

Deep learning for image analysis quick introduction

E. Decencière

Mines Paris
PSL Research University
Center for Mathematical Morphology



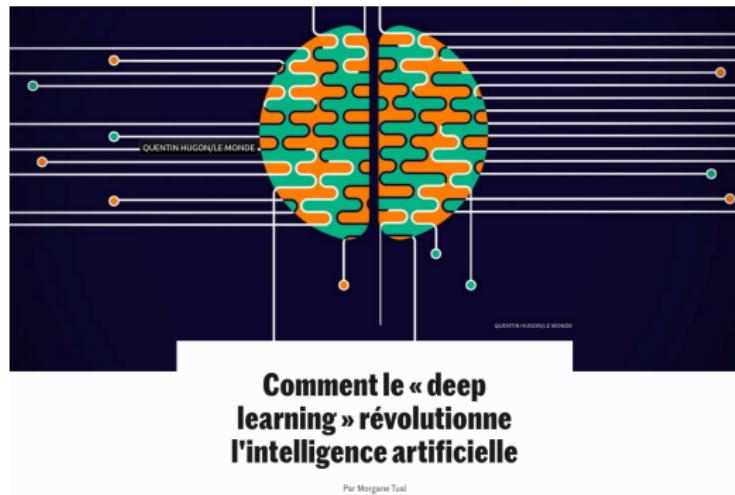
Contents

- 1 Introduction
- 2 Artificial neural networks
- 3 Application to images
- 4 Autoencoders and generative adversarial networks
- 5 Conclusion

Contents

- 1 Introduction
- 2 Artificial neural networks
- 3 Application to images
- 4 Autoencoders and generative adversarial networks
- 5 Conclusion

The rise of deep learning

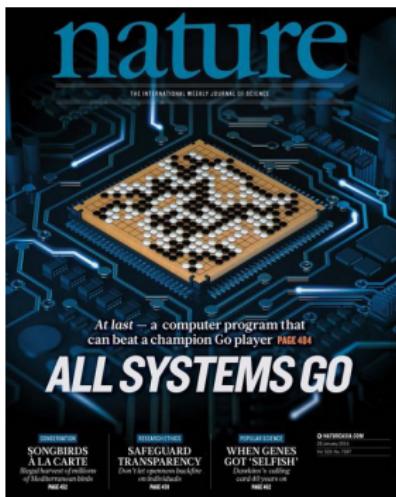


**Comment le « deep
learning » révolutionne
l'intelligence artificielle**

Par Morgane Teul

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

Contents

- 1 Introduction
- 2 Artificial neural networks
- 3 Application to images
- 4 Autoencoders and generative adversarial networks
- 5 Conclusion

Artificial neural networks and deep learning history

- 1958: Perceptron [Rosenblatt, 1958].

Artificial neural networks and deep learning history

- 1958: Perceptron [Rosenblatt, 1958].
- 1979: Convolutional neural networks [Fukushima, 1979].

Artificial neural networks and deep learning history

- 1958: Perceptron [Rosenblatt, 1958].
- 1979: Convolutional neural networks [Fukushima, 1979].
- 1980's: Backpropagation algorithm [Werbos, 1982, LeCun, 1985].

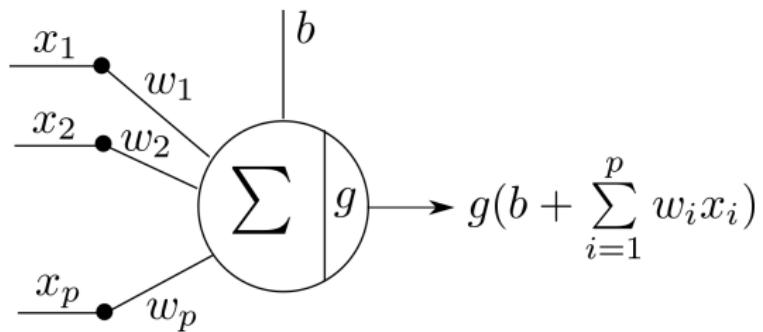
Artificial neural networks and deep learning history

- 1958: Perceptron [Rosenblatt, 1958].
- 1979: Convolutional neural networks [Fukushima, 1979].
- 1980's: Backpropagation algorithm [Werbos, 1982, LeCun, 1985].
- 2006-: Implementations on Graphical Processing Units

Artificial neural networks and deep learning history

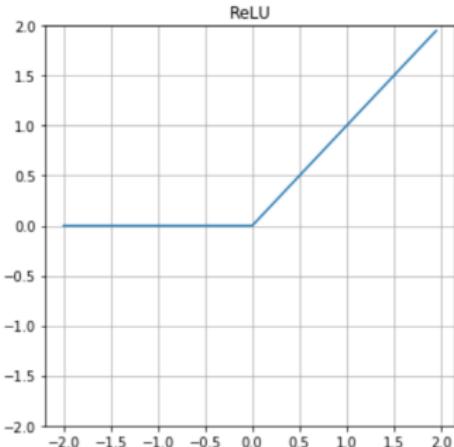
- 1958: Perceptron [Rosenblatt, 1958].
- 1979: Convolutional neural networks [Fukushima, 1979].
- 1980's: Backpropagation algorithm [Werbos, 1982, LeCun, 1985].
- 2006-: Implementations on Graphical Processing Units
- 2012: Imagenet image classification won by a convolutional neural network [Krizhevsky et al., 2012].

Artificial neuron



Activation: rectified linear unit (ReLU)

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

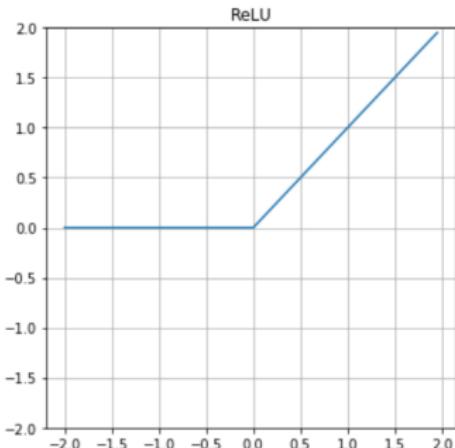


Remarks

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

Activation: rectified linear unit (ReLU)

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

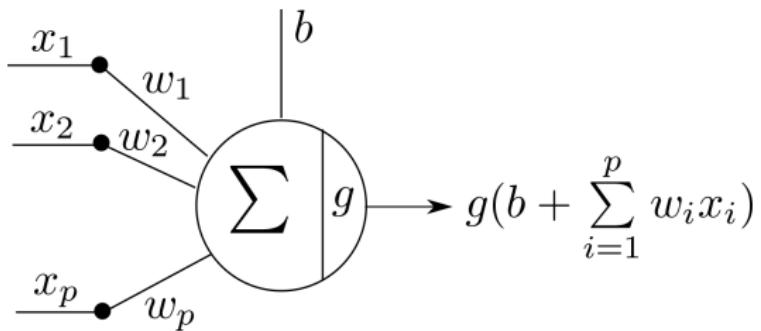


Remarks

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

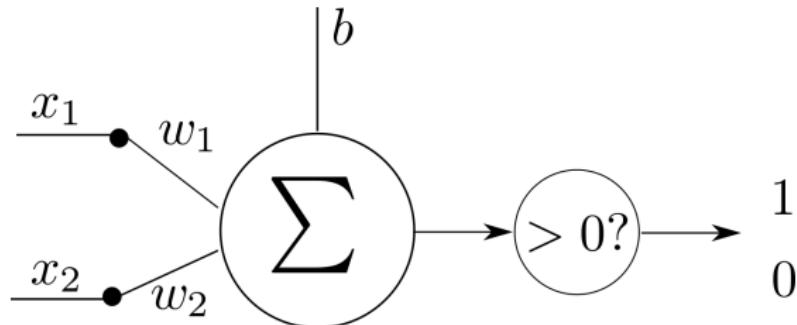
ReLU is the most commonly used activation function.

What can an artificial neuron compute?



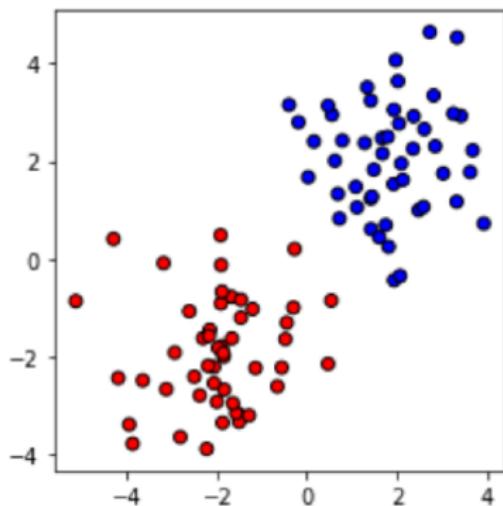
In \mathbb{R}^p , $b + \sum_{i=1}^p w_i x_i = 0$ corresponds to a hyperplane H . For a given point $\mathbf{x} = \{x_1, \dots, x_p\}$, decisions are made according to the side of the hyperplane it belongs to.

Example

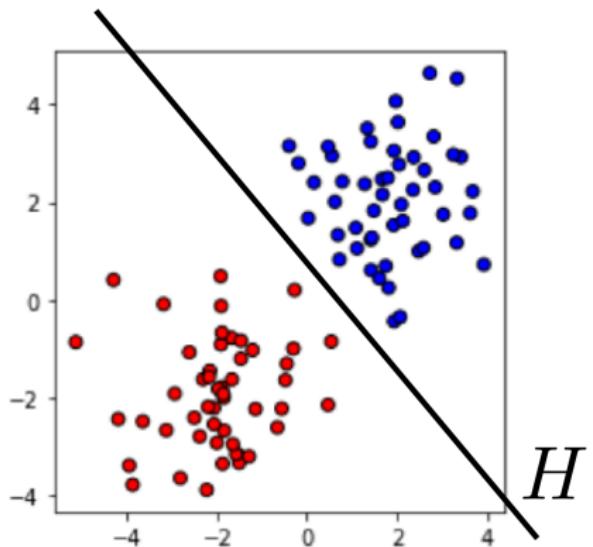


- $p = 2$: 2-dimensional inputs (can be represented on a screen!)
- Activation: binary
- Classification problem

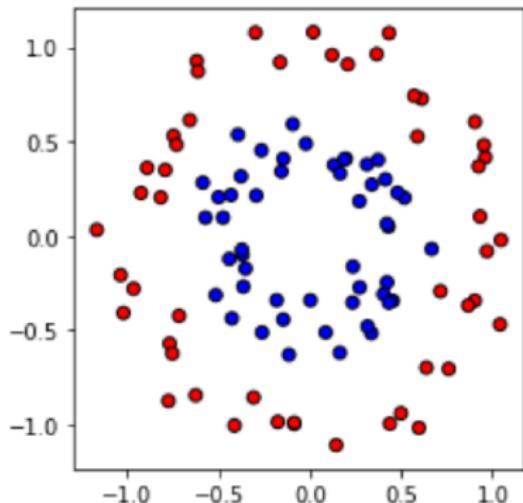
Gaussian clouds



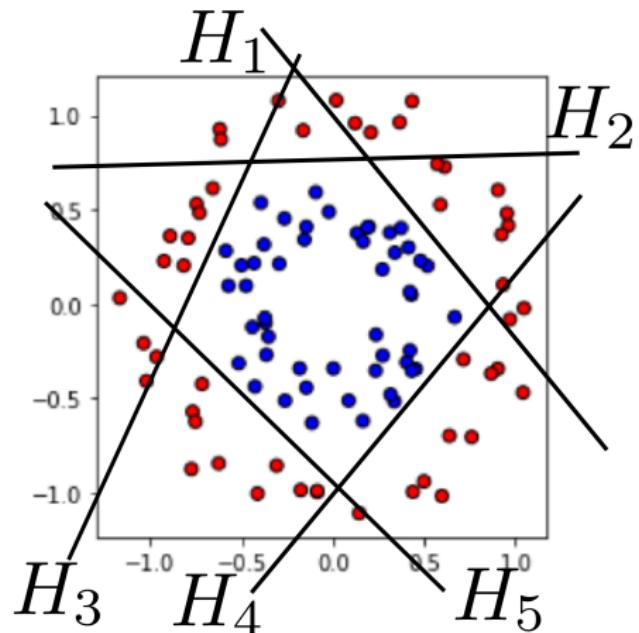
Gaussian clouds



Circles



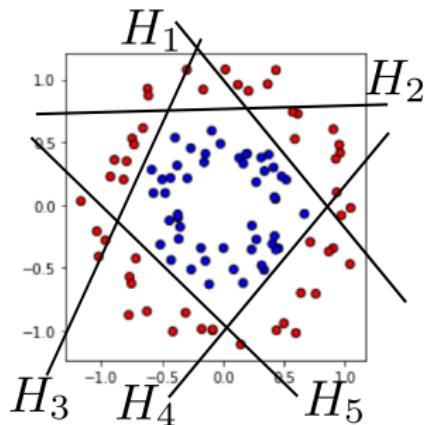
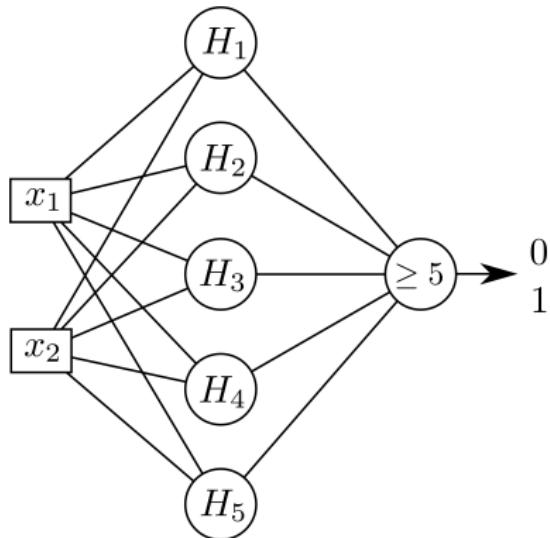
Circles



Playing with artificial neural networks

<https://playground.tensorflow.org>

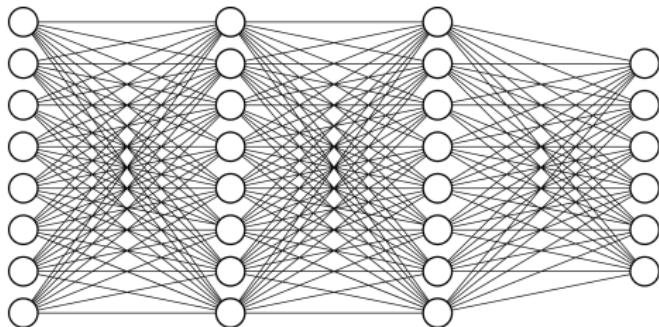
Solution



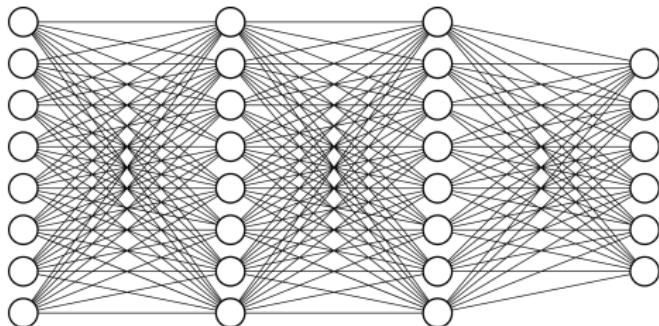
Universal approximation theorem
[Cybenko, 1989, Hornik, 1991]

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



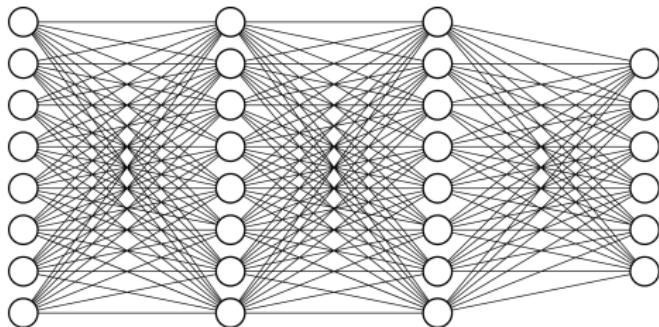
Multi-layered perceptron



Deep learning

- Artificial neural networks with *many* layers.

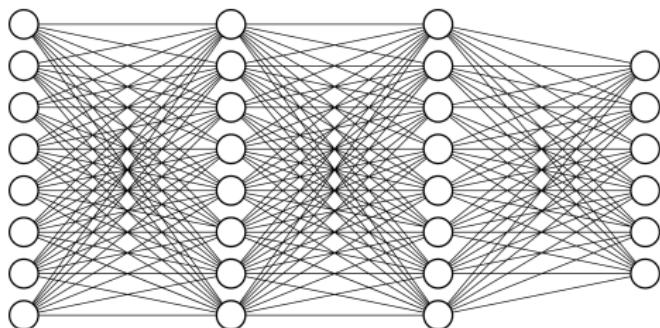
Multi-layered perceptron



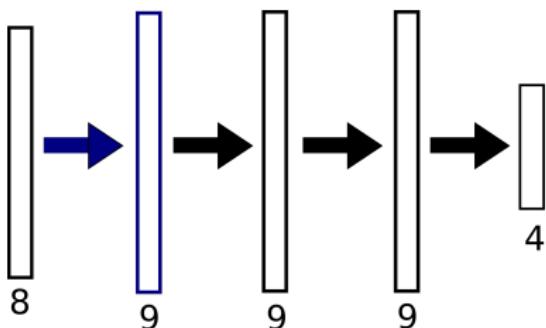
Deep learning

- Artificial neural networks with *many* layers.
- Features get more specific with depth

Graphical representation of NNs



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



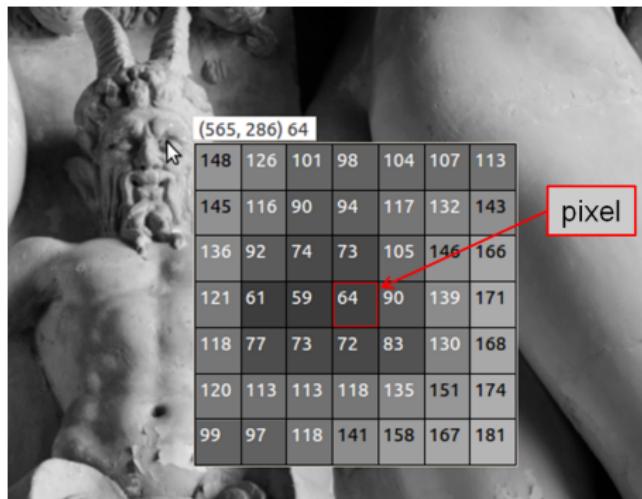
Learning with artificial neural networks

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

Contents

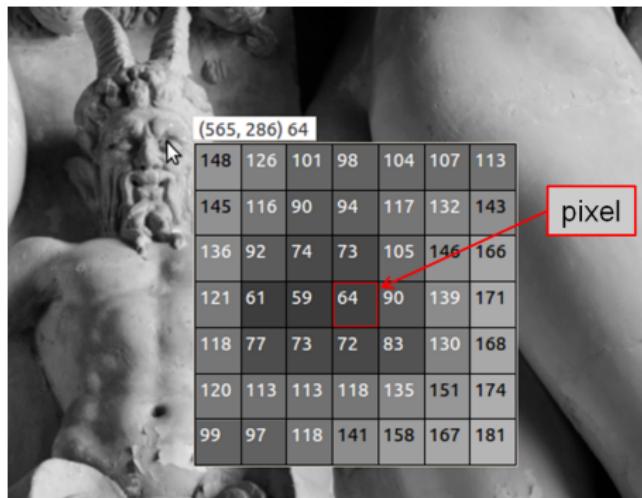
- 1 Introduction
- 2 Artificial neural networks
- 3 Application to images
- 4 Autoencoders and generative adversarial networks
- 5 Conclusion

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.

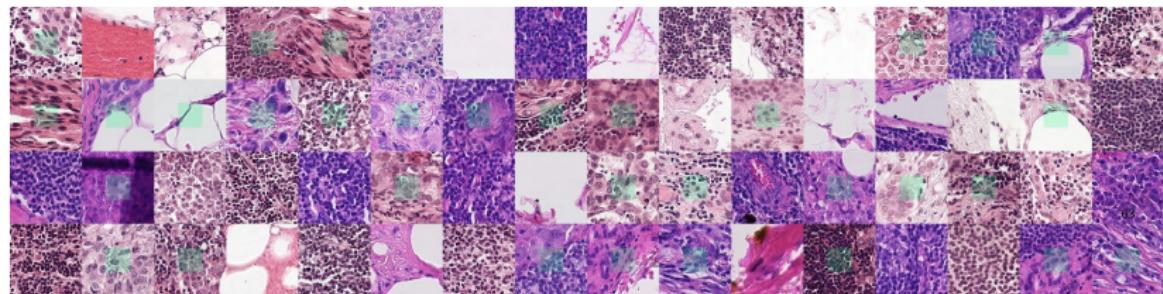
The role of annotated image databases

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

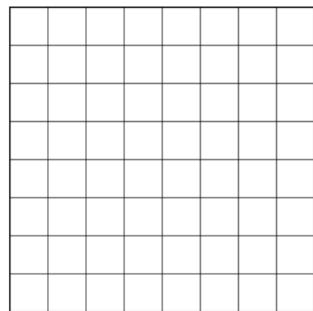
- Image class
- Measure(s) obtained from the image
- Position of objects within the image
- Segmentation

PatchCamelyon database

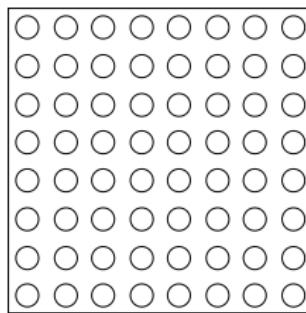
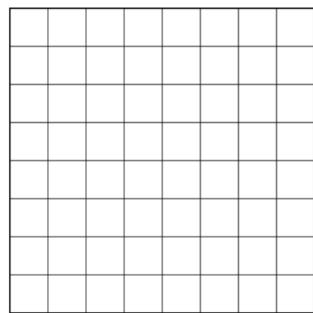


- 327 680 images of size 96×96
- Binary label (tumor tissue in center region or not)
- <https://github.com/basveeling/pcam>

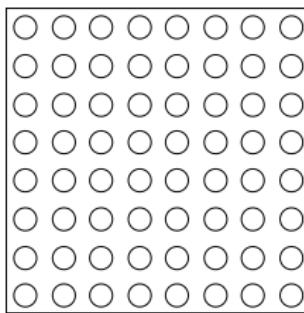
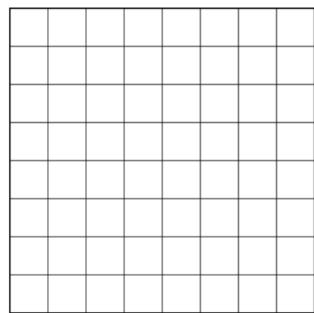
Layers representation



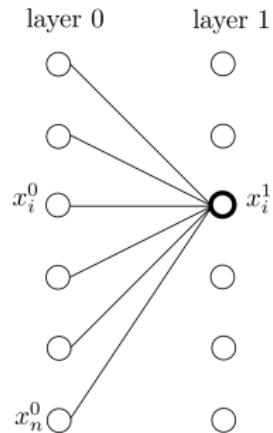
Layers representation



Layers representation

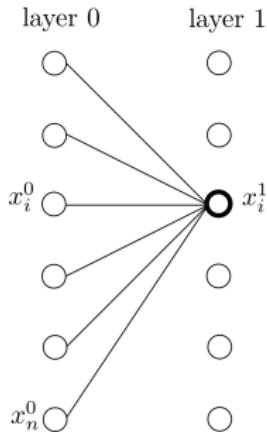


Towards convolutional layers

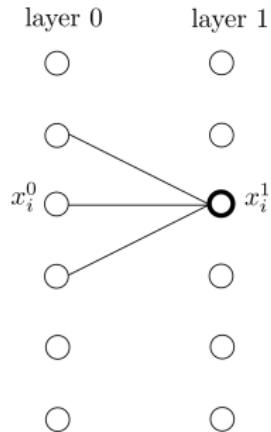


Fully connected layer:
 $n(n + 1)$ weights

Towards convolutional layers

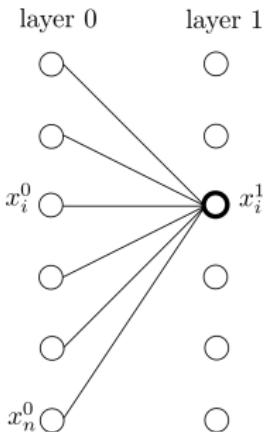


Fully connected layer:
 $n(n + 1)$ weights

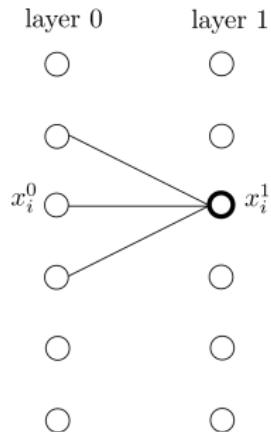


Locally conn. layer:
 $n(s + 1)$ weights

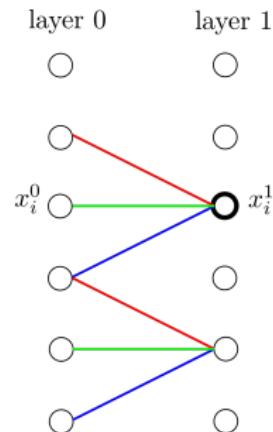
Towards convolutional layers



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



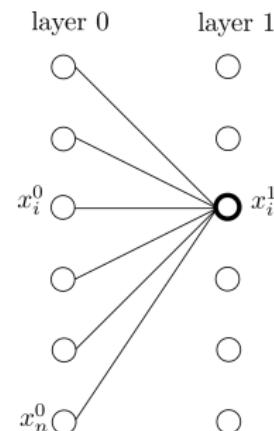
Locally conn. layer:
 $n(s + 1)$ weights



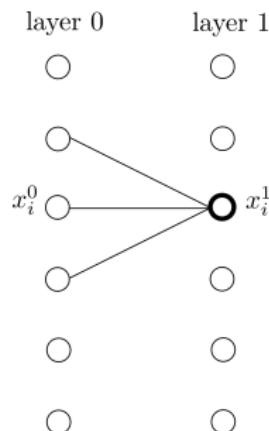
Weight replication: $s + 1$ weights.
Convolutional layer.

Towards convolutional layers: some figures

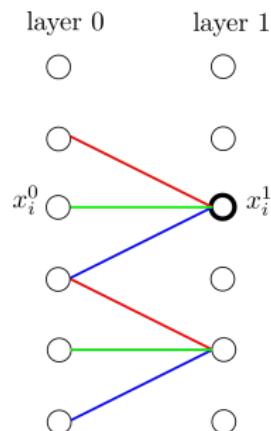
- 3×3 convolutions: $s = 9$
- Toy image: $n = 28 \times 28 = 784$
- Typical image: $n = 1000 \times 1000 = 10^6$



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



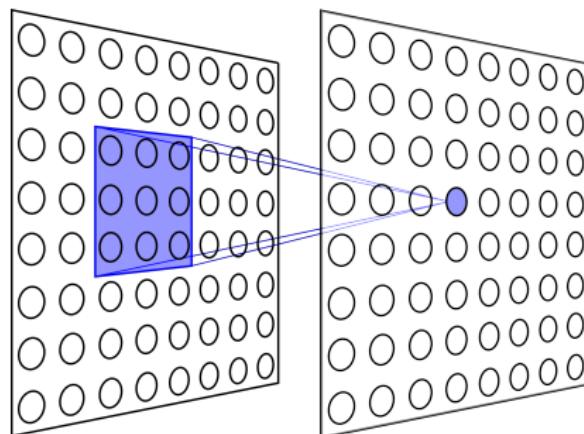
Locally conn. layer:
 $n(s + 1)$ weights
7840
 10^7



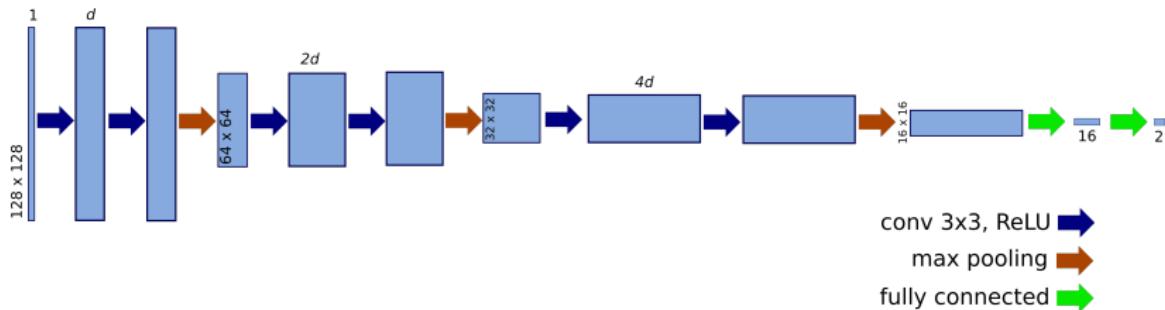
Weight replication: $s + 1$ weights.
10
 10^7

Convolutional layer illustration in 2D

- Illustration of a convolution of size 3×3

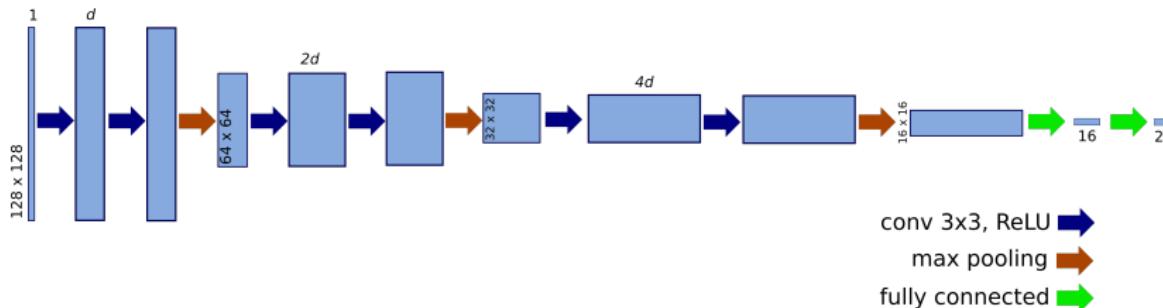


1D representations



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

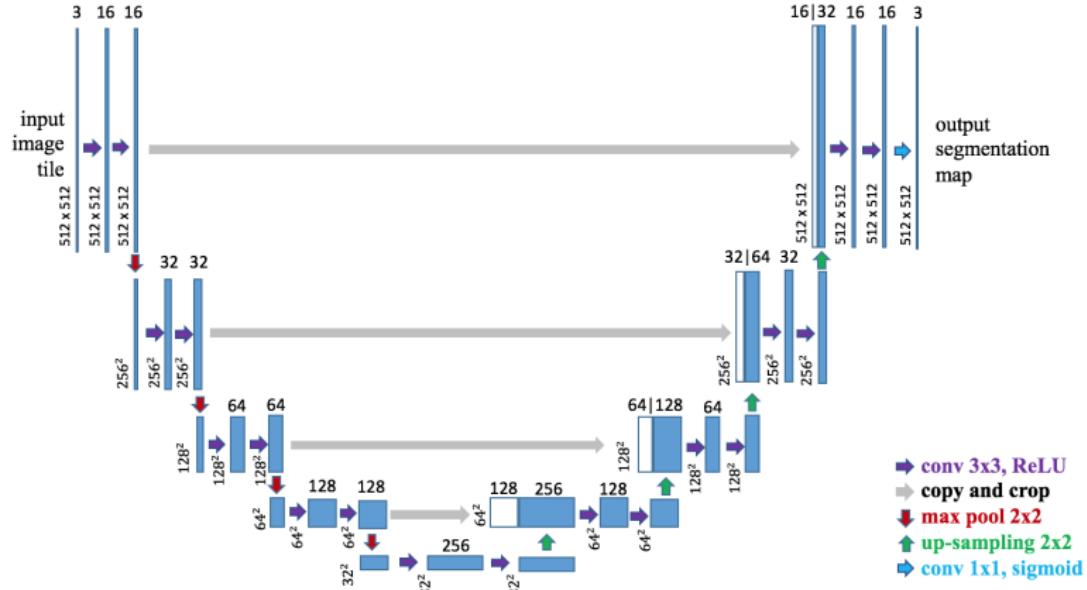
1D representations



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).

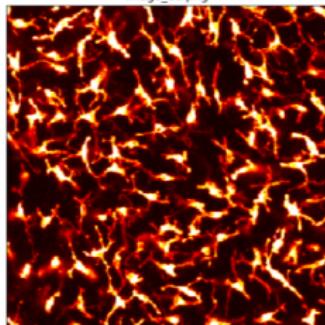
U-Net architecture [Ronneberger et al., 2015]



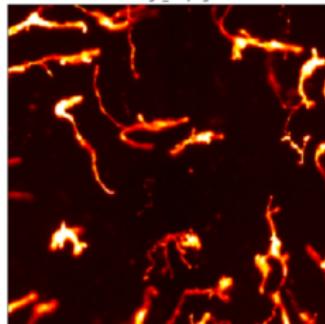
Example: counting cells

image

image_60.png

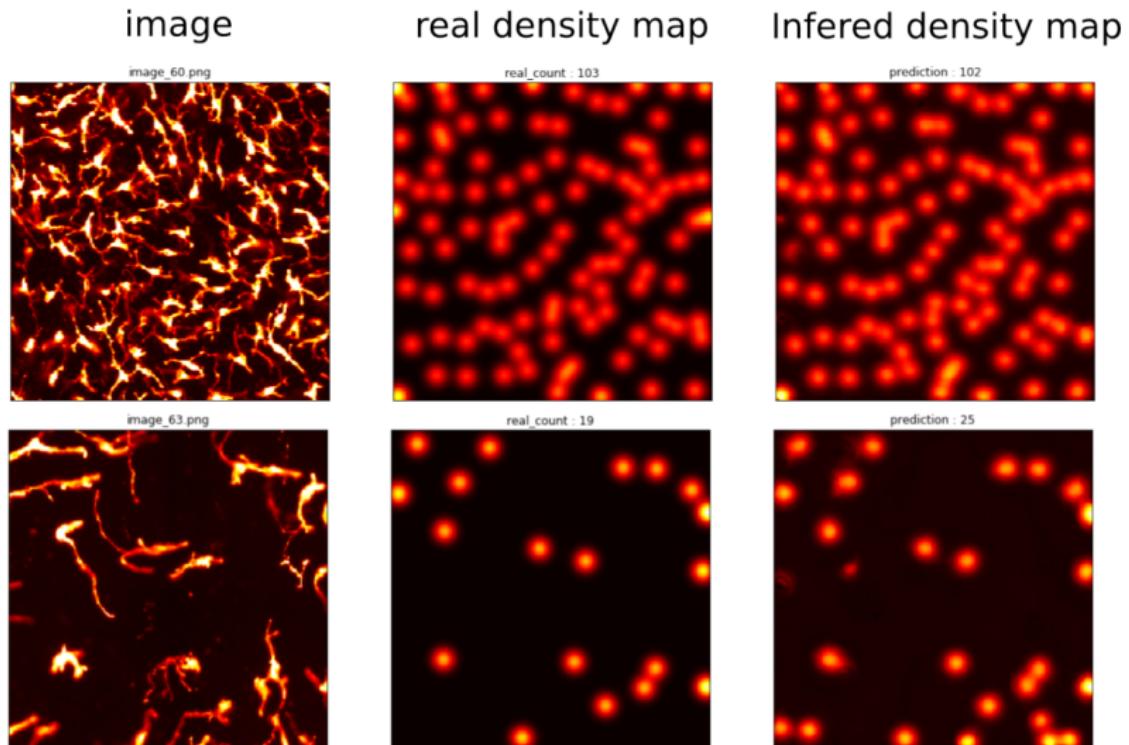


image_63.png



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

Counting cells



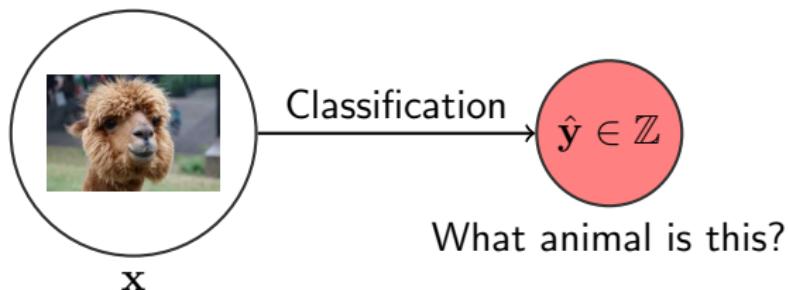
Credits: Tristan Lazard, master thesis. In collaboration with L'Oréal.

Contents

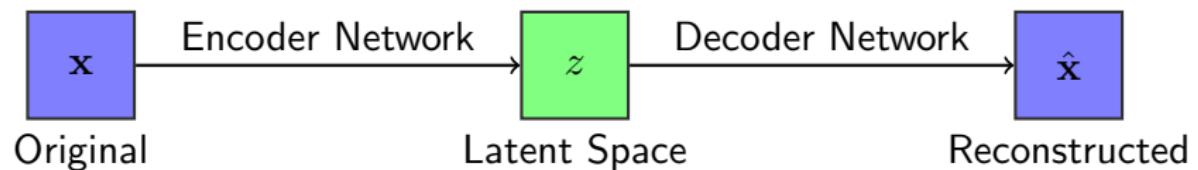
- 1 Introduction
- 2 Artificial neural networks
- 3 Application to images
- 4 Autoencoders and generative adversarial networks
- 5 Conclusion

Supervised Learning

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

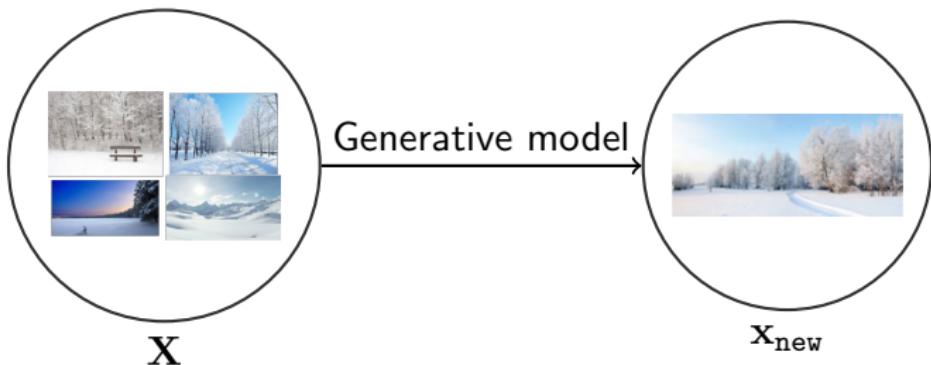


Autoencoders

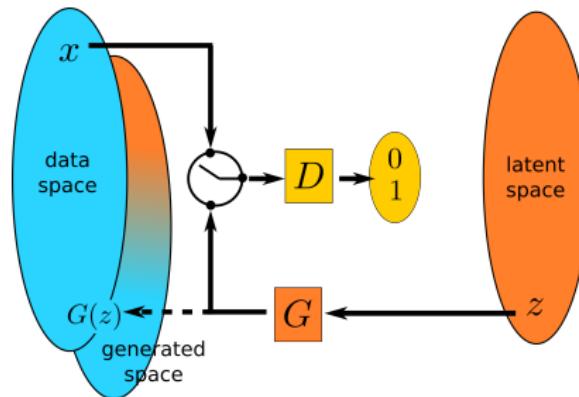


Unsupervised learning: Generative Models

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

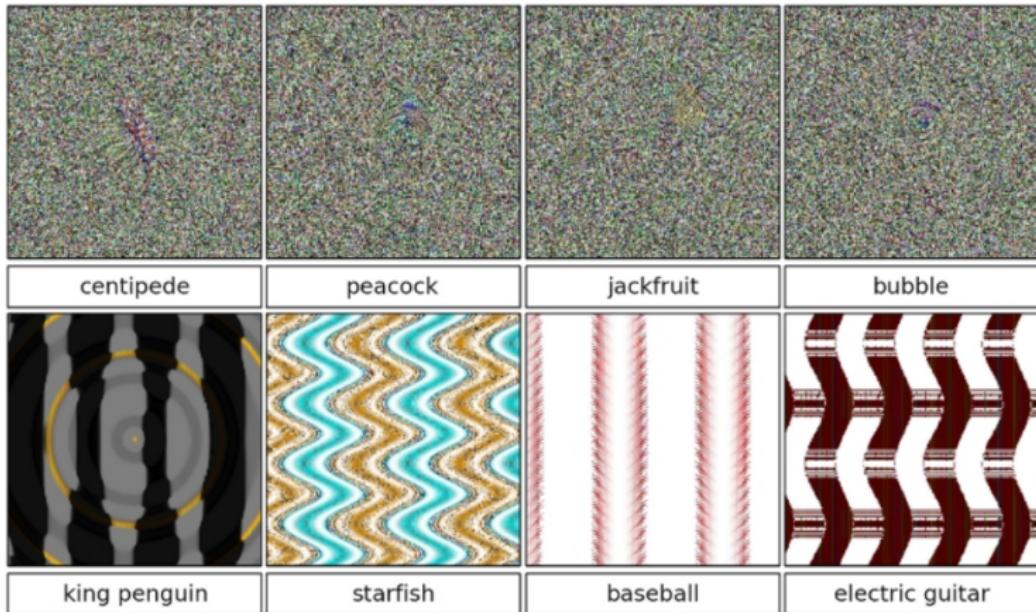
- 1 Introduction
- 2 Artificial neural networks
- 3 Application to images
- 4 Autoencoders and generative adversarial networks
- 5 Conclusion

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]



References |

- [Cybenko, 1989] Cybenko, G. (1989). Approximations by superpositions of a sigmoidal function. *Mathematics of Control, Signals and Systems*, 2:183–192.
- [Fukushima, 1979] Fukushima, K. (1979). Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position- Neocognitron. *ELECTRON. & COMMUN. JAPAN*, 62(10):11–18.
- [Goodfellow et al., 2014] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014). Generative Adversarial Nets. In *Advances in Neural Information Processing Systems 27*, pages 2672–2680. Curran Associates, Inc.
- [Hornik, 1991] Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural Networks*, 4(2):251–257.
- [Krizhevsky et al., 2012] Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. In Pereira, F., Burges, C. J. C., Bottou, L., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc.
- [LeCun, 1985] LeCun, Y. (1985). Une procedure d'apprentissage pour reseau a seuil asymmetrique (A learning scheme for asymmetric threshold networks). In *proceedings of Cognitiva 85*.

References II

- [Nguyen et al., 2015] Nguyen, A., Yosinski, J., and Clune, J. (2015). Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 427–436.
- [Ronneberger et al., 2015] Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In Navab, N., Hornegger, J., Wells, W. M., and Frangi, A. F., editors, *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, number 9351 in Lecture Notes in Computer Science, pages 234–241. Springer International Publishing.
- [Rosenblatt, 1958] Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, 65(6):386–408.
- [Werbos, 1982] Werbos, P. J. (1982). Applications of advances in nonlinear sensitivity analysis. In Drenick, R. F. and Kozin, F., editors, *System Modeling and Optimization*, Lecture Notes in Control and Information Sciences, pages 762–770, Berlin, Heidelberg. Springer.