Deep learning for image analysis quick introduction

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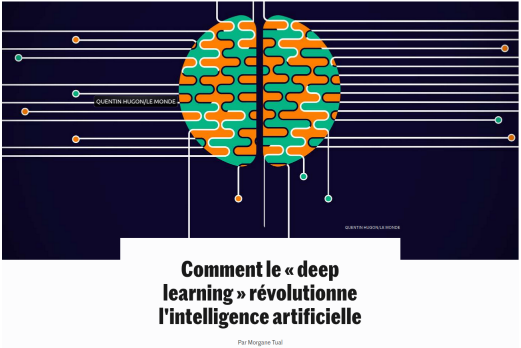
Contents

Contents

The rise of deep learning



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

The rise of deep learning

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

Contents

Artificial neural networks and deep learning history

- 1958: Perceptron [Rosenblatt, 1958].

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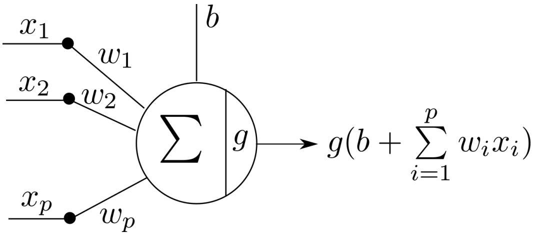
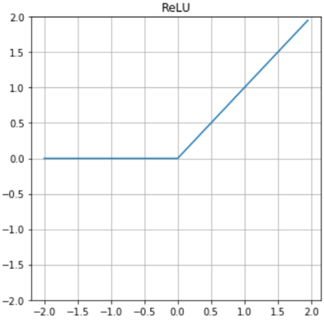
- 1980's: Backpropagation algorithm [Werbos, 1982, LeCun, 1985].
- 2006-: CNN implementations using Graphical Processing Units (GPU): up to a 50 speed-up factor.
- 2012: Imagenet image classification won by a convolutional neural network [Krizhevsky et al., 2012].

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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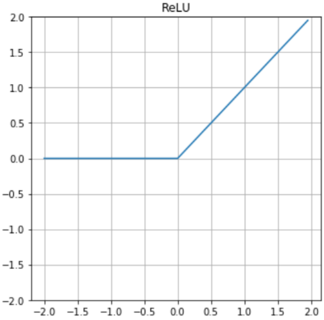

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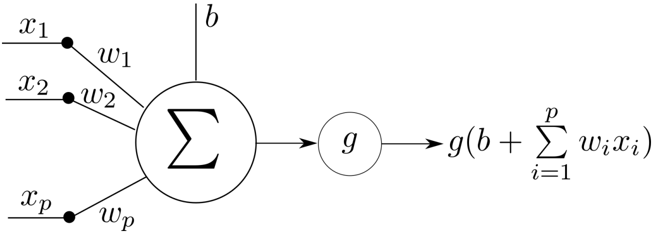
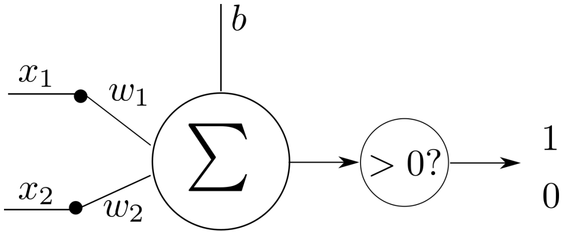
ReLU is the most commonly used activation function.

What can an artificial neuron compute?



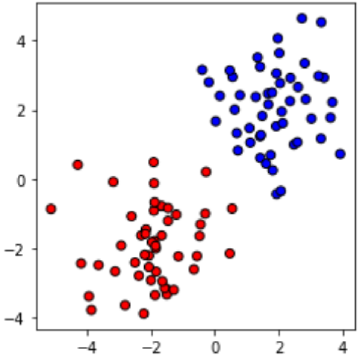
In $\mathbb{R}^p$, $b + \sum_{i=1}^{p} w_i x_i = 0$ corresponds to a hyperplane H. For a given point $\mathbf{x} = \{x_1, \ldots, x_p\}$, decisions are made according to the side of the hyperplane it belongs to.

Example of what we can do with a neuron

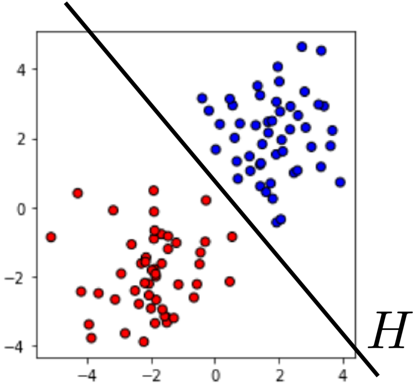


- $p = 2$: 2-dimensional inputs (can be represented on a screen!)
- Activation: binary
- Classification problem

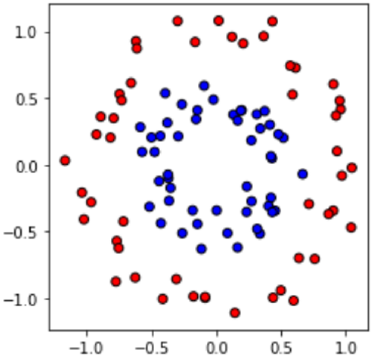
Gaussian clouds



Gaussian clouds



Circles



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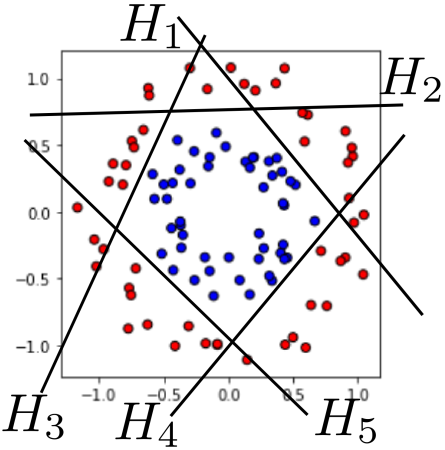
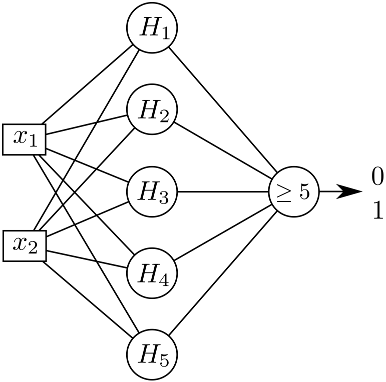
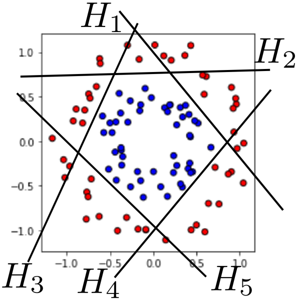


Solution



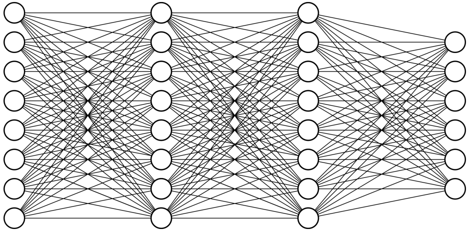


Universal approximation theorem [Cybenko, 1989, Hornik, 1991]

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

Multi-layered perceptron

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



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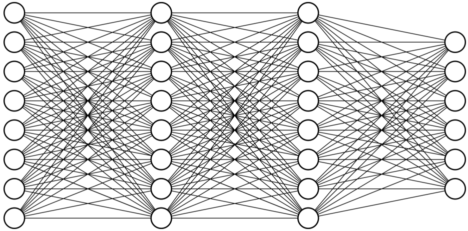
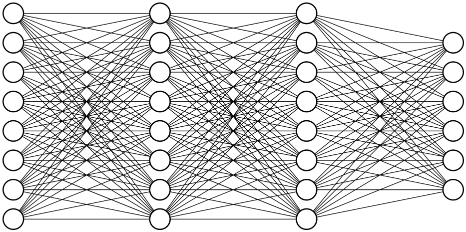
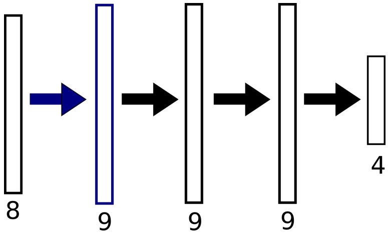


Deep learning

Artificial neural networks with *many* layers.

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

Contents

A picture is worth a thousand words

Grey level values around the left eye of the faun

A picture is worth a thousand words

Grey level values around the left eye of the faun

- Deep learning excels in image analysis.

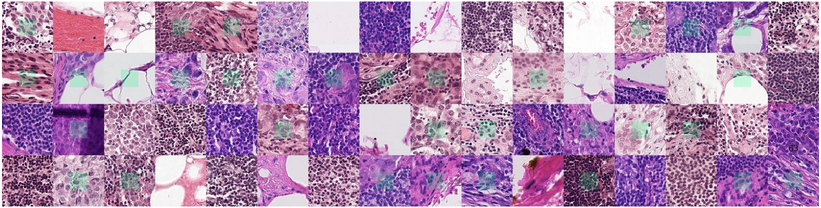
The role of annotated image databases

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

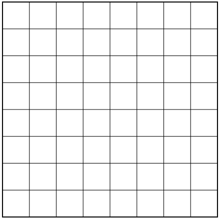
PatchCamelyon database



- $327\,680$ images of size 96×96
- Binary label (tumor tissue in center region or not)
- `https://github.com/basveeling/pcam`

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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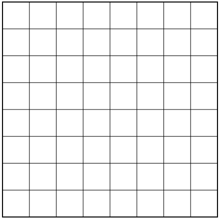

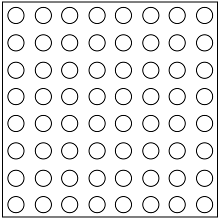

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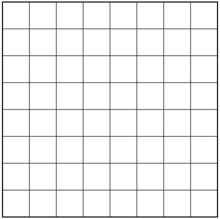
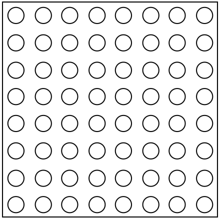
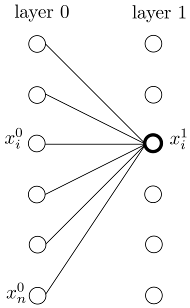


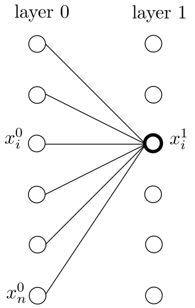


Towards convolutional layers



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

Towards convolutional layers



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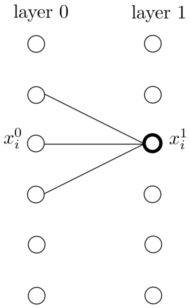
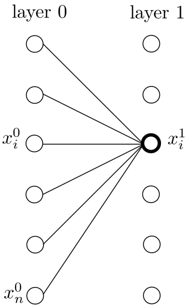


Locally conn. layer:
$n(s+1)$ weights

Towards convolutional layers



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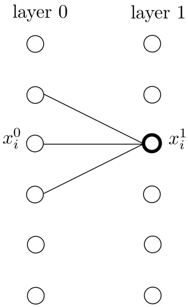

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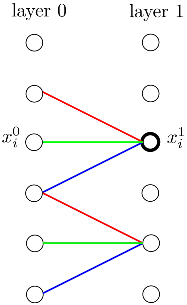
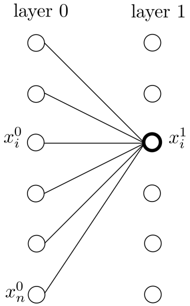


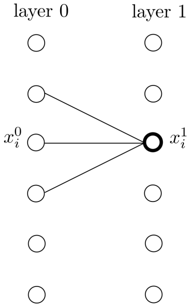
Weight replication: $s+1$ weights.
Convolutional layer.

Towards convolutional layers: some figures

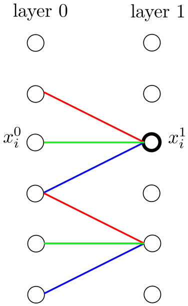
- 3×3 convolutions: $s = 9$
- Toy image: $n = 28 \times 28 = 784$
- Typical image: $n = 1000 \times 1000 = 10^6$



Fully connected layer:
$n(n+1)$ weights
$\approx 6.10^5$
$\approx 10^{12}$



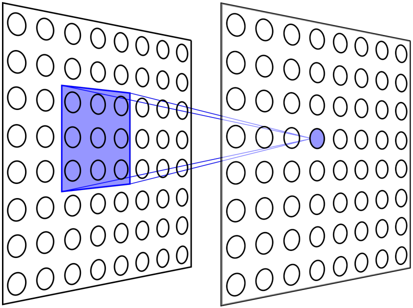
Locally conn. layer:
$n(s+1)$ weights
7840
10^7



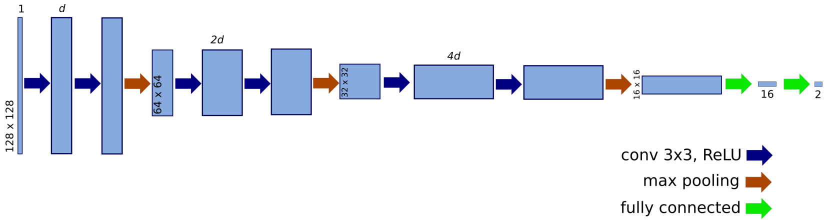
Weight replication: $s+1$ weights.
10
10

Convolutional layer illustration in 2D

- Illustration of a convolution of size 3×3

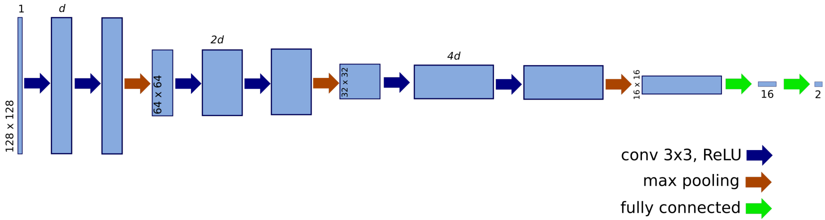


1D representations



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

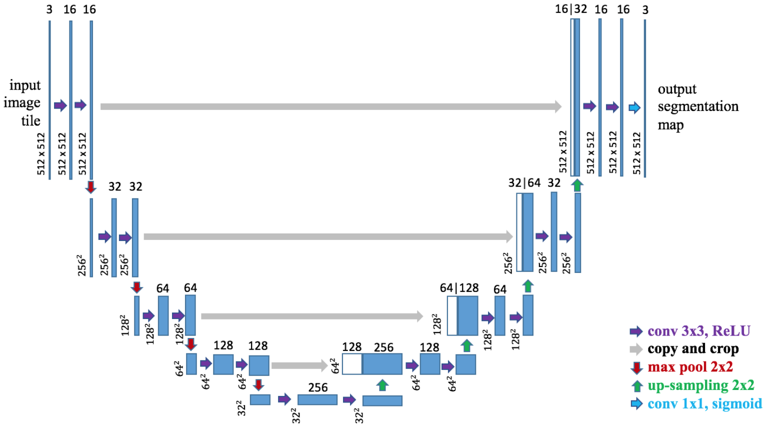
1D representations



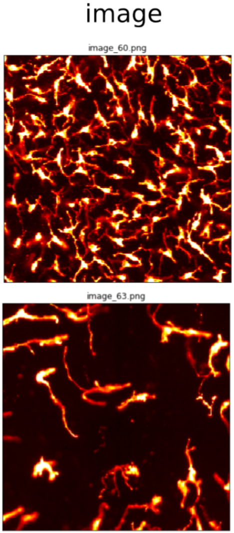
This NN was used to estimate the position of the center of the macula on fundus images.

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]

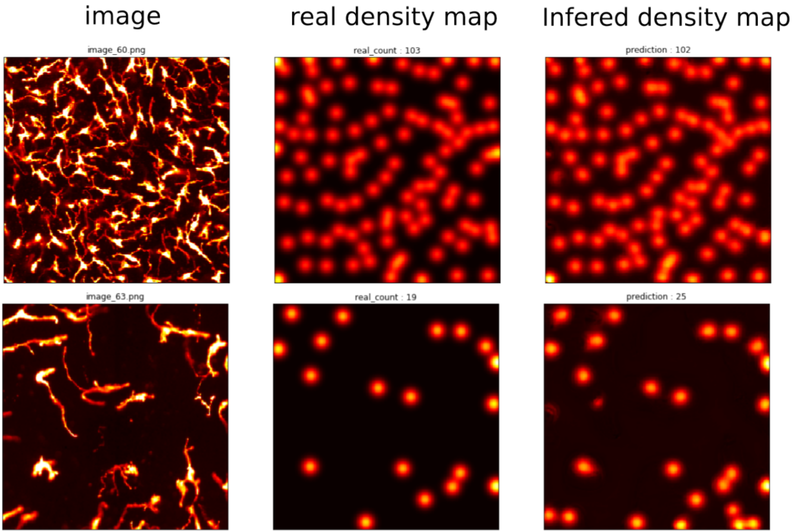


Example: counting cells



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

Counting cells



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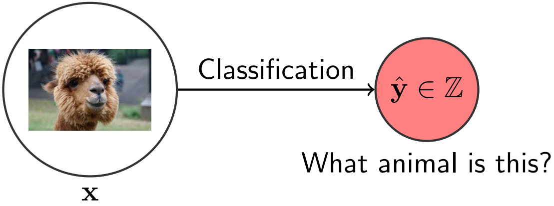
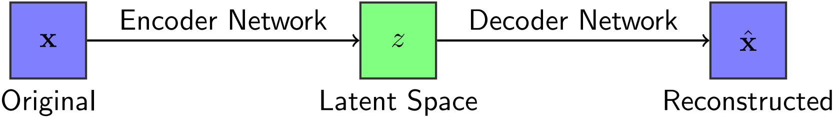
Contents

Supervised Learning

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

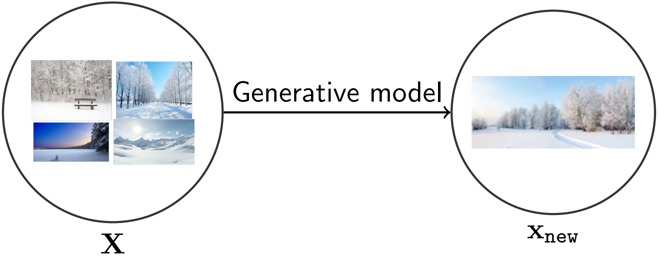


Autoencoders

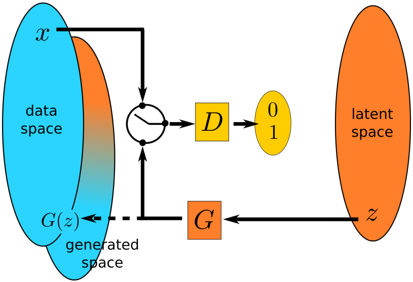


Unsupervised learning: Generative Models

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 generator G is optimized so that the produced images are classified as real by the discriminator

Which face is real?

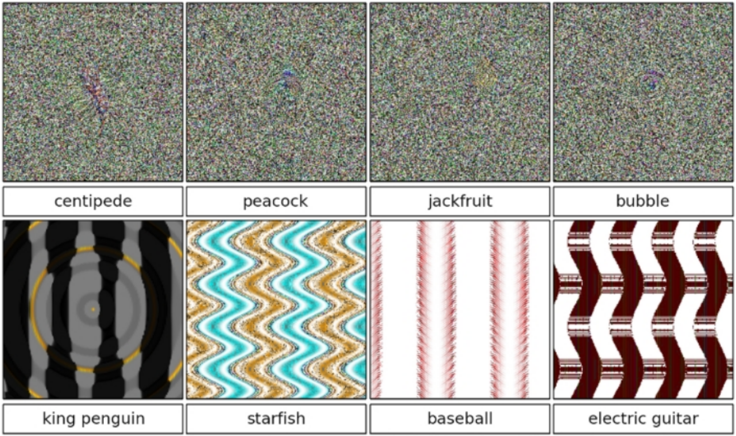
https://www.whichfaceisreal.com/

Contents

Conclusion

- Deep learning allows to learn complex transformations between tensors, thanks to:
  - Smart methods and algorithms.
  - Lots of annotated data.
  - Specialized hardware (for learning).
- Drawbacks:
  - Interpretability problem.
  - Why does deep learning work so well?
  - Deep learning can be easily fooled.
- General artificial intelligence is still far away

ConvNets can be fooled [Nguyen et al., 2015]



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