

IFT6390

Fondements de l'apprentissage machine

Learning terminology

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Learning from examples



“horse”



“horse”



“horse”

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

Categories of problems (tasks) in machine learning

Supervised learning

- Classification
- Regression

Non-supervised learning

- Density estimation (learn the distribution of examples)
- Clustering
- Dimensionality reduction
- Feature extraction

Reinforcement learning

(not scheduled for this class)

Example of classification problem

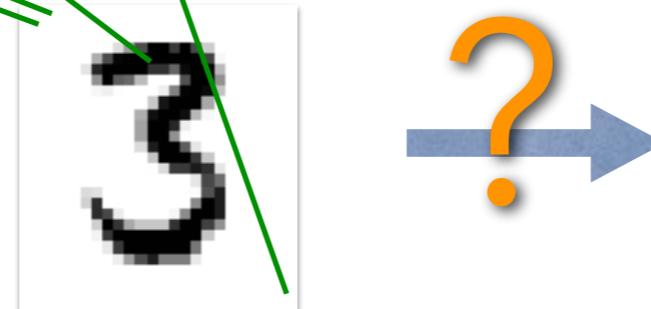
entry x_i

(vector representation)

$$x \in \mathbb{R}^d$$

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

Test point:
(new x)



2	2
2	2
2	2
2	2
2	2
3	3
3	3
3	3
3	3
3	3

training set

label y_i

*Learning is not
memorizing*

*It is the ability to
generalize to unseen
cases!*

2 or 3?

Data representation

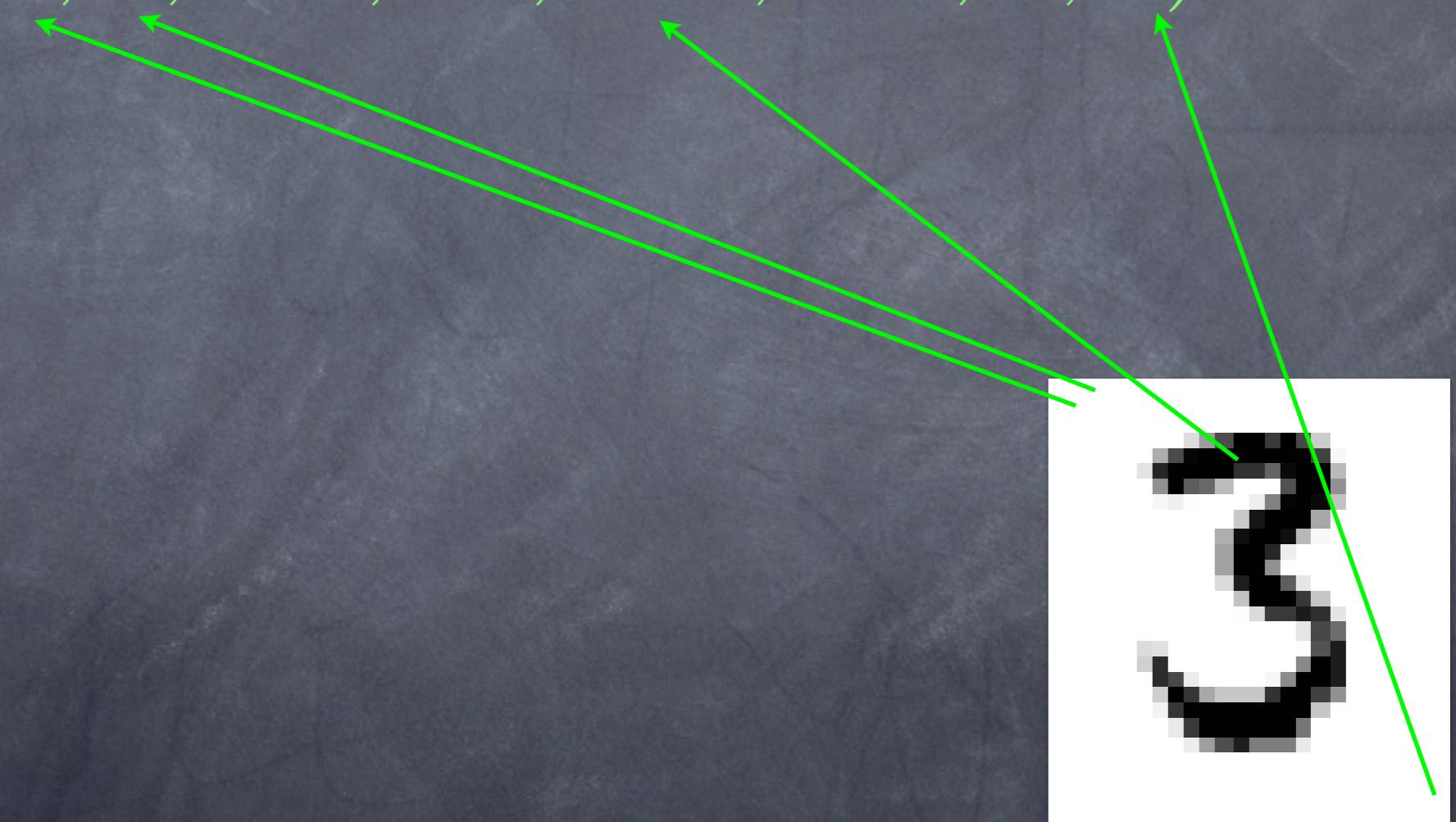
- Most learning algorithms require a **vector representation** of the examples
- Numerical vectors of fixed dimension d

$$x \in \mathbb{R}^d$$

ex: $x = (0, 0, \dots, 54, 120, \dots, 0, 0)$

Example: raw vector representation of
an image (bitmap) in grayscale

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



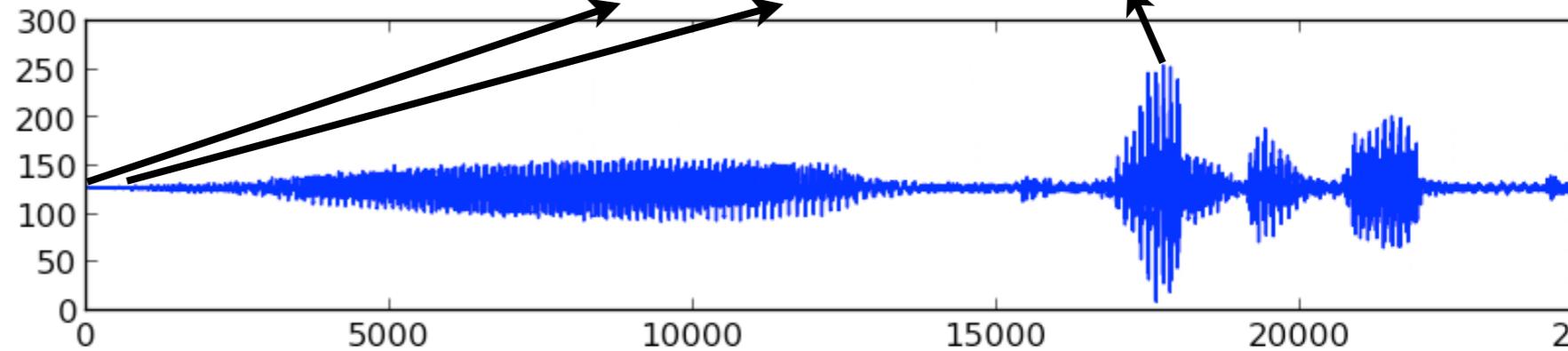
Transform an example into a vector representation $\mathbf{x} \in \mathbb{R}^d$

Raw representation:

$$\mathbf{x} \in \mathbb{R}^d$$

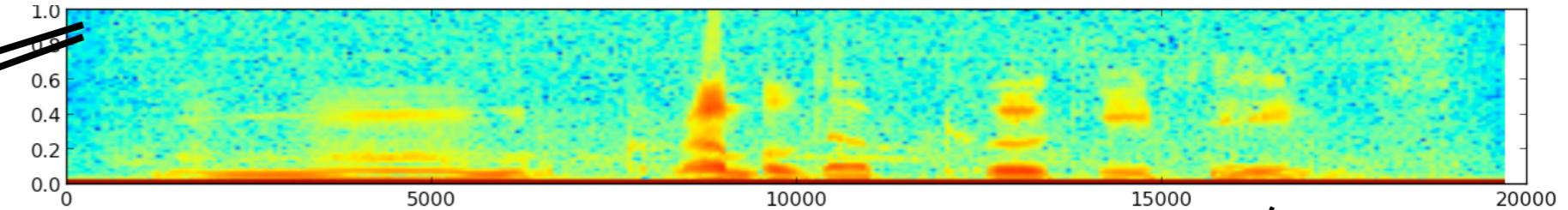
$$x = (0, 0, \dots, 54, 120, \dots, 0, 0)$$

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



Or feature extraction from pre-processing:

$$x = (, , , , \dots)$$



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

OR vector of handmade features:

ex: Histograms of Oriented Gradients

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

Another possibility: Characteristic traits describe the inputs (features, descriptors)

$$\mathbf{x} = (\text{feature 1}, \text{feature 2}, \dots, \text{feature d})$$

- ⦿ Often designed manually to facilitate the task of learning (feature engineering).
- ⦿ eg. to represent a natural image (vision): SIFT descriptors.
- ⦿ eg. to represent a document: frequency of occurrences of certain words (bag of words).
eg. feature k = how many times the word "plane" appears in the document.

Training set

number
of
examples
 n

input:



targets:

"horse"

input:



targets:

"cat"

etc...

input:



targets:

"horse"

Test point:



?

Dimensionality
of input

d

inputs: X

(vector of features)

X_1

(3.5, -2, ..., 127, 0, ...)

+1

Y_1

preprocessing,
feature
extraction

X_n

$X_{n,2}$

(6.8, 54, ..., 17, -3, ...)

+1

Y_n

$\mathcal{X} = (5.7, -27, \dots, 64, 0, \dots) \rightarrow ?$

?

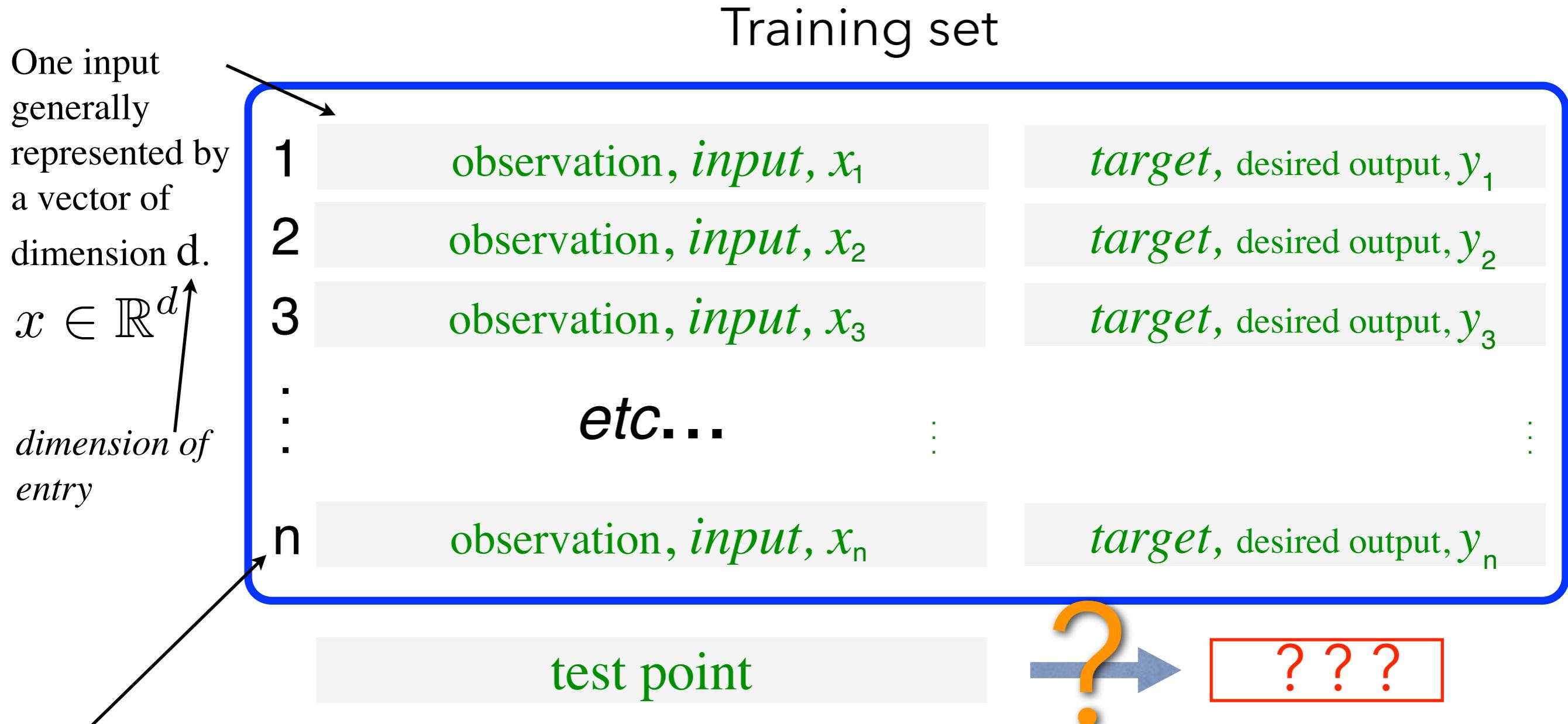
Importance of the problem dimension

⇒ Determines which learning algorithms are applicable or not (because of their algorithmic complexity).

- Number of examples: **n**
(often in the millions of more)
- Dimension of input: **d**
how many features we are using
(often in the order of 100 to 1000, sometimes in the 10s of thousands)
- Dimensions of the target we want to predict eg., number of classes **m** (often low, sometimes thousands)

→ A dataset will often be organized
in a matrix $n \times (d+1)$ or $n \times (d+m)$

Terminology of supervised learning



size of the dataset, number of examples, or “samples”

We are looking for an algorithm that produces an **output** that is a good prediction of the target. This algorithm finds a good **function $x \rightarrow y$**

Terminology of supervised learning

- When the target is a class label, a categorical variable (indicating which class or category the entry belongs to, among many) is said to be a **CLASSIFICATION** problem. (we often use an integer as a label).
- When the target is one (or more) real values to predict, we talk about a **REGRESSION** problem.

When we do not have an explicit target, we are in the context of **unsupervised learning**.

Learning tasks

Supervised learning = predict a target y from the input x

- y represents a category or “class”
 ⇒ classification (binary or multiclass)
- y is a real value
 ⇒ regression

} predictive models

Unsupervised learning: no explicit target (label) y

- modeling the distribution of x
 ⇒ density estimation
- discover an underlying structure in x
 ⇒ clustering
 ⇒ dimensionality reduction (eg. for visualisation)

} descriptive models

Learning tasks

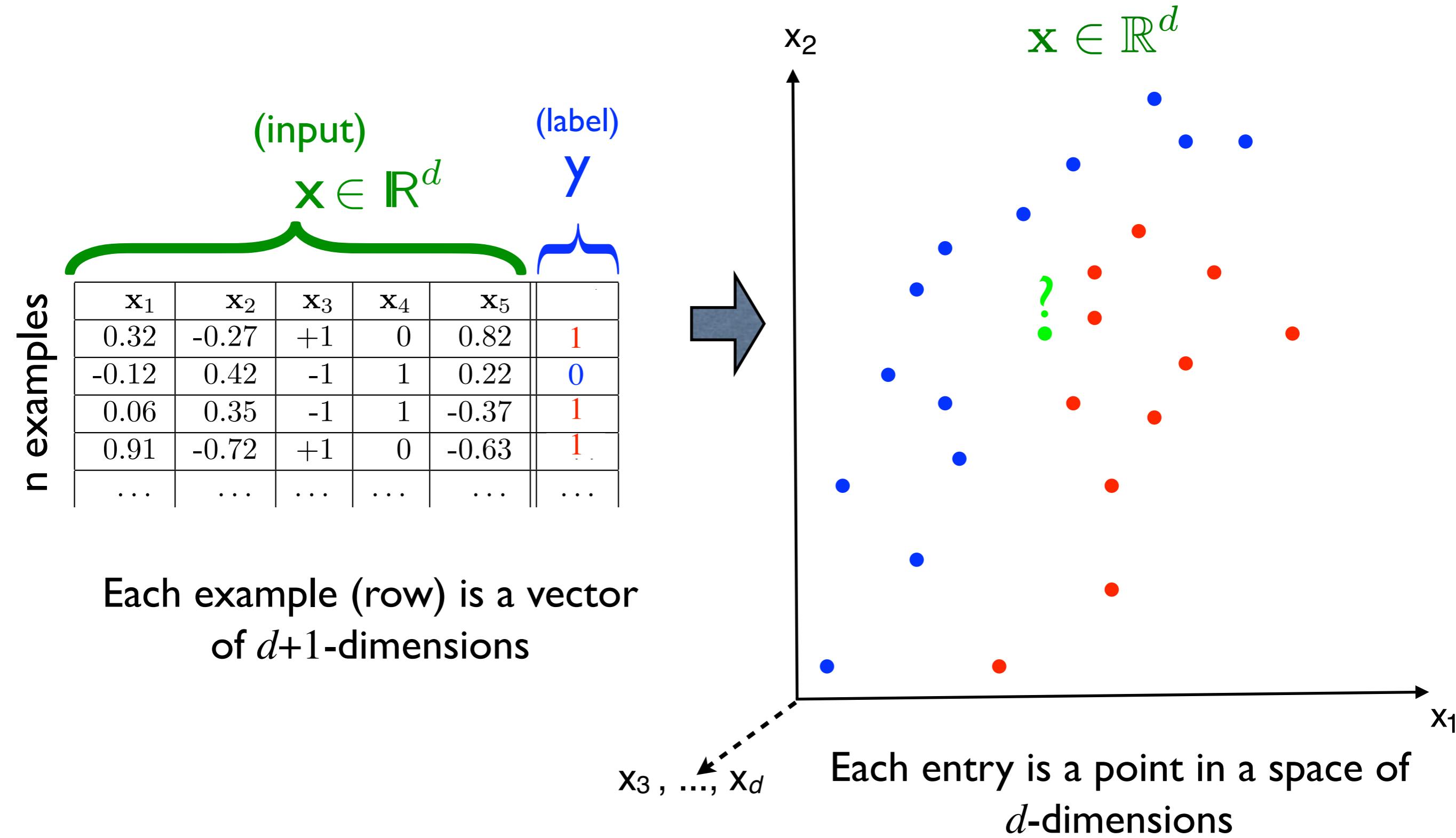
Semi-supervised learning:

same goal as supervised learning, but using both labeled (with target) and unlabeled examples.

Reinforcement learning

an artificial agent must learn to decide what actions to perform in a changing environment to maximize a total reward.

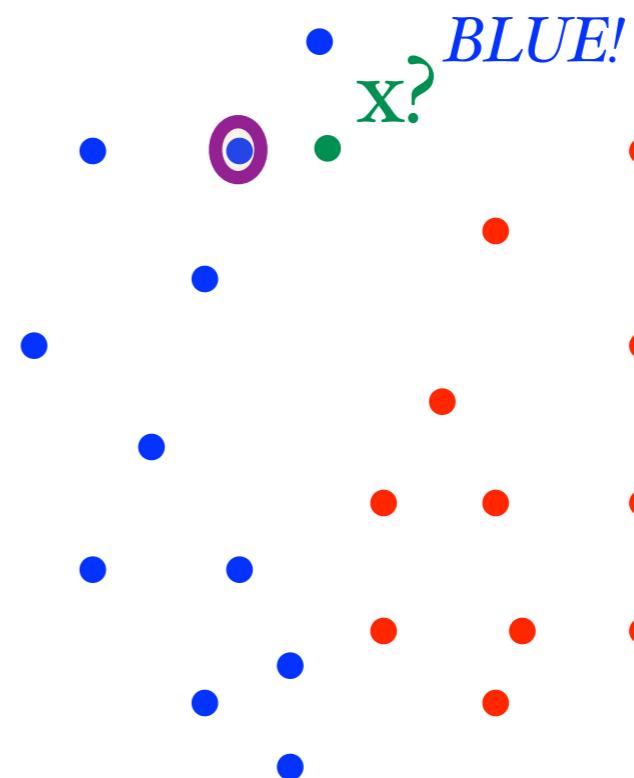
Data set seen as a scatter plot in a high-dimensional vector space



The nearest neighbor algorithm

For a test point x :

- We find the **nearest neighbour** of x within the training set by some measure of distance (eg Euclidean distance).
- We associate x with the class of this nearest neighbor.

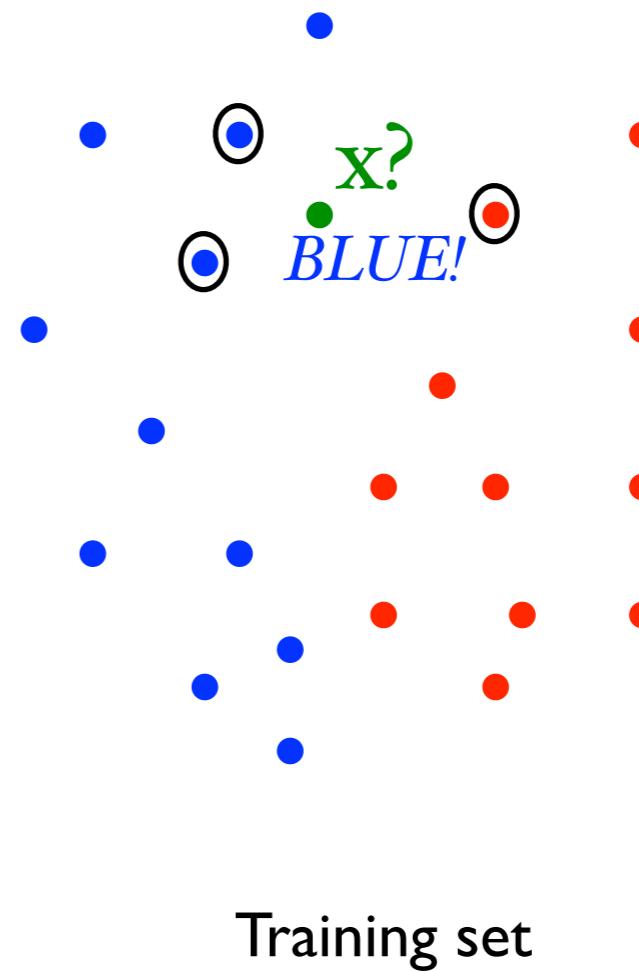


The k-nearest neighbors algorithm (k-NN)

For a test point x :

$k=3$

- We find the **k nearest neighbors** of x within the training set apprentissage by some measure of distance (eg Euclidean distance).
- We associate x with the class of the **majority** of neighbors.



Short review of vectors

(of dimension d)

■ what is a vector? mathematical,
computer, graphic representations ...

■ Euclidean distance

■ norms

■ scalar product

■ efficient calculation of the distance
from a point to a set of points

The notion of level of representation

