

The Perceptron

LIN 313 Language and Computers
UT Austin Fall 2025
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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

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

Language model probabilities

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

$$P(a|b) = \frac{P(b|a) \times P(a)}{P(b)} \quad \text{BAYES LAW}$$

conditional
independence
assumption

$$P(a|b, c) = P(a|b) \times P(a|c)$$

substituting:
our events

$$P(\text{candidate} | \text{korekt}, \text{great}) = P(\text{candidate} | \text{korekt}) \times P(\text{candidate} | \text{great})$$

$$P(\text{cand} | \text{korekt}, \text{great}) = \frac{P(\text{cand} | \text{great}) \times P(\text{korekt} | \text{candidate}) \times P(\text{candidate})}{P(\text{korekt})}$$

apply Bayes
Law

ignore the
denominator

$$P(\text{cand} | \text{korekt}, \text{great}) = P(\text{cand} | \text{great}) \times P(\text{korekt} | \text{cand}) \times P(\text{cand})$$

→ apply this formula to each ~~word~~ candidate (see next page)

Problem 2: Bayesian Spelling Correction

Part 2: the bigram model

Error model probabilities

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Language model probabilities

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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. $P(\text{candidate} \mid \text{korekt}, \text{great}) = P(\text{candidate} \mid \text{great}) \times P(\text{korekt} \mid \text{candidate}) \times P(\text{candidate})$

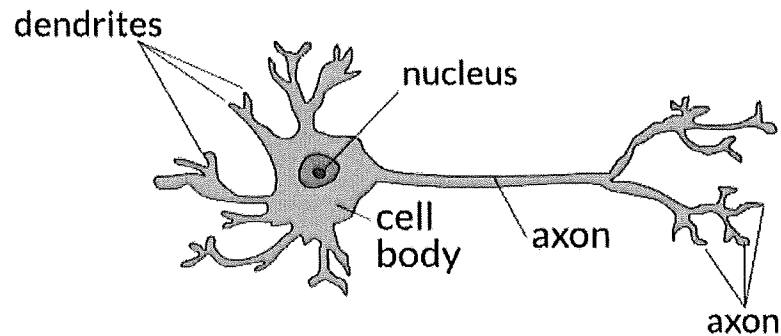
Apply the formula to each candidate:

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?

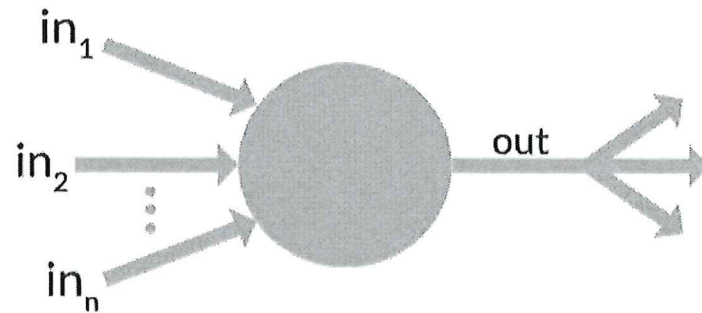
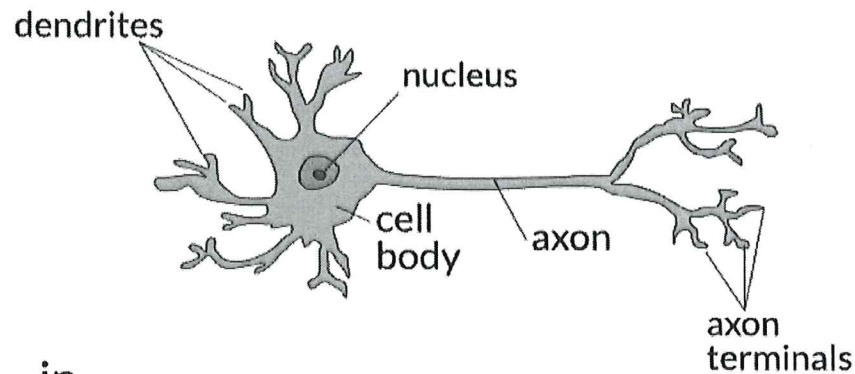
- new model for AI
- interconnected nodes weight bias
- layer
- output \leftarrow input
- logistic regression
- SGD (stochastic gradient descent)

What is a neuron?



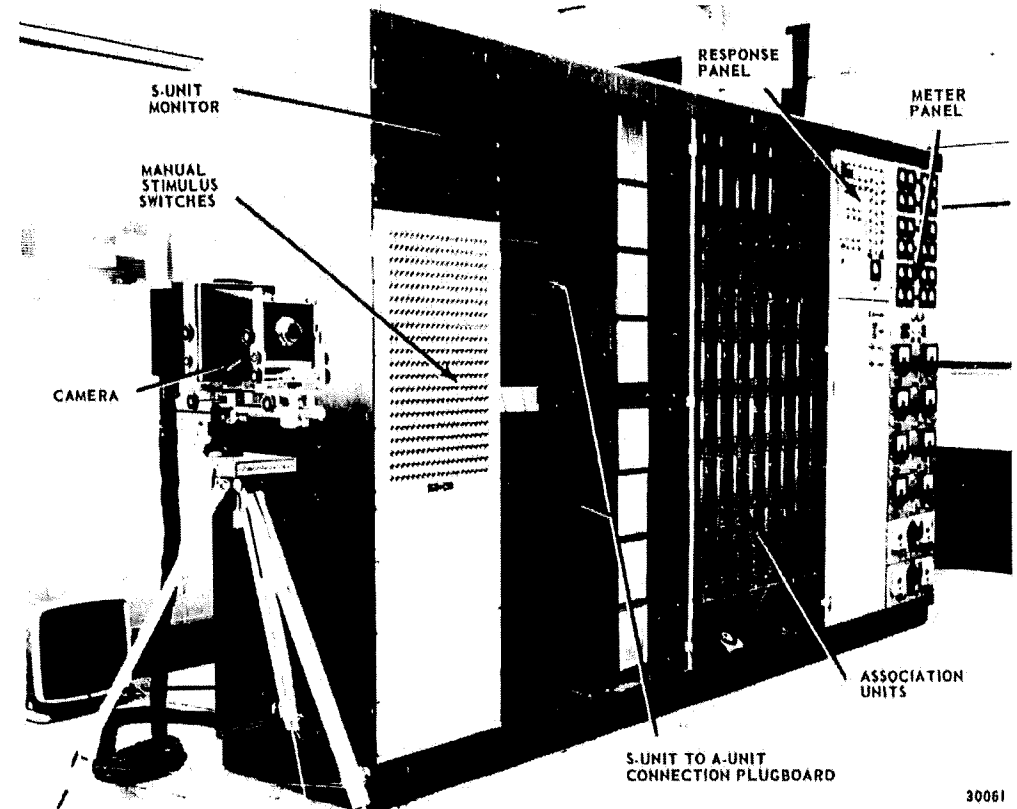
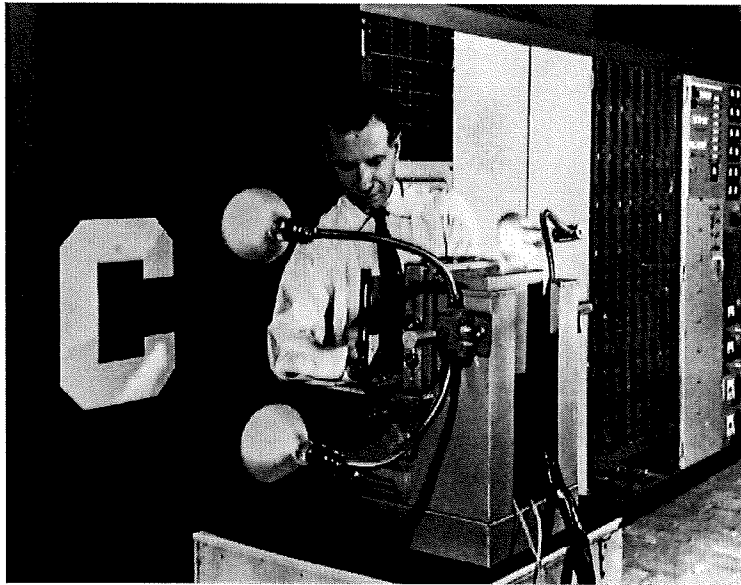
- a very long cell
- **dendrites** collect stimuli from other cells, chemical signals
- if the **action potential** is reached, the neuron fires

The Artificial Neuron (McCulloch-Pitts, 1943)



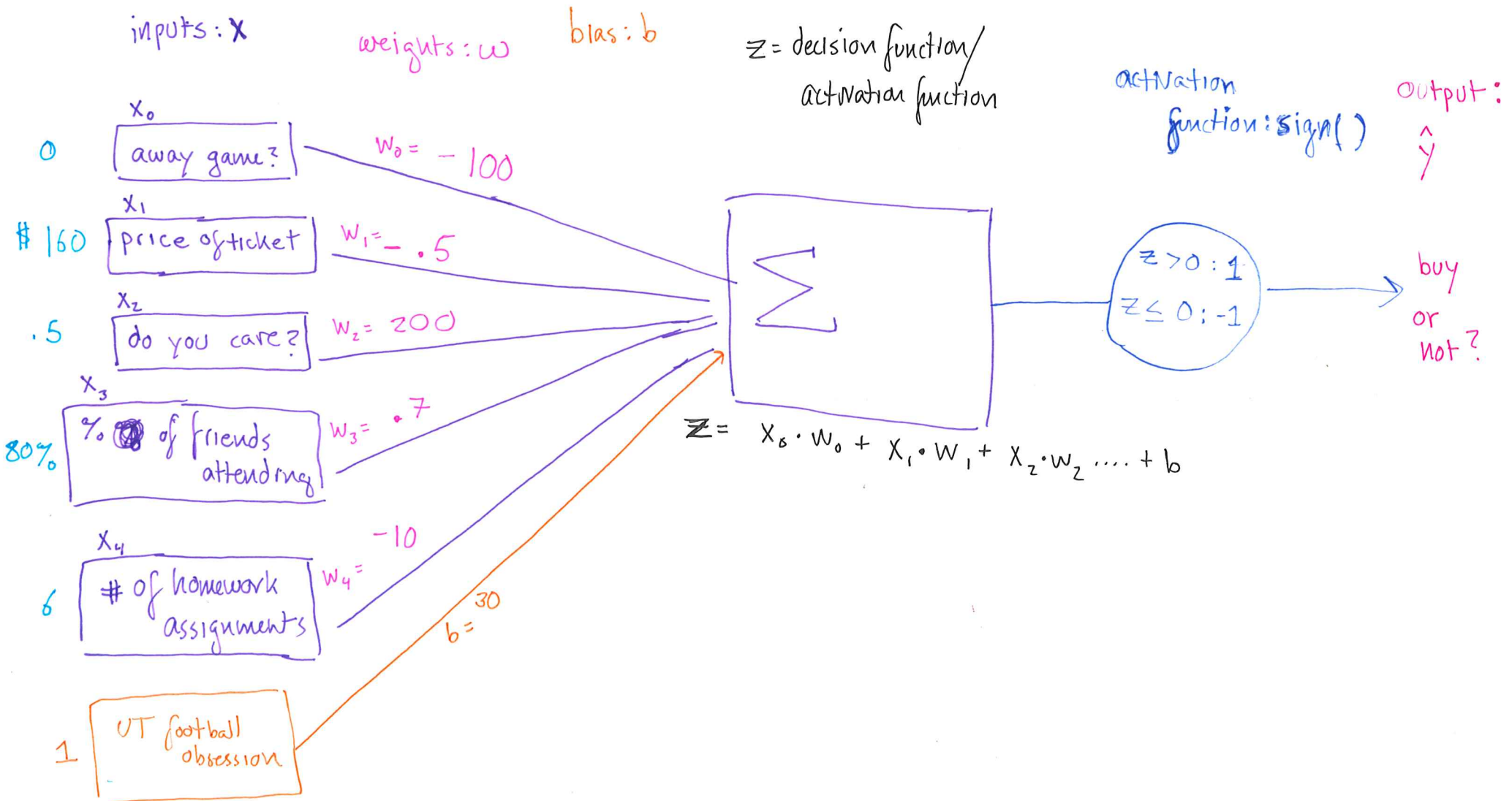
- binary inputs (either on or off)
- summation function / *decision function*
 - adds up the input values
- some *activation function*
 - decides whether to fire

The Perceptron (Rosenblatt, 1958)

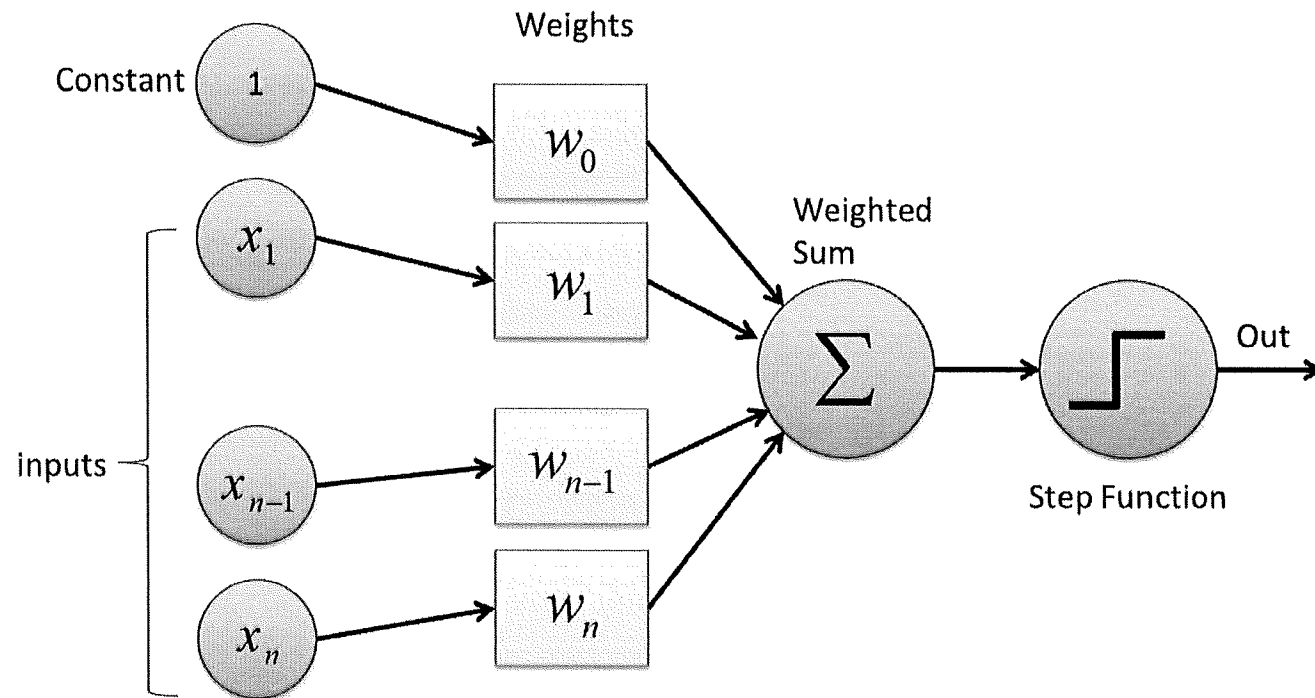


Perceptron Intuition

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

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

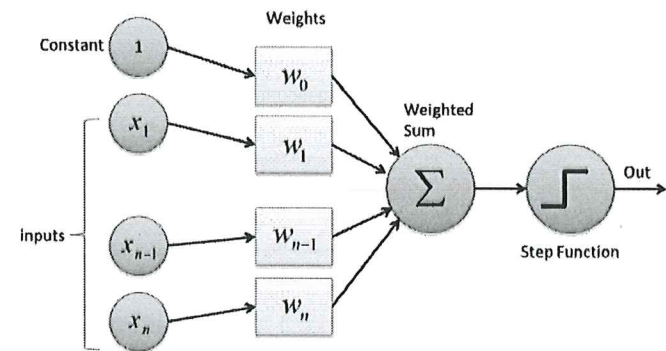
Handwritten annotations:
 - "y hat" points to \hat{y}
 - predicted value points to \hat{y}
 - weighted sum points to z
 - step function points to sign

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

Handwritten annotations:
 - weighted sum points to z
 - equivalent points to the summation term

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

$\hat{y} = \vec{W} \cdot \vec{X} + b$



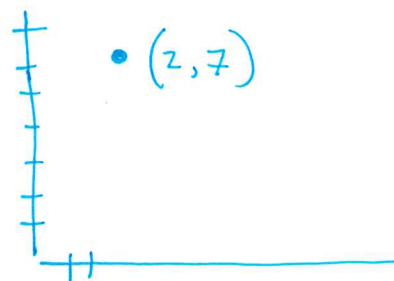
Vectors

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

A vector is an ordered list of numbers. $[1, -2, 0.3]$

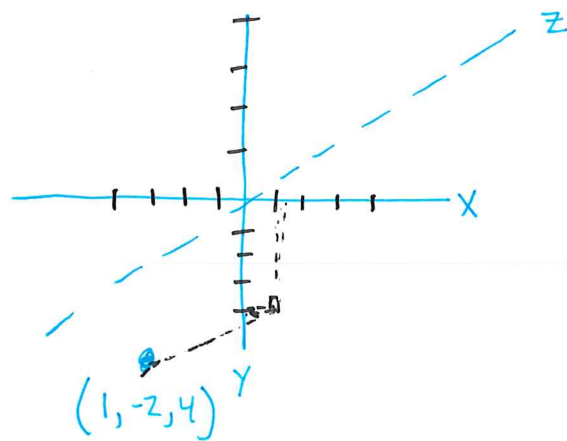
An ordered pair is a vector. $(2, 7)$

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



A vector is an ordered pair with more numbers $[1, -2, 4]$

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 ($w_1 w_2 \dots w_l$)

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

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

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

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