Département d'informatique et de recherche opérationnelle

# IFT6390
# Fondements de l'apprentissage machine

First class:

**INTRODUCTION**

Professor: Ioannis Mitliagkas
Slides adapted from: Pascal Vincent

# Today

- Getting to know the class (very general discussion, hardly any technical content).
- Webpage on Studium
  https://studium.umontreal.ca
- 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

**Undergraduate version of this class (in French)**

**IFT3395 Fondements de l'apprentissage machine**

Automne

- Offert en 3ème année de bac,

**Advanced course presenting a formalism and essential techniques for learning**

**IFT6269 Modèles graphiques probabilistes et apprentissage**

Automne

Automne

**Limited capacity, very interesting premise**

**IFT6757 Autonomous vehicles (Duckietown)**

# 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

Hiver Course that goes deeper into the fundamental math

IFT6085(?) Theoretical principles for deep learning

Hiver New mathematical course by Guillaume Rabusseau

IFT???? Linear algebra/Spectral Methods in ML

FIRST PART

# Course plan

## and other practical information

# You can find information..

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

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

IFT6390-A-A18
Fondements de l'apprentissage machine
If not, please send me an email

# 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...)

There will be reminders for all essential mathematical notions ...

# 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, however we can accommodate:
  - Homework and exams can be submitted in French
  - Come talk to me if you still have questions!

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 représentations.

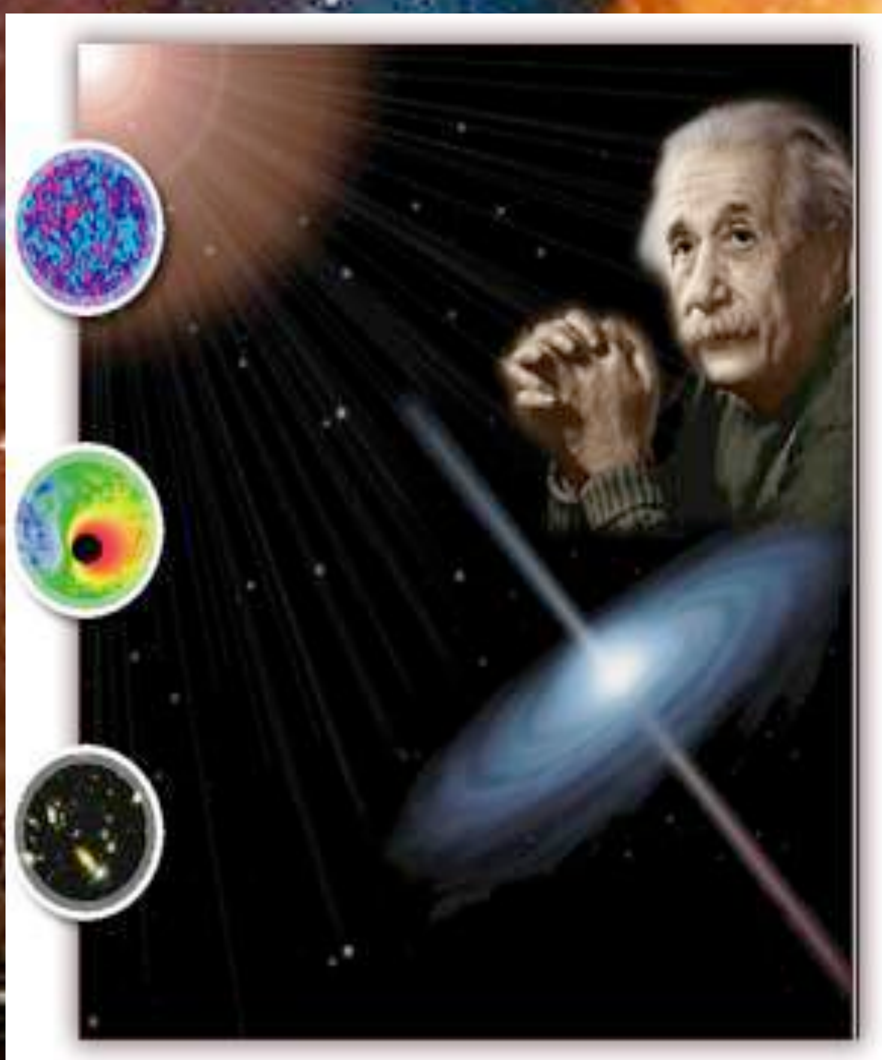
## Scientific curiosity

# Three great mysteries

## Scientific curiosity

# Three great mysteries

The universe,
space / time
energy / matter



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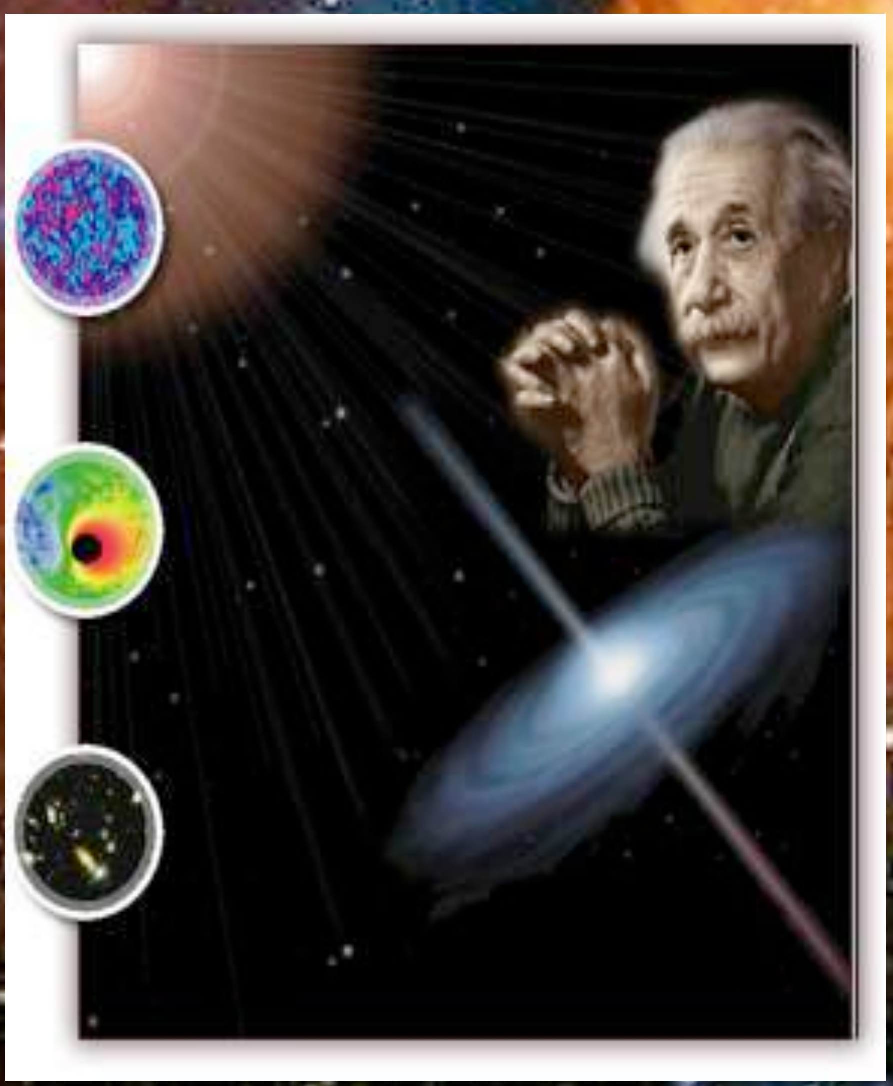

Life

Scientific curiosity

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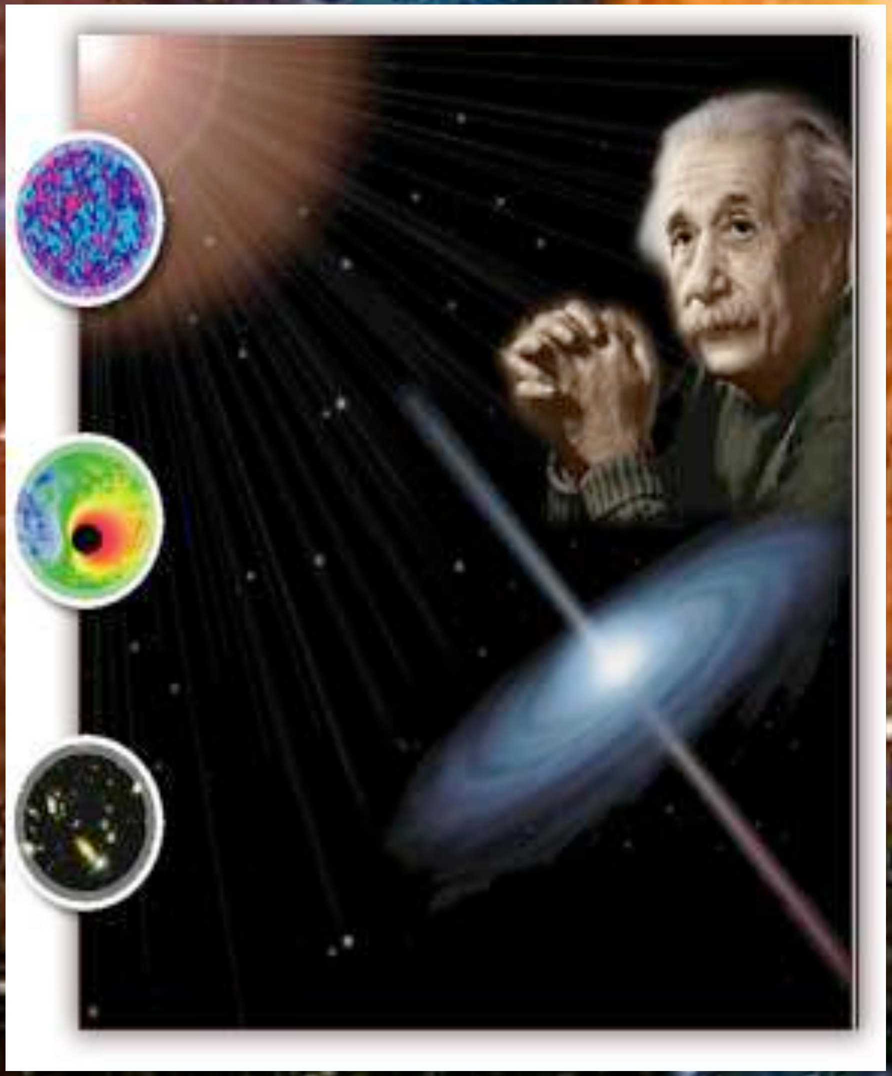


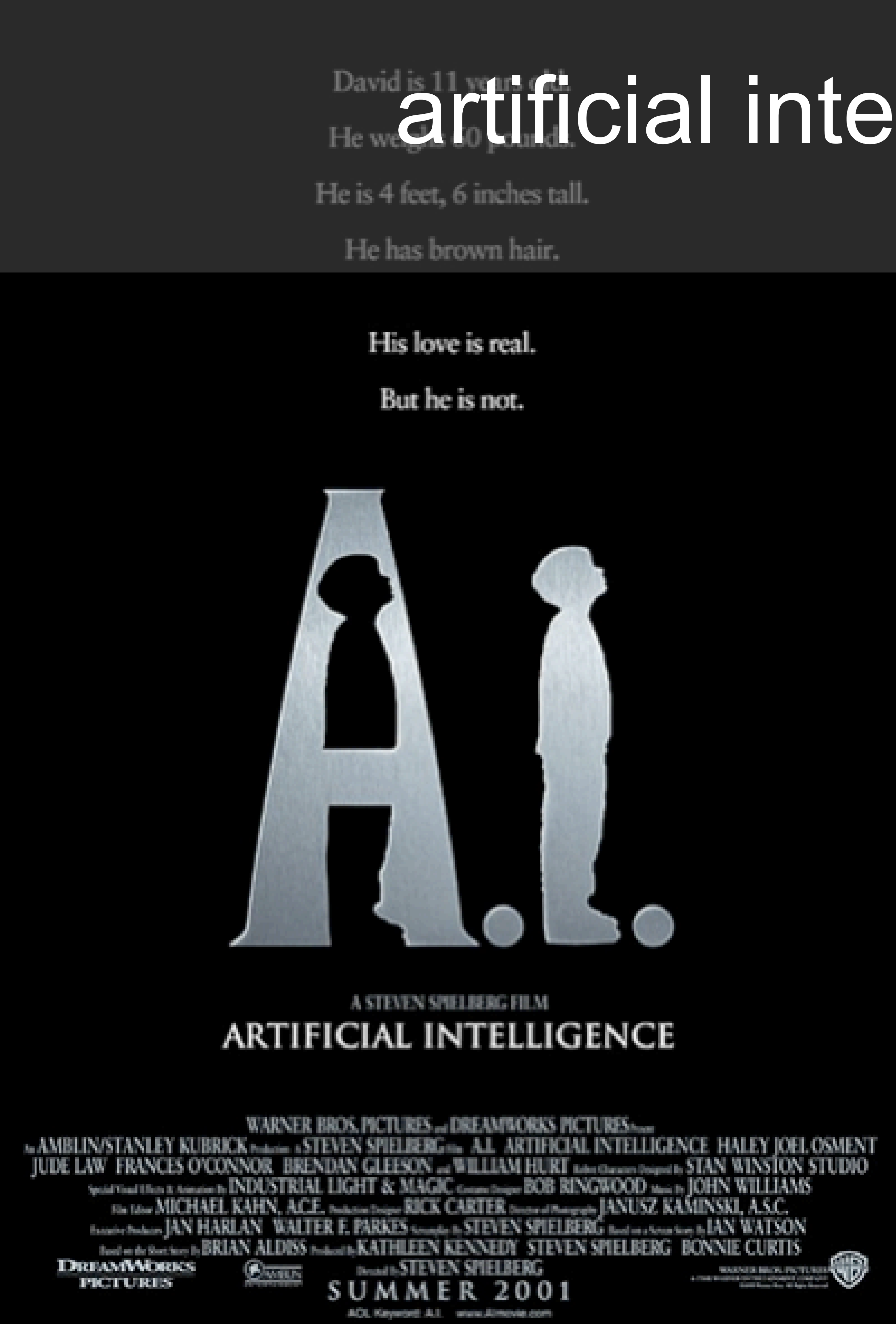
Life

Intelligence,
Consciousness

# Natural intelligence: a brain that learns, adapts

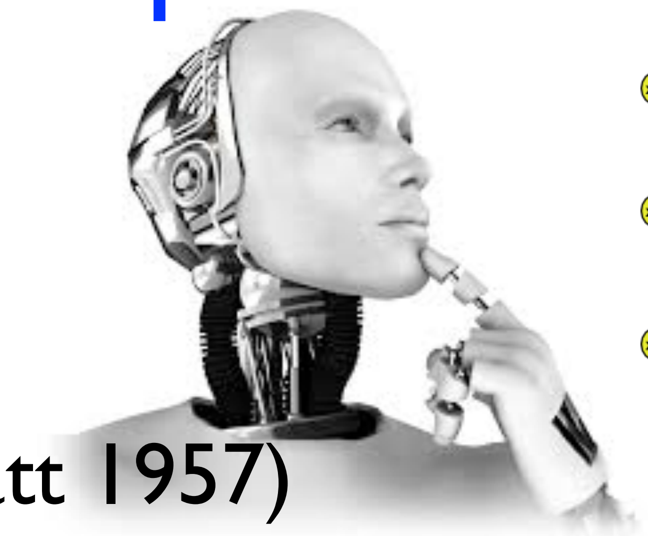
- $10^{11}$ neurons,
  $10^{14}$ synapses
- Complex network of neurons
- Learning: the modification/adaptation of synapses

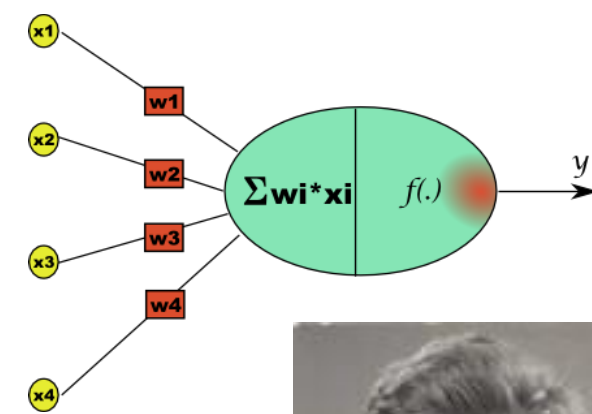
# artificial intelligence…




# The origins of machine learning

## Historical perspective



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  Artificial Intelligence

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

- Two approaches historically different in AI

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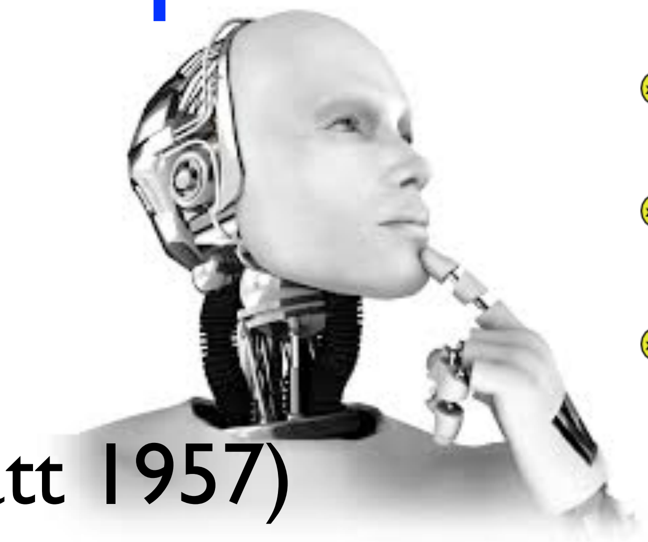

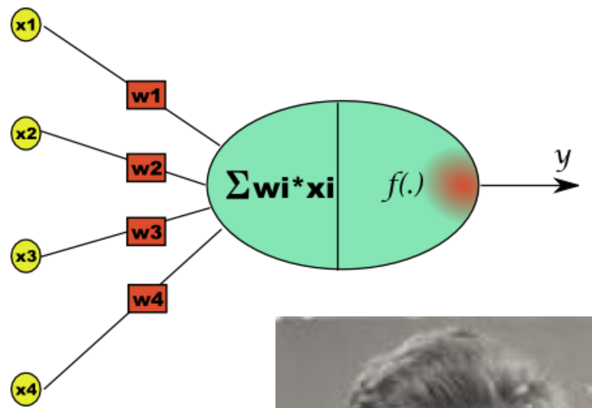


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⇨ network of neurones
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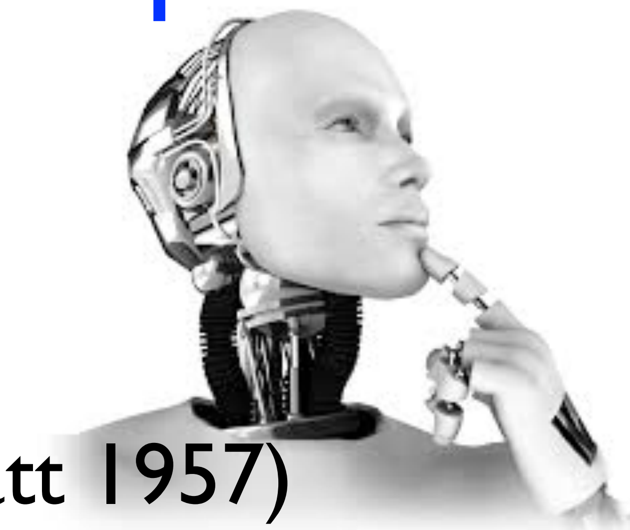

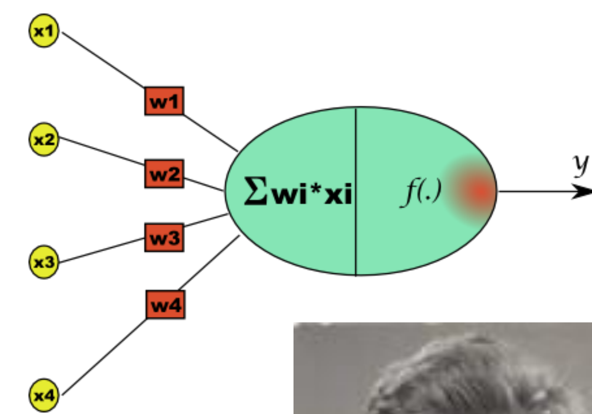


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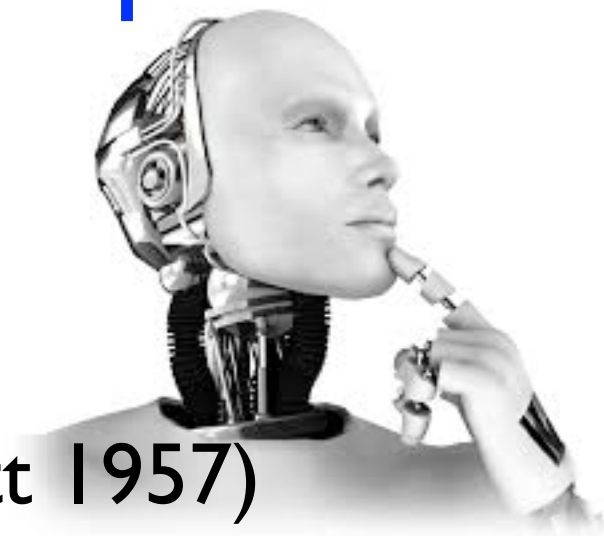

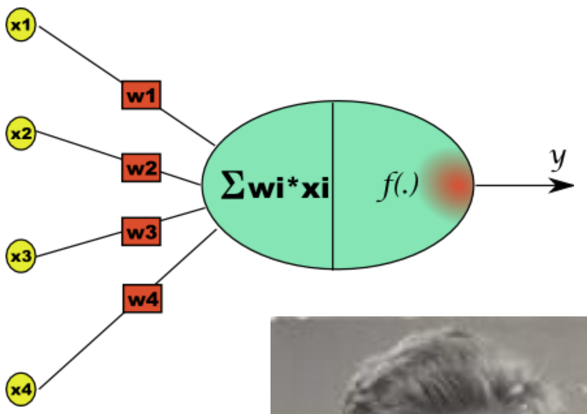


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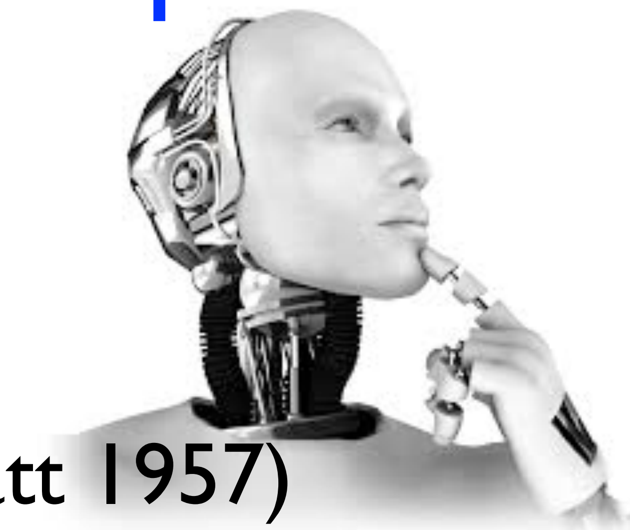

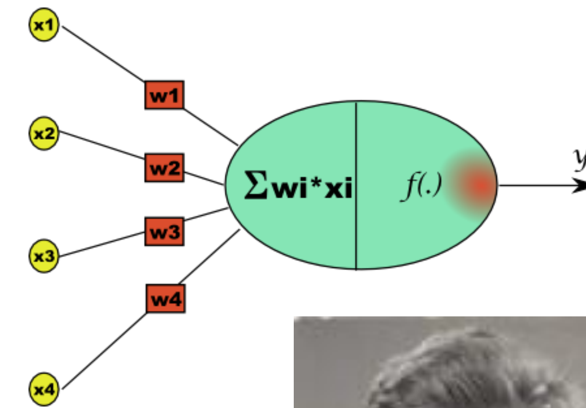


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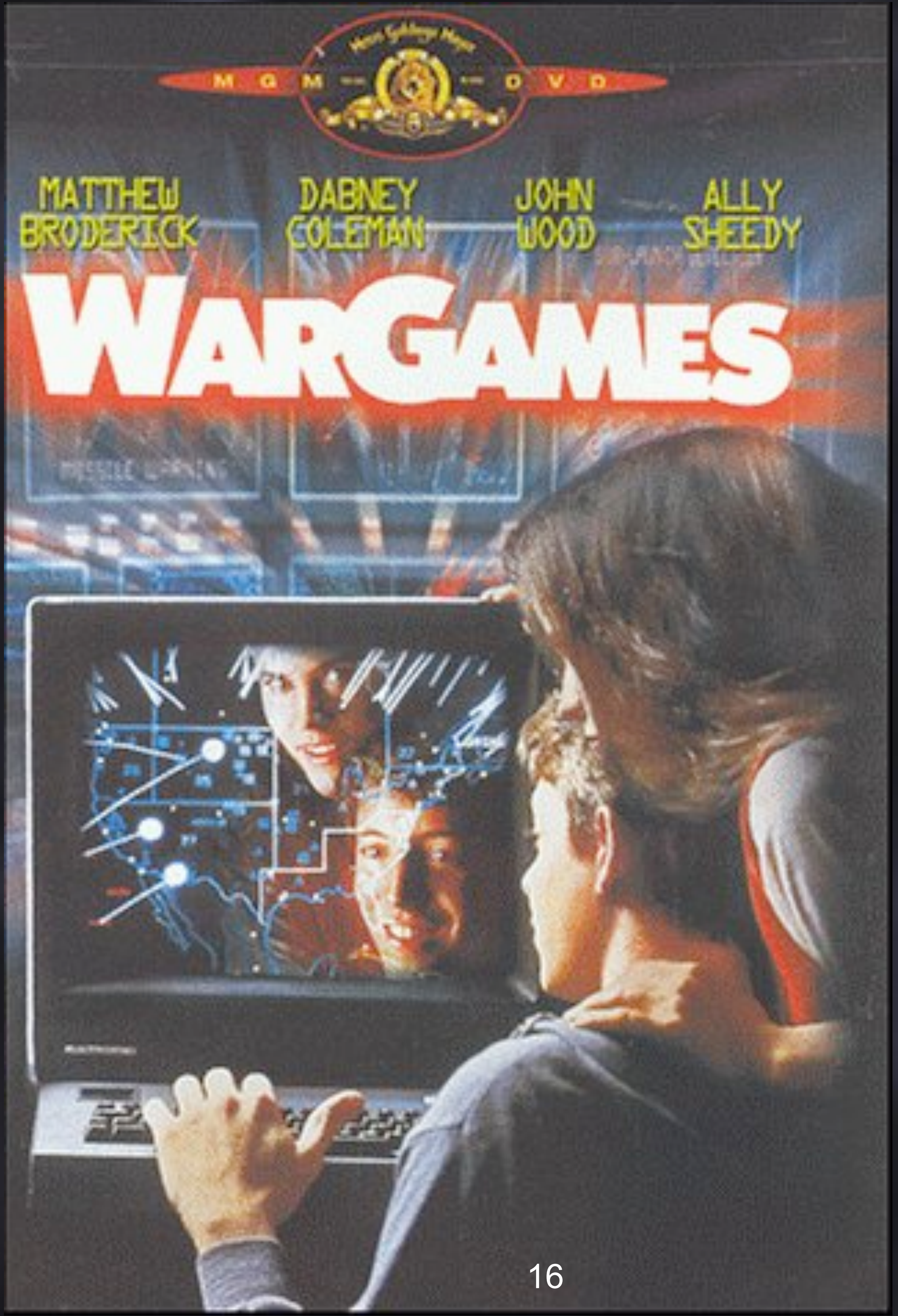
Learning and probabilistic models have largely won
➪ machine learning (apprentissage machine)

# A.I. in science fiction

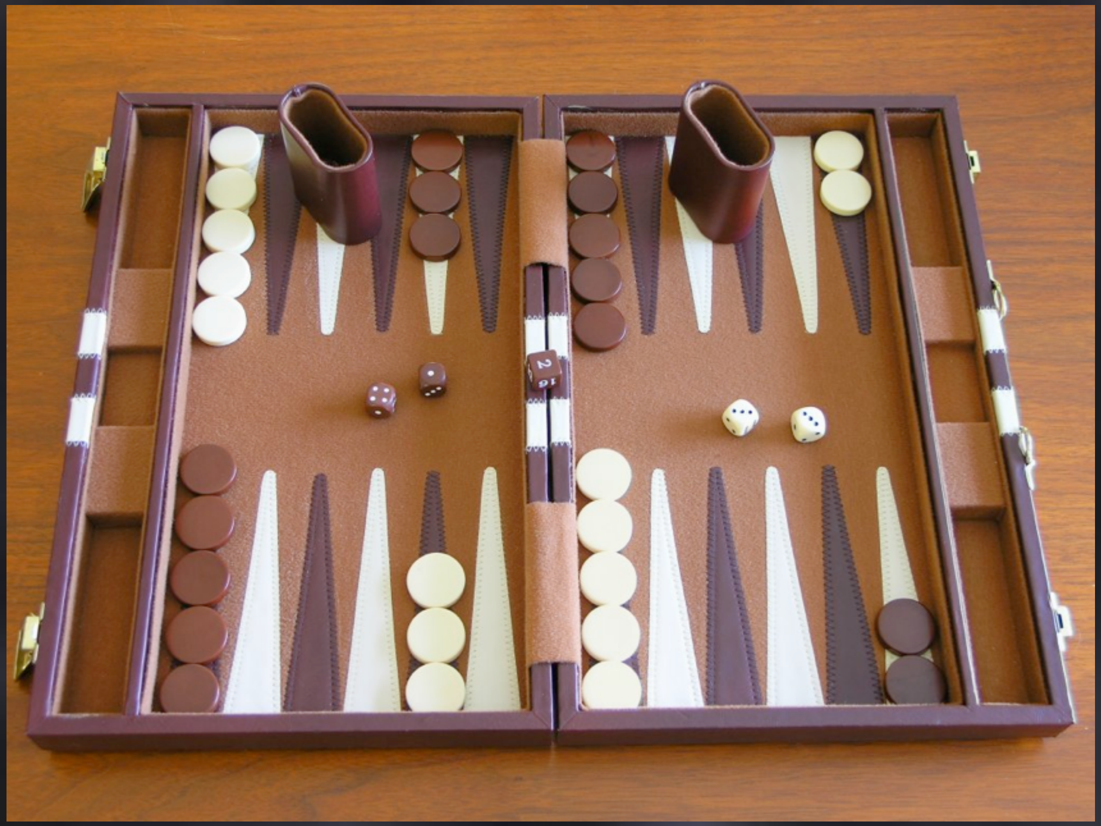
- 1983: In WarGames, a computer learns by playing against itself to play tic-tac-toe and do "global thermonuclear war".



# in reality…

## Backgammon

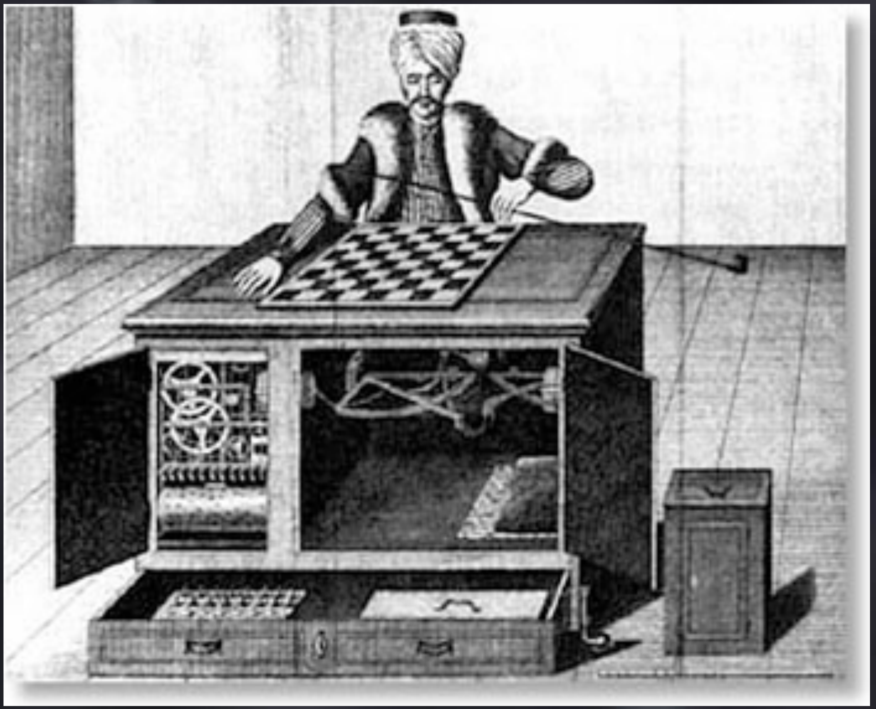
- 1995: TD-gammon, an artificial neural network trained by playing 200 000 games of backgammon against itself, plays at a level equivalent to the best players in the world (Tesauro 1995).



# 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!

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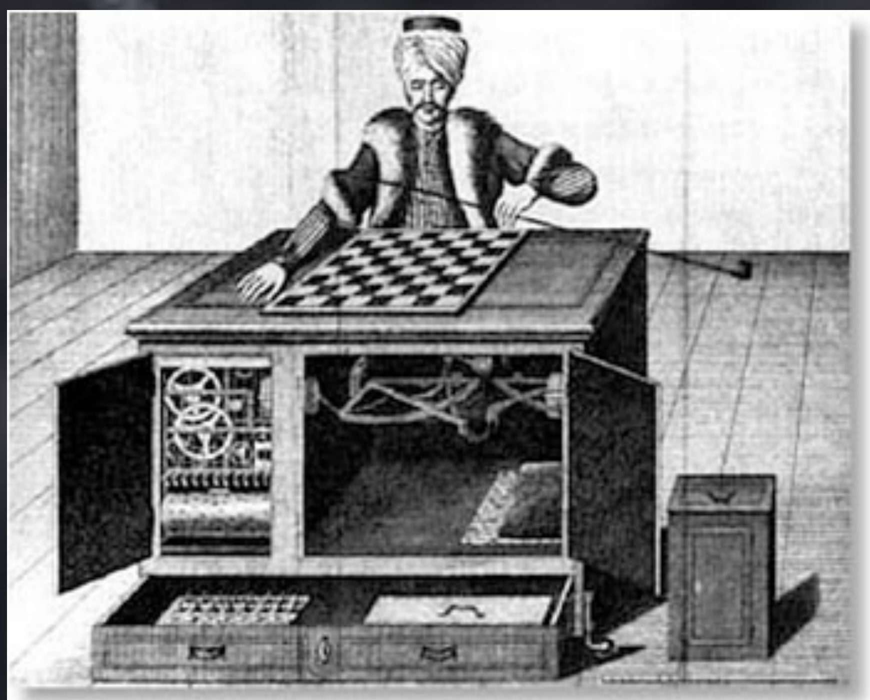

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1997: Garry Kasparov vs «Deep Blue» of IBM

# 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!

# 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”)

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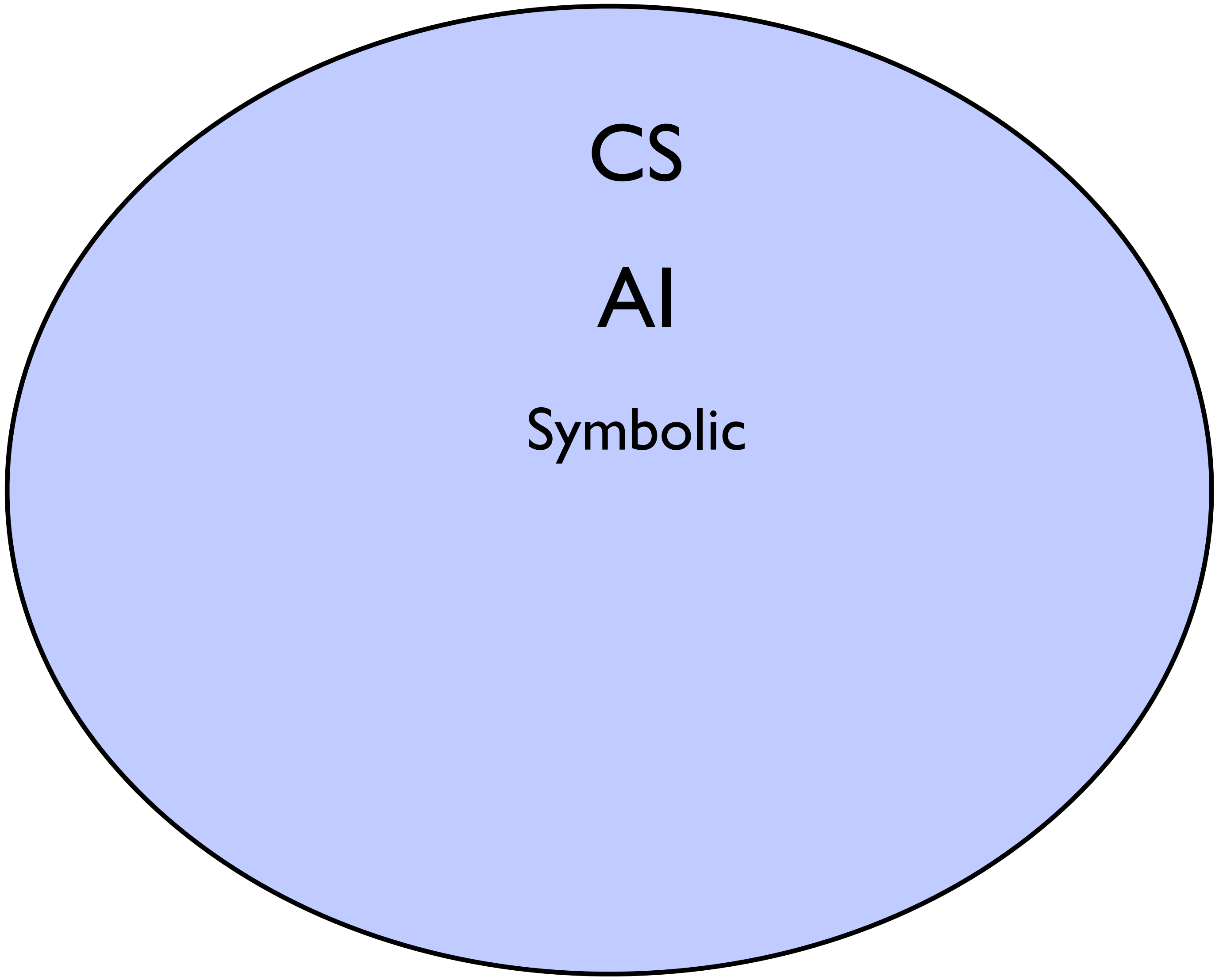

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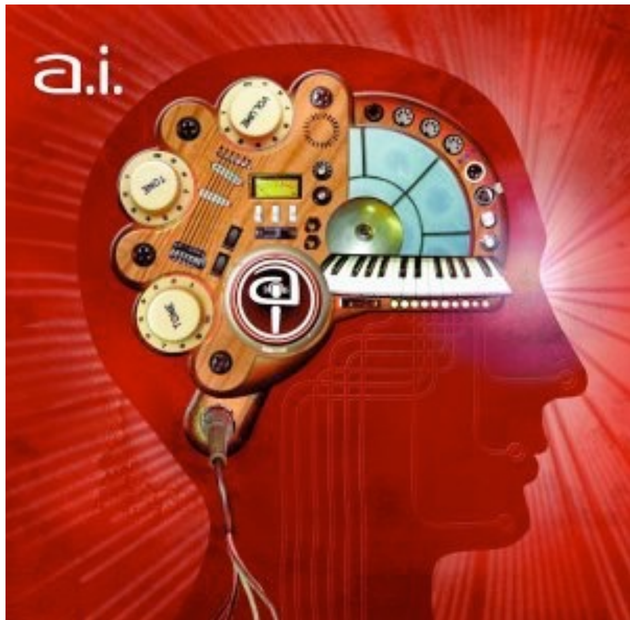


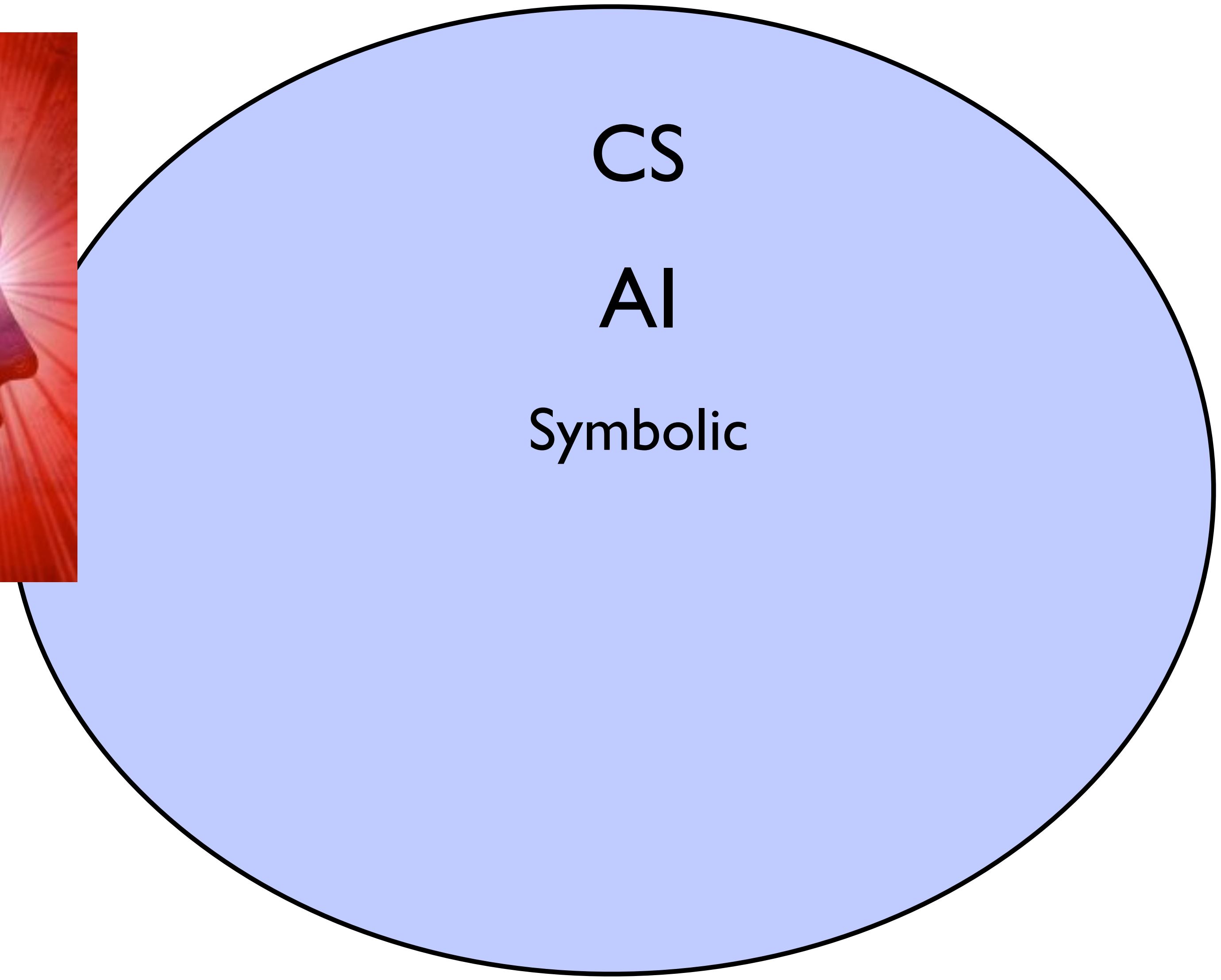

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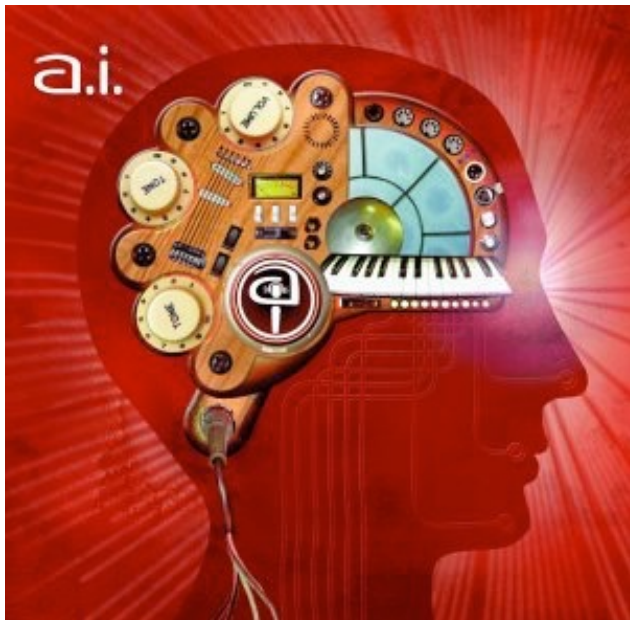


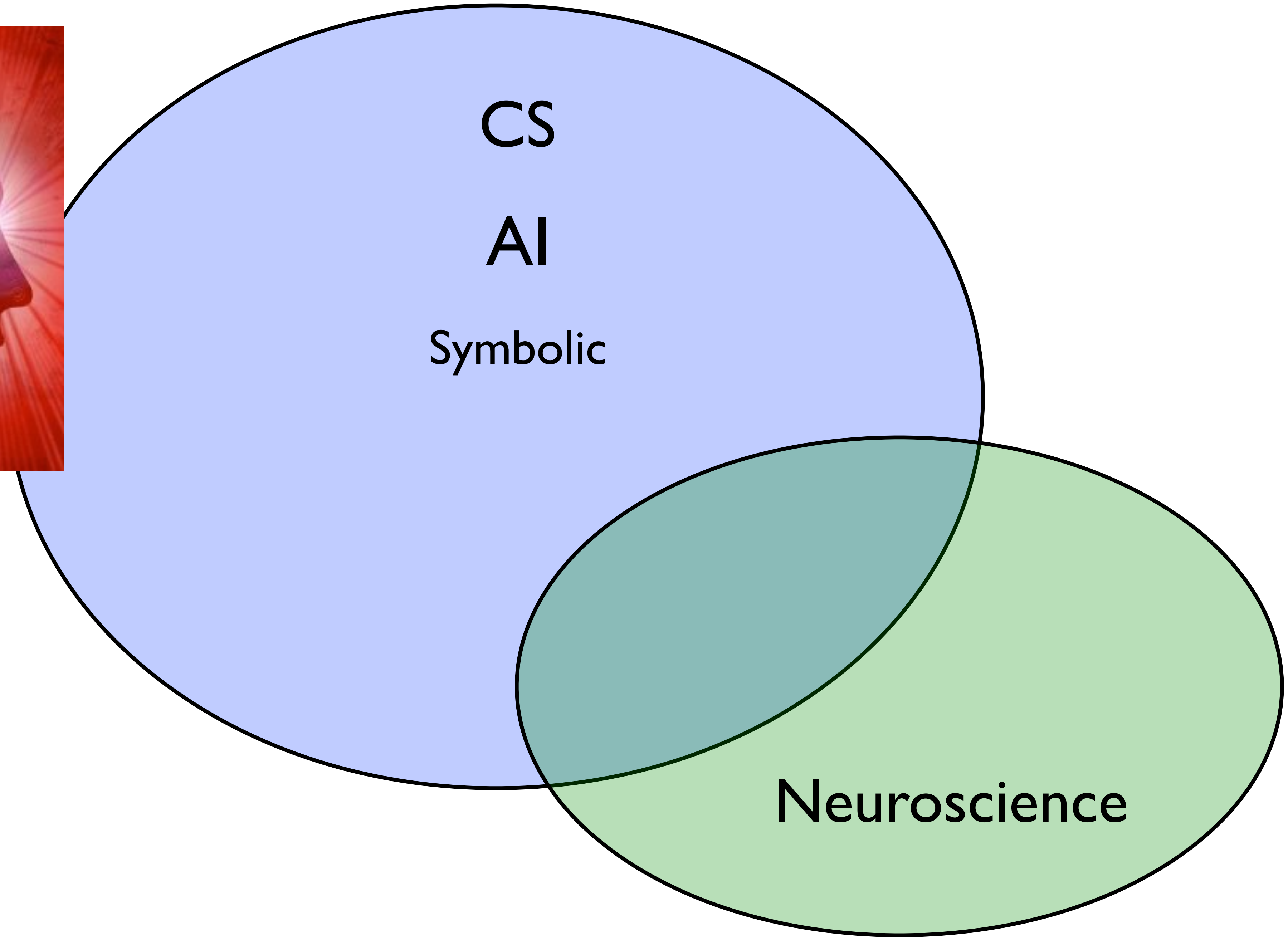

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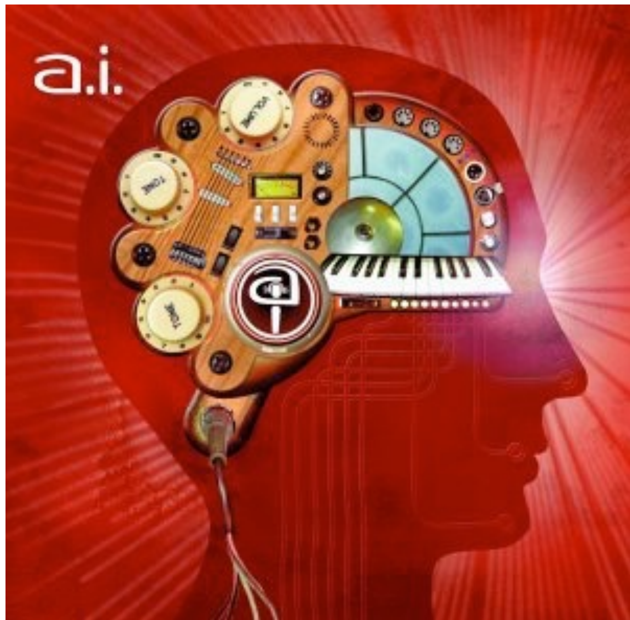


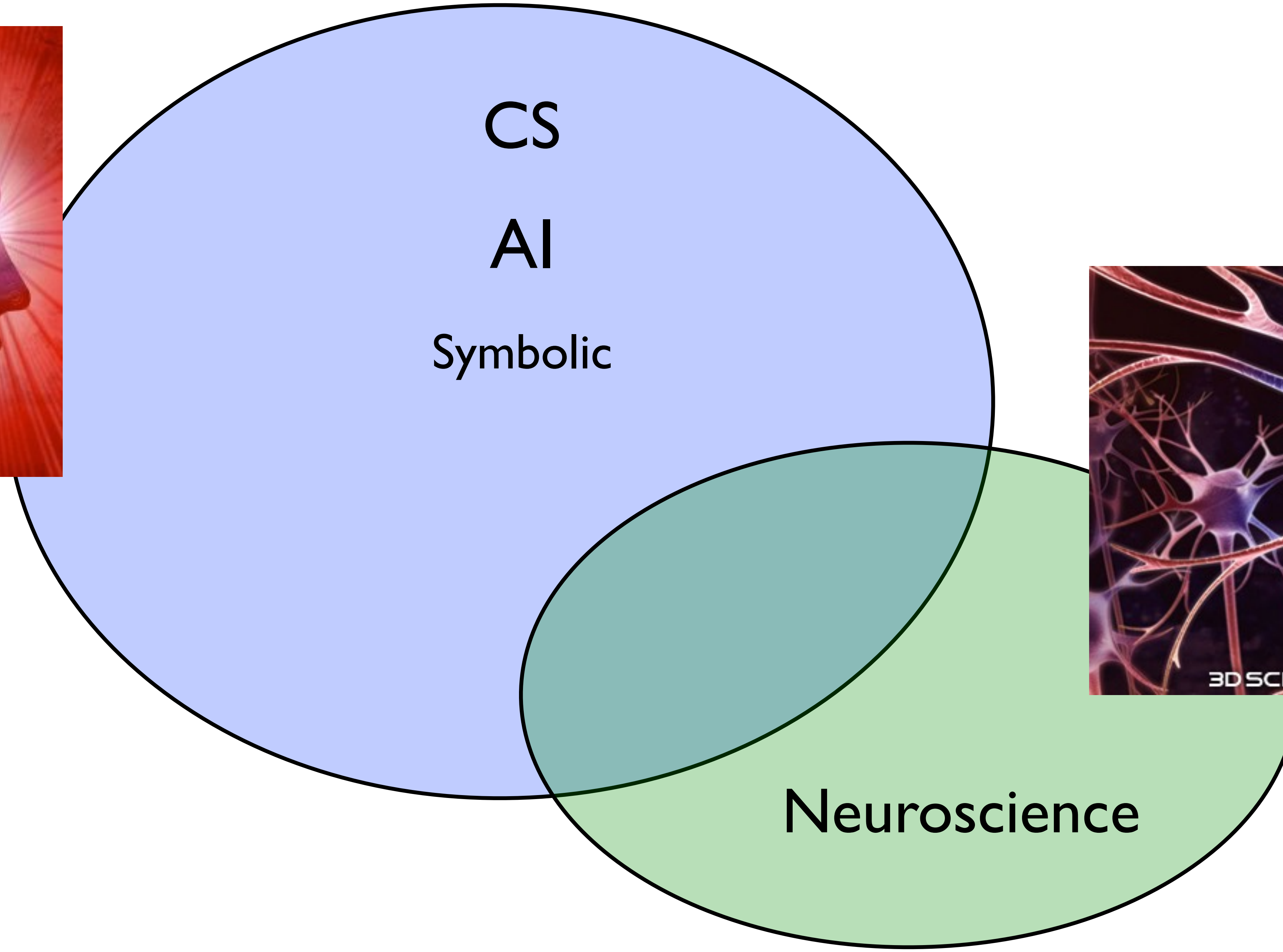


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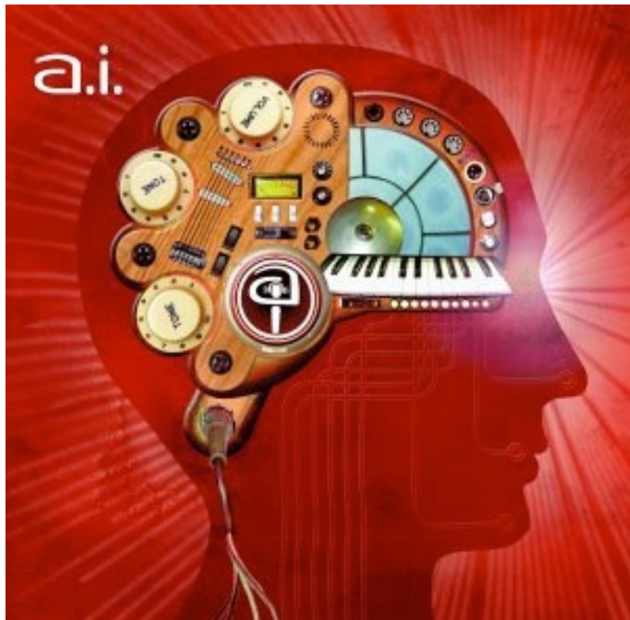


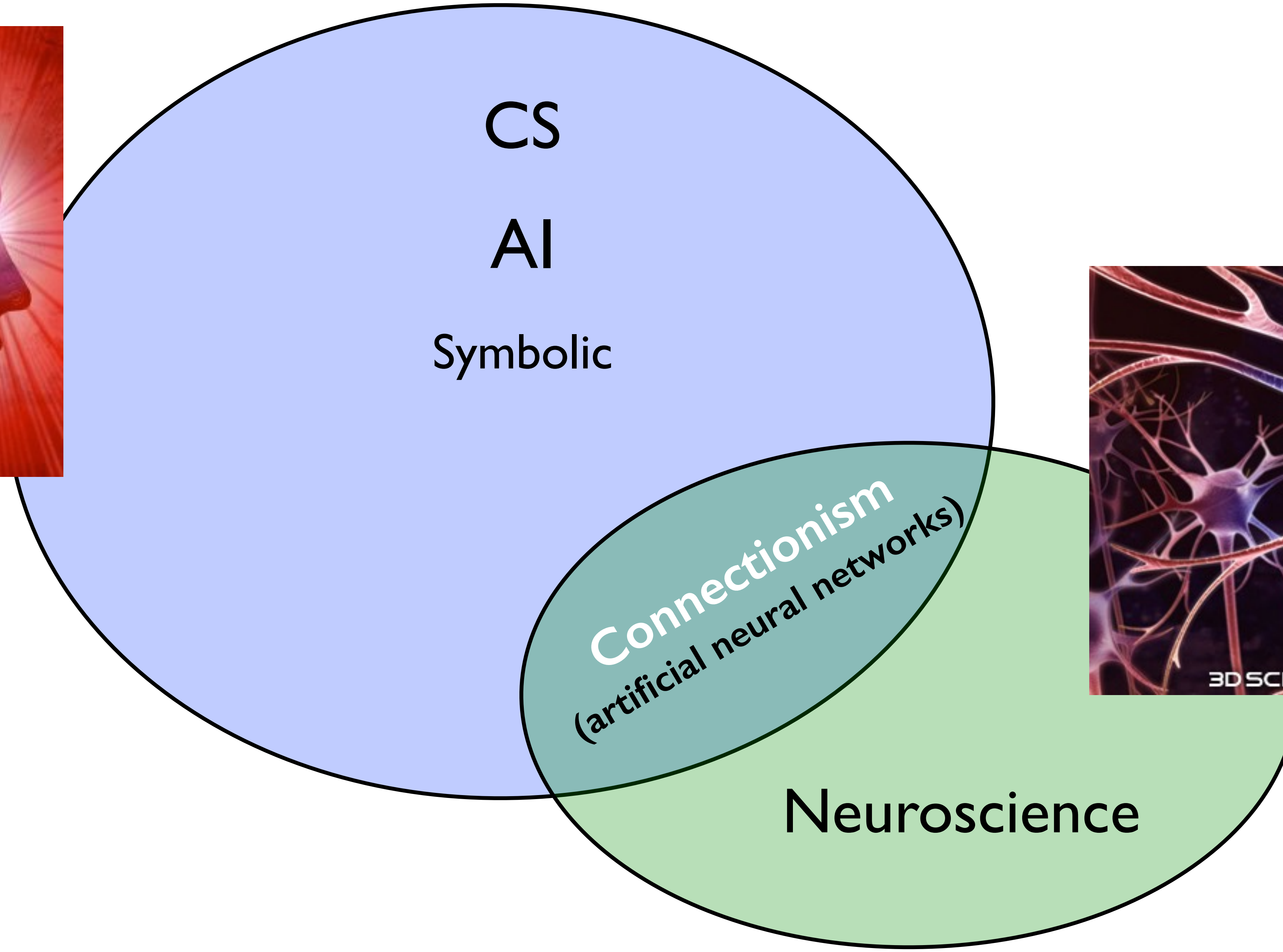


# The role of learning in modern AI

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

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apprentissage

machine

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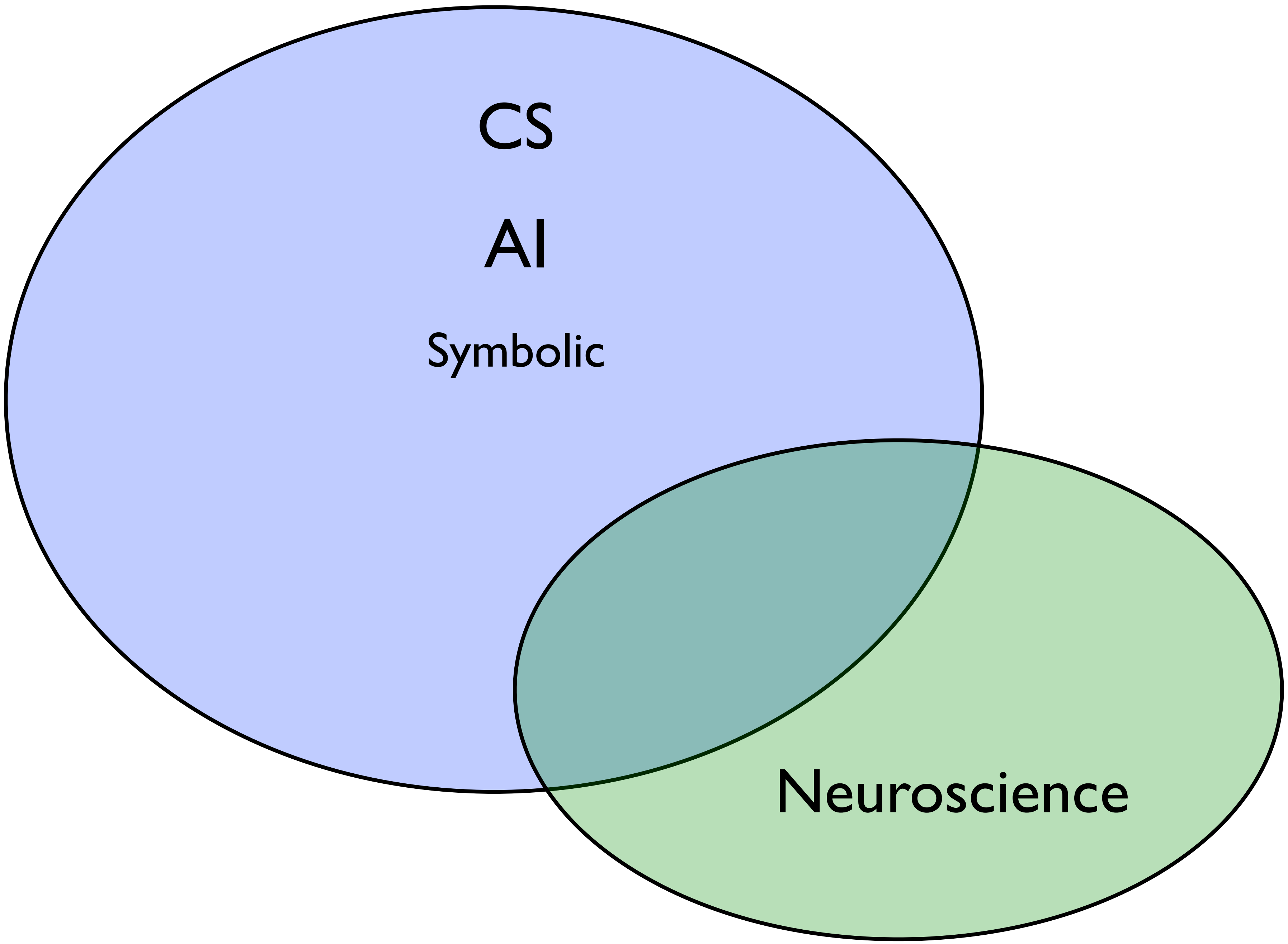

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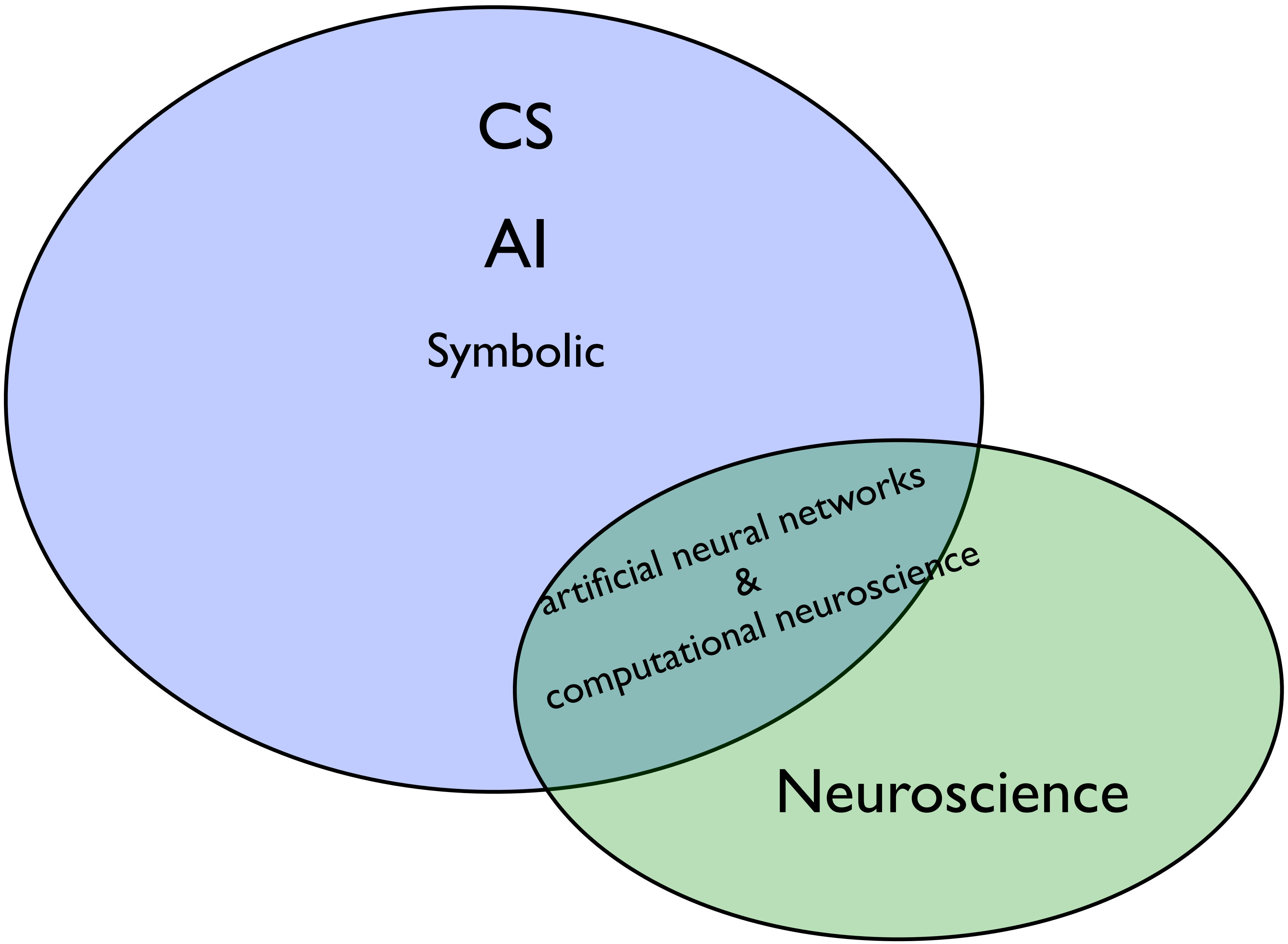

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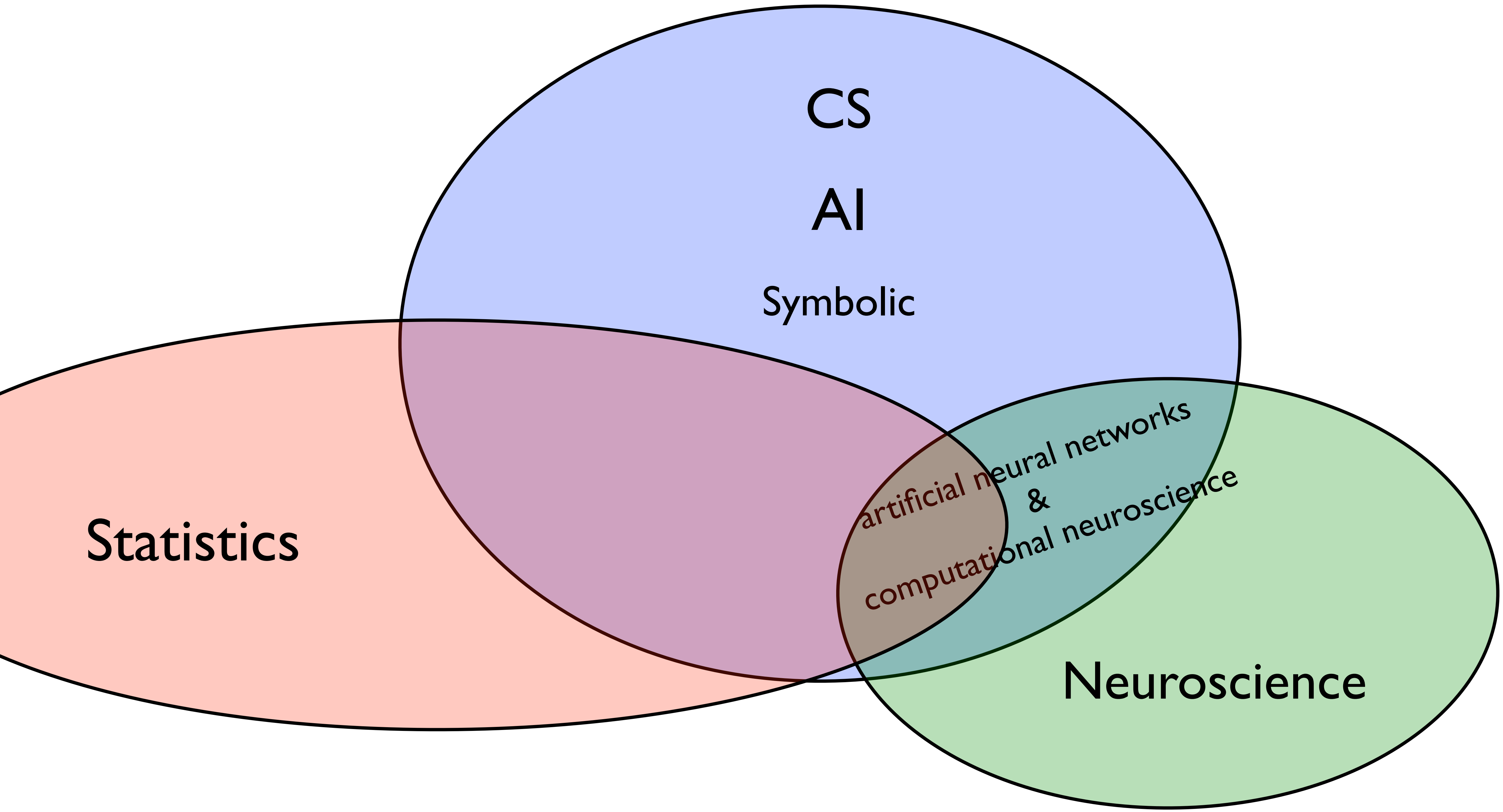

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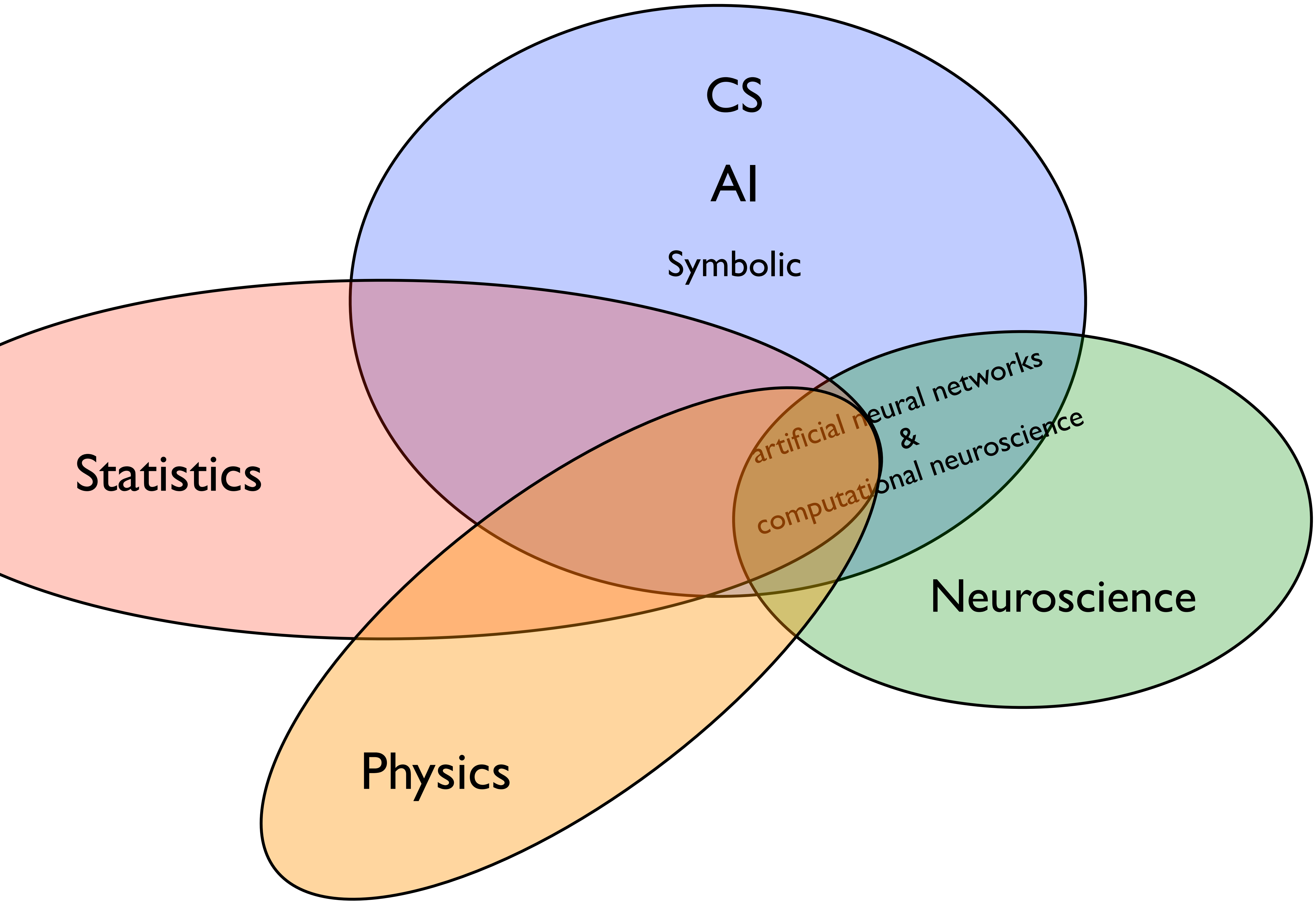

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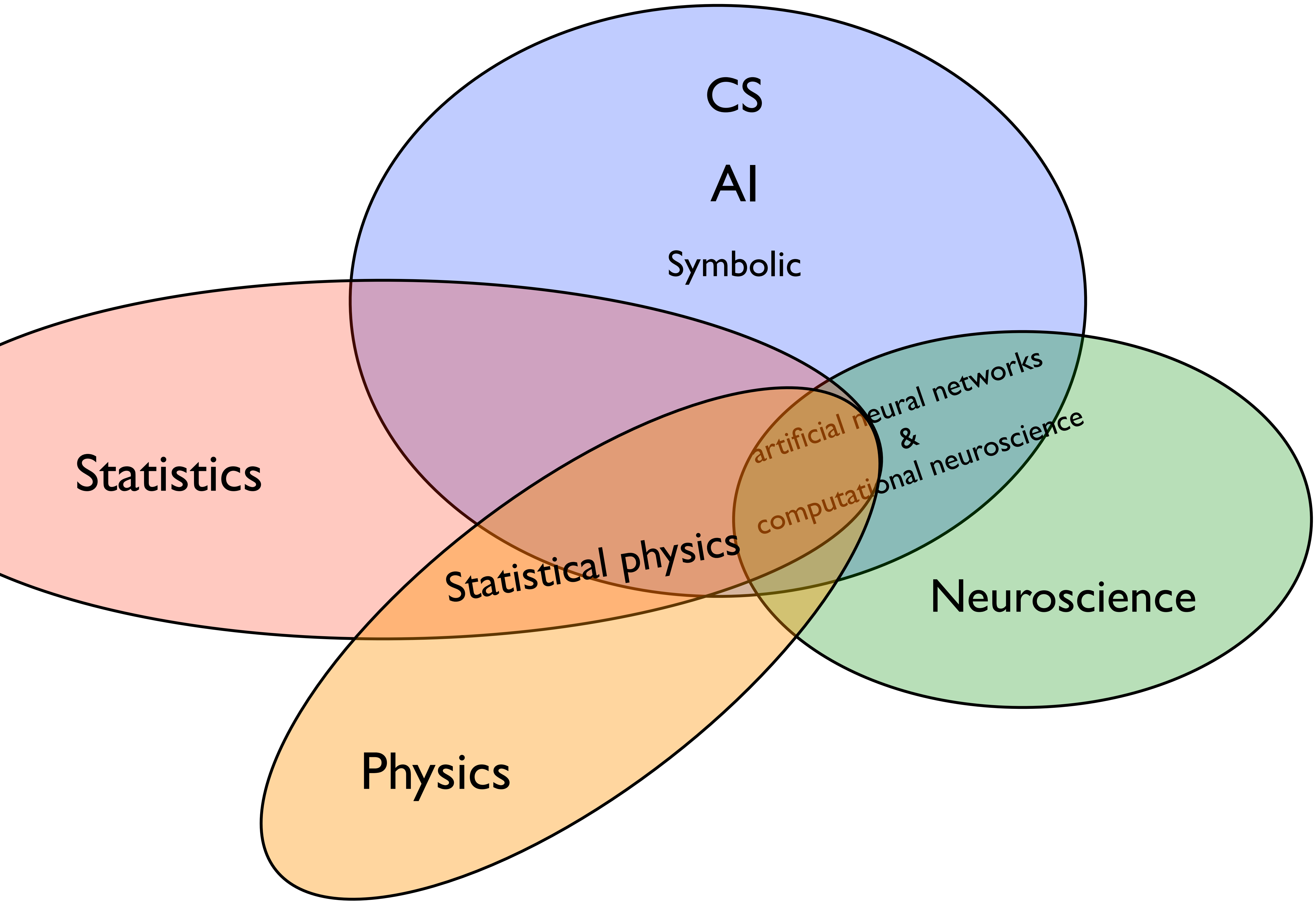

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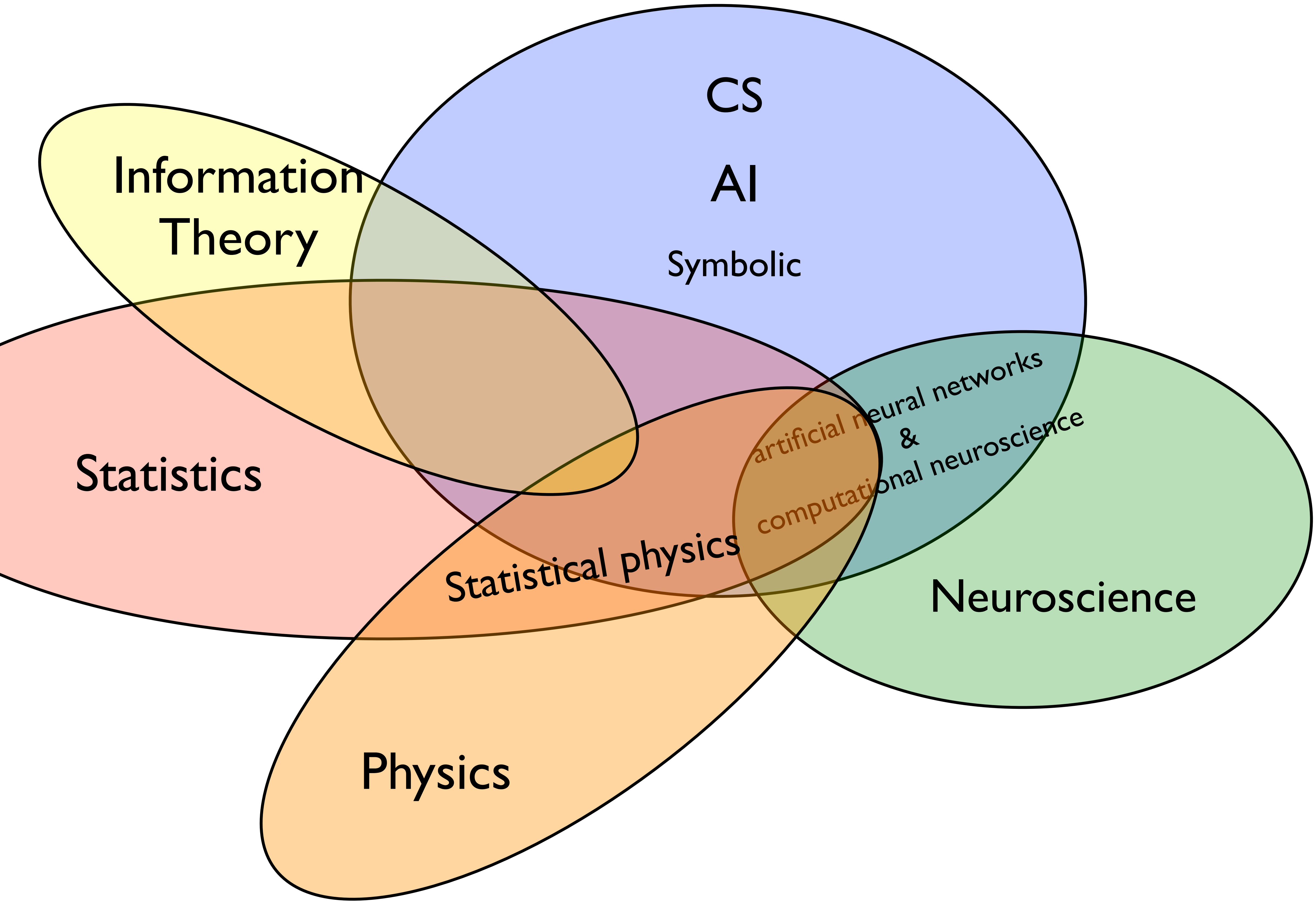

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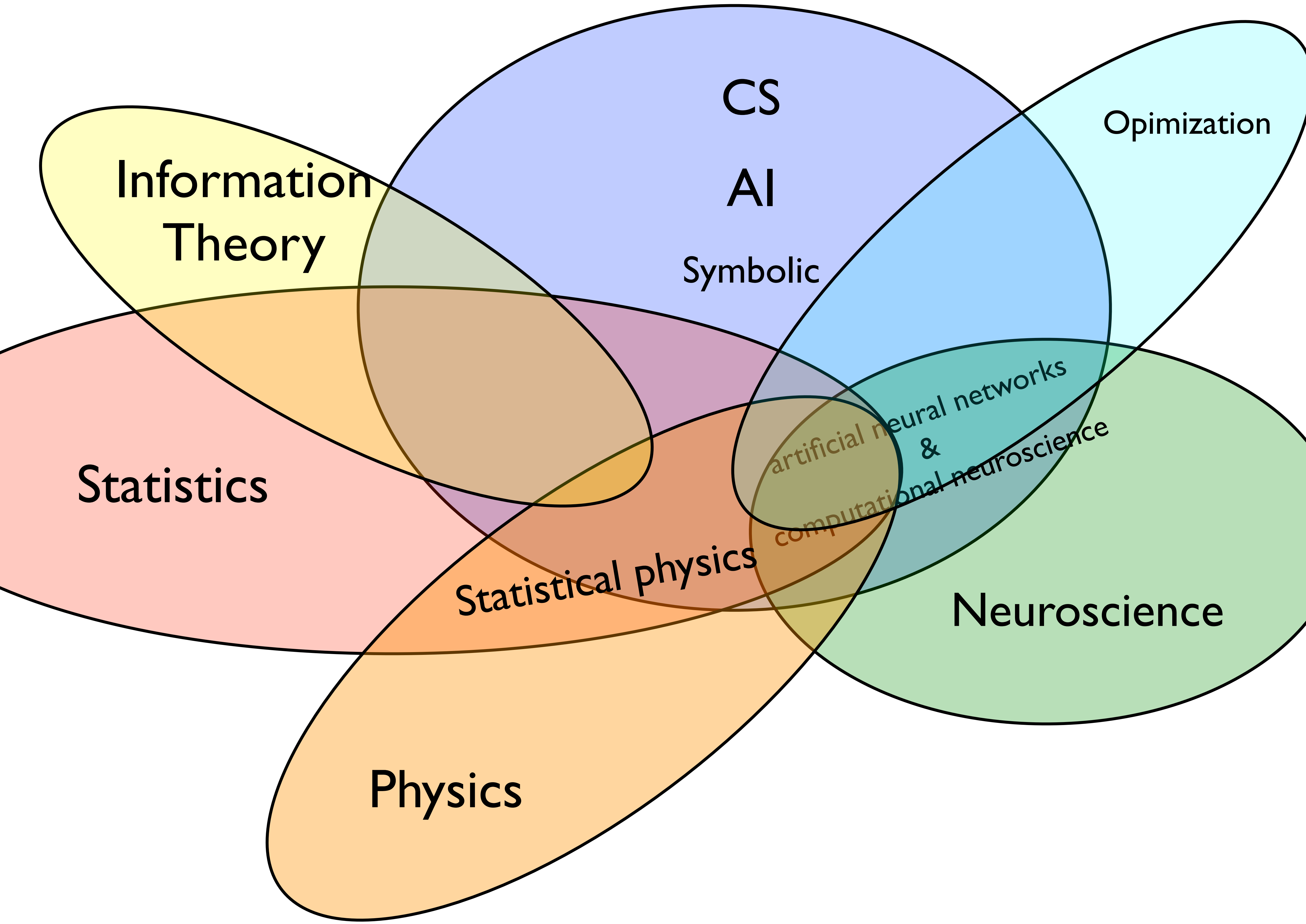

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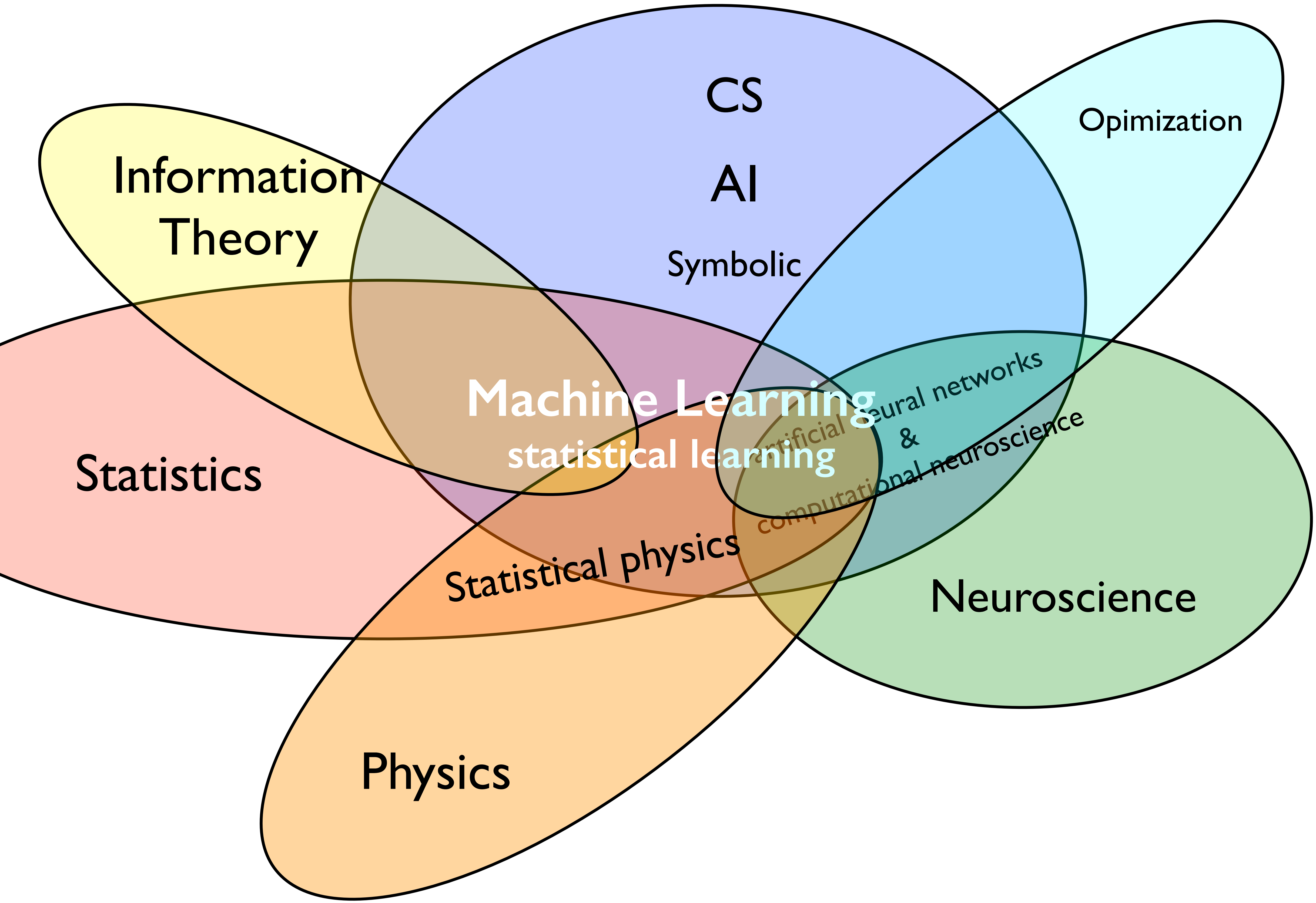

# What is ML?

Perspective of a (hypnotized) user

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Perspective of a (hypnotized) user

- A field of scientific study (=witchcraft) which
- researches the fundamental principles (magic formulas)
- and **develops the** **algorithmes** (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...

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# 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!**

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"horse"

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

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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

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# Ex: Character recognition

Training set

# Ex: Character recognition

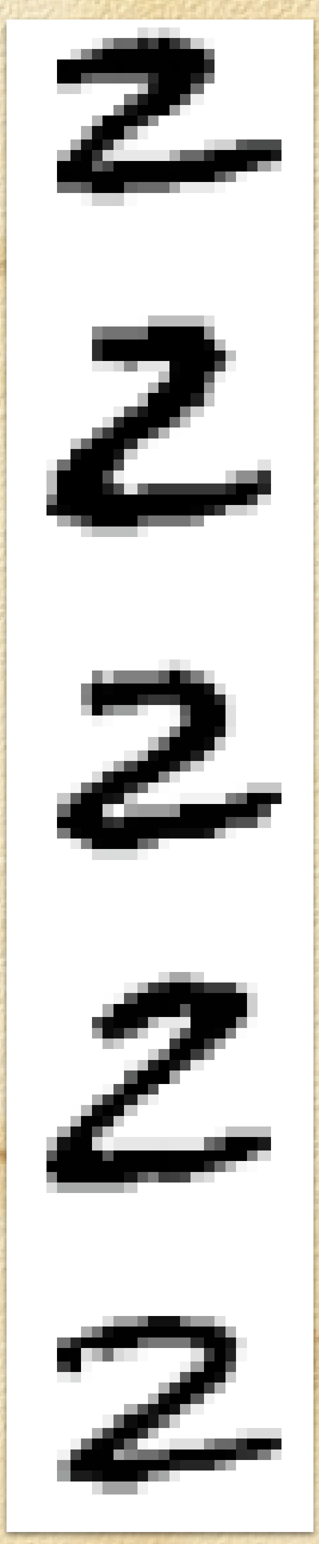
Training set

2

# Ex: Character recognition

Training set

**2**

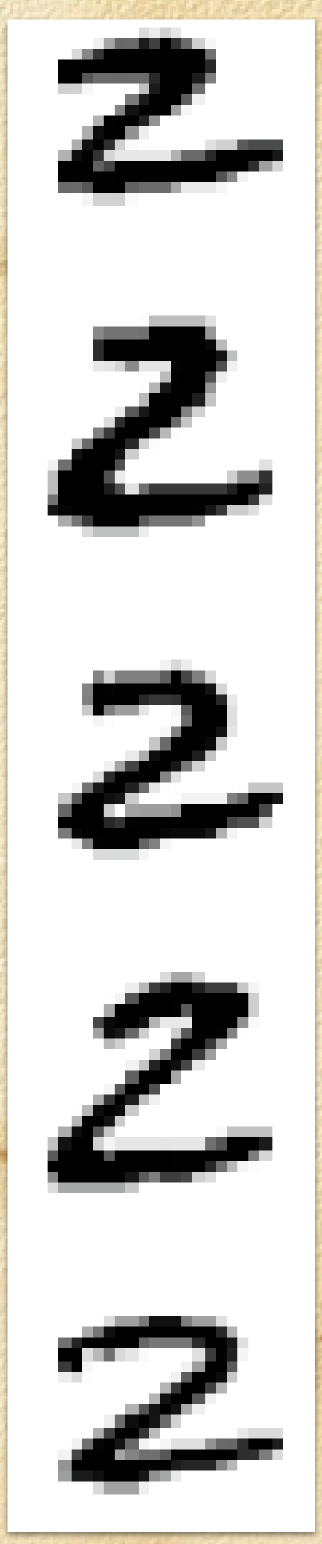


# Ex: Character recognition

Training set

2

3



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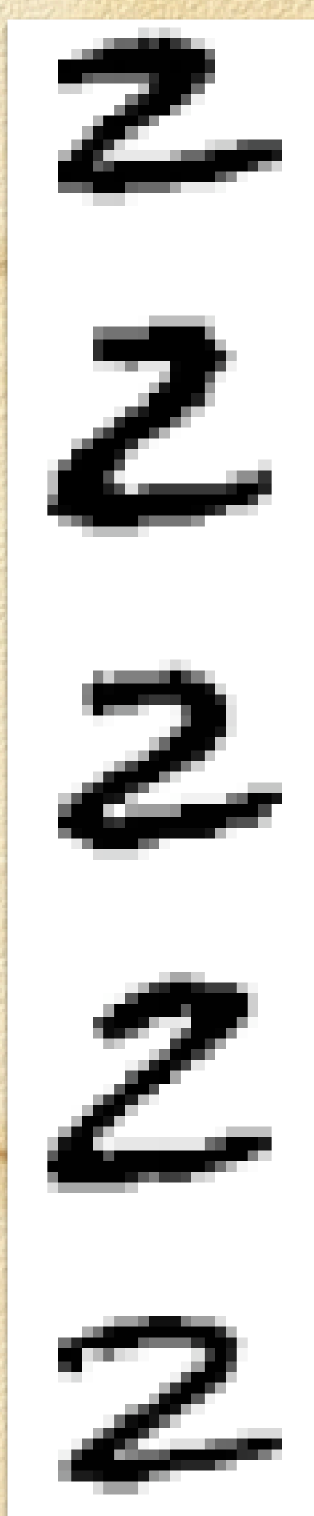

3

# Ex: Character recognition

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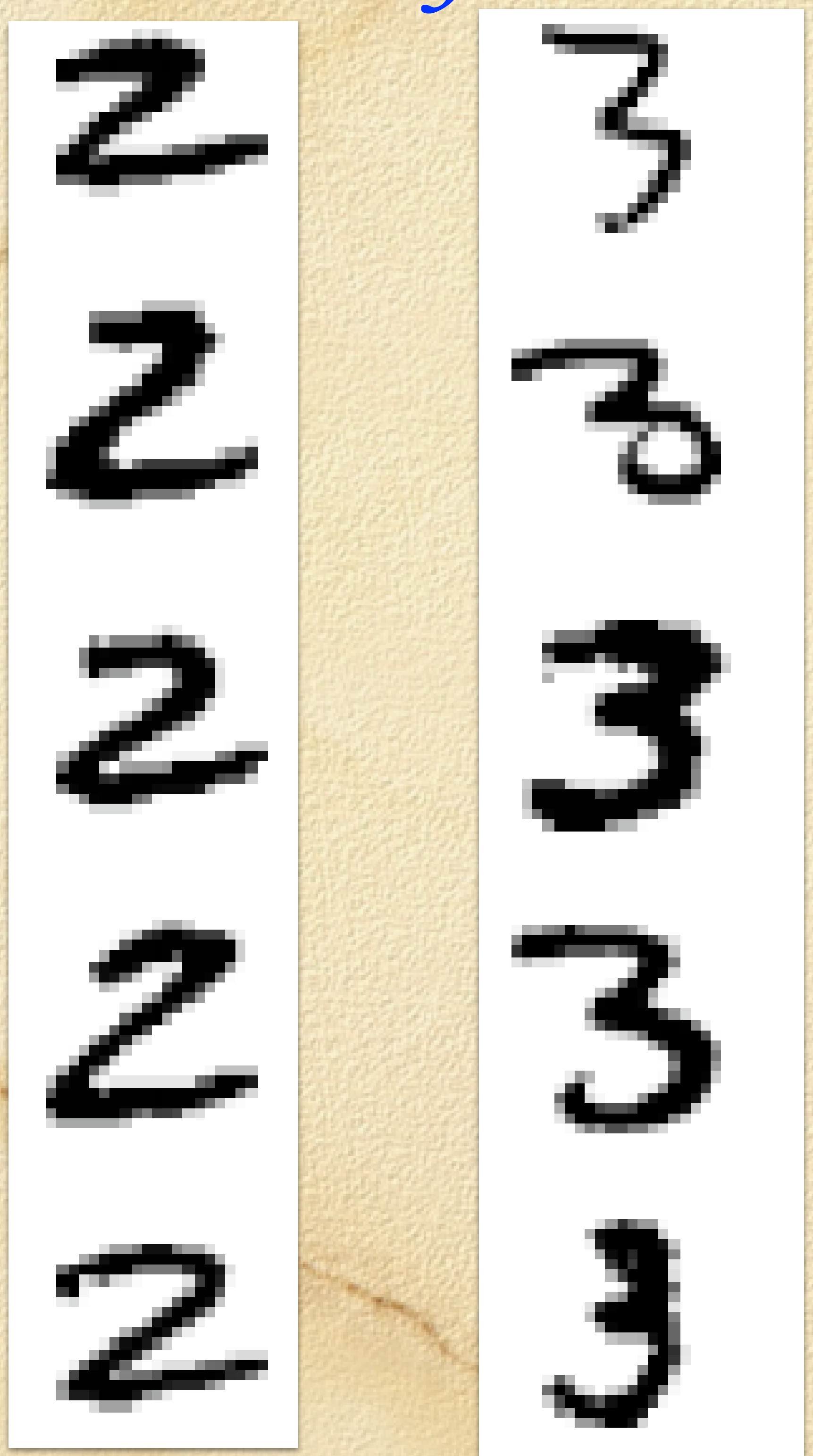
2 3



Test point

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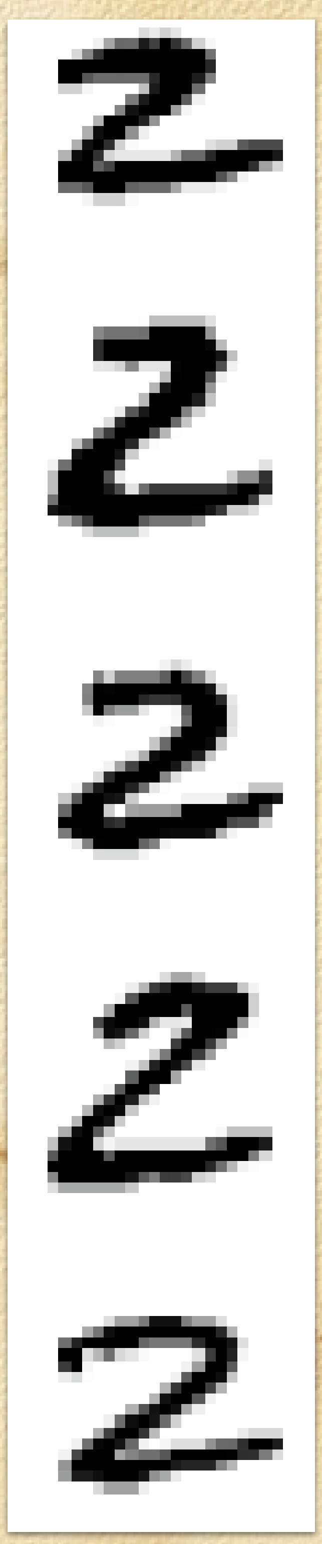

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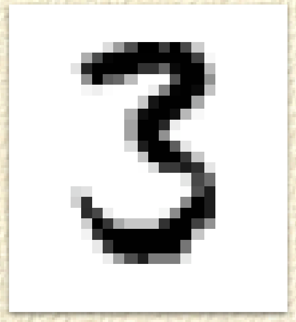

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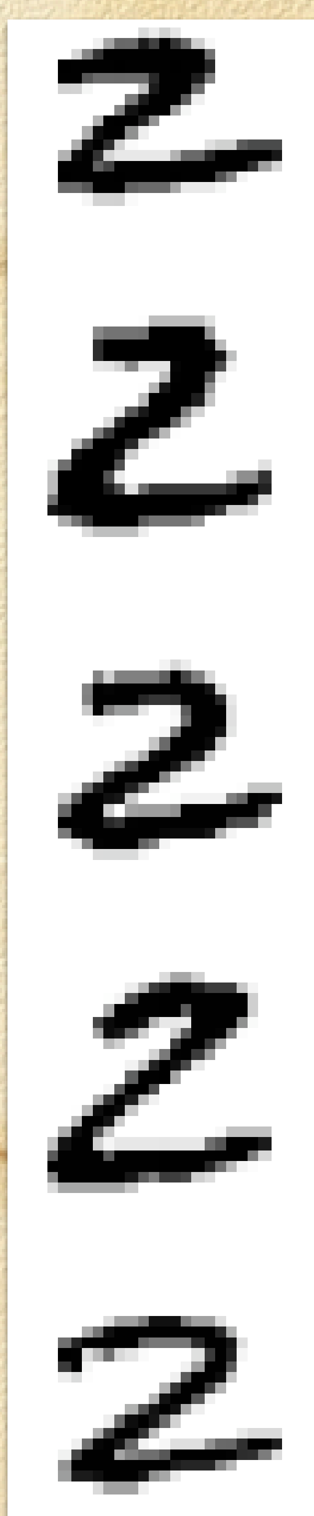
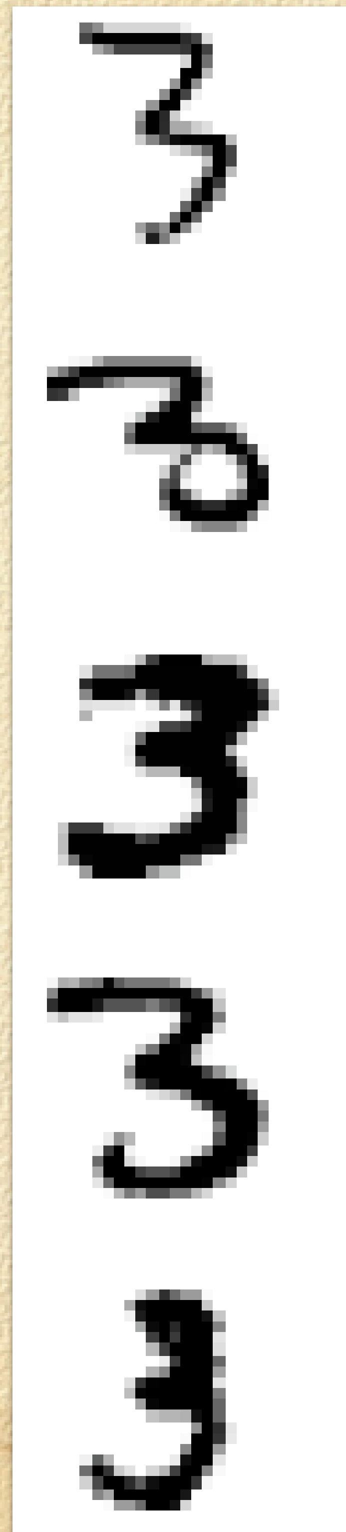
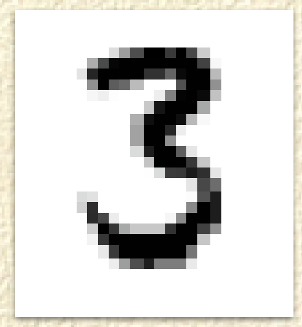




Test point

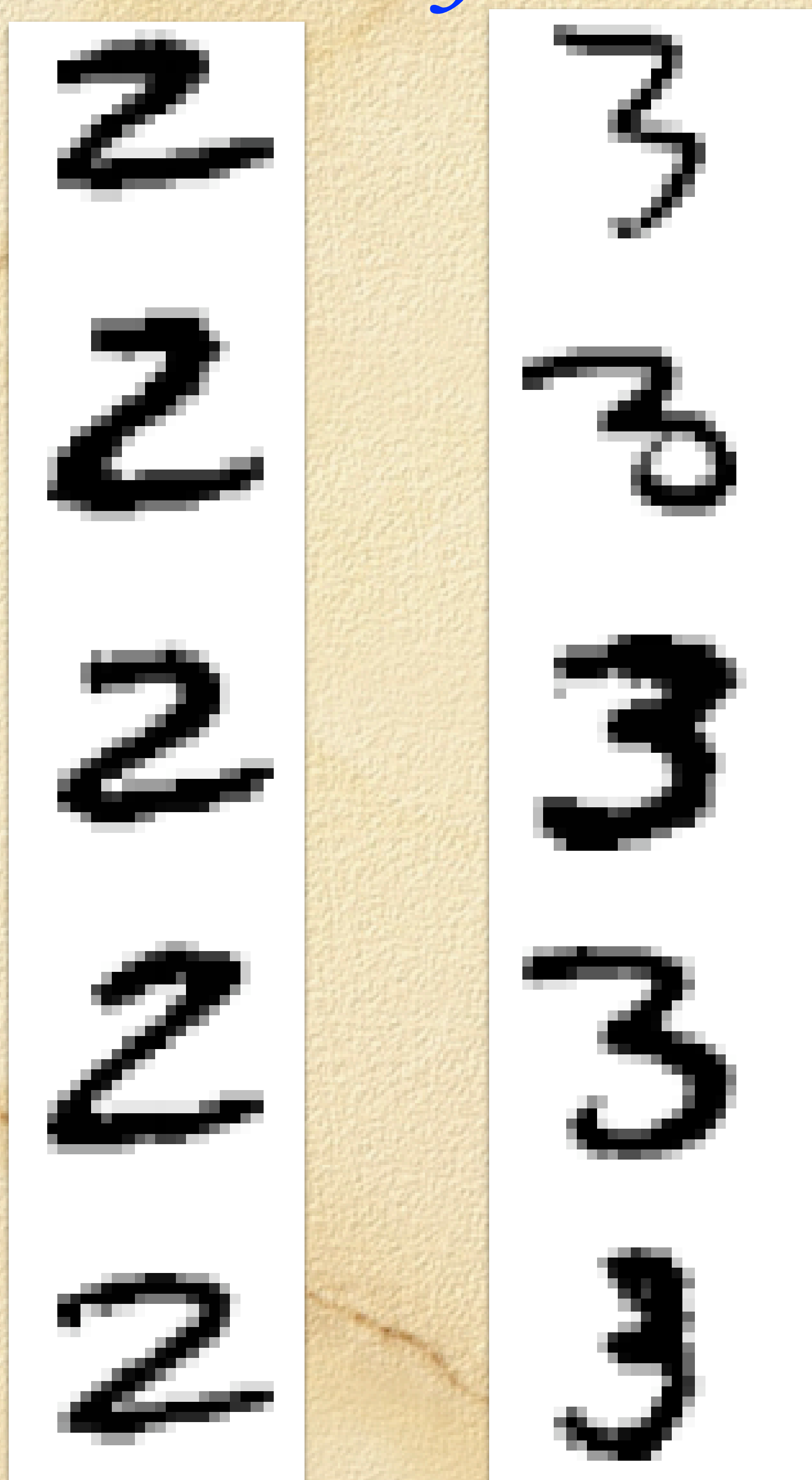


2 or 3 ?

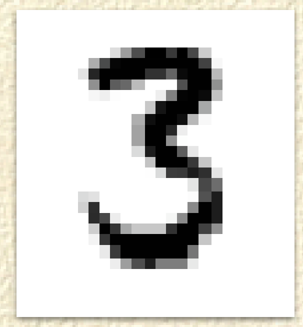
# Ex: Character recognition

Training set

2 3



Test point



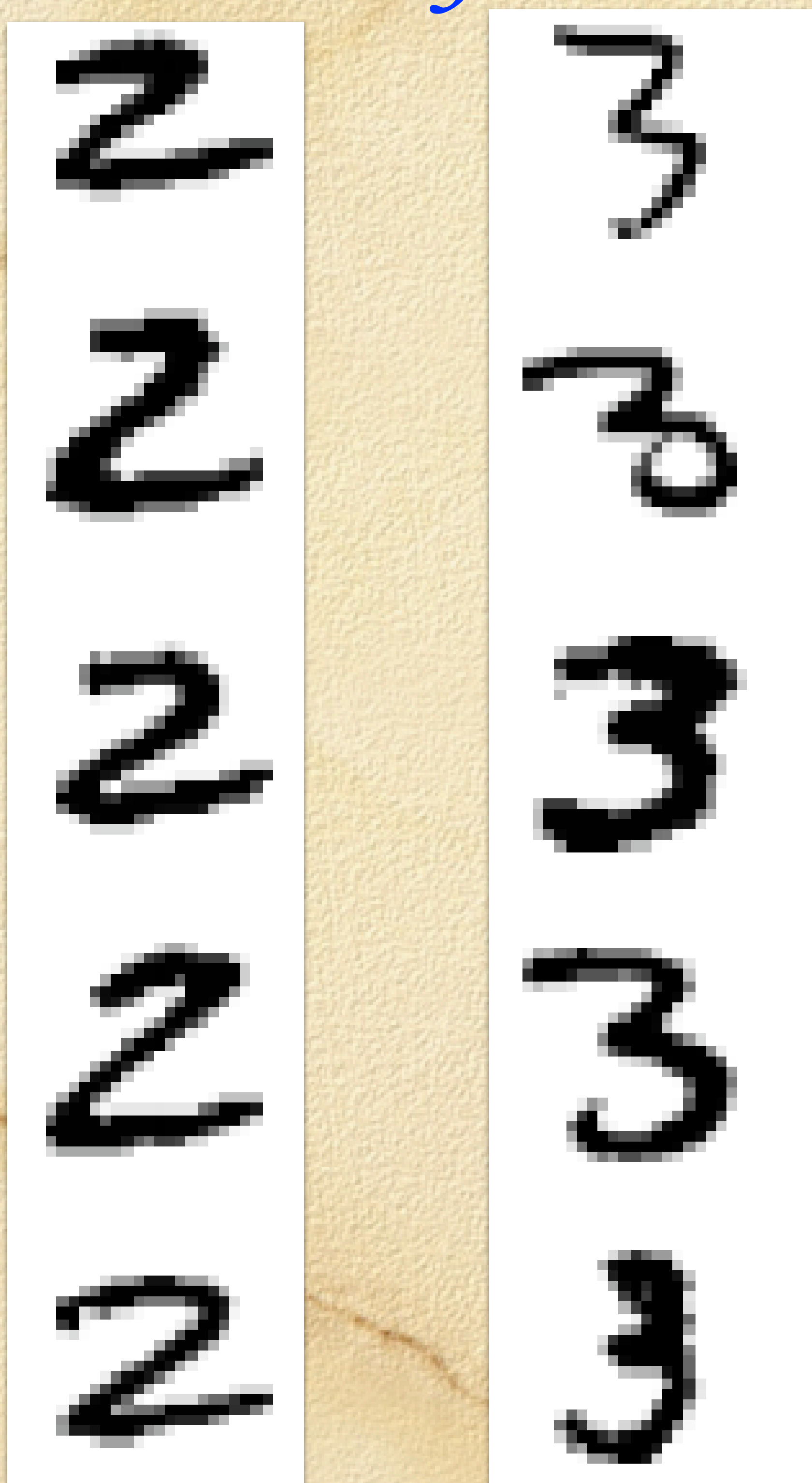
2 or 3 ?

*Learning is not simply memorizing…*

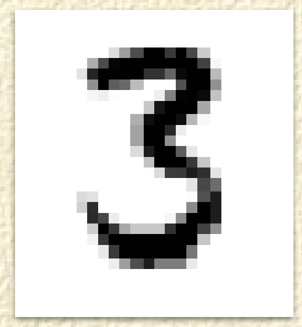
# Ex: Character recognition

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

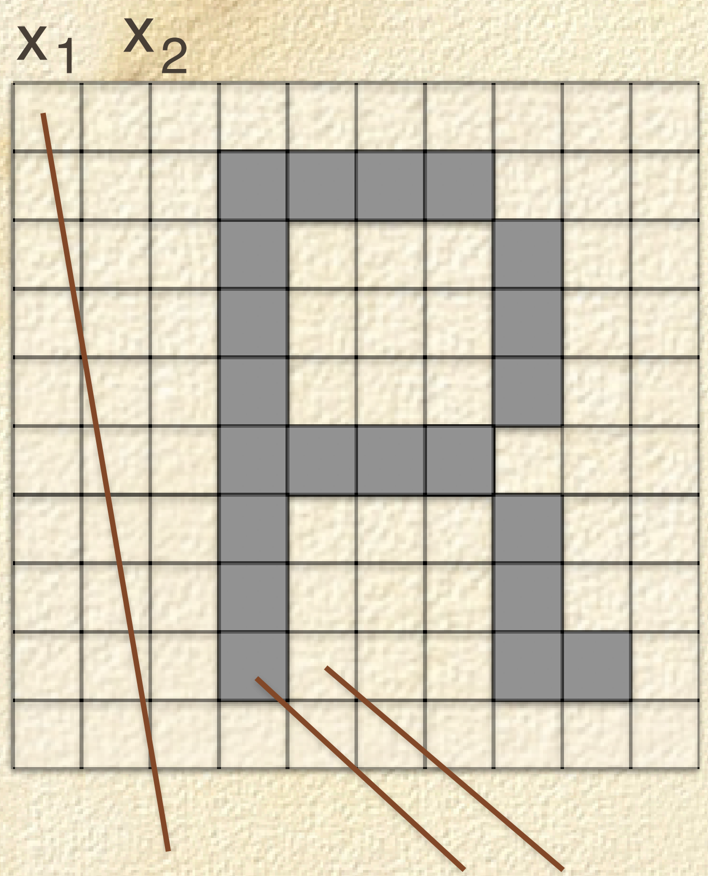
- Statistics: branch of mathematics
  - Importance of rigor and theoretical guarantees
  - Strong assumptions and hypothesis tests
- Machine learning:
  branch of Artificial Intelligence (computer science)
  - Grand ambition: intelligence!
  - We take inspiration from everything we can
    (neuroscience, 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.

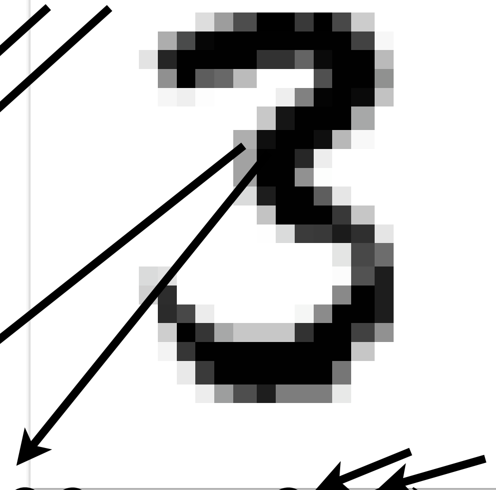
# Vector representation of a data example




x = ( 0, 0, ... , 140, 0, ... )

x vector in $R^d$

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

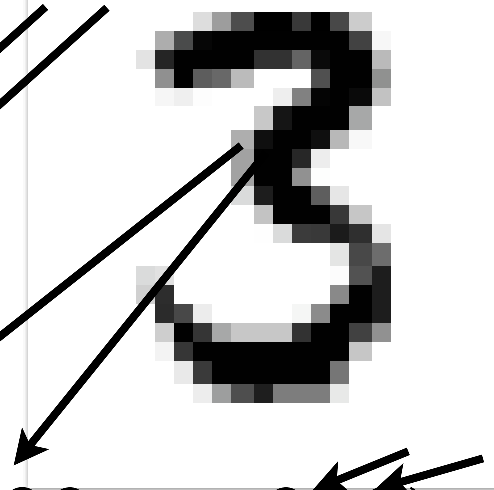


Gross representation:

$x = (0, 0, ..., 54, 120, ..., 0, 0)$

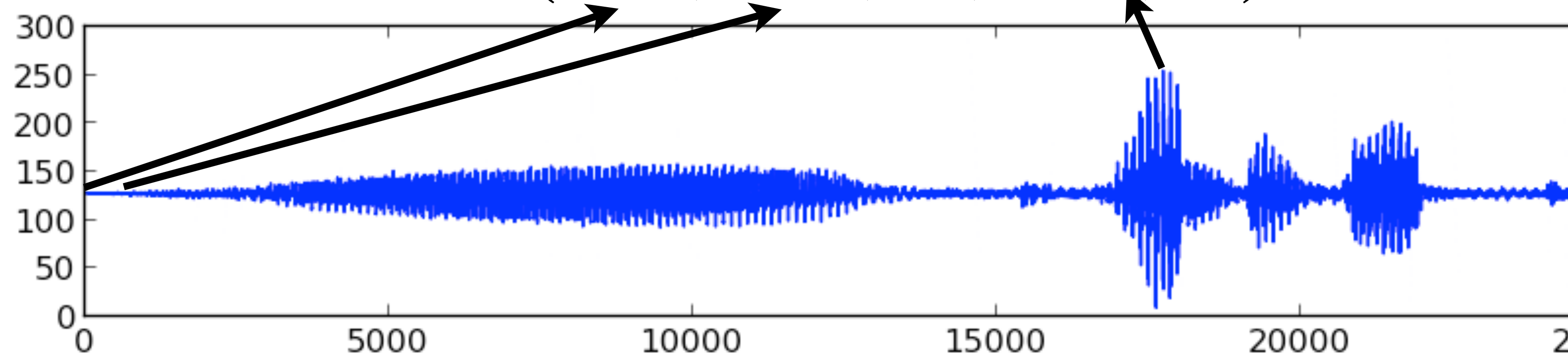
# Transform an example into a vector representation $\mathbf{x} \in \mathbb{R}^d$

Gross representation:

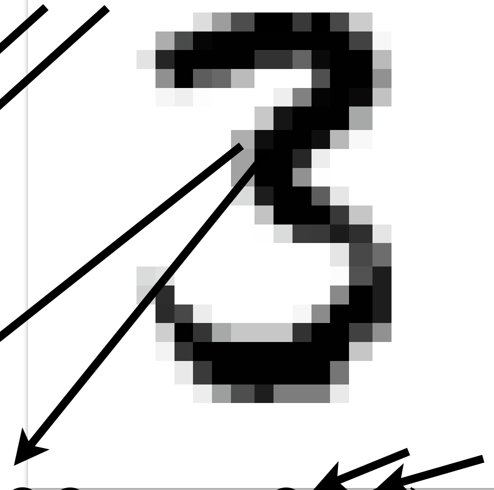


$$x = (0, 0, \ldots, 54, 120, \ldots, 0, 0)$$

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



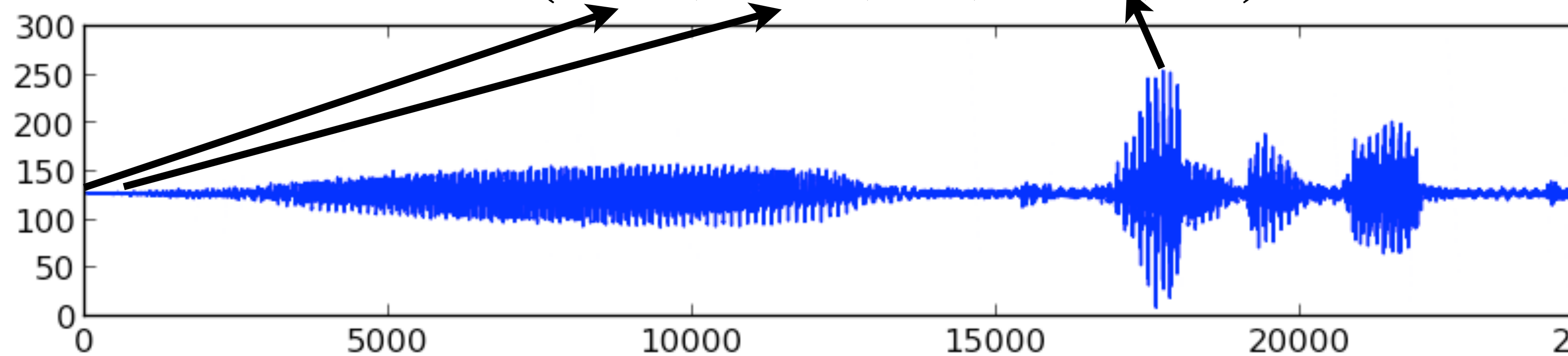
# Transform an example into a vector representation $\mathbf{x} \in \mathbb{R}^d$



Gross representation:

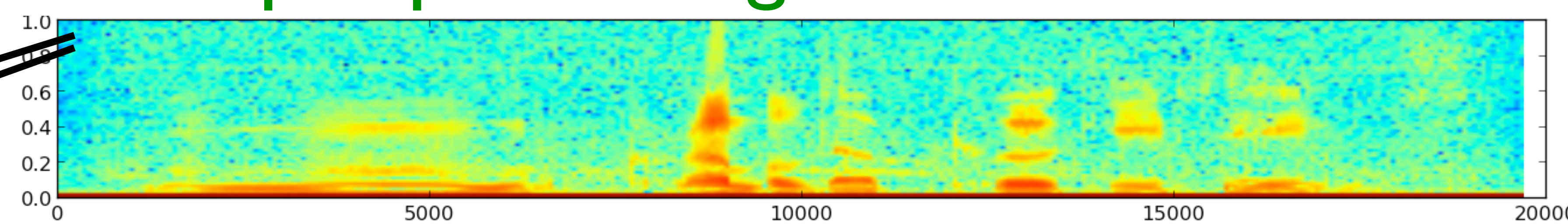
$x = (0, 0, ..., 54, 120, ..., 0, 0)$

$x = (125, 125, ..., 250, ...)$




Or feature extraction from pre-processing:

$x = (\ ,\ \ ,\ \ ,\ \ ,\ ....)$



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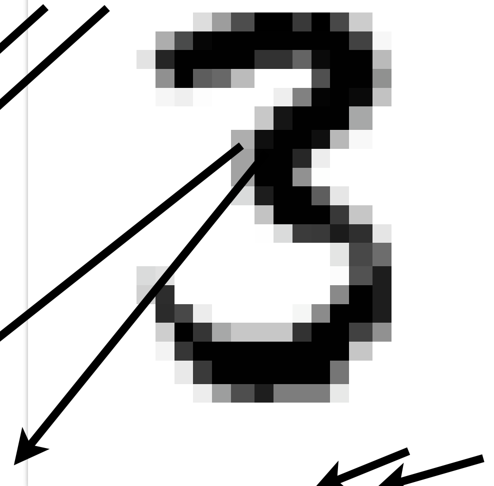
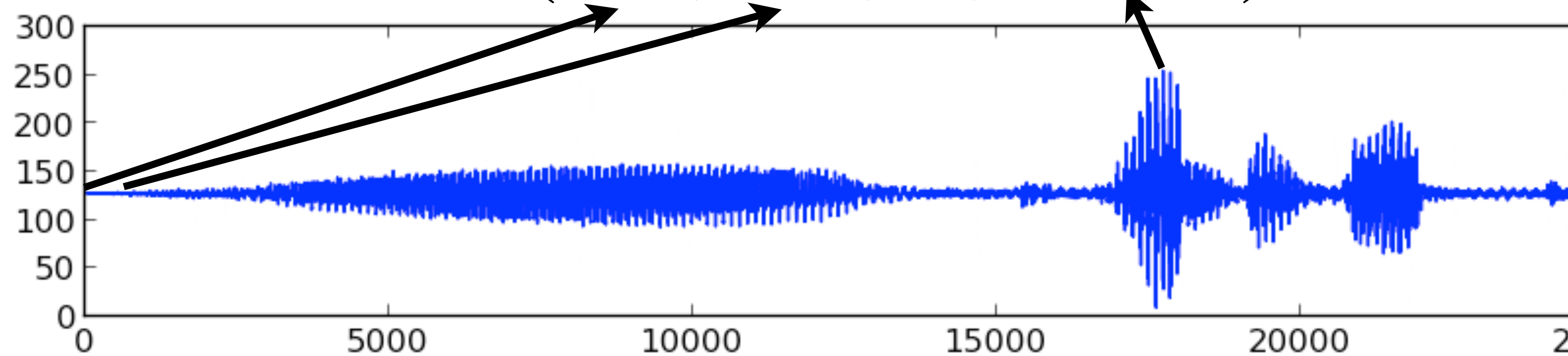


## Gross representation:

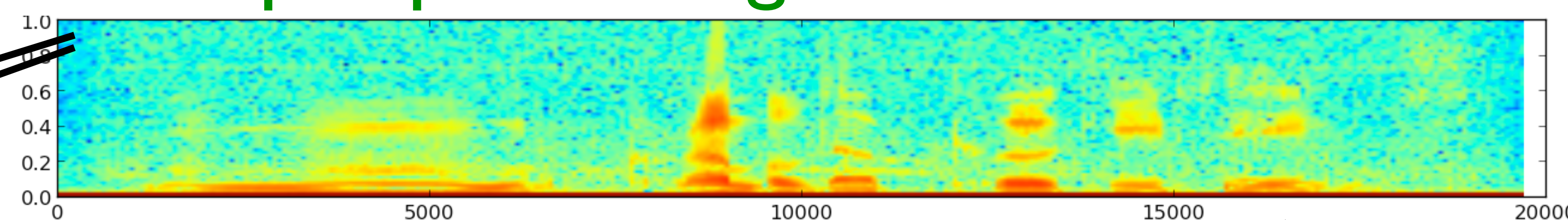
$$x = (0, 0, \ldots, 54, 120, \ldots, 0, 0)$$

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




## Or feature extraction from pre-processing:

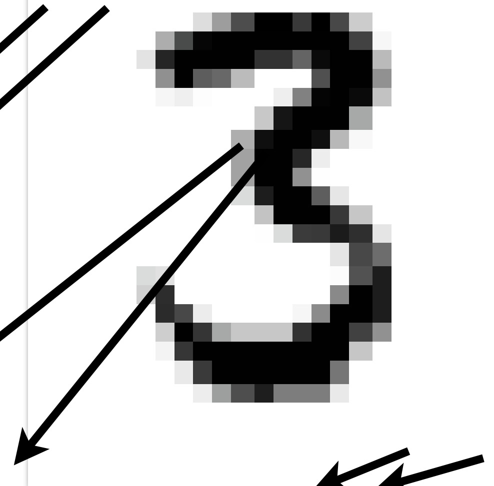
$$x = ( , \quad , \quad , \quad , \quad \ldots.)$$




we the jumped jumping run elephant dog cat horse

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

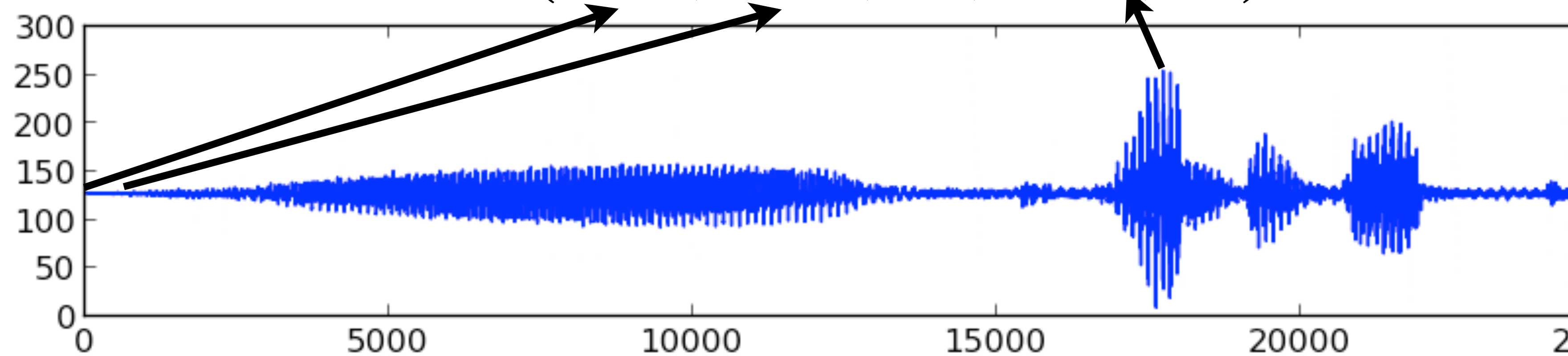
# Transform an example into a vector representation $\mathbf{x} \in \mathbb{R}^d$



## Gross representation:

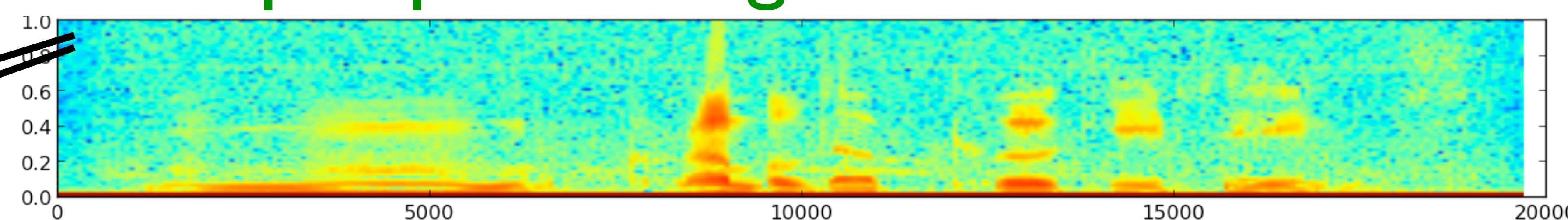
$x = (0, 0, ..., 54, 120, ..., 0, 0)$

$x = (125, 125, ..., 250, ...)$




## Or feature extraction from pre-processing:

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




we the jumped jumping run elephant dog cat horse

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

## 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

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

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

n examples

| $\mathbf{x}_1$ | $\mathbf{x}_2$ | $\mathbf{x}_3$ | $\mathbf{x}_4$ | $\mathbf{x}_5$ | |
|---|---|---|---|---|---|
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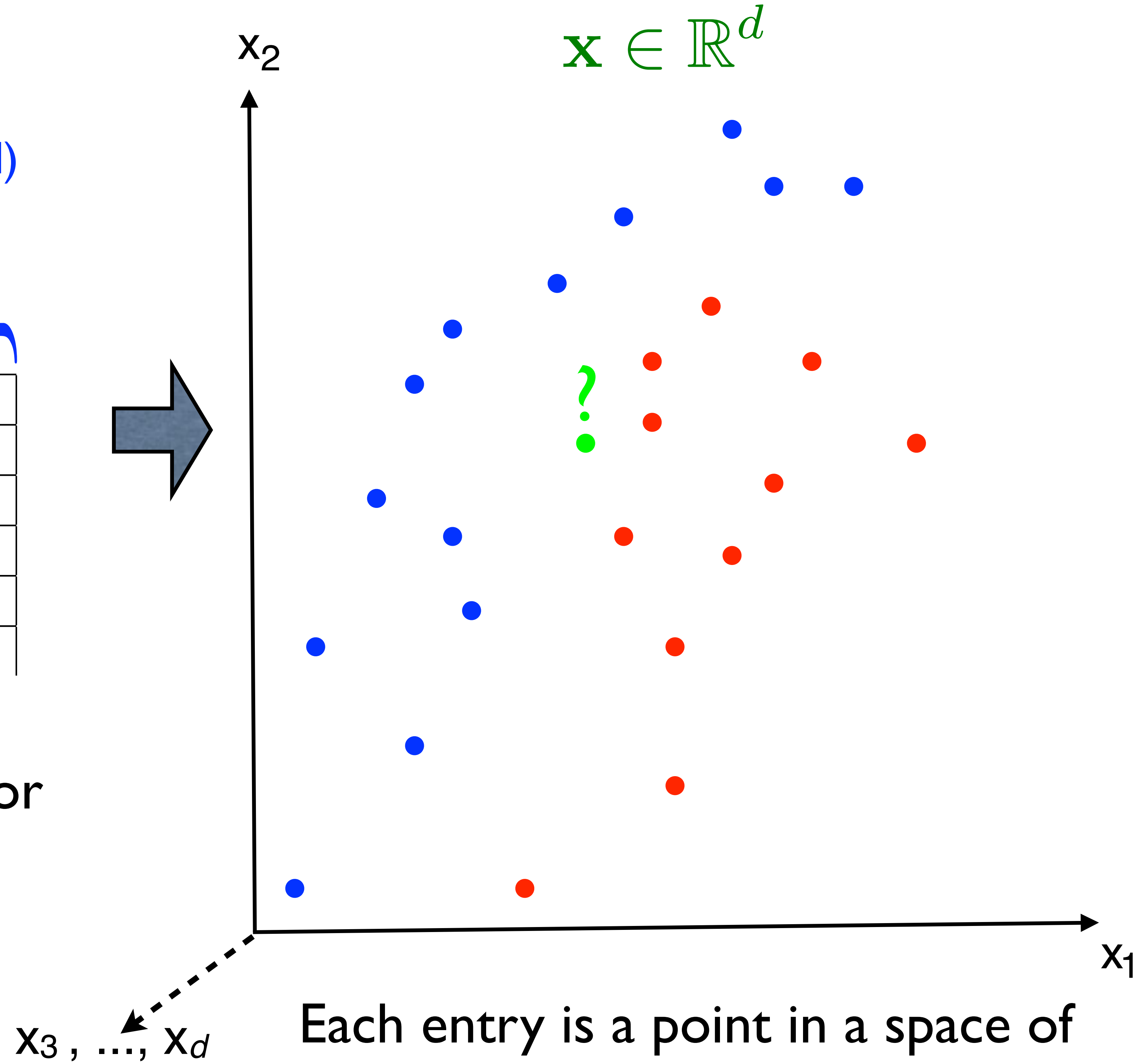
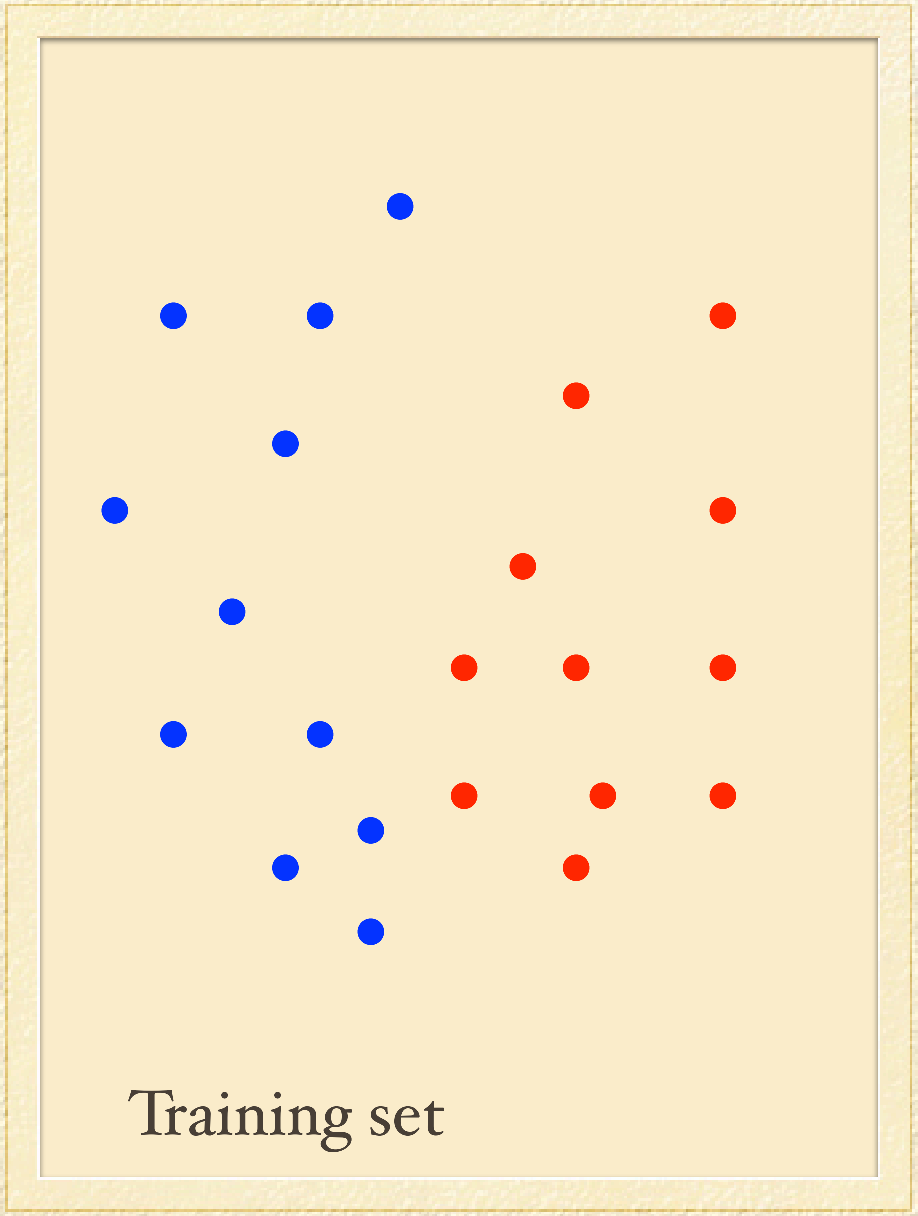
| ... | ... | ... | ... | ... | ... |

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



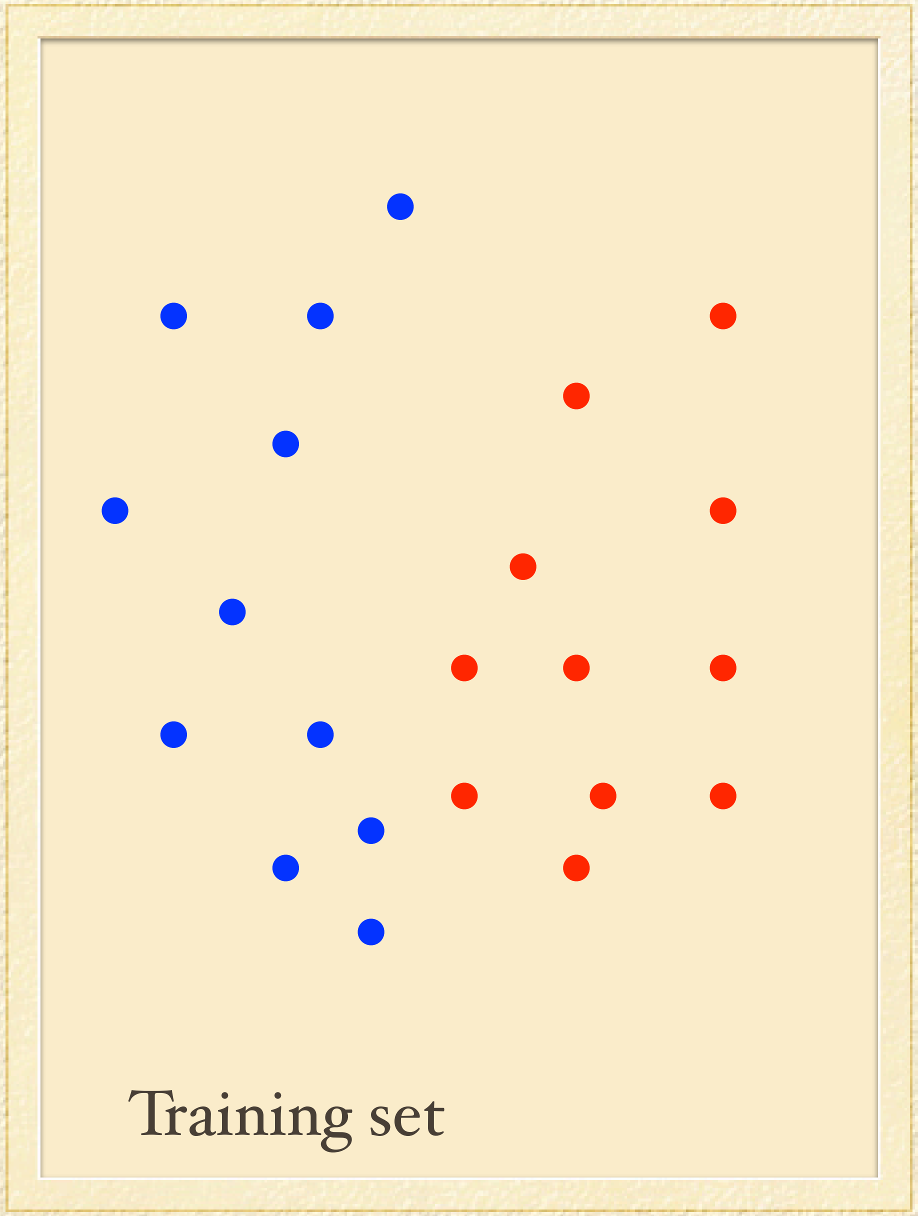

Each entry is a point in a space of $d$-dimensions

# Ex: the nearest neighbor algorithm



# Ex: the nearest neighbor algorithm

For a test point x:



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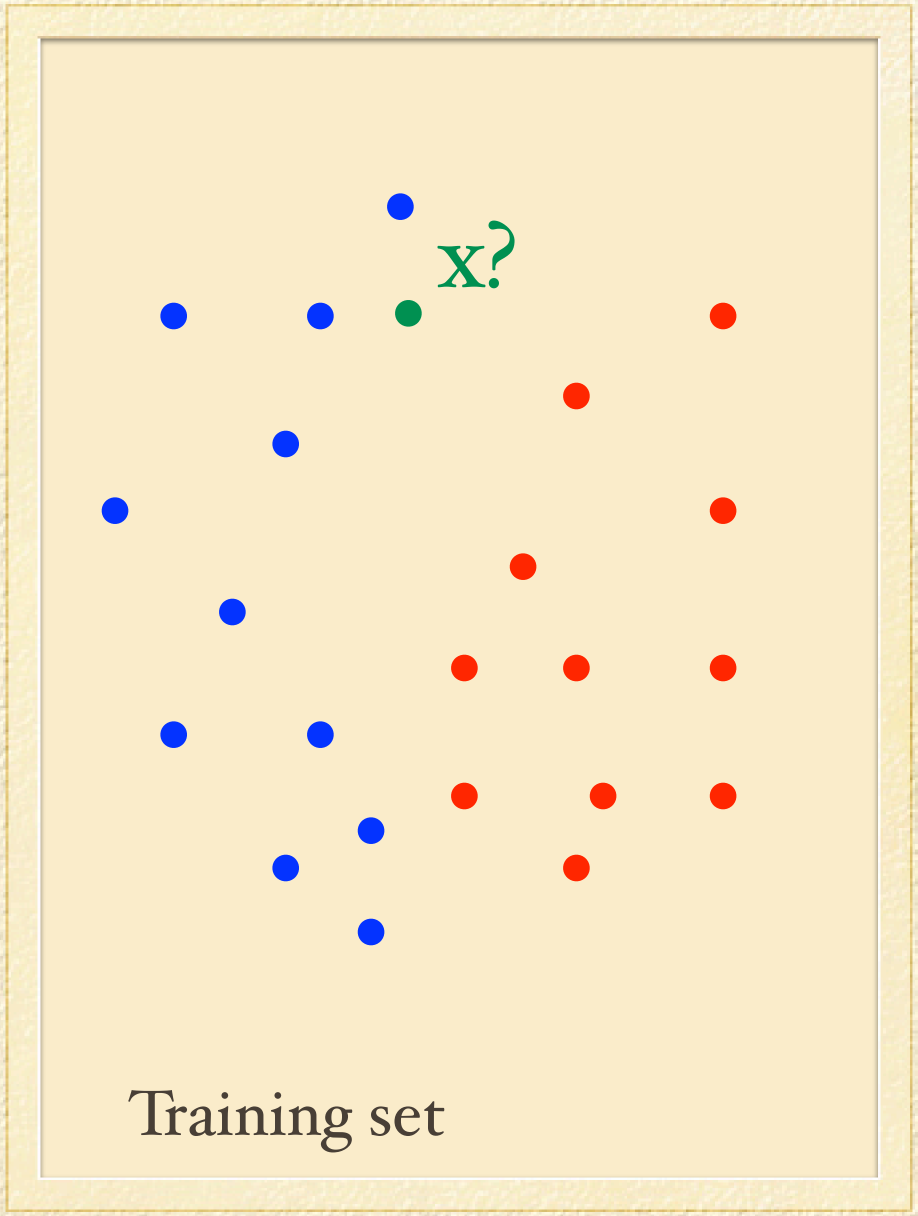
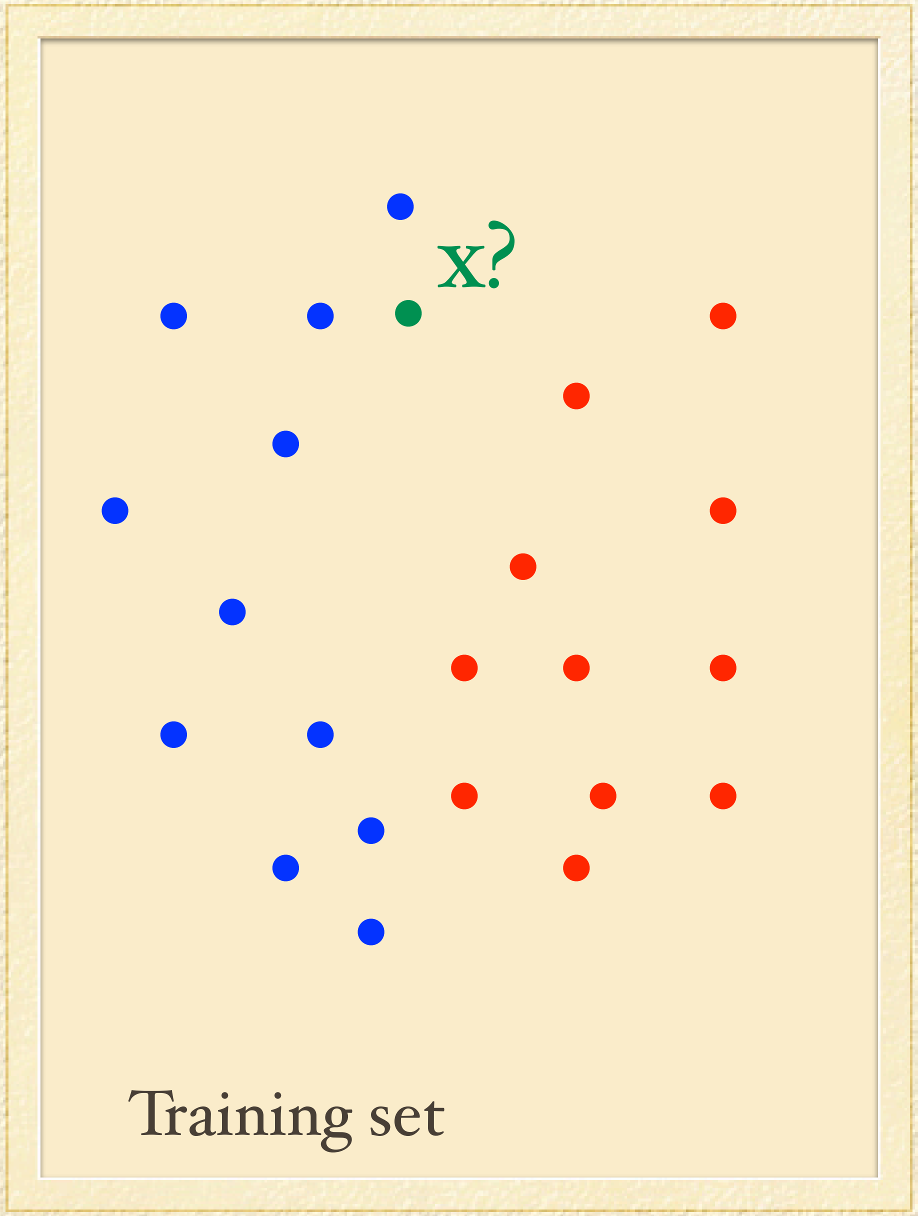


# Ex: the nearest neighbor algorithm

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).



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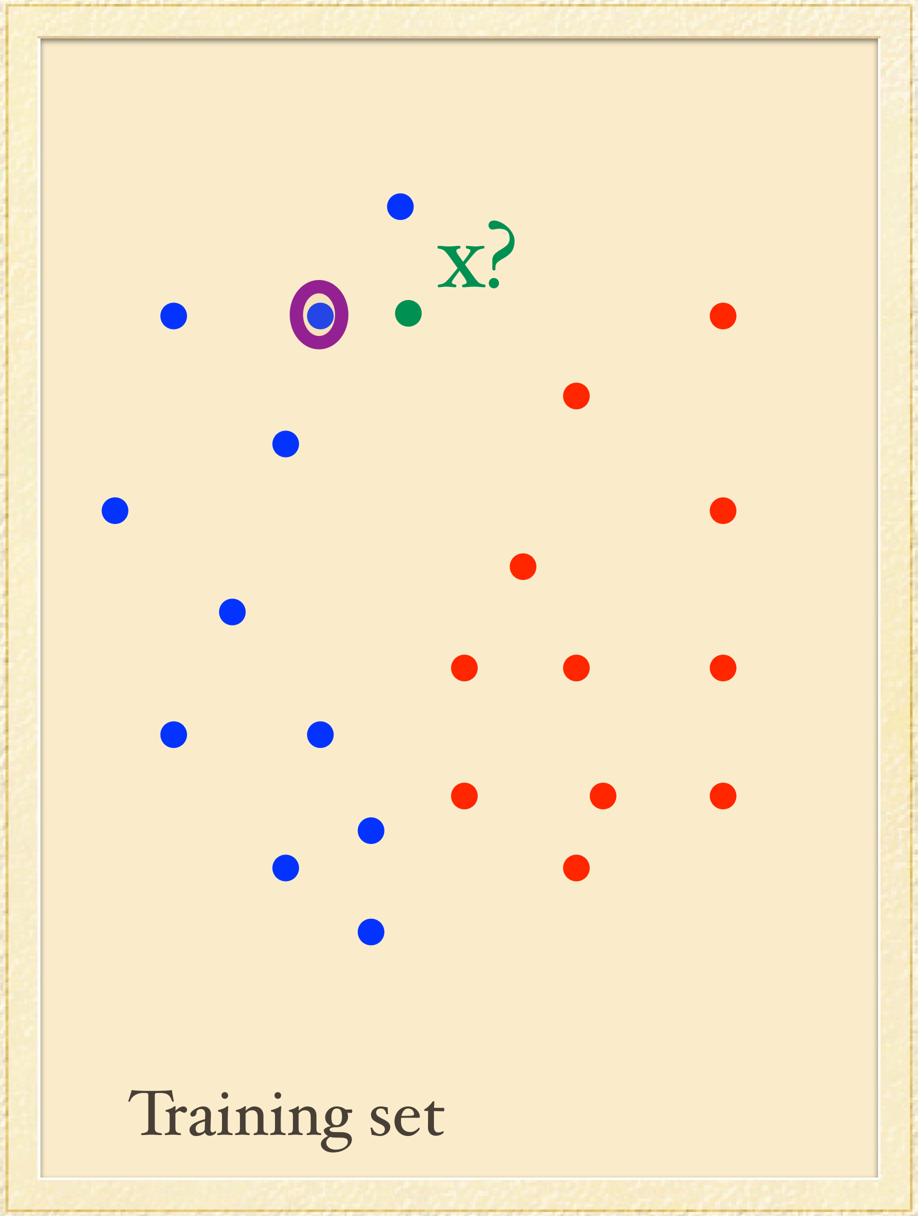
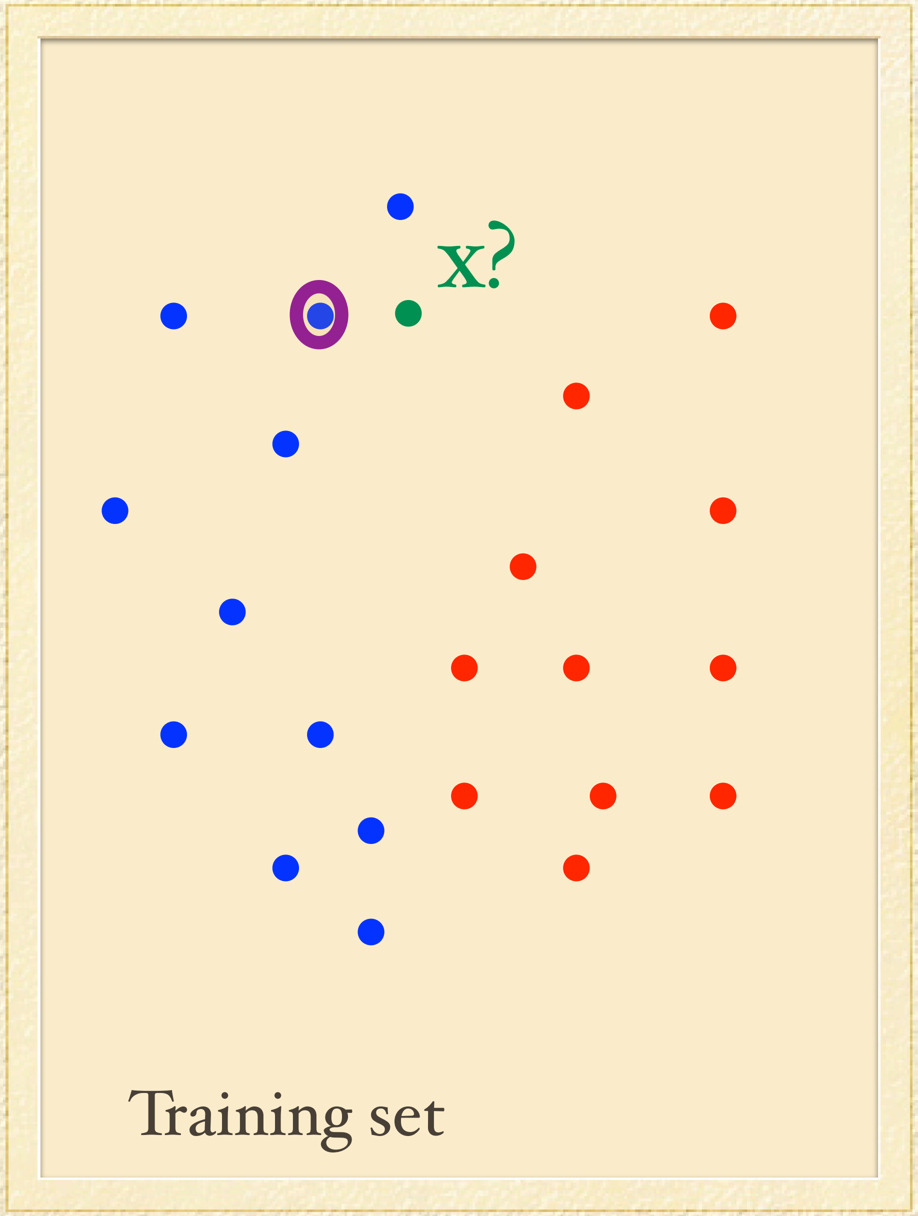


# Ex: the nearest neighbor algorithm

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.



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