

Convolutional neural networks

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Correction TP 1

- Utilisation de Google Drive
- Optimiser le réseau pour les bases Moons et Circles
 - Meilleures valeurs de q et lr ?
- Codage de l'entropie croisée et de sa dérivée. **Attention à la dernière activation!**
- Comparaison:
 - Besoin d'une base de **test**.
 - Quantification.

Contents

- 1 Introduction
- 2 Application of fully connected NNs to image classification
- 3 From fully-connected layers to convolutional layers
- 4 Building convolutional networks
- 5 Some classical architectures
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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

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?

Extracting semantic information from an image



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Designing computer vision systems that are able to extract semantic information from an image is a difficult task.

Image analysis applications

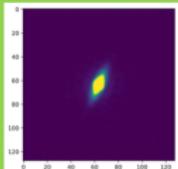
image → valeur	image → image (segmentation)
 → oiseau	 → Base COCO
 → 50,2	 → Dong et al., ECCV 2014



Image analysis applications

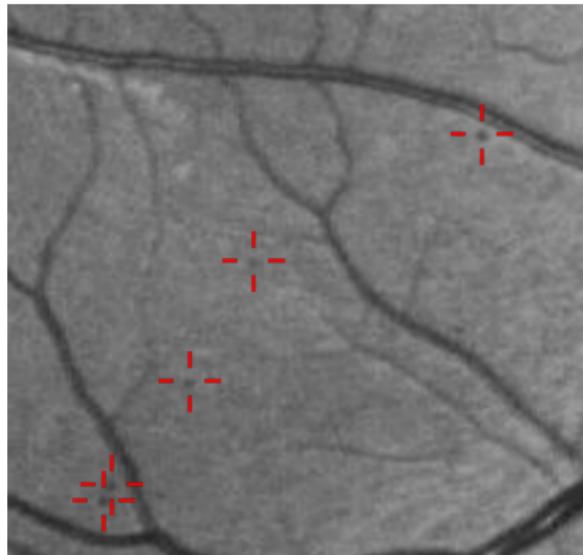
- classification
- quantification
- object localization
- segmentation
- transformation (filtering, in-painting, editing, colorization...)
- image caption generation
- 2D to 3D (stereo matching, 3D reconstruction, ...)
- motion estimation
- style transfer
- compression
- anomalous image detection
- image generation
- etc.

Image processing approach

- Build a geometrical model for the objects of interest
- Implement this model using image processing operators

Image processing approach

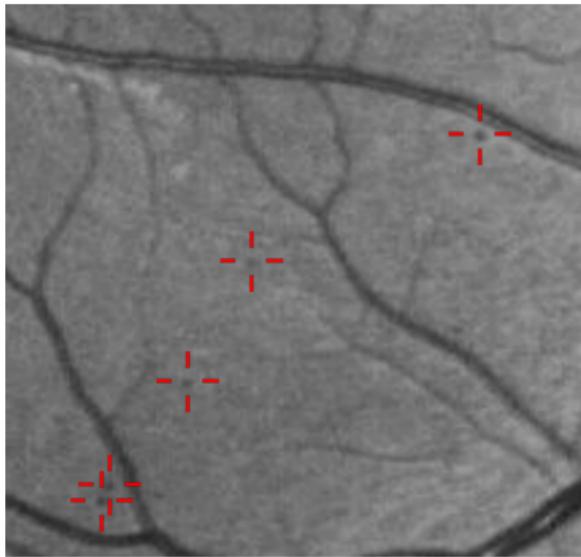
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Detail of eye fundus image with microaneurysms to be detected

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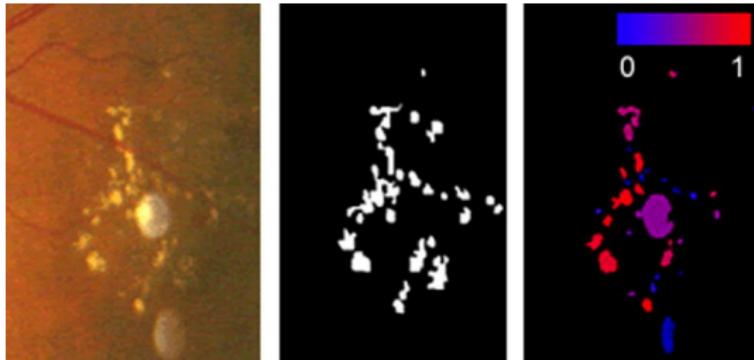
- ⊕ This approach works correctly when the objects are not too complex.
- ⊖ If objects are difficult to model, machine learning methods can bring a solution.

Classical machine learning approach

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

Classical machine learning approach

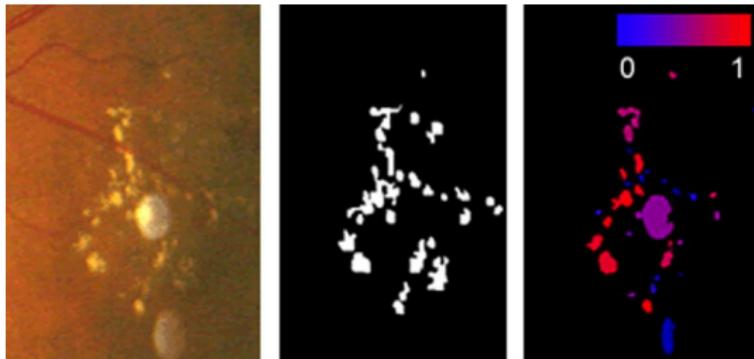
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Exudates segmentation: original image, ground-truth and candidates with associated probabilities obtained with machine learning

Classical machine learning approach

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Exudates segmentation: original image, ground-truth and candidates with associated probabilities obtained with machine learning

- ⊕ Works well with 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

- 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
 - ⊖ Extensive computing resources needed

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 [?]

- 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
- It has been used since 1998
- Human performance on a similar database (NIST) is reported to be around 1.5% error [?]
- Best methods, based on convolutional neural networks, give around 0.21% test error.

MNIST database



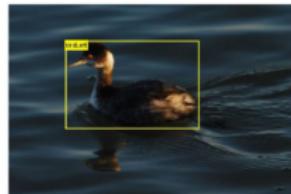
Credits: Images from MNIST assembled
by Josef Stepan (licensed under CC
BY-SA 4.0)

Pascal VOC project [?, ?]

This project organized a challenge from 2005 to 2012, divided into several tasks, including an image classification task.

Pascal VOC image classification task (2012)

Train/val: 11 540 images where the presence of 20 categories of objects was annotated. The test dataset is unknown and tests are run online (still available).



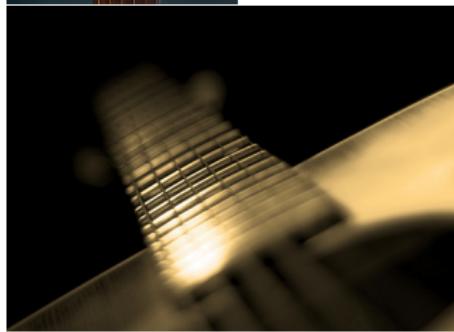
ImageNet project [?]

Since 2010, ImageNet organizes an annual challenge: The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), that constituted a breakthrough in the design of image analysis challenges by its size.

Image classification task (since 2012)

- Training: 1 281 167; validation: 50 000; test: 100 000.
- 1 000 classes (90 dog breeds!).

ImageNet projet

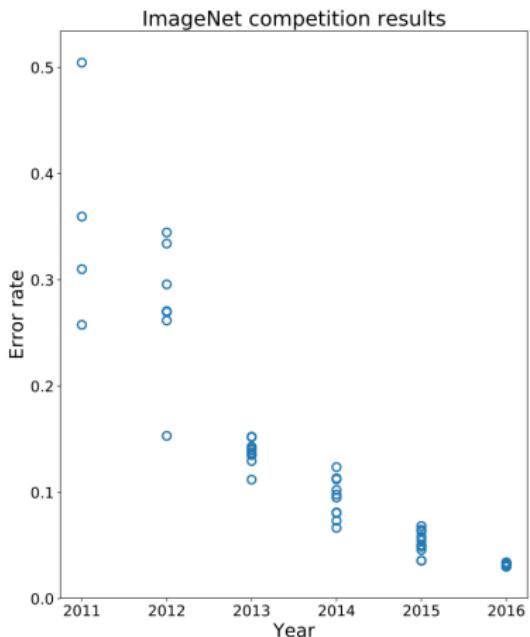


Examples from the *acoustic guitar* class

Deep learning achievements

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

2012: *AlexNet* [?] won this challenge by a large margin



Deep learning achievements (cont.)

- 2011: first super-human performance, IJCNN 2011 traffic sign recognition contest [?]



- 2012: visual object detection (Mitosis detection in breast cancer histology [?])
- 2012: segmentation competition (neuronal membranes in electron microscopy images [?])

Deep learning achievements (cont.)

- 2016: AlphaGo beats Lee Sedol, one of the best go players, in a 5-game match



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

CNN and *ConvNet*

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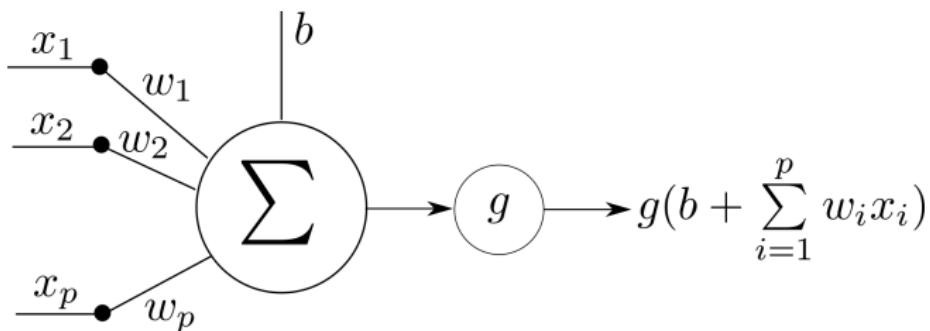
CNN and *ConvNet*

Our first task: image classification!

Contents

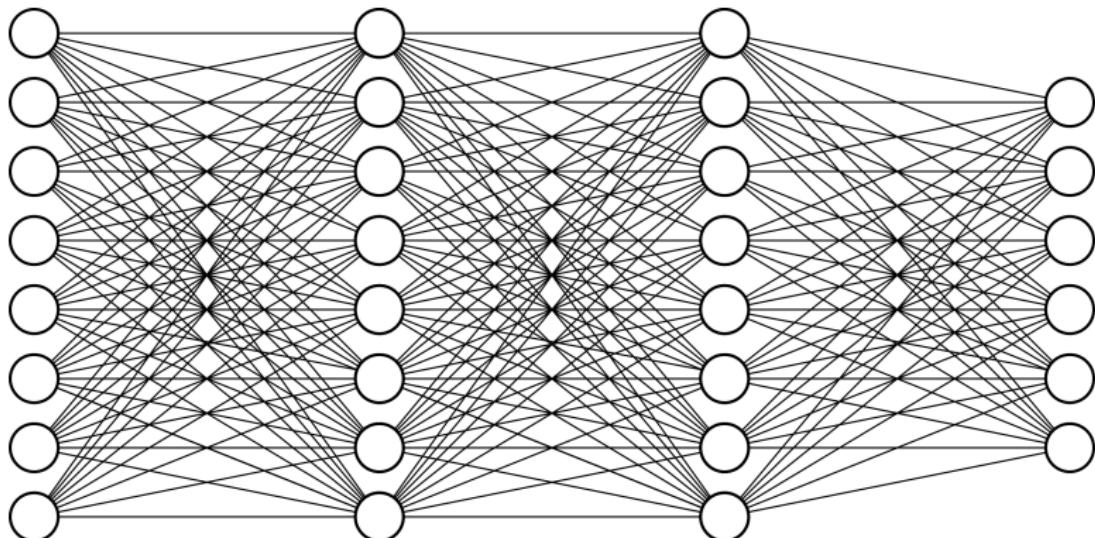
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Reminder: Artificial neuron



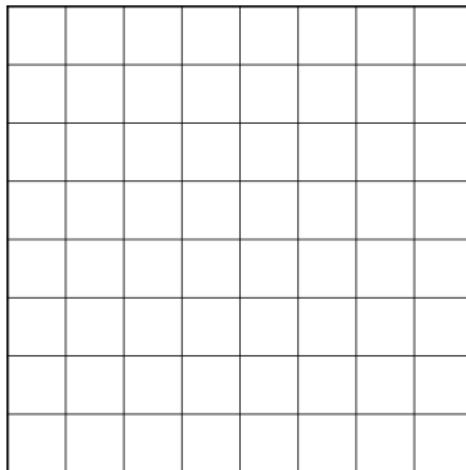
- b, w_1, \dots, w_n are the neuron parameters, to be learnt
- g is the activation or transfer function

Reminder: Neural network



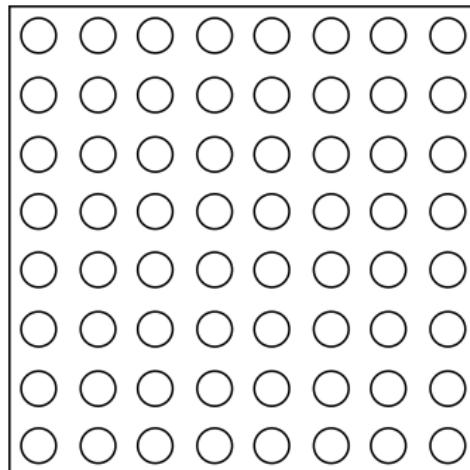
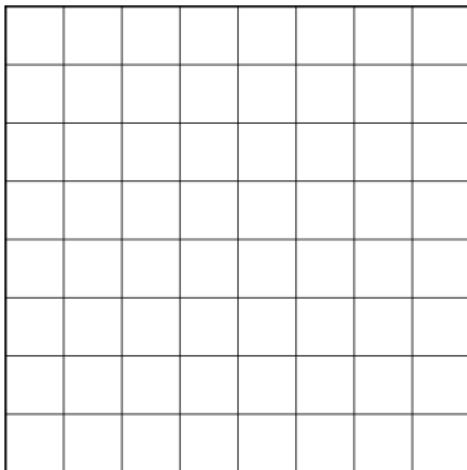
Input image, input neurons

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



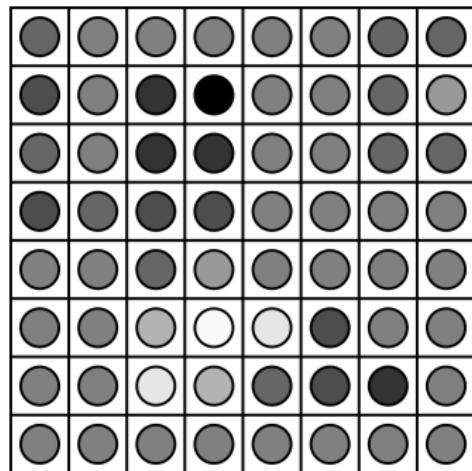
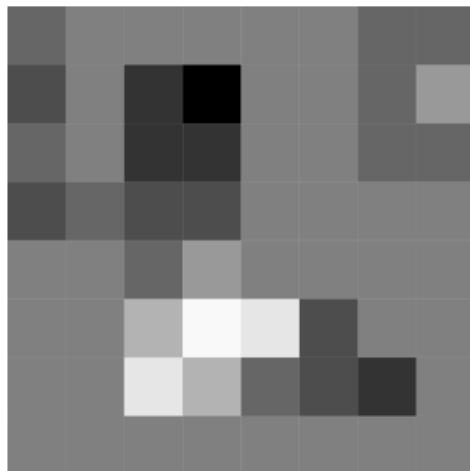
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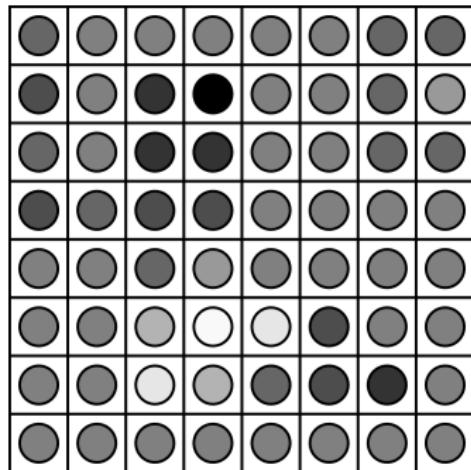
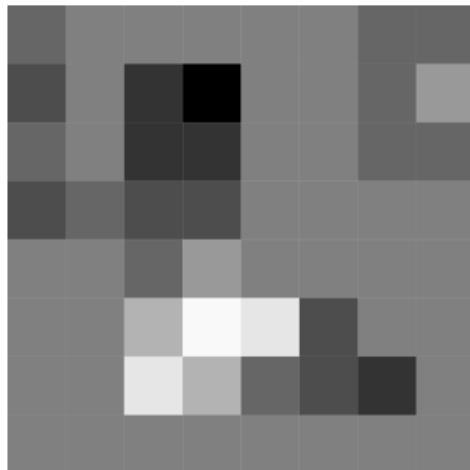


Image preprocessing

Often, the input image is modified to make the optimization of the model easier.

Image classification problem

Classification problem:

- Input: image
- 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 $\mapsto [1, 0, 0, 0]$
- Label 1 $\mapsto [0, 1, 0, 0]$
- Label 2 $\mapsto [0, 0, 1, 0]$
- Label 3 $\mapsto [0, 0, 0, 1]$

This is called **one-hot encoding**. The resulting vector is a one-hot vector.

Activations

Different activations (typically ReLU) can be used in the intermediate layers.

Concerning the last layer: Given that the aim is a vector containing zeros except for a one, two designs are commonly used:

- Use a sigmoid as last activation
- Last layer: a softmax operator

Softmax operator

Definition

The softmax operator $\sigma : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is given by:

$$\forall \mathbf{x} \in \mathbb{R}^d, \forall k \in \{1, \dots, d\} : \quad \sigma(\mathbf{x})_k = \frac{e^{\mathbf{x}_k}}{\sum_{i=1}^d e^{\mathbf{x}_i}}$$

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Some properties

- $0 < \sigma(\mathbf{x})_k < 1$
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Example

$$\mathbf{x} = \begin{pmatrix} 10.1 \\ 0 \\ -4.3 \\ 1.33 \end{pmatrix} \quad \sigma(\mathbf{x}) \approx \begin{pmatrix} 0.9998 \\ 0.000041 \\ 0.00000056 \\ 0.00016 \end{pmatrix}$$

Loss function for classification: cross-entropy

The preferred loss function for classification is cross-entropy:

For \mathbf{y} in $\{0, 1\}^d$ and $\hat{\mathbf{y}}$ in $]0, 1[^d$:

$$H(\mathbf{y}, \hat{\mathbf{y}}) = - \sum_{i=1}^d \mathbf{y}_i \log(\hat{\mathbf{y}}_i)$$

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- Note that the binary cross-entropy we previously saw is a particular case of cross-entropy.

Image classification with a fully-connected NN

Input

The input image, containing p pixels, is transformed into a vector of length p .

Output

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

Image classification with a fully-connected NN

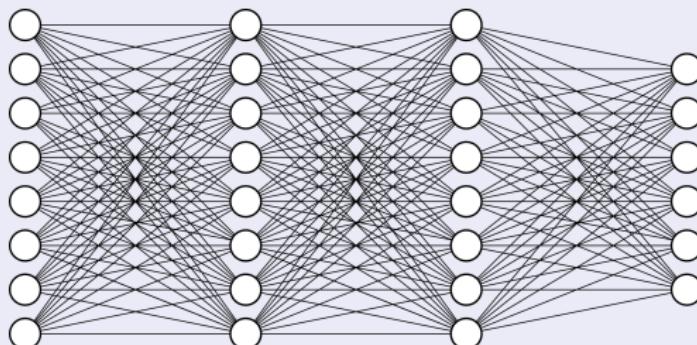
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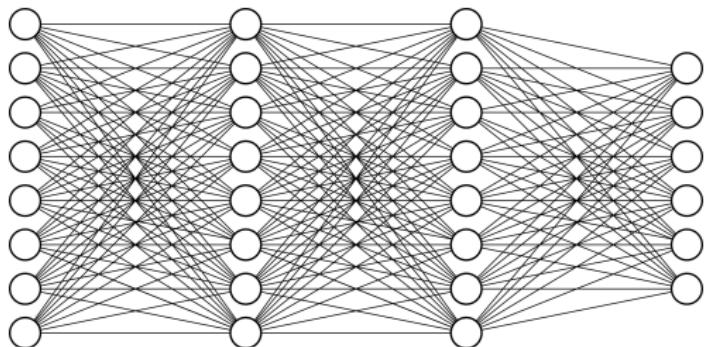
Example: image of size 4×2 , 4 possible classes



Flatten

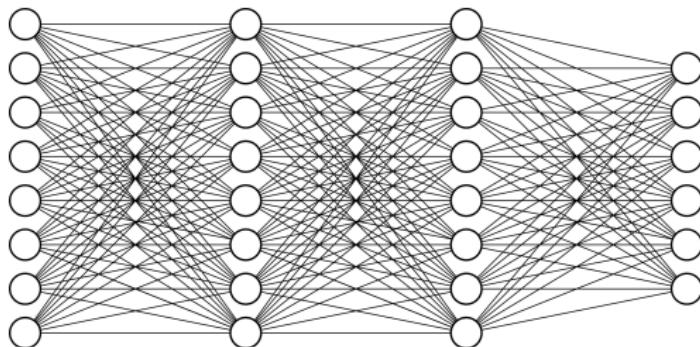
- Transforms an array into a vector
- Loss of spatial information
- This is typically done to transition between a convolutional layer and a fully-connected one.

Image classification using a fully-connected NN



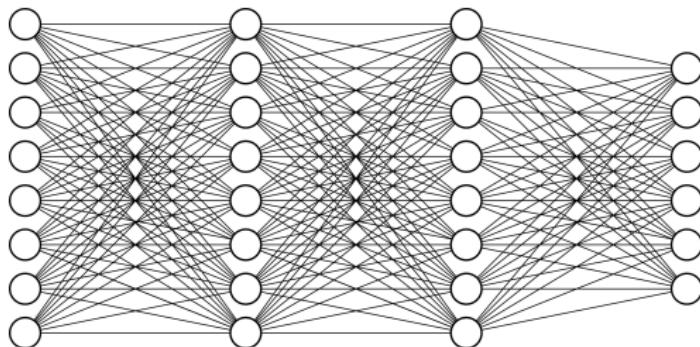
- A small image contains at least 100 000 pixels

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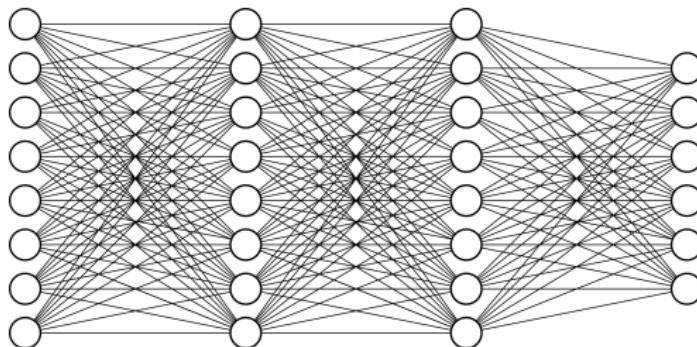
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Image classification using a fully-connected NN



- A small image contains at least 100 000 pixels
- The number of parameters between two layers of that size is $10^5 \times (10^5 + 1)!$
- This approach is not feasible...
- Moreover, this approach does not take into account the local structure of images.

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:

- NN solely composed of fully-connected layers 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.

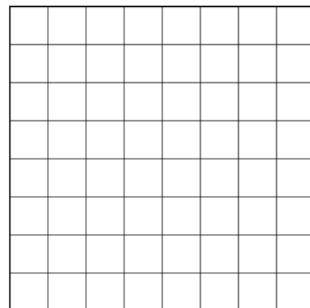
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Layers representation

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.

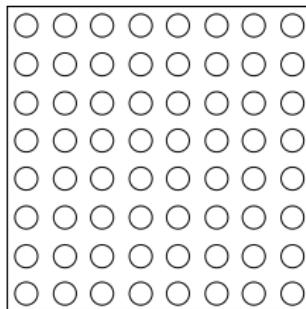
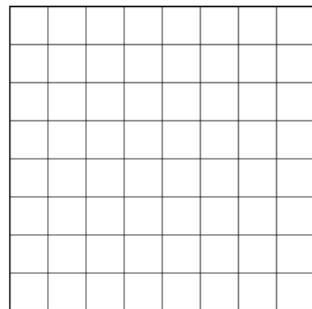
We represent some connections between neurons. Each such connection is associated to a weight. The bias are not represented, to avoid clutter, but must not be forgotten.



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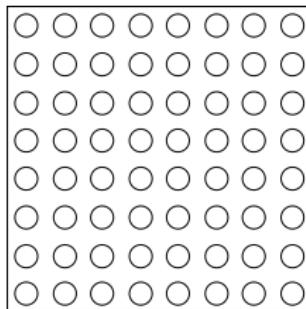
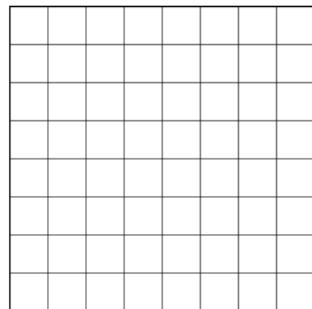
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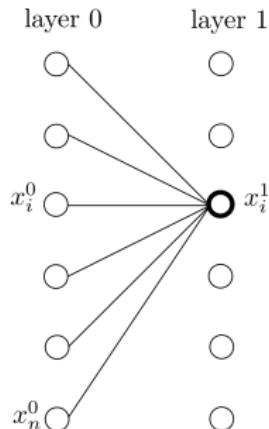
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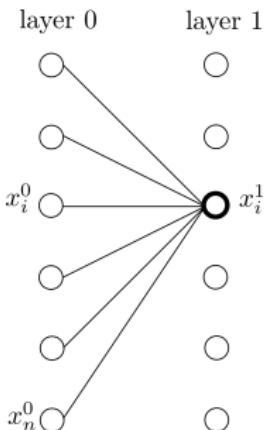


Towards convolutional layers

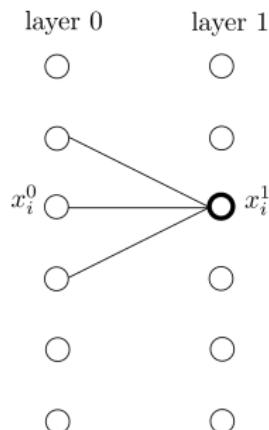


Fully connected layer:
 $n \times n$ weights and n bias:
 $n(n + 1)$ parameters

Towards convolutional layers

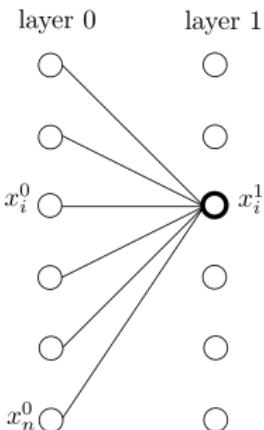


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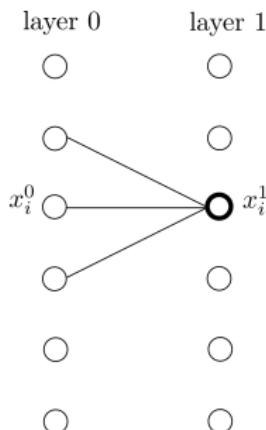


Locally conn. layer:
 $n(s + 1)$ parameters

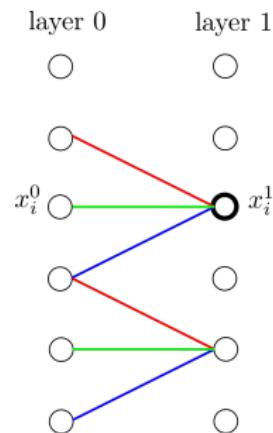
Towards convolutional layers



Fully connected layer:
 $n \times s$ weights and s bias:
 $n(s + 1)$ parameters



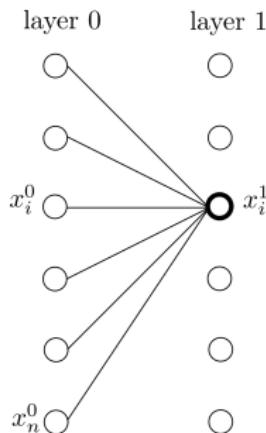
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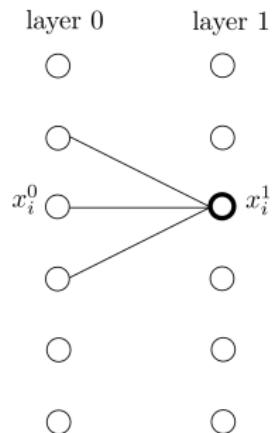
Weight replication: $s + 1$ parameters.
Convolutional layer.

Towards convolutional layers: some figures

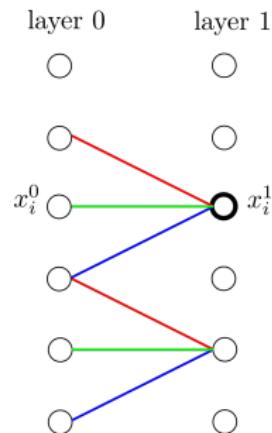
- 3×3 convolutions: $s = 9$
- Toy image: $n = 28 \times 28 = 784$
- Typical image: $n = 1000 \times 1000 = 10^6$



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

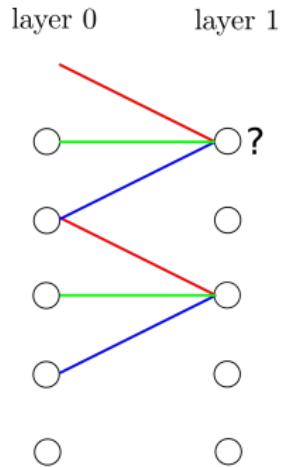


Locally conn. layer:
 $n(s + 1)$ parameters
7840
 10^7



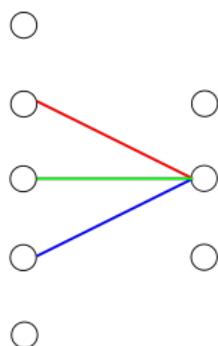
Weight replication: $s + 1$ parameters.
10
10

Dealing with borders



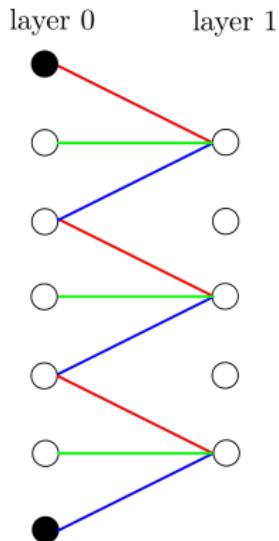
First solution: keep only well defined outputs

layer 0 layer 1



- Pros:
 - border effect disappears
- Cons:
 - Lack of flexibility

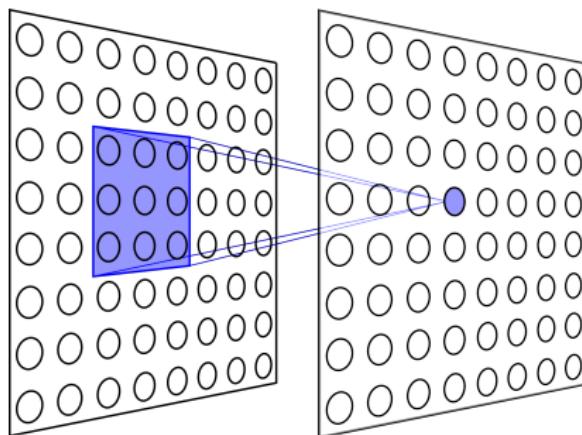
Second solution: zero padding



- Pros:
 - More flexible architecture
- Cons:
 - Border effect still present

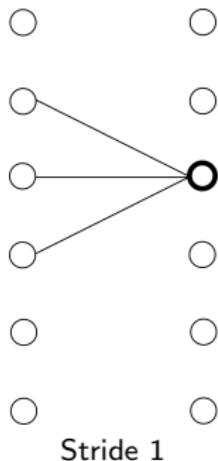
Convolutional layer illustration in 2D

- Illustration of a convolution of size 3×3



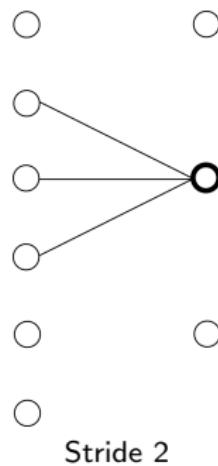
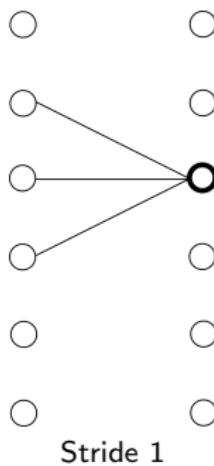
Stride

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



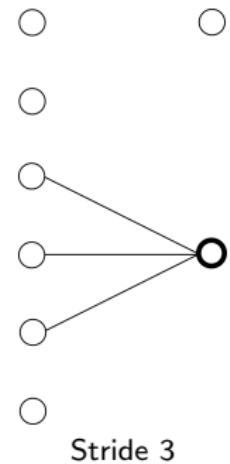
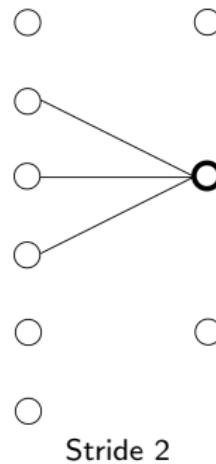
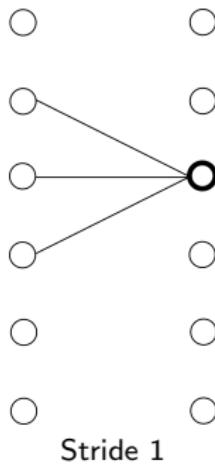
Stride

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



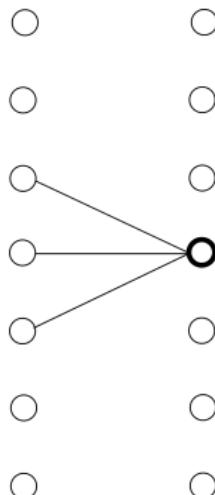
Stride

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



Dilated convolutions

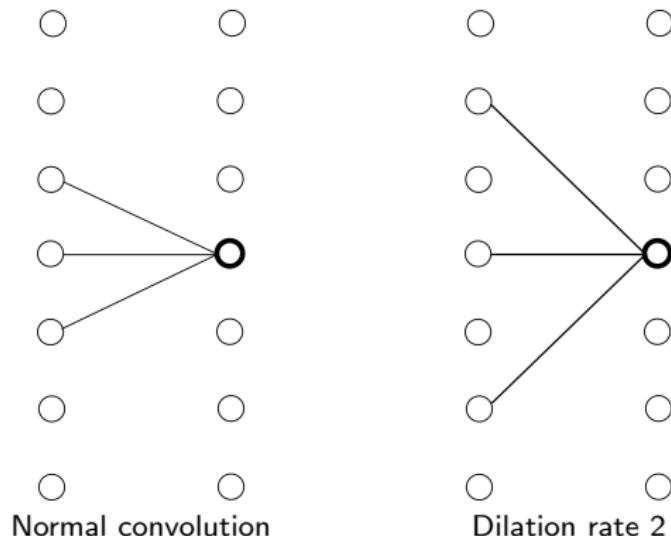
Dilated convolutions are used to increase the size of the receptive field of the network.



Normal convolution

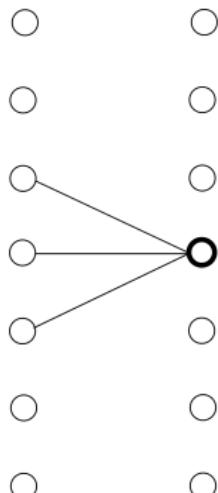
Dilated convolutions

Dilated convolutions are used to increase the size of the receptive field of the network.

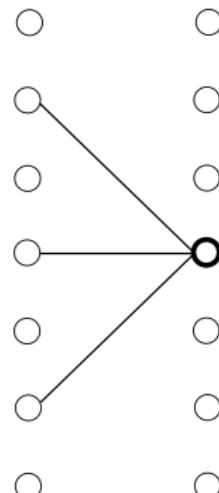


Dilated convolutions

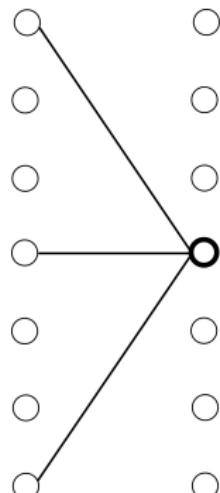
Dilated convolutions are used to increase the size of the receptive field of the network.



Normal convolution

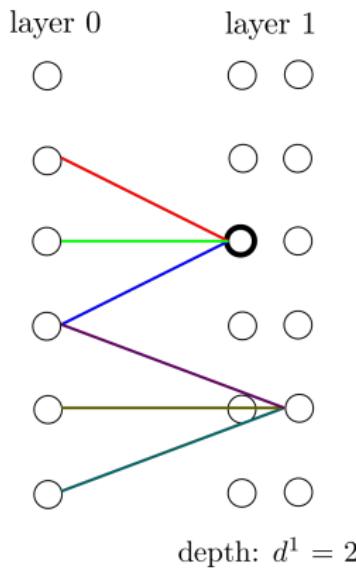


Dilation rate 2



Dilation rate 3

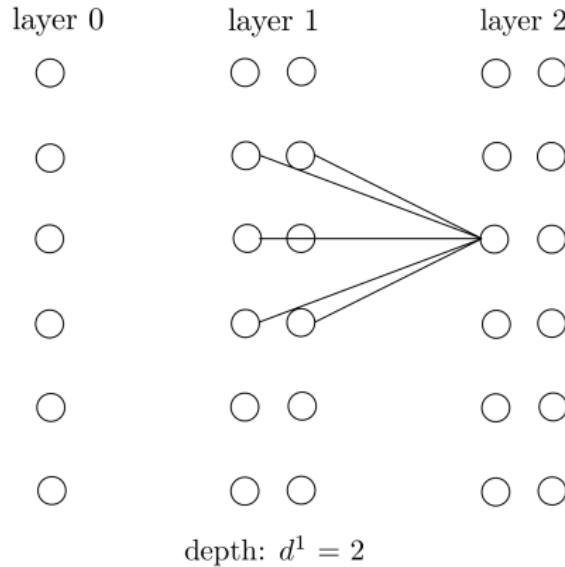
Several filters in the same convolutional layer



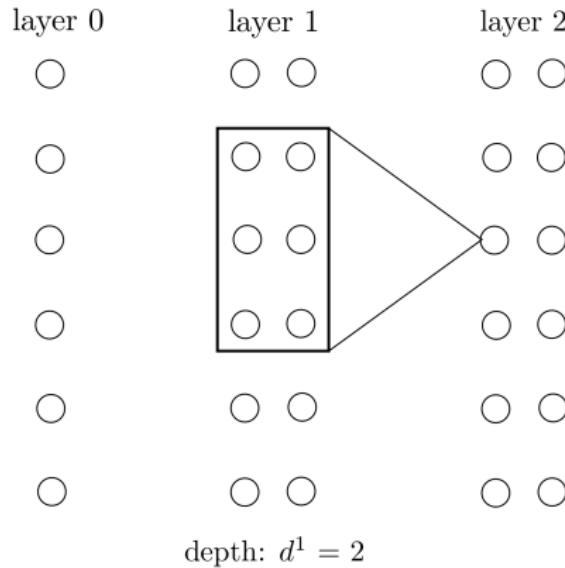
Note on vocabulary

The depth of a layer is often called the **number of filters**.

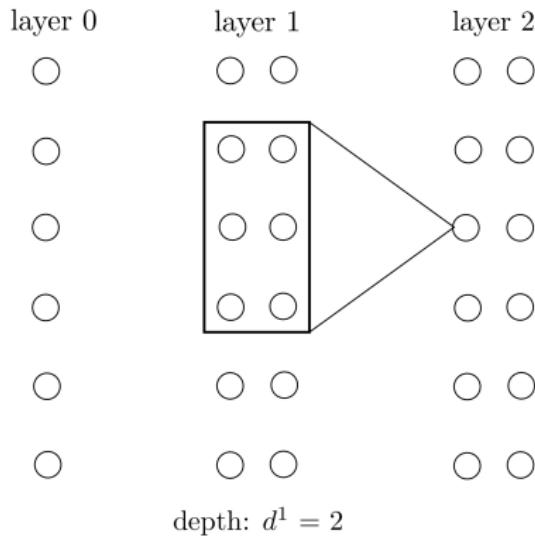
Several filters in the same convolutional layer



Several filters in the same convolutional layer

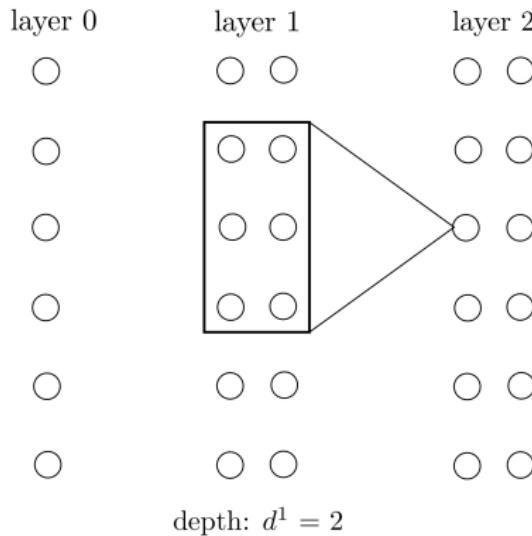


Consequences on the parameter number



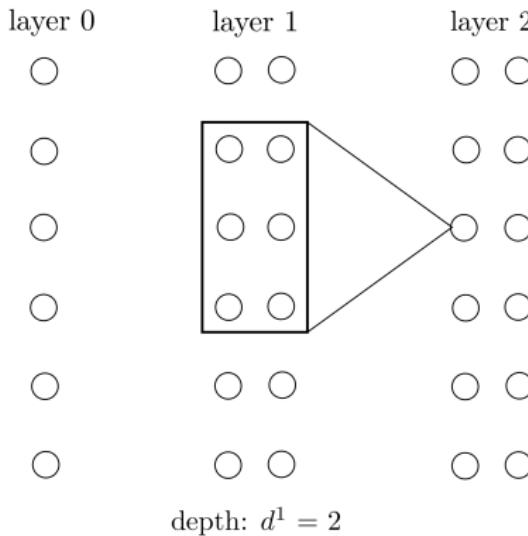
- How many parameters do we have in layer 1?

Consequences on the parameter number



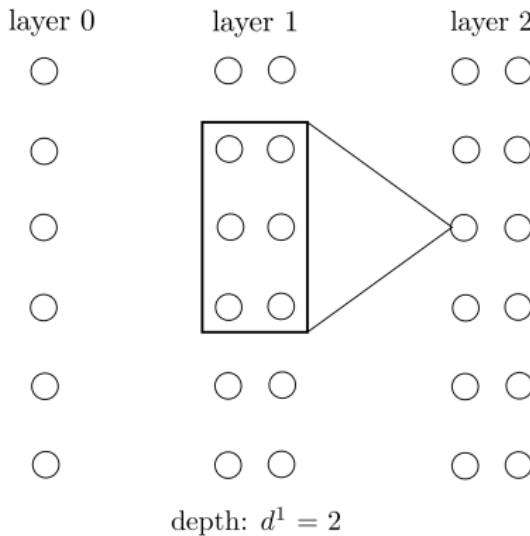
- How many parameters do we have in layer 1?
- $d^1 \times (s + 1)$

Consequences on the parameter number



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

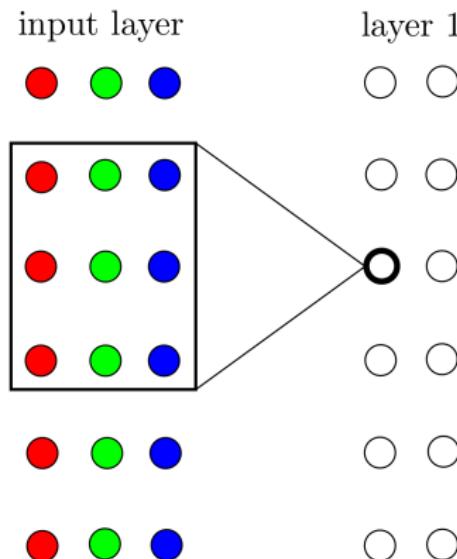
Consequences on the parameter number



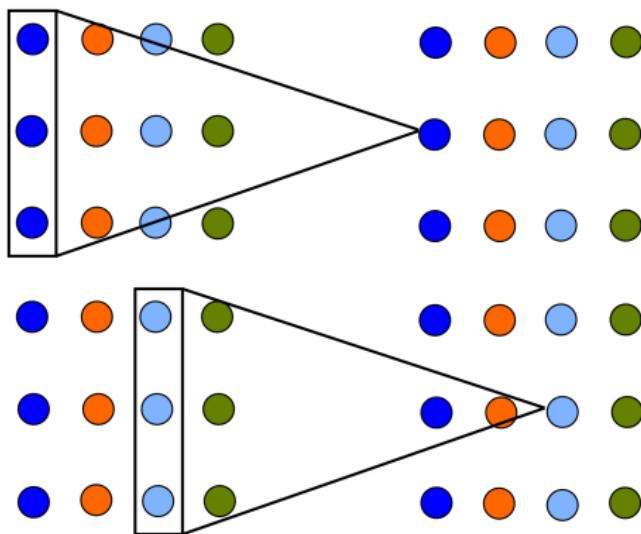
- How many parameters do we have in layer 1?
- $d^1 \times (s + 1)$
- In layer 2?
- $d^2 \times (d^1 \times s + 1)$

Multi-valued images

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



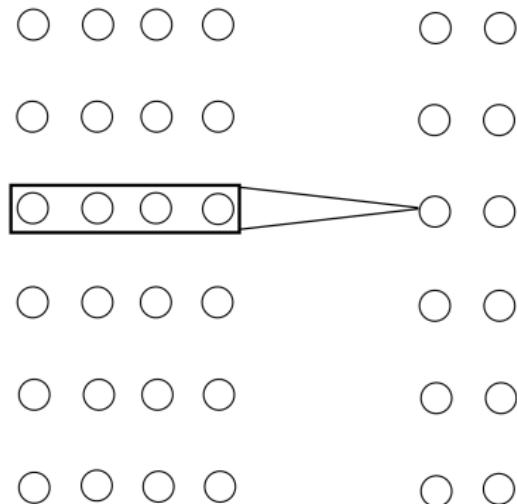
Depth-wise convolution



- The previous layer must contain the same number of filters
- The number of parameters is drastically reduced
- These layers are interesting when combined with 1×1 convolutions...

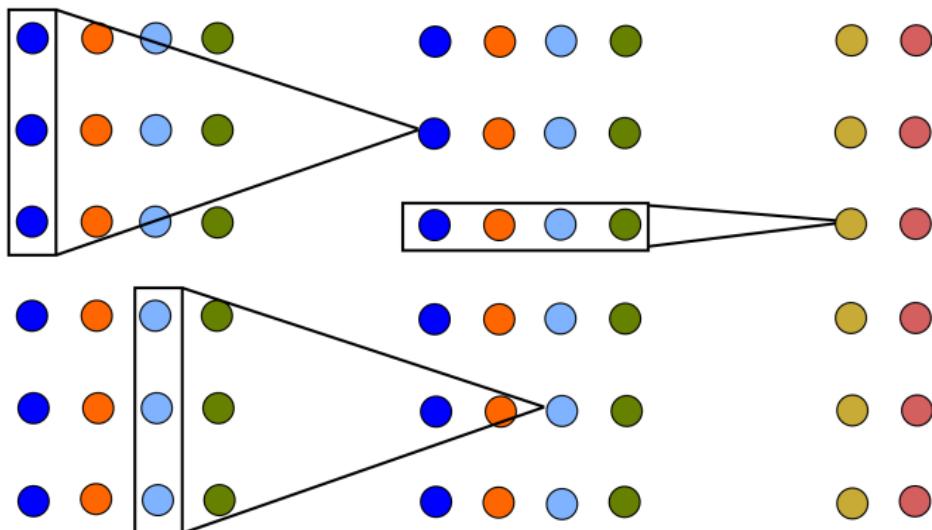
Dimension reduction

1×1 convolutions are used to reduce the number of filters - this is called by some authors *dimension reduction*.



Decomposed convolution

The combination of depth-wise with 1×1 convolutions gives decomposed convolutions.



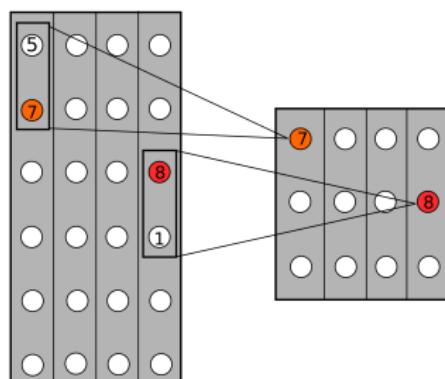
They are somehow a factorization of classical convolutions. Thus they allow reducing the number of parameters.

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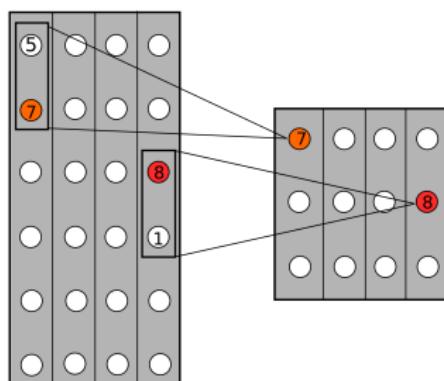
Max pooling

- Convolutional networks often contain subsampling steps. A common way of doing this today is by using *max pooling* layers with stride 2.
- Sampling is only applied along the spatial dimensions, not along the dimension of the filters.



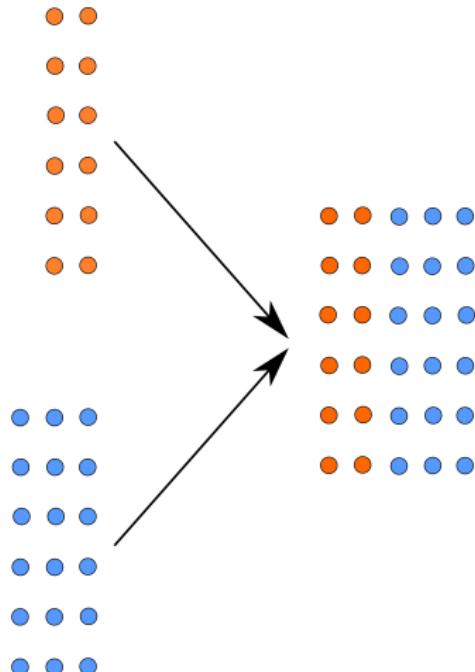
Max pooling

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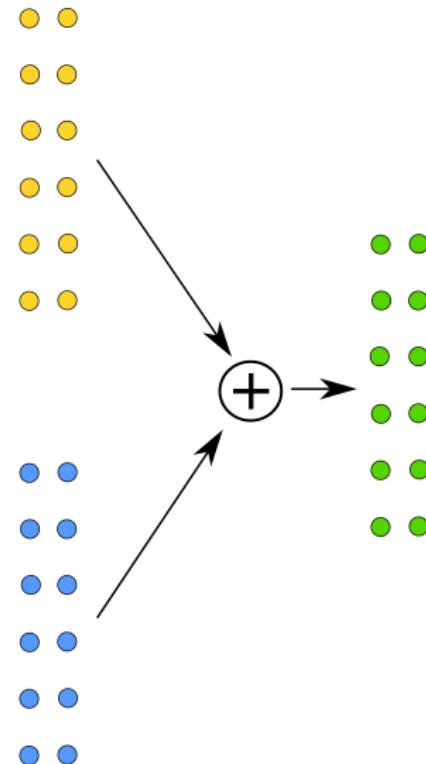


Note however a current trend that consists in using convolutional layers with a stride of 2

Branch merging: concatenation



Branch merging: addition

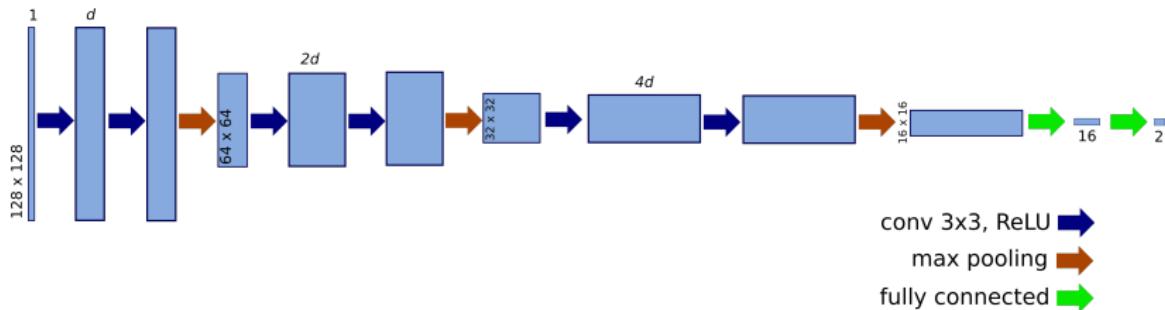


Main components of a convolutional neural network

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

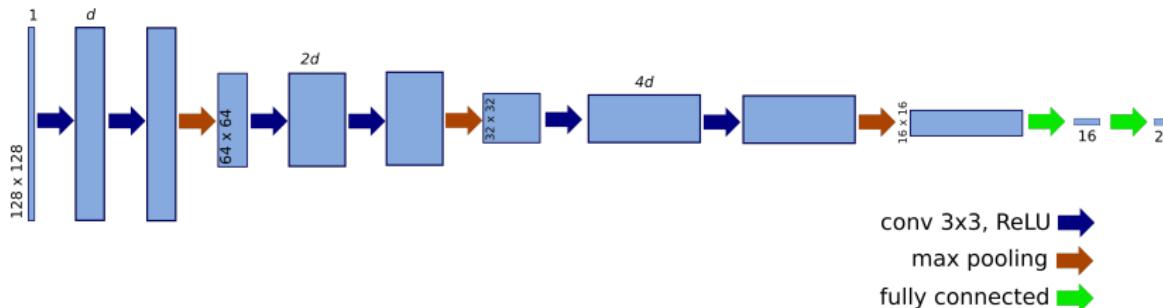
- ① Several iterations of: One or several convolutional layers, with increasing depth, followed by max pooling
- ② A few fully connected layers

1D representations



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

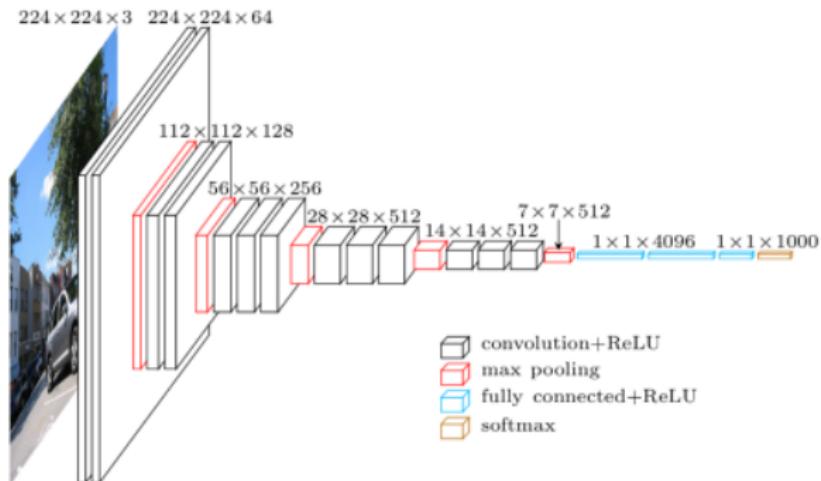
1D representations



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).

2D representations



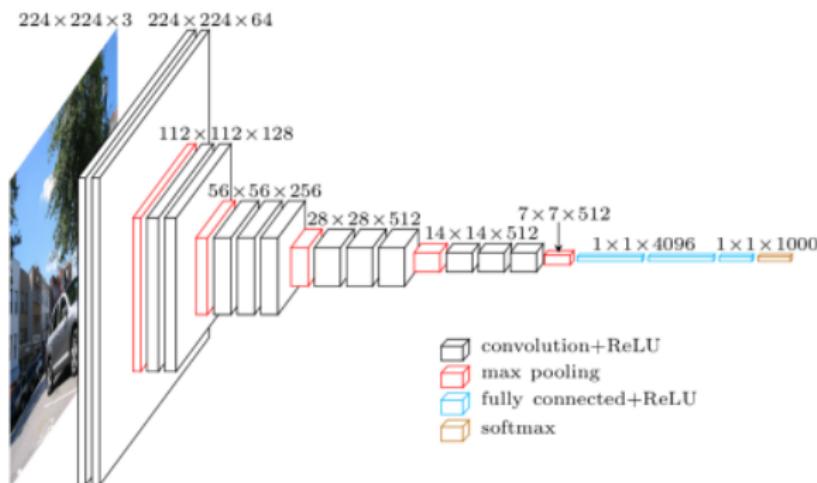
Credits: VGG16 (From
<https://www.cs.toronto.edu/~frossard/post/>)

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VGGnet

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

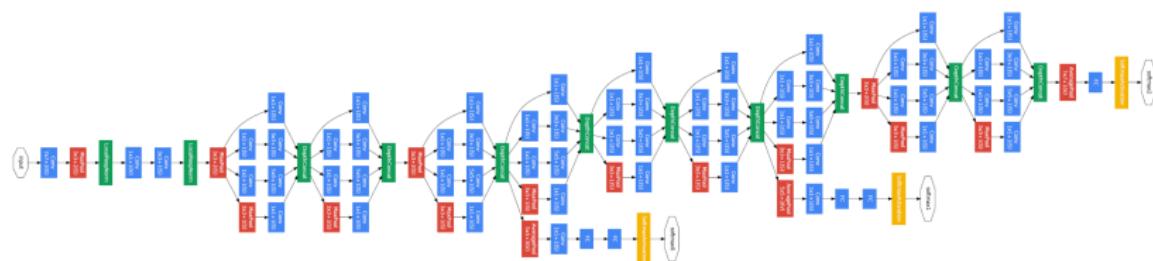


Credits: VGG16 (From
<https://www.cs.toronto.edu/~frossard/post/>)

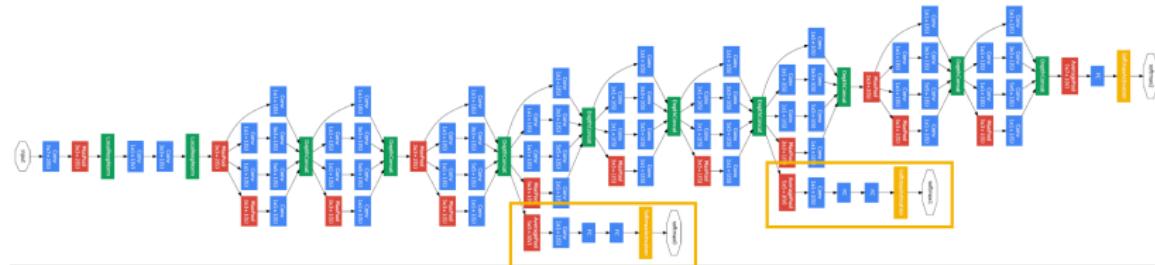
GoogLeNet

This is an architecture based on Inception v1 principles.

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

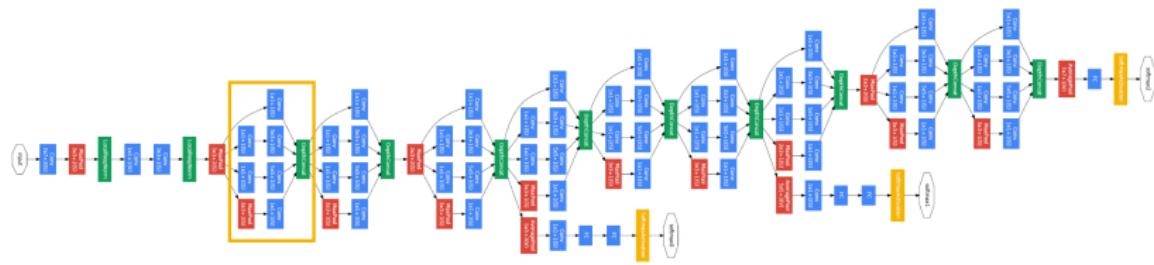


GoogLeNet review



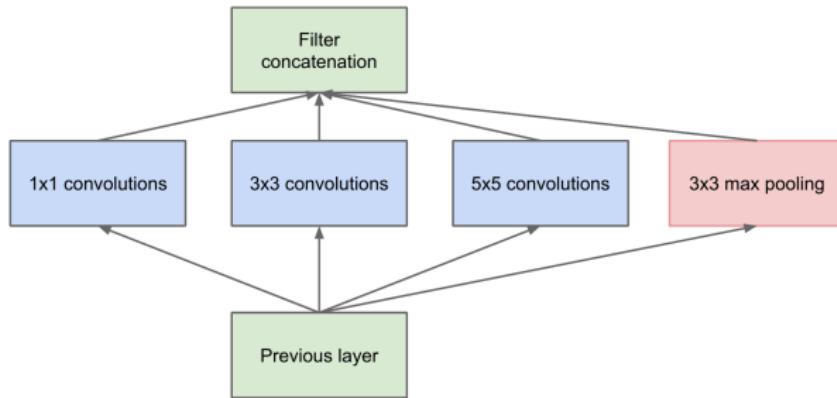
- Two extra outputs are added
- They are added to the final output with a 0.3 weight
- They help propagate gradient through the low levels of the network

GoogLeNet review

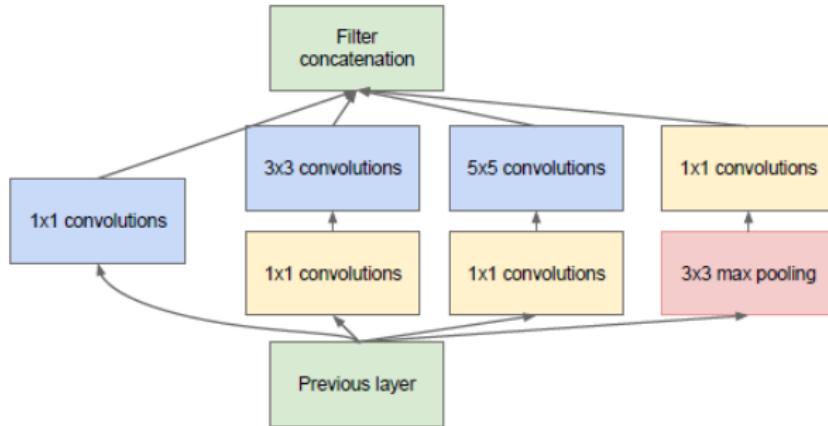


- 9 inception modules

Inception module: “naive version”

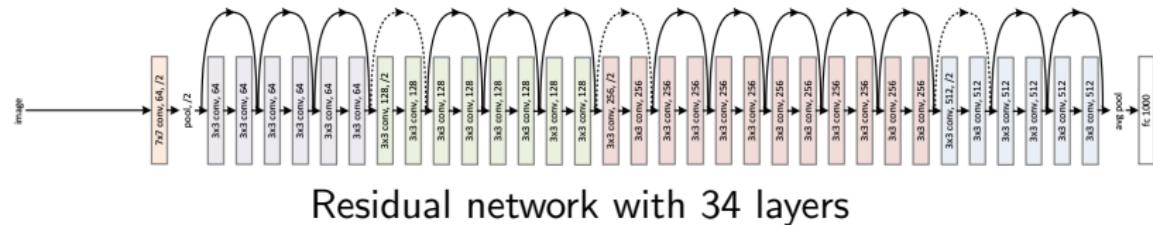


Inception module



- 1×1 convolutions are used to keep the number of parameters low.

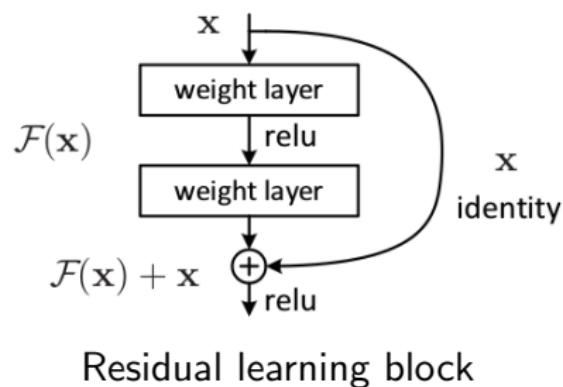
ResNet



- 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 [?]

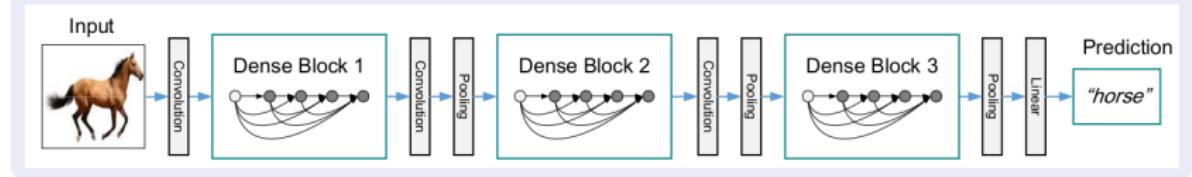
ResNet module

- Skip connections help backpropagation

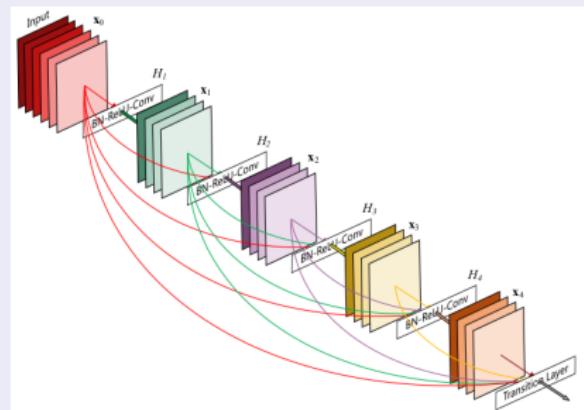


DenseNet[?]

Architecture

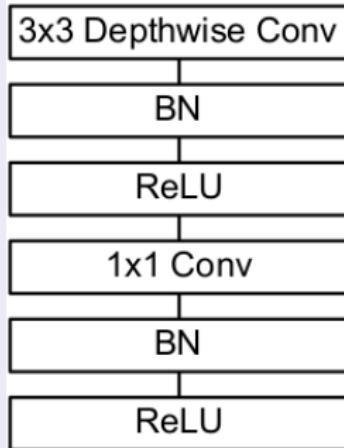


Dense block



MobileNet [?]

Depth-wise separable convolution



Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Number of parameters: 4 million.

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Some deep learning libraries

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

- Tensorflow, by Google (Apache licence)
- PyTorch, Torch (Facebook - BSD licence)
- Caffe (Univ. of California, Berkeley - BSD licence)
- Microsoft Cognitive Toolkit (MIT licence)
- MatConvNet (for MatLab users)

Comments

- Most of these libraries are distributed with very permissive licences
- Most of them use Python as prototyping language
- **Keras** is a very easy to use interface to Tensorflow.

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 based on deep learning
- Its applications are ubiquitous
- Not only we can improve on existing tasks, but we can also treat some problems in a completely different way (for example, image generation).

Limitations

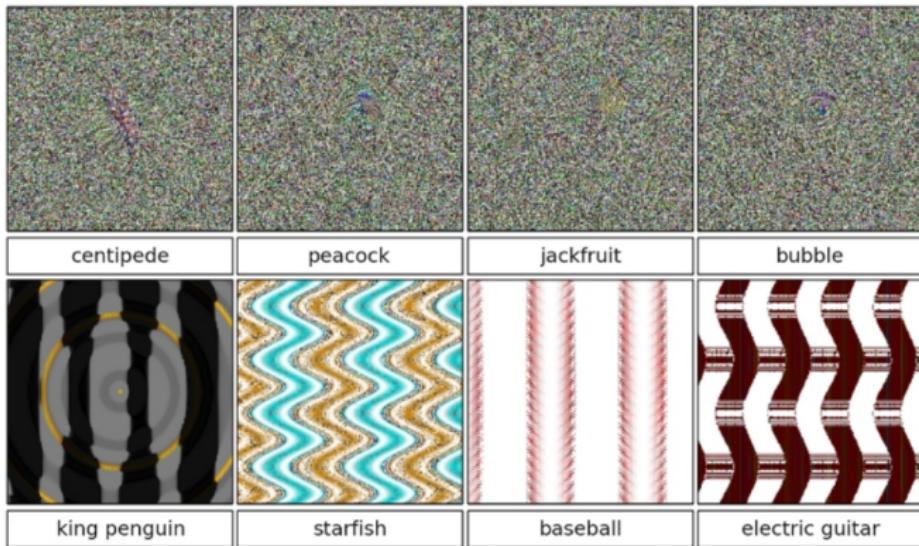
For a deep-learning solution to work, you need:

- Enough annotated data
- A lot of fiddling (different architectures; hyper-parameters; optimization)
- Expensive, energy hungry, computing resources

Moreover, these models lack interpretability.

ConvNets can be fooled

Deep learning can produce astonishing results [?]...



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