DD2421
Introduction to Artificial Neuronal Networks

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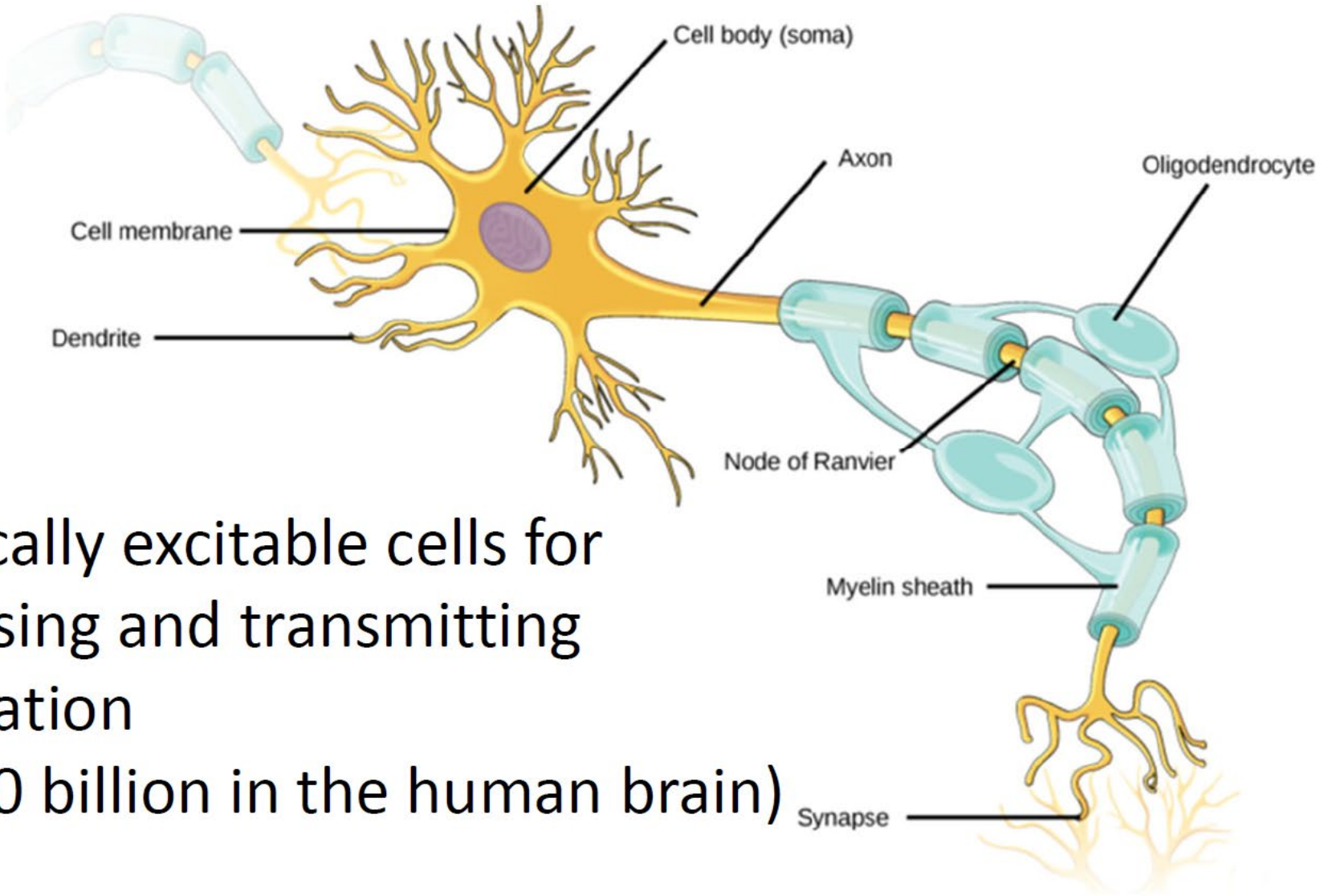
Overview

- Biological Neurons
- Artificial Neurons
- What can a single Neuron do?
- From Neurons to Networks
- How to Train a Neuronal Network
- Tricks of the Trade … how to get your Network working
- Software Example
- Other classes of Neuronal Network

Biological Neurons

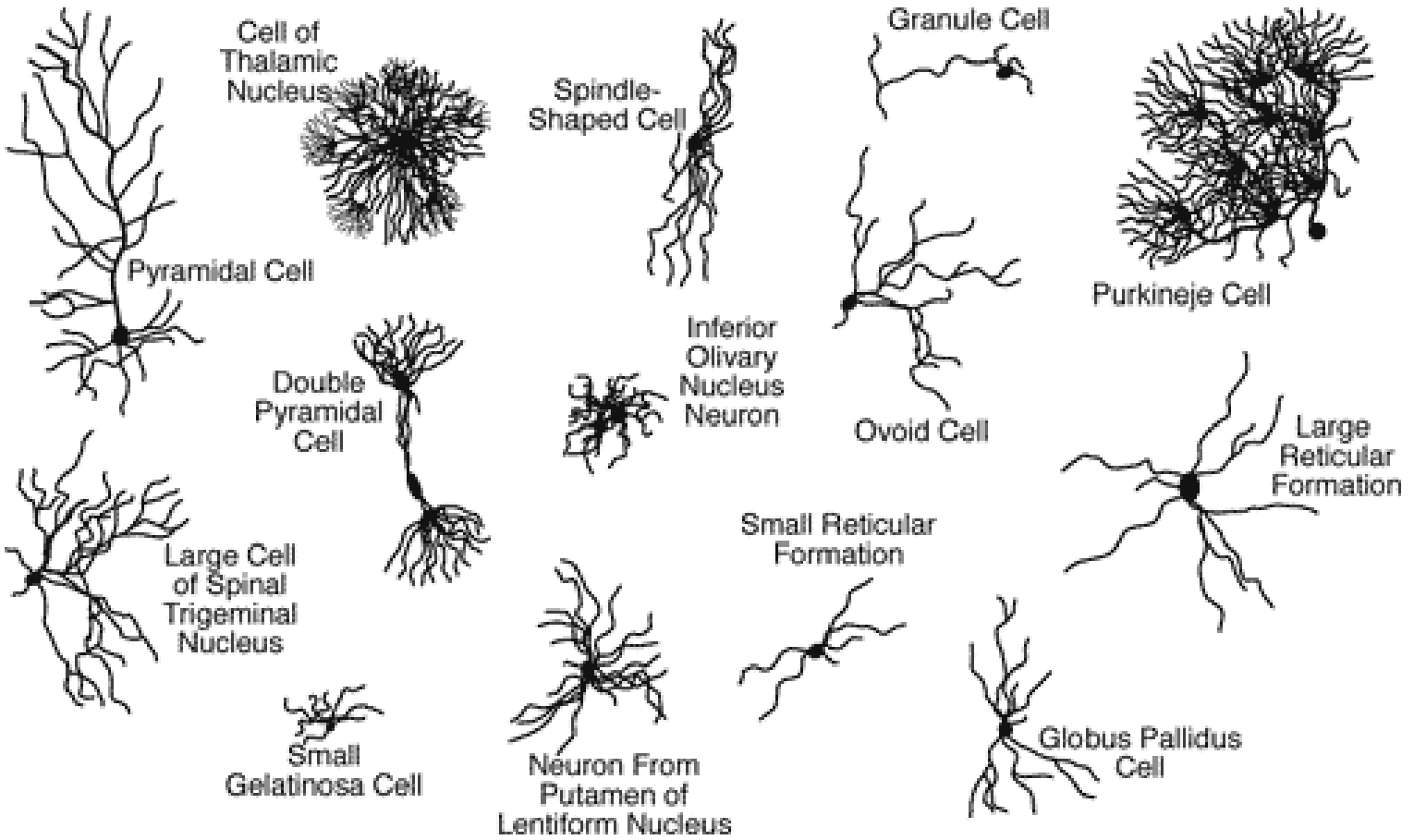


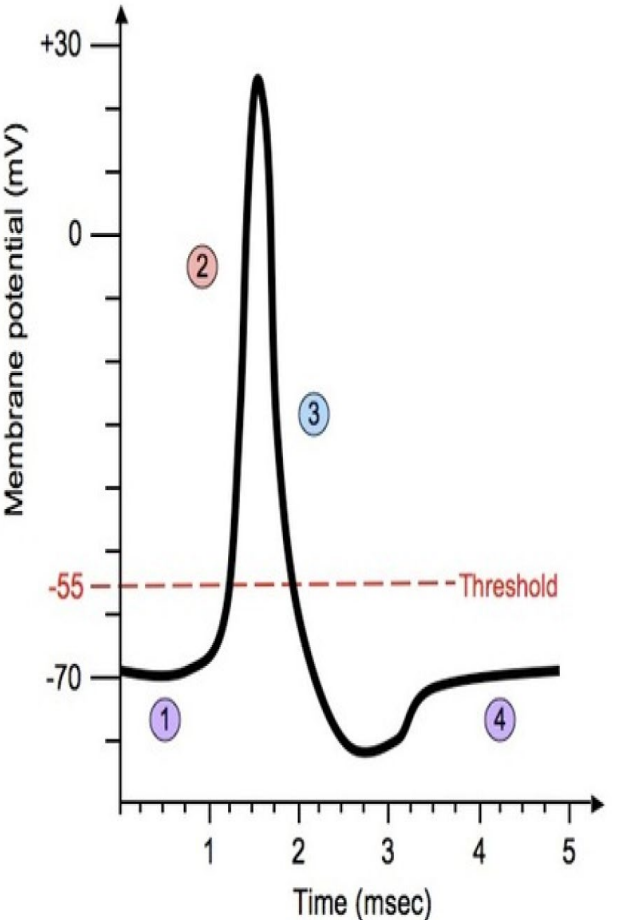
electrically excitable cells for processing and transmitting information
(ca. 100 billion in the human brain)

Biological Neurons

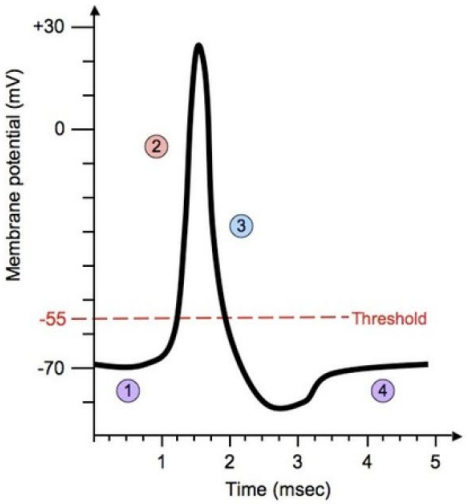
A large variety of cell types, but similar function:

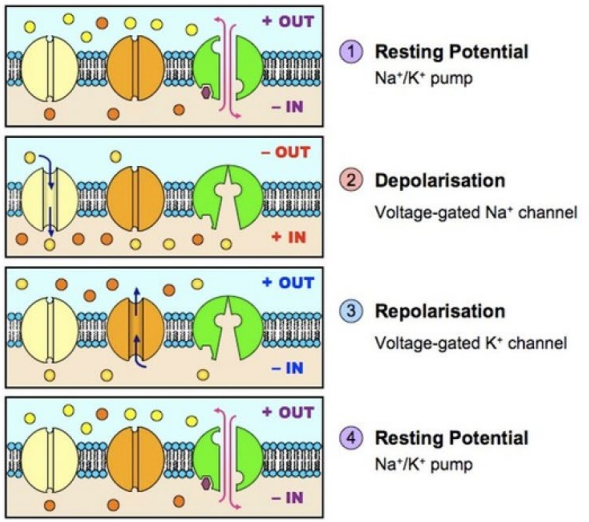
(leaky) Integrate and Fire

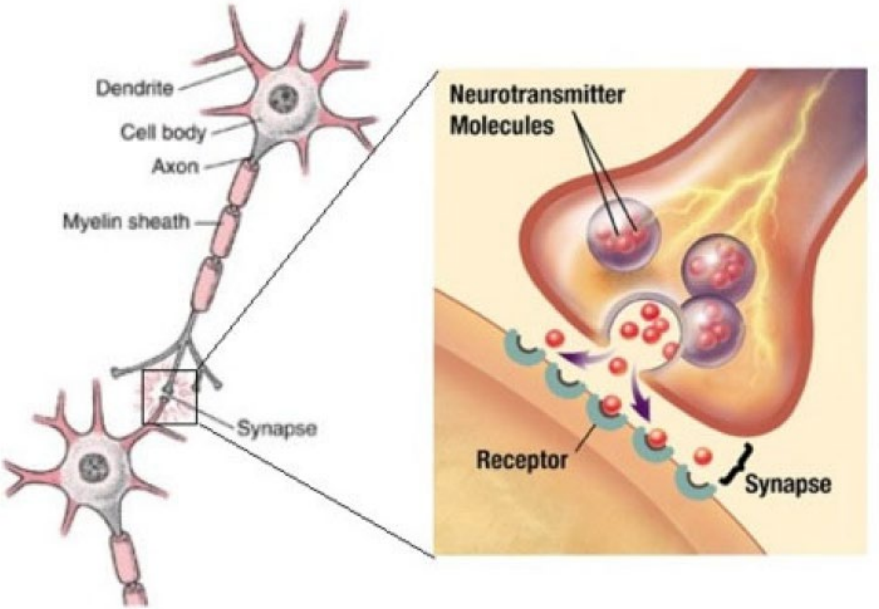




Biological Details





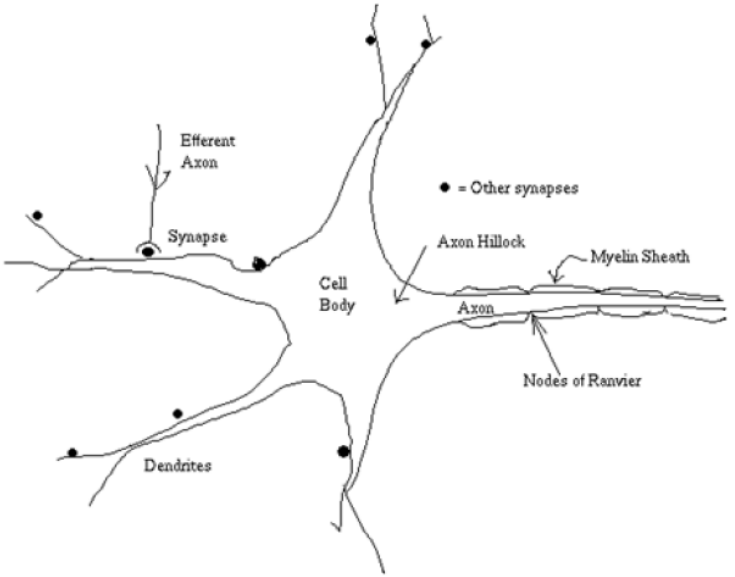


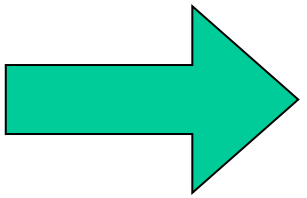
More details on neuroscience? KTH CST course in P4

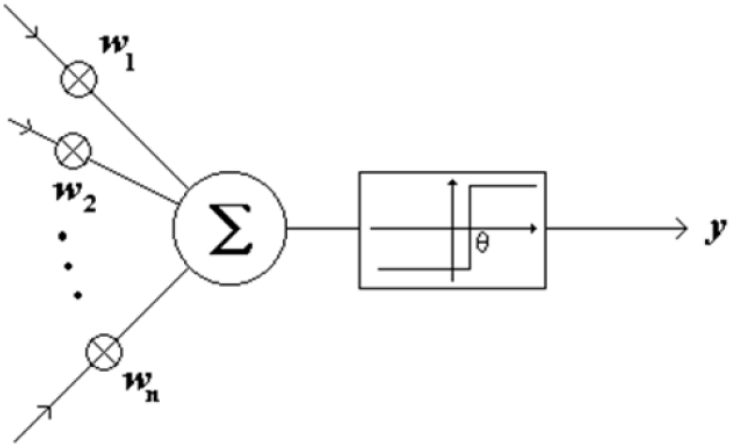
https://www.kth.se/social/course/DD2401/

Artificial Neuron

From Biology to Technology



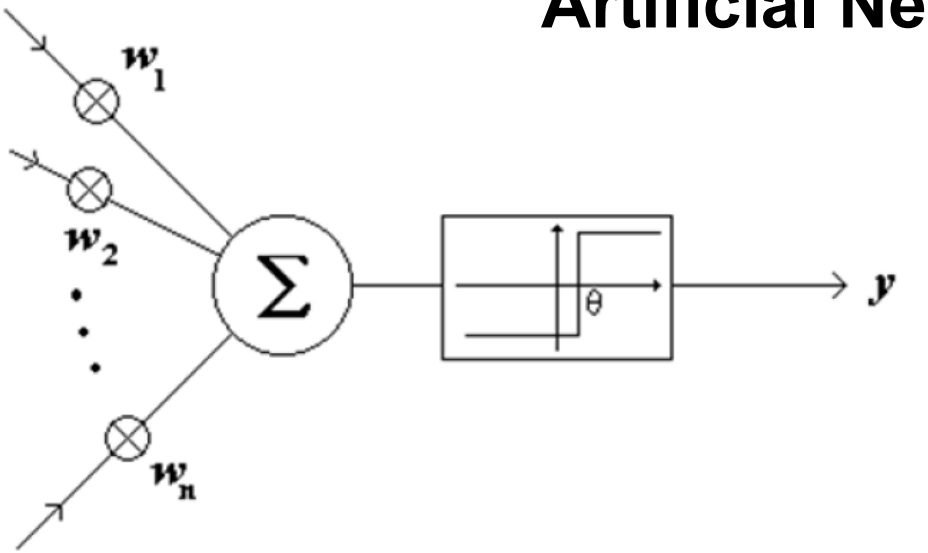




- *Analog Leaky Integration*
- *Asynchronous Operation*
- *Spiking Communication*
- *Energy Efficient Implementation*

?

Artificial Neuron



- Discrete Summation of Weighted Input
- Centrally Clocked System
- Continuous Values Communication (events → rates)
- Von Neumann Computing Architectures

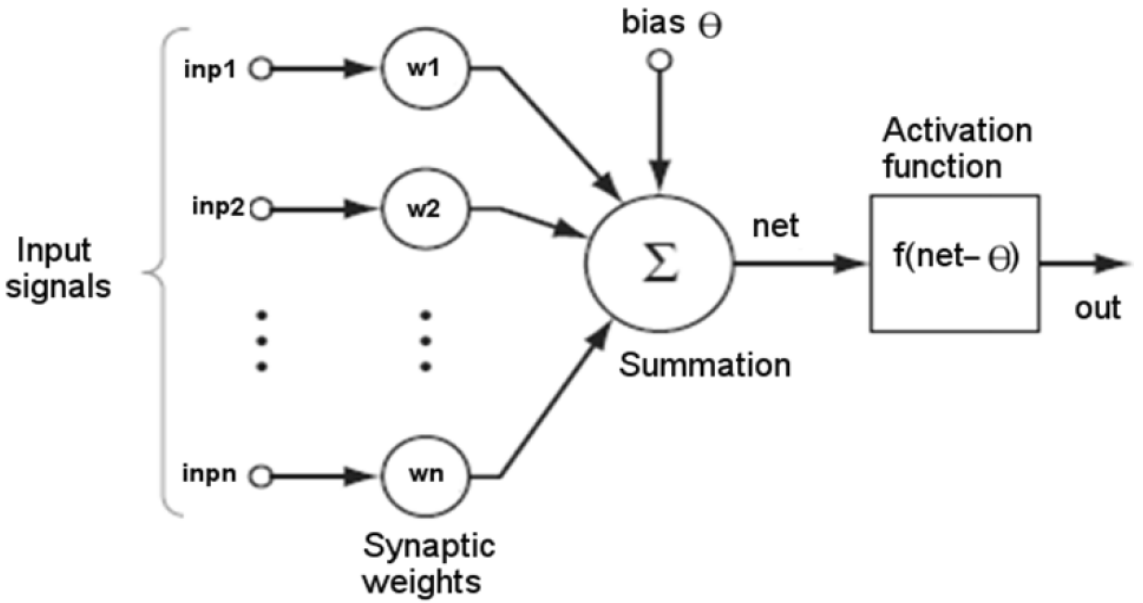
We transition to a technical abstraction, the *Perceptron*, which can get implemented on computers (time: 1970s)

A one-slide history of Neurons and Neuronal Networks

- 1940's McCulloch and Pitts Neuronal Description
  Donald Hebb "The Organization of Behaviour"
- late 1960's Rosenblatt's Perceptron
- 1970's Minsky and Papert's criticism (1969), first *AI winter.*
  Concerns and unsolved obstacles led to lower interest and poor funding
- 1980's Hopfield's impact (self-learning)
- 1990's training through error-backpropagation (1986)
- 2000's more mathematically rigorous statistical learning theory
- 2000's more computing power → deep neural networks

Applications today: Pattern recognition: classification and clustering; General interpolation problems; Data representations, coding and compression; Signal processing; Time series prediction; System identification; Decision support (e.g. medical or industrial diagnostics); Memory storage, modelling; Optimization, combinatorial problems

What can a Single Neuron do?



The **net input** of the neuron is given by

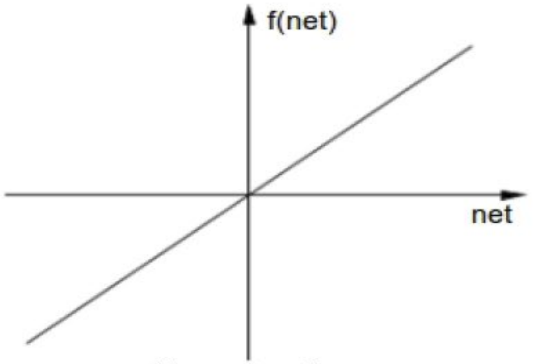
$$net = \sum_{i=1}^{n} p_i w_i = p_1 w_1 + p_2 w_2 + \cdots + p_n w_n$$

whereas the output of the neuron is computed as

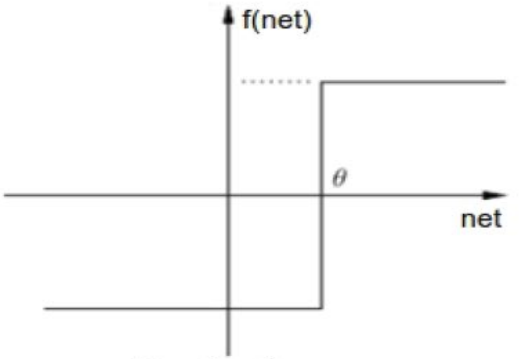
$$out = f(net - \theta)$$

... anything ... depending on the activation function $f(\cdot)$

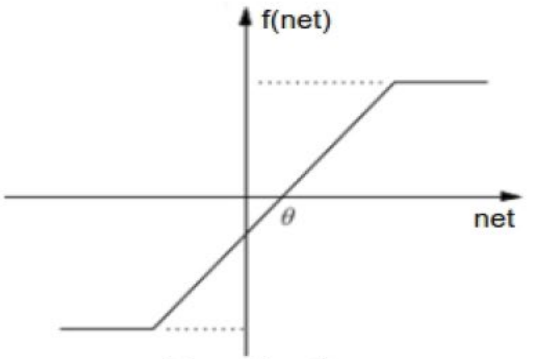
Typical Activation Functions $f(\cdot)$



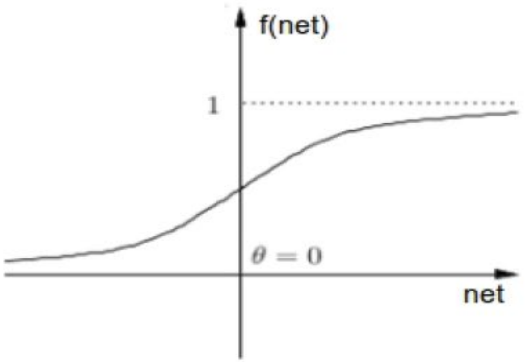
Linear function



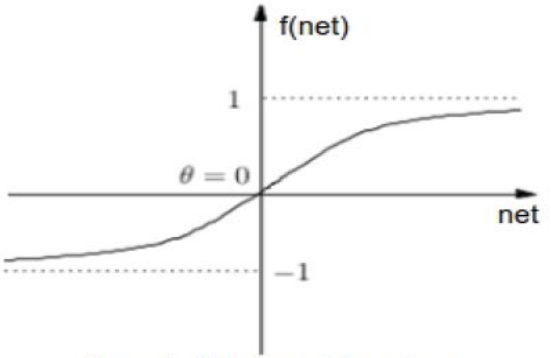
Step function



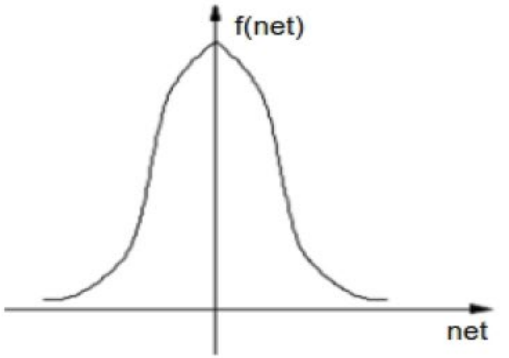
Ramp function



Sigmoid function



Hyperbolic tangent function



Gaussian function

By hand-selecting the activation function, we can allow arbitrary functionality.

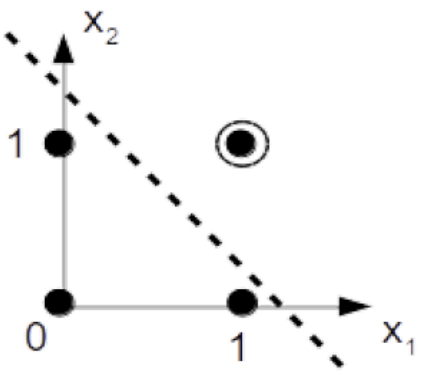
But we can't know a-priory!

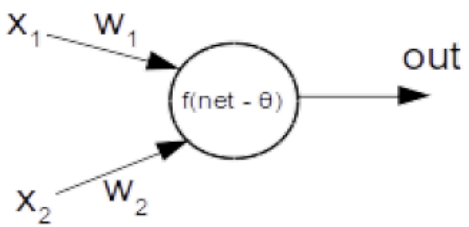
Hence, we require a generic system that works independent of activation function.

What can a Single Neuron do?

Assume a **LINEAR activation function**. "Boolean Logic" Classification on 2-dimensional input, decision based on out ≥ 0 or <0

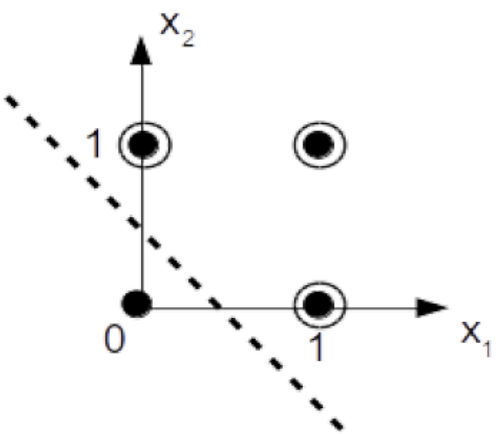
AND problem

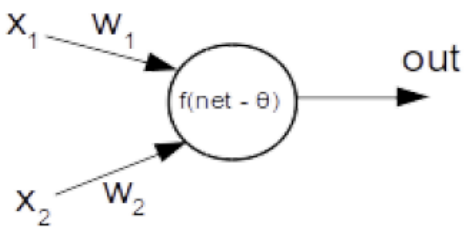




Sample solution:
$w_1 = w_2 = 0.8$
$\theta = 1$

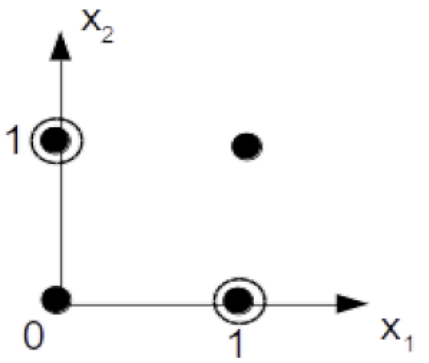
OR problem





Sample solution:
$w_1 = w_2 = 0.8$
$\theta = 0.5$

XOR problem



Sample solution:
The problem is not linearly separable → we need a **multi-layer perceptron**

Training Neurons Networks

SUPERVISED LEARNING (labeled training data exists)

Idea: use the error produced by a neuron to adjust its weights

Error metric of a neuron

$$E(t) = \sum_{p=1}^{P_T} \left(t_p(t) - out_p(t) \right)^2$$

t_p target output
$out_p(t)$ current output

Weight update for a neuron *i*

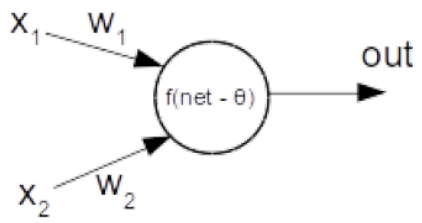
$$w_i(t) = w_i(t-1) + \Delta w_i(t)$$

$$\Delta w_i(t) = \eta \left(\frac{-\partial E(t)}{\partial w_i(t)} \right)$$

This updates all neuronal input weights w_i for a all data point *p*, subject to the current weights.

Training a single neuron, real-world example

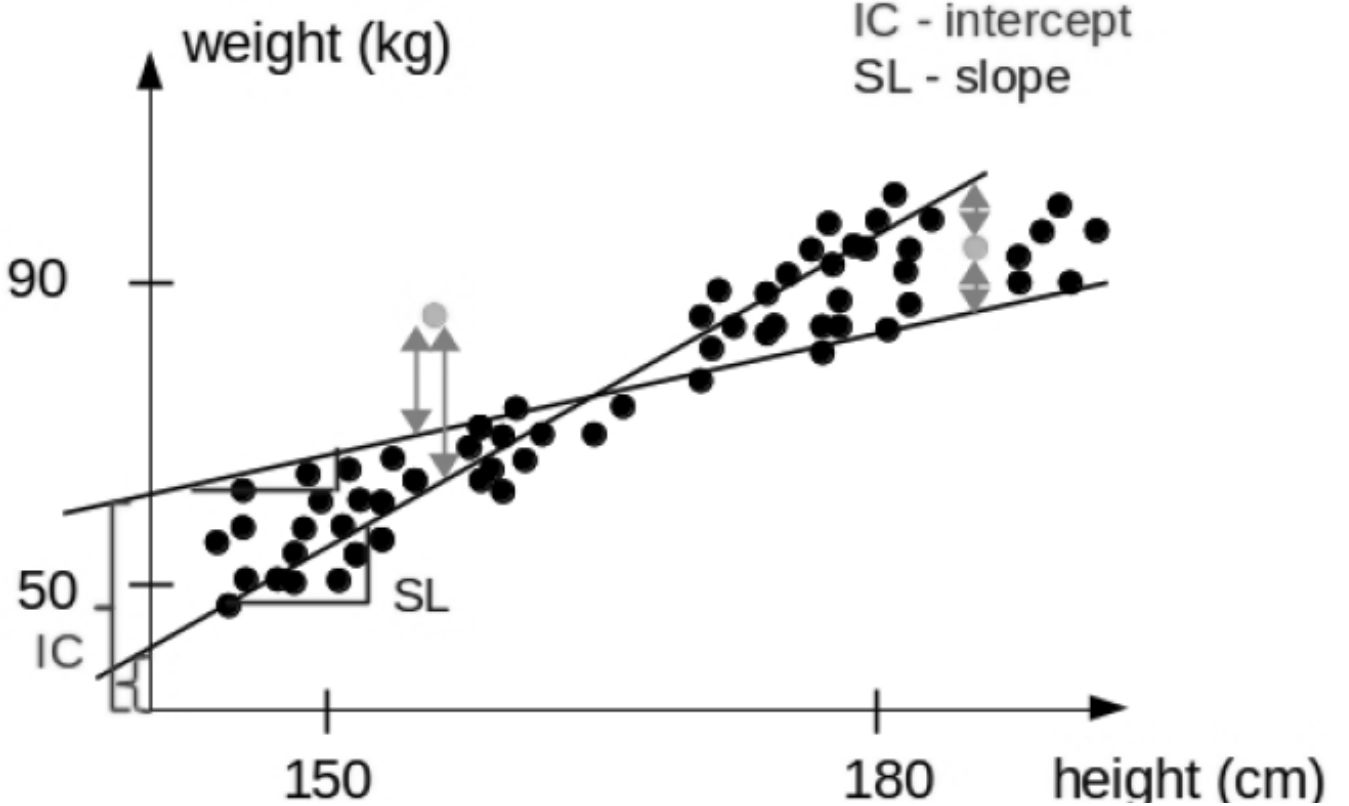
height



weight

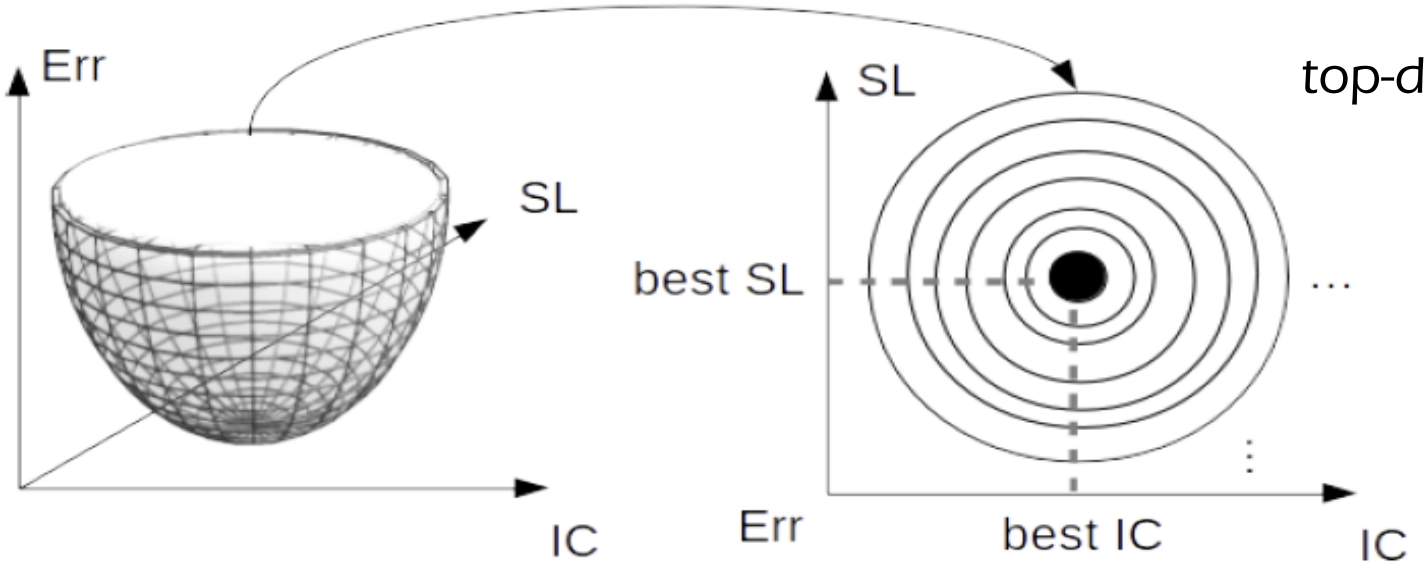
Bias offset
(= const 1)

weight = w1*height + w2*bias
= SL * height + IC



Every new data point will adjust SL and IC such that ultimately the best matching linear approximation is encoded in w_1, w_2

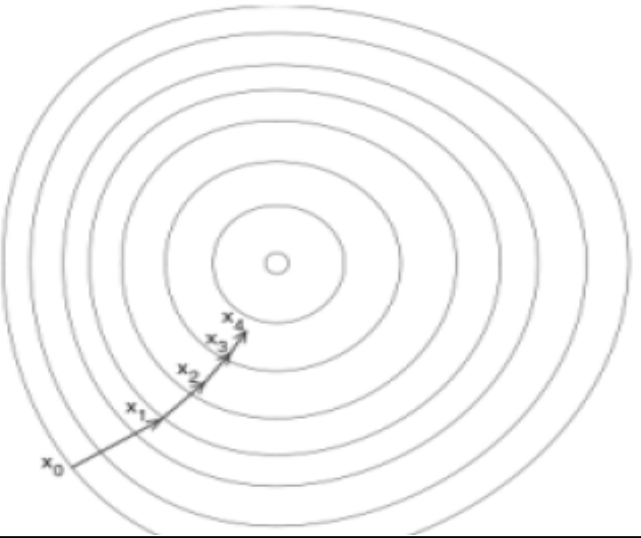
Training a single neuron, real-world example



top-down projection

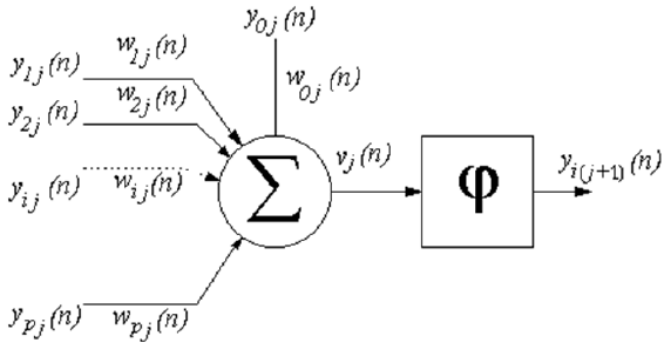
How do we achieve this? In order to guide the search for the suitable parameters Gradient Descent is used:

1. Pick **random initial values** for IC/SL (e.g. x_0)
2. **Calculate the gradient** with respect to each model parameter (i.e. IC,SL)
3. **Update the parameters** in the **direction** of the negative **gradient**
4. **Repeat** 2 and 3 until **convergence** (e.g. $x_{1...4}$)



From Neurons to Networks

Single neuron "node"



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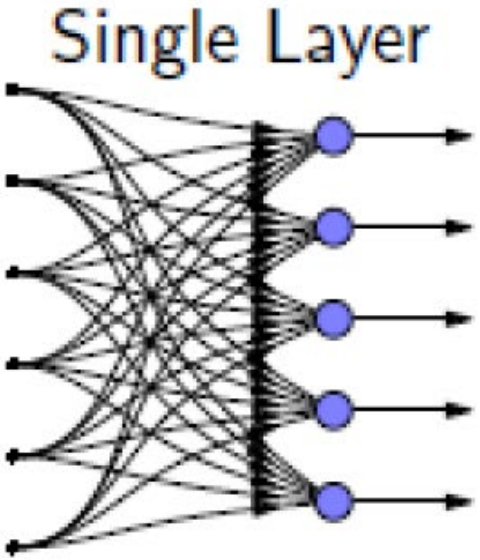
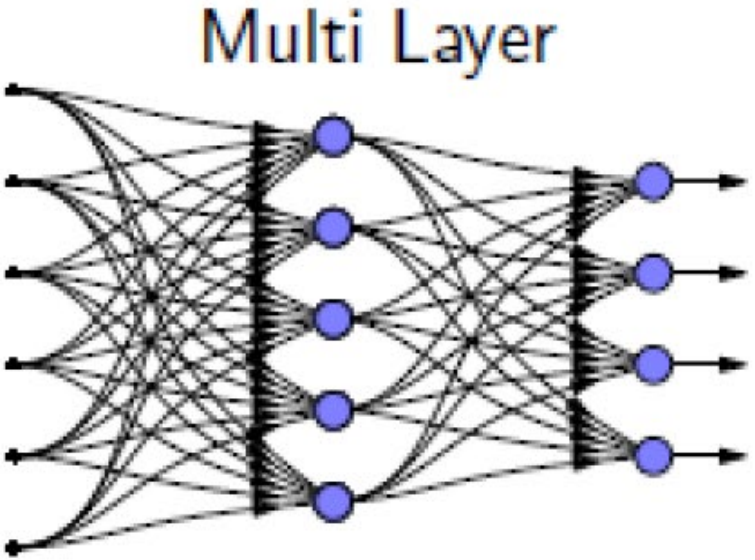
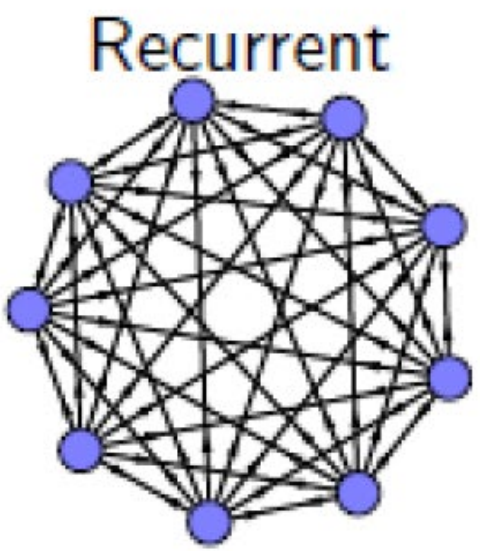
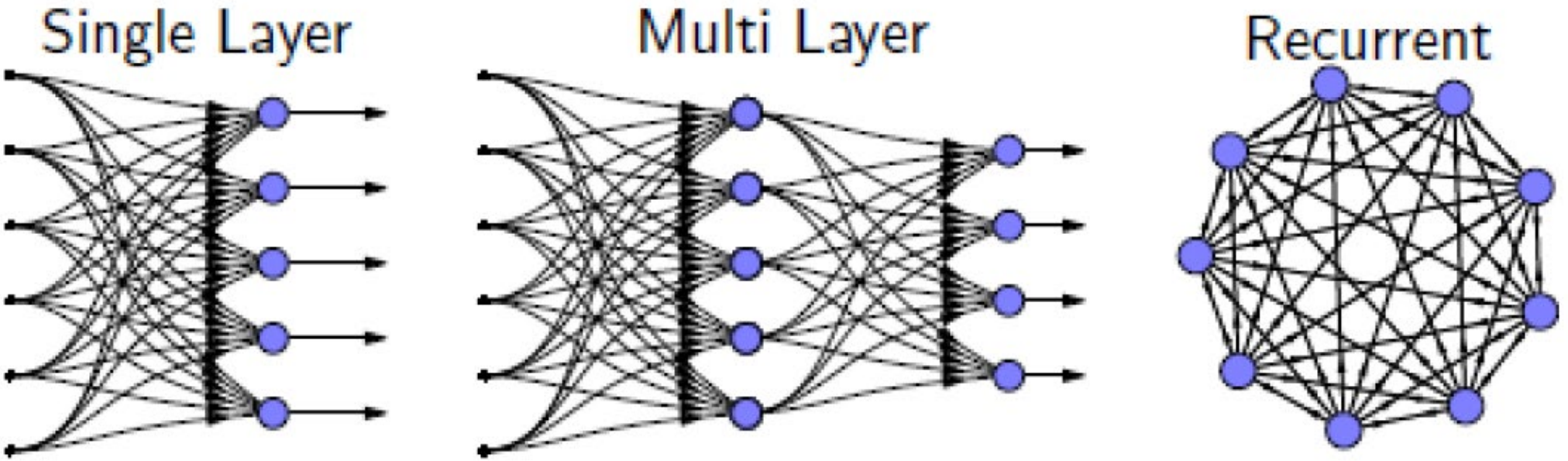
Neuronal Networks







Neuronal Networks

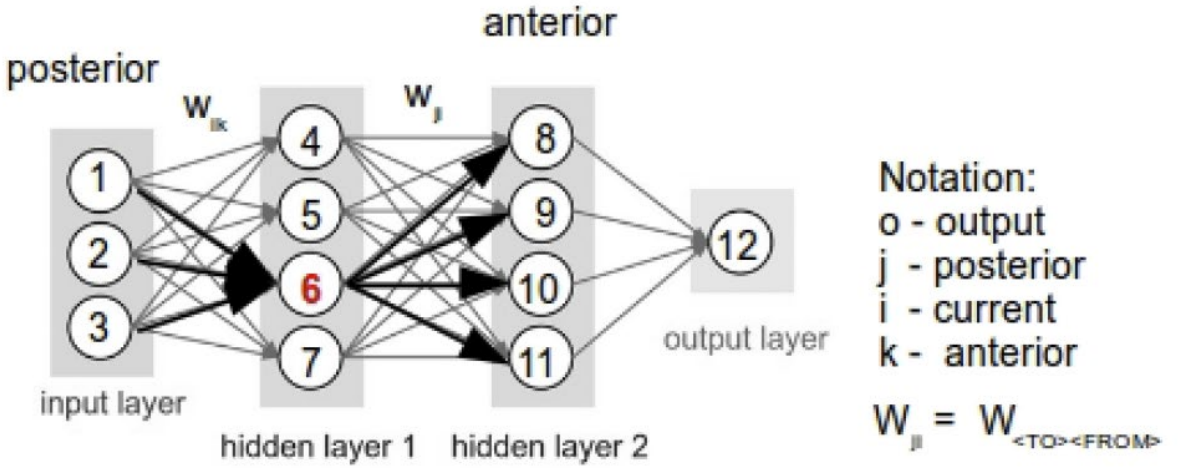


Main Challenges

- Which structure to use?
- How to train (adjust weights) given a particular problem?
  We learned how to do for one neuron, but for networks?
- (How to provide sufficient computing power?)

How to train Neuronal Networks

- We can not simply train neurons in a network, as the "desired output" (t_p) is unknown for neurons in middle layers
- Instead, **ERROR BACKPROGATION** through the network



$$\Delta w_{ik}(t) = f'\left(net_i(t)\right) \cdot \sum_{j \in P} \delta_j(t) \cdot w_{ji}(t) \cdot f\left(net_k(t)\right)$$

$$\delta_i(t) = f'\left(net_i(t)\right) \cdot \sum_{j \in P} \delta_j(t) \cdot w_{ji}(t)$$

Tricks of the Trade – how to get your network working

1. Weight Initialization

   initialize all weights to **small random** numbers

2. Input / Output Normalization

   output: use linear output neuron
   input: try to normalize to [-1 .. +1] or close to that

3. Use Small Weight Update η

   Constant or time dependent $\eta(t)$.

4. Avoid local minima in weight space

   Simulated Annealing, multiple independent runs

Tricks of the Trade – how to get your network working

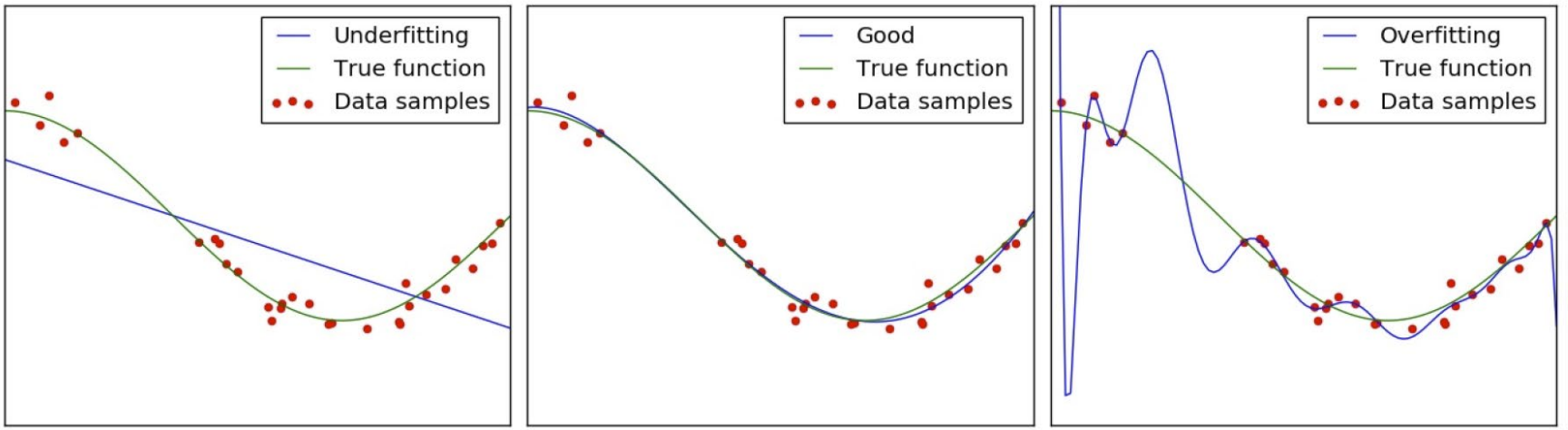
5. Network size

   Complete mystery; rules of thumb, fan-in / fan-out (projections)

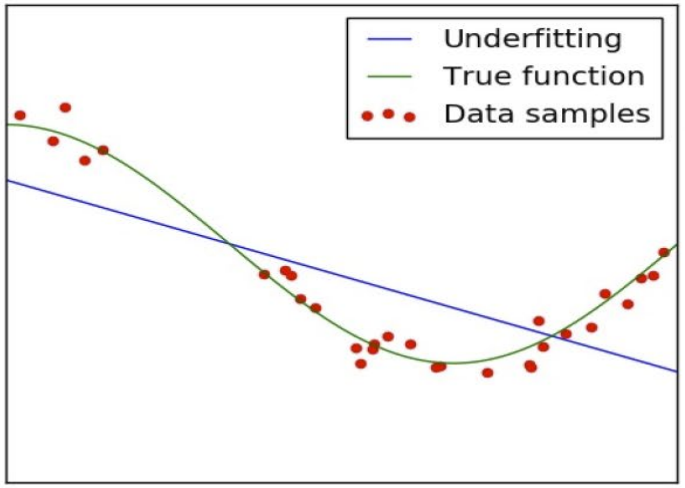
6. Vanishing Gradient

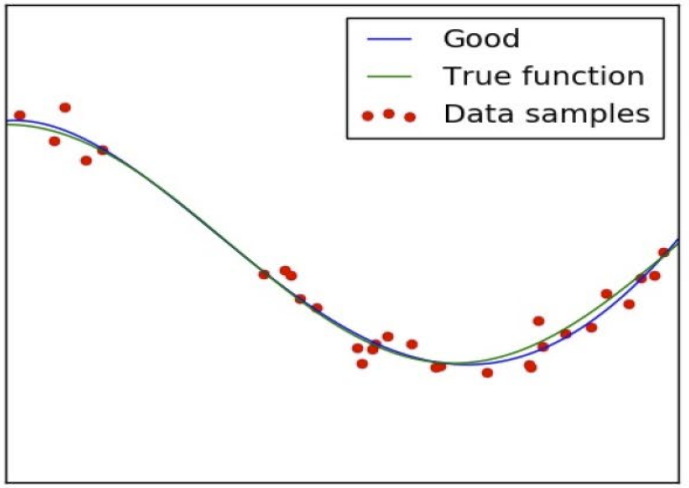
   multiple layers significantly reduce the available gradient

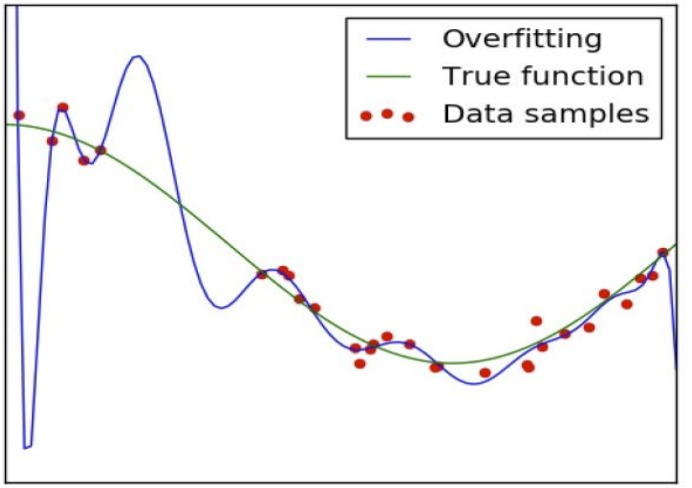
7. Overtraining / Overfitting



Overtraining / Overfitting

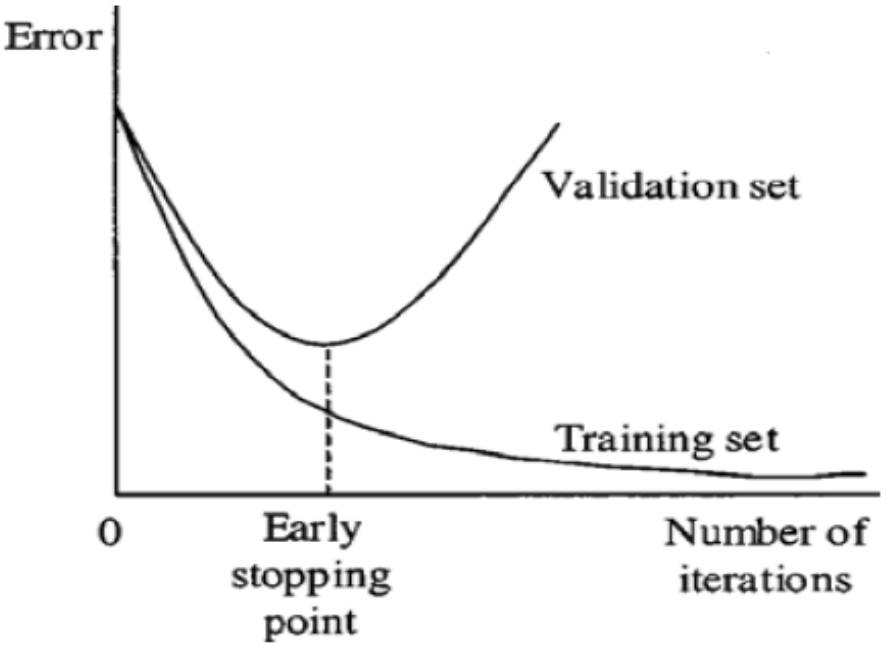






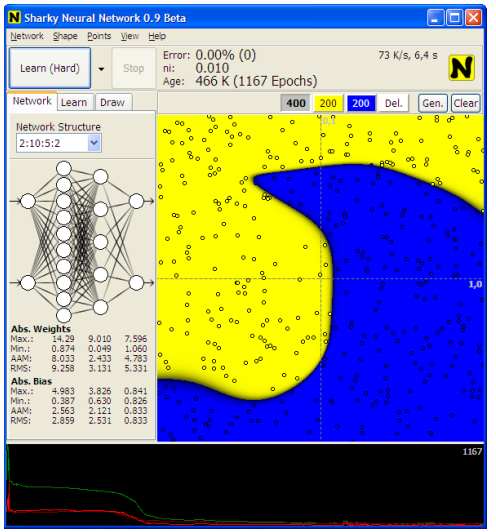
Split available data in two sets
-) 70% Training Data
-) 30% Validation

Train on training data only,
evaluate on Validation data,
STOP training as performance drops



Software Example Neuronal Nets

- Google for “Neuronal Network Online Software Simulation” or similar
- http://www.sharktime.com/en_SharkyNeuralNetwork.html



- https://grey.colorado.edu/emergent/index.php/Comparison_of_Neural_Network_Simulators

Other Forms of Neuronal Networks

- Recurrent Neuronal Networks
  - Liquid State Machine

- Unsupervised Learning
  - Hebbian Networks
  - Kohonan Self-Organizing Maps

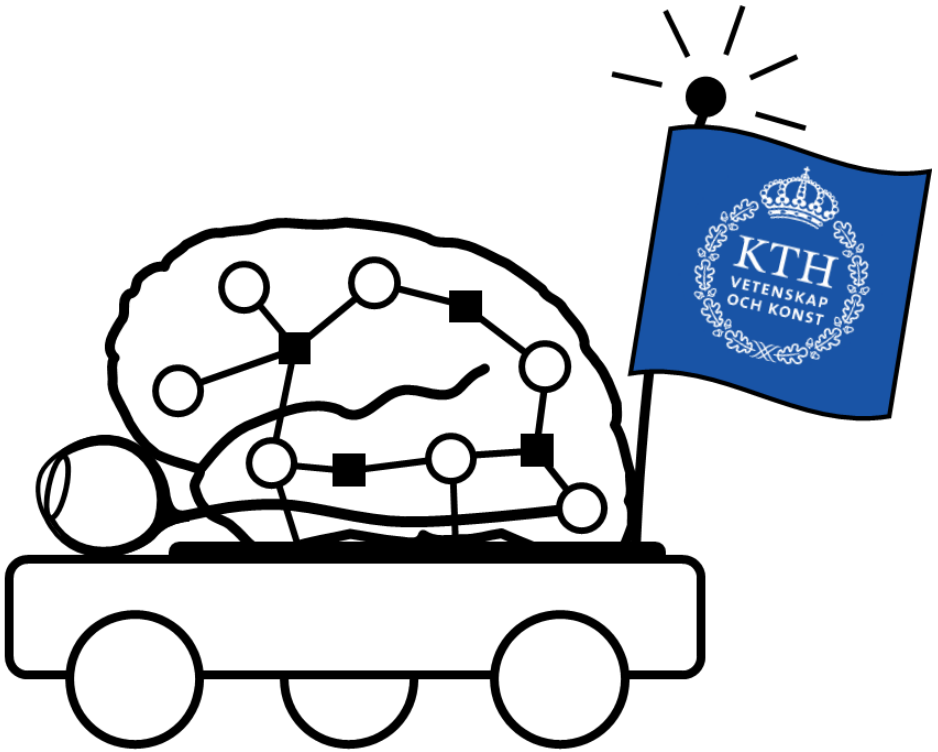
- Deep Neuronal Networks
  - Deeeeeep

more interest in this topic?

KTH DD2437 – Artificial Neural Networks and Deep Architectures

A Brief Introduction to Our Own Research

NCS



Computation in Brains

Getting to know your Brain

- 1.3 Kg, about 2% of body weight
- 10^{11} neurons
- Neuron growth
  250.000 / min (early pregnancy)
  … but also loss, 1 neuron/second

“Operating Mode” of Neurons

- Analog leaky integration in soma
- Digital pulses (spikes) along neurites
- 10^{14} stochastic synapses
- Typical operating “frequency”
  ≤100Hz, typically ~10Hz, asynchronous

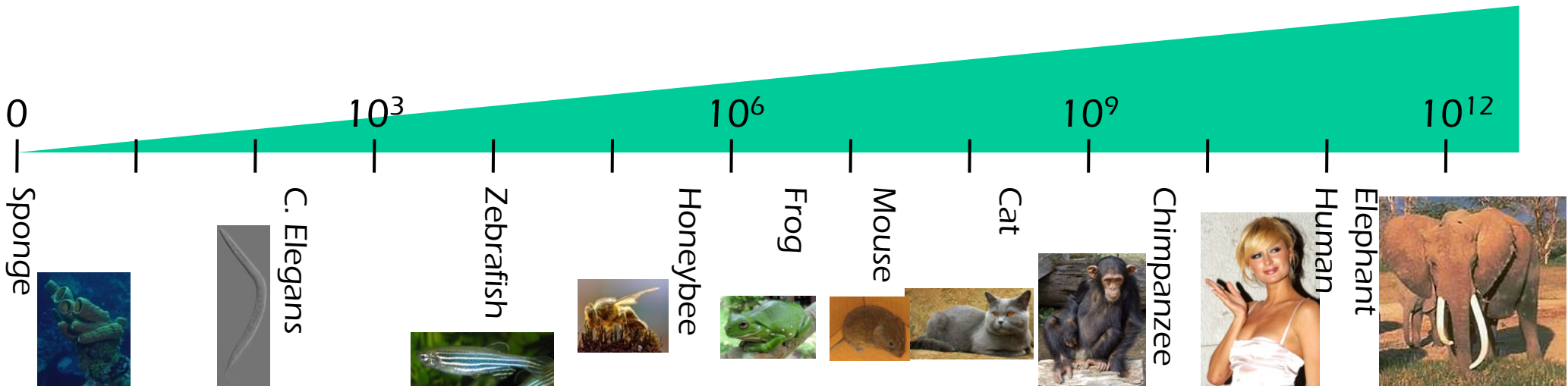
... and in Machines

Getting to know your Computer’s CPU

- 50g, largely irrelevant
- 10^{10} transistors (SPARC M7, 2015)
- ideally no modification over lifetime

“Operating Mode” of CPUs

- Digital Boolean logic processing
- Digital signal propagation
- Reliable remote storage of data
- Typical operating frequency
  Several GHz, synchronous

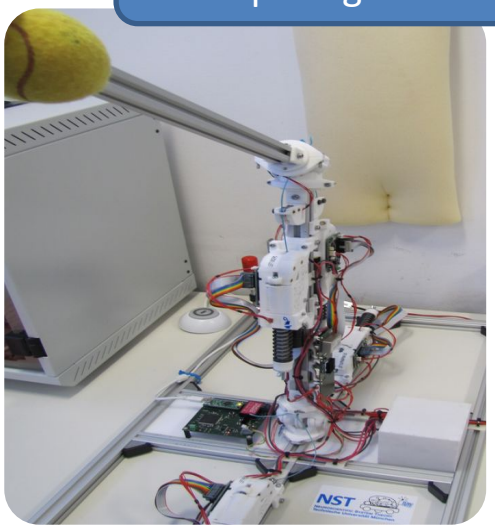


Real-Time Neuronal Information Processing in Closed-Loop Systems

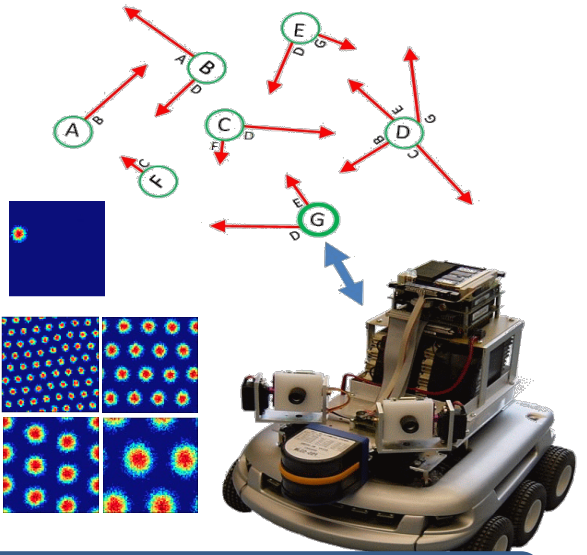
- Event-Based Neuromorphic Vision
- Information Processing in Distributed Neuronal Circuits
- Neuromorphic Real-Time Computing and Control
- Self-Construction and Organization of Neuronal Circuits

Event-Based Neuromorphic Vision

Neuromorphic Real-Time Computing and Control



Information Processing in Distributed Neuronal Circuits

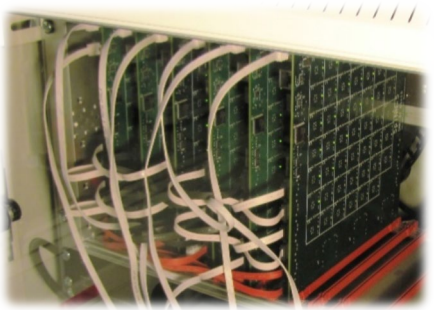


Self-Construction and Organization of Neuronal Circuits

Neuro Computing Hardware Systems

CPU/GPU

- Software Neuronal Net Simulation
- High Energy
- Central Code and Data Memory
- Limited Communication Bandwidth
- Limited Parallelism
- High System Clock



SpiNNaker

- Software Neuronal Net Simulation
- Reduced Energy
- Distributed Code and Data Memory
- Optimized for Spiking Communication
- Massive Parallelism
- Reduced System Clock

TrueNorth

- Neuronal Circuits in Digital Hardware
- Low Energy
- Function given by Synaptic Connectivity
- Limited Local Spiking Communication
- Expandable Parallelism
- Low System Clock

Spikey

- Neuronal Circuits in Analog Hardware
- Minimal Energy
- Function given by Synaptic Connectivity
- (Limited Local Spiking Communication)
- (Limited Parallelism)
- Real-time Accelerated System Clock

KTH VETENSKAP OCH KONST

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