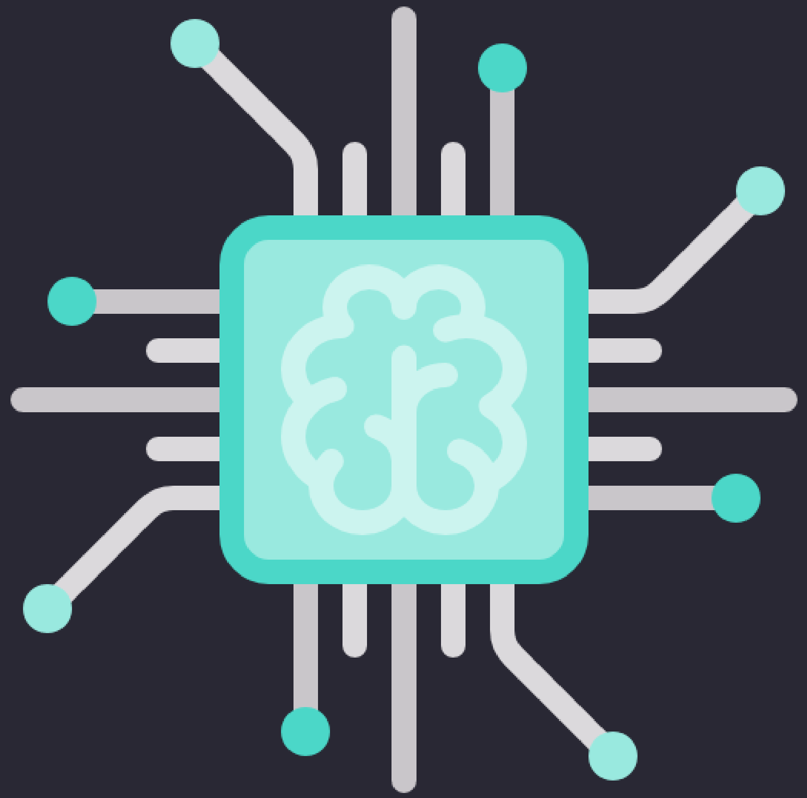
Deep Dissection

Understanding the ins and outs of Neural Networks

by Diogo Pinto



The road ahead

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Motivation

- Why deep learning
- Playground

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Fundamentals

- Derivatives & Chain rule
- Perceptron
- Sigmoid function & Cross-entropy

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- Forward propagation
- Error computation
- Back propagation
- Parameters update

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Implementation

- Binary Classification – Census Income dataset

Who are you people? 👀

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- Who is used to work with **Python**?

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- Who already did something **close to this**?

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- Who likes **matrices and letters** in the place of numbers?

Who are you people? 👀

- Who is used to work with **Python**?
- Who already did something **close to this**?
- Who likes **matrices and letters** in the place of numbers?
- Who had a good night of **sleep**?

Assumptions

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- A bit of **Algebra** and **Calculus**

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- Introductory level of **Machine Learning** knowledge

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Difficulty can be calibrated, give feedback!

Motivation

Why am I here?

"Don't limit your challenges, challenge your limits"

Unknown

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10110
11110

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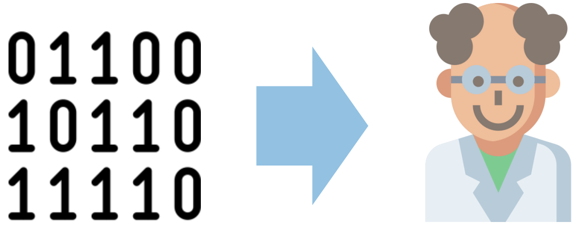

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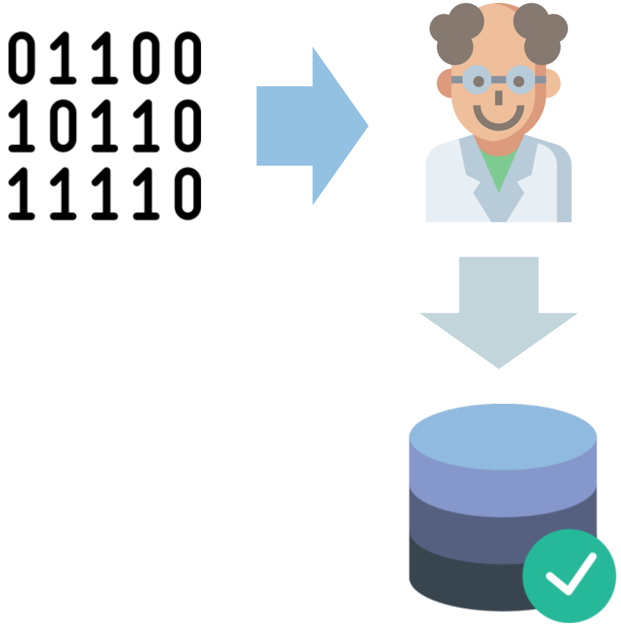

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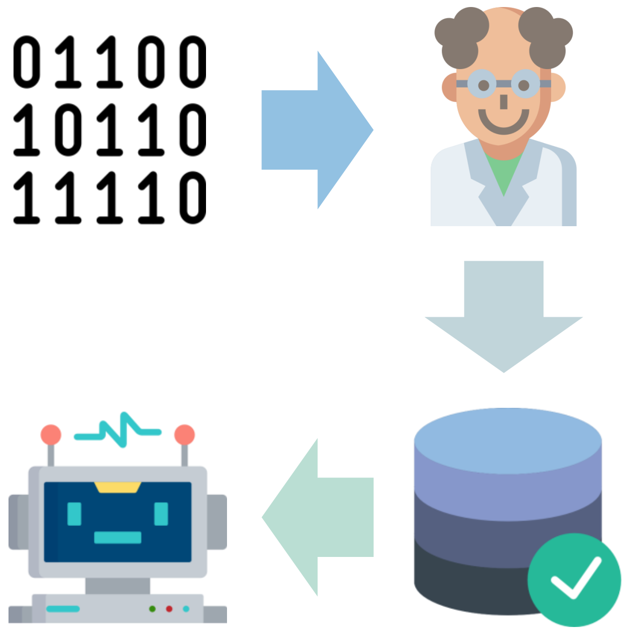

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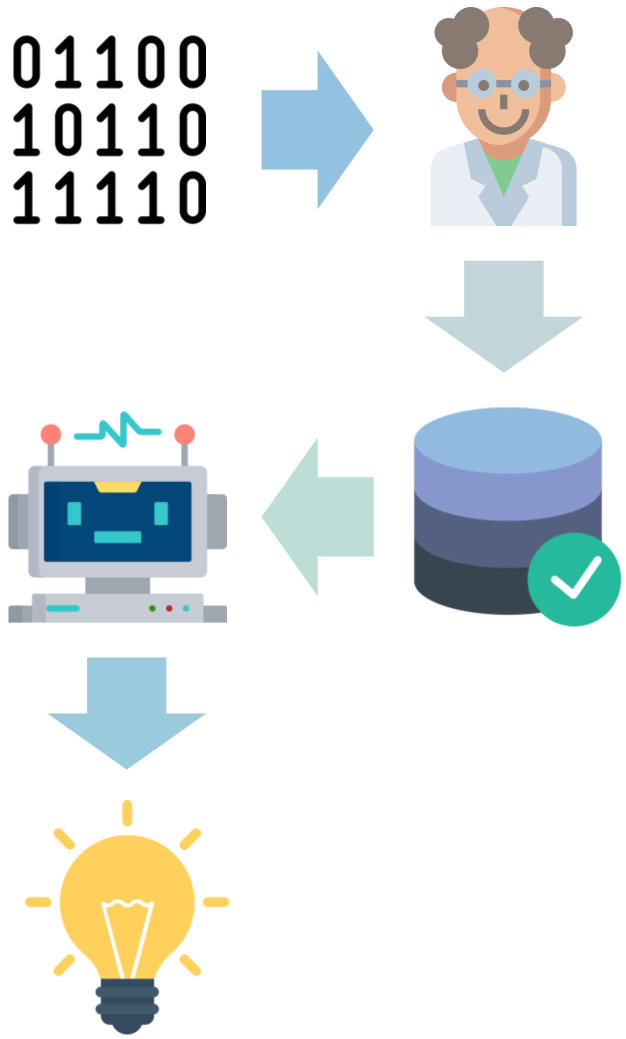

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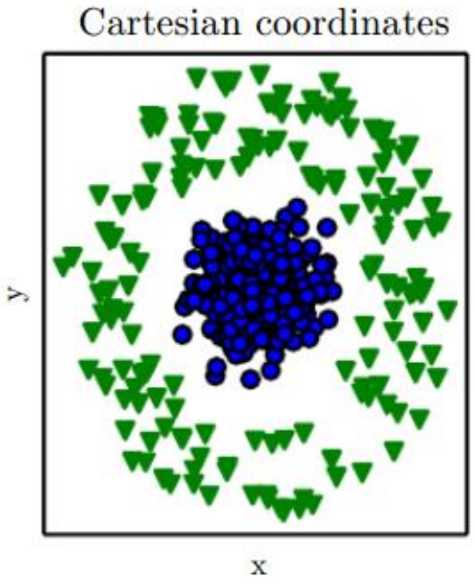

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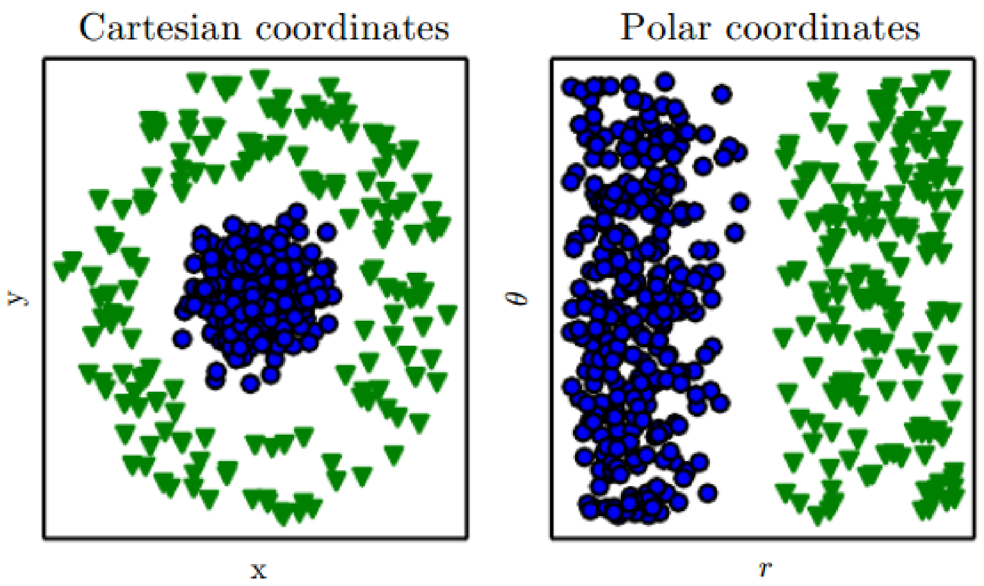

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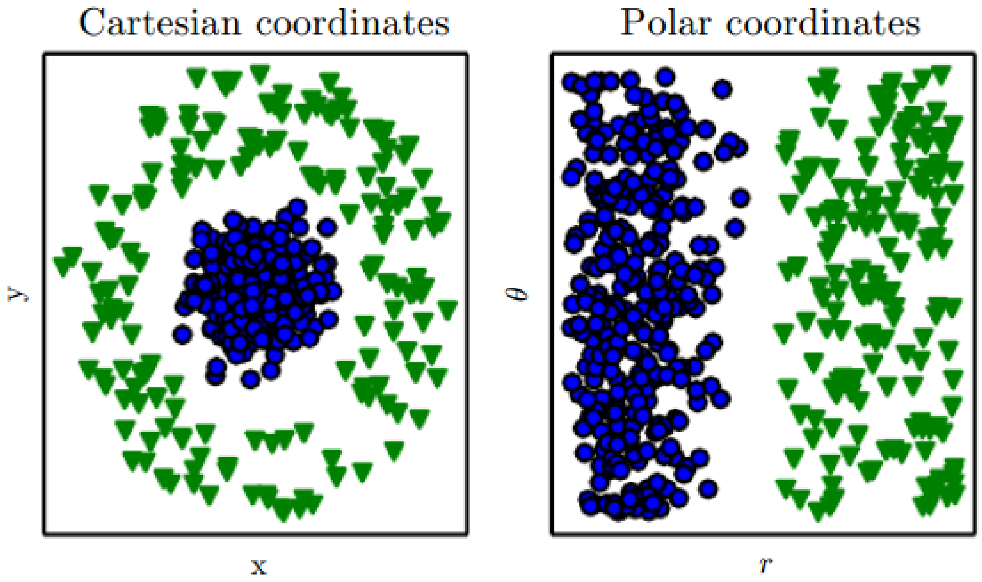
  - Identifying the **sources of influence**
  - Disentangle them



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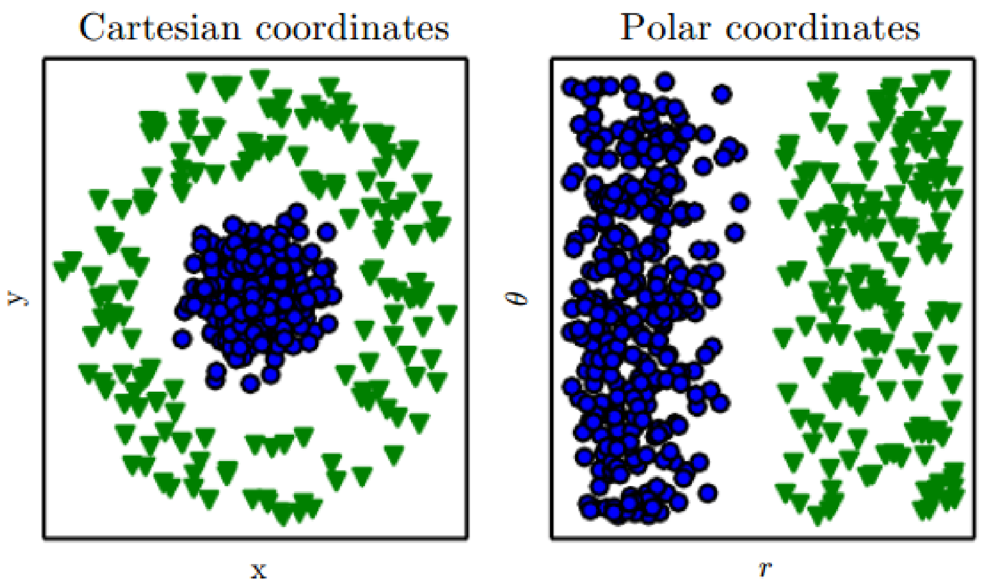

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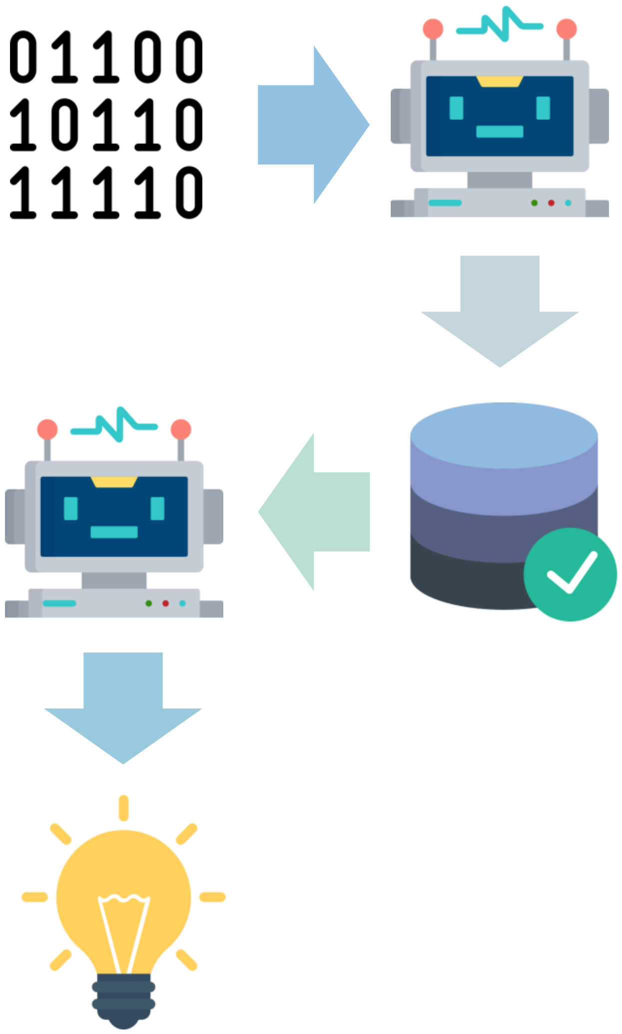

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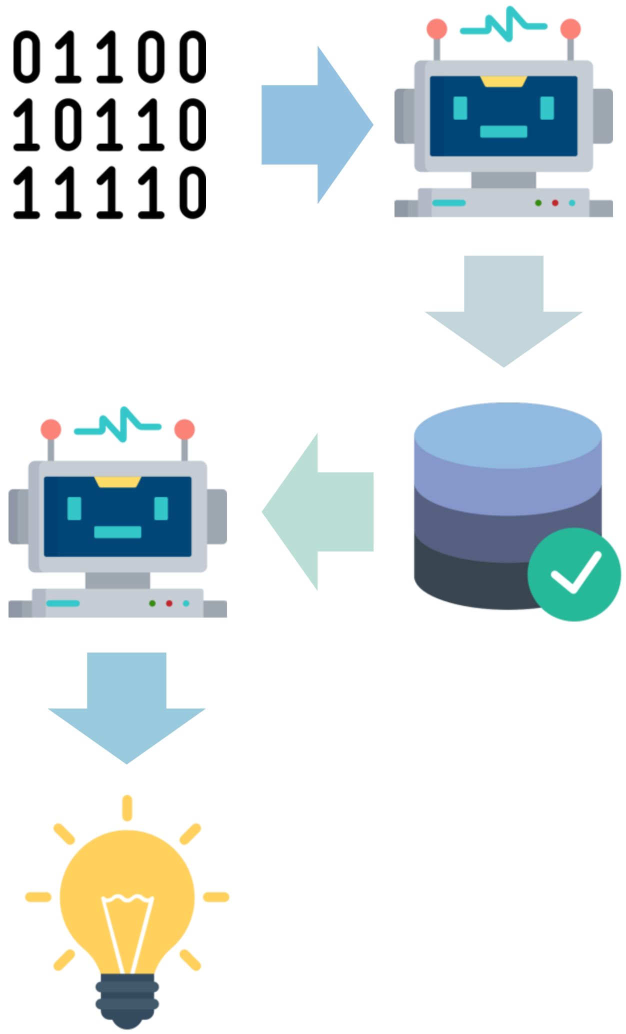
  - Learning **high-level concepts** can be as hard as the original problem



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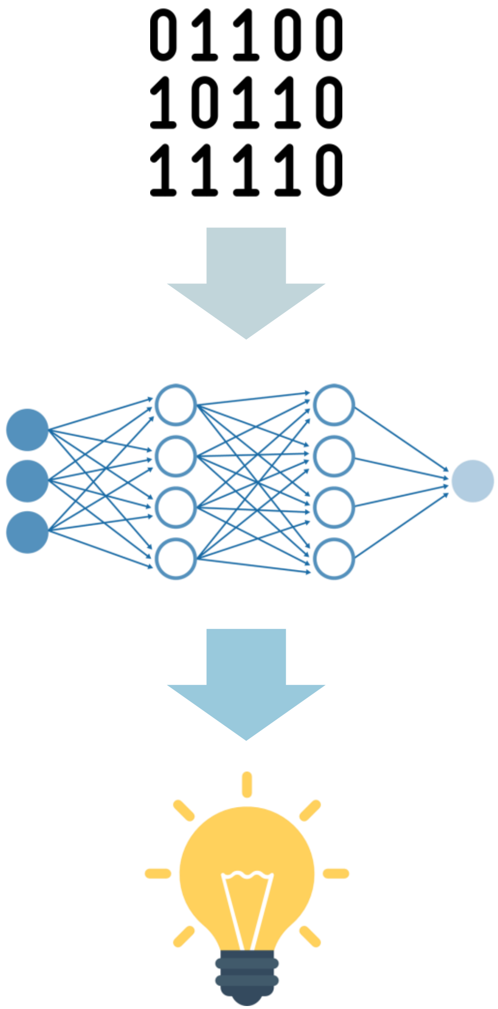

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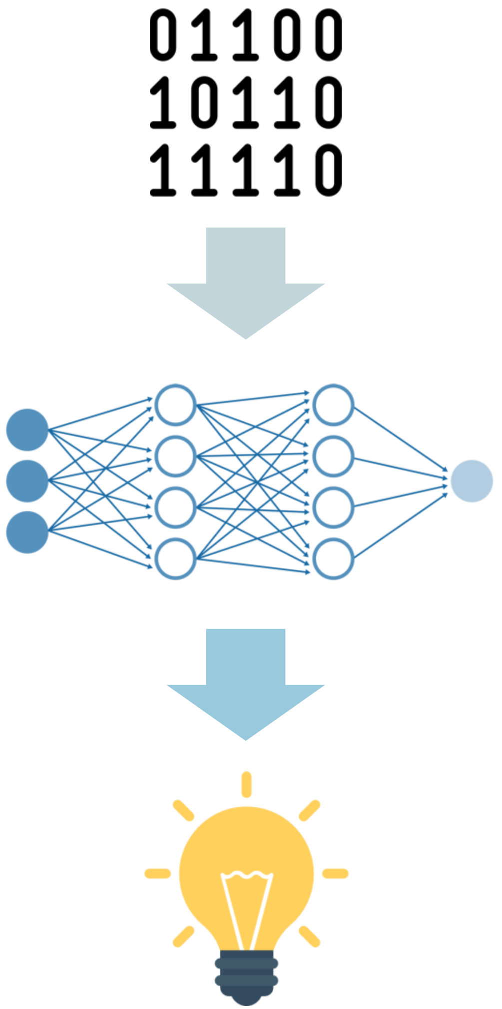
- Deep learning tackles this heads on
  - **Hierarchical combination** of simpler concepts into more complex ones



A quick visual demo…

[Neural Networks Playground]

Fundamentals

What do I need to know?

"You can't build a great building on a weak foundation."

Gordon B. Hinckley

It’s Calculus Time 🎉

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- Derivatives

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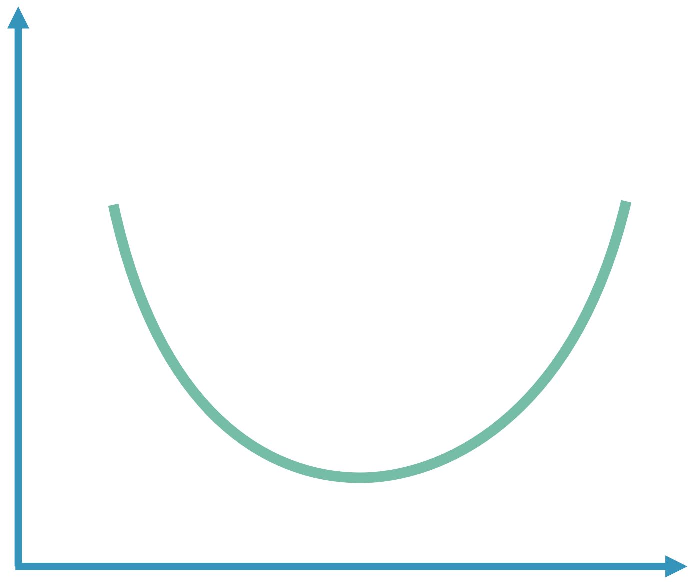

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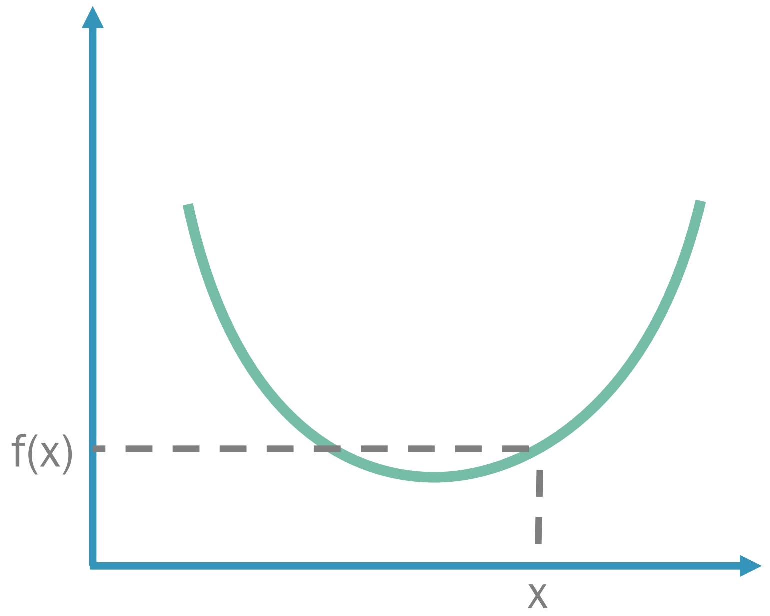

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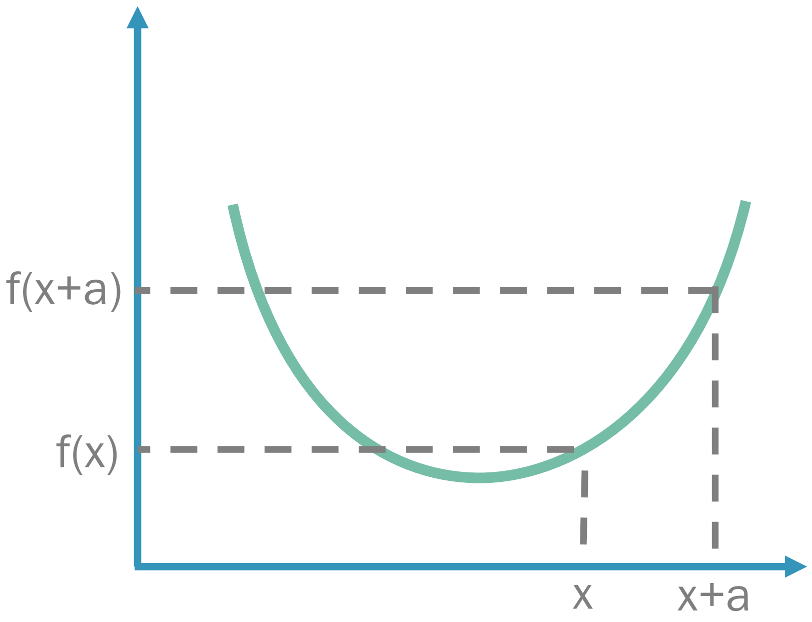

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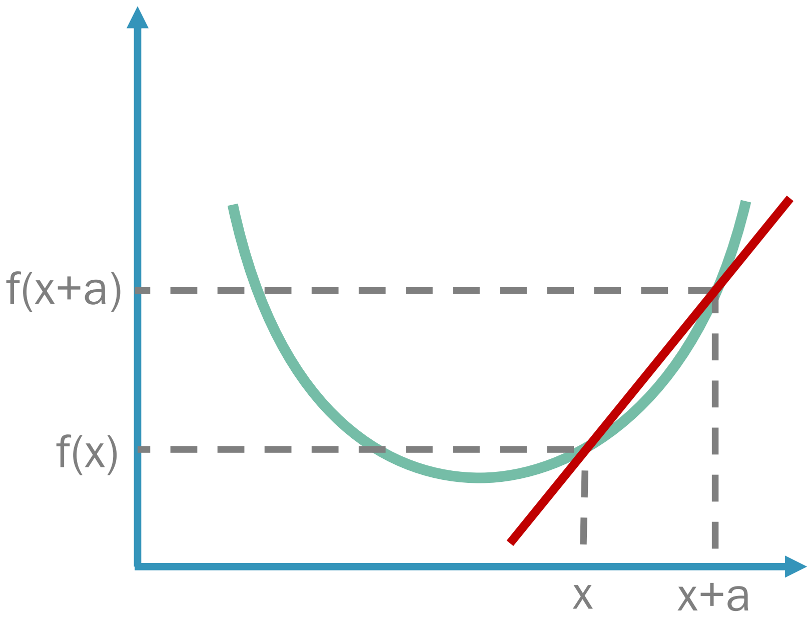

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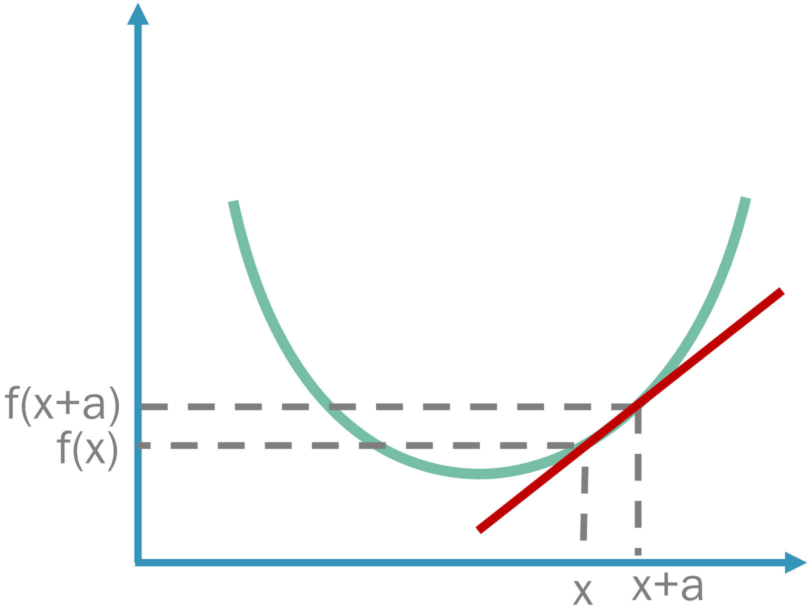

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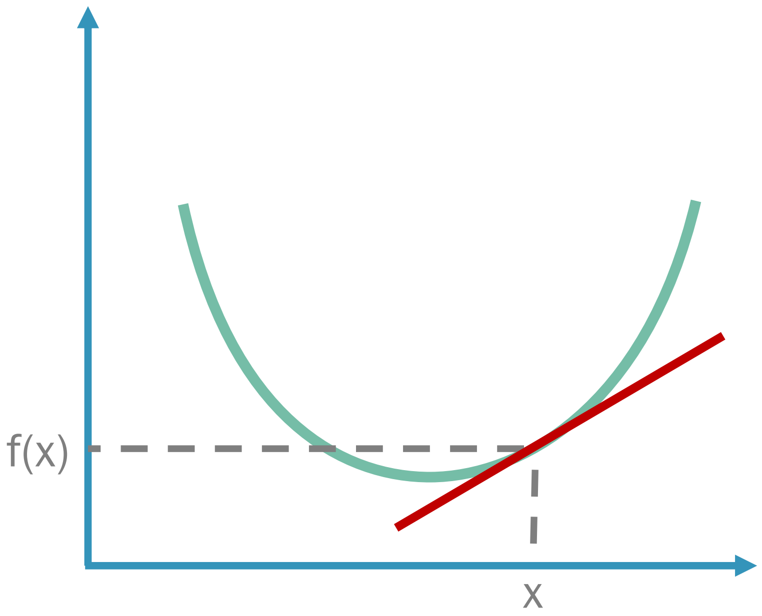

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- Derivatives
  - $y = f(x)$
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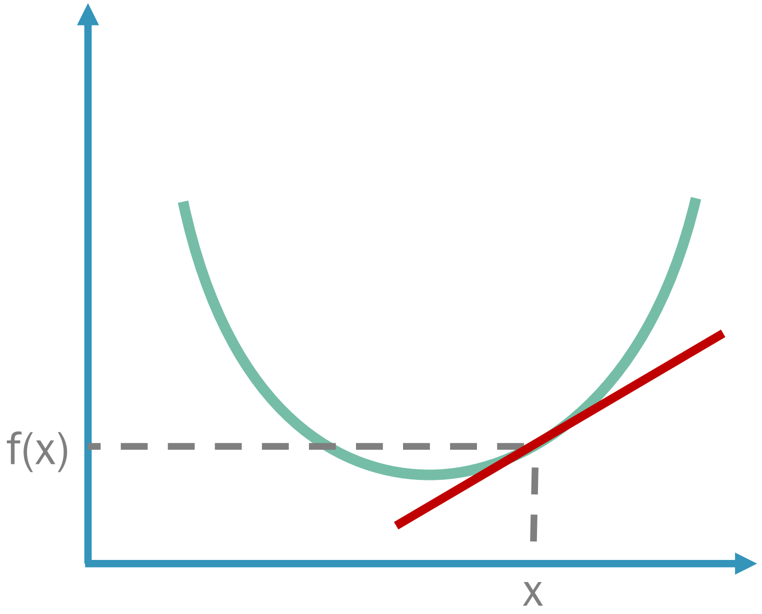
  - $\lim_{a \to 0} \frac{f(x+a)-f(x)}{(x+a)-x}$ or $\frac{dy}{dx}$



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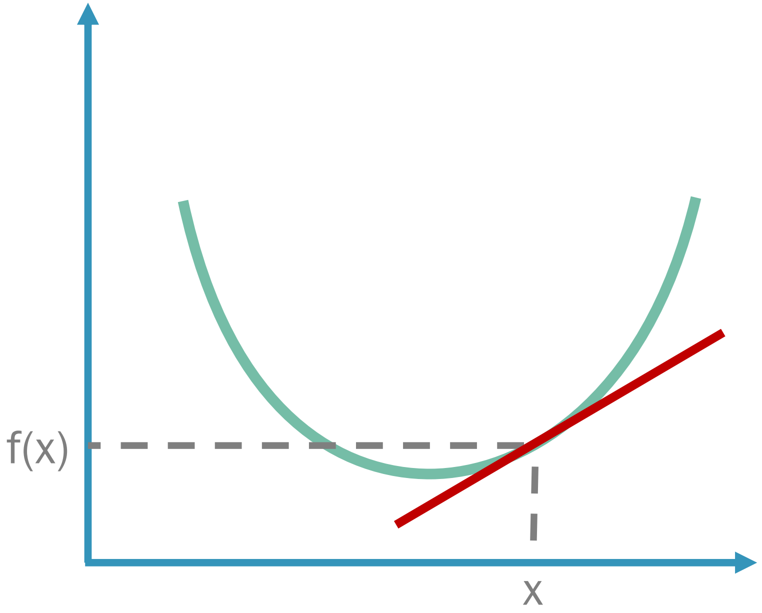

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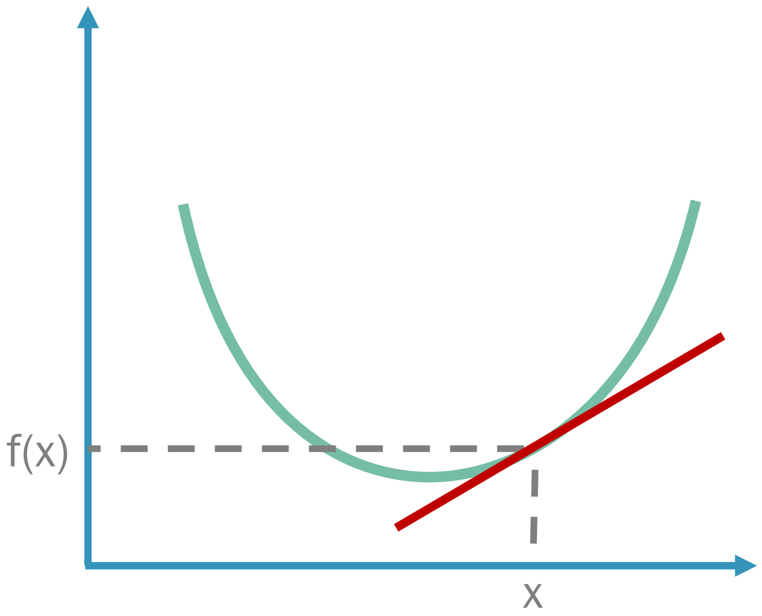

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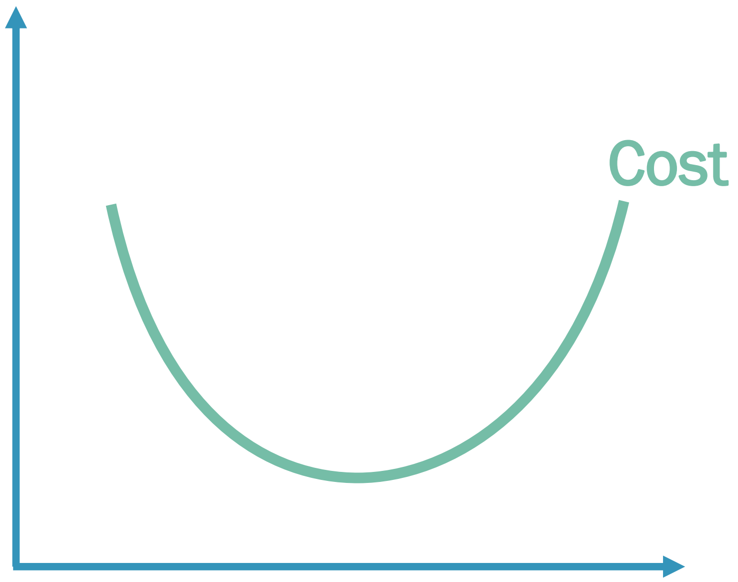

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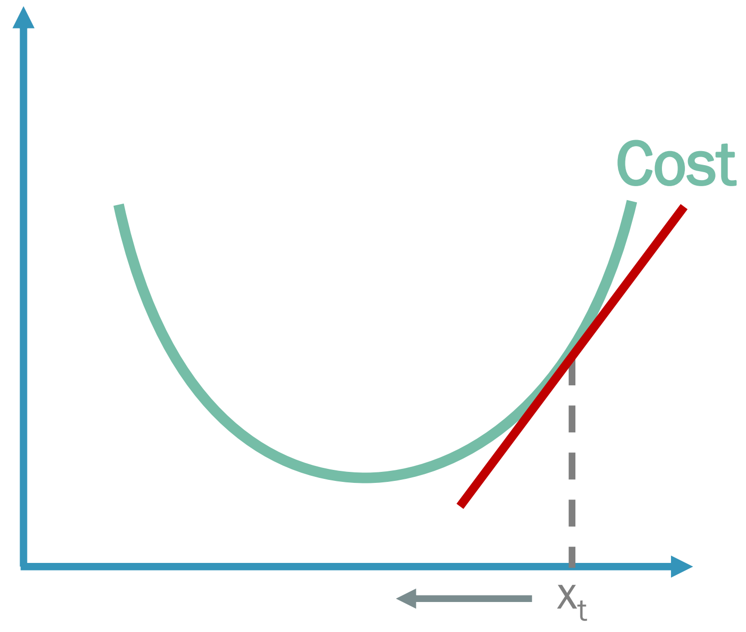

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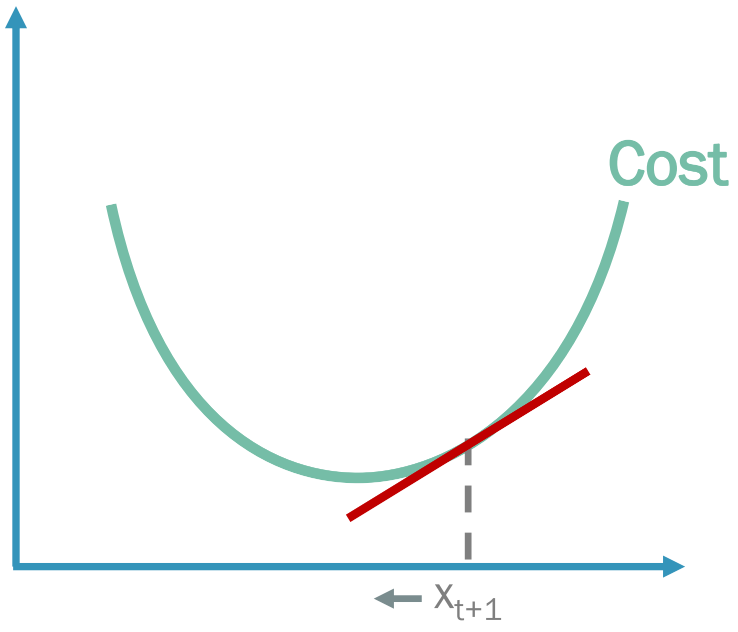

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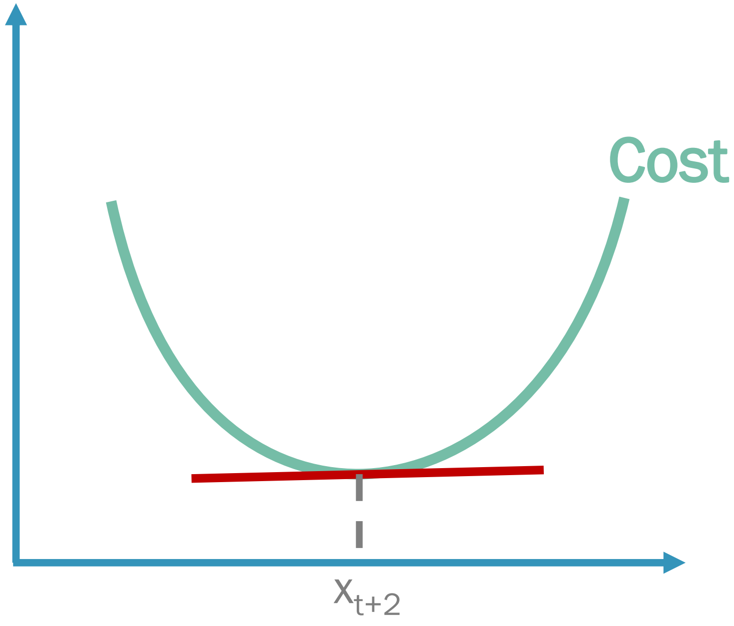

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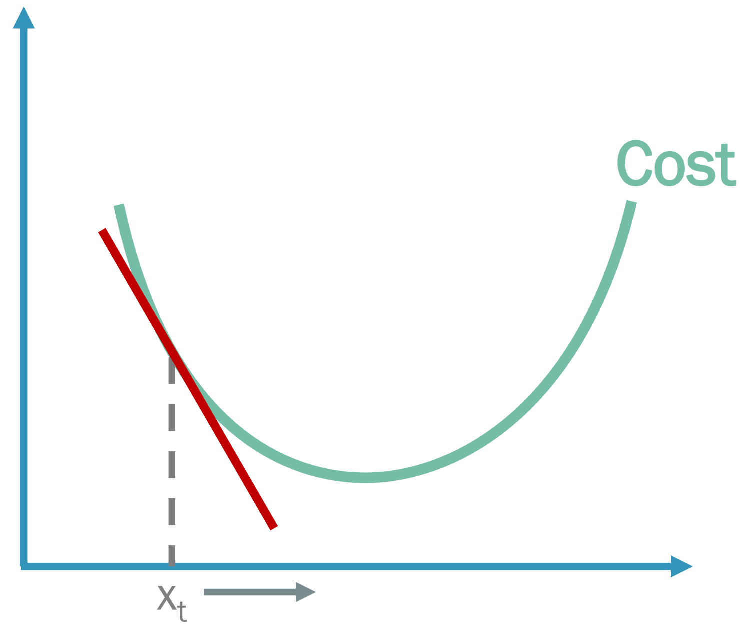

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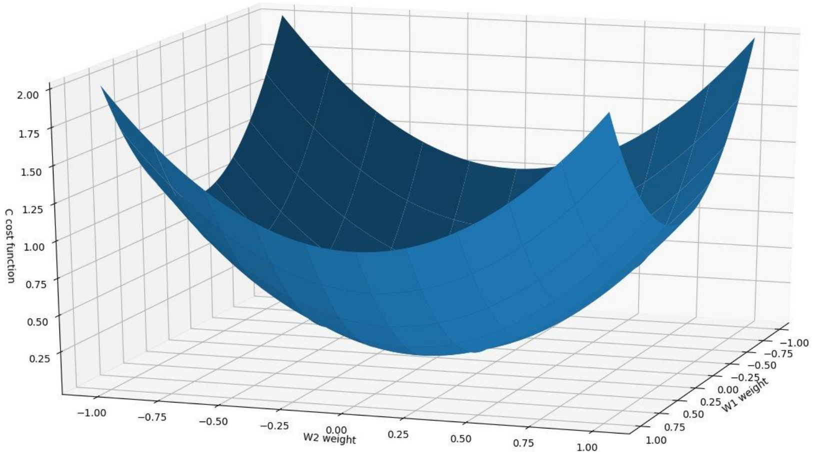

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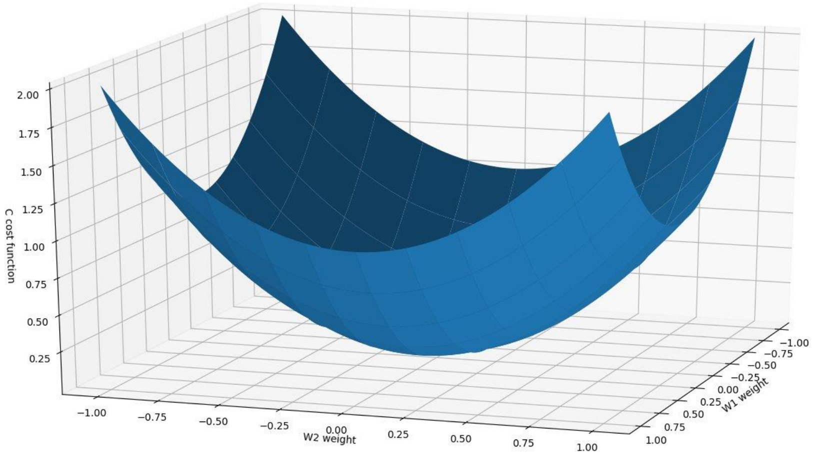
  - How a small change in $\boldsymbol{x_i}$ changes **y**, keeping all $\boldsymbol{x_{k \neq i}}$ constant



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  - $\frac{\partial y}{\partial x}$ instead of $\frac{dy}{dx}$

The chain rule of derivatives

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$$\frac{d}{dx} g\big(f(x)\big) = \frac{dg}{df}\frac{df}{dx}$$

Perceptron

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- Linear binary classifier

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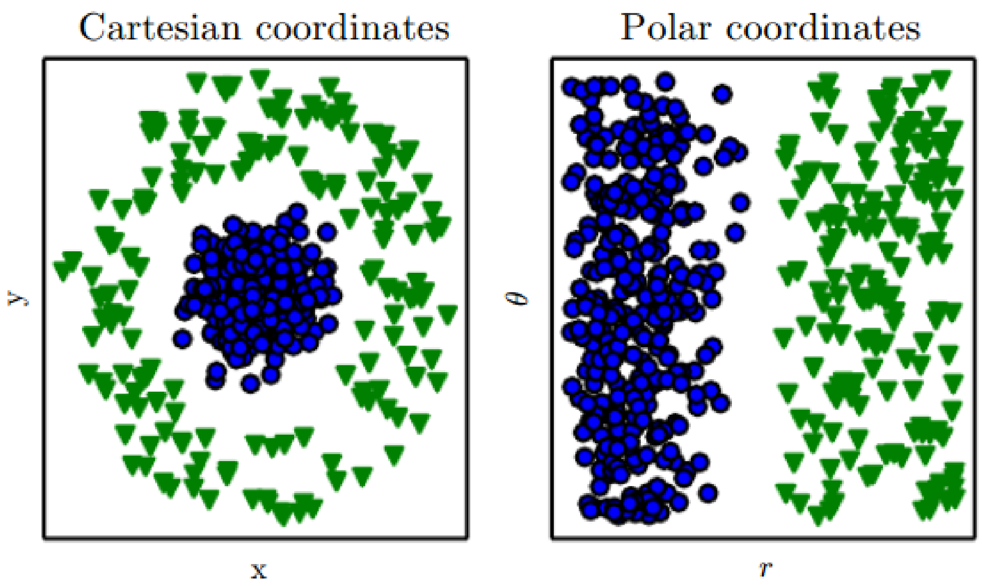
  - Linearly separable data



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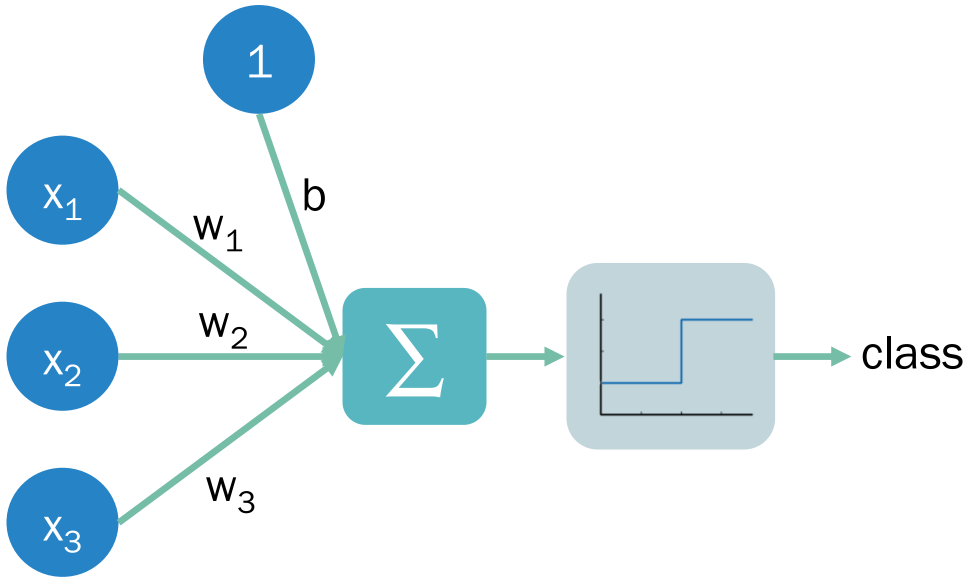

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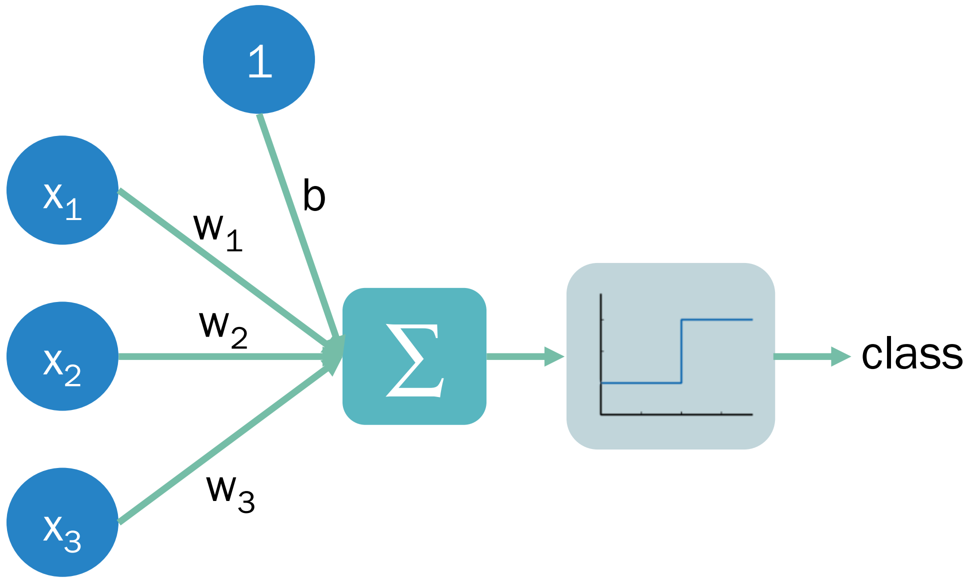
- **Components**
  - Input values



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- **Components**
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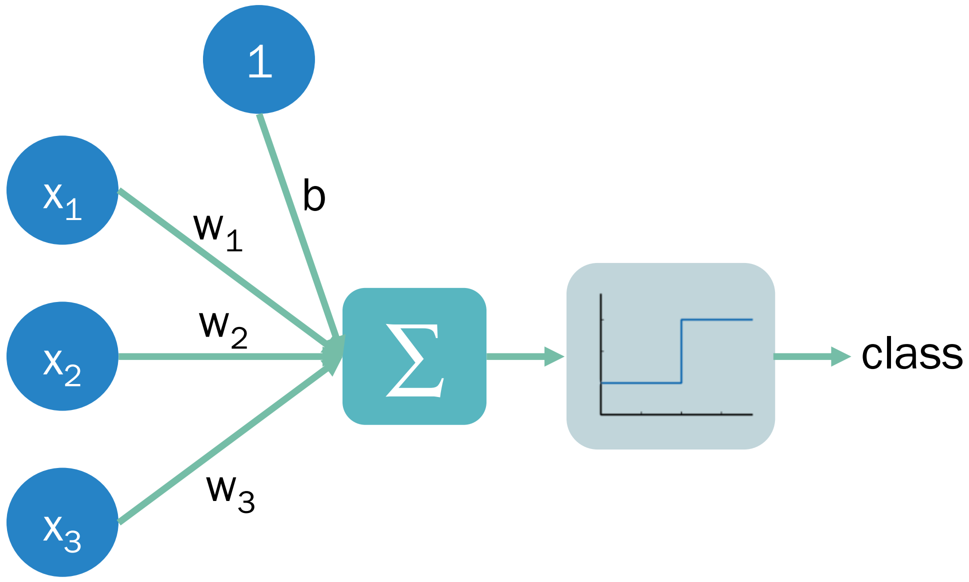
  - Weights and Biases



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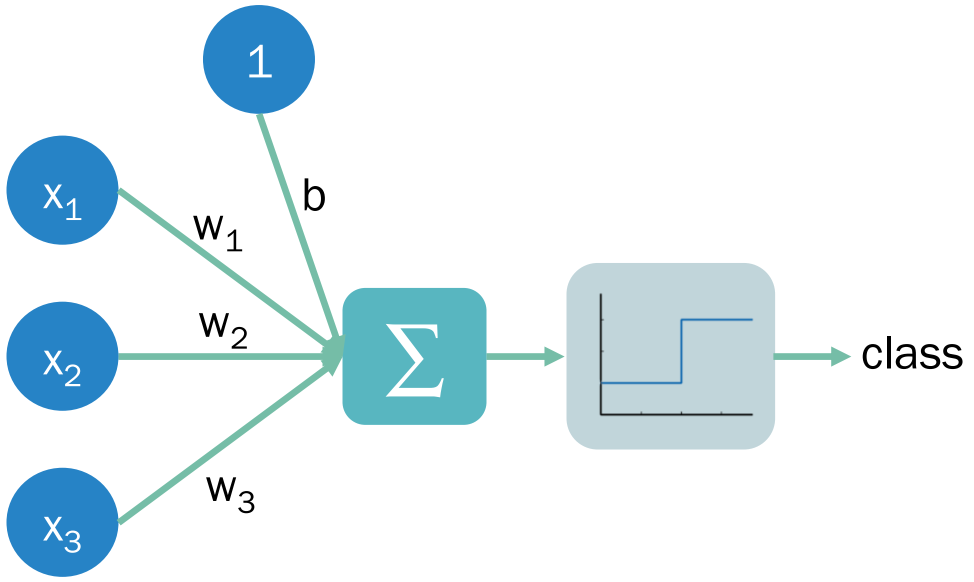
  - Sum



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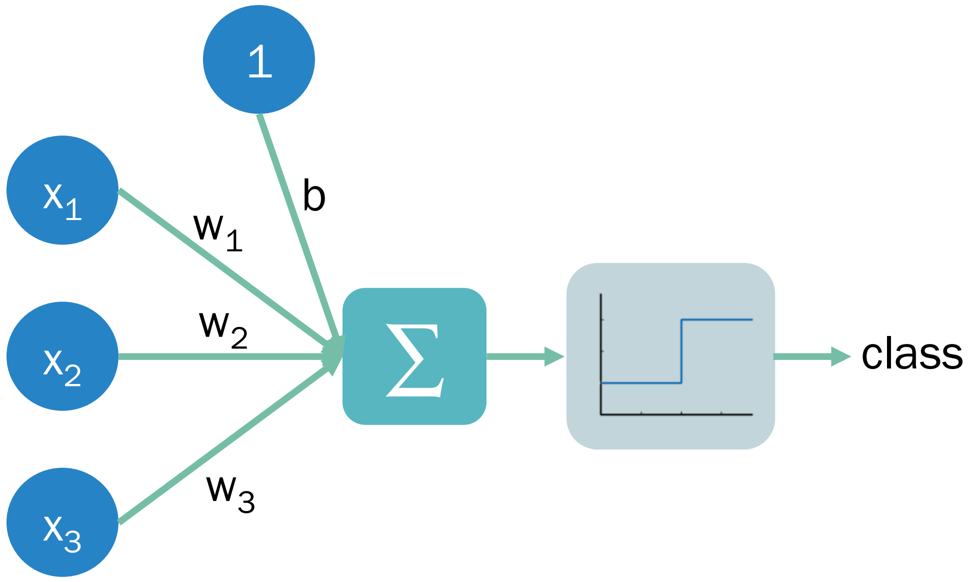

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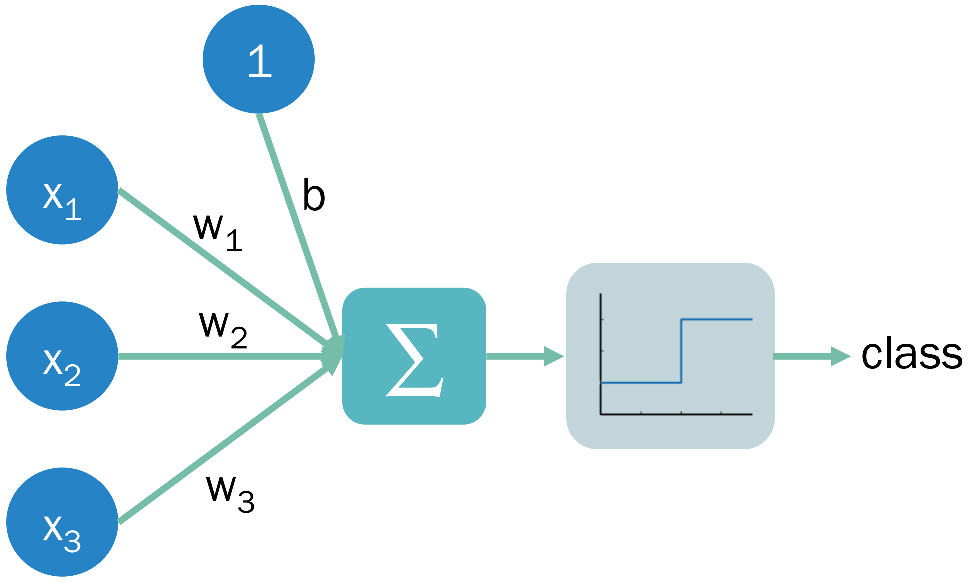
  - Weight update from errors *(training)*



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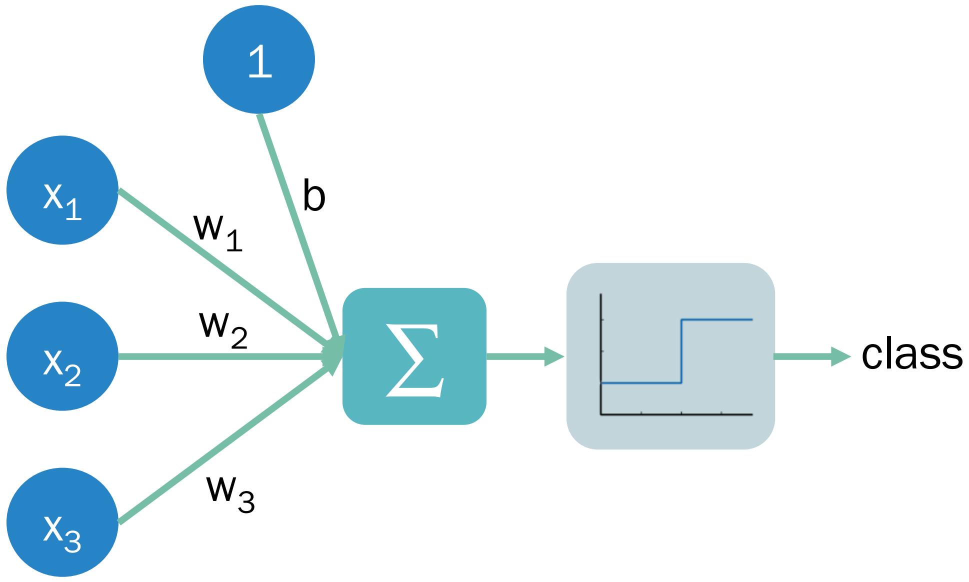
- **Steps**



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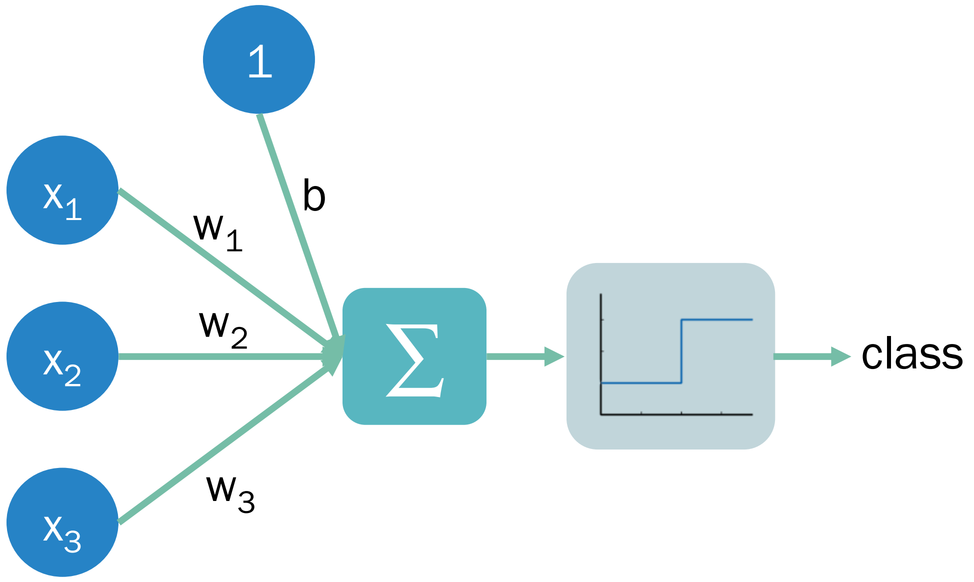
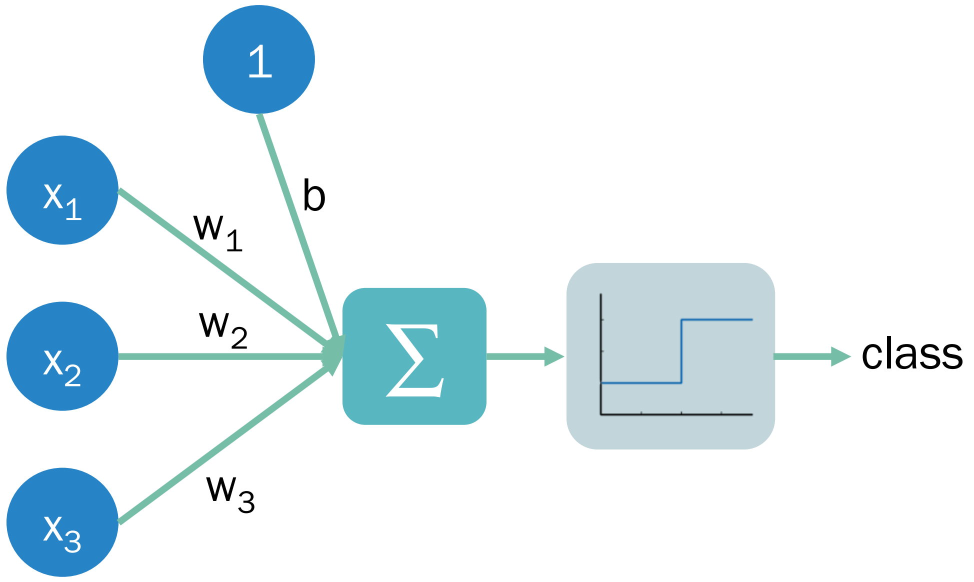
  - Weight update from errors *(training)*
- Steps
  1. Multiply inputs by the weights



Perceptron

- Linear binary classifier
  - Linearly separable data
  - One out of two classes
  - Supervised learning
- **Components**
  - Input values
  - Weights and Biases
  - Sum
  - Activation function
  - Weight update from errors *(training)*
- **Steps**
  1. Multiply inputs by the weights
  2. Add up the values



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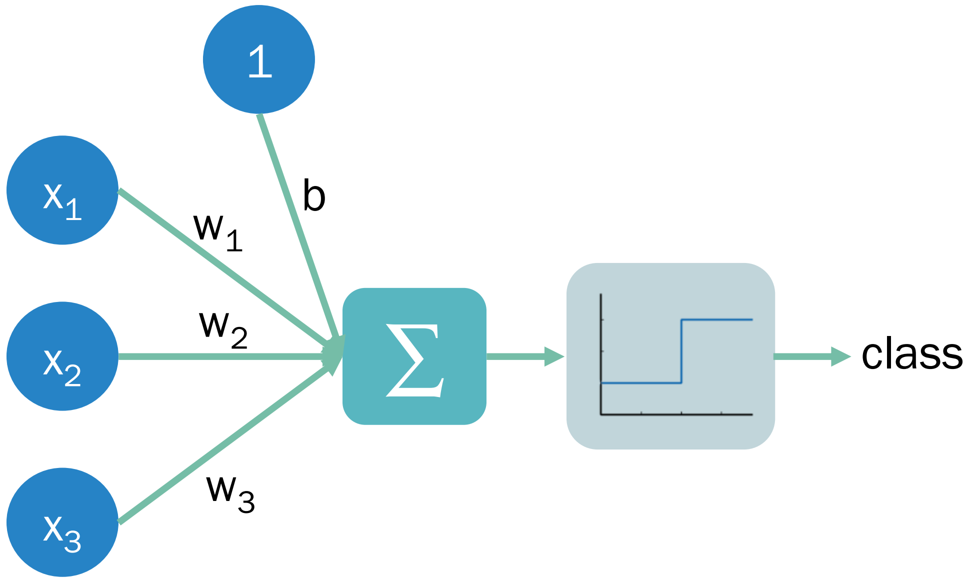

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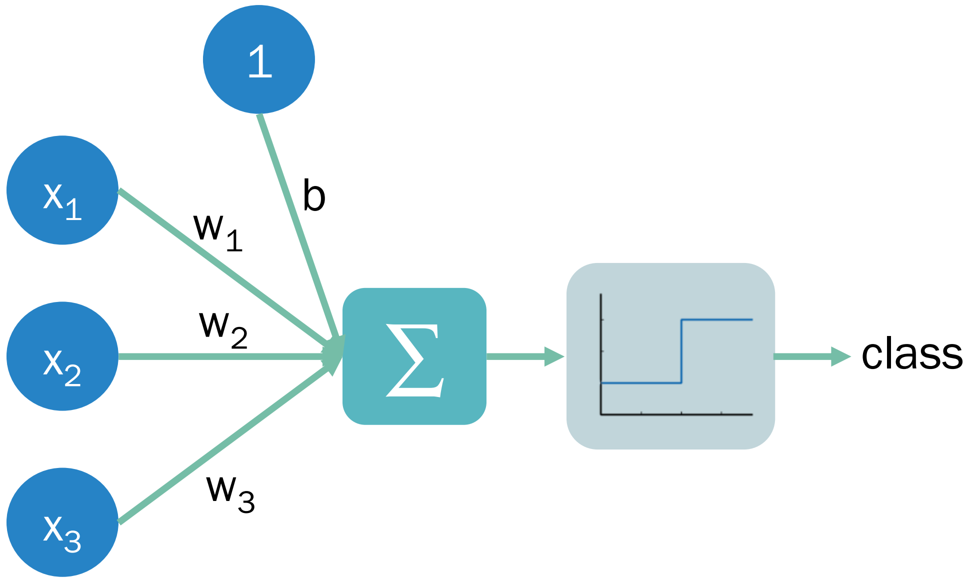

Step & Error functions

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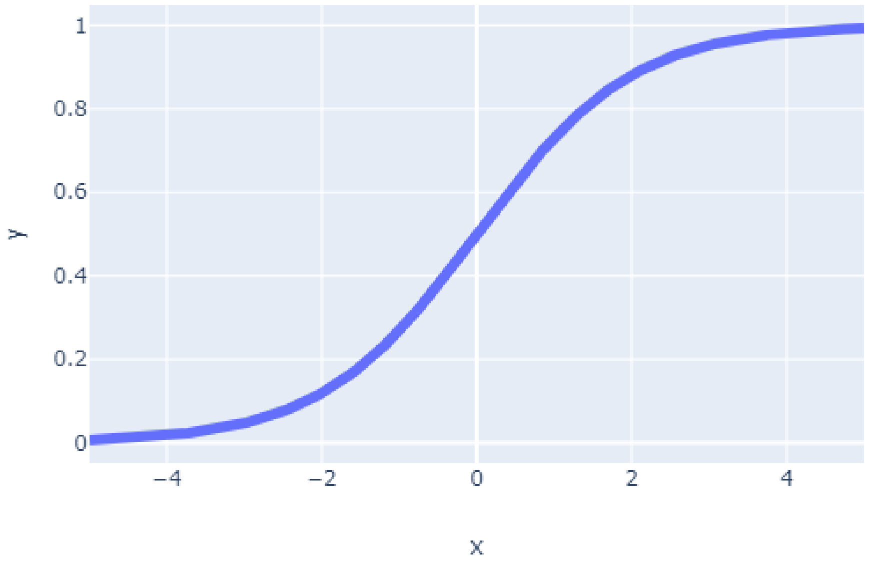
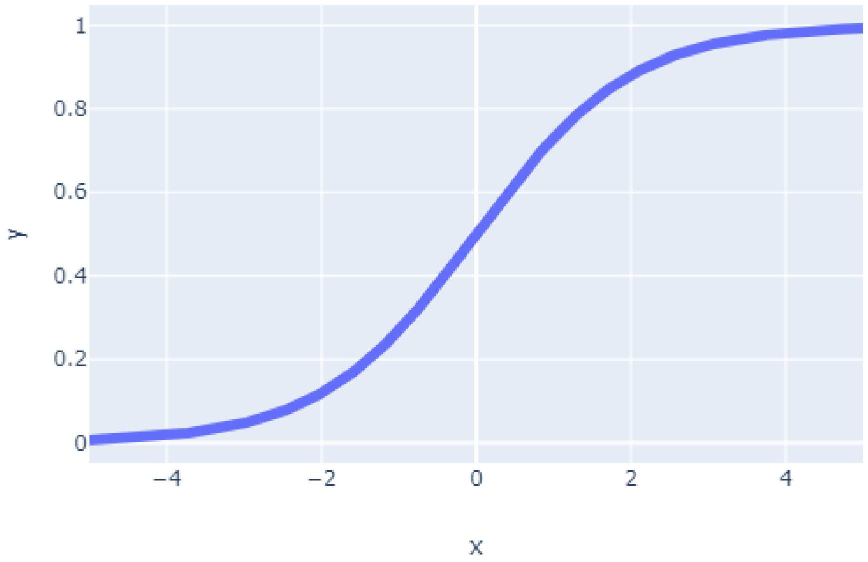
- Sigmoid function



Step & Error functions

- Sigmoid function
  - $\frac{1}{1+e^{-x}}$
  - Can be interpreted as probability



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  - $-\sum_i (t_i \ln(y_i) + (1-t_i)\ln(1-y_i))$
  - Distance between two distributions
  - Rooted on information theory
    - Huffman coding

The Internals

Is it all a black box?

"For every action there is an equal and opposite reaction"

Newton's 30rd Law of Motion

Setup

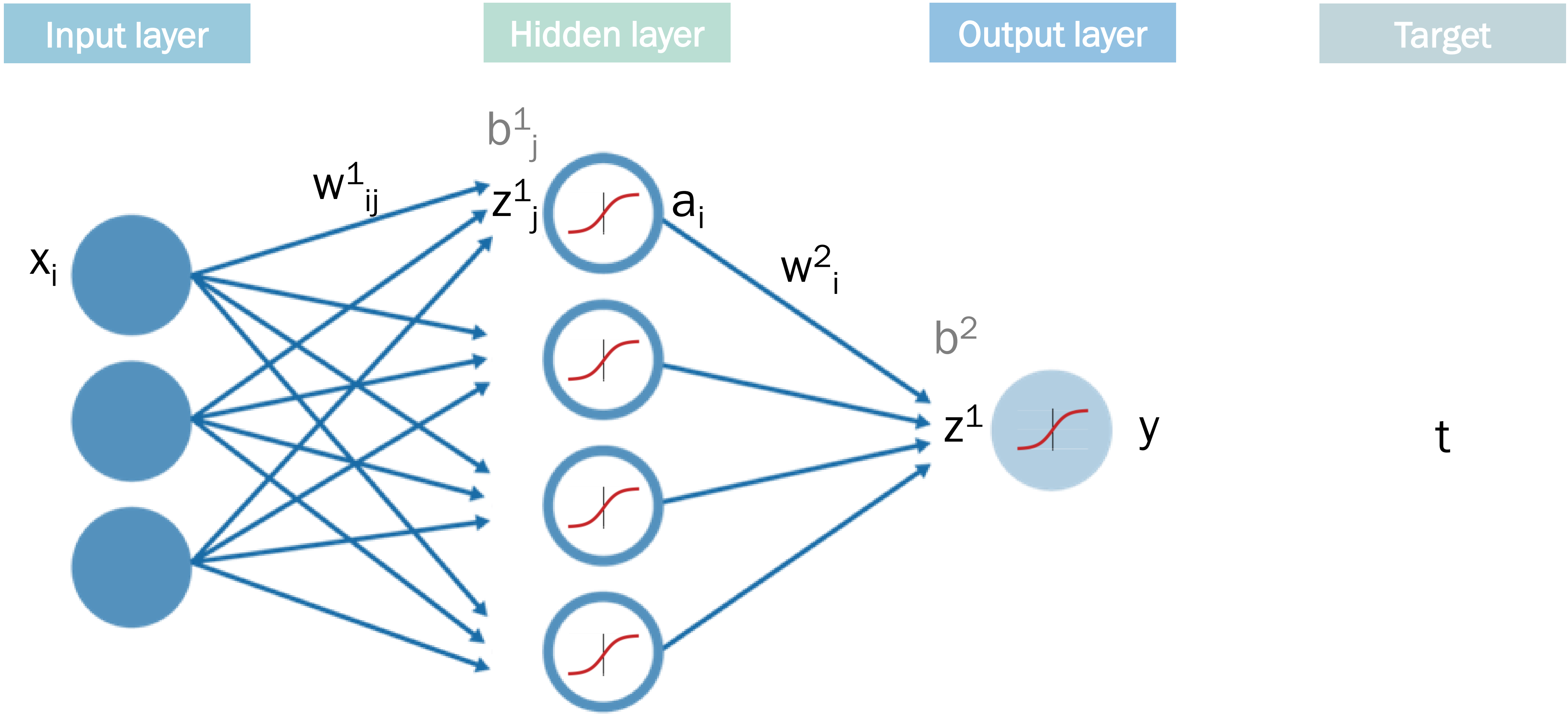
Single datum

Binary classification problem

Objective:

$$\arg\min_{w,b} Error$$

Anatomy of a neural network



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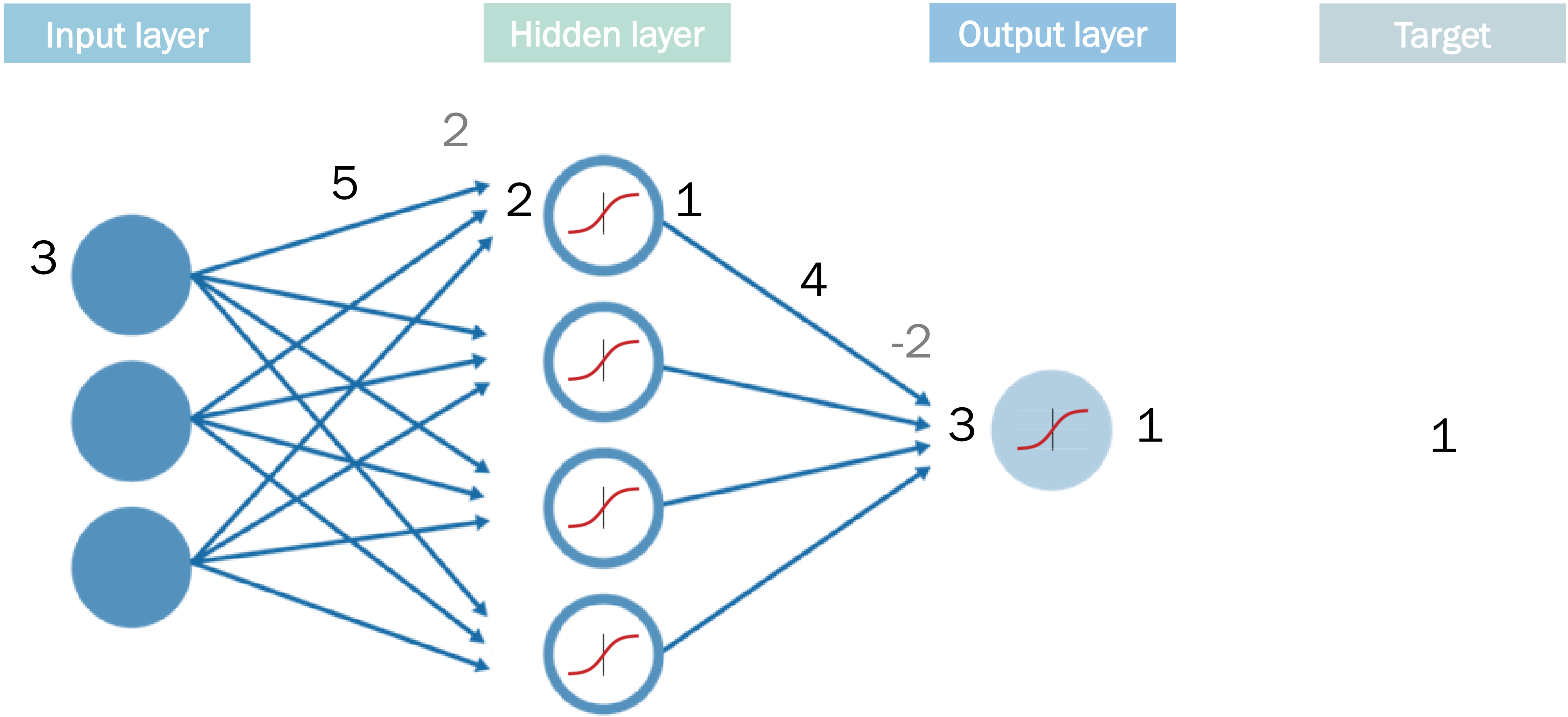

Derivation Steps

Forward Propagation

Error Computation

Back Propagation

Parameters update

Implementation

Does it even work?

"Machines take me by surprise with great frequency."

Alan Turing

Just a tiny bit more of fundamentals 😅

- Dot product of two matrices

```python
import numpy as np

a = np.random.normal(size=(100, 50))
b = np.random.normal(size=(50, 100))

# dot product of `a` and `b`?
```

Just a tiny bit more of fundamentals 😅

- Dot product of two matrices
  - **Iterating** over the arrays
    - 247 ms

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a = np.random.normal(size=(100, 50))
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# dot product of `a` and `b`

c_slow = np.zeros((100, 100))

for i in range(a.shape[0]):
    for j in range(b.shape[1]):
        acc = 0
        for k in range(a.shape[1]):
            acc += a[i, k] * b[k, j]
        c_slow[i, j] = acc
```

Just a tiny bit more of fundamentals 😅

- Dot product of two matrices
  - **Iterating** over the arrays
    - 247 ms
  - Numpy's dot product
    - 110 μs

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import numpy as np

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c = a.dot(b)
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http://bit.ly/2GFMIJP


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Today I learned

What we did:

- Derived the math behind traditional neural networks for binary classification
- Implemented and evaluated them using Numpy

Potential paths of exploration:

- Regression
  - Mean squared error
- Multiclass
  - Softmax activation
  - Cross entropy
- Refactor the implementation
- …

Bibliography

- *Deep Learning* by Goodfellow et al. for images and inspiration
- Notes on Backpropagation
- Census income dataset from UCI Repository
- Visual Information Theory by Christopher Olah
- Neural Networks MOOC by Geoffrey Hinton
- What the Hell is a Perceptron by Sagar Sharma

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Thank you

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