

# FROM LINEAR ALGEBRA TO MACHINE LEARNING

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# OVERVIEW

Motivation

Vectors

Examples

Conclusions

## MOTIVATION

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# MOTIVATION

- **Linear algebra** is important to understand machine learning.
- As well as **calculus**, **probability theory**, and **statistics**.
- It is rewarding to take the **hard path** to learn machine learning (IMHO).

# LEARNING FROM ERRORS

```
30 # compute distances using self-created function
31 distances2 <- matrix(nrow=size, ncol=size)
32 for (p in 1:size) {
33   for (q in 1:size) {
34     row_p = iris2[p,]
35     row_q = iris2[q,]
36     distances2[p, q] <- euclidean_distance(row_p, row_q)
37   }
38 }
```

# LEARNING FROM ERRORS

```
14 # function for calculating Euclidean Distance
15 euclidean_distance <- function(p, q) {
16     ed = 0
17     for (i in 1:4) {
18         ed <- ed + (p[,i] - q[,i]) ^ 2
19     }
20     ed <- sqrt(ed)
21     return(ed)
22 }
```

## VECTORS



# A VECTOR IS A COLLECTION OF NUMBERS

$$\vec{a} = \mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$



## LENGTH OF A VECTOR

$$|\mathbf{a}| = \sqrt{\sum_{i=0}^n a_i^2}$$

## DISTANCE BETWEEN VECTORS

$$\begin{aligned}d(\mathbf{a}, \mathbf{b}) &= \|\mathbf{a} - \mathbf{b}\| \\ &= \sqrt{\sum_{i=0}^n (a_i - b_i)^2}\end{aligned}$$

## DOT PRODUCT

$$\begin{aligned} \mathbf{a} \cdot \mathbf{b} &= \sum_{i=0}^n a_i b_i \\ &= a_0 b_0 + a_1 b_1 + \dots + a_n b_n \end{aligned}$$

So,

$$\begin{aligned} \mathbf{a} \cdot \mathbf{a} &= a_0 a_0 + a_1 a_1 + \dots + a_n a_n \\ &= a_0^2 + a_1^2 + \dots + a_n^2 \\ &= |\mathbf{a}|^2 \end{aligned}$$

## EXAMPLES

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WINTER IS COMING

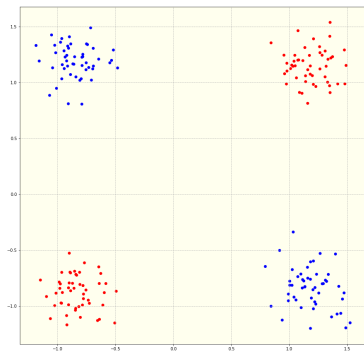
A white sword graphic is positioned vertically, with its hilt at the top and its blade pointing downwards. The blade of the sword is shaped like the letter 'I', which is used as the letter 'I' in the word 'IS' of the phrase 'WINTER IS COMING'. The sword is centered between the words 'WINTER' and 'COMING'.

# THE AI WINTER IS COMING

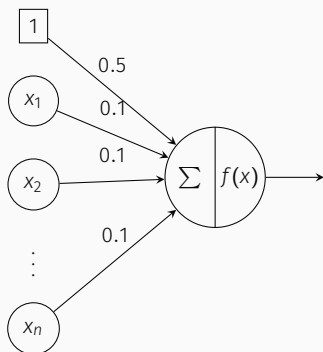
- Is really coming? No.
- However, we already had an AI winter.
- The research on neural nets was stopped for many years, after Minsky and Papert proved that a single layer perceptron was not able to deal with the exclusive-or problem.

# TOY DATASET

$b_{11}$	$b_{12}$	1
$b_{21}$	$b_{22}$	0
$b_{31}$	$b_{32}$	1
...	...	...
$b_{n1}$	$b_{n2}$	1



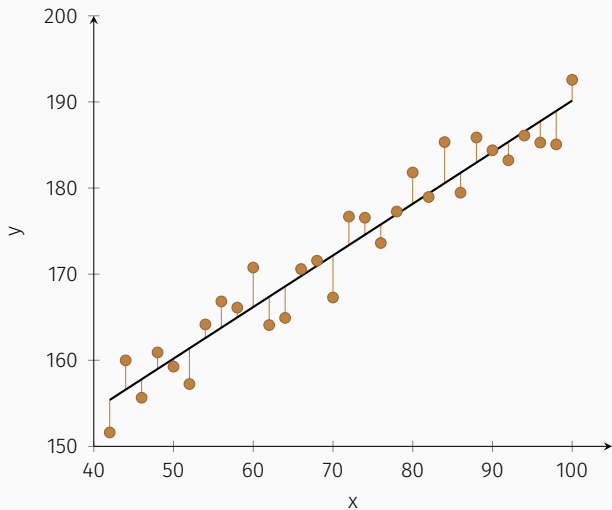
# PERCEPTRON



$x_0$	$x_1$	$\Sigma$	$f(x)$
1	1	$1 \times 0.5 + 1 \times -1 = -0.5$	0
1	0	$1 \times 0.5 + 0 \times -1 = 0.5$	1



# LINEAR REGRESSION



# LINEAR REGRESSION

- We want to calculate the intercept  $a$  and the slope  $b$ .

$$\arg \min_{a,b} \sum_i (y_i - (ax_i + b))^2 = \arg \min_w \|Xw - \mathbf{y}\|^2$$

- The solution to this optimization problem is:

$$\mathbf{w}^* = (X^T X)^{-1} X^T \mathbf{y}.$$

## CONCLUSIONS

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## MORE TOPICS WE SHOULD CHECK

- **Gradient descent** is a beautiful optimization algorithm, basically, we multiply matrices to many times.
- **Eigenvectors** and **eigenvalues**; some dimensionality reduction techniques are based on eigendecomposition.
- Be aware that **numerical instabilities** can happen, and avoid these ones.

## REFERENCES

- **Mathematics for Machine Learning: Linear Algebra** by Coursera.
- **The Math of Intelligence** by Siraj Raval.
- **Deep Learning Book** by Bengio and Goodfellow, has a chapter summarizing which linear algebra topics you need to learn neural networks.

Thank you.

Questions?

Comments?