

# The Perceptron

LIN 313 Language and Computers  
UT Austin Fall 2025  
Instructor: Gabriella Chronis

# Admin

- HW 2 grades posted this afternoon
- HW 3 due 10/15

# Overview 10/8

- Review homework
- Artificial Neurons
  - components
    - weights
    - bias
    - activation
- The Perceptron Algorithm
  - vector notation
  - dot product
  - use the algorithm to predict outputs from inputs

# Problem 2: Bayesian Spelling Correction

## Part 2: the bigram model

### Error model probabilities

- $P(\text{korekt} \mid \text{correct}) = .034$
- $P(\text{korekt} \mid \text{kraken}) = .007$
- $P(\text{korekt} \mid \text{carrot}) = .015$

### Language model probabilities

- $P(\text{correct} \mid \text{great}) = 0/1013 = 0$
- $P(\text{kraken} \mid \text{great}) = 5/1013 = 0.004935$
- $P(\text{carrot} \mid \text{great}) = 1/1013 = 0.000987$

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Derive the formula we are going to use:

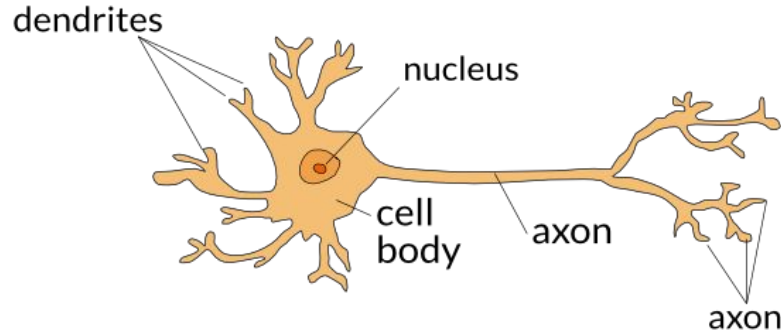
1. conditional independence assumption
  - a.  $P(a \mid b, c) = P(a \mid b) \times P(a \mid c)$
2. Substitute our events
  - a.  $P(\text{candidate} \mid \text{korekt}, \text{great}) = P(\text{candidate} \mid \text{great}) \times P(\text{candidate} \mid \text{korekt})$
3. We already have  $P(\text{candidate} \mid \text{great})$ .
4. We need  $P(\text{candidate} \mid \text{korekt})$ . Use Bayes Law
  - a.  $P(\text{candidate} \mid \text{korekt}, \text{great}) = P(\text{candidate} \mid \text{great}) \times P(\text{korekt} \mid \text{candidate}) \times P(\text{candidate}) / P(\text{korekt})$
5. We will be comparing these probabilities, so we can ignore the denominator because it's the same for all
  - a.  $P(\text{candidate} \mid \text{korekt}, \text{great}) = P(\text{candidate} \mid \text{great}) \times P(\text{korekt} \mid \text{candidate}) \times P(\text{candidate})$

Apply the formula to each candidate:

1. correct
  - a.  $P(\text{correct} \mid \text{korekt}, \text{great}) \propto P(\text{correct} \mid \text{great}) \times P(\text{korekt} \mid \text{correct}) \times P(\text{correct})$
  - b.  $P(\text{correct} \mid \text{korekt}, \text{great}) \propto 0 \times 0.034 \times 0.000845$
  - c.  $P(\text{correct} \mid \text{korekt}, \text{great}) \propto 0$
2. kraken
  - a.  $P(\text{kraken} \mid \text{korekt}, \text{great}) \propto P(\text{kraken} \mid \text{great}) \times P(\text{korekt} \mid \text{kraken}) \times P(\text{kraken})$
  - b.  $P(\text{kraken} \mid \text{korekt}, \text{great}) \propto 0.004935 \times 0.007 \times 0.000264$
  - c.  $P(\text{kraken} \mid \text{korekt}, \text{great}) \propto 9.11988\text{e-}9$
3. carrot
  - a.  $P(\text{carrot} \mid \text{korekt}, \text{great}) \propto P(\text{carrot} \mid \text{great}) \times P(\text{korekt} \mid \text{carrot}) \times P(\text{carrot})$
  - b.  $P(\text{carrot} \mid \text{korekt}, \text{great}) \propto 0.000987 \times 0.015 \times 0.000211$
  - c.  $P(\text{carrot} \mid \text{korekt}, \text{great}) \propto 3.123855\text{e-}9$

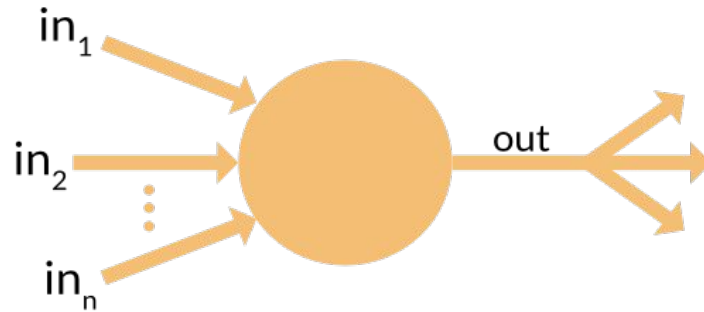
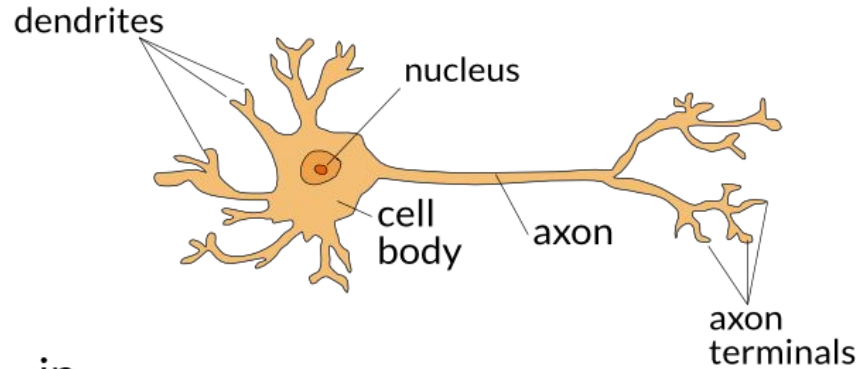
What is a neural network?

# What is a neuron?



- a very long cell
- **dendrites** collect stimuli from other cells, chemical signals
- if the **action potential** is reached, the neuron fires

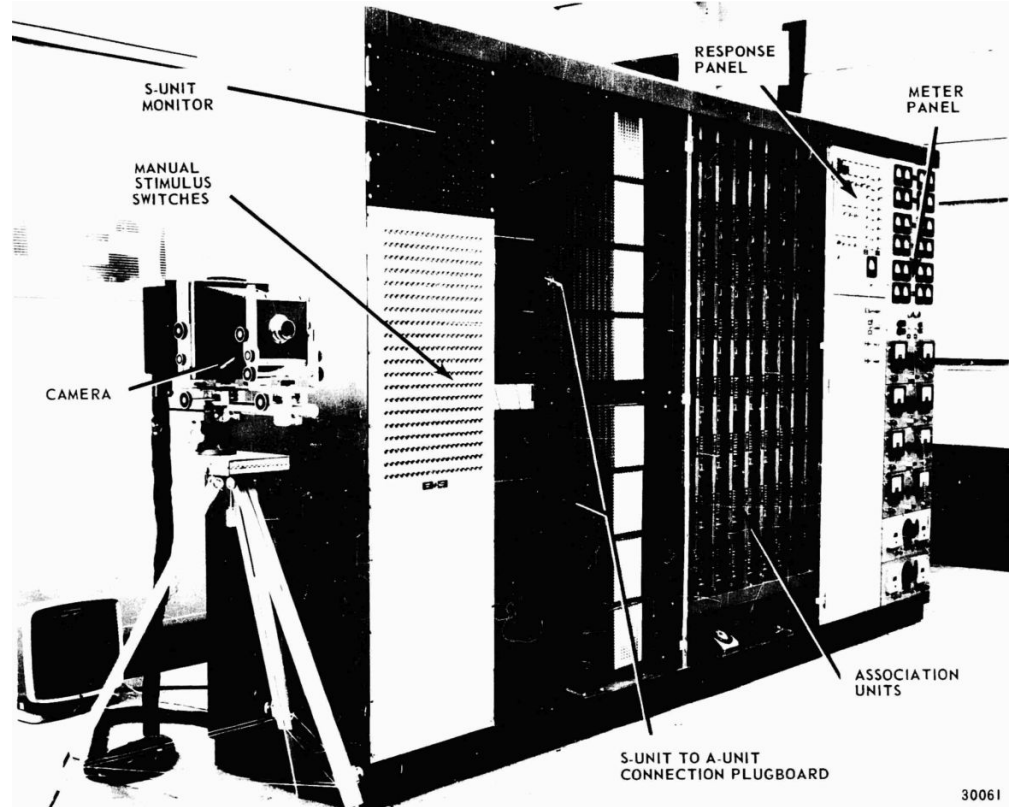
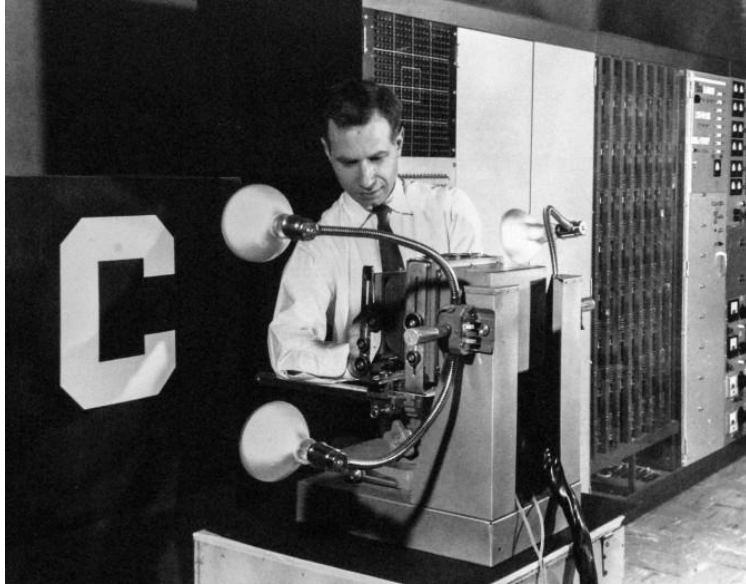
# The Artificial Neuron (McCulloch-Pitts, 1943)



- binary inputs (either on or off)
- summation function
  - adds up the input values
- some *activation function*
  - decides whether to fire



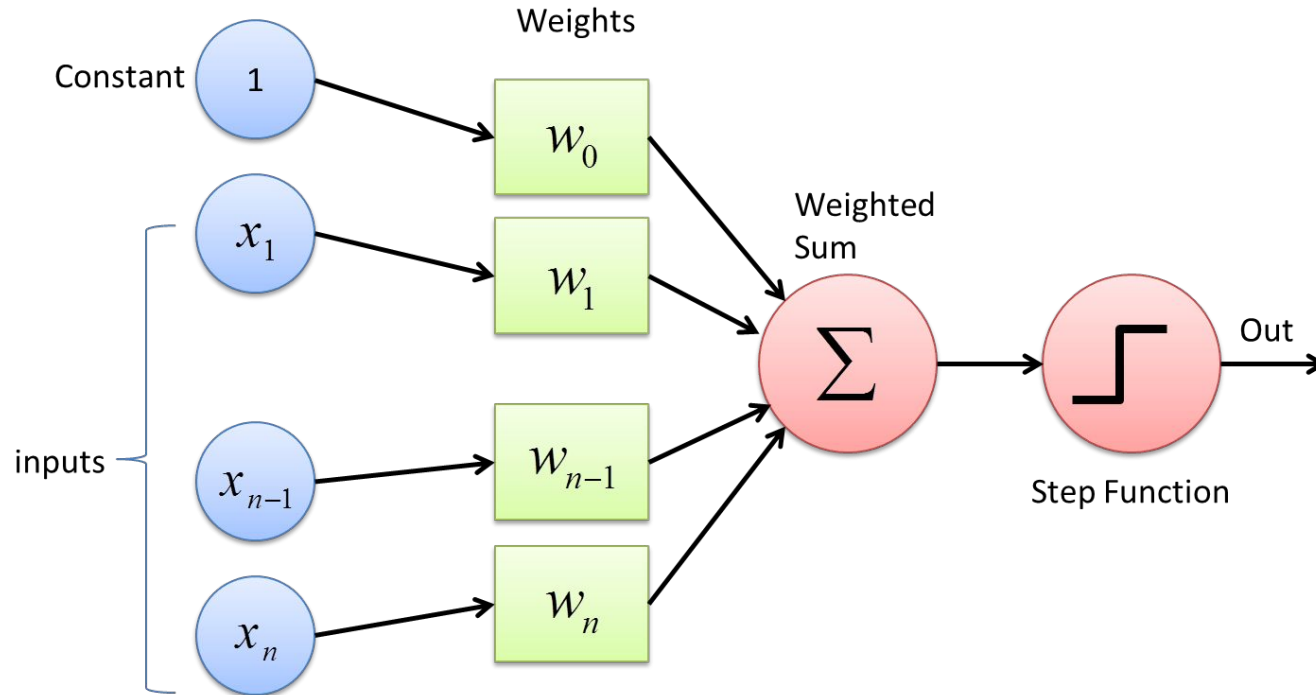
# The Perceptron (Rosenblatt, 1958)



# Perceptron Intuition

Should you buy a ticket to the next UT Game?

# The Perceptron Algorithm



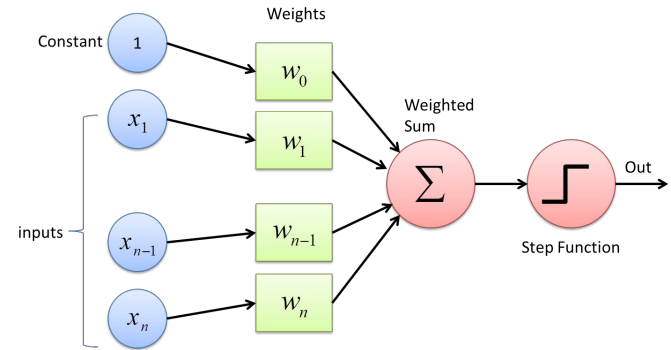
# The Perceptron Algorithm

formalized as an equation, the Perceptron looks like this

$$\hat{y} = \text{sign}(z) = \begin{cases} 1, & \text{if } z > 0 \\ 0, & \text{if } z \leq 0 \end{cases}$$

$$z = \left( \sum_{i=1}^n w_i x_i \right) + b$$

$$z = (x_1 * w_1) + (x_2 * w_2) + (x_3 * w_3) + \dots + (x_n * w_n) + b$$



# Vectors

The equation gets simpler if we think of the input as vectors.

A vector is an ordered list of numbers.

An ordered pair is a vector.

An ordered pair has a **geometric interpretation**.

A vector is an ordered pair with more numbers

A vector also has a geometric interpretation

# The Perceptron Algorithm (again)

$$\hat{y} = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b)$$

$\mathbf{w}$  is the weight vector ( $w_1 w_2 \dots w_i$ )

$\mathbf{x}$  is the input vector ( $x_1 x_2 \dots x_i$ )

$b$  is the bias, still a regular number

$\text{sign}()$  is the activation function

$\mathbf{w} \cdot \mathbf{x}$  is the **dot product** of  $\mathbf{w}$  and  $\mathbf{x}$

*the **dot product** is just shorthand for the weighted sum!*

## The Dot Product Definition

$$\mathbf{a} = \langle a_1, a_2, a_3 \rangle \quad \mathbf{b} = \langle b_1, b_2, b_3 \rangle$$

$$\mathbf{a} \cdot \mathbf{b} = a_1 b_1 + a_2 b_2 + a_3 b_3$$

# Vector Dot Products

(

# Putting it all together

What does a **forward pass** through the Perceptron look like for our UT example?

$$\hat{y} = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b)$$

It's an away game. two of my friends are actually going, but I'm broke and I have to write an essay and finish a lab write up this weekend.

$\mathbf{w} =$

$\mathbf{x} =$

$b =$



# Putting it all together

What does a **forward pass** through the Perceptron look like for our UT example?

$$\hat{y} = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b)$$

It's a home game, the weather is balmy. I have a ton of homework but all of my friends are going.

$\mathbf{w} =$

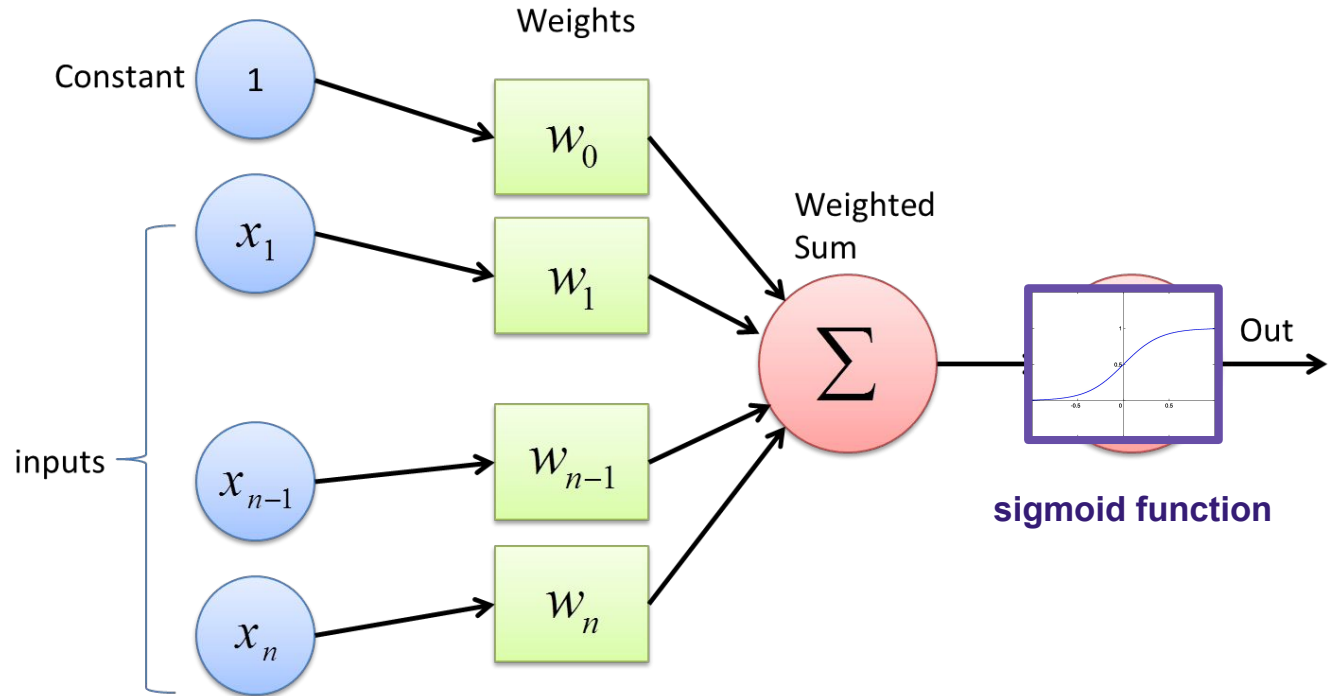
$\mathbf{x} =$

$b =$

# Linear Regression

The only difference is the activation function that we choose!

Linear regression uses the **sigmoid** activation function



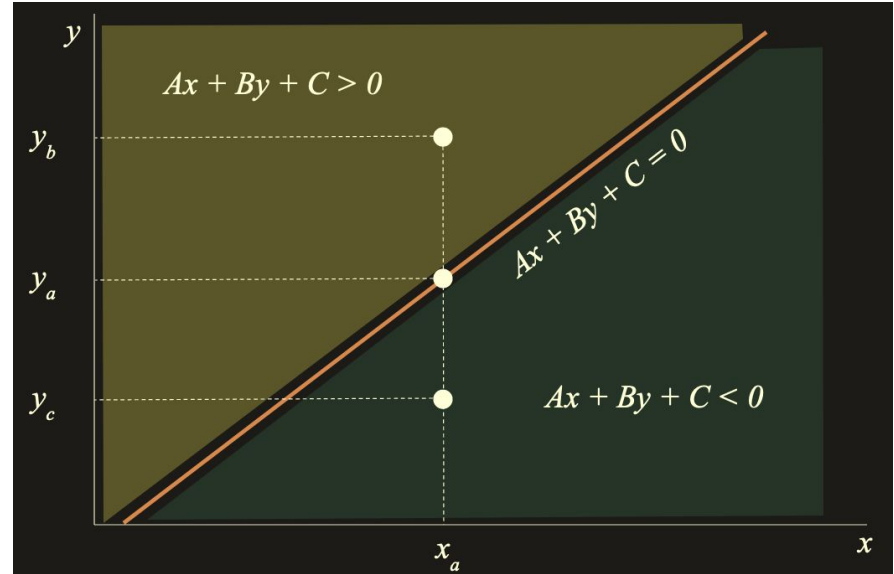
# Geometric Interpretation

we can make decision function (the weighted sum) into an equation for a line:

$$w_1x_1 + w_2x_2 + b = 0$$

Rewrite that line in standard  $y=mx+b$  form

$$x_2 = -(w_1/w_2)x_1 - (b/w_2)$$



⚠ Note: This is assuming that the coefficients are **positive**. If not, the top region could perhaps be where  $Ax + By + C < 0$  instead and the bottom be  $Ax + By + C > 0$ . You will see this as you interact with a model later in the post.

<https://karthikvedula.com/2024/01/05/visualizing-the-perceptron-learning-algorithm/>

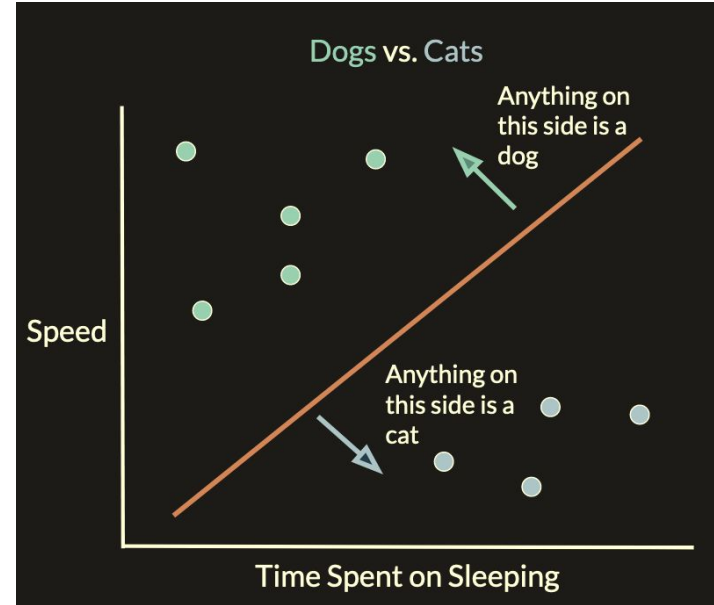
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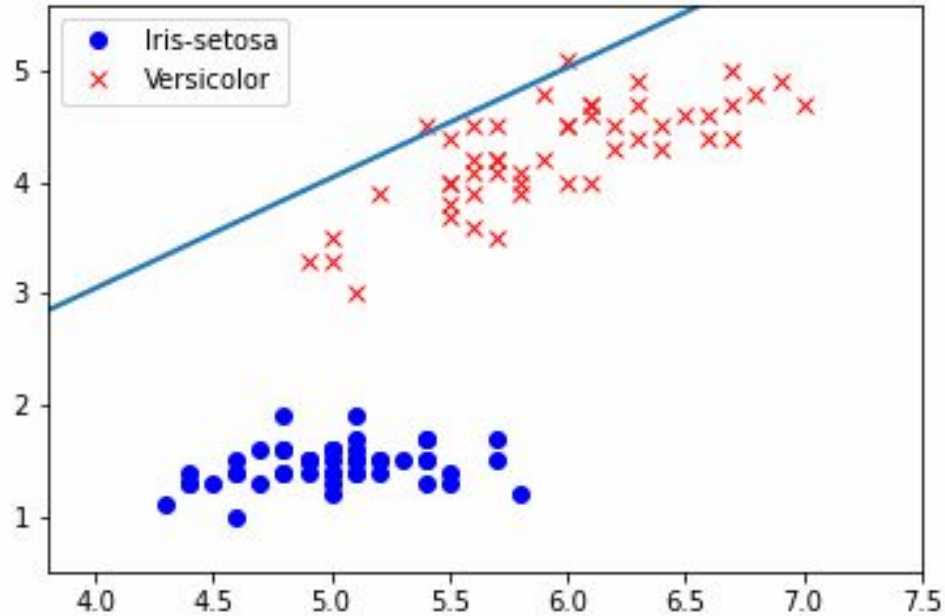
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# Perceptron Learning (next class)



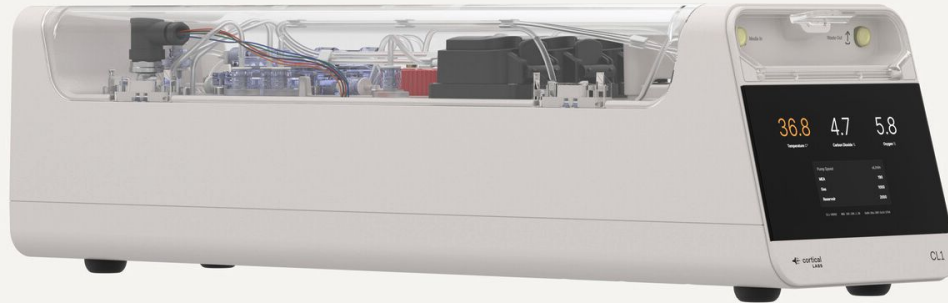
# Interactive Demos

- perceptron: <https://karthikvedula.com/2024/01/05/visualizing-the-perceptron-learning-algorithm/>
- perceptron: <https://perceptron.streamlit.app/>
- dot product: <https://maththebeautiful.com/dot-product/>

# If ever the twain shall meet...

Introducing the world's first biological neural network: <https://corticalabs.com/cl1>

## Silicon meets neuron



Real neurons are cultivated inside a nutrient rich solution, supplying them with everything they need to be healthy. They grow across a silicon chip, which sends and receives electrical impulses into the neural structure.