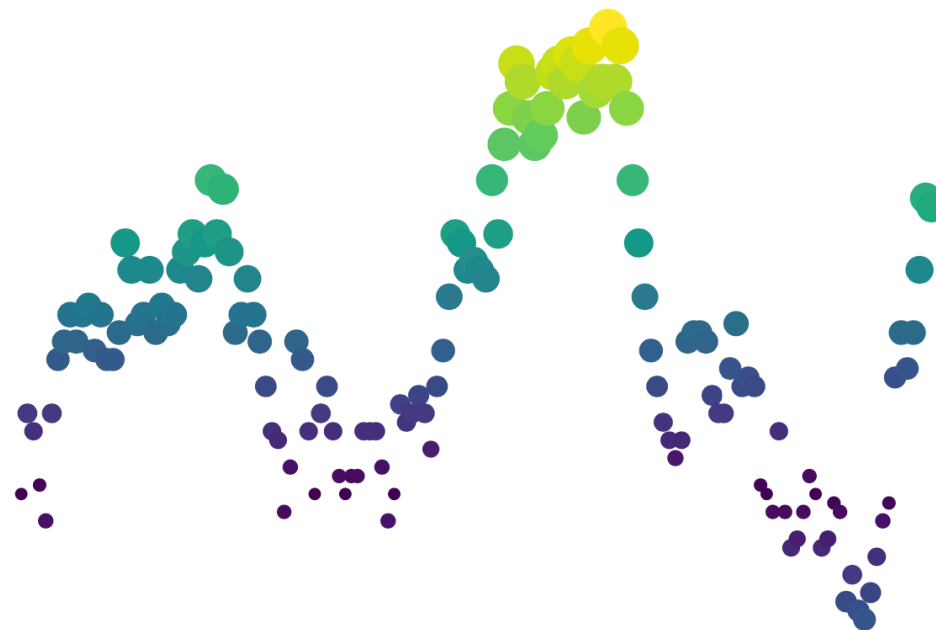
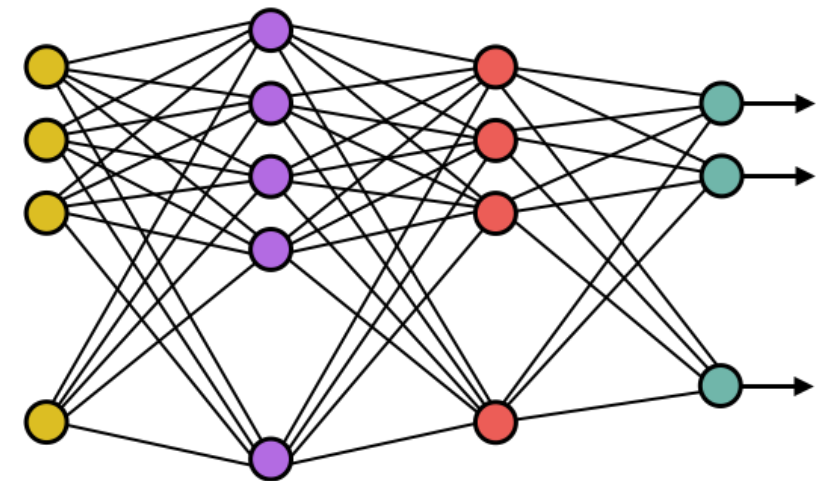
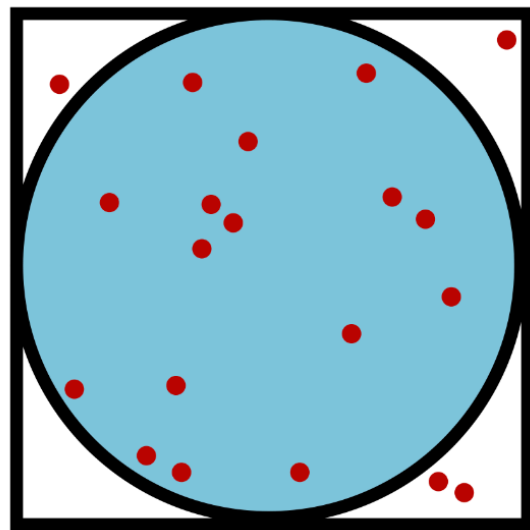


# Numerical Methods

**Lauren Hayward**  
**PSI START Online School**



# Last lecture: Monte Carlo methods in statistical physics

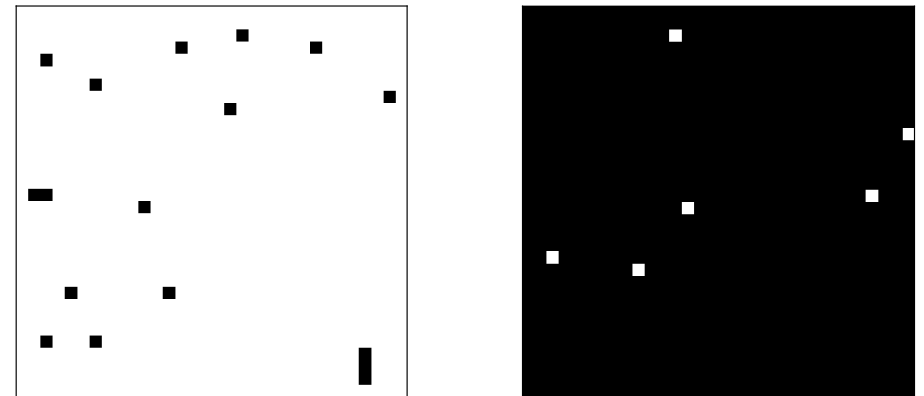
**Ising model in 2D:** 
$$E = -J \sum_{\langle ij \rangle} s_i s_j$$

**At high temperatures:**



Paramagnetic phase

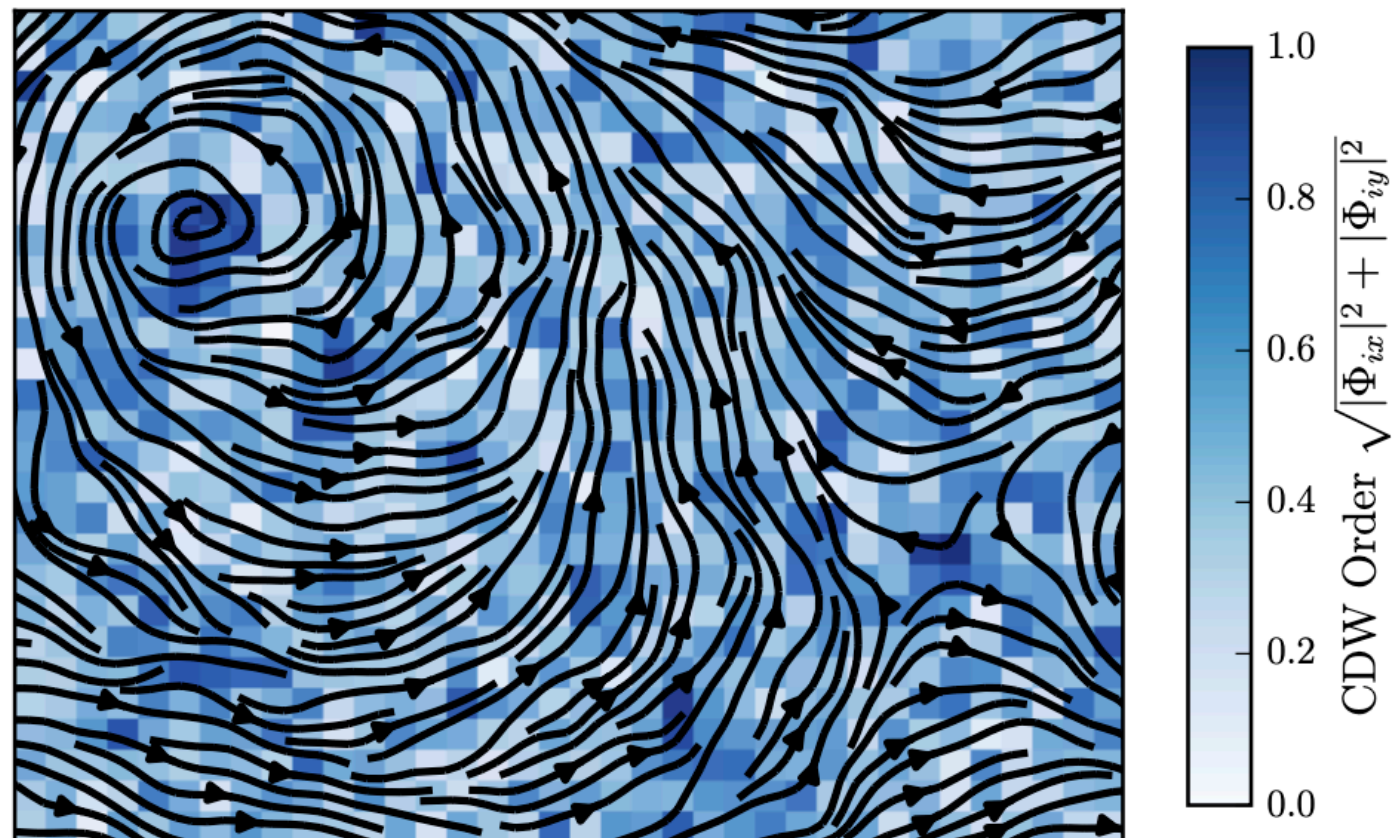
**At low temperatures:**



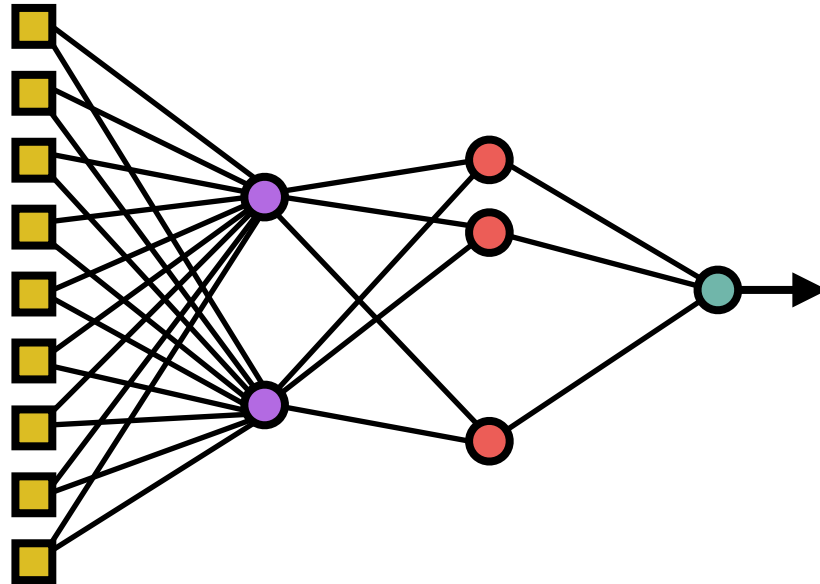
Ferromagnetic phase

# Monte Carlo to study high-temperature superconductivity

$$H = \frac{\rho_s}{2} \sum_{\langle ij \rangle} \left[ \sum_{\alpha=1}^2 (n_{i\alpha} - n_{j\alpha})^2 + \lambda \sum_{\alpha=3}^6 (n_{i\alpha} - n_{j\alpha})^2 \right] \\ + \frac{\rho_s a^2}{2} \sum_i \left[ g \sum_{\alpha=3}^6 n_{i\alpha}^2 + g' \left( \sum_{\alpha=3}^6 n_{i\alpha}^2 \right)^2 + w \left[ \left( n_{i3}^2 + n_{i4}^2 \right)^2 + \left( n_{i5}^2 + n_{i6}^2 \right)^2 \right] \right]$$



# Outline for today



## Machine learning and neural networks

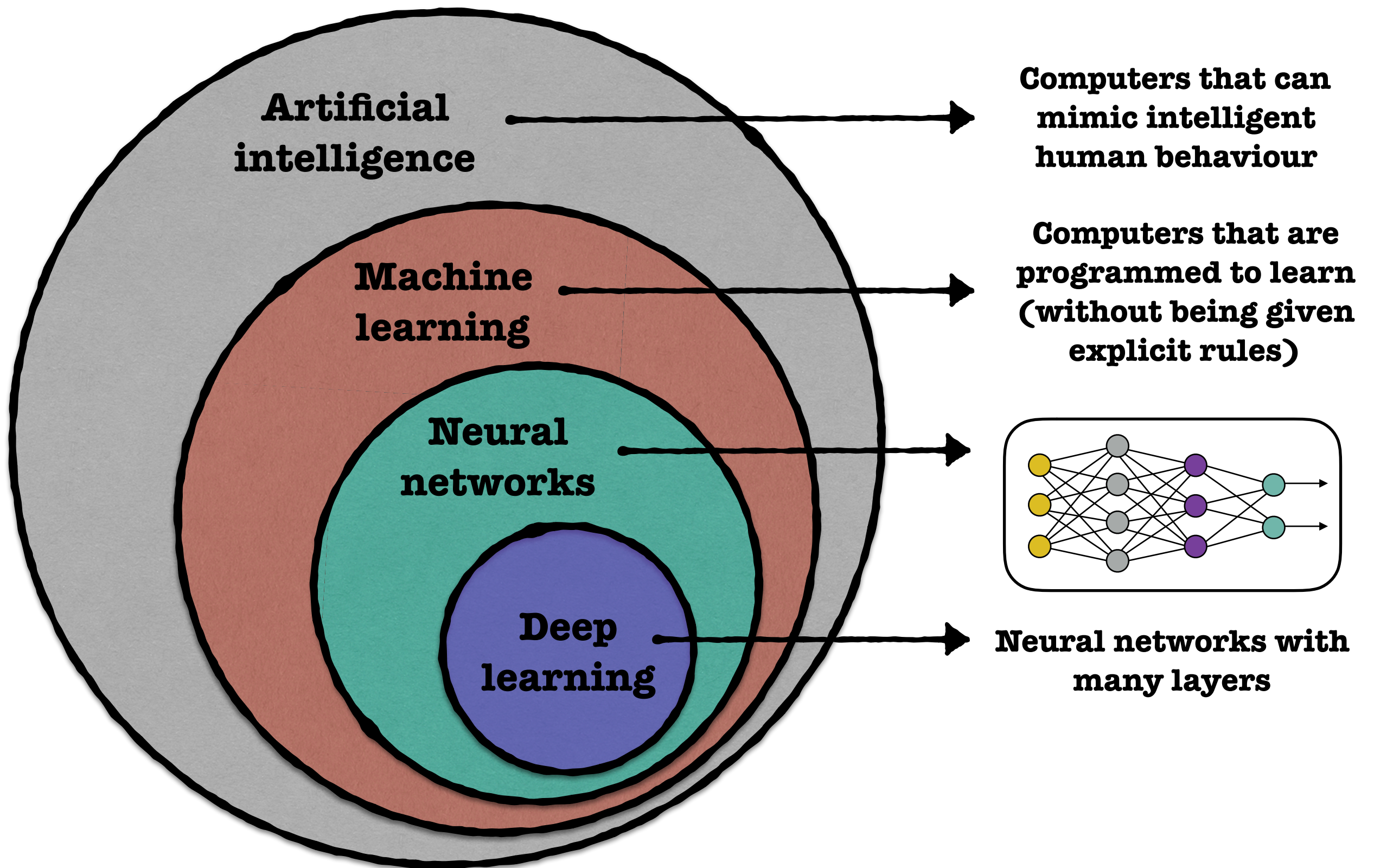
- ▶ Feedforward neural network architecture: layers, weights, biases, activation functions
- ▶ Feedforward neural networks in PyTorch

# What is machine learning?

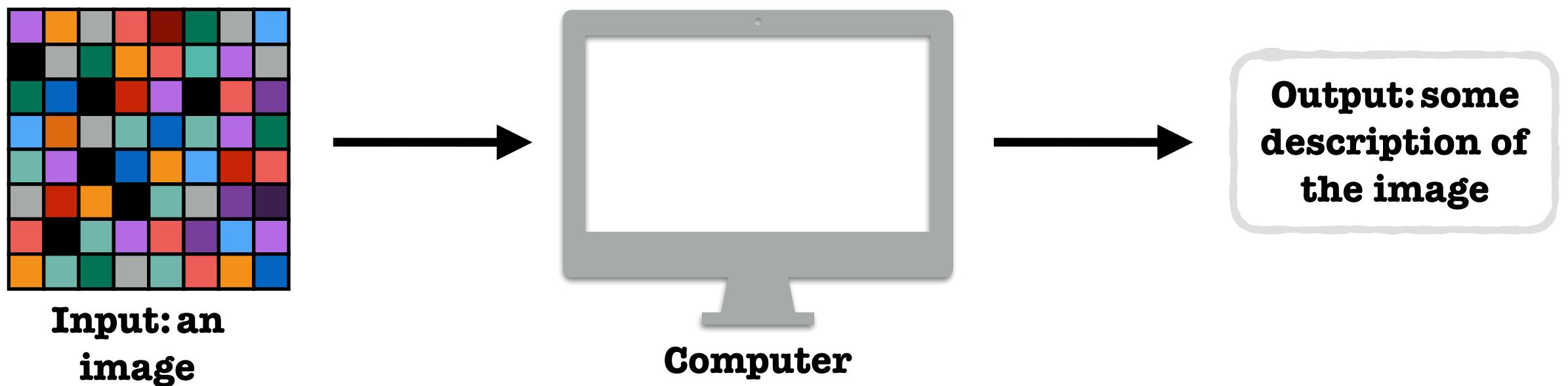
**Machine learning:** training computers to detect and characterize features from data

Compare with a goal of **statistical physics:** predicting and explaining macroscopic phenomena (features) from microscopic quantities (data)





# Application of neural networks: classifying images

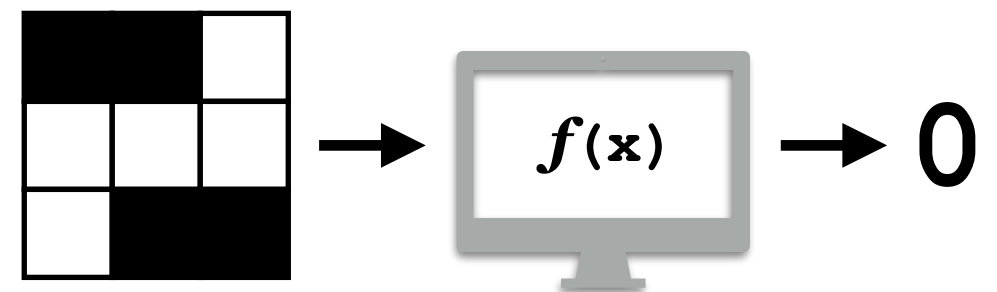
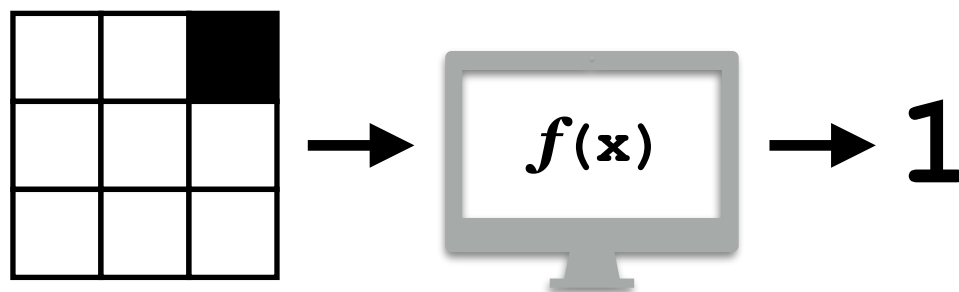
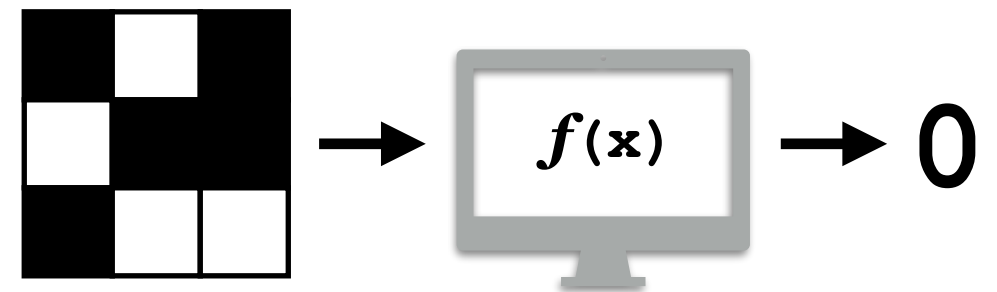
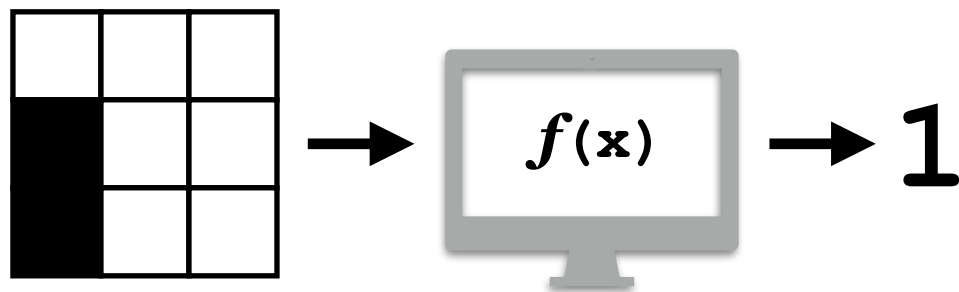


**Or, more mathematically:**



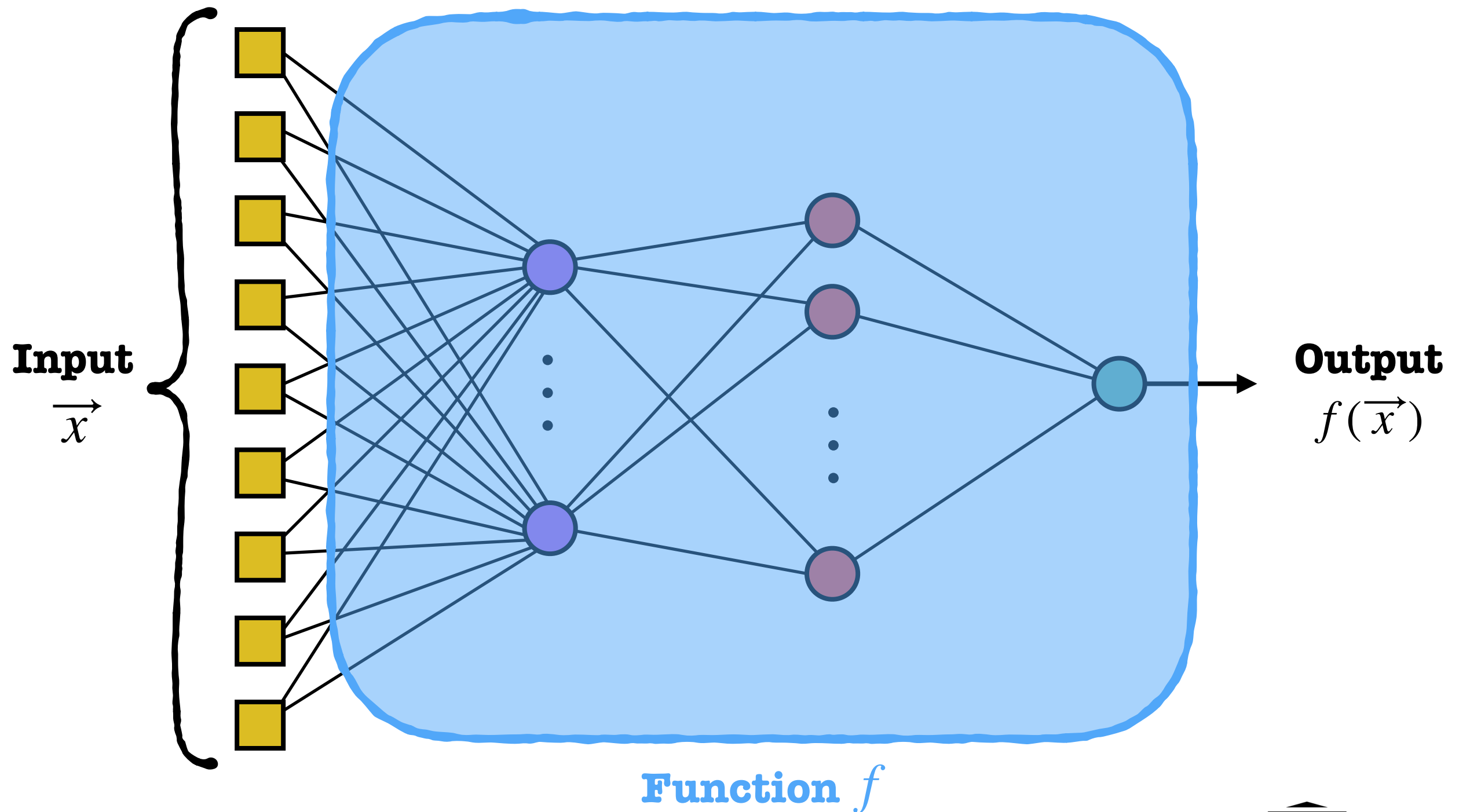
# Application of neural networks: classifying images

**Example: identifying whether an image contains one rectangle**

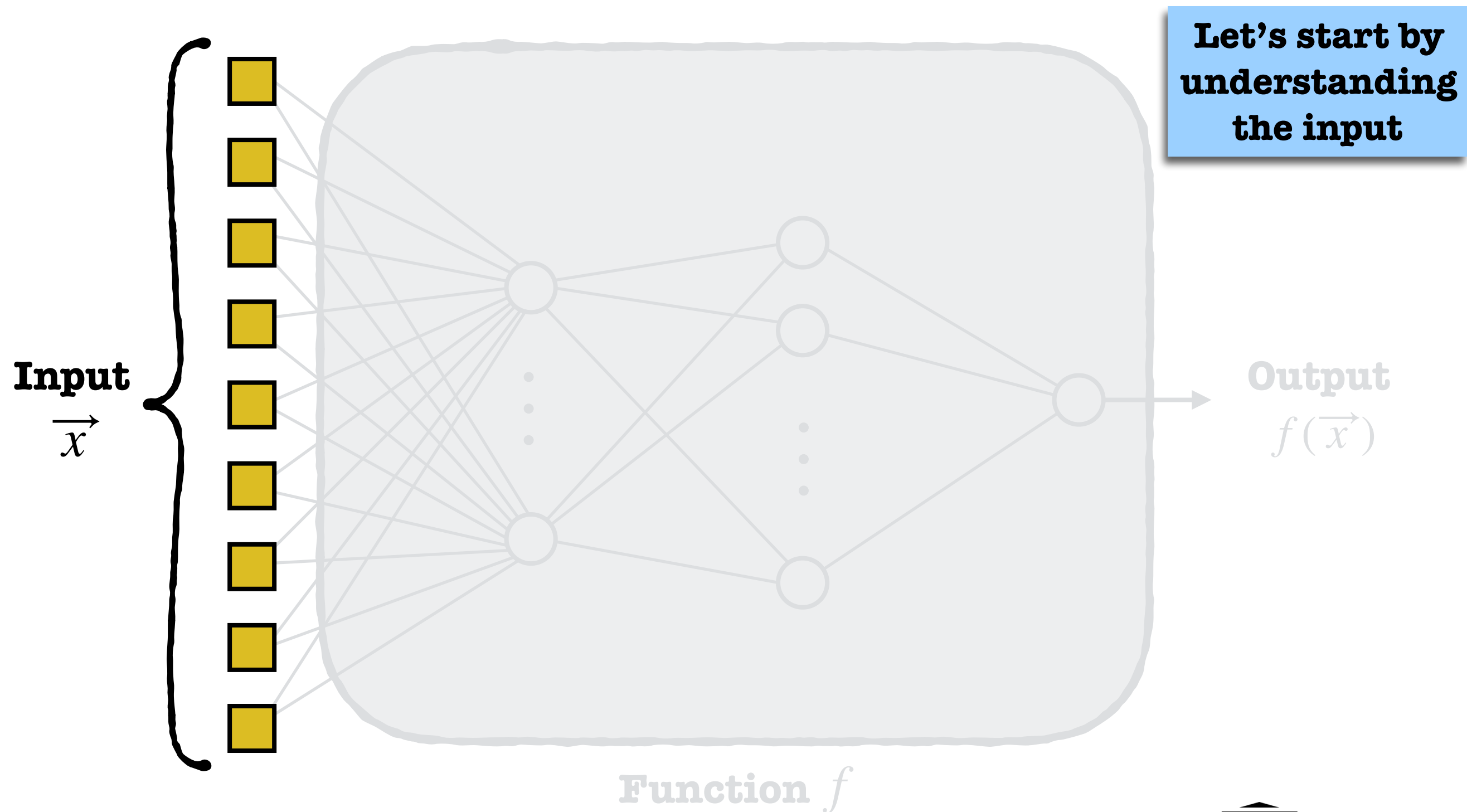




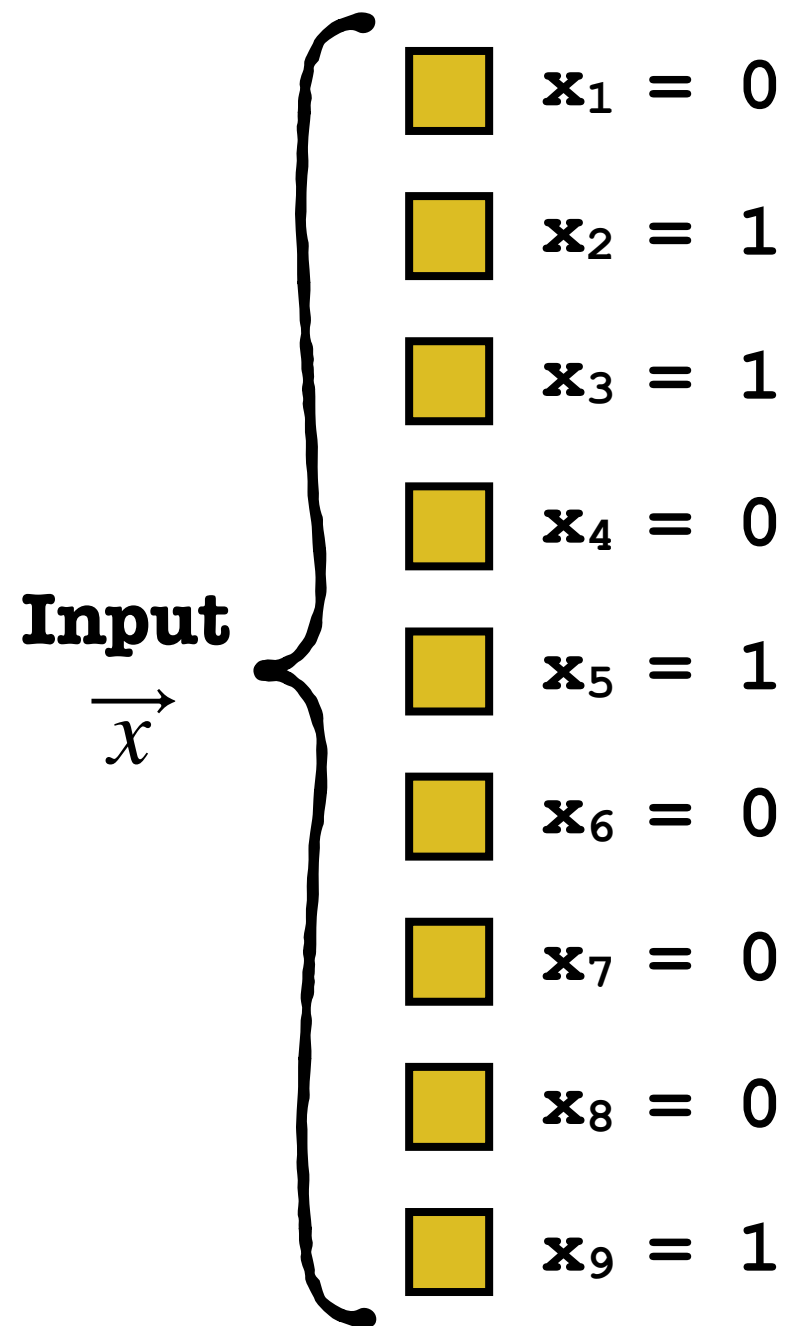
# Feedforward neural network



# Feedforward neural network



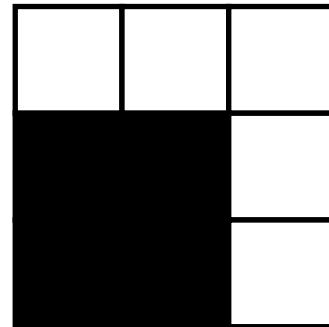
# Neural network input



$$\vec{x} = [0, 1, 1, 0, 1, 0, 0, 0, 1]$$

# Neural network input

How do we translate

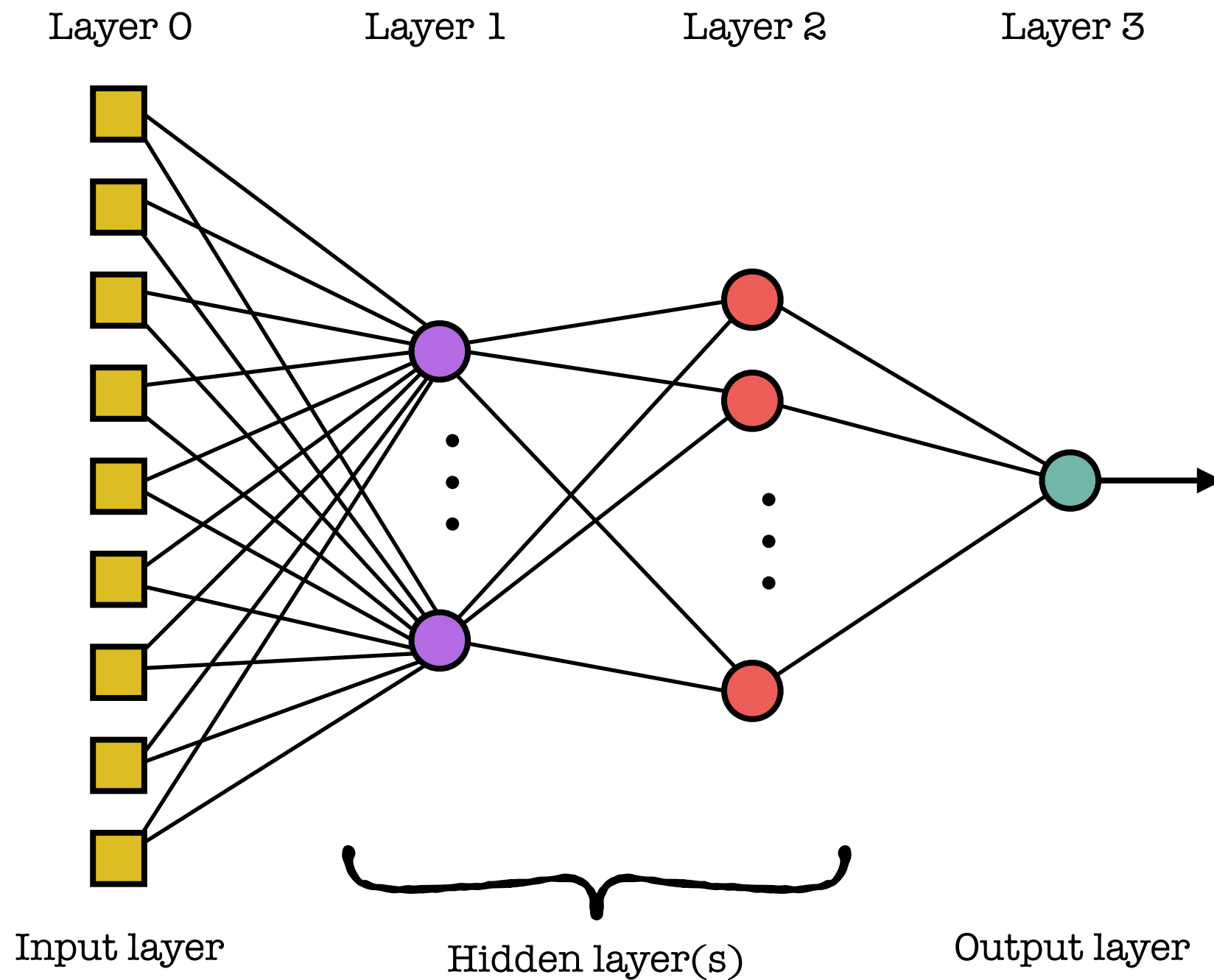


into an input for the neural network?

$\mathbf{x}_1 = 0$	$\mathbf{x}_2 = 0$	$\mathbf{x}_3 = 0$
$\mathbf{x}_4 = 1$	$\mathbf{x}_5 = 1$	$\mathbf{x}_6 = 0$
$\mathbf{x}_7 = 1$	$\mathbf{x}_8 = 1$	$\mathbf{x}_9 = 0$

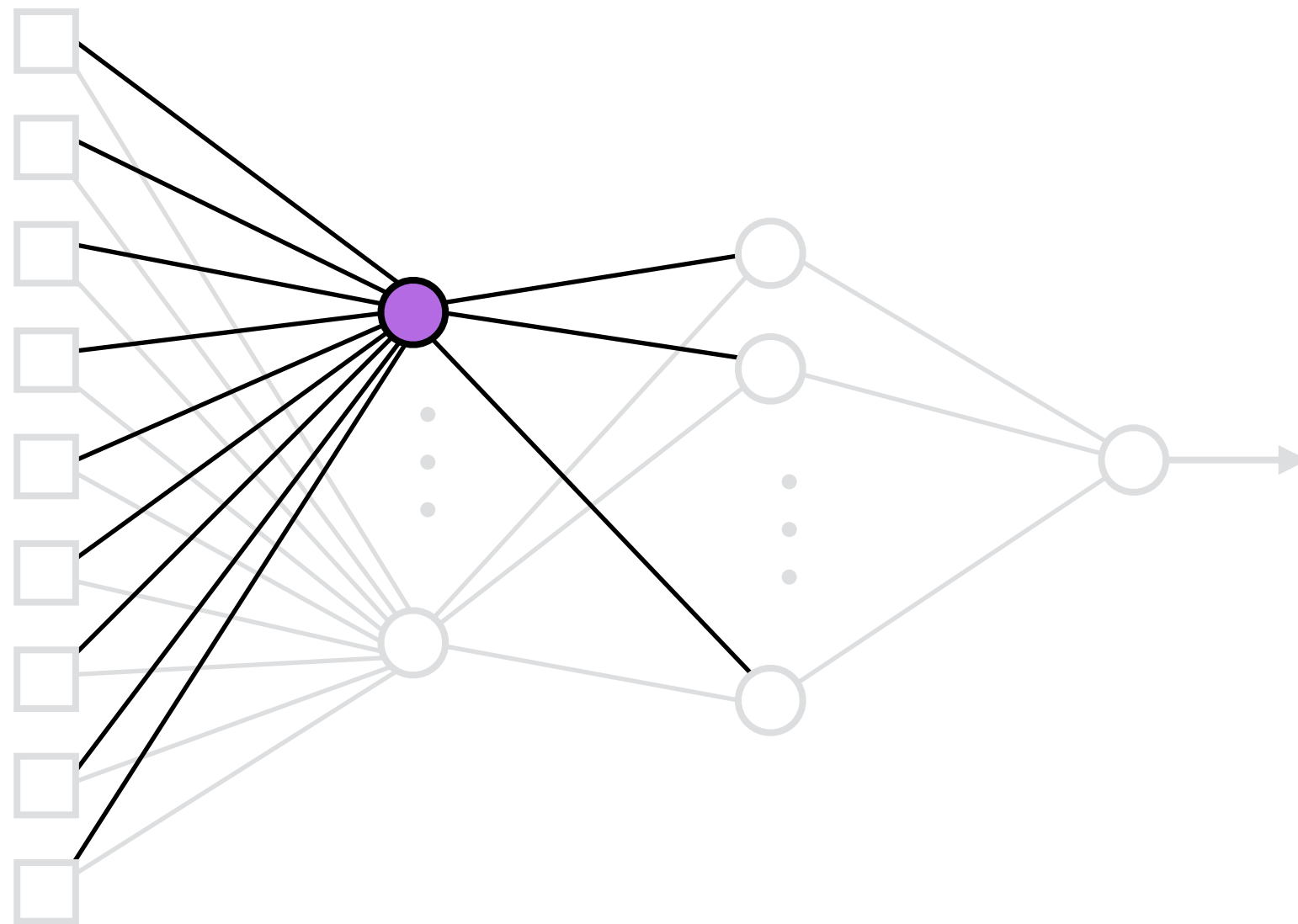
$$\vec{x} = [0, 0, 0, 1, 1, 0, 1, 1, 0]$$

# Neural networks layers



# Neuron output

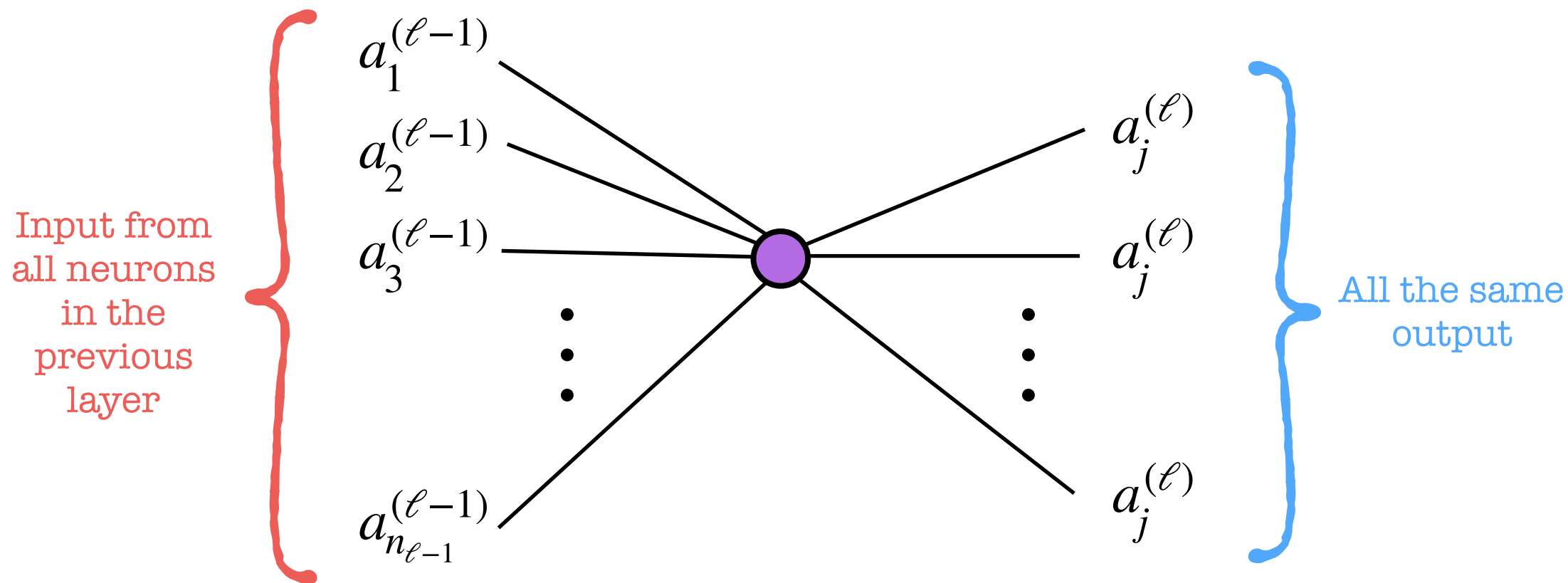
Let's zoom in on the  $j^{\text{th}}$  neuron in layer  $\ell > 0$





# Neuron output

Let's zoom in on the  $j^{\text{th}}$  neuron in layer  $\ell > 0$



The output from this neuron is: 
$$a_j^{(\ell)} = g_\ell \left( \sum_{i=1}^{n_{\ell-1}} a_i^{(\ell-1)} W_{ij}^\ell + b_j^\ell \right)$$

# Neuron output

$$a_j^{(\ell)} = g_\ell \left( \sum_{i=1}^{n_{\ell-1}} a_i^{(\ell-1)} W_{ij}^\ell + b_j^\ell \right)$$

The diagram illustrates the components of the neuron output equation. The equation is  $a_j^{(\ell)} = g_\ell \left( \sum_{i=1}^{n_{\ell-1}} a_i^{(\ell-1)} W_{ij}^\ell + b_j^\ell \right)$ . The terms are color-coded:  $g_\ell$  is in a purple box,  $W_{ij}^\ell$  is in a blue box, and  $b_j^\ell$  is in a red box. Arrows point from these boxes to their respective descriptions below the equation: a purple arrow from  $g_\ell$  points to "non-linear activation function", a blue arrow from  $W_{ij}^\ell$  points to "weight for each link", and a red arrow from  $b_j^\ell$  points to "bias for each neuron".

non-linear  
**activation  
function**

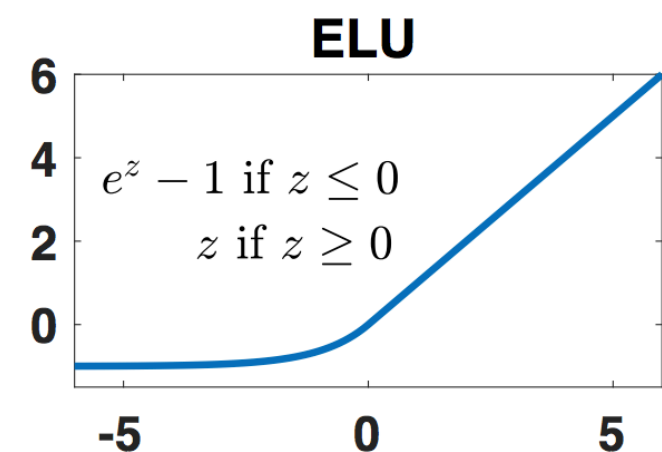
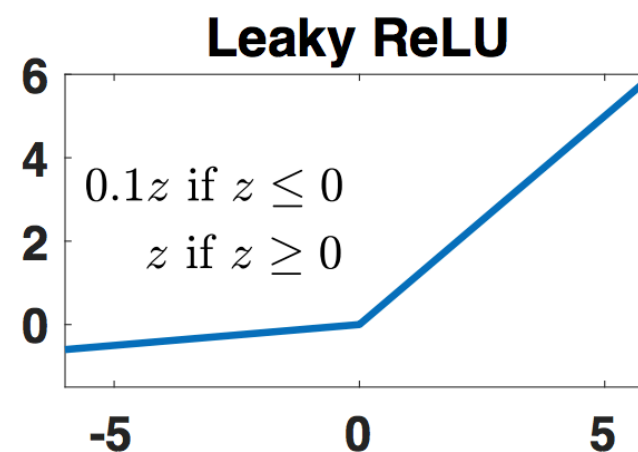
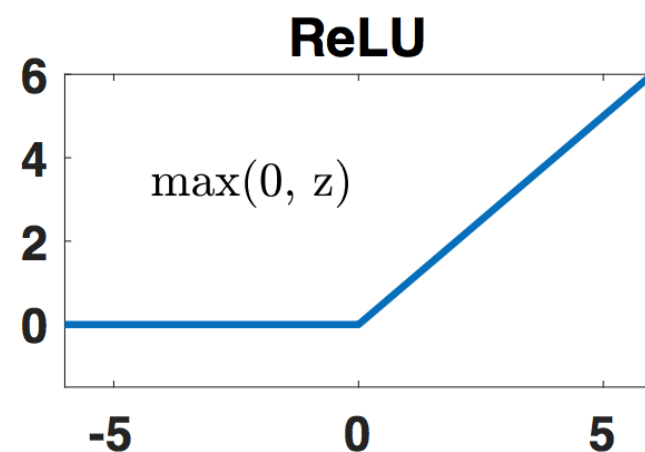
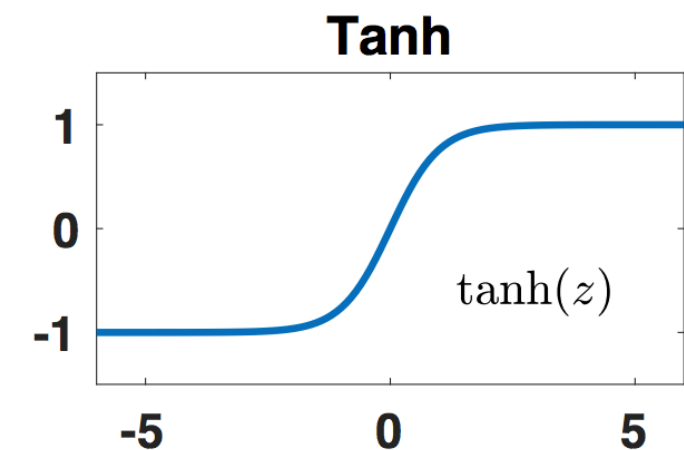
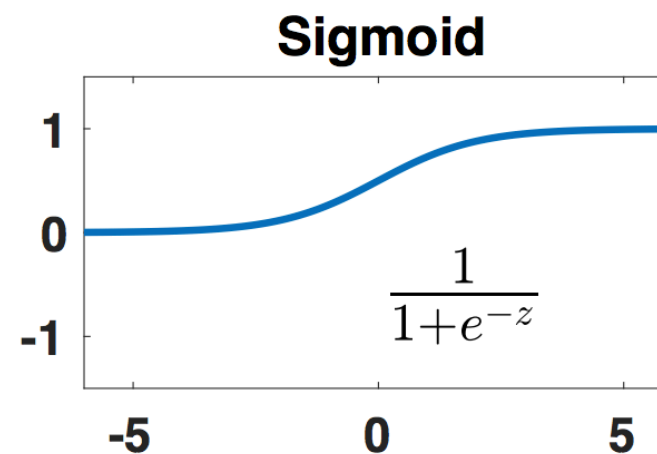
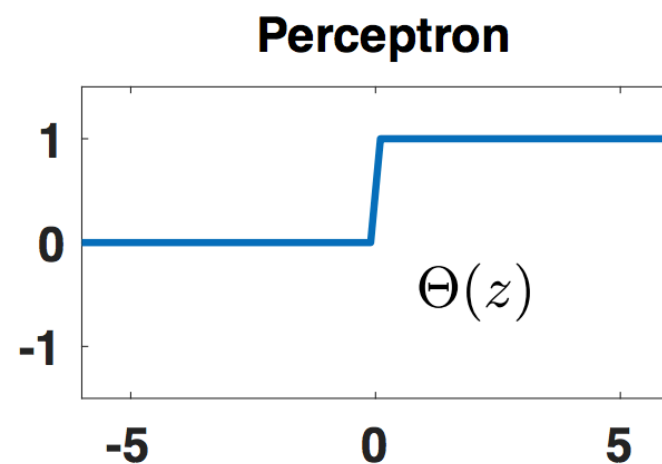
**weight**  
for each  
link

**bias**  
for each  
neuron

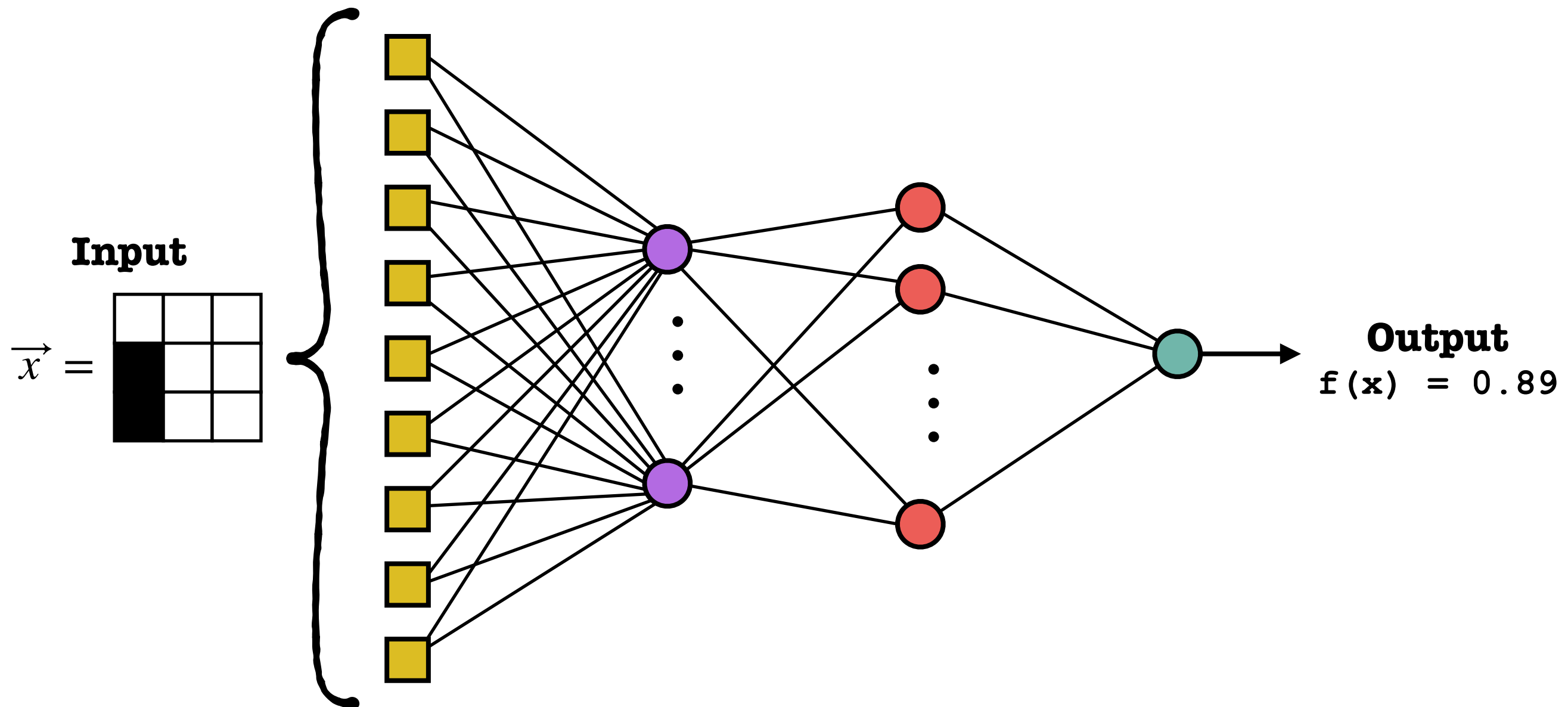
The weights and biases are adjusted as the network **learns**.

# Activation functions

We can choose various non-linear activation functions  $g_\ell$ , such as:



# Neural network output

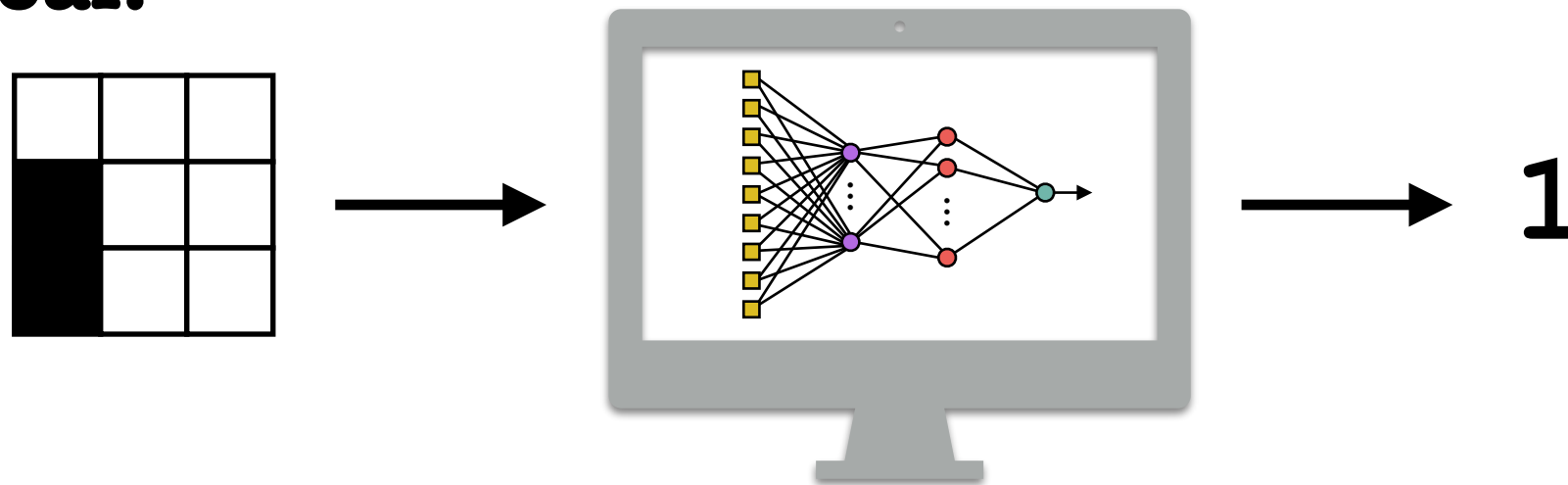


**What does this output mean?**

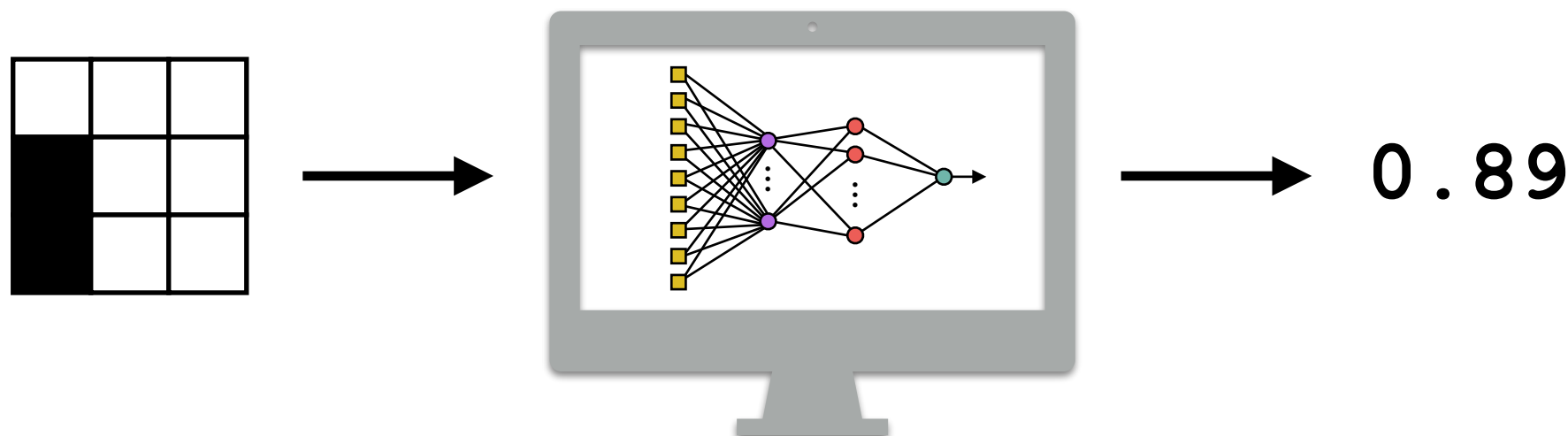
# Neural network output

Recall that our goal is to identify whether an image contains one rectangle

**Goal:**



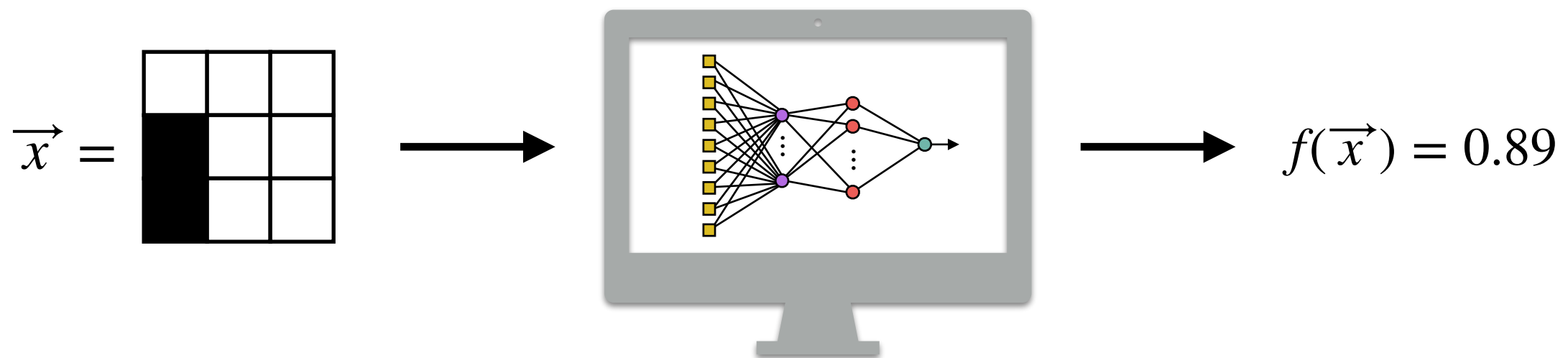
**What we might find:**



Our network is 89% sure that the input contains one rectangle.

# Neural network output

In other words, our network might give the output:



While the true answer should be:  $y_{\text{true}}(x) = 1$

**We would like to choose the weights  $W$  and biases  $b$  such that the difference between  $f(x)$  and  $y_{\text{true}}(x)$  is as small as possible.**



# Neural network output

We would like our neural network to classify all possible inputs using the same weights and biases.

