ELTE | FACULTY OF INFORMATICS

EMBODIED INTELLIGENCE

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ELTE | IK

DEPARTMENT OF ARTIFICIAL INTELLIGENCE

Topics

- Cognitive robotics
- Computational intelligence
- Cognitive model of the iPhonoid robot partner
- Evolutionary robotics
- Biologically-inspired robot locomotion

Cognitive robotics

Introduction, motivations

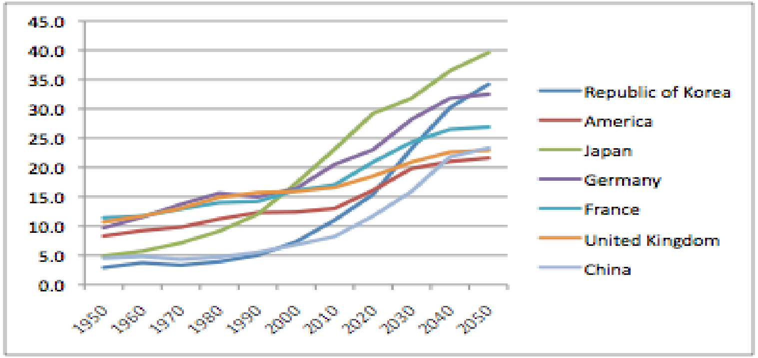
Motivations

- Recently various types of intelligent robots were developed to perform tasks in real environments such as houses, commercial facilities, and public facilities
- In order for robots to be used in close collaboration with humans, there are major technological challenges that need to be overcome
- A human-friendly robot should have human-like intelligence and cognitive capabilities to co-exist with human
- Application area → lonely people, e.g. elderly

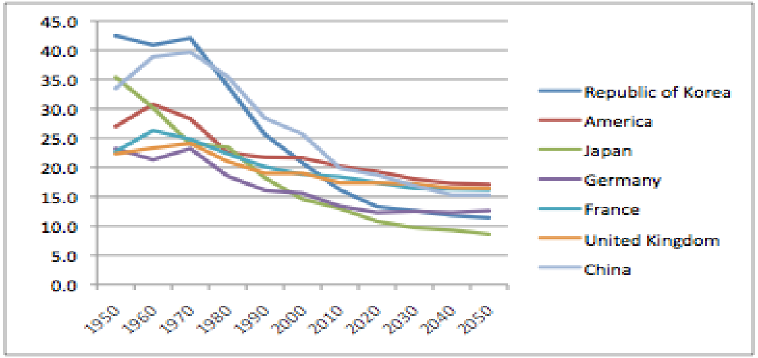
The Aging Society Problem

- The number of elderly people living alone is increasing
- There is an imbalance between the increasing number of elderly people and the decreasing number of births
- The elderly people who live alone or separated from their family have the lack of communication and movement that may decline cognitive ability and cause dementia.

Dependent population：
Over 65 Age



Dependent population：
Under 15 Age



Reference
・UN, World Population Prospects: The 2008 Revision
・「Census」(Japan ; Statistics Bureau)

Robot Partner Solution for Elderly People Social Support Environment

- Thursday, September 11, 2014
- Set-up the "Robotic Revolution Initiative Council" to create a 5-year plan
- Set targets to increase the size of the robot market: double the use of robots in manufacturing, and increase their use in non-manufacturing (home robot) including the service sectors by a factor of 20

Source

Cognition

- Cognition: (Oxford Dictionaries)
  - The mental action or process of acquiring knowledge and understanding through thought, experience, and the senses.
  - A perception, sensation, idea, or intuition resulting from the process of cognition.
  - Origin: from latin ‘cognitio’ meaning ‘get to know’

Cognitive Science

- Comprises psychology, artificial intelligence, philosophy, neuroscience, linguistics, anthropology, sociology, biology, and others
- Problems: memory organization, learning, decision mechanisms, logic, planning, neural networks, brain organization, etc.

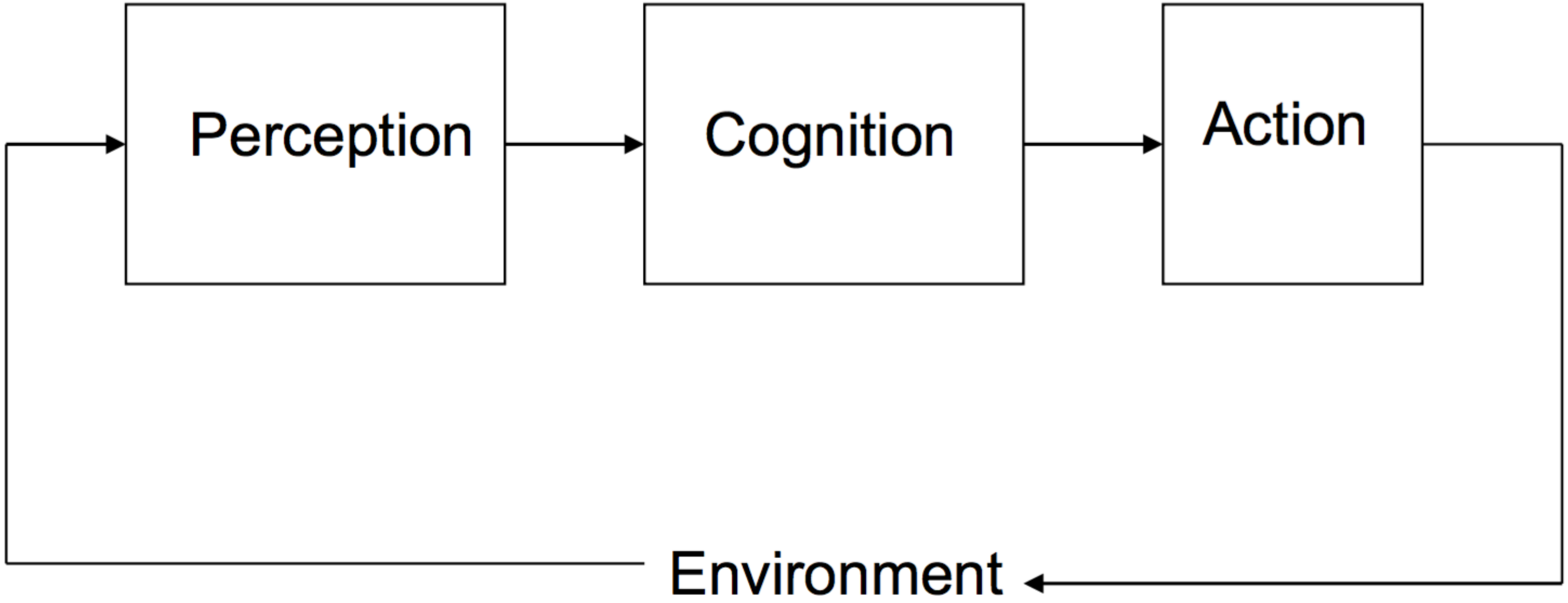
Cognitive Robotics

- Cognitive robotics is concerned with endowing robots with mammalian and human-like cognitive capabilities to enable the achievement of complex goals in complex environments. Cognitive robotics is focused on using animal cognition as a starting point for the development of robotic computational algorithms, as opposed to more traditional Artificial Intelligence techniques, which may or may not draw upon mammalian and human cognition as an inspiration for algorithm development.

Cognitive Robotics

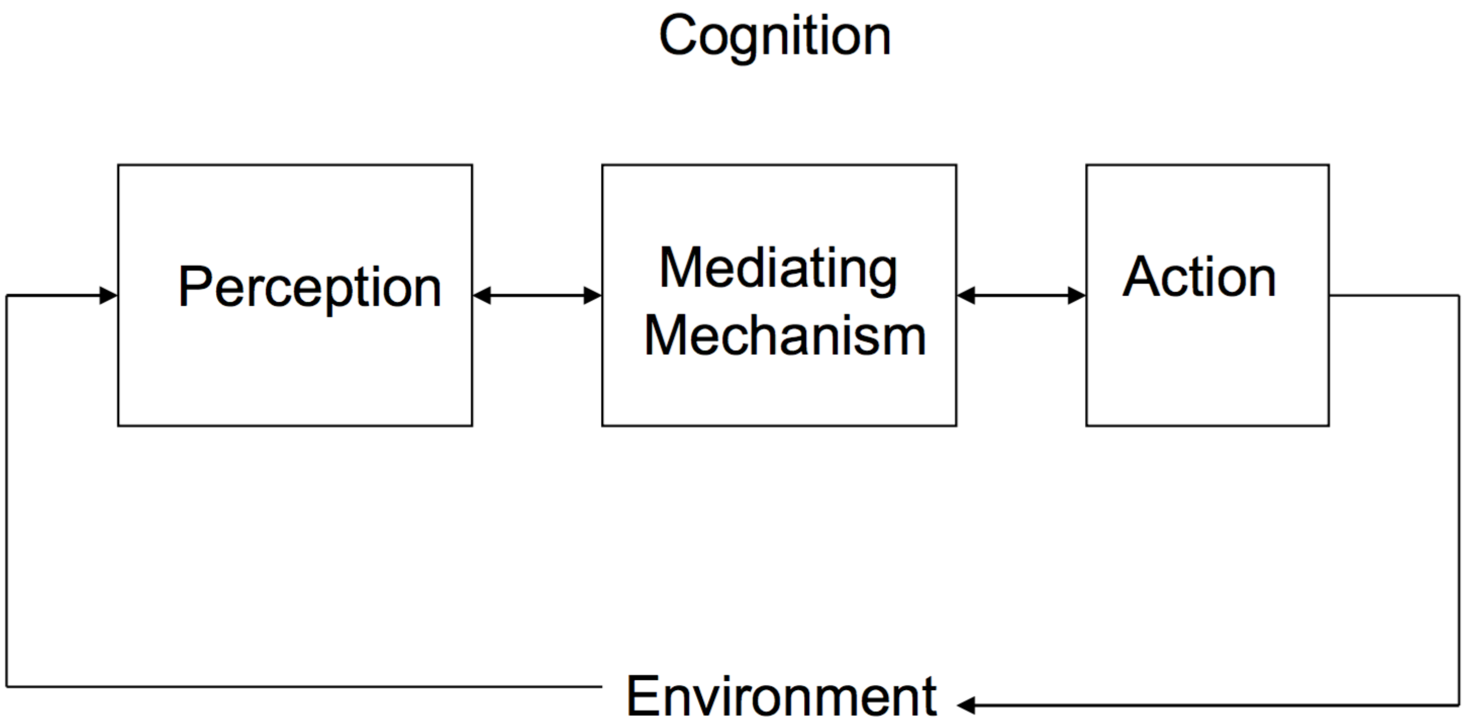
- Robotics + Cognitive Science
  - create robots with cognitive abilities
  - create robots that are human-like
- Cognitive Science → Robotics
  - use cognitive science to improve robots
- Robotics → Cognitive Science
  - use robots to test cognitive science theories
  - use robots to compare different cognitive architectures
  - use robots to identify problems and questions about cognition
  - use robots as a platform to learn about cognition

A Traditional Cognitive Architecture



- sense
- plan
- act

Embodied and Situated Cognition

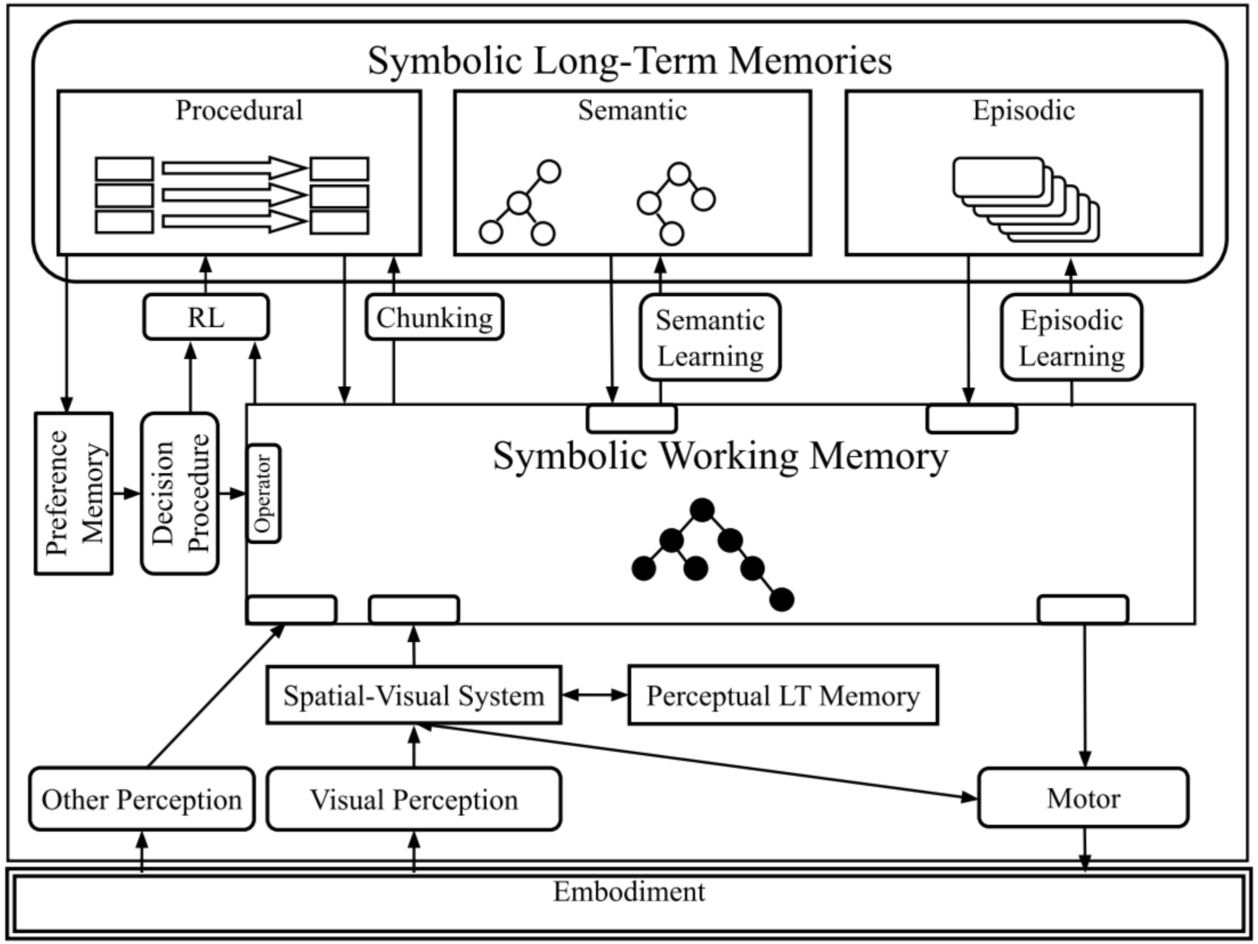


- Solutions are found, and cognition takes place, through interaction with environment

Soar Cognitive Architecture

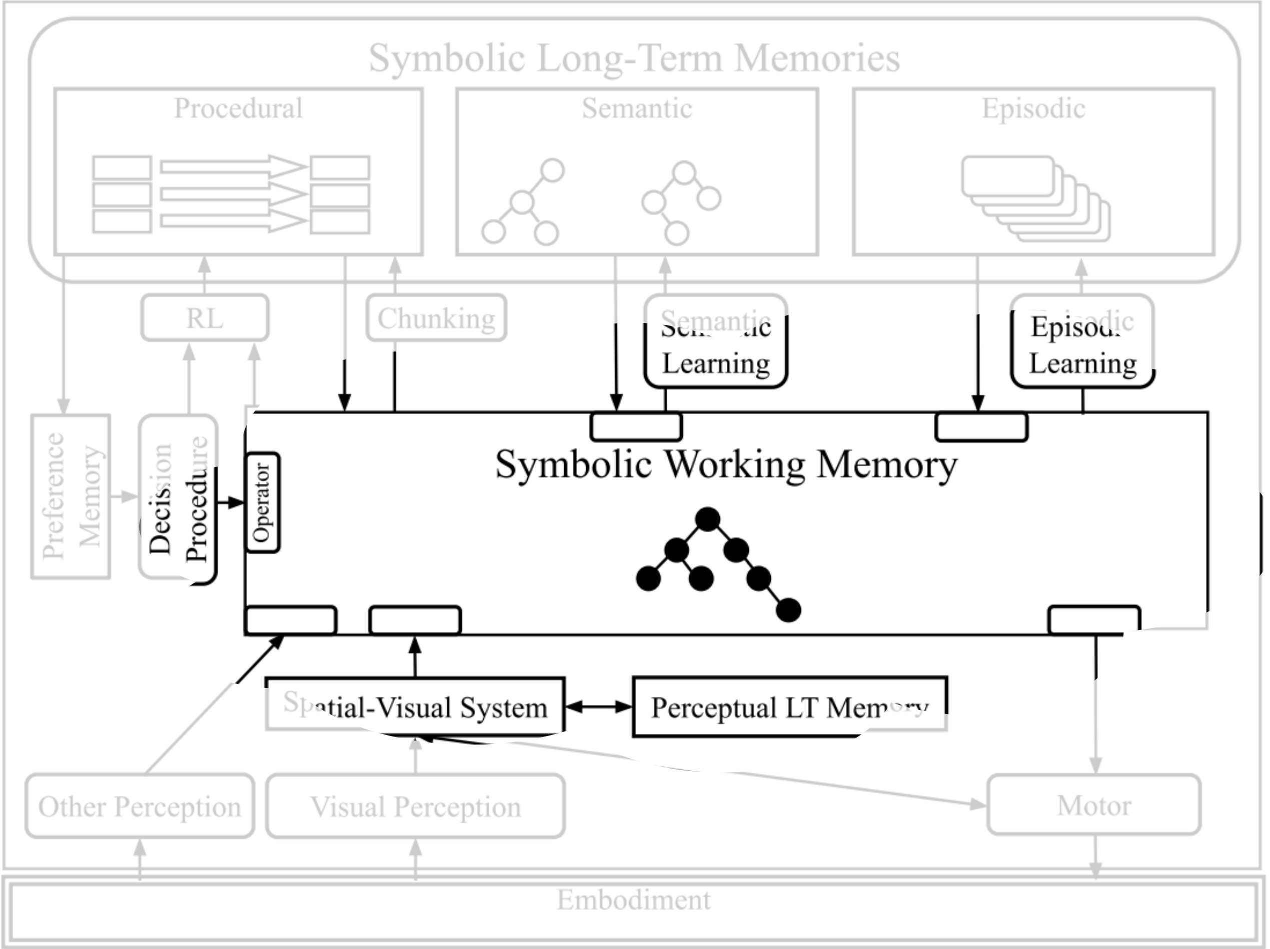
- Control of an embodiment depends on the structures in Working Memory, which are manipulated by each long-term memory system.

- Cognitive cycle: a unit of decision making or action selection for internal and external acts based on the current state of an agent. It has a real timescale (often 50ms for modeling human behavior) that characterizes the requirement to react quickly with respect to a given task and environment.



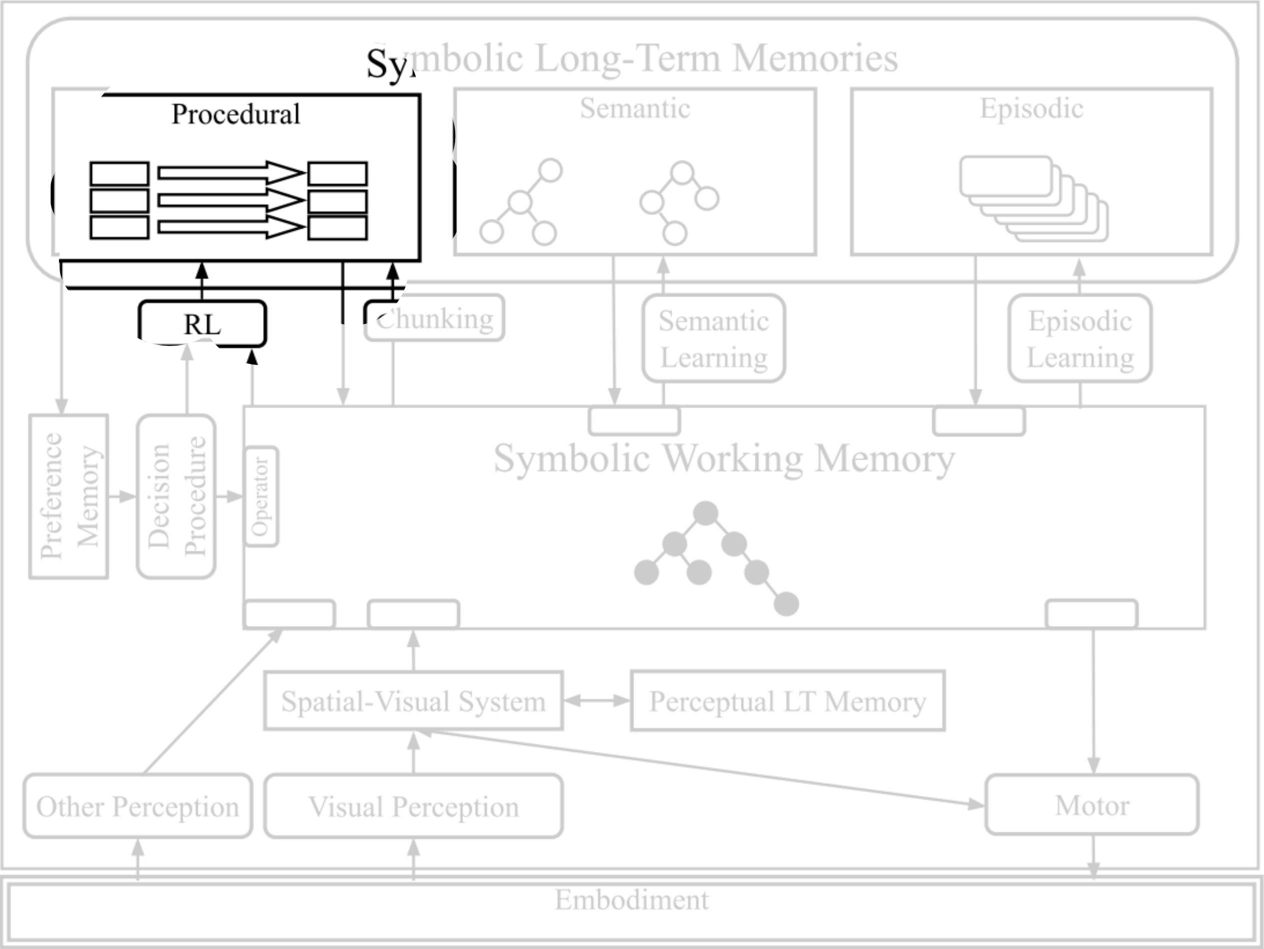
Working memory

- Working memory: a temporary global space within which representations from perception and long-term memories can be dynamically composed. Working memory interfaces with declarative long-term memory through buffers that cue for retrieval and contain retrieved memory elements. This memory also contains information about goals and actions. Agent behavior typically depends on procedural memory control of working memory elements.



Procedural memory

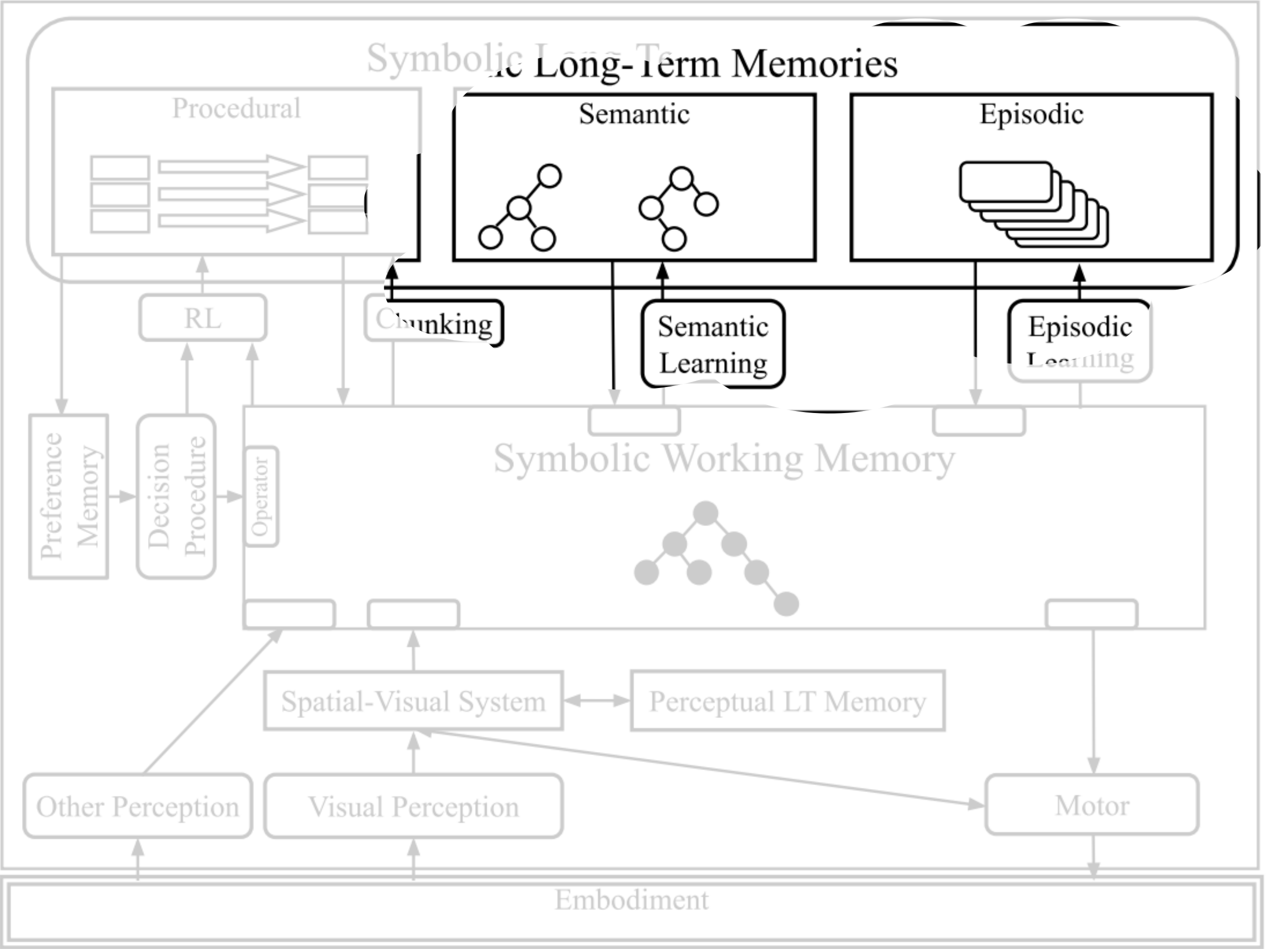
- Procedural memory: a long-term memory system with knowledge about actions and in particular how to initiate them (for external actions) and how to execute them (for internal actions). This is usually implemented with if-then rules. Procedural memory can also contain additional knowledge for action preferences that can be learned with reinforcement learning mechanisms. Procedural memory inspects and modifies working memory, and only has access to declarative long-term memory elements if they are retrieved into working memory.



Declarative long-term memory

Declarative long-term memory: a long-term store for facts and concepts. In some systems (such as Soar), this is split into episodic and semantic memory. It contains persistent symbolic relations.

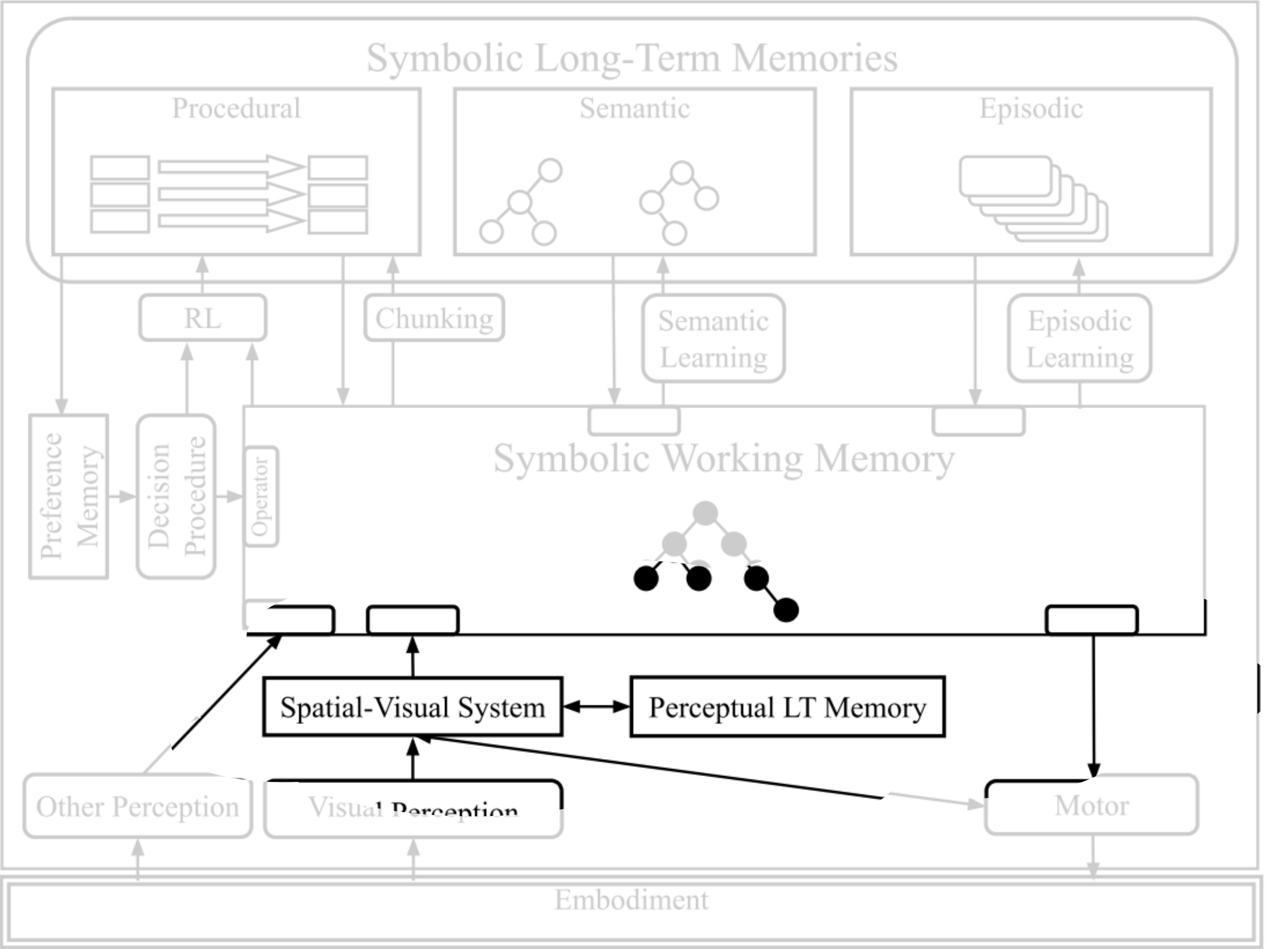
- Semantic memory: long-term declarative memory for facts. The definition for a word is stored here.
- Episodic memory: long-term declarative memory for contextualized experiential knowledge. It is a temporally-ordered log of an agent's history. A memory including the use of a word in context is stored here.



Buffers

- Perception Buffer: a representation of sensor data that is passed to working memory. This can directly interact with motor control (as in control loops).

- Motor Buffer: a subset of working memory contents that initiate and control external action and interact with an embodiment.



Cognitive Architectures - Common Points

- Recognition and categorization
- Decision making and choice
- Perception and situation assessment
- Prediction and monitoring
- Problem solving and planning
- Reasoning and belief maintenance
- Execution and action
- Interaction and communication
- Remembering, reflection, and learning

Human Cognition

- Working memory is very limited
- Long-term memory is selective: we forget things
- Memory is constructive: we misremember things
- Language is ambiguous and fuzzy
- Reasoning is often flawed
- and so on

- All of these things are necessary for us to function effectively in real time in different and changing environment

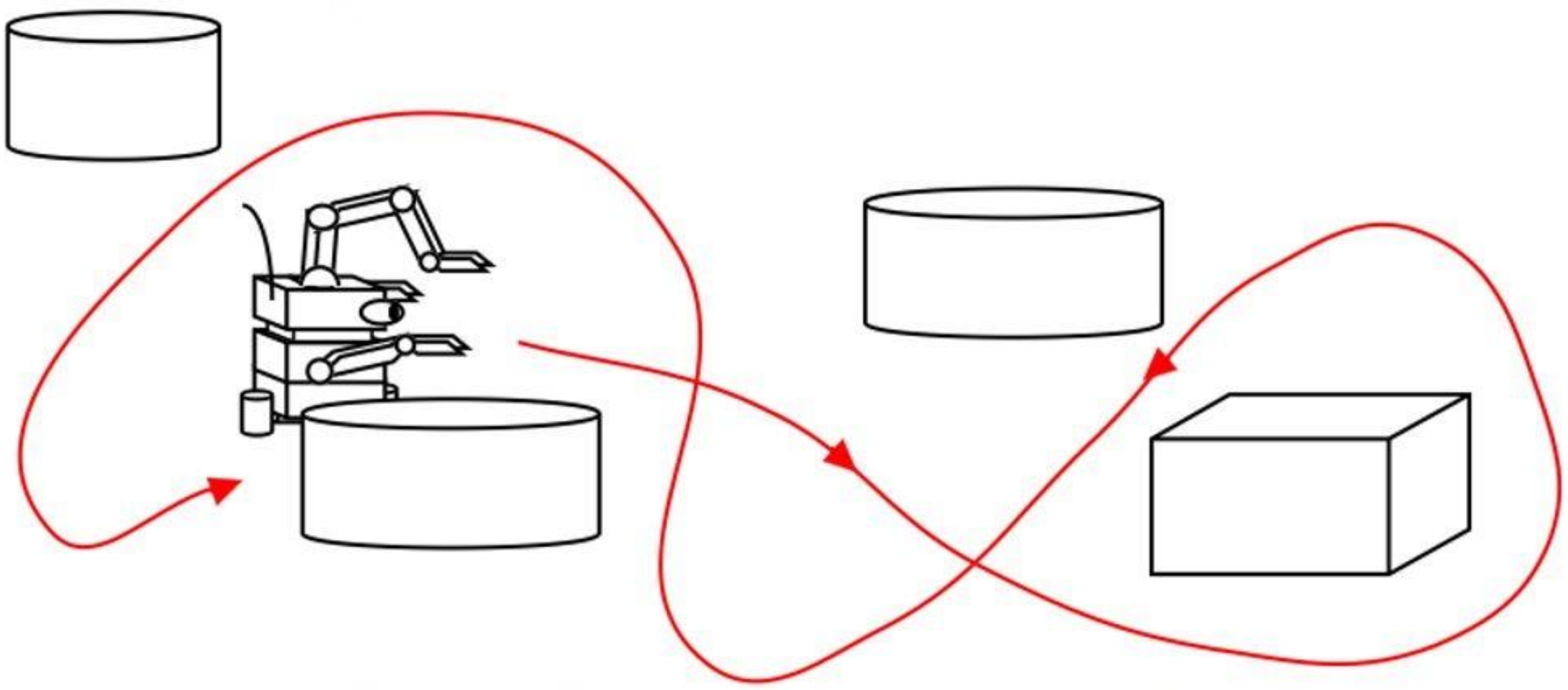
Adaptivity

Learning, evolution, adaptation

- Learning:
  - Changes will be made after the evaluations
  - Learning is the purpose of change
- Evolution:
  - Evaluations happen after the changes
  - Evolution is the result of change
- Adaptation:
  - Changes occur after evaluations or as a result of adaptation to environmental conditions

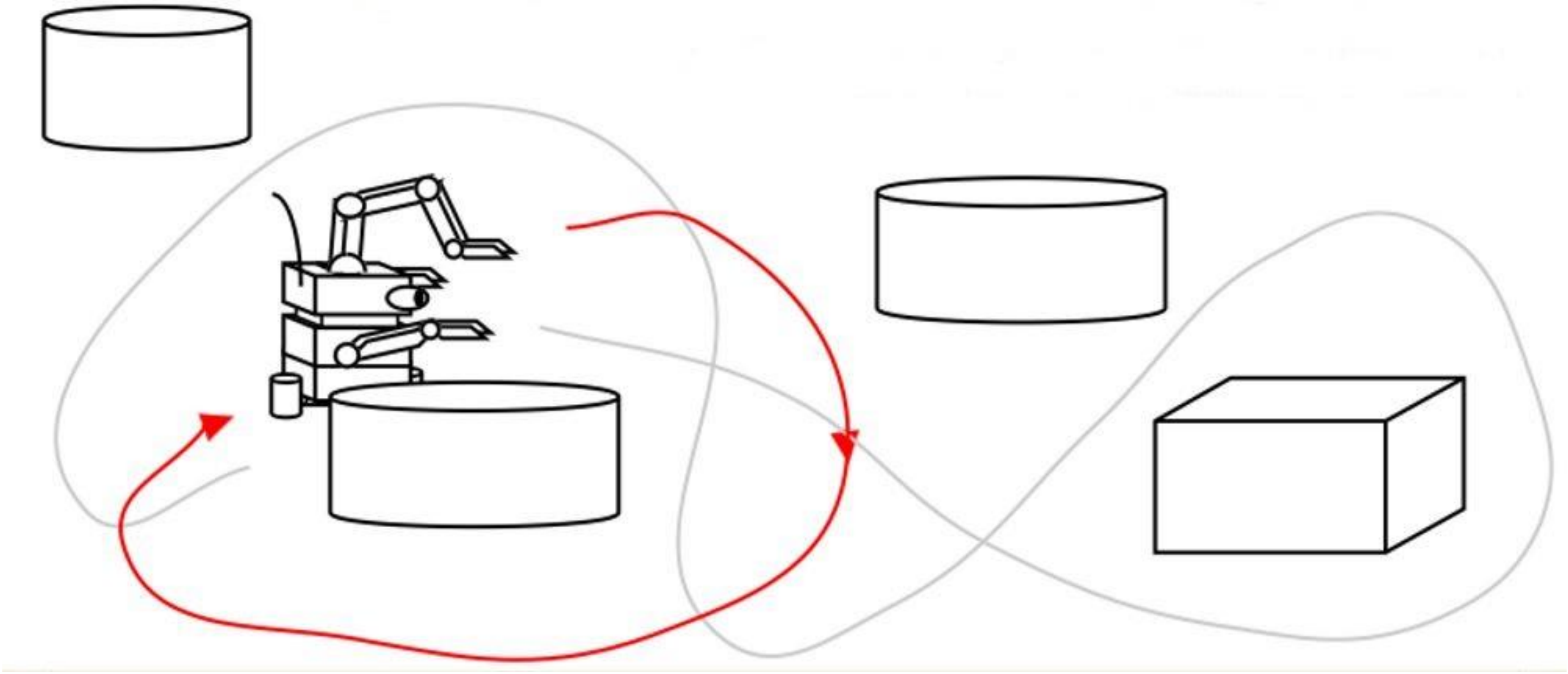
Adapting to the environment - self-adaptation

- The robot adapts to a given environment by changing its behavior



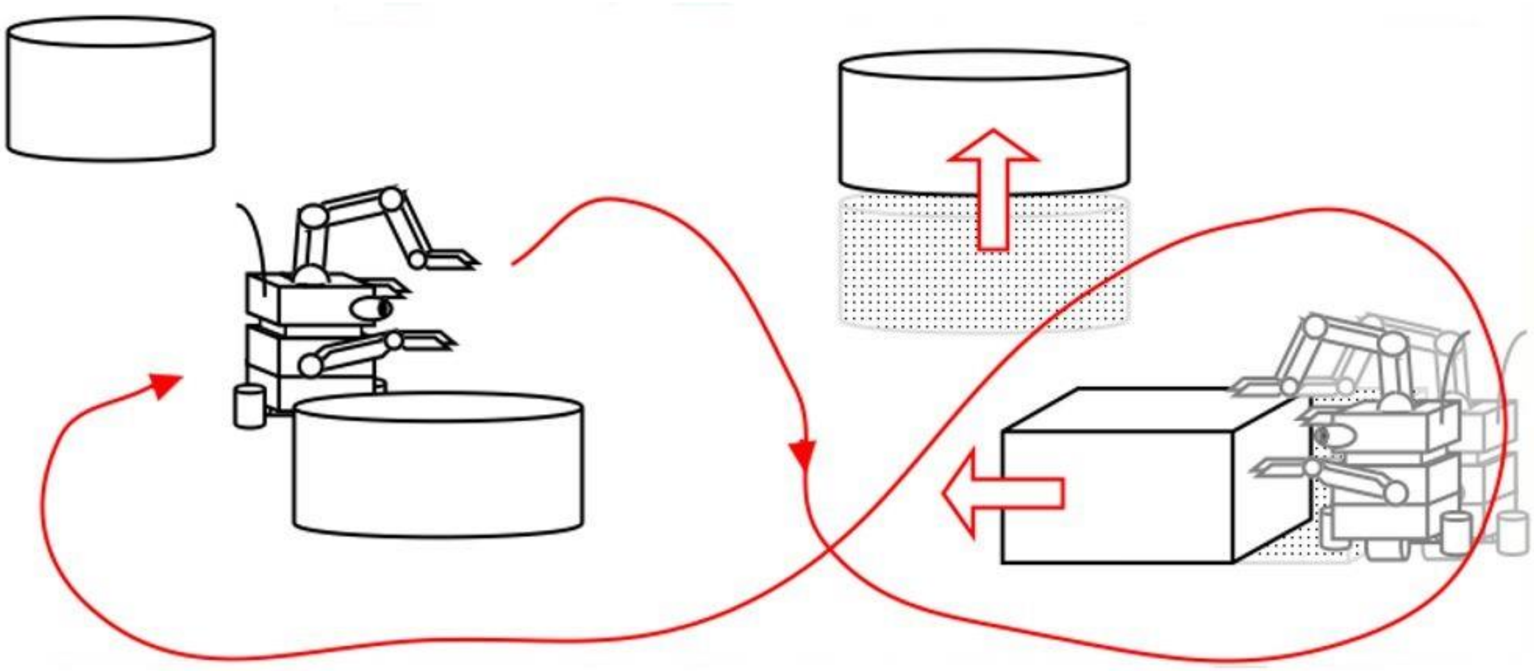
Adapting to the environment - selective adaptation

- The robot adapts to a given environment by choosing the right local environment (like a migratory bird)



Adapting to the environment - constructive adaptation

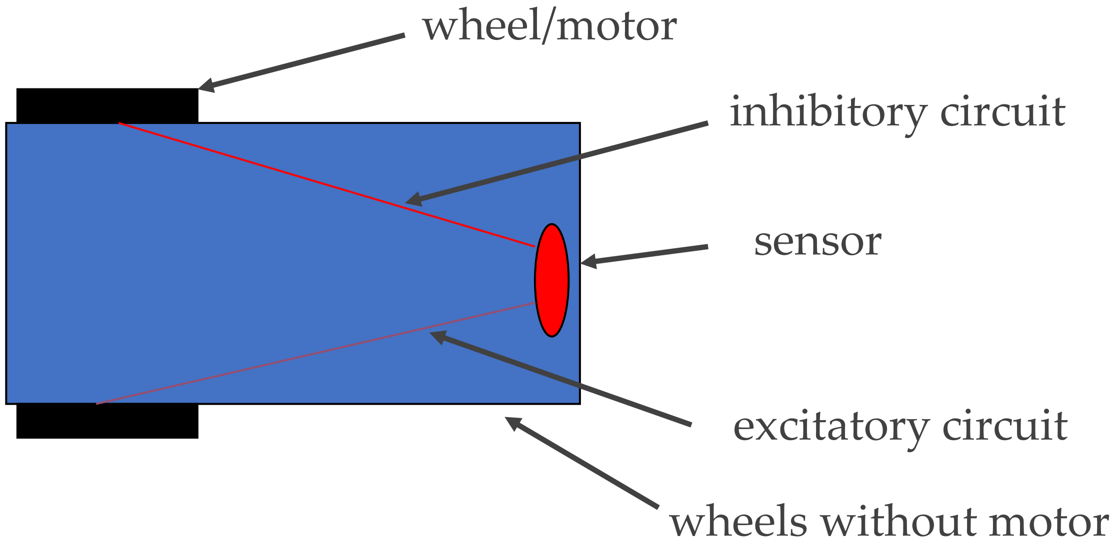
- The robot adapts to a given environment by rebuilding the environment (like a human)



Braitenberg vehicles

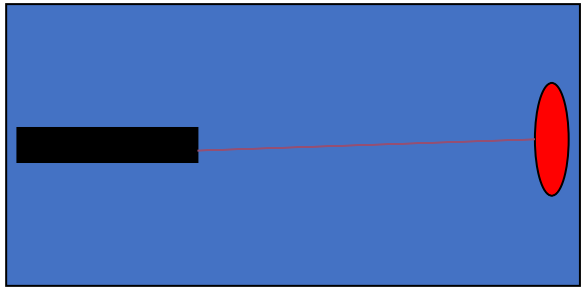
Braitenberg vehicles

- Complex behavior can also be achieved with simple elements
- Complex behavior does not necessarily hide a complex inference mechanism



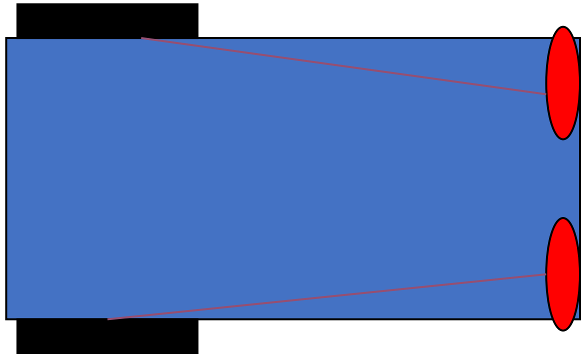
Inhibitory circuit: when the sensor is activated, the motor slows down
Excitatory circuit: when the sensor is activated, the engine accelerates

Vehicle 1 - life



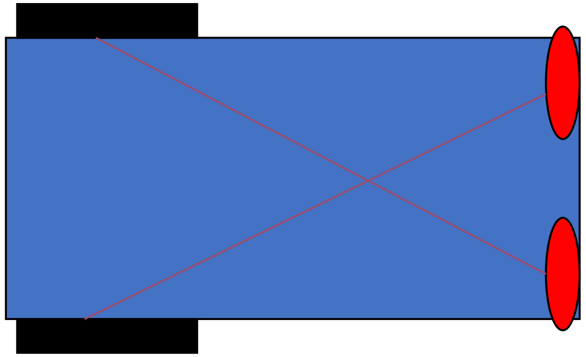
- It has one sensor
- Excitatory circuit
- It is always moving.
- Assuming a temperature sensor: the warmer the place the faster the motion

Vehicle 2a - fear



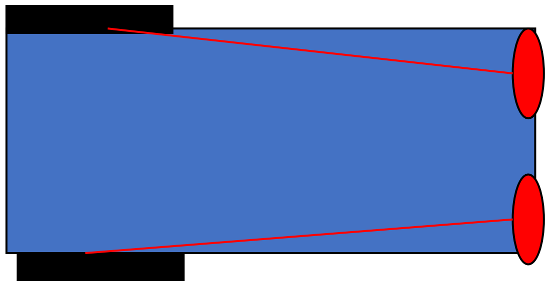
- It has two sensors
- Two excitatory circuits
- Assuming a light sensor, when the light source is closer to one of the sensors, it is activated more and the vehicle starts to move away from the source
- If both sensors are activated equally, it will "attack" the source

Vehicle 2b - aggression



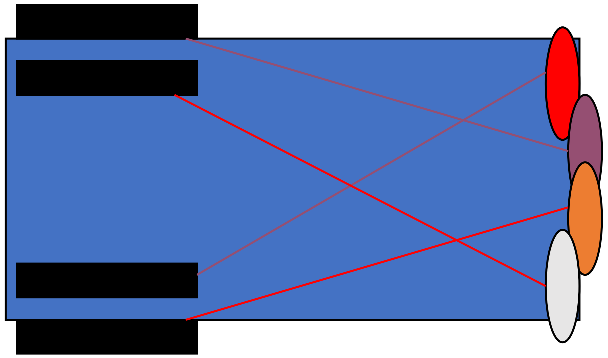
- It has two sensors
- Two excitatory circuits, cross-connected
- Attacks the source in all cases

Vehicle 3a - love



- It has two sensors
- Two inhibitory circuits
- It keeps going until it finds a source. Then it slows down and stops.
- If one side sees the source, the vehicle turns in that direction.
- In the case of cross-connected circuits (3b), the reaction is similar, but it is "interested" in other, stronger sources

3c vehicle - knowledge



Red: light sensor
Purple: temperature sensor
Orange: organic matter detector
Grey: oxygen detector

- It has four different types of sensors
- It has the capabilities of the previous vehicles
- Turns towards light, dislikes heat, likes organic matter, seeks oxygen
- Able to perform some of the brain functions of simpler organisms

Conclusions

- Other types:
  - e.g. vehicle 4b: all couplings are both inhibitory and excitatory, but in a non-monotonic way, i.e. the motors increase and decrease their speed in a non-linear way
- We only really understand machines if we have created them ourselves, otherwise not sure
- If we do not know the internal structure of a machine, we tend to overestimate its complexity

Computational intelligence

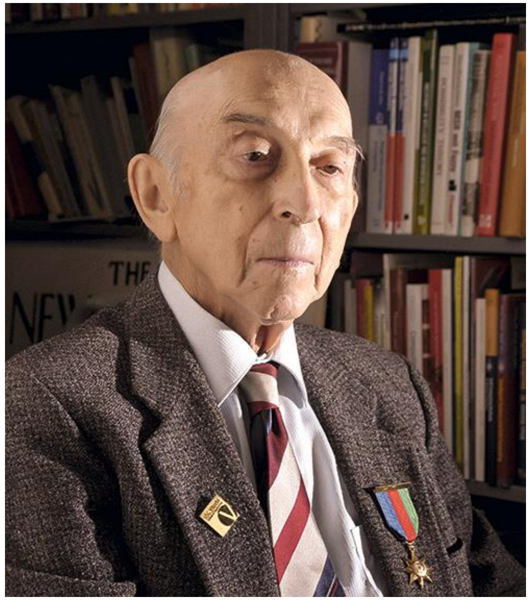
Computational intelligence

- The three main subfields of Computational Intelligence (CI) are:
  - Fuzzy systems
  - Neural networks
  - Evolutionary computation
- CI techniques can provide approximate solutions for complex problems cannot be handled by classical methods
- CI techniques can balance well between the computational complexity and the accuracy of the solution
- CI can be used for wide range of problems including statistical tasks, data mining problems, pattern recognition, prediction, optimization
- It has various applications in many fields such as engineering, economics, logistics and so on

Fuzzy systems

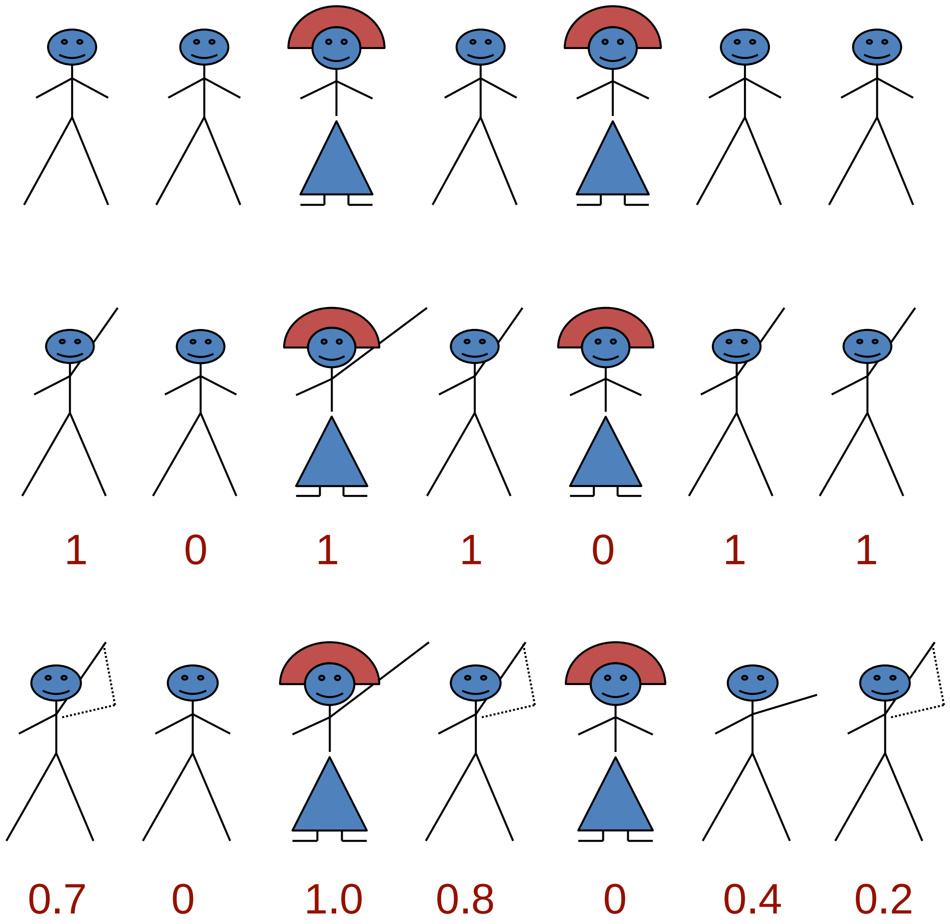
Fuzzy sets, fuzzy logic

- Fuzzy: blurred, vague
- Lotfi A. Zadeh (1965): fuzzy set theory for expressing the imprecision existing in linguistic concepts
- Fuzzy logic: Zadeh, 1973
- Fuzzy inference using linguistic rules:
  - Zadeh: 1973
  - Mamdani: 1975



- Blurry border:
  - e.g..: „tall people”: how much is a person with a known height element of this set?
- Partial membership: between 0 and 1: there is somebody who belongs more, there is somebody who belongs less
- To what extent does x belong to the set?
  ↳ membership function

An example



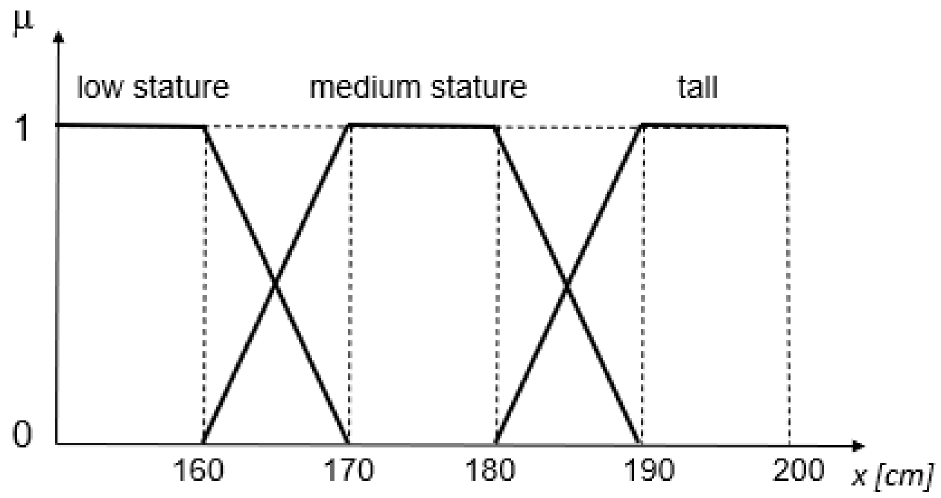
- E.g. A class of student
- The universe of discourse: X

- "Who does have a driver's licence?"
- A subset of X=A (crisp) set
  $\chi_A(X)$ = characteristic function

- "Who can drive very well?"
  $\mu(X)$ = membership function

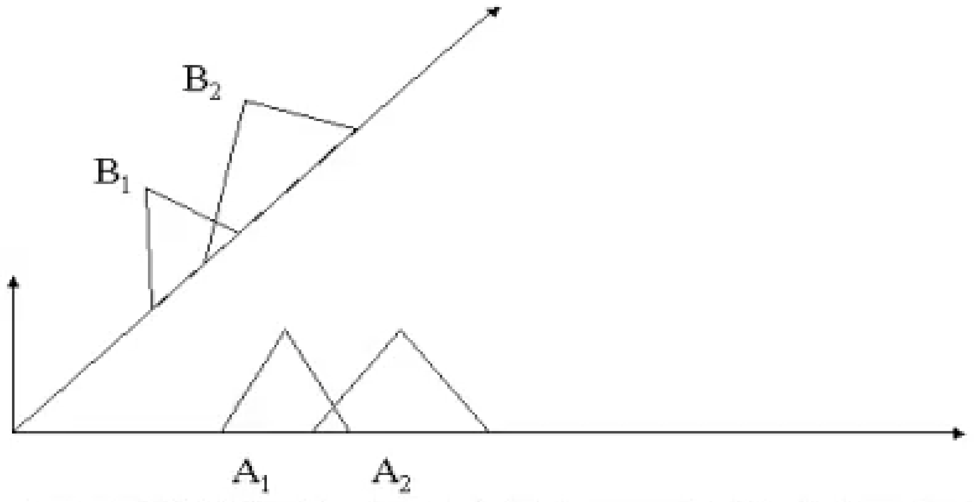
Another example

- An example to describe people's height by 3 fuzzy sets
- The sets can partly overlap each other
- A person may belong to more than one set, with different membership values



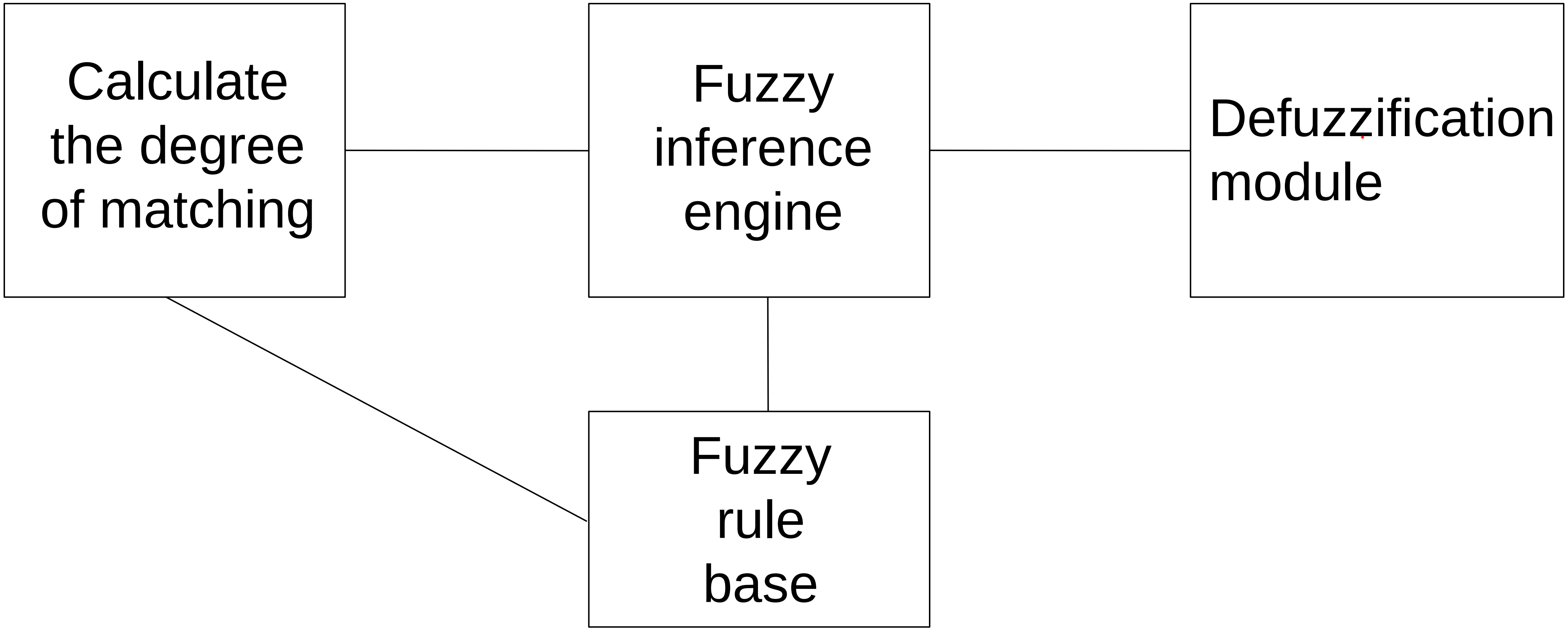
Fuzzy rules

- **IF** $x = A$ **THEN** $y = B$
  - where A is the antecedent of the rule, B is its consequent
  - example: **If** traffic is heavy in this direction **then** keep the green light longer
- Fuzzy rule base

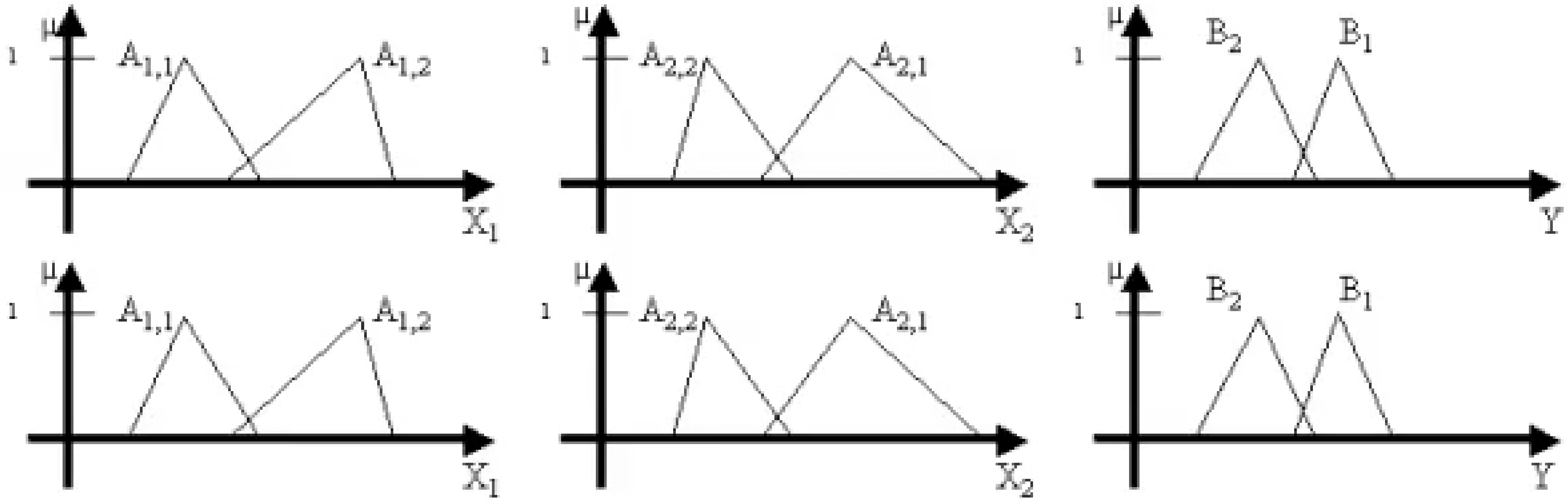


Fuzzy rule base (R) containing two fuzzy rules R_1: $A_1 \rightarrow B_1$, R_2: $A_2 \rightarrow B_2$

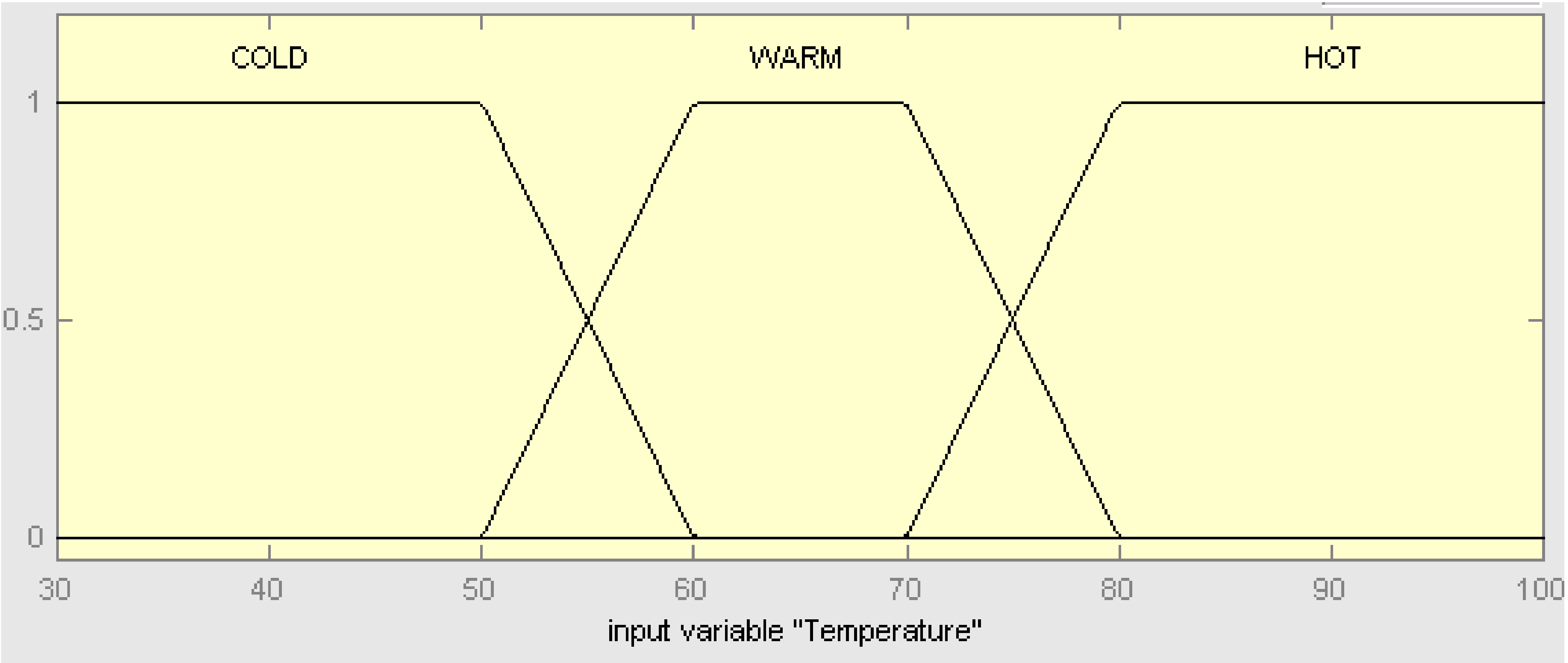
General scheme of a fuzzy system



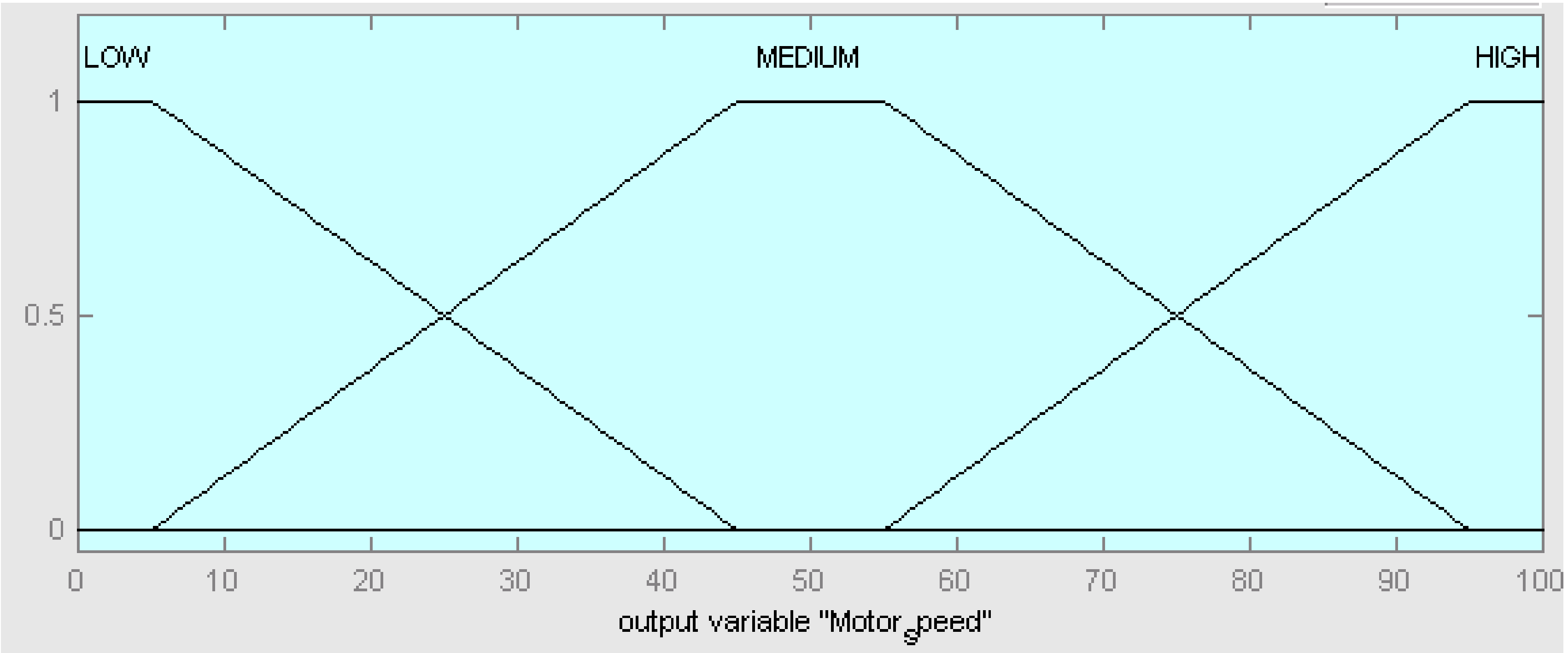
The inference mechanism



Fuzzy systems: an example



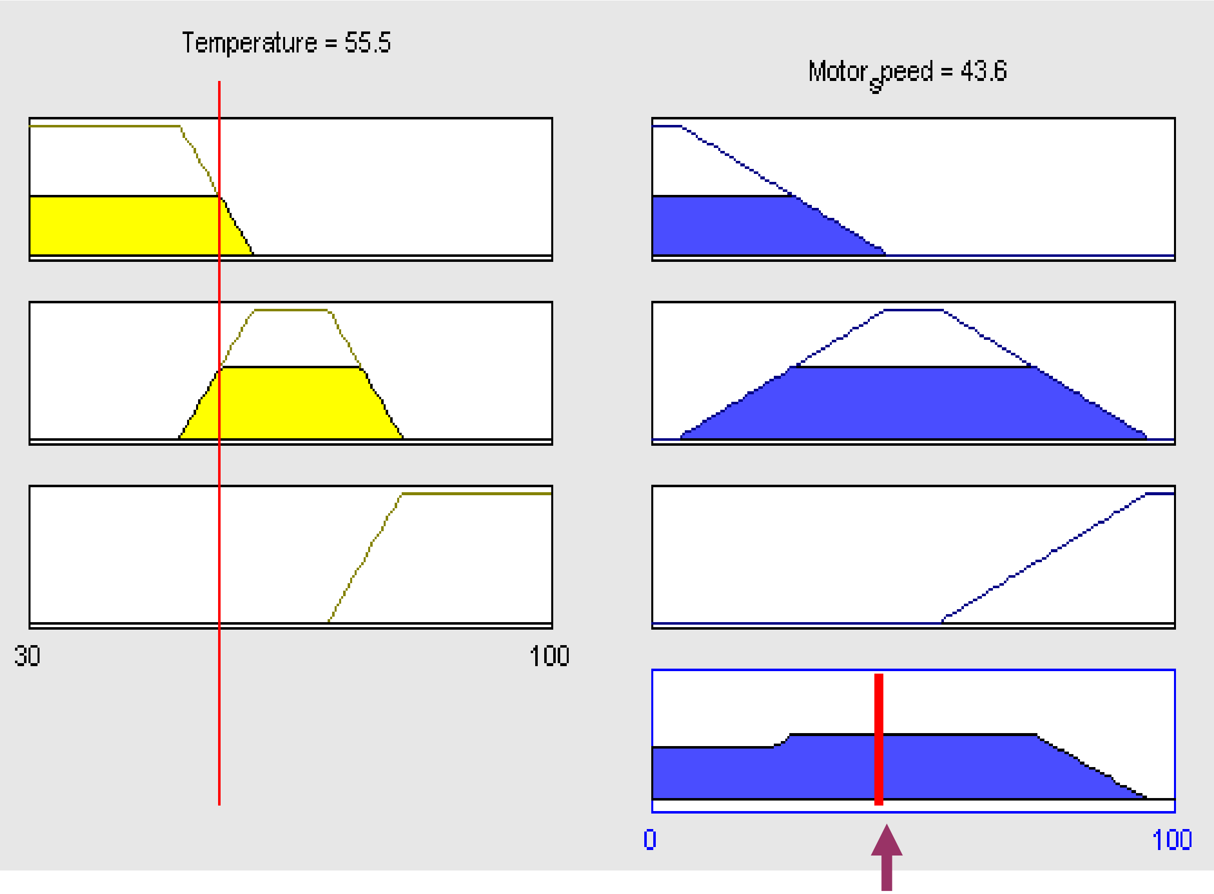
The rules



IF *temperature* is COLD **THEN** *motor_speed* is LOW
IF *temperature* is WARM **THEN** *motor_speed* is MEDIUM
IF *temperature* is HOT **THEN** *motor_speed* is HIGH

The inference mechanism

- Rule 1
- Rule 2
- Rule 3



Neural networks

Unsupervised learning

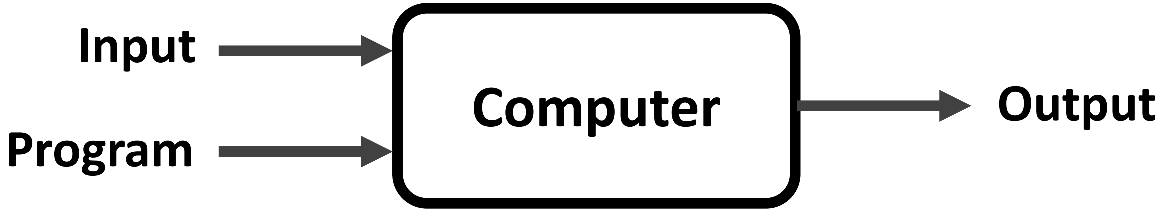
Supervised learning

label

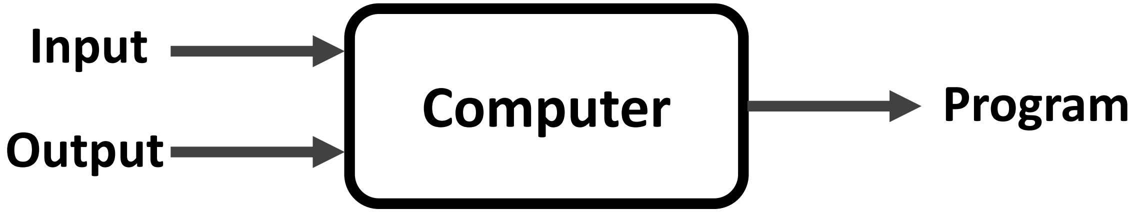
dog **cat** **bird**

Learning - Programming

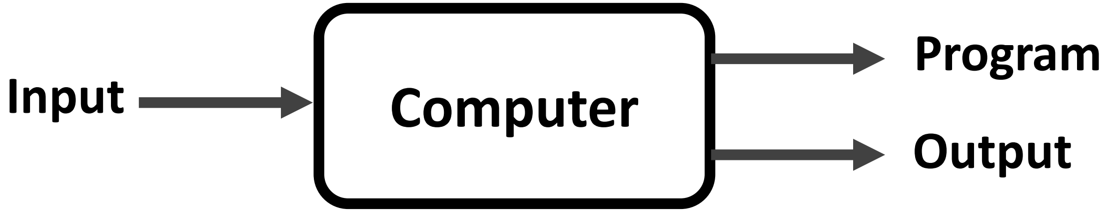
- Traditional computer programming:



- Supervised learning:

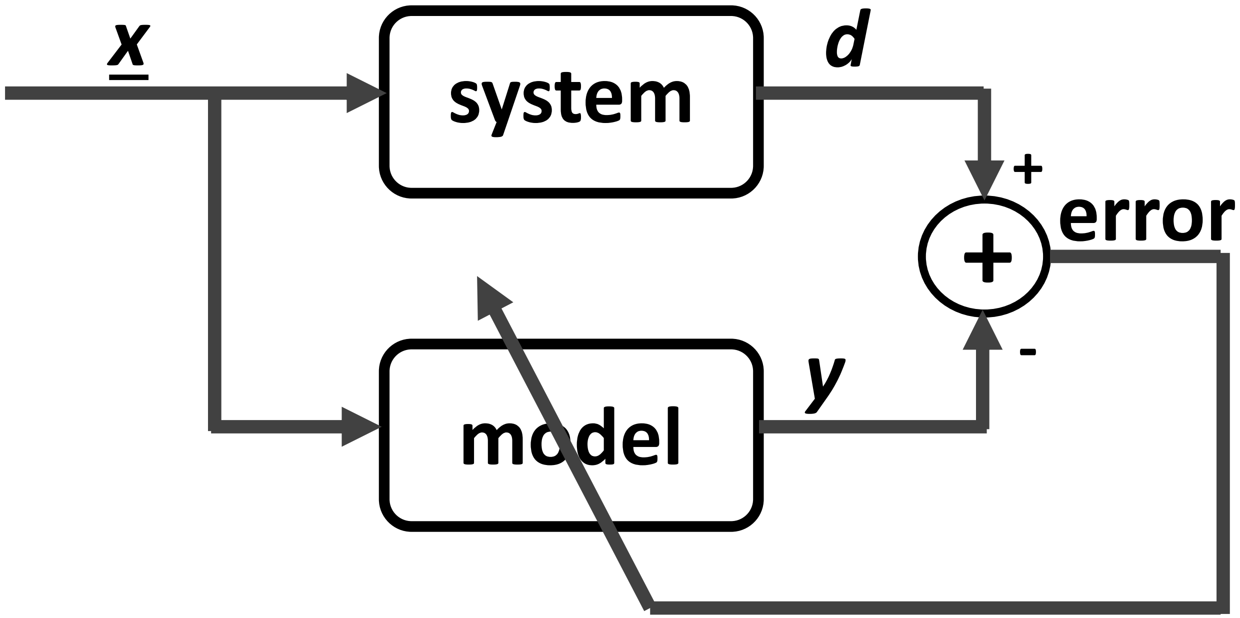


- Unsupervised learning:



Supervised learning

- given: input-output training patterns $(x_1^{(p)}, x_2^{(p)}, \ldots, x_n^{(p)}, d^{(p)})$
- p: number of patterns, n-dimensional input, scalar output

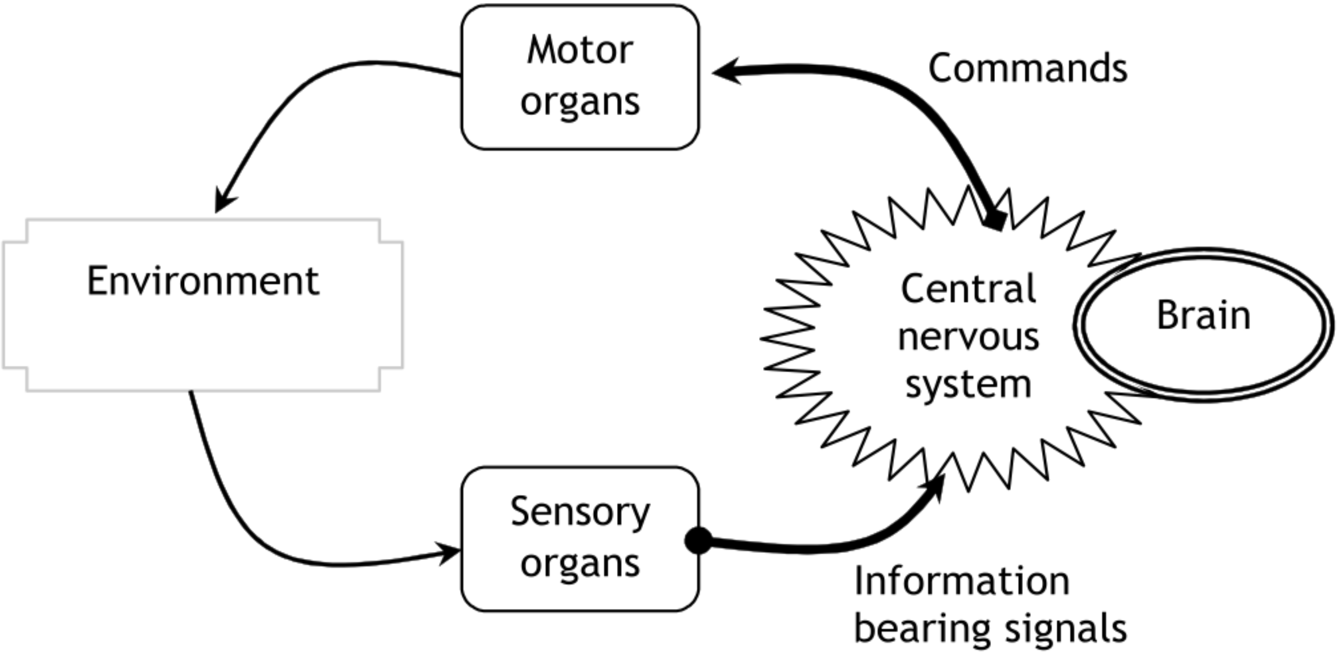


Supervised learning

- **Representation:**
  - rule based system
  - fuzzy system
  - decision tree
  - neural network
  - support vector machine
  - etc.
- **Evaluation:**
  - error
  - accuracy
  - cost
  - entropy
  - etc.
- **Optimization:**
  - gradient based algorithm
  - evolutionary algorithm
  - etc.

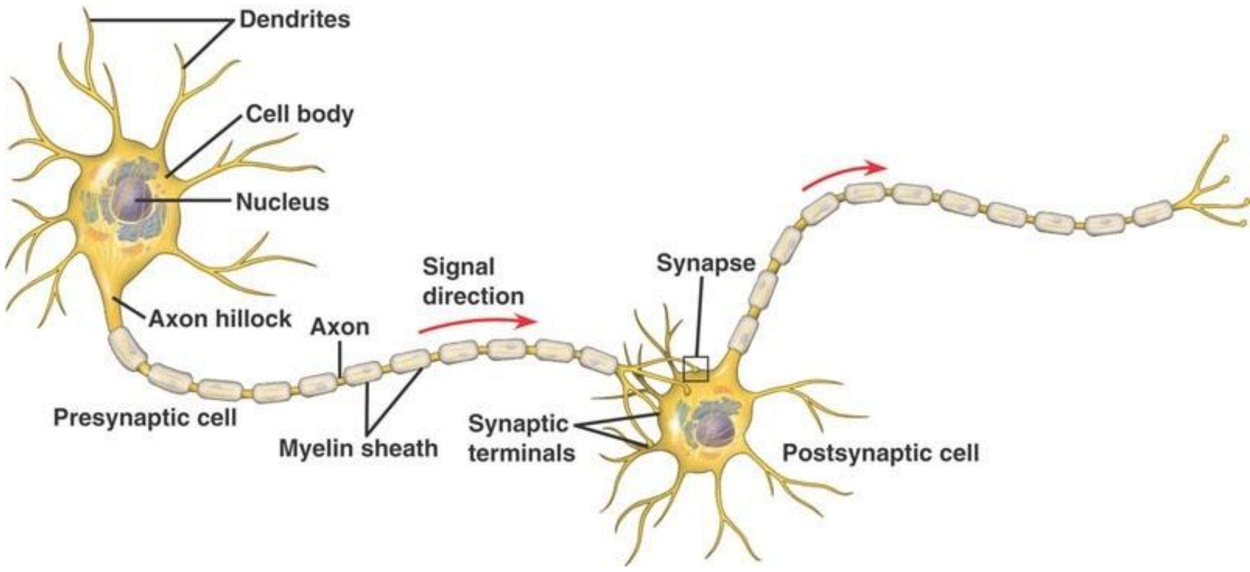
Human nervous system

- Human nervous system is a very **complex** system capable of **thinking, remembering, problem solving, making decision** and etc.



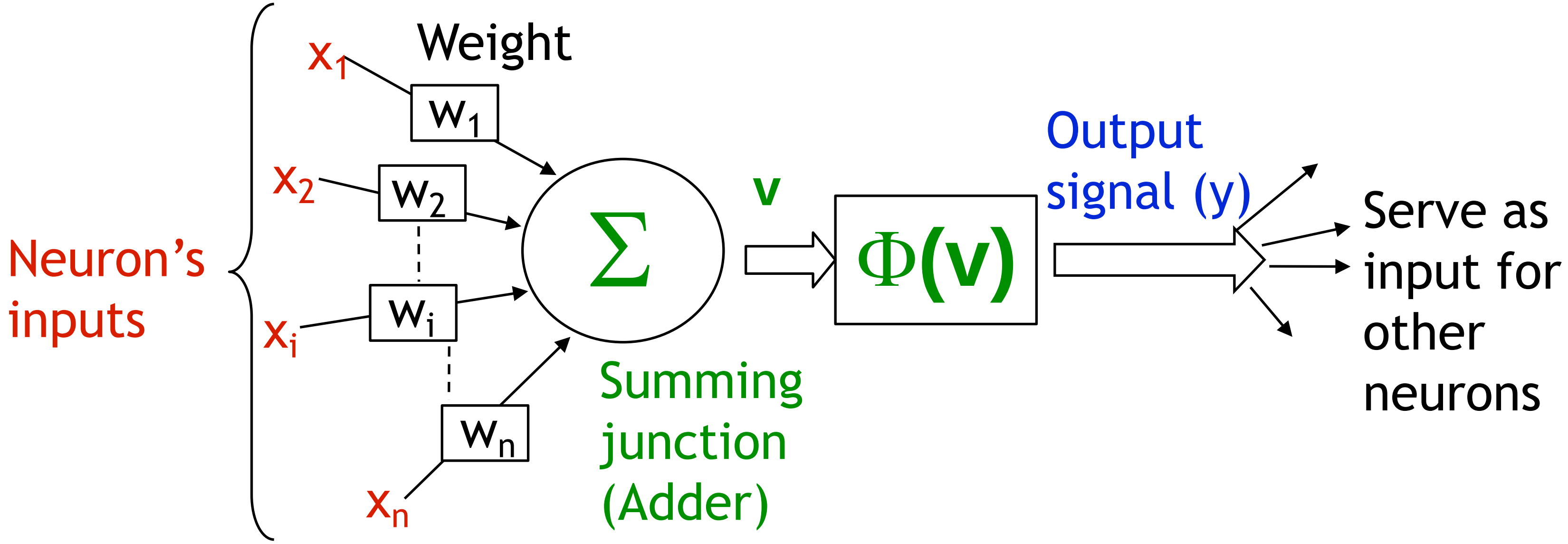
Basic Mechanisms of Neurons

- Dendrites: Inputs
- Axons: Outputs
- Cell body: Leaky integrator
- Cell-cell intersection: Synapse
- Neurotransmitters:
  Emitted into synaptic space by the presynaptic cell's action potencial
- On the postsynaptic side, presynaptic activations induce potential jumps based on the synapse's characteristics

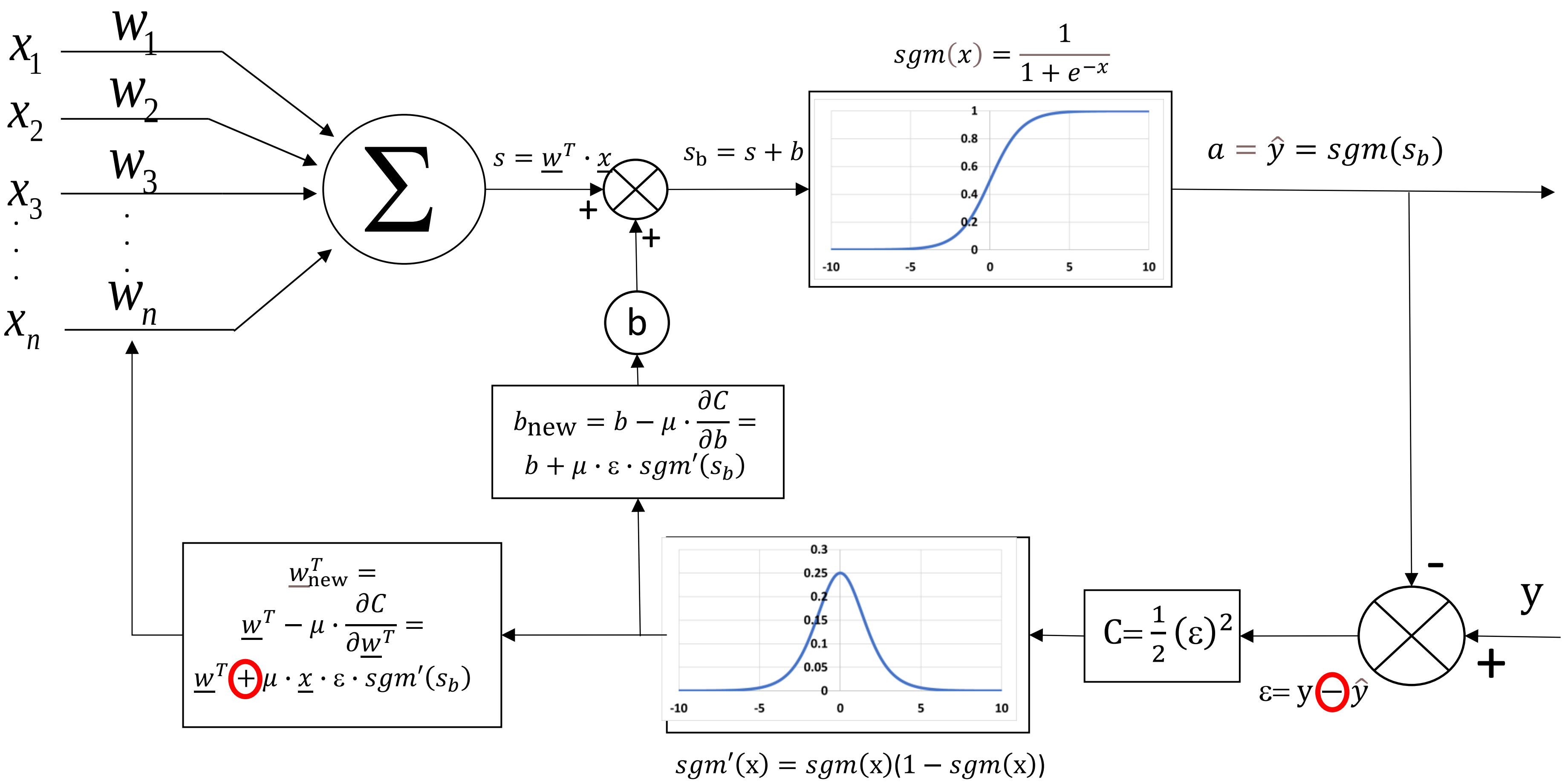


Artificial neuron

- An information processing unit that is fundamental of an artificial neural network.
- A mimicking model for biological neuron.



Neuron’s learning

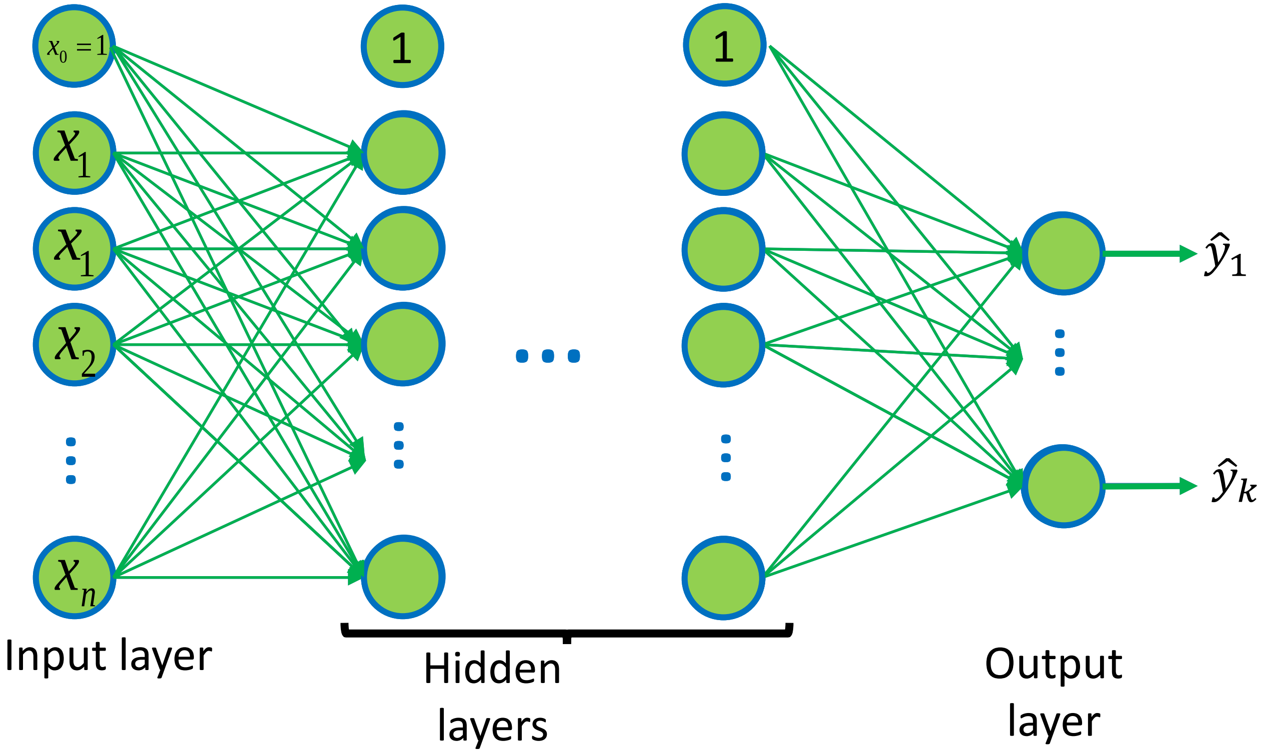


μ: *learning rate*
a: *activation*
$\hat{y}$: *output*
y: *desired output*
$\underline{x}$: *inputs*

Artificial Neural Networks

- A neuron can only perform some simple information processing; therefore it is not able to solve complex problems.
- However, neurons can be interconnected to deliver collective complex behavior and thus they can be used for solving complex problems.
- By connecting neurons we get Artificial Neural Network (ANN) which is a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain to yield a network with rather complex behavior.
- In ANN, neurons (processing elements) are organized into a sequence of layers with full or partial connection between the layers

Artificial Neural Networks



$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{n=1}^{k}\left(y_n^{(p)} - \hat{y}_n^{(p)}\right)^2$$

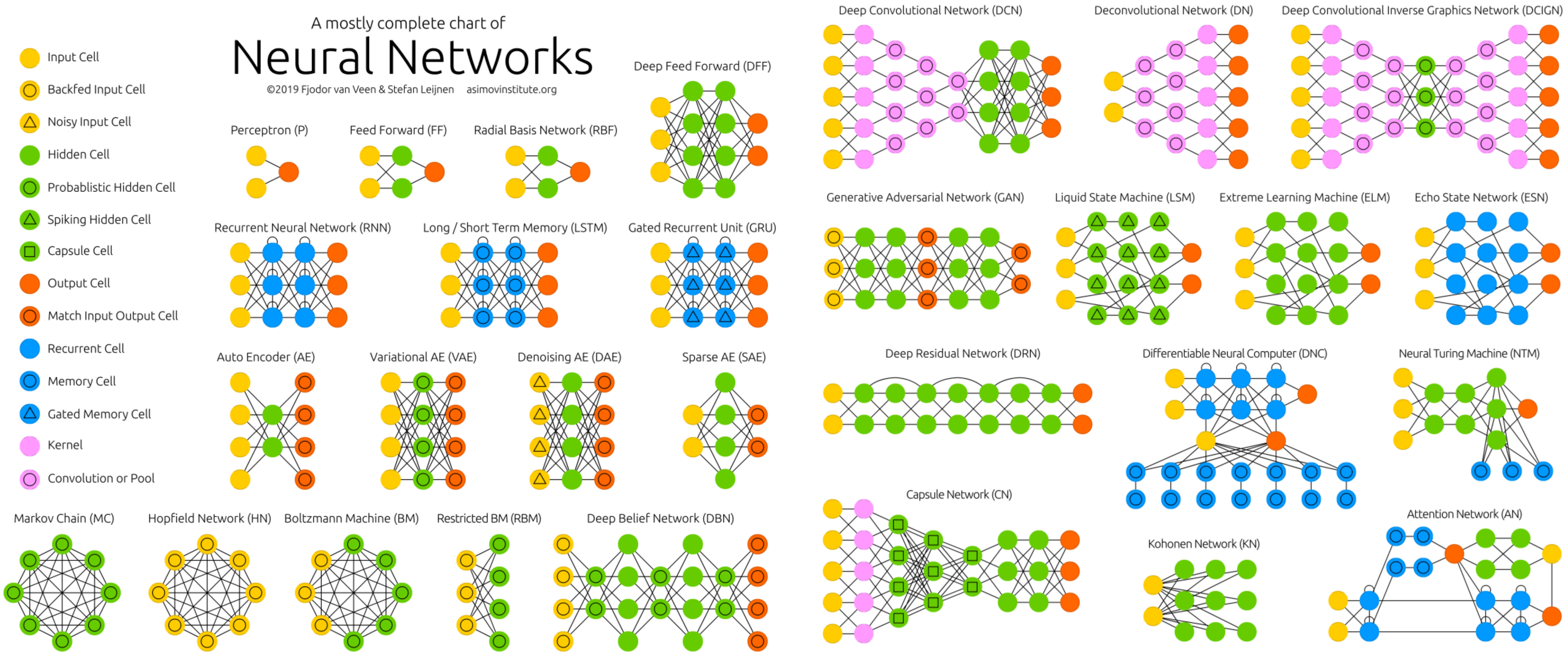
$$\frac{\partial E}{\partial \underline{a}^{(L+1)}} = -\sum_{p=1}^{P}\sum_{n=1}^{k}\left(y_n^{(p)} - \hat{y}_n^{(p)}\right)$$

$$\underline{\delta}^{(l)} = f'^{(l)}_{act}\left(\underline{s_b}^{(l)}\right) \cdot \underline{\underline{W}}^{T\,(l+1)} \cdot \underline{\delta}^{(l+1)}$$

$$\frac{\partial E}{\partial \underline{\underline{W_b}}^{T\,(l)}} = \underline{\delta}^{(l)} \cdot \underline{a}^{T\,(l-1)}$$

$$\underline{\underline{W_{b\_new}}}^{T\,(l)} = \underline{\underline{W_b}}^{T\,(l)} + \mu \cdot \frac{\partial E}{\partial \underline{\underline{W_b}}^{T\,(l)}}$$

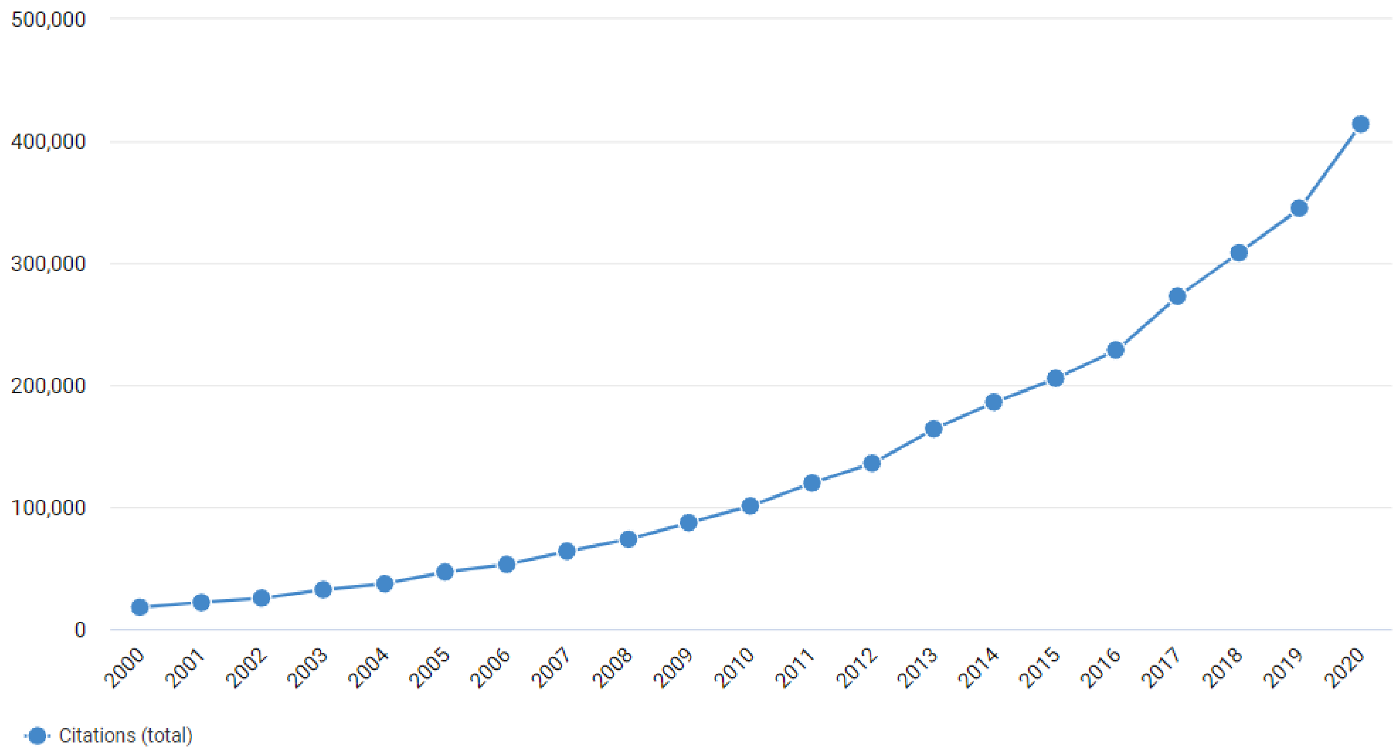
Overview of neural networks



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

Motivations for spiking neural networks

- Biological plausibility
- Energy efficiency
- Parallel computation
- Deeper analysis of human nervous system



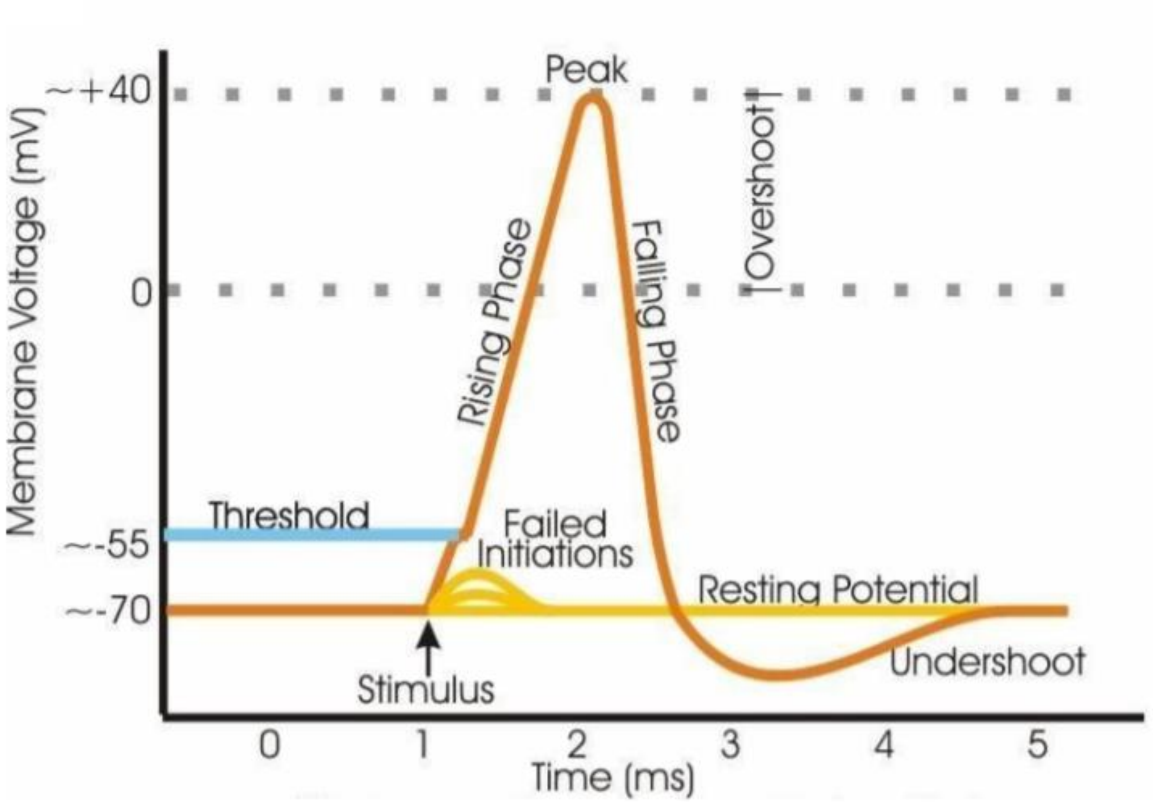
http://www.dimensions.ai

Action Potentials

- Dynamic behavior
- Thresholding mechanism
- Spike (short bursts with close to uniform amplitude)
- Refractory state
- Resting potential

- Cause: Voltage dependent active ion transport through the membrane

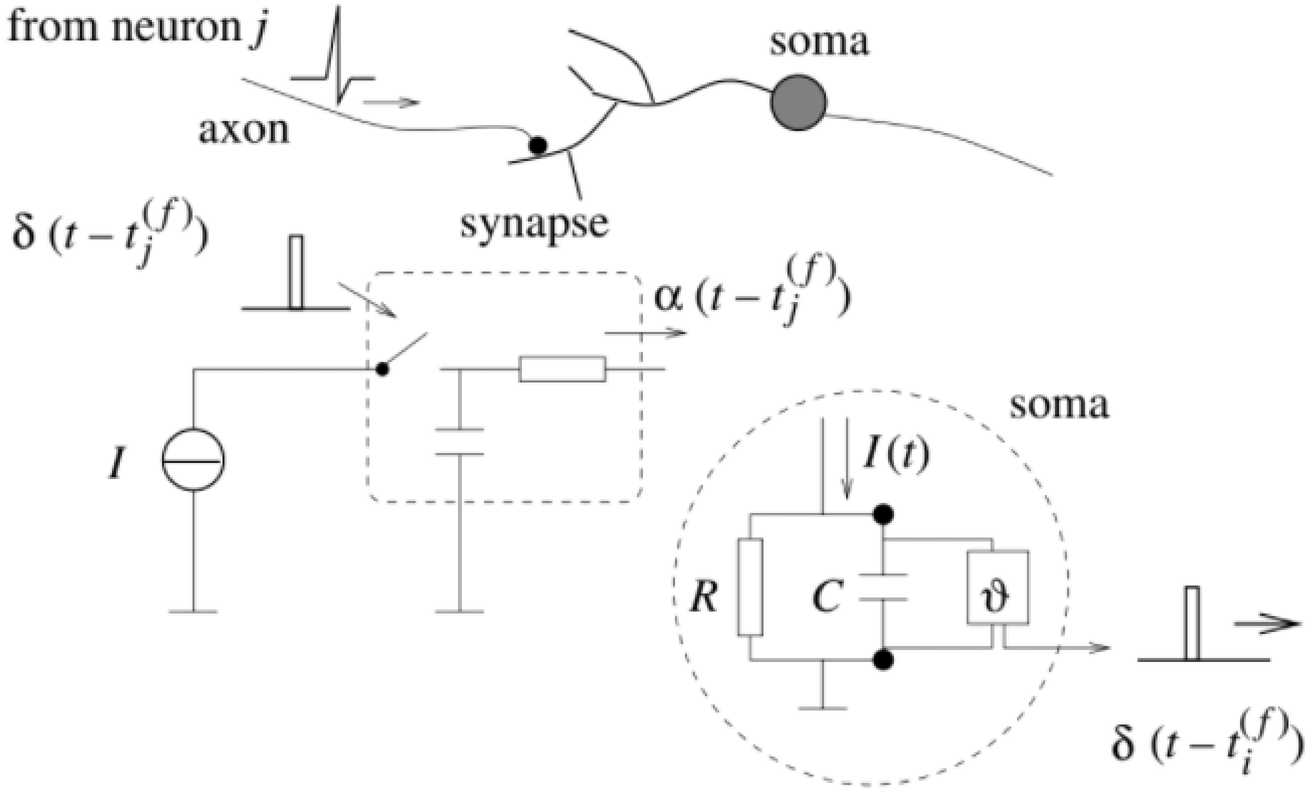
- Thresholding can be interpreted as a step activation function
(non-differentiable)



A. Tsitiridis: Biologically – inspired machine vision, PhD thesis, 2012.

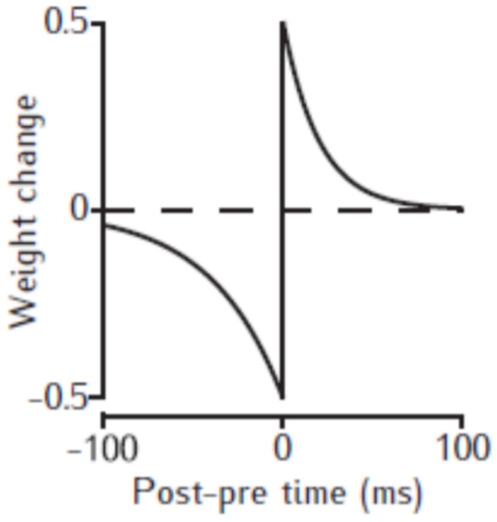
Mathematical Modelling: Integrate & Fire

- Cell body integrates inputs over time: capacity
- Leaky integrator, loses potential when not fed with inputs: resistor
- Comparator works as the thresholding mechanism
- Inputs are discrete uniform events in time with a constant effect shifted in time: alpha circuit operated by a switch



Hebbian Learning and Spike-Timing-Dependent Plasticity

- Synapses learn based on pre- and postsynaptic spikes
- Biologist Donald O. Hebb described as:
  „Fire together, wire together.”
- Unsupervised
- Local rule applied for every neuron-pair separately
- This learning rule is applied in STDP
  (Spike-timing-dependent plasticity)
- Weight change is inversely proportional to the elapsed time between activations
- This rule can be multiplicative too
- Second order general form exists



$$\frac{dw_{ij}}{dt} = a_0 + S_i(t) \cdot \left[a_1^{pre} + \int_0^\infty a_2^{pre,post}(s) \cdot S_j(t-s)\, ds \right] + \\ + S_j(t) \cdot \left[a_1^{post} + \int_0^\infty a_2^{post,pre}(s) \cdot S_i(t-s)\, ds \right]$$

Kistler & van Hemmen, 2001.

Simplified Non-leaky Integrate and Fire Model

- Membrane potential is derived from the sum of the old value of membrane potential, the sum of incoming synaptic spikes, and the external potential

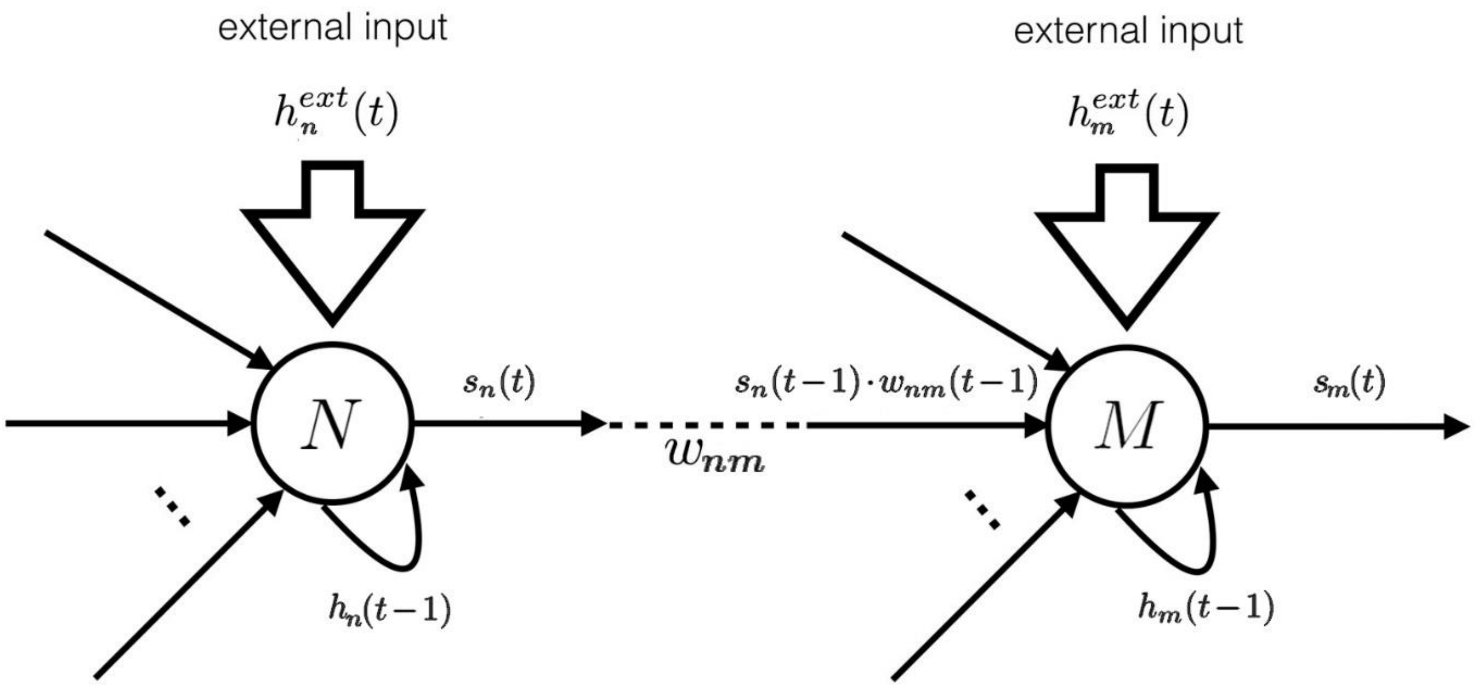
$$h_m(t) = h_m(t-1) + \sum_{n=1}^{N} s_n(t-1) \cdot w_{nm}(t-1) + h_m^{ext}(t)$$

- Upon the membrane potential becomes greater than the threshold, an output spike is generated

$$s_m(t) = \begin{cases} 1 & \text{if } h_m(t) \geq \theta \\ 0 & \text{otherwise} \end{cases}$$

Simplified Non-leaky Integrate and Fire Model

- The definition of spiketime is the exact moment of simulation when a spike is generated.
- When no spike is generated, the spiketime is interpreted as the timestep after the simulation finishes.



$$\hat{t}_i = \begin{cases} t & \text{where } s_i(t) = 1 \\ t_{max} + 1 & \text{if } s_i(t) \equiv 0 \end{cases}$$