Convolutional neural networks

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Contents

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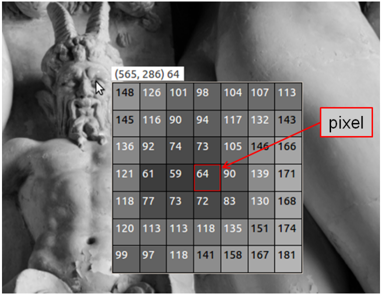
A picture is worth a thousand words

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.



Grey level values around the left eye of the faun

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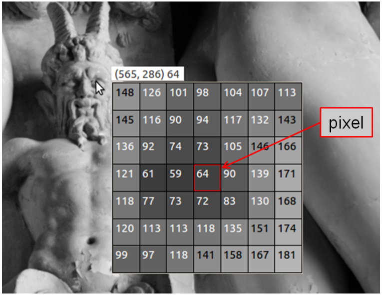

Grey level values around the left eye of the faun

Examples

- Grey level 2D images: infrared, microscopy, topography
- Colour images: camera photos
- Grey level 3D images: computed tomography scan
- Colour image sequences: video, motion pictures
- $d > 3$: multi-spectral imaging

What is special about images?

- Local structure
- Spatial redundancy
- Scale redundancy [Glasner et al., 2009]

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?

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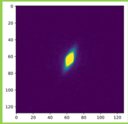
Designing computer vision systems that are able to extract semantic information from an image is a difficult task.

Image analysis applications

image → valeur

→ oiseau



→ 50,2

Tuccillo et al, 2018

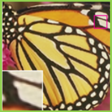
image → image

(segmentation)

→

Base COCO

→



Dong et al., ECCV 2014

Génération d’images

→

Isola et al, 2017

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.

Classical image processing approach

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

Credits: [zhang et al., 2011]

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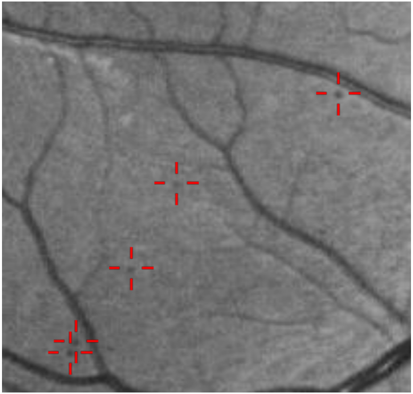

Detail of eye fundus image with microaneurysms to be detected

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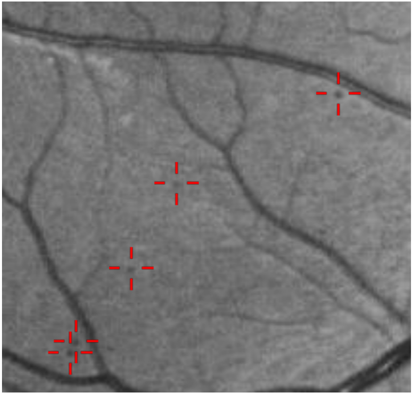

Detail of eye fundus image with microaneurysms to be detected

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

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

Credits: [zhang et al., 2011]

Classical machine learning approach

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

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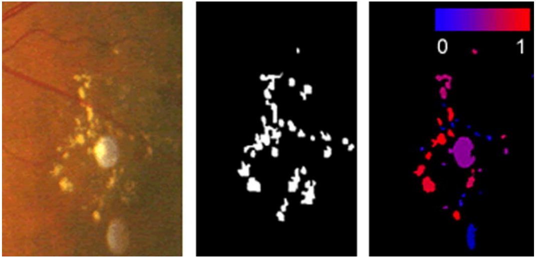

Exudates segmentation: original image, ground-truth and candidates with associated probabilities obtained with machine learning

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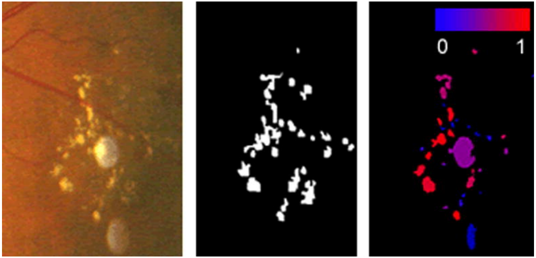


Exudates segmentation: original image, ground-truth and candidates with associated probabilities obtained with machine learning

$\oplus$ Works well with the right features

$\ominus$ An expert is required to define those features - and this can be a long process

$\ominus$ Annotated data is required

Credits: [Zhang et al., 2014]

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 [Lecun et al., 1998]

- The Modified National Institute of Standards and Technology (MNIST) database contains $60\,000$ training images of hand-written digits, and $10,000$ test images.
- Image size: 28×28
- It has been used since 1998
- Human performance on a similar database (NIST) is reported to be around 1.5% error [Simard et al., 1993]
- Best methods, based on convolutional neural networks, give around 0.21% test error.

MNIST database

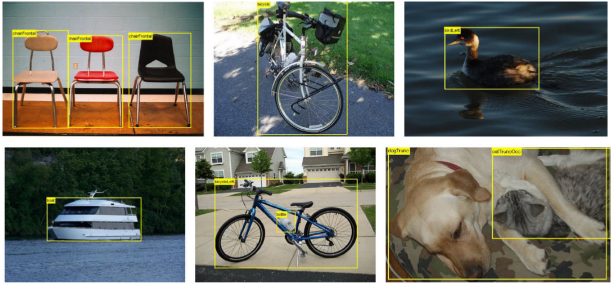
Credits: Images from MNIST assembled by Josef Stepan (licensed under CC BY-SA 4.0)

Pascal VOC project [Everingham et al., 2010, Everingham et al., 2014]

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).



Credits: From [Everingham et al., 2014]

ImageNet project [Russakovsky et al., 2015]

Since 2010, ImageNet organizes and 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!).

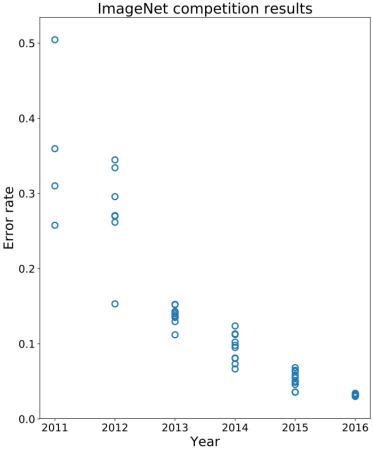
ImageNet projet

Examples from the *acoustic guitar* class

Deep learning achievements

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

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



Deep learning achievements (cont.)

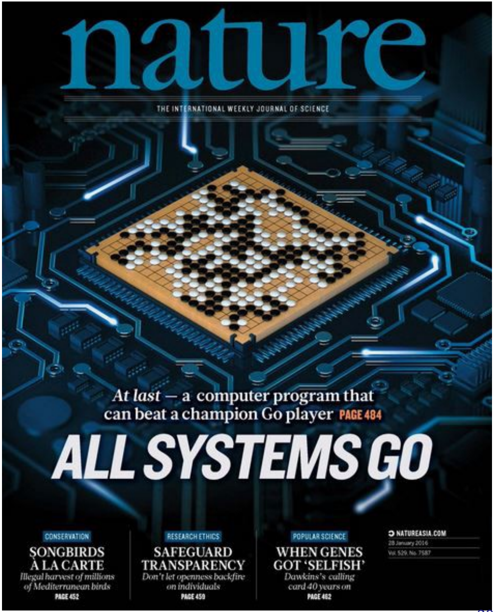
- 2011: first super-human performance, IJCNN 2011 traffic sign recognition contest [Cireșan et al., 2011]

- 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])

Credits: [Stallkamp et al., 2011]

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*

Convolutional neural networks in deep learning

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Acronyms

CNN and *ConvNet*

Our first task: image classification!

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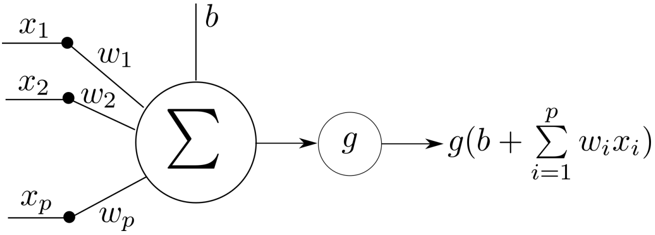
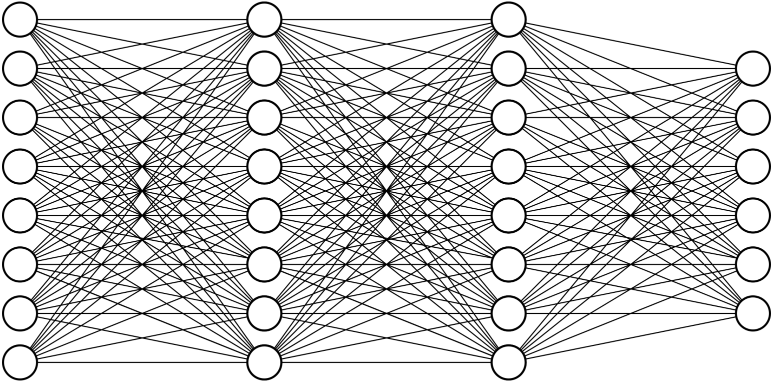
Reminder: Artificial neuron



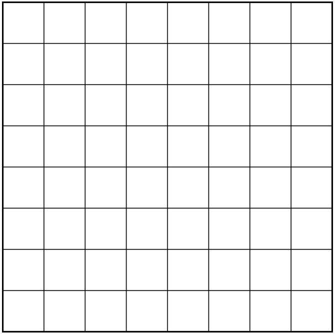
- $b, w_1, \dots, w_n$ are the neuron parameters, to be learnt
- g is the activation or transfer function

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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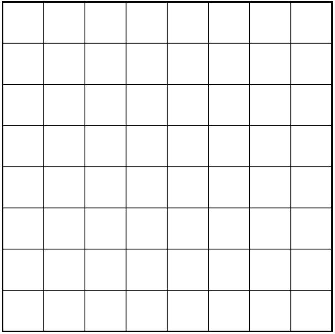

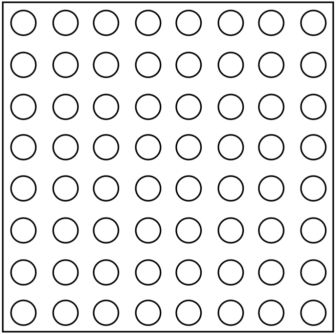

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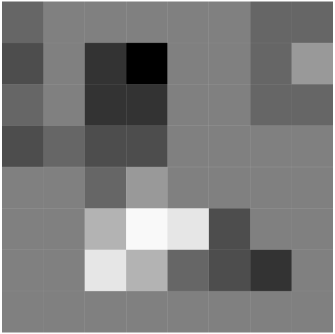

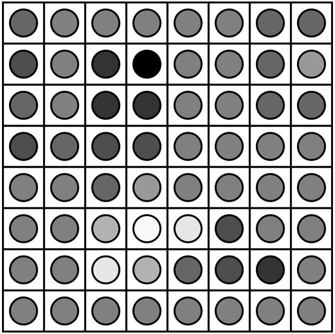

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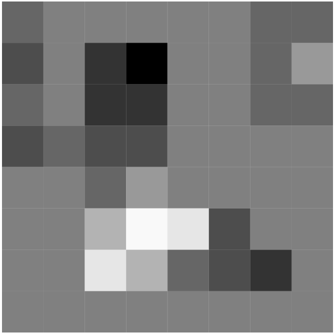

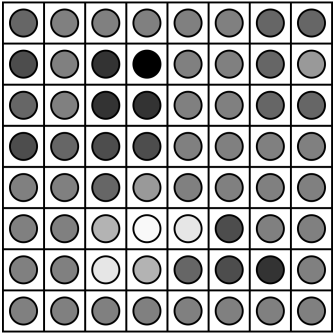

Image preprocessing

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

Image classification problem

Classification problem:

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

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 $3 \longmapsto [0, 0, 0, 1]$

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 $\sigma : \mathbb{R}^d \to \mathbb{R}^d$ is given by:

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

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

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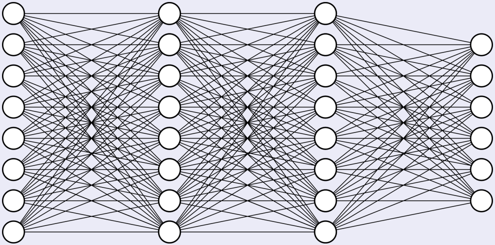
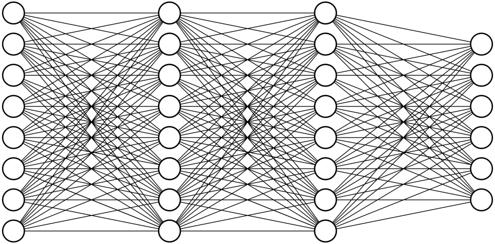
Example: image of size 4×2, 4 possible classes



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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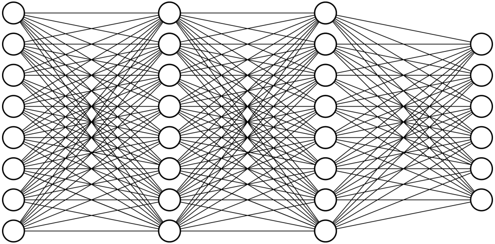

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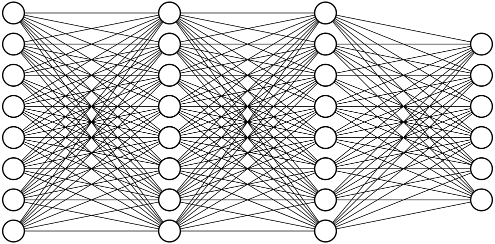

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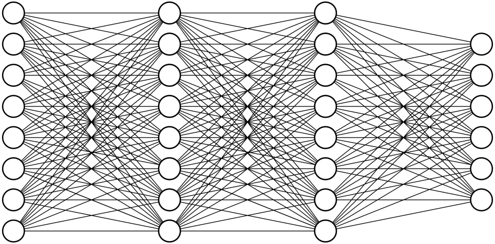

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- The number of parameters between two layers of that size is $10^5 \times (10^5 + 1)$!
- This approach is not feasible...
- Moreover, this approach does not take into account the local structure of images.

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

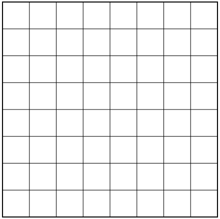
Today:

- 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.

Contents

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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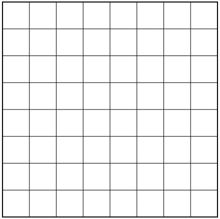

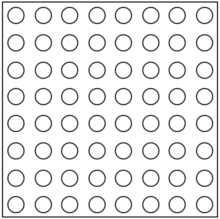

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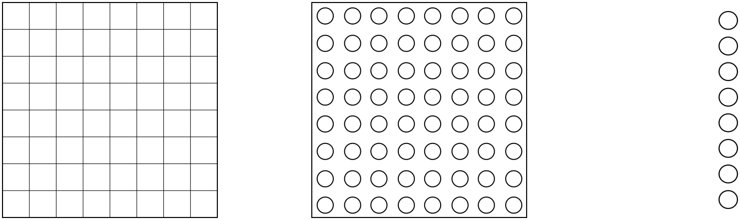
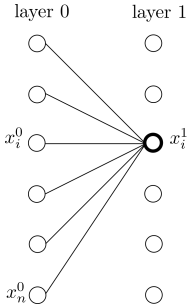


Towards convolutional layers



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

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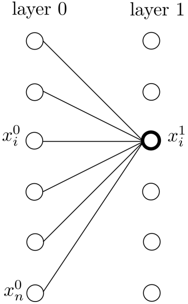

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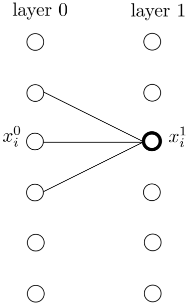

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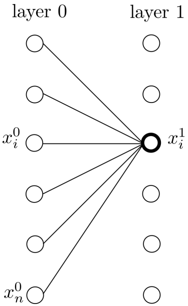

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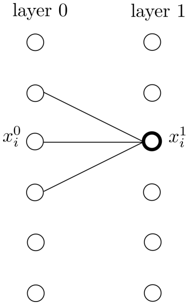

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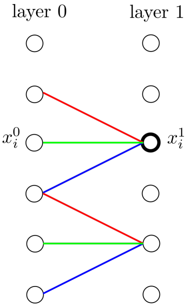
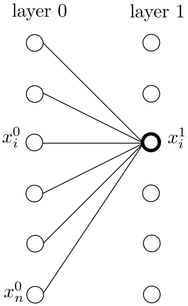


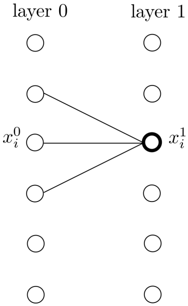
Weight replication: $s+1$ parameters.
Convolutional layer.

Towards convolutional layers: some figures

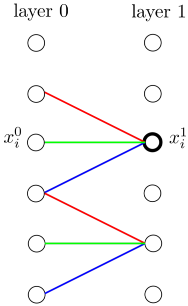
- 3×3 convolutions: $s = 9$
- Toy image: $n = 28 \times 28 = 784$
- Typical image: $n = 1000 \times 1000 = 10^6$



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

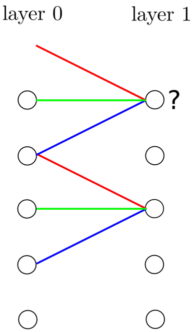


Locally conn. layer:
$n(s+1)$ parameters
7840
10^7

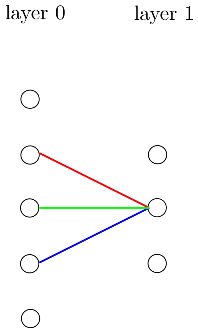


Weight replication: $s+1$
parameters.
10
10

Dealing with borders

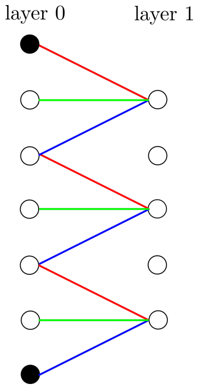


First solution: keep only well defined outputs



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

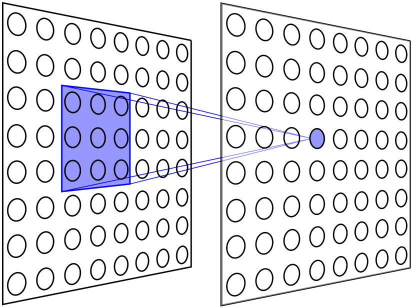
Second solution: zero padding



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

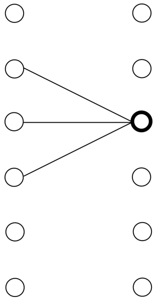
Convolutional layer illustration in 2D

- Illustration of a convolution of size 3×3



Stride

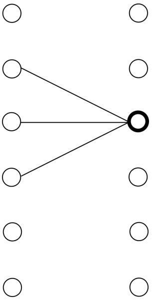
A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.

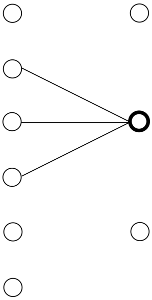


Stride 1

Stride

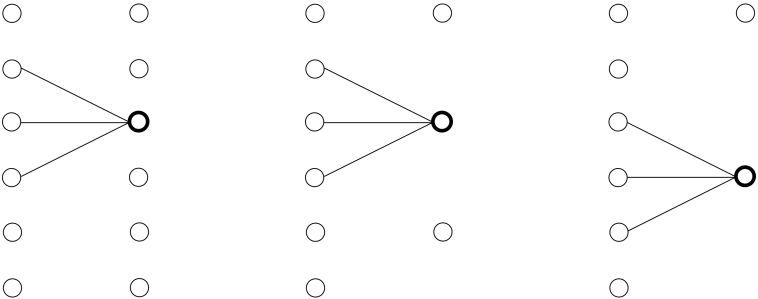
A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.





Stride

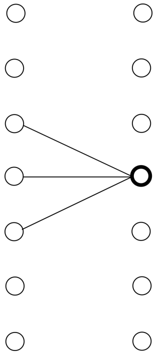
A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.



Stride 1 Stride 2 Stride 3

Dilated convolutions

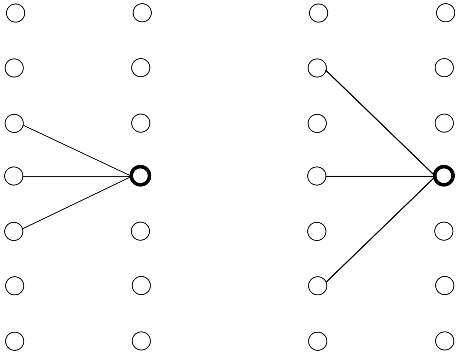
Dilated convolutions are used the increase the size of the receptive field of the network.



Normal convolution

Dilated convolutions

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

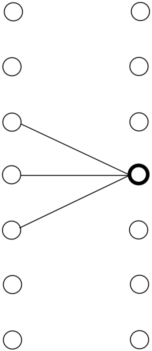


Normal convolution

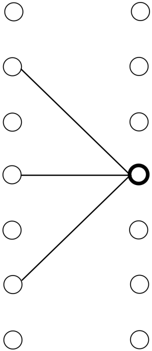
Dilation rate 2

Dilated convolutions

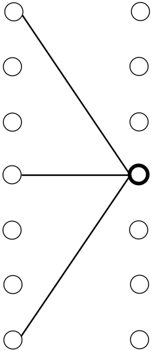
Dilated convolutions are used the increase the size of the receptive field of the network.



Normal convolution

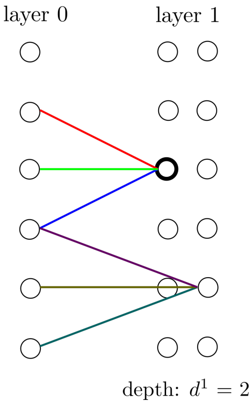


Dilation rate 2



Dilation rate 3

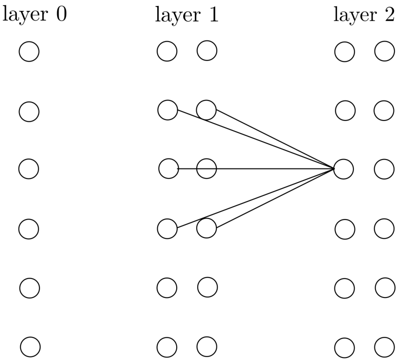
Several filters in the same convolutional layer



Note on vocabulary

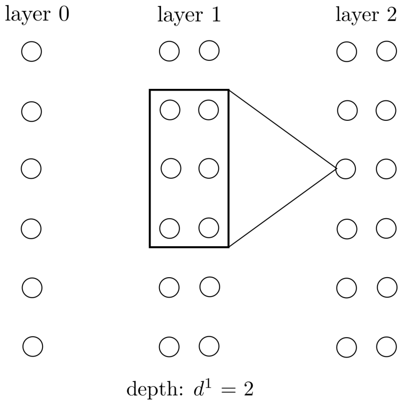
The depth of a layer is often called the number of filters.

Several filters in the same convolutional layer

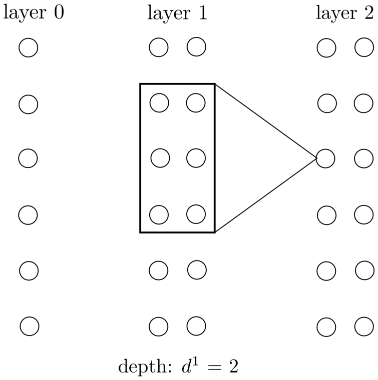


depth: $d^1 = 2$

Several filters in the same convolutional layer

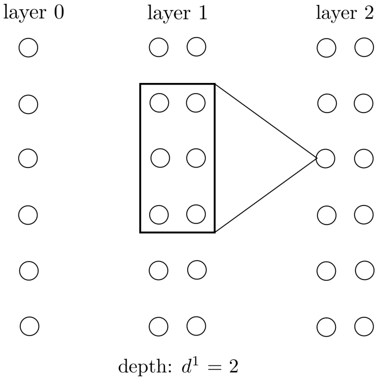


Consequences on the parameter number



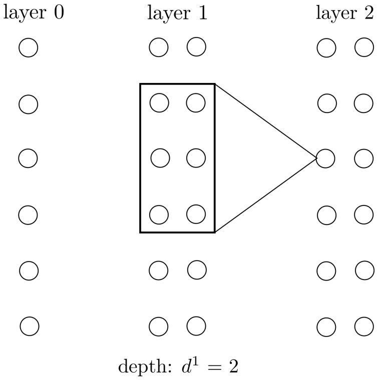
- How many parameters do we have in layer 1?

Consequences on the parameter number



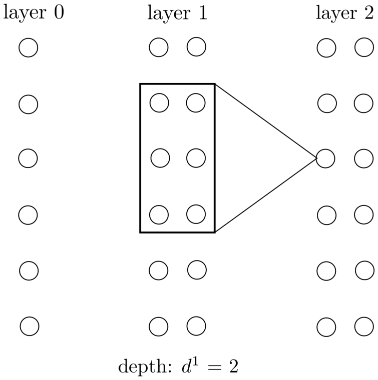
- How many parameters do we have in layer 1?
- $d^1 \times (s+1)$

Consequences on the parameter number



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

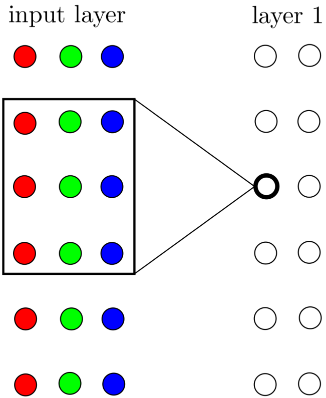
Consequences on the parameter number



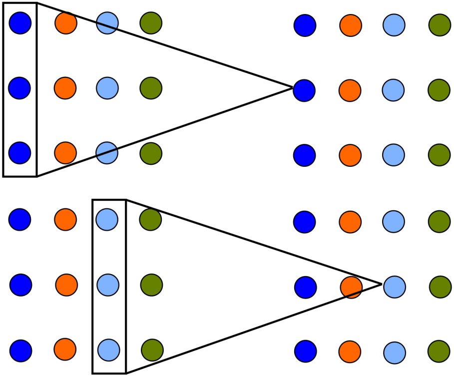
- How many parameters do we have in layer 1?
- $d^1 \times (s+1)$
- In layer 2?
- $d^2 \times (d^1 \times s + 1)$

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



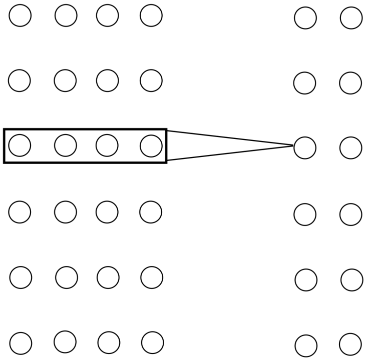
Depth-wise convolution



- 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...

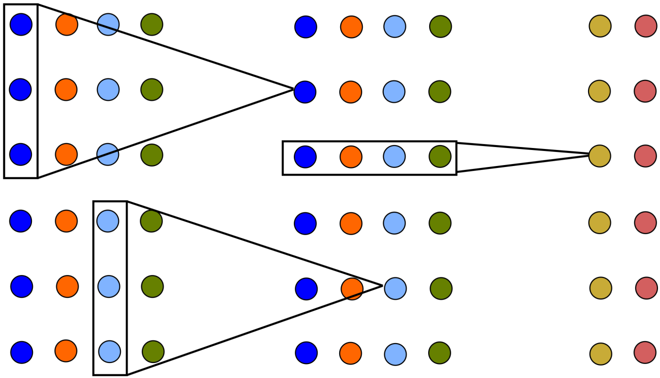
Dimension reduction

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.

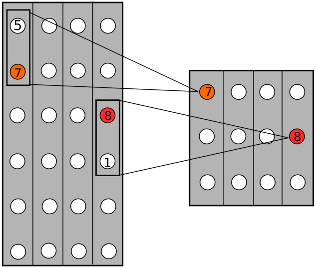


They are somehow a factorization of classical convolutions. Thus they allow reducing the number of parameters.

Contents

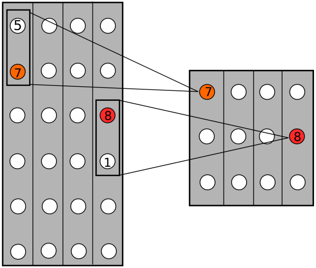
Max pooling

- 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.



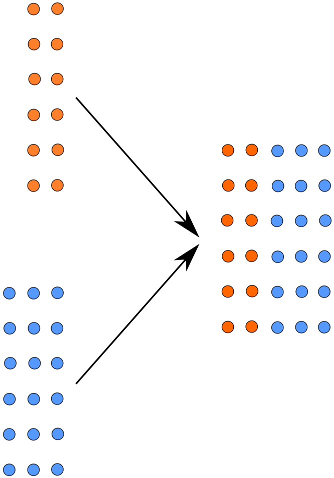
Max pooling

- 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.

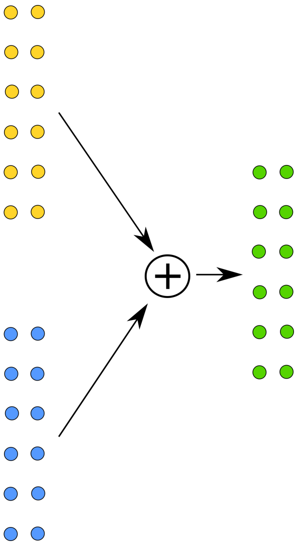


Note however a current trend that consists in using convolutional layers with a stride of 2

Branch merging: concatenation



Branch merging: addition

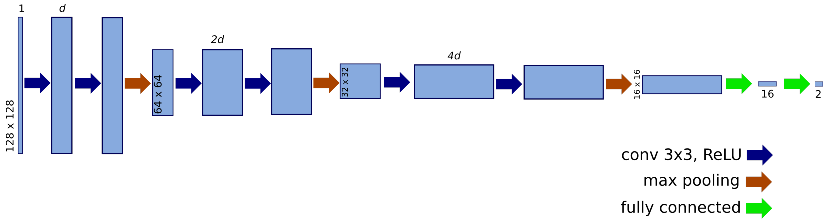


Main components of a convolutional neural network

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

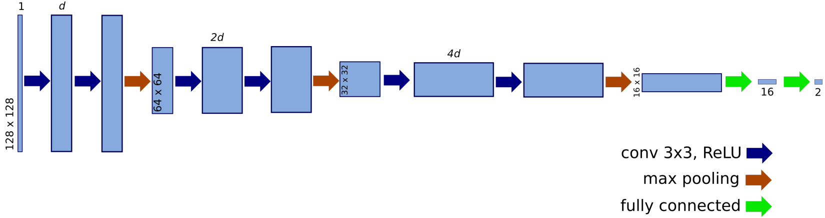
1. Several iterations of: One or several convolutional layers, with increasing depth, followed by max pooling
2. A few fully connected layers

1D representations



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

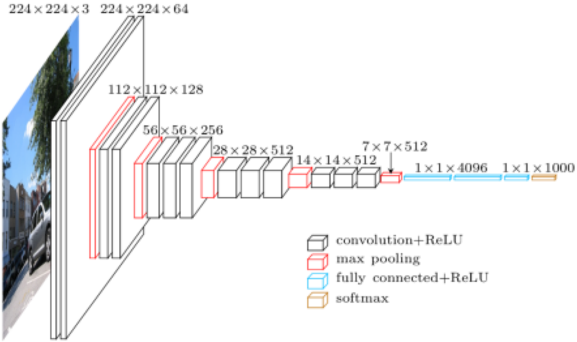
1D representations



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

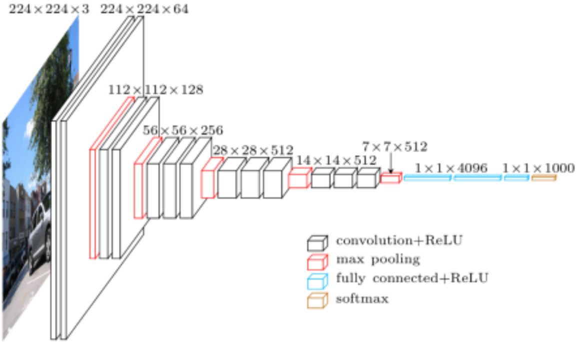


Credits: VGG16 (From
https://www.cs.toronto.edu/ frossard/post/

Contents

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.

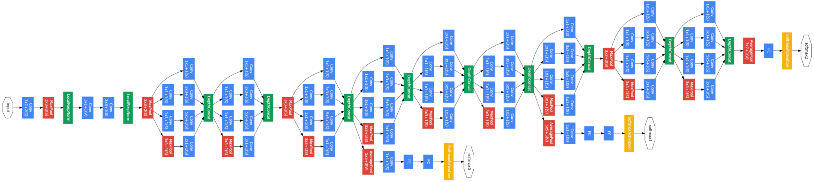


Credits: VGG16 (From https://www.cs.toronto.edu/ frossard/post/

GoogLeNet

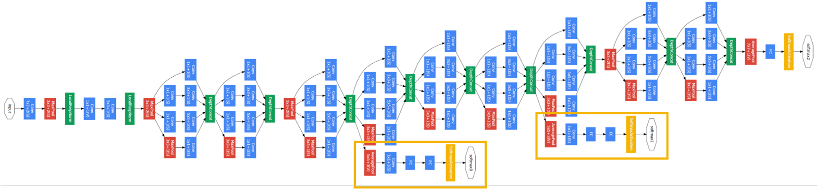
This is an architecture based on Inception v1 principles.

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



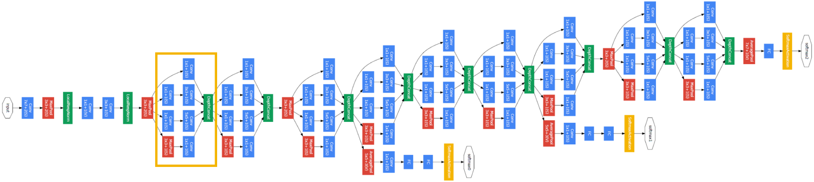
Credits: From [Szegedy et al., 2014]

GoogLeNet review



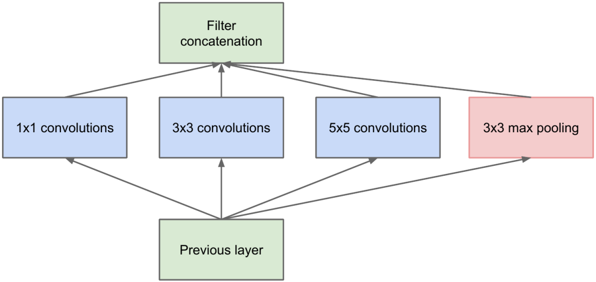
- Two extra outputs are added
- They are added to the final output with a 0.3 weight
- They help propagate gradient through the low levels of the network

GoogLeNet review



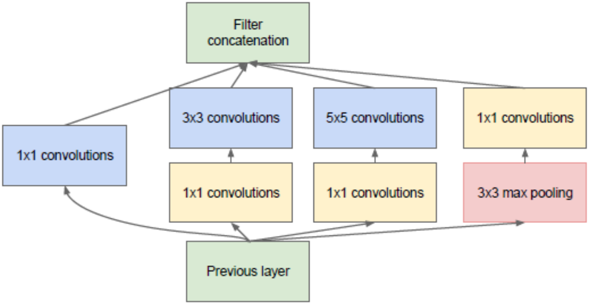
- 9 inception modules

Inception module: “naive version”



Credits: From [Szegedy et al., 2014]

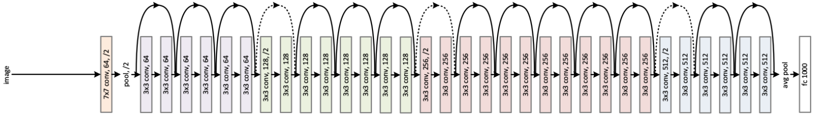
Inception module



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

Credits: From [Szegedy et al., 2014]

ResNet

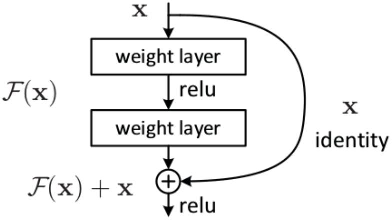


Residual network with 34 layers

- 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]

ResNet module

- Skip connections help backpropagation

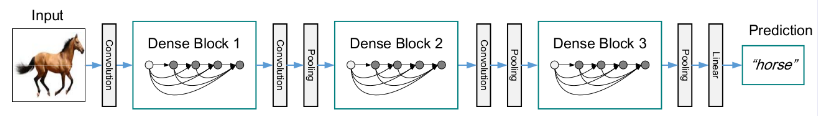


Residual learning block

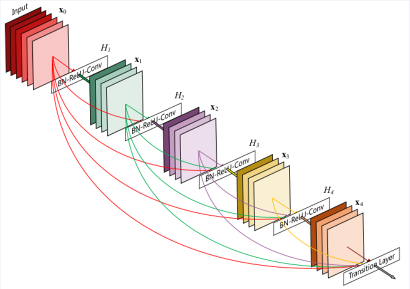
Credits: From [He et al., 2015]

DenseNet[Huang et al., 2018]

Architecture

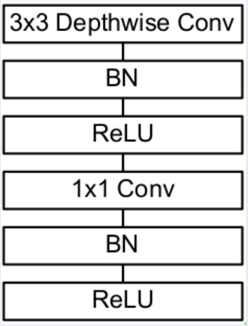


Dense block



MobileNet [Howard et al., 2017]

Depth-wise separable convolution



Number of parameters: 4 million.

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	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ 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	$1 \times 1 \times 1000$

Contents

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

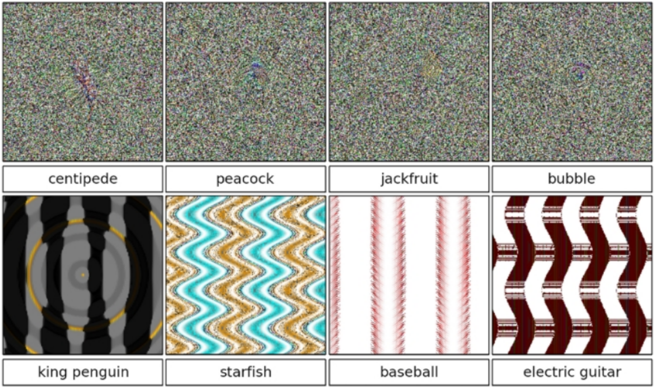
For a deep-learning solution to work, you need:

- 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 [Nguyen et al., 2015]...



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[Everingham et al., 2010] Everingham, M., Van Gool, L., Williams, C. K. I., Winn, J., and Zisserman, A. (2010). The Pascal Visual Object Classes (VOC) Challenge. *International Journal of Computer Vision*, 88(2):303–338.

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[Huang et al., 2018] Huang, G., Liu, Z., van der Maaten, L., and Weinberger, K. Q. (2018). Densely Connected Convolutional Networks. *arXiv:1608.06993 [cs]*. arXiv: 1608.06993.

[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.

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