



# **CS 540 Introduction to Artificial Intelligence**

## **Perceptron**

**University of Wisconsin-Madison**

**Fall 2022**



# Part I: Single-layer Neural Network

# How to classify

## Cats vs. dogs?

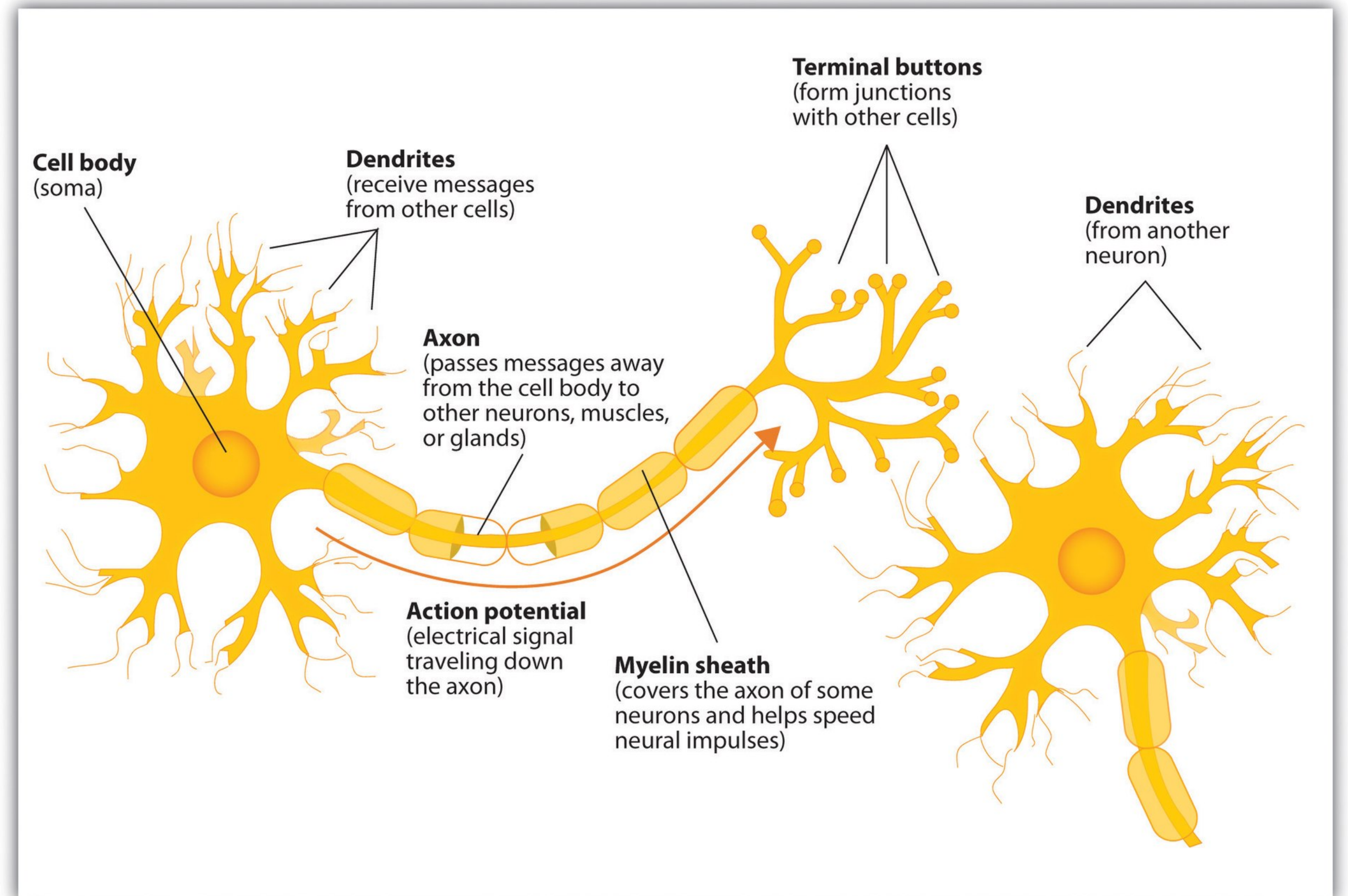


# Inspiration from neuroscience

- Inspirations from human brains
- Networks of **simple** and **homogenous** units



(wikipedia)

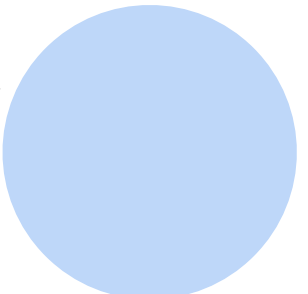
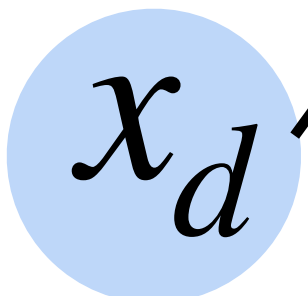
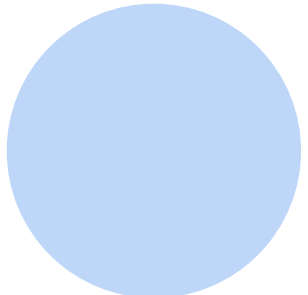
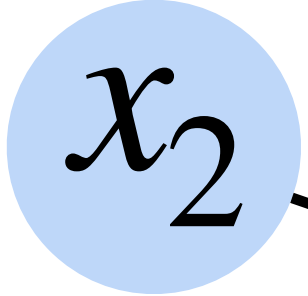
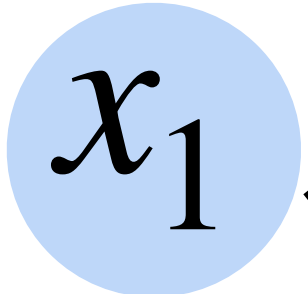


# Perceptron

Cats vs. dogs?



Input



Output

# Linear Perceptron

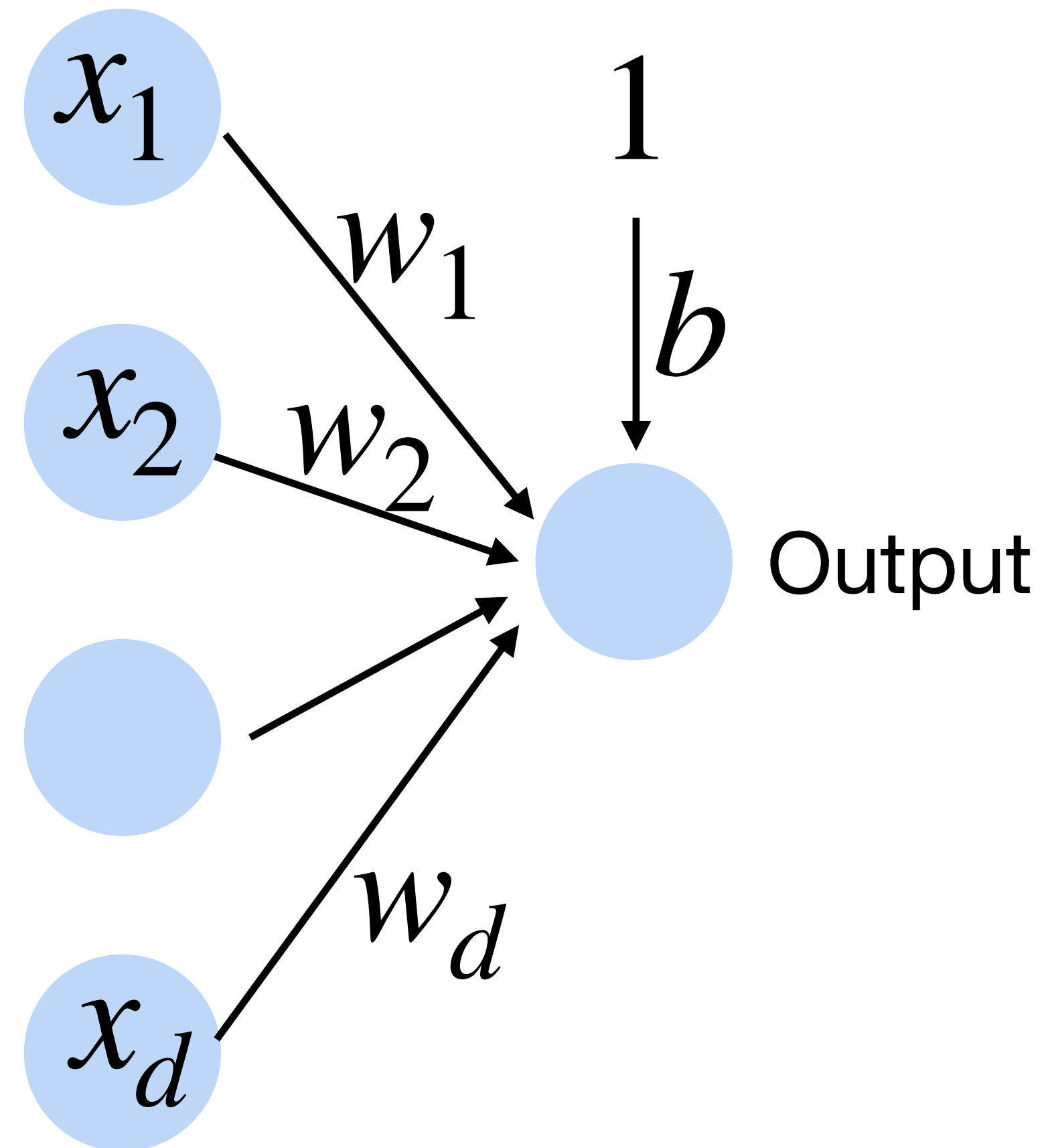
- Given input  $\mathbf{x}$ , weight  $\mathbf{w}$  and bias  $b$ , perceptron outputs:

$$f = \langle \mathbf{w}, \mathbf{x} \rangle + b$$

Cats vs. dogs?



Input



# Perceptron

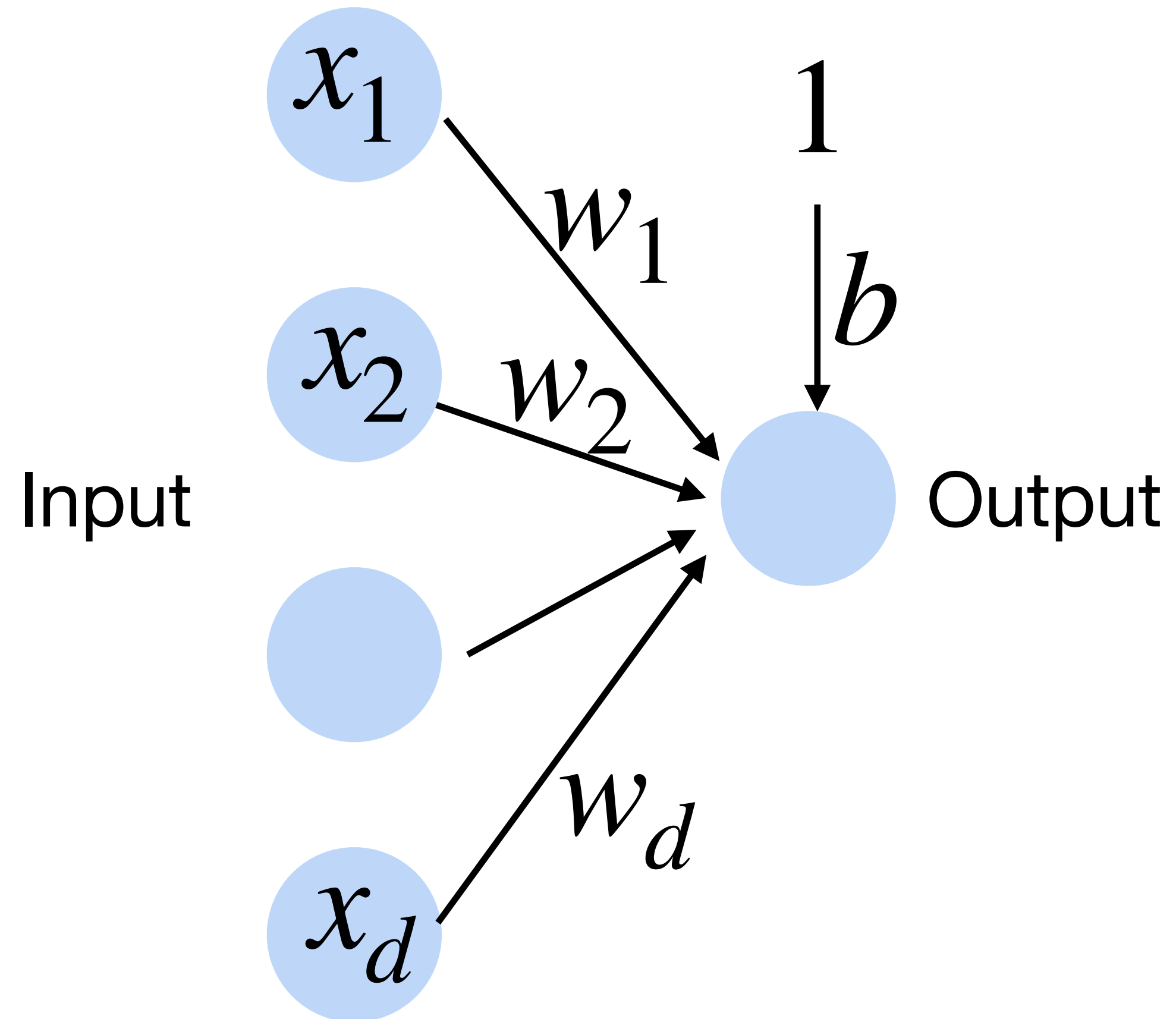
- Given input  $\mathbf{x}$ , weight  $\mathbf{w}$  and bias  $b$ , perceptron outputs:

$$o = \sigma(\langle \mathbf{w}, \mathbf{x} \rangle + b)$$

$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

Activation function

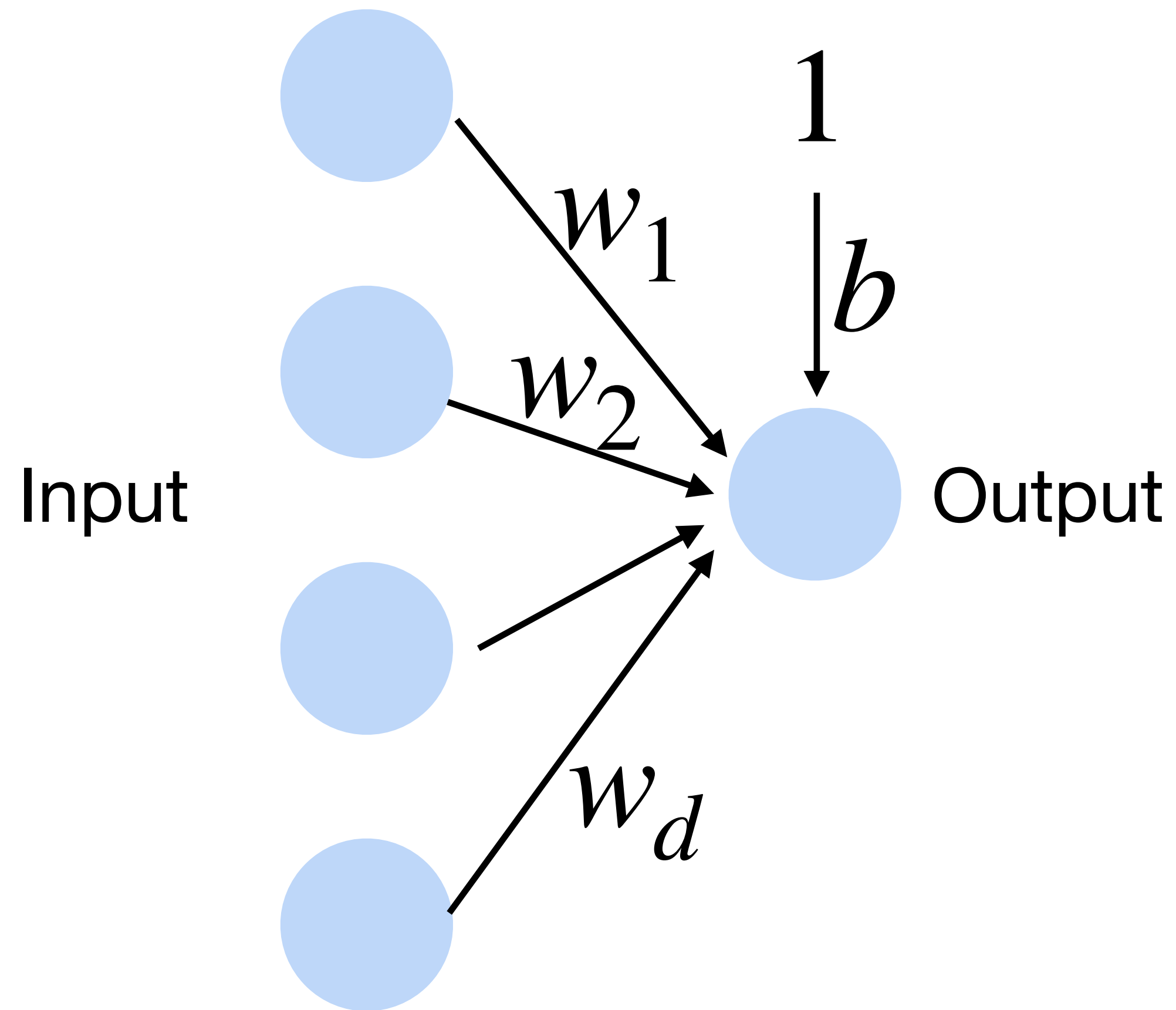
Cats vs. dogs?



# Perceptron

- Goal: learn parameters  $\mathbf{w} = \{w_1, w_2, \dots, w_d\}$  and  $b$  to minimize the classification error

Cats vs. dogs?





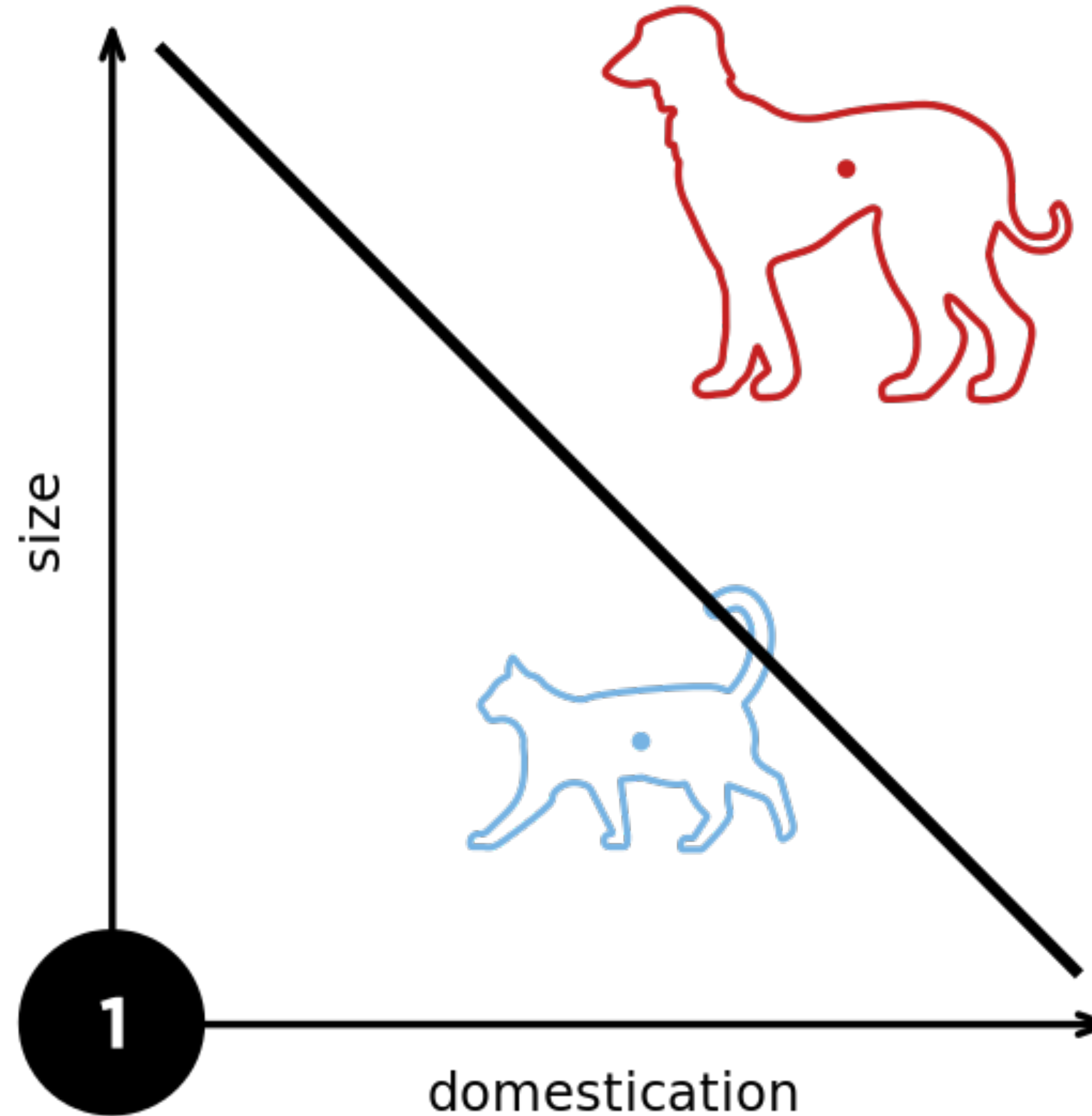
# Training the Perceptron

x augmented with dimension of constant 1

## Perceptron Algorithm

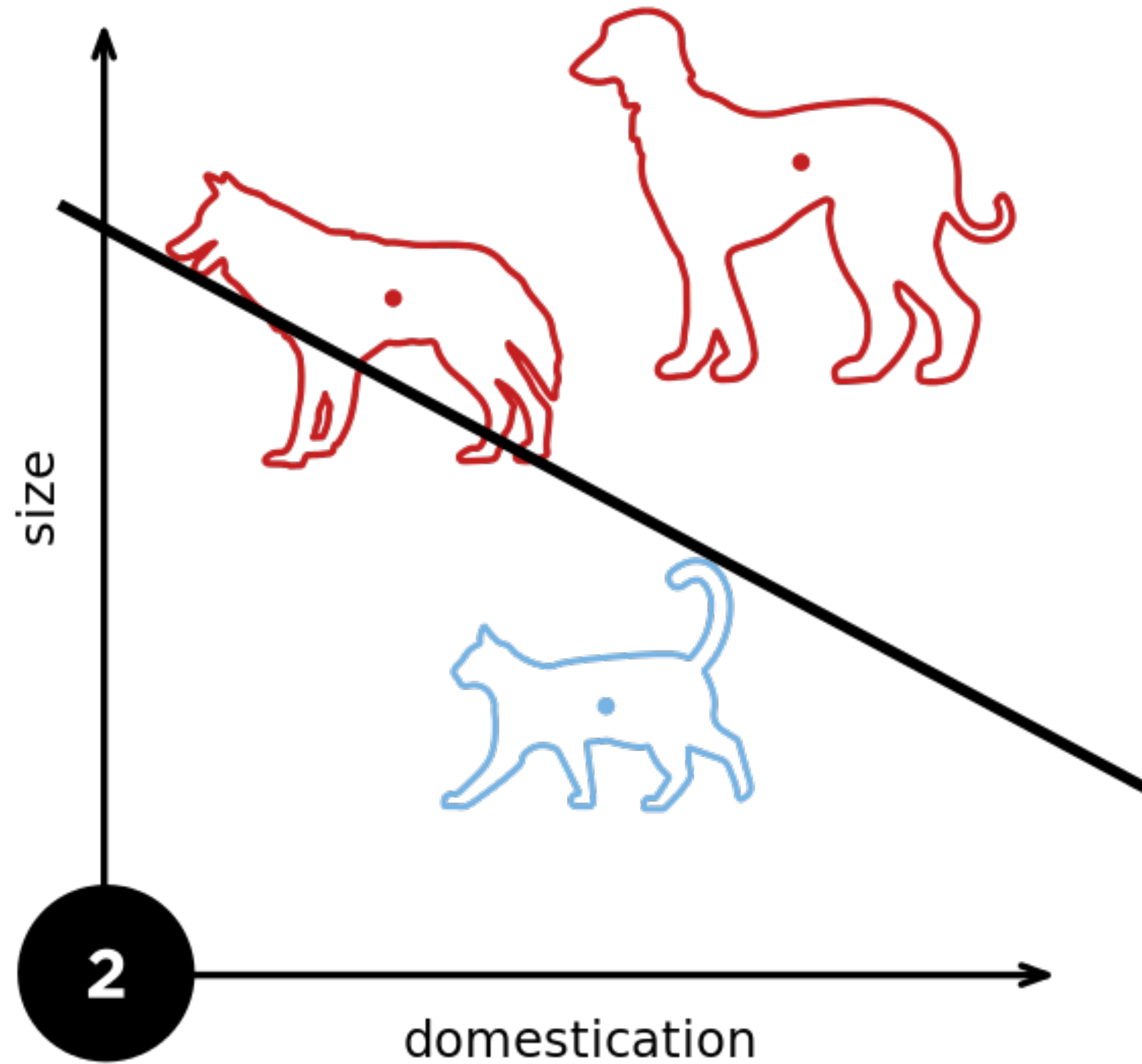
```
Initialize  $\vec{w} = \vec{0}$  // Initialize  $\vec{w}$ .  $\vec{w} = \vec{0}$  misclassifies everything.
while TRUE do // Keep looping
   $m = 0$  // Count the number of misclassifications,  $m$ 
  for  $(x_i, y_i) \in D$  do // Loop over each (data, label) pair in the dataset,  $D$ 
    if  $o_i \neq y_i$  then // If the pair  $(\vec{x}_i, y_i)$  is misclassified
       $\vec{w} \leftarrow \vec{w} + x_i$  if  $y_i = 1$ ,  $\vec{w} \leftarrow \vec{w} - x_i$  if  $y_i = 0$ 
       $m \leftarrow m + 1$  // Counter the number of misclassification
    end if
  end for
  if  $m = 0$  then // If the most recent  $\vec{w}$  gave 0 misclassifications
    break // Break out of the while-loop
  end if
end while // Otherwise, keep looping!
```

# Perceptron



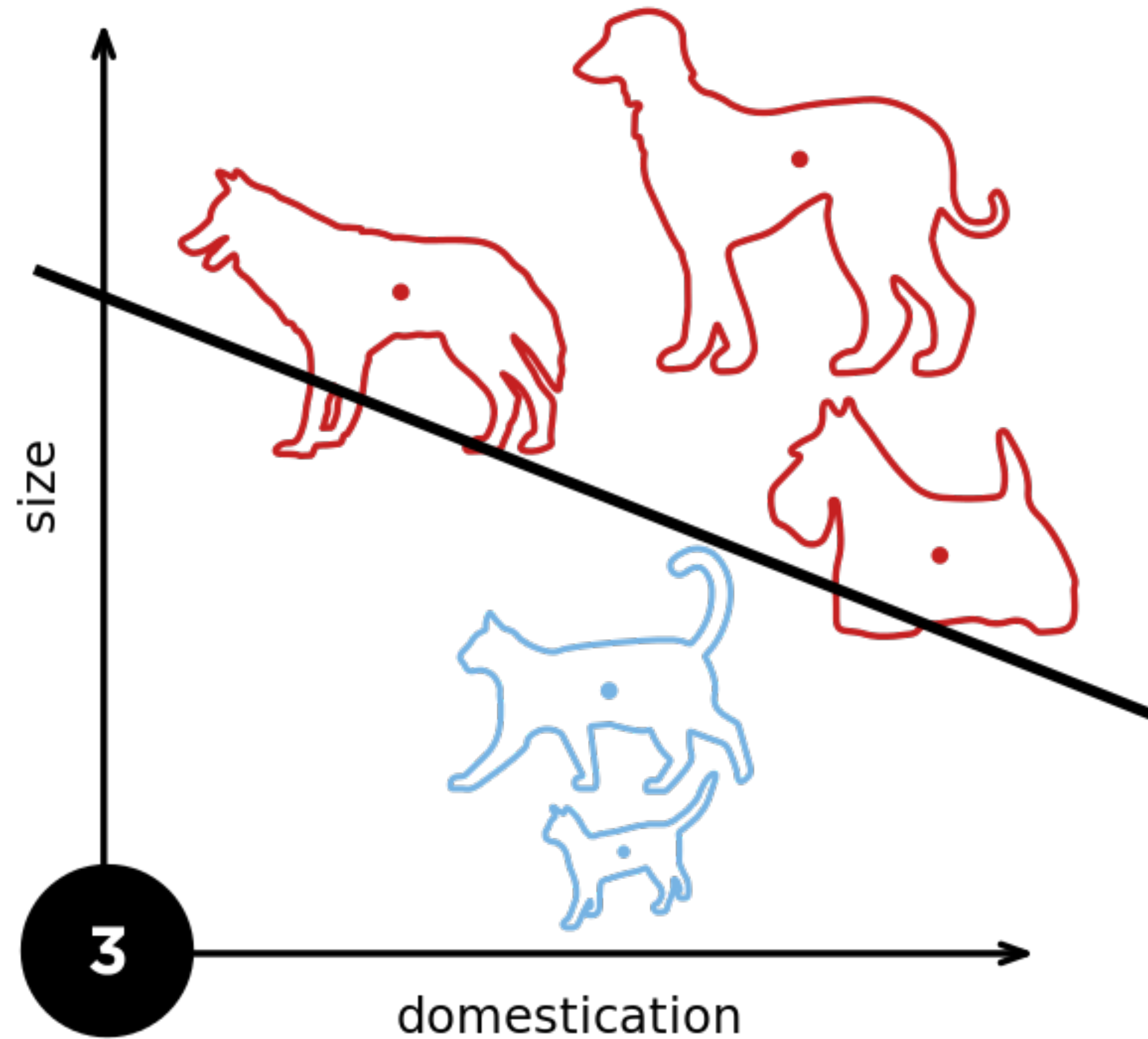
From wikipedia

# Perceptron



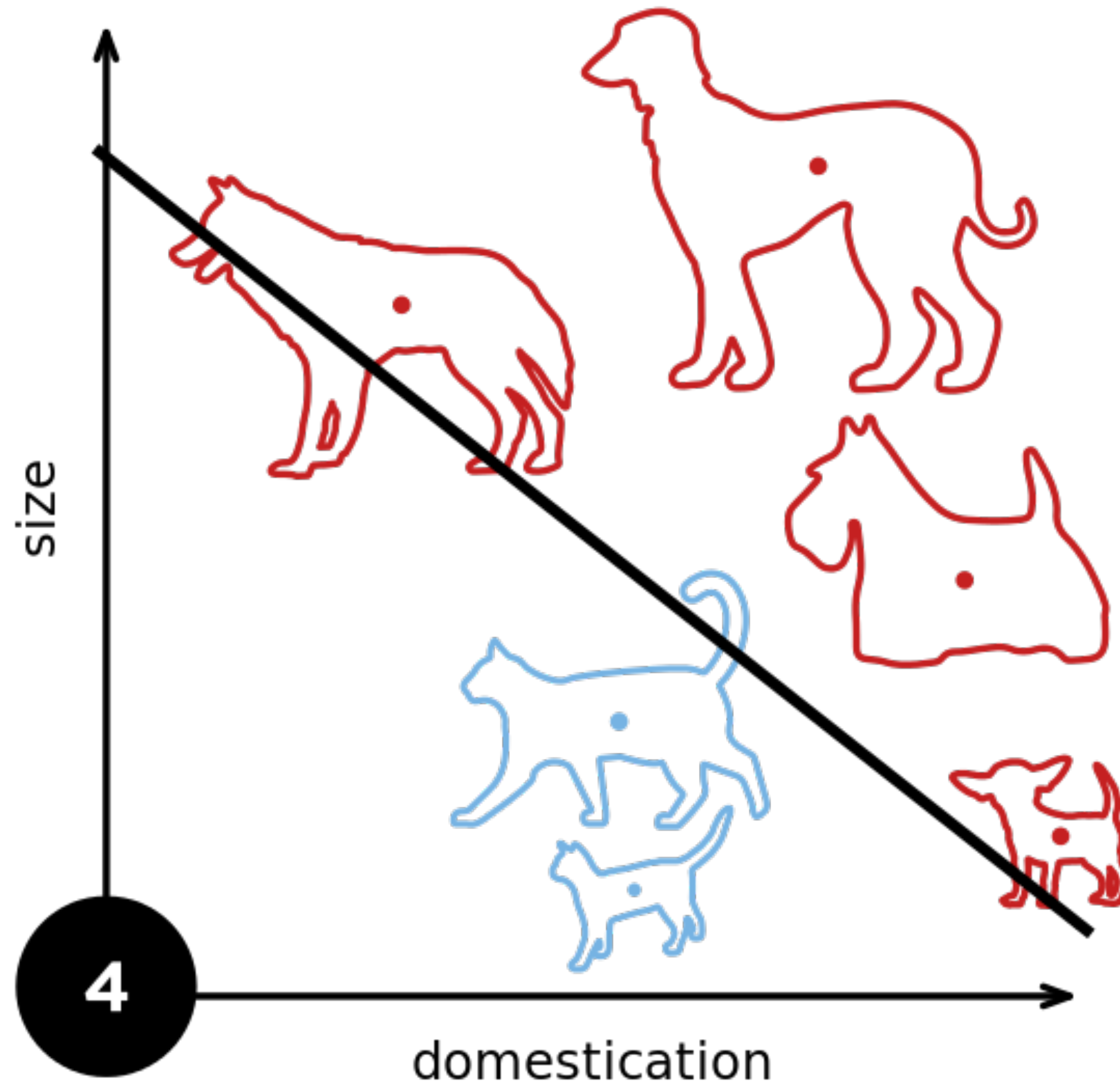
From wikipedia

# Perceptron



From wikipedia

# Perceptron



From wikipedia

# Example 2: Predict whether a user likes a song or not



model



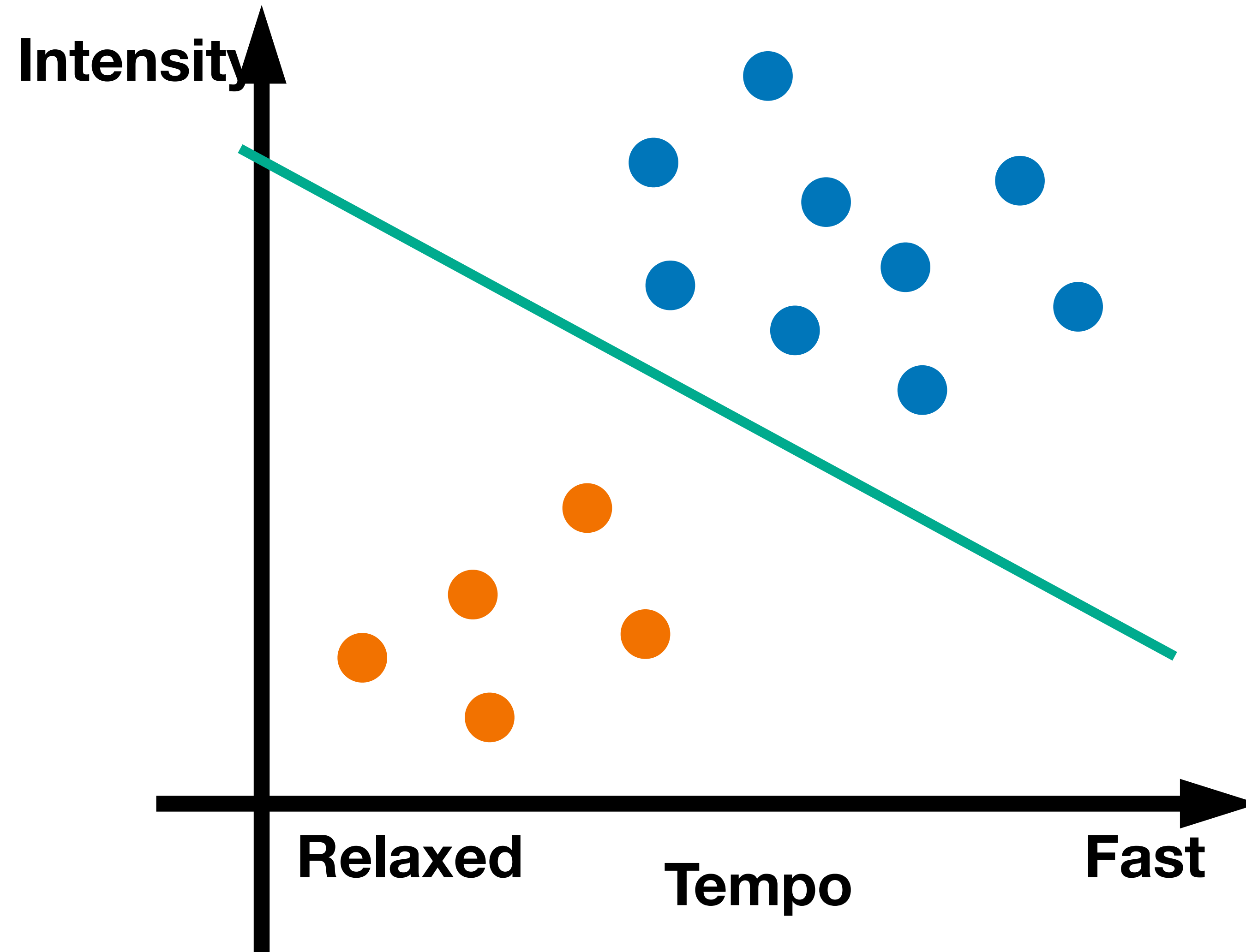
# Example 2: Predict whether a user likes a song or not Using Perceptron



User Sharon

● DisLike

● Like



# Learning AND function using perceptron

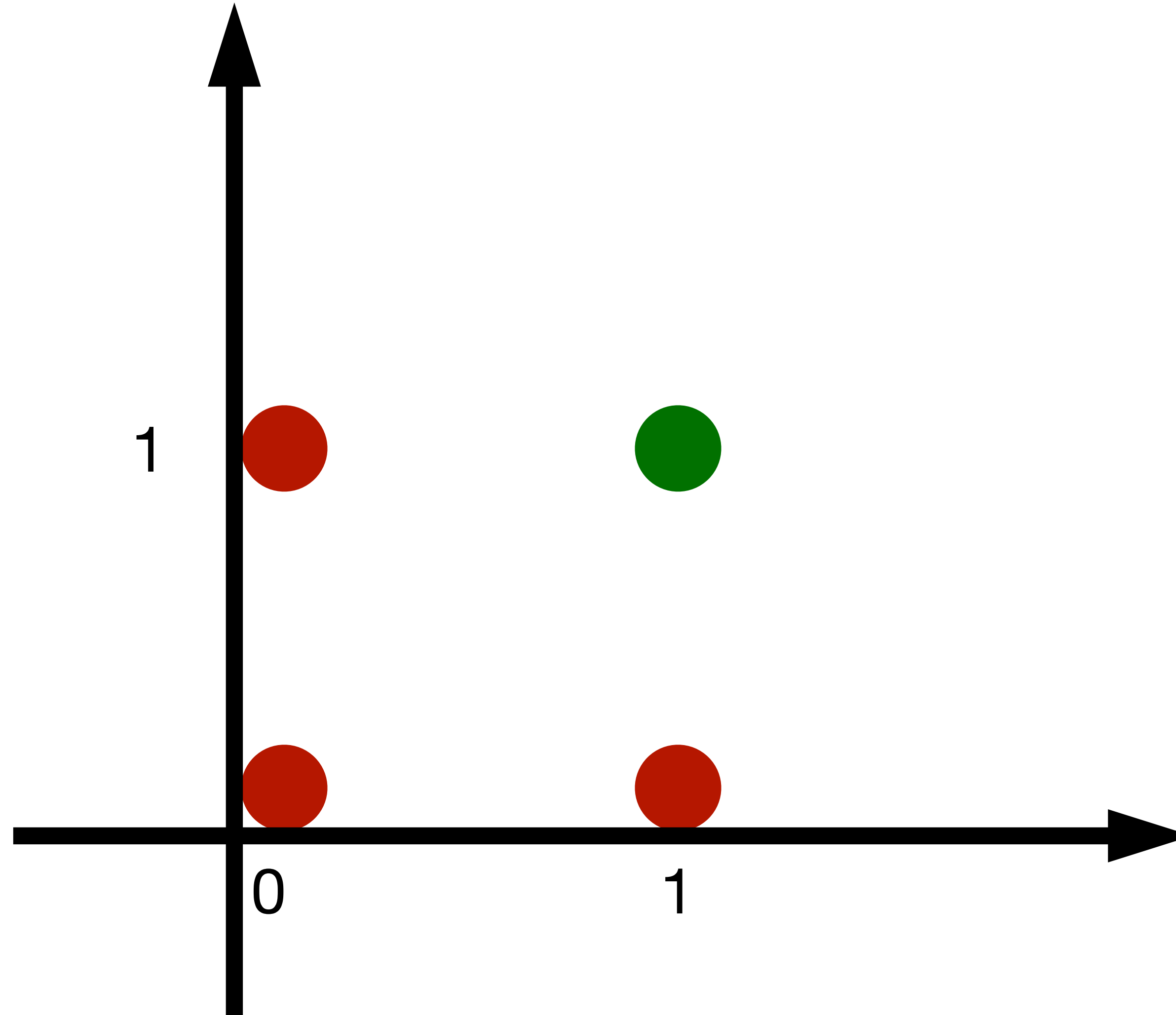
The perceptron can learn an AND function

$$x_1 = 1, x_2 = 1, y = 1$$

$$x_1 = 1, x_2 = 0, y = 0$$

$$x_1 = 0, x_2 = 1, y = 0$$

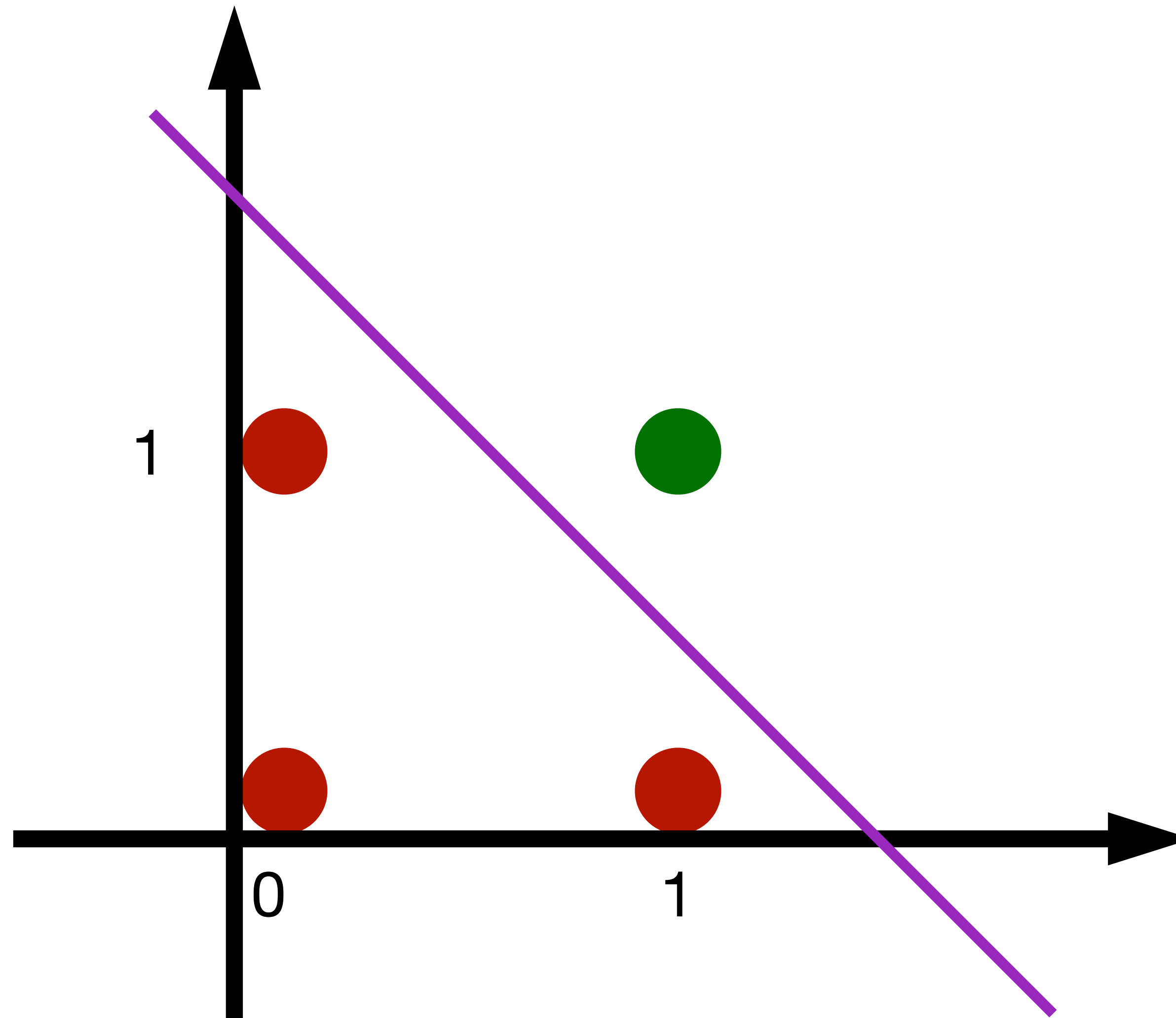
$$x_1 = 0, x_2 = 0, y = 0$$





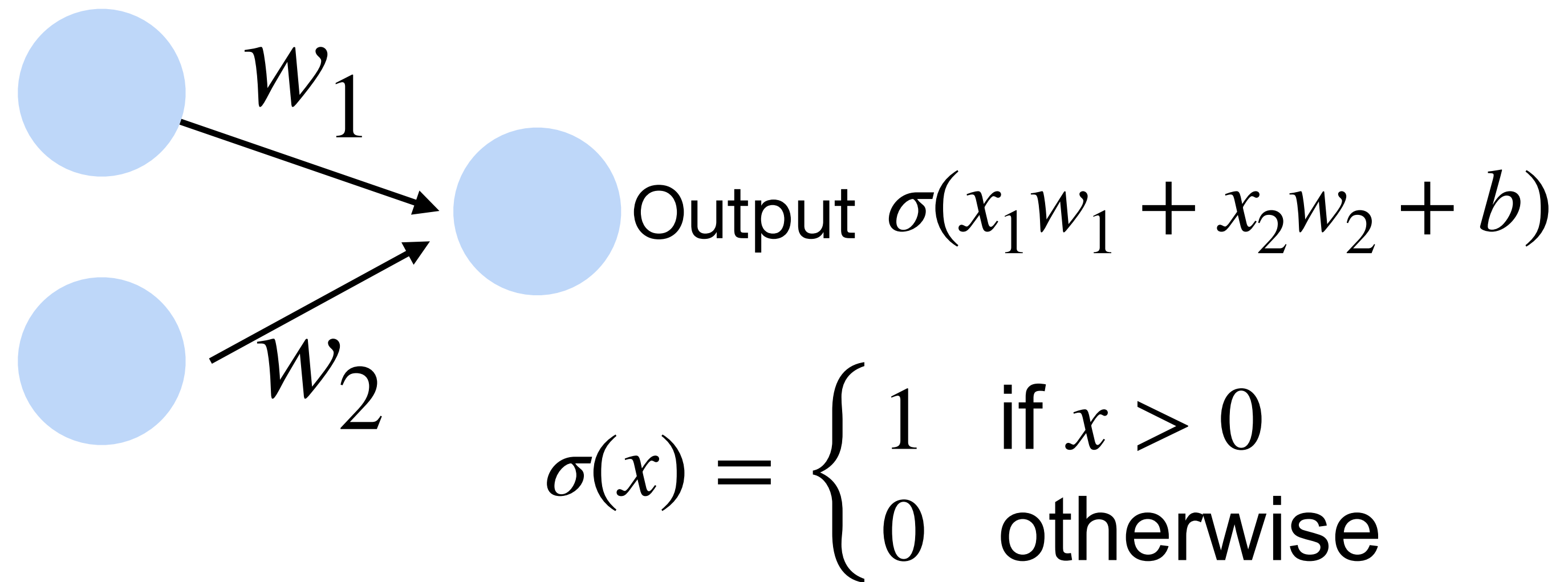
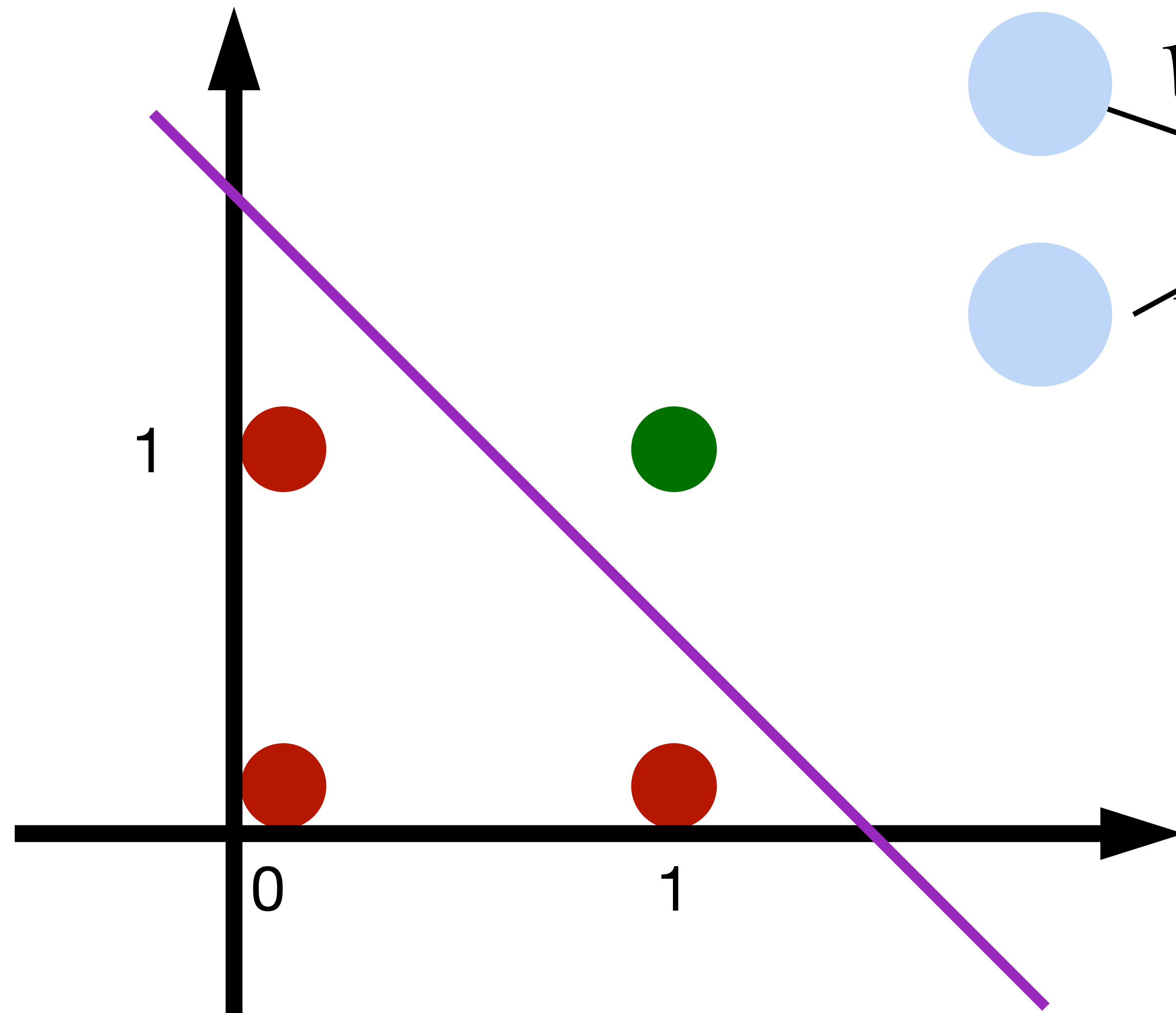
# Learning AND function using perceptron

The perceptron can learn an AND function



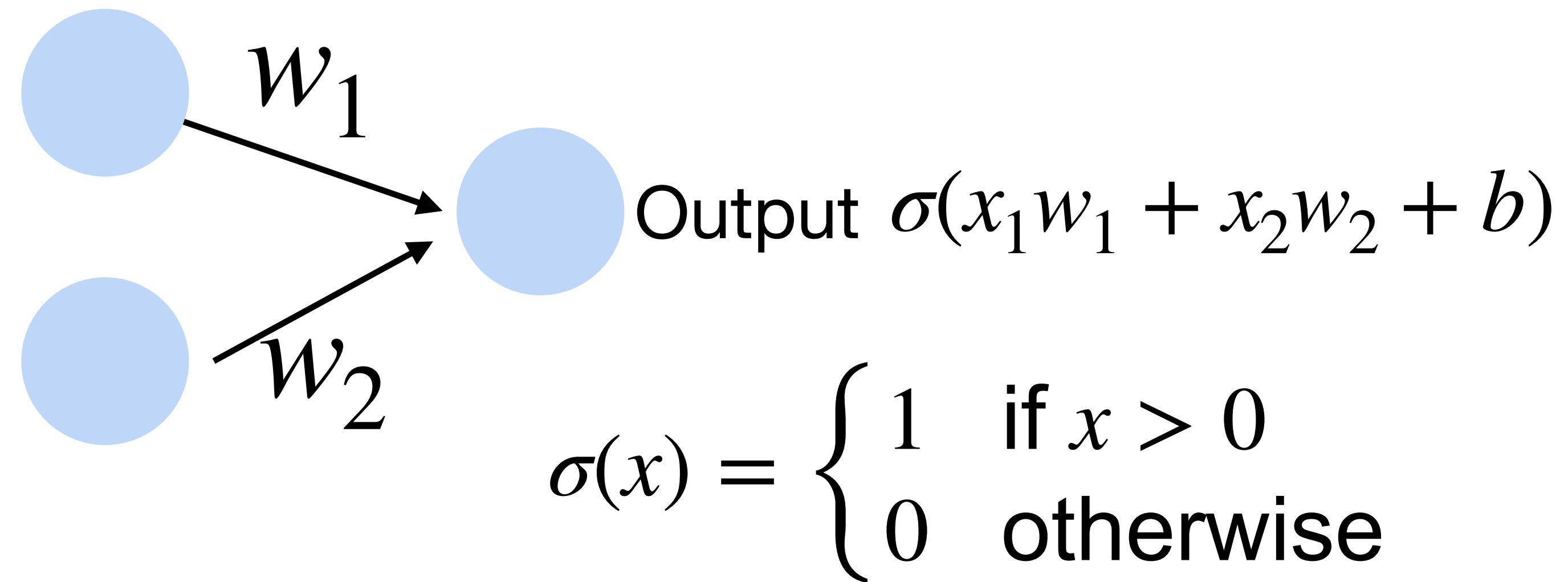
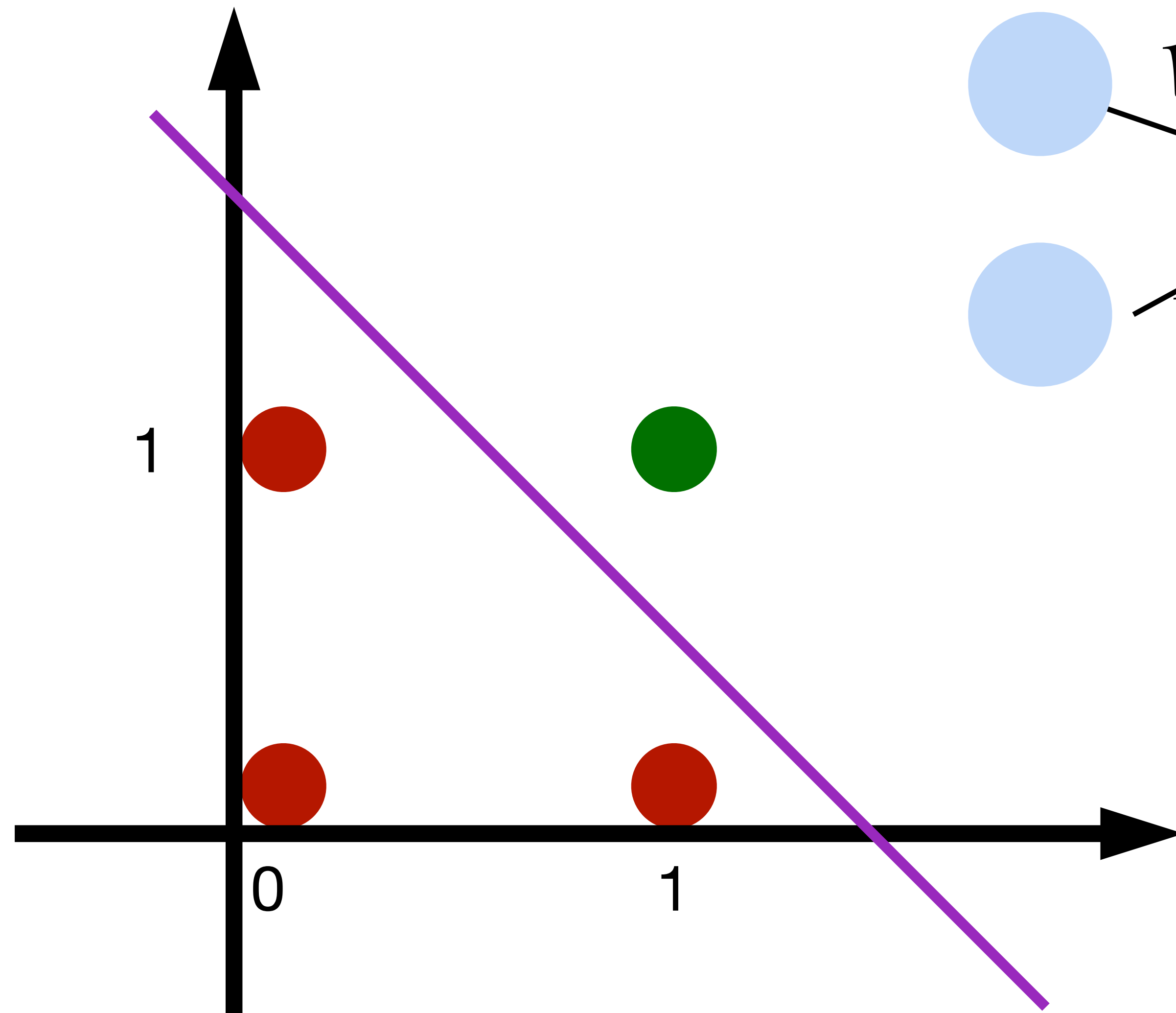
# Learning AND function using perceptron

The perceptron can learn an AND function



# Learning AND function using perceptron

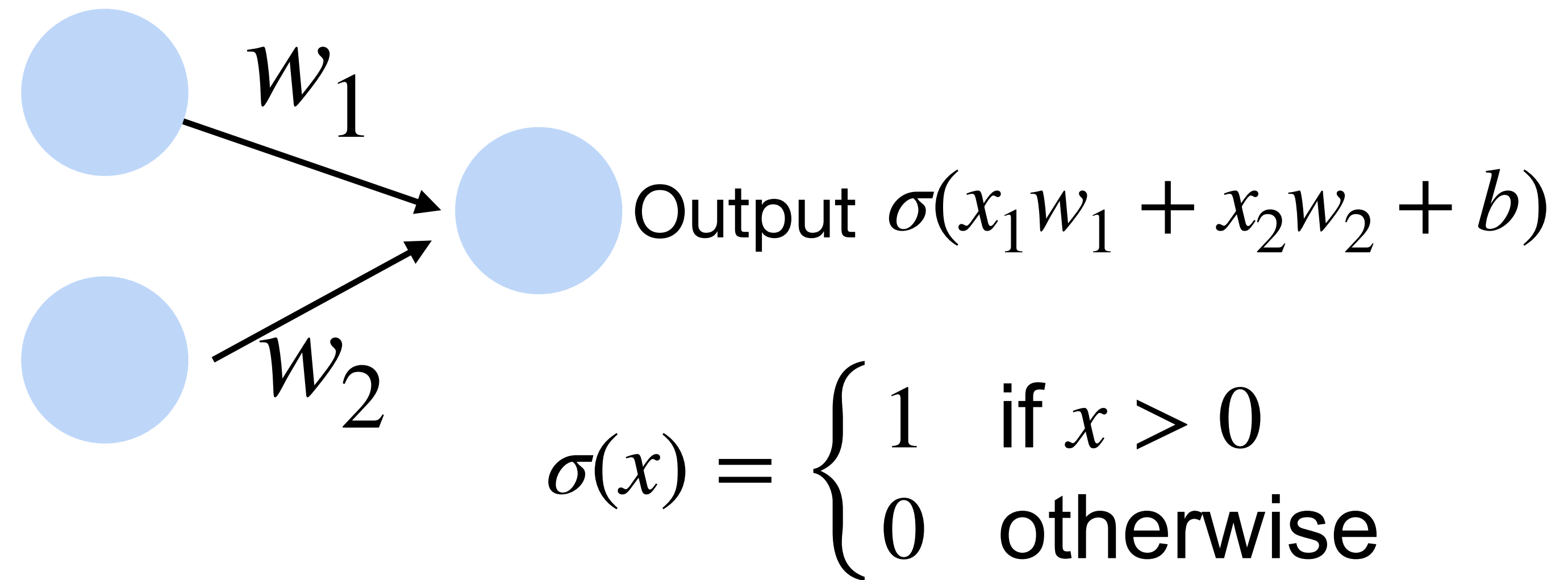
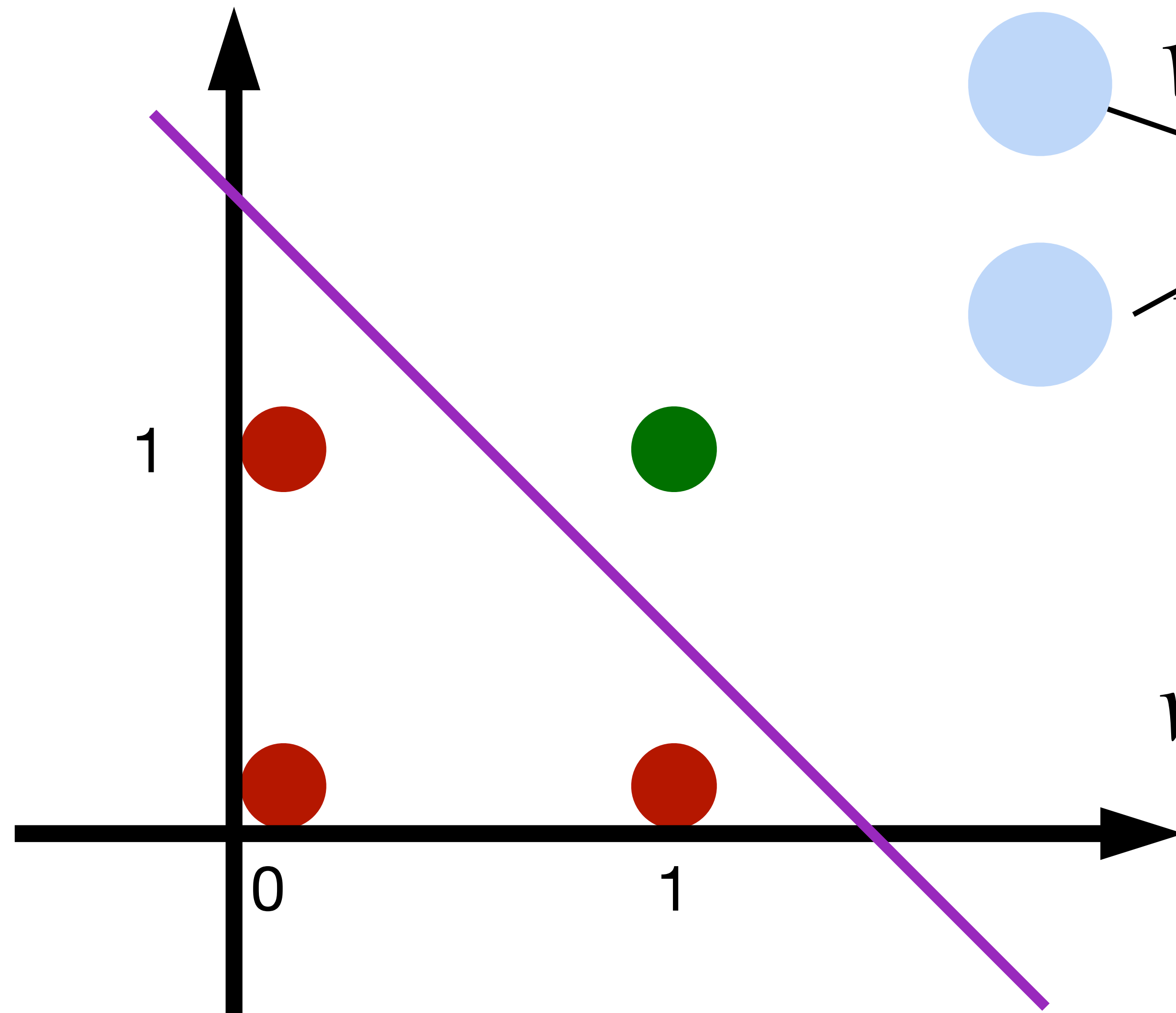
The perceptron can learn an AND function



What's  $w$  and  $b$ ?

# Learning AND function using perceptron

The perceptron can learn an AND function



$$w_1 = 1, w_2 = 1, b = -1.5$$

# Learning OR function using perceptron

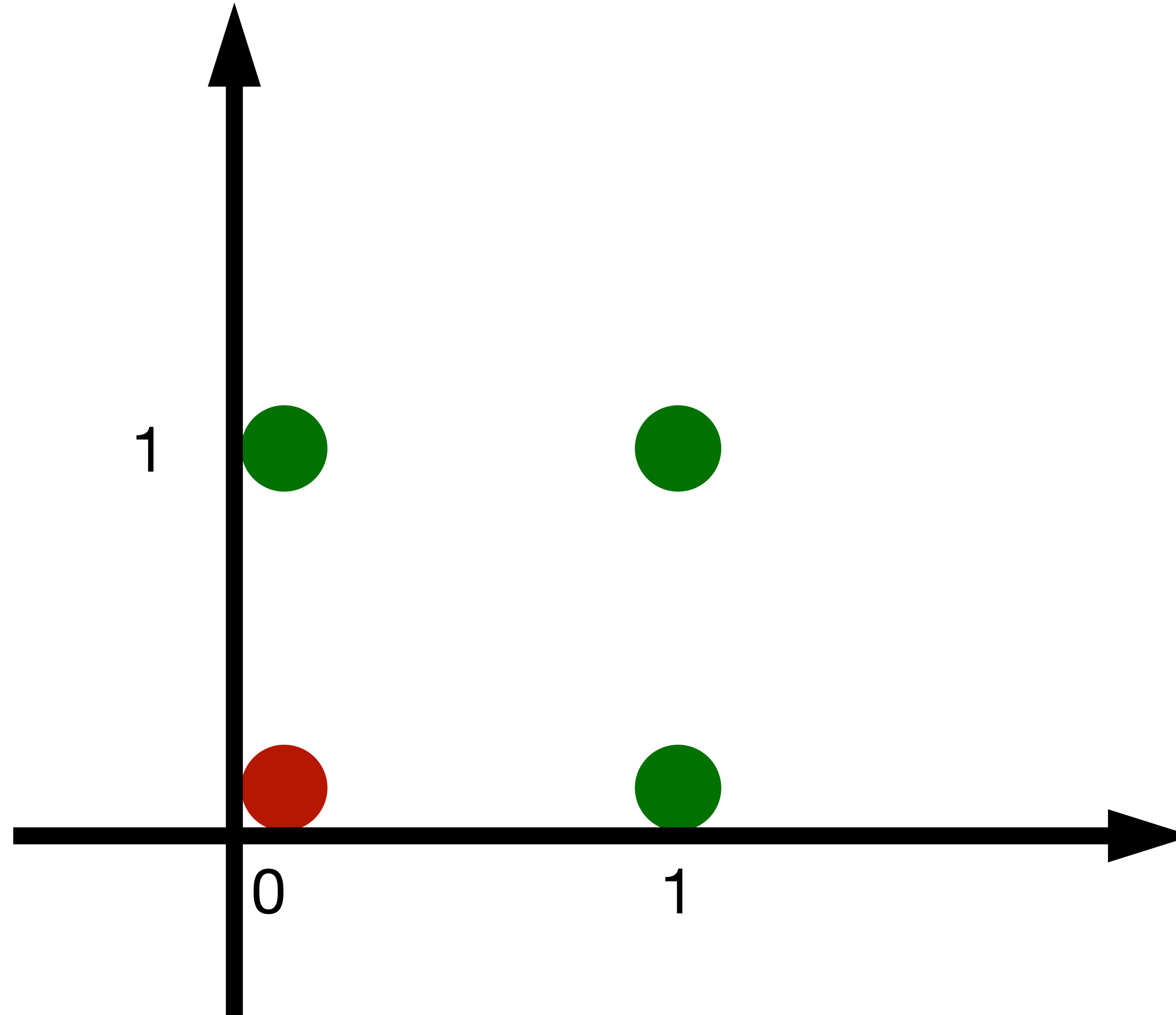
The perceptron can learn an OR function

$$x_1 = 1, x_2 = 1, y = 1$$

$$x_1 = 1, x_2 = 0, y = 1$$

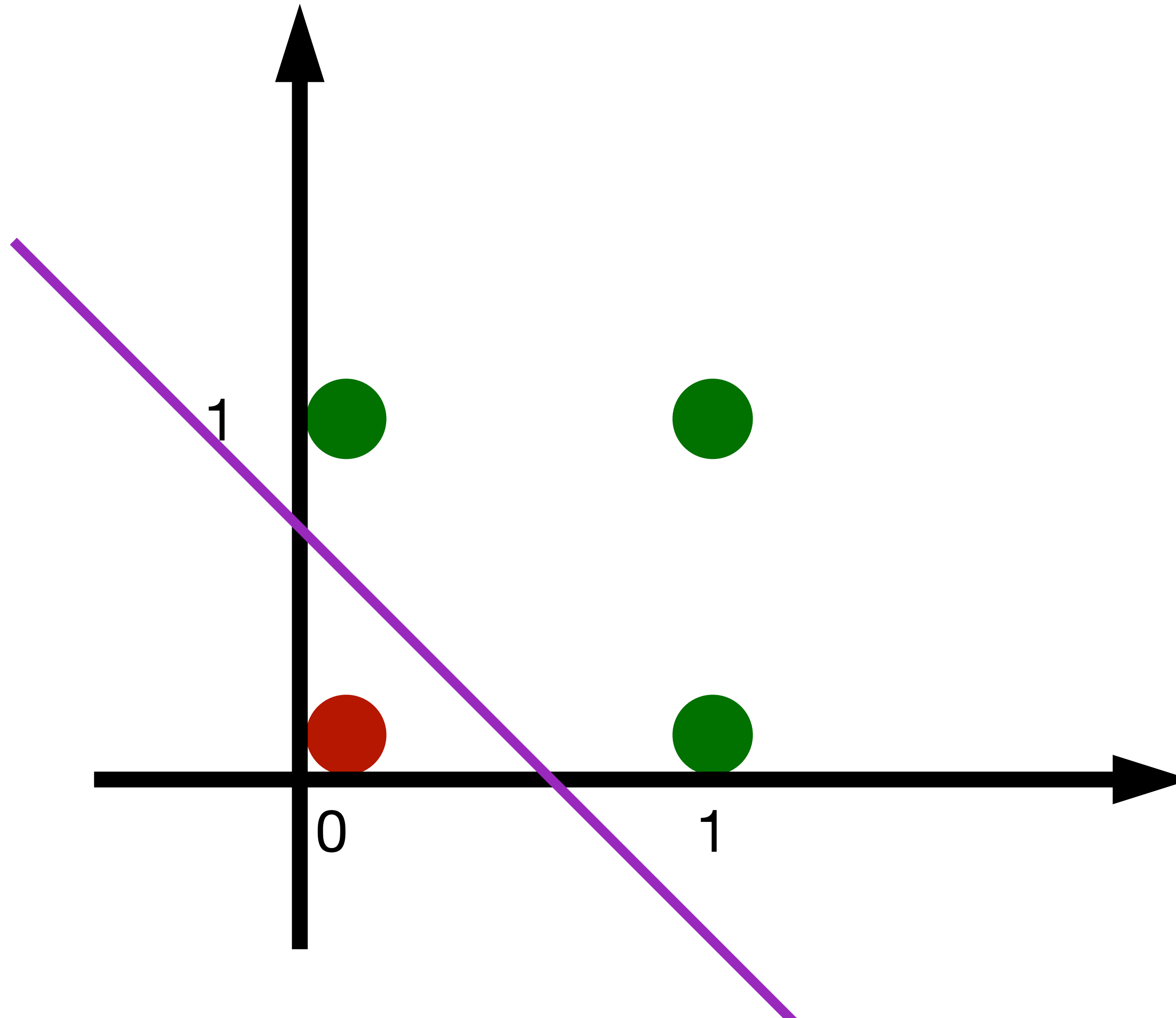
$$x_1 = 0, x_2 = 1, y = 1$$

$$x_1 = 0, x_2 = 0, y = 0$$



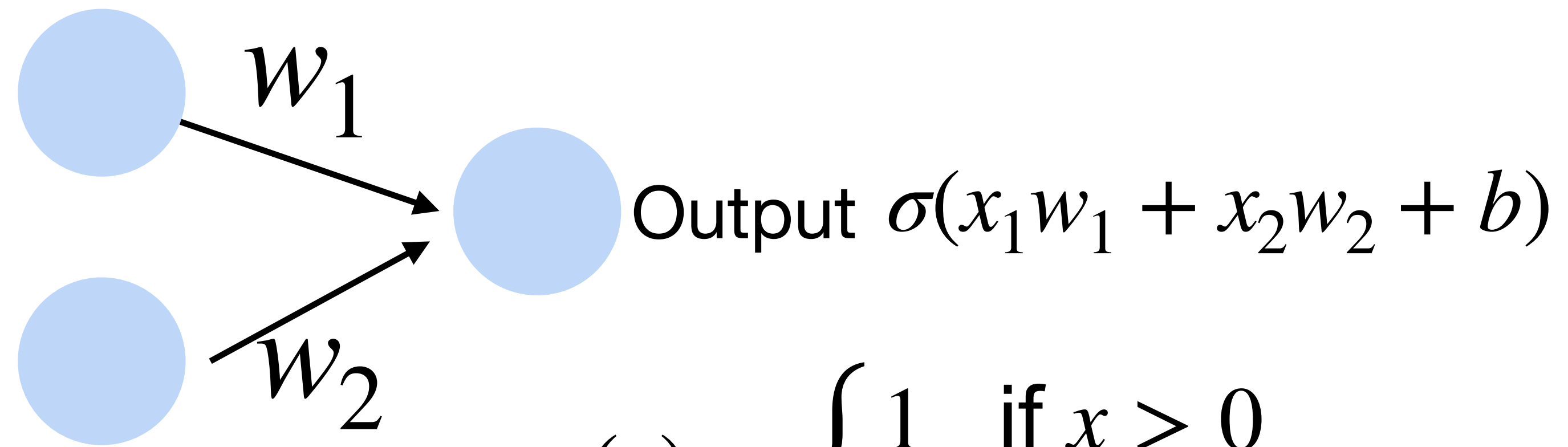
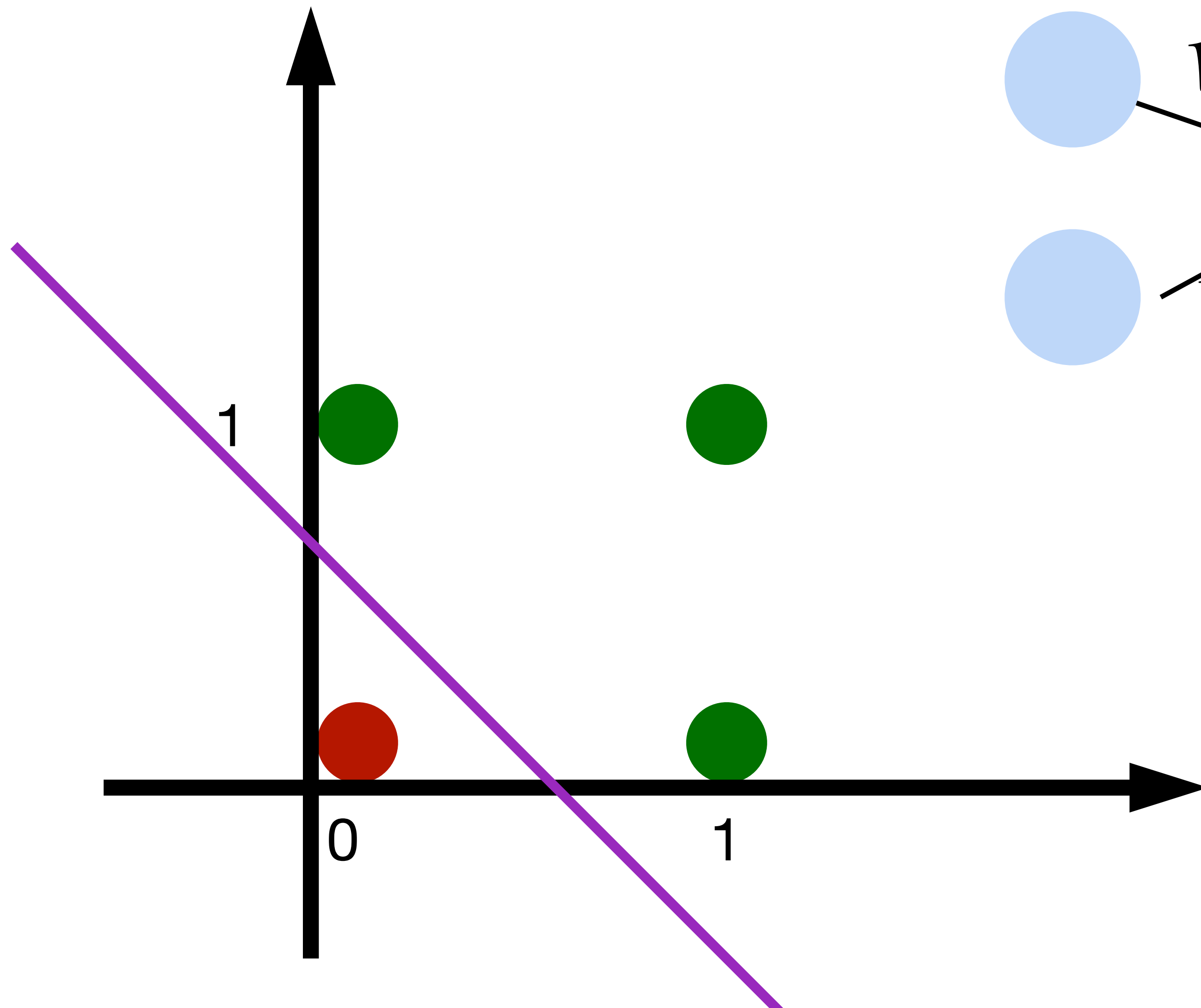
# Learning OR function using perceptron

The perceptron can learn an OR function



# Learning OR function using perceptron

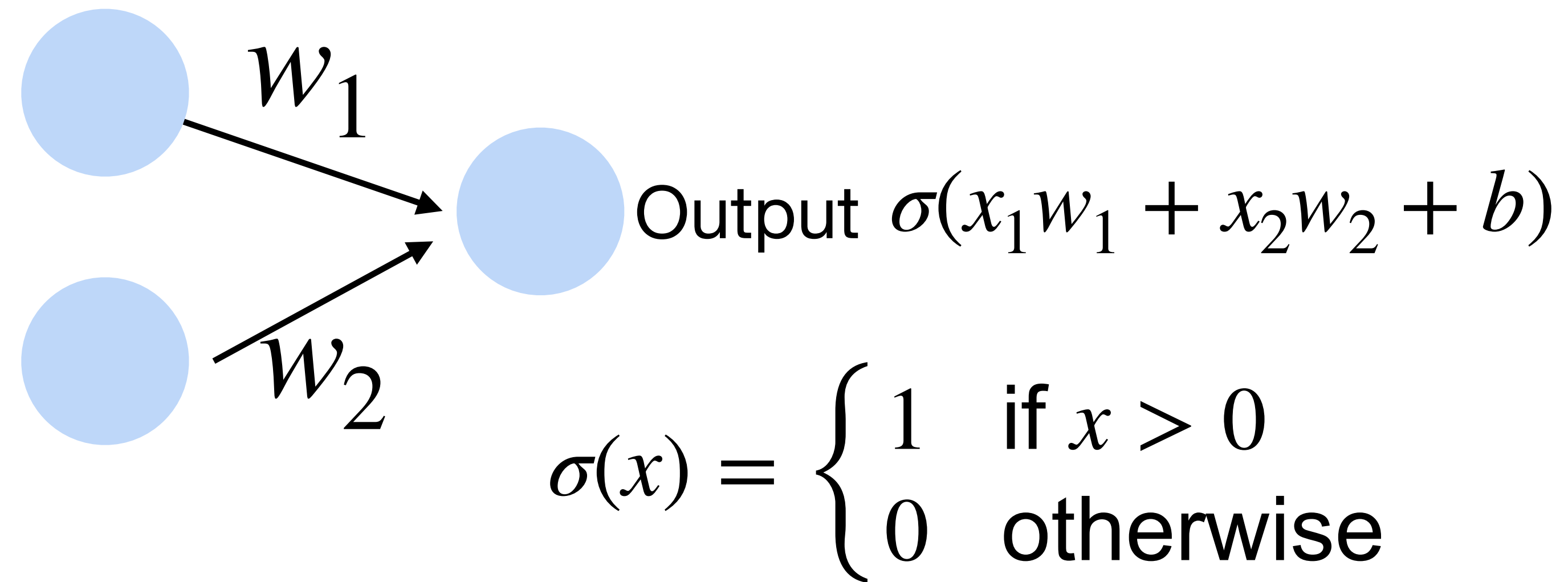
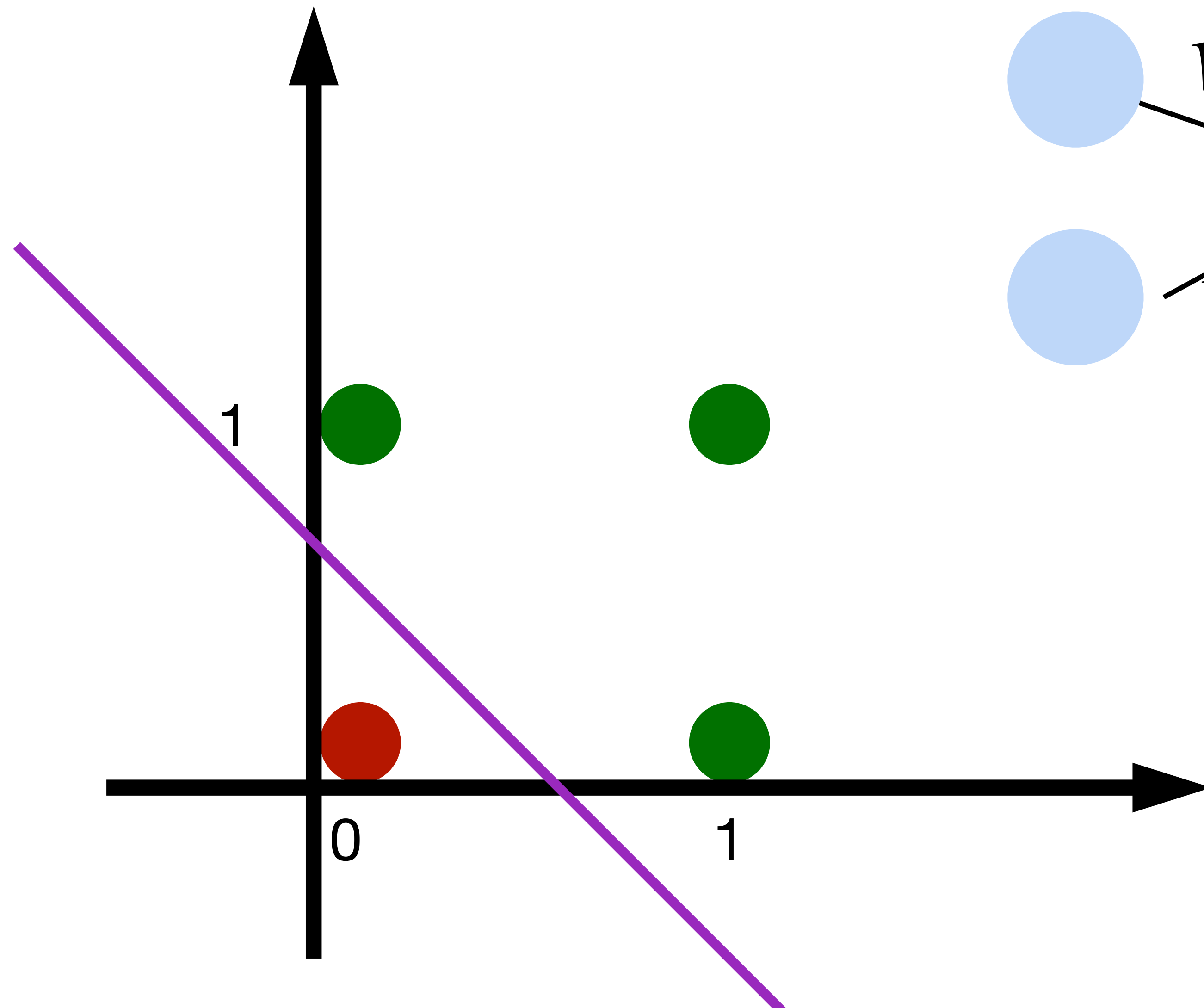
The perceptron can learn an OR function



$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

# Learning OR function using perceptron

The perceptron can learn an OR function

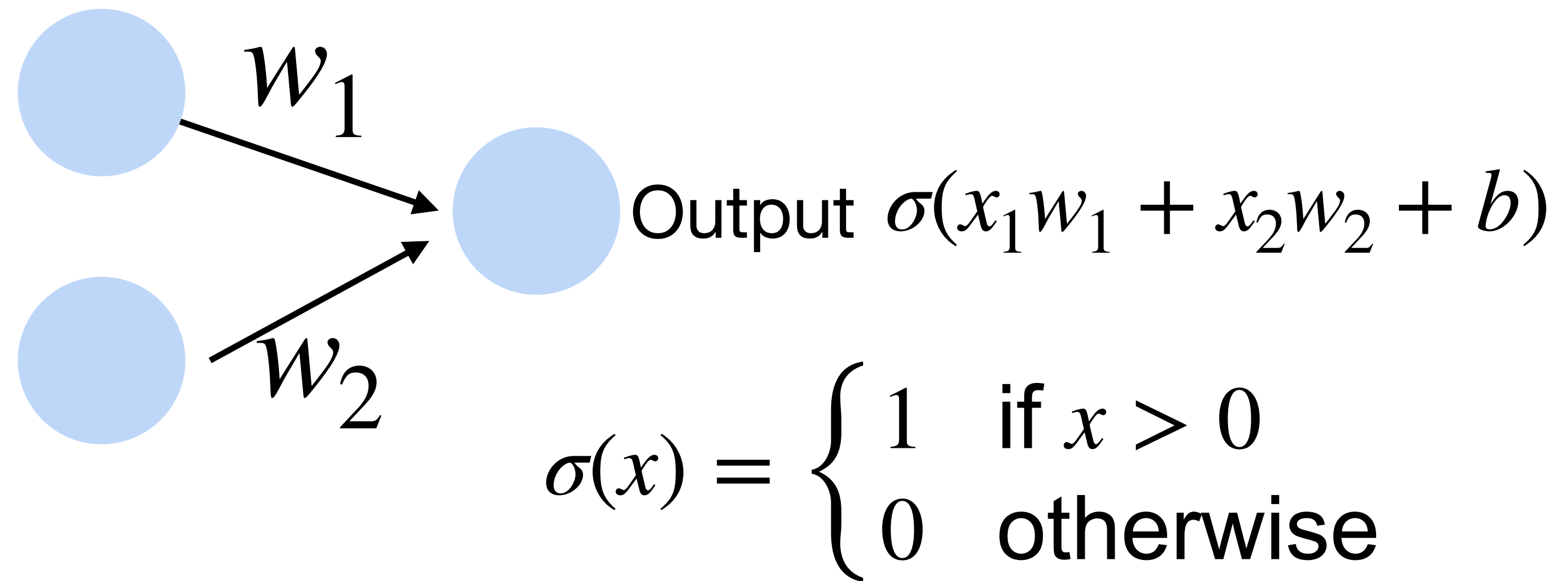
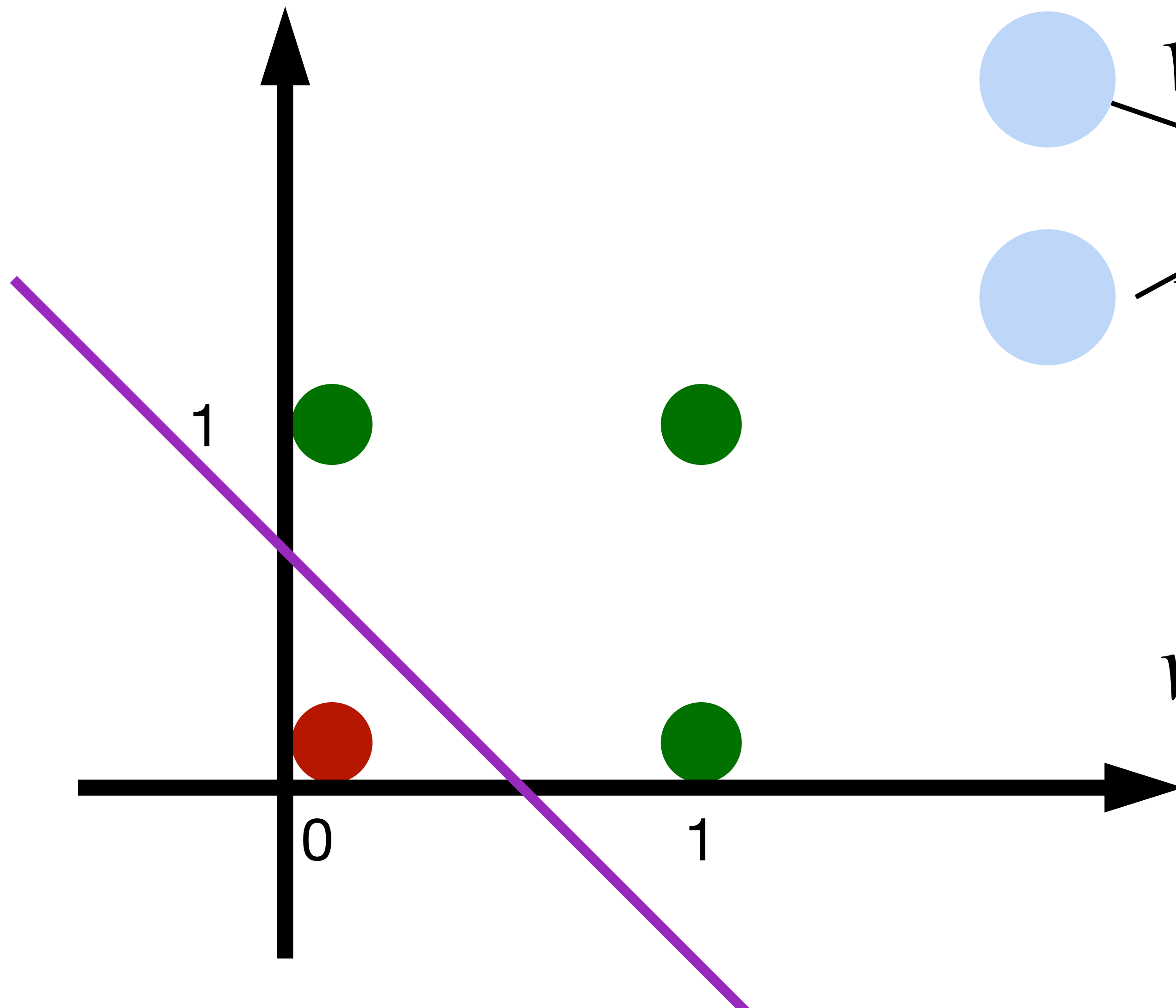


What's  $w$  and  $b$ ?



# Learning OR function using perceptron

The perceptron can learn an OR function



$$w_1 = 1, w_2 = 1, b = -0.5$$

# Learning NOT function using perceptron

The perceptron can learn NOT function (single input)



$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$



# Learning NOT function using perceptron

The perceptron can learn NOT function (single input)



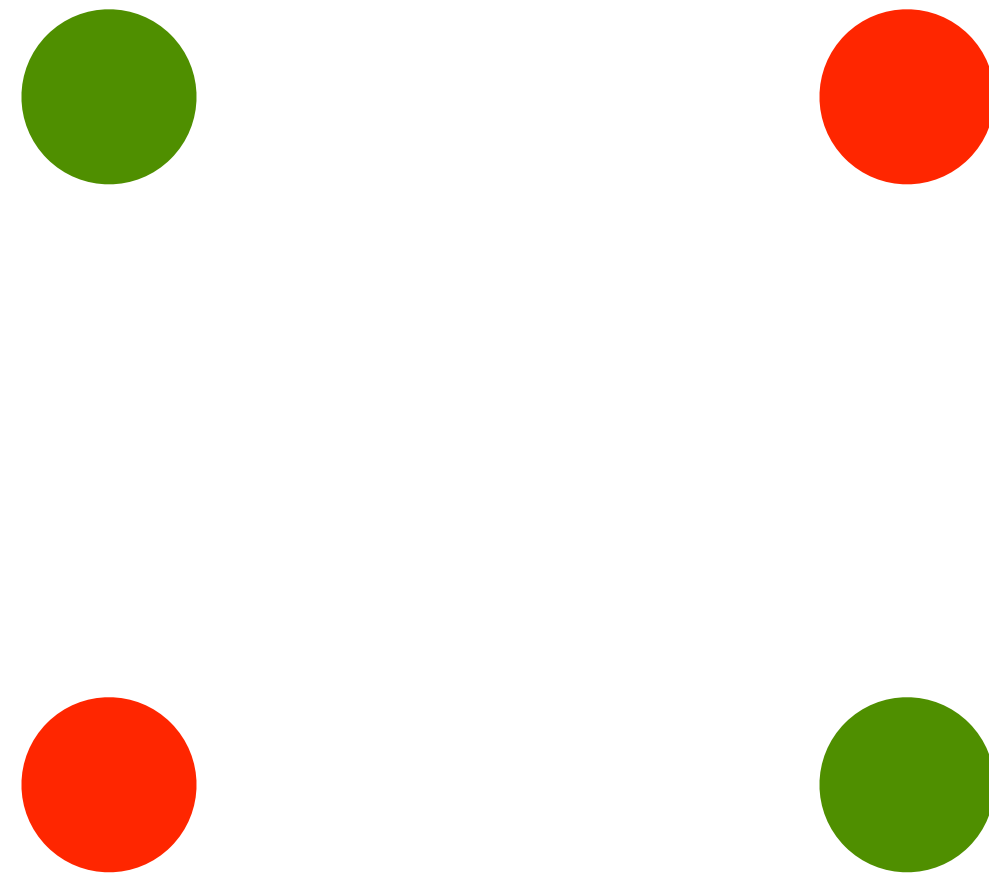
$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$w_1 = -1, b = 0.5$$



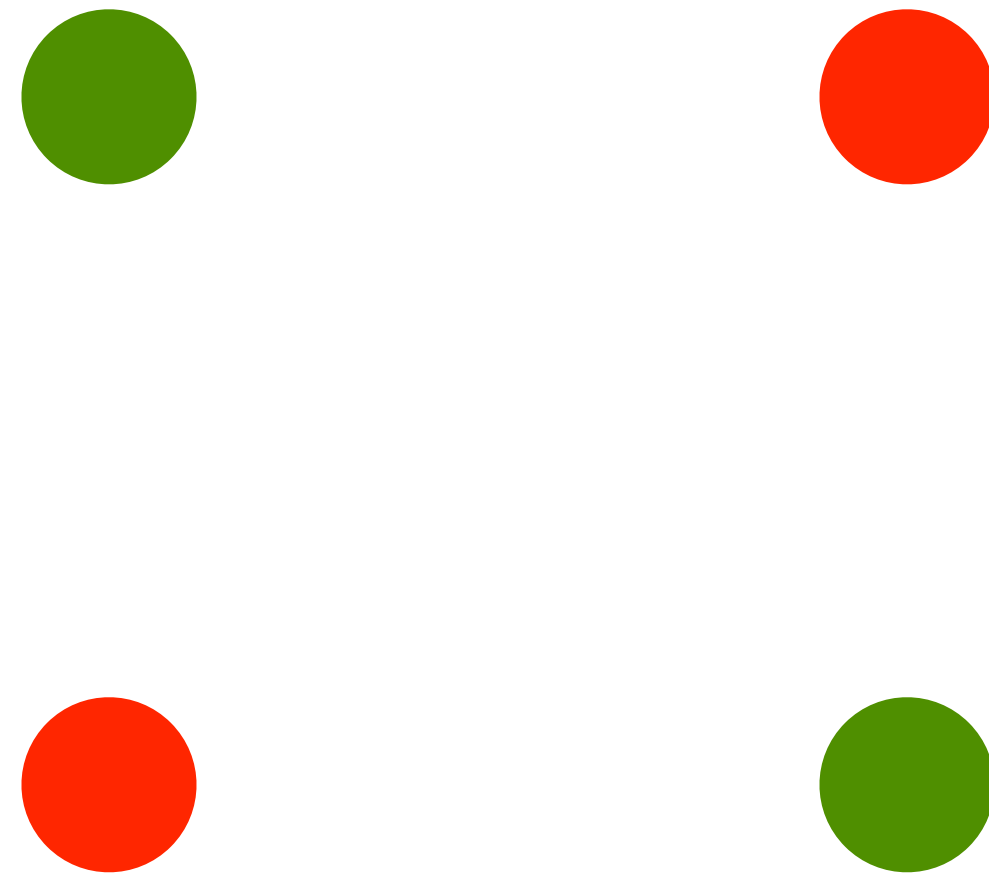
# XOR Problem (Minsky & Papert, 1969)

The perceptron cannot learn an XOR function  
(it can only generate linear separators)



# XOR Problem (Minsky & Papert, 1969)

The perceptron cannot learn an XOR function  
(it can only generate linear separators)



This contributed to the first AI winter

# Quiz Break

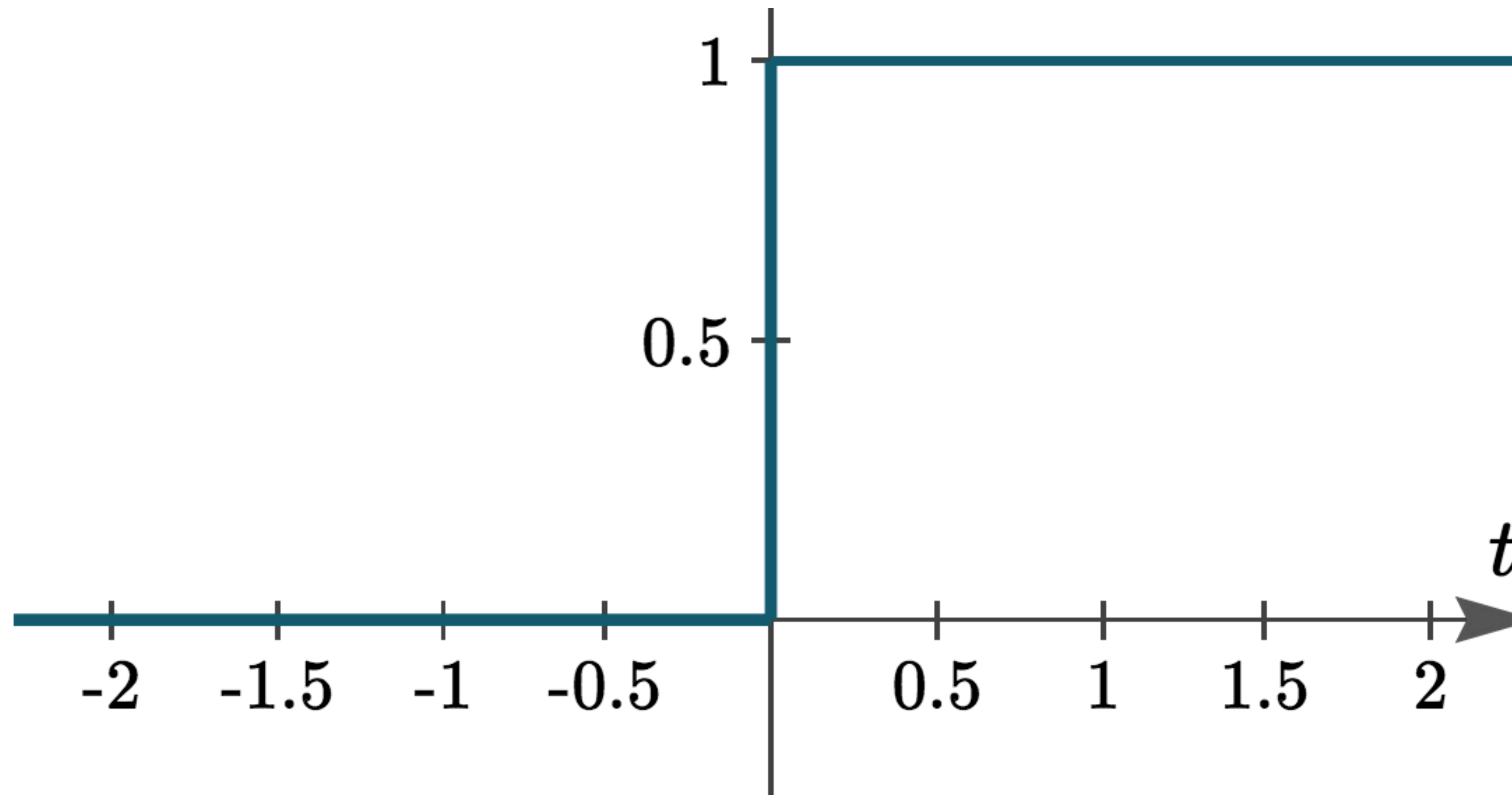
Perceptron can be used for representing:

- A. AND function
- B. OR function
- C. XOR function
- D. Both AND and OR function

# Step Function activation

Step function is discontinuous, which cannot be used for gradient descent

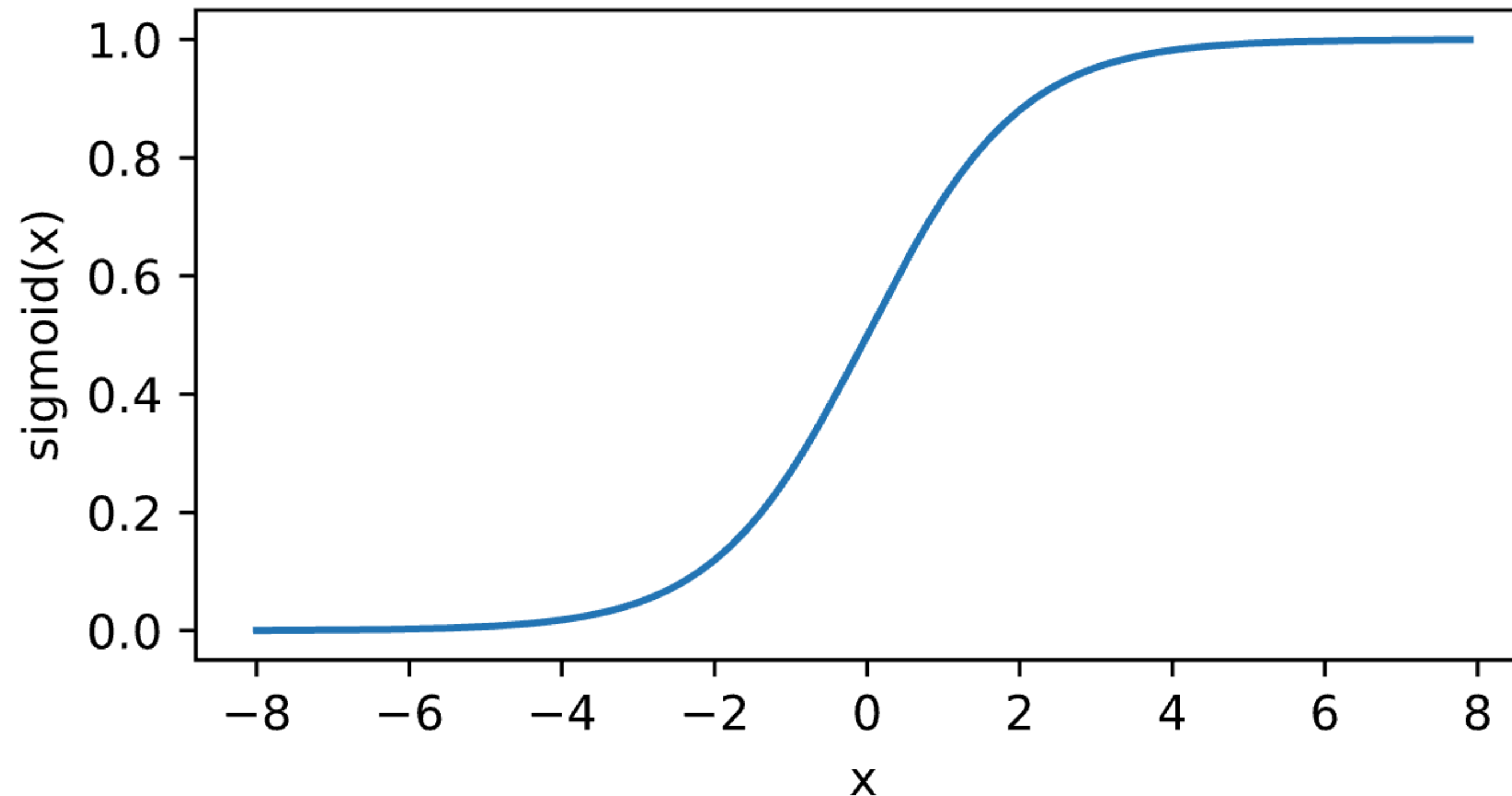
$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$



# Sigmoid/Logistic Activation

Map input into  $[0, 1]$ , a **soft** version of  $\sigma(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$

$$\sigma(z) = \text{sigmoid}(z) = \frac{1}{1 + \exp(-z)}$$



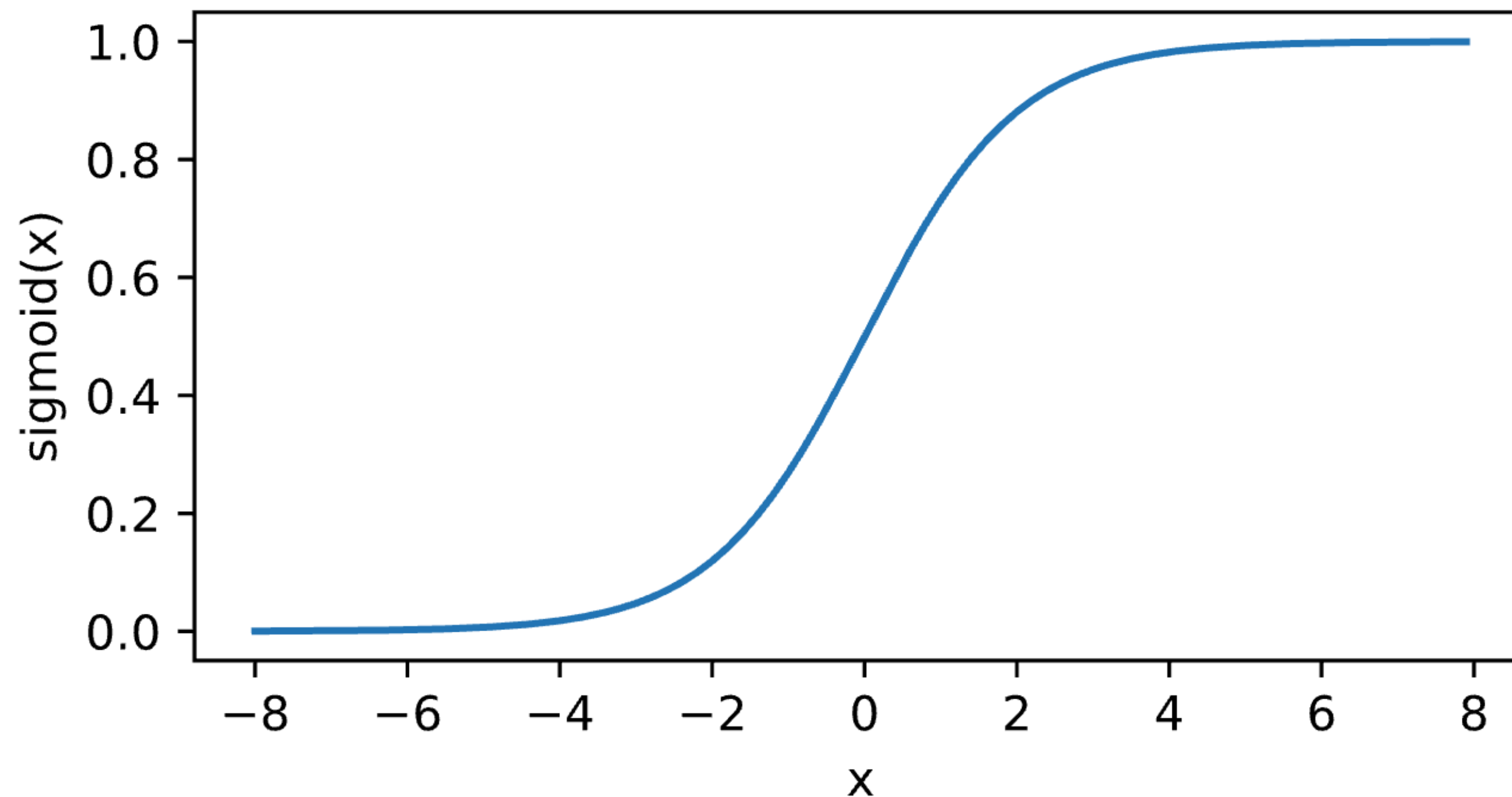


# Logistic regression

$$\mathbf{x} \in \mathbb{R}^d, y = \{-1, +1\}$$

$$p(y = 1 | \mathbf{x}) = \sigma(\mathbf{w}^T \mathbf{x}) = \frac{1}{1 + \exp(-\mathbf{w}^T \mathbf{x})}$$

$$p(y = -1 | \mathbf{x}) = 1 - \sigma(\mathbf{w}^T \mathbf{x}) = \frac{1}{1 + \exp(\mathbf{w}^T \mathbf{x})}$$



# Logistic regression

Given:  $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$        $\mathbf{x} \in \mathbb{R}^d, y = \{-1, +1\}$

Training: maximize likelihood estimate (on the conditional probability)

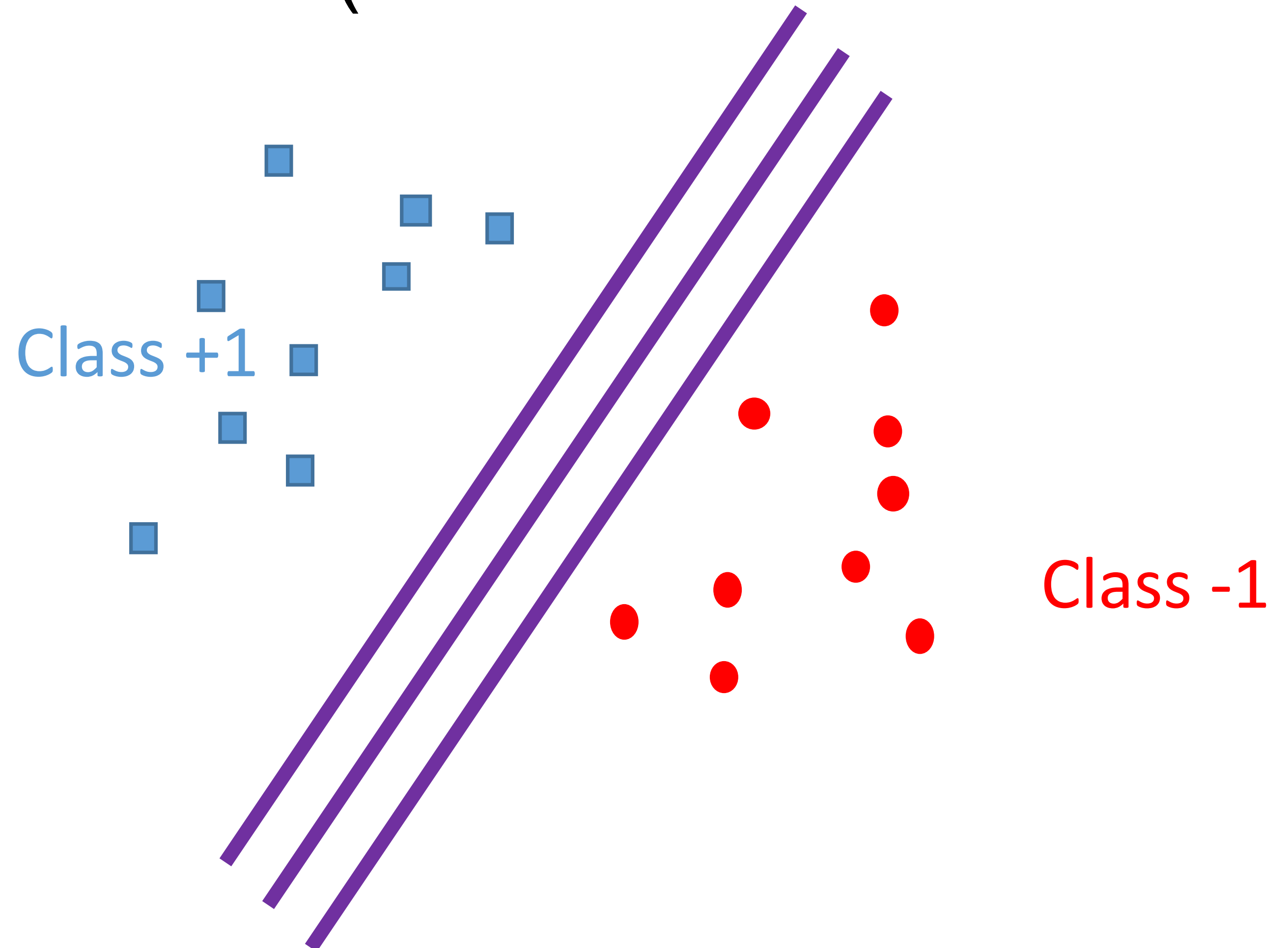
$$\max_{\mathbf{w}} \sum_i \log \frac{1}{1 + \exp(-y_i \mathbf{w}^T \mathbf{x}_i)}$$

# Logistic regression

Given:  $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$       $\mathbf{x} \in \mathbb{R}^d, y = \{-1, +1\}$

Training: maximize likelihood estimate (on the conditional probability)

When training data is linearly separable, many solutions



# Logistic regression

Given:  $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$       $\mathbf{x} \in \mathbb{R}^d, y = \{-1, +1\}$

Training: maximum A posteriori (MAP)

$$\min_{\mathbf{w}} \sum_i -\log \frac{1}{1 + \exp(-y_i \mathbf{w}^T \mathbf{x}_i)} + \frac{\lambda}{2} \|\mathbf{w}\|_2^2$$

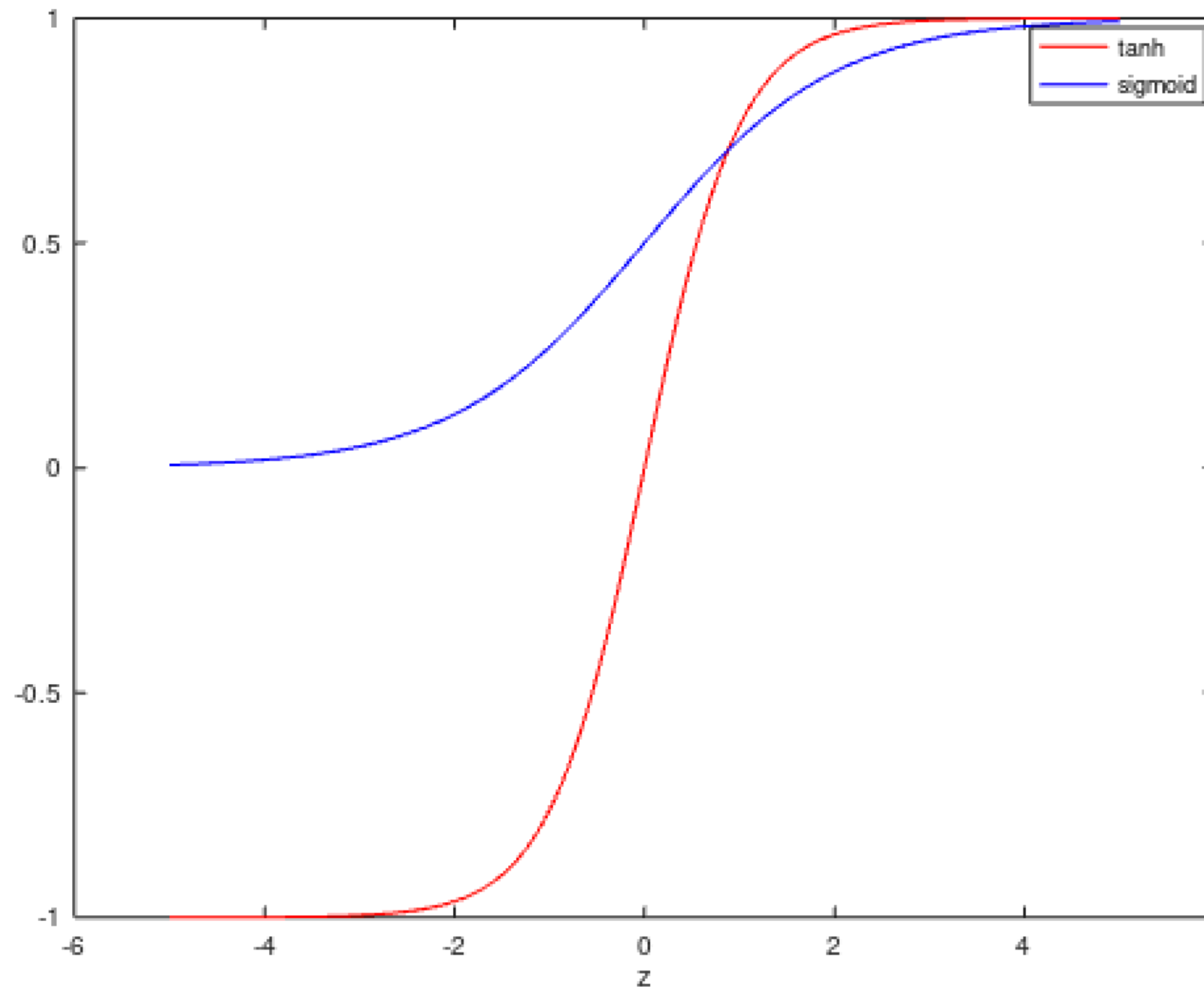
- Convex optimization
- Solve via (stochastic) gradient descent

# Tanh Activation

Map inputs into  $(-1, 1)$

$$\sigma(z) = \tanh(z) = \frac{1 - \exp(-2z)}{1 + \exp(-2z)}$$

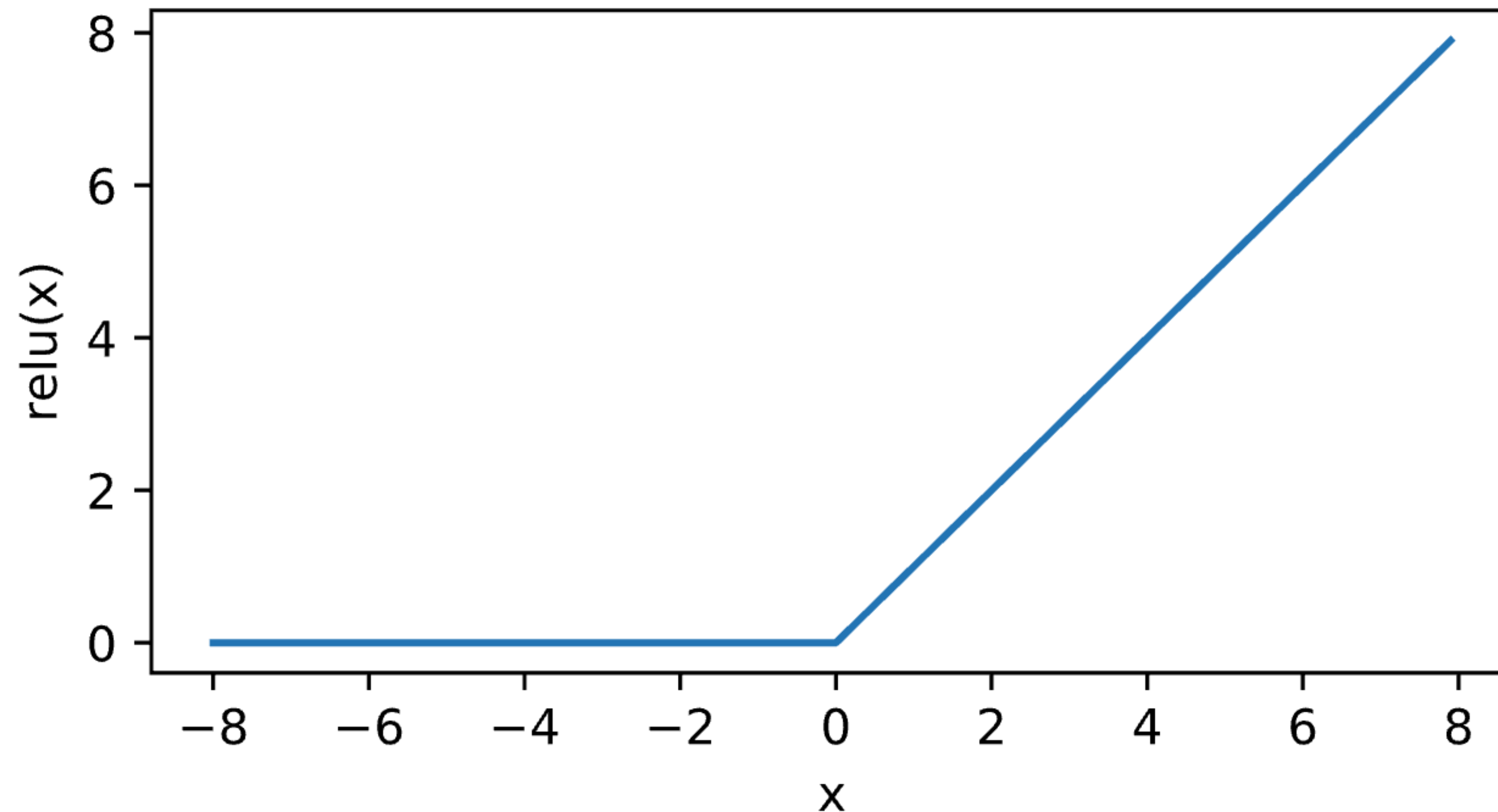
$$\tanh(z) = 2\text{sigmoid}(2z) - 1$$



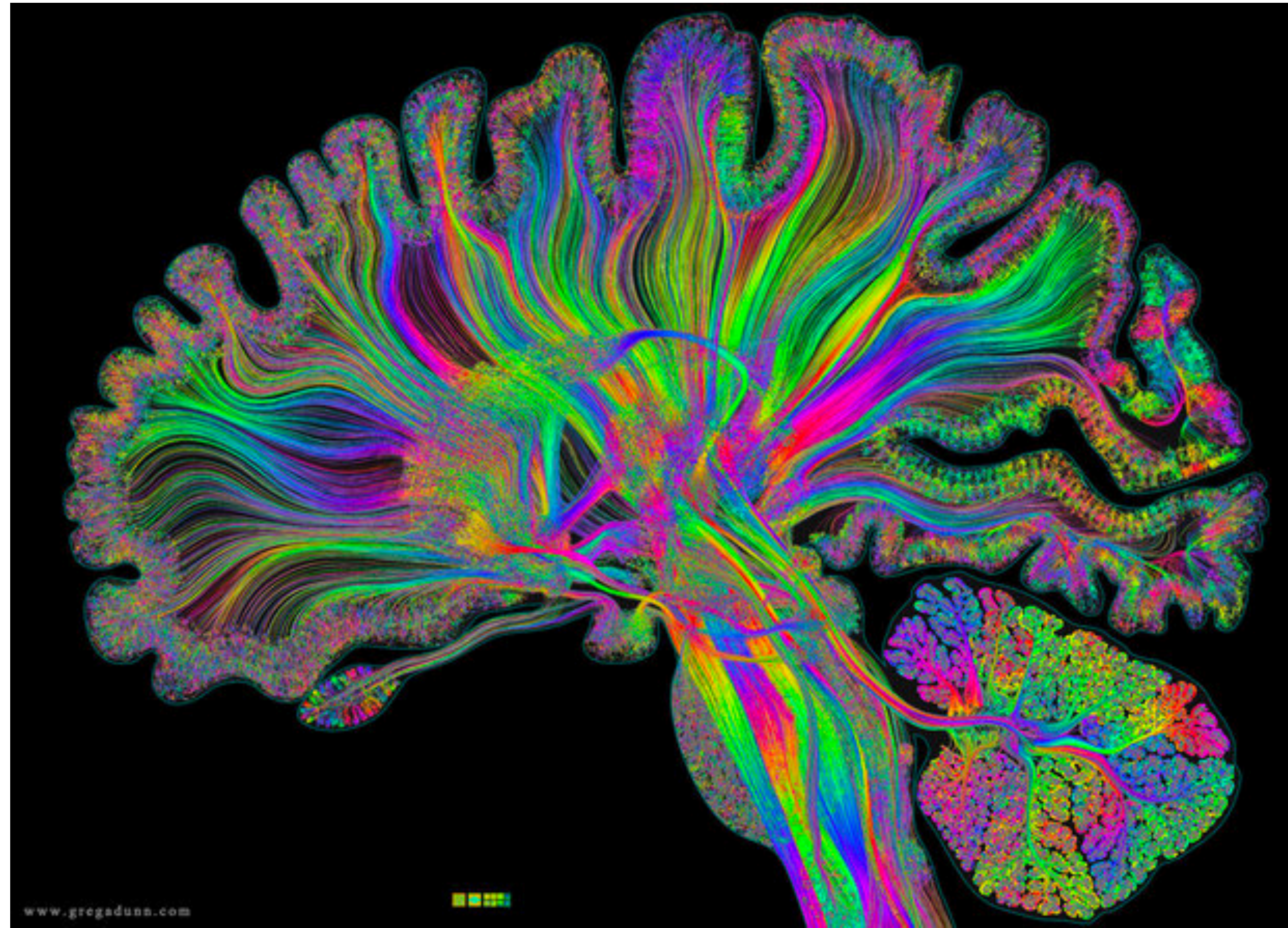
# ReLU Activation

ReLU: rectified linear unit (commonly used in modern neural networks)

$$\text{ReLU}(x) = \max(x, 0)$$



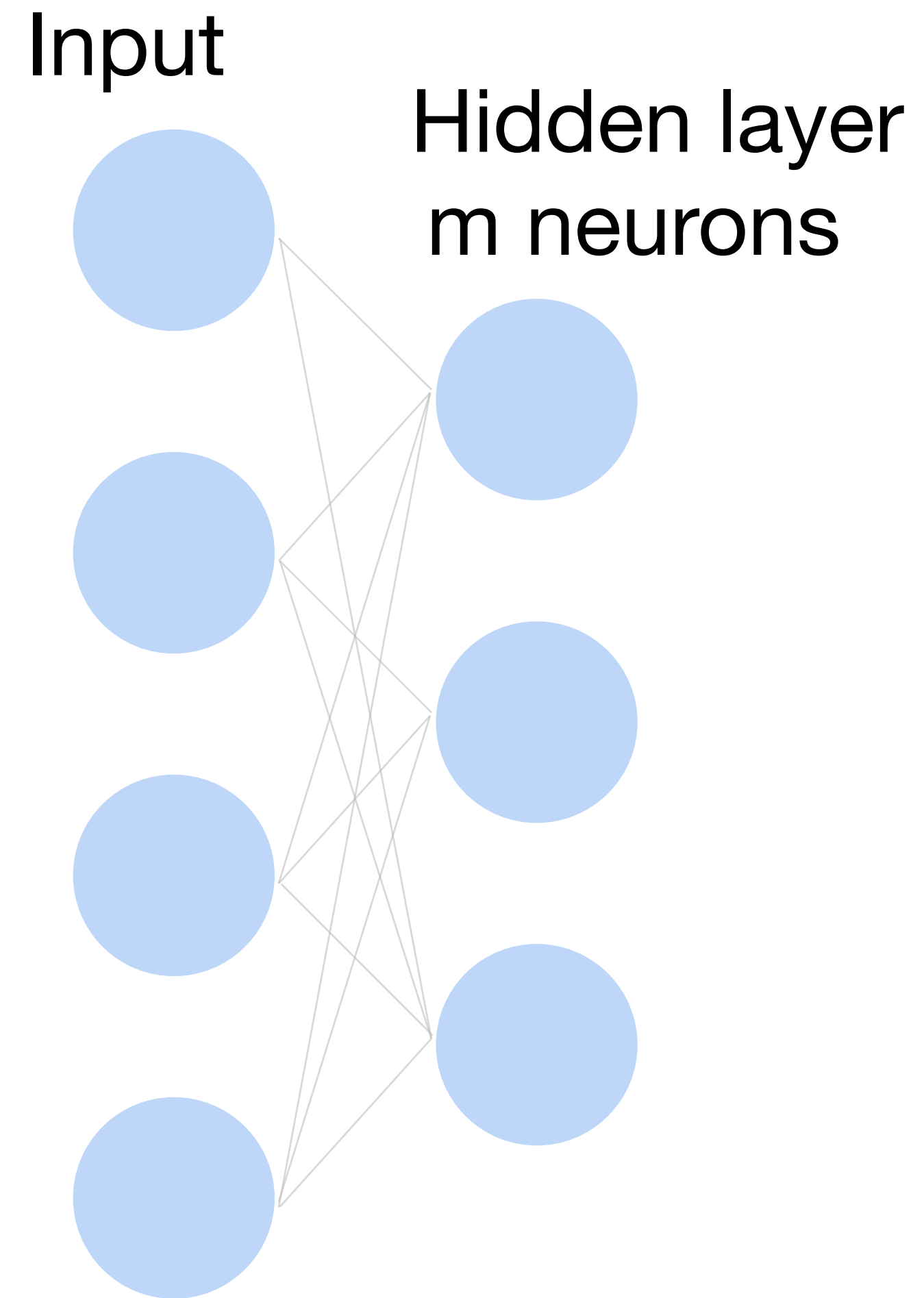
# Multilayer Perceptron



# Single Hidden Layer

## How to classify

Cats vs. dogs?

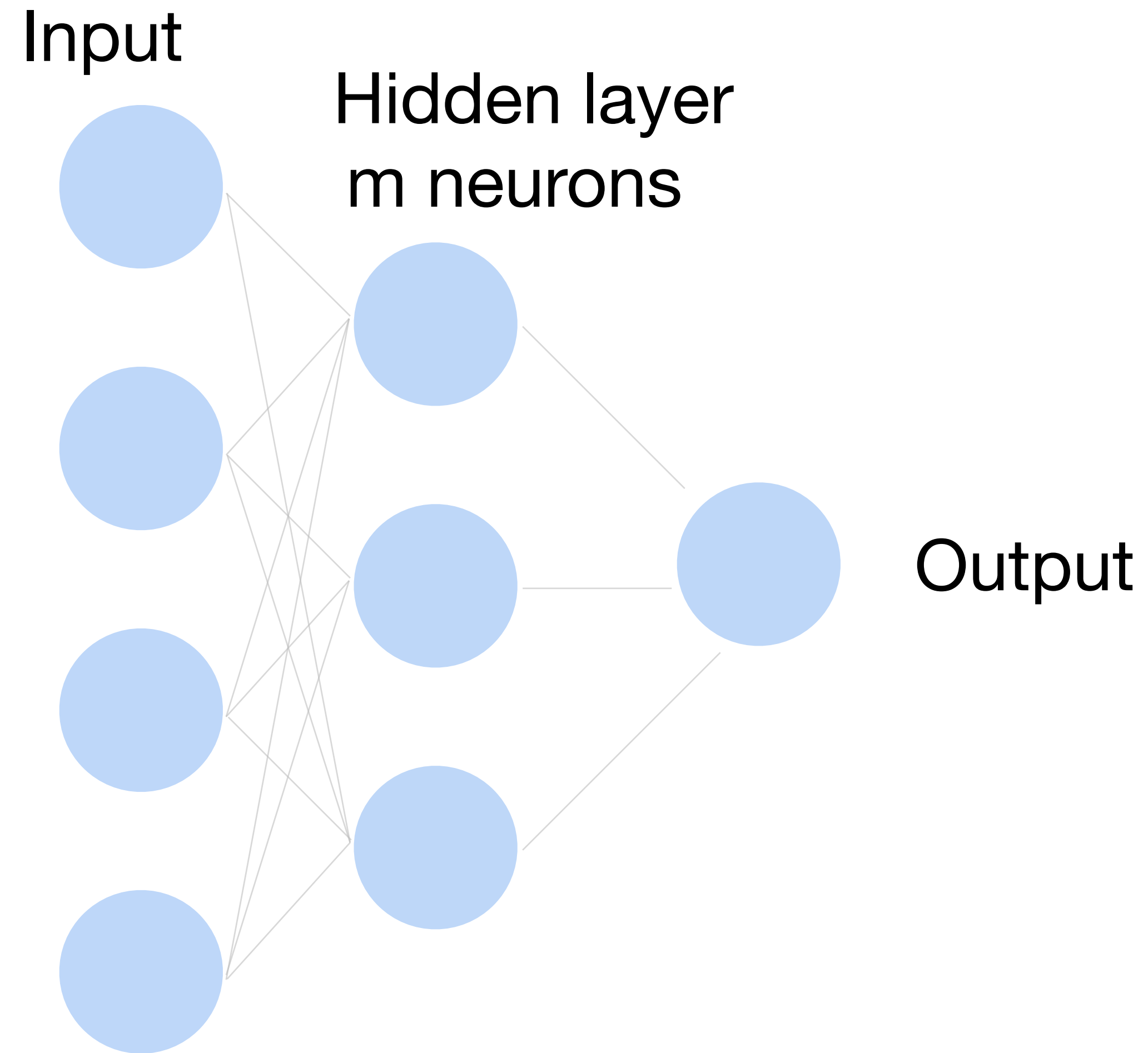




# Single Hidden Layer

## How to classify

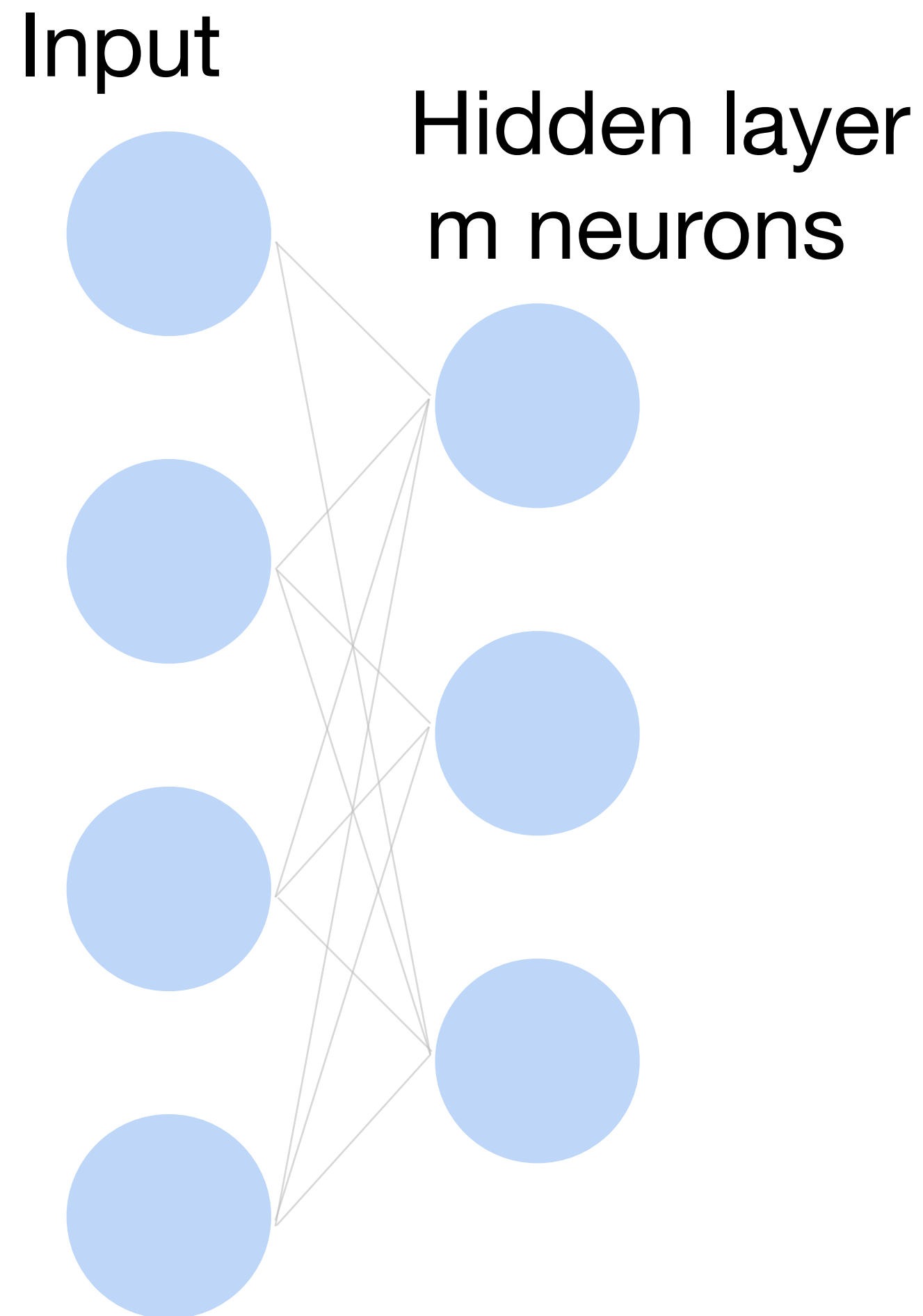
Cats vs. dogs?



# Single Hidden Layer

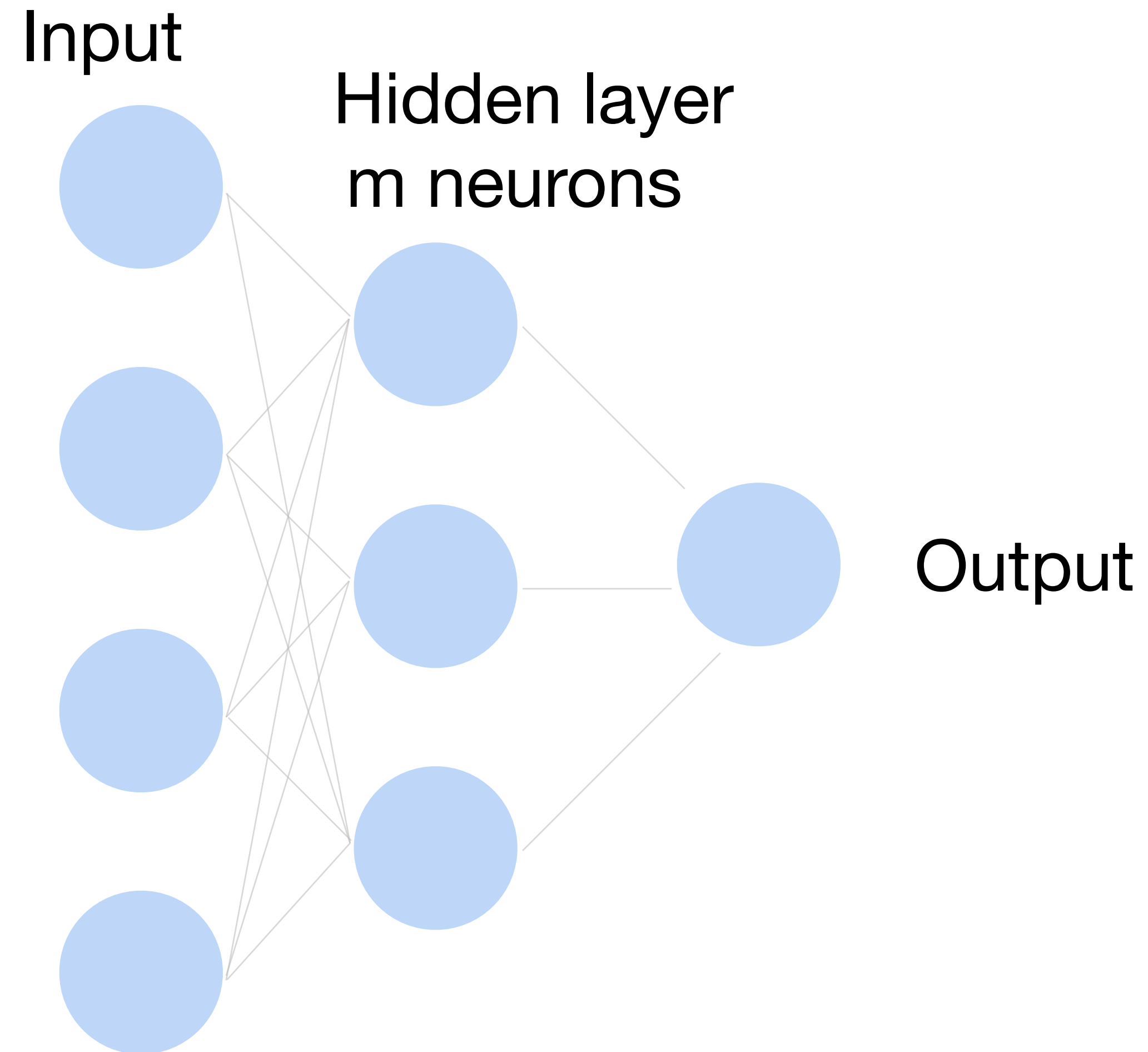
- Input  $\mathbf{x} \in \mathbb{R}^d$
- Hidden  $\mathbf{W} \in \mathbb{R}^{m \times d}$ ,  $\mathbf{b} \in \mathbb{R}^m$
- Intermediate output  
 $\mathbf{h} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$

$\sigma$  is an element-wise  
activation function

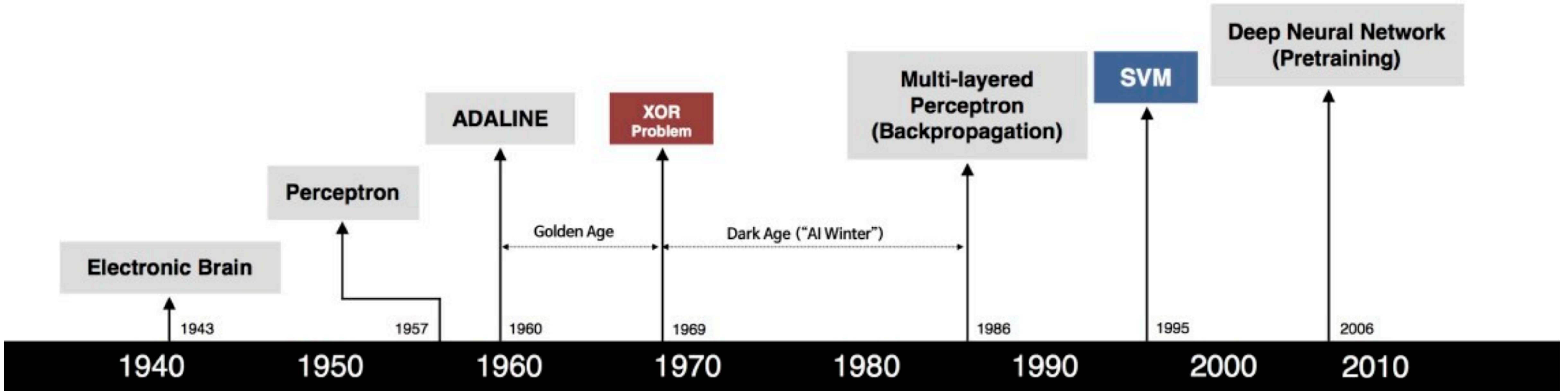


# Single Hidden Layer

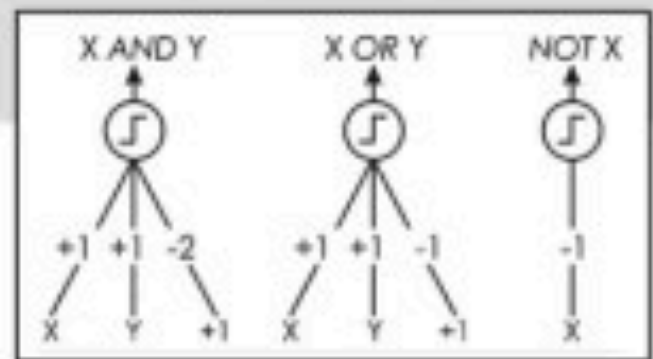
- Output  $\mathbf{f} = \mathbf{w}_2^T \mathbf{h} + b_2$



# Brief history of neural networks



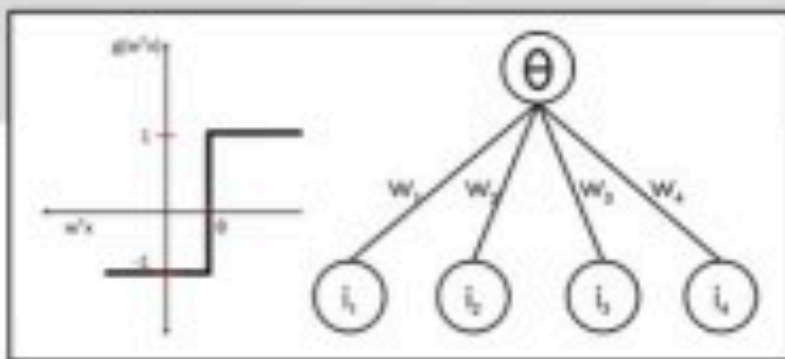
S. McCulloch - W. Pitts



- Adjustable Weights
- Weights are not Learned



F. Rosenblatt



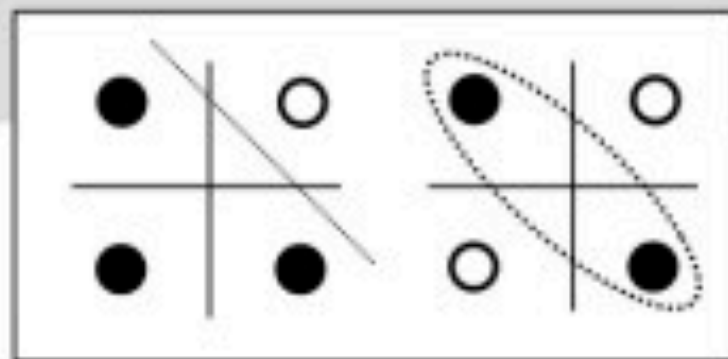
- Learnable Weights and Threshold



B. Widrow - M. Hoff



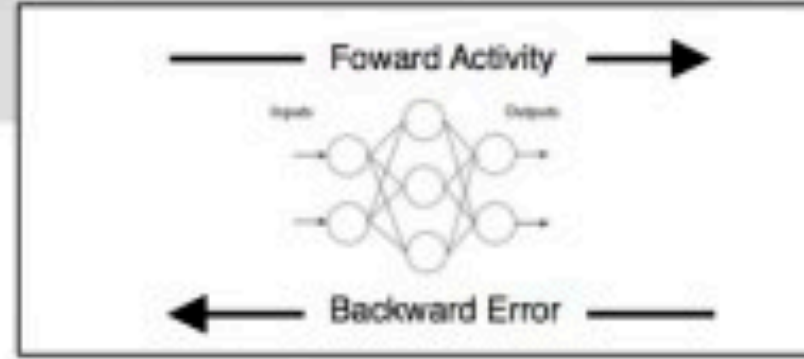
M. Minsky - S. Papert



- XOR Problem



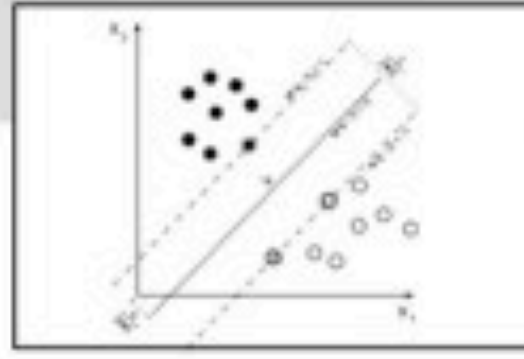
D. Rumelhart - G. Hinton - R. Williams



- Solution to nonlinearly separable problems
- Big computation, local optima and overfitting



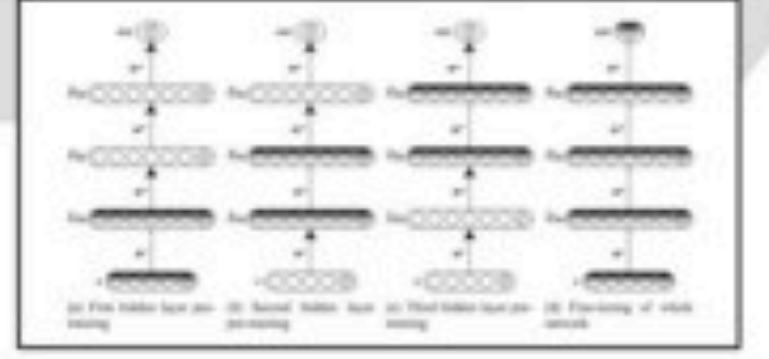
V. Vapnik - C. Cortes



- Limitations of learning prior knowledge
- Kernel function: Human Intervention



G. Hinton - S. Ruslan



- Hierarchical feature Learning

# What we've learned today...

- Single-layer Perceptron
  - Motivation
  - Activation function
  - Representing AND, OR, NOT
- Brief history of neural networks