

# Lecture 2

## Introduction to Neural Networks

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# Planning

- Image classification
- Linear Classifier
- Neural networks
- Lab Assignments

# Image Classification

# Image Classification

- **Motivation of image classification (recognition):** assign one label (from a fixed set of categories) to each input image
- **Example:** given the following image, assign probabilities to 4 labels {dog, cat, hat, mug}

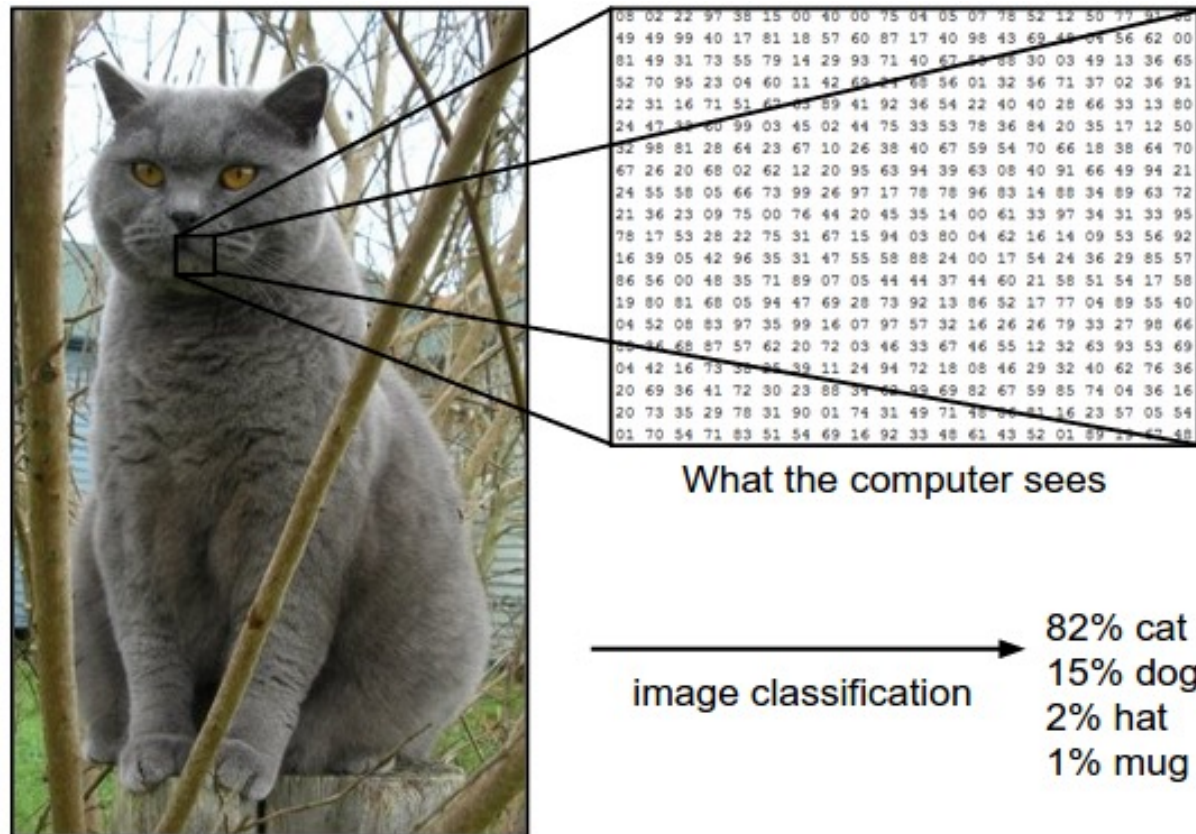


Image credits: [cs231n](#)

# Image Classification

- **Challenges:** the task is trivial for human, but very challenging for a computer !

Viewpoint variation



Scale variation



Deformation



Occlusion



Illumination conditions



Background clutter



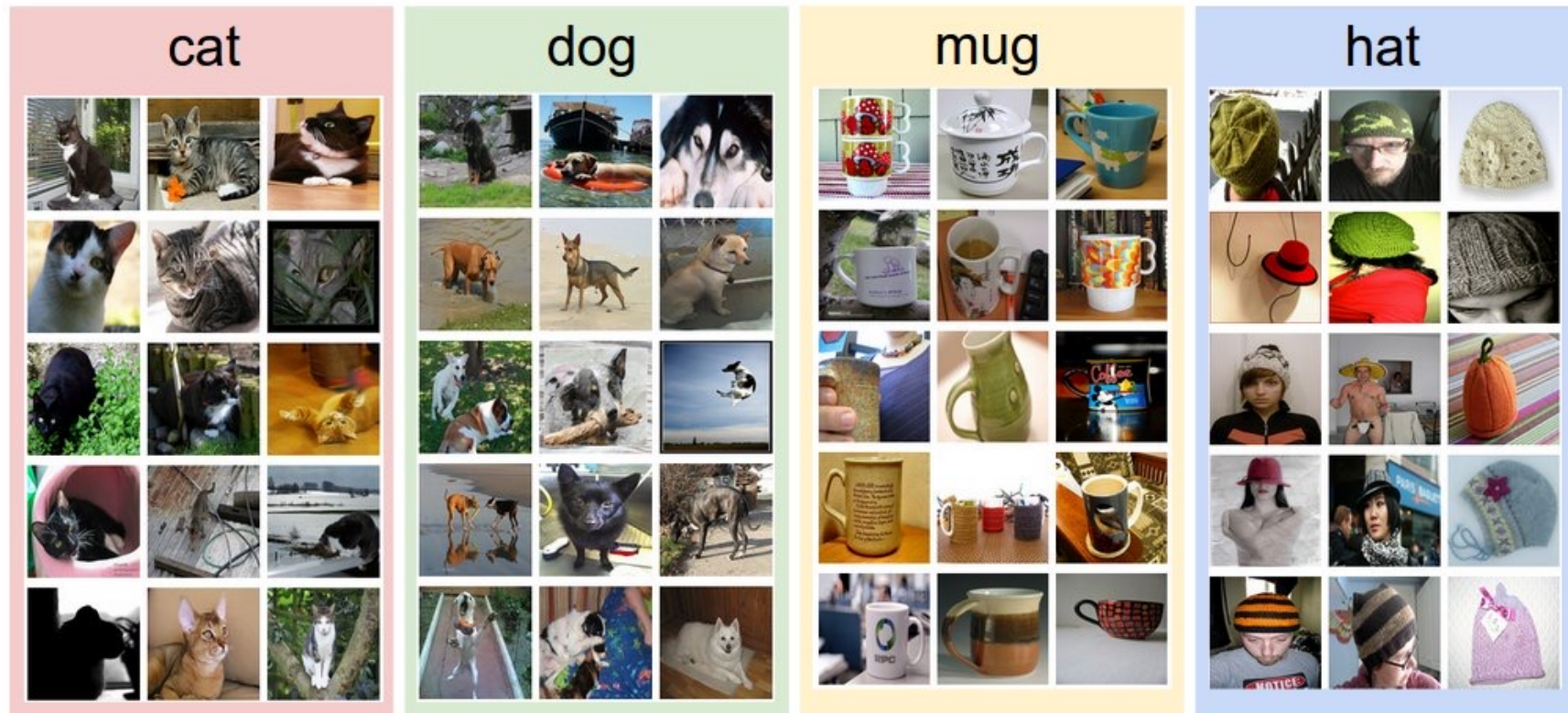
Intra-class variation





# Image Classification

- **Data-driven approach:** learn from a training dataset including labeled images



*In practice, we may have thousands of classes and hundreds of thousands of images per class.*

# Nearest Neighbor classifier

- **Principle:** compare the test image to each training image → choose the closest one (lowest distance)

- L1 distance 
$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

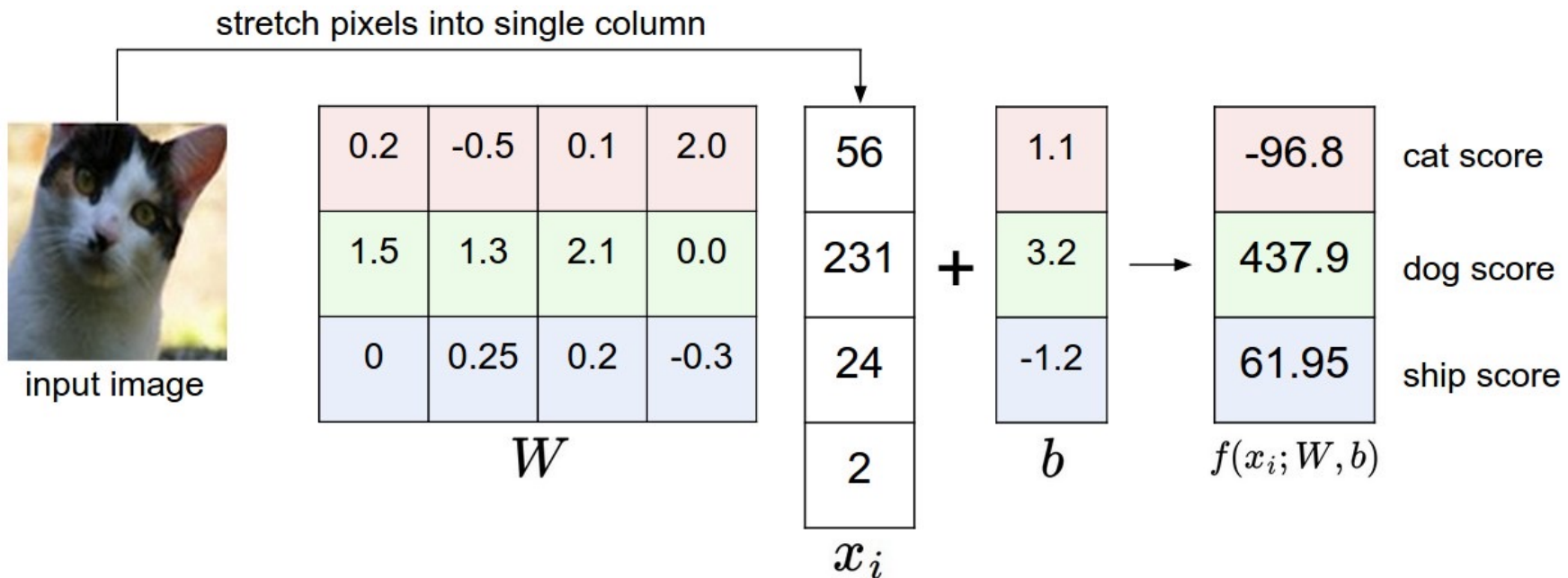
- L2 distance 
$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$

test image					training image					pixel-wise absolute value differences				
56	32	10	18		10	20	24	17		46	12	14	1	
90	23	128	133		8	10	89	100		82	13	39	33	
24	26	178	200	-	12	16	178	170	=	12	10	0	30	→ 456
2	0	255	220		4	32	233	112		2	32	22	108	

→ It does not work because of the previous challenges !!!!

# Linear Classification

- **Principle:** use the linear mapping  $f(x_i, W, b) = Wx_i + b$

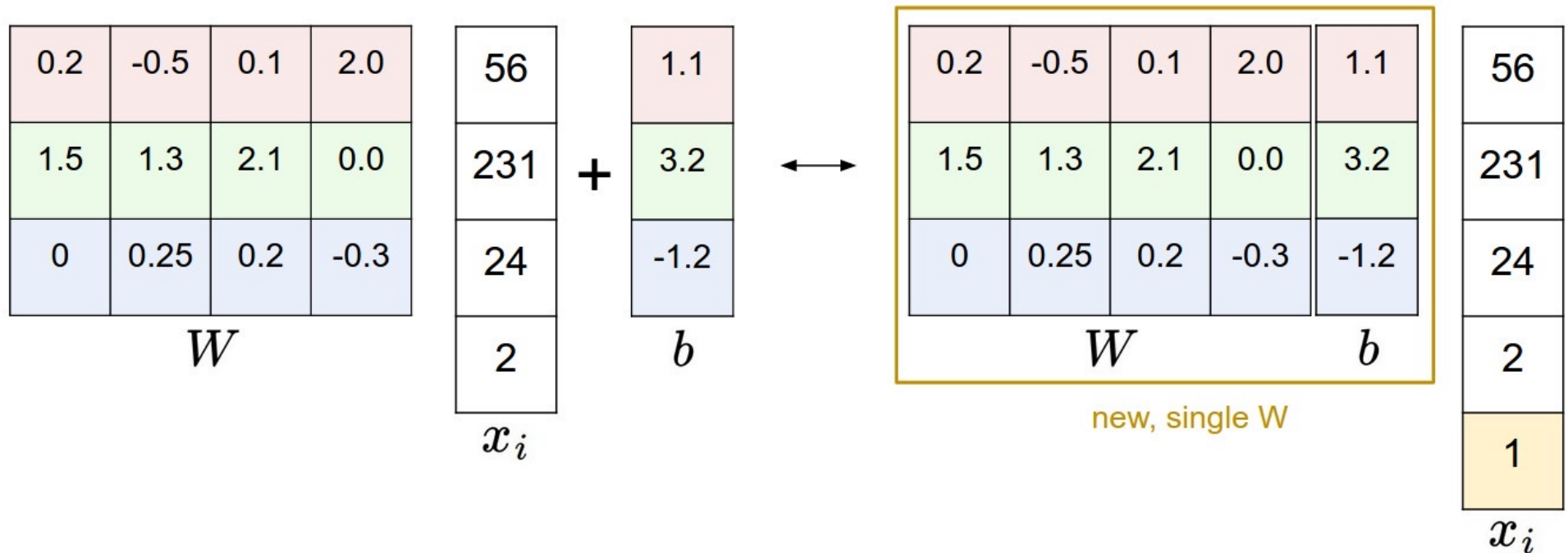


- We need to learn the parameters (weights  $W$  and bias vector  $b$ ) using the training dataset.
- Once they are learned, simply pass the test image and compute the class probabilities
- Matrix multiplication and addition → very fast



# Linear Classification

- **Bias trick:** in common, we simplify the couple  $(W, b)$  as one



- We extend the vector  $x_i$  with one additional dimension (bias dimension)
- Our linear mapping now becomes

$$f(x_i, W) = Wx_i$$

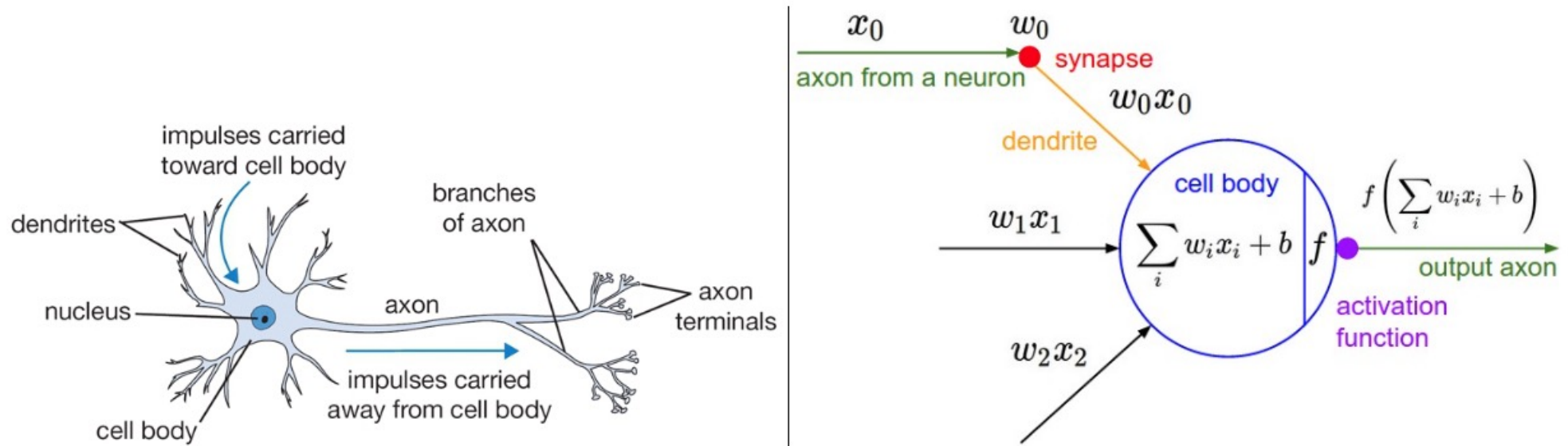
# Linear Classification

- **Training:** input each pair of image and label  $(x_i, y_i)$  to update weights  $\mathbf{W}$  (by using a loss function). The training objective is to minimize the loss
- Usually, we use the **cross-entropy loss**.
- Testing: use the computed  $\mathbf{W}$  to predict a label  $\hat{y}_k$  for a test image  $x_k$
- **Further reading:** *loss function, gradient descent, back-propagation*

# Neural networks

# Neural networks

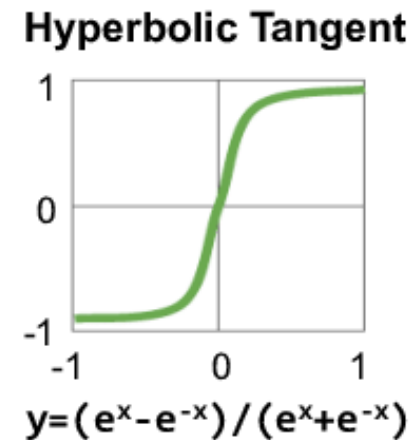
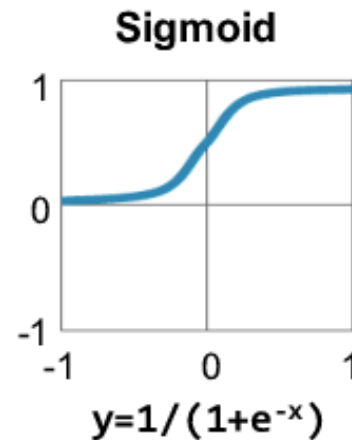
Inspired by the goal of modeling biological neural systems with an activation function :



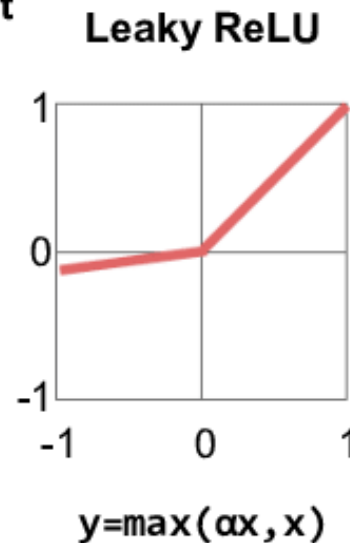
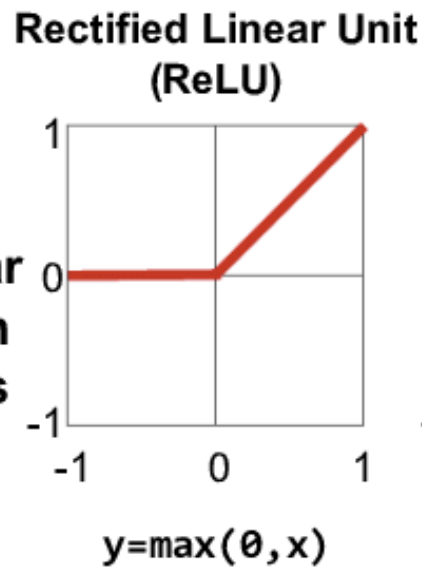
- Each neuron performs a dot product with the input and its weights, adds the bias and applies the non-linearity (or activation function)
- Biological neuron models are much more complex !!!

# Neural networks

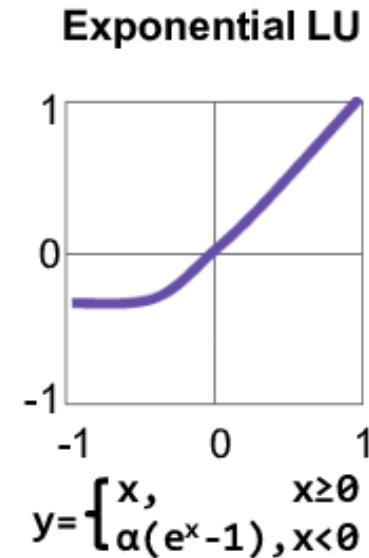
**Traditional  
Non-Linear  
Activation  
Functions**



**Modern  
Non-Linear  
Activation  
Functions**

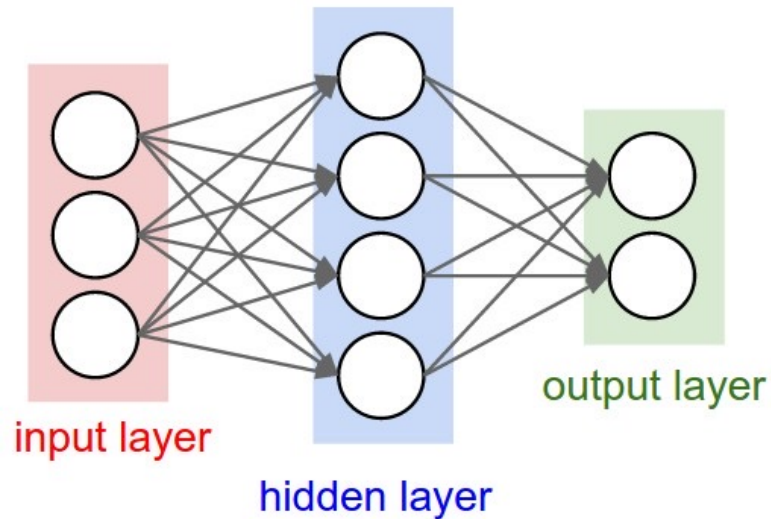


$\alpha = \text{small const. (e.g. 0.1)}$



# Neural networks

## One-layer neural networks

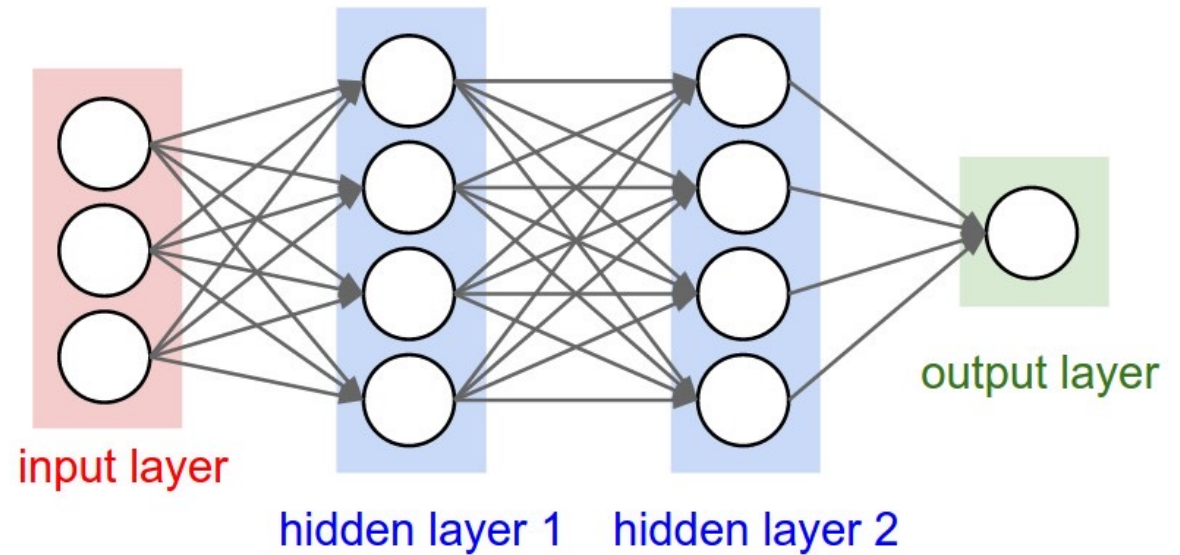


- This network has  $4 + 2 = 6$  neurons (not counting the inputs),  $[3 \times 4] + [4 \times 2] = 20$  weights and  $4 + 2 = 6$  biases, for a total of 26 learnable parameters.
- Attention: the output layer neuros commonly do not have an activation function !!! It is usually take to represent the class score (i.e. classification layer)



# Neural networks

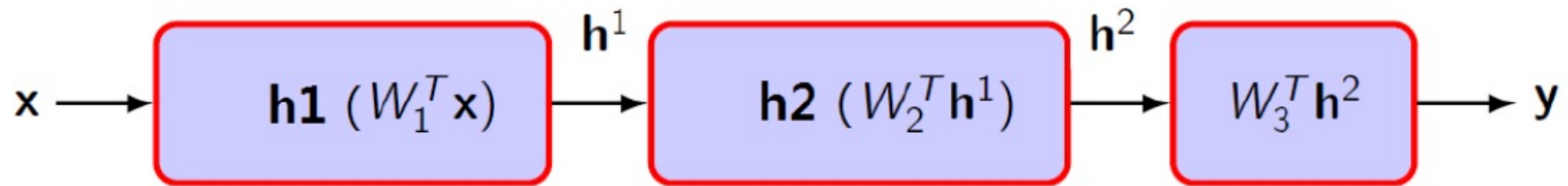
## Two-layer neural networks



- The network has  $4 + 4 + 1 = 9$  neurons,  $[3 \times 4] + [4 \times 4] + [4 \times 1] = 12 + 16 + 4 = 32$  weights and  $4 + 4 + 1 = 9$  biases, for a total of 41 learnable parameters.
- Also named **Multi-Layer Perceptrons (MLPs)**

# Neural networks

## Simplified notations

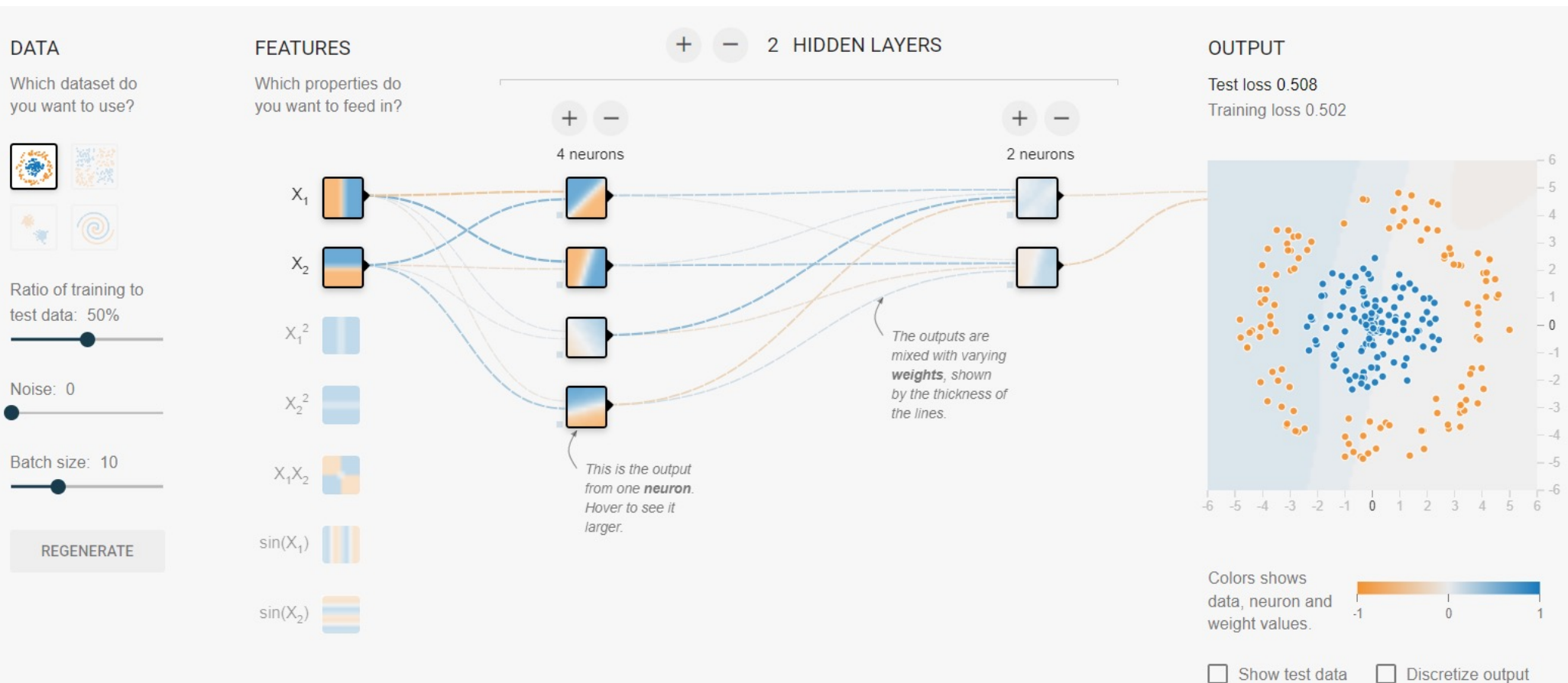


- $x$ : input
- $y$ : output
- $W_i$ : set of parameters (weights) of the  $i^{th}$  layer
- $h^i$ : output of the  $i^{th}$  layer
- $hi$ : activation function of the  $i^{th}$  layer (i.e., *sigmoid*, *ReLU*, *leaky ReLU*, etc.)

# Neural networks

## Visualization of neural networks

<https://playground.tensorflow.org/>



# Lab assignments

**Practical lab: Training neural networks on the MNIST dataset (for handwritten digit recognition) using Pytorch.**

- **Download, complete and submit** the notebook from Moodle **(R3A13\_lab1\_assign.ipynb)**
- Note that you need to submit **your compiled notebook with all outputs**

# References and Sources

- **Convolutional neural networks for visual recognition** - Stanford

<https://cs231n.github.io/>

- **Neural networks and deep learning** (free online book)

<http://neuralnetworksanddeeplearning.com/index.html>

- **Machine learning course** – Oxford

<https://www.cs.ox.ac.uk/people/nando.defreitas/machinelearning/>

- **Neural network course** - Hugo Larochelle

[https://info.usherbrooke.ca/hlarochelle/neural\\_networks/content.html](https://info.usherbrooke.ca/hlarochelle/neural_networks/content.html)

- **Deep learning course** – François Fleuret

<https://fleuret.org/dlc/>