Université de Montréal
Département d'informatique et de recherche opérationnelle

IFT6390
Fondements de l'apprentissage

INTRODUCTION

Professor: Ioannis Mitliagkas
Slides adapted from: Pascal Vincent

Mila

Today

- Getting to know the class (very general discussion, hardly any technical content).
- Class communication
- The objectives, the plan of the class, the evaluation and grading…
- Informal presentation of the domain of machine learning.

Other machine learning classes offered at DIRO

Automne

Graduate version of this class (in English)

IFT6390 Fondements de l'apprentissage machine

Automne

Advanced course presenting a formalism and essential techniques for learning

IFT6269 Modèles graphiques probabilistes et apprentissage

Automne

Limited capacity, very interesting premise

IFT6757 Autonomous vehicles (Duckietown)

Automne

Data Science class

IFT6758 Science des données

Other machine learning classes offered at DIRO

Advanced course presenting cutting-edge research in artificial neura networks and deep learning

Hiver

IFT6266 Algorithmes d'Apprentissage / Apprentissage de représentations

Course that goes deeper into the fundamental math

Hiver

IFT6085 Theoretical principles for deep learning

Theory course: Linear and Multi-linear algebra in ML

IFT6760A Linear algebra/Spectral Methods in ML

Hiver

New Reinforcement Learning course

IFT6760C

FIRST PART

Course plan

and other practical information

Communication!

Step 1: Public website

`http://mitliagkas.github.io/ift6390-ml-class/`

Very important, complete and up-to-date information on what to expect about the class

STATIC

Read very carefully!

Especially the **prerequisites** page.

Step 1.5: Studium

On the StudiUM webpage:
https://studium.umontreal.ca

If you are registered, in the menu «mes cours» (my courses) you should see:

IFT6390-A-A20
Fondements de l'apprentissage machine

If not, your registration might not be yet finalized.

Show of hands: registered, received announcement?

We will only use it to give you access to Piazza and gradescope.
Will not be updated.

Step 2: Piazza

For questions, discussion and announcements:
https://piazza.com/umontreal.ca/fall2020/ift6390

We have invited all registered students.
You should have received announcement.

THE MOST IMPORTANT RESOURCE!!

Make sure you check frequently.
Make sure you receive Piazza emails

Step 3: Gradescope

For questions, discussion and announcements:
https://piazza.com/umontreal.ca/fall2020/ift6390

We have invited all registered students.
You should have received announcement.

THE MOST IMPORTANT RESOURCE!!

Make sure you check frequently.
Make sure you receive Piazza emails

Email?

Not possible. Class is too big.

If you already have access to Piazza, please ask your questions on the forum.

Only exception: personal, sensitive questions.

Communication and info

1. Public website
2. Piazza
3. Gradescope

Content and prerequisites

Flavor of the class

The course requires some comfort on both mathematics & computer science

- Linear algebra
  (vectors, matrices, ...)
- Probability, statistics
  (random variable, distribution, expectaton, ...)
- Analysis
  (partial derivatives...)
- Algorithms
  (and complexity)
- Data structures
- Programming
  (Python environment +numpy+matplotlib…)

IMPORTANT: Study the 'prerequisites' page on the public website

THIS CLASS IS HARD

Goal for first 2-3 weeks:
Decide if this class is for you

I will point you to resources to cover any gaps in math and programming.

Labs will help!!

==> HEAVY first month for some of you

Overall, graduate class with lots of work

Grade breakdown

Weekly quizzes (10%)

Lab midterm exam (10%)
Individual programming exam (Oct ??)

Homework (30%):
3 sets, theory and programming, submitted individually (except third set)

Data competitions (30%):
Two competitions during two halves of class

Final exam (20%):
Theory exam on all material (date TBA, most likely take-home exam)

Flavor of the class

- Educational material comes from various sources (pay attention to mathematical notations!).
- The course will be given in english
  ––> Details in next slide

Language

- Graduate class
  - Largely international students
  - Research performed in English
  - Conferences, workshops, journals
- All of the material will be in English, but we can accommodate:
  - Homework, exams and questions on Piazza can be submitted in French

SECOND PART

Informal presentation of the domain of machine learning

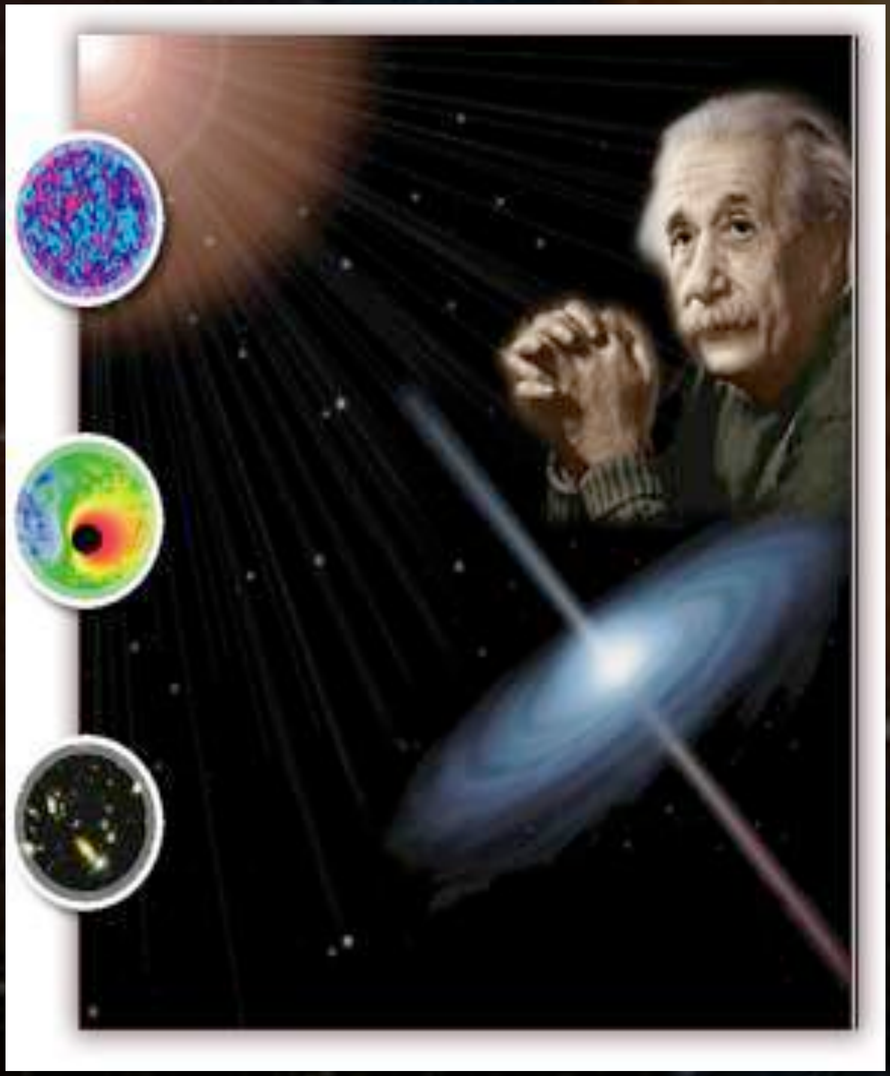
On the schedule today

- The role of learning in modern Artificial intelligence.
- The founding disciplines of learning.
- The domains of application of learning.
- Examples of types of problems in learning.
- Data representations.

Scientific curiosity

Three great mysteries

The universe,
space / time
energy / matter



Life

Intelligence,
Consciousness

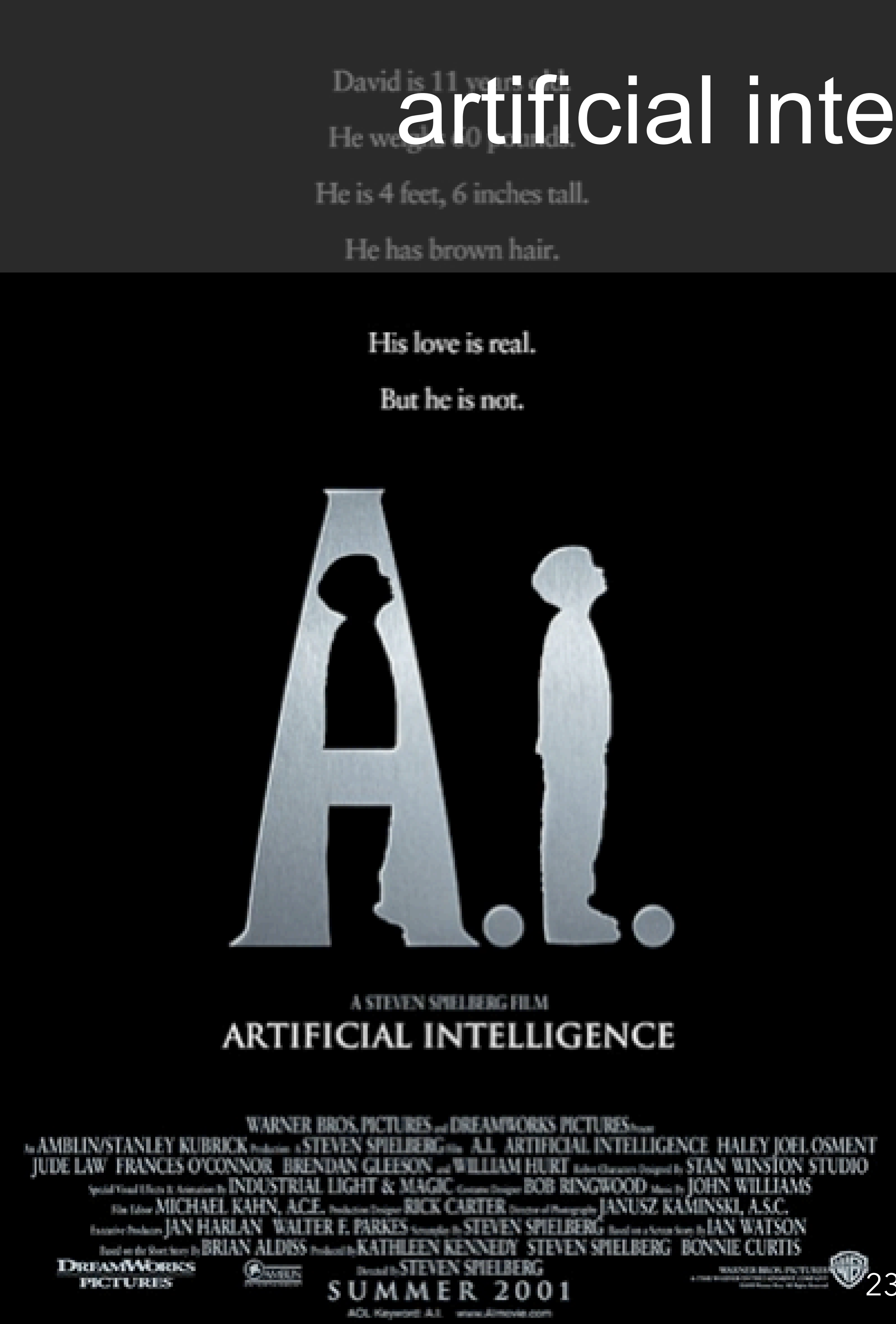
Natural intelligence: a brain that learns, adapts

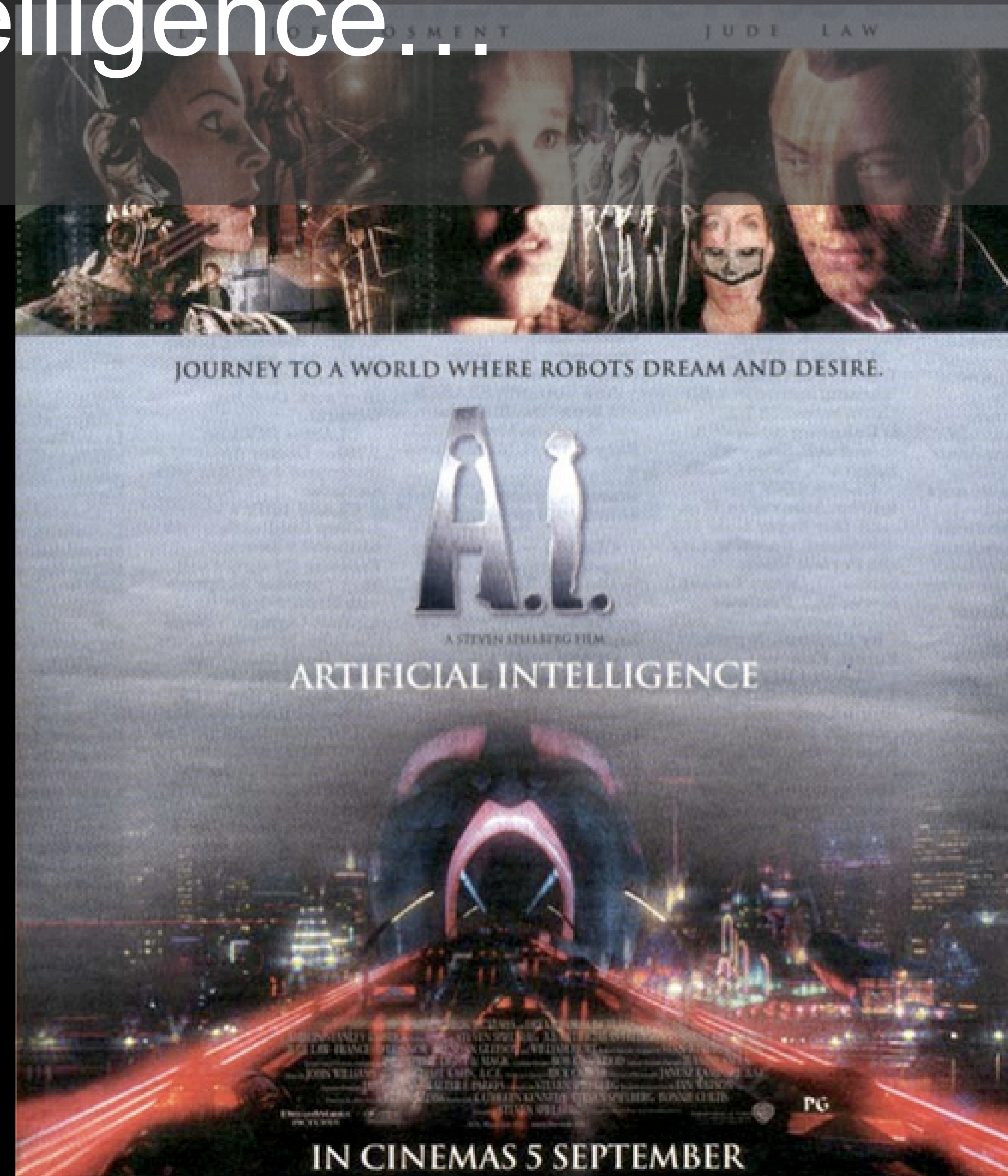
- 10^{11} neurons,
  10^{14} synapses

- Complex network of neurons

- Learning: the modification/adaptation of synapses

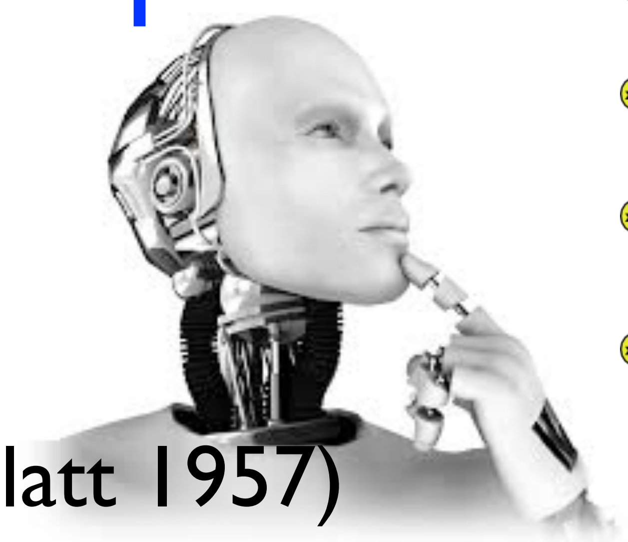
artificial intelligence…

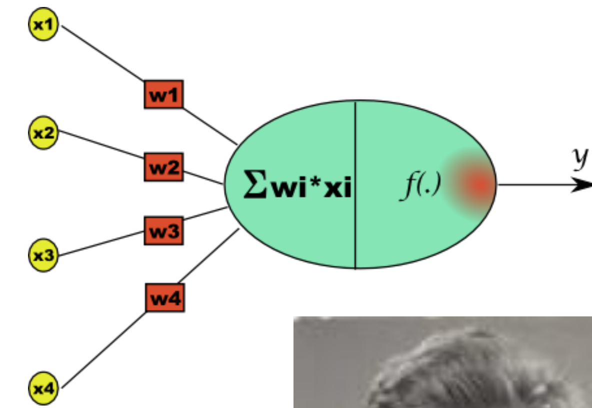




The origins of machine learning

Historical perspective





- Born from an ambitious goal:
  Artificial Intelligence

- <u>Founding project:</u>
  The **Perceptron** (Frank Rosenblatt 1957)
  First artificial neuron **learning** from examples

- Two approaches historically different in AI

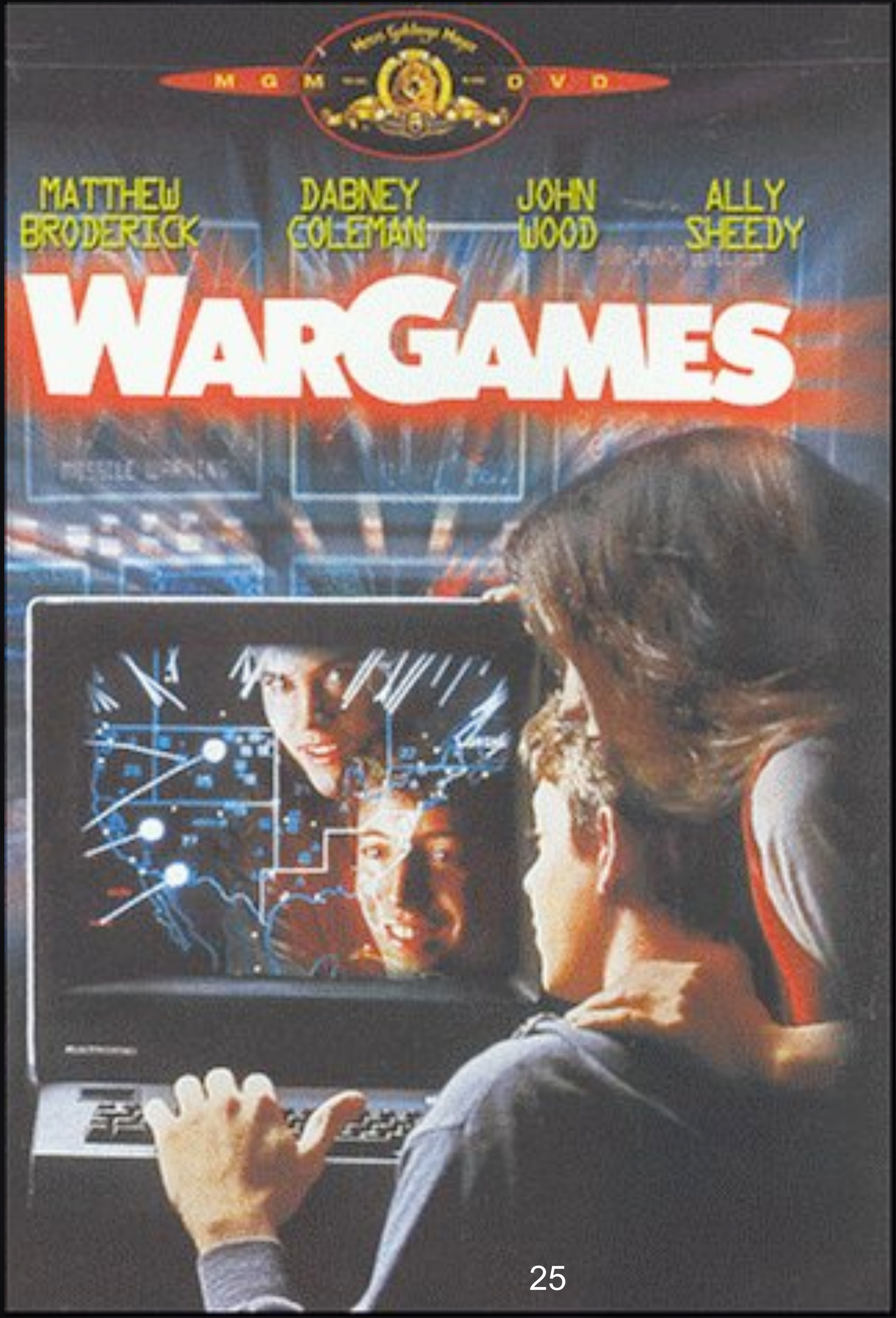
Inspired by the brain:
➪ network of neurones
learning from examples
➪ artificial perception.

«Classic» AI is symbolic:
Centered around logical reasoning
➪ <u>No learning</u> (hand-coded rules)
➪ <u>no handling of uncertainty</u>
Finally added with Bayes Nets…

Learning and probabilistic models have largely won
➪ machine learning (apprentissage machine)

A.I. in science fiction

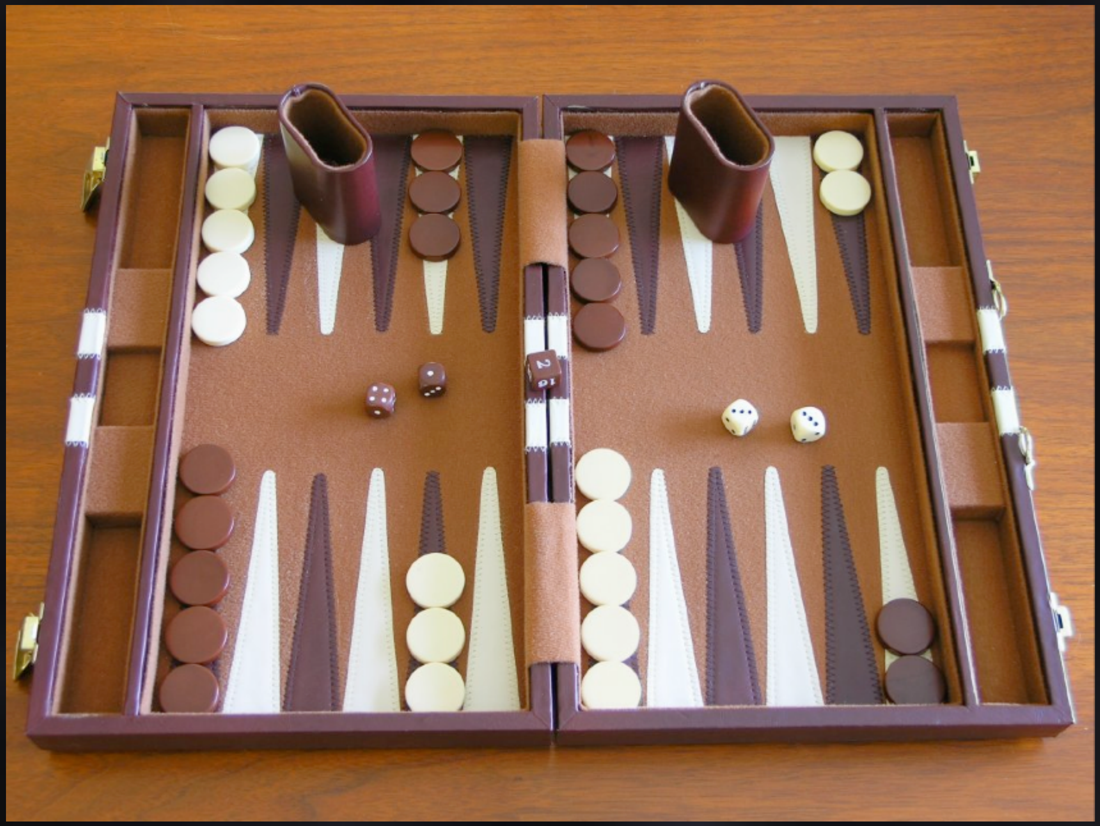
- 1983: In WarGames, a computer learns by playing against itself to play tic-tac-toe and do "global thermonuclear war".



in reality…

Backgammon

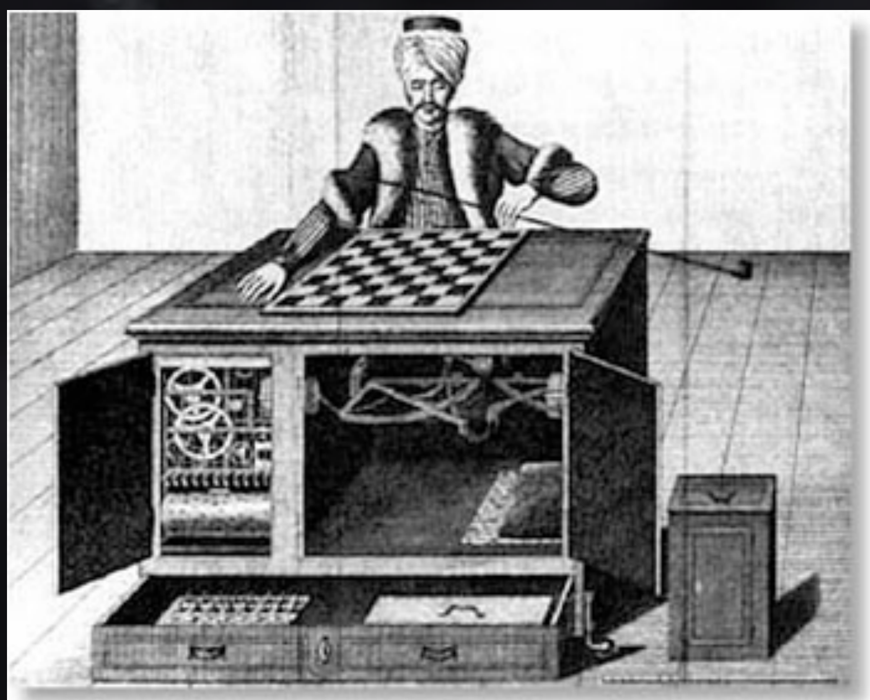
- 1995: TD-gammon, an artificial neural network trained by playing 200 000 games of backgammon against itself, plays at a level equivalent to the best players in the world (Tesauro 1995).



In chess

(Example of success of a "classic" AI approach)

1770: «Mechanical turk» automatic chess player



Won against Napoleon Bonaparte and Benjamin Franklin

A hoax!

1997: Garry Kasparov vs «Deep Blue» of IBM

At Geopardy

- February 2011: Watson, an IBM system, defeats the human champions of Geopardy.

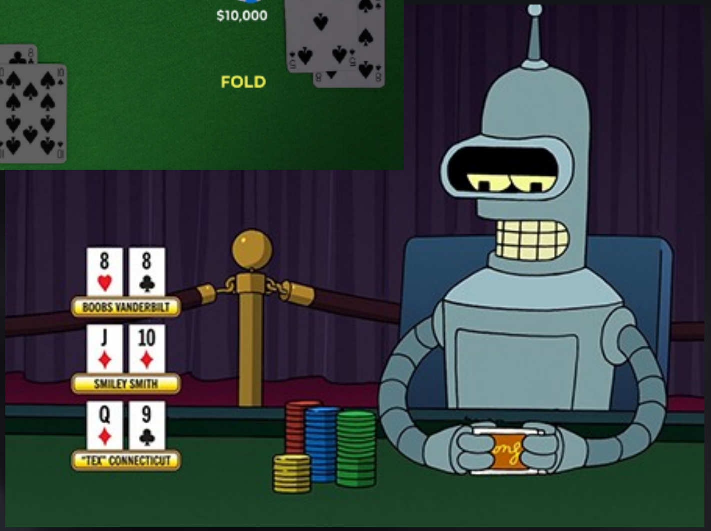
- Used machine learning on large database of textual data.

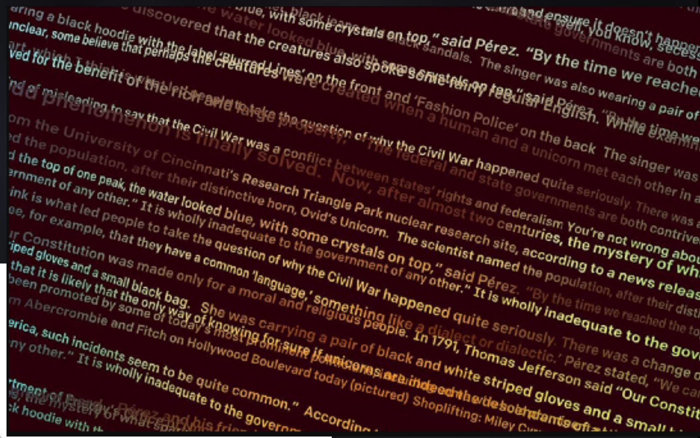
March 2016

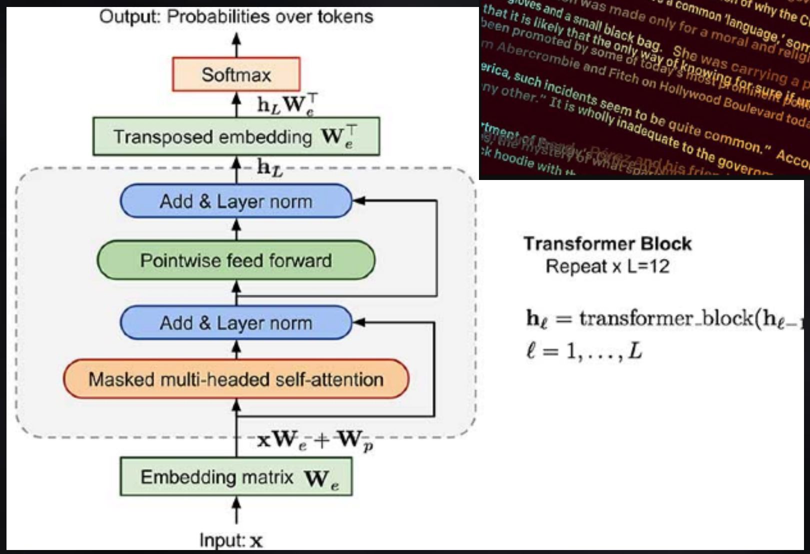
AlphaGo

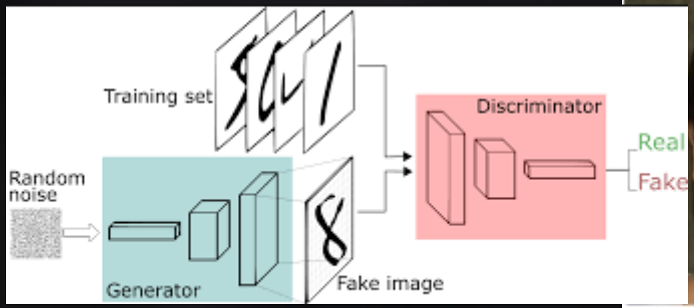
GO: one of the rare table games where human champions still had a large lead.
Not anymore!

More recent advances









Learning is at the heart of modern successes of AI

And it is not just for games

- Google search
- Computer vision systems
- Voice recognition (eg. Siri)
- Smart product recommendations: Netflix / Amazon / …
- Autonomous vehicles
- Autonomous robots etc…

Applications

- Traditional applications: recognizing forms/ patterns
  - handwriting, speech, fingerprints
  - expert humans do these well
  - **moderate** amount of data, number of attributes, numbers of classes
  - **moderate** noise and ambiguity

Applications

- Modern applications:
  - data mining, large scale text mining, financial predictions, ranking web hits (Google), analysis of genetic expression
  - expert humans do not exist
  - **enormous** amount of data, number of attributes, numbers of classes
  - **increased** noise and ambiguity

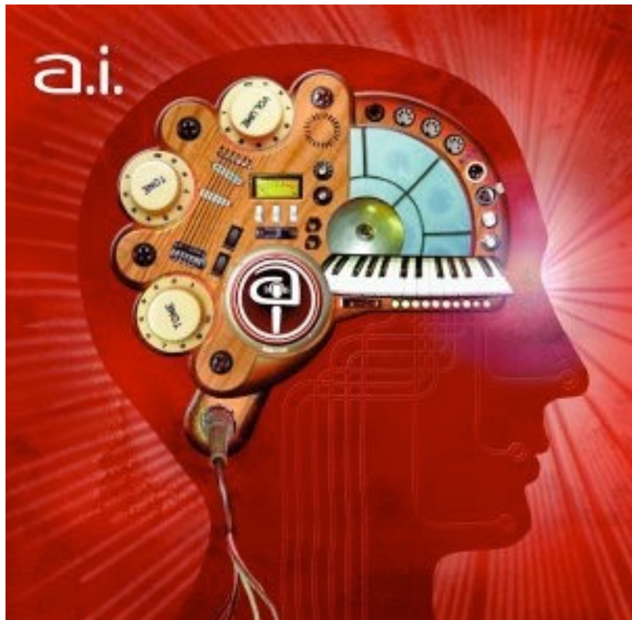
Applications

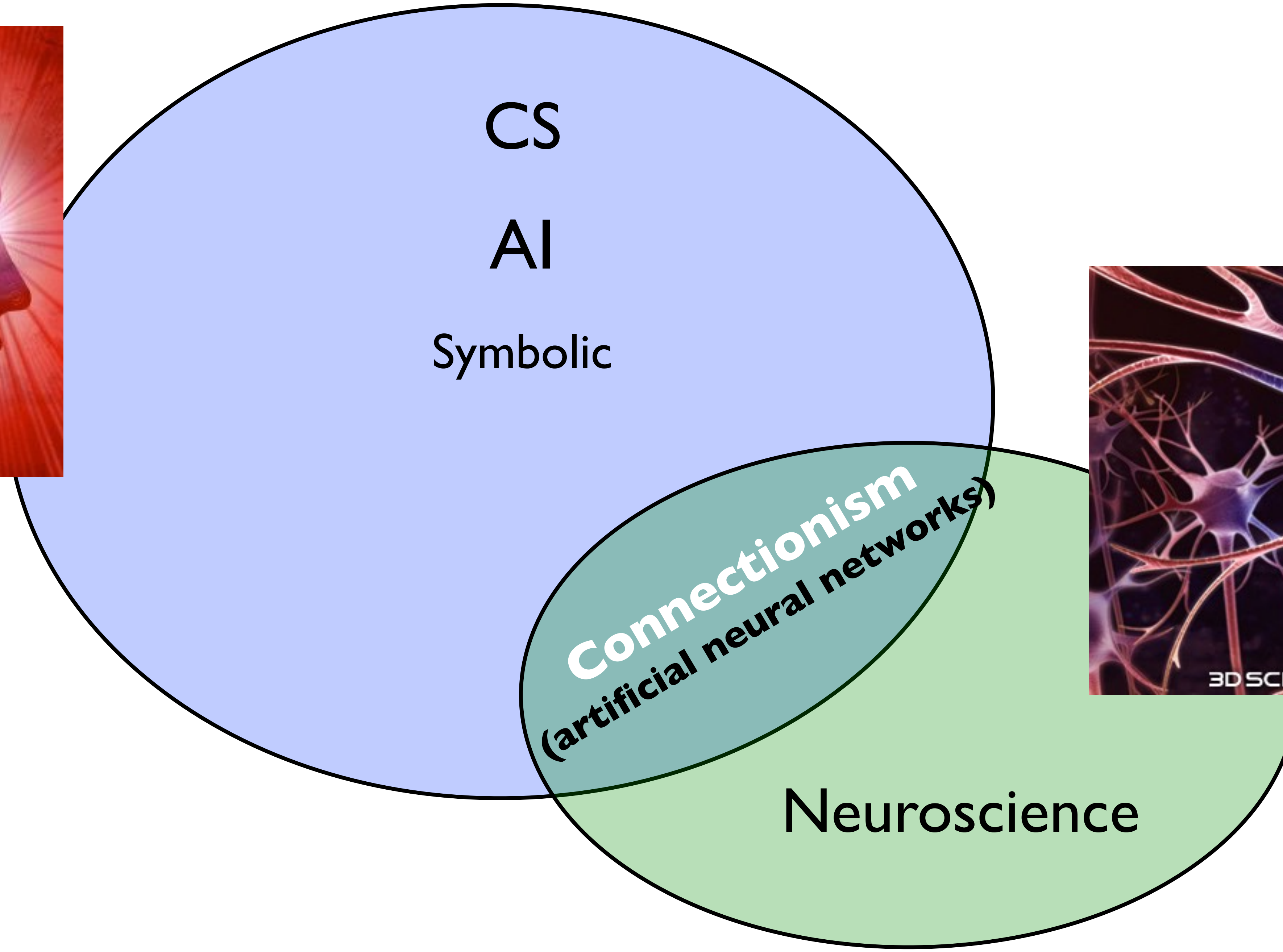
- Pattern recognition
  - handwriting
  - speech
  - fingerprints
  - images
- Mining text
  - Google
  - text classification
- Natural language processing
  - predicting the next word
  - disambiguation of meaning
  - predicting the part of speech (POS)
- Software engineering
  - Predicting stability
  - Better testing (*)
  - Security (*)

Applications

- Data mining
  - direct marketing
  - prediction of bonuses
- Bioinformatics
  - predicting the risk of cancer
  - detecting disease
  - drug discovery
- Collaborative filtering
  - product recommendations
  - personalized medicine

The vision of AI
in **1957** (Rosenblatt, "Perceptron")





The role of learning in modern AI

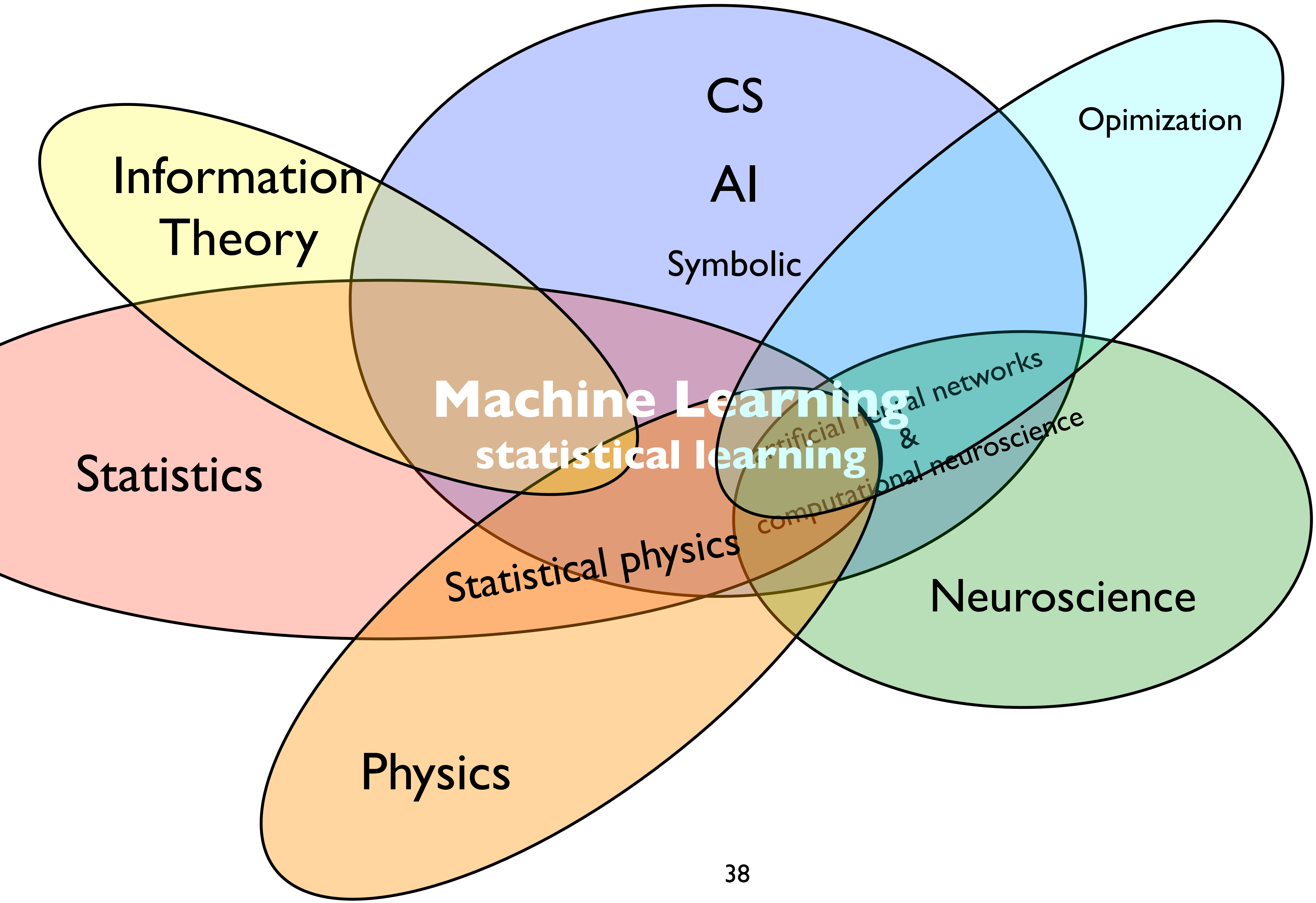
- "Connectionist" AI has matured, is mathematical, has given rise to machine learning – neural networks are part of ML.
- "Classic AI", having integrated uncertainty, gave rise to probabilistic graphical models (Bayesian networks), whose parameters can be learned.

apprentissage

machine

- The fundamental role of learning and a probabilistic approach is largely recognized.

Current vision of founding disciplines



What is ML?

Perspective of a (hypnotized) user

- A field of scientific study (=witchcraft) which
- researches the fundamental principles (magic formulas)
- and **develops the algorithms** (magical incantations/ spells)
- capable of using the collected data to (automagically) **produce** *predictive* functions to apply on similar data (in the future!)

The basic ingredient of ML is...

- Collected from nature, from the internet, industrial processes.
- Arrive in many formats, structured / unstructured, rarely clean, often messy.
- In learning we want to see our data as a **list of examples** (or we will transform them in that form)

- ideally ***many*** *examples* of the *same nature*.

➡ preferably with each example, *a vector of numbers* (or we will transform them in that form)

Learn from **examples!**

"horse"

"horse"

"horse"

Principle much more general than to write by hand, starting from scratch, an algorithm to recognize a horse ...

You know how to program: how would you do it?

“Classic” algorithms vs learning

- Classic approach:
  - formal description of the constraints of entry and desired output
  - understanding of the computational problem
  - **design** of an algorithmic solution, based on this understanding
  - **increased** noise and ambiguity
- Problems:
  - Incomplete understanding
  - Algorithmic solution can be very expensive

“Classic” algorithms vs learning

- Learning approach:
  - data (examples) of the form **(input, output)**
  - **partial** understanding of the computational problem: a priori knowledge
  - **learning:** searching within a large class of functions

- Important:

For ML to work, we need (sometimes a lot of) data.
The more data we have, the better results we get.

Learning

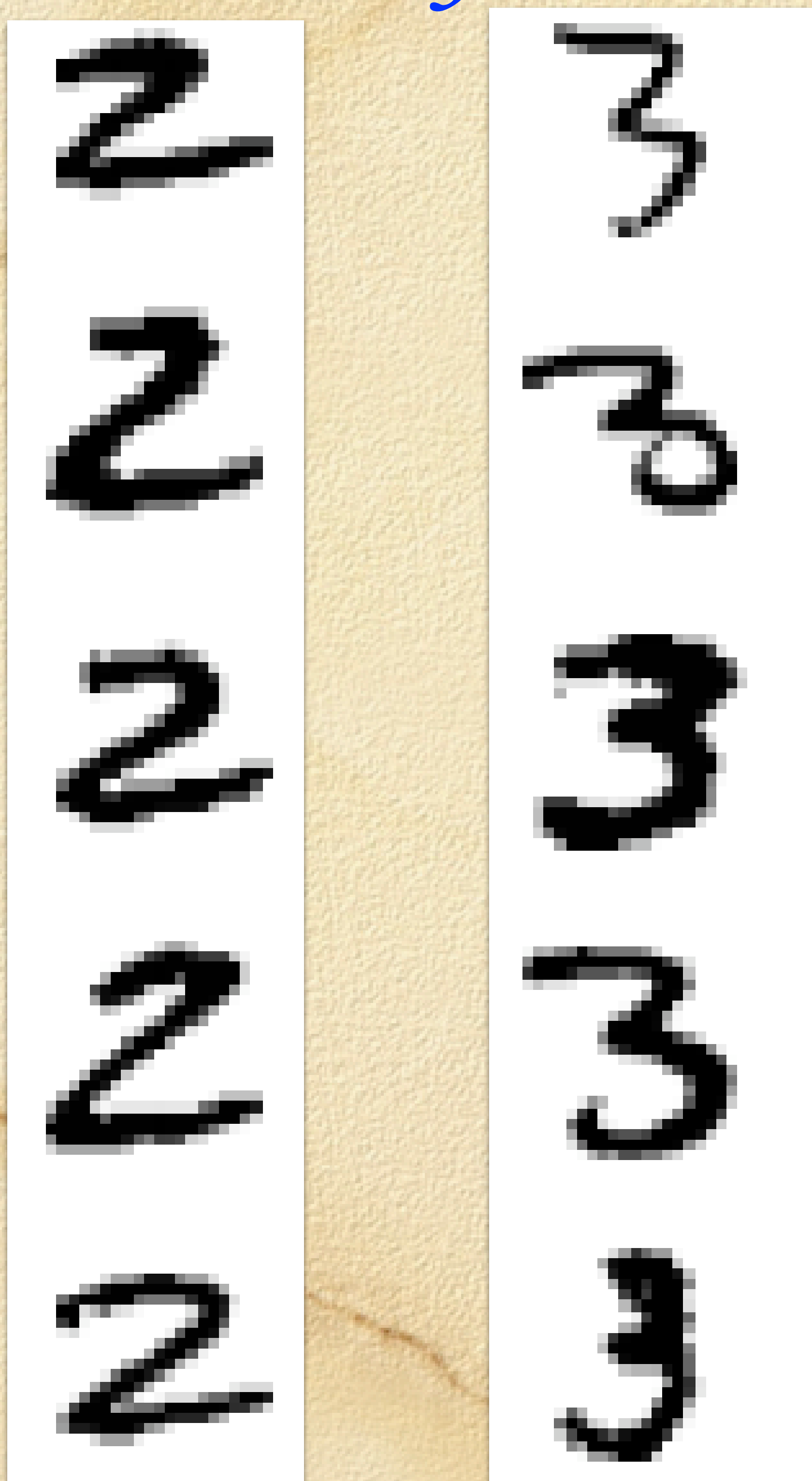
- An essential characteristic of natural intelligence
- Learning **by heart** vs **inductive** reasoning
- Key word: **generalization**
- Typical learning situation:

1. We are given examples (data)
2. We are then presented with a **new example** and we have to make a decision/prediction.

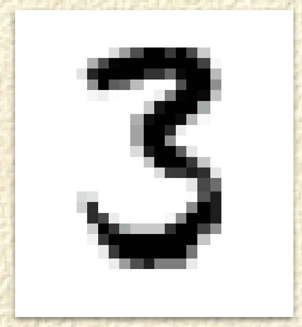
Ex: Character recognition

Training set

2 3



Test point



2 or 3 ?

Learning is not simply memorizing…

It is to be able to generalize!

on new examples that we have not before seen

Categories of learning problems

- Classification
  - Task: **Classify** new examples in discrete categories
- Regression
  - Task: make a **real-valued prediction** for each example
- Density estimation
  - Task: decide if new example resembles seen examples

Machine learning? or Statistics?

a lot in common but with a difference in point of view

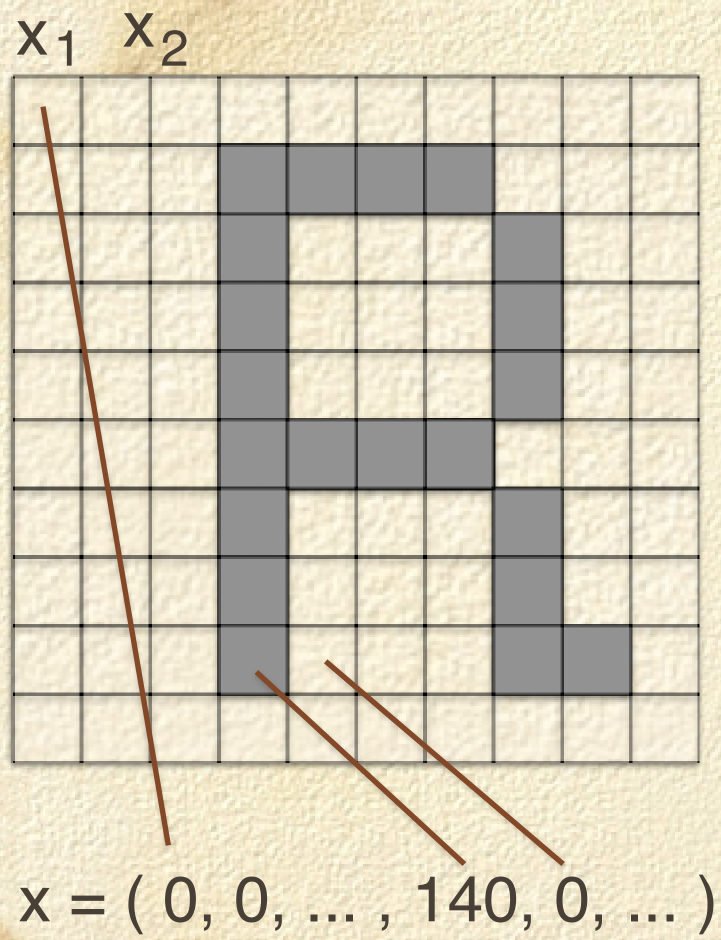
- Statistics: branch of mathematics
  - Importance of rigor and theoretical guarantees
  - Strong assumptions and hypothesis tests
- Machine learning:
  branch of Artificial Intelligence (computer science)
  - Grand ambition: intelligence!
  - We take inspiration from everything we can
    (neuroscience, statistics, physics, information theory, ...)
  - The important fact is that ML works! ☺
    Pragmatic approach.

Data-mining?

or machine learning? or statistics?

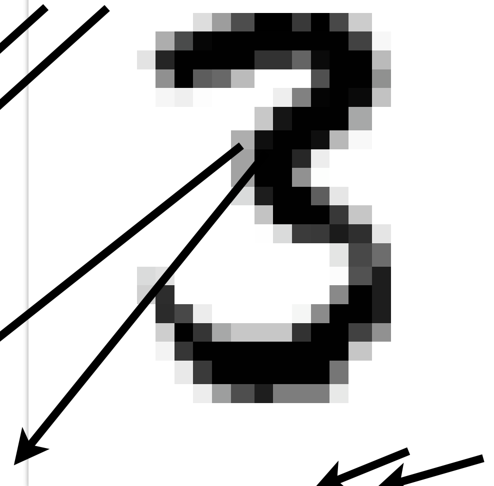
- Statistics and machine-learning = theoretical studies and algorithmic developments for data analysis / learning.
- data-mining = use of these techniques on big industrial problems (big datasets).
    - Challenges related to size: scaling problems
    - Practical approach.

Vector representation of a data example



x vector in R^d

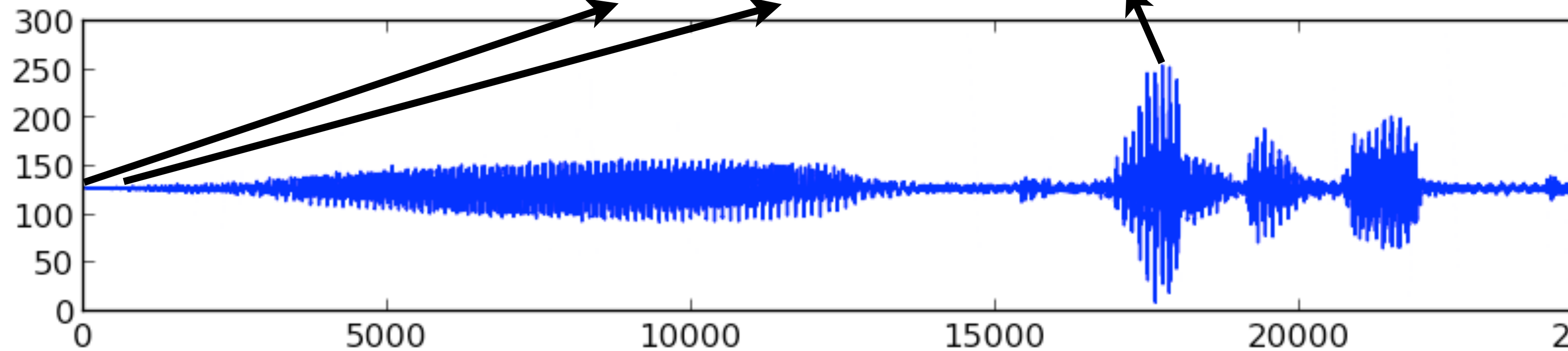
Transform an example into a vector representation $\mathbf{x} \in \mathbb{R}^d$



Gross representation:

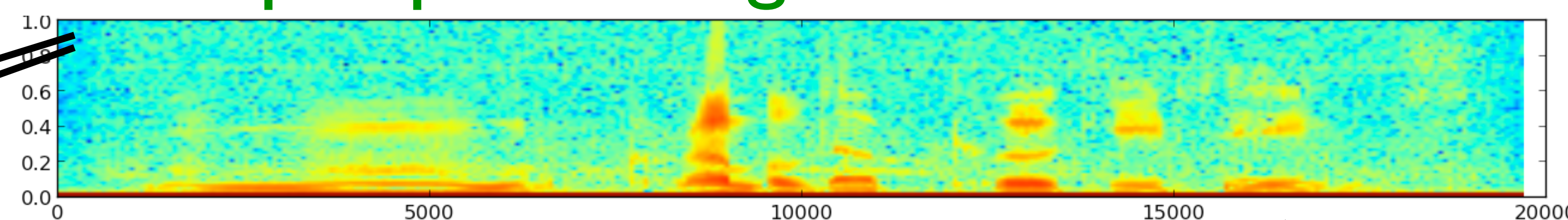
$x = (0, 0, \ldots, 54, 120, \ldots, 0, 0)$

$x = (125, 125, \ldots, 250, \ldots)$



Or feature extraction from pre-processing:

$x = (, \quad , \quad , \quad , \quad \ldots)$



we the jumped jumping run elephant dog cat horse

Bag of words for «The cat jumped»: $x = (\ldots 0 \ldots, 0, 1, \ldots 0 \ldots, 1, 0, 0, \ldots, 0, 0, 1, 0, \ldots 0 \ldots$

OR vector of handmade features:

$x = (\text{feature } 1, \ldots, \text{feature } d)$

ex: Histograms of Oriented Gradients

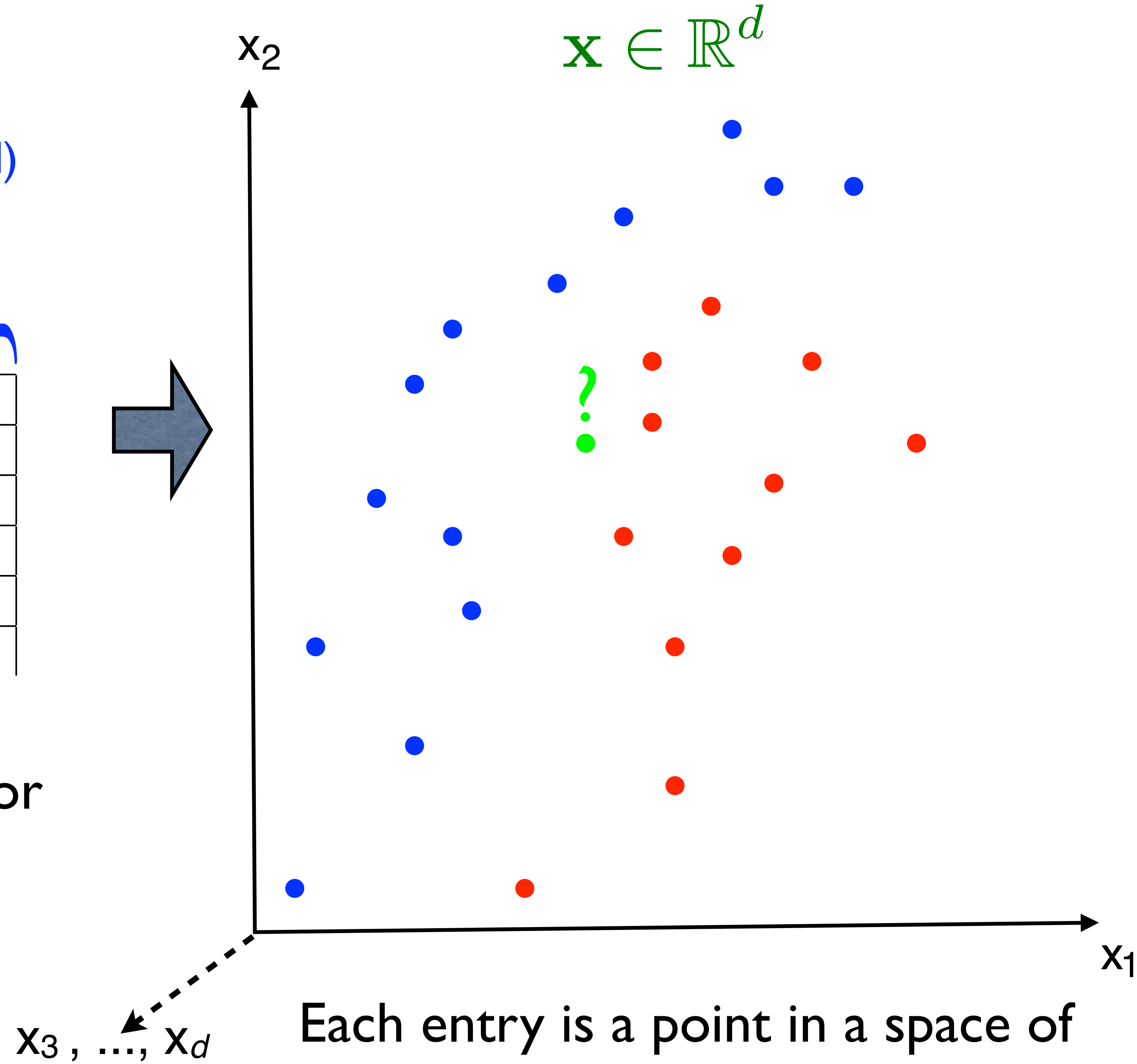
Data set seen as a scatter plot in a high-dimensional vector space

(input) $\mathbf{x} \in \mathbb{R}^d$ (label) y

n examples

$\mathbf{x}_1$	$\mathbf{x}_2$	$\mathbf{x}_3$	$\mathbf{x}_4$	$\mathbf{x}_5$	
0.32	-0.27	+1	0	0.82	1
-0.12	0.42	-1	1	0.22	0
0.06	0.35	-1	1	-0.37	1
0.91	-0.72	+1	0	-0.63	1
...	...	...	...	...	...

Each example (row) is a vector of d+1-dimensions



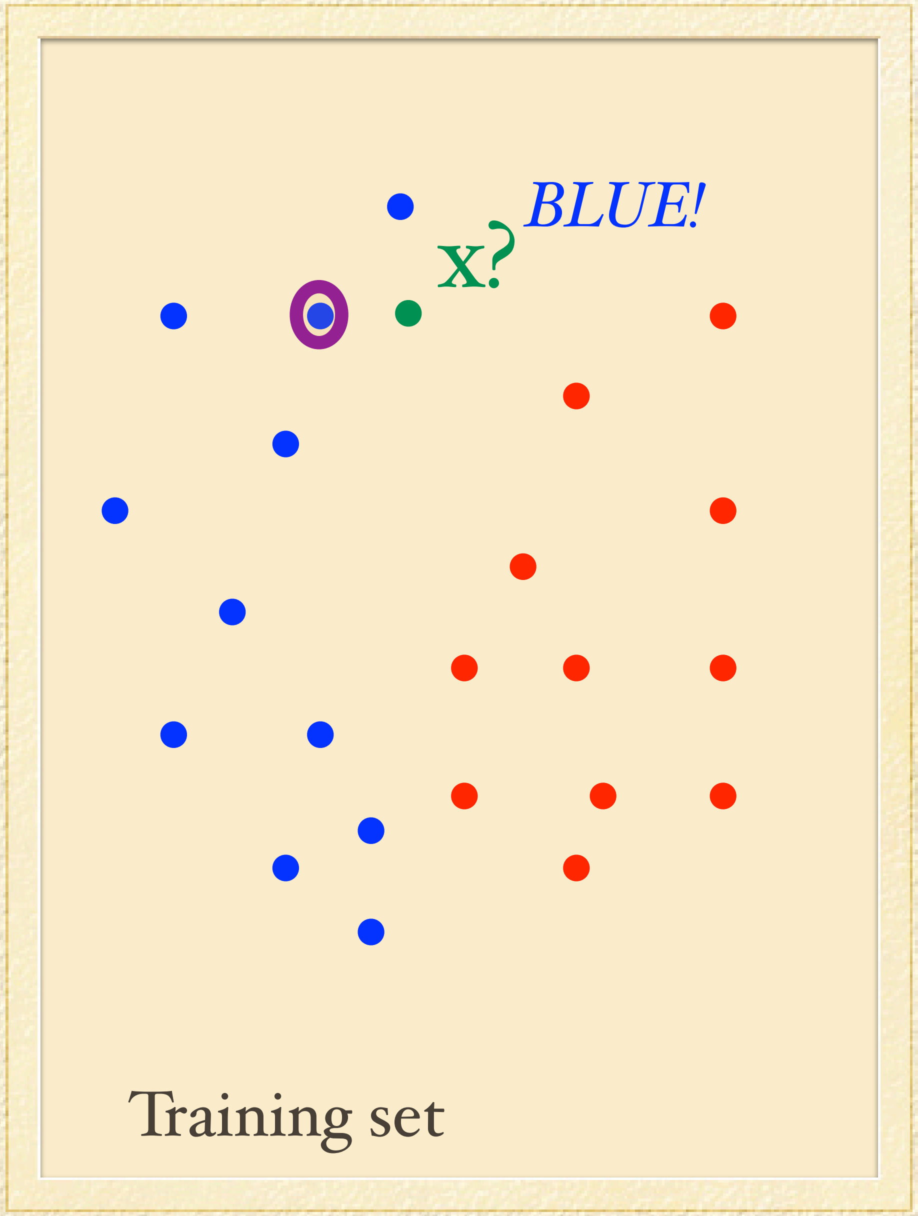
Each entry is a point in a space of d-dimensions

Ex: the nearest neighbor algorithm

For a test point x:

- We find the **nearest neighbour** of x within the training set apprentissage by some measure of distance (eg Euclidean distance).

- We associate x with the class of this nearest neighbor.



Représentation des données:

Notion de niveau de représentation