Artificial “Neural Networks”

The questions to ask

Jean Feydy

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Écoles Normales Supérieures de Paris et Paris-Saclay

About me

Jean Feydy (2016-2019) :

- PhD student with Alain Trouvé, ENS Cachan,
  Computational anatomy.
- Teaching assistant for Gabriel Peyré, M2 MVA and ENS Paris,
  Mathematical foundations of data sciences.
- Son of Antoine Feydy, PUPH at the Paris-Cochin hospital,
  Specialist of **musculoskeletal imaging.**

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However, this idea now allows us to implement
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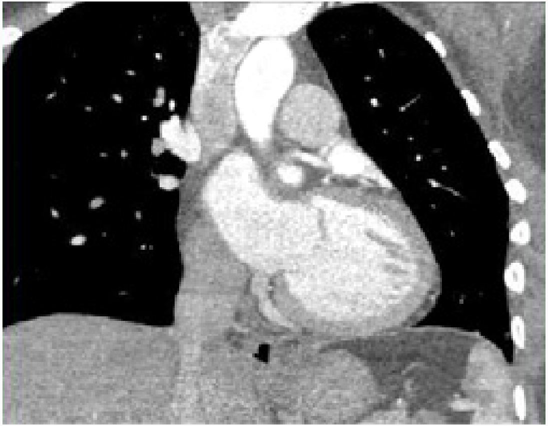
As physicians, how can you look at these
methods with a **critical eye**?

What can we see on a medical image?

One image : three levels of analysis [EPW11, Man11]



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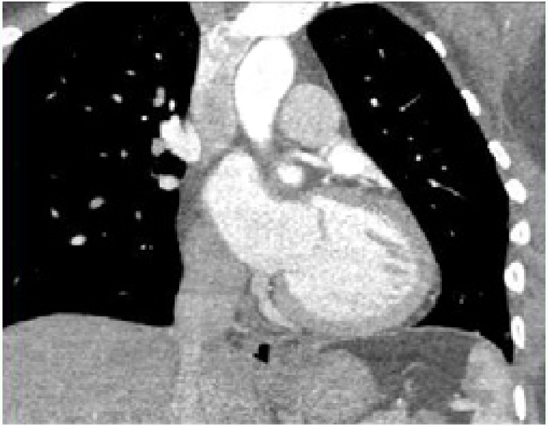

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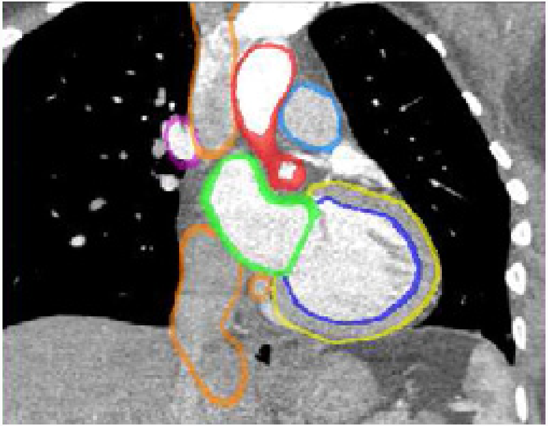

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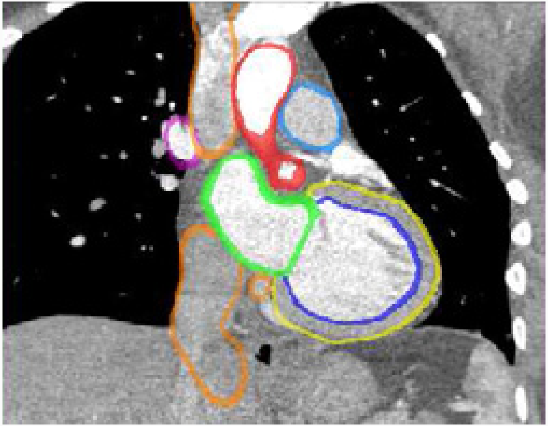

One image : three levels of analysis [EPW11, Man11]

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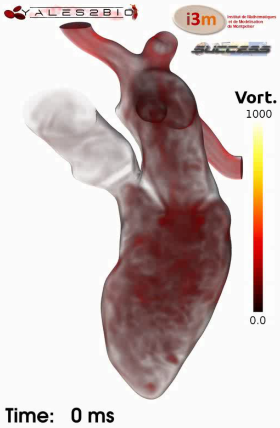

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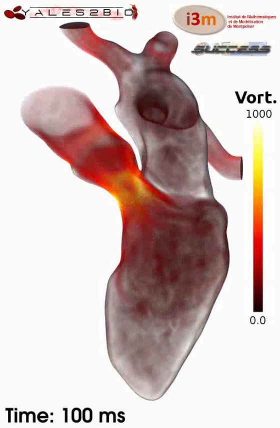

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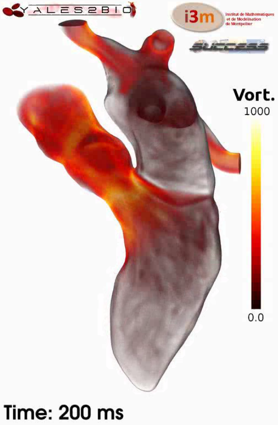

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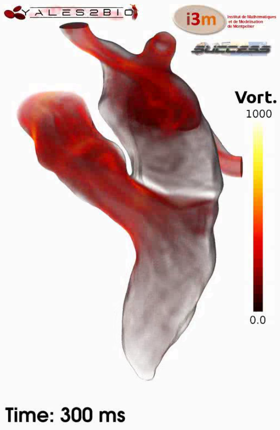

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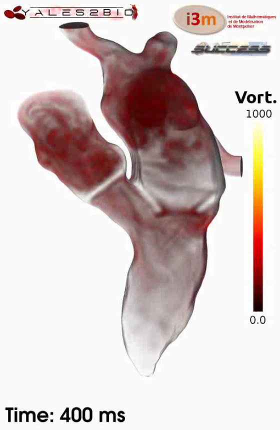

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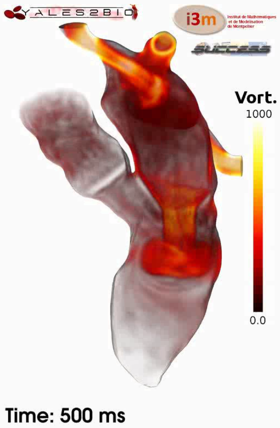

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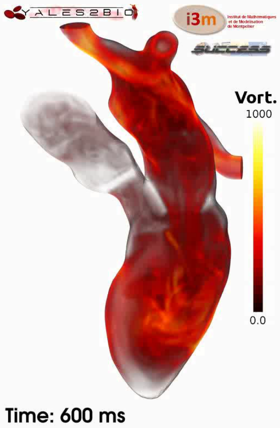

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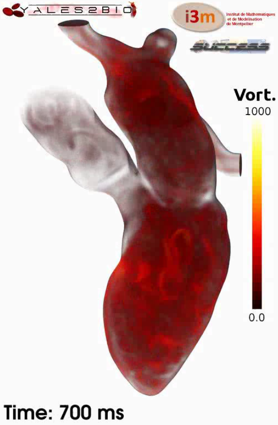

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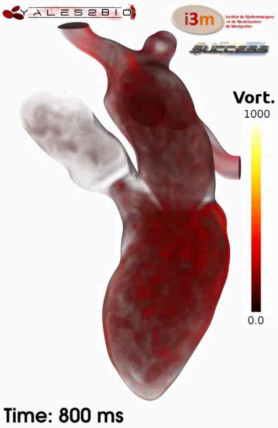

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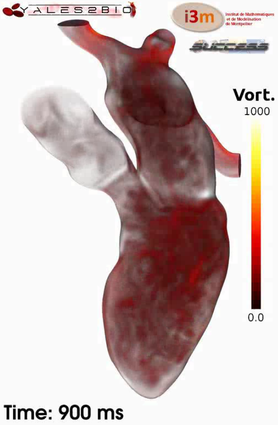

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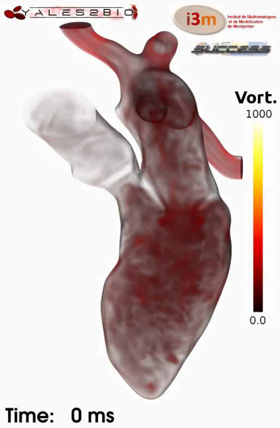

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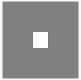
Let's discover the most fundamental of all imaging theories: Texture analysis through **multi-scale filtering**.

Filtering, aka. “convolution product”

Convolution (i.e. weighted average of the neighboring pixels) :

Cheap generalization of the **product** “$a \cdot x$”,
parameterized by the coefficients of a **small filter** φ.



$\star$

$=$

φ $\qquad$ x $\qquad$ $\varphi \star x$

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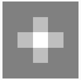 $\star$  $=$ 

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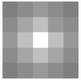
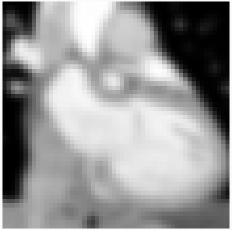
 $\star$  $=$ 

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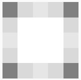

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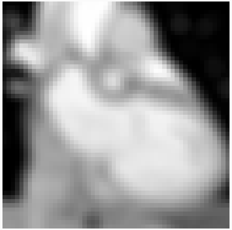

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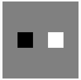
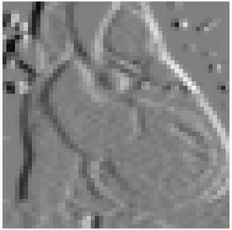
 $\star$  $=$ 

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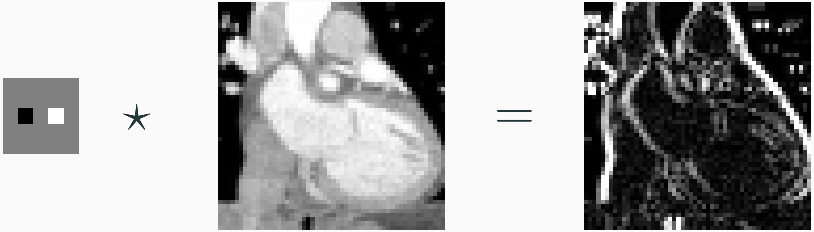

$\varphi \qquad\qquad x \qquad\qquad |\varphi \star x|$

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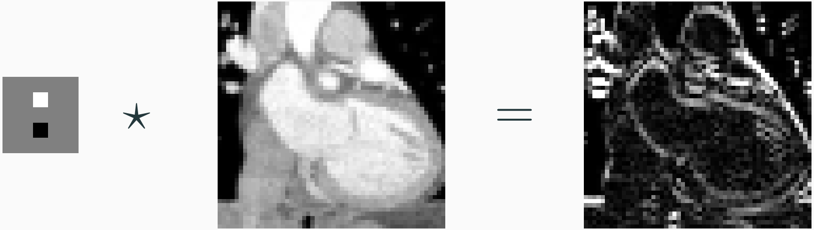

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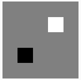

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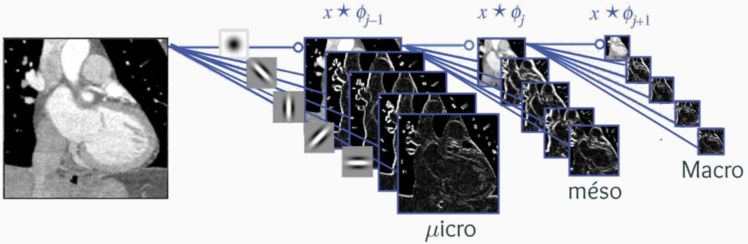
Multi-scale prior on images

Wavelet theory (1990∼2010 ; Meyer, Mallat, Daubechies...) :

Small filters + cascading zoom-out operations [Mal16]:



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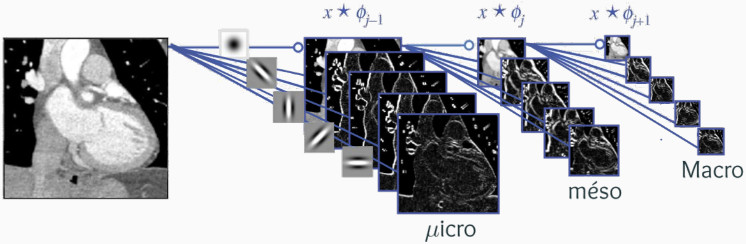

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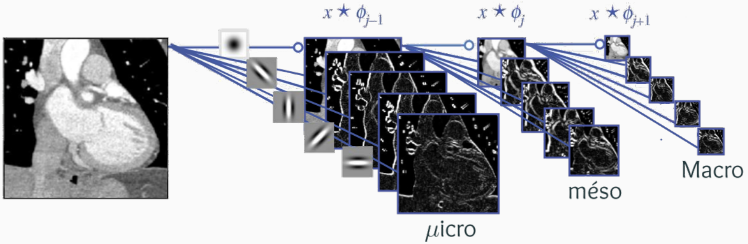

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$\Longrightarrow$ **JPEG2000** format, standard of the movie industry.

That's it for classical models.
What about neural networks?

“Supervised learning” = regression

We have:

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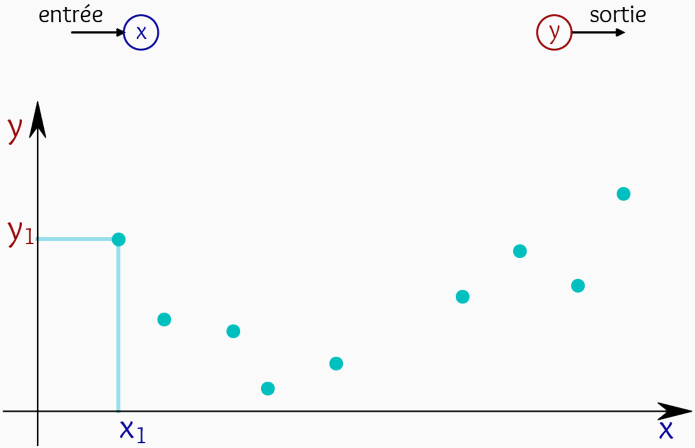
Let’s find, step by step, a value $\mathbf{w}_{\text{optimal}}$ of the parameters that minimizes **the average error on the predictions.**

A toy dataset, in dimension 1



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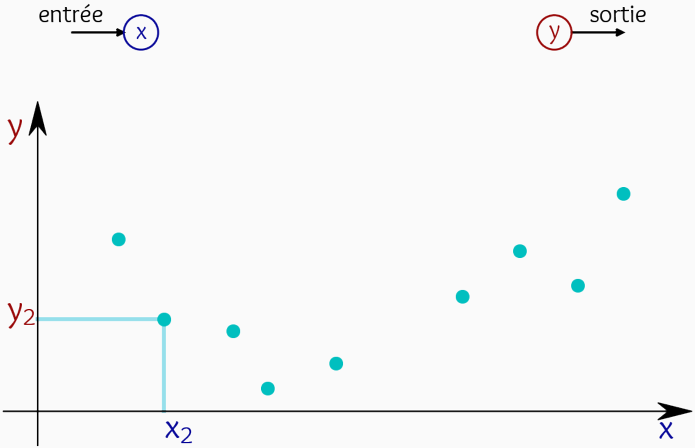

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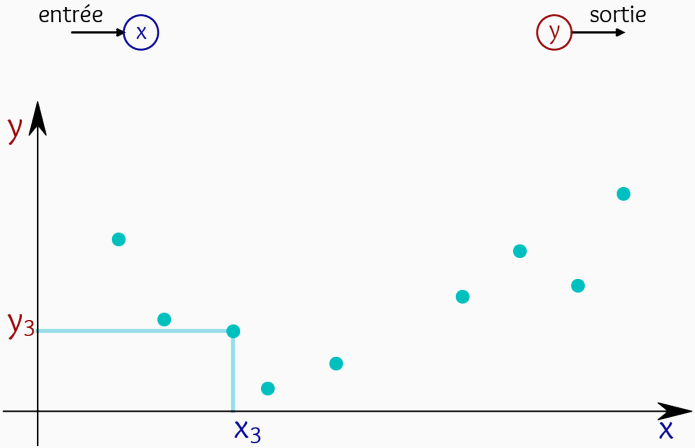

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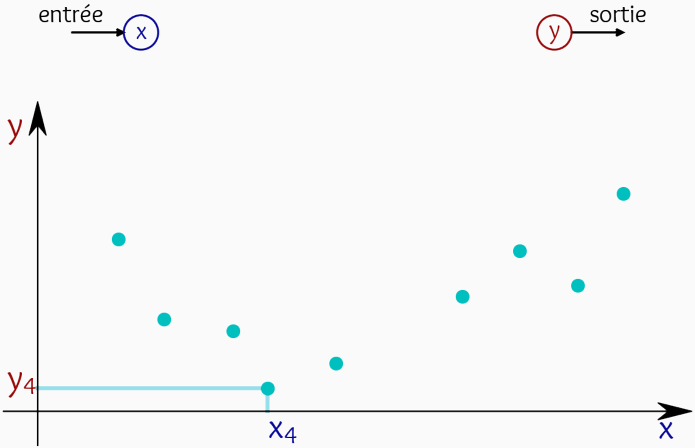

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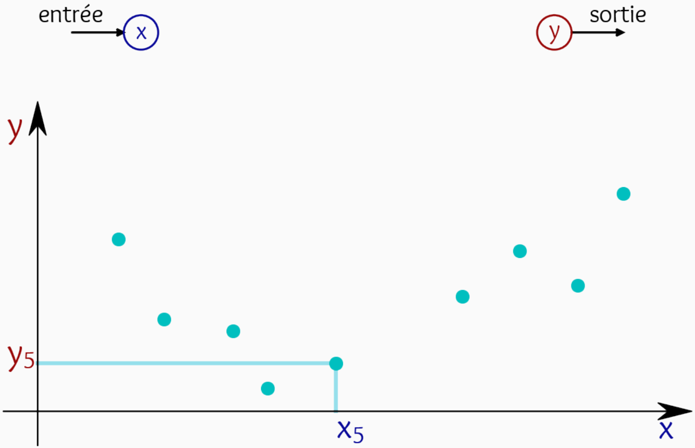

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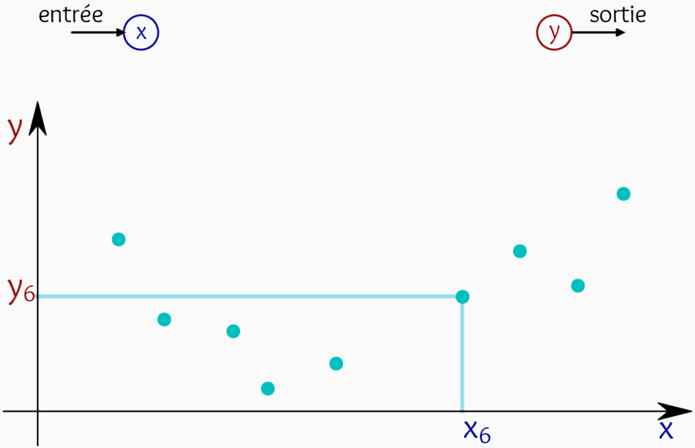

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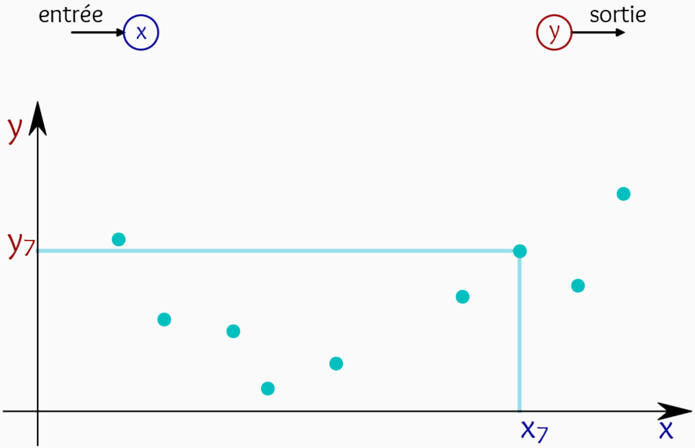

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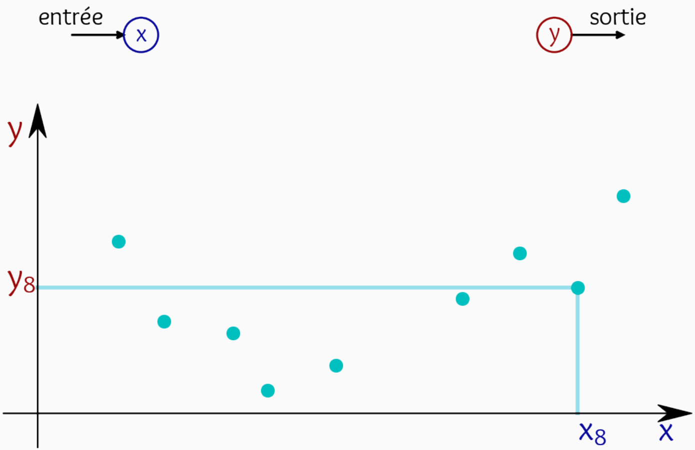

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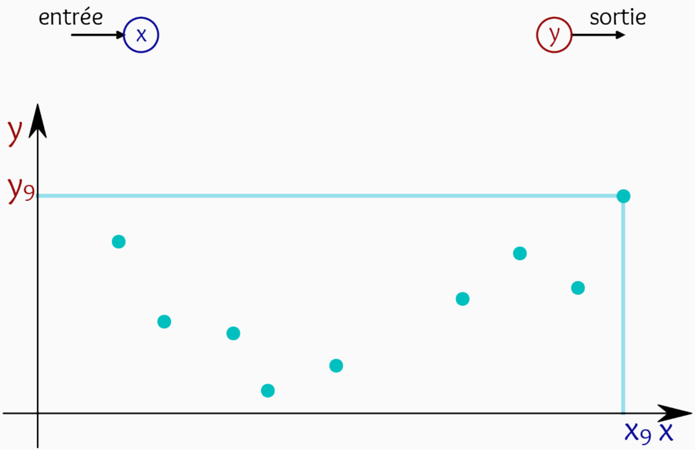
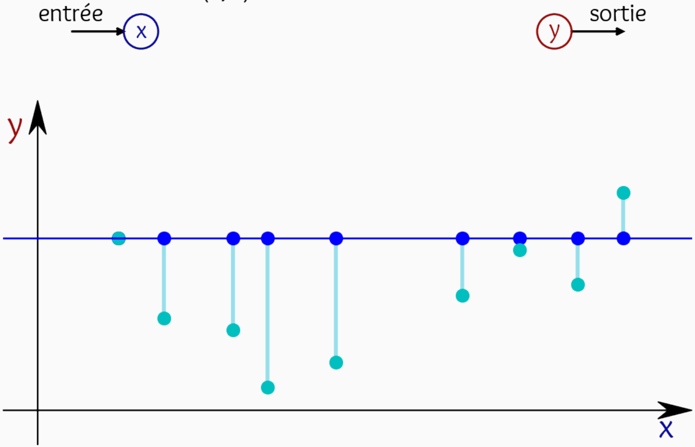


A fundamental example: linear regression

$$F(a, b; x) = a \cdot x + b$$
$$(a, b) = +0.00,\ +0.25$$



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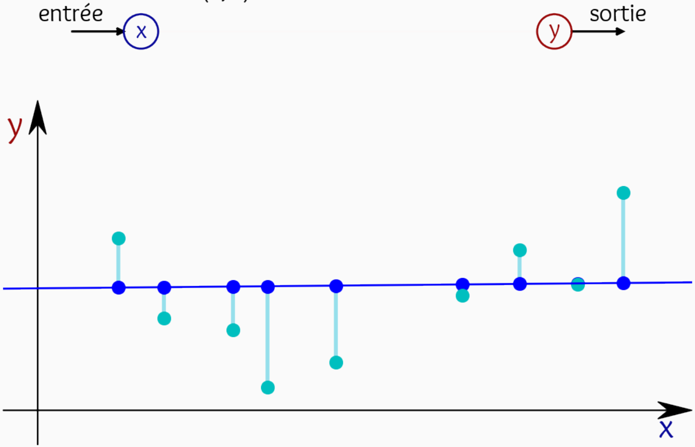
$$F(a,b;x) = a \cdot x + b$$
$$(a,b) = +0.01,\ +0.18$$



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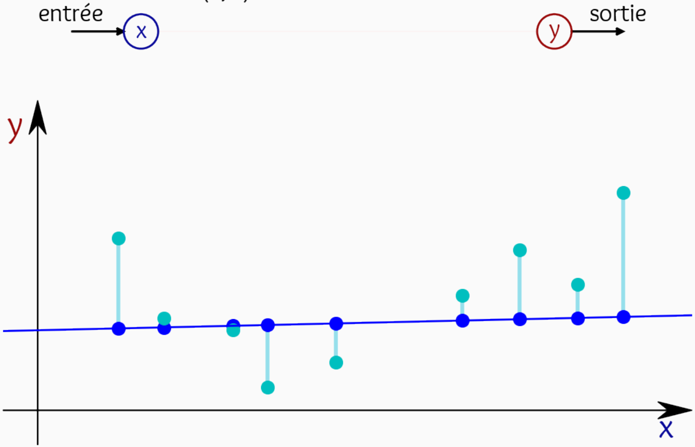
$$F(a,b;x) = a \cdot x + b$$
$$(a,b) = +0.02,\ +0.12$$



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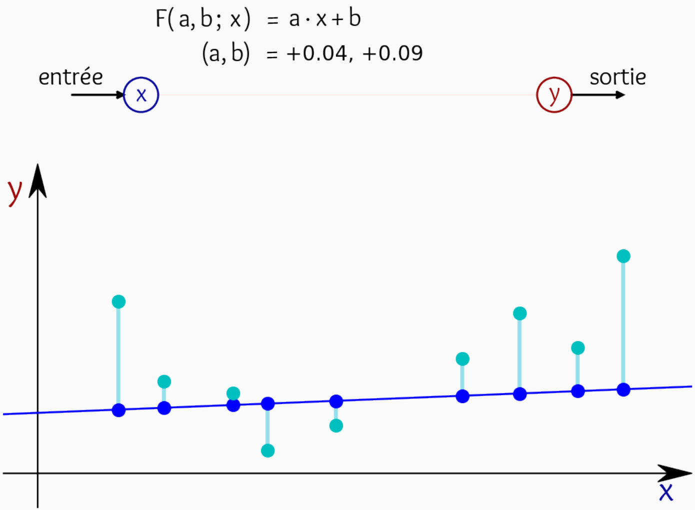

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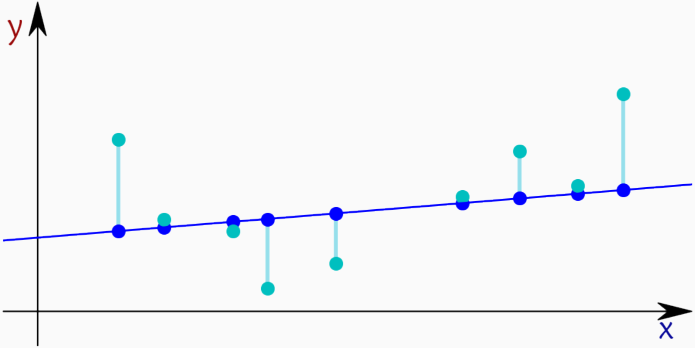
$$F(a, b; x) = a \cdot x + b$$
$$(a, b) = +0.08,\ +0.11$$



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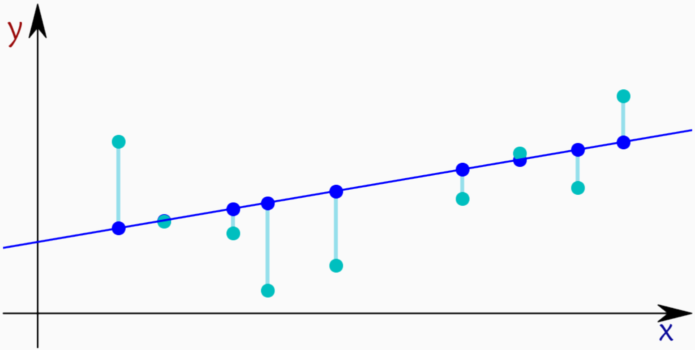
$$F(a, b; x) = a \cdot x + b$$
$$(a, b) = +0.17,\ +0.10$$



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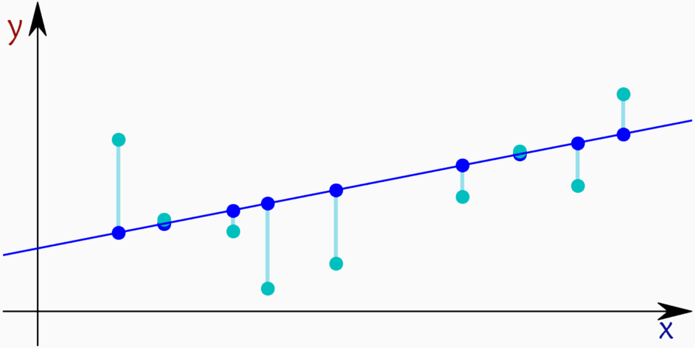

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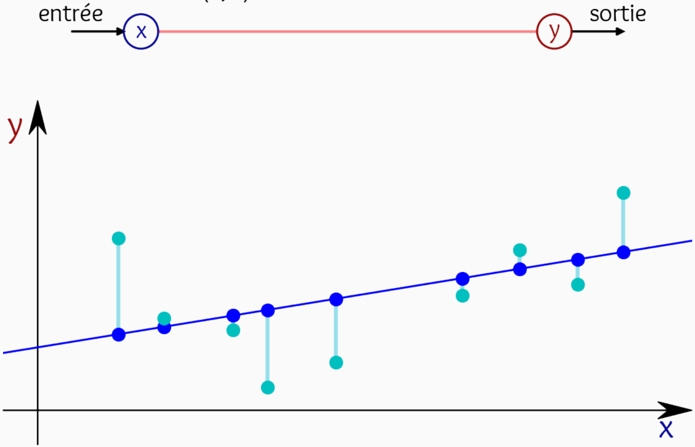

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$$F(a, b; x) = a \cdot x + b$$
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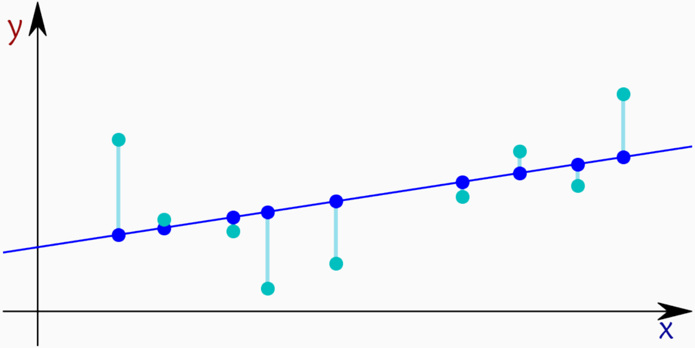

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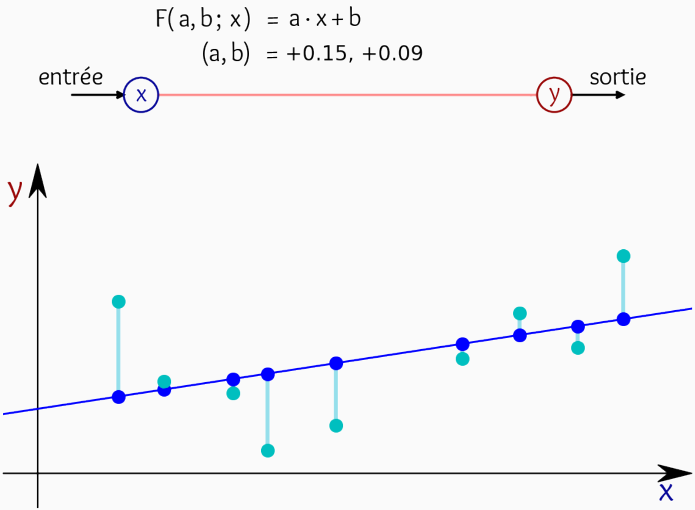
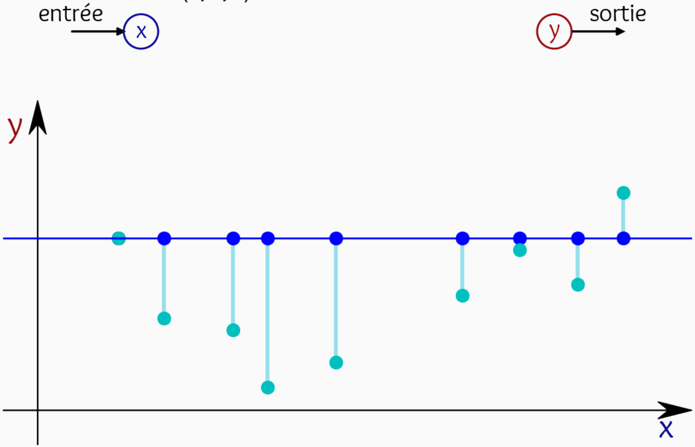


A slightly more complex model: quadratic regression

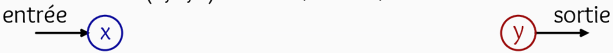
$$F(a, b, c; x) = a \cdot x^2 + b \cdot x + c$$

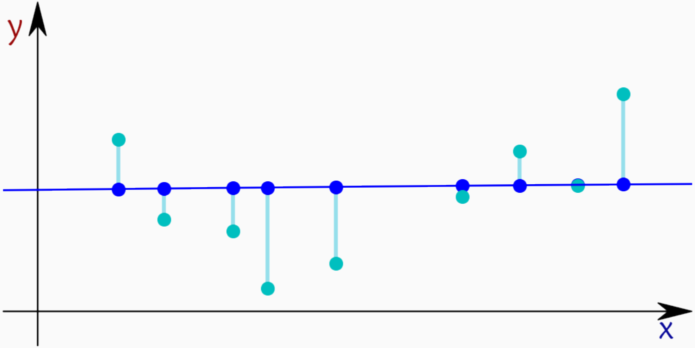
$$(a, b, c) = +0.00,\ +0.00,\ +0.25$$



A slightly more complex model: quadratic regression

$$F(a,b,c;x) = a \cdot x^2 + b \cdot x + c$$
$$(a,b,c) = -0.00,\ +0.01,\ +0.18$$





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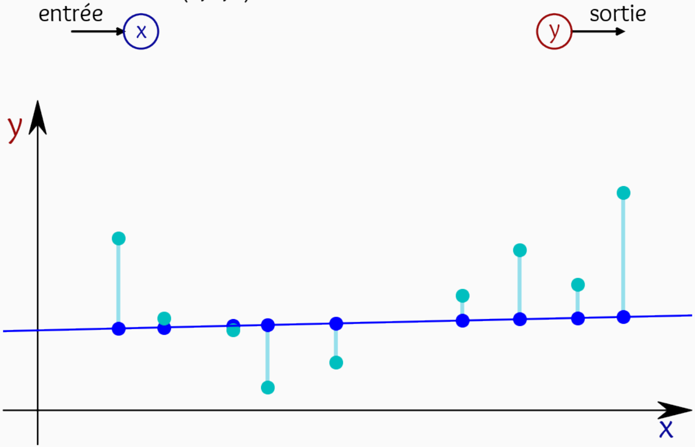
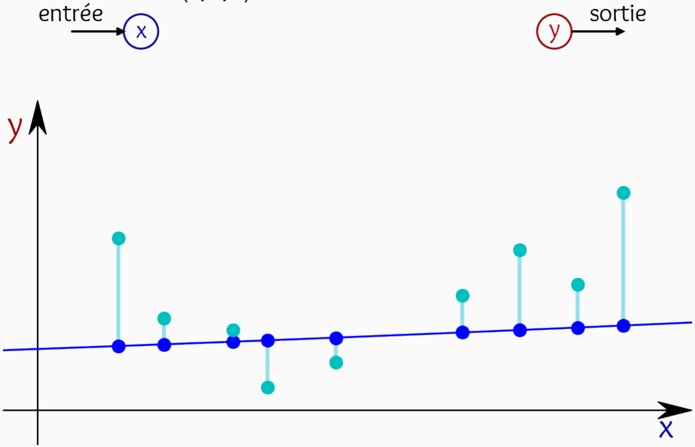
$$F(a, b, c; x) = a \cdot x^2 + b \cdot x + c$$

$$(a, b, c) = -0.00,\ +0.02,\ +0.12$$



A slightly more complex model: quadratic regression

$$F(a,b,c;x) = a \cdot x^2 + b \cdot x + c$$
$$(a,b,c) = +0.00,\ +0.04,\ +0.09$$



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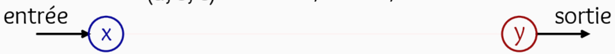
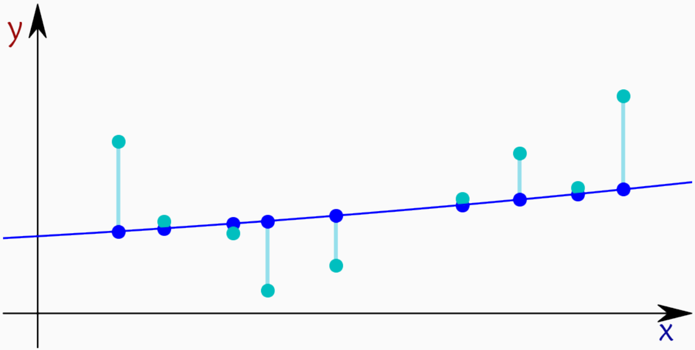
$$(a, b, c) = +0.03,\ +0.08,\ +0.11$$





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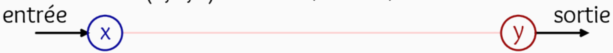

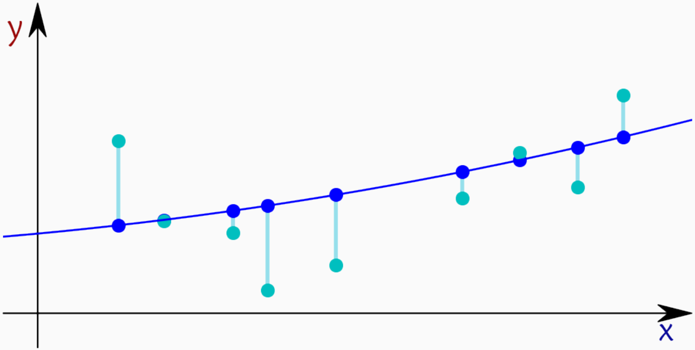

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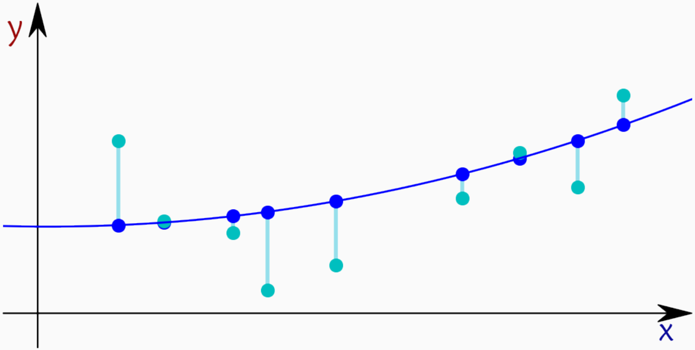
$$F(a, b, c; x) = a \cdot x^2 + b \cdot x + c$$

$$(a, b, c) = +0.21,\ +0.18,\ +0.13$$



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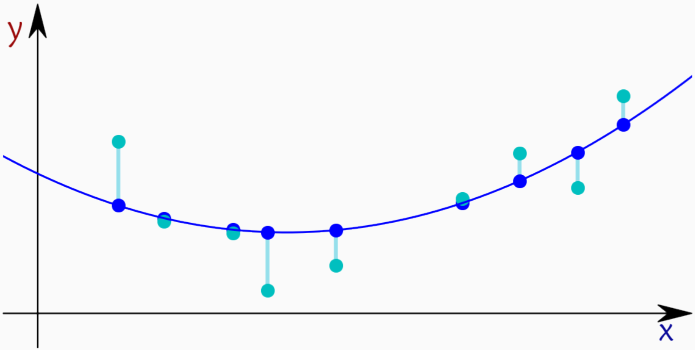
$$F(a, b, c; x) = a \cdot x^2 + b \cdot x + c$$

$$(a, b, c) = +0.66,\ +0.12,\ +0.20$$



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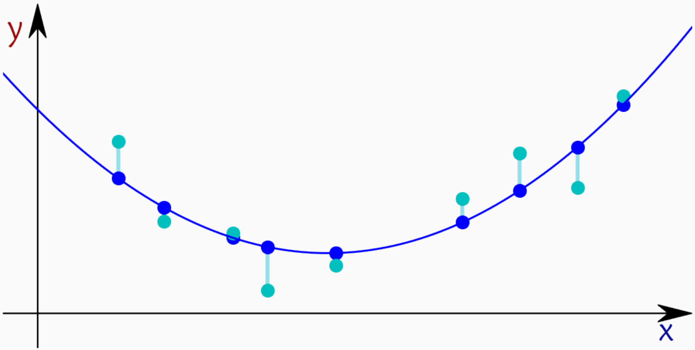
$$F(a, b, c; x) = a \cdot x^2 + b \cdot x + c$$
$$(a, b, c) = +1.18,\ +0.07,\ +0.30$$



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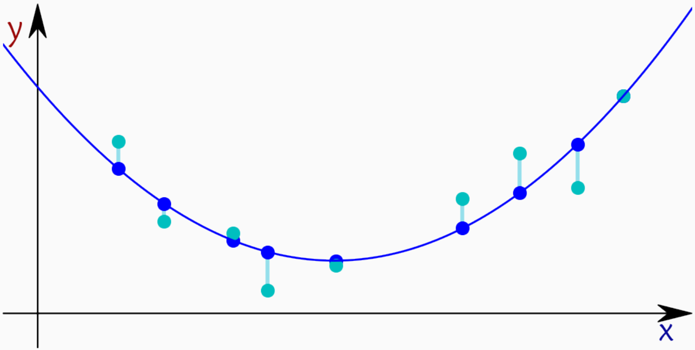

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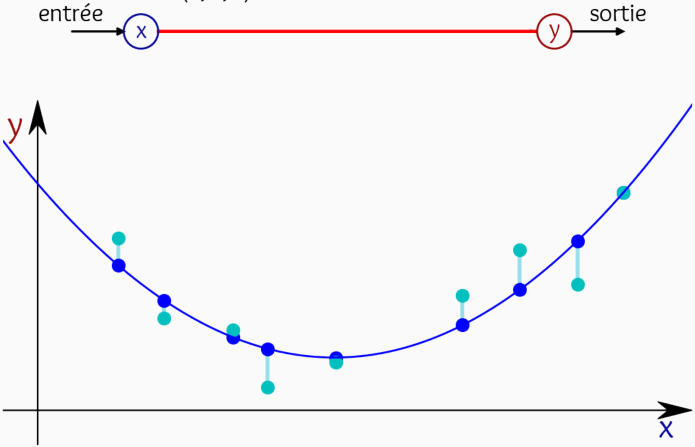

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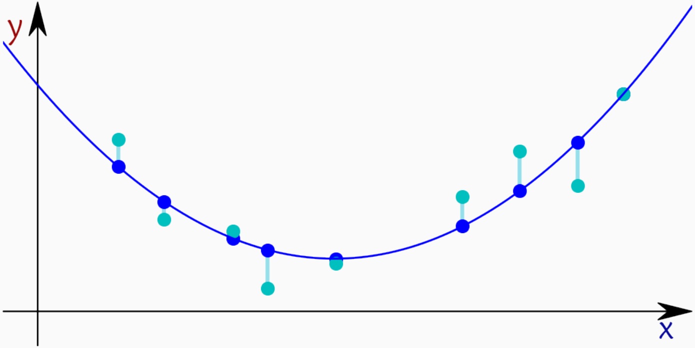
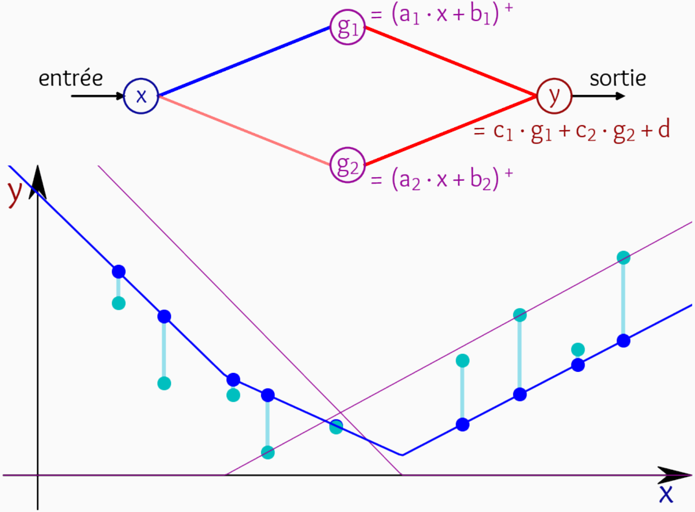


Let's complexify our model with intermediate variables...



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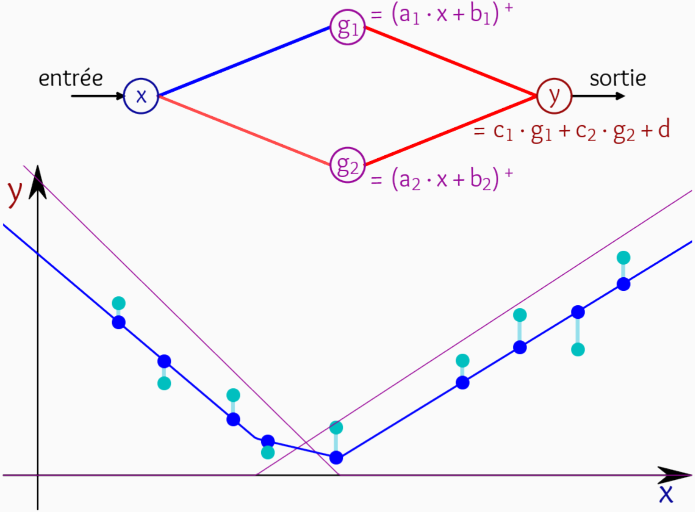

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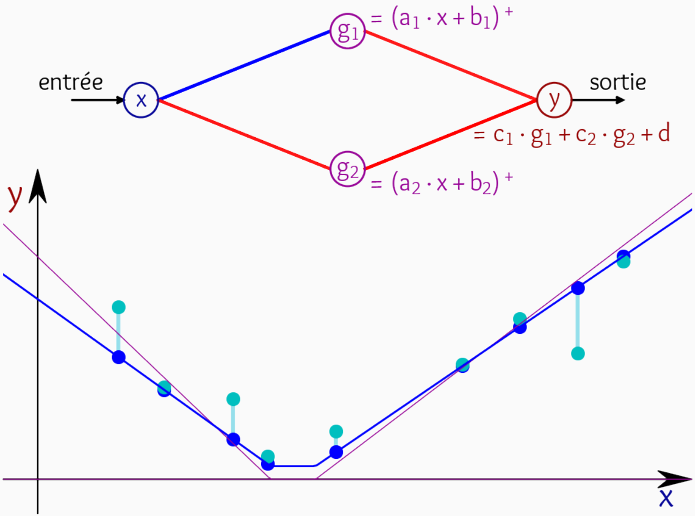

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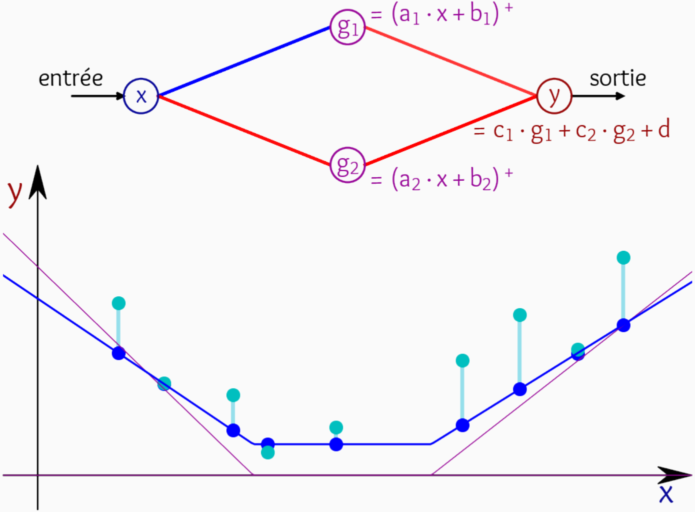

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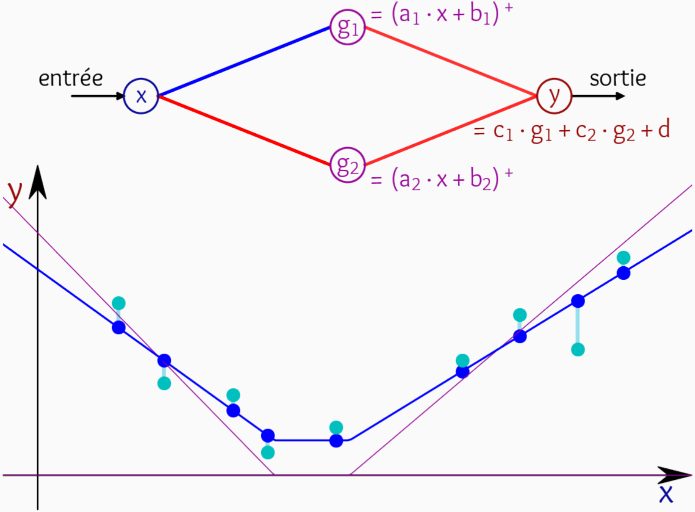

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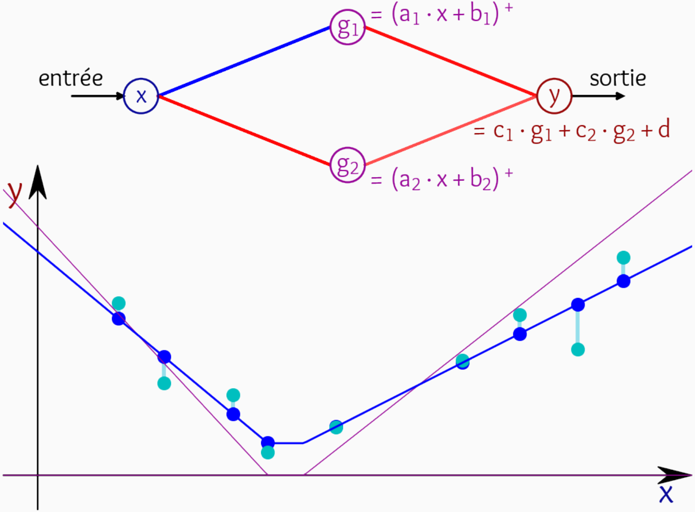

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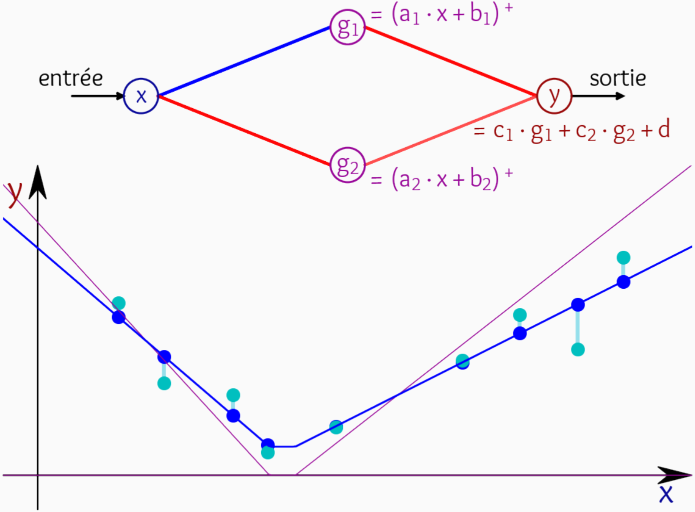

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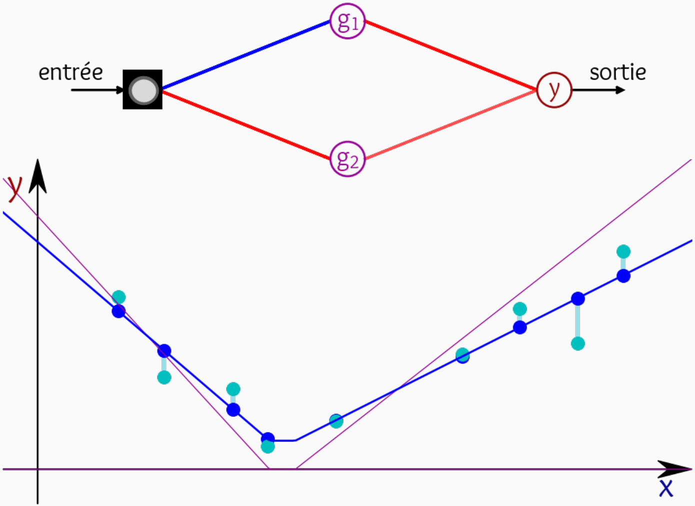

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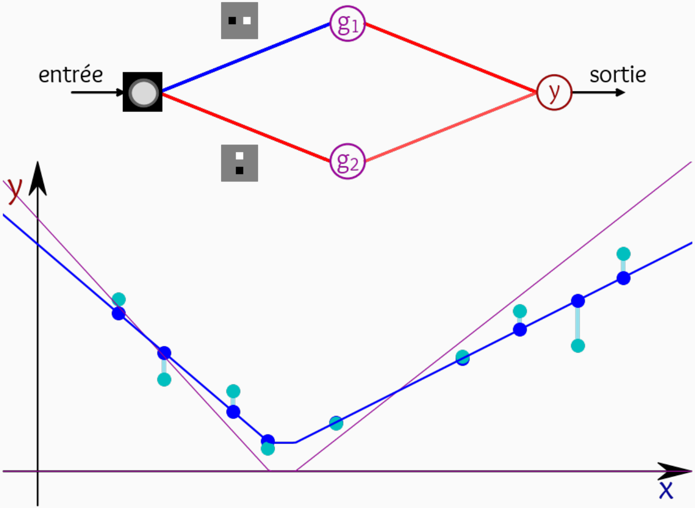

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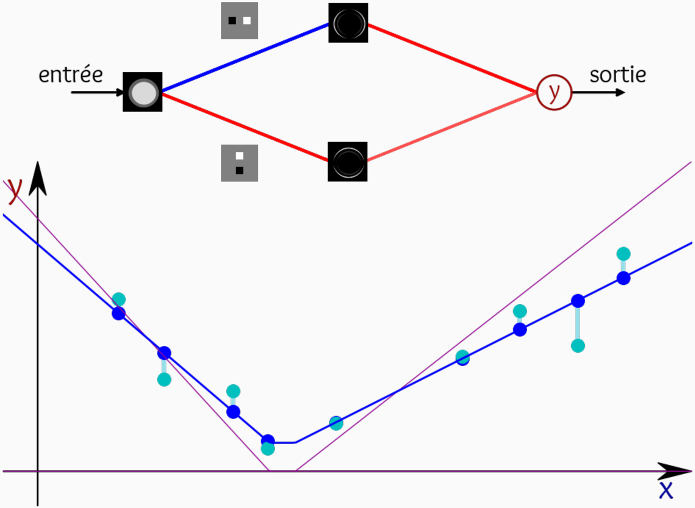

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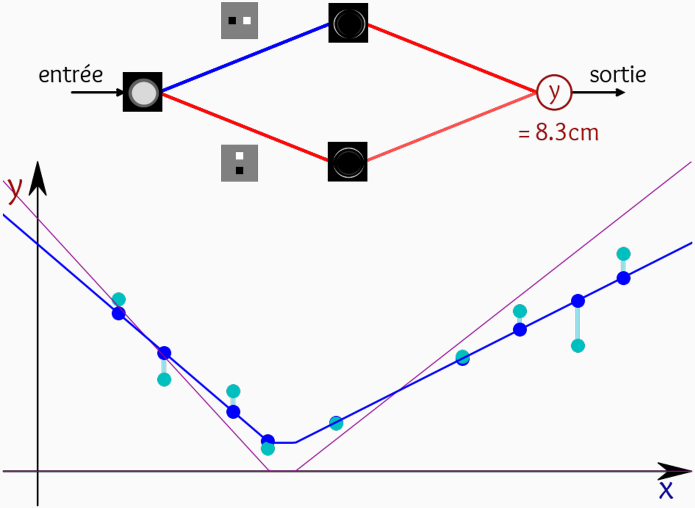

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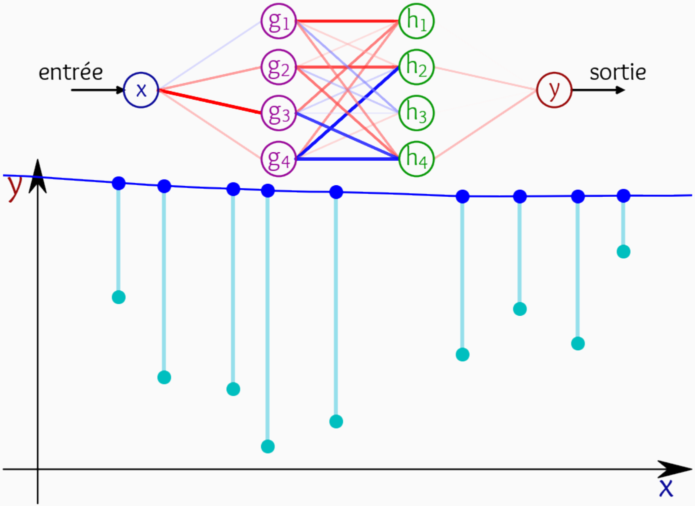

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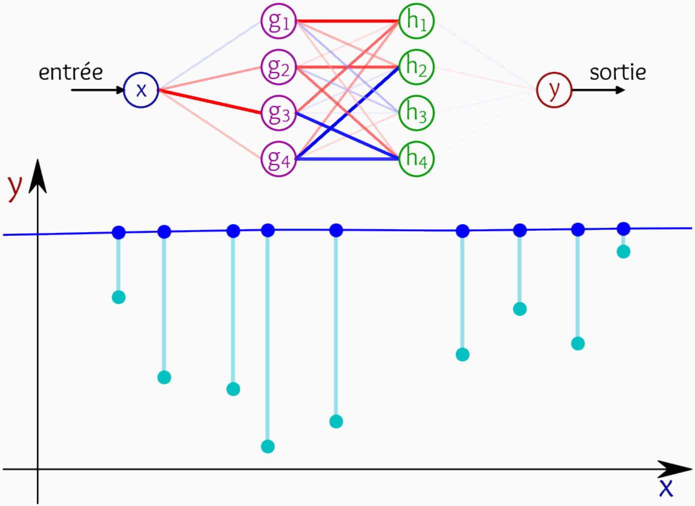

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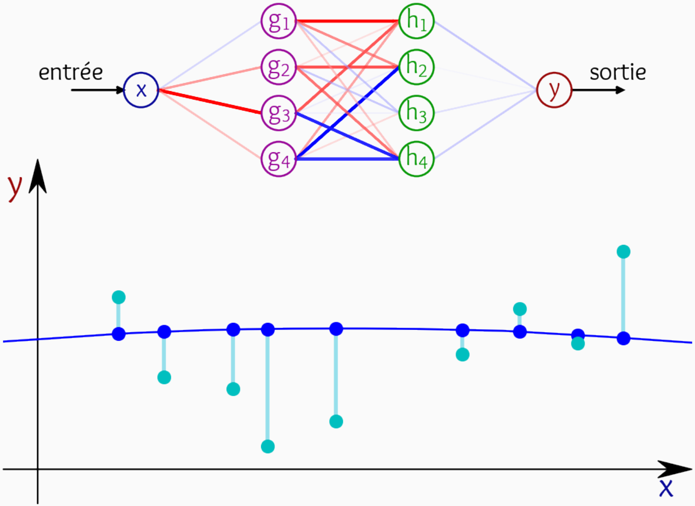

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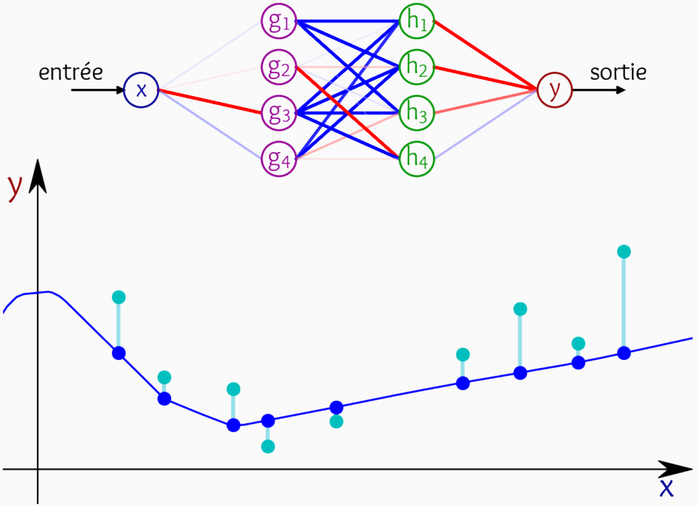

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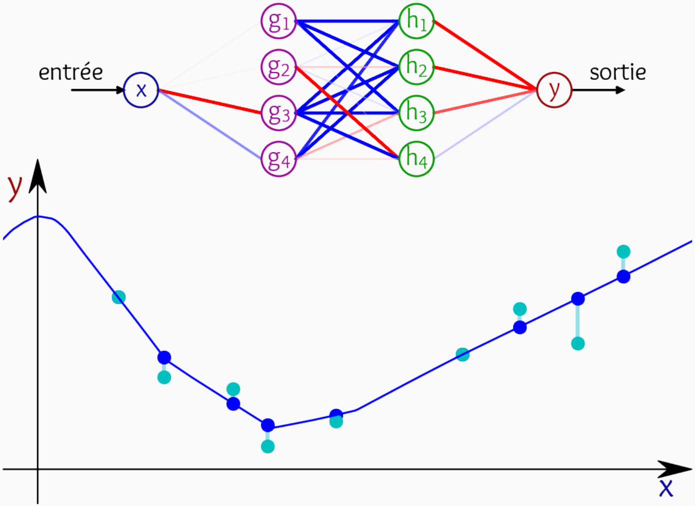

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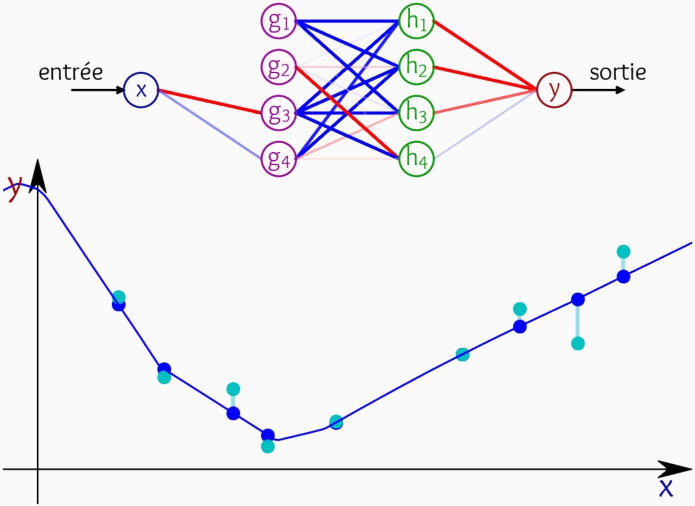

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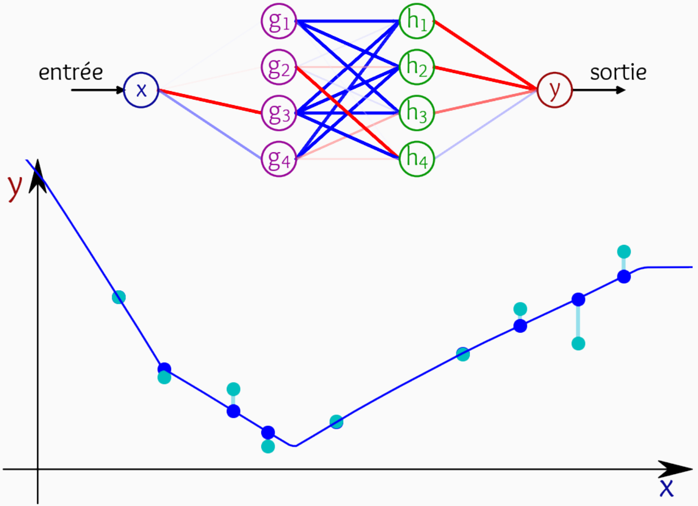

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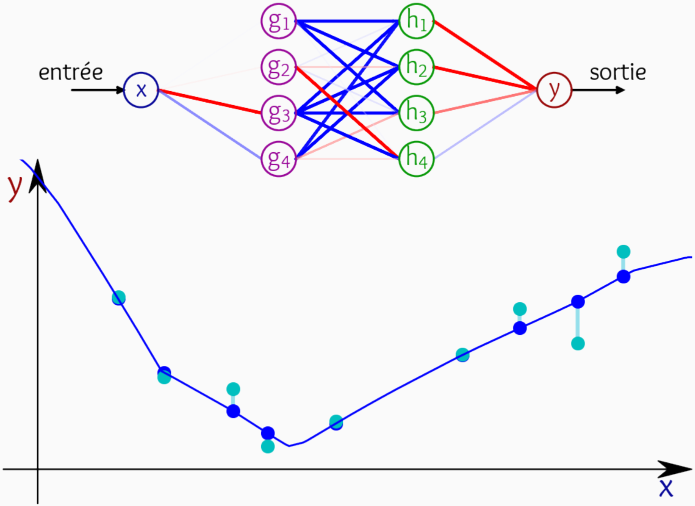

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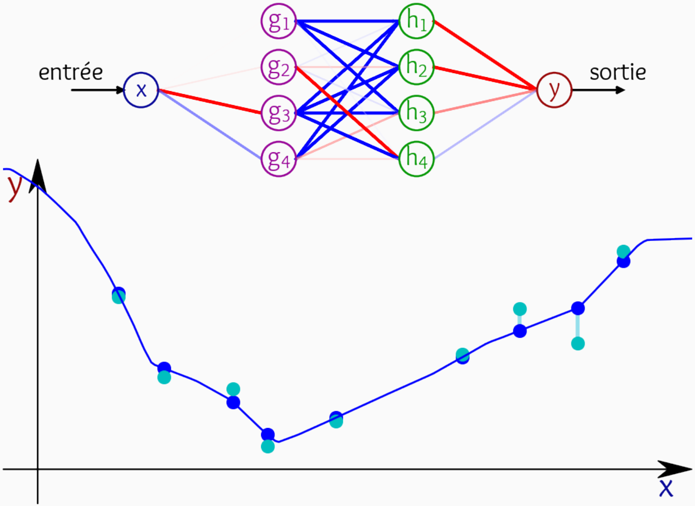

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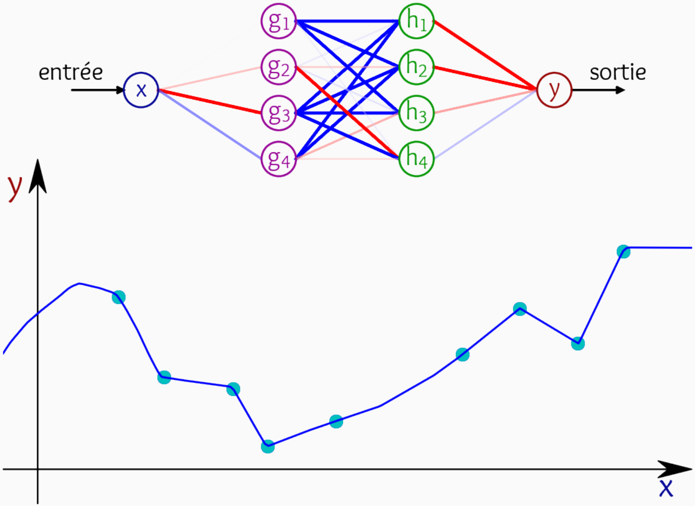

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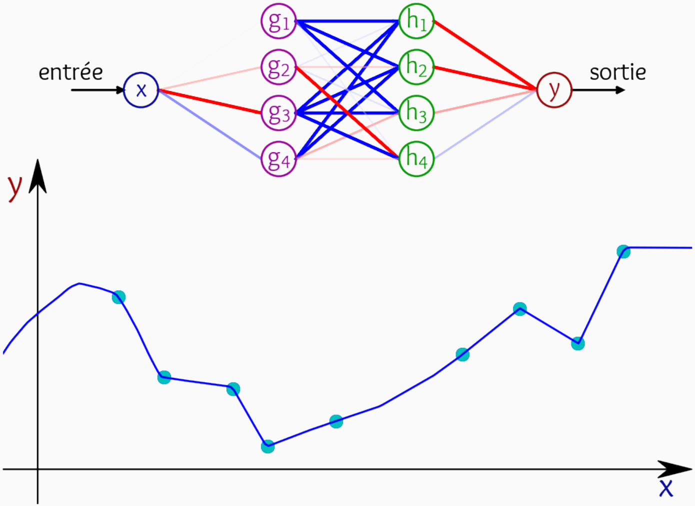

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Is it good enough?

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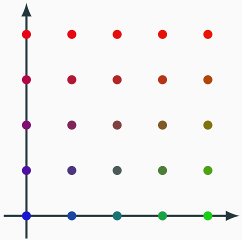

2 numbers
$\rightarrow 5^2$ samples

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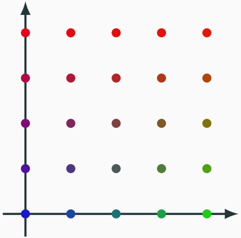

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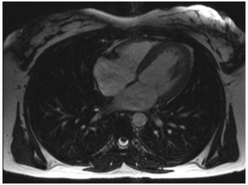

$128 \cdot 128$ numbers

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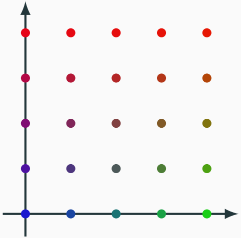

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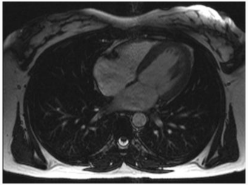

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The set of all 2D/3D images is **way too large**
to be sampled with a satisfying accuracy.

In medical imaging, a good model $F(w; x) \simeq y$ should:

Encode **a sensible prior** on the data

Can I understand a heart MRI as a deformed template?

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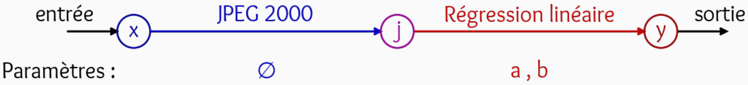
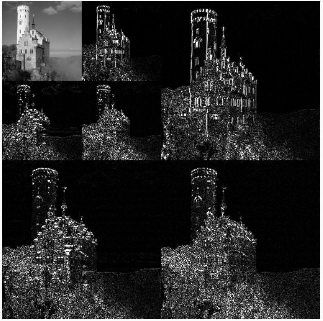
$\Longrightarrow$ **Let's combine "regression" with "JPEG2000" !**

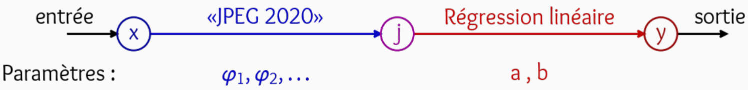
Analysis through multi-scale filtering :
$\Longrightarrow$ Convolutional Neural Networks

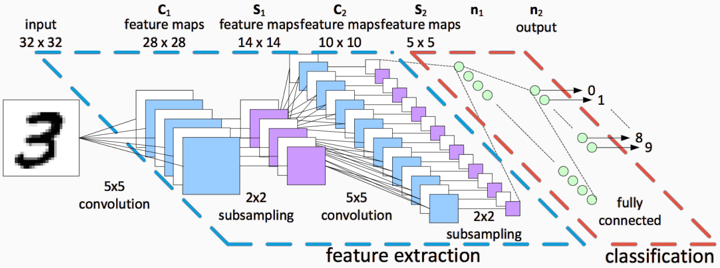
Classical signal processing [Dam] :





Modern signal processing [PMC11] :





Convolutional Neural Networks: an excellent compromise

JPEG2000 relies on a model $F(\mathbf{w}\,;x\,) \simeq y$ that is:

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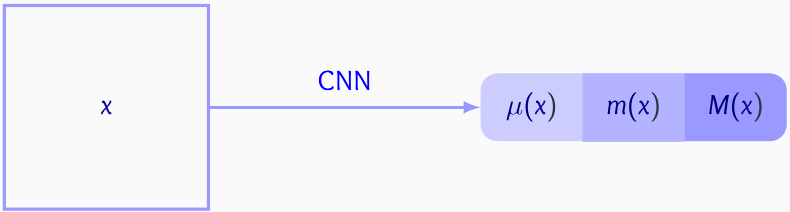
By **tuning its parameters** on a labeled database,
we get a **CNN** $\simeq$ problem-dependent "JPEG2020".



An iconic application: Deep Art [NN16]

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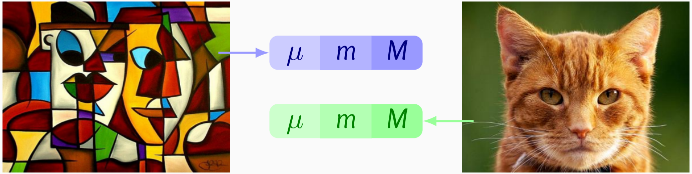

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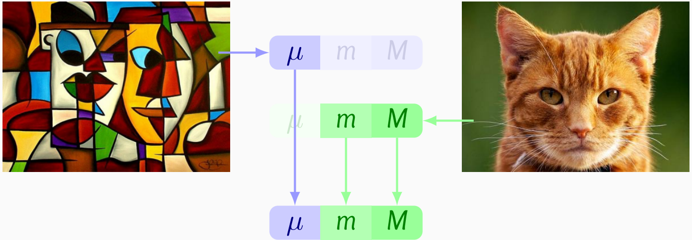

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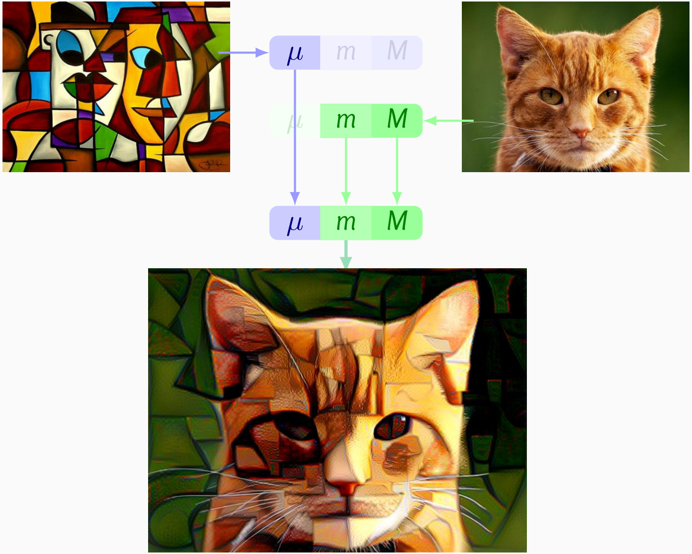

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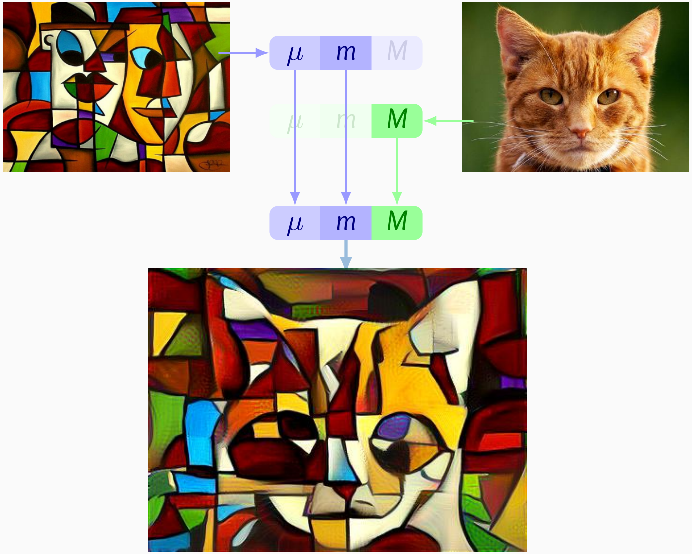

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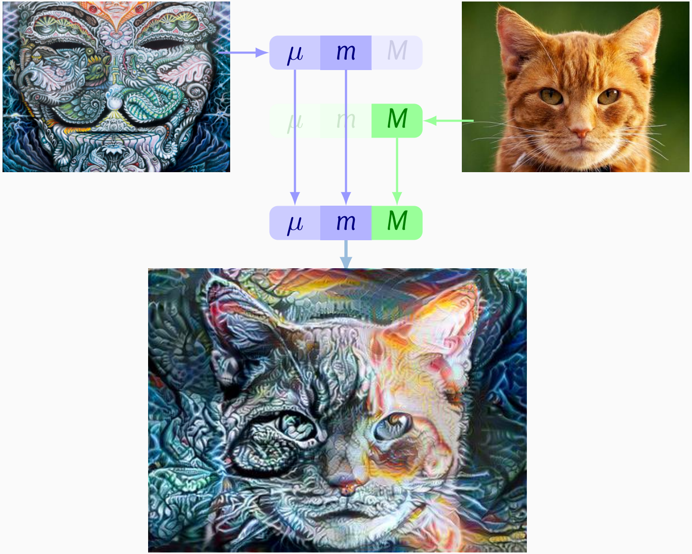

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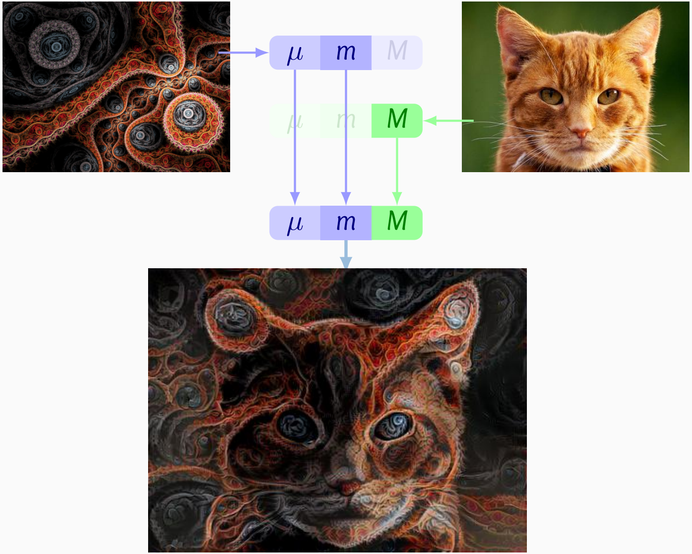

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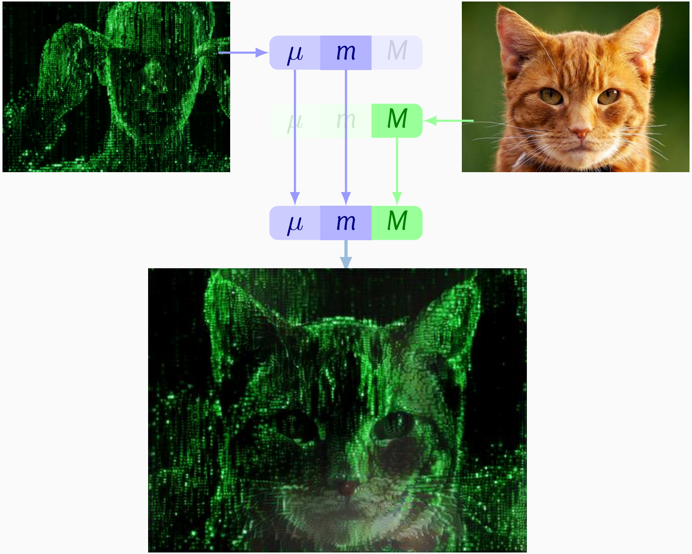

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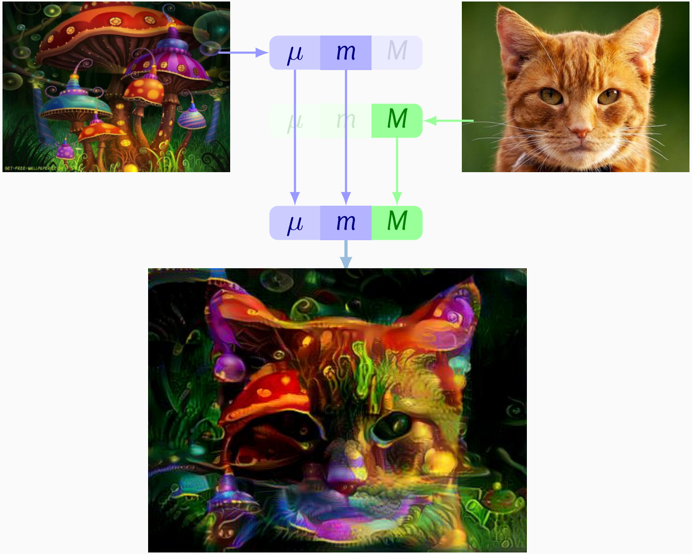

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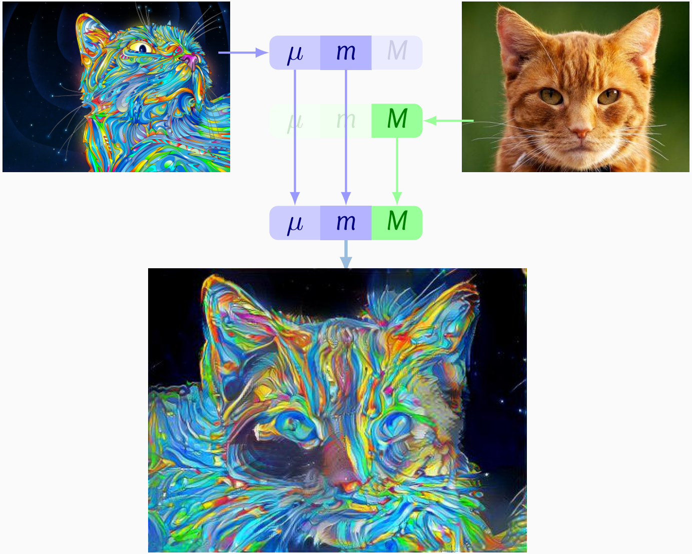

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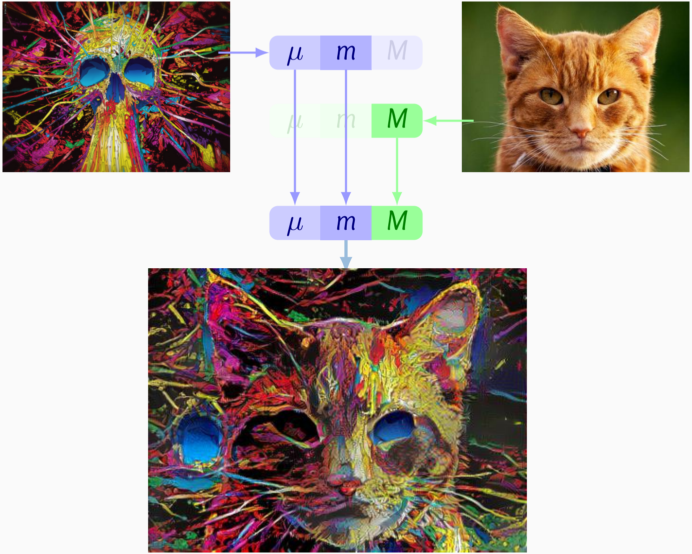

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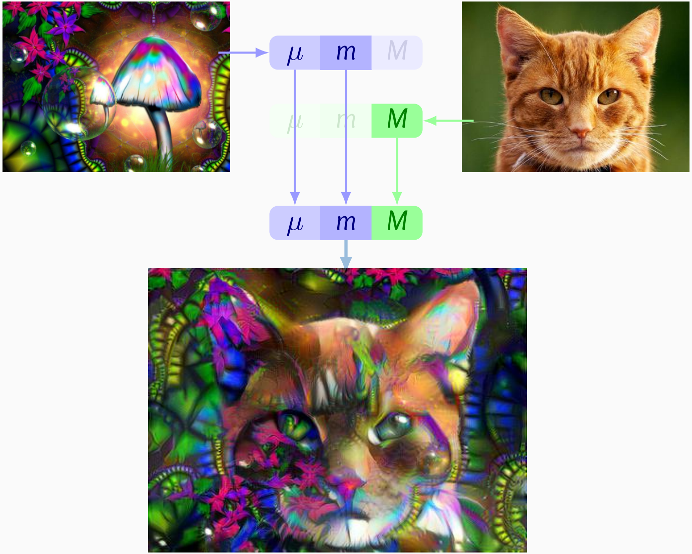

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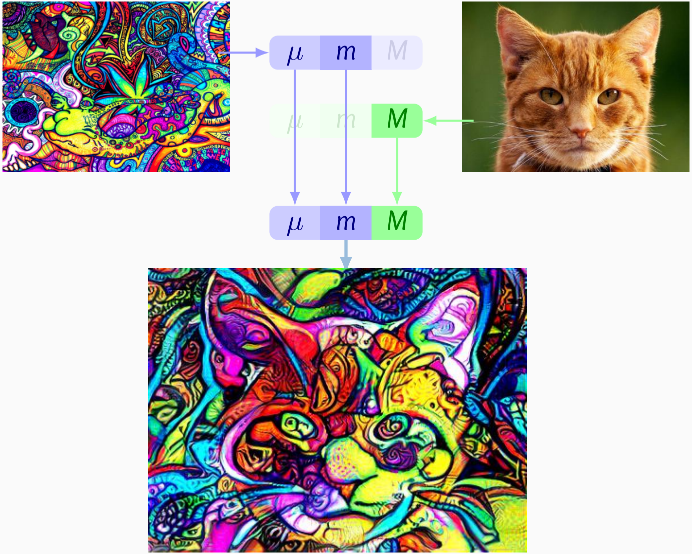

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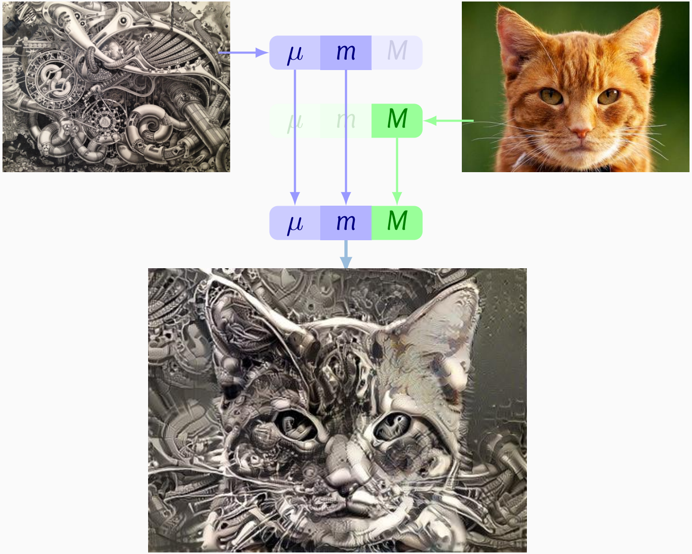

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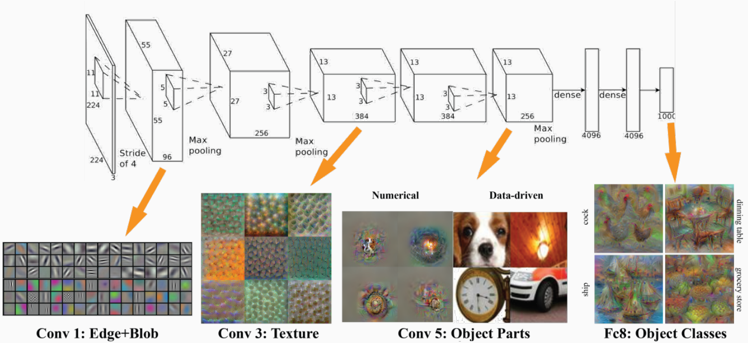
What researchers have in mind [WZTF]:



$\mu(x)$ $\quad m(x)$ $\quad M(x)$

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CNNs perform **feature detection**, nothing more, nothing less [NYC15]:

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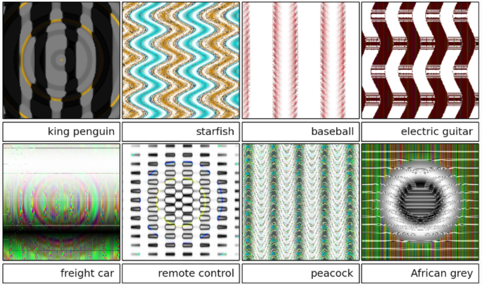

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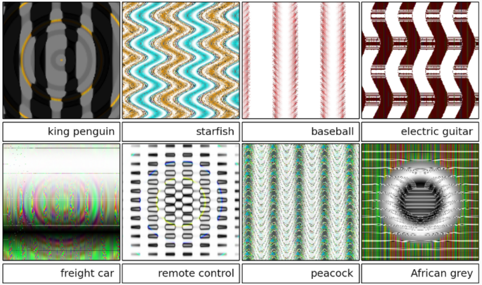

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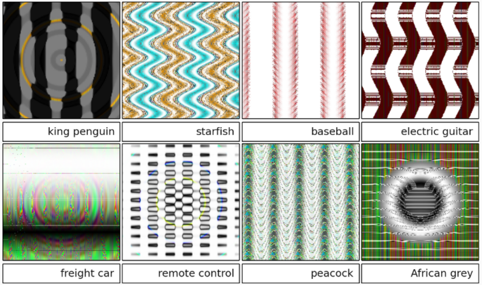

Unfortunately : **structured** anatomical models are **way** more expensive.

(that's my job...)

Conclusion

Old ideas, fancy words

As we've seen :

Multi-layer perceptron $\Longleftrightarrow$ Neural network

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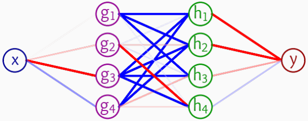

$\overset{?}{\Longleftrightarrow}$

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An image processing software **always** relies on a **simplistic model** of the data.

There is no miracle.

Keep in mind

When facing an “AI” product :

- **« Show me what doesn’t work. »**

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Going further :

Cours de **Sciences des données** au Collège de France,

`www.college-de-france.fr/site/stephane-mallat/`

Jetez un œil à la leçon inaugurale, très accessible !

AI+Radiology MasterClass

sites.google.com/view/masterclassiaimagerie/home

My notebooks are available: www.math.ens.fr/~feydy/Teaching/

Thank you for your attention.

Any questions ?

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