

# Introduction to deep learning 1/?

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02.11.22

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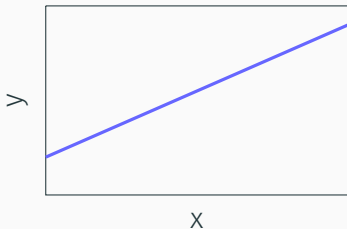
1. Building an artificial neural network (ANN)
2. Training the ANN
3. Transformation to a Convolutional Neural Network (CNN)

## Building a neural network: Linear regression

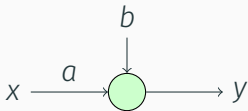
$$y = ax + b$$

# Building a neural network: Linear regression

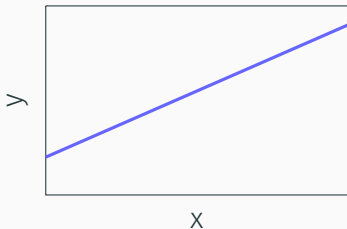
$$y = ax + b$$



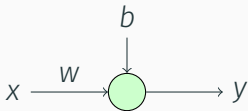
# Building a neural network: Linear regression



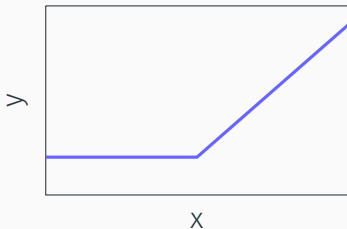
$$y = ax + b$$



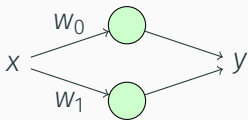
## Building a neural network: Artificial neuron



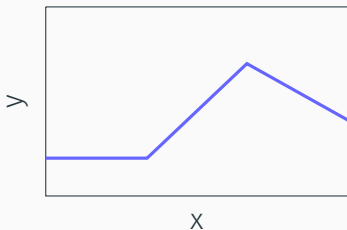
$$y = \max(0, wx + b)$$



## 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

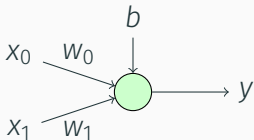


## Building a neural network: Universal approximation theorem

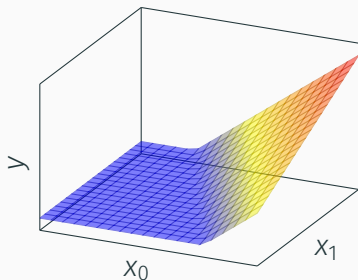
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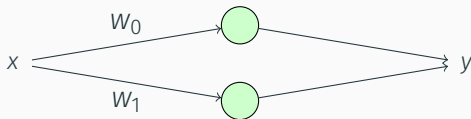
# Building a neural network: Increasing dimensionality



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

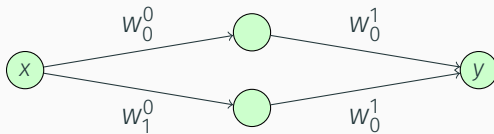


# Building a neural network



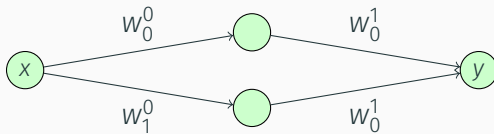
$$y = \max(0, w_0x + b_0) + \max(0, w_1x + b_1)$$

# 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



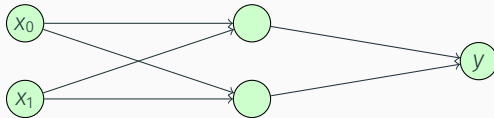
Input

Hidden

Output

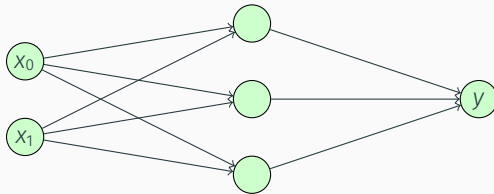
$$y = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x + b_{1,0}) + b_1)$$

# Building a neural network



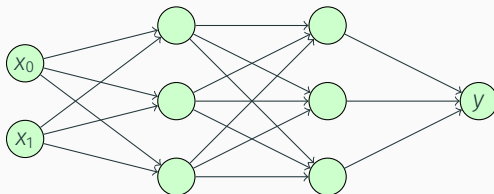
$$y = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^0 * x_1 + b_{0,1}) + b_1)$$

# 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



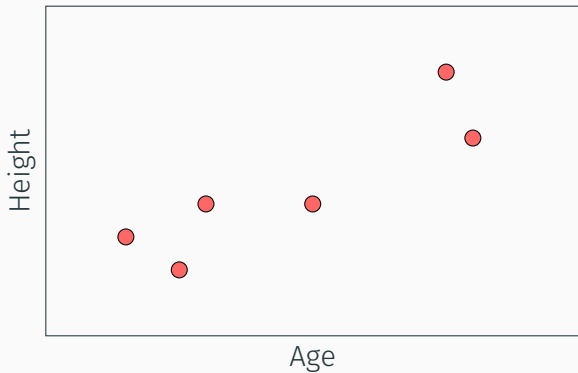
$$\begin{aligned}
 y = & \max(0, w_{0,0}^2 * \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + \\
 & w_{1,0}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^+ * w_1 + b_{0,1}) + \\
 & w_{2,0}^1 * \max(0, w_{0,2}^0 * x_0 + w_{1,2}^+ * w_1 + b_{0,2}) + \\
 & b_{1,0}) + \\
 & w_{1,0}^2 *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



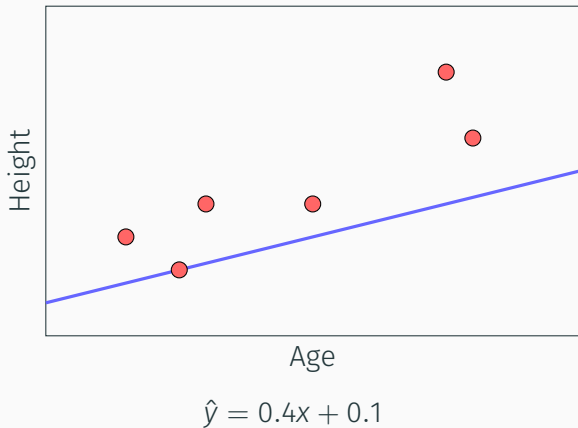
## Building a neural network: Summary

- 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

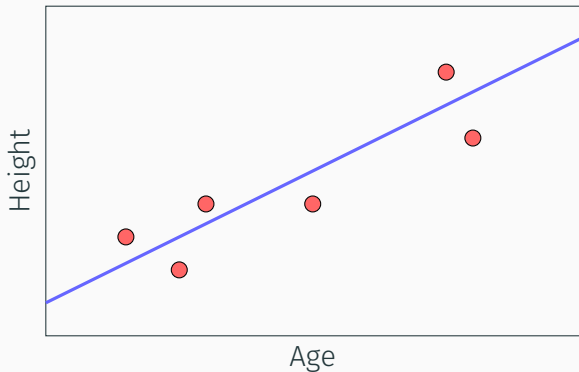
## Training a neural network: Loss functions



## Training a neural network: Loss functions

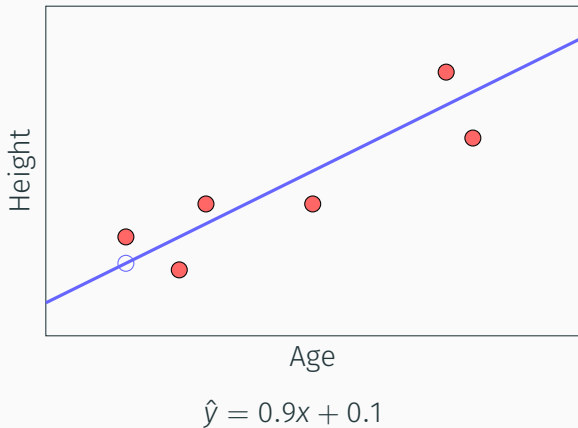


## Training a neural network: Loss functions

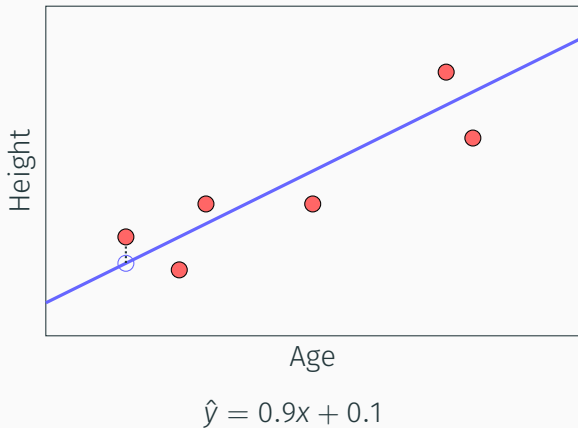


$$\hat{y} = 0.9x + 0.1$$

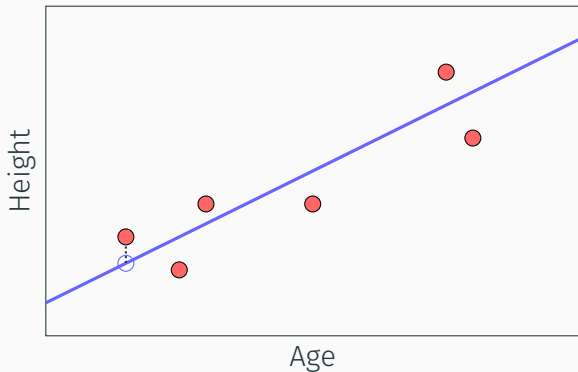
## Training a neural network: Loss functions



## Training a neural network: Loss functions



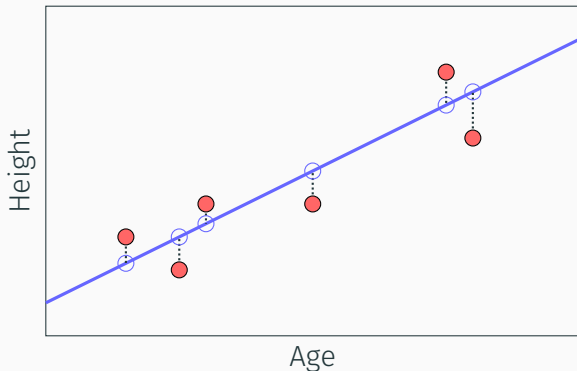
## Training a neural network: Loss functions



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

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

# Training a neural network: Loss functions



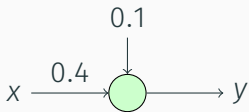
$$\hat{y} = 0.9x + 0.1$$

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

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

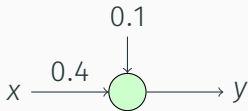


## Training a neural network: Gradient descent



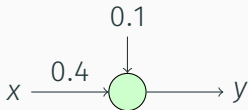
$$y = 0.4x + 0.1 \quad \text{loss} = (y - \hat{y})^2$$

## Training a neural network: Gradient descent



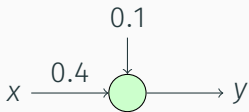
$$0.16 = 0.4 * 0.15 + 0.1 \quad 0.019 = (0.3 - 0.16)^2$$

## Training a neural network: Gradient descent



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

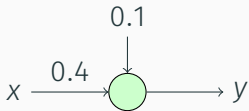
## Training a neural network: Gradient descent



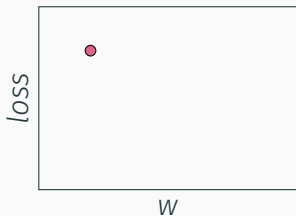
$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$

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) weighted by  $w$  (0.4), plus the bias  $b$  (0.1), squared to yield the loss (0.019). Red arrows indicate the mapping of variables:  $w$  points to 0.4,  $x$  points to 0.15,  $b$  points to 0.1,  $y$  points to 0.3,  $\hat{y}$  points to 0.15, and  $loss$  points to 0.019.

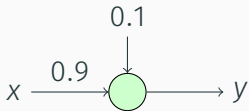
## Training a neural network: Gradient descent



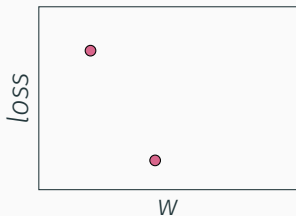
$$(0.3 - (0.4 * 0.15 + 0.1))^2 = 0.019$$



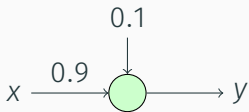
## Training a neural network: Gradient descent



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



## Training a neural network: Gradient descent



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

