

# Introduction to deep learning 1/?

---

Esten Høyland Leonardsen

02.11.22

UiO:Life Science, University of Oslo



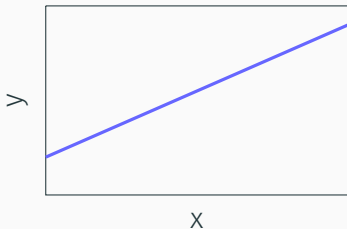
1. Building an artificial neural network (ANN)
2. Training the ANN
3. Transformation to a Convolutional Neural Network (CNN)

## Building a neural network: Linear regression

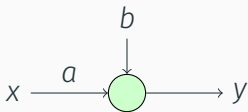
$$y = ax + b$$

# Building a neural network: Linear regression

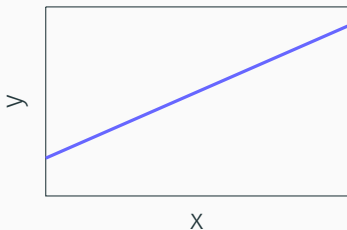
$$y = ax + b$$



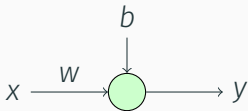
# Building a neural network: Linear regression



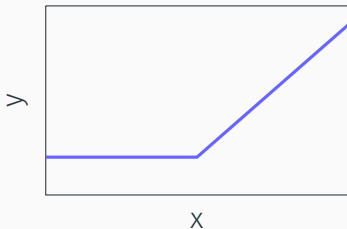
$$y = ax + b$$



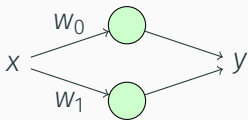
## Building a neural network: Artificial neuron



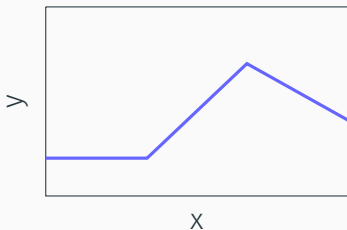
$$y = \max(0, wx + b)$$



## Building a neural network: Artificial neural network (ANN)



$$y = \max(0, w_0x + b_0) + \max(0, w_1x + b_1)$$



## Building a neural network: Universal approximation theorem

*"Any relationship that can be described with a polynomial function can be approximated by a neural network with a single hidden layer."*

- Some guy in the 80s, probably

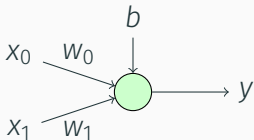


# Building a neural network: Universal approximation theorem

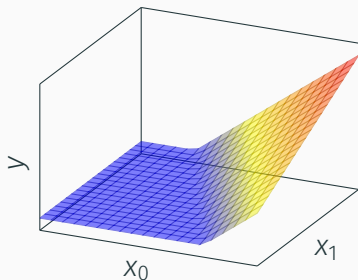
*"Any relationship that can be described with a polynomial function can be approximated by a neural network with a single hidden layer."*

- Some guy in the 80s, probably

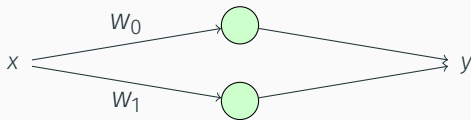
# Building a neural network: Increasing dimensionality



$$y = \max(0, w_0x_0 + w_1x_1 + b)$$

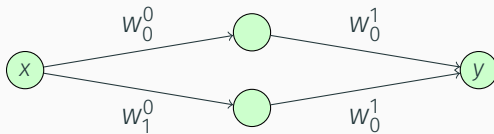


# Building a neural network



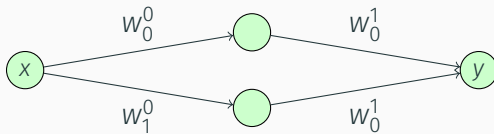
$$y = \max(0, w_0x + b_0) + \max(0, w_1x + b_1)$$

# Building a neural network



$$y = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x + b_{1,0}) + b_1)$$

# Building a neural network



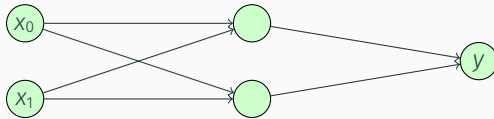
Input

Hidden

Output

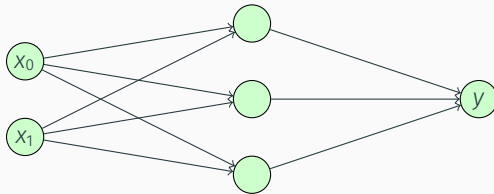
$$y = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x + b_{1,0}) + b_1)$$

# Building a neural network



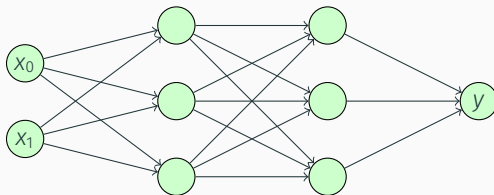
$$y = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^0 * x_1 + b_{0,1}) + b_1)$$

# Building a neural network



$$y = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^0 * x_1 + b_{0,1}) + w_{2,0}^1 * \max(0, w_{0,2}^0 * x_0 + w_{1,2}^0 * x_1 + b_{0,2}) + b_1)$$

# Building a neural network



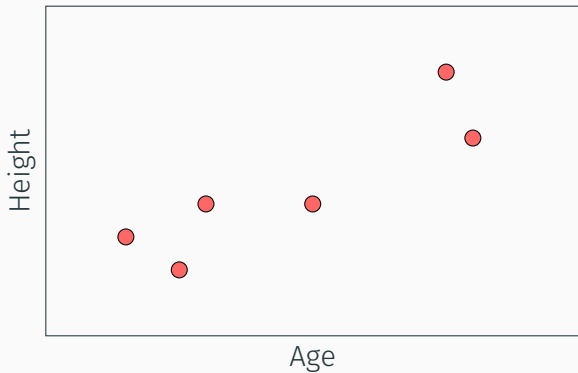
$$\begin{aligned}
 y = & \max(0, w_{0,0}^2 * \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + \\
 & w_{1,0}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^+ * w_1 + b_{0,1}) + \\
 & w_{2,0}^1 * \max(0, w_{0,2}^0 * x_0 + w_{1,2}^+ * w_1 + b_{0,2}) + \\
 & b_{1,0}) + \\
 & w_{1,0}^2 * \max(0, w_{0,1}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + \\
 & w_{1,1}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^+ * w_1 + b_{0,1}) + \\
 & w_{2,1}^1 * \max(0, w_{0,2}^0 * x_0 + w_{1,2}^+ * w_1 + b_{0,2}) + \\
 & b_{1,1}) + \\
 & w_{2,0}^2 * \max(0, w_{0,2}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + \\
 & w_{1,2}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^+ * w_1 + b_{0,1}) + \\
 & w_{2,2}^1 * \max(0, w_{0,2}^0 * x_0 + w_{1,2}^+ * w_1 + b_{0,2}) + \\
 & b_{1,2}) + \\
 & b_2)
 \end{aligned}$$



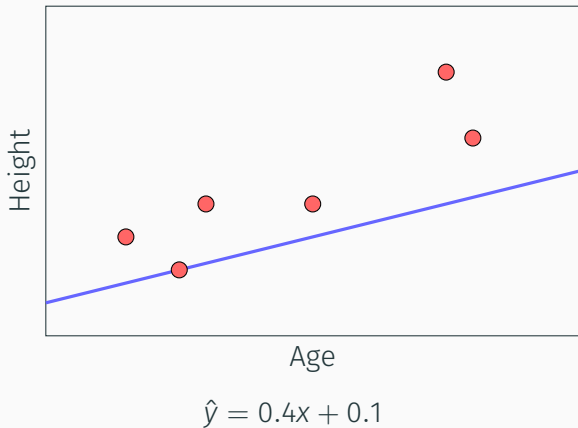
## Building a neural network: Summary

- Artificial neurons are (linear) weighted sums wrapped in non-linear activation functions
- Multiple artificial neurons stacked together in a layerwise fashion comprise an artificial neural network
- Artificial neural networks allow us to model arbitrarily complex relationships between inputs and outputs

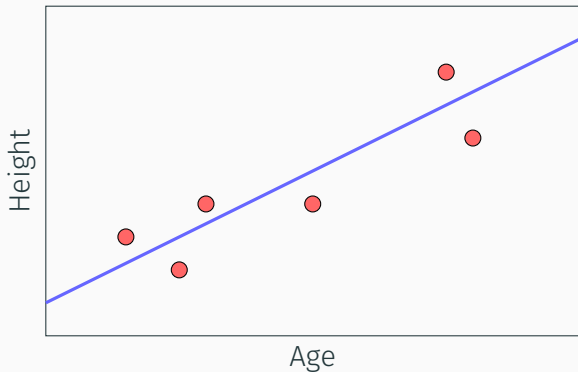
## Training a neural network: Loss functions



## Training a neural network: Loss functions

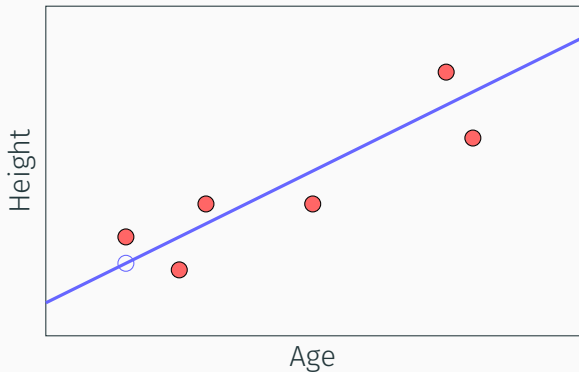


## Training a neural network: Loss functions



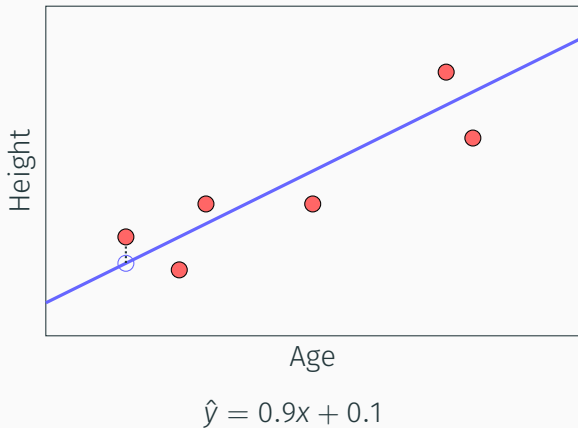
$$\hat{y} = 0.9x + 0.1$$

## Training a neural network: Loss functions

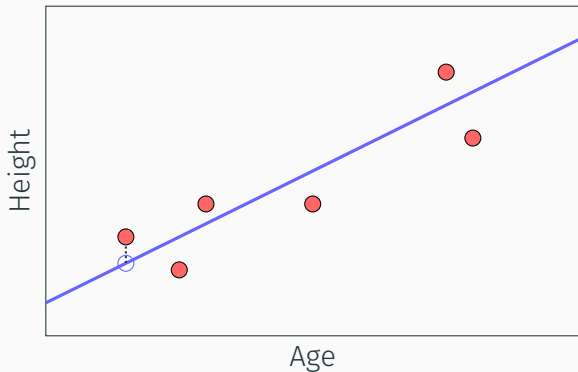


$$\hat{y} = 0.9x + 0.1$$

## Training a neural network: Loss functions



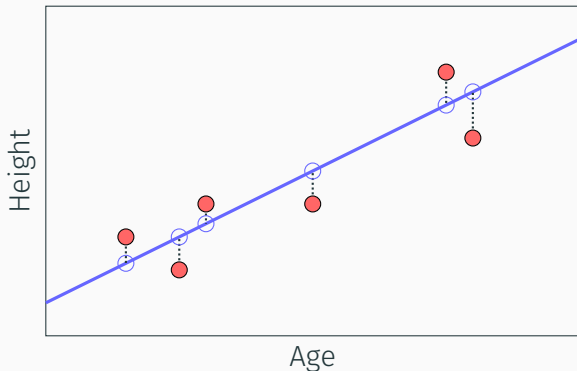
## Training a neural network: Loss functions



$$\hat{y} = 0.9x + 0.1$$

$$error_i = |\hat{y} - y|$$

# Training a neural network: Loss functions



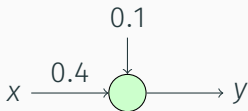
$$\hat{y} = 0.9x + 0.1$$

$$\text{error}_i = |\hat{y} - y|$$

$$\text{mse} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

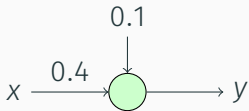


## Training a neural network: Gradient descent



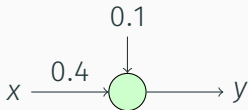
$$y = 0.4x + 0.1 \quad \text{loss} = (y - \hat{y})^2$$

## Training a neural network: Gradient descent



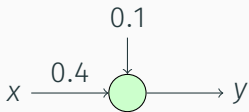
$$0.16 = 0.4 * 0.15 + 0.1 \quad 0.019 = (0.3 - 0.16)^2$$

## Training a neural network: Gradient descent



$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$

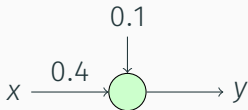
## Training a neural network: Gradient descent



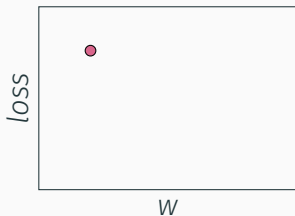
$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$

Diagram illustrating the calculation of the loss for a single neuron. The equation shows the difference between the target  $y$  (0.3) and the predicted value  $\hat{y}$  (0.15) after applying the weight  $w$  (0.4) and bias  $b$  (0.1). The result is the loss, 0.019.

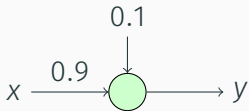
## Training a neural network: Gradient descent



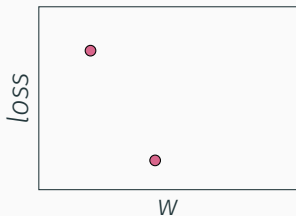
$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$



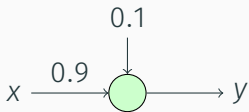
## Training a neural network: Gradient descent



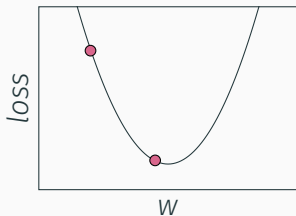
$$(0.3 - (0.9 * 0.15 + 0.1))^2 = 0.004$$



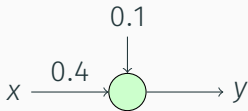
## Training a neural network: Gradient descent



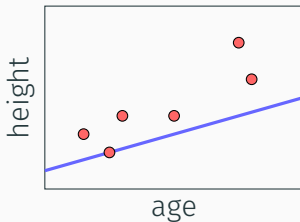
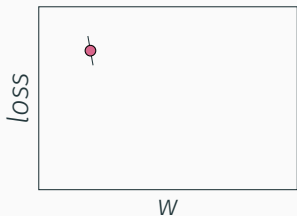
$$(0.3 - (0.9 * 0.15 + 0.1))^2 = 0.004$$



# Training a neural network: Gradient descent

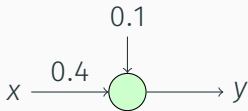


$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$

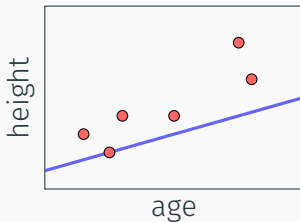
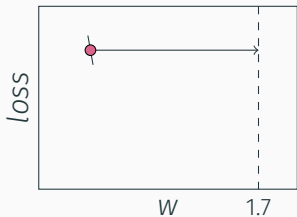




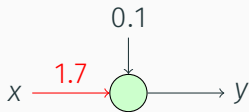
# Training a neural network: Gradient descent



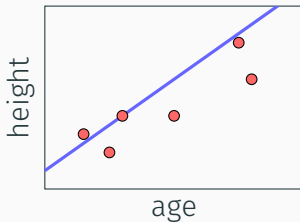
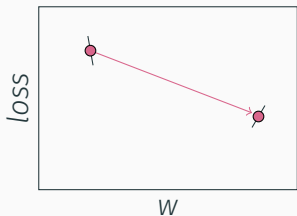
$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$



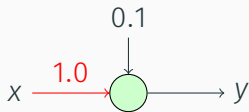
# Training a neural network: Gradient descent



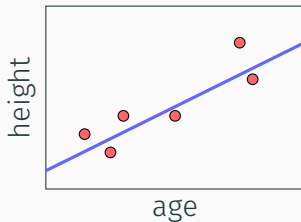
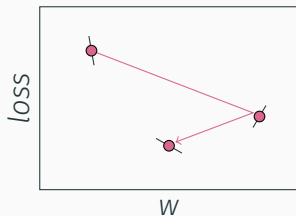
$$(0.3 - (1.7 * 0.15 + 0.1))^2 = 0.003$$



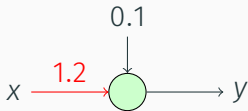
# Training a neural network: Gradient descent



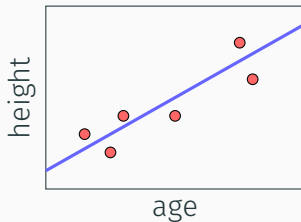
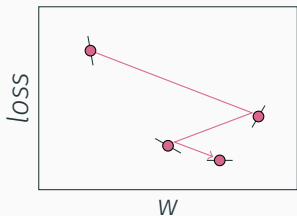
$$(0.3 - (1.0 * 0.15 + 0.1))^2 = 0.002$$



# Training a neural network: Gradient descent



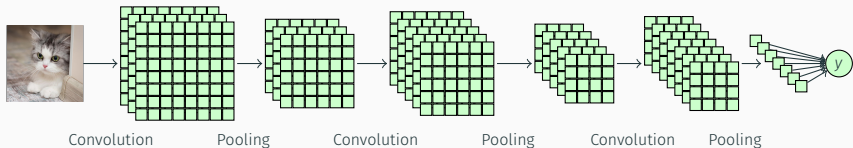
$$(0.3 - (1.2 * 0.15 + 0.1))^2 = 0.000$$



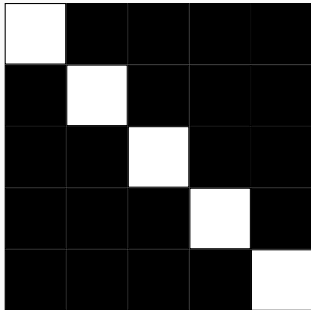
# Training a neural network: Summary

- The loss function is a precise formalization of what we want the model to learn
- Calculating the gradient allows us to see how we can update the parameters of the model to decrease the loss
- Using gradient descent we can update the parameters sequentially until we have the perfect model with zero loss

# Convolutional neural networks: Architecture

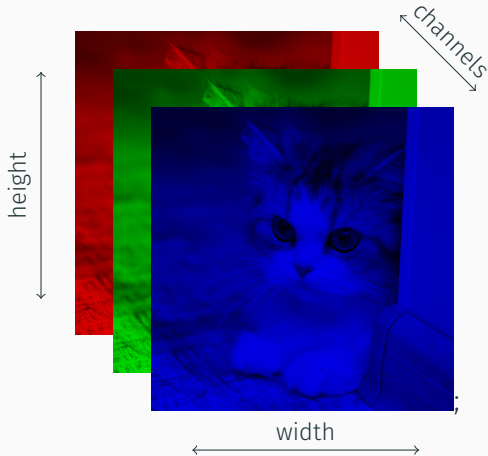


# Convolutional neural networks: Images



1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

# Convolutional neural networks: Images





# Convolutional neural networks: Convolution

0	0	1
0	1	0
1	0	0

 $*$ 

1	0	0
0	1	0
0	0	1

# Convolutional neural networks: Convolution

0	0	1
0	1	0
1	0	0

 $*$ 

1	0	0
0	1	0
0	0	1

0\*1

# Convolutional neural networks: Convolution

0	0	1
0	1	0
1	0	0

 $*$ 

1	0	0
0	1	0
0	0	1

$$0*1+0*0$$

# Convolutional neural networks: Convolution

0	0	1
0	1	0
1	0	0

 $*$ 

1	0	0
0	1	0
0	0	1

$$0*1+0*0+1*0$$

# Convolutional neural networks: Convolution

0	0	1
0	1	0
1	0	0

\*

1	0	0
0	1	0
0	0	1

$$0*1+0*0+1*0+0*0$$

# Convolutional neural networks: Convolution

0	0	1
0	1	0
1	0	0

 $*$ 

1	0	0
0	1	0
0	0	1

$$0*1+0*0+1*0+0*0+1*1+0*0+1*0+0*0+0*1=1$$

# Convolutional neural networks: Convolution

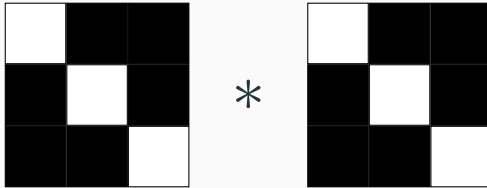
1	0	0
0	1	0
0	0	1

 $*$ 

1	0	0
0	1	0
0	0	1

$$1*1+0*0+0*0+0*0+1*1+0*0+1*0+0*0+1*1=3$$

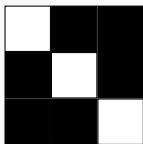
# Convolutional neural networks: Convolution



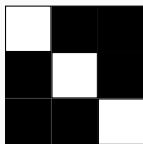
$$1*1+0*0+0*0+0*0+1*1+0*0+1*0+0*0+1*1=3$$



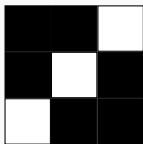
# Convolutional neural networks: Convolutional layers



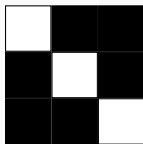
\*



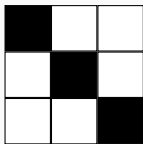
= 3



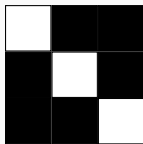
\*



= 1



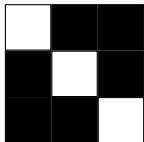
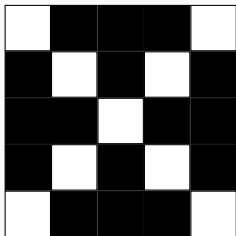
\*



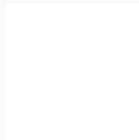
= 0

# Convolutional neural networks: Convolutional layers

Image

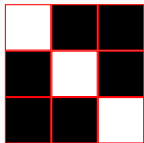
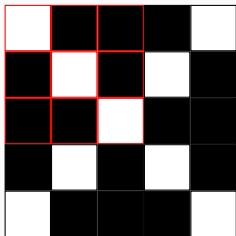


Pattern 1



# Convolutional neural networks: Convolutional layers

Image

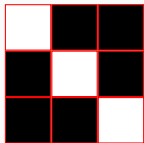
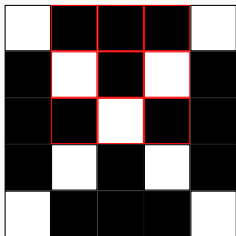


Pattern 1

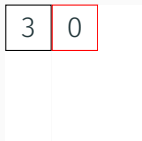
3

# Convolutional neural networks: Convolutional layers

Image

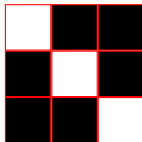
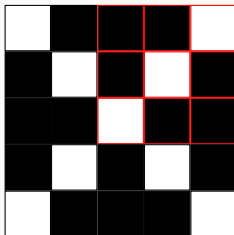


Pattern 1



# Convolutional neural networks: Convolutional layers

Image

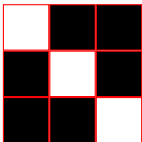
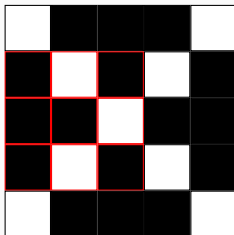


Pattern 1

3	0	1

# Convolutional neural networks: Convolutional layers

Image

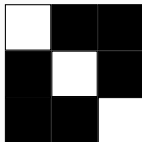
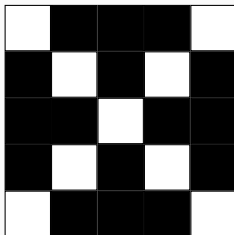


Pattern 1

3	0	1
0		

# Convolutional neural networks: Convolutional layers

Image

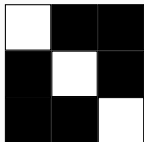
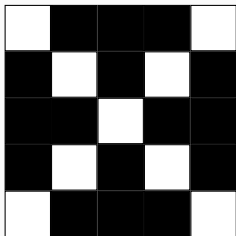


Pattern 1

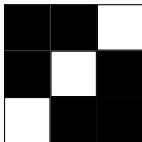
3	0	1
0	3	0
1	0	3

# Convolutional neural networks: Convolutional layers

Image



Pattern 1



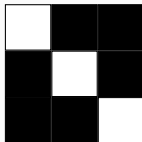
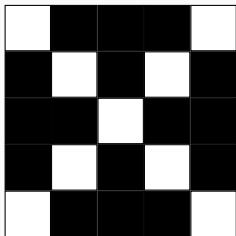
Pattern 2

	1	0	3
	0	3	0
	3	0	1

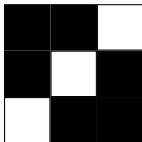


## Convolutional neural networks: Convolutional layers

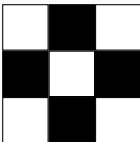
Image



### Pattern 1



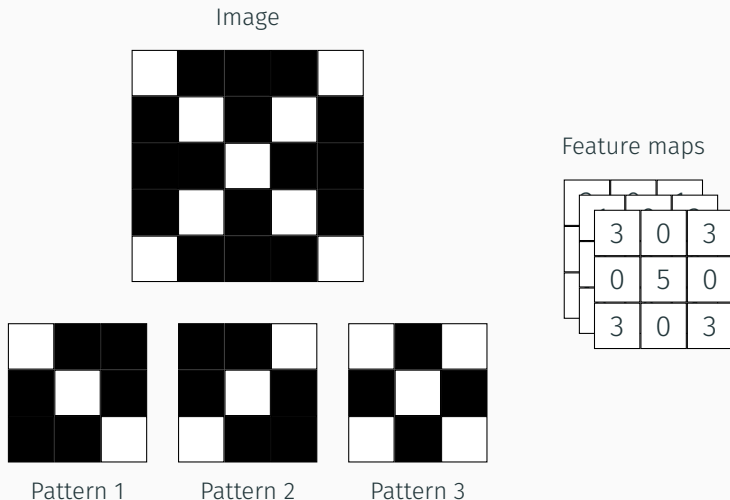
## Pattern 2



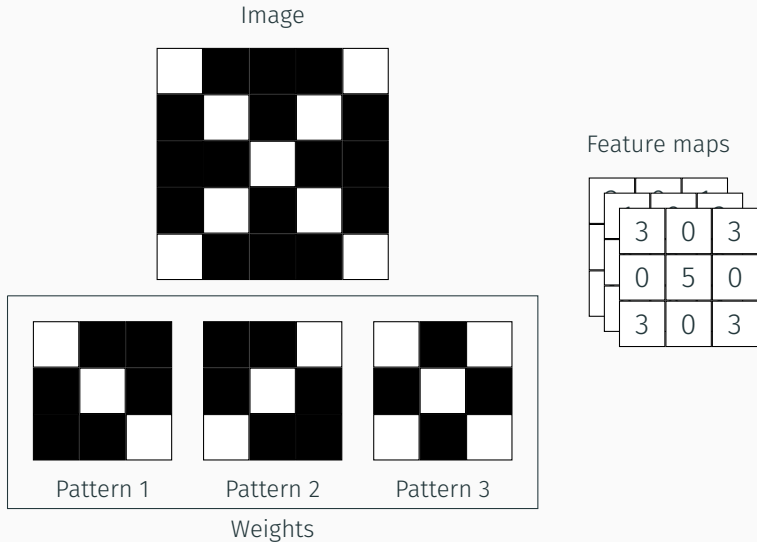
### Pattern 3

3	0	3
0	5	0
3	0	3

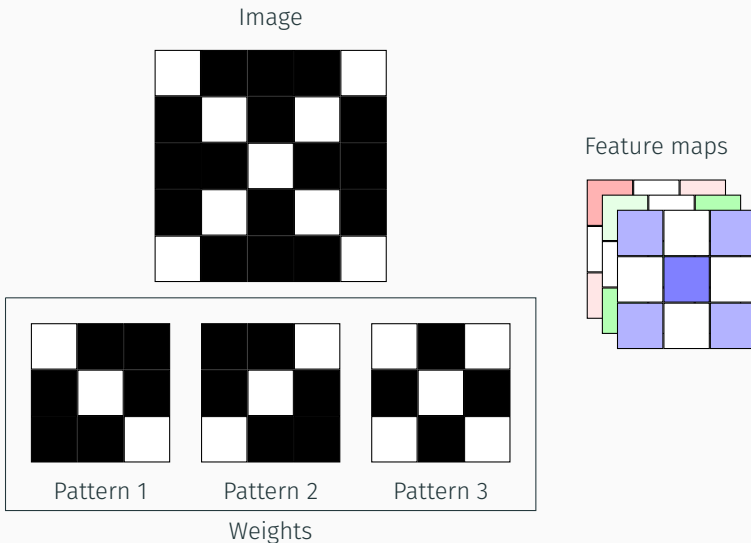
# Convolutional neural networks: Convolutional layers



# Convolutional neural networks: Convolutional layers



# Convolutional neural networks: Convolutional layers



# Convolutional neural networks: Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

# Convolutional neural networks: Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

5

# Convolutional neural networks: Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

5	7
---	---

# Convolutional neural networks: Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

5	7
13	



# Convolutional neural networks: Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

5	7
13	15

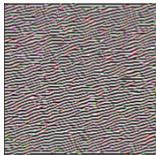
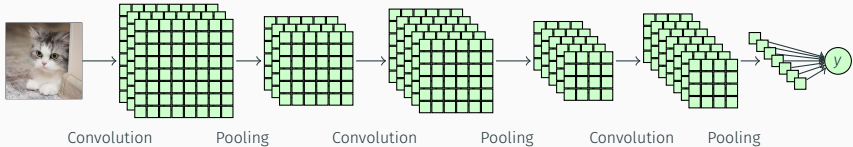
# Convolutional neural networks: Pooling

Feature map

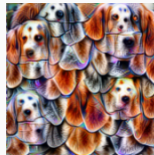
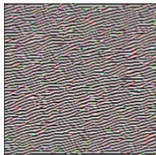
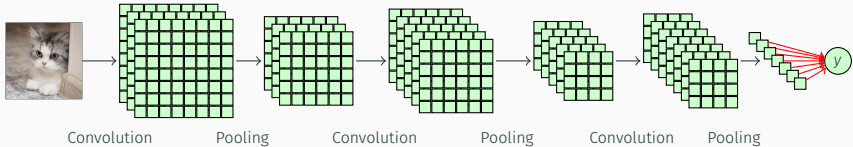
0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

5	7
13	15

# Convolutional neural networks: Architecture



# Convolutional neural networks: Architecture



# Convolutional neural networks: Summary

- Images in computers are stored as matrices of numbers
- The convolution operation is a pattern matcher
- A convolutional layer is a battery of pattern matchers where the patterns are learned during training
- The pooling operation reduces spatial dimensions and distills information
- A convolutional neural network consists of alternating convolution and pooling
- Alternating convolution and pooling in practice means looking for more and more abstract patterns spanning larger and larger region of the images
- The final layer of the network makes a prediction based on the patterns it has found