

Deep Learning & Applied AI

Data, features, and embeddings

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SAPIENZA
UNIVERSITÀ DI ROMA

Data awareness

Machine learning involves dealing with **data**.

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

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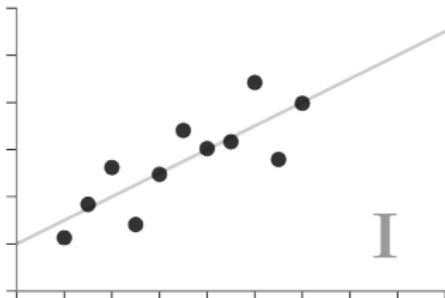
What do you do when you have a problem involving data?

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

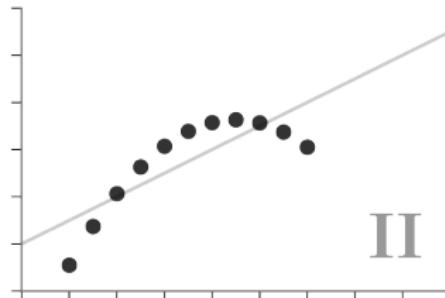


Anscombe's Quartet

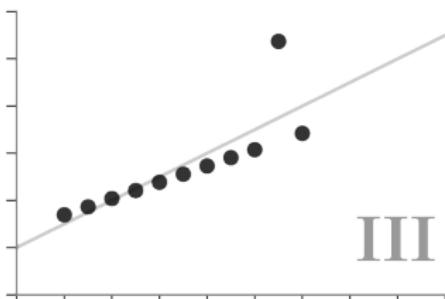
Each dataset has the same summary statistics (mean, standard deviation, correlation), and the datasets are *clearly different*, and *visually distinct*.



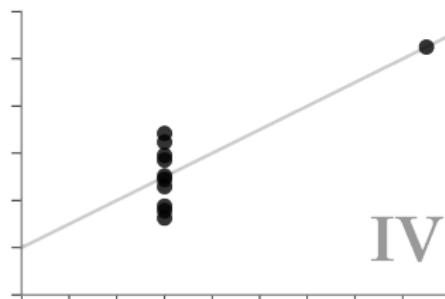
I



II



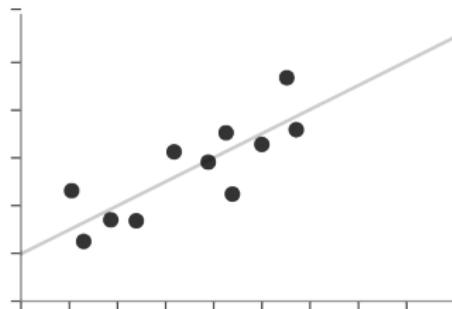
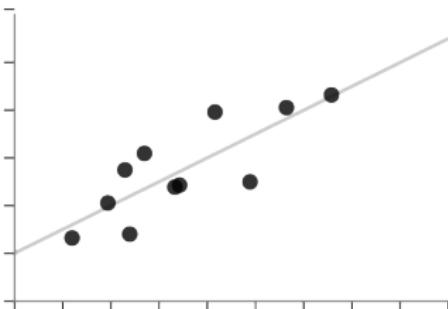
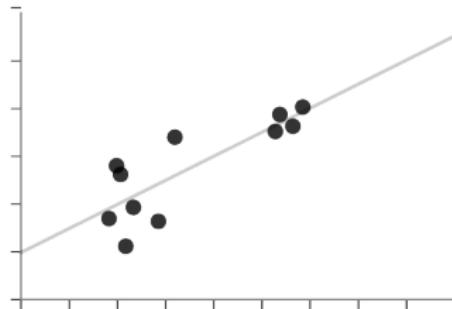
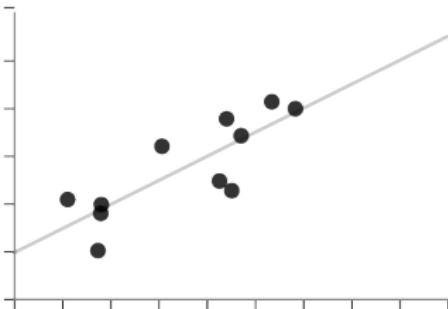
III



IV

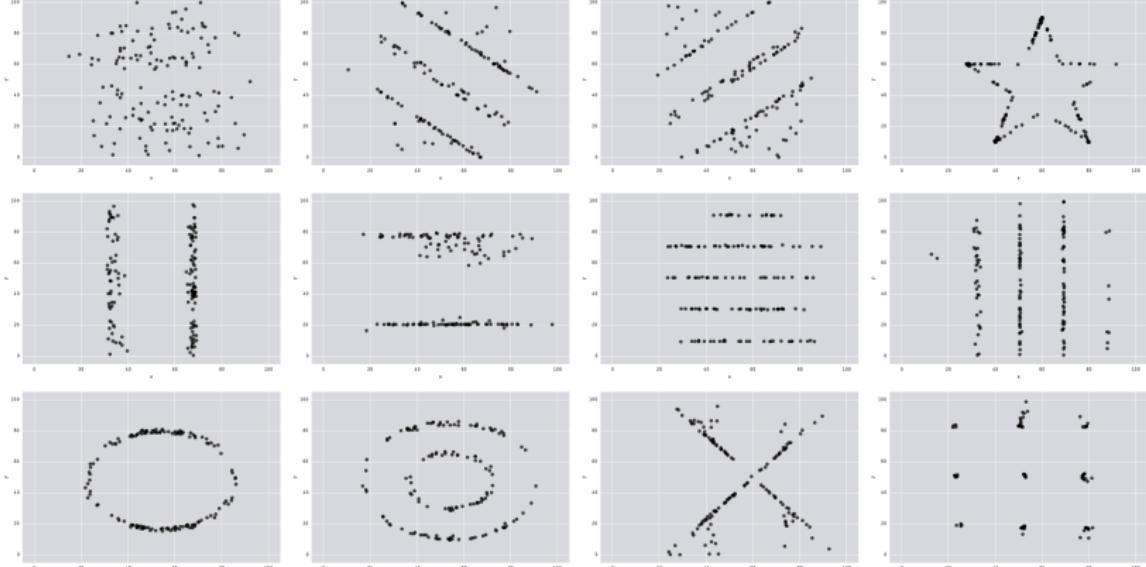
X Unstructured Quartet

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:



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It will not always be easy to visualize.

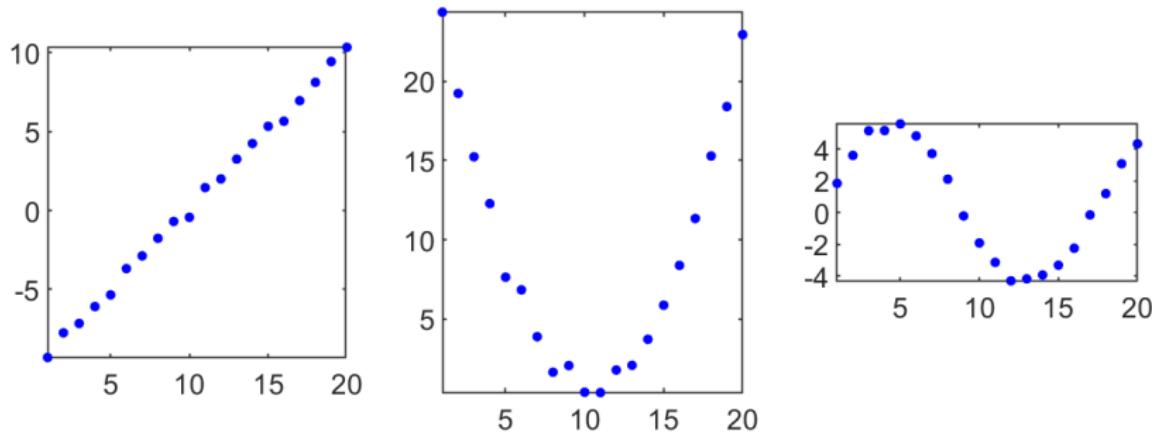
Difficult cases: **high-dimensional** data, **no physical access** to data, **implicit** access to data (e.g. latent spaces).

Models for describing the data

Learning is about **describing** the **process**, or **model**, that yields a given output from a given input.

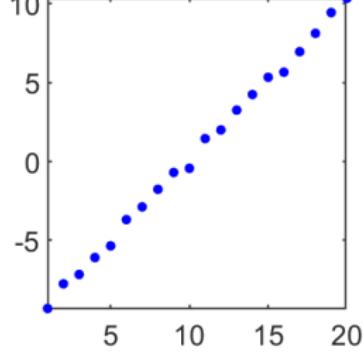
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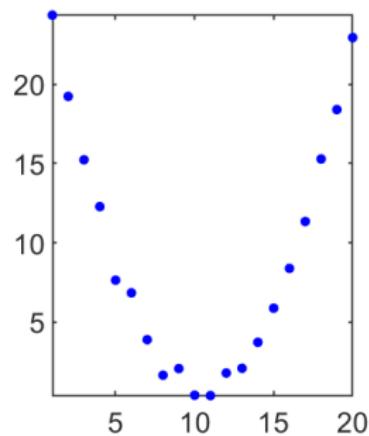


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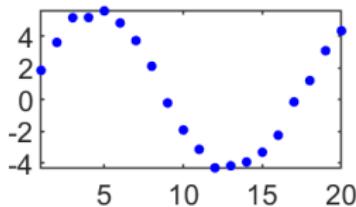
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$$y = ax + b$$



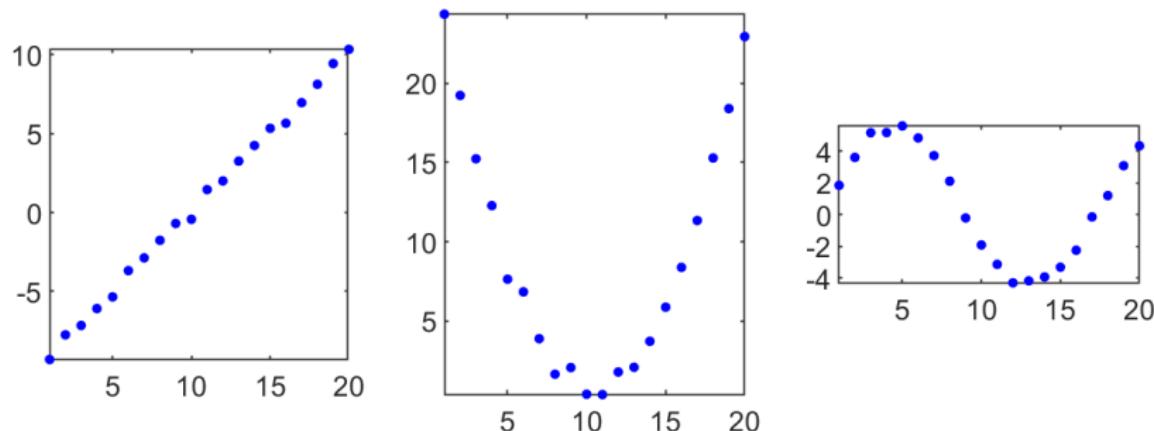
$$y = ax^2 + bx + c$$



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

Models for describing the data

Learning is about **describing** the **process**, or **model**, that yields a given output from a given input.



$$y = ax + b$$

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

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

Our model might use **prior knowledge** on the data.

Third plot: the data comes from a periodic process.

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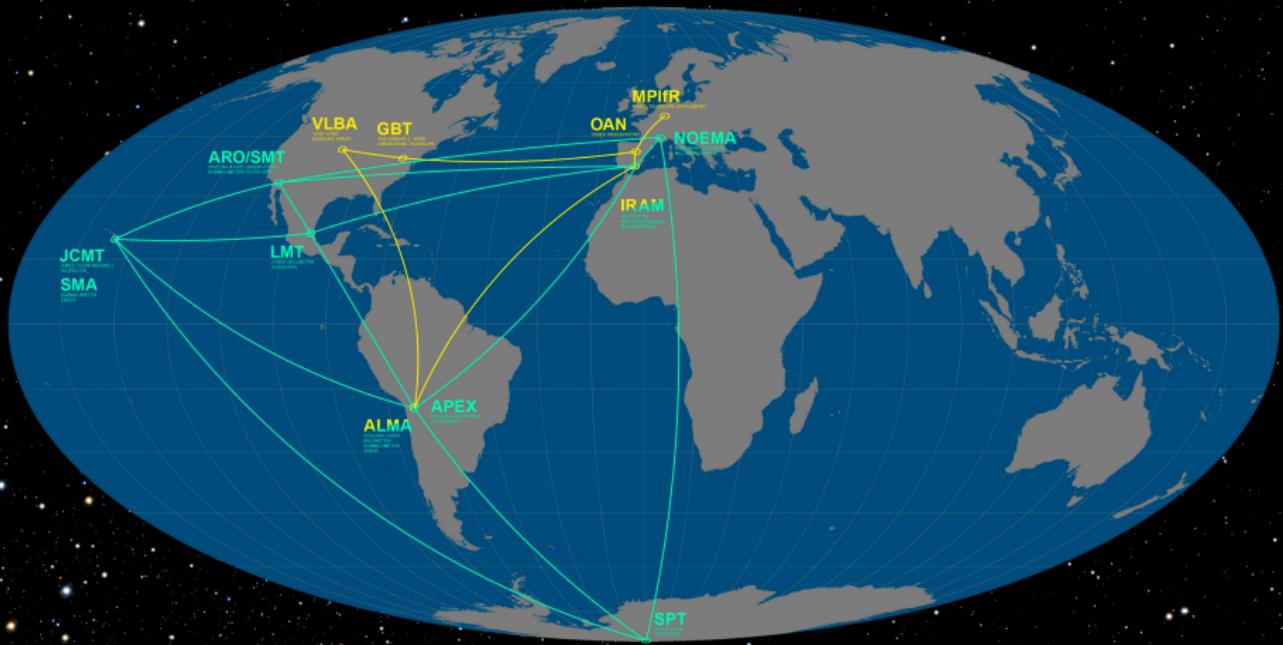
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All these encode some expected behavior.

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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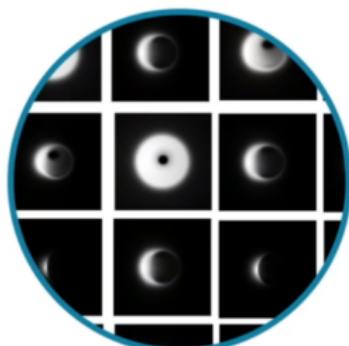
It is an ill-posed **inverse problem**:

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

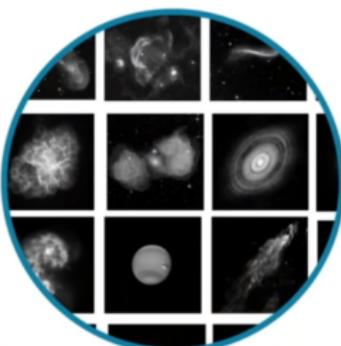
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black holes



astronomy

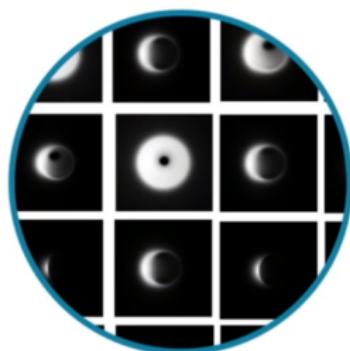


everyday

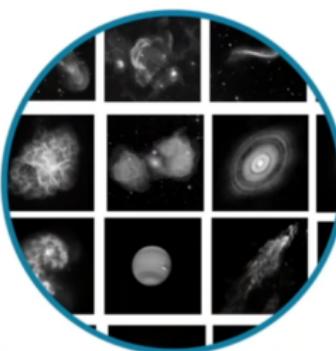
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black holes
unreliable



astronomy



everyday

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

Bouman et al, "Computational imaging for VLBI image reconstruction", CVPR 2016

Reliability of the prior: fairness

AI learns what humans teach.

The data provided by human can be **highly biased**.

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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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The data provided by human can be **highly biased**.

Bias in the training dataset is still an open problem!

Some possible causes:

- **Skewed sample:** a tiny initial bias grows over time, since future observations confirm prediction.

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

Explaining the data

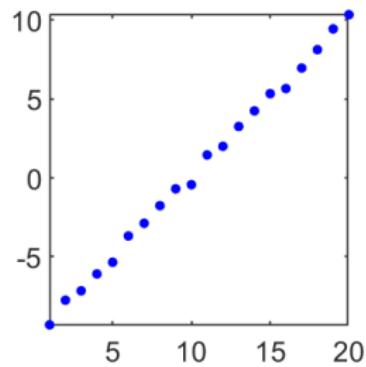
Learning is about discovering a **map** from input to output.

"Finding a model explaining the data" means determining the map.

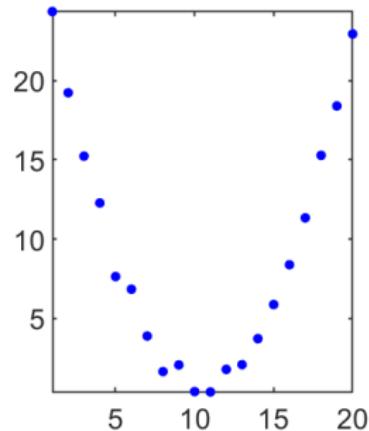
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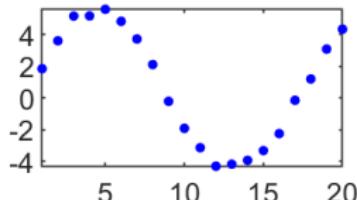
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Key assumption: the data has an
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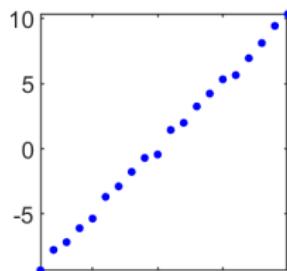
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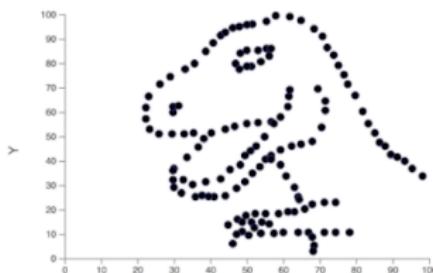
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Key assumption: the data has an underlying structure.

This structure is almost never captured by a simple expression.



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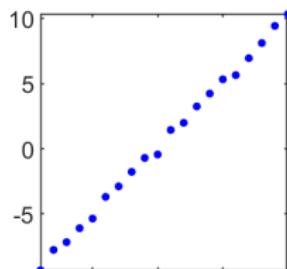
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$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} a_x \\ a_y \end{pmatrix} t + \begin{pmatrix} b_x \\ b_y \end{pmatrix}$$



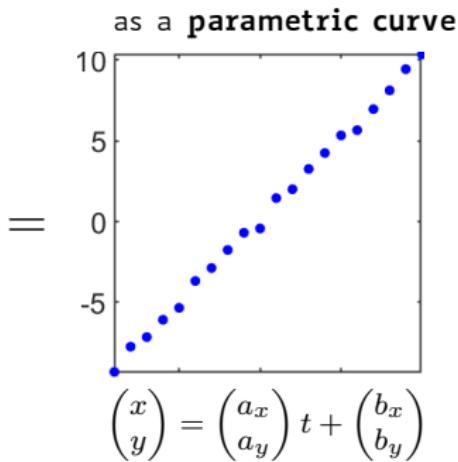
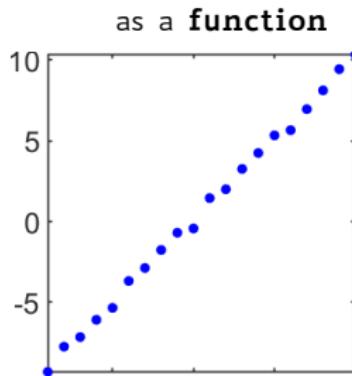
(not a function in 1D)

Clearly, data is not always one-dimensional.

Choosing a representation

The same data can be described in different ways.

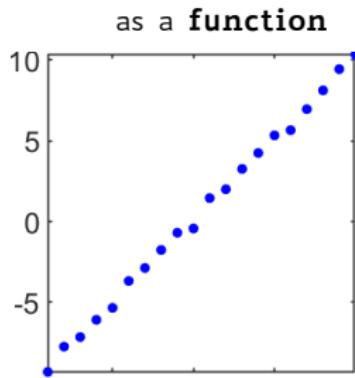
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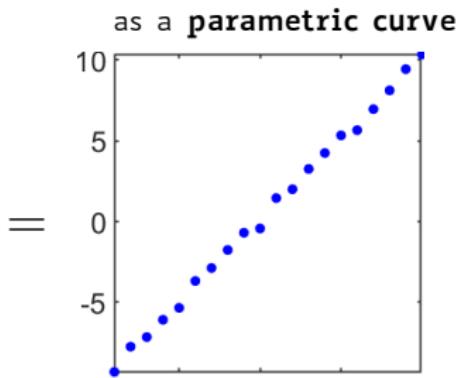
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$$y = ax + b$$

2 weights



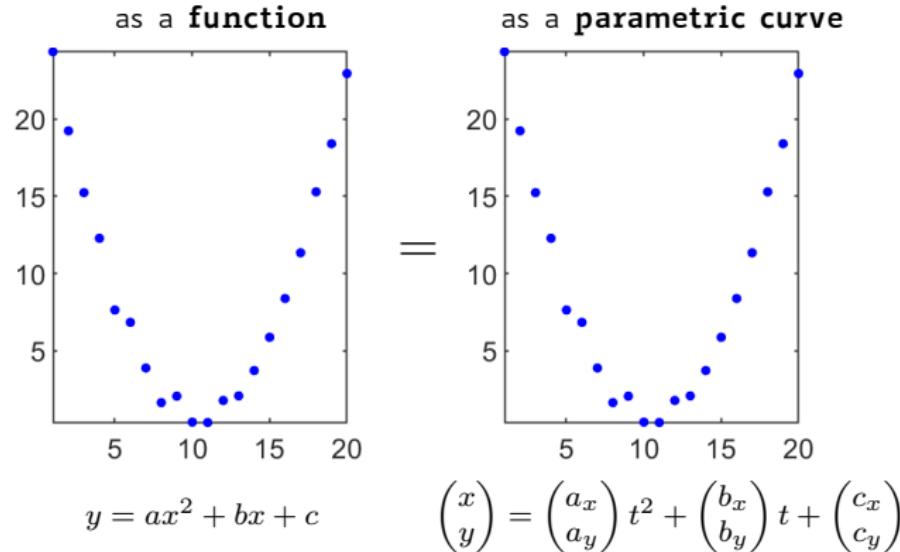
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4 weights

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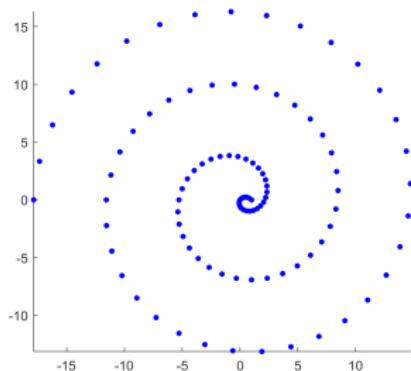


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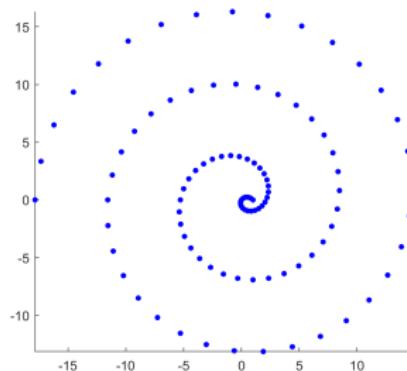
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What is the "right" way?

as a **function**



as a **parametric curve**



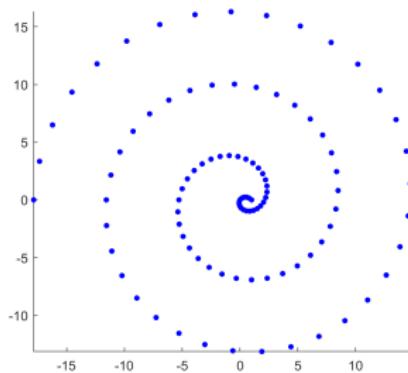
=

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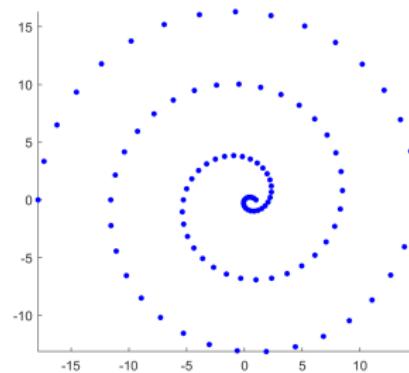
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=

y is not a function of *x*

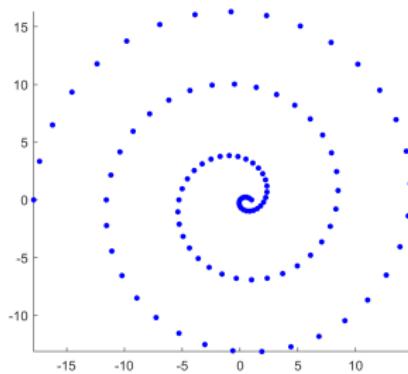
$$\begin{pmatrix} x \\ y \end{pmatrix} = a \begin{pmatrix} \cos t \\ \sin t \end{pmatrix} (a - t)$$

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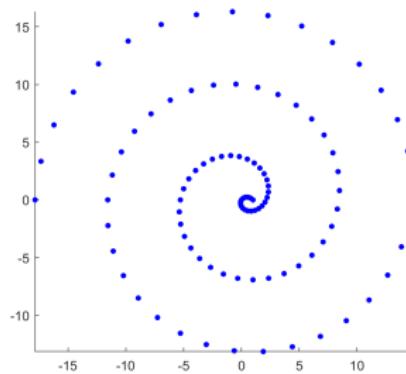
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$$r = a\theta \quad (\text{polar coordinates})$$

as a **parametric curve**



=

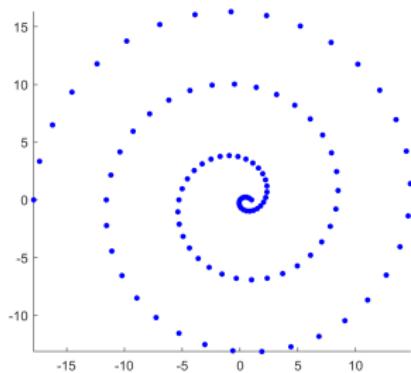
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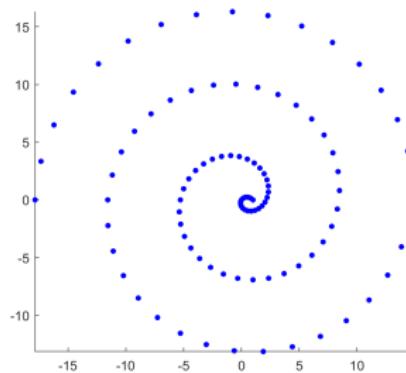
as a **function**



$$r = a\theta$$

linear!

as a **parametric curve**



=

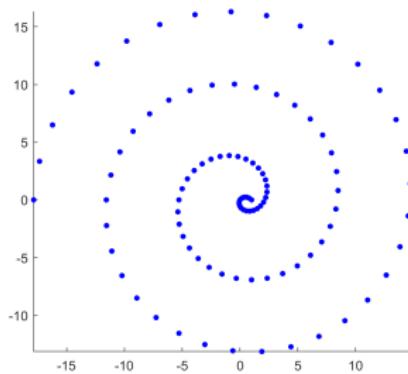
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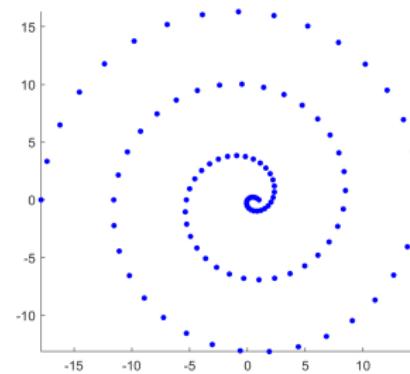
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Trade-off between #weights and simplicity

The curse of dimensionality

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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: ~ 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?

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.



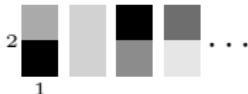
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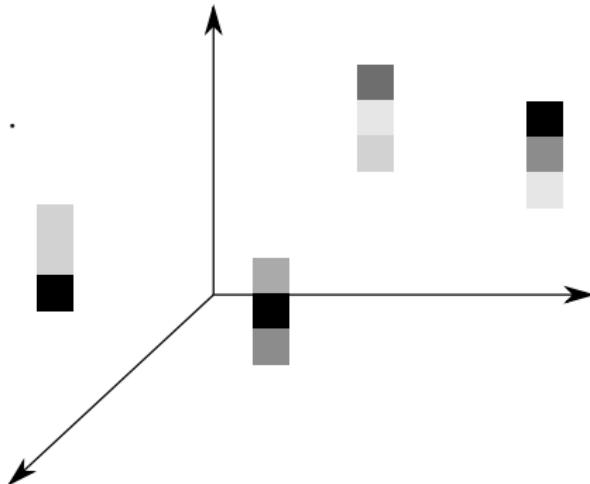
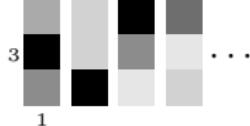
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Similarly, with 3 pixels we get:



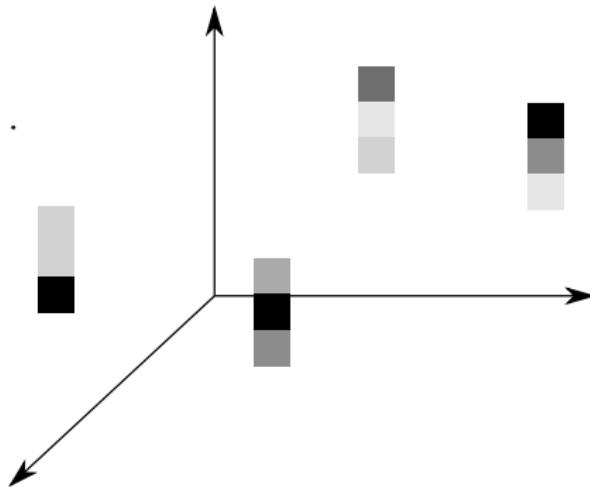
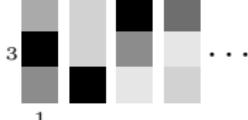
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Each image is a point in one dimension.



Similarly, with 3 pixels we get:



Each new dimension increases **sparsity** of the point cloud.

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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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To discover a pattern, we need **exponentially** many observations as we have dimensions!

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

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Two options:

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

Favor simplicity

Let's play a game:

2, 4, 8, . . .

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

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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

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

Also: when feasible, add more data!

Features

Assume each data point $x \in \mathcal{D} \subset \mathbb{R}^n$ is the result of a synthesis process:

$$\sigma : F \mapsto x$$

which takes a set of **features** F and composes them into x .

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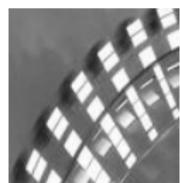
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Example

An image $x \in \mathbb{R}^{w \times h}$ is composed by pixels.

If each pixel of x is a feature, then σ simply sums them up:


$$= \alpha_1 \begin{bmatrix} \cdot \\ \vdots \\ \cdot \end{bmatrix} + \alpha_2 \begin{bmatrix} \cdot \\ \vdots \\ \cdot \end{bmatrix} + \alpha_3 \begin{bmatrix} \cdot \\ \vdots \\ \cdot \end{bmatrix} + \dots$$

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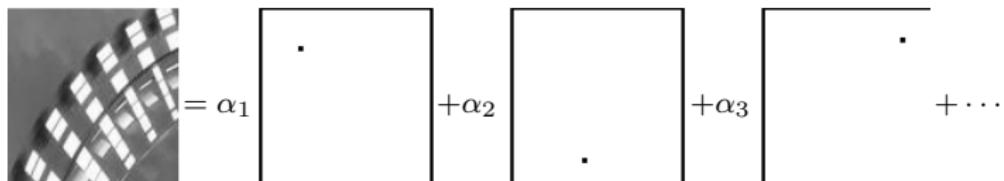
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$$\text{Image} = \alpha_1 \begin{array}{|c|} \hline \cdot \\ \hline \end{array} + \alpha_2 \begin{array}{|c|} \hline \\ \hline \cdot \\ \hline \end{array} + \alpha_3 \begin{array}{|c|} \hline \\ \hline \\ \hline \cdot \\ \hline \end{array} + \dots$$

In this case, the **feature space** F is spanned by individual pixels.

Each feature (each pixel) represents a dimension.

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α_i are the **weights** in the representation of x .

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In this **particular case**, the feature space is a **vector space** and σ is **linear**.

Features

Having one feature per pixel is extremely wasteful!

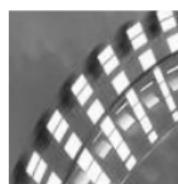
Curse of dimensionality: `features >> observations`

Features

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Curse of dimensionality: **features** \gg **observations**

What does **really** characterize our image?


$$= \sigma(\quad , \square, _)$$

The equation shows a grayscale image of a checkered surface on the left, followed by an equals sign, then the mathematical symbol for the sigmoid function (σ), and finally three input features: a gray square, a white square with a black border, and a horizontal black line.

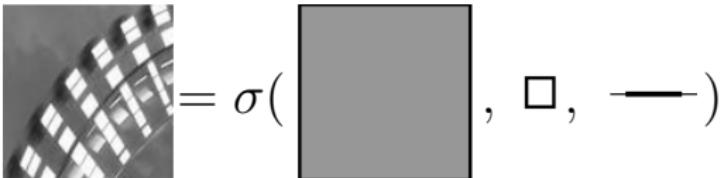
In general, the transformation σ acts **nonlinearly** on the features.

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Curse of dimensionality: **features \gg observations**

What does **really** characterize our image?



A grayscale image of a checkered surface is shown on the left, followed by an equals sign. To the right of the equals sign is a mathematical expression: $\sigma(\quad, \square, \text{---})$. The first argument of the σ function is represented by a gray square, the second by a white square with black outlines, and the third by a black horizontal line.

In general, the transformation σ acts **nonlinearly** on the features.

The output of σ is called an **embedding** of the data point.
For the data point $x \in \mathcal{D} \subset \mathbb{R}^n$, the **embedding space** is \mathbb{R}^n .

Invariances

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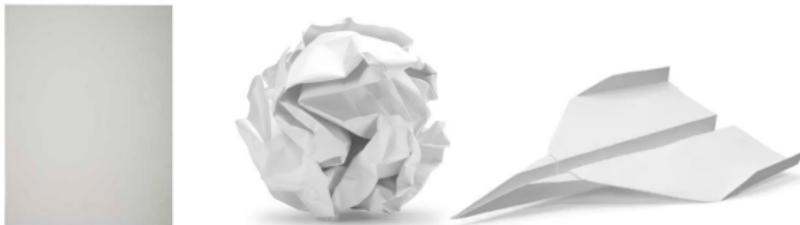
Example: A sheet lives naturally in \mathbb{R}^2



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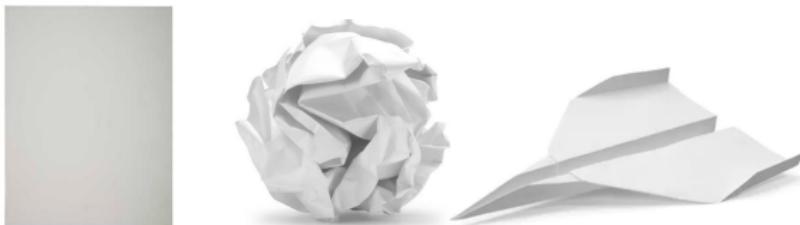


Three different embeddings of the **same object**

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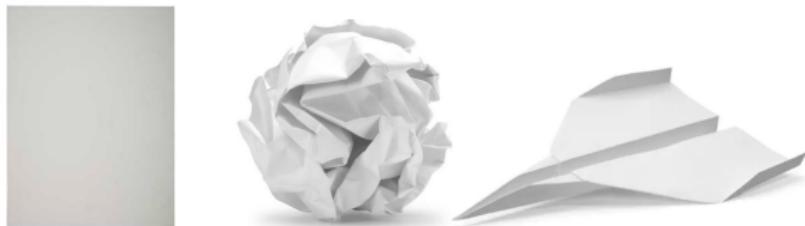


Three different embeddings of the **same** object
Q: what is preserved in all these embeddings?

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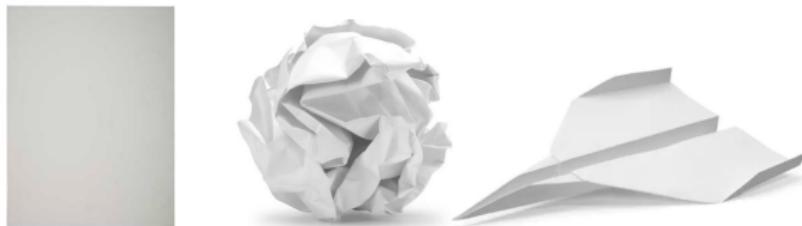


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Three different embeddings of the **same** object
A: **distances** are preserved in all the embeddings

Challenge: discover what **intrinsic** properties are preserved; these properties characterize the data.

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Latent feature: directional illumination

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Latent feature: directional illumination

3 params for the light source position + **1** param for light intensity

Latent features

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We talk about **latent** features. Direct access to the embedding only.

Discovering latent features involves discovering:

the "true" embedding space for the data
+
the **transformation** between the two spaces

General idea: find & discard **non-informative** dimensions.

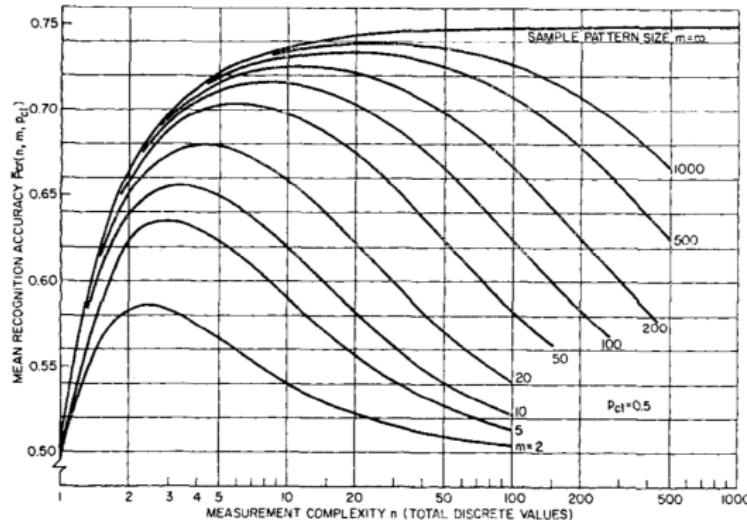
Optimal dimensionality

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The effect of different dimensions, captured by **Hughes phenomenon**:



There is an optimal dimension which maximizes accuracy.

Hughes, "On the mean accuracy of statistical pattern recognizers", IEEE TIT 1968

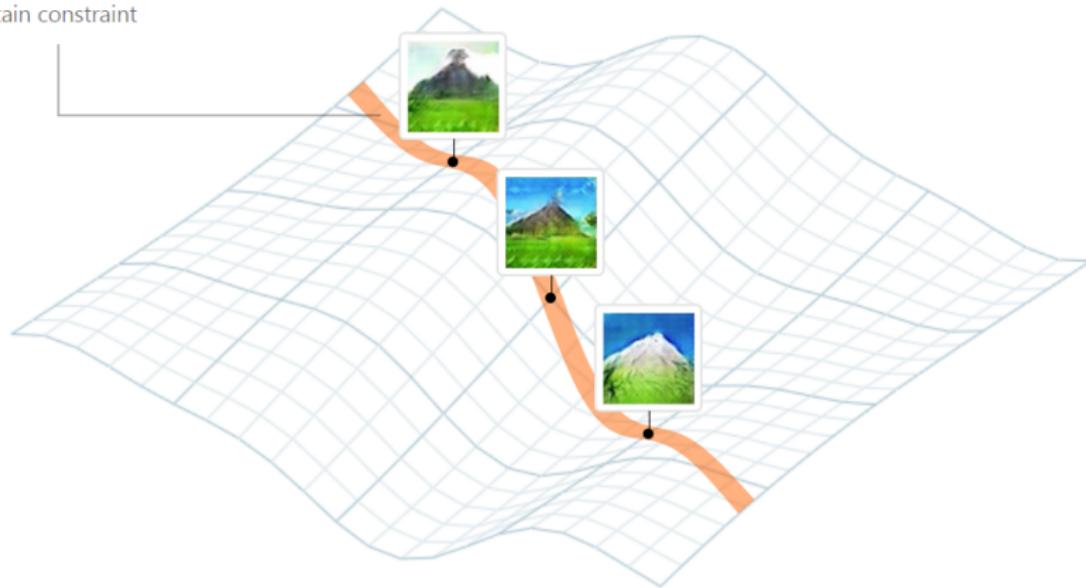
The manifold hypothesis

Deep learning assumes that the input data lives on some underlying **non-Euclidean** structure called a **manifold**.

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Subspace of all images
that satisfy the
mountain constraint



Features are task-driven

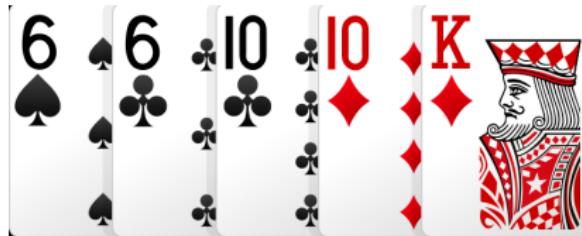
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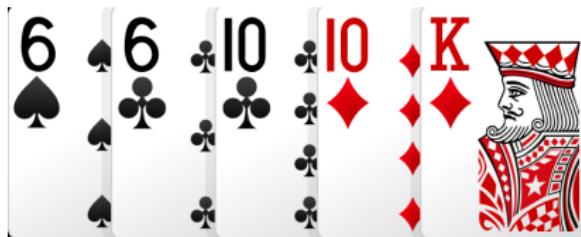


Is color important?

Features are task-driven

How are features extracted from given data?

Speaking about features only makes sense if we are given a **task** to solve!



Is color important?

Rank, suit, and color are generic features, but **specific problems** determine what features are important for that task.

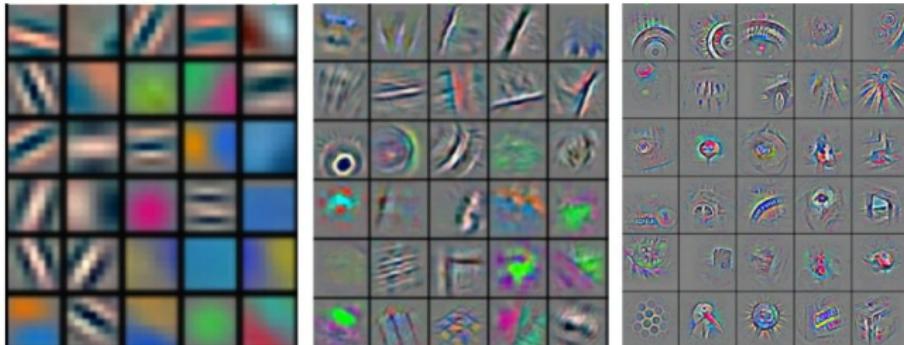
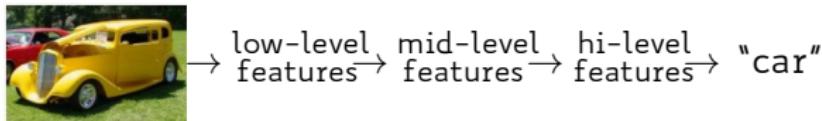
What counts in spades, does not count in poker.

Deep learning is a **task-driven** paradigm
to extract patterns and **latent features**
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However, features are not always the focus of deep learning; rather, they are instrumental for the given task.

Example: Visual classification



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>

Distill post on t-SNE:

<https://distill.pub/2016/misread-tsne/>