

# Machine Learning: Neural Networks

CSE 415: Introduction to Artificial Intelligence  
University of Washington  
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## Outline

- History of neural networks research
- The Perceptron
- Examples
- Training algorithm
- Fundamental training theorem

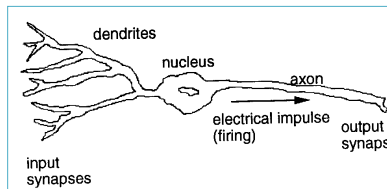
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## The Biological Neuron



The human brain contains approximately  $10^{11}$  neurons.

**Activation process:**

Inputs are transmitted electrochemically across the input synapses  
Input potentials are summed.

If the sum reaches a threshold, a pulse moves down the axon. (The neuron has “fired”.)

The pulse is distributed at the axonal arborization to the input synapses of other neurons.

After firing, there is a refractory period of inactivity.

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## History of Neural Networks Research

1943 McCulloch & Pitts model of neuron.

$$n_i(t+1) = \Theta(\sum_j w_{ij} n_j(t) - \mu_i), \quad \Theta(x) = \begin{cases} 1 & \text{if } x \geq 0; \\ 0, & \text{otherwise.} \end{cases}$$

1962 Frank Rosenblatt's book gives a training algorithm for finding the weights  $w_{ij}$  from examples.

*Principles of neurodynamics: Perceptrons and the theory of brain mechanisms*

1969 Marvin Minsky and Seymour Papert publish *Perceptrons*, and prove that 1-layer perceptrons are incapable of computing image connectedness.

1974-89, 1982: Associated content-addressable memory.

Backpropagation: Werbos 1974, Parker 1985, Rumelhart, Hinton, & Williams 1986.

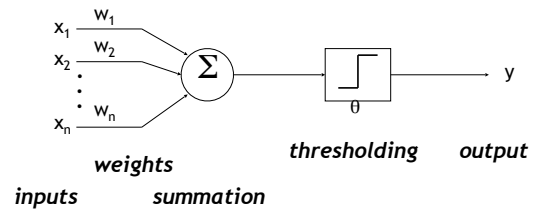
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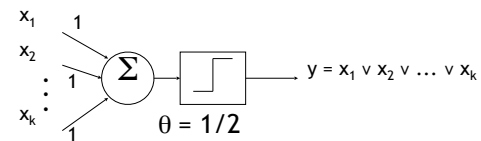
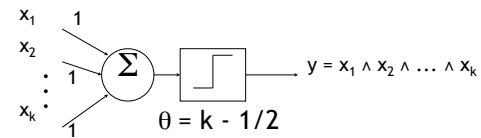
## The Perceptron



$$y = \begin{cases} 1 & \text{if } \sum w_i x_i \geq \theta; \\ 0, & \text{otherwise.} \end{cases}$$

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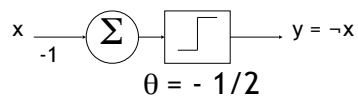
## Perceptron Examples: Boolean AND and OR.



$$x_i \in \{0, 1\}$$

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## Perceptron Examples: Boolean NOT



$$x_i \in \{0, 1\}$$

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## Perceptron Example: Template Matching

-1	-1	1	-1	-1
-1	1	-1	1	-1
1	1	1	1	1
1	-1	-1	-1	1
1	-1	-1	-1	1

weights  $w_1$  through  $w_{25}$

$$x_i \in \{-1, 1\}$$

$$\theta = 25 - \epsilon$$

Recognizes the letter A provided the exact pattern is present.

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## Perceptron Training Sets

Let  $X = X^+ \cup X^-$  be the set of training examples.

$S_X = \langle X_1, X_2, \dots, X_k, \dots \rangle$  is a *training sequence* on  $X$ , provided:

- (1) Each  $X_k$  is a member of  $X$ , and
- (2) Each element of  $X$  occurs infinitely often in  $S_X$ .

An element  $e$  occurs *infinitely often* in a sequence

$z = \langle z_1, z_2, \dots \rangle$

provided that for any nonzero integer  $i$ , there exists a nonnegative integer  $j$  such that there is an occurrence of  $e$  in

$z_i, z_{i+1}, \dots, z_j$ .



## Perceptron Training Algorithm

Let  $X = X^+ \cup X^-$  be the set of training examples. and let  $S_X = \langle X_1, X_2, \dots, X_k, \dots \rangle$  be a training sequence on  $X$ .

Let  $w_k$  be the weight vector at step  $k$ , and let  $\theta_k$  be the threshold at step  $k$ .

Choose  $w_0$  and  $\theta_0$  arbitrarily. For example.  $w_0 = (0, 0, \dots, 0)$ ,  $\theta_0 = 1$ .

Each each step  $k$ ,  $k = 0, 1, 2, \dots$

Classify  $X_k$  using  $w_k$ .

If  $X_k$  is correctly classified, take  $w_{k+1} = w_k$ .

If  $X_k$  is in  $X^-$  but misclassified, take  $w_{k+1} = w_k - c_k X_k$  and  $\theta_{k+1} = \theta_k + c_k$

If  $X_k$  is in  $X^+$  but misclassified, take  $w_{k+1} = w_k + c_k X_k$  and  $\theta_{k+1} = \theta_k - c_k$

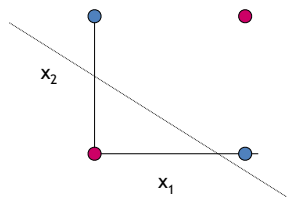
The sequence  $c_k$  should be chosen according to the data. Overly large constant values can lead to oscillation during training. Values that are too small will increase training time. However,  $c_k = c_0/k$  will work for any positive  $c_0$ .



## Perceptron Limitations

Perceptron training always converges if the training data  $X^+$  and  $X^-$  are linearly separable sets.

The boolean function XOR (exclusive or) is not linearly separable. (Its positive and negative instances cannot be separated by a line or hyperplane.) It cannot be computed by a single-layer perceptron. It cannot be learned by a single-layer perceptron.



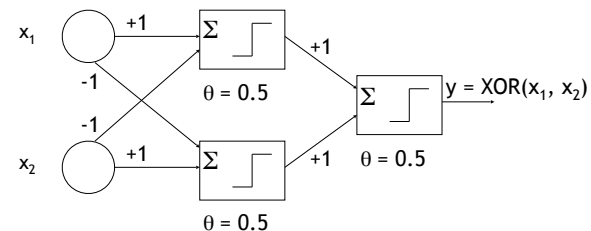
$$X^+ = \{ (0, 1), (1, 0) \}$$

$$X^- = \{ (0, 0), (1, 1) \}$$

$$X = X^+ \cup X^-$$



## Two-Layer Perceptrons





## Two-Layer Perceptrons (cont.)

Two-Layer perceptrons are computationally powerful.

However: they are not trainable with a method such as the perceptron training algorithm, because the threshold units in the middle level “block” updating information; there is no way to know what the correct updates to first-level weights should be.