

Deep Learning

3.1 Perceptron

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Threshold Logic Unit

- ① First Mathematical Model for a neuron

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$$f(x) = \mathbb{1}(w \sum_i x_i + b \geq 0)$$

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- ③ **No learning; heuristics approach**

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⑤

$$f(x) = \begin{cases} 1 & \text{when } \sum_i w_i x_i + b \geq 0 \\ 0 & \text{else} \end{cases}$$

Perceptron

- ① For simplicity we consider +1 and -1 responses

$$\sigma(x) = \begin{cases} 1 & \text{when } x \geq 0 \\ -1 & \text{else} \end{cases}$$



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- ③ \mathbf{w} are referred to as weights and b as the bias

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- ④ Mechanism for learning weights

Weights and Bias

① Why are the weights important?

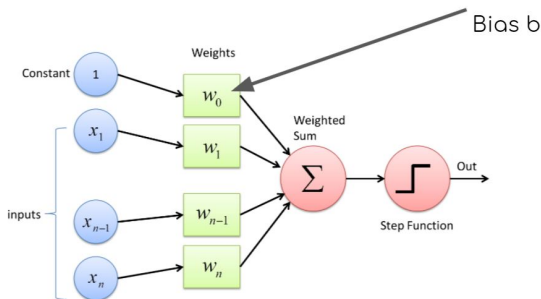


Figure credits: DeepAI

Weights and Bias

- ① Why are the weights important?
- ② Why is it called 'bias'? What does it capture?

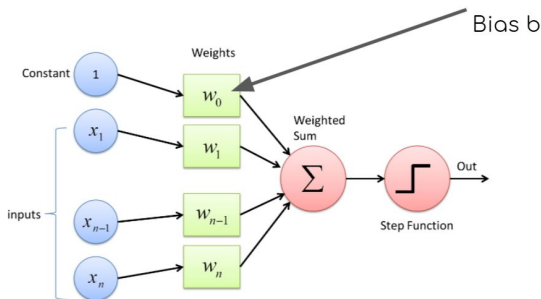


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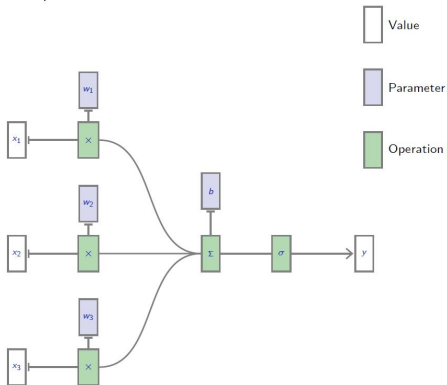


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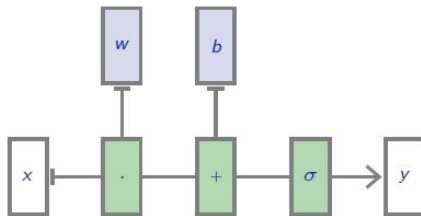


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 $\mathbf{w}_{k+1} = \mathbf{w}_k + y_{n_k} \cdot \mathbf{x}_{n_k}$

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- ④ Note that the bias b is absorbed as a component of \mathbf{w} and \mathbf{x} is appended with 1 suitably

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▶ Colab Notebook: Perceptron

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- ② Stops as soon as it finds a separating boundary
- ③ Other algorithms maximize the margin from boundary to the samples