

Deep learning for image analysis quick introduction

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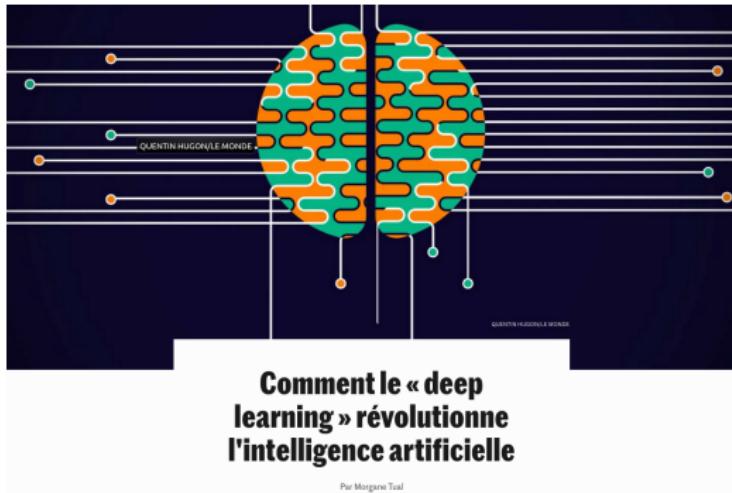
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The rise of deep learning



**Comment le « deep
learning » révolutionne
l'intelligence artificielle**

Par Morgan Teal

Le Monde, juillet 2015

The rise of deep learning



Nature, 2016

The rise of deep learning

Le prix Turing récompense trois pionniers de l'intelligence artificielle (IA)

L'association américaine ACM a remis son prestigieux prix aux chercheurs français, canadien et britannique : Yann LeCun, Yoshua Bengio et Geoffrey Hinton.

Par David Larousserie · Publié le 27 mars 2019 à 11h01 - Mis à jour le 29 mars 2019 à 12h11

Le Monde, mars 2019

Pour Elon Musk, l'intelligence artificielle pourrait menacer la civilisation

L'entrepreneur américain, qui a fondé Tesla, a alerté les politiques américains sur la nécessité de réguler l'intelligence artificielle.

Par **Le Figaro**

Publié le 18/07/2017 à 06:00, mis à jour le 18/07/2017 à 11:25

Le Figaro, juillet 2017

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Artificial neural networks and deep learning history

- 1958: Rosenblatt's perceptron [Rosenblatt, 1958]

Artificial neural networks and deep learning history

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- 1979: Neocognitron (convolutional neural network architecture) [Fukushima, 1979, Fukushima, 1980]

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- 1980's: the backpropagation algorithm ([Werbos, 1982]; see also the work of LeCun [LeCun, 1985])

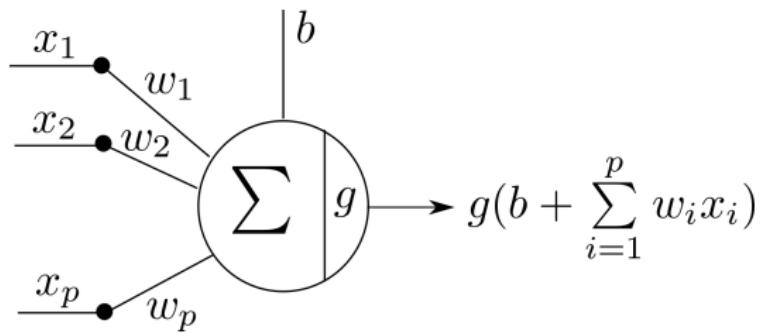
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- 2006-: CNN implementations using Graphical Processing Units (GPU): up to a 50 speed-up factor.

Artificial neural networks and deep learning history

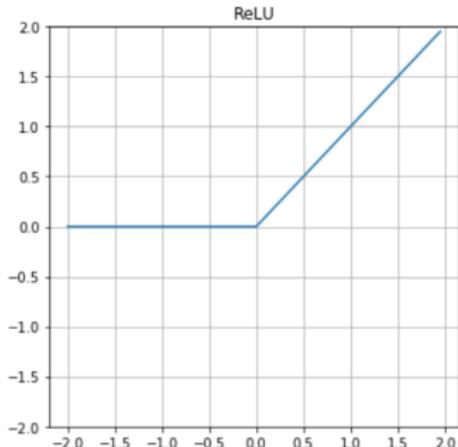
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- 1980's: the backpropagation algorithm ([Werbos, 1982]; see also the work of LeCun [LeCun, 1985])
- 2006-: CNN implementations using Graphical Processing Units (GPU): up to a 50 speed-up factor.
- 2012: Imagenet image classification won by a CNN with AlexNet [Krizhevsky et al., 2012].

Artificial neuron



Activation: rectified linear unit (ReLU)

$$g(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

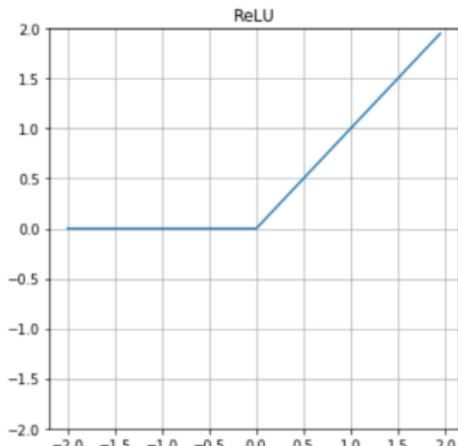


Remarks

- + Usable gradient when activated
- + Fast to compute
- + High abstraction

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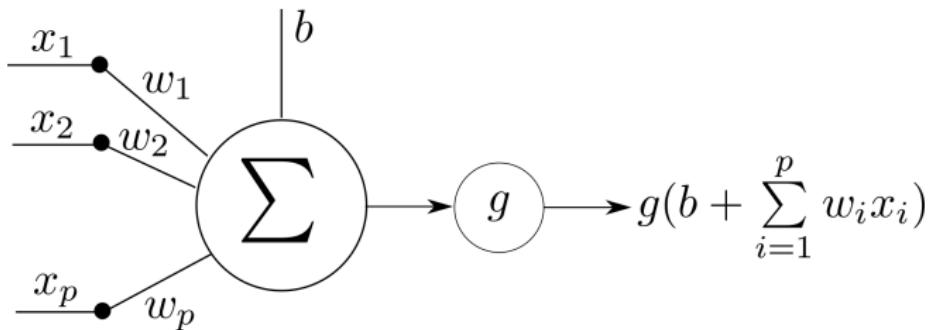


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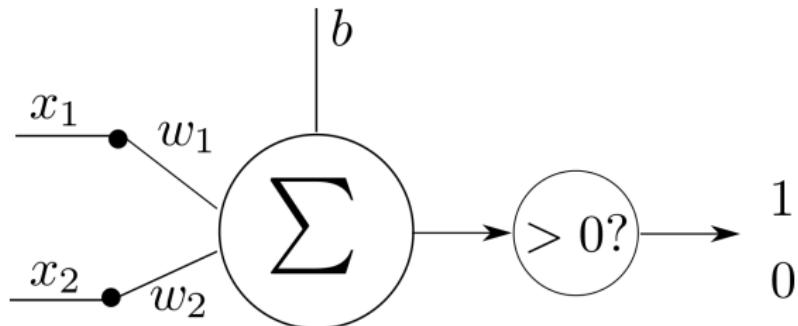
ReLU is the most commonly used activation function.

What can an artificial neuron compute?



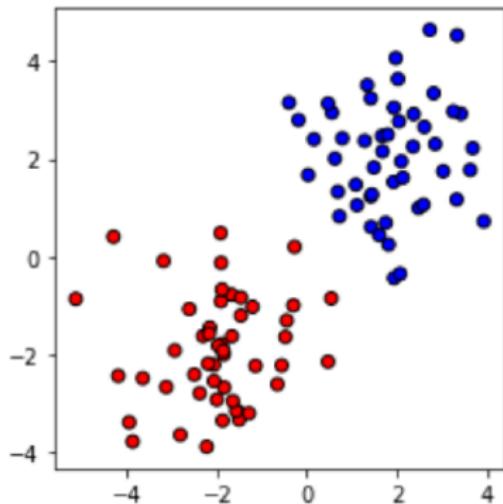
In \mathbb{R}^p , $b + \sum_{i=1}^p w_i x_i = 0$ corresponds to a hyperplane H . For a given point $\mathbf{x} = \{x_1, \dots, x_p\}$, decisions are made according to the side of the hyperplane it belongs to.

Example of what we can do with a neuron

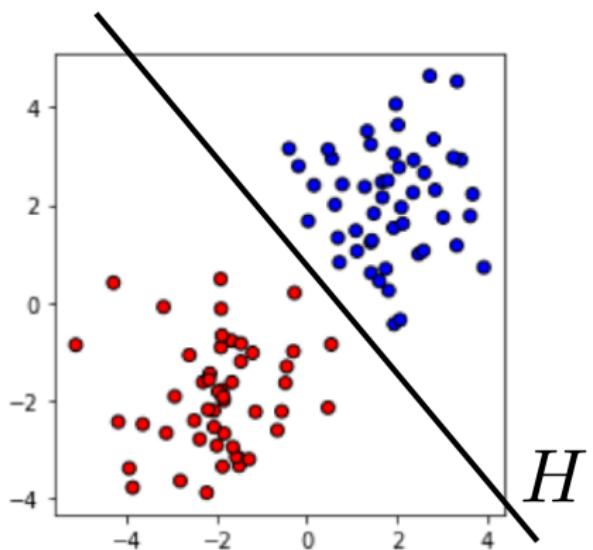


- $p = 2$: 2-dimensional inputs (can be represented on a screen!)
- Activation: binary
- Classification problem

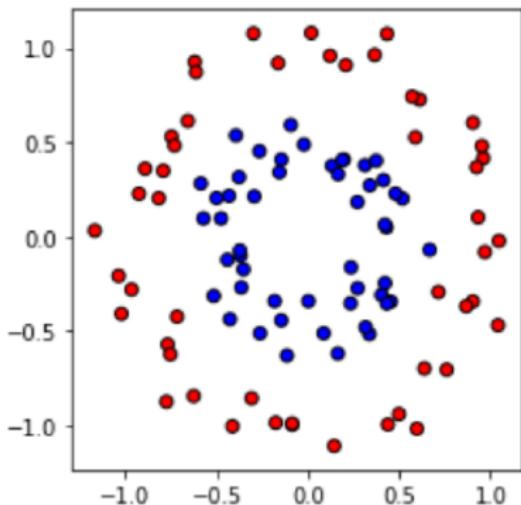
Gaussian clouds



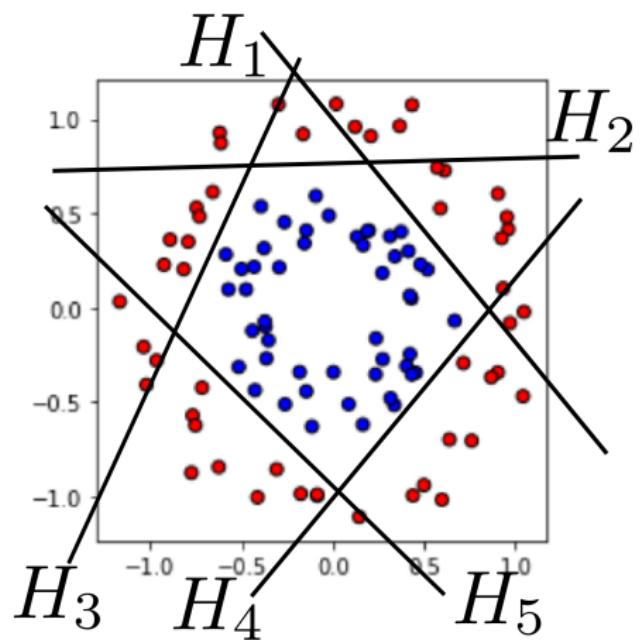
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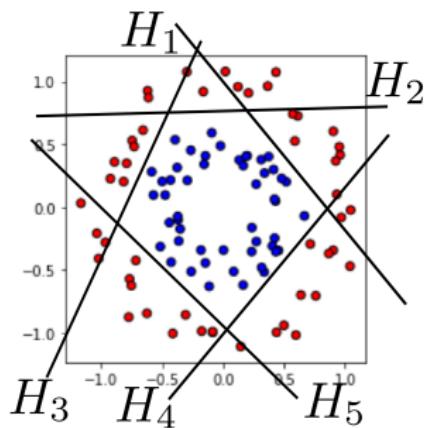
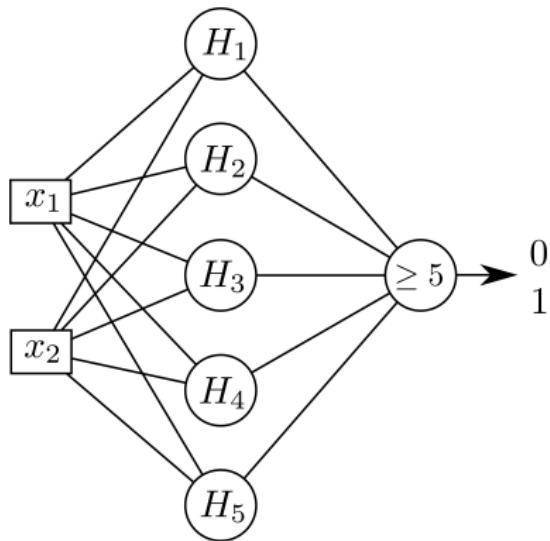
Circles



Circles



Solution

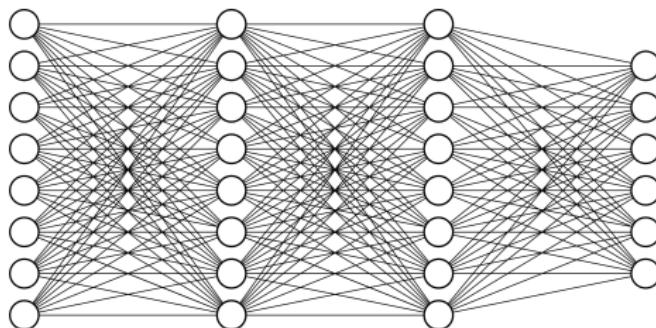


Universal approximation theorem
[Cybenko, 1989, Hornik, 1991]

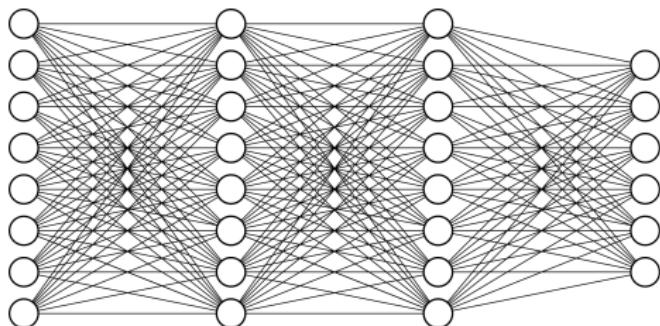
Any continuous real-valued function of $[0, 1]^p$ can be approximated by an artificial neural network with a single hidden layer.

Fully-connected layers

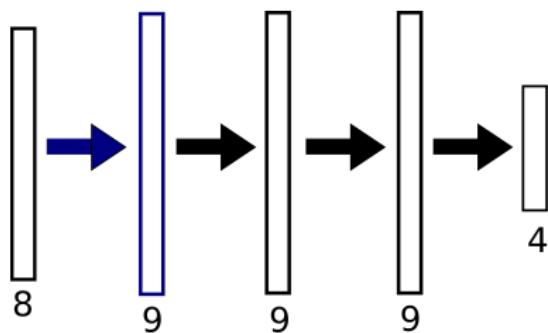
- A layer is said to be fully-connected if each of its neurons is connected to all the neurons of the previous layer



Graphical representation of NNs



- Data is organized into arrays, linked with operators
- A layer corresponds to an operator between arrays.



Learning with artificial neural networks

- Constitute your learning, validation and test sets
- Define a loss function
- Use gradient descent (backpropagation) to minimize the loss

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A picture is worth a thousand words

Definition

- Classically, an image is a matrix of values belonging to $[0, \dots, 255]$ (grey level images) or to $[0, \dots, 255]^3$ (color images).
- More generally, an image is a q -dimensional array of values belonging to R^d .



Grey level values around the left eye of the faun

The role of annotated image databases

Image databases including *annotations* (typically some kind of high level information) are essential to the development of *supervised* machine learning methods for image analysis.

Annotations

- Image class
- Measure(s) obtained from the image
- Position of objects within the image
- Segmentation

MNIST database [Lecun et al., 1998]

- The Modified National Institute of Standards and Technology (MNIST) database contains 60 000 training images of hand-written digits, and 10,000 test images.
- Image size: 28×28

A 10x10 grid of handwritten digits, likely from the MNIST dataset. The digits are arranged in a grid pattern. The digits are handwritten in black ink on a white background. The digits are: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9.

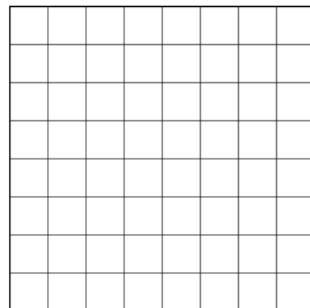
0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7	7	7
8	8	8	8	8	8	8	8	8	8
9	9	9	9	9	9	9	9	9	9

Credits: Images from MNIST assembled
by Josef Stepan (licensed under CC
BY-SA 4.0)

Layers representation

For illustration purposes, in the following slides images and filters will be displayed as rows of neurons – these can be seen as 1D arrays or as sections of 2D arrays.

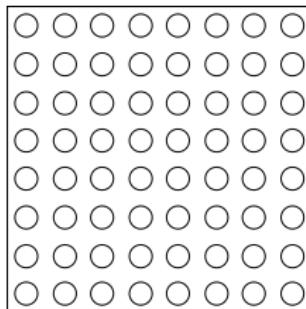
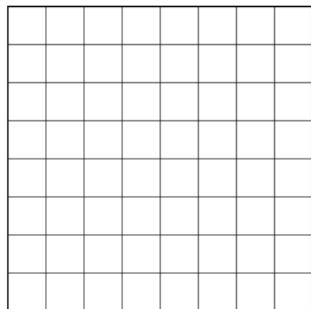
We represent some connections between neurons. Each such connection is associated to a weight. The bias are not represented, to avoid clutter, but must not be forgotten.



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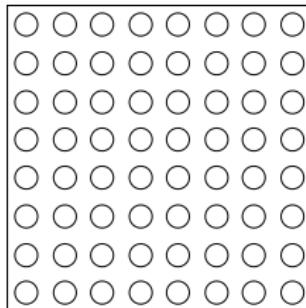
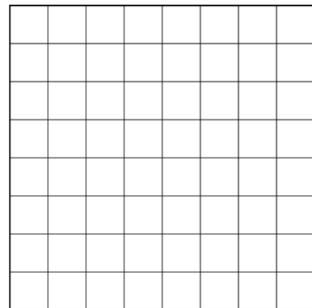
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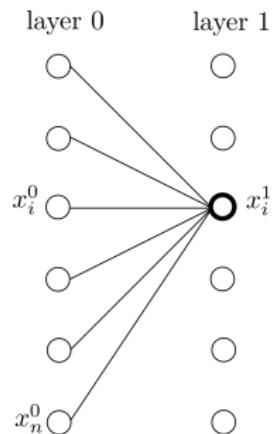
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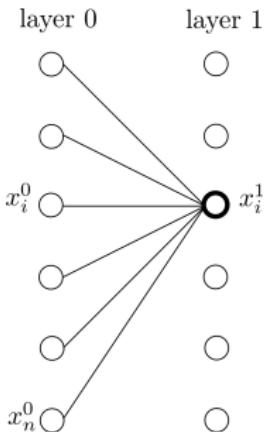


Towards convolutional layers

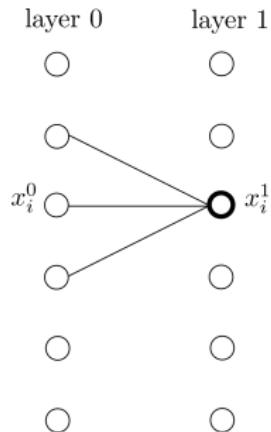


Fully connected layer:
 $n(n + 1)$ weights

Towards convolutional layers

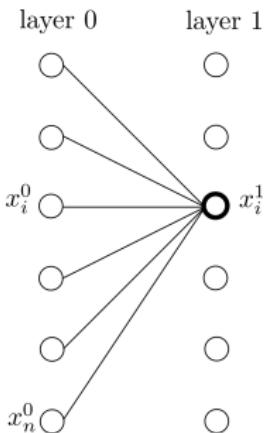


Fully connected layer:
 $n(n + 1)$ weights

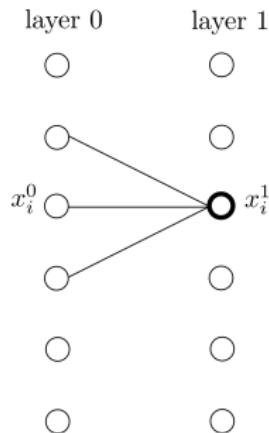


Locally conn. layer:
 $n(s + 1)$ weights

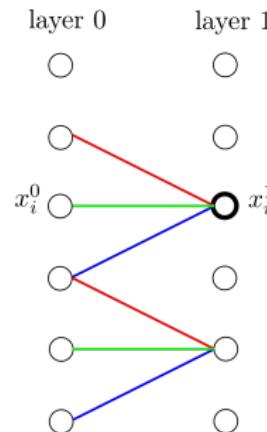
Towards convolutional layers



Fully connected layer:
 $n(n + 1)$ weights



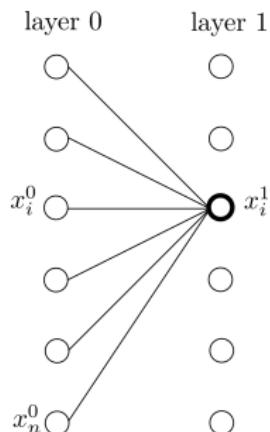
Locally conn. layer:
 $n(s + 1)$ weights



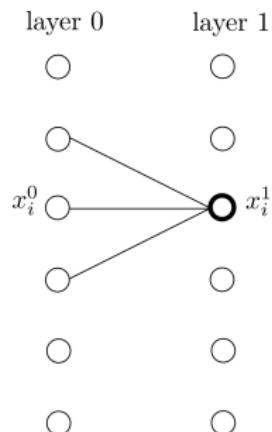
Weight replication: $s + 1$ weights.
Convolutional layer.

Towards convolutional layers: some figures

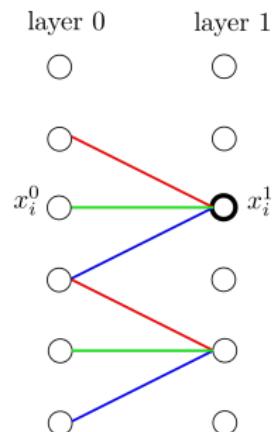
- 3×3 convolutions: $s = 9$
- Toy image: $n = 28 \times 28 = 784$
- Typical image: $n = 1000 \times 1000 = 10^6$



Fully connected layer:
 $n(n + 1)$ weights
 $\approx 6 \cdot 10^5$
 $\approx 10^{12}$



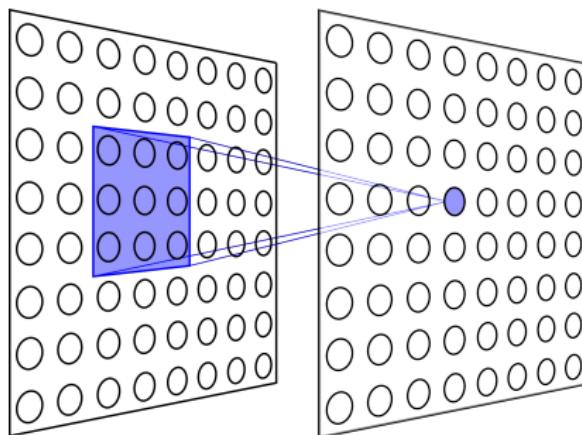
Locally conn. layer:
 $n(s + 1)$ weights
7840
 10^7



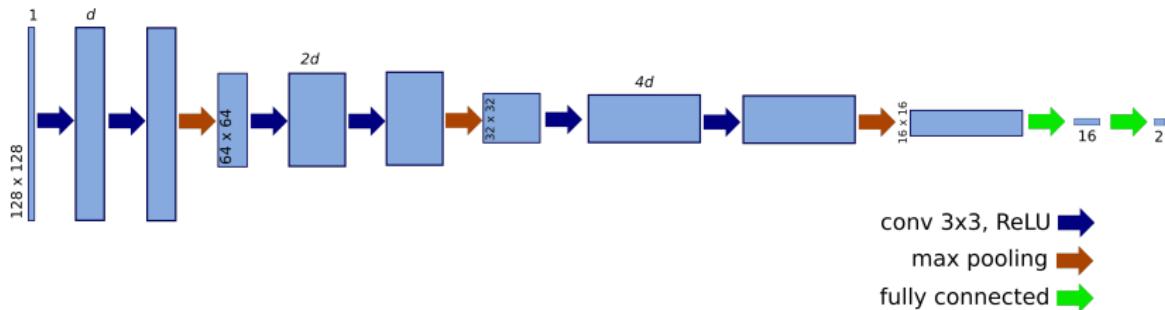
Weight replication: $s + 1$ weights.
10
10

Convolutional layer illustration in 2D

- Illustration of a convolution of size 3×3

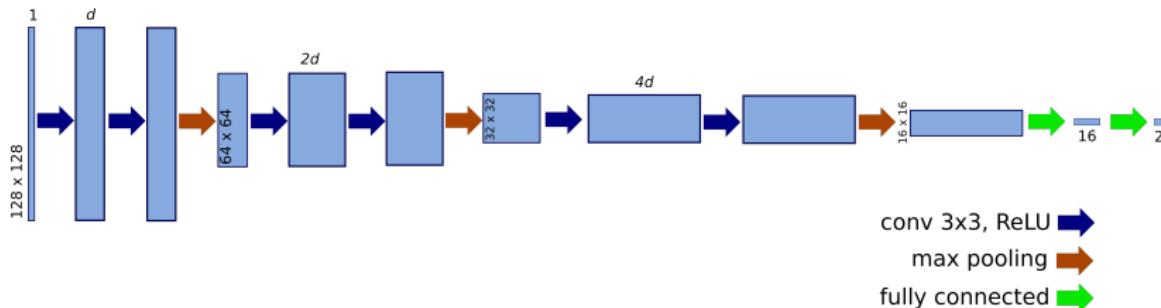


1D representations



Credits: NN is work of Robin Alais et al.
Fundus image by Mikael Häggström, used
with permission (CC0).

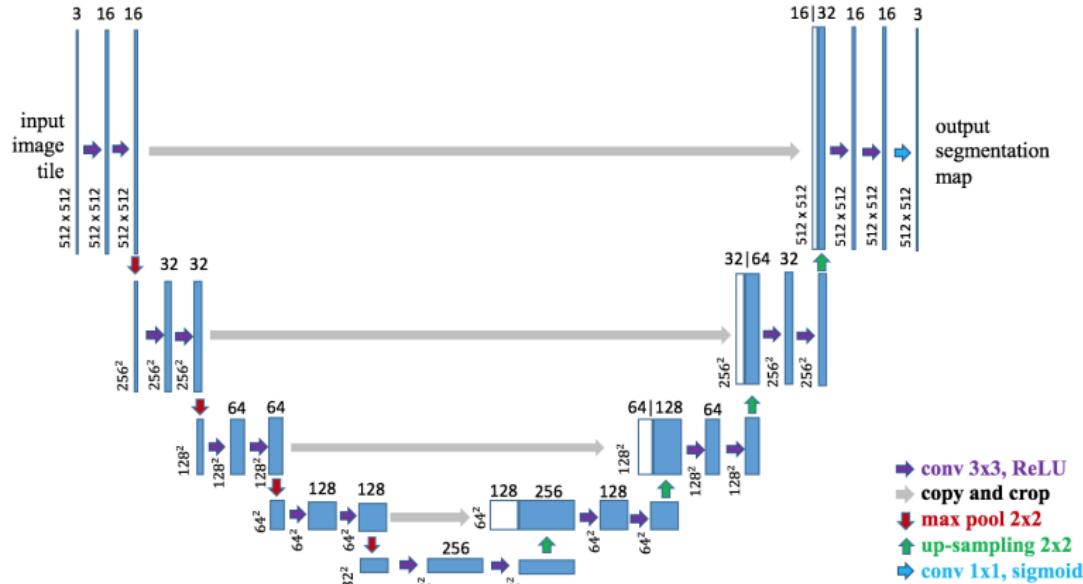
1D representations



This NN was used to estimate the position of the center of the macula on fundus images.

Credits: NN is work of Robin Alais et al.
Fundus image by Mikael Häggström, used with permission (CC0).

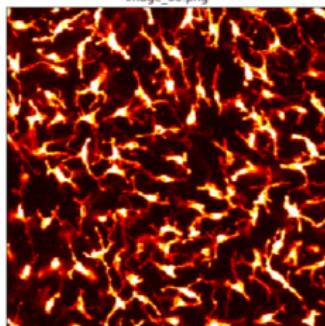
U-Net architecture [Ronneberger et al., 2015]



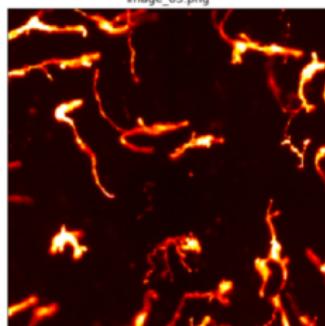
Example: counting cells

image

image_60.png

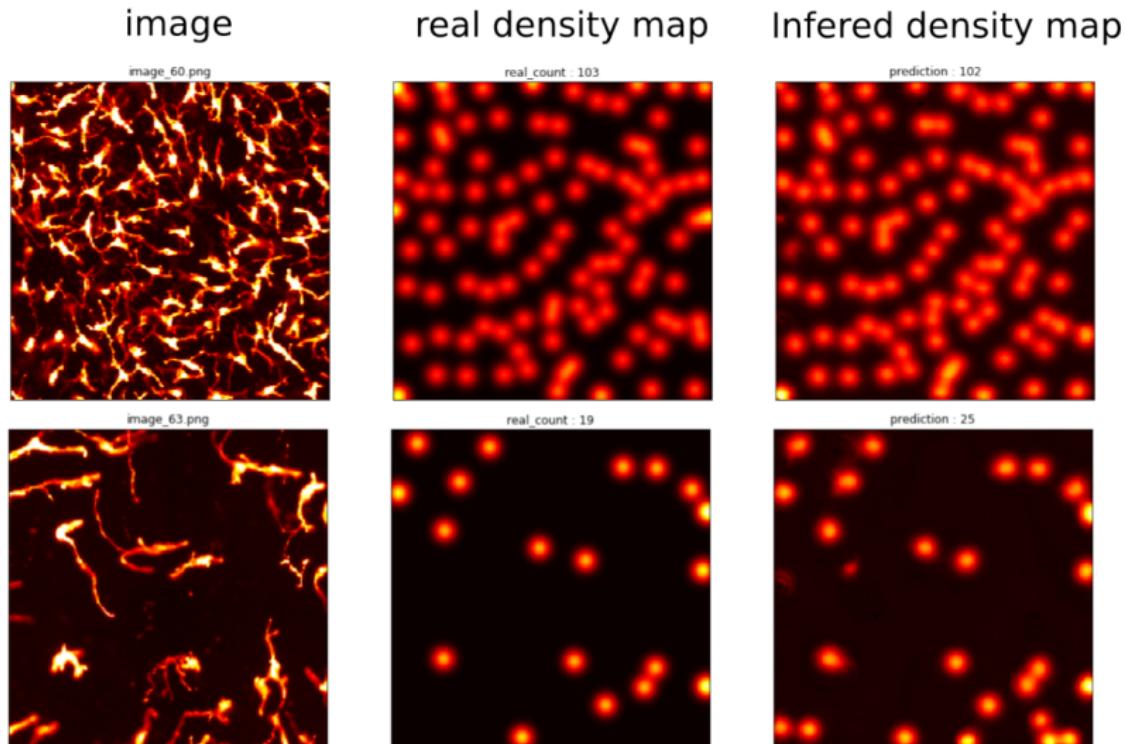


image_63.png



Credits: Tristan Lazard, master thesis. In collaboration with L'Oréal.

Counting cells



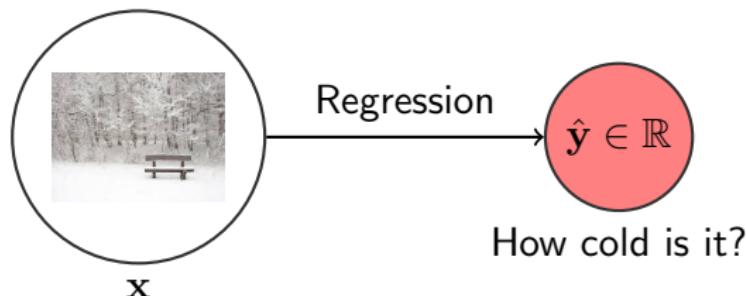
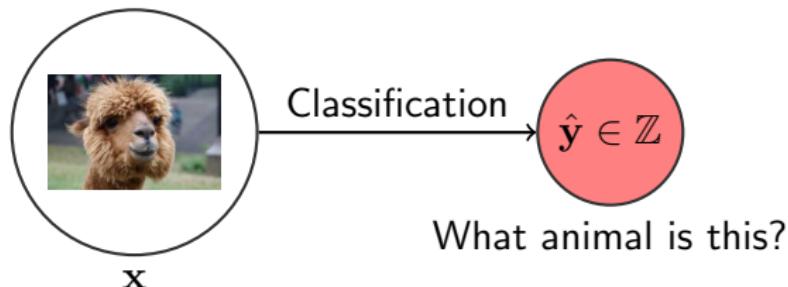
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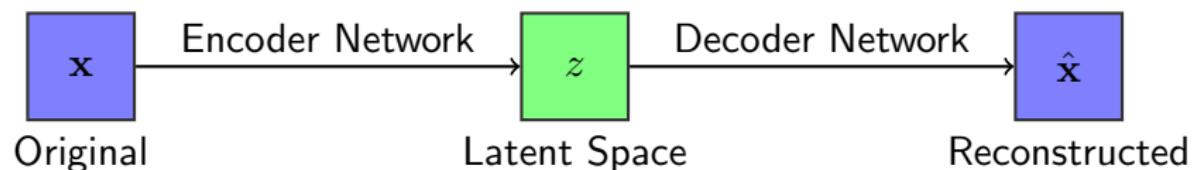
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Supervised Learning

Given a labeled dataset (\mathbf{X}, \mathbf{Y}) , we would like to learn a mapping from data space to label space.

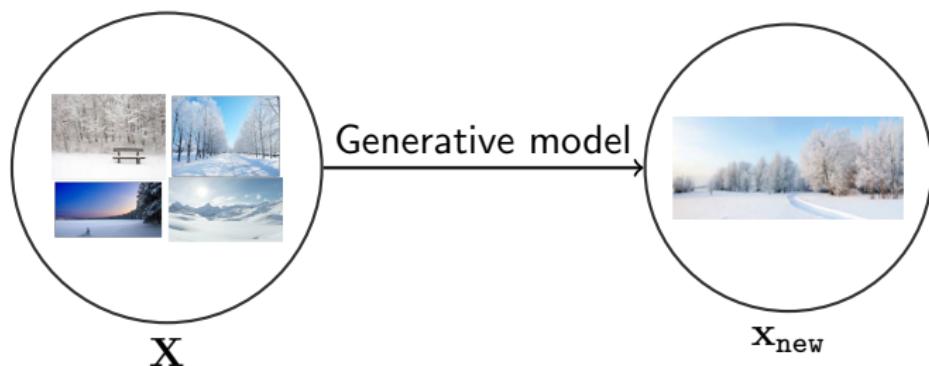


Autoencoders

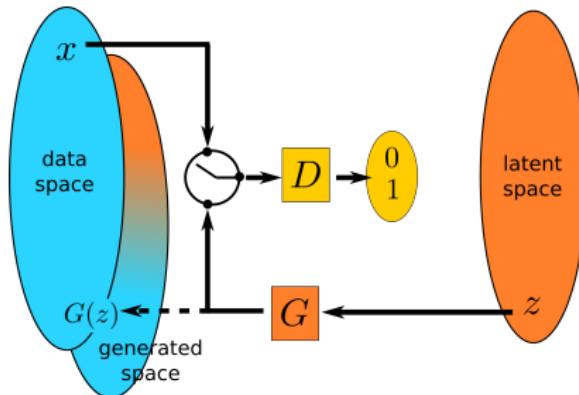


Unsupervised learning: Generative Models

Given an unlabeled dataset (\mathbf{X}), we would like to learn: How to generate a new observation from the same distribution (unknown) of dataset?



Generative adversarial networks [Goodfellow et al., 2014]



- The **discriminator** D is optimized so that it correctly classifies images as real (1) or fake (0)
 - The decoder or **generator** G is optimized so that the produced images are classified as real by the discriminator

Which face is real?

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Conclusion

- Deep learning allows to learn complex transformations between tensors, thanks to:
 - Smart methods and algorithms
 - Lots of data
 - Specialized hardware
- General artificial intelligence is still far away

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