

# PSY9511: Seminar 7

## Deep learning for computer vision tasks

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07.11.24



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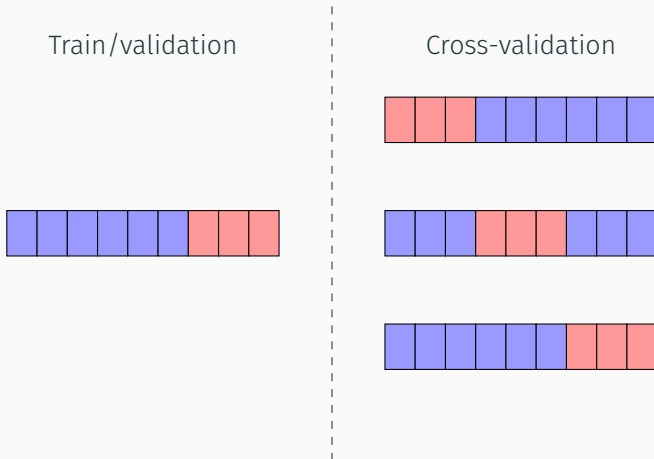
1. Exercise 4
2. Deep learning
  - Motivation
  - (Deep) neural networks
  - Training procedure
3. Convolutional neural networks for computer vision

# Weekly exercises

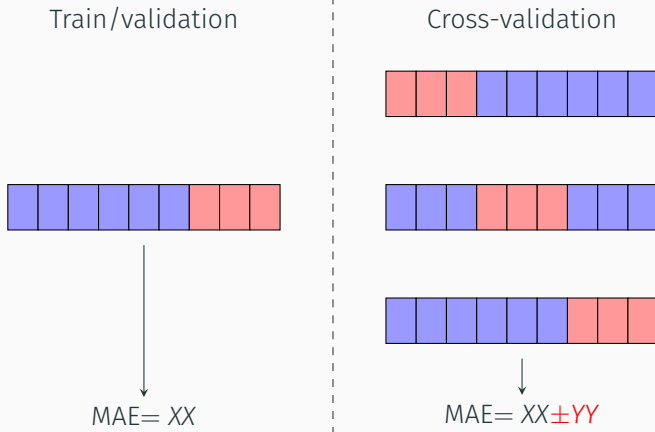
- The weekly exercises are **mandatory**
- The deadlines are **strict**



# Validation procedures



# Validation procedures



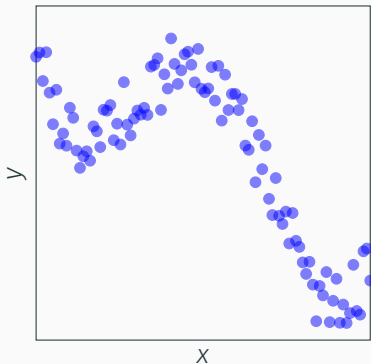
# Deep learning

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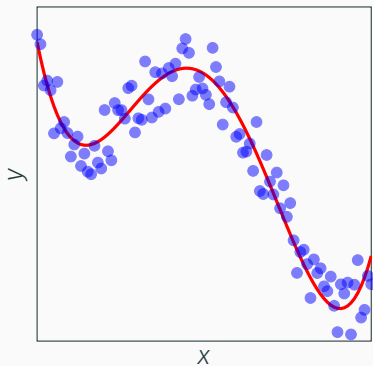


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# Deep learning: Motivation



# Deep learning: Motivation

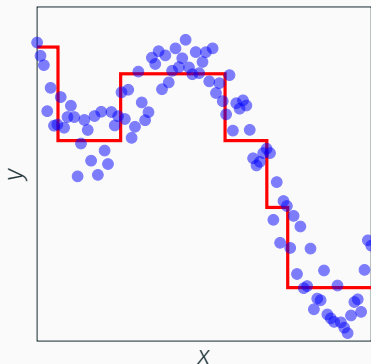


$$\hat{y} = s(x)$$





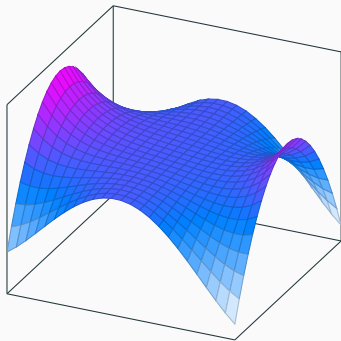
# Deep learning: Motivation



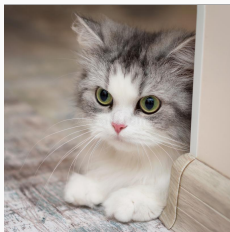
$$\hat{y} = \begin{cases} 4 & \dots \\ 3 & 0.2 \leq x < 0.6 \\ 1.5 & \dots \end{cases}$$



# Deep learning: Motivation



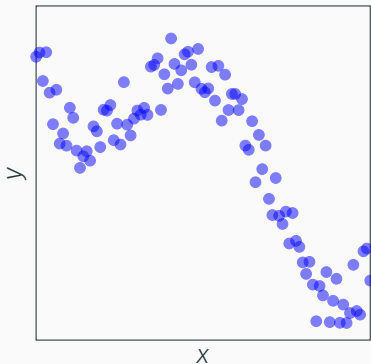
# Deep learning: Motivation



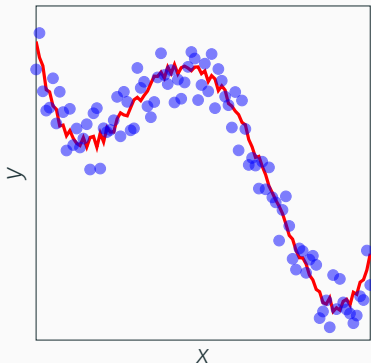
The cat wagged  
its tail



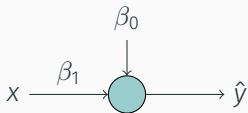
# Deep learning: Motivation



# Deep learning: Motivation

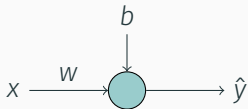


# Deep learning: Artificial neural networks



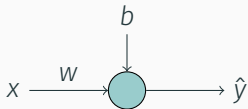
$$\hat{y} = \beta_0 + \beta_1 x$$

# Deep learning: Artificial neural networks

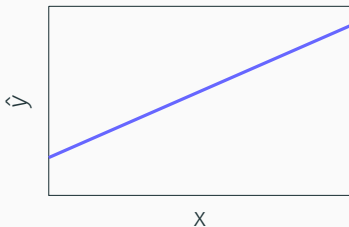


$$\hat{y} = wx + b$$

# Deep learning: Artificial neural networks

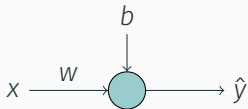


$$\hat{y} = wx + b$$



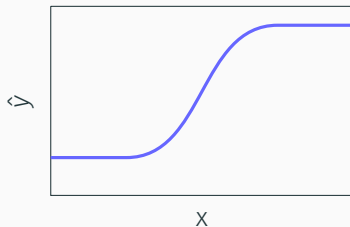


# Deep learning: Artificial neural networks

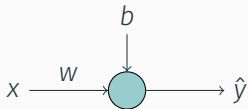


$$\hat{y} = \frac{e^x}{1 + e^x}$$

Sigmoid

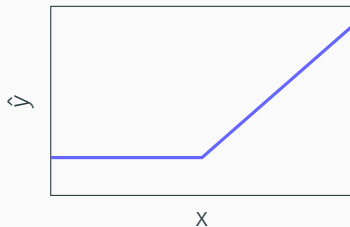


# Deep learning: Artificial neural networks

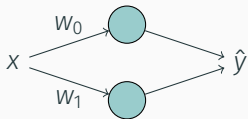


$$\hat{y} = \max(0, wx + b)$$

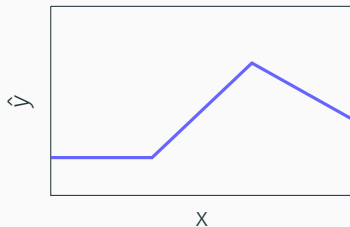
Rectified Linear Unit (ReLU)



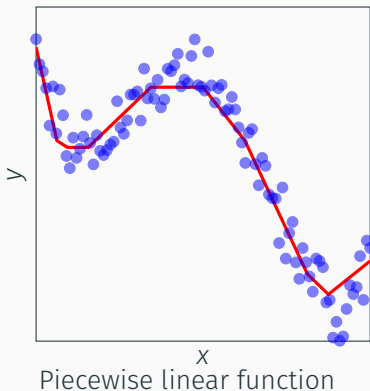
# Deep learning: Artificial neural networks



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



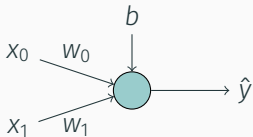
# Deep learning: Artificial neural networks



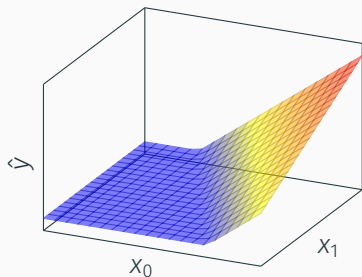
## Universal approximation theorem:

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

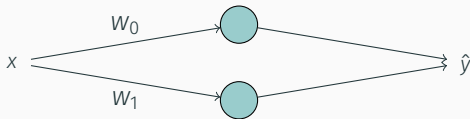
# Deep learning: Artificial neural networks



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

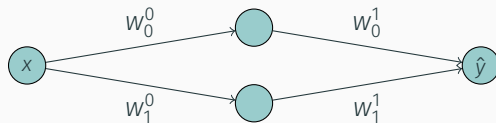


# Deep learning: Artificial neural networks



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

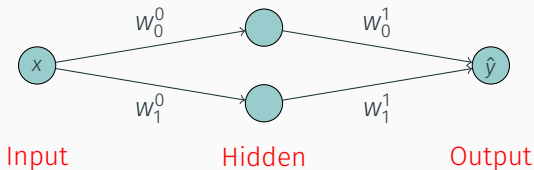
# Deep learning: Artificial neural networks



$$\hat{y} = \max(0, w_0^1 * \max(0, w_0^0 * x + b_0^0) + w_1^1 * \max(0, w_1^0 * x + b_1^0) + b_0^1)$$

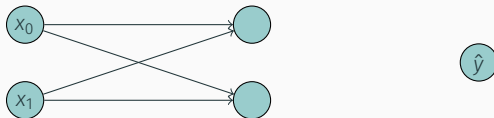


# Deep learning: Artificial neural networks



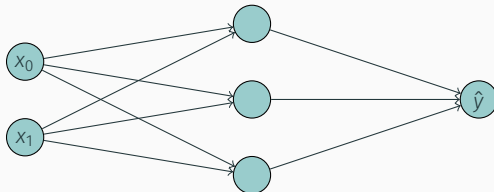
$$\hat{y} = \max(0, w_0^1 * \max(0, w_0^0 * x + b_0^0) + w_1^1 * \max(0, w_1^0 * x + b_1^0) + b_1^1)$$

# Deep learning: Artificial neural networks



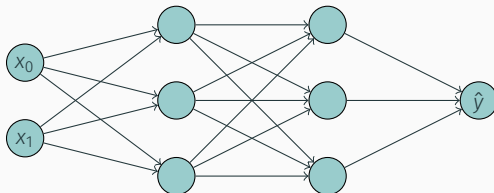
$$\hat{y} = \max(0, w_{0,0}^1 * \max(0, w_{0,0}^0 * x_0 + w_{1,0}^0 * x_1 + b_{0,0}) + w_{1,0}^1 * \max(0, w_{0,1}^0 * x_0 + w_{1,1}^0 * x_1 + b_{0,1}) + b_1)$$

# Deep learning: Artificial neural networks



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

# Deep learning: Artificial neural networks



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

# Deep learning: Artificial neural networks

Artificial neural networks: Combines artificial neurons, simple computational units that compute a non-linear function of their inputs, in a computational graph

- Can approximate arbitrarily complex polynomial functions (given enough neurons)
- Neurons are organized in layers, and we expand a model in width (e.g. more neurons per layer) or depth (e.g. more layers)

