浙江大学爱丁堡大学联合学院
ZJU-UoE Institute

Lecture 11 - Introduction to neural networks

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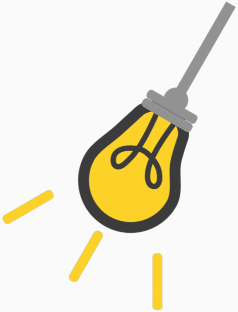
- Describe artificial neural networks (ANNs).
- Explain the learning process of ANNs.
- Explain the concept of gradient descent.



Introduction

Artificial neural networks

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Each neuron takes in a number of inputs, performs some calculation on these inputs and outputs anothe value.

The connections between neurons (**edges**) are weighted, so that different inputs might influence the results in different ways.

Typically, neural networks consists of layers of these nodes.

Why using neural networks?

- Used in many field - adaptable to many problems
- Sufficiently complex networks can approximate any function
- Image analysis / computer vision has vastly benefitted from ANN (specifically CNN) as they can extract complex information from images
- Downside: often network computation is difficult to interpret

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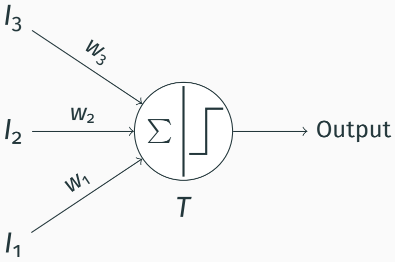
Today we will introduce **shallow networks**, and will move onto **deep networks** in the next lectures.

Single layer ANN

The McCulloch-Pitts Neuron

- Linear threshold unit (LTU)
- The first type of artificial neuron developed in 1943 by McCulloch and Pitts
- Little resemblance to biological neurons
- Only very simple (binary) operation possible
- Inputs can only be 0 or 1, weights could be +1 or -1 (excitatory or inhibitory)
- A simple **threshold** *T* decides the binary output.



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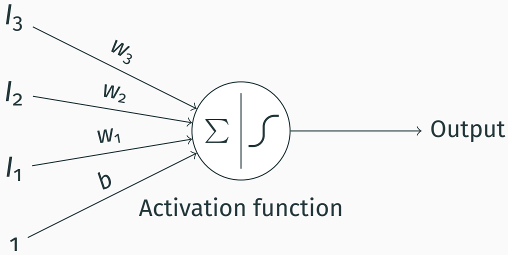
- Learns: $$f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0, \\ 0 & \text{otherwise} \end{cases}$$

  x: vector of input features
  w: vector of weights
  b: bias



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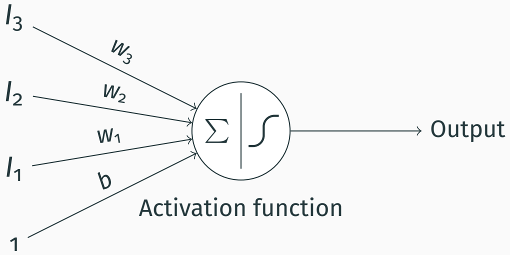
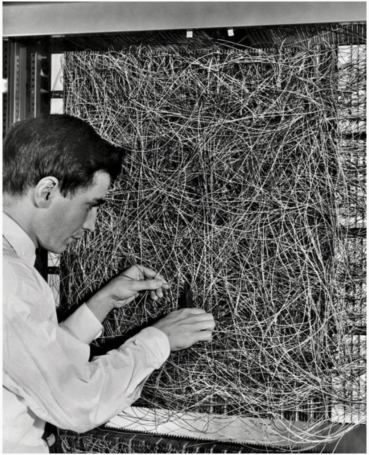
- Includes an **activation function** (e.g. a sigmoid), which can introduce non-linearity in the system, allowing to model complex functions.
- Includes a **bias term**, which allows shifting the activation function.

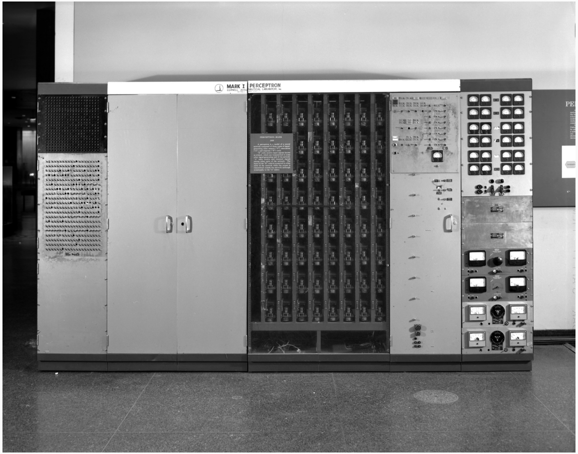


A little historical side note...

The perceptron was built as an actual machine!

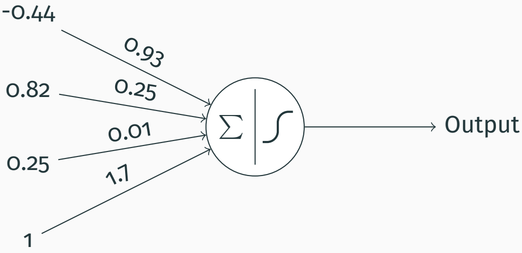


Frank Rosenblatt with a Mark I Perceptron computer in 1960



A Mark I Perceptron computer - National Museum of American History

The calculations performed by a ANN are very simple.

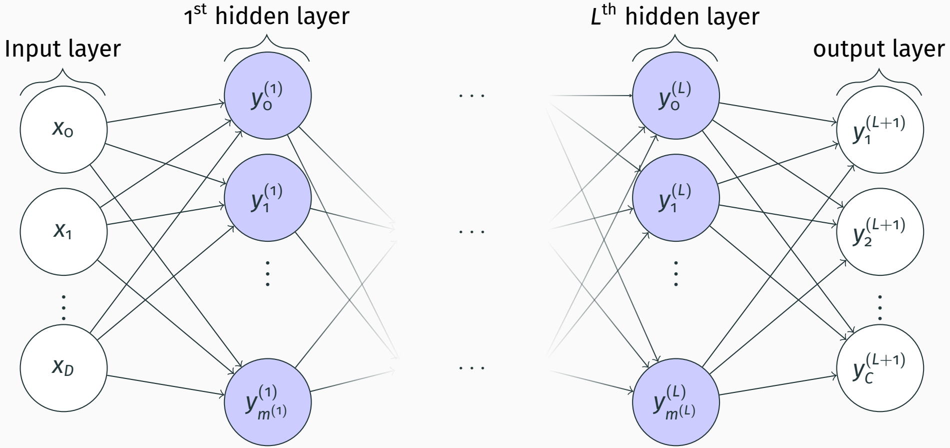


We calculate: $\sum_i (x_i \cdot w_i) + b = 0.25 * 0.01 + 0.82 * 0.25 - 0.44 * 0.93 + 1.7 = \mathbf{1.498}$ and we pass it through the activation function.

For example, using the sigmoid we get $\frac{1}{1+e^{-1.498}} = \mathbf{0.9}$.

Multi-layer perceptrons

We can extend the perceptron to a **multi-layer perceptron** (MLP).



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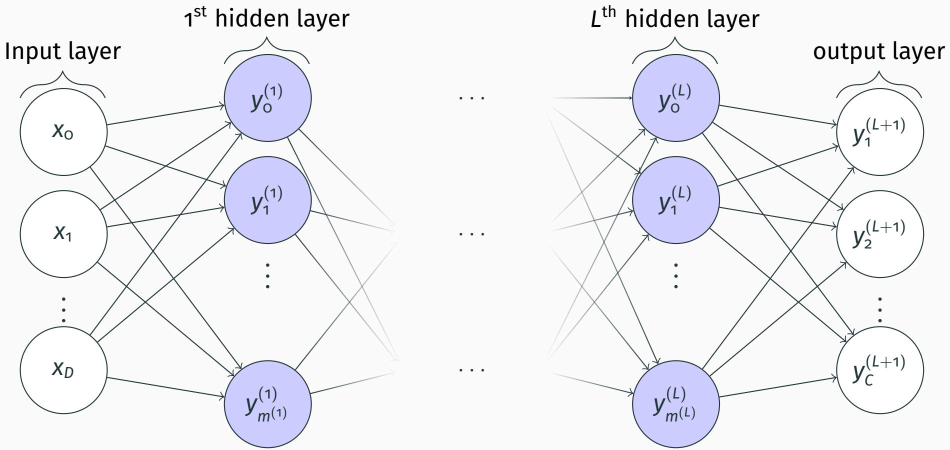

MLPs have one or more **hidden layers** that are connected to the input layer. By increasing the complexity of the network, it can perform much more complex tasks.

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- We repeat this process until we reach the output layer.

Activation function

Several activation functions are used in ANNs. They are used to introduce non-linearity in the ANN.

Some of the most common are:

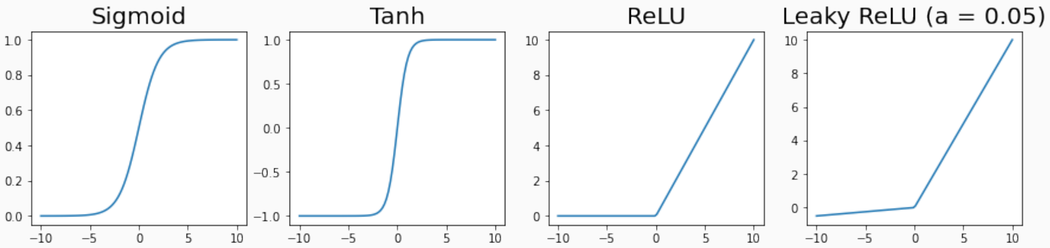
- Sigmoid
- Hyperbolic tangent (tanh)
- Rectified linear unit (ReLU)
- Leaky ReLU

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$\mathrm{ReLU}(x) = \max(0, x)$$

$$\mathrm{ReLU}(x, a) = \max(a \cdot x, x)$$

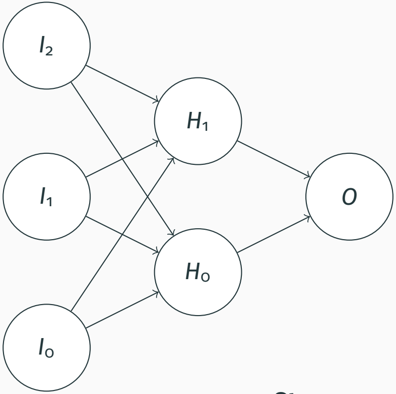


Optimization (how does the ANN learn?)

Backpropagation

Once the forward propagation is complete, we can start **backpropagation**.

This is the process of improving the weights of each node to minimise the error in the output of the network.



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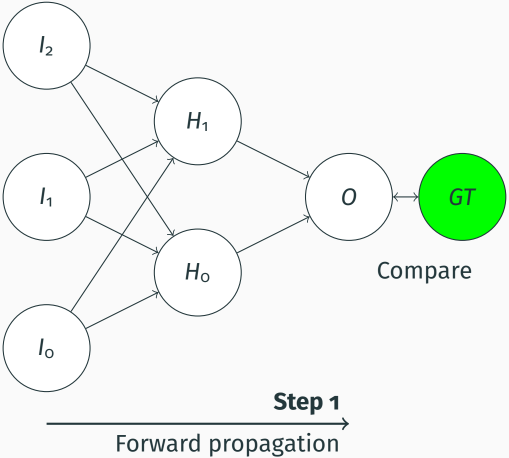

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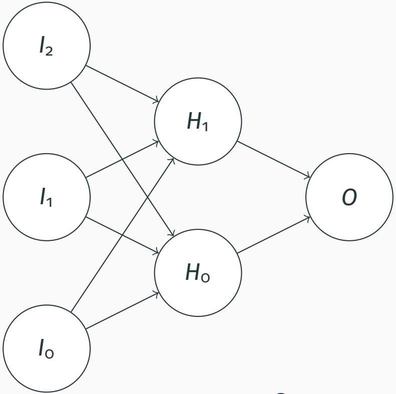

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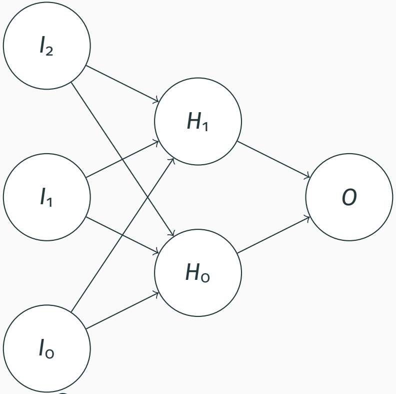

Step 2

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One of the most common optimizers is **gradient descent** (or some of its variations).

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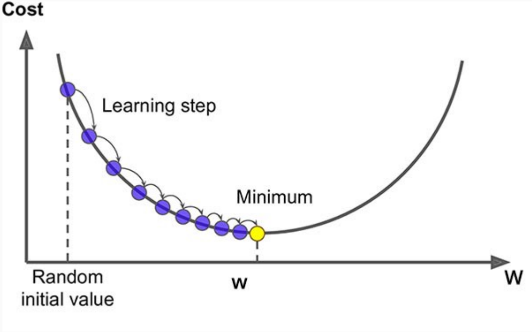
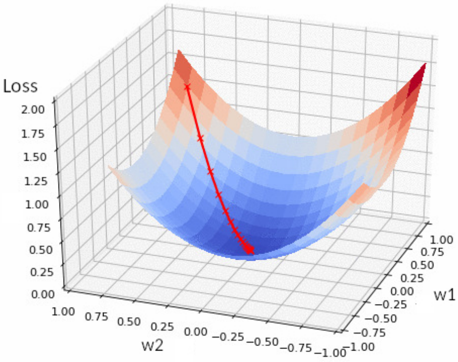


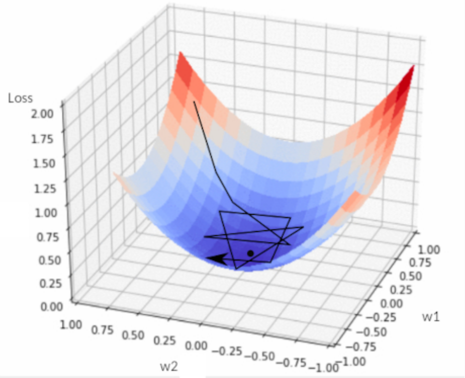
$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \nabla J(\mathbf{w})$$

$\leftarrow$ While the image shows a single weight, in reality we need to do this for the (very) large number of parameters in the network!

Learning rate

The choice of learning rate is key!





Next lecture...

Having a general understanding of ANNs, we will look at more complex networks and start talking about deep learning!