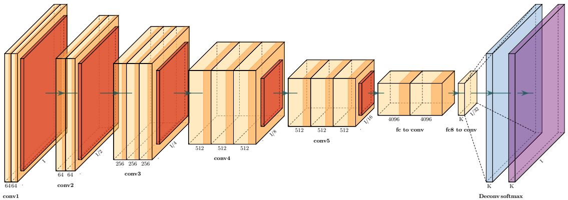

Convolutional Neural Networks

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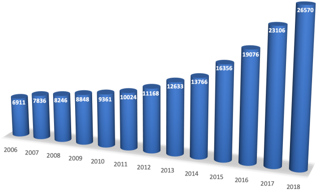
Convolutional Neural Networks (CNNs)

- Dedicated to computer vision problems and more generally to any problem with a spatial (or sequential) structure.
- Change the classical paradigm of image analysis



Number of publications per year (IEEE+Springer+Elsevier)

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Some applications

Deep is everywhere ;-):

- Medicine
- Security
- Internet
- Art
- NLP
- Games
- Images and videos analysis
- Vocal synthesis
- Pattern matching
- Autonomous driving
- Robotics
- Domotics
- Many More

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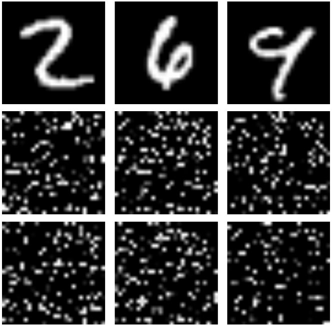
MLP and images

Why ?

- *A question of size*: a 512$\times$ 512 RGB image = 786 432 values.
  Let's build a 1 hidden layer MLP, producing an image from an image.
  Then the number of parameters to train is approximatively $6.19.10^{11}$,
  more than 1Tb in memory $\rightarrow$ untractable.
- *A question of information*: pixel values may be related (correlated) to the values surrounding the pixel position $\rightarrow$ a 1D representation cannot easily handle this.
- *A question of invariance*: a representation meaningful at a certain location should be used everywhere

MLP and images

- A 2-layer MLP can easily classify MNIST data, BUT images are vectorized : $28 \times 28 \rightarrow 784 \times 1$
- What if pixels values are shuffled ?



Original images

Shuffled images

Another set of 2,6 and 9

How can you recognize the digits ???

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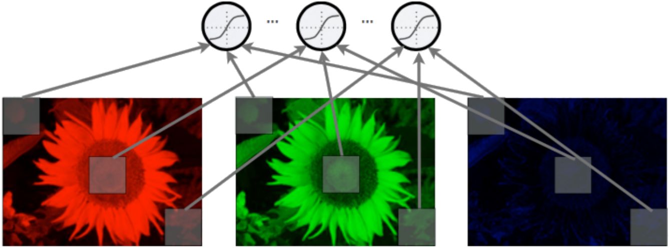
Convolutional Neural Networks (CNN)

Key ideas of CNN

- *Local connectivity*: each neuron is connected to a patch in the image, not to the whole set of pixels.
- *Convolution layers* apply the same linear transformation locally everywhere while preserving the signal structure.
- *Parameter sharing* across patches, allows to be equivariant to translation.
- *Pooling layers* allows to be pseudo invariant to local translations and noise.



Convolution

Definition

In 1D, convolution (cross-correlation) between f and g:

$$f \circledast g(x) = \sum_{y+z=x} f(y).g(z) = \sum_{y} f(y)g(x+y)$$

In 2D: $g(x,y) = w \circledast f(x,y) = \sum_{m}\sum_{n} w(m,n).f(x+m,y+n)$

w: convolution Kernel (or filter) applied to image f.

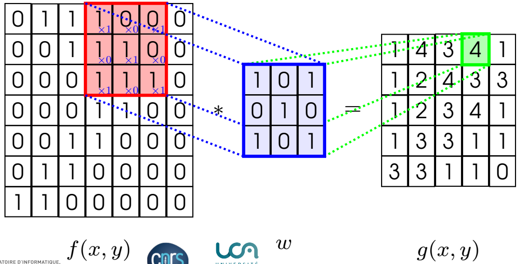
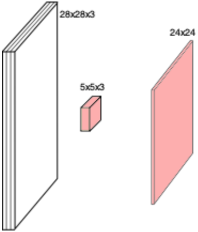


FIGURE: Exemple de convolution discrÃ¨te

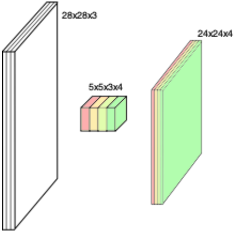
Convolution

- For multichannel images (eg color images), convolutions are usually computed for each channel and summed.
- Mutiple convolutions

$\Rightarrow$ Convolutions applied to *tensors*.



$$w \circledast f(x,y) = \sum_{i=0}^{2} w_c \circledast f_c(x,y)$$



4 kernels 5$\times$ 5 on color images

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Convolution layer

Let

- $\boldsymbol{x}$ be the input tensor of size $C \times H \times W$.
- $\boldsymbol{k}$ be a kernel of size $C \times h \times w$ ($h \times w$ = *receptive field*)
- $\boldsymbol{y}$ be the output tensor (the *feature map*), resulting from the convolutions.

A convolution layer implements K convolutions, using K kernels k.

$\boldsymbol{y}$ is of size $K \times (H - h + 1) \times (W - w + 1)$ and

$$(\forall k) \quad \boldsymbol{y}(i,j) = \sum_{c=0}^{C-1} (\boldsymbol{x}_c \circledast \boldsymbol{k}_c)(i,j) + b_{ij}$$

The k's and b are shared parameters to learn.

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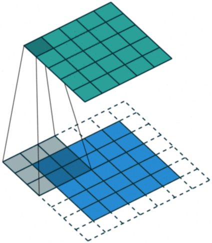
Convolution layer

Additional Parameters

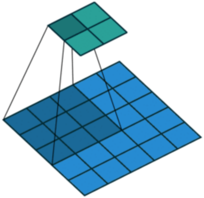
- *padding*: size of a zeroed frame added arount the input
  $\rightarrow$ controls the spatial dimension of the feature map
-
-



Convolution layer

Additional Parameters

- *padding*: size of a zeroed frame added arount the input
  $\rightarrow$ controls the spatial dimension of the feature map
- *stride*: step size when moving the kernel across the signal
  $\rightarrow$ reduces the spatial dimension of the feature map
-



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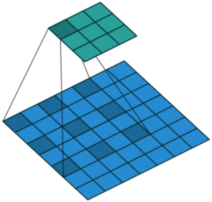
Convolution layer

Additional Parameters

- *padding*: size of a zeroed frame added arount the input
  $\rightarrow$ controls the spatial dimension of the feature map
- *stride*: step size when moving the kernel across the signal
  $\rightarrow$ reduces the spatial dimension of the feature map
- *dilation*: modulates the expansion of the kernels without adding weights.
  $\rightarrow$ increases the units receptive field size without increasing the number of parameters



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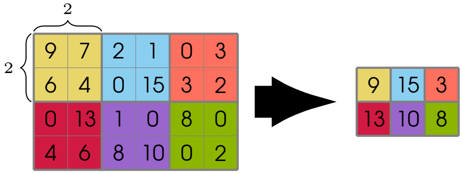
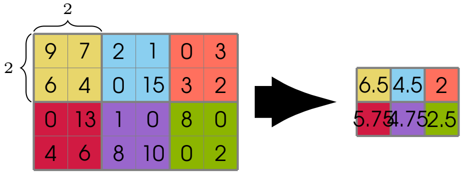
Pooling layer

Pooling $\approx$ downsampling: considers a receptive field of size $h \times w$ and replaces the set of values by the max, the mean (main pooling operations)



$\mathbf{2} \times \mathbf{2}$ max pooling



$\mathbf{2} \times \mathbf{2}$ average pooling

Pooling layer

- No parameter to learn !
- Pooling layers provide invariance to any permutation inside one cell.
- pseudo-invariance to local translations.
- Interesting if we care more about the presence of a pattern rather than its exact position.

Other typical layers

- *Activation*: add an activation function after the output of a layer (can be integrated in the layer itself).
- *Dropout*: randomly sets input units to 0 with a given frequency at each step during training. Helps prevent overfitting.
- *Batch normalization*: applies a transformation that maintains the mean output close to 0 and the output standard deviation close to 1. Works differently during training and during inference. Fasten the training process.
- *Fully connected* = MLP

Additional ressource

See Slides "Normalization" and "Dropout".

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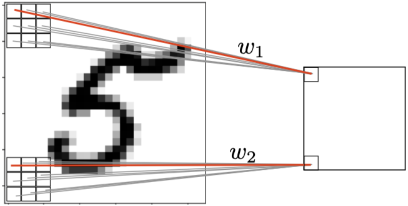
Backpropagation in CNN

Same concept as for MLP: multivariable chain rule, with weight sharing constraint.

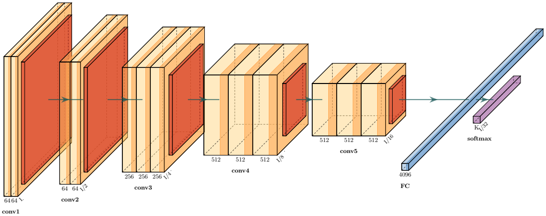


$$w_1 = w_2 = w_1 - \frac{\eta}{2}\left(\frac{\partial \mathcal{L}}{\partial w_1} + \frac{\partial \mathcal{L}}{\partial w_2}\right)$$

Additional ressource

See slides "Optimization for deep Learning" and "weight initialization"

- Classical architectures: succession of (Conv -Activation -Pooling) blocks + fully connected layer(s) + softmax (for classification)



- Since 2014, several other architectures proposed.

See...

Lectures “CNN architectures” & “Transfer Learning”.

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STATE OF THE ART

Method	# Params	Extra Data	ImageNet Top-1	ImageNet Top-5	ImageNet-ReaL [6] Precision@1
ResNet-50 [24]	26M	–	76.0	93.0	82.94
ResNet-152 [24]	60M	–	77.8	93.8	84.79
DenseNet-264 [28]	34M	–	77.9	93.9	–
Inception-v3 [62]	24M	–	78.8	94.4	83.58
Xception [11]	23M	–	79.0	94.5	–
Inception-v4 [61]	48M	–	80.0	95.0	–
Inception-resnet-v2 [61]	56M	–	80.1	95.1	–
ResNeXt-101 [78]	84M	–	80.9	95.6	85.18
PolyNet [87]	92M	–	81.3	95.8	–
SENet [27]	146M	–	82.7	96.2	–
NASNet-A [90]	89M	–	82.7	96.2	82.56
AmoebaNet-A [52]	87M	–	82.8	96.1	–
PNASNet [39]	86M	–	82.9	96.2	–
AmoebaNet-C + AutoAugment [12]	155M	–	83.5	96.5	–
GPipe [29]	557M	–	84.3	97.0	–
EfficientNet-B7 [63]	66M	–	85.0	97.2	–
EfficientNet-B7 + FixRes [70]	66M	–	85.3	97.4	–
EfficientNet-L2 [63]	480M	–	85.5	97.5	–
ResNet-50 Billion-scale SSL [79]	26M	3.5B labeled Instagram	81.2	96.0	–
ResNeXt-101 Billion-scale SSL [79]	193M	3.5B labeled Instagram	84.8	–	–
ResNeXt-101 WSL [42]	829M	3.5B labeled Instagram	85.4	97.6	88.19
FixRes ResNeXt-101 WSL [69]	829M	3.5B labeled Instagram	86.4	98.0	89.73
Big Transfer (BiT-L) [33]	928M	300M labeled JFT	87.5	98.5	90.54
Noisy Student (EfficientNet-L2) [77]	480M	300M unlabeled JFT	88.4	98.7	90.55
Noisy Student + FixRes [70]	480M	300M unlabeled JFT	88.5	98.7	–
Vision Transformer (ViT-H) [14]	632M	300M labeled JFT	88.55	–	90.72
EfficientNet-L2-NoisyStudent + SAM [16]	480M	300M unlabeled JFT	88.6	98.6	–
Meta Pseudo Labels (EfficientNet-B6-Wide)	390M	300M unlabeled JFT	90.0	98.7	**91.12**
Meta Pseudo Labels (EfficientNet-L2)	480M	300M unlabeled JFT	**90.2**	**98.8**	91.02

Source: Meta Pseudo Labels, Hieu Pham et al. (01/2021)

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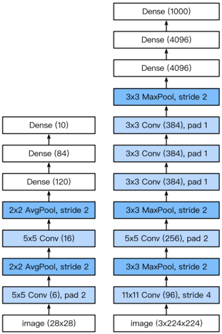
Examples

Two classical (and old) architectures

- LeNet-5 (LeCun et al, 1998): 61 706 trainable parameters
- AlexNet (Krizhevsky et al, 2012): 61 100 840 trainable parameters



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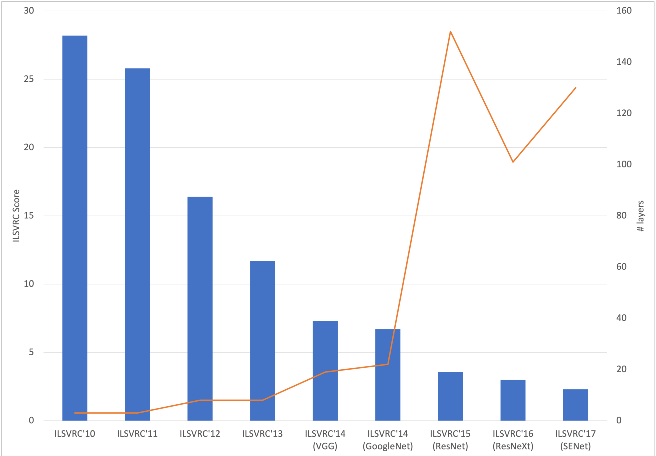
THE DEEPER, THE BETTER ?

Image Large Scale Visual Recognition Challenge (Classification task)



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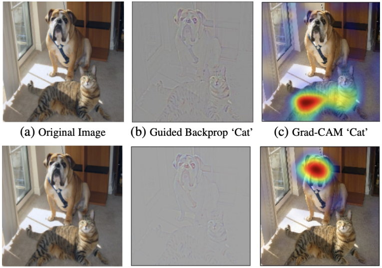
Inside the CNN

What we can do

- filters $\rightarrow$ images
- distributions of activations on a batch of samples
- gradient of the response with respect to the input
- create a synthetic image that maximize a given filter



(a) Original Image (b) Guided Backprop 'Cat' (c) Grad-CAM 'Cat'

(g) Original Image (h) Guided Backprop 'Dog' (i) Grad-CAM 'Dog'

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Inside the CNN

It seems that

- the first layers encode edges, directions and colorimetric properties
- directions and colors are combines to "textures"
- these patterns combine to more complex patterns → semantic