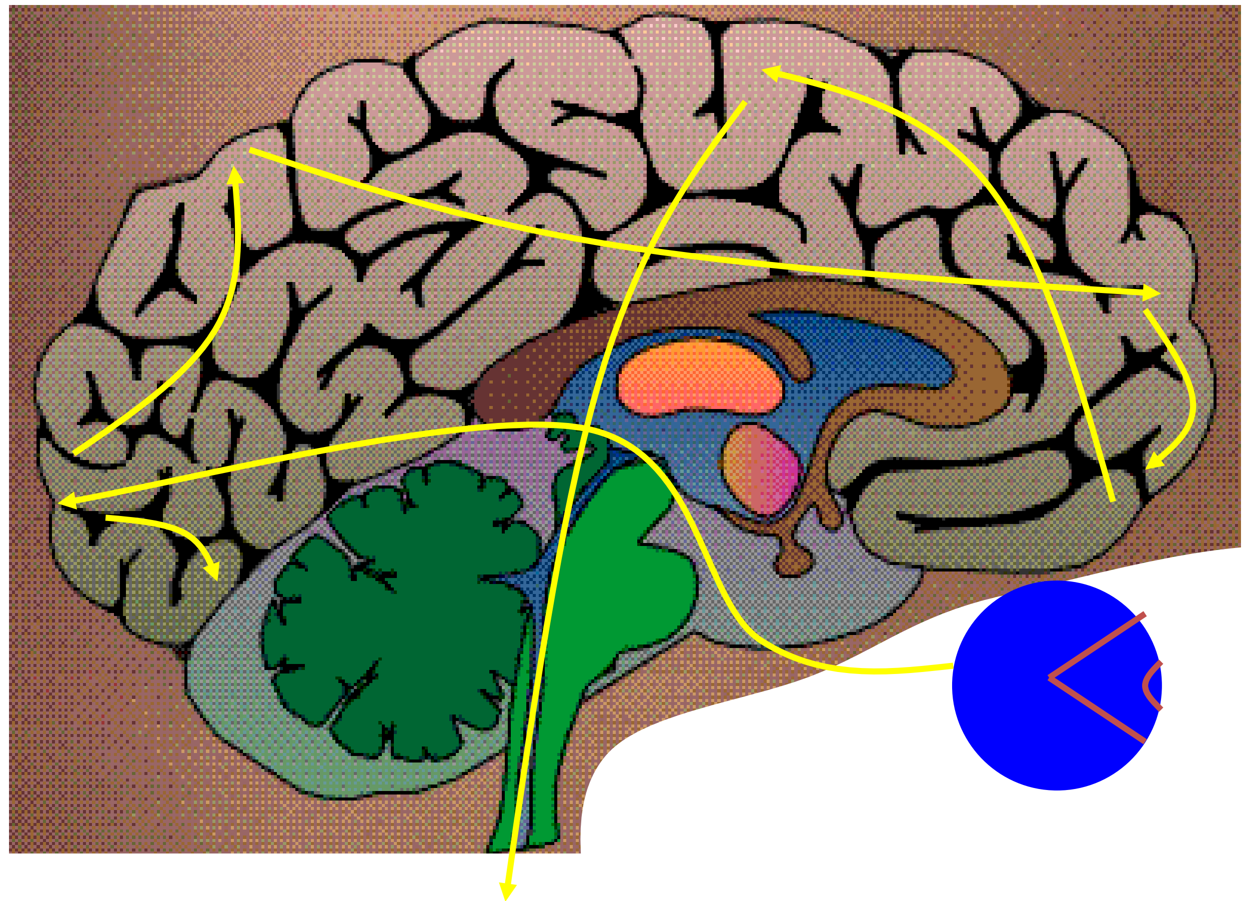
Artificial Neural Networks

Wulfram Gerstner

EPFL, Lausanne, Switzerland

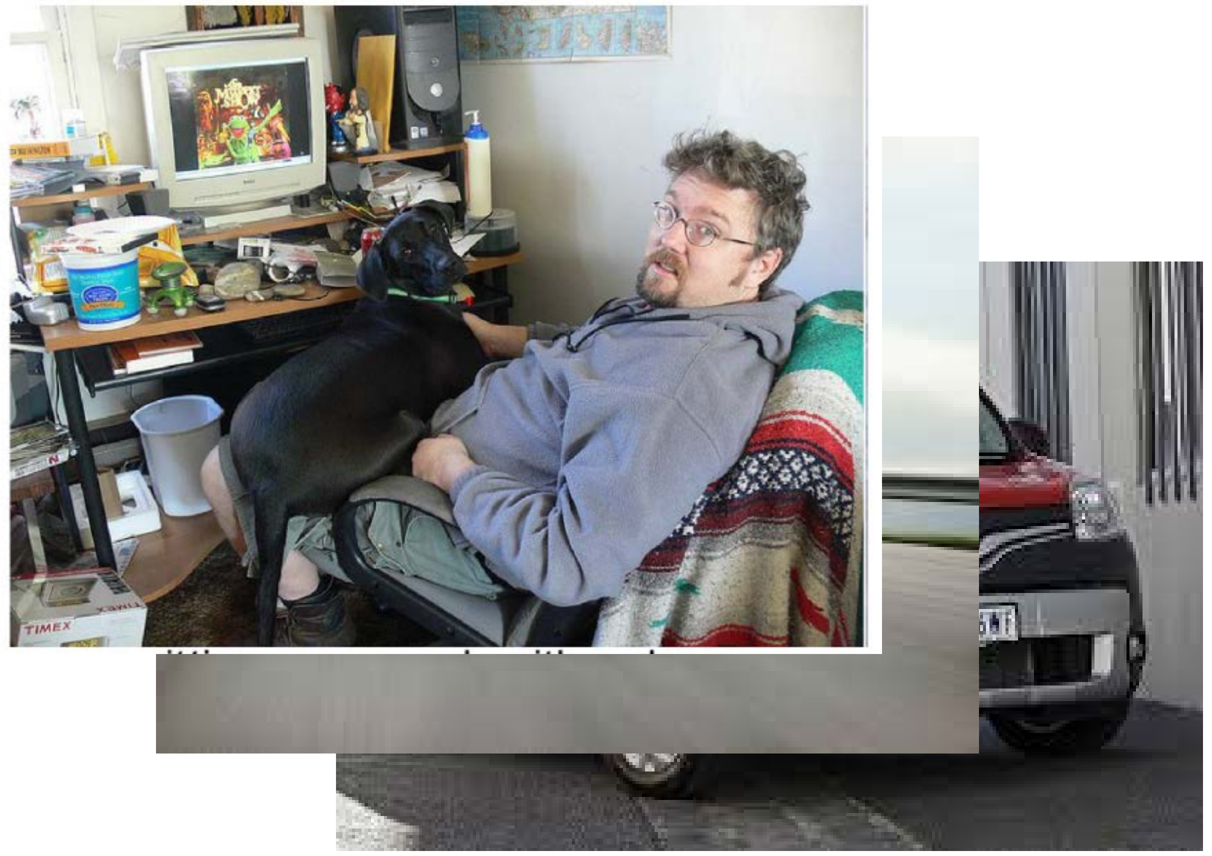
The brain: Cortical Areas

motor
cortex



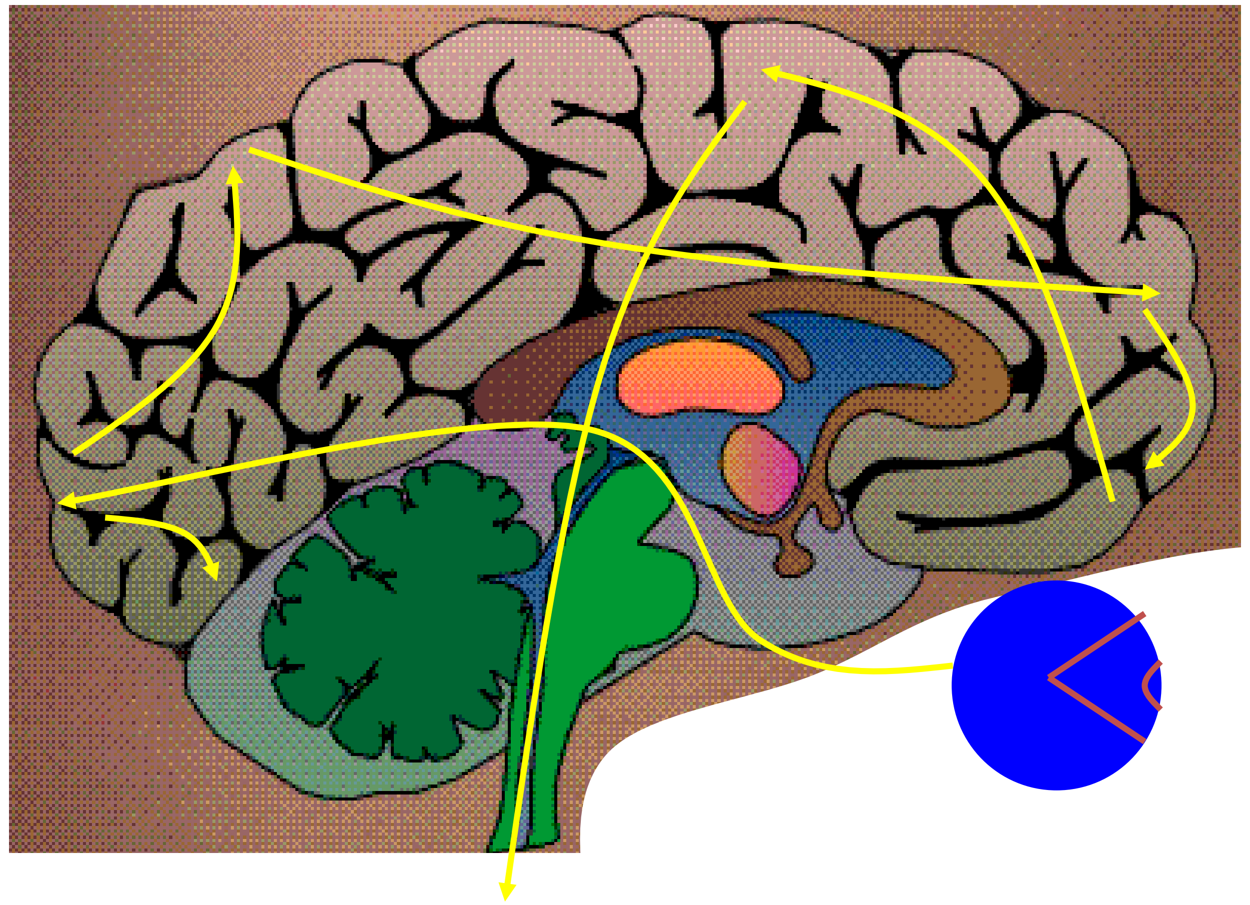
visual
cortex

frontal cortex



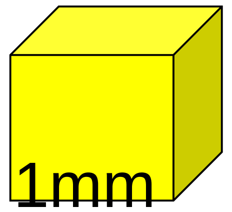
to
muscles

The brain: Cortical Areas



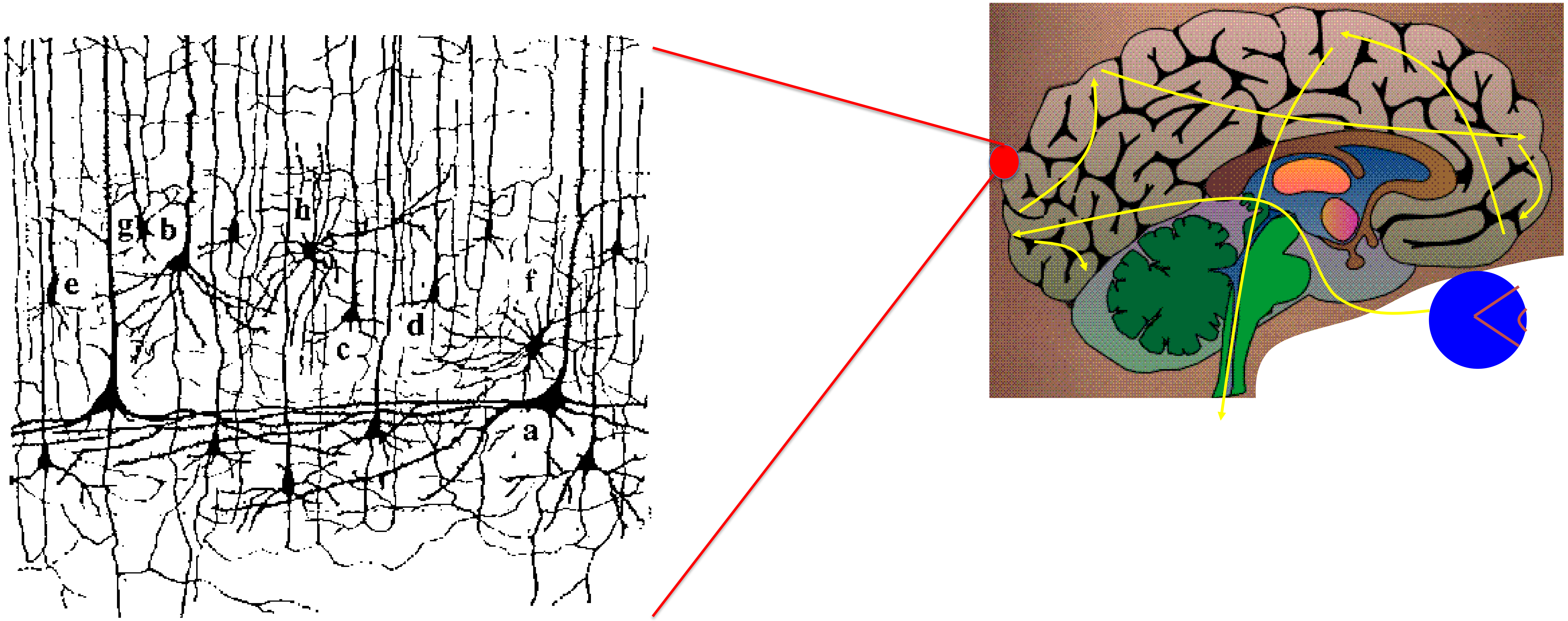
The Brain: zooming in

1mm



10 000 neurons

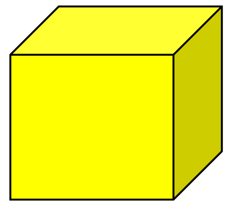
3 km of wire



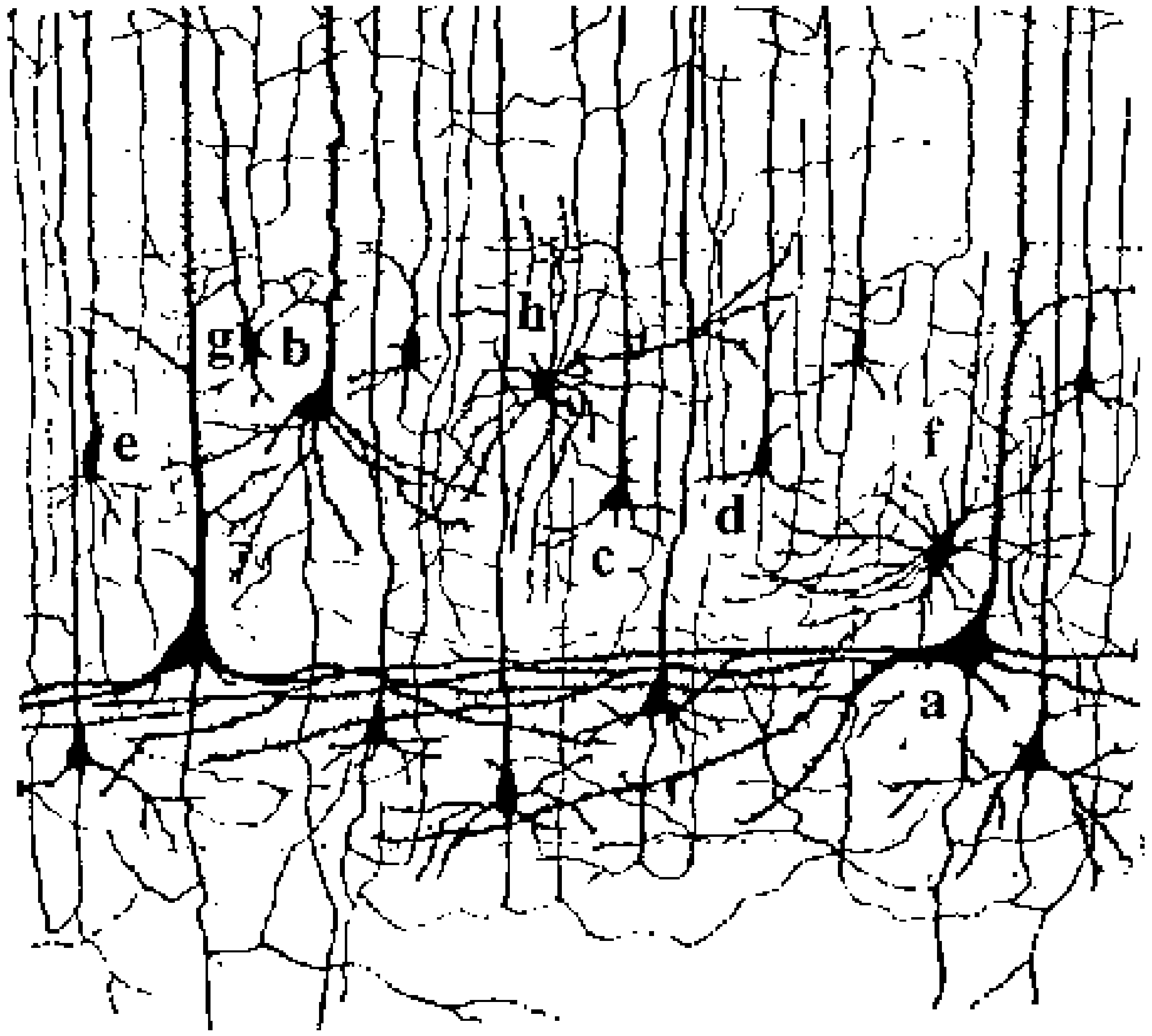
Ramon y Cajal

The brain: a network of neurons

1mm

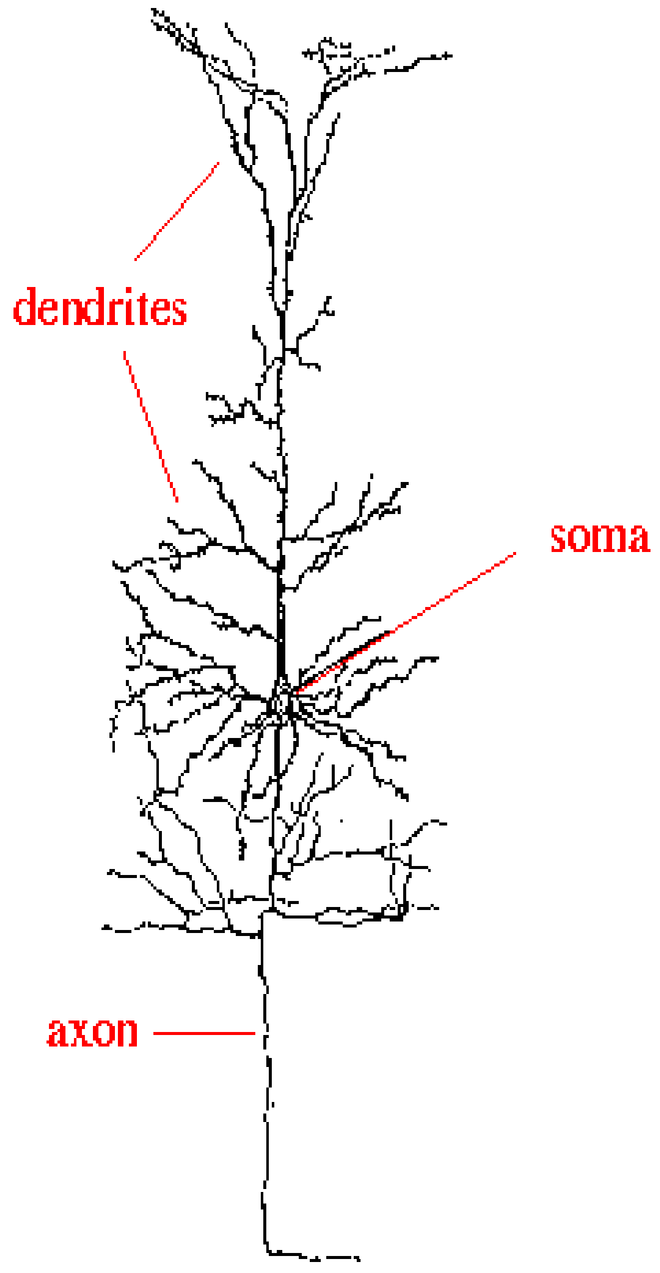


10 000 neurones
3 km de cablage

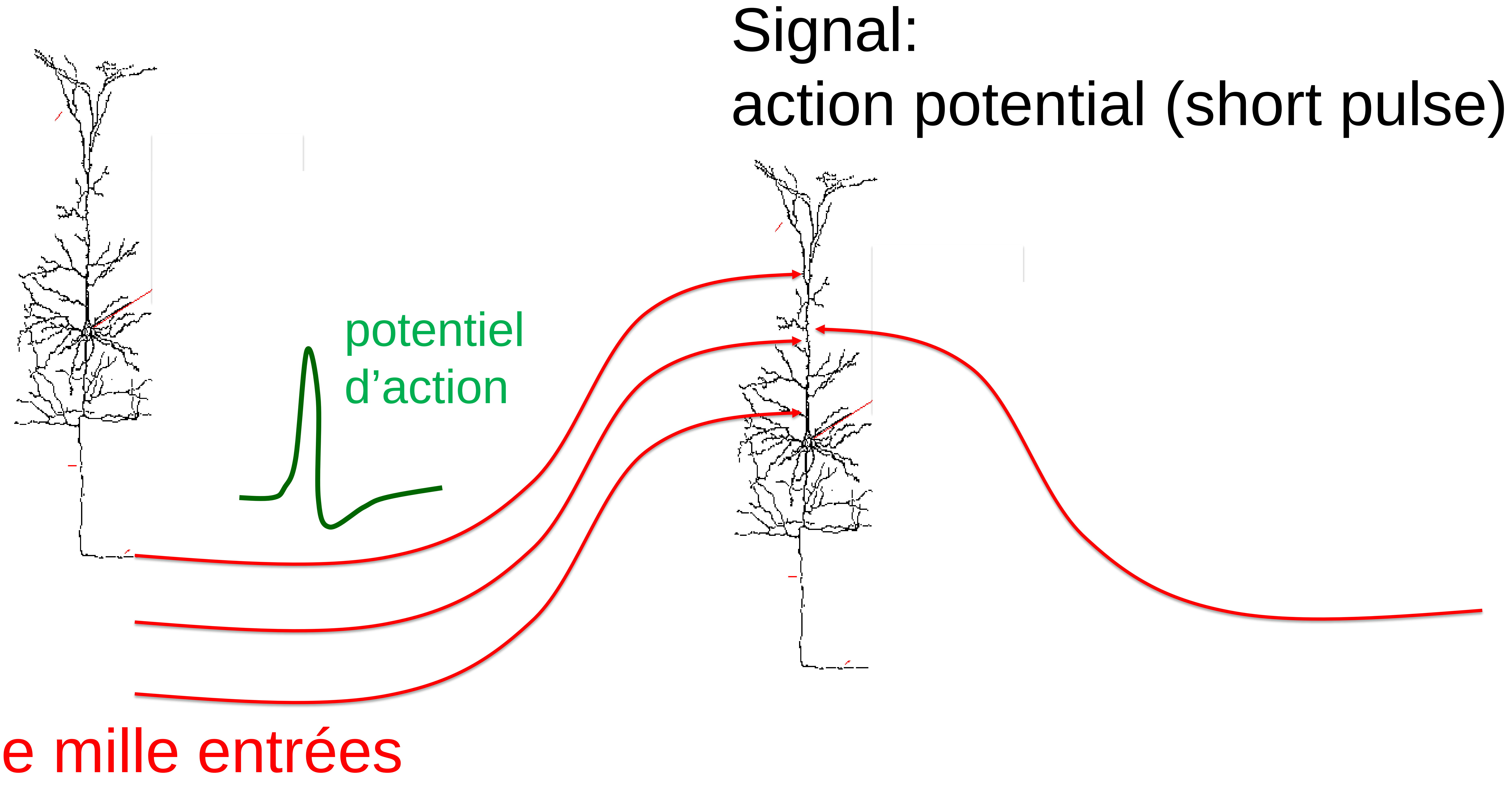


Ramon y Cajal

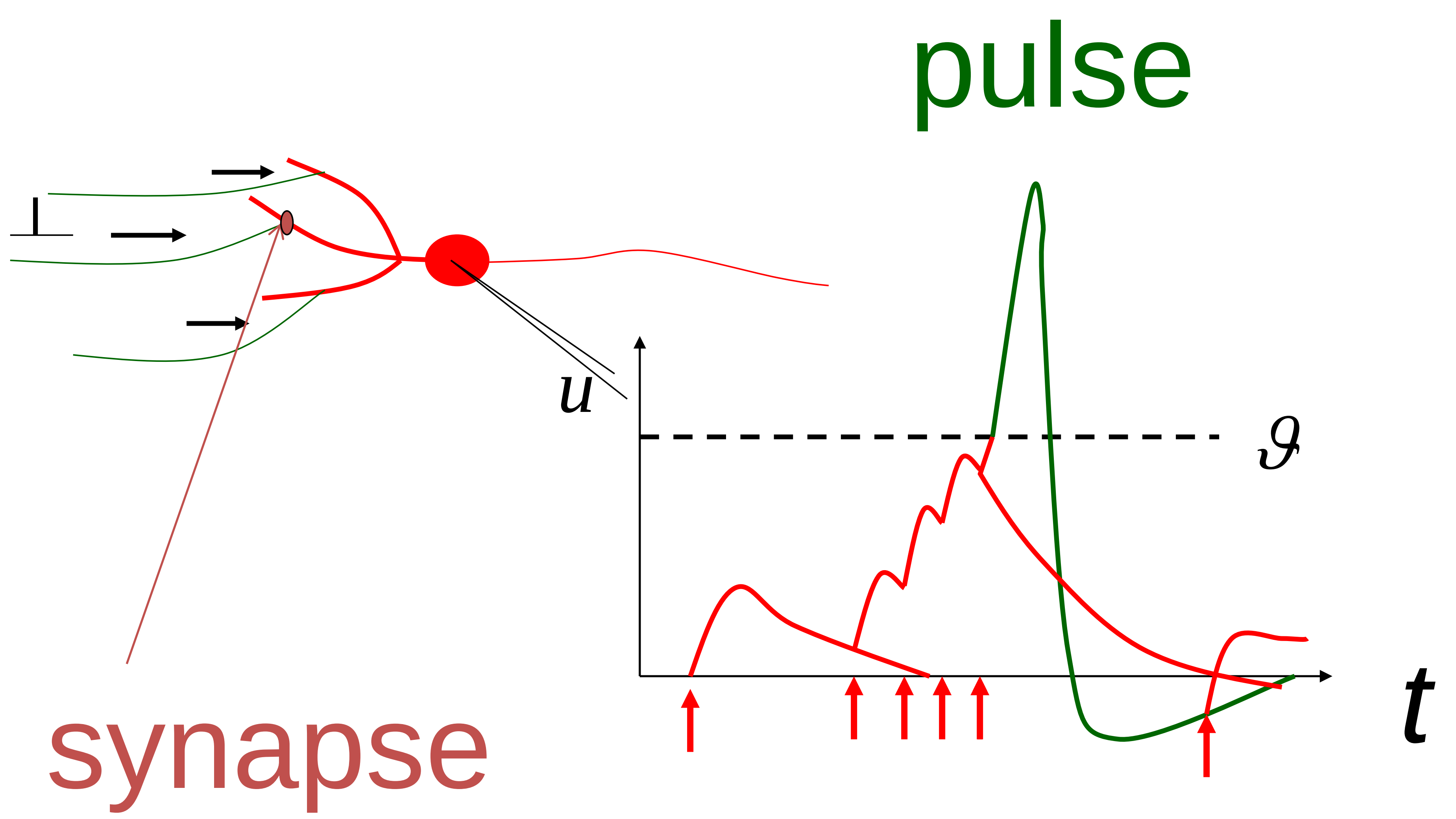
Signal:
Potentiel d’action (impulsion)



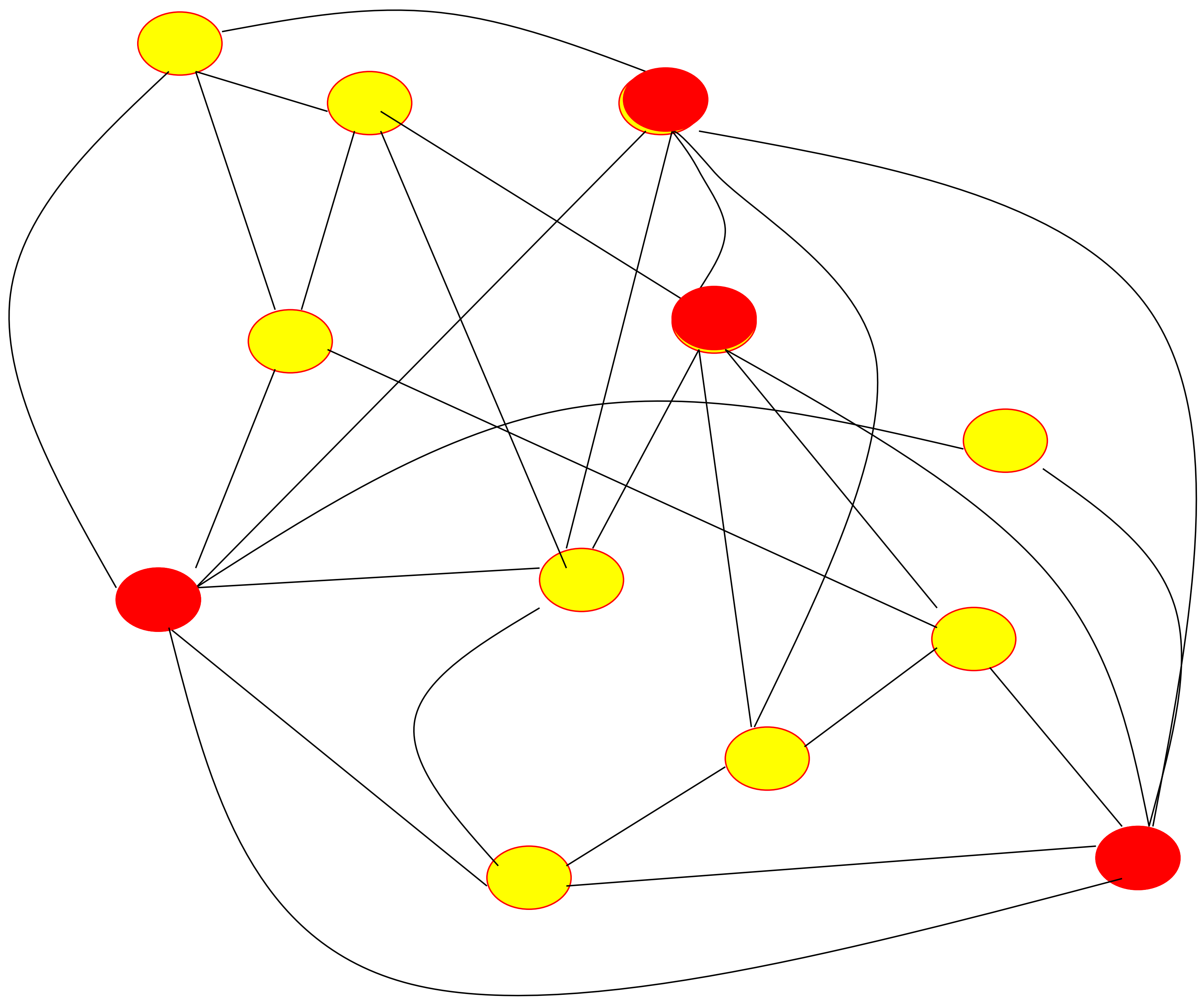
The brain: signal transmission



The brain: neurons sum their inputs

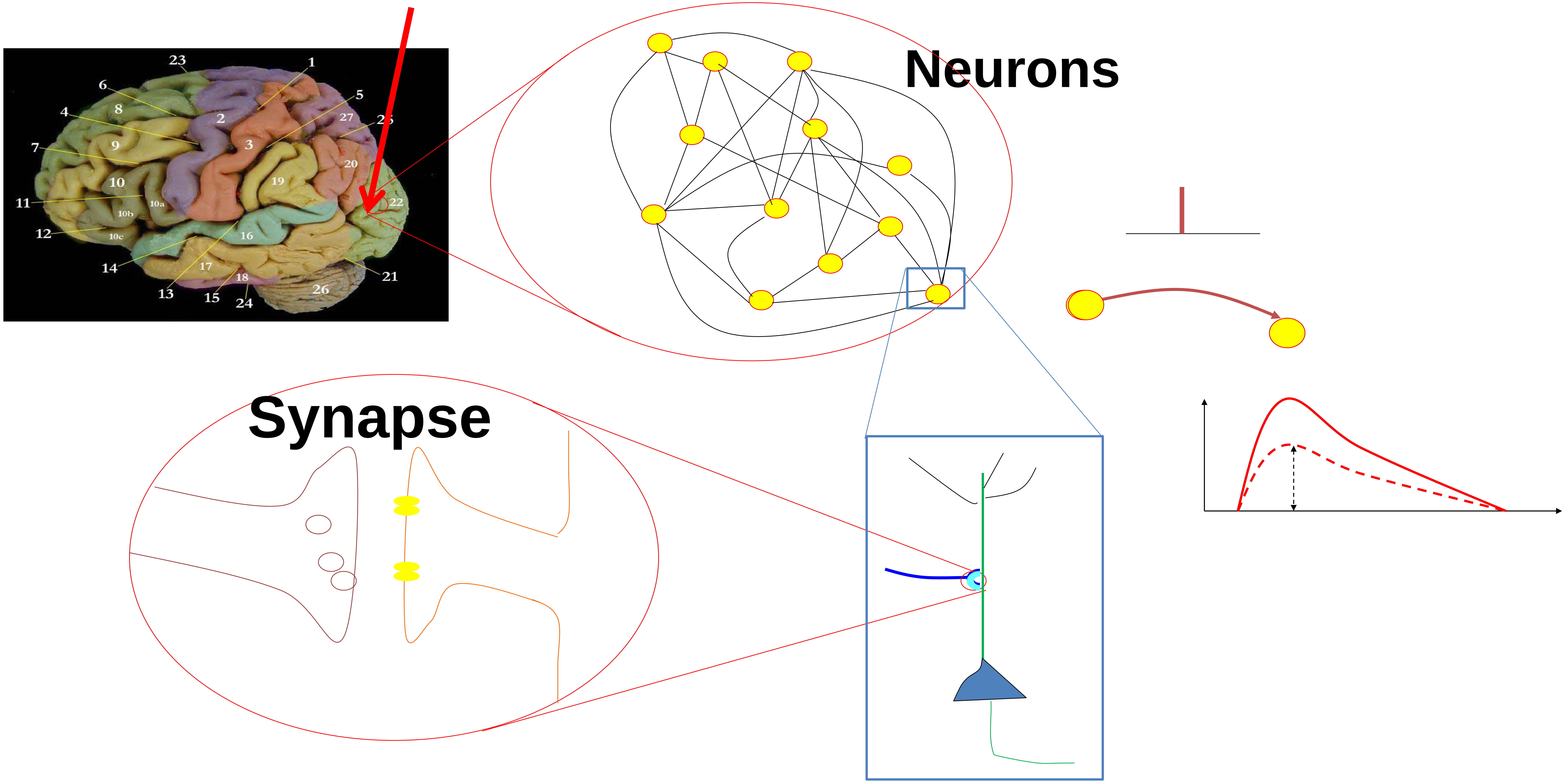


Summary: the brain is a large network of neurons



Active neuron

Learning in the brain: changes between connections



learning = change of connection

Artificial Neural Networks

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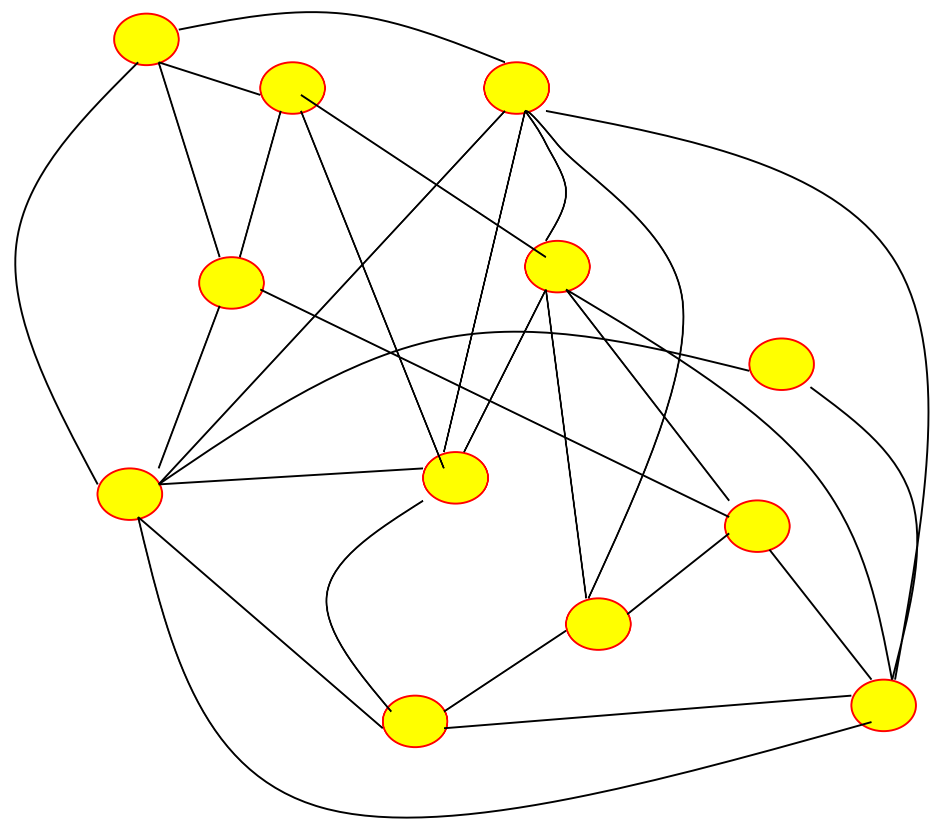
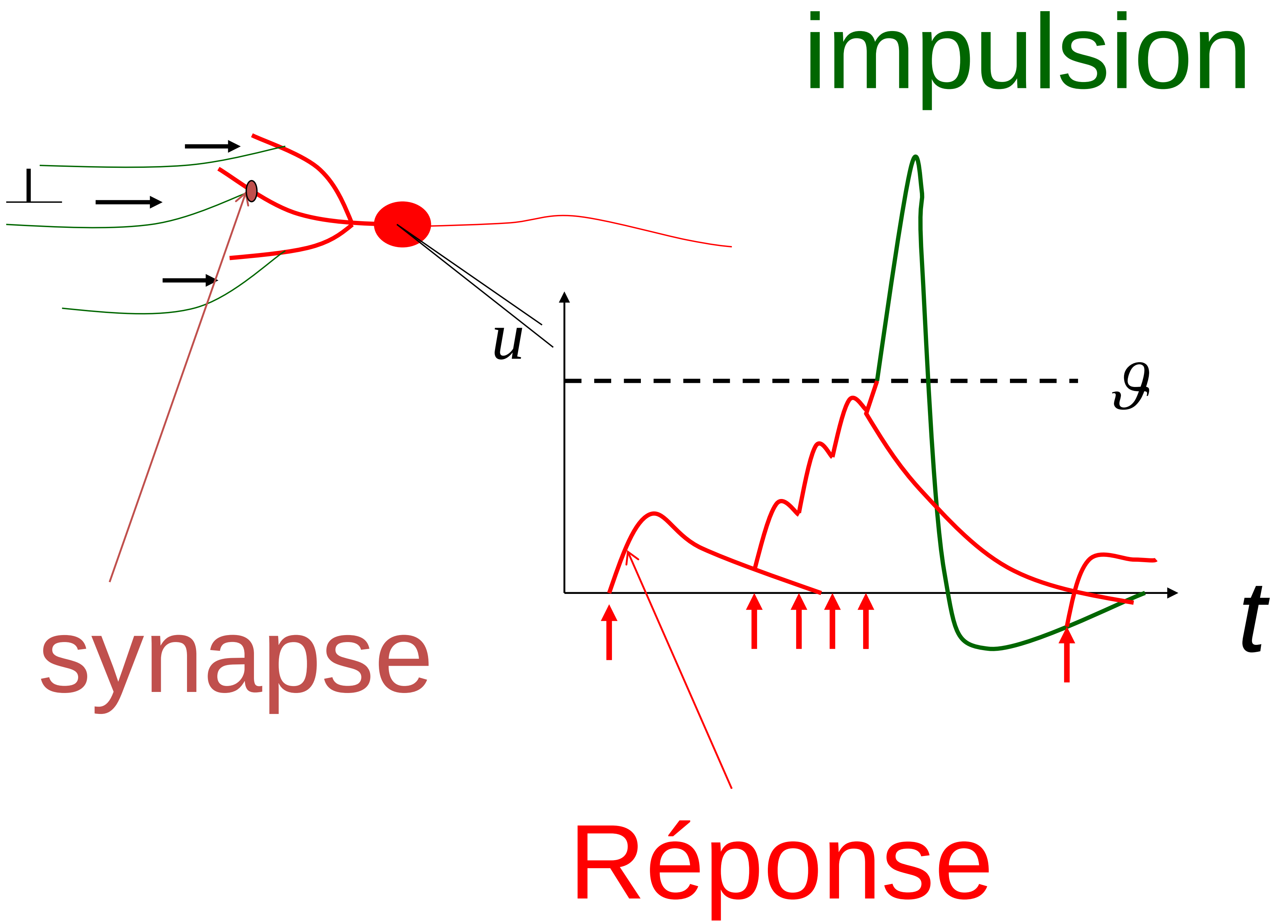
1. The brain
2. Artificial Neural Networks

Modeling: artificial neurons





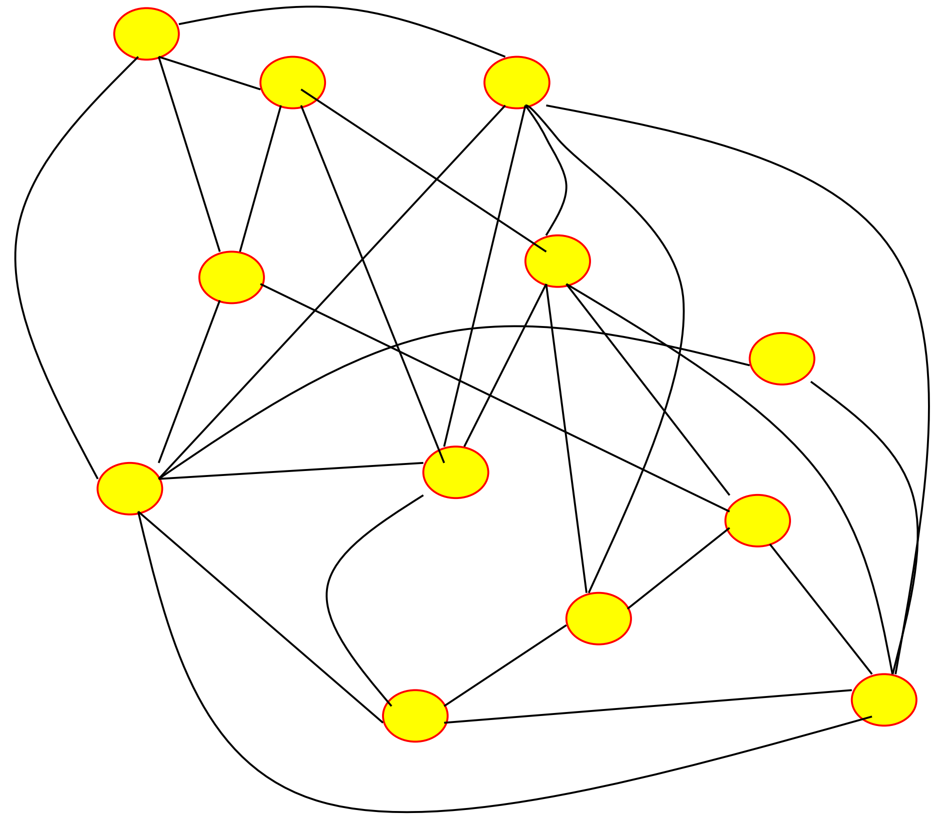
-responses are added
-pulses created at threshold
-transmitted to other

→ Mathematical description

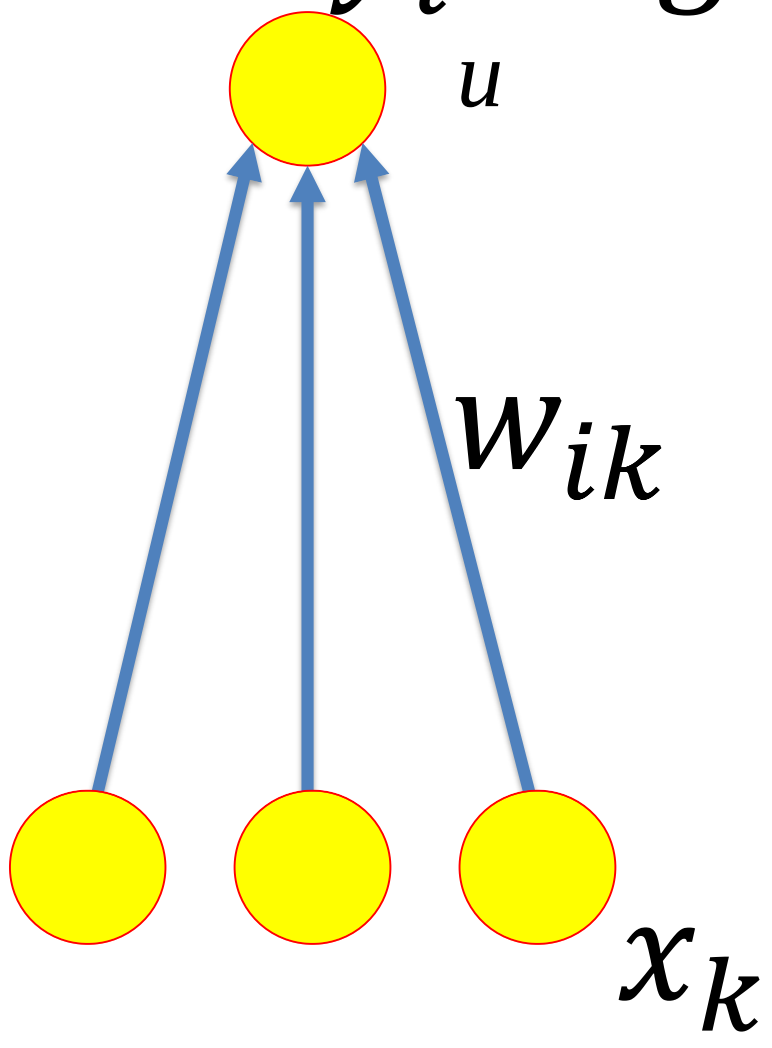
Modeling: artificial neurons

forget spikes: continuous activity x

forget time: discrete updates



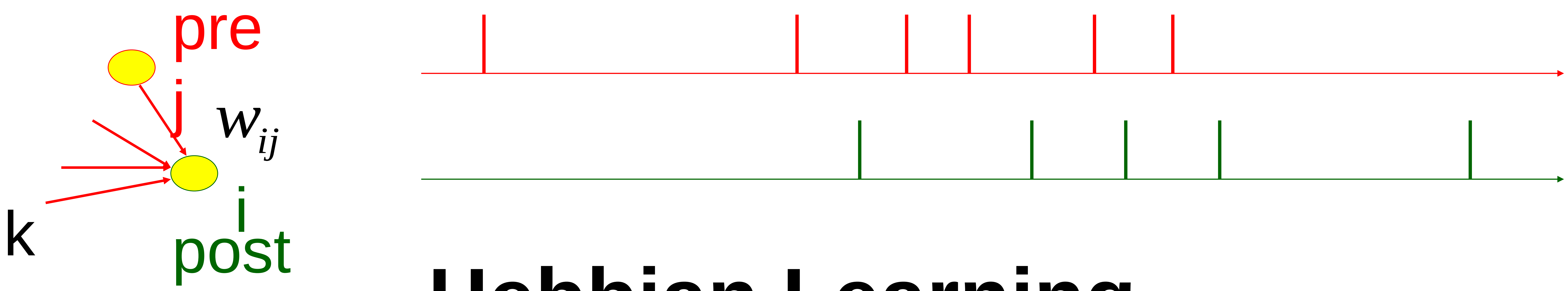
$$y_i = g\left(\sum_k w_{ik}\, x_k\right)$$



weights = adaptive parameters

Learning of connections in biology

Where do the connection weights come from?



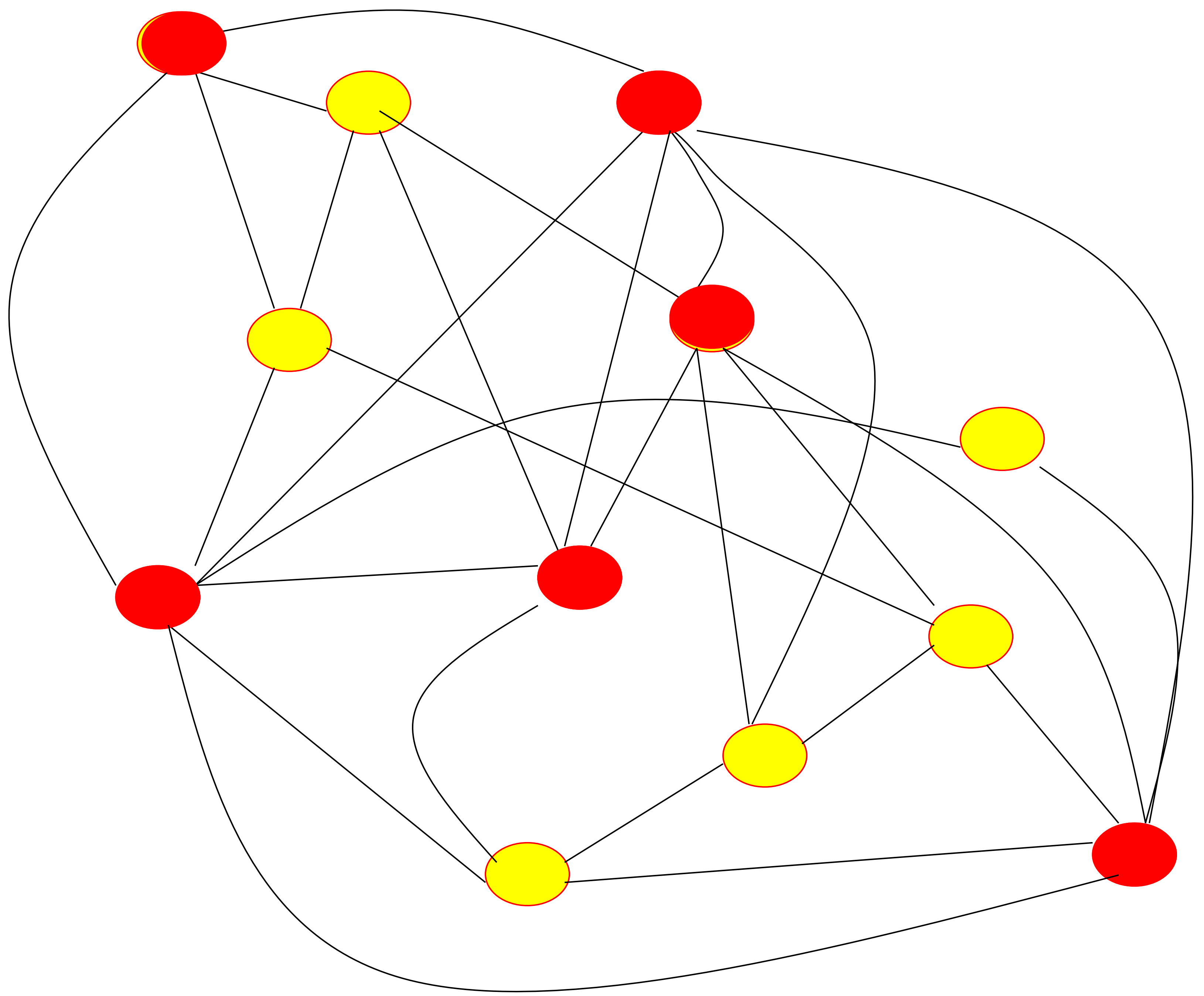
Hebbian Learning

When an axon of cell **j** repeatedly or persistently takes part in firing cell **i**, then j's efficiency as one of the cells firing i is increased

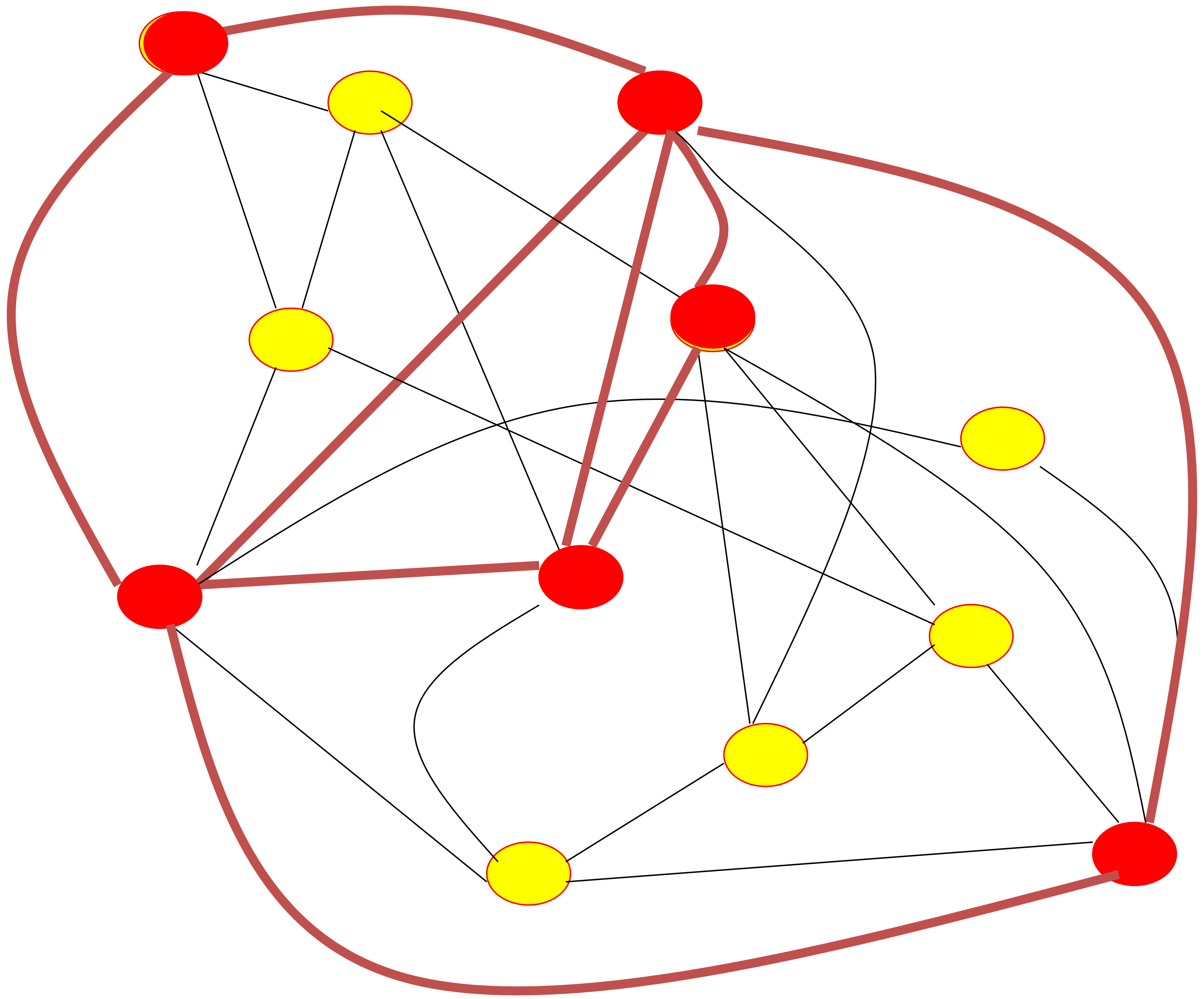
Hebb, 1949

- local rule
- simultaneously active neurons

Hebbian Learning of Associations



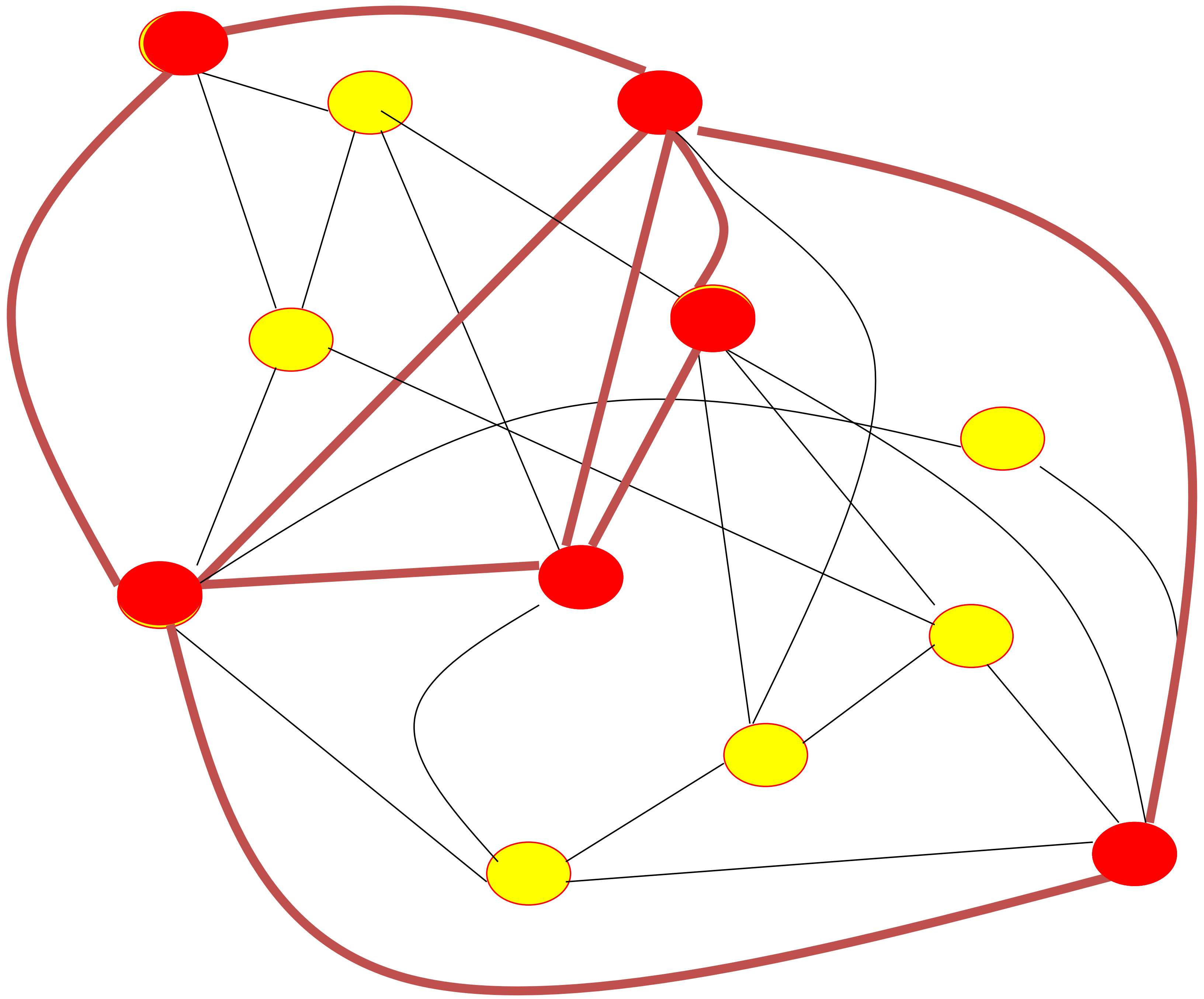
Hebbian Learning of Associations

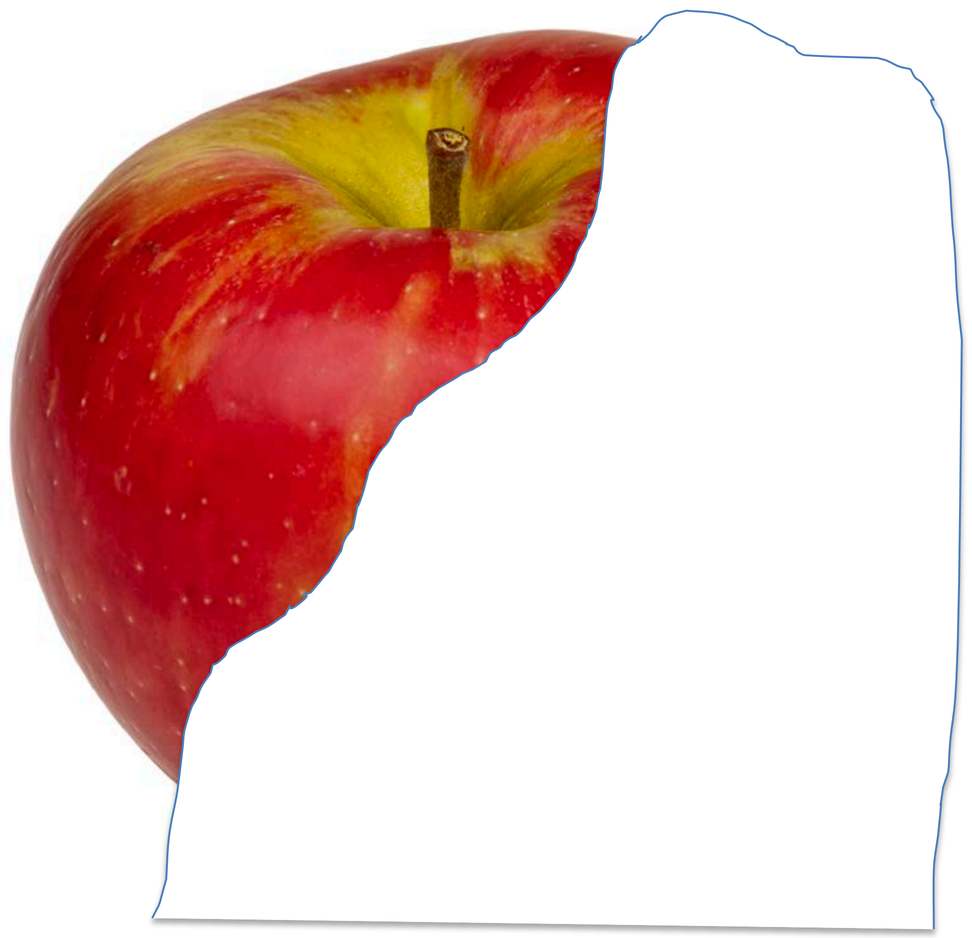


item memorized by change of synaptic weights

Hebbian Learning: Associative Recall

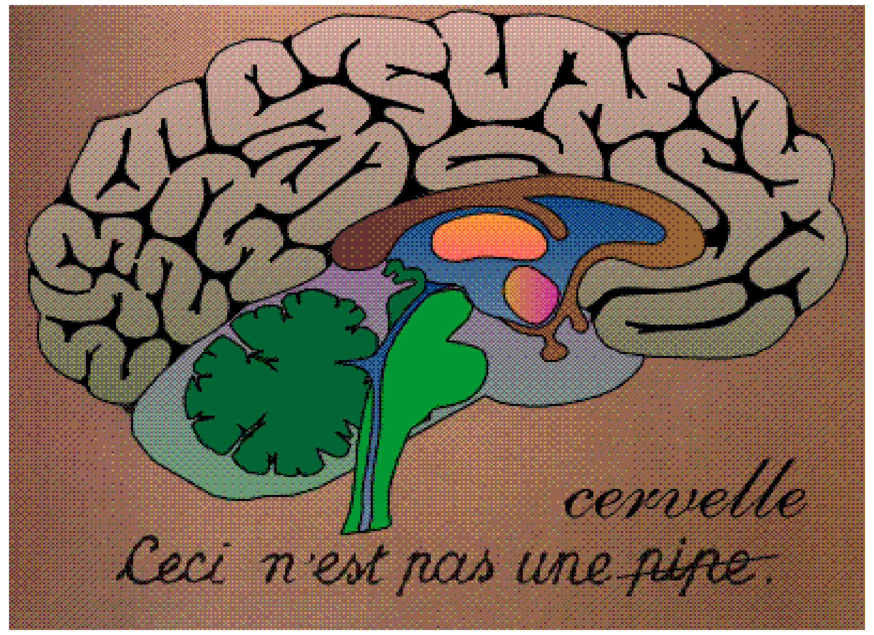
Recall:
Partial info



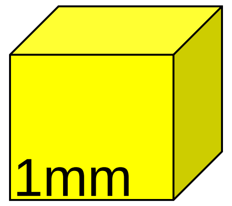


item recalled

Neurons and Synapses form a big network



Brain



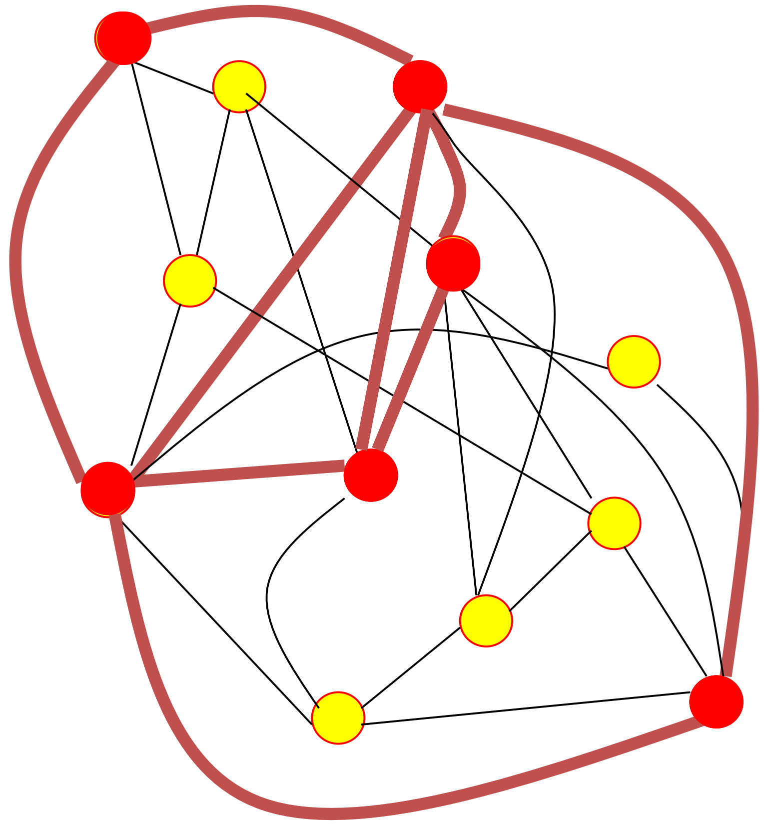
1mm

10 000 neurons
3 km of wire

10 billions neurons

10 000 connexions/neurons

memory in the connections



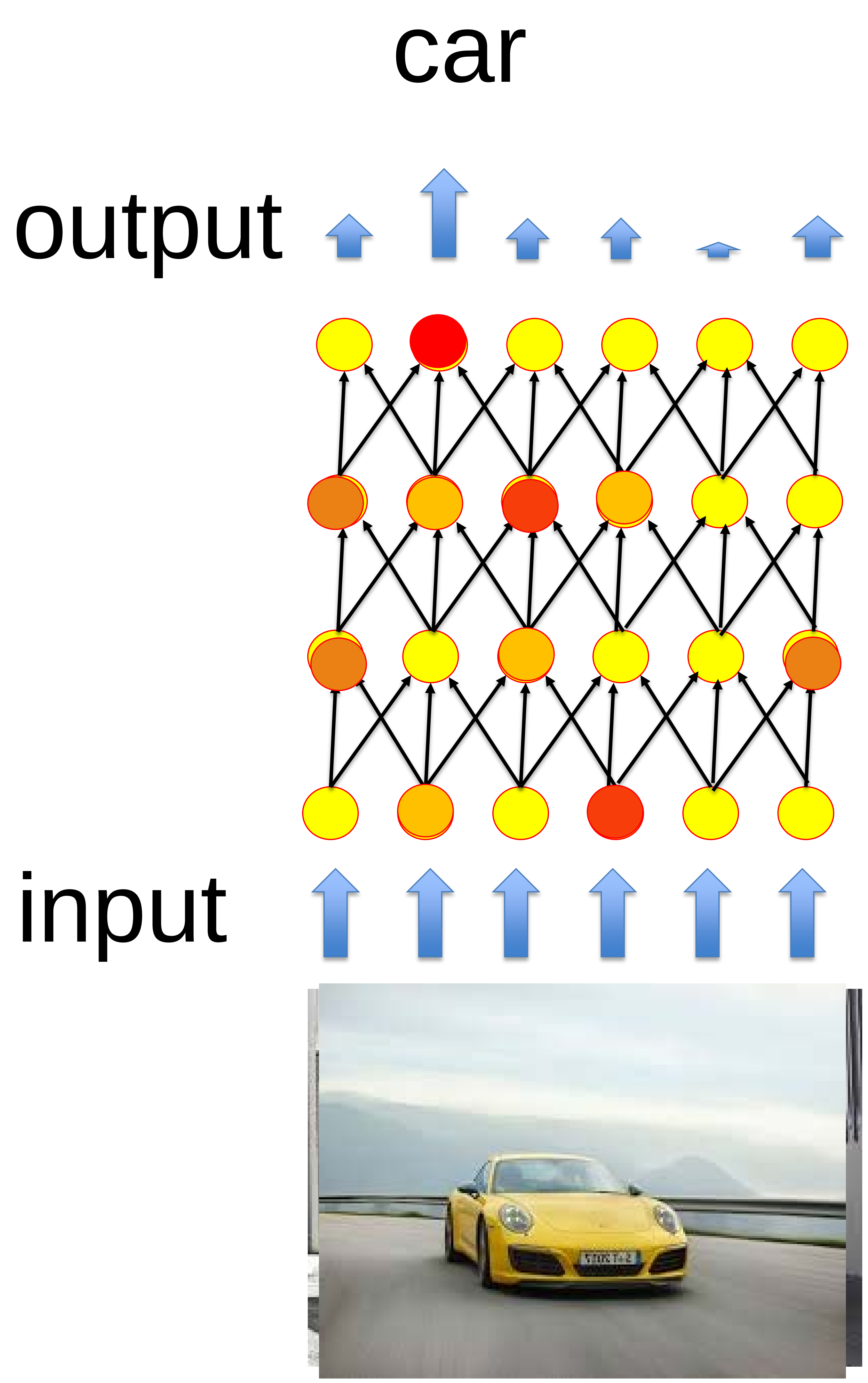
Distributed Architecture

No separation of processing and memory

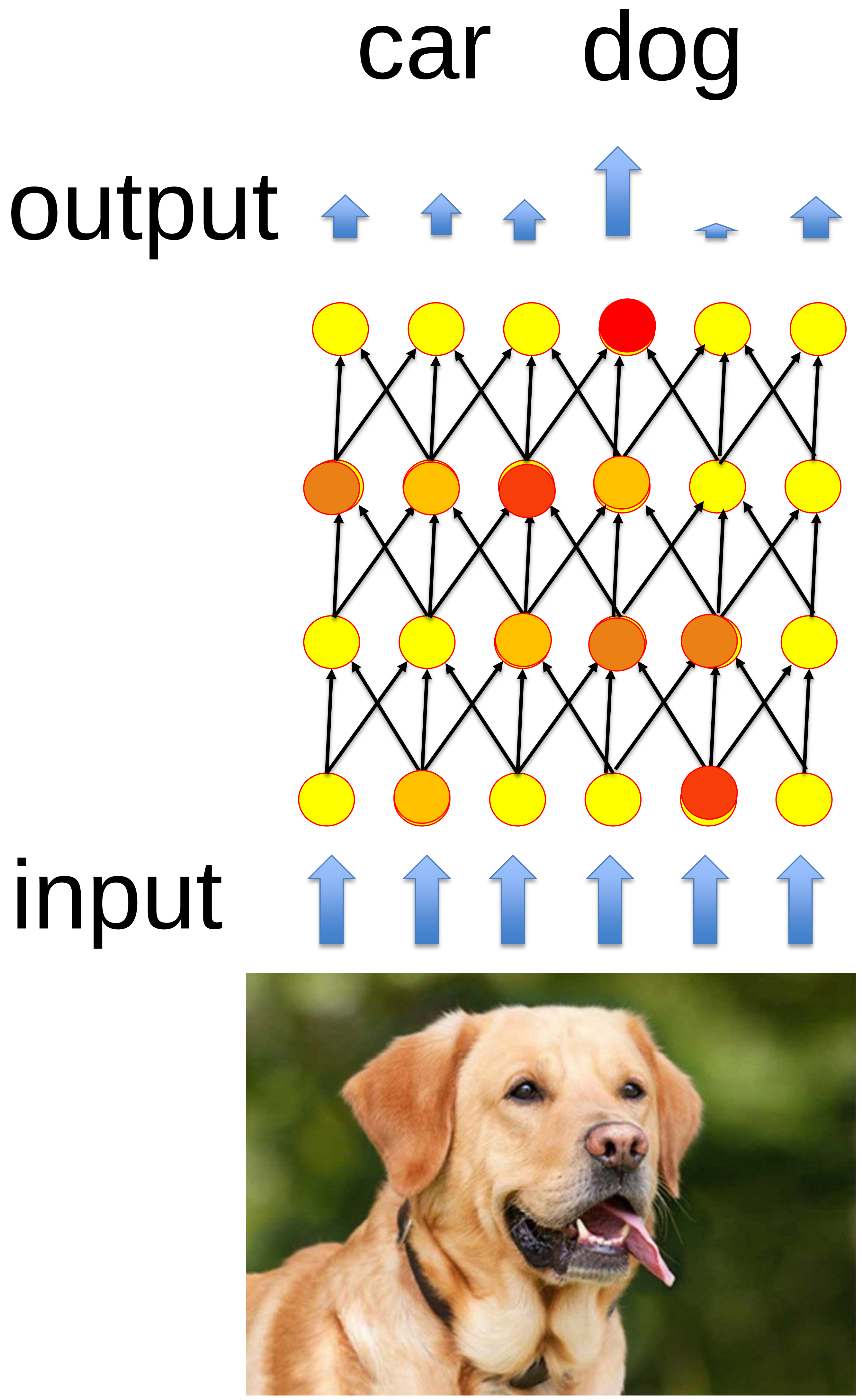
Quiz: biological neural networks

[ ] Neurons in the brain have a threshold.
[ ] Learning means a change in the threshold.
[ ] Learning means a change of the connection weights
[ ] The total input to a neuron is the weighted sum of individual inputs
[ ] The neuronal network in the brain has no recurrent connections and no feedback connections

Artificial Neural Networks for classification



Artificial Neural Networks for classification



Aim of learning:
Adjust connections such that output is correct (for each input)

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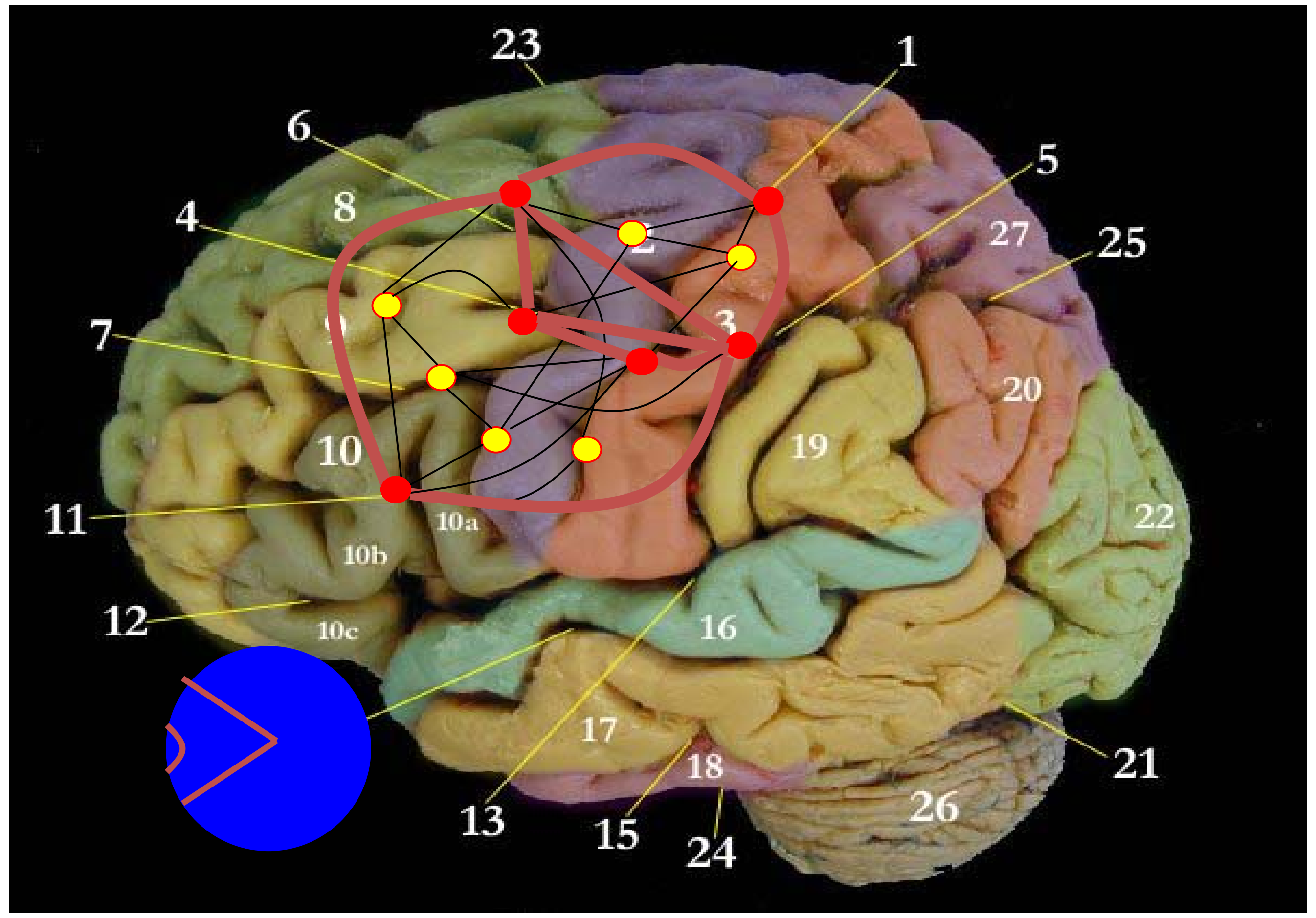
2. Artificial Neural Networks
   - for classification
   - for action learning

Artificial Neural Networks for action learning

Coactivation of 2 neurones:

- Connections strengthened
- Facilitates to repeat same action

Even the mistakes?

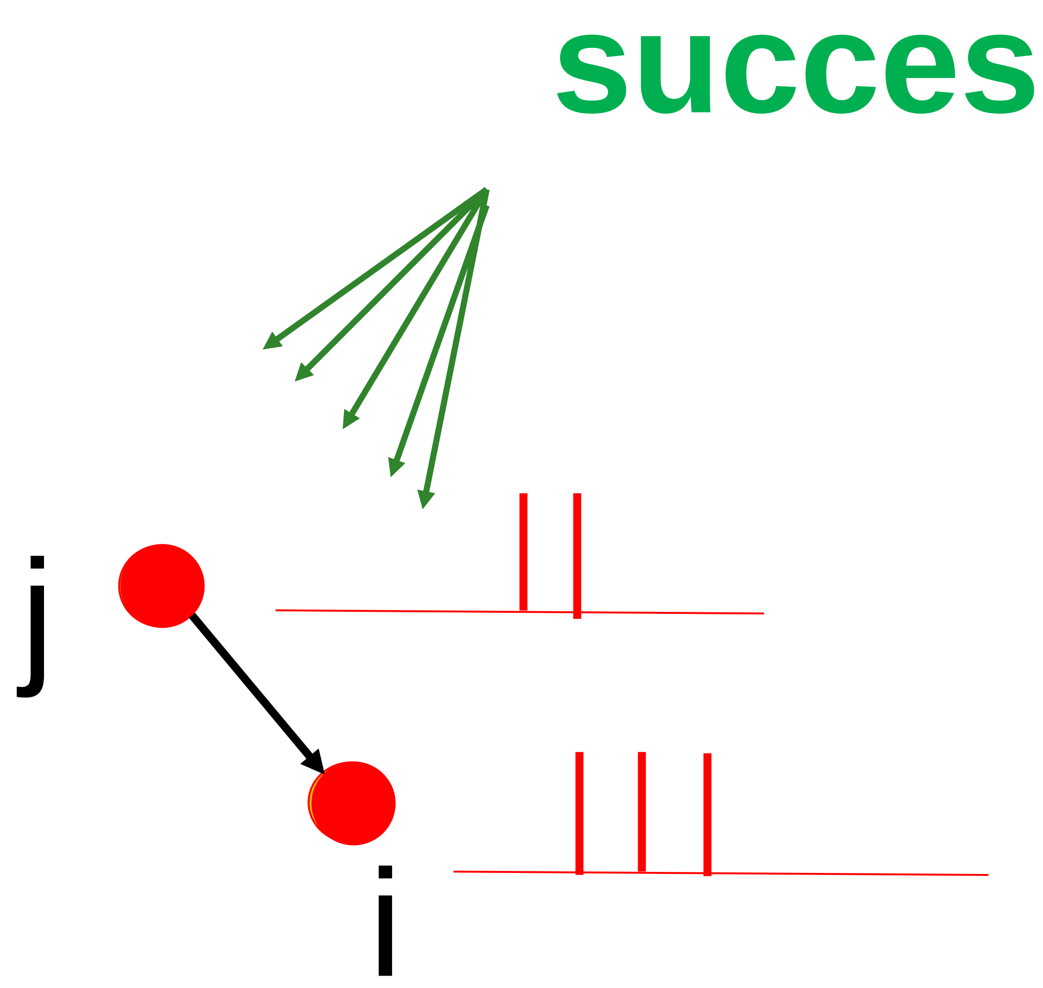


Missing:

Value of action

- ‘goodie’ for do
- ‘success’
- ‘compliment’

Modeling – the role of reward



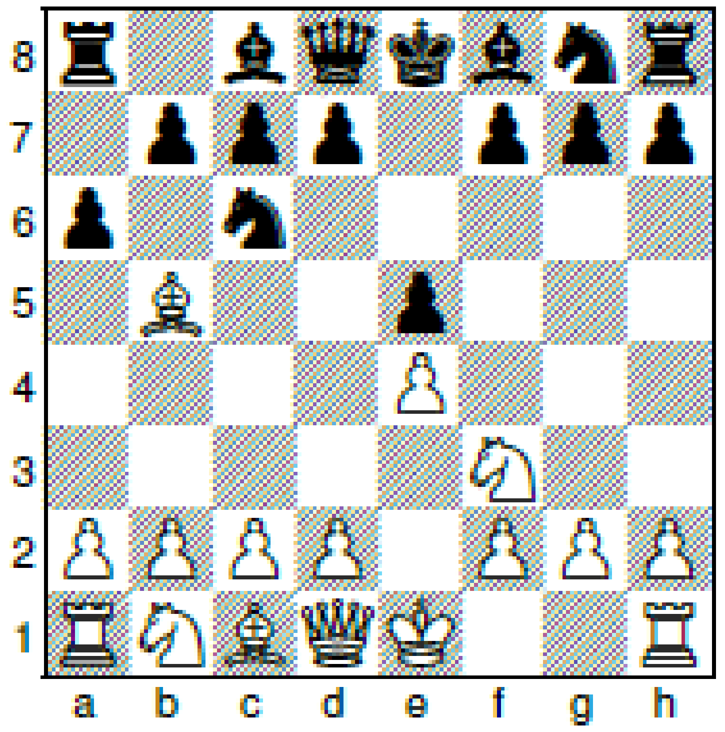
Three factors for changing a connection

- activity of neuron j
- activity of neurone i
- success

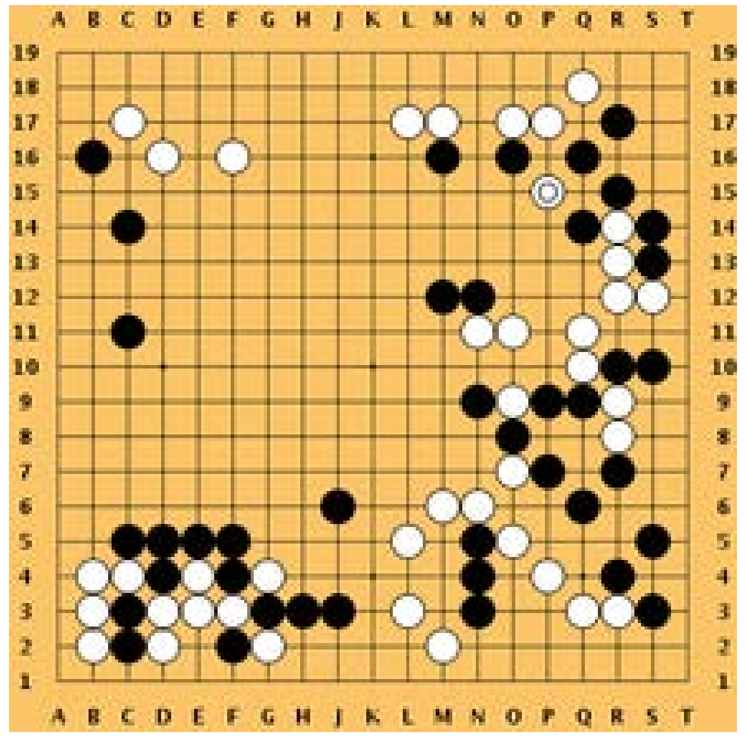
Barto 1985, Schultz et al. 1997; Waelti et al., 2001; Reynolds and Wickens 2002; Lisman et al. 2011

Deep reinforcement learning

Chess



Go



Artificial neural network (*AlphaZero*) discovers different strategies by playing against itself.

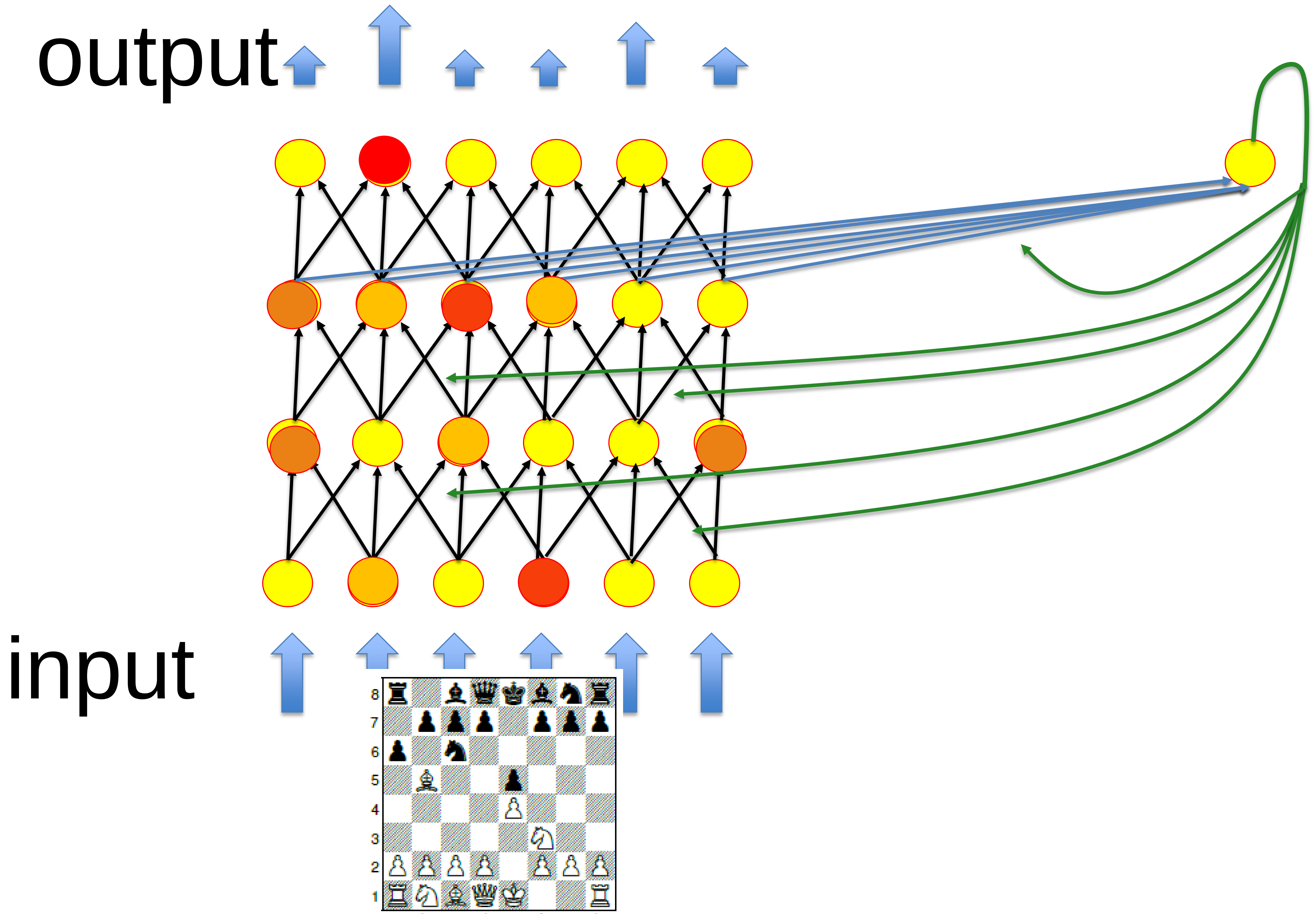
In Go, it beats Lee Sedol

Deep reinforcement learning

Network for choosing action

action:
Advance king

2^e output for value of action:
probability to win



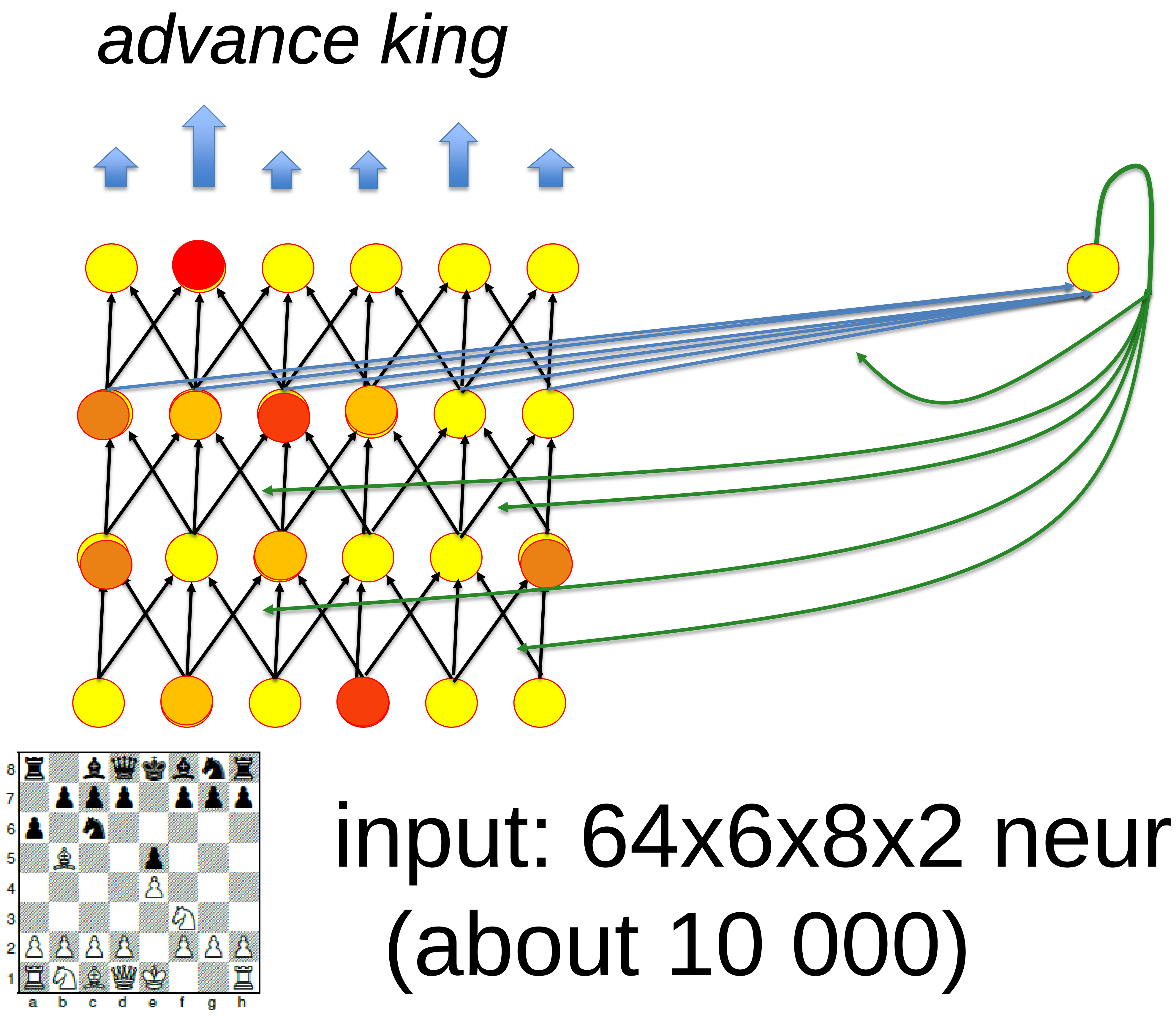
learning:
- change connections

aim:
- Predict value of position
- Choose next action to win

Deep reinforcement learning (alpha zero)

Silver et al. (2017) , Deep Mind

output: 4672 actions



input: 64x6x8x2 neuronss
(about 10 000)

Training 44Mio games (9 hours)

Planning:
potential sequences
(during 1s before playing next action)

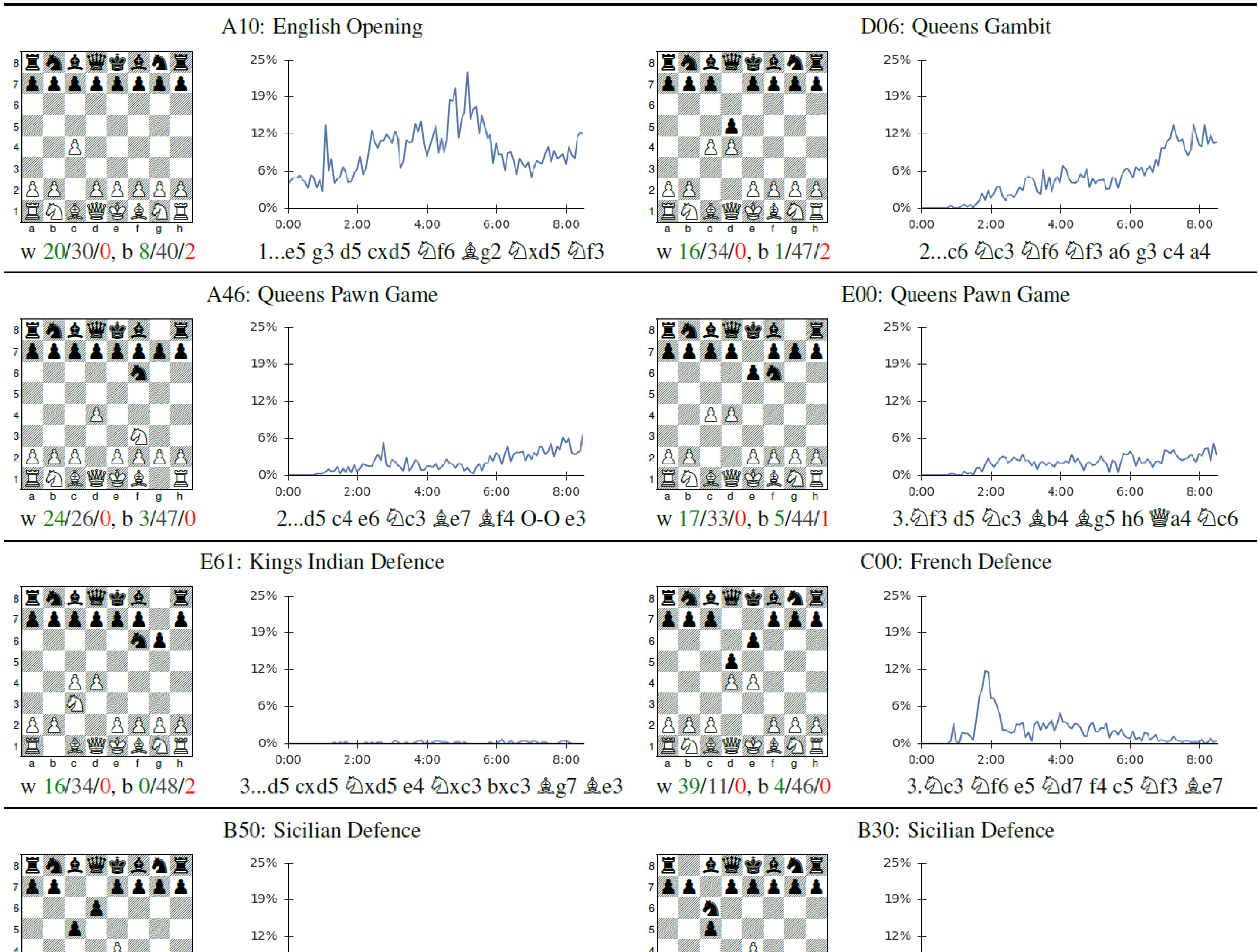
Deep reinforcement learning (alpha zero)

Chess:

-discovers classic openings

-beats best human players

-bets best classic AI algorithms



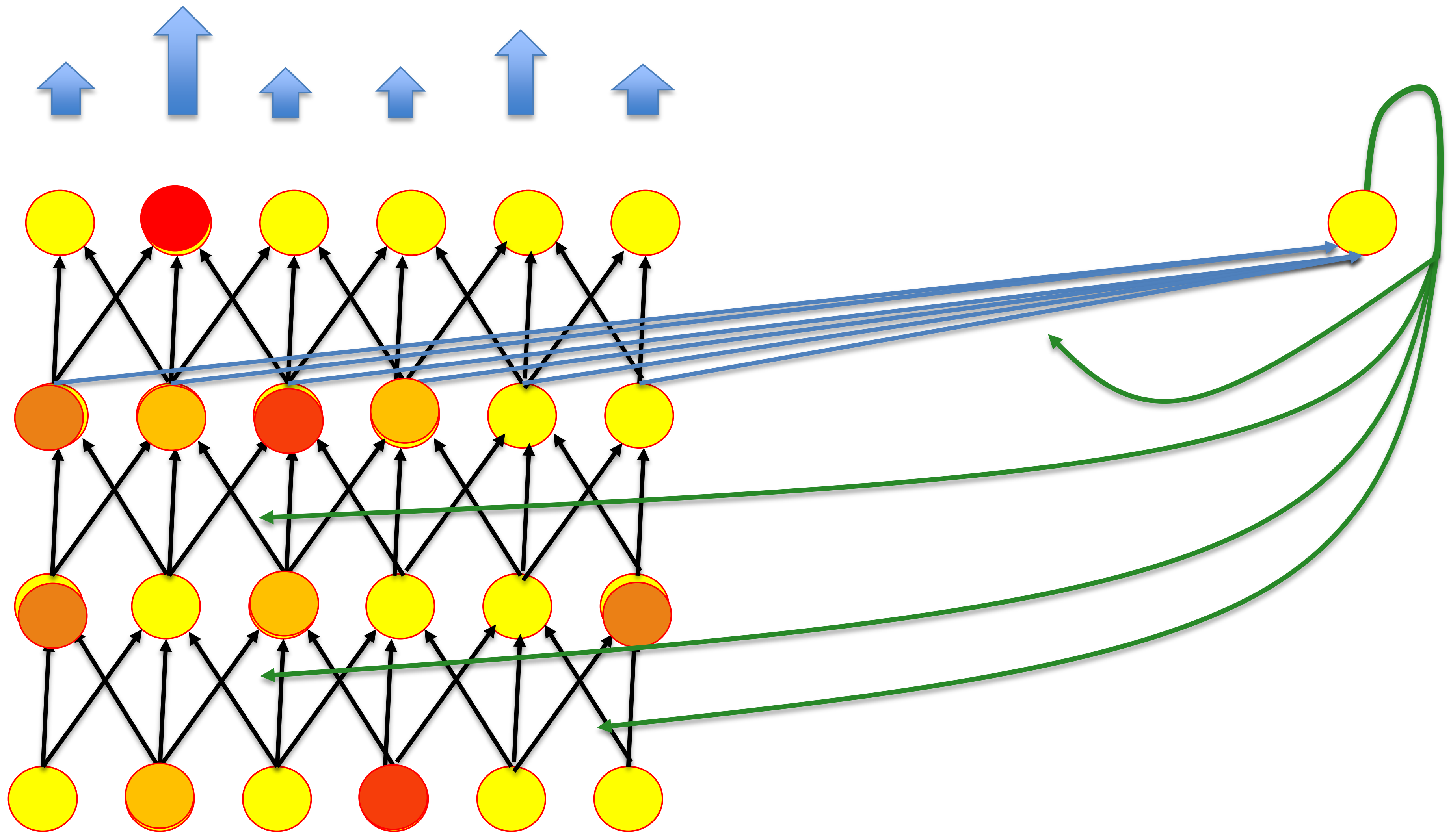
Self-driving cars

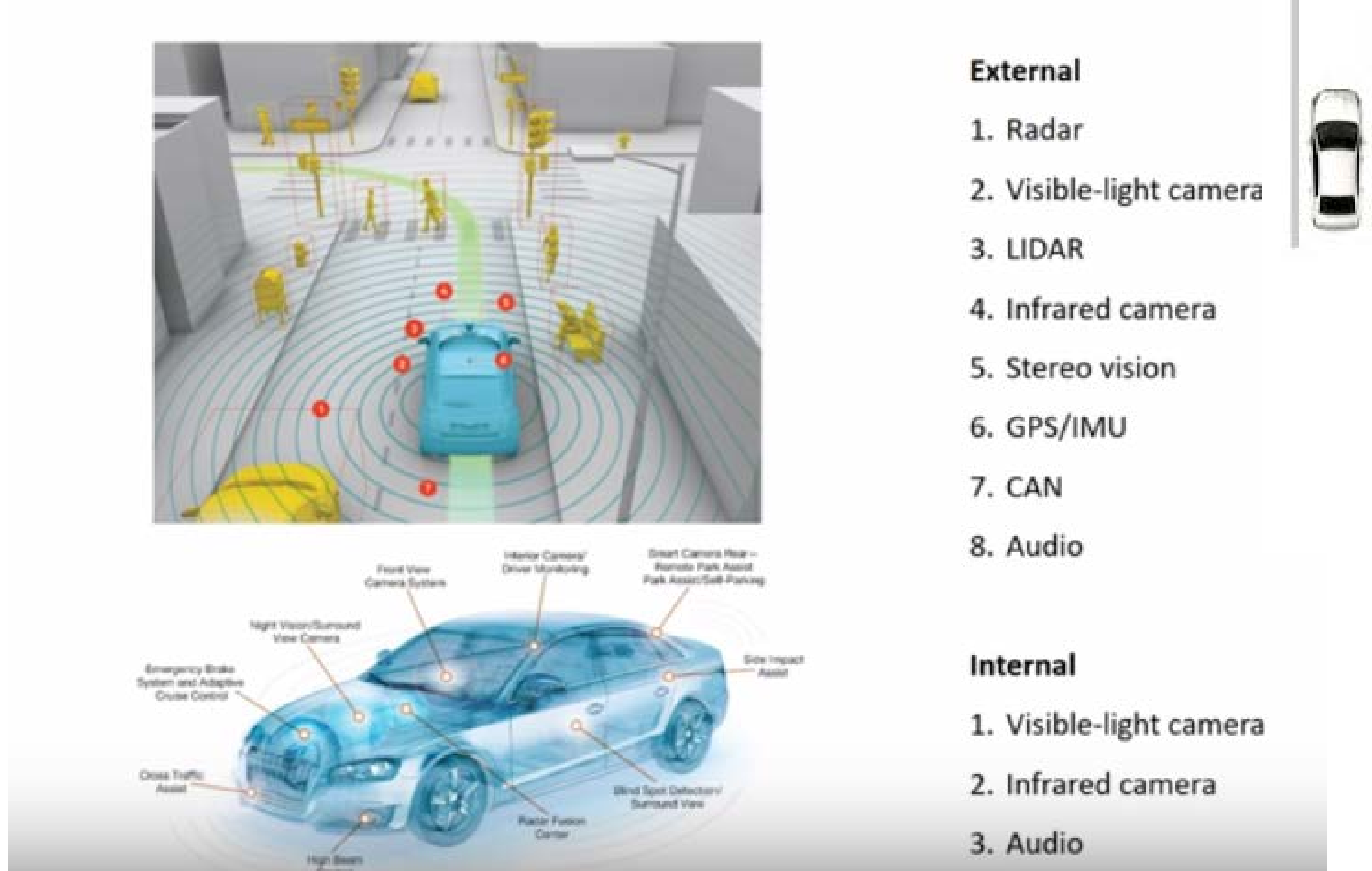
https://selfdrivingcars.mit.edu/

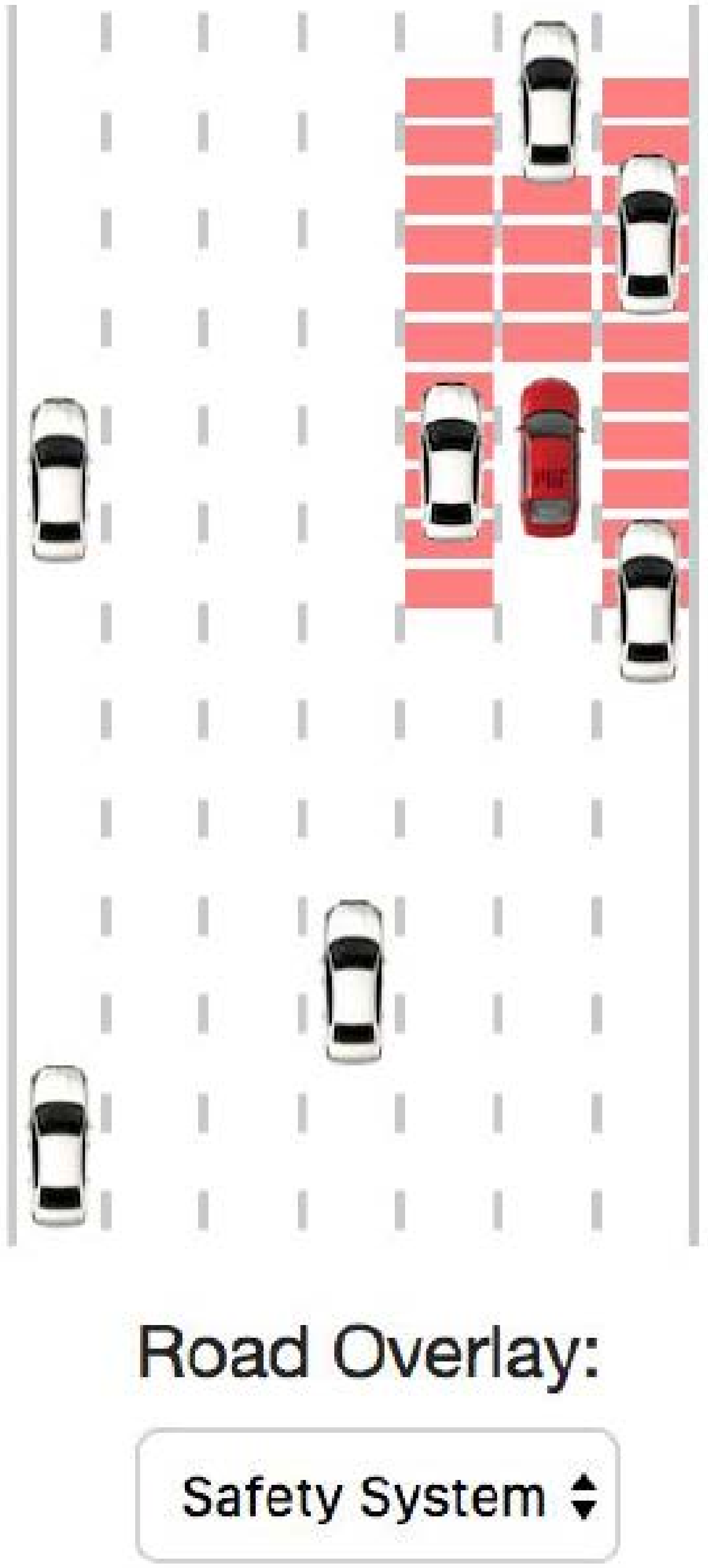
Lex Friedman, MIT

advance and accerate

Value: security, duration of travel







Artificial Neural Networks

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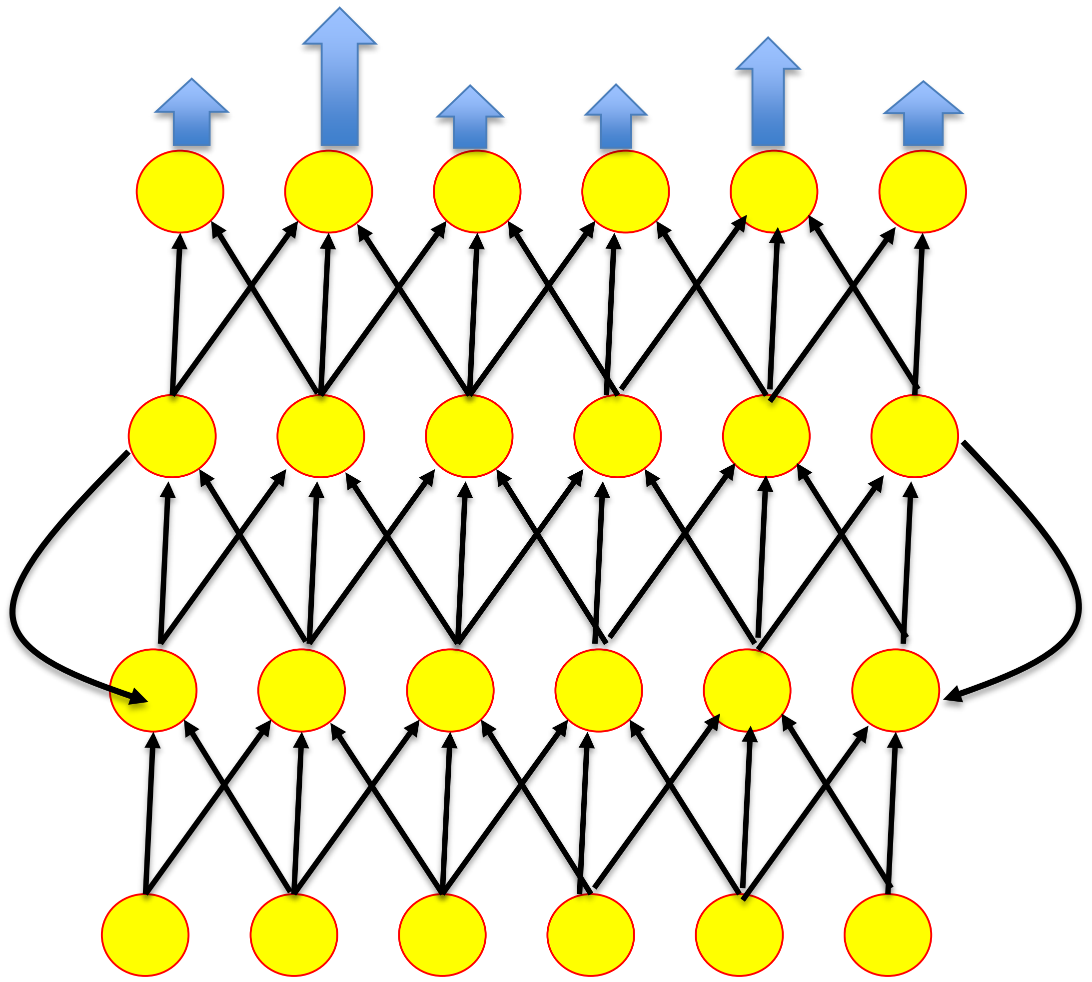
EPFL, Lausanne, Switzerland

1. The brain
2. Artificial Neural Networks
   - for classification
   - for action learning
   - for sequences (music, translation, speech)

Deep networks with recurrent connections

‘a man sitting on a couch with a dog’



Network desribes the image with the words:

‘a man sitting on a couch with a dog’

(Fang et al. 2015)

Quiz: Classification versus Reinforcement Learning

[ ] Classification is based on rewards
[ ] Reinforcement learning is based on rewards
[ ] Reinforcement learning aims at optimal action choices
[ ] Classification aims at predicting the correct category such as ‘car’ or ‘dog’

Artificial Neural Networks

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EPFL, Lausanne, Switzerland

1. The brain
2. Artificial Neural Networks
   - for classification
   - for action learning
   - for sequences
3. Overview of class

Artificial Neural Networks

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1. Simple perceptrons for classification
2. Backprop and multilayer perceptron
3. Statistical Classification by deep networks
4. Deep learning:
   regularization and tricks of the trade
5. Complements to deep learning
6. Sequence predictions and LSTMs
7. Convolutional networks
8. Reinforcement learning1: TD learning
9. Reinforcement learning2: SARSA
10. Reinforcement learning3: Policy Gradient
11. Deep Reinforcement learning
12. Applications

Artificial Neural Networks

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EPFL, Lausanne, Switzerland

1. Simple perceptrons for classification
2. Backprop and multilayer perceptron
3. Statistical Classification by deep networks ← miniproject1
4. Deep learning:
   regularization and tricks of the trade
5. Complements to deep learning
6. Sequence predictions and LSTMs ← miniproject2
7. Convolutional networks
8. Reinforcement learning1: TD learning
9. Reinforcement learning2: SARSA
10. Reinforcement learning3: Policy Gradient ← miniproject3
11. Deep Reinforcement learning
12. Applications

Miniprojects (MPs): we use software package ‘Keras’

- hand in 2 (or 3) out of 3 projects
- graded on a scale of 1-6
- average grade of MPs counts 1/3 toward final grade
- we do fraud detection interviews
- you get three weeks for each MP
- MP can be done alone or in group of two students
- interview for final MP is in first week after end of classes

→ **plan ahead!!**

Written exam:

- counts 2/3 toward final grade
- no tools allowed (no calculator, no cell phone, no paper, no book)
- ‘mathy’

Exercise sessions as follows:

- hand-out of exercise sheet ***n*** Friday of week ***n***
- You work on it until Thursday of week ***n+1***
- Solutions posted at noon, Thursday ***n+1***
- Friday week ***n+1*** by 10:00 am: you vote for the one exercise that you want to be explained
- Friday week ***n+1*** at 12:00 am. This exercise is explained on the blackboard + Q&A

  \+ Q&A for miniprojects

TA's:
- Dr. Johannni Brea
- Dane Corneil
- Florian Colombo
- Teo Stocco

Artificial Neural Networks

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EPFL, Lausanne, Switzerland

- The math is developed on the blackboard
- There are no written course notes!!
- All of the contents are standard textbook material

Choose a textbook that you like:

For first half of class:

- *Pattern Recognition and Machine Learning*, C.M Bishop, 2006
- *Neural Networks for Pattern Recognition*, C.M. Bishop, 1995
- *Deep Learning*, Ian Goodfellow et al., 2017 (also online)

For second half of class:

- *Reinforcement learning,* R. Sutton+ A. Barto (2^{nd} ed, online)

Artificial Neural Networks

Prerequisits:

CS433, Pattern Classification and Machine Learning
(Profs Jaggi+Urbanke)

Rules:

If you have taken this class: please ask many questions

If you have not taken this class: please do not complain

Artificial Neural Networks

Learning outcomes:

- apply learning in deep networks to real data
- assess/evaluate performance of learning algorithms
- Elaborate relations between different mathematical concepts of learning
- judge limitations of learning algorithms
- propose models for learning in deep networks

Transversal skills:

Access and evaluate appropriate sources of information
Manage priorities
work through difficulties, write a technical report

Artificial Neural Networks

Work load:

4 credit course → 6 hours per week for 18 weeks

(1 ECTS = 27 hours of work)

Questions?

… before we start

TA’s this year:

- Dr. Johannni Brea
- Dane Corneil
- Florian Colombo
- Teo Stocco

Artificial Neural Networks: Lecture 1
Simple Perceptrons for Classification

Wulfram Gerstner
EPFL, Lausanne, Switzerland

Objectives for today:

- understand classification as a geometrical problem
- discriminant function of classification
- linear versus nonlinear discriminant function
- perceptron algorithm
- gradient descent for simple perceptrons

1. The problem of Classification

car (yes or no)

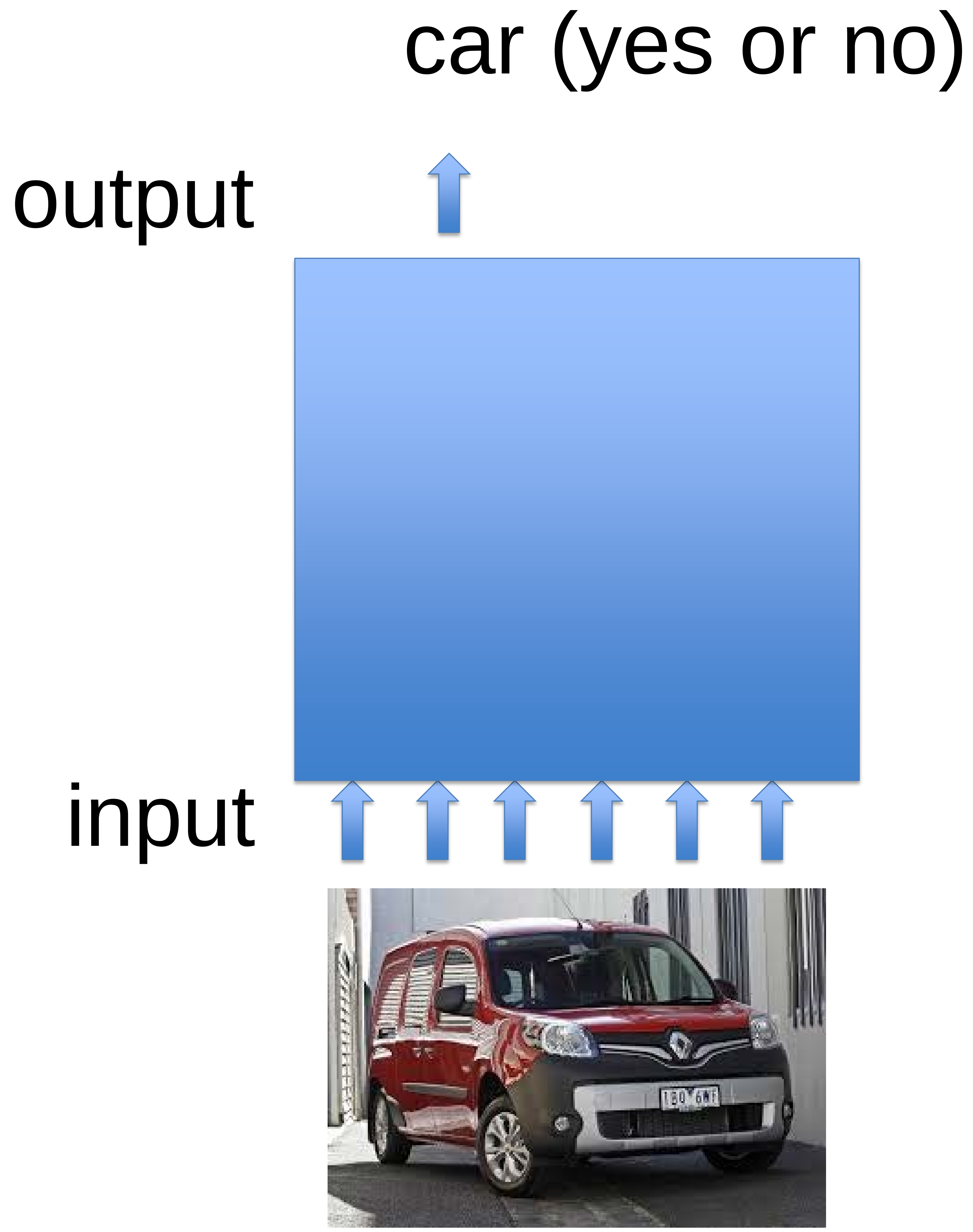
output

the classifier

input

1. The problem of Classification

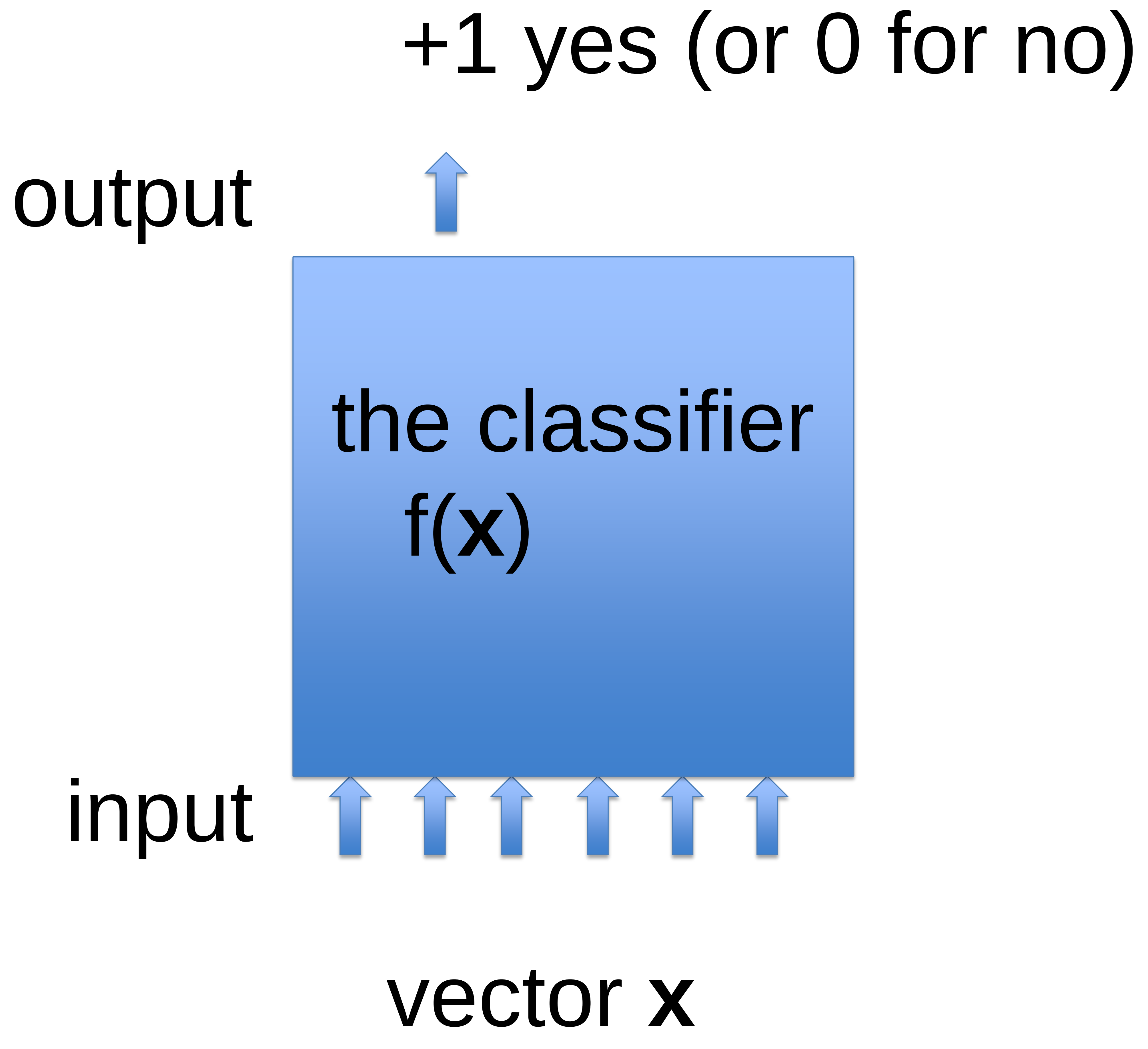
Blackboard 1:
from images to vector



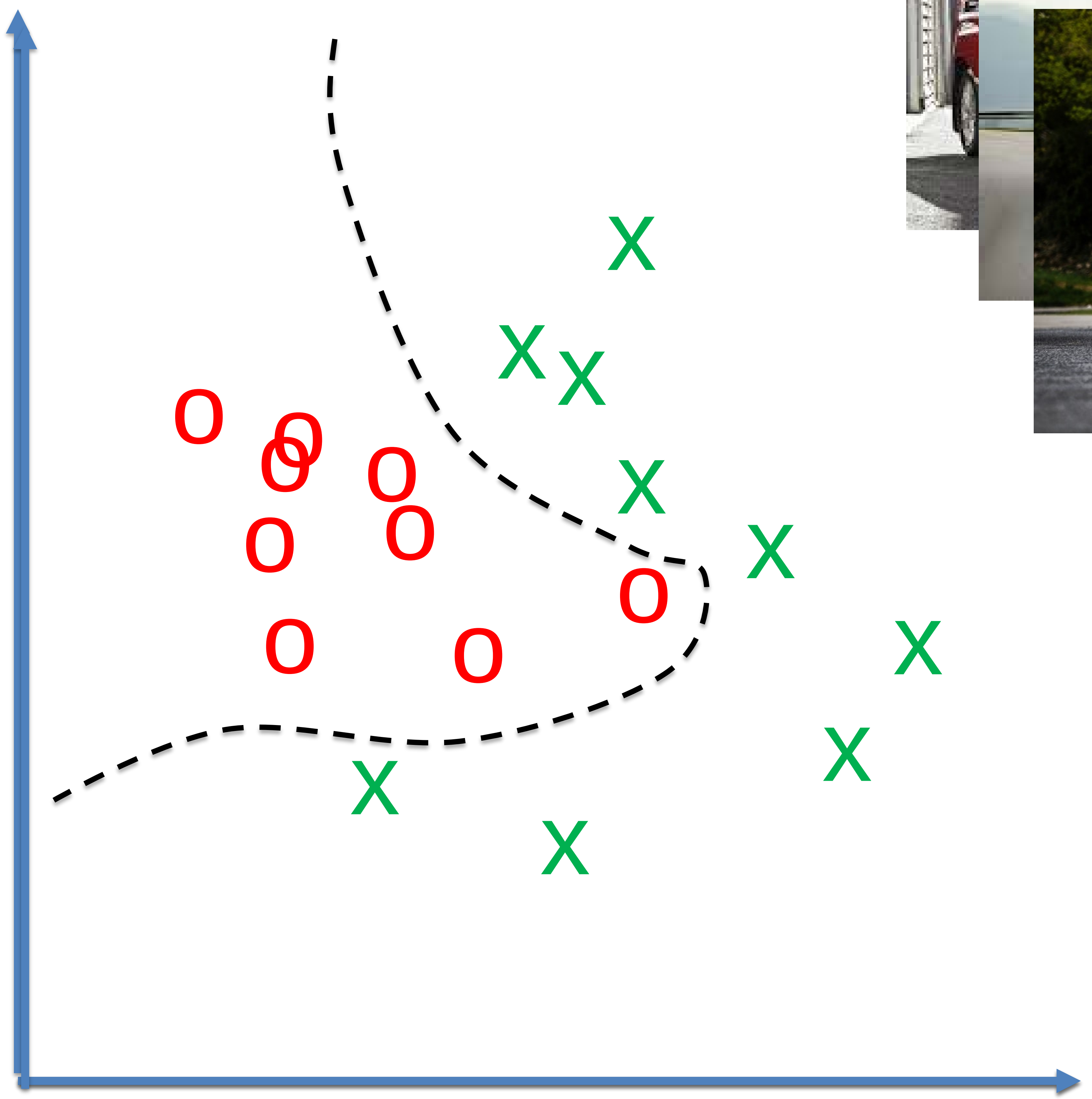
Blackboard 1:

from images to vector

1. The problem of Classification



1. Classification as a geometric problem



Blackboard 2:

from vectors to classification

Blackboard 2:

from vectors to classification

1. Classification as a geometric problem

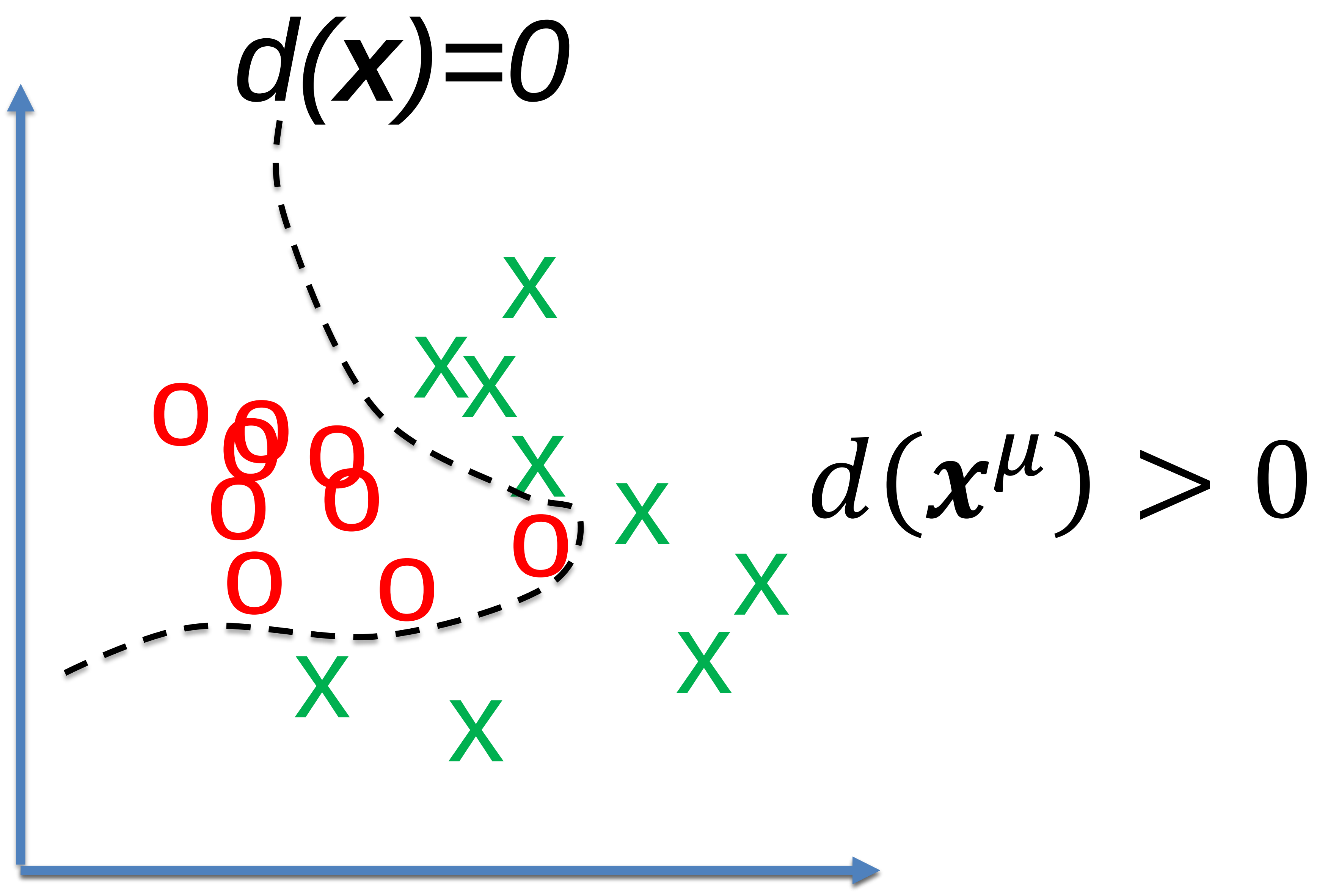
Task of Classification

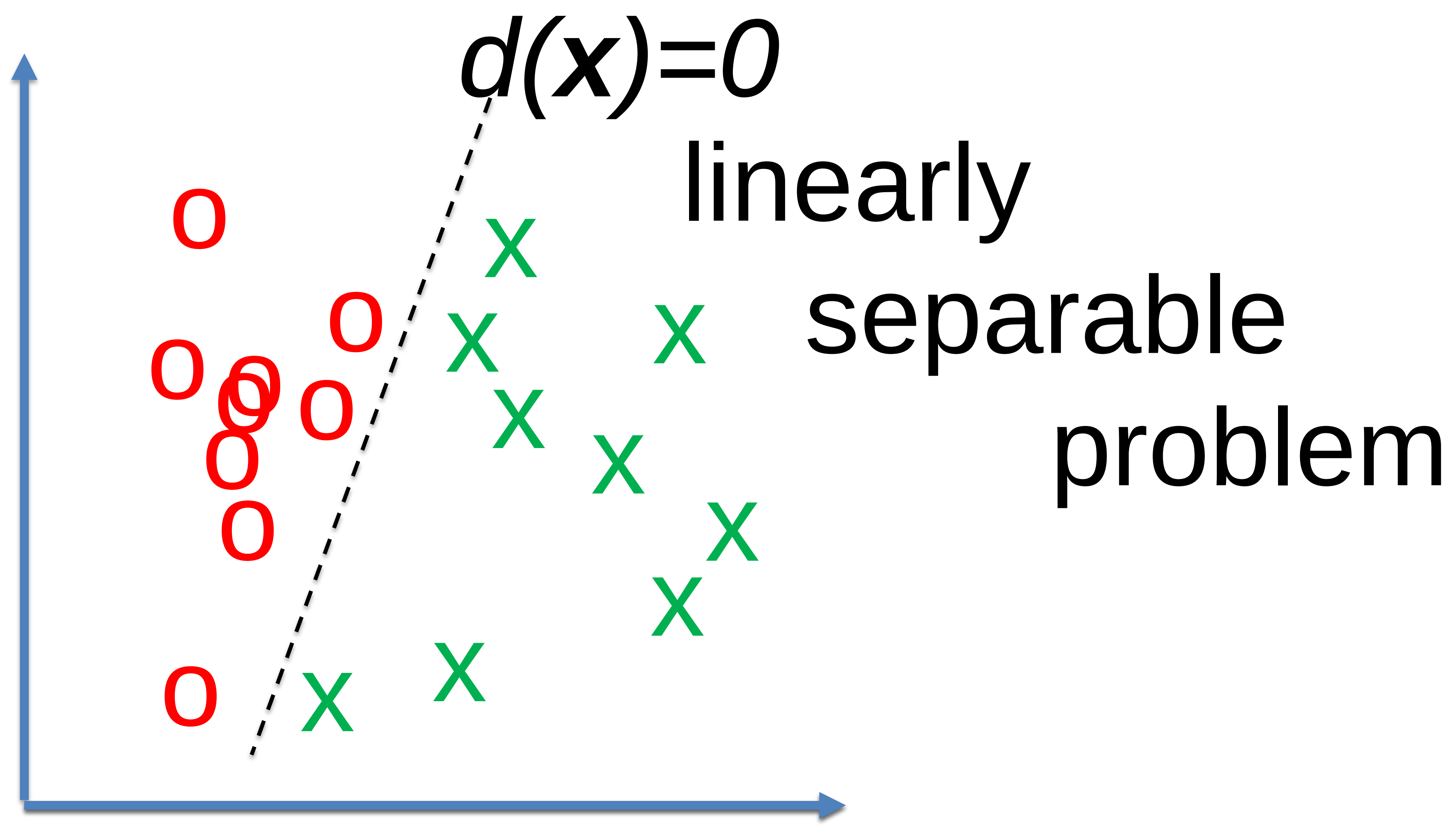
= find a **separating surface** in the high-dimensional input space

Classification by **discriminant function** $d(\mathbf{x})$

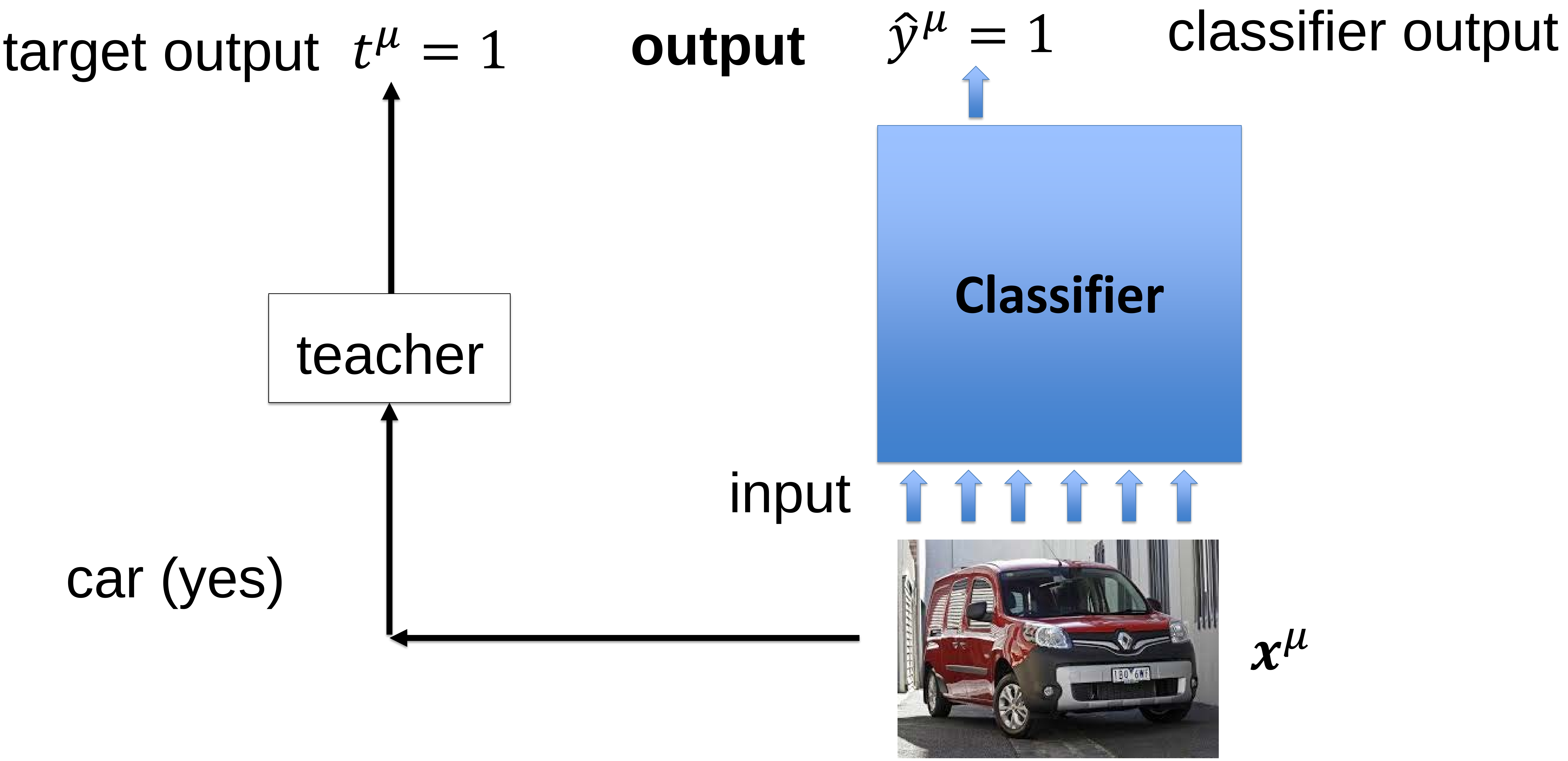
→ $d(\mathbf{x})=0$ on this surface; $d(\mathbf{x})>0$ *for all positive examples* $\mathbf{x}$

$d(\mathbf{x})<0$ *for all counter examples* $\mathbf{x}$





2. Data base for Supervised learning



2. Data base for Supervised learning

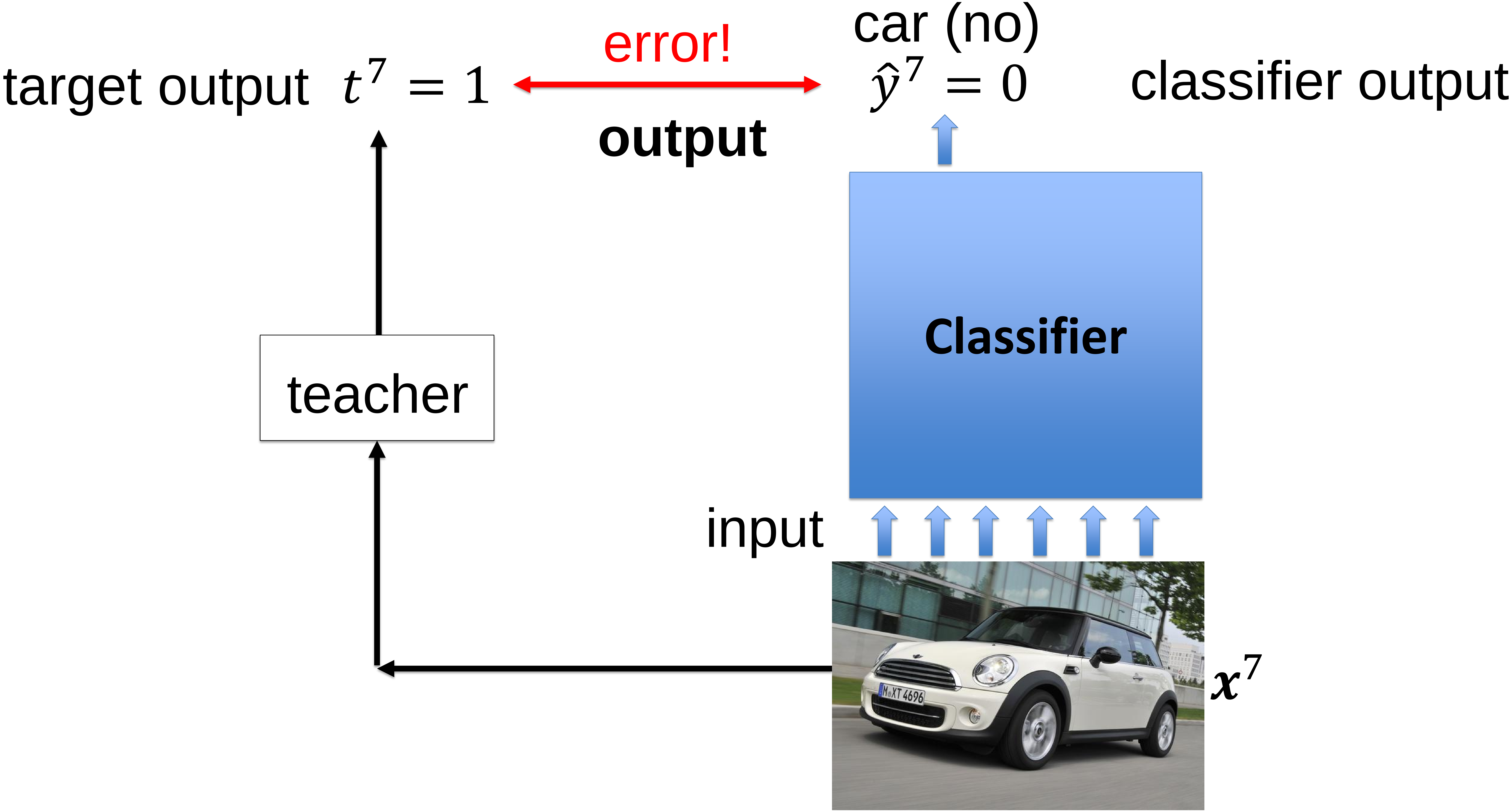
P data points $\{ \quad (\boldsymbol{x}^{\mu}, t^{\mu}) \quad , \qquad 1 \le \mu \le P \quad \};$

input target output

$t^{\mu} = 1$ car =yes

$t^{\mu} = 0$ car =no

2. Data base for Supervised learning



2. Data base for Supervised learning

P data points $\{ \quad (\boldsymbol{x}^\mu, t^\mu) \quad , \qquad 1 \le \mu \le P \quad \};$

input target output

for each data point $\boldsymbol{x}^\mu$, the classifier gives an output y^μ

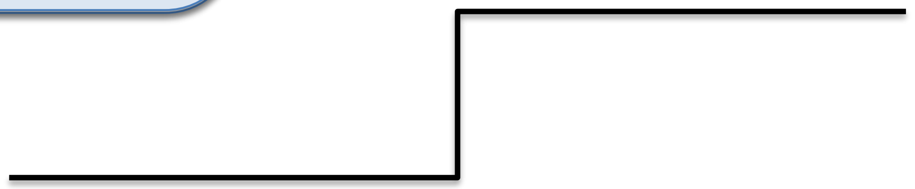
→ **use errors** $\hat{y}^\mu \neq t^\mu$ **for optimization of classifier**

Remark: for multi-class problems $\mathbf{y}$ and $\boldsymbol{t}$ are vectors

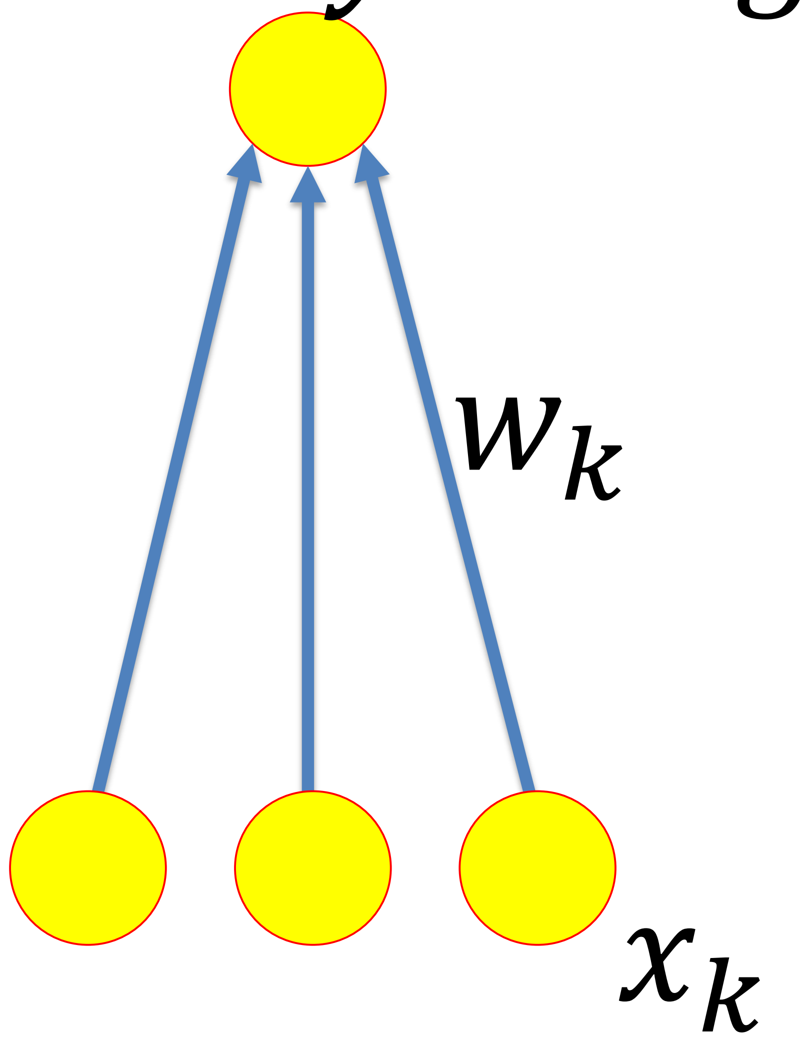
3. Single-Layer networks: simple perceptron

Blackboard 3:
hyperplane

$$\hat{y} = g(a') = \begin{cases} +1 \text{ if } a' > \vartheta \\ 0 \text{ if } a' < \vartheta \end{cases}$$



$$\hat{y} = g\left(\sum_k w_k \, x_k\right)$$



output $\hat{y} = f(\boldsymbol{x})$

vector $\boldsymbol{x}$

Blackboard 3:

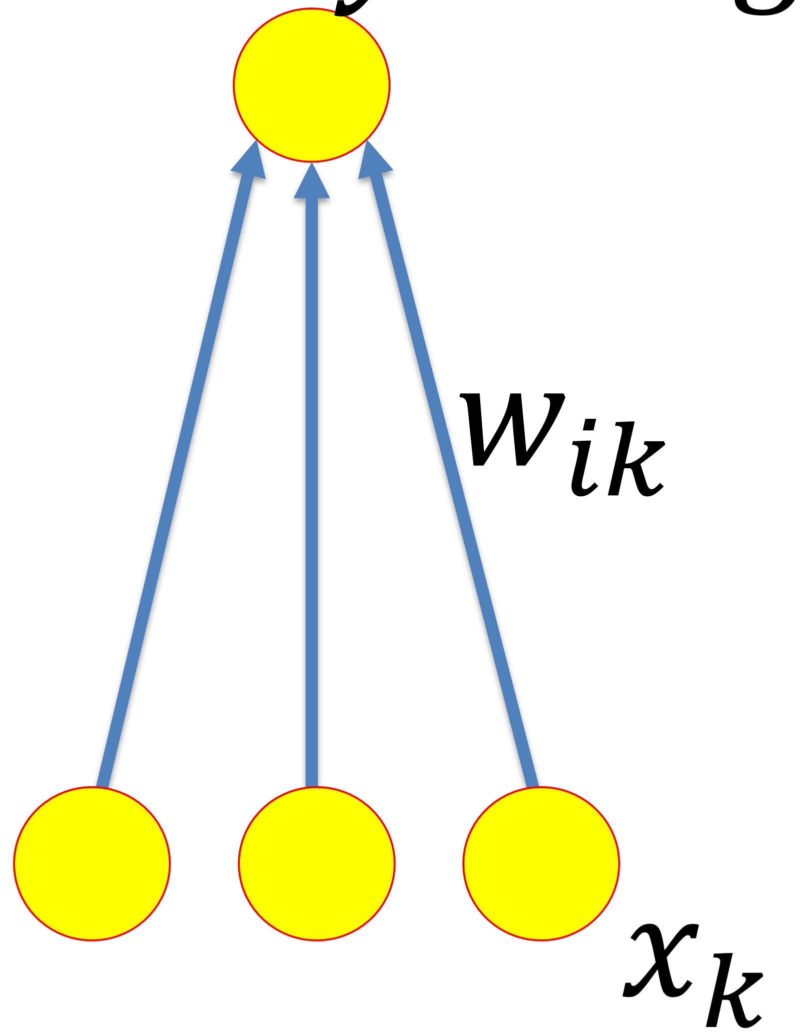
hyperplane

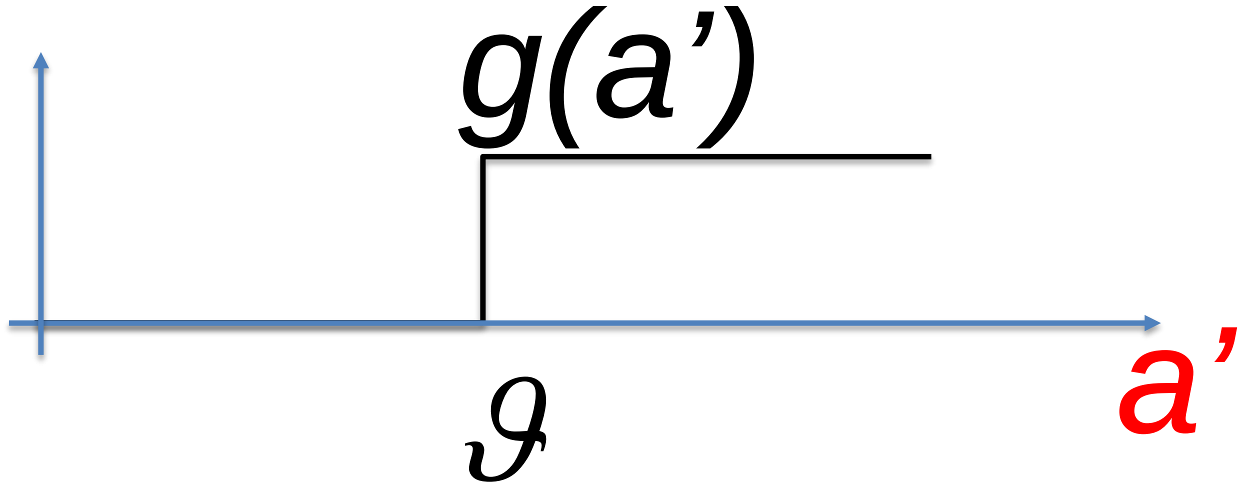
3. Single-Layer networks: simple perceptron

$$\hat{y}^{\mu} = 0.5[1 + sgn(\underbrace{\textstyle\sum_k w_k\, x_k - \vartheta)]}_{a}$$

output

$$\hat{y}^{\mu} = g\left(\underbrace{\sum_k w_k\, x_k}_{a'}\right)$$





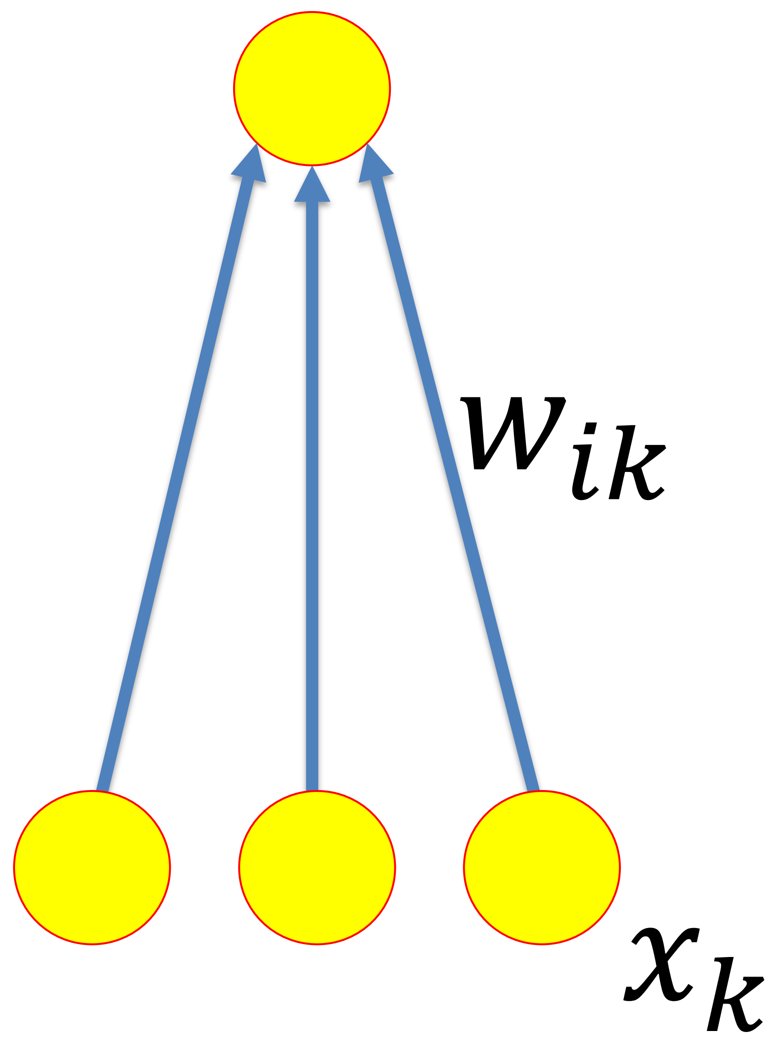
$$g(a') = \begin{cases} 1 & \text{if } a' > \vartheta \\ 0.5 & \text{if } a' = \vartheta \\ 0 & \text{if } a' > \vartheta \end{cases}$$

input

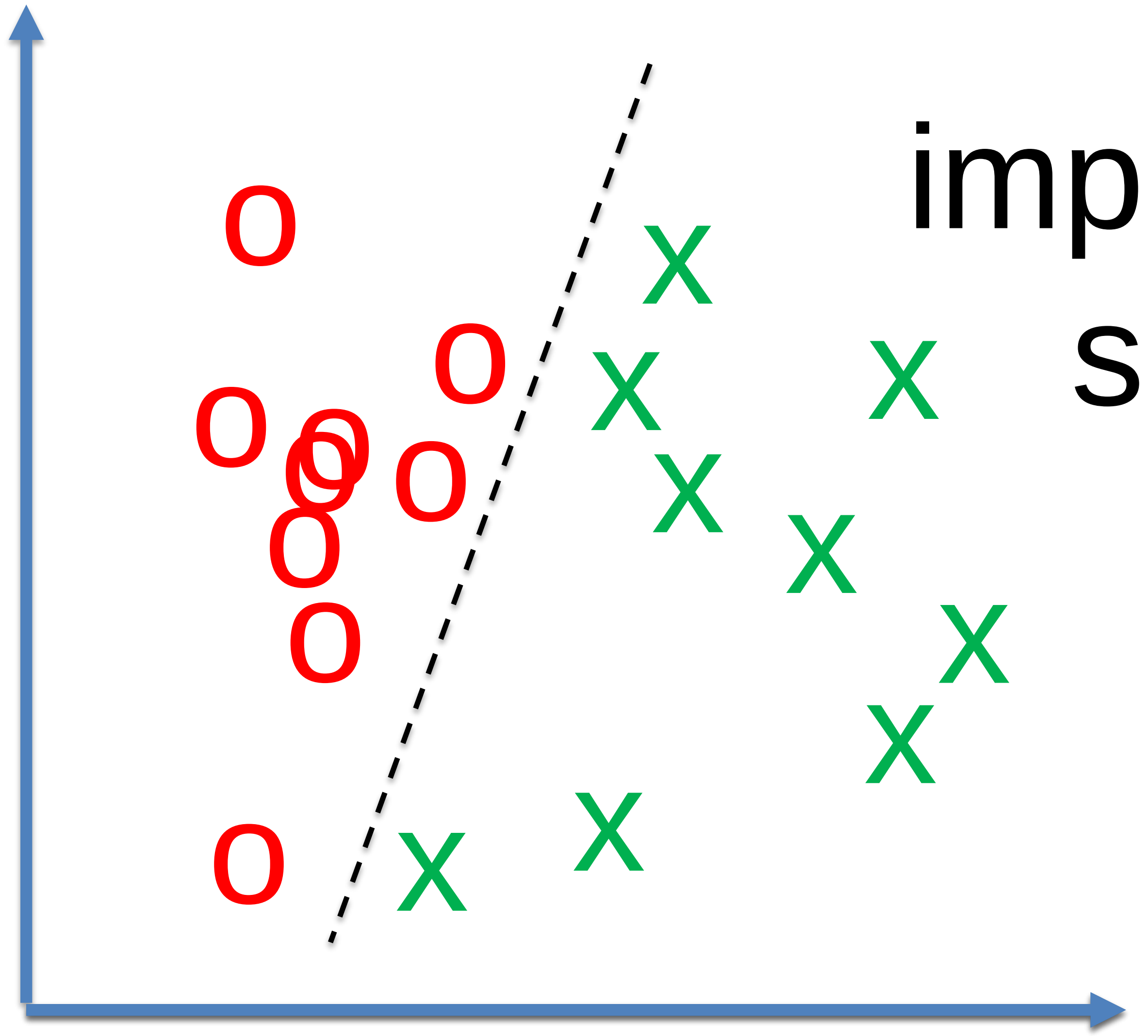
vector $\boldsymbol{x}$

3. Single-Layer networks: simple perceptron

$$\hat{y} \quad = 0.5[1 + sgn(\sum_k w_k \, x_k - \vartheta)]$$



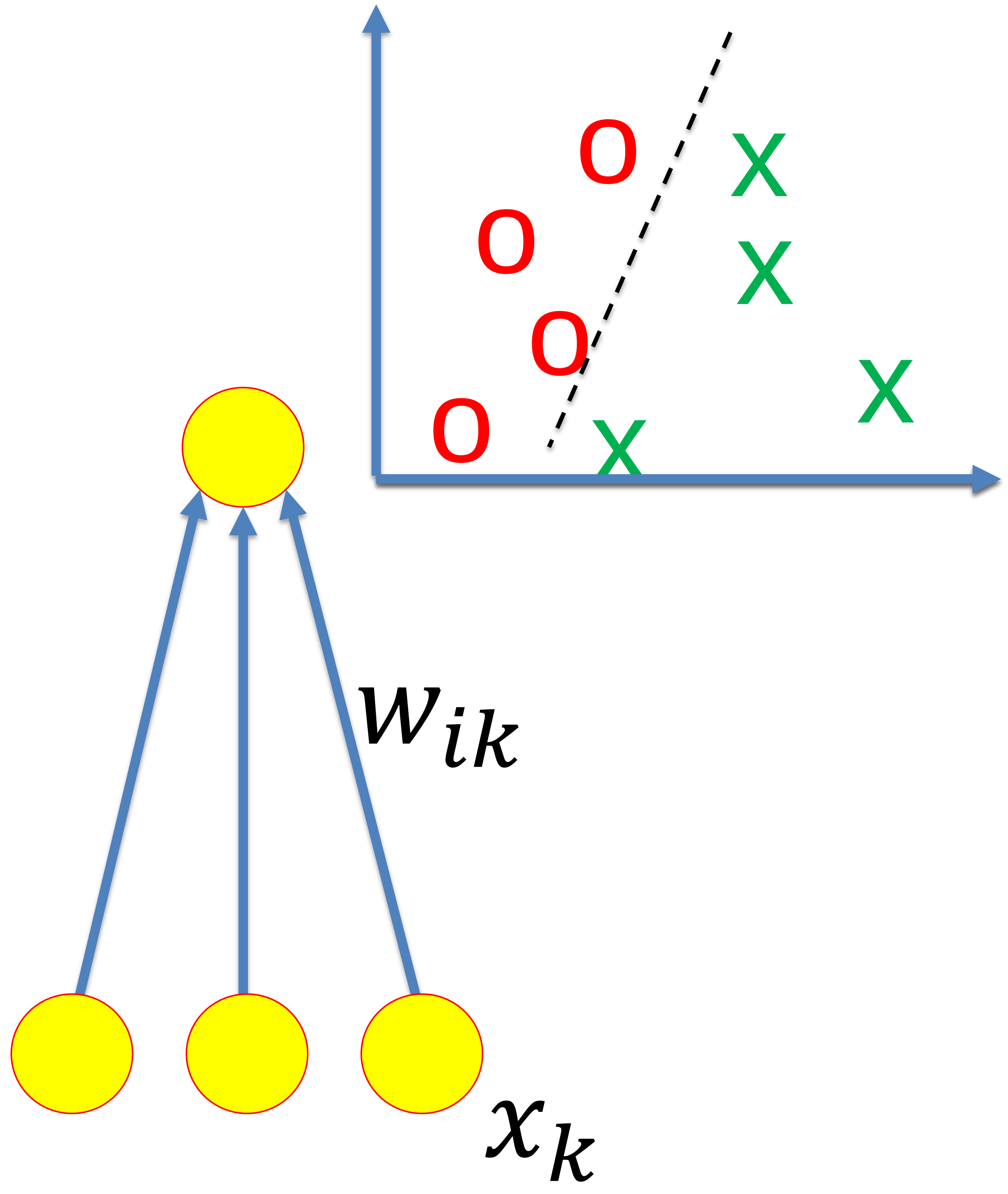
$$d(\boldsymbol{x}) = \sum_k w_k \, x_k - \vartheta = 0$$



imposes a linear separation

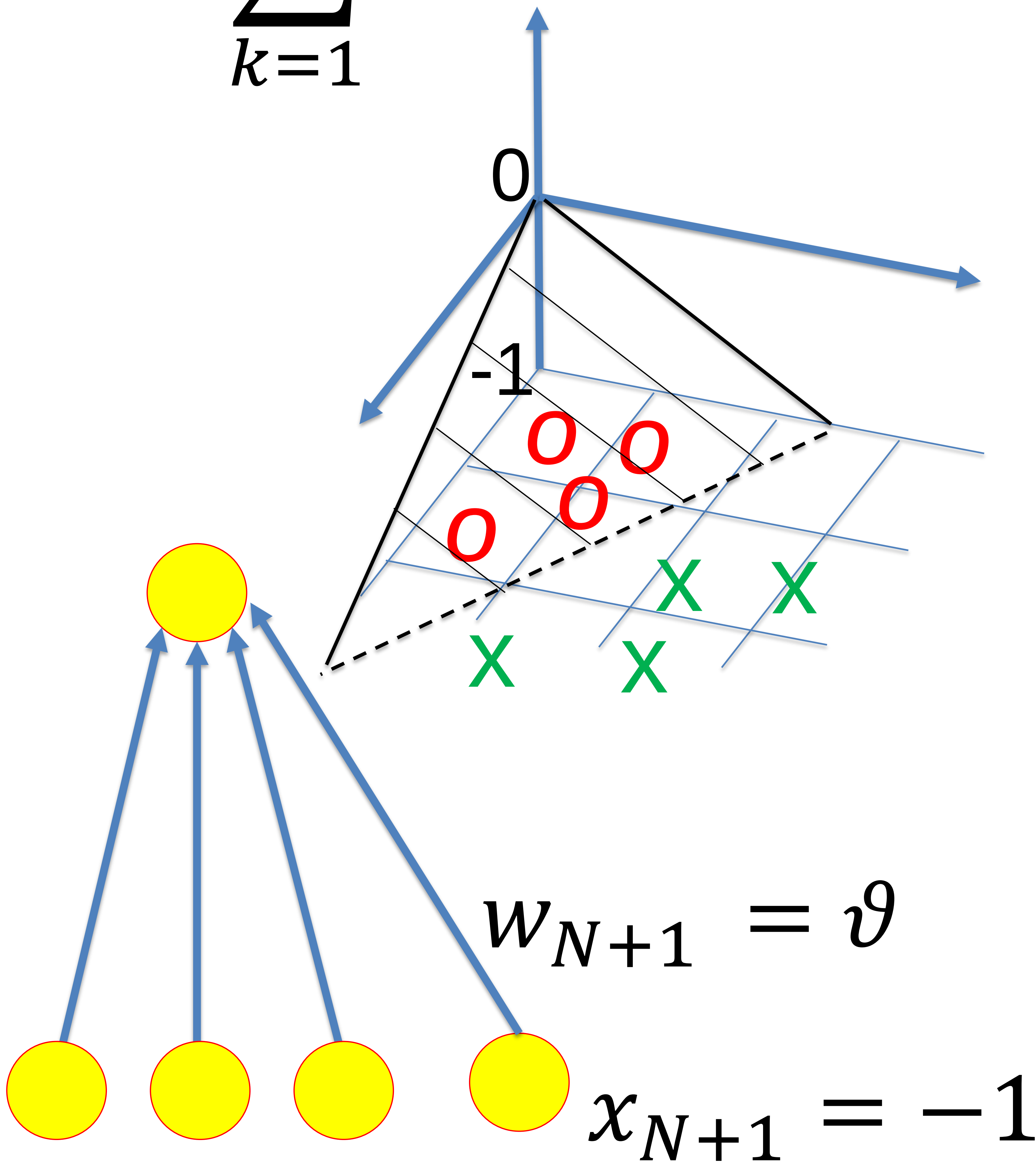
3. remove threshold: add a constant input

$$d(\boldsymbol{x}) = \sum_{k=1}^{N} w_k\, x_k - \vartheta \;= 0$$



$\boldsymbol{x} \in R^N$

$$d(\boldsymbol{x}) = \sum_{k=1}^{N+1} w_k\, x_k \;= 0$$



$\boldsymbol{x} \in R^{N+1}$

3. Single-Layer networks: simple perceptron

a simple perceptron

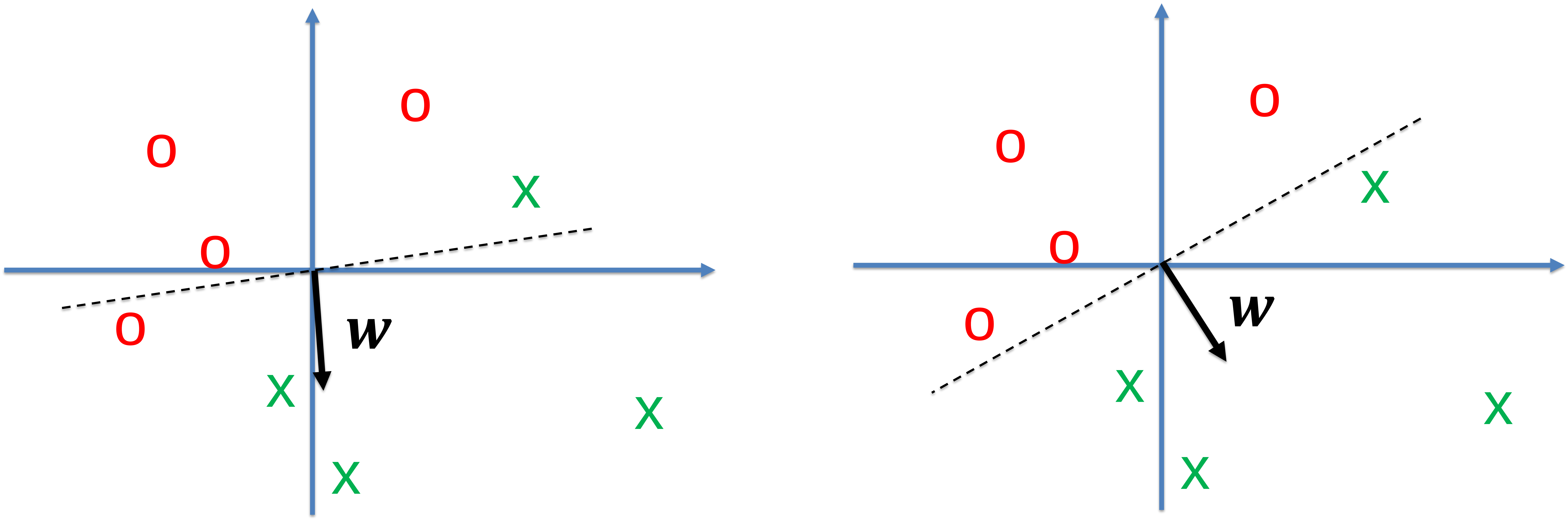
- can only solve linearly separable problems
- imposes a separating hyperplane
- for $\vartheta = 0$ hyperplane goes through origin
- threshold parameter ϑ can be removed by adding an input dimension

→ in ***N+1*** dimensions hyperplane always goes through origin

- We can **adapt the weight vector** to the problem

4. Perceptron algorithm: turn weight vector (in N+1 dim.)

$$hyperplane:\ d(\boldsymbol{x}) = \sum_{k=1}^{N+1} w_k\, x_k = \boldsymbol{w}^T \boldsymbol{x} \ = 0$$



4. Perceptron algorithm: turn weight vector

Blackboard 4:
geometry of perceptron algo

$$\Delta \boldsymbol{w} \sim \boldsymbol{x}^{\mu}$$

Perceptron algo (in N+1 dimensions):

- set $\mu = 1$

(1) cycle many times through patterns

- choose pattern μ
- calculate output

$$\hat{y}^{\mu} = 0.5[1 + sgn(\boldsymbol{w}^T \boldsymbol{x}^{\mu})]$$

- update by

$$\Delta \boldsymbol{w} = \gamma [t^{\mu} - \hat{y}^{\mu}] \boldsymbol{x}^{\mu}$$

- iterate $\mu \leftarrow (\mu + 1) mod \boldsymbol{P}$, back to (1)

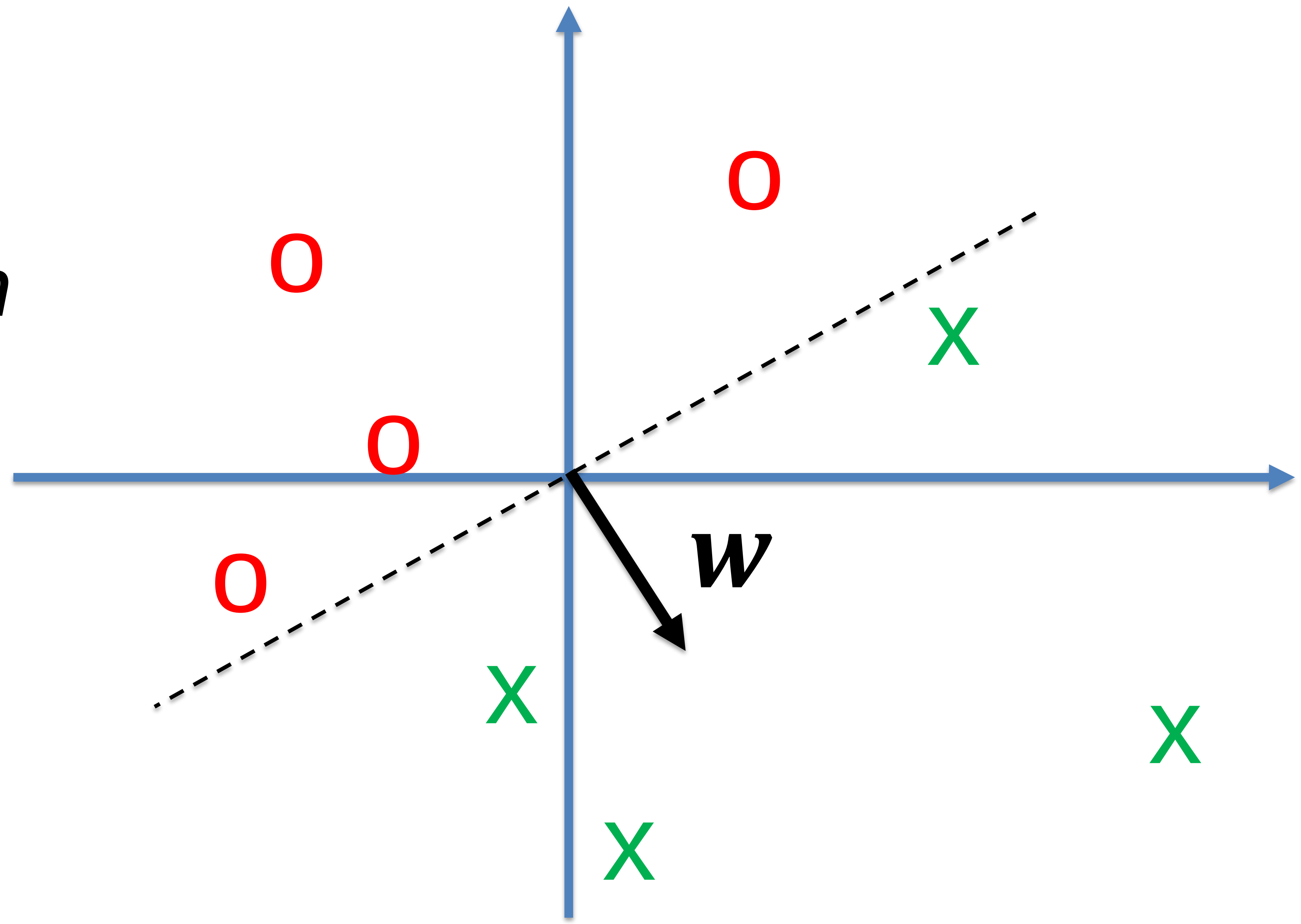
(2) stop if no changes for all ***P*** patterns

Blackboard 4:
geometry of the perc. algo

4. Perceptron algorithm: theoreom

If the problem is linearly separable, the perceptron algorithm converges in a finite number of steps.

Proof: in many books, e.g., Bishop, 1995,
Neural Networks for Pattern Recognition



Quiz: Perceptron algorithm

The **input vector has *N* dimensions** and we apply a perceptron algorithm.

[ ] A change of parameters corresponds always to a rotation of the separating hyperplane in N dimensions.

[ ] A change of parameters corresponds always to a rotation of the separating hyperplane in N+1 dimensions.

[ ] An increase of the length of the weight vector implies an increase of the distance of the hyperplane from the origin in N dimensions.

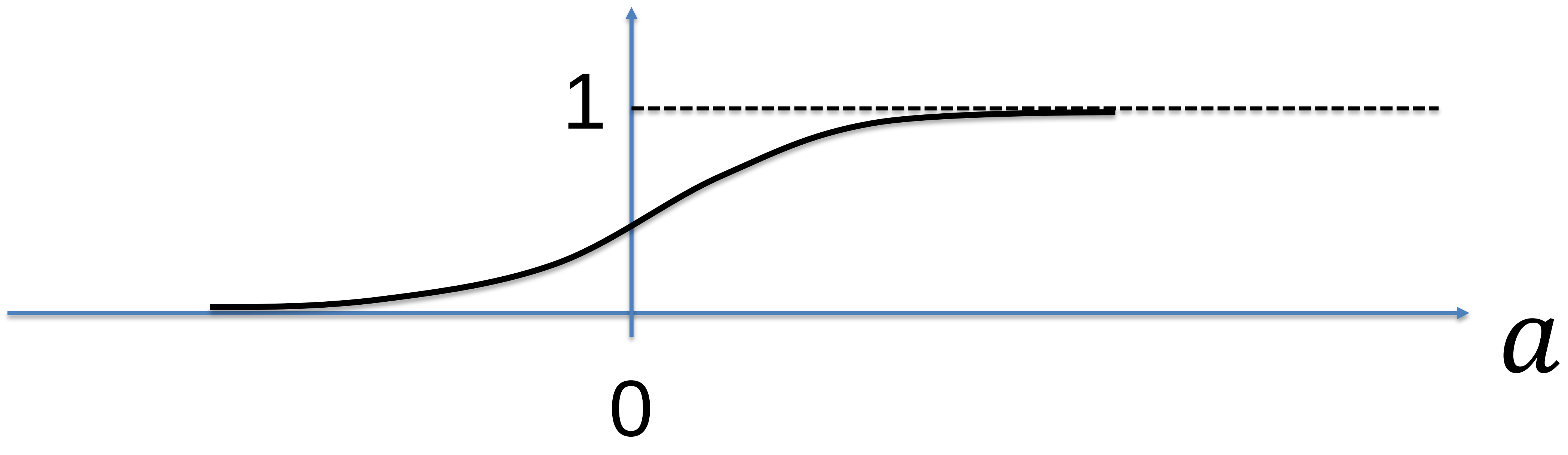
[ ] An increase of the length of the weight vector implies that the hyperplane does not change in N dimensions

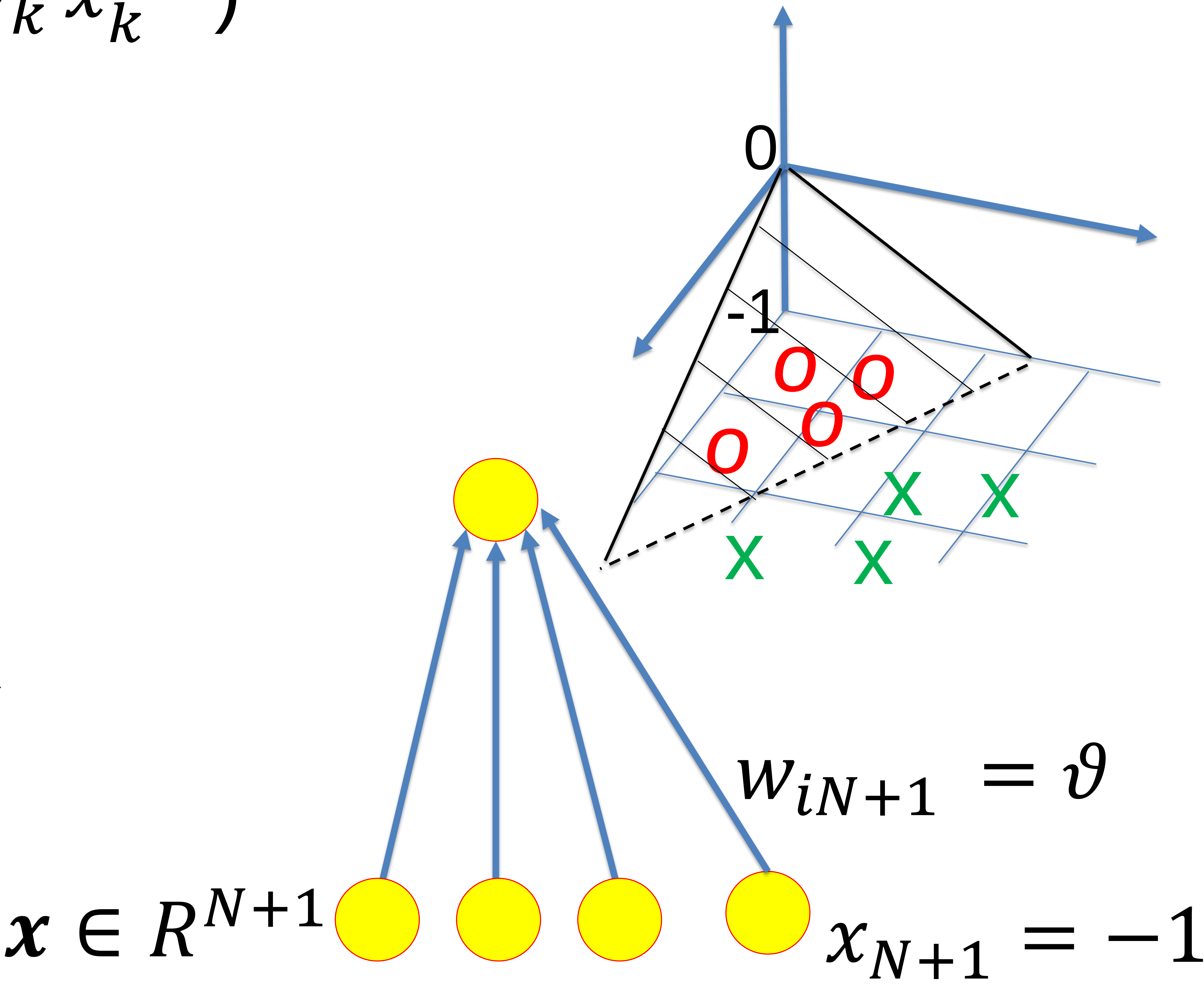
[ ] An increase of the length of the weight vector implies that the hyperplane does not change in N+1 dimensions

5. Sigmoidal output unit

$$\hat{y}^{\mu} = g(\boldsymbol{w}^T \boldsymbol{x}^{\mu}) = g(\textstyle\sum_{k=1}^{N+1} w_k \, x_k^{\mu} \;)$$

$$g(a) = \frac{\exp(a)}{1 + \exp(a)}$$





5. Supervised learning with sigmoidal output

target output $t^7 = 1$ ⟷ error! ⟷ $\hat{y}^7 = 0.2$ classifier output

output

$\boldsymbol{f}(\boldsymbol{x}^7) = g(\boldsymbol{w}^T \boldsymbol{x}^\mu)$

Classifier

teacher

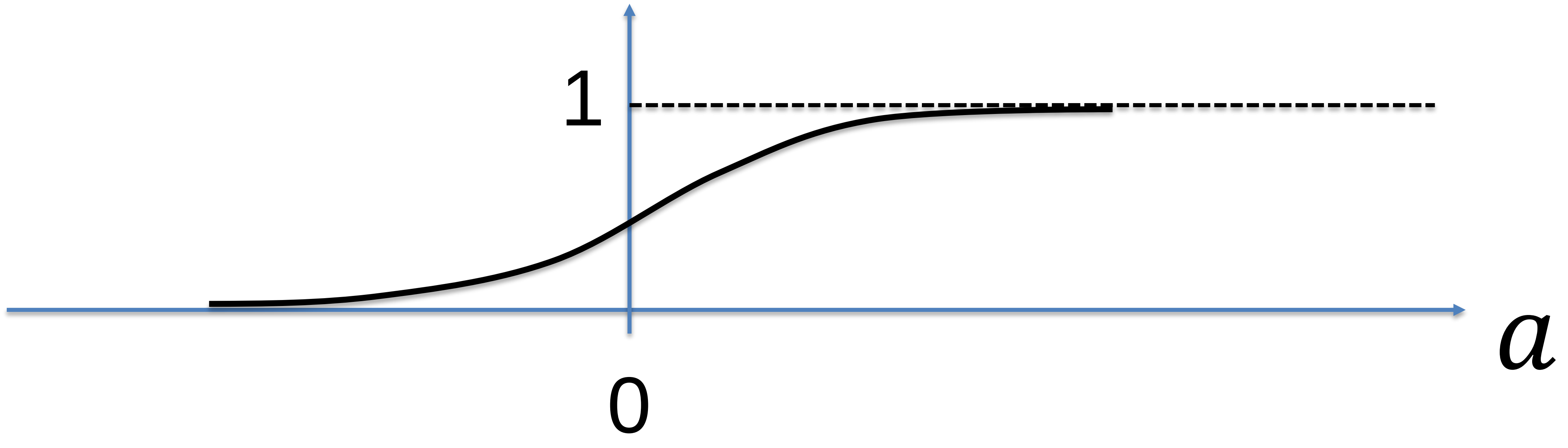
input

$\boldsymbol{x}^7$

5. Supervised learning with sigmoidal output

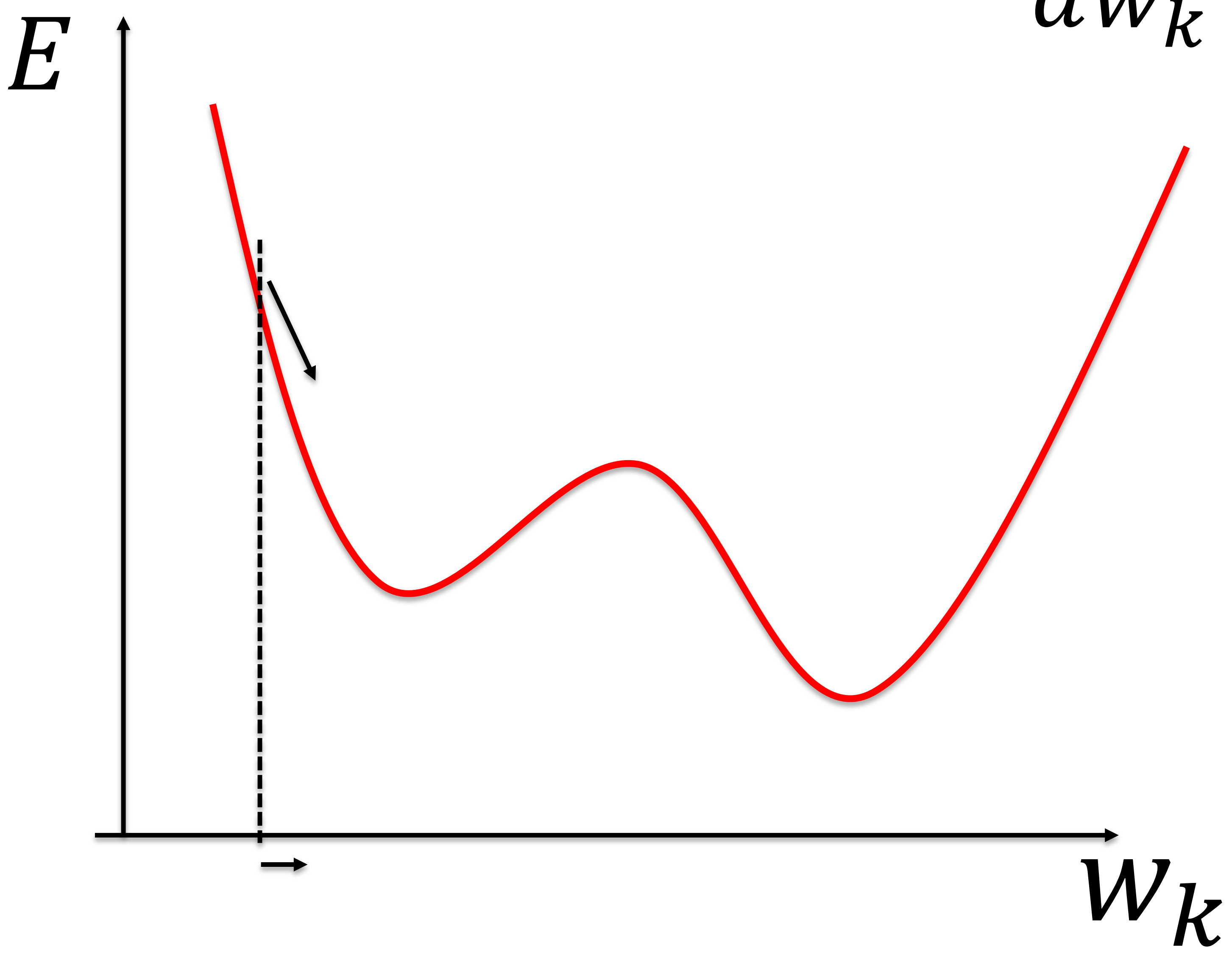
define error

$$E(\boldsymbol{w}) = \frac{1}{2}\sum_{\mu=1}^{P}\left[t^{\mu} - \hat{y}^{\mu}\right]^2$$

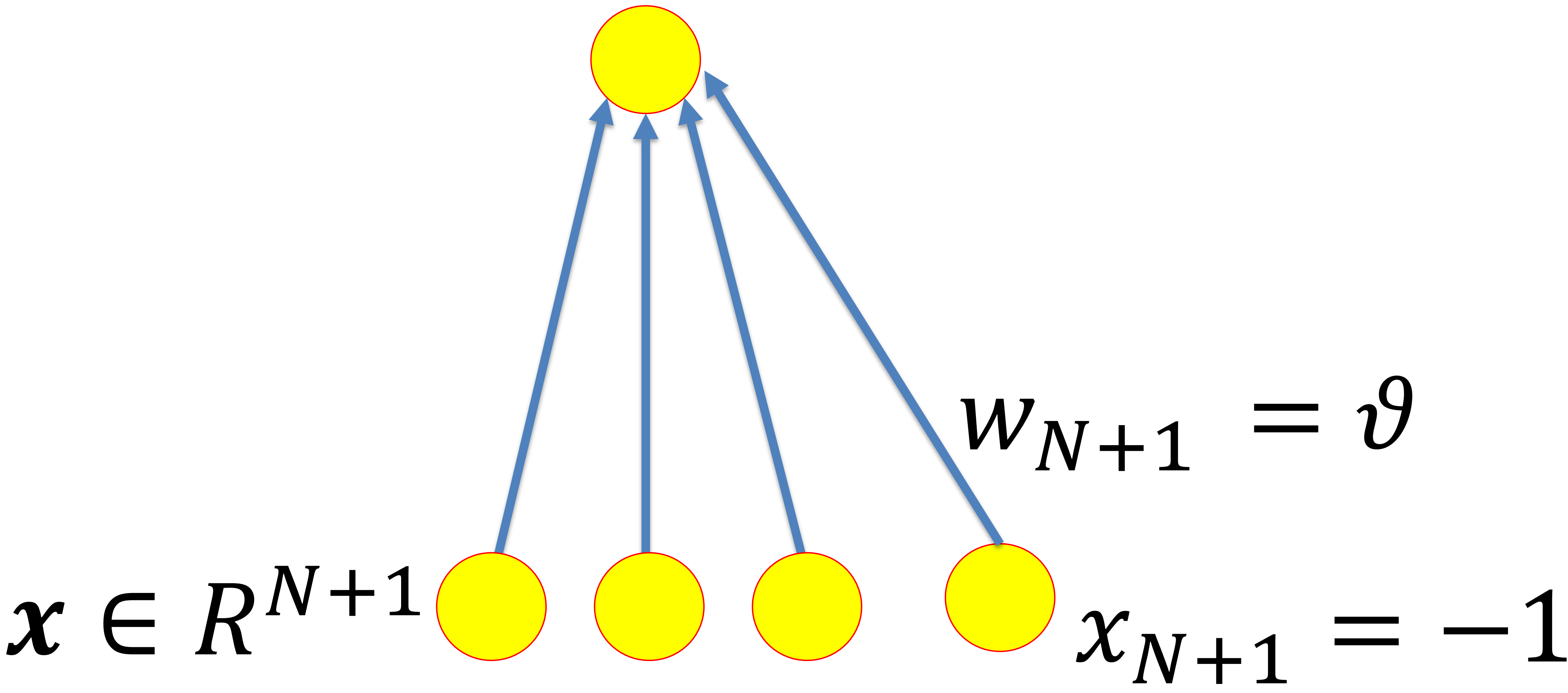


gradient descent

$$w_k = -\gamma \frac{dE}{dw_k}$$



$$\hat{y}^{\mu} = g(\boldsymbol{w}^T \boldsymbol{x}^{\mu})$$



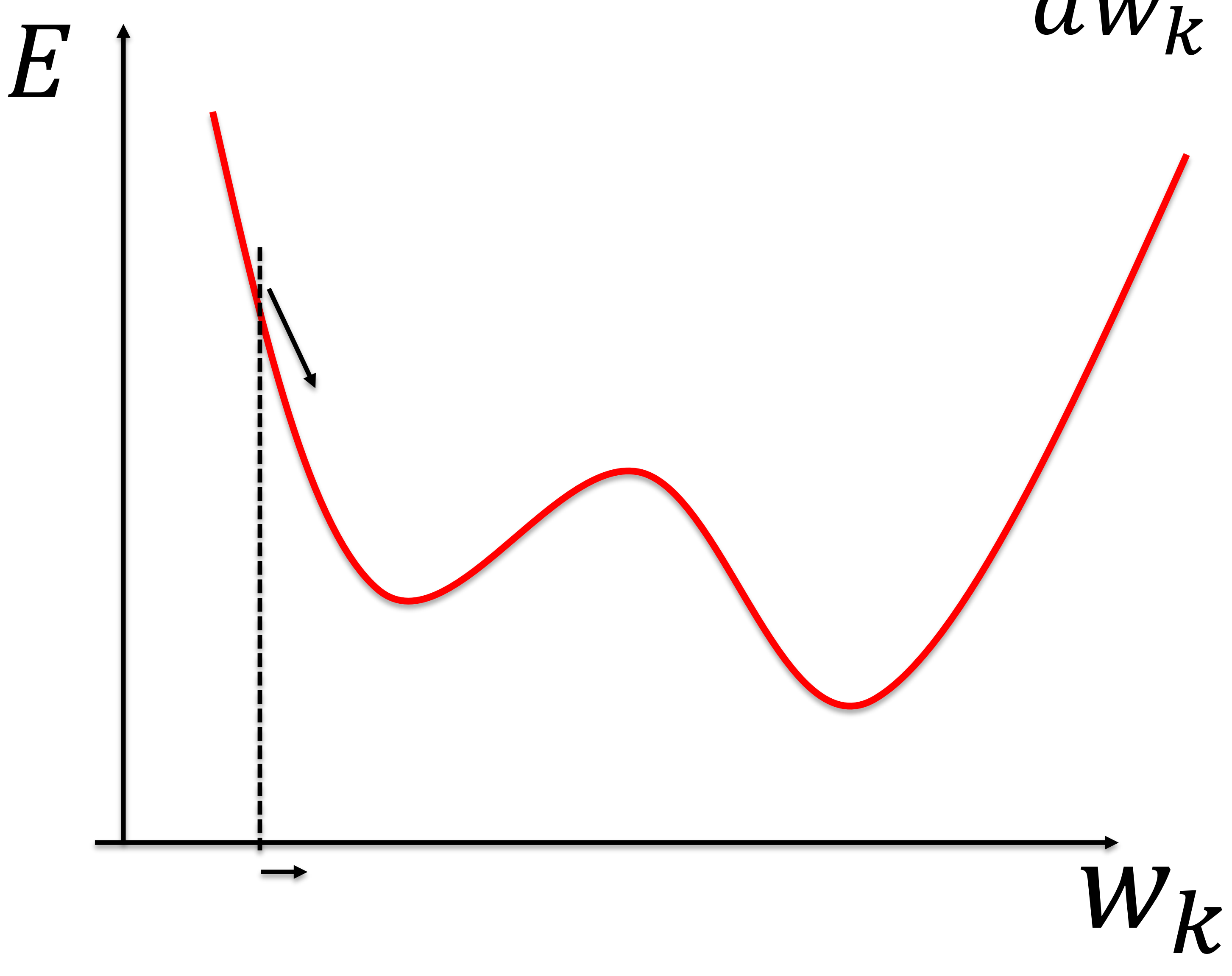
6. gradient descent

Quadratic **error**

$$E(\boldsymbol{w}) = \frac{1}{2}\sum_{\mu=1}^{P}\left[t^{\mu} - \hat{y}^{\mu}\right]^2$$

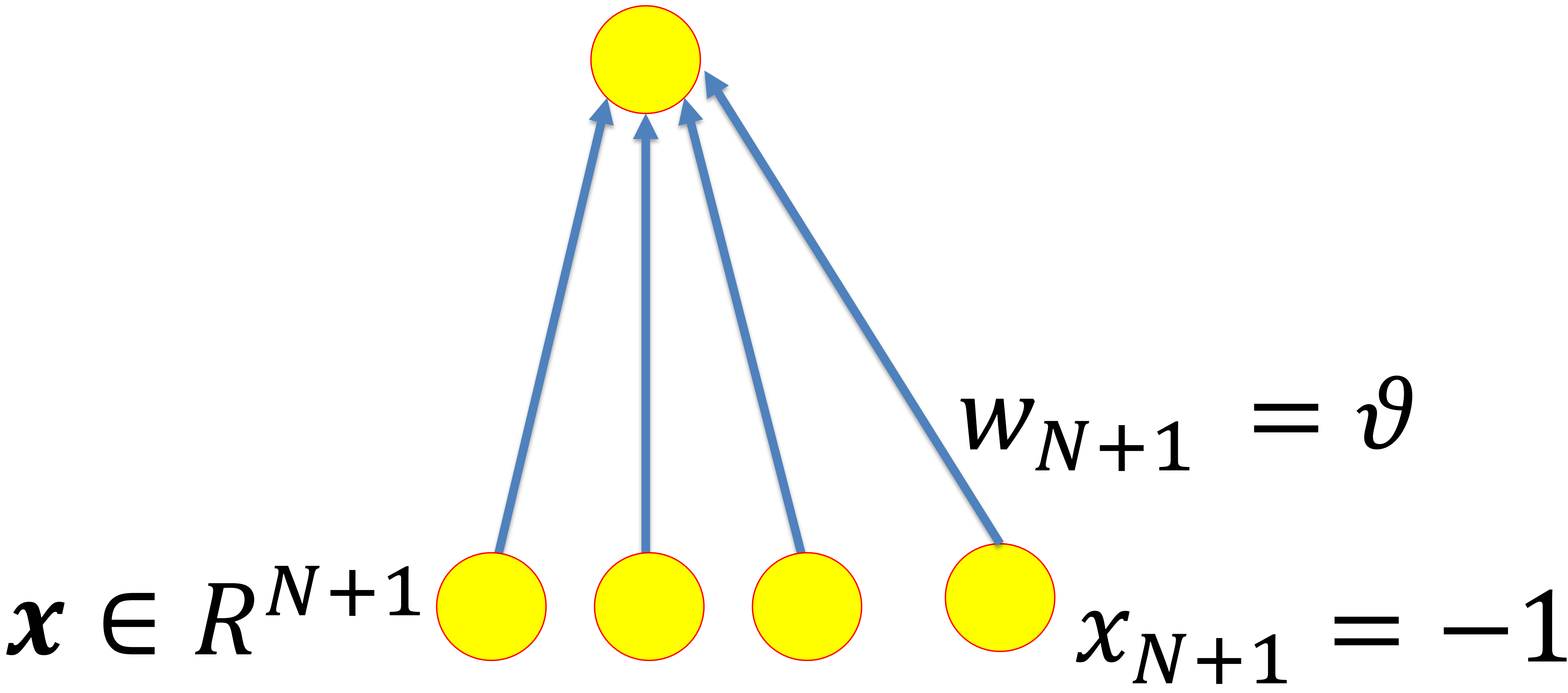
gradient descent

$$w_k = -\gamma \frac{dE}{dw_k}$$



Exercise 1.1 now:
- *calculate gradient (1 pattern)*
- *geometrical interpretation?*

$$\hat{y}^{\mu} = g(\boldsymbol{w}^T \boldsymbol{x}^{\mu})$$



Exercise 1.1 now:

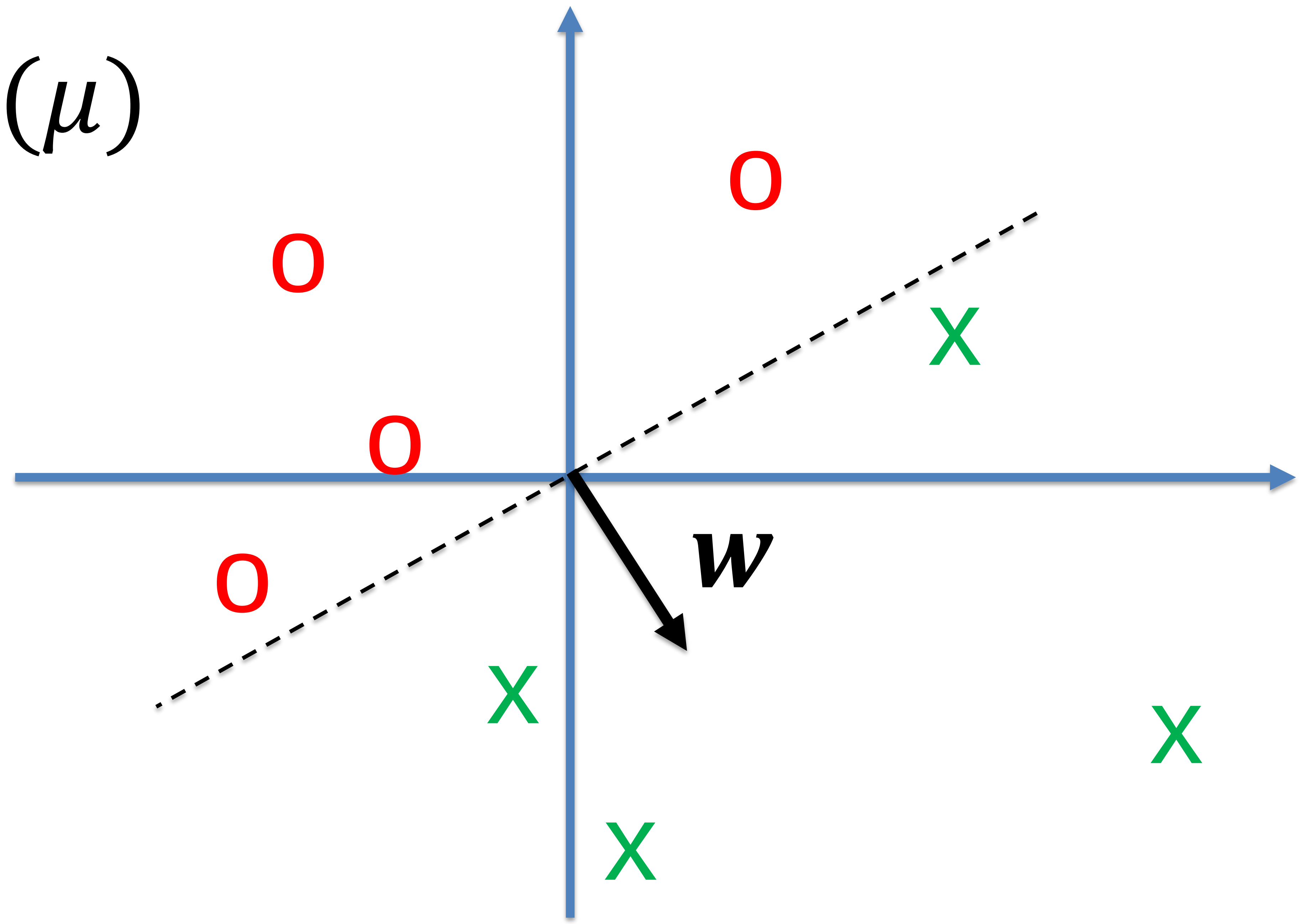
- calculate gradient (1 pattern)

- geometrical interpretation?

6. Gradient descent algorithm

$$\Delta \boldsymbol{w} = \gamma \delta(\mu) \boldsymbol{x}^{\mu}$$

- stepsize depends on (signed) output mismatch $\delta(\mu)$ for this data point
- change implemented even if ‘correctly classified
- compare with perceptron algorithm



Summary for today:

- understand classification as a geometrical problem
- discriminant function of classification
- linear versus nonlinear discriminant function
- perceptron algorithm
- gradient descent for simple perceptrons

Reading for this week:

Bishop, Ch. 4.1.7 of

Pattern recognition and Machine Learning

or

Bishop, Ch. 3.1-3.5 of

Neural networks for pattern recognition

Motivational background reading:

Silver et al. 2017, Archive

Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm

Goodfellow et al., Ch. 1 of

Deep Learning

The END