Convolutional neural networks

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A picture is worth a thousand words

Definition

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

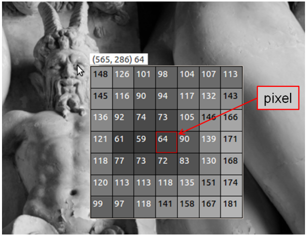

Figure: Grey level values around the left eye of the faun.

Designing computer vision systems that are able to extract semantic information from an image is a difficult task. How can we build systems that extract meaning from an image?

Extracting semantic information from an image

- Where is the phone? (localization task)
- How many mugs are there? (quantification task)
- Is there a window in the room?
- At what time of the day was the photograph taken?

Image processing approach

- Build a mathematical model for the objects you are interested in
- Implement this model using image processing operators

\+ This approach works correctly when the objects are not too complex.

\- If objects are difficult to model, machine learning methods can bring a solution.

Classical machine learning approach

- Compute features from the image
- Apply machine learning to those features

+ Works well when you engineer the right features
- An expert is required to define those features - and this can be a long process
- Annotated data is required

Deep learning approach

Modern neural networks approach

- Directly take as input the image pixels
- The network is supposed to build its own features

+ Good (impressive!) results

- A large amount of annotated data is required

Some accomplishments

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

2012: *AlexNet* [Krizhevsky et al., 2012] won this challenge by a large margin

The database contains more that 1 million training images, belonging to 1000 different classes (including 120 dog breeds!).

Some accomplishments (cont.)

- 2011: first super-human performance, IJCNN 2011 traffic sign recognition contest [Cireșan et al., 2011]
- 2012: visual object detection (Mitosis detection in breast cancer histology [Cireșan et al., 2013])
- 2012: segmentation competition (neuronal membranes in electron microscopy images [Ciresan et al., 2012])
- 2016: AlphaGo beats Lee Sedol, one of the best go players, in a 5-game match

Deep learning applications with images

- classification
- object localization
- semantic segmentation
- instance segmentation
- transformation (filtering, in-painting, editing, colorization...)
- quantification
- compression
- image caption generation
- 2D to 3D (stereo matching, 3D reconstruction, ...)
- motion estimation
- Style transfer
- Anomalous image detection
- Image generation

Convolutional neural networks in deep learning

- They are pivotal to many of the successes achieved by neural networks these recent years
- They are interesting for dealing with regular structured data, such as images (or board games!)

Acronyms

Two acronyms are used for convolutional neural networks in the literature: *CNN* and *ConvNet*.

Essential milestones

- 1979: Neocognitron (CNN architecture) [Fukushima, 1979, Fukushima, 1980]
- 1989: Backpropagation applied to CNNs [LeCun et al., 1989]
- 2006, 2010: GPU implementation [Chellapilla et al., 2006, Cireșan et al., 2010]

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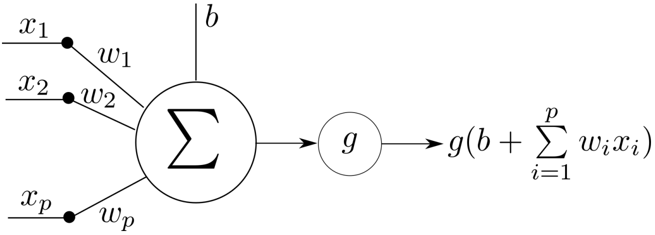
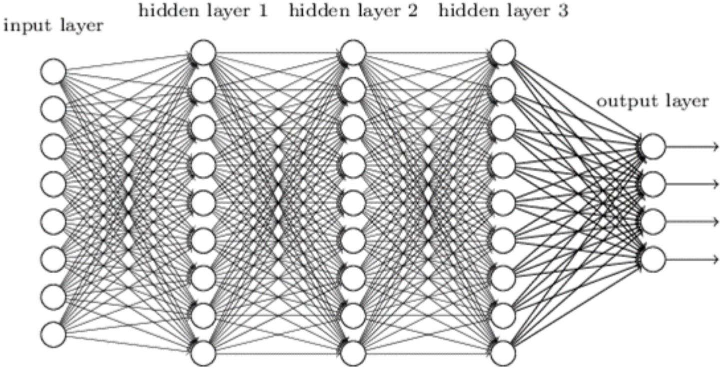
Artificial neuron



- $b, w_1, \ldots, w_n$ are the neuron parameters, to be learnt
- g is the activation or transfer function

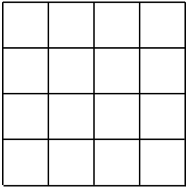
Neural network



(from http://www.jtoy.net)

Input image, input neurons

In the scalar case (single-valued images), each input pixel is considered as an input neuron.



Input image, input neurons

In the scalar case (single-valued images), each input pixel is considered as an input neuron.

Image classification problem

Classification problem:

- Input: image $\mathbf{x}$
- Output: class $y \in \{label_1, label_2, \dots, label_q\}$

Class coding

Often, classes are denoted by integers, but this is only a coding commodity. For instance, it would be meaningless to use a regression approach for this problem.

Class coding

If there are q possible classes, then a class will be coded as a vector $\mathbf{y}$ of length q. If its class is r then for $0 \leq i < q$:

$$\mathbf{y}[i] = \begin{cases} 1, & \text{if } i = r \\ 0, & \text{otherwise} \end{cases}$$

Example with 4 classes

- Label $0 \longmapsto [1, 0, 0, 0]$
- Label $1 \longmapsto [0, 1, 0, 0]$
- Label $2 \longmapsto [0, 0, 1, 0]$
- Label $3 \longmapsto [0, 0, 0, 1]$

Image classification with a neural network

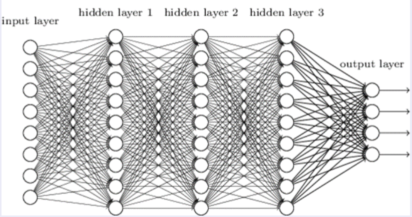
Input

Scalar image is transformed into a vector of length p.

Output

For q classes, the output will be a vector of length q.

Example: image of size 4×2, 4 possible classes



Activation of the last layer

Loss function for classification: cross-entropy

Conclusion on fully-connected networks for image classification

Fully connected layers:

- scale badly to large size images
- do not take into account the local structure of images

Today:

- Fully-connected networks are almost never used for image analysis.
- Fully-connected layers are only used in the middle (auto-encoders) or at the end (classification) of the pipeline.

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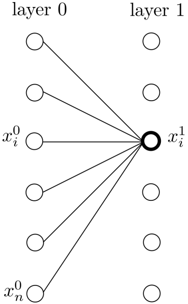
Towards convolutional layers

In the following slides, for illustration purposes, we will consider one-dimensional images



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

Towards convolutional layers

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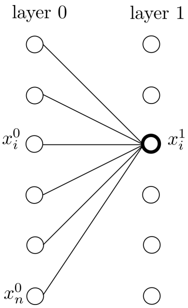
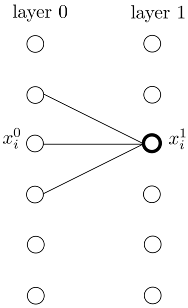


Fully connected layer: $n(s+1)$ weights



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

Towards convolutional layers

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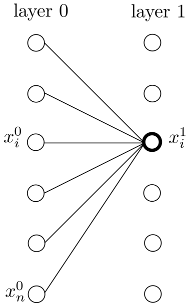

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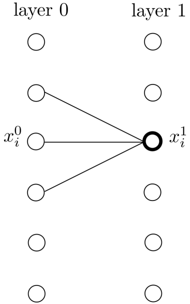

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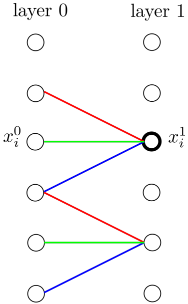

Weight replication: $s+1$ weights

Towards convolutional layers

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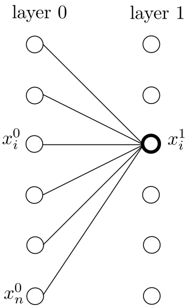
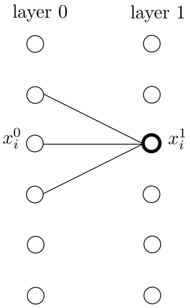
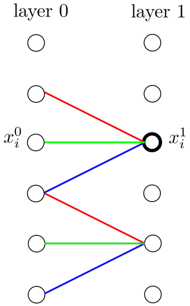


Fully connected layer: $n(s+1)$ weights



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

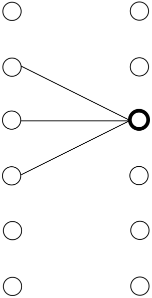


Weight replication: $s+1$ weights

A convolutional layer computes a convolution, plus a constant, of the precedent layer.

Stride

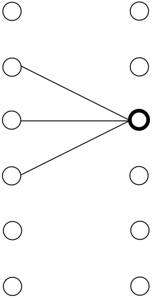
A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.

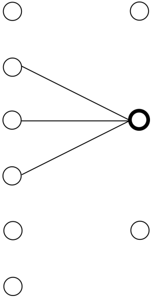


Stride 1

Stride

A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.

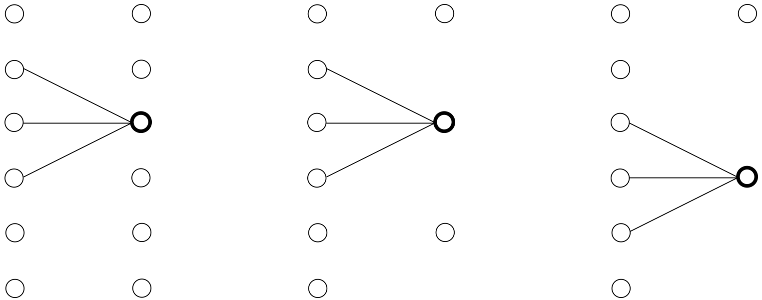




Stride 1 Stride 2

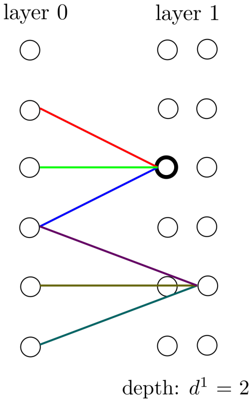
Stride

A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.

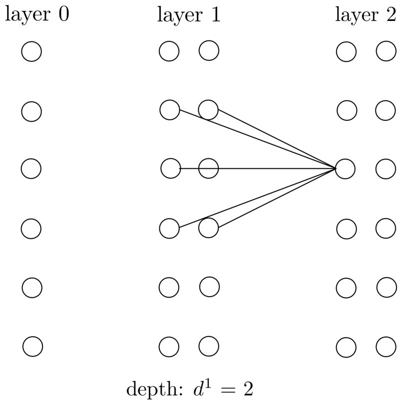


Stride 1 Stride 2 Stride 3

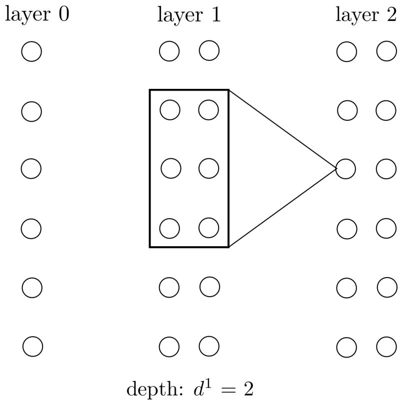
Several filters in the same convolutional layer



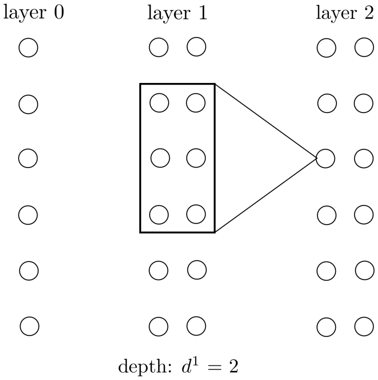
Several filters in the same convolutional layer



Several filters in the same convolutional layer

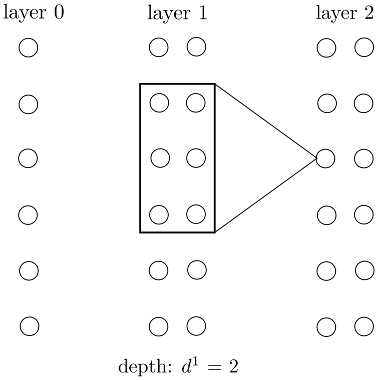


Consequences on the parameter number



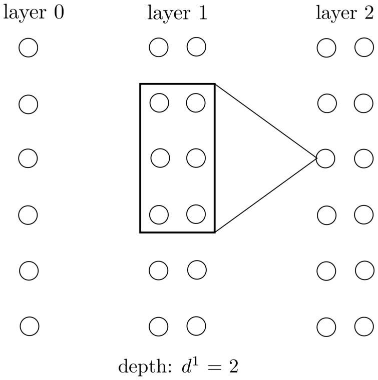
- How many parameters do we have in layer 1?

Consequences on the parameter number



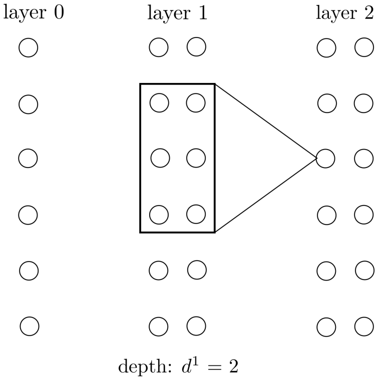
- How many parameters do we have in layer 1?
- $d^1 \times (s+1)$

Consequences on the parameter number



- How many parameters do we have in layer 1?
- $d^1 \times (s+1)$
- In layer 2?

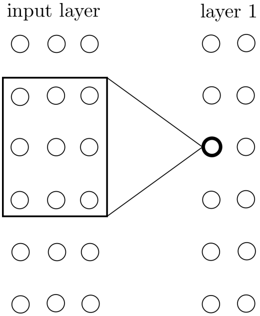
Consequences on the parameter number



- How many parameters do we have in layer 1?
- $d^1 \times (s+1)$
- In layer 2?
- $d^2 \times (d^1 \times s + 1)$

Multi-valued images

An input image with p channels (for instance à colour image with 3 channels) can be represented by an input layer of depth 3



Some properties

- Translation invariance
- Efficient implementation using matrix operations and graphical processing units

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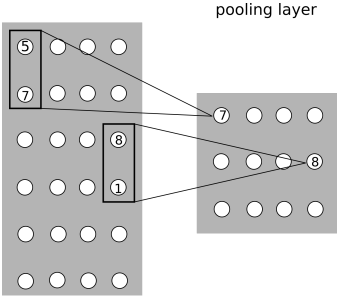
Max pooling

- Convolutional networks often contain subsampling steps. These can be done using strides of 2 or more within convolutional layers or, as it is common practice today, using *max pooling* layers.
- Sampling is only applied along the spatial dimensions, not along the dimension of the filters.



Skip connections

Main components of a convolutional neural network

Many successful architectures, especially for image classification, follow the same pattern:

1. Several iterations of: One or several convolutional layers, with increasing depth, followed by max pooling
2. A few fully connected layers

VGGnet

- Proposed by K. Simonyan and A. Zisserman from the University of Oxford [Simonyan and Zisserman, 2014]
- Runner-up in the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2014.
- Number of parameters (VGG16): 138 million.

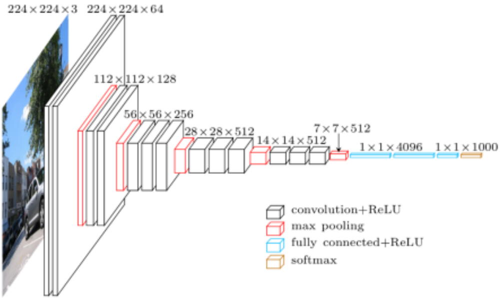


Figure: VGG16 (From https://www.cs.toronto.edu/ frossard/post/vgg16/)

GoogLeNet (a.k.a. Inception v1)

- Winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2014.
- Number of parameters: *only* 5 million.

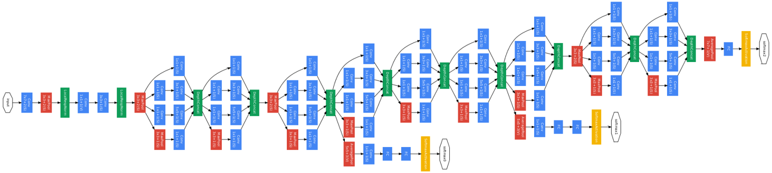


Figure: From [Szegedy et al., 2014]

ResNet won the following year...

Inception module

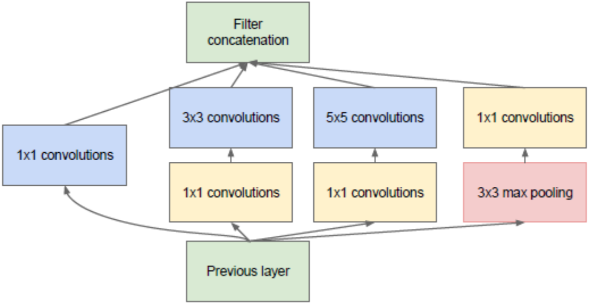


Figure: From [Szegedy et al., 2014]

ResNet

- Winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2015.
- The authors tested up to 1202 layers. They reported no training difficulties, but overfitting [He et al., 2015]

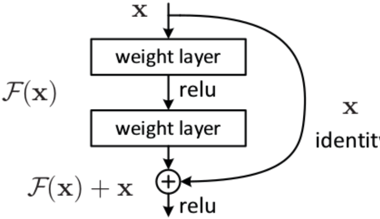


Figure: Residual learning block (from [He et al., 2015])

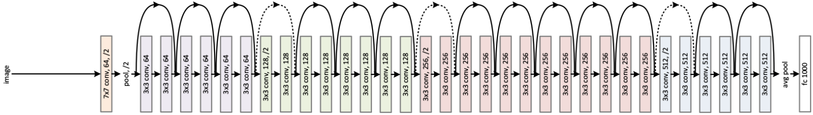


Figure: Residual network with 34 layers (from [He et al., 2015])

Current trends

- Small convolutions (3×3)
- Dimension reduction using 1×1 convolutions
- Increasing number of layers
- Skip connections

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Designing a convolutional neural network

- Network architecture
- Hyper-parameter setting
- Optimization method and parameters

Learning, specially for complex networks, can be difficult. It is always time consuming.

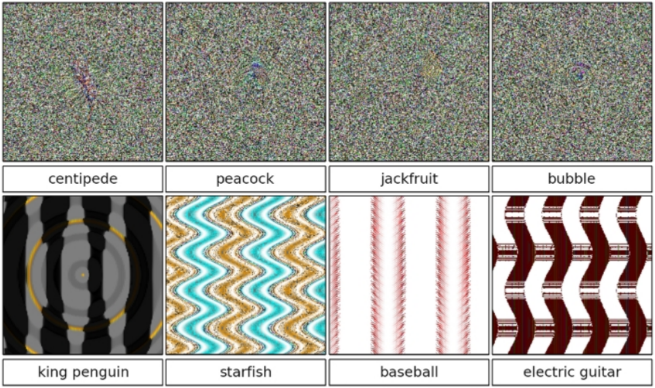
Using an existing network

- Replicate network architecture and hyper-parameters
- Load weights

With standard libraries this is very simple. Prediction time is usually fast.

ConvNets can be fooled

Deep learning can produce astonishing results [Nguyen et al., 2015]...



Main deep learning libraries

Deep learning is a very competitive domain, where code sharing is very common.

- Theano
- Torch
- Tensorflow
- Caffe
- MatConvNet

Keras

Keras is a very easy to use interface to Theano and Tensorflow.

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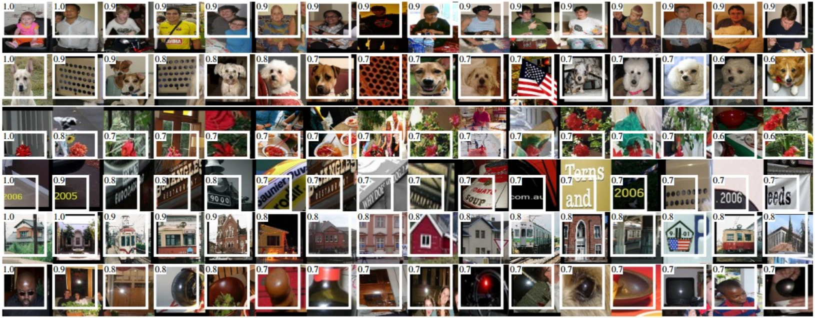
Visualizing at least what we don't understand

We do not fully understand today where the good performances of deep learning come from. But we can at least have a look at what is going on inside the networks.

- Neuron outputs (activations)
- Filter values
- "Important" pixels

Maximal neuron activation

Which images maximally activate a given neuron?
[Girshick et al., 2014]



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A revolution in image analysis

- Deep learning has brought an undeniable break-through in image analysis (as in other fields)
- A significant part of research efforts in image analysis today is base on deep learning
- Its applications are ubiquitous

Limitations

For a deep-learning solution to work, you need:

- Enough annotated data
- A lot of fiddling (different architectures; hyper-parameters; optimization)
- One (or, even better, several) powerful GPUs

Moreover, these models lack interpretability.

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