# Neural Networks

## Simple ANNs

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1

## Topics

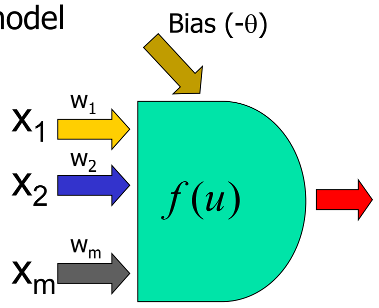
- Perceptron
  - Basics
  - Training
  - Test
  - Example
- Adaline
  - Basics
  - Differences

 2

2

# Perceptron

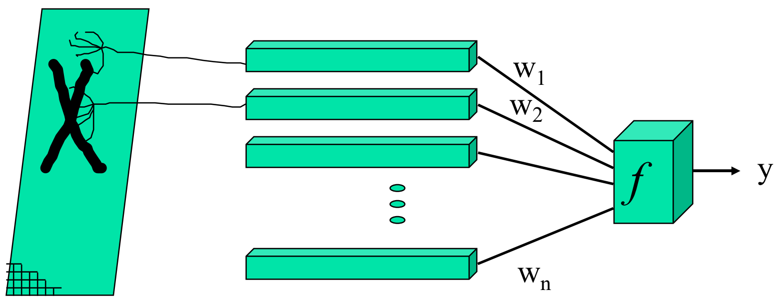
- First ANN implementation
  - Rosemblat, 1958
  - McCulloch-Pitts neuron model
- Training
  - Supervised
  - Error correction
    - $w_i(t)= w_i(t\text{-}1) + \Delta w_i$
      - $\Delta w_i = \eta x_i \delta$
      - $\Delta w_i = \eta x_i (y - f(\mu))$
- Convergence theorem




 3

3

# Perceptron architecture

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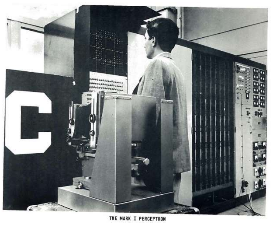
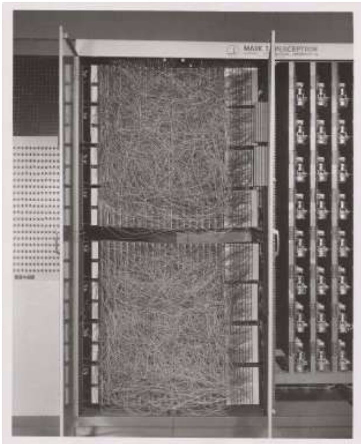
4

## Perceptron implementation

- First implementation:
  - Mark I Perceptron
  - Cornell Aeronautical Laboratory, USA

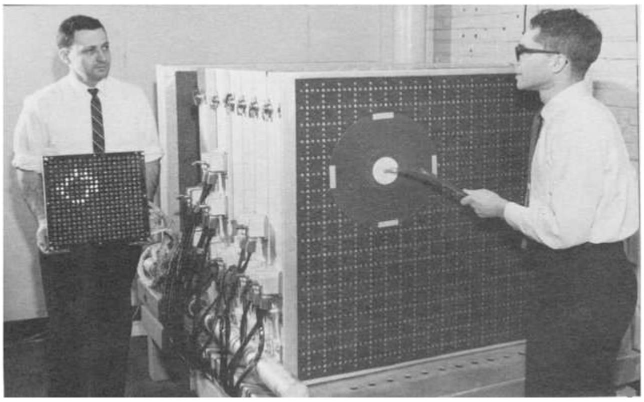




 5

5

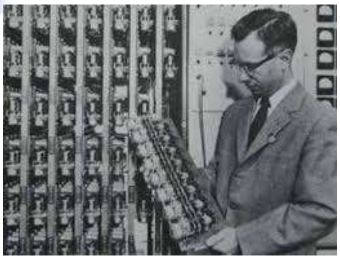
## Starting the implementation

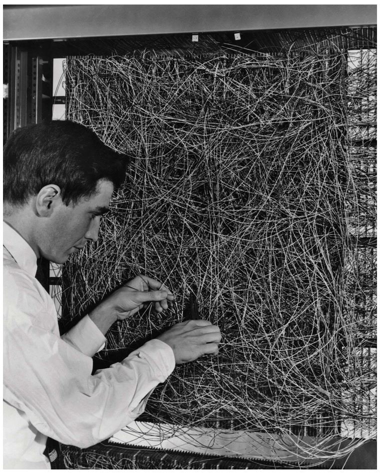


 6

6

## Preparing the Perceptron

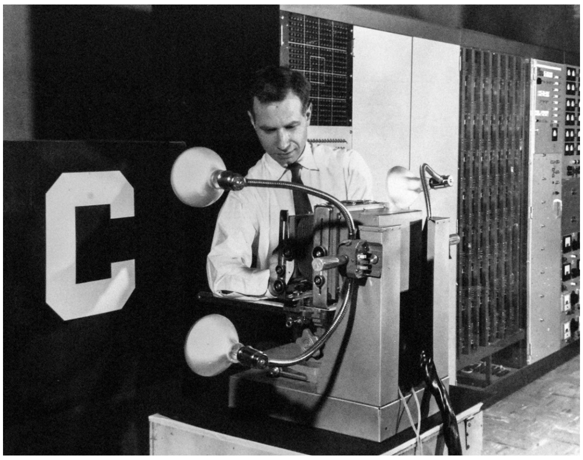




7

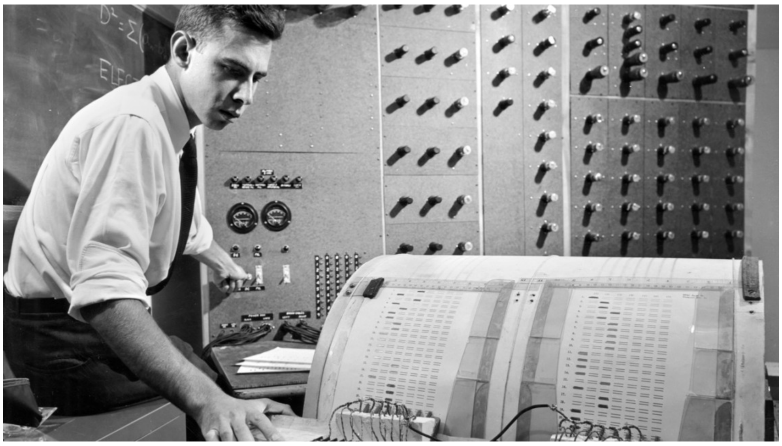
## Concluding Perceptron



8

# Perceptron working





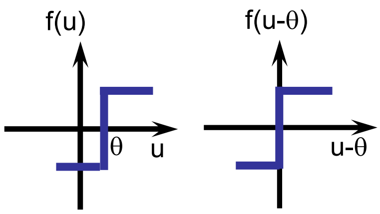
# Perceptron

- Answer / network output
  - Applies threshold activation function on total input sum received by a neuron

$$u = \sum_{i=1}^{m} x_i w_i$$

$$f(u) = \begin{cases} +1 \text{ if } u \geq \theta \\ -1 \text{ if } u < \theta \end{cases}$$

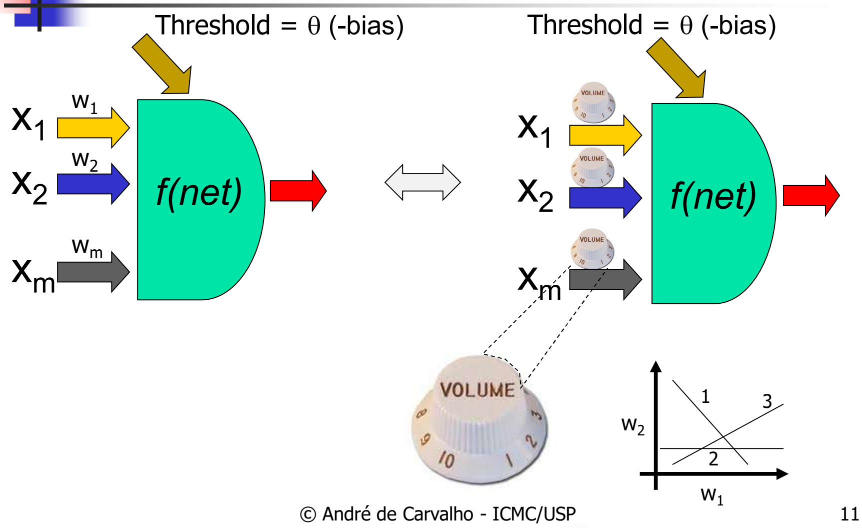
$$net = \sum_{i=0}^{m} x_i w_i$$




f(u-θ) = sinal (u-θ)
f(net) = f(u-θ)

## Training

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11

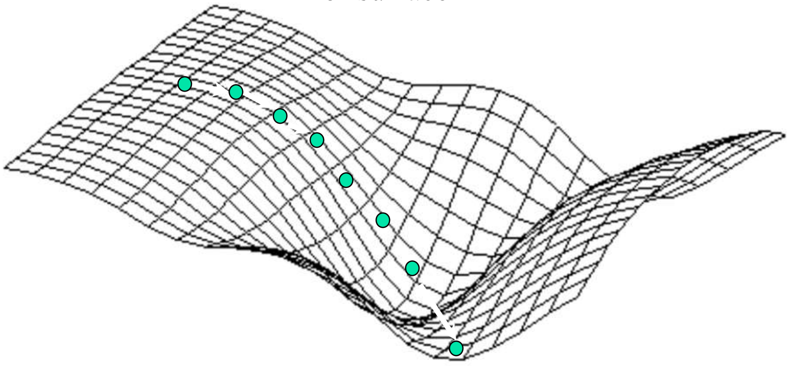
## Training algorithm

*initialise all weighes with $w_j = 0$*
***repeat***
    ***for*** *each training example (X, d)* ***do***
        *calculate the network output y*
        ***if*** *($d \neq y$)*
        ***then*** *update weight value*
***until*** *an acceptable error is achieved*

18/12/2019 André de Carvalho 12

12

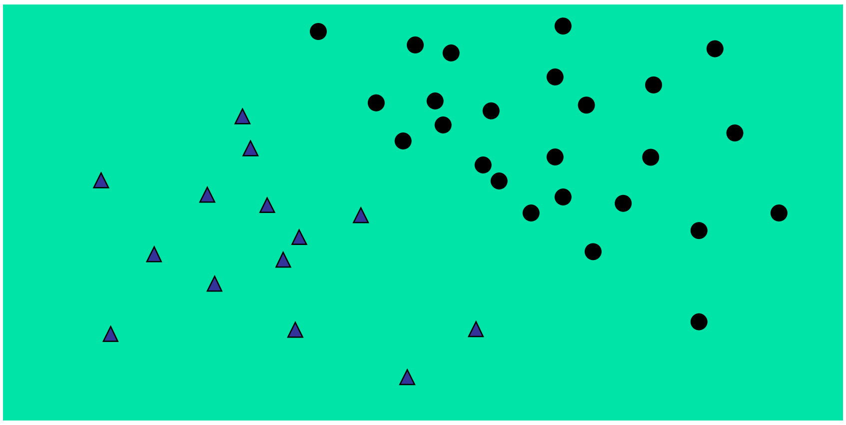
# Training






13

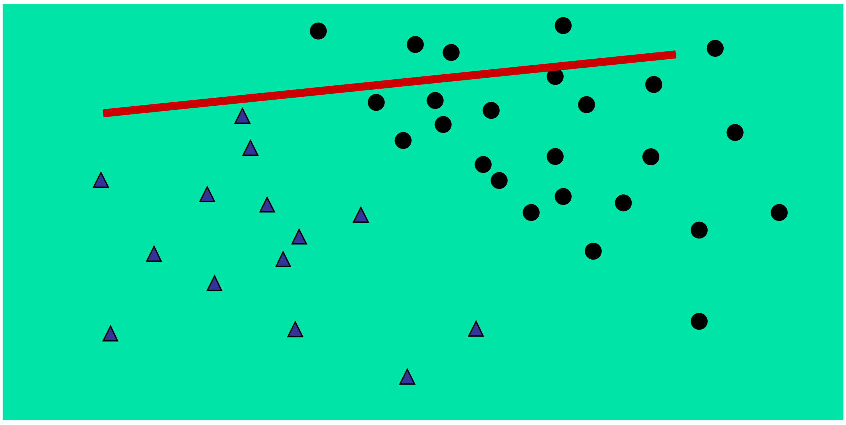
# Training moving borders



14

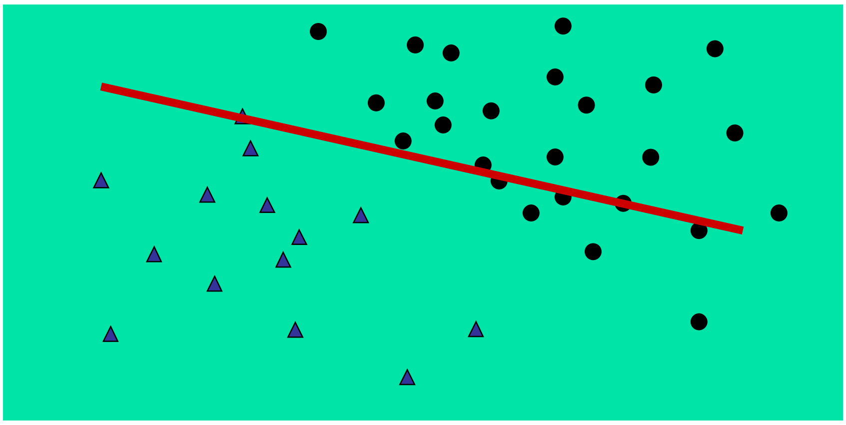
## Training moving borders





15

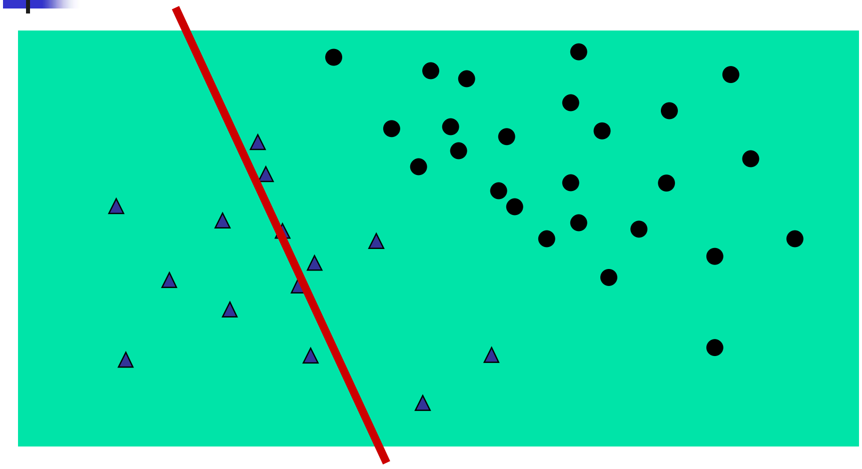
## Training moving borders





16

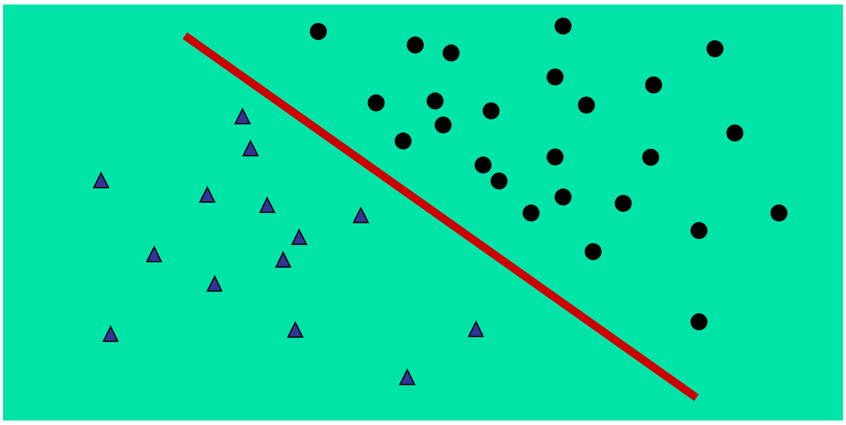
## Training moving borders



 17

17

## Training moving borders



 18

18

## Test

***for*** *each test example X do*
*present X to the network input*
*calculate network output y*
***if*** *(y= -1 )*
***then*** *X* $\in$ *class A*
***else*** *X* $\in$ *class B*

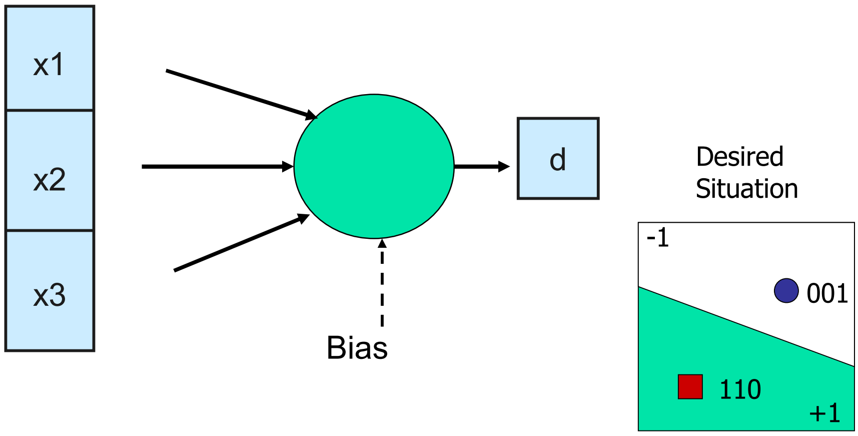




## Example

- Given a Perceptron network with:
  - Three input terminals, using the following initial weights $w_0 = 0{,}4$, $w_1 = -0{,}6$ e $w_2 = 0{,}6$, and threshold $\theta = 0{,}5$:
    - Teach the networks with the training dataset (001, -1) and (110, +1)
      - Using as learning rate $\eta = 0{,}4$
    - Define the class for the samples: 111, 000, 100 e 011

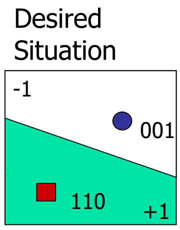
# Example






21

# Example: item a)



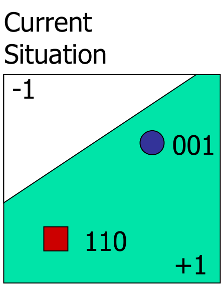

a) Train the network

a.1) For the input pattern 001 (d = -1)

Step 1: define the network output

u = 0(0.4) + 0(-0.6) + 1(0.6) -1(0.5) = 0.1

y = u = +1 (since 0.1 $\geq$ 0)




Step 2: adjust weights (d $\neq$ y)

$w_0$ = 0.4 + 0.4(0)(-1 - (+1)) = 0.4

$w_1$ = -0.6 + 0.4(0)(-1 - (+1)) = -0.6

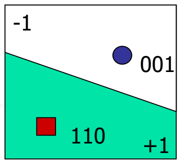
$w_2$ = 0.6 + 0.4(1)(-1 - (+1)) = -0.2

$w_3$ = 0.5 + 0.4(-1)(-1 - (+1)) = 1.3



22

Desired Situation




# Example: item a)

## a) Train the network

### a.2) For the input pattern 110 (d = +1)

Step 1: define the network output

$u = 1(0.4) + 1(-0.6) + 0(-0.2) -1(1.3) = -1.5$

$y = u = -1$ (since $-1.5 < 0$)

Step 2: adjust weights ($d \neq y$)

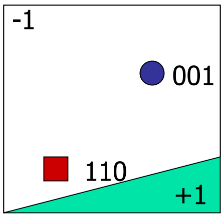
$w_0 = 0.4 + 0.4(1)(1 - (-1)) = 1.2$

$w_1 = -0.6 + 0.4(1)(1 - (-1)) = 0.2$

$w_2 = -0.2 + 0.4(0)(1 - (-1)) = -0.2$

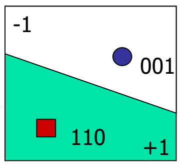
$w_3 = 1.3 + 0.4(-1)(1 - (-1)) = 0.5$

Current Situation






Desired Situation




# Example: item a)

## a) Train the network

### a.3) For the input pattern 001 (d = -1)

Step 1: define the network output

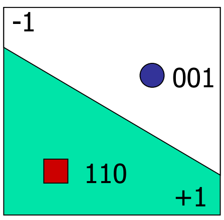
$u = 0(1.2) + 0(0.2) + 1(-0.2) -1(0.5) = -0.7$

$y = u = -1$ (since $-0.7 < 0$)

Step 2: adjust weights ($d = y$)

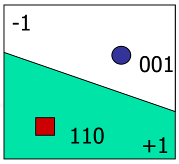
Since $d = y$, there is no need to adjust the weights

Current Situation



## Example: item a)

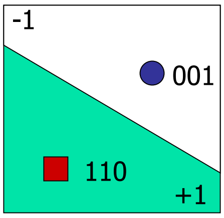
Desired Situation




a) Train the network

a.4) For the input pattern 110 (d = +1)

Current Situation




Step 1: define the network output

$u = 1(1.2) + 1(0.2) + 0(-0.2) -1(0.5) = +0.7$

$y = u = +1$ (since $0.7 > 0$)

Step 2: adjust weights ($d = y$)

Since $d = y$, there is no need to adjust the weights





## Example: item b)

b) Test the network

b.1) For the input pattern 111

$u = 1(1.2) + 1(0.2) + 1(-0.2) -1(0.5) = 0.7$

$y = u = 1$ (since $0.7 \geq 0$) ) $\Rightarrow$ class 1

b.2) For the input pattern 000

$u = 0(1.2) + 0(0.2) + 0(-0.2) -1(0.5) = -0.5$

$y = u = -1$ (since $-0.5 < 0$) $\Rightarrow$ class 0

## Example: item b)

b) Test the network

b.3) For the input pattern 100

$u = 1(1.2) + 0(0.2) + 0(-0.2) +1(-0.5) = 0.7$

$y = u = 1$ (since $0.7 \geq 0$) $\Rightarrow$ class 1

b.4) For the input pattern 011

$u = 0(1.2) + 1(0.2) + 1(-0.2) -1(0.5) = -0.5$

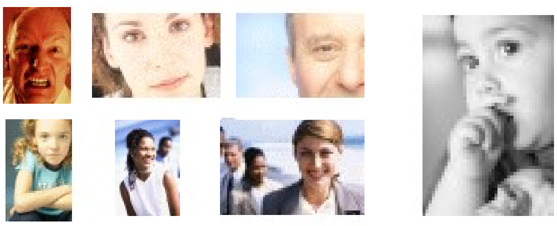
$y = u = -1$ (since $-0.5 < 0$) $\Rightarrow$ class 0





## Example 2

- Distinguish male face images from female face images



## Example 2

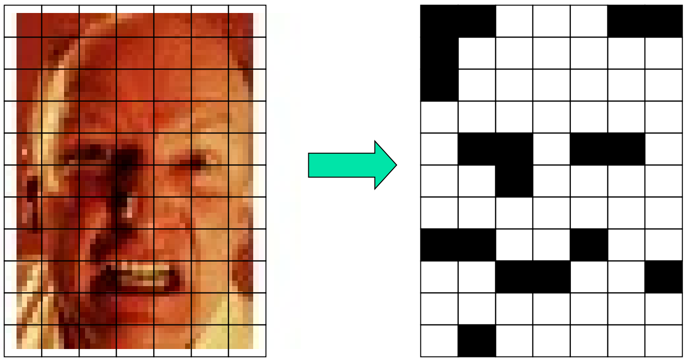
- Distinguish male face images from female face images
  - Use images directly
    - Matrix of pixels
  - Use features extracted from the image
    - Distance between components from the face (Ex. eyes)
    - Texture
      - Moustache, Hair, Beard





## Example 2

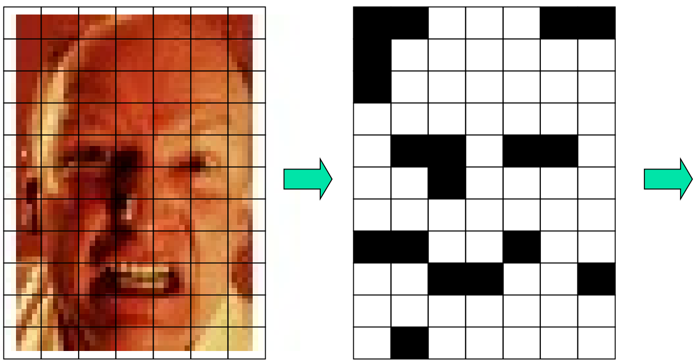
## Example 2





31

## Example 2



1 1 0 0 0 1 1
1 0 0 0 0 0 0
1 0 0 0 0 0 0
0 0 0 0 0 0 0
0 1 1 0 1 1 0
0 0 1 0 0 0 0
0 0 0 0 0 0 0
1 1 0 0 1 0 0
0 0 1 1 0 0 1
0 0 0 0 0 0 0
0 1 0 0 0 0 0



32

## Example 3

- Consider the following patients

| Name | Fever | Dizzy | Spots | Pain | Diagnosis |
|---|---|---|---|---|---|
| John | yes | yes | small | yes | ill |
| Peter | no | no | large | no | healthy |
| Mary | yes | yes | small | no | healthy |
| Joe | yes | no | large | yes | ill |
| Ann | yes | no | small | yes | healthy |
| Lyn | no | no | large | yes | ill |





## Example 3

- Consider the following patients

| Fever | Dizzy | Spots | Pain | Diagnosis |
|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 1 |
| 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 |
| 1 | 0 | 1 | 1 | 1 |
| 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 1 |

## Example 3

- Train a Perceptron network to distinguish:
  - Potentially healthy patients
  - Potentially ill patients
- Test the network for the following new cases
  - (Louis, no, no, small, yes)
  - (Laura, yes, yes, large, yes)





## Adaline

- Problem with Perceptron:
  - Weight adjustment does not take into account the true distance between
    - Produced output and desired output
- Adaline network
  - Proposed by Widrow and Hoff in 1960
  - Also based on McCulloch-Pitts nodes

## Adaline

- Training
  - Supervised
  - Error correction (LMS, delta rule)
    - $\Delta w_{ij} = \eta x_i(d_j - y_j)$ $(d \neq y)$
    - $\Delta w_{ij} = 0$ $(d = y)$
    - Gradual weight adjustment
      - Takes into account the distance between the desired output (d) and the produced output (y)

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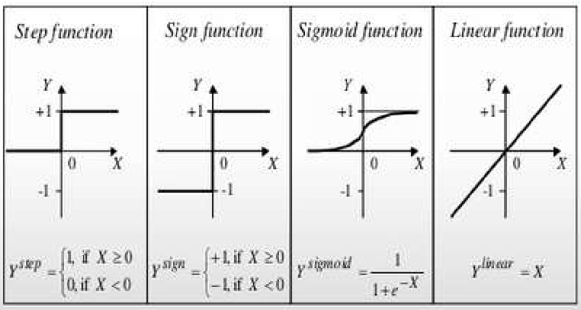
37

## Activation functions

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38

## Quiz 1

- What is the main difference between Perceptron and Adaline?
  - A) Learning rule
  - B) Architecture
  - C) Activation function
  - D) Learning paradigm



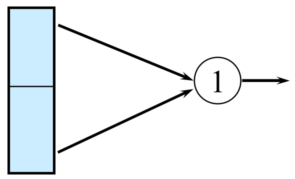


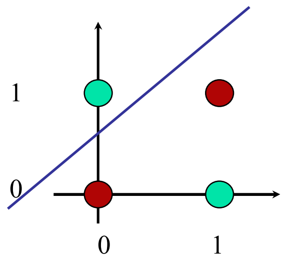

## A bit of history

- (1969) Minsky & Papert analysed the Perceptron network and pointed out its limitations
  - Could only deal with linear separable problems
    - Not with XOR and parity
  - Largely reduced the research activity in ANNs

# Perceptron limitation

$0, 0 \rightarrow 0$
$0, 1 \rightarrow 1$
$1, 0 \rightarrow 1$
$1, 1 \rightarrow 0$

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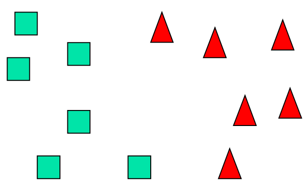
41

# Perceptron

- Linearly separable patterns



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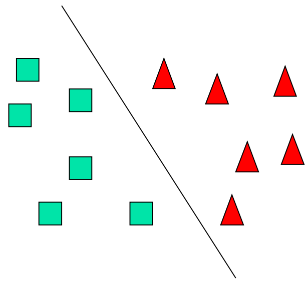
42

## Perceptron

- Linearly separable patterns







## Perceptron limitation

- One-layer networks can only deal with linearly separable problems
- A large number of important application problems are non-linearly separable
- Many problems have more than 2 classes
  - Multiclass problems

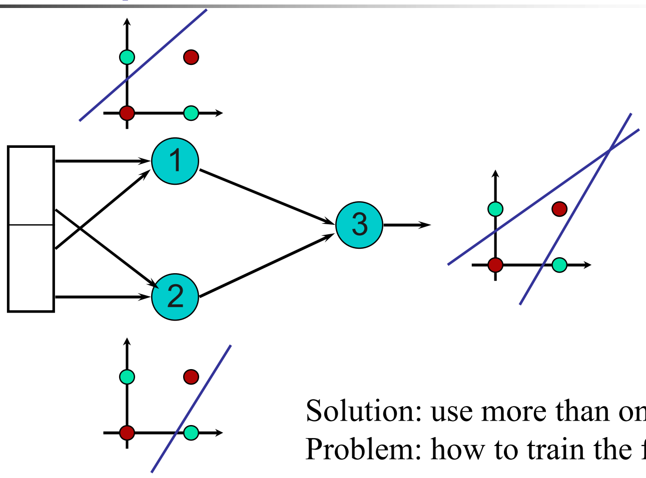
## Quiz 2

- What is the main difference between Perceptron and Adaline?
  - A) Learning rule
  - B) Architecture
  - C) Activation function
  - D) Learning paradigm



45

## Perceptron limitation




Solution: use more than one layer
Problem: how to train the first layers



46

# Next:
# MLP Neural Networks