Machine Learning workshop

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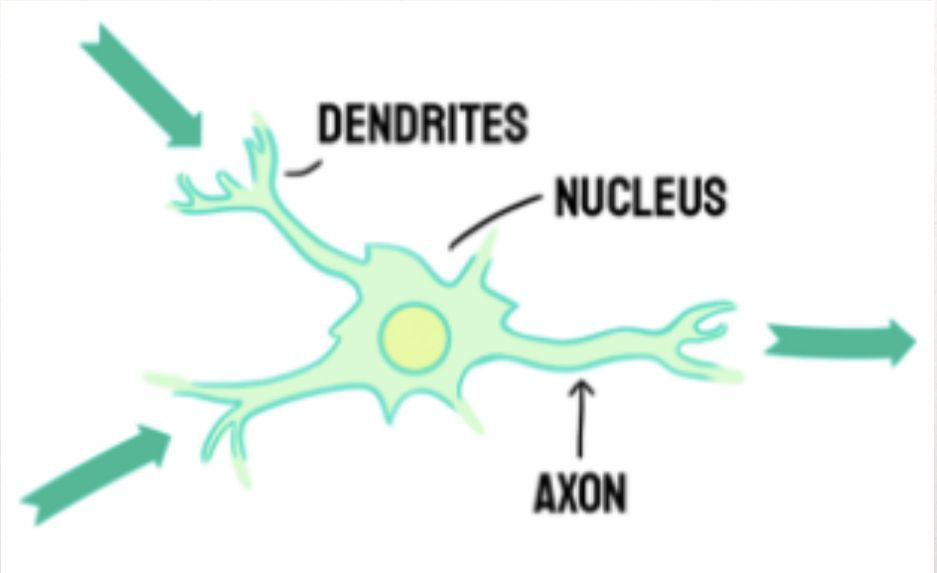
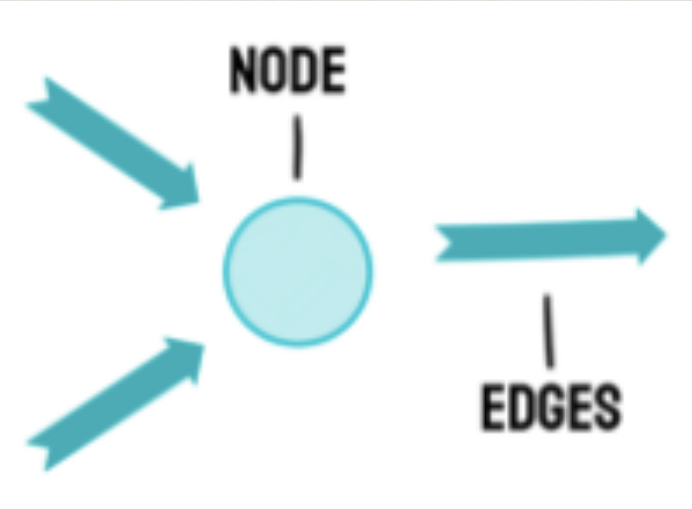
Brief introduction to **Neural Networks** (NN)

Artificial NNs inspired from Biological NNs

Biological Neural Network (BNN)



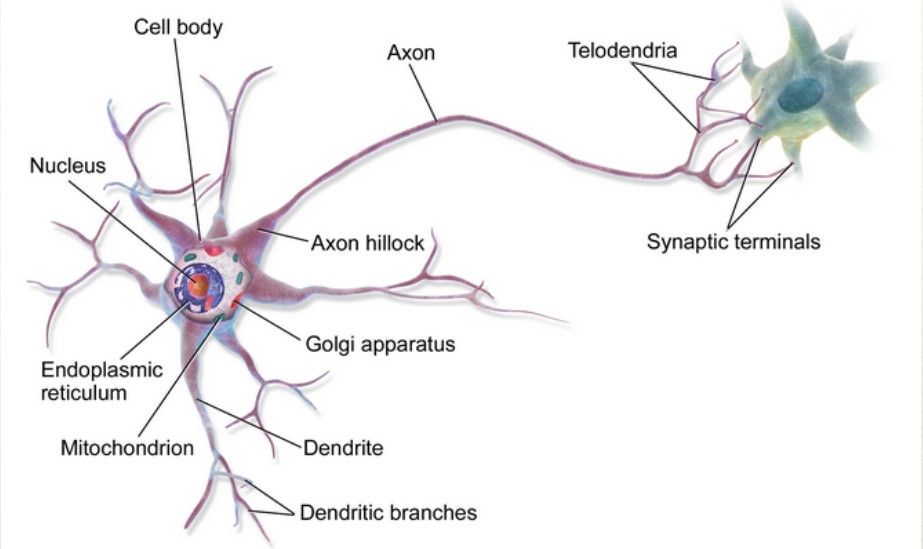
Artificial Neural Network (ANN)



From BNN to ANN

ANN as simulation of Biological NN

- NN are developed by simulating networks of human neurons



The human neuron has a cell body, a number of input wires (*dendrites*) and an output wire (*axon*)

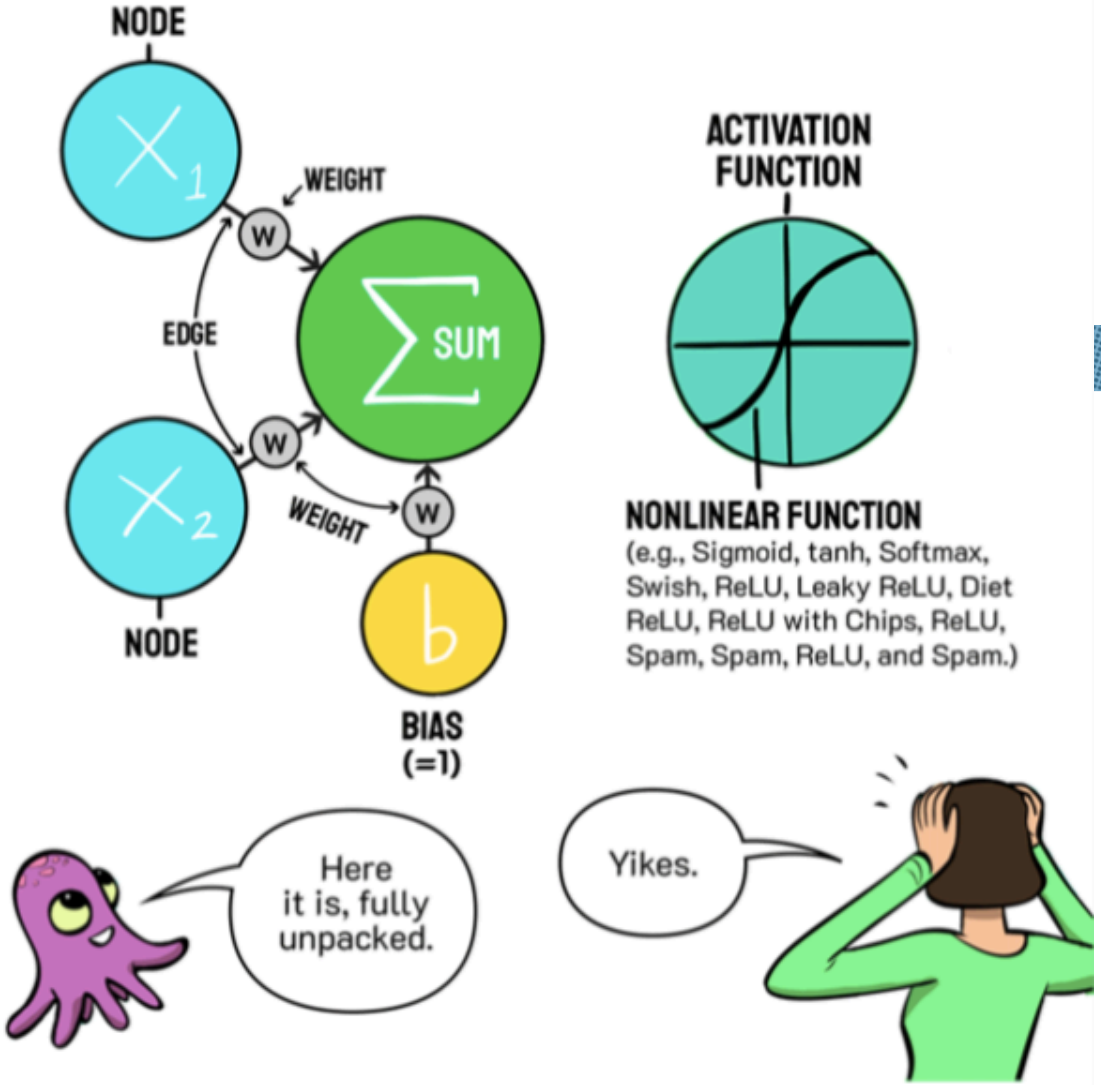
- we can think of it as a **computational unit** that gets inputs, computes, and spits output to other neurons (which we will call **nodes** or **units**)
- we can think of it simply as a **logistic unit** that computes some h as a sigmoid

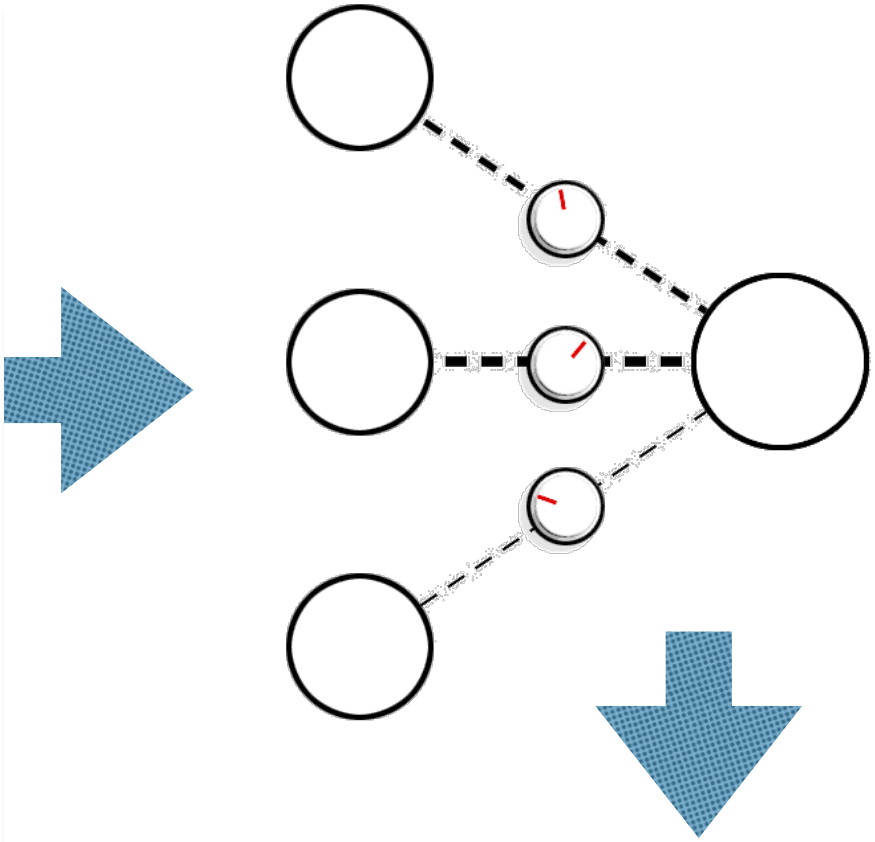
Communication in BNNs is done via pulses of electricity

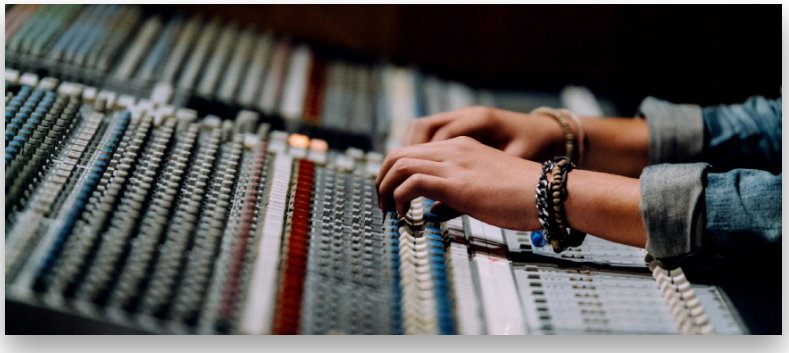
- we can think of **I/O** passing in/out **numerical values**
- a **wide** network..

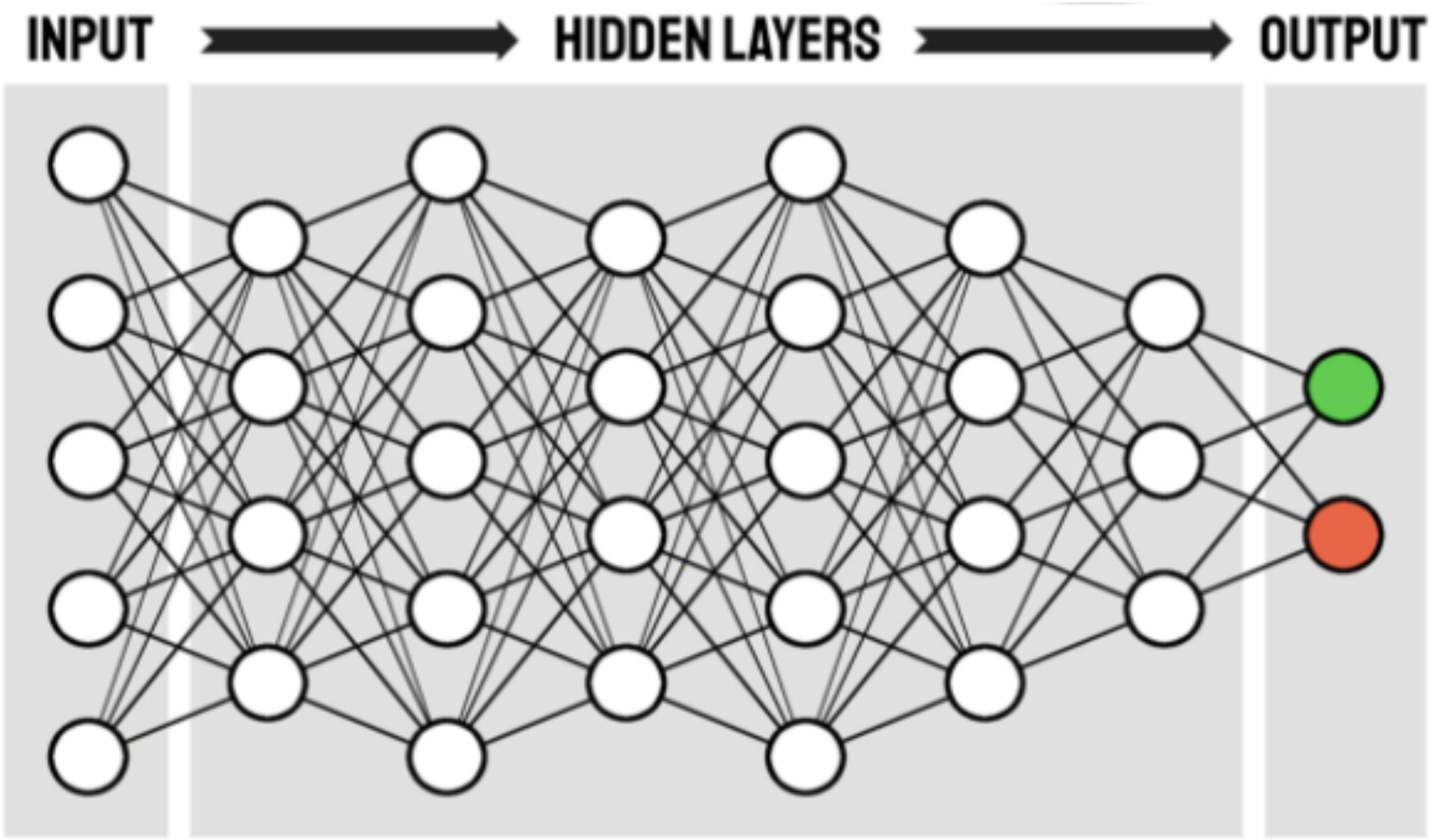
Vastly oversimplified model.. → see next

All boils down to a set of optimal "weights"








INPUT
HIDDEN LAYERS
OUTPUT

Why NNs as ML algorithms?

Important to model **non-linear relationships among attributes**.

NNs are at the very core of **Deep Learning**

- versatile, powerful, scalable

Ideal to tackle large and highly complex ML tasks, such as:

- classifying billions of **images** (e.g., Google Images)
- powering **speech recognition** services (e.g. Siri, Alexa, ..)
- **recommending** the best videos to watch to *O*(100M) users every day (e.g. YouTube)
- **learning to beat humans** in very specific tasks (e.g. from medical applications - e.g. radiology - to gaming - e.g. Go and DeepMind's AlphaZero)

Brief history of NNs

1943 (!): first introduction by McCulloch and Pitts

- a neurophysiologist and a mathematician
- "A Logical Calculus of Ideas Immanent in Nervous Activity",
- the first ANN architecture in human history
  - a simplified computational model of how biological neurons might work together in animal brains to perform complex computations using propositional logic

1960s: the successes of ANNs stopped - the "**first AI winter**"

Early 1980s: revival of interest in connectionism, new architectures, better training techniques. Slow progress, though.

1990s: other (not NN) powerful ML techniques were invented, e.g. SVMs . Seemed to offer better results and stronger theoretical foundations than ANNs - the "**second AI winter**"

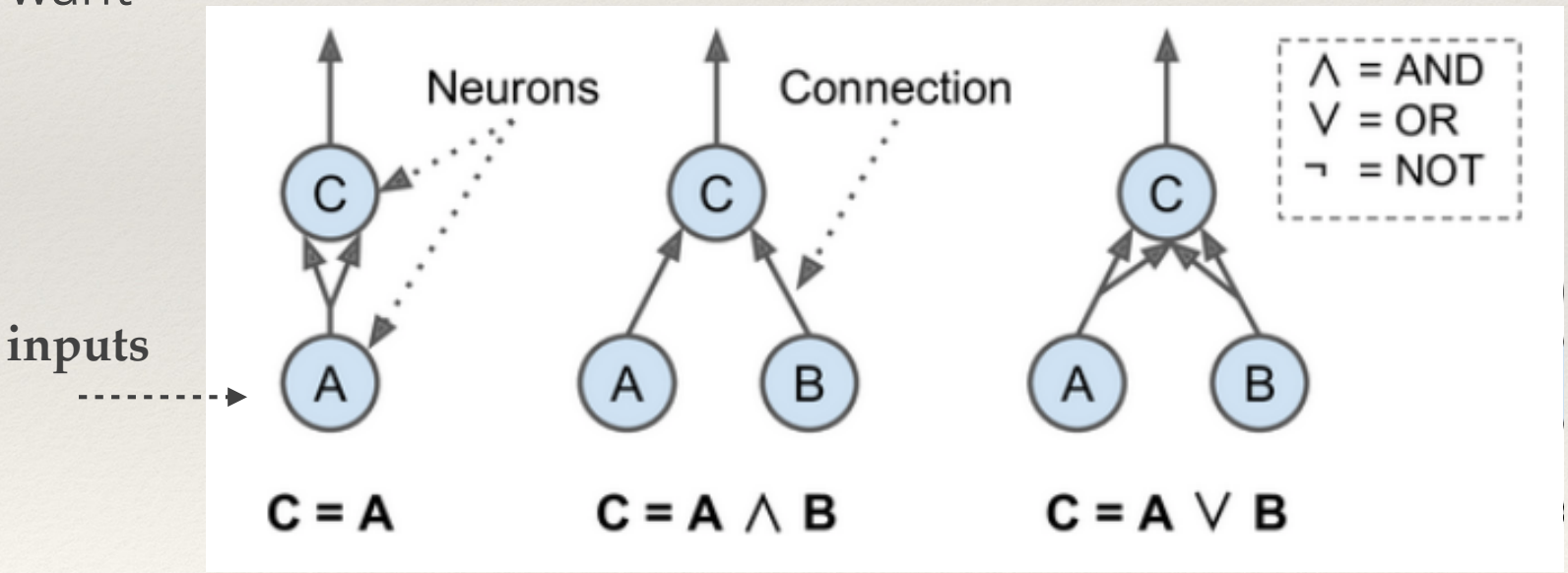
2000s-2010s: a new "AI spring": why now? will it last?

Logical computation with neurons

The McCulloch/Pitts model for a biological neuron was later called "**artificial neuron**"

- it has 1 (or more) **binary (on/off) inputs** and 1 **binary** output (*NOTE: all binaries!*)
- it activates its output when more than a certain number of its inputs are active (e.g. 2 in the examples below)

They showed that even with such a simplified model it is possible to build a network of artificial neurons that computes **any basic logical proposition** you want

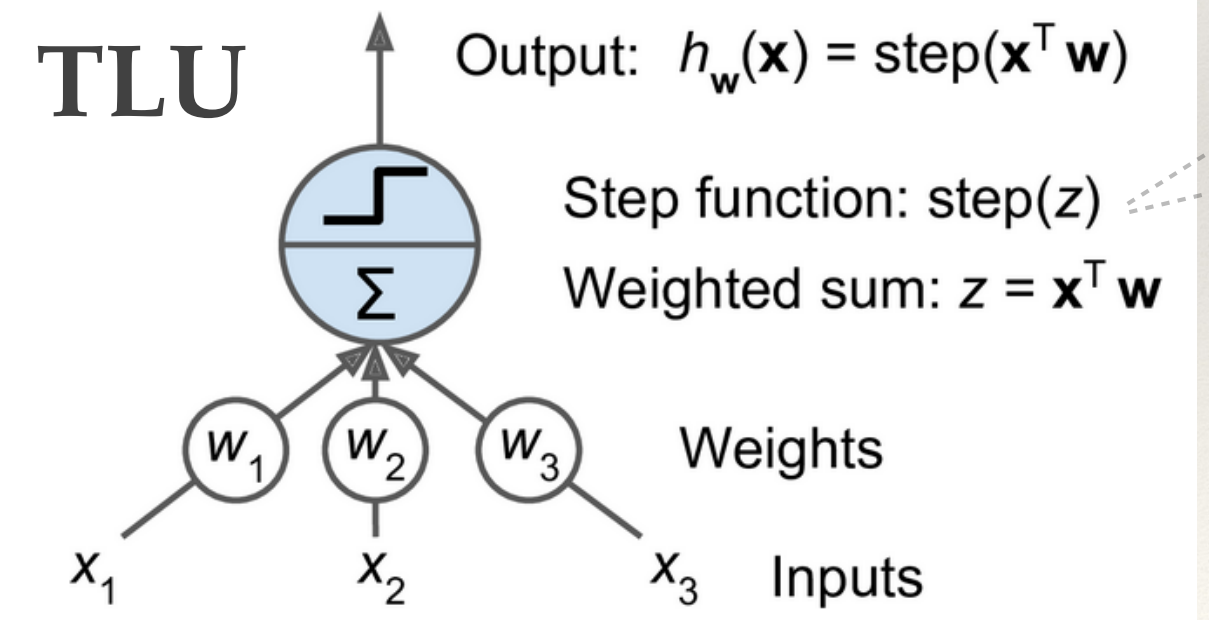


Imagine yourself how to combine them to form more complex logical functions

The **TLU** and the Perceptron

1957, Rosenblatt: "Perceptron" as one of the simplest possible ANN architectures, based on a slightly modified artificial neuron, called **threshold logic unit** (**TLU**) or linear threshold unit (LTU)

- the **inputs/output** are now **numbers** (not binary on/off) values
- each input connection is associated with a **weight**
- the TLU computes a **weighted sum of its inputs**, applies a **step function** to that sum, and **outputs** the result



$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

$$\text{sgn}(z) = \begin{cases} -1 & \text{if } z < 0 \\ 0 & \text{if } z = 0 \\ +1 & \text{if } z > 0 \end{cases}$$

1 single TLU can act as a simple **linear binary classifier**

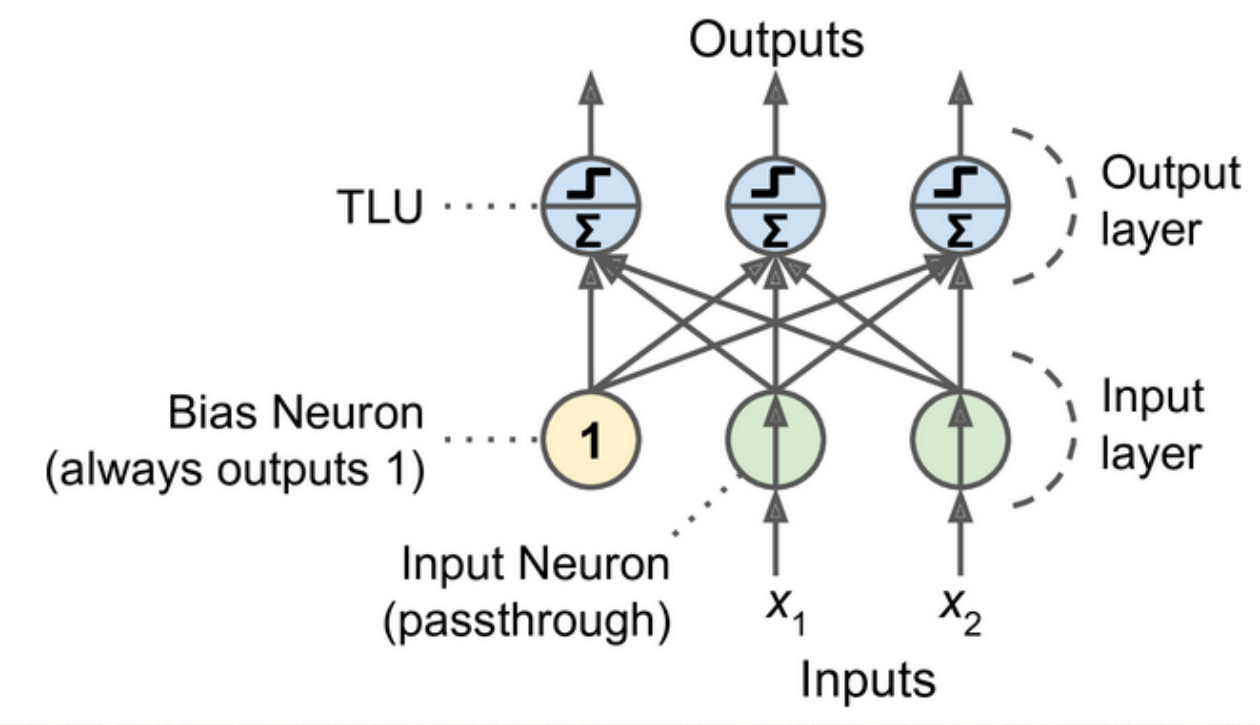
- linear combination of the inputs, and depending of the thresholds → positive/ negative class (just like Logistic Regression classifier or a linear SVM !)

The TLU and the **Perceptron**

A **Perceptron** is then composed of **a single layer of TLUs** with each TLU connected to all the inputs

- in the **input layer**, an extra bias feature is generally added ($x_0 = 1$), via a "**bias neuron**" that just outputs 1 all the time.
- When all the neurons in a layer are connected to all the neuron in the previous layer (i.e. here the input neurons), it is called a **fully-connected** or **dense** layer

This Perceptron can classify instances simultaneously into 3 different binary classes, which makes it a **linear multi-class classifier**



Training a **Perceptron**

Input from biology and neurosciences

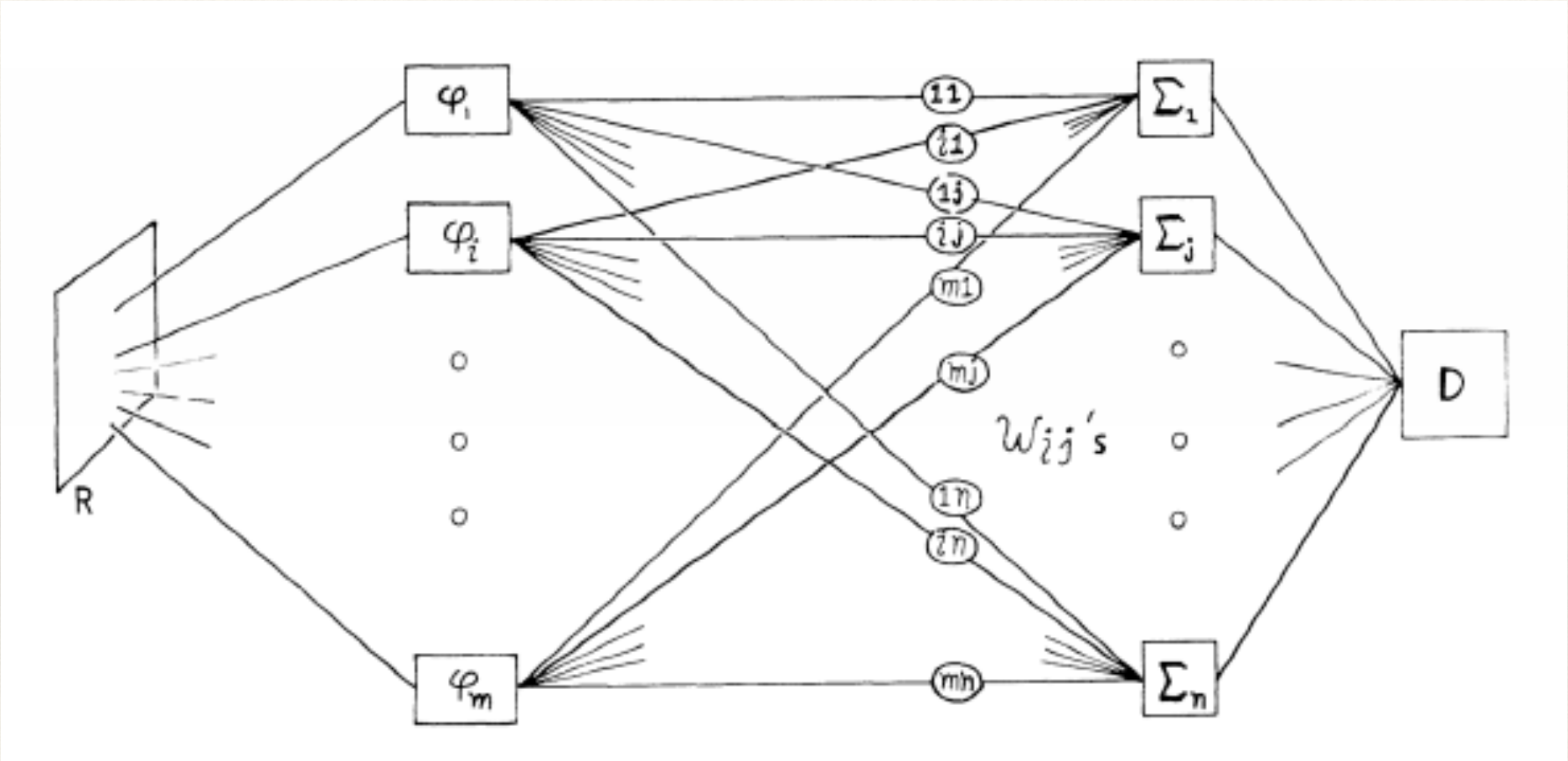
- *1949, Hebb; "Organization of Behavior"*
- **Hebb's rule** (Hebbian learning): when a biological neuron triggers another neuron, the connection between these two neurons **grows stronger**
  - Lowel: "**Cells that fire together, wire together**"

Largely inspired by Hebb's rule, the Perceptron training algorithm proposed by Rosenblatt was a **weight update**

- the Perceptron is fed one training instance at a time. For each instance it makes its prediction(s). For every output neuron that produced a wrong prediction, it reinforces the connection weights from the inputs that would have contributed to the correct prediction

Multi-Layer Perceptron (MLP)

1969, Minsky/Papert, "Perceptrons", the monograph



A picture very similar to the ones we still draw today!

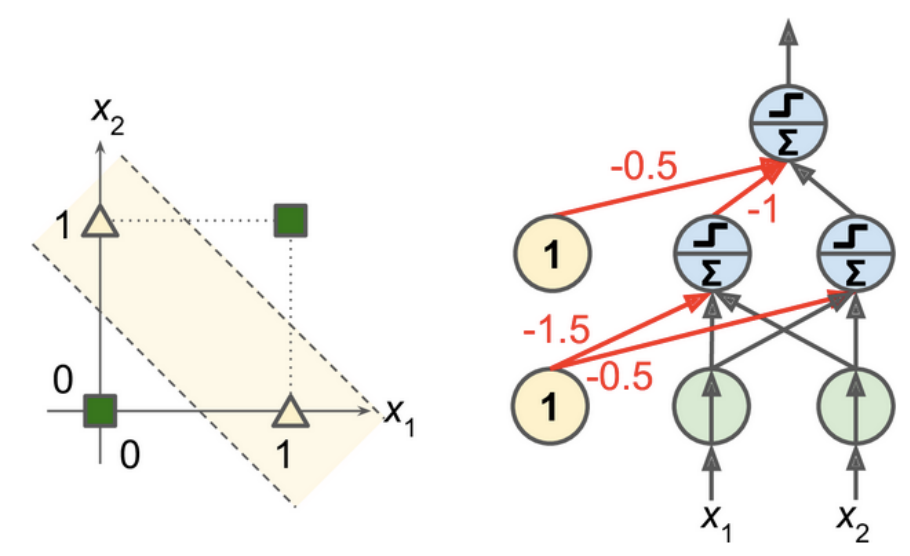
Multi-Layer Perceptron (MLP)

Minsky/Papert:

- serious weaknesses of Perceptrons highlighted, in particular its incapability of solving relatively trivial problems, e.g. the exclusive OR (XOR) classification problem
- Well, true of any other linear classification model (e.g. Logistic Regression classifiers).. but **researchers had expected much more from Perceptrons!** Great disappointment. People dropping off the field..

But.. it soon turned out most limitations of Perceptrons could be eliminated by **stacking multiple Perceptrons**!

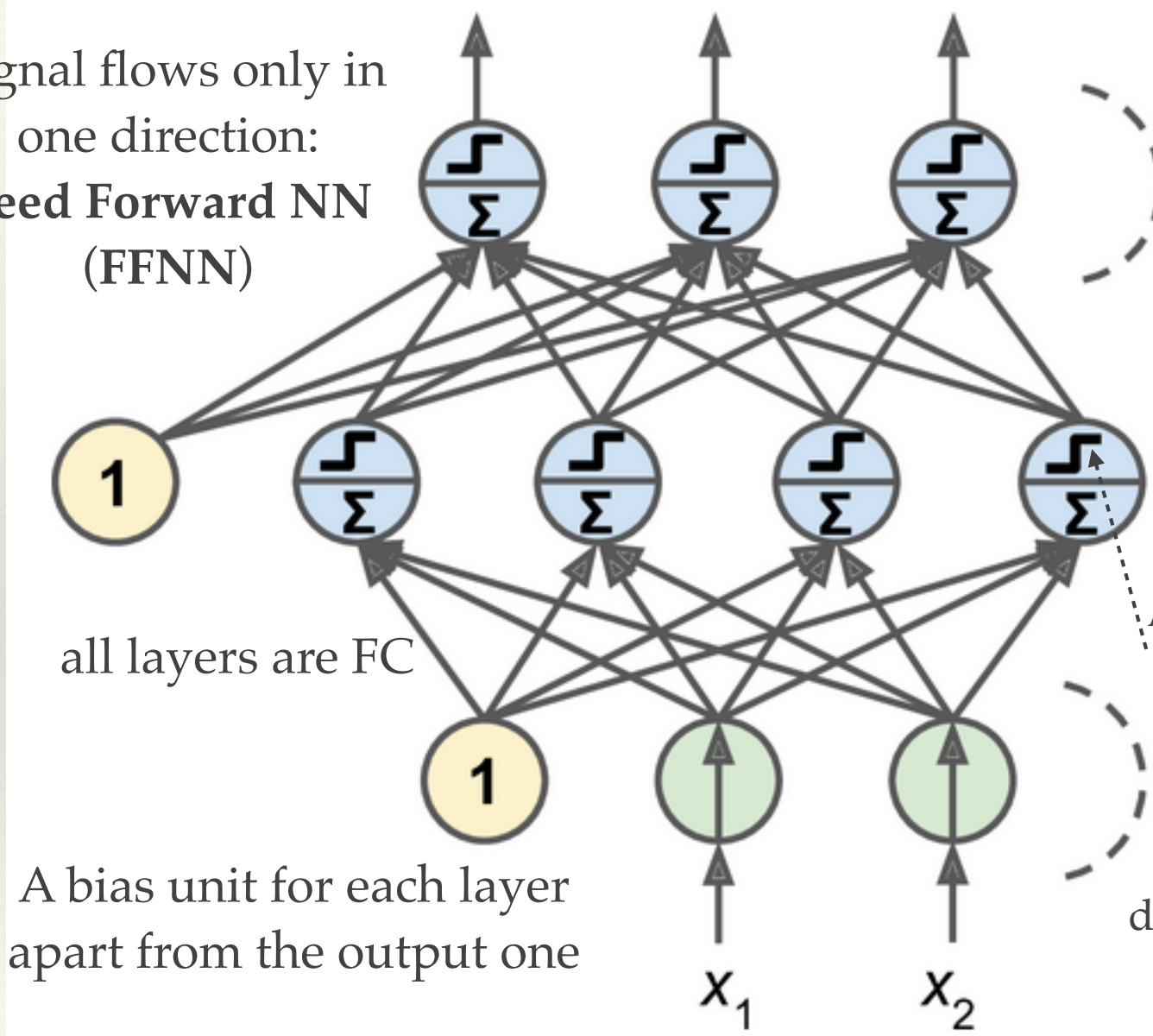
- the resulting ANN is called a **Multi-Layer Perceptron (MLP)**



Note that **you added an entire brand new layer** to the original Perceptron architecture

(see next)

MLP - FCNN - FFNN



Signal flows only in one direction: **Feed Forward NN (FFNN)**

layers of TLUs

Output layer

Hidden layer

Input layer

Activation functions important to have some non-linearity between layers

all layers are FC

A bias unit for each layer apart from the output one

deep stack of hidden layers?
→ **Deep NN (DNN)**
(Deep Learning sometimes used also for shallow, non deep, NN)

Training a **MLP**: the **BP algo**

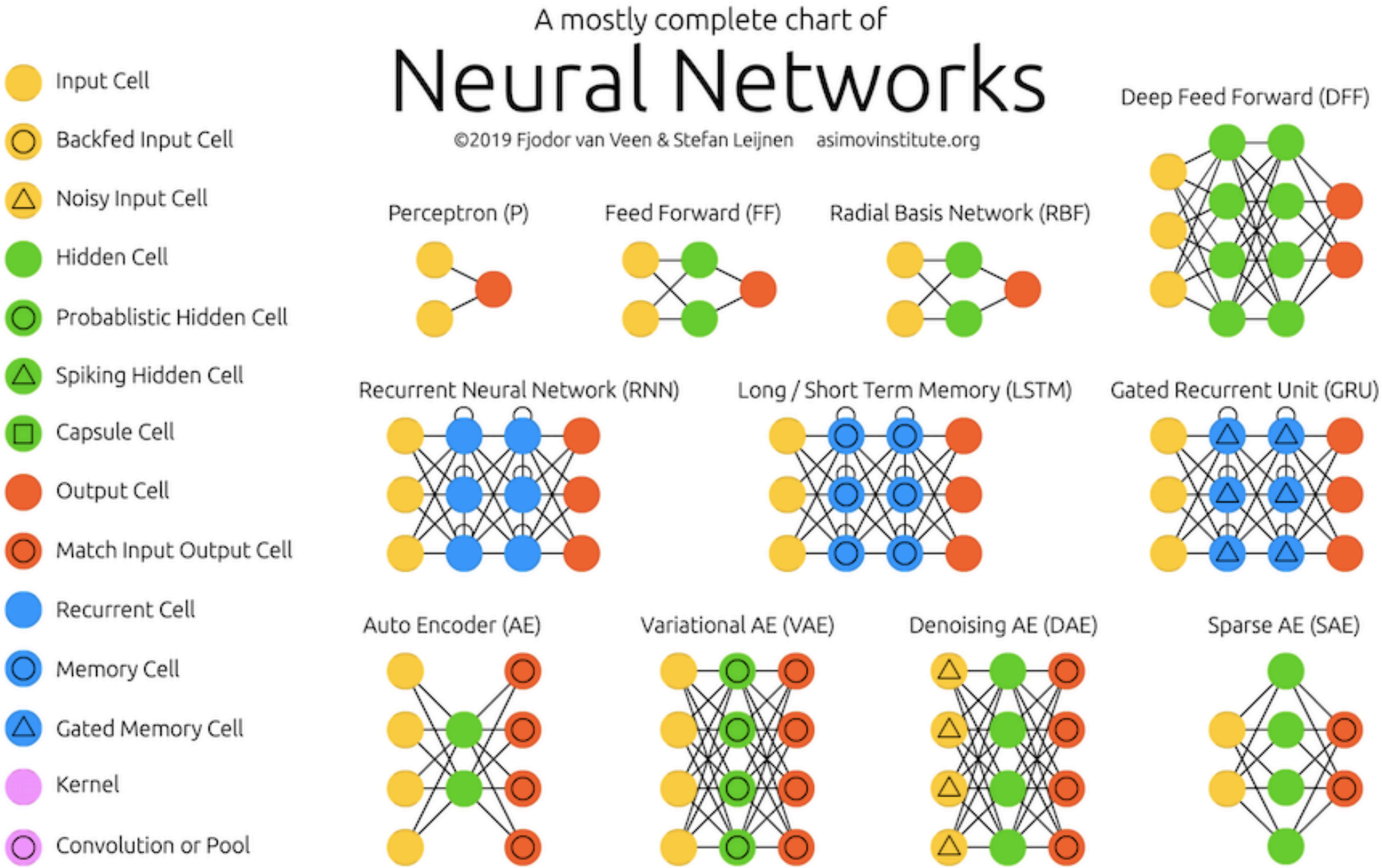
For many years, researchers struggled to find a way to train MLPs.

1986, Rumelhart/Hinton/Williams introduced the **back-propagation** (**BP**) **training algorithm** - still used today

BP algo in one sentence:

- For each training instance, the BP algo first makes a prediction (**forward** pass), measures the error, then goes through each layer in reverse to measure the error contribution from each connection (**backwards**/reverse pass), and finally slightly tweaks the connection weights to reduce the error (in a GD step).
- the whole process is iteratively repeated - in **epochs** - until the network converges

https://www.asimovinstitute.org/neural-network-zoo/



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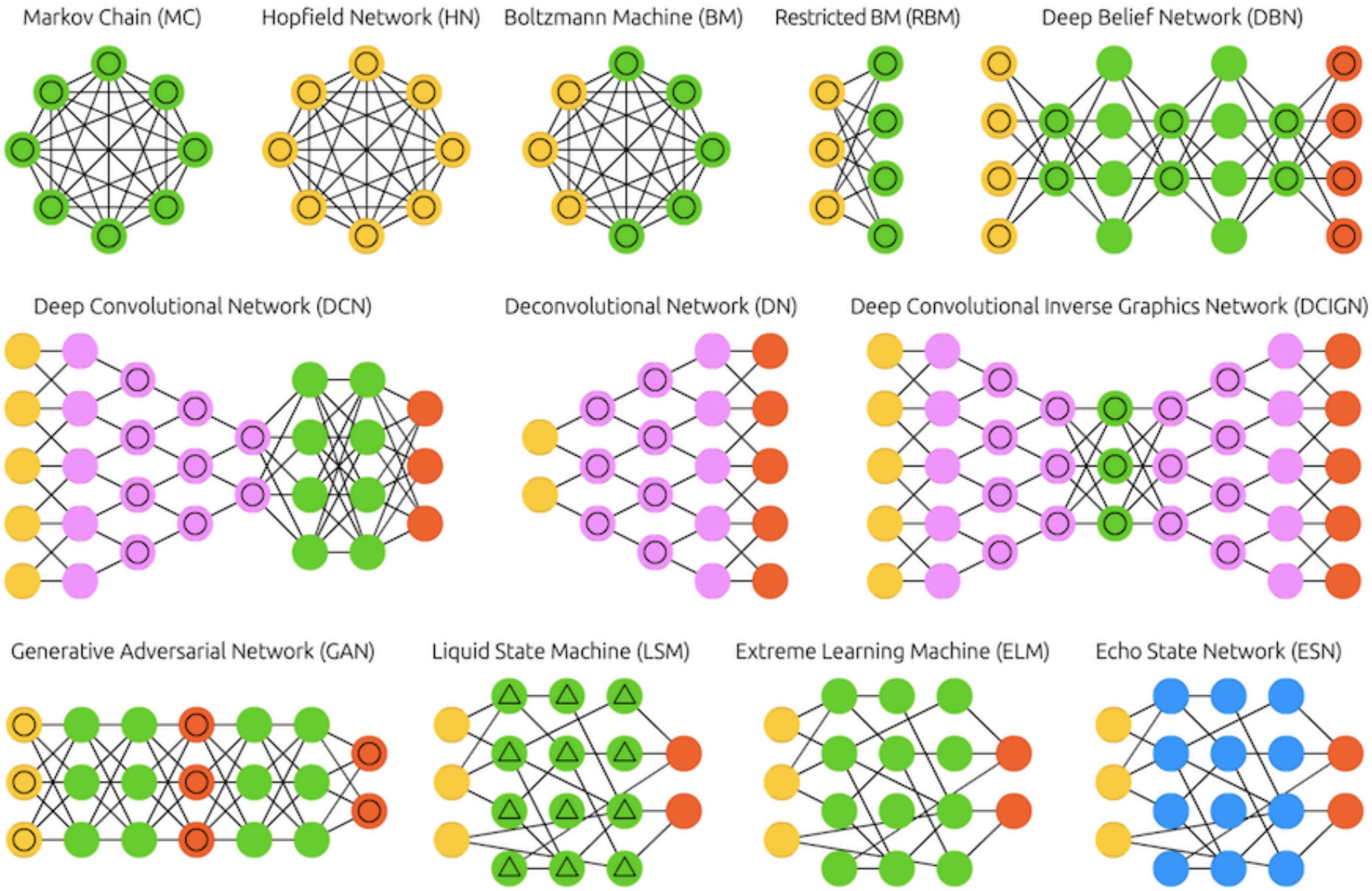

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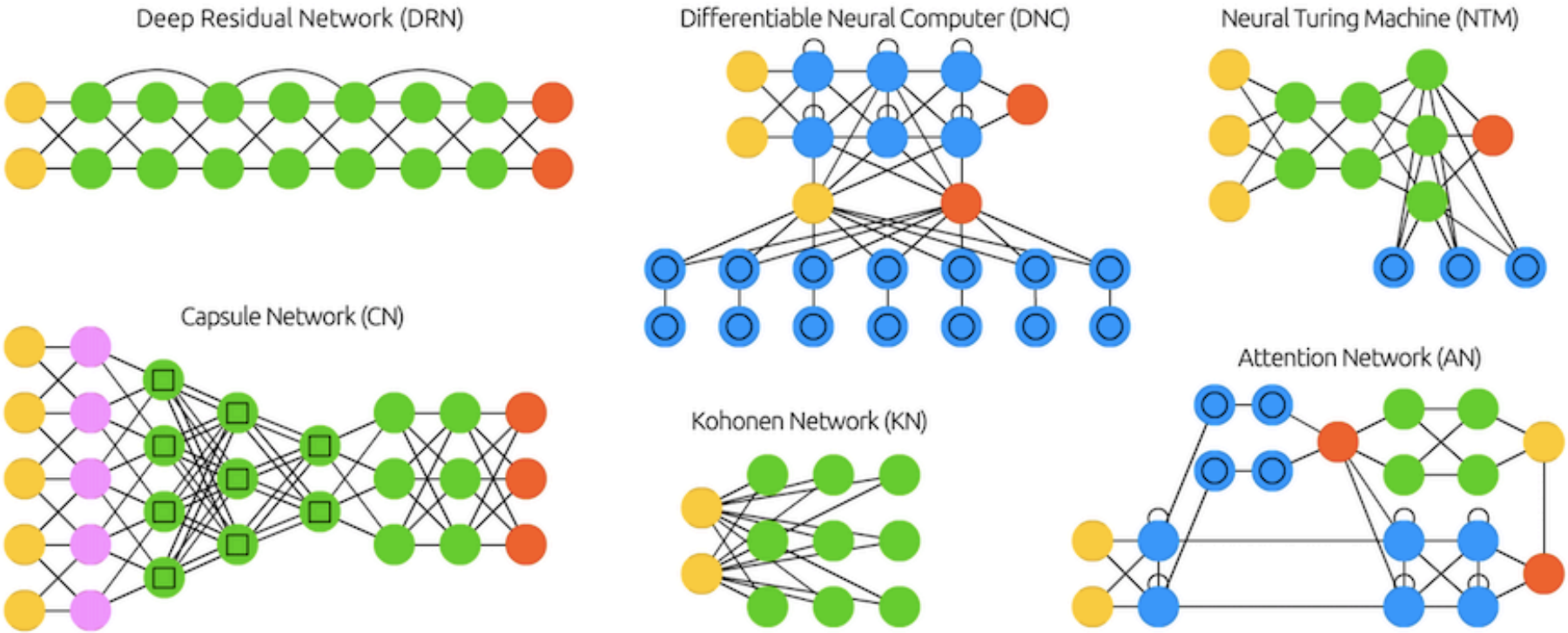

That's it,
for our **Intro to NNs**