Redes convolucionales

Aprendizaje automático

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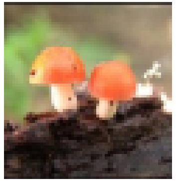
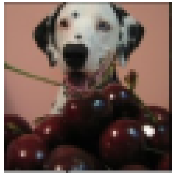
Agenda

- Redes Neuronales Convolucionales (CNNs)
- Por qué no utilizar feed forward NNs?
- Convolución
- Pooling
- Stride
- Ejemplos

Clasificación de imágenes

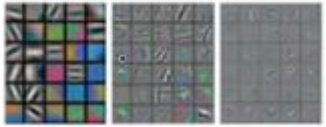
Image	Category
	mushroom
	cherry
...	...

Feed-forward NNs

Propiedades de señales naturales

- Main assumption :
  - Data (images, videos, speech) is compositional, it is formed of patterns that are:
    - Local (Hubel-Wiesel 1962)
    - Stationary (shared patterns)
    - Hierarchical (multi-scale)





- ConvNets leverage the compositionality structure :
  - They extract compositional features and feed them to classifier, recommender, etc (end-to-end systems).


Computer Vision

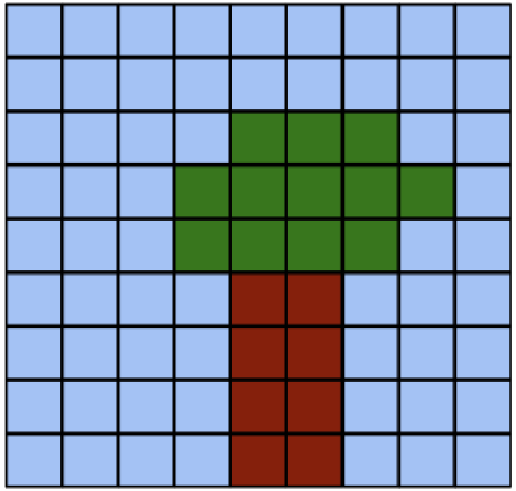

NLP


Speech


Game of Go

https://www.youtube.com/watch?v=Iiv9R6BjxHM&list=PLLHTzKZzVU9eaEyErdV26ikyolxOsz6mq&index=24

Propiedades de señales naturales



A digital image is a 2D **grid of pixels.**

https://storage.googleapis.com/deepmind-media/UCLxDeepMind_2020/L3%20-%20UUCLxDeepMind%20DL2020.pdf

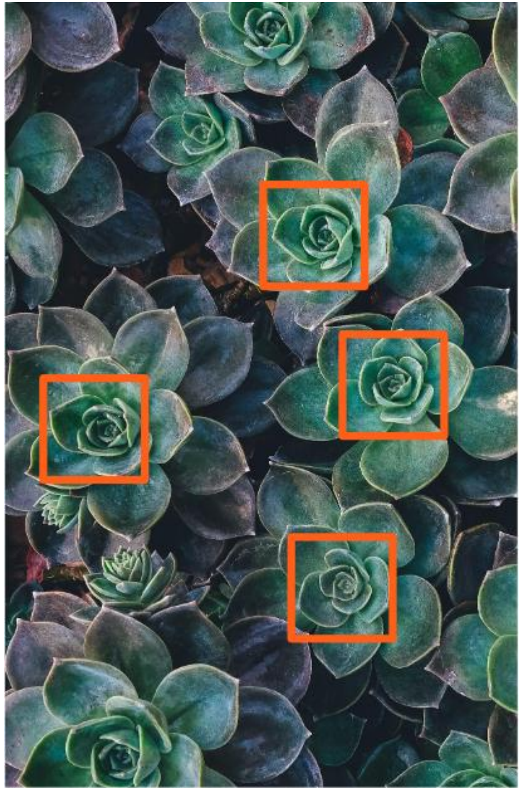
Localidad y estacionariedad

Locality: nearby pixels are more strongly correlated

Translation invariance: meaningful patterns can occur anywhere in the image

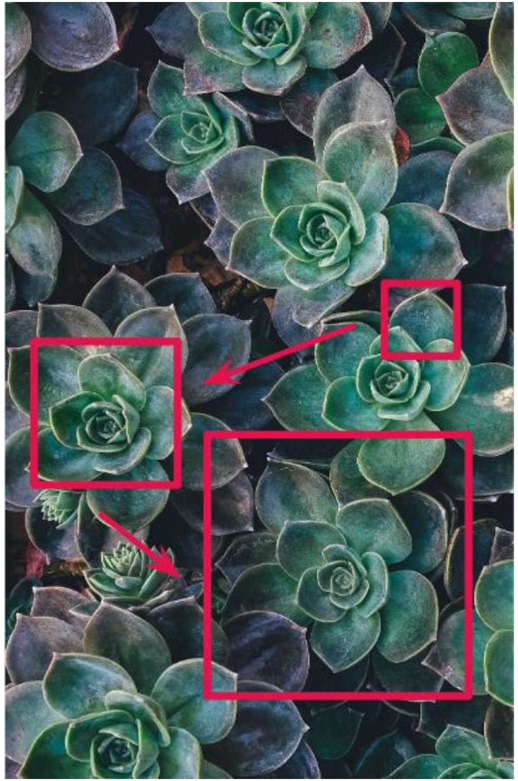
Estacionariedad: Translation invariance

Utilizando la estructura de las imágenes



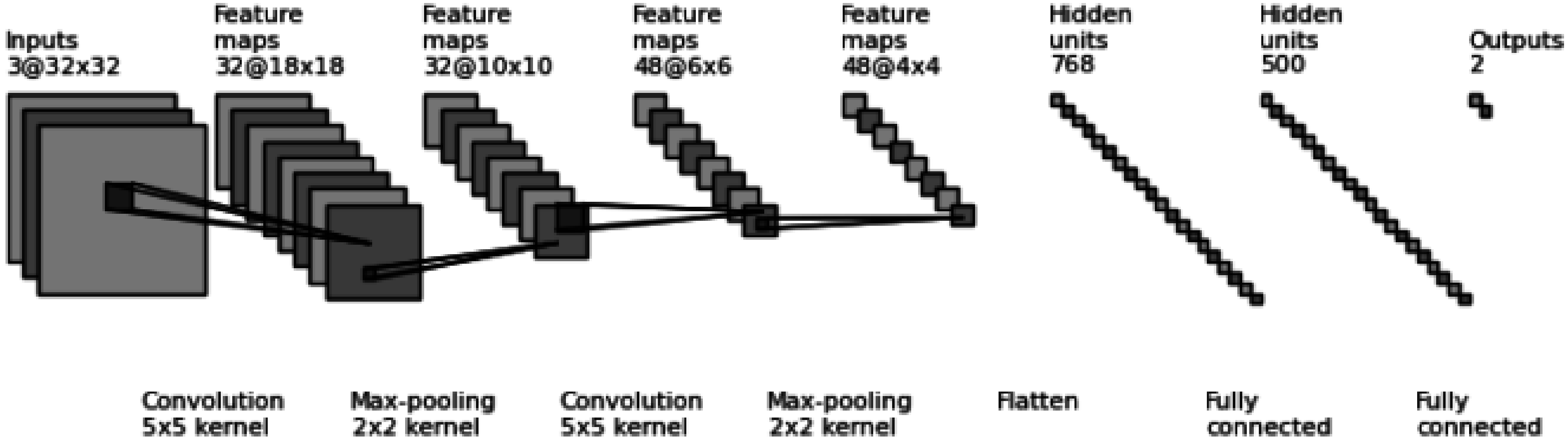
Weight sharing: use the same network parameters to detect local patterns at many locations in the image

Utilizando la estructura de las imágenes

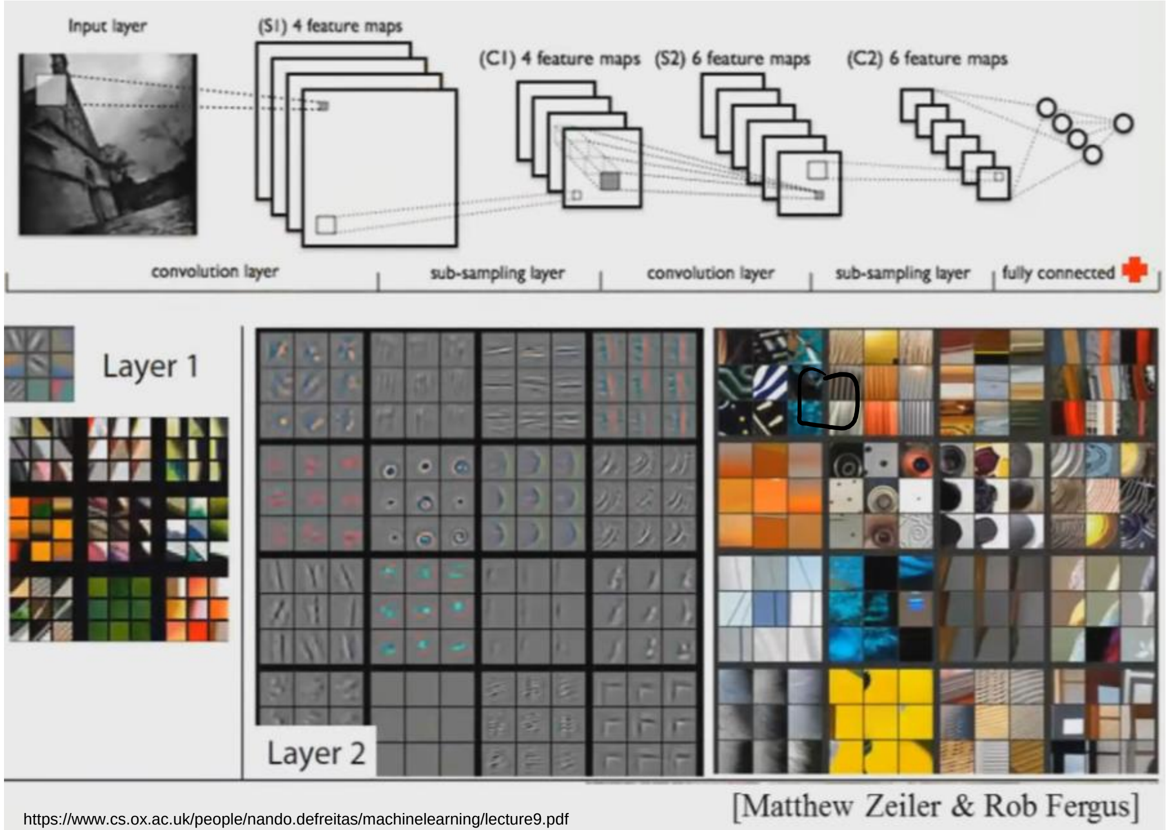


Hierarchy: local low-level features are composed into larger, more abstract features

Estructura de la red convolucional

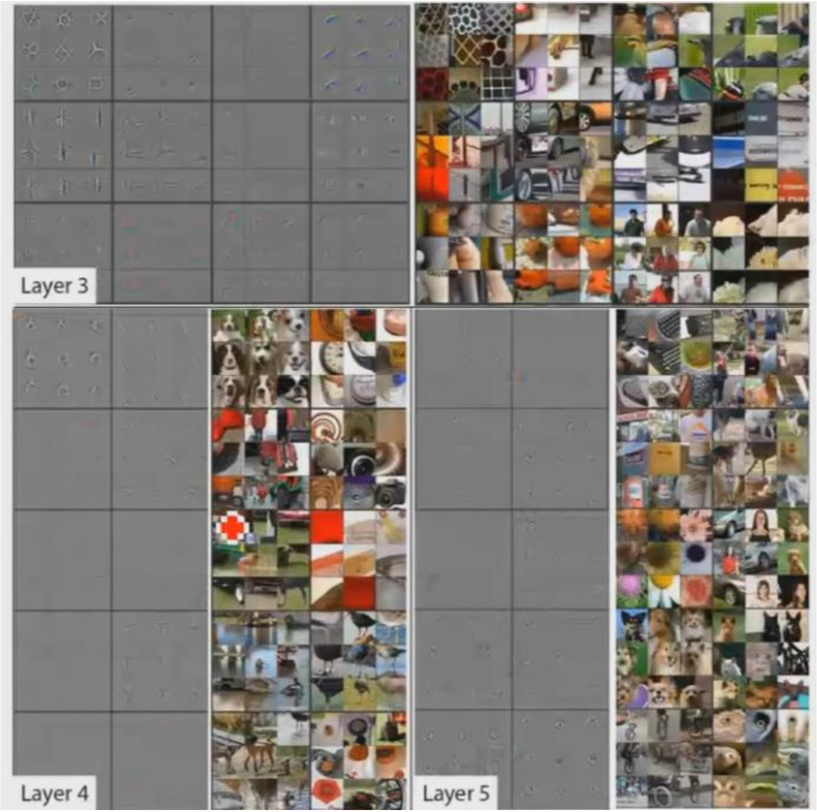


Ejemplos

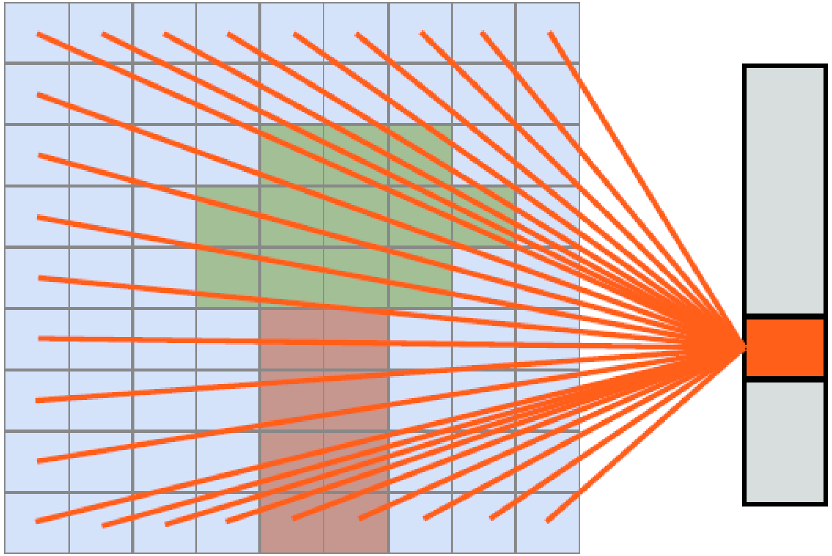


https://www.cs.ox.ac.uk/people/nando.defreitas/machinelearning/lecture9.pdf

Ejemplos



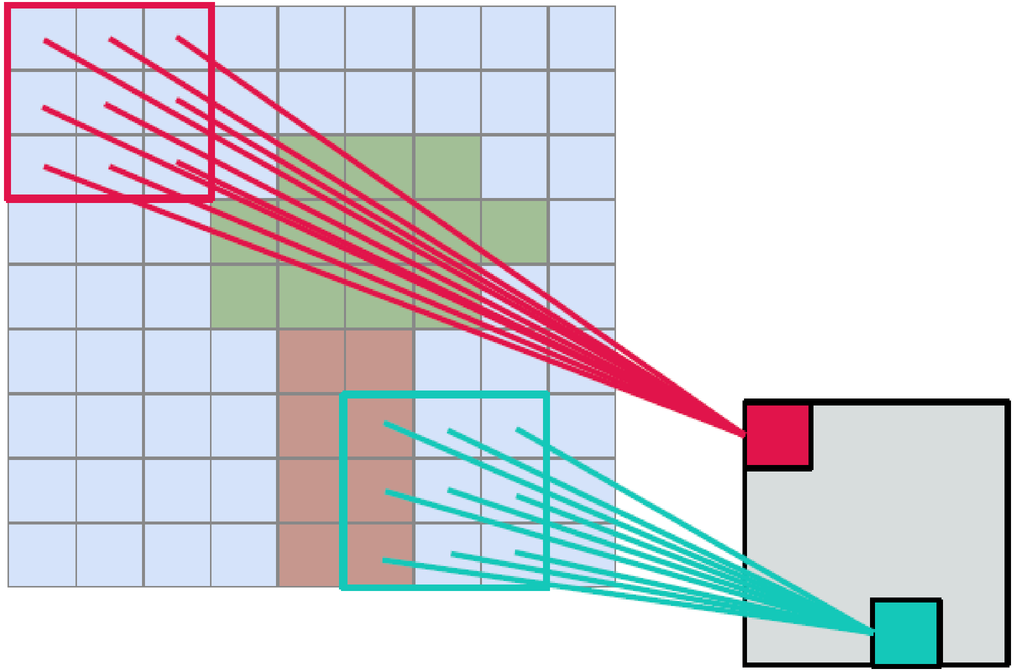
De capas completamente a localmente conectadas a



fully-connected unit

$$y = \sum_{i \in \text{image}} \mathbf{w}_i \mathbf{x}_i + b$$

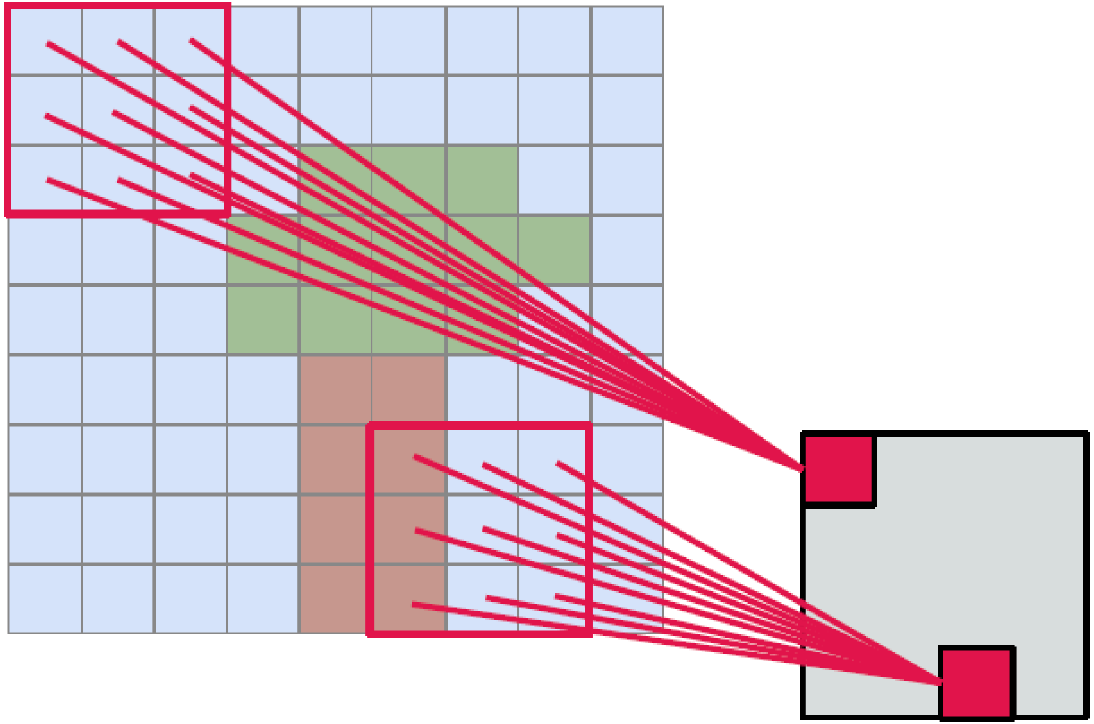
De capas completamente a localmente conectadas a



$$y = \sum_{i \in 3\times 3} \mathbf{w}_i \mathbf{x}_i + b$$

locally-connected units
3×3 receptive field

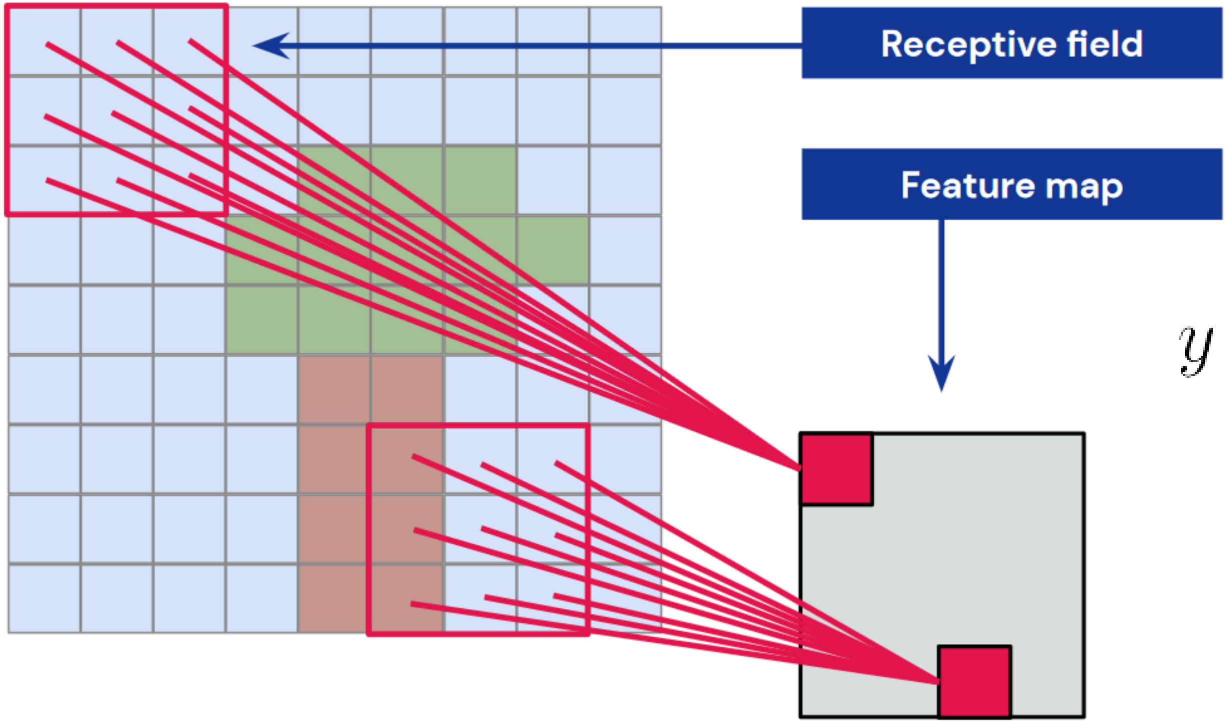
De capas completamente a localmente conectadas a



$$y = \mathbf{w} * \mathbf{x} + b$$

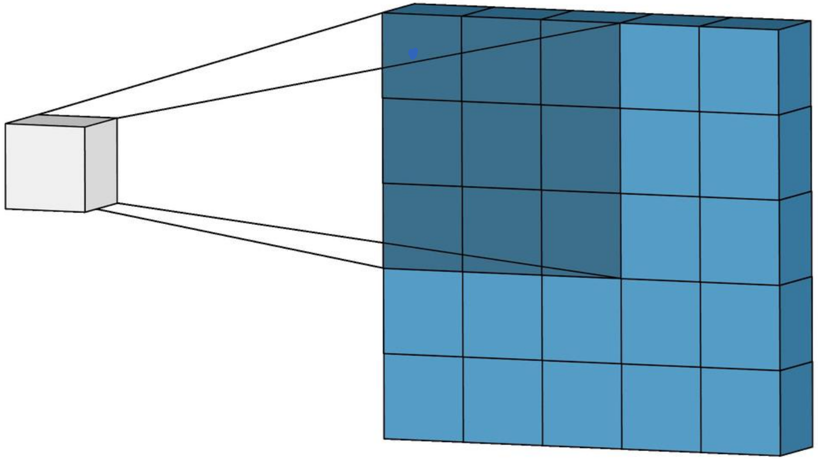
convolutional units
3X3 receptive field

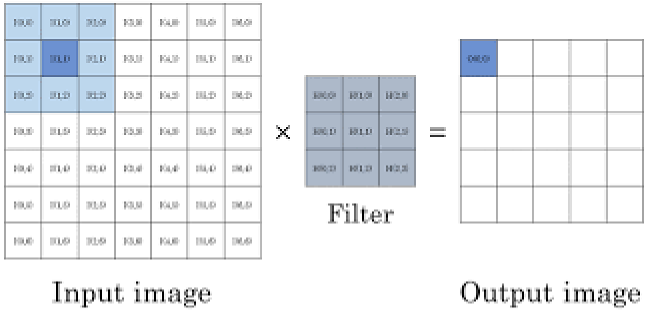
Receptive field



$$y = \mathbf{w} * \mathbf{x} + b$$

Convolución



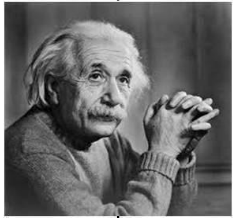


$$y = \mathbf{w} * \mathbf{x} + b$$

$$H_{out} = H_{in} - K + 1$$

$$W_{out} = W_{in} - K + 1$$

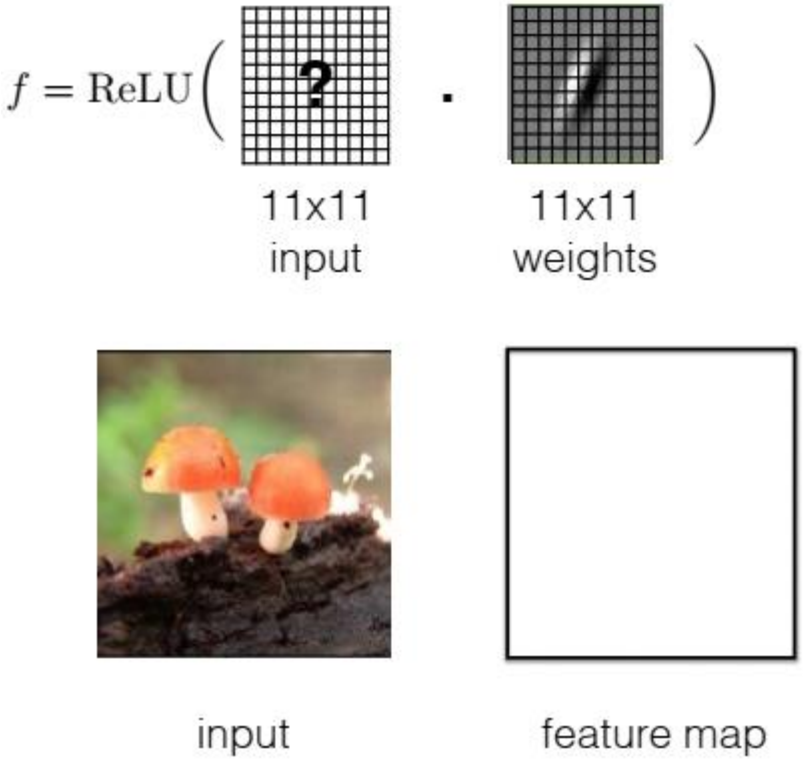
Detección de bordes



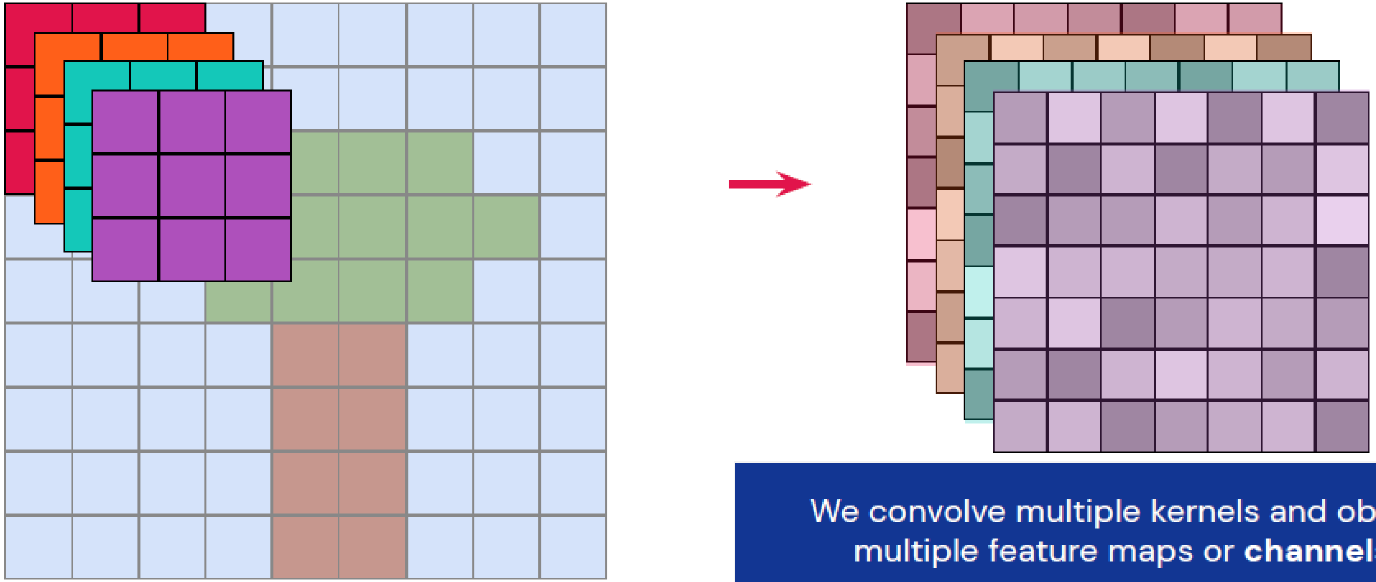
-1	0	+1
-2	0	+2
-1	0	+1

+1	+2	+1
0	0	0
-1	-2	-1

Convolución en CNNs

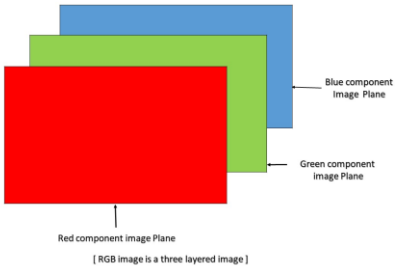


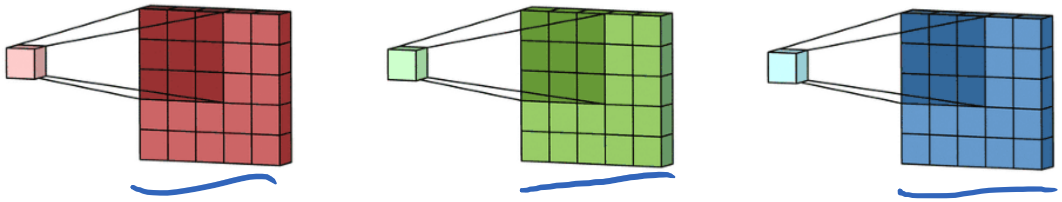
Convolución 2D

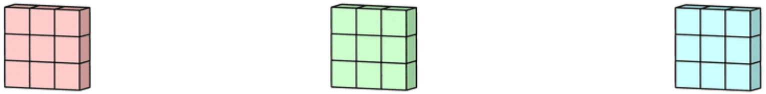


We convolve multiple kernels and obtain multiple feature maps or **channels**

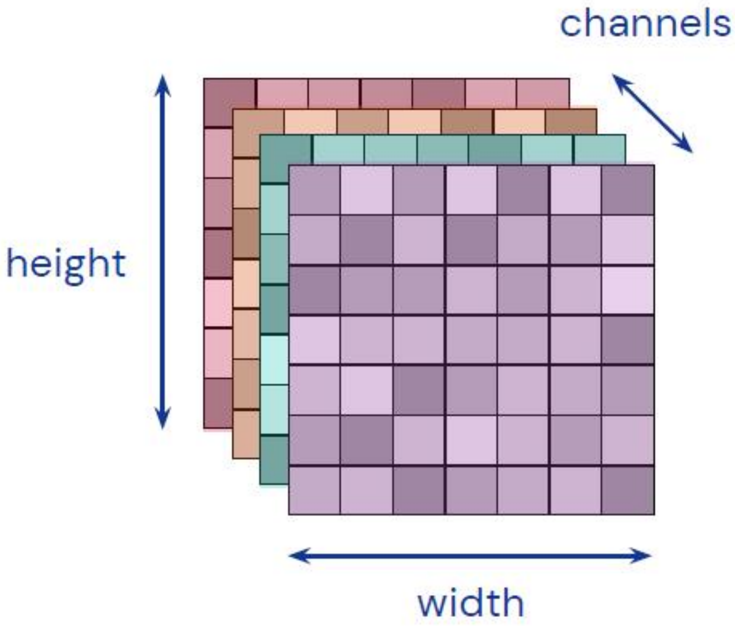
Convolución 2D



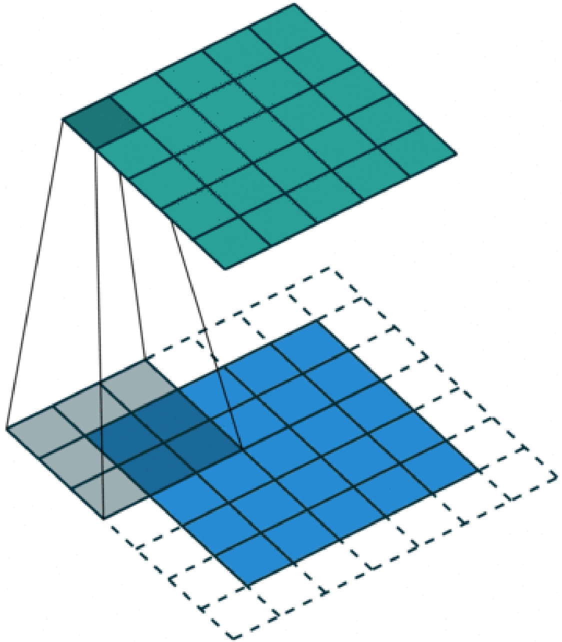


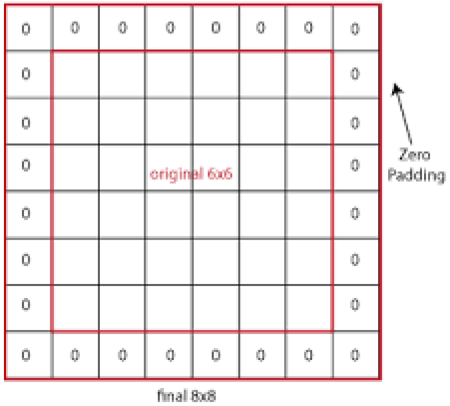


Entradas, salidas y tensores



Padding





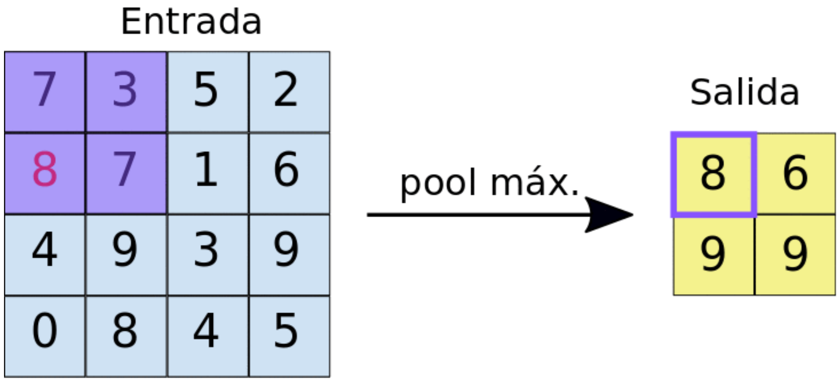
$$W_{out} = W_{in} + 2p - K + 1$$

$$H_{out} = H_{in} + 2p - K + 1$$

https://github.com/vdumoulin/conv_arithmetic

Pooling

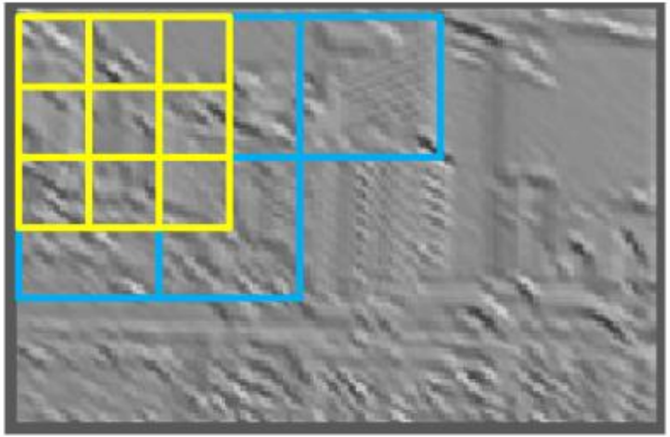
Queremos saber si en un cuadro aparece una característica pero no exáctamente donde



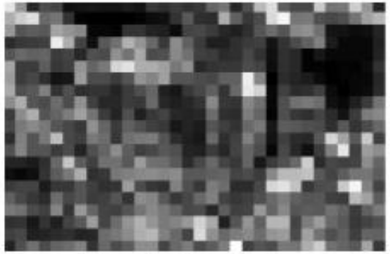
$$H_{out} = H_{in} - K + 1$$

$$W_{out} = W_{in} - K + 1$$

Pooling

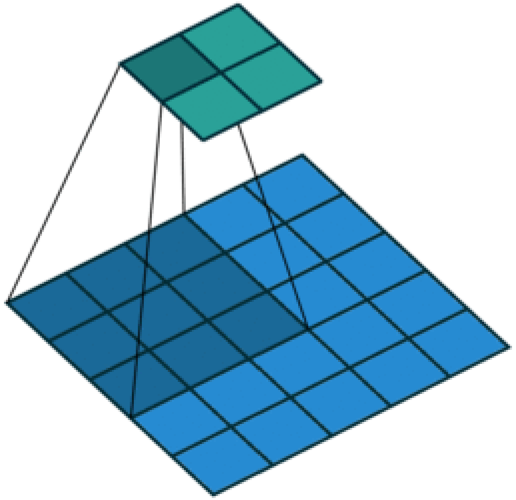


feature map



feature map
after max pooling

Stride



$$H_{out} = \frac{H_{in}+2p-K}{s} + 1$$

$$W_{out} = \frac{W_{in}+2p-K}{s} + 1$$

s: Stride
p: Padding
K: Kernel size
Hin: *Input Heigh* ***Hout:*** Output Heigh
Win: *Input Width* ***Wout:*** Output width

Grafo computacional

fully connected

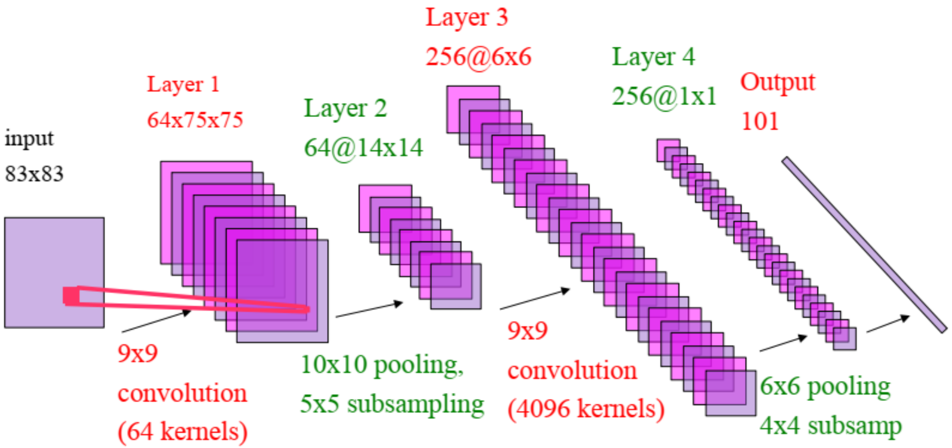
input

convolution

nonlinearity

pooling

Convolutional Neural Network

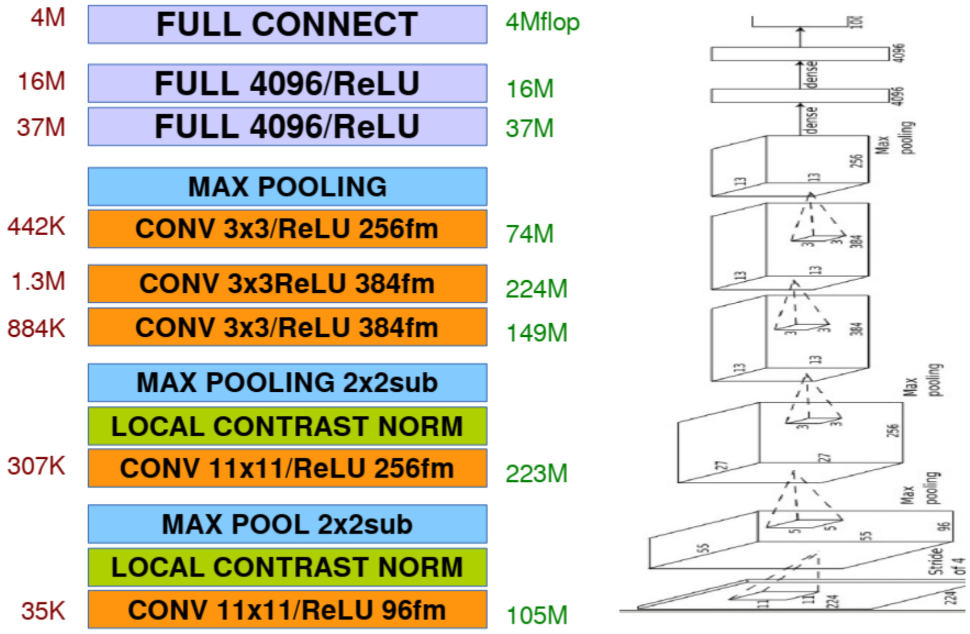


- Non-Linearity: half-wave rectification, shrinkage function, sigmoid
- Pooling: average, L1, L2, max
- Training: Supervised (1988-2006), Unsupervised+Supervised (2006-now)

(LeCun 13')

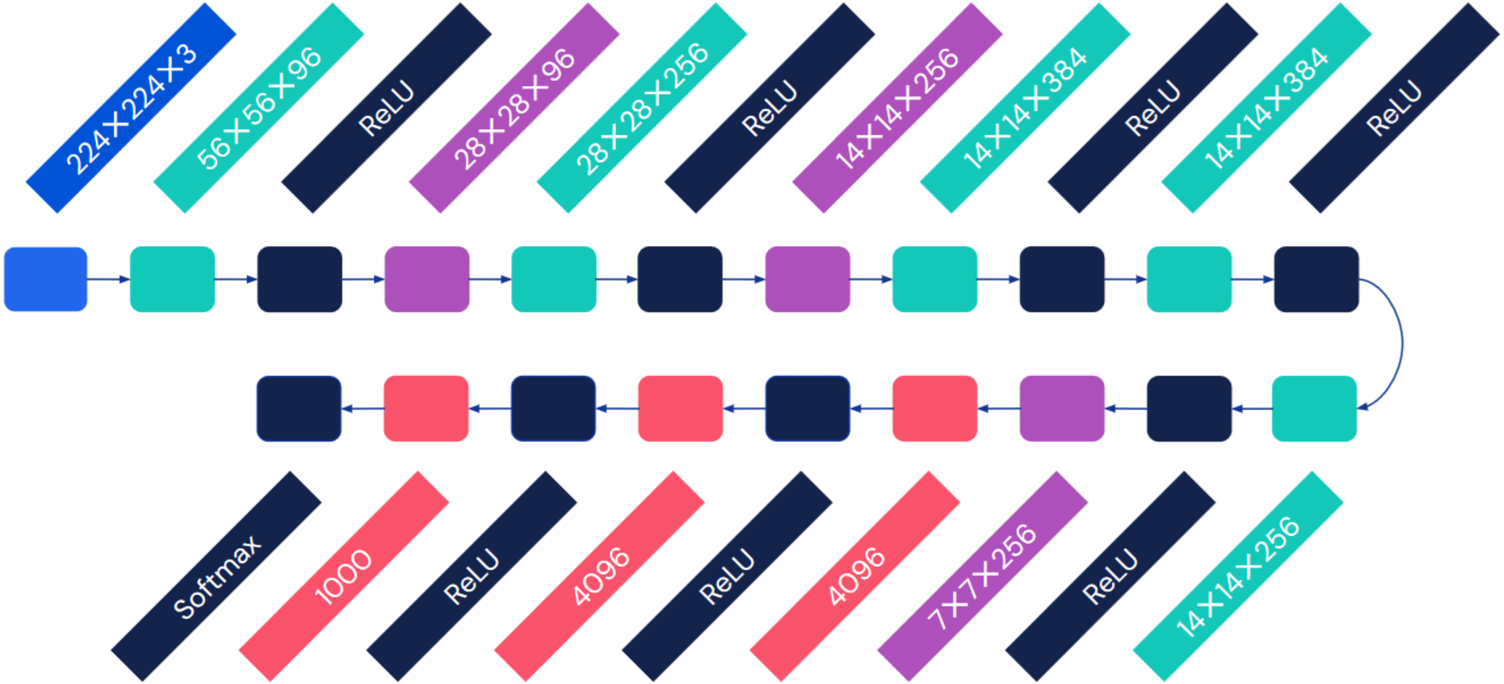
AlexNet

- 1000 categories, 1.5 Million labeled training samples
- Won the 2012 ImageNet LSVRC. 60 Million parameters, 832M MAC ops



(Krizhevsky et al., 12')

AlexNet



224X224X3
56X56X96
ReLU
28X28X96
28X28X256
ReLU
14X14X256
14X14X384
ReLU
14X14X384
ReLU
14X14X256
ReLU
7X7X256
4096
ReLU
4096
ReLU
1000
Softmax

Convolutional Neural Network

96 convolutional filters on the first layer
(filters are of size 11x11x3, applied across
input images of size 224x224x3)

(Krizhevsky et al., 12')

Batch normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \text{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_\mathcal{B} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_\mathcal{B})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_\mathcal{B}}{\sqrt{\sigma_\mathcal{B}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \text{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Figure from Ioffe et al. (2015)

Want to learn more?

Ioffe, S.; Szegedy, C.
Batch normalization: Accelerating deep network training by reducing internal covariate shift International conference on machine learning (2015)

Reduces sensitivity to **initialisation**

Introduces stochasticity and acts as a **regulariser**

Segmentación semántica