Machine Learning

Talking sense about data

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SAPIENZA
UNIVERSITÀ DI ROMA

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Data awareness

Machine learning involves dealing with data.

What do you do when you have a problem involving data?

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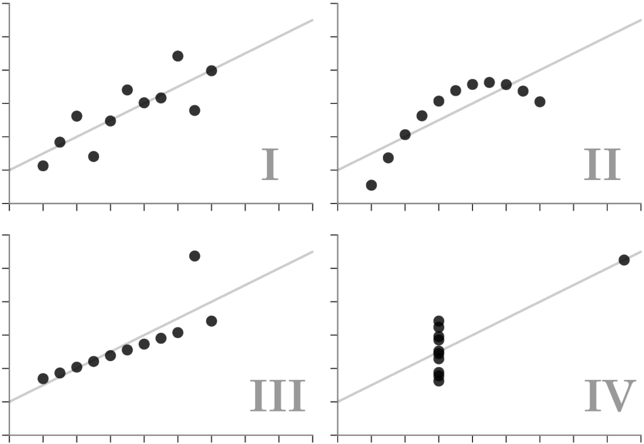
First thing: **look at the data!**

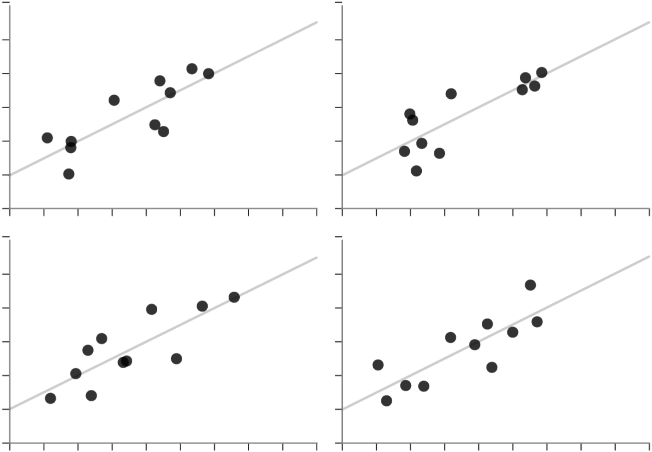
Anscombe’s Quartet

Each dataset has the same summary statistics (mean, standard deviation, correlation), and the datasets are *clearly different*, and *visually distinct*.



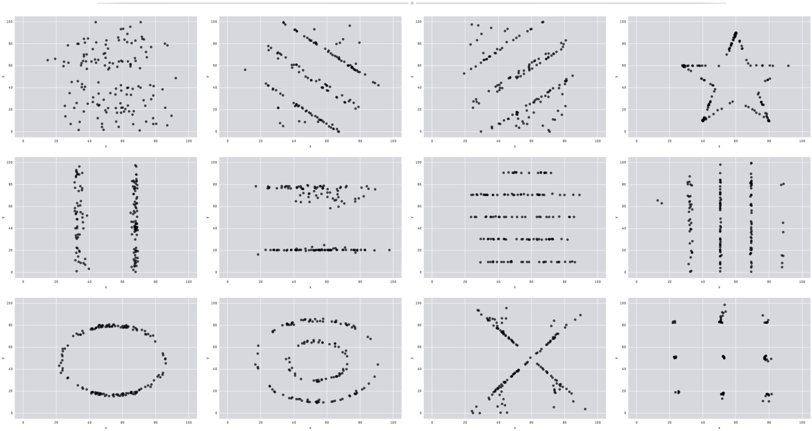
✗ Unstructured Quartet

Each dataset here also has the same summary statistics. However, they are not *clearly different* or *visually distinct*.



The datasaurus dozen

All these datasets have the same summary stats to 2 decimal places:



Matejka and Fitzmaurice, SIGCHI 2017

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It will not always be easy to visualize.

Difficult cases: high-dimensional data, no physical access to data, implicit access to data (e.g. latent spaces).

Models for describing the data

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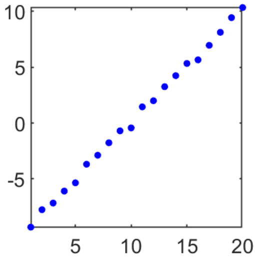

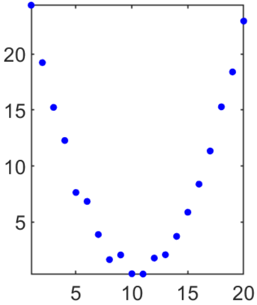

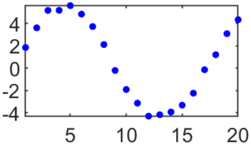

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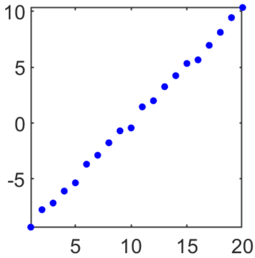
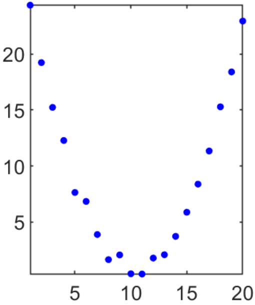


$$y = ax + b$$



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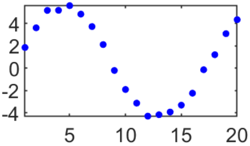

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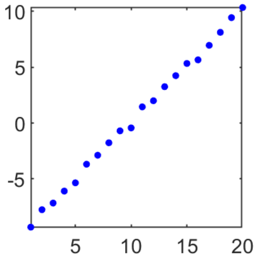

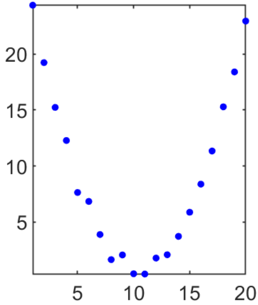

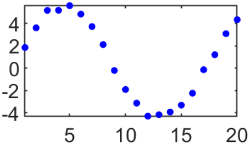

$y = ax + b$ $\quad$ $y = ax^2 + bx + c$ $\quad$ $y = a\sin(x) + bx + c$

Our model might use prior knowledge on the data.

For example, in the third plot, we might know *a priori* that the data actually comes from a periodic process.

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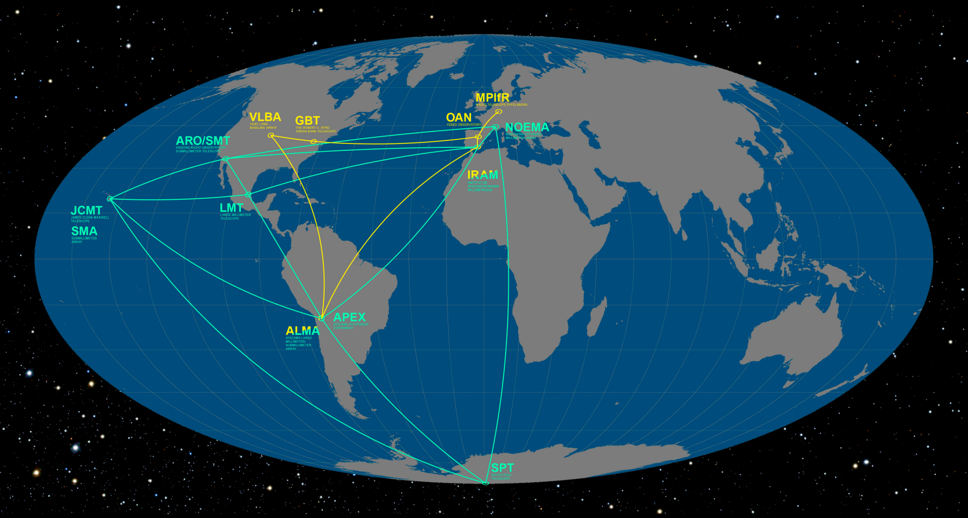
All these encode, to different extents, some expected behavior.

Event Horizon Telescope



Reliability of the prior: imaging the black hole

Problem: reconstruct an image from a sparse set of spectral measurements (VLBI imaging).

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It is an ill-posed inverse problem:

- Infinite number of possible images explain the data

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Problem: reconstruct an image from a sparse set of spectral measurements (VLBI imaging).

It is an ill-posed inverse problem:

- Infinite number of possible images explain the data
- Optimization heavily relies on priors.
  Find an explanation that respects prior assumptions about the "visual" universe while still satisfying the observed data.

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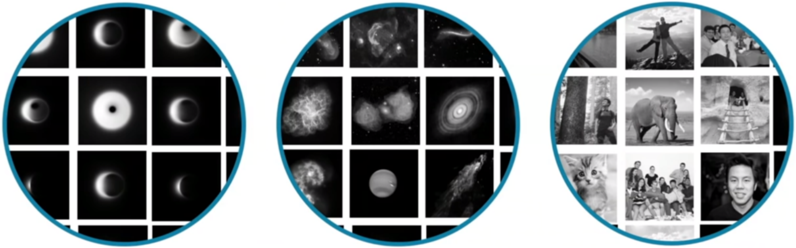

black holes astronomy everyday

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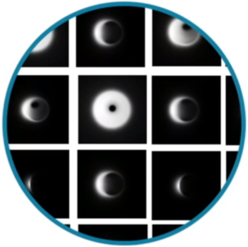
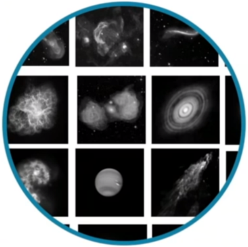


black holes
unreliable



astronomy

everyday

Black holes are dangerous! They will yield what one expects to obtain.

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Reliability of the prior: fairness

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	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. *(Source: ProPublica analysis of data from Broward County, Fla.)*

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Search query	Work experience	Education experience	Profile views	Candidate	Xing ranking
Brand Strategist	146	57	12992	male	1
Brand Strategist	327	0	4715	female	2
Brand Strategist	502	74	6978	male	3
Brand Strategist	444	56	1504	female	4
Brand Strategist	139	25	63	male	5
Brand Strategist	110	65	3479	female	6
Brand Strategist	12	73	846	male	7
Brand Strategist	99	41	3019	male	8
Brand Strategist	42	51	1359	female	9
Brand Strategist	220	102	17186	female	10

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Bias in the training dataset is still an open research problem!

Some possible causes:

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Assessing data and prior reliability is crucial for any learning-based system.

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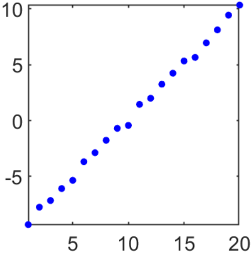

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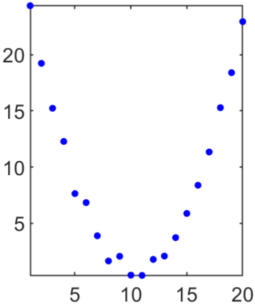

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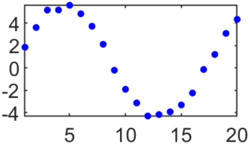

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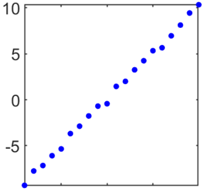
This structure is almost never captured by a simple expression.



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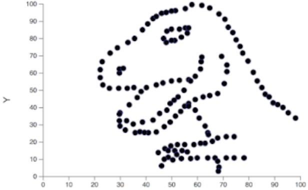

$?$

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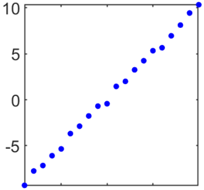

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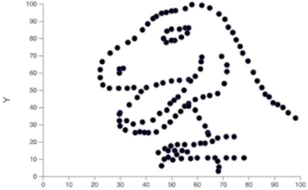


(not a function in 1D)

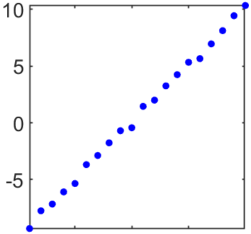
Clearly, data is not always one-dimensional.

Choosing a representation

The same data can be described in different ways.

What is the "right" way?

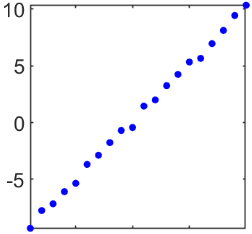
as a function



$$y = ax + b$$

$=$

as a parametric curve



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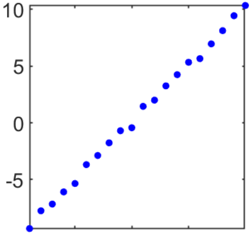
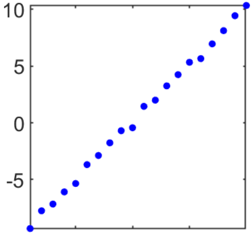


$$y = a x + b$$

2 weights

$=$

as a parametric curve



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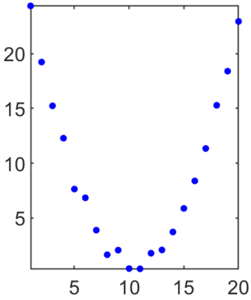
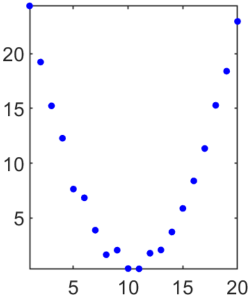


$$y = ax^2 + bx + c$$

=

as a **parametric curve**



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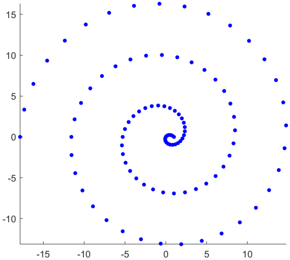

$=$

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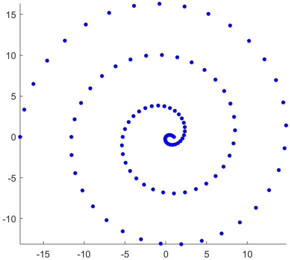

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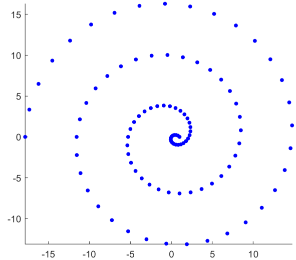
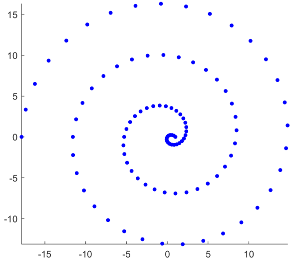


y is not a function of x

$=$

as a **parametric curve**



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

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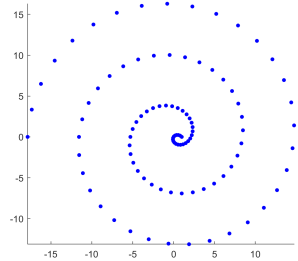
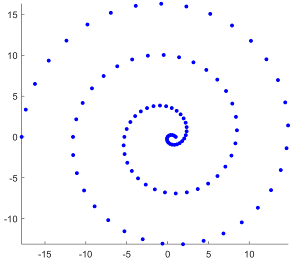


$r = a\theta$
(polar coordinates)

$=$

as a parametric curve



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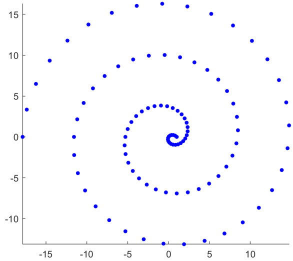
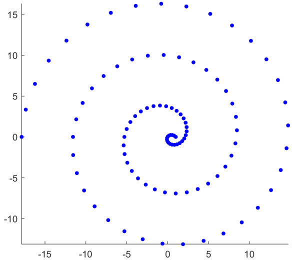


$r = a\theta$

linear!

$$=$$

as a **parametric curve**



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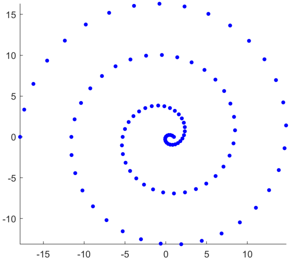

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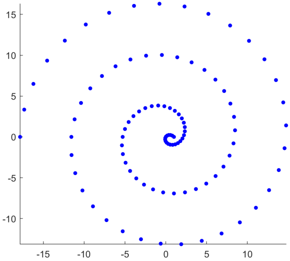

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Trade-off between #weights and simplicity

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For example, a $w \times h$ image has wh dimensions.

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

Example: $\sim$1 megapixel photo (grayscale) has $\sim 10^6$ dimensions.

The curse of dimensionality

Of course, data can have more than 1 or 2 dimensions.

For example, a $w \times h$ image has wh dimensions.

The value of each coordinate is given by the gray value at that pixel.
Then, the entire image is one point in a wh-dimensional space.

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

Example: ~1 megapixel photo (grayscale) has $\sim 10^6$ dimensions.

Are all those dimensions significant?

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For simplicity, consider 1×1 images, i.e., consisting of one single pixel.

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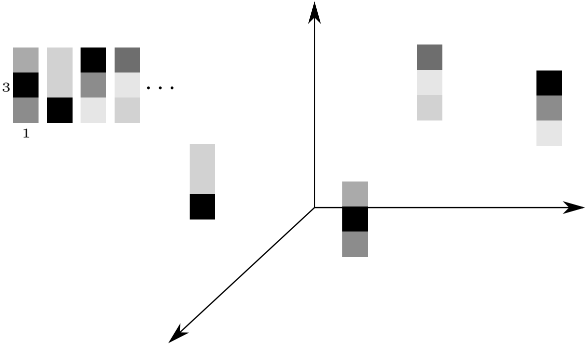
Similarly, with 3 pixels we get:

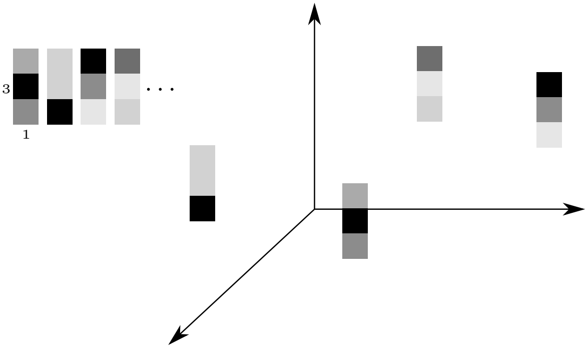


The curse of dimensionality

For simplicity, consider 1×1 images, i.e., consisting of one single pixel.

Each image is a point in one dimension.

Similarly, with 3 pixels we get:



Each new dimension increases sparsity of the point cloud.

The curse of dimensionality

A dataset of natural images will be extremely sparse in $\mathbb{R}^{w \times h}$, since each region of space is observed very infrequently.

New samples are less likely to fall close to the previous ones.

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If n data points cover well the space of 1-dimensional images, then n^d data points are required for d-dimensional images.

More data points make interesting structures emerge

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To cover the space entirely, we need exponentially many observations as we have dimensions!

If n data points cover well the space of 1-dimensional images, then n^d data points are required for d-dimensional images.

Two options:

1. **Increase** the dataset
2. **Decrease** the dimensions

Favor simplicity

Let's play a game:

$$2, 4, 8, \ldots$$

Rules:

- **Task:** Discover the rule I used to produce the sequence
- Give me a number: I'll tell you if it's next in sequence or not
- **Once you're sure**, tell me the rule

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Occam's razor: Among competing hypotheses, select the one with the fewest assumptions.

Also: when feasible, add more data!

Suggested reading

Blog post on the datasaurus:
https://www.autodeskresearch.com/publications/samestats

TED talk on the idea behind imaging the black hole:
https://www.youtube.com/watch?v=BIvezCVcsYs

VLBI reconstruction dataset:
http://vlbiimaging.csail.mit.edu/

Paper on the black hole imaging technique:
https://arxiv.org/pdf/1512.01413.pdf

Tutorial video and slides on ML fairness:
https://nips.cc/Conferences/2017/Schedule?showEvent=8734