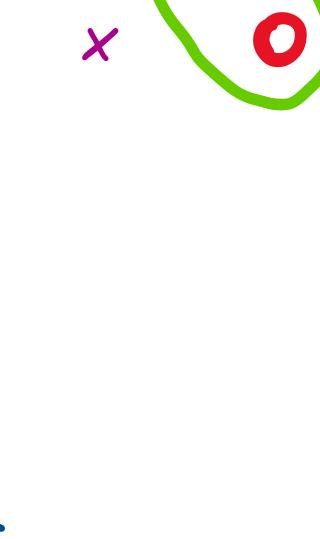


XOR PROBLEM AND MULTI-LAYER PERCEPTRON (MLP)

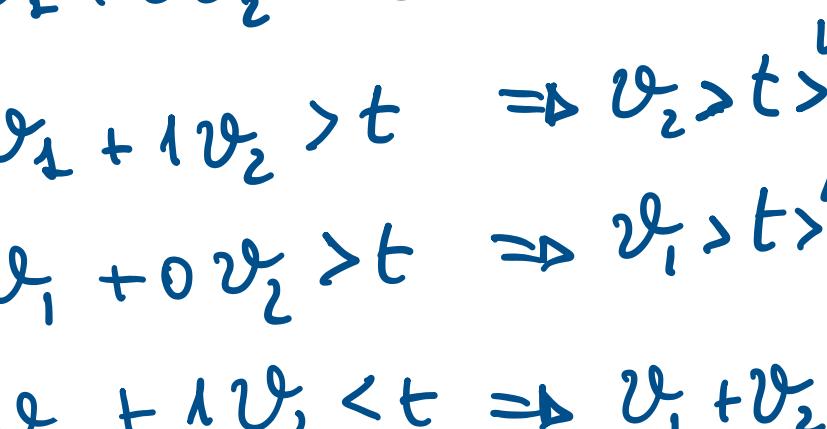
(PAG 62, CAP 3, SECTION 3.2.2 OF THE GOOD NEURAL NETWORK A SYSTEMATIC INTRODUCTION)

MINSKY AND PAPERT (1969) DEMONSTRATED THAT
THE XOR PROBLEM CANNOT BE SOLVED BY A PERCEPTRON

INPUT 1	INPUT 2	OUTPUT
1	1	0
1	0	1
0	1	1
0	0	0



PERCEPTRON MODEL



$$\begin{aligned} 0w_1 + 0w_2 < t &\Rightarrow t > 0 \quad (\text{IF THE } t \text{ IS VALID}) \\ 0w_1 + 1w_2 > t &\Rightarrow w_2 > t > 0 \\ 1w_1 + 0w_2 > t &\Rightarrow w_1 > t > 0 \quad \left[\begin{array}{l} w_1 > 0 \\ w_2 > 0 \end{array} \right] \Rightarrow w_1 + w_2 > 2t \\ 1w_1 + 1w_2 < t &\Rightarrow w_1 + w_2 < t \end{aligned}$$

⇒ THERE IS NO CONFIGURATION FOR A PERCEPTRON WHICH SOLVES XOR PROBLEM

PERCEPTRON CAN COMPUTE ONLY LINEAR DECISION BOUNDARIES!

TO SOLVE ⇒ ADD HIDDEN LAYER

PROBLEM ⇒ HOW TO TRAIN?
HOW TO DETERMINE HIDDEN PARAMETERS?

NON-LINEAR SEPARABILITY

WHEN POINTS WITH LABEL $y=1$ CANNOT BE SEPARATED WITH A LINE (HYPERPLANE) FROM THOSE WITH LABEL $y=0$ THEN THE PROBLEM IS NOT PERCEPTRON COMPUTABLE

⇒ PERCEPTRON CAN COMPUTE ONLY FUNCTIONS ON SET OF SEPARABLE POINTS

DEFINIZIONE LINEARE SEPARABILITÀ 3.3 N-N A SYSTEMATIC APPROACH

TWO SETS OF POINTS A AND B IN A m -DIMENSIONAL SPACES ARE CALLED LINEAR SEPARABLE IF \exists REAL NUMBER w_1, \dots, w_m , EXIST, SUCH THAT EVERY POINT $(x_1, \dots, x_m) \in A$ SATISFIES $\sum_{i=1}^m w_i x_i \geq w_{m+1}$ AND EVERY POINT $(x_1, \dots, x_m) \in B$ SATISFIES $\sum_{i=1}^m w_i x_i < w_{m+1}$

HOW MANY LINEAR SEPARABLE FUNCTIONS OF m BINARY ARGUMENTS EXISTS?

$m=2 \Rightarrow 14$ OUT OF 16 POSSIBLE BOOLEAN FUNCTIONS ARE SEPARABLE (LINEARLY)

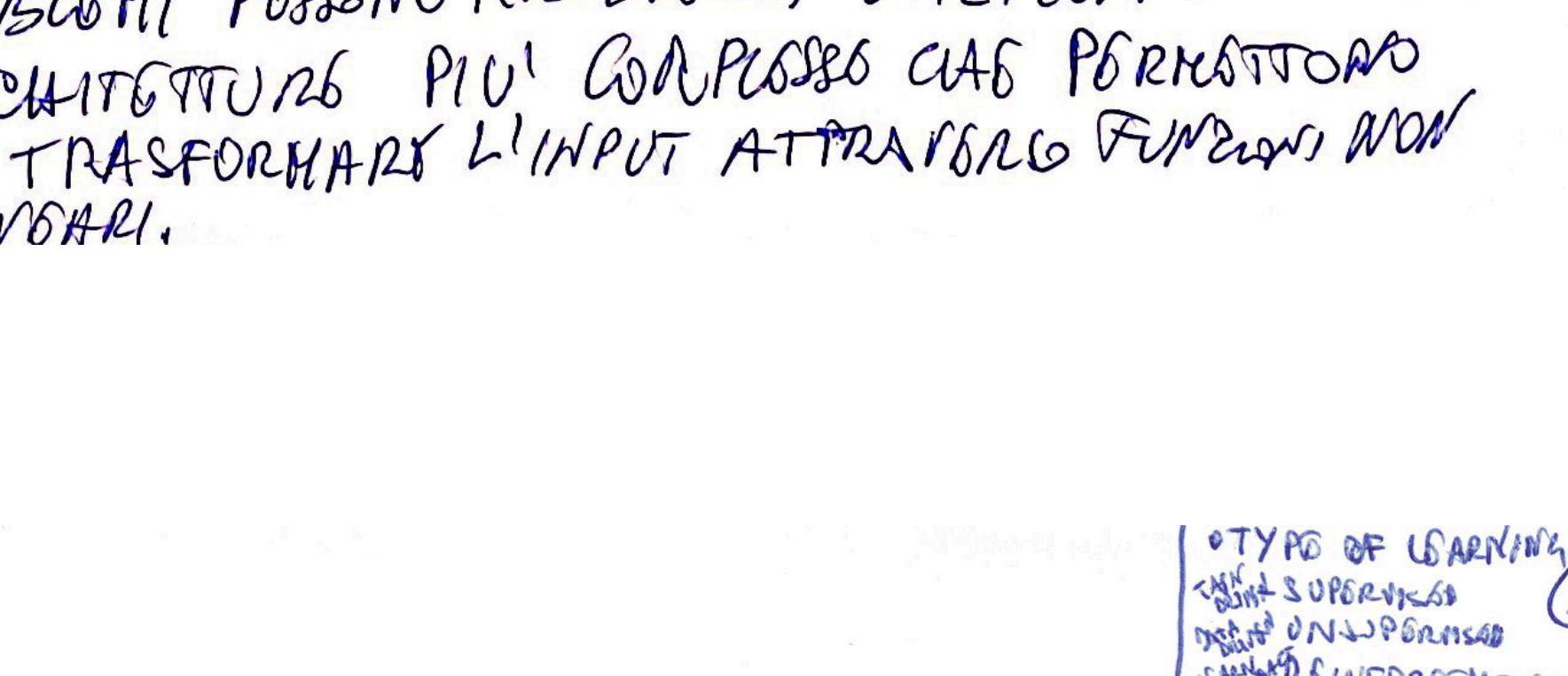
$m=3 \Rightarrow 104$ OUT OF 256 ARE LINEARLY SEPARABLE

$m=4 \Rightarrow 1882$ OUT OF 65536 FUNCTIONS ARE LINEARLY SEPARABLE

THESE IS NO FORMULA WHICH EXPRESSES THIS AS FUNCTION OF m

[WE CAN GET THAT INCREASING m THE PROBABILITY OF A FUNCTION TO BE LINEAR SEPARABLE DECREASE DRAMATICALLY
NOTE: USUALLY OUR INPUT IS HIGH WRT m (AND CONTINUOUS)]

XOR NETWORK



$$a_1 = \begin{cases} 1 & \sum w_i x_i > t \\ 0 & \sum w_i x_i \leq t \end{cases}$$

$$(1,1) \quad a_1 = 1 \quad a_2 = 1 \quad \text{SOL 3} \quad a_3 = 0$$

$$(1,0) \quad a_1 = 1 \quad a_2 = 0 \quad \text{SOL 2}$$

? COMPUTE FOR $(0,1)$ AND $(0,0)$ → EXERCISE

MULTIPLE HYPERPLANES

IN SUM PROBLEMI CHE NON SONO RISOLVIBILI

USCIRSI DA UNA FUNZIONE LINEARE. TALI PROBLEMI POSSONO RISOLVERSI UTILIZZANDO

ARCHITETTURE PIÙ COMPLICATE CHE PERMETTONO DI TRASFORMARE L'INPUT ATTIVANDO FUNZIONI NON LINEARI.

CAPITOLO 6.1.2

6.1.3

NN A SYSTEMATIC INTRODUCTION

- ① RECUP PERCEPTRON MODELL (SUPERVISED LEARNING ALGORITHM)
 - 1) MODEL: PARAMETRIZED FUNCTION, ONE WEIGHT COMPONENT.
 - 2) TRAINING SET: $x^{(i)} \in \mathbb{R}^n$, $y^{(i)} \in \{0,1\}$: SET M COPPIE $(x^{(i)}, y^{(i)})$
 - 3) LEARNING ALGORITHM - ROSENBLATT 1958 KARTH
 - 4) PERFORMANCE MEASURE (COST FUNCTION):

GOAL: CLASSIFICATION - BINARY $y^{(i)} \in \{0,1\}$

$$\min_j J(j) = 0$$

② TRAINING SET, VALIDATION SET, TEST SET

• RANDOM SPLITTING

• CROSS VALIDATION

③ EVALUATION ON TEST (SAME AS COST FUNCTION)

④ CAN WE USE FOR REGRESSION? ⇒ NO SIGN FUNCTION

• CAN WE INTERPOT IN A PROB FASHION? ⇒ SIGNUM (NON LINEAR)

• KERNEL & BASIS FUNCTION REPRESENTATION

• LINEAR SEPARABILITY? DEFINITION RISPETTO AL LINEAR PERCEPTRON; HOW MANY

• XOR PROBLEM ⇒ POSSIBLY SOLUTION ⇒ PROBLEM WITH LEARNING

• NON SEPARABILITY & LINEAR MACHING? DICOTOMIES

NON SEPARABILITY & LINEAR MACHING

$$X = \{x^{(1)}, x^{(2)}, \dots, x^{(m)}\} \in \mathbb{R}^d$$

- GIVEN m points THERE ARE 2^m DICOYMIES (POSSIBILITY OF SEPARATION)

For 2 points up to 2 dicotomies

- ONLY \sqrt{d} DICOYMIES ARE LINEAR SEPARABLE

- WITH $m > d$ THE PROBABILITY THAT X IS LINEARLY SEPARABLE GOES TO 0 VERY FAST



• TYPE OF LEARNING

• SUPERVISED

• INPUT & OUTPUT

• LINEAR & NON LINEAR

• RECOGNIZER METHODS

• CLASSIFICATION

• LEARNING THE THRESHOLD

• CHANGE DATA

• ADD PARAMETERS TO THE MODEL

• DATA NORMALIZATION

• EACH COMPONENT

$x_j - \bar{x}_j / \sigma_j$; $x_j - \bar{x}_j / \max(x_j) - \min(x_j)$

⇒ $x_j \in [0,1]$

• DATA NORMALIZATION

$\bar{x}_j = \frac{1}{m} \sum_{i=1}^m x_j^{(i)}$

$\sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^m (x_j^{(i)} - \bar{x}_j)^2}$

$\mu_j = \frac{1}{m} \sum_{i=1}^m x_j^{(i)}$