Lecture 1:

AI and Deep Learning

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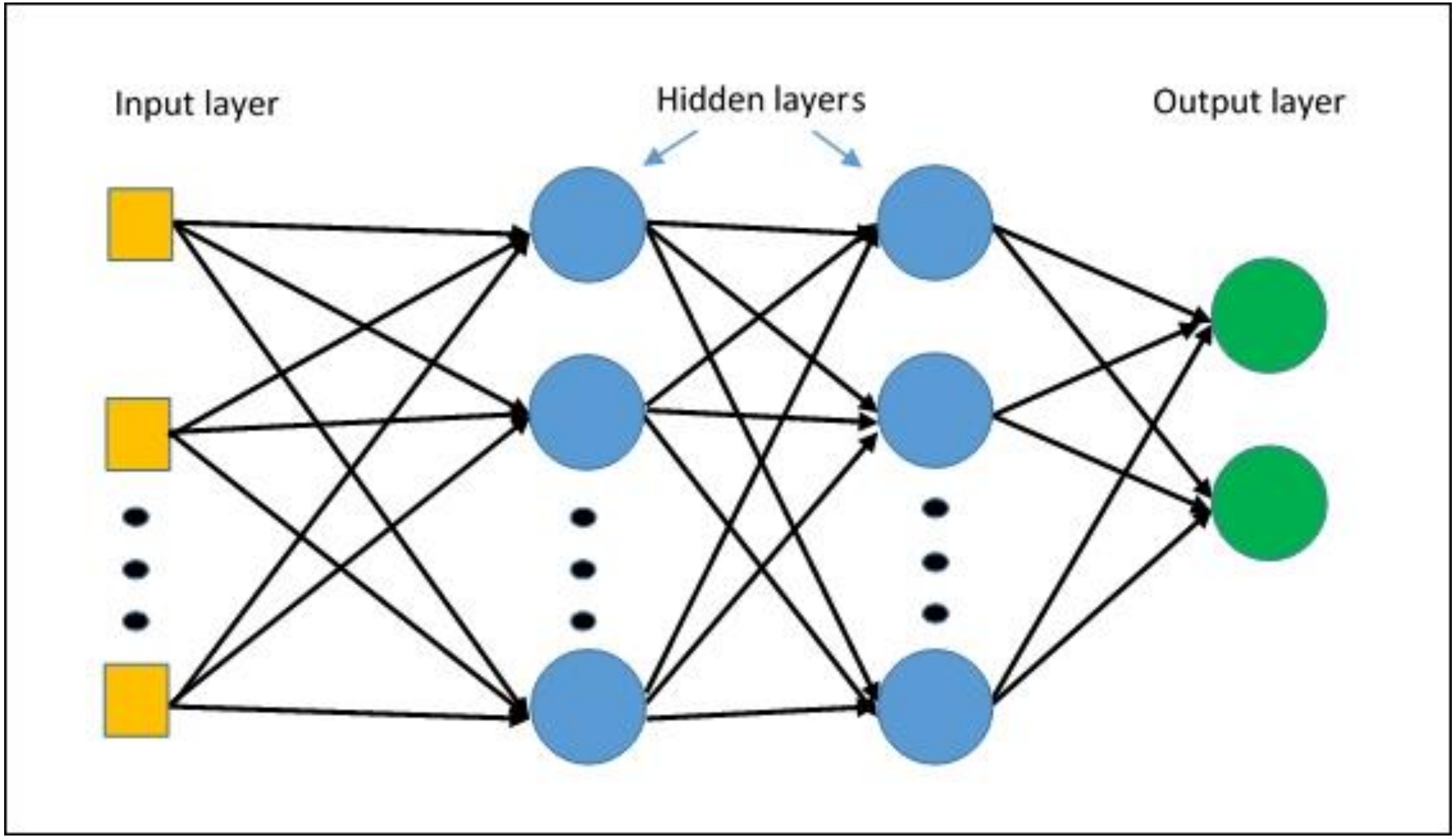
Milano, 13/09/2021

PhD School – Learning on 3D geometries

LA STATALE Università degli Studi di Milano
SAPIENZA Università di Roma

What



We will have a **deeper** description …

Image from "Getting Started with TensorFlow", G. Zaccone, 2016

When

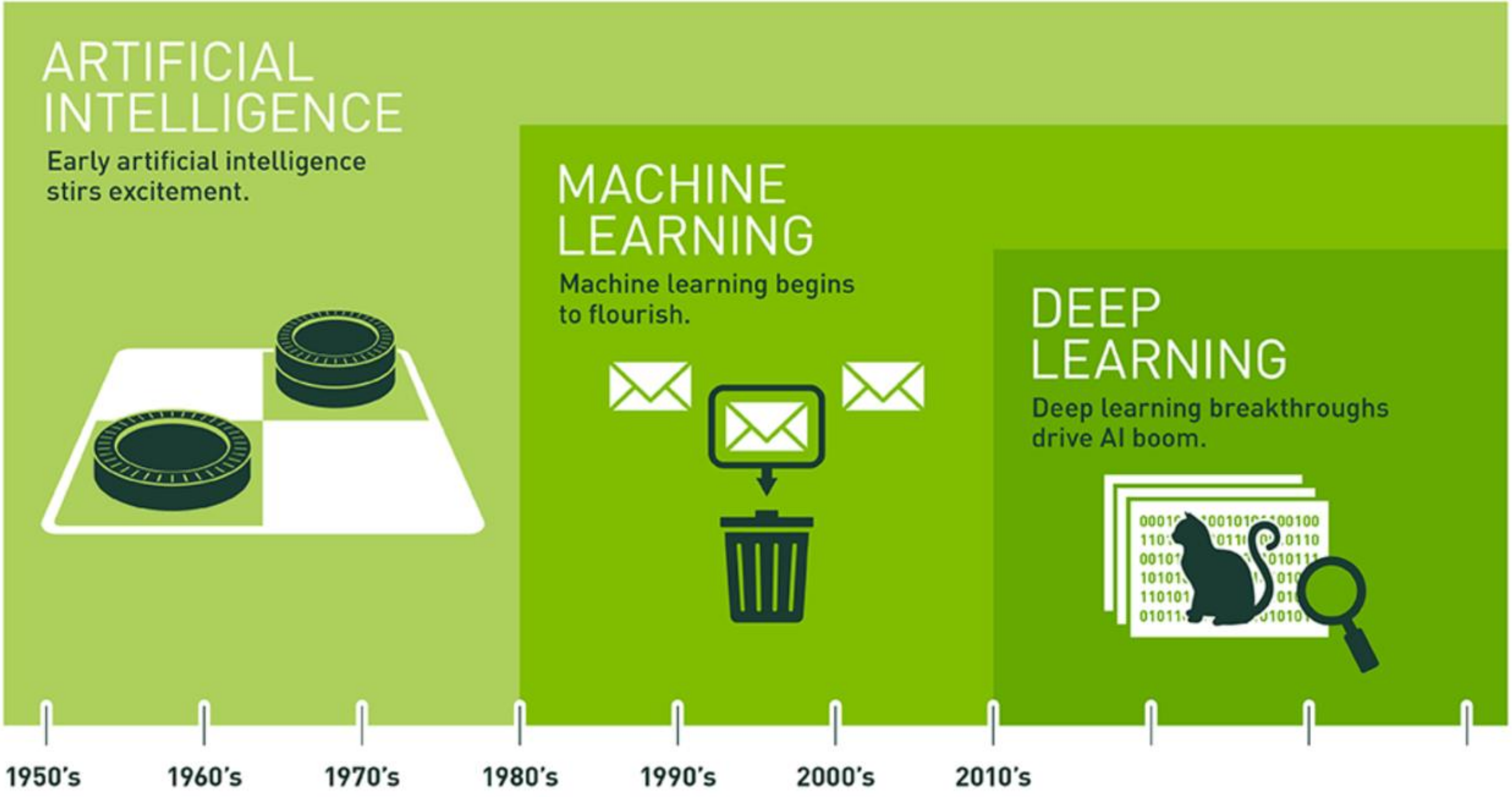
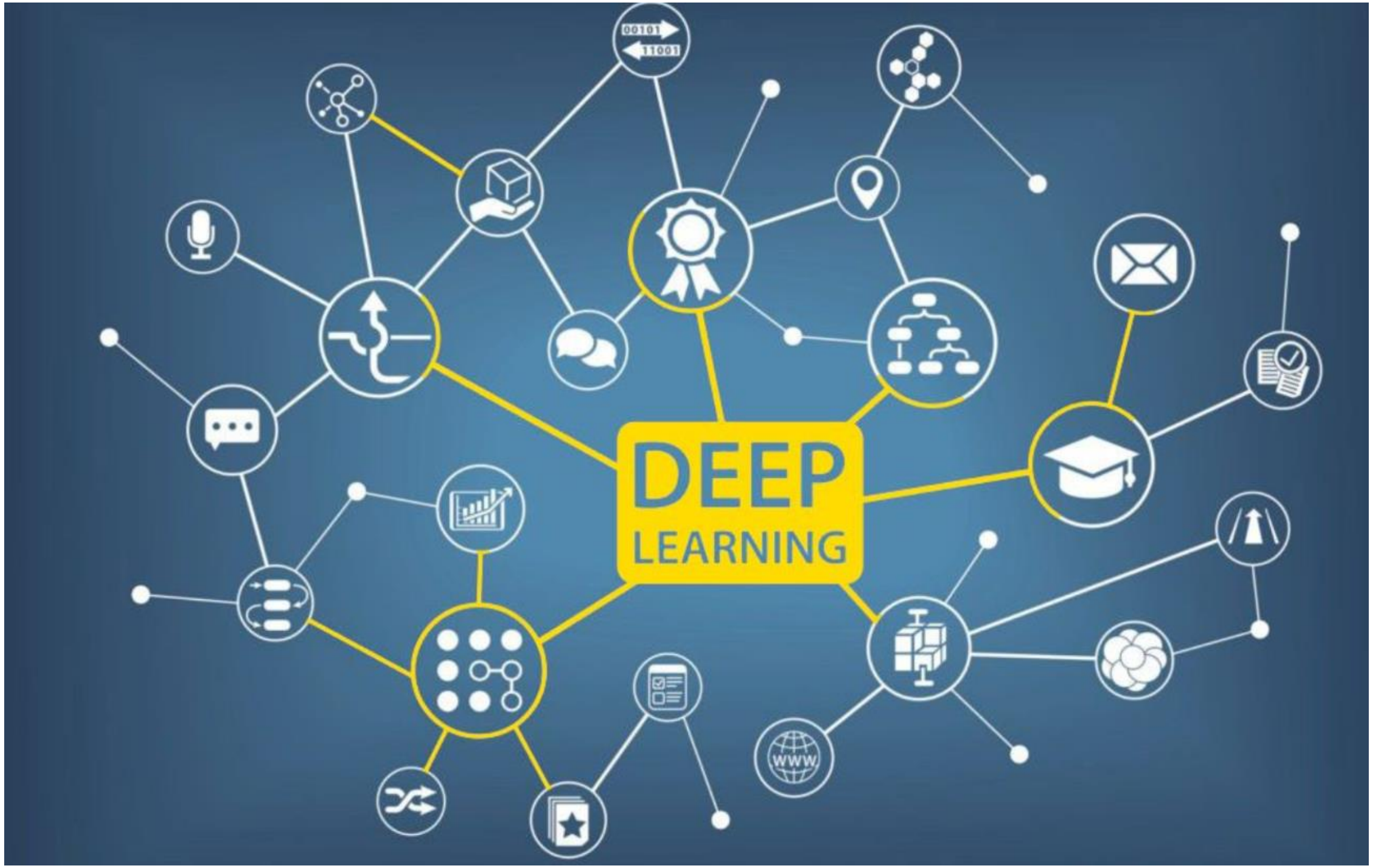


Image by Michael Copeland, NVIDIA

Slide credit E. *Rodolà*

Where



Nowadays, Deep Learning and AI are everywhere

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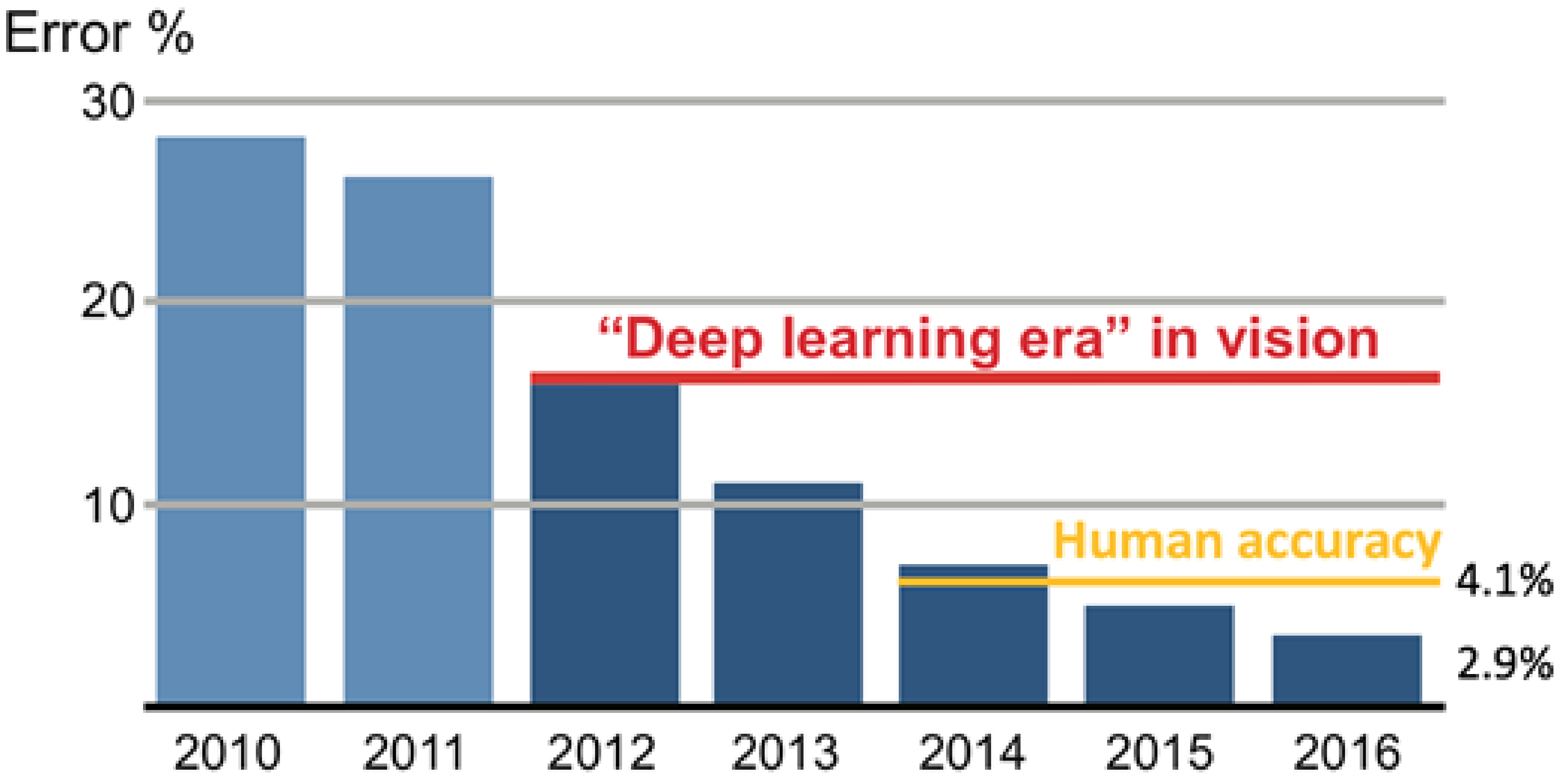
Why



ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

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How

Exploiting and extracting information that is contained in the data.

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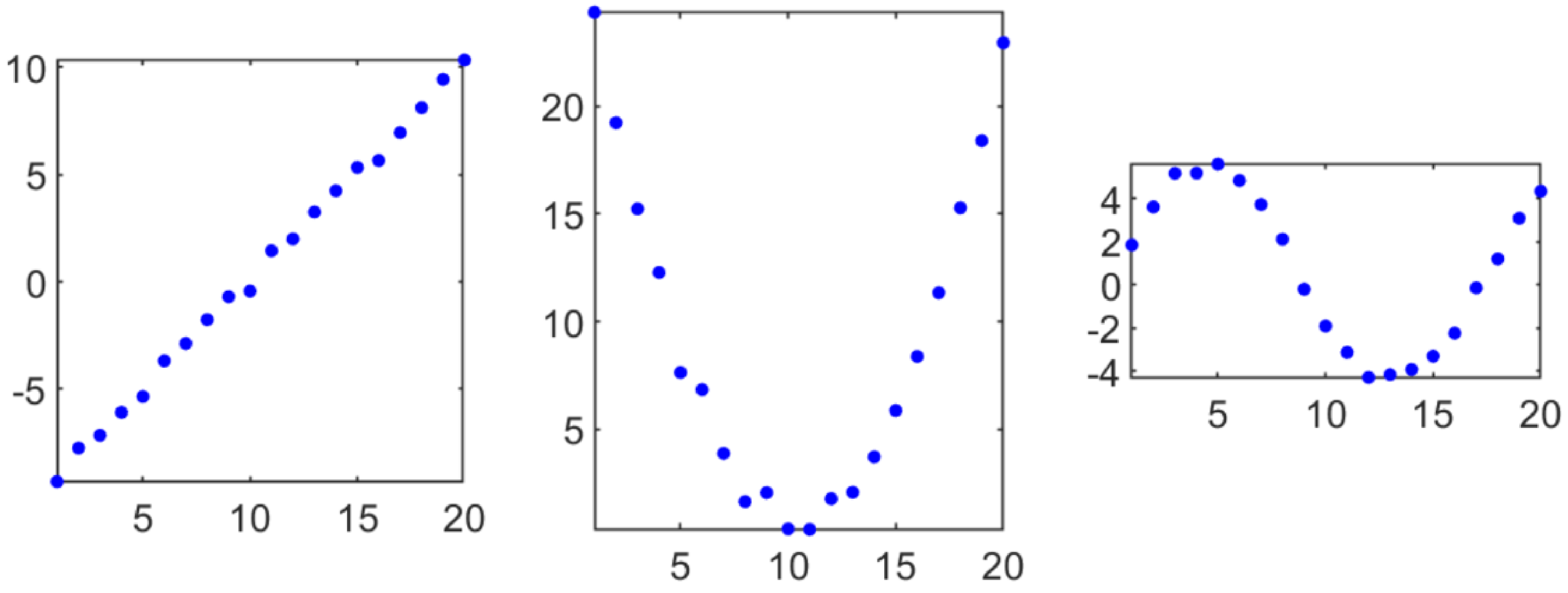
Learning

Learning = find a description of data

Or even better: describe the process (or model) that associates a given output from a given input



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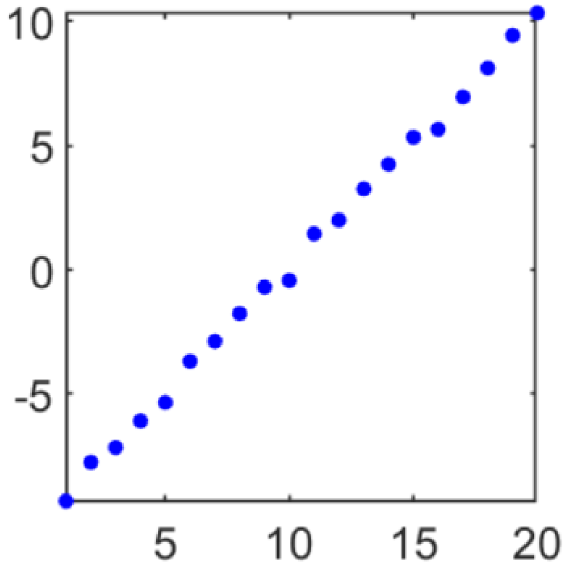
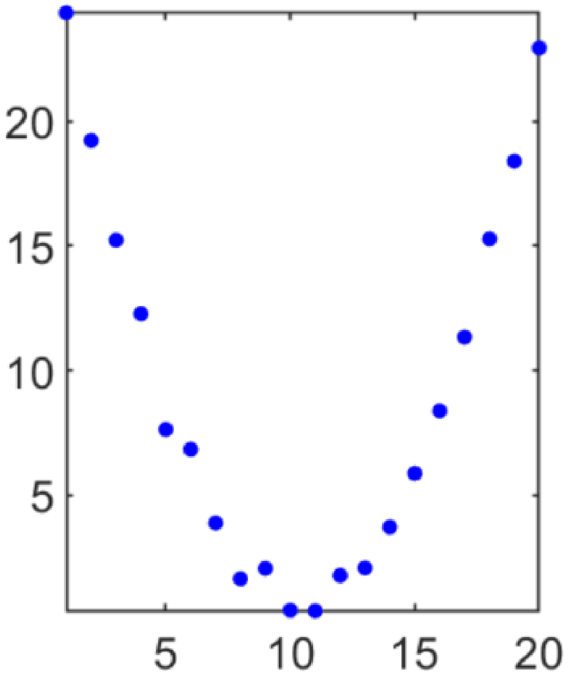
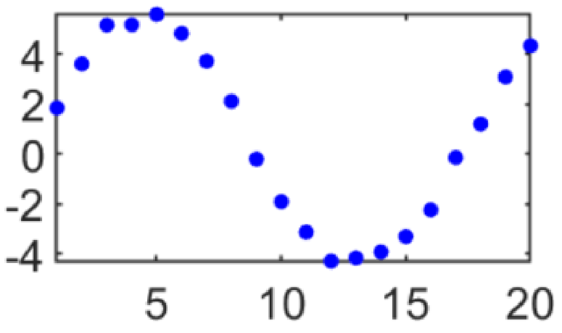
An example







$y = ax + b$

$y = ax^2 + bx + c$

$y = ax^3 + bx^2 + cx + d$

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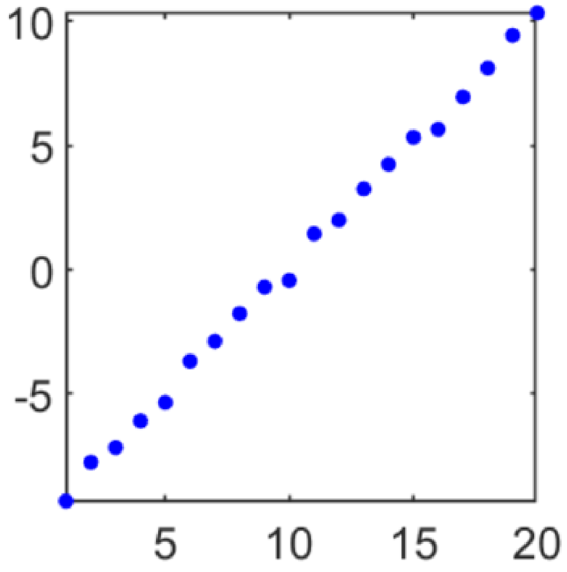
Not only data



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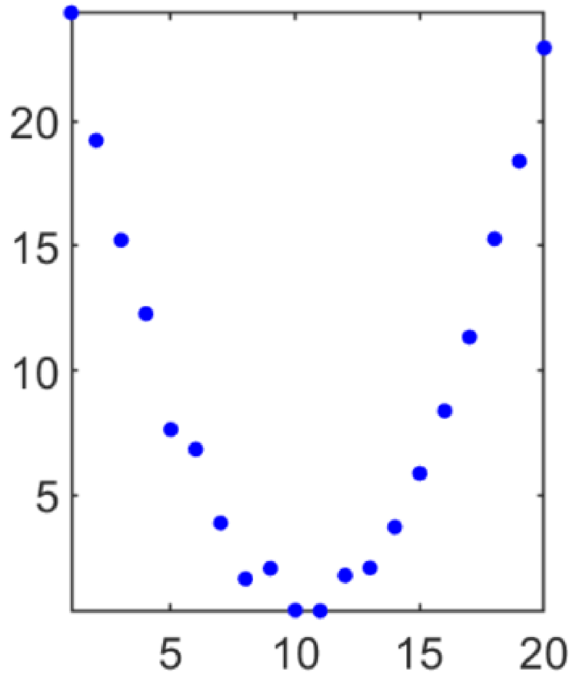
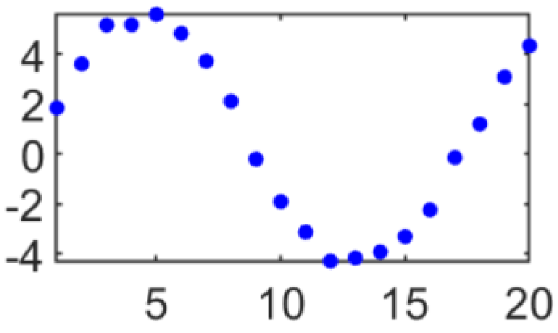


$$y = ax^2 + bx + c$$



$$y = ax^3 + bx^2 + cx + d$$

In addition, we could know something about the data or about the process (Prior Knowledge)

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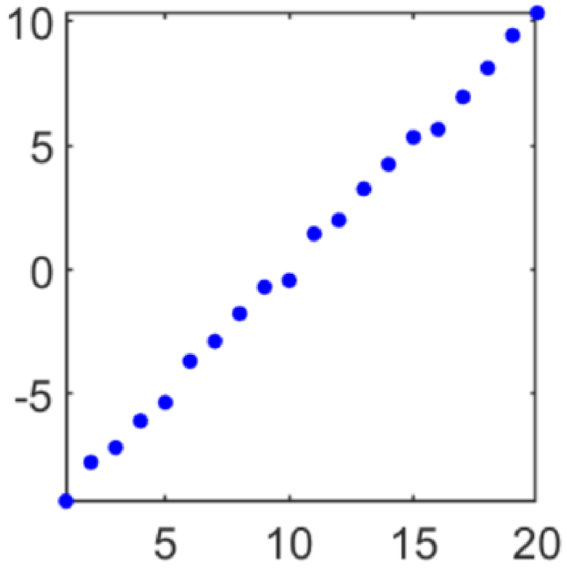
Not only data



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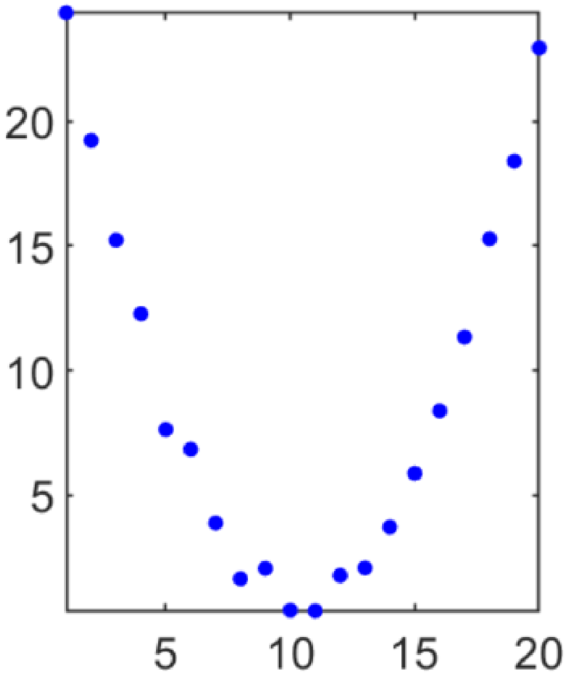

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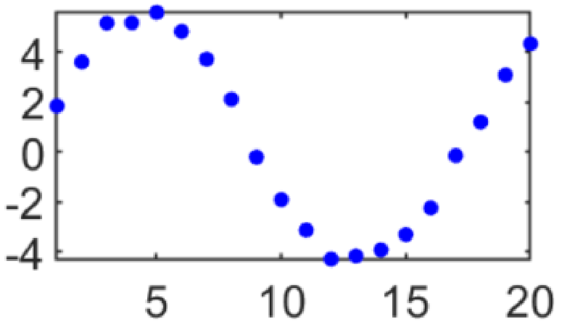

$$y = a\sin(x) + bx + c$$

In the third example, we could know that the process is **periodic**

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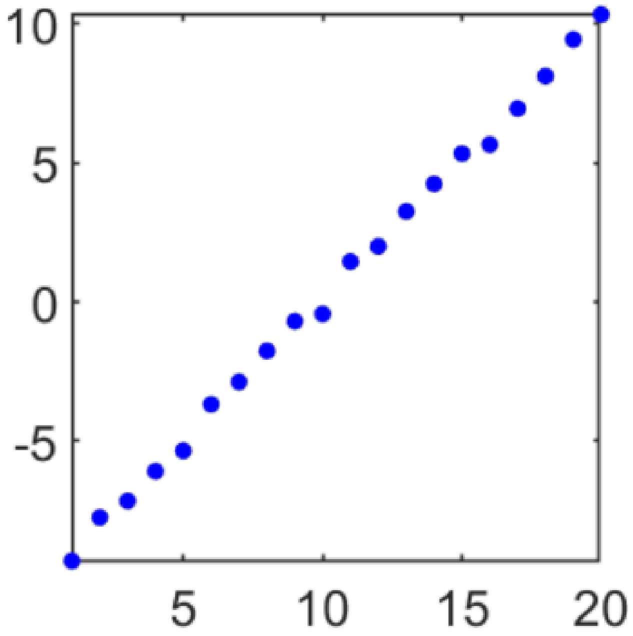
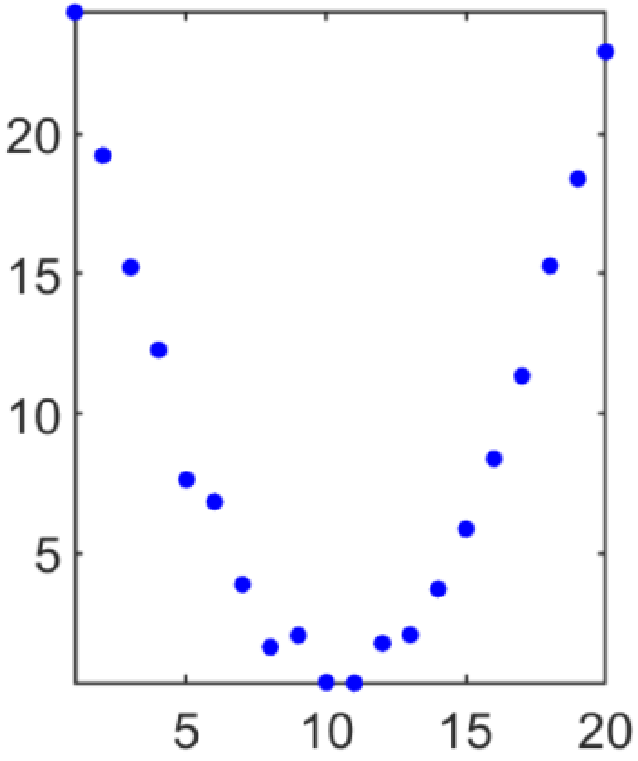
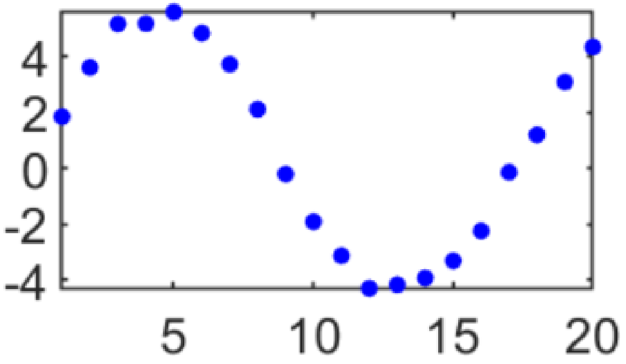
Model = map (function)

Learning = discovery the **map** from **input** to **output**







$y = ax + b$

$y = ax^2 + bx + c$

$y = a\sin(x) + bx + c$

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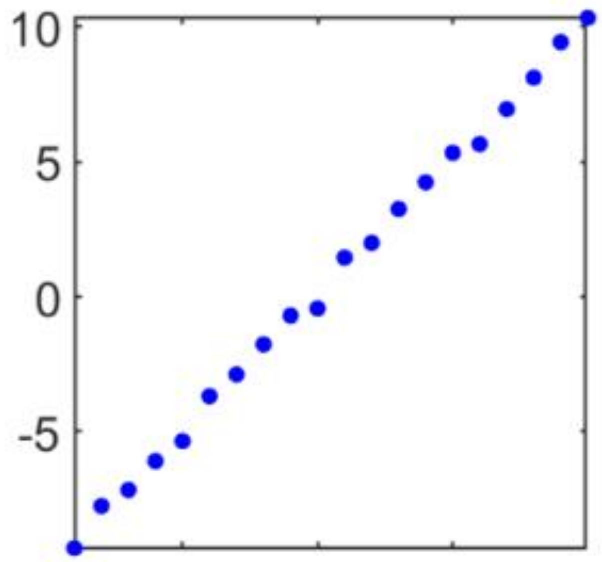
Data structure

Key assumptiomn: the data has an underlying structure



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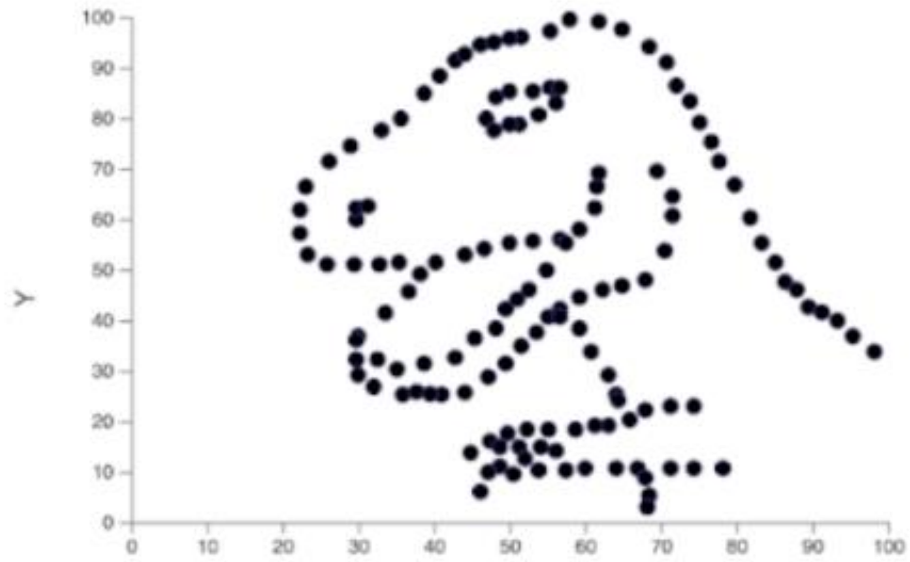

?

This structure is not usually well-described by simple functions

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Data structure

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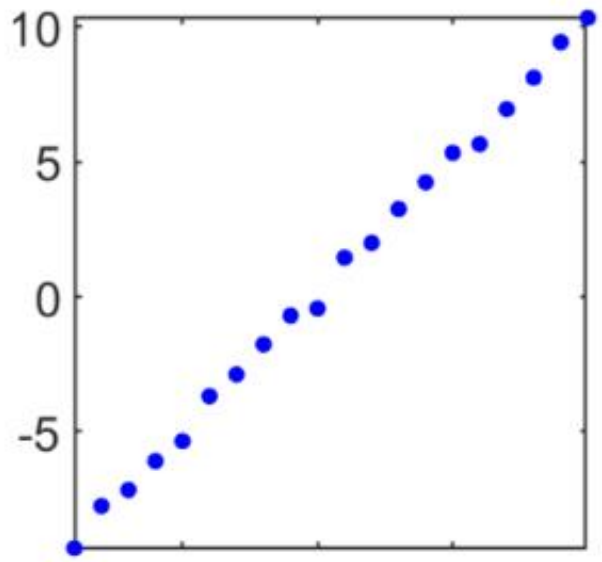

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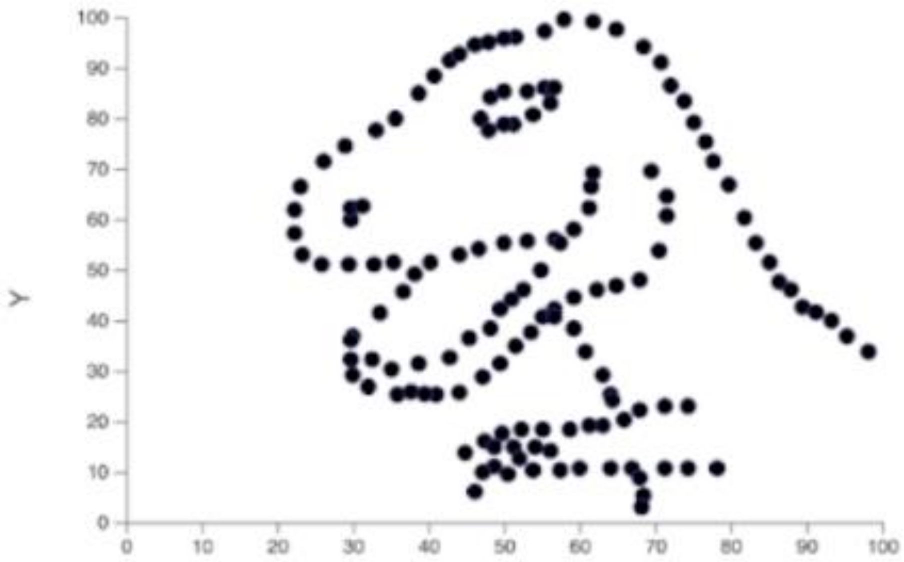

?

This structure is not usually well-described by **LINEAR** functions

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Data structure

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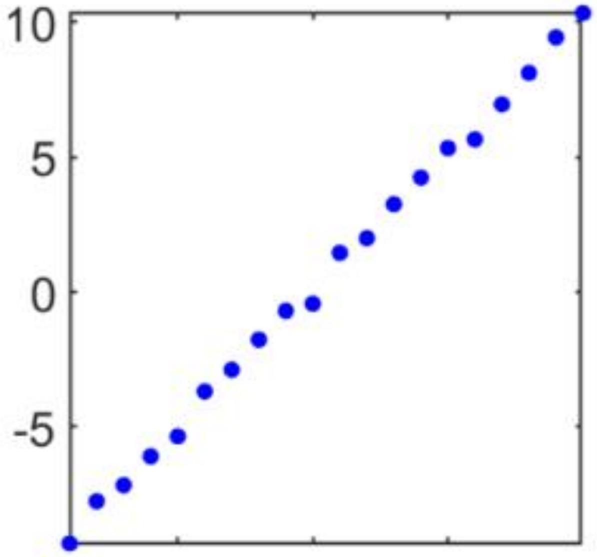

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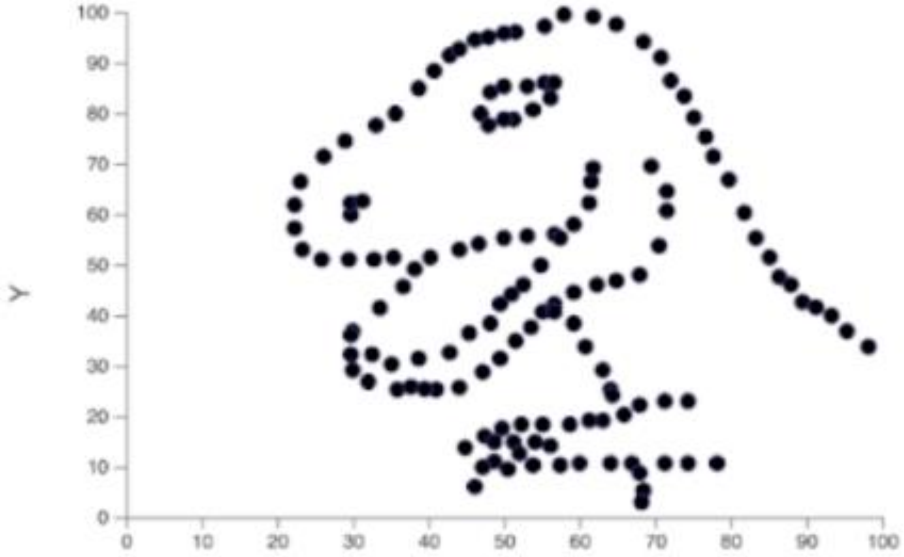

?

Data and functions could be not 1D

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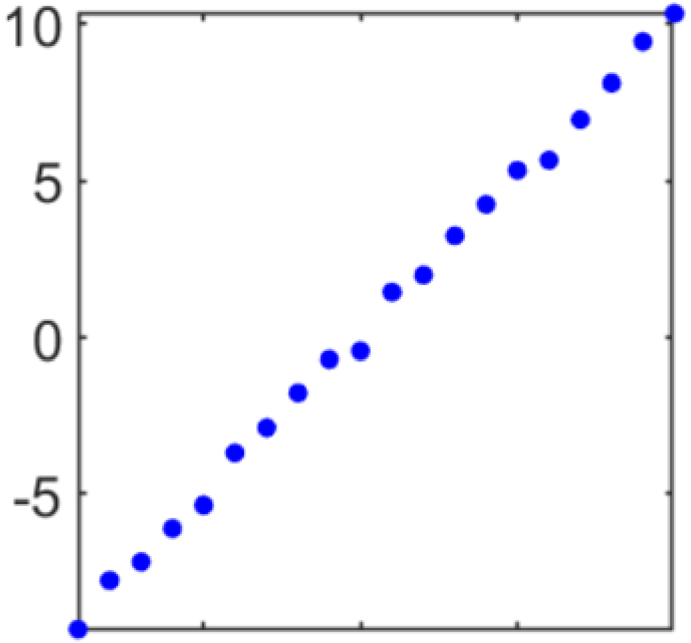
Not a unique representation

There are different models that could represent the same data

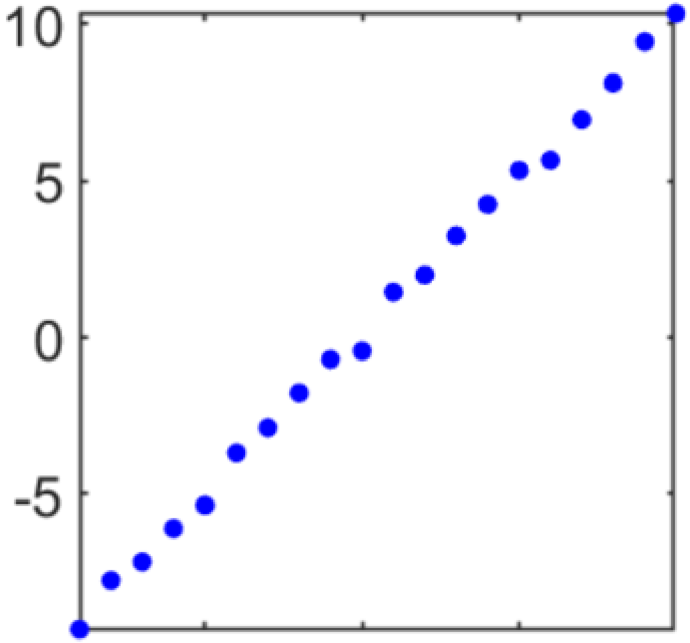
as a **function**



$$y = ax + b$$

$=$

as a **parametric curve**



$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} a_x \\ a_y \end{pmatrix} t + \begin{pmatrix} b_x \\ b_y \end{pmatrix}$$

Not a unique representation

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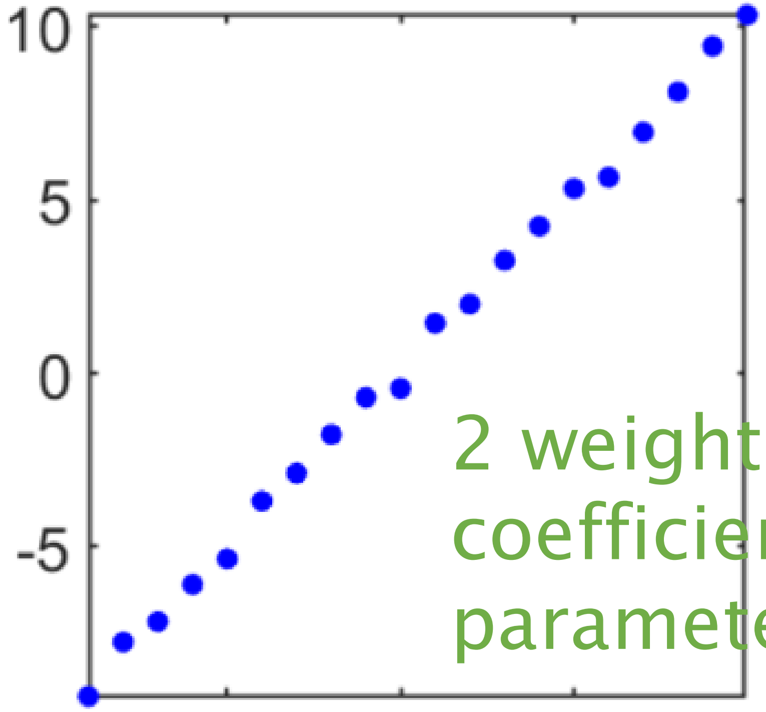
as a **function**

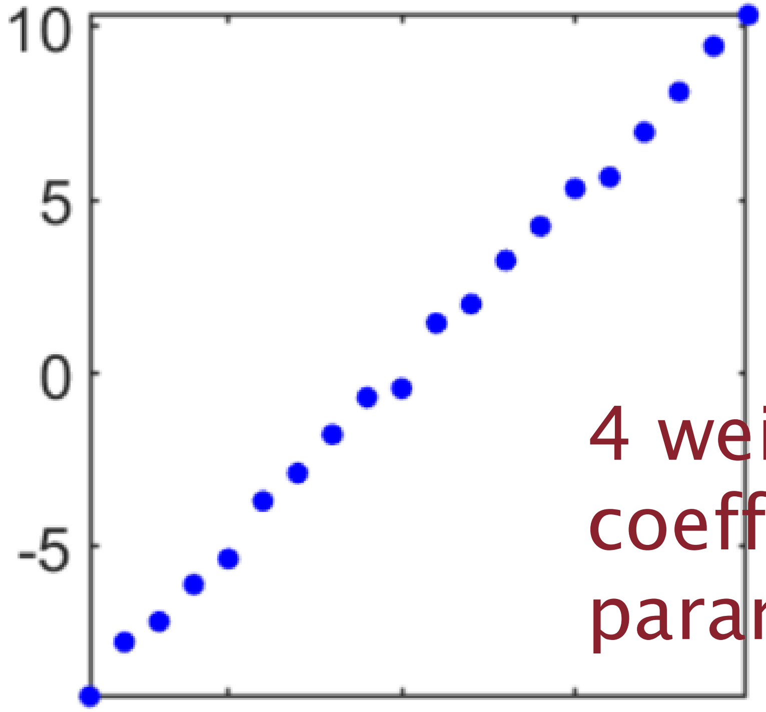


2 weights
coefficients
parameters

$$y = ax + b$$

=

as a **parametric curve**



4 weights
coefficients
parameters

$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} a_x \\ a_y \end{pmatrix} t + \begin{pmatrix} b_x \\ b_y \end{pmatrix}$$

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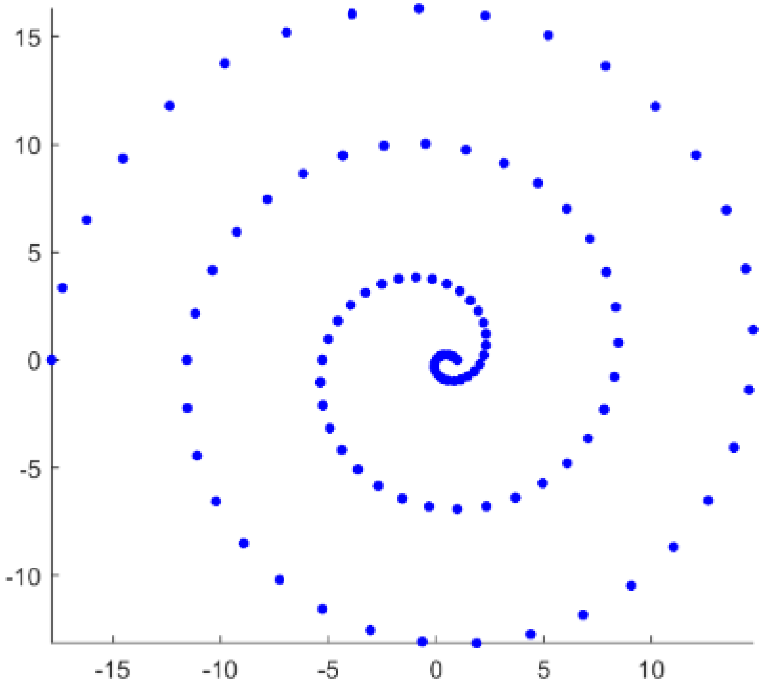
The right representation

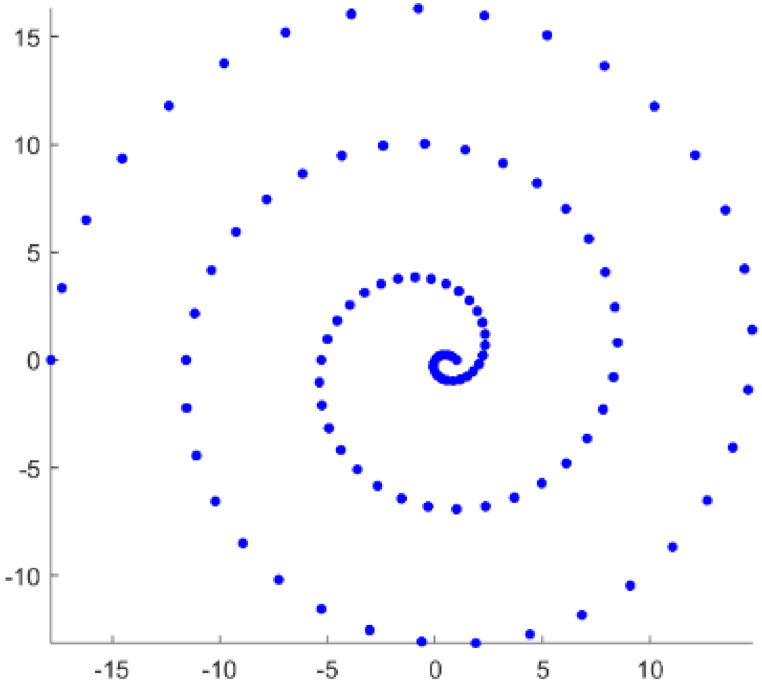
There are different models that could represent the same data

as a **function**



=

as a **parametric curve**



y is not a function of x

$$\begin{pmatrix} x \\ y \end{pmatrix} = a \begin{pmatrix} \cos t \\ \sin t \end{pmatrix} (a - t)$$

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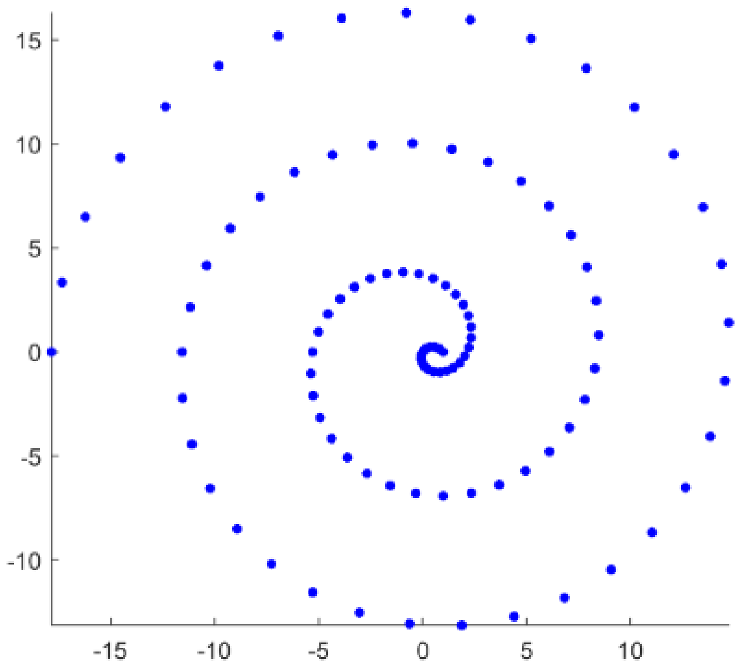
The right representation

There are different models that could represent the same data

as a **function**

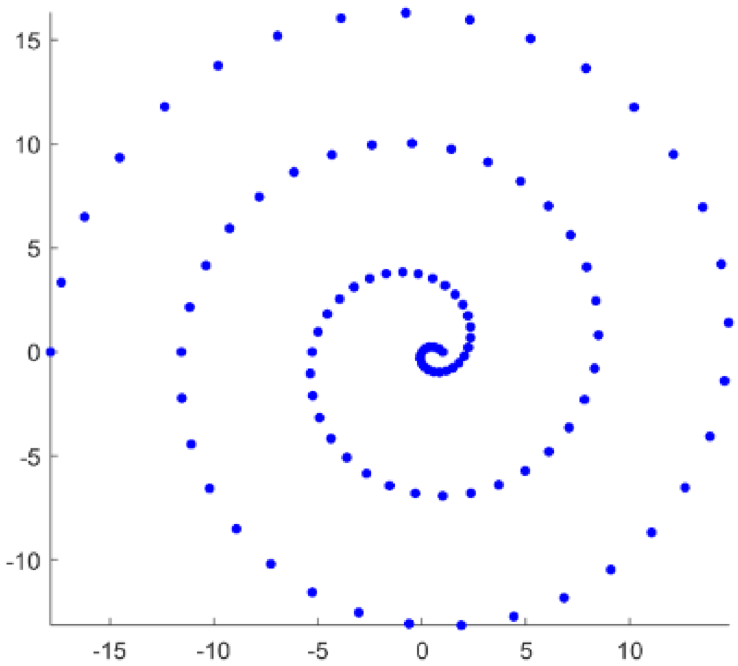


$$r = a\theta$$

(polar coordinates)

=

as a **parametric curve**



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The right representation

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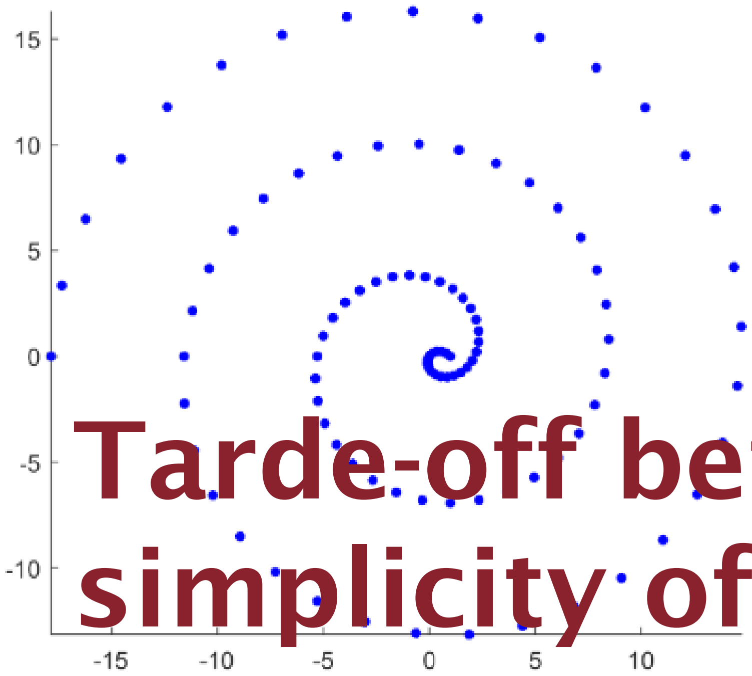
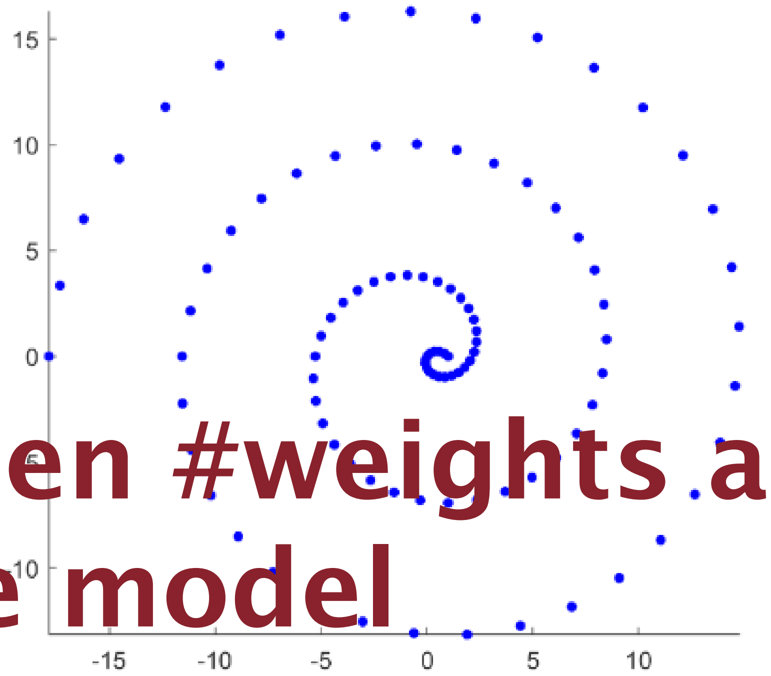


$=$

as a **parametric curve**



Tarde-off between #weights and simplicity of the model

$$r = a\theta$$

linear!

$$\begin{pmatrix} x \\ y \end{pmatrix} = a \begin{pmatrix} \cos t \\ \sin t \end{pmatrix} (a - t)$$

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Data dimensionality

Data can have more than dimension 1 or 2

A $h \times w$ image is represented by a vector of size hw each entry of which is the gray value at the corresponding pixel

$\in \mathbb{R}^{w \times h} \cong \mathbb{R}^{wh}$

A ~1 megapixel image (grayscale) has $\sim 10^6$ dimensions

Not all these dimensions are informative

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Need for Data

A dataset of natural images will be extremely sparse in $\mathbb{R}^{h \times w}$

And some regions of this space will be observed very frequently

Tarde-off between #dimensions and Amount of data required

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Need for Priors

Priors help to better understand the data

If we can assume some priors on the data we will be able to select a more meaningful representation to model the data-distribution

One common prior assumed in deep learning is the **Manifold hypothesis**

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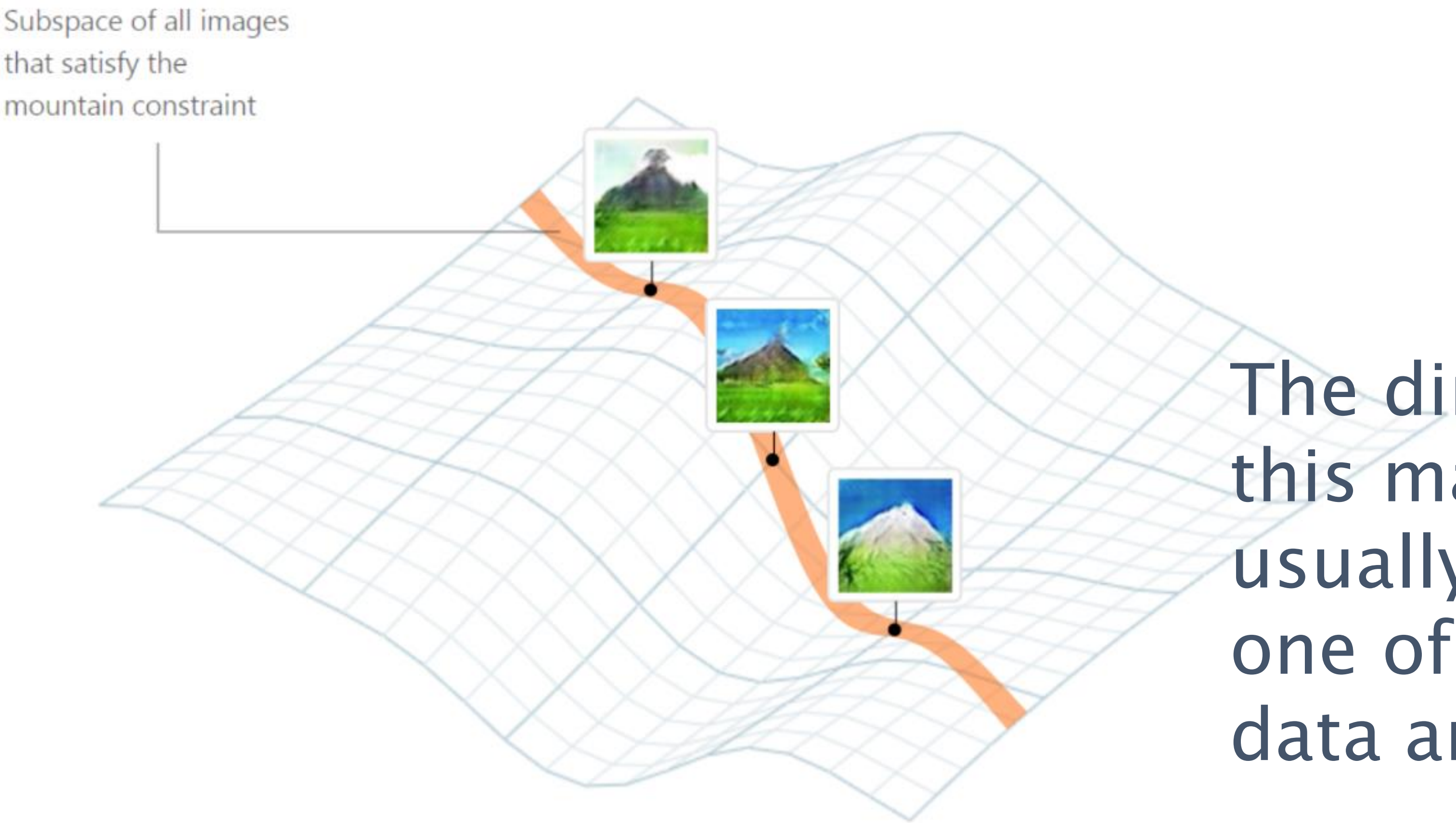
Manifold Hypothesis

The input data lives in a some underlying non-Euclidean structure called a Manifold



The dimensionality of this manifold are usually smaller than the one of the space where data are represented.

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AI and applications

The AI techniques are exploited in several applications

- Economy and finance
- Social analysis
- Agriculture
- Cybersecurity
- Education
- Healthcare
- Media
- Commerce (e-commerce)
- Manufacturing
- Automotive
- …

We usually imagine them applied to audio signals or images

AI and Images (2D)

Many outstanding results have been achieved on applications that involve images (computer vision)

Due to the huge amount of data of this kind available ImageNet contains 1.281.167 training images, 50.000 validation images and 100.000 test images

Why Geometric deep Learning?

Pixels (**Euclidean**)

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Why Geometric deep Learning?

Geometry (Non-**Euclidean**) Pixels (**Euclidean**)

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Geometric deep Learning

1. Data are not organized on a fixed grid or template

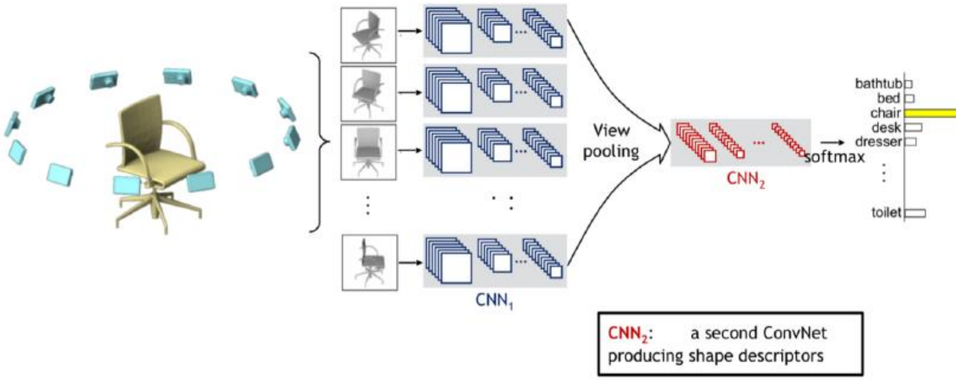
2. Different representation are possible (as we will see)

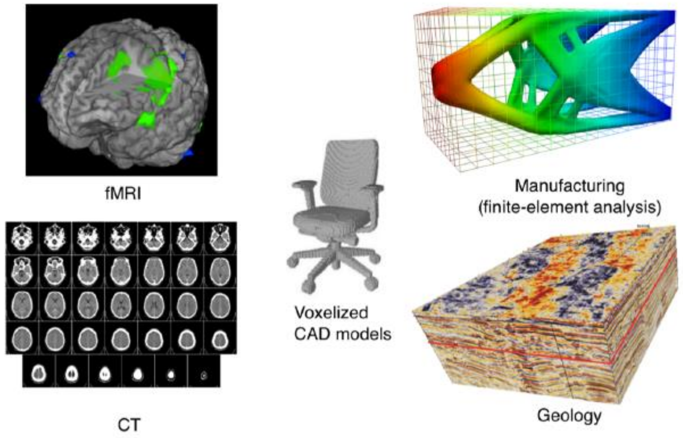
3. More Rigid transformations are possible

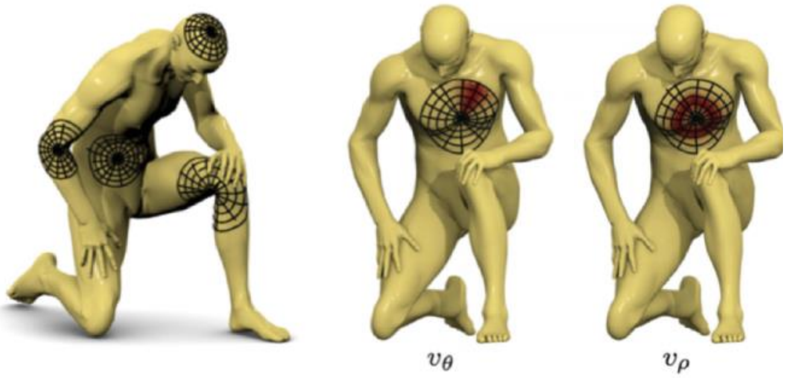
4. Limited amount of data available

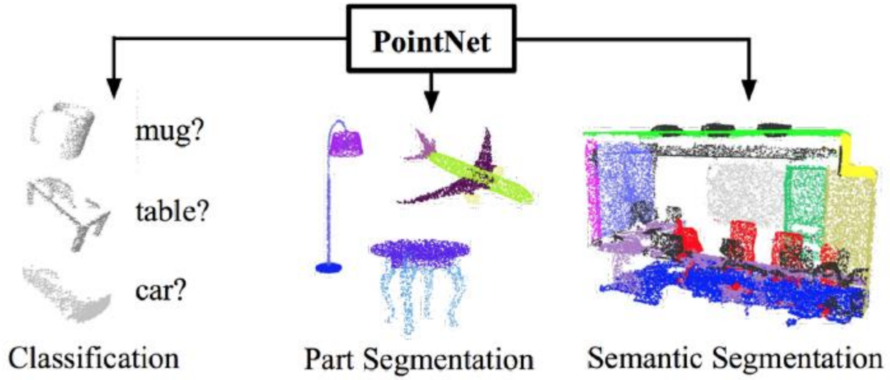
5. Limited amount of information available (labels, segmentations,..)

We can learn on 3D geometries









The main scope of this course is to see some of the solutions that have been proposed in the last decade