

Lecture 9:

Neural Networks based Cases

Chapter 4, Chapter 18

Additional reference

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Outline

- Neural Networks
- Case 1: NN for Didabot
- Case 2: NN for the Braitenberg vehicles
- Case 3: Embedded NN for DAC
- Summary

Lecture 8: Beyond Classical search

Neural networks

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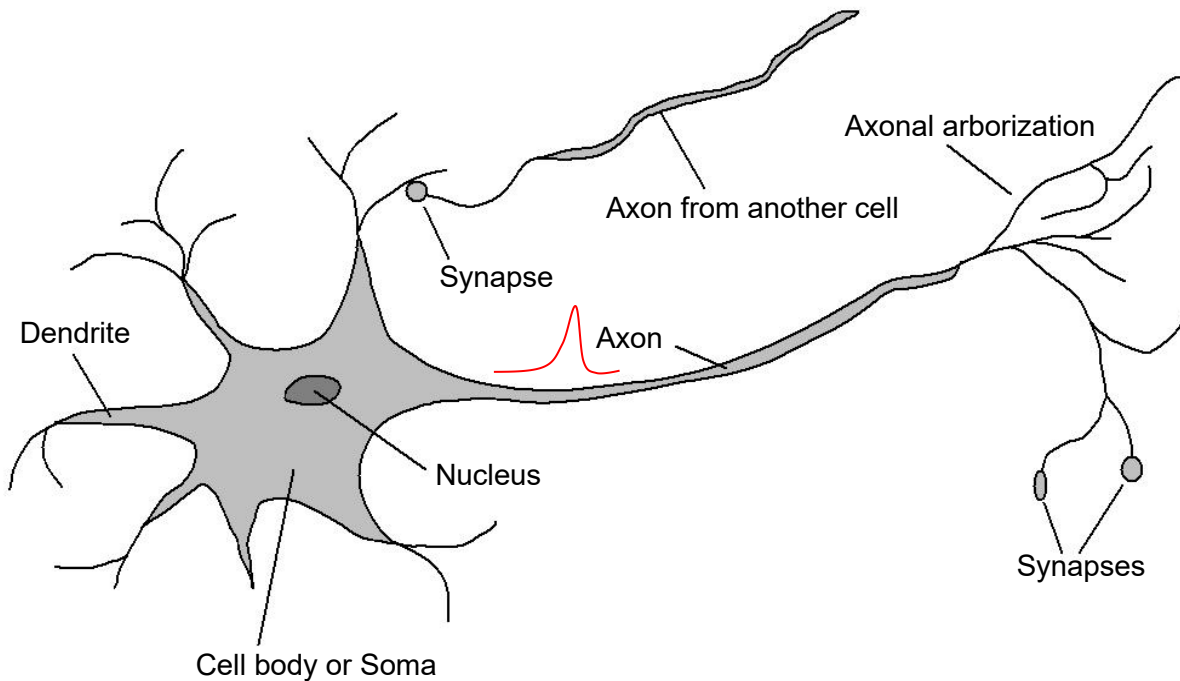
WeChat group: U10M12018.01 人工智能（英）群

Outline

- Brains
- Neural networks
- Perceptrons
- Multi-layer Perceptrons
- Applications of neural networks
- Evolving a neuro controller for robots
- Summary

Brains

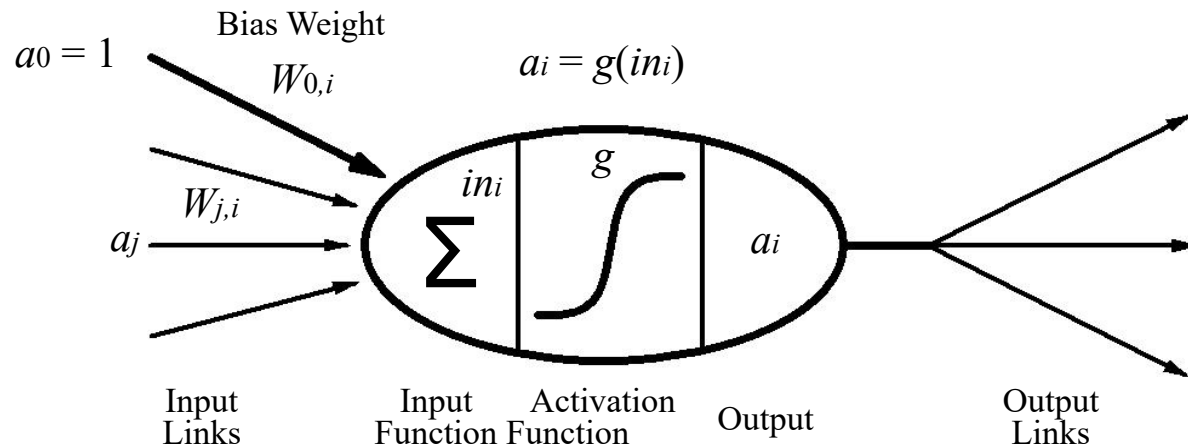
10^{11} neurons of > 20 types, 10^{14} synapses, 1ms–10ms cycle time
Signals are noisy “spike trains” of electrical potential



McCulloch–Pitts “unit”: M-P model of neuron

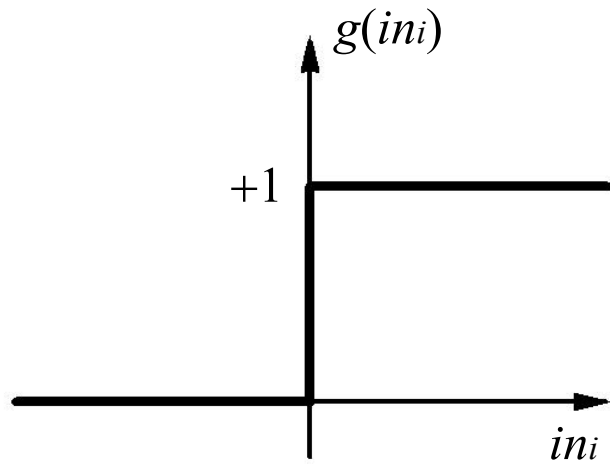
Output is a “squashed” linear function of the inputs:

$$a_i \leftarrow g(in_i) = g \sum_j W_{j,i} a_j$$

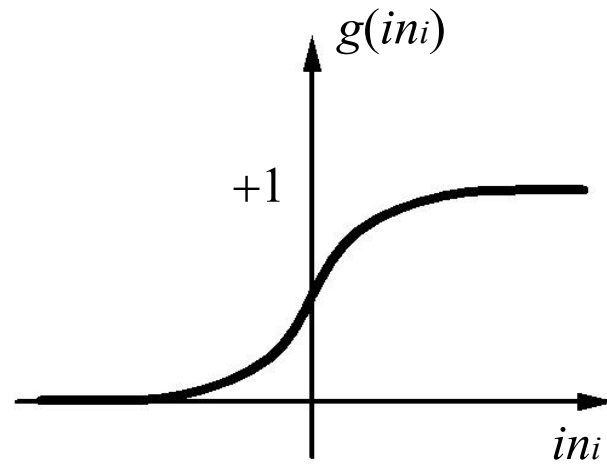


A gross oversimplification of real neurons, but its purpose is to develop understanding of what networks of simple units can do

Activation functions



(a)



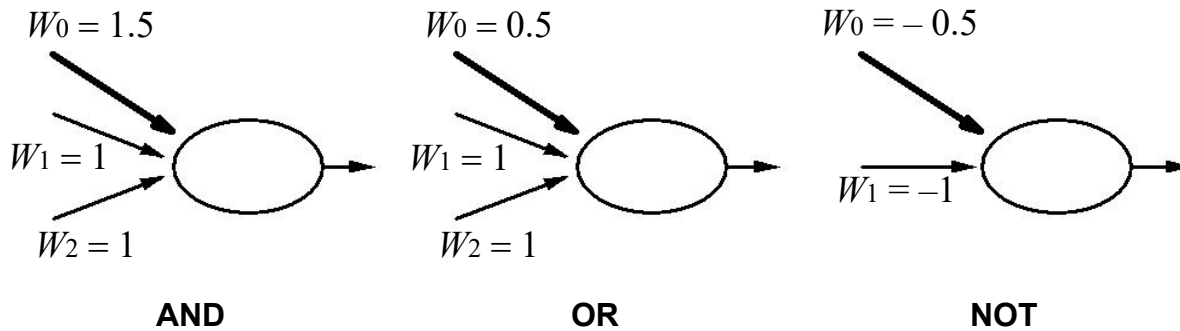
(b)

(a) is a **step function** or **threshold function**

(b) is a **sigmoid function** such as $1/(1 + e^{-x})$, $(1 - e^{-x}) / (1 + e^{-x})$

Changing the bias weight $W_{0,i}$ moves the threshold location

Implementing logical functions



McCulloch and Pitts: every Boolean function can be implemented

Network structures

Feed-forward networks:

- single-layer perceptrons
- multi-layer perceptrons

Feed-forward networks implement functions, have no internal state

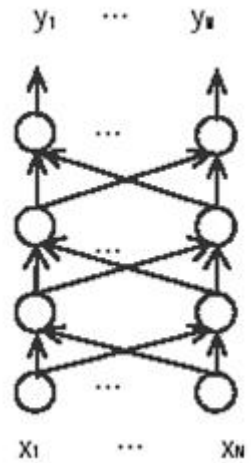


Figure 1 one MLP

Recurrent networks:

- Hopfield networks have symmetric weights ($W_{ij} = W_{ji}$)
 $g(x) = \text{sign}(x)$, $a_i = \pm 1$; holographic associative memory
- Boltzmann machines use stochastic activation functions,
 \approx MCMC in Bayes nets
- recurrent neural nets have directed cycles with delays
 \Rightarrow have internal state (like flip-flops), can oscillate etc.

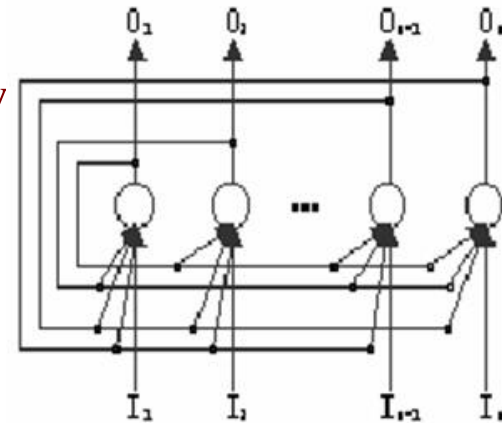


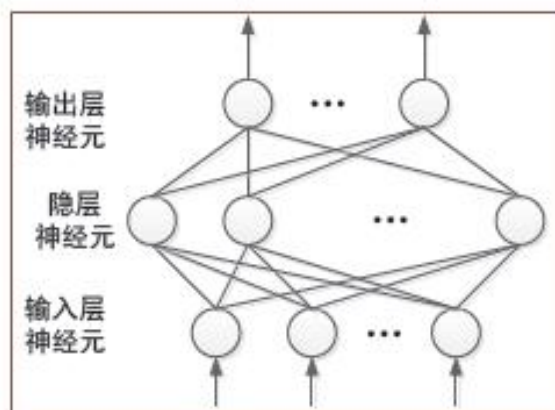
Figure 2 one RNN

Deep learning networks:

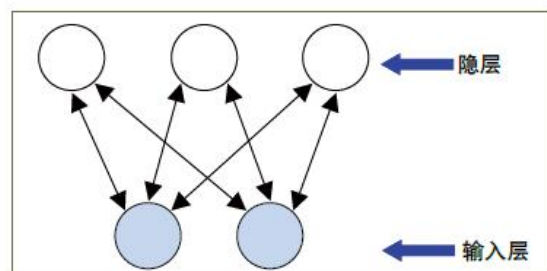
- Boltzmann machines
- Deep Believable Networks

• DBNN: Deep learning

- RBM
- BP



(a) BPN



(b) RBM

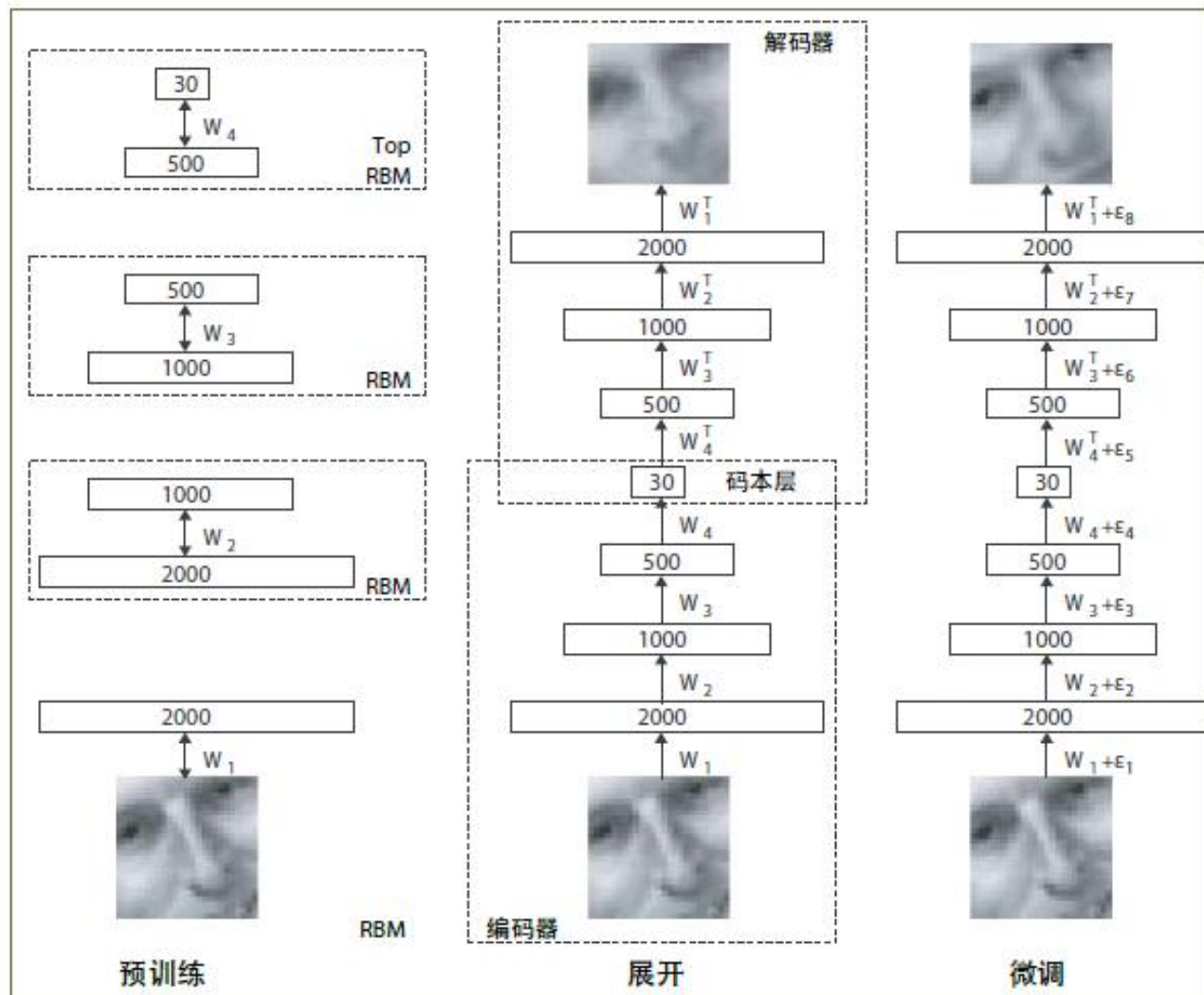
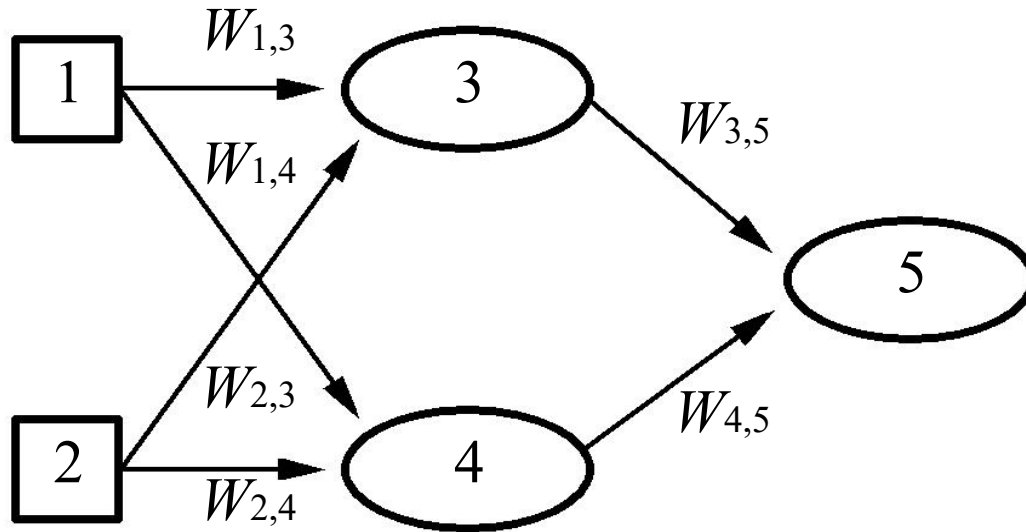


Figure 3 one DLNN

Feed-forward example

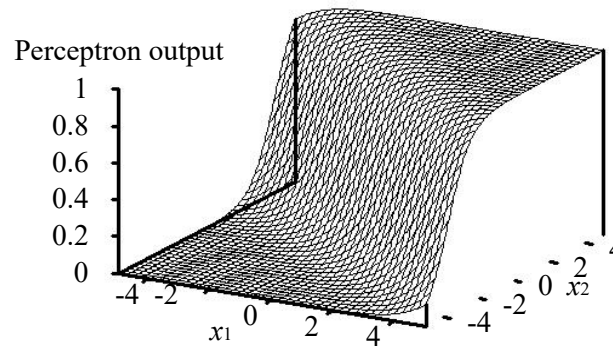
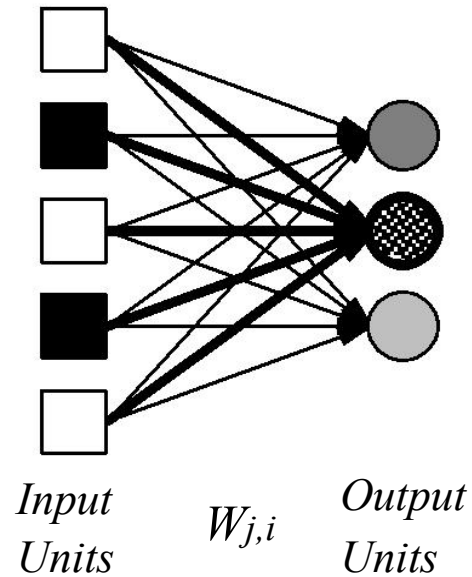


Feed-forward network = a parameterized family of nonlinear functions:

$$\begin{aligned} a_5 &= g(W_{3,5} \cdot a_3 + W_{4,5} \cdot a_4) \\ &= g(W_{3,5} \cdot g(W_{1,3} \cdot a_1 + W_{2,3} \cdot a_2) + W_{4,5} \cdot g(W_{1,4} \cdot a_1 + W_{2,4} \cdot a_2)) \end{aligned}$$

Adjusting weights changes the function: do learning this way!

Single-layer perceptrons



Output units all operate separately—no shared weights

Adjusting weights moves the location, orientation, and steepness of cliff

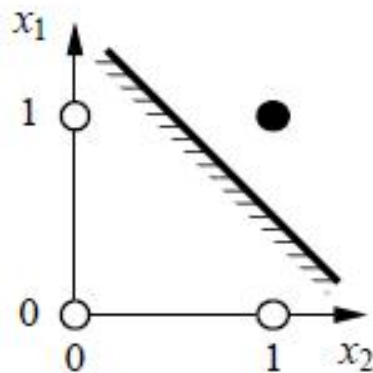
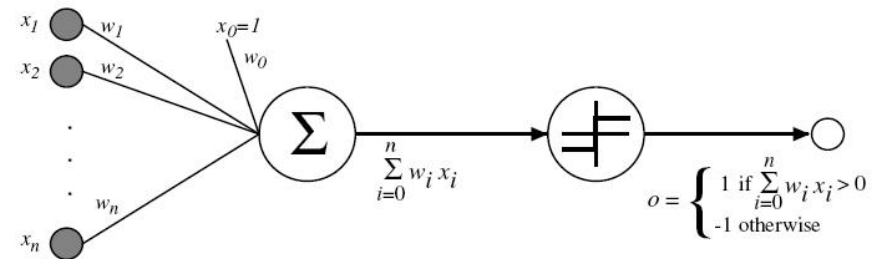
Expressiveness of perceptrons

Consider a perceptron with g = step function (Rosenblatt, 1957, 1960)

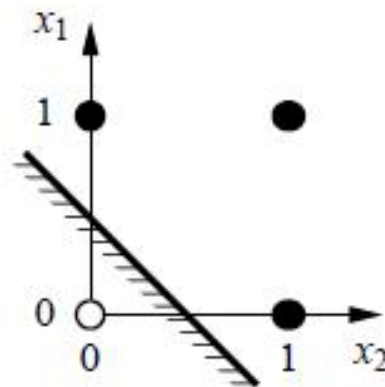
Can represent AND, OR, NOT, majority, etc., but not XOR

Represents a **linear separator** in input space:

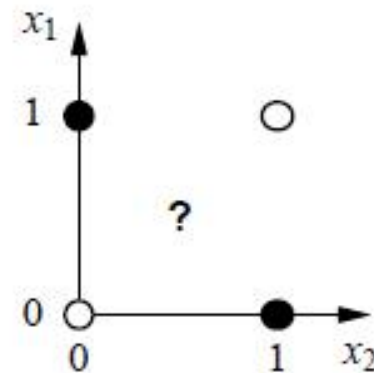
$$\sum_j W_j x_j > 0 \text{ or } W \cdot x > 0$$



(a) x_1 and x_2



(b) x_1 or x_2

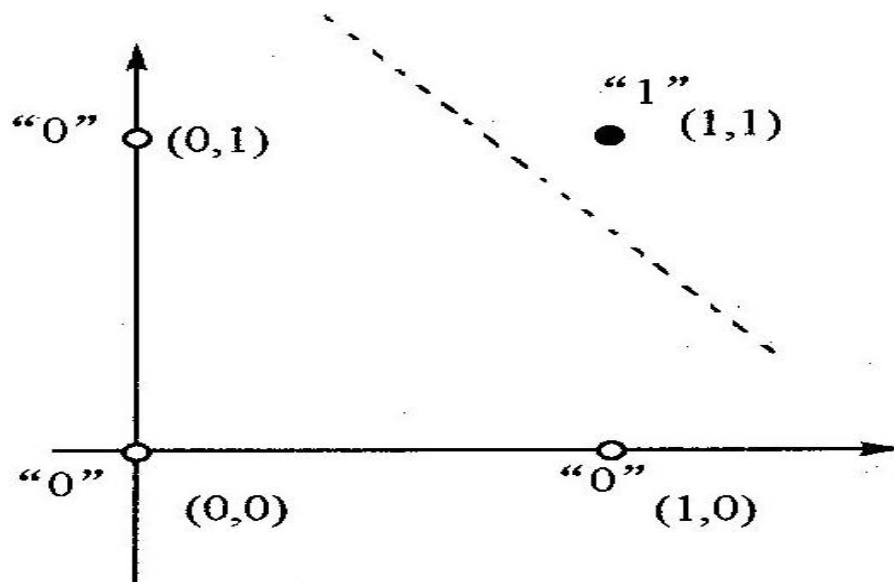


(c) x_1 xor x_2

Minsky & Papert (1969) pricked the neural network balloon because of **Perceptrons**

Table 2-1 “AND” 表2-1 “与”

x_1	x_2	$x_1 x_2$	$Y=w_1x_1+w_2x_2-b=0$	条 件
0	0	0	$Y=w_1\cdot 0+w_2\cdot 0-b<0$	$b>0$
0	1	0	$Y=w_1\cdot 0+w_2\cdot 1-b<0$	$b>w_2$
1	0	0	$Y=w_1\cdot 1+w_2\cdot 0-b<0$	$b>w_1$
1	1	1	$Y=w_1\cdot 1+w_2\cdot 1-b\geq 0$	$b\leq w_1+w_2$

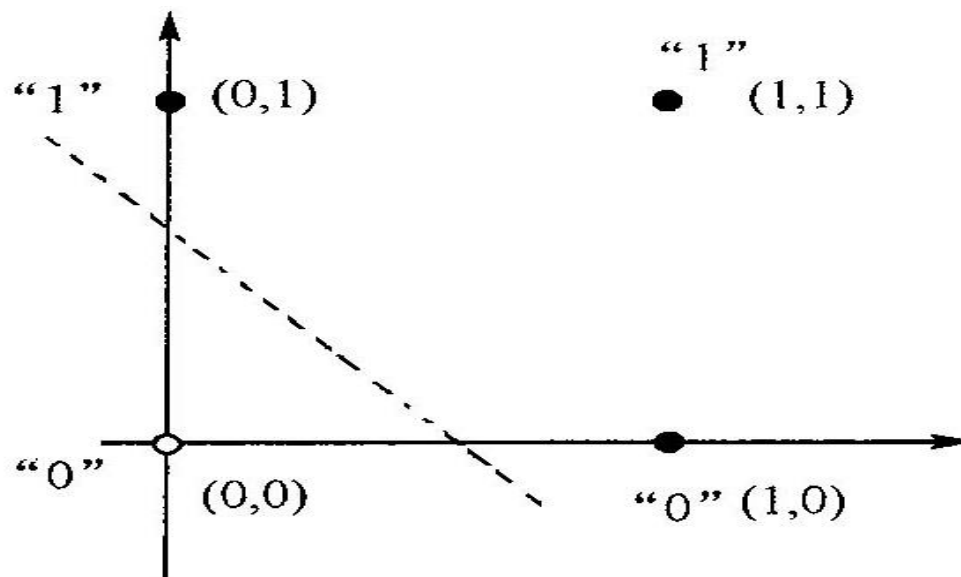


“与”

$$w_1 = 1, w_2 = 1, b = 1.5$$

Table 2-2 “OR” 表2-2 “或”

x_1	x_2	$x_1 x_2$	$Y=w_1 x_1 + w_2 x_2 - b=0$	条 件
0	0	0	$Y=w_1 \cdot 0 + w_2 \cdot 0 - b < 0$	$b > 0$
0	1	1	$Y=w_1 \cdot 0 + w_2 \cdot 1 - b \geq 0$	$b \leq w_2$
1	0	1	$Y=w_1 \cdot 1 + w_2 \cdot 0 - b \geq 0$	$b \leq w_1$
1	1	1	$Y=w_1 \cdot 1 + w_2 \cdot 1 - b \geq 0$	$b \leq w_1 + w_2$

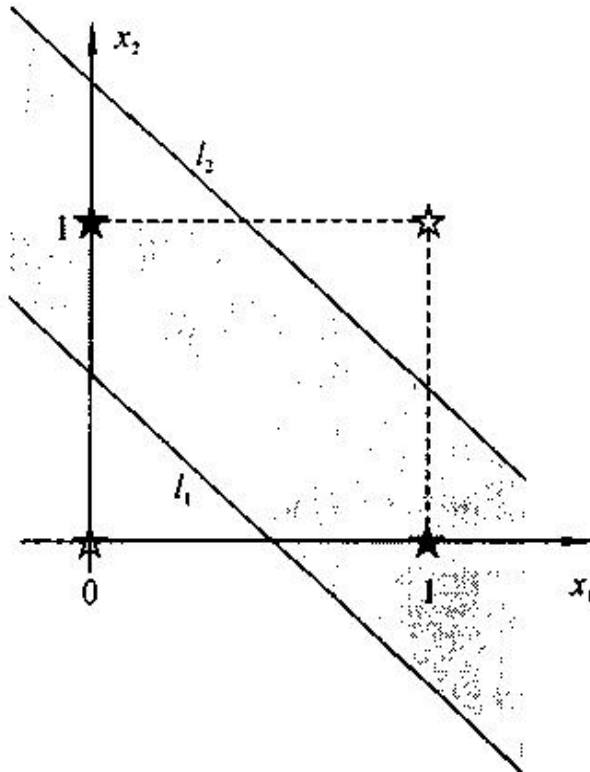


“或”

$$w_1 = 1, w_2 = 1, b = 0.5$$

XOR based on Perceptrons

Ideas!



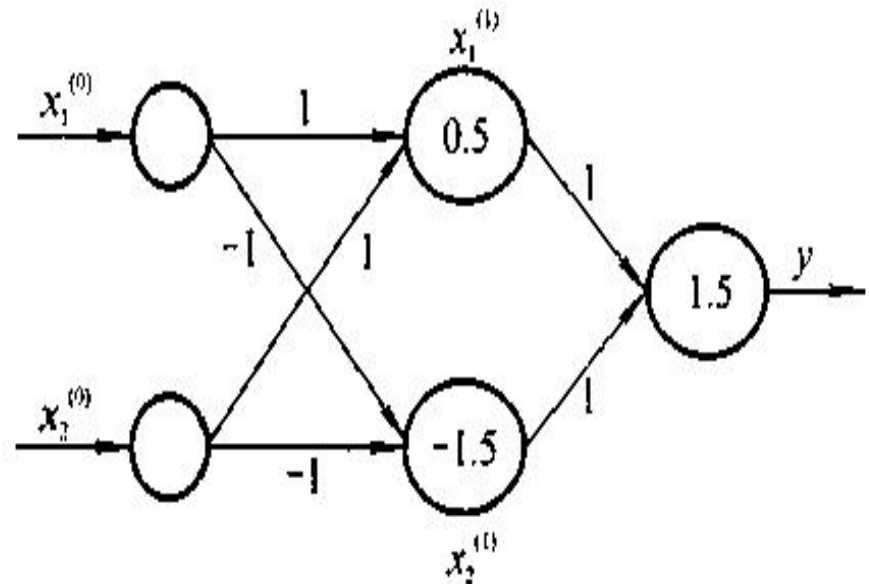
Four rules expressed for XOR:

IF $x_1=0$ AND $x_2=0$ THEN $y=0$

IF $x_1=0$ AND $x_2=1$ THEN $y=1$

IF $x_1=1$ AND $x_2=0$ THEN $y=1$

IF $x_1=1$ AND $x_2=1$ THEN $y=0$



Perceptron learning

Learn by adjusting weights to reduce **error** on training set

The **squared error** for an example with input x and true output y is

$$E = \frac{1}{2} \text{Err}^2 = \frac{1}{2} (y - h_{w(x)})^2,$$

Perform optimization search by **gradient descent**:

$$\begin{aligned} \frac{\partial E}{\partial w_j} &= \text{Err} \times \frac{\partial \text{Err}}{\partial w_j} = \text{Err} \times \frac{\partial}{\partial w_j} (y - g(\sum_{j=0}^n w_j x_j)) \\ &= -\text{Err} \times g'(\text{in}) \times x_j \end{aligned}$$

Simple weight update rule:

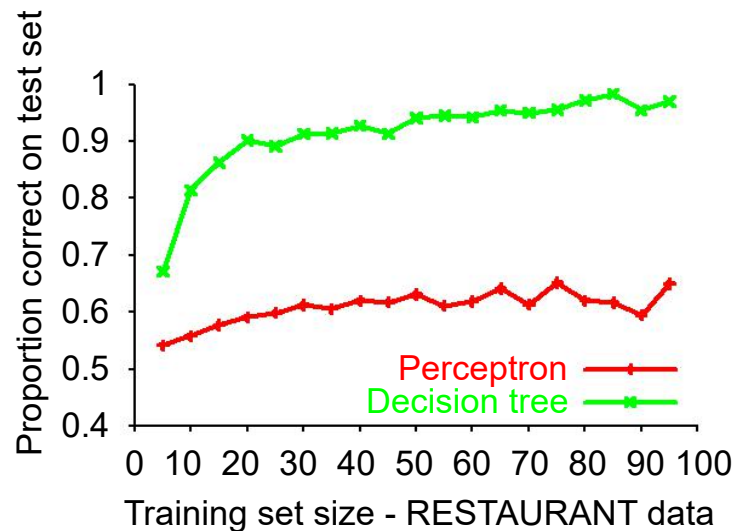
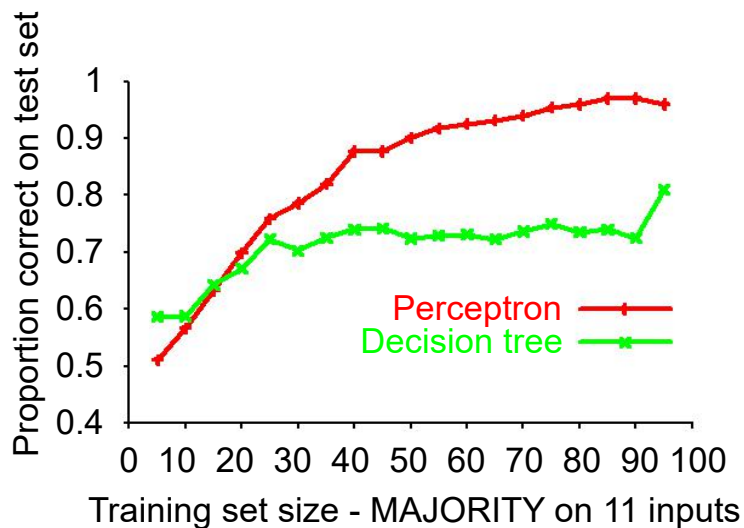
$$w_j \leftarrow w_j + \alpha \times \text{Err} \times g'(\text{in}) \times x_j$$

E.g., +ve error \Rightarrow increase network output

\Rightarrow increase weights on +ve inputs, decrease on -ve inputs

Perceptron learning contd.

Perceptron learning rule converges to a consistent function
for any linearly separable data set



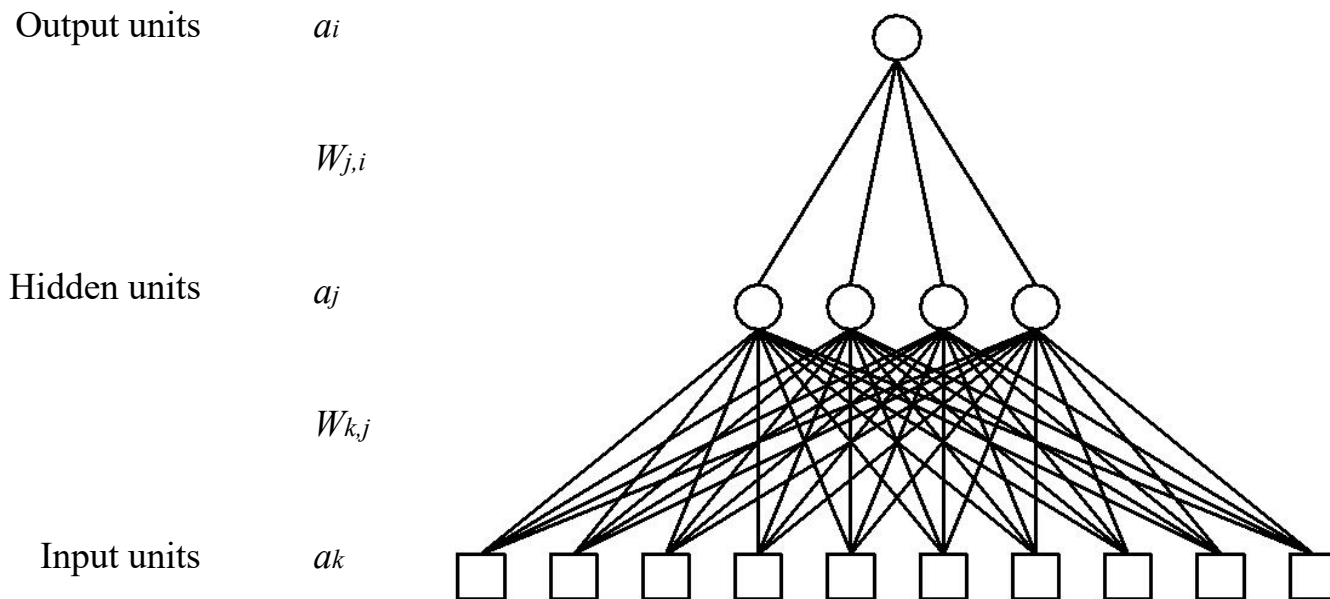
Perceptron learns majority function easily, DTL is hopeless

DTL learns restaurant function easily, perceptron cannot represent it

Why?



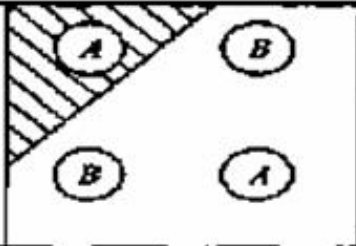
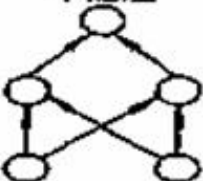

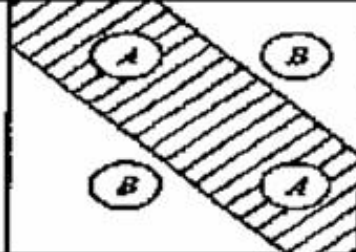
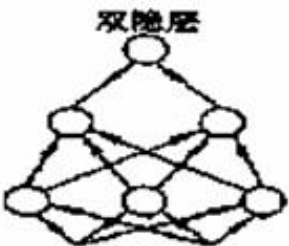

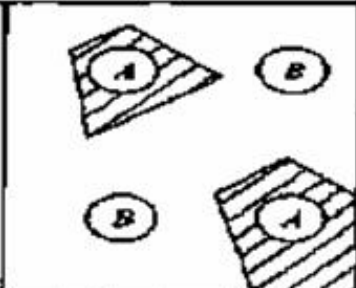
Multilayer perceptrons

Layers are usually fully connected;
numbers of **hidden units** typically chosen by hand



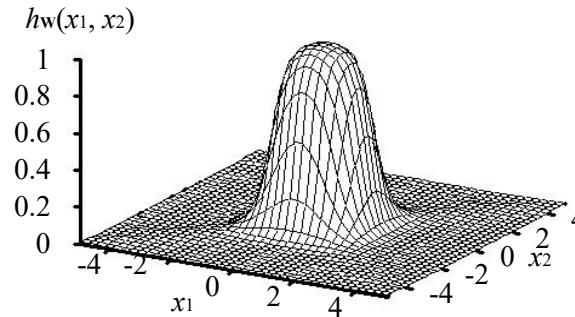
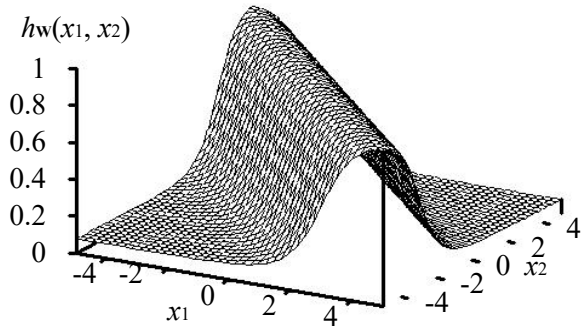
Expressiveness of MLPs

Structure and decision region for Perceptrons

结构	决策区域类型	区域形状	异或问题
<p>无隐层</p> 	<p>由一超平面分成两个</p>		
<p>单隐层</p> 	<p>开凸区域或闭凸区域</p>		
<p>双隐层</p> 	<p>任意形状(其复杂度由单元数目确定)</p>		

Expressiveness of MLPs

All continuous functions w/ 2 layers, all functions w/ 3 layers



Combine two opposite-facing threshold functions to make a ridge

Combine two perpendicular ridges to make a bump

Add bumps of various sizes and locations to fit any surface

Proof requires exponentially many hidden units (cf DTL proof)

Back-propagation learning

Output layer: same as for single-layer perceptron,

$$W_{j,i} \leftarrow W_{j,i} + \alpha \times a_j \times \Delta_i$$

where $\Delta_i = \text{Err}_i \times g'(in_i)$

Hidden layer: **back-propagate** the error from the output layer:

$$\Delta_j = g'(in_j) \sum_i W_{ji} \Delta_i$$

Update rule for weights in hidden layer:

$$W_{k,j} \leftarrow W_{k,j} + \alpha \times a_k \times \Delta_j .$$

(Most neuroscientists deny that back-propagation occurs in the brain)

Back-propagation derivation

The squared error on a single example is defined as

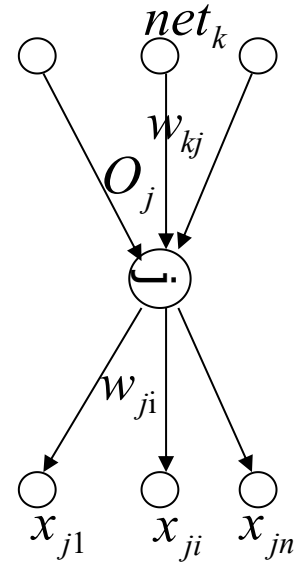
$$E = \frac{1}{2} \sum_i (y_i - a_i)^2,$$

where the sum is over the nodes in the output layer.

$$\begin{aligned} \frac{\partial E}{\partial W_{j,i}} &= -(y_i - a_i) \frac{\partial a_i}{\partial W_{j,i}} = -(y_i - a_i) \frac{\partial g(in_i)}{\partial W_{j,i}} \\ &= -(y_i - a_i) g'(in_i) \frac{\partial in_i}{\partial W_{j,i}} = -(y_i - a_i) g'(in_i) \frac{\partial}{\partial W_{j,i}} (\sum_j W_{j,i} a_j) \\ &= -(y_i - a_i) g'(in_i) a_j = -a_j \Delta_i \end{aligned}$$

Back-propagation derivation contd.

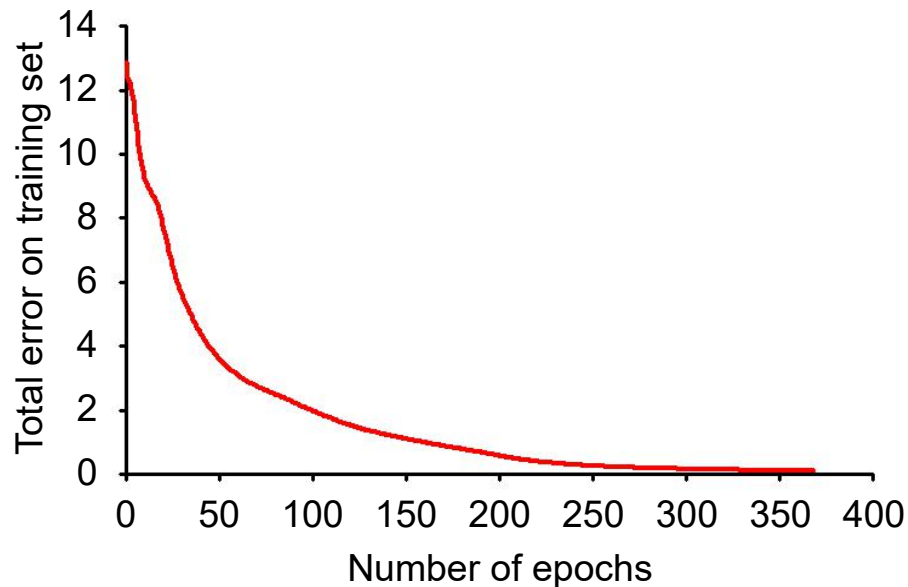
$$\begin{aligned}
 \frac{\partial E}{\partial W_{k,j}} &= - \sum_i (y_i - a_i) \frac{\partial a_i}{\partial W_{k,j}} = - \sum_i (y_i - a_i) \frac{\partial g(in_i)}{\partial W_{k,j}} \\
 &= - \sum_i (y_i - a_i) g'(in_i) \frac{\partial in_i}{\partial W_{k,j}} = - \sum_i \Delta_i \frac{\partial}{\partial W_{k,j}} (\sum_j W_{j,i} a_j) \\
 &= - \sum_i \Delta_i W_{j,i} \frac{\partial a_j}{\partial W_{k,j}} = - \sum_i \Delta_i W_{j,i} \frac{\partial g(in_j)}{\partial W_{k,j}} \\
 &= - \sum_i \Delta_i W_{j,i} g'(in_j) \frac{\partial in_j}{\partial W_{k,j}} \\
 &= - \sum_i \Delta_i W_{j,i} g'(in_j) \frac{\partial}{\partial W_{k,j}} (\sum_k W_{k,j} a_k) \\
 &= - \sum_i \Delta_i W_{j,i} g'(in_j) a_k = - a_k \Delta_j
 \end{aligned}$$



Back-propagation learning contd.

At each **epoch**, sum gradient updates for all examples and apply

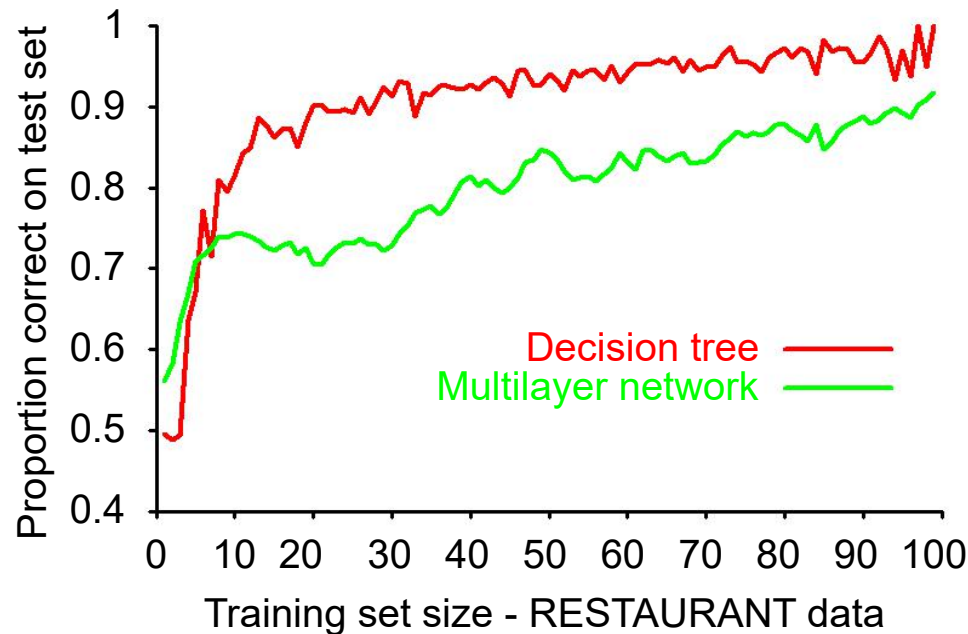
Training curve for 100 restaurant examples: finds exact fit



Typical problems: slow convergence, local minima

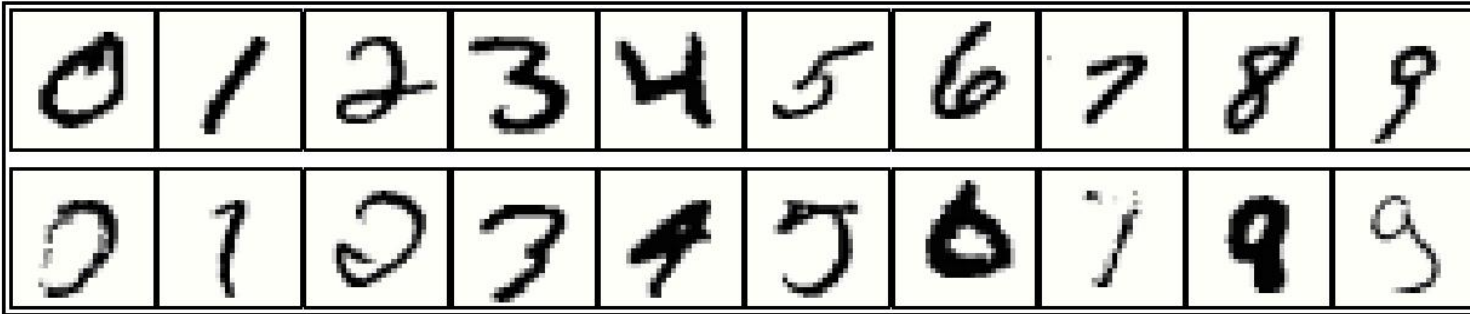
Back-propagation learning contd.

Learning curve for MLP with 4 hidden units:



MLPs are quite good for complex pattern recognition tasks,
but resulting hypotheses cannot be understood easily

Handwritten digit recognition



3-nearest-neighbor = 2.4% error

400–300–10 unit MLP = 1.6% error

LeNet: 768–192–30–10 unit MLP = 0.9% error

Current best (kernel machines, vision algorithms) \approx 0.6% error

Summary

Most brains have lots of neurons; each neuron \approx linear–threshold unit (?)

Perceptrons (one-layer networks) **insufficiently expressive**

Multi-layer networks are **sufficiently expressive**; can be trained by gradient descent, i.e., error ***back-propagation***

Many applications: speech, driving, handwriting, fraud detection, etc.

Engineering, cognitive modelling, and neural system modelling subfields have largely diverged

Back-propagation Algorithm: Pros and Cons

Pros: good learning algorithm for MLP

Cons: local optima, time consuming

Assignment

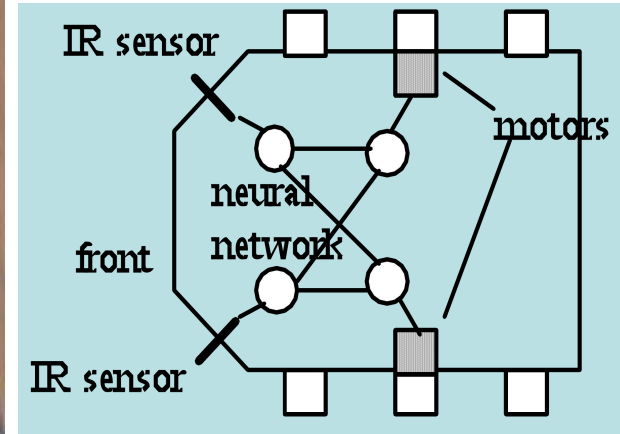
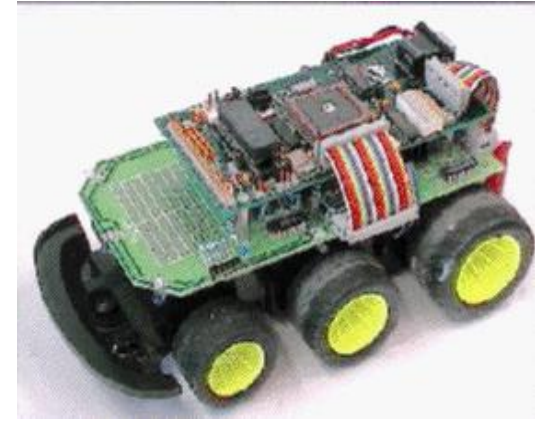
- Readings: Chap 18.6, 18.7
- Exercises: 18.19
- Additional exercises:
 - Exercise 1: Compute a NN to realize function XOR based on Perceptrons.
 - Exercise 2: Prove the formula of BP Algorithm based.

*Handed in next Tuesday

Case1: Evolving a neural controller for an agent

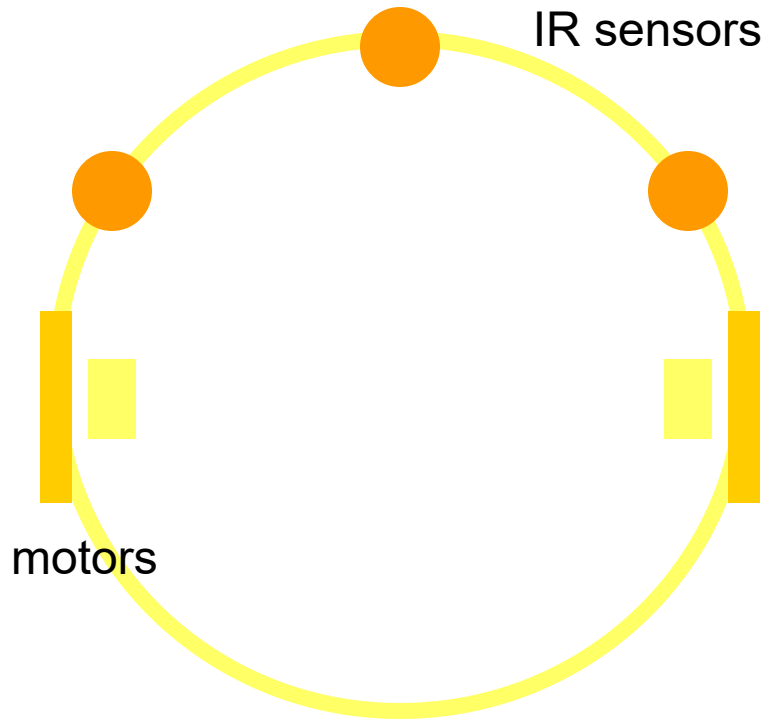


arena with Styrofoam cubes



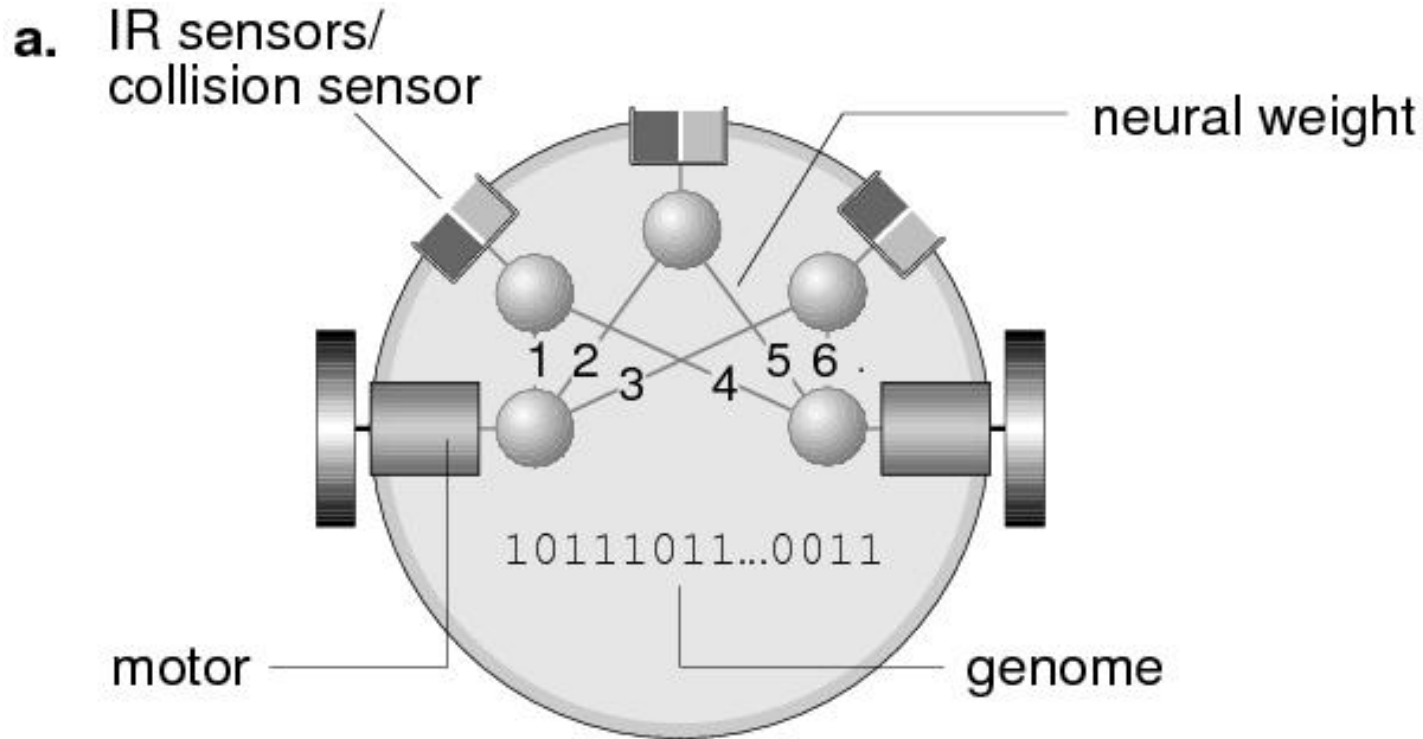
Didabot:
simple robot
for didactical purposes

Scheme 1: Evolving a neural controller for an agent



how to proceed?

Encoding in genome



b.

initial genome	1101	0110	0001	0011	1010	1100
encodes weights (numbers)	1	2	3	4	5	6

c.

initial weights after "development"	.37	-.1	-.43	-.3	.16	.3
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Encoding in genome “development”

1. take the one single individual with the highest fitness
2. choose another individual from the population at random, irrespective of fitness, for sexual reproduction
3. add the fittest individual to the new population

fittest individual (highest rank)

1 2 3 4 5 6

initial genome 0011 0101 0010 0111 1010 1010

encoded weights -.3 -.17 -.37 .03 .17 .17

other individual

1 2 3 4 5 6

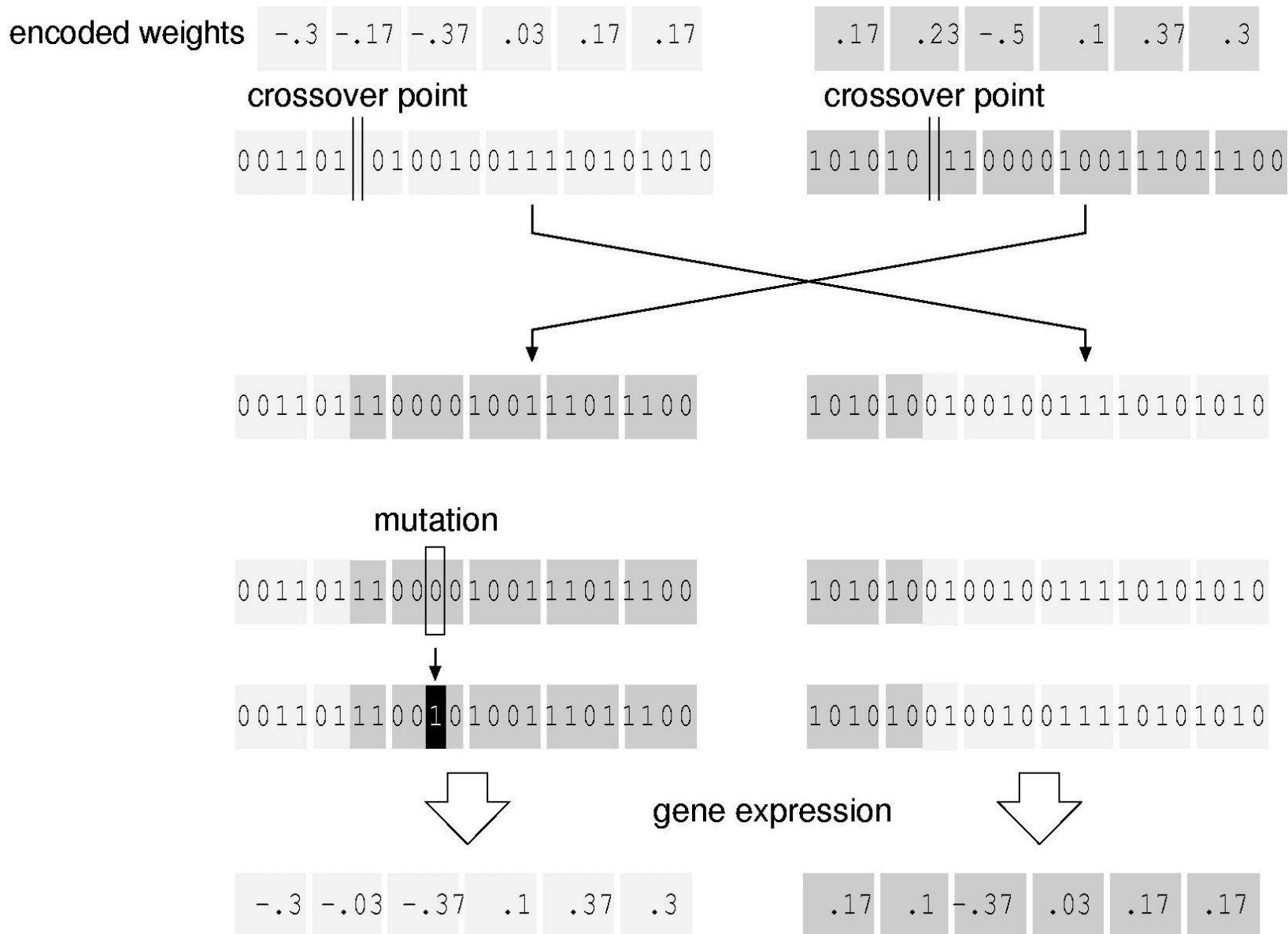
1010 1011 0000 1001 1101 1100

.17 .23 -.5 .1 .37 .3

encoding	development	selection	reproduction
<ul style="list-style-type: none"> • binary • many-character • real-valued 	<ul style="list-style-type: none"> • no development (phenotype = genotype) • development with and without interaction with the environment 	<ul style="list-style-type: none"> • “roulette wheel” • elitism • rank selection • tournament • truncation • steady-state 	<ul style="list-style-type: none"> • mutation • crossover

Reproduction: Crossover and mutation

“development”



Case 2: NN based scheme for the Braitenberg vehicles

- Readings: **Additional** reference
- Exercises
 - **2 Additional exercises**
 - The Braitenberg vehicles
 - The “Swiss Robots”

Assignment (Additional)

1. The Braitenberg vehicle in figure 3 implement its controllers with a simple neural network which has two layers of neurons; starting from the top sides, the first layer receives inputs from the sensors and sends its outputs to the second layer, while the neurons in the second layer drive the motors of the robot. The picture shows a schematic representation of a mobile robot. Assume that it is moving at a default (slow) speed.

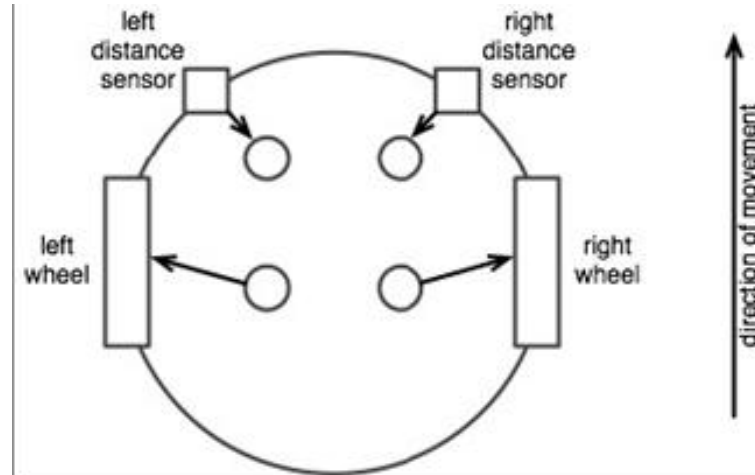


Figure 3

- Implement a simple neural network by connecting the neurons (small circles) in order to implement the obstacle avoidance behavior (i.e., while moving in the environment, the robot avoids the obstacle that it senses by means of the IR sensors). You do not need to specify the weights of the connections; just say whether each connection is excitatory (+) or inhibitory (−). There are several ways to achieve this, just come up with ONE solution.
- Are there any inspirations for you to design an intelligent robot?

Assignment (Additional)

2. In his book “Vehicles: Experiments in Synthetic Psychology”, Braitenberg describes, among other things the following vehicles:

- a) The “love” vehicle likes to stay as close to a light source as possible.
- b) The “aggression” vehicle tries to destroy the light sources by colliding with them.
- c) The “fear” vehicle flees away from any light source.
- d) The “explorer” vehicle slows down at each light source and then goes to the next one.

As shown in the following figure 3, each robot possesses two light sensors as well as either positive or negative connections to the motors. All connections have the same absolute weight values. The signs of the weights are given in the head of the corresponding arrows. The signal amplitude of the light sensors is here proportional to the intensity of detected light.

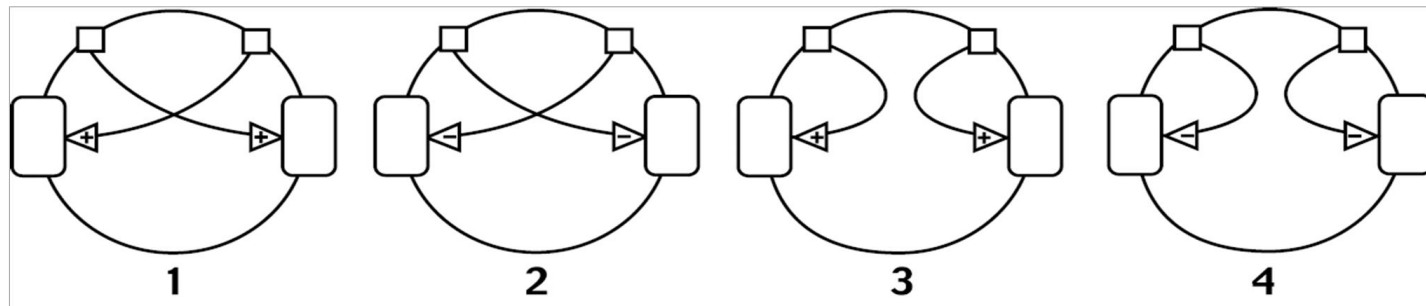


Figure 3

- (1) **(8 points)** The task is to assign to each robot schema as in figure 3 the correct behavior (a, b, c or d) – write the respective character next to the number.
- (2) **(4 points)** What happens if you keep the same connections but you move the position of the right sensor to the left side of the robot (just next to the left sensor) in Figure 3?
- (3) **(3 points)** What conclusions can you derive from the experiment assumed in above (2)?

Assignment (Additional)

3. “SWISS ROBOTS” are a set of simple robots, each robot as shown in Figure 1 was equipped with two motors, one on the left and one on the right, and two infrared sensors, one front left and one front right.



- What intelligent behaviors do you think emerged from the “Swiss Robots” after you watched the video illustration as in figure 1?
- What are the robots really doing when we think in agent’s perspective –situated perspective?
- Are there any inspirations for you to design an intelligent robot?

Case 3: embedded NN for DAC

Introduction to neural networks for
Distributed Adaptive systems

-[Video based SHAIL2011-6](#)

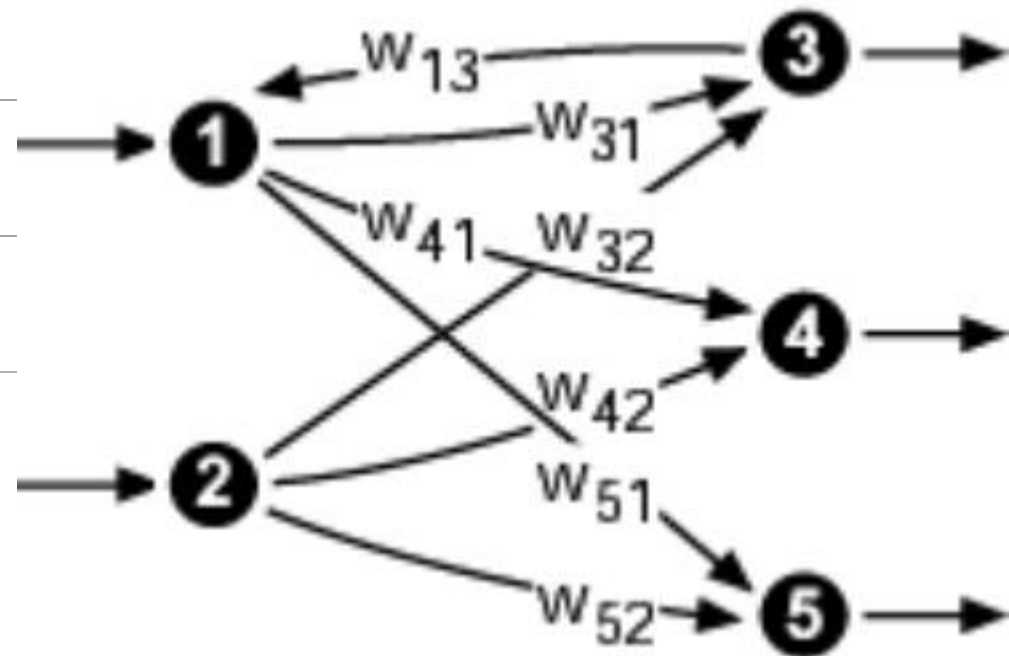
Artificial Neural Network: Representations (Connectivity)

	node 1	node 2	node 3	node 4	node 5
node 1	0	0	0.8	0	0
node 2	0	0	0	0	0
node 3	0.7	0.4	0	0	0
node 4	1.0	-0.5	0	0	0
node 5	0.6	0.9	0	0	0

Matrix

feed-forward network
with one recurrent
connection

Graph



The five basics of neural networks

- embedding
- node characteristics
- connectivity
- propagation rule
- learning rule

(details, see later)

Neural networks for robotics

NN popular in robotics

- ability for learning and generalization
- graceful degradation
- coping with non-linearities
- well-investigated
- easy to manipulate and build

Embedded Artificial Neural Networks

DAC – Distributed Adaptive Control

Khepera robot

Initial design decisions

“low-level specifications”

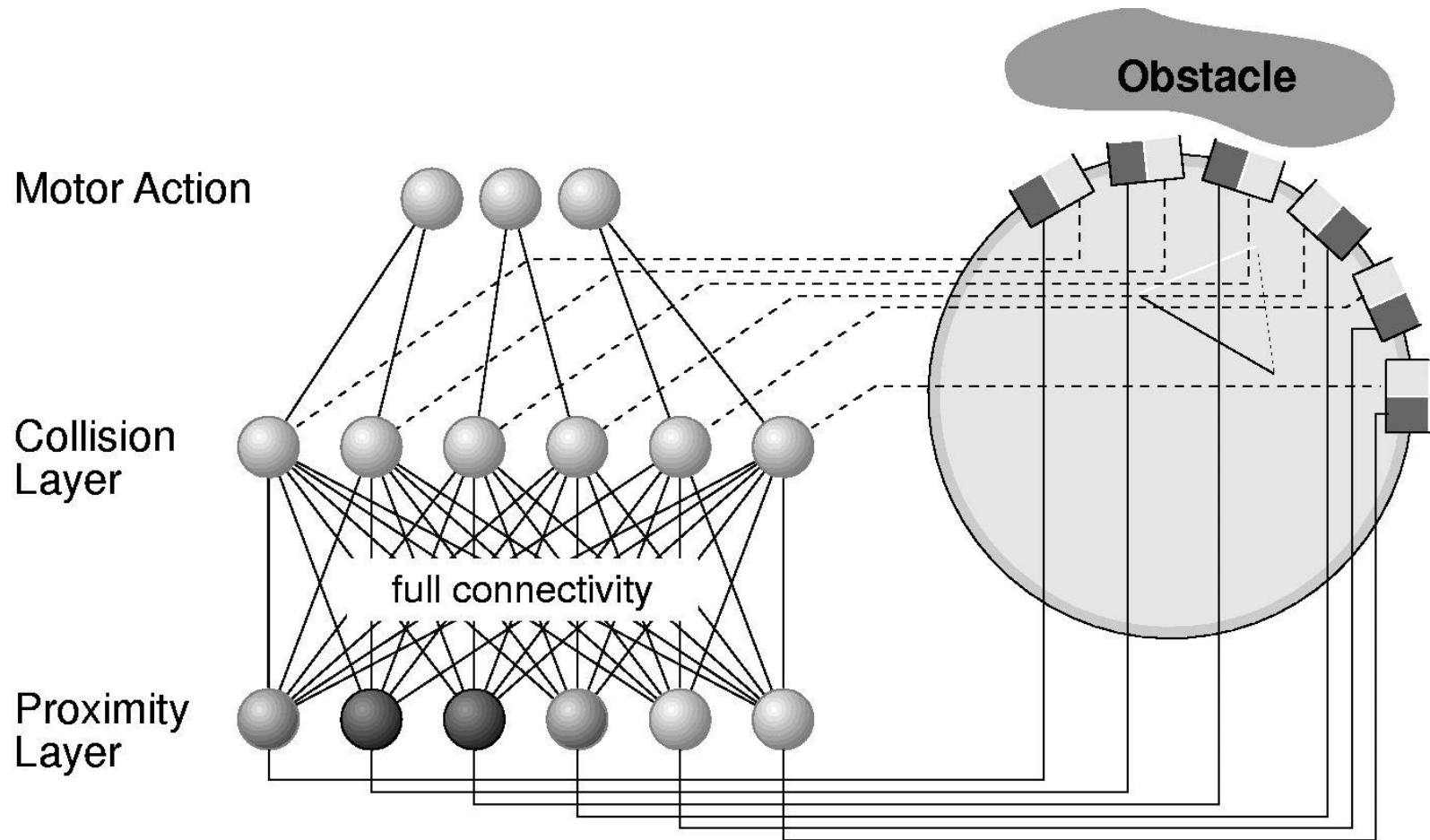
- sensors
- motor system
- default forward speed
- basic reflexes:
 - hitting obstacle on right, turn left
 - hitting obstacle on left, turn right
 - turn towards light source (left and right)

DAC – Distributed Adaptive Control

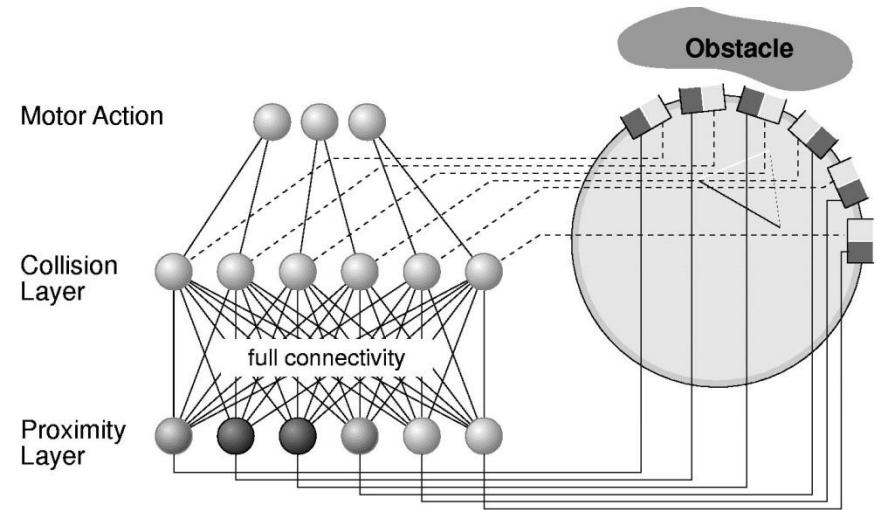
Embedding the neural network

Khepera robot

DAC - the embedded neural network



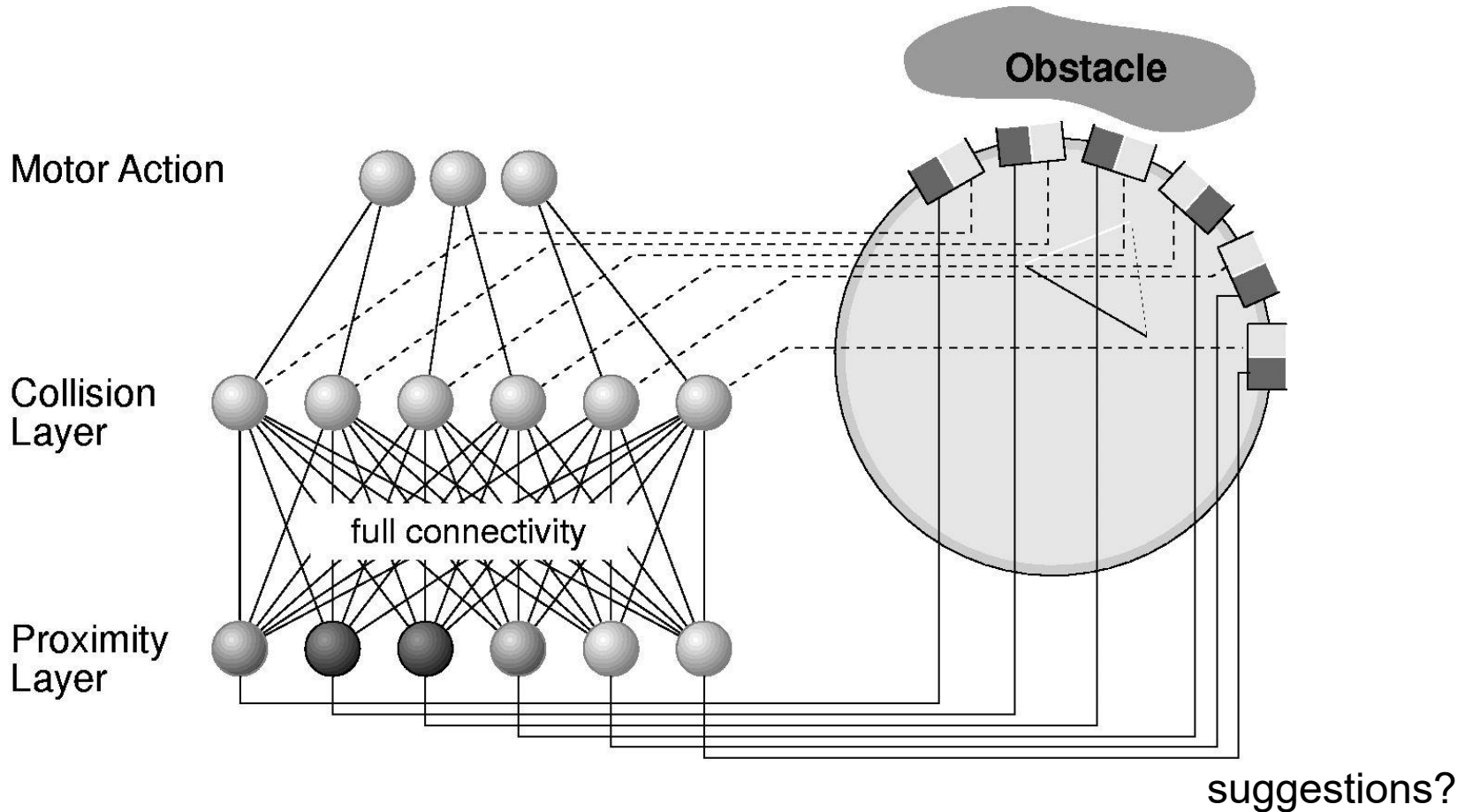
DAC - the embedded neural network formal description



Hebbian Learning (learning rule)

“When an axon of cell A is near enough to excite a cell B and repeatedly ... takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.” (Donald Hebb, 1949)

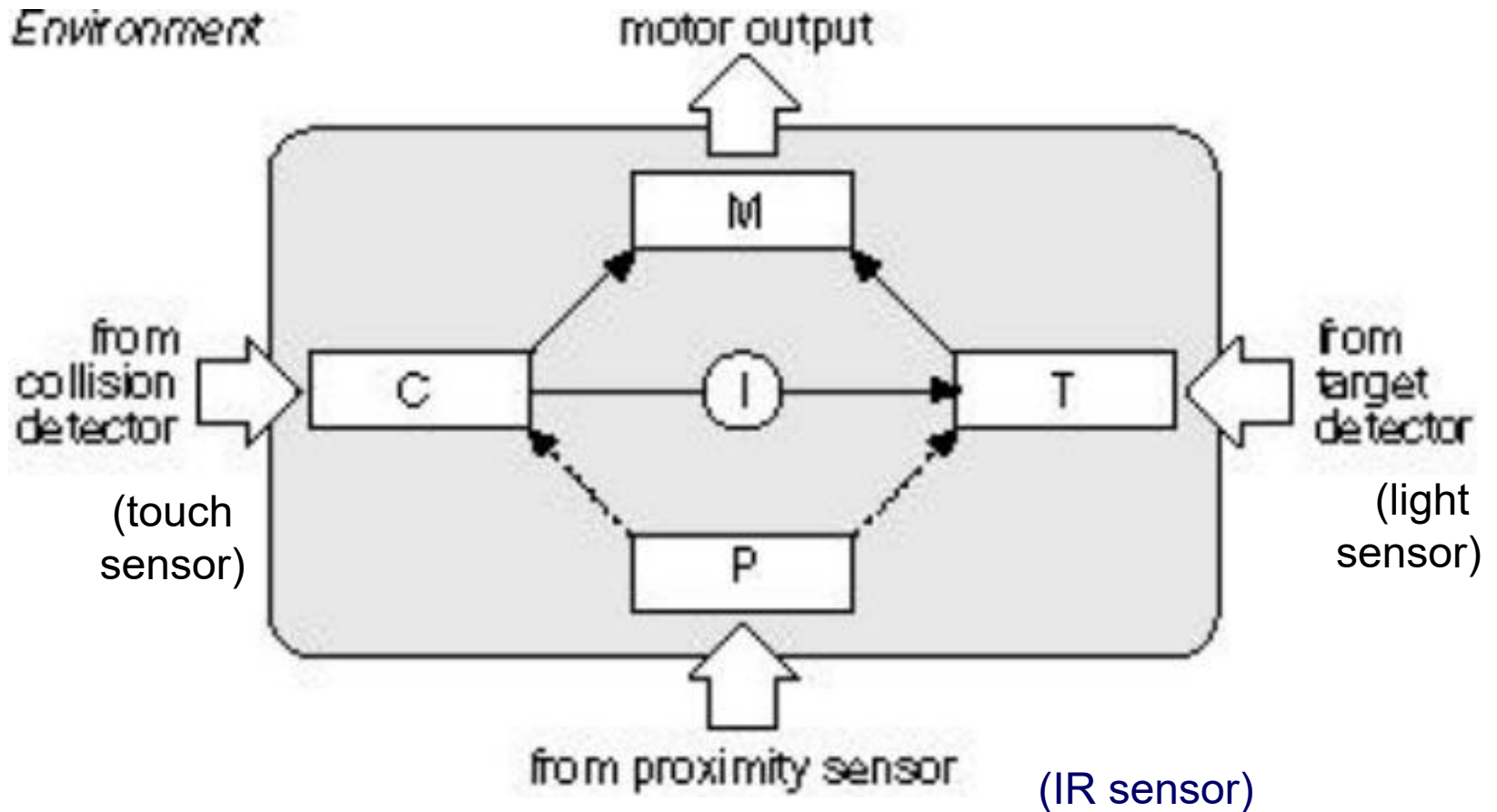
What will happen?



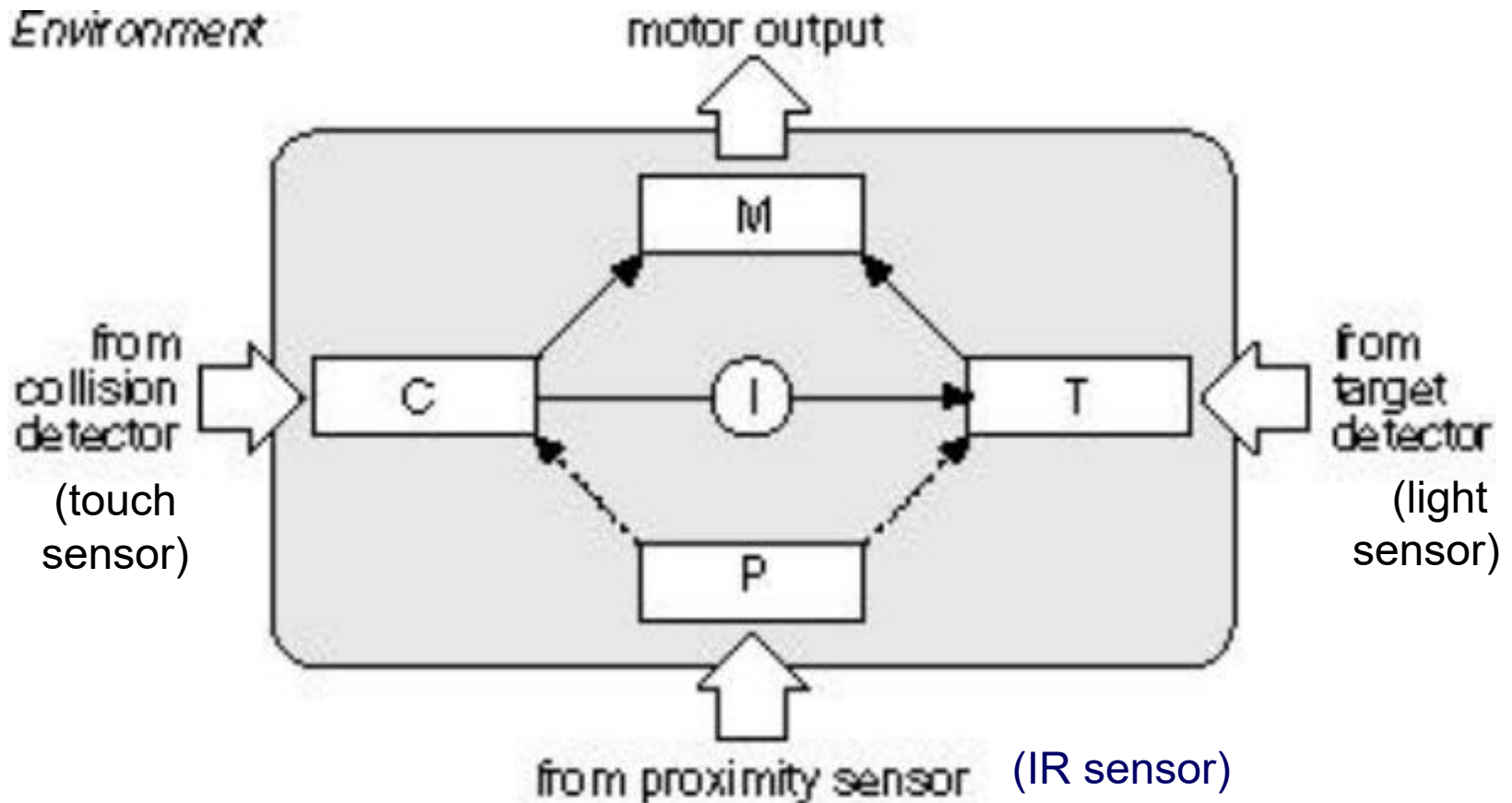
Learning obstacle avoidance

- touch sensors (on/off)
- pre-programmed reflexes based on touch sensors
- proximity sensors
- partial overlap → extraction of mutual information
- proximity sensors start taking over from touch sensors
→ DAC demonstration

Including the light-turning reflex



Including the light-turning reflex

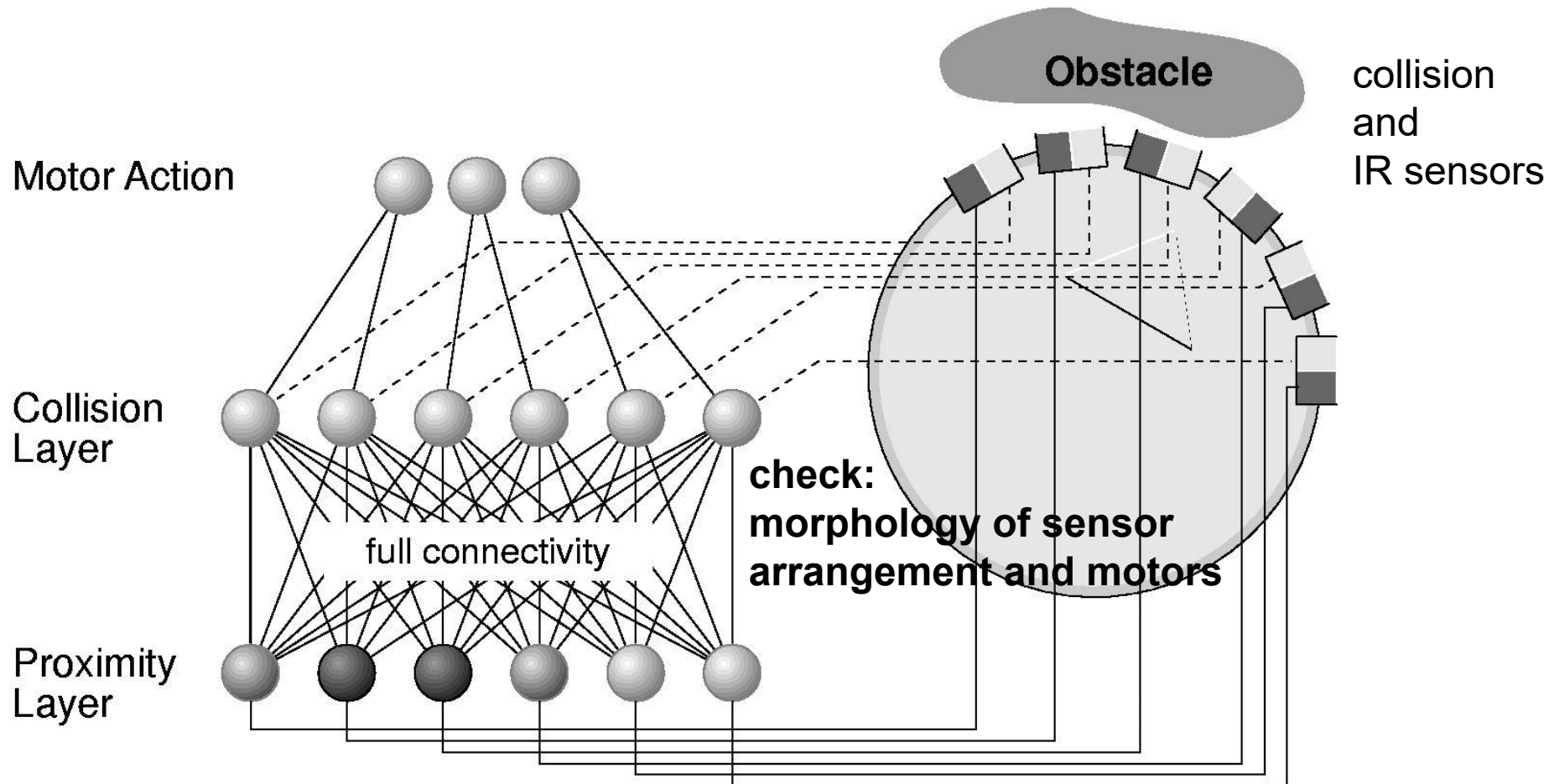


Summary: The Five Basics of Neural Networks

- ***Embedding the Network in the Agent***
- Connectivity
- Characteristics of the Nodes
- Propagation Rule
- Learning Rule

The function of neural networks can only be understood if it is known how they are embedded into a physical system interacting with the real world.

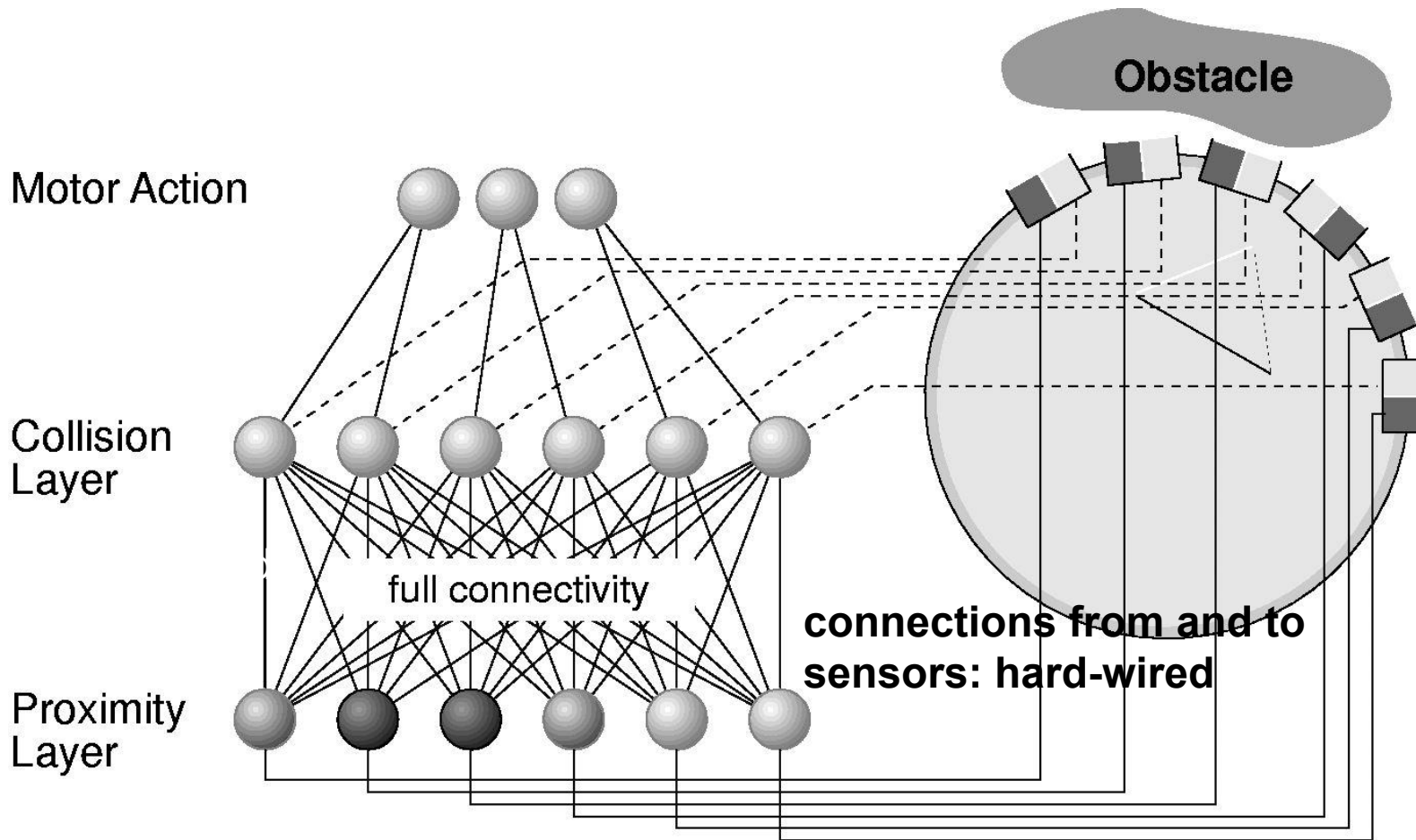
DAC - the embedded neural network (embedding)



The Five Basics of Neural Networks

- Embedding the Network in the Agent
- ***Connectivity***
- Characteristics of the Nodes
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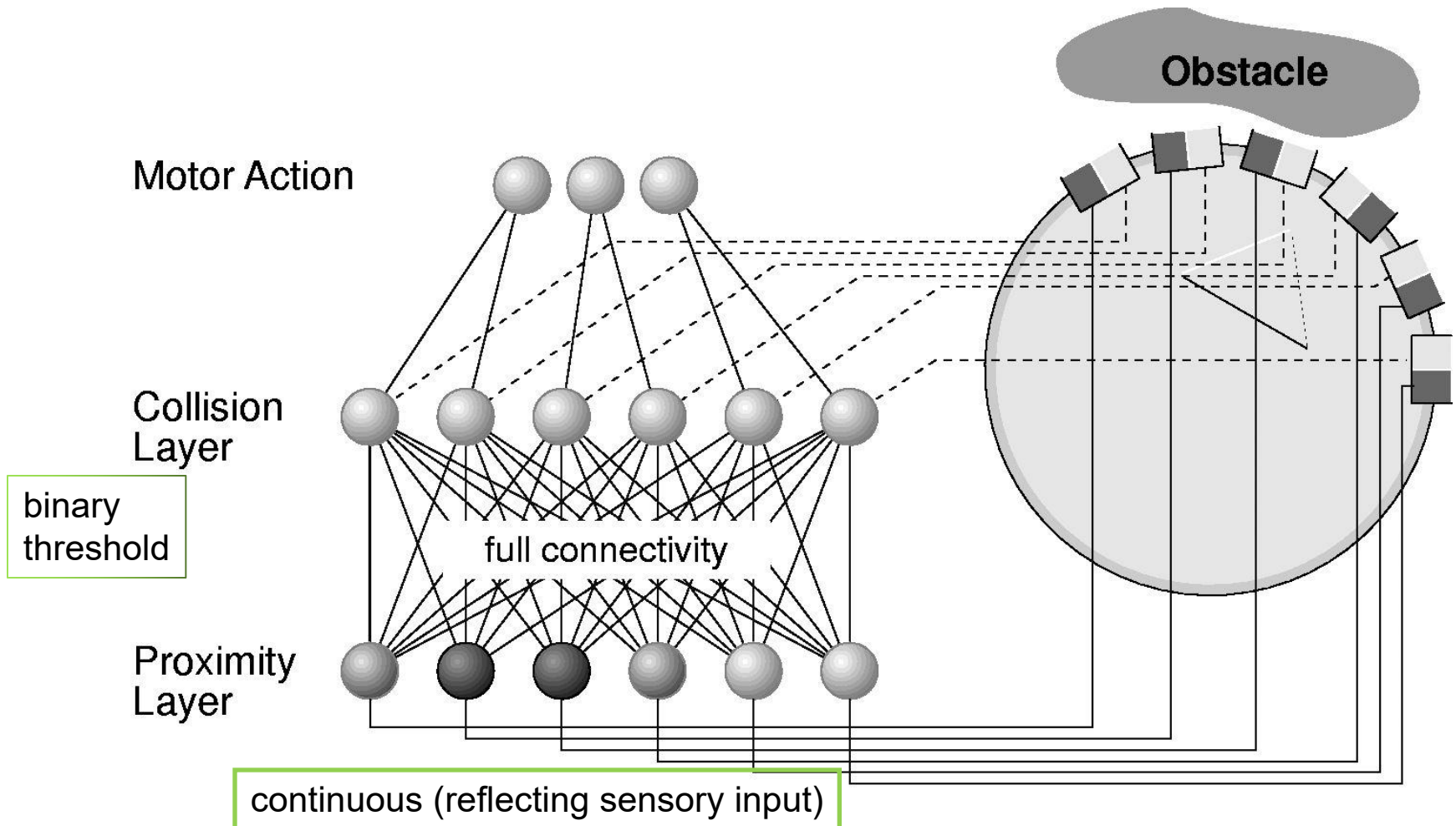
DAC - the embedded neural network (connectivity)



The Four or Five Basics of Neural Networks

- Embedding the Network in the Agent
- Connectivity
- ***Characteristics of the Nodes (see formulas)***
- Propagation Rule
- Learning Rule

DAC - the embedded neural network (node characteristics)



The Four or Five Basics of Neural Networks

- Embedding the Network in the Agent
- Connectivity
- Characteristics of the Nodes
- *Propagation Rule → synchronized steps*
- Learning Rule

The Four or Five Basics of Neural Networks

- Embedding the Network in the Agent
- Connectivity
- Characteristics of the Nodes
- Propagation Rule
- *Learning Rule → Hebbian learning*

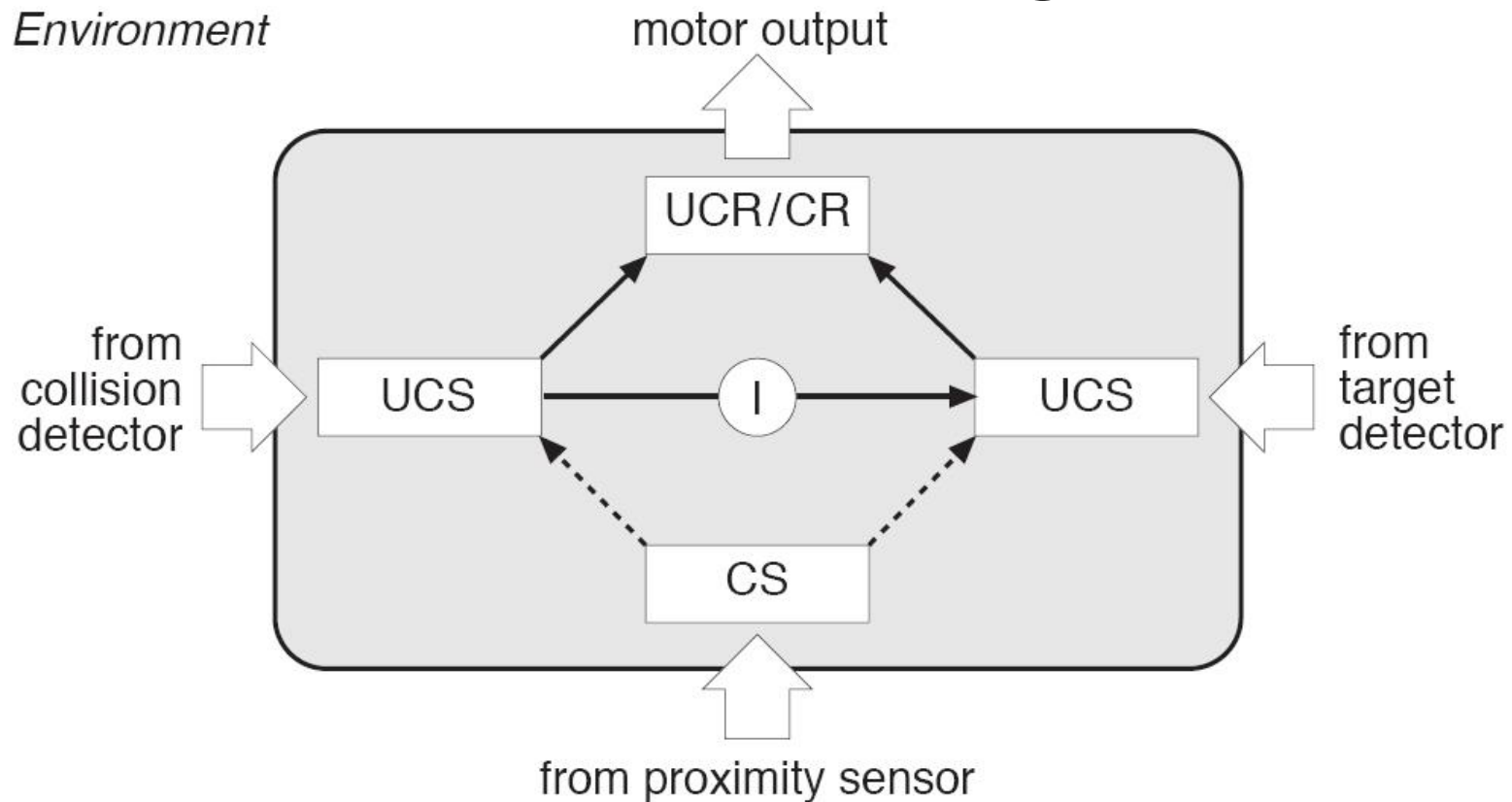
Learning rule - and forgetting

formulas 5.7, 5.8, and 5.9 on p161 of
“Understanding Intelligence”

Summary of the DAC architecture

- learning to “anticipate” obstacles (“hallucination?”)
→ F-O-R
- collision sensors, proximity sensors: different physical processes → redundancy principle
- induction of information structure (mutual information through physical interaction with environment) → principle of sensory-motor coordination
- change of sensor morphology → correlations lost
- robust behavior (noise and fault tolerance; generalization)
- learning continuous (Hebbian learning): impossibility not to learn
- forgetting (“active” forgetting)
- very simple abstractions but extremely powerful

DAC as a model of classical conditioning



From: "Understanding intelligence"

The DAC architecture, interpreted in terms of classical conditioning. The activations of the proximity sensors are the conditioned stimuli. The unconditioned stimuli are modeled as the activations of the collision or target (light) sensors. The motor responses are stored in the unconditioned response field. The CR and the UCR are identical.

Summary

- Neural networks: outlook
 - BP/Hebbian learning/.....
 - supervised, non-supervised, reinforcement
 - Deep learning: DNN, CNN, GNN,.....
 - Interpretability of neural networks
- More challenging in NN

Assignment

- Readings: Chap 18.6, 18.7
- Exercises
 - Exercises: 18.19
 - Additional exercises:
 - Exercise 1: Compute a NN to realize function XOR based on Perceptrons.
 - Exercise 2: Prove the formula of BP Algorithm based.
 - Exercise 3*: training a neuro controller for the robot “Braitenberg vehicle” mentioned in our course, and give one answer
 - *Handed in next Tuesday