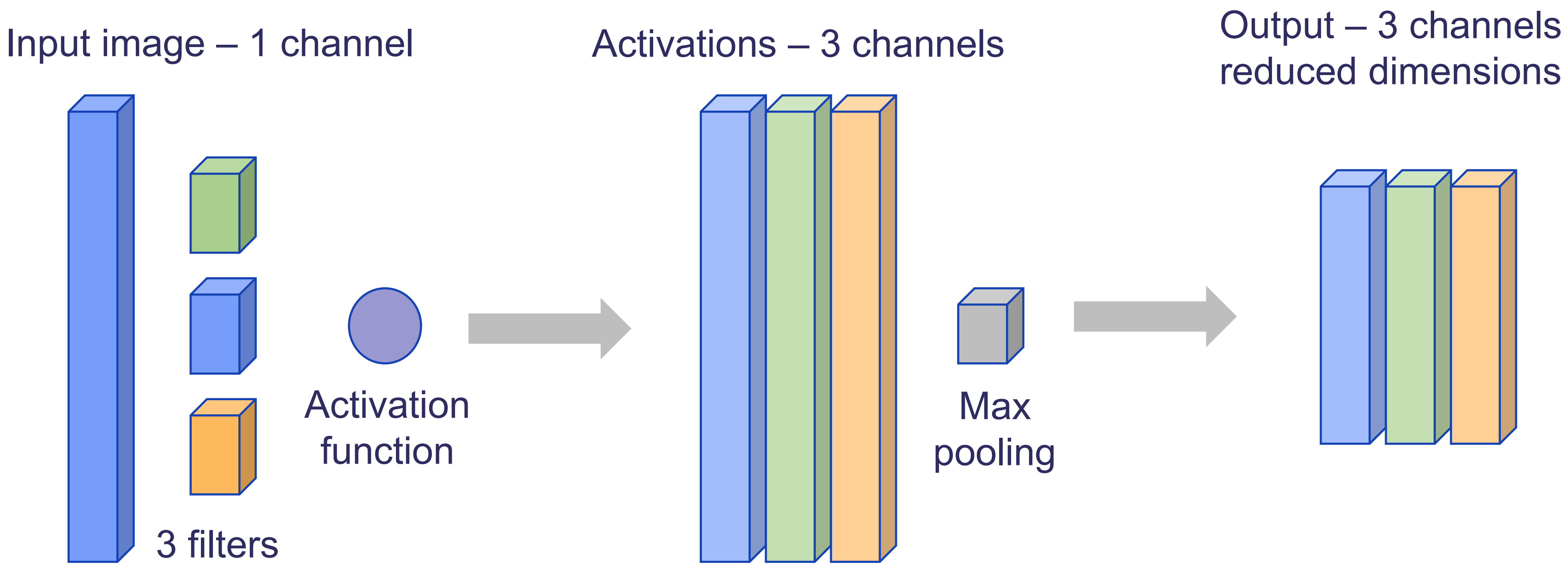
# CONVOLUTION IN ACTION: POOLING

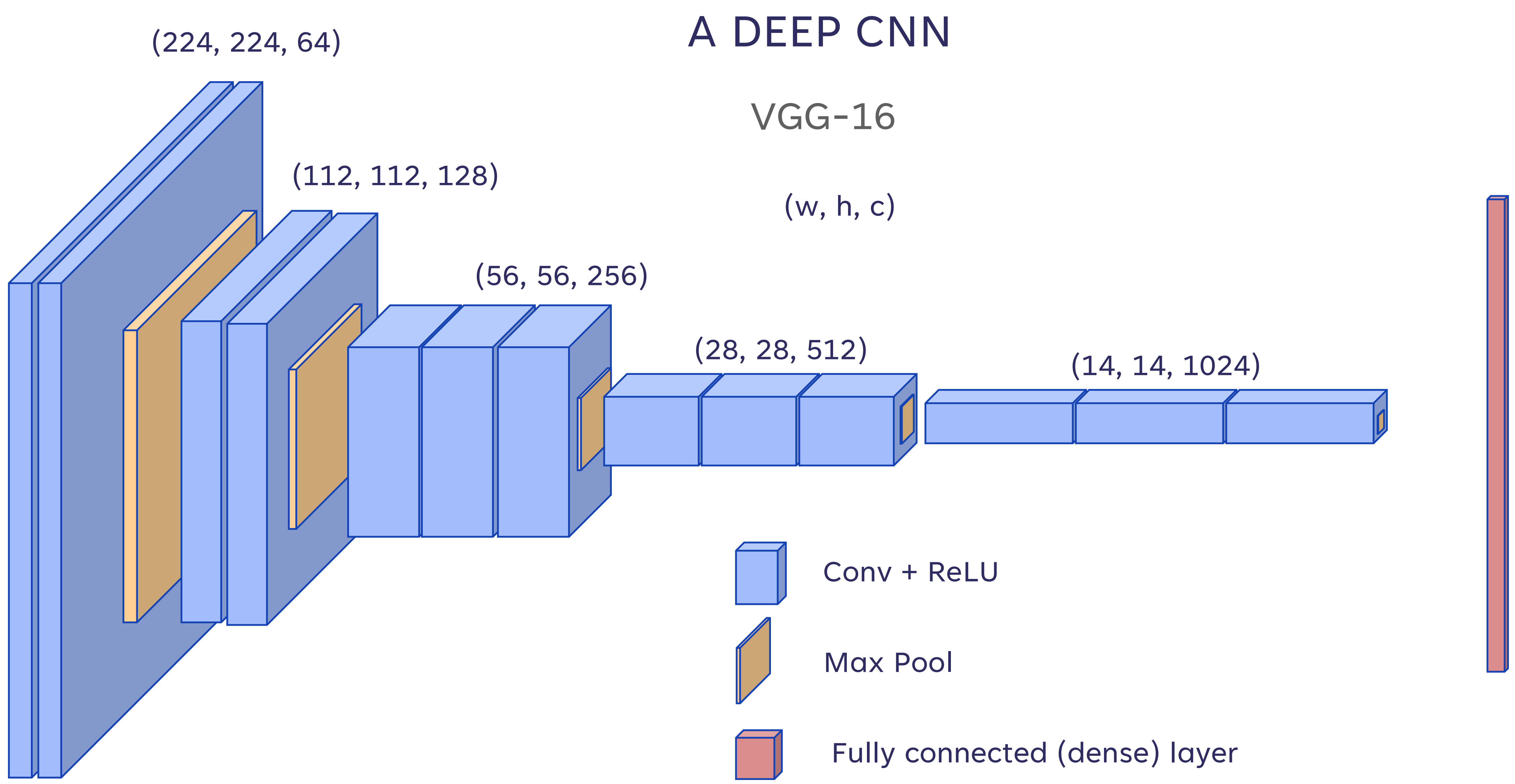
Pooling **compresses information** content between layers




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

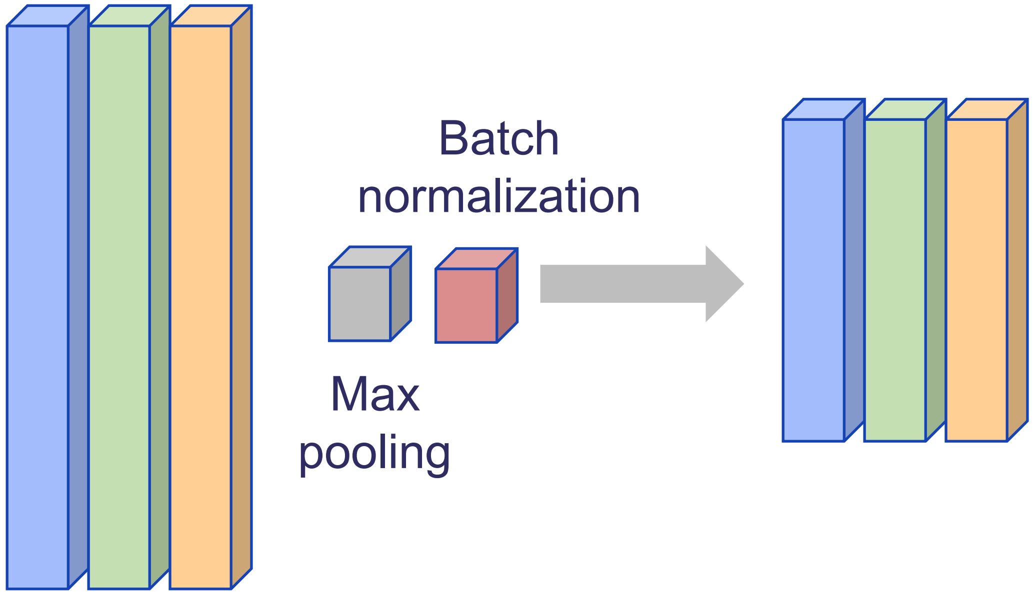
# CONVOLUTION IN ACTION: PUTTING IT TOGETHER




A DEEP CNN
VGG-16
(224, 224, 64)
(112, 112, 128)
(w, h, c)
(56, 56, 256)
(28, 28, 512)
(14, 14, 1024)
Conv + ReLU
Max Pool
Fully connected (dense) layer

# BATCH NORMALISATION

Normalise the outputs from intermediate layers



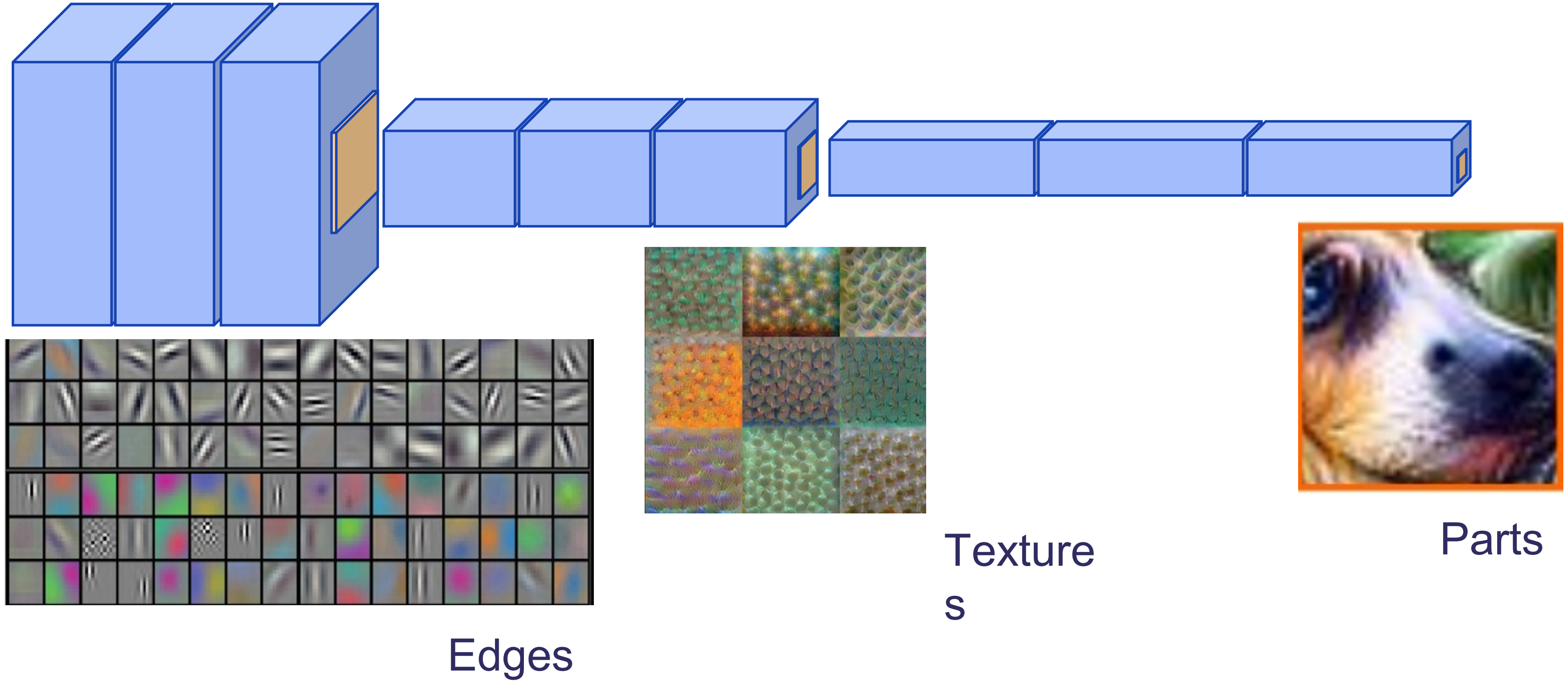

Makes weights deep in the NN more robust to changes early in the NN

# 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)
```

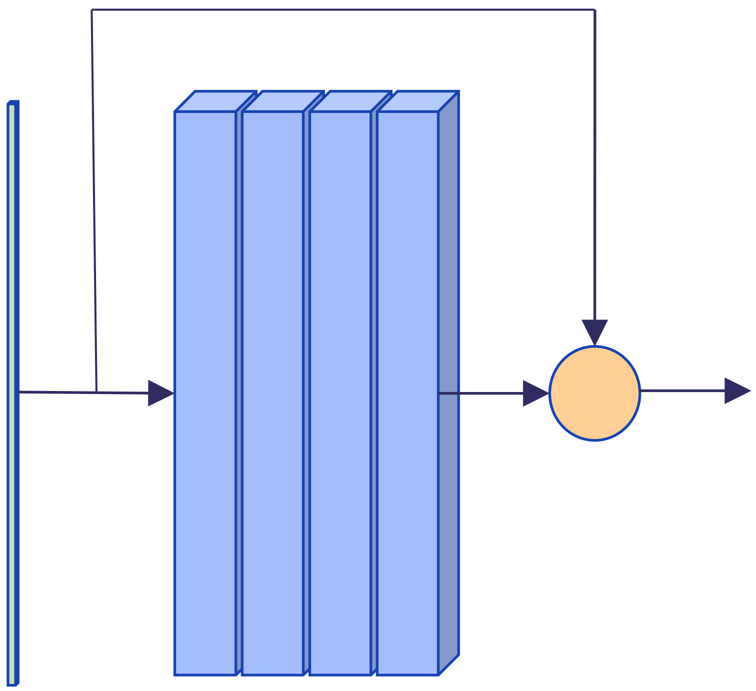
# Hierarchy of filters

- 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

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