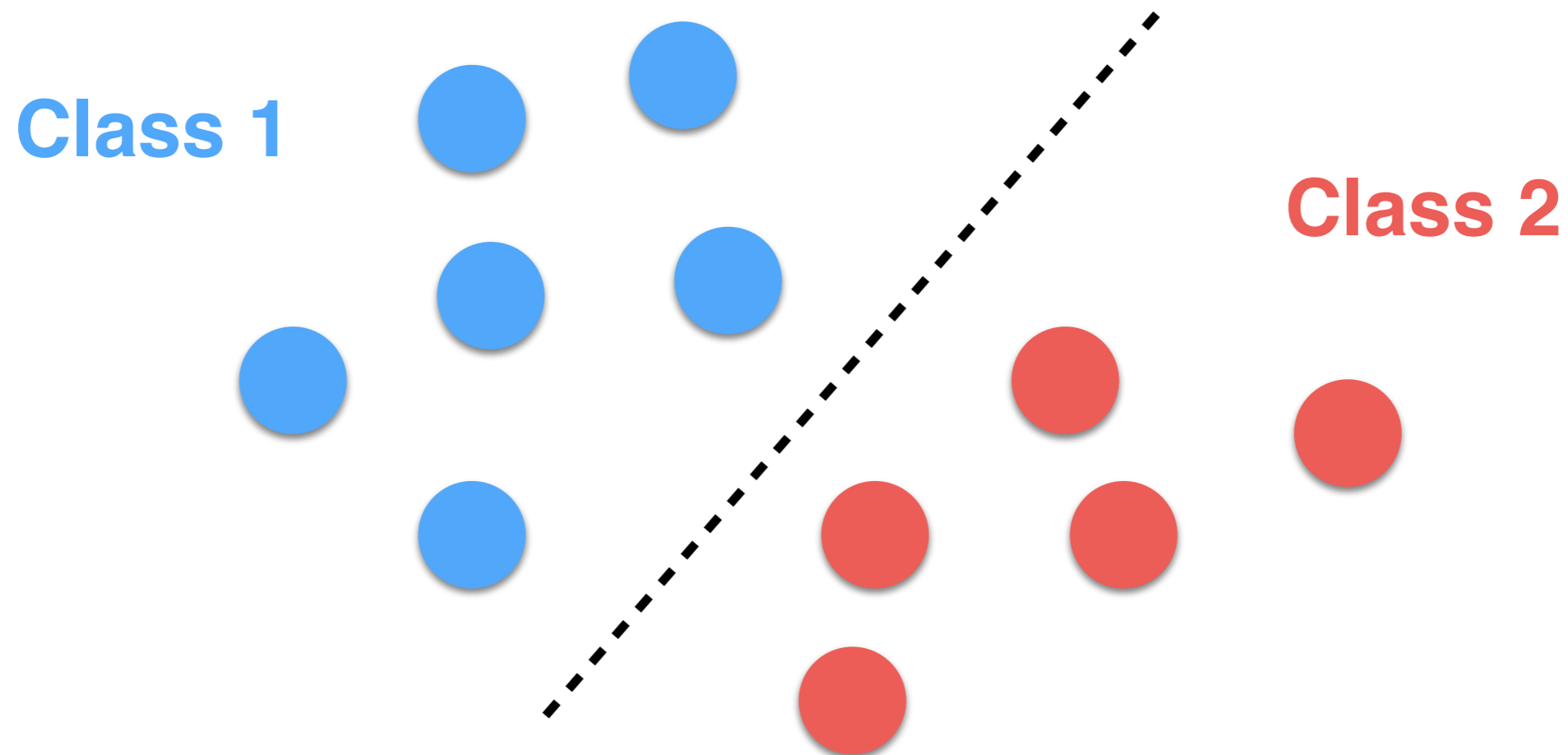


Segmentation with Machine Learning

Machine Learning

- Machine learning algorithms work very well for classification: drawing a plane or hyperplane to divide to classes of samples.
- Similarly to k-Means this works for segmentation too!




Machine Learning



Training
Set



Model



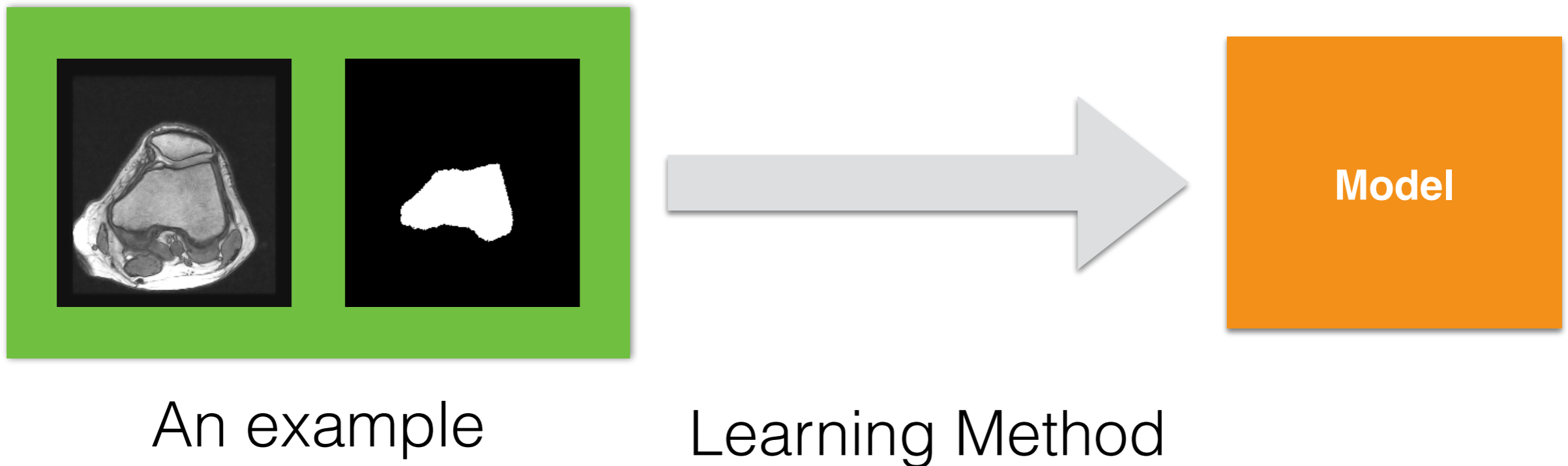
Learning
Method

Machine Learning

- There are two steps:
 - Learning
 - Evaluation

Machine Learning: Learning

- We need to collect examples and transfer that knowledge into a model.

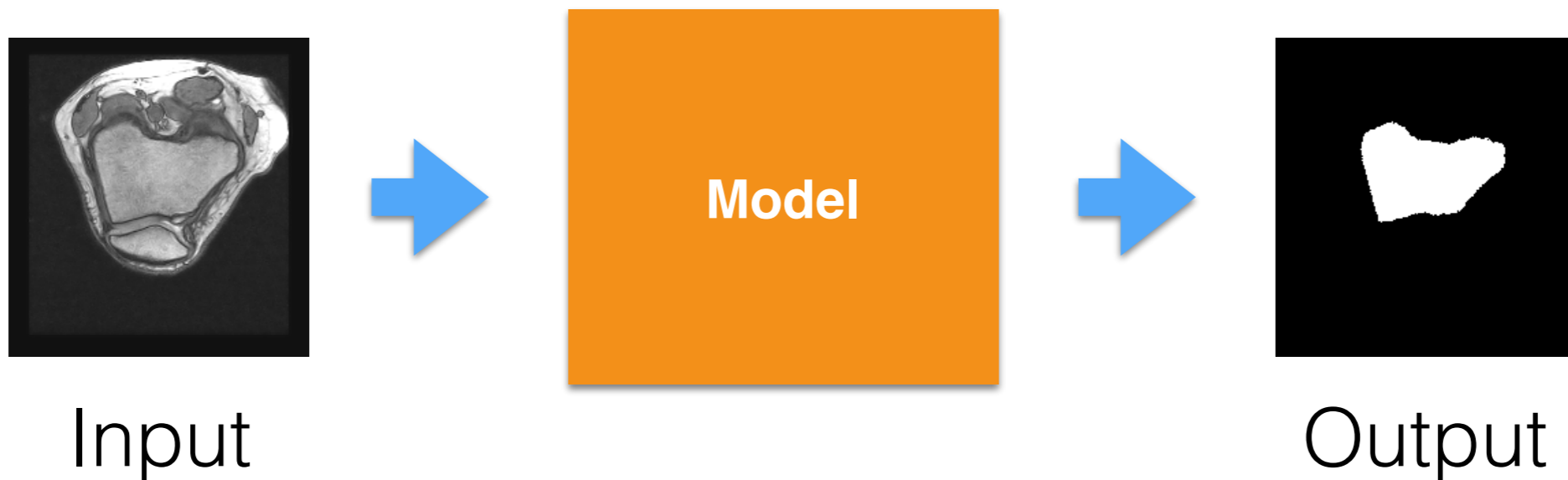


Machine Learning: Learning

- **Training set:** a dataset of n couples: input and output. The bigger the better! (at least 10,000 couples for high-quality segmentation). This represents a knowledge to be trained. “*Learn by example*”; i.e., supervised learning.
- **Learning Method:** a mathematical model/function that transfers the knowledge of the training set to the model.
- **Model:** a mathematical model that can store the knowledge of the dataset into its parameters (called **weights**).

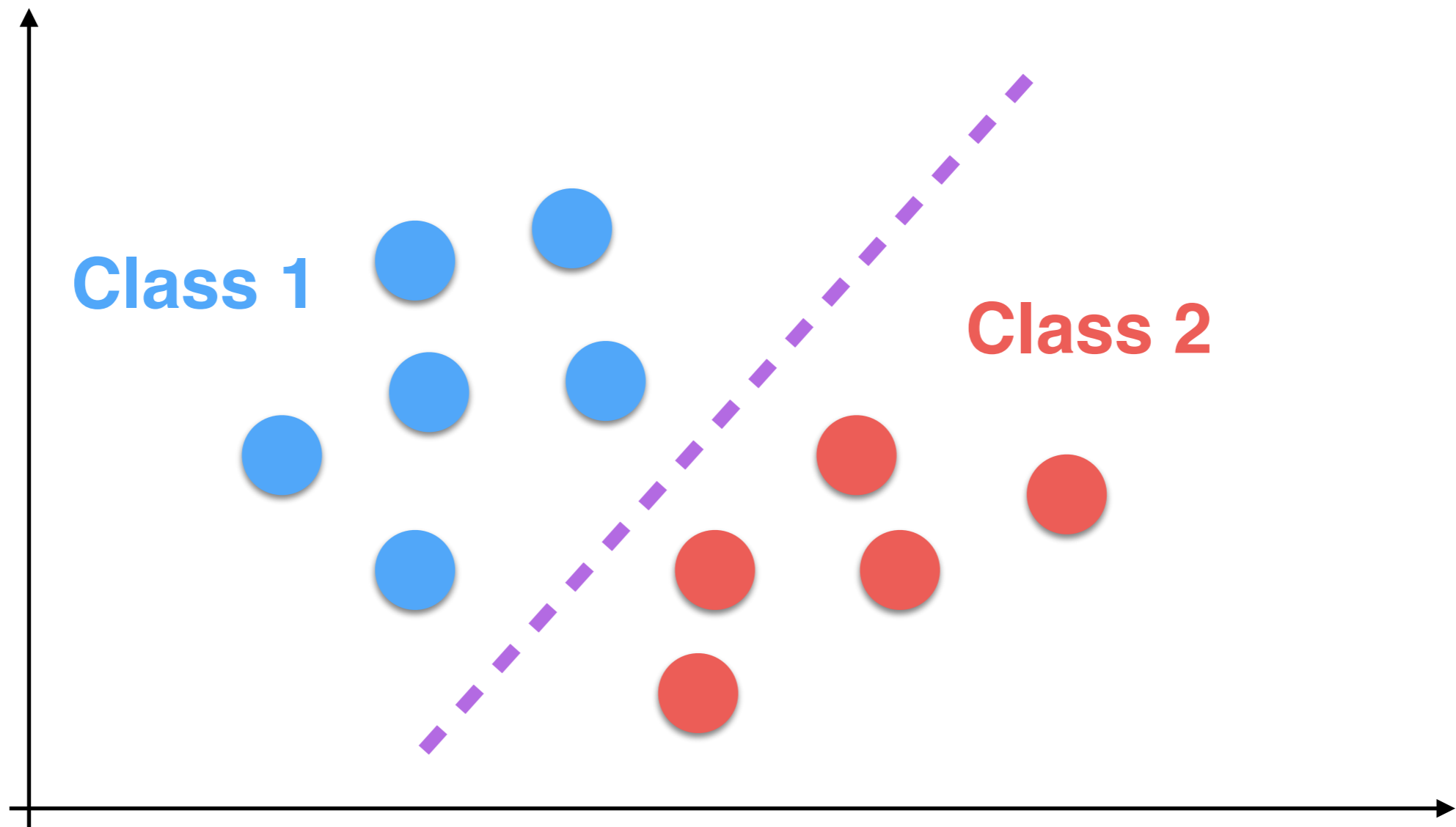
Machine Learning: Evaluation

- After learning the dataset, we just need to pass data to the model (i.e., we evaluate it) to get results:



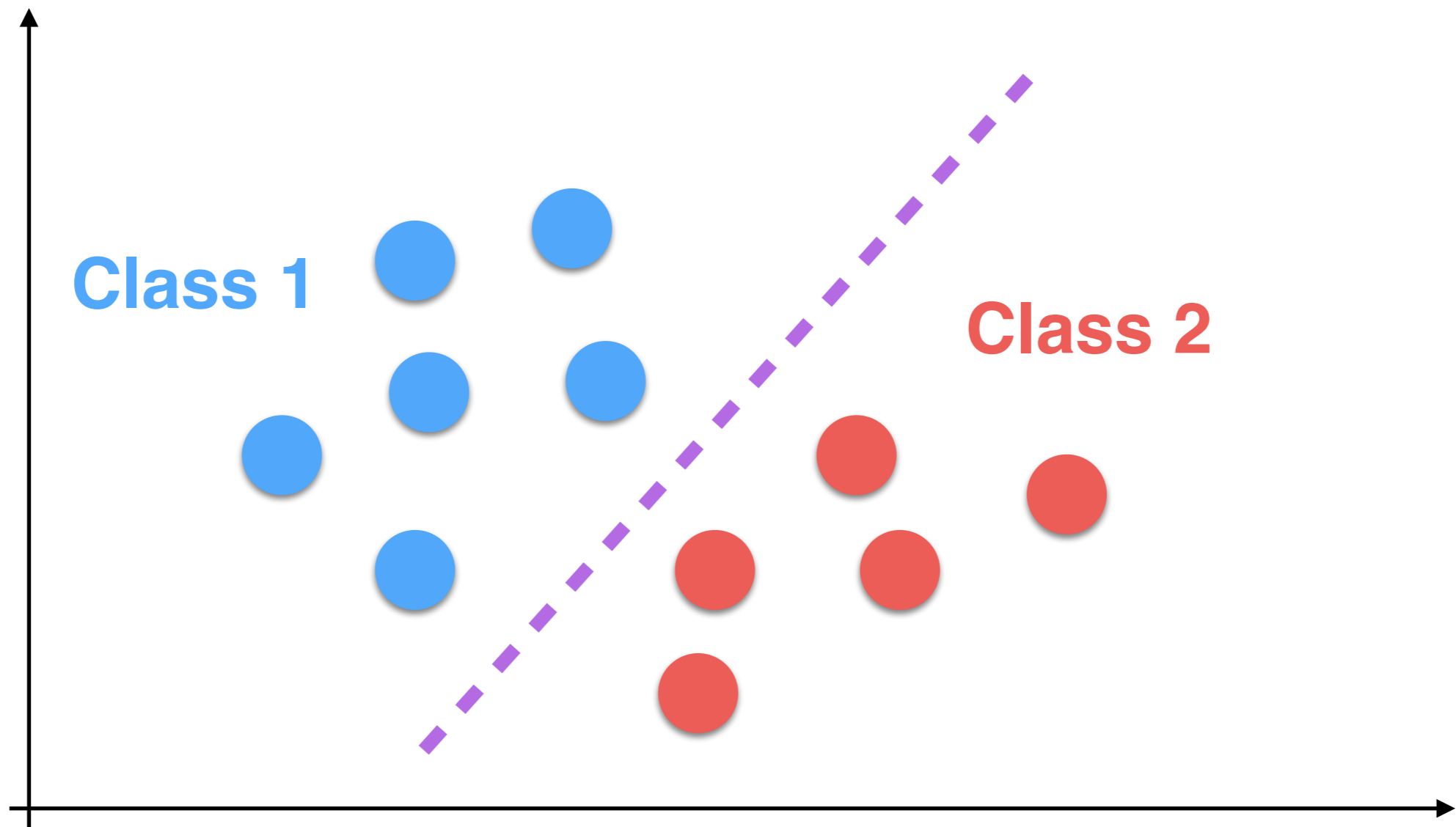
A Simple Example

Machine Learning



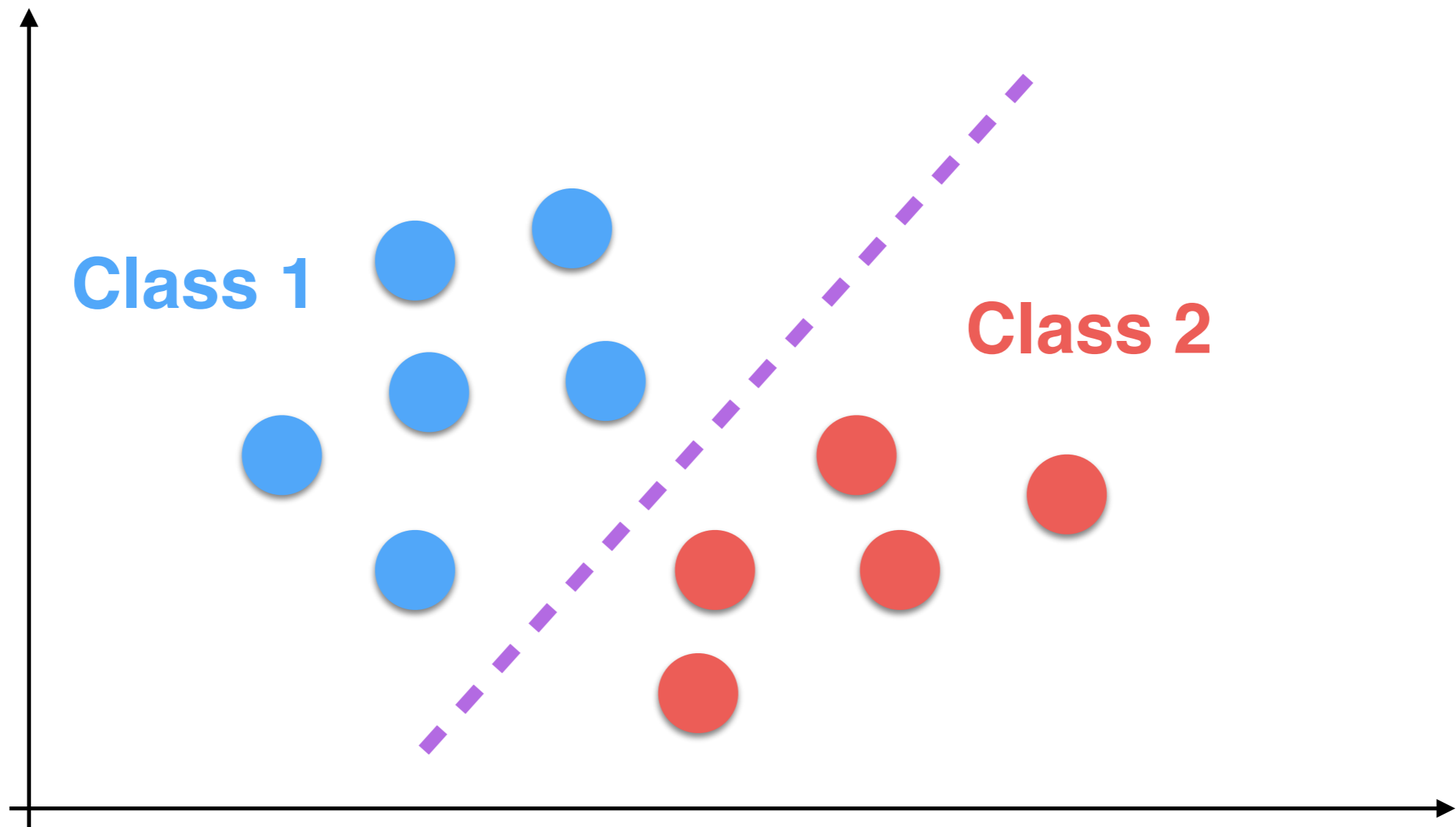
$$h : \mathbb{R}^n \rightarrow \{\text{Class 1, Class 2}\}$$

Machine Learning



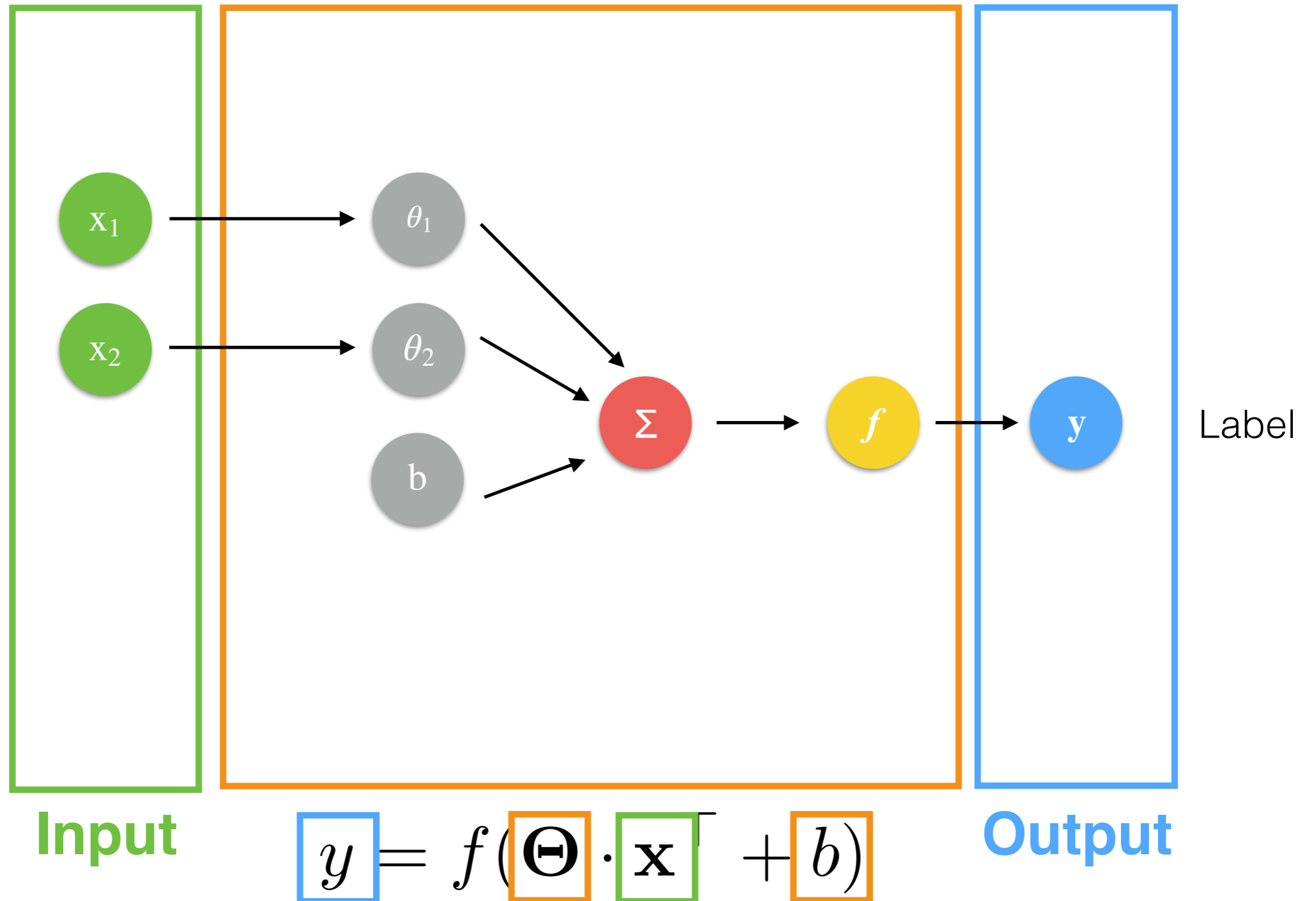
$$h : \mathbb{R}^2 \rightarrow \{0,1\}$$

Machine Learning



$$h(\mathbf{x}) = \begin{cases} 1 & \text{if } (\mathbf{x} \cdot \Theta + b) > 0 \\ 0 & \text{otherwise} \end{cases}$$

Neural Networks: A Model



Machine Learning: Neural Networks

- The idea is to “mimic the neurons” in our brains:
 - A neuron receives multiple inputs or stimuli, that we can represent as a vector \mathbf{x} .
 - Depending on previous knowledge, Θ , a neuron can react to \mathbf{x} , and if the stimulus is strong enough there is an activation
 - The reaction to stimuli is typically modeled as a dot product between \mathbf{x} and Θ .

Neural Networks: The Activation Function

- To add non-linear effect to h , we apply a non-linear function f that is called the **activation function**.
- It can be defined in many ways. For example:

$$f(z) = \frac{1}{1 + e^{-z}} \quad f(z) = \begin{cases} 1 & \text{if } z \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

- This is because the result has to be either belonging or not to a class; i.e., our area of interest.

Neural Networks: Learning

- We need to collect m couples (\mathbf{x} and y).
- We need to minimize an error function J :

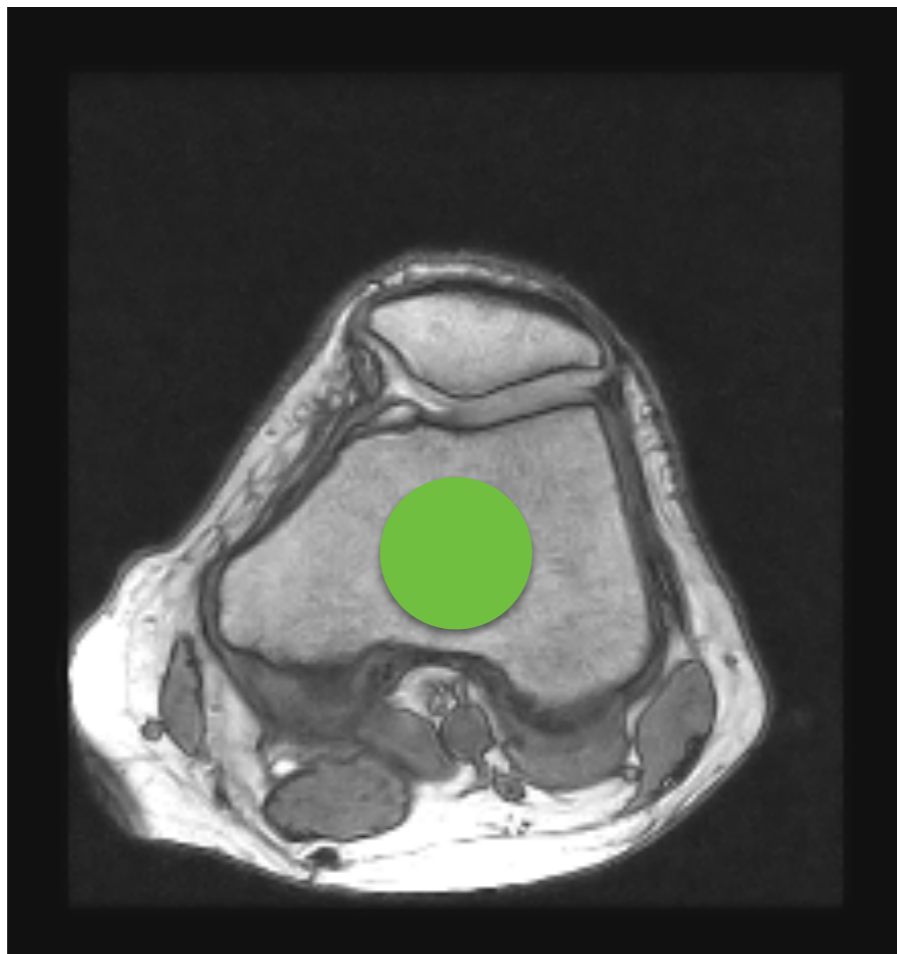
$$J(\Theta) = \frac{1}{2} \sum_{i=1}^m \left(f(\mathbf{x}^i \cdot \Theta^\top + b) - y^i \right)^2 \quad \text{with } f(x) = x$$

- How do we minimize it?
 - Gradient descent
 - Starting solution for theta? Random values in $[0, 1]$!

A Segmentation Example

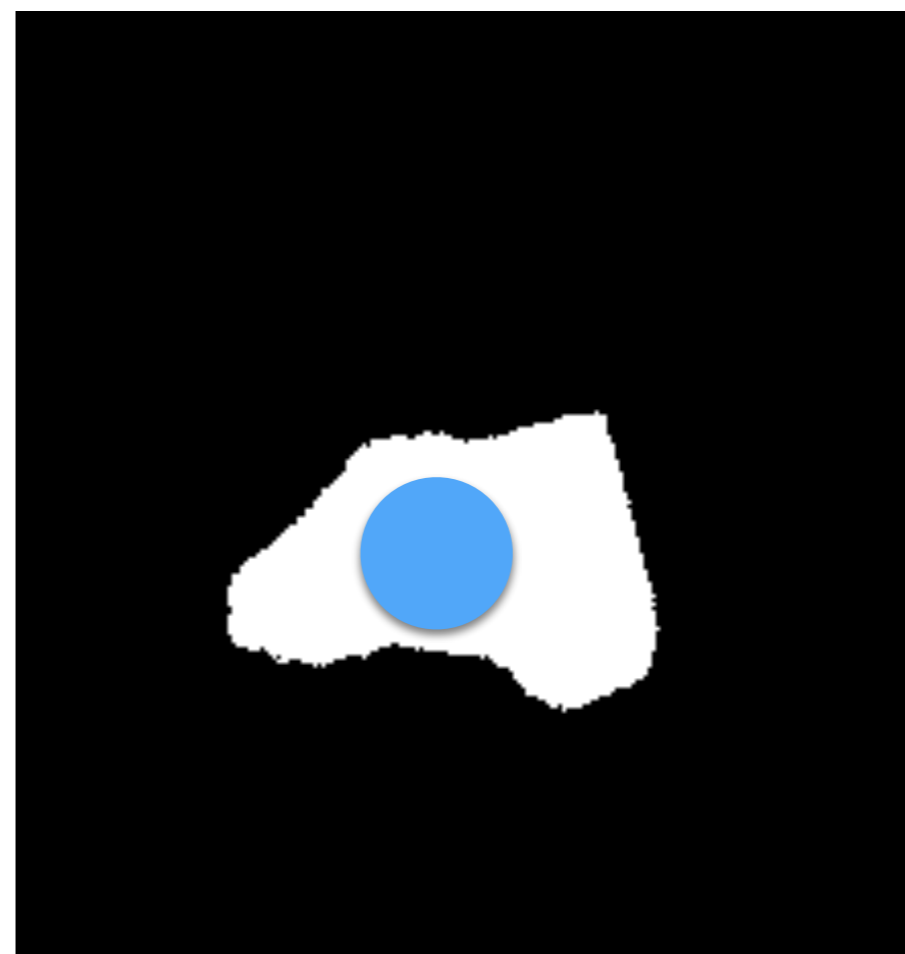
Neural Networks: Training Set (1)

Input



$$\mathbf{x} = \{100, 100, 0.78\}$$

Output



$$y = 1$$

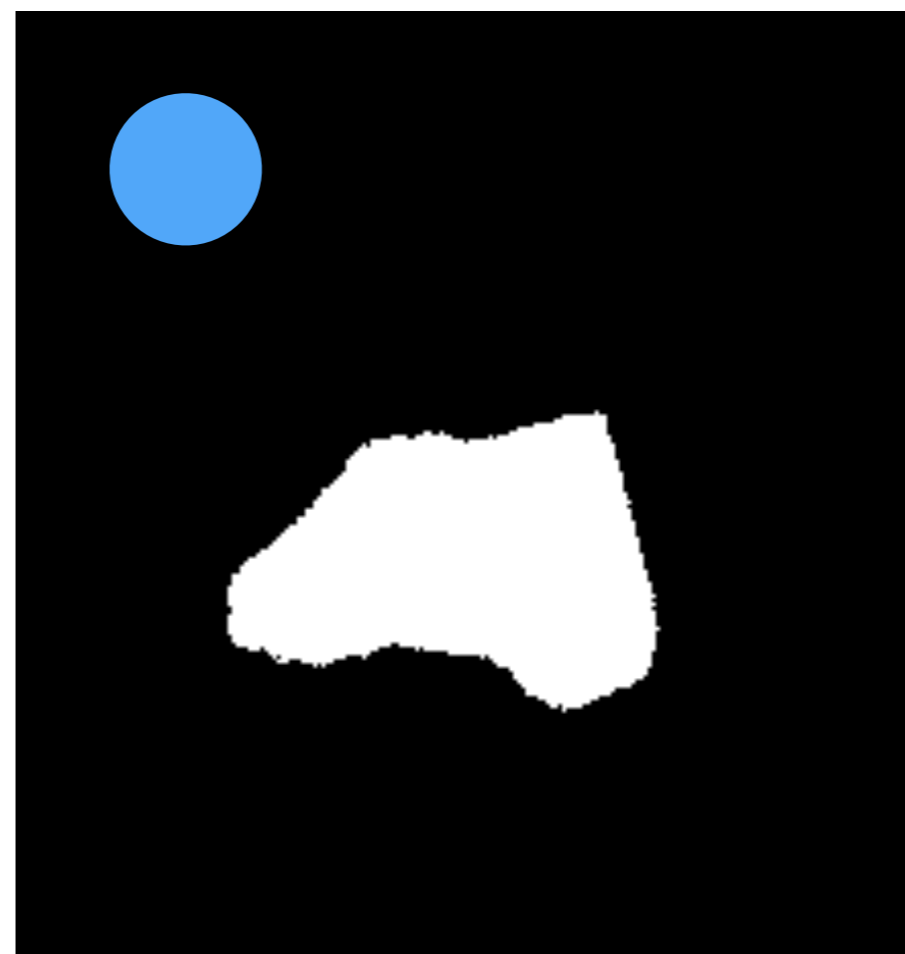
Neural Networks: Training Set (2)

Input



$$\mathbf{x} = \{20, 20, 0.039\}$$

Output

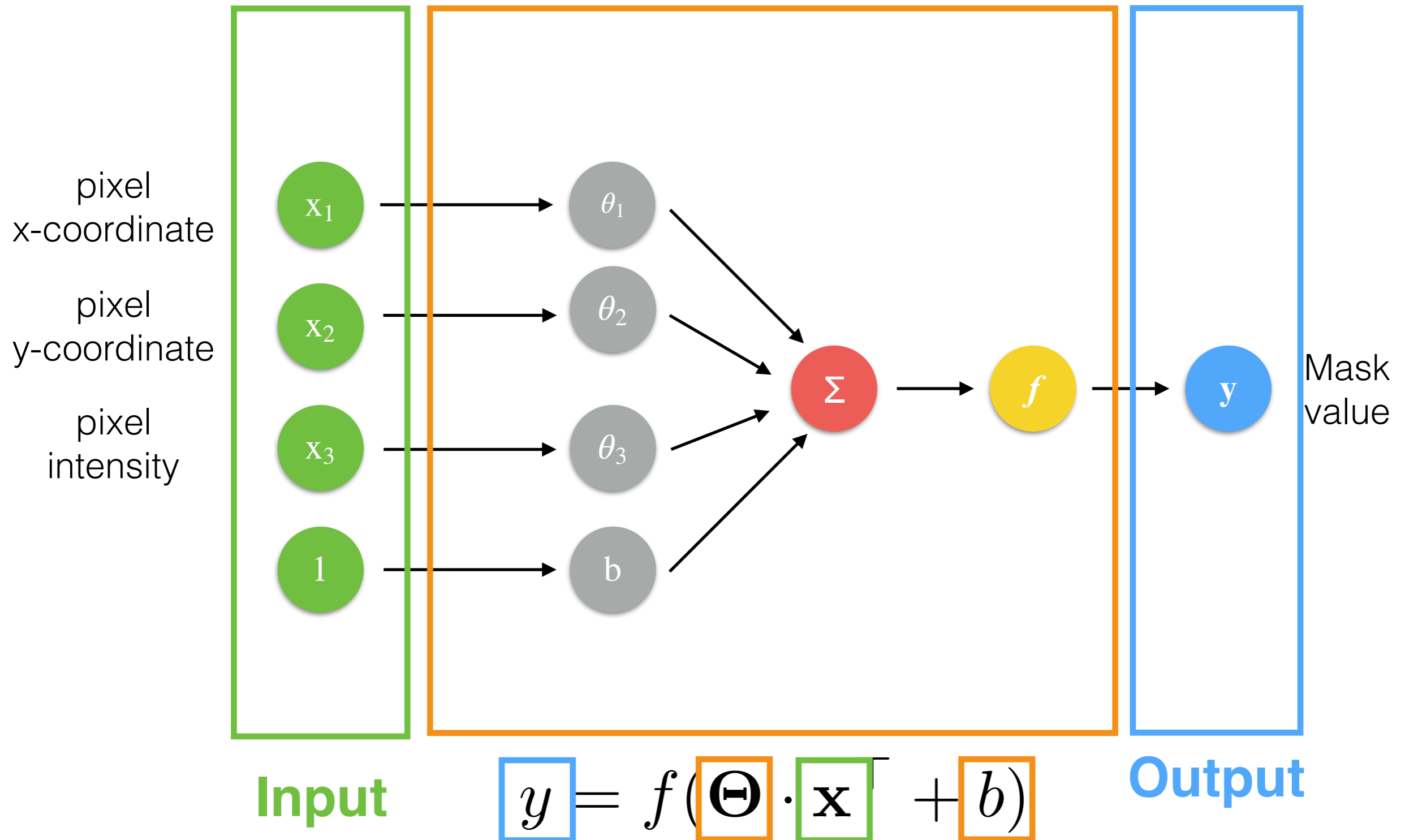


$$y = 0$$

Machine Learning: Training Set (3)

- The training set needs to be balanced:
 - The same amount of examples for both classes:
ROI and background

Neural Networks: A Model



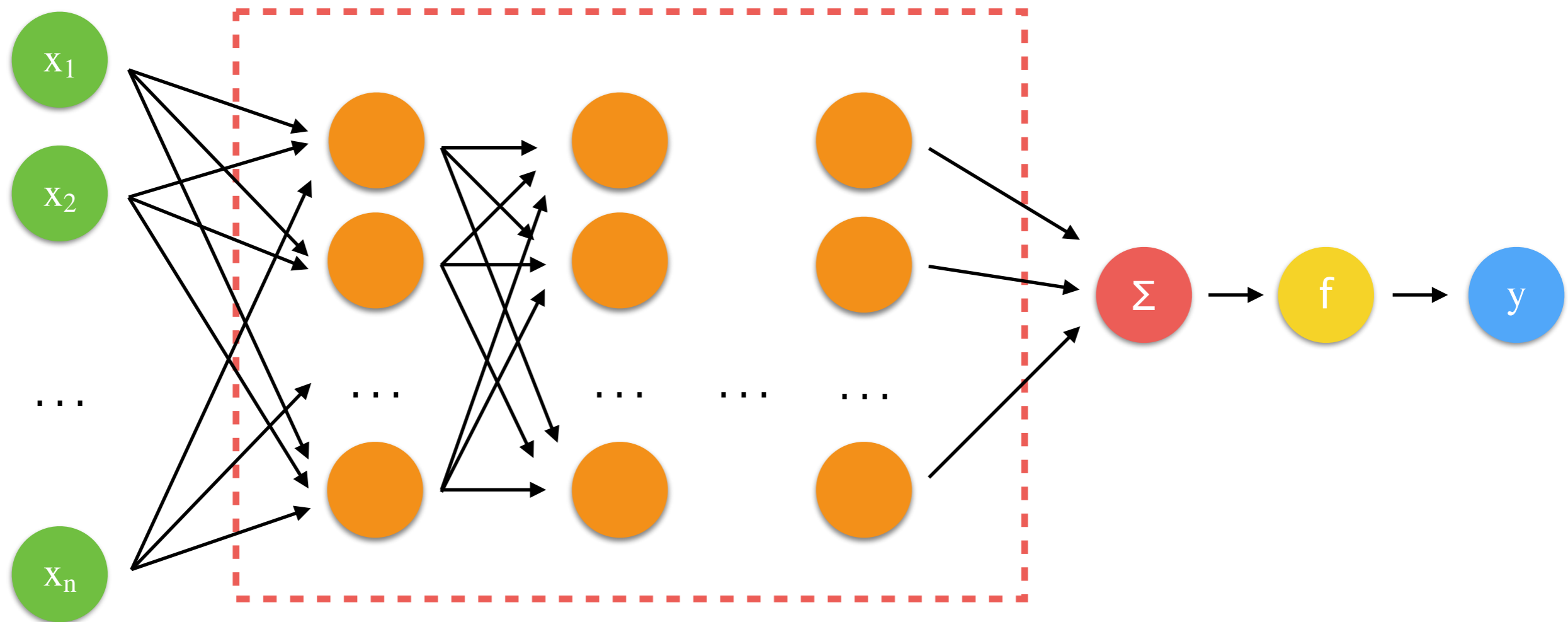
More Complex Examples

More Complex Nets

- To achieve high-quality results, a network needs to “see” and “understand” more data at the same time; not only a couple such as the pixel coordinates+pixel intensity and its classification as in the previous example!
- We need to use more pixels/voxels at the same time:
 - How?
 - Adding and mixing more neurons

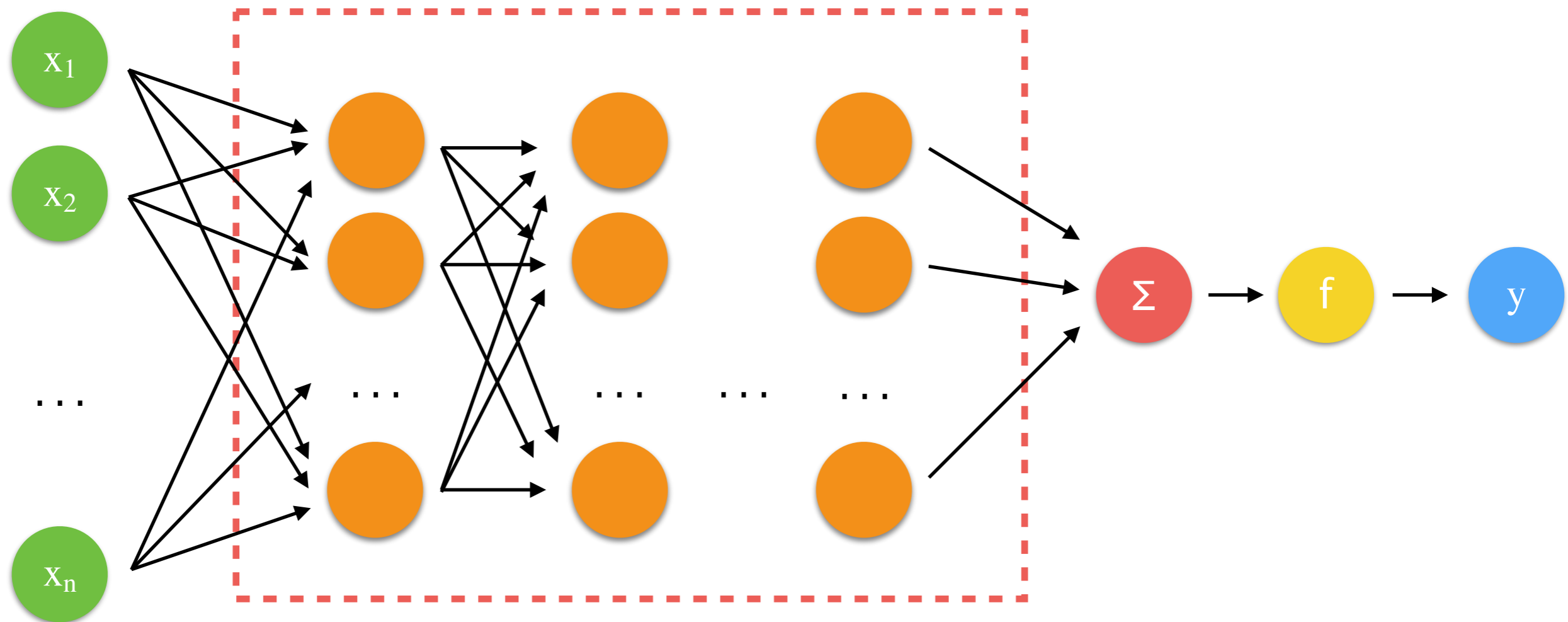
Neural Networks: Bigger Networks



Hidden Layers



Neural Networks: Bigger Networks

Hidden Layers



  $y = f(\Theta \cdot \mathbf{x}^\top + b)$

Neural Networks

- Advantages:
 - fully automatic!
 - computationally fast to evaluate (not the learning though); especially using GPUs.
- Disadvantages:
 - they required many many examples: more than 1,000 to get some decent result; better $> 10,000$ training example!

that's all folks!